ASSESSING AVALANCHE PROBLEMS FOR OPERATIONAL AVALANCHE FORECASTING BASED ON DIFFERENT MODEL CHAINS INTERNATIONAL SNOW SCIENCE WORKSHOP 2023, BEND, OREGON

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ABSTRACT:
Snow-cover models were initially developed to assist with operational avalanche forecasting, but the full potential has yet to be exploited. There are excellent possibilities for filtering and summarizing the overwhelming amount of information. Therefore, researchers intend to provide easy-to-grasp visualizations to facilitate the integration of snow-cover models into the forecaster's workflow. In recent years, avalanche forecasting services have transitioned into a rather process-based workflow of regional avalanche danger, which starts with identifying the prevailing avalanche problems. We adapted a post-processing algorithm to support this approach and used snow cover model data to assess avalanche problems. The algorithm is solely based on the snow cover model output and, thus, capable of providing an avalanche problem nowcast and forecast with various model chains. For the winter season 2021/22, SNOWPACK simulations driven by an automated weather station in a region of Tyrol in the Austrian Alps, modeled avalanche problems show a fairly similar behavior as the forecaster's assessment. Looking into detail, the model assigns a Persistent Weak Layer Problem earlier but for a shorter period. Furthermore, the algorithm provides valuable information to time the Wet Snow Problem in individual aspects. Overall, these algorithm demonstrates models' benefit in deciding when and where problems develop and for how long they are critical. Our work aims to merge traditional forecasting with the modeling world to pave the way toward the integration of automatic avalanche problem identification.

Keywords: avalanche problems, SNOWPACK, simulations, forecasting, model chains, avalanche danger assessment

1. INTRODUCTION

The major role of avalanche forecasting services is analyzing the current and to publish a daily report with the future avalanche situation. The assessment process for those reports still follows a very traditional setup: Based on expert knowledge and field observations combined with weather, and sometimes snowpack models, forecasters assess in a mostly subjective manner the prevailing avalanche conditions and inform the public and authorities on the expected hazard. Snow cover modeling, however, will allow us to close observation gaps and process in a systematic manner large amount of weather and snow data. Therefore, various promising approaches are in development, already demonstrating the advantages when allowing snowpack modeling to have a stronger influence on the avalanche hazard assessment process. Pérez-Guillén et al. (2022) showed the potential and quality of assigning automatically avalanche danger levels using 1-D physics-based SNOWPACK simulations in combination with machine-learning algorithms. Again based on machine-learning approaches, Mayer et al. (2023) demonstrated that their simulation-based snowpack stability index, P-unstable (Mayer et al., 2022) is closely related to natural avalanche activity and outperforms classical stability indices such as the natural stability index (Sn38). Reuter et al. (2022) derived an algorithm to provide an automated classification of avalanche problems based on results of SAFRAN - SURFEX/ISBA-Crocus - MEPRA (S2M) and SNOWPACK simulations. The major goal was to provide an objective approach for classifying avalanche problems in order to determine present and future snow avalanche climatology.

With snow cover modeling, however, avalanche forecasters are confronted with an overwhelming amount of information and either may not have the time or the experience to interpret them in a correct

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and efficient way. Consequently, there is the need to access this tremendous data and information treasure within the snow cover modeling world more easily. First methods and products are in development: For example, Herla et al. (2022) averaged and clustered thousands of simulated snow profiles by repetitively applying snow profile alignment and similarity assessment algorithm based on dynamic-time-warping of Herla et al. (2021). The resulting reference profiles can provide a quick overview for predefined warning regions or suggest an objective clustering of regions considering similarities in the snow stratigraphy.

In 2022 the European Avalanche Warning Services (EAWS) agreed on the so-called avalanche problems (Fig. 1) as the entry point for their novel workflow on assessing the regional avalanche danger level (EAWS, 2017, 2022). However, the assessment of avalanche problems is still subjective and influenced by the forecaster's experience and education.

