Statistical Downscaling Techniques for Global Climate Model Simulations of Temperature and Precipitation with Application to Water Resources Planning Studies

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1. Introduction

Downscaling is a term used to describe the process of relating information or data at relatively coarse spatial and temporal scales to desired products at finer spatial and temporal scales. In the case of climate impacts assessments, the process is commonly used to relate monthly simulations of temperature (T) and precipitation (P) data at approximately 200km resolution archived by a global climate model (GCM) to finer-scale information needed to drive a hydrologic model or other application model (e.g. daily data at 1/16th degree resolution needed to drive the VIC hydrologic model used in the studies described in this report—See Chapter 5).

Downscaling approaches are generally designed to introduce fine-scale regional information, while preserving the most important and well-resolved climate signals that the models generate in response to greenhouse forcing. Because GCMs do not resolve the coastal mountains or smaller mountain ranges like the Cascades, east-west temperature and precipitation gradients in the Pacific Northwest are not appropriately simulated in the models, and attempts to use this data in its raw form will produce highly erroneous results. One can argue that large-scale features, such as north-south gradients along the west coast of the U.S., are better resolved because storm tracks in the cool season are related to large-scale storm systems that GCMs can resolve reasonably well (Salathé 2006). The position of the dominant storm track, however, can be strongly biased, and these biases can be different for different climate models, which creates difficulties when attempting to interpret changes at relatively small spatial scales (i.e. a particular river basin). Different climate models also show wide variations in their ability to accurately reproduce the key features of regional climate, and the quality of the time series behavior of different models also varies widely. Some models simulate a reasonably accurate ENSO cycle, for example, whereas others simulate this important driver of PNW climate relatively poorly. Some models may have too much interannual variability, others too little, etc.

GCM simulations of precipitation are much more problematic than those for temperature, and each GCM produces a unique sequence of decadal scale precipitation variability that makes comparisons between different GCM precipitation signals in a given future time frame problematic. This is particularly true in the PNW, where systematic changes in annual precipitation simulated by GCMs are relatively small, and decadal variability remains an important driver of future impacts in any given future decade (Mote and Salathé in press). These aspects of the simulations highlight the need for a multi-model ensemble approach to understanding regional climate changes.

Climate change studies to support water planning typically use GCM simulations to define scenarios of future changes in temperature and precipitation and related hydrologic variables such as snowpack, evaporation, or streamflow (Salathé *et al*. 2007). Approaches for downscaling GCM simulations can be broadly classified as "statistical" and "dynamical" downscaling techniques. Statistical downscaling methods are based on robust relationships between large-scale parameters that are well-resolved by a global model and observations at smaller spatial scales. In general, any number of large-scale fields may be used to predict a fine-scale parameter. For example, sea-level pressure and atmospheric moisture fields may be used to downscale regional precipitation. Dynamic downscaling techniques employ regional climate models, using relatively fine grid spacing (10-50km), to explicitly simulate fine-scale meteorological processes and feedback mechanisms. In particular, regional climate models incorporate fine-scale topographic features (e.g. the Cascade mountain range in the PNW) that are not accounted for in GCM simulations (Salathé *et al*. 2007).

There is currently great interest in dynamical downscaling techniques because they have the potential to explicitly simulate the spatial and temporal variability of changes in meteorological variables from first principles and to simulate local changes in temperature or precipitation that are potentially different from the climate signals from the global model (Salathé *et al.* in press). These approaches, however, are still strongly limited by the computational requirements of the models used (which ultimately limits the number of realizations that can be produced). Furthermore, bias inherited from both the GCM simulation that drives the meso-scale model at the outer boundary combined with bias generated by the meso-scale models themselves can be substantial (Wood *et al.*

2004). Thus use of dynamic downscaling does not eliminate the need for statistical bias correction and downscaling. Given that dynamic downscaling approaches are still emerging as a practical resource for water planning, we will limit ourselves in this paper to a discussion of statistical downscaling approaches used in the studies described in this report. Salathé *et al*. (2007; 2010) provide an overview of dynamic downscaling approaches and the results for a recent case study for those interested in more details on this topic.

In this paper we will describe in detail two commonly used statistical downscaling approaches, develop a third approach which is a hybrid between the two methods, and discuss the strengths and limitations of each approach for various water planning applications. The paper is intended to provide a technical guide for water planning and management professionals who need to select a downscaling approach for particular water resources planning or assessment applications and is also intended to serve as a technical reference for the specific methods used for the Columbia Basin Climate Change Scenarios Project (CBCCSP) described in this report. The three downscaling approaches discussed in this chapter have been fully implemented in our study to provide meteorological inputs to the 1/16th degree VIC and 150m DHSVM hydrologic model implementations described in Chapter 5 and 6 of this report.

2. Downscaling Methodology

In this section, we first describe a process for selecting scenarios from the available GCMs, describe two statistical downscaling approaches that have been widely applied in previous water planning studies, and finally develop the methods for a third approach which is a hybrid between the two existing approaches, exploiting the relative strengths of each. For water planning studies, changes in daily minimum and maximum temperature (T) and precipitation (P) are the primary inputs needed to drive hydrologic models (See Chapter 5 and 6, this report), which in turn, produce natural streamflow scenarios needed for various water resources applications. Following Widmann et al. (2002) methodology, we use the GCM-simulated precipitation and temperature as the predictors for regional precipitation and temperature. While other parameters may improve downscaling skill in some regions, for the Pacific Northwest, the temporal variability of regional precipitation is well represented by large-scale precipitation simulations, which makes it a suitable predictor for statistical downscaling. Other variables needed for hydrologic simulation (such as humidity and solar radiation) are derived from T and P data in the hydrologic models used in this study (Maurer *et al.* 2002; Elsner *et al.* 2010, Chapter 5 and 6, this report).

