A FRAMEWORK FOR THE QUANTITATIVE ASSESSMENT OF NEW DATA STREAMS IN AVALANCHE FORECASTING

by

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TABLE OF CONTENTS

TABLE OF CONTENTS CONTINUED

LIST OF TABLES

Table | Page

LIST OF TABLES CONTINUED

LIST OF FIGURES

LIST OF FIGURES CONTINUED

LIST OF FIGURES CONTINUED

LIST OF FIGURES CONTINUED

Table Page

LIST OF FIGURES CONTINUED

Table Page

LIST OF FIGURES CONTINUED

Table Page

ABSTRACT

Data used by avalanche forecasters are typically collected using weather stations, manual field-based observations (e.g., avalanche events, snow profiles, stability tests, personal observations, public observations, etc.) and weather forecasts (“traditional observations”). Today, snow cover observations can be delivered via remote sensing (e.g., satellite data, UAV, TLS, time-lapse camera etc.). Forecasting operations can also use statistical forecasting, weather models, and physical modeling to support decisions. This paper presents a framework and methodology to quantify the impact these new, complex data streams have on the formulation of, and associated uncertainty of, avalanche forecasting. We use data from a case study in Norway. Avalanche forecasters in Norway assessed size (D), likelihood, avalanche problem, and hazard level for a highway corridor in Grasdalen, Stryn Norway. The control groups were given access to traditional observations. The experimental groups were given access to the same traditional data, but also near-real-time snow surface LiDAR data (“RS+”). In case study one the RS+ (n=10) consensus findings were a hazard level two steps lower than the control group (n=10). In case study two the traditional (n=10) and RS+ groups’ (n=7) consensus findings assessed the northeastern avalanche path at the same hazard level. Assessing the southwestern slide path, the traditional group (n=10) and RS+ group (n=9) had the same consensus finding for hazard level. In 2 of 3 case studies, the RS+ groups had fewer selections for size, likelihood, and avalanche problem which indicates reduced uncertainty in their forecasts. Throughout the 2022-2023 winter season Norwegian Public Roads Administration avalanche forecasters performed a real-time experiment throughout the season – with and without additional RS+ data when forecasting. They agreed on hazard level in 6 of 10 forecasts. In the other 4 forecasts, RS+ forecasters assessed the hazard level higher than traditional data forecasts. When RS+ data reveals aspects of conditions that traditional observations did not detail, RS+ forecasters adjust their selections in the hazard matrix, resulting in greater clustering of their predictions, indicating reduced uncertainty. Due to uncertainty associated with avalanche forecasting, this framework for assessment should be used to track avalanche forecast efficacy and build a qualitative and quantitative historical record.

CHAPTER ONE

INTRODUCTION

Applied Avalanche Forecasting for Public Roads

Snow avalanches pose a hazard to numerous public roadways throughout the world, and avalanche forecasters are tasked with determining the likelihood of avalanche events on a given day (Schaerer, 1989; Stethem, 2003; Hendrikx et al., 2013). Highway avalanche forecasters develop a plan to mitigate avalanche paths and close roads based on the information available to their operation. There are two types of operational avalanche mitigation measures, short-term measures, and long-term measures used to reduce avalanche hazard. Long-term mitigation is a passive, infrastructure focused mitigation process, which includes corridor route planning/avoidance, berms, snowsheds, tunnels, catching basins, etc. (Hendrikx et al., 2020). Short-term avalanche mitigation is an active process informed by an operational framework and the avalanche forecast, and it includes the use of explosives (e.g. hand charges, remote avalanche mitigation systems (RAMS), helicopter charges, explosive trams, etc.) to reduce the avalanche hazard (Hendrikx et al., 2020). For this project, avalanche mitigation refers to short-term avalanche mitigation measures and the complexities of using an operational framework and avalanche forecasting to inform short-term mitigation.

Since closing a road is costly, a proportionate amount of avalanche mitigation is necessary (Schaerer, 1989). Most importantly, highway avalanche forecasters want to avoid a scenario where the road is open, and an avalanche hits the road because that type of exposure to avalanche hazard is involuntary (CAA, 2016). Therefore, highway avalanche forecasters work to reduce their uncertainty about instabilities (McClung, 2002a). McClung (2002b) explains that applied avalanche forecasting comes down to answering: "Given the information, what action should be taken?" Also, he explains, forecasting involves decisions at each of the three stages of forecasting: (1) data collection and integration, (2) analysis, and (3) objective, collective decision/action (McClung, 2002b). McClung (2002b) expands on stage 3 by suggesting forecasters make collective decisions using a formalized process to reduce bias and make consistent decisions. The idea of a formalized process built the Conceptual Model of Avalanche Hazard (CMAH) (Figure 1) — this conceptual model seeks to reduce bias from human perception and reduce uncertainty about the avalanche hazard, which captures McClung (2002b) stages of forecasting (Statham et al., 2018). These papers and conceptual models have provided suggestions for guiding operations, corridor forecasting, ski patrolling, public forecasting, and many other organizations that are required to assess avalanche hazard—these tools aim to reduce errors in human perception. To continue reducing human error this work will explore these concepts through the development of a workflow and methodology to assess what changes when highway avalanche forecasters have access to more data when making critical decisions. The following section will review the literature on expert decision-making across fields where an experts' decisions have an impact on another person's life.

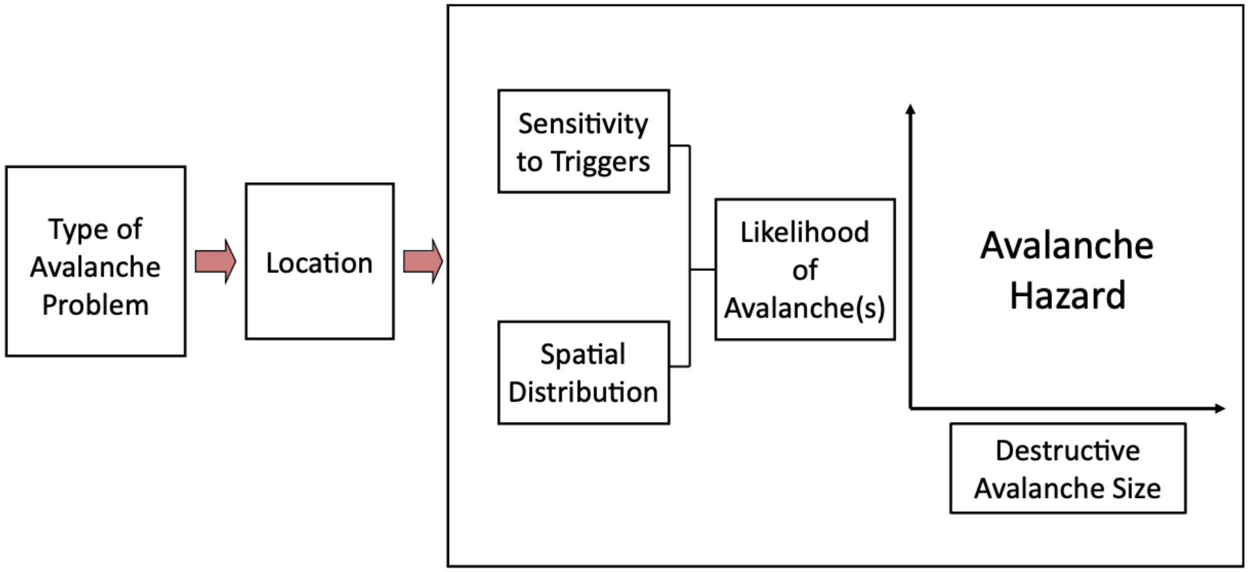


Figure 1. Conceptual Model of Avalanche Hazard used for assessing pertinent observations during hazard assessment process from Statham et al., 2018.

Literature Review

Merriam-Webster defines a decision as “a determination arrived at after consideration” (“Decision,” n.d.). This definition makes it clear that arriving at a decision is a problem-solving process requiring consideration. Decision theory is often split into two categories: normative (optimal decision making) and descriptive (how decisions are made) decision theories (Rapoport, 1994). This area of social science has intersected with research on the behavior of people in avalanche terrain. For instance, there are descriptive studies investigating the causes of avalanche accidents and the decision-making frameworks utilized by backcountry experts (McCammon, 2000, 2002, 2004, 2009; Landrø et al., 2020a, 2020b). For instance, McCammon in his series of papers explored the heuristic traps that seemed to reoccur while reviewing avalanche incidents across North America. Landrø in 2020a and 2020b detailed the tools experts use to make a decision about the avalanche hazard in the field, and he looked at when they disregard that tool and use their experience. Landrø also analyzed which tools experts teach to beginner backcountry users (Landrø et al., 2020a, 2020b). All this work is descriptive, but McCammon's work sought a normative impact. His work identified how decisions resulting in accidents were made experts (McCammon, 2000, 2002, 2004, 2009). However, his work is often miscommunicated in avalanche education (Johnson et al., 2020). Recently, studies have identified the biases of only analyzing avalanche accidents and a closer look at why recreationalists are sometimes inclined to engage in increased risk while in avalanche terrain (Johnson et al., 2020; Mannberg et al., 2020). Despite several studies exploring the decision-making of people in the backcountry, there are few studies exploring the decisions of avalanche forecasters while writing a forecast.

In avalanche forecasting much of the research focuses on risk calculations and decision aids for hazard assessment and planning along hazardous roads and railways (e.g., Schaerer, 1989; Hendrikx & Owens, 2008; Bründl et al., 2009; Statham et al., 2018). The CMAH model does not explicitly discuss the decision theory used to formulate the conceptual model. However, it does identify the benefit of a well-defined framework to reduce bias and increase consistency (Statham et al., 2018). It is apparent that CMAH is rooted in decision theory, but it does not provide the context to understand why a decision aid like this is necessary for more accurate, consistent decisions when experts are faced with uncertainty. A qualitative study examines the challenges faced by 22 public avalanche forecasters in maintaining consistency (Hordowick, 2022). It explores their decision-making process amidst uncertainty, offering insights into the nuance of avalanche problems being added or removed from public forecasts (Hordowick, 2022). Finally, studies are now looking at forecaster consistency with problems and hazard communication (Jamieson et al., 2015; Mitterer, 2023; Walcher, 2023).

The rest of the avalanche related decision-making research is far more normative in its exploration of avoiding human perception errors as a forecaster and reducing uncertainty (McClung, 2002a; Jamieson et al., 2015). McClung's work is not based on a quantitative study of operational avalanche forecasting — the research is from McClung's experience and interactions with the avalanche industry (McClung, 2002a). This study aims to emphasize the findings of descriptive theory research across various fields. It will underscore the importance of gaining a deeper understanding of the decision-making processes of avalanche forecasters. Such insights are crucial for enhancing the development of decision aids and monitoring methods, ensuring avalanche operations adapt effectively as snow science evolves.

Medical Experts and Avalanche Experts

In developing a decision aid for an operational forecasting team there needs to be an understanding of expert systems and knowledge acquisition. Dreyfus and Dreyfus' (2005) research explains that there are five stages to becoming an expert: (1) novice, (2) advanced beginner, (3) competence, (4) proficiency, and (5) expertise, and these stages help people gain experience to strengthen their skill set. Everyone is an expert in something—Dreyfus and Dreyfus (2005) use the example of walking or driving, which is a crude skill, but some people become experts in subtle skills like music or sports. Similarly, operational forecasting is a subtle skill that integrates several pieces of data, developed from a learned experience forecasting along hazardous corridors. Subtle skills are born from smaller margins of error (Dreyfus & Dreyfus, 2005). So, a skill like avalanche forecasting requires subtle discriminations for expertise, because small differences in actions result in large differences in results (Dreyfus & Dreyfus, 2005). They ultimately conclude that experts are not using rules; rather, they are discriminating between thousands of special cases seen during their career, and they cannot always communicate their methods (Dreyfus & Dreyfus, 2005). Interestingly enough, LaChapelle (1980) and Landrø (2020b) found similar behaviors in avalanche forecasters and experts. Dreyfus and Dreyfus (2005), exploring medical surgeons in the real world, explain that rule-based approaches only build competence while expert-based systems preserve expert performance. This research is important for understanding how experts become an expert, and the research also shows experts are not immune to errors. McClung (2002a) also saw that experts are still prone to errors in human perception, and he aimed to reduce it by identifying human biases.

Dreyfus and Dreyfus' (2005) research is directly applicable to operational forecasting because operational forecasters, much like medical experts, are making decisions that directly impact the life of another human being while the forecaster themselves is relatively free from harm. Landrø et al. (2020a) defines avalanche experts as a person spending "[…] a large share of his/her daily work in avalanche prone terrain, performing real-life decision-making on behalf of themselves and in some cases others, and has done this for many winter seasons." Landrø et al. (2020a, 2020b) focused on experts with personal exposure to avalanche terrain. However, both Landrø et al. (2020a, 2020b) and Dreyfus and Dreyfus (2005) report that experts are using experience that is hard for their experts to verbalize when problem solving. Given this similarity, as Dreyfus and Dreyfus (2005) and Landrø et al. (2020a; 2020b) suggest, then an empirical study is needed to identify what operational forecasters are using to make decisions and how they acquired knowledge to become an expert.

Aiding the Experts

Since most experts aren't exclusively using rules to make decisions, it is interesting that human error still exists among experts and decision aids are still taught. Some research suggests that humans using their experiences do not place enough weight on rare events (Hertwig & Erev, 2009; Newell et al., 2016). Additionally, recent personal experience heavily influences risk assessment (Weber, 2006). This recency bias is detailed in McClung 2002a. Moreover, descriptions of risk probability, like a weather forecast or climate change, typically cause humans to overweight and overestimate rare events (Hertwig & Erev, 2009; Weber, 2006). Which is why CMAH acknowledges uncertainty within its definitions of likelihood and the entire framework itself (Statham et al., 2018).

Considering the breadth of problems forecasters must account for, these studies on experience and description outcome probabilities are overly simple. Naturally, experience and description gaps may be more relevant for studying novice recreationists and how they acquire knowledge. Moreover, these issues about descriptions of probabilities are important to public avalanche forecasting. Despite those connections, operational forecasters learn and acquire knowledge through their training and experience as a forecaster, and decisions made by experience and intuition are not always correct and sometimes are overly conservative (Wegwarth et al., 2009).

To solve problems with uncertainty, complicated probabilistic risk, and human perception error, heuristics were introduced to aid the decision-maker. These decision aids are often called "fast and frugal decision trees," which create a framework with decision points to improve (1) accuracy, (2) fast decisions, and (3) good decisions with limited information (frugality)

(Wegwarth et al., 2009). Wegwarth et al. (2009) found that emergency room doctors more accurately admitted cardiac patients to the coronary care unit when using a fast and frugal decision tree as opposed to intuition or the use of a detailed decision aid—the underlying study led Wegwarth to conclude that adaptable heuristics can help doctors reduce variation in their care of patients. Similarly, operational forecasters could use heuristics in situations where they frequently make conservative decisions. Expert weather forecasters report using heuristics when issuing severe weather warnings, and find them necessary when they have incomplete information in a short timeline where extensive deliberation and analysis are not necessary (Stuart et al., 2007). This is relevant because humans can only process so much information at once (Hardman & Macchi, 2004). Luan & Reb (2017) found similar results while researching experts making managerial decisions—expert managers used heuristics or heuristic-like approaches as decisions became more complex. This led them to conclude that identifying information that experts found important for decision-making could help organizations better understand how experts make decisions (Luan & Reb, 2017). Given this literature, some form of heuristics when applied by experts is effective because experts know how to improvise.

The research of heuristics suggests that experts can use them because they know when to use the tool and when to ignore the tool. If the decision aids are adaptable to the standards used by a group of experts, then avalanche forecasters can have useful tools when decisions become more complex. Developing these tools is challenging. First, they require an empirical study of how and when experts exclude information in complex forecasting situations. Furthermore, the avalanche industry would need to agree upon a success rate for avalanche forecasting—a challenge for operations that often have different standards for mitigation.

Collective Intelligence of Experts

In applied avalanche forecasting, McClung (2002a) described 14 common biases that could negatively impact a forecaster. 1. Search for supportive evidence, 2. Inconsistency, 3. Conservatism, 4. Recency, 5. Frequency, 6. Availability, 7. Illusory Correlations, 8. Selective perception, 9. Making a decision based on the 'authority' or 'ego' of a person, 10. Underestimating uncertainty, 11. Optimism, wishful thinking, 12. Anchoring, 13. Use of rules of thumb, 14. Guide-client relationship and peer pressure. Three of these biases (8, 11, and 14) prescribe seeking collective opinions or decisions from other forecasters to encourage objective decision-making (McClung, 2002a). Although collective intelligence is suggested as a resolution to bias in avalanche forecasting in LaChapelle (1980), McClung (2002a, 2002b), and (Jamieson et al., 2015), there is no data to support why or if this resolution will improve a forecast.

Research has found that groups of people are typically better at problem-solving than a single person (Krause et al., 2010; Radcliffe et al., 2019). In a systematic review of collective intelligence in medical decision-making, Krause et al. (2009) explain that some studies have found that radiologists, pathologists, and dermatologists make more accurate assessments when several experts review the data and make a collective decision. Collective intelligence in the medical industry has connections to operational avalanche forecasting because most forecasters build a consensus forecast with a team before choosing mitigation strategies. If collective intelligence has the same impact on avalanche forecasting, it could improve forecasts. Bunting and Groszkruger (2016), collecting best practices for clinicians recommended teams of medical experts should be used to reduce error in diagnosis. Radcliffe et al. (2019) suggest that more research should be done to show there is an improvement in patient outcomes when collective intelligence is used, and the diagnostic process is more accurate. This approach would show that collective intelligence does more for patient outcomes than reducing the chance of clinician error. Similarly in avalanche forecasting, a review of collective forecasting and individual forecasting could show that there is a quantifiable impact on decision-making when a group of experts builds a forecast. However, to determine success there needs to be tools that assess success like the operationalization of the avalanche activity index (Logan & Greene, 2023, Schweizer et al., 2003).

Synthesis of the Literature

Much like the experts in medicine, sports, and music, operational forecasters have used their experience to establish a subtle skill. These subtle skills provide them with some autonomy in navigating complex problems, but operational forecasters, like most professionals, aim to minimize human error in their decision-making. LaChapelle (1980), McClung (2002a, 2002b), Jamieson et al. (2010, 2015), and Statham et al. (2018) provide ideas that inform the industry on how avalanche forecasters should anticipate and resolve errors that reduce uncertainty and produce a forecast that answers the key questions avalanche forecasters need to ask. These pieces of forecasting guidance give forecasters a place to start—especially when data and evidence become more complex.

The literature makes three suggestions that have optimized performance in parallel industries. One, experience-based experts are needed because they can efficiently move through complex problems, but their experiences are still subject to errors in human perception. Two, experts who use decision aids can be more effective because they have a wealth of knowledge that allows them to determine when to use the tools or improvise. Three, teams of experts will make more accurate decisions and reduce error when compared to one expert.

Assessing decisions made under uncertainty is not easy because uncertainty inherently suggests that the outcome is unknown to the decision-maker. Therefore, best practice recommendations will establish a standard to measure all forecasting operations. Like surveys of medical experts, an empirical review of how experts are making decisions and using heuristics will help formulate a comprehensive framework that will be widely accepted by experts in the industry. Moreover, the wealth of research in medical decision-making will be more comparable if the behavior of operational forecasters is quantified like many medical decision-making works.

LaChapelle (1980) and McClung (2002a, 2002b) discuss the elements of avalanche forecasting and its intersection with human perception. Uncertainty is a principal issue in avalanche forecasting because of variability and human perceptions of variability (McClung 2002a; 2002b). In avalanche forecasting this is important because on any given day an observations relevance is changing. To work through this uncertainty data can be classified by its entropy: (1) snowfall and weather factors have the most informational entropy (class I), (2) snowpack factors (e.g., grain type, stratigraphy, temperature profile, etc.) are neutral (class II), and (3) direct information about stability like observed avalanches have the least informational entropy (class III) (McClung, 2002b). In reducing uncertainty, forecasters prefer low entropy data (e.g., evidence of avalanches). Moreover, certain observations are more meaningful for certain avalanche problems (Jamieson et al., 2010).

All these studies have built a wealth of normative decision theory and risk reduction in applied avalanche forecasting. Moving forward, like meteorological forecasting and modern medicine, new data streams will emerge in forecasting, and if the industry has a metric to assess a forecasting operation the impact of new data can be measured. Despite advances in data collection and data types, the addition of new, complex data creates a greater cognitive load on the decision makers. This is true even when the information is reliable and relevant (Darioshi & Lahav, 2021). Moreover, the ease of use, defaults, automation, and emotion can manipulate a user and drive the user to make less rational decisions (Darioshi & Lahav, 2021).

Studies on new, complex data in avalanche forecasting have explored the calibration and validation of technology that provides information about stratigraphy, snowfall, and avalanches (e.g., Donahue & Hammonds, 2022; Sanderson et al., 2022; Morin et al., 2020; McCormack & Vaa 2019; Peitzsch et al., 2018; Schmid et al., 2016; Hendrikx et al., 2013; Matzl & Schneebeli, 2006). Few studies explore the integration of new data into a forecaster's workflow, and the data's impact on forecaster uncertainty and forecast quality.

Research Question

This study aims to find the changes avalanche forecasters make to the hazard ratings of their avalanche forecast, when they have more complex data sets available. The hazard ratings represent the final product of an avalanche forecast, determined after assessing the size, likelihood, and specific avalanche problems for the forecast period. Our goal is to present a case-study that illustrates a methodology to assess the impact of adding new data streams into the avalanche forecasting process. The objective of this study is to answer if data entropy from remotely sensed data result in a statistically significant change in forecasting: (1) avalanche size, (2) likelihood(s), (3) avalanche problem type, and (4) avalanche hazard level? Data entropy is central to this question because it defines the level of uncertainty associated with data; therefore, increased data entropy increases the uncertainty in the avalanche forecast (McClung, 2002b).

To answer this question avalanche forecasters for public corridors were interviewed to develop a framework to assess the effectiveness and impact of new data streams when added to an avalanche forecasting operation that already has a robust system for forecasting their corridors. A series of scenarios were then used to assess if any change occurred when avalanche forecasters were given different types of data. To measure what changes and by how much those elements changed, this study looked at the four elements of the Norwegian Public Roads Administration's avalanche forecast, (1) avalanche size on the destructive potential scale ("D"), (2) likelihood of avalanches as a probability, (3) avalanche problem type, and (4) avalanche hazard level on a scale of 1 to 4. Additionally, this study used those same measurements for actual forecasts written during the 2022 – 2023 avalanche forecasting season for 10 different days. This project is part of a larger project, Geohazard Survey from Air – remote decision support with focus on avalanche applications (GEOSFAIR). (https://www.vegvesen.no/fag/fokusomrader/forskning-innovasjon-og-utvikling/pagaende-programmer-og-prosjekter/geosfair/). For the scenarios this project used avalanche forecasters from the Norwegian Public Roads Administration (NPRA), Norwegian Geotechnical Institute (NGI), Norwegian Water Resources and Energy Directorate (NVE), municipal forecasters, and professional observers. It is anticipated that this work will clearly demonstrate how avalanche size on the D scale, likelihood, problem type, and ultimately hazard level change when new data streams are introduced, and what impact that additional data has on forecaster uncertainty.

CHAPTER TWO

METHODS

The proposed draft framework was initially based on relevant literature (as presented in Chapter 1), and the experience of my practitioner and scientific partners. Additionally, I interviewed public corridor forecasters outside of the project for feedback. The following section provides details on this process, and the final framework used for shaping our case studies.

Development of a Framework

We developed a framework to assess avalanche mitigation decisions made by operational forecasters (Figure 2). The framework was developed to increase consistency, which aids us in reliably assessing decision-making across operations. However, we did not want to change the way an operation builds a forecast because it would not accurately capture the decision-making process. Therefore, I conducted 3 semi-structured interviews with corridor forecasters to ensure that the framework was realistic. The interviews are listed in Appendix A. I spoke with John Stimberis, a supervisor and avalanche forecaster for Interstate 90 in Washington state. I also spoke with Matt McKee, the Avalanche Program Manager and sole avalanche forecaster for the Alaskan Railroad. I also spoke with Jim Kennedy, the Avalanche Program Director for the Alaska Department of Transportation, and Tim Glassett, the Avalanche and Artillery Program Manager at the Alaska Department of Transportation. These interviews have specifically informed the framework shown in Figure 2.

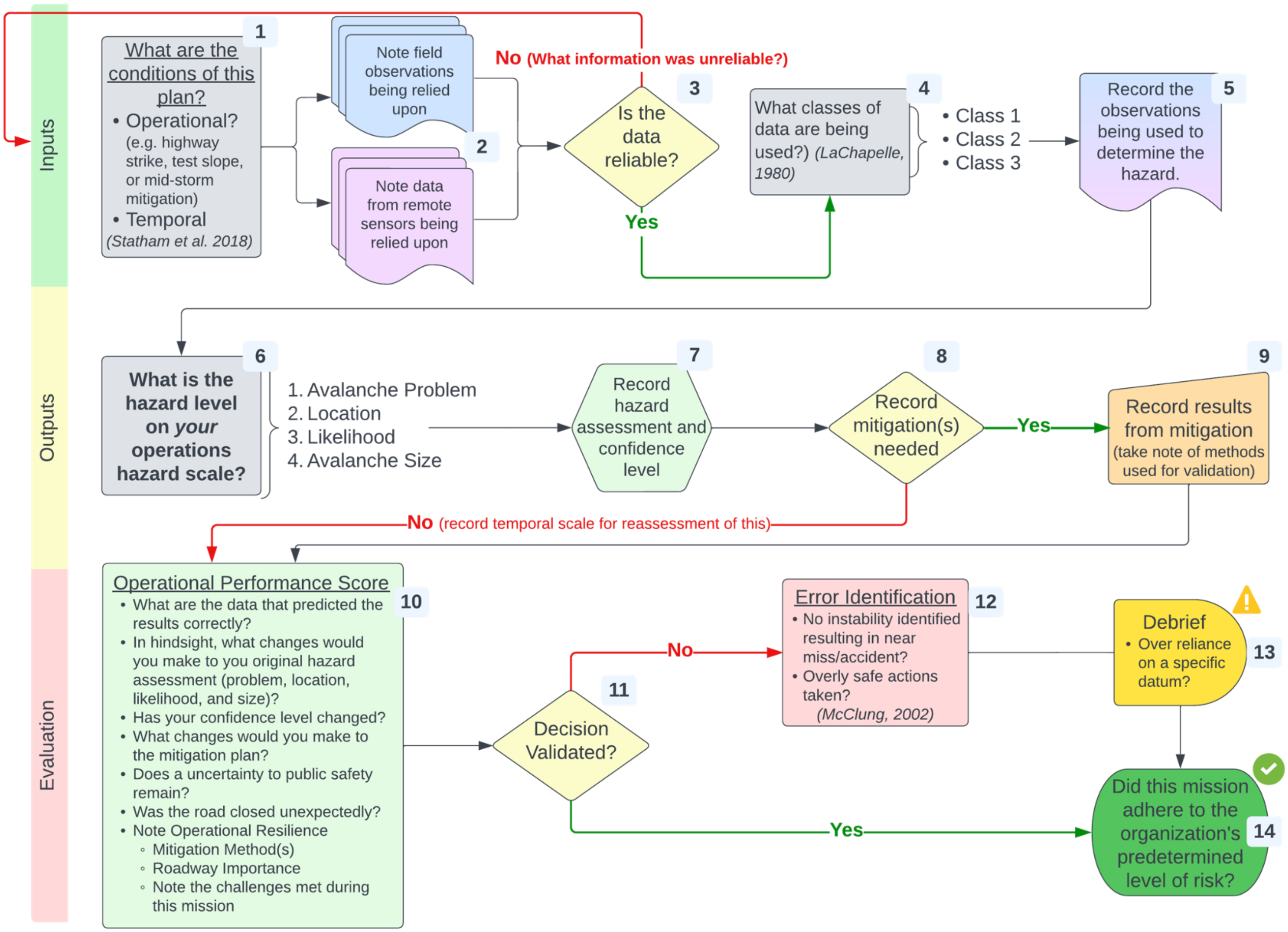


Figure 2. The framework and experimental design developed that shows the steps of the avalanche forecasting process for operations with mitigation.

Figure 2 splits avalanche forecasting into three different processes, represented by the three rows, (i) inputs, (ii) outputs, and (iii) evaluation, and within these processes each step is numbered (1 to 14). Stages i and ii expands upon McClung 2002b's three stages of avalanche forecasting, and stage iii adds steps to formalize and encourage debriefing, an often-informal step in avalanche forecasting (Appendix A, Figure A2). The input stage (row i) is where avalanche forecasters begin to develop a plan. The interviews with forecasters showed that this process is somewhat standardized based on collective operational experience gathering observations in these slide paths. In step 1 an operation recognizes and defines the operational scale and the temporal scale for the forecast (Statham et al., 2018). Doing so establishes the standards by which an operation uses to measure successful outcomes later in the decision framework. At step 2 the forecasters receive and/or collect observations from their varying data streams as they normally would for their operation. At step 3 the forecaster reaches a decision point where they must determine the reliability of the data. For field observations in the United States of America this looks like using the methods in the most current version of the Snow Weather and Avalanche Guidelines (SWAG) (AAA, 2022). For observation types produced with the aid of computer modeling and instrumentation there is no industry specific guidance in a professional document like the SWAG. In fact, the interviews of avalanche forecasters made it clear that in practice the use of more advanced data streams in corridor forecasting is few and far between in those locations. If the data is determined to be reliable, step 4 shows the process of breaking this data down into the three classes of data based on its uncertainty. Here, forecasters are seeking the data with the highest level of certainty that is relevant to the avalanche problem

(LaChappelle, 1980; Jamieson et al., 2010). Step 5 was created so forecasters remember to record which observations were the most relevant for a given day.

After assessing and organizing the data, the forecaster needs to build a plan and act (row ii). In the outputs lane step 6 starts to build on CMAH—here, a forecaster needs to convert the observations into a standardized language about avalanche size, location, likelihood, and problem to arrive at an appropriate hazard level, which is step 7. At this step the forecaster should note their confidence level in the forecast because it informs an assessor about the forecaster's agreement with the data (Mastrandrea et al., 2010). This is something the Colorado Avalanche Information Center (CAIC) has started to use when assessing their avalanche forecasts (Logan & Greene, 2023). Step 8 uses the hazard level assessment to inform the need for mitigation, which can include closing roads, using explosives, metering traffic, or other measures typically used by the operation. After Step 8, if no mitigation is needed there is an option to define a scale to reassess that decision before starting over with a new forecast. Step 9 can be skipped if no mitigation is needed; otherwise, recording the results from mitigation using the operation's standard format is required when mitigation is used. The interviewees made it clear that recording results from explosives is a standard procedure at their operations. Additionally, recording mitigation is valuable for validating a forecast, which Techel and Schweizer (2017) used when verifying regional avalanche forecasts.

After a forecast is produced, it is wise to assess and debrief the forecast—the evaluation lane provides talking points for operations (row iii). During the interviews, operations found this step challenging and said it often took place in a more casual context like informal conversations. Step 10 is a way to facilitate helpful conversations about adjusting a forecast or taking note of something missed. After debriefing the forecast, step 11 asks the operation to validate their decision (e.g. was the operation correct in not closing the road this morning?). Sometimes the feedback at step 11 can be obvious like an avalanche accident, and sometimes the feedback has its own uncertainty because the lack of an avalanche does not mean the operation was correct. Some operations are looking at taking a more objective approach to assessing and validating the avalanche forecast. The CAIC backcountry avalanche forecasters assess forecasts using a hindcast produced by an independent forecaster (assessor) (Logan & Greene, 2023). The CAIC provides an assessor with critical information and the actual weather that occurred that day, as opposed to the original weather forecast (Logan & Greene, 2023). The assessor writes the correct forecast, and the forecasts and confidence level can be reviewed by the operation (Logan & Greene, 2023). This method is far more objective than casual conversations, but it is time consuming, and it is not something the CAIC does in the middle of the season. Therefore, operations without access to weather models with these capabilities can use more qualitative talking points in step 10 to answer the question in step 11. Additionally, at this step, operations using explosives for avalanche hazard mitigation have an opportunity to validate their forecasts (Techel & Schweizer, 2017). However, the uncertainty from observations adds to the uncertainty of mitigation results — the well documented incidents of post-mitigation release of avalanches make it clear that results from mitigation are not a perfect assessment tool (Baugher et al., 2023).

