Utility of Gridded Observations for Statistical Bias-Correction of Climate Model Outputs and its Hydrologic Implication over West Central Florida

기후 모델 결과의 통계적 오차 보정과 수문 모델링 적용을 위한 격자 단위 자료의 유용성 평가

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ABSTRACT

강우의 관측망 확장과 위성 자료 및 기후 모델을 이용한 격자 단위자료가 개발 및 보급됨에 따라 다양한 자료의 분야별 활용성에 대한 연구의 필요성이 제기되고 있다. 본 연구에서는 지역 기후 모델 산출물의 오차 보정을 위한 격자 관측자료의 활용성을 평가하였다. 또한 통합 분포형 수문모델을 이용하여, 보정한 기후모델 결과의 수문 모의를 위한 기후 입력 자료로써의 적합성을 검토하였다. 보정된 결과는 각 관측자료의 월별 평균 강우량과 공간 분포를 비교적 잘 재현하였다. 한편 연강우량 시계열에 있어 그 양상은 잘 재현된 가운데 보정되지 않은 오차를 일부 포함하는 것으로 나타났다. 이는 점 관측자료로부터 추정된 시험 지역내 172개 소유역에 대한 일평균 강우량 자료와 비교해 볼 때 관측자료의 형식이나 정확성보다 기후모델의 불확실성에 기인하는 것으로 판단된다. 수문 모의 결과, 격자 자료를 이용하여 보정한 강우 입력자료는 수문 모델의 검보정에 이용된 소유역 단위 강우 자료를 이용한 결과에 상응하는 활용성을 보여주었다. 또한 강우의 공간 분포를 고려하지 않고, 시험유역 전체에 대한 평균 강우량을 입력 자료로 이용한 결과를 통해 기후 자료의 공간 분포와 관측 밀도의 중요성을 확인하였다.

Keywords: Regional climate model (RCM); bias-correction; gridded observation; hydrologic simulation; integrated hydrologic model (IHM)

1. INTRODUCTION

General circulation models (GCMs) have been considered robust tools to develop climate scenarios for impact assessments (Karl and Trenberth, 2003) as climate modelers endeavor to improve GCM skill by incorporating more aspects of the complexities of the global atmospheric system. However, GCMs have also been considered to be insufficient for further applications (e.g., used for hydrologic and agricultural modeling) especially at regional scales because of deficiencies of coarse resolution and physical uncertainty (Dibike and Coulibaly, 2005; Giorgi et al., 2001).

Numerous researchers have pointed out that downscaling and bias-correction are essential processes to employ

GCMs for regional applications (McGregor, 1997; Fowler et al., 2007). By themselves, GCMs have significant limitations in reproducing regional climate and meteorological variables from GCMs are commonly subject to systematic errors (Graham et al., 2007). Dynamical downscaling of GCMs using Regional Climate Models (RCMs) propagate the errors from GCMs by using biased GCM outputs as initial and boundary conditions; thus bias-correction using historic observations is typically necessary (Hwang et al., 2011; Murphy, 1999; Wood et al., 2004). It should be noted that despite the deficiencies, dynamical downscaling is a matter of great interest in climate research because RCMs are not limited by the mathematical assumptions inherent to statistical downscaling and RCMs have often been found to accurately reproduce local climatology. However, RCMs require sufficient care in their application since model performance can vary by region and season due to different physical configurations and parameterizations (Fowler et al., 2007).

For downscaling and bias-correction, various types of observations can be used according to the purpose of the

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study. The inconsistency between the spatio-temporal resolution of observations and model output can limit the effectiveness of downscaled and bias-corrected model output. Raw RCM results are often bias-corrected using point observations despite the discord of resolutions. When applicable models (e.g., hydrologic model or crop model) require point/basin inputs, bias-correction with the available observations used for model calibration or verification would provide the direct inputs for the models.