2.1 Observed Meteorological Dataset

An observed meteorological data set implemented at 1/16th degree resolution has been implemented for the PNW (Chapter 3, this report). This data set serves as the basis for the GCM bias correction procedures (Section 2.4.1), and is also used to provide an observed daily time series which used in the two temporal disaggregation schemes described below.

2.2 Selecting Emissions Scenarios and Ranking GCM Performance

To provide inputs to the downscaling process, the first step is to select greenhouse gas emissions scenarios and a group of GCMs. GCM simulations are carried out by a number of independent research groups worldwide, and use emissions scenarios generated for the Intergovernmental Panel on Climate Change (IPCC) assessment as inputs (SRES REF). The results of these modeling efforts are archived and distributed as the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. Although GCMs simulate a number of meteorological variables, we will confine our discussion to T and P which are the key inputs to hydrologic model applications.

2.2.1 Selecting Emissions Scenarios

Following the selection criteria developed by Mote and Salathé (2010), the IPCC "A1b" and "B1" emissions scenarios were selected for use in the study. The A1b scenario represents a medium emissions scenario associated with increasing greenhouse gases (and simulated PNW temperatures) through the end of the 21st century. The B1 scenario reflects significant greenhouse gas mitigation which begins to stabilize greenhouse gas concentrations (and simulated warming) by the end of the 21st century (Mote and Salathé 2010).

2.2.2 Evaluating and Ranking of Global Climate Models

The performance of global climate models may be evaluated using a variety of metrics depending on the qualities most important to a particular study. In general, the ranking will be dependent on the metric used, and it is impossible to make an unqualified selection of the "best" climate models. Although skill in simulating the 20th century climate is one commonly used metric for evaluating GCMs, good performance for this metric does not guarantee that a model will give a realistic simulation of climate change associated with increasing greenhouse forcing (i.e. skill in reproducing historical variability and realistic greenhouse gas sensitivity are not necessarily related). For these reasons, the accepted approach to assessing climate change impacts is to use as large an ensemble of climate models as is computationally feasible. Model rankings, then, may be used to reduce the size of the ensemble by rejecting models that perform less well (*e.g.* Overland and Wang 2007). For this study, we have used projections based on a selection of 10 global models whose 20th century simulations have the smallest bias in temperature and precipitation and that simulate the most realistic annual cycle in these parameters. These 10 models are sufficient to span the range of future climate change while reducing the computational demands of an even larger ensemble.

For particular applications, other qualities of the models may be important, such as the ability to simulate interannual variability associated with El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and other natural climate processes. A number of studies have addressed these issues, for example AchutaRao and Sperber (2006) for tropical ENSO, Overland and Wang (2007) for arctic climate variability, Brekke *et al*. (2008) for the State of California, and Reichler and Kim (2008) for global performance. Issues specific to the Pacific Northwest are addressed by Mote and Salathé (2010), including an analysis of North Pacific variability of temperature, precipitation, and sea-level pressures, which is a good indicator of skill in simulating ENSO and PDO teleconnections and other large-scale climate processes that influence the region. Here, we summarize model rankings for 20th century bias, a global performance index (AchutaRao and Sperber 2006), and North Pacific variability (Mote and Salathé 2010). Table 1 provides the ranking for the 10 models used in this report.

The five "best" models are shown in Table 2, based on the best combined rankings for Bias and North Pacific variability only. Note that incorporating the global metric (which is not available for ECHO-G) identifies the highest combined rank for four of the five models selected using only bias and North Pacific variability as the ranking criteria.

Table 1. Model ranking based on three metrics, 20th C bias, global climate patterns, North Pacific variability, and the sum of the Bias and North Pacific ranks. (A rank of 1 reflects the best performance, and a rank of 10 reflects the worst performance in the individual metrics.)

Model	Bias	Global	North Pacific	Sum All	Sum Bias and NP
UKMO-HadCM3	1	3	8	12	9
CNRM-CM3	2	7	4	13	6
ECHAM5/MPI-OM	3	2	3	8	6
ECHO-G	4	-	2	-	6
PCM	5	9	7	21	12
CGCM3.1(T47)	6	4	1	11	7
CCSM3	7	5	9	21	16
IPSL-CM4	8	8	10	26	18
MIROC3.2(medres)	9	6	5	20	14
UKMO-HadGEM1	10	1	6	17	16

Table 2. Five best models based on combined bias and North Pacific variability metrics in Table 1

Model	Bias	Global	North Pacific	Sum All	Sum Bias and NP
CNRM-CM3	2	7	4	13	6
ECHAM5/MPI-OM	3	2	3	8	6
ECHO-G	4	-	2	-	6

CGCM3.1(T47)	6	4	1	11	7
UKMO-HadCM3	1	3	8	12	9

2.3 Delta Method Downscaling Approaches

The so called "delta method" is conceptually very simple and has been widely applied in water planning studies, particularly in earlier studies (prior to about 2000) when GCM resolution was typically very coarse and the models were only capable of simulating regional-scale changes in T and P (e.g. Lettenmaier *et al.* 1999). Although some variations have been developed, a common application of the delta method will apply monthly changes in temperature and precipitation from a GCM, calculated at the regional scale, to an observed set of station or gridded temperature and precipitation records that are the inputs to a hydrologic model. The meteorological variables from the GCM simulation are typically averaged over an historic period from a control simulation and a future period from a scenario simulation to estimate the changes. Mote and Salathé (2010), for example, compared simulations from twenty GCMs, averaged over the entire PNW, for a 30-year window centered on the 1980s (1970-1999) to three future 30-year windows centered on the 2020s (2010-2039), 2040s (2030-2059), and 2080s (2070-2099). For this study, we use the gridded historical meteorological dataset described above. Changes in mean climate, calculated for each calendar month, are applied at daily time scale for each 1/16th degree grid cell, as follows:

For all grid cells in the domain:

$$P_{new} = P_{obs} * P_{fact} \quad (1)$$

where P_{fact} is the ratio of the CGM simulated mean precipitation from the future time period relative to the historic period (1970-1999), averaged over the geographical region of interest, in this case, the states of Washington, Oregon, and Idaho.

$$T_{new} = T_{obs} + T_{delts} \quad (2)$$

where T_{delta} is the difference in the CGM simulated mean temperature from the future time period relative to the historic period, averaged over the geographical region of interest.

