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Future Projections of Daily Precipitation and Its Extremes in Simulations of 21st Century Climate Change

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Future Projections of Daily Precipitation and Its Extremes in Simulations of 21st Century Climate Change

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Dedication

This report is dedicated to my loving parents, who passed on a respect for education, and to my girlfriend, Yongfei Zhang, without whose caring support it would not have been possible.

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Abstract

Future Projections of Daily Precipitation and Its Extremes in Simulations of 21st Century Climate Change

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The current generation of climate models in the Coupled Model Intercomparison Project Phase 5 (CMIP5) is used to assess the future changes in daily precipitation and its extremes. The simple average of all the models, i.e. the multi-model ensemble mean (MMEM), has been widely used due to its simplicity and better performance than most individual models. Weighting techniques are also proposed to deal with the systematic biases within the models. However, both methods are designed to reduce the uncertainties for the study of climate mean state. They will induce problems when the climate extremes are of interest.

We utilize a Bayesian weighting method to investigate the rainfall mean state and perform a probability density function based assessment of daily rainfall extremes. Satellite measurement is used to evaluate the short historical period. The weighting method can be only applied to regions rather than hemispheric scale, and thus three

tropical regions including the Amazon, Congo, and Southeast Asia are studied. The method based on the Gamma distribution for daily precipitation is demonstrated to perform much better than the MMEM with respect to the extreme events. A use of the Kolmogorov-Smirnov statistic for the distribution assessment indicates the method is more applicable in three tropical wet regions over land mentioned above. This is consistent with previous studies showing the Gamma distribution is more suitable for daily rainfall in wet regions. Both methods provide consistent results.

The three regions display significant changes at the end of the 21st century. The Amazon will be drier, while the Congo will not have large changes in mean rainfall. However, both of the Amazon and Congo will have large rainfall variability, implying more droughts and floods. The Amazon will have 7.5% more little-rain days (defined as > 0.5 mm/d) and 4.5 mm/d larger 95th percentile for 2092-2099, and the Congo will have 2.5% more little-rain days and 1 mm/d larger 95th percentile. Southeast Asia will be dryer in the western part and wetter in the eastern part, which is consistent with the different changes in the 5th percentile. It will also experience heavier rainfall events with much larger increases in the 95th percentile. The future changes, especially the increase in rainfall extremes, are very likely associated with the strengthening of hydrological cycle.

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CHAPTER I

INTRODUCTION

The tropical rainforests play a crucial role in the climate system [*Cox et al*., 2008; *Lewis et al*., 2011]. It accounts for large amount of global terrestrial photosynthesis, and future changes of rainfall over these regions are important for determining global carbon-climate feedbacks [*Cox et al*., 2004]. Particularly, climate change associated with anthropogenic forcings such as the release of greenhouse gases (GHGs) has a strong impact on the bioproductivity of rainforests, fire risk, agriculture, and hydropower production in the Amazon, and significantly contributes to the variations of global atmospheric carbon dioxide concentration [*Ackerley et al*., 2011; *Asner*, 2009; *Chen et al*., 2011; *Friedlingstein et al*., 2006]. How we can assess these changes and warn the public with more reliable evidence closely depends on the development of climate models.

Nowadays a large number of observational data sets and model outputs are available from different modeling groups around the world to study the current climate as well as future projections [*IPCC*, 2007]. However, global models from Couple Model Intercomparison Project Phase 3 (CMIP3) were shown to have highly variable biases in precipitation and its seasonality over Amazon rainforest [*Li et al*., 2006; *Vera et al*., 2006]. Such biases and lack of investigation of their causes contribute to large uncertainty in projecting future changes of the atmospheric CO_2 concentration and

climate [*Friedlingstein et al*., 2006]. Since the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4), considerable efforts have been made to reduce dry biases in the climate models that participated in the IPCC Fifth Assessment Report (CMIP5). CMIP5 includes more than 50 models from 24 modeling groups with generally higher resolution and more ensemble members for individual experiments [*Taylor et al*., 2012]. Are rainfall climatology, variability and their controlling processes realistically represented in CMIP5 models? If not, what are the main causes of such model uncertainty? How we can evaluate these data sets, analyze their potential biases and use them for our specific use closely depends on our understanding of statistical tools.

These General Circulation Models (GCMs) have a wide range of climate response for future climate projections both globally and regionally, although using the same scenarios for greenhouse gas concentration increases [*IPCC*, 2007]. A commonly used approach is to treat equally all models and average them; the resulting multi-model ensemble mean (MMEM) is demonstrated superior to most if not all individual models [*Gleckler et al*., 2008; *Lambert and Boer*, 2001].

The MMEM may not be the best approach when most models tend to have biases of the same direction, i.e. systematic biases [*IPCC*, 2010]. For instance, most models simulate excessively dry conditions over the Amazon in the dry season resulting in a similar bias for the MMEM. Alternative approaches, in which models are weighted according to their agreement with observations in simulating current climate using a Bayesian framework, have been proposed by previous studies [*Jupp et al*., 2010;

Räisänen and Ylhäisi, 2012; *Räisänen et al*., 2010; *Rammig et al*., 2010; *Tebaldi and Knutti*, 2007; *Tebaldi et al*., 2004; *Tebaldi et al*., 2005]. In this work, I employ a Bayesian method, adapted from several previous studies, to weight the CMIP5 models in order to reduce the dry biases over the tropics [*Jupp et al*., 2010; *Rammig et al*., 2010]. However, one should notice that a consensus as to what is a robust weighting technique has not yet been reached [*IPCC*, 2007; 2010; *Räisänen et al*., 2010], partly due to subjective prior input and statistical assumptions [*Knutti et al*., 2010; *Tebaldi and Knutti*, 2007].

Both the MMEM and weighted methods could be problematic when the focus is climate extremes that are not Gaussian-distributed, e.g. daily precipitation. The averages are expected to cancel out extreme values especially in regions where models have large disagreement, and the true distribution for the specific variable substantially narrows [*Räisänen and Ylhäisi*, 2012; *Scoccimarro et al*., 2013].

Many documented distributions have been explored to understand daily precipitation [*Buishand*, 1978; *Hanson and Vogel*, 2008; *Wilks*, 1998], and the Gamma distribution is considered to have a better goodness of fit [*Thom*, 1958; *Watterson and Dix*, 2003]. One good example is the inclusion of fitting a Gamma distribution for precipitation when the Standard Precipitation Index (SPI), a widely accepted standard for drought monitoring, is calculated [*McKee et al*., 1993]. Moreover, one appealing reason why the MMEM is widely used and reported in the Intergovernmental Panel on Climate Change Fourth Assessment Report [*IPCC*, 2007] is its simplicity. Therefore, this study focuses on utilization of the understanding of probability distribution of daily rainfall in a

simple framework using multi-model ensembles to analyze future changes. We also do not consider the ability of the models to reproduce the tendencies of rainfall extremes and assume stationary processes when evaluating the reconstructed daily rainfall distribution [*Scoccimarro et al*., 2013].

We use the recently published model outputs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) designed for the IPCC Fifth Assessment Report (AR5). The data sets as well as observations are described in Chapter 2. The methodologies of weighting models and fitting the daily rainfall distribution for the TRMM data and the models are introduced in Section 3. In Chapter 4, the mean rainfall and fitted distributions are compared, and the methods are evaluated in historical time period. In Chapter 5, future changes of mean rainfall and precipitation extremes are discussed in the three tropical regions. Our main results are summarized and some issues are discussed in Chapter 6.

