AN APPLIED VALIDATION AND VERIFICATION FRAMEWORK FOR COMPUTER-ASSISTED PUBLIC AVALANCHE FORECASTING

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ABSTRACT: Computer-assisted avalanche forecasting models are increasingly used to support operational avalanche forecasting, yet robust and repeatable validation frameworks remain limited. This work presents a unified validation and verification system designed for operational public avalanche forecast teams to continuously validate snowpack structure, an instability model, and an avalanche danger rating model. We propose multiple verification use cases that serve as benchmarks for the validation system. Snowpack simulations are evaluated against manual snowpit observations using methods built upon dynamic time warping. Additionally, modeled temperature profiles are evaluated against measured temperatures observed throughout the snowpack. Modeled instability metrics and danger level forecasts were evaluated against backcountry observations, which were used to derive the Avalanche Activity Index (AAI) and human forecasted danger levels. AAI was calculated using the weighted sum of the frontal areas of reported avalanches. Results demonstrate that validating SNOWPACK against manual observations and measured snowpack temperatures leads to measurable comparisons in snowpack structure representation, while instability and danger level validation contextualize modeled outputs and foster a benchmark for performance. The proposed framework emphasizes relative performance, operational relevance, and repeatability rather than exact layer-by-layer model agreement, aligning model evaluation with the needs of practicing forecasters. This work provides a foundation for developing automated, scalable validation systems that support more reliable operational avalanche forecasting.

KEYWORDS: Artificial intelligence, avalanche forecasting, modeling and quantitative forecasting, validation and verification

1. INTRODUCTION

SNOWPACK (SP) is a physically based numerical model that simulates the thermal, mechanical, and mass-balance evolution of the seasonal snow cover, developed by SLF in Davos, Switzerland (Lehning et al. 1999). The model treats snow as a three-component porous medium of ice, liquid water, and moist air, solving coupled differential equations for heat transfer, water transport, water vapor diffusion, and mechanical settlement (Bartelt and Lehning, 2002; Lehning et al., 2002a, b). The model is driven by meteorological data from automated weather stations, and has been adapted to utilize forecasted model data to produce predicted snowpack properties (Bellaire et al., 2011). In order for avalanche forecasters to trust and effectively utilize SP in their operational workflow, methods for quantifying model performance and communicating model accuracy and limitations are needed (Thacker et al., 2004). Internal feedback sessions with avalanche forecasters at the Utah Avalanche Center (UAC) showed that uncertainty about model accuracy and limitations has not prevented operational use of SP, but initially slowed adoption and limited forecaster trust in its outputs (Brackelsberg et al., 2026). As verification and validation are a primary process for building confidence and credibility in numerical models (Thacker et al., 2004), quantifying model performance and verifying its functionality may increase usage amongst avalanche forecasters.

Although SP has been widely applied in avalanche forecasting and snow research, relatively few studies have presented operational validation frameworks that continuously assess model performance against field observations. Herla et al. (2021) first developed a computational method to align and quantitatively compare manual snow profile observations to modeled profiles by adapting methods of Dynamic Time Warping (DTW). This work provides a backbone for other validation work (Herla, et al. 2024) and systems that can be adapted to compare simulated SP profiles against human observations. Palomaki and Miller (2023) validated SP outputs against ten manually observed snow profiles during the 2020-2021 season using the DTW-based similarity method of Herla et al. (2021). Palomaki and Miller (2023) reported similarity scores between 0.21 and 0.62, with 1 representing perfect similarity, and showed the models consistently struggled to accurately represent crusts. Herla et al. (2024) additionally built upon prior work by developing a method to

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quantify, at a large scale, how well an operational weather and snowpack model chain represents concerning persistent weak layers and crusts observed in the field. This work provides a comprehensive operational validation for using SP in public avalanche forecasting.

