ASSESSING THE IMPACT OF PRECIPITATION INPUTS ON SNOWPACK SIMULATIONS IN WESTERN CANADA

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ABSTRACT: Public avalanche forecasters in Canada increasingly rely on snowpack models to augment manual observations for avalanche hazard assessments, but several studies have recently demonstrated that precipitation inputs are one of the key sources of uncertainty in snowpack simulations. To address this challenge, this study evaluates the impact of precipitation data from four different sources—the Canadian High-Resolution Deterministic Prediction System (HRDPS), an operational adjustment to HRDPS by Avalanche Canada (AvCan), the operational HRDPS-Canadian Precipitation Analysis System (CaPA), and a new experimental version of CaPA (CaPA-Exp)—on snowpack simulations at 28 weather stations across western Canada over three winter seasons (2020-2022). For each station, we compare the snowpack structure of a reference simulation constrained by daily observed snowpack height with simulations driven by the four different precipitation data sources. To make these comparisons, we compute relative differences in snowpack height, differences in the prevalence of key grain types, and differences in the number of simulated weak layers to describe the snowpack structure. Linear mixed effects regression models are then used to explore the effect of precipitation data source, season, season period, and region on these performance measures. Our results show that simulations with all four precipitation data sources overestimate HS when compared to the reference simulations, but the CaPA-Exp analysis product is generally closest to the reference. However, regional differences exist, and CaPA-Exp is not always the best choice. The results of this study can help Canadian avalanche forecasters better understand the strengths and weaknesses of different precipitation products for snowpack simulations.

KEYWORDS: Snowpack models, precipitation, uncertainty, snow depth, validation.

1. INTRODUCTION

In recent years, avalanche forecasters have transitioned from relying exclusively on field observations for their avalanche hazard assessments to increasingly incorporating snowpack simulations into forecasting practices. These simulations are produced by numerical models that simulate the physical characteristics of the seasonal snowpack throughout the winter based on input data from meteorological observations or numerical weather prediction (NWP) models (Herla et al., 2022; Morin et al., 2020). Globally, the most commonly used snowpack models include the Swiss SNOWPACK (Lehning et al., 1999), and the French Crocus (Brun et al., 1989; Vionnet et al., 2012), but SnowGrid (Olefs et al., 2013) is also utilized in specific regions of Austria (Morin et al., 2020). Since avalanche conditions can vary substantially across space and time (Schweizer et al., 2008), these models can help forecasters understand regional snowpack conditions and assess avalanche hazard in locations and/or times with limited information (Herla et al., 2022; Morin et al., 2020).

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Snowpack simulations inherently include uncertainties from a variety of sources including the accuracy and reliability of meteorological inputs, the spatial representativeness of the input data, as well as the numerical representation of physical processes in the models (i.e., model parameterizations) (Morin et al., 2020). Various recent studies have identified precipitation input as a major source of uncertainty in snowpack modelling and examined its impact. Horton and Haegeli (2022), for example, compared snow depths predicted by the weather–snowpack model chain of Avalanche Canada with data from automated and manual observations to assess the impact of precipitation inputs on model accuracy. The study found substantial differences in how the model performed in different mountain ranges with snow depth being overpredicted in the Coast range and underpredicted in many parts of the interior Rocky Mountains. An examination of the snowpack simulations in the different ranges showed that the impacts errors were more severe in the Rocky Mountains where faceting is more sensitive to snow depth. Raleigh et al. (2015) explored how forcing errors impact snow variable simulations and concluded that models are most sensitive to bias errors. Furthermore, Ritcher et al. (2020) found that the simulated stability of weak layers in simulations is highly sensitive to precipitation errors.

Possible solutions for addressing the issue of precipitation input errors include incorporating more accurate precipitation products, which is what we will explore in this paper, or using an ensemble approach to derive a more broadly supported precipitation estimate and explicitly quantify the associated uncertainty.

