METEOROLOGICAL AND SNOWPACK PROPERTIES ASSOCIATED WITH CRUST-ADJACENT PERSISTENT WEAK LAYERS

PART 2: APPLYING THEORY TO OBSERVED PATTERNS

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ABSTRACT: Over the past nine seasons, ten substantial melt-freeze crusts formed in avalanche start zones along Turnagain Pass, in the heart of Alaska's Chugach National Forest. Near-crust faceting was frequently observed after crusts were buried, producing a persistent weak layer that would often become a forecasting challenge for weeks or months to come. Massive dry and wet slab avalanche cycles and dangerous near-misses were credited to the facets that developed above, within laminations of, or below these crusts. However, not all crusts developed a weak layer that would produce long-term avalanche activity.

This study explores weather and snowpack observations that may help avalanche practitioners anticipate long-term avalanche problems on crust-adjacent persistent weak layers. A companion paper reviews existing research related to crusts and persistent instability, identifying long- and short-term cumulative loading, temperature trends, and stability test results as potential indicators of problematic crust-adjacent weak layers. Here, we explore the practical utility of applying these factors as predictors of crust-related avalanche activity by comparing them against two groupings of well-documented crusts at Turnagain Pass: (1) those with a weak layer that ultimately produced persistent avalanche activity, and (2) those with short-lived or no reactivity. We use Support Vector Machines to identify loading and temperature thresholds that separate active and inactive seasons. We then use a simple contingency table analysis to explore the best ways to apply stability test results and individual loading event magnitude toward predicting avalanche activity. This work highlights the utility of previously-identified predictors, with an emphasis on putting theory into practice. We also identify areas for potential future work along these lines, and ways to improve current practices to improve our ability to anticipate avalanche activity on crust-adjacent persistent weak layers.

KEYWORDS: crust, persistent weak layer, machine learning

1. INTRODUCTION

Predicting avalanches failing on persistent weak layers that form above, within laminations of, or just below a crust is a challenge to avalanche forecasting operations. One of the biggest challenges is anticipating whether observed crust-adjacent instability is short lived, or whether it has the potential to produce large-scale destructive avalanches weeks or months after a crust is buried. This challenge has led to a body of research – in the form of case studies, theory, lab experiments, and forecasting frameworks – that provides avalanche practitioners with tools to evaluate crusts.

A companion paper (Moderow et al. 2024) reviews this growing body of work, in search of potential indicators that can help avalanche forecasting operations differentiate between conditions that produce long term, crust-adjacent instability, and conditions where long term issues are less likely. This paper tests several potential indicators – namely cumulative precipitation, temperature trends, and stability test results – on a set of substantial crusts observed in the Chugach National Forest over nine seasons.

Turnagain Pass is located on the north end of the Kenai Peninsula in Southcentral Alaska, USA, approximately 60 km (40 mi) southeast of Anchorage (Figure 1). The Seward Highway runs over Turnagain Pass, reaching a maximum elevation of 300m (1000'). The corridor provides excellent access to the Kenai Mountains, and is among the busiest winter backcountry recreation areas in Alaska for motorized and non-motorized recreationists. This area is the core forecast zone for the Chugach National Forest Avalanche Center (CNFAC).

The Kenai Mountains rise from sea level to approximately 900-1,350m (3,000-4,500') in elevation. The region's snow climate varies significantly over short distances. Interannually, the forecast zone has been shown to exhibit characteristics of maritime, continental, and intermountain snow climates (Wagner, 2012).

The CNFAC maintains a public database of snowpack and avalanche observations (CNFAC,

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2024). We examined these records and weather station data from the 2015/16 season through 2023/24 and identified ten substantial crust layers that formed early in the season and were the focus of CNFAC observations and avalanche forecasts for weeks to months after they were buried. Weak layers associated with some of these crusts would go on to produce avalanches 2-8 weeks after burial, while others would act as a reactive interface for only a few days after burial.

