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DATA ARTICLE

Multivariate Canadian Downscaled Climate Scenarios for CMIP6 (CanDCS-M6)

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Abstract

Canada-wide, statistically downscaled simulations of global climate models from the Sixth Coupled Model Inter-comparison Project (CMIP6) have been made available for 26 models using a new multivariate approach and an improved observational target dataset. These new downscaled scenarios comprise daily simulations of precipitation, maximum temperature, and minimum temperature at 1/12° resolution across Canada. Simulations from each of the 26 downscaled global climate models span a historical period (1950–2014), and three future Shared Socio-economic Pathways (SSPs) representing low (SSP1 2.6), moderate (SSP2 4.5) and high (SSP5 8.5) future emissions from 2015 to 2100. Results from an evaluation of the multivariate downscaling method over Canada yield improved performance in replicating multivariate and compound climate indices compared to previously used univariate downscaling methods. This Multivariate Canadian Downscaled Climate Scenarios for CMIP6 (CanDCS-M6) dataset is intended to facilitate climate impacts assessments, hydrologic modelling, and analysis tools for presenting climate projections.

KEYWORDS

Canada, climate scenarios, CMIP6, downscaling, multivariate

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1 | INTRODUCTION

Future scenarios from global climate models produced as part of the Sixth Coupled Model Inter-comparison (CMIP6; Eyring et al., 2016) are widely used for quantifying the impacts of climate change both globally (IPCC Sixth Assessment Report; Masson-Delmotte et al., 2021) and for Canada (Bush et al., 2022). Obtaining information from these models about future climate impacts in Canada at provincial, regional, and local scales generally requires additional post-processing of these simulations (Zhang et al., 2019). Systematic biases that can exist between large-scale model simulations and observations (Kim et al., 2020; Sillmann et al., 2013) are often reduced through the application of statistical downscaling methods to adjust model output using information from gridded observational datasets (Benestad et al., 2008). Thus, in practice, the term ‘downscaling’ refers to both bias correction of raw model output and a decrease in its horizontal resolution. An example of this in the Canadian context is the previous treatment of model simulations from the Fifth Coupled Model Inter-comparison (CMIP5; Taylor et al., 2011) using the Bias Correction/Constructed Analogues with Quantile mapping reordering downscaling method (BCCAQv2; Cannon et al., 2015; Werner & Cannon, 2015). These simulations have been widely used in myriad applications and are used by climate services portals including climatedata.ca, the Climate Atlas of Canada, and Power Analytics and Visualization for Climate Science, among others.

Many downscaling methods like BCCAQv2 adjust coarse-scale simulations to match the statistical properties of a target (observational) dataset using a univariate approach, in which different variables (e.g. daily precipitation, daily maximum and minimum temperature) are considered independently (Lange, 2019; Wilcke et al., 2013). Univariate downscaling methods can be effective at correcting biases in the distributions of individual variables (Li et al., 2010) but can omit or represent poorly certain phenomena defined by combinations of multiple variables (Maraun, 2016; Zscheischler et al., 2019). Compound extreme events (Zscheischler & Seneviratne, 2017) in particular can have significant negative impacts and the frequency of such events can be underestimated when the contributing variables are adjusted separately (Singh et al., 2021). To account for dependence between different variables, multivariate methods have been developed to bias correct both univariate and multivariate distributions across several variables using different approaches (Cannon, 2018; Mehrotra & Sharma, 2016; Piani & Haerter, 2012). While generally more computationally expensive, using a multivariate downscaling approach

can enable analyses of compound or multi-variable phenomena using the resulting bias corrected simulations (François et al., 2020).

The Multivariate Canadian Downscaled Climate Scenarios for CMIP6 (CanDCS-M6) dataset is intended to provide a consistent, Canada-wide ensemble of future scenarios for applications including climate impacts assessments, infrastructure design, hydrologic and impact modelling, engagement and outreach, and analysis tools. The CanDCS-M6 ensemble builds on the previous Univariate Canadian Downscaled Climate Scenarios for CMIP5 (CanDCS-U5) and CMIP6 (CanDCS-U6) produced using the univariate BCCAQv2 downscaling method. Similar to the existing CanDCS datasets, CanDCS-M6 provides daily surface meteorological variables of precipitation, and maximum and minimum temperature for both historical simulations and multiple future emissions pathways. Scenarios in CanDCS-M6 are produced by downscaling simulations from CMIP6 using the N-dimensional Multivariate Bias Correction (MBCn; Cannon, 2018) method with a new target observational dataset for calibration.

MBCn has become frequently used in the recent downscaling literature in multivariate analysis applications. It has been used to downscale hydro-climatic variables more effectively in snow-dominated watersheds in Canada (Eum et al., 2020), alpine catchments in Europe (Meyer et al., 2019), and many other examples elsewhere. It has also been applied solely as a bias correction method to improve target datasets used in downscaling (Asong et al., 2020). Similarly, inter-variable dependence in ensemble weather forecasts has been improved using MBCn as a statistical post-processing tool (Whan et al., 2021). MBCn has also been applied solely as a bias correction method to ensembles of regional climate model simulations. The CanLEAD dataset is a version of the CanRCM4 Large Ensemble that has been bias-corrected with MBCn using two gridded observational datasets (Cannon et al., 2021; Singh et al., 2021). The North American phase of CORDEX (NA-CORDEX) has produced versions of the regional climate model (RCM) simulations that have been bias-corrected with MBCn and two gridded datasets covering North America (McGinnis & Mearns, 2021). Each of these applications represents examples where MBCn is used to reduce biases in individual variables within datasets while maintaining the relationships between those variables.

The following sections describe the work undertaken to synthesize the new calibration dataset, evaluate the performance of MBCn in multivariate downscaling for Canada, and provide downscaled simulations of CMIP6 models for Canada using these components. Section 2 summarizes the CMIP6 models selected for downscaling, explains the

development of the PCIC-Blend observational dataset, and describes the MBCn method. PCIC-Blend combines components of existing and recent gridded observations to produce a Canada-wide dataset with an improved representation of daily precipitation in particular (Section 2.2). Section 2.3 summarizes the implementation of MBCn to produce the CanDCS-M6 scenarios. Section 3 describes the evaluation of MBCn against other univariate and multivariate methods, with performance evaluated using an ensemble of regional climate model simulations. Finally, dataset access is described in Section 4, and potential limitations and applications of the CanDCS-M6 scenarios are discussed in Section 5.

2 | DATA DESCRIPTION AND DEVELOPMENT

2.1 | CMIP6 climate models and scenarios

Simulations from CMIP6 used in CanDCS-M6 were obtained from global climate models (GCMs) participating in the Scenario Model Inter-comparison Project (ScenarioMIP; O'Neill et al., 2016). Models to be down-scaled were chosen from GCMs employing the historicalALL and Tier 1 ScenarioMIP Shared Socio-economic Pathways (SSPs; Gidden et al., 2019; Riahi et al., 2017) including those with low (SSP1 2.6), moderate (SSP2 4.5), and high (SSP5 8.5) future emissions. These SSPs are similar to the Representative Concentration Pathways (RCPs; Vuuren et al., 2011) used in CanDCS-U5. Specific GCMs were selected for downscaling based on satisfying data completeness criteria including availability of daily precipitation, maximum and minimum temperature between 1950 and 2100 following the historicalALL and three future SSP emissions scenarios. All models that satisfied the completeness criteria were acquired using the Earth System Grid Federation data distribution platform (Williams et al., 2009). At the deadline at which point the CMIP6 GCM list had to be finalized for this analysis (September 2021), 26 GCMs were identified that satisfied all completeness criteria. The list of GCMs selected and acquired is provided in Section S1 in the Appendix S1.

Among the ensemble of 26 CMIP6 global climate models selected are three models with sporadic, anomalously high daily maximum temperature outliers ($>50^{\circ}\text{C}$) that are believed to originate from model component errors leading to the accumulation of sensible heat at the surface. These include two Met Office Hadley Centre (MOHC) models, HadGEM3-GC31-LL and UKESM1-0-LL, and one model from the Korean Meteorological Administration (KACE-1-0-G). The issues associated with the MOHC models

are noted in the Earth System Documentation Errata at errata.es-doc.org with the following identifier: 76b3f818-d65f-c76b-bfd8-cae5bc27825c. While the modelling centre responsible for these models recommends omitting such events from analysis or further use, such a solution would introduce problems in generating statistically downscaled scenarios. Rather than omitting maximum temperature values based on a fixed threshold, we have implemented a method to detect and correct anomalously high maximum temperature values that occur within the downscaling domain used in CanDCS-M6. Employing the resulting corrected model maximum temperatures when downscaling prevents the anomalous values from being propagated into the downscaled outputs. A complete description of the detection and correction method is provided in Section S5 in the Appendix S1.

2.2 | Observational calibration dataset

Observations used in CanDCS-M6 for calibration were developed by combining three gridded observational datasets that interpolate quality-controlled weather station data for Canada and western North America. The first is an updated version of the Natural Resources Canada meteorological dataset, produced by interpolating Adjusted and Homogenized Canadian Climate Data (AHCCD; Vincent et al., 2012) weather stations using the Australian National University Spline (ANUSPLIN; Hopkinson et al., 2012) method (NRCANmet_v2; McKenney et al., 2011). The updated version incorporates a recent third-generation AHCCD dataset with improved and extended observation record lengths (AHCCDv3; Vincent et al., 2020). Downscaled scenarios in CanDCS-U5 and CanDCS-U6 were produced using an earlier version of NRCANmet (NRCANmet_v1) developed using the previous second-generation AHCCD stations (Vincent et al., 2012). This NRCANmet_v1 dataset is also often referred to as 'ANUSPLIN observations' in other literature. The second observational dataset is the Adjusted Precipitation Dataset for Canada (NRCANmet_Adj; MacDonald et al., 2021). This gridded precipitation dataset was produced by interpolating stations from the Adjusted Daily Rainfall and Snowfall dataset (Wang et al., 2017), in which station observations were quality-controlled and corrected to account for various effects leading to measurement underestimation. The third product is the Pacific Climate Impacts Consortium (PCIC) meteorology for Northwest North America dataset (PNWNAmets; Werner et al., 2019). This dataset extends beyond Canada to include Alaska and the northwestern United States and was created by interpolating long-term, quality-controlled weather

station observations guided by high-resolution climatologies from the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al., 2008).

