TAMPA BAY WATER CLIMATE VARIABILITY AND PROJECTIONS ON REGIONAL WATER SUPPLIES PROJECT
TECHNICAL REPORT

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INTRODUCTION

Rainfall and temperature variability at multiple time and space scales profoundly affect both water demand fluctuations and supply availability. In support of effective water resource management and efficient groundwater/surface water source rotation that enhances system reliability, Tampa Bay Water is seeking to develop more robust climate forecasts and simulation techniques. In 2007, Tampa Bay Water initiated a project with University of Florida to assess the usefulness of various climate indices, climate forecasts and climate model predictions as input into the agency's hydrologic models.

Tampa Bay Water uses a variety of hydrologic and statistical models as part of their effort at risk-based management of short- and intermediate-term operations and long-range planning. The operational models include the Short Term Demand Forecast Model (STDF), surface water artificial neural network models (SWANN), and Groundwater ANN Models (GWANN). The planning models include the Long Term Demand Forecasting System (LTDFS), the Flow Modeling System (FMS), and the Integrated Hydrologic Model/ Integrated Northern Tampa Bay Application (IHM/INTB). These models relate inputs, such as rainfall, temperature, pumping or diversions, to outputs such as water levels, storage levels or flows. Rainfall is the most important input for all of these models. For deterministic hydrologic models (e.g. IHM/INTB) rainfall is needed as a highly spatially and temporally distributed product. On the other hand statistical models (e.g. GWANN and FMS) typically require a spatially or temporally aggregated rainfall forecasts, or utilize historic rainfall recorded at specific locations and times.

PHASE I: APRIL 2007- DECEMBER 2011

Task 1: Assess benefits of incorporating rainfall forecasts into Tampa Bay Water's Ground Water Artificial Neural Network (GWANN) set of models

Results: The GWANN models currently generate 1-week to 4-week forecasts of groundwater levels at 58 monitoring wells in the Tampa Bay region using recent observed rainfall, pumping and groundwater levels, and a rainfall forecast that assumes that the same rainfall observed in the week prior to the forecast will occur over the next 4 weeks. Results of this effort showed that overall the GWANN models exhibited low sensitivity to rainfall forecast method. Based on the Root mean square error statistic (RMSE) averaged over all 58 monitoring wells, model results for 2006 and 2007 indicated that using a perfect rainfall forecast, using the long-term median weekly rainfall as the forecast for each of the next 4 weeks, and using the long-term median 4-week rainfall split equally over the next 4 weeks, all modestly reduced model prediction error over using the current method. However, the Theils' U statistic averaged over all 58 monitoring wells showed that the naïve model (using last week's groundwater level as the forecast for future groundwater levels) performed better than GWANN for predicting groundwater levels in both 2006 and 2007 regardless of which rainfall forecast was used. These investigations indicated that, in its present form, improved rainfall forecasts will not significantly improve the GWANN model performance, regardless of forecast method. Structural changes to the GWANN models, such as retraining the neural networks using forecast rainfall or other forecast climate indices; or extending the forecast/planning horizon beyond four weeks may be necessary before improved rainfall forecasts can reduce model prediction errors.

Complete details on the results of this task were provided in the Interim Report submitted to Tampa Bay Water in October 2008.

Task 2: Assess benefits of incorporating rainfall forecasts into Tampa Bay Water's Surface water flow Modeling System (FMS).

Results: The FMS model currently generates 1-month to 12-month forecasts of surface water flows at 5 locations using recent surface water flow levels, and an internal rainfall forecast based on a historic rainfall patterns at the Plant City rainfall station. Initial FMS model evaluations compared the model performance using its existing rainfall forecast to using 'perfect' monthly rainfall as the forecast. The 90% confidence interval band was reduced by 14% (Bell Shoals) to 48% (De-adjusted S160) when using the perfect rainfall forecast in 2006, and 19% (Bell Shoals) to 64% (Hillsborough River Dam) when using the perfect rainfall forecast in 2007. These results indicated a potential for improving model performance if better rainfall forecasts can be incorporated into the FMS model system.

Complete details on the results of this task were provided in the Interim Report submitted to Tampa Bay Water in October 2008. This effort also resulted in the following peer reviewed publication:

Hwang, S., Martinez, C.J., and T. Asefa. 2012. Assessing the benefits of incorporating rainfall forecasts into monthly flow forecast system of Tampa Bay Water, Florida. Journal of the Korean Society of Agricultural Engineers 54(4): 127-135. doi: 10.5389/KSAE.2012.54.4.127

Task 3: Generate monthly realizations of climate indices from historical data and provide recommendations for incorporating into Tampa Bay Water models.

Results: The goal of this task was to identify climate patterns related to monthly and seasonal rainfall, streamflow, and demand in the Tampa Bay region and to recommend climate indices that could be used to improve forecasts of these variables. As part of this work a review of online climate analysis tools was conducted to evaluate their suitability for use in the Tampa Bay Region.

Lagged linear correlation maps were produced between seasonal mean rainfall, streamflow, and demand with seasonal means of each of three gridded climate variables: sea surface temperatures, sea level pressures, and 500mb geopotential heights. Lagged correlation maps were produced for regional means/totals and for individual stations in order to examine the variability of results. Lagged composite anomaly maps of the gridded climate variables were then created for extreme seasonal hydrologic events (e.g. 10th and 90th percentiles). Based on the patterns found by lagged correlation and composite analyses, indices of each climate variable were identified for further analysis. Each index was evaluated using lagged Pearson's product moment correlation and Spearman's rank correlation of monthly and seasonal values.

The most significant results, in terms of correlation magnitude and persistence, were found with indices of El Niño - Southern Oscillation (ENSO). The Niño 3 and Niño 3.4 sea surface temperature indices and the station-based and reanalysis-based Southern Oscillation Indices (SOI and eqSOI, respectively) were found to show significant and coherent correlations at lead-times up to nine months. The variability of these relationships during different phases of the Atlantic Multidecadal Oscillation (AMO) was then examined. Significant differences were found between different time periods of the AMO, however no clear pattern between phases was found. It is recommended that one of the identified ENSO indices be employed when developing climate-based forecasts. However, it is also recommended that the strength and pattern of the relationship be verified according to the time-period of historical data used to develop forecasts or train models.

Complete details on the results of this task were provided in the Interim Report submitted to Tampa Bay Water in August 2009.

Task 4: Evaluate the ability of the mesoscale regional climate model MM5 to predict precipitation over the Tampa Bay region

Results: This task quantitatively evaluated the ability of the fifth-generation Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5) to reproduce observed spatiotemporal variability of precipitation in the Tampa Bay region over the 1986–2008 period. The National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis data were used as initial and boundary conditions for MM5. Use of the NCEP–NCAR reanalysis data for boundary conditions is advantageous because it removes the confounding factors of potential biases related to retrospective Global Climate Model (GCM) process simulation, and thus provides a more objective measure of the skill of the MM5 downscaling accuracy.

Raw MM5 model results were positively biased; therefore, the raw model precipitation outputs were bias corrected at 53 long-term precipitation stations in the region using the cumulative distribution function (CDF) mapping approach. CDF mapping effectively removed the bias in the mean daily, monthly, and annual precipitation totals and improved the RMSE of these rainfall totals. Observed daily precipitation transition probabilities were also well predicted by the bias-corrected MM5 results. Nevertheless, significant error remained in predicting specific daily, monthly, and annual total time series. After bias correction, MM5 successfully reproduced seasonal geostatistical precipitation patterns, with higher spatial variance of daily precipitation in the wet season and lower spatial variance of daily precipitation in the dry season. Bias-corrected daily precipitation fields were kriged over the study area to produce spatiotemporally distributed precipitation fields over the dense grids needed to drive the IHM/INTB model. Cross validation at the 53 long-term precipitation gauges showed that kriging reproduced observed rainfall with average RMSEs lower than the RMSEs of individually bias-corrected point predictions. Results indicate that although significant error remains in predicting actual daily precipitation at rain gauges, kriging the bias-corrected MM5 predictions over a hydrologic model grid produces distributed precipitation fields with sufficient realism in the daily, seasonal, and interannual patterns to be useful for multidecadal water resource planning in the Tampa Bay region.

