CLIMATE CHANGE SCENARIO GENERATION AND UNCERTAINTY ASSESSMENT USING HIERARCHICAL BAYESIAN MODEL AND WAVELET BASED STOCHASTIC MODEL

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Abstracts The research presented here represents a collaborative effort with the SFWMD on developing scenarios for future climate for the SFWMD area. The project focuses on developing methodology for simulating precipitation representing both natural quasi-oscillatory modes of variability in these climate variables and also the secular trends projected by the IPCC scenarios that are publicly available. This study specifically provides the results for precipitation modeling. The starting point for the modeling was the work of Tebaldi et al that is considered one of the benchmarks for bias correction and model combination in this context. This model was extended in the framework of a Hierarchical Bayesian Model (HBM) to formally and simultaneously consider biases between the models and observations over the historical period and trends in the observations and models out to the end of the 21st century in line with the different ensemble model simulations from the IPCC scenarios. The low frequency variability is modeled using the previously developed Wavelet Autoregressive Model (WARM), with a correction to preserve the variance associated with the full series from the HBM projections. The assumption here is that there is no useful information in the IPCC models as to the change in the low frequency variability of the regional, seasonal precipitation. This assumption is based on a preliminary analysis of these models historical and future output. Thus, preserving the low frequency structure from the historical series into the future emerges as a pragmatic goal. We find that there are significant biases between the observations and the base case scenarios for precipitation. The biases vary across models, and are shrunk using posterior maximum likelihood to allow some models to depart from the central tendency while allowing others to cluster and reduce biases by averaging. The projected changes in the future precipitation are small compared to the bias between model base run and observations and also relative to the inter-annual and decadal variability in the precipitation.

INTRODUCTION

The South Florida Water Management District faces many related challenges in assessing threats to future water supplies given the prospect of anthropogenic climate change. These include impacts due to changes in the timing and magnitude of rainfall, temperature and winds, and due to sea level rise. Prior work done by the SFWMD and others in the region has developed downscaling capacity for rainfall simulations based on projections by General Circulation Models for different climate change scenarios, and has also investigated the possibility of integrating low frequency climate oscillations, such as El Nino Southern Oscillation and the Atlantic Multi-decadal Oscillation. An integrated approach for developing consistent and

appropriate scenarios across precipitation and temperature that reflects both historical variability and trends and also the projections from the climate change models has not so far been attempted. Also, only a limited analysis of the biases and the uncertainty in the projections of these variables has been done.

A number of products that provide scenarios for projected future climate change are available. The primary sources usually referenced are those related to the IPCC Climate Change scenarios under different assumptions of anthropogenic impacts in the 21st century used in General Circulation Models of the Ocean and Atmosphere (GCMs). Precipitation and temperature have been downscaled (often separately) to station or regional values using a variety of methods. Significant biases and uncertainties in these projections are found and have been documented. Some of these relate to the average and standard deviation of monthly or daily values, and schemes for bias correction and uncertainty reduction using model averaging have been developed. These need to be specifically evaluated for the SFWMD domain for this set of models.

The Florida region has been shown to have persistent inter-annual and decadal modes of climate variability. Unfortunately, these are not captured very well by the current generation of GCMs. Prior work has shown how historical and paleo data can be used to simulate multi-scale rainfall variations for use with SFWMD. The extension of these methods to spatially and temporally consistent scenarios for precipitation and temperature is still needed. The objectives of the study were to provide climate change scenario with associated uncertainties, and extend the existing downscaling tools to simulations of seasonal rainfall using the climate change information that was derived through the Hierarchical Bayesian Model.

METHODOLOGY

Tebaldi et al. (2005) considered only changes in the long-term mean of rainfall and temperature. The proposed scheme in this study takes into account changes in mean and variance simultaneously. Moreover, the biases in mean and variance are differentiated from the base scenario and future scenario in a systematic way using a Hierarchical Bayesian model. We also consider a linear trend parameter in the model, thus allowing for a systematic nonstationarity, rather than just an epochal shift in the mean. This is a generalization of the “delta” approach used by *Tebaldi et al.* (2005). We are specifically interested in an assessment of the biases in the mean and the variance of precipitation and temperature as simulated by the IPCC models, unlike simply an assessment of the projected change in the mean, which is the focus of the Tebaldi et al work. The reason for this interest is that since the equations of the climate system are highly nonlinear, large biases in the state variables simulated in the past when GCM simulations are constrained by historical greenhouse gas and solar output forcings point to systematic deficiencies in the representation of key climate processes. The GCM simulations have been loosely calibrated to the historical global temperature record – specifically a variety of process parameterizations and forcings have been tested and sub-selected or adjusted such that key features of the long term global temperature trend from the 20th century are adequately or credibly reproduced. Similarly, some GCM’s have also made an effort to reproduce ENSO like variability through specific ocean-atmosphere interaction parameterizations. However, while these global or specific features may be tuned now, regional simulations such as those of interest