Environment and Climate Change Canada (ECCC) currently has several operational deterministic precipitation products suitable for snowpack modelling. They include the High-Resolution Deterministic Prediction System (HRDPS), the operational NWP model run by the Canadian Meteorological Centre on a 2.5 km horizontal grid (Milbrandt et al., 2016), and the HRDSP-Canadian Precipitation Analysis System (CaPA), which combines the HRDPS precipitation output with observations from weather stations, weather radars and satellites to create the best possible estimate of the precipitation field (Mahfouf et al., 2007; Fortin et al., 2018). While CaPA has been validated and optimized for the flat regions of the Canadian Prairies (e.g., Boluwade et al., 2018; Lespinas et al., 2015; Zhao, 2013), it has known weaknesses in mountainous regions due to low number of available relevant stations and various algorithmic challenges (Carrera et al., 2010; Fortin et al., 2018; Schirmer and Jamieson, 2015; Madore et al., 2023). These shortcomings make it difficult to use CaPA for driving snowpack simulations for operational avalanche forecasting in western Canada.

To address the challenges, Horton and Haegeli (2022) created a method to scale the HRDPS precipitation values based on differences of modeled and observed weekly changes in the height of the snowpack (HS), and Madore et al., (2023) developed a new experimental version of CaPA that takes advantage of additional automated observation networks relevant for avalanche forecasting in western Canada.

Together, this results in four related but distinct precipitation fields: 1) the original HRDPS, 2) the operational adjustments to the HRDPS values implemented in Avalanche Canada's operational snowpack model chain (AvCan), 3) the operational version of CaPA, and 4) the experimental version of CaPA (CaPA-Exp). While there is a considerable body of research evaluating the quality of HRDPS and CaPA predictions including some avalanche-motivated studies focusing on HS (see earlier references), but to our knowledge, there has not been any validation studies that examine the other two precipitation products (CaPA-Exp and AvCan) and provide a more comprehensive perspective on the impact of the different precipitation fields on the structure of the simulated snowpack that is so important for avalanche forecasting.

The objective of this study is to complement the existing research by developing an approach for examining the impacts of the four precipitation products on HS and the structure of the simulated snowpack. The results of our study help to create a better awareness of the strengths and weaknesses of the different precipitation products on regional-scale snowpack simulations in western Canada.

2. METHODS

Widespread, continuous direct snow profile observations would be the ideal dataset for examining how well snowpack simulations driven by different precipitation products reflect reality. However, since such datasets do not exist in western Canada, we approached our research question by computing reference simulations at a network of stations with hourly observations of HS. By forcing the height of the simulated snowpack to match the observed, we produce our best possible guess of the snowpack structure based on the actual precipitation at a given location. The simulations using the different precipitation products can then be compared against these reference simulations. While the use of a simulated reference might seem suboptimal initially, it actually helps to completely isolate the effect of the precipitation product and eliminate any other sources that result in differences between simulated and observed snowpacks.

2.1 Study location and data sources

Our study area encompassed the mountainous regions of southwestern Canada, characterized by the maritime Coast Mountains, the continental Rocky Mountains, and the transitional Columbia Mountains (Fig. 1). Each of these mountain ranges has distinct geographical features, storm patterns, and snow and avalanche climates (Shandro & Haegeli, 2018). Our study period included three winter seasons (2019/20 to 2021/22), each starting on September 1 and ending on May 15.

Our dataset for the reference simulations consisted of observed hourly HS observations from 28 suitable British Columbia (26) and Alberta (2) automated snow weather stations (Fig. 1). Our inclusion criteria required the stations to be within 600 vertical m of the local treeline elevation (Horton and Haegeli, 2022), less than 400 vertical m away from the closest HRDPS grid point, have at least 250 days of observation per winter, and data gaps needed to be shorter than 40 days. If we ended up with multiple stations within a single Avalanche Canada forecast subregion (Buhler et al., 2023), we only included the highest one to avoid redundancy and ensure a more even representation across the study area.

