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Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods

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Abstract

Downscaling of climate model data is essential to most impact analysis. We compare two methods of statistical downscaling to produce continuous, gridded time series of precipitation and surface air temperature at a 1/8-degree (approximately 140 km^2 per grid cell) resolution over the western U.S. We use NCEP/NCAR Reanalysis data from 1950–1999 as a surrogate General Circulation Model (GCM). The two methods included are constructed analogues (CA) and a bias correction and spatial downscaling (BCSD), both of which have been shown to be skillful in different settings, and BCSD has been used extensively in hydrologic impact analysis. Both methods use the coarse scale Reanalysis fields of precipitation and temperature as predictors of the corresponding fine scale fields. CA downscales daily large-scale data directly and BCSD downscales monthly data, with a random resampling technique to generate daily values. The methods produce comparable skill in producing downscaled, gridded fields of precipitation and temperatures at a monthly and seasonal level. For daily precipitation, both methods exhibit some skill in reproducing both observed wet and dry extremes and the difference between the methods is not significant, reflecting the general low skill in daily precipitation variability in the reanalysis data. For low temperature extremes, the CA method produces greater downscaling skill than BCSD for fall and winter seasons. For high temperature extremes, CA demonstrates higher skill than BCSD in summer. We find that the choice of most appropriate downscaling technique depends on the variables, seasons, and regions of interest, on the availability of daily data, and whether the day to day correspondence of weather from the GCM needs to be reproduced for some applications. The ability to produce skillful downscaled daily data depends primarily on the ability of the climate model to show daily skill.

1 Introduction

Climate models are the primary tool to evaluate the projected future response of the atmosphere-land-ocean system to changing atmospheric composition (MacCracken et al., 2003; Stocker et al., 2001), and they underpin most climate change impacts studies (Wilby and Harris, 2006). However there is a mismatch between the grid resolution of current climate models (generally hundreds of kilometers), and the resolution needed by environmental impacts models (typically ten kilometers or less). Downscaling is the process of transforming information from climate models at coarse resolutions to a fine spatial resolution. Downscaling is necessary, as the underlying processes described by the environmental impact models are very sensitive to the nuances of local climate (Hidalgo et al., 2007[1]), and the drivers of local climate variations, such as topography, are not captured at coarse scales.

There are two broad categories of downscaling: dynamic (which simulates physical processes at fine scales) and statistical (which transforms coarse-scale climate projections to a finer scale based on observed relationships between the climate at the two spatial resolutions). Dynamic downscaling, nesting a fine scale climate model in a coarse scale model, produces spatially continuous fields of climate variables, thus preserving some spatial correlation as well as physically plausible relationships between variables. However, dynamic downscaling is very computationally intensive, making its use in impact studies limited, and essentially impossible for multi-decade simulations with different global climate models and/or multiple greenhouse gas emission scenarios. Thus, most impacts studies rely on some form of statistical downscaling, where variables of interest can be downscaled using historical observations. There has been extensive work developing and intercomparing statistical downscaling techniques for climate impact studies (Giorgi et al., 2001; Wilby and Wigley, 1997).

Statistical downscaling is typically used to predict one variable at one site, though

[1] Hidalgo, H. G., Dettinger, M. D., and Cayan, D. R.: Downscaling daily precipitation and temperature fields over the U.S. with constructed analogues, J. Climate, in review, 2007.

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some techniques for simultaneous downscaling to multiple sites for precipitation have been developed (Harpham and Wilby, 2005; Wilks, 1999). However, for studies of some climate impacts such as river basin hydrology, it is important to downscale simultaneous values of multiple variables (such as precipitation and temperature) over large, heterogeneous areas, while maintaining physically plausible spatial and temporal relationships, though few downscaling techniques have been developed to do this.

In this study we compare two methods of statistical downscaling to produce continuous, gridded time series of precipitation (P) and surface air temperature (T) at a fine resolution over a large spatial domain. These two methods are termed constructed analogues (CA, Hidalgo et al., 2007[1]; van den Dool, 1994) and bias correction and spatial downscaling (BCSD, Wood et al., 2004). The CA method has been shown to have significant skill in reproducing the variability of daily P and T over the contiguous United States (U.S.), in particular in the western coast (Hidalgo et al., 2007[1]). The BCSD method has been shown to provide downscaling capabilities comparable to other statistical and dynamical methods in the context of hydrologic impacts (Wood et al., 2004).

The main conceptual difference between the two methods compared here is that the daily correspondence of the coarse resolution and the fine resolution patterns is maintained in the CA method, while in the BCSD the monthly patterns are conserved but daily patterns are resampled randomly, and therefore the daily correspondence is not conserved. In this way, CA is designed to use the simulated daily sequences from a climate model (at a coarse spatial resolution) and downscales each simulated day, while BCSD downscales monthly simulated climate model output and randomly generates daily sequences to match the monthly values. While randomly resampling daily sequencing within a month has been shown to have a negligible impact for monthly and seasonal river basin hydrologic statistics (Wood et al., 2002), for impacts related to shorter-term extremes (e.g. heat waves, air quality episodes, flood peaks), changes in daily sequencing will be important. Where a climate model exhibits skill in simulating daily variability, CA would capture that skill, while BCSD would reflect climatological intra-month variability. Thus, the two methods will be expected to distinguish themselves only inasmuch as the large-scale climate exhibits skill at the daily time scale.

