HYDROLOGIC IMPLICATIONS OF DYNAMICAL AND STATISTICAL APPROACHES TO DOWNSCALING CLIMATE MODEL OUTPUTS

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Abstract. Six approaches for downscaling climate model outputs for use in hydrologic simulation were evaluated, with particular emphasis on each method's ability to produce precipitation and other variables used to drive a macroscale hydrology model applied at much higher spatial resolution than the climate model. Comparisons were made on the basis of a twenty-year retrospective (1975–1995) climate simulation produced by the NCAR-DOE Parallel Climate Model (PCM), and the implications of the comparison for a future (2040–2060) PCM climate scenario were also explored. The six approaches were made up of three relatively simple statistical downscaling methods – linear interpolation (LI), spatial disaggregation (SD), and bias-correction and spatial disaggregation (BCSD) – each applied to both PCM output directly (at T42 spatial resolution), and after dynamical downscaling via a Regional Climate Model (RCM – at 1/2-degree spatial resolution), for downscaling the climate model outputs to the 1/8-degree spatial resolution of the hydrological model. For the retrospective climate simulation, results were compared to an observed gridded climatology of temperature and precipitation, and gridded hydrologic variables resulting from forcing the hydrologic model with observations. The most significant findings are that the BCSD method was successful in reproducing the main features of the observed hydrometeorology from the retrospective climate simulation, when applied to both PCM and RCM outputs. Linear interpolation produced better results using RCM output than PCM output, but both methods (PCM-LI and RCM-LI) lead to unacceptably biased hydrologic simulations. Spatial disaggregation of the PCM output produced results similar to those achieved with the RCM interpolated output; nonetheless, neither PCM nor RCM output was useful for hydrologic simulation purposes without a bias-correction step. For the future climate scenario, only the BCSD-method (using PCM or RCM) was able to produce hydrologically plausible results. With the BCSD method, the RCM-derived hydrology was more sensitive to climate change than the PCM-derived hydrology.

1. Introduction

An improved understanding of the interactions between ocean, land and atmosphere has led to definitive advances in the ability to forecast weather and climate using complex models of the ocean-land-atmosphere system (e.g., Betts et al., 1997; Livezey et al., 1997; Shukla, 1998; Koster et al., 1999). Despite improved skill in weather and climate forecasts, hydrologists struggle with how best to use forecast information in applications such as water resource planning, management

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and conservation as well as irrigation and drainage for sustainable development. The lack of spatial specificity and accuracy have rendered weather and climate forecasts inadequate for hydrologic applications that have serious ramifications to stakeholders and the society at large (Stern and Easterling, 1999).

One factor that has limited the use of climate forecast information in hydrological prediction is the scale mismatch between climate model output and the spatial scale at which hydrological models are applied – typically some subdivision, either natural (subcatchment) or gridding of a watershed (e.g., Lettenmaier et al., 1999; Wood et al., 2002; Wilby et al., 2000). Various studies have evaluated downscaling methods designed to bridge this gap, particularly in terms of their ability to reproduce surface temperature and precipitation fields (IPCC, 2001; Leung et al., 2003). The methods that have been most widely used include dynamical modeling by nesting a regional climate model (RCM – see Leung et al., 2004) within a general circulation model (GCM) (Cocke and LaRow, 2000; Leung et al., 1999; Giorgi and Mearns, 1991; Kim et al., 2000; Yarnal et al., 2000), statistical or empirical transfer functions that relate local climate to GCM output (Hewitson and Crane, 1996; Wilby and Wigley, 1997; Wilby et al., 1998) and climate-anolog procedures (IPCC, 1996). Still other methods (e.g., Charles et al., 1999) combine dynamical and statistical procedures. Murphy (1999) showed that while dynamical and statistical downscaling approaches yield similar reproductions of current climate (e.g., Wilby et al., 2000), they can nonetheless differ significantly in their projections of future climate conditions. Studies by Murphy (1999), Kidson and Thompson (1998) and Wilby et al. (2000) further suggest the need to bias correct climate model output to assure meaningful results in applications like hydrologic and water resources assessments.

The papers in this special issue report results from the pilot phase of the Department of Energy Accelerated Climate Prediction Initiative (ACPI), which used GCM scenarios of future climate produced by the DOE-NCAR Parallel Climate Model (PCM; Washington et al., 2000; Dai et al., 2004). A variety of methods were used in ACPI projects to downscale PCM output. Dettinger et al. (2004) studied water resources impacts of climate change projected by PCM in several subbasins of the Sacramento–San Joaquin River basin after adjustment of historical climate model output to match daily observed precipitation and temperature statistics. Payne et al. (2004) utilized variations of the probability mapping methods described by Wood et al. (2002) for spatial downscaling and bias correction of both global and regional climate model outputs in their investigation of water resources impacts of climate change in the Columbia River Basin (CRB). VanRheenen et al. (2004) and Christensen et al. (2004) used similar approaches in studies of the Sacramento–San Joaquin and Colorado River basins, respectively. All of these studies used different methods to downscale and bias correct the global or regional model outputs in order to produce realistic simulations of hydrologic conditions of the current climate. It is worth noting that this is a de facto minimum standard of any useful downscaling method for hydrologic applications: the historic (observed) conditions must be reproducible.

Few studies have evaluated the differences among various downscaling methods based on their implications for hydrological predictions (Crane et al., 2002; Wilby et al., 2000). There remain critical questions, for instance, about the value of dynamic downscaling, given that biases inevitably remain that must be removed, usually by subsequent application of statistical methods. With these questions in mind, we evaluated six different methods of downscaling from global or regional models to the still finer scale of a grid based hydrological model (specifically, the Variable Infiltration Capacity, or VIC model). Included are three statistical downscaling methods – linear interpolation (LI), spatial disaggregation (SD) and bias-corrected spatial disaggregation (BCSD) – applied either directly to PCM outputs or to dynamically downscaled (to intermediate resolution) PCM output, i.e., to the output of a regional climate model. The six methods were compared through application to a retrospective climate simulation, and those that performed best were also applied to a future climate scenario. The spatial domain of all comparisons was the Columbia River Basin (CRB) of the U.S. Pacific Northwest (PNW) region (see Payne et al., 2004 for background).

2. Approach

The general approach was to simulate land surface energy and water fluxes using the VIC macroscale hydrological model (see Section 2.2), driven by meteorological outputs from PCM with and without intervening dynamical downscaling using a regional climate model. Results of a twenty-year climate-hydrology scenario were evaluated by comparison with a retrospective observational analysis of surface climate and hydrologic conditions. Implications of the more successful of the approaches were also explored for a future climate run. The observational analysis is discussed in Section 2.1, the models and simulations in Section 2.2, and the downscaling methods in Section 2.3. Sampling error issues are discussed in Section 2.4.

2.1. OBSERVATIONAL ANALYSIS

The observed climatological and hydrological fields used to evaluate the downscaled climate model outputs were taken or derived from the hydroclimatic retrospective analysis of Maurer et al. (2002), which is based on a $\frac{1}{8}$-degree hydrologic simulation of land surface energy and water variables run at a 3 hour timestep over the continental U.S. for the period 1950–2000. We used average monthly temperature and soil moisture, total monthly precipitation, runoff and evaporation, and basin-averaged monthly snow water equivalent. The climate variables (precipitation and temperature) for the 20-year retrospective period (approximately

1976–96) were taken directly from the Maurer et al. (2002) dataset, and the hydrologic ones were generated via a retrospective simulation of the 20 year period (with a 2 year hydrologic model spin-up, producing an initial model state from which all retrospective runs were started), driven by climate variables taken from the same gridded observations.

2.2. MODELS AND SIMULATIONS

We used output from two climate models: PCM, and the RCM of Leung et al. (2004) for that portion of their domains included within the VIC model's 1/8-degree representation of the PNW. The PNW domain is divided by the Cascade Mountain range into coastal basins draining to the west, and all of the CRB. Almost all of the region has a winter-dominant precipitation regime in which most of the annual precipitation is derived from frontal systems originating in the North Pacific, the majority of the moisture from which falls on the west slopes of the Cascades. Although much drier, the CRB to the east receives winter precipitation mostly as snow (in the mountains of British Columbia, Canada, and Idaho and Montana), much of which contributes to a strong seasonal runoff peak in the late spring and early summer. Figure 1 shows the study domain, along with the PCM and RCM grid alignments (T42 or 2.8125 degrees latitude/longitude for PCM, and 1/2-degree latitude/longitude for RCM). Also shown are the PCM and RCM average annual precipitation and temperature climatologies for the period 1975–95, at the resolution of each climate model, and the observed 1/8-degree climatology described in Section 2.1. The figure shows the effect of RCM's higher spatial resolution relative to PCM (PCM represents the PNW region with about 20 grid cells, while RCM uses about 500, and the observed 1/8-degree climatology has about 6400).

The climate scenarios and climate model simulations used in the study are described in greater detail elsewhere in this issue (Dai et al., 2004 (for PCM); Leung et al., 2004 (for RCM)), but in brief, they resulted from retrospective historical simulation and future climate simulations, based on a observed historical greenhouse gas and aerosol emissions for the historical run, and 'business as usual' (BAU) global emissions future climate. Because the RCM simulations were of length 20 years (using a subset of longer PCM sequences to represent boundary conditions), all analyses were based on the 20-year simulations for both PCM and RCM for the periods designated 'RCM subset' in Table 1 to avoid sample length differences. The run designations used in Table 1 are consistent with other papers in this issue (specifically Dai et al., 2004; Leung et al., 2004).

