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Review of scenario selection and downscaling methods for the assessment of climate change impacts on hydrology in the United States pacific northwest

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Abstract:

This paper reviews methods that have been used to evaluate global climate simulations and to downscale global climate scenarios for the assessment of climate impacts on hydrologic systems in the Pacific Northwest, USA. The approach described has been developed to facilitate integrated assessment research in support of regional resource management. Global climate model scenarios are evaluated and selected based on historic 20th century simulations. A statistical downscaling method is then applied to produce a regional data set. To facilitate the use of climate projections in hydrologic assessment, additional statistical mapping may be applied to generate synthetic station time series. Finally, results are presented from a regional climate model that indicate important differences in the regional climate response from what is captured by global models and statistical downscaling. Copyright © 2007 Royal Meteorological Society

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INTRODUCTION

Some of the most important anticipated impacts of climate change are expressed through hydrologic processes such as streamflow, snowpack, and flooding. Modelling these impacts requires high-resolution regional data for future scenarios of temperature and precipitation. The science of climate change at global and regional scales is quite advanced, and climate simulations are typically downscaled to as fine as 10–50 km grids or to station locations. While there remains significant research to be done to fully understand climate dynamics at these scales and to bolster confidence in future scenarios, the current climate modeling is adequate for many applications in hydrology. A principal challenge is linking global climate simulations to existing computational tools and institutional mechanisms within an integrated assessment. For example, under global climate change, system impact assessment is complicated by the constantly shifting underlying climate trends within large year-to-year variability (Arnell, 1996). The analysis of water resource systems and their reliability, yield, and specific event frequency, generally assumes a static state that can be described statistically using a time series of historic events, and depends on using the observed record of the past to estimate the probability of future events. The observed record is assumed to be statistically stationary so that all events are equally probable and these probabilities are assumed to carry into the future. Typically, climate projections are based on transient simulations from multiple projected emissions scenarios and climate models. While this approach can generate a large number of projections based on various models and emissions scenarios, it does not correspond well to the current approach in resource management.

This paper reviews methods developed by the Climate Impacts Group (CIG) at the University of Washington for integrated assessment of climate change impacts in the Pacific Northwest, United States. This research focuses on four diverse yet connected natural systems of the Pacific Northwest (fresh water, forests, salmon and coasts) and the socioeconomic and/or political systems associated with each. Hydrologic processes are central to the climate impacts in all sectors; thus, downscaling climate scenarios for hydrologic simulations forms the basis for quantitative analyses.

Many of the approaches we have developed are based on empirical corrections to simulated climate data. These corrections are based on a relationship between the observed statistics of a parameter and the simulation of that parameter for equivalent climate conditions. This relationship is then used to correct the simulation of that parameter for future climate conditions. In its simplest form, that relationship could be a simple perturbation to correct a bias. In the quantile mapping, however, the

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full probability distribution is taken into account. For example, the temperature simulated by a given model for present-day conditions at a given location may be 5 °C too cold compared with observations. For the future climate, one would add 5 °C to all values simulated at that location to correct this bias. The bias may be simply a lapse-rate correction for unresolved topography or it may stem from a deficiency in the model physics. These methods rely on the availability of data from a historic, or base-climate, simulation produced by the global climate model under consideration. The base-climate simulation must conform as closely as possible to the external forcings (greenhouse gas and aerosol concentrations, solar output, and volcanic aerosol loading in the stratosphere) present during the observed record. This simulation is then the reference state against which future changes are compared.

This paper begins with a description of the selection and evaluation of the global climate scenarios, followed by a review of statistical downscaling methods including a new approach to synthesize data suitable for resource management studies, and finally, we discuss the implications of new information provided by high resolution mesoscale modeling.

All data presented in this paper are publicly available for download over the Internet. Downscaled climate scenario data for the Pacific Northwest may be found at; <http://www.cses.washington.edu/data/ipccar4/>. We have also developed an interactive web-based mapping tool to allow comparisons of the various scenarios, available from the above web page.

SCENARIOS FOR PNW CLIMATE CHANGE

The collection of global climate simulations performed for the International Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) (Alley *et al*., 2007) provide an excellent standardized set of scenarios for climate impacts studies. There is considerable variability among the projections from various modeling groups and among the emissions scenarios considered. Ideally, a large ensemble of climate models and scenarios is used in impacts studies, but for some applications, computational demands may necessitate considering only a limited set of scenarios. In such a case, the selection must be done carefully in order to select models that accurately depict the historic climate of the region of interest and scenarios that span as broad a range of future climate change as a much larger ensemble would. To guide in this selection for the Pacific Northwest, we have considered simulations of the models for 20th century conditions as well as the range of changes for the 21st century. We consider only temperature and precipitation in our evaluation since these parameters most significantly define the hydrologic response to climate change, which in turn produces the most significant impacts.

For this study, a selection of simulations performed for the IPCC AR4 was analyzed. Simulation data are available from the IPCC Data Archive at Lawrence Livermore National Laboratory (<http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php>). Here we consider as a baseline climate the 1900–2000 simulations for historic conditions. For future climate we consider the 2000–2100 simulations for the A2 and B1 emissions scenarios from the IPCC Special Report on Emissions Scenarios (Nakicenovic *et al*., 2000). Specifically, we present results from ten models: HADCM3, ECHAM5, CCSM3, PCM1, CNRM-CM3, CSIRO-MK3 MIROC-3.2, IPSL-CM4, CGCM-3.1, and GISS-ER, which provides ten simulations for the 20th century and 20 simulations for the 21st century (ten for each emissions scenario). All analysis presented for the model comparison and statistical downscaling is based on the monthly mean results provided at the above web archive. For the regional model, we use the ECHAM5 A2 simulation, for which we obtained 6 hourly output. Including variants of the models used in this study, there are simulations from 24 models with monthly simulation data available from the IPCC, some with multiple realizations. Thus, we present results from a substantial subset of the available models that illustrates the range of expected results. The methods described here could easily be applied to the full suite of models.

