TOWARDS IMPROVED SNOWFALL ESTIMATIONS IN THE CANADIAN MOUNTAINS IN SUPPORT OF AVALANCHE HAZARD ASSESSMENT

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ABSTRACT: Snowfall significantly influences avalanche hazards in mountainous regions, and accurately estimating snow properties in Canada's vast mountains remains challenging due to limited observations. Snow simulation with numerical weather prediction (NWP) models often addresses this challenge. To improve the precipitation of the High Resolution Deterministic Prediction System (HRDPS), the Canadian Precipitation Analysis (CaPA) is an interesting avenue. Nevertheless, the current version of CaPA underestimates winter precipitation in mountainous regions due to a limited number of stations within those areas and algorithmic limitations. To improve the quality of CaPA's solid precipitation product in mountainous areas, an experimental version at 2.5 km grid spacing covering western Canada and the northwestern part of the United States (US) was implemented. New wind quality control parameters were tested to increase the number of assimilated stations in winter. Then, new precipitation observations from additional networks in mountainous areas were assimilated. The results from those experiments were evaluated at both local and regional scales. At a local level, the variability of solid precipitation between experiments was examined within Glacier National Park (GNP) (Canada) using manual snow boards and an automated rain gauge network. At a regional level, the Crocus detailed snowpack model, driven by the 2.5km CaPA experiment precipitation combined with atmospheric forecasts from HRDPS, was used to assess snow distribution over the experimental area. Preliminary results showed good improvement by the CaPA experiments over the HRDPS at GNP. The simulation with new assimilated networks performed best in the park. The snow simulation at the regional scale showed promising results when compared with multiple field observations and automated stations.

Keywords: Solid precipitation estimation, snowpack modeling, mountains

1. INTRODUCTION

Snowfall amounts play a significant role in shaping avalanche hazards in mountainous regions over time and space. However, accurately estimating the spatial distribution of snow properties in the vast Canadian mountains is a difficult task due to the region's immense size and limited observational data. To address the scarcity of ground observations, researchers have explored the integration of numerical weather prediction (NWP) models coupled with snow models (Bellaire et al., 2011; 2013; Quéno et al., 2016). This approach has been employed to advance various aspects of avalanche hazard forecasting, such as assessing surface hoar spatial variability (Horton and Jamieson, 2016), monitoring wet avalanche activities (Bellaire et al., 2017), and identifying weak layers (Bellaire and Jamieson, 2013). Nevertheless, the accuracy of snow simulations is intricately linked to the precision of the data input.

Environment and Climate Change Canada (ECCC) operates the High-Resolution Deterministic Prediction System (HRDPS) (Milbrandt et al., 2016). This NWP system delivers a 48-hour weather forecast four times daily on a 2.5 km horizontal grid and is presently utilized by Avalanche Canada for avalanche risk assessment in Canadian avalanche-prone regions. However, recent research by Horton and Haegeli (2022) has identified biases in HRDPS precipitation forecast affecting snowpack simulations and related avalanche hazard assessment. One potential solution to this issue is the use of the Canadian Precipitation Analysis (CaPA) (Fortin et al., 2015; Lespinas et al., 2015; Mahfouf et al., 2007). CaPA used ground observations and radar data to adjust the forecasted HRDPS precipitation

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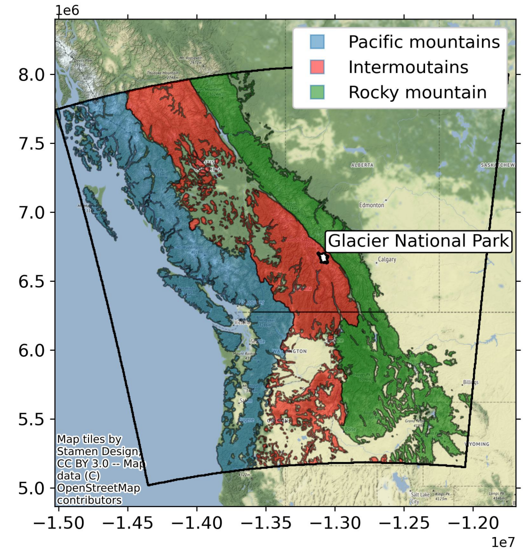

Figure 1: The experimental extent (outlined by the black frame) is located in the western part of Canada and encompasses the northwest region of the United States. It includes three distinct mountainous areas and encompasses Glacier National Park (marked within the frame).