Note that multiplicative perturbations are used for precipitation to avoid potential sign problems (i.e. the potential to calculate negative precipitation using an additive approach), and additive perturbations are used with T to avoid problems with T not being on an absolute scale (i.e. the centigrade scale is zero at the freezing point of water at standard pressure, not at absolute zero).

To give an example, suppose an analysis of a particular GCM simulation showed 2 C warming in January for a future 30-year window, with an increase in P of 10%. In this case $T_{delta} = 2.0$, and $P_{fact} = 1.1$. These perturbations are applied uniformly over the entire domain at a daily time scale to the full timeseries of observations. Thus daily gridded observations of T and P are forced to reproduce a region-wide change in the long-term mean for each month estimated from the raw GCM data. Many features of the original time series and spatial variability of the gridded observations are preserved by the delta method, and any bias in the mean in the GCM simulations is automatically removed during the process. Changes in the seasonality of temperature and precipitation are captured, but the climate change perturbation is the same at all points in the region. The only fine-scale information (spatial or temporal) comes from the observed dataset.

2.3.1 Advantages and Limitations of the Delta Method

A key advantage of the delta method is that observed patterns of temporal and spatial variability from the gridded observations are preserved, and comparison between future scenarios and observations is straightforward and easily interpreted. The time sequence of events matches the historic record in the gridded data sets, facilitating direct comparison between the observations and future scenarios. For example, particular drought years in the historic record can be directly compared in the historic and future simulations. Bias from the GCMs is not introduced, and the spatial resolution of the

GCM (which is different for different GCMs) is not very important given that the changes are calculated at the regional scale. Thus the delta method facilitates a direct comparison of different GCMs with different error characteristics, different patterns of spatial and temporal variability, etc. In the PNW, which is strongly affected by the El Nino Southern Oscillation (ENSO), the ability of a particular GCM to simulate the variability of tropical sea surface temperatures (and the large-scale teleconnections to the PNW associated with these variations) is an important element of the time series behavior of the scenario. By discarding the temporal information from the GCM and forcing the behavior of T and P in the future scenario to match observed patterns associated with ENSO, the delta method facilitates the comparison of changes in T and P from GCMs with potentially very different performance in this regard.

The strengths of the delta method are also its key limitation, because, by design, no information about possibly altered temporal or spatial information is extracted from the GCM simulations. So, for example, while some monthly information about the regional-scale intensity of climatic extremes from the GCM simulation is captured by the delta method, no information from the GCM about potentially changing *interarrival time*, *duration, or spatial extent* of climatic extremes (e.g. droughts and floods) is captured by the delta method. Likewise, only changes in monthly means are captured, and other potential changes in the probability distributions of T and P are ignored. Thus a key limitation of the delta method is that potential changes in the variability or time series behavior of T and P are not captured by the approach.

2.4 Bias Correction and Statistical Downscaling

The statistical downscaling technique that has come to be called Bias Correction and Statistical Downscaling (BCSD) was first developed in seasonal to interannual forecasting applications (Wood et al. 2002) and has been widely applied in monthly time scale climate change studies in the West in recent years (e.g. Payne *et al.* 2004; Kristiansen *et al.* 2004; Van Rheenen *et al.* 2004; Vicuna *et al.* 2007). The approach is carried out in three essentially distinct steps:

1. Statistical bias correction of GCM simulations of T and P at the GCM grid scale and monthly time step,
2. Spatial downscaling from the GCM grid to the grid scale of interest (in our case $1/16^{th}$ degree),
3. Temporal disaggregation from monthly to daily time scales

We describe each of these steps below.

2.4.1 Statistical Bias Correction

Statistical bias correction is carried out by first aggregating the gridded T and P observations to the GCM grid scale (typically about 200km resolution), and then using quantile mapping techniques to remove the systematic bias in the GCM simulations (Wood *et al.* 2002). Quantile mapping techniques work by creating a one-to-one mapping between two cumulative distribution functions (CDFs): one based on the GCM simulations and the second based on the aggregated observations. The mapping process is based on a simple nonparametric lookup procedure (Figure 1). If the GCM simulation of T or P for a particular month represents the estimated Xth quantile in the cumulative distribution function for the GCM simulations over a certain period, then the Xth quantile is looked up in the cumulative distribution function for the aggregated T or P observations for the same period, and this new value becomes the "bias corrected" GCM value for that month (Figure 1). After applying this procedure, by construction, the bias corrected GCM simulations have the same CDF as the aggregated observations for the training period used to construct the two CDFs. It should be noted that no assumptions about the nature of the two probability distributions is required, and the process fully preserves the nature of the extremes in the observed CDF. For this study, the mapping between GCM values and aggregated observed values is based on a 1950-1999 training period. The bias in the model is assumed to be constant and to extend to future simulations as well. (This assumption is well supported by the experiments carried out by Salathé (2004) who showed, using split sample tests of 20^{th} century climate records, that the bias correction process performed equally well when trained on Pacific Decadal

Oscillation (PDO) warm phase epochs and validated on cool phase PDO epochs, as when trained on cool phase epochs and validated on warm phase epochs.) The CDF is allowed to evolve in the bias-adjusted future projection (in response to the systematic changes in the raw simulations), but with the bias relative to the observed climate removed. The output of this process is a bias corrected version of the large-scale GCM monthly time series for T and P for the entire GCM monthly time series (in our case from 1950-2099).