2 Data sources and methods

2.1 Data sources

Daily P, maximum and minimum temperature at 1/8 degree resolution (approximately 140 km^2 per grid cell) were obtained from the University of Washington Land Surface Hydrology Research group (http://www.hydro.washington.edu), the development of which is described in Maurer et al. (2002). The data are daily station observations interpolated onto a regular grid, with precipitation adjusted for compatibility with the Parameter-elevation Regressions on Independent Slopes (PRISM, Daly et al., 1994) dataset. This dataset constitutes the main dataset in the calibration and evaluation the performance of the downscaling processes in this study.

We use the National Center of Environmental Prediction and the National Center of Atmospheric Research (NCEP/NCAR) reanalysis (hereinafter reanalysis, Kalnay et al., 1996) as a surrogate for a General Circulation Model (GCM), which is then downscaled and compared to observations. Reanalysis data are available on a T62 Gaussian grid (approximately 1.9° square), a resolution comparable to current generation of GCMs. Due to the assimilation of atmospheric observations, it represents the best possible simulation capability of a GCM, though it still can exhibit substantial regional biases, especially in precipitation (Maurer et al., 2001; Widmann and Bretherton, 2000; Wilby et al., 2000). Another favorable characteristic of reanalysis data is the availability of daily precipitation and temperature data, which is often not archived for long, climate change simulations by modeling groups. Additionally, the P and T daily variability in the reanalysis has been shown to be plausible in some locations in the Western U.S. (Widmann and Bretherton, 2000), and the existence of skill in daily statistics of GCM output will be a major factor distinguishing the downscaling methods compared in this study.

2.2 "Observed" and "projected" time period definitions

We used 1950–1976 reanalysis precipitation and temperature as the period representing the "observations," and 1977–1999 as "projections," similar to past studies (e.g. Salathé, 2003; Wilby et al., 2000). These two periods have differing characteristics, with the second period reflecting the temperature increase of recent decades, as well as a phase shift in the Pacific Decadal Oscillation (PDO, Mantua et al., 1997) from cool phase (through 1976) to warm phase (1977 through at least the mid-1990s) (Mantua and Hare, 2002). The PDO influences North American climate in a similar manner to the El Niño Southern Oscillation (ENSO), though by contrast with ENSO, PDO persists for decades. PDO has been correlated with precipitation, temperature, and hydrologic anomalies (Cayan, 1996; Hamlet and Lettenmaier, 1999), showing strong correlations especially for the Pacific Northwest. The magnitude of observed warming trends in the Western U.S. of 1–3°C over the second half of the 20th century are non-uniform through the region and are not fully explained by the PDO shift (Stewart et al., 2005). Precipitation trends over recent decades are even more non-uniform spatially and variable through time (Mote et al., 2005). For the spatial domain used in this study, the latter period is warmer by 0.2°C and wetter by 7%, with the means of the two periods differing with high confidence (>90%, based on a 1-tailed t-test). In this way, while not dramatically warmer, the period used as projections in this study serves as a proxy for a changed climate from the one used to train the downscaling methods.

2.3 Bias-correction & spatial downscaling (BCSD)

The bias-correction and spatial downscaling (BCSD) method of Wood et al. (2004) is an empirical statistical technique in which the monthly precipitation and temperature output from a GCM are downscaled. The method was originally developed for adjusting GCM output for long-range streamflow forecasting (Wood et al., 2002) and was later adapted for use in studies examining the hydrologic impacts of climate change in the Western U.S. (Christensen et al., 2004; Payne et al., 2004; Van Rheenen et al., 2004). The technique uses a quantile-based mapping (Panofsky and Brier, 1968) of the probability density functions for the monthly GCM precipitation and temperature onto those of gridded observed data, spatially aggregated to the GCM scale. This same mapping is applied to the 21st century GCM simulations. This allows the mean and variability of a GCM to evolve in accordance with the GCM simulation, while matching all statistical moments between the GCM and observations for the base period. This technique has compared favorably to different statistical and dynamic downscaling techniques (Wood et al., 2004) in the context of hydrologic impact studies. The method is computationally efficient and has thus been applied to studies downscaling multiple, extended GCM simulations for hydrologic impact studies (Cayan et al., 2007; Christensen and Lettenmaier, 2007; Maurer, 2007).

To recover daily values historical months are selected at random and each day in the selected month is rescaled identically (using a multiplicative factor for precipitation and an additive factor for temperature) to match the projected monthly total precipitation and average temperature. In this way the BCSD method, as applied in this study, does not account for changes in the statistics of climate variability at scales less than monthly that may be projected by a GCM, and is not expected to exhibit skill at projecting statistics of daily extremes above simply assuming climatological daily variability. In other, more spatially limited settings, adjusting the random selection of the historic sequence used in rescaling based on climate similarity has been used (Salathé, 2005). However, applying that conditioning technique requires the ability to characterize the entire domain by mean monthly precipitation, which is only possible on much smaller domains than that used in this study.