CHAPTER II

DATA SETS

2.1. CMIP5 Models

The CMIP5 models are designed to support the release of the IPCC 5th Assessment Report (AR5). This study examines daily precipitation in the historical and RCP8.5 experiments. Twelve models are used, including CanESM2, CCSM4, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-CC, HadGEM2-ES, INM-CM4, IPSL-CM5A-LR, MIROC5, MPI-ESM-LR, and MRI-CGCM3. Some information of these models is summarized in Table 1. Since the TRMM rainfall product is available from 1998, we compare 2092-2099 in RCP8.5 runs with 1998-2005 in historical runs to assess the future changes of rainfall distribution at the end of the 21st century. The more than 2000 samples in each grid box of the 8-year periods are adequate to assess distribution. The majority of the models provide multiple ensemble runs for each experiment. Given that the focus of this study is to construct rainfall distribution rather than the mean state and the average of all runs would reduce random variability in each simulation, we utilize one ensemble member from each model for this particular purpose [*IPCC*, 2010] which already provides enough samples to estimate the parameters. The model outputs are collected by the Program for Climate Model Diagnosis and Intercomparison (PCMDI).

One of the most important parts in the IPCC report is the assessment of General

Table 1. A description of the twelve CMIP5 models

Model	**Institute (Country)**	**Ens**	**Components (Resolution)**	**Calendar**
CanESM2	Canadian Centre for Climate Modelling and Analysis (Canada)	5	**Atm**: CanAM4 (AGCM15i, T63L35) **Ocn**: CanOM4 (OGCM4.0 256×192L40)	No leap
CCSM4	National Center for Atmospheric Research (USA)	6	F09_g16 (0.9×1.25_gx1v6)	No leap
GFDL-CM3	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	5	**Atm**: AM3 (2.0° lat ×2.5° lon) **Ocn**: MOM4.1 (1.0° lat ×1.0° lon, enhanced tropical resolution: 1/3 on the equator)	No leap
GFDL-ESM2G	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	1	**Atm**: AM3 (2.0° lat ×2.5° lon) **Ocn**: TOPAZ (Tripolar, 360×210, L63)	No leap
GFDL-ESM2M	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	1	**Atm**: AM3 (2.0° lat ×2.5° lon) **Ocn**: MOM4.1 (1.0° lat ×1.0° lon, enhanced tropical resolution: 1/3 on the equator)	No leap
HadGEM2-CC	Met Office Hadley Centre (UK)	3	**Atm**: HadGAM2 (N96L60) **Ocn**: HadGOM2 (Lat: 1.0-0.3 Lon: 1.0 L40)	360 d/y
HadGEM2-ES	Met Office Hadley Centre (UK)	4	**Atm**: HadGAM2 (N96L38) **Ocn**: HadGOM2 (Lat: 1.0-0.3 Lon: 1.0 L40)	360 d/y
INM-CM4	Institute for Numerical Mathematics (Russia)	1	**Atm**: 1.5° lat ×2.0° lon **Ocn**: ?	No leap
MIROC5	AORI, NIES, and JAMSTEC (Japan)	4	**Atm**: AGCM6 (T85L40) **Ocn**: COCO4.5 (256×224, L50)	No leap
IPSL-CM5A-LR	Institut Pierre Simon Laplace (France)	4	**Atm**: LMDZ4 (96×95×39, 1.875° lat ×3.75° lon) **Ocn**: ORCA2 (2×2L31, 2.0° lat ×2.0° lon)	No leap
MPI-ESM-LR	Max Planck Institute for Meteorology (Germany)	3	**Atm**: ECHAM6 (T63L47) **Ocn**: MPIOM (GR15L40)	Gregorian
MRI-CGCM3	Meteorological Research Institute (Japan)	5	**Atm**: GSMUV (Tl159L48) **Ocn**: MRI.COM3 (1×0.5, L51)	Gregorian

Circulation models (GCMs) from more than 20 participated modeling centers. One common view about these GCMs is that they are not all performing well on simulating climate mean state as well as the variability. Also, well-developed modeling centers do not necessarily have better GCMs, especially in the study of regional climate. For instance, Geophysical Fluid Dynamics Lab (GFDL) models have significant dry bias in the dry season of the Amazon [*Bombardi and Carvalho*, 2009; *Dai*, 2006]. This is associated with the bias in Intertropical Convergence Zone (ITCZ) [*Doi et al*., 2012; *Yin et al*., 2012].

2.2. Reference data

The Tropical Rainfall Measuring Mission (TRMM), as a join mission between the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA), is designed to facilitate our understanding of rainfall distribution and variability within the tropics. It coincides with our focus and serves as the reference for the assessment of the historical rainfall distribution. TRMM 3B42 algorithm (version 7) provides adjusted merged-infrared (IR) daily rainfall amount at $0.25°\times0.25°$ spatial resolution [*Huffman et al*., 2007]. TRMM and CMIP5 data are interpolated into $2.5°\times2.5°$ resolution in order to facilitate our comparison at each grid box. TRMM 3B42 can be accessed at NASA Goddard Earth Sciences (GES) Data and Information Services Center (DISC).

CHAPTER III

METHODOLOGY

3.1. Bayesian Weighting Techniques

Several approaches have been proposed to combine all the information provided by these models to study future projections. The MMEM may be biased when systematic biases exist either due to common issues in the parameterizations or initial assumptions. One suggestion is to put more weights on better performing models. The Bayesian method to weight the models used in this report is adapted from previous studies [*Jupp et al*., 2010; *Rammig et al*., 2010].

A discrete uniform prior is assigned to the model weights. This is rather like an informative prior since the MMEM does provide improvements for comparison with the observations in terms of climate mean state [*Gleckler et al*., 2008]. Two steps are taken to set up the likelihood. Firstly, The difference in the means between the models and observation is assessed to construct the first-step posterior. The sample variance is calculated in Equation (1):

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(m_i - \frac{1}{N}\sum_{i=1}^{N}m_i)^2 \quad (1)$$

where m_i is the ith model data. Then a climate index is calculated in Equation (2):

$$C_i = (m_i - O)^2 \quad (2)$$

where O is the observation. The likelihood is then defined as:

$$f(d|weights) = \exp(-\frac{C_i}{2\sigma^2}) \quad (3)$$

The second-step weights are given more to the models with closer distribution with that of the observation. Before that, the mean climate biases need to be removed first:

$$\log b_{i,t} = \log m_{i,t} - \overline{\log m_{i,t}}^t + \overline{\log O_t}^t \quad (4)$$

Kolmogorov-Smirnov (KS) statistic is used to assess the consistence of distribution and construct the final likelihood, and details about the KS statistic will be introduced in Chapter 3.3.

After the final posterior weights are obtained, we compare the results from weighted average of model outputs (WGT) against MMEM.

3.2. Construction of daily rainfall distribution

Establishing a probability density function to investigate daily rainfall distribution has long been a popular topic in the fields of meteorology, engineering, and others. Several studies suggest that so far the two parameter Gamma distribution function may be appropriate for daily rainfall assessment [*Buishand*, 1978; *Thom*, 1951; *Wilby*, 2002], while some other distributions are also proposed to have a good fit [*Burgueño et al*., 2005; *Wilks*, 1998]. One good example of the Gamma fit is the Standard Precipitation Index (SPI), widely-used nowadays and designed to enhance drought monitoring [*McKee et al*., 1993]. The calculation of the SPI is performed by first fitting a Gamma

distribution to monthly rainfall values where the two parameters are maximum likelihood estimates (MLEs) [*Thom*, 1958]. For daily precipitation, the Gamma distribution also has better, if not the best, goodness of fit for wet days and regions [*Buishand*, 1978; *Thom*, 1951; *Watterson and Dix*, 2003].