The availability and quality of meteorological data varies from location to location and is often sparse in many regions. The spatial distributions of available observations have been found to be inadequate to support efficient hydrologic modeling in some cases (Elder et al., 2008). To cope with this limitation much effort has been taken to generate estimates of observational meteorological data throughout the United States (especially precipitation and temperature) through national projects (e.g., GEWEX (Global Energy and Water cycle Experiment) Continental-Scale International Project (GCIP)). Therefore it is worthwhile to evaluate the utility of various available observations (e.g., point, basin, and gridded data) for bias correction.

Hwang et al. (2011) applied the MM5 (the Pennsylvania State University (PSU)-National Center for Atmospheric Research (NCAR) Fifth-Generation Mesoscale regional climate Model; Grell et al., 1994) model and bias-corrected precipitation predictions using available point observations over west central Florida. They evaluated dynamically downscaled and bias-corrected reanalysis data at each station and found good agreement between results and observations. In addition, the errors (for precipitation timing and temporal variability) in bias-corrected MM5 output and its hydrologic implications were discussed in detail by Hwang et al. (2012).

The goal of this study was to investigate the utility of available observations at different scales for bias-correction of RCM outputs and to evaluate the accuracy of surface hydrologic predictions (streamflow and springflow) produced using the bias-corrected MM5 outputs to drive the Integrated Hydrologic Model (IHM). This study bias-corrected the results of Hwang et al. (2011) from 1989 to 2006 using basin-based areal averaged observations and gridded precipitation observations from Maurer et al. (2002) available

over the United States. Finally, the IHM, developed for the regional water supply system by Tampa Bay Water, was run using each bias-corrected climate data to examine the hydrologic implications of different types of meteorological observations. In addition to the bias-corrected data, spatially averaged observed precipitation estimates over the model domain (i.e., daily spatial average of the basin precipitation time series) was used to drive the IHM model to evaluate the importance of accurately representing the spatial variability of precipitation.

II. METHODS AND MATERIALS

1. Study Area

The hydrologic model domain defined in this study was bordered by the Gulf of Mexico, USA and inland groundwater flow lines (Fig. 1). The area is located in the west central Florida region (i.e., Tampa Bay region) and extends

Fig. 1 Map depicting the study area, model basin configuration, and location of hydrologic target stations. Solid and dashed grids represent grid configuration and resolution of MM5 and G obs., respectively

to the eastern boundary of Southwest Florida Water Management District (SWFWMD). Tampa Bay is a large, natural harbor and estuary along the Gulf of Mexico on the west central coast of Florida. The aquifer system in this area consists of both areas of semi-confined Floridan aquifer recharged by means of leakage from the overlying surficial aquifer and areas where the aquifer is unconfined and receives direct recharge from vadose zone infiltration. West central Florida includes karst topography and thus rapid groundwater discharge through the springs (Florea, 2008). The complexity of the geology and its unique properties over the region impede accurate hydrologic modeling. In the study area, average annual rainfall for the study period from 1989 to 2006 was 1295 mm. In general, evapotranspiration (ET) consumes the largest portion of precipitation, approximately 70 % of annual precipitation. A variety of land types cover the study area, including urban (22 %), grassland (25 %), forest (15 %), agricultural (6 %), mined land (7 %), water (4 %), and wetlands (21 %). Because this area is a dominantly rainfall-driven system and has a humid subtropical climate, an accurate prediction of climate forcing and change of climate variability have been important issues in time-scale varying water planning.

2. Models and Data

A. Mesoscale regional climate model

Many researchers have applied MM5 to a variety of regions for both retrospective and future climate studies (e.g., Colle et al., 1999; Zhong et al., 2005). A review of the MM5 model (e.g., physical schemes and domain configuration) and its applications over the U.S. were provided by Hwang et al. (2011). This study employed the 9×9 km² grid MM5 precipitation, maximum temperature and minimum temperatures predictions from Hwang et al (2011).