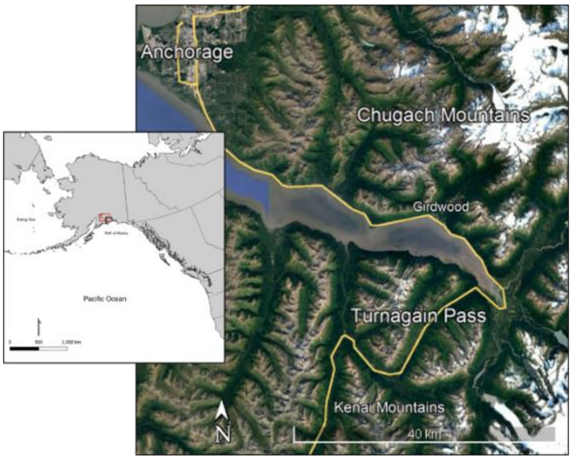

Figure 1: Location and study area. Data: Google Earth (2024), World Bank (2020), Nat. Res. Can. et al. (2010).

It can be a challenge to anticipate whether a crust will evolve into a persistent problem, or if avalanche activity will be short lived. In many cases, the only way this question gets answered is by observing a large avalanche, either triggered intentionally during mitigation work conducted by other operations near the CNFAC forecast area, or with an accident or near-miss in the backcountry. Once a crust forms and is then buried it can be difficult to assess stability based on snowpack structure alone, which will often have one or more of the following characteristics whether the crust/facet layer produces avalanches or not:

- ~1-2mm faceted grains above and below the crust.
- Laminations of crusts and facets that form a layer 20-30 cm thick or more.
- Moist or wet grains in a thick layer below the crust.
- A slab overlying the crust/weak layer complex, increasing in thickness over time.

While we commonly refer to avalanches failing above or below these crusts, the weak layers that produced the avalanches were almost always faceted grains immediately above, below or between laminated layers within the crusts. For ease of communication in this paper, we will simply refer to avalanches as failing ‘above’ ‘below’ or ‘within’ crusts.

This paper uses weather and avalanche records from a public backcountry forecasting operation to identify effective predictors of persistent avalanche problems associated with buried crusts. We investigate the cumulative precipitation above crusts and average air temperatures following crust formation to explore conditions that may or may not drive faceting near the crust. We also explore loading events immediately prior to avalanche activity, and the effectiveness of common stability tests as indicators of reactivity, to detect conditions that may predict avalanche activity in the short-term. By exploring all of these characteristics – which were identified in Moderow et al. (2024) as some potential predictors of instability – we are investigating properties related to weak layer and slab development in the weeks following crust burial, as well as shorter-term indicators of avalanche activity.

2. METHODS

Between the 2015/16 and 2023/24 seasons there were 10 substantial crusts that formed at and above treeline (750m or 2500’) within the CNFAC advisory area. We divide these crusts into two main groups – the ‘active’ group, which was associated with avalanches up to 8 weeks after burial, and the ‘inactive’ group, which may have produced direct-action avalanches in the days following burial, but would not go on to produce avalanches later in the season. A substantial crust was one of sufficient thickness and hardness that it was observable in snow pit walls for weeks or months after formation. These crusts were the result of rain on snow and/or multi-day warming events that raised temperatures well above freezing at and above treeline on Turnagain Pass. To take into account future loading events and to observe each crust for several months before wet avalanche problems dominate the region, only crusts that formed by mid-January are analyzed.

2.1 <u>Cumulative Precipitation</u>

We characterize the cumulative precipitation above a crust by tracking the precipitation beginning on day 1 after a crust forms, through day 100. We use Support Vector Machines (SVM) to identify a precipitation threshold that separates the active group from the inactive group (Awad and Khanna, 2015). In this case, SVM is an effective alternative to similar statistical regression methods because it works well with smaller datasets and does not make assumptions about the underlying distribution of a dataset (Kecman, 2005). Additionally, SVM is less prone to overfitting than artificial neural networks (Awad and Khanna, 2015). This can make the SVM model more reliable in predicting future data points.

