**Bias Correction of Global and Regional Models Simulated Daily
Precipitation and Surface Temperature over Southeast Asia**

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Submission to Global and Planetary Change

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ABSTRACT

The quantile mapping (QM) method was applied to adjust the biases of the global and regional climate models (GCM and RCMs) simulated daily precipitation and surface mean temperature over Southeast Asia regions based on APHRODITE dataset. Output from four different RCMs as well as their driving GCM in CORDEX-EA archive were corrected to examine the added value of RCMs dynamical downscaling in the context of bias adjustment. The result shows that the RCM biases are comparable to that of the GCM biases. In some instances, RCMs amplified the GCM biases. Generally, QM method substantially improves the biases for both precipitation and temperature. However, the bias adjustment method works better for surface mean temperature and less so for daily precipitation. The large inter-models variability is reduced remarkably after bias adjustment. Nevertheless, the bias adjustment tends to weaken the precipitation trends although it does not generally alter the sign of the trends. Hence, RCMs downscaling is crucial to simulate the correct local and regional climate trends prior to bias adjustment in areas where GCMs fail to resolve climate change signals. Overall, study indicates that a bias corrected RCM simulation provided additional improvement to the sub-regional temporal features compared to their forcing GCM.

Key words: Southeast Asia, bias adjustment, global climate model, regional climate model

1. Introduction

In the past few decades, climate modeling groups have markedly improved their global climate models (GCMs) simulations (CMIP, 2015; Gulizia et al., 2015; PCMDI, 2015). For instance, the global climate simulation experiments derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5) have been widely used for future global climate predictions (e.g. Meehl et al., 2009; Taylor et al., 2012). Several studies have highlighted issues related to biases and uncertainties in the CMIP5 models simulations (Taylor et al., 2012; Brekke and Barsugli, 2013; Su et al., 2013; Wang et al., 2014). Specifically, most of the CMIP5 models show less skill in precipitation simulation over regions with complex topography (Mehran et al., 2014). Meanwhile, a number of downscaling techniques have been developed to deal with the inadequacies in GCMs (Maraun et al., 2010). These downscaling methods are categorized into two types: dynamical, a model-based methodology where a regional climate model (RCM) is forced by lateral boundary conditions from GCM output to simulate the local scale processes over a smaller region using finer grids (e.g. Giorgi and Mearns, 1991, 1999; Wang et al., 2004; Fowler et al., 2007); and empirical downscaling, where a statistical relationship is constructed between large scale climate variables (predictors) and observed local variables (predictands) (e.g. Hewitson and Crane, 1996; Bates et al., 1998; Charles et al., 2004; Wilby et al., 2004).

Dynamical downscaling with a RCM offers a physically realistic approach compared to statistical downscaling because RCMs have the same representations of atmospheric dynamical and physical processes as GCMs (Maraun et al., 2010; Lafon et al., 2013). However, RCMs may still produce considerable systematic errors (Frei et al., 2003; Suklitsch et al., 2008, 2011; Johnson and Sharma, 2012). The systematic errors in both GCMs and RCMs hinder direct utilization of the simulated output for regional and local climate impact studies (e.g. Wilby et al., 2000; Wood et al., 2004; Fowler et al., 2007; Randall et al., 2007;

Piani et al., 2010; Chen et al., 2011; Hagemann et al., 2011; Rojas et al., 2011; Haddeland et al., 2012; Johnson and Sharma, 2012; Lafon et al., 2013). Thus, a number of post-processing techniques by adjusting the GCMs or RCMs output towards observed characteristics are widely used in climate impact studies (e.g. Kidson and Thompson, 1998; Murphy, 1999; Wilby et al., 2000; Piani et al., 2010; Ehret et al., 2012; Teutschbein and Seibert, 2012; Muerth et al., 2013; Wilcke et al., 2013; Casanueva et al., 2015).

A range of bias adjustment methods have been developed and improved (see Themeßl et al., 2011 for a comprehensive overview) for local climate impact studies. These methods include delta change method (Hay et al., 2000), multiple linear regression (Hay and Clark, 2003), local intensity scaling (Schmidli et al., 2006), monthly mean correction (Fowler and Kilsby, 2007), gamma-gamma transformation (Sharma et al., 2007), analog methods (Moron et al., 2008), fitted histogram equalization (Piani et al., 2010), and quantile mapping (Wood et al., 2004; Sun et al., 2011). The bias adjustment methods have often been criticized for its non-physical basis of applications (Wood et al., 2004; Liang et al., 2008; Hagemann et al., 2011; Chen et al., 2011; Teutschbein et al., 2011; Dosio et al., 2012; Ehret et al., 2012; Teutschbein and Seibert, 2012; Muerth et al., 2013). Ehret et al. (2012) argued that the bias adjustment is often used in an invalid way and was developed under the pressure in response to needs for climate impact studies (Vannitsem, 2011). Hence, it was developed from the perspective of necessity rather than validity (Ehret et al., 2012).

