Projected extreme climate indices in the java island using cmip5 models

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Abstract. Climate change has brought great environmental impacts that cause economic disruption as it causes extreme climate phenomena such as floods and droughts. The projection of precipitation and temperature is crucial to develop the adaptation and mitigation options, as well as to improve the operational strategies in various sectors. This study used Coupled Model Intercomparison Project Phase 5 (CMIP5) that consists of 29 GCMs to make the projection of precipitation and temperature (2011–2100), along with daily observational data from 16 stations over the Java island for 20 years (1986–2005) to evaluate the models. Spatial and temporal correlation method was used to evaluate the climate models and 5 GCMs with the best performance were selected to project the precipitation and temperature. A bias correction method called Simple Quantile Mapping (SQM) was used to adjust the climate models to better represent the observational data. Representative Concentration Pathway (RCP)4.5 dan RCP8.5 scenarios were chosen and the extreme weather events were depicted using the Expert Team for Climate Change Detection and Indices (ETCCDI), which includes annual total precipitation (Prcptot), consecutive dry days (CDD), consecutive wet days (CWD), monthly maximum temperature (TXx) and monthly minimum temperature (TNn). Using the multi model ensemble (MME) from the 5 best GCMs, the projection of 5 extreme climate indices over Java island shows a relative increase to the historical period.

1. Introduction
Climate change can be defined as changes in the average weather conditions or changes in the distribution of weather events to the average conditions [1]. Climate change refers to changes in climate conditions that can be identified (for example, using statistical tests) by changes in average or variability in their properties, lasting for a long period of time (usually decades or more). Human activity has changed the composition of the atmosphere and the surface of the earth. Some of these changes have a direct or indirect impact on the earth energy balance which then trigger climate change. Current climate change is mainly caused by the increase of the concentration of Greenhouse...
Gases (GHG) in the atmosphere [2]. The minimum period to determine changes in climate scale is 30 year period. Studies regarding climate change should consider the past, current, and future climatic condition, so the analysis between timescale should be integrated. In the future changing climate, the changes of climatic parameters will disrupt life in many ways, for instance, threats of biodiversity, seawall erosion, and storms [3]. Climate change affects the frequency and intensity of extreme weather events [4]. In the last 30 year period, the annual precipitation and temperature in Indonesia has shown a significant increase [5]. The average temperature has increased as much as 0.3°C since 1900. Despite the overall increase over the Indonesian region, some regions experience decreases in precipitation amount [6].

Global climate models (GCMs) are the main tools to depict the future climate projection in global and regional scale. The information derived from those models are used in the policy making related to the adaptation and mitigation efforts, particularly to simulate precipitation and temperature. GCM is numerical model that consist of data from various climatic parameters and the best way to simulate large scale climatic condition. However, it is hard to make projection for small spatial scale as GCMs resolution tend to be coarse (±300 km x 300 km or 2.5°) [7]. Climate models are numerical representations of the climate system based on the processes of physical, chemical and biological components, interactions between components, feedback processes and taking into account all or part of them. Coupled Model Intercomparison Project Phase 5 (CMIP5) is a set of coupled climate models that has been used extensively for climate projection, detection and attribution, and other climate sensitivity studies. CMIP5 was developed in 2013 and is the first integrated model climate configuration that does not require flux adjustments (artificial adjustments applied in climate model simulations to prevent them from entering unrealistic climatic conditions). This model was issued by various institutions in the world. Good simulation of the current climate state without using flux adjustments is a big advancement when the model was developed and is still better compared to other models in this regard [8].

The purpose of this study is to project the future extreme climate conditions (2011-2100) in Java island based on a global modeling scenario that has been bias corrected with ground station data over the island of Java. So that based on the description of the future extreme climate projections generated from the study, adaptation, and mitigation measures can be carried out on Java to reduce the impact of life losses and material losses that can be caused.

2. Methodology

2.1 Data

![Figure 1. The location of 16 meteorological stations of BMKG on the Java island used in the Study.](image)

The observational data used in this study is the daily observation of precipitation, maximum and minimum temperature. The observational data from 16 meteorological stations that belongs to the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) over Java island (Figure 1.) for 20 year period (1986 – 2005). Models used were the CMIP5 models that consist of 29 GCMs (Table 1). In this study, the 1986 – 2005 period is defined as the baseline period, whereas
the 2011 – 2100 period is the projection period. Two scenarios were used, which are the RCP4.5 and RCP8.5 scenarios.