Figure 1: The five avalanche problems according to EAWS standards: New Snow, Wind Slab, Persistent Weak Layers, Wet Snow, Gliding Snow (EAWS, 2017)

To address this topic, we refined Reuter et al. (2022)'s algorithm to obtain an objective first guess of the prevailing avalanche problem(s). To this end, we extended it with the possibility to evaluate slope simulations, not only flat field simulations, and the post-processing tool now copes with a new model chain, i.e. snow cover simulations initialized by observed snow profiles (Binder & Mitterer, 2023). We also enhanced the concept of the *Wet Snow Problem* by treating multiple cycles with different on-set points according to Mitterer et al. (2016). A brief description of these new features follows in the Data and Methods section. Then, we test and evaluate the algorithm against the forecast avalanche problem(s) in one forecasting region of Tyrol for a period with an increased number of avalanche incidents during the 2021/22 winter season. Here, we only show results for SNOWPACK simulations driven by automated weather stations and focus on the assessment of the *Persistent Weak Layer* and *Wet Snow Problem*. In this context, we discuss how this information can be visualized for a practical avalanche danger assessment and how it can enhance the process of avalanche forecasting.

2. DATA AND METHODS

2.1. Input data for SNOWPACK

In order to obtain the evolution and the layering within the snowpack, we used the 1-D snow cover model SNOWPACK (Bartelt & Lehning, 2002; Lehning et al., 2002). The model was driven on various automated weather stations (AWS) within the so called EUREGIO (Provinces of Tyrol, South Tyrol and Trentino in the Eastern European Alps), however, we will focus on the results of the AWS in the *Axamer Lizum*, which is a well equipped weather station in a ski-resort nearby Innsbruck, Austria. Simulations were performed for the flat field site of the AWS and 38° virtual slopes, i.e. for the main aspects north, east, south and west. The AWS provides air temperature, humidity, wind speed, wind direction, snow height, and incoming short wave radiation. In addition to the traditional, AWS-based SNOWPACK simulations, we established a new model chain where we initialized SNOWPACK with an observed snow profile and forced it with numerical weather prediction model data (Binder & Mitterer, 2023). Typically, operational snow profiles do not include density measurements, a required parameter for the simulations. We, therefore, apply the hand-hardness parameterisation of Monti et al. (2014) to gain the density for each layer based on the layer's grain type and hand hardness (Binder & Mitterer, 2023).

2.2. Avalanche problem algorithm

Reuter et al. (2022) established an algorithm to identify and track potential weak layers and assign avalanche problems based on flat field simulations. This was done to study snow and avalanche climatology. We transferred the initial MatLab code to Python and extended the algorithms in order to address operational constraints in a more flexible way. We enhanced the treatment of the *Wet Snow Problem* to address several aspects and process additional wet-cycles according to Mitterer et al. (2016). In addition, we generated a pre-processing tool to identify potential weak layers of simulations initialized by observed snow profiles.

New Snow and Persistent Weak Layer Problem

The main concept of the algorithm to identify the *New Snow* or the *Persistent Weak Layer Problem* can be broken down to the following major decision points.

- The algorithm identifies potential weak layers (pWL) when they develop close to the old snow surface and distinguishes between

Table 1: Thresholds for assigning avalanche problems according to Reuter et al. (2022) and Mitterer et al. (2016)

Avalanche problem	Stability criterion	Artificial triggering	Natural release
New Snow	Expected time to failure (h)	-	18
	Critical crack length (m)	0.3	0.32
	Failure initiation criterion (-)	1	-
Persistent WL	Expected time to failure (h)	-	18
	Critical crack length (m)	0.42	0.42
	Failure initiation criterion (-)	-	1.31
Wet Snow	LWC_{index} (-)	-	0.33 (1st cycle); 1
	Days of isothermal state (days)	-	≤ 3

non-persistent grain types and persistent grain types.

- If a pWL has been identified, the algorithm checks for a cohesive slab (i.e., if slab height $\geq 0.2\ m$ and slab density $\geq 120\ kg/m^3$). With this check, the algorithm identifies the combination of the potential weak layer and a slab, supporting failure initiation and crack propagation.
- If the cohesive slab criterion is fulfilled, various stability criteria as e.g. the critical crack length according to Reuter et al. (2015), expected time to failure according to Conway and Wilbour (1999) and failure initiation criterion according to Reuter et al. (2015).
- If the stability criteria meets certain thresholds, (listed in Table 1) the prevailing avalanche problem is assigned.
- If a new persistent weak layer is buried, the previous persistent WL is treated as old persistent weak layer, only triggerable with secondary release mechanisms. (Reuter et al., 2022)

