Future changes of hydroclimatic extremes in western North America using a large ensemble: The role of internal variability

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Abstract

Increases in the intensity and frequency of extreme events in Western North America (WNA) can cause significant socioeconomic problems and threaten existing infrastructure. In this study we analyze the impacts of climate change on hydroclimatic extremes and assess the role of internal variability over WNA, which collectively drain an area of about 1 million km$^2$. We used gridded observations and downscaled precipitation, maximum and minimum temperature from seven General Circulation Models (GCMs) that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) and a large ensemble of CanESM2 model simulations (CanESM2-LE; 50 members) for this analysis. Spatial and temporal changes of eight climate extreme indices are assessed over the historical (1981-2010) and future (2060-2089) time periods. In addition, changes in extreme events with high return periods are analyzed based on the extreme value theory. To better understand the effects of internal climate variability on the hydroclimatology of WNA we assess the relations between 14 Low Frequency Variability Modes (LFVMs), with three different time lags, and the regional temperature and precipitation. The correlation between each LFVM and the principle component of temperature and precipitation over the spatial domain is computed using Maximum Covariance Analysis (MCA). Robustness of the results is further evaluated using composite analysis. Results show that the intensity and frequency of extreme precipitation and temperature are projected to increase over WNA. The uncertainties due to internal variability (represented by CanESM2-LE) are significant and comparable to those arising from GCM structures. El Nino Southern Oscillation, Trans-Polar Index (TPI), Southern Annular Mode (SAM), Eastern Pacific (EP) and West Pacific (WP) are found to be dominant LFVMs that can significantly influence WNA’s hydroclimatic variables.
Keywords

Hydroclimatic extremes, climate change, internal variability, precipitation, temperature, runoff, western North America, Low frequency variability mode, CLIMDEX, composite analysis, maximum covariance analysis
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Acronyms

*.nc = NetCDF .................................................................................................................. 23
ACCESS1-0 = ARC Centre of Excellence for Climate System Science ............................... 25
ACCESS1-3 = ARC Centre of Excellence for Climate System Science ............................... 25
AO = Arctic Oscillation ....................................................................................................... 8
BCCA = Bias Correction Constructed Analogues ............................................................... 25
BCCAQ = Bias Correction/Constructed Analogues with Quantile mapping reordering
approach ............................................................................................................................ 24
BCCI = Bias Corrected Climate Imprint .............................................................................. 25
CanESM2 = Canadian Centre for Climate Modelling and Analysis .................................. 25
CanESM2-LE = CanESM2- Large Ensemble ..................................................................... 26
CaRB = Campbell River Basin .......................................................................................... 20
CCA = Canonical Correlation Analysis ............................................................................. 35
CCSM4 = University Corporation for Atmospheric Research (UCAR) ............................ 25
CDD = maximum number of consecutive dry days .......................................................... 5
CLIMDEX = Climate extreme indices ................................................................................ 4
CMIP3 = Coupled Model Intercomparison Project Phase 3 ............................................. 11
CMIP5 = Coupled Model Intercomparison Project Phase 5 ............................................. 11
CNRM-CM5 = Centre National de Recherches Meteorologiques / Centre Europeen de
Recherche et Formation Avancees en Calcul Scientifique .............................................. 25
CRB = Columbia River Basin .......................................................................................... 16
DMI = Dipole Mode Index ................................................................................................. 8
EA = East Atlantic .............................................................................................................. 8
ENSO = El Nino Southern Oscillation .............................................................................. 7
EOF = Empirical Orthogonal Function .................................................................15
EP = Eastern Pacific .............................................................................................8
ETCCDI = Expert Team on Climate Change Detection and Indices ..................11
EVT = Extreme Value Theory ...............................................................................5
FRB = Fraser River Basin .....................................................................................18
GEV = Generalized Extreme Value .....................................................................14
GP = generalized Pareto ......................................................................................30
GSL = Growing Season Length ..........................................................................5
HadGEM2-ES = Met Office Hadley Centre ESM .............................................25
HIV = Human Immunodeficiency Viruses ...........................................................1
IPCC = Intergovernmental Panel on Climate Change .........................................3
MCA = Maximum Covariance Analysis ...............................................................9
MCA1 = MCA mode 1 .........................................................................................59
MPI-ESM-LR = Max Planck Institute for Meteorology (MPI-M) ....................25
NAO = North Atlantic Oscillation ......................................................................8
NP = North Pacific ..............................................................................................17
NTA = North Tropical Atlantic ...........................................................................8
PC = Principal Component ................................................................................16
PDF = Probability Density Function ..................................................................31
PDO = Pacific Decadal Oscillation .....................................................................8
PDSI = Palmer Drought Severity Index ...............................................................16
PNA = Pacific/North American Pattern ................................................................8
R10 = number of days with precipitation greater than 10 mm .......................5
R95pTOT = total amount of precipitation exceeding the 95th percentile of the climatological distribution for wet days .................................................................5
RCM = Regional Climate Model ................................................................. 13
RCP = Representative Concentration Pathway ........................................... 3
RX5day = monthly maximum consecutive 5-day precipitation ....................... 5
SAM = Southern Annular Mode ................................................................. 8
SCF = Square Covariance Fraction .......................................................... 36
SDII = simple precipitation intensity index ................................................. 5
SOI = Southern Oscillation Index ............................................................. 8
SST = Sea Surface Temperature ............................................................... 16
SVD = Singular Value Decomposition ....................................................... 16
tasmax = maximum daily temperature ..................................................... 32
tasmin = minimum daily temperature ....................................................... 32
TNn = minimum Temperature ................................................................ 5
TPI = Trans Polar Index .......................................................................... 8
TXx = maximum temperature .................................................................. 5
UPRB = Upper Peace River Basin ............................................................ 19
WP = West Pacific .................................................................................. 8
Chapter 1

1. Introduction

This section discusses hydroclimatic extreme events (including precipitation, temperature and runoff), their driving mechanisms, examples of historical events, and the role of climate change and internal variability followed by the thesis outline in the end.

1.1. Hydroclimatic extreme events

Definition of extreme events varies between different disciplines. Politicians and journalists define them as any event with an important consequence. According to this definition, a heavy rainfall that cause no flooding is not considered an extreme event. Pandemics such as HIV or flu are extreme societal events. Other examples include large benefit/loss in market turbulence, embezzlement in politics, earthquake and landslide in geoscience, flood and drought in natural science. Hydrologists define extreme events as deviations from the usual trend of the observed or simulated variable (such as precipitation, temperature, runoff), or as unusual/unexplainable events regardless of their impacts (Albeverio, Jentsch and Kantz, 2006). In general, the tails of a probability distribution of a variable are considered as extremes.

Extreme events, such as floods and droughts, commonly occur in North America (NA) as well as other regions around the world resulting in significant socioeconomic consequences. Examples include flooding in central Arizona on July 24th in 1990, which was initiated by heavy rainfall and locally strong winds. Texas faced severe drought conditions starting from October 2010 with an average precipitation amount of 14.8 inches recorded in 2011, as the driest year for Texas. The Fraser river basin was flooded in May 1972. Potential flooding was
predicted based on above-average snow survey records in February. Temperature rise contributed to snowmelt in May 2018 and resulted in massive flooding in British Columbia as well. It caused thousands of residents to be displaced in Grand Forks, Osoyoos with some on alert in Chilliwack.

Increases in the severity and frequency of extreme events, due to natural or human-induced causes, can result in severe damages and losses in the future. Understanding historical changes of the characteristics of extremes and the driving mechanisms is essential for their accurate future predictions.

1.2. Changes in extreme events

According to the Clausius-Clapeyron relationship increases in the atmospheric temperature would raise its moisture holding capacity resulting in more severe and more frequent extreme events. Therefore, in a changing climate more intense flooding, caused by heavier rainfall among others, are expected to occur in many regions around the world particularly the ones that are categorized as wet areas. Temperature increases would also increase the evapotranspiration rates and reduce the average rainfall rates particularly in dry areas resulting in severe drought conditions. Therefore, societies and infrastructure are more vulnerable to hydroclimatic extreme events under climate change. In addition, internal climate variability, due to the chaotic nature of the atmospheric and oceanic processes play a significant role in modulating extreme events particularly at the regional scales.
1.2.1 Impacts of climate change on extreme events

Climate is an average state of weather prevailing in an area over a long period of time. The global climate has always been oscillating, however observational data shows that the average global temperature has been increasing over the past decades particularly since 1980s. There is strong evidence that these observed changes are associated with anthropogenic greenhouse effects caused by human-induced emissions via industrialization (Najafi et al., 2015). Greenhouse gasses (GHGs), including carbon dioxide, methane, water-vapor, nitrous oxide, among others, can trap the long-wave radiation emitted from the Earth’s surface into the atmosphere resulting in increases in the Earth’s surface temperature. Since 19th century global GHG concentrations have been increasing steadily (van Vuuren et al., 2011). Because of the lack of knowledge of future GHG concentrations, the Intergovernmental Panel on Climate Change (IPCC) has introduced four distinct GHG emission scenarios, representing possible range of future GHG concentrations, called Representative Concentration Pathways (RCPs) 2.6, 4.5, 6.0 and 8.5 (Stocker et al., 2013). Total radiative forcing, which is a cumulative measure of human emissions of GHG levels, is used to define different RCPs by the end of 2100.

The global average temperature has increased by 2°C over the past 35 years because of the human influence (Northon, 2017). Although the average rate of temperature changes is not large (compared to daily and seasonal variations), even the consequences of small temperature changes are significantly destructive. Rising temperature can intensify the hydrological cycle and increase the severity and frequency of extremes through increased evapotranspiration, snow cover declines, glacial retreats, rising sea levels, warming oceans, shrinking ice sheets, heavy rainfall, among others (Wuebbles, Fahey and Hibbard, 2017). These changes can threaten infrastructure and local communities and leads to decreased snow, glacial treats, rising
sea levels, warming oceans, shrinking ice sheets and extreme events (Wuebbles, Fahey and Hibbard, 2017).

![Global Mean Surface Temperature](image)

**Figure 1.** Global mean surface temperature (Hansen et al., 2010)

As Figure 1 shows two main characteristics of the global mean surface temperature changes including climate signals, i.e. the long-term trends and projections of the climate system, and noise, i.e. internal climate variability. The climate signal (or the forced response) represents the effects of climate change or the fingerprints of anthropogenic GHG emissions in long-term temperature trends. In this study we analyze the impacts of climate change on hydroclimate extremes using parametric and non-parametric statistical methods.

Statistical analysis is required to analyze the impacts of climate change on extreme events and quantify the uncertainties. In this study, we use parametric and non-parametric methods based on Extreme Value Theory (EVT) and climate extreme indices (CLIMDEX), which are quantitative metrics that show changes in extreme temperature and precipitation at the monthly and annual scales. CLIMDEX includes 27 standardized indices calculated from daily weather
data that are defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Karl, Nicholls and Ghazi, 1999a; Zhang et al., 2005). In this study, CLIMDEX indices are used to assess spatial and temporal variability of hydroclimatic extremes, quantify the uncertainties in climate change impacts on extremes, evaluate GCMs, and characterize climate signal and internal variability of extremes.

We selected eight CLIMDEX indices, which represent the intensity (I) and frequency (F) of extreme Pr & T (e.g. growing length, drying days, very high precipitation etc.). These include three temperature-based indices: Growing Season Length (GSL; F), maximum temperature (TXx; I), minimum Temperature (TNn; I); and five precipitation indices including the number of days with precipitation greater than 10 mm (R10; F), monthly maximum consecutive 5-day precipitation (RX5day; I), simple precipitation intensity index (SDII; I), total amount of precipitation exceeding the 95th percentile of the climatological distribution for wet days (i.e. daily RR ≥ 1.0mm) (R95pTOT; F), and maximum number of consecutive dry days (i.e. RR < 1mm; F) (CDD), which is a precipitation based drought index.

Additionally, we analyzed extreme precipitation and temperature values at the tails of their corresponding probability distributions. Extreme Value Theory (EVT) was used to analyze the stochastic behavior of extreme values and characterize events that have relatively long return periods (~100 years). Extreme value distributions are fitted to the observed and simulated extremes over the historical and future periods, the corresponding parameters are inferred using available methods such as Maximum Likelihood Estimation (MLE), and extreme events with specific return periods and the corresponding uncertainties are determined.
Impacts of climate change on streamflow

Increases in the intensity and frequency of hydroclimatic extremes (Touma et al., 2015; Pagán et al., 2016) would challenge water resources management. For example, lengthening drought durations in arid and semi-arid regions can cause difficulties in releasing the minimum environmental flows from the reservoirs. Increases in precipitation, however, demands more storage in reservoirs and attention for downstream water releases (Carlton and Kandathil, 2013). Therefore, any changes in hydroclimatic variables, especially precipitation, can have significant consequences for recreational activities, dam operations, ecosystems and water quality upstream and downstream of the reservoirs (Naz et al., 2018).

