International Congress on Environmental Modelling and Software

7th International Congress on Environmental Modelling and Software - San Diego, California, USA - June 2014

Jun 16th, 2:00 PM - 3:20 PM

Uncertainty Transfer in Modeling Layers: From GCM to downscaling to hydrologic surface-groundwater modeling

John F. Mejia
Desert Research Institute Division of Atmospheric Sciences, John.Mejia@dri.edu

Richard G. Niswonger
United States Geological Survey

Justin Huntington
Desert Research Institute, Division of Hydrologic Sciences

Mejia, John F.; Niswonger, Richard G.; and Huntington, Justin, "Uncertainty Transfer in Modeling Layers: From GCM to downscaling to hydrologic surface-groundwater modeling" (2014). *International Congress on Environmental Modelling and Software*. 11.
https://scholarsarchive.byu.edu/iemssconference/2014/Stream-B/11

International Environmental Modelling and Software Society (iEMSs)
7th Intl. Congress on Env. Modelling and Software, San Diego, CA, USA,
Daniel P. Ames, Nigel W.T. Quinn and Andrea E. Rizzoli (Eds.)
http://www.iemss.org/society/index.php/iemss-2014-proceedings

Uncertainty Transfer in Modeling Layers: From GCM to downscaling to hydrologic surface-groundwater modeling

John F. Mejia[1], **Richard G Niswonger**[2], **Justin Huntington**[3]
1.Desert Research Institute Division of Atmospheric Sciences, Reno, Nevada, john.mejia@dri.edu
2. United States Geological Survey, USGS, Carson City, Nevada
3. Desert Research Institute, Division of Hydrologic Sciences, , Reno, Nevada

Abstract: In this presentation we show how model uncertainty is transferred from GCMs to hydrologic model results for different downscaling strategies. We use a USGS Groundwater and Surface-water FLOW (GSFLOW) model applied to three small catchments in the northeastern Lake Tahoe basin. A framework is developed for assessing the benefits and difficulties associated with using historical and future climate projections from CMIP3 and CMIP5 datasets for hydrologic investigations. Here we downscale 10 km gridded GCM climate data to a 60m grid using daily values from climate stations and PRISM average monthly climate. Hydrologic model results show that an ensemble/probabilistic station-based downscaling approach provides reasonable downscaled climate data that can be used to evaluate sub-regional scale impacts in hydrologic processes.

Keywords: CMIP3, CMIP5, statistical downscaling, GSFLOW, hydroclimate, simulated uncertainty.

1. INTRODUCTION

Climate variability in mountainous regions occurs over much smaller spatial scales than is represented in GCMs. GCM climate data must be downscaled in mountainous regions to accurately simulate runoff magnitudes and volumes. Climate station data measured in mountain regions can be used to downscale GCM data; however, results vary widely depending on the GCM and downscaling method. Data from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Projects Phase 3 and 5 GCM simulated output (hereafter CMIP3 - Meehl et al. 2007- and CMIP5 -Taylor et al. 2012-) are downscaled here, and hydrologic simulations forced by these data are used to evaluate downscaling methods. In addition, downscaled products such as the BCSD (Maurer et al. 2010), BCCAv2 (Brekke et al. 2013), NARCCAP (Mearns et al. 2012) are included in this analysis and further downscaled for evaluation using hydrologic simulations. An important conceptual component of the methods presented herein is the evaluation of downscaled GCM climate through the use of hydrologic simulation, climate station data, and measured streamflow.

Future climate projections for the 21st century indicate large changes in water resources of Western U.S. that are outside the variability measured during the historical measurement period. Resilience of water resources infrastructure to these extreme climate conditions is of great concern to water resources planner and managers. Any efforts to address and reduce the uncertainty in climate change assessments will support more effective adaptation and mitigation strategies. In this paper we address how uncertainty is transferred from GCMs to hydrologic simulations using GSFLOW, an integrated physically-based hydrologic model (Markstrom et al., 2008). A high resolution model of the mountainous watersheds in the Sierra-Nevada is used to represent distributed precipitation as rain and snow, and the resulting watershed processes (Huntington and Niswonger 2012; Mejia et al. 2012). GSFLOW simulations of the Tahoe region provide a rigorous evaluation of how well GCM climate information can be used to provide meaningful estimation of daily streamflow volumes for current and future climate conditions. We highlight some of the expected benefits and difficulties in using the newly developed

CMIP5 datasets for climate change related water resources evaluations. Progress in the downscaling of climate data to mountainous regions is presented using ensemble/probabilistic approaches. Initial efforts are described to expand this methodology to other hydrological modeling frameworks.