In order to assess the performance of the models at simulating present-day climate and to compare the future trends simulated by the models, we examine time series of the regional mean temperature and precipitation. The Pacific Northwest is taken as the region between 124 and 111° west longitude, 42–49° north latitude: Washington, Oregon, Idaho, and western Montana. Models have different resolutions, but the number of model grid points enclosed in this latitude-longitude box is typically 12–20. The regionally averaged time series are simply the average of these gridcell values for each month. Owing to coarse spatial resolution, models represent little significant spatial structure within the region (*i.e.* due to topography, land use, or land-water interactions), and variations in model climate across the region are small. Since the topography and land use are not realistically represented at this scale, these variations are not necessarily indicative of what one would expect at the local scale. Thus, the regional mean is a reasonable spatial size to capture well-resolved features in the simulation while removing noise.

20th century simulations

To evaluate the skill of the various models in capturing Pacific Northwest climate, we compare the regional time series from each model against observations from the 20th century. There are various ways to represent the 'observed' regionally averaged temperature and precipitation. A common approach is to average weather station data into 'climate divisions' (geographical zones that are assumed to have internally uniform climate characteristics) and combine the climate divisions into a regional average with area weighting. The drawback of this approach is that it underrepresents the contribution of high terrain, which has very few weather stations,

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to the regional average. A better estimate horizontally interpolates and vertically extrapolates observations to a uniform, high-resolution grid using a simple model of the variations of temperature and precipitation with elevation and slope (Daly *et al.*, 1994). This approach, however, would be unsuitable for comparing with climate model output, which does not resolve the terrain. A third approach is to use a reanalysis simulation, where observed data are assimilated into a weather prediction model at the spatial resolution typical of climate models; here we use data from the NCEP/NCAR Reanalysis Project (NNRP) (Kalnay *et al.*, 1996). We have chosen to use station data and NNRP datasets for comparisons to the global models depending on the parameter of interest.

To assess model performance for the Pacific Northwest, we compare the bias in the long-term monthly mean temperature and precipitation relative to the observed climate. Model bias may arise from various effects, and may not necessarily indicate that the model cannot correctly capture the large-scale climate change signal. For example, the coarse resolution of the regional topography in the global models may misrepresent the mean elevation of the region, which would introduce a simple lapse rate bias that could easily be corrected; by using NNRP data for this comparison, however, we minimize this effect. We have also examined the climatological seasonal cycle of each model as compared to the observed seasonal cycle. The ability of a model to correctly capture the transitions between seasons depends on its ability to correctly simulate many important regional meteorological and land-surface processes. Thus, this comparison may be a better test of the model's ability to capture climate change than looking only at model bias. For purposes of model evaluation, we use the 30-year period 1970–1999 to establish the simulated and observed base climate since observations are of better quality during this period. We have considered a number of metrics to evaluate the models, but present here the bias in annual mean temperature and precipitation relative to the observed climatology represented by the NNRP data.

There is no consistent temperature bias among the climate models relative to NNRP, with some models showing a warm and some a cold bias (Figure 1(a)). The dashed lines indicate the standard deviation of the NNRP annual mean temperatures, which gives an indication of the magnitude of bias in the models as compared to interannual variability. Most models are within one standard deviation of the reanalysis climatology. Three models show a markedly larger bias than the others. The GISS model shows a strong warm bias and the PCM and CGCM each show a moderate cold bias. The NNRP Pacific Northwest annual mean temperature is 2.4 °C colder than the annual mean temperature derived from climate division data. Thus, relative to the climate

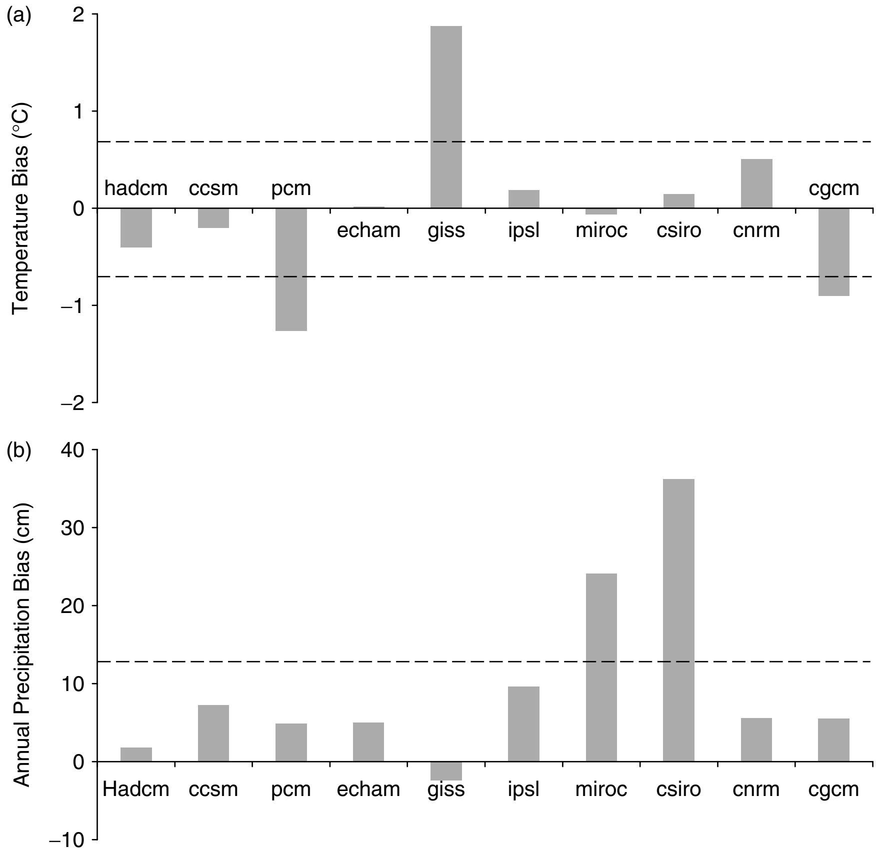

Figure 1. Difference (°C) between Pacific Northwest annual mean temperature for each model and NCAR–NCEP Reanalysis for 1970–1999. Horizontal lines indicate one standard deviation in the interannual variability of the NCAR–NCEP temperature for 1970–1999. (b) as (a) but for annual total precipitation in cm.