Table 1. Characteristics of the CMIP5 model used in the study [9].

| No | GCM Name | Modeling Group | Resolution |
|----|----------|----------------|------------|
| 1  | bcc-csm1-1-m | Beijing Climate Center, China Meteorological Administration | 320 x 160 |
| 2  | bcc-csm1-1   | Beijing Climate Center, China Meteorological Administration | 128 x 64  |
| 3  | CanESM2     | Canadian Centre for Climate Modelling and Analysis, Canada | 128 x 64  |
| 4  | CCSM4       | National Center for Atmospheric Research, United States | 288 x 192 |
| 5  | CESM1-BGC   | National Science Foundation, Department of Energy, NCAR, USA | 288 x 192 |
| 6  | CESM1-CAM5  | National Science Foundation/Department of Energy, NCAR, USA | 288 x 192 |
| 7  | CMCC-CM     | Centro Euro-Mediterraneo sui Cambiamenti Climatici, Italy | 480 x 240 |
| 8  | CMCC-CMS    | Centro Euro-Mediterraneo sui Cambiamenti Climatici, Italy | 192 x 96  |
| 9  | CNRM-CM5    | National Centre of Meteorological Research, France | 256 x 128 |
| 10 | CSIRO-Mk3-6-0 | CSIRO in collaboration with the Queensland Climate Change Centre of Excellence, Australia | 192 x 96  |
| 11 | FGOALS-g2   | Chinese Academy of Sciences, and Center for Earth System Science, China | 128 x 60  |
| 12 | FGOALS-s2   | Chinese Academy of Sciences, and Center for Earth System Science, China | 128 x 108 |
| 13 | GFDL-CM3    | Geophysical Fluid Dynamics Laboratory, United States | 144 x 90  |
| 14 | GFDL-ESM2G  | Geophysical Fluid Dynamics Laboratory, United States | 144 x 90  |
| 15 | GFDL-ESM2M  | Geophysical Fluid Dynamics Laboratory, United States | 144 x 90  |
| 16 | HadGEM2-CC  | Met Office Hadley Centre, United Kingdom | 192 x 145 |
| 17 | HadGEM2-ES  | Met Office Hadley Centre, United Kingdom | 192 x 145 |
| 18 | HadGEM2-AO  | National Institute of Meteorological Research, Korea Meteorological Administration | 192 x 145 |
| 19 | inmcm4      | Institute of Numerical Mathematics, Russia | 180 x 120 |
| 20 | IPSL-CM5A-LR | Institut Pierre Simon Laplace, France | 96 x 96   |
| 21 | IPSL-CM5A-MR | Institut Pierre Simon Laplace, France | 144 x 143 |
| 22 | IPSL-CM5B-LR | Institut Pierre Simon Laplace, France | 96 x 96   |
| 23 | MIROC-ESM  | Tokyo, National Institute for Environmental Studies, and JAMSTEC, Japan | 128 x 64  |
| 24 | MIROC-ESM-CHEM | Tokyo, National Institute for Environmental Studies, and JAMSTEC, Japan | 128 x 64  |
| 25 | MIROC5      | Tokyo, National Institute for Environmental Studies, and JAMSTEC, Japan | 256 x 128 |
| 26 | MPI-ESM-LR  | Max Planck Institute for Meteorology, Germany | 192 x 96  |
| 27 | MPI-ESM-MR  | Max Planck Institute for Meteorology, Germany | 192 x 96  |
| 28 | MRI-CGCM3   | Meteorological Research Institute, Japan | 320 x 160 |
| 29 | NorESM1-M   | Norwegian Climate Centre, Norway | 144 x 96  |

