ASSESSING SNOWPACK STRATIGRAPHY ACCURACY BASED ON DIFFERENT INPUT DATA: INSIGHTS FOR OPERATIONAL AVALANCHE FORECASTING

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ABSTRACT: Avalanche forecasters and snow scientists use physically based snow stratigraphy models to fill spatial and temporal gaps in field-based snow profile observations. These models generate stratigraphy predictions using meteorological input from automated weather stations (AWS) or numerical weather prediction (NWP) models. The choice of input data is often determined by data availability or convenience instead of giving full consideration to the most appropriate source for a particular application. For example, while AWS may provide weather observations that better represent a particular site, they have large up-front costs and require specialized personnel to service and maintain. The goal of this study is to quantify the accuracy of snow stratigraphy produced by the SNOWPACK model driven by different input data, with a particular focus on cost-benefit analysis for operational avalanche forecasting. We generate modeled snow profiles at a field site in the Bridger Range of southwestern Montana, USA, using a) observations from an AWS at the field site and b) NWP output from the NOAA High-Resolution Rapid Refresh (HRRR) model. Validation data consist of a season-long time series of 10 manual snow profiles. We use dynamic time-warping (DTW) to quantify the overall and grain-type categorized similarities between modeled and in-situ observed profiles that are collocated in time and in space. Based on the similarity results, we present a cost-benefit analysis that considers the cost of installing and maintaining an AWS alongside the improved representation of snow depth, grain size, and weak layer types.

KEYWORDS: snow cover model, automated weather station, numerical weather prediction, similarity

1. INTRODUCTION

Avalanche forecasters and snow scientists use physically based snow stratigraphy models, including SNOWPACK (Bartelt and Lehning, 2002) and Crocus (Vionnet et al., 2012) to fill spatial and temporal gaps in field-based snow profile observations. These models generate stratigraphy predictions using meteorological input data, including air temperature, humidity, wind, net radiation, and precipitation. Although initial demonstrations of snow models used input data from automated weather stations (AWS) to predict one-dimensional stratigraphy at individual points (Lehning et al., 1999), spatially distributed, interpolated predictions soon followed by employing three-dimensional models (e.g., ALPINE3D; Lehning et al., 2006) and networks of AWS or output from numerical weather prediction (NWP) models as input data (Bellaire et al., 2011; Bellaire and Jamieson, 2013). These strategies are especially effective for modeling snow on regional scales where AWS and in situ observations are sparse or unavailable, and have been employed over many regions (Morin et al., 2020), including the Canadian Rocky Mountains (Horton and Haegeli, 2022), the French Alps (Vionnet et al., 2019), and the Swiss Alps (Richter et al., 2021; Pérez-Guillén et al., 2022). However, NWP output may not provide a good representation of true weather conditions at a particular area of interest, especially in mountainous terrain. The spatial resolution of NWP models (often on the order of a few kilometers) may be too coarse to resolve fine-scale terrain features that are important for localized orographic precipitation events (Goger et al., 2016; Lehner and Rotach, 2018). Unrepresentative data derived from NWP models will result in unrepresentative modeled stratigraphy.

Various commercial and non-profit operations that may wish to incorporate snow models into their avalanche forecasting workflows typically have limited human and material resources. Installation of an AWS at an area of interest would provide high-quality input data for a snow stratigraphy model but presents a significant up-front cost. On the other hand, NWP output from many weather models is freely available but accessing and preparing NWP output for stratigraphy model input data is not always straightforward. Regardless of the input data, configuring and running a stratigraphy model is a specialized skill that may require an operation to hire new personnel. Additionally, the benefits derived from these costs are

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not always easily determined. Forecast operations in different regions may place more or less value on a model's ability to reproduce different characteristics of the snowpack. For example, new snow totals may be the most important parameter for a maritime operation, while accurate representation of deeper persistent weak layers may be most important for a continental operation. A model that produces reasonable snow depths but fails to accurately represent snowpack structure may provide value for some forecasting operations but could seem relatively useless for others. Quantitative interpretation of model results with respect to different snow characteristics can help forecasters assess the potential utility of incorporating such models into operational forecasting workflows.

In this paper we present a case study to examine the stratigraphic accuracy of the SNOWPACK model based on input data from AWS observations and NWP output. We use dynamic time warping (DTW) to assess the overall and layer-specific similarities between the modeled profiles and in situ profiles at our study site (Herla et al., 2021). Finally, we contextualize our results for small- to medium-scale operational avalanche forecasting using a cost-benefit analysis.