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division data, models show a bias of 2.4 °C less than the bias relative to the NNRP temperature. All models are substantially colder than the climate-division climatology. The difference between the climate division mean and the NNRP mean follows from the distribution of stations relative to the regional topography (mostly in low areas) and the coarse sampling of the topography by the NNRP. Consequently, the NNRP value is more representative of what one may expect from global climate models.

Figure 1(b) shows the bias in mean annual total precipitation in cm with the standard deviation of the NNRP precipitation shown by the dashed line. The temperature biases are not systematically related to precipitation biases, and the three models with large temperature biases yield small precipitation biases as compared to the other models. All but the GISS model produce somewhat more precipitation than the NNRP. Two models (MIROC and CSIRO) show considerable wet biases that exceed the standard deviation of annual precipitation in the NNRP data.

Another facet of 20th century climate that can be evaluated is the trend in temperature. For the global average, many models simulate a warming rate similar to the 0.6 °C warming observed over the 20th century. Since the trends in temperature observed over the late 20th century are associated with greenhouse forcing, and this forcing is included in the global model simulations, we should expect the observed and simulated trends to correspond. To represent the regional trend in temperature over the 20th century, we use station observations from the U.S. Historical Climatology Network (USHCN) data rather than NNRP. Since the temperature trend is less dependent on model resolution, station observations are a better representation of the warming. Interannual variability has a much greater influence at the regional scale compared to the global mean, so the regional warming due to greenhouse gas forcing could be contaminated by variability in atmospheric circulation; nonetheless, six of the models simulate a warming for the Northwest in the neighbourhood of the observed warming (Figure 2). Three models simulate very little trend (CSIRO, HADCM, MIROC) while one simulates a much larger trend (CGCM). We do not perform the same comparison for precipitation since the variability in precipitation observed for the Pacific Northwest over the 20th century is dominated by interannual and interdecadal variability. Since these variations are not related to external forcing, we do not expect them to correspond between observations and models.

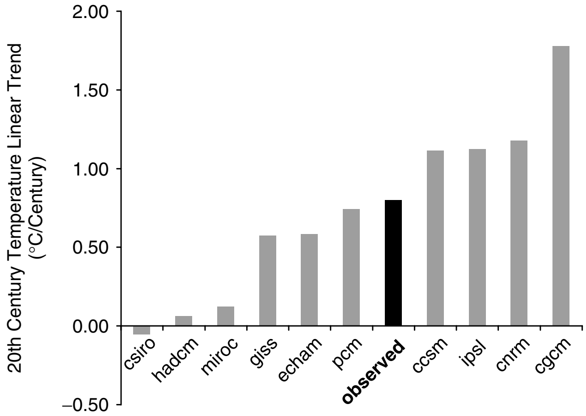

Figure 2. 20th century linear trend in temperature for the Pacific Northwest during the 20th century for each of the ten models from simulations forced by observed changes in greenhouse gases. The observed trend based on the U.S. Historical Climatology Network (USHCN) is shown in black.

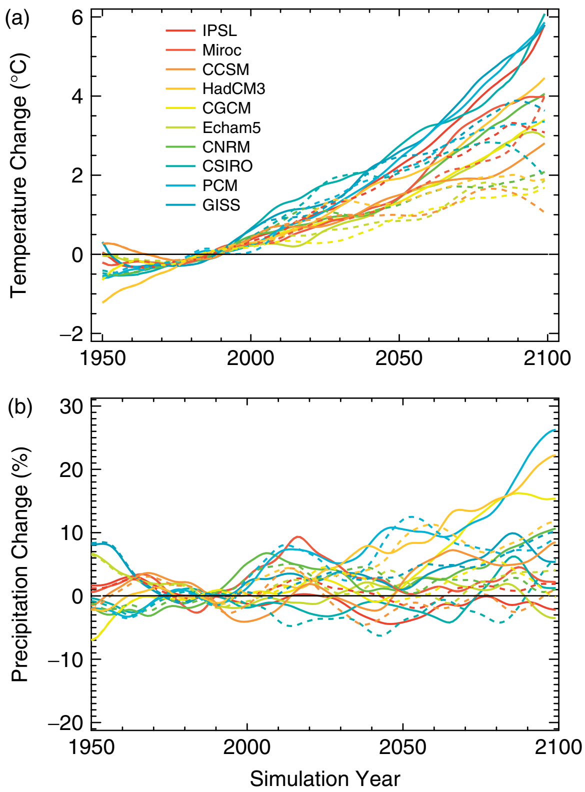

Figure 3. Simulated Pacific Northwest climate change for (a) temperature and (b) as a relative percentage for precipitation. Differences are computed relative to the 1990s, in °C for temperature and % for precipitation. Individual annual values are smoothed as described in the text. A2 scenarios are solid, B1 dashed. This figure is available in colour online at www.interscience.wiley.com/ijoc

Scenarios for the 21st century

The regionally averaged warming for the 21st century, relative to the 1990s, is shown for all 20 simulations in Figure 3(a). The simulated annual mean temperatures are smoothed using locally weighted regression (Cleveland, 1993) with parameters chosen to emphasize timescales greater than about 10 years and the average from 1990 to 1999 is subtracted. Note that the A2 (solid lines) and B1 (dashed lines) scenarios show very similar warming upto about 2050, only diverging in the later part of the century. This divergence of the two scenarios follows from the markedly different emissions, but the different scenarios do not impact warming rates in the near term. Note also, the range of warming rates in the 20th century for the various models. Warming projected for the end of the 21st century ranges from about 1.5 to 6 °C if both emissions scenarios are considered. The standard deviation of Pacific Northwest annual mean temperature for 1950–1999 from the NNRP reanalysis is 0.7 °C. Thus, the simulated 21st century warming for most models (and all A2 simulations) exceeds natural variability within the first few decades.

