Multi-Model Ensemble Analysis of Runoff Extremes for Climate Change Impact Assessments

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Abstract

In this study multi-model ensemble analysis of extreme runoff is performed based on eight regional climate models (RCMs) provided by the North American Regional Climate Change Assessment Program (NARCCAP). Hydrologic simulation is performed by driving the Variable Infiltration Capacity (VIC) model over the Pacific Northwest region, for historical and future time periods. Extreme event analysis is then conducted using spatial hierarchical Bayesian modeling (SHB). Ensemble merging of extreme runoff is carried out using Bayesian Model Averaging (BMA) in which spatially distributed weights corresponding to each regional climate model are obtained. Comparison of the residuals before and after the multi-model combination shows that the merged signal generally outperforms the best individual signal. The climate model simulations show close performance regarding maximum and minimum temperature and wind speed, however, the differences are more pronounced for precipitation and runoff. Between-model variances increase for the future time series compared to the historical ones indicating larger uncertainties in climate change projections. The combined model is then used to predict projected seasonal runoff extremes and compare them with historical simulations. Ensemble average results suggest that seasonal extreme runoff will increase in most regions in particular the Rockies and west of the Cascades.

1. Introduction

Extensive global climate model (GCM) simulations have been conducted in recent years including the Coupled Model Intercomparison Project–Phase 3 (CMIP3) with a coordinated set of global coupled climate model experiments which are also assessed in the Intergovernmental Panel on Climate Change fourth assessment report (Meehl et al., 2007). Additionally CMIP5 experiments, incorporating about 20 modeling groups, are another continued effort for multi-model intercomparison and analysis (Najafi et al., in press; Taylor et al., 2012). These experiments are based on pre-defined scenarios of projected greenhouse gas and air pollutant emissions and land use, such as the representative concentration pathways (RCPs) corresponding to CMIP5 and the special report on emission scenarios (SRES) in CMIP3, which are carried out in order to assess changes in the oceanic-atmospheric quantities.

Aside from a plethora of statistical downscaling approaches currently available (Najafi et al., 2011c; Wood et al., 2004), several regional-scale programs have been established in order to meet the increasing demand for finer spatio-temporal resolution climate datasets. These include the Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects (PRUDENCE) project (Christensen and Christensen, 2007), followed by the Ensembles-Based Predictions of Climate Changes and Their Impacts (ENSEMBLES) project (Van der Linden and Mitchell, 2009) which provides suite of regional datasets representing projected climate variations; the STAtistical and Regional dynamical Downscaling of EXtremes for European regions (STARDEX) project (Goodess et al., 2007); the Coordinated Regional Climate Downscaling Experiment

(CORDEX) (Jones et al., 2011); and the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al., 2012).

These experiments are used for climate change impact assessment as well as uncertainty quantification (Mearns et al., 2009). Fowler et al. (2007) combined the results of RCMs from the PRUDENCE ensemble, assuming the models have equal skill. Nonparametric bootstrapping was used for probabilistic estimates of extreme precipitation. Fowler and Ekström (2009) further proposed a weighting scheme based on the spatial characteristics and extreme precipitation statistics of the RCMs and observations. Their results indicated that when all RCMs are driven by a single GCM, the model weighting does not significantly impact results. Studies on combining the outputs from multiple RCMs suggest that incorporating a weighting procedure based on the model performance during a training period would enhance the simulation results (Casanova and Ahrens, 2009; Kug et al., 2008). Multi-model ensemble studies using RCM simulations have been generally focused on climate variables such as temperature (Kang et al., 2012; Smith et al., 2009; Tebaldi et al., 2005) and precipitation (Fowler and Ekström, 2009; Halmstad et al., 2012; Mailhot et al., 2011). Kang et al. (2012) proposed a Bayesian hierarchical model to combine winter temperature from six RCMs in Phase-I of NARCCAP experiments. Zhu et al. (2012) performed a Bayesian model averaging of the extreme rainfall intensities using the RCM simulations provided by NARCCAP.

