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High-Resolution Meteorological Forcing Data for Hydrological Modelling and Climate Change Impact Analysis in Mackenzie River Basin

Zilefac Elvis Asong[1], Mohamed Ezzat Elshamy[1], Daniel Princz[1], Howard Simon Wheater[1], John W. Pomeroy[1, 2], Alain Pietroniro[1, 2, 3] and Alex Cannon[4]

[1]Global Institute for Water Security, University of Saskatchewan, 11 Innovation Blvd, Saskatoon, SK, Canada S7N 3H5

[2]Centre for Hydrology, University of Saskatchewan, 121 Research Drive, Saskatoon, SK, Canada S7N 1K2

[3]Environment and Climate Change Canada, 11 Innovation Blvd, Saskatoon, SK, Canada S7N 3H5

[4]Climate Research Division, Environment and Climate Change Canada, BC V8W 2Y2, Victoria, Canada

***Corresponding author:**
Phone: +1 306 491 9565
Email: *elvis.asong@usask.ca*

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Abstract:

Cold regions hydrology is very sensitive to the impacts of climate warming. Impacts of warming over recent decades in western Canada include glacier retreat, permafrost thaw and changing patterns of precipitation, with increased proportion of winter precipitation falling as rainfall and shorter durations of snowcover, and consequent changes in flow regimes. Future warming is expected to continue these trends. Physically realistic and sophisticated hydrological models driven by reliable climate forcing can provide the capability to assess hydrological responses to climate change. However, the provision of reliable forcing data remains problematic. Hydrological processes in cold regions involve complex phase changes and so are very sensitive to small biases in the driving meteorology, particularly in temperature and precipitation, including precipitation phase. Cold regions often have sparse surface observations, particularly at high elevations that generate a large amount of runoff. This paper aims to provide an improved set of forcing data for large scale hydrological models for climate change impact assessment. The best available gridded data in Canada is from the high resolution forecasts of the Global Environmental Multiscale (GEM) atmospheric model and outputs of the Canadian Precipitation Analysis (CaPA) but these datasets have a short historical record. The EU WATCH ERA-Interim reanalysis (WFDEI) has a longer historical record, but has often been found to be biased relative to observations over Canada. The aim of this study, therefore, is to blend the strengths of both datasets (GEM-CaPA and WFDEI) to produce a less-biased long record product (WFDEI-GEM-CaPA) for hydrological modelling and climate change impacts assessment over the Mackenzie River Basin. First, a multivariate generalization of the quantile mapping technique was implemented to bias-correct WFDEI against GEM-CaPA at 3h × 0.125° resolution during the 2005-2016 overlap period, followed by a hindcast of WFDEI-GEM-CaPA from 1979. The derived WFDEI-GEM-CaPA data are validated against station observations as a preliminary step to assess its added value. This product is then used to bias-correct climate projections from the Canadian Centre for Climate Modelling and Analysis Canadian Regional Climate Model (CanRCM4) between 1950 –

2100 under RCP8.5, and an analysis of the datasets shows the biases in the original WFDEI product have been removed and the climate change signals in CanRCM4 are preserved. The resulting bias-corrected datasets are a consistent set of historical and climate projection data suitable for large-scale modelling and future climate scenario analysis. The final product (WFDEI-GEM-CaPA, 1979-2016) is freely available at the Federated Research Data Repository at http://dx.doi.org/10.20383/101.0111 (Asong et al., 2018) while the original and corrected CanRCM4 data are available at https://doi.org/10.20383/101.0162 (Asong et al., 2019).

Subject Keywords: cold regions processes, observations, bias correction, Mackenzie River Basin

1 Introduction

Accurate and reliable weather and climate information at the basin scale is in increasingly high demand by policy-makers, scientists, and other stakeholders for various purposes such as water resources management (Barnett et al., 2005), infrastructure planning (Brody et al., 2007), and ecosystem modelling (IPCC, 2013). Particularly, the potential impacts of a warming climate on water availability in snow-dominated high latitude regions continue to be a serious concern given that over the past several decades, these regions have experienced some of the most rapid warming on earth (Demaria et al., 2016; Diffenbaugh et al., 2012; Islam et al., 2017; Martin and Etchevers, 2005; Stocker et al., 2013). The on-going science suggests that these warming trends are resulting in the intensification of the hydrologic cycle, leading to significant recent observed changes in the hydro-climatic regimes of major river basins in Canada and globally (Coopersmith et al., 2014; DeBeer et al., 2016; Dumanski et al., 2015). Changes in the timing and magnitude of river discharge (Dibike et al., 2016), shifts in extreme temperature and precipitation regimes (Asong et al., 2016b; Vincent et al., 2015) and changes in snow, ice, and permafrost regimes are anticipated (IPCC, 2013). Substantial evidence also indicates that the long-held notion of stationarity of hydrological processes is becoming invalid in a changing climate. As pointed out by Milly

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et al. (2008), this loss of stationarity means that there will be an increase in the likelihood and frequency of extreme weather and climate events, including floods and droughts.

Water resources in most land areas north of 30° N are heavily dependent on natural water storage provided by snowpacks and glaciers, with water accumulated in the solid phase during the cold season and released in the liquid phase during warm events and the warm season. Particularly, the Canadian Rocky Mountains, the hydrological apex of North America with headwater streams flowing to the Arctic, Atlantic and Pacific oceans, constitutes an integral part of the global hydrological cycle (Fang et al., 2013). Flows in these high elevation headwaters depend heavily on meltwater from snowpacks and glaciers. However, given that it is characterized by a highly varying cold region hydroclimate, studies indicate that it is in these high elevation regions where climate variability and change is expected to be most pronounced in terms of its impacts on water supply (Beniston, 2003; Kane et al., 1991; Prowse and Beltaos, 2002; Woo and Pomeroy, 2011). More physically realistic and sophisticated hydrological models driven by reliable climate forcing information can enhance our ability to assess short- and long-term regional hydrologic responses to increasing variability and uncertainty in hydro-climatic conditions in a changing climate. Nonetheless, hydrological processes in cold regions involve complex phase changes and so are very sensitive to small biases in the driving meteorology, particularly in temperature and precipitation.