2.4 Constructed analogues

The Constructed Analogues (CA) method is described in detail in Hidalgo et al. (2007)[1]. The pattern to be downscaled (target pattern) is estimated using a linear combination of previously observed patterns (library) that are similar to the target pattern. The target patterns are the 1977 to 1999 Reanalysis patterns. The linear estimate at the coarse scale of each of daily target pattern is called the analogue. The downscaled estimate is constructed by applying the regression coefficients obtained at the coarse-scale, to the high-resolution patterns corresponding to the same days used to derive the analogue. In this application of the CA, the library patterns were composed of the coarsened version of the Maurer et al. (2002) data, aggregated to the resolution of the Reanalysis (T62) from 1950 to 1976 along with the corresponding 1/8 degree versions for the same days. As in Hidalgo et al. (2007)[1], the estimation of the target pattern was constructed using as predictors the "best" 30 analogues (based on the pattern root mean square error (RMSE) distance with the target) selected from a window of potential patterns that is climatologically ±45 days apart from the target.

Mathematically, for each day and variable to be downscaled, if we define $Z_{\text{analogues}}$ as the matrix of 30 best predictors from the 1950 to 1976 library at the coarse resolution and $P_{\text{analogues}}$ the corresponding 1/8 degree resolution patterns for the same days, the downscaled estimate $\hat{P}_{\text{downscaled}}$ is given by:

$$\hat{P}_{\text{downscaled}} = P_{\text{analogues}} \left[\left(Z'_{\text{analogues}} Z_{\text{analogues}} \right)^{-1} Z'_{\text{analogues}} \right] Z_{\text{obs}} \qquad (1)$$

Where Z_{obs} is the target pattern, corresponding to the matrices of the Reanalysis patterns. Details on the derivation of Eq. (1) can be found in Hidalgo et al. (2007)[1].

2.5 Comparison of methods

First, we assess the ability of the different methods to simulate average monthly precipitation and temperature. Second we compare both downscaling methods using metrics of daily precipitation and temperature extremes.

2.5.1 Monthly and annual assessment

The monthly skill is characterized using correlations between the monthly averages of the downscaled estimates and the monthly averages of the Maurer et al. (2002) data. In addition, the biases in the climatological precipitation and temperature were computed. Scatter plots for different locations in California are also produced for assessment of the performance of the methods at point scales.

2.5.2 Comparison based on daily precipitation and temperature indices

To characterize precipitation and temperature at the daily scale, we use indices that were developed as part of the Statistical and Regional dynamical Downscaling of Extremes for European regions (STARDEX) effort, which provides standard diagnostics for systematic inter-comparison of different downscaling methods (e.g., Harpham and Wilby, 2005; Haylock et al., 2006). Statistics were computed on a seasonal (December–February; March–May; June–August; September–November) and annual level at each 1/8° grid cell in the western United States. In computing the statistics (for the projection period of 1977–1999) for each grid cell, if fewer than 15 years were available for calculation of the statistic (such as many occurrences of zero precipitation amounts), that index was excluded for that grid cell.

Correlations were calculated for the years 1977–1999 between downscaled (CA or BCSD) and the gridded observed data (Maurer et al., 2002) for each statistic. Correlations are computed on seasonal (winter = December–February; spring = March–May; summer = June–August; fall = September–November). For plotting, the square of the correlation coefficient r^2 is used. To test the hypotheses that the correlation at each grid cell was zero, a Fisher's transform was applied to the Pearson correlation coefficients and a p-value (the probability that a non-zero correlation was reported when the downscaled and observed data are actually uncorrelated) was computed. A similar approach was used to test the hypotheses that the correlations produced by the two downscaling techniques are statistically the same.

3 Results and discussion

3.1 Monthly and seasonal skill

The correlation between monthly averages of downscaled P and T and the Maurer et al. (2002) observations is shown in Fig. 1. An interpolation of the reanalysis data to the fine scale (1/8 degree) grid is also shown as a reference or as a third "method" of downscaling the coarse scale data. For precipitation, the BCSD shows a larger area with very strong correlations, but the BCSD and CA downscaling methods are generally comparable when contrasted with the lower skill of the interpolated reanalysis. Figure 2 shows the root mean square error (RMSE) for the BCSD and CA are comparable for precipitation, and the BCSD method has lower RMSE over a larger region than CA for temperature. However, both methods exhibit much lower RMSE than the cubic interpolation, indicating that both downscaling methods provide substantial increases in skill at generating local climate features at the monthly scale.

For the Mojave Desert gridpoint, Fig. 3a shows that the correlations for precipitation and temperature are comparable for the CA and BCSD methods, with both methods slightly underestimating P and T but with high correlations. For the Madera gridpoint (Fig. 3b), located in California's Central Valley, the CA method shows weaker correlations than the BCSD for P and slightly stronger correlations for T, though again the two methods are very similar. For Madera and Yosemite (Fig. 3c), the CA method generally underestimated P, while the BCSD generally underestimated T.

A plot of the biases in P and T can be found in Fig. 4. In general the P biases are of similar magnitude for BCSD and CA, with larger biases occurring in similar locations for both methods (both generally along prominent mountain ranges), highlighting the difficulty in downscaling large-scale precipitation in areas of complex terrain. BCSD underestimates T to a greater degree than CA for the Upper Colorado River Basin, California's San Joaquin Valley and the Canadian portion of the Columbia River Basin, though there is some spatial correspondence in the regions with over- and under-estimation of T in both methods.