Complete details on the results of this task can be found in the following peer-reviewed publication:

Hwang, Syewoon, Wendy Graham, José L. Hernández, Chris Martinez, James W. Jones, Alison Adams, 2011: Quantitative Spatiotemporal Evaluation of Dynamically Downscaled MM5 Precipitation Predictions over the Tampa Bay Region, Florida. J. Hydrometeor, ***12****, 1447–1464. doi: http://dx.doi.org/10.1175/2011JHM1309.1*

Task 5: Evaluate the ability of statistically downscaled GCM retrospective simulations to predict daily precipitation over the Tampa Bay region

Results: There are a number of statistical techniques that downscale coarse climate information from global circulation models (GCM). However, many of them do not reproduce the small-scale spatial variability of precipitation exhibited by the observed meteorological data which can be an important factor for predicting hydrologic response to climatic forcing in the Tampa Bay region. In this task a new downscaling technique (bias-correction and stochastic analog method, BCSA) was developed to produce stochastic realizations of bias-corrected daily GCM precipitation fields that preserve the spatial autocorrelation structure of observed daily precipitation sequences. This approach was designed to reproduce observed spatial and temporal variability as well as mean climatology.

The BCSA method was used to downscale 4 retrospective GCM precipitation predictions (1961 to 1999) over the state of Florida and compared the skill of the method to the results obtained with the commonly used bias-correction and spatial disaggregation (BCSD) approach, bias-correction and constructed analog (BCCA) method, and a modified version of BCSD which reverses the order of spatial disaggregation and bias-correction (SDBC). Spatial and temporal statistics, transition probabilities, wet/dry spell lengths, spatial correlation indices, and variograms for wet (June through September) and dry (October through May) seasons were calculated for each method.

Results showed that (1) BCCA underestimated mean climatology of daily precipitation while the BCSD, SDBC and BCSA methods accurately reproduced it, (2) the BCSD and BCCA methods underestimated temporal variability because of the interpolation and regression schemes used for downscaling and thus, did not reproduce daily precipitation standard deviations, transition probabilities or wet/dry spell lengths as well as the SDBC and BCSA methods, and (3) the BCSD, BCCA and SDBC methods under-estimated spatial variability in precipitation resulting in under-prediction of spatial variance and over-prediction of spatial correlation, whereas the new stochastic technique (BCSA) accurately reproduced observed spatial statistics for both the wet and dry seasons. This task underscored the need to carefully select a downscaling method that reproduces all precipitation characteristics important for the hydrologic system under consideration if local hydrologic impacts of climate variability and change are going to be accurately predicted. For the Tampa Bay Water region, where reproducing small-scale spatiotemporal precipitation variability is important, the BCSA method is recommended for use over the BCSD, BCCA, or SDBC methods.

Complete details on the results of this task can be found in the following peer-reviewed publication:

Hwang, S., and W. Graham, Development and comparative evaluation of a stochastic analog method to downscale daily GCM precipitation, Hydrol. Earth Syst. Sci. Discuss., 10, 2141–2181, doi:10.5194/hessd-10-2141-2013.

Task 6: Evaluate the ability of statistically downscaled GCM retrospective simulations to simulate retrospective streamflow when used to drive the IHM-INTB model

Results: This task applied three statistical downscaling methods: 1) bias-correction and spatial disaggregation at daily time scale (BCSD_daily), 2) a modified version of BCSD which reverses the order of spatial disaggregation and bias-correction (SDBC), and 3) the bias correction and stochastic analog method (BCSA) developed in Task 5) above to downscale retrospective General Circulation Model daily precipitation outputs to the sub-basin scale for west-central Florida. Each downscaled climate input dataset was then used in the IHM-INTB model to examine differences in ability to simulate retrospective streamflow characteristics.

Results showed that the BCSD_daily method consistently underestimated mean streamflow because the highly spatially-correlated small precipitation events produced by this method resulted in overestimation of evapotranspiration. Highly spatially-correlated large precipitation events produced by the SDBC method resulted in overestimation of the standard deviation of wet season daily streamflow and the magnitude/frequency of high streamflow events. BCSA showed better performance than the other methods in reproducing spatiotemporal statistics of daily precipitation and streamflow.

This task demonstrated that differences in statistical downscaling techniques propagate into significant differences in streamflow predictions, and underscored the need to carefully select a downscaling method that reproduces precipitation characteristics important for the hydrologic system under consideration.

Complete details on the results of this task can be found in the following publication that has been submitted for peer review:

Hwang, S., and W. Graham, Hydrologic importance of spatiotemporal variability in statistically downscaled daily GCM precipitation predictions, Journal of the American Water Resources Association, in review, 2013.

PHASE II – JANUARY 2012-DECMBER 2013

Task 1: Assess the utility of dynamically-downscaled regional reanalysis data to predict streamflow in west central Florida using IHM-INTB

Results: This task evaluated the reliability of using dynamically-downscaled, bias-corrected reanalysis data (i.e. regional reanalysis data) to predict streamflow in the Tampa Bay Region using the IHM-INTB model. Four different sets of global reanalysis data (NCEP/NCAR-R1, NCEP-DOE-R2, ERA40, and 20CR) that were previously downscaled using two Regional Climate Models (RCM) (MM5 and the Regional Spectral Model, RSM) were obtained, bias-corrected on a daily basis using the CDF-mapping approach, and used to drive the IHM-INTB model.

All raw dynamically-downscaled reanalysis datasets accurately estimated the annual cycle of daily maximum and minimum temperature, except the NCEP/NCAR R1+MM5 data which consistently underestimated daily maximum temperature. All raw regional reanalysis precipitation data significantly overestimated precipitation, particularly for the dry season. Bias-correction using the CDF-mapping approach effectively removed biases in the temporal mean and standard deviation of both the daily precipitation and temperature predictions. Biases in the mean monthly and mean annual precipitation totals were removed by CDF-mapping on a daily basis, but the standard deviation of the monthly and annual precipitation totals were not accurately reproduced. Furthermore inaccuracies in actual daily precipitation time series aggregated into monthly and annual rainfall total time series that showed significant and temporally persistent errors.

Precipitation timing errors produced by bias-corrected regional reanalysis data were propagated and enhanced by non-linear streamflow generation, groundwater flow and storage processes in the hydrologic model and produced significant errors in both actual and mean daily, monthly and annual streamflow and groundwater level predictions. In general it was determined that the accuracy of the streamflow predictions produced by the bias-corrected downscaled reanalysis data was not sufficient for short term (monthly to annual) decision making, but may be satisfactory for long term (decadeal) planning purposes. Results of this task indicated that similarly bias-corrected dynamically downscaled retrospective and future GCM projections should be suitable for assessing potential hydrologic impacts of future climate change in the Tampa Bay region.

Complete details on the results of this task can be found in the following peer reviewed publications:

Hwang, S., W. Graham, A. Adams, and J. Guerink, Assessment of the utility of dynamically-downscaled regional reanalysis data to predict streamflow in west central Florida using an

integrated hydrologic model, Regional Environmental Change, doi: 10.1007/s10113-013-0406-x, 2013.

Hwang, S., W. Graham, J. Guerink, and A. Adams, Hydrologic implications of errors in bias-corrected regional reanalysis data for west-central Florida, Journal of Hydrology, in review, 2013.

Task 2: Assess potential regional climate change impact on streamflow over Tampa Bay region using retrospective predictions and future projections from the FSU COAPS Land-Atmosphere Regional Ensemble Climate Change Experiment for the Southeast United States at 10-km resolution (CLARREnCE10).

The CLARREnCE10 dataset, http://floridaclimateinstitute.org/resources/data-sets/regional-downscaling, includes retrospective (1969-2000) and future (2039-2070, A2 scenario) predictions from three GCMs that were dynamically downscaled to 10-km resolution using the FSU RSM (see Figure 1). The three GCMs selected by FSU for downscaling were the Community Climate System Model (CCSM), the Hadley Centre Coupled Model, version 3 (HadCM3) and the Geophysical Fluid Dynamics Laboratory GCM (GFDL). Emission scenarios were generated by the Intergovenmental Panel on Climate Change (IPCC) and are described in IPCC Special Reports on Emission Scenarios (IPCC 2000). Scenarios were developed that describe different storylines about possible future social, economic, technological and demographic developments. The emission scenarios have internally consistent relationships that were used to describe future pathways of greenhouse gas emissions. The A2 scenario describes a very heterogeneous world and represents “high future emissions". Projected CO_2 concentrations are used to estimate the effects on the earth’s radiative energy budget, and this is the key forcing input used in global climate model simulations of the future.