2. THE GCM LAYER

An in-depth analysis of the GCM biases over western U.S. was presented by Mejia et al. (2014) and this work is highlighted here with emphasis on hydrologic investigation. Climate information from the CMIP3 and CMIP5, including atmospheric states in addition to precipitation and temperature, have played a significant role in the assessment of climate variability and change for the IPCC fourth and fifth Assessment Reports (IPCC-AR4, 2007; IPCC-AR5 in prep.). When averaged over the globe, most Atmosphere-Ocean General Circulation Models (AOGCMs) used in both CMIP3 and CMIP5 show acceptable skill in predicting average surface temperatures for historical climate. The multi-model ensemble of global averaged surface temperature spreads randomly about the observed value, and tends to be more accurate than the results from any one individual realization of the ensemble. However, models exhibit less skill at sub-continental and regional scales, and often there are similarities in deficiencies among many models, indicating that models suffer important errors related to spatial scale and structural error.

This situation has led to climate assessment studies using composites or subsamples of CMIP3 and CMIP5 according to their individual skill evaluated by region or by individual or combination of parameters (Knutti et al. 2010). Ensemble subsample selection, or weighting depending on based on ensemble member performance, is highly sensitive of the intended application, region of interest, and the metrics implemented (Glecker at al. 2008). Even though the skill of model results will improve by using such ensemble or composited approaches (Stott and Fotest 2007; Knutti et al. 2010), these improvements may not be realized outside of historical climate records, such as for projections of climate change.

Figure 1 shows GCM surface temperature (T2m) and precipitation biases for Western U.S. (North American Monsoon, Sierra Nevada and Cascades, and the Intermoutain West), using CMIP3 and CMIP5 and AMIP3 and AMIP5 participant GCMs. All GCM models implemented in this analysis are also used as input for the BCSD, BCCA, NARCCAP downscaling procedures. Ensemble model performance is measured as the bias relative to the UDel (Willmott and Matsuura 2001) annual means for the period 1980-1999 and relative to other observational products[1]. A striking result is the poor to moderate agreement between observational-based data sets over all the regions. Bias varies widely among regions and GCMs. Fig. 1 shows that the multi-model ensemble bias median surface temperature for all GCMs is within ~1°C, but the CMIP5 and AMIP5 models exhibit greater spread in the bias among the ensemble members compared to CMIP3 and AMIP3, respectively. However, the CMIP3 and CMIP5 tend to be colder relative to AMIP3 and AMIP5 (about ~2°C over the NAM and the Intermountain West regions). Over all regions, positive precipitation (wet) biases are robust between the CMIP3 and CMIP5 as more than 75% of the models are above all the observed gridded averages. These wet biases are closely related to the cold surface temperature biases in each region (not shown). Further, the wet biases exhibited by CMIP3 and CMIP5 are also large relative to AMIP3 and AMIP5. The distributions of surface temperature and precipitation biases indicate that when coupled GCMs (CMIP3 and CMIP5) are restored to the observed SSTs (AMIP3 and AMIP5) the simulation improves dramatically over NAM and marginally over the Intermountain West and the Sierra Nevada and Cascades. The results over the NAM region agree with Liang at el. (2008), which showed that most of these biases are related to overestimation and early onset of the monsoon season. They also showed that such biases are not systematically related to physics configuration of the models, or resolution, with the role of adjacent oceans SSTs playing a partial role in the GCM response. Most of these wet biases are more pronounced during the cold season (not shown) suggesting that systematic links other than those simply related to monsoon circulation and processes likely are responsible in this region. CMIP5 has greater spread among models in precipitation biases over the NAM region, as well as wetter biases relative to CMIP3 (which is consistent with previous work; Sheffield et al. 2012; Geil et al. 2013). These outstanding ensemble wet biases have been partly associated with the well-documented systematic biases on daily precipitation distribution, where the

---

[1] NNRP (Kalnay et al. 1996), CMAP (Xie and Arkin 1997), NARR (Mesinger et al. 2006), CFSR (Saha et al. 2010), and GPCP (Adler et al. 2003).

frequency of light (heavy) precipitation intensities tend to be overestimated (underestimated) (De Angelis et al. 2013).

