Extreme precipitations and temperatures over the U.S. Pacific Northwest : A comparison between observations, reanalysis data and regional models

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Abstract

We examine extreme precipitation and temperature indices in the R2 reanalysis data and the nested WRF (Weather Research and Forecasting) and HadRM (Hadley Centre Regional Model) simulations at HCN (Historical Climatology Network) stations over the United States Pacific Northwest during 2003-2007. The WRF and HadRM simulations driven by the R2 reanalysis data represent the observed extreme precipitations reasonably well: correlation coefficients are high and statistically significant, and slopes are close to 1. The WRF Domain 3 with its highest resolution (~12 km) shows the best statistical performance when compared to the 36-km WRF Domain 2 and 25-km HadRM. The R2 reanalysis data represent the timing of rain-bearing storms over the Pacific Northwest well; however, the reanalysis have the worst performance at simulating both extreme precipitation indices and extreme temperature indices when compared to the WRF and HadRM simulations. Improvement in the extreme temperature indices is also noted for WRF and HadRM simulations when compared to the R2 reanalysis data. These results suggested that the R2 reanalysis data, and by extension global climate model simulations, are not sufficient for examining extreme precipitations and temperatures due to their coarse resolutions. Nevertheless, the large-scale forcing for extreme events is represented by the reanalysis so that these events may be simulated in the regional models.
1. Introduction

Extreme weather events such as heat waves, floods, droughts or storms can lead to severe societal and economical impacts. Over the recent decades, the costs of the extreme events have increased dramatically (UNEP, 2002) and they are expected to change in frequency and/or intensity in a warming climate (IPCC, 2007; Tebaldi et al. 2006). Global climate models have long predicted the link between a warmer climate and changes in extreme weather events (IPCC, 2007). More recently, there has been some observational evidences of this. For instance, Allan and Soden (2008) demonstrated a direct link between a warmer climate and an amplification of precipitation extremes in tropical areas using satellite observations.

Global models are powerful tools to investigate climate change on large scales. However, such models do not represent local topography and other surface characteristics well due to their coarse horizontal resolution (~150-300 km). Therefore, they might face difficulties in adequately resolving the interactions of large-scale weather systems with local terrain and mesoscale processes that are important for causing localized extreme weather events. Note that the United States Pacific Northwest is especially challenging for global models since this region is characterized by complex terrain that includes mountainous ranges and land-sea contrasts (see Fig. 1).
To capture the fine-scale features such as orographic precipitation, land-sea breeze, rain shadows and wind storms, regional climate models with a more realistic representation of the complex terrain and heterogeneous land surfaces are needed (Mass et al., 2002; Leung et al., 2003a, b). Recently, Salathé et al. (2008) showed markedly different trends in temperature and precipitation over the Pacific Northwest between MM5-based regional climate simulation and the driving global models, presumably due to mesoscale processes not being resolve at coarse resolution. Later, Zhang et al. (2009) looked at the simulations from two limited-area coupled land-atmosphere models: the Weather Research and Forecasting (WRF) model and the Hadley Centre Regional Model (HadRM) over the same region. They noted improvement of the regional models performance over the large-scale driving data in generally resolving the observed precipitation and temperature. However, few studies have been dedicated to regional models performance in terms of extreme weather events despite the tremendous interest in such phenomena.

In this study, we will focus on extreme precipitations and temperatures and compare the R2 reanalysis and the WRF and HadRM simulations with observations. This is a first and necessary step towards the projection of future changes in extreme weather events on regional scales. This work is organized as follows. The models and experimental design are briefly described in Sections 2 and 3, respectively. A comparison of models simulations with observations is discussed in Section 4. Major conclusions and discussions are presented in Section 5.
2. Models Description

2.1 WRF Model

The WRF model is a state-of-the-art, next-generation mesoscale numerical weather system designed for short-term weather forecast as well as long-term climate simulation (http://www.wrf-model.org). It is a non-hydrostatic model, with many different choices for physical parameterizations suitable for a broad spectrum of applications across scales ranging from meters to thousands of kilometers. The physics package includes microphysics, cumulus parameterization, planetary boundary layer (PBL), land surface models (LSM), longwave and shortwave radiation (Skamarock et al. 2006).