The SVM model is fit using each day as an independent observation, which has an observed value of cumulative SWE above the crust as the explanatory variable, and whether the crust evolved to be ‘active’ or ‘inactive’ as the response. In order to explore the variability in predictive strength of cumulative precipitation over time, we fit an SVM model using cumulative precipitation from day one through the first week, second week, third week, etc. up to 100 days after the crust was formed. We use a bootstrapping technique (Effron and Tibshirani, 1985) to estimate the predictive accuracy for each case. For each of the time periods of interest, we randomly assign 80% of the daily cumulative precipitation observations to a training dataset to train an SVM model. We assess the predictive accuracy of each model by predicting the class (i.e. ‘active’ or ‘inactive’) of each day in the remaining 20% of the dataset and counting the number of correct assignments. For each time frame (1-week, 2-week, etc.), we fit the model 10,000 times, with each run randomly assigning new training and test datasets. We compare mean percent prediction accuracy (i.e. the percentage of correct daily assignments to ‘active’ or ‘inactive’ groups) for each time frame to identify the time period with the best predictive performance.

After identifying the optimal time frame for the SVM, we fit an SVM model using the full set of daily observations within that optimized time period and plot the SVM decision boundary, which represents the cumulative precipitation threshold separating active and inactive crusts, using the time frame with the highest accuracy rate.

2.2 Temperature Trends

We use a similar SVM bootstrapping technique described in section 2.1 to explore predictive potential for daily average temperature during different time frames following crust formation. We use the same training and test data sizes, and number of model runs as described in section 2.1, using daily average temperature as the predictor rather than cumulative SWE. We explore predictive potential for days 1-7, 7-14, 14-28 and so on up until day 100. We then select the model for the optimal time frame based on predictive accuracy and plot the SVM decision boundary as in section 2.1.

In addition to daily temperatures, we also explore the phase of the crust layer at the time it was buried. Anecdotal observations suggest that crust layers may be more likely to produce avalanches weeks after formation when they are buried wet, i.e. before they have a chance to freeze. This is in alignment with the melt layer recrystallization process described in Birkeland (1998). Moderow et al. (2024) describe multiple studies in which this process has been observed in controlled experiments and documented in the field. However, it is unclear whether melt layer recrystallization would be more prone to persistent avalanche issues than faceting due to the large temperature gradients observed adjacent to already frozen crust layers (Hammonds, 2015). We explore the melt/freeze layer phase at time of burial (i.e. frozen or not) as a potential indicator of problematic crust layers by looking at the proportion of active crust layers that were buried wet vs. frozen, and comparing that to the proportion of inactive crust layers that were buried wet vs. frozen.

2.3 Stability Tests

It can be a challenge to use stability tests to assess the reactivity of weak layers associated with buried crusts, particularly after they have been buried for a long time. Even so, in the absence of clear signs of an unstable snowpack (e.g., avalanche activity or collapsing) the best (or sometimes only) indicator of weak layer instability is often stability test results. Considering this, we evaluate the utility of stability tests in inferring crust layer reactivity by investigating stability test results for the active avalanche seasons shared publicly by avalanche professionals through the Observations platform on the CNFAC website (CNFAC, 2024). These stability tests include the Propagation Saw Test (PST), Extended Column Test (ECT), and Compression Test (CT). We explore four cases:

I. Unstable test results defined by a PST End with cut length of less than half of the column, or an ECTP, regardless of the number of taps.
II. Unstable results as defined in case I *or* any CT with a score of less than 21
III. Unstable results as defined in case I *or* any CT with fracture character SP or SC, or shear quality Q1 or Q2.
IV. Unstable results defined by any of the three cases described above qualifying as ‘unstable’.