2. METHODS

2.1 Study Site

Data were collected at the study site as part of the field experiment detailed in Miller et al. (2022). The study site (45.834 N, −110.935 E) is a sheltered meadow at 2240 m above sea level surrounded by steep, sub-alpine mountain terrain within the Bridger Range of southwest Montana, USA (Figure 1). The Bridger Range has an intermountain snow and avalanche climate (Mock and Birkeland, 2000), with average December through March temperatures of −3.5 to −7 ◦C and average annual snowfall of approximately 7.5 m measured at nearby Bridger Bowl Ski Area. The site has been host to a number of avalanche-related studies over the past 20 years (Deems, 2002; Landry et al., 2004; Lundy et al., 2001; Van Peursem et al., 2016).

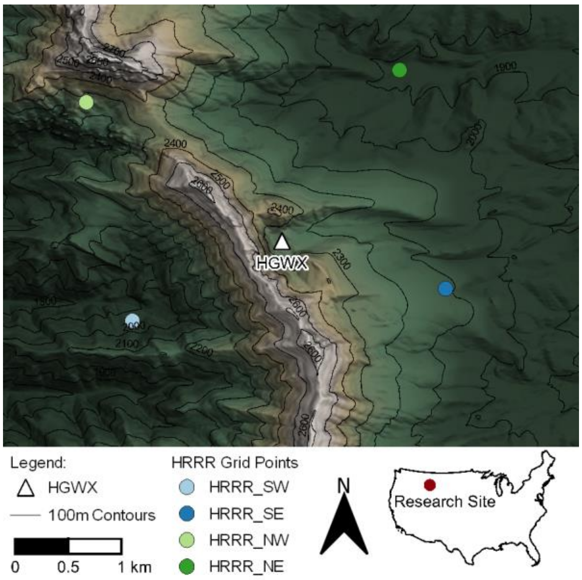

Figure 1: Study site overview in the Bridger Range of southwest Montana, USA.

2.2 Field data collection

We installed an AWS at the field site (hereafter called HGWX) on January 7, 2021, that measured air temperature, relative humidity, wind speed and direction, four-component radiation, and snow depth at hourly intervals through April 25, 2021 (Figure 2). Snow was already on the ground on the installation date, so we took a full snowpit profile in order to initialize SNOWPACK. During data collection, the internal heater for the upward-facing pyranometer failed, which resulted in some erroneous measurements of incoming shortwave radiation when the sensor was coated with ice. We replaced these bad data using measured outgoing shortwave radiation (the downward-facing pyranometer did not suffer from icing issues) and a parameterized albedo based on the elapsed time since the last snow event.


Figure 2: Photograph of study site with HGWX AWS and in situ snow profile collection from April 11, 2021.

In addition to the snow profile on the installation date, we collected nine snow profiles over the course of the study period immediately adjacent to HGWX. For each snow profile we recorded grain type, grain size, and hand hardness for each layer, and conducted density and temperature profiles over the full depth of the pits. We use these nine snow profile observations to validate model results.

2.3 *Numerical weather prediction data*

We used the High Resolution Rapid Refresh (HRRR) v4 atmospheric model (Dowell et al., 2022) to provide NWP input data for SNOWPACK. The HRRR model is run every hour and generates a 60+ hour forecast on a 3-km grid over the contiguous United States. For this study we use only HRRR analysis data, i.e., data from the *f00* file generated every hour (see Dowell et al., 2022, for more information about file structure). We selected the four closest points on the 3-km HRRR grid to our study site (Figure 1) and downloaded the necessary variables to run SNOWPACK at each of the points. A comparison of HGWX and HRRR variables revealed that modeled snow depth and snow water equivalent (SWE) were poor representations of true snow conditions at the field site. Instead, we use an accumulated precipitation variable from HRRR that represents the water content of both liquid and solid precipitation to drive SNOWPACK.

2.4 *SNOWPACK model simulations*

We used the one-dimensional snow cover model SNOWPACK (v3.5) for this study (Bartelt and Lehning, 2002). We initiated the model runs with the field collected snow profile from January 7, 2021, and modeled at an hourly time step through April 25, 2021. We used standard model settings except applying the “NIED” water transport method for snow because it is capable of modeling more complex water movement than the standard “bucket” method (Hirashima et al., 2010). We ran model simulations for HGWX and each of the four nearest HRRR gridpoint inputs.