In this work, the microphysics and convective parameterizations used were the WRF Single-Moment 5-class (WSM5) scheme (Hong et al. 2004) and the Kain-Fritsch scheme (Kain and Fritsch 1993), respectively. The WSM5 microphysics explicitly resolves water vapor, cloud water, rain, cloud ice, and snow. The Kain-Fritsch convective parameterization utilizes a simple cloud model with moist updrafts and downdrafts that includes the effects of detrainment and entrainment. The land-surface model used was the NOAH (National Centers for Environmental Prediction - NCEP, Oregon State University, Air Force, and Hydrologic Research Lab) LSM 4-layer soil temperature and moisture model with canopy moisture and snow cover prediction (Chen and Dudhia 2001). The LSM includes root zone, evapotranspiration, soil drainage, and runoff, taking
into account vegetation categories, monthly vegetation fraction, and soil texture. The
PBL parameterization used was the YSU (Yonsei University) scheme (Hong et al., 2006)
which is an updated version of Hong and Pan (1996). This scheme includes counter-
gradient terms to represent heat and moisture fluxes due to both local and non-local
gradients. Atmospheric shortwave and longwave radiations were computed by the NCAR
CAM (Community Atmospheric Model) shortwave scheme and longwave scheme
(Collins et al. 2004), respectively.

2.2 HadRM Model

HadRM (Jones et al. 2004) is the third-generation regional climate model (HadRM3H)
developed at the UK Met Office Hadley Centre. It is a limited-area, high-resolution
version of the atmospheric general circulation model HadAM3H (Gordon et al. 2000;
Johns et al. 2003). HadRM is a hydrostatic version of the fully primitive equations.
Model parameterizations include dynamical flow, horizontal diffusion, clouds and
precipitation, radiative processes, gravity wave drag, land surface and deep soil (Jones et
al. 2004).

The horizontal resolution of the HadRM model grid is 0.22°x0.22° (although a resolution
of 0.44°x0.44° is also available). The HadRM latitude-longitude grid is rotated in a way
that the equator lies inside the region of interest. This permits quasi-uniform grid box
area over the region of interest with a minimum horizontal resolution of ~25 km at the rotated equator.

HadRM was released as part of the PRECIS (Providing REgional Climates for Impacts Studies) package ([http://precis.metoffice.com](http://precis.metoffice.com)). This package also includes software to allow processing and display of the model output data. The PRECIS package is flexible, user-friendly and computationally inexpensive. It can easily be applied over any regions of the globe to provide detailed climate information for regional climate studies and climate impacts assessment.

3. Experimental Design

The experimental design follows Zhang et al. (2009) and is briefly described here.

WRF was set up by using multiple nests (Fig. 1a). The outermost domain at 108 km resolution covers nearly the entire North American continent and much of the eastern Pacific Ocean and the western Atlantic Ocean. The second domain at 36 km resolution encompasses the continental U.S. and part of Canada and Mexico. The innermost domain at 12 km resolution covers the U.S. Pacific Northwest (Fig. 1b). 31 vertical levels were used in the model with the highest resolution (~20 – 100 m) in the boundary layer. One-way nesting was applied in this study.
We chose the highest available resolution (~25 km) for the domain of HadRM (Fig. 1a). The HadRM model domain includes a large part of the eastern Pacific Ocean, Western U.S. and part of Mexico and Canada to better represent the synoptic weather systems that affect the Pacific Northwest. There are 19 vertical hybrid levels in HadRM spanning from the surface to 0.5 mb.

The WRF and HadRM runs were initialized at 0000 UTC December 1, 2002 and ended at 0000 UTC December 31, 2007. The first one-month simulations by WRF and HadRM were regarded as model spin-up. The initial and lateral boundary conditions were interpolated from the NCEP-DOE (Department of Energy) AMIP-II (Atmospheric Model Intercomparison Project) Reanalysis (R-2) data (Kanamitsu et al. 2002). The lateral boundary conditions were updated every six hours for both models. SST was updated every six hours in WRF using the RTG_SST (Real-Time, Global, Sea Surface Temperature) analysis (ftp://polar.ncep.noaa.gov/pub/history/sst) developed and archived at NCEP. In HadRM, SST was taken from a combination of the monthly HadISST (Hadley Centre’s sea ice and sea surface datasets; http://badc.nerc.ac.uk/data/hadisst) and weekly NCEP observed datasets (http://www.cdc.noaa.gov/cdc/reanalysis/reanalysis.shtml). The simulations from both WRF and HadRM models were output every hour.
4. Results

We will focus on extreme weather indices for which a 5-year simulation is adequate. Definition of these extreme weather indices based on daily maximum and minimum temperatures and precipitation are described in Table 1.