Bayesian model averaging (BMA) has gained much attention in multi-model ensemble merging of hydro-climate predictions (Duan et al., 2007; Kharin and Zwiers, 2002; Najafi et al., 2011a; Najafi et al., 2012; Raftery et al., 2005). BMA is a statistical technique which provides weighted average of the individual models based on their performances in the

training period. It considers the probability distribution function (PDF) of each model simulation and provides a combined PDF based on the optimized weights and variances assigned to each model. This method has been successfully applied to various hydro-climatic quantities including regional weather forecast of surface temperature and sea level pressure (Raftery et al., 2005), runoff (Duan et al., 2007; Najafi et al., 2011b), precipitation and wind forecasting (Sloughter et al., 2010; Sloughter et al., 2007; Zhu et al., 2012) as well as the humidity field (Yang and Wang, 2012). Further enhancements of ensemble combination by merging data assimilation techniques (Moradkhani et al., 2012; Moradkhani et al., 2005) with BMA was introduced by Parrish et al. (2012). The success of Bayesian model combination has motivated this study to conduct multi-model ensemble merging of runoff extremes, as obtained from a hydrologic model driven by different RCMs, using this probabilistic approach.

This study is performed over the Pacific Northwest (PNW) (as shown in Figure 1 of *Najafi and Moradkhani, 2013b*) which covers the Columbia River Basin (CRB). Winter (October-March) precipitation dominates the hydrologic characteristics of PNW (Miles et al., 2000). Precipitation in the mountains is higher especially on the western slopes of the Olympics, Coast mountain range and the Cascades. The region is climatically divided by the Cascade Mountains. Low elevation regions west of the Cascades are largely rain dominated while the regions located on the east are snow dominated.

Outputs from eight downscaled RCMs were used to force the VIC hydrologic model (Liang et al., 1994) followed by hierarchical Bayesian modeling of extreme runoffs (Najafi and Moradkhani, 2013a; Najafi and Moradkhani, 2013b). In this study Bayesian averaging of precipitation, temperature, wind speed, and runoff time series is separately conducted.

Spatially distributed BMA weights corresponding to each RCM are obtained, and the uncertainties related to the historical and projected runs are quantified.

In Section 2 of the paper a discussion of the NARCCAP datasets and the corresponding regional climate models is provided along with an introduction to the observational data. In Section 3 the steps for ensemble modeling of runoff extremes are explained including a brief introduction to the downscaling approach, the VIC hydrologic model, spatial hierarchical Bayesian modeling of extremes, and Bayesian model averaging. Section 4 provides the results of the model combination followed by a summary of the study along with the concluding remarks in Section 5.

2. Regional Climate Models

The North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al., 2012; Mearns et al., 2009) comprises several regional climate models (RCMs). It aims at producing higher resolution datasets for climate change impact assessments and uncertainty quantification. RCMs generally have varying dynamical formulations and physical parameterizations including different sub-grid scale turbulence, radiative transport, boundary layer effects and moist processes. NARCCAP experiments are performed over similar spatio-temporal domains, which include the United States, Canada and Northern Mexico. Phase-I of the experiments which are conducted over the time period of 1979-2004, are based on the National Center for Environmental Prediction (NCEP-2) reanalysis boundary conditions and are taken as substitute for observations. The lateral boundary conditions include energy, moisture and momentum fluxes. In the second phase of the experiments, fully coupled global climate models replaced the NCEP reanalysis.

118 Simulations are performed in 50-km horizontal resolution, over the periods of 1971-2000
119 and 2041-2070 based on the SRES A2 emission scenario. In this scenario the CO₂
120 concentration is expected to reach 575 and 870ppm (parts per million) by the middle and
121 the end of the 21st century.