Step 12 and 13 can be skipped if the decision was validated. If the decision was not validated step 12 reviews McClung 2002b Operational Risk Band, which suggests operations should fall between taking too much risk and not taking enough risk, sometimes defined as a margin of safety (Jamieson et al., 2015). Step 12 asks the operation to look critically at why they took too much or too little risk, and step 13 asks them to see if that problem started at the observational stage. Finally, step 14 looks at making sure operations performed within the bounds that they believe is appropriate for their operation.

Study Area

The study area where we applied our framework was in Western Norway, Highway 15 on its way from Stryn to Grotli passes through the avalanche paths of Sætreskarsfjellet Mountain at 1,606 meters above sea level (61.99105°N, 7.28282°E). A large path on the NE face of Sætreskarsfjellet has 640 meters of vertical run, and avalanches can easily reach the road (Figure 3). There is a 200-meter snow gallery and a line of breaking mounds, which do not completely protect the road from larger avalanches. Mitigation with explosives is an option with buried charges in the start zone of the NE facing path. The start zone of the smaller southerly facing path is much lower than the northerly slide path. The southerly facing slide is far smaller, but even a small avalanche is more likely to hit the road. Additionally, its proximity to a tunnel entrance and exit makes debris on the road very hazardous for motorists.

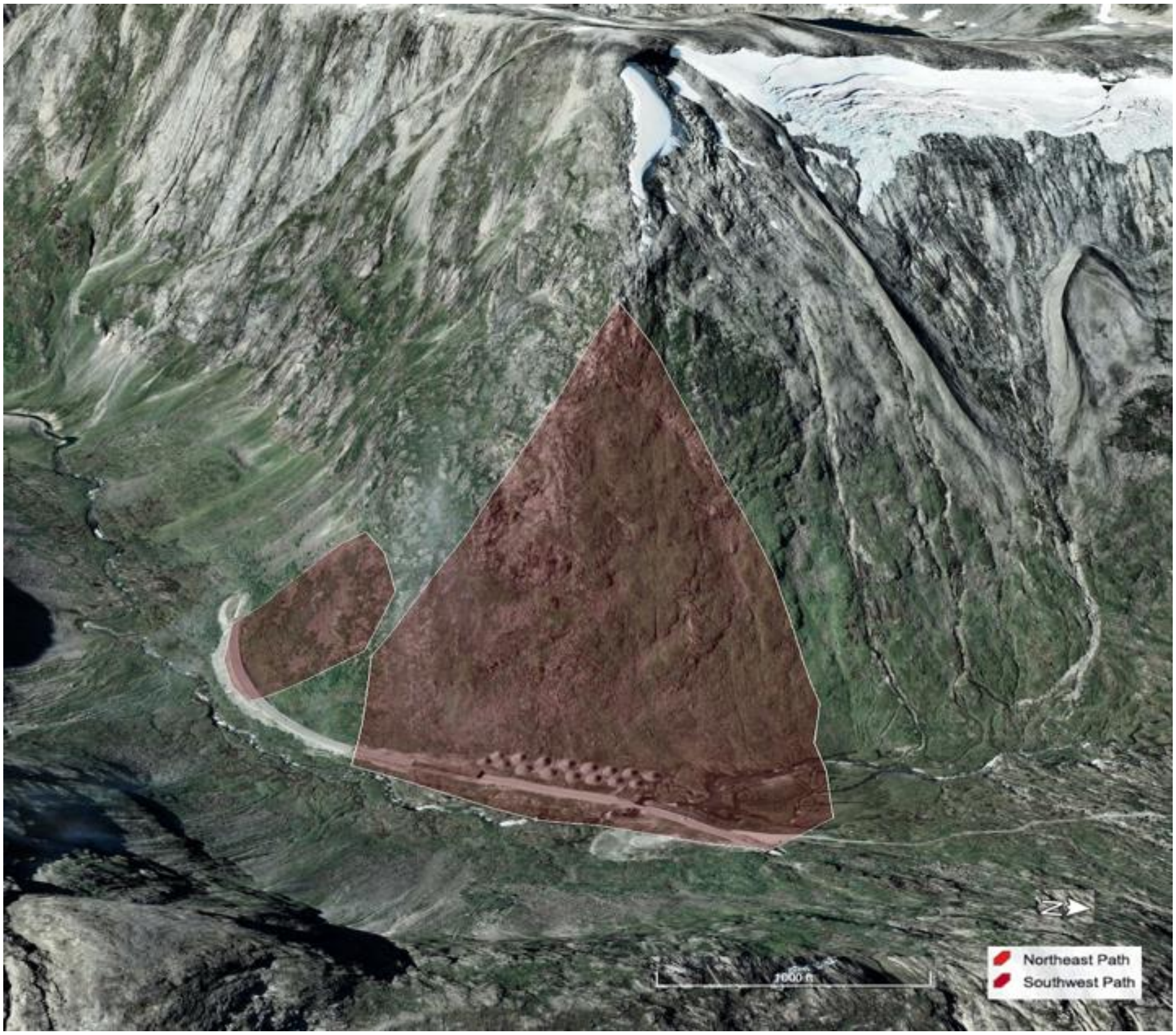


Figure 3. NE and SW slide path of Sætreskarsfjellet Mountain above highway 15 used in this study.

Development of Case Studies

Observations collected during the forecasting season of 2022-2023 were used to develop two case studies. Each case study had two versions: one with traditional observations (i.e., weather forecasts, weather station data, public snowpack observations, web camera images, and snow profiles) and a second version with all of the same traditional observation and remote sensing observations (RS+). The RS+ included (1) Unmanned Aerial Vehicle (UAV) derived slope scale digital elevation models of the snow surface in the start zones; (2) slope scale snow erosion and deposition since the last LiDAR scan, and; (3) the traditional observations. Participants in our survey received a case study with traditional observations and a case study with RS+. Therefore, all the participants had one case study as the control group using traditional observations, and one case study as the experimental group with the RS+. Note that these two inputs are shown in Figure 2, in the "Inputs" lane, in step 2. Survey participants (n=20) were a combination of highway avalanche forecasters, public forecasters, and professional observers based in Norway that had prior experience writing internal or public forecasts. All the survey participants have seen this avalanche path in person, and they were familiar with its characteristics.

Two forecasters at the Norwegian Public Roads Administration (NPRA) provided input about the types of information available to the case study participants based on the resources highway forecasters typically use to write a forecast. Next, those data and observations were compiled and sent to each of the participants.

Participants were randomly assigned to one version of the case study. Next, the participants were instructed to look through the information and fill out the same hazard rating matrix used by NPRA forecasters (Figure 4). The Hazard Rating Matrix allows the participants to select the destructive (D) avalanche size (D1-D5), likelihood (unlikely – very likely), avalanche problem type (new snow, wind slab, persistent weak layer, wet snow, and glide). These selections ultimately determine the hazard level scale shown in Figure 5. Participants can record multiple sizes, likelihoods, and avalanche problems in the matrix. Each participant also wrote a brief description of the data they relied upon to write their forecast. No time limit was given to complete the matrix and short written statement.

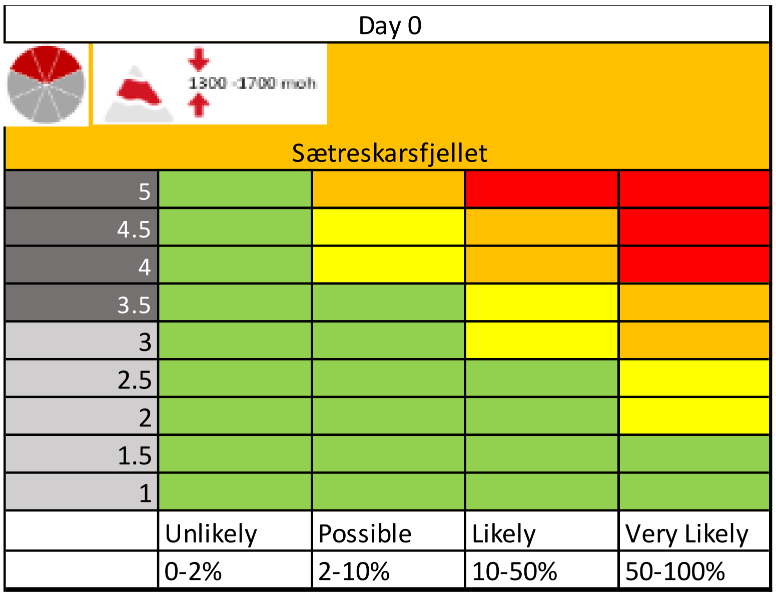


Figure 4: Norwegian Public Roads Administration Hazard Matrix used by participants to record their assessment of avalanche size, likelihood, problem, and road hazard level (translated to English).

Hazard Level		**Recommended Caution**
	Green	Normal Attention
	Yellow	Increased Awareness
	Orange	Some Restrictions
	Red	Extensive Restrictions

Figure 5: Norwegian Public Roads Administration Avalanche Hazard Level scale (Humstad, 2016).

Case Study One Description

Case study one, was based on a storm that started on February 20, 2023, and continued through the morning of February 21, 2023. The aim was for participants to provide a road forecast in accordance with the NPRA matrix and provide a hazard level for the next 24 hours, which would expire on February 22, 2023, at 12:00 PM. This format was used to closely follow the forecasting schedule of the NPRA.

The participants using traditional data received remote weather station data at 1,300 meters above sea level. This station included hourly data of windspeed and direction, and air temperature for the last 24 hours (12:00 PM February 20, 2023, to 12:00 PM February 21, 2023). Additionally, they were given 24 hours of remote weather station data from 600 meters above sea level that included windspeed and direction, air temperature, and snow and snow water equivalent (SWE) data. For this case study, new precipitation at 600m was 10 cm overnight. They were also provided with three static webcam photos of the road and avalanche path. The photos showed that the webcam lens was iced over at 2:07 PM on February 20, it was snowing at 1:11 AM on February 21, and there were clearing skies at 7:49 AM on February 21. They were provided with the previous days avalanche forecast, and a weather forecast for the next 24 hours that showed another 20-30 cm of snow possible. Next, they were provided with the public avalanche forecast, two field observations from NPRA employees. The NPRA observations, which were a link to real observations on Norway's avalanche observation website Varsom Regobs (Observation 1, Observation 2). Observation 1 explained that there was a crust found while touring in the area on February 16, 2023. Observation 2 called attention to a natural size D3 avalanche releasing prior to mitigation on the morning of February 21, 2023. Additionally, the participants received a report about road conditions, and a report from a NPRA employee that mitigation at 11:00 AM released a size D3 avalanche with a vertical run of 450 meters.

The participants that had access to the remotely sensed data (i.e., RS+) received the same traditional data as described, and they received four additional images from the LiDAR scan post mitigation on February 21, 2023. Three images of the slope scale snow surface digital elevation models showed the results of the mitigation. In addition, they were also provided an image of the slope scale erosion and deposition since the last scan on February 20, 2023 (Figure 6).

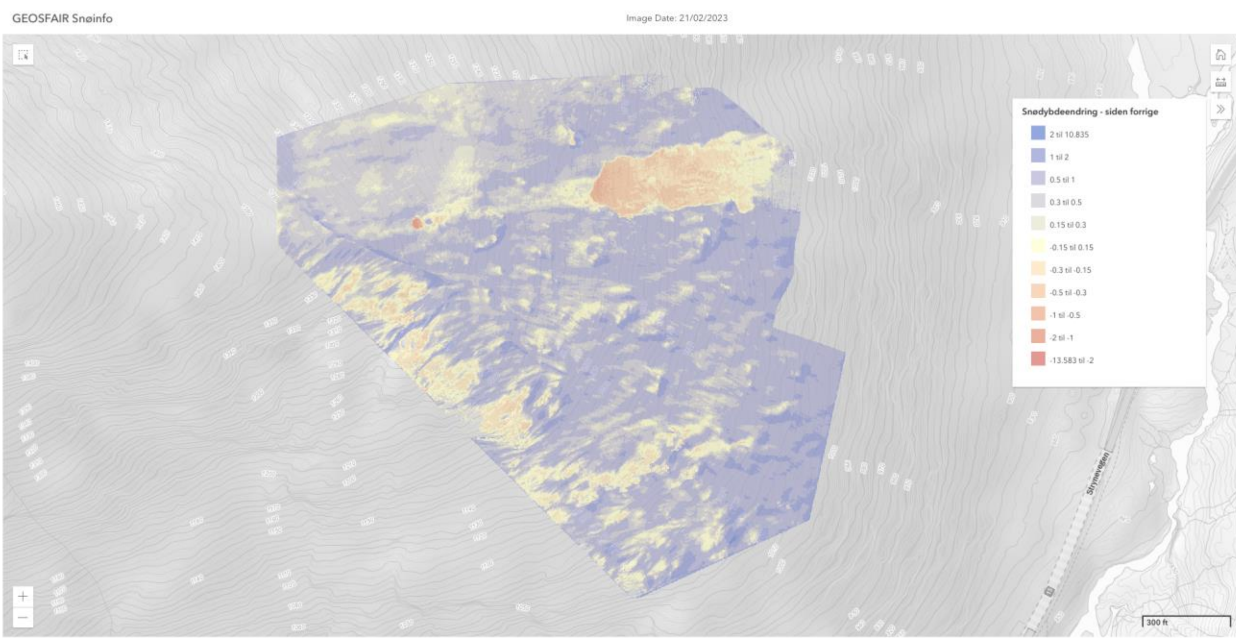


Figure 6. Slope scale erosion deposition showing mitigation displaced 0.5 – 1 meter of snow, and there were 1-2 meters of new snow from the storm overnight. Blue indicates deposition, and yellow/red indicates wind erosion or removal of snow from mitigation.

Case Study Two Description

Case Study Two was based on a wind event that started in the late afternoon on February 21, 2023, and continued through the morning of February 22, 2023. Just as in Case Study One, participants provided a road forecast in accordance with the NPRA matrix and a hazard level for the next 24 hours, which would expire on February 23, 2023, at 12:00 PM. In Case Study Two the participants were asked to fill out a separate hazard matrix for the large NE slide path and the smaller SW slide path. These separate forecasts are designated as Case Study Two: NE and Case Study Two SW throughout this paper.

The participants using traditional data received remote weather station data at 1,300 meters above sea level. This station included hourly data of windspeed and direction, and air temperature for the last 24 hours (12:00 PM February 21, 2023, to 12:00 PM February 22, 2023). Additionally, they were given 24 hours of remote weather station data from 600 meters above sea level that included windspeed and direction, air temperature, and snow and snow water equivalent (SWE) data. For this case study, there was a trace of new precipitation at 600m overnight. They were also provided with three static webcam photos of the road and avalanche path. The photos showed that it was sunny with a wind affected snow surface on the large northeastern slide path at 1:02 PM on February 21, it was windy and sunny at the road level at 2:32 PM on February 21, and it was windy and foggy at 11:56 AM on February 22. They were provided with the previous days avalanche forecast, and a weather forecast for the next 24 hours that showed less than 5 cm of snow possible. Next, they were provided with the public avalanche forecast, two field observations from NPRA employees. The NPRA observations, which were a link to real observations on Norway's avalanche observation website Varsom Regobs (Observation 1, Observation 2). Observation 1 explained that there was an avalanche released during mitigation on February 21, 2023. Observation 2 explained that there was a crust found while touring in the area on February 16, 2023.

The participants that had access to the remotely sensed data (i.e., RS+) received the same traditional data as described, and they received five additional images from the LiDAR on February 22, 2023. Two images of the slope scale snow surface digital elevation models showed a wind affected snow surface on the northeastern slide path. A slope scale erosion and deposition image since the last scan on February 21, 2023, of this same slide path showed over two meters of snow erosion. They were provided with a slope scale digital elevation model image of the smaller southwest facing slide path, which showed a small avalanche and a debris pile. The slope scale erosion and deposition map since the last scan on February 21, 2023, showed varied erosion and deposition throughout the path.

Development of Real-Time Forecast Comparison

Throughout the 2022-2023 season highway forecasters with the NPRA that forecast for highway 15 performed real-time forecasts throughout the season – with and without RS data. One forecaster would forecast for the day like they normally would using traditional observations, and on a day where there was data from a UAV a second forecaster would write a forecast using traditional observations and UAV data—the RS+ data set. Looking back at Figure 2, this process would take the forecasters all the way to step 8. In the following days the forecasters would get together and write a hindcast/consensus forecast and agree on size, likelihood, avalanche problem, and hazard level, which would look like completing steps 9 through 14. This idea is rooted in the benefit of collective intelligence across a wide range of professional fields (Krause et al., 2010; Radcliffe et al., 2019).

Case Study Data Analysis

First, basic descriptive statistics were examined for traditional data and the RS+ version of the case study (i.e., median, mode, and interquartile ranges (IQR)). Next, we used statistical testing to highlight the differences between the versions of the case study. A Mann-Whitney U test was used for the ordinal variables (size, likelihood, and hazard level). A Pearson χ^2 test was used for the nominal variable of avalanche problem. These tests were used to compare the results of a traditional data forecast to that of a RS+ forecast. This case study is a small sample size, which should be kept in mind while interpreting these results. For statistical comparisons we considered *p*-values less than 0.05 to be statistically significant.

Next, contingency tables (i.e., "heat maps") showing the frequencies of size and likelihood were differenced from one another. Traditional data was subtracted from RS+ data to determine this difference. Lastly, contingency tables were used to show the frequency of size and avalanche problem as well as likelihood and avalanche problem.

Real-Time Forecasts Data Analysis

Quantitatively assessing these data is challenging as the sample size is incredibly limited due to the nature of avalanche forecasting—similarly to other studies of snow science this set of conditions exists on a small temporal scale. Additionally, without a consensus forecast it is difficult to assess, which forecast is correct. This would require an additional study to choose parameters that make a forecast good, and it requires weather models that hindcast the weather (Logan & Greene, 2023). Furthermore, relying on consensus hindcasts in the middle of the season is not a practical application of employee resources due to the time constraints during winter months. Assessing the quality of a forecast can take close to 20-30 hours, and it requires many resources to provide reliable data for hindcasting purposes (Logan & Greene, 2023). Additionally, these datasets amplify the potential for bias between forecaster experience level and comfort with traditional and RS+ observations. Therefore, drawing quantitative conclusions from these sets is not appropriate. Instead, this data set is assessed qualitatively after compiling summaries of the two forecasts. Additionally, two days were explored more closely because a consensus forecast was written.

CHAPTER THREE

RESULTS

The case studies and the real-time forecasts resulted in two different data sets that cannot be combined, or directly compared. Therefore, the case studies and real-time forecasts each have their own results sections. Additionally, on two occasions in the real-time forecasts, a consensus forecast was written, and those two results are talked about in their own results section.

Case Study One

Case Study One had 21 participants with 20 recording valid responses. There were 10 participants in scenario one, with traditional data. The 10 participants had a total of 45 responses in the hazard matrix (Table 1), as a forecaster is able, and permitted to provide multiple responses. All the responses to this question were valid. There were 11 participants in scenario two with RS+ data. Out of the 11 respondents one was invalid because they previously participated in writing a forecast with traditional data. The 10 participants had a total of 46 valid responses in the hazard matrix (Table 2).

Table 1: Case study one, central tendencies and dispersion of traditional data responses

Traditional Data and Observations (n = 45)

Variable	*Median*	*Mode*	*IQR*
Problem	NA	Wind Slab	NA
Size (D)	3	3.5	2.5 – 3.5
Likelihood	Likely	Likely	Possible – Likely
Hazard Level	Some Restrictions	Some Restrictions	Normal Attention – Some Restrictions

Table 2: Case study one, central tendencies and dispersion of RS+ responses

Remotely Sensed Data Plus Traditional Data (n = 46)

Variable	*Median*	*Mode*	*IQR*
Problem	NA	Wind Slab	NA
Size (D)	2.5	2.5	2 - 3
Likelihood	Possible	Possible	Possible - Likely
Hazard Level	Normal Attention	Normal Attention	Normal Attention – Increased Awareness

<u>Size</u>

The participants with traditional data selected a size D3 avalanche 24.4% of the time, while another 24.4% of the participants selected a size D3.5 (Figure 7). The median was a size D3, and the mode was a size D3.5 (Table 1). The participants with RS+ selected a size 2.5 23.9% of the time (Figure 7), and they had a median and mode of D2.5 (Table 2). For size, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was not statistically significant (*p*-value 0.197) when RS+ data was added to the scenario.

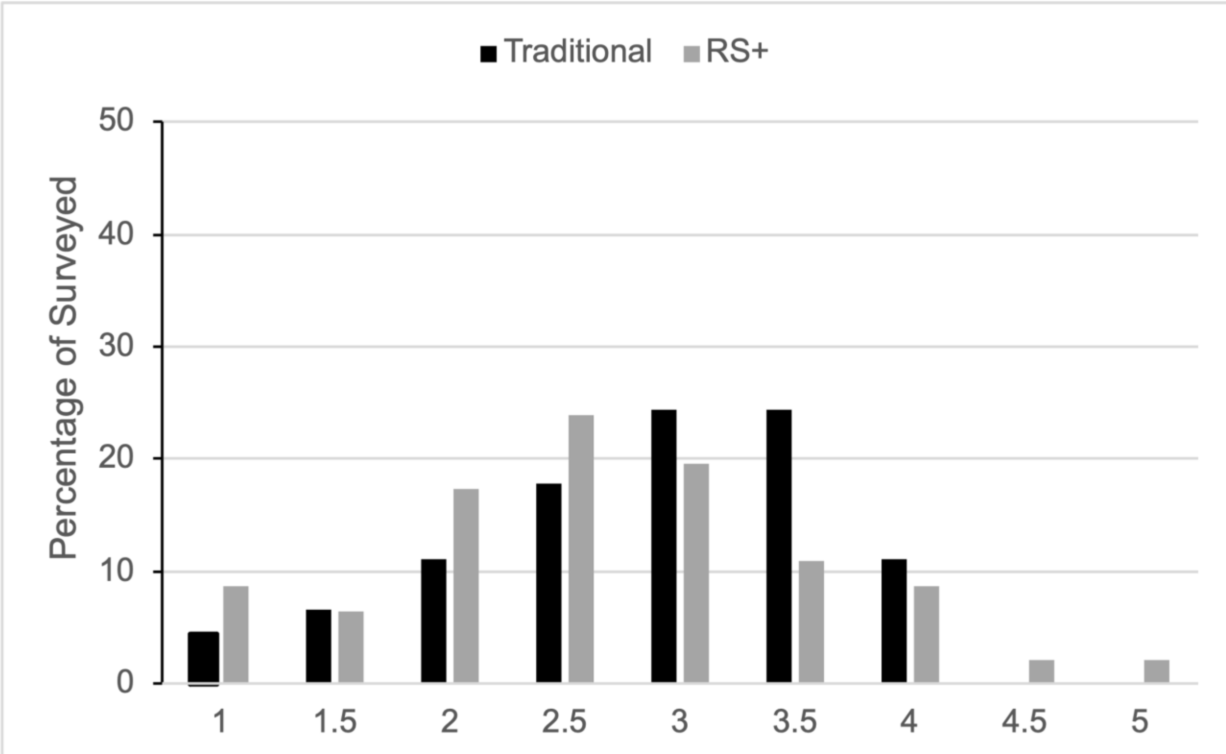


Figure 7. Case study one, frequency distribution of avalanche size (D) selected by the participants.

Likelihood

48.9% of the participants with traditional data said an avalanche was likely (Figure 8). The median and mode for this response was likely (Table 1). 34.8% of the participants with RS+ data said an avalanche was possible and another 34.8% said an avalanche was likely (Figure 8). The median and mode likelihood for this response was possible (Table 2). For likelihood, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was statistically significant (p-value 0.014) when RS+ data was added to the scenario.

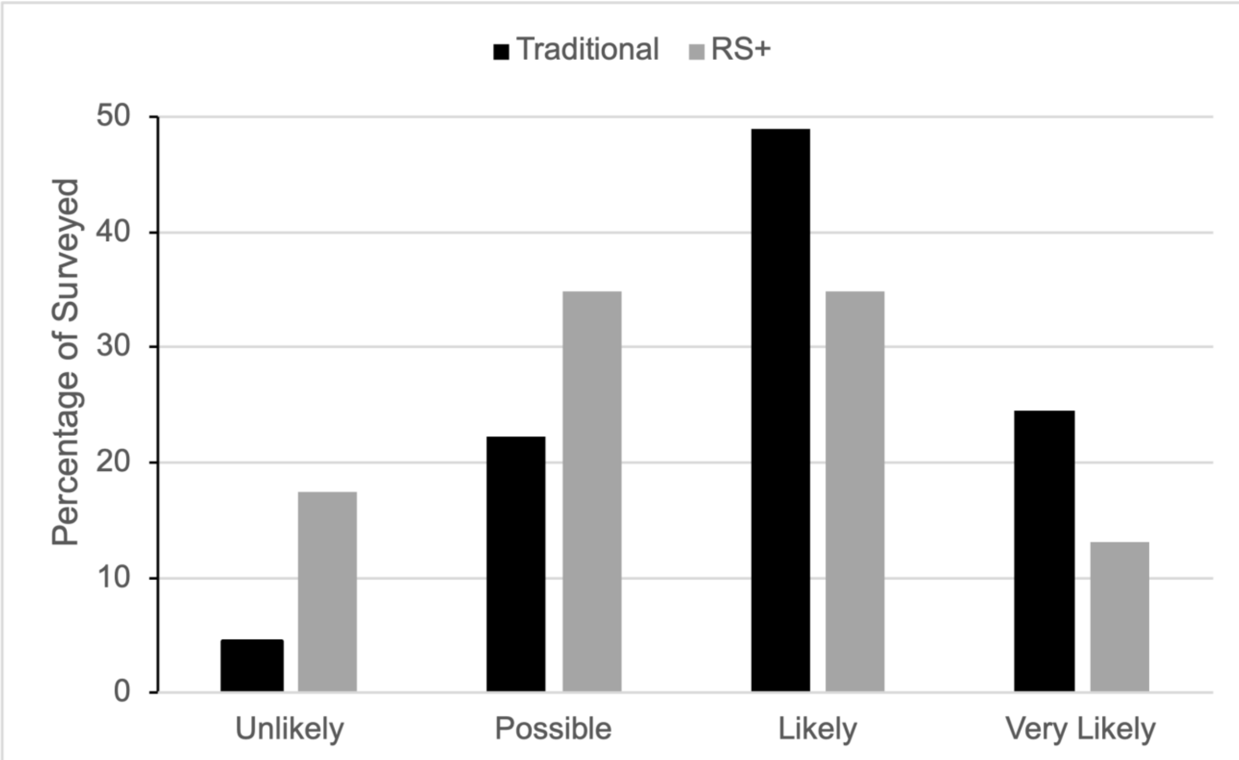


Figure 8. Case study one, frequency distribution of likelihood selected by the participants.

<u>Avalanche Problem Type</u>

The avalanche problem in both versions of the case study was most frequently a wind slab problem. With traditional data wind slab was selected 60.0% of the time (Figure 9). The participants with traditional data had 22.2% of the responses as a persistent weak layer (PWL) problem. RS+ participant responses selected a wind slab problem 73.9% of the time (Figure 9). Additionally, the mode was a wind slab problem for both scenarios of the case study (Table 1,2). For avalanche problem type, a nominal variable, we conducted a Pearson χ^2 test. The difference between the two groups was statistically significant (p-value 0.021) when RS+ data was added to the scenario.

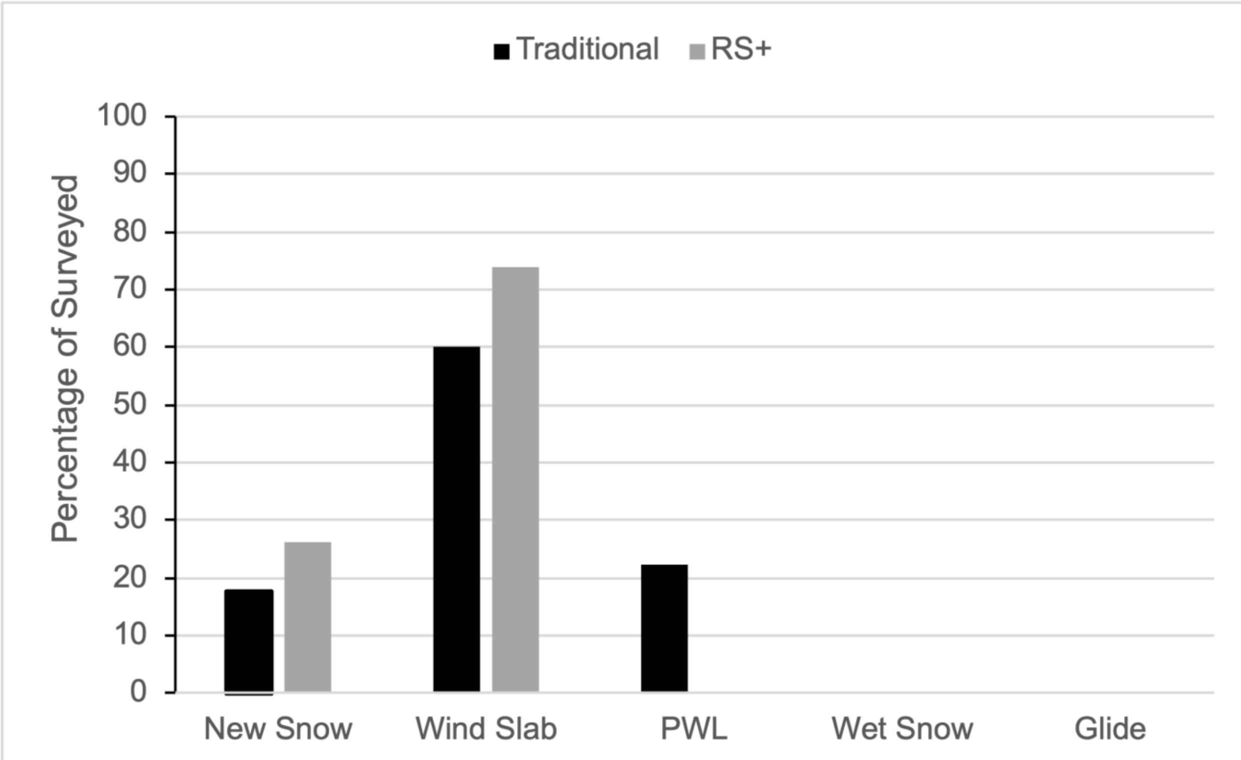


Figure 9. Case study one, frequency distribution of avalanche problem selected by the participants.

<u>Hazard Level</u>

Based on the location of likelihood and size the hazard level the participants derived the hazard level for highway 15. Participants using traditional data placed 37.8% of their selection at a hazard level as some restrictions (level 3 of 4) (Figure 10). The participants with traditional data had an IQR of 2 with a spread from normal attention (level 1 of 4) to some restrictions (level 3 of 4) (Table 1).

The participants with RS+ data had 58.7% of their selections in normal attention (1 of 4) (Figure 10). These same participants had an IQR of 1, with a spread from normal attention (level 1 of 4) to increased awareness (level 2 of 4) (Table 2). For avalanche hazard level, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was statistically significant (*p*-value < 0.001) when RS+ data was added to the scenario.