Figure 3(b) shows the simulated changes in precipitation. The yearly simulated values are expressed as the percent change in annual total precipitation from 1990 to 1999. Data are smoothed as for temperature (Figure 3(a)). While the observed trend in temperature is substantial when compared with the interannual variability for the 20th century, this is not true for annual total precipitation. The 1950–2000 standard deviation of NNRP annual precipitation is 16%, around a mean of 81 cm. Thus, the fluctuations in the past overshadow the trends predicted by all but the wettest scenarios in the future (Figure 3(b)). There is a consensus among the models for modest increases in precipitation under climate change with no model indicating a drying trend. Changes in precipitation are rather small in the models, with the exception of the CSIRO, IPSL, and CGCM simulations for the A2 scenario. While the trend is small compared to interannual variability, this shift may be significant given the consensus among models. Even a small shift in the mean would have substantial implications for the frequency of extreme events. Furthermore, increases in precipitation are more substantial for the rainy season, November through January (Salathé, 2006).

Another way to view the scenarios is to consider the changes from the present to some time in the future. For resource planning, for example, the period of the 2040s is a useful time horizon. To remove interannual variability, it is best to consider the mean over a 30-year time slice centred on the period of interest. Thus, we represent the 2040s as the mean from 2030 to 2060. To illustrate the range of temperature and precipitation scenarios for the 2040s, we may plot the change in temperature on one axis and the change in precipitation on another axis (Figure 4; asterisks mark the coordinates of each model). Models fall into three clusters, which are indicated by shaded areas on Figure 4. The largest and tightest cluster is centred around the multi-model mean change of 1.7 °C and small precipitation increase (ECHAM5, CSIRO, CNRM, and PCM); a second cluster includes two models with large (8.5%) increases in precipitation (CGCM and IPSL); a third contains models with small decreases in precipitation (HADCM, GISS, CCSM), and the MIROC model is alone in depicting a modest precipitation increase and large warming. Unlike the situation with the global mean, where the precipitation change and temperature change of models tend to be correlated, there seems to be no correspondence between temperature change and precipitation change in the northwest. This is likely due to the effects of changes in the North Pacific storm track on precipitation (Salathé, 2006), which is not well correlated with local temperature.

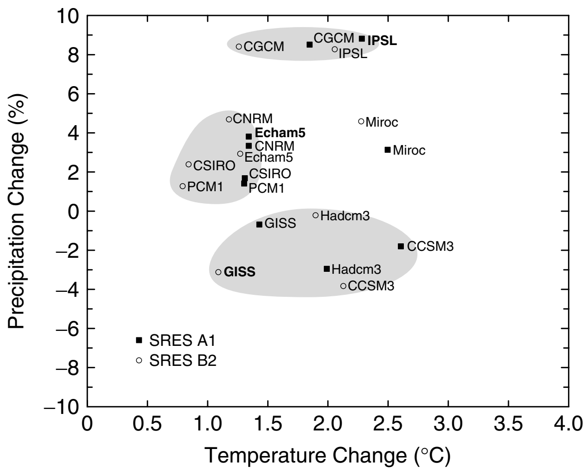

Figure 4. Scatterplot of change in annually averaged temperature and precipitation for each of the 20 scenarios simulated for the '2040s' (i.e. 2030–2059 minus 1970–1999). Three clusters and associated 'marker' scenarios are highlighted.

For detailed climate impacts studies that require extensive modeling, it may not be feasible to use all available scenarios. In this case, a subset of the models that spans the temperature and precipitation range of interest, or that exposes critical system sensitivities, may be selected. For example, three scenarios highlighted in Figure 4 represent each cluster of models: (1) a relatively high rate of warming and large increase of precipitation (the IPSL A2 scenario); (2) a middle-of-the-road scenario (ECHAM5 A2); and (3) a low-warming, drier scenario (GISS B1). In selecting these marker scenarios, the model's 20th century performance has also been taken into account. Both IPSL and ECHAM5 show excellent results for 20th century temperature and precipitation and the 20th century temperature trend. While GISS shows a large temperature bias, it is the only 'cool-dry' future scenario, and does represent the 20th century temperature trend and precipitation well. We stress that the ranking of these scenarios is not the same for other decades, and that for situations where seasonality may play a role other models may better represent the extremes in the range of possibilities.

In fact, there are marked differences in the seasonality of the climate change signal. In most models, the simulated warming is largest for summer (June–August). Three of the models (HadCM3, CNRM, GISS) produce substantially more (at least twice as much) warming in summer than in winter, and all but PCM and CGCM have greater warming in summer than in winter. This result stands in contrast to the common assumption that winter warming exceeds summer warming, and may result from soil moisture feedbacks. The result also has implications for increased water demand and more frequent forest fires. Precipitation changes are largest in winter (December–February), and tend to be positive. In summer, precipitation declines slightly in most scenarios.

STATISTICAL DOWNSCALING

While global simulations indicate large-scale patterns of change associated with natural and anthropogenic climate forcing, they cannot capture the effects of narrow mountain ranges, complex land/water interaction, or regional variations in land-use. Thus, it is necessary to develop robust approaches for applying global simulations at the regional scale. To that end, a number of methods, ranging from statistical downscaling to regional climate models, have been applied to bridge the gap between global climate models and local impacts. Global models generally are run at a resolution of 100–300 km and regional studies require a resolution of 10–50 km or finer. For hydrologic impact studies, surface temperature and precipitation are the most important parameters to acquire from the global models for input to hydrologic simulations. For the Pacific Northwest, a resolution of at least 15 km or 1/8-degree is required to resolve the slopes and elevations of the important mountain ranges. We have employed two techniques for downscaling to this resolution, a statistical method described in this section and a regional climate model described later in this paper.