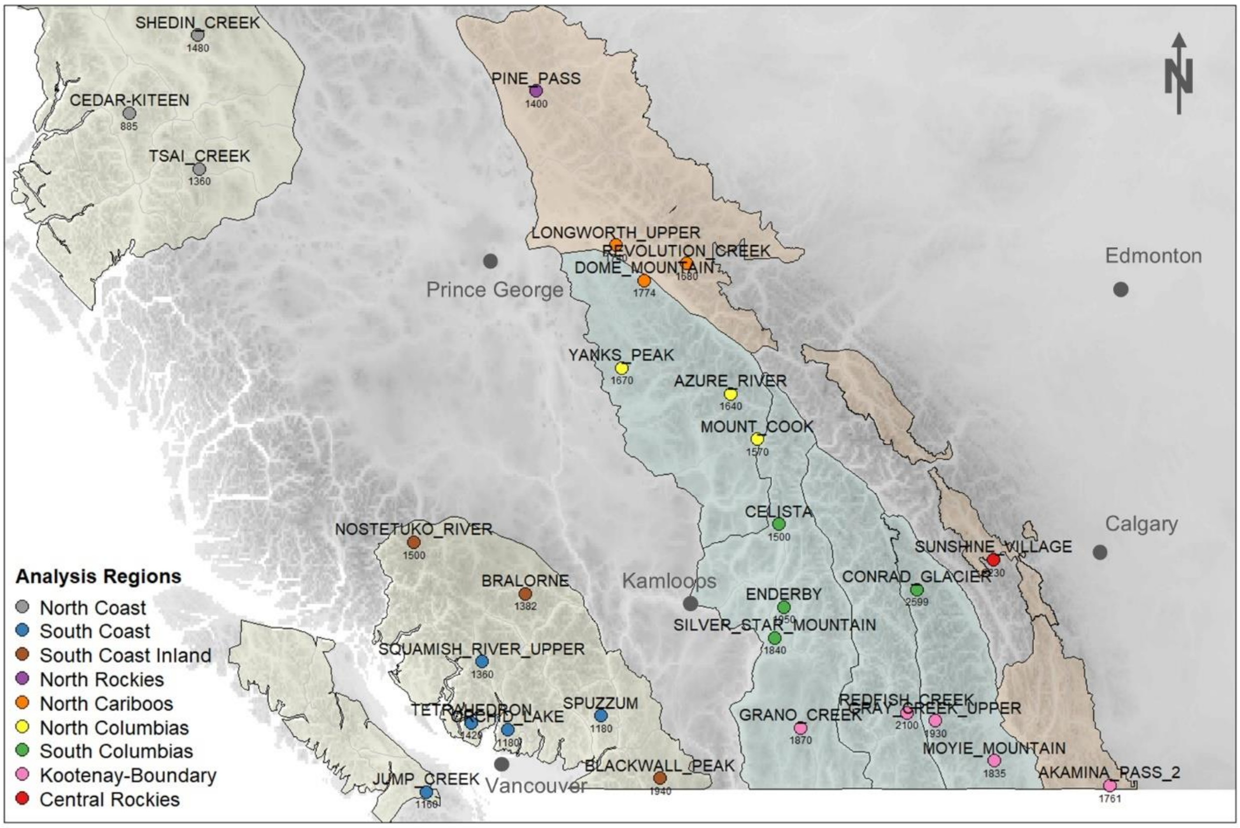

Figure 1: Map of southwestern Canada showing study area with study sites grouped by analysis regions as indicated by colored dots. Background polygons show avalanche forecast regions grouped by main mountain ranges (Coast range: yellow; Columbia Mountains: green; Rocky Mountains: orange).

Avalanche Canada provided the HRDPS and AvCan datasets from their data archive. The operational adjustment of the HRDPS precipitation values in the operational snowpack model chain developed by Horton and Haegeli (2022) scales the HRDPS values based on differences of modeled and observed weekly changes in HS. If differences at a site exceed 10%, the local hourly precipitation amounts from the HRDPS for the last week are scaled to produce the observed change in HS.

CaPA and CaPA-Exp data was provided by Alexandre Langlois' research team at the University of Sherbrooke. While CaPA only uses ECCC's own proprietary network of weather sites, the CaPA-Exp precipitation values are further corrected by incorporating weather observations from additional third-party networks relevant for avalanche forecasting in western Canada including Kananaskis Country (n = 5), Parks Canada (n = 17), British Columbia Ministry of Transportation and Infrastructure (n = 110), and Glacier National Park (n = 5).