3. DOWNSCALING AND THE DRIZZLE PROBLEM

Large scale Global Climate Models (GCMs) are not well suited for estimating flow volumes draining from small watersheds. Complex orographic features are not adequately resolved in relatively coarse GCMs: typically, the smoothed elevation affects temperature, and orographic effects generate errors in precipitation amounts. To increase GCM applicability, several methods have been implemented to downscale climate to fine temporal and spatial scales; however, more work is required to evaluate how these downscaling methods affect simulated climate and hydrology in mountainous regions that are topographically complex.

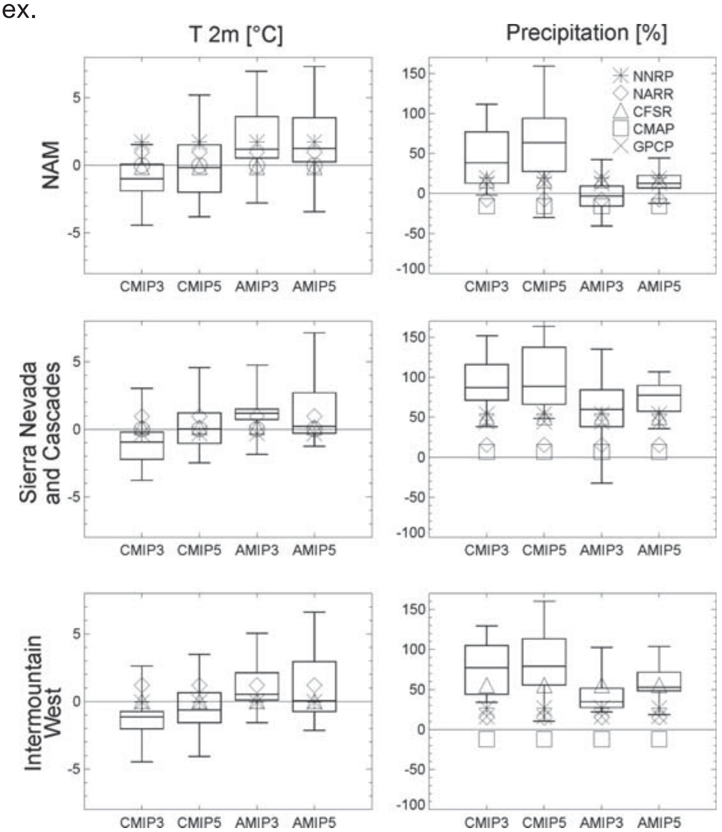

Figure 1 CMIP3, CMIP5, AMIP3, and AMIP5 regional ensemble distributions (box and whisker plots) for surface temperature (left panels) and precipitation (right panels) biases, evaluated during 1981 to 2000. Spatial averages (from top to bottom) for the North American Monsoon (NAM), Sierra Nevada and Cascades, and Intermountain West. Gridded observations from University of Delaware are used as reference; for robustness in bias estimations, differences relative to other gridded data are also shown (symbols). Each box plot is defined as the median and inter-quartile range and the upper and lower limits from each GCM ensemble. Modified from Mejia et al. (2014).

Of note is that even though the model spread in CMIP3 and CMIP5 projections is relatively similar, CMIP5 incorporates previously ignored factors and more refined processes and components of the climate systems (Taylor et al. 2012). Hence, uncertainty in the newer CMIP5 models appears to be lower than the CMIP3 models as CMIP5 models incorporate more climate system processes. In light of the aforementioned GCM biases and deficiencies, it is important to evaluate the extent to which correction and spatial disaggregation made by the BCSD or BCCA statistical downscaling approaches obscures realistic climate features that could be important to hydrologic impact investigations.

Statistical downscaling (SD) of GCM output is an inexpensive and common method to increase climate resolution, while removing biases, which consists in data transformations originally at ~1°-2° grid sizes to 10 km or finer grids. Available GCM SD information for the U.S. include: the Bias-Correction Constructed

Analogues (BCCA; CMIP3, Maurer et al. 2010; CMIP5, Brekke et al. 2013) at daily time increments and grid size of 1°/12; other SD data products include the 30-arcsecond monthly global data (Mosier et al. 2013) and daily NASA Earth Exchange (NEX) Downscaled Climate Projections (Thrasher et al. 2013) only for CMIP5. Previous studies showed different challenges associated with application of downscaling approaches for small-scale (60 m^2 grids) impact studies where it was shown that a second level of downscale/bias corrections were required (Mejia et al. 2012), especially for complex terrain, or applications that downscale to individual climate stations. This second level of downscale/bias corrections that are applied to downscaled GCM results are referred to herein as *double-statistical downscaling* or *2SD*, and is done using quantile–quantile distribution mapping (Mejia et al., 2012; Huntington and Niswonger, 2012).