Statistical downscaling has an important advantage over a regional model in that it is computationally efficient and allows the consideration of a large set of climate scenarios. Over the 50-year time horizon, the variation in projected change is far greater among the various models than among emissions scenarios. Therefore, to fully account for this uncertainty, a multi-model ensemble is the most appropriate approach.

For statistical downscaling of future climate scenarios, the method must be based on predictors that can capture the effects of climate change, and not just of climate variability. For example, while sea-level pressure patterns govern the local variability in precipitation, we might anticipate that climate warming may increase precipitation rates even within similar circulation regimes. Thus, we have investigated several combinations of predictors (Widmann *et al*., 2003) and have found that large-scale precipitation from the global model is a robust predictor for Pacific Northwest precipitation. Important additional variability, due to the interaction of atmospheric circulation and the topography, is captured by including sea-level pressure as a secondary predictor. Similarly, the large-scale surface air temperature is a robust predictor for regional temperature. In contrast to precipitation, there is little additional skill in including a circulation parameter, so this single predictor is sufficient.

The statistical downscaling method used for scenarios developed by the Climate Impacts Group is based on methods described by Wood *et al*. (2002), Widmann *et al*. (2003), and Salathé (2005). As in Wood *et al*. (2002), the monthly mean global climate model data are bias-corrected to map the observed statistical distributions of temperature and precipitation onto the climate model. The bias-corrected climate model is then downscaled to 1/8-degree resolution. For precipitation the 'dynamical scaling' method presented in Widmann *et al*. (2003) is used; for temperature the method described in Salathé (2005) is used. The statistical downscaling is based on 1/8-degree gridded observed temperature and precipitation (Maurer *et al*., 2002). In all cases, the statistical downscaling parameters are fit independently for each climate model using a 20th century climate simulation that matches the period of observations. Typically, we use a 50-year period, 1950–1999, for the fitting. Any simulation from the global model may then be downscaled using these parameters. We apply the downscaling to simulations from the global models described in the previous section. Specifically, we use three 100 year simulations from each model, the 20th century run and the SRES A2 and B1 scenarios for the 21st century. By downscaling the 20th century simulation, we may perform hydrologic simulations based on the 20th century scenario and evaluate climate change signals relative to the historic record.

In the first step of the downscaling, bias correction is applied to the global model grids using a quantile mapping. Since bias-correction is performed on the climate model grid, the 1/8-degree observational data are aggregated to the grid of the climate model under consideration. Observed and simulated data for the period 1950–1999 are used to form transfer functions based on the cumulative distribution function (CDF) for each parameter for each calendar month. Temperature and precipitation simulated by the climate model are then bias corrected using the transfer function, assuring that the bias-corrected simulation returns the observed CDF during the training period (1950–1999). For example, at each grid cell of a specific model and calendar month, we have a series of 50 monthly mean temperatures for each year, t, of the base climate simulation, $T_{model}^{base}(t)$. From the aggregated 1/8-degree data, we have a corresponding observed time series, $T_{obs}^{base}(t)$. We construct from these the CDF for the model, $C_{model}^{base}(T)$and the inverse cumulative distribution for the observed data, $\tau_{obs}^{base}(C)$. TheCDF, $C(T)$, is the fraction of years in the time series with temperature less than T for the calendar month under consideration. The bias-corrected temperature for year t and the given calendar month at this grid cell is then given by $\hat{T}(t) = \tau_{obs}^{base}\{C_{model}^{base}[T_{model}(t)]\}$ where $T_{model}(t)$ is the series of simulated monthly mean temperatures for the calendar month over the full simulation (1900–2000 for the historic run, 2000–2100 for future scenarios). This process is repeated for each grid cell in the domain and for each calendar month. Precipitation is also bias-corrected using the same technique. Figure 5 shows an example of the bias correction. Three time series of monthly mean January temperature for a particular grid point (47.6N, 121.9W) are shown in Figure 5(a): the aggregated temperature from the observed dataset (OBS), the raw ECHAM5 temperature for the same period from the 20th century simulation, and this result after bias correction. The CDF for the observed and modeled time series are shown in Figure 5(b); by construction, the bias corrected model yields the sameCDF. Bias correcting the global model to the full observed probability distribution is an important step for hydrologic applications. The

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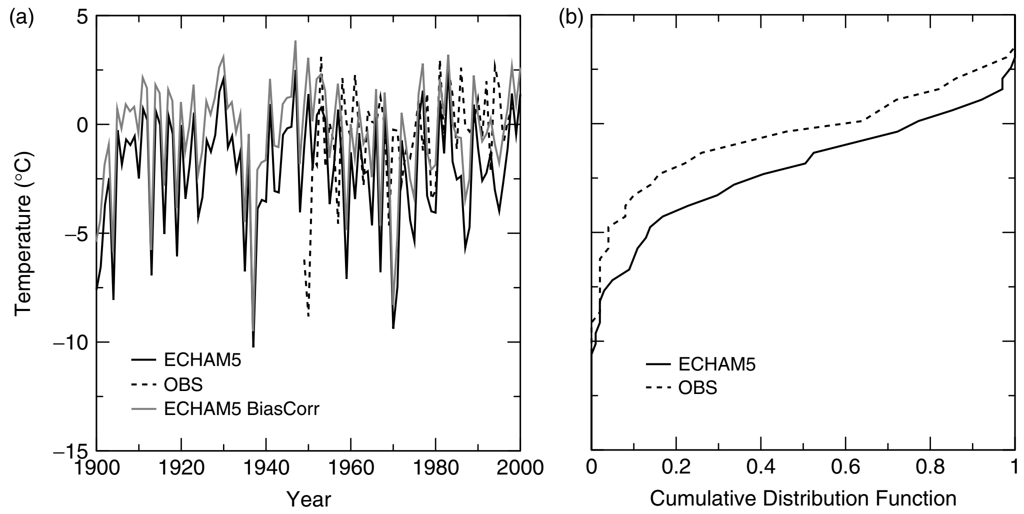

Figure 5. Time series of January temperature (°C) from the ECHAM5 model (solid line), gridded observations (dotted line), and bias-corrected ECHAM model (gray line) at a selected grid cell. (b) Cumulative distribution functions for the time series in (a).

downscaled 20th century simulation from any model will reproduce the observed probability distribution of temperature and precipitation, and by extension, hydrologic simulations based on the downscaled data will reproduce the observed distribution of streamflow. This is helpful in using multiple models for hydrologic assessment since all climate change runs may be readily compared against a baseline run using the 20th century simulation.

