Bias correction of daily precipitation from downscaled CMIP5 climate projections over the Indonesian region

F Amsal, H Harsa, A Sopaheluwakan, U A Linarka, R P Pradana and R Satyaningsih

Center for Research and Development, Agency for Meteorology Climatology and Geophysics (BMKG), Jakarta 10720, Indonesia

ferdikaamsal@gmail.com

Abstract. Global Climate Models (GCMs) have been the primary source of information for constructing climate scenarios, and they provide the basis for climate change impacts assessments of climate change for a range of scales, from global down to regional scale. Due to the coarse spatial resolution, the GCM outputs have to be downscaled to resolve the scale discrepancy between the resolutions required for impact assessments and the model’s resolution. However, it is important to bias-correct (BC) the raw climate projection outputs which ideally correct the discrepancy between a model’s climate and the observed historical climate. In this study the results of bias correction of daily precipitation over the Indonesian region from downscaled CMIP5 GCM climate simulations using an optimized configuration of the Regional Climate Model (RegCM) for a baseline period of 16 years (1990–2005) with respect to observation is discussed in detail. The statistical bias correction method validated in this study is based on the initial assumption that both observed and simulated intensity distributions are well approximated by the Gamma distribution and the correction is made by matching the quantiles of the Gamma cumulative distribution functions. Overall, the results suggest that when the bias-correcting is applied on dynamically downscaled model, it improved the skill in simulating the precipitation over Indonesia and this is a useful tool for further regional downscaling studies.

Keywords : Global Climate Models, CMIP5, Regional Climate Model, Gamma distribution.

1. Introduction
Precipitation is one of important climate variables for several sectors such as hydrology, health, agriculture, food supply. Those sectors eventually might affect social and economic sectors. Precipitation also the most sensitive to model formulation because of its dependence on parameterization schemes and their interaction with the model dynamics [1]. The International Panel on Climate Change (IPCC) have stated that warmer climate in the future are likely to increase the frequency and intensity of the extreme precipitation events [2]. Therefore, it is crucial to have reliable model output particularly in impact studies of extreme precipitation in the context of the climate change.

Global Climate Models (GCMs) have been used as the primary source of information to understand and quantify such extreme events for both the present-day climate and possible future climates. However, GCMs are generally run at coarse resolution and therefore not all processes, especially those on mesoscales, are reasonably simulated for regional scale [3]. This may lead to misrepresentations of
extreme precipitation event [4,5]. To bridge this resolution gap, dynamical and/or statistical downscaling techniques were applied in order to obtain plausible regional climate change projections [1,6].

The dynamical downscaling approach is based on regional climate models (RCMs) running over limited geographical domains with boundary conditions given by the GCM to be downscaled [3]. These RCMs explicitly solve mesoscale atmospheric processes and provide spatially and physically consistent outputs. However, they still have considerable biases [7,8,9], which are typically adjusted in practical applications using a variety of bias correction (BC) methods. Formally, in the BC downscaling approach, the target variable (e.g., precipitation) simulated by the RCM is directly corrected against the available local-scale observations using appropriate statistical techniques [1,10,11].

This study aims to applying statistical bias correction to regional climate model output and evaluate the performance of the bias correction. In Section 2, we describe the data and methodology used in this study. The results are discussed in Section 3, followed by conclusions in Section 4.

2. Data and methodology

2.1. Datasets

In this study we use the Regional Climate Model system RegCM4 [12] to downscale CSIRO Mk3.6. RegCM4 is a hydrostatic and compressible model that uses sigma-p vertical coordinates, run on an Arakawa B-grid. RegCM4 has the dynamical core of the mesoscale model version 5 (MM5) developed by the National Center for Atmospheric Research (NCAR) and Pennsylvania State University [14]. It incorporates the radiation scheme of the NCAR Community Climate System Model version 3 (CCSM3) [15,16] for radiation and infrared spectra, following Collins et al. [17]. The Biosphere-Atmosphere Transfer Scheme (BATS) for land-surface processes follows Dickinson et al. [18] and Gao et al. [19]. The CLM [20] is also available as the land-surface scheme in RegCM4. To represent urban and suburban environments, two new land-use types have been added to BATS in RegCM4. Urban development modifies the surface albedo and alters the surface energy balance; it also heavily affects runoff and evapotranspiration. To describe the land–atmosphere exchanges of energy, momentum, water and carbon, RegCM4 uses Community Land Model version CLM3.5 [21], which applies a series of biogeophysically-based parameterizations. Moreover, RegCM4 uses other physical processes, including those of Holtslag et al. [22] for the Planetary Boundary Layer (PBL) and Zeng et al. [23] for ocean flux parameterization approaches. Multiple cumulus convection schemes are available in RegCM4. The new scheme allows the user to select either Grell or Emanuel in the function of the ocean-land mask. The Arakawa–Schubert type closure or the Fritsch and Chappell [24,25] type closure are available for use in the Grell convective parameterization scheme.