122 NARCCAP includes six RCMs (CRCM, ECP2, HRM3_ MM5I, RCM3, and WRFG) that are
123 driven by four GCMs including the Canadian Global Climate Model version 3
124 (CGCM3, (Flato, 2005)), the NCAR Community Climate Model version 3 (CCSM3, (Collins et
125 al., 2006)), the Geophysical Fluid Dynamics Laboratory (GFDL) Climate Model version 2.1
126 (CM2.1, (Anderson et al., 2004)), and the United Kingdom (UK) Hadley Centre Climate
127 Model version 3 (HadCM3, (Gordon et al., 2000)). Each RCM is nested within different
128 GCMs resulting in suite of RCM-GCM simulations. In this study data from eight RCM_GCM
129 combinations, which were available at the time these analyses were performed, are
130 considered including CRCM_cgcm3, CRCM_ccsm, HRM3_gfdl, HRM3_hadcm3, RCM3_gfdl,
131 RCM3_cgcm3, WRFG_cgcm3 and WRFG_ccsm.

132 RCMs provide hydro-climatic simulations at 3-hourly as well as daily time series at each
133 50km grid cell. Daily precipitation (mm/day), daily maximum and minimum temperature
134 (K) as well as zonal and meridional wind speeds (m/s), were used to drive VIC.

135 The observed climatological fields were taken from the retrospective analysis of (Maurer
136 et al., 2002). These daily datasets are mostly calculated values based on other observations
137 rather than direct measurements. These datasets consist of 1/8° gridded precipitation,
138 temperature and wind time series covering the period of January 1949 until July 2000.

It should be noted that there are systematic biases within RCM outputs for several reasons including the lateral boundary forcing and the model structures. In this study bias correction was performed at the resolution of the observational data based on the quantile mapping approach. For the individual months the cumulative distribution functions (CDFs) of each $1/8^\circ$ cell and the closest RCM grid were matched over the historical period of 1971-2000. The changes at each quantile were then applied on the future CDFs of the corresponding RCM grid cell. In this approach, the RCM biases are assumed to be stationary in time, implying that they remain constant for the historical and projected simulations. This assumption is one of the limitations of the statistical downscaling methods.

3. Methodology

Using the $1/8^\circ$ observed climatological data as well as downscaled NARCCAP simulations the VIC hydrologic model was driven. VIC estimates snow accumulation and melt, soil moisture, evapotranspiration, surface runoff as well as baseflow. Modeling is performed at a daily time step for the historical time period of 1971-2000 and future period of 2041-2070 by considering three layers of soil. Five elevation bands are considered to better characterize the snow processes at each grid cell. Simulations are made based on the water balance equations assuming that the surface temperature is equal to the surrounding air temperature. The resulting runoff (mm) at each cell is considered for the hydrologic extreme analysis. The model has been calibrated and validated by Maurer et al. (2002) and similar model parameters are used in this study. Further information on hydrologic modeling and extreme analysis (as briefly discussed below) is provided in (Najafi and Moradkhani, 2013a; Najafi and Moradkhani, 2013b).

3.1. Runoff Extreme Analysis based on Hierarchical Bayesian Modeling

Extreme value analysis has been developed to characterize the tail of a distribution (Coles, 2001). The generalized extreme value distribution (GEV) was used to represent the seasonal maximum runoffs. GEV is defined as:

$$F(y|\mu, \sigma, \kappa) = \exp \left\{ - \left[1 + \kappa \left(\frac{y - \mu}{\sigma} \right) \right]^{-1/\kappa} \right\}, \quad (1)$$

where μ, σ and κ are the location, scale and shape parameters respectively and $1 + \kappa(y - \mu)/\sigma > 0$.

The τ -year return level extreme event can be obtained from:

$$z_\tau = \mu - \frac{\sigma}{\kappa} \left[1 - (-\log(1 - 1/\tau))^{-\kappa} \right], \quad (2)$$

Spatial hierarchical Bayesian models were recently proposed to combine rare extreme data from different locations in order to increase sample size and produce more reliable estimates (Cooley et al., 2007; Sang and Gelfand, 2009; Schliep et al., 2010).