A new calibration target dataset for CanDCS was developed from the three existing observational datasets to incorporate the positive attributes from each while addressing certain known performance issues. For observations of precipitation there was a specific question of whether the new precipitation observations address the known dry bias present in NRCANmet_v1 in British Columbia and Yukon (Werner et al., 2019). NRCANmet_v2 precipitation displayed a significant dry bias over all of Canada compared to NRCANmet_v1 and therefore was not considered for use in a new target dataset (not shown). Results from (MacDonald et al., 2021) suggested that NRCANmet_Adj precipitation displays improved performance primarily in northern and eastern Canada, which is reflected in the differences between precipitation from NRCANmet_Adj and NRCANmet_v1 (Figure 1). Most of eastern Canada displays increased precipitation totals in the NRCANmet_Adj dataset, with the largest increases

in Atlantic Canada resulting in better agreement with AHCCDv3 station observations (Figure 2). Overall dry biases present in NRCANmet_v1 that amount to -172 mm/year averaged across all AHCCDv3 stations in the region are substantially reduced to an average bias of -36 mm/year in NRCANmet_Adj. Conversely in western Canada, specifically in BC and Yukon, NRCANmet_Adj displays similar or even less precipitation than in NRCANmet_v1 (Figure 1), indicating elements of the dry bias present in NRCANmet_v1 persist in NRCANmet_Adj precipitation in this region. A map displaying the regions of Canada, such as BC and Yukon, is provided in Figure S1 in the Appendix S1.

To further confirm this underestimation in NRCANmet_Adj precipitation, one aspect of the evaluation in (Werner et al., 2019) has been repeated, here comparing the PNWNAmet and NRCANmet_Adj datasets with precipitation from the Agricultural and Rural Development Act (ARDA) weather station network. These stations operated in BC between 1965 and 1991 and were not used in generating either the NRCANmet

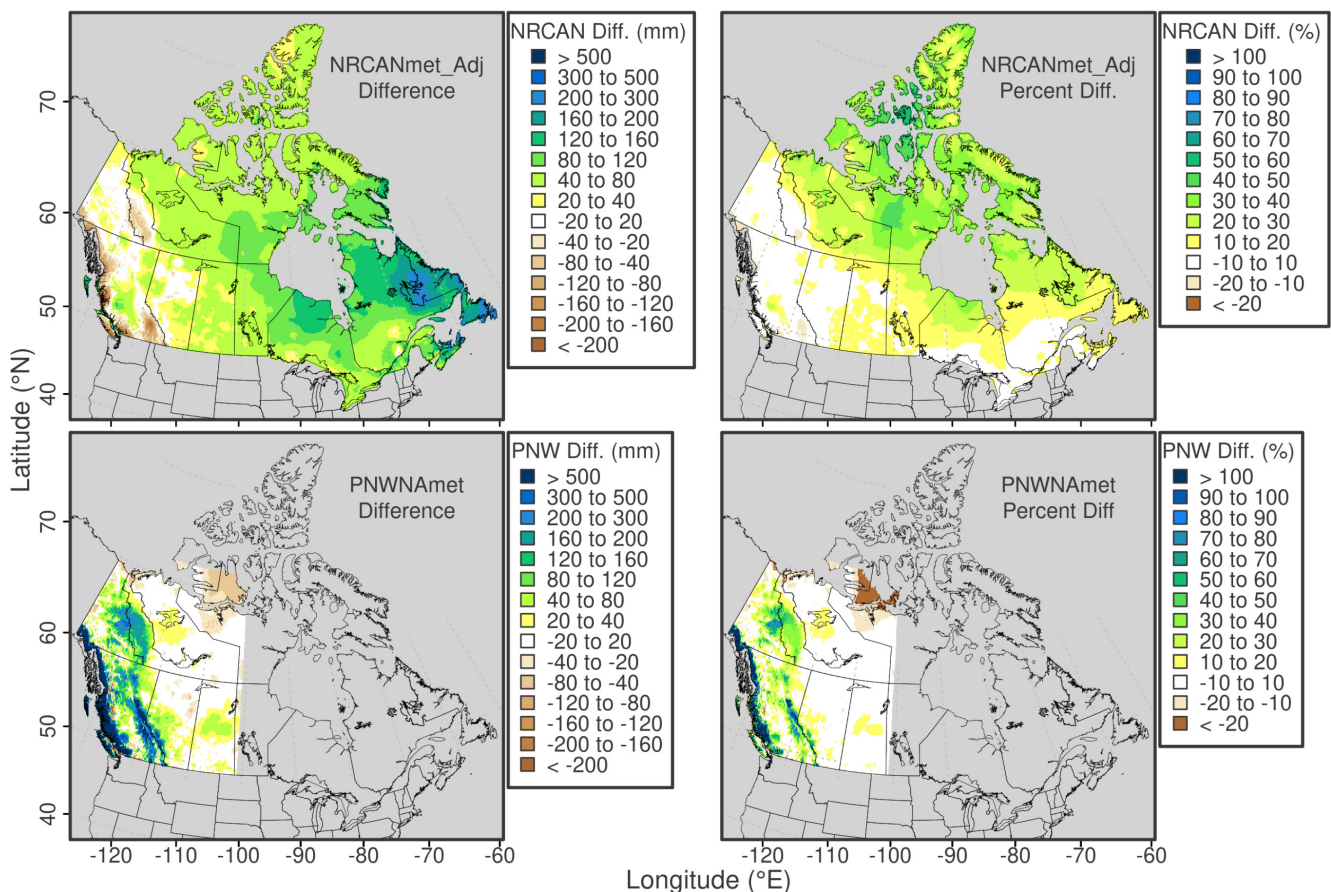


FIGURE 1 Comparison of average annual total precipitation from the NRCANmet_Adj and PNWNAmet datasets with NRCANmet_v1 gridded observations for Canada. The left panels display the absolute differences (NRCANmet_Adj—NRCANmet_v1 and similar for PNWNAmet) and the right panels display the relative differences $([NRCANmet_Adj - NRCANmet_v1] / NRCANmet_v1 \times 100\%)$ and similar for PNWNAmet), both calculated for 1950–2010.

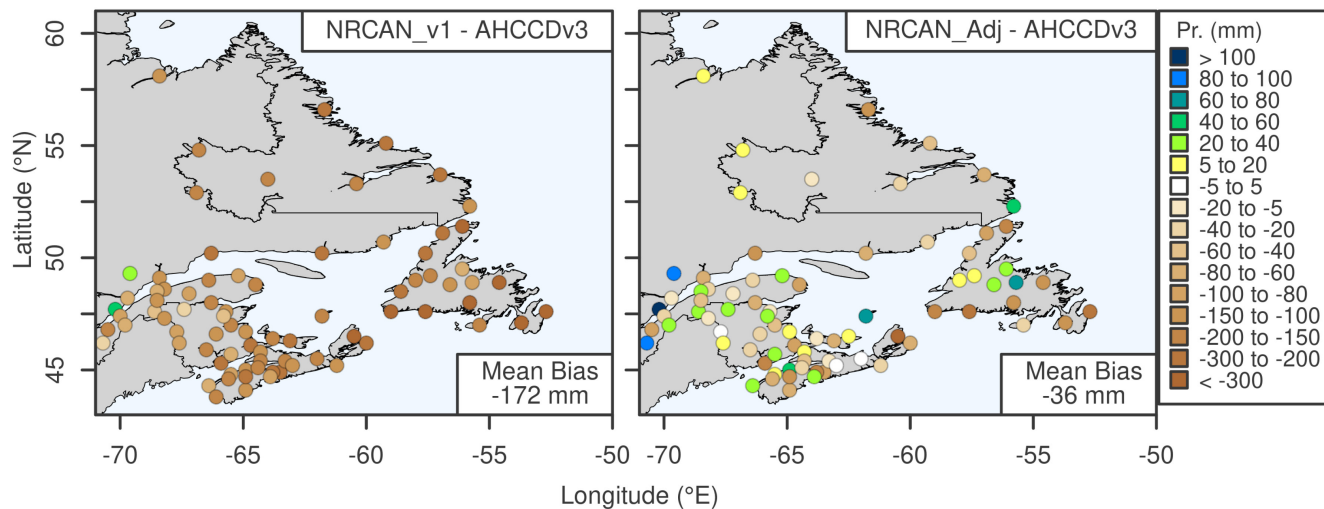


FIGURE 2 Average annual total precipitation from the NRCANmet_v1 and NRCANmet_Adj datasets for Atlantic Canada. The panels display differences between both NRCANmet gridded observations and AHCCDv3 station observations in Atlantic Canada. Differences are calculated using all valid days in the AHCCDv3 station records between 1950 and 2010 to overlap with the NRCANmet_v1 and NRCANmet_Adj datasets. The left panel displays differences for NRCANmet_v1—AHCCDv3 and the right panel for NRCANmet_Adj—AHCCDv3.