A set of sensitivity experiment in RegCM4 physical parameterizations for Southeast Asia region has been conducted, combining six cumulus parameterization schemes and three ocean surface flux schemes [26,27,28]. Following this experiment, in this study RegCM4 was run with the main configuration as shown in Table 1.

| Model physics                          | Scheme selected in this study |
|----------------------------------------|-------------------------------|
| Planetary Boundary Layer (PBL) scheme  | Holtslag PBL [22]             |
| Radiation scheme                       | CCSM                          |
| Large scale moisture                   | SUBEX                         |
| Land-surface treatment                 | BATS1e                         |
| Cumulus parameterization               | MIT Emanuel                   |
| Ocean flux scheme                      | Zeng et al. [23]              |

As reference data for statistically correcting the aforementioned climate model output we use the Tropical Rainfall Measuring Mission (TRMM) 3B42 product [30]. The precipitation estimates are available for spatial resolution of $0.25^\circ \times 0.25^\circ$ and temporal resolution of 3 hourly. The bias correction in this study covers the period of 1990-2005.
2.2. Methodology
The quantile mapping (QM) has been widely used in RCMs, e.g. by Piani et al. [30] and Ngai et al. [31]. QM is an empirical statistical technique that matches the quantile of simulated model values to the observed values at the same quantile. The technique is applied by first constructing the cumulative distribution function (CDF) of each datasets, the model and the reference. The quantile of each value in the model is extracted using model’s CDF. This process yields a new dataset consisting quantile value of each model datum. Using this dataset, an inversion procedure is carried out to every quantile datum by looking up a value in reference data that lies on the same quantile with the datum being observed. To illustrate the methodology, the QM is applied to a dataset generated randomly (Figure 1). The black line denotes the synthetic observed data while the red line represents the synthetic model data.

The method was then applied to the daily precipitation of RegCM4 output. We evaluate the performance of the bias correction in three ways. First, we compare the seasonal bias of uncorrected and corrected precipitation of RegCM4 compared to TRMM data. Second, we analyse the performance of the method by comparing the number of wet days for each month over all the period of the study. Third, we examine extreme precipitation in terms of RX1DAYS and 95\textsuperscript{th} percentile of seasonal mean.

![Figure 1. QM simulations using 1000 set (observation and model) of random sampling](image)

3. Result and discussion
3.1. Bias corrected monthly and seasonal precipitation
Figure 2(a) shows quantile-quantile (Q-Q) plots of the uncorrected and corrected RegCM4 precipitation against the TRMM estimated precipitation for each month and in all grid boxes of the domain. The uncorrected RegCM4 output tends to underestimate low precipitation but overestimate high precipitation in all months. After bias correction, the corrected quantiles are close to the observation. RegCM4 also shows a large monthly mean bias on each grid and these occur almost in every month, even though the standard deviation is relatively constant (Figure 2(b)). The standard deviations of the bias of corrected model output are more varied from month to month compared to the standard deviations of the bias of the uncorrected one.
Figure 2. (a) Q-Q Plot of monthly mean precipitation (above) and the mean bias of uncorrected and (b) corrected ReGCM4 monthly mean precipitation in each grid (below).

The spatial distribution of mean biases in monthly total precipitation for each season are shown in Figure 3. The largest systematic bias over land area occurred in the centre part of Sumatera island, north of Sulawesi island, and the centre of Papua island, where the large biases are observed almost in all month. All these regions are characterized by high topography and therefore physically affect most of the heavy precipitation in the model, which result in profound differences between the observation and the model. Big negative of the relative bias occurs in mountain range from December to May. We also can see in almost all other seasonal and regional regions cases, observational estimates are within the range of the model simulation (bias ± 500 mm/month). After applying bias correction, precipitation
biases generally decrease in all seasons. This is consistent with the previous study conducted by Ngai et al. [31].