To better understanding the impact of climate change on streamflow, we use a hydrological model (setup and calibrated by BC-Hydro) to assess the projected changes of regional streamflow.

1.2.2 Internal variability

Internal variability originates from internal processes within the climate system and the interactions between the atmosphere, ocean and land surface components (i.e. soil, vegetation etc.). Characterization and prediction of internal variability (noise; Figure 1) are quite challenging because of the complexities that exist in this natural system. However it is critical to understand and distinguish the influence of internal climate variability and forcing signals on hydroclimatic extremes for future policy making, and planning and design of civil infrastructure (Deser, Knutti, et al., 2012; Deser, Phillips, et al., 2012). The effects of internal
variability are more noticeable in precipitation compared to temperature particularly at regional scales (Deser, Knutti, et al., 2012; Fischer, Beyerle and Knutti, 2013; Xie et al., 2015).

**Low Frequency Variability Modes (LFVMs)**

Large-scale atmospheric circulations can affect the regional weather patterns of many regions around the world and last for several days, weeks, months, or years. LFVMs are large-scale anomalies that refer to periodic patterns of pressure and circulation over a vast area. The chaotic changes of the sea-level pressure between two regions can lead to changes in sea surface temperature (SST) that can affect the hydroclimate of many regions around the world. Low Frequency Variability Modes (LFVMs) are generally defined based on the anomalies of pressure or temperature at a specific time period. There are several teleconnection patterns that span over the Pacific and Atlantic oceans including El Niño Southern Oscillation (ENSO), which is defined as the anomaly of spatially averaged SST over the equatorial Pacific Ocean. Since teleconnection patterns commonly remain for a relatively long time (they might last for weeks to several years), they are also referred to as preferred modes of low-frequency variability.

The most common and important LFVMs affecting NA are associated with the anomalies that occur over the Pacific and Atlantic oceans including changes in the tropical SSTs (Barnston et al., 1991). The well-known examples of internally generated variabilities in North America (NA) include Pacific Decadal Oscillation (PDO), ENSO, Atlantic Multidecadal Oscillation (AMO) and North Atlantic Oscillation (NAO). ENSO is known as one of the most influential LFVMs that can affect the variability of global extreme precipitation (Dai et al., 1997). We
analyzed the effects of 14 teleconnection signals on hydroclimatic extremes over western North America (WNA; Table 1).

<table>
<thead>
<tr>
<th>Teleconnection name</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arctic Oscillation</td>
<td>AO</td>
</tr>
<tr>
<td>Dipole Mode Index</td>
<td>DMI</td>
</tr>
<tr>
<td>East Atlantic</td>
<td>EA</td>
</tr>
<tr>
<td>Eastern Pacific</td>
<td>EP</td>
</tr>
<tr>
<td>North Atlantic Oscillation</td>
<td>NAO</td>
</tr>
<tr>
<td>El Niño-Southern Oscillation</td>
<td>Nino3.4</td>
</tr>
<tr>
<td>North Tropical Atlantic</td>
<td>NTA</td>
</tr>
<tr>
<td>El Niño-Southern Oscillation</td>
<td>ONI</td>
</tr>
<tr>
<td>Pacific Decadal Oscillation</td>
<td>PDO</td>
</tr>
<tr>
<td>Pacific/North American Pattern</td>
<td>PNA</td>
</tr>
<tr>
<td>Southern Annular Mode</td>
<td>SAM</td>
</tr>
<tr>
<td>Southern Oscillation Index</td>
<td>SOI</td>
</tr>
<tr>
<td>Trans Polar Index</td>
<td>TPI</td>
</tr>
<tr>
<td>West Pacific</td>
<td>WP</td>
</tr>
</tbody>
</table>

**Teleconnection impacts on extreme events**

Considering that LFVMs can influence regional hydroclimatic variables, there are two main questions that need to be addressed: which teleconnection signals can affect the hydroclimatic variables at a specific region? and how much can they explain the hydroclimatic variabilities? We used two statistical approaches to address these questions including composite analysis and maximum covariance analysis.

Composite analysis is a straightforward, non-parametric approach to analyze basic structural characteristics of hydroclimatic extreme events, including possible impacts of large-scale
variability modes on regional extremes (Zhang et al., 2010). Maximum Covariance Analysis (MCA) is a systematic approach to characterize the relationships between LFVMs and hydroclimatic variables. MCA analyzes the patterns, between a spatio-temporally varying hydroclimatic variable and LFVMs, which explain a maximum fraction of covariance between them. Wilks, (2015) showed that MCA is a suitable approach to capture atmospheric and oceanic processes. MCA analyzes the dominant modes of interaction robustly because of its comprehensive assessment of the relationship between the space-time datasets (Frankignoul, Chouaib and Liu, 2011).

1.3. Research Objectives

The overall objective of this research is to assess the observed and projected changes of hydroclimatic extreme events in WNA and understand the driving mechanisms. The first objective is to evaluate simulated changes of extreme hydroclimatic variables based on a Large Ensemble (LE) of downscaled General Circulation Models (GCMs) using gridded observations over western NA. The second objective is to assess future spatial and temporal changes in extreme Pr&T under climate change. The third objective is to characterize the uncertainties in GCM structures and model initialization and understand the roles of climate change and internal variability in characterizing extremes. The fourth objective is to quantify the influence of LFVMs on extremes over the study region. And the fifth objective is to assess projected changes in runoffs in selected watersheds in western NA using the large suite of downscaled GCMs.
1.4. Research questions

The following questions are addressed in this research:

- How do the spatial patterns of observed and GCM simulated extreme events compare in terms of both frequency and intensity?
- How do frequency and intensity of extreme events in WNA change under climate change?
- Are there consistencies between parametric and non-parametric analyses of extreme events?
- What are the uncertainties of GCMs? Are they reliable for further studies over the region?
- What is the relationship between LFVMs and hydroclimatic variables? Which LFVMs affect hydroclimatic variables in WNA and to what extent?
- What are projected changes in streamflow over the region?

1.5. Thesis organization

Chapter 2 provides a review of the literature related to climate change and its impacts on hydroclimatic extreme events. The first two sections of this chapter are about non-parametric and parametric approaches that are used to characterize climate extremes. It then discusses the effects of LFVMs.

Chapter 3 describes the methodology used to assess the impacts of climate change and LFVMs.

Chapter 4 presents the results, followed by summary and conclusions in Chapter 5.
Chapter 2

2. Literature review

According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) the global average surface temperature has increased by 0.85°C ± 0.20°C during 1880-2012 based on several observed datasets (Field et al., 2014). The warming rate has almost doubled between 1956-2005 compared to the last 100 years (1906-2005) (IPCC AR4) (Solomon et al., 2007). It is widely recognized that the resulting changes in extremes can be more significant compared to the means, and it is not possible to estimate extreme events, under climate change, by shifting the location of the climatological distribution (Katz and Brown, 1994; Najafi and Moazami, 2016). Previous studies on the historical and projected changes of the hydroclimate confirm that changes in the tails of a variable’s distribution (e.g. precipitation) are not consistent with changes in its mean (Klein Tank et al., 2003; Robeson, 2004; Kharin and Zwiers, 2005). In addition, changes in the tails of the temperature distribution may not be symmetric implying that Max/Min temperature may vary differently.

2.1. Assessment of Climate Change Impacts on Hydroclimatic Extremes

Climate Extreme Indices

Climate extreme indices (known as CLIMDEX) are defined by the Expert Team on Climate Change Detection and Indices (ETCCDI). These indices are used to represent projected extreme events based on simulated Pr&T from GCMs participating in the Coupled Model Intercomparison Projects Phase 3 (CMIP3) and Phase 5 (CMIP5) (Karl, Nicholls and Ghazi,
Observed changes of climate variables have been voiced since late 1950s (Tebaldi et al., 2006; Najafi, Zwiers and Gillett, 2016, 2017a, 2017b). Frich et al. (2002) analyzed both frequency and intensity of extreme events during the second half of the 20th century using 10 CLIMDEX indices. Their results show that global average Pr&T have increased in the late 20th century. A year after that Kiktev et al. (2003) analyzed the spatially distributed trends of six Pr&T based climate extreme indices using gridded observations and simulations. Their results were consistent with those of Frich et al. (2002). Alexander et al. (2006) assessed the global changes of extreme Pr&T during the 20th century using 27 indices. Their results showed that in the second half of the 20th century cold nights decreased by almost 70% while the number of warm nights and the intensity of temperature increased, with varying patterns around the world.

Since the beginning of 21st century, a number of studies have attempted to determine the observed and projected changes of extreme events under climate change. Using 10 Pr&T-based indices and a suite of Atmosphere-Ocean General Circulation Models (AOGCMs) Tebaldi et al., (2006) found that both temperature- and precipitation-based extreme indicators (representing frequency and intensity of extremes) will increase in the future. A study conducted by Sillmann and Roeckner (2008) showed that GCMs could capture the observed climatological large-scale patterns of six Pr&T-based indices. They also found projected global temperature increases over the 21st century as well as increases in precipitation intensity particularly in wet regions. Orlowsky and Seneviratne (2012) compared the characteristics of extreme events at the end of this century with current conditions at seasonal time-scale. Their results showed increases in high temperature events, decreases in cold extremes and non-uniform patterns of change in precipitation-related extremes. Sillmann et al. (2013) provided an overview of projected changes of climate extremes over the 21st century relative to a
reference period (1981-2000). They used different scenarios of climate change simulations using GCMs from the Coupled Model Intercomparison Project Phase 3 (CMIP3) and Phase 5 (CMIP5). Their results showed a disagreement on the sign of precipitation-based indices between models for some regions. Minimum temperature changes are more significant on a daily basis than maximum temperature, and most noticeable Pr&T changes occur under Representative Concentration Pathway (RCP) 8.5.

Although it is important to study the impacts of climate change on extreme events globally, it is also critical to characterize and determine changes in regional extreme events at a high spatial and temporal resolution to better understand and predict their socio-economic impacts. Future changes of extreme events and the role of climate variability are the primary concerns in determining the impacts of climate change (Tebaldi et al., 2006). Klutse et al. (2018) examined two precipitation and seasonal drought indices over West Africa under two global warming rates of +1.5 °C and +2 °C. They used a suite of 25 Regional Climate Models (RCMs) nested within 10 GCMs. Results showed increases in dry days and decreases in wet days over the study region. Ongoma et al. (2018) analyzed the variability of extreme events in the Equatorial East Africa over the 21st century. They used an ensemble of 18 (24) CMIP5 GCM precipitation (temperature) simulations based on RCPs 4.5&8.5 emission scenarios. Significant increases in the intensity and frequency of extreme temperature as well as increases in precipitation variability are projected by the end of the 21st century.

Although these aforementioned studies’ results are important for stakeholders’ long-term plans, they are mostly based on relatively coarse resolution data. In order to have a more accurate and precise overview of changes in extreme events, we need to use finer resolution data.
Extreme value theory

Analyzing the present and future characteristics of extreme Pr&T is critical for water management. Precipitation, which is the main component of the hydrological cycle, is characterized by natural spatial and temporal climate variability and anthropogenic human influence (Field, Christopher B., 2012). Extreme Value Theory (EVT) is a parametric statistical approach to work with probability distributions of extreme data. It has been widely used in hydroclimatic studies to analyze trends and estimate extremes with specific return periods. Beniston et al. (2007) compared changes of European heat waves, heavy precipitation, drought, windstorms, and storm surges over the historical and projected periods using RCMs. Their results showed that heavy precipitation will increase in central and northern Europe and will decrease in the south by the end of the 21st century. Fowler et al. (2007) used RCMs over Europe to assess the model uncertainty in simulating the future and historical changes of extremes using Generalized Extreme Value (GEV) distribution. They found that RCMs project increases in the intensity of both short and long-duration extreme precipitation for most parts of Europe, although individual model projections show varying results. They state that both the resolution and the number of ensemble members can affect the projection changes.