2.2 Method
The statistical downscaling gives specific information for the climate change studies with affordable computational abilities [10]. Before being downscaled, 29 GCMs were ranked based on the proximity pattern, both spatially and temporally, using the correlation method. The correlation analysis has been used to investigate the closeness of both parameter, with x being the modeled precipitation and y as the observational precipitation. The correlation coefficient used were calculated using the following formula (1) below:

\[
 r_{xy} = \frac{n \sum x_i y_i - (\sum x_i)(\sum y_i)}{\sqrt{[n \sum x_i^2 - (\sum x_i)^2][n \sum y_i^2 - (\sum y_i)^2]}}
\] (1)
Simple quantile mapping (SQM) is an algorithm to bias correct a time series data, for instance the precipitation and temperature [11]. The bias correction method consists of methods to scale the mean, variance, and higher distribution moment by parametric [12] and non-parametric techniques [13]. Previous studies had shown that non-parametric bias correction method called SQM, gives higher ability that systematically reduce biases in climate models, in particular to precisely reproduce temporal trend from weather variables and compatible to hydrological applications [14]. The quantile mapping fits the cumulative distribution function (CDF) $F_{o,h}$ and $F_{m,h}$ from each model ($x_{(m,h)}$) and observational data ($x_{(o,h)}$). This then leads to this transfer function (2) [11] below:

$$\hat{x}_{m,p}(t) = F_{o,h}^{-1}\{F_{m,h}[x_{m,p}(t)]\}$$  \hspace{1cm} (2)

To bias correct the $x_{m,p}(t)$, the modelled value at $t$ was projected and was written with subscript $p$. If the CDF and the inverse of CDF (the quantile function) were modelled empirically from data, the algorithm was illustrated with the help of quantile plot, which is the scatter plot between empirical quantile of observational data and modelled data (the value that was sorted from all sample when the sample number of the observation and model are the same). SQM, like all statistical post-processing algorithm, depend heavily on the assumption that climate model biases that will be fixed was stationary [11]. After being projected for the RCP4.5 and RCP8.5 scenarios, the precipitation data for 2011 – 2100 period was obtained, then the extreme climate indices were calculated (Table 2), which includes the annual total precipitation, cumulative dry days, cumulative wet days, monthly maximum temperature, and monthly minimum temperature, which will be analysed for the future period (2011-2100).

### Table 2. Selected of 5 extreme climate indices of ETCCDI used in the study [15].

| Indices | Variable | Description | Unit |
|---------|----------|-------------|------|
| Prcptot | Precipitation | Annual total precipitation in wet days, (daily precipitation ≥1mm) | days |
| CDD     |          | Maximum length of dry spell, maximum number of consecutive days with daily precipitation <1mm | days |
| CWD     |          | Maximum length of wet spell, maximum number of consecutive days with daily precipitation ≥1mm | mm  |
| TXx     | Temperature | Monthly maximum value of daily maximum temperature | °C |
| TNn     | Temperature | Monthly minimum value of daily minimum temperature | °C |

### 3. Results and Discussion

#### 3.1 raw GCM Rank

The rank was calculated based on 4 criteria, which was the spatial correlation of precipitation, temporal correlation of precipitation, the spatial correlation of temperature, and temporal correlation of temperature. The correlation analysis between all 29 GCMs and the observation in 16 stations was done and 5 best GCMs were selected. The precipitation pattern over Java island is known as the monsoonal pattern that has one precipitation peak and one low in one year period [16]. Based on Table 3, the temporal pattern closeness between GCMs and observational data is apparent with correlation of more than 0.8 for 5 GCMs, which was then used as the justification to use those 5 GCMs. The GCMs used were CESM1-CAM5, FGOALS-g2, MRI-CGCM3, FGOALS-s2, and CMCC-CM. On the other hand, the spatial correlations were lower than the temporal correlation (0.4 for precipitation, 0.5 for temperature).
Table 3. The results for raw GCM Rank based on the correlation coefficient value.