The goal of this research is to develop a framework for verifying and validating SP model outputs generated from weather data recorded at a single point-location in Little Cottonwood Canyon located in the Wasatch Mountains of Northern Utah. Model verification is supported through an ice-block test, where SP model outputs are compared to a block of ice given a modified SMET and an initial snow (.sno) input files. Model validation is supported by comparing outputs against manually observed snowpits based on methods of DTW, as well as comparing snowpack temperature outputs against measured snowpack temperatures at the study site. Furthermore, downstream model outputs such as the instability model (Mayer et al. 2022) and avalanche danger model (Pérez-Gullién et al. 2022) were validated against human-observed avalanches and human-produced avalanche danger ratings. The proposed framework emphasizes relative performance, operational relevance, and repeatability rather than exact layer-by-layer model agreement, aligning model evaluation with the needs of practicing forecasters.

2. METHODS

2.1 Study Site

The Atwater study plot (40.59148, -111.63778) is located at an elevation of 2,667 meters in Little Cottonwood Canyon, UT, across the road from Alta Ski Area (figure 1). The study plot is located on flat terrain and is maintained by the U.S. Department of Agriculture, Utah Department of Transportation, University of Utah, and UAC. The study plot includes typical SNOTEL measurements such as snow water equivalent (SWE), precipitation accumulation, air temperature, snow depth, soil moisture and temperature. Additional instrumentation augments measurements for the surface energy balance providing data to drive the SP model. Two collocated snowpack temperature sensing devices were deployed to assess and quantify SP's heat transfer modeling skill. A shielded thermocouple array (K-type) and Beaded Stream temperature cable captured snowpack temperature at multiple heights above the ground on 5-minute intervals.

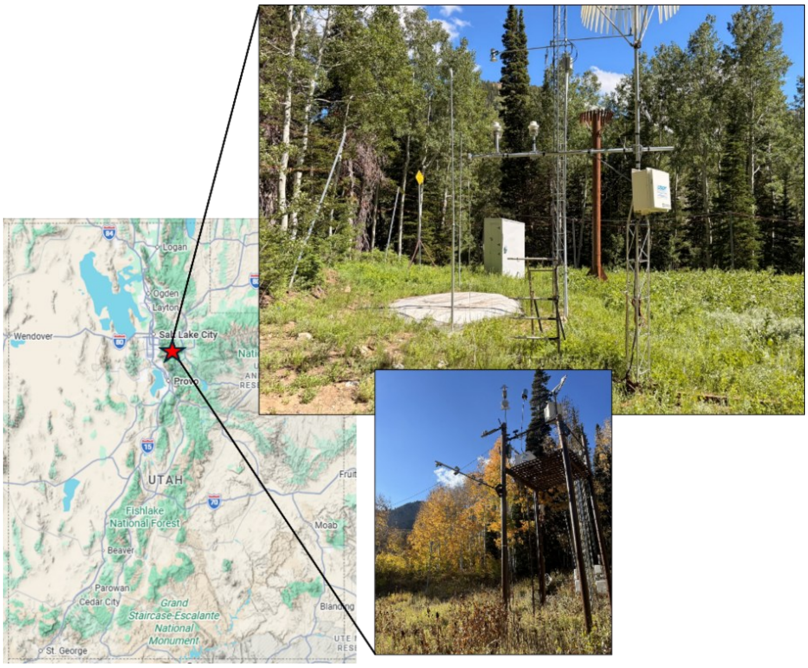

Figure 1: Location of the Atwater study plot at Alta, Utah. The inset photograph is of the SNOTEL instruments and the collocated snow temperature instruments (Beaded Stream and thermocouple array).

2.2 SNOWPACK Verification

To ensure that SP behaves as expected and repeatedly, a verification method was developed to confirm that the model reproduces expected behavior and remains physically consistent under a given set of parameters. An Ice Block Test (IBT) was developed to ensure daily repeatability, verify new versions of SP and evaluate new configuration settings. The IBT begins by initializing SP with a single ice layer, then running the model under stable, cold (-10°C), dry conditions for seven days. The verification test then evaluates whether key state variables remain within predefined physical tolerances. These variables include the presence of the ice layer, layer thickness (+/- 1.0 cm), temperature (+/- 2.0 K), ice volume fraction (+/- 0.03), liquid water content (maximum limit = 1.0%), and density (+/- 20.0 kg/m^3). If all state variables remain within their specified tolerance ranges, the IBT passes and the model configuration is considered verified.