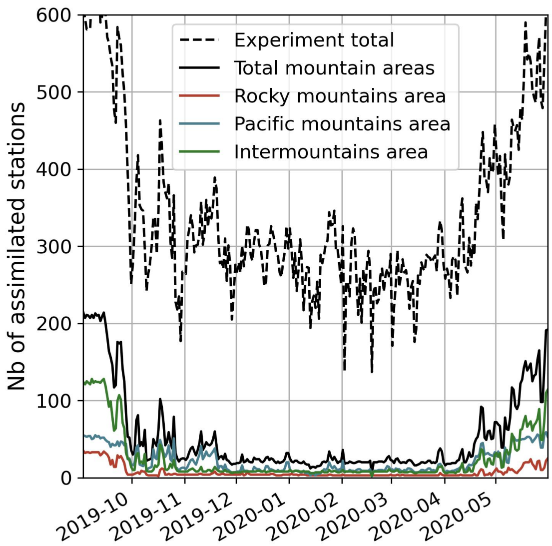

Figure 2: Number of assimilated stations for the three mountainous areas identified (Canadian part) and for the whole experimental extend (including the United States).

data and produce an adjusted precipitation grid. CaPA covers the entirety of Canada, with the exception of some Arctic islands, and the northern part of the United States. However, challenges exist in using these models effectively in the context of snow simulations, as highlighted by Schirmer and Jamieson (2015). The difficulties arise from the undercatch bias of rain gauges in measuring solid precipitation (Goodison et al., 1998). This leads to the rejection of automated stations when the air temperature at the station is below $0°C$ during the quality control (QC) of CaPA (Lespinas et al., 2015). The implementation of radar measurement is not implemented during solid precipitation which limits the amount of precipitation data use to correct the HRDPS grid (Fortin et al., 2018). Finally, the spatial interpolation doesn't account for the altitude.

The project aims to enhance the Canadian Precipitation Analysis (CaPA) to better support avalanche hazard forecasting. To address the challenge of limited observation networks, additional precipitation gauge networks that were not part of the operational CaPA version underwent QC for an experimental CaPA version with HRDPS. Experimental CaPA versions are evaluated on two scales. On a local level, the study examines snowfall variability within Glacier National Park (Canada) using a high-density network of manual snowboards and automatic rain gauges. It assesses how new snow is distributed within a 2.5-kilometer CaPA grid pixel in relation to elevation and the digital elevation model grid used by the model. On a regional level, the Crocus detailed snowpack model (Vionnet et al., 2012), driven by the 2.5-kilometer CaPA precipitation data combined with HRDPS atmospheric forecasts, is used to evaluate snow distribution across the experimental area, with a particular focus on mountain ranges and Avalanche Canada's forecasting areas.

2. METHODOLOGY

2.1. Study site

The experimental version of CaPA used in the project operates on a subset of the HRDPS model grid. This experimental zone is located in the western part of Canada and the northwest part of the United States (Figure 1). Its southern boundary is at $41.5°$ latitude, and the northern boundary is at $57.5°$ latitude, with a tolerance of $\pm 0.5°$ along each boundary. This setup mitigates border effects within our primary area of interest, the Canadian avalanche-prone regions. The results are analysed for three mountain ranges based on the classification by Snethlage et al. (2022). In Canada, this classification corresponds well with the snow climate zones of western Canada, as defined by Shandro and Haegeli (2018). These mountain areas include the Pacific Mountains on the west coast, associated with the maritime snow climate; the Rocky Mountains on the eastern limits of the mountainous region, associated with the continental snow climate; and the Intermountain region, which covers the ranges in between and