Johnson and Sharma (2012) suggested a cascade of adjustments where GCM output is first downscaled by using an RCM and the remaining biases are removed using a bias adjustment method. This leads to the question of whether the incorporation of RCM downscaling as an intermediate step can actually contribute to a better result (Ahmed et al., 2013; Halmstad et al., 2013; Eden et al., 2014). Halmstad et al. (2013) reported that the bias adjustment is required to add value to RCMs simulations. Meanwhile, Eden et al. (2014)

argued that this post-processing method can also be applied to the GCMs output directly (e.g. Li et al., 2010; Maraun et al., 2010; Piani et al., 2010; Themeßl et al., 2011; Eden et al., 2012). Relatively, few studies have focused on the comparison between the post-processing of RCM and GCM simulations (Halmstad et al., 2013; Eden et al., 2014). Eden et al. (2014) found that there is no clear added value of the intermediate RCM downscaling step with respect to a stochastic post-processing. Their study shows that the bias-corrected GCM simulations yield better results compare to the bias-corrected RCM simulations. The extent to which RCMs downscaling as an intermediate step is necessarily to improve the local scale climate projections remains illusive and it is likely depending on the performance of RCMs-GCMs simulation over a specific location. Hence, the comparison of bias-corrected RCM and bias-corrected GCM is required in order to determine the appropriate uses of the bias adjustment in the RCMs-GCMs modeling chain in a specific domain.

The objectives of this study is to demonstrate the added value of RCM as an intermediate step to GCM with respects to the bias adjustment of different RCM simulations over the Southeast Asia region. The paper is structured as follows. Data and methodology are described in section 2 and 3 respectively. Section 4 presents the comparison of uncorrected and corrected RCMs/GCM simulations with respect the observation. Finally, summary and conclusions are provided in section 5.

2. Data

Gridded daily precipitation (PR) and surface mean temperature (Tmean) from January 1979 to December 2005 with a resolution of $0.25^{\circ} \times 0.25^{\circ}$ provided by the Asian Precipitation-Highly-Resolved Observational Data Integration Towards the Evaluation of Water Resources project (Yatagai et al., 2009; APHRODITE, 2015) were used as observation. Five RCMs participating in the Coordinated Regional Climate Downscaling Experiment for

East Asia (CORDEX-EA) of the World Climate Research Program (WCRP) were used in this study (Giorgi et al., 2009; Oh et al., 2014; Yu and Xiang, 2015). These RCMs experiment include: (1) the Hadley Centre Global Environmental Model version 3 regional climate model (HadGEM3RA), (2) the Regional Climate Model version 4.0 (RegCM4), (3) the Weather Research and Forecasting (WRF) model, (4) the Mesoscale Model version 5 (MM5) model, and (5) the Regional Spectral Model (RSM). Model details and configurations are listed in Table 1 (CORDEX-EA 2015). These RCMs are driven by the Atmosphere-Ocean coupled Hadley Center Global Environmental Model version 2 (HadGEM2AO) (Martin et al., 2011; Baek et al., 2013; ENES/ESGF, 2015) and the output of the simulation is made available at the CORDEX East Asia project website (<https://cordex-ea.climate.go.kr/main/modelsPage.do>).

The domain of the study covers the Southeast Asia region (Fig. 1). The domain is further divided into twenty sub-regions for regional statistics computation. The RCMs and GCM output were re-gridded onto the same observation grid points of $0.25^{\circ} \times 0.25^{\circ}$. The bias adjustment calibration period covers January 1979 to December 1992 and the period from January 1993 to December 2005 was used for validation. The study focuses on two seasons, winter season (December-January-February, DJF) and summer season (June-July-August, JJA).

3. Bias adjustment method

The focus of the study is to evaluate the performance of bias adjustment of multiple RCMs output compare to that directly corrected from the forcing GCM with the dynamical downscaling as an intermediate step. Only one bias adjustment method is considered. The quantile mapping (QM) bias adjustment method is used to adjust the model biases. The QM method has been widely used in hydrological applications (Dettinger et al., 2004; Wood et al.,

2004; Boé et al., 2007) and bias correction of RCMs (Dobler and Ahrens, 2008; Piani et al., 2010). Teutschbein and Seibert (2012) showed that while all bias correction methods tested in their study were able to correct the daily mean values, only QM method is capable to correct others statistical properties (i.e. standard deviation or percentiles) for both precipitation and temperature.