These test results were then compared to observed avalanche activity in the region, with ‘observed unstable’ assigned to days of crust-adjacent avalanches or observed collapses. Days were designated ‘unstable’ beginning on the first day of individual avalanche cycles and ending on the last day of observed avalanche activity. This approach allows us to examine the effectiveness of the ECT/PST and the CT and to look at the best way to incorporate test results to achieve the highest accuracy. For each of the four cases, we generate contingency tables (Table 1) and calculate summary statistics commonly used in assessing stability test effectiveness (e.g. Birkeland et al., 2023). Specifically, we calculate:

- Probability of Detection (POD), which is the number of unstable test results that correspond with unstable conditions, or True Unstable/Total Observed Unstable;
- Probability of False Detection (POFD), which may also be described as the false unstable

rate, or False Unstable/Total Observed Stable; and

- False Alarm Ratio (FAR), which may also be described as the false stable rate, or False stable/ Total observed unstable.

Table 1: Example contingency table used to summarize stability test results.

		Observed	
		Unstable	*Stable*
Predicted	*Unstable*	True Unstable	False Stable
	Stable	False Unstable	True Stable

2.4 Loading events prior to avalanches

The final variables we investigate are the 1-, 3-, and 7-day loading thresholds prior to avalanche activity. These time frames align with the thresholds identified in previous studies, described by Moderow et al. (2024). We identify 44 days of natural or human-triggered avalanche activity in our dataset and an additional 4 days where no avalanches were observed but collapsing was reported, and investigate the cumulative loading in these three time periods prior to the observed avalanches.

We calculate the mean value for 1-, 3-, and 7-day loading periods, and split the data into two groups; those days during which signs of instability or avalanche activity were observed, and those days when no signs of instability were observed. For each time period, we calculate the mean SWE total for the 'unstable' days. We assume any SWE value exceeding this mean value to indicate an 'unstable' predictor, and any SWE total less than the mean value as a 'stable' predictor. We use these predicted values to generate similar contingency tables as in section 2.3, and calculate the same descriptive statistics for those contingency tables (i.e. POD, POFD, FAR).

3. RESULTS

3.1 Cumulative precipitation

There is an apparent difference in total cumulative precipitation between active and inactive crust layers, with active layers often receiving less precipitation than inactive layers (Figure 2).

Cumulative precipitation during the first week following crust formation is a very poor indicator for whether a crust will be a problem or not (Figure 3), with average predictive accuracy of 0.65 (n = 10,000, sd = 0.11). After day 7, there is a sharp increase in model performance from weeks 2-3 (mean = 0.75, sd = 0.07 and 0.06, respectively) which slowly tapers off after that. In other words, the data are showing that the best window for using cumulative SWE to predict whether a crust will be a problem in the long term is in the 2-3 weeks following crust formation.

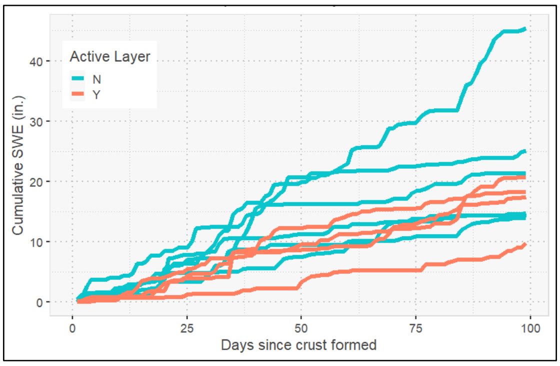

Figure 2: Cumulative SWE above crusts for 100 days after the crust formed. Each line represents one of the ten crusts in our dataset. 'Active' crusts are colored red, while 'inactive' crusts are in blue. The x-axis shows the number of days since the crust formed.

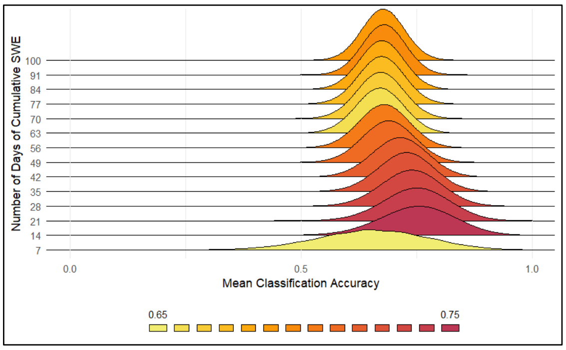

Figure 3: Ridge plot histograms of model performance for each time frame. Darker colors with a peak further to the right of the chart indicate higher percent accuracy

The decision boundary defined by the SVM for days 1-21 models a cumulative SWE threshold that separates days belonging to the 'active' group from days belonging to the 'inactive' group (Figure 4). For a given day after crust formation, if cumulative SWE falls above the threshold the crust layer is more likely to be inactive, and if the cumulative SWE falls below the threshold the crust layer is more likely to produce avalanches in the long term.