The hydrologic model used in this study, the Variable Infiltration Capacity (VIC) model of Liang et al. (1994, 1996, 1999) is a semi-distributed grid-based hydrological model which parameterizes the dominant hydrometeorological processes taking place at the land surface-atmosphere interface. The VIC model has been implemented previously for the CRB, and the calibration procedure and results are described in Nijssen et al. (1997) and Payne et al. (2004). VIC model

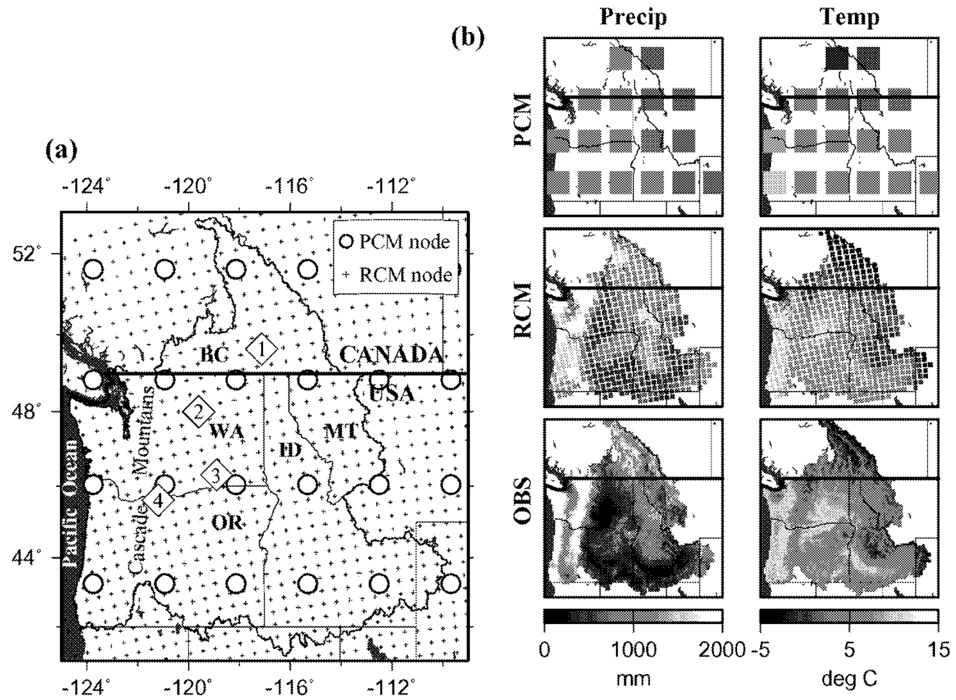

Figure 1. (a) PNW domain with PCM and RCM model grids and four streamflow simulation locations (diamonds: 1 – Corra Linn; 2 – Chief Joseph; 3 – Ice Harbor; and 4 – The Dalles). (b) PNW annual average 1979–95 model climatologies for total precipitation and average temperature at PCM's T42 and RCM's 1/2-degree resolutions, and the 1/8-degree observed climatology of Maurer et al. (2002).

Table I
Simulations used in this study

Run	Description	Run period	RCM subset
B06.22	Historical (greenhouse CO_2 + aerosols forcing)	1870–2000	10/1975–9/1995
B06.44	Climate change (BAU6, future scenario forcing)	1995–2099	7/2040–6/2060

climate inputs for this study were daily precipitation, maximum and minimum temperature, and daily average wind speed, for each 1/8-degree model grid cell (other forcing variables – specifically downward solar and longwave radiation, and dew point – were derived using methods described by Maurer et al., 2002). Because VIC was run at a finer spatial resolution than the climate models, a downscaling step (methods described in the next section) to bridge the resolution gap between climate model and VIC was implemented, whether PCM or RCM output was used. The VIC model was applied to the entire PNW study domain of Figure 1, although the hydrologic analysis was confined to the CRB drainage upstream of the Dalles, OR, a domain identical to that used by Payne et al. (2004). The primary difference between the VIC model used for this study and the Payne et al. (2004) implementation was grid resolution: we used 1/8- rather than 1/4-degree longitude and latitude to afford a greater resolution gap for the downscaling method evaluation. Streamflow results are reported for four locations shown in Figure 1: Kootenai River at Corra Linn Dam, Columbia River at Chief Joseph Dam, Snake River at Ice Harbor Dam, and the Columbia River at the Dalles, OR. These reflect, roughly, streamflow effects in the Canadian portion of the basin, the middle and upper Columbia River, the Snake River drainage, and the entire basin. Figure 2 shows simulated streamflow at these locations when VIC was driven by observed precipitation and temperature. The simulations generally reproduce the observed long term monthly mean hydrograph and also capture interannual flow variation.

2.3. DOWNSCALING METHODS

For each of the climate model runs summarized in Table I, we compared six approaches for downscaling climate model output: three model output post-processing approaches – linear interpolation (LI), spatial disaggregation (SD) and bias-corrected spatial disaggregation (BCSD) – each applied to PCM output directly and to RCM output, which represents an intermediate dynamical downscaling step. To distinguish between three direct PCM output methods and the three RCM output methods, a prefix of PCM – or RCM – is used with the post-processing method designator. Regardless of the method, the climate model output fields that were downscaled were the same: monthly mean temperature (T_{avg}) and total precipitation (P_{tot}), at the climate model resolution. Each downscaling procedure reproduced these as input fields for the VIC model at 1/8-degree resolution, and an additional step was taken to disaggregate the monthly fields into daily time series required by VIC (daily precipitation, maximum and minimum temperature). This final disaggregation step is identical to that used in Wood et al. (2002), and is summarized briefly in Section 2.3.1 below. Sections 2.3.2 and 2.3.3 summarize the SD and LI approaches, primarily focusing on their differences from BCSD.

2.3.1. *Bias Correction of Climate Model Output, Followed by Spatial Disaggregation (BCSD)*

For direct use of PCM output, T_{avg} and P_{tot} forcings from each climate model cell centered within the study region were treated individually for purposes of bias correction. For bias removal, a quantile-based mapping (e.g., the empirical transformation of Panofsky and Brier, 1968) was constructed from the PCM model climatology to the observed monthly climatology for each variable (T_{avg} and P_{tot}). The observed climatology was derived from Maurer et al. (2002) for the period 1975–95, re-gridded and averaged to the PCM grid resolution. The PCM climatology was taken from modeled T_{avg} and P_{tot} from the B06.22 simulation for the same period. The mapping from PCM to observed climatology was subsequently

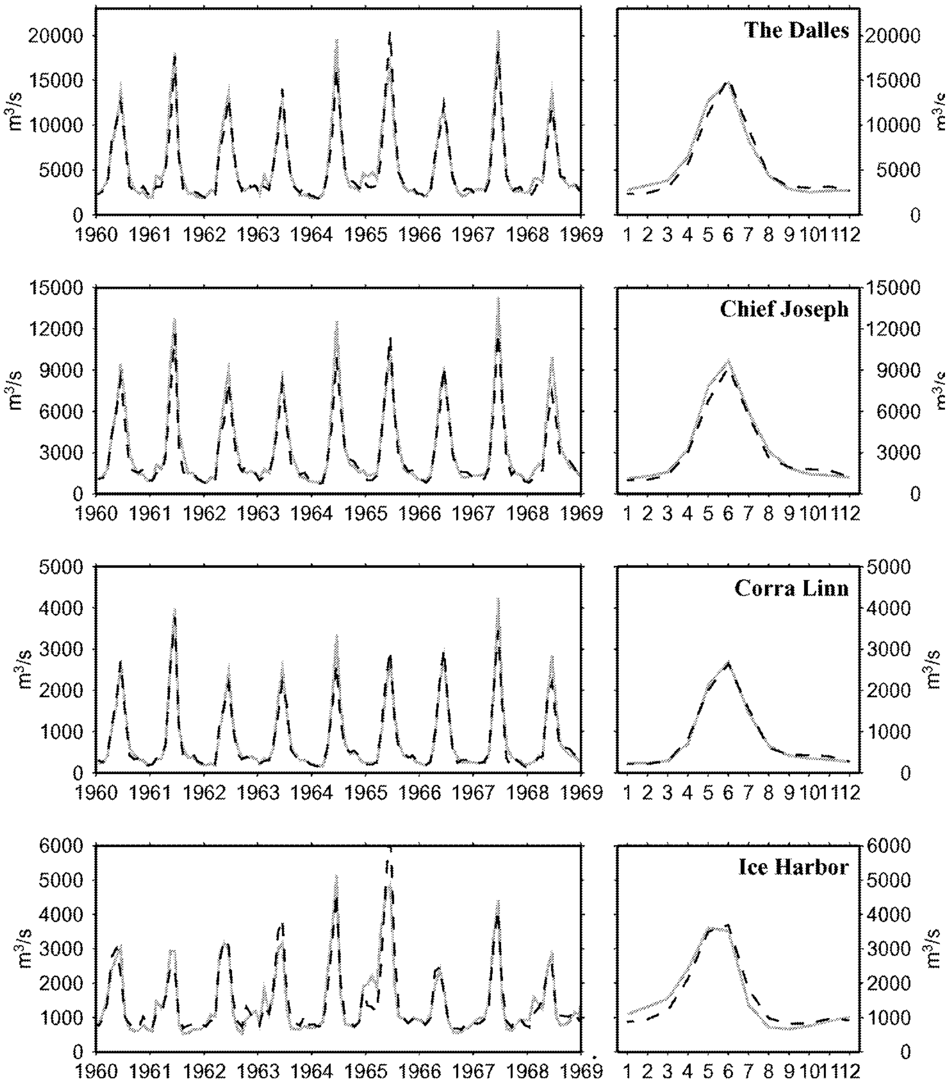

Figure 2. VIC model streamflow validation results for four routing locations (naturalized observations, solid gray; simulated, dashed). A subset timeseries from the validation period is shown at left, the monthly mean hydrographs at right.

applied to the PCM raw output, translating it to a plausible range with respect to historical observations. The mapping was performed at the resolution of the PCM output, hence the adjustments vary spatially at the PCM grid scale and by month. For the BAU scenarios, the PCM cell-specific temperature shift (monthly averages relative to the B06.22 retrospective run monthly averages) were removed from the uncorrected PCM output before, and replaced after, the bias-correction step. For the BAU runs, this step was needed because the BAU temperature distribution was quite different from that of the climate model historic run. When the temperature shift was removed, the spread of the BAU run temperature distribution was near the historical range, enabling the bias-correction step to be applied with little extrapolation. The basic assumption of this approach is that the variability of the BAU run temperature distributions will remain similar to the retrospective run variability, despite the BAU mean shift.