In the next step, the bias-corrected climate model is spatially downscaled using the techniques employed in Salathé (2005). For temperature, the bias-corrected climate model data is sampled onto the 1/8-degree grid. The mean difference between the bias-corrected model and the 1/8-degree data for each calendar month during the training period (1950–1999) is computed to form a perturbation factor. The downscaled temperature is then formed by adding the factor for the appropriate calendar month to the monthly simulated temperature for each month of the simulated scenario. For precipitation, a similar method is employed using a multiplicative scaling factor. In the simple case, the scaling factor is the mean ratio of simulated and observed precipitation on the 1/8-degree grid over the training period. In the 'dynamical scaling', the scaling factor is modified to account for the interaction of large-scale winds and regional topography in distributing precipitation across the region.

The output from this downscaling is a transient, monthly time series on a 1/8-degree grid. The monthly values may be temporally disaggregated to daily values by re-sampling the historic data set. To produce a daily weather sequence that is consistent with the monthly mean state, an appropriate analog month must be selected. We select this analog as the historic month whose monthly mean spatial precipitation pattern most closely matches the month to be disaggregated and corresponds to the same calendar month. The pattern match is accomplished using empirical orthogonal functions (EOFs) analysis with spatial EOFs derived from the historic record. The downscaled month is projected onto the three leading EOFs and the analog month is found by minimizing the difference between the resulting three principal components and the principal components for the historic months. The daily sequence of temperature and precipitation at each grid point from this analog month is scaled by the ratio of the downscaled monthly mean to the analog monthly mean to yield a daily time series with the appropriate monthly mean.

The daily, transient, regional climate grids can then be used as forcings in regional scale hydrologic models. This approach is useful for projecting future trends in hydrologic phenomenon, such as regional snow cover, soil moisture, and streamflow volumes over large, continental scale areas such as the Columbia or Colorado River basins. The downscaled data are publicly available for download (see <http://www.cses.washington.edu/data/ipccar4/>) for use in various applications.

MAPPING TO STATIONS

Many existing tools used in hydrologic resource management are based on data from meteorological stations. The microclimate of a given station may not be well represented by the downscaled grid due to factors such as elevation or land use. Consequently, interpolating or sampling the downscaled grid to generate a station time series may not be appropriate. However, we expect the climate change signal at a station would correspond to the grid cell that contains the station. Thus, we have developed a technique to map the downscaled grid onto stations of interest.

This process uses quantile mapping similar to the method for bias-correcting global models described above. The monthly time series of temperature and precipitation are extracted from the gridded downscaled data for the historic and future climate simulations. Transformation relationships are defined for each calendar month by mapping CDFs for the downscaled historic climate simulation to the CDFs for the observed station data. The time series for the future climate simulation can then be mapped to the station location using these relationships. As with the gridded downscaled data, the station data can be temporally disaggregated using a process of selective resampling.

THE USE OF TRANSIENT SCENARIOS FOR IMPACTS STUDIES

Using climate models to forecast impacts on water resources presents an unusual challenge in representing the climate of a region. Climate is the average weather over a period of time, which assumes that the long-term average of climate parameters do not change over time. By design, however, climate change impact studies consider the effects of changes in the long-term average climate state. Since the range of natural variability is comparable to the rate of climate change predicted for the early 21st century, understanding the combined effects of natural variability and long-term change presents an important challenge to climate impacts assessment. If we use a short range of years (typically 10 or 30 years) to describe the average climate at some point in the future, as has been done in climate impact studies (e.g. Lettenmaier *et al*., 1999; Palmer and Hahn, 2002) the variability within that time slice is often less than what has been observed over centennial scales. Extreme events are defining events when describing the sustainability of a water resource; therefore, it is very important to include these events in any representation of potential future climate. If, however, the range is extended much beyond 30 years, the secular trend in the data due to climate change becomes conflated with the natural variability and the assumption of static climate is no longer valid. Accordingly, a 30-year time slice appears to be the best compromise for this approach despite necessarily truncating the range of variability.

Many water resources planning and allocation decisions are based upon statistical metrics that are calculated using observed historic values over a 50–100 year period. Assessing how these metrics may shift due to the impacts of climate change requires being able to examine the full range of potential variability. The process can be greatly complicated when using transient climate scenarios in which the rate of change is as great as, or greater than, the natural variability seen within the standard planning horizon. For example, a change in magnitude of the 50-year flood event might be expected to occur over the next 25 years, yet the use of 30-year time slices or transient scenarios cannot readily provide such information. One option for addressing the truncated range of variability when using subsets of climate data is to create a synthetic time series that includes both the full range of observed, historic variability and the shifted climate statistics appropriate for a specific future time frame. To form such a time series, we map the statistical properties of the future time series onto the historic observed time series. In so doing, we assume the historic natural variability is preserved in the future, but with shifted statistical properties. Specifically, we use a quantile mapping process, as in the station mapping, to map the CDF derived from a short future time slice (e.g. 30 years) onto the long historic observed station data (e.g. 100 years). This balances the need for a short sample to capture future trends, taken from the climate projection, and a long sample, taken from the historic record, to capture the range of natural variability.