2.3 SNOWPACK Structure Validation

To validate SP outputs against manually recorded reference data, a validator tool was created based on the snow profile alignment tool from Herla et al. (2021) to compare modeled profiles with observed snow profiles collected at the Atwater study plot. Twenty-three snow profile observations were collected between January 2024 and March 2026 (CAAML file format). For each reference pit, the tool runs a DTW alignment between the modeled and reference layer sequences. Each layer is treated as a discrete object described by a grain type and a hand hardness integer (1-6 scale). Grain similarity is looked up from the 10x10 Herla et al. (2021) matrix. Hardness similarity is calculated as the difference between modeled and reference hardness, subtracted from 1, and divided by 5. To enable comparisons among snow profiles with different numbers of layers, DTW scores were normalized by dividing the total alignment cost by the path length. Finally, normalized DTW scores were subtracted from 1 to provide a more intuitive score of 0 (no representation) to 1 (perfect representation).

2.4 SNOWPACK Temperature Validation

To validate SP outputs against measured temperature data, a thermal validation tool was created to compare modeled internal snowpack temperature and thermal diffusivity against measured, height-resolved sensor data from two independent sensing methods. These independent sensors include an array of solar-shielded K-type thermocouples and a Beaded Stream digital temperature cable at the Atwater Study Plot within the snow. Beaded Stream sensors are located 50 cm, 75 cm, 105 cm, 135 cm, 165 cm, 195 cm, 225 cm, 255 cm, and 285 cm above the ground. Thermocouple sensors are located 50 cm, 80 cm, 105 cm, and 135 cm above the ground. Sensor data is restricted to only the rows physically inside the snowpack, between the ground and the snow surface. Temperature comparisons are made both continuously (using the modeled height grid subsampled at a given value) and at the sensor heights (using the exact physical height of sensors) as a consistency check. Sensors located 40 cm from the snow surface are excluded from comparisons to avoid errors due to solar loading. To fill the near-surface comparison, surface temperature readings are used to fit a second-order polynomial to the closest buried temperature sensor. Additionally, since SP records temperature at the top of each layer, ground level is assigned the temperature of the lowest model element. Unlike the structure validation method, which is reliant on manually observed and submitted snowpit profiles, temperature data is collected hourly and can be evaluated more frequently.

In addition to validation against temperature values, comparing the thermal diffusivity of modeled and observed snowpacks can provide additional physical insights. This approach is still under development and may help validate the physical heat transfer parameterizations in the model. SP does not directly output thermal diffusivity; therefore, diffusivity is derived from conductivity, density, and the assumption that the snow's specific heat behaves like pure ice (Yen, 1981). We build on Oldroyd et al. (2012), who successfully measured thermal diffusivity with an array of snowpack thermocouples in the field. While results are absent from the work presented here, we include this methodology as an important part of a validation framework that can be derived from these measurements.

2.5 Instability Model Validation

To validate SP derived P-unstable (Mayer et al. 2022) instability outputs, an Avalanche Activity Index (AAI) was developed using avalanche data reported to the UAC from public observers between October 2023 and May 2026. Backcountry users reported widths and depths which were used to compute the avalanche frontal area, as run lengths are typically absent from human submitted observations. These reported frontal areas were binned into five categories using methods similar to Mayer et. al (2022) and Schweizer et. al (2003). An estimated run length of 304 meters was used to achieve an area binning function. The AAI is a weighted sum of reported avalanches over a day, weighted by size (equation 1), where w_i is the weight associated with each avalanche size and N_i is the number of avalanches associated with a given weight.

$$AAI = \sum_{i=1}^{n} w_i \times N_i \tag{1}$$

Reported avalanches were compared to the P-unstable instability outputs between the 2023-2024 and 2025-2026 seasons. To capture days where no avalanches were reported, the avalanche danger level was used (null days). This avoided self-correlation between high AAI values and high instability model values. When the average danger level was less than level two (moderate) and no avalanches were reported, the AAI was assigned to a value of zero. A confusion matrix was used to assess the instability metric, where a threshold of instability was defined as AAI greater than 1.0 and instability model values above 0.77.

