

An Improved Dynamical Downscaling for the Western United States

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1. Introduction

A quantitative assessment of climate change impacts on water management depends heavily on the knowledge of basic climate variables, such as precipitation and temperature, and how they might change over time. The approach of dynamical downscaling - nesting regional climate models (RCMs) within general circulation models (GCMs) - has shown promise in producing climate information at scales useful to e.g. water managers (Leung et al. 2006). Organized efforts such as the European project PRUDENCE (Christensen et al. 2007) and the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al. 2009) have demonstrated the value of dynamical downscaling on regional climate projections. However, a significant degree of uncertainty in regional downscaling still exists. The uncertainties are more so in mountainous and drought-prone regions such as the western United States (U.S.) (Lo et al. 2008), as this region of the U.S. is projected to experience significant warming and precipitation reduction that portend a drying climate scenario (IPCC 2007). Hence, an assessment of climate projection uncertainties is paramount.

The western U.S. relies both economically and socially on the development of winter mountain snowpack and the timely release of its retained water (Gleick and Chalecki 1999). Decreasing and early melting of the snowpack across the western U.S. have occurred during the past century (Cayan et al. 2001; Pierce et al. 2008) and are expected to continue due to a warming climate (McCabe and Wolock 1999; Leung et al. 2004). RCMs are envisaged to be a crucial tool to simulate future projections at finer scales. However, a recent analysis on change in snow property (Gillies et al. 2011) have noted that most NARCCAP models tend to produce persistent cold biases in the surface over the western U.S., thus leading to an overestimation of the snowfall and the snow depth. Analyzing several mesoscale forecast models, Coniglio et al. (2010) have observed similar cold biases in daily minimum temperature, which are attributable to the models' inability to break down the morning inversion layer quickly enough. Such cold biases are most serious in the interior West. While temperature biases alone may be corrected by statistical methods, these documented cold biases in RCMs can and do alter the climate projections; this is because the amount of available water in the atmosphere is also a function of evapotranspiration, which changes exponentially with temperature variations (Nash and Gleick 1993). Moreover, the impacts

of such temperature biases on many derived variables (such as snow) cannot be statistically corrected in the downscaling.

Precipitation simulation has been a challenge in the western U.S. as well. A study by Wang et al. (2009) (hereafter WGTG) examined the precipitation seasonal and interannual variabilities simulated by six RCMs that participated in NARCCAP (models described in Figure 1). The results of WGTG indicated that all the models driven by reanalysis data persistently overestimated the winter precipitation amounts but underestimated summer precipitation amounts. Such biases, which are consistent with those found in other simulations over the western U.S. (Leung et al. 2004; Caldwell et al. 2009; Qian et al. 2010), result in a severe distortion of the seasonal cycle, particularly over regions that are further inland (cf. areas B, C, & D in Figure 1). For instance, the distinct semi-annual variation of the Wasatch Range (area B) was simulated as a winter-dominant annual cycle by all models, while the dry spring and wet summer in the Colorado Rockies (area C) were portrayed erroneously as wet spring and dry summer in 3 out of 6 models. Among these common biases, the monsoon rainfall (area D) was severely underestimated by 5 models resulting in an incorrect winter-predominant precipitation regime. WGTG further showed that the overprediction in the winter precipitation leads to a “false association” with the El Niño-Southern Oscillation (ENSO) while in reality, the ENSO-precipitation correlation is quite low in this region (e.g., Dettinger et al. 1998). What is more, recent observational studies (e.g., Anderson et al. 2010) point out that the summer precipitation in southwest U.S. has increased over the past half century and is associated with a broader coverage through enhanced monsoon rainfall. However, such an observation contradicts the projected decrease in summer precipitation over the same region by the IPCC (2007). Given the ubiquitous RCM biases in the monsoon rainfall – as is evident in Figure 1 – the reliability of climate projections downscaled from RCMs remains highly uncertain.

The challenge in regional downscaling is further exemplified by the projected changes in winter precipitation over the western U.S. (Figure 2) simulated by two NARCCAP models: the Canadian RCM (left) and the UC-Santa Cruz RCM3 (right), both of which are downscaled from the Canadian GCM Version 3. Despite apparent agreement in precipitation changes at higher latitudes, the downscaled results for the subtropics and monsoon affected regions are noticeably different between the two models, particularly in the Southwest. In this region, the CRCM simulated an overall increase in winter precipitation, while the RCM3 simulated much less of an increase and even has some areas experiencing a decrease. Since these projections were forced by the same GCM boundary conditions, their discrepancies pose a concern regarding the extent to which climate change scenario is representative. Such discrepancies are compounded further when it comes to the evaluation of RCMs downscaled output. Conventional detection and attribution methods (e.g., Hegerl et al. 2006) are generically developed from signal processing and so, require a large number of simulations to generate ensemble means; this requires a significant capacity in computing resources. At present, few operational institutions are capable of this level of computation and data storage. Thus, a more efficient performance measure is needed to evaluate simulation discrepancies as has been revealed in Figures 1 and 2.