to the SFWMD may exhibit significant systematic biases due to a lack of adequate representation of the climate processes that affect the region. Moreover, in the process of tuning the models to specific attributes, other attributes may be actually worse. For instance, some of the models that now "reproduce" ENSO, do indeed generate ENSO events with a plausible frequency that matches the key frequency band in the observations. However, the amplitudes of the oscillation, as well as the specific areas that correspond to "hot spots" in the Pacific Ocean, and hence strong tropical convection may have significant biases. These can translate into significant alterations of the nature of the teleconnections of interest for land precipitation and temperature. Since all such biases are difficult to diagnose, we focus on the identification of the biases in the domain of interest to the SFWMD. If the biases are much larger in magnitude than the uncertainty across the ensemble runs from a particular model or even across the models, then the results from the GCM should be viewed as systematically wrong, and even the delta approach to projecting climate change should be viewed with suspicion. Future projections in a nonlinear climate system will likely behave very differently than those projected by these GCMs particularly if the biases for historical simulations are relatively large. Biases in the mean and variance are modeled formally. We do not attempt to model the biases in the low frequency (inter-annual and longer) structure at this point, but do explore them empirically using wavelet analysis.

Hierarchical Bayesian Multi-model Ensemble Model (HBMME) The observed seasonal rainfall are assumed to follow a Normal distribution, $Yobs \sim N(\mu, \sigma^2)$, with mean($\mu$) and standard deviation(σ). The assumption of normal distributions is considered reasonable due to the aggregation over a season and over an area. In addition, quantile plots of observations and model data for each GCM against the theoretical normal distribution show normal distribution. To begin with, the time series is centered with $Tc = (N/2+1)$ so that the intercept μ can be regarded as the mean value of the climate condition for present and future period. The parameter α refers to a linear trend that is to be derived from the observations.

$$Y_{obs,t} \sim N(\mu + \alpha(t - Tc), \sigma^2) \tag{1}$$

Next, we consider the representation of the observations by the IPCC GCMs. We consider an additive bias B_i and a multiplicative bias γ_i in the ith GCM model:

$$Y_{base,t} \sim N(\mu + \mathrm{B}_i + \alpha(t - Tc), \sigma^2 \gamma_i) \tag{2}$$

The prior distributions of the parameters for the base scenario model are specified as follows. The bias parameters are shrunk across the GCMs, to reduce potential sampling variability. The two levels of modeling consider a prior or uncertainty distribution for each parameter, and a non-informative distribution for the prior associated with each hyper parameter. The hyper-parameters μ_B, σ_B, μ_γ and σ_γ for the bias terms are introduced to shrink across the GCMs, and then these hyper-parameters that can be interpreted as the average bias across the GCMs and the associated variance. These hyper-parameters have a non-informative prior in turn as follows: $\mu \sim N(\mu_\mu, \sigma_\mu)$, $\mathrm{B}_i \sim N(\mu_B, \sigma_B)$, $\alpha \sim N(\mu_\alpha, \sigma_\alpha)$, $\gamma_i \sim N(\mu_\gamma, \sigma_\gamma)$, $\sigma \sim Ga(k, \theta)$, $\mu_B \sim N(\mu_{\mu_B}, \sigma_{\mu_B})$, $\sigma_B \sim Ga(k_{\sigma_B}, \theta_{\sigma_B})$, $\mu_\gamma \sim N(\mu_{\mu_\gamma}, \sigma_{\mu_\gamma})$, $\sigma_\gamma \sim Ga(k_{\sigma_\gamma}, \theta_{\sigma_\gamma})$

For the distribution of climate change, a mean shift ($\Delta\mu$) and a variance change(λ_i) are employed in the model. $Y_{future,t}$ is treated as an observation in the model although $Y_{future,t}$ is unobserved. This allows an estimation of the variance(σ_f) of the precipitation for the scenario period. $Y_{future,t}$ can thus be estimated as a missing value in the Hierarchical Bayesian model. Moreover, the additive and multiplicative biases with the parameter ΔB_i and γ_i can change between the control and scenario periods. Therefore, the bias, bias change and true change under climate change are combined into additive changes for the mean and a multiplicative change for the standard deviation, respectively. The equations for the final projection and the bias corrected projection for a particular model being combined are given as:

$$Y_{future,t} \sim N(\mu + \Delta\mu + (\alpha + \Delta\alpha)(t - Tc), \sigma^2 \sigma_f{}^2) \tag{3}$$
$$Y_{future,i,t} \sim N(\mu + \Delta\mu + \mathrm{B_i} + \Delta\mathrm{B_i} + (\alpha + \Delta\alpha)(\mathrm{t - Tc}), \sigma^2 \sigma_f{}^2 \gamma_i \lambda_i)$$

