Before machine learning: validating historical SNOWPACK simulations for avalanche hazard forecasting in Glacier National Park, B.C., Canada.

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ABSTRACT: Accurate avalanche hazard forecasting depends on reliable snow and weather information, which is often unavailable in the complex mountainous terrain where hazards are greatest. This limits the availability of training data for emerging machine learning approaches to avalanche hazard assessment.This study lays the groundwork for such a model for Glacier National Park (GNP), British Columbia, Canada, by validating snow cover simulations produced by the MeteoIO/SNOWPACK/Alpine3D model chain driven by four gridded meteorological forcing datasets spanning reanalyses, a regional climate model, and a numerical weather prediction model. Each dataset is downscaled using subgridding and terrain-adapted interpolation techniques. Modelled snow cover properties are then compared against an extensive record of snow profiles and instability tests collected by the Avalanche Control Section between the 1999-2000 and 2022-2023 seasons, using the profile similarity approach. This work establishes a validated historical simulation framework upon which future machine learning approaches to avalanche hazard forecasting in GNP can be built.

KEYWORDS: Avalanche forecasting, SNOWPACK/Alpine3D, Model validation, Weak layer identification, Meteorological forcing data, Glacier National Park

1. INTRODUCTION

In Canada, snow avalanches, hereafter referred to as avalanches, are the deadliest winter natural hazard (Stethem et al., 2003). Most accidents involve recreational mountain users, including snowmobilers (42%), skiers and snowboarders (25%), hikers (15%), and mountaineers (5%) (Canada, 2021). However, avalanches also pose significant risks to roads and infrastructure. Glacier National Park (GNP), located in British Columbia, Canada, is a region where avalanches impact both backcountry users and critical infrastructure, namely the Trans-Canada Highway (TCH) and Canadian Pacific Railway (CPR). This vital transportation corridor passes through an 18-kilometer section of GNP, commonly known as Rogers Pass, which is considered a highly active avalanche zone. Over the past 50 years, 134 avalanche paths in Rogers Pass have generated more than 63,470 avalanches that have reached either the TCH or CPR (Koestel, 2024). As one of Canada's main transportation corridors, even a one-hour closure of Rogers Pass is estimated to impact approximately $4 million in economic activity, while a full-day closure can affect upwards of $96 million (Rogers Pass Mountain Safety Team, 2026).

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Given the critical importance of maintaining safe and open transportation routes, accurate assessments of snow and weather conditions are essential to predict avalanche hazard. Current avalanche forecasting services rely on key data sources such as manual snow profile observations, weather forecasts, and weather station data, synthesized through the forecaster's expert judgment (Statham et al., 2018). However, data availability in mountainous and avalanche-prone terrain is often limited, and automated weather stations are frequently absent and/or scarce from many of the elevations and aspects relevant to avalanche forecasting. Gridded meteorological products, including numerical weather prediction (NWP) and reanalysis datasets, offer a means of overcoming these observational gaps, providing spatially continuous forcing data where direct measurements do not exist.

To reduce reliance on this expertise-driven process, statistical approaches have long been used to complement forecaster judgment. Early efforts used logistic regression, nearest-neighbour, and classification tree models driven directly by observed or forecasted weather variables (e.g Gau-

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thier et al., (2017), Hendrikx et al., (2014), and Hendrikx et al., (2014)), later extending to machine learning algorithms trained directly on NWP output (Gauthier et al., 2025). Other approaches broadened this input further by combining meteorological variables with topographic and geological information (Choubin et al., 2019); yet even this more complete input set omitted snow cover conditions entirely, a simplification that limits the ability of such models to capture the specific stratigraphic processes governing persistent weak layers formation and evolution. Recently, incorporating physically simulated snow cover stratigraphy, rather than weather and terrain variables alone, has been shown to improve predictive performance (Mayer et al., 2022; Viallon-Galinier et al., 2023).

However, snow cover models often produce a wide range of output parameters that must be interpreted to extract meaningful insights (Morin et al., 2020). To address this complexity, machine learning tools offer a promising solution by integrating multiple variables into predictive models. In the avalanche research community, several recent studies have demonstrated the potential of these approaches (e.g. Hendrick et al., (2023), Mayer et al., (2022), Mayer et al., (2023), Viallon-Galinier et al., (2023), Pérez-Guillén et al., (2022), and Pérez-Guillén et al., (2025)).