Spatial disaggregation imposed sub-PCM grid scale spatial variability on the bias-corrected, PCM-scale forcings. The monthly time step, bias-corrected PCM-scale BAU scenario time series were spatially interpolated to the hydrology model grid cell centers. Anomaly fields (multiplicative for P_{tot}, and additive for T_{avg}, different for each calendar month), developed from the observed climatological monthly means (for T_{avg} and P_{tot}) were applied to the resulting ⅛-degree monthly variable fields as follows: (a) observed monthly mean T_{avg} and P_{tot} 1975–95 averages were aggregated to the climate model scale (T42 or ½-degree), and then interpolated back to the ⅛-degree scale, exactly as the climate model scale forcings were interpolated; (b) the differences (for T_{avg}) or ratios (for P_{tot}) between the ⅛-degree monthly mean T_{avg} and P_{tot} and the interpolated monthly mean fields were calculated to create the anomaly fields. The mean monthly sets of anomaly fields so constructed, when applied to timeseries of interpolated climate model-derived fields, added spatial variability to the smooth ⅛-degree field created by the interpolation step. The spatial disaggregation created VIC-scale monthly forcing time series corresponding to the PCM-scale time series, but reflecting VIC-scale spatial structure.

Finally, a temporal disaggregation step was used to form daily time step inputs for the VIC model. The monthly forcing time series were replicated using scaled or shifted daily patterns sampled from the historic record, at the hydrology model resolution. Month-long daily patterns of precipitation and temperature (more specifically minimum and maximum temperature, with T_{avg} defined as their average) were sampled for each monthly timeseries by picking a year from the 50-year climatology period at random. Each sampling year was used for the entire CRB domain to preserve a degree of synchronization in the weather components driving hydrologic response. The daily patterns were then scaled (for P_{tot}) and shifted (for T_{avg}) to match the monthly timeseries (in T_{avg} and P_{tot}) created by applying the interpolated, bias-corrected PCM anomalies to the VIC cell climatological means. Various screening methods were applied to the precipitation patterns to ensure that rescaling did not result in unrealistic values. The same temporal disaggregation step was applied in all six methods, to avoid confounding the results by differences in the derivation of daily weather patterns. The rationale for use of monthly rather than daily or sub-daily climate model outputs is discussed in Wood et al. (2002).

Application of the BCSD method to RCM output was as described above, with the following differences:

- Instead of PCM output for T_{avg} and P_{tot}, RCM's dynamically downscaled monthly T_{avg} and P_{tot} at ½-degree were used. A ½-degree observed climatology was developed for bias-correction by aggregation from the Maurer et al. (2002) archive.
- The spatial disaggregation began with bias-corrected ½-degree monthly fields rather than the PCM resolution fields.

Note that RCM is driven with a more comprehensive set of PCM output fields than the limited surface variables used in our hydrologic downscaling (see Leung et al., 2004 for details).

2.3.2. *Spatial Disaggregation of Climate Model Output, without Bias Correction (SD)*

The SD approach was similar to the BCSD method, except that the PCM or RCM output fields were interpolated to the ⅛-degree VIC model grid without the intervening bias-correction step.

2.3.3. *Spatial Linear Interpolation of Climate Model Output (LI)*

The LI procedure was similar to BCSD, except that the PCM output fields or RCM output fields were linearly interpolated to the hydrologic model grid cells without the intervening bias-correction step, and without spatial disaggregation. The LI approach is intended to provide a baseline for comparison with the other methods because it adds the least additional information to the raw output of the climate model. More elaborate interpolation approaches exist that draw from ancillary information sources (e.g., using elevation data to estimate precipitation gradients across an interpolation space, as in Hutchinson, 1995), to yield a more intelligent distribution of the interpolated data. These methods arguably fall closer to the category of spatial disaggregation (SD), and are not considered in this paper, given our inclusion of a separate SD method.

2.4. METHOD DISCUSSION

The success of two of the techniques – BC and SD – depend on the stability over time of the probability distributions used to correct climate model bias and to impose spatial variability, respectively. In the retrospective assessment, the probability distributions were estimated from the same simulation period that was being downscaled. Hence the distributions at first glance appear to yield unbiased results after downscaling – although it should be understood that even in this case, the historic period provides only an estimate to the underlying statistical populations of the variables being downscaled, and there is bias associated with the short record length from which the probability distributions were estimated. Had the corrections been applied to another retrospective period, the effect of bias resulting from the relatively short record length used to estimate the probability distributions would have been more apparent. If the timeseries of the variables in question are stationary and the variance is relatively small, this should be a somewhat minor issue, as even small samples (e.g., $N = 20$, as in this paper) will not produce large sampling biases, at least in the estimation of the means of derived hydrologic variables. On the other hand, for variables with larger bias, and/or estimation of variables near the tails of the probability distributions, the problem is potentially important – notwithstanding that it can be alleviated by use of a longer period of coincident historical observations and climate simulation.

As noted in Section 2.3.1, for the BAU climate downscaling the sampling bias issue is compounded by the need to estimate unbiased probability distributions of *future* climate with which to adjust the climate model biases. We recognized through exploratory data analysis that the PCM P_{tot} distribution changes are small enough that the retrospective period can be used to estimate these distributions, but the shift in the climate model T_{avg} distributions cannot be ignored. Our approach to minimizing bias in future T_{avg} distributions and the required assumptions is described in Section 2.3.1.

A thorough investigation of the sampling bias issues associated with estimation of probability distributions from short record lengths is beyond the scope of this paper. Instead, we report here a brief investigation of the implications. The goal is to estimate the extent to which biases in results could arise from errors in estimating probability distributions of the underlying variables. The discussion applies to the means of derived variables, and to the BC method only.

Using a Monte Carlo framework, 500 pairs of samples of 20 years of P_{tot} and T_{avg} (each year drawn randomly with replacement) were taken from the observed 1950–99 PCM-scale record over the CRB domain, and from the spatial means, monthly probability distributions of sampling errors were estimated. These are shown in Figure 3 (panels a and b) by the 95% confidence limits, together with the mean of the 50-year period. For precipation, the largest errors were roughly 20–25% in winter and spring, while the largest temperature errors were 1–2 °C in winter, and 0.9 °C in spring. It should be noted that winter and spring precipitation and temperature are the dominant meteorological variables affecting streamflow.

In this limited investigation, it was not feasible to carry this analysis through the hydrologic simulation. Instead, we estimated the effects of the precipitation and temperature variation on peak season runoff using 2000 randomly drawn non-consecutive 20-year samples from the simulated runoff associated with the full 50-year period. Figure 3c shows the variation in mean monthly May–August (MJJA) runoff associated with variations in mean monthly December–March (DJFM) CRB-average precipitation and temperature. While the May–August runoff is relatively insensitive to temperature variations, absolute changes (in mm) were approximately half the absolute winter precipitation changes (in mm). Figure 3d shows the variation in May runoff as a fraction of June runoff associated with variations in April–June (AMJ) precipitation and temperature. The runoff fraction ranges from approximately 0.85, for the retrospective climate, to approximately 1.15 for a shift in peak flow commonly associated with moderate climate warming