While ongoing efforts continue to improve the physics schemes in RCMs, a different set of challenge lies in the inherent biases of the GCM forcing data. That is, even if an RCM can produce a realistic regional climate when driven by observations, any biases in the parent

GCM will inevitably distort the downscaled climate (e.g., Lo et al. 2008). An example from our recent in-house study shows just such an effect (Figure 3): the reanalysis-driven simulation of the Weather Research and Forecasting (WRF) model produced a realistic temperature downscaling over the western U.S. (Figures 3a and 3b); however, temperature downscaled from a GCM revealed widespread cold biases (Figure 3c). Similar temperature biases were also reported by Caldwell et al. (2009).

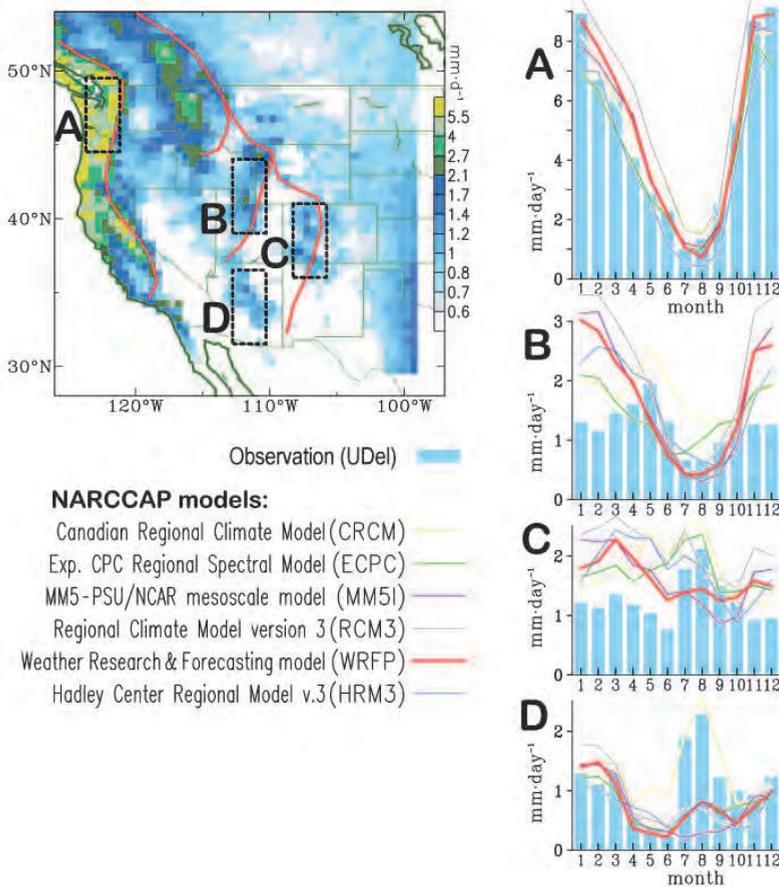


Fig. 1. Cold season (Nov-May) precipitation distribution and monthly observed (bar) and simulated (lines) precipitation at four designated areas. Modified from Wang et al. (2009).

These results strongly suggest that realistic regional downscaling is only achievable with a calibrated RCM driven by an un-biased GCM forcing. In this chapter, we propose an economic and efficient method to reduce uncertainties in climate projections, with a specific focus on the western U.S. Model settings and data sources necessary for developing this method are introduced in Section 2. Simulation design is outlined in Section 3. Results and discussions are presented in Section 4. A summary and some conclusions are given in Section 5.

DJF Precip 2041-2070 minus 1971-2000

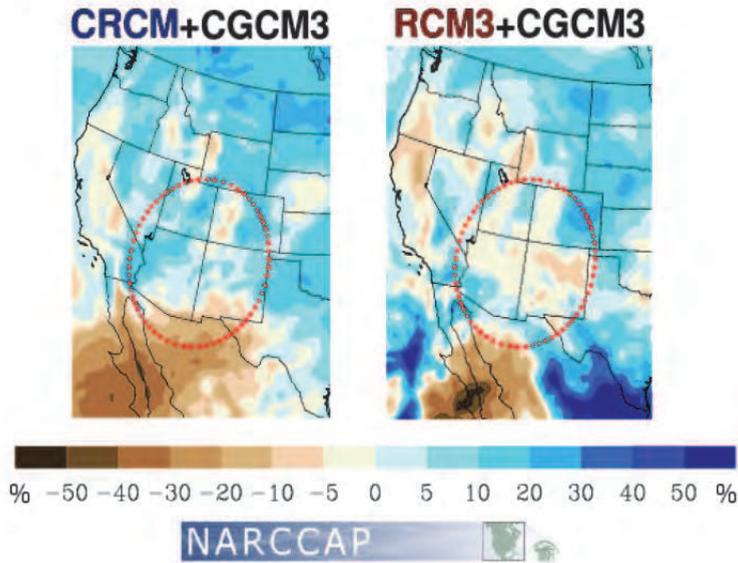


Fig. 2. Difference of winter precipitation in percentage between periods of 2041-2070 and 1971-2000 downscaled from CGCM3 by CRCM (left) and RCM3 (right) of the NARCCAP. The Southwest region with large discrepancy is circled.