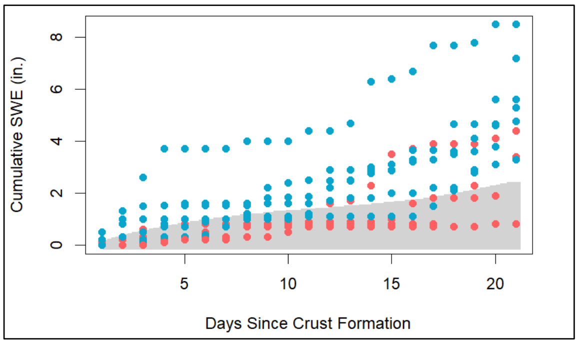

Figure 4: Threshold defined by SVM decision boundary for weeks 1 through 3 following crust formation. An observation falling within the gray shaded region is more likely to belong to the 'active' group, while an observation falling above that threshold is more likely to belong to the 'inactive' group.

3.2 *Temperature Trends*

In both the active and inactive groups, the number of crusts buried wet is exactly equal to the number of crusts buried after they have a chance to freeze (Figure 5).

Looking at daily average temperatures following crust formation, the SVM performed the strongest during weeks one and two, with an accuracy rate of 70% and 73%, respectively (Figure 6). In general, the active crusts had colder average temperatures than the inactive crusts. SVM performance drops sharply beyond week 2, accurately classifying around 55% of the observations.

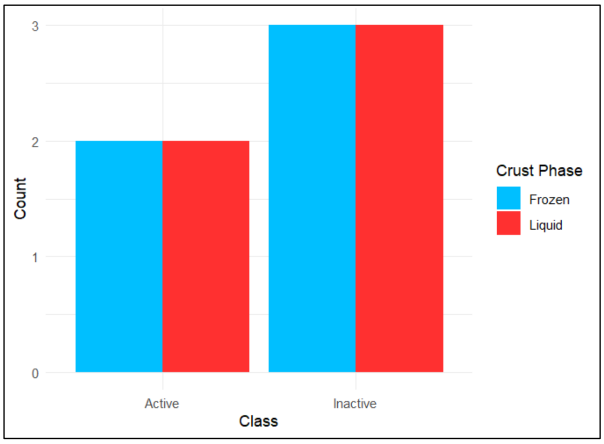

Figure 5: Number of crusts buried frozen (blue) or moist/wet (red). Active crusts are grouped on the left, inactive crusts are grouped on the right. For both groups the number of 'wet' crusts is exactly equal to the number of frozen crusts.

The SVM decision boundary in Figure 6 defines the threshold separating the 'active' group from the 'inactive' group. In general, the 'active' group observed colder temperatures during the first two weeks after the crust formed. If a daily average temperature falls below the threshold (in the gray shaded area of the chart), the observation is more likely to belong to the 'active' group. This relationship is not as clear as the cumulative SWE threshold described in section 3.1, which is also reflected in the slightly lower model accuracy.

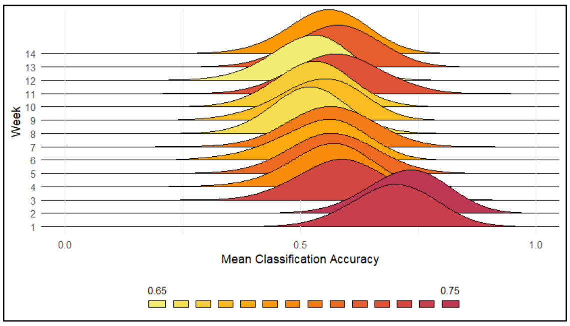

Figure 6: Mean SVM accuracy using daily average temperature to predict activity group membership. Note the sharp decline in predictive accuracy after week 2.