Wet Snow Problem

Increasing liquid water content (LWC) in the snowpack leads to a loss of stability. The increase in LWC is due to snow melting, which is forced by radiative fluxes (balance of short-wave and long-wave), sensible heat (air temperature advection at snow surface), or rain (latent energy). Mitterer and Schweizer (2013) introduced the liquid water content index (LWC_{index}) and identified it as a reliable index to define the onset of wet snow instabilities. The LWC_{index} can be used to determine three periods: (I) decrease of stability (LWC_{index} increases towards 1), (II) timing of maximum instability ($LWC_{index} \geq 1$) and (III) return to stability ($LWC_{index} \geq 1$ and isothermal snowpack for more than 3 days). For the avalanche problem algorithm, the LWC for every aspect is extracted of the SNOWPACK simulations. As soon as the LWC crosses a threshold of 0.01 (representing a $LWC_{index} = 0.33$) the situation is supposed to be critical and a *Wet Snow Problem* is assigned. We keep the problem as long as the LWC_{index} stays above 0.33 and the snowpack has not reached an isothermal state for more than three consecutive days. This wet snow instability can undergo several cycles. After completing the first cycle (reaching $LWC_{index} = 0.33$) the LWC may decrease again (dry out) beneath this threshold. If so, the threshold for reassigning the *Wet Snow Problem* (new cycle) increases to a $LWC_{index} \geq 1$ (Mitterer et al., 2016).

Extensions of algorithm for snow profile input

The initial algorithm focused on the identification of potential weak layers from the moment they are buried. This approach is suitable for simulations starting from the very beginning of the season, however, for simulations initiated by observed snow profiles this information is not available. Therefore, we refer to the relative threshold sum approach (RTA) to identify the location of potential weak layers (Monti & Schweizer, 2013). The RTA takes six different factors into account: grain size (of pWL) , difference in grain size (between two adjacent layers), difference in hardness (between two adjacent layers), grain type, slab thickness and failure layer depth. The RTA delivers no direct information on stability, but been proven to reliably detect structural weaknesses, characterizing potential weak layers.

3. RESULTS AND DISCUSSION

In the following we describe the results for the avalanche problem algorithm for one AWS in the *Axamer Lizum* throughout the winter season 2021/22. We will first present and discuss the decision path of the algorithm for assessing the *Persistent Weak Layer Problem* and then focus on the *Wet Snow Problem*. To give an overview on the prevailing avalanche conditions, Figure 2 (a) shows the evolution of the avalanche danger level over the

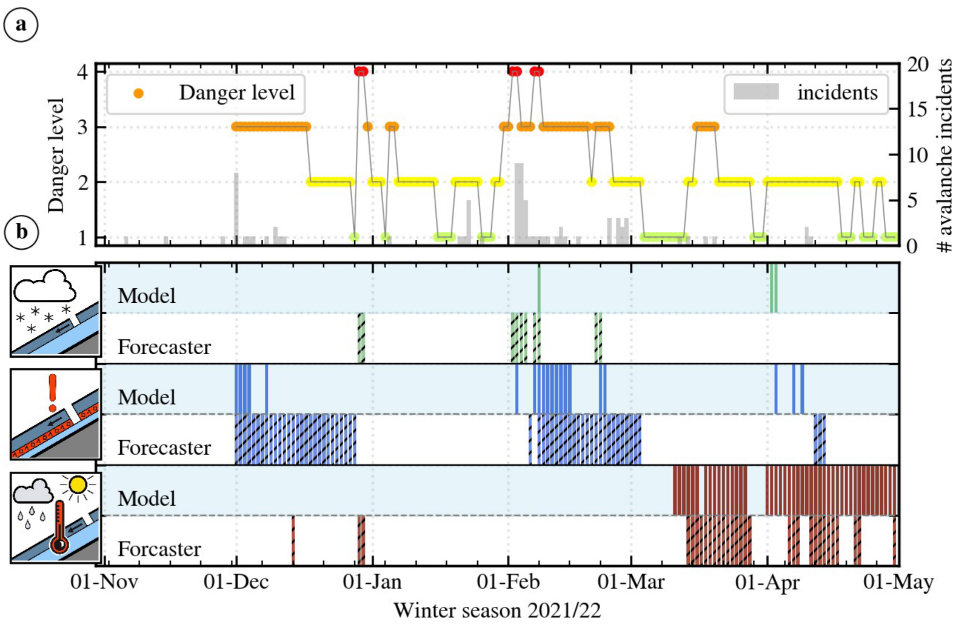

Figure 2: (a.) Evolution of the maximum avalanche danger level per day in Tyrol during the winter season 2021/22 and reported avalanche incidents with people involvement by grey bars. (b.): Avalanche problems assigned by the model in the blue shaded area compared to the avalanche problem assigned by the avalanche warning service Tyrol for the surroundings of the AWS *Axamer Lizum*.