2.6 Danger Level Model Validation

To validate SP derived danger level outputs (Pérez-Gullién et al. 2022), modeled danger levels were compared to UAC forecasted danger levels on North, East, South, and West facing upper-elevation slopes (above 2,895 meters). Despite the elevation difference between the site and the forecast elevation band, the site is known to have a representative upper-elevation snowpack for the Salt Lake forecast region. Forecasts were pulled between January 2024 and March 2026 and compared with modeled danger levels for the same period. Modeled values were plotted against the random forest predicted danger level and the average modeled danger level for each day in the observation period. Validation was assessed by an ordinal confusion matrix per aspect along with Cohen's kappa, bias, and percentage of exact agreement. Pearson's correlation coefficient, Spearman's correlation coefficient, bias, mean average error, root mean squared error, symmetric mean absolute error percentage, and standard deviation residual were calculated to continue to assess the fitted linear regression.

3. RESULTS

3.1 SNOWPACK Verification

An IBT test is performed for every new iteration of SP being used or tested (i.e. a new SP version is released, a new configuration setting is being tested, etc.) to ensure the model hasn't broken or altered fundamental snow physics. Figure 2 displays a successful IBT test for a SP model. If the IBT fails, the model cannot proceed further in the operational pipeline, and root cause analysis is initiated.

```
Parsing: ICE_TEST_ice_block.pro
  Total timesteps : 57
  With snow/ice   : 57

Checking assertions ...
  Comparing 2024-12-01 00:00:00 → 2024-12-08 00:00:00
  [PASS] Thickness  initial=10.00 cm  final=10.00 cm  drift=0.00 cm  tol=±1.0 cm
  [PASS] Temperature  initial=-10.01 °C  final=-10.08 °C  drift=0.06 K  tol=±2.0 K
  [PASS] Ice fraction  initial=0.900  final=0.900  drift=0.0000  tol=±0.030
  [PASS] Max LWC  0.00%  limit=1.0%
  [PASS] Density  initial=825.3 kg/m³  final=823.8 kg/m³  drift=1.5  tol=±20.0

[PASSED] All ice block assertions satisfied.
```

Figure 2: Output from the Ice Block Test used to verify the functionality of SP models.

3.2 SNOWPACK Structure

To assess the degree to which SP outputs represent human-observed snow stratigraphy at the Atwater study plot, a DTW-based validator tool is used. Figure 3 displays the kernel distribution of DTW-based validation scores of the Atwater model between the 2023-2024 and 2025-2026 seasons. Note the bimodal distribution in seasons 2023-2024 and 2025-2026. This can be attributed to the time of the season when observers submitted snow profiles. It should be noted that various observers were leveraged and pits were collected at irregular intervals. Despite these challenges these datasets offer a benchmark for validating the model's skill. Future concentrated efforts to improve the quality and regularity of snowpit observations will be prioritized as these data sets provide operational value.

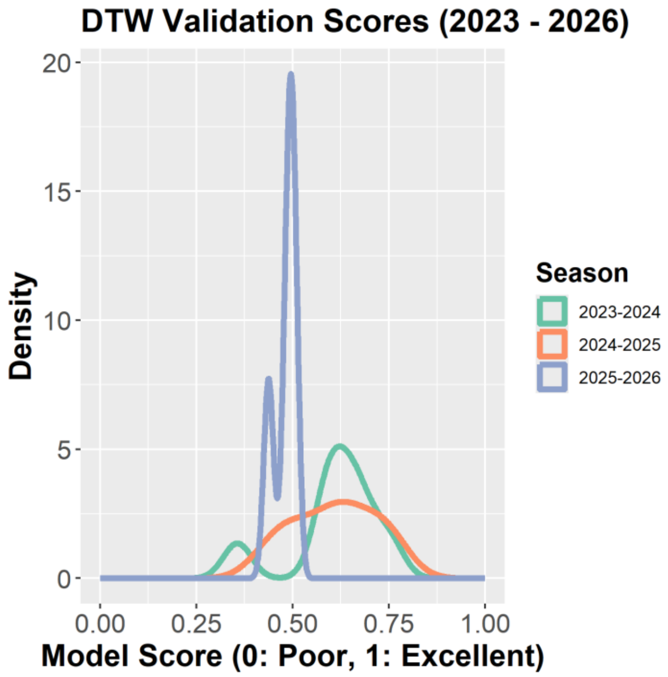

Figure 3: SP structure validation scores from 2023 through 2026. A score of 0 indicates no agreement between SP and observed data, while a score of 1 indicates perfect agreement.

