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ENGINEERING JOURNAL

Bias Correction of Seasonal Rainfall Forecasts of Thailand from General Circulation Model by Using the Ratio of Gamma CDF Parameter Method

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Abstract – **Water management needs rainfall forecasts for planning and responding to flood and drought events. Variation in rainfall can affect water usage activities and reservoir operation. Recently, the seasonal forecasting of rainfall has been conducted based on the relationship between rainfall on a continent and sea surface temperature of an ocean, which then can be used to forecast rainfall patterns for El Nino and La Nina phenomena. General circulation models are an alternative tool that provides seasonal rainfall forecasts. However, their resolution is too coarse to be applied on a river basin and country scale because they employ a mathematical model of the general circulation of planetary atmosphere and ocean to forecast the seasonal rainfall on a global scale. In order to improve the accuracy of rainfall forecasts for both spatial and temporal purposes, the seasonal rainfall forecast data from general circulation models must be downscaled to the station level before they can be utilised in hydrological applications or water planning, This research attempts to develop a new bias correction technique to downscale seasonal rainfall forecasts by using the ratio of gamma CDF parameters with data from three global circulation models including CCM3V, ECHAM4.5, and GFDL. The performance of each bias corrected general circulation model is evaluated by some goodness of fit measures such as root mean square error, mean square error, and sum absolute error. This bias correction method was demonstrated to be able to improve the quality of global circulation model data in both temporal and spatial terms, and CCM3V provides better results compared to other models.**

Keywords – Seasonal rainfall forecasting, Bias Correction, General circulation model, Gamma CDF.

1. INTRODUCTION

It is necessary to have rainfall forecasts in order to manage water operations. Water operations in practice can be employed for flood and drought forecasting and warnings, providing effective rainfall forecasts which can assist farmers in planning paddy rice production to avoid losses from variations in rainfall. More advanced rainfall forecasting technologies have been developed, and among them is the global circulation model (GCM). GCM is a tool used to simulate the future climate on monthly and seasonal basis. It is a dynamic model which couples together atmospheric and oceanic models thereby providing high accuracy forecasts on a global scale. However its forecasting results are still too coarse to be used for water management in the river basin. Therefore GCM precipitation forecasts need to be downscaled to the station level before being applied to the hydrological system on a river basin scale. Statistical downscaling can be described as the process of linking coarse resolution climate model output to fine resolution station-level data via statistical relationships with the purpose of correcting model biases at the local scale [1].

Previous published research on the relationship between sea surface temperature and monsoon rainfall is available. In [2] a statistical forecasting method that adopted the traditional linear regression and a local polynomial-based nonparametric method was analysed and discussed. A statistical method for a 6-month period forecast based on hierarchical clustering method was presented in [3, 4] in which the method identified patterns of years that exhibited the highest similarity as measured by 3 monthly tele-connection indices.

Many researchers have applied the statistical downscaling method to the General Circulation Model. A statistical downscaling model to forecast northern China summer rainfall (NCSR) using outputs of the real-time seasonal Climate Forecast System, version 2 (CFSv2) was discussed in [5]. The forecast predictors from the CFSv2 included sea level pressure, 850-hPa meridional wind, and 500-hPa geopotential height. The results showed better forecast skills than the original CFSv2 for all lead months, except the 3-month-lead example. A new bias correction method that conserved the changes in mean and standard deviation of the uncorrected model of simulated data and compared it to five other bias-correction methods using monthly temperature and precipitation data simulated from 12 GCMs in the Coupled Model Intercomparison Project (CMIP3) archives was applied in [6]. Artificial neural networks (ANN) have been applied to a statistically downscaling global climate model (GCMs) during the rainy season at meteorological site locations in Bangkok, Thailand [7], which reported that the downscaled results of the present period showed a good agreement with station precipitation data.

The objective of our research was to develop a new bias correction technique that downscales seasonal rainfall forecasts by using the ratio of gamma CDF parameters. The performance of the bias corrected seasonal GCM rainfall forecasts was evaluated by sum absolute error and mean in the spatial term.