course of the winter-season 2021/22 for the warning region where the AWS *Axamer Lizum* is located. In addition to the colored dots representing the avalanche danger levels, we plotted reported avalanche incidents in the surroundings of the AWS. The avalanche conditions represent an average winter season in Tyrol with two critical periods, reaching high avalanche danger level-4; one at the end of December and one at the beginning of February. Especially the second period was characterized with several avalanche incidents. Figure 2 (b) displays the avalanche problem assignment given by the forecaster (bars in white shaded area of the plot) and detected by the algorithm (blue shaded area in the plot). Overall the model appears to have a fairly similar behavior in assigning avalanche problems as the forecast. In more detail, there are distinctions in the beginning and duration of each problem. As for the *Persistent Weak Layer Problem*, illustrated in the third panel, the model appears to assign it during the same periods, albeit not prolonged as indicated by the forecaster. The *Wet Snow Problem* assignment of the model and forecaster, in the fourth panel, exhibits a significant similarity in depicting the problem.

Persistent Weak Layer Problem

For the detailed analyses of the *Persistent Weak Layer Problem* we focus on the critical conditions prevailing the period with high avalanche danger level-4 at the beginning of February 2022. Figure 3 (a) shows the problem assignment by model and forecaster, (b) the checks relevant for the algorithm to give the *Persistent Weak Layer Problem*, with ticks indicating if thresholds are exceeded. Figure 3 (c) displays the evolution of the total snow height, and the 24-hour and 48-hour of new snow, while (d) and (e) give detailed information on the relevant criteria presented in Table 1.

The model identifies the *Persistent Weak Layer Problem*, on the 3 February, a few days earlier than the forecaster (on the 6 February), but assigned it for one day only. Both forecaster and model drop the problem after a day, to reassign it for a longer period (starting from 7, respectively 8 February). In contrast to the forecaster, the model drops the problem on 15 February. With the snowfall event around 22 January, a potential persistent weak layer is buried but the cohesive slab criteria, in this case the slab height, is not fulfilled. Therefore it is not assessed as critical. The precipitation event from 3 February, buried a weak layer, created a cohesive slab and reached critical stability. For the upcoming days the (potential) weak layer is present, but the overlaying slab, with thin slab height, does not support the crack propagation. With the next snowfall on 6 February, the weak layer is reactivated and propagation and initiation criteria are fulfilled. The snowfall event on 15 February buried a new persistent weak layer. This new layer, overlaid by a thin slab, does not fulfill the slab height criteria, therefore no stability criteria are calculated and no problem is assigned. Although the previous persistent WL could still be triggered directly, it is not assigned due to the secondary release treatment of deep persistent