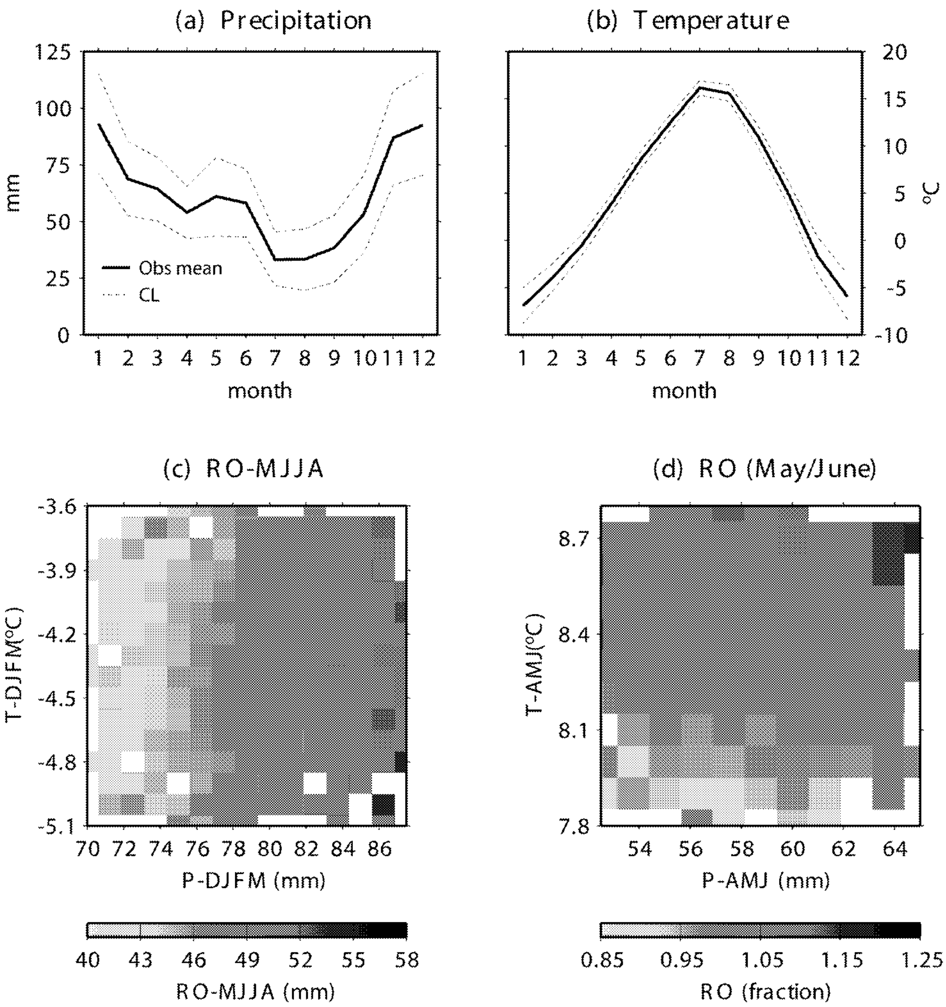

Figure 3. Sampling error 95% confidence limits for monthly precipitation (a) and temperature (b); (c) correspondence of mean May–August runoff (RO-MJJA) with mean December–March (DJFM) precipitation and temperature; and (d) correspondence of ratio of May runoff to June runoff with April–June (AMJ) precipitation and temperature.

in this region. The implications of precipitation and temperature sampling error for runoff, at the extremes, are that a 1 °C warm bias in spring temperature, about the same magnitude as the 0.975 non-exceedence sampling error, is sufficient to produce the entire shift, and a winter precipitation negative bias could produce a 20% summer runoff reduction. On the other hand, as the results in Section 3 show, these runoff biases are minor relative to the distortions arising from a failure to bias correct climate model output, even using a short correction period.

These results are not comprehensive, but illustrate that the 20 year scenario lengths used here are on the shorter end of the size needed to produce robust correction distributions for application to different scenario periods. Again, the magnitude of these errors can be reduced by increasing the length of the retrospective period, although it should be noted that the rate of error reduction is expected to go roughly as the ½ power of the record length, so even using the entire 50-year period of historic observations (and assuming RCM runs of this length were made) would only reduce the errors by a factor of about 1.6.

3. Results

Results are presented first for the retrospective climate simulation, followed by the future climate simulation, and each is compared to the observational analysis described in Section 2.1. Results include (a) temporally averaged spatial climate fields (monthly total precipitation, P_{tot}, and monthly average air temperature, T_{avg}) for December and July (which reflect winter and summer conditions); (b) associated spatially averaged variables (P_{tot}, T_{avg}, evapotranspiration, snow water equivalent or SWE, runoff and soil moisture); and (c) monthly average streamflow (runoff routed through a stream network) at four locations in the CRB shown in Figure 1.

3.1. RETROSPECTIVE ANALYSIS (OCTOBER 1975–SEPTEMBER 1995)

3.1.1. *Spatial Analyses of Precipitation, Temperature and Snow Water Equivalent*
For December and July, observed P_{tot} and T_{avg} (Figures 4 and 5) are compared with the PCM and RCM-derived retrospective simulation (B06.22) results. For precipitation, the main features of the observed climatology (top row, Figure 4) are a spatial divide between higher precipitation to the west of the Cascade Mountains (which run north-south at about longitude 121–122° W – see Figure 1) and lower precipitation to the east, and a temporal divide between wet and dry in winter (December) and summer (July), respectively. A less pronounced feature is associated with the higher precipitation areas in Canada, Idaho and Montana, which correspond primarily to higher elevations. The LI results show that PCM simulates the west-east gradient toward lower precipitation in December, and somewhat reproduces the reverse in the July, but not surprisingly fails to capture any elevation-dependent features (hence at the local scale is biased almost everywhere, even though the basin average bias is moderate). The RCM better resolves these spatial features, but shows a wet tendency in December (except in coastal areas and British Columbia, where it is too dry), and a dry tendency in July. Spatial disaggregation (SD) alone leads to better representation of precipitation for PCM, greatly reducing the December local precipitation biases and nearing RCM's performance with LI. Because of RCM's better resolution, RCM-SD closely resembles RCM-LI, although SD appears to exacerbate RCM-LI local biases in some

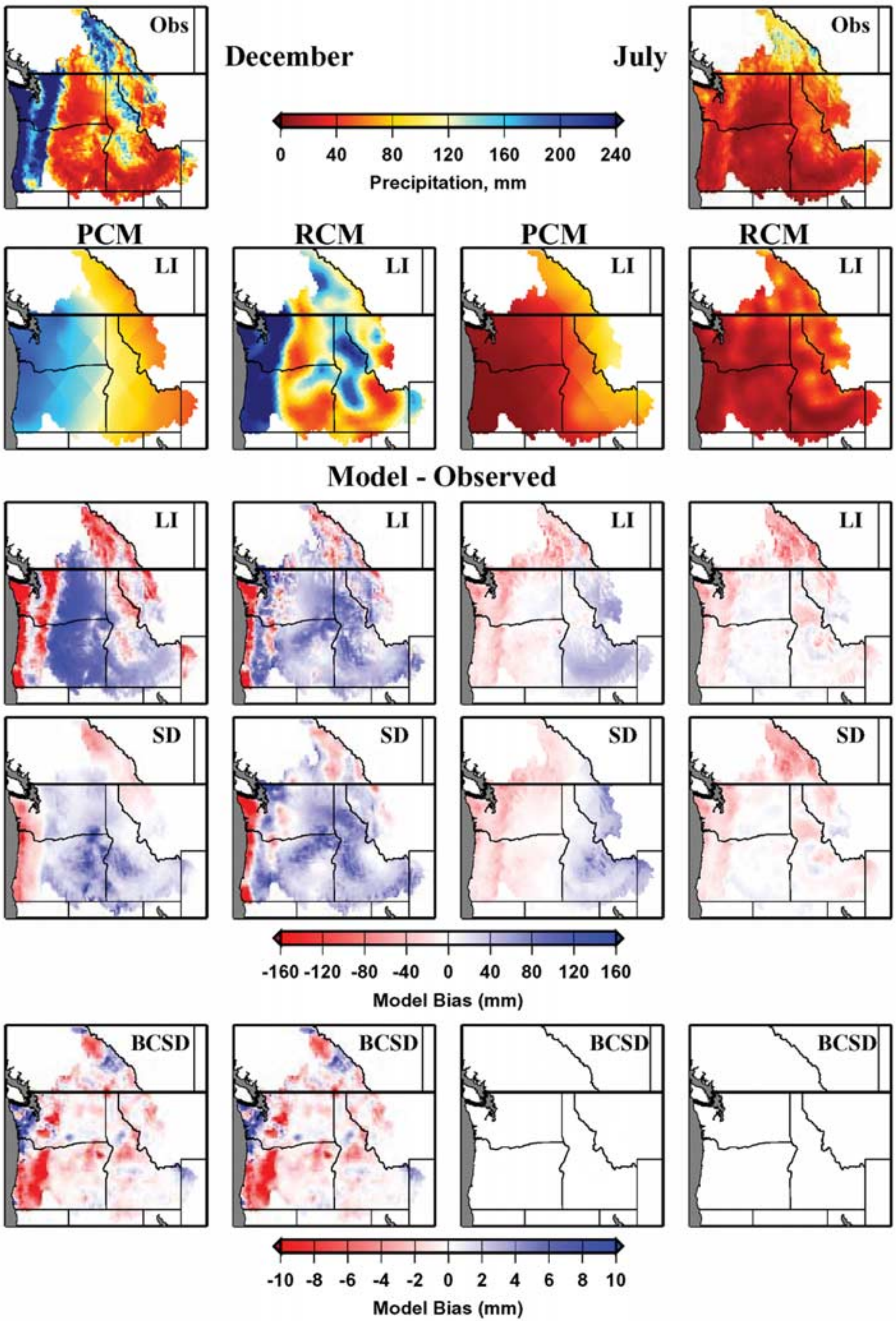

Figure 4. December and July total precipitation for the PCM and RCM-driven retrospective simulations (1975–95), and for each downscaling method, as compared with the observed climatology (top row) for the same period. LI method values are shown in the second row, below which are differences from observed values for the LI, SD and BCSD methods.