Extreme value theory has the flexibility to characterize nonstationary extremes by including additional explanatory variables or covariates such as time (Katz, 2013). Westra et al. 2013 determined the trends of the annual maximum precipitation events using global ground-based observations. Based on a nonstationary generalized extreme value analysis they found significant association between extreme precipitation and globally averaged near-surface temperature. Two-thirds of the stations showed an increase in the trends of extreme precipitation events. Sun et al. (2015) analyzed the effects of El-Nino Southern Oscillation (ENSO) as a low frequency variability signal on extreme precipitation using a Bayesian
regional extreme value model. They used 7000 high quality observation sites and took Southern
Oscillation Index (SOI), an index to measure ENSO, as a covariate to characterize the changes
in extreme precipitation. Their results showed that ENSO affected regions globally and
confirmed that ENSO is an important Low Frequency Variability Mode (LFVM) worldwide,
specifically in winters. Fix et al. (2018) used a 30-member ensemble under the RCP8.5
scenario and a 15-member ensemble under the RCP4.5 scenario to fit a nonstationary
distribution to determine temporal changes of extreme precipitation.

We compared changes of extreme precipitation and Max/Min temperature by fitting a GEV
distribution to their spatial annual maxima using high resolution gridded data in historical and
future time periods.

2.2. Impacts of LFVMs

LFVMs can significantly affect hydroclimatic variables over NA particularly in winters (Zhang
et al., 2010). Hurrell and Van Loon (1997) found PDO as an influential driver of the North
American climate. Low-flows over Western Canada are influenced by warm/dry conditions
during El Niño and positive phases of PDO and PNA (Bonsal and Shabbar, 2008). The effects
of ENSO, as a dominant LFVM, on the frequency of heavy precipitation was examined over
contiguous United States (Cayan, et al 1999; Gershunov and Cayan, 2003). Positive phase of
NAO was found to reduce the average winter precipitation over Canada (Stone, Weaver and
Zwiers, 2000).

Time-dependent spatial fields of data

Matrix method from linear algebra is a way of finding spatial and temporal structures in
datasets. Empirical Orthogonal Function (EOF) finds the structure that explains the maximum
variance of a two-dimensional dataset (i.e. one dimension represents its structure and the other
one is the dimension that the realization of the structure is sampled from (Briggs, 2007)).
Assuming that the structure dimension of a two-dimensional dataset represents coordinates of
the observed records (e.g. location of each grid or point) and the sampling dimension is time,
the analysis will result in a set of structures in the spatial dimension, which are called EOF’s.
Another set of structures that are related to one-to-one to the EOF’s are called Principal
Components (PC’s). Maximum Covariance Analysis is one of the approaches to find both
EOF’s and PC’s of two two-dimensional datasets. MCA is a widely used approached; however,
it is alternatively referred as Singular Value Decomposition (SVD) because the main process
of the methodology of MCA is done by SVD (Mo, 2003).
Large-scale linear relationship of two hydroclimatic variables have been studied since the late
20th century. Shabbar and Bonsal (2004) used Maximum Covariance Analysis (MCA) to find
how Canadian temperature linearly co-varies with the dominant patterns of the northern
hemisphere atmospheric and global oceanic circulation. Their results confirmed that ENSO has
a significant role in variability of winter cold and warm spells over Canada. Shabbar and
Skinner (2004) analyzed the linear relationship between Palmer Drought Severity Index (PDSI)
over Canada and previous winter Sea Surface Temperature (SST) patterns. They estimated
modes of MCA that explain more than 80% of the covariance between PDSI and SST.
According to their results, summer moisture availability in Canada is affected by ENSO,
Pacific Decadal Oscillation (PDO) and their interrelationship. Joly and Voldoire (2009) applied
MCA to find regions in West Africa where precipitation co-varies with ENSO using
observations and 16 CMIP3 GCM simulations in the 20th century. They showed that the
developing phase of ENSO influences West African Monsoon. Zarekarizi, et al. 2018 assessed
the relationship between a few precipitation-based extreme indices and climate tele-
connections over the Columbia River Basin (CRB) over the historical period using PMCA.
They found that East Pacific (EP), Western Pacific (WP), East Atlantic (EA) and North Atlantic Oscillation (NAO) are influential signals.

The impacts of LFVMs, specifically ENSO, strongly depend on the their timing onsets and the time lag of atmospheric response (Joly and Voldoire, 2009). Therefore, we analyze the relations between 14 LFVMs and average/extreme Pr&T considering three monthly lags. In addition, we quantify the contribution of each teleconnection to the variability of each component over western NA.

**Composite Analysis**

Composite analysis is a useful technique in meteorology or climatology to determine which LFVMs can significantly affect hydroclimatic variables. Kenyon and Hegerl (2010) used ground-based observations to determine the effects of LFVMs (including ENSO, NAO and North Pacific (NP)) on the global extreme precipitation. Zhang, et al. (2010) identified the statistical relationship between LFVMs (ENSO, PDO and NAO) and winter maximum daily precipitation over NA. They showed that increased likelihood of extreme precipitation over Southern NA corresponds to the positive phase of ENSO and PDO. Tan et al. (2016) analyzed the impacts of LFVMs (including ENSO, PDO and NAO) on monthly and seasonal maximum daily precipitation. Their results, based on composite analysis, showed that extreme precipitation is influenced by NAO patterns over almost half of stations in Canada, while relatively three fourths of the stations are statistically influenced by ENSO and PDO patterns.

In this study, we performed a comprehensive analysis of the relationships between average/extreme precipitation and temperature and almost all important LFVMs over WNA using composite analysis and observed gridded data.
Chapter 3

3. Methodology

3.1. Study area

The study area in WNA is located between the Pacific Ocean on the West and the Rocky and Columbia Mountain Ranges on the East. It has a complex topography and includes parts of British Columbia (BC) and Alberta (AL) in Canada, and four states in the USA (Washington, Oregon, Idaho and Montana) with a total area of 958,000 km$^2$ (Figure 2). We investigated extreme temperature, precipitation and runoff and their driving mechanisms over 4 major river basins including Fraser, Peace, Columbia and Campbell.

The Fraser River Basin (FRB) is one of the largest watersheds in western Canada that includes densely populated urban areas (such as the city of Vancouver) and diverse ecosystems. Almost 67% of BC’s population live in FRB with considerable socio-economic and cultural activities. It drains the western slopes of the North American Cordillera. FRB lies between the Coast Mountains and the Continental Divide, which originates from BC’s northeast (near Jasper, Alberta) and drains into the Pacific Ocean in the southwest. Due to its relatively large area (230,000 km$^2$) and elevation diversity (varies from the sea level to 4000m), it includes different climate zones (12 ecoregions and 9 biogeoclimatic zones (Shrestha et al., 2012)). The area ranges from dry interior plateaus and wet fertile valleys nearest the Pacific west coast to snowy mountains of the eastern Rockies. FRB’s major tributaries include the Stuart, Nechako, Quesnel, Chilcotin, Thompson and Harrison Rivers. According to gridded observations data derived from Environment and Climate Change Canada’s climate station observations, the mean annual temperature in FRB varies between -5°C to 10°C and its precipitation ranges between 200 mm–5000 mm.
The Peace River Basin (PRB) located in Northern British Columbia and extending to Alberta drains an area of approximately 101,000 km$^2$. It stretches from BC’s border to the Smoky river comprising small rivers and creeks such as Hines, Jack, McLean, Lathrop and Sweeney Creeks and Eureka, Clear, and Montagneuse Rivers, and a number of lakes, including the George Lake. The Wapiti-Smoky River, which drains the front ranges of the Rockies, is the main tributary downstream. PRB plays a major role in hydropower generation and is regulated by the W.A.C. Bennett Dam and companion Williston Lake Reservoir (Romolo et al., 2006). PRB originates from the Rocky Mountains and passes 1100 km before flowing into the Southwestern tip of the Lake Athabasca. The elevation of PRB ranges from 400m to 2800m, while the range of its continental climate average is between -11.7°C in January and 12.4°C in July. Most of the annual precipitation over the PRB occurs between October-April and relatively 51% of the precipitation falls as snow (Najafi, Zwiers and Gillett, 2017a).

The Columbia River Basin (CRB), also known as “the most managed river system in the world” (with many dam and flow control structures) (Nehlsen, Williams and Lichatowich, 1991), consists of the third largest river in the USA in terms of the flow volume (i.e. Columbia River). The Columbia river is 1954 km long and drains and area of approximately 616,417 km$^2$. The Kootenai and Flathead/Pend ‘Oreille Rivers, which cross the United States-Canada border, the Snake and Willamette Rivers are its major tributaries. The CRB is mainly a snowmelt driven (nival) system (Pulwarty and Redmond, 1997) and receives most of its precipitation in the winter and the remaining 20% in June to August. Almost half of CRB’s runoff outflows from 16% of the basin that lies in Canada. CRB has a wide range of average annual precipitation from almost 200mm over eastern Rockies, including the Snake River basin, to more than 1500mm in the coastal mountains. The temperature of CRB, as a humid-continental climate basin, varies between -9.2°C in January to 13.3°C in July.
The Campbell River Basin (CaRB) is in between the dry east and wet west coast climate in the Vancouver Island in southwestern Canada. The Campbell River is 33km long, originates from Strathcona provincial park and drains an area of 1193 km$^2$. CaRB consists of three lakes (Buttle Lake and Upper Campbell Lake, Lower Campbell Lake and John Hart Lake) has a mixture of nival/pluvial regime. CaRB has high streamflow volume during Falls and Springs and low flows in the summers (Mandal, Srivastav and Simonovic, 2016). CaRB’s elevation varies significantly compared to its area and ranges between 139–2200m with an average elevation of 932m. Average minimum January temperature is -4°C, while the average maximum July temperature is 16°C. CaRB is among the basins that receive great amount of precipitation in western Canada with a total average annual precipitation of 5716mm (Bennett, Werner and Schnorbus, 2012). CaRB receives almost 80% of its precipitation between October to March and 45% of the total precipitation falls as snow (Najafi, Zwiers and Gillett, 2017b).
This study analyzes the hydroclimatic extreme events and determine their relationship with large-scale climate variabilities over four key basins in Pacific Northwest (FRB, UPRB, CRB and CaRB) covering more than 958 thousand square kilometers (Figure 2). Not only the area is so large to use high-resolution data for, but also the elevation varies a lot within the study area, which makes the precipitation and temperature over the study area fluctuated.

Moreover, the impact of climate change on streamflow is assessed over the Kootenay (Kootenai) River Basin (KRB). The KRB (Figure 3) is a major river basin in southeastern British Columbia and northern Montana and Idaho in the United States. The KRB, whose outlet is Skookumchuck, is the second largest tributaries of the Columbia River. The length of KR is 781 kilometres and it originates from its headwaters in the Kootenay Ranges of the Canadian
Rockies with the mean elevation of 1800 meters. The KRB is divided into three sub-watersheds draining approximately 13000 km². The range of temperature is from below freezing in winters to 30 °C in summers. The annual peak flows of the KRB exceed 660 m³/s routinely.

Figure 3. Kootenay River Basin

3.2. Data

The analyses are conducted using high-resolution observations and simulations at 1/16° spatial and daily temporal resolution. This section describes downscaled data, gridded observations, General Circulation Models and Large Ensemble climate simulations used in this study.
3.2.1. Daily Gridded Observation

Daily gridded observed precipitation, Max/Min temperature at 1/16° spatial and daily temporal resolution are provided by the hydrology team at the Pacific Climate Impacts Consortium (PCIC) that covers 1951-2010. Observation dataset is obtained in NetCDF (*.nc) file format and is accessed and analyzed using R statistical programming language.

3.2.2. General Circulation Models

Hydroclimatic extremes are influenced by internal variability, natural (e.g. changes in solar radiation, volcanic eruptions) and anthropogenic forcing factors (e.g. increases in GHG concentrations including CO2, CH4 etc.). General Circulation Models (GCMs) are complex atmosphere-ocean-land numerical models that are commonly used to understand changes of extreme events in response to human-induced climate change and the role of internal variability/forcing response and predict projected changes in hydroclimatic variables in the future. We use a set of GCM simulations that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Meehl et al., 2000). In addition, we use a large set of simulations (50 ensemble runs) from a single GCM (i.e. CanESM2) to better understand the uncertainties in model structures and initialization, the role of internal variability and forcing response in hydroclimatic extremes of WNA, and predict the projected changes of extreme events (Tebaldi and Knutti, 2007; Tebaldi, Arblaster and Knutti, 2011; Deser, Knutti, Solomon and Adam S Phillips, 2012; von Storch and Zwiers, 2013).
**GCM Downscaling**

GCMs contain large-scale information of the hydroclimate system (including forcing responses and internal variabilities), however they have a coarse spatial resolution and cannot be used to analyze hydroclimatic extremes at local scales particularly in regions with complex topography (Mearns *et al.*, 2001). Downscaling, which is the process of translating coarse resolution GCM simulation outputs to regional hydroclimatic variables at fine spatiotemporal resolution, is commonly categorized into two approaches: statistical downscaling and dynamical modeling (Haylock *et al.*, 2006; Najafi, Moradkhani and Wherry, 2011). In dynamical downscaling, Regional Climate Models (RCMs) are nested within GCMs to represent the historical/future physical processes at a high resolution (Christensen and Christensen, 2004; Pal, Giorgi and Bi, 2004; Frei *et al.*, 2006; Fowler *et al.*, 2007; Wood *et al.*, 2004). This approach is computationally demanding and can be time consuming. The other drawback of dynamical downscaling is the dependency of RCMs on boundary conditions obtained from GCMs and lack of transferability to different regions (Mandal, Srivastav and Simonovic, 2016).