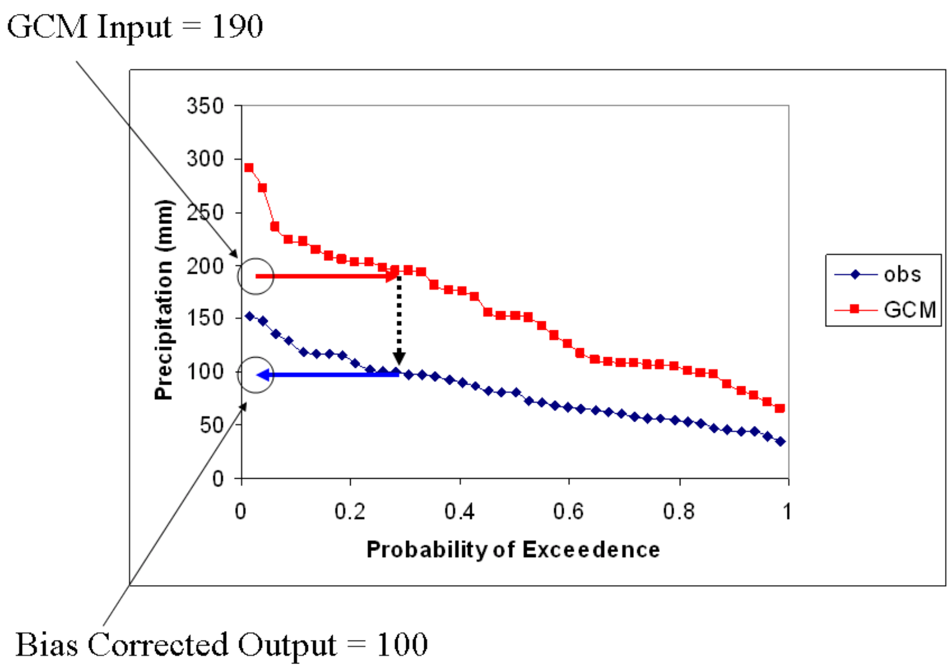

Figure 1. Schematic diagram showing the quantile mapping process used for GCM bias correction.

2.4.2 Spatial Downscaling

After large-scale bias correction, the monthly T and P values at the GCM grid scale are interpolated to the fine scale grid (1/16th degree). Our version of this approach uses an inverse square weighting using four nearest neighbors. These values are then scaled to produce the fine-scale spatial variability of the gridded observations. For precipitation, a multiplicative factor is applied, and, for temperature, an additive factor is applied. The factors are computed for each calendar month as the ratio or difference between the GCM and observed values for the period 1970-1999. Thus the bias-corrected, large-scale anomalies are used to estimate a time series of monthly values at the fine grid scale.   Note that anomalies based on 1970-1999 are used in this step to establish a common baseline with the traditional delta method approaches described above.

2.4.3 Temporal Disaggregation

Finally, the monthly time series at each grid cell is temporally disaggregated to daily time scale by a random sampling of observed daily variability represented by a carefully screened set of relatively wet months. The choice of relatively wet conditions as the basis of the basis of the temporal downscaling step is intended to minimize the occurrence of a relatively wet month being paired to a relatively dry daily time series at the grid scale, which can create unrealistically large daily precipitation values. In the most recent version of the code that we use here, an arbitrary ceiling of 150% of the observed maximum precipitation value for each cell is also imposed by "spreading out" very large daily precipitation values into one or more adjacent days. The value of precipitation for the month is preserved, however.

2.4.4 Advantages and Limitations of the BCSD Method

The BCSD approach is conceptually attractive in comparison with the relatively simple delta method because it extracts more information from the GCM simulations. The transient time series behavior of the monthly GCM simulations, although bias corrected, is largely preserved by the downscaling, and the large-scale spatial variability of the GCM simulations of T and P is also incorporated in the final results. Although the daily patterns within the month are extracted from observations, the changes in precipitation and temperature extremes are potentially very different in comparison with delta method approaches that only perturb the mean monthly value on a regional basis. The use of the BCSD for multiple GCMs facilitates a very straightforward approach to estimating the uncertainty of outcomes in any future time period using ensemble methods. BCSD downscaled transient runs also contain realizations of interannual and interdecadal variability that may be different from those in the historic record. As noted above, the BCSD approach has been widely applied in a number of large-scale, monthly water planning studies (e.g. Payne *et al.* 2004; Christensen *et al.* 2004), and at these spatial and temporal scales the approach has worked reasonably well.

As for the delta method approach, the source of the strengths of the BCSD method is also the source of its limitations. Incorporating more information from the GCM simulations is not necessarily valuable if the information is of poor quality, and in the context of an ensemble analysis, the results may be difficult to interpret if the quality of information varies substantially from GCM to GCM. Extracting a time series directly from the GCM provides an explicit transient realization that is potentially valuable, however, as discussed in Section 2.1 many GCMs do not accurately simulate interannual climate variability in the PNW, which raises concerns about the accuracy of the future time series as well. Another limitation is that the climate change signal in temperature and precipitation relies only on information represented in the global model. As noted in the introduction, the spatial patterns in GCM data (particularly east-west gradients) are not reliable since the terrain features that determine spatial variability in the climate are not represented in the global models. Widmann *et al*. (2002) introduced an approach intended to improve the downscaling of terrain effects by considering both the large-scale precipitation and circulation patterns from the GCM simulations (Salathe *et al*. 2004).

Finally, due to the disaggregation of monthly data, daily time step realizations from BCSD downscaling have been found to frequently contain unrealistic daily precipitation estimates, especially at smaller spatial scales of interest in water resources planning. These artifacts of the downscaling approach can occur, for example, when a relatively wet future condition is paired at specific grid locations with a relatively dry month used for daily disaggregation. In effect a few isolated storms in the dry month are made much larger to reflect the relatively wet month from the GCM simulation. Although the version of the BCSD code used in this study places some quantitative (but essentially arbitrary) limits on increases in daily precipitation during the temporal disaggregation step (see Section 2.3.3), the effects on daily precipitation must be interpreted with caution. We should note that these daily time step artifacts are not at all related to GCM signals, which are incorporated only at monthly time scales (Maurer and Hidalgo 2008).