The prior distributions of the parameters for the future scenario model are as follow. The hyper parameters such as $\mu_{\Delta B}$, $\sigma_{\Delta B}$, μ_λ and σ_λ for shrinkage across the GCMs are introduced as follows: $\Delta\mu \sim N(\mu_{\Delta\mu}, \sigma_{\Delta\mu})$, $\Delta B_i \sim N(\mu_{\Delta B}, \sigma_{\Delta B})$, $\Delta\alpha_i \sim N(\mu_{\Delta\alpha}, \sigma_{\Delta\alpha})$, $\lambda_i \sim N(\mu_\lambda, \sigma_\lambda)$, $\sigma_f \sim Ga(k_f, \theta_f)$, $\mu_{\Delta B} \sim N(\mu_{\mu_{\Delta B}}, \sigma_{\mu_{\Delta B}})$, $\sigma_{\Delta B} \sim Ga(k_{\sigma_{\Delta B}}, \theta_{\sigma_{\Delta B}})$, $\mu_\lambda \sim N(\mu_{\mu_\lambda}, \sigma_{\mu_\lambda})$, $\sigma_\lambda \sim Ga(k_{\sigma_\lambda}, \theta_{\sigma_\lambda})$

Wavelet Based Autoregressive Model (WARM) In our analyses of the IPCC scenarios, the historical or base scenarios, may or may not reproduce the inter-annual variability seen in the observations over the same period. In earlier work, ENSO, NAO and AMO influences have been identified in different seasons for the S. Florida rainfall and temperature. Initially, we considered a formal model for the bias estimation and correction for each significant low frequency component. However, in the work presented here, we have considered a simpler model, that considers the low frequency structure in the historical data only and not the changes in this structure for the future as simulated by the GCMs. We considered the separation of the historical data into "noise" and low frequency signal. The low frequency signal is then modeled using a Wavelet Autoregressive Moving Average Model (WARM) developed by *Kwon et al*. (2006), while the noise term is modeled as an ARMA process but with the variance adjusted to reflect the potential change in variance indicated by the Hierarchical Bayesian Model for the climate change simulation. The projected change in the mean seasonal precipitation is then added to complete the future projection. The basic structure of the WARM model is described in this section. Consider a time series x_t , $t = 1, \ldots, N$, recorded at monthly, that exhibits quasi-oscillatory, low frequency variations at intraseasonal, interannual and longer time scales, as seen in many hydroclimatic time series. Consider the decomposition of this series into K component series R_{kt} that represent "signal" and a residual term ε_t .

$$x_t = \sum_{k=1}^{K} R_{kt} + \varepsilon_t \tag{4}$$

The decomposition considers that there are K orthogonal or independent series that carry the low frequency information, and the residual, ε_t, is a stochastic process. The notion is that the dynamics of each of these terms (R_{kt} and ε_t) is simpler to model using an autoregressive model than an autoregressive model for the composite dynamics of all the components. Since the wavelet components and the residual series are orthogonal by construction, the component and residual autoregressive models can then be added together to generate time series simulations. In general, each could be modelled using an appropriate time series technique (e.g., linear of nonlinear). Here, we consider a linear autoregressive model for each term, leading to the following model structure:

$$\begin{aligned} x_t &= \sum_{k=1}^{K} AR(R_{kt}; p_k) + AR(\varepsilon_t; p) \\ &= \sum_{k=1}^{K}\left(\sum_{i=1}^{p_k} \alpha_{k,i} R_{t-i,k} + v_{t,k}\right) + \sum_{j=1}^{p} \beta_j \varepsilon_{t-j} + \omega_t \end{aligned} \tag{5}$$

Here, p_t is the order of an autoregressive model fit to the kth signal, $\alpha_{k,i}$ are the corresponding autoregression coefficients; p is the order of an autoregressive model fit to the stochastic process ε_t, with β_j as the associated autoregression coefficients, and $v_{t,k}$ and ω_t are independent, identically distributed, noise processes. Noting that the order (p_k or p) of each autoregressive model and the coefficients of each autoregression in (5) can be estimated using standard time series methods (e.g., Maximum Likelihood and Akaike Information Criteria) the procedures for the selection of the "signals" R_{kt} in the decomposition in equation (4) are described as per time series. Here, we have used the Morlet wavelet, defined as $\varphi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}$, where ω_0 is a frequency.

STUDY AREA AND DATA

Both observational data and output from the GCMs are summarized in this section. We need to clarify between current climate data that comes from observations and model projections that come from models only. Our variable of interest is the precipitation, but the same methods can be applied to other climate variables. The model can also be extended to multivariate modeling of the changes in precipitation. However, this is a little more difficult to accomplish for WARM, unless an extension to modeling the co-spectrum is introduced. We present results for four season precipitation for control (1971-2000) and scenario period (2031-2060).

Rainfall Data Monthly averages within a climatic division have been calculated by giving equal weight to stations reporting and precipitation within a division. Period of record is 1895 through latest month available, updated monthly. Figure 1 shows the distribution of monthly rainfall during 1895-2008. We select MJJ seasonal rainfall and ASO seasonal rainfall beginning May 1st and August 1 corresponding to the first and second mode of the peak rainy season over the South Florida for the period 1895 to 2008. We also select the NDJ seasonal rainfall and FMA seasonal rainfall beginning November 1st and February 1 corresponding to the first and second mode of the dry rainy season over the South Florida for the period 1895 to 2008.

