Climate Change Scenario Generation and Uncertainty Assessment: Multiple variables and potential hydrological impacts

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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.

핵심용어 : Climate Change, Hierarchical Bayesian Model, Bias, Multi Model Ensemble(MME)

1. 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

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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.

2. METHODOLOGY

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.

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

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:

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

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.

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 is given as:

$$Y_{future,t} \sim N(\mu + \Delta\mu + (\alpha + \Delta\alpha)(t - Tc), \sigma^2 \sigma_f^{\,2}) \qquad (3)$$

$$Y_{future,i,t} \sim N(\mu + \Delta\mu + \mathrm{B_i} + \Delta\mathrm{B_i} + (\alpha + \Delta\alpha)(\mathrm{t} - \mathrm{Tc}), \sigma^2 \sigma_\mathrm{f}^{\,2} \gamma_\mathrm{i} \lambda_i)$$

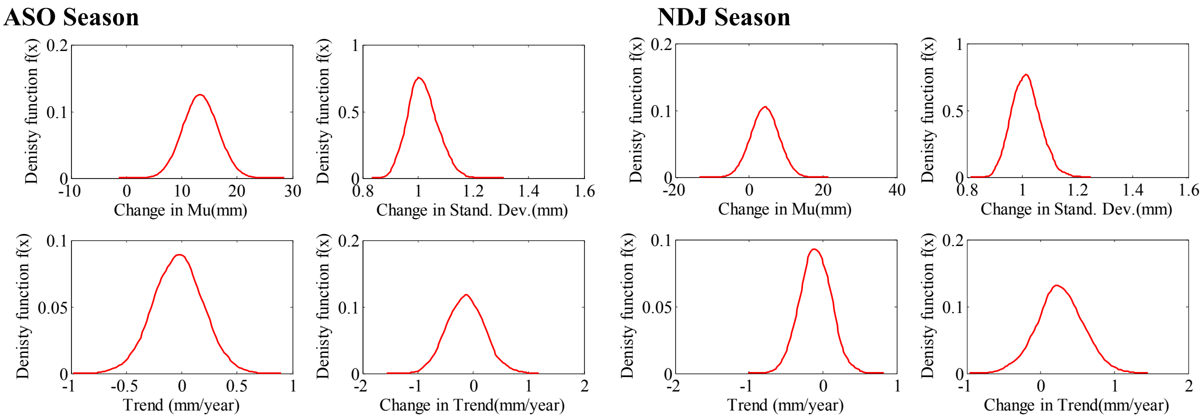

Figure 1. Posterior densities for change in mean precipitation (Δμ), change in variance, trend (tr) and change in trend(Δtr) in the ASO and NDJ season.

3. RESULTS AND DISCUSSION

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 1 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

4. 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 precipitation 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.

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