In order to understand the underlying distribution of daily precipitation and verify the advantage of Gamma fitting, we compare four different distributions for the TRMM data. They are Exponential (EXP), Gamma (GAM), Generalized Pareto (GPA), and Generalized Extreme Value (GEV) distributions, and their corresponding probability density functions (PDFs) are given in Table 2. These four distributions have been proposed by previous studies to assess daily rainfall and have different performance for specific situations [*Hanson and Vogel*, 2008; *Papalexiou and Koutsoyiannis*, 2013; *Toreti et al*., 2013]. The stationary processes are assumed for the 8-year time period in order to assess the goodness of fit of the statistical model on the basis of adequate data points. The comparisons of the distributions are discussed in Chapter 4.2.

Based on the comparisons, we further utilize the Gamma distribution to fit daily rainfall in each model and reconstruct it across the models in a similar manner with the multi-model ensemble mean (MMEM), as described in Equation (5):

$$GAMM(x;\xi,\theta) = \frac{(\overline{\theta})^{-\overline{\xi}}}{\Gamma(\overline{\xi})} x^{\overline{\xi}-1} e^{-\frac{x}{\overline{\theta}}} \tag{5}$$

where GAMM is the reconstructed daily rainfall distribution function. Γ is Gamma function where $\Gamma(\overline{\xi}) = (\overline{\xi} - 1)!$. $\overline{\xi}, \overline{\theta}$ are the averages of the shape and scale parameters for the models:

$$\overline{\xi} = \frac{\sum_{i=1}^{M} \xi_i}{M}, \overline{\theta} = \frac{\sum_{i=1}^{M} \theta_i}{M} \tag{6}$$

M is the number of models. ξ_i and θ_i are the shape and scale parameters for *i*th model, respectively, and they are obtained as MLEs $\hat{\xi}_i$ and $\hat{\theta}_i$. $\hat{\theta}_i$ is easy found by taking the derivative of log-likelihood with respect to θ_i and given by:

$$\hat{\theta}_i = \frac{\sum_{j=1}^{n} x_j}{n \cdot \hat{\xi}_i} \tag{7}$$

where x_j are samples and n is the sample size. The two-parameter log-likelihood then reduces to one-parameter space. However, taking the derivative and setting it equal to zero does not yield a closed-form solution for $\hat{\xi}_i$. Therefore, we employ Newton's iteration method to obtain the root of the likelihood equation given by:

$$\psi(\hat{\xi}_i) = \frac{1}{n}\sum_{j=1}^{n} \log x_j - \log(\frac{1}{n}\sum_{j=1}^{n} x_j) + \log \xi_{i0} \tag{8}$$

where ψ is the digamma function, defined as the logarithmic derivative of the gamma function. ξ_{i0} is the initial value of ξ_i and can be obtained by using the method of moments:

Table 2. The probability density functions (PDFs) of the four distributions assessed for daily precipitation

Name	**PDF**
Exponential (EXP)	$f(x;\lambda)=\lambda e^{-\lambda x}, x\geq 0$
Gamma (GAMM)	$f(x;\xi,\theta)=\frac{\theta^{-\xi}}{\Gamma(\xi)}x^{\xi-1}e^{-\frac{x}{\theta}}, x>0$
Generalized Pareto (GPA)	$f(x;\xi,\mu,\theta)=\frac{1}{\theta}(1+\frac{\xi(x-\mu)}{\theta})^{-\frac{1}{\xi}-1}, x\geq\mu(\xi\geq 0)$
Generalized Extreme Value (GEV)	$f(x;\xi,\mu,\theta)=\frac{1}{\theta}(1+\frac{\xi(x-\mu)}{\theta})^{-\frac{1}{\xi}-1}$ $\cdot\exp[-(1+\frac{\xi(x-\mu)}{\theta})^{-\frac{1}{\xi}}], x>\mu-\frac{\theta}{\xi}(\xi>0)$

$$\xi_{i0} = \left(\frac{\sum_{j=1}^{n} x_j}{n \cdot \sigma_x}\right)^2 \tag{9}$$

where σ_x is the standard deviation of the samples.

This method using Equation (5) is appropriate to assess rainfall distribution since the distributions for the models tend to scatter around the true distribution implying the averages of the two parameters for the models can reduce the distribution bias, and thus this method inherits some of the benefits of the MMEM from the distribution perspective.

3.3. A Statistic for Evaluation of Distribution

We use the Kolmogorov-Smirnov (KS) statistic *D* to evaluate modeled daily rainfall distribution against that from TRMM. D_i is defined as the absolute maximal distance of the empirical cumulative distribution functions (CDF) between TRMM and *i*th model:

$$D_i = \max\left|CDF_0(x) - CDF_i(x)\right| \tag{10}$$

The applications are discussed and well documented in previous studies [*Feldl and Roe*, 2011; *Jupp et al*., 2010].

Since the distribution is of more concern than climatology, the spatio-temporal mean bias is corrected in Equation (11) before the evaluation:

$$\log M_{i,s,t}^{new} = \log M_{i,s,t} - \left\langle \overline{\log M_{i,s,t}} \right\rangle + \left\langle \overline{\log O_{i,s,t}} \right\rangle \tag{11}$$

where the angle brackets denote a temporal mean and the overbars denote a spatial mean. *O* is the observation and M_i is the *i*th model. *s* and *t* represent space and time,

respectively.

Thus, we can regard the KS statistic D_i as a measure of the difference between the empirical CDF of the TRMM daily rainfall product and bias-corrected CDF of the *i*th model, and smaller D_i indicates better performance on rainfall distribution for the *i*th model. We also compare this method with the MMEM using the KS statistic.

CHAPTER IV

HISTORICAL EVALUATIONS

4.1. Comparisons of rainfall climatology

The posterior weights for the CMIP5 models are shown in Figure 1 for the Amazon, Congo, and Southeast Asia. Models H, J, and L are primarily selected for the Amazon; models C and H are selected for the Congo; and models C, F, and I are selected for Southeast Asia. The other models for specific regions are assigned with almost 0 weights primarily due to their significant bias occurred during the algorithm. The result for the Amazon is consistent with my previous work showing that the large inter-model variability exists. The better performance of these three models is a result of more reasonable surface conditions as well as Inter Tropical Convergence Zone (ITCZ). Thus, the application of purely statistical tools can be an underlying signature of important physical processes.

Figure 2 indicates the weighting method (WGT) partly corrected the dry bias for the Amazon region. The underestimates of rainfall by the MMEM are clearly seen over the whole area and are dominant over the northern part, up to 4 mm/d less than the observation. The WGT shows a significant reduction of the dry biases in the whole domain, especially the southern part, implying the use of multi-model ensembles can modulate the rainfall spatial pattern adjusted to be consistent with the observation for regional structure. However, the WGT does not reduce the bias for the Congo and