Methods: The daily precipitation and temperature data for the retrospective predictions from each GCM were bias-corrected using a CDF mapping approach. Three different methods for estimating the required CDFs were used (see Figure 2):

1. Monthly CDFs were estimated using all daily data for each calendar month (total 12 CDFs)
2. Daily CDFs were estimated using a moving window of ±15 days around the day to be bias-corrected (total 365 CDFs)
3. Daily CDFs were estimated using a moving window of ±30 days around the day to be bias-corrected (total 365 CDFs)

To develop future scenarios two different methods were used:

1. Direct Bias Correction method: The bias for a particular daily value of precipitation or temperature was assumed to be the same in the retrospective and future periods. Thus for each daily future projection the bias-correction for the retrospective prediction with that same value was applied (see Figure 2).

2. Delta method: The differences between the monthly CDFs of raw retrospective and future CLAREnCE10 precipitation and temperature predictions at each percentile were used to adjust the observed monthly CDF to produce a future CDF. The future CDF was used to produce the future time series for each variable from the observed times series.

The bias-corrected dynamically downscaled retrospective and future daily precipitation and temperature data were then used as inputs for the IHM-INTB model. All other parameters, forcing terms and initial boundary conditions for hydrologic simulation were identical to those used in the calibrated model.

<u>Temperature Results:</u>

Figure 3 compares the spatial distribution of the observed and raw CLAREnCE10 daily minimum temperature (Tmin) over the Tampa Bay region for the thirty year retrospective and future time periods. Figure 4 compares the spatial distribution of the observed and raw CLAREnCE10 retrospective and future mean daily maximum temperature (Tmax). All retrospective downscaled GCMs reasonably reproduced the range of values for the observed mean Tmax and Tmin. Note that the bias-corrected results reproduce very similar spatial distributions of mean Tmax and Tmin to the observations because the bias-correction process maps raw CLAREnCE10 CDFs to observed CDFs on a grid-by-grid basis. The retrospective and future spatial distributions of daily mean Tmax and Tmin predictions were found to be very similar for a given GCM. This is due to the fact that the regional climate model uses the same physical schemes and geographic data (e.g., topography, land cover, etc.) for the retrospective and future simulations for each simulation but uses different boundary conditions from the appropriate GCM. All downscaled GCM projections consistently estimated a 2-3^{o}C increase in mean daily maximum and minimum temperatures over the study area for the future period (2039~2070) under the A2 emission scenario.

Figure 5 compares the monthly mean Tmax and Tmin of the observed, raw and bias-corrected CLAREnCE10 data for the retrospective and future periods. This figure indicates that the annual cycle of observed mean Tmax and Tmin were accurately reproduced by all three GCMs, and that the relatively small biases were successfully removed by bias-correction. Figure 6 compares the predicted change in future monthly mean Tmax and Tmin for each GCM in the CLAREnCE10 experiment. Raw CLAREnCE10 results predict that the average monthly increase of temperature will range from 1^{o}C to 3 ^{o}C, and bias corrected results predict an average monthly increase of approximately 1^{o}C to 3 ^{o}C. The predicted monthly changes for the raw results (Figure 6 left column) are the mean of monthly change factors used in the 'delta method'. There is some variation among the different GCM results, with CCSM showing a different annual cycle of temperature change compared to the HadCM3 and GFDL results. In all cases the difference among bias-correction techniques was smaller than the difference among GCMs.

<u>Precipitation Results:</u>

Figure 7 compares the spatial distribution of the observed and raw CLAREnCE10 predicted daily precipitation over the Tampa Bay region for the thirty year retrospective and future time periods. This figure shows significant differences in the spatial pattern of precipitation among GCMs, and significant differences between the raw retrospective GCMs and the observed data. In particular, the retrospective CCSM predictions significantly underestimate the observed mean precipitation over the entire study area. As with the temperature results, spatial patterns of retrospective and future mean precipitation were similar for each individual GCM. However, unlike the temperature results the magnitude of precipitation change from the retrospective to future period varied among the GCMs. Precipitation was predicted to decrease for CCSM, remaining approximately equal for HadCM3, and increase for GFDL.

Figure 8 shows the annual cycle of mean precipitation for the raw and bias-corrected CLAREnCE10 data for the retrospective and future periods. While the raw retrospective HadCM3 and GFDL results reproduce the seasonal cycle of precipitation fairly well, the raw retrospective CCSM results fail to reproduce the summer rainy season. Figure 9 compares the predicted change in future precipitation change (future-retrospective) for the three raw and bias-corrected GCMs. Figure 9, left column are the monthly mean change factors used in 'delta method'. The bias-corrected CCSM predicts a decrease in precipitation for all months in the future. The bias-corrected HadCM3 shows a slight increase in precipitation in the winter months and a decrease in the summer months. GFDL shows a significant decrease in July precipitation but increases in precipitation for most months of the year. As with the temperature results, the differences among the GCMs were much greater than the differences among the bias-correction methods.

Streamflow Results:

Figure 10 compares the annual cycle of mean monthly streamflow predicted by the IHM-INTB model using bias-corrected retrospective predictions and future scenarios to both historic streamflow observations and the calibrated IHM-INTB model results for the Alafia and Hillsborough Rivers. Differences between retrospective and future predicted mean monthly streamflow for each future scenario are plotted in Figure 11. These results show that predicted changes in the annual cycles of future streamflow for each GCM generally follow its predicted mean monthly precipitation change pattern (Figure 9). The differences among the GCMs were much greater than the differences among the bias-correction methods, with CCSM predicting significantly lower mean monthly streamflow throughout the entire year, HadCM3 predicting a slight decrease in mean monthly streamflow in July and August, and GFDL predicting an increase in streamflow throughout most of the wet season (June through October).

Figure 12 compares the 7Q10 High Flow estimated from streamflow simulations for the Alafia and Hillsborough Rivers using the downscaled and bias-corrected GCM results and the calibrated IHM-INTB model. Note that the 7Q10 High Flow is the annual 7-day maximum streamflow that is expected to occur on average in 1 year out of 10. These results show that the HadCM3 and GFDL predict a higher 7Q10 in the future for the Alafia River and a similar 7Q10 in the future for the Hillsborough river, while the CCSM predicts a much lower 7Q10 in the future for both rivers.

Figure 13 compares the retrospective and future mean annual evapotranspiration (ET), and the ET to precipitation ratio averaged over the study area, to the calibrated IHM-INTB model estimate. The future HadCM3 and GFDL results predict an increase of ET compared to the retrospective and calibrated results, with some variations among the bias-correction methods. In contrast, the CCSM results predict a significant decrease of mean annual ET and a significant increase in the ET to precipitation ratio due to the predicted decrease in precipitation for all months (Figure 7 through 9).

Results of this task show that although each of the GCMs predicts a consistent increase in future temperature, differences among future precipitation estimates propagate into significant differences in future streamflow predictions. In other words, the precipitation signal overwhelms the temperature signal in predicting hydrologic implications of projected future changes. The high uncertainty in precipitation and thus streamflow estimates across the three GCMs considered here indicates that additional GCM predictions (with multiple greenhouse gas emission scenarios) must be examined before any actionable recommendations can be made. Due to the extreme time and computational expense associated with dynamic downscaling for GCMs, statistical downscaling of the larger set of GCMs using the BCSA method developed by Hwang and Graham (2013) is recommended.

A manuscript is currently being prepared on this work for submission to a peer reviewed journal.