Accurately simulating precipitation is one of the main deficiencies of GCMs. GCMs tend to create erroneously high seasonal, diurnal, and spatial variability of precipitation (Meehl at al. 2007; Maloney et al. 2012). Further, convective processes are solve implicitly and appear to be triggered more frequently than observed. Hence, GCMs have a strong tendency of overestimating frequencies of low precipitation intensities (i.e., the drizzle problem; Day 2006; DeFlorio et al. 2013). This problem results in errors in the frequency distribution of precipitation intensity and duration (i.e., the spell-length), and therefore, also affects local feedback mechanisms and hydroclimate processes. Errors in GCM-based hydrologic simulation associated with the drizzle problem are evaluated using simulated output from GSFLOW. In the present work, daily precipitation and minimum and maximum temperature data from Mt Rose SNOTEL and Tahoe City NWS stations are used for hydrologic calibration and GCM station-based downscaling (see Huntington and Niswonger 2012 for weather station and GSFLOW modeling details).

Fig. 2 shows the number of precipitation days simulated by GCMs on days when no precipitation was measured at climate stations for the BCCA data, and the CMIP3 and CMIP5 GCMs. These GCMs overemphasize low intensity precipitation events by twofold. Relative to present time, late 21st BCCA output shows a slight decrease of precipitation events. It is evident that common SD approaches exhibit the drizzle problem and additional corrections are necessary to remove this error. We removed unrealistic drizzle by estimating the optimum threshold (P0), where values of historical daily precipitation lesser than or equal to P0 are set to zero so the frequency of days with precipitation matches the observed frequency for both historical and future climate. After P0 is optimized (on average around 0.84 mm day-1), monthly accumulations are bias-corrected following the same method as in 2SD; this approach is refer to *2SD-no-drizzle*.

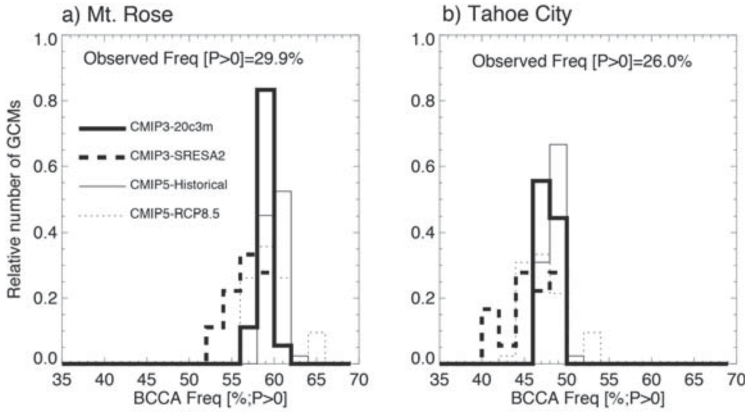

Figure 2 Frequency of days (%) with precipitation for (a) Mt Rose and (b) Tahoe City using BCCA for present and future CMIP3 and CMIP5 nearest grid points. Observed frequencies are also shown.

BCCA and the 2SD and or 2SD-nodrizzle assume stationarity of the statistical estimates over the largest timescales and neglects surface physical feedbacks between temperature and precipitation. To evaluate simulated errors climate associated with the drizzle problem, simulated hydrologic conditions are analyzed for the aforementioned climate products and GCMs. These comparisons are used to evaluate whether downscaled/bias corrected GCM results can provide reasonable representation of climate for regional scale hydrologic impact studies. Benefits that are provided by various downscaling and bias correction methods are evaluated.

4. HYDROLOGIC MODEL (GSFLOW)

GSFLOW is a coupled groundwater and surface water flow model based on the integration of the Precipitation-Runoff Modeling System (PRMS) and the Modular Ground-Water Flow Model (MODFLOW-NWT) (Leavesley et al., 1995; Niswonger et al., 2008; Markstrom et al. 2008). Application of GSFLOW to watersheds in the Sierra-Nevada for climate-change analysis was presented by Huntington and Niswonger (2012), and evaluation downscaled GCM climate results was presented by Mejia et al. (2012).