2. STUDY AREA

Thailand is located in the tropical zone of South-East area of the continent between latitude 5°37' N - 20°27' and longitude 97°22' – 105°37' covering 513,115 square kilometers. The climate of Thailand is under the influence of the southwest monsoon and northeast monsoon which are of a seasonal character. The southwest monsoon, which starts in May, brings a stream of warm moist air from the Indian Ocean towards Thailand causing abundant rain over the country, especially on the windward side of the mountains. Rainfall during this period is caused not only by the southwest monsoon, but also by the Inter Tropical Convergence Zone (ITCZ) and tropical cyclones, which produce a large amount of rainfall. The onset of monsoons varies to some extent. The southwest monsoon usually starts in mid-May and ends in mid-October, while the northeast monsoon normally starts in mid-October and ends in mid-February. According to the climate pattern and meteorological conditions, Thailand may be divided into 5 parts: Northern, Northeastern, Central, Eastern, Southeastern, and Southwest, as shown in figure 1.

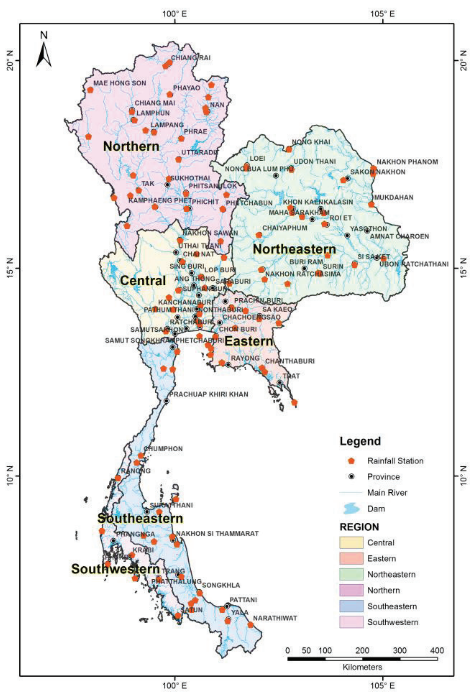

Figure 1 Studied area and rainfall stations

3. DATA USED

The rainfall data from 106 rain gauge stations were collected from the Thai Meteorological Department (TMD). The distribution of the rainfall stations in the study is shown in figure 1. The seasonal forecast general circulation model (GCM) precipitation data includes CCM3.6.6, ECHAM4.5 and GFDL AM2–LM2. CCM3.6.6 is the latest version of the NCAR Community Climate Model [8]. ECHAM4.5 is the series evolving originally from the spectral weather prediction model of the European Centre for Medium Range Weather Forecasts (ECHAM4.5; [9], ECMWF; [10]). GFDL AM2–LM2 is a global atmosphere and land model for climate research [11]. The forcing scenarios include persistence sea surface temperature (SST) anomalies (psst) and scenario SST anomalies (ssst). The description of GCM precipitation dataset is shown in Table 1. The GCM-simulated monthly precipitation data is validated against the corresponding observed data from 2001 to 2015.

Table 1 The description of GCMs used in this study

Model	Originating Group	Resolution (latitude x longitude)	Time period
CCM3.6.6	National Center for Atmospheric Research	2.76°X2.81°	12/2004 – 10/2015
GFDL AM2–LM2	U.S. Dept. of Commerce/NOAA/ Geophysical Fluid Dynamics	2.0° X 2.5°	8/2004 – 10/2015
ECHAM 4.5	Max Planck Institute for Meteorology	2.76°X2.81°	9/2001 – 10/2015

4. METHODOLOGY

4.1 Rational of Gamma CDF Parameter Method

In [6] a bias correction method from Gamma distribution for long term precipitation (Pr) prediction was proposed. The method first corrects statistical parameters for each of the baseline and projection period, and then monthly Pr are corrected using the quantile-based mapping method with the bias-corrected statistical parameters, mean and coefficient of variation (CV), estimated by the method of moment. This method conserves the changes of mean and standard deviation of the uncorrected model simulation data before and after bias-correction, and hence the CV is conserved. We propose a new method similar to [6], but use the maximum likelihood method to estimate parameters, instead of the method of moment.