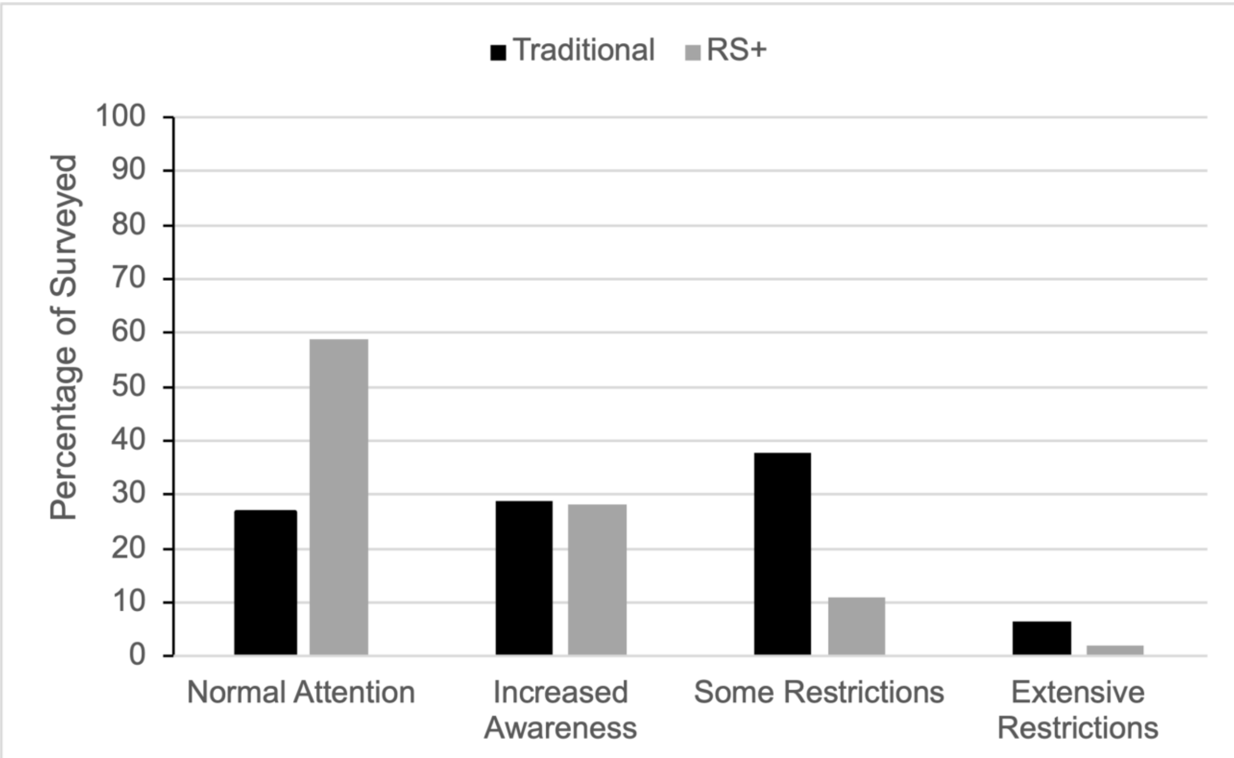
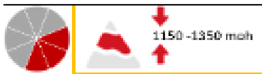


Figure 10. Case study one, frequency distribution of hazard level selected by the participants.

Heat Maps

The heat maps show the most frequent occurrence of size and likelihood, which allows us to assess what the consensus hazard level would be if it was overlayed the NPRA's hazard matrix. Additionally, the heat maps show where the answers for size and likelihood cluster on the hazard level matrix (Figure 11).



Case Study One, Traditional - Sætreskarsfjellet Total n: 10, Responses n: 45				
5	0.0%	0.0%	0.0%	0.0%
4.5	0.0%	0.0%	0.0%	0.0%
4	2.2%	2.2%	6.7%	0.0%
3.5	2.2%	6.7%	11.1%	4.4%
3	0.0%	4.4%	15.6%	4.4%
2.5	0.0%	4.4%	8.9%	4.4%
2	0.0%	4.4%	2.2%	4.4%
1.5	0.0%	0.0%	2.2%	4.4%
1	0.0%	0.0%	2.2%	2.2%
	Unlikely	Possible	Likely	Very Likely
	1	2	3	4

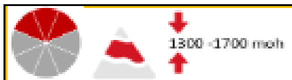
Case Study One, RS+ - Sætreskarsfjellet Total n: 10, Responses n: 46				
5	2.2%	0.0%	0.0%	0.0%
4.5	2.2%	0.0%	0.0%	0.0%
4	4.3%	2.2%	2.2%	0.0%
3.5	2.2%	6.5%	2.2%	0.0%
3	4.3%	8.7%	6.5%	0.0%
2.5	2.2%	8.7%	6.5%	6.5%
2	0.0%	4.3%	13.0%	0.0%
1.5	0.0%	2.2%	2.2%	2.2%
1	0.0%	2.2%	2.2%	4.3%
	Unlikely	Possible	Likely	Very Likely
	1	2	3	4

Figure 11. Case study one, overlay of traditional matrix and contingency chart for traditional data on the left and RS+ data on the right. Hatching represents cells with more than 10% of the responses.

Heat Map Differencing

The heat maps were differenced from one another to highlight where the increases and decreases in the selections on the hazard matrix occurred, where positive values indicate an increase in responses from RS+ scenario participants for that cell value, and a negative percentage is a decrease, relative to the traditional scenario. Differencing RS+ responses from traditional data responses shows the participants with RS+ data reduced the number of responses from a size D2.5 to D4 in the likely category (Table 3). RS+ participants increased their responses in the lower likelihoods compared to those with traditional data (Table 3).

Table 3. Case study one, difference of RS+ hazard matrix responses subtracted from traditional data of the hazard matrix responses. Hatching represents cells with a 10% increase in responses.



Heat Map Difference (RS+ - Traditional)					% Totals
5	**2.2%**	**0.0%**	**0.0%**	**0.0%**	2.2%
4.5	**2.2%**	**0.0%**	**0.0%**	**0.0%**	2.2%
4	**2.1%**	**0.0%**	**-4.5%**	**0.0%**	-2.4%
3.5	**0.0%**	**-0.1%**	**-8.9%**	**-4.4%**	-13.6%
3	**4.3%**	**4.3%**	**-9.0%**	**-4.4%**	-4.9%
2.5	**2.2%**	**4.3%**	**-2.4%**	**2.1%**	6.1%
2	**0.0%**	**-0.1%**	**10.8%**	**-4.4%**	6.3%
1.5	**0.0%**	**2.2%**	**0.0%**	**-2.3%**	-0.1%
1	**0.0%**	**2.2%**	**0.0%**	**2.1%**	4.3%
	Unlikely	Possible	Likely	Very Likely	
	0-2%	2-10%	10-50%	50-100%	
% Totals	12.9%	12.6%	-14.1%	-11.4%	

<u>Avalanche Problem and Size</u>

Using a contingency table with the avalanche problem and size to find the most frequently selected size and the problem for that size. The participants with traditional data had 46.7% of the results as a wind slab from size 2.5 to a size 3.5 (Table 4). The highest frequency for a new snow problem was a size 1.5 at 6.7% (Table 4).

Table 4: Case study one, avalanche type and size contingency table for traditional data

	1	**1.5**	**2**	**2.5**	**3**	**3.5**	**4**	**4.5**	**5**	**% Totals**
New Snow	4.4%	6.7%	2.2%	0.0%	2.2%	2.2%	0.0%	0.0%	0.0%	17.8%
Wind Slab	0.0%	0.0%	4.4%	11.1%	17.8%	17.8%	8.9%	0.0%	0.0%	60.0%
PWL	0.0%	0.0%	4.4%	6.7%	4.4%	4.4%	2.2%	0.0%	0.0%	22.2%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	4.4%	6.7%	11.1%	17.8%	24.4%	24.4%	11.1%	0.0%	0.0%	

For the participants with RS+ data 43.4% of the responses were wind slab problems from a size 2 to a size 3 (Table 5). The new snow problems had their highest frequency as a size 2.5 at 8.7%.

Table 5: Case study one, avalanche type and size contingency table for RS+

	1	1.5	2	2.5	3	3.5	4	4.5	5	% Totals
New Snow	2.2%	2.2%	2.2%	8.7%	6.5%	4.3%	0.0%	0.0%	0.0%	26.1%
Wind Slab	6.5%	4.3%	15.2%	15.2%	13.0%	6.5%	8.7%	2.2%	2.2%	73.9%
PWL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	8.7%	6.5%	17.4%	23.9%	19.6%	10.9%	8.7%	2.2%	2.2%	

Avalanche Problem and Likelihood

A contingency table was used for avalanche problem and likelihood to find the most frequently selected likelihood and the problem for that likelihood. The participants with traditional data selected the wind slab problem as possible to likely 48.9% of the time (Table 6). And 17.8% of the responses were new snow problems with a likelihood of likely to very likely (Table 6).

Table 6: Avalanche Type and Likelihood Contingency Table for Traditional Data

	Unlikely	Possible	Likely	Very Likely	% Totals
New Snow	0.0%	0.0%	8.9%	8.9%	17.8%
Wind Slab	0.0%	15.6%	33.3%	11.1%	60.0%
PWL	4.4%	6.7%	6.7%	4.4%	22.2%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	4.4%	22.2%	48.9%	24.4%	

The frequencies of likelihood and problem type in the case study with RS+ data showed 52.2% of the responses from participants found a wind slab was possible to likely (Table 7). Also, 17.4% of the participants recorded that a new snow problem was possible to likely (Table 7).

Table 7: Avalanche Type and Likelihood Contingency Table for RS+

	Unlikely	Possible	Likely	Very Likely	% Totals
New Snow	0.0%	8.7%	8.7%	8.7%	26.1%
Wind Slab	17.4%	26.1%	26.1%	4.3%	73.9%
PWL	0.0%	0.0%	0.0%	0.0%	0.0%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	17.4%	34.8%	34.8%	13.0%	

Case Study Two

This case study asked the participants to produce two hazard level matrixes for two different slide paths. Case Study Two is split into two sections, and the data is divided in the same manner. This section begins with Case Study Two, which represents the large slide path in Figure 3 facing the NE, and the section ends with Case Study Two SW, which represents the smaller slide path in Figure 3.

Case Study Two – Large NE Path

Case Study Two, northeast had 19 participants with 17 recording valid responses. There were 10 participants in scenario two, northeast, with traditional data. The 10 participants had a total of 36 responses in the hazard matrix (Table 8). All the responses to this question were valid. There were 9 participants in scenario two with RS+ data. Out of the 9 respondents two were invalid because they did not provide an answer in the hazard matrix. The 7 participants had a total of 23 valid responses in the hazard matrix (Table 9).

Table 8: Case study two, NE path, central tendencies and dispersion of traditional data responses

Traditional Data and Observations (n = 36)

Variable	*Median*	*Mode*	*IQR*
Problem	NA	Wind Slab	NA
Size (D)	2.5	2.5	1.5 – 3
Likelihood	Possible	Unlikely	Unlikely – Possible
Hazard Level	Normal Attention	Normal Attention	Normal Attention – Normal Attention

Table 9: Case study two, NE path, central tendencies and dispersion of RS+ responses

Remotely Sensed Data Plus Traditional Data (n = 23)			
Variable	*Median*	*Mode*	*IQR*
Problem	NA	Wind Slab	NA
Size (D)	2.0	2.0	1.5 – 2.5
Likelihood	Possible	Possible	Unlikely – Possible
Hazard Level	Normal Attention	Normal Attention	Normal Attention – Normal Attention

Size

The participants with traditional data selected a size D2.5 avalanche 25.0% of the time (Figure 12). The median was a size D2.5, and the mode was a size D2.5 (Table 8). The participants with RS+ selected a size D2 26.1% of the time (Figure 12), and they had a median and mode of D2 (Table 9). For size, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was not statistically significant (*p*-value 0.098) when RS+ data was added to the scenario.

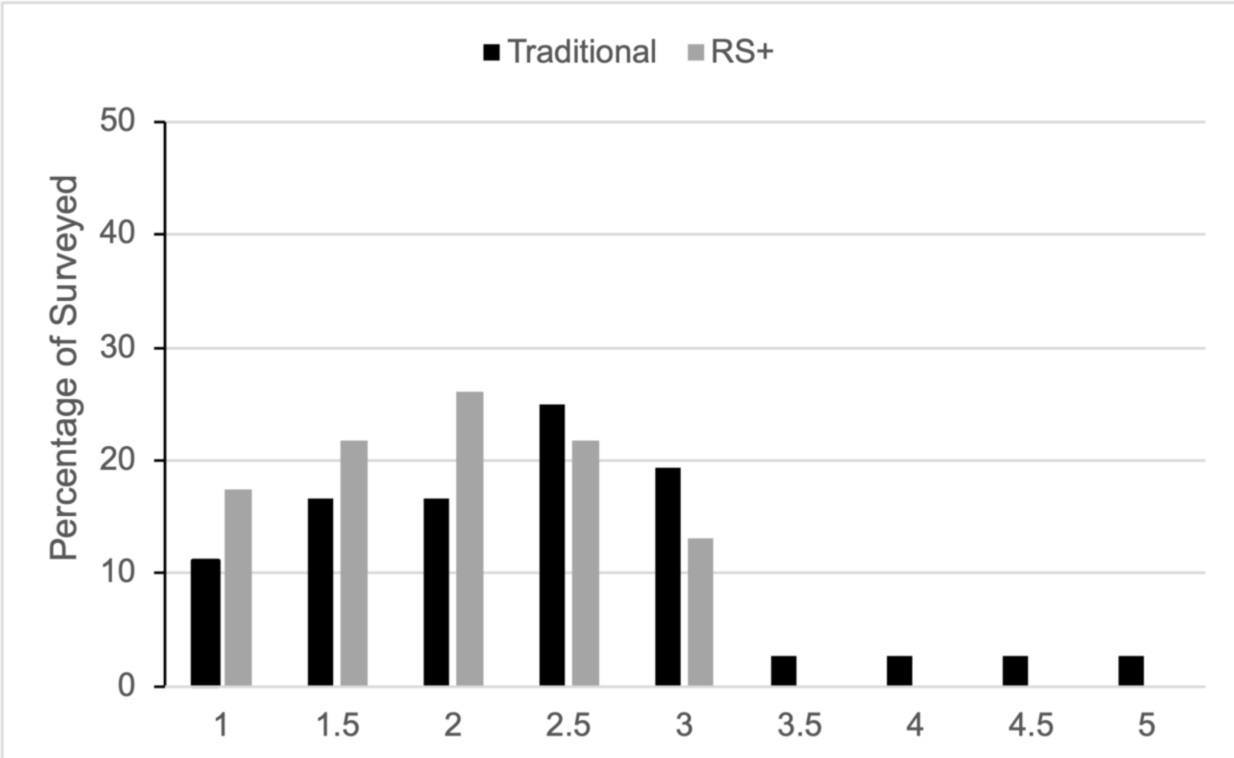


Figure 12. Case study two, NE path, frequency distribution of avalanche size selected by the participants.

Likelihood

The participants with traditional data selected unlikely for the likelihood 44.4% of the time (Figure 13). The median for this response was possible, while the mode was unlikely (Table 8). Among the participants with RS+ data, 39.1% said an avalanche was unlikely and another 39.1% said an avalanche was possible (Figure 13). The median and mode likelihood for this response was possible (Table 9). For likelihood, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was not statistically significant (*p*-value 0.512) when RS+ data was added to the scenario.

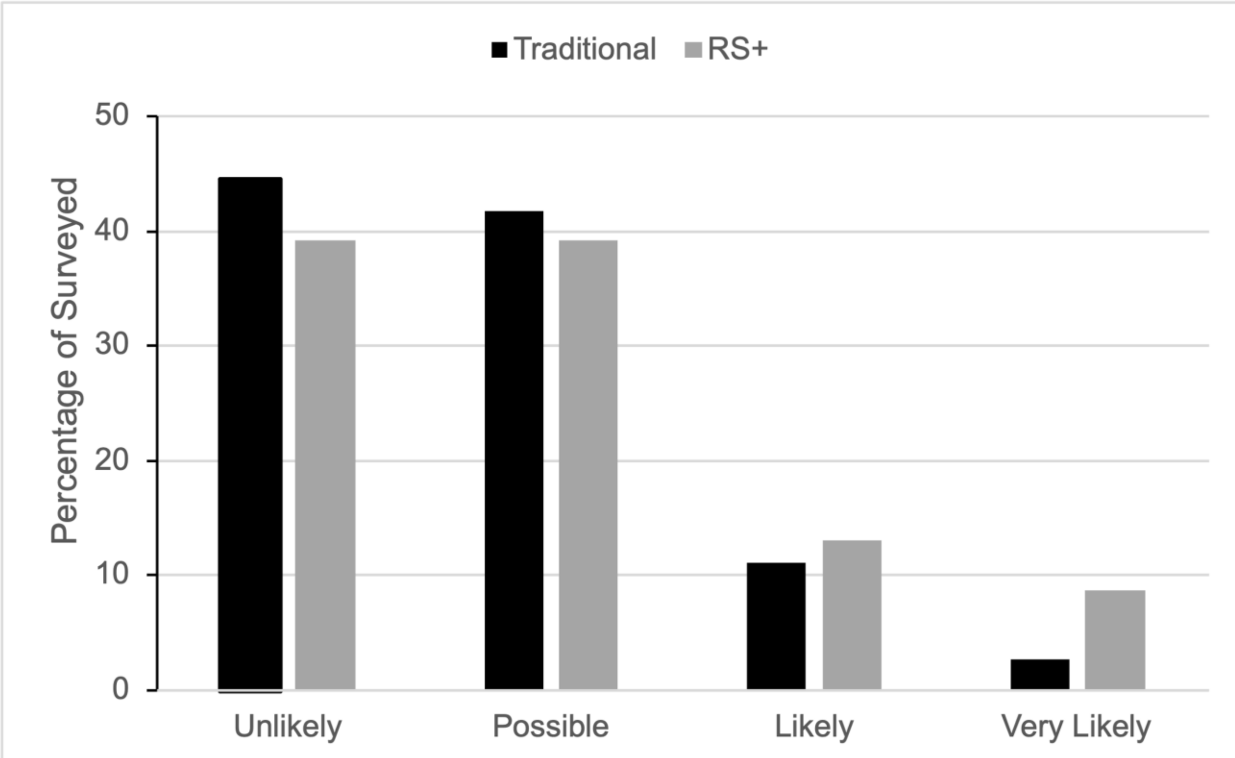


Figure 13. Case study two, NE path, frequency distribution of likelihood selected by the participants.

Avalanche Problem Type

The avalanche problem in both versions of the case study was most frequently a wind slab problem. With traditional data wind slab was selected 91.7% of the time (Figure 14). The participants with traditional data had 8.3% of the responses as a new snow problem. RS+ participant responses selected a wind slab problem 73.9% of the time and a PWL 17.4% of the time (Figure 14). Additionally, the mode was a wind slab problem for both scenarios of the case study (Table 8,9). For avalanche problem type, a nominal variable, we conducted a Pearson χ^2 test. The difference between the two groups was not statistically significant (p-value 0.148) when RS+ data was added to the scenario.

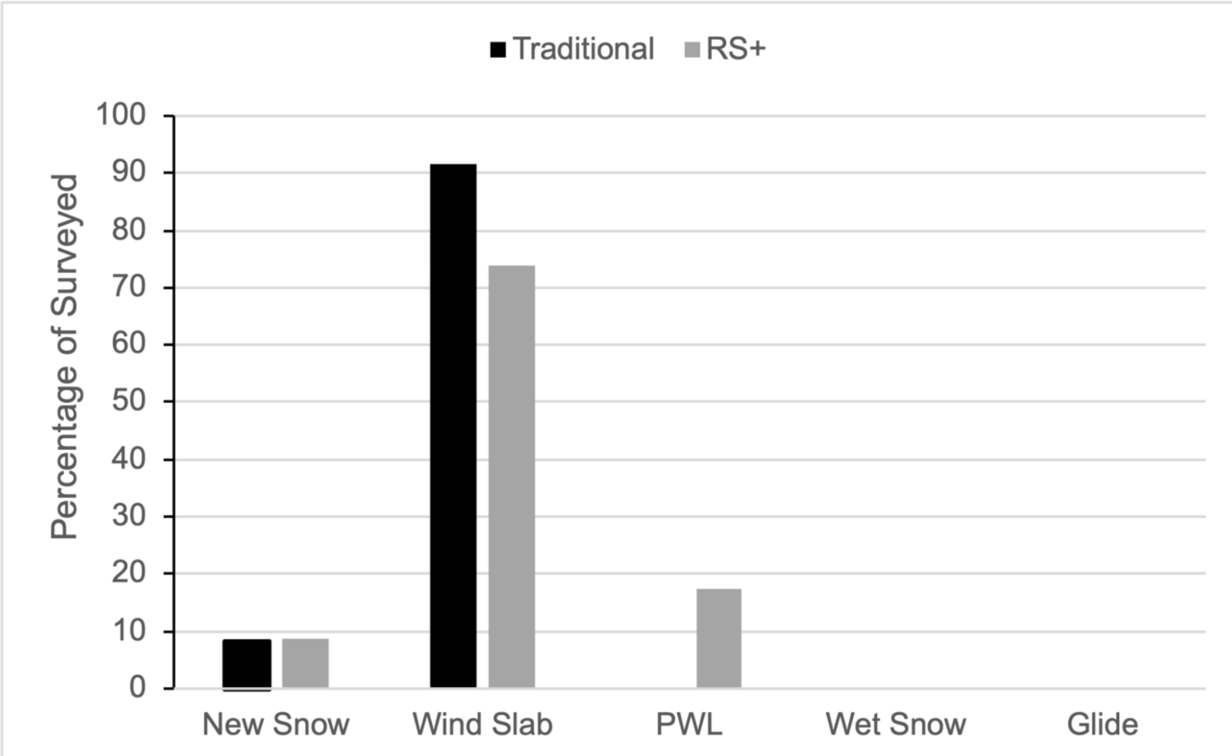


Figure 14. Case study two, NE path, frequency distribution of avalanche problem selected by the participants.

Hazard Level

Participants using traditional data placed 91.7% of their selections at a hazard level as normal attention (level 1 of 4) (Figure 15). The participants with traditional data had an IQR of zero with most of their selections as normal attention (Table 8). There were 3 selections or 8.3% of selections in the "some restrictions" (level 2 of 4) category.

The participants with RS+ data had 82.6% of their selections in normal attention (level 1 of 4) (Figure 15). These same participants had an IQR of zero (Table 9). For avalanche hazard level, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was not statistically significant (p-value 0.267) when RS+ data was added to the scenario.

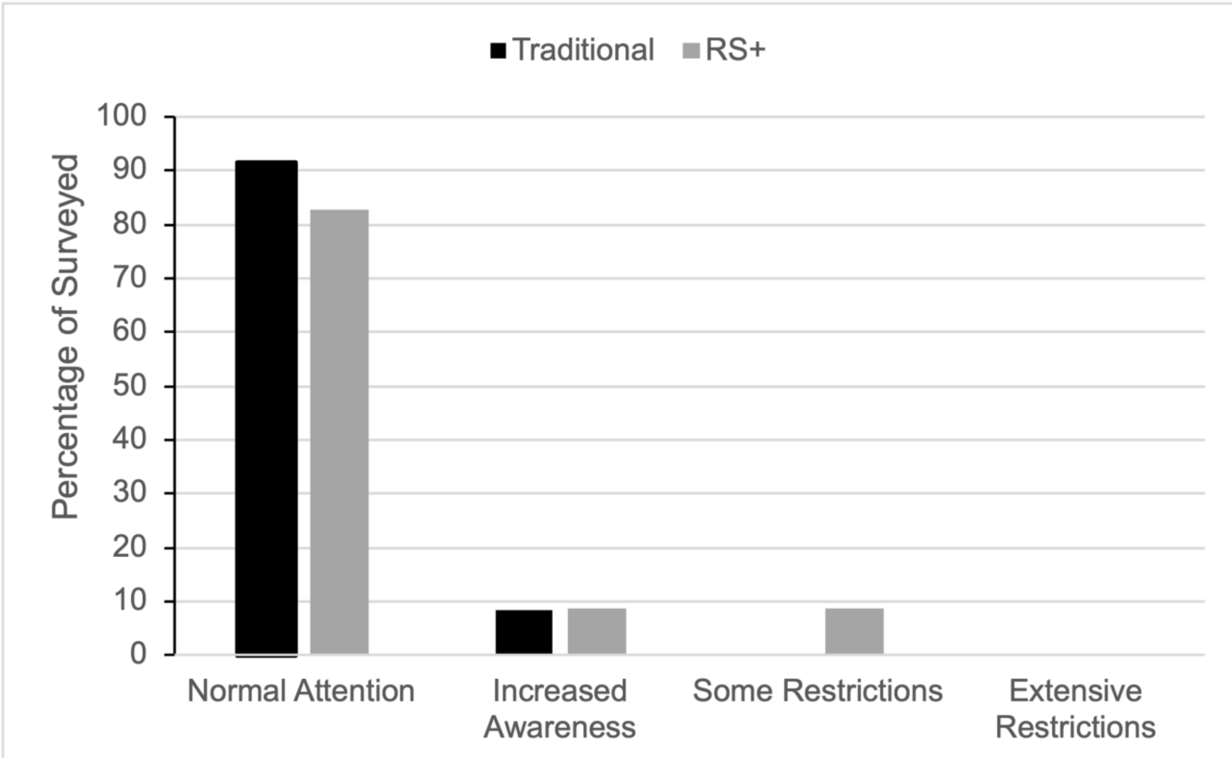


Figure 15. Case study two, NE path, frequency distribution of hazard level selected by the participants.

Heat Maps

The heat maps show the most frequent occurrence of size and likelihood, which allows us to assess what the consensus hazard level would be if it was overlayed the NPRA's hazard matrix. Additionally, the heat maps show where the answers for size and likelihood cluster on the hazard level matrix (Figure 16).

Case Study Two, Traditional - Sætreskarsfjellet NE Total n: 10, Responses n: 36				
5	2.8%	0.0%	0.0%	0.0%
4.5	2.8%	0.0%	0.0%	0.0%
4	2.8%	0.0%	0.0%	0.0%
3.5	2.8%	0.0%	0.0%	0.0%
3	13.9%	5.6%	0.0%	0.0%
2.5	8.3%	11.1%	5.6%	0.0%
2	5.6%	11.1%	0.0%	0.0%
1.5	2.8%	11.1%	2.8%	0.0%
1	2.8%	2.8%	2.8%	2.8%
	Unlikely	Possible	Likely	Very Likely
	1	2	3	4

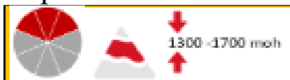
Case Study Two, RS+ - Sætreskarsfjellet NE Total n: 7, Responses n: 23				
5	0.0%	0.0%	0.0%	0.0%
4.5	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%
3.5	0.0%	0.0%	0.0%	0.0%
3	4.3%	0.0%	4.3%	4.3%
2.5	4.3%	8.7%	4.3%	4.3%
2	4.3%	21.7%	0.0%	0.0%
1.5	13.0%	4.3%	4.3%	0.0%
1	13.0%	4.3%	0.0%	0.0%
	Unlikely	Possible	Likely	Very Likely
	1	2	3	4

Figure 16. Case study two, NE path, overlay of traditional matrix and contingency chart for traditional data on the left and RS+ data on the right. Hatching represents cells with more than 10% of the responses.

Heat Map Differencing

The heat maps were differenced from one another to highlight where the increases and decreases in the selections on the hazard matrix occurred, where positive values indicate an increase in responses from RS+ scenario participants for that cell value, and a negative percentage is a decrease, relative to the traditional scenario. Differencing RS+ responses from traditional data responses shows the participants with RS+ data decreased the number of responses in D2-5 being unlikely (Table 10). While they increased the responses for size D1 to D1.5 in the likely categories and D2 in the possible category (Table 10). RS+ participants also increased their responses in likely and very likely for size D2.5-D3 (Table 10).

Table 10. Case study two, NE path, difference of RS+ hazard matrix responses subtracted from traditional data of the hazard matrix responses. Hatching represents cells with a 10% increase in responses.



	Heat Map Difference (RS+ - Traditional)				% Totals
5	-2.8%	0.0%	0.0%	0.0%	-2.8%
4.5	-2.8%	0.0%	0.0%	0.0%	-2.8%
4	-2.8%	0.0%	0.0%	0.0%	-2.8%
3.5	-2.8%	0.0%	0.0%	0.0%	-2.8%
3	-9.5%	-5.6%	4.3%	4.3%	-6.4%
2.5	-4.0%	-2.4%	-1.2%	4.3%	-3.3%
2	-1.2%	10.6%	0.0%	0.0%	9.4%
1.5	10.3%	-6.8%	1.6%	0.0%	5.1%
1	10.3%	1.6%	-2.8%	-2.8%	6.3%
	Unlikely	Possible	Likely	Very Likely	
	0-2%	2-10%	10-50%	50-100%	
% Totals	-5.3%	-2.5%	1.9%	5.9%	

<u>Avalanche Problem and Size</u>

Using a contingency table with the avalanche problem and size to find the most frequently selected size and the problem for that size. The participants with traditional data had 80.5% of the results as a wind slab from size D1 to a size D3 (Table 11). The frequency of a new snow problem ranged from a size D1 to a size D2 at 2.8% (Table 11).

Table 11: Case study two, NE path, avalanche type and size contingency table for traditional data

	1	1.5	2	2.5	3	3.5	4	4.5	5	% Totals
New Snow	2.8%	2.8%	2.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.3%
Wind Slab	8.3%	13.9%	13.9%	25.0%	19.4%	2.8%	2.8%	2.8%	2.8%	91.7%
PWL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	11.1%	16.7%	16.7%	25.0%	19.4%	2.8%	2.8%	2.8%	2.8%	

For the participants with RS+ data 73.9% of the responses were wind slab problems from a size D1 to a size D3 (Table 12). The new snow problems had their highest frequency as a size D1 and D1.5 (Table 12). A PWL was also selected 17.4% of the time, and the avalanche size ranged from D1.5 to D3 (table 12).

Table 12: Case study two, NE path, avalanche type and size contingency table for RS+

	1	1.5	2	2.5	3	3.5	4	4.5	5	% Totals
New Snow	4.3%	4.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.7%
Wind Slab	13.0%	13.0%	21.7%	17.4%	8.7%	0.0%	0.0%	0.0%	0.0%	73.9%
PWL	0.0%	4.3%	4.3%	4.3%	4.3%	0.0%	0.0%	0.0%	0.0%	17.4%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	17.4%	21.7%	26.1%	21.7%	13.0%	0.0%	0.0%	0.0%	0.0%	

<u>Avalanche Problem and Likelihood</u>

A contingency table was used for avalanche problem and likelihood to find the most frequently selected likelihood and the problem for that likelihood. The participants with traditional data selected the wind slab problem as unlikely to possible 80.5% of the time (table 13). And 8.3% of the responses were new snow problems with a likelihood of possible to likely (Table 13).

Table 13: Case study two, NE path, avalanche type and likelihood contingency table for traditional data

	Unlikely	Possible	Likely	Very Likely	% Totals
New Snow	0.0%	5.6%	2.8%	0.0%	8.3%
Wind Slab	44.4%	36.1%	8.3%	2.8%	91.7%
PWL	0.0%	0.0%	0.0%	0.0%	0.0%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	44.4%	41.7%	11.1%	2.8%	

The frequencies of likelihood and problem type in the case study with RS+ data showed 38.9% of the responses from participants found a wind slab was unlikely to possible (Table 14). Also, 8.7% of the participants recorded that a new snow problem was unlikely (Table 14).

Table 14: Case study two, NE path, avalanche type and likelihood contingency table for RS+

	Unlikely	Possible	Likely	Very Likely	% Totals
New Snow	8.7%	0.0%	0.0%	0.0%	8.7%
Wind Slab	13.9%	25.0%	5.6%	5.6%	50.0%
PWL	5.6%	2.8%	2.8%	0.0%	11.1%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	28.1%	27.8%	8.3%	5.6%	

<u>Case Study Two: SW Slide Path</u>

Case Study Two, southwest had 19 participants with 19 recording valid responses. There were 10 participants in scenario two, southwest, with traditional data. The 10 participants had a total of 39 responses in the hazard matrix (Table 15). All the responses to this question were valid. There were 9 participants in scenario two with RS+ data. All the responses to this question were valid. The 9 participants had a total of 23 valid responses in the hazard matrix (Table 16).