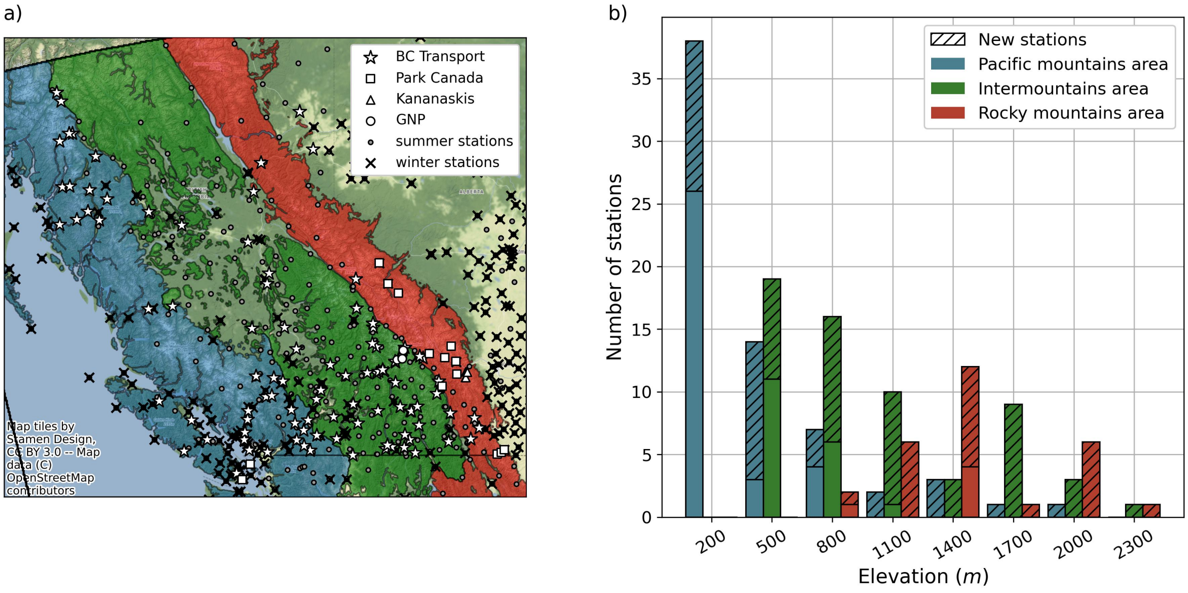

Figure 3: (a) Original stations assimilated in summer (grey circles) and winter (black circles), along with the new network of stations (white circles) assimilated by CaPA. (b) Distribution of elevation for all weather stations within the three mountainous areas. The hatched portion of the bar represents the new stations assimilated.

represents the transitional snow climate. For the present work, we focus on the Canadian part of the simulation domain.

At a local scale, our study is centered over Glacier National Park in British Columbia. This park hosts Canada's largest Avalanche Control Program and has the critical responsibility of safeguarding the Trans-Canada Highway, which serves as the primary transportation route in western Canada. Multiple weather stations are strategically positioned at varying elevations within the park along the highway, with five stations equipped with rain gauges ranging from high to low maintenance. Our primary study site is located on Mount Fidelity at the Fidelity station, situated on the western border of the park at an elevation of 1905 meters. Mount Fidelity is part of the Selkirk Mountains, located in the Intermountain zone adjacent to the Rocky Mountains zone.

2.2. New Network Assimilation

Accessibility and maintenance challenges often lead to a scarcity of weather stations in mountainous regions. The operational version of the CaPA model assimilates data from networks maintained by either ECCC or third-party partners. For example, in Western Canada, BC Forest contributes data from its network, adding a total of 228 weather stations to the analysis. Unfortunately, these stations are only available in the summer months, as they are not maintained during the winter. This limitation contributes to the scarcity of stations from November to May (Figure 2).