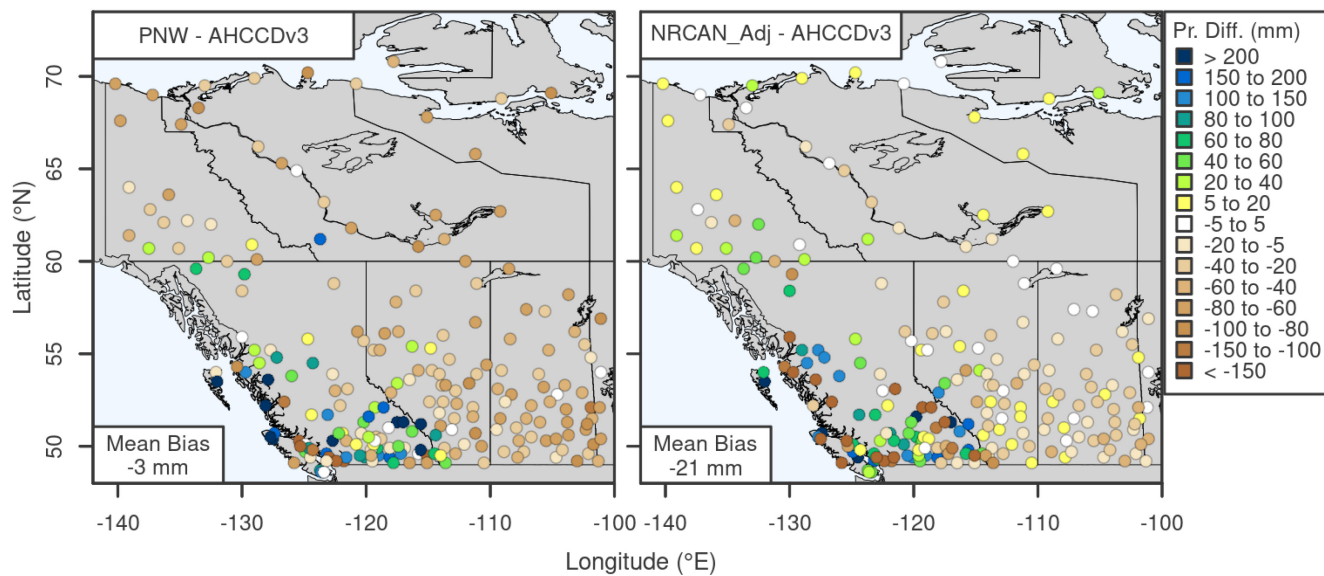


FIGURE 3 Comparison of annual total precipitation between PNWNAmet and NRCANmet_Adj gridded observations and AHCCDv3 stations in western Canada. Differences are calculated using all valid days in the AHCCD records between 1950 and 2012 to overlap with the gridded datasets. The left panel displays differences for PNWNAmet—AHCCDv3 and the right panel for NRCANmet_Adj—AHCCDv3.

or PNWNAmet datasets, thus making them an independent means of assessment. The overall average difference in annual total precipitation among all ARDA stations is 67 mm/year for PNWNAmet and -131 mm/year for NRCANmet_Adj. Among the 20 stations above 1000 m, the average difference is 36 mm/year for PNWNAmet and -140 mm/year for NRCANmet_Adj. Large negative biases in NRCANmet_Adj are also concentrated in the islands of Haida Gwaii, the Rocky Mountains near 55° N, and coastal sites near Vancouver Island. Similar patterns of bias are also present when the datasets are compared

with AHCCDv3 stations (Figure 3). Differences between the datasets illustrate that while PNWNAmet underestimates precipitation amounts at many sites in the Prairie provinces, NRCANmet_Adj precipitation displays large negative biases in coastal and mountainous areas of BC, with positive precipitation biases in the central interior of BC. While these differences at individual stations display strong spatial variability, the overall biases at western Canada stations are drier in NRCANmet_Adj (-21 mm/year) than in PNWNAmet (-3 mm/year). In these regions, precipitation in PNWNAmet reflects the added

information provided from the PRISM dataset, which also leads to improved representation in BC (Werner et al., 2019).

Differences in precipitation between NRCANmet_Adj and AHCCDv3 stations in the rest of Canada are shown in Figure S2 in the Appendix S1. Results for Northern Canada largely resemble those shown in the region above 60° N in the right-hand panel of Figure 3. Annual precipitation in Manitoba and western Ontario display the same modest underestimation in NRCANmet_Adj as for the other Prairie provinces visible in Figure 3. At sites in central Ontario and Quebec, NRCANmet_Adj displays greater spatial variability in the sign and magnitude of the differences, similar to the results shown in the right-hand panel of Figure 2.

Daily maximum and minimum temperatures among the three observational datasets display much greater similarity. Differences between temperatures from NRCANmet_v2 and NRCANmet_v1 are negligible since both datasets use the same methodology and similar, primarily ECCC station data sources. Differences between temperatures from PNWNAmet and NRCANmet_v2 are also negligible over most of western Canada, with the exception of Yukon, where PNWNAmet exhibits higher temperatures. Figure 4 displays average daily bias values in maximum and minimum temperatures at 25 AHCCDv3 stations. Over the Yukon region as a whole, temperatures from the NRCANmet_v2 grid cells display an overall cold bias (−0.28°C for maximum temperature and −0.14°C for minimum temperature), while temperatures from PNWNAmet display smaller differences (0.02°C for maximum temperature and 0°C for minimum temperature). There is considerable variability among individual stations, however, and the regions with the greatest differences between PNWNAmet and NRCANmet_v2 temperatures do not coincide with station observations. Overall, colder biases in the NRCANmet_v2 temperature series help explain why temperatures in the PNWNAmet gridded observations are warmer than those in NRCANmet_v2 and suggest that at these locations, PNWNAmet is in closer agreement with station observations. Larger differences along the Alaska border and the northwestern part of Yukon may reflect a warm bias in PNWNAmet temperatures in this region and suggest further examination is necessary in any updates or revisions to the dataset.

Given the relative similarity in temperatures among the three observational datasets, addressing the precipitation biases was a priority to ensure the downscaled simulations accurately represent precipitation conditions in Canada. Therefore, we concluded that constructing a blended dataset combining PNWNAmet in the west of Canada and with NRCANmet_Adj elsewhere would provide an improved

calibration dataset of precipitation over much of Canada compared to NRCANmet_v1. Temperatures were then produced by combining PNWNAmet with NRCANmet_v2 using the same blending approach. The optimal area over which to combine NRCANmet and PNWNAmet was guided by dataset performance compared to station observations, and a diagonal blending region to the east of the Rocky Mountain range was selected to combine the precipitation and temperature datasets. Blending the PNWNAmet and ANUSPLIN datasets was performed using a weighted average applied with a two-dimensional sigmoid function (equation 1) to provide a smooth transition between the datasets:

$$w = \frac{1}{[1 + \exp((x - x_0)/a)] [1 + \exp((y - y_0)/b)]} \quad (1)$$

In the region of overlap, daily values of the blended dataset were created by combining PNWNAmet with weight w and NRCANmet with weight $1-w$, spanning the range $[0,1]$, where w is a function of the longitude x and latitude y coordinates. The central values of x_0 and y_0 define where the weighting for both datasets is equal to $\frac{1}{2}$, and both x_0 and y_0 are also linear functions of the coordinates. The width of the blending region is determined by the a and b parameters, both of which were set to 1 corresponding to a blending region of approximately 8° wide to provide a gradual transition between the two datasets. The blending region is centred on a transect that extends from 134° W, 70.6° N near Tuktoyaktuk, Yukon to 108° W, 49° N on the border between Saskatchewan and Montana. The gradual and wide blending region is located within parts of both datasets where spatial features are more homogeneous, both due to smoother topography and reduced station density, which also avoids blending features with strong precipitation or temperature gradients.

Prior to blending the NRCANmet_v2 and PNWNAmet temperature datasets, any occurrences of temperature reversals (daily minimum temperature > daily maximum temperature) in the NRCANmet_v2 data were corrected. Such reversals had already been corrected in the PNWNAmet dataset (Werner et al., 2019). Weather station records from the AHCCDv3 stations were used wherever possible to apply corrections. Examination of the annual largest temperature reversals for the 1950–2017 period revealed that locations where the absolute magnitude of the reversals was <4°C were randomly distributed, while reversals with magnitude >4°C were more spatially coherent. For reversals with absolute magnitudes of less than 4°C, the default correction was to swap the values of maximum and minimum temperature following the procedure for PNWNAmet. If the reversal exceeded 4°C, the