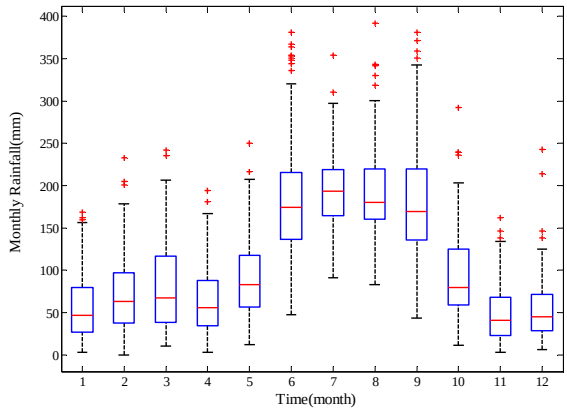

Figure 1. Annual precipitation distribution as calculated over 100 years data, seventy five percent of the rain occurs in MJJ (May-July) and ASO(August-October).

Climate Change Scenario The recent availability of the multi-model climate simulations of the Inter-governmental Panel on Climate Changes 4th Assessment Report (IPCC-AR4) provides a state-of-the-art tool with which to assess future water resources. The following subset of the IPCC-AR4 coupled models and corresponding runs are used in this work. Most of the models have a horizontal resolution of around 2 degree. The outputs of the climate of the 20th Century experiment (20C3M) are used to describe the climate for the period 1970–1999, while those from the 720 ppm stabilization experiment (SRES A1B) are used to represent the changes under a climate change scenarios for the period 2001–2090. Seasonal mean precipitation fields for both the present climate and climate change scenarios are computed as averages over all available members. The same number of members from each model is used to calculate the present and projected climate. The precipitation climatology is analyzed in South Florida for August-September-October (ASO) and November-December-January (NDJ). A comparison of bias for monthly distribution of precipitation is described by Figure 2. The GCM runs show significant biases in the amplitude of the annual cycle while the shape of the annual cycle does match that of the observations for many of the GCMs. As shown in Figure 2, it would not make sense to directly use the GCMs because the variance of precipitation derived by climate model is too much biased in terms of scale and location associated with precipitation distribution.

Table 1. GCMs list used in this study

GCM	Ensemble Member		GCM	Ensemble Member	
	20C3M	A1B		20C3M	A1B
CGCM3.1(T47)	5	5	IPSL CM4	1	1
CNRM CM3	1	1	MIROC3.2	3	1
CSIRO MK3.0	3	1	ECHO G	3	3
GFDL CM2.1	3	1	ECHAM5/ MPI-OM	4	4
GISS AOM	2	2	MRI CGCM 2.3.2	5	5
GISS EH	5	3	CCSM3.0	6	7
FGOALS G1.0	3	0	PCM	4	0
INGV ECHAM4	1	1	UKMO HadCM3	2	1
INM CM3.0	1	1	UKMO HadGEM1	2	1

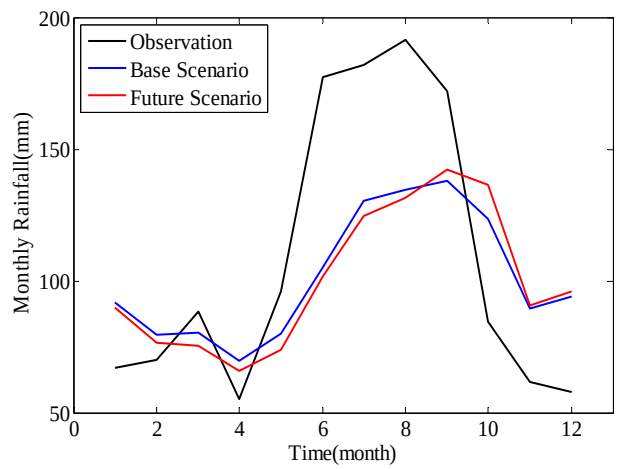

Figure 2. Monthly rainfall distribution for observation, base scenario and future scenario.

RESULTS AND DISCUSSION

The main interest in this section is to present the additive biases of mean, multiplicative biases of variance, changes in mean, change in variability and change in trend as identified by the HBM. We present all the distribution associated with the biases and the changes. These parameters are estimated by maximizing the joint posterior likelihood across observations and models. Since the likelihood is difficult to evaluate analytically as a function of the parameters, a Markov Chain Monte Carlo algorithm is used to identify the optimal parameter values and the associated posterior probability distributions. A normality test is performed in order to assure model assumption of normal distribution of precipitation in the Hierarchical Bayesian Model. The Q-Q plot is used to check whether or not the precipitation could have come from normal distribution that is used as probability distribution of the precipitation in this study. It seems that the assumption of normal distribution for the observed precipitation, control runs and scenario runs is not invalid given the Q-Q plot. For ASO and NDJ seasons, the main focus is to quantify the biases in mean and variance in the climate model and estimate mean shift, variability change and trend change. In this regard, the posterior distributions of additive bias for control run $\mathbf{B}_i$, additive bias for simulation run $\Delta\mathbf{B}_i$, multiplicative bias for control run $\boldsymbol{\gamma}_i$ and multiplicative bias for simulation run $\boldsymbol{\lambda}_i$ are derived. Finally, the posterior distributions of $\Delta\mu$, σ_f, and $\Delta\alpha$ are provided for each seasonal rainfall.