2.5 *Quantitative profile similarity analysis*

To quantify the accuracy of SNOWPACK model results we use the dynamic time warping (DTW) method from the *sarp.snowprofile* and *sarp.snowprofile.alignment* packages developed by Herla et al. (2021) for the R programming language (R Core Team, 2019). The DTW method ingests two snow profiles, identifies corresponding layering, and resamples and rescales the layers of a query profile (modeled in this study) to that of the reference profile (observed in this study). To calculate similarity, layers of the aligned profiles are mapped and the distances between the full set of matched layers are combined into an overall similarity score. This score can be further divided into separate similarity scores for new snow (precipitation particles and decomposing fragments), bulk grains (rounds, facets, rounding facets, and melt forms), weak layers (surface and depth hoar), and crusts (melt freeze crusts and ice forms). These four layer-specific similarity scores are weighted differently in the calculation of the overall similarity score; weak layer and crust scores are weighted more heavily to accentuate their importance in avalanche forecasting applications.

We calculate similarity scores between observed in situ snow profiles and all SNOWPACK modeled outputs, both AWS-driven and NWP-driven, in all snow layer categories. We also use the averageSP function in the sarp.snowprofile.alignment package to create an average HRRR profile from the four individual grid points. This produces a representative profile for the regional conditions around the study site, but we note that this is different from spatially interpolating the snow profiles using a physically based model such as ALPINE3D.

3. RESULTS AND DISCUSSION

3.1 *AWS - HRRR comparison*

The HRRR modeled data captured each of the weather patterns measured at HGWX but did have easily identifiable biases. HGWX consistently recorded colder air temperatures than all of the HRRR model grid points (Figure 3). The seasonal mean air temperature differences ranged from +0.29 to +2.82°C for the four HRRR model grid points. To correct for these warm biases, we subtracted the seasonal mean difference from each observation in the timeseries, at each of the four HRRR points.

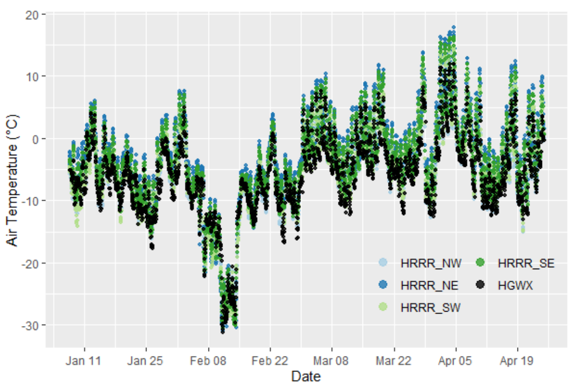

Figure 3: Air temperatures as modeled by the nearest four HRRR grid points (blue and green) before bias-correction and recorded at HGWX (black).

Incoming shortwave radiation recorded at HGWX was substantially less than modeled radiation at all of the HRRR points (Figure 4). Cumulative daily incoming shortwave radiation at all HRRR points was 35.5 - 56.2% higher throughout the duration of this study. This directly affects the modeled consolidation and melt of surface snow. We attribute this difference to localized terrain effects at our study site, which are not present at the HRRR points. At the site, HGWX is installed near the base of a 300 m ridge with steep walls immediately to the west. Recorded incoming shortwave radiation drops sharply around 14:00-16:00 local time during the winter when the sun moves behind this ridge. The HRRR points are far enough away from the site that they are not influenced by this local terrain feature, though we question whether this effect would be well-represented at the 3 km spatial resolution of the HRRR model. We did not make any adjustments to the HRRR solar radiation values before using the data to drive the SNOWPACK model.

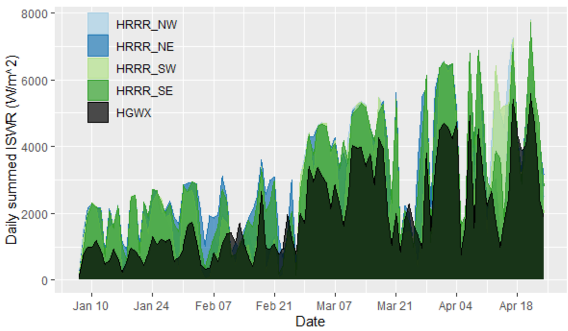

Figure 4: Daily summed incoming shortwave radiation as modeled by the nearest four HRRR points (blue and green) and recorded at HGWX (black).