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Trends produced by a GCM are not explicitly corrected toward observations with either the CA or BCSD methods. Thus, as illustrated in Fig. 5, the large-scale temperature trends (which are not large for the projected period) are translated to the fine scale without generating fine-scale detail that may be present in the observations. BCSD, by extracting the temperature trend prior to bias-correction and replacing it afterward, exactly reproduces the large scale trends, while CA has a tendency to somewhat suppress them. The differences between large-scale trends simulated by reanalysis and observed station trends have been extensively explored (Kalnay and Cai, 2003; Kalnay et al., 2006). These differ due to many factors, notably because reanalysis does not reflect impacts of land use changes as well as other local and regional changes to clouds, snow, soil moisture, or instrumental changes (Trenberth, 2004; Vose et al., 2004). Regardless, in general, trend simulation by a coupled GCM during the 20th century is not directly comparable to observed trends, since low-frequency natural oscillations can masquerade as trends (Knowles et al., 2006), and the phase of oscillations in an unconstrained GCM simulation would not be expected to mimic observations. Thus, correcting trends in a GCM toward observed trends would be a questionable practice.

3.2 Daily skill

There is only modest skill with either the CA and BCSD method for dry (20th percentile) daily precipitation extremes in winter (Fig. 6), and this is generally focused in coastal areas of the Pacific Northwest. Other seasons show lower skills. There is no statistically confident difference between the methods for this measure. For wet (90th percentile) daily precipitation conditions both methods show some skill in winter, when most precipitation occurs (Fig. 7). The CA method exhibits higher correlations over certain regions such as the Sierra Nevada in California, but as with dry daily extremes, there is no statistically significant difference in the skills exhibited by the two methods.

In Fig. 8 the r^2 values between observations and the two downscaling methods for simulating the maximum number of dry days per season are shown. The starkest difference is in winter, where in the southern half of the domain the CA downscaling technique better captures dry day sequences than the BCSD. In approximately 22% of the grid cells where CA has better skill than BCSD, the difference is also statistically significant ($p<0.1$). For seasons other than winter, the CA technique still shows better skill than BCSD overall, though there are more grid cells where BCSD shows better skill. Overall, at an annual level the two techniques are statistically indistinguishable, with only 5% of the grid cells showing differences in correlation between observations and each of the two methods that are statistically significant at the $p=0.1$ level, far fewer than would be expected by chance. This shows that temporal aggregation of daily extreme statistics can mask seasonal skill differences.

The skill of the methods at simulating the observed maximum number of consecutive wet days in each season, while not shown, has results similar to those of Fig. 8, where the highest skill and the greatest difference between the two methods is in winter, and in the Southern half of the domain. In winter, 23% of the grid cells exhibit statistically significant differences between the skill levels of the two methods. Again, at the annual level, the skill at reproducing observed patterns of maximum consecutive numbers of wet days is much less statistically distinguishable than in the Winter.

In Fig. 9 the skill at reproducing extreme low temperature statistics, expressed as the 10th percentile daily temperature in each season is shown. In winter and fall, the CA method has much higher skill than BCSD, with 30% of the grid cells showing statistically significant differences between the methods. In the North, roughly corresponding to the Columbia River basin, the difference is most apparent. In this same region, however, the BCSD method shows greater skill in spring. Thus, the choice of most appropriate downscaling technique may depend not only on the statistic being analyzed, but also the region and season of focus.

In Fig. 10 the downscaling skill for reproducing observed daily warm anomalies, expressed as the 90th percentile temperature is illustrated. As was demonstrated above, the skill of the downscaling for daily temperature extremes exceeds that for precipitation extremes. While the downscaling of average seasonal temperatures for the two downscaling methods was shown to be comparable, high temperature extremes are better simulated with the CA downscaling, most notably in Central California and the Great Basin in summer. For seasons other than summer, less than 7% of the grid cells showed differences between the skills of the two downscaling techniques, much less than would be expected by chance at 90% confidence, indicating the methods are statistically indistinguishable for these seasons.

It is interesting to note in Fig. 10 that the lack of significant skill with either method along large portions of the coast in the summer and fall. This shows that the assumptions of stationarity embedded in either statistical downscaling method (where large-scale weather patterns are related to historically observed fine scale observations) at the scale used in this study may not be valid for the coastal climate in this region, where local effects due to sea breeze and coastal upwelling affect extremes, and the relationship between large scale and fine scale climate may be changing (Lebassi et al., 2007[2]).

4 Conclusions

At a monthly time scale, the two downscaling methods considered here, CA and BCSD, produce comparable skills in producing downscaled, gridded fields of precipitation and temperatures given coarse-scale reanalysis data as a surrogate GCM. The skill for temperature downscaling is considerably greater than that for precipitation, with precipitation showing much greater spatial variability in skill level.

Considering daily precipitation, both methods exhibit some skill in reproducing observed wet and dry extremes, generally in the Pacific Northwest, and the difference between the methods is not significant. This reflects the general low skill in daily precipitation variability in the large-scale reanalysis data over the domain, thus neither method can generate the skill absent in the large-scale signal. For reproducing fine

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scale observed consecutive sequences of wet and dry days, the CA method shows greater skill in winter in the Southwest. For other seasons and in other regions the methods are in general not statistically different.

The skill in downscaling daily temperature extremes exceeds that for precipitation extremes. For low temperature extremes, the CA method produces greater downscaling skill than BCSD for fall and winter seasons. For high temperature extremes, CA demonstrates higher skill then BCSD in summer, though for other seasons differences are not significant.