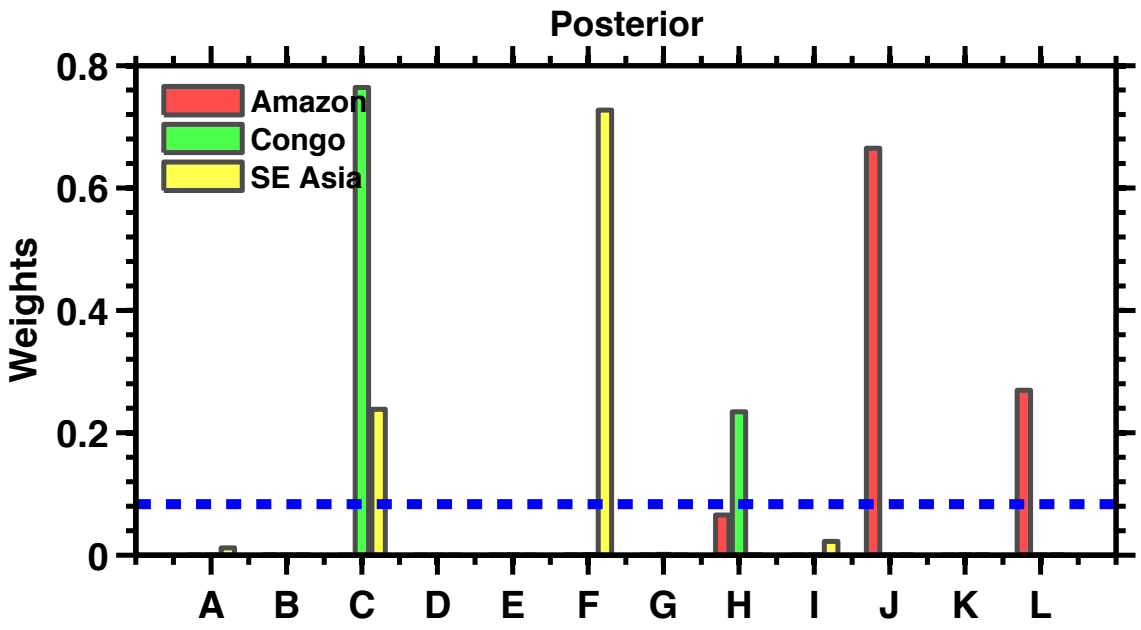

Figure 1. The posterior weights of the 12 models for the three tropical regions. The Amazon is selected as the rectangular region of 75°W-55°W, 15°S-5°N; the Congo is selected as of 15°E-30°E, 7.5°S-5°N; and South Asia is selected as of 95°E-155°E, 10°S-5°N.

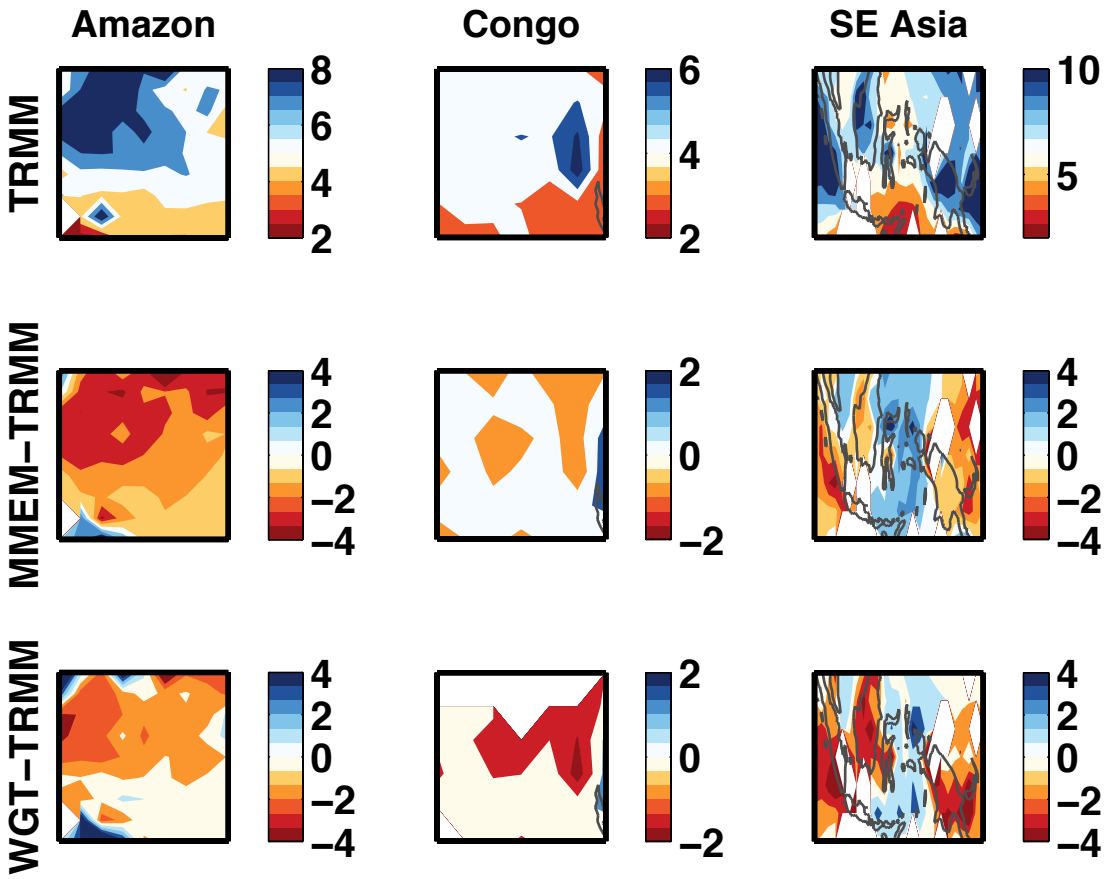

Figure 2. The rainfall climatology from TRMM for the three tropical regions (first row), the difference between the MMEM and TRMM (second row), and the difference between the WGT and TRMM (third row). The unit is mm/d.

Southeast Asia. Two reasons might be responsible for this issue. One is that we also consider the difference in area-averaged rainfall distribution as one important step of the penalties for weighting. While one model might have less bias for the climatology, a significant bias in distribution would also lower its weight. Also, the WGT method is not designed for each grid since energy and hydrological budgets need to be maintained. Therefore, a weighted average of three models is likely to increase bias in sub-regions.

4.2. Comparisons of distributions

Figure 3a compares the Gamma-fitted daily rainfall with the empirical TRMM data in order to check whether the daily rainfall reasonably follows the Gamma distribution. Relatively small values of the KS statistic in oceanic areas especially the tropics, South Pacific Convergence Zone (SPCZ), tropical rainforest regions, the western US, and the Tibetan Plateau indicate the true distribution of daily rainfall may approximately follow the Gamma distribution. Figure 3b compares the four distributions by ranking the KS statistic from low to high. Among them, the Gamma distribution outperforms over most areas of the tropics and subtropics, while the GPA distribution is the best for the Sahara Desert, Middle East, and some other grids. The GEV distribution is only the best for very few grids, and the EXP distribution is considered as the worst. Given the fact that the Gamma distribution is in the best daily rainfall fitting family as well as the unjustified GPA location assumption and slow convergence to a GPA/GEV shape, we use the method in Equation (5) to reconstruct the daily rainfall distribution for CMIP5 models.