Table 1 displays the minimum, first quartile, median, mean, third quartile, and maximum validation scores across each of the three prior seasons. Validation scores from the 2025-2026 season are noticeably different from the two prior seasons. This may be due to the abnormal presence of crusts within the snowpack at the Atwater study plot, which are a known grain type that SP has difficulty representing (Herla, et al 2024). Palomake and Miller (2023) found similarity scores between 0.21 and 0.62, where a score of 1 represents perfect similarity, and showed the models consistently struggled to accurately represent crusts. This framework can additionally be used to test the sensitivity of SP outputs to differing configuration settings.

Table 1: A summary of validation scores for the Atwater model from the 2023-2024, 2024-2025, and 2025-2026 seasons.

Season	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
2023-2024	0.357	0.589	0.629	0.613	0.672	0.754
2024-2025	0.450	0.526	0.619	0.607	0.694	0.742
2025-2026	0.438	0.473	0.490	0.480	0.498	0.504
All Seasons	0.357	0.500	0.605	0.587	0.658	0.754

3.3 SNOWPACK Temperature

Results of the thermal validator tool compare modeled temperature against measured temperature readings from the thermocouple and Beaded Stream instrumentation. Figure 4 displays comparisons between temperature data from the 2025-2026 season. Measured temperature is observed in Figure 4 (left) from the Beaded Stream temperature cable. Figure 4 (middle) shows the modeled snowpack temperature from SP and Figure 4 (right) shows the difference (model-observed) temperature. Similar findings were observed from the thermocouples (omitted here). As shown, the Atwater SP model consistently held a cold bias in the lower and mid-snowpack layers, while holding a warm bias at upper-level snowpack layers. A congruency of this trend between Thermocouple and Beaded Stream data indicates that the vertical interpolation of reference data is reliable. This approach may serve as a physical check to ensure reliable, and consistent model results with a physical baseline at specific sites.

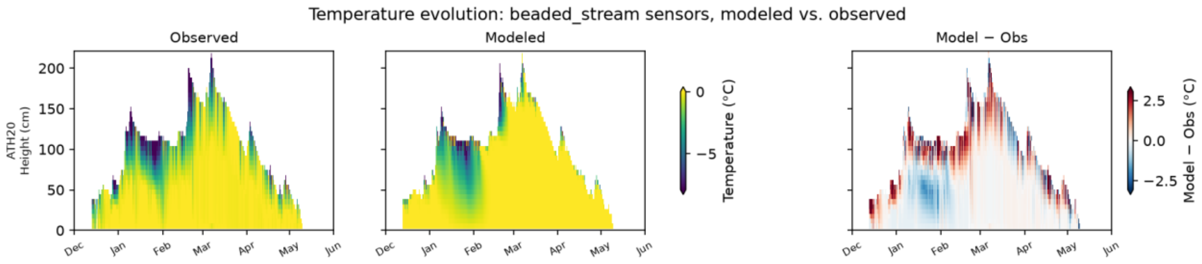

Figure 4: Modeled and observed snowpack temperatures from the 2025-2026 winter season. Results display observed temperatures recorded by Beaded Stream temperature cable.

3.4 Instability Model

Figure 5 displays a 2x2 agreement table between predicted instability (>0.77 threshold) and actual stability (AAI). Following the approach of Hutter et al. (2021), who used Cohen's kappa (κ) to assess agreement among avalanche forecasters' classifications, we computed κ to quantify agreement between these two classification schemes. Observed agreement was 62.3% (n = 193/310), compared to an expected chance agreement of 49.6%, yielding κ = 0.25, which falls in the "fair" range according to Landis and Koch (1977). Disagreement between the two schemes was asymmetric. The model over-predicted instability in 107 cases (34.5%) where conditions were actually stable, while missing only 10 cases (3.2%) of actual instability. This pattern suggests the model's predicted instability threshold is liberal (over-sensitive) relative to observed AAI-based stability, at the cost of overall agreement.