Statistical downscaling methods find empirical linear/nonlinear relationships between large scale predictors (i.e. GCM outputs) and local scale predictands (e.g. local precipitation) using a variety of statistical techniques (Wilby and Wigley, 1997). One of the advantages of statistical downscaling is its simplicity and flexibility (requiring relatively straightforward modifications for use at various locations) compared to dynamical downscaling approach. Which has made it popular among researchers.

In this study, we used GCM simulations that are downscaled statistically using a state-of-the-art method called Bias Correction/Constructed Analogues with Quantile mapping reordering (BCCAQ) and provided by PCIC (Werner and Cannon, 2016). This method combines Bias
Correction Constructed Analogues (BCCA) with Bias Corrected Climate Imprint delta method (BCCI) and is suitable for the analysis of extreme events (Cannon, Sobie and Murdock, 2015).

**CMIP5 GCMs**

We analyzed outputs from seven CMIP5 GCMs (including precipitation, minimum and maximum temperature) for historical (1981-2010) and future (2060-2089) time periods, which include ACCESS1-0, ACCESS1-3, CanESM2, CCSM4, CNRM-CM5, HadGEM2-ES, and MPI-ESM-LR (Table 2). All GCMs are downscaled using the BCCAQ approach based on the Representative Concentration Pathway (RCP)8.5 (Werner and Cannon, 2016).

<table>
<thead>
<tr>
<th>GCM</th>
<th>Institution</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS1-0</td>
<td>ARC Centre of Excellence for Climate System Science</td>
</tr>
<tr>
<td>ACCESS1-3</td>
<td>ARC Centre of Excellence for Climate System Science</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
</tr>
<tr>
<td>CCSM4</td>
<td>University Corporation for Atmospheric Research (UCAR)</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Meteorologiques / Centre Europeen</td>
</tr>
<tr>
<td></td>
<td>de Recherche et Formation Avancees en Calcul Scientifique</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Met Office Hadley Centre ESM</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max Planck Institute for Meteorology (MPI-M)</td>
</tr>
</tbody>
</table>
CanESM2 Large Ensemble (LE) Simulations

A large ensemble of 50 climate simulations based on the CanESM2 model (CanESM2-LE) are used to distinguish the uncertainties in model structure and internal variability and assess the roles of forcing responses and variability in regional hydroclimatic extremes. These simulations represent changes in the initialization of the CanESM2 GCM. Hence, the modeling uncertainty boundary would cut off due to the unit structure of the simulation model. Similar to other GCMs, we used downscaled precipitation, minimum and maximum temperature over the historical (1981-2010) and future (2060-2089) periods. The Large Ensemble simulations have been downscaled by PCIC to 1/16° resolution using BCCAQ under the RCP8.5 emission scenario (Werner and Cannon, 2016).

All datasets are obtained in *.nc file format and are accessed and analyzed using R statistical programming language.

3.3. Methods

The statistical and process-based models to assess the impacts of climate change and LFVMs on hydroclimatic extremes in WNA are described in this section, which include: climate extreme indices, Generalized Extreme Value distribution, composite analysis, maximum covariance analysis and hydrological modeling. Figure 4 briefly demonstrates the flowchart of methodologies.
3.5.1. Climate extreme indices

Climate extreme indices (i.e. CLIMDEX) were defined by Expert Team on Climate Change Detection and Indices (ETCCDI). Most of these indices represent moderate extremes that occur at least once a year (Zhang et al., 2011). There are 27 CLIMDEX indices available that are based on daily data from which 16 are temperature-based and 11 are precipitation-based. Some indices can be used to estimate hydroclimatic extremes with long return periods using annual maximum data with sufficient length (Zhang et al., 2011).
CLIMDEX can be divided into two categories. One that characterizes the amounts of maximum/minimum temperature and precipitation and the other that measure the number of days in a year when extremes exceed certain threshold (Zhang et al., 2011). Analysis of both types of indices are critical for the design and planning of structure and infrastructure, agricultural and water resources management. Through a comprehensive literature review, we selected eight indices that best represent the intensity and frequency of extreme temperature (3 indices) and precipitation (5 indices) (Karl, Nicholls and Ghazi, 1999b; Zhang et al., 2005). These indices are described in Table 3.

**Table 3. Climate extreme indices (CLIMDEX) that are analyzed in this study**

<table>
<thead>
<tr>
<th>Index Name</th>
<th>ID</th>
<th>Definition</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Growing Season Length</td>
<td>GSL</td>
<td>Annual¹ count between the first span of at least 6 days with daily mean temperature TG &gt;5°C and the first span after July 1st (Jan 1st in SH) of 6 days with TG &lt;5°C. Let TGij be daily mean temperature on day i in year j. Count the number of days between the first occurrence of at least 6 consecutive days with TGij &gt; 5°C and the first occurrence after 1st July (Jan 1st in SH) of at least 6 consecutive days with TGij &lt; 5°C.</td>
<td>days</td>
</tr>
<tr>
<td>Max Tmax</td>
<td>TXx</td>
<td>Let TXx be the daily maximum temperatures in month k, period j. The maximum daily maximum temperature each month is then TXxkj = max(TXxkj).</td>
<td>°C</td>
</tr>
</tbody>
</table>

¹ Annual means Jan 1st to Dec 31st in the Northern Hemisphere (NH); July 1st to June 30th in the Southern Hemisphere (SH).
<table>
<thead>
<tr>
<th>Min Tmin</th>
<th>TNn</th>
<th>Let TNn be the daily minimum temperatures in month k, period j. The minimum daily minimum temperature each month is then TNnkj=min(TNnkj) °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Heavy Precipitation Days</td>
<td>R10</td>
<td>Let RRij be the daily precipitation amount on day i in period j. Count the number of days where RRij ≥ 10mm days</td>
</tr>
<tr>
<td>Max 5-day Precipitation Amount</td>
<td>RX5day</td>
<td>Let RRkj be the precipitation amount for the 5-day interval ending k, period j. Then maximum 5-day values for period j are Rx5dayj = max (RRkj) mm</td>
</tr>
<tr>
<td>Simple Daily Intensity Index</td>
<td>SDII</td>
<td>Let RRwj be the daily precipitation amount on wet days, w (RR ≥ 1mm) in period j. If W represents number of wet days in j, then: [ SDII_j = \frac{\sum_{w=1}^{W} RR_{wj}}{W} ] mm/day</td>
</tr>
<tr>
<td>Very Wet Days</td>
<td>R95pTOT</td>
<td>Let RRwj be the daily precipitation amount on a wet day w (RR ≥ 1.0mm) in period i and let RRw95 be the 95th percentile of precipitation on wet days in the 1961-1990 period. If W represents the number of wet days in the period, then: [ R95_{pTOT} = \sum_{w=1}^{W} RR_{wj} \quad where \quad RR_{wj} &gt; RR_{w95} ] mm</td>
</tr>
</tbody>
</table>
Let $RR_{ij}$ be the daily precipitation amount on day $i$ in period $j$. Count the largest number of consecutive days where $RR_{ij} < 1\text{mm}$.

### 3.5.2. Generalized Extreme Value Distribution

Extreme Value Theory (EVT) is an effective statistical approach to analyze extremes that can occur beyond the range of available data (Cooley, 2013), which is suited for engineering design. Using this parametric method the return levels and return periods of desired events can be found to quantify and describe the related risks (Coles et al., 2001; Najafi and Moradkhani, 2013, 2014). Return period is defined as the “average recurrence interval” or the average time between reoccurrence of an event (Olsen, Lambert and Haimes, 1998). Given this definition, an $m$-year return level event (such as a 50-year flood) is associated with a return period of $m$ years. Return level is assume to be unchanged throughout the study time period under the stationary assumption (Coles et al., 2001).

EVT fits a theoretically justified distribution to a subset of records of extremes. Two common approaches to extract the subset of extreme data are: a) Peaks over threshold (POT) and b) Block Maxima. Let $\{X_t\}$ denote a time series of the quantity of interest, for example daily total precipitation. Based on POT a threshold is defined and data exceeding the threshold are selected as extreme events. The theory recommends modeling the threshold exceedance data using Generalized Pareto (GP) distribution or an equivalent point process representation (Dupuis, 1999).
The other approach is to categorize data into blocks of time (e.g. annual) and take the maximum value of each block (Block Maxima). Consequently, the number of selected extremes will be equal to the number of blocks. The blocks should be fixed and large enough to assume that the asymptotic results provide a good approximation (Cooley, 2013; Najafi and Moradkhani, 2013). Annual blocks of 30 years (1981-2010) were chosen in this study. Thus, the theory recommends fitting a Generalized Extreme Value (GEV) distribution. GEV includes Gumbel, Fréchet and Weibull distributions, also known as type I, II and III extreme value distributions, respectively (Früh et al., 2010) having the flexibility to take a continuous range of shapes. GEV is characterized by three parameters:

- Location parameter ($\mu \in \mathbb{R}$) moves the entire distribution along the x-axis.
- Scale parameter ($\sigma > 0$) modifies the peak of the distribution. In other words, it stretches or shrinks the distribution.
- Shape parameter ($\zeta \in \mathbb{R}$) describes the tail of the distributions and determines the type of the GEV distribution i.e. Gumbel (unbounded), Fréchet (heavy upper tailed) and Weibull (bounded) distributions corresponding to $\zeta = 0$, $\zeta > 0$, and $\zeta < 0$, respectively.

GEV’s Probability Density Function (PDF) is shown in equation 1.

Equation 1.

$$f(z = \frac{x - \mu}{\sigma}) = \begin{cases} 
\frac{1}{\sigma} \exp\left(-\left(1 + \frac{z}{\zeta}\right)^{1/\zeta}\right) \left(1 + \frac{z}{\zeta}\right)^{-1} \zeta, & \zeta \neq 0 \\
\frac{1}{\sigma} \exp(-z - \exp(-z)), & \zeta = 0
\end{cases}$$

where $\zeta$, $\sigma$, $\mu$ are the shape, scale, and location parameters, respectively.

GEV distribution range is defined based on the shape parameter ($\zeta$) in equation 2:
Equation 2.

\[
\begin{cases}
1 + \frac{\zeta x - \mu}{\sigma} > 0, & \text{for } \zeta \neq 0 \\
-\infty < x < +\infty, & \text{for } \zeta = 0
\end{cases}
\]

In this study, we calculate the annual maximum precipitation, and annual maximum/minimum temperature (tasmax/tasmin) based on gridded observations over the historical period and GCMs/LE runs over the historical and future periods. GEV distribution is fitted to the annual max/min data using the Maximum Likelihood Estimation (MLE) method. Common design return periods include the 2-, 10-, 25-, 50-, 100-, and even 500-years. The values of aforementioned return periods can be calculated based on the statistics of the flow record. Given the available data and their associated length, extreme Pr&T events with return periods of 50 and 100 years (i.e. exceedance probabilities of 2% and 1%) are estimated for the observed and simulated datasets for each time period.

3.5.3. Composite Analysis

Composite analysis is a statistical method to determine some of the basic structural characteristics of a meteorological or climatological phenomenon that is difficult to observe in totality (e.g. large-scale climate circulations, hurricanes, etc.). We determined the impacts of 14 Low Frequency Variability Modes (LFVMs) on western North America (WNA)’s tasmin, tasmax and maximum precipitation over extended winter (November-December-January-February) based on composite analysis (Zhang, Wang, Zwiers and Groisman, 2010). Analysis was conducted over each 1/16° grid.

The composites of low (X_{low}) and high (X_{high}) values of temperature/precipitation were calculated for 5 highest and lowest phases of LFVMs over 1945-2012. X_{low} and X_{high}
correspond to the cold and warm phase of each LFVM for each grid during winter, respectively.