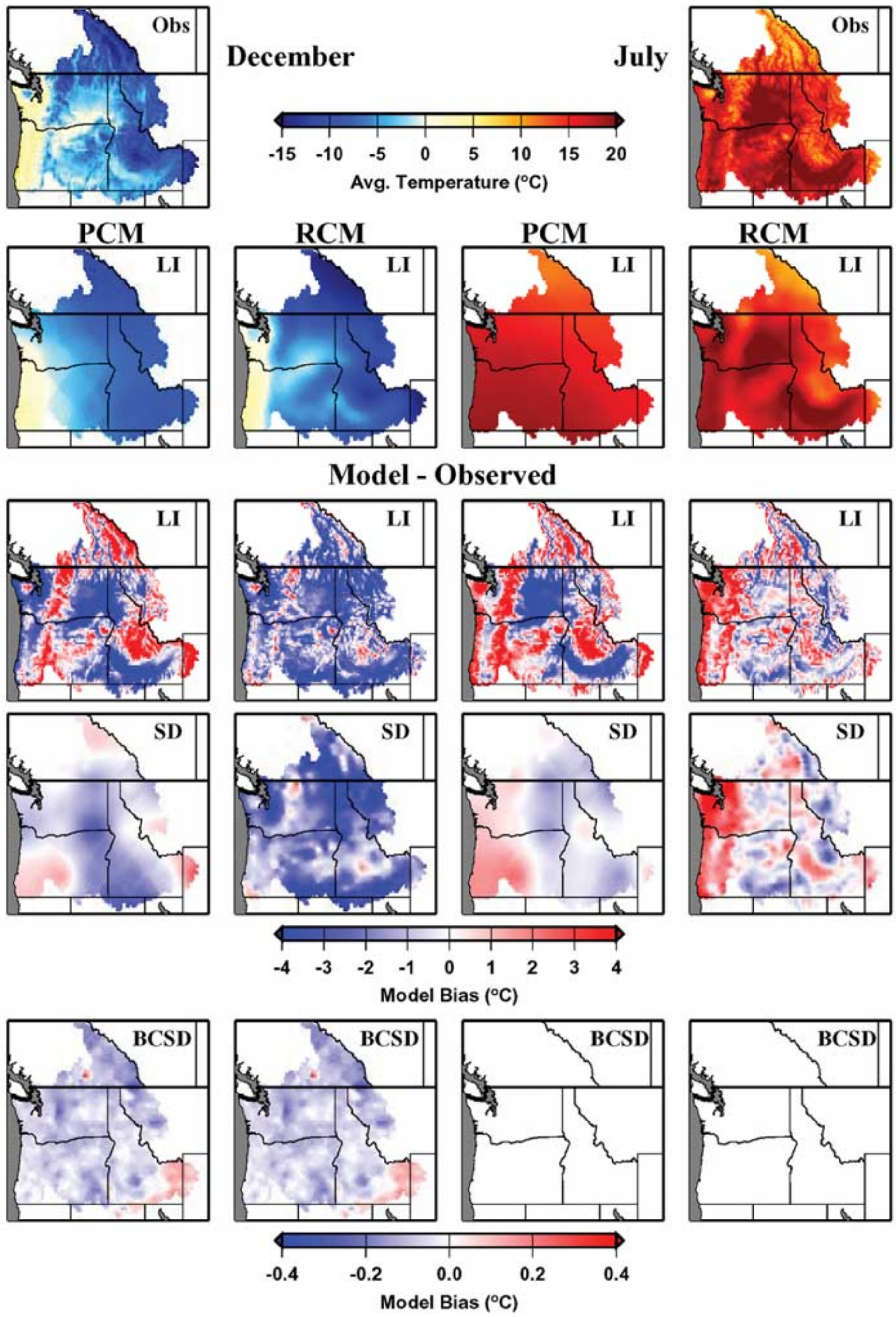

Figure 5. December and July average temperature for the PCM and RCM-driven retrospective simulations (1975–95), and for each downscaling method, as compared with the observed climatology (top row) for the same period. LI method values are shown in the second row, below which are differences from observed values for the LI, SD and BCSD methods.

areas while improving them in others. BCSD reduces differences between observed and simulated P_{tot} in both December and July to within 1–2% of observed.

The main feature of the observed climatology for T_{avg} (top row, Figure 5) is a cooling gradient, present both in winter (December) and summer (July), from southwest to northeast, which is moderated primarily by elevation, and secondarily by humidity effects associated with lower precipitation east of the Cascades Mountains (which, along with the Snake River plain in the southeast, is clearly identifiable in the observed climatology). The interpolated PCM-LI and RCM-LI results both capture the primary gradient, but RCM is clearly superior in resolving the temperature range and spatial distribution across the basin. Both models show cold and warm biases in the lower and higher elevation areas, respectively, but these are much stronger in PCM, particularly in December. For PCM, the SD method alone removes much of the spatial elevation related bias for July and December, leaving broad scale biases of a few degrees or less. (It should be noted, however, that this apparent agreement is somewhat deceptive, as the hydrological model is quite sensitive even to temperature biases of this magnitude). For RCM, SD may also smooth biases arising from the finer resolution of the observed climatology, but RCM's initial biases, for the most part, remain. BCSD improves the results to the point that the PCM and RCM T_{avg} simulations match the observed means to within a few tenths of a degree Celsius in December, and a few hundredths of a degree Celsius in July.

For the CRB domain (upstream of the Dalles, OR, bordered to the west by the Cascade Mountains rather than the Pacific Ocean), the simulated average April 1 snow water equivalent (SWE) (Figure 6) reflects the effects of winter and spring temperature and precipitation. PCM-LI completely fails to capture both the magnitude and spatial distribution of SWE, and although interpolated RCM distributes snow correctly, it has a high bias, particularly in the Snake River plain, western Montana and eastern Oregon. With SD, PCM derived results improve greatly, despite leaving a high bias in eastern Oregon and central Idaho and a low bias in BC. For RCM, SD makes little difference. For both PCM and RCM, the BCSD method eliminates most of the bias inherent in using both RCM and PCM outputs directly, although some small differences between the two are evident, and some very localized biases remain (such as in the northern part of the study domain).

3.1.2. *Basin-Average Monthly Analysis*

The basin average monthly analysis (Figure 7) shows that the LI and SD methods produce nearly the same basin-wide precipitation and temperature signals for each model. In dynamical downscaling, however, there are no physically-based mechanisms that constrain the simulation to preserve PCM's basin mean precipitation or temperature. In this example, while the RCM changes the PCM temperature signal only slightly (leaving a cold winter and spring bias), it worsens the bias in the seasonality of precipitation, particularly the high bias in fall and winter. For RCM, with the LI and SD methods, the high bias in fall and winter precipitation leads

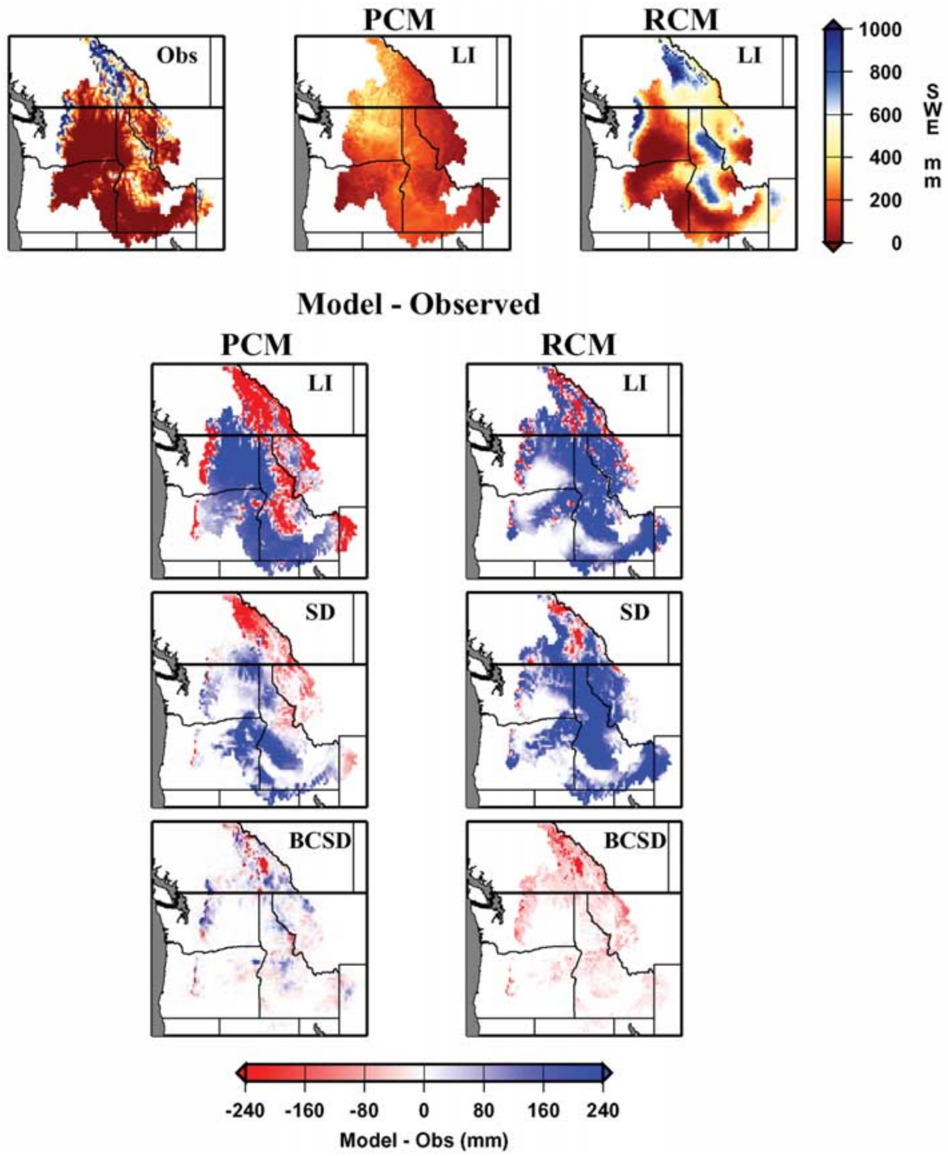

Figure 6. Average April 1 SWE simulation for the retrospective 1975–95 climate simulations, compared with the observed (simulated by the VIC model forced with observations) climatology for the same period (top left). LI method values are shown to the right of the observed values; rows 2–4 contain differences from observed values for the LI, SD and BCSD methods.

to an oversimulation of SWE, soil moisture and summer evaporation. For PCM, the results are varied, with SWE and runoff undersimulated for the LI method and oversimulated for the SD method, but soil moisture and summer evaporation oversimulated for both. SD has little effect on the interpolated results for RCM, but as before, greatly changes the interpolated results for PCM. The BCSD method, by definition, forces the mean and variance of the PCM and RCM output to equal the observed distribution, so for precipitation and temperature, the PCM and RCM BCSD results cannot be discriminated (in top row panels of Figure 7) from the observed climatology. For hydrologic variables, however, the exacting monthly corrections of precipitation and temperature alone do not eliminate all biases relative to the observed hydroclimatology. Note that PCM and RCM BCSD runoff shifts slightly earlier in the year, SWE is reduced, and soil moisture is slightly out of phase as compared with values simulated directly using VIC forced with gridded observations.