The gamma distribution is parameterized in terms of a shape parameter (α) and an inverse scale parameter (β), called a rate parameter. The gamma cumulative distribution function can be derived as in equation (1).

$$F(x: \alpha, \beta) = \int_0^x f(u; \alpha, \beta) du = \frac{\gamma(\alpha, \beta x)}{\Gamma(\alpha)} \quad (1)$$

where $\gamma(\alpha, \beta x)$ is the lower incomplete gamma function.

The shape and inverse scale parameters are estimated as in equations (2) and (3).

$$\alpha = \frac{\mu^2}{SD^2} \quad (2)$$

$$\beta = \frac{SD^2}{\mu} \quad (3)$$

The bias corrected mean (μ_{cor}) and standard deviation (SD_{cor}) are calculated as in equations (4) and (5).

$$\mu_{cor} = \frac{\mu_p \mu_o}{\mu_b} \quad (4)$$

$$SD_{cor} = \frac{SD_p SD_o}{SD_b} \quad (5)$$

where μ_p is mean of the predicted rainfall data, μ_o is the mean of the observed rainfall data, μ_b is the mean of the baseline of GCM rainfall data, SD_p is standard deviation of the predicted rainfall data, SD_o is the standard deviation of the observed rainfall data, and SD_b is the standard deviation of the baseline of GCM rainfall data.

The bias corrected rainfall (x_{cor}) is estimated from the inverse of cumulative distribution function of original GCM precipitation by using the bias corrected mean (μ_{cor}) and standard deviation (SD_{cor}) from equations (4) and (5), in (6).

$$x_{cor,i} = F^{-1}\left(F\left(x_{p,i}; \alpha_p, \beta_p\right); \alpha_{cor}, \beta_{cor}\right) \quad (6)$$

where F is the original CDF of the gamma distribution with bias corrected parameters.

In addition, the root mean square error (RMSE), the mean absolute error (MAE), the sum absolute error, mean and standard deviation are used to compare the bias corrected GCM rainfall.

4.2 Rational of Gamma CDF Parameter Method

The bias correction is conducted as follows:

1) Collect observed rainfall data from Thai Meteorological Department.
2) Download the GCM rainfall data from International Research Institute for Climate and Society at http://iridl.ldeo.columbia.edu/SOURCES/.IRI/.FD/.GCM/.
3) Extract the GCM rainfall for Thailand and match the GCM rainfall data in grid format to observed station data.
4) Investigate the quality of observed and GCM rainfall data and fill any missing values.
5) Develop the bias correction of seasonal rainfall forecasting technique.
6) Apply the bias correction technique to seasonal GCM rainfall forecasts.
7) Validate the bias corrected GCM rainfall by comparing with the corresponding GCM dataset of same period using goodness of fit measures.
8) Forecast bias corrected GCM rainfall in July 2015 to October 2015.

The inverse distance weighting (IDW) interpolation method [12] is adopted to interpolate the bias corrected results in station level to spatial map.

5. RESULTS

5.1 Bias Corrected Rainfall Validation

The performance of the bias correction technique can be evaluated by using goodness of fit measures such as root mean square error (RMSE) and mean absolute error (MAE). The comparisons between the original and the bias corrected GCM are shown in Table 2. The results show that this bias correction method can reduce the root mean square error (RMSE) by between 8.28% to 31.35% and reduce the mean absolute error (MAE) by between 5.10% to 31.86% when compared with the original GCM rainfall. Furthermore, the mean and standard deviation of the bias corrected GCM rainfall are close to those of the observed rainfall with the difference of -3.0% to 0.9% and -25.6% to -15.4%, respectively (Table 3).