Climate Change Study for Precipitation

Posterior Density of Seasonal Rainfall The posterior predictive density given all data is shown in Figure 3. The uncertainties associated with the parameters are fully integrated into the proposed Hierarchical Bayesian framework so that the different GCMs projections are not only using their data but also depend on other models. In order to show biases of the climate model, the posterior distribution of the precipitation for the climate model (Y_{base}) is provided with the red dashed line. The solid blue line is for observed precipitation (Y_{obs}) while the solid red line is for the seasonal rainfall in the scenario period ($Y_{future,t}$) which is corrected for the control bias. It

was found that the mean shift $\Delta\mu$ is quite small compared to the mean and variance biases as shown in Figures. The change in mean of the precipitation for 2031-2060 period is not significant given the posterior predictive density function. The ASO and NDJ season shows slight change in mean which is about 15mm and 5mm. With respect to the variance, all the seasons showed increased variability under consideration of climate change as shown in Figure 6. We will further investigate the changes in the last section.

Posterior Density of Additive Model Bias In this section, the posterior distributions of additive bias for control run ($\mathbf{B}_i$) and additive bias for simulation run ($\Delta\mathbf{B}_i$) are discussed. The posterior densities for additive model biases for the different GCMs are presented in Figure 4. In Figure 4, the solid red lines are for the control biases (B) and the dashed blue lines for the scenario biases (B+ΔB). The additive control bias shows mostly negative values during the ASO season. It means that the climate models usually underestimate precipitation during the wet season which was to be expected. However, the additive bias during dry season does show clear positive values. The additive control bias $\mathbf{B}_i$ and the additive simulation bias ($\mathbf{B}_i + \Delta\mathbf{B}_i$) are almost identical which means that the additive simulation bias $\Delta\mathbf{B}_i$ is relatively small compared to the additive control bias $\mathbf{B}_i$. The additive bias for individual model $\mathbf{B}_i$ has common mean and variance for shrinkage in the Hierarchical Bayesian model. As discussed early, the posterior distribution of the parameters are estimated over Hierarchical Model which allow us to use all the information between different climate models.

Posterior Density of Multiplicative Model Bias In this section, the posterior distributions of multiplicative bias for control run ($\boldsymbol{\gamma}_i$) and multiplicative bias for simulation run ($\boldsymbol{\lambda}_i$) are discussed. The posterior densities for multiplicative model biases for the different GCMs are presented in Figure 5. In Figure 5, the solid red lines are for the multiplicative control biases ($\boldsymbol{\gamma}_i$) and the dashed blue lines for the multiplicative scenario biases ($\boldsymbol{\gamma}_i\lambda_i$). The multiplicative control bias $\boldsymbol{\gamma}_i$ shows large variability compared to the multiplicative simulation bias $\boldsymbol{\lambda}_i$.