Cold regions often have sparse surface observations, particularly at the high elevations that generate a major amount of runoff. The effects of mountain topography and high latitudes are currently not well reflected in the observational record. Ground-based measurements (e.g. gauges) are limited especially over the Canadian Rocky Mountains, and suffer from gross inaccuracies associated with cold climate processes (Asong et al., 2017; Wang and Lin, 2015; Wong et al., 2017). The advent and use of weather radar systems have addressed some of the short-comings of gauge coverage, at least where radar exists. Unfortunately, in Canada, for example, the spatial coverage of weather radar is limited to the

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southern (south of 55° N) part of the country (Fortin et al., 2015b). Recently, improved satellite products have emerged such as the Global Precipitation Measurement (GPM) mission that provides meteorological information at fine spatiotemporal resolutions and regular intervals. But, the GPM is still at its early stage and only covers the region south of 60° N (Asong et al., 2017; Hou et al., 2014).

The capability of the current generation of Earth System Models (ESMs) to represent meteorological variables is therefore of major interest for hydrological climate change impact studies in cold regions watersheds. Despite commendable progress being made, raw outputs from regional and global ESMs still differ largely from observational reference meteorology due partly to spatial scale mismatches and systematic biases (Taylor et al., 2012). Therefore, ESM outputs are often downscaled and biases are adjusted statistically before being used in hydrological simulations (Asong et al., 2016b; Chen et al., 2013; Chen et al., 2018; Gudmundsson et al., 2012). Recent research has demonstrated that bias correction, including adjustment of the dependence between driving variables, can lead to more realistic hydrological simulations in cold regions watersheds where the response of the system is sensitive to accumulation and melt of snow and ice (Meyer et al., 2019).

Apart from uncertainty due to the many empirical statistical techniques which have been developed to post-process ESM outputs (Maraun, 2016), the quality and length of the reference observational data set for bias correction remains a major issue (Reiter et al., 2016; Schoetter et al., 2012; Sippel et al., 2016). In Canada and other regions of North America, regional gridded data sets such as the combined Global Environmental Multiscale (GEM) atmospheric model forecasts (Yeh et al., 2002) and the Canadian Precipitation Analysis—CaPA (Mahfouf et al., 2007) have been found to perform comparably to ground observations, both statistically and hydrologically (Alavi et al., 2016; Boluwade et al., 2018; Eum et al., 2014; Fortin et al., 2015a; Gbambie et al., 2017; Wong et al., 2017). However, the duration of GEM-CaPA is too short to be used to directly correct ESM climate due to unsynchronized internal variability—the recommended minimum record length for bias correction is 30 years (Maraun, 2016;

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Maraun et al., 2017). Other gridded products such as the EU WATCH ERA-Interim reanalysis—WFDEI (Weedon et al., 2014) and Princeton (Sheffield et al., 2006) have a longer historical record, but have been found to be biased relative to observations over Canada (Wong et al., 2017) and the United States (Behnke et al., 2016; Sapiano and Arkin, 2009). However, the WFDEI reanalysis has been found to outperform other long-record gridded products (Chadburn et al., 2015; Park et al., 2016; Wong et al., 2017).

Because of sparse observational network, few gridded climate datasets exist that contain the necessary meteorological variables to drive physically-based land surface models at sub-daily temporal resolution north of 55° N in North America. Because the combination of the GEM and CaPA datasets has been shown to perform relatively well in these regions, the intent here is to use these datasets to bias-correct the WFDEI dataset, which contains a sufficient length of record for bias-correcting climate projection datasets. Aside from its short record length, a limitation of the GEM-CaPA dataset for wider use for hydrological models is that the wind, temperature, and humidity variables are available only at the 0.995 sigma(σ) level (approximately 40 m, varying in time and space; herein referred to as the "40 m" level) across the full length of record. The WFDEI dataset contains these variables at the surface level, which is more typically used by hydrological models. Therefore, the bias correction effectively modifies the source surface level data to reproduce the climate found at the 40 m level of the reference dataset (GEM-CaPA). Many regional and large-scale land surface hydrological models are perfectly capable of using climate data at this atmospheric level. Thus, no effort is made to interpolate the product back to surface level. In addition, the bias-corrected dataset at an effective 40 m level can then be used to bias-correct these same fields from the CanRCM4 dataset, which are at the same 0.995 σ level as in the reference dataset (GEM-CaPA). The analysis results in a bias-corrected set of historical and projected climate data that is consistent in time and considers the regional topography and climate effects of GEM and CaPA, and is suitable to drive large-scale simulations of distributed hydrological models for assessing climate change impacts in data sparse regions.

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The aim of this study, therefore, is to combine the strengths of both datasets (GEM-CaPA and WFDEI) to produce a less-biased long record product (WFDEI-GEM-CaPA) using a multi-stage bias correction framework. First, a multivariate generalization of the quantile mapping technique was implemented to bias-correct WFDEI against GEM-CaPA at 3h × 0.125° resolution during the 2005-2016 period, followed by a hindcast of WFDEI-GEM-CaPA from 1979. Subsequently, a 15-member initial condition ensemble of the CanESM2 ESM (historical and RCP8.5 scenarios), which have been dynamically downscaled at 0.44° (50 km) resolution using the fourth generation Canadian Regional Climate Model (CanRCM4), are sourced from the Canadian Centre for Climate Modelling and Analysis. A multivariate bias correction algorithm is applied to the CanRCM4 outputs (1950 – 2100) to adjust the data against WFDEI-GEM-CaPA. The bias-corrected products are important for developing distributed hydrological models as well as for assessing climate change impacts over the Mackenzie River basin (MRB), which constitutes a testbed for the Changing Cold regions Network (CCRN) project's large-scale hydrological modelling strategy and is the case study for the current analysis.

2 Methodology

2.1 Study area

The study area is the Mackenzie River Basin (MRB) which is the largest river basin in Canada and the largest river draining from North America to the Arctic Ocean (Fig. 1). It drains an area of about 1.8 million km^2 and discharges more than 300 km^3 of freshwater to the Beaufort Sea in the Arctic each year. The basin drains parts of British Columbia, Alberta, Saskatchewan, the Northwest Territories and the Yukon Territory in northwestern Canada. The western tributaries are relatively steep as they originate from the Canadian Rocky Mountains while the eastern tributaries have milder topography with several interconnected lakes and swamps. With a wide variety of climatic conditions such as the cold temperate, mountain, subarctic and arctic zones, about 75% of the basin is underlain by continuous and discontinuous permafrost.