2.2 Snowpack simulations

We used SNOWPACK version 3.4.5 (Lehning et al., 1999) to simulate the evolution of the seasonal snowpack at the 28 station locations in two different ways: precipitation product-specific and reference simulations. Whereas air temperature, relative humidity, wind speed, and incoming shortwave and longwave radiation were sourced from HRDPS for all simulations, the precipitation data was simulation specific. CaPA and CaPA-Exp precipitation data was resampled from 24-hour to hourly values using the same relative timings as the HRPDS hourly data. Uniform flat-field settings were applied at all study station locations. Lapse rate corrections were applied to adjust precipitation, air temperature, and relative humidity values from the model grid point elevation to match the elevation of the corresponding weather station using the downscaling methods described by Thornton et al. (1997). Seasonal simulations started on Sept 1, when the ground was assumed to be snow free and ran until May 1 of the following year. To maintain stability in snow height during simulation, wind transport and erosion were deliberately disabled.

Reference simulations were generated using lapse-rate corrected hourly precipitation values (PSUM) from the HRDPS, but to ensure consistency with the observed height of the snowpack at the station, the SNOWPACK parameter ENFORCE_MEASURED_ SNOW_HEIGHTS was set to TRUE, forcing SNOWPACK to match the measured HS and represent the amount and properties of new snow accumulation more accurately.

2.3 Data analysis

To examine differences in snowpack height and structure of the simulations with different precipitation products, we calculated several performance indicators in relation to the reference simulation:

- The relative difference in HS,
- Differences in the proportion of key grain types within the snowpack: rounded grains (RG); faceted crystals and depth hour (FC & DH); melt-freeze crusts and ice formations (MFcr & IF),
- Differences in unstable layer counts for specific grain types: non-persistent layers (PP, DF & RG); persistent layers (FC, DH & SH).

To make the results from deep and shallow snowpack areas more comparable, we chose to compute relative differences in HS compared to absolute differences, which we used in all other comparisons.

Each performance indicator was computed for all simulation types and seasons for a select subset of dates (1 and 15 of each month from Oct. 1 to May 1). Thinning the dataset this way substantially reduced the issue of autocorrelations, decreased redundancies, and made the analysis of the extensive dataset more efficient.

Once the performance indicators were calculated, we used linear mixed effects regression models to isolate and examine the biases of the different sources of precipitation data on the snowpack simulations. The regression approach allowed us to isolate the effect of the source of precipitation data from other potential factors affecting the quality of the simulations, and the random effects enabled us to properly account for the hierarchical structure of our dataset.

We conducted our entire analysis in R (version 4.2.3; R Core Team, 2024) and used the lmer function of the lme4 package (Bates et al., 2015) to estimate the linear mixed effects models for each performance indicator. We started the analysis for each performance indicator by regressing the difference to the reference simulation against the following categorical predictor variables: season, season period, analysis region, and source of precipitation data. *Season* included the categorical values 2020, 2021, and 2022, and the levels of the *season period* predictor were 'Early season' (Oct. 1 to Dec. 15), 'Main season' (Dec. 16 to Mar. 15), and 'Late season' (Mar. 16 to May 1). To account for regional differences in our analysis, we divided the 28 stations included in our study into nine distinct *analysis regions* (Fig. 1) based on spatial distribution and operational experience. Please note that the regions 'North Rockies' and 'Central Rockies' only include one station each (Pine Pass and Sunshine Village respectively). The final predictor variable included in the regression analyses was the *source of the precipitation data* which included the levels 'HRDPS', 'AvCan', 'CaPA', and 'CaPA-Exp'. To understand the performance of the different sources of precipitation data in more detail, we also included its interaction effects with all other predictor variables when we estimated the regression parameters for the first time. *Date* and *station* were included as random effects to account for the repeated measures and address potential correlations within groups.