Thus current versions of the BCSD downscaling approach are probably best applied to GCM simulations which simulate the monthly time series behavior of the historic period for the region in question relatively accurately. Use of these results is also best confined to monthly analysis at moderate to large spatial scales because of downscaling artifacts which can produce questionable daily precipitation estimates, particularly at smaller spatial scales. Use of the BCSD approach for daily flood risk analysis, for example, would probably not be a good choice, both because the size of storms is not necessarily realistic, and precipitation extremes can be exaggerated as discussed above.

2.5 Hybrid Delta Approach

As discussed in the introduction, the hybrid delta (HD) downscaling technique is a new approach developed specifically for the CBCCSP to support applications that require realistic daily time step information at relatively small spatial scales. It combines some of the best features of the traditional delta method and BCSD approaches discussed above, while avoiding many of the limitations of each. In particular, the method preserves the time series behavior and spatial correlations from the gridded T and P observations (a key advantage of the traditional delta method), but transforms the entire probability distribution of the observations at monthly time scales based on the bias corrected GCM simulations (a key advantage of the BCSD method).

The approach begins by applying the BCSD approach to produce a monthly time series of T and P, downscaled to the fine-scale grid ($1/16^{th}$ degree in our case) as described in Section 2.3.1 and 2.3.2 above. Monthly data for a future 30-year window at each grid cell location are segregated into individual calendar months (i.e. all the Januarys, Februarys, etc.) and these data are then ranked from highest to lowest value. An unbiased quantile estimator is used to assign a plotting position to the data for each calendar month based on the Cunnane formulation (Stedinger *et al.* 1993):

$$q = (i - 0.4)/(n + 0.2) \qquad (3)$$

where q is the estimated quantile (or probability of exceedance) for the data value of rank position i (rank position 1 is the highest value), for a total sample size of n. Historic T and P observations are processed in the same manner for each calendar month and grid cell.

The final steps in the HD downscaling approach use the same quantile mapping approaches discussed in Section 2.3.1, but the technique is inverted in this case to achieve a different objective. Instead of bias correcting a GCM simulation to match observations, the observations are re-mapped onto the bias corrected GCM data to produce a set of transformed observations reflecting the future conditions. Figure 2 shows a schematic of the final steps in the data processing sequence. The process is probably best described by giving an example. For each individual grid cell, a T or P value from the observed monthly time series is mapped from the observed quantile position for that calendar month to the corresponding quantile from the bias corrected GCM data associated with a future scenario. (I.e. if October 1916 from the observed time series is the 87th percentile of all the Octobers in the observed time series, this monthly value is mapped to the 87th percentile of all the bias corrected GCM Octobers for the future scenario.) To produce a daily time series, the daily values within the observed month are then rescaled so that they reproduce the new monthly value. The entire observed time series of T and P at each grid cell is perturbed in this manner using the observed and GCM distributions for each calendar month, resulting in a new time series that has the statistics of the bias corrected GCM data for the future period, but essentially preserves the time series and spatial characteristics of the gridded T and P observations.

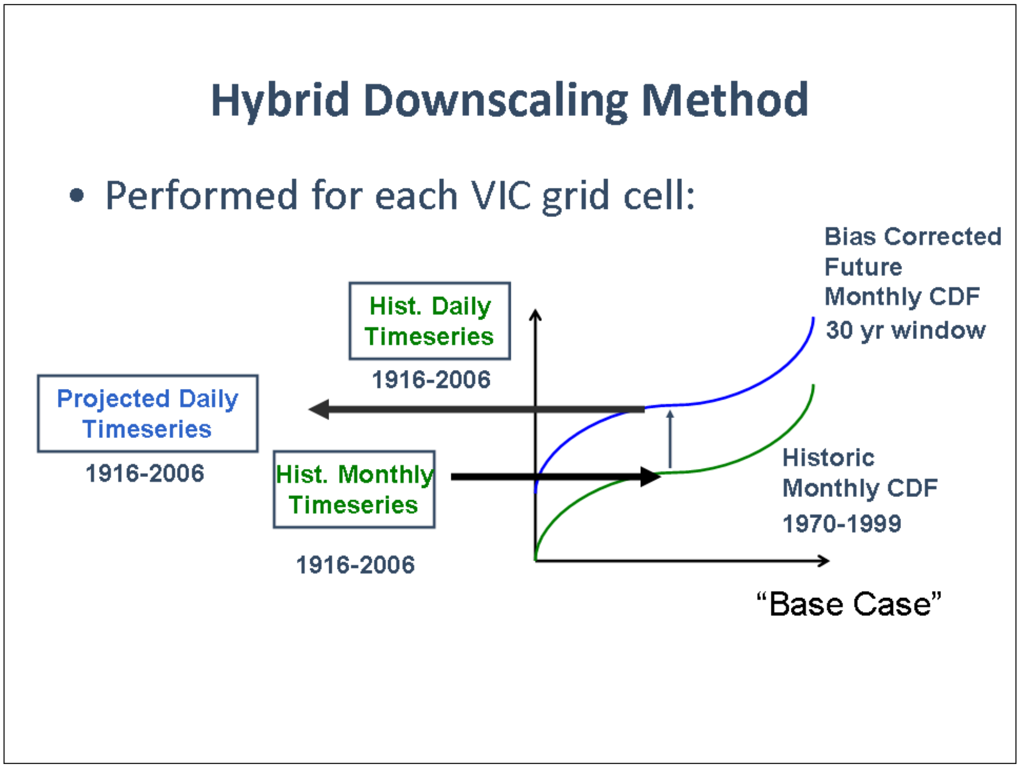

Figure 2 Schematic diagram of the final data processing steps for the hybrid delta downscaling method.