The hierarchical model is based on a likelihood function which depends on time and space:

$$p_1(y_i|\mu_i, \sigma_i, \kappa_i) = \prod_{i=1}^S \prod_{t=1}^T \frac{1}{\sigma_i} \left[1 + \kappa_i \left(\frac{y_{it} - \mu_i}{\sigma_i} \right) \right]^{-1/\kappa_i - 1} \times \exp \left\{ - \left[1 + \kappa_i \left(\frac{y_{it} - \mu_i}{\sigma_i} \right) \right]^{-1/\kappa_i} \right\} \quad (3)$$

y_{it} is the annual maximum runoff at cell i in time t . T is the total number of years for each of the historical and future periods and S the total number of cells. To characterize uncertainties in model parameters, it is assumed that each GEV parameter follows a normal distribution rather than constant values (Banerjee et al., 2004; Cooley and Sain, 2010):

$$p_2(\theta_i|\lambda_{\theta}, U_{i,\theta}, \tau_{\theta}^2) = N\left(X_{i,q}'\lambda_{\theta,q} + U_{i,\theta}, \frac{1}{\tau_{\theta}^2}\right) \quad (4)$$

where $X_{i,q}'$ and $\lambda_{\theta,q}$ with $\theta \sim \mu, \sigma, \kappa$ represent the covariates (i.e. explanatory variables such as the geographic coordinates, physical and hydro-climatologic characteristics that are associated with each cell) and their corresponding factors respectively; τ_{θ}^2 is the precision parameter (inverse of the variance). $U_{i,\theta}$ represents the spatial random effect parameters and accounts for the dependencies between GEV parameters. i denotes each grid cell, q the number of covariates and q' the number of their associated factors ($q' = q+1$). The procedure for spatial hierarchical Bayesian modeling of runoff extremes, is further illustrated in Figure 2 of *Najafi and Moradkhani, 2013b*.

3.2. Bayesian Model Averaging

BMA is a probabilistic method for multi-model ensemble merging, based on post-processing of deterministic models over a training period (Duan et al., 2007; Najafi et al., 2011b; Raftery et al., 2005). Each ensemble member ' m_n ' is assigned an individual probability distribution function $p(y|m_n)$, which describes the probability of observing hydro-climatic variable ' y ' conditional on model m_n being the best model. The posterior probability of each model m_n being correct given the measured data O (i.e. $p(m_n|O)$) is taken as the weight assigned to that model, with all weights summing to unity. The resulting PDF associated with ' y ' is a weighted average of each constituent PDF and can be assessed based on the law of total probability:

$$p(y) = \sum_{n=1}^N p(y|m_n, O) p(m_n|O) \quad (5)$$

where O is the observed runoff. Hydrologic variables generally follow non-Gaussian distributions. In order to satisfy the Gaussian assumption the Box-Cox transformation (Sakia, 1992) was applied over the simulated runoffs (f_n) prior to BMA implementation. The prior distribution $p(y|f_n, O)$ is generally assumed to be a Gaussian distribution, $N(y|f_n, \sigma_n^2)$ with f_n as the mean and σ_n as the standard deviation.

Based on Eq. 5, the log-likelihood function is defined by:

$$l(w_1, \dots, w_n, \sigma^2) = \sum_{n=1}^N w_n \cdot \sum_{t=1}^T N(y_t^{obs} | f_{n,t}, \sigma_n^{iter}) \quad (6)$$

The Maximum Likelihood (ML) estimates of the unknown values of $p(f_n|O)$ (i.e. w_n) and σ_n are obtained using the iterative procedure of the EM algorithm which swaps between Expectation and Maximization steps (Duan et al., 2007; McLachlan and Krishnan, 2007; Raftery et al., 2005). In the Expectation step a latent variable is defined based on the parameter values $\theta = w_n, \sigma_n \{n=1,2,3,\dots,N\}$:

$$\hat{z}_{n,t}^{iter} = \frac{N(y_t | f_{n,t}, \sigma_n^{(iter-1)})}{\sum_{n=1}^N N(y_t^{obs} | f_{n,t}, \sigma_n^{(iter-1)})} \quad (7)$$

where $N(y_t | f_{n,t}, \sigma_n^{(iter-1)})$ is a normal PDF with the mean of $f_{n,t}$ and standard deviation of $\sigma_n^{(iter-1)}$. In the Maximization step the parameters ' θ ' are estimated given the values of $z_{n,t}$:

$$w_n^{Iter} = \frac{1}{T} \sum_{t=1}^T z_{n,t}^{Iter} \quad (8)$$

$$\sigma_n^{2^{Iter}} = \frac{\sum_{t=1}^T \hat{z}_{n,t}^{Iter} \cdot (y_t^{obs} - f_{n,t})^2}{\sum_{t=1}^T \hat{z}_{n,t}^{Iter}} \quad (9)$$