We also scaled the precipitation at each of the four points using a multiplier (15 for this study) to correct for underestimation bias. This type of precipitation bias correction has been utilized in other studies (Bellaire et al., 2011, 2013).

3.2 <u>Modeled and observed snow profile comparison</u>

Calculated snow profile similarities between in situ observed and SNOWPACK modeled profiles resulted in overall similarity scores between 0.62 and 0.21 (Figure 5). The HGWX-derived simulations consistently outperformed all HRRR-derived simulations in all similarity categories when tested against the observed profiles. Within the HRRR-derived profiles, we note that input data from the points on the west side of the Bridger Range ridgeline resulted in higher similarities to observed profiles than points on the east side of the ridge, even though the study site itself is east of the ridge. We hypothesize that this is due to poor terrain representation on the 3 km HRRR grid but requires more investigation to be certain.

For all modeled profiles, weak layer similarity is the highest but also shows the largest range. For example, profiles from the HGWX, both HRRR points west of the Bridger Range ridgeline, and the average HRRR profile all have at least one comparison date with a weak layer similarity score of 1.0. However, these perfect similarity scores are for the April 24 profiles, where the observed and modeled profiles contained a single layer of basal depth hoar of similar thickness that counted toward the weak layer category in the similarity analysis. All modeled profiles scored their minimum weak layer similarity with the January 14 comparison, after only one week into the experiment. On this date the modeled profiles feature a rapidly grown layer of depth hoar to ~40 cm thick during a period of cold clear weather, which contrasted with the observed 7 cm thick layer of depth hoar.

New snow and bulk grain similarity scores displayed considerable variation across the modeled profiles. New snow similarity scores ranged from 0.91 to 0, and the extremely low values are the result of either missed precipitation or mis-characterized (rain instead of snow) events. Bulk grain similarity ranged from 0.64 to 0.07 and was generally well captured by all models with the exception of the HRRR southern grid point modeled profiles.

Crusts consistently had the lowest similarity scores throughout the season. We attribute these low scores to a persistent melt freeze crust seen in the midpack of our SNOWPACK simulation outputs that was never observed in the field. This consistently mis-represented crust layer is also the primary contributor to our relatively low overall similarity scores due to the preferential weighting of weak layers and crusts.

We also compared the HGWX-derived and HRRR-derived model profiles directly (Figure 6), instead of using the observed profiles as the reference. These results indicate that the representation of crusts and precipitation particles have the largest variation between the two input datasets, with closer agreement in weak layer representation. Again, we note that the HRRR points on the opposite side of the Bridger Range ridgeline from the HGWX have higher similarity to HGWX-derived profiles.

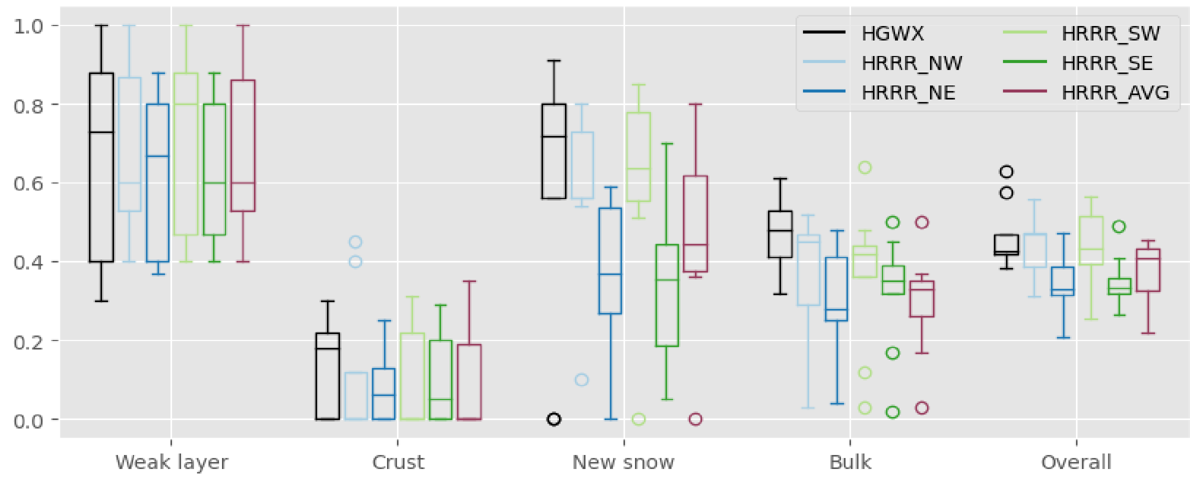

Figure 5: Similarity scores between observed in situ snow profiles and different SNOWPACK model output broken into weak layer, crusts, precipitation particles, bulk grains, and overall profile similarities.