Simulated values that are outside the observed quantile map (which can occur because we use a relatively short window from 1970-1999) are interpolated using standard anomalies (i.e. standard deviations from the mean). Although this approach ostensibly assumes a normal distribution, it was found during testing to be much more stable than more sophisticated approaches. In particular, the use of Extreme Value Type I (EV1) distributions for extending the tail of the probability distributions was found to be highly unstable in practice and introduced large errors in daily extremes in many grid cells.

The key difference between the hybrid delta approach and the traditional delta method is that the entire probability distribution at monthly time scale is adjusted to reflect the GCM data. Thus changes in the mean, variance, skewness or other statistical features of the GCM data are reproduced explicitly in the future scenarios. Unlike the BCSD approach, however, which can produce highly unrealistic daily time series behavior (particularly for P), the approach maintains realistic values by closely aligning the time series and spatial behavior of the future values with the gridded observations. In particular, the random pairing of wet future months with dry observed months that frequently produces unrealistic daily precipitation values in the BCSD approach is completely avoided. The HD method also provides a static 91-year climate time series representing a 30-year future time horizon. This has an advantage in comparison with the BCSD method in allowing better representation of statistical parameters such as return periods of climatic or hydrologic extremes that are of interest to water resources planners.

3. Comparison of Three Downscaling Methods

To illustrate some of the key differences between the different downscaling approaches described above, in this section we show the spatial distribution of temperature and precipitation changes for January over the PNW for a single GCM, simulated natural streamflow for a moderate sized basin on the east side of the Cascades (The Yakima River at Parker USGS 12505000), and simulated flood risk for the Kettle River at Westbridge (Environment Canada 08NN003) in British Columbia.

Figure 3 shows the spatial variability of average changes in January precipitation and average temperature over the PNW. Note that the traditional delta method approach would show a constant change over the entire domain, whereas the BCSD and hybrid delta maps show considerable spatial variability. For example, in the Yakima River basin (outlined in Figure 3) temperatures are much warmer than for the region as a whole, and the northern portions of the Columbia basin show much larger increases in precipitation than other parts of the domain. The spatial variation in temperature in the BCSD and hybrid delta runs has a substantial influence on the loss of snowpack (and resulting streamflow timing shifts) in the hydrologic simulations (Figure 4). Similarly estimates of flood risk for the Kettle River (Figure 5) are markedly different for the ensemble of hybrid delta method simulations (which shows little systematic change in flood risk) in comparison with the traditional delta method approach (which shows strong declines in flood risk). These differences are related to the spatial distribution of precipitation changes incorporated in the hybrid delta approach.

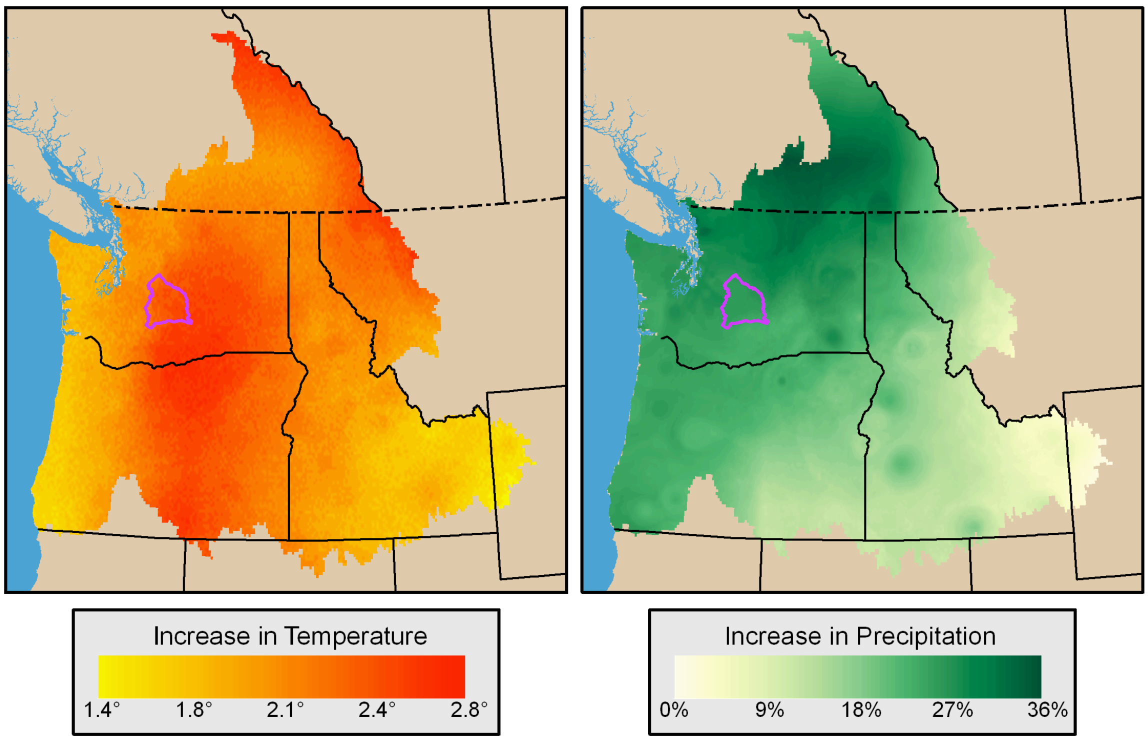

Figure 3. Spatial plots of changes in January average temperature (left, in˚C) and precipitation (right, in %) for the 2040s for the CGCM3 (T47) GCM and A1b emissions scenario. The outline of the Yakima River basin upstream of USGS 12305000 (Yakima River at Parker) is shown for reference.