The daily maximum and minimum temperatures (Tmax and Tmin) are obtained from simulated hourly temperature with terrain adjustment performed in the same way as in Zhang et al. (2009). The terrain adjustment is performed in order to account for differences in altitude between the station and the model grid point. To summarize, we compute the local daily lapse rate ($\lambda_r$) at each station location using the following formula:

$$\lambda_r = \frac{1}{n} \sum_{i=1}^{n} \frac{|T_r - T_i|}{|h_r - h_i|}$$

where $T$ represents the surface air temperature from the model simulation and $h$ the terrain elevation of the grid cell. The $r$ and $i$ subscripts stand for the grid cell of reference (for which the lapse rate is computed in the WRF and HadRM domains) and one of the four closest grid cells, respectively. Note that among these four neighborhood grid cells, only the ones with an elevation at least 100 m higher or lower than the grid cell of reference were used in this formula. Otherwise, the standard lapse rate of 6.5°C/km was used. Finally, the computed lapse rates were constrained to the interval of 2 to 7°C/km in
agreement with what has been observed (Mote et al. 2009). We noticed a rather small
difference between using this computed lapse rate and the standard one. For R2, we still
used the standard lapse rate. No lapse rate was applied to precipitation.

4.1 Extreme Precipitation Indices

For extreme precipitation, we mainly focus on annual number of days with precipitation
over certain thresholds (10, 20 and 40 mm), annual number of wet days, maximum
number of consecutive wet (dry) days, simple daily precipitation index, annual total
precipitation in wet days and monthly maximum precipitation within 1 day and 5
consecutive days.

Figure 2 shows the tail of the normalized probability density function (pdf) of daily
precipitation greater than 70 mm over the 5-year period with all stations combined.
Station observations show 26 days with daily precipitation greater than 100 mm; the
regional climate models simulate frequencies of 32, 41 and 34 days, for WRF Domain 2,
Domain 3 and HadRM, respectively. However, the reanalysis data never generates
precipitation greater than 100 mm and severely underestimates the number of days with
precipitation between 70 and 100 mm. Notice in Fig. 2 that regional climate models seem
to generally overestimate the amount of days with daily precipitation lower than 130 mm.
Scatter plots for the number of days with daily precipitation greater than 10, 20 and 40 mm are presented in Fig. 3; each point represents the results for a single HCN station and for a single year over the 5-year period. Correlation coefficients and linear regression slopes are given in each panel and indicate how well the simulations capture the variation in extreme precipitation across the region. All correlation coefficients presented in this figure are significant at significance level of 0.05 based on t-statistics, except for the number of days with precipitation greater than 40 mm in R2. There is a clear tendency of decreasing correlation coefficient with increasing threshold which suggests that models have increasing difficulties in resolving the increasingly heavy precipitations. The R2 reanalysis persistently shows the lowest correlation coefficients and slopes. For instance, the correlation coefficient is merely 0.46 with a slope of 0.14 for number of days with precipitation greater than 40 mm/day. Among the regional models, WRF Domain 3 always shows the highest correlation coefficients which is probably related to a better representation of the domain due to its higher resolution. Note also that WRF tends to overestimate extreme precipitations.

Hence, the regional models show improvement over the R2 reanalysis data in getting the magnitude of extreme precipitations closer to observations. However, it is important to know whether or not the models also get the timing of extreme precipitations right. Assuming that the timing of the rain-bearing storms is determined by the large-scale forcing data, we examined the probability of occurrence of a wet day in the reanalysis
data and regional models on days when the observed daily precipitation is greater than a certain threshold (Fig. 4). More than 80% of the time, when rain is observed, the reanalysis data also generate precipitation (Fig. 4). This percentage increases to more than 93% when the observed daily precipitation is greater than 10mm. Similar probabilities are noted in the regional models (Fig. 4), confirming that timing of precipitation in the regional models is dictated by the reanalysis data.