This process allows a climate change signal to be captured from the global climate model via shifts in climate variable CDFs, while also allowing for a longer time series that contains all of the extreme events in the observed record. The magnitude of these events is shifted to correspond with the altered climate signal from the global climate model. The long-term climate trends from the global climate model data have been removed so that the station scale dataset contains a long climatic sequence that is not complicated by the presence of an underlying trend, but instead, can be considered as a steady-state approximation of the climate at one point in time, but that contains the full range of potential variability.

REGIONAL CLIMATE MODEL

Statistical downscaling has been of considerable value in producing scenarios for climate impacts assessment. Dynamical downscaling through the use of regional climate models, is a promising tool with several advantages over statistical methods, as discussed extensively in the literature (Fowler *et al*., 2007; Giorgi and Mearns, 1999; Hellstrom *et al*., 2001; Leung *et al*., 2003; Mearns *et al*., 1999). For the Pacific Northwest, however, previous work using a regional climate model at 50 km resolution showed little added value over statistical methods (Wood *et al*., 2004). The primary reason for this result is that the regionally important mesoscale processes and feedbacks require much finer spatial resolution to be properly simulated. Research on real-time weather forecasting for the Pacific Northwest (Mass *et al*., 2003) using the MM5 mesoscale model (Grell *et al*., 1993) has shown that a resolution of 15 km or less is required to capture the orographic effects, land-water contrasts, and mesoscale circulations that characterize the regional climate and weather. To improve on the representation of regional climate change from statistical downscaling, we have employed a regional climate modelling system based on this real-time weather forecasting system (Salathe *et al*., 2007). To account for the geographical details as discussed above, the regional model simulations are performed at 15 km resolution.

We present here results from downscaling the A2 scenario simulation of the ECHAM5 global model, which was included in the analysis of Section 2. This model uses the fifth-generation atmospheric general circulation model developed at the Max Planck Institute for Meteorology (Roeckner E, *et al*. The atmospheric general circulation model ECHAM 5. PART I:

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Model description, MPI-Report 349, 127 pp, 2003) coupled to the Max Planck Institute ocean model (MPI-OM). As shown in Figure 1, this model shows relatively small biases in simulated 20th century temperature and precipitation relative to the NCAR-NCEP Reanalysis and (Figure 2) simulates a 20th century warming trend similar to the observed trend. Furthermore, the climate change response of the ECHAM5 A2 simulation is central among the various models for both temperature and precipitation (Figure 4). Thus, this model provides a good middle-of-the road scenario for Pacific Northwest climate change. Model output at 6-h intervals was obtained from the CERA WWW Gateway at; <http://cera-www.dkrz.de/CERA/index.html>; the data are managed by World Data Center of Climate <http://www.mad.zmaw.de/wdcc/>. ECHAM5 was run at T63 spectral resolution, which corresponds to a horizontal grid spacing of approximately 150 km at mid-latitudes.

Regional simulations open up a broad range of impacts applications that are not served by statistical downscaling, such as air quality modelling (Avise *et al*., 2006). Furthermore, many resource managers are already familiar with mesoscale model output from work with real-time weather forecasts, so the results dovetail into existing management tools. Most importantly, however, these results show changes in hydrologic processes not captured by the statistical downscaling that could have considerable importance in impacts assessment. We present here two examples that show a different warming trend in the regional model than in the statistical downscaling. Thus, the physical downscaling of the ECHAM5 simulation introduces a more varied regional response to climate change than is suggested by the raw model output or the statistical downscaling.

The first example is straightforward: warming is intensified in regions where snow cover is lost due to the snow-albedo feedback. This feedback is also important in global climate model simulations, where polar warming is amplified relative to lower latitudes (Holland and Bitz, 2003). Coarse-resolution models, however, do not realistically represent the effect at regional scales since they do not resolve the slopes and elevations of the local topography. Regional models of sufficiently fine resolution may represent these features and thus simulate this feedback in detail. Snow-albedo feedback follows from the decreased albedo of the underlying land surface relative to snow and the consequent increased absorption of solar radiation when snow cover is lost. Figure 6(a) shows the difference in the warming from 1990–1999 to 2045–2054 for the ECHAM5 model between the statistical downscaling and from the regional model downscaling. This difference is calculated as the temperature change from 1990–1999 to 2045–2054 in the regional model minus the temperature change from 1990–1999 to 2045–2054 in the statistical downscaling. Thus, positive values indicate greater warming in the regional model than the statistical downscaling and negative values indicate less warming in the regional model. Relative to the global model, the regional model produces amplified warming along the western slopes of the Cascades and in the high plateaus of Eastern Washington and Oregon. This amplified warming is produced by increased absorption of solar radiation at the surface as snow cover is eliminated and albedo decreases (Figure 6(b)). The effect is most pronounced near the present-day snowline where snow cover is most sensitive to temperature changes.

A second effect follows from mesoscale circulation established by the local temperature gradients in spring (March–April–May). Warming of the continental interior, relative to the oceans, establishes an anomalous on-shore pressure gradient, as can be seen from the 1000-hPa height field (change from 1990s to 2050s, Figure 7(a)). This pressure gradient increases the climatological onshore flow and produces increased low-level cloudiness as indicated by the concentration of cloud water (change from 1990s to 2050s, Figure 7(b)). Increased cloudiness reduces the incident solar radiation at the surface, producing a coolling effect during the day. As in DJF, there is substantial snow loss in this season, with associated increase in surface albedo. The albedo effect more than makes up for the loss of incident solar radiation, yielding a net increase in shortwave absorption at the surface. Thus, there is an amplified warming in the mesoscale simulation relative to the raw global model for MAM; if cloud cover were not simulated to increase, this amplification would be even greater.