The QM adjusts for errors in the shape of distribution of the modeled data with reference to the observed distribution. Due to the differences in the distribution of variables, an additive adjustment is often used for the temperature (e.g. Eisner et al., 2012; Thrasher et al., 2012) and multiplicative adjustment for the precipitation (e.g. Bennett et al., 2011). For a value in the modeled data, its quantile with respect to the distribution was estimated. The observations correspond to the similar quantile is determined from the observed distribution. A change factor is calculated to be used for the modeled values adjustment. A multiplicative factor is used for the daily precipitation (Eqs. 1 and 2), as follows

$$F_r = P_{obs}(r) / P_{sim}(r) \quad (1)$$

$$P'_{sim}(r) = F_r \times P_{sim}(r) \quad (2)$$

and the additive factor is used for the daily temperature (Eqs. 3 and 4),

$$F_r = T_{obs}(r) - T_{sim}(r) \quad (3)$$

$$T'_{sim}(r) = F_r + T_{sim}(r) \quad (4)$$

where r indicates the r -quantile under consideration. The factor, F_r is applied to adjust the modelled data values of the similar quantile outside the reference period.

In this algorithm, the quantile values are calculated from the empirical distribution of both the observed and the modelled data directly instead of pre-fitting a parametric distribution to the sample data (e.g. Ines and Hansen, 2006; Li et al., 2010; Piani et al., 2010). The approach is motivated by the work of Gudmundsson et al. (2012) who argued that non-

parametric methods usually produced a better performance as compared to the parametric methods in the context of QM bias adjustment.

4. Results and discussions

4.1. Bias corrected daily precipitation and surface mean temperature

Fig. 2 shows the comparison of empirical cumulative density distribution (ECDF) of the raw and the bias-adjusted (BC) daily PR and Tmean for the validation period (1993-2005), area-averaged over the whole Southeast Asia region (region above 30° N is excluded, see Fig. 1 for domain). After applying QM bias adjustment, the distance between model and observation is reduced and the adjusted distributions match the observation better. The bias-corrected PR is closer to observed distribution for both JJA and DJF seasons.

Fig. 3 shows quantile-quantile (Q-Q) plots of the uncorrected and corrected GCM and RCMs data against the observed PR and Tmean for both DJF and JJA season. The raw GCM/RCM output tends to overestimate PR but underestimate Tmean for both seasons. After QM bias adjustment, the corrected quantiles are getting closer to the observation (especially for Tmean). It is noted that the uncorrected quantiles show larger inter-models variations for both PR and Tmean. Generally, result shows that the performance of QM is better for Tmean compared to PR.

The biases of the GCM and RCMs spatial distribution with respect to the observed mean climatology (1993-2005) are shown in Fig. 4 for PR and Fig. 5 for Tmean, respectively. Generally, the raw GCM/RCMs downscaling simulations present a remarkable overestimation (underestimation) for PR (Tmean) during DJF. Besides, Tmean biases of the raw GCM/RCMs downscaling are larger in DJF compare to JJA. Note that the model biases remain or even elevated in some RCMs. Some regional model amplifies the biases of GCMs instead of reducing them. By applying QM, PR (Tmean) biases are largely reduced over

equatorial regions (northern part of the domain) in both JJA and DJF seasons. The inter-model variability is greatly reduced by bias adjustment, especially for regions with large biases. After adjustment, the bias corrected PR biases show a very similar spatial pattern between models.

The Taylor diagrams (Taylor, 2001) in Fig. 6 summarize the results of seasonal climatology spatial agreement for PR and Tmean in terms of correlation coefficients, root mean square errors (RMSE) and standard deviations. Figure shows that the QM method considerably improves the GCM and RCMs simulations with higher spatial correlation values especially for Tmean. Besides, there is a notable reduction in model spread where the RMSE is minimized and standard variation values are closer to the observation. The bias-corrected GCM output yields equally good skills as the bias-corrected RCM simulation in terms of spatial distribution.