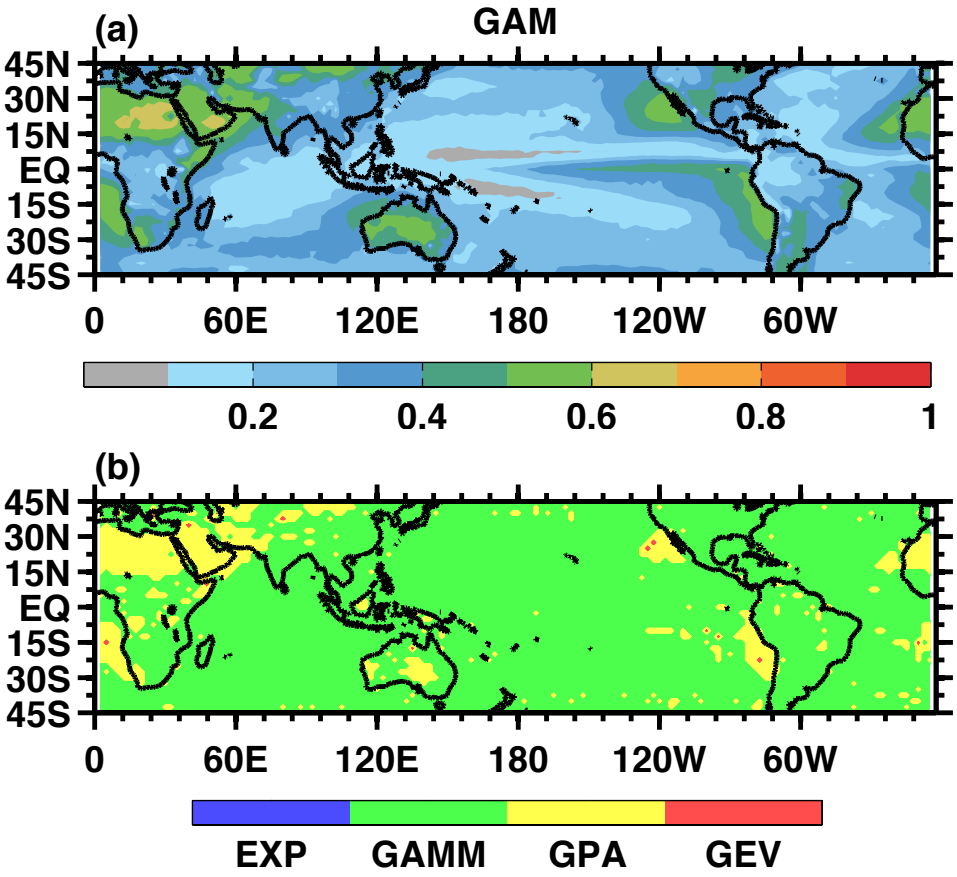

Figure 3. (a) The KS statistic between the empirical and Gamma-fitted TRMM data, and (b) the pattern of best distribution indicated by the smallest KS statistics

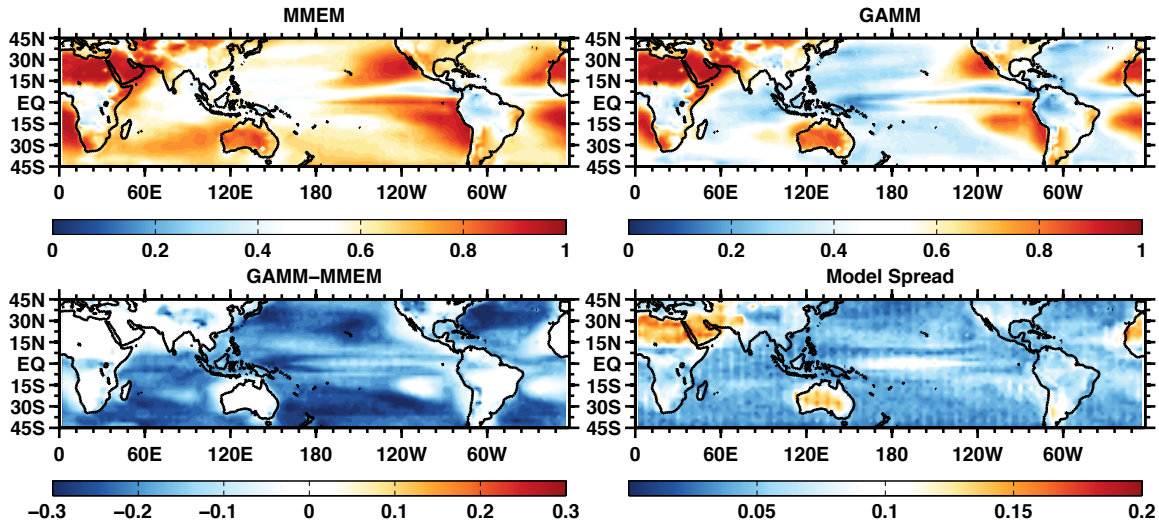

Figure 4. The KS statistic for the (a) MMEM, (b) GAMM, (c) its difference between the GAMM and MMEM, and (d) model spread of changes in the KS statistic among Gamma-fitted and original model outputs

4.3. Evaluation of the GAMM method

Figure 4 shows the KS statistic for the MMEM, GAMM compared with TRMM and their difference. For the MMEM, the KS statistic is generally larger than 0.5 over the entire domain between 45°S and 45°N except for tropical South America and central Africa (Figure 4a), implying a significant difference between the distributions of the TRMM and MMEM. The GAMM method has reasonable application over the tropical rainforest regions including the Amazon, Congo, and Southeast Asia with the KS statistic values smaller than 0.4, although it is still poor for the drier regions including the east coast of the Americas and the Africa continent, the Sahara, West Asia, and Australia (Figure 4b). The GAMM improves the daily rainfall distribution over all the oceanic areas and some land areas including the western US, the Tibetan Plateau, and tropical rainforest regions (Figure 4c).

Figure 4d shows the model spread of changes in the KS statistic among Gamma-fitted and original model outputs between 2092-2099 and 1998-2005. As shown, the values are generally smaller than 0.1, except the Sahara, West Asia, and Australia. Compared with Figure 4b, the model spread is smaller indicating that daily rainfall in the models does not have much change in the distribution function and approximately follows Gamma distribution in the future to the same degree as the present, despite the change of shape and scale parameters.

Figure 5 and 6 show the 5^{th} and 95^{th} percentile for the TRMM, its difference between the MMEM and TRMM, and between the GAMM and TRMM. The 5^{th} percentile for TRMM daily rainfall is generally 0 mm/d for the entire domain between

45°S and 45°N (Figure 5a). However, it is larger than 2 mm/d for the MMEM in regions of the tropical oceans and SPCZ, the western North Pacific and Atlantic, and the tropical rainforest regions (Figure 5b). In none of the grids, the MMEM is better than at least half of the individual models. The GAMM largely reduces the biases, although some weak differences (<1 mm/d) still exist over the western Pacific on the two sides of the equator (Figure 5c). It also shows in most of the regions the GAMM has less bias than at least 6 models, except subtropical Pacific and Atlantic.

Figure 6a and 6b show the MMEM produces much smaller rainfall for the 95th percentile over the wet regions indicated by the TRMM, with a rainfall reduction more than 20-30 mm/d. The MMEM is better than at least 6 models over the east coast of the Americas and the Africa continent, southern Indian Ocean, the Sahara, West Asia, and partial Tibetan Plateau. The GAMM can reduce the biases especially over the three tropical rainforest regions despite of 10-20 mm/d biases in other regions (Figure 6c). Interestingly, the regions where the GAMM is better than at least half of the models are also the regions with relative small KS values (Figure 4b) almost compensate the poor applications of the MMEM, especially the tropical regions.

The larger biases for the MMEM over the regions in Figure 3a and 3b is because daily rainfall extremes are largely canceled out by taking the average of the models over these regions, indicating greater inter-model variability. The larger biases in the 95th percentile than the 5th percentile imply that individual models tend to not produce right-tailed distribution of precipitation (heavy rains) especially in the global wet regions. The improvements by the GAMM method show that it can be reasonable to study the changes

in daily rainfall extremes using this method.