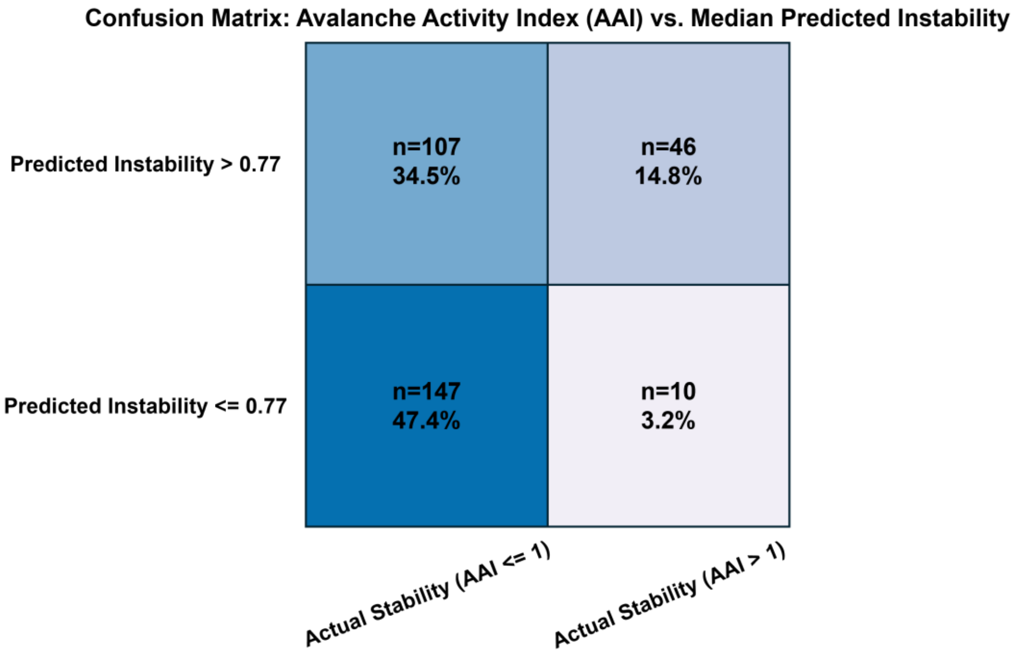

Figure 5: Agreement table of predicted instability (> 0.77) and AAI-based instability (AAI > 1) between October 2023 and May 2026.

3.5 Danger Level Model

Figure 6 displays modeled avalanche danger against UAC forecasted avalanche hazard at upper-elevation slopes facing North, East, South, and West. The percent of exact agreement ranges from 51.5% to 54.9%, and κ ranges within 0.29-0.33. This suggests "fair" agreement (Landis and Koch, 1977), and is only modestly better than random chance. Agreement is concentrated when the modeled and forecasted avalanche danger is moderate or considerable. Additionally, the model consistently over-forecasted on slopes facing North, East, and West, while the model may under-forecast on South facing slopes.