The choice of most appropriate downscaling technique depends in part on the variables, seasons, and regions of interest. For precipitation, and impacts driven predominantly by precipitation, there is little distinction between the two methods, and the general lack of skill at a daily timescale in the large-scale reanalysis-simulated climate provides little incentive to favor either downscaling method. The presence of skill in the daily reanalysis temperature data allows the CA method to show superior skill compared to BCSD at reproducing local temperature extremes in some seasons and locations.

As noted by Hidalgo et al. (2007)[1] one drawback to using daily P and T fields from a GCM is that the biases in the variance exhibited by the GCM will be reconstructed by the CA technique in the downscaled fields. While the reanalysis data used here as a surrogate GCM can be considered a best possible GCM, since it assimilates observed data, there are still substantial biases in some surface variables, and in particular for this study, precipitation. Actual GCM output reproduces precipitation extremes less reliably than reanalyses (Kharin et al., 2005), which could reduce the skill of the CA method. Although the CA method works with anomalies and therefore biases in the mean of the GCM are not transferred to the fine scale results, some kind of bias correction is needed to remove biases in the variance of the GCM when the CA is to be applied to actual GCM data.

A limitation common to both methods is that the greatest skill of both methods is obtained when the precipitation and temperature fields of the GCM are used as "pre-

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dictors". However, as noted in Hidalgo et al. (2007)[1] these fields may be depicted less accurately than other potential predictor variables in the GCM (for example atmospheric circulation fields). These considerations are model dependent and should be kept in mind when downscaling data from actual GCM. Regardless of the technique, a final caveat is that of Charles et al. (1999), who noted the validation of a downscaling technique using historic data does not imply it will be equally valid under changed future climate conditions. While both techniques used in this study are shown to provide skill in downscaling, any future changes to the relationships between large scale and fine scale climate cannot be anticipated by them.

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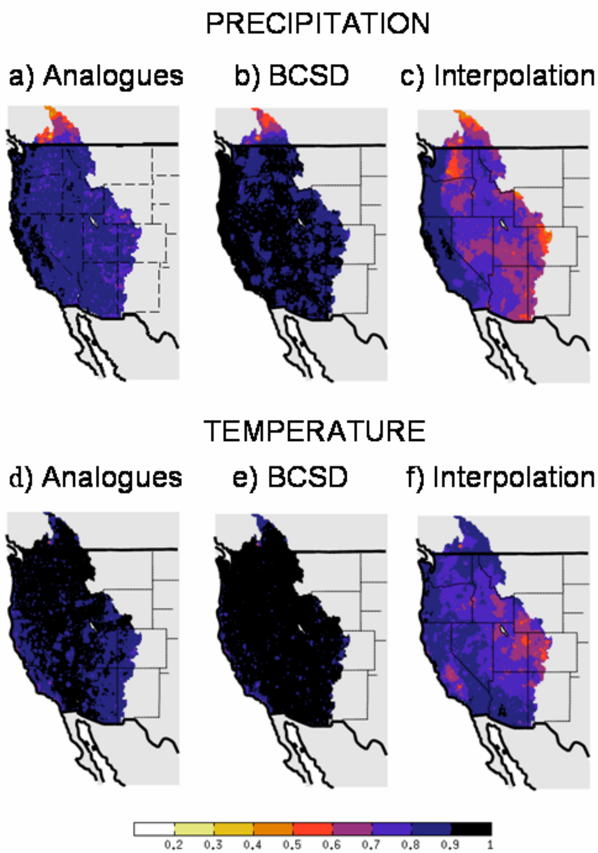

Fig. 1. Month to month correlation coefficients between observations from Maurer et al. (2002) dataset and downscaling estimates using three different approaches: the CA (left panel), the BCSD (middle panel) and a cubic interpolation of the large scale field.

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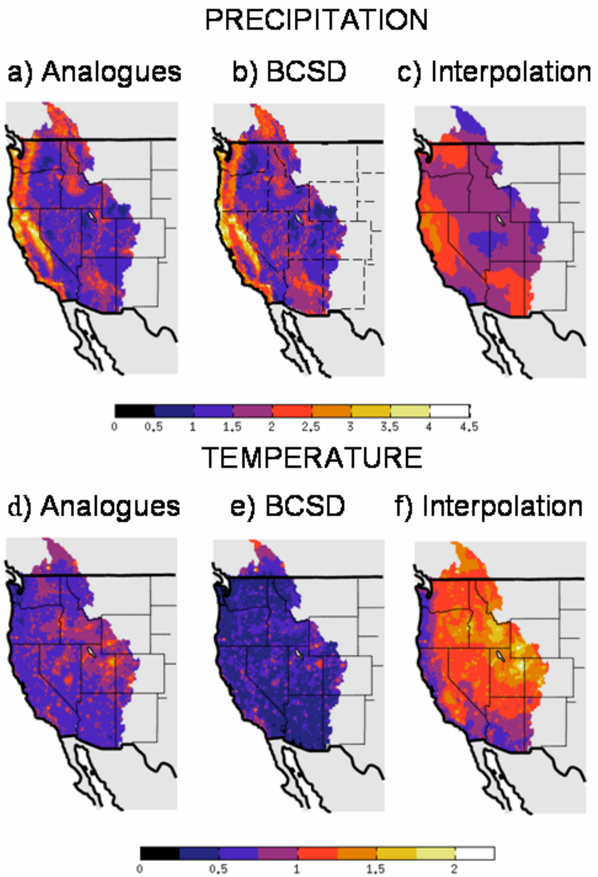

Fig. 2. Same as Fig. 1 but for the RMSE. Values in (mm day^{-1})$^{1/2}$ for precipitation and °C for temperature.