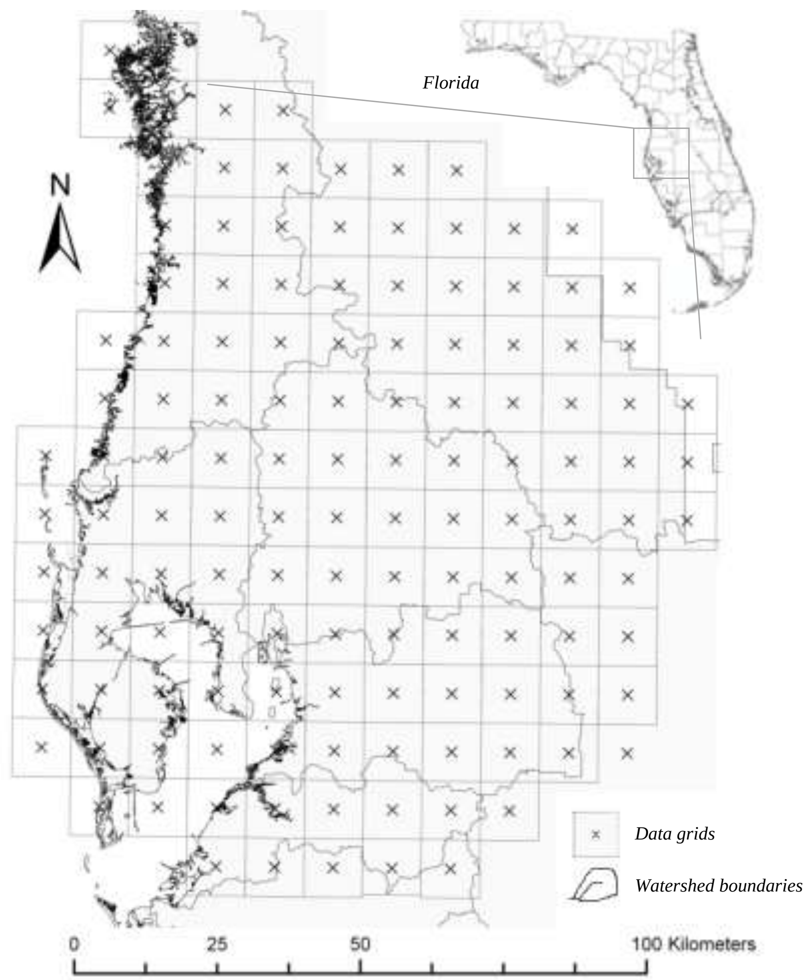

Figure 1. The study area (Tampa Bay region, Florida) and grid configuration of the CLAREnCE10 data.

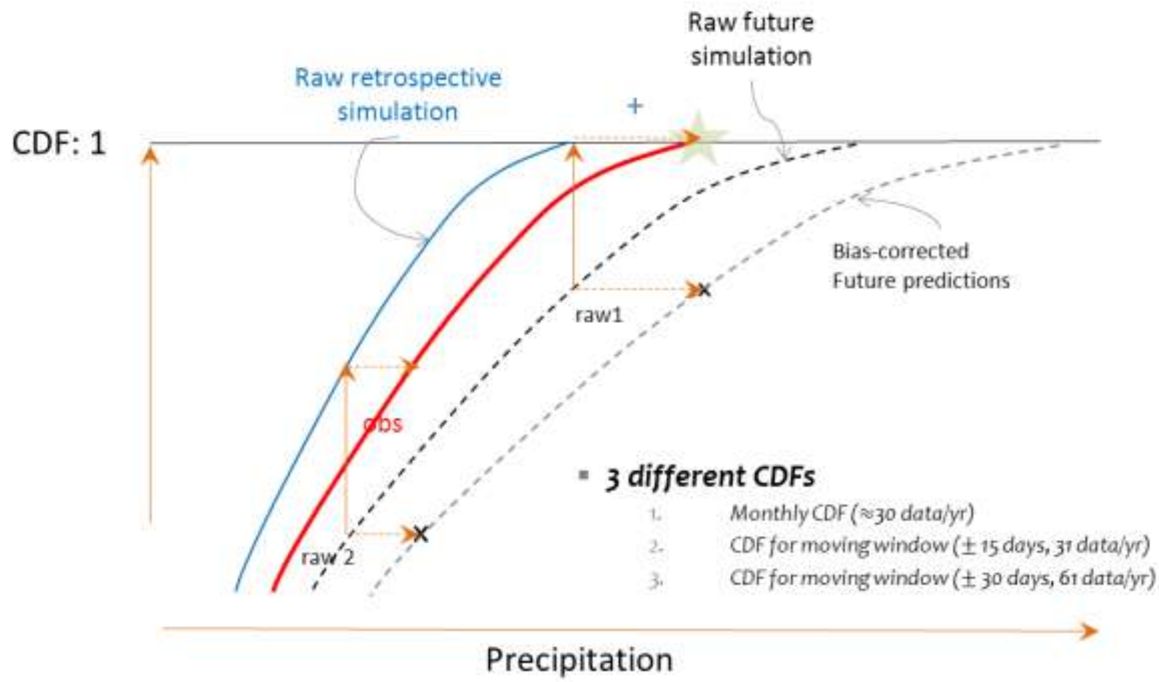

Figure 2. Schematic representation of bias-correction procedures (i.e., CDF mapping) used in this study. The process is conducted for each monthly cdf, or daily moving window cdf independently.

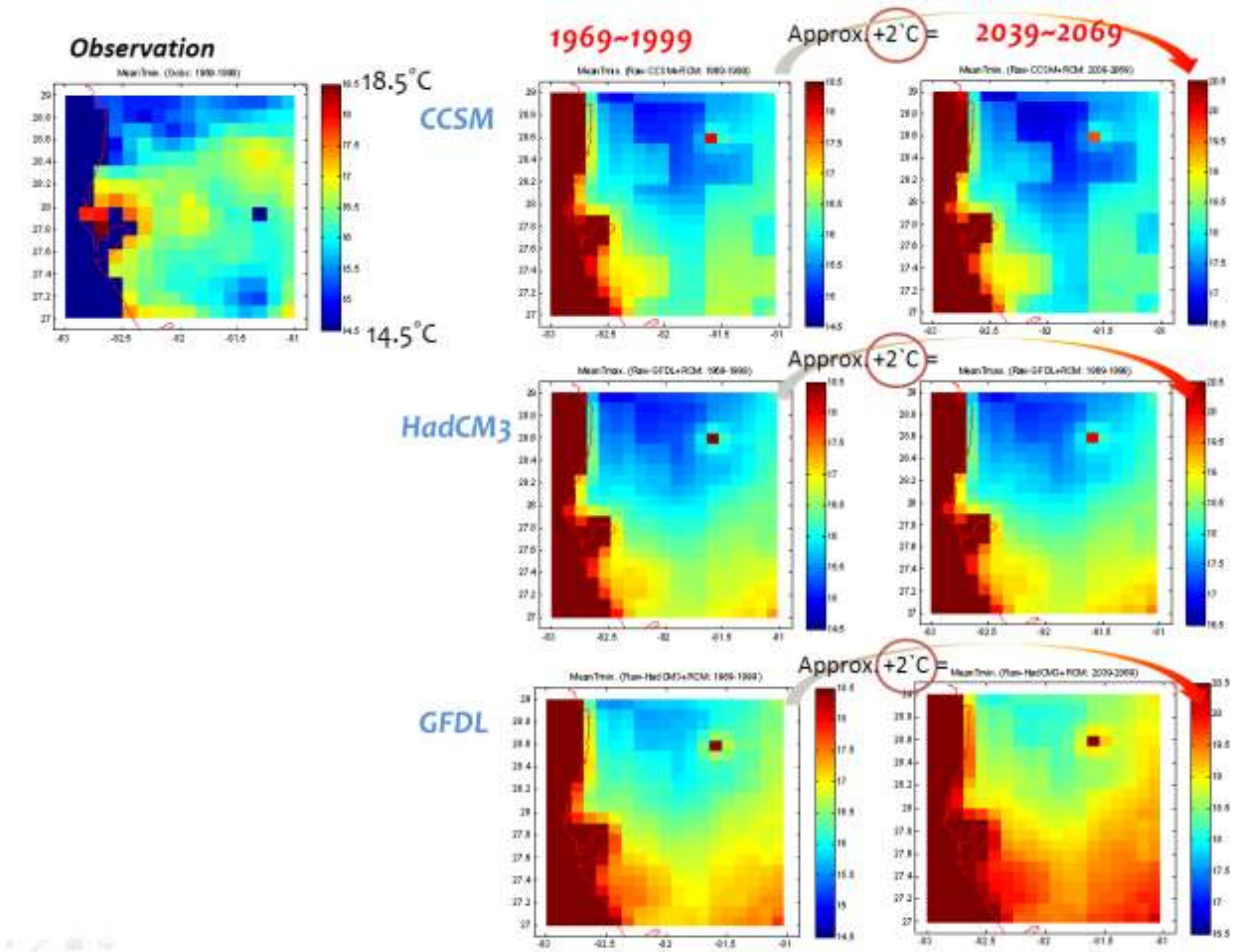

Figure 3. Comparison of spatial distributions of the observed (upper left), raw retrospective (middle column) and future (right column) mean daily Tmin. Note that the scales are different for the retrospective and future simulations.