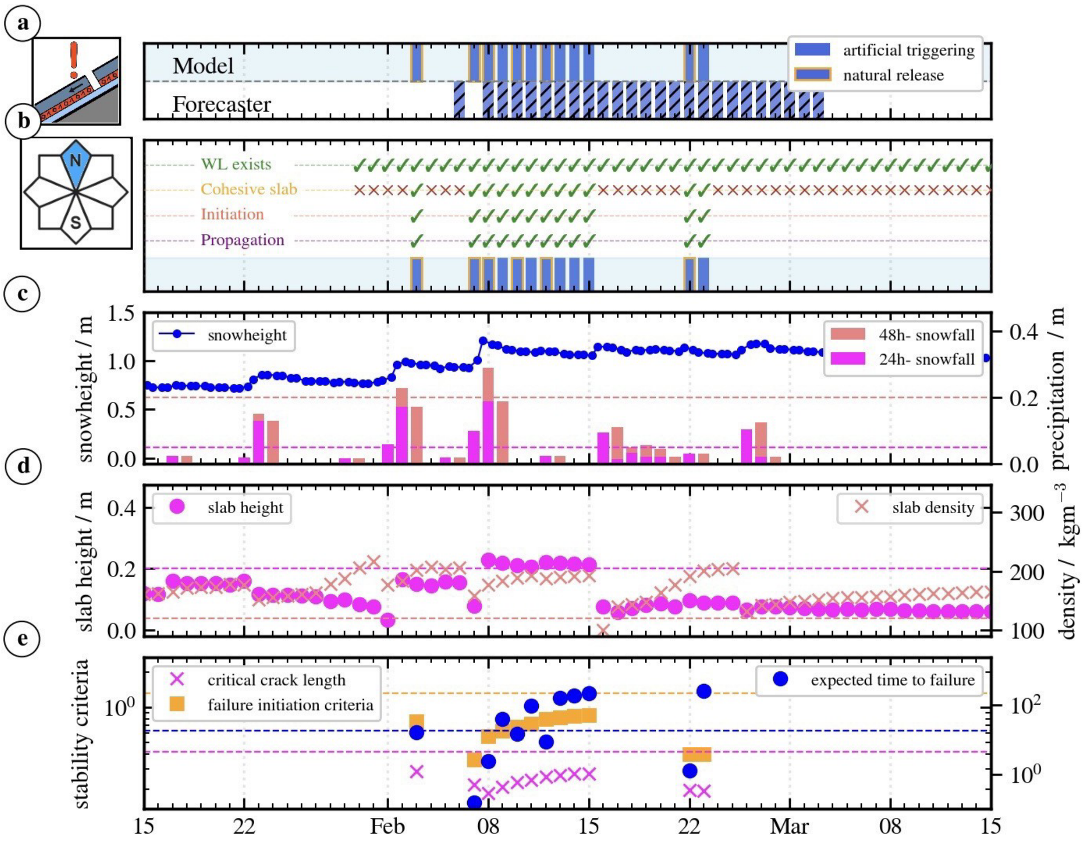

Figure 3: Persistent Weak Layer assignment for the AWS *Axamer Lizum* and its surroundings for the period of February till March 2021 valid for northern aspects. (a.) Assigned by the algorithm in the upper shaded area respectively by the avalanche warning service Tyrol in the white shaded area. (b.) Problem assessment for simulations for the north-facing slopes. (c.) Total snow height in meters, measured at the AWS as well as the 24-hour solid precipitation and 48-hour precipitation. (d.) Cohesive slab criteria as slab height in meters and the density of the new snow. (e.) Stability criteria composed by critical crack length, failure initiation, expected time to failure.