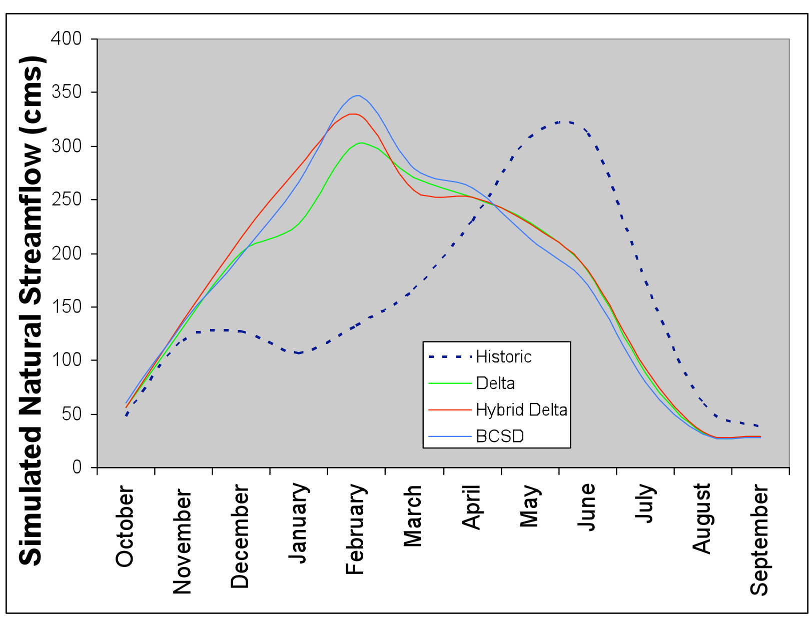

Figure 4 Long-term mean simulated monthly hydrograph for the Yakima River at Parker (USGS 12505000) for historical condition and three different downscaling approaches applied to the 2040s A1b CGCM3 (T47) GCM scenario. Historic, delta, and hybrid delta averages are calculated from the 30-year window associated with "1970-1999", BCSD values are averaged from the 30-year window from 2030-2059 in the transient simulation.

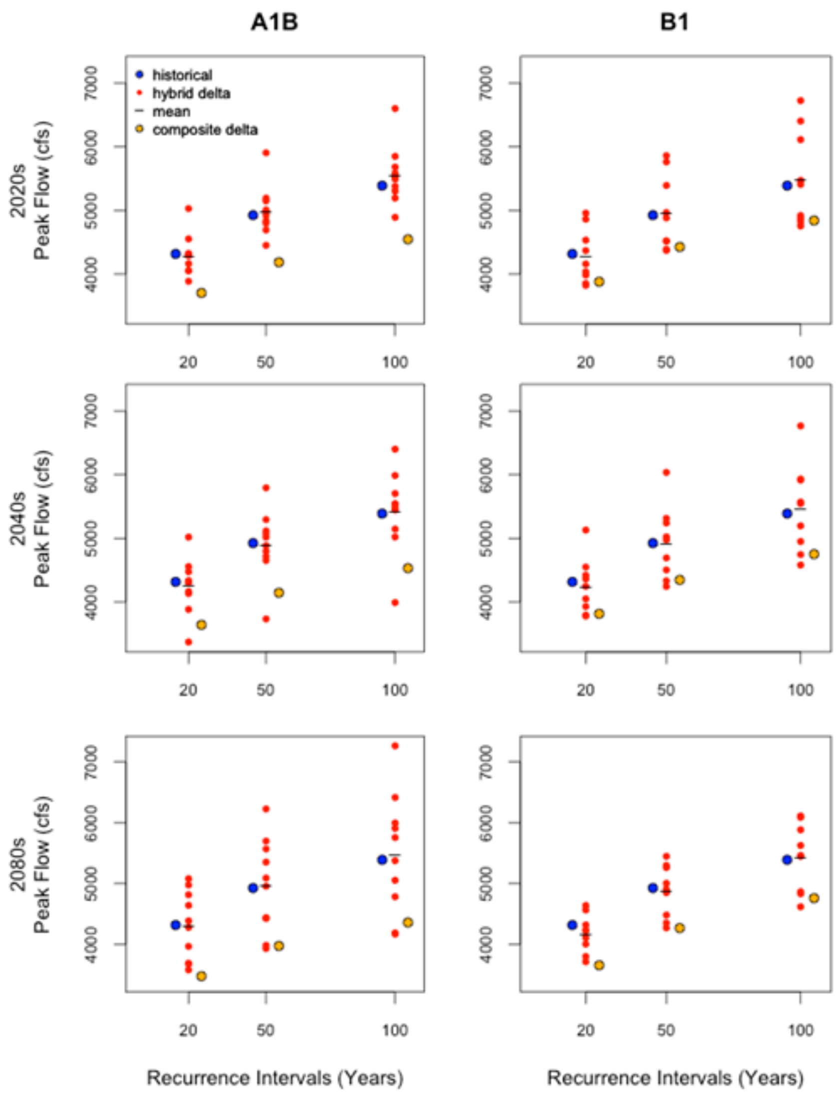

Figure 5 Estimates of flood risk at the 20, 50, and 100 year recurrence interval for the Kettle River at Westbridge (Environment Canada 08NN003). The figures show flood risk for historical simulations (single blue dot), an ensemble of 10 hybrid delta scenarios (range of red dots), and the associated delta method scenario (yellow dot), respectively.

4. Guide to Applications

In this section we discuss choice of downscaling technique for particular water planning applications. Table 1 summarizes a number of key features of the three statistical downscaling approaches outlined in Section 2.