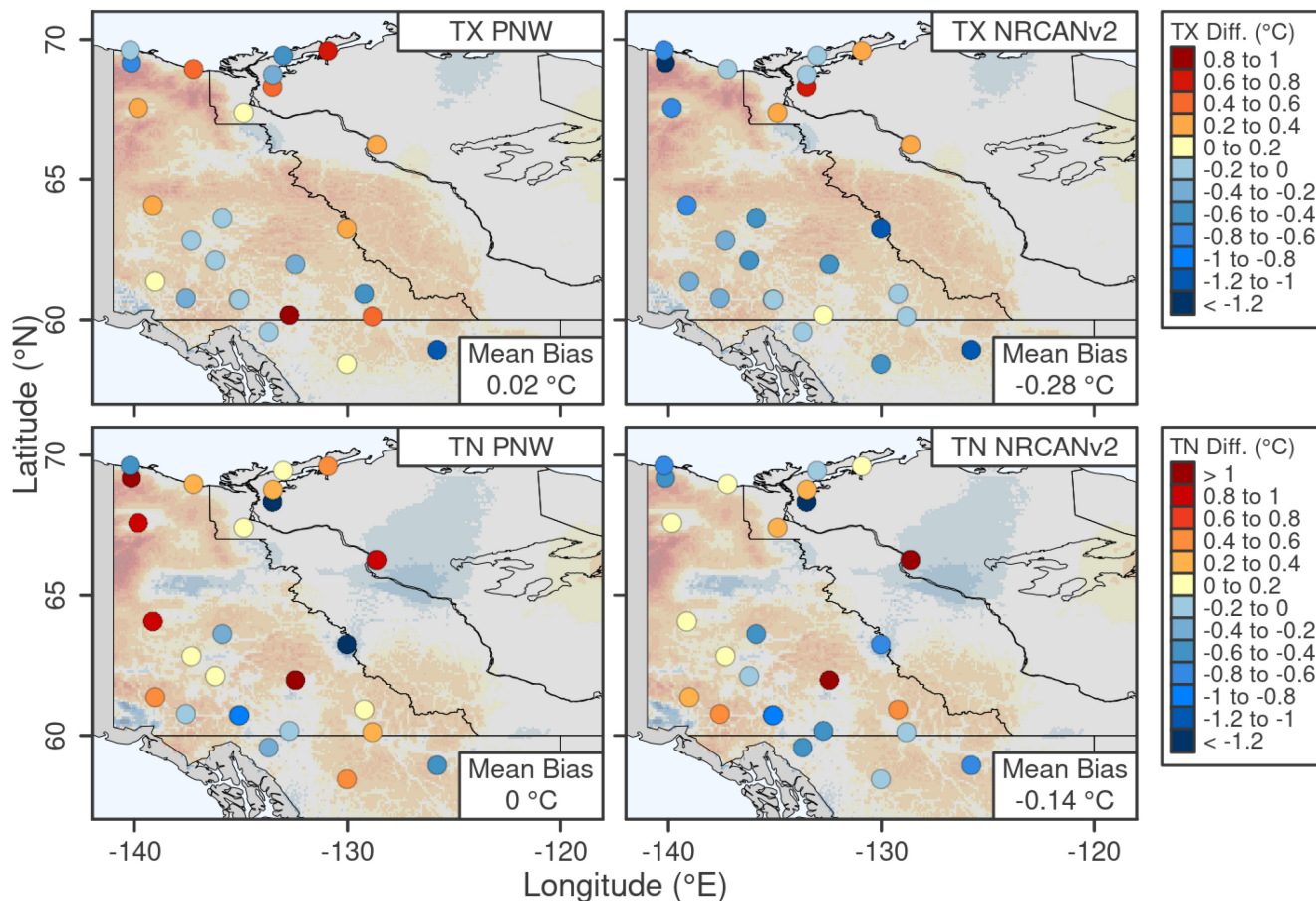


FIGURE 4 Comparison of daily maximum and daily minimum temperature biases between PNWNAmet and NRCANmet_v2 gridded observations and AHCCDv3 station observations in northwestern Canada. Biases are calculated for all valid days in the AHCCD station records between 1950 and 2012 to overlap with the PNWNAmet and NRCANmet_v2 datasets and are then averaged over the entire record. The top row displays differences in daily maximum temperature for PNWNAmet—AHCCDv3 (left) and NRCANmet_v2—AHCCDv3 (right). The bottom row displays corresponding panels for daily minimum temperature differences. Gridded data displayed in the background of each panel shows the differences between the datasets and NRCANmet_v1.

nearest AHCCDv3 stations were used to infer which of the maximum or minimum temperature values was most likely erroneous and then corrections were applied using the station diurnal temperature ranges.

The resulting blended observational dataset (denoted as ‘PCIC-Blend’) spans 1950–2012 and incorporates the improvements in PNWNAmet, NRCANmet_v2, and NRCANmet_Adj made since the development of NRCANmet_v1. In particular, the combination of PNWNAmet in western Canada and NRCANmet_Adj in eastern Canada provides a superior representation of precipitation in PCIC-Blend when compared to station observations. Regarding temperatures, there is more limited added value in PCIC-Blend as PNWNAmet and NRCANmet_v2 exhibit similar values to NRCANmet_v1 over the regions in which the datasets overlap, except for the Yukon region described in Figure 4, where neither shows superior performance compared to station observations. The main benefits from PCIC-Blend

temperatures are the correction of temperature reversals across all of Canada and the use of the latest AHCCDv3 in NRCANmet_v2.

2.3 | Multivariate downscaling method

The method used here to generate downscaled scenarios that maintain inter-variable dependencies is N-dimensional Multivariate Bias Correction (MBCn; Cannon, 2018). MBCn extends univariate quantile delta mapping (QDM), in which projected changes from the driving model input are applied to bias-corrected simulations at each quantile (Cannon et al., 2015). In this modified form of quantile mapping, relative changes from the driving model are maintained in the resulting bias-corrected simulation. In MBCn, QDM is first applied to the N variables independently to adjust the marginal distributions of the input data to match those from the

calibration target. Correcting the multivariate distribution is then performed using an N -dimensional probability distribution transform function originally developed for colour correction in image processing (Pitié et al., 2007). Linear combinations of the input and target variables are formed by random orthogonal rotation to produce rotated distributions. The marginal distributions of the rotated input variables are then corrected using QDM to match those of the target before being rotated back. When applied repeatedly, the multivariate distribution of the input variables will converge to that of the target variables. A complete description of the procedure can be found in Cannon, 2018. For this application of MBCn, $N=3$ corresponds to the three variables of daily precipitation, maximum temperature, and minimum temperature.

Downscaling with MBCn in this application was implemented using Climate Imprint (CI; Hunter & Meentemeyer, 2005) as a pre-processing step to provide an initial bias correction using monthly climatologies and to apply a first step of spatial disaggregation from coarse-scale to the target resolution. Given the large difference in spatial resolutions that generally exists between coarse driving model input (~ 250 km) and fine-scale target data (~ 10 km), the spatial interpolation of anomalies that occurs within CI was performed in sequential steps. Beginning with the initial coarse-scale resolution, each interpolation step increased spatial resolution by 0.5 degrees (~ 50 km) to reduce the incidence of spatial artefacts that can otherwise occur in a direct interpolation between disparate resolutions. The MBCn method was then applied to adjust precipitation, maximum temperature, and minimum temperature simultaneously at each grid cell at this target resolution. When producing downscaled scenarios from the CMIP6 simulations, both the CI and MBCn applications were calibrated using the 1951–2012 period available from the PCIC-Blend observational dataset. A schematic diagram of the procedure to produce the CanDCS-M6 scenarios is shown in Figure 5.

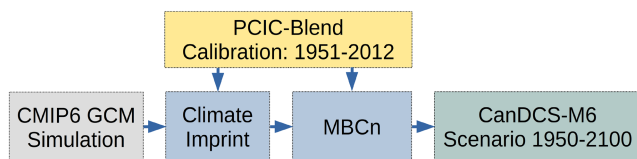


FIGURE 5 Schematic diagram of the multivariate downscaling method used to produce the CanDCS-M6 scenarios. Model simulations from CMIP6 are first bias-corrected and spatially disaggregated to the target resolution using Climate Imprint, with monthly climatologies obtained from PCIC-Blend. MBCn is then applied to each grid cell to adjust the marginal and multivariate distributions of the simulated variables, again calibrated using PCIC-Blend to produce the CanDCS-M6 scenario for the entire period of the input CMIP6 simulation.

3 | EVALUATION

Evaluation of the multivariate MBCn downscaling method was conducted using RCM simulations from the CanRCM4-Large Ensemble (ECCC, 2018) under a perfect model framework. In this approach, RCM data can be used as pseudo-observations to evaluate downscaling method performance at future time intervals. Simulations of CanRCM4 precipitation and temperature were first aggregated to a coarser resolution using 5×5 CanRCM4 grid cells to act as ‘GCM’ input (at $\sim 2.5^\circ$). Historical CanRCM4 data from the same realization in its standard resolution (nominally 0.44°) was used as the target dataset during a 1951–2010 calibration period. Downscaled simulations were then compared against the corresponding fine scale CanRCM4 run acting as pseudo-observations for the future simulation period. The evaluation was performed using realizations from the CanRCM4-Large Ensemble across a domain covering all of Canada below 75° N (determined by the northern extent of the CanRCM4 domain) and part of the northern United States (above 40° N).

The performance of MBCn was also considered relative to the univariate method BCCAQv2 that was used previously to create downscaled scenarios and to an additional multivariate method selected for comparison from a suite of other multivariate methods. Bivariate Conditional Bias Correction (BCBC; Piani & Haerter, 2012) is a two-stage approach in which one variable is first downscaled using a standard univariate method, after which a second variable is sorted into groups organized according to magnitudes from the first variable and then downscaled separately within each group. In the implementation of BCBC used here, downscaled temperature values were used as the first variable and the univariate method used was QDM. Precipitation values were then downscaled, conditional on temperature values produced using QDM. Any derived temperature indices where BCBC and QDM values are displayed are therefore identical. In the precipitation comparisons, two versions of BCBC were also considered: one conditional on daily maximum temperature, BCBC (TX), and the other conditional on daily minimum temperature, BCBC (TN). Comparisons between the multivariate methods, BCCAQv2 and CanRCM4, were measured using both univariate and multivariate metrics, and selected examples are shown here. Spatial differences are shown using climatologies from the end of the simulation period (2071–2100) where differences between the downscaled simulations and CanRCM4 values are largest. A schematic illustrating the evaluation procedure is shown in Figure 6.