4.1. Uncertainty due to the drizzle problem and climate change signal

Table 1 shows GSFLOW ensemble (CMIP3-20CM3 and CMIP5-Historical) root mean squeare error (RMSE) compared against the GSFLOW model forced by measured climate and calibrated to various other observed hydrologic variables. Of note is that the 2D-nodrizzle exhibit improvements in historical hydroclimate simulations relative 2SD downscaling approach for both CMIP3 and CMIP5 ensembles. With few exceptions, individual members show similar behavior, indicating that downscaling and bias corrections can be used to remove some error related to the drizzle problem. Errors caused by the drizzle problem are not too large as to obscure future trends in climate change for high emission scenarios during late 21st century. Table 2 shows the signal-to-noise ratio, with the signal measured as the scenario-based hydroclimate trend from *future* minus *present* annual mean, and with the noise derived from RMSE from Table 1. Note that both 2SD and 2SD-no-drizzle approaches lead to similar hydroclimate change assessments as indicated by similar signal-to-noise ratios. Results indicate that only surface or near-surface hydroclimate parameters show significant trends under the outlined uncertainty, while groundwater variables are less sensitive. However, errors in the temporal variability at daily to seasonal temporal scale impacts runoff processes and thus, indirectly affects groundwater recharge timing and amounts.

Table 1 Historical CMIP3 and CMIP5 RMSE for both 2SD and 2SD-nodrizzle approaches.

	gwflow2strms		**uzf_recharge**		**basinsoilmoist**		**basinpweqv**		**basinsroff**		**streambed_loss**		**gwflow2strms**	
	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle
CMIP3	0.2140	0.1496	0.298	0.213	15.94	11.61	23.57	20.33	0.0539	0.0529	0.0050	0.0038	0.054	0.033
CMIP5	0.2170	0.1498	0.318	0.229	17.38	13.28	24.79	19.47	0.0520	0.0498	0.0053	0.0039	0.056	0.036

gwflow2strms: Volumetric flow rate of ground-water discharge to stream reaches [10^5 m^3 day^-1]

basinpweqv: Total volume of water in snowpack storage for watershed [10^5 m^3]

basinstrmflow: Volumetric flow rate of streamflow leaving the watershed [10^5 m^3 day^-1]

uzf_recharge: Volumetric flow rate of recharge from the unsaturated zone to the saturated zone [10^5 m^3 day^-1]

basinsoilmoist: Total volume of soil water in capillary reservoirs of soil zone for watershed [10^5 m^3]

basinpweqv: Volume of water in snowpack storage [10^5 m^3]

basinsroff: Volumetric flow rate of the sum of Hortonian (Horton, 1933) and Dunnian surface runoff (Dunne and Black, 1970) to streams [10^5 m^3 day^-1]

sat_change_stor: Change in saturated-zone storage [10^5 m^3]

streambed_loss: Volumetric flow rate of stream leakage to unsaturated and saturated zones [10^5 m^3]

gwflow2strms: Volumetric flow rate of ground-water discharge to stream reaches [10^5 m^3 day^-1]

Table 2 Ensemble signal-to-noise ratios. Signal is estimated as the difference of annual mean parameters during the 2100-2080 and 2000-1980 time slices, while we assume the noise is derived from the RSME shown in Table1. Values larger than 1 indicate a significant signal.

	basinppt		**basinstrmflow**		**uzf_recharge**		**basinsoilmoist**		**basinpweqv**		**basinsroff**		**streambed_loss**		**gwflow2strms**	
	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle	2SD	2SD-nodrizzle
CMIP3	0.27	0.31	-0.12	-0.04	-0.21	-0.25	-1.558	-2.235	-2.356	-3.017	0.7326	0.8373	0.21	0.23	-0.60	-0.82
CMIP5	0.54	0.56	0.34	0.56	0.00	0.01	-1.387	-1.964	-2.584	-3.504	1.3947	1.5497	-0.04	-0.08	-0.08	-0.10