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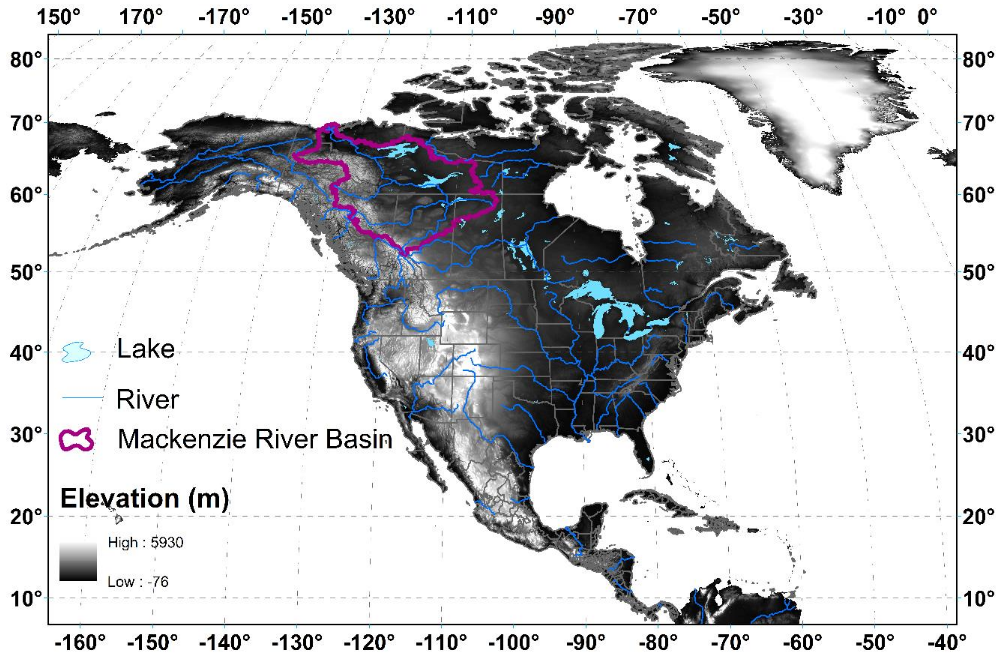

Figure 1: Location of the Mackenzie River Basin in North America.

2.2 Data sources

2.2.1 Gridded GEM-CaPA product

Hourly archived forecast data from the GEM model were acquired from Environment and Climate Change Canada (http://collaboration.cmc.ec.gc.ca/cmc/cmoi/product_guide/submenus/rdps_e.html, last access: 28 September 2018). The fields include downward incoming solar radiation, downward incoming longwave radiation and pressure at the surface, as well as specific humidity, air temperature, and wind speed at approximately 40 m above ground surface. The 40 m level was used because surface level variables at 1.0 σ (approximately at 2 m for temperature and humidity, and 10 m for wind speed) are only available in the archive from 2010 onward. The GEM data are approximately 24 km resolution from October 2001, approximately 15 km from June 2004, and approximately 10 km resolution from November 2012, and are provided on a rotated latitude/longitude grid in Environment and Climate

Change Canada—ECCC 'standard file' format. The archived data are of former operational forecasts, and contain model outputs from versions of GEM prior to 2.0.0 through 5.0.0.

6-Hourly total precipitation data from the complementary CaPA product (http://collaboration.cmc.ec.gc.ca/cmc/cmoi/product_guide/submenus/capa_e.html, last access: 28 September 2018) were also acquired. The analysis incorporates observed precipitation from meteorological weather stations, and more recently from radar, into the precipitation field from GEM. The CaPA data are approximately 10-km resolution from January 2002, also on a rotated latitude/longitude grid in ECCC 'standard file' format. The data contain reanalysis outputs from CaPA 2.4b8 from 2002-2012, and of former operational analyses from versions of CaPA 2.3.0 through 4.0.0 from November 2012 onward.

The variables from GEM and CaPA were spatially interpolated and re-projected to a regular latitude/longitude grid at 0.125° resolution. For data from GEM, the interpolation was done using a bilinear algorithm, while data from CaPA were interpolated using nearest neighbour (Schulzweida et al., 2004). Where necessary, the GEM fields were converted to SI units and CaPA was converted to a precipitation rate in SI units for better compatibility with some hydrological models.

2.2.2 Gridded WFDEI product

The gridded WFDEI meteorological forcing data has a global 0.5° spatial resolution and 3-h time step covering the period 1979-2016 (http://www.eu-watch.org/data_availability, last access: 25 July 2018). Weedon et al. (2014) used the ERA-Interim surface meteorology data as baseline information to derive the WFDEI product. Firstly, ERA-Interim data were interpolated at half-degree spatial resolution to match the land–sea mask defined by the Climatic Research Unit (CRU) of the University of East Anglia, Norwich, England. Subsequently, corrections for elevation and monthly bias of climate trends in the ERA-Interim fields were applied to the interpolated data. The WFDEI data have two sets of precipitation data: the Global Precipitation Climatology Centre product (GPCC) and CRU Time Series version 3.1 (CRU TS3.1).

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Preprint. Discussion started: 31 July 2019
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Thus, two variants of the WFDEI product are available—WFDEI-GPCC and WFDEI-CRU. The WFDEI-CRU data set was used here because it goes up to 2016, whilst the WFDEI-GPCC had only been updated until 2013 at the time of our analysis.

2.2.3 Station observations

To evaluate the added value of bias-correcting WFDEI against GEM-CaPA, *in situ* hourly precipitation totals at 9 stations located across the MRB were utilized (Fig. 2). This station network is maintained by Environment and Climate Change Canada (ECCC) (http://climate.weather.gc.ca/historical_data/search_historic_data_e.html, last access: 15 March 2019). Only precipitation (which is available at the surface for all data sets) is validated in this study because of the differences in heights between other gridded variables such as air temperature, specific humidity, and wind speed (see Sections 2.3 and 3.1) and the ECCC station data. The data were extracted for the period from 01 January 2005 to 31 December 2016. Out of 81 stations located over the MRB (Fig. 2), 9 of these stations were found to have less than 10% of missing data (calculated at daily timescale) between this period and were retained for further consideration (see Table 1 for additional information on the 9 stations retained for further analysis). This dataset is hereafter referred to as ECCC-S (S for station).