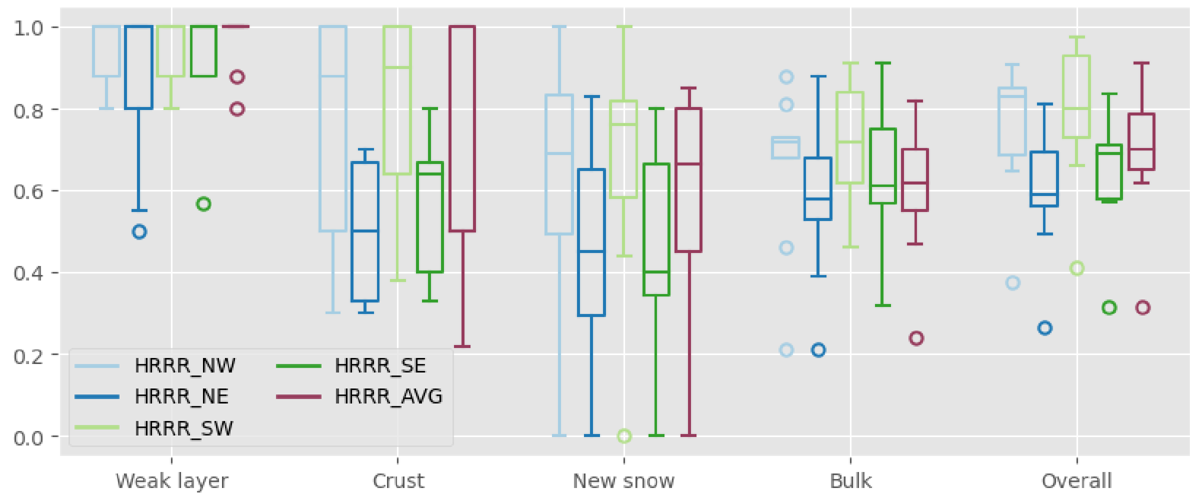

Figure 6: Similarity scores between HRRR-derived SNOWPACK model output compared to HGWX-derived output.

3.3 <u>Individual profile similarities</u>

We additionally analyzed two sets of profiles, mid-winter (February 10) and spring (April 11), to provide further insight into model discrepancies and strengths during the 2021 winter (Figure 7).

A sizable storm deposited approximately 80 cm of new snow at the study site in the two days prior to the February 10 profile, then air temperatures dropped gradually to -15°C at the time of field work. When compared to the observed profile from February 10, the HGWX-derived and HRRR-derived profiles have the same similarity scores for crusts (0.0) and weak layers (0.88). Only one thin (1 cm) pencil-hard crust layer was recorded in the observed profile at 63 cm from the ground, yet both modeled profiles featured thick melt-freeze crusts 10-20 cm thick at knife hardness resulting in the 0 similarity score. The high weak layer similarity score of this set is related to the single weak layer of basal depth hoar quantified in the similarity analysis found in all profiles. The HGWX-derived profile has slightly higher similarity scores than the HRRR average profile for both new snow (0.83, 0.79, respectively) and bulk grains (0.41, 0.4, respectively), which results in a higher overall similarity for HGWX (0.53, 0.52, respectively).