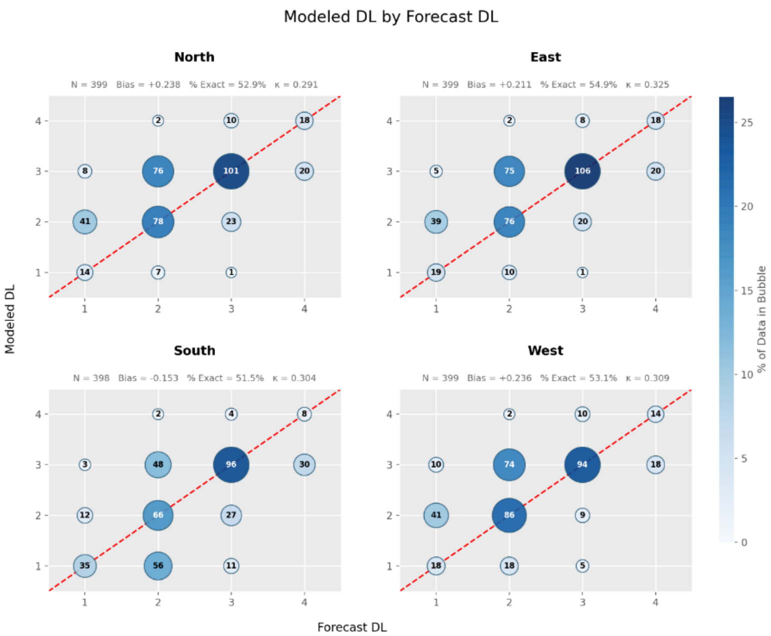

Figure 6: Modeled vs. forecasted danger level for upper-elevation slopes (above 2,895 meters) between January 2024 and May 2026.

4. DISCUSSION

This work represents a collection of approaches and techniques for benchmarking quantitative operational avalanche modeling skills. The frequency and timing of these assessments depend on the operational requirements. The verification tests are run at a minimum during code pulls and during the assessment of new source code. Expanding the verification tests are underway. Validation of subsequent models shall be performed at a minimum seasonally during annual reporting or during development of new models or adjustments to existing models. New models or features added to the operational tool chain are submitted with benchmarking and validation protocol to understand model performance. These assessments serve to extend model reliability, transparency on model skill, and to ensure repeatability. Additionally, adding validation sites at multiple regions may help local benchmarking and contextualize model results to the local forecasting zone.

The framework provided here is designed for SP modeling at a single point-location weather station. Model input data is reliant on consistent, quality data from the Atwater weather station, and gaps in data may impact model outputs and downstream forecaster tools. Gaps in weather station data are resolved by downscaling HRRR weather model data and backfilling during times of fault data (Szczerbinski et al, 2026). Structural validation depends on human-submitted snowpack observations, which are subject to observer bias. Additionally, AAI is dependent on human-submitted avalanche observations, which are self-reported estimates of avalanche width and depth. Furthermore, not all avalanches are reported. This verification and validation framework is additionally used to test model configurations, new model site locations, and tools to ensure weather data quality.

5. CONCLUSION

This work provides a verification and validation framework for computer-assisted public avalanche forecasting operations. The framework emphasizes operational relevance, repeatability, and relative performance rather than exact layer-by-layer matching. This framework and its results will serve as a benchmark for continuous model improvements and for transparency to forecasters and operational users.

Model verification via an Ice Block Test ensures that downstream model tools function properly and flags potential errors in configuration settings. Structural model validation showed a reasonable to moderate representation compared to human observations, but degraded during seasons with an abnormal presence of crusts. Temperature validation often revealed a modeled cold bias in lower and mid-snowpack while holding a warm bias closer to the snow surface. The P-unstable instability model showed a liberal bias, over-predicting instability relative to AAI-based observations. The danger level model showed fair agreement by Cohen's kappa, with a tendency to over-forecast on North, East, and West aspects and under-forecast on South-facing slopes.

We also aim to use this verification and validation framework to continually improve model representation. Changes to SP configuration settings that lead to different model outputs can be compared against baseline model validation metrics and assessed for improvements in snowpack representation. The ability to assess model performance also helps when establishing new locations for SP modeling. In addition to the Atwater location, SP modeling is currently being deployed at Trail Lake weather station in the Uinta Mountains in northeastern Utah, at Deer Valley Resort in the Wasatch Mountains, and at the Tony Grove weather station in Logan, Utah. These locations represent different snowpack types, and the configuration settings optimized for Atwater are not necessarily optimal for these other point locations.

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REFERENCES

Bellaire, S., Jamieson, J. B., and Fierz, C., 2011. Forcing the snow-cover model SNOWPACK with forecasted weather data, The Cryosphere, 5, 1115–1125, https://doi.org/10.5194/tc-5-1115-2011.

Brackelsberg, C., Pagnucco, P., Morrison, T., 2026. Implementation of snowpack and machine learning models in an operational forecasting workflow. In: Proceedings of the International Snow Science Workshop, Whistler, BC, October 2024.