3.1.3. *Monthly Average Streamflow*

The plots of monthly average streamflow in Figure 8 show the implications of the downscaling methods for different parts of the basin. At The Dalles, RCM's high precipitation bias leads to oversimulation of runoff for both the SD and LI methods; whereas for PCM, the LI results are reasonably close to observed, while the SD method oversimulates runoff. The same is true for PCM at Ice Harbor, while at Corra Linn and Chief Joseph, SD improves runoff simulation. For RCM, the SD and LI methods yield similar streamflows, and these are much improved relative to PCM streamflows at Corra Linn and Chief Joseph, but are worse (due to oversimulation) at Ice Harbor. The SD step in all cases reduces the difference between interpolated PCM streamflow and RCM-LI streamflow. This reflects the fact that RCM inherited large scale bias from PCM and therefore streamflows simulated using the RCM-LI outputs are similar to those simulated by PCM-SD. The BCSD method greatly improves streamflow simulation relative to the other methods for both PCM and RCM, at all four sites, although the small bias toward earlier runoff remains. The PCM and RCM BCSD results are essentially identical, more or less by construct.

3.2. BAU ANALYSIS (JULY 2040–JUNE 2060)

3.2.1. *Spatial Analyses of Precipitation, Temperature and Snow Water Equivalent*

Because of the large biases resulting from the LI and SD methods for the retrospective climate period, results for BCSD only are discussed for the BAU climate. LI spatial plots are shown, however, to help illustrate the differences between the BAU and retrospective scenarios.

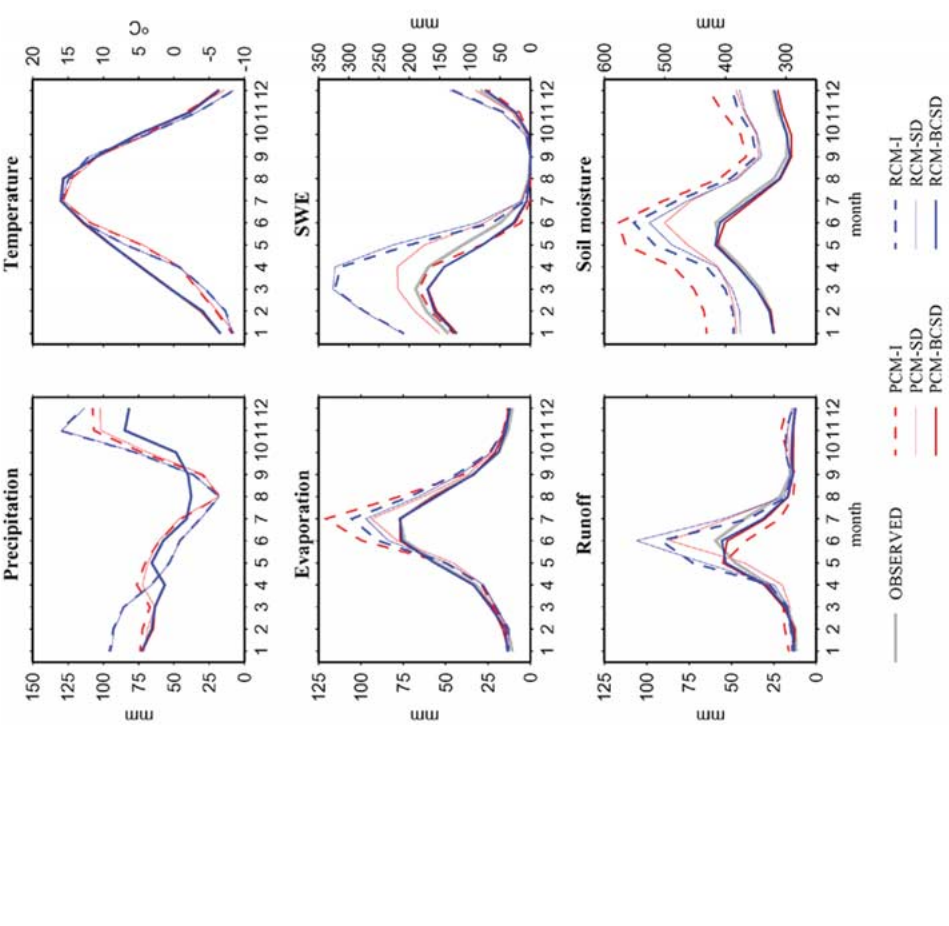

Figure 7

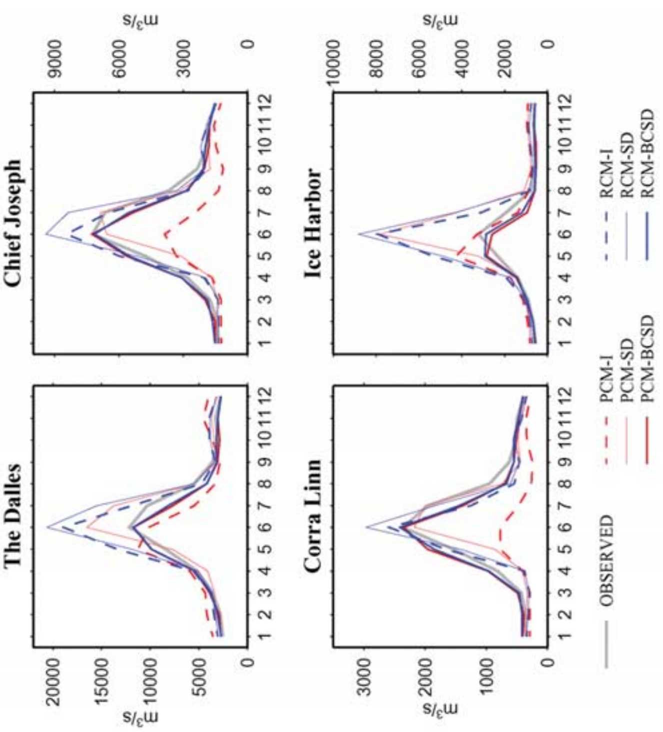

Figure 8

For the BAU simulations, after BCSD, the primary changes in precipitation (top row, Figure 9), as compared with the observed climatology and with the retrospective climate simulation results (second row, Figure 4), are an intensification of precipitation in the northwest and northeast parts of the domain, a drying in the southeast in December, and a moderate drying over most of the region in July. The BCSD results for both models are quite similar, but RCM simulates greater precipitation in some areas in December (particularly west of the Cascade Mountains and in the mountains of Idaho) and less precipitation in the eastern part of the basin in July.

For temperature (Figure 10), the BAU simulations from PCM and RCM preserved the spatial patterns from each model's retrospective simulation (Figure 5), but are uniformly about 3 and 1.8 °C warmer in winter and July, respectively, a difference that PCM-BCSD and RCM-BCSD simulated almost identically. The two approaches nonetheless lead to differences of up to ½ °C in places.

For precipitation and temperature, the RCM-PCM differences with BCSD appear in most cases to be reasonably consistent with tendencies present in the retrospective simulations before any adjustment (e.g., comparing RCM-PCM differences in the LI rows of Figures 4 and 5). For example, the RCM's BAU climate is wetter than PCM's to the west of the Cascade Mountains, where it is also wetter in the retrospective LI approach. The RCM BAU's Snake River basin is warmer than PCM in July, while in the retrospective simulations, that area is both warmer and drier before bias correction. In winter, the reverse is true (as it is for the eastern rim of the domain). These differences are consistent with the RCM's colder, wetter bias in those areas in the retrospective simulations. Although these differences are damped out in the retrospective BCSD, they filter through BCSD in the BAU simulations.

For the BAU climate April 1 SWE (Figure 11), the BCSD method with RCM and PCM yields significantly less snow for each model, relative to their retrospective SWE results. RCM has less SWE relative to PCM except in the northern tip of the basin, where the RCM BAU is both colder and wetter than the PCM BAU in December.

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Figure 7. CRB areal averages of climate and hydrology variables for the retrospective 1975–95 climate simulations, compared with the observed climatology (i.e., observed precipitation and temperature, and simulated hydrologic variables based on these observations) for the same period (note that the PCM and RCM BCSD methods produce monthly mean precipitation and temperature that are indistinguishable from the observed in the figure).

Figure 8. Streamflow at four locations (see Figure 1) for the retrospective 1975–95 climate simulations, compared with the observed (simulated by the VIC model driven with observations) climatology for the same period.