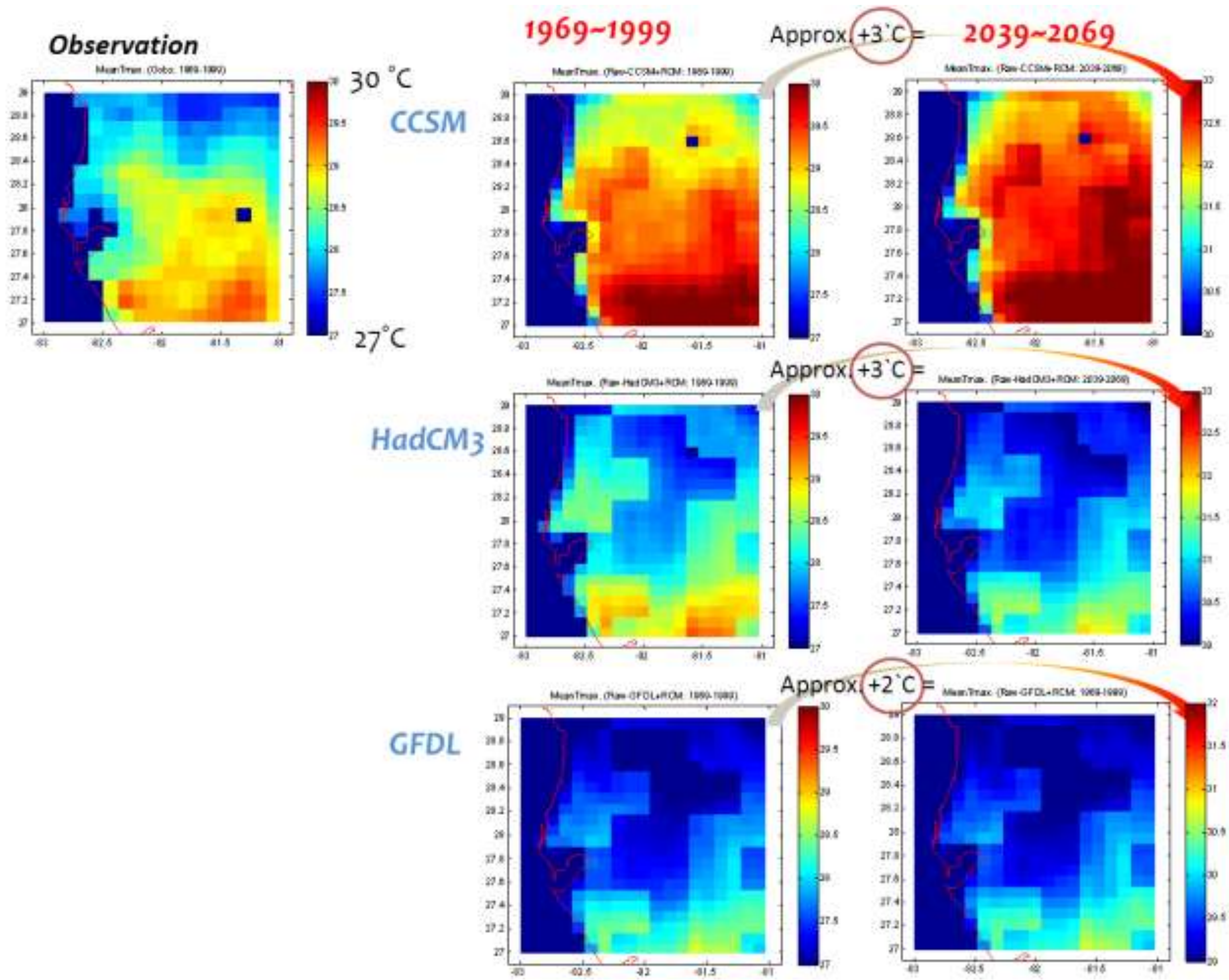

Figure 4. Comparison of spatial distributions of the observed (upper left), raw retrospective (middle column) and future (right column) mean daily Tmax. Note that the scales are different for the retrospective and future simulations.

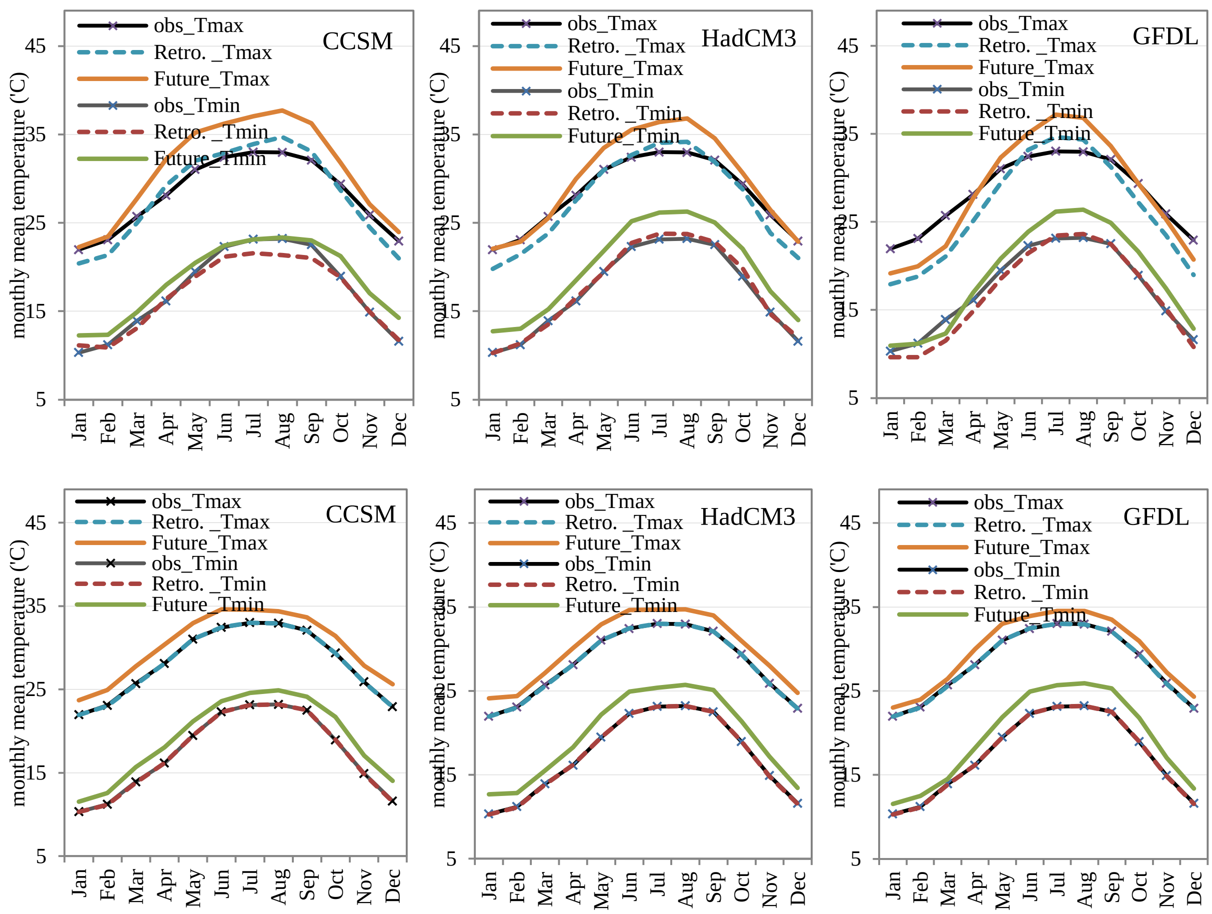

Figure 5. Monthly mean of Tmax and Tmin of raw (upper row) and bias-corrected (bottom row) CLAREnCE10 data (i.e., CCSM (first column), HadCM3 (second column), and GFDL results (third column)) using monthly CDFs for retrospective (1969-2000) and future (2039-2070) periods. The variation among bias-corrected results using the other methods (i.e., daily moving window) were negligible and thus shown here.