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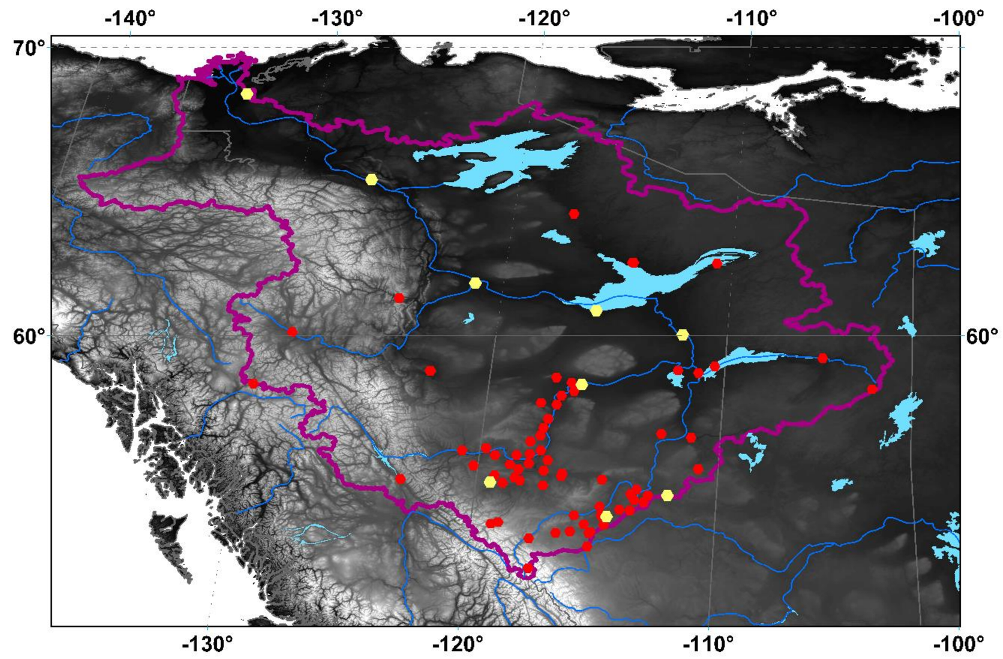

Figure 2: Spatial distribution of the initial 81 ground-based precipitation gauges (red and yellow dots) over the study area during the period 2005 – 2016. Data screening for missing values (10% threshold used here) resulted in 9 of these stations (yellow dots) being retained for further analysis.

Table 1: List of observation stations used for validating the various gridded historical products between 2005 – 2016. The 'percent missing' column indicates the percentage of missing values for each station over the period 2005 – 2016

Station name	Station_id	Province	Latitude	Longitude	Elevation	Percent missing
FORT VERMILION	30495	AB	58.38	-116.04	289	7.14
BARRHEAD CS	30641	AB	54.09	-114.45	648	1.89
BEAVERLODGE RCS	30669	AB	55.2	-119.4	745	6.14
LAC LA BICHE CLIMATE	30726	AB	54.77	-112.02	567	1.19
INUVIK CLIMATE	41883	NT	68.32	-133.52	103	4.91
FORT SMITH CLIMATE	41884	NT	60.03	-111.93	203	3.19
HAY RIVER CLIMATE	41885	NT	60.84	-115.78	164	0.66
FORT SIMPSON CLIMATE	41944	NT	61.76	-121.24	168	0.46
NORMAN WELLS CLIMATE	43004	NT	65.29	-126.75	93.6	3.45

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2.2.4 Climate model outputs

The historical and future climate simulations utilized in this study are part of the CanRCM4 large ensemble which consists of 50 members and downscaled at horizontal spatial resolutions of 0.44° (50 km). These CanESM2 simulations had been produced initially by the Canadian Sea Ice and Snow Evolution Network (CanSISE) Climate Change and Atmospheric Research (CCAR) Network project (https://www.cansise.ca/, last access: 24 April 2019). The input data for the historical period, i.e., 1950 – 2005 as well as the future (2006 – 2100) RCP simulations of CanRCM4 were provided by the parent ESM (CanESM2) as specified in the Coupled Model Intercomparison Project Phase 5 (CMIP5) guidelines. The data are sourced from the Canadian Centre for Climate Modelling and Analysis (CCCma) at www.cccma.ec.gc.ca/data/canrcm/CanRCM4 (last access: 6 March 2019). This study utilized 15 members of the 0.44 degrees resolution product at 1-h time step and values were aggregated to 3-h resolution prior to bias correction. The seven forcing variables needed for driving the CCRN MESH model (https://wiki.usask.ca/display/MESH/About+MESH, last access: 10 May 2019) and which were bias-corrected in the current study are included in Table 2.

2.3 Data processing and bias correction workflow

The workflow for the multi-stage bias correction is shown in Fig.3. Bias correction was done after aggregating 1-h GEM-CaPA estimates to 3-h (the values at each time step represent the mean of the previous 3-h period, to make it consistent with WFDEI) and interpolating both WFDEI and GEM-CaPA to 0.125° resolution. For bias correction, a multi-stage approach was implemented as follows. A multivariate generalization of the quantile mapping technique (Cannon, 2018) which combines quantile delta mapping (Cannon et al., 2015) and random orthogonal rotations to match the multivariate distributions of two data sets was implemented to bias-correct WFDEI against GEM-CaPA at 3-h*0.125° resolution during the 2005-2016 period. Models were fitted to data for each calendar month while accounting for inter-variable dependence structure. Using the fitted models (2005-2016), a hindcast was made of WFDEI between

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Preprint. Discussion started: 31 July 2019
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1979-2004. Finally, the corrected WFDEI data derived from the fitted (2005-2016) and hindcast (1979-2004) periods were concatenated to obtain the bias-corrected WFDEI-GEM-CaPA product (1979-2016).