4.2. Future seasonality hydroclimate projections

Future climate projections that consider increased greenhouse gas emission scenarios show there is a potential to cause large changes in hydrology and water resources on the Sierra Nevada. Figure 3 shows historical and future monthly mean GSFLOW output for selected parameters using all available CMIP3 (18 ensemble members) and CMIP5 (42 ensemble members) GCMs and the 2SD-no-drizzle downscaling approach. Future hydroclimate projections in the Tahoe basin show that a combination of a slight increase in precipitation (Table 2) and increase in temperature (not shown) produce net decreases in water stored in snow pack, with the snow-melt pulse occurring 1-month earlier relative to historical simulations (Fig. 3a). Fig. 3a also shows that the amount of water in snowpack is more sensitive during the cold season relative to the warm season, as indicated by the ensemble spread. GSFLOW results show specific characteristics of changes in seasonality of surface and groundwater hydrologic parameters. For example, the future streamflow ensemble mean shifts earlier in time and leads to decreases in minimum flows relative to the historical period (Fig 3b). These changes in seasonality of surface parameters are related to changes in groundwater recharge (Fig. 3c), with a small decrease in storage according to CMIP3 ensemble and rather negligible changes according to CMIP5 ensemble (Table 1). Our results agree with previous work performed in the basin (Pierce et al. 2008; Coats at al. 2010; Huntington and Niswonger 2012) and more generally over Western U.S. (Wood et al. 2004; Stewart et al. 2005) for snow dominated catchments when simulated under a warmer climate. The simulations herein do not consider future land-use/land cover changes, including those related to potential impact of local or remote air quality, where black carbon can potentially impact snowpack, thus hydroclimate changes (Hadley et al. 2010).

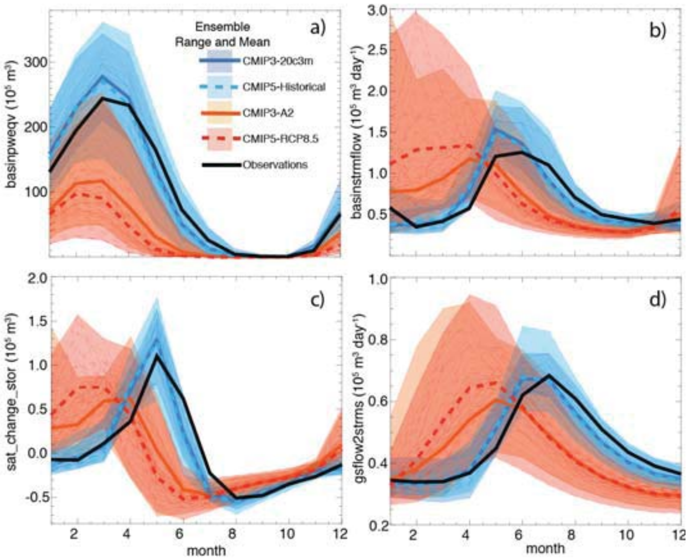

Figure 3 Monthly mean GSFLOW output using 2SD-no-drizzle approach on CMIP3 and CMIP5 BCCA for present (1981-2000) and future (2081-2100) simulated meteorology. Panels show basin average (a) volume of water in snow pack, (b) streamflow, (c) change in saturated zone storage, and (d) groundwater to stream discharge. Reference GSFLOW is based on observed meteorology (solid black lines). See Table 2 for long name of shown parameters.

5. CONCLUDING REMARKS

In this paper, we applied a double statistical downscaling approached and evaluated how uncertainty in simulated climate affects hydrological assessments using an integrated surface-water and groundwater flow model. Our analysis helps to address several questions related to the uncertainty introduced by downscaling methods used for hydrologic impact studies of small mountainous watersheds. Our results also provide updated estimates of the future hydrologic conditions using the latest models from CMIP5 ensembles, and a better estimate of the uncertainties and range of possibilities from GCMs and downscaling methods. We also evaluated how uncertainty is transferred from GCMs and downscaling/bias corrections to hydrologic simulations.

Our analysis indicates that CMIP3 and CMIP5 GCM results exhibit biases that are correlated for precipitation and temperature results. Bias correction does not alleviate these errors in climate projections. Daily results from the BCSD products have been widely used; however, as shown in the results presented herein, this dataset still exhibits common problems inherited from GCM structural deficiencies. We have implemented a refined statistical downscaling technique to improve and facilitate implementations of BCSD and other downscaling approaches when station-based projections are needed. For example, our results show that partially fixing the drizzle problem in the station-based downscaling datasets improves GSFLOW simulated hydrologic fluxes. However, several questions still remain about the optimal level of refinement, and the extent to which the correction of the drizzle problems introduces additional physical inconsistencies between parameters (i.e., between temperature and precipitation), and other well-known problems in statistical downscaling procedures. This study also provides insight regarding the accuracy of simulated future hydrologic conditions in mountainous regions in mid-latitude high-elevation areas. For example, these results will also have applicability to the entire Sierra Nevada range and adjacent areas.