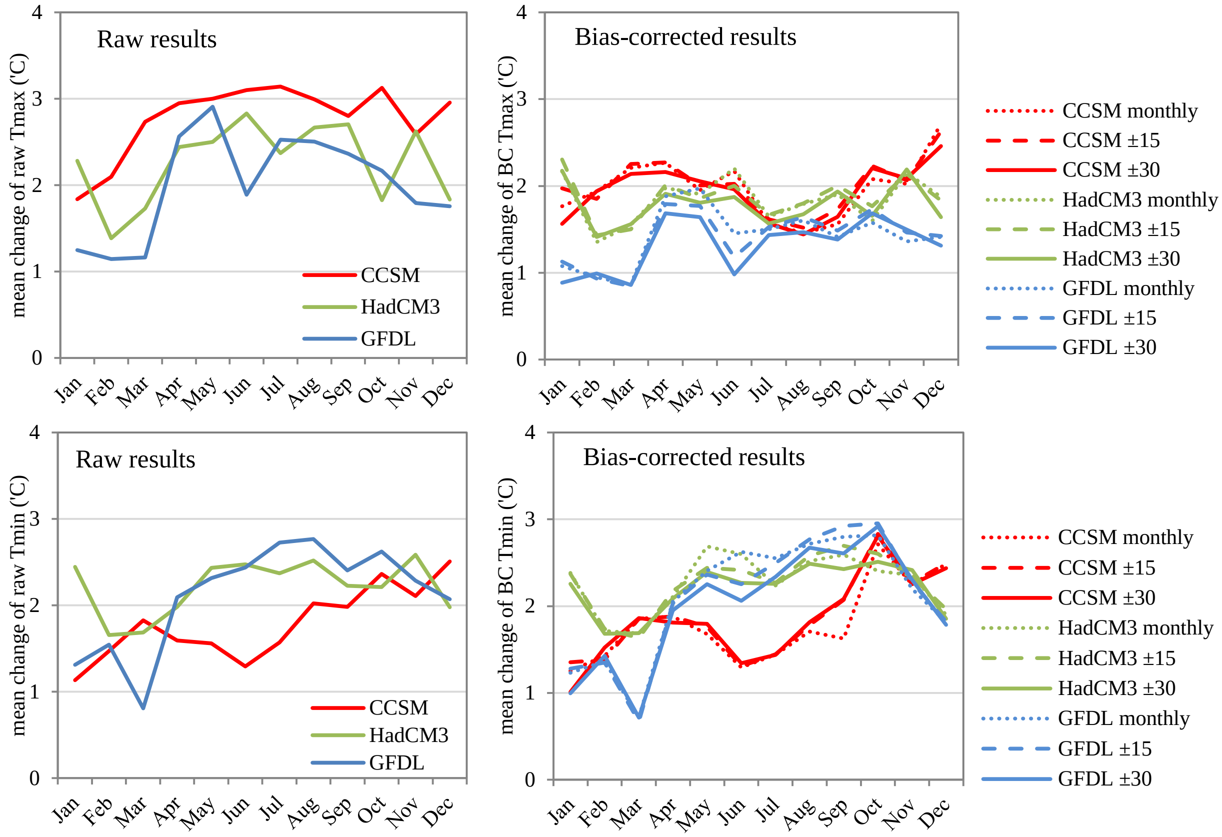

Figure 6. Predicted change in future monthly mean Tmax (upper row) and Tmin (bottom row) for each GCM. Differences for the bias-corrected results using 3 different methods are presented in right column.

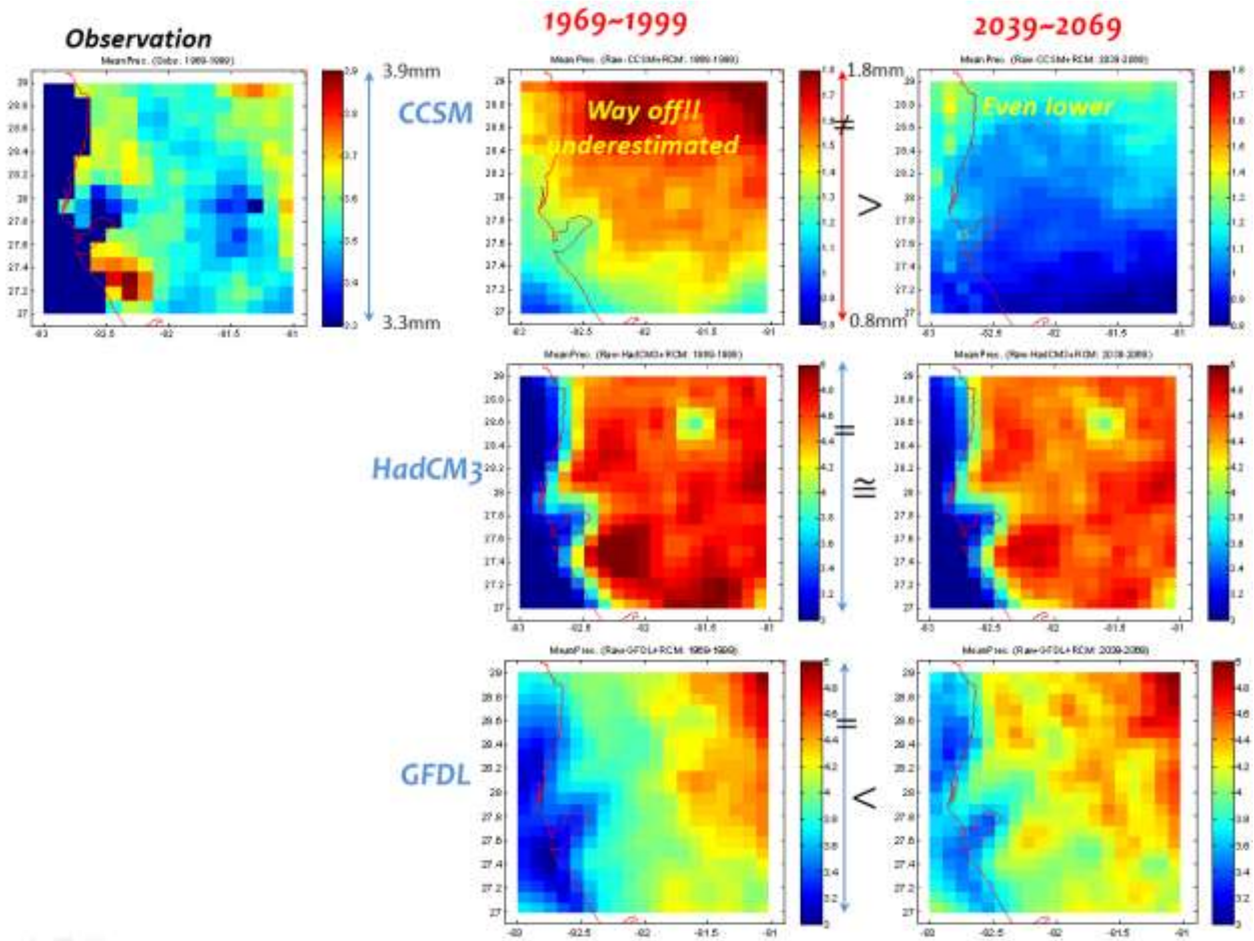

Figure 7. Comparison of spatial distributions of the observed (upper left), raw retrospective (middle column) and future (right column) mean daily preciptiation. Note that the scales are identical for the retrospective and future but different among the GCMs.