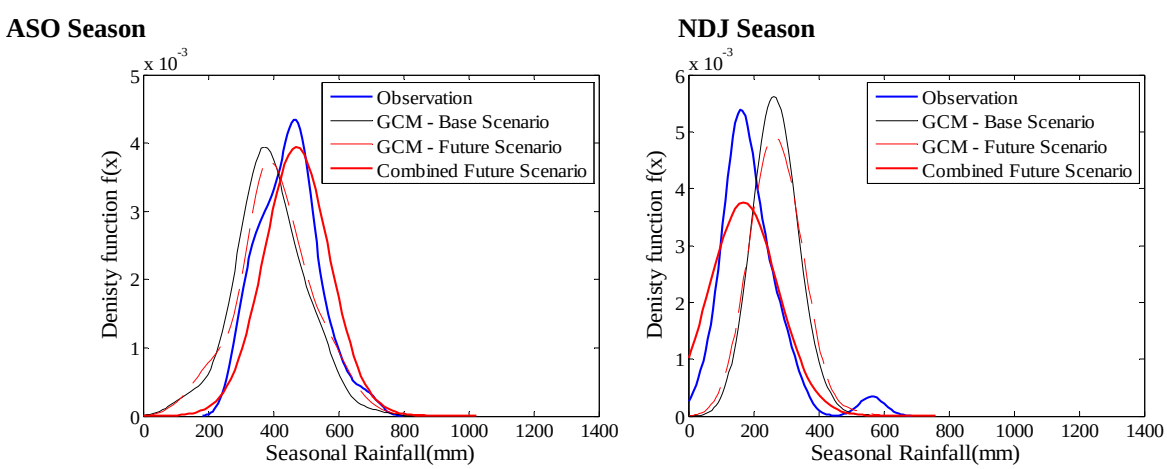

Figure 3. Posterior predictive densities for seasonal rainfall

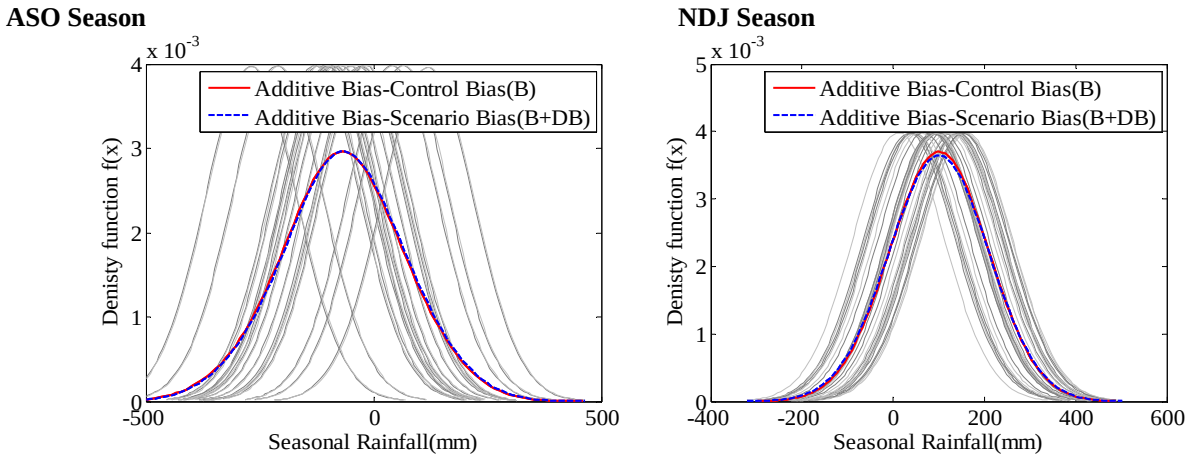

Figure 4. Posterior densities for additive model biases for the different GCMs.

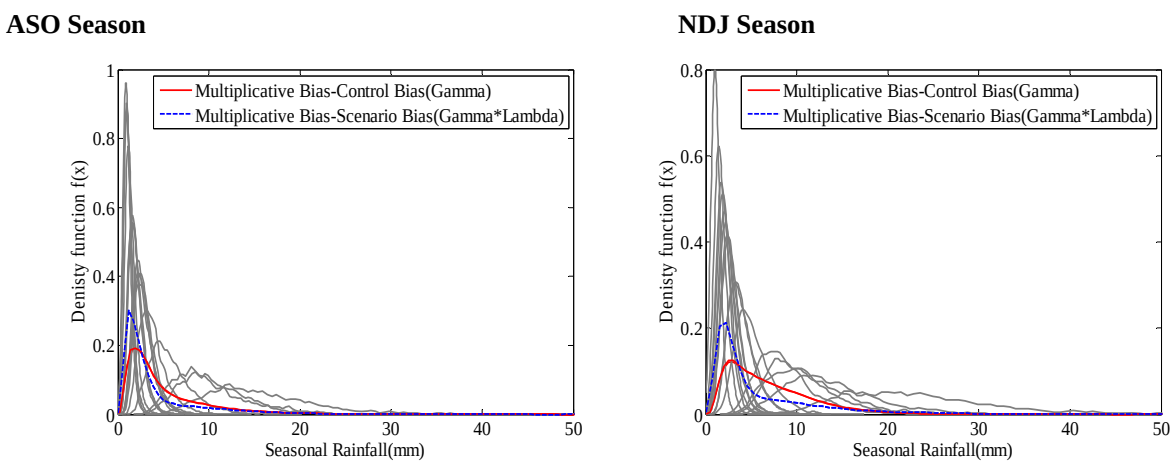

Figure 5. Posterior densities for multiplicative model biases for the different GCMs.

Posterior Density of Changes In this section, the posterior distribution the mean change ($\Delta\mu$), variance change (σ_f) and trend change ($\Delta\alpha$) is illustrated and discussed for each season in South Florida. Figure 6 describes change in mean, variance and trend under climate change. For ASO season, there is a mild increase in mean, and the peak of the posterior distribution of $\Delta\mu$ locates around 15mm. The increased change in variability seems to be expected for ASO season given posterior distribution of σ_f, but the peak of the posterior distribution is about 1.1 that means small tendency toward an increase in variability. There is no evidence for increase or decrease trend for control run and simulation period. For NDJ season, there is slight positive change in mean. The peak of the posterior distribution of $\Delta\mu$ locates around 5mm. The change in variability doesn't seems to be expected for NDJ season given posterior distribution of σ_f, but the peak of the posterior distribution is about 1.0 that means no tendency toward an increase or a decrease in variability. The high probability of small negative trend for the control period

was found by the posterior distribution of slope parameter α, but the change in trend $\Delta\alpha$ becomes positive slope meaning that the negative trend will be no longer significant under climate change condition