Yet the reliability of any downstream machine learning model is fundamentally constrained by the physical simulations it is trained or applied on. Snow cover simulations themselves inherently accumulate errors from their meteorological inputs and from deficiencies in the underlying model formulation (Herla et al., 2024; Herla et al., 2021). Any machine learning layer built on top of these simulations, however sophisticated, is therefore also exposed to this accumulated error. Establishing the validity of the snow cover simulations that feed into these approaches is therefore not a peripheral concern, but a foundational requirement for their eventual adoption in operational avalanche forecasting.

This paper addresses this need to validate snow cover simulations in GNP, produced by the MeteoIO/SNOWPACK/Alpine3D model chain, driven by four different gridded meteorological forcing datasets. These simulations are evaluated against an extensive record of observed snow profiles and instability tests collected in the park between the 1999-2000 and 2022-2023 winter seasons. This work provides the necessary foundation upon which future machine learning approaches to avalanche hazard forecasting in GNP can be reliably built, by establishing a validated historical baseline of model performance across whole-profile stratigraphy, weak layer identification, and slab characteristics.

2. STUDY AREA

This study is based in GNP, located in the Selkirk Range of the Columbia Mountains (fig 1). This region is characterized by high annual precipitation and significant snowfall, averaging around 1,600 mm annually at an altitude of 1,320 m, 69% of which falls as snow (Fitzharris, 1987). It is categorized as a transitional snow climate (Hägeli and McClung, 2003; Haegeli and McClung, 2007), characterized by deep snow cover and annual variability between maritime and continental influences. As mentioned earlier, the region is highly avalanche-prone, experiencing approximately 2,000 observed avalanches each winter (Koestel, 2024; Imbach et al., 2025a). GNP's avalanche hazard is characterized by a comparatively high prevalence of storm slab hazard situations, alongside a lower prevalence of deep persistent slab problems, particularly surface hoar layers, relative to other transitional-climate ranges in the region (Shandro and Haegeli, 2018).

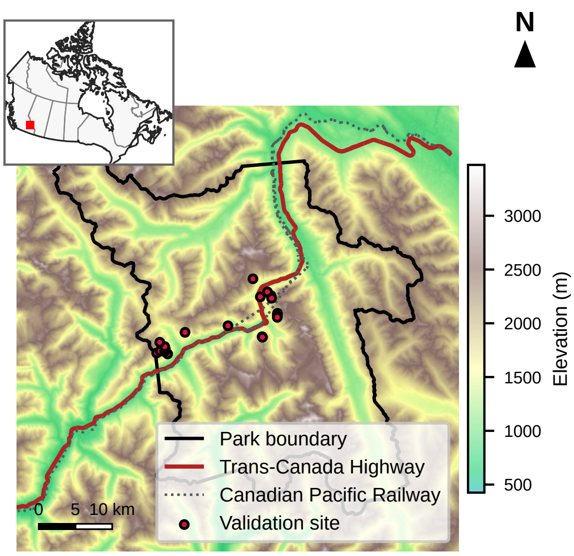

Figure 1: Study area map of Glacier National Park (GNP), British Columbia, Canada. The background shows a hillshaded 100 m digital elevation model colored by elevation. The map also shows the outline of GNP and the Trans-Canada Highway.

3. DATA

Four different forcing meteorological datasets were selected, validated, and compared to observed snow profile data collected by the Rogers Pass Mountain Safety Team (MST). This multi-dataset approach allowed for a better performance analysis of forcing data with differing spatial resolution, temporal coverage, and origin (NWP, reanalysis, or regional climate model).