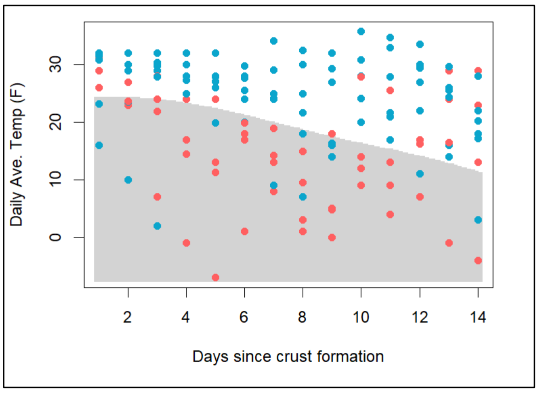

Figure 7: Threshold defined by the SVM decision boundary for daily average temperature during weeks 1 and 2 following crust formation.

3.3 *Stability Tests*

The ECT and PST, when used without a CT, had a 35% POD. In other words, during time periods where a crust-adjacent weak layer was producing avalanches, these two tests accurately classified conditions as such 35% of the time. The tests had a POFD of 19%, and FAR of 65%. (Table 2).

When the CT score is included (without fracture character or shear quality), we observe a POD of 32%, with a POFD of 23% and a FAR of 68%.

When the fracture character and shear quality are included (without CT score), we observe a POD of 40%, with 35% POFD and 60% FAR. If we incorporate ECT, PST, CT score, fracture character, and shear quality, designating the test result as 'unstable' if any of these methods produces an unstable score, we see a POD of 48%, with POFD of

18% and FAR of 52%. Contingency tables for all four cases are shown in Table 3.

	True Positive (POD)	*False Unstable (POFD)*	*False Stable (FAR)*
1-Day	0.29	0.18	0.71
3-Day	0.44	0.23	0.56
7-Day	0.44	0.28	0.56

Table 2: Summary statistics for four different approaches to applying stability tests.

	True Positive (POD)	*False Unstable (POFD)*	*False Stable (FAR)*
ECT/PST	0.35	0.19	0.65
ECT/PST + CT Score	0.32	0.23	0.68
ECT/PST + CT Fracture Character	0.40	0.35	0.60
Holistic	0.48	0.18	0.52

Table 3:Contingency tables for four approaches to applying stability tests.

ECT/PST

		Observed	
		Unstable	*Stable*
Predicted	*Unstable*	21	3
	Stable	39	13

ECT/PST + CT Taps

		Observed	
		Unstable	*Stable*
Predicted	*Unstable*	27	6
	Stable	58	20

ECT/PST + CT Fracture Character

		Observed	
		Unstable	*Stable*
Predicted	*Unstable*	32	9
	Stable	49	17

Holistic

		Observed	
		Unstable	*Stable*
Predicted	*Unstable*	36	9
	Stable	39	41

3.4 Precipitation loading events prior to avalanches

The 24-hour loading increment had a 29% TPR, with a 18% POFD and 71% FAR. The 3- and 7-day increments had 23% and 28% POFD, respectively, with 44% POD, and 56% FAR (Table 4). Boxplots of these data show considerable overlap between the 'stable' and 'unstable' groups for each loading increment, with many large storms recorded within the 'stable' group (Figure 8).

Table 4: Summary statistics for each loading increment as a predictor of instability.

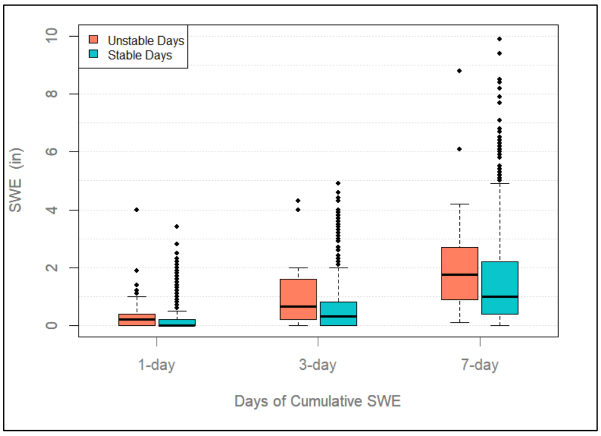

Figure 8: Boxplots of 1-, 3-, and 7-day loading increments, separated by 'stable' and 'unstable' days.