Another factor affecting the low station assimilation during winter is the QC applied by CaPA, which rejects all automatic station measurements when the temperature is below $0°C$ and the wind above 0.6 m s^{-1}. This QC was put in place due to a negative bias in small precipitation amounts in CaPA when solid precipitation was assimilated (Lespinas et al., 2015). Recent experiments have shown promising results by adjusting the wind threshold for automated stations from $0.6m/s$ to $3m/s$ (Feng et al., in review). This modification enables us to conduct a baseline experiment with a minimum number of stations during the winter. The limited presence of stations in mountainous areas is clearly evident in Figure 2, especially when compared to the total number of stations assimilated for the entire experiment, which includes stations located outside the mountainous areas depicted in Figure 1.

In our simulations, we incorporated data from three distinct station networks, each playing a crucial role in enhancing our model's accuracy and reliability (Figure 3). The Kananaskis Network, provided by the University of Saskatchewan, is strategically located at the boundary between the Rocky Mountains and the adjacent plains, in the southeastern region. This network comprises five well-maintained stations. The precipitation data from these stations were QC beforehand and thus, were directly assimilated into our simulations. The Parks Canada Network, our second resource, consists of 17 stations strategically positioned across various park areas within the experimental zones. Those stations were filtered beforehand for erroneous data and then assimilated. The third network added to our simulations is from BC Transport, featuring a total of 97 stations. Precipitation data from this network were corrected with a segmented neutral aggregating filter (NAF-SEG) (Ross et al., 2020) to remove negative noise without affecting the total accumulated precipitation. All the stations from the three networks have air temperature and wind speed measurements that are needed to be QC within CaPA. Finally, within the Parks network, we identify a subnetwork situated in GNP. The five stations that are located there are considered to be accurate. All stations within GNP are directly incorporated into the simulation without undergoing the standard CaPA QC procedures.

2.3. CaPA simulation configuration

The new experimental setup was implemented on a subgrid of the HRDPS domain, as defined in Sect. 2.1. The selected time range for the analysis spanned from September 2019 to May 2022. Each simulated year focused on the winter season, resulting in three sets of simulations (2019-2020, 2020-2021, 2021-2022) for each experiment. For reference, we conducted a CaPA experiment using the same parameters as the operational CaPA. This experiment referred to as *CaPA_oper*, served as the baseline for our other simulations. It was essential to account for potential changes in the background grid size that could impact spatial interpolation and to ensure a consistent dataset for comparison. The second configuration, *CaPA_ws3ms*, focused on the winter assimilation of more stations in the current network used by CaPA. To achieve this, we followed the methodology outlined by Feng et al., (view) and modified the wind threshold for the CaPA QC of solid precipitation measured by automated stations. The threshold was changed from $0.6m/s$ to $3m/s$. Finally, we assimilated the new network of stations described in Sect (*CaPA_NewNetworks*). 2.2. The background configuration for this experiment was the same as *CaPA_ws3ms* with the implementation of the $3m/s$ threshold on the new dataset with the exception of the GNP stations, which were force and by-passed CaPA QC.

2.4. Validation at Glacier National Park

The work conducted at GNP aimed to assess the local precipitation variability in various CaPA experiments. Particular emphasis was placed on the Fidelity station, which stands out as the most frequently visited by park technicians and is known for its high accuracy, especially in precipitation measurements. To estimate the local variability of precipitation, we evaluated four snowstorm events at five different elevations, ranging from 979m to 1923m around the station. Clean snowboards were strategically placed before each snowstorm, and measurements of snow water equivalent, height, and density were taken afterward. This work was intended to correct the precipitation bias due to the elevation difference between the Fidelity station elevation and the CaPA/HRDPS elevation grid point. The output of simulations *HRDPS*, *CaPA_oper* and *CaPA_NewNetworks* of winter 2020-2021 was used to evaluate the impact of assimilating the new networks in GNP and at the Fidelity station.