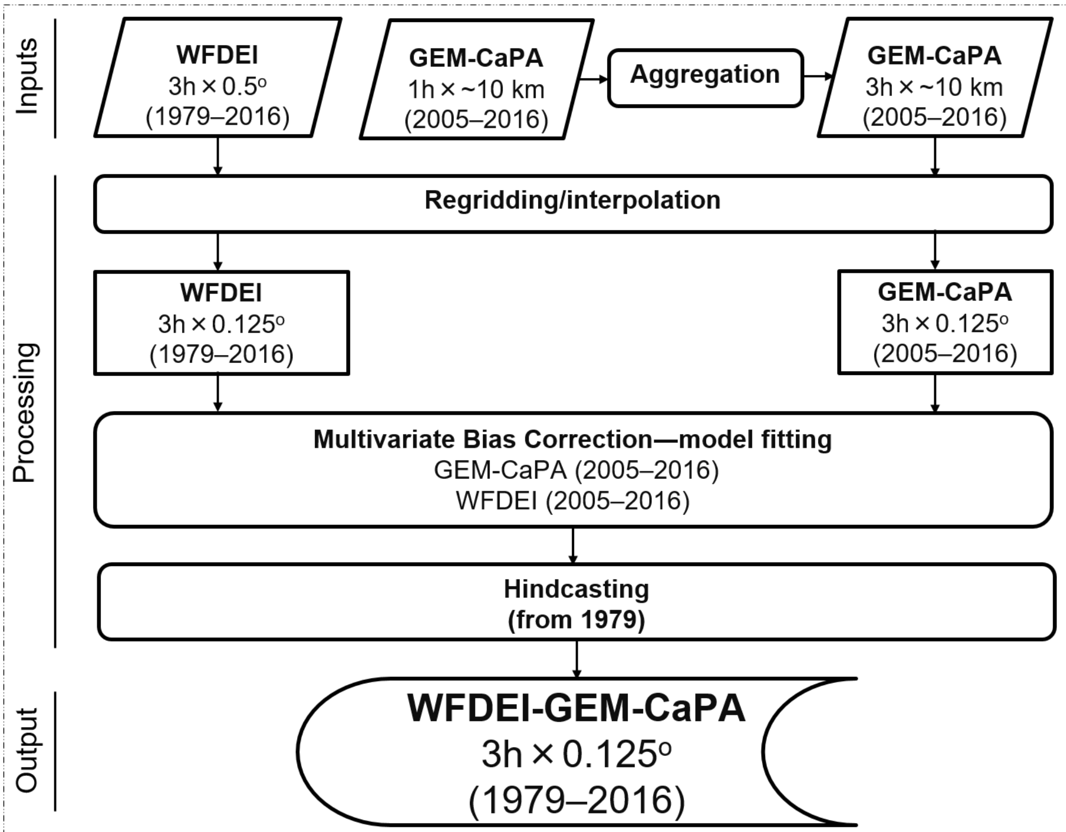

Figure 3. A schematic representation of inputs and bias correction procedure used to produce the WFDEI-GEM-CaPA meteorological forcing data set.

For bias-correcting the 15-member CanRCM4 initial condition ensemble against the WFDEI-GEM-CaPA product, CanRCM4 was also spatially interpolated to match the WFDEI-GEM-CaPA specifications using nearest neighbour interpolation. The multivariate bias correction (MBCn) technique (described above) transfers all aspects of the WFDEI-GEM-CaPA continuous multivariate distribution to the corresponding multivariate distribution of variables from CanRCM4 during the 1979 – 2008 calibration period (also known here as historical period). Subsequently, when applied to future projections, changes

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Preprint. Discussion started: 31 July 2019
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in quantiles of each variable between the historical and future period are also preserved. Models were fitted to data for each calendar month and for each grid point while preserving the dependence structure among variables. The historical data sets used in the fitting procedure include WFDEI-GEM-CaPA (1979 – 2008) and CanRCM4 (1979 – 2008). Using the fitted models, quantiles of CanRCM4 output from 1950 – 2100 were changed. To evaluate the need to bias-correct CanRCM4, performance of the bias correction scheme, as well the impact of bias correction on the climate change signal, the seasonal cycle of all 7 variables is assessed over three 30-year periods: 1979–2008 (referred hereafter as 1990s); 2021–2050 (referred to hereafter as 2030s) and 2071–2100 (referred to hereafter as 2080s).

3 Results and discussion

3.1 Bias correction of WFDEI

Table 2 presents an overview of the seven variables processed in this study. Note that the GEM 40 m variables are used directly to correct WFDEI surface level variables (2 m temperature, 2 m specific humidity, and 10 m wind speed). Therefore, the corrected WFDEI-GEM-CaPA data reflect 40 m elevations above the surface. The spatial coverage of the WFDEI-GEM-CaPA data is the same as the areal extent of the MRB (Figs. 1 and 2). The suitability of the bias correction algorithm to reproduce the observed seasonal cycle and inter-annual variability of the variables was assessed for the fitting (2005-2016) and hindcast (1979-2004) periods. Data extracted over the entire Mackenzie River basin is used to demonstrate the quality of the bias correction exercise and uniqueness of the resulting output. Fig. 4 shows the seasonal cycle for GEM-CaPA, WFDEI and WFDEI-GEM-CaPA during the fitting period. Overall, the monthly distributions show that the bias was removed for all variables resulting in the very close distributions between GEM-CaPA and WFDEI-GEM-CaPA. The bias was particularly large for wind speed, an important variable for both alpine and prairie blowing snow redistribution calculations (Pomeroy and Li, 2000), but was successfully removed. Fig. 5 shows the mean annual time series of the seven variables over the 1979-2016 period. It is noticeable that the bias is corrected while the inter-annual variability is well preserved

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between WFDEI and WFDEI-GEM-CAPA, except for shortwave radiation where the inter-annual variability is not fully preserved as shown by the correlation between the WFDEI and WFDEI-GEM-CaPA annual series. However, this should not be a major issue when impact models are driven using these data.

Table 2: List variables processed in this study with heights and units in each dataset.