CONCLUSION

To establish scenarios for climate impacts assessment, we considered ten global climate models from the IPCC Fourth Assessment (Alley *et al*., 2007). The 20th century simulations from these models were compared against observations from the same period in order to evaluate the models. Most models performed well in the 20th century simulation, with two or three showing deficiencies in some measures of the Pacific Northwest climate. The SRES A2 and B1 simulations from these models span a wide range of potential increases in temperature and precipitation for the Pacific Northwest. For further modelling in impacts studies, either the full set may be considered or, when resources are limited, a subset that represents the range of changes in temperature and precipitation found in the full ensemble. Thus, even when only a small number of scenarios are used, a large ensemble must be considered in the early stages to better estimate the projected range of climate change and to guide scenario selection.

We have developed a statistical downscaling method appropriate for producing high-resolution scenarios of temperature and precipitation for the Pacific Northwest. This method maps the observed statistical properties of temperature and precipitation onto the global model simulation. For downscaling, global model temperature is the large-scale predictor for regional temperature; global model precipitation and sea-level pressure are predictors

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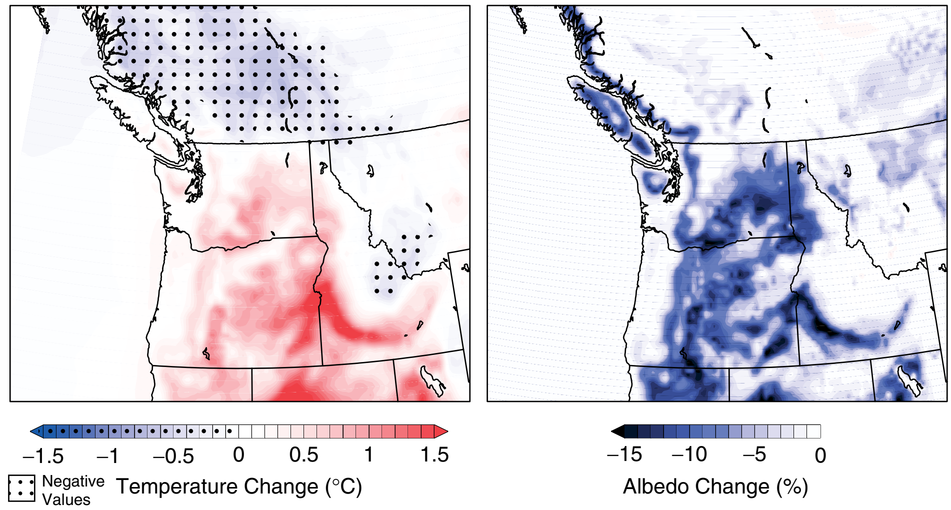

Figure 6. Difference in warming from 1990s to 2050s simulated by the ECHAM5 global climate model and by the MM5 regional model for December–January–February. Positive values indicate greater warming in the regional model. (b) Percent change in December–January–February surface albedo in the regional model from 1990s to 2050s. This figure is available in colour online at www.interscience.wiley.com/ijoc

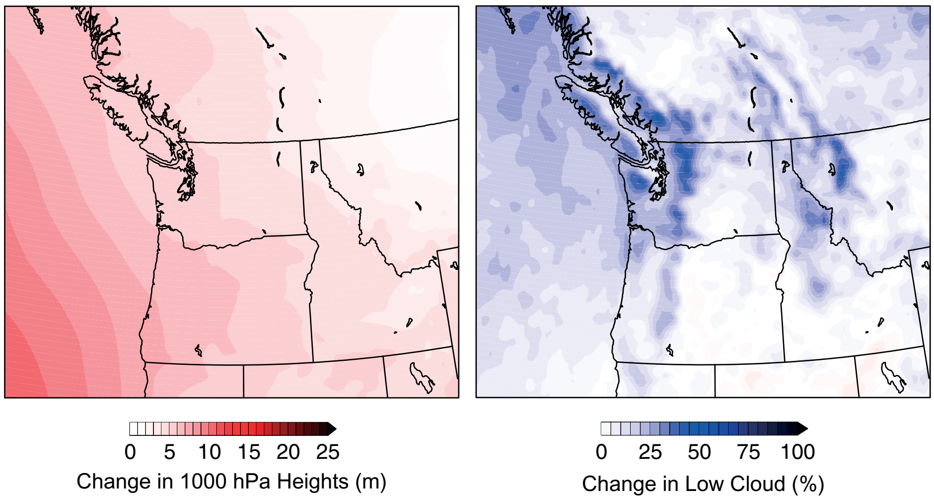

Figure 7. Change in March–April–May 1000 hPa heights in regional model simulation from 1990s to 2050s (b) Percent change in March–April–May low cloud concentration from 1990s to 2050s. This figure is available in colour online at www.interscience.wiley.com/ijoc

for regional precipitation. These predictors ensure that the climate change signal from the global model is captured and transferred to the regional scenario. Furthermore, by forcing the probability distribution of events in the downscaled data, hydrologic simulations using the downscaled 20th century simulation from any model should return the statistical distribution of hydrologic events observed for that century. To facilitate integration of the downscaled data into water resource management tools, we have developed additional processing techniques to map the data to stations and to synthesize stationary climate time series. In this way, various downscaled data may be produced appropriate to specific applications. Gridded transient data are appropriate in many research contexts. Station-mapped transient time series are appropriate for many hydrologic simulations where the transient climate change signal is of interest. The stationary time series may be used for modelling water resource systems where parameters such as reliability, yield, and specific event frequency are of primary interest and long time series are required to produce the required statistics.

While statistical downscaling is a valuable tool in impacts assessment due to the ability to consider many climate scenarios and very long time series, there are important mesoscale responses to climate change that are not captured. To produce meaningful simulations of these effects for the Pacific Northwest, a high-resolution model (15 km resolution or better) is required to capture the land surface and topographic structures that control the mesoscale climate. Owing to the computational resources required, only few scenarios and short time slices are feasible. From such studies, however, we can identify processes that may be important in determining climate impacts in the region. Specifically, we identify changes in the surface radiation budget caused by the loss of snow and increased cloudiness that produce localized amplifications of the warming predicted by the global model.

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