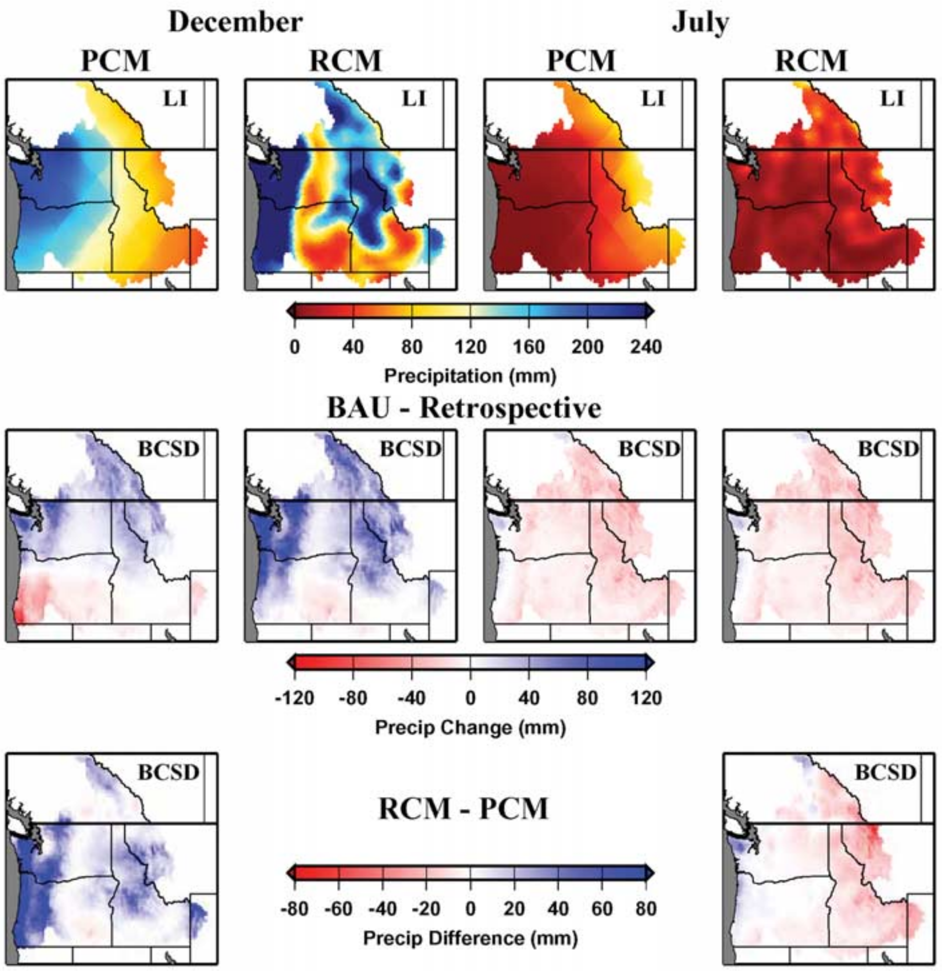

Figure 9. December and July total precipitation for the PCM and RCM-driven BAU future climate simulations (2040–60). With LI only (top row); (second row) differences in BAU BCSD results for PCM and RCM from their retrospective BCSD results; (third row) differences between RCM-BCSD and PCM-BCSD results.

3.2.2. *Monthly Basin Average and Streamflow Analyses*

In the monthly analysis of basin average variables (Figure 12), the BAU RCM and PCM with BCSD approaches both have increased spring and decreased summer precipitation, although PCM precipitation is greater than RCM, except in fall. BAU temperature increases are nearly identical for the two approaches, hence different hydrologic results for the basin-averages variables follow more from precipitation differences. Soil moisture and evaporation are higher in PCM-BCSD, moderating the effect of PCM's higher precipitation on runoff, which is only slightly higher for PCM than for RCM. For both approaches, the peak runoff comes about one month earlier, but for RCM-BCSD, volume also decreases. Basin-average BAU

SWE declines relative to retrospective SWE, but without much difference between approaches (despite the spatial differences in Figure 11). Relative to the retrospective results, the BAU streamflow (Figure 13) shows an even larger seasonality shift toward higher winter-spring flows, and lower summer ones, relative to the observed climatology. Although equally shifted, the RCM BCSD streamflows are more sensitive to climate warming (with decreases in volume in addition to the shift) than the PCM-BCSD flows. This effect is exaggerated at Ice Harbor (near the mouth of the Snake River), where flow does not benefit from the RCM-BCSD's relatively higher spring snowpack in the Canadian headwaters of the CRB.

4. Conclusions

The foregoing results of spatial analyses for December and July, and monthly analyses of basin averaged climate and hydrology variables and streamflow were chosen to characterize spatial and temporal differences arising from six different approaches to downscaling climate model output. We recognize that there are some difficulties in diagnosing hydrologic effects from one-month 'summer' and 'winter' snapshots of climate variables, even coupled with the continuous monthly analyses of basin averaged variables. Nonetheless, we draw the following conclusions from the retrospective analysis:

- With BCSD (in contrast to the two other postprocessing choices), a dynamical downscaling step does not lead to large improvements in retrospective hydrologic simulation relative to direct use of GCM output.
- Linear interpolation of PCM or RCM output is insufficient to support plausible hydrologic simulation, even over large areas, despite the fact that RCM moderates PCM-derived hydrologic biases relative to the $1/8$-degree observed climatology.
- If large-scale climate model outputs are relatively unbiased, applying spatial disaggregation (SD) to impose subgrid spatial variability improves hydrologic simulations, but substantial local biases will remain. After SD, for example, hydrologic (e.g., SWE and runoff) and streamflow simulations derived from the PCM output produce similar results to the finer scale RCM outputs after LI.
- If the climate fields are biased, SD alone may exacerbate biases locally (while leaving the basin average bias unchanged), particularly for precipitation, with the result that the downscaled climate variables may be unsuitable for use in hydrologic simulation.

Hydrologic simulation is sufficiently sensitive to biases in the basin mean and spatial distribution of precipitation and temperature at the monthly level, that nearly all local bias must be removed from climate inputs. This is particularly true

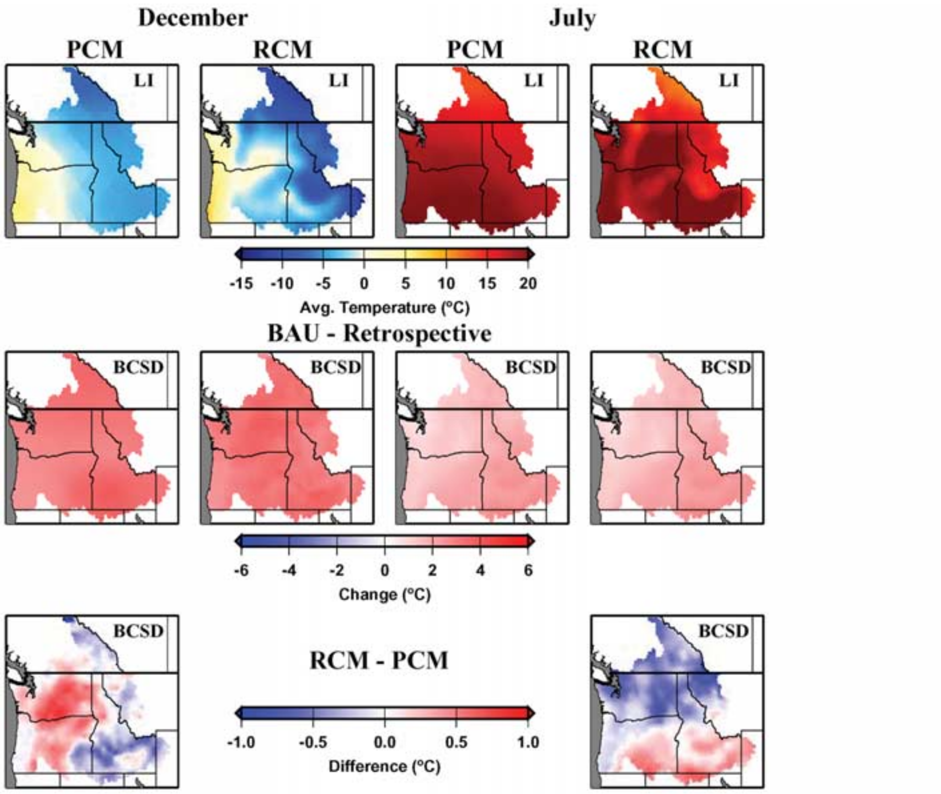

Figure 10

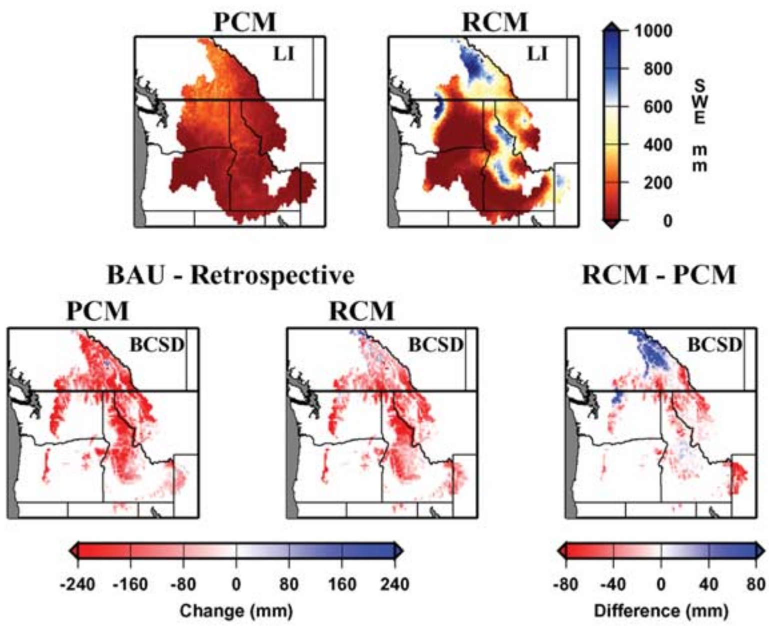

Figure 11

where seasonal snowpack transfers moisture input to the soil column and runoff from one season to the next. A primary conclusion of the retrospective study is that, although the BCSD method successfully reproduces observed hydrology using biased climate model simulation outputs from both PCM and RCM, the monthly temporal scale used in correction of climate model precipitation and temperature, separately, fails to rectify more subtle differences between climate model simulation and observed climate. Interdependencies between precipitation and temperature (for example, the frequency of wet-warm and wet-cold winters) are not addressed by the BCSD method, nor are the characteristics of seasonal distributions of precipitation and temperature arising from temporal autocorrelation in climate variables. Although the RCM may augment PCM in simulating these dynamics, after the BCSD method, the RCM and PCM retrospective hydrology simulations (with residual biases) were nonetheless nearly identical.