The convergence criterion is defined as $l(\theta^{Iter}) - l(\theta^{Iter-1}) \leq \varepsilon$ where ε is the specified threshold.

The mean and variance of BMA are obtained from:

$$E(y|O) = \sum_{n=1}^N w_n f_n \quad (10)$$

$$Var(y|O) = \sum_{n=1}^N w_n [f_n - E(y|O)]^2 + \sum_{n=1}^N w_n \sigma_n^2 \quad (11)$$

The variance consists of two constituents, the between model variance (1st part of summation in eq. 11) and the within model variance (2nd part of summation). As for the downscaling approach, similar stationarity assumption holds for the estimated weights.

3.3. Ensemble Merging of Extreme Runoff

The 100-yr return level runoffs corresponding to the observed datasets and different RCMs are obtained using the spatial hierarchical Bayesian model, as discussed in section 3.1, which pools data from different locations and provides robust estimates of low frequency extreme events (Cooley et al., 2007; Najafi and Moradkhani, 2013b).

In order to merge the multi-model ensemble runs, Bayesian model averaging of runoff time series is performed at individual grid cells, and the calculated BMA weights are

applied on the extreme runoffs corresponding to each RCM. Similar weights in the historical period are used to obtain the multi-model average results for the projected extreme runoffs. The results are compared with two other scenarios: 1) Taking the ensemble mean of VIC forcing signals including precipitation, temperature and wind speed followed by VIC simulation and extreme value analysis, 2) Driving VIC with individual RCM outputs, then combining the resulting runoffs followed by extreme analysis. In both scenarios the extreme runoffs are expected to be averaged out resulting in underestimated predictions. In addition averaging the inputs could affect the dependence of variables as discussed in (Hanel et al., 2013; Knutti et al., 2010).

Spatial assessment of model performances is performed based on the estimated weights at each grid cell, where better models are assigned higher weights. The between model variances (and correspondingly standard deviations) are considered to represent uncertainties arising from different RCMs in hydrologic impact assessments.

4. Results

The spatial distribution of the estimated BMA weights assigned to the downscaled daily precipitation over 1971-2000 are shown in Figure 1. Although the bias correction approach has significantly enhanced the simulations, results show that the simulations do not perfectly match with the observation. The use of more advance bias correction (postprocessing) methods by mean of copula functions can be explored in future studies (Madadgar and Moradkhani, 2014). The RCM3_gfdl, CRCM_ccsm and HRM3_gfld appear to receive higher weights as compared to the other RCMs. Lowest weights are assigned to RCM3_cgcm3 indicating that this model has the worst performance. To the north of the

253 Rockies, and most regions west of the Cascades higher weights are assigned to
254 HRM3_hadcm3, HRM3_gfdl and RCM3_gfdl.

255 Similar analyses were conducted for the maximum and minimum temperatures and wind
256 speed. Analysis of the maximum temperature indicates that the RCMs are almost equally
257 weighted. However, the HRM3_hadcm3 and the WRFG_ccsm are assigned slightly higher
258 weights compared to the others on the north of Rockies and west of the Cascades (not
259 shown). BMA weights obtained based on the minimum temperature values also tend to be
260 very close among the eight RCMs. The only exception is HRM3_hadcm3 which receives
261 slightly higher weights than the other RCMs. Similar results are obtained for the wind
262 speed. The weights corresponding to temperature and wind speed suggest that the RCMs
263 are performing almost equally well in estimating these variables. Therefore, the multi-
264 model average results would be similar to a strategy where all the RCMs are equally
265 weighted. This is contrary to the precipitation estimates (Figure 1) where differences
266 between model weights from various RCMs as well as the spatial variability within
267 individual RCMs are significant.