| GCM Name       | Spatial Precipitation Correlation | Temporal Precipitation Correlation | Spatial Temperature Correlation | Temporal Temperature Correlation | GCM Rank Total |
|----------------|----------------------------------|-------------------------------------|--------------------------------|----------------------------------|----------------|
| CESM1-CAM5     | 0.3                              | 0.8                                 | 0.5                            | 0.9                              | 1              |
| FGOALS-g2      | 0.2                              | 0.7                                 | 0.4                            | 0.9                              | 2              |
| MRI-CGCM3      | 0.2                              | 0.8                                 | 0.5                            | 0.9                              | 3              |
| FGOALS-s2      | 0.1                              | 0.8                                 | 0.2                            | 0.9                              | 4              |
| CMCC-CM        | 0.2                              | 0.8                                 | 0.4                            | 0.8                              | 5              |
| CESM1-BGC      | 0.1                              | 0.8                                 | 0.5                            | 0.9                              | 6              |
| CCSM4          | 0.0                              | 0.8                                 | 0.5                            | 0.9                              | 7              |
| HadGEM2-ES     | 0.2                              | 0.7                                 | 0.0                            | 0.9                              | 8              |
| GFDL-CM3       | 0.1                              | 0.8                                 | 0.2                            | 0.9                              | 9              |
| NorESM1-M      | -0.2                             | 0.7                                 | 0.5                            | 0.9                              | 10             |
| bcc-csm1-1-1   | -0.1                             | 0.8                                 | 0.4                            | 0.8                              | 11             |
| GFDL-ESM2G     | 0.2                              | 0.8                                 | 0.0                            | 0.9                              | 12             |
| HadGEM2-AO     | 0.3                              | 0.8                                 | 0.0                            | 0.9                              | 13             |
| IPSL-CM5B-LR   | 0.1                              | 0.7                                 | 0.3                            | 0.9                              | 14             |
| bcc-csm1-1-m   | 0.1                              | 0.8                                 | 0.1                            | 0.9                              | 15             |
| MPI-ESM-LR     | -0.2                             | 0.4                                 | 0.5                            | 0.9                              | 16             |
| MPI-ESM-MR     | -0.3                             | 0.5                                 | 0.4                            | 0.9                              | 17             |
| CSIRO-Mk3-6-0  | -0.2                             | 0.8                                 | 0.2                            | 0.9                              | 18             |
| CMCC-CMS       | -0.4                             | 0.6                                 | 0.2                            | 0.8                              | 19             |
| IPSL-CM5A-LR   | 0.0                              | 0.7                                 | 0.2                            | 0.9                              | 20             |
| CanESM2        | -0.2                             | 0.6                                 | 0.3                            | 0.9                              | 21             |
| CNRM-CM5       | 0.0                              | 0.8                                 | 0.1                            | 0.9                              | 22             |
| HadGEM2-CC     | 0.2                              | 0.8                                 | 0.0                            | 0.9                              | 23             |
| GFDL-ESM2M     | 0.2                              | 0.8                                 | 0.0                            | 0.9                              | 24             |
| MIROC5         | 0.0                              | 0.7                                 | 0.0                            | 0.9                              | 25             |
| IPSL-CM5A-MR   | 0.1                              | 0.7                                 | 0.0                            | 0.9                              | 26             |
| inmcm4         | 0.2                              | 0.6                                 | 0.1                            | 0.8                              | 27             |
| MIROC-ESM      | -0.1                             | 0.4                                 | 0.0                            | 0.9                              | 28             |
| MIROC-ESM-CHEM | -0.1                             | 0.4                                 | -0.1                           | 0.9                              | 29             |

3.2 Results of Boxplot for selected of 5 Extreme Climate Indices of ETCCDI

In this section, the SQM bias correction algorithm is applied to precipitation, maximum air temperature and the minimum air temperature of the 5 GCM data for the historical period and future period based on from 16 meteorology station points. Historical analysis and projections were carried out for precipitation, minimum air temperature and maximum air temperature using 5 GCM with the highest ranking, namely CESM1-CAM5, FGOALS-g2, MRI-CGCM3, FGOALS-s2, CMCC-CM, obtained from CMIP5. The best 5 corrected GCMs were then processed to calculate the 5 extreme climate indices of ETCCDI, which is total annual total precipitation (Prcptot), consecutive dry days (CDD), consecutive wet days (CWD), monthly maximum temperature (TXx) and monthly minimum temperature (TNN) for the historical periods and the future period. All the extreme climate indices of the historical period and the future period were plotted in boxplots. For the historical period, the bias of the 5 GCM and multi model ensemble (MME) plots were compared. For the 5 GCMs and MME data projections, the 5 GCMs were evaluated in their changes in the future period compare to the historical period.