3.1 | Univariate indices

Univariate indices used in the evaluation are derived exclusively from either daily precipitation, daily maximum temperature, or daily minimum temperature. Examples include annual and seasonal averages of precipitation or temperature, degree days, return levels, and Climdex indices of extremes (Zhang et al., 2011). Simulated temperature values from BCCAQv2 and MBCn show very similar performance when compared to CanRCM4 over the evaluation area. Where differences do exist between

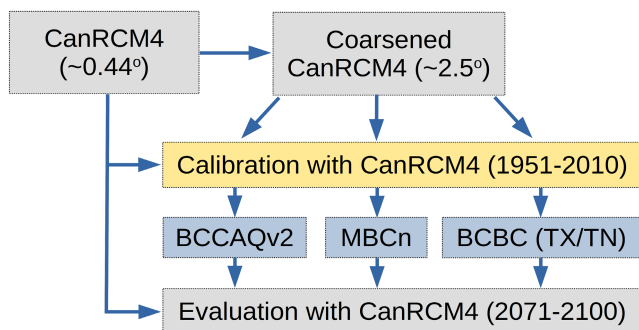


FIGURE 6 Schematic diagram of the procedure used to compare performance between the univariate and multivariate downscaling methods. Under the perfect model framework, CanRCM4 is coarsened to 2.5 and used as the input simulation. Each method is calibrated using the original CanRCM4 dataset during 1951–2010 to produce downscaled simulations during 1950–2100. Performance of the methods is then evaluated by comparing the downscaled results with CanRCM4 during the last 30 years in the simulations (2071–2100).

the downscaled simulations and CanRCM4, the biases appear similar in location and magnitude in both BCCAQv2 and MBCn. This close agreement is evident as assessed by calculating the root-mean-squared error (RMSE) between the downscaled simulation climatologies and CanRCM4 temperature-derived climatologies (Table 1). These RMSE values were computed for the 2071–2100 period and illustrate similar magnitudes of spatial differences between downscaled and RCM climatologies for Canada. To provide an indication of the added-value obtained by applying either of the downscaling methods, RMSE values are calculated from precipitation and temperature values obtained using bilinear interpolation of the coarse-scale inputs to RCM resolution. Results from these comparisons are shown in the ‘Interp.’ columns of Table 1 and display substantially greater differences relative to CanRCM4 compared to the downscaled simulations.

Precipitation indices simulated by BCCAQv2 and MBCn also show broadly similar patterns of accumulation and both methods display biases compared to CanRCM4. Precipitation from BCBC conditional either on daily maximum (BCBC (TX)) or minimum temperature (BCBC (TN)) displays biases over an expanded area and generally with higher magnitudes compared to the other methods. Table 2 displays average spatial RMSE across Canada for several precipitation-derived indices of accumulation and frequency for the 2080s. Figures displaying differences between the downscaled simulations and CanRCM4 for selected indices from Table 2 are shown in Section S4 of the Appendix S1. A majority of these indices have the lowest

TABLE 1 Spatial root-mean-squared-error (RMSE) for temperature-derived indices from the BCCAQv2 and MBCn downscaling methods, and bilinear interpolation (Interp.) when compared to CanRCM4, averaged over Canada for the period 2071–2100.

Temperature variable	Units	Spatial RMSE			Relative RMSE		
		BCCAQv2	MBCn	Interp.	BCCAQv2	MBCn	Interp.
Cooling degree days (CDD)	DD	13.3	11.2	47.5	2.5	2.1	14.7
Heating degree days (HDD)	DD	61.3	61.2	259.4	2.7	2.7	14.1
Growing degree days (GDD)	DD	40.9	36.7	140.5	2.7	2.4	14.2
Summer max. temperature	°C	0.42	0.38	1.71	4.6	4.2	23.1
Winter min. temperature	°C	0.60	0.62	1.86	6.9	7.0	27.3
20-year max. temperature	°C	0.81	0.80	3.5	7.7	7.6	39.4
20-year min. temperature	°C	1.52	1.55	3.8	9.5	9.6	37.9
Frost days (FD)	Days	6.22	5.96	12.8	11.1	10.5	22.1
Ice days (ID)	Days	4.45	4.33	10.3	6.8	6.7	16.0
Grow. seas. length (GSL)	Days	13.2	10.7	16.9	19.1	16.2	23.6
Diurnal temp. range (DTR)	°C	0.12	0.10	0.91	5.9	4.8	13.5
Summer days (SU)	Days	1.36	1.21	7.8	4.2	3.8	20.4
Tropical nights (TR)	Days	1.58	1.45	3.9	4.8	4.7	17.6

Note: Indices in the bottom half of the table are selected from the set of Climdex indices of extremes. Relative RMSE values are normalized using the spatial standard deviation of the climatological values for each index.

TABLE 2 Spatial root-mean-squared-error (RMSE) comparing climatologies of daily precipitation-derived indices between the downscaling methods, bilinear interpolation (Interp.) and CanRCM4. RMSE is calculated between all matching grid cells from the downscaling simulation climatology and CanRCM4 climatology and is displayed relative to the CanRCM4 climatology as a percentage.

Spatial RMSE relative difference (%) in 2071–2100					
Precipitation variable	BCCAQv2	MBCn	BCBC (TX)	BCBC (TN)	Interp.
Annual precipitation	3.3	3.2	3.5	3.4	16.2
Summer precipitation	4.0	3.8	5.1	4.8	8.2
Winter precipitation	5.9	7.2	9.1	8.2	23.3
20-year max. precip.	18.4	17.8	18.4	18.7	55.2
Consec. dry days (CDD)	10.5	7.6	15.3	13.1	23.7
Consec. wet days (CWD)	10.6	8.3	12.9	12.7	36.9
Precip > 1 mm (R1mm)	3.0	2.9	3.7	3.8	18.6
Precip > 10 mm (R10mm)	7.2	6.9	7.6	7.5	22.3
Precip > 95 th % ile (R95p)	8.1	7.5	8.6	8.5	17.4
Precip > 99 th % ile (R99p)	15.3	15.3	15.8	16.1	22.5
Max 1-day Pr. (RX1day)	7.9	7.9	8.1	8.4	34.8
Max 5-day Pr. (RX5day)	6.8	5.4	8.9	7.7	23.7

Note: Indices in the bottom part of the table are selected from the set of Climdex indices of extremes.

spatial RMSE values in the MBCn simulated precipitation while BCBC precipitation produces generally higher RMSE depending on the index. In many cases, however, the magnitude of the difference between methods tends to be small. All of the methods yield much better agreement with CanRCM4 compared to the bilinearly interpolated precipitation. Overall, the similarities between projected temperature and precipitation changes for CanRCM4 and the downscaled simulations suggest that the transfer functions obtained from the calibration period continue to perform well under strong transient climate change.

3.2 | Multivariate indices

Multivariate indices are calculated using some combination of daily maximum, daily minimum temperature, and daily precipitation. Effective simulation of dependencies between precipitation and temperature variables is important in simulating phenomena such as drought, fire weather, snow, and other related processes. Of particular interest is whether dependencies between precipitation and temperature that are present in CanRCM4 simulations are replicated by the different downscaling methods. Applying a multivariate downscaling method such as BCBC or MBCn is meant to incorporate these

dependencies in the resulting simulations where they may have been missed using the univariate BCCAQv2 method. Here, results are shown using precipitation-as-snow, analysis of dependence between daily precipitation and temperature, and compound extreme events to illustrate how the different methods compare in replicating inter-variable relationships.

3.2.1 | Precipitation-as-snow

Indices using a combination of temperature with precipitation yield larger differences between the different downscaling approaches. For example, annual total precipitation-as-snow (PAS), where precipitation that occurred when daily average temperature was below freezing is classified as snow, is more effectively replicated by MBCn than BCCAQv2 or either BCBC application (Figure 7). Sections of the continental interior show underestimation of annual total PAS of up to 30% in BCCAQv2 and BCBC, much more than occurs in MBCn. There are also substantial differences between the two BCBC methods, with BCBC (TN) simulating 20% less PAS in the Prairies and western US, and 10% to 20% more PAS in Atlantic Canada compared to BCBC (TX). Spatial RMSE of PAS from MBCn (RMSE = 13.1 mm) is only two-thirds