268 BMA is performed over runoff estimates from VIC hydrologic modeling based on different
269 RCMs. The assigned weights show significant spatial variability between RCMs (Figure 2).
270 The results indicate that CRCM_ccsm and WRFG_ccsm generally receive the highest
271 weights, while HRM3_hadcm3, RCM3_cgcm3 and RCM3_gfdl have the lowest values.

272 The weights assigned to each RCM can be regarded as indicators of its performance. Figure
273 3 shows the 90% range of the weights for each hydro-climate quantity corresponding to
274 the individual RCMs. The average performances between the models are approximately

similar regarding the maximum and minimum temperatures along with the wind speed. The medians are close to 0.125 (or 1/8) meaning that the models are almost equally weighted. The differences between models are more apparent with respect to precipitation and runoff estimates. This signifies the dissimilarities between regional climate models in simulating precipitation and hydrologic variables such as runoff. High spatial variations between the assigned weights also exist in runoff and precipitation as compared with the other quantites.

As indicated in section 3.3 the proposed method for ensemble merging of extremes is compared with two other strategies: 1) ensemble merging of climatological signals before hydrologic modeling and extreme analysis and 2) ensemble merging of runoff simulations before extreme analysis. Figure 4 shows the comparison between the estimated 100-yr runoffs from the three model combination strategies, and the ones estimated based on the observed gridded dataset as shown on the first column. Results from three strategies are shown on the second to fourth columns of Figure 4 respectively. As expected the two strategies in which signals are combined before extreme analysis tend to under-estimate the extreme runoffs in most of the region during all seasons. However, they capture the seasonal trend of extreme events showing highest extremes on the west of the Cascades along with the Olympics during winter which tends to decrease by spring and summer and again increase during fall. In the Rockies, where runoff is dominated by snowmelt, the extreme runoffs tend to increase in spring and summer then decrease in fall and winter when most of the precipitation falls and is stored as snow.

The biases corresponding to each model combination method are shown in Figure 5. The two strategies in which Bayesian model averaging is applied before the extreme analysis

provide negatively biased extreme estimates (under-estimation of the 100-yr runoffs). The biases are strong west of the Cascades and in the Rockies during spring through fall. The strategy in which the obtained BMA weights are assigned to extremes shows considerably lower bias.

The mean absolute errors of the estimated 100-yr runoffs (mm) from the Bayesian model averaging of extremes and its constituting models are compared in Table 1. The results indicate that BMA outperforms the best model during the spring and summer, while it outperforms most of the individual models in other seasons.

The between model variances are calculated for each grid cell based on Eq. 11, and the corresponding standard deviations are shown for the historical (red) and future (blue) time periods in Figure 6. The two peaks on the left side of each figure showing high between model standard deviations correspond to the Coast Range ($\sim 123^\circ$ W) and the Cascades ($\sim 121^\circ$ W) on the west. From Figure 6 the between model deviations considerably increase over the future period especially on west of the Cascades and close to the Pacific coast. This indicates an increased model uncertainty in hydrologic extreme analysis for the future compared to the historical period, based on the assumption that the model weights and biases are stationary in time. The spatial means of the between model deviations (median of all the standard deviations for individual grid cells) increase by approximately 52%, 80%, 133% and 210% during winter, spring, summer and fall respectively.

The multi-model ensemble averages of the 100-yr return level runoffs are shown for all seasons in Figure 7. The results show that in winter time extreme runoff increases in the

future, in particular over the Cascades and Olympics Mountains while it decreases in eastern Oregon and west of Idaho. In spring the results show future increases over the Rockies, especially in the Canadian portion of the Columbia River Basin, as well as west of the Cascades and the Olympics Mountains. The runoffs generally decrease in summer, while showing slight increases on the west coast. Fall season will experience increased extreme runoffs on west of the Cascades and the Rockies. There are slight increases in almost all other grid cells as well.