Scatter plots of annual number of wet days (daily precipitation greater than 1 mm; Fig. 5a) simulated and observed at each station show overestimation not only in the regional models but also in the R2 reanalysis. Correlation coefficient and slope for R2 are 0.52 and 0.39, respectively. Correlations for the regional models are higher than for R2, with the WRF Domain 2 showing the highest correlation coefficient (0.78) while HadRM showing the best slope (0.64) among the regional models.

Scatter plots of the maximum number of consecutive wet days (Fig. 5b) show overestimation in R2 and regional models. The correlation coefficients between R2 and the regional climate models are similar. The slopes for the R2 reanalysis and HadRM model are comparable and better than the slopes for the WRF model. In comparison, the maximum number of consecutive dry days are underestimated by R2 and regional models (Fig. 5c). This is consistent with the overestimation of the annual number of wet days (Fig. 5a) as well as the maximum number of consecutive wet days (Fig. 5b). The
correlation coefficients and the slopes for the maximum number of consecutive dry days are rather small (between 0.40 and 0.56 for correlations and between 0.30 and 0.46 for slopes). However, among the regional models WRF Domain 3 shows slightly better correlation coefficient and slope. For the annual number of wet days, maximum number of consecutive wet days, and maximum number of consecutive dry days we do not find substantial improvement from the regional climate models over the driving data. This result is consistent with the goals of dynamical downscaling. The timing and number of rain-bearing storms are determined by the large-scale forcing fields and the regional models cannot modify this timing.

Scatter plots of simple daily precipitation index defined as the average daily precipitation on wet days are displayed in Fig. 5d. Correlation coefficients are higher and slopes are closer to 1 for regional models than for the R2 reanalysis with the highest correlation coefficient and the best slope noted for WRF Domain 3 among the regional domains. As mentioned before, the timing of rain-bearing storms in regional models is determinate by the large-scale driving data; however, the magnitude strongly depends on the interactions of the local terrain with the large-scale weather systems. Regional models, with their improved representation of local terrain, better resolve orographic precipitation and yield precipitation intensities closer to the observations. This result can also be seen in the spatial distribution of simple daily precipitation index (Fig. 6) where larger (smaller) precipitation intensities occur on windward (leeward) side of the Cascade Range in
observations and regional model simulations while the R2 reanalysis data displays a relatively homogeneous pattern and a smaller gradient between wind- and leeward regions.

Figure 5e presents the scatter plots of annual total precipitation in wet days; this measure is the product of the precipitation index and the number of wet days. The benefit of regional climate models over the R2 reanalysis data is clear in this figure as evidenced in higher correlation coefficients and slopes closer to 1. This is also clearly indicated by the geographical distribution of the annual total precipitation in wet days (Fig. 6). Although the correlation coefficient of WRF Domain 3 is the highest among the regional domains, note that this domain also overestimates the annual total precipitation in wet days due to the already discussed overestimation of the annual number of wet days (Fig. 5a).

Figure 7 presents scatter plots of maximum 1-day and 5-day accumulated precipitation for each calendar month over the 5-year period. The correlation coefficients between the R2 reanalysis and the observations for 1- and 5-day maximum precipitation are 0.60 and 0.69, respectively. These values are slightly lower than those for the regional models. However, the slopes for the regional models are considerably better and closer to 1 than those for the reanalysis data. Severe underestimation of the observed precipitation is noted in the R2 reanalysis data especially for 1-day maximum precipitation greater than 100 mm and 5-day accumulations greater than 200 mm. Here again, WRF Domain 3 with
its highest resolution exhibits the highest correlation coefficients and the best slopes amongst the regional domains.

To summarize, the above analysis suggests that the R2 reanalysis data resolves the timing of the rain-bearing storms relatively well; however, R2 reanalysis data shows poor performance in capturing extreme precipitation events. This suggests that the reanalysis data adequately represent the well-resolved fields such as moisture flux and synoptic storms. Because of this, extreme precipitation can be adequately simulated in regional models given boundary conditions. This is especially true for WRF Domain 3, which shows the best statistical performance amongst the regional domains, indicating the importance of model resolution in simulating extreme precipitation. This conclusion should likewise apply when using regional models to downscale global climate models with similar resolution to the R2 reanalysis.