Prior to the April 11 field day, a small storm deposited 6 cm of new snow atop 30 cm of mixed melt forms, melt freeze crusts, and ice lenses from interspersed diurnal warming over the previous two weeks. The difference in similarity scores between HGWX-derived (0.58) and HRRR-derived (0.47) models increased for the April 11 profiles. The gap in similarity is primarily due to differences in weak layer (0.88 and 0.60 for HGWX and HRRR, respectively) and bulk grain (0.32 and 0.03, respectively) similarity scores. All models handle the crust-melt-form matrix of the upper snowpack well, while the midpack exhibits the

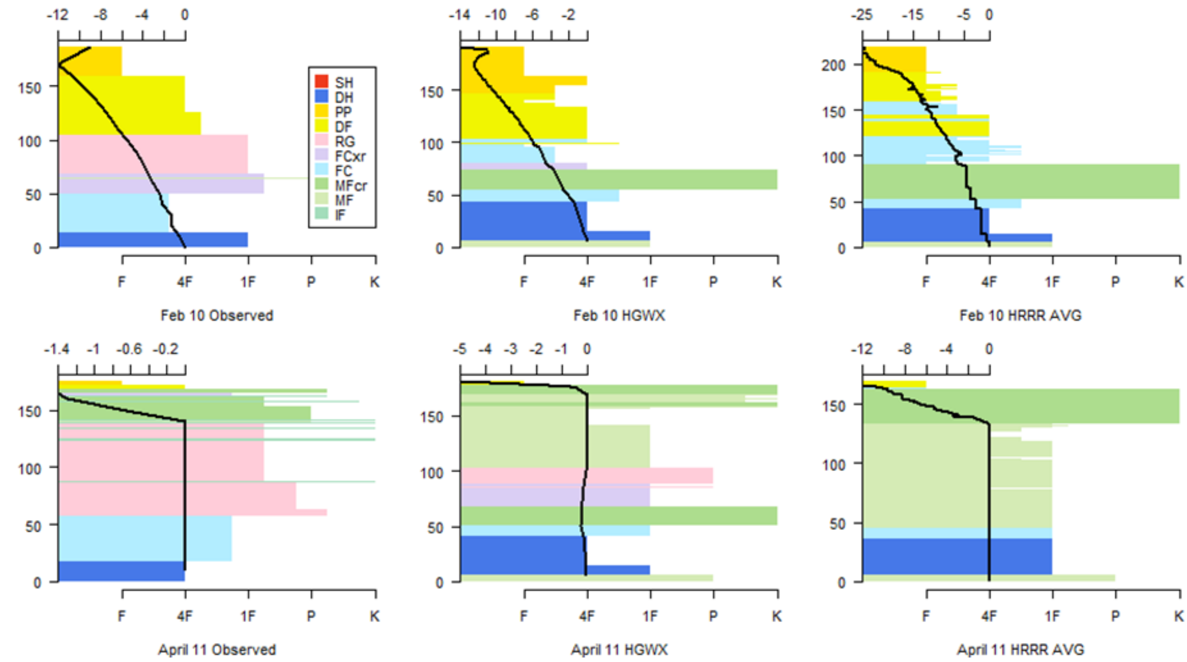

Figure 7: Observed, HGWX modeled and HRRR average modeled snow profiles from February 10, 2021 (top row), and April 11, 2021 (bottom row).

greatest differences. The midpack of the observed April 11 profile is isothermic but contains thick (~50 cm) layers of rounded grains that transition to facets below 57 cm from the ground. The HGWX-derived temperature profile is not completely isothermic and contains a mixture of rounded grains, melt forms, and rounding facets. The HRRR-derived profile exhibits a very similar temperature profile to that of the observed profile yet contains only melt forms (i.e., wet snow). We attribute these moisture related differences primarily to the increased solar radiation at the HRRR points.

We note that the results presented here could vary widely for other case studies. For example, AWS- and NWP-derived model profiles might be more similar if an NWP point is located closer to the site of interest. Terrain complexity is also an important factor, and NWP-derived profiles could better represent a site of interest if the site is not highly influenced by small-scale topographic features.

4. COST BENEFIT ANALYSIS

The AWS-derived SNOWPACK model profiles had higher similarity scores than NWP-derived model profiles when compared to in situ observations. In this case study, the largest improvement was in the representation of new precipitation amounts throughout the season and bulk grain layers during the transition from dry to wet snow in the spring. In order to access these benefits, operational avalanche forecast centers will need to devote resources to the installation and maintenance of an AWS. Estimated costs for a fully equipped AWS with all necessary sensors, data logger, batteries, and solar panels are approximately $20,000 from a reputable manufacturer, plus additional expenses for radio equipment for automated data transfer.