5.2 Forecasting Evaluation

The accuracy of the bias correction GCM rainfall data in forecasting can be evaluated in spatial terms by comparing the sum absolute errors (SAE), and it is found that this bias correction method can reduce the bias of CCM3V by between 9% and 21%, ECHAM4.5 by between 1% and 33%, and GFDL 50% to 62% (Table 4), with the exception that SAEs of GFDL show increasing values in October. Spatial bias correction can also be seen from the mean in different regions of Thailand. Table 5 shows that all bias-corrected GCM rainfall data sets provide good results in North, Central, and Northeastern regions with the average difference under 20% compared to the observed rainfall dataset. The CCM3V and ECHAM4.5 show underestimated results with an average of 7.63% and 7.67%, respectively, while the GFDL shows overestimated results with an average of 10% compared to the observed rainfall. The GFDL with psst forcing in figure 2 shows the difference from the mean for the month of September at -0.5% while CCM3V and ECHAM4.5 produce the difference about -15% and -12% compared to the observed rainfall.

Table 2 Comparisons of goodness of fit measures between original and bias corrected (BC) GCM rainfall

Measure	GCM	Forcing	Original (mm/month)	BC (mm/month)	%Difference
RMSE	CCM3V	psst	128.69	120.01	-8.71
		ssst	128.76	120.62	-8.28
	ECHAM4.5	psst	133.70	119.21	-10.42
		ssst	135.38	121.05	-10.16
	GFDL	psst	174.50	119.88	-31.35
		ssst	167.87	117.64	-30.08
MAE	CCM3V	psst	87.89	84.88	-5.44
		ssst	88.08	85.36	-5.10
	ECHAM4.5	psst	94.28	84.05	-10.87
		ssst	96.56	86.35	-10.62
	GFDL	psst	122.98	84.04	-31.86
		ssst	119.12	82.48	-30.96

Remark Original is original GCM rainfall and BC is bias corrected GCM rainfall.

Table 3 Comparison of mean and standard deviation between original and bias corrected (BC) GCM rainfall

Measure	GCM	Forcing	Observed (mm/month)	Original (mm/month)	% Diff	BC (mm/month)	% Diff
Mean	CCM3V	psst	147.3	115.5	-21.5	148.3	0.7
		ssst	147.3	116.4	-21.0	148.6	0.9
	ECHAM4.5	psst	144.6	135.2	-6.5	140.9	-2.6
		ssst	144.6	141.5	-2.2	140.3	-3.0
	GFDL	psst	146.6	188.5	28.6	145.4	-0.8
		ssst	146.6	185.2	26.4	143.5	-2.1
SD	CCM3V	psst	139.3	81.2	-41.7	117.5	-15.6
		ssst	139.3	81.8	-41.3	117.9	-15.4
	ECHAM4.5	psst	137.4	102.2	-25.6	109.3	-20.5
		ssst	137.4	98.4	-28.4	107.1	-22.1
	GFDL	psst	139.1	155.9	12.0	108.2	-22.3
		ssst	139.1	146.5	5.3	103.5	-25.6

Remark Original is original GCM rainfall and BC is bias corrected GCM rainfall.

Table 4 Comparison of sum absolute error (SAE) between original and bias corrected GCM (BC) rainfall

Measure	Forcing	Dataset	Jul	Aug	Sep	Oct
CCM3V	psst	Original	10,620	11,830	11,806	7,025
		BC	8,786	10,109	9,888	6,359
		%Diff	-17%	-15%	-16%	-9%
	ssst	Original	10,714	11,869	11,857	7,164
		BC	8,841	9,434	9,686	6,337
		%Diff	-17%	-21%	-18%	-12%
ECHAM4.5	psst	Original	13,399	13,089	11,028	7,050
		BC	10,324	9,141	10,609	6,739
		%Diff	-23%	-30%	-4%	-4%
	ssst	Original	13,577	12,766	10,727	6,916
		BC	10,286	8,565	9,954	6,818
		%Diff	-24%	-33%	-7%	-1%
GFDL	psst	Original	24,176	30,371	25,030	10,635
		BC	12,091	12,144	9,526	13,458
		%Diff	-50%	-60%	-62%	27%
	ssst	Original	26,822	31,272	28,290	11,779
		BC	13,271	12,755	10,800	12,281
		%Diff	-51%	-59%	-62%	4%