	WFDEI		GEM-CaPA		WFDEI-GEM-CaPA	
Variable	**Height**	**Unit**	**Height**	**Unit**	**Height**	**Unit**
Precipitation	Surface	kg m^{-2} s^{-1}	surface	kg m^{-2} s^{-1}	surface	kg m^{-2} s^{-1}
Air Temperature	2 m	K	40 m	K	40 m	K
Specific Humidity	2 m	kg kg^{-1}	40 m	kg kg^{-1}	40 m	kg kg^{-1}
Wind Speed	10 m	m s^{-1}	40 m	m s^{-1}	40 m	m s^{-1}
Surface Pressure	Surface	Pa	Surface	Pa	Surface	Pa
Surface Downwelling Shortwave Radiation	Surface	W m^{-2}	Surface	W m^{-2}	Surface	W m^{-2}
Surface Downwelling Longwave Radiation	Surface	W m^{-2}	Surface	W m^{-2}	Surface	W m^{-2}

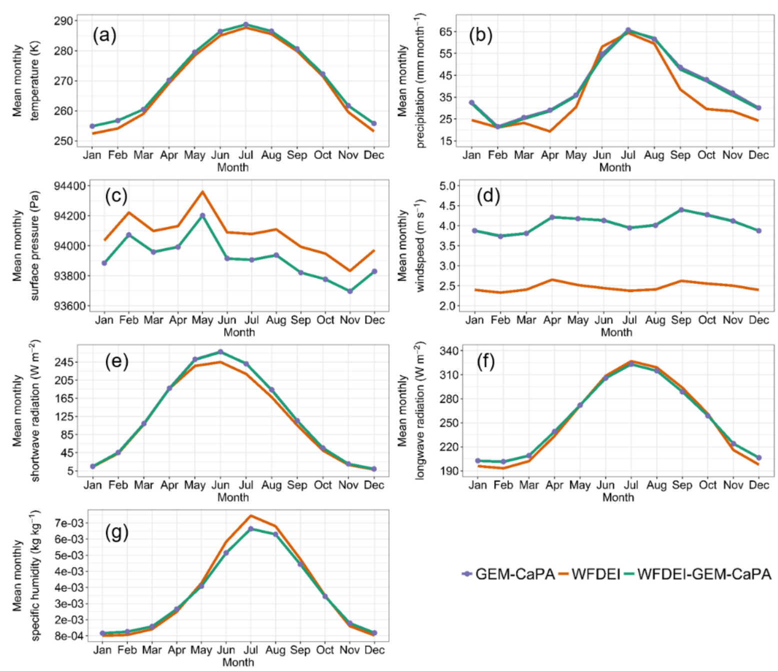

Figure 4: Seasonal cycle of GEM-CaPA (dark slate blue), WFDEI (orange) and bias corrected data—WFDEI-GEM-CaPA (green) for air temperature (a), precipitation (b), surface pressure (c), wind speed (d),

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shortwave radiation (e), longwave radiation (f), and specific humidity (g) during the fitting period (2005-2016).

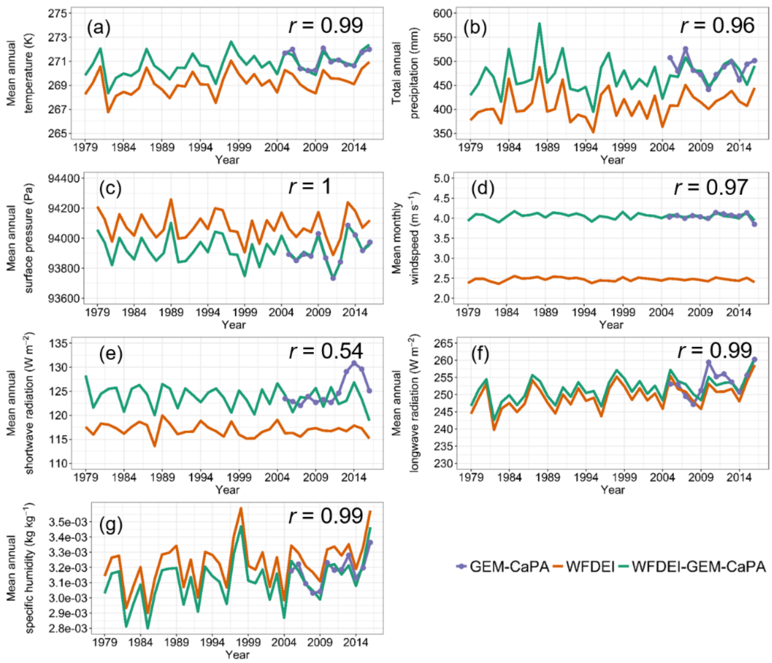

Figure 5: Time series of GEM-CaPA (dark slate blue), WFDEI (orange) and bias corrected data—WFDEI-GEM-CaPA (green) for air temperature (a), precipitation (b), surface pressure (c), wind speed (d), shortwave radiation (e), longwave radiation (f), and specific humidity (g) during the periods 2005-2016 (GEM-CaPA) and 1979-2016 (WFDEI and WFDEI-GEM-CaPA). The correlation (*r*) between the WFDEI and WFDEI-GEM-CaPA annual series is indicated for each variable.

The foregoing analyses have shown that the bias in the WFDEI data was removed for both the fitting and hindcast periods. However, some potential limitations remain—for example, WFDEI was interpolated directly from 0.5° to 0.125° and bias-corrected against GEM-CaPA at 0.125°. The interpolation does not add any event-scale spatial variability for a variable like precipitation which is very variable across different scales. These issues have been reviewed extensively by Cannon (2018), Maraun (2013), Maraun et al. (2010), and Storch (1999).

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3.2 Validation of gridded products against station observations

In this section, the WFDEI-GEM-CaPA product is validated against station observations (ECCC-S) as a way to indicate the benefit of bias-correcting WFDEI against GEM-CaPA. As mentioned in Section 2.2.3, the validation focusses on precipitation given that the other variables are issued at different heights (e.g. 2m vs 40m) for various data sets. Thus, the height differences preclude direct validation of other variables against the ECCC-S data which are measured at the surface. Validation is performed for the 2005 – 2016 period using monthly precipitation totals. Figure 6 shows the percentage of missing values by year for each of the 9 stations. Fort Simpson Climate has the most 'completeness' of records while Beaverlodge RCS and Fort Vermilion have the least, particularly between 2013 – 2015 where about 30% of the records are missing for some years (e.g. 2013 and 2014). It is worth mentioning that all of the 81 stations located over the MRB had no data before the year 2000 (see Table S1 in the supplementary material). The station metadata in Table S1 was last downloaded from the ECCC website on April 11, 2019. To compare stations against gridded products, the corresponding precipitation series of gridded products for each gauge was obtained by combining the surrounding four grid cells via bilinear interpolation.