- **High Resolution Deterministic Prediction System (HRDPS)** (Milbrandt et al., 2016): A spatially gridded (~2.5 km, 195 cells intersecting the GNP domain) NWP model, and the current operational forcing standard used for avalanche forecasting in GNP. Data are available from the 2017-2018 season to present, allowing simulations to be extended in near real-time as new operational output becomes available.
- **ERA5-Land** (Muñoz Sabater, J., 2019): A high-resolution (~9 km, 30 cells intersecting the GNP domain) global reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), used here to cover the 1999-2000 to 2022-2023 period, with a data record extending back to 1950.
- **6th Generation Canadian Regional Climate Model (CRCM6/GEM5)** (Girard et al., 2014; Roberge et al., 2024; Llerena et al., 2023): A regional climate model (~12 km, 16 cells intersecting the GNP domain) developed at ESCER/UQAM, from the GEM5 forecast model (McTaggart-Cowan et al., 2019) originally developed at Environment and Climate Change Canada (ECCC). Run in hindcast configuration, driven by the ERA5 global reanalysis (Hersbach et al., 2020) over the 1981-2023 period and the whole North American domain (CORDEX North America domain). Used here to cover the 1999-2000 to 2022-2023 period, with data available back to 1980. Beyond its hindcast capability, this model also offers future climate projections, opening the possibility of using this same validated workflow to study the impacts of climate change on snow cover conditions and avalanche hazard in GNP.
- **Canadian Surface Reanalysis (CaSR V3.2)** (Khedhaouiria et al., 2026): A high-resolution (~10 km, 30 cells intersecting the GNP domain) surface reanalysis dataset built on the Canadian Precipitation Analysis (CaPA) system of Environment and Climate Change Canada (ECCC). Used here to cover the 1999-2000 to 2022-2023 period, with data available back to 1980.

Observed snow profile data used for validation were collected by Parks Canada avalanche professionals and forecasters (Imbach et al., 2025b). Specific sites were selected with the help of MST staff, based on their regular use throughout the season as reference locations for assessing snow cover stability. In total, 17 sites were selected, totaling more than 850 observed snow profiles and more than a 1,000 instability test results (compression test, extended column test, rutschblock test, propagation saw test) spanning the 1999-2000 to 2022-2023 seasons. These sites span an elevation range of 1,312 to 2,308 m and multiple aspects, providing varying conditions needed to evaluate the model's performance under the varied terrain and snow cover conditions relevant to avalanche forecasting in the park.

4. METHODS

4.1. Model chain parameters

All four forcing datasets were subgridded following the method of Billecocq et al., (2024), developed and validated for GNP. Each native grid cell of a given forcing dataset is first converted into a virtual weather station: its centroid is recomputed to the nearest pixel of a high-resolution digital elevation model (DEM), minimizing the elevation mismatch between the coarse forcing cell and the underlying terrain. Air temperature (K), relative humidity (scale of 0-1), and incoming longwave radiation (W/m^2) are then bias-corrected for the resulting elevation difference. Precipitation (mm) is corrected using a fixed fractional lapse rate derived from field measurements (0.0011 mm per m of elevation difference), and wind speed (m/s) is downscaled using a sky-view-factor approach to account for terrain sheltering unresolved at the native forcing resolution.

The resulting virtual weather stations were spatially interpolated with MeteoIO (Bavay and Egger, 2014) to a 100 x 100 m DEM resolution, before running SNOWPACK-Alpine3D (Bartelt and Lehning, 2002; Lehning et al., 2006) at each grid cell using the energy-balance module, with terrain radiation correction enabled. Snow drift and runoff modules were disabled, as this study focuses on the vertical stratigraphy of the simulated snow cover rather than terrain-scale redistribution or meltwater routing. Each seasonal simulation was initialized from bare ground on September 2, with no snow cover state carried over between seasons.