3.2.1 Annual total precipitation in wet days. The output of the original selected 5 GCM for the bias for the Prcptot boxplot indices is shown in Figure 2.a, which shows that its mean, median and boxplot patterns that were still not close to the observational value. The outputs of the CESM1-CAM5 and MRI-CGCM3 models is an overestimation, while the outputs of the FGOALS-g2, FGOALS-s2, and CMCC-CM models underestimate the value of the observations. MME results from 5 GCMs also
showed an underestimated value of the value of their observations. The bias correction process is needed so that the output data from the GCM model simulations represent the observational data better. After the bias correction was done, in Figure 2.b it is shown that the mean and median Prcptot of 5 GCMs are closer to the mean and median precipitation observations where the ratio of precipitation values are not too far. MME results from 5 GCMs were very close to the observations. This shows that MME can be used to represent Prcptot on average for all 16 stations over the island of Java in future period.

Figure 2. Boxplot for indices of Prcptot observation, 5 GCMs, and MME for historical periods (a. left) Prcptot output before bias correction (b. right) Prcptot output after bias correction.

Figure 3 is the 5 GCM projections that has been corrected using the SQM algorithm for the period 2011 to 2100 for precipitation variables. Figures 3.a and 3.b show that the average annual precipitation of 16 meteorological stations on Java island increases in the future for both scenarios compared to the historical period (see figure 2.b) with a higher increase in the amount of rainfall in the RCP8.5 scenario. For the 2011-2100 period, all 5 GCMs show different pattern in the boxplot. The mean and median values for Prcptot until 2100 does not exceed 3000 mm/year except for the FGOALS-g2 model in the RCP8.5 scenario. For MME in both RCP4.5 and RCP8.5 scenarios for the amount of annual precipitation shows a relatively closer pattern. The outlier values in the projection period reaches values above 5000 mm/year, namely in the FGOALS-s2 model in RCP4.5 and the MRI-CGCM3 model in RCP8.5 which was not found in the historical period.

Figure 3. Boxplot for Prcptot future projections of 5 GCMs and MME after the bias correction (a. left) Prcptot output of the RCP4.5 Scenario (b. right) Prcptot output of the RCP8.5 Scenario.
3.2.2 Maximum length of dry spell, maximum number of consecutive days. The output of the selected 5 original GCMs of the CDD boxplot indices is shown below. In Figure 4.a it is shown that the mean, median and 5 GCM boxplot patterns are quite far from the observation value. The intricacies of some of the original model outputs are still underestimated compared to observed values. The MME yielded from the original 5 GCMs output also shows the underestimated value of the observations value. After the bias correction is done, in Figure 4.b was shown that the mean and median values of some models were closer to the mean value of observational precipitation, namely CMCC-CM and FGOALS-g2 even though the median and maximum and minimum ranges still have significant differences. The mean value of MME resulted from 5 GCMs was close enough to the value of the observations, but for the median and maximum and minimum ranges, the values of successive dry days are still quite different. The CDD value of observation ranged of 20 days to 95 dry days while the MME has smaller range of 30 to 50 consecutive dry days.

![Figure 4](image.png)

**Figure 4.** Boxplot for indices of CDD observation, 5 GCMs, and MME for historical periods (a. left) CDD output before bias correction (b. right) CDD output after bias correction.

Figure 5 is plots of boxplots of 5 GCM projections which has been corrected using the SQM algorithm for the 2011 to 2100 period for consecutive dry days. Figures 5.a and 5.b show that the average CDD of 16 meteorological stations on Java island increases in the future in both scenarios compared to the historical period (see figure 4.b). The CSM1-CAM5 model shows a fairly large range of CDD values, 12 to 175 dry days respectively in the RCP4.5 and 15 days to 190 consecutive dry days. The 5 GCM shows a boxplot pattern that is different in between the historical and the projection period of 2011 to 2100, but the 5 GCM shows a relatively similar pattern for the RCP4.5 and RCP8.5 scenarios. For dry days MME, consecutively for both RCP4.5 and RCP8.5 scenarios, the range is relatively small in the projection period, which is 20 to 70 consecutive dry days in the 2011 – 2100 period.
Figure 5. Boxplot for CDD future projections of 5 GCMs and MME after the bias correction (a. left) CDD output of the RCP4.5 Scenario (b. right) CDD output of the RCP8.5 Scenario.