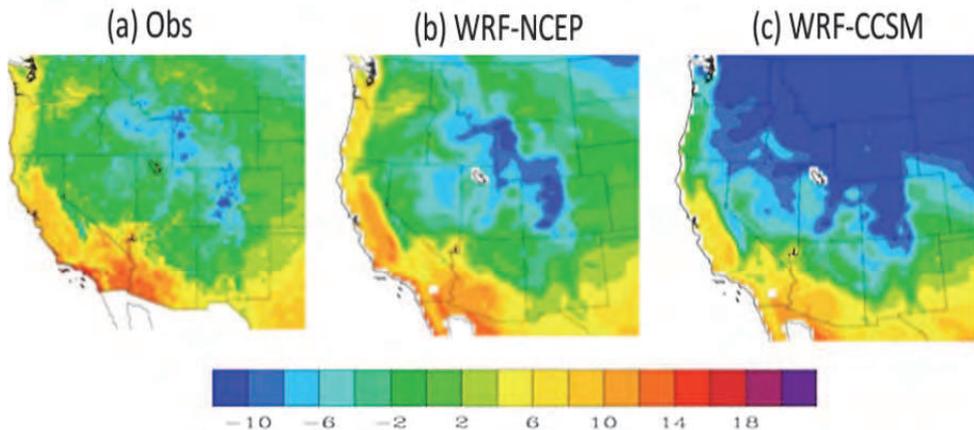


Fig. 3. Surface temperature (°C) in December 1999 from a) PRISM (Parameter-elevation Regressions on Independent Slopes Model) data (4 km), b) coupled WRF-CLM simulations driven by the National Centers for Environmental Prediction reanalysis data I (NCEP-1) (30 km), and c) WRF-CLM simulations driven by CCSM (30 km).

2. Model and data sources

We used the latest version WRF model (version 3.2) for the dynamical downscaling. Figure 4 shows the simulation domain centered over the western U.S. but also covering adjacent areas including the Pacific. We decided upon a 30 km resolution to better account for the complex terrain of the region, but at the same time comparable to the 50 km resolution of NARCCAP. The WRF model was configured with 28 vertical sigma layers from the surface to the 50 hPa level. In addition, the WRF model was coupled to the Community Land Model version 3.5 (CLM), hereafter WRF-CLM. The CLM was designed to describe snow, soil, and vegetation processes for global and regional applications (Bonan et al. 2002; Jin et al. 2010a, b); this latest version includes a 5-layer snow scheme, a 10-layer soil scheme, and a single layer vegetation scheme. The vegetation involves solar radiation reflected and absorbed by the canopy as well as its transfer within the canopy (Sellers 1985). Up to 10 sub-grids per model grid are included in CLM to represent sub-grid heterogeneity of the land surface. The surface is classified into 24 land categories, including different types of vegetation, bare soil, oceans, lakes, wetlands, and glaciers. The soil layer is divided into 19 categories defined as percentages of sand and clay.

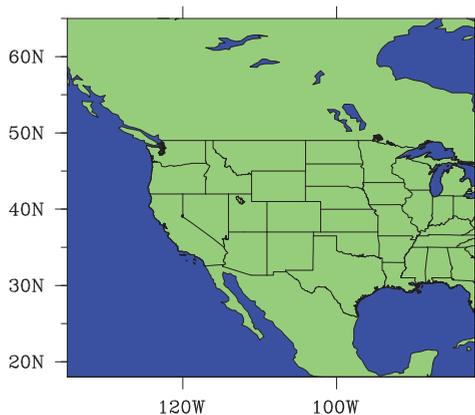


Fig. 4. Proposed simulation domains for the WRF model at 30 km resolution.

Reanalysis to drive the WRF model was obtained from the National Centers for Environmental Prediction-Department of Energy Global Reanalysis II (NCEP-2; Kanamitsu et al. 2002) available 1979-present. The GCM to drive the WRF model is the Community Climate System Model (CCSM) used in the IPCC Fourth Assessment Report. Other observational data sets used in this study included monthly $0.5^\circ \times 0.5^\circ$ gridded precipitation and temperature (Legates and Willmott 1990), the North American Regional Reanalysis at a 32-km resolution (NARR; Mesinger et al. 2006), and 4-km precipitation and temperature data from the PRISM.

For downscaling evaluations, we used the NARCCAP output. NARCCAP's six RCMs (including WRF) were driven by NCEP-2 reanalysis and a set of atmosphere-ocean general circulation models (AOGCMs) over a domain that covers the continental U.S. and much of Canada. The AOGCMs (including CCSM) were forced with the A2 Emissions Scenario which has cumulative CO_2 concentrations projected to be around 575 ppm by the middle of

the 21st century. Reanalysis-forced simulations were also produced for the period 1979-2004; those simulations were analyzed by WGTG. For climate downscaling, the RCMs are nested in the AOGCMs for the historical period 1971-2000 and for a future period 2041-2070. All the RCMs were run at a spatial resolution of 50 km. For details about NARCCAP see Mearns et al. (2009) and their website at <http://www.narccap.ucar.edu/>.

3. Simulation framework

To assess the range of projection uncertainties in regional downscaling, we conducted (1) a physics-calibrated RCM that was forced by (2) a set of bias-corrected GCM data, (3) to produce a set of calibrated/corrected downscaling data, and (4) to evaluate this data set with control simulations as well as the NARCCAP output. These approaches are illustrated schematically in (Figure 5) and are detailed further.