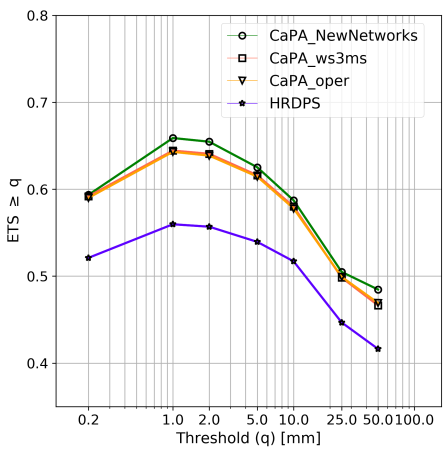

Figure 4: ETS results for the CaPA experiments and the *HRDPS*. The evaluation was done using automated stations and manual stations (119 stations).

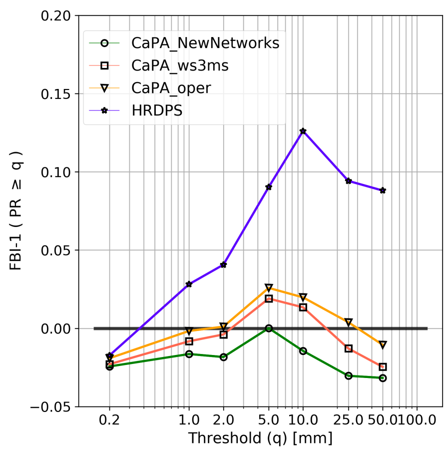

Figure 5: FBI results for the CaPA experiments and the *HRDPS*. The evaluation was done using automated stations and manual stations (119 stations).

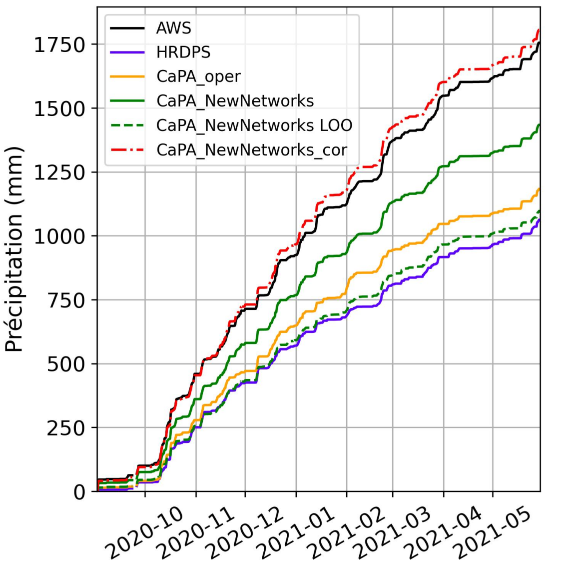

Figure 6: Cumulative precipitation of the Automated Weather Station (*AWS*), *HRDPS*, *CaPA_oper*, *CaPA_NewNetworks* and with the Leave One Out evaluation for the 2020-2021 season at Fidelity. *CaPA_NewNetworks_cor* shows the precipitation accumulation corrected for altitude.

2.5. Regional snow validation

Simulations were carried out with the detailed snowpack model Crocus (Vionnet et al., 2012) to assess the impact of the different precipitation datasets on snow cover evolution across the mountains of Western Canada. The version of Crocus described in Vionnet et al. (2022) was used in this study. Atmospheric driving data other than total precipitation were taken from successive short-term HRDPS forecasts as in Horton and Haegeli (2022) and Vionnet et al. (2022). The simulations were carried out over three winters from 1 September 2019 to 30 June 2022 at a resolution of 2.5 km on the same grid as the CaPA experiments. Three precipitation datasets described in Sect. 2.3 were considered:*HRDPS*, *CaPA_oper* and *CaPA_ws3ms*. The precipitation phase was derived using the near-surface wet bulb temperature (Vionnet et al., 2022).

Snowpack simulations were evaluated using manual and automatic snow depth measurements across the three regions of interest in Western Canada (Figure 1). These data were obtained from the CanSWE dataset (Vionnet et al., 2021) and the Canadian avalanche community and BC Transport (Horton and Haegeli, 2022). Only stations with actual elevation within 200 m from the elevation of the selected grid point were kept for the analysis. This selection was applied to limit the impact on snow simulations of errors in the precipitation phase and amount resulting from elevation differences between the model and the observations.