4.2 Extreme Temperature Indices

For extreme temperatures, we examined 1) the annual number of frost days, 2) the number of summer days, 3) the annual number of days with Tmax greater than 30 and 35°C, and 4) the monthly extreme values of Tmax and Tmin. The results are presented in Figs. 8 and 9.
R2 is comparable to regional climate models in terms of correlation coefficients for the number of frost days but with a better slope (Fig. 8a). This might be related to large deficiencies in the regional climate models during night time (Zhang et al., 2009). As also noted in Zhang et al. (2009), during the same 5-year simulation period, a warm bias of Tmin on the order of 2°C is identified over the Pacific Northwest in both model simulations. This warm bias tends to reduce the number of frost days in the regional models. Also, cold bias of Tmin on the order of 1°C is noted in the R2 reanalysis and might be responsible for larger number of frost days. These biases are reflected in the scatter plots with the R2 reanalysis showing the majority of the points above the 1:1 line and the regional model results falling below the line.

For the number of summer days and the number of days with Tmax greater than 30 and 35°C (Figs 8b, c and d), the regional models consistently show higher correlation coefficients and significantly better slopes compared to the R2 reanalysis. Severe underestimation identified in these categories in the R2 reanalysis might be related to the cold bias of Tmax on the order of 3°C (Zhang et al., 2009). As pointed out in the same paper, the regional models with higher resolution tend to partially reduce this large bias to values less than 1°C.

All scatter plots in Fig. 8 display a larger spread in R2 than in regional models suggesting that regional models better represent the spatial pattern of extreme temperatures.
compared to R2, even with a lapse-rate correction applied. Temperature is primarily dictated by large-scale weather systems with fine scale features (e.g. land cover, albedo, soil moisture, cloudiness) playing a secondary role in modulating the local temperatures. Large-scale driving data such as the R2 reanalysis usually captures the large-scale weather systems well. However, the improved resolution of the regional models is better able to represent mesoscale processes (Salathé et al, 2008) and land-surface characteristics, which yields the narrower spreads in the scatter plots.

The correlation coefficients and slopes for the extreme temperature indices (Fig. 8) do not differ significantly between the regional domains in contrast to the extreme precipitation indices. This suggests that higher resolution does not lead to better model performance beyond a certain threshold. This may be in part due to the lapse rate correction, which accounts for the lack of high-resolution terrain and, as opposed to topography, land cover types are likely well-resolved even at 36-km grid spacing.

Figure 9 shows the annual extreme Tmax and Tmin. Note that these annual maximum and minimum extremes basically refer to summer and winter extremes, respectively. For the annual maximum value of daily Tmax (Fig. 9a), the correlation coefficient and slope corresponding to the R2 reanalysis are 0.59 and 0.61, respectively. The regional models show considerably higher correlation coefficients (~0.80) and much better slopes (~0.90). In terms of annual minimum values of Tmin (Fig. 9b), the correlation coefficients and
slopes corresponding to the regional models do not differ appreciably from those for the R2 reanalysis except for HadRM regional model which shows a rather low slope (0.53).

The R2 reanalysis strongly underestimates the annual minimum value of Tmin by as much as about 8°C (Fig. 9b). The WRF domains both show small bias in the annual minimum value of Tmin while HadRM shows a warm bias of the order of ~3°C. This suggests that the regional models have warm biases which might offset the large cold biases of R2 in winter.

5. Conclusions and Discussion

This work examines the performance of two regional models, WRF and HadRM in simulating several indices of extreme temperature and precipitation for the U.S. Pacific Northwest during a five-year period (2003-3007).