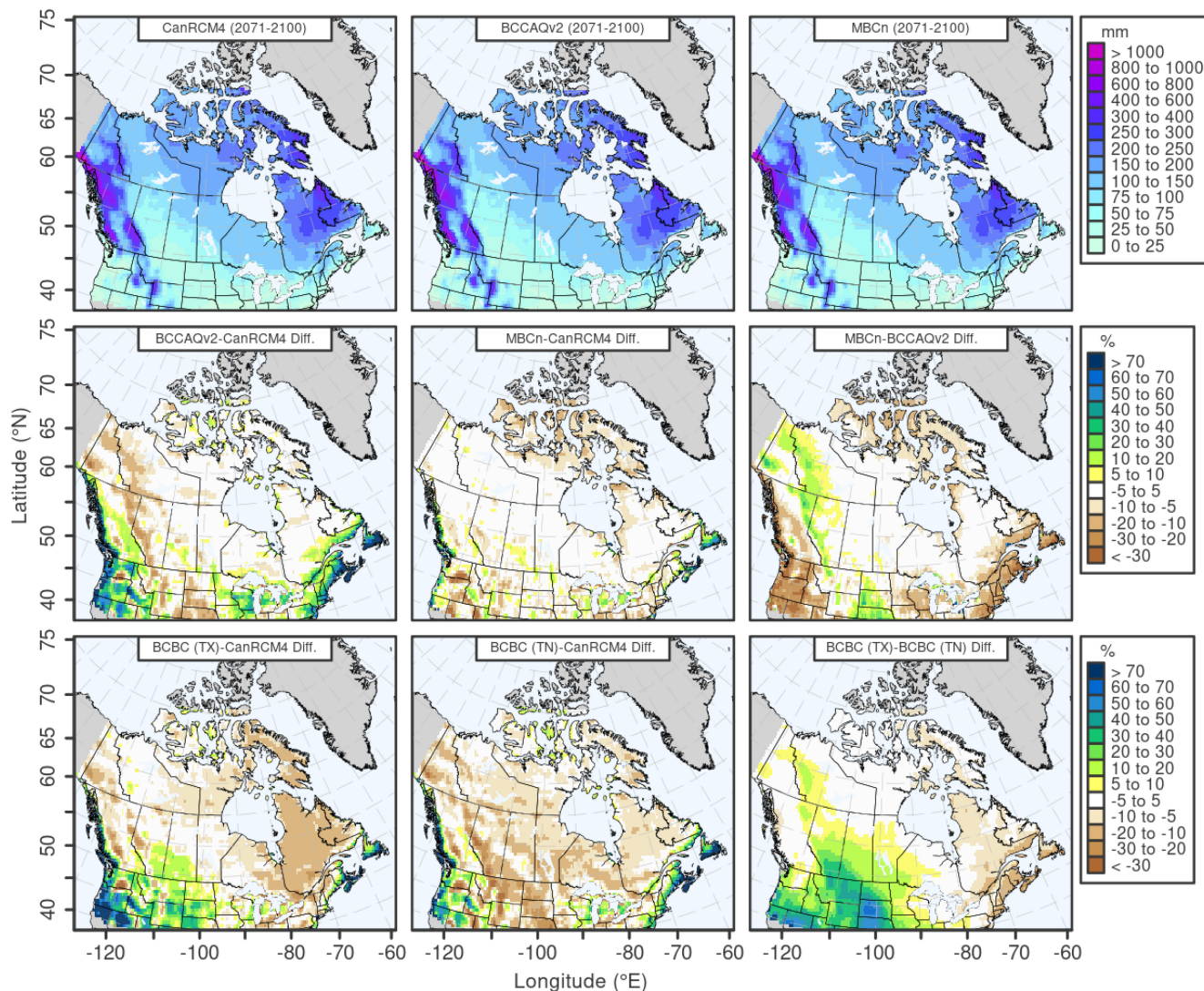


FIGURE 7 Average annual total precipitation-as-snow (PAS) climatologies during 2071–2100. The top row displays 30-year climatologies from CanRCM4 and the two downscaled simulations driven by coarsened CanRCM4 (BCCAQv2 and MBCn). The bottom row displays the differences between the two downscaled simulation climatologies and the RCM climatology (left and middle), and the difference between the two downscaled climatologies (right).

of that of BCCAQv2 (RMSE=18.3 mm) or BCBC (BCBC (TX) RMSE=18.2 mm; BCBC (TN) RMSE=19.6 mm). All methods overestimate the amount of PAS along both coasts, where below-freezing temperatures are infrequent and total PAS is low in the future climate; however, the extent of this effect is reduced in BCBC (TX) and MBCn.

3.2.2 | Dependence between pairs of daily variables

Spearman, or rank correlation, is useful for characterizing the dependence between two variables following different distributions since it is defined based on the ranks rather than the values of the variables considered (François

et al., 2020). Here, Spearman correlation values are calculated for combinations of daily time series of precipitation and maximum temperature, precipitation and minimum temperature, and maximum temperature and minimum temperature separately for each season. Correlation values are calculated at each grid cell in CanRCM4 and each downscaled simulation during 2071–2100. In addition to BCCAQv2 and MBCn, Spearman correlation results are shown only for BCBC (TX), as values from BCBC (TN) are effectively the same.

Spearman correlation between maximum and minimum temperature is effectively the same in the downscaled simulations as in CanRCM4. Only in summer are any differences notable and these occur primarily in the western US region covered in this comparison,

with small differences in western Canada. For most of Canada maximum and minimum temperature are strongly correlated and the downscaled simulations replicate the values in these regions well. Figures 8 and 9 display Spearman correlation values between precipitation and maximum or minimum temperature for winter and summer during 2071–2100. The BCCAQv2 method tends to underestimate the strength of correlations seen between winter precipitation and temperature in CanRCM4 (Figure 8). MBCn reproduces these correlations much better, as does BCBC, except for a persistent underestimation in the northeast coastal regions. Results from coastal regions may be affected by the influence of ocean grid cells in these regions that can be incorporated when producing coarsened CanRCM4. Similar results are seen for summer precipitation and minimum temperature (Figure 9), though in parts of central and western Canada both BCCAQv2 and the BCBC simulations display low Spearman correlation values of opposite sign to those in CanRCM4 and MBCn. Correlation values for the spring and fall months display greater similarities compared to CanRCM4, and where biases are present, they resemble lower magnitude versions of those visible in the winter and summer months.

Some degradation of the rank chronology can be expected from BCCAQv2 because of the univariate approach to downscaling precipitation and temperature and from the reordering step in the downscaling algorithm using spatial analogues. Reordering of the daily sequence occurs

within each calendar month in the quantile delta mapping (QDM) output in BCCAQv2 according to the ranks of events taken from the analogues. Reordering is performed in an effort to reduce the excessive smoothness that can occur in the QDM output and represent patterns of spatial variability more accurately using information from the spatial analogues. The MBCn and BCBC methods do not use the reordering step of BCCAQv2 and therefore are not subject to this effect to the same degree.

3.3 | Compound extreme events

Compound extreme events measure combined occurrences of daily precipitation and temperature extreme events. The compound events used in this analysis are determined by counting precipitation and temperature events above or below specified thresholds (Tencer et al., 2014). Thresholds are defined for each day of the year using sliding windows of multiple days centred on the specified day (15 days for precipitation and 3 days for temperature) to calculate percentiles. For example, a wet, warm maximum temperature compound event is defined as a day with precipitation >75th percentile and daily maximum temperature >90th percentile. Eight types of compound events are considered using combinations of wet or dry precipitation and warm or cold maximum and minimum temperature. Thresholds for the events are calculated for 2070–2099, with the interval shifted 1 year

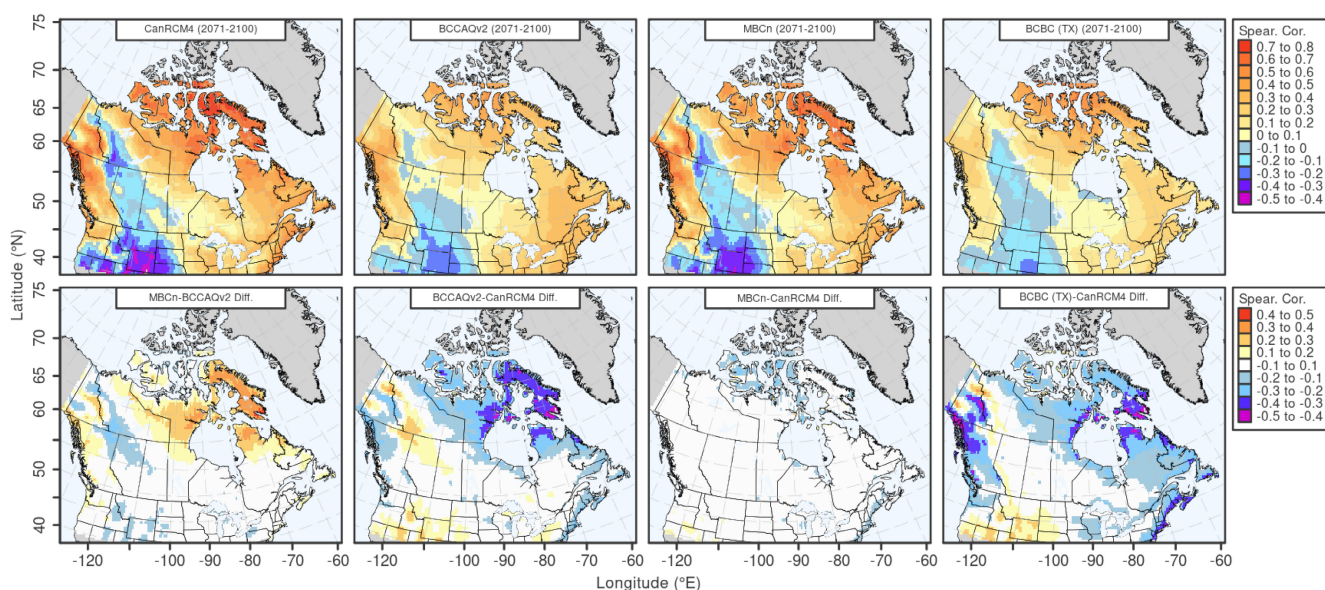


FIGURE 8 Spearman correlation between winter precipitation and maximum temperature during 2071–2100. The top row displays Spearman correlation values from CanRCM4 and the three downscaled simulations driven by coarsened CanRCM4 (BCCAQv2, MBCn, BCBC (TX)). From left to right, the bottom row displays the differences in correlation values between the MBCn and BCCAQv2 simulations, as well as differences between the three downscaling methods and CanRCM4. Results from BCBC (TN) are effectively the same as for BCBC (TX) and are not shown.

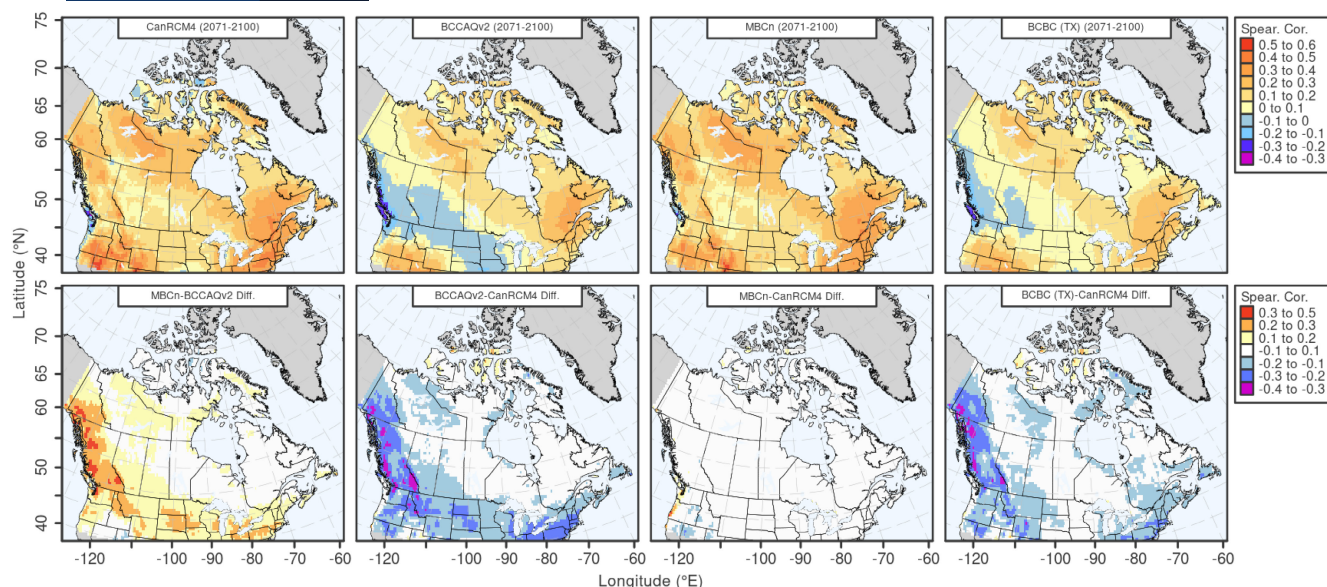


FIGURE 9 Same as Figure 8, but for Spearman correlation values of summer precipitation and minimum temperature.