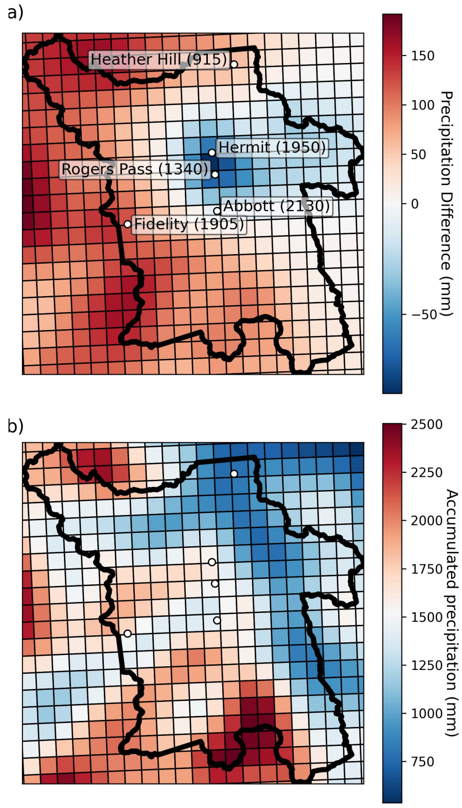

Figure 7: (a) Difference in accumulated precipitation for *CaPA_NewNetworks* and *CaPA_oper* over the GNP area for 2020-2021. (b) Accumulated precipitation for the *CaPA_NewNetworks* over the GNP area for 2020-2021.

3. PRELIMINARY RESULTS

3.1. Simulation performance

The evaluation of the simulation quality was done using equitable threat score (ETS) (Figure 4) and the frequency bias index (FBI) (Figure 5) as described in Lespinas et al., (2015. The FBI measures the ratio of forecasted event frequency to observed event frequency. We have adjusted its definition to make it 0 when frequencies match and positive/negative when forecasts exceed/fall short of observations. ETS measures the fraction of correctly predicted forecast/analysis values. A score of 1 on the ETS indicates a perfect forecast/analysis, and values less than 0 indicate no skill. All simulations performed better than the *HRDPS* on both scores. The CaPA simulations greatly improved the accuracy of the simulation for the smaller range of precipitation (<10mm) as shown with the higher ETS score in Figure 4. The assimilation of the new network showed a small improvement in ETS but few changes in the FBI compared with the other simulations.

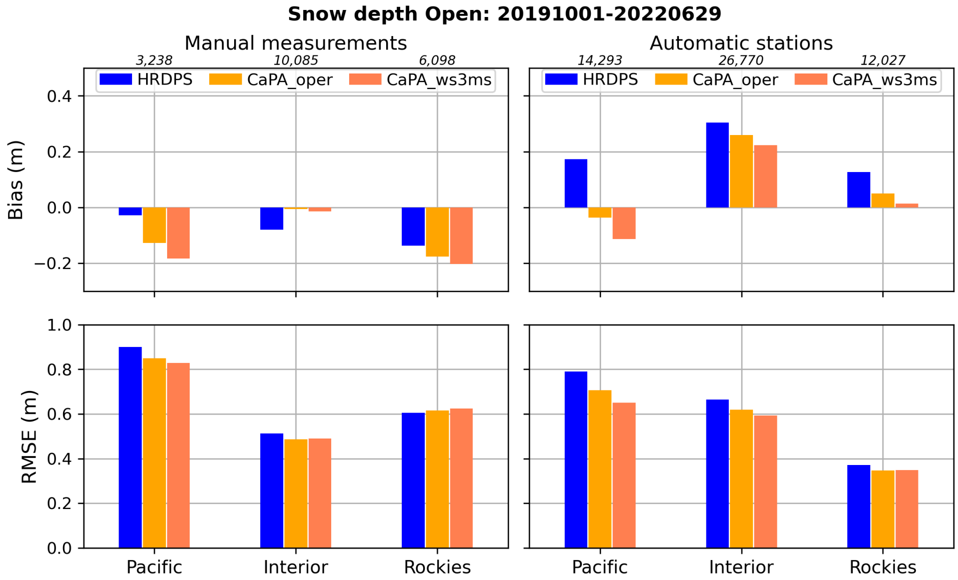

Figure 8: Snow depth (m) mean bias (top row) and RMSE (bottom row) against data from manual measurements (left) and automatic stations (right) for Crocus simulations. The number above the figures corresponds to the number of observations available during the study period: 1 September 2019 to 29 June 2022. The location of the evaluation regions is shown in Figure 1