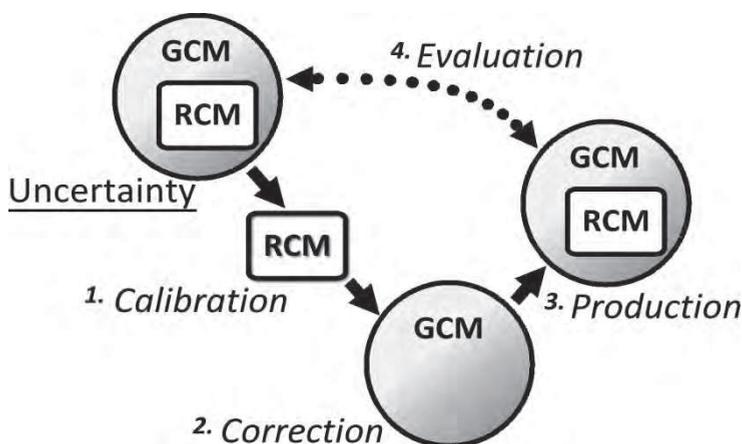


Fig. 5. Schematic illustration of the simulation framework.

(1) WRF model calibration and validation

Winter precipitation is primarily a large-scale process linked more closely to cloud microphysics than cumulus convection (Grubišić et al. 2005; Yuan et al. 2008), while summer monsoonal precipitation is mainly a cumulus convection process and is sensitive to the microphysics involved (e.g., Yang et al. 2009). Consequently, treatments to suppress any excessive winter precipitation often results in loss of summer precipitation; likewise, methods to increase summer convective rainfall can easily enhance the already overestimated winter precipitation. With this challenge in mind, we calibrated the WRF model by first obtaining the best microphysics scheme for winter and second, tested the cumulus convective schemes for summer but retaining the selected microphysics scheme in winter. The purpose was to correct the biases in seasonal precipitation in order to simulate an accurate annual cycle.

(2) CCSM output bias correction

In order to reduce the impact of GCM biases on regional downscaling, any GCM forcing data can be “corrected” prior to being used to drive any dynamic downscaling. The goal

here is to have the CCSM output to approximate the reanalysis data so that the calibrated WRF-CLM can achieve consistent performance when driven by the CCSM. An initial step for a bias correction was to apply statistical downscaling techniques on the CCSM forcing data. Statistical downscaling generally consists of (a) the development of statistical relationships between observed climate variables and large-scale predictors, and (b) the application of such relationships to the GCM output (Wilby et al. 1998). Here, we modified the technique somewhat by developing a regression model for each variable between the CCSM and the reanalysis towards eliminating their climatological differences. This type of analysis generates a set of "climatologically viable" CCSM data to force WRF-CLM.

(3) Downscaling for the western U.S.

Using the calibrated WRF-CLM forced by corrected CCSM boundary conditions, we produced regional climate simulations for the western U.S. Three sets of data were generated: (a) those driven by reanalyses, b) those driven by the original CCSM, and (c) those driven by the climatologically corrected CCSM. These three sets of simulations were evaluated against each other and with observations. A comparison with NARCCAP outputs ensue to provide an uncertainty assessment.

4. Results

4.1 WRF-CLM calibration and validation

Through Fourier analysis, WGTG decomposed the seasonality of western US precipitation into an annual cycle (1st harmonic) and a semiannual cycle (2nd harmonic). These annual and semiannual precipitation cycles were subjected to Empirical Orthogonal Function (EOF) analysis, obtaining two leading modes for each cycle. In the annual cycle, EOF1 and EOF2 represent a winter-summer seesaw and a spring-fall oscillation, respectively. The winter-summer seesaw depicts a precipitation pattern divided by the Rocky Mountains, reflecting the seasonal march of upper-level winds interacting with the orography. The spring-fall oscillation and the semiannual cycle both reveal an oscillating dipole between the northwest and the southwest; the latter cycles are particularly sensitive to convective precipitation. Figure 6 shows the results from the NARCCAP simulations depicting the combined spring-fall and EOF1-semiannual modes (left) of precipitation in Colorado (area C in Figure 1), in comparison to the EOF2-semiannual mode (right). It is apparent in Figure 6 that most models produced a distorted seasonal cycle due to an overly strong spring-fall oscillation and an out-of-phase semiannual cycle; the WRF model was among them.

Winter precipitation overprediction over terrain has been a common deficiency within many Bulk Microphysical Parameterization schemes (BMPS), because most BMPS treat snow and graupel as two separate categories without partial riming within the cloud; correcting this error would help improve the amounts of cloud water and reduce the surface precipitation over windward slopes (Colle and Lin 2010). We have found through various experiments that cumulus parameterization schemes (CPSs) have very little impact on winter precipitation amounts in the western US. Thus, we focused on the microphysics coupled with the WRF model and selected one that is most effective in reducing the overprediction of precipitation. After obtaining the optimal microphysics scheme for winter precipitation it was used for sensitivity testing of CPSs for summer precipitation. By experimenting with the full combination of BMPS and CPSs available in WRF-CLM, we selected the Morrison 2-moment BMP (Thompson et al. 2008) that reduces the most of the overprediction bias. We

also found that the Grell-Devenyi ensemble CPS – a multi-closure, multi-parameter, ensemble method (Grell and Devenyi 2002) – most accurately reflected the summer precipitation in the Southwest monsoon region. The inclusion of CLM also improves the precipitation simulation in the western U.S., as has been shown in Jin et al. (2010a, 2010b).