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Daily vs. monthly climate data in statistical downscaling

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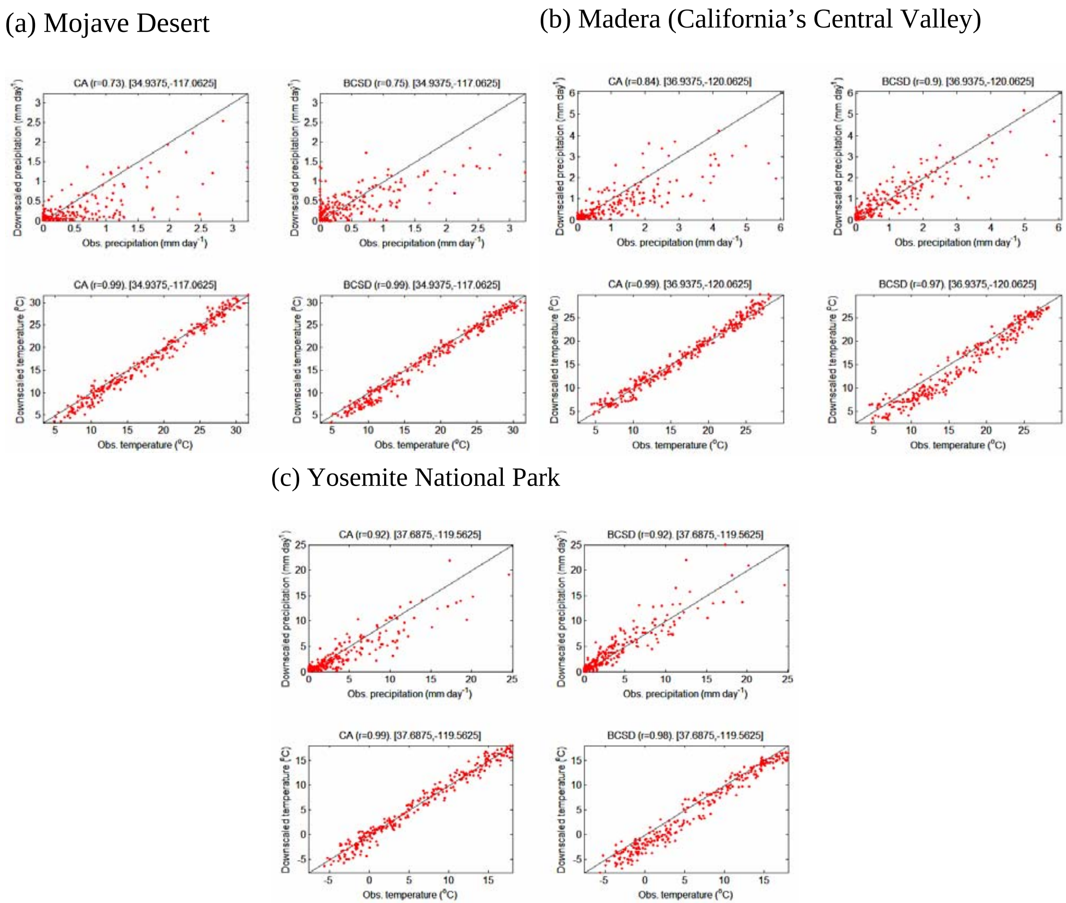

Fig. 3. Scatter plot of observed versus downscaled precipitation and air temperature for three grid cells.

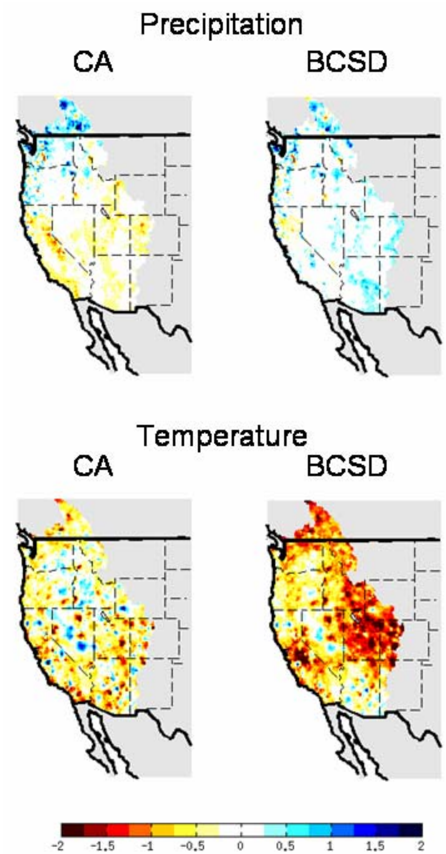

Fig. 4. Biases in mean precipitation (mm day^{-1}) and temperature (°C) using CA and BCSD methods.