The impact of a specific LFVM on the local precipitation/temperature is estimated by the composite difference between 5 year averages ($\bar{X}_{\text{low}} - \bar{X}_{\text{high}} = \Delta \bar{X}$) (Zhang, Wang, Zwiers, Groisman, et al., 2010). We used bootstrapping to test whether the effects of LFVMs are statistically significant. To put it in detail, the averages of extended winter maximum daily precipitation for two 5-year randomly selected are computed for each grid. Then the difference of the averages is computed ($\Delta \bar{X}_i$). Using a Monte Carlo resampling approach 1000 estimates of $\Delta \bar{X}_i$ are generated. If $\Delta \bar{X}$ is equal to or smaller than 2.5th percentile of $\Delta \bar{X}$ or it is equal to or larger than 97.5th percentile of $\Delta \bar{X}$ the association between the hydroclimatic variable and the corresponding LFVM is statistically significant at the 5% significance level. Figure 5 shows how composite analysis works.

![Figure 5. Composite Analysis flowchart](image-url)
This process is repeated for each LFVM for each grid cell. Since hydroclimatic extreme events (e.g. precipitation and temperature) commonly occur locally at (sub)daily scales while large-scale climate variabilities (i.e. LFVMs) are usually seasonal (Zhang, Wang, Zwiers, Groisman, et al., 2010), we also determined the association between hydroclimatic variables and LFVMs considering time lags of one and two months.

3.5.4. Maximum Covariance Analysis

Maximum Covariance Analysis (MCA) captures the patterns of two space-time datasets that explain the maximum fraction of covariance between them. MCA is a general decomposition of the covariance matrix between two datasets that have one dimension in common (e.g. time) (Levine et al., 2013). Consider two matrices $X[m \times n]$ and $Y[q \times n]$, where $n$ is the number of samples (e.g. time) and $m$ and $q$ are the numbers of standardized $X$ and $Y$ variables, respectively ($X$ represents temperature or precipitation spatially distributed over the study region and $Y$ represents LFVMs). Therefore, $n$ is the same-sized dimension whereas $m$ and $q$ are different among $X$ and $Y$ matrices. Covariance matrix between $X$ and $Y$ is calculated:

Equation 3.

$$C = \frac{1}{n} \times X \times Y^T$$

where $C$ is the covariance matrix between $X$ and $Y$ and $T$ represents the transpose of matrix $Y$.

Singular Value Decomposition (SVD) is then applied on the covariance matrix ($C$):

Equation 4.

$$C = \frac{1}{n} \times X \times Y^T = U\Sigma V^T$$
Singular values are the square roots of the eigenvalues between X and Y. U and V are \([m \times r]\) and \([p \times r]\) matrices representing the singular vectors of spatial patterns of X and Y, respectively. In other words, U and V are different patterns such that the projected data onto these patterns (shown in equation 5 and 6) exhibit maximum covariance with the projection onto any other patterns. \(\Sigma\) is a diagonal matrix \([r \times r]\) \((r \leq \min(m, q, n - 1))\) The diagonal values of \(\Sigma\) are non-negative singular values \(\sigma(i = 1, 2, ..., r)\) arranging in descending order with \(r \leq \min(m, q, n - 1)\). In other words, each \(\sigma\) shows the strength of pair of patterns of MCA. The first pair of U and V (singular vectors) explains the largest fraction of the quadratic covariance (first \(\sigma\)), and other pairs describe largest fractions of the quadratic covariance not explained by previous pairs.

Temporal expansion coefficients of left and right field structures (X and Y matrices) are described as matrices A and B whose columns are time series, which characterize each variability mode of LFVMs. To put it in different words, A and B are the projected X and Y onto the patterns (U and V). The \([n \times r]\) matrices A and B should satisfy the following equations.

Equation 5.

\[
A = X^T \times U
\]

Equation 6.

\[
B = Y^T \times V
\]

Since we standardized the left field dataset (X), and the right field dataset (Y) is already standardized (large-scale climate anomalies) the results of MCA are not very different from Canonical Correlation Analysis (CCA) except the orthonormality of MCA singular vectors to each other and uncorrelated expansion coefficients (Mo, 2003). The results of each modes of
MCA are assessed through the Square Covariance Fraction (SCF) defined as equation 7. The proportion of covariance explained by the each pattern is shown by SCF.

Equation 7.

\[ SCF_k = \frac{\sigma_k^2}{\sum \sigma_i^2} \]

Where \( k \) represents each mode of MCA (i.e. \( k = 1, 2, \ldots, r \)).

In this study matrix \( X \) refer to a) spatial average precipitation b) spatial maximum precipitation and c) average temperature over extended winter for more than half of a century (i.e. 1950-2010) and matrix \( Y \) refers to 14 large-scale climate variability modes (LFVMs) over extended winter within the same period of time with 3 different time lags (i.e. no lag, one- and two-month lags). First column of \( U \) and \( V \) (\( U_k \) and \( V_k \)) are respectively the coefficient related to \( X \) and \( Y \) for the mode 1 of MCA that has the largest fraction of quadratic covariance. Furthermore, first column of \( A \) and \( B \) (\( A_k \) and \( B_k \)) are the temporal expansion coefficient related to \( X \) and \( Y \), respectively.
Chapter 4

4. Results and discussion

The results obtained from the analysis of hydroclimatic extremes and the driving mechanisms are presented in this section. Observed and simulated annual maximum (AM) precipitation (Pr) and temperature (T) are analyzed, followed by non-parametric extreme analysis based on CLIMDEX to assess the impacts of climate change on an annual/monthly basis and evaluate temporal changes. We then discuss the historical and projected extremes based on the parametric EVT approach. Finally, the relationships between LFVMs and regional hydroclimatic extremes are presented.

4.1. Temporal changes of the annual maximum precipitation and temperature

Temporal changes in the AM Pr&T are assessed for each river basin using high-resolution gridded observation, a large ensemble of 50 simulations based on CanESM2-LE and 7 GCMs (Single Run GCMs or SR_GCMs). Table 4 shows the average future (2060-2089) changes of the annual maxima compared to 1981-2010 based on multi-model ensemble means. Overall, the annual hydroclimatic maxima (i.e. Pr&T) are projected to increase in the future based on CanESM2-LE and CMIP5 GCMs. PRB has the lowest precipitation increase of 5.04 mm (7.44 mm) according to CanESM2-LE (SR_GCMs), while CaRB has the largest change in the AM precipitation with 21.39 mm (18.3 mm) increase according to CanESM2_LE (SR_GCMs ). CRB is projected to get warmer at a slower rate compared to the other three basins with 6.86°C (6.56°C) increase in maximum tasmax and 6.91°C (5.97°C) increase in maximum tasmin based on CanESM2_LE (SR_GCMs). FRB shows the highest rate of increase with 8.98°C (7.3°C)
increase in maximum tasmax and 7.75°C (6.84°C) increase in maximum tasmin based on CanESM2_LE (SR_GCMs).

Table 4. The changes of AM from historical to future period over WNA (FRB, PRB, CRB, CaRB)

<table>
<thead>
<tr>
<th>hydroclimatic variables</th>
<th>FRB</th>
<th>UPRB</th>
<th>CRB</th>
<th>CaRB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CanESM2_LE GCM</td>
<td>CanESM2_LE GCM</td>
<td>CanESM2_LE GCM</td>
<td>CanESM2_LE GCM</td>
</tr>
<tr>
<td>max Pr (mm)</td>
<td>10.45</td>
<td>7.68</td>
<td>0.04</td>
<td>7.44</td>
</tr>
<tr>
<td>max tasmax (°C)</td>
<td>8.98</td>
<td>7.3</td>
<td>8.94</td>
<td>8.19</td>
</tr>
<tr>
<td>max tasmin (°C)</td>
<td>7.75</td>
<td>6.84</td>
<td>7.46</td>
<td>6.6</td>
</tr>
</tbody>
</table>

Relative changes of the AM precipitation and temperature over WNA from the historical to the future periods are shown in Table 5. Highest relative increases in Max precipitation are projected to occur in FRB at 30% (23%) followed by CRB at 29% (24%) based on CanESM2_LE (SR_GCMs), respectively. AM tasmax is projected to increase in PRB by 30% (28%) in the future followed by FRB with 29% (24%) increase according to CanESM2_LE (SR_GCMs). AM tasmin increases are relatively large over the entire WNA (> 50%) with lowest increases of 43% (38%) in CRB based on CanESM2_LE (SR_GCMs).

Table 5. Same as table 4 but in percentage

<table>
<thead>
<tr>
<th>hydroclimatic variables</th>
<th>FRB</th>
<th>UPRB</th>
<th>CRB</th>
<th>CaRB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CanESM2_LE GCM</td>
<td>CanESM2_LE GCM</td>
<td>CanESM2_LE GCM</td>
<td>CanESM2_LE GCM</td>
</tr>
<tr>
<td>max Pr</td>
<td>30</td>
<td>23</td>
<td>14</td>
<td>24</td>
</tr>
<tr>
<td>max tasmax</td>
<td>29</td>
<td>24</td>
<td>30</td>
<td>28</td>
</tr>
<tr>
<td>max tasmin</td>
<td>58</td>
<td>55</td>
<td>56</td>
<td>52</td>
</tr>
</tbody>
</table>

Spatially averaged temporal changes of the AM precipitation, tasmax and tasmin over FRB, PRB, CRB and CaRB based on observations, and downscaled GCM simulations are shown in Figures 6-9. Shaded colors (blue for SR_GCMs and red for CanESM2_LE) show the 2.5-97.5% uncertainty ranges of GCM simulations. Uncertainties in the projected hydroclimatic extremes are higher compared to the historical ones, which implies that the corresponding variabilities would increase in the future.
Highest variations of AM tasmax are seen in CaRB that vary between 22.5°C in 1999 to 30.2°C in 2007. Max precipitation shows larger variability compared with Max tasmin and tasmax. CaRB has the largest variability in AM precipitation, between 48mm in 1985 and 110mm in 2004, possibly because of its close distance to the Pacific Ocean. The CRB has the highest variability in Max tasmin with 12.4°C in 1993 and 16.4°C in 2006.
Figure 6. Changes in the AM precipitation, tasmax and tasmin over FRB. The black solid line represents the observations; blue and red shades show the 95th quantiles of seven GCMs and 50 CanESM2-LE runs, respectively, over historical (1981-2010) and future (2060-2089) periods.

Figure 7. Changes in the AM precipitation, tasmax and tasmin over PRB. The black solid line represents the observations; blue and red shades show the 95th quantiles of seven GCMs and 50 CanESM2-LE runs, respectively, over historical (1981-2010) and future (2060-2089) periods.
Figure 8. Changes in the AM precipitation, tasmax and tasmin over CRB. The black solid line represents the observations; blue and red shades show the 95th quantiles of seven GCMs and 50 CanESM2-LE runs, respectively, over historical (1981-2010) and future (2060-2089) periods.
Figure 9. Changes in the AM precipitation, tasmax and tasmin over CoRB. The black solid line represents the observations; blue and red shades show the 95th quantiles of seven GCMs and 50 CanESM2-LE runs, respectively, over historical (1981-2010) and future (2060-2089) periods.

CanESM2_LE captures the observed variability of AM Pr&T better than SR_GCMs based on the corresponding values of the P-factor (Table 6), which is defined as the percentage of observations that lie within the given uncertainty bounds. P-factors vary between 0 and 1 showing the worst and best performance of the ensemble simulation, respectively. The
uncertainty ranges of the CanESM2_LE, however, are larger compared to those of SR_GCMs, based on the values of the R-factor, which represents the average width of the uncertainty bounds divided by the standard deviation of the observations (Table 7). In other words, CanESM2_LE capture the variables better partly because they have larger uncertainty bounds.