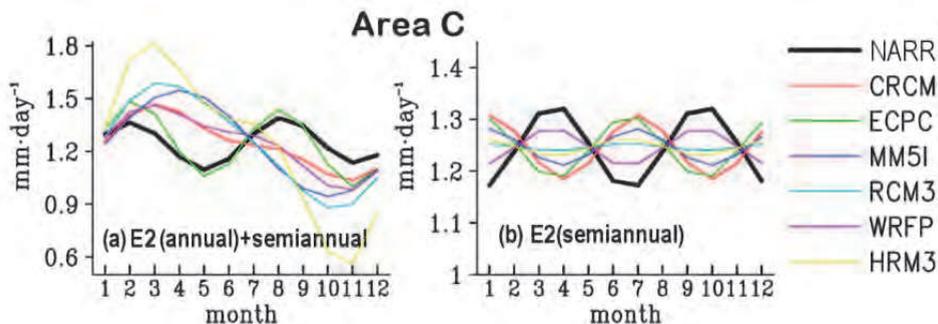


Fig. 6. Precipitation reconstructions in area C (Fig. 2) from the combined spring-fall mode and the first semiannual mode (left) and second semiannual mode. Modified from Wang et al. (2009).

To illustrate the calibration effectiveness, we present the result in 2008. The control run was forced by the NCEP-2 with the same physics packages as the NARCCAP WRF, denoted as WRF(Ctrl). Figure 7 shows the monthly precipitation of WRF(Ctrl) over the Wasatch Range (area B in Figure 1) and northern Arizona (area D). Compared to the observations (blue histograms), precipitation biases similar to those in Figure 1 still prevail – overestimation in cold-season amounts and underestimation in warm-season amounts. Next we applied the calibration, denoted as WRF(Exp). Except for the optimal BMPs and CPS settings and the coupling with CLM, the rest of model parameters (e.g., land surface physics and boundary layer schemes) remained the same as in WRF(Ctrl). As shown in Figure 7 (red lines), precipitation in WRF(Exp) already reveals a marked improvement towards a more accurate seasonal variability where reduced winter precipitation and the enhanced summer (monsoon) rainfall are more adequately simulated. A further improvement is revealed in the summer daily precipitation events. As shown in Figure 8 (left) across 37°N, pronounced diurnal rainfall episodes occurred during 4-12 August 2008. However, the diurnal rainfall signal is very weak in WRF (Ctrl) resulting in less than a half of the observed amounts falling over the terrain (middle). But this is remedied by WRF(Exp) substantially increases the diurnal rainfall leading to a more realistic seasonal distribution (right). The precipitation frequency is also enhanced.

4.2 Forcing data correction and WRF simulations for the western U.S.

In previous analysis (Figure 3), we saw that WRF-CLM could produce reasonably accurate simulations if forced with the reanalysis data. However, when the model is forced with CCSM data it generated unrealistic simulations that were obviously biased. To reduce the bias, which in this case was inherited from the CCSM, we developed a set of statistical functions between the forcing variables in CCSM and NCEP-2. These statistical functions covered various timescales including a diurnal range (6 hr data), season and annual cycles,

and climate mean state. The training period for the statistical functions is 1979-1999. The statistical functions followed those used in Dettinger et al. (2004) and Miller et al. (2008). The point to note is that the differences between CCSM and NCEP-2 are minimized

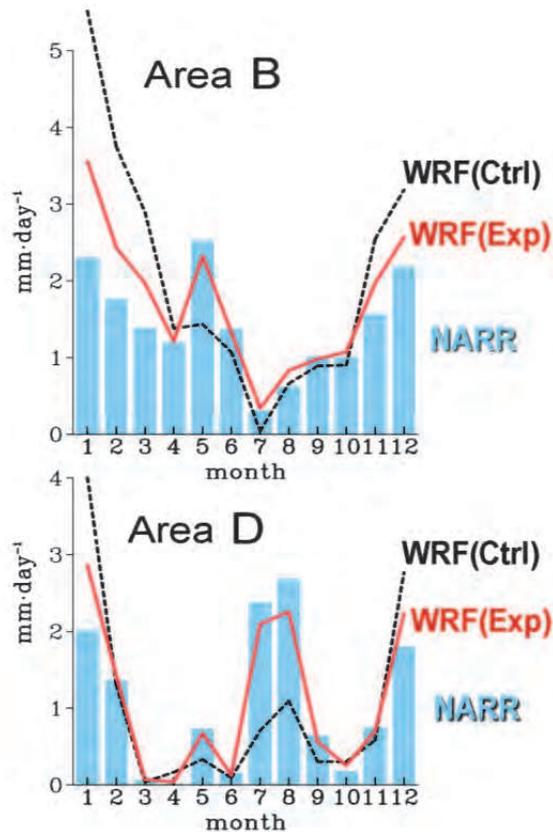


Fig. 7. Monthly precipitation of 2008 in areas B and D from the observation (bars), WRF(Ctrl) (black dashed line), and WRF(Exp) (red solid line). The observation here uses the North American Regional Reanalysis (NARR).