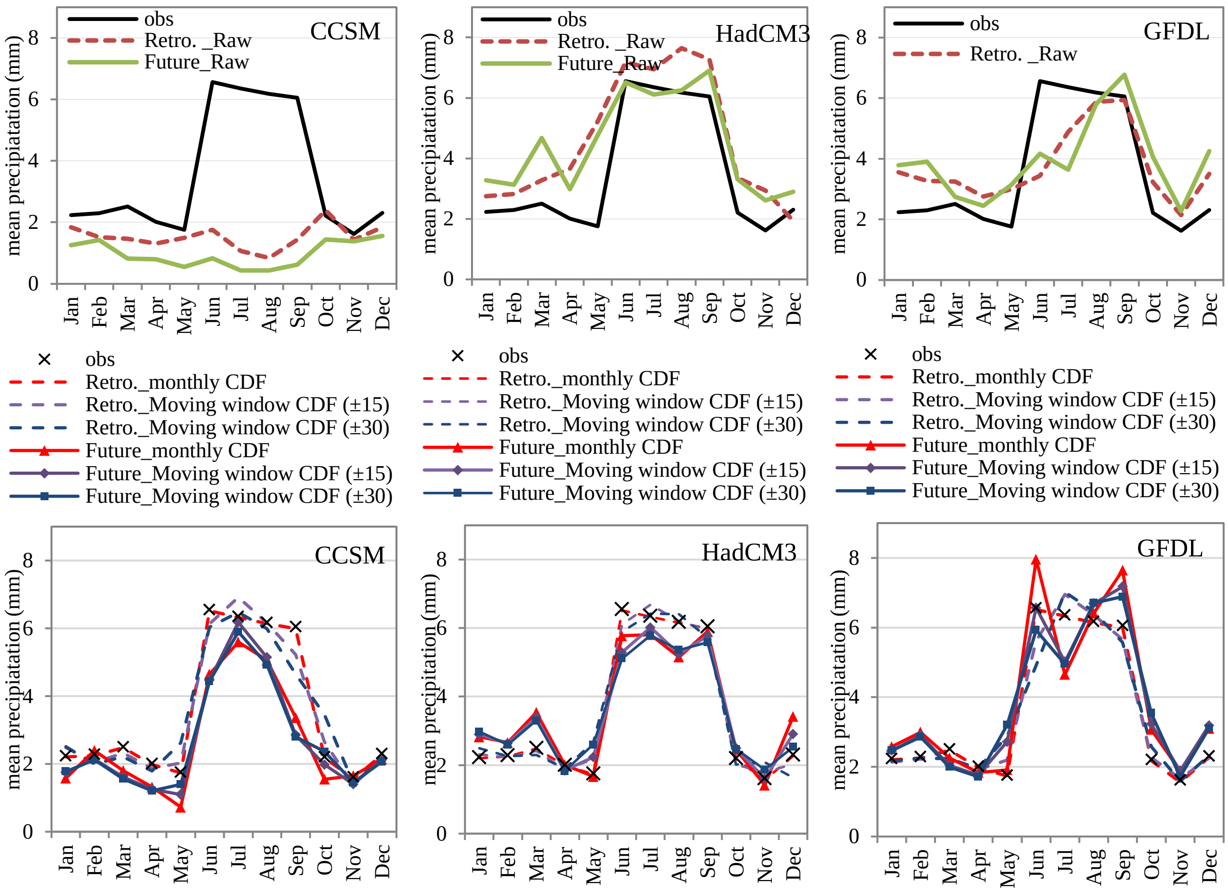

Figure 8. Daily mean precipitation of raw (upper row) and bias-corrected (bottom row) CLAREnCE10 data (i.e., CCSM (first column), HadCM3 (second column), and GFDL results (third column)) for retrospective (1969-2000) and future (2039-2070) periods.

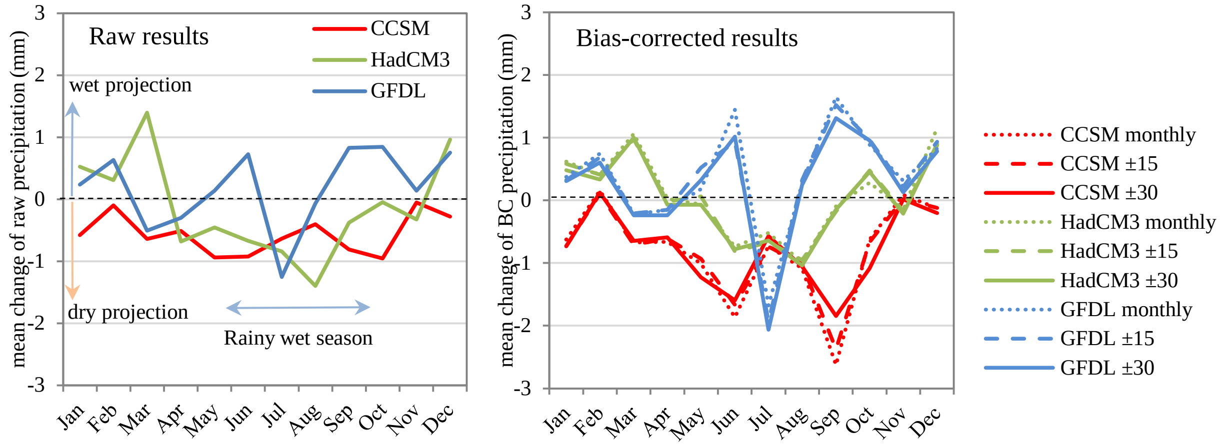

Figure 9. Predicted change in future mean precipitation for each GCM. Differences for the bias-corrected results using 3 different methods are presented in right column.

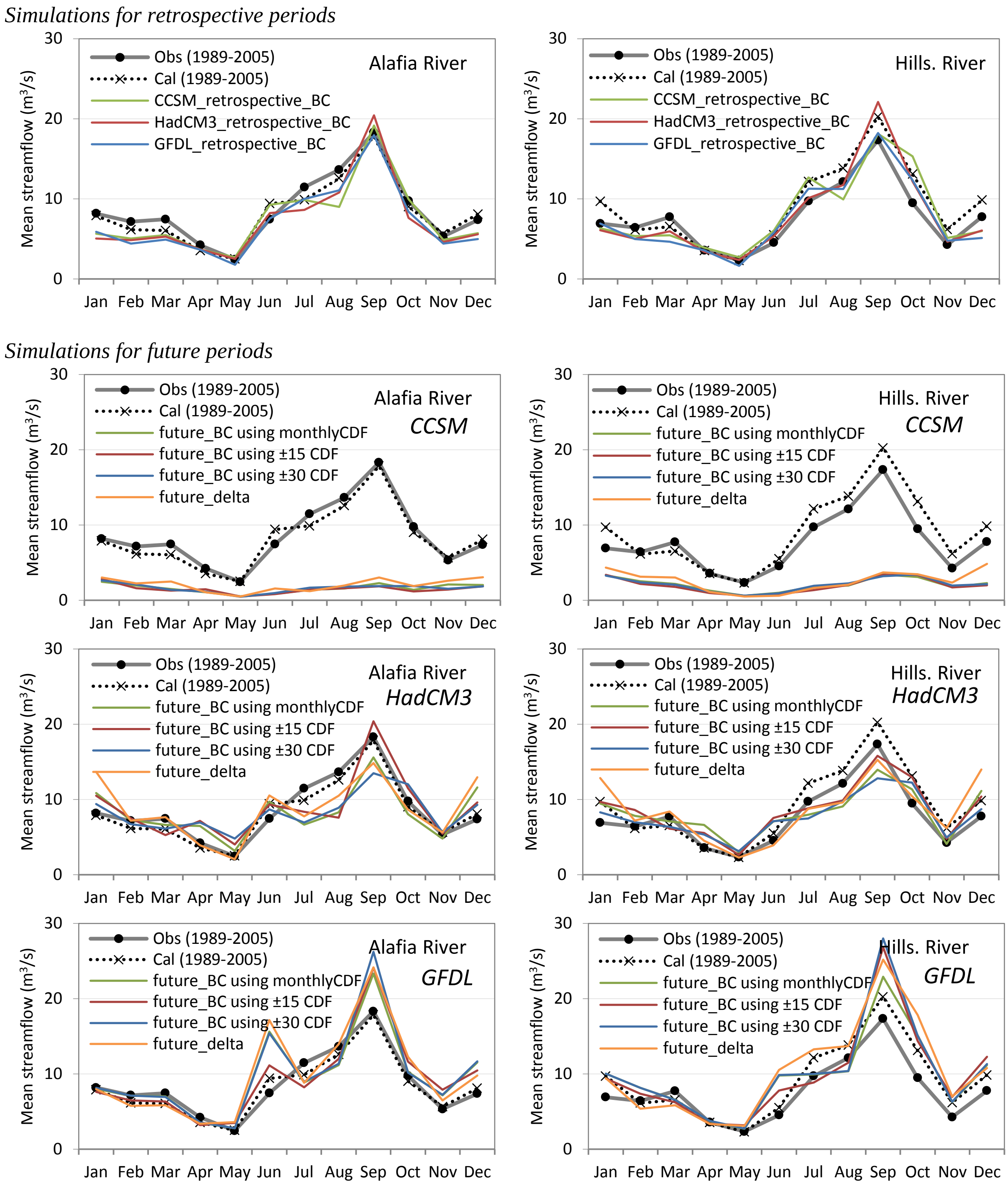

Figure 10. Simulated daily mean streamflow using bias-corrected retrospective CLAREnCE10 data (1969-2000, first row) and future data (2039-2070: CCSM (second row), HadCM3 (third row), and GFDL (fourth row)) for Alafia River (right column) and Hillsborough River (left column).