Table 5 Comparison of mean between observed and bias corrected GCM (BC) rainfall

Observed/ GCM	Forcing	Month	North	South West	South East	Central	East	North East	Whole Country
		Mean (mm/month)							
Observed		Jul	281.9	235.4	231.5	179.7	130.1	178.9	216.1
		Aug	258.8	334.0	286.7	165.1	148.8	212.6	230.1
		Sep	239.4	335.1	350.3	260.7	261.7	225.5	257.4
		Oct	176.7	232.4	210.8	160.7	191.4	131.9	167.8
		Difference (%)							
CCM3V	psst	Jul	-48.1%	-43.2%	-44.3%	-8.7%	93.4%	11.5%	-20.9%
		Aug	-25.9%	-65.1%	-61.0%	4.0%	48.7%	4.5%	-18.2%
		Sep	0.4%	-58.1%	-60.6%	-24.4%	-8.9%	6.6%	-15.3%
		Oct	19.1%	-14.8%	-6.1%	23.6%	40.6%	53.6%	24.4%
	ssst	Jul	-41.9%	-54.7%	-54.3%	-7.5%	80.8%	11.3%	-20.7%
		Aug	-25.7%	-61.3%	-56.6%	9.8%	54.6%	7.8%	-15.4%
		Sep	-5.1%	-50.8%	-54.3%	-23.4%	-5.0%	4.4%	-15.6%
		Oct	12.9%	-16.1%	-8.0%	20.7%	42.6%	49.9%	20.8%
ECHAM4.5	psst	Jul	-45.4%	-44.5%	-46.3%	-26.1%	31.2%	3.3%	-27.0%
		Aug	-13.2%	-23.7%	-17.9%	17.4%	72.1%	4.7%	-2.3%
		Sep	-2.1%	-25.4%	-36.3%	-20.0%	3.0%	-1.2%	-11.0%
		Oct	-0.4%	-20.8%	-26.5%	3.2%	13.4%	25.9%	2.6%
	ssst	Jul	-36.8%	-16.9%	-25.1%	-16.9%	50.3%	9.6%	-16.0%
		Aug	-9.7%	-15.5%	-13.0%	16.9%	66.9%	4.2%	-0.3%
		Sep	-4.8%	-20.8%	-34.7%	-22.9%	-1.9%	-3.7%	-12.7%
		Oct	-3.3%	-3.4%	-11.2%	4.4%	17.8%	24.7%	5.3%
GFDL	psst	Jul	-21.1%	-30.0%	-36.9%	3.5%	76.6%	27.0%	-3.8%
		Aug	10.2%	-20.4%	-20.2%	39.9%	91.5%	37.4%	18.4%
		Sep	-1.1%	5.1%	-14.1%	-16.1%	8.9%	12.3%	-0.5%
		Oct	-35.3%	80.4%	70.9%	-16.7%	3.1%	2.5%	2.9%
	ssst	Jul	-15.4%	-11.1%	-20.2%	11.9%	91.4%	38.2%	6.2%
		Aug	13.7%	-14.0%	-13.0%	43.4%	91.9%	47.0%	24.4%
		Sep	4.4%	12.3%	-6.3%	-9.5%	18.9%	26.3%	8.3%
		Oct	-28.2%	115.3%	104.7%	2.6%	32.8%	24.4%	22.9%