TABLE 3 Spatial root-mean-squared-error (RMSE) comparing annual average climatologies of compound extreme events between the downscaling methods and CanRCM4.

Threshold	BCCAQv2	MBCn	BCBC(TX)	BCBC(TN)
Temperature	Wet events (Pr. > 75th%)			
TX > 90th %	2.12 (2.07, 2.16)	0.75 (0.71, 0.79)	2.28 (2.22, 2.31)	2.18 (2.12, 2.26)
TX < 10th %	1.15 (1.13, 1.16)	0.42 (0.40, 0.44)	1.07 (1.06, 1.09)	1.06 (1.05, 1.08)
TN > 90th %	1.39 (1.36, 1.43)	0.77 (0.76, 0.77)	1.34 (1.26, 1.41)	1.28 (1.19, 1.40)
TN < 10th %	0.84 (0.82, 0.86)	0.46 (0.44, 0.48)	0.65 (0.61, 0.69)	0.67 (0.60, 0.72)
Temperature	Dry events (Pr. < 11 mm)			
TX > 90th %	2.84 (2.83, 2.86)	1.22 (1.18, 1.26)	2.64 (2.58, 2.68)	2.54 (2.44, 2.65)
TX < 10th %	2.39 (2.37, 2.43)	0.92 (0.91, 0.92)	2.34 (2.23, 2.48)	2.37 (2.13, 2.58)
TN > 90th %	2.97 (2.85, 3.05)	1.25 (1.21, 1.28)	2.19 (2.10, 2.25)	2.14 (1.96, 2.30)
TN < 10th %	3.76 (3.73, 3.81)	0.91 (0.89, 0.93)	2.68 (2.50, 2.89)	2.51 (2.12, 2.82)

Note: RMSE is calculated between all matching grid cells from the downscaling simulation climatology and CanRCM4 climatology for 2070–2099 and then spatially averaged over all of Canada. Values in the brackets denote the minimum and maximum spatial RMSE values from the downscaled CanRCM4 runs. All values are in units of events per year.

earlier compared to previously shown climatologies to accommodate the sliding window calculations.

Over the evaluation area, simulated compound events calculated using MBCn precipitation and temperature are closer in agreement with those from CanRCM4 compared to the other methods in all cases. Spatial RMSE values for all eight compound event types, comparing events calculated from downscaled simulations with those from CanRCM4, are shown in Table 3. Common to all compound event results is that the biases observed in the BCCAQv2 simulations are reduced in both sets of BCBC simulations but are not reduced to the same degree as in the MBCn simulations. While average spatial RMSE values suggest MBCn captures event occurrence more

effectively, all methods exhibit spatially variable performance. Warm (maximum temperature > 90th percentile) and dry (precipitation < 1 mm) events (Figure 10) are underestimated by all methods in western North America, particularly over mountain ranges. The same events are underestimated by BCCAQv2 in northern Quebec and around Hudson Bay, extending into the Prairies. BCCAQv2 and the BCBC methods also overestimate the frequency of warm, dry events in the eastern Arctic, central United States, and eastern seaboard.

Cold, dry compound events (Figure 11) display a systematic underestimation in the frequency of occurrence in BCCAQv2 and both BCBC methods. The lower simulation values appear most acute again in the mountains of

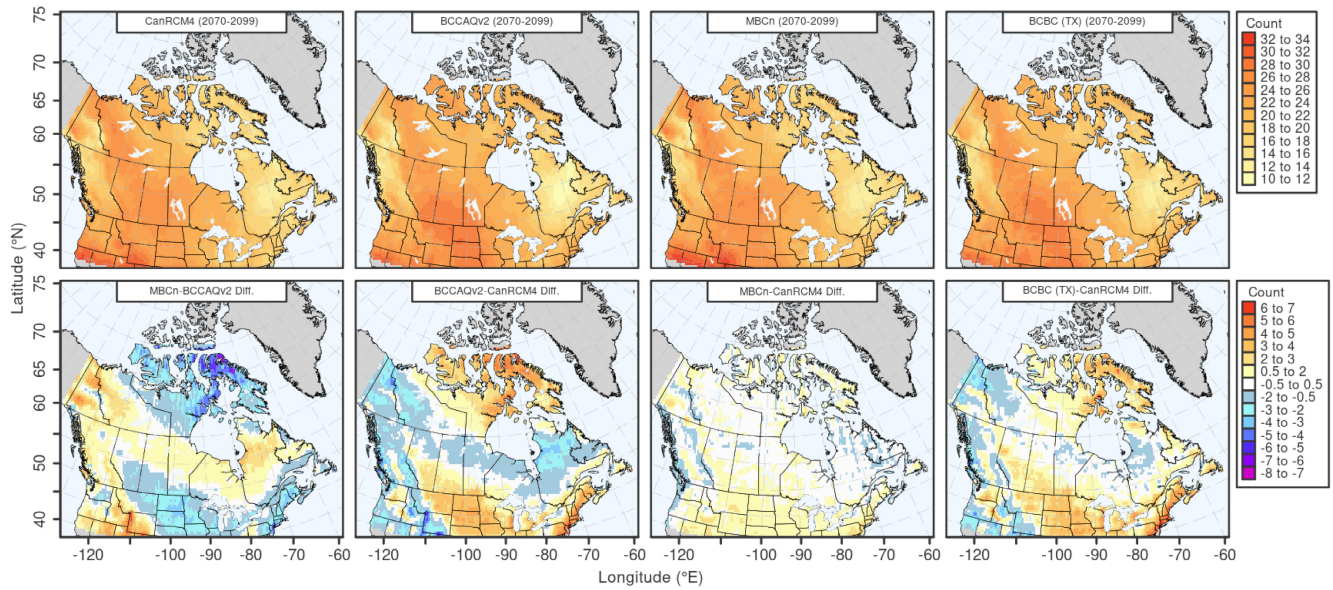


FIGURE 10 Annual average warm and dry compound extreme events during 2071–2100. Events are defined as Daily maximum temperature > 90th percentile and daily precipitation < 1 mm. The top row displays values from CanRCM4, BCCAQv2, MBCn, and BCBC (TX). From left to right, the bottom row displays the differences in compound extreme events between the MBCn and BCCAQv2 simulations, as well as differences between the three downscaling methods and CanRCM4. Results from BCBC (TN) are effectively the same as for BCBC (TX) and are not shown.

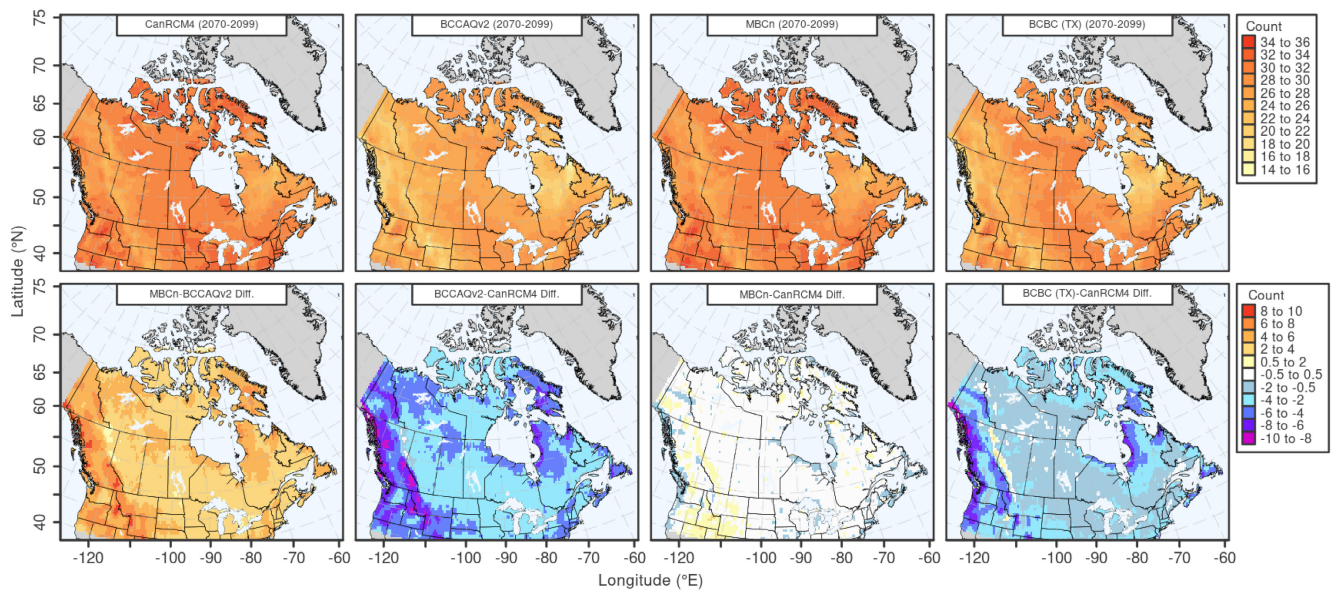


FIGURE 11 Same as Figure 10, but for daily minimum temperature < 10th percentile and daily precipitation < 1 mm.

western North America and eastern Canada. In contrast, the MBCn simulations display very little difference from CanRCM4, with only minor overestimation in the western United States. For the BCBC simulations, selecting either maximum or minimum temperature as the conditional variable makes little difference in the simulation of compound events.