Table 15: Case study two, SW, central tendencies and dispersion of traditional data responses

Traditional Data and Observations (n = 39)

Variable	*Median*	*Mode*	*IQR*
Problem	NA	Wind Slab	NA
Size (D)	2.0	1.5	1.5 – 2.5
Likelihood	Possible	Unlikely	Unlikely – Possible
Hazard Level	Normal Attention	Normal Attention	Normal Attention – Normal Attention

Table 16: Case study two, SW, central tendencies and dispersion of RS+ responses

Remotely Sensed Data Plus Traditional Data (n = 27)

Variable	*Median*	*Mode*	*IQR*
Problem	NA	Wind Slab	NA
Size (D)	2.0	2.5	1.5 – 2.5
Likelihood	Possible	Unlikely	Unlikely - Likely
Hazard Level	Normal Attention	Normal Attention	Normal Attention – Normal Attention/Increased Awareness

Size

The participants with traditional data selected a size D1.5 avalanche 25.6% of the time (Figure 17). The median was a size D2, and the mode was a size D1.5 (Table 15). The participants with RS+ selected a size D2.5 29.6% of the time (figure 17), and they had a median of a size D2 and mode of D2.5 (Table 16). For size, an ordinal variable, we conducted a Mann-

Whitney U test. The difference between the two groups was not statistically significant (p-value 0.379) when RS+ data was added to the scenario.

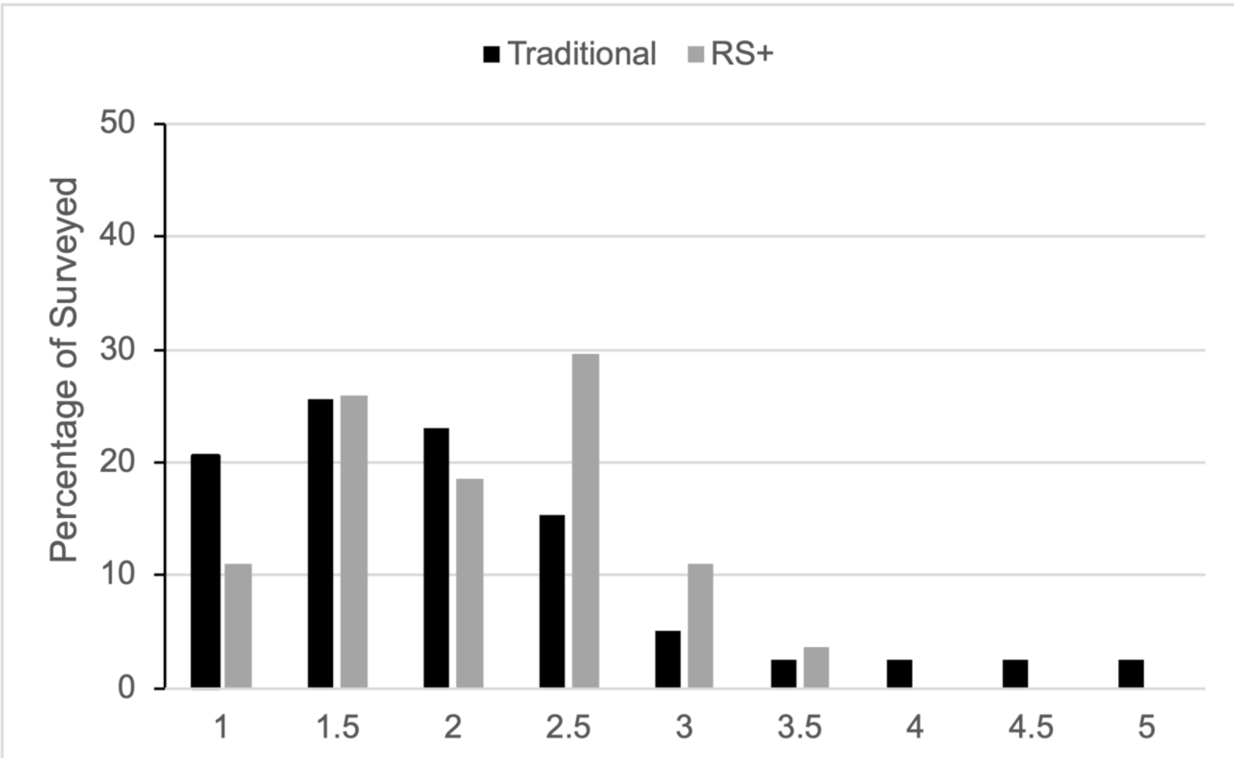


Figure 17. Case study two, SW path, frequency distribution of avalanche size selected by the participants.

<u>Likelihood</u>

The participants with traditional data selected unlikely for the likelihood 43.6% of the time and possible 43.6% of the time (Figure 18). The median for this response was possible, while the mode was unlikely (Table 15). Among the participants with RS+ data, 37.0% said an avalanche was unlikely (Figure 18). The median this response was possible while the mode was unlikely (Table 16). For likelihood, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was not statistically significant (p-value 0.290) when RS+ data was added to the scenario.

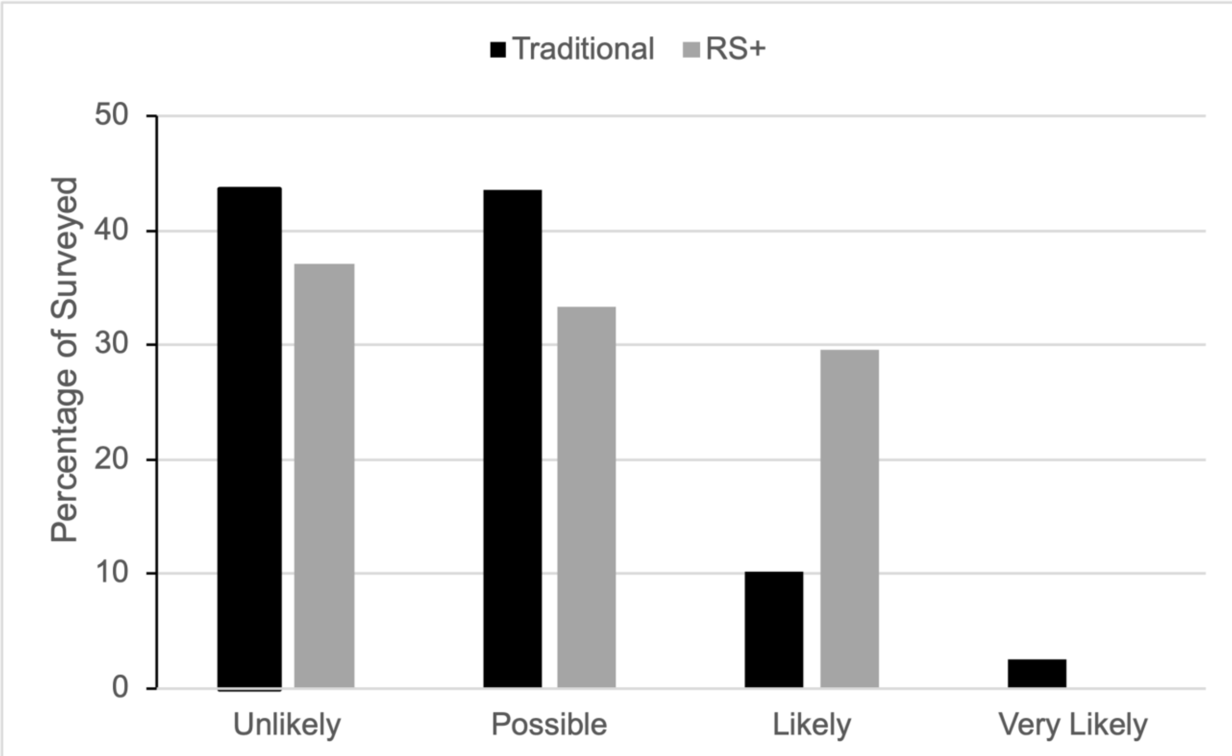


Figure 18. Case study two, SW path, frequency distribution of likelihood selected by the participants.

Avalanche Problem Type

The avalanche problem in both versions of the case study was most frequently a wind slab problem. With traditional data, wind slab was selected 64.1% of the time (Figure 19). The participants with traditional data had 28.2% of the responses as a new snow problem. RS+ participant responses selected a wind slab problem 81.5% of the time and a PWL 14.8% of the time (Figure 19). Additionally, the mode was a wind slab problem for both scenarios of the case study (Table 15, 16). For avalanche problem type, a nominal variable, we conducted a Pearson χ^2 test. The difference between the two groups was statistically significant (p-value 0.008) when RS+ data was added to the scenario.

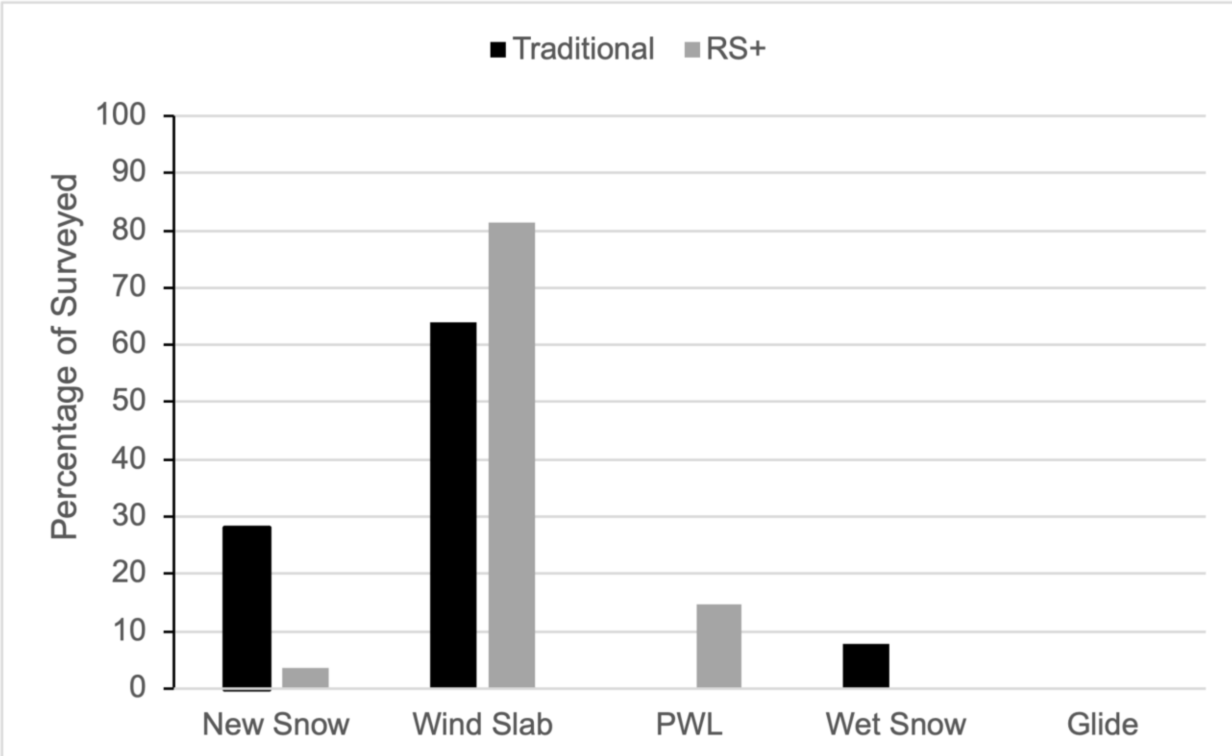


Figure 19. Case study two, SW path, frequency distribution of avalanche problem selected by the participants.

Hazard Level

Participants using traditional data placed 94.9% of their selections at a hazard level as normal attention (level 1 of 4) (Figure 20). The participants with traditional data had an IQR of zero with most of their selections as normal attention (Table 15). There were 2 selections or 5.1%, in the “some restrictions” (level 2 of 4) category.

The participants with RS+ data had 74.1% of their selections in normal attention (level 1 of 4) (Figure 20). These same participants had an IQR of 0.5, showing that the first quartile was normal attention, but the third quartile was between normal attention and increased awareness (Table 16). For avalanche hazard level, an ordinal variable, we conducted a Mann-Whitney U test. The difference between the two groups was statistically significant (p-value 0.014) when RS+ data was added to the scenario.

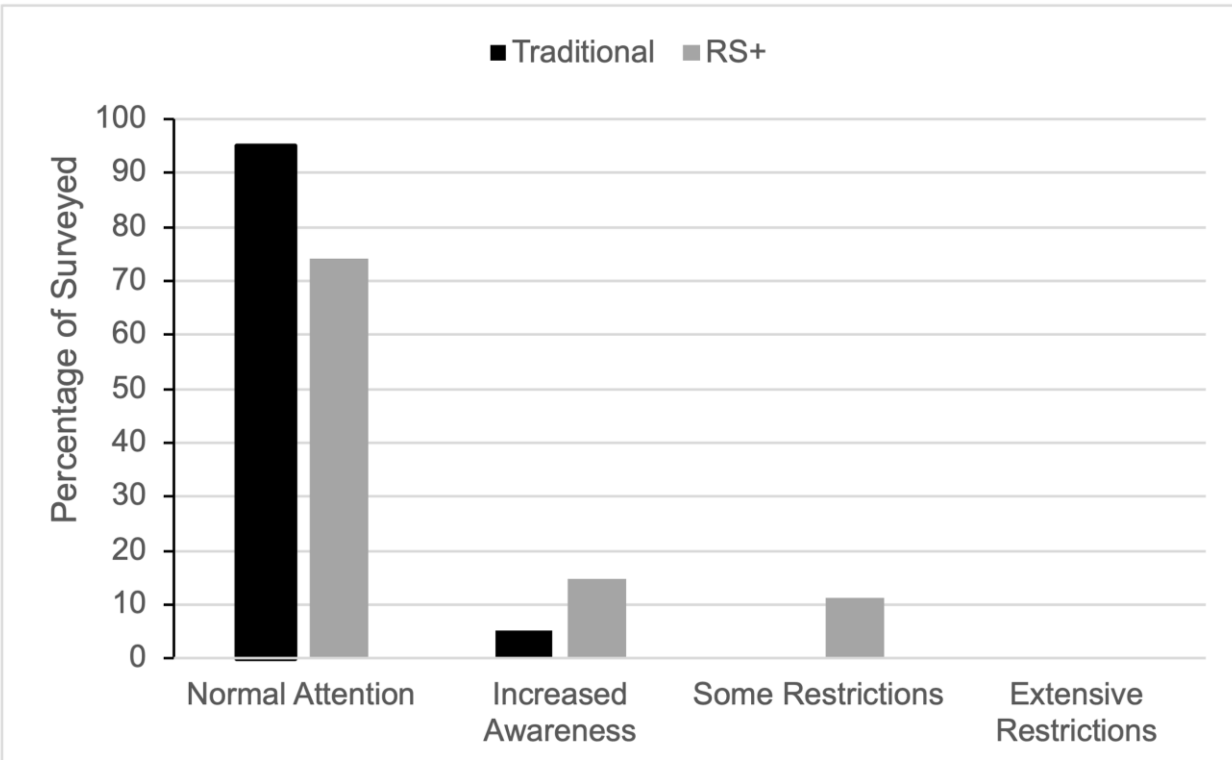


Figure 20. Case study two, SW path, frequency distribution of hazard level selected by the participants.

Heat Maps

The heat maps show the most frequent occurrence of size and likelihood, which allows us to assess what the consensus hazard level would be if it was overlayed the NPRA's hazard matrix. Additionally, the heat maps show where the answers for size and likelihood cluster on the hazard level matrix (Figure 21).

Case Study Two, Traditional - Sætreskarsfjellet SW Total n: 10, Responses n: 39				
5	2.6%	0.0%	0.0%	0.0%
4.5	2.6%	0.0%	0.0%	0.0%
4	2.6%	0.0%	0.0%	0.0%
3.5	2.6%	0.0%	0.0%	0.0%
3	2.6%	2.6%	0.0%	0.0%
2.5	5.1%	7.7%	2.6%	0.0%
2	7.7%	12.8%	2.6%	0.0%
1.5	12.8%	10.3%	2.6%	0.0%
1	5.1%	10.3%	2.6%	2.6%
	Unlikely	Possible	Likely	Very Likely
	1	2	3	4

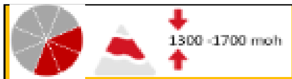
Case Study Two, RS+ - Sætreskarsfjellet SW Total n: 9, Responses n: 27				
5	0.0%	0.0%	0.0%	0.0%
4.5	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%
3.5	0.0%	0.0%	3.7%	0.0%
3	0.0%	3.7%	7.4%	0.0%
2.5	7.4%	11.1%	11.1%	0.0%
2	7.4%	7.4%	3.7%	0.0%
1.5	14.8%	7.4%	3.7%	0.0%
1	7.4%	3.7%	0.0%	0.0%
	Unlikely	Possible	Likely	Very Likely
	1	2	3	4

Figure 21. Case study two, SW path, overlay of traditional matrix and contingency chart for traditional data on the left and RS+ data on the right. Hatching represents cells with more than 10% of the responses.

Heat Map Differencing

The heat maps were differenced from one another to highlight where the increases and decreases in the selections on the hazard matrix occurred, where positive values indicate an increase in responses from RS+ scenario participants for that cell value, and a negative percentage is a decrease, relative to the traditional scenario. Differencing RS+ responses from traditional data responses shows the participants with RS+ data increased the number of responses in D2.5 to D3 being likely (Table 17). While they decreased the responses for likelihood in all the other categories (Table 17). There were no increases or decreases greater than 10% in any of the cells in Table 17.

Table 17. Case study two, SW path, difference of RS+ hazard matrix responses subtracted from traditional data of the hazard matrix responses.



Heat Map Difference (RS+ - Traditional)					% Totals
5	-2.6%	0.0%	0.0%	0.0%	-2.6%
4.5	-2.6%	0.0%	0.0%	0.0%	-2.6%
4	-2.6%	0.0%	0.0%	0.0%	-2.6%
3.5	-2.6%	0.0%	3.7%	0.0%	1.1%
3	-2.6%	1.1%	7.4%	0.0%	6.0%
2.5	2.3%	3.4%	8.5%	0.0%	14.2%
2	-0.3%	-5.4%	1.1%	0.0%	-4.6%
1.5	2.0%	-2.8%	1.1%	0.0%	0.3%
1	2.3%	-6.6%	-2.6%	-2.6%	-9.4%
	Unlikely	Possible	Likely	Very Likely	
	0-2%	2-10%	10-50%	50-100%	
% Totals	-6.6%	-10.3%	19.4%	-2.6%	

Avalanche Problem and Size

Using a contingency table with the avalanche problem and size to find the most frequently selected size and the problem for that size. The participants with traditional data, 41.0% of the wind slab problems fell between a size D1.5 and a D2.5 (Table 18). The frequency of a new snow problem was highest from a size D1 to a size D1.5 (Table 18).

Table 18: Case study two, SW path, avalanche type and size contingency table for traditional data

	1	1.5	2	2.5	3	3.5	4	4.5	5	% Totals
New Snow	12.8%	12.8%	2.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	28.2%
Wind Slab	7.7%	12.8%	15.4%	12.8%	5.1%	2.6%	2.6%	2.6%	2.6%	64.1%
PWL	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Wet Snow	0.0%	0.0%	5.1%	2.6%	0.0%	0.0%	0.0%	0.0%	0.0%	7.7%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	20.5%	25.6%	23.1%	15.4%	5.1%	2.6%	2.6%	2.6%	2.6%	

For the participants with RS+ data, the frequencies were highest between a size D1.5 to D2.5 (Table 19). The new snow problems were only selected for a D1.5 (Table 19). A PWL was also selected for a size D2.5 to D3.5 (Table 19).

Table 19: Case study two, SW path, avalanche type and size contingency table for RS+

	1	1.5	2	2.5	3	3.5	4	4.5	5	% Totals
New Snow	0.0%	3.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.7%
Wind Slab	11.1%	22.2%	18.5%	22.2%	7.4%	0.0%	0.0%	0.0%	0.0%	81.5%
PWL	0.0%	0.0%	0.0%	7.4%	3.7%	3.7%	0.0%	0.0%	0.0%	14.8%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	11.1%	25.9%	18.5%	29.6%	11.1%	3.7%	0.0%	0.0%	0.0%	

<u>Avalanche Problem and Likelihood</u>

A contingency table was used for avalanche problem and likelihood to find the most frequently selected likelihood and the problem for that likelihood. The participants with traditional data selected the wind slab problem as unlikely to possible 53.8% of the time (Table 20). And the new snow problem had the highest frequency as possible (Table 20).

Table 20: Case study two, SW path, avalanche type and likelihood contingency table for traditional data

	Unlikely	Possible	Likely	Very Likely	% Totals
New Snow	10.3%	15.4%	2.6%	0.0%	28.2%
Wind Slab	33.3%	20.5%	7.7%	2.6%	64.1%
PWL	0.0%	0.0%	0.0%	0.0%	0.0%
Wet Snow	0.0%	7.7%	0.0%	0.0%	7.7%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	43.6%	43.6%	10.3%	2.6%	

The frequencies of likelihood and problem type in the case study with RS+ data showed 62.9% of the responses from participants found a wind slab was unlikely to possible (Table 21). Also, 14.8% of the responses recorded a PWL was possible to likely (Table 21).

Table 21: Case study two, SW path, avalanche type and likelihood contingency table for RS+

	Unlikely	Possible	Likely	Very Likely	% Totals
New Snow	3.7%	0.0%	0.0%	0.0%	3.7%
Wind Slab	33.3%	29.6%	18.5%	0.0%	81.5%
PWL	0.0%	3.7%	11.1%	0.0%	14.8%
Wet Snow	0.0%	0.0%	0.0%	0.0%	0.0%
Glide	0.0%	0.0%	0.0%	0.0%	0.0%
% Totals	37.0%	33.3%	29.6%	0.0%	

Case Study Data Summary

A summary of results from the case studies is show in Table 22. First, in both case studies the mode for the forecasted avalanche problem was a wind slab problem for both groups (Table 22). Second, in all the case studies there was a difference in the central tendency of the two participants groups for the forecasted avalanche size (D) (Table 22). Participants with RS+ data in case study one and two NE forecasted a smaller avalanche size (D) (Table 22). For avalanche size (D) in case study two SW, the RS+ participants mode was a larger avalanche size, than the mode of the traditional participants. Third, the median and mode of the forecasted likelihood of avalanches were lesser amongst RS+ participants in case study one, and greater amongst RS+ participants in case study two NE. Case study two SW showed the same median and mode across the groups. The result of these differences in size and likelihood across the case studies resulted in the participant groups forecasting the hazard level to be less hazardous in case study one, while the other case study resulted in the same forecasted avalanche hazard level.

Table 22: Data summary of case study one and two results

Case Study	**Variable**	**Median**		**Mode**	
		Traditional	*RS+*	*Traditional*	*RS+*
One	Problem	NA	NA	Wind Slab	Wind Slab
	Size	3.0	2.5	3.5	2.5
	Likelihood	Likely	Possible	Likely	Possible
	Hazard Level	Some Restrictions	Normal Attention	Some Restrictions	Normal Attention
Two NE	Problem	NA	NA	Wind Slab	Wind Slab
	Size	2.5	2.0	2.5	2.0
	Likelihood	Possible	Possible	Unlikely	Possible
	Hazard Level	Normal Attention	Normal Attention	Normal Attention	Normal Attention
Two SW	Problem	NA	NA	Wind Slab	Wind Slab
	Size	2.0	2.0	1.5	2.5
	Likelihood	Possible	Possible	Unlikely	Unlikely
	Hazard Level	Normal Attention	Normal Attention	Normal Attention	Normal Attention

Real-Time Forecasts

There were 17 forecasts written by a forecaster with RS+ data. 7 were invalid because they lacked a hazard matrix and/or a corresponding traditional forecast. Therefore, there are 10 valid forecasts. The 8 forecasts without a consensus are summarized in Table 23. The two forecasts with a corresponding consensus forecast are summarized in Table 24.

The forecasts summaries below show the avalanche forecast for the next 12 hours. The weather summaries are translated to English. The quoted and paraphrased words about the weather are from the internally published forecast that used traditional observations. The weather forecast from the forecaster with traditional observations was selected because it does not rely on

UAV data, and the internally published forecast is double checked by a supervisor at the NPRA. The hazard matrixes from the forecasters are in Appendix D. Two forecasts included wind to transport snow in the written weather forecast (January 31 and February 16, 2023). Two weather forecasts contain new snow problems (March 16 and March 20, 2023). February 1, February 16, March 13, and March 15, 2023 have calm weather in the weather forecast.

Table 23. Real-time forecast summaries, n=8

Date and Weather Summary	**Forecast Summary**		**Hazard Level**	
	Traditional	*RS+*	*Traditional*	*RS+*
January 31, 2023 “On Tuesday afternoon and evening, about 5 cm of snow is forecast with winds (6-9 m/s) from the southwest.”	New snow avalanches size (D) 2 – 2.5 are possible	Wind slab avalanches size (D) 2.5 – 3 are possible, new snow avalanches size (D) 1.5 are likely	Normal Attention (1 of 4)	Increased Awareness (2 of 4)
February 1, 2023 “Wednesday […] nice weather and calm winds are expected.”	Wind slab avalanches size (D) 1.5 are unlikely	Wind slab avalanches size (D) 2.5 – 3 are unlikely, wind slab avalanches size (D) 1.5 are possible, new snow avalanches size (D) 1.5 are likely	Normal Attention (1 of 4)	Normal Attention (1 of 4)

Table 23 continued.

Date and Weather Summary	Forecast Summary		Hazard Level	
	Traditional	*RS+*	*Traditional*	*RS+*
February 3, 2023 "The precipitation forecast for Friday night did not materialize. For the rest of Friday and Saturday, fine weather and calm winds are expected until windy weather on Saturday evening."	Wind slab avalanches size (D) 1.5 are unlikely, persistent slab avalanches size (D) 1.5 are unlikely, wet snow avalanches size (D) 1 are unlikely	Wind slab avalanches size (D) 3 are unlikely	Normal Attention (1 of 4)	Normal Attention (1 of 4)
February 16, 2023 "On Friday and Saturday, precipitation will fall as snow in the start zones. Most of the precipitation will come with winds from the NW, up to light gales."	Wind slab avalanches size (D) 1 – 1.5 are unlikely	Wet snow avalanches size (D) 1 are unlikely to possible	Normal Attention (1 of 4)	Normal Attention (1 of 4)
March 13, 2023 "Calm wind conditions and little precipitation. Cold"	Persistent slab avalanches size (D) 3 are unlikely, Wind slab avalanches size 2 – 3 are possible, new snow avalanches size (D) 2 are possible, wind slab avalanches size (D) 2 – 2.5 are likely	Wind slab avalanches size (D) 1 – 2 are unlikely, persistent slab avalanches size (D) 3 are possible	Increased Awareness (2 of 4) falling to Normal Attention (1 of 4)	Increased Awareness (2 of 4)

Table 23 continued.

Date and Weather Summary	**Forecast Summary**		**Hazard Level**	
	Traditional	*RS+*	*Traditional*	*RS+*
March 15, 2023 “Storm from the south/southeast and 20mm of precipitation [starting Thursday.]”	Persistent slab avalanches size (D) 2 are unlikely, new snow avalanches size (D) 1.5 are unlikely to possible, wind slab avalanches size (D) 1.5 are unlikely to possible, wind slab avalanches size (D) 2 are possible	Persistent slab avalanches size (D) 1.5 – 3 are unlikely	Normal Attention (1 of 4)	Normal Attention (1 of 4)
March 16, 2023 “Storm from south/southeast and 20mm of precipitation from Thursday evening and through Friday.”	Persistent slab avalanches size (D) 2.5 are possible to likely, wind slab avalanches size (D) 2.5 are likely	Persistent slab avalanches size (D) 2.5 – 3 are possible to likely	Normal Attention (1 of 4) rising to Increased Awareness (2 of 4)	Some Restrictions (3 of 4)
March 20, 2023 “Windy weather on Wednesday may transport snow. 10 cm of fresh snow is possible above 1200 meters above sea level.”	Persistent slab avalanches size (D) 2.5 are unlikely, wind slab avalanches size (D) 2 are unlikely to possible	Persistent slab avalanches size (D) 2.5 are unlikely	Normal Attention (1 of 4)	Normal Attention (1 of 4)

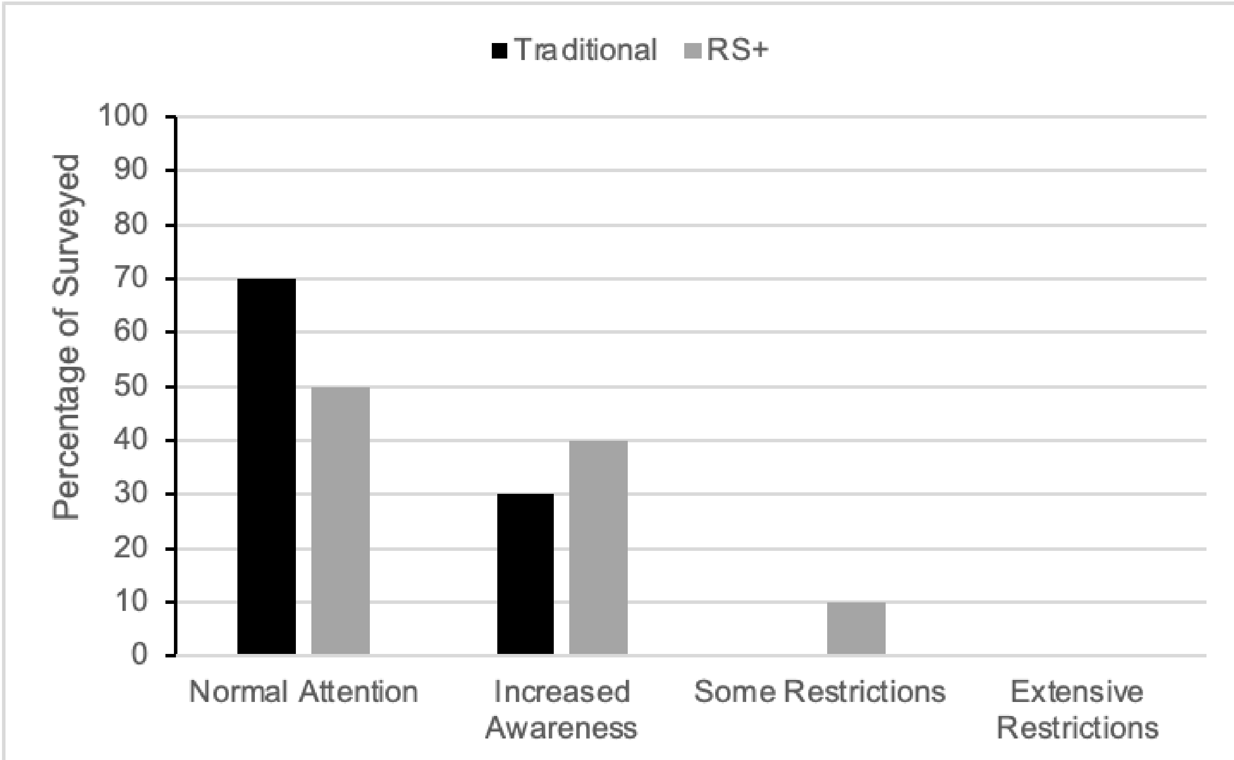


Figure 22. Real-time forecasts frequency distribution of hazard level selected by NPRA forecasters (this also includes the two instances where a consensus forecast was written, n=10)

<u>Real-Time Forecasts with Consensus Forecast</u>

These are summaries of the avalanche forecasts that had a traditional forecaster, a RS+ forecaster with UAV data, and a consensus forecast was written (Table 24). The summaries also include comments from the forecasters after they wrote the consensus. On February 17, 2023, there was a difference between the two hazard levels. This resulted in a consensus forecast that agreed with the traditional forecaster. On March 3, 2023, that was a combining of avalanche size and likelihoods in the consensus so that both forecasters had their forecast incorporated in the consensus forecast.