4.2. Performance Analysis

To evaluate the Alpine3D/SNOWPACK model chain against GNP snow profile record, we used the snow profile alignment tool of (Herla et al., 2021), implemented in the R package *sarp.snowprofile.alignment* (Herla et al., 2020). This tool uses dynamic time warping (DTW) to align the modeled profile to the observed reference profile: the modeled snow height is first rescaled, then layers are matched based on a multi-dimensional distance combining grain type and hand hardness, which we weighted 60/40, avoiding penalizing an otherwise well-simulated layer for a depth offset relative to the observation. This is especially important considering that NWP and gridded input weather data can carry a negative precipitation bias (Billecocq et al., 2024; Bellaire et al., 2013; Côté et al., 2017). Once aligned, a whole-profile similarity score (sim_{prof}), ranging from 0 (highly dissimilar) to 1 (identical), was computed and scaled with the relative threshold approach (RTA) (Monti and Schweizer, 2013) to give more weight to thin weak layers. As this continuous score lacks an established absolute benchmark, it is most informative as a comparative tool across forcing datasets and seasons, with HRDPS, the current operational NWP standard for Canadian avalanche forecasting (Herla et al., 2024), serving as a practical reference point. sim_{prof} was computed for every observed snow profile in the GNP dataset against each of the four forcing datasets, to identify which best reproduces the observed stratigraphy.

Whole-profile similarity offers a generally good understanding of model performance, but lacks the specificity needed in an operational mindset (Herla et al., 2024). Such validation says little about whether the model captures the specific weak layer responsible for an observed instability. To address this, we assessed each forcing dataset's model output against instability test results (compression test, rutschblock, extended column test, and propagation saw test) recorded by Parks Canada crews. Instability test records were less frequent and less consistent in the historical database before the 2017-2018 season. Thus, this weak layer and slab analysis was restricted to the 2017-2018 to 2022-2023 seasons, while whole-profile similarity was assessed over the full 1999-2000 to 2022-2023 record. For each instability test, the observed failure layer was identified in the reference profile by its recorded depth and grain type, then located in the modeled profile through the same DTW alignment described above. We define sim_{gtype} as this matched layer's grain-type similarity, quantifying whether the model reproduces the correct grain type at the correct depth for the weak layer responsible for the observed instability. A match was classified as a hit when $sim_{gtype} \geq 0.8$. Because every instability-test occurrence is assigned a best-candidate matched layer by construction, this hit rate is recall-like rather than a full precision-recall characterization, as there is no natural source of false positives in this matching scheme. We similarly define sim_{slab} as a grain+hardness similarity score (0.6/0.4 blend, as in the whole-profile alignment) restricted to the layers between the surface and the matched weak layer. sim_{prof} and sim_{slab} are therefore directly comparable, as both derive from the same continuous 0.6/0.4 grain+hardness blend restricted to different depth ranges; sim_{gtype}, by contrast, is drawn from a discrete grain-type similarity lookup and is best interpreted through the hit-rate threshold defined above. This approach tests whether the model reproduces the correct stratigraphy at three levels: whole profile, weak layer identification, and overlying slab characteristics.

5. RESULTS

5.1. Whole-profile similarity

Over their full available records, whole-profile similarity (sim_{prof}) medians ranged from 0.454 (CRCM6) to 0.505 (HRDPS), with ERA5-Land and CaSR falling between (0.458 and 0.473, respectively; Figure 2a). HRDPS's record is limited to the 2017-18 to 2022-23 seasons ($n = 270$), reflecting the shorter length of its numerical-weather-prediction archive, while CRCM6, ERA5-Land, and CaSR each span the full 1999-2000 to 2022-23 record ($n = 861$). Restricting the comparison to the 2017-18 to 2022-23 period common to all four datasets narrows this gap: median sim_{prof} ranged from 0.448 (ERA5-Land) to 0.505 (HRDPS), with CRCM6 and CaSR falling between (0.449 and 0.459, respectively; Figure 2b). Across the full 24-season record available for CRCM6, ERA5-Land, and CaSR, season medians fluctuated within a roughly 0.41 to 0.52 band with no apparent directional trend.