### 3.2. The number of wet-days characteristics

Figure 4 shows a distinctive wet and dry seasonal pattern as observed by TRMM due to the Asian-Australian monsoon, which affects Southeast Asia and Australia through the winds from the southeast and northwest during the cooler and warmer months, this is respectively to the Indonesian monsoon type based on the rainfall patterns and characteristics. Therefore, we can see the effect of ITCZ over the middle of Indonesia region. We also can see that the observation can capture the effect of warm pool over western Pacific Ocean and eastern Indian Ocean that is related to the surface evaporation exposure time, marked by increasing the likelihood of cumulus formation due to greater convection over warmer seas.

RegCM4 was able to simulate the north–south rainfall gradient realistically over Indonesia, as shown in Figure 5. However, the model tends to shift the number of days with precipitation so that in boreal autumn (September-October-November; SON) we can see longer wet-days over Sumatera. The model underestimates the number of wet-days over the sea and overestimate them over the land. The model was also able to capture the orographic precipitation and mostly drive the longer period of rainfall over the high topography area such as the middle of Sumatera island, northern Sulawesi island, and southern Papua island.

QM bias correction was realistically able to improve the model simulation so that we can see most of the pixel on the corrected model have a similarity with the observation (Figure 6). We can see the same pattern of wet-days period over Indonesia region.
Figure 4. TRMM (observation) mean monthly number of wet-days

Figure 5. CSIRO (model) mean monthly number of wet-days
Figure 6. Mean monthly number of wet-days after bias correction

3.3 Extreme precipitation
Extreme value distributions are fitted to these data in order to evaluate rare precipitation events, such as one-day amounts that are exceeded on average only every 20 years.

Figure 7. Mean monthly of daily maximum precipitation (RX1DAY) different TRMM – CSIRO (observation – uncorrected model)
Figure 8. Mean monthly of daily maximum precipitation (RX1DAY) different TRMM – Corrected CSIRO (observation – corrected model)

Figure 9. Percentile 95 of seasonal mean of daily precipitation
4. Conclusion

From this study we have investigated how well the quantile mapping bias correction method improve the performance of the RCM for a set of precipitation indices. The analysis focuses on precipitation over Indonesia region. The results from this study would serve as a useful reference for an extended evaluation of regional climate models over the study area. We assess that RegCM without bias correction have shown large uncertainty in climate but the bias correction tool helped to simulate the reliable climate output with reference to observed climate data. Therefore for framing of better management practices, adaptation programme and planning and policy-making based on climate model output, we must ensure to develop the more reliable and validated regional climate scenarios before using that. Our future work also aims to characterize spatial variability over a larger region of Southeast Asia using gridded precipitation products.

References

[1] Maraun D, Wetterhall F, Ireson AM, Chandler RE., Kendon EJ, Widmann M, Brienen S, Rust H W, Sauter T, Theemel M, Venema VKC, Chun KP, Goodess CM, Jones RG, Onof C, Vrac M, and Thiele-Eich I 2010 Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user Rev. Geophys. 48 RG3003

[2] Intergovernmental Panel on Climate Change (IPCC) 2007 Summary for policymakers, in climate change 2007: The Physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change, ed Solomon S et al. (Cambridge: Cambridge University Press) pp1–18

[3] Giorgi F and Mearns L O 1991 Approaches to regional climate change simulation: A review Rev. Geophys. 29 191-216

[4] Willems P, Arnbjerg-Nielsen K, Olsson J, and Nguyen VTV 2012 Climate change impact assessment on urban rainfall extremes and urban drainage: methods and shortcomings Atmos. Res. 103 106-118

[5] Tabari H., Taye MT, and Willems P 2015 Water availability change in central Belgium for the late 21st century Global Planet. Change 131 115–123

[6] Fowler HJ, Blenkinsop S, and Tebaldi C 2007 Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling Int. J. Climatol. 27 1547–78

[7] Christensen JH, Boberg F, Christensen OB, and Lucas-Picher P 2008 On the need for bias correction of regional climate change projections of temperature and precipitation Geophys. Res. Lett. 35 L20709

[8] Herrera S, Fita L, Fernandez J, and Gutierrez JM 2010 Evaluation of the mean and extreme precipitation regimes from the ENSEMBLES regional climate multimodel simulations over Spain J. Geophys. Res. 115 D21117

[9] Turco M, Sanna A, Herrera S, Llasat M-C, and Gutiérrez JM 2013 Large biases and inconsistent climate change signals in ENSEMBLES regional projections Clim. Change 120(4) 859–869