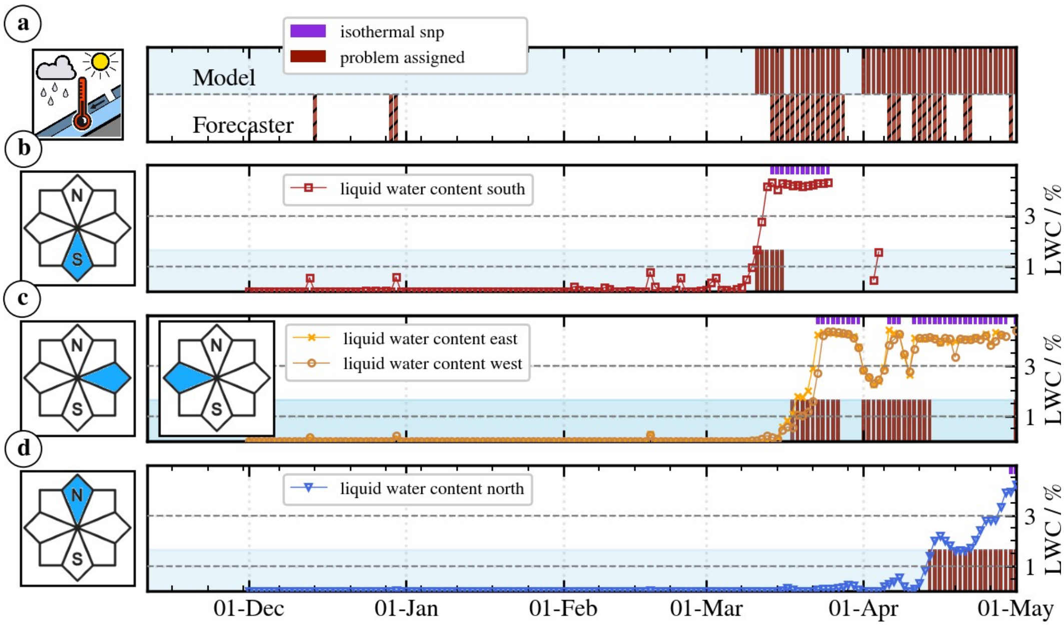

Figure 4: *Wet Snow Problem* assignment for the AWS *Axamer Lizum* and its surroundings for the winter season 2021/22: (a.) Assigned by the algorithm in the upper shaded area and by the avalanche warning service Tyrol in the white shaded area. Simulated LWC in % per volume for (b.) south- , (c.) east- and west- and (d.), north-facing slopes. Small purple bars on top-axis of the graphs indicate the days of isothermal state; red bars indicate whenever the algorithm hits the threshold for assigning a *Wet Snow Problem.*

problems. Only after several minor snowfall events till the 22 February the algorithm detects avalanche conditions again.

The *Persistent Weak Layer Problem* is generally hard to assess, as it is based on processes happening within the snowpack. It is barely identified without field observations such as snow profiles. In addition, it is responsible for severe incidents. Numerical simulations suggest an objective identification of *Persistent Weak Layer Problem(s)*, depending on aspect, timing of development and duration of persistence. Forecasters tend to keep the *Persistent Weak Layer Problem* longer than it might be necessary. Still, we have to keep in mind that in contrast to the avalanche bulletin, SNOWPACK only supplies point information and no spatially distributed information.

Wet Snow Problem

Figure 4 (a) shows the modeled *Wet Snow Problem* and the forecaster's assessment, (b) to (d) the liquid water content (LWC) in percent per volume and the days of isothermal state for the four main aspects of our virtual slope simulations. The spring season in the surroundings of the AWS *Axamer Lizum* was dominated by several melt-induced events driven by air temperature advection and solar radiation. The model assigned the critical state of the *Wet Snow Problem* to the sunnier slopes first. Hence, simulations of southern aspects reached the critical threshold on the 11 March, while the east-facing on the 17 and west-facing slopes on the 18 March. Although the southern slopes get unstable initially, they return to stable conditions after six days with four days of isothermal state. The eastern and western aspects underwent several wet snow cycles until the end of the season. North-facing slopes followed at the end of the season, forced by temperature advection. This slope specific visualization of the LWC can support forecasters in timing the beginning and end of *Wet Snow Problem(s)* on various aspects.

4. CONCLUSION AND OUTLOOK

In conclusion, this study focused on analyzing the performance of an avalanche problem algorithm for the AWS located in *Axamer Lizum* during the winter season 2021/22. The results were presented and discussed for two main avalanche problems: the *Persistent Weak Layer Problem* and the *Wet Snow Problem*. Regarding the *Persistent Weak Layer Problem*, the model demonstrated a generally similar behavior to the forecaster's assignment. Differences were observed in the initiation and duration of the problem. Detailed analysis revealed that the model identified the problem a few days earlier than the forecaster, but assigned it for a shorter period. The simulation indicated that the problem persisted for nine days, while the forecaster dropped it after a day, only to reassign it for a longer period. The analysis pointed out that simulations using SNOWPACK can provide valuable information about *Persistent Weak Layer Problem(s)*, aiding in their identification and duration assessment. In situations where the stratigraphy exhibits several persistent WLs, only the uppermost is referred directly for the *Persistent Weak Layer Problem*. This might lead to an underestimation of surface near older persistent weak layers. Therefore, we suggest an evaluation of the treatment for older persistent weak layers, covering primary and secondary release mechanisms. The simulations for the *Wet Snow Problem* confirmed typical observations, e.g. that the southern aspect experienced the problem first. The eastern and western aspects underwent several wet snow cycles throughout the season. The algorithm can facilitate aspect-specific challenges to support forecasters. In summary, this study underscores the potential of SNOWPACK simulations to enhance avalanche hazard assessment by providing valuable insights into *Persistent Weak Layer* and *Wet Snow Problem(s)*. While the model exhibited some disparities compared to human forecasters, its capabilities in early problem identification and duration assessment offers a valuable complement to traditional forecasting methods. Furthermore, the aspect-specific characteristics highlight the need for tailored forecasting approaches to address varying conditions across different slopes.

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