Since the values of the relative difference in HS is bound at the lower end by -100% (means there is no snow in the simulation at all while the reference simulation has a snowpack), we added 1 and log-transformed the values to produce a more normally distributed dependent variable for the regression analysis. All other performance indicators exhibited normal distributions centered around zero and were included in the regression analysis without any pre-processing.

To evaluate the contributions of the fixed effects, we calculated Type II Wald chi-squared tests using the Anova function of the car package (Fox & Weisberg, 2019). Only significant variables and interactions (p-values < 0.05) were kept in each iteration of the model development. For evaluating the performance of the final model, we used the check_model function from the performance package (Lüdecke et al., 2021) and visually checked for issues. Furthermore, we employed the compare_performance function from the same package to calculate the conditional and marginal R^2 values for the final models.

To visualize the results of our regression analyses, we used functions from the effects (Fox, 2003) and sjPlot (Lüdecke, 2023) packages to produce effects plots. These plots illustrate the effect of a particular predictor variable on the dependent variable averaged across all other predictor variables.

3. RESULTS

After starting our regression analysis for the relative difference in HS with all possible predictor variables and their interactions with the source of the precipitation data, our final model only included season period, source of precipitation data, region and the interaction between region and source of precipitation data (Table 1). While the main effect of region was not significant itself, we retained it in the model due to the significant associated interaction effect. Season and all other interactions did not emerge as significant contributors.

Across the entire dataset, HS was overestimated in the simulations by +11% relative to the reference simulations (i.e., observed HS) as indicated by the significantly positive intercept (p-value < 0.001). However, several additional patterns emerged.

Table 1: Type II Wald Chi-Squared test statistics for significant variables and interactions (IA) in the final regression model for relative differences in HS (Df: degrees of freedom).

Variable	*Test statistic*	*Df*	*p-value*
Season period	28.8	2	< 0.001
Source of precip. data	24.8	3	< 0.001
Region	9.2	8	0.328
Interaction of Region-Source of precipitation data	73.1	24	< 0.001

The parameter estimates for *season period* show that HS is generally overpredicted in the main and late season by an average of +15% and +16% relative to the reference simulation (Fig. 2, left panel). The overprediction is significantly higher (+24%) in the early season when the snowpack is shallower, and the same absolute differences in HS result in larger relative differences. The fact that none of the confidence intervals cross the zero line shows that the average bias relative to the reference simulation is statistically significant in all season periods. The insignificance of the interaction effect between season period and sources of precipitation data indicates that this seasonal pattern applies to all four simulations, and there are no substantial differences between them.

The significance of the main effect for *source of precipitation data* shows that there are statistically significant differences in how the simulations with the four different data sources perform (Fig. 2, central panel). When everything else is controlled for, HRDPS overpredicted HS by +17% relative to the reference simulations, AvCan overpredicted by +20%, CaPA by +21%, and CaPA-Exp by +14%. Therefore, CaPA-Exp is closest to the reference simulations, but the overprediction bias is still significant as shown by the confidence interval that does not cross the zero line.

The right panel of Fig. 2 illustrates the combined effect of source of precipitation data, analysis region and their interaction effect. Looking at the general regional pattern, we can observe that in the Coast Mountains, the predictions of HS from all sources are closest to the reference simulations in the North Coast region, and the overprediction increases as we go to the South Coast region and increases even further in the South Coast Inland region, where it is the highest in the entire dataset (ranges from +40% for HRDPS to +57% for CaPA).

The North Rockies region is the only region where we see a substantial underprediction of HS (ranges from -32% for AvCan to -52% for CaPA-Exp). However, it is important to note that this analysis region only includes a single study site (Pine Pass), which is also reflected in the large confidence intervals.