Figure 8 compares the seasonal multi-model average 100-yr runoffs for the historical and future time periods. Each circle represents a grid cell in the region with the ones above the splitting line showing increases in extreme runoffs. Approximately 90% of the grid cells show increased extreme runoff during winter and spring, while only 60% of the cells show increases in the summer. During the fall season almost all grid cells are expected to experience increased extreme runoffs. A linear regression model was fitted to the historical and future time series over each season. The generated scaling factors (i.e. β in $Y=X\beta+\alpha$) for each season are shown in Table 2. Results show overall increases in runoff extremes in the future time period.

5. Summary and Conclusions

Eight RCM_GCM combinations including CRCM_cgcm3, CRCM_ccsm, HRM3_gfdl, HRM3_hadcm3, RCM3_gfdl, RCM3_cgcm3, WRF3_cgcm3 and WRF3_ccsm were considered for the extreme ensemble merging. Analyses were based on the downscaled precipitation, temperature and wind speed, the VIC hydrologic model simulations, and the spatial

341 hierarchical Bayesian model estimates of the extreme runoff. Ensemble average results by
342 means of Bayesian model averaging were then compared to the individual estimations.

343 BMA was applied on the daily runoff simulations obtained from VIC based on different
344 RCMs. The estimated weights for all cells were applied on the predicted 100-yr runoffs
345 corresponding to individual RCMs in order to obtain the ensemble average results for both
346 the historical and future time periods. BMA performance was satisfactory as it
347 outperformed the best model during spring and summer seasons. The BMA weights were
348 spatially uniform regarding the temperature and wind speed, however, they varied
349 considerably for precipitation and runoff suggesting that there is large spatial variation in
350 RCM performances with respect to these quantities.

351 The between model variability was also quantified which showed that fall has the highest
352 variability in the future compared to its historical period.

353 Overall the multi-model results show increases in the extreme runoffs in the future in most
354 regions, particularly over the high elevations, such as the north of Rockies during spring.
355 The results also suggest that less than half of the PNW area will experience reduced
356 extreme events during summer, while extreme events are projected to increase for almost
357 the entire PNW during fall. These results suggest substantial shift in the seasonality of peak
358 stream-flow, mainly from summer to spring for several regions of the Pacific Northwest.

359 In this study the downscaling process was based on the quantile mapping approach and no
360 further adjustments for wet-day frequency or future extremes were applied. In addition
361 downscaling of the RCM_GCM variables for the future period was based on stationarity
362 assumption, that the biases between observations and simulations obtained for historical

period would remain unchanged. Similar assumption was made regarding the BMA weights that were applied on the projected simulations. However, models with high performance skills in the historical period do not necessarily show future prediction skill (Reifen and Toumi, 2009). Also Uncertainties arise due to the weighting process (Hesselbjerg Christensen et al., 2010) depending on the individual model error uncertainties as well as the degree of model error correlation and the relative magnitude of the unpredictable noise (Weigel et al., 2010).

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521

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7a

Figure 7b

Figure 8

Table 1

Table 1: Comparison of the mean absolute errors of the estimated 100-yr return level runoffs (mm) from BMA and the individual models.

Seasons	BMA	WRFG_cgcm3	WRFG_ccsm	RCM3_cgcm3	RCM3_gfdl	HRM3_hadcm3	HRM3_gfdl	CRCM_cgcm3	CRCM_ccsm
Winter	2.84	3.26	3.17	3.37	3.27	7.98	3.03	3.8	2.78
Spring	2.48	3.02	3.05	3.64	3.25	5.65	3.27	3.24	2.92
Summer	1.99	2.16	2.03	2.68	2.5	3.48	2.65	2.64	2.42
Fall	2.11	2.49	1.76	2.61	2.9	2.18	2.54	2.62	2.66

Table 2

Table 2: Calculated scaling factors based on the linear regression model of the future (Y) and historical (X) simulations.

Season	Mean	2.5% CI	97.5% CI
Winter	1.112	1.1	1.118
Spring	1.31	1.3	1.32
Summer	1.051	1.044	1.058
Fall	1.242	1.237	1.248