based upon bilinear regression parameters that were derived during their training period. As an example, Figure 9 shows the regression-corrected CCSM annual temperature and precipitation in the southwestern U.S. (42°N 114.3°W , 32°N 102°W) versus the original simulation. The original CCSM appears to overestimate the trends in both temperature and precipitation. However, the statistically corrected temperature and precipitation time series are in good agreement with the PRISM data during the historical period (1895-1999), a result we consider to enhance the reliability of future projections (2000-2099), which are being generated for further studies. We then applied this regression-based correction method to all variables in the CCSM used to force WRF-CLM. These variables included air temperature, moisture, geopotential height, wind, and sea surface temperature, all of which were updated at a 6-hour frequency.

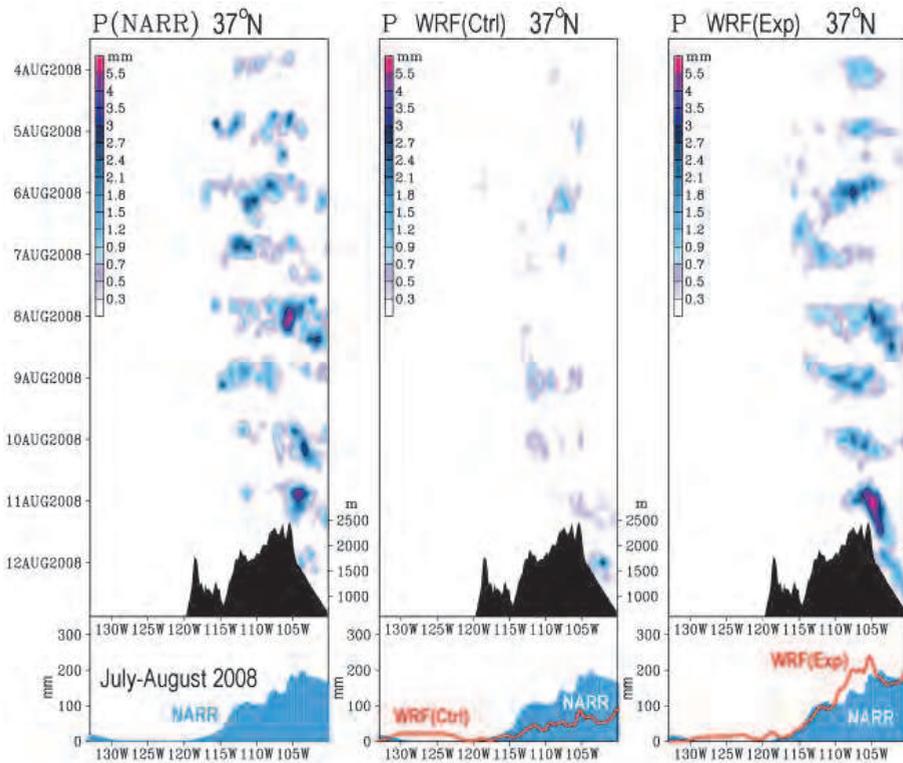


Fig. 8. Longitude-time cross sections of precipitation averaged at 37-40°N from 3 August to 12 August 2008 with the July-August accumulation (bottom), derived from the NARR (left), WRF(Ctrl) (middle), and WRF(Exp) (right). Terrain is illustrated as black shadings.

Figure 10 shows the winter (December-February) precipitation for the western U.S. averaged over the period 1989-1999, including two sets of gridded observations: PRISM (Figure 10a) and the University of Delaware data (Figure 10b). Note that even these observations exhibit some apparent differences, especially at high elevations over mountain ranges along the Rockies. Nevertheless, the WRF simulation forced with the NCEP-2 data (Figure 10c) is in good agreement with both observation data sets, with an average bias of 26 mm/month over the entire simulation domain compared to PRISM. However, when the same WRF-CLM is forced with the original CCSM output, the model severely overestimates the precipitation and the domain-wide averaged bias doubles to 59 mm/month. This difference clearly demonstrates the inherited biases from the CCSM forcing data - biases that are difficult to diagnose. After correcting the CCSM forcing data through the aforesaid statistical functions, the result (Figure 10e) exhibits a marked improvement - the domain-averaged bias was reduced to 31 mm/month.