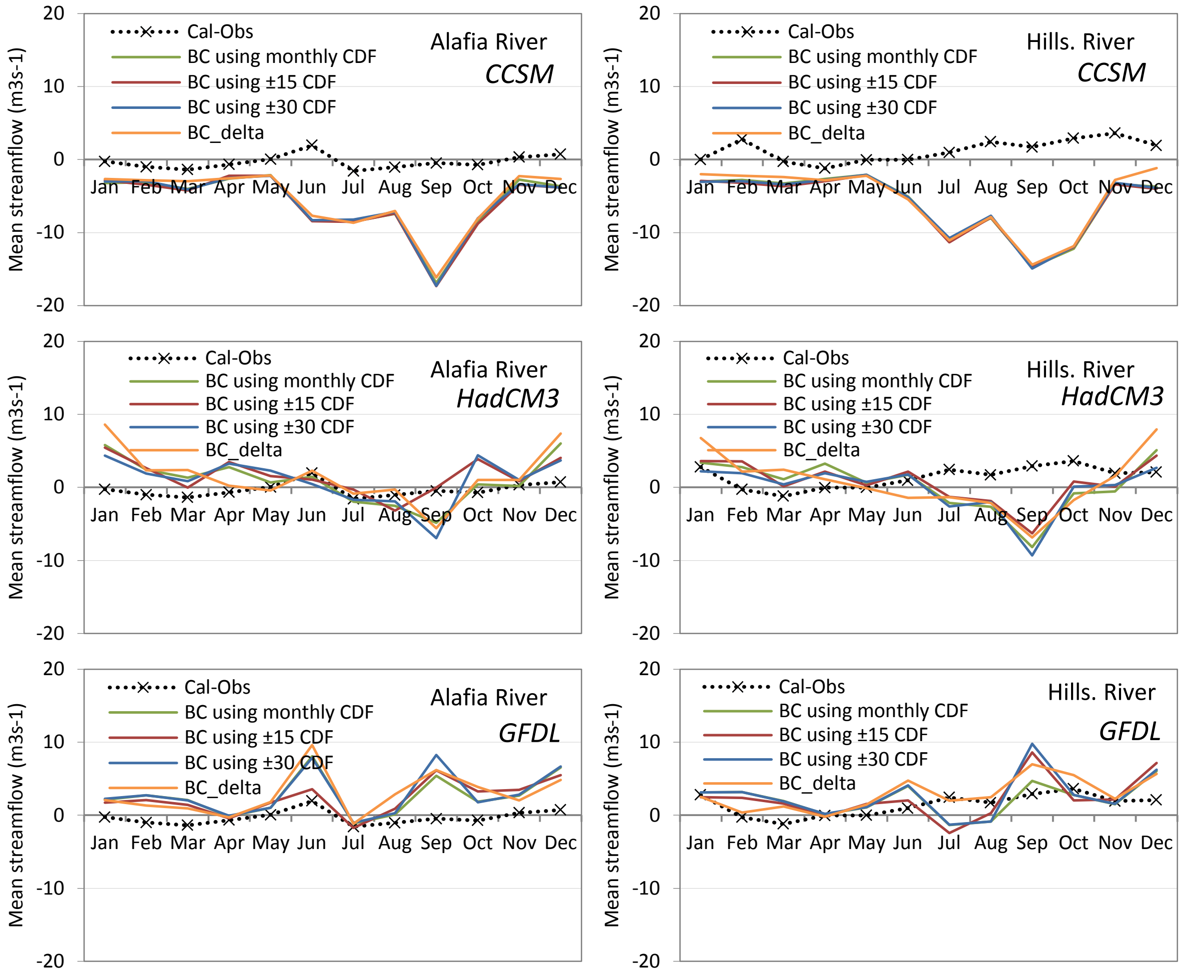

Figure 11. Predicted change in future streamflow simulations for CCSM (first row), HadCM3 (second row), and GFDL (third row) for Alafia River (right column) and Hillsborough River (left column).

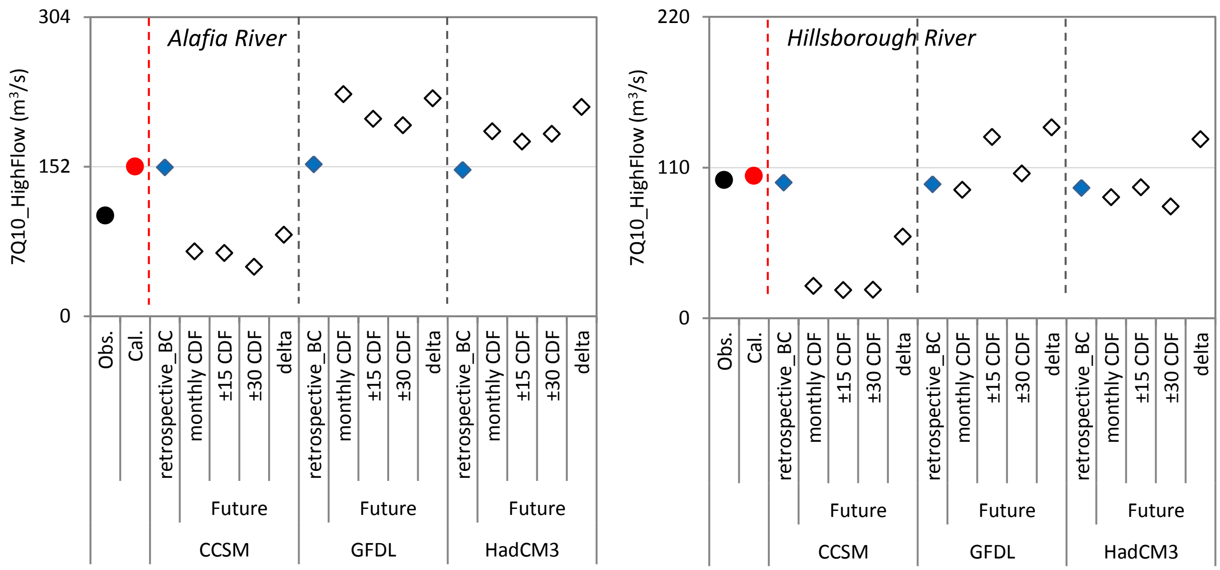

Figure 12. Comparison of the calibrated, retrospective and future 7Q10_HighFlow (top row) estimated from streamflow simulations for Alafia River and Hillsborough River using the downscaled GCM results.

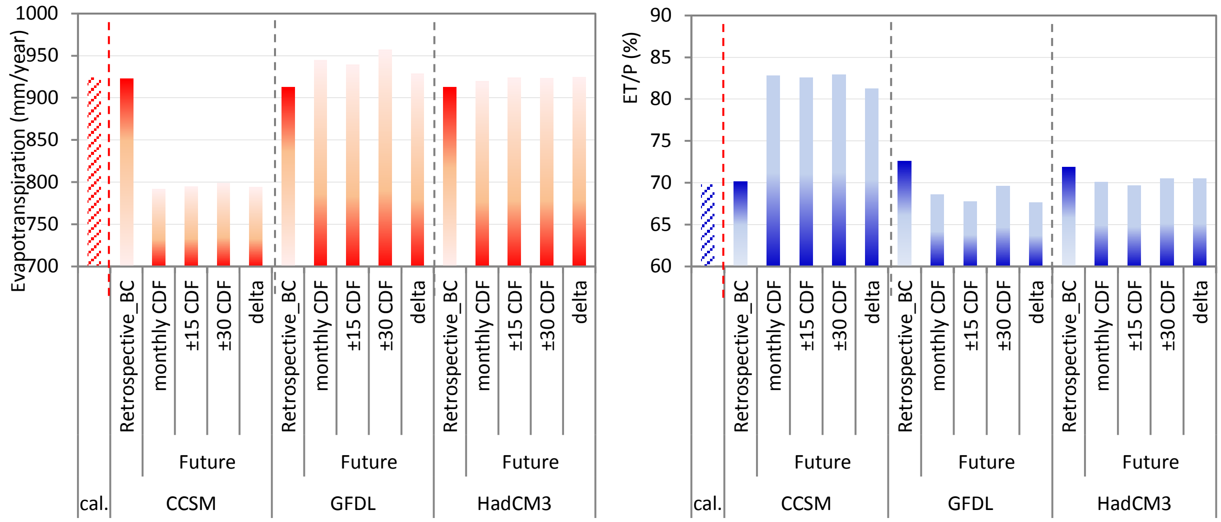

Figure 13. Comparison of calibrated, retrospective and future mean annual evapotranspiration (right column) and evapotranspiration ratio to precipitation (left column), averaged over the study area.