Table 24. Real-time forecast summaries with a consensus forecast, n = 2

Date and Weather Summary	**Forecast Summary**			**Hazard Level**		
	Traditional	*RS+*	*Consensus*	*Traditional*	*RS+*	*Consensus*
February 17, 2023 "Precipitation as snow throughout the [next 2.5 days]. Wind from W and NW becoming NW gale Saturday."	Wind slab avalanches size (D) 2 – 2.5 are possible, wind slab avalanches size 2 are likely	Wind slab avalanches size (D) 2 – 2.5 are possible, wind slab avalanches size 2 – 2.5 are likely	Wind slab avalanches size (D) 2 – 2.5 are possible, wind slab avalanches size 2 are likely	Normal Attention (1 of 4)	Increased Awareness (2 of 4)	Normal Attention (1 of 4)
Consensus Forecast Comments Summary	We agree on probability but differ on avalanche size. The RS+ forecaster assumed a worst-case scenario with avalanches stepping down to a weak layer. The RS+ forecaster agrees with the traditional forecast and reduced size and hazard level.					
March 3, 2023 "Precipitation and cold weather is expected throughout the weekend, and winds up to stiff gales from the northwest."	Wind slab avalanches size (D) 2.5 – 3 are possible, wind slab avalanches size (D) 2.5 are likely	Wind slab avalanches size (D) 3 are possible, wind slab avalanches size (D) 2 are likely, wind slab avalanches size (D) 1 are very likely	Wind slab avalanches size (D) 2.5 – 3 are possible, wind slab avalanches size (D) 2 – 2.5 are likely, wind slab avalanches size (D) 1 are very likely	Increased Awareness (2 of 4)	Increased Awareness (2 of 4)	Increased Awareness (2 of 4)
Consensus Forecast Comments Summary	"Uncertainty - with less precipitation/NW does not move in as far, the danger will be lower. There is uncertainty about the extent of weak layers high in the snow cover after cold and clear weather before the precipitation started on Friday."					

CHAPTER FOUR

DISCUSSION

Decision uncertainty is inherent in avalanche forecasting, and the inductive process of avalanche forecasting process uses uniform processes like CMAH to minimize uncertainty (LaChapelle, 1980; Statham et al., 2018). New and complex data can complicate this process because data has varying degrees of uncertainty (McClung, 2002b, Jamieson et al., 2015). One concern with all data is increased data entropy (McClung, 2002b). New data types, like UAV imagery, can exist as class I, II, or III observations. When UAV data is a class I observation like an image of an avalanche, it will have the least amount of data entropy. However, it can also be an observation of snowfall or weather conditions and be classified as class III data with the most entropy. Uncertainty and the meaning of a datum is a characteristic of data collection and a frequent problem in avalanche forecasting (Jamieson et al., 2015). Dreyfus and Dreyfus' (2005) research shows that this is where expertise is important—it allows a decision maker to use their experience to separate the signal from the noise, which looks like using the right observation about the right avalanche problem in avalanche forecasting (Jamieson et al., 2010). When new data becomes available, experience can be limited. However, literature from other industries suggest that there are effective ways to build competence. Decision aids like CMAH, comprehensive frameworks, and fast and frugal trees can help as the industry builds experience with new data types (Wegwarth et al., 2009). Furthermore, the avalanche industry can lean on the experience of expert weather forecasters that have seen their industry expand to include more complex data for forecasting (Stuart et al., 2007). Finally, collective intelligence, which was frequently mentioned by avalanche forecasting supervisors during their interviews, should continue to be a part of the avalanche forecasting process. The literature suggests it is effective (LaChapelle, 1980; McClung, 2002a; Krause et al., 2010; Jamieson et al., 2015; Radcliffe et al., 2019). Moreover, the comments from the results of real-time forecasts with a consensus forecast (Table 24) show that a forecaster in both scenarios changed their mind when they came together to make a consensus forecast. Using literature from other professions and qualitative results from this study, there are ways to reduce uncertainty when a new data is added to a forecasting operation.

In addition to data entropy, there is uncertainty in the accuracy of the measurement, and the science being used to observe a phenomenon (Jamieson et al., 2015). That is why data is evaluated for reliability in avalanche forecasting (Figure 2 step 3). Moreover, new, complex data requires avalanche forecasters to learn new computing techniques and interpretive skills, like when they view Figure 6. These interfaces can not only increase the cognitive load on forecasters, but application interfaces and automation can manipulate the forecasters (Darioshi & Lahav, 2021). The case studies show that there were significant changes in the forecast in case study one and case study two SW because they had some variables with *p*-values less than 0.05. In those studies, the participants with RS+ data selected fewer boxes in the hazard matrix, indicating a stronger grasp of the size and likelihood of avalanche problems. Additionally, in case study two NE there was little difference between the forecasts, which could indicate that the introduction of new information did not increase the cognitive load of the participants with RS+ data. Furthermore, the similarity in responses from case study two NE suggests that new biases were not introduced when RS+ data was presented to participants. The following sections explore how these results from the case studies and real-time forecasts show there was some change in the forecasts, and what that means for the future of avalanche forecasting.

Case Study One

The forecasted size and likelihood were one step higher for those with traditional data than those with RS+ data (Table 22). The mode for participants with traditional data was a size D3.5 while the mode for RS+ participants was a size D2.5. Also, the mode for likelihood from participants with traditional data was likely, while the mode for participants with RS+ data was possible. Looking at the products created by those with traditional data we found that the avalanche size was consistently rated larger than the avalanche size of those with RS+ data. The observations provided to a participant with traditional data was limited to field reports of a size D3 avalanche and an obscured web camera image. A participant with RS+ data received a LiDAR digital elevation model that allowed them to see mitigation results more clearly.

The IQR for size and likelihood also reflects this same one step change in the range of hazard-level responses. Moreover, the tails of the range for those with RS+ data show 17.4% of the selections were classified as unlikely whereas only 4.4% of the responses from traditional data were categorized as unlikely. In fact, those with traditional data selected very likely 24.4% of the time while those with RS+ data selected very likely 13.1% of the time. Almost half of the participants (48.9%) with traditional data agreed on the likelihood as likely. Whereas the participants with RS+ data were split between possible (34.8%) and likely (34.8%).

A product of this one step change in size and likelihood resulted in a two-step change in hazard level, which would significantly alter the restrictions for highway management in Norway. This shows the value of increased forecaster confidence because it allows the forecaster to select fewer boxes, which can prevent increasing the hazard due to forecaster uncertainty. In case study one the RS+ participants had more detailed, visual data about the impact of mitigation. This is class I data, which has the least amount of data entropy, which reduces uncertainty about the instability—the goal of avalanche forecasting. The mode forecast for hazard level among traditional participants responses was some restrictions—the RS+ participants most frequently selected normal attention. The frequency distribution for those with RS+ data in figure 8 shows 58.7% of responses falling in the normal attention (1 of 4) category. Figure 8 also shows the disagreement among the responses of participants with traditional data. Combining this information, we see that those with RS+ found that smaller avalanches were at a lower likelihood; therefore, we find more agreement with hazard level among RS+ participants suggesting a reduction in uncertainty. For likelihood and hazard level, despite the small sample sizes, there were *p*-values below 0.05. Although this is a small sample size, this result suggests that the RS+ data significantly impacted the choices made by those with RS+ data.

When we consider the avalanche problem type, initially, the results seem uniform with both groups selecting wind slab problems most frequently. However, the participants with traditional data selected a PWL problem while the RS+ participants did not. Despite both groups having access to an observation stating that a crust was found four days prior in the area. Although it could not be proven that this observation alone was the significant factor in traditional participants choosing a PWL, it is important to note that traditional data participants had fewer observations to read through. With fewer observations there is a lower cognitive load, and cognitive load reduction can help manage the mental calculations required in forecasting (Darioshi & Lahav, 2021). However, fewer observations can also influence the value a user places on each observation. And fewer observations can make each data point a more accessible memory when the forecaster records their avalanche problem. Furthermore, PWLs are an avalanche problem that is complex for many forecasters (Hordowick, 2022). This type of uncertainty—where scientific knowledge does not fully understand a phenomenon can heavily influence a forecaster (Jamieson et al., 2015). McClung 2002b discusses how bias 6, availability, can cause forecasters to rely on specific, uncommon events easily recalled to and other relevant information is excluded. McClung's resolution to this problem is using computer assisted forecasting. Moreover, McClung 2002b suggests that that bias 12, anchoring, occurs when forecasters extrapolate avalanche problems to area where it might be irrelevant. Although the PWL layer was observed in this area, the observation was important to those with traditional data despite post mitigation results indicating that the PWL was not reactive. Although we cannot pinpoint which bias influenced the uncertainty of the traditional participants, the results show that the group was more uncertain about the forecast.

A forecaster with LiDAR imagery could be influenced by the digital elevation models and erosion maps because it was four detailed images about class I data—avalanche observations. McClung 2002b discusses this as bias 4, recency. The recent information about an avalanche may cause an RS+ participant to ignore the PWL problem reported earlier in the week and trend towards a wind slab and new snow problem. Additionally, less forecaster uncertainty and therefore increased confidence does not necessarily mean the forecast is more accurate (McClung, 2002b). These data from the RS+ observations could contribute to overconfidence and introduce a new bias that is not captured in older studies about forecaster decision-making. However, since the information from the UAV was class I data, it is important to consider that this is a critical, low entropy observation. Here, we found a *p*-value less than 0.05 for avalanche problem, which suggest the RS+ data significantly influenced the response to the avalanche problem.

Case Study Two: NE Slide Path

The northeastern facing slide path on this weather day experienced a substantial wind event that eroded nearly two meters of snow. Both the traditional data participants and the RS+ participants seemed to identify this and settle on small, low likelihood avalanches for the next 24 hours. For avalanche size, the RS+ participants (median and mode of D2) were only a half-step smaller than the traditional data participants (median and mode of D2.5). All participants were provided with wind data, but more importantly, both groups had visual representation of the wind event. The traditional participants had still web camera imagery that showed windy conditions, and the RS+ group had the web camera stills and erosion maps showing a loss of nearly two meters of snow. The small difference in the avalanche size forecasted may highlight how the RS+ participants had more detailed information about the wind event. There was little variation in likelihood among the participants. The only variation was the traditional participants had a mode of unlikely while the RS+ participants had a mode of possible. Ultimately the similarities between these groups resulted in high *p*-values and a hazard level of normal attention being selected in both scenarios. This is an important finding for this study because it suggests that the addition of RS+ data had a neutral outcome; therefore, RS+ data did not introduce a new bias that was more detrimental than the biases of traditional forecasters.

An interesting result in this survey is that traditional participants recorded 36 responses in their hazard matrixes, and the RS+ participants recorded 23 responses. This suggests more forecaster certainty in the RS+ participant assessment of the size and likelihood of a given avalanche problem. Unfortunately, for the northeastern slide path two invalid responses from RS+ participants make it hard to be confident in that conclusion. Although this sample size is even smaller than case study one, for this scenario the *p*-values suggest that UAV LiDAR data did not significantly change the four variables in this scenario.

Case Study Two: SW Slide Path

Traditional data for this scenario had limited information about the south facing slide path. The RS+ participants had LiDAR derived DEM and an erosion and deposition map. The southerly facing slide path in this scenario is far smaller, but even a small avalanche is more likely to hit the road. For avalanche size, the medians for both groups of participants were a size D2. However, the mode for traditional participants was a size D1.5 while the RS+ participants had a mode of D2.5. This is apparent in the heat map differencing figure, which shows a 14.2% increase in size D2.5 avalanches by RS+ participants, which is the largest increase in an avalanche size category across all three case studies (Table 17). This is important because the data available to the RS+ participants showed a detailed DEM with a visible avalanche (Appendix B, Figure B4).

For likelihood, both groups assessed the median and mode as possible and unlikely respectively. However, the IQR for likelihood was different. For participants with traditional data the IQR was unlikely to likely, and those with RS+ had an IQR from unlikely to possible (Table 15, 16). Looking at the tails in the frequency graphs (Figure 18) of the RS+ participants we see far more participants selecting a likelihood of likely. In fact, Figure 18 shows that there was a

19.4% increase in selections of likely, which was the largest increase in a likelihood across the heat map differencing figures.

The one step change in size and likelihood was not large enough to change the avalanche hazard level from normal attention. One issue in using this idea to measure changes in the forecast between groups is that this avalanche path is small, even higher likelihood avalanches will not necessarily raise the hazard level. However, the hazard level and avalanche problem type have a *p*-value less than 0.05. Although this is a small sample size, the frequency distributions provide more context.

More RS+ participants were selecting wind slab and PWL problems as opposed to new snow problems. Additionally, more RS+ participants selected increased awareness (level 2 of 4) and some restrictions (level 3 of 4). Looking at the data provided to the participants, the RS+ participants had an avalanche observation in the LiDAR data and more clear information about the impact wind had on the southerly slide path, which is a good observation for this problem (Jamieson et al., 2010). Although, the avalanche is hard to see in the image, the LiDAR imagery showed deposition, which was more information about the south facing slide path than the traditional participants received.

Again, in this case study the traditional respondents had far more responses (39) than the RS+ participants (27). With a similar number of participants, it is appropriate to look at this closer. The frequency distribution of avalanche size shows that every size of avalanche was selected at least once by a traditional participant. Alternatively, the RS+ participants did not select an avalanche size larger than a D3.5. This raises the question if RS+ participants were more certain in their selections, or if other explanations like a misunderstanding of the hazard matrix resulted in this pattern.

McClung 2002b notes that more information can increase confidence. (It should be noted that confidence does not suggest accuracy (McClung, 2002b.)) The right type of data about the avalanche problem can reduce uncertainty (Jamieson et al., 2010), and here, as in case study one, the reduction in hazard matrix selections suggest that UAV data was the right information about the pertinent avalanche problem. With this happening a second time, this suggest an increase in forecaster confidence due to the decrease in responses in the hazard matrix. A decrease in responses suggest higher confidence in a forecast because it means the forecaster is more certain about the size and likelihood of a particular avalanche problem, which results in a more precise avalanche hazard level. CMAH also discusses how uncertainty is built into definitions of likelihood (Statham et al., 2018). And the hazard matrix from the NPRA allows for a similar range of possibilities of size and likelihood, much like a confidence interval (Statham et al., 2018). Therefore, a reduction in responses that clusters around a certain size and likelihood suggests increased confidence.

Real-Time Forecasts and Consensus Forecasts

In all 10 real-time forecasts, which includes the two cases with a consensus forecast, the forecasters agreed on the hazard level 6 out of 10 times. Out of those 6 times the hazard level was normal attention (level 1 of 4) 5 times (Table 23, 24). Only once was the hazard level higher than normal attention and agreed upon, which was on March 3, 2023, at increased awareness (level 2 of 4). Logically, this makes sense because Figure 4 shows that green, normal attention makes up much of the hazard matrix. In the other 4 instances the RS+ forecaster assessed the hazard level to be higher than the traditional forecaster. The frequency distribution in Figure 22 emphasizes this phenomenon.

There are several reasons why this methodology for establishing which forecast is better is problematic. Also, it is challenging to determine if the change in the forecast were caused by the additional data stream. First, the stakes are far higher for the traditional forecaster—they are writing a real forecast. The RS+ forecaster is writing an additional forecast on a day where they were not originally able to forecast. Second, using these events as a data set is challenging because the ability for this methodology to succeed required a LiDAR scan of the area. This meant that sometimes LiDAR scans were only taken when the weather was good enough for UAV pilots to travel to the study area. Unfortunately, that is not when the most complex avalanche conditions exist, which contributes to several results in normal attention (level 1 of 4). Additionally, when complex avalanche conditions exist it is hard to image an operation using their resources to write a forecast that will not be used. Lastly, managing this project and asking forecasters to come together and write a consensus forecast during the season is time consuming (Logan & Greene, 2023). For instance, sometimes a RS+ forecast was written, but there was no traditional forecast because the NPRA does not forecast every day when the hazard level is at normal attention (level 1 of 4).

The limited dataset shows a tendency for forecasting a higher hazard level when a forecaster had RS+ data. The consensus forecasts comments in Table 24 show how some discussion can help improve the forecast, and this corroborates the qualitative suggestions of McClung 2002b, Jamieson et al. 2015 and CMAH. On February 17, 2023, the traditional forecaster helped the RS+ forecaster feel more certain about a weak layer that was recently buried by new snow. And on March 3, 2023, the RS+ forecaster helped the traditional forecaster write a more complete forecast that included size (D) 1 avalanches as very likely. This methodology could be fruitful with an operation that has scrupulous record keeping, and an operation with the ability for employees to review old weather forecasts, observations, and web camera images to assess forecasts in the offseason (Logan & Greene, 2023).

Overall Discussion

The results suggests that additional information, in this case from UAV LiDAR scans of the snow surface, changes the assessment of the avalanche hazard post-mitigation and prior to mitigation. The results of fewer selections in the hazard matrix from case study one and case study two SW confirm McClung 2002b and Jamieson et al. 2010's qualitative findings that the right type of information can reduce uncertainty for a forecaster. In case study one the RS+ participants determined that although the likelihood was "likely" the avalanche size was much smaller than the traditional participants believed, which resulted in a lower hazard level. In case study two SW the RS+ participants had fewer responses in the hazard matrix suggesting more certainty in their selections of size and likelihoods. Following the principles of CMAH for hazard assessment this suggests a decrease in uncertainty (Statham et al., 2018). Furthermore, this study shows that a case study approach presented to a group of forecasters can be a methodology to assess the impact additional data could have on forecasting products and outcomes. In addition to looking at what changed and how that influenced forecaster certainty, this approach could also highlight overly conservative decision making when using rules or being subject to biases. When non-experts make difficult decisions they often use rules or heuristics, which is one of McClung 2002b's biases as well as a sometimes effective tool for learning that can be based on expert approaches (Luan & Reb, 2017). Determining if a data stream is causing an operation biases and negative outcomes, and using forecasters more familiar with the new, complex data to teach the operation would improve the roll out of new data.

A goal of this study was to find how new data streams will impact the cognitive load of an avalanche forecaster and ultimately the products they create. This study asked forecasters with a range of experiences with traditional data and complex data, years forecasting, and types of forecasting because that more accurately reflects the make-up of an avalanche forecasting operation. For example, an avalanche forecaster with one year of professional experience could have studied remote sensing at a university, while a forecaster with 15 years of professional experience has limited exposure to remote sensing technology (Darioshi & Lahav, 2021).

With a small sample size, it is unrealistic to make strong statements about statistical differences because small changes in the data have a large influence on the results of statistical tests. Therefore, we suggest that this same methodology is valuable in assessing how new data impacts a forecaster, and if that change is desirable with respect to operational decision making.

A challenge of this study is measuring that impact because knowing which forecast is correct or the most accurate is influenced by data entropy and forecaster uncertainty (Schweizer et al., 2003; Techel & Schweizer, 2017; Logan & Greene, 2023). During high avalanche hazard (large size (D) and increased likelihood) or low avalanche hazard (small size (D) and decreased likelihood) the presence or lack of avalanche observations can provide increased feedback because there is decreased uncertainty in the observation classes. However, between these two bounds of an avalanche hazard level is where an operation can see increased uncertainty from the lack of feedback about avalanche activity. To reduce uncertainty operations using avalanche mitigation with explosives can gain additional feedback from mitigation results (Jamieson et al., 2015). Although mitigation and the choice of when and where to use mitigation has its own level of uncertainty, the experimental design of this project shows why mitigation is a valuable piece of information that can be used in forecast assessment during the evaluation stage of the framework (Figure 2, step 10 and 11).

This case study approach testing changes to a forecasting workflow can assess the impact of those changes. It can also help an operation more effectively prepare for possible problems by indicating possible biases from an observation type. Finally, it can indicate when a technology is less helpful to an operation. For example, results from a case study following this methodology that show minimal change in forecaster responses would need to be compared to the relative investment to acquire this stream of additional information. However, any cost-benefit analysis should always consider that even a marginal gain in forecast quality could mean the difference in potential lives lost or saved, so this analysis should be undertaken with great care. It should be noted that this study is testing for changes in four specific variables that focus on uncertainty reduction in forecasting, rooted in the CMAH (Statham et al., 2018). It does not test for other possible value of technology (e.g., employee safety enhancement, resource and time management, etc.).

Ultimately, avalanche operations with extensive mitigation plans and several team members stand to benefit from the framework, case study, and real-time forecast methodology. For instance, some North American ski patrols have several employees that are actively engaged with frequent avalanche mitigation, and they are intimately familiar with the terrain. A group like this would benefit from the framework because it can ensure all employees are on the same page for a forecasting workflow. Additionally, these groups could use the case study approach with real events during early season training, and the assessors would have historical data to determine which group of forecasters was correct based on mitigation results. Additionally, the larger number of forecasters on a ski patrol and more opportunities for mitigation provides feedback for real-time forecast assessment, which could improve the quality of consensus forecasting and the results from such a study. Additionally, a highway operation with active mitigation programs and several tools to monitor avalanche conditions can confirm forecasts with mitigation.

In addition to operations benefiting from this methodology, some forecasting operations stand to benefit from the results of this study. The results suggest that when an observation from the UAV data provided more information about an avalanche condition the responses decreased, or clustered in a smaller area; thus, decreasing forecaster uncertainty. Therefore, avalanche operations that struggle to monitor start zones due to safety concerns or the remoteness of an area, much like the NPRA, stand to benefit from a data type that prevents forecasters from exposing themselves to an avalanche hazard.

Furthermore, remote or data sparse regions will likely have more uncertainty in the instability due to the lack of observations. A tool, like a UAV or other autonomous data stream, provides spatial and temporal observations of remote areas on a consistent, predictable scale. Here, the NPRA is gaining snow surface and erosion/deposition observations of two avalanche paths that are distant from work centers and are exposed to avalanche hazard. Spatially consistent observations of this path can provide valuable data as the snow cover changes throughout the season, and these observations help build a historical record of noteworthy conditions that remain accessible online. Additionally, temporally consistent UAV observations (e.g., 24 hour, 12 hour, weekly, etc.) provide a reliable observation when other observation types are unattainable. By contrast, traditional observations can be spatially inconsistent because snow pits are destructive; thus, they are not dug in the same place throughout the season. Observations of a fine, fixed area (e.g., weather stations, study plots, snow profiles) have varying scales of application, increasing their uncertainty (Jamieson et al., 2015). Lastly, the spatial and temporal scale of these samples are sometimes convenient or historical. Although the value of the RS+ data consistency was not expressly tested with this methodology, the case studies suggest that RS+ forecasters provided with an observation that the traditional observations did not highlight or capture reduced uncertainty about the instability.

Another benefit of more consistent data from UAV's or other autonomous data streams, is that it provides a visual representation of the season's snow cover. This is important because it can be used for improved record keeping, which could be used as a tool for the assessment of avalanche forecast accuracy when using the framework (Figure 2, stage iii). Moreover, these consistent observations could be used for in season assessments of the forecasts by building a historical record of images from UAVs. Particularly in step 10 of Figure 2, forecasters could note surprising results and compare past and present UAV data of avalanche paths. Again, this data was not used for this purpose during this project, but the ability for forecasters to gain confidence in their forecasts based on historical precedent could be a natural use of these products.

Building a case study based on real observations and data is relatively easy. And isolating the new data or the data delivery method by only providing it to the experimental group can show the tendencies of each group. Using an internal hazard level scale as presented here, or a more traditional danger scale (i.e., European or North American Danger Scale) is a robust approach to look at how step changes occur. Some of the most important data comes from the movement of the central tendencies. Additionally, we can derive the reduction in uncertainty by looking at the IQR and contingency tables of likelihood and size compared with the avalanche problem.

CHAPTER FIVE

CONCLUSIONS AND FUTURE WORK

This study shows that adding an advanced data stream to a forecaster's workflow will change the outcome of the forecast. Case study one resulted in a one-step change in hazard level when avalanche forecasters were given RS+ data and a two-step change in size and likelihood. The RS+ participants set a lower hazard level (normal attention (level 1 of 4)) than the traditional participants (some restrictions (level 2 of 4)). The likelihood, avalanche problem, and hazard level all had p-values less than 0.05.

In case study two, for the large northeastern slide path, both groups of participants set the avalanche hazard level at normal attention. There was a half-step change in the avalanche size, with traditional participants selecting a size D2.5 while the RS+ participants selected a size D2. None of the four variables had a p-value less than 0.05. In case study two, for the smaller SW slide path, both groups of participants set the avalanche hazard level at normal attention. However, there was a one-step change in the mode of the avalanche size from the traditional participants at D1.5 to RS+ participants at D2.5. The avalanche problem and hazard level had a p-value less than 0.05. The participants with RS+ data selected far fewer boxes in the hazard matrix suggesting greater confidence in their assessment.

For the real-time forecasts throughout the season when the weather was calm the forecasters agreed on 3 of 4 forecasts. When snow was in the weather forecast the RS+ forecaster had a one-step higher hazard level in 2 of 3 forecasts. When wind and snow was in the weather forecast the forecasters agreed 2 of 3 times, and the RS+ forecaster had a higher hazard level once. The consensus forecasts showed that one RS+ forecaster overestimated the size of the avalanches. The forecast for March 3, 2023, the showed that the RS+ forecaster was certain of small avalanches being very likely, and those avalanches were ultimately added to the consensus forecast.

This paper presents a workable methodology to better understand and assess the impact of new data products on the avalanche forecasting process, and outcomes. However, it comes with limitations on time, resources, and capacity of humans working in a dynamic environment. If those limitations were removed the first step in this study would be applying the case study approach to several different forecasting operations (e.g., public, transportation corridors, ski resorts, private mines, etc.) across different climates. Additionally, those case studies would test different types of data streams (e.g., satellite data, UAV, TLS, time-lapse camera, SNOWPACK, statistical forecasting, internal weather models, AI assistance etc.). This would allow for broader conclusions to be drawn on each data type. Additionally, developing an assessment tool for the case study responses would allow for assessing forecast accuracy, and our conclusions could go further in assessing the success of a data type. Also, using more tools to analyze and visualize how the hazard levels are shifting from traditional users to new data type users. Lastly, determining the impact new, complex data will have on recreational users is an inevitable next step as this data becomes publicly available.

Next, the real-time forecasting methodology could be improved so a quantitative assessment is possible. First, an operation with a history of consistent record keeping practices would be needed so the study could take place over several years of operation. This would allow for conclusions to be drawn about the impact the data has on different weather events and seasonal snowpacks. Much like other assessments used to analyze the accuracy of avalanche forecasts there needs to be a correct forecast. Some suggest using a hindcasting weather model with the relevant observations, and this work used a consensus forecast based on the idea of collective intelligence. Additionally, operations that use mitigation will have another valuable tool for assessing forecasts. These methods would be useful to compare during a forecast analysis. The next big step would be scaling this process up so machine learning could analyze new data and make a hindcast that is best given the known results of the weather and additional observations. Then this data could be available for forecasters by the next morning so they could continue to adjust their forecasts throughout the year. This process of in season feedback from consistent UAV observations, could provide information on forecast efficacy and build a qualitative and quantitative record for improved assessment with the use of the framework (Figure 2).

This case-study approach is valuable to the avalanche forecasting community because avalanche operations are continually looking for ways to get more observations in their forecast area, and there is little research on how data streams change forecaster behavior. As costs of new products decrease, more avalanche forecasters will have the opportunity to get observations from complex data streams. Before more complex data streams become a part of an operation's suite of products, operations should know if the data results in outcome neutral forecasts, at a bare minimum. Ideally, they should be outcome positive, and operations should avoid data that increases confusion and leads to negative outcomes. Carefully interpreting that data and using existing observation techniques to determine which observations are relevant will be critical at the onset. This case-study approach illustrates how an organization could quantify the impact a new flow of information has on their forecasting team. Avalanche forecasting operations should be aware of the impact new data additions have on pool of observations available to a forecaster, or the impact of data delivery improvements or changes. The case studies show what is possible in assessing a new addition or changes to a professional forecaster’s workflow.

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APPENDICES

APPENDIX A

FORECASTER INTERVIEWS

Step 1:

This is a project from Norway where they are equipping drones with sensors to support the decisions being made by avalanche forecasters. They are supporting some of my thesis work.

My questions: Will this additional data improve forecaster decision making?

- Two products
    1. A framework that conceptualizes the decision-making process of an operational forecaster and where the major decision points are.
    2. An assessment metric for the quality of the forecast and mitigation decision
- How?
    1. Test if a forecaster with remote sensing data makes a better forecast by comparing their forecast to a forecaster with traditional observations only
        - In real time in Norway
        - Scenario using real data with other operational forecasters
    2. Interview experts to determine ways they would like to assess their decisions after a day of mitigation even when everything goes according to plan.

Step 2: Interview

1. What is your role within your organization?
    a. Supervisor/manager and forecasts 30-50% forecasting?

2. Can you walk me though your decision-making process for mitigation, opening, or closing the railroad in your own words?
    a. Modified forecaster funnel. Arrive look at big picture, area forecast discussion from NWS, look at a table based QPF product in 6hr increments, look at an hourly in 4k or 4/3k looking at 12-24 hour period. Timing of precip and possibly the end and intensities. Intensity and timing is most important. Then. Look at local wx in corridor. Wind, temp, precip. Go to study plot and dig into the snowpack, new snow, surface obs, profile, perform relevant tests (typically ECT), look at recent bonding. Then take obs back to office. Compile what all that means. Find hazard to most likely affect highway. 1 the ones that run first. 2 Also may involve catchments, do we have a buffer or not? Then determine if we need to shoot sooner or later. Then Schedule control work. Schedule is based largely on instability AND operational availability (don't do in middle of shift change). If confident about not doing anything then he will take direct ops and communicate with Alpental about release characteristics and runout. Factor that in. Last case for a decision dig more profiles or get eyes on paths.
    b. Throughout day there might be more things that happen on small scale. Look at more model runs, do an obs drive, ski area obs, study plot obs. Also, wx station data at the finger tips.
    c. Wx station data very important. Ridge sites to know free air temp is really important. There is specific data relevant to certain situations.

Figure A1 Continued.

3. Is there any type of data you wish you had, but you do not have it?
    a. Added a lysimeter to get outflow.
        i. Picked up the idea from NZ. 10 foot square slab with a drain center. The snowpack builds up and measures the water coming out scaled for a larger catchment. Operationally good for rain on snow for when it comes through. Then it helps when we get a steady state.
        ii. This shows how a snowpack will absorb some water.
    b. Now he knows some paths that are good indicator paths. Path specific release information is really important. Wishes he had this.
    c. Find out how much catchment is available. Drone with snowpack height is helpful but not part of the operation.

4. Is there something you think your operation needs to be more successful or reduce the stress on forecasters?
    a. For specific paths this would really help. If you know a small slide is going exceed the catchment.
    b. Hard to get eyes on the path, but clouds and heavy precip.
5. Is there something you think your operation needs to be more successful or reduce the stress on forecasters?

6. What does your rating system look like?

    a. Came from TARP group.
        i. Has more to do with operational outcomes
        ii. No hazard, nothing scheduled, under evaluation, scheduled, ongoing, full pass closure (permission to travel)

7. Mitigation technology?
    a. Artillery (used infrequently, once a year). Not as effective and takes a lot of time to set it up.
    b. Homemade trams to move large shots. 25lb anfo
    c. No RAMS for I90. Stevens pass has some.
        i. White pass not much
        ii. Then some hand charges on smaller passes.

Step 3: Walk through flowchart

1. Is there anything that sticks out when you look at this that you see and think there is no way we do anything like this and there is no need to do it in the future?

2. Are your operational objectives well defined by your operation?

    a. 12 – 24 hour timing is important. They need weather and avy info.

Figure A1 Continued.

   b. Summing up weather can be a quick conversation. Most stuff on I90 is concern about run out.

3. What type of data is available to your forecasters?

4. Do you currently have any data that is sometimes unreliable?

   a. The study plot is really small scale. With a less experienced forecaster this could be too little.
   b. ECT may not always be relevant (think surface hoar)
   c. Every couple of years new people come, but they have a level of previous experience. Still takes a few years to get it all together.

5. Do you use any version of the Conceptual Model of Avalanche Hazard?
   a. Not specifically. Use a similar method.
   b. Send out a weather and avalanche outlook to interested parties. Uses a rating system for operational base. Then another internal form that is distributed, with obs and relevant information, slides, naturals, etc.
   c. Concise and objective as possible.