B. Integrated Hydrologic Model (IHM)

The Tampa Bay region has a strong interaction among the hydrologic components (e.g., streams, wetlands, lakes, and aquifers) (Geurink and Basso 2011). In order to model the complex system, Tampa Bay Water and SWFWMD developed an integrated surface/subsurface hydrologic model coupling the EPA Hydrologic Simulation Program-Fortran

(HSPF; Bicknell et al., 2001) and the USGS MODFLOW96 (Harbaugh and McDonald, 1996) for surface water and groundwater modeling, respectively (Geurink et al., 2006). IHM provides reasonable simulation of the complex interactions of surface water and groundwater features in shallow water-table environments. The model can be characterized as a deterministic, semi-distributed-parameter, semi-implicit real-time formulation, with variable time steps and spatial discretization (Ross et al., 2004). The IHM model was calibrated and verified for the Northern Tampa Bay Region (called the Integrated Northern Tampa Bay model) using hydrologic observations from 1989 to 2006 (Geurink and Basso 2011). The north and east boundaries of the study domain follow Floridan aquifer flow lines and the southern boundary is placed far enough from the area of interest for this study to minimize the influence of the general head boundary (Geurink et al., 2006; Hwang et al., 2012). IHM model domain is shown in Fig. 1.

C. Data used in the study

This study chose two streamflow stations (Alafia River and Hillsborough River, Fig. 1) to evaluate hydrologic responses, based on their importance to water supply operations/management over the study area. Additionally, two springflow stations (Lithia and Weeki Wachee) were also chosen for evaluation because groundwater is a major source of public water supply in Florida and it is directly related to springflow. The stations are located in the northern part and southern part of the domain, respectively. In general Weeki Wachee springflow comes from the unconfined Floridan aquifer and Lithia springflow comes from the semi-confined Floridan aquifer. In the unconfined Floridan aquifer region, spring discharge from the Floridan aquifer near the coastline replaces surface runoff.

Two sets of precipitation data were used for bias-correction of the MM5 predictions focused over the IHM model domain: 1) 172 basin-based areal precipitation data for each model basin used for calibration and verification of the IHM model, 2) 1/8 degree ($\sim 12 \times 12$ km²) gridded observations of precipitation over the west central Florida from 1989 to 1999 (Maurer et al., 2002). The areal daily precipitation data for each basin were generated from available station observations (> 300 stations over the

model domain) using Thiessen polygons and area-weighted method by Geurink and Basso (2011). The daily gridded observations (daily and monthly precipitation, maximum, minimum, and average temperature, and wind speed) at 1/8 degree spatial resolution are archived in netCDF format and available at http://hydro.engr.scu.edu/files/gridded_obs/daily/ncfiles/. These products are available over the entire U.S. Approximately 100 grids of the gridded data covered entire study domain including 172 basins (Fig. 1). This paper refers basin-based areal estimates and gridded data described above to B obs. (Basin-based observation) and G obs. (Gridded observation), respectively.

3. Methodology

Based on obtained data, this study ran IHM using B obs., MM5 results that were bias-corrected using B obs. (BC_B MM5), and MM5 results that were bias-corrected using G obs. and then point-kriged onto the basin centroids (BC_G MM5) as input of IHM for hydrologic application. The framework of the study was schematically represented in Fig. 2.

Fig. 2 Schematic framework of the study

A. Statistical bias-correction

This research used a quantile mapping approach for

bias-correction using the observed and simulated cumulative distribution functions (CDFs). The brief procedure is as follows: 1) CDFs of daily observations and simulations at each basin or grid were generated; 2) the percentile of each forecasted value was mapped to the CDF of observations using the same percentile; 3) the second step was repeated for each simulated value. The bias-correction procedure was conducted independently for each calendar month.

Maximum and minimum daily temperature predictions (Tmax and Tmin) were also bias-corrected for each calendar month using a similar approach as done for precipitation, but we bias-corrected mean temperature and then used the corresponding Tmax and Tmin for each corrected mean temperature. This approach avoids unrealistic results (e.g., corrected Tmin could occasionally be greater than Tmax) and also allow the bias-corrected results to preserve observed daily temperature range (Tmax-Tmin). This paper does not discuss bias-corrected temperature results because the study is focusing on differences among precipitation data assuming that the biases of temperature is not significantly affecting hydrologic responses and biases in temperature are small enough for reasonable hydrologic simulation.