5.2. Slab similarity

Slab similarity (sim_{slab}), restricted to the segment from the surface to the model layer matched to each weak-layer failure observed from recorded instability tests ($n = 1021$). Median values clustered

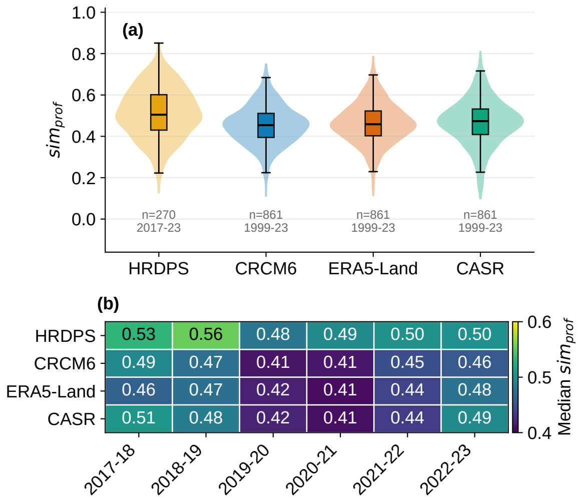

Figure 2: Whole-profile similarity (sim_{prof}) between modeled observed snow profiles at GNP. (a) Whisker Plot showing the distribution of sim_{prof} for each forcing input dataset covering different span (i.e. 2017-18 for HRDPS and 1999-2000 for all three other forcing input data). (b) Heatmap showing the median sim_{prof} by forcing dataset and season, restricted to the 2017–18 to 2022–23 period common to all four datasets.

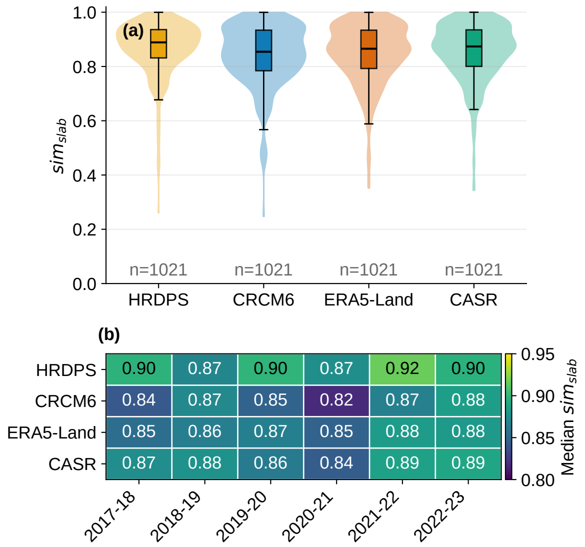

Figure 3: Slab similarity (sim_{slab}) between simulated and observed snow profiles, restricted to the segment from the surface to the model layer matched to each observed weak-layer failure. (a) Whisker Plot showing the distribution of sim_{slab} by forcing dataset. (b) Heatmap showing the median sim_{slab} by forcing dataset and season.

tightly across forcing datasets, ranging from 0.854 (CRCM6) to 0.889 (HRDPS), with ERA5-Land and CaSR falling between (0.865 and 0.874, respectively; Figure 3a). This range was considerably narrower than the spread observed for sim_{prof}, and slab similarity values were substantially higher overall than whole-profile similarity values over the same period.

5.3. Weak-layer grain-type identification

Pooled across all four forcing datasets ($n = 4252$ instability-test occurrences), the overall hit rate was 69.9% (Table 1). Hit rates were broadly similar across forcing datasets, ranging from 67.2% (ERA5-Land) to 72.4% (CRCM6). Hit rate varied with the depth offset between the observed failure and the matched model layer, peaking at 75.0% for moderate offsets (10-20 cm) and declining to 60.9% beyond 40 cm.

6. DISCUSSION

6.1. Why validation must precede machine learning adoption

Snow cover models are increasingly used not only as standalone forecasting tools but also as the physical foundation underlying statistical and machine learning approaches to avalanche forecasting (e.g. Mayer et al., (2022), Pérez-Guillén et al., (2022), and Hendrick et al., (2023)). In either case, the trustworthiness of these downstream applications depends directly on how accurately the underlying simulations represent real snow conditions (Herla et al., 2024; Herla et al., 2021). The Swiss operational use of SNOWPACK and the machine learning model is a great working example of how first validating and establishing confidence in the underlying model chain affects operational trust and performance (Herwijnen et al., 2023; Techel et al., 2025). The results presented here provide this same foundation for GNP: across four independent forcing datasets, the MeteoIO/SNOWPACK/Alpine3D model chain reproduced observed snow stratigraphy, from whole-profile structure through to weak-layer identification and overlying slab characteristics, establishing the baseline that this kind of downstream adoption requires.