4.3 Long-term trend in the Western U.S.

The reanalysis-driven calibration simulation for the period 1979-2004 (in line with NARCCAP) is promising in the context of the provision of useful assessments for projection

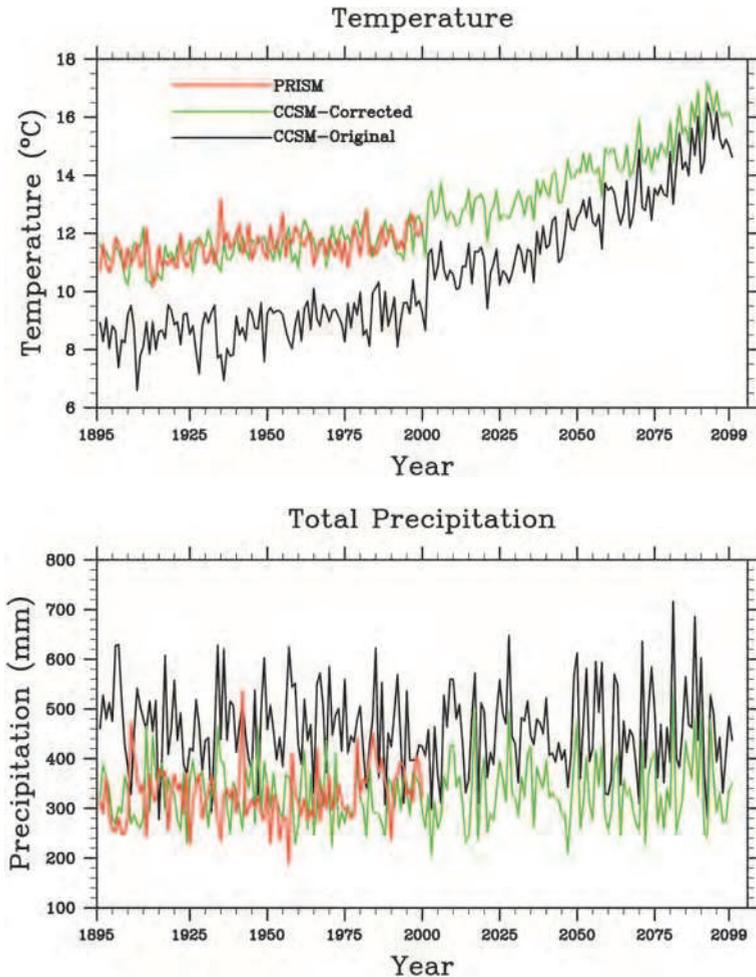


Fig. 9. CCSM projections of annual temperature (left) and precipitation (right) over the southwestern U.S. The black line is for the original CCSM projections, the green line is for statistically-corrected CCSM projections, and the red line is for PRISM data. In this project we will use a similar method to correct the CCSM forcing data for WRF-CLM.

uncertainties. Figure 11 shows the linear trends in precipitation over the central western U.S. (Areas B and C in Figure 1) simulated from the six reanalysis-driven NARCCAP models. Except for the Hadley Center RCM (HRM3), none of the models capture the observed downtrend in precipitation. After the calibration process as described in Section 4.1 was applied, WRF-CLM simulated a much more realistic precipitation trend. It is therefore reasonable to expect that, by evaluating climate projections made from the calibrated/corrected downscaling against the original and existing (i.e. NARCCAP) ones, the uncertainty range of the climate projections can be quantified. We may also be able to address the challenge outlined in Figure 2, that is, to identify a representative projection with physically based assessment and with higher confidence.