Wet events calculated using the top 25th percentile of daily precipitation occur less frequently overall and

the differences between the downscaled methods and CanRCM4 are correspondingly smaller. MBCn produces too few wet, warm minimum temperature events (daily minimum temperature > 90th percentile) in parts of western North America, while the other methods display even lower values over larger areas (Figure 12). For wet, cold events (daily maximum temperature < 10th percentile) MBCn replicates the values from CanRCM4 over Canada well, with low biases in the western United States, while

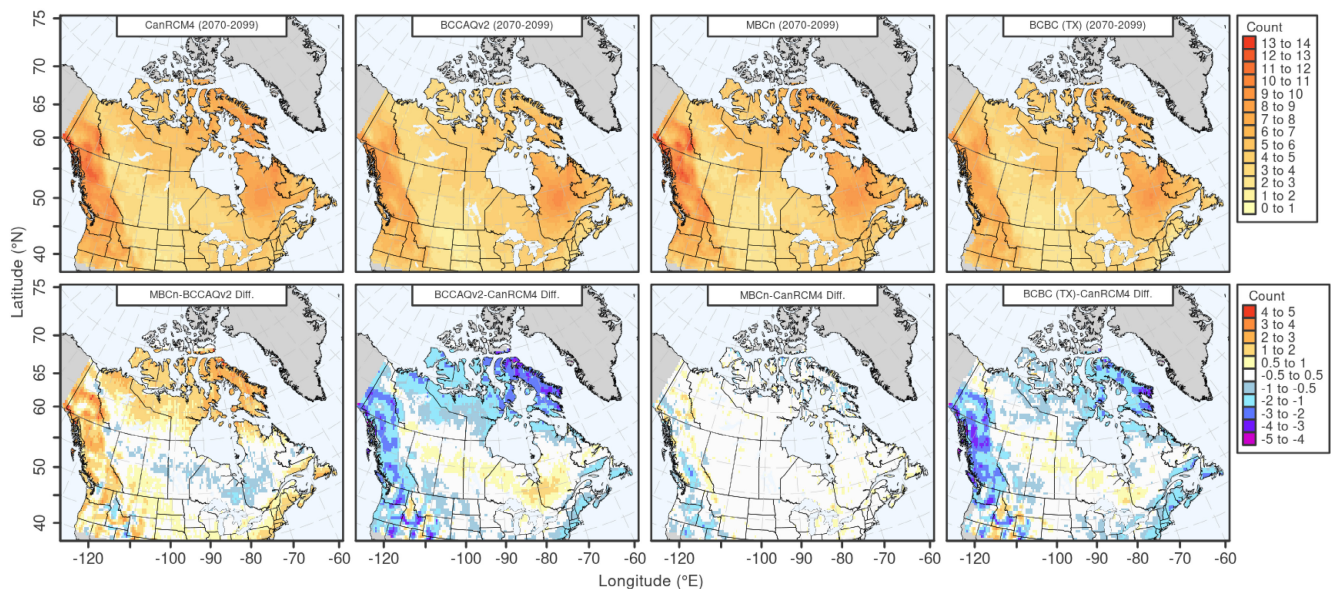


FIGURE 12 Same as Figure 10, but for daily minimum temperature >90th percentile and daily precipitation >75th percentile.

the other methods underestimate their frequency by a few events per year in most of the domain. Among all compound event types, areas where differences are small (one to two events per year) may result from sampling uncertainty and could be diminished by the addition of more CanRCM4 runs in the analysis. Regions with greater differences, mainly in the dry events, suggest the presence of more substantive differences between the downscaling methods. The choice of precipitation threshold may also influence the results. While 1 mm is commonly used to separate wet from dry events in model simulations, coarsening CanRCM4 may lead to an increase in the apparent frequency of these events. Each downscaling method will then need to compensate with both magnitude and frequency adjustments. Using the 1 mm definition in this case, in most locations wet and dry compound events calculated from MBCn downscaled simulations exhibit closer agreement with CanRCM4 than the other methods.

4 | DATASET ACCESS

Both the PCIC-Blend gridded observational dataset and CanDCS-M6 simulations for Canada are available for download from the Pacific Climate Impacts Consortium Data Portal (<https://www.pacificclimate.org/data>). PCIC-Blend can be accessed from [pacificclimate.org/data/daily-gridded-meteorological-datasets](https://www.pacificclimate.org/data/daily-gridded-meteorological-datasets), while the CanDCS-M6 (as well as CanDCS-U6 and CanDCS-U5) datasets can be accessed from [pacificclimate.org/data/statistically-downscaled-climate-scenarios](https://www.pacificclimate.org/data/statistically-downscaled-climate-scenarios). Files for all datasets are provided as binary netcdf files with dataset-specific information provided within the file metadata following CF Metadata

Conventions CF-1.7 CMIP-6.2. Through the data portal tools, spatial and temporal subsets of the datasets can be selected using user-defined boundaries. Simulations from CanDCS-M6 can also be obtained separately for each driving CMIP6 GCM, emissions pathway (SSP), and variable (precipitation, maximum temperature, and minimum temperature). Additionally, lists of representative subsets for Canada and five sub-regions using selected GCMs from CanDCS-M6 are provided to enable analysis with smaller ensemble sizes. Subset lists and a complete description of the selection methodology are provided on the CanDCS-M6 download page in the ‘Model Subsets (CMIP6)’ subsection.

5 | POTENTIAL DATASET USE AND LIMITATIONS

The CanDCS-M6 scenarios can facilitate climate impact assessments, further applications such as hydrologic, agricultural, or snow modelling, and the development of analysis tools for delivering climate projections. The provision of daily values of precipitation and temperatures in the downscaled scenarios will enable a wide variety of potential further processing or derived calculations. While the dataset represents an improvement over previous versions, the scenarios remain subject to certain limitations. The ensemble of CMIP6 GCMs selected represents an ‘ensemble of opportunity’ (Tebaldi & Knutti, 2007) that is unlikely to yield a systematic sampling of all potential climate projections. Among the CMIP6 models selected are some exhibiting substantially higher warming compared to other models

in Canada (Sobie et al., 2021). As MBCn preserves the signal of projected change from the driving GCM, the downscaled scenarios largely replicate these same features. Ongoing work regarding emergent constraints (Liang et al., 2020; Tokarska et al., 2020) may suggest forming ensembles from these models could require weighting or constraining individual GCM scenarios. Each downscaled scenario also involves a single realization for each model (except for CanESM5), and the simulations are corrected using a reference period from the same realization. This can lead to an underestimation of internal variability during this period in the resulting downscaled scenario (Cannon et al., 2021).

Finally, the calibration dataset originates from gridded observations developed from interpolated station data. In many parts of Canada, particularly northern regions, station coverage is sparse. In such regions, spatial features in the downscaled scenarios may be overly smooth in appearance. Interpolation artefacts reflecting available station locations may also be visible for indices derived from single days such as annual extreme values. As the calibration dataset is used to correct all GCM simulations, these spatial features may be common to all scenarios. When conducting analysis in these data-sparse areas, simulations from additional sources such as dynamically downscaled RCMs provided by CORDEX (McGinnis & Mearns, 2021) or CanLEAD (Cannon et al., 2021) may provide further insight or information for comparison to the statistically downscaled CanDCS-M6 simulations.

6 | CONCLUSIONS

The relative performance of BCCAQv2, MBCn, and BCBC in downscaling precipitation and temperature for Canada highlights situations where multivariate downscaling methods can differ from a univariate approach. Among multivariate indices, those that involve daily precipitation and temperature display the greatest differences between methods. Downscaled simulations from MBCn replicate these compound indices more effectively in Canada than the other methods, though differences are minor for some locations and indices. While BCBC displays improved performance in replicating some aspects of inter-variable dependence better than BCCAQv2, the level of improvement does not match MBCn, particularly for compound events. Simulation of univariate indices is effectively the same in BCCAQv2 and MBCn, while the BCBC simulations exhibit some degradation in performance for certain indices. As both BCCAQv2 and MBCn employ quantile delta mapping to correct the marginal distributions of the input data, similar performance among univariate indices is expected. MBCn does incur significant additional

computational cost, however, which may be a consideration for applications where results for univariate are of greater interest. Where information about multivariate indices is required, simulations from MBCn provide a more accurate representation of these quantities. The extensive use of MBCn in myriad other applications also provides further evidence of the utility of this method, and greater confidence in the performance of the methodology in addition to the evidence presented here.

The CanDCS-M6 scenarios, therefore, employ MBCn as the multivariate method to produce downscaled CMIP6 GCM simulations in conjunction with the new PCIC-Blend calibration target dataset. These new downscaled scenarios deliver daily simulations of precipitation, maximum temperature, and minimum temperature across Canada for 26 GCMs following three future emissions pathways between 1950 and 2100. The implementation of MBCn to deliver downscaled scenarios for Canada also offers the potential to expand the set of variables beyond the current set of daily precipitation and temperature. As observational and reanalysis datasets with additional variables become available at higher resolution and longer temporal coverage, multivariate downscaling will enable the production of scenarios encompassing these expanded datasets and allow for analysis of indices beyond those derived from precipitation and temperature.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

OPEN RESEARCH BADGES



This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at <https://www.pacificclimate.org/data>.

DATA AVAILABILITY STATEMENT

The Multivariate Canadian Downscaled Climate Scenarios for CMIP6 (CanDCS-M6) are available for download from the Pacific Climate Impacts Consortium Data Portal (<https://www.pacificclimate.org/data/statistically-downs>

caled-climate-scenarios). The PCIC-Blend gridded observational dataset developed to calibrate the downscaled scenarios can be accessed from <https://www.pacificclimate.org/data/daily-gridded-meteorological-datasets>.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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