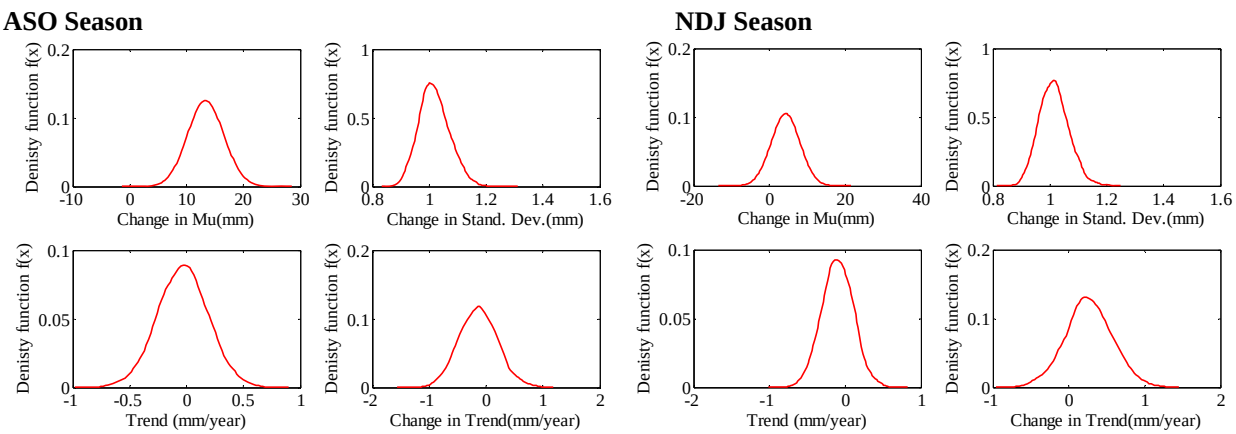

Figure 6. Posterior densities for change in mean precipitation (Δμ), change in variance, trend (tr) and change in trend(Δtr) in the ASO and NDJ season.

Stochastic Simulation of Precipitation with GCMs In this section, a hybrid scheme to simulate future climate scenario using a wavelet transform based stochastic simulation technique (WARM) with the GCM information such as change in mean and trend. The WARM model was formulated and applied to each of the series to isolate spectral components that are statistically significant over the full period of record and to then reconstruct their time and frequency modulated signal over the period of record. This signal and the residual terms are then modeled as an autoregressive process (or ARMA process), and the simulations from each of these components are then aggregated. The strategy is shown to do very well at capturing the underlying low frequency variability as well as the marginal distributions of the target variables. Thus, the proposed way is to utilize the WARM model to characterize underlying low frequency in the conjunction with GCMs in order to include nonstationary issues driven by climate change. The change in mean and trend that is estimated quantitatively from the previous section is added onto the WARM simulation. Finally, the future scenario for precipitation, $Y_{fs}(t)$, can be formulated as follow:

$$Y_{fs}(t) = \sum_{k=1}^{K}\left(\sum_{i=1}^{p_k}\alpha_{k,i}R_{t-i,k} + v_{t,k}\right) + \sum_{j=1}^{p}\beta_j\varepsilon_{t-j} + \omega_t + \left(\Delta\mu + \Delta tr(t)\right) \tag{12}$$

where, $\Delta\mu$ is the change in mean and Δtr is the change in trend in the future. The posterior densities of the values are derived in the previous stage. As an example for the hybrid simulation, ASO seasonal rainfall is presented. First, the WARM simulation is made for the ASO seasonal rainfall. 110 years Observed data are used. We note that 60 year band has a GWP level higher than the significance level. In Figure 7, one could conclusively conclude that WARM is able to reproduce the observed spectrum over the frequency band of fitting. Figure 8 illustrates the projected simulation of rainfall for the period 2001-2010. As shown in Figure 8, there is a

discrepancy between WARM simulation and WARM + GCM simulation. Note that the presented differences are affected by the change in mean and trend.

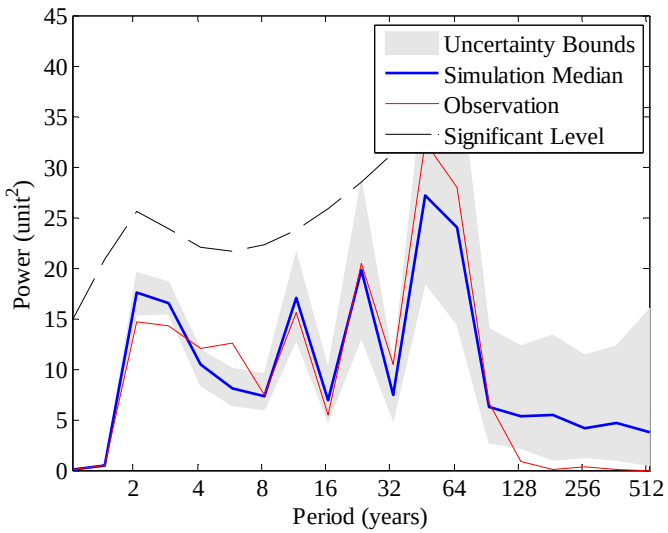

Figure 7. Comparison of global wavelet spectrum between observation and WARM simulation