3.2. Local validation

A comparison of accumulated precipitation at the Fidelity station revealed varying degrees of underestimation compared to the Automated Weather Station (AWS) (Figure 6). *HRDPS* exhibited the most significant underestimation, with the *CaPA_oper* also notably underestimating precipitation. The *CaPA_NewNetworks* simulations, while still underestimating precipitation, showed improvement primarily due to the inclusion of the Fidelity station in the analysis. This improvement was confirmed by Leave One Out analysis, which excludes the Fidelity station from *CaPA_NewNetworks*s, resulting in decreased precipitation likely due to newly assimilated stations in less snowy areas within the Park. The experiment with the snow board led to a lapse rate correction factor of 1.2591 for the elevation difference between the station (1905m) and the pixel covering the Fidelity site (1577m). Applying this correction coefficient, *CaPA_NewNetworks_cor* slightly overestimated AWS precipitation.

The influence of nearby stations on the difference between *CaPA_NewNetworks* and *CaPA_NewNetworks* LOO is evident in Figure 7a, illustrating the assimilation impact of new stations. Hermit and Roger's Pass stations recorded less precipitation, reducing simulated values, while the Fidelity station recorded more. The evaluation of the accumulation with *CaPA_NewNetworks*(Figure 7b) shows well the terrain's effect on the simulated values.

3.3. Snowpack simulations at regional scale

Figure 8 shows the error metrics (Bias and Root Mean Squared Error, RMSE) for the simulations of snow depth in the three regions of interest. It makes the distinction between automatic and manual measurements due to the differences in spatial representativeness. Indeed, manual measurements include multi-point snow courses collected along transects, whereas automatic stations measure snow depth in an area restricted to a few m^2. Results from the experiment *CaPA_NewNetworks* are not included yet.

The Pacific region is characterized by the largest error in absolute value in terms of RMSE (Figure 9a) due to the large snow accumulation in this region. The CaPA experiments lead to an improvement of snowpack simulations compared to the HRDPS forcing as illustrated by the reduction of RMSE for both manual and automatic stations (Figure 8). In particular, the *CaPA_ws3ms* experiment shows a strong improvement in RMSE throughout the Pacific region with the exception of the northwesternmost part of the region (Figure 9). This improvement is partially due to a reduction of snow accumulation in this region where the HRDPS overestimates winter precipitation (Horton and Haegeli, 2022). However, the *CaPA_ws3ms* experiments have a negative bias in snow depth for both manual and automatic stations suggesting that stations affected by wind-undercatch may be assimilated by this configuration of CaPA.