B. Kriging process

IHM requires basin-based areal precipitation data as input because the model discretizes the surface-water domain into 172 basins as shown in Fig. 1. For this reason the use of gridded observations for bias-correction at each grid require post-processing to estimate areal precipitation for basins to be directly used as input to IHM. MM5 precipitation that was bias-corrected using gridded observations was interpolated onto each basin centroid using point-kriging to generate basin-based inputs for the model. This approach was introduced by Hwang et al. (2011) who showed that kriging bias-corrected RCM predictions onto point locations reproduced observed rainfall with lower errors comparing to the RCM predictions bias corrected at individual points.

C. Error statistics

This study quantified the accuracy of bias-corrected

climate predictions (i.e., daily, monthly and annual total precipitation) and hydrologic model simulations (i.e. daily and monthly streamflow and springflow discharge), using the mean error (ME) and the root mean square error (RMSE); the coefficient of determination R^2 and the coefficient of efficiency E (Nash and Sutcliffe, 1970) were also used to evaluate hydrologic model performance. It should be noted that in this study, hydrologic simulation results using MM5 predictions were evaluated by comparison to calibrated IHM results rather than measurements to focus on the hydrologic implications of differences in climatic forcing data. Whereas error statistics for calibrated results were calculated using observations, error statistics for other simulations were calculated based on calibrated results to quantify differences between the simulated and calibrated IHM results.

IV. RESULTS AND DISCUSSION

1. Bias-Corrected MM5 Results

Bias-corrected MM5 precipitation predictions were evaluated by comparison to observed data. Fig. 3 compares the mean monthly precipitation and annual total precipitation over the study period from 1989 to 2005 for B obs., G obs., BC_B MM5, and BC_G MM5. We found that while BC_B MM5 mean monthly predictions closely matched the

observations, BC_G obs. showed comparable results but with slightly higher monthly mean errors (see Table 1). This is likely due to the fact that sub-basin based observations are available for the entire study period, but gridded observations only to 1999 were used in the study. Using observations that coincide exactly with the simulation

Table 1 The mean monthly and annual averaged precipitation of basin and gridded observations and mean error (ME) of mean monthly MM5 precipitation predictions

Units: mm	Basin obs. (89'~06')	Gridded obs. (89'~99')	BC_B MM5	BC_G MM5
	Monthly precip.		Mean error	
Jan	65.68	63.29	1.16	3.22
Feb	69.91	81.22	-1.65	0.26
Mar	71.69	93.05	3.06	1.53
Apr	61.74	63.71	-1.76	-5.02
May	53.02	89.35	-0.73	-10.66
Jun	202.75	173.40	-6.57	-13.86
Jul	192.90	185.86	-2.39	5.81
Aug	182.60	184.79	2.33	6.80
Sep	172.26	170.18	8.59	13.94
Oct	69.10	79.91	-3.37	-8.35
Nov	41.13	51.87	6.65	8.12
Dec	71.18	57.91	-2.39	4.35
avg.	104.50	107.88	0.24	0.51
Annual total precipitation				
Avg.	1272.82	1302.39	1255.26	1304.56
Stdev.	213.82	204.95	323.85	247.46

Fig. 3 Comparison of (a) the mean monthly precipitation and (b) annual total precipitation time series for IHM basin observations (B obs.), gridded observations (G obs., available through 1999), bias-corrected MM5 results using B obs. (BC_B MM5), and bias-corrected MM5 using G obs. (BC_G MM5). The bright and dark gray zones represent total data range and 5 to 95 percentile of B obs. over the 172 sub-basins

period would remove most of the temporal mean bias. In this paper however, we used all available observations for bias correction because this approach is analogous to what would be appropriate when GCM predictions/forecasts are employed for simulation periods that do not necessarily coincide with the period of record. When the period of record used for bias correction and the simulation period do not exactly coincide, small temporal biases can be expected due to differences in data over the averaging intervals. Hwang et al., (2011 and 2012) have previously shown that while raw MM5 results tend to overestimate the monthly precipitation over the study region, the bias-corrected mean daily and monthly predictions accurately

reproduce the point observations that were used for bias-correction.