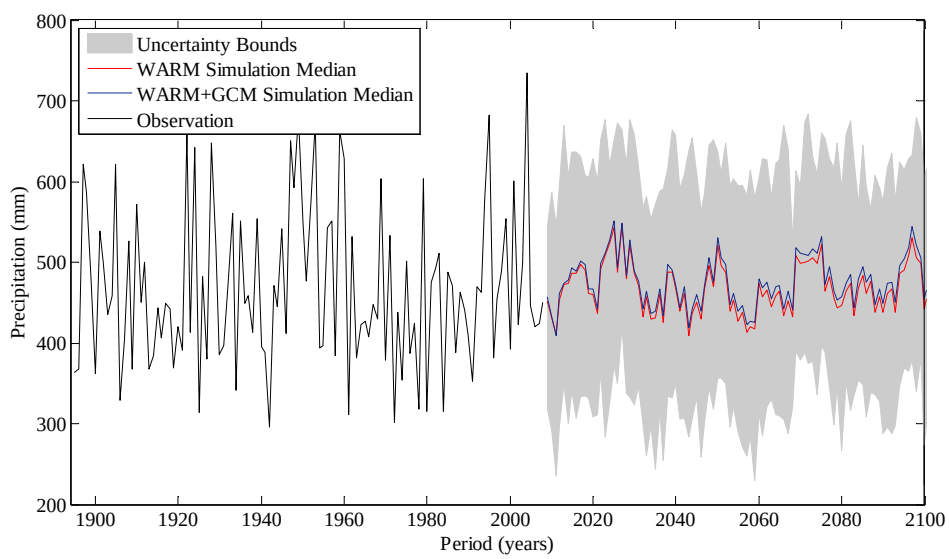

Figure 8. Projected simulation of ASO seasonal rainfall for the period 2001-2100 using the hybrid stochastic model.

SUMMARY AND DISCUSSION

A new model was introduced for simultaneously estimating the bias in the mean and variance, as well as the trends in these parameters in the observations and the IPCC scenarios for the 20th century and for the projected scenarios for the 21st century. The biases in the models for simulations for S. Florida are generally much larger than the uncertainty across models and also than the projections of future changes in these parameters (2031-2060). Modest increase or no

changes in the mean and modest increases in the variability are identified shrinking across the models. The Hierarchical Bayesian Model developed simultaneously models the evolution of each model and uses information across models to shrink the biases to a common mean and variance. Thus, each model gets a posterior probability distribution for each bias term (mean and variance) and trend terms. However, the ensemble mean of the biases and of the future values for the mean and variance are also generated as a byproduct. In this respect, the model improves on the Bayesian delta approach model of *Tebaldi et al.* (2005). The large biases identified are disquieting at first glance. Since they come from physically based models, one suspects that the physics is not adequate for describing the seasonal precipitation process for S. Florida. However, one expects downward biases in variability and potentially in the mean as the averaging spatial scale of the rainfall process increases, i.e., if the GCM grid boxes considered are much larger than the domain analyzed for the observations, then one can actually expect such differences. An investigation into multiscale spatial averaging of rainfall could indeed reveal whether the bias between the average seasonal precipitations for Division 4 is indeed significantly different from what would be expected from spatial averaging. If this is the case, then the bias correction as provided here is indeed quite reasonable and necessary. In terms of applications and projections of climate change, the conclusion from the analyses presented here is that at least for seasonal precipitation, the projected changes in the mean and the variance are likely to be relatively small, especially compared to the bias and the parameter/projection uncertainty. Consequently, it is still important to focus on the large dynamic range of inter-annual, decadal and inter-decadal variations in seasonal precipitation that are experienced in the region.

The key point is that particularly for the low frequencies identified as significant, there is considerable uncertainty as to the spectral power. This is seen even in simulations generated using WARM from the historical record. Consequently, we consider a strategy where we model the changes in the mean and variance using the Hierarchical Bayesian model, and can generate future simulations from this model. If a specific n year future period is of interest for projections, one can then directly produce realizations for the mean and variance of precipitation for that period. Indeed, one can generate simulations that also include the linear trends in the mean and variance over this period. However, if there is interest in preserving the time series structure in these simulations, e.g., for multi-year drought or wet period analysis, then one can add those components using WARM, with an appropriate adjustment for the error variance for the noise term. This is the strategy we currently recommend and can provide the software routines for.
There is an intriguing possibility for extending the model developed here to directly consider the following extensions:

REFERENCES

Kwon, H.-H., Lall, U. and Khalil, A.F. (2007) Stochastic simulation model for nonstationary time series using an autoregressive wavelet decomposition: Applications to rainfall and temperature, Water Resour. Res., doi:10.1029/2006WR005258.

Tebaldi, C., Smith, R.L., Nychka, D., Mearns, L.O. (2005) Quantifying uncertainty in projection of regional climate change: a Bayesian approach to the analysis of multimodel ensembles. J Clim 18:1524–1540.