**Table 6. P-factors of CanESM2_LE and SR_GCMs for four key river basins over WNA (FRB, PRB, CRB, CaRB)**

<table>
<thead>
<tr>
<th>hydroclimatic variables</th>
<th>FRB</th>
<th>UPRB</th>
<th>CRB</th>
<th>CaRB</th>
</tr>
</thead>
<tbody>
<tr>
<td>max Pr (mm)</td>
<td>0.93</td>
<td>0.83</td>
<td>0.93</td>
<td>0.67</td>
</tr>
<tr>
<td>max tasmax(°C)</td>
<td>0.97</td>
<td>0.87</td>
<td>0.73</td>
<td>0.87</td>
</tr>
<tr>
<td>max tasmin(°C)</td>
<td>0.9</td>
<td>0.67</td>
<td>0.93</td>
<td>0.7</td>
</tr>
</tbody>
</table>

**Table 7. R-factors of CanESM2_LE and SR_GCMs for four key river basins over WNA (FRB, PRB, CRB, CaRB)**

<table>
<thead>
<tr>
<th>hydroclimatic variables</th>
<th>FRB</th>
<th>UPRB</th>
<th>CRB</th>
<th>CaRB</th>
</tr>
</thead>
<tbody>
<tr>
<td>max Pr (mm)</td>
<td>3.73</td>
<td>2.88</td>
<td>3.69</td>
<td>2.19</td>
</tr>
<tr>
<td>max tasmax(°C)</td>
<td>4.38</td>
<td>3.12</td>
<td>4.94</td>
<td>3.19</td>
</tr>
<tr>
<td>max tasmin(°C)</td>
<td>4.1</td>
<td>2.92</td>
<td>4.38</td>
<td>2.93</td>
</tr>
</tbody>
</table>

**4.2. Spatial changes in indices of extreme precipitation and temperature for WNA**

This section presents the projected changes of climate extreme indices over WNA at a relatively high resolution (i.e. 1/16°) under climate change. Spatial distribution of temperature-intensity (TNN, TXX and frequency: CDD) and precipitation-based (intensity: GSL, R10 and frequency: R95PTOT, RX5day and SDII) indices (i.e. CLIMDEX) are calculated using gridded observations, CanESM2_LE and SR_GCM simulations over the historical (1981-2010) and future (2060-2089) time periods.
West CRB is the warmest region in WNA in terms of the average TNN during the late 20th century, while the coldest regions over the same period are north PRB and northwest FRB along the Coast Mountains (Figure 10). We calculate the multi-model averages of the downscaled CanESM2_LE (50 members) and SR_GCMs (7 members) runs at each grid cell over WNA. Simulations represent the historical spatial patterns of TNN accurately over the entire domain except west central FRB and CRB where they underestimate the observed temperature. Both simulations show future increases in TNN over all locations, however CanESM2_LE projects more intense increases.

Upper CRB, along the Columbia Mountains, west central regions of PRB, western FRB and CaRB, which is a coastal basin, show the lowest TXX values over the late 20th century, while the warmest region is in west central CRB (Figure 10). Both CanESM2_LE and SR_GCMs ensemble means represent the spatial variations of TXX over the historical period throughout the domain accurately. According to future simulation, the entire WNA will face a significant increase in the intensity of TXX particularly over FRB, along Coast Mountains, and CRB, along Columbia Mountains. CanESM2_LE project more intense TXX projections compared to SR_GCMs.
Figure 10. Spatial average Changes of TNN and TXX based on gridded observations, CanESM2_LE and SR_GCM simulations over the historical (1981-2010) (first rows) and future (2060-2089) (second rows) periods over WNA.
Regions in the center and west of CRB have higher frequencies of consecutive dry days over the late 20th century compared to other parts of WNA, while the least number of consecutive dry days occur along eastern FRB and central PRB (Figure 11). Similar to TNN both GCM ensembles slightly underestimate the consecutive dry days in west central CRB and upper PRB. The frequencies of dry days in a row are projected to increase over CaRB and southwestern FRB and decrease in parts of central CRB. Areas that are affected by increases in TXX and TNN (temperature-based) and CDD (precipitation-based) can experience dramatic hydroclimatic conditions that can cause severe socioeconomic consequences.

West CRB has the longest growing season length over WNA and is the most suitable region for cultivation (Figure 11). Areas with the lowest TXX values (Upper CRB, along the Columbia Mountains, center to west of PRB, western FRB and CaRB, which is a coastal basin) have shorter growing season lengths compared to the other regions in WNA. Both CanESM2_LE and SR_GCMs capture the observed spatial pattern of this temperature-based extreme index in terms of frequency. Based on these simulations the length of the growing season is projected to increase in the future period throughout the entire domain with the longest records in west, south and central parts of CRB and shortest records in northwestern PRB.
Figure 11. Spatial average Changes of CDD and GSL based on gridded observations, CanESM2_LE and SR_GCM simulations over the historical (1981-2010) (first rows) and future (2060-2089) (second rows) periods over WNA.
The figures of spatial average number of days, precipitation in very wet days, precipitation intensity and 5-day maximum precipitation are shown in appendix 1-2. The coastal regions including southwest FRB, western parts of CRB and CaRB, and the mountainous areas including eastern parts of CRB and FRB and central PRB, which are along the Upper Rocky Mountains and Columbia Mountains, have the highest number of wet days (Appendix 1). Southern and central parts of CRB, central and west central FRB have the lowest number of wet days in the late 20th century. The average numbers of observed wet days over the entire domain are well represented by CanESM2_LE and SR_GCMs ensemble means. The number of wet days with more than 10 mm precipitation is projected to increase over western PRB and parts of the Rockies, with less pronounced changes in other parts of WNA.

The spatial pattern of the average precipitation in very wet days (R95) over WNA is similar to the one for the number of wet days (Appendix 1) showing largest values in southwestern FRB, western parts of CRB, CaRB, eastern CRB and FRB and central PRB. Both CanESM2-LE and SR_GCMs project increases in R95 over northern PRB and northern Rockies in the future period.

Results for the 5-day maximum precipitation are similar to those of R95PTOT (Appendix 2). An outlook of the spatial changes of precipitation intensity is shown in appendix 2 with high intensities over southwest to west and southeast to east of the domain, while the area in between (the midline of WNA) has the lowest precipitation intensity. The spatial observation pattern of precipitation was captured by both CanESM2_LE and SR_GCMs. Climate simulations project that precipitation rate will intensify over most parts of the domain (except parts of the central WNA), mainly along upper Rocky Mountains and Columbia Mountains.
4.3 Temporal changes of extreme indices

Monthly climatologies of the precipitation and temperature-based extreme indices based on gridded observation and CanESM2_LE and SR_GCMs ensemble simulations over the historical and future periods are shown in Figure 12. Highest 5-day maximum precipitation values (RX5day) occur over November, December, January and February. Both downscaled CanESM2_LE and SR_GCMs simulations represent the monthly climatology of RX5day reasonably well with CanESM2_LE slightly underestimating the observed values except for January and June when they overestimate the observations. RX5day is projected to decrease in July and increase in the extended winter period (Nov-Feb). CanESM2_LE shows lower (higher) values for the future RX5day in July (January) compared to SR_GCMs, with differences 4 and 8 mm, respectively.

Monthly variations of temperature-based extreme indices (TXX and TNN; Figure 12) are also represented by downscaled CanESM2_LE and SR_GCMs simulations well. However, SR_GCM ensemble mean slightly underestimates (overestimates) the observed TXX/TNN in spring and summer (extended winter). Both TXX and TNN are projected to increase throughout the year in the future. CanESM2_LE shows higher increases compared to SR_GCMs from July until October (by almost 3°C). July will remain as the warmest month with a climatological average of 37°C (34°C) according to CanESM2_LE (SR_GCMs).

A noticeable change in the future is that the number of months when the average minimum tasmin (TNN) becomes more than 0°C. Both ensembles show that 5 months of the year (May, June, July, August and September) will have climatologies above 0°C, while the number of months with TNN above 0°C was 3 (June, July and August) during the historical period.
Figure 12. Monthly variation of RX5day, TXx and TNN based on gridded observations (black dashed line), CanESM2_LE and GCM simulations for historical (1981-2010) (green and blue dashed line associated with CanESM2_LE and SR_GCMs, respectively) and future (2060-2089) (red and brown dashed line associated with CanESM2_LE and SR_GCMs, respectively) periods.

Temporal changes of 8 CLIMDEX indices over the historical and future periods based on gridded observations, CanESM2_LE and SR_GCM simulations (means and the corresponding uncertainties based on the 2.5%-97.5% quantile ranges) are shown in Figures 13 (temperature-based and consecutive dry days) and 14 (precipitation-based).
The temporal variations of TNN and TXX are represented by the 95% quantile ranges of both ensembles well, with CanESM2_LE showing higher values for the P&R-factors (more representative uncertainty bounds with wider ranges) compared to SR_GCMs (Figure 13, Table 8). The observed average TNN is -25.1°C, which is projected to increase to -14.9°C (-16.6°C) based on CanESM2_LE (SR_GCMs). The differences between the future and historical TNN means are 9.5°C and 7.7°C according to CanESM2_LE and SR_GCMs, respectively. Similarly, the observed average TXX value of 29°C is projected to increase to 37.3°C (35.8°C). The differences between the future and historical TXX means are 7.8°C (6.5°C) according to CanESM2_LE (SR_GCMs). In addition, the means of the projected TNN and TXX simulations are larger than the historical maxima in WNA.

Temporal variabilities of CDD and GSL are captured well by both ensembles (Figure 13). While CanESM2-LE captures the observed changes better compared to SR_GCMs (according to the P-factors shown in Table 8), it has a larger uncertainty range (R-factors in Table 8). The average number of observed consecutive dry days is 13 days, which is projected to increase to 13.5 (12.6) days. CanESM2_LE (SR_GCMs) simulations project slight increases of 0.21 (1.5) days in CDD in the future. The observed average GSL is 174.6 days, which is projected to increase to 236 (225) days according to CanESM2_Le (SR_GCMs) simulations, respectively. GSL is projected to increase by 60 (48.3) days in the future.
Figure 13. Historical (1981-2010) and projected (2060-2089) changes of TNN, TXX, CDD and GSL based on gridded observation (solid black line), CanESM2_LE (left side) and SR_GCM (right side) simulations. Red and blue dashed lines are 95th quantile of simulations (CanESM2_LE on the left and SR_GCMs on the right side) for historical and projection period, respectively. Solid green line is the temporal average of CanESM2_LE/SR_GCM simulations. The solid red and blue lines are the mean of the historical and projection period, respectively.
Similar to temperature-based indices, the temporal variations of the precipitation-based indices (representing the frequency and intensity of extremes) including R10, R95PTOT and RX5day are better captured by CanESM2_LE compared to SR_GCMs (higher P-factors; Table 9) because of their larger uncertainty ranges. As shown in Figure 14, both simulated ensembles project increases in the frequency of heavy precipitation (R10) (10.4 and 7.3 days corresponding to CanESM2-LE and SR-GCMs, respectively) compared to observations (1.9 days). Differences between the future and historical R10 simulations are 6.8 (3.9) days. The observed R95PTOT value of 100.8 mm is projected to increase to 136.1 and 120.6 mm based on CanESM2_LE and SR_GCM, respectively over WNA. The corresponding differences between the future and historical R95PTOT simulations are 32.8 mm and 17.9 mm, respectively. Simple daily precipitation intensity (SDII) is also projected to increase by 0.52 mm (0.36 mm). The observed value of 3.2 mm is projected to be 4 (3.8) mm based on CanESM2_LE (SR_GCMs).

Overall, the results show that the intensity and frequency of temperature- and precipitation-based extreme indices are projected to increase in WNA. Large ensemble simulations based on a single model (CanESM2-LE) show larger uncertainty ranges compared to an ensemble of single simulations from multiple GCMs with different structures. Also, CanESM2-LE projects more intense/frequent extreme events compared to SR-GCMs.

Table 8. P-factor and R-factor of CanESM2_LE and SR_GCMs for TNN, TXX, CDD and GSL

<table>
<thead>
<tr>
<th>Factors</th>
<th>CLIMDEX</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TNN (°C)</td>
</tr>
<tr>
<td>CanESM2_LE GCM</td>
<td>0.9</td>
</tr>
<tr>
<td>R-factor</td>
<td>3.63</td>
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</table>
Figure 14. Historical (1981-2010) and projected (2060-2089) changes of R10, R95PTOT, RX5day and SDII based on gridded observation (solid black line), CanESM2_LE (left side) and SR_GCM (right side) simulations. Red and blue dashed lines are 95th quantile of simulations (CanESM2_LE on the left and SR_GCMs on the right side) for historical and projection period, respectively. Solid green line is the temporal average of CanESM2_LE/SR_GCM simulations. The solid red and blue lines are the mean of the historical and projection period, respectively.
Table 9. P-factor and R-factor of CanESM2_LE and SR_GCMs for R10, R95PTOT, RX5day and SDII

<table>
<thead>
<tr>
<th>Factors</th>
<th>R10 (day)</th>
<th>R95PTOT (mm)</th>
<th>RX5day (mm)</th>
<th>SDII (mm/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2_LE GCM</td>
<td>0.83</td>
<td>0.83</td>
<td>0.67</td>
<td>0.87</td>
</tr>
<tr>
<td>CanESM2_LE GCM</td>
<td>0.57</td>
<td>0.67</td>
<td>0.7</td>
<td>0.53</td>
</tr>
<tr>
<td>P-factor</td>
<td>0.83</td>
<td>0.67</td>
<td>0.87</td>
<td>0.7</td>
</tr>
<tr>
<td>R-factor</td>
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<tr>
<td>R-factor</td>
<td>2.46</td>
<td>2.11</td>
<td>1.98</td>
<td>2.18</td>
</tr>
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</table>

### 4.4. Spatial distributions of extreme Pr&T with 50- and 100-year return levels

The results of the parametric extreme analysis (based on the GEV distribution) show that mountains in the east and west parts of WNA are most susceptible to extreme precipitation events (Figure 15). Southwestern FRB, western parts of CRB, CaRB, eastern CRB and FRB and central PRB experience the highest observed 50-year precipitation events (between 55-150 mm) while the diagonal line from southeast to northwest of WNA receives the lowest 50-year precipitation (between 12-34 mm). Both CanESM2_LE and SR_GCM simulations capture the spatial distribution of extreme precipitation over the historical period except northwestern FRB where they underestimate the observations. CanESM2_LE and SR_GCM simulations project increases in the 50-year precipitation events over the future period in the range of 60-150 mm along the eastern and western mountains of WNA and 15-60 mm over the areas in between the mountains.
CRB has the highest 50-year tasmax (between 30-42°C) (Figure 16) and tasmin (between 14-22°C) (Figure 17) based on the gridded observation, while west and east parts of FRB and western PRB have the lowest tasmax (between 18-30°C) and tasmin (between 7-14°C). Both simulated ensembles capture the spatial pattern of extreme tasmax and tasmin over the WNA, however SR_GCM (CanESM2_LE) underestimate (overestimate) the tasmax (tasmin) over eastern PRB.
Figure 16. Tasmax 50-year return level based on historical period (1981-2010) (first row) and on future period (2060-2089) (second row) over WNA using gridded observation (left column), CanESM2_LE (middle column) and SR_GCM (right column) simulations.