Herla, F., Horton, S., Mair, P., and Haegeli, P., 2021. Snow profile alignment and similarity assessment for aggregating, clustering, and evaluating snowpack model ouput for avalanche forecasting, Geosci. Model Dev., 14, 239–258, https://doi.org/10.5194/gmd-14-239-2021.

Herla, F., Haegeli, P., Horton, S., and Mair, P., 2024 A large-scale validation of snowpack simulations in support of avalanche forecasting focusing on critical weak layers, Nat. Hazards Earth Syst. Sci., 24, 2727–2756, https://doi.org/10.5194/nhess-24-2727-2024.

Hutter, V., Techel, F., and Purves, R. S., 2021. How is avalanche danger described in textual descriptions in avalanche forecasts in Switzerland? Consistency between forecasters and avalanche danger, Nat. Hazards Earth Syst. Sci., 21, 3879–3897, https://doi.org/10.5194/nhess-21-3879-2021.

Landis, J. R. and Koch, G. G., 1977. The measurement of observer agreement for categorical data, Biometrics, 33, 159–174, https://doi.org/10.2307/2529310.

Lehning, M., Bartelt, P., Brown, B., Russi, T., Stöeckli, U., Zimmerli, M., 1999. SNOWPACK model calculations for avalanche warning based upon a new network of weather and snow stations. Cold Reg. Sci. Technol. 30, 145 – 157.

Lehning, M., Bartelt, P., 2002. A physical SNOWPACK model for the Swiss avalanche warning Part I: Numerical Model. Cold Reg. Sci. Technol. 35, 123-145.

Lehning, M., Bartelt, P., Brown, B., Fierz, C., Satyawali, P., 2002a. A physical SNOWPACK model for the Swiss avalanche warning: Part II. Snow Microstructure. Cold Reg. Sci. Technol. 35,147 – 167.

Lehning, M., Bartelt, P., Brown, B., Fierz, C., 2002b. A physical SNOWPACK model for the Swiss avalanche warning: Part III. Meteorological forcing, thin layer formation and evaluation. Cold Reg. Sci. Technol. 35, 169 – 184.

Mayer, S., van Herwijnen, A., Techel, F., and Schweizer, J., 2022. A random forest model to assess snow instability from simulated snow stratigraphy, The Cryosphere, 16, 4593–4615, https://doi.org/10.5194/tc-16-4593-2022.

Oldroyd, H. J., Higgins, C. W., Huwald, H., Selker, J. S., and Parlange, M. B., 2012. Thermal diffusivity of seasonal snow determined from temperature profiles, Adv. Water Resour., 55, 121–130, https://doi.org/10.1016/j.advwatres.2012.06.011.

Palomaki, R. T. and Miller, Z. S., 2023. Assessing SNOWPACK stratigraphy accuracy based on different input data: insights for operational avalanche forecasting, in: Proceedings, International Snow Science Workshop, Bend, OR, USA, 287–294.

Pérez-Guillién, C., Techel, F., Hendrick, M., Volpi, M., van Herwijnen, A., Olevski, T., Obozinski, G., Perez-Cruz, F., and Schweizer, J., 2022. Data-driven automated predictions of the avalanche danger level for dry-snow conditions in Switzerland, Nat. Hazards Earth Syst. Sci., 22, 2031–2056, https://doi.org/10.5194/nhess-22-2031-2022.

Schweizer, J., Kronholm, K., and Wiesinger, T., 2003. Verification of regional snowpack stability and avalanche danger, Cold Reg. Sci. Technol., 37, 277–288, https://doi.org/10.1016/S0165-232X(03)00070-3.

Szczerbinski, R., Morrison, T., Talty, M., and Steenburgh, J., 2026. Snowpack model sensitivity to observational and weather model inputs, in: Proceedings, International Snow Science Workshop, Whistler, Canada, October, 2026.

Thacker, B., Doebling, W., Hemez, F., Anderson, M., Pepin, J., and Rodriguez, E., 2004. Concepts of model verification and validation, Los Alamos National Laboratory, Los Alamos, NM, USA, Report LA-14167-MS.

Yen, Y. C., 1981. Review of thermal properties of snow, ice and sea ice, CRREL Report 81-10, U.S. Army Cold Regions Research and Engineering Laboratory, Hanover, NH, USA.