4. DISCUSSION

The results of the SVM analysis provide a visual tool that puts daily observations into context with previously documented events and can potentially reduce the uncertainty in predicting whether a crust is going to be problematic in the long term. The tool requires very little work in real-time. For example, if a new crust has just been buried and a forecaster is assessing whether it is going to produce avalanches in the weeks to come, they can plot the daily cumulative SWE on top of that recent crust, overlaid on the SVM threshold, and see where the current season is tracking compared to the ten cases studied in this project. If the current season is tracking above the cumulative SWE and average daily temperature thresholds, there is a much smaller chance it will produce long-term avalanche problems than if it is below those thresholds. Using this approach, cumulative SWE appears to be a slightly better predictor than daily average temperature, although both factors may help to resolve some uncertainty.

The SVM for the ideal time frame – the 2-3 weeks after crust formation – can accurately separate 'stable' and 'unstable' seasons ~75% of the time. That's a similar rate to previous attempts at using various models to predict avalanche activity (e.g. Hendrikx et al., 2014; Marienthal et al., 2015; Schirmer et al., 2009). This also confirms prior research that identifies initial crust burial depth and weather conditions as important early indications of potential long-term instability (Moderow et al., 2024). This relationship between cumulative SWE and average temperature is a major factor driving snow metamorphism near the recently formed crust. Based on what we are seeing from this dataset the observed trends of lower SWE totals and cooler average temperatures corresponding with long-term instability indicate the temperature gradient in 1-3 weeks following crust formation is a key player driving instability. A larger temperature gradient above the crust would likely promote faceting and weak layer formation, which can lead to longer-term instability.

Interestingly, our data do not show any difference in avalanche behavior between crusts that are buried wet or frozen. This may simply be a result of using a small dataset, or it may suggest two different processes driving metamorphism adjacent to melt/freeze layers. Melt layer recrystallization relies on the presence of liquid meltwater within the melt layer at the time of burial by a relatively colder layer of new snow (Birkeland, 1998). This sets up a temperature gradient that is strong enough to drive faceting above the melt layer, which will be slower to freeze once insulated by the new snow. This process is different from the very large temperature gradients Hammond et al. (2015) observed adjacent to crystalline ice lenses within a snow sample in the laboratory. These gradients were influenced by the physical properties of the ice layer, which is a very efficient heat conductor and has lower thermal contact resistance than adjacent snow layers. Our findings suggest that both of these processes occur in the field, and both have the potential to contribute to forming a problematic weak layer. It is worth noting that most of the observations in this study reported crusts forming on top of a snowpack that is either moist or wet and remains so several days or weeks after the crust is buried. Thus, there was likely a strong temperature gradient present whether the crust was frozen or not at the time of burial.

Our data clearly show stability tests do not perform well with this type of avalanche problem. We can improve performance by including more info (i.e. different kinds of tests with taps and fracture character), but only marginally. By including all of the available stability test information, tests were only able to accurately capture unstable avalanche conditions 48% of the time. If CT results are included using the score alone, we actually see a drop in POD as compared to only performing an ECT or PST, as well as an increase in both False Stable and False Unstable rates. It isn't until we include fracture character and CT score, along with ECT or PST tests in our assessment where we see improved performance. It is important to note that in this dataset, even with the most comprehensive use of tests, the false stable rate exceeds the true stable rate. Therefore we need to consider more than just stability test scores when assessing persistent weak layers associated with crusts.