The spatial patterns of mean monthly precipitation for dry (October through January and February through May), and wet seasons (June through September) over the domain were mapped in Fig. 4. Generally, the results indicate that bias-correction of MM5 using point observations and gridded observations reproduced the observed mean spatial structure of B obs. and G obs. precipitation fields, respectively. However, the spatial pattern of the gridded data showed some differences from the spatial pattern of the basin-based data especially for wet season months. This is due to the different period of record for the gridded

Fig. 4 Spatial distribution of mean monthly precipitation for dry (first row; Oct., Nov., Dec., and Jan., second row; Feb., Mar., Apr., and May), and wet seasons (bottom row; Jun., Jul., Aug., and Sep.) for IHM sub-basin observations (B obs. (1989~2006), first column), bias-corrected MM5 results using B obs. (BC_P MM5 (1989~2006), second column), gridded observations (G obs. (1950~1999), third column), and bias-corrected MM5 using G obs. (BC_G MM5 (1989~2006), forth column). Units of precipitation are mm

observations (1950 to 1999) compared to MM5 simulation (1986 to 2008) and the comparatively coarse resolution of the gridded data (12 km²). As expected, the mean precipitation fields of G obs. were spatially over-correlated comparing to those of B obs. as shown in Fig. 4 likely due to the coarser grid spacing of G obs. than basin density.

2. IHM Simulation Results

Error statistics, the mean monthly discharge and the cumulative distribution function (CDF) of daily streamflow were used to evaluate streamflow results. Table 2 summarizes model error and performance scores for the daily and monthly streamflow and springflow simulations for the target stations. The IHM model results using BC_G MM5 precipitation showed larger underestimation of total daily and monthly streamflow volume (larger negative ME) but slightly smaller error in capturing temporal variability (smaller RMSE and larger E) at the target stations compared to the results using BC_B MM5.

Fig. 5 compares mean monthly streamflow volume predicted by the climate input datasets at the target stations. At both locations mean monthly streamflow volume was similar for all predictions during the January through May dry season, but both the MM5 predictions and the spatially averaged rainfall significantly underestimated flow during the early portion of the wet season (June–August) compared to the calibrated results. The BC_B MM5 results peak higher than the calibration result in the wet season (see Fig. 5 and Table 2) mainly due to the occasional over-estimation of precipitation during the wet season. The streamflow simulation errors tend to exponentially increase as the annual total precipitation increases and, increase approximately linearly with mean RMSE of daily precipitation (Fig. 6). Additionally, Fig. 7 shows the total water budget over the domain by major category for each of the climate inputs. The water budget comparison shows that underestimated total streamflow using spatially averaged precipitation and BC_G MM5 were associated with over-estimated total ET over the domain.

The BC_B MM5 and BC_G MM5 climate datasets showed

Table 2 Error statistics for daily and monthly streamflow and springflow simulations using basin precipitation observations, MM5 predictions (i.e., BC_B MM5 and BC_G MM5), and spatially averaged precipitation observations. Units for ME and RMSE are m³/s