Results presented herein provide some indication that downscaling and bias correction can alleviate some of the structural errors present in GCM climate results. Evaluation and improvement of transferability of existing bias correction methods between station or gridded measurements and downscaled approaches (statistical and dynamical) are, therefore, required for regional scale hydrologic impact studies. For example, the significance of stationarity assumptions used for downscaling and bias correction methods needs further analysis. Additionally, more study is required on the role of model bias and the neglect of feedbacks among climate variables.

6. ACKNOWLEDGMENT

This material is based upon work supported by the USBR WaterSmart program (#R11Ap81455) and the Desert Research Institute (DRI). We also acknowledge the modeling groups for making their model output available for analysis: the Program for Climate Model Diagnosis and Intercomparison (PCMDI) for collecting and archiving this data and the WCRP's Working Group on Coupled Modelling (WGCM) for organizing the model data analysis activity and BCCA for their downscaling efforts. The second author of this paper was supported by the USGS Groundwater Resources Program through the Office Of Groundwater.

7. REFERENCES

Adler, Robert F., and Coauthors, 2003: The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979–Present). J. Hydrometeor, 4, 1147–1167. doi: http://dx.doi.org/10.1175/1525-7541(2003)004<1147:TVGPCP>2.0.CO;2

Brekke, Levi, 2013, Bridget L. Thrasher, Edwin P. Maurer, Tom Pruitt, 2013: Downscaled CMIP3 and CMIP5 Climate Projections; http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/techmemo/downscaled_climate.pdf

De Angelis, Anthony M., Anthony J. Broccoli, Steven G. Decker, 2013: A Comparison of CMIP3 Simulations of Precipitation over North America with Observations: Daily Statistics and Circulation Features Accompanying Extreme Events. J. Climate, 26, 3209–3230. doi: http://dx.doi.org/10.1175/JCLI-D-12-00374.1

DeFlorio, M. J., D. W. Pierce, D. R. Cayan, A. J. Miller, 2013: Western U.S. Extreme Precipitation Events and Their Relation to ENSO and PDO in CCSM4, Journal of Climate, e-View doi: http://dx.doi.org/10.1175/JCLI-D-12-00257.1

Geil, K. L., Y. L. Serra and X. Zeng, 2013: Assessment of CMIP5 Model Simulation of the North American Monsoon System. J. Climate, accepted.

Hadley, O. L., Corrigan, C. E., Kirchstetter, T. W., Cliff, S. S., & Ramanathan, V., 2010: Measured black carbon deposition on the Sierra Nevada snow pack and implication for snow pack retreat. Atmospheric Chemistry and Physics,10 (15), 7505-7513.

Huntington, J.L. and R.G. Niswonger, 2012: Role of surface-water and groundwater interactions on projected summertime streamflow in snow dominated regions: An integrated modeling approach, Water Resources Research, 48, W11524, doi:10.1029/2012WR012319.

Knutti, R., G. Abramowitz, M. Collins, V. Eyring, P.J. Gleckler, B. Hewitson, and L. Mearns, 2010: Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections. In: Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combining Multi Model Climate Projections [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, and P.M. Midgley (eds.)]. IPCC Working Group I Technical Support Unit, University of Bern, Bern, Switzerland.

Leavesley, G.H., and Stannard, L.G., 1995: The precipitation-runoff modeling system—PRMS, in Singh, V.P., ed., Computer Models of Watershed Hydrology: Highlands Ranch, Colo., Water Resources Publications, p. 281-310.

Liang, Xin-Zhong, Jinhong Zhu, Kenneth E. Kunkel, Mingfang Ting, Julian X. L. Wang, 2008: Do CGCMs Simulate the North American Monsoon Precipitation Seasonal–Interannual Variability?. J. Climate, 21, 4424–4448.doi: http://dx.doi.org/10.1175/2008JCLI2174.1

Maloney, E. and co-authors, 2012: North American Regional Climate in CMIP5 Experiments: Part II: Assessment of 21st Century Projections. J. Climate. Manuscript in preparation.