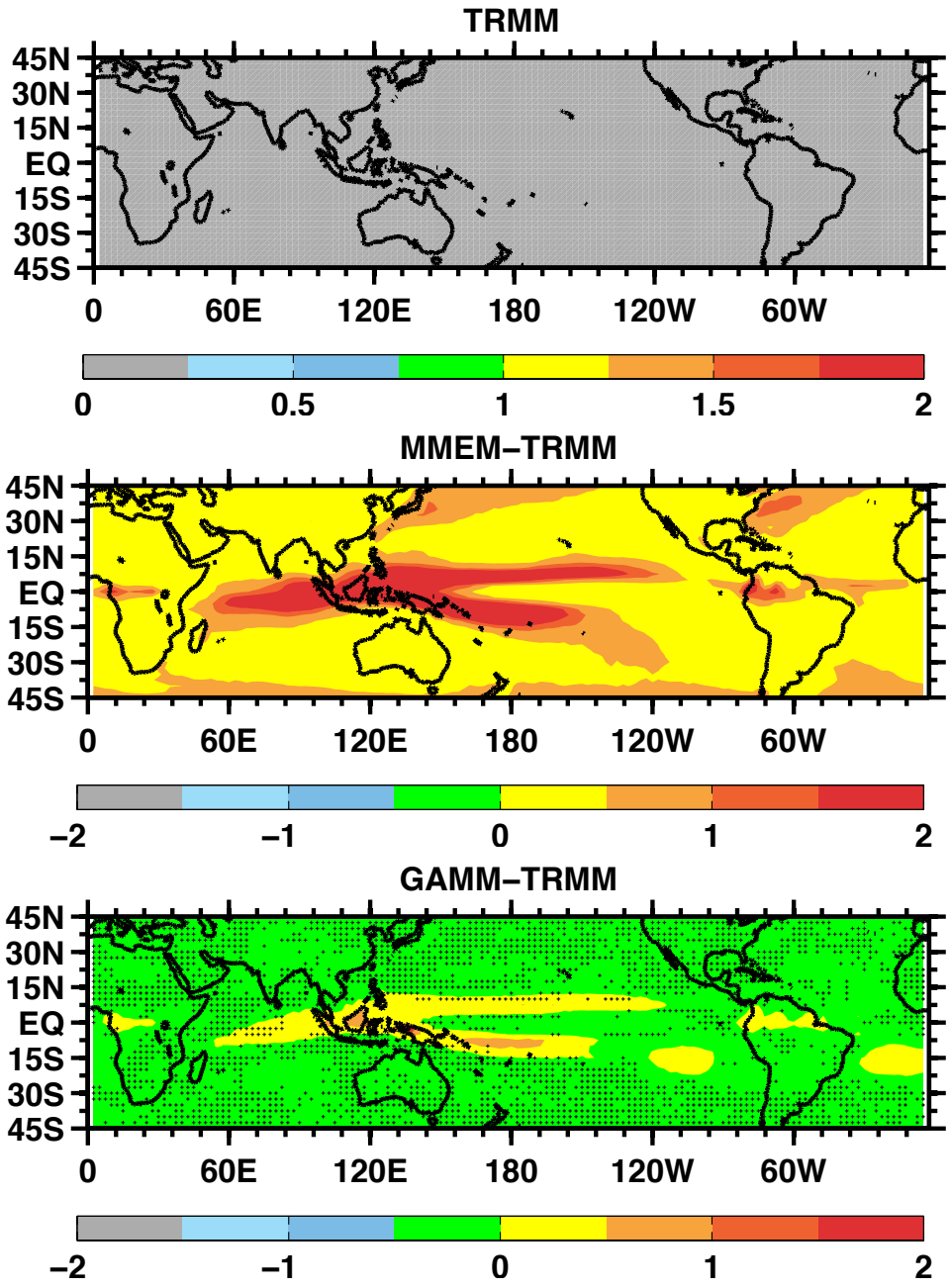

Figure 5. The 5th percentile for (a) the TRMM, (b) its difference between the MMEM and TRMM, and (c) between the GAMM and TRMM. The unit is mm/d. Regions are stippled where the MMEM or GAMM is better than at least arbitrary half of the models.

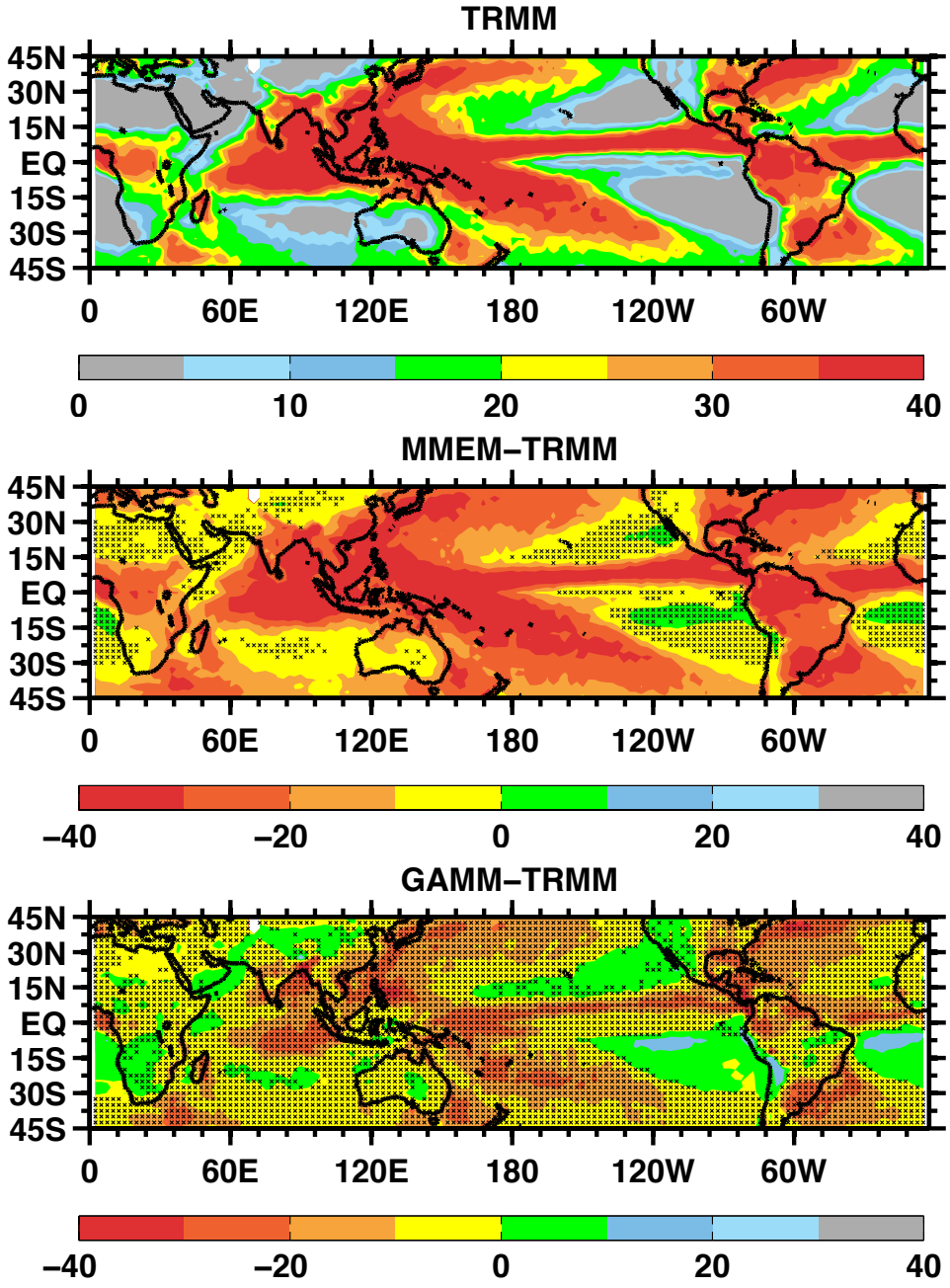

Figure 6. The 95th percentile for (a) the TRMM, (b) its difference between the MMEM and TRMM, and (c) between the GAMM and TRMM. The unit is mm/d. Regions are stippled where the MMEM or GAMM is better than at least arbitrary half of the models.