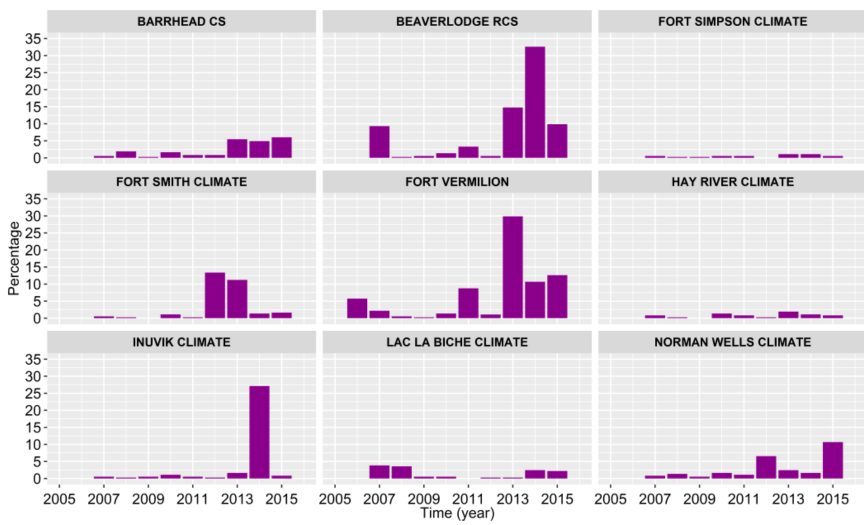

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Figure 6: Percentage of missing values for the 9 selected stations. The percentages are computed on daily precipitation totals.

In terms of precipitation totals, Fig. 7 depicts quantile–quantile (Q–Q) plots of monthly precipitation from WFDEI-GEM-CaPA, WFDEI and CaPA compared against ECCC-S. As expected, although with noticeable differences across the MRB, CaPA agrees well with ECCC-S since some or all of these meteorological stations are assimilated by the CaPA system. WFDEI tends to overestimate the observed precipitation amounts in Barrhead CS and Beaverlodge RCS while it underestimates precipitation amounts greater than ~50 mm in locations such as Fort Simpson, Hay River, Norman Wells, and Inuvik. Overall, 1) CaPA performs better than WFDEI, and 2) correcting WFDEI against CaPA adds value to the WFDEI data set, thus the reason for the close agreement between WFDEI-GEM-CaPA and ECCC-S. All three products tend to underestimate high precipitation amounts in Norman Wells although CaPA and WFDEI-GEM-CaPA compare relatively more closely to ECCC-S than does WFDEI. Note that extracting data from grid points does not only have the effect of smoothing the area averages, but comparing grid point estimates to station values may not provide a clear picture of the quality of a gridded product. However, this diagnostic analysis can provide preliminary insights into the potential performance of a data set.

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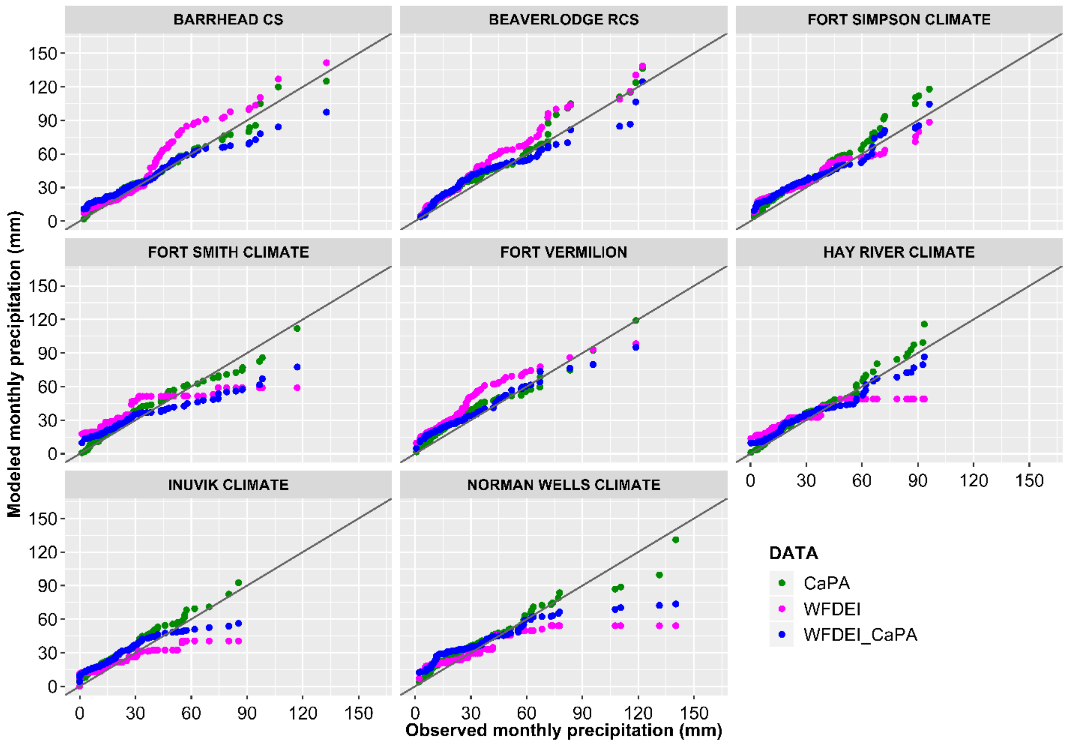

Figure 7: Quantile-quantile plots of modelled (CaPA, WFDEI and WFDEI-GEM-CaPA) and observed monthly precipitation totals.

3.2 Bias correction and future climate projections

In this section, the need to bias-correct the CanRCM4 outputs is shown and whether the simulated climate change signal was preserved after applying MBCn to the CanRCM4 outputs is determined. Figure 8 shows the climatological seasonal cycle of all 7 variables which are required to drive the MESH model for the MRB. First, between April and October, CanRCM4 overestimates the observed (i.e. WFDEI-GEM-CaPA) daily precipitation amounts and specific humidity during the historical period. This is also true in the case of daily mean wind speed in the cold months (October to April). However, it underestimates the wind speed in the warm season (May to September). Surface pressure is underestimated during September to May and overestimated in the summer (June to August). For the other variables (e.g. air

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temperature and radiation), CanRCM4 is able to simulated closely the observed seasonal cycle although biases still exist. These biases necessitated the application of the MBCn algorithm on the raw CanRCM4 outputs. The MBCn algorithm removed the bias in the CanRCM4 simulations during the fitting period (1990s) as can be judged from the close fit between WFDEI-GEM-CaPA and the unbiased CanRCM4 output (corr_1990s). On the projected climate change signal, there is a projected change in the amplitude of all variables but not a shift in the phase of the cycle over the MRB with global warming. Precipitation, specific humidity and longwave radiation are projected to increase in the future, with larger changes expected in the warm season (April – October) while air temperature is projected to increase, particularly in the cold months (October – March). These climate change signals are very much well preserved after applying MBCn to the CanRCM4 simulations.