Maraun, D., 2013: Bias Correction, Quantile Mapping, and Downscaling: Revisiting the Inflation Issue. J. Climate, 26, 2137–2143. doi: http://dx.doi.org/10.1175/JCLI-D-12-00821.1

Markstrom, S.L., Niswonger, R.G., Regan, R.S., Prudic, D.E., and Barlow, P.M., 2008: GSFLOW—Coupled ground-water and surface-water flow model based on the integration of the Precipitation-Runoff Modeling System (PRMS) and the Modular Ground-Water Flow Model (MODFLOW-2005): U.S. Geological Survey Techniques and Methods 6-D1, 240 p.

Maurer, E.P., H.G. Hidalgo, T. Das, M.D. Dettinger, and D.R. Cayan, 2010: The utility of daily large-scale climate data in the assessment of climate change impacts on daily streamflow in California, Hydrology and Earth System Sciences, 14, 1125-1138, doi:10.5194/hess-14-1125-2010.

Mearns, Linda O., and Coauthors, 2012: The North American Regional Climate Change Assessment Program: Overview of Phase I Results. Bull. Amer. Meteor. Soc., 93, 1337–1362. doi: http://dx.doi.org/10.1175/BAMS-D-11-00223.1

Meehl, G. A., C. Covey, T. Delworth, M. Latif, B. McAvaney, J. F. B. Mitchell, R. J. Stouffer, and K. E. Taylor, 2007: The WCRP CMIP3 multi-model dataset: A new era in climate change research, Bulletin of the American Meteorological Society, 88, 1383-1394. DOI: 10.1175/BAMS-88-9-1383

Mejia, J. F., Huntington, J., Hatchett, B., Koracin, D. and Niswonger, R. G., 2012: Linking Global Climate Models to an Integrated Hydrologic Model: Using an Individual Station Downscaling Approach. Journal of Contemporary Water Research & Education, 147: 17–27. doi: 10.1111/j.1936-704X.2012.03100.x

Mejia, J.F., Koračin1, D, and E.M. Wilcox, 2014: Effect of Coupled GCM SST Biases on Simulated Climate of the Western U.S., Submitted J. of Climate.

Mosier, T. M., Hill, D. F. and Sharp, K. V. (2013), 30-Arcsecond monthly climate surfaces with global land coverage. Int. J. Climatol.. doi: 10.1002/joc.3829

Niswonger, R.G., Panday, Sorab, and Ibaraki, Motomu, 2011: MODFLOW-NWT, A Newton formulation for MODFLOW-2005: U.S. Geological Survey Techniques and Methods 6–A37, 44 p.

Pierce DW, Barnett, T.P., Hidalgo, H., Das, T., Bonfils, C., Santer, B., Bala, G., Dettinger, M., Cayan, D., Mirin, A, Wood, A., and Nozawa, T., 2008: Attribution of declining western U.S. snowpack to human effects. J. of Climate, 21: 6425-6444.

Saha, S., and Coauthors, 2010: The NCEP Climate Forecast System Reanalysis. Bull. Amer. Meteor. Soc. 91: 1015-1057.

Sheffield, J., et al., 2012: North American Climate in CMIP5 Experiments. Part I: Evaluation of 20th Century Continental and Regional Climatology. J. Climate, submitted.

Stewart I, Cayan, D. R. ,and Dettinger, M. 2005. Changes toward earlier streamflow timing across western North America. Jour. Clim. 18: 1136-1155.

Stott, Peter A.and Chris E. Forest, 2007: Ensemble climate predictions using climate models and observational constraints, Phil. Trans. R. Soc. A, 365, 2029–2052, doi:10.1098/rsta.2007.2075

Taylor, K.E., R.J. Stouffer, G.A. Meehl, 2012: An Overview of CMIP5 and the experiment design." Bull. Amer. Meteor. Soc., 93, 485-498, doi:10.1175/BAMS-D-11-00094.1.

Thrasher B, Xiong J, Wang W, Melton F, Michaelis A, et al., 2013. Downscaled climate projections suitable for resource management. Eos Trans AGU 94: 321–323.doi: 10.1002/2013eo370002

Willmott, C. J., and K. Matsuura, 2001: Terrestrial air temperature and precipitation: Monthly and annual time series (1950–1999) Version 1.02. [Available online at http://climate.geog.udel.edu/~climate.

Wood, A. W., L. R. Leung, V. Sridhar and D. P. Lettenmaier, 2004: Hydrologic Implications of Dynamical and Statistical Approaches to Downscaling Climate Model Outputs, Climatic Change 62: 189–216, 2004.