6.2. Historical slab and whole profile similarity

Whole-profile similarity showed no evidence of degradation across the 24-season record available for CRCM6, ERA5-Land, and CaSR, with season medians fluctuating within a consistent band rather than trending downward. Furthermore, despite well-documented precipitation biases in NWP and reanalysis products (Billecocq et al., 2024; Bellaire et al., 2013; Côté et al., 2017), slab similarity

Table 1: Weak-layer grain-type hit rate ($sim_{gtype} \geq 0.8$) by forcing dataset, pooled across all instability test types ($n = 1063$ per dataset).

Model	Median sim_{gtype}	Mean sim_{gtype}	% exact match	Hit rate
HRDPS	0.8	0.746	43.4%	72.0%
CRCM6	0.9	0.765	48.5%	72.4%
ERA5-Land	0.8	0.743	46.6%	67.2%
CaSR	0.8	0.747	46.4%	68.0%
Pooled	0.8	0.750	–	69.9%

clustered tightly across all four forcing datasets, in contrast to the wider spread observed for whole-profile similarity. Because sim_{slab} and sim_{prof} are computed from the same underlying alignment, restricted to different depth ranges, part of this narrower spread is a property of the shorter slab segment accumulating less alignment cost than a full profile, and should not be read as fully independent confirmation of higher slab-level skill. Even accounting for these caveats, the finding remains practically useful: it shows the model chain performs consistently regardless of which forcing dataset is used, supporting its application across different historical periods and regions of the park. It also strengthens the case for applying this validated workflow beyond the historical record: because CRCM6 additionally provides future climate projections, this same model chain could be used to study projected changes in snow cover conditions and avalanche hazard in GNP under a changing climate.

Site-specific patterns in this stability, by elevation, aspect, or individual location, are not addressed here and are reserved for a forthcoming, more detailed paper, which will also validate the downscaled and subgridded meteorological forcing values themselves against recorded weather station observations, and complement this analysis with SNOWPACK simulations driven directly by weather station data at station locations, providing a further point of comparison between modelled and recorded conditions.

6.3. Weak-layer grain-type identification as an operational anchor

Correctly identifying the weak layer responsible for an observed instability is central to avalanche hazard assessment, since avalanche release is governed by failure at this specific layer rather than by the snow cover as a whole (Schweizer et al., 2003). A pooled hit rate of 69.9% for correctly identifying weak-layer grain type at the matched model layer represents a meaningful, though incomplete, indicator of model performance. This hit rate can be interpreted as an empirical estimate of the probability that the model correctly identifies a given weak layer's grain type, offering forecasters and downstream machine learning applications alike an operationally interpretable measure of expected reliability. This figure should also be interpreted alongside the slab-level agreement demonstrated above: even where whole-profile similarity is modest, the model chain appears comparatively capable of representing the specific structure a forecaster's judgment depends on.

7. CONCLUSION

This study establishes a validated historical baseline for MeteoIO/SNOWPACK/Alpine3D snow cover simulations in Glacier National Park, evaluated against an extensive record of observed snow profiles and instability tests spanning up to 24 winter seasons. Across four independent meteorological forcing datasets, the model chain reproduced observed snow stratigraphy, showed no evidence of performance degradation over multiple decades, and achieved a meaningful weak-layer grain-type identification rate of nearly 70%, with slab-level accuracy notably robust regardless of which forcing dataset was used. This stability supports the use of these forcing datasets for retrospective avalanche analysis extending well beyond the recent period covered by HRDPS alone.

Together, these results provide the validated physical foundation required before machine learning approaches to avalanche hazard forecasting can be reliably developed for GNP. Future work will build on this baseline with a site-specific analysis across elevation and aspect, validation of the downscaled and subgridded meteorological forcing values against recorded weather station observations, SNOWPACK simulations driven directly by weather station data at station locations, and application of this validated workflow to CRCM6's future climate projections to assess projected changes in snow cover conditions and avalanche hazard under a changing climate. Building on this validated foundation, future work will also focus on developing machine learning approaches to avalanche hazard forecasting in GNP, the central motivation for establishing this baseline in the first place.

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