6. How do you decide to mitigate? Is there an operational standard here?
   a. No, intuition and experience.
   b. If its uncertain-lean towards closure or control
   c. We don’t just shoot it because. Want certainty and confidence.
7. Validation?
   a. Can mostly see what happens when we place shots or ski down after control work to confirm results. Artillery spot is the least able to know.
8. Conversation about mitigation results
   a. Conversations can depend on snow structure conversations about results.
      i. New snow not a convo
   b. Deep persistent, more nervous about it. May gain some more knowledge and give it some time.

9. Looking at the operational performance score do you think you have data on these pieces so you could measure this if I provided some sort of scoring scale?
   a. A metric like this is really dependent on an avalanche release. Also, traffic volumes and maintenance work required. Traction and maintenance—untangling this is hard.
   b. Guessing size before mitigation could be helpful.
   c. Verbal outcome on what was the most helpful piece of information.

10. What does feedback after a decision like mitigation, closing, or opening after a period of danger look like for your organization? Do you measure accuracy?

Figure A1 Continued.

   a. Make avalanche report after mitigation. Runout and start stop. Blast record kept. An do the best to record all naturals.
   b. Get to see very active paths before they hit road because of catchments.

11. Looking at error types rooted in uncertainty… McClung says type 1 is a failure to claim instability and an accident occurs. Type 2 is an overly conservative decision. Is there any use of this in reviewing incidents?

12. Does your operation have a predetermined level of risk?

13. Are there any big decision points that I'm missing?

14. Would you be willing to participate in an exercise where your operation uses data from an event that happened at your operation in the past, and we add some piece of remote sensing to compare forecaster outcomes?

15. Is there anyone else you think I should talk with about the framework? QPF to get accuracy and see 72 hour change. Measure accuracy—more reliable

Figure A1. John Stimberis, Avalanche Forecaster at Washington State Department of Transportation Interview

Step 1: Would it be okay if I record this conversation?

This is a project from Norway where highway forecasters are equipping drones with sensors to support the decisions being made by avalanche forecasters. Norway is supporting some of my thesis work.

My questions: Will this additional data improve forecaster decision making?

- Two products
   1. A framework that conceptualizes the decision-making process of an operational forecaster and where the major decision points are.
   2. An assessment metric for the quality of the forecast and mitigation decision
- How?
   1. Test if a forecaster with remote sensing data makes a better forecast by comparing their forecast to a forecaster with traditional observations only
      - In real time in Norway
      - Scenario using real data with other operational forecasters
   2. Interview experts to determine ways they would like to assess their decisions after a day of mitigation even when everything goes according to plan.

Step 2: Interview

1. What is your role within your organization?

Figure A2 Continued.

a. Only forecaster. Large zone, avalanche problems from seward—mile 16 to mile 84. Huge swath of the railroad. 16 avalanche paths in those 70 miles. Risk has to do with exposure—sometimes storm but no freight. Sometimes a barge cannot cross. Hazard with no risk because freight isn't coming. Some team work with highway—road crew nervous about RR sometimes.
    i. Barges are stalled in icy straits.
b. Highrails sometimes at risk because workers on road. Employees on road. Can close off so they don't cross it.
c. Some paths have radar detection. Avalanche in front of train most dangerous.
d. Trains travel at 15 mph through leading up to slide path.
e. Some pressure to not close to get trains moving they can ice in.
    i. RR splits at MM 61—goes to woddyier. Then avy paths 62 to 16 all the way Seward not active business wise. Logistically problems—rather stop a train than let it get hit. Some economic pressure—so we shoot
f. 5th season. Only been a 4 for half a day.
g. 3, 2 and 1 mostly. Mostly lives at 2

2. What does data collection look like within your organization—what information is available?
    a. 2 weather stations in avalanche terrain towards Seward—less frequent traffic zone. More avalanche terrain less traffic. One NRCS, one AKRR.
        i. Water, snow depth (just total snow), ETI gauge when its raining
    b. Wind site (temp and rh and wind)
    c. Alyeska mid mountain site is best piece of data and wind site on Max's Mountain
    d. Wind stations rime up. So stations slightly lower are better. Most terrain in his zone is 3,000'
    e. Some wind stations only work 30-40% of time
    f. Site at portage—extra wet. RACS system and weather station on a path near this site coming in future. Add a LIDAR on to the RAC.
    g. Wants avalanche detection. Favorite data is infrasound. Wishes he had it. Some trouble with wind and infrasound.
    h. Most avalanches are dry that turn wet. Dry release… hit wet band and turns into wet slide.
    i. Infrasound triangulates—anything around 1.+ something hit road in LCC. Shows how far it went on the map. What path. And can give full track info by time.
    j. Field data is stolen from Chugach
        i. Area isn't accessible.
        ii. Can't always get up the tracks to get data.
        iii. Tracks weak layers from public forecast

3. Can you walk me though your decision-making process for mitigation, opening, or closing the railroad in your own words?

4. Is there any type of data you wish you had, but you do not have it?

Figure A2 Continued.

a. Additional people
b. Wants info before weather clears
c. Snowpack data—hard to get high elevation data.
d. LiDAR not number one—could track things better. Watch it for next time

5. Is there something you think your operation needs to be more successful or reduce the stress on forecasters?

6. What does your rating system look like?

    a. Mirrors 1-5 scale
        i. Really low threat, almost none
        ii. Storm but not worries—folks have to call in and out and wear beacon, clean up
        iii. Beacon, avy training, call in and out of slides, maybe control
        iv. Not going out. Control work, definitely. No track authority given. Only avy crew
        v. So bad we can't even do work.

7. What tech do you have mitigation

    a. Techs shoot with Howitzer.
    b. Scary part is clearing debris—exposing crews to this. Really shoots a lot to clear hangfire if he has a big avalanche down.

Step 3: Walk through flowchart

1. Is there anything that sticks out when you look at this that you see and think there is no way we do anything like this and there is no need to do it in the future?

2. Are your operational objectives well defined by your operation?

3. What type of data is available to your forecasters?

4. Do you currently have any data that is sometimes unreliable?

5. Do you use any version of the Conceptual Model of Avalanche Hazard?

6. How do you decide to mitigate? Is there an operational standard here?

7. Looking at the operational performance score do you think you have data on these pieces so you could measure this if I provided some sort of scoring scale?

Figure A2 Continued.

8. What does feedback after a decision like mitigation, closing, or opening after a period of danger look like for your organization? Do you measure accuracy?

9. Looking at error types rooted in uncertainty… McClung says type 1 is a failure to claim instability and an accident occurs. Type 2 is an overly conservative decision. Is there any use of this in reviewing incidents?

10. Does your operation have a predetermined level of risk?

11. Are there any big decision points that I'm missing?

12. Would you be willing to participate in an exercise where your operation uses data from an event that happened at your operation in the past, and we add some piece of remote sensing to compare forecaster outcomes?

13. Is there anyone else you think I should talk with about the framework?

14. The more data you get the better you are?

    a. Compare UDOT to Somewhere else

Figure A2. Matt McKee Avalanche Forecaster at Alaskan Railroad interview

Step 1:

This is a project from Norway where they are equipping drones with sensors to support the decisions being made by avalanche forecasters. They are supporting some of my thesis work.

My questions: Will this additional data improve forecaster decision making?

- Two products
    1. A framework that conceptualizes the decision-making process of an operational forecaster and where the major decision points are.
    2. An assessment metric for the quality of the forecast and mitigation decision
- How?
    1. Test if a forecaster with remote sensing data makes a better forecast by comparing their forecast to a forecaster with traditional observations only
        - In real time in Norway
        - Scenario using real data with other operational forecasters
    2. Interview experts to determine ways they would like to assess their decisions after a day of mitigation even when everything goes according to plan.

Step 2: Interview

8. Could you briefly describe the area you are responsible for forecasting?

Figure A3 Continued.

   a. 9 years of forecasting the Girdwood highway. Under Jim and Matt for a couple of years. All on the Seward Highway. South Central Alaska.

9. What is your role within your organization?
   a. Avalanche specialist, and state wide artillery program manger (Jim). Worked at Alyeska for several years. South Central Alaska. Milepost 104 to milepost 18. Portage, glacier highway, and hope. 7 gun mounts.

10. Can you walk me though your decision-making process for mitigation, opening, or closing the railroad in your own words?
    a. Line up a gun mission—only travel corridor to Kenai peninsula. No preventative road closures. Monitor 17 or 18 weather stations. Gun or heli mission. Daisy bell not used often. Small road closure during out missions.
    b. Campbell scientific, nrcs sites, and other stations used by AKRR and Alyeska.
    c. SWE, Wind speed and direction, 3 different climate zones
    d. Need more swe data, communications (needs satellites)
    e. Noaa spot forecasts, awg,
    f. Historical monitoring in a seasonal temporal scale
    g. Network of all avalanche groups—meet once a week.
    h. Overload it and seeing what is going on. Fast decision making.
       i. Gut feeling, intuition, see what went on. Moving quickly and dynamically.

11. Is there any type of data you wish you had, but you do not, have?
    a. Snow distribution is awesome, super helpful but it needs to be operational. If you can track this with artificial and naturals
    b. Radar stuff to see start zones and how far things are running

12. Is there something you think your operation needs to be more successful or reduce the stress on forecasters?
    a. More people and money!
    b. Really good reliable precip data at mid elevations
    c. Ski area had great precip sites—at least felt like you could back up decisions
       i. Driving hours to get eyes on things. Want live information.

13. Is there something you think your operation needs to be more successful or reduce the stress on forecasters?

14. What does your rating system look like?

    a. 1-5 scale
    b. 1: low hazard
    c. 2:
    d. 3: 10-12 days a year

Figure A3 Continued.

e. 4: 10-15
f. 5: 20+ years
g. Rating system could be improved upon. No time to do this now—be nice to nail things down. Put a general forecast out and individually call managers.

15. Mitigation technology?
16. Feedback loop?
    a. No formal. Talk it over with team but not
    b. Not formally spelled out
    c. Liability—
    d. Most pressure comes from internal, 66,000 people coming and going, doctor's appointments

Step 3: Walk through flowchart

16. Is there anything that sticks out when you look at this that you see and think there is no way we do anything like this and there is no need to do it in the future?

17. Are your operational objectives well defined by your operation?

18. What type of data is available to your forecasters?

19. Do you currently have any data that is sometimes unreliable?

20. Do you use any version of the Conceptual Model of Avalanche Hazard?

21. How do you decide to mitigate? Is there an operational standard here?

22. Looking at the operational performance score do you think you have data on these pieces so you could measure this if I provided some sort of scoring scale?

23. What does feedback after a decision like mitigation, closing, or opening after a period of danger look like for your organization? Do you measure accuracy?

24. Looking at error types rooted in uncertainty… McClung says type 1 is a failure to claim instability and an accident occurs. Type 2 is an overly conservative decision. Is there any use of this in reviewing incidents?

25. Does your operation have a predetermined level of risk?

26. Are there any big decision points that I'm missing?

Figure A3 Continued.

27. Would you be willing to participate in an exercise where your operation uses data from an event that happened at your operation in the past, and we add some piece of remote sensing to compare forecaster outcomes?

28. Is there anyone else you think I should talk with about the framework?

Figure A3. Tim Glassett and Jim Kennedy avalanche forecasters at Alaska Department of Transportation interview

APPENDIX B

CASE STUDY POWERPOINT PRESENTATIONS

Figure B1. Case study presentation for case study one with traditional data

Scenario for Forecasting With Traditional Data

Read through the following relevant observations and fill out the matrix.

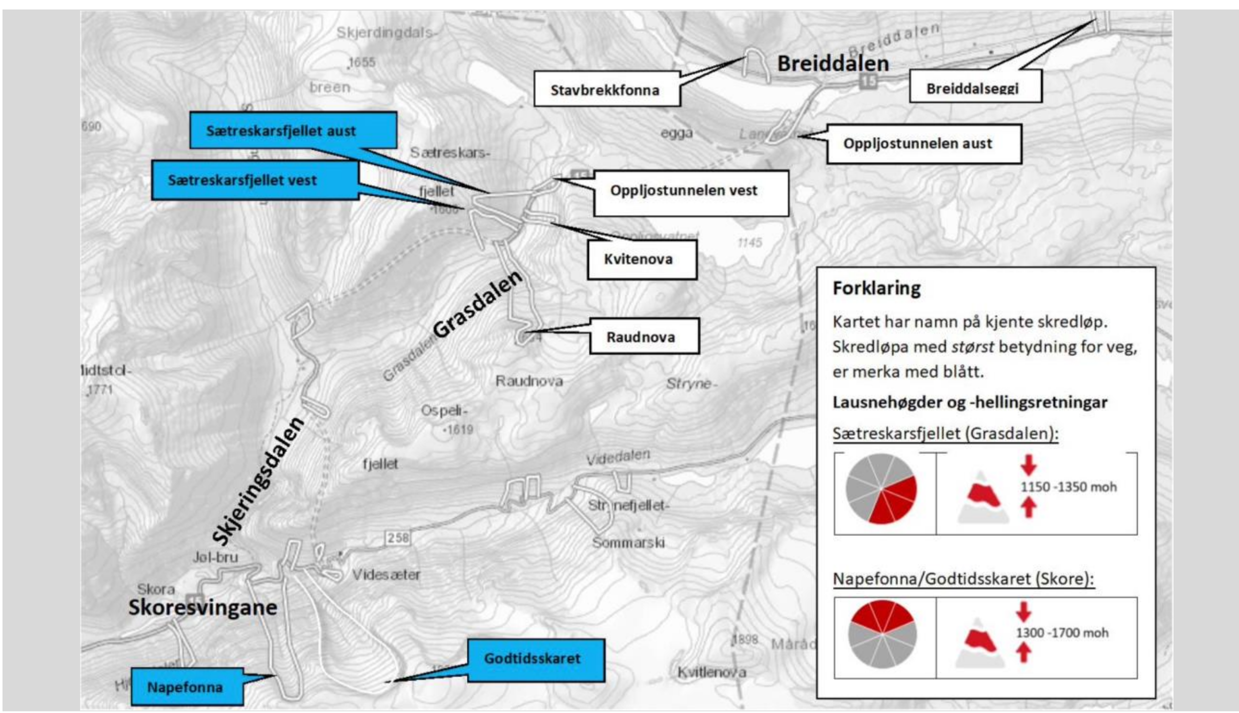

Figure B1 Continued.

Sætreskarsfjellet Characteristics

- Sætreskarsfjellet aust is an east facing slope
- Sætreskarsfjellet vest is a south facing slope
- Start zone slope angle: 38º

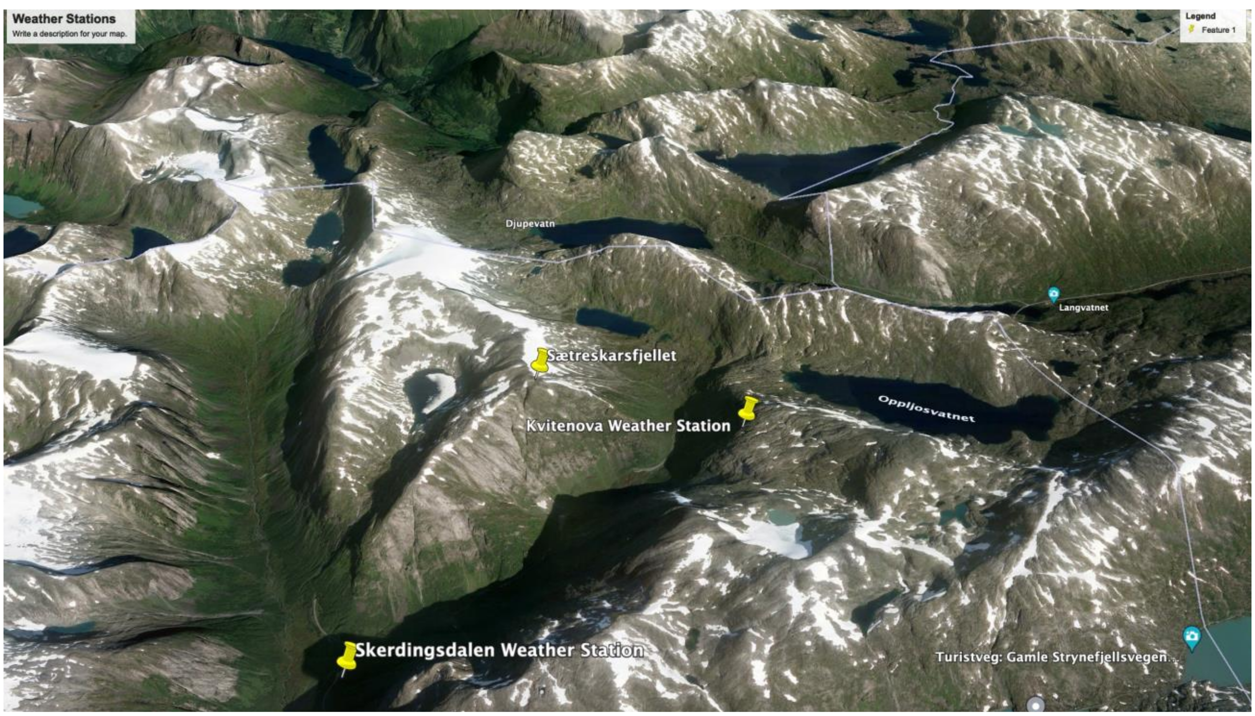

Figure B1 Continued.

Kvitenova Weather Station at 1,300 m

Tidspunkt	Vindhastighet (m/s)	Vindretning (0 - 360°) (º)	Vindkast (m/s)	Maks. vindkast siste 10 minutter (m/s)	Vindkastretning (0 - 360°) (º)
20.02.2023 12:00	13.0	265.0	13.7	23.1	243.0
20.02.2023 13:00	14.9	262.0	21.2	21.2	248.0
20.02.2023 14:00	14.0	267.0	0.0		0.0
20.02.2023 15:00	15.8	265.0	17.1	20.4	237.0
20.02.2023 16:00	32.8	266.0	36.3	41.7	264.0
20.02.2023 17:00	14.6	248.0	17.5	19.9	237.0
20.02.2023 18:00	16.8	252.0	30.7	30.7	258.0
20.02.2023 19:00	10.6	255.0	10.5	15.1	261.0
20.02.2023 20:00	10.6	262.0	12.4	15.5	257.0
20.02.2023 21:00	5.2	264.0	5.3	6.6	256.0
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20.02.2023 23:00	4.7	280.0	7.3	7.3	288.0
21.02.2023 00:00	10.6	299.0	16.0	16.0	325.0
21.02.2023 01:00	9.1	306.0	12.1	12.1	319.0
21.02.2023 02:00	6.4	301.0	6.9	9.2	328.0
21.02.2023 03:00	6.7	300.0	7.9	9.5	325.0
21.02.2023 04:00	7.2	305.0	8.9	8.9	336.0
21.02.2023 05:00	4.1	294.0	4.5	6.0	337.0
21.02.2023 06:00	3.1	296.0	3.5	4.4	360.0
21.02.2023 07:00	2.1	291.0	2.8	3.2	357.0
21.02.2023 08:00	2.2	262.0	2.6	2.8	69.0
21.02.2023 09:00	3.4	86.0	4.7	5.3	84.0
21.02.2023 10:00	1.3	125.0	1.6	2.1	137.0
21.02.2023 11:00	4.0	91.0	5.2	5.7	80.0

Skjerdingsdalen Weather at 600 m

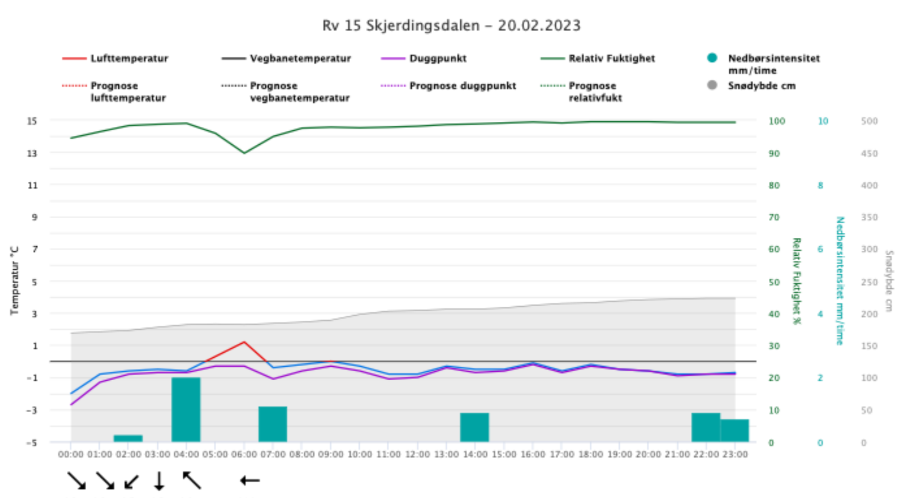


Figure B1 Continued.

Road at the Bottom of Sætreskarsfjellet Aust Overnight

Sætreskarsfjellet Yesterday (Lens Iced Over)

Figure B1 Continued.

Sætreskarsfjellet at 0749

February 19 and 20 RV 15 Awareness Level

	Søndag 19.2		Mandag 20.2			
	Oransje: Enkelte restriksjoner		Rødt: Omfattende restriksjoner			
Grasdalen						
Skoresvingane						
Skredproblem	Fokksnø		Fokksnø			

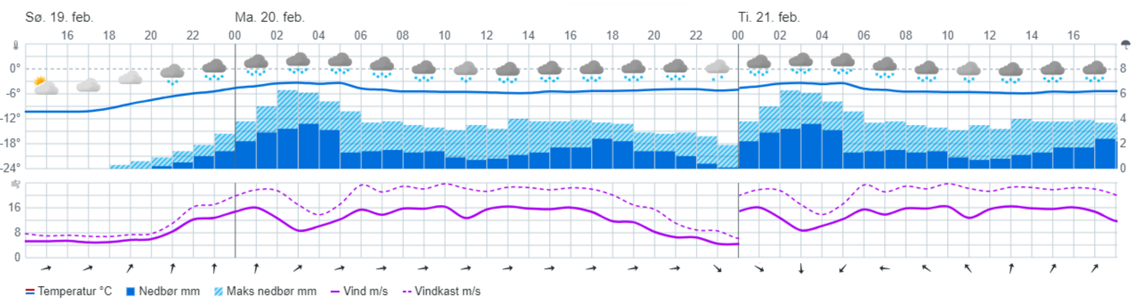
20.2 Skredvarsel

«Før siste dagers snøfall var snødekket påvirket av varme opp til minst 1400 moh (regobs 329958). Snøoverflaten bestod da for det meste av skare. Under skaren er det fortsatt fokksnø med tørr og kald snø. Siste tre dager kan det kommet mellom 70 og 100 mm nedbør i området. Sammen med kuling fra vest har dette ført til tykke fokksnøflak i leområder. Skarelag/svake lag i Sætreskarsfjellet har ikke stor sammenhengende utbredelse på grunn av at det har vært oppstikkende rygger og steiner i området, helt til siste døgns snøfall. I Napefonna kan svake lag være mer sammenhengende.»

Figure B1 Continued.

Kvitenova Forecast at 1400 m

- Monday Morning Update: «Varmfront med over 40 mm nedbør som snø i løsneområdene med stiv kuling fra vest hele mandag og tirsdag. Brøytemannskap melder at det er kommet 20-30 cm snø siste døgn.»



Avalanche Forecast and Observations

- Indre Fjordane Regional Forecast
- Observation 1
- Observation 2
- Tore calls you at 1100 to tell you that the explosive released a size 3 avalanche that had a vertical run of 450 meters. You cannot see the results on the webcam because it has started to snow again. Tore says it is snowing at a rate of 1 cm/hr in Grasdalen.

Figure B1 Continued.

Bakgrunn/forklaring

Avtalte nivå

Nivå skredfare		Aktsemd (tilrådd nivå)	Tiltak (tilrådd nivå, typiske restriksjonar)
	Grønt	Normal merksemd	Ingen spesielle tiltak, normal drift
	Gult	Auka merksemd	Dagleg skredvarsling Unngå manuelle operasjonar (t.d. kosting av skilt)
	Oransje	Enkelte restriksjonar	Restriksjonar på arbeidsoperasjonar (fresegrøft, opphald i Grasdalen) Unngå kolonne ved ugunstig vindretning Stenging kan skje på kort varsel. Ev. opning kan vurderast. Vurdere skredkontroll
	Rødt	Omfattande restriksjonar	Stengt veg Unngå arbeid i spesifisert område Vurdere skredkontroll

Record the Problem and Awareness Level for February 21 at Sætreskarsfjellet

Skredproblem	
Nysnø	N
Fokksnø	F
Vedvarande svakt lag	Vsl
Våt snø	V
Glideskred	G

Skredstørrelse	
Små	1
Middels	2
Store	3
Svært store	4
Ekstreme	5

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure B2. Case study presentation for case study one with RS+ data

Scenario for Forecasting With Drone Data

Read through the following relevant observations and fill out the matrix.

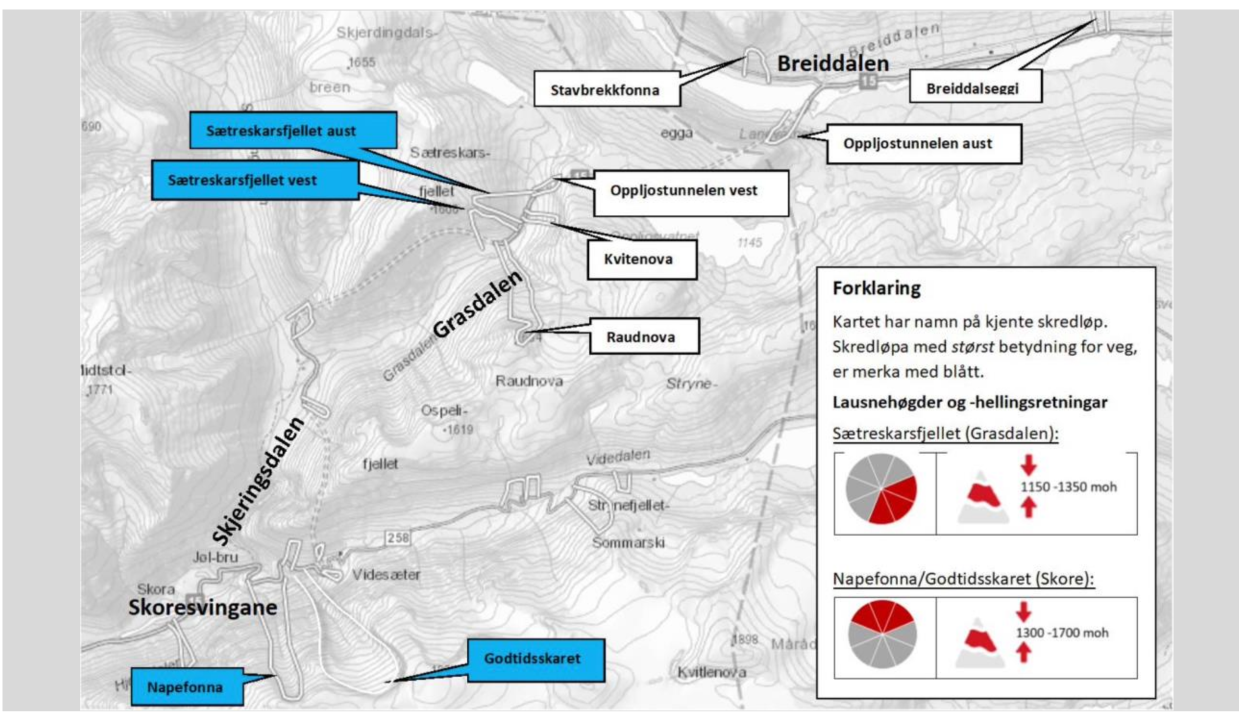


Figure B2 Continued.

Sætreskarsfjellet Characteristics

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- Sætreskarsfjellet vest is a south facing slope
- Start zone slope angle: 38º

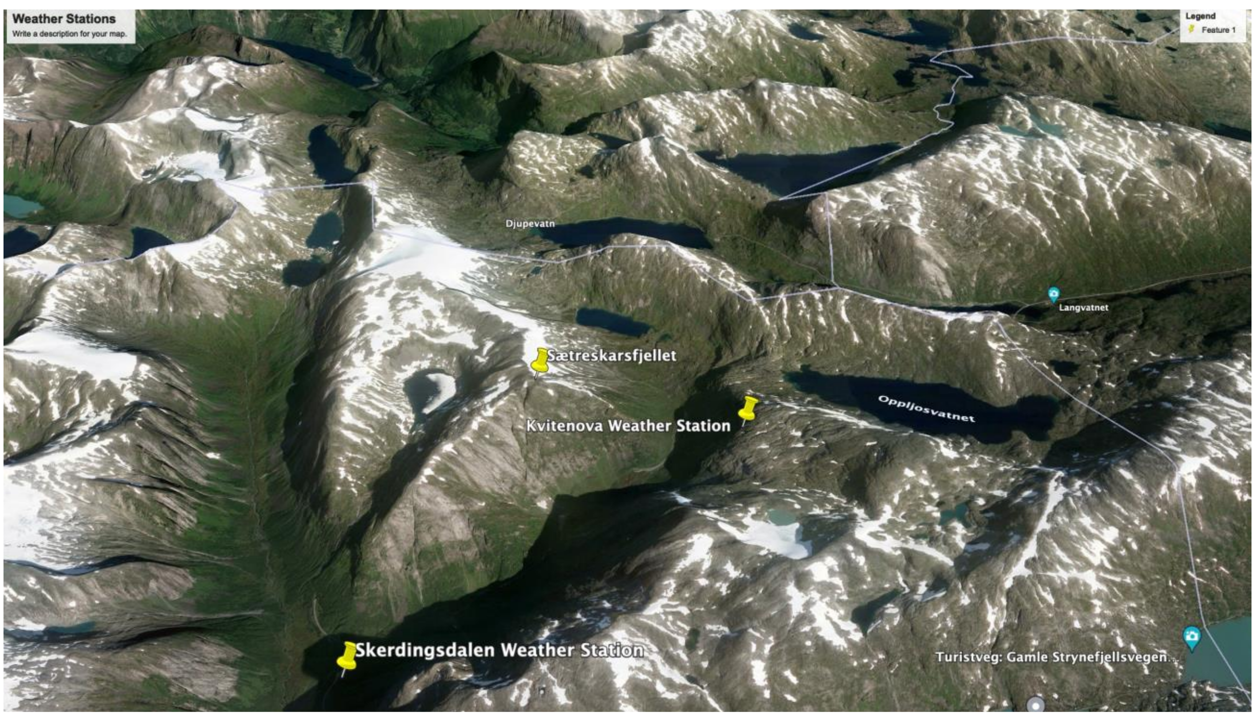

Figure B2 Continued.

Kvitenova Weather Station at 1,300 m

Tidspunkt	Vindhastighet (m/s)	Vindretning (0 - 360°) (º)	Vindkast (m/s)	Maks. vindkast siste 10 minutter (m/s)	Vindkastretning (0 - 360°) (º)
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Skjerdingsdalen Weather at 600 m

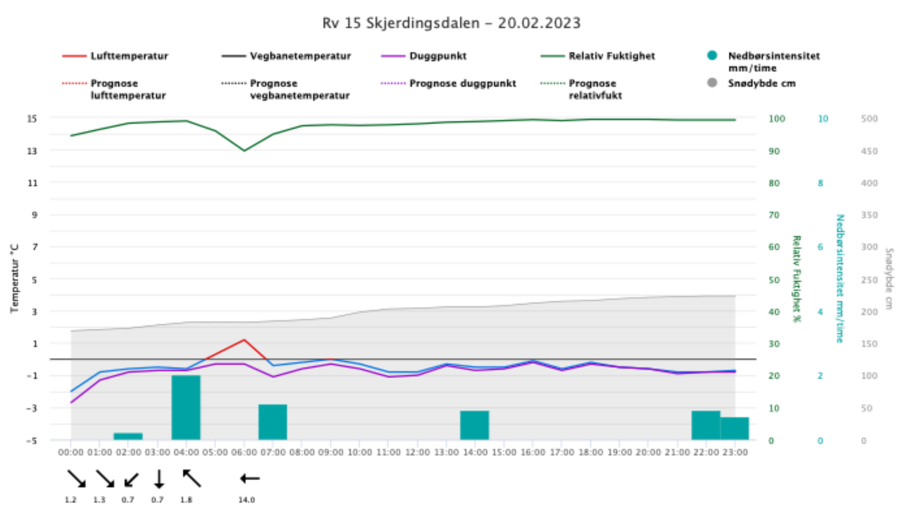


Figure B2 Continued.