Incremental SWE loading in the days prior to avalanche activity also had poor predictive performance, with low POD and high FAR. This supports what we tend to observe in the field – even when dealing with a known weak layer, we often see large storms that do not produce avalanches, and we often see avalanches after relatively small loading events. However, a closer look at the record does reveal some important patterns:

1. Precipitation loading events only produced avalanches when the total cumulative SWE above the crust was between 9.1-40.6 cm (3.6"-16") since the crust had formed. Once there was greater than 40.6 cm (16") of cumulative SWE above the crust, we did not observe any activity attributed to precipitation loading as the primary driver of instability, regardless of the magnitude of the individual loading event.
2. In the 93 precipitation loading events over the course of this study, 14 had natural and/or human triggered avalanches associated with them. The flip side of this statistic is that 85% of loading events did not produce avalanches.
3. Avalanches occurred during/after the second through sixth precipitation loading events after the crust formed, but never after the 7th or later.

5. LIMITATIONS AND FUTURE WORK

This study covers a small geographic area over a short time period. Although we have hundreds of days of observations, we are only comparing nine separate seasons. While this smaller dataset made it possible to look a little closer at each individual crust, it also limits our ability to apply these findings to a larger population. While the tools and trends we've described in this paper may indeed be useful and accurate, they may still need to be refined or adjusted. For example, the SVM method assumes all observations are independent. While this assumption is valid for comparing data among seasons (which is the goal of this project), it is not accurate to describe the data structure within seasons. This may impact the true predictive power of the SVM method, and is important to consider while evaluating future crust/weak layer combinations.

It seems worth exploring other ways to use the cumulative loading prior to observed avalanche activity as a predictor, since that is likely a key factor that we have not yet been able to capture. For example, considering individual loading events as a percentage of the total load above the crust may provide more insight than simply using the magnitude of the loading event on its own.

Although we explored meteorological variables that may be associated with weak layer formation, this work did not examine the predictive power of weak layer characteristics like grain size, density, or hardness. Although this data is becoming increasingly available as more professionals publish detailed observations on platforms such as SnowPilot (Chabot et al., 2004), it was often missing from the observations we examined to compile the dataset we used in this study.

While this paper examined several meteorological variables that would directly impact weak layer formation, our analysis of factors that influence slab characteristics is limited. A modelling approach using snowpack characteristics for both the slab and the weak layer may resolve some of the uncertainty that still remains. There may be much to gain by investigating changes in slab stiffness immediately prior to avalanche activity.

This project highlights the importance of including multiple types of data in assessing this particular type of avalanche. Future work may be able to build on this concept by pursuing other machine learning methods like Random Forests, Bayesian Networks, or Gradient Boosting, for example, to incorporate a variety of data to assess stability related to crust-adjacent weak layers and develop forecasting frameworks to aid in forecasting for this type of problem.

6. CONCLUSION

In describing the state of the art of avalanche forecasting, LaChapelle (1980) concluded 'Avalanche forecasting thus is seen to be the cumulative integration through time of a widely diverse body of information'. Over 40 years later, our work here supports his conclusion. We have found that individual indicators such as stability test results or storm totals do not perform well on their own as predictors of stability when faced with the problem of crust-adjacent persistent weak layers. However, we did draw some key conclusions that can better help forecasters anticipate activity on this type of weak layer in the future:

- Tracking cumulative SWE loading on top of a recently formed crust can be a very useful tool in predicting whether a weak layer will form and whether a crust will pose a problem in the long term, or if avalanche activity will be short-lived.
- Although stability tests have their limitations, performance may be improved by incorporating results from multiple tests rather than just one. It is important to consider both propagation potential/fracture character as well as the load required for initiation (i.e. number of taps) and use the weakest result to make an assessment.
- We have documented problematic crust layers whether they are buried cold or wet. Therefore, we cannot assume that a crust problem will be short-lived simply because of the phase in which it was buried.

Ultimately, there is still a large amount of uncertainty in forecasting for this type of problem. With a higher uncertainty and the potential for large avalanches, a more cautious mindset is warranted when forecasting for and traveling on a snowpack with crust-adjacent persistent weak layers.

7. ACKNOWLEDGEMENTS

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