CHAPTER V

FUTURE CHANGES

5.1. Rainfall mean state

Figure 7 shows the mean rainfall changes at the end of 21st century (2092-2099) compared with the current climate (1998-2005). The changes are more significant toward the dry end indicated by WGT especially in the northern Amazon, while the drier changes are less than 0.5 mm/d by MMEM. This is consistent with larger surface temperature increases by WGT than MMEM (not shown), given the relationship between temperature and precipitation over the tropics. The change over the Congo is not very large both by the WGT and the MMEM. However the changes over Southeast Asia demonstrate spatial differences. The eastern part will be wetter and the western part will be drier. This actually is very likely to be consistent with an enhanced tropical hydrological cycle in the 21st century. If this method gave us stronger confidence on the modeled future projections, the results would warn the entire society about related issues of the civilization progress and environmental protection.

5.2. Rainfall extremes

Given the appropriate application of the GAMM method (Figure 3) and common interests in the three tropical rainforest regions (the Amazon, Congo, and Southeast Asia), Figure 8 shows the changes in rainfall extremes in these regions. We utilize

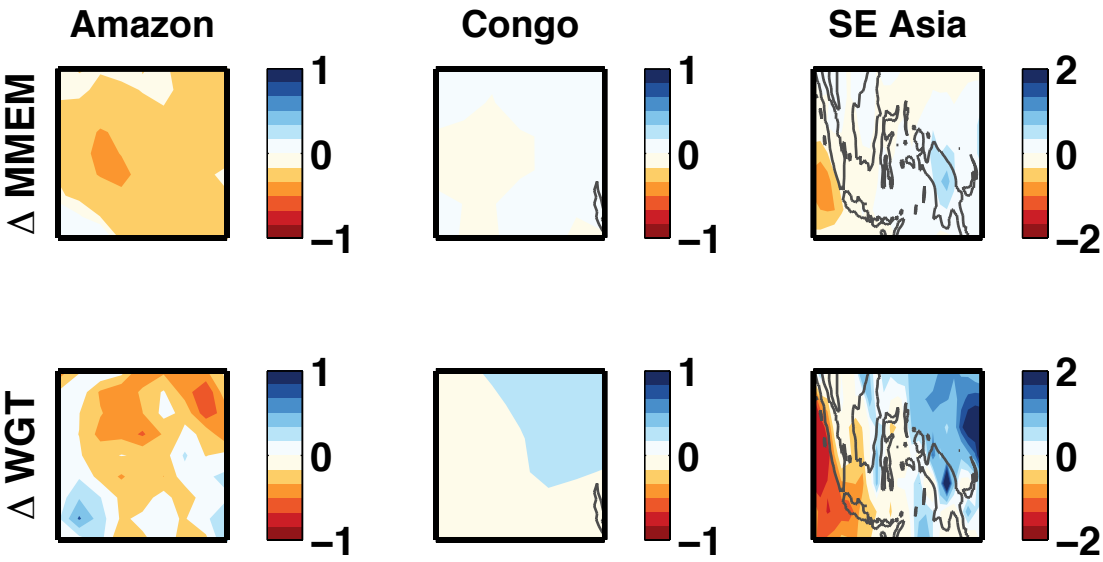

Figure 7. The rainfall changes (2092-2099 minus 1998-2005) from the MMEM (first row) and WGT (second row) for the three tropical regions. The unit is mm/d.

percentage change of little-rain days (defined as < 0.5 mm/d) for the Amazon and Congo considering that the 5th percentile is normally 0 mm/d in places where the dry season is adequately long and rainfall seasonality is clear [*Fu et al*., 2013]. We also look at three different 8-year time period in the 21st century (2032-2039, 2062-2069, and 2092-2099) in order to discover whether the changes are hidden in some possible interannual or decadal phenomenon. The results from the GAMM method are compared with that from the MMEM.

The three regions display significant changes throughout the 21st century. The Amazon, from the GAMM method, will have 7.5% more little-rain days and 4.5 mm/d larger 95th percentile at the end of the 21st century, indicating greater daily rainfall variability and more rainfall extremes. The results from the MMEM show similar direction of changes with much smaller magnitude, i.e. 2.5% more little-rain days and 1 mm/d larger 95th percentile at the end of the 21st century. Changes from both GAMM and MMEM are significant visually, especially for the dry days. The GAMM method shows quite similar results for the Congo basin, 5% more little-rain days and 4 mm/d larger 95th percentile for 2092-2099. Although the MMEM shows a same change in heavy rainfall with smaller magnitude, it does not have clear change in the little-rain days. Since Southeast Asia almost has 0 percentage of little-rain days, we still use the 5th percentile to represent the dry condition. An insignificant change in the 5th percentile actually results from an increase in the western Pacific and a decrease in the eastern Indian Ocean (not shown). It also shows positive change of the 95th percentile, with 17 mm/d larger for the GAMM and 5 mm/d larger for the MMEM respectively for 2092-2099.