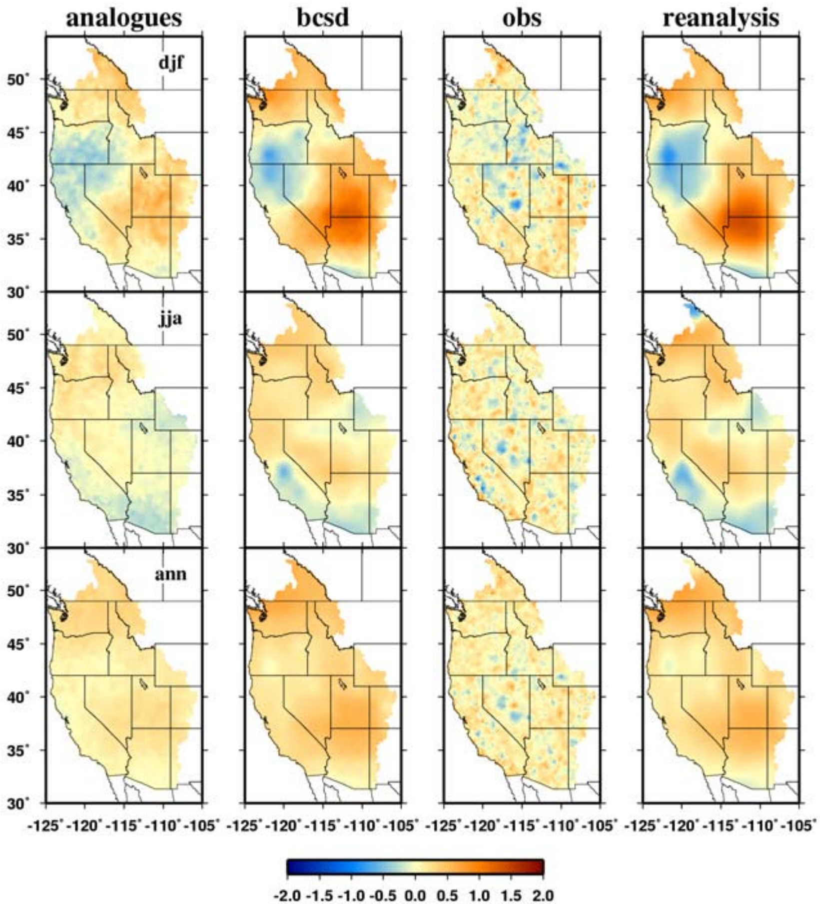

Fig. 5. Comparison of trends produced by downscaling with CA, BCSD, observed trends, and trends in the interpolated reanalysis data set. Values are in ˚C/decade for the projected period of 1977–1999.

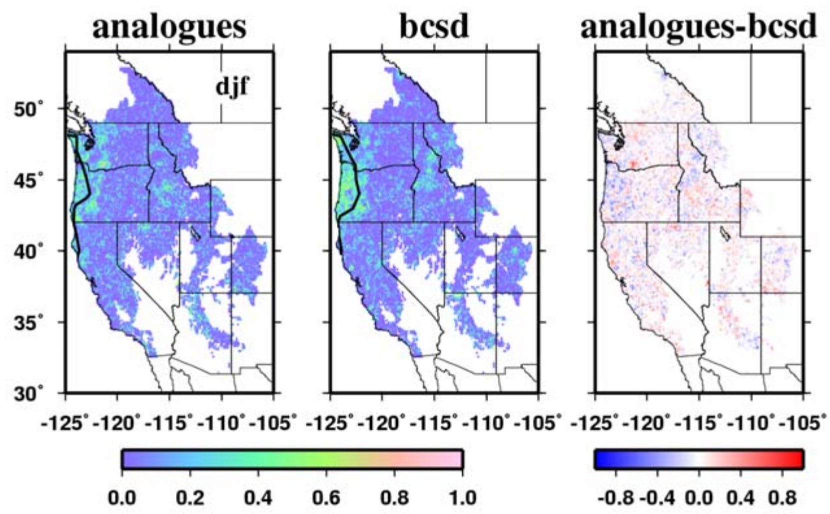

Fig. 6. r^2 values between observations and CA (left panel) and BCSD (center panel) for the 20th percentile (dry) daily precipitation statistic for winter season (as indicated in right panel). Right panel shows the difference between the two. The contour line delineates regions where the r^2 values achieve 90% confidence. Areas are absent if they have an inadequate number of years to compute the statistic.

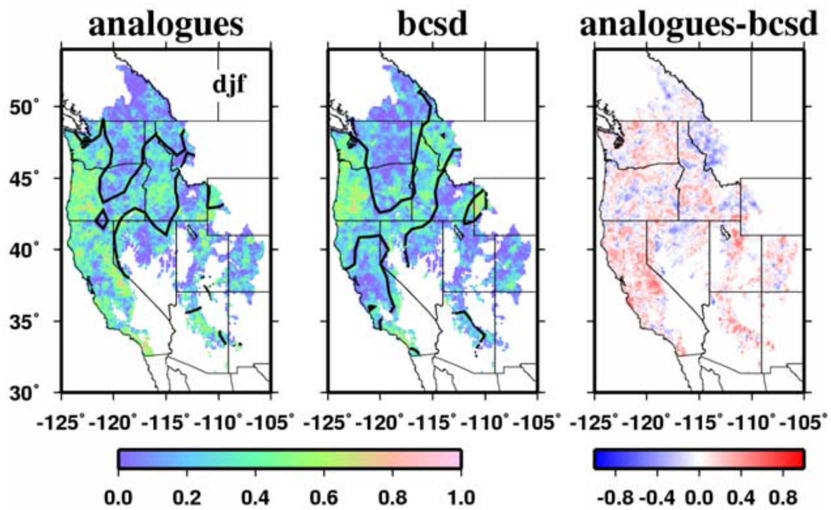

Fig. 7. Same as Fig. 5 but for the 90th percentile (wet) daily precipitation statistic.