Station name	Error statistics	Daily results evaluation				Monthly results evaluation			
		Precipitation scenarios							
		vs. Obs.	vs. calibrated IHM results			vs. Obs.	vs. calibrated IHM results		
		Calibrated	BC_B MM5	BC_G MM5	Avg. precip.	Calibrated	BC_B MM5	BC_G MM5	Avg. precip.
Alafia River at Lithia	ME	− 0.36	− 0.94	− 1.29	− 1.03	− 0.36	− 0.92	− 1.27	− 1.03
	RMSE	7.65	17.34	15.06	8.73	3.21	9.46	8.49	4.69
	E	0.69	− 0.20	0.10	0.70	0.89	0.14	0.31	0.79
	R ²	0.77	0.22	0.21	0.72	0.94	0.39	0.37	0.81
Hillsborough River near Zephyrhills	ME	0.19	− 0.56	− 0.76	− 0.90	0.19	− 0.55	− 0.76	− 0.89
	RMSE	2.84	11.48	9.91	3.86	1.44	6.38	6.21	2.47
	E	0.94	0.04	0.29	0.89	0.97	0.48	0.51	0.92
	R ²	0.94	0.33	0.34	0.90	0.98	0.54	0.52	0.93
Weeki Wachee spring	ME	− 0.15	− 0.07	0.06	− 0.47	− 0.15	− 0.07	− 0.08	− 0.47
	RMSE	0.45	1.27	1.19	0.61	0.43	1.26	1.11	0.60
	E	0.80	− 0.60	− 0.40	0.64	0.81	− 0.58	− 0.23	0.64
	R ²	0.83	0.12	0.12	0.87	0.84	0.11	0.13	0.77
Lithia spring	ME	0.01	− 0.02	− 0.02	− 0.05	0.01	− 0.07	− 0.05	− 0.05
	RMSE	0.24	0.19	0.17	0.09	0.23	0.21	0.19	0.09
	E	0.45	0.68	0.72	0.93	0.49	0.58	0.68	0.92
	R ²	0.50	0.66	0.68	0.94	0.55	0.44	0.42	0.55

no significant differences in terms of springflow simulation (Table 2 and Fig. 5). Interestingly, BC_G MM5 climate inputs provided slightly better results for springflow stations. This result may indicate that mean monthly springflow could be reasonably predicted using gridded observations for bias-correction in areas where there are significant surface-groundwater interactions because the BC_G MM5

method predicted smaller spatial errors of climate inputs and thus smaller timing of errors as well when compared to BC_B MM5.

Fig. 8 shows the CDFs for each climate input dataset over the ranges of streamflow and springflow. Exceedence probability analysis (especially for streamflow) was significant for water resources decisions at target stations.

Fig. 5 Comparison of simulated mean monthly streamflow and springflow for each target station

Fig. 6 The relationship between the mean RMSE of streamflow simulations over the model domain and (a) annual precipitation predictions and (b) mean RMSE of daily precipitation predictions for each year

For all stations deviations between the various climate dataset CDFs were found, with the average precipitation case over-predicting streamflow exceedences in the ranges of interest (allowable for extraction) for streamflow locations. At both the Hillsborough River and the Alafia River locations the BC_B MM5 dataset over-predicted the CDF values (i.e. under-predicted exceedence probabilities) over the entire range of interest especially at the lower limit for streamflow withdrawal, implying more low flow events and less surface water availability for public supply than the calibrated values would indicate. On the other hand, the BC_G MM5 matched the calibrated streamflow exceedence probabilities well throughout the flow range of interest at the Hillsborough River, but slightly over-estimated the CDF value (under-estimated exceedence probabilities) for flows between 7 m³/s and 30 m³/s at the Alafia River.

Whereas the MM5 daily precipitation CDF was corrected to be identical to the daily CDF of observed precipitation through the bias correction process, and as a result mean

monthly precipitation over the study period were virtually identical, streamflow responses evaluated in this study

Fig. 7 Comparison of the total water budget over the domain by major category for calibrated results, spatially averaged, and MM5 climate scenarios

Fig. 8 Comparison of cumulative distribution function (CDF) of daily streamflow (left column) and monthly springflow (right column) for calibrated results and the simulations with precipitation scenarios. The arrow ranges on the figures indicate the permitted thresholds range for streamflow withdrawals

indicate that reproducing more detailed precipitation characteristics (i.e. actual annual totals, seasonal distribution, inter-event duration, precipitation intensity, and spatial distribution) is important to accurately capture both the monthly mean streamflow and the daily streamflow CDF. Furthermore, simulation accuracy of the temporal mean streamflow condition does not imply that the variability, change, and impacts of extreme events that are important for hydrologic applications have been adequately predicted.