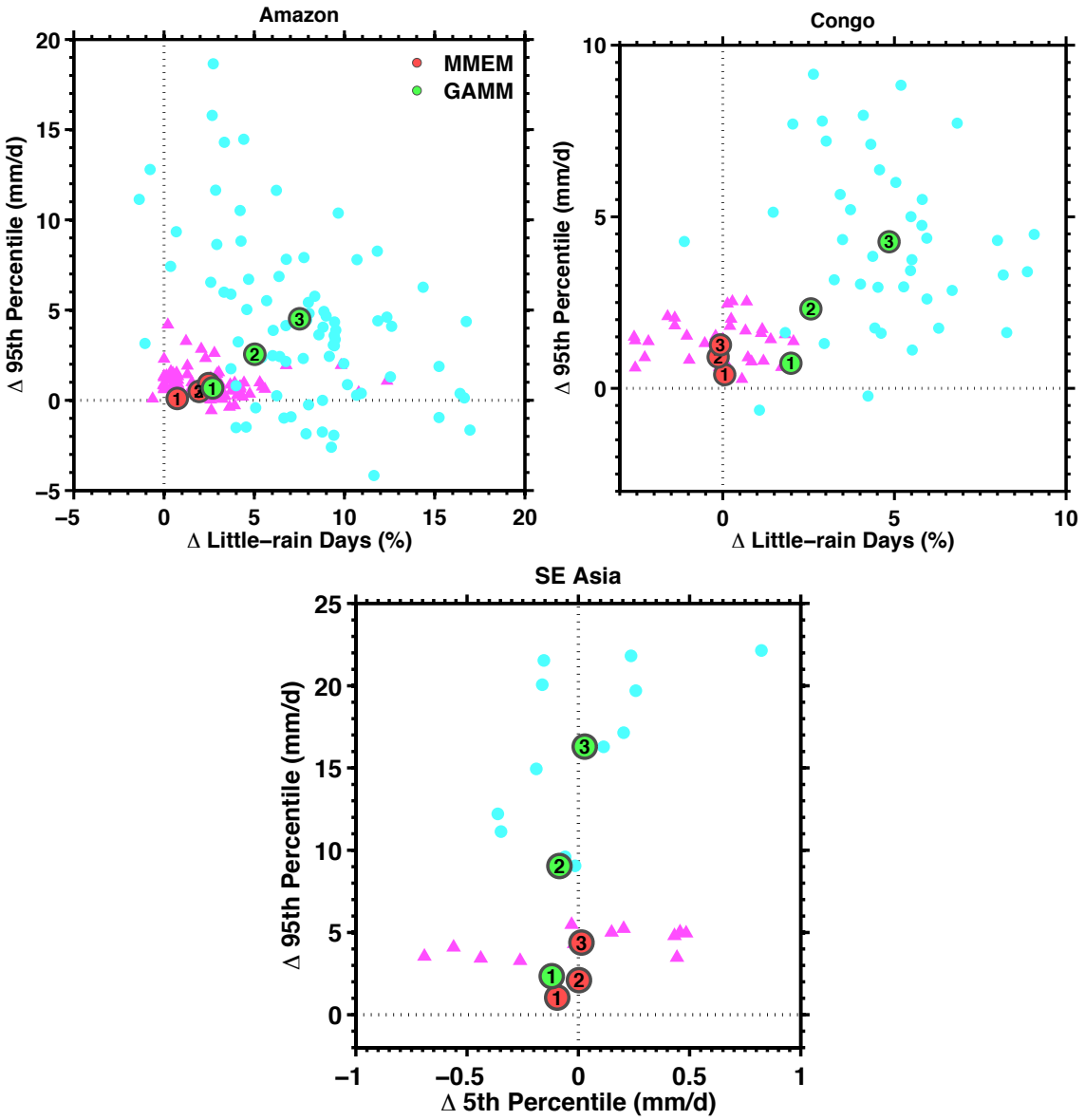

Figure 8. Scatter plot of changes in little-rain days and 95th percentile for the Amazon and Congo, and changes in 5th and 95th percentile for Southeast Asia. The oceanic grids have been removed. Numbered circles represent different time periods: "1" for 2032-2039, "2" for 2062-2069, and "3" for 2092-2099. Red is from the MMEM and green is from the GAMM. Magenta triangles are all the grids for the period of 2092-2099 from the MMEM, while cyan circles are those from the GAMM.

Despite of some discrepancies in the changes of the dry condition and different magnitude, changes of heavy precipitation are all positive for the tropical lands for both GAMM and MMEM. These are consistent with previous studies using different methodologies [*Min et al*., 2011; *Westra et al*., 2013]. One reason is due to an intensification of the hydrological cycle implied by the atmospheric and surface heat budget [*Trenberth*, 2011]. This is even clear for the Pacific Walker circulation with an upward branch located at the western Pacific. Another explanation is that shifted sea surface temperature change, e.g. ENSO pattern change, can also alter the rainfall distribution in the tropics.

CHAPTER VI

CONCLUSIONS AND DISCUSSION

This report utilizes two statistical methods to understand the mean rainfall and precipitation extremes, respectively. The first one is to weight the newly published IPCC models based on Bayesian theory and climate index. The mean climate state and rainfall distribution assessed by Kolmogorov-Smirnov statistic are investigated to construct the two-step posterior. The dry biases over the Amazon in most models are largely reduced using the weighting techniques, and the better models selected are consistent with their better performance in physical processes that are related to precipitation over the Amazon. Although the method does not reduce the bias over the Congo and Southeast Asia, it may reduce underlying distribution bias. The future changes from the WGT method are similar to those from the MMEM, but with larger magnitude.

Many studies using multi-model ensembles focus on how to improve the simulations of climate mean state and reduce inter-model uncertainties [*Blázquez and Nuñez*, 2012; *Räisänen et al*., 2010; *Tebaldi et al*., 2005]. Either the simple MMEM or weighting techniques can serve to handle these issues. However, when climate extremes and their future changes are of interest, studies are normally based on individual models that are more variable-dependent [*Kharin et al*., 2005; *Sun et al*., 2006].

At monthly time scale, the MMEM could still be applicable to assess temperature and rainfall extremes since it is approximately Gaussian-distributed [*Räisänen and*

Ylhäisi, 2012; *Tebaldi and Knutti*, 2007; *Tebaldi et al*., 2005]. Yet for daily precipitation extremes, the unweighted or weighted means are not quite applicable since extreme values would be largely reduced as a result of reduced random variability across different simulations. Here we propose a probability density function based method of constructing daily precipitation distribution in the CMIP5 multi-model ensembles. The method assumes that daily rainfall is Gamma-distributed and employs the MLEs for the shape and scale parameters. Making the averages of the parameters for the models is of the similar manner with the MMEM technique since the distributions for individual models scatter around the true one defined as the observation. We then use the KS statistic to evaluate whether the constructed distribution is close to that from the TRMM product.

Unsurprisingly, the method provides a better way than the MMEM to assess the daily rainfall distribution in tropical rainforest regions as indicated in Figure 2. The biases in the 5^{th} and 95^{th} percentile have also been largely reduced in these regions (Figures 3 and 4). The future changes in the 21^{st} century have been investigated in the tropical regions where the method is appropriate enough. The Amazon and Congo will experience enhanced rainfall variability implying dryer condition and heavier rainfall, while Southeast Asia will have right-hand shifted rainfall distribution with increased rainfall amount. The results are consistent with a recent study on changes of rainfall extremes in CMIP5 models with different assessment [*Scoccimarro et al*., 2013].

One limitation of this method is that it can only be applied to rainfall assessment of specific regions. The fundamental assumption that Gamma distribution fits daily

rainfall is more suitable for wet days and wetter regions (Figure 2a) [*Buishand*, 1978; *Thom*, 1951]. How we can loose the assumption and develop new methodology for global regions is beyond the scope of this study. Given the large inter-model variability for the tropics and subtropics, possibly due to model deficiencies of simulating upward velocity and representing organized convective systems [*O'Gorman and Schneider*, 2009; *Toreti et al*., 2013], our method provides an alternative way to assess the future changes of daily rainfall extremes in the tropical land regions, and indicates similar with *O'Gorman* [2012]. Finally the future development of these models for reducing the detected rainfall biases, e.g. dry biases in the Amazon, can increase our confidence in drawing conclusions for predictions.

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Vita

Lei Yin was born in Suzhou, China, in 1987, and was named for the thunderstorm that accompanied his birth. Growing up in a family filled with the smell of math, he was deeply affected by his grandpa and uncle who were both high-school math teachers and doomed to his teenage years of practicing algebra and geometry into long hours of the night. Nevertheless, the 1998 deluge in southern China almost destroyed his home and entirely changed his impression of the nature of our planet. After seeing the horror of disasters that affect human beings, Lei chose atmospheric science as his undergraduate major so that he would be armed with more than his dream, a dream of having less fear of natural threats.

He enjoyed his four years at Nanjing University, where not only did he take excellent care of school curriculum, but also built confidence, patience, and diligence. Thanks to advanced training in mathematics and physics that his field offered, Lei acquired a wide spectrum of knowledge in basic sciences and felt wholly prepared to enter the real world of manipulating details, i.e. scientific research.

While attending the Jackson School of Geosciences at The University of Texas at Austin, he worked on detecting climate changes over South America as a Ph.D. student. His research centered on recognizing the basic physical processes and dynamics contributing to climate variability and change on all time scales, understanding the relative importance of natural variability and anthropogenic forcing, and revealing the

potential influence of air-land interactions behind the hydrological cycle. After delving more into the science, he realized the importance of computational and mathematical tools in his research area. Thus, he also spent much time on taking courses to obtain a systematic overview of these applications. He first accomplished the Portfolio in Applied Statistical Modeling, and then finished the M.S. in Statistics in School of Natural Sciences at UT-Austin.

Equipped with the knowledge of both statistics and climate science, Lei is concurrently pursuing the Ph.D. in geological sciences. He is still on his path toward the mysterious mist of the future; of one thing he is sure: whatever the place he occupies, his priority will always be to serve society as a whole.

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This report was typed by Lei Yin.