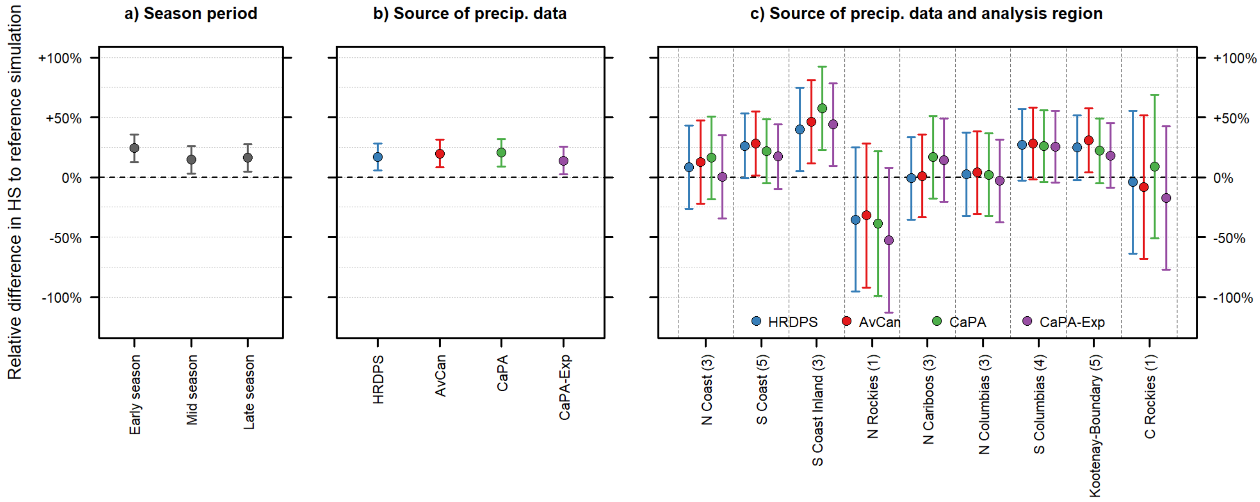

Figure 2: Effects plots for the main effect of season period (left panel), main effect of source of precipitation data (center panel), and the combined main and interaction effects for source of precipitation data and analysis region (right panel) for relative difference in HS in relation to the reference simulations, which are represented by the horizontal dashed line at zero. Positive values indicate the simulations overpredict HS, whereas negative values represent underpredictions. Vertical lines represent the 95% confidence interval of the point estimates. Confidence intervals that do not cross the zero line indicate statistically significant biases and the chance that the simulations produce the same HS estimates as the reference simulation are less than 5%. The numbers in brackets in the region labels on the x-axis in the right panel represent the number of study sites included in each analysis region.

Simulations of HS are generally very close to the reference simulation in the northern parts of the Columbia Mountains (North Cariboos and North Columbias), but we have consistent over predictions of HS by all simulations in the South Columbia and Kootenay-Boundary analysis regions. And finally, in the central Rocky Mountains region, the simulations with all four precipitation sources result in HS estimates around the reference simulation. However, this analysis region also only includes a single study site (Sunshine Village), and the presented estimates should be interpreted with caution.

Overall, the pattern that CaPA-Exp produces lower HS estimates closest to the reference simulation holds for most analysis regions, but there are some notable exceptions. In the South Coast Inland region, HRDPS provides the best estimate for HS while CaPA-Exp still represents an improvement over CaPA. At the single study site in the North Rockies, the lower HS values produced by the CaPA-Exp exasperate the general underprediction of HS in this region. Another interesting outlier is the North Cariboo region, where HRDPS and AvCan produce HS values very close to the reference simulation, while CaPA and CaPA-Exp produce snowpacks that are too deep. At Sunshine Village, the only station in the Central Rockies region, the difference between CaPA and CaPA-Exp is larger than in other regions, and CaPA-Exp produces the prediction furthest away from the reference simulation. At this study site, HRDPS provides the HS estimate closest to the reference simulation.

It is worth noting that the confidence intervals in the right panel of Fig. 2 are relatively wide and many of them cross the zero line. This means that in most cases, we cannot infer from our analysis with 95% confidence that the deviations from the reference simulation apply to simulations with the different precipitation data sources in general. The only analysis region where the 95% confidence intervals consistently do not cross the zero line is the South Coast Inland region. However, the magnitudes of the observed deviations are substantial in many analysis regions, and the confidence intervals are heavily dependent on our sampling approach, which was rather conservative (i.e., included few samples). Hence, we recommend focusing on the point estimates and interpreting the confidence intervals with caution.