In addition to these up-front costs to purchase AWS equipment, we estimate that initial AWS installation and ongoing maintenance during the season require between 1-2 weeks of devoted personnel hours. In the United States, avalanche forecasters are often hired through federal agencies at the GS7 level, corresponding to a salary of up to $23.98 per hour. AWS installation and maintenance at this rate costs between $960–1920. We note that these costs can rise considerably if sensors malfunction or break during the winter season, which is not uncommon in harsh alpine environments. In situ snow profile collection is necessary to validate model performance, but we do not anticipate additional costs in this regard as digging pits already represents a significant portion of a forecaster's duties. However, prioritizing in situ data collection at the AWS location may prevent broader observations across the forecasting region.

Regardless of the input data source, avalanche forecasting operations implementing snow stratigraphy modeling within their workflows will need to budget additional personnel hours for the task. Although NWP data are generally free to download, accessing and processing the data to be usable as stratigraphy model input requires considerable programming expertise. Similarly, installing and operating snow cover models are not always straightforward. We estimate at least one month of devoted personnel hours for an employee with some familiarity with coding and weather models, for an estimated cost of $3850. Once initial computer workflows are set the process can be largely automated for daily forecasting, bringing the time requirement down to an estimated 15 minutes per day to incorporate model output into operational forecasts.

Integrating snow cover models into avalanche forecasting operations has both short- and long-term benefits. In the short-term, snow cover models capture critical weak layer deposition that emerge from brief meteorological moments (Horton et al., 2014). Subtle grain metamorphism or deposition due to specific meteorological conditions are challenging to observe overnight as a forecaster, but are captured by snow cover models, potentially reducing forecast uncertainty. In the long-term, models provide a basis for tracking specific weak layer progression throughout the season in a specific location (Bellaire et al., 2011, 2013). Having a consistent grasp of one location's conditions allow forecast teams to orient valuable field time toward additional locations, improving their spatial understanding of the snowpack and critical weak layer distributions. Additionally, scaling snow cover models up to multiple locations and elevations within an operation reduces spatial uncertainty in snowpack structure, especially in data-sparse areas (Herla et al., 2022).

We also note that the benefits of snow cover model integration into operational forecasting are not immediately available. Our case study illustrates the importance of calibrating the modeled inputs to match field conditions. Specifically, we corrected temperature and precipitation using observations from the AWS at our study site. Similar meteorological input tuning could be completed without an AWS through repeated model runs with minor input tweaks and output comparison to observed snow profiles (Horton and Haegeli, 2022). As observations are collected over multiple seasons, the validation dataset becomes richer and likely encapsulates a wider range of snowpack conditions. This enables a more robust validation of the stratigraphy model and can increase understanding of the utility of the tool for a particular operation and site.

We close this cost-benefit analysis with some thoughts on the relative strengths and weaknesses of AWS-derived and NWP-derived stratigraphy models. With radio or cellular transmission, it is possible to obtain live data from an AWS, while some NWP output may have a lag time of minutes to hours before it can be accessed and downloaded. Assuming an AWS site is well chosen and the instrumentation is properly installed, AWS observations will provide a more accurate representation of the snowpack at a site of interest, which is likely to result in more accurate stratigraphy models. The observations are easily validated and data files are typically more approachable than NWP output. However, up-front equipment costs are high, and sensor malfunction mid-season can result in a data gap of days to weeks or longer. NWP output has no up-front direct costs and data availability is highly reliable, and provides opportunity to scale modeling efforts from a single point to much larger regions (e.g., Horton and Haegeli, 2022). However, this method potentially represents a larger technical hurdle and, in most cases, will result in a less accurate representation of the snowpack for specific locations.

5. CONCLUSION

We used input data derived from both AWS observations and NWP models to drive a snow stratigraphy model at a field site in southwest Montana, USA. AWS-derived modeled profiles showed higher quantitative similarity scores to in situ observations than NWP-derived profiles, especially for new snow and bulk grain layers. We attribute the lower performance of NWP-derived models to poor representations of terrain and its local influence on incoming shortwave radiation in the NWP inputs. We also observed the creation of additional melt freeze crusts in all SNOWPACK modeled outputs that did not align with our field collected profiles. While the particular similarity scores are unique to our study site, the analysis and methodology detailed here can broadly serve as a template for avalanche forecast operations to assess the potential utility of stratigraphy models for their specific workflows. Forecasting operations can expect personnel costs of approximately $4000 for initial implementation of any snow stratigraphy modeling, plus an additional $22,000 for up-front AWS equipment costs, installation, and ongoing maintenance.

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DISCLAIMER

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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