3.2.3 Maximum length of wet spell, maximum number of consecutive days. The output of the original selected 5 GCMs for the CWD indices in Figure 6.a shows that the value of the 5 GCM overestimate the observation value of an average of 16 meteorological stations on the island of Java which ranges from 10 days to 16 consecutive wet days. We note that the CESM1-CAM5 model is much overestimating of around 43 days up to 75 wet days in a row. MME results from the original 5 GCM output also show an upper estimate value of the observation value. After bias correction was done, in Figure 6.b it was shown that the value of the 5 GCM range and the observation value are close even though the range of maximum, minimum, mean and median values of some 5 models are still above the observation value. The 5 GCM after correction showed a boxplot pattern that is relatively close to a small range. The MME value of 5 GCM after bias correction with SQM can be closer to the observational value.

Figure 6. Boxplot for indices of CWD observation, 5 GCMs, and MME for historical periods (a. left) CWD output before bias correction (b. right) CWD output after bias correction.

Figure 7 displays 5 GCM projections that have been corrected using the SQM algorithm for the 2011 - 2100 period for the consecutive wet day variables. Figures 7.a and 7.b show that CWD on average over all 16 meteorological stations have increased in terms of its mean and median values. In the historical period we found the average of the models are having 15 consecutive wet days while in the projection period the mean and median of 5 GCMs and MME gives approximately 16 to 18 consecutive wet days. From the maximum range in the future period for both scenarios compared to
the historical period (see figure 6.b), there is a slight increase in the CWD indices. The 5 GCM in both scenarios show relatively similar boxplot patterns.

![Boxplot for CWD future projections of 5 GCMs and MME after the bias correction](image)

**Figure 7.** Boxplot for CWD future projections of 5 GCMs and MME after the bias correction (a. left) CWD output of the RCP4.5 Scenario (b. right) CWD output of the RCP8.5 Scenario.

### 3.2.4 Monthly maximum value of daily maximum temperature

The output of selected 5 original GCMs for the maximum temperature indices is show in Figure 8.a. The value of 5 GCM varies, with the CESM1-CAM5 model, FGOALS-g2, FGOALS-s2, MRI-CGCM3 underestimate the observation values while the CMCC-CM overestimate the average observation value of 16 meteorological stations over the 9island of Java which ranges from 33,0°C to 35,5°C. After bias correction, in Figure 8.b it is shown that the minimum and maximum range values, with the mean and median 5 GCM and observation values are close to each other. The MME value of 5 GCMs for the TXx indices after the bias correction with SQM is adjusted to be closer to the observation value in the range of 34,0°C to 35,5°C.

![Boxplot for indices of TXx observation, 5 GCMs, and MME for historical periods](image)

**Figure 8.** Boxplot for indices of TXx observation, 5 GCMs, and MME for historical periods (a. left) TXx output before bias correction (b. right) TXx output after bias correction.

Figure 9 displays 5 GCM projections that have been corrected using the SQM algorithm for the period 2011 to 2100 for maximum temperature variables. Figures 9.a and 9.b show that the average TXx of 16 meteorological stations on Java island out of 5 GCMs show increases in the minimum value, mean, median, maximum in TXx in the projection period based on the scenario RCP4.5 and RCP8.5. Observed values ranged from 33,0°C to 35,5°C (figure 8.b) while the projected values in the 2011-2100 period with the RCP4.5 scenario ranged from 35,5°C to 37,0°C based on the MME, while the other 5 GCMs pointed to a relatively close mean value from the MME. For the projection, RCP8.5 scenario shows a higher temperature increase than the RCP4.5 scenarios for the 5 GCMs and MME. The mean of the 5 GCMs for the RCP8.5 scenario shows that the average is approximately 37,0°C with a maximum temperature range ranging from 34,2°C to 41,0°C.
3.2.5 Monthly minimum value of daily minimum temperature. The output of selected 5 original GCMs for the minimum temperature indices is shown in Figure 10.a. The value of the 5 GCMs consistently overestimate ranges from 20.9°C to 25.8°C compared to the average observation value of 16 meteorological stations on the island of Java which ranges from 17.5°C to 19.8°C. After the bias correction is done, Figure 8.b shows that the values of the 5 GCMs model are still varied but are quite close to the value of the observations. The MME value of 5 GCMs for the TNn indices after bias correction with SQM is sufficient to resemble the observation value in the range of 17.4°C to 19.5°C.