Figure 17. Tasmin 50-year return level based on historical period (1981-2010) (first row) and on future period (2060-2089) (second row) over WNA using gridded observation (left column), CanESM2_LE (middle column) and SR_GCM (right column) simulations.
Figure 16-17 show that 50-year tasmax and tasmin are projected to increase with CanESM2_LE showing more increases. The highest 50-year tasmax occurs over CRB and central FRB between 40°C and 50°C according to the SR_GCM and CanESM2_LE simulations, while the latter projects larger increases in tasmax (Figure 16). Both CanESM2_LE and SR_GCM simulations project increases in the 50-year tasmin throughout WNA, however the latter shows less increases (Figure 17). Based on the SR_GCM ensemble mean tasmin values will increase to 23-30°C over CRB, however according to CanESM2_LE more regions including CRB, central FRB and eastern PRB are projected to experience this range of 50-year tasmin.

The geographical pattern of 100-year precipitation is relatively similar to 50-year precipitation (shown in Appendix 3), while the range of the maximum 100-year precipitation is 62mm to 150mm. The range of the minimum 100-year precipitation is 13-38 mm. PRB is the only basin where both CanESM2_LE and SR_GCM simulations underestimate the observed 100-year precipitation.

More than 50% of WNA is projected to face 30mm increase of 100-year precipitation (Appendix 3). The range of the future maximum 100-year precipitation is 79-170 mm for the areas located in southwestern FRB, western parts of CRB, CaRB, eastern CRB and FRB and central PRB. The lowest 100-year precipitation is projected to occur over the diagonal line from southeast to northwest of WNA with a range of 16-50 mm. SR_GCM simulations project higher values for the 100-year precipitation events compared with CanESM2_LE.

CRB is projected to have the highest 100-year tasmax (between 38-42°C) (Appendix 4) and tasmin (between 14-22°C) (Appendix 5) based on the gridded observation. West and east parts of FRB and western PRB have the lowest 100-year tasmax (between 18-32°C) and tasmin.
(between 7-14°C). Both CanESM2_LE and SR_GCM ensembles capture the spatial pattern of 100-year tasmax and tasmin over WNA, although they underestimate (overestimate) the tasmax (tasmin) over eastern PRB.

The difference between 100-year tasmax (Appendix 4) or tasmin (Appendix 5) using historical and projected simulations is 1.5°C (1°C). However, projections based on CanESM2_LE simulations show larger areas with severe temperature.

4.5. Impacts of low frequency variability modes on WNA’s hydroclimatic variables

Maximum Covariance Analysis

Using maximum covariance analysis (MCA) we analyze the effects of low frequency variability models (LFVMs) on hydroclimatic variables. Figure 18 shows the correlation between 14 LFVMs and the temporal expansion coefficient of the average temperature (MCA mode 1) considering three different time lags (i.e. no lag, one month lag and two months lag). The MCA mode 1 (MCA1) explains 97%, 98% and 98% of the Square Covariance Fraction (SCF) associated with 0-, 1- and 2-month lags, respectively. These SCF values are quite high considering the level of variability of the input data, seasonality, and the relatively high temporal resolution (daily time scale). Correlation values between different LFVMs (no-lag) and the average temperature (based on MCA1) are: EP (+0.3), NAO (-0.36), ENSO (+0.39), SOI (-0.32) and TPI (+0.3). These values are comparable for other time-lags of one-month: EP (0.36), NAO (-0.3), ENSO (0.3), PNA (-0.31), SAM (0.43) and SOI (-0.39) and two-month: NAO (-0.4), PNA (-0.49), SAM (0.3) and SOI (-0.37) as lag LFVMs.
The correlation between LFVMs with different time lags and the temporal expansion coefficients of the average and maximum precipitation (MCA mode 1) are shown in Figures 19 and 20, respectively. LFVMs that have the highest impact on WNA’s average precipitation include (no lag): ENSO (-0.44), ONI (-0.42), TPI (-0.35) and SOI (0.47) (Figure 19), and the corresponding ones for the maximum precipitation include: ENSO (-0.34), AO (-0.33), TPI (-0.32), EA (-0.31), and SOI (0.4) (Figure 20).
The highest correlations between one-month lag LFVMs with the average precipitation over WNA (based on MCA1) are ONI (-0.41), ENSO (-0.41), TPI (-0.36) and SOI (0.52), and for the two-month lag LFVMs are ONI (-0.39), ENSO (-0.36), TPI (-0.33), PDO (-0.3), SAM (0.35) and SOI (0.46).

The high correlated one-month LFVMs with the maximum precipitation are TPI (-0.32), ENSO (-0.32), PDO (-0.31), AO (-0.3), EA (-0.3), SAM (0.3) and SOI (0.43). Furthermore, maximum precipitation is correlated with PDO (-0.38), EA (-0.33), TPI (-0.32), ENSO (-0.3), SAM (0.34) and SOI (0.4) as two-month lag LFVMs.
The covariance explained by MCA1 between different lags of LFVMs and the average precipitation (91%, 89% and 86% associated with 0-, 1- and 2-month lags, respectively) is high considering the variability of the input data. In contrast, MCA1 explains lower covariance between different lags of LFVMs and the maximum precipitation (65%, 67% and 68% 0-, 1- and 2-month lags, respectively).

**Composite Analysis**

The statistically significant relationships between 14 LFVMs and extreme hydroclimatic variables are found using composite analysis. Overall, precipitation extremes particularly over the mountainous regions of WNA (over eastern CRB and FRB and central PRB) are more likely to be influenced by LFVMs compared with temperature.
The 5 highest and lowest values of LFVMs are shown in Table 10. Figures 21-25 show the most significant composite differences (based on the results of this study) in the average of extended winter maximum daily precipitation (Max precip), tasmax and tasmin for the two 5-year groups.

Table 10. 5 lowest and highest LFVM years

<table>
<thead>
<tr>
<th></th>
<th>No lag</th>
<th>One-month lag</th>
<th>Two-month lag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lowest</td>
<td>Highest</td>
<td>Lowest</td>
</tr>
<tr>
<td>AO</td>
<td></td>
<td></td>
<td></td>
</tr>
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<tr>
<td>NTA</td>
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</tr>
<tr>
<td>Year</td>
<td>ONI</td>
<td>PDO</td>
<td>PNA</td>
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<tr>
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</table>

Overall, the intensity of the extended winter Max precip in high LFVM years tends to be larger compared to years when LFVMs are low. The red hatched areas show statistically significant
relationships between LFVMs and local hydroclimatic extremes. While Max precip over extended winter is found to be influenced by all 14 large-scale climate oscillations, half of LFVMs have no statistically significant impacts on maximum daily tasmax nor maximum daily tasmin (i.e. AO, DMI, EA, EP, ONI, PDO and TPI), although the differences in these variables in different phases of LFVMs can reach up to 11°C and 7°C in some regions, respectively.

EA has significant negative relations with Max precip considering all lags (Figure 21). However, two-month lag’s EA has maximum impact on maximum precipitation over western, north-eastern and central parts of CRB, east and west of FRB and south of CaRB. The effects of EA over WNA have not been investigated previously.
Extended winter Max precip has positive (eastern CRB) and negative (west and east parts of FRB, central and western CRB and eastern CaRB) relations with NAO (Figure 22).

Maximum daily tasmax (Max tasmax) over northern PRB, central and parts of southern CRB have negative relations with one-month lag NAO. Moreover, one-month lag NAO has
statistically significant negative impact over the borders of the CRB, entire the CaRB, eastern FRB and center of the PRB.

Max precip over eastern and parts of southwestern PRB has positive relationship with Nino3.4 (an ENSO index), while western and eastern CRB and parts of southwestern FRB have negative relations with Nino3.4 (Figure 23). The areas that have statistically significant relations with Nino3.4 are consistent between different time lags.
Max tasmax and tasmin show positive relations with One-month lag’s Nino3.4 over a small area in southern CRB.

**Figure 23.** Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of Nino3.4 with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.

No-month lag’s NTA has significant positive relation with Max precip over central CRB, western FRB, northern and western PRB (Figure 24).

In addition, No-month lag’s NTA has significant positive relations with Max tasmin/tasmax over the entire WNA (except central and western parts of FRB and western CRB).
Figure 24. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of NTA with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.

Max precip has negative correlation with WP over western, southern and partially eastern CRB regardless of when WP starts (Figure 25). No-month lag’s WP has the maximum influence on Max precip, with positive relations over northern FRB and eastern PRB.
One-month lag’s WP has negative relation with Max tasmax over CRB, western FRB and northern PRB, and with Max tasmin over western and southeastern CRB and the entire PRB except its western parts.

Figure 25. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of WP with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 6-14 show the spatial significant impact of AO, DMI, EP, ONI, PDO, PNA, SAM, SOI and TPI, respectively on hydroclimatic extreme values.

As shown in Appendix 6, AO starting in October (one-month lag) has the most significant impact on Max precip over extended-winter. It has statistically significant negative relation with local precipitation in eastern and western FRB and CRB and the entire CaRB, and positive relation with the ones in the north of PRB.

No-month lag’s DMI (no lag), has statistically significant negative relations with Max precip (Appendix 7) affecting small regions over northeastern and southeastern CRB and western FRB.

EP has relatively small negative impacts over varying spatial locations (considering different time lags) (Appendix 8). One-month lag’s EP affects Max precip in western CRB and southern PRB. Furthermore, eastern CRB is significantly affected by No-month lag’s EP.

No-month lag’s ONI has positive relation with Max precip over central and eastern PRB, while two-month lag’s ONI has negative relation with Max precip over western and parts of eastern CRB and central FRB (Appendix 9).

As Appendix 10 shows, PDO significantly influences western and eastern CRB (negative correlation) in terms of Max precip, with the maximum impact at a two-month time lag.

two-month lag’s PNA has the strongest negative correlation with Max precip over central PRB and southeastern CRB, while a small area in eastern CRB is positively correlated with PNA (Appendix 11). PNA is one of the most important and influential LFVMs on Max tasmin/tasmax over WNA. The Max tasmax of almost the entire WNA as well as Max tasmin (except southeastern PRB, western FRB and southern CRB) are affected by two-month lag’s PNA.
As Appendix 12 shows, SAM has a statistically significant positive relation with Max precip particularly with a two-month lag. It affects Max precip over eastern CRB, central and southern FRB and eastern PRB. Max tasmin over eastern CRB and northeastern FRB is influenced by two-month lag’s SAM, while the one over a small area in western CRB is affected by One-month lag’s SAM.

One-month lag’s SOI has a positive relation with Max precip (Appendix 13) over eastern and western CRB, while two-month lag’s SOI influences Max precip over relatively similar area.

Max tasmax over a small region in western CRB and Max tasmin of a large area over PRB and central FRB are significantly affected by One-month lag’s SOI.

TPI, with different lags, has statistically significant impact on Max precip (Appendix 14). No-month lag’s TPI has both positive relation with precip over PRB and northwest FRB and negative relation over eastern CRB. Its maximum impact occurs when TPI starts in September (two months lag) with positive relations over northeastern and southeastern PRB and negative relations over western and eastern CRB.