4.2. The added value of RCMs to GCMs prior to bias adjustment

The RCMs added value is generally referred as the ability of regional models to providing additional climate change signals that are not resolved in the coarser resolution GCMs (Feser et al., 2011; Di Luca et al., 2013). This is arguably a crucial step prior to bias adjustment as the bias correction methods are not expected to modify the original climate change signals. In the past few years, a number of studies have addressed the issue of added value given by RCMs (e.g. Duffy et al., 2006; Feser, 2006; Seth et al., 2007; Prömmel et al., 2010; Di Luca et al., 2013; Mariotti et al., 2014; Torma et al., 2015). Added value of RCM is likely noticeable only at regional scale and likely very region dependent, as the large scales processes are expected to be better resolved by GCMs. Focus on identifying regions where RCMs do add significant value should be at greater concern, although RCMs simulations

may not add significant value to all aspects of climate change predictions (Di Luca et al., 2012).

In current study, the Southeast Asia domain was divided into 20 sub-regions for regional statistics computation (see Fig. 1 for sub-regions location) to examine the added value of RCMs compared to the driving GCM on regional scales, in the context of bias adjustment. Fig. 7 displays the observed, simulated and corrected PR annual cycle by both GCM and RCMs, and statistics of annual cycle (1993-2005) area averaged over the 20 sub-regions. Fig. 8 shows the same result except for Tmean. Generally, the bias adjustment reduces the amplitude of annual cycle for both variables (except region R12 for Tmean). The two panels in second row of figure show statistics comparison of the simulated and bias-corrected annual cycle with respects to observation annual cycle. Results indicate that overall the correlation coefficients and root mean square errors (RMSE) of GCM/RCMs simulated annual cycle are greatly improved after bias adjustment. Besides, the added value of RCMs on sub-regional characteristics was identified. Over some regions (e.g. R9-R14), the correlation coefficients and RMSE skills of raw/corrected RCMs eventually scored higher than the raw/corrected GCM. RCM was able to reproduce better annual cycle compared to GCM after the bias adjustment. In addition, the application of QM varies across the models as some RCMs (e.g. HadGEM3-RA and WRF) do provide more skillful results compared to others after applying the QM.

The effect of QM bias adjustment on trends in seasonal PR is illustrated in Fig. 9 (DJF) and Fig. 10 (JJA). The trend is calculated based on the complete full data period from 1979 to 2005. Result shows that QM tends to deflate the negative trend in both seasons. Thus, the negative trends become weaker after bias adjustment. However, the QM did not change the sign of PR trends in general. Although the effect of QM bias adjustment on PR trends is marginal, there is a tendency for QM to modify PR trends and this is consistent with the

previous studies (e.g. Maraun, 2013; Maurer and Pierce, 2014). If the trends are affected after bias adjustment, the changes of climate model output can have significant impacts on the downstream impact studies where the results maybe misrepresented (Maraun, 2013). In some regions, results showed that the RCMs may reproduce the correct seasonal PR trends (especially the equatorial regions and the coastal area of East Asia), even though their forcing GCM simulated a wrong trend sign. The PR trends are strongly influence by the climate model itself compared to bias adjustment in terms of spatial distribution and there are added values by RCMs as they improved the PR trends over some regions compared to their forcing GCM before the application of bias adjustment.

5. Summary and conclusions

The QM bias adjustment method was applied to correct GCM- and RCM-simulated daily PR and Tmean over Southeast Asia region based on the APHRODITE dataset. Both RCMs (HadGEM3-RA, RegCM4, WRF, MM5 and RSM) and their driven GCM (HadGEM2-AO) simulations were used, in order to compare the effectiveness of direct adjustment of GCM output and that of correcting the dynamically downscaled output.

Result suggests that biases of spatial mean climatology in PR and Tmean are largely removed for both seasons by applying QM method. The model biases vary between RCMs due to differences of model characteristics and parameterizations. However, the inter-model variability is greatly reduced after correction. The result indicates that raw RCMs biases are in general comparable to the raw GCM biases. While in some cases, RCM amplified the model biases. The QM has largely improved the GCM/RCMs spatial correlation and RMSE for both PR and Tmean. The correlation coefficients of annual cycles with respects to the observation are closer to observed values especially for Tmean after bias adjustment. Generally, QM method shows better result for the adjustment of daily surface mean

temperature compared to daily precipitation. The bias adjustment modified the precipitation trends but did not alter the sign of precipitation trend in general. Dynamically downscaling with RCMs prior to bias adjustment provides additional improvement to the sub-regional temporal characteristics (annual cycle and trends) compared to GCMs.