Table 1: Key Features of the Different Downscaling Approaches

Feature	**Delta Method**	**BCDC**	**Hybrid Delta**
Source of interannual and interdecadal climate variability	Observations	GCM	Observations
Source of interarrival time and duration of droughts and floods	Observations	GCM	Observations
Source of spatial variability	Observations	Observations/GCM	Observations/GCM
Captures change in mean T and P mean from climate model?	Yes	Yes	Yes
Captures change in variance of T and P from climate model?	No	Yes	Yes
Captures change in monthly T and P extremes?	No	Yes	Yes
Captures change in daily T and P extremes?	Yes, but only via changes in monthly means	Yes, but only via changes in monthly statistics	Yes, but only via changes in monthly statistics
Future monthly T and P statistics directly comparable with observations?	Yes	Yes (but not necessarily at relatively small spatial scales)	Yes

Future daily T and P statistics directly comparable with observations?	Yes	No	Yes

4.1 Applications of the Delta Method

The delta method is often applied in the context of an easily interpreted sensitivity analysis, or when a few model runs are intended to capture the consensus of a suite of T and P changes from a group of climate model simulations. In applications where the time series behavior of T and P is a key driver of outcomes (e.g. in the case of estimating drought statistics) and is not necessarily simulated well (or equally well) for different GCMs, the choice of the delta method may avoid these difficulties. In applications where a large number of realizations of variability for a consistent level of systematic change is desirable (e.g. for testing a water supply system for reliability), the delta method provides a very straight-forward framework for the analysis. Delta method experiments are also a good framework for sensitivity analysis of changes in flood and low flow risks associated with systematic warming and changes in mean monthly precipitation statistics (see for example Mantua et al. in press).

4.1.1 Delta Method Runs for the Columbia Basin Climate Change Scenarios Project

For the PNW, we currently have 91 years of observed climate (1916-2006), to which a number of delta method perturbations can be applied. This can be accomplished either in an ensemble mode (i.e. one run per individual GCM), or in a consensus mode (i.e. average changes in T and P from all GCMs encompassed in a single run). For this study, we have chosen to focus on the latter approach and provide six traditional delta method runs, representing the consensus of changes in T and P for the 10 best climate models (discussed above) for three future time periods and two emissions scenarios. These are also essentially the same six scenarios that formed the core of the Washington Climate Change Impacts Assessment (Elsner et al. in press).

4.2 Applications of the BCSD Approach

One of the key advantages of the BCSD approach is that it provides a transient realization that explicitly reproduces the monthly time series behavior of the GCM T and P simulations, in our case from mid-20th century to the end of the 21st century. Thus for analyses that are potentially sensitive to changing time series behavior, the BCSD may provide useful information that is missing from the delta method or HD runs. For example, potentially changing drought inter-arrival and duration statistics would probably be best analyzed using a BCSD approach, because the time series behavior of T and P is a key determinant of these statistics. Likewise, any analysis that is focused on rates of change through time is well served by the BCSD approach. For example, trends in the date of peak snow water equivalent or the centroid of timing of streamflow can only be examined in the context of a transient run.

Another advantage of the BCSD approach is that any future time period can be analyzed, as compared to delta method and HD runs which impose changes from a fixed 30-year future period on a long historic record of observed variability. So, for example, an analysis of the 30-year period centered on the 2060s is easily extracted from a BCSD transient run without making new hydrologic model runs.

Since daily time step data are generated by a non-physical disaggregation of monthly-mean climate model output, considerable caution should be exercised in using daily results associated with BCSD approaches, and in general the analysis should be confined to bi-weekly or monthly analysis at medium to large spatial scales. So, for example, analysis of flood risk (which is strongly influenced by daily precipitation statistics) would not, in general, be a good application for BCSD approaches, particularly at smaller spatial scales. Basin-wide hydropower studies in the Columbia River basin at monthly time step, however, would probably be well served by the BCSD approach (see e.g. Payne et al. 2004).

4.2.1 BCSD Runs for the Columbia Basin Climate Change Scenarios Project

For the current study, we provide 10 BCSD runs associated with the 5 best GCMs (see Section 2.1) and two emissions scenarios (A1b and B1). This choice of only the five best GCMs for analysis reflects the fact that, without reasonable reproduction of historic climate variability by the GCM, it is hard to argue that explicitly incorporating this information in the downscaling is valuable. Furthermore A1b and B1 results are not dramatically different until late in the 21st century, so a total of 10 runs over the two scenarios provides enough sample size for a reasonably detailed analysis of model uncertainty for the different GCMs for the 2020s and 2040s. For the 2080s the spread of results are dominated by emissions uncertainties rather than modeling sensitivity (Mote and Salathé in press), so having a relatively small sample of GCMs is probably less important.

4.3 Applications of the Hybrid Delta Approach

Because the HD approach incorporates the strengths (and avoids most of the limitations) of both delta method and BCSD approaches, we are recommending that this approach be used as the primary product for most kinds of water resources analyses. The HD approach is suitable for water resources planning at both daily and longer time scales, supports analysis of daily hydrologic extremes such as flood and low flow risk, and provides consistency across a range of spatial scales that is comparable to that produced by hydrologic model simulations using observed T and P data. In particular, results at smaller spatial scales are less likely to be affected by daily time step disaggregation artifacts that are commonly encountered in products produced using the BCSD approach. Although duration and inter-arrival time of droughts are essentially those of the historic record in the HD products, the effects of changing drought intensity associated with changing probability distributions of monthly T and P statistics can be analyzed using the HD approach at daily time scales. Furthermore, without daily time step data from the global models, there is not a secure basis for projecting changes in the daily statistics of T and P under climate change. Indeed, such changes are best studied using high-resolution regional climate models that can simulate the physical processes that control such changes (Salathé *et al.* in press).

4.3.1 Hybrid Delta Runs for the Columbia Basin Study

Sixty future Hybrid Delta runs will be produced for the CBCCSP based on the ten best GCMs, three future time periods, and two emissions scenarios. This strategy will produce a relatively large sample size to support a detailed uncertainty analysis of key hydrologic variables for each future time period.

5. Conclusions

A number of different statistical downscaling approaches have been developed to provide gridded T and P data at local-scales derived from large-scale, monthly GCM simulations of T and P. Both the traditional Delta Method, and widely used BCSD approach have different strengths and limitations, and are most suitable for different kinds of applications. The Hybrid Delta method developed in this study combines the key strengths of each approach, while largely avoiding the limitations of each. Although a few specific applications can only be addressed using the transient products produced by the BCSD approach, the Hybrid Delta approach can be used successfully in most water resources applications. For this reason we have chosen to use the Hybrid Delta method as the corner stone of the hydrologic analysis in the CBCCP.

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