Road at the Bottom of Sætreskarsfjellet Aust Overnight

Sætreskarsfjellet Yesterday (Lens Iced Over)

Figure B2 Continued.

Sætreskarsfjellet at 0749

LiDAR Sætreskarsfjellet Aust 21.02.2023 at 0900

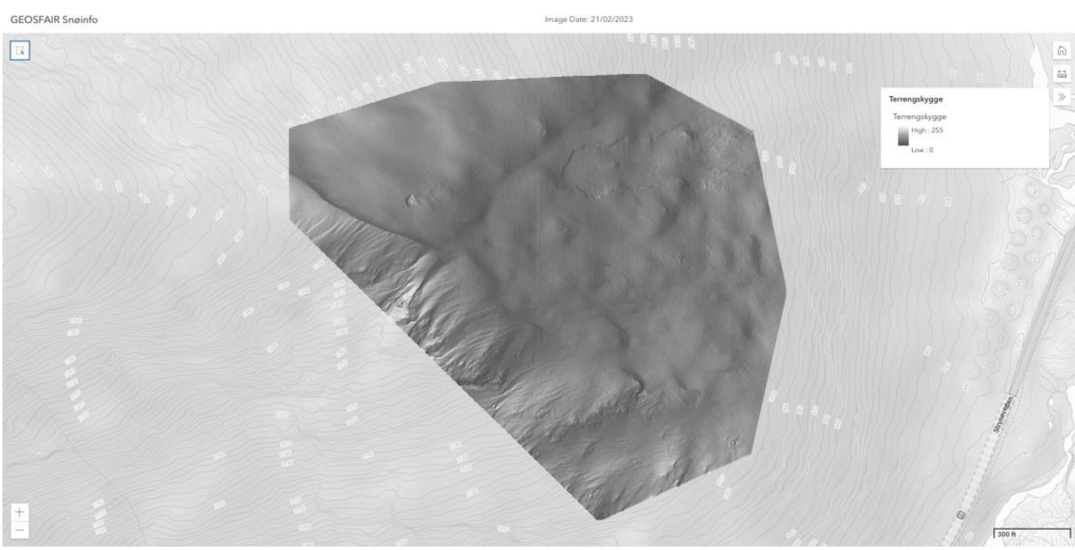
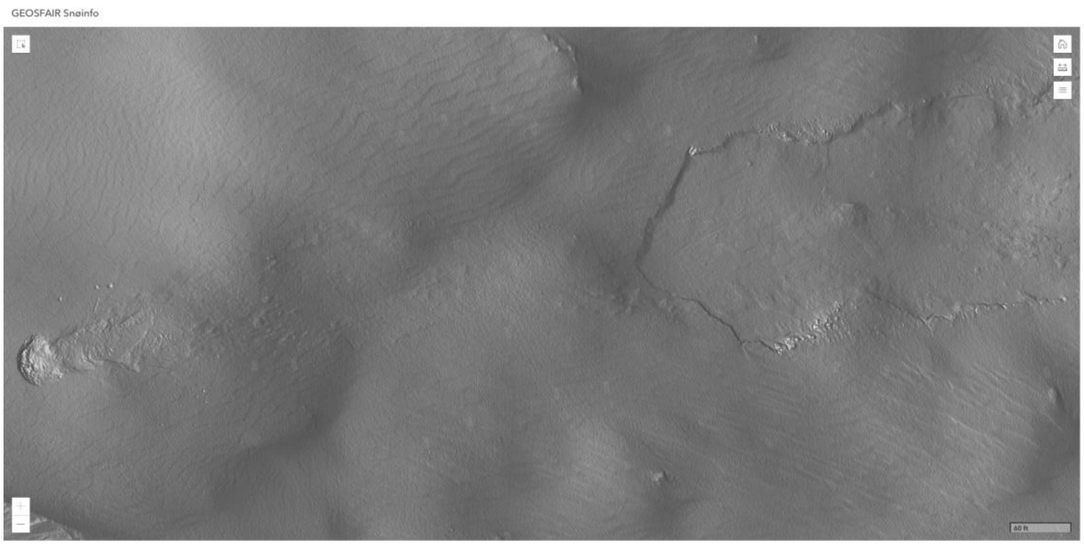


Figure B2 Continued.

Sætreskarsfjellet Mitigation Result



Sætreskarsfjellet Mitigation Result

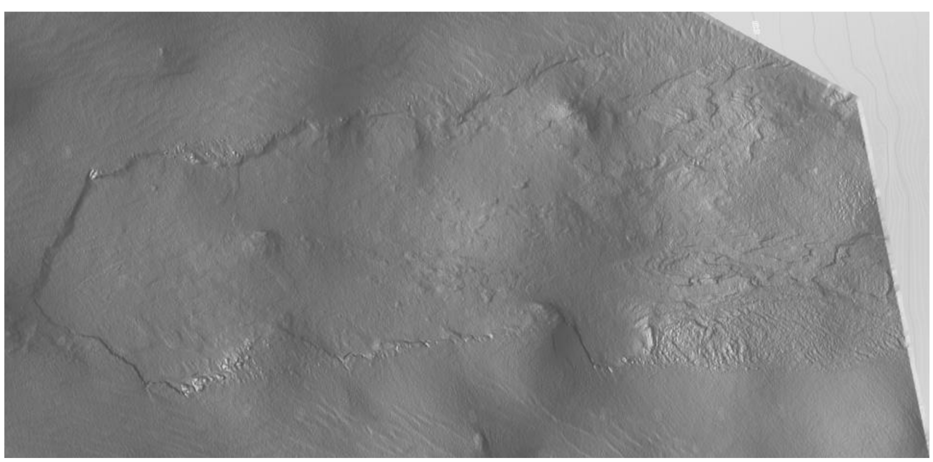
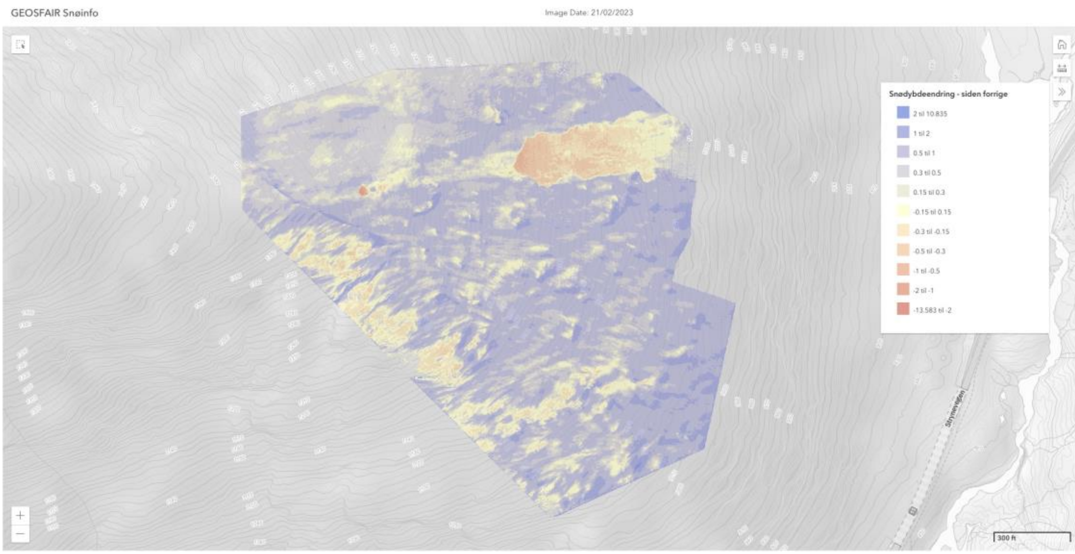


Figure B2 Continued.

Storm Erosion/Deposition Sætreskarsfjellet



February 19 and 20 RV 15 Awareness Level

Søndag 19.2			**Mandag 20.2**
Oransje: Enkelte restriksjoner			Rødt: Omfattende restriksjoner
Grasdalen			
Skoresvingane			
Skredproblem	Fokksnø		Fokksnø

20.2 Skredvarsel

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Figure B2 Continued.

Kvitenova Forecast at 1400 m

- Monday Morning Update: «Varmfront med over 40 mm nedbør som snø i løsneområdene med stiv kuling fra vest hele mandag og tirsdag. Brøytemannskap melder at det er kommet 20-30 cm snø siste døgn.»

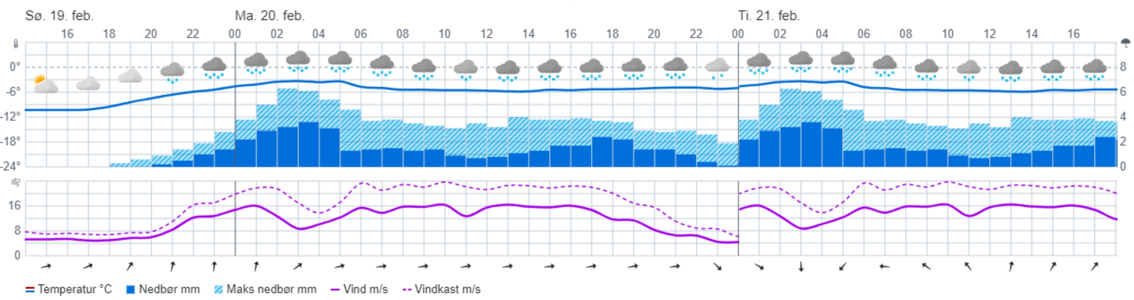

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Figure B2 Continued.

Bakgrunn/forklaring

Avtalte nivå

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	Rødt	Omfattande restriksjonar	Stengt veg Unngå arbeid i spesifisert område Vurdere skredkontroll

Record the Problem and Awareness Level for February 21 at Sætreskarsfjellet

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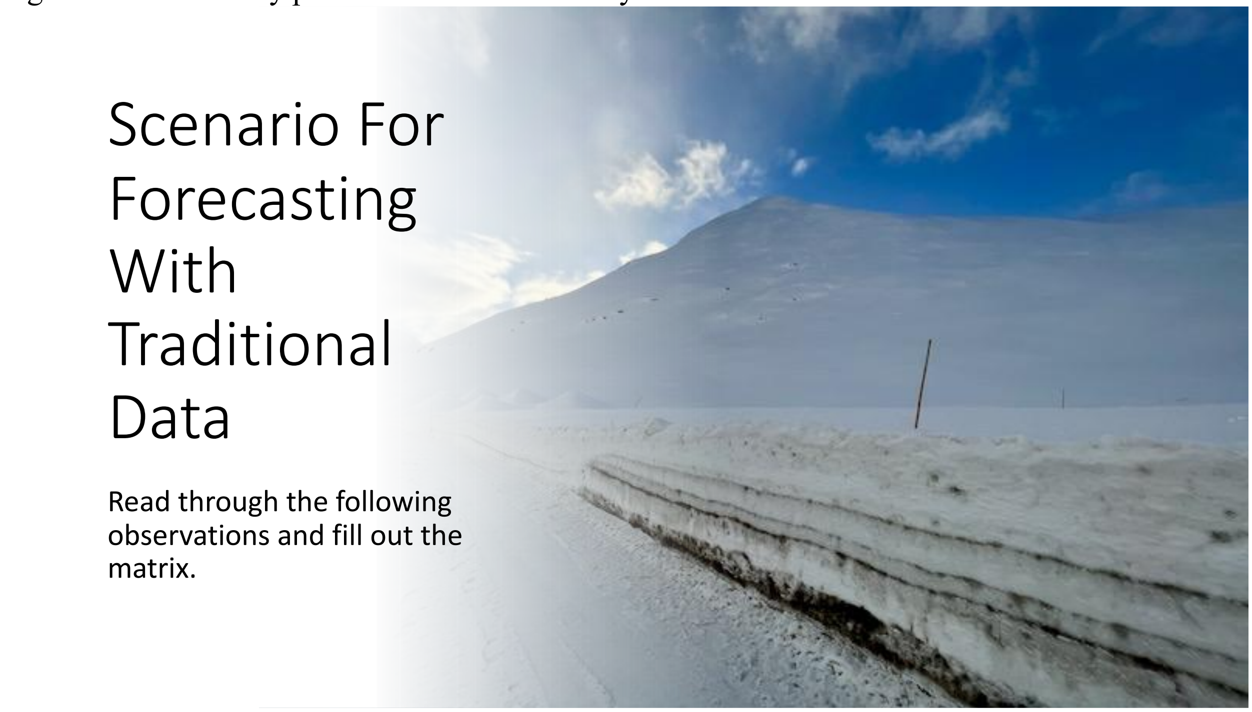
Nysnø	**N**
Fokksnø	**F**
Vedvarande svakt lag	**Vsl**
Våt snø	**V**
Glideskred	**G**

Skredstørrelse	
Små	**1**
Middels	**2**
Store	**3**
Svært store	**4**
Ekstreme	**5**

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure B3. Case study presentation for case study two with traditional data



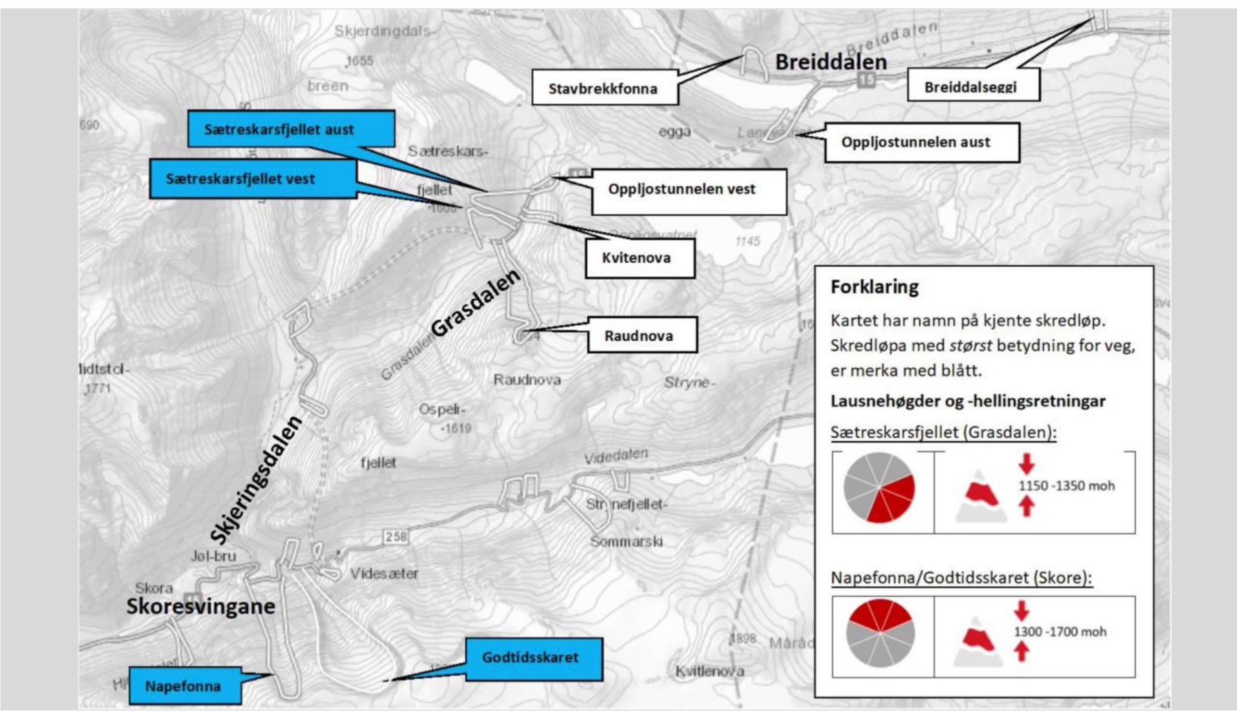


Figure B3 Continued.

Sætreskarsfjellet Characteristics

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- Start zone slope angle: 38º

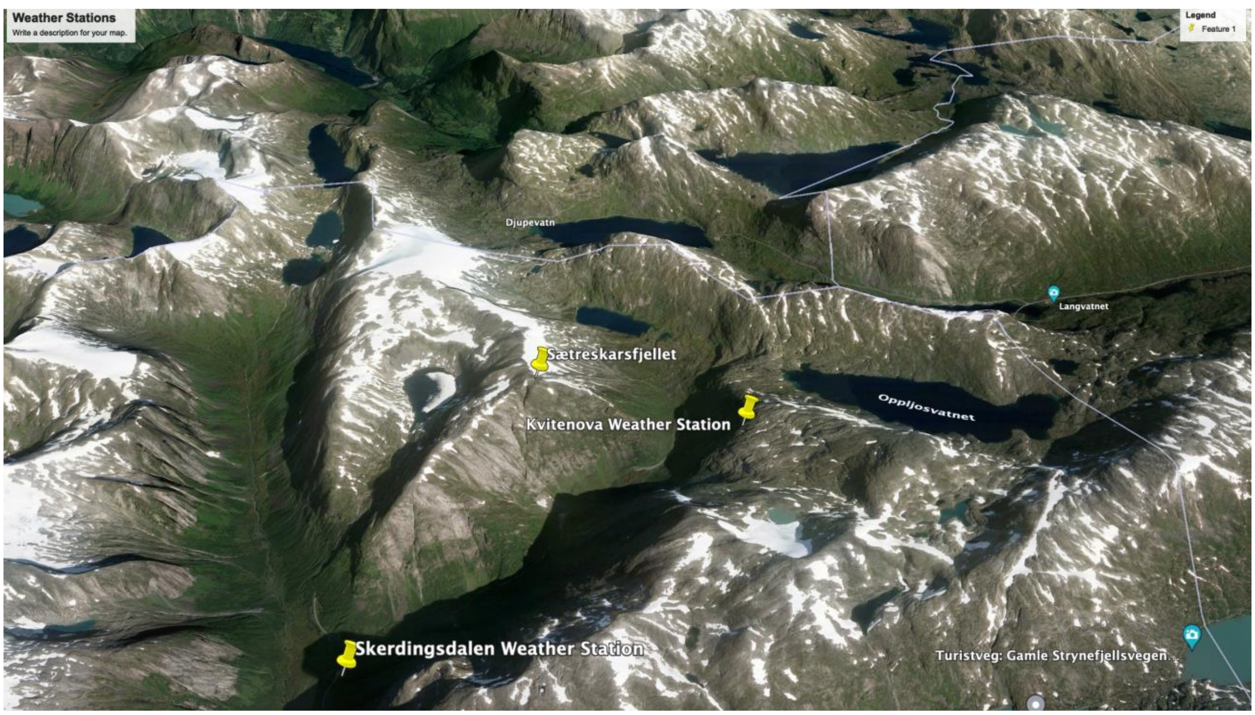

Figure B3 Continued.

Kvitenova Weather at 1,300 m

Tidspunkt	Vindhastighet (m/s)	Vindretning (0 - 360°) (º)	Vindkast (m/s)	Maks. vindkast siste 10 minutter (m/s)	Vindkastretning (0 - 360°) (º)
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21.02.2023 16:00	1.3	324.0	1.3	2.4	358.0
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21.02.2023 20:00	1.4	146.0	1.7	2.3	157.0
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22.02.2023 00:00	4.4	152.0	6.0	6.9	146.0
22.02.2023 01:00	3.8	150.0	4.6	5.5	163.0
22.02.2023 02:00	3.2	148.0	3.7	6.3	138.0
22.02.2023 03:00	5.1	164.0	6.6	7.0	159.0
22.02.2023 04:00	4.2	174.0	6.0	6.0	177.0
22.02.2023 05:00	6.6	165.0	7.1	8.8	166.0
22.02.2023 06:00	5.3	155.0	7.2	7.2	155.0
22.02.2023 07:00	4.7	156.0	7.3	8.5	157.0
22.02.2023 08:00	3.6	204.0	5.5	6.7	184.0
22.02.2023 09:00	8.5	185.0	8.2	13.7	194.0
22.02.2023 10:00	9.0	177.0	10.6	14.5	183.0
22.02.2023 11:00	5.6	205.0	7.3	10.6	199.0
22.02.2023 12:00	6.8	195.0	9.0	13.0	214.0

Skjerdingsdalen Weather at 600 m

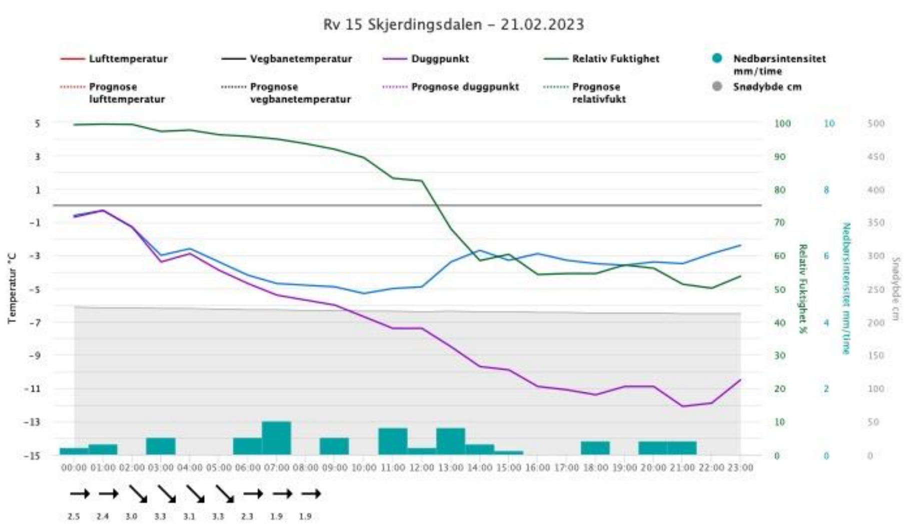


Figure B3 Continued.

Road at the Bottom of Sætreskarsfjellet Aust Yesterday

Sætreskarsfjellet Aust Yesterday

Figure B3 Continued.

Current Conditions

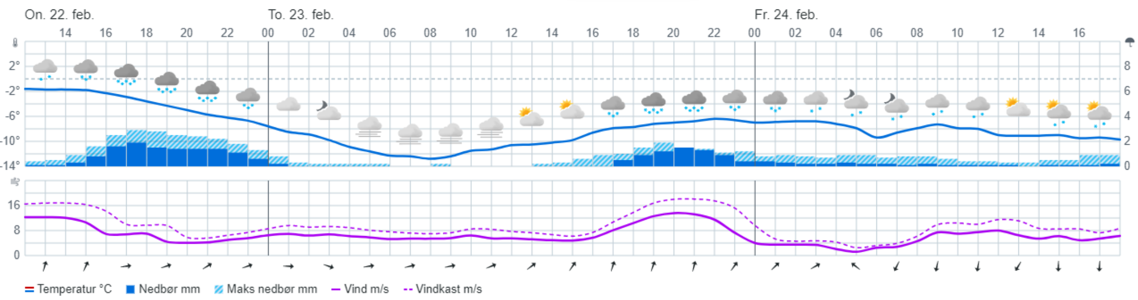
February 21 RV 15 Awareness Level

Trisdag 21.2	
Grønt: Normal merksemd	
Grasdalen	
Skoresvingane	
Skredproblem	Fokksnø

Figure B3 Continued.

Kvitenova Forecast at 1400 m

- Wednesday Morning Update: «Onsdag er det oppholdsvær, og frisk bris av skiftende retning. På Grotli er temperaturen -6 °C. I Skjæringsdalen er det +1 °C.»



Avalanche Forecast and Observations

- [Indre Fjordane Regional Forecast]
- [Observation 1]
- [Observation 2]

Figure B3 Continued.

Bakgrunn/forklaring

Avtalte nivå

Nivå skredfare		Aktsemd (tilrådd nivå)	Tiltak (tilrådd nivå, typiske restriksjonar)
	Grønt	Normal merksemd	Ingen spesielle tiltak, normal drift
	Gult	Auka merksemd	Dagleg skredvarsling Unngå manuelle operasjonar (t.d. kosting av skilt)
	Oransje	Enkelte restriksjonar	Restriksjonar på arbeidsoperasjonar (fresegrøft, opphald i Grasdalen) Unngå kolonne ved ugunstig vindretning Stenging kan skje på kort varsel. Ev. opning kan vurderast. Vurdere skredkontroll
	Rødt	Omfattande restriksjonar	Stengt veg Unngå arbeid i spesifisert område Vurdere skredkontroll

Record the Problem and Awareness Level for February 22 at Sætreskarsfjellet Vest

Skredproblem	
Nysnø	N
Fokksnø	F
Vedvarande svakt lag	Vsl
Våt snø	V
Glideskred	G

Skredstørrelse	
Små	1
Middels	2
Store	3
Svært store	4
Ekstreme	5

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure B3 Continued.

Record the Problem and Awareness Level for February 22 at Sætreskarsfjellet Aust

Skredproblem	
Nysnø	N
Fokksnø	F
Vedvarande svakt lag	Vsl
Våt snø	V
Glideskred	G

Skredstørrelse	
Små	1
Middels	2
Store	3
Svært store	4
Ekstreme	5

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure B4. Case study presentation for case study two with RS+ data

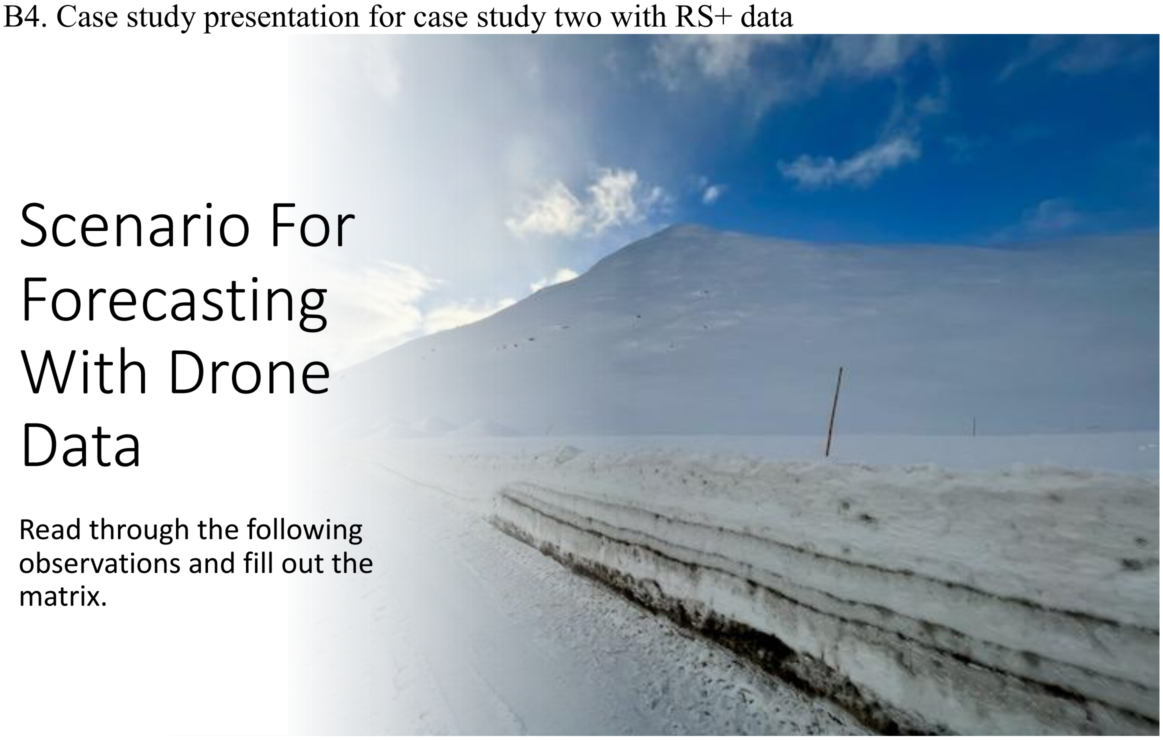
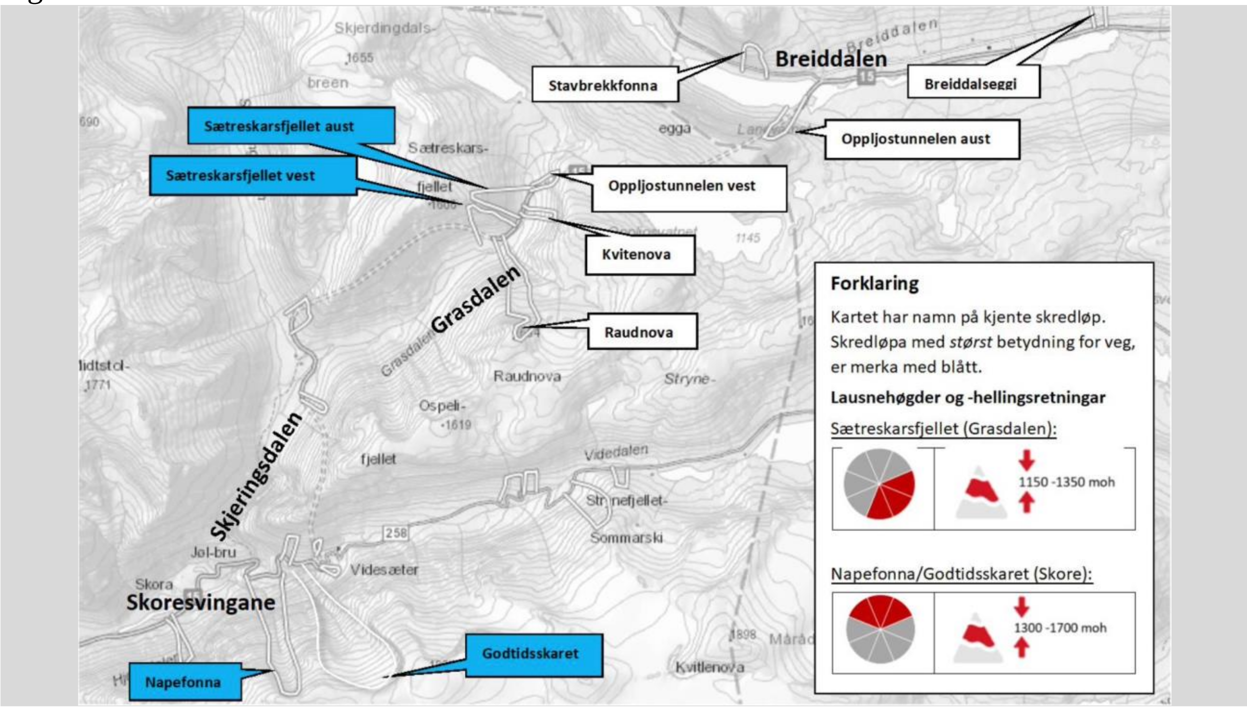


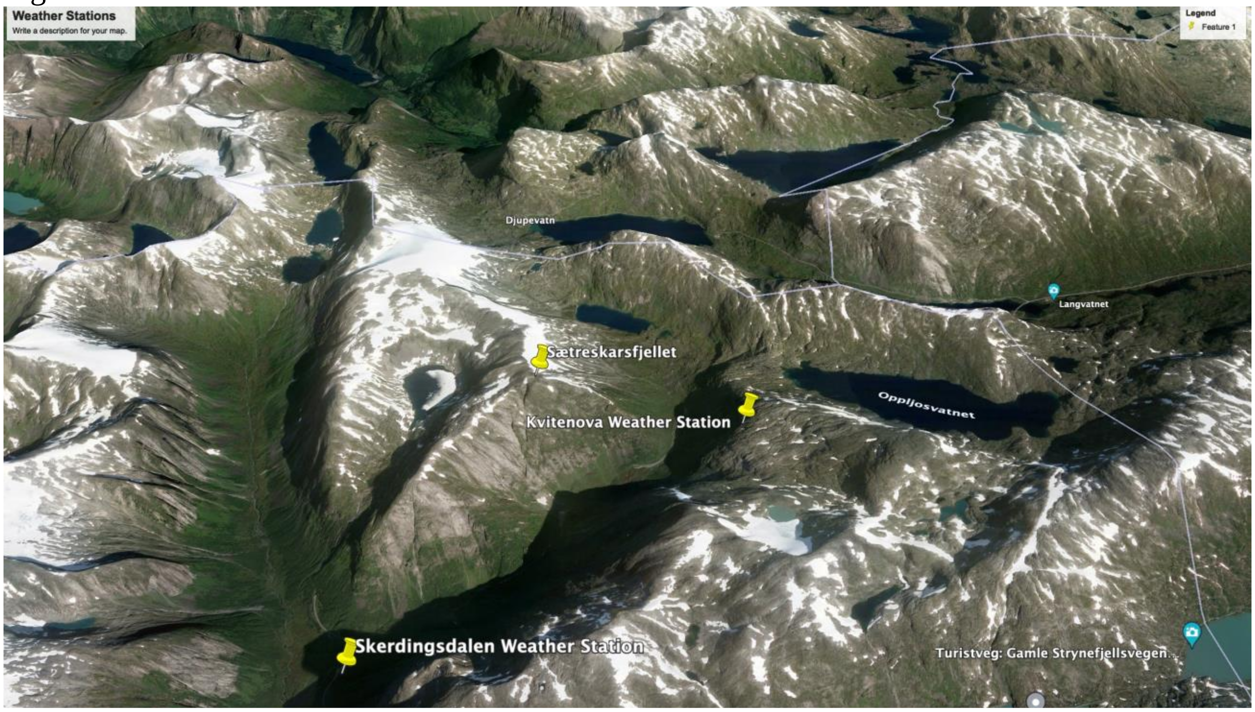
Figure B4 Continued.