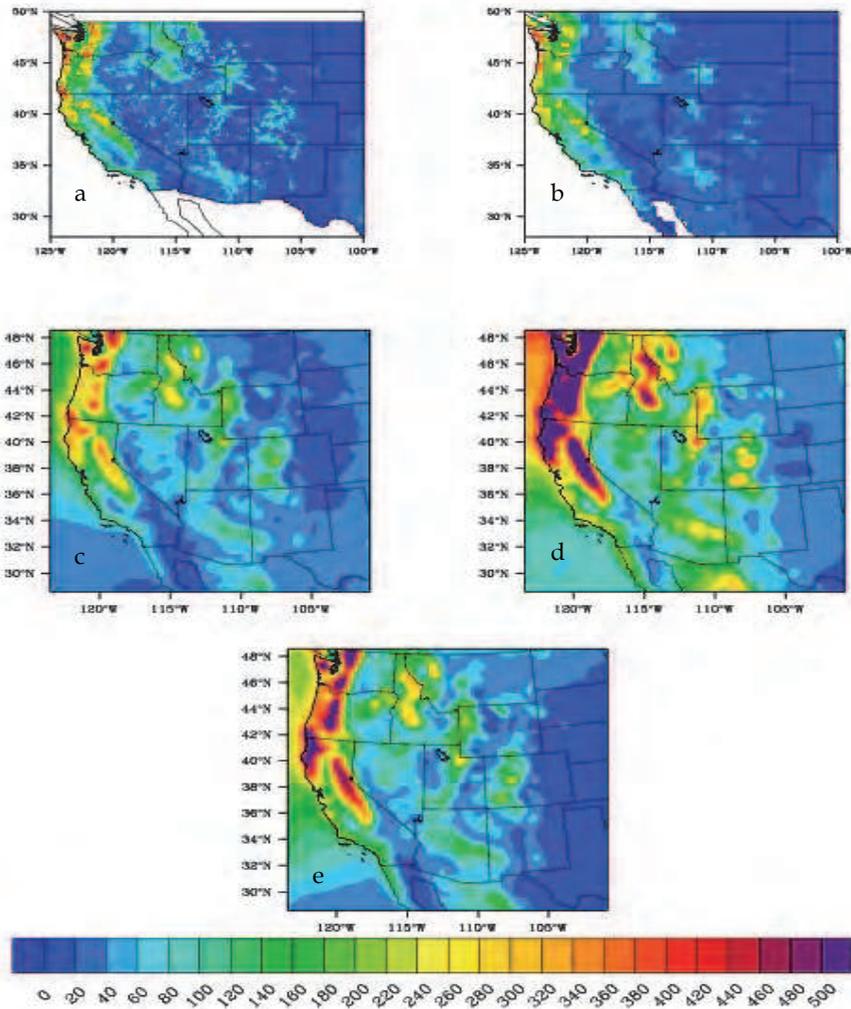


Fig. 10. Winter (December, January, and February) precipitation and observations and simulations averaged over the period of 1989-1999. a) PRISM data; b) University of Delaware observations; c) WRF forced with NCEP; d) WRF forced with original CCSM output; e) WRF forced with the regressed CCSM output.

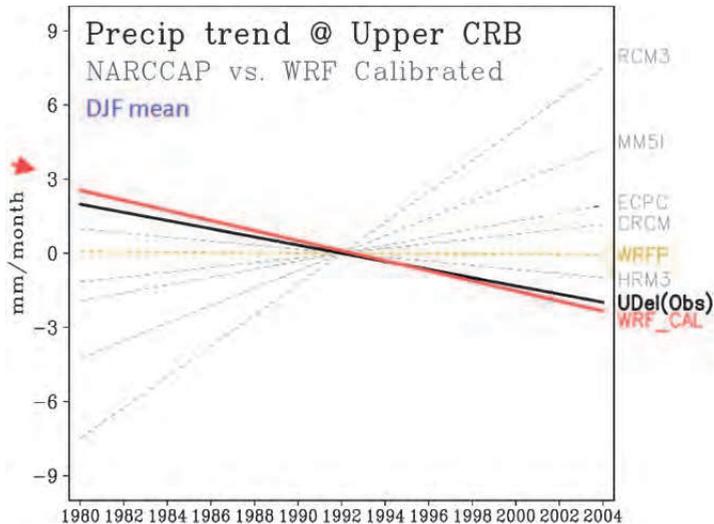


Fig. 11. Least-square trends in winter (December-February) precipitation averaged over Areas B and C (as in Figure 1) simulated by 6 NARCCAP models (grey; WRF in golden), calibrated WRF-CLM forced by NCEP-2 (red), and the University of Delaware observation (black) for the period 1979-2004. Year 1979 is omitted to avoid potential spin-up problems.

5. Summary and conclusions

Proper interpretation of climate projections that exhibit a wide range of uncertainties has been a challenge for the management of water resources. The common detection and attribution method validating GCM simulations is expensive when it comes to dynamical downscaling because of the large ensemble members required. In this chapter we demonstrated an economic approach through effective combination of dynamical and statistical downscaling towards reducing the range of projection uncertainties. The demonstration consists of (1) calibration of a regional climate model (WRF-CLM) towards realistic precipitation seasonal cycles, (2) data correction of a global climate model (CCSM) to minimize climatological biases of the forcing variables, and (3) generation of regional downscaling from (1) and (2) followed by evaluation against existing climate downscaling (NARCCAP) to quantify and reduce the range of projection uncertainties. We focused on the Upper Colorado River Basin of the western U.S. not only because of its critical role in the western water resource, but also because this region has complex precipitation seasonal cycles and that these cycles were not simulated properly by the NARCCAP models.

Our analyses showed that the calibrated simulation successfully reduced overprediction of windward precipitation amounts and reasonably captured the monsoon precipitation. This subsequently improved seasonal variability in precipitation when compared to that produced by the NARCCAP models. The improved simulation revealed a realistic long-term trend in precipitation that was not captured by the same model prior to the calibration. In addition, GCM forcing data corrected from climatological biases produced a downscaled climate that was significantly improved over that driven by original GCM forcing data. Consequently, by comparing the calibrated/corrected regional downscaling with existing

ones such as those provided by NARCCAP, the range of uncertainties in those baseline projections (i.e. NARCCAP) can be quantified. Subsequently, the water management community will have a better tool in assessing future water needs. A long-term (2000-2100) climate simulation derived from the calibrated/corrected regional downscaling is being generated with an expected complete date in summer 2011.

6. Acknowledgment

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This book provides an interdisciplinary view of how to prepare the ecological and socio-economic systems to the reality of climate change. Scientifically sound tools are needed to predict its effects on regional, rather than global, scales, as it is the level at which socio-economic plans are designed and natural ecosystem reacts. The first section of this book describes a series of methods and models to downscale the global predictions of climate change, estimate its effects on biophysical systems and monitor the changes as they occur. To reduce the magnitude of these changes, new ways of economic activity must be implemented. The second section of this book explores different options to reduce greenhouse emissions from activities such as forestry, industry and urban development. However, it is becoming increasingly clear that climate change can be minimized, but not avoided, and therefore the socio-economic systems around the world will have to adapt to the new conditions to reduce the adverse impacts to the minimum. The last section of this book explores some options for adaptation.

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