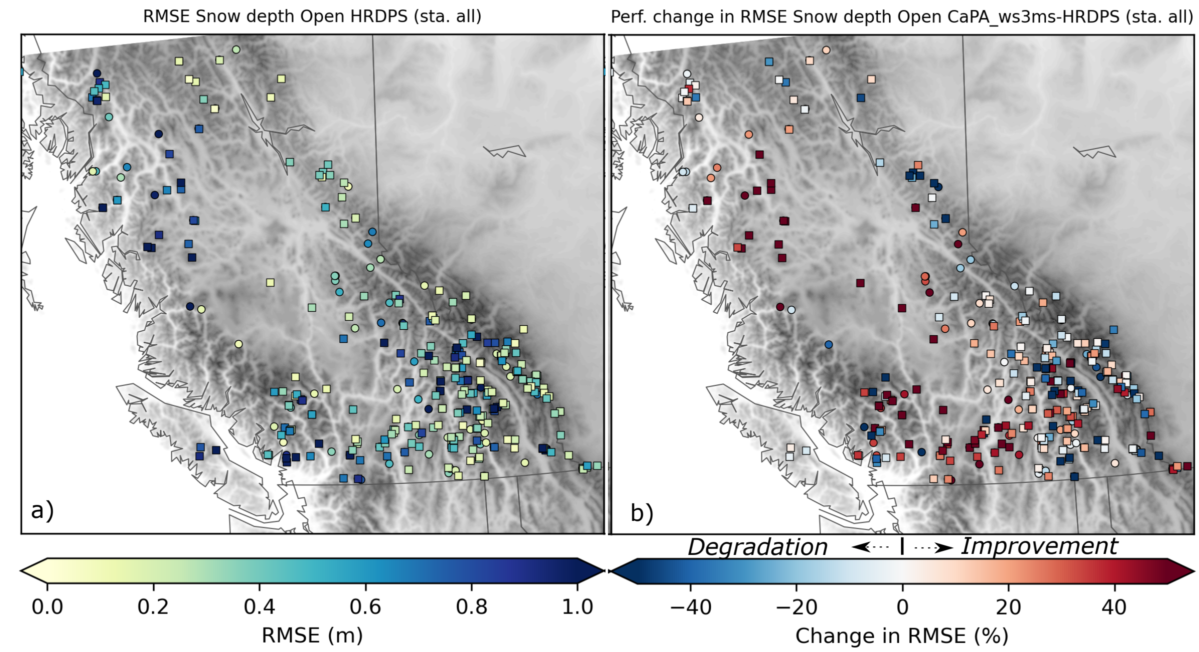

Figure 9: (a) Spatial distribution of snow depth RMSE against data from manual measurements (square) and automatic stations (round) for the *HRDPS* experiment. (b) Performance change in RMSE (in %) between the *CaPA_ws3ms* and the *HRDPS* experiments. A positive (negative) performance change denotes an improvement (degradation) in snowpack simulations.

In the Interior region, the CaPA experiments improve the bias and RMSE compared to the HRDPS forcing for both manual and automatic stations. Figure 9b shows that the improvements are mainly found in the southwestern part of this region. Results are more contrasted in the south-eastern part of this region, illustrating the need to carry out an analysis at a refined spatial scale. In the Rockies, the impact of the CaPA experiments is also contrasted (Figure 8 and 9b). Indeed, they lead to an overall degradation with manual stations (slight increase in RMSE and an increase in negative bias) whereas an overall improvement is found with automatic stations (slight decrease in RMSE and a reduction of positive bias). Additional analysis is required to better understand the differences of error metrics between manual and automatic, in particular the spatial and altitudinal representativeness of each network.

3.4. Conclusions and perspectives

The first results of this research project illustrate the benefit of the Canadian Precipitation Analysis system (CaPA) to estimate snowfall amount and drive snowpack simulations in the mountains of Western Canada. Adding quality-controlled data from high-mountain networks improved the quality of the precipitation analysis at the local and regional scales. Snowpack simulations driven by CaPA also showed promising improvements across the different snow climates of Western Canada.

These preliminary results will orient the next steps of the project. First, the effect of wind-undercatch on the precipitation measurements will be corrected for the additional mountain networks considered in the project. Then, more advanced spatial interpolation methods will also be considered to better account for the effects of elevation on the precipitation distribution. These modifications will be tested using the high-density SNOTEL network measuring precipitation in the mountains of the Western US. Finally, the improved CaPA precipitation estimates will be used as input to the avalanche hazard forecasting system of Avalanche Canada to test the impact of CaPA on avalanche hazard assessment.

ACKNOWLEDGEMENT

This work was funded by the Canadian Search and Rescue New Initiatives Fund the Natural Sciences and Engineering Research Council of Canada (NSERC), the Canadian Foundation for Innovation (CFI) and the Centre d'études nordiques (CEN). The authors would like to acknowledge significant contributions from Simon Horton and Pascal Haegeli from Simon Fraser University and Avalanche Canada. The authors also underline the great and continuous support from the Glacier National Park avalanche safety team for their field support and data access.

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