For the spatially averaged observed rainfall data, the timing of peak streamflow was aligned with calibration results for all locations. Using the spatially averaged precipitation, which preserved the observed temporal precipitation patterns, also underestimates average daily and monthly streamflow volumes at the target stations. The decrease in streamflow was likely due to lower spatial variability (see Fig. 4) and higher frequency of small precipitation events (greater than 0 but less than 10 mm/day) resulting in higher ET (Fig. 7) and thus lower runoff. The simulations using BC_B MM5 predictions more accurately reproduced calibrated ET and total streamflow leaving the domain. However the temporal trend in streamflow response was better simulated with the spatially homogeneous observed precipitation input compared to both MM5 predictions (as measured by reduced RMSE and increased E). This indicates that the timing of precipitation and antecedent moisture conditions is important factors in predicting the timing of streamflow.

The spatially-averaged uniform precipitation generally resulted in underestimation of the mean monthly springflow (Fig. 5) and overestimation of the frequency of lower flow (Fig. 8) at the target stations compared to calibrated results most likely due to increased ET (Fig. 7) and strong interaction between surface and subsurface hydrologic system. The flow predictions with bias-corrected MM5 climate inputs (i.e., BC_B MM5 and BC_G MM5) also underestimated calibrated flow for all target stations, although the results were better than for spatially averaged precipitation. This indicates that for hydrologic applications, preserving the spatial variability of climate inputs is at least as important as preserving the spatially averaged temporal patterns.

V. CONCLUSIONS

In this research, basin-based areal observations and gridded observations were applied to bias-correct precipitation predictions from the MM5 mesoscale climate model in west central Florida, USA. The goal of the study was to investigate the utility of available observation data (but at different spatial resolutions) for bias-correction and its hydrologic implications. Simulated hydrologic responses for streamflow, and spring discharge were examined and compared for climate input datasets including observed data and two forms of dynamically downscaled and bias-corrected reanalysis data using MM5. The Integrated Hydrologic Model (IHM) was used as the hydrologic simulator to deterministically predict hydrologic responses for each climate input dataset from 1989 to 2005. Spatially averaged observed precipitation over the model domain was used to evaluate the importance of accurately representing the spatial variability of precipitation. Bias-corrected precipitation predictions from MM5 were compared to observed data used to calibrate the IHM model. Streamflow and springflow simulations using the MM5 predictions and spatially averaged precipitation were compared to calibrated hydrologic results for the target stations.

The results showed that biases in the precipitation estimates were effectively removed by the bias-correction process using both datasets (i.e., B obs. and G obs.). The monthly mean and annual total precipitation time series for gridded observations were reliably consistent with those of basin-based observations. While the bias-corrected monthly mean precipitation was accurately matched to the observed results that were used for bias-correction, the temporal trend of observed annual precipitation were reproduced by bias-corrected climate predictions but with some biases. The observed cumulative distribution functions for daily precipitation, mean monthly precipitation and the spatial pattern of mean seasonal precipitation were well reproduced by bias-corrected predictions.

Based on the comparison of monthly streamflow and streamflow CDFs, IHM results using MM5 precipitation bias-corrected using gridded observations (BC_G MM5) showed comparative results to those of bias-corrected

results using basin-based observations (BC_B MM5). Both MM5 predictions appeared to have some errors compared to either observations or calibrated results. In particular, for springflow stations BC_G MM5 climate inputs provided slightly better results indicating that mean monthly springflow could be reasonably predicted using gridded observations for bias-correction. Furthermore the BC_G MM5 successfully reproduced the calibrated streamflow exceedence probabilities around the flow range of interest for water diversion.

The spatially averaged observations accurately reproduced the annual cycle of mean monthly streamflow and springflow. However, significant underestimations of streamflow and springflow, especially for the wet season, were found and were likely due to lower spatial variability and higher frequency of small precipitation events resulting in higher ET loss. These results indicate that for hydrologic applications, preserving the spatial variability of climate inputs is at least as important as preserving the spatially averaged temporal patterns.

Overall, this study demonstrated that Maurer et al.'s gridded observations would be usable for statistical adjustment of climate model output for hydrologic modeling applications. Additionally, the accurately in reproducing spatial variability/correlation of precipitation is important when used as input for a physically distributed hydrologic model and for rainfall-driven regions with spatially variable climate characteristics.

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