While the described patterns are interesting and the overall variance captured by our model is 53% (conditional R^2), it is important to note that only 14% is captured by the included fixed effects (marginal R^2). This means that most of the captured variance is associated with the random effects of study site and to a much lesser degree date. This means that there are considerable variations within the analysis regions presented in Fig. 2, and the observed regional patterns should not be applied to individual stations without further analysis. However, since our focus is on regional scale avalanche forecasting, we stayed with the regional analysis.

The results of our regression analyses for snowpack structure (proportion of grain types and the number of unstable weak layers) closely follow the patterns of the HS deviations. In general, simulations that overpredict HS also have higher proportions of rounded grains and higher numbers of unstable non-persistent weak layers relative to the reference simulation. Alternatively, simulations that underpredict HS are generally associated with higher proportions of depth hoar or faceted crystals. A more detailed presentation of the results for the snowpack structure performance indicators is beyond the scope of this ISSW paper, but interested readers are referred to Krawetz (in prep.) for more information.

4. DISCUSSION

Our analysis of simulated HS in western Canada generally aligns with those of the most recent studies evaluating the performance of different precipitation products in the context of avalanche forecasting. Horton and Haegeli (2022) concluded that HRDPS overestimates HS in the Coast and Columbia Mountains, and underestimates HS in the Rockies which is generally consistent with our results. Our results show slight underestimations in the South Columbias, and estimations close to the reference in the North Coast and North Columbias. However, the results of our study do not align with the findings of Horton and Haegeli (2022) for the estimation of HS using the AvCan product. For the Coast Mountains, the study reported a large reduction in precipitation, whereas we found a small increase in snowpack height for AvCan. In the North Columbias, their study indicated a small reduction in precipitation, whereas our results showed a small increase. Additionally, for Kananaskis in the Central Rockies, their study noted a large increase in precipitation, but our findings revealed a small decrease in underestimation in the North Rockies and a small increase in underestimation in the Central Rockies. The main reason for these differences is the evolution of the adjustments in the AvCan product. Whereas Horton and Haegeli (2022) used fixed bias corrections, the version of AvCan used in this study employed conditional weekly corrections. Furthermore, the HS validation datasets used by Horton and Haegeli (2022) also included practitioner observations reported in the InfoEx, the daily information exchange among Canadian avalanche safety programs.

Madore et al. (2023) concluded that CaPA and CaPA-Exp generally perform better than HRDPS, which only partially aligns with the findings of our study for HS. While CaPA-Exp performed the best overall, CaPA performed the worst overall, although very close to AvCan. However, despite the improvements, CaPA-Exp still overestimates HS. The findings from this study also show regional differences in the performance of CaPA and CaPA-Exp, but these patterns should be interpreted with caution due to the relatively low marginal R^2.

Finally, Schirmer and Jamieson (2015) used winter precipitation data from CaPA and two NWP models, HRDPS and GEM15 through snow depth comparison of snow depth sensors and automated snow weather stations across western Canada. The study concluded that winter precipitation amounts were systematically underestimated by NWP models, which is not consistent with the systematic overestimation of HS found in this study. While the authors acknowledge that their results were inconsistent with other studies in this field at that time, the use of different and older versions of weather models are likely additional reasons for the observed differences with the present study.

While our analysis revealed some interesting regional patterns, the relatively large differences between the conditional and marginal R^2 highlight that much of the variance included in the data is associated with the random effect for study sites. Readers should therefore interpret the regional patterns with caution.

5. CONCLUSION

We employed a linear mixed effects regression analysis approach to simultaneously examine the biases of four different precipitation products on simulated HS at 28 study sites in western Canada where hourly HS observations are available. The simulations with all four precipitation data sources overestimate HS when compared to the reference simulations (i.e., observed HS), but CaPA-Exp is generally closest to the reference. However, regional differences exist, and CaPA-Exp is not always the best choice.

The results of this study can help Canadian avalanche forecasters better understand the strengths and weaknesses of different precipitation products for snowpack simulations. To provide deeper insight, future studies should examine the effects at smaller spatial scales in more detail.

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