Our analysis indicates that the R2 reanalysis data represent the timing and intensities of rain-bearing storms over the Pacific Northwest well; however, the R2 reanalysis data consistently show less correspondence with observed extreme precipitation indices when compared to the WRF and HadRM simulations. This is explained by the rather coarse resolution of the R2 reanalysis system that cannot simulate the magnitude of locally intense precipitation, which depends on the influence of local complex terrain on large-
scale weather systems. Thus, the R2 reanalysis data provide realistic large-scale boundary conditions necessary for driving regional climate models and allow the regional models to simulate locally intense precipitation events that are not captured in the reanalysis. This conclusion may also hold true for dynamically downscaling global climate models provided they simulate realistic large-scale patterns. Comparing regional simulations at multiple grid spacing and two models illustrates the importance of fine grid spacing in simulating extreme precipitation.

The WRF and HadRM simulations resolve the observed extreme precipitation indices reasonably well as reflected by high correlation coefficients and slopes close to 1 in terms of the extreme precipitation indices. The improvement of the regional models over the R2 reanalysis data in simulating the extreme precipitation events are primarily related to the better representation of the local complex terrain by the regional models. The WRF Domain 3 with its highest resolution always shows the best statistical performance when compared to the WRF Domain 2 and HadRM.

Appreciable improvement in the extreme temperature indices is also noted for WRF and HadRM when compared to the R2 reanalysis data. This is likely related to the capability of the regional models in resolving mesoscale processes that are associated with complex terrain. Daily temperature variability is primarily controlled by large-scale weather systems; however, mesoscale processes can modulate the temperature fields in a non-
trivial way especially over complex terrain. An improvement in simulating extreme temperature indices at finer grid spacing is found even with a lapse-rate correction applied to model results, so elevation is not the primary issue producing better local temperature simulations. Extremes in temperature depend also on radiative transfer, boundary layer dynamics, and latent and sensible heat transfer with the surface. These in turn depend on surface properties such as vegetation, snow cover, surface albedo, and soil moisture and temperature. The fine grid spacing of the regional models is necessary to adequately resolve local variations in these surface properties and provide realistic simulations of extreme temperatures.

HadRM and WRF are generally comparable in their performance in resolving the observed precipitation and temperature extremes at horizontal resolutions on the order of tens of kilometers, although HadRM with its higher resolution (~20 km) than the WRF Domain 2 (~36 km) does not necessarily show improved performance over the WRF Domain 2. This is probably related to different physics and dynamics parameterizations between the two models. It is noted that HadRM is a hydrostatic model with less flexibility in horizontal resolution but is computationally inexpensive to run while WRF is a complex modeling system with horizontal resolutions ranging from meters to thousands of kilometers but is computationally expensive to run.
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References:


Zhang, Y., V. Dulière, P. Mote and E.P. Salathé Jr., 2009: Evaluation of WRF and
HadRM Mesoscale Climate Simulations over the United States Pacific Northwest.