In conclusions, this study has demonstrated that QM is a useful method to improve biases of daily precipitation and mean temperature from both GCM and RCMs simulations. Furthermore, the study recognizes the need of RCMs downscaling as an intermediate step prior to bias adjustment. The incorporation of dynamical downscaling prior to bias adjustment showed some added value on sub-regional temporal scales over Southeast Asia region. If the focus is on local or sub-regional scales over Southeast Asia regions, the implication of this study suggests that using a bias adjusted RCMs simulation as input for the impact studies would provide better results compared to their host GCM. The skills of QM may vary with the choices of RCMs. Meanwhile, only one bias adjustment method was considered in current study. Multiple bias adjustment approaches should be considered for future studies, in order to assess the uncertainties associated with the bias adjustment method in climate change impact studies. Although the global and regional climate models continue to being improved, the bias adjustment is a useful method to bridge the mismatch between climate models and climate impact studies at the time being.

Acknowledgments

This research was done as part of the PhD study of the first author and is funded by the National University of Malaysia (UKM), Grants ICONIC-2013-001 and AP-2013-005. This research is also related to the Asia Pacific Network for Global Change Research Grants (ARCP-17NMY-Tangang / ST-2013-017, ACRP-07CMY-Tangang / ST-2015-003). We acknowledge the Asian Precipitation–Highly-Resolved Observational Data Integration

Towards Evaluation of the Water Resources (APHRODITE) for making freely available daily precipitation and surface mean temperature products. We acknowledge also the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

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595 **Table captions**

596 **Table 1.** CORDEX East Asia Regional Climate Model Configurations.

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620 **List of Figs.**

621 **Fig. 1.** The domain study and area for 20 sub-regions.

622 **Fig. 2.** Observed, uncorrected and corrected ECDF distribution of daily (a)-(b) PR and (c)-(d)
623 Tmean for DJF (top) and JJA (bottom) from 1993 to 2005.

624 **Fig. 3.** The Q-Q plot of seasonal daily PR and Tmean. Uncorrected (black circles) and
625 corrected (gray triangles) simulated (a)-(b) PR and (c)-(d) Tmean against observation
626 for DJF (top) and JJA (bottom).

627 **Fig. 4.** (a) DJF and (b) JJA seasonal biases of uncorrected (top) and corrected (bottom) PR of
628 GCM and five RCMs (from the left, HadGEM2AO, HadGEM3RA, RegCM4, WRF,
629 MM5 and RSM) compared to observation for the validation period 1993 to 2005.

630 **Fig. 5.** As in Fig. 4. but for Tmean.

631 **Fig. 6.** Taylor diagrams for the seasonal climatology of (a)-(b) PR and (c)-(d) Tmean for DJF
632 (top) and JJA (bottom). The circles are uncorrected models while triangles for the
633 corrected models.

634 **Fig. 7.** Top: Sub-regional (a) observed, uncorrected and corrected annual cycle for PR.
635 Bottom: (b) Correlation coefficients and (c) RMSE of uncorrected and corrected
636 annual cycle with respect to observation (Model: from the left, HadGEM2AO,
637 BCHadGEM2AO, HadGEM3RA, BCHadGEM3RA, RegCM4, BRegCM4, WRF,
638 BCWRF, MM5, BCMM5, RSM and BCRSM).

639 **Fig. 8.** As in Fig. 7. but for Tmean.

640 **Fig. 9.** DJF seasonal precipitation trends (1979–2005) for (a) observation, (b)-(g) uncorrected
641 and (h)-(m) corrected models.

642 **Fig. 10.** As in Fig. 9. but for JJA.

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644 **Table 1.** CORDEX East Asia Regional Climate Model Configurations.

Model		HadGEM3RA	RegCM4	MM5	WRF	RSM
Institute		Korea Meteorological				
		Administration/National Institute		Konju National	Seoul National	Seoul National
		of Meteorological Research		University	University	University
		(KMA/NIMR)				
Physics	Radiation	General 2stream	CCM3	CCM2	RRTM	Chou
	Cloud	Mixed phase	SUBEX	Resiner II	WSM3	diagnostic microphysics
	Convection	Revised mass-flux	Emanuel	KF2	KF2	SAS
	Non-local PBL	Lock et al.	Holtstag	YSU	YSU	YSU
	Land	MOSE II	CLM3	CLM3	NOAH	NOAH
	Nudging	No	Yes	Yes	Yes	Yes

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Fig. 1. The domain study and area for 20 sub-regions.

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Fig. 2. Observed, uncorrected and corrected ECDF distribution of daily (a)-(b) PR and (c)-(d) Tmean for DJF (top) and JJA (bottom) from 1993 to 2005.

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