4.6. Streamflow

The results of daily streamflow based on Raven hydrological modeling over the KRB confirms high variability of streamflow. Taking observed streamflow as reference, Figure 26 shows that streamflow simulated by GCMs has high variability than CanESM2 LE over historical period. Variability of streamflow based on CanESM2 LE is less than that of GCMs over both historical and future period. The range of daily streamflow based on gridded observation is
from 43 cms in 1981 to 4106 cms in 1997, while mean of CanESM2_LE (GCMs) smoothen the range from 65 cms in 1981 to 2697 cms in 2010 (53 cms in 1981 to 2859 cms in 2007).

Figure 26. Temporal streamflow based on gridded observation (first row), CanESM2_LE (second row) and GCMs (third row)

Figure 27 and 28 show the 95th quantile of daily streamflow based on GCMs and CanESM2_LE, respectively. Comparison of figure 26 and 27-28 shows that the mean of both
GCMs and CanESM2_LE smoothen the extremes of streamflow. In other words, in order to analyze the streamflow, simulation quantiles capture the observed streamflow better.

![Figure 27. 95th quantile of historical and future simulated streamflow based on GCMs (blue shadow) and observed streamflow based on gridded observation (solid black line)](image)

The mean of both simulations overestimate (underestimate) the minimum (maximum) observed streamflow (Figure 26). On the other side, when observed streamflow is simulated based on quantiles, simulations (Figure 27-28) quantitatively capture not only the observed streamflow, but also its variability.
Based on table 11, CanESM2_LE 95th quantile has a better performance in simulating the daily streamflow over the KRB compared with that of GCMs. Table 11 shows that CanESM2_LE 95th quantile captured the observed streamflow (P-factor 0.92) more than GCMs 95th quantile (P-factor .84). Moreover, the 95th quantile based on CanESM2_LE has a narrower width (R-factor 1.05) compared with GCMs (R factor 1.21).
Table 11. P&R-factors of simulated daily streamflow based on CanESM2_LE and GCMs

<table>
<thead>
<tr>
<th></th>
<th>LE</th>
<th>GCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-factor</td>
<td>1.05492</td>
<td>1.21344</td>
</tr>
<tr>
<td>P-factor</td>
<td>0.92018</td>
<td>0.84448</td>
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</table>

Figure 29 shows the maximum daily streamflow based on observed gridded, CanESM2_LE and GCMs. Having said that the variability of maximum daily streamflow is high, both CanESM2_LE and GCMs underestimated the observed maximum daily streamflow. Although CanESM2_LE underestimated the maximum daily streamflow less than GCMs, the maximum daily streamflow based on GCMs captured the variability of observation better than CanESM2_LE.
Figure 29. Maximum daily streamflow over the KRB based on observed gridded observation (black line), CanESM2_LE (red line) and GCMs (green line) over historical (top) and future (bottom) period

Both CanESM2_LE and GCMs simulated a higher maximum daily streamflow over future period. In other words, CanESM2_LE (GCMs) simulates that the range of maximum daily streamflow would change from 1286-2697 cms (1259-2859 cms) to 3975-6430 cms (2649-5117 cms). Noted that both simulations underestimated the observed daily maximum streamflow, their projection of daily maximum streamflow might be underestimated. It means the actual daily maximum streamflow at the end of century might be higher than what simulations projected.
Chapter 5

5. Conclusion

In this study, we analyzed the simulated extreme events from 7 GCMs (single runs) and a large ensemble of 50 climate simulations based on the CanESM2 model, compared them with gridded observations over the historical period (1981-2010), and determined the projected changes of extremes over the future period (2060-2089).

Historical changes of hydroclimatic extremes show that CanESM2_LE better captures the temporal variability of the observations compared to SR_GCM as it has a larger uncertainty range. Both ensembles project increases in the intensity of maximum values of daily maximum precipitation, maximum temperature and minimum temperature over WNA under the RCP8.5 emission scenario. Precipitation variability over high elevation and coastal regions are high showing larger uncertainties in the projected estimates compared to temperature.

Non-parametric analysis of extreme events (CLIMDEX) based on CanESM2_LE showed larger projected values for temperature-based quantities compared to SR_GCMs. Despite differences in the projected intensities, both ensembles show that Max tasmax and tasmin would dramatically increase resulting in changes in the precipitation regime and higher rates of snowmelt in the future. Coast Mountains (western FRB) are projected to increases in maximum tasmin by an average of 10°C that make the region vulnerable to winter rain-on-snow and snowmelt flooding. SR_GCM simulations better determine the spatial patterns of temperature-based indicators compared to CanESM2-LE.

Both ensembles underestimate the number of observed consecutive dry days and project slight increases over southern and western CRB in the future. This implies that southern CRB is projected to face severe droughts with an average of 50 days of consecutive dry days. The length of growing season is simulated well by both ensembles, and is projected to increase over
the entire WNA. Northwest CRB is projected to have the longest growing season length for almost $\frac{3}{4}$ of a year.

CanESM2_LE has a better performance in simulating precipitation-based climate extreme indices than temperature-based ones. Historically, western and eastern WNA received more precipitation compared to other regions. Intense precipitation is projected to be more frequent and intense over WNA particularly in mountainous areas (Coast Mountains, Columbia Mountains and Rocky Mountains). In addition, the spatial patterns of precipitation-based indices are different from the spatial patterns of temperature-based indices.

The spatial pattern of 50 and 100-year precipitation, with 1 in 50- and 100 chance of occurring in any given year, is similar to the spatial pattern of non-parametric precipitation-based CLIMDEX indices. 50 and 100-year precipitation events over western and eastern WNA (Coast Mountains, Columbia Mountains and Rocky Mountains) are more severe compared to the rest of the domain. While extended areas are projected to receive more intense precipitation in the future, the intensity of 50 and 100-year events are also simulated to increase by an average of 30mm according to CanESM2_LE and SR_GCM ensembles.

Both 50 and 100-year Max tasmin are found to be above 0°C throughout WNA in the future based on the multi-model ensemble means. The corresponding values are projected to increase by 5°C in average and up to 13° in some areas over PRB, CRB and RB. This can potentially jeopardize the snowpack (as a natural storage of water) over the mountainous areas.

CRB is found to be the hottest basin in WNA in terms high Max/Min temperature based on both parametric and non-parametric analysis of extremes. CRB and parts of the mountainous areas of FRB are projected to have the highest 50 and 100-year temperature extremes.

In this research, we characterized the contribution of EA, SAM, TPI and WP to WNA’s precipitation variability in addition to several other LFVMs such as AO, ENSO, PDO and
NAO, which have been analyzed in previous studies (Stone, Weaver and Zwiers, 2000; Gershunov and Cayan, 2003; Zhang et al., 2010; Tan, Gan and Shao, 2016; Whan and Zwiers, 2017). We determined the relationship between 14 low frequency variability models (with 0-, 1-, and 2-month time lag) and hydroclimatic variables over WNA using MCA. Accordingly, the average temperature over WNA is positively correlated with EP, ENSO, PDO and SAM and negatively correlated with NAO, PNA and SOI. The average precipitation is found to be positively correlated with SAM and SOI and negatively correlated with ENSO, ONI, PDO and TPI. Maximum precipitation has a negative relation with AO, EA, ENSO, PDO and TPI. In addition, there is a stronger positive relation between maximum precipitation and SAM and SOI compared with that of the average precipitation.

The spatial patterns of the dependencies between LFVMs and local hydroclimatic extremes are assessed using composite analysis. Results show that LFVMs can influence the averages of the extended winter maximum daily precipitation and temperature over western, eastern and northern regions of WNA. Max precip is influenced by no-month lag’s AO, EA, ENSO, NAO, NTA, TPI and WP (i.e. no time lag). In addition, One-month lag’s AO, EA, ENSO, PDO, SAM, SOI and TPI (i.e. one-month lag) and two-month lag’s EA, ENSO, PDO, SAM, TPI, and WP (i.e. two-month lag) can significantly affect parts of WNA.

Results show that no-month lag’s NTA is the most influential LFVM that can affect max tasmax/tasmin over the entire WNA except areas on the west. One-month lag’s ENSO and SAM are found to affect these variables over the southern parts of CRB, while SOI significantly affects them over northern and western PRB. WP and NAO can significantly affect western and eastern parts of WNA, respectively. Overall, NTA and WP are dominant LFVMs that can contribute to extreme temperature variations in large regions of WNA, while others such as ENSO and PDO can affect parts of WNA.
Appendix

Appendix 30. Spatial average Changes of R10 and R95 based on gridded observations, CanESM2_LE and SR_GCM simulations over the historical (1981-2010) (first rows) and future (2060-2089) (second rows) periods over WNA.
Appendix 31. Spatial average Changes of RX5day and SDII based on gridded observations, CanESM2_LE and SR_GCM simulations over the historical (1981-2010) (first rows) and future (2060-2089) (second rows) periods over WNA.
Appendix 32. Precipitation 100-year return level based on historical period (1981-2010) (first row) and on future period (2060-2089) (second row) over WNA using gridded observation (left column), CanESM2_LE (middle column) and SR_GCM (right column) simulations.

Appendix 33. Tasmax 100-year return level based on historical period (1981-2010) (first row) and on future period (2060-2089) (second row) over WNA using gridded observation (left column), CanESM2_LE (middle column) and SR_GCM (right column) simulations.
Appendix 34. Tasmin 100-year return level based on historical period (1981-2010) (first row) and on future period (2060-2089) (second row) over WNA using gridded observation (left column), CanESM2_LE (middle column) and SR_GCM (right column) simulations.
Appendix 35. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of AO with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 36. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of DMI with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 37. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of EP with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 38. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of ONI with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 39. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of PDO with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 40. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of PNA with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 41. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of SAM with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 42. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of SOI with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
Appendix 43. Differences in the extended winter hydroclimatic variables (Precipitation: first row, maximum temperature: second row, minimum temperature: third row) averaged from 5 years associated with highest and lowest value of TPI with three different lags (no lag: first column, one month lag: second column, two months lag: third column). Shadowed areas are those grids whose differences are statistically significant.
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January 2019).


Curriculum Vitae

NAME
Mohammad Hasan (Jason) Mahmoudi

POST-SECONDARY EDUCATION AND DEGREE
University of Tehran 2012 - 2016
Bachelor of Water Engineering (top ranked student)

HONORS AND REWARDS
• Top ranked in Class of 2012 at University of Tehran
• Awarded Erasmus Mundus Scholarship in 2015
• Admitted to Graduate Program (Master) of the Department of Water Engineering, Without Taking the National Entrance Exam as a Reward of Top Position in B.Sc. Class.
• 2018 CatIQ's Canadian catastrophe award winner

VOLUNTEER EXPERIENCE
• Student mentorship (University of Western Ontario) summer 2018
• English teacher for Orphan and poor children summer 2011
• English teacher for Orphan and poor children summer 2012

CONFERENCES
• Mahmoudi M.H., Najafi M.R., Werner A.T., Schnorbus M., AGU Fall Meeting 2018, “Changes In Extreme Temperature And Precipitation Events In The Pacific Northwest: Effects Of Climate Change And Natural Variability”, December 2018
• Mahmoudi M.H., Najafi M.R., Werner A.T., Schnorbus M., 2018 Joint Meeting of the CGU-CSSS-CIG-CSAFM-ESSSA - Scientific Program, Niagara Falls, “Changes in extreme daily temperature and precipitation over Western Canada based on a large ensemble of climate change simulations”, June 2018
• Mahmoudi M.H., Najafi M.R., Werner A.T., Schnorbus M., Environmental risk modelling and extreme events, Université de Montréal, “Projected Changes in Extreme Precipitation over the Fraser and Campbell River Basins in Western Canada”, August 2017


• Velayati S., Mahmoudi M., National Conference of Water Crisis in Iran and the Middle East, Shiraz; 03/2015 - “introducing Barout formation as an aquifer formation in North and Northeast of Iran” http://www.civilica.com/PaperWATERCONF01-ATERCONF01_115.html

JOURNALS

• Gavili S., Sanikhani H., Kisi O., Mahmoudi M., 2016. Evaluation of several soft computing methods in monthly evapotranspiration modeling (Case Study: Kurdistan Province, Iran). Meteorological Applications Journal; Article ID: MET1676

PROJECTS

• Ecotourism of Iran National Climate Change Report in 2015
• Assessment of Risk Map of Qazvin Aquifer
• Assessment of Intrinsic groundwater vulnerability of coastal aquifer using GALDIT Index; Case Study: Golestan Province
• Assessment of climate change impact on extreme precipitation and temperature over western North America (WNA)
• The impact of teleconnections signals on extreme precipitation over WNA