Like seasonal climate variability, interannual climate variability is only represented by the downscaling methods described in this paper via those characteristics that are directly transmitted to the downscaled values. For instance, while the methods ensure that the long term model-based monthly climatology (and to a large extent) the hydrology will resemble the observed hydroclimatology, they do not guarantee that the interseasonal or interannual sequencing of different climate regimes (e.g., dry/wet periods such as the 1988 drought or 1993 midwestern U.S. flooding) in a retrospective climate model simulation will be accurately simulated. Extratropical interannual climate variability, particularly for precipitation, is not predicted well by GCMs (e.g., Lau et al., 1996), even given observed ocean boundary forcings, far less in free-running climate integrations that form the basis for many climate change studies. Given retrospective boundary conditions, however, many climate models (PCM included, as noted in Zhu et al., 2004) simulate long-term average annual and seasonal climate characteristics (for means and other statistics) reasonably well, which is the rationale for using these models in climate impact assessments. Approaches that combine climate model estimates of changes in characteristics which climate models simulate well with observation-derived information about poorly simulated climate characteristics (e.g., interannual variability, subgrid spatial variability) may be a fruitful area for future investigations.

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Figure 10. December and July average temperature for the PCM and RCM-driven BAU future climate simulations (2040–60). With LI only (top row); (second row) differences in BAU BCSD results for PCM and RCM from their retrospective BCSD results; (third row) differences between RCM-BCSD and PCM-BCSD results.

Figure 11. Average April 1 SWE simulation for the PCM and RCM-driven BAU future climate simulations (2040–60). LI method results (top row); (second row, left) PCM and RCM BCSD differences between BAU and retrospective results; (second row, right) differences between RCM-BCSD and PCM-BCSD results.

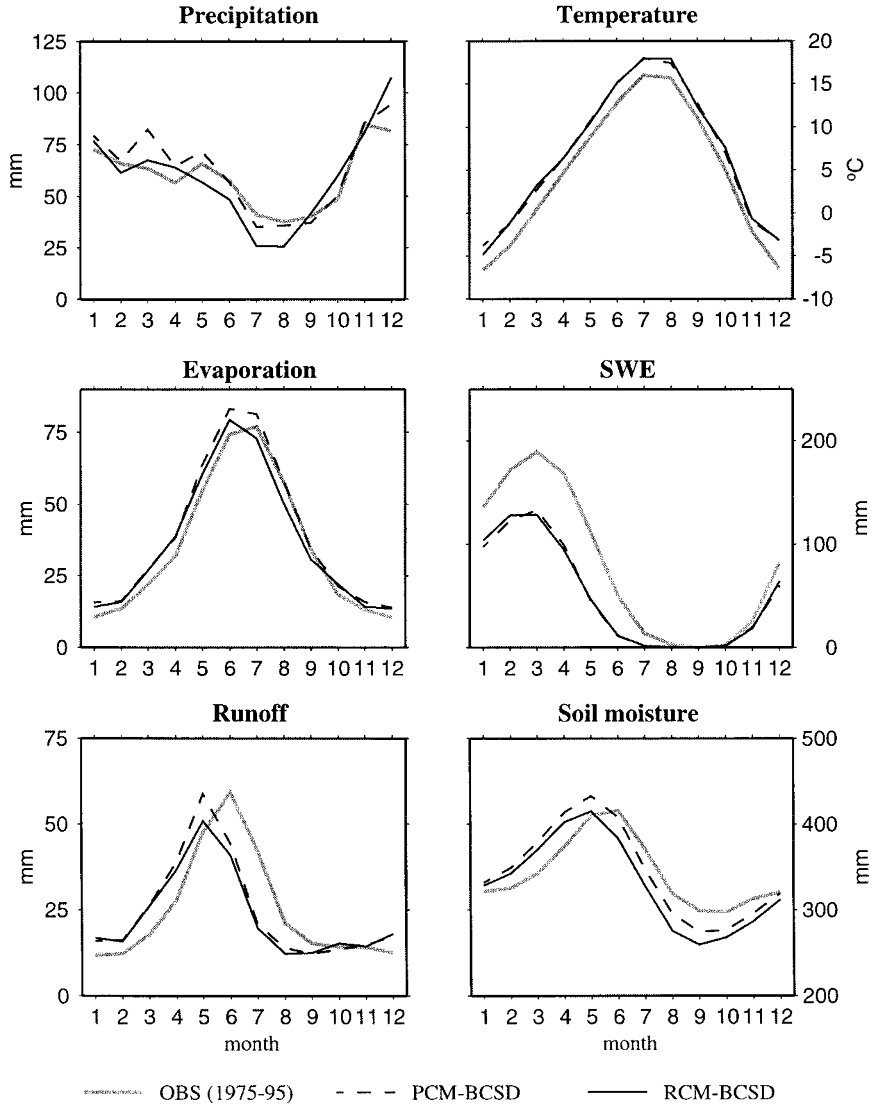

Figure 12. CRB areal averages of climate and hydrology variables for the PCM and RCM-driven BAU future (2040–60) climate simulations, compared with the observed 1975–95 climatology (i.e., observed precipitation and temperature, and simulated hydrologic variables based on these observations).

When applied to the future (BAU) climate scenarios, the BCSD method yielded the only consistently plausible streamflow simulations, whether or not dynamical downscaling was also used. A significant conclusion, however, is that dynamically downscaling the climate model scenarios before applying the BCSD method yielded results showing greater hydrologic sensitivity to climate change in the CRB than PCM-BCSD (i.e., without dynamical downscaling). The RCM's initial biases in the spatial simulation of temperature and precipitation that were removed for

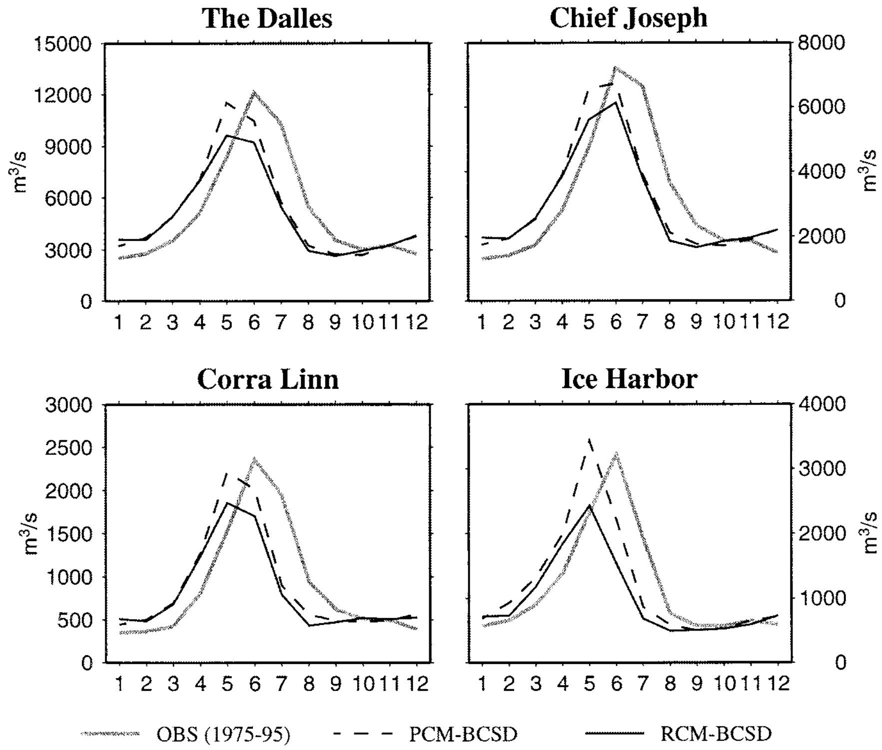

Figure 13. Streamflow at four locations (see Figure 1) for the PCM and RCM-driven BAU future (2040–60) climate simulations, compared with the observed 1975–95 climatology (simulated by the VIC model driven with observations).

the retrospective scenarios appeared to provide tendencies that produce the model differences for the BAU climate. Charles et al. (1999) note that for climate change assessments, the inclusion in statistical downscaling approaches of an atmospheric moisture prediction variable (in this case, one other than surface precipitation – perhaps one more confidently simulated by climate models) can lead to convergence in the results of statistical and dynamical approaches.

The greater hydrologic sensitivity to the BAU climate found using RCM-BCSD compared to PCM-BCSD may imply that fully coupled land-atmosphere models like RCM have a role to play in climate change analysis. The hydrologic differences are the combined result of differences between the PCM and RCM simulated warming signals, and differences in their precipitation characteristics. Leung et al. (2004) showed larger warming in the BAU scenario at the higher elevations that may be associated with snow-albedo feedback effects (a dependence also found in observations by Beniston et al. (1997), and other regional climate simulations: Giorgi et al. (1997), Leung and Ghan (1999), and Kim (2001)). A one way coupling of large scale climate models with high resolution hydrologic models cannot recover the effects of the missing regional scale climate change signatures. Where such regional signatures can be shown to be important (*and* can be accurately represented) in a subgrid scheme, they argue for higher resolution modeling or at least subgrid treatments in fully coupled land-atmosphere models for the study of climate change effects.

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