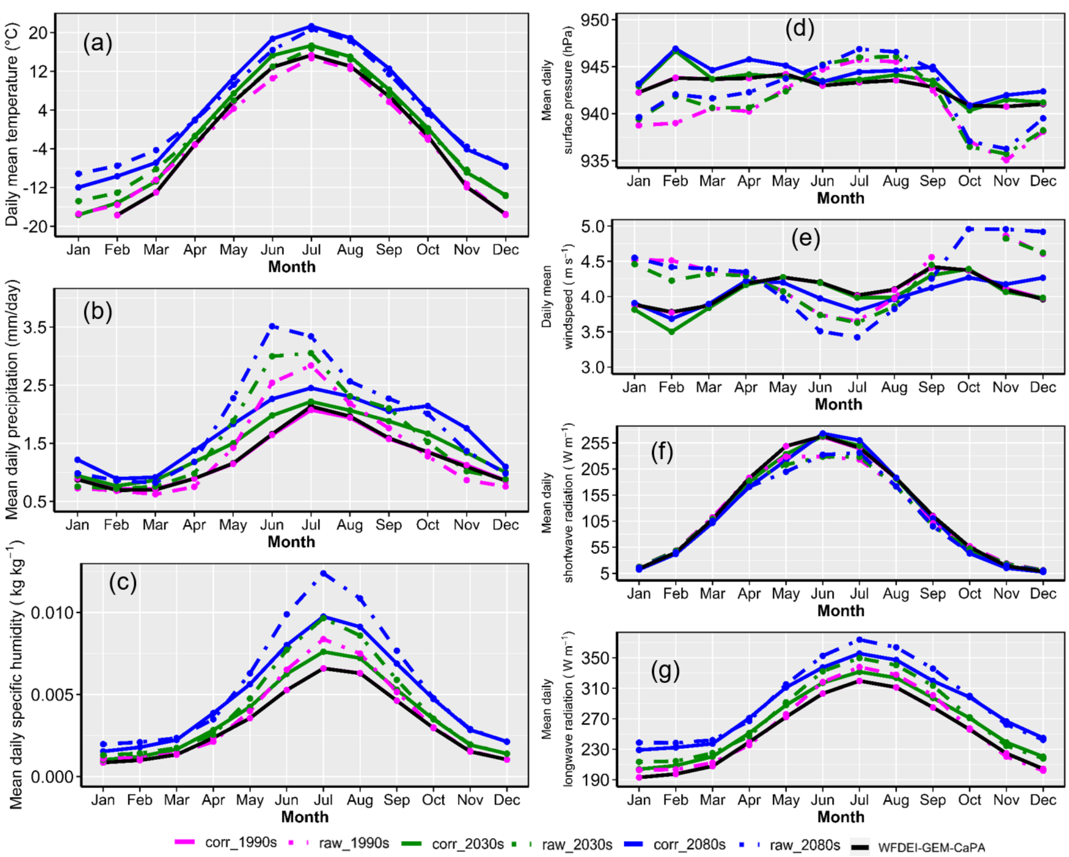

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Figure 8: Seasonal cycle of WFDEI-GEM-CaPA, raw and bias-corrected CanRCM4 data for air temperature (a), precipitation (b), specific humidity (c), surface pressure (d), wind speed (e), shortwave radiation (f), and longwave radiation (g) during the periods 1979–2008; 2021–2050 and 2071–2100.

4 Conclusions

Cold regions hydrology is very sensitive to the impacts of climate warming. More physically realistic hydrological models driven by reliable climate forcing can provide the capability to assess hydrological responses to climate variability and change. However, cold regions such as the Mackenzie River Basin often have sparse surface observations, particularly at high elevations where a large amount of runoff is generated. By making this long-term dataset available, it is hoped that it can be used to better understand and represent the seasonal/inter-annual variability of hydrological fluxes and the timing of runoff, and their long-term trends. This data set is also valuable for bias correction of climate model projections to assess potential impacts of future climate change on the hydrology and water resources of the basin.

The raw CanRCM4 outputs were found to have systematic biases which required bias correction towards WFDEI-GEM-CaPA. There are clear discrepancies between the seasonal cycle of WFDEI-GEM-CaPA, raw, and bias-corrected CanRCM4 data. For example, the CanRCM4 simulated climatological daily mean precipitation in June over the MRB between 1979 – 2008 is ~2.5 mm/day while the observed value is ~1.5 mm/day. This results in a 1.0 mm/day wet bias which can have various implications for quantifying water resources availability, management and adaptation in a future changed climate. Therefore, it is crucial to produce the bias-corrected CanRCM4 outputs prior to using the data to drive large scale hydrological models for climate change impacts analysis in the MRB. Nevertheless, the WFDEI-GEM-CaPA data used here as the reference have uncertainties (although it is superior to WFDEI as shown in Fig. 7) and should be used with caution especially from the perspective of over-interpreting impact model outputs.

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5 Data availability

The final product (WFDEI-GEM-CaPA, 1979-2016) is freely available at the Federated Research Data Repository at http://dx.doi.org/10.20383/101.0111 (Asong et al., 2018) while the original and corrected CanRCM4 data are also freely available at https://doi.org/10.20383/101.0162 (Asong et al., 2019).

6 Author contribution

Z.E., H.W., J.P., A.P., and M.E. conceived of and designed the experiment. D.P. preprocessed the GEM-CaPA data, A.C. developed the bias correction model code and guided the computing procedures while Z.E. performed the computations. M.E extracted the sample data used in generating Fig.4 and 5. Z.E. prepared the manuscript with contributions from all co-authors.

7 Competing interests

The authors declare that they have no conflict of interest.

8 Acknowledgements

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