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Table 1. Definition of extreme precipitation and temperature indices.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Definition</th>
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<tbody>
<tr>
<td>1</td>
<td>Annual number of days with daily precipitation greater than 10 mm</td>
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<td>2</td>
<td>Annual number of days with daily precipitation greater than 20 mm</td>
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<td>3</td>
<td>Annual number of days with daily precipitation greater than 40 mm</td>
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<tr>
<td>4</td>
<td>Annual number of wet days when daily precipitation greater than 1 mm</td>
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<td>5</td>
<td>Maximum number of consecutive wet days with daily precipitation greater</td>
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<td>than 1 mm</td>
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<td>6</td>
<td>Maximum number of consecutive dry days with daily precipitation less than</td>
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<td>1 mm</td>
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<td>7</td>
<td>Simple daily precipitation index (the average daily precipitation on a</td>
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<td></td>
<td>wet day)</td>
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<td>8</td>
<td>Annual total precipitation in wet days</td>
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<td>9</td>
<td>Monthly maximum 1-day precipitation</td>
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<td>10</td>
<td>Monthly maximum 5-day precipitation</td>
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<tr>
<td>11</td>
<td>Number of frost days with daily minimum temperature less than 0°C</td>
</tr>
<tr>
<td>12</td>
<td>Number of summer days with daily maximum temperature greater than 25°C</td>
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<tr>
<td>13</td>
<td>Number of days with daily maximum precipitation greater than 30°C</td>
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<tr>
<td>14</td>
<td>Number of days with daily maximum precipitation greater than 35°C</td>
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<tr>
<td>15</td>
<td>Annual maximum value of daily maximum temperature</td>
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<tr>
<td>16</td>
<td>Annual minimum value of daily minimum temperature</td>
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* The indices and their definition follow primarily the recommendations from the CLIVAR (Climate Variability And Variability) Expert Team on Climate Change Detection and Indices
Figure 1. (a) WRF model domains with two nests (Domain 1, 2, 3) and HadRM domain, and (b) WRF innermost domain (Domain 3) and terrain height (m). Shadings in (a) represent terrain height (m) for the corresponding WRF domain. Grid spacing for each domain is: WRF Domain 1, 108 km; WRF Domain 2, 36 km; WRF Domain 3, 12 km; and HadRM Domain, 25 km. USHCN stations in the states of Washington, Oregon and Idaho are represented by filled black circles in (b).
Figure 2. Normalized probability distribution function of daily precipitation at USHCN stations location from observations (thick black), R2 reanalysis (dash-dotted) and WRF Domain 2 (dotted gray), WRF Domain 3 (black) and HadRM (gray) simulations. Precipitation is in mm.
Figure 3. Scatter plots of annual number of days with daily precipitation greater than 10 (a), 20 (b) and 40 mm (c) between observations and R2 reanalysis data (first column) and between observations and WRF Domain 2, WRF Domain 3 and HadRM simulations (second, third and fourth columns, respectively). Each point reflects the extreme index at one USHCN station for each year over the 5-year period. The two numbers in each scatter plot correspond to the correlation coefficient and linear regression slope, respectively. Except for the number of days with precipitation greater than 40 mm in R2, all correlation coefficients are significant at a significance level of 0.05 based on t-statistics.
Figure 4. Probability of a wet day in the reanalysis data (black), WRF Domain 2 (light gray), WRF Domain 3 (medium gray) and HadRM (dark gray) given that the corresponding observed daily precipitation is greater than a certain threshold (0.1, 10, 20, 30, 40 and 50 mm). The probability is computed at each station location, then spatially averaged.
Figure 5. Scatter plots of various precipitation indices between observations and R2 reanalysis (first column) and between observations and WRF Domain 2 (second column), WRF Domain 3 (third column) and HadRM (fourth column) simulations. Each point reflects the extreme index at one USHCN station for each year over the 5-year period. The two numbers in each scatter plot correspond to the correlation coefficient and linear regression slope, respectively. All correlation coefficients are significant at a significance level of 0.05.
Figure 6. Geographical distributions of simple daily precipitation index (top 5 panels) and annual total precipitation in wet days (bottom 5 panels) for USHCN observations, R2 reanalysis and WRF Domain 2, WRF Domain 3 and HadRM simulations at stations location. The Cascade crest is represented by the dotted line.
Figure 7. Scatter plots of monthly maximum 1-day (a) and 5-day (b) accumulated precipitation between observations and R2 reanalysis (first column) and between observations and WRF Domain 2, WRF Domain 3 and HadRM simulations (second, third and fourth column, respectively). Each point reflects the extreme index at one USHCN station for each calendar month over the 5-year period. Precipitation is given in mm. The two numbers in each scatter plot correspond to the correlation coefficient and linear regression slope, respectively. All correlation coefficients are significant at a significance level of 0.05.
Figure 8: Scatter plots of temperature indices between observations and R2 reanalysis (first column) and between observations and WRF Domain 2, WRF Domain 3 and HadRM simulations (second, third and fourth column, respectively). Each point reflects the extreme index at one USHCN station for each year over the 5-year period. The two numbers in each scatter plot correspond to the correlation coefficient and linear regression slope, respectively. All correlation coefficients are significant at a significance level of 0.05. Temperature is given in degree Celsius.
Figure 9. Scatter plots of annual maximum value of Tmax (a) and annual minimum value of Tmin (b) between observations and R2 reanalysis (first column) and between observations and WRF Domain 2, WRF Domain 3 and HadRM simulations (second, third and fourth column, respectively). Each point reflects the extreme index at one USHCN station for each year over the 5-year period. The two numbers in each scatter plot correspond to the correlation coefficient and linear regression slope, respectively. All correlation coefficients are significant at a significance level of 0.05. Temperature is given in degree Celsius.