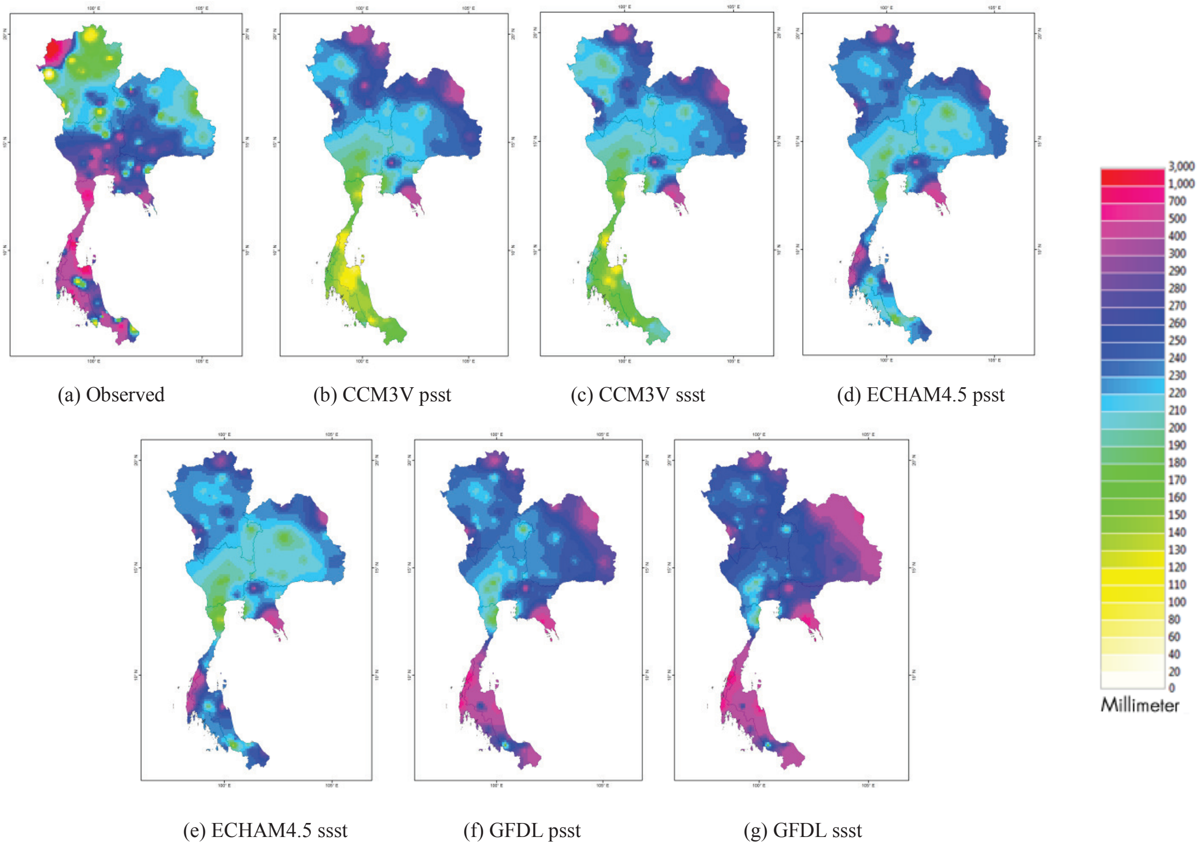

Figure 2 Comparisons of the observed and bias corrected GCM rainfall in September, 2015

6. Conclusion

The study results show that the ratio of gamma CDF parameter bias correction method can improve the quality of seasonal forecasting GCM. It can reduce the biases of an original GCM dataset in spatial terms of between 1% to 62%. The bias corrected GCM rainfall provides a good result in the North, Central and Northeastern areas of Thailand. The bias corrected CCM3V rainfall provides better results compared to other models.

7. Acknowledgment

The authors gratefully acknowledge the contributions of Thai Meteorology Department for observed rainfall data distribution, and many thanks to Mr. Roy Morien of the Naresuan University Language Centre for his editing assistance and advice on English expression in this manuscript.

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