[10] Marzban C, Sandgathe S, and Kalnay E 2006 MOS, perfect prog, and reanalysis Mon. Weather Rev. 134(2) 657–663

[11] Ruiz-Ramos M, Rodríguez A, Dosio A, Goodess C, Harpham C, Mínguez M, and Sánchez E 2016 Comparing correction methods of RCM outputs for improving crop impact projections in the Iberian Peninsula for 21st century Clim. Change 134(1–2) 283–297

[12] Giorgi F et al 2012 RegCM4: model description and preliminary tests over multiple CORDEX domains Clim. Res. 52 7–29

[13] Collier M, Jeffrey S, Rotstain L, Wong K, Dravitzki S, Moeseneder C, et al. 2011 The CSIRO-Mk3-6-0 Atmosphere-Ocean GCM: participation in CMIP5 and data publication MODSIM 2011 - 19th International Congress on Modelling and Simulation (Perth) (Modelling and Simulation Society of Australia and New Zealand Inc) pp 2691-97

[14] Grell GA, Dudhia J, and Stauffer DR 1994 A description of the fifth-generation Penn State/NCAR Mesoscale Model (MM5) NCAR Tech. Note, NCAR/TN-398+STR pp 122

[15] Kiehl JT, Hack J, Bonan G, Boville B, Briegleb B, Williamson D, and Rasch P 1996 Description of the NCAR Community Climate Model (CCM3) Technical Report 30 NCAR/TN-420+STR, National Center for Atmospheric Research, Boulder, Colorado, pp 152

[16] Collins WD and others 2006 The Community Climate System Model Version 3 (CCSM3) J. Climate 19 2122-43
[17] Dickinson RE, Henderson-Sellers A, and Kennedy PJ 1993 Biosphere-atmosphere transfer scheme (BATS) version 1e as coupled to the NCAR Community Climate Model NCAR Technical Note NCAR/TN-387+STR p 72

[18] Gao X et al. 2006 Projected changes in mean and extreme precipitation over the Mediterranean region from high resolution double nested RCM simulations Geophys. Res. Lett. 33 L03706

[19] Oleson KW, Niu Gy, Yang ZL, Lawrence DM and others 2008 Improvements to the Community Land Model and their impact on the hydrologic cycle J. Geophys. Res. 113 G01021

[20] Tawfik AB, Steiner AL 2011 The role of soil ice in land–atmosphere coupling over the United States: a soil moisture precipitation winter feedback mechanism J. Geophys. Res. 116 D02113

[21] Holtslag A, de Bruijn E, Pan HL 1990 A high resolution air mass transformation model for short-range weather forecasting Mon. Weather Rev. 118 1561–75

[22] Zeng X, Zhao M, Dickinson RE 1998 Intercomparison of bulk aerodynamic algorithms for the computation of sea surface fluxes using TOGA COARE and TAO data J. Clim. 11 2628–44

[23] Fritsch JM and Chappell CF 1980 Numerical prediction of convectively driven mesoscale pressure systems. Part I: Convective parameterization J. Atmos. Sci. 37 1722–33

[24] Juneng L, Tangang F, Chung J, Ngai S, Tay T, Narisma G, et al. 2016 Sensitivity of Southeast Asia rainfall simulations to cumulus and air-sea flux parameterizations in RegCM4 Climate Research 69(1) 59–77

[25] Ngo-Duc T, Tangang FT, Santisirisomboon J, Cruz F, Trinh-Tuan L., Nguyen-Xuan T, et al. 2016 Performance evaluation of RegCM4 in simulating extreme rainfall and temperature indices over the CORDEX-Southeast Asia region International Journal of Climatology 37 1634-47

[26] Cruz FT, Narisma GT, Dado JB, Singhruck P, Tangang F, Linarka UA, et al. 2017 Sensitivity of temperature to physical parameterization schemes of RegCM4 over the CORDEX-Southeast Asia region. International Journal of Climatology 37 5139-53

[27] Huffman GJ, Adler RF, Bolvin DT, Gu G, Nelkin EJ, Bowman KP, et al. 2007 The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales Journal of Hydrometeorology 8 38–55

[28] Piani C, Haerter J, and Coppola E 2010 Statistical bias correction for daily precipitation in regional climate models over Europe Theor. Appl. Climatol. 99 187–192

[29] Ngai ST, Tangang F, and Juneng L 2017 Bias correction of global and regional simulated daily precipitation and surface mean temperature over Southeast Asia using quantile mapping method Global and Planetary Change 149 79–90