Figure 9. Boxplot for TXx future projections of 5 GCMs and MME after the bias correction (a. left) TXx output of the RCP4.5 Scenario (b. right) TXx output of the RCP8.5 Scenario.

Figure 10. Boxplot for indices of TNn observation, 5 GCMs, and MME for historical periods (a. left) TNn output before bias correction (b. right) TNn output after bias correction.

Figure 11 displays 5 GCM projections that have been corrected using the SQM algorithm for the period 2011 to 2100 for maximum temperature variables. Figures 11.a and 11.b show that TNn on an average of 16 meteorological stations on Java island out of 5 GCMs increases in terms of the minimum value, mean, median, maximum in TNn in the projection period based on the scenario RCP4.5 and RCP8.5. Observation values ranged from 17.5°C to 19.8°C (figure 10.b) while the projected values in the 2011-2100 period with the RCP4.5 scenario ranged from 18.5°C to 21.8°C based on MME, while the other 5 GCMs addressed the mean values that varied with MME. The FGOALS-g2 model shows the mean, median and range values lower than the other 4 GCMs in the historical period and the projection period for the RCP4.5 and RCP8.5 scenarios. For the projection scenario RCP8.5 shows a higher temperature increase than the RCP4.5 for 5 GCMs and MME scenarios.
Figure 11. Boxplot for TNn future projections of 5 GCMs and MME after the bias correction (a. left) TNn output of the RCP4.5 Scenario (b. right) TNn output of the RCP8.5 Scenario.

3.3 Percent change of future Extreme Climate Indices based on MME. In this part, the analysis of the projected extreme climate indices were divided into three parts, the near time period (2011–2040), the medium time period (2041–2070), and far time period (2071–2100) for both RCP4.5 and RCP8.5 scenario. The relative change of percentage over projection and historical period was calculated to assess the magnitude of change of the extreme climate indices. The MME of the projections were calculated from 5 GCMs that were selected before (Table 3).

There is a significant increase in the MME of all climate indices selected. The cumulative precipitation show increases in both the RCP4.5 and RCP8.5 scenarios, for all time period. The magnitude of changes are higher in the later time periods. The CDD and CWD indices also show relative increase to the historical period, that implies the more intense seasons (dry season tends to be dryer, wet season tend to be wetter). The TXx and TNn indices show consistent increases, which means that the whole distribution of temperature will be shifted to the right. Not a single indices experience decrease in the future period. The details of the percentage increase for the 5 extreme indices are tabulated in Table 4 below.

| Climate Indices | Future Change of RCP4.5 | Future Change of RCP8.5 |
|-----------------|------------------------|------------------------|
|                 | Near (2011-2040) | Middle (2041-2070) | Far (2071-2100) | Near (2011-2040) | Middle (2041-2070) | Far (2071-2100) |
| Preptot         | 9 % | 11 % | 17 % | 5 % | 17 % | 32 % |
| CDD             | 7 % | 10 % | 5 % | 7 % | 11 % | 12 % |
| CWD             | 9 % | 8 % | 10 % | 8 % | 17 % | 17 % |
| TXx             | 3 % | 6 % | 7 % | 4 % | 7 % | 12 % |
| TNn             | 6 % | 11 % | 13 % | 7 % | 15 % | 23 % |

4. Conclusion
Based on the spatial and temporal correlation analysis of all 29 GCMs with observational data, the 5 best models were chosen to represent the future projection of temperature and precipitation over Java. Those 5 GCMs were CESM1-CAM5, FGOALS-s2, MRI-CGCM3, FGOALS-s2, and CMCC-CM. However, those GCMs output still shows biases to the ground observation, therefore, the simple quantile mapping method was used to adjust the model outputs.

Using RCP4.5 and RCP8.5 projections, the 5 climate indices chosen experience relative increase in the 2011–2100 period, compared to the historical period. Using 3 different periods, near time period (2011–2040), medium time period (2041–2070), and far time period (2071–2100), the 5 climate
indices experience various increases as well. The highest increase was obtained for the annual total precipitation parameter, that implies the risk of extreme precipitation in the future.

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