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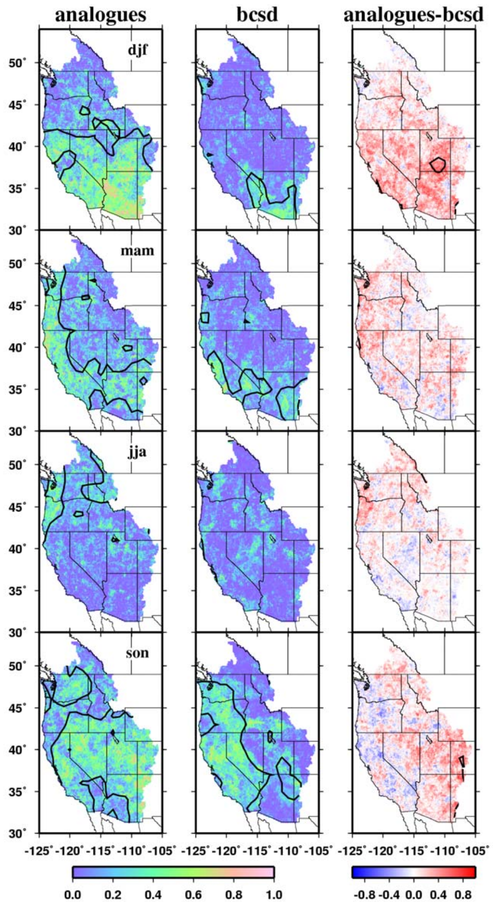

Fig. 8. Same as Fig. 5, but for maximum number of consecutive dry days per season. Each row corresponds to the season indicated in the right panel of that row.

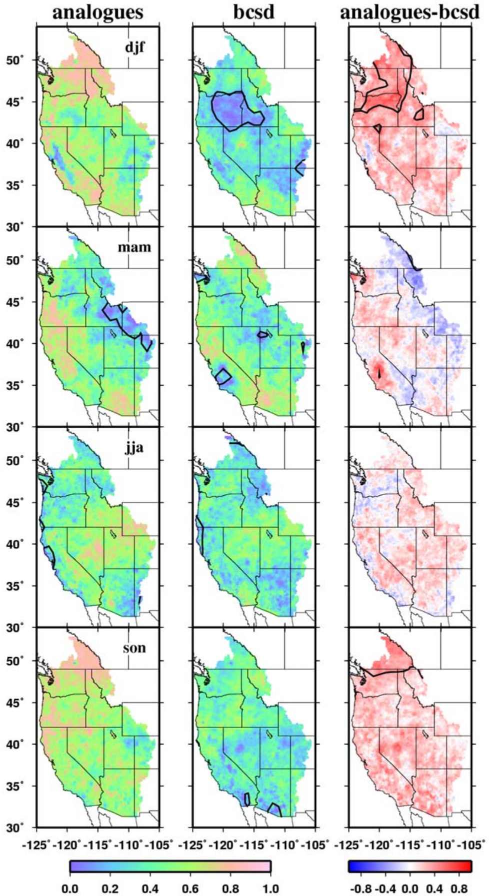

Fig. 9. Same as for Fig. 7, but for 10th percentile (cool) daily temperature in each season.

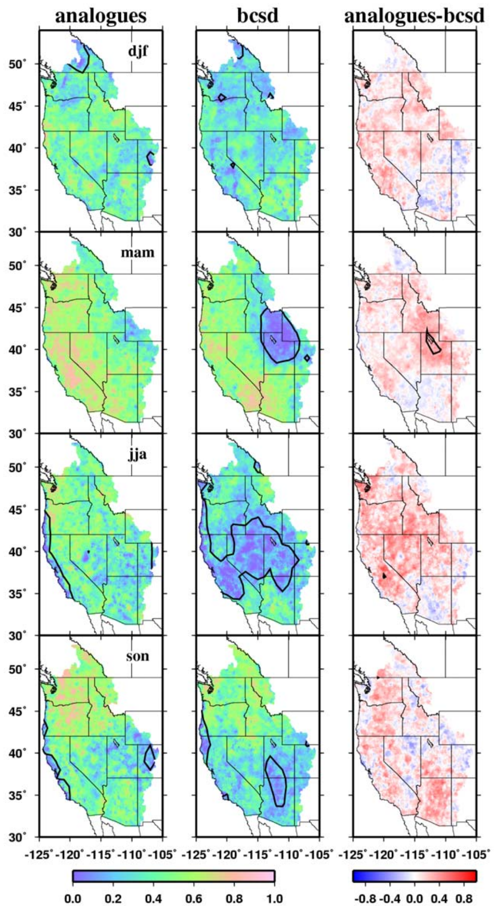

Fig. 10. Same as for Fig. 7, but for 90th percentile (warm) daily temperature in each season.