Sætreskarsfjellet Characteristics

- Sætreskarsfjellet aust is an east facing slope
- Sætreskarsfjellet vest is a south facing slope
- Start zone slope angle: 38º

Figure B4 Continued.

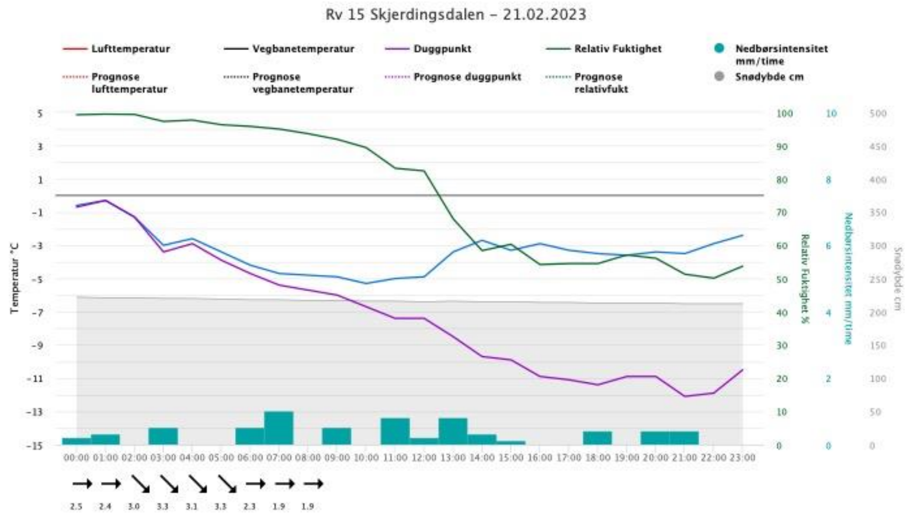


Kvitenova Weather at 1,300 m

Tidspunkt	Vindhastighet (m/s)	Vindretning (0 - 360°) (º)	Vindkast (m/s)	Maks. vindkast siste 10 minutter (m/s)	Vindkastretning (0 - 360°) (º)
21.02.2023 12:00	4.9	101.0	5.6	7.2	112.0
21.02.2023 13:00	1.9	100.0	3.4	3.8	88.0
21.02.2023 14:00	2.0	206.0	3.3	3.6	195.0
21.02.2023 15:00	2.0	218.0	3.7	3.7	236.0
21.02.2023 16:00	1.3	324.0	1.3	2.4	358.0
21.02.2023 17:00	1.0	251.0	1.9	2.5	276.0
21.02.2023 18:00	1.6	191.0	1.5	3.2	195.0
21.02.2023 19:00	1.1	196.0	1.8	2.5	167.0
21.02.2023 20:00	1.4	146.0	1.7	2.3	157.0
21.02.2023 21:00	1.4	238.0	2.9	2.9	212.0
21.02.2023 22:00	2.7	135.0	2.8	4.4	140.0
21.02.2023 23:00	3.3	155.0	2.5	5.6	163.0
22.02.2023 00:00	4.4	152.0	6.0	6.9	146.0
22.02.2023 01:00	3.8	150.0	4.6	5.5	163.0
22.02.2023 02:00	3.2	148.0	3.7	6.3	138.0
22.02.2023 03:00	5.1	164.0	6.6	7.0	159.0
22.02.2023 04:00	4.2	174.0	6.0	6.0	177.0
22.02.2023 05:00	6.6	165.0	7.1	8.8	166.0
22.02.2023 06:00	5.3	155.0	7.2	7.2	155.0
22.02.2023 07:00	4.7	156.0	7.3	8.5	157.0
22.02.2023 08:00	3.6	204.0	5.5	6.7	184.0
22.02.2023 09:00	8.5	185.0	8.2	13.7	194.0
22.02.2023 10:00	9.0	177.0	10.6	14.5	183.0
22.02.2023 11:00	5.6	205.0	7.3	10.6	199.0
22.02.2023 12:00	6.8	195.0	9.0	13.0	214.0

Figure B4 Continued.

Skjerdingsdalen Weather at 600 m



Road at the Bottom of Sætreskarsfjellet Aust Yesterday

Figure B4 Continued.

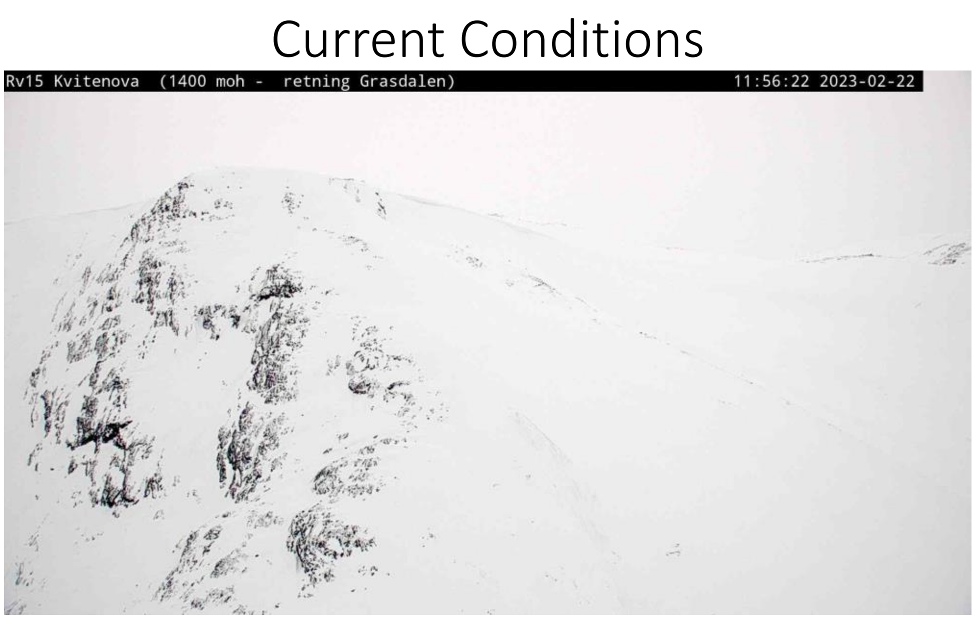
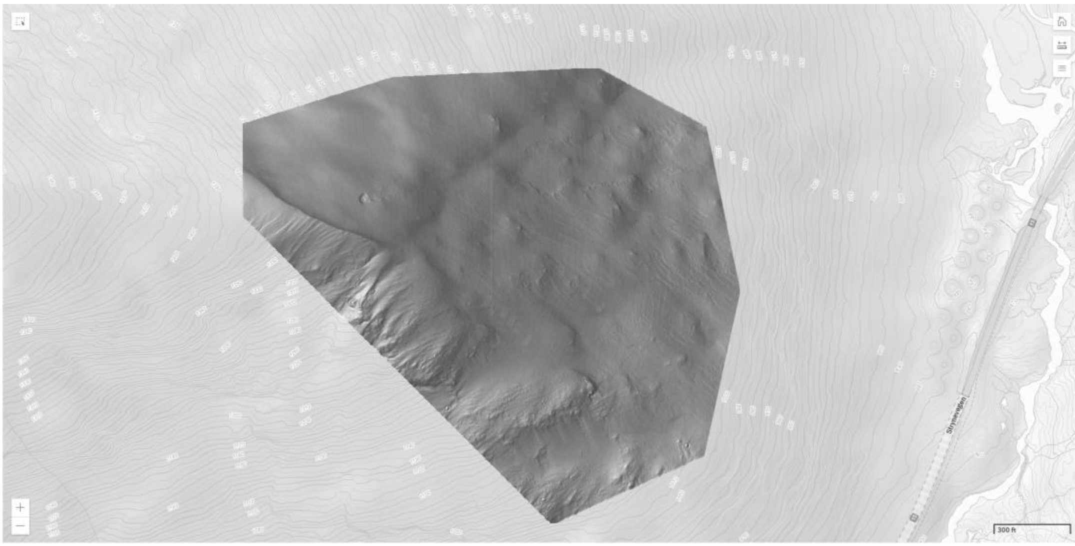


Figure B4 Continued.

LiDAR Sætreskarsfjellet Aust



Sætreskarsfjellet Aust Start Zone

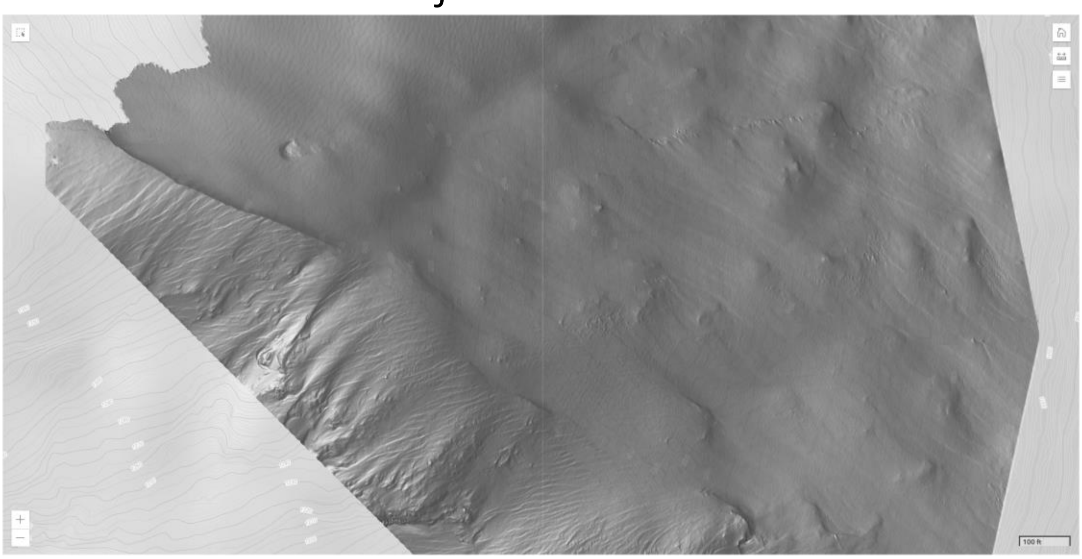
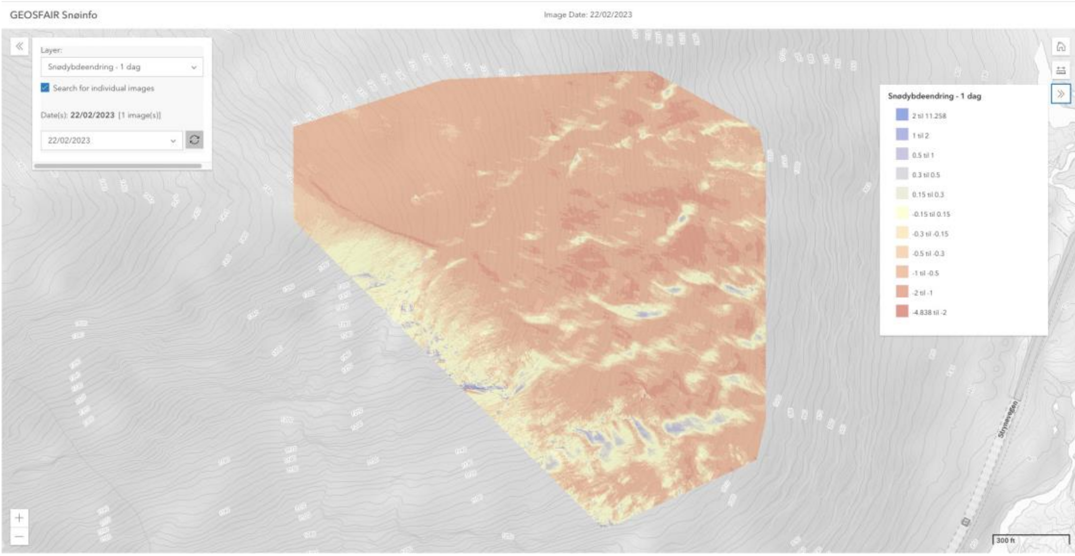


Figure B4 Continued.

24 hr Erosion/Deposition in Sætreskarsfjellet Aust



Sætreskarsfjellet Vest Start Zone

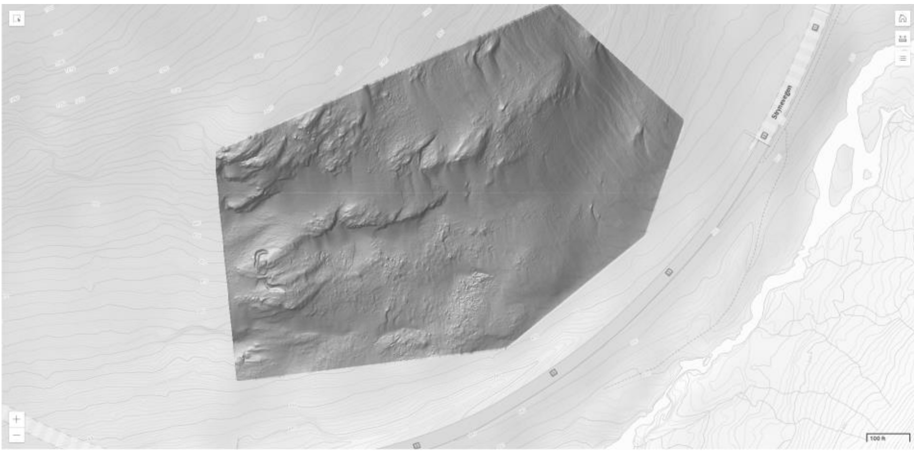
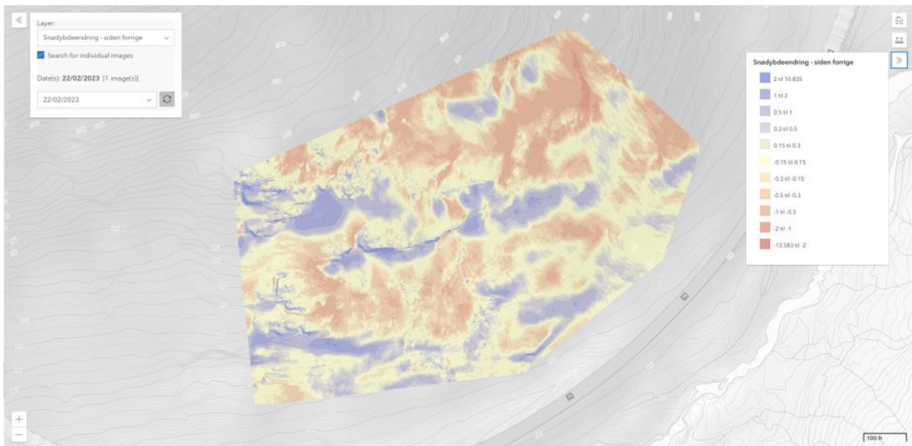


Figure B4 Continued.

24 hr Erosion/Deposition in Sætreskarsfjellet Vest



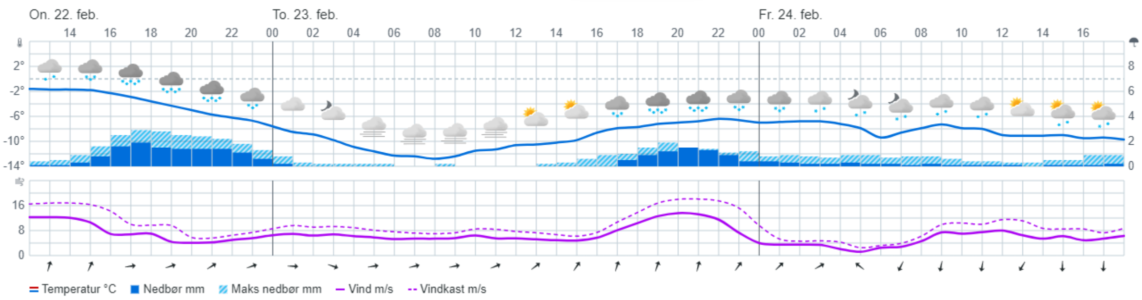
February 21 RV 15 Awareness Level

Trisdag 21.2	
Grønt: Normal merksemd	
Grasdalen	
Skoresvingane	
Skredproblem	Fokksnø

Figure B4 Continued.

Kvitenova Forecast at 1400 m

- Wednesday Morning Update: «Onsdag er det oppholdsvær, og frisk bris av skiftende retning. På Grotli er temperaturen -6 °C. I Skjæringsdalen er det +1 °C.»



Avalanche Forecast and Observations

- Indre Fjordane Regional Forecast
- Observation 1
- Observation 2

Figure B4 Continued.

Bakgrunn/forklaring

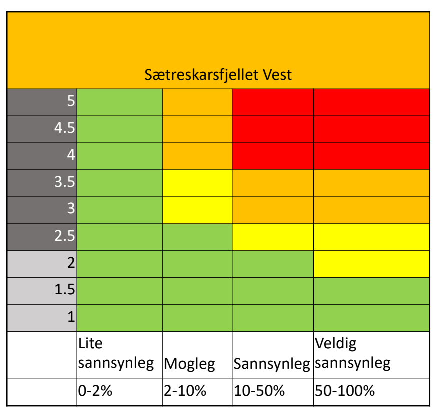
Avtalte nivå

Nivå skredfare		Aktsemd (tilrådd nivå)	Tiltak (tilrådd nivå, typiske restriksjonar)
	Grønt	Normal merksemd	Ingen spesielle tiltak, normal drift
	Gult	Auka merksemd	Dagleg skredvarsling Unngå manuelle operasjonar (t.d. kosting av skilt)
	Oransje	Enkelte restriksjonar	Restriksjonar på arbeidsoperasjonar (fresegrøft, opphald i Grasdalen) Unngå kolonne ved ugunstig vindretning Stenging kan skje på kort varsel. Ev. opning kan vurderast. Vurdere skredkontroll
	Rødt	Omfattande restriksjonar	Stengt veg Unngå arbeid i spesifisert område Vurdere skredkontroll

Record the Problem and Awareness Level for February 22 at Sætreskarsfjellet Vest

Skredproblem	
Nysnø	N
Fokksnø	F
Vedvarande svakt lag	Vsl
Våt snø	V
Glideskred	G

Skredstørrelse	
Små	1
Middels	2
Store	3
Svært store	4
Ekstreme	5



Record the Problem and Awareness Level for February 22 at Sætreskarsfjellet Aust

Skredproblem	
Nysnø	**N**
Fokksnø	**F**
Vedvarande svakt lag	**Vsl**
Våt snø	**V**
Glideskred	**G**

Skredstørrelse	
Små	**1**
Middels	**2**
Store	**3**
Svært store	**4**
Ekstreme	**5**

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

APPENDIX C

SCENARIO RESPONSES

Sætreskarsfjellet				
5				
4.5				
4			F	
3.5			N	F
3				N
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C1. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3			F	F
2.5				
2				
1.5			N	N
1			N	N
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C2. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5			F	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C3. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5			F	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C4. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5		F		
3			F	
2.5				
2			N	
1.5				N
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C5. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5		F		
3			F	
2.5				
2			N	
1.5				N
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C6. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5		F	F	
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C7. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5		F	F	
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C8. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4			(F)	
3.5			F	
3			F	
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C9. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4	Vsl	F	F	
3.5	Vsl	F	F	
3		F	F	
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C10. Case study one traditional data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3		F		
2.5				
2			F	
1.5				N
1				N
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C11. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5		F	F	
2		F	F	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C12. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5		F	F	
2		F	F	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C13. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5		F	F	
2		F	F	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C14. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3				
2.5		F	F	
2		F	F	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C15. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4		F	F	
3.5			F	
3				
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C16. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5		N		
3			N	
2.5				N
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C17. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5		N		
3			N	
2.5				N
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C18. Case study one RS+ data response

Sætreskarsfjellet				
5				
4.5				
4				
3.5				
3		F/N		
2.5		F/N	F/N	
2			F/N	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C19. Case study one RS+ data response

Sætreskarsfjellet				
5	F			
4.5	F			
4	F			
3.5	F			
3	F			
2.5	f	f		
2		F	F	
1.5		F	F	
1		F	f	
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C20. Case study one traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2	F			
1.5		F		
1			N	
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C21. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3	F			
2.5	F			
2		N		
1.5		N		
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C22. Case study two traditional data response

Sætreskarsfjellet Øst				
5	F			
4.5	F			
4	F			
3.5	F			
3	F			
2.5	F			
2	F	F		
1.5	F	F		
1	f	f		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C23. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5	F			
2		F		
1.5			F	
1				F
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C24. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3	F			
2.5				
2		F		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C25. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3		F		
2.5		F	F	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C26. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5		F		
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C27. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3	F			
2.5		F		
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C28. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3	F			
2.5		F		
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C29. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3		F		
2.5		F	F	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C30. Case study two traditional data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3			F	F
2.5		F	F	F
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C31. Case study two RS+ data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2		F		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C32. Case study two RS+ data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	F, N			
1	F, N			
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C33. Case study two RS+ data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2		VSL		
1.5			VSL	
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C34. Case study two RS+ data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5				
2		F		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C35. Case study two RS+ data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3				
2.5		F		
2		F		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C36. Case study two RS+ data response

Sætreskarsfjellet Øst				
5				
4.5				
4				
3.5				
3	Vsl			
2.5	Vsl			
2	F	F		
1.5	F	F		
1	F	F		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C37. Case study two RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2	F			
1.5		F		
1			N	
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C38. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2	F	N		
1.5	F	N		
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C39. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5	F			
4.5	F			
4	F			
3.5	F			
3	F			
2.5	F			
2	F			
1.5	F,n	F,n		
1	F,n	F,n		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C40. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5	F			
2		F		
1.5			F	
1				F
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C41. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2		v		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C42. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5		V		
2		V		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C43. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5		F		
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C44. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	N			
1		N		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C45. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	N			
1		N		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C46. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3		F		
2.5		F	F	
2		F	F	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C47. Case study two SW traditional data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3		F		
2.5			F	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C48. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	F	F		
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C49. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2		F		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C50. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5				
2	F			
1.5	F,N			
1	N			
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C51. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3			VSL	
2.5		VSL	VSL	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C52. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5	F	F		
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C53. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5			Vsl	
3			F	
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C54. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5			F	
2			F	
1.5			F	
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C55. Case study two SW RS+ data response

Sætreskarsfjellet Vest				
5				
4.5				
4				
3.5				
3				
2.5	F	F		
2	F	F		
1.5	F	F		
1	F	F		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure C56. Case study two SW RS+ data response

APPENDIX D

REAL-TIME FORECAST MATRIXES

1150 -1350 moh

Strekke B - Grasdalen (Sætreskarsfjellet)

5				
4.5				
4				
3.5				
3				
2.5		N		
2		N		
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

1150 -1350 moh

Strekke B - Grasdalen (Sætreskarsfjellet)

5				
4.5				
4				
3.5				
3		F		
2.5		F		
2				
1.5			N	
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D1. Hazard Matrixes from January 31, 2023, traditional on left, RS+ on right

1150 -1350 moh

Strekke B - Grasdalen (Sætreskarsfjellet)

5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	F			
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

1150 -1350 moh

Strekke B - Grasdalen (Sætreskarsfjellet)

5				
4.5				
4				
3.5				
3	F			
2.5	F			
2				
1.5		F	N	
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D2. Hazard Matrixes from February 1, 2023, traditional on left, RS+ on right

1150 -1350 moh

Strekke B - Grasdalen (Sætreskarsfjellet)

5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	F/VsL			
1	V			
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

1150 -1350 moh

Strekke B - Grasdalen (Sætreskarsfjellet)

5				
4.5				
4				
3.5				
3	F			
2.5				
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D3. Hazard Matrixes from February 3, 2023, traditional on left, RS+ on right

1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5	F			
1	F			
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3				
2.5				
2				
1.5				
1	V	V		
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D4. Hazard Matrixes from February 16, 2023, traditional on left, RS+ on right

1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3	Vsl	F		
2.5		F	F	
2		F, N	F	
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3		Vsl		
2.5				
2	F			
1.5	F			
1	F			
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D5. Hazard Matrixes from March 13, 2023, 2023, traditional on left, RS+ on right

1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3				
2.5				
2	Vsl	F		
1.5	F, N	F, N		
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3	Vsl			
2.5	Vsl			
2	Vsl			
1.5	Vsl			
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D6. Hazard Matrixes from March 15, 2023, traditional on left, RS+ on right

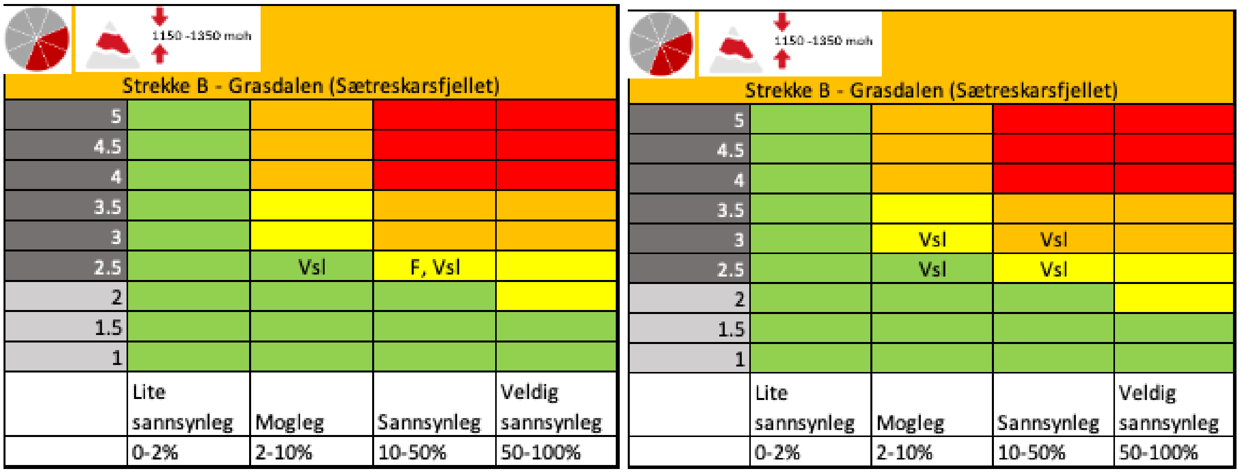


Figure D7. Hazard Matrixes from March 16, 2023, traditional on left, RS+ on right

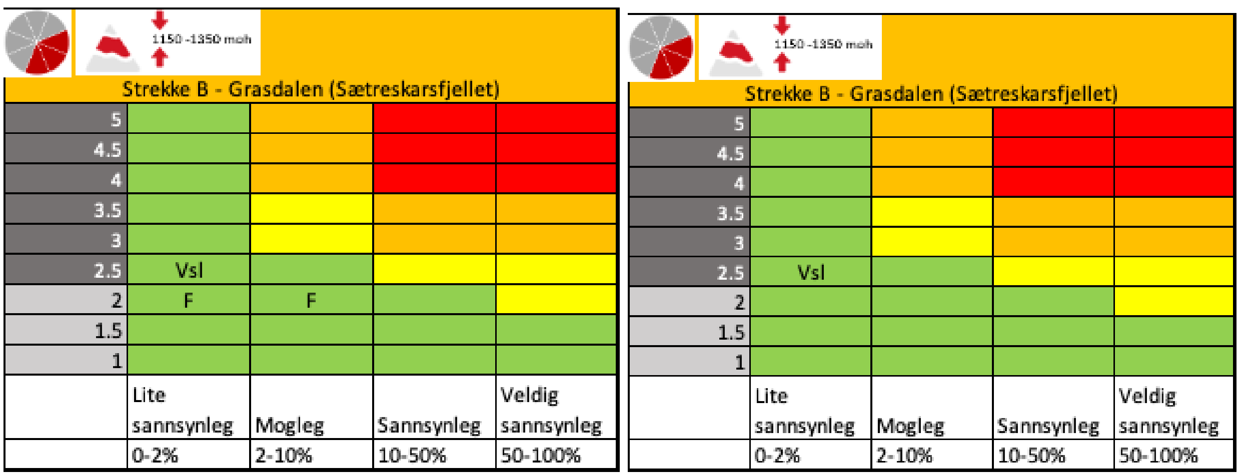


Figure D8. Hazard Matrixes from March 20, 2023, traditional on left, RS+ on right

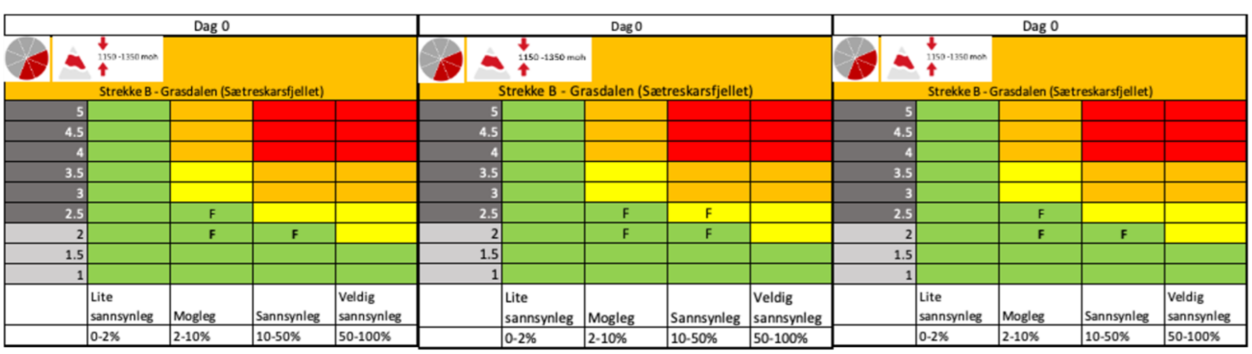


Figure D9. Hazard matrixes from February 17, 2023 avalanche forecast with a consensus matrix. From left to right traditional, RS+, consensus

Dag 0				
1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3		F		
2.5		F	F	
2				
1.5				
1				
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Dag 0				
1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3		f		
2.5				
2			f	
1.5				
1				f
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Dag 0				
1150 -1350 moh				
Strekke B - Grasdalen (Sætreskarsfjellet)				
5				
4.5				
4				
3.5				
3		f		
2.5		F	F	
2			f	
1.5				
1				f
	Lite sannsynleg	Mogleg	Sannsynleg	Veldig sannsynleg
	0-2%	2-10%	10-50%	50-100%

Figure D10. Hazard matrixes from March 3, 2023 avalanche forecast with a consensus matrix. From left to right traditional, RS+, consensus