Evaluation of Two Bias-Correction Methods for Gridded Climate Scenarios over Japan

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Abstract

Bias corrected climate scenarios over Japan were developed using two distinct methods, namely, the cumulative distribution function-based downscaling method (CDFDM) and Gaussian-type Scaling approach (GSA). We compared spatial distribution, monthly variation, and future trends. The seasonal distribution of bias-corrected data using CDFDM closely followed the original general circulation model (GCM) outputs. GSA overestimated the amount of precipitation by 12–18% in every season because of an unsuitable assumption on the probability distribution. We also examined the contributions of each source of the uncertainty in daily temperature and precipitation indices. For daily temperature indices, GCM selection was the main source of uncertainty in the near future (2026–2050), while different Representative Concentration Pathways (RCPs) resulted in large variability at the end of the 21st century (2076–2100). We found large uncertainty using the bias-correction (BC) methods for daily precipitation indices even in the near future. Our results indicated that BC methods are an important source of uncertainty in climate risk assessments, especially for sectors where precipitation plays a dominant role. An appropriate choice of BC, or use of different BC methods, is encouraged for local mitigation and adaptation planning in addition to the use of different GCMs and RCPs.

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1. Introduction

Climate change may lead to variations in atmospheric circulation and meteorological field, which has the potential to affect human health, agricultural yields, water resources, and more. In order to evaluate impacts of the changing climate and consider mitigation and adaptation measures, global circulation models (GCMs) provide the main sources of information regarding future projections. As GCM simulations often contain systematic errors, bias-correction (BC) is essential to use their outputs for impact assessments (e.g., Gomez-Garcia et al. 2019; Iizumi et al. 2017; Maraun et al. 2017). For example, within the framework of the Inter-Sectoral Impact Model Intercomparison Project 2b (ISI-MIP2b; Frieler et al. 2017), four GCMs were selected from the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012), and a trend-preserving approach (Hempel et al. 2013) was applied to examine the impacts of climate change on a global scale.

Meteorological observation networks have recently been developed around the world. Grid-based datasets derived from stationary measurements, observational satellites data and modeled results have become available (e.g., Harris et al. 2014; Yatagai et al. 2009; Ohno et al. 2016). The gridded format enables straightforward evaluation of modeled data. In Japan, 1-km-gridded data sets were developed (Ohno et al. 2016) mainly based on station data from the Japan Meteorological Agency (JMA), which encouraged application of various climate impact studies at a regional scale. However, future climate scenarios that encompass multiple variables over a long period with spatially high resolution have not been available so far.

Future climate projections are subject to considerable uncertainties (e.g., Giorgi and Francisco 2000). To depict a more complete picture of the uncertainties in projected climate scenarios, understanding the contributions of each source of uncertainty is important. Some studies have attempted to quantify and examine the several sources of uncertainty in future projections (e.g., Sillmann et al. 2013; Ishizaki et al. 2012). However, there are few studies that have systematically evaluated the uncertainties in climate projections associated with different BC methods (Iizumi et al. 2017). For example, intercomparison of BC methods over Japan remain unreturned due to the lack of multiple climate scenarios based on the same GCM and various BC methods. Here we developed gridded climate scenarios based on two different BC methods using multiple GCMs and Representative Concentration Pathways (RCPs). The skill of BC methods to reproduce observed spatial distribution of mean state, monthly variation, and future trends were validated. We also examined the contribution of each source of the uncertainty in the corrected climate projections.

2. Data and method

Four GCMs were selected from CMIP5; MIROC5, MRI-CGCM3, HadGEM2-ES, and GFDL-CM3. Regarding the GHGs emission pathways, RCP2.6 and RCP8.5 were used. These were selected as common scenarios for the S-8 project, that aimed to provide a synthetic national multi-sector climate impact assessment, based on the reproducibility and variation in temperature rise around the Japan region (Hanasaki et al. 2012). Many researchers have used these GCMs to perform impact assessments in Japan throughout recent years. As reference data, we used the Agro-Meteorological Grid Square Data (Ohno et al. 2016). This dataset was developed using the Automated Meteorological Data Acquisition System (AMeDAS) by JMA and its accuracy was confirmed by comparing the gridded values to observations at the closest station (Ohno et al. 2016).

Table 1 shows a detailed description of the two databases developed and used here. One was developed in this study (Ishizaki 2020) based on the CDFDM proposed by Iizumi et al. (2010, 2011, 2012, 2014, 2017). It is a non-parametric method in which the several is identified and corrected in each percentile. The CDF for the calibration period was conducted for early- (January to June) and late-seasons (July to December), respectively. Daily observational data from 1980 to 2018 were utilized to maximize the reference period because the length of the data period would affect the range of variation in the corrected data, especially in a non-parametric correction method like CDFDM. As the historical period was defined up to 2005 in CMIP5, we employed daily GCM data from 1967 to 2005 to define the GCM error. This dataset was referred to as the CDFDM data.

The second dataset was corrected by the Gaussian-type scaling approach (GSA) of Haerter et al. (2011). Reference clima-
was calculated for 2005−2050. After 2050 for RCP2.6, the trend component was fixed by the linear trend value at 2050 (Nishimori et al. 2019). This dataset was referred to as he GSA data.

Note that the reference periods were not the same between CDFDM and GSA because they were developed under the different frameworks. Both bias correction methods were applied over land only due to the coverage of the reference data. We calculated daily temperature and precipitation indices, which are known as the Expert Team on Climate Change Detection and Indices (ETCCDis), to compare the projection ranges associated with different GCMs, RCPs, and BCs.

3. Results

3.1 Reproducibility of spatial distribution

Since each BC method had different target moments, features, and base periods, reproducibility would be expected to be different even in past periods. We compared bias, root mean square error (RMSE), and Taylor skill (Taylor 2001), with respect to the spatial distribution of temperature and precipitation averaged between 1981 and 2005 (Fig. 1). The MIROC5 model was found to have a warm bias throughout the season and the RMSE exceeded 5°C in winter. Although the RMSE was greatly reduced by the CDFDM approach, a warm bias of 0.4°C on the annual average was found. On the other hand, the data corrected by the GSA exhibited almost no bias in any season and the RMSE was almost zero. Compared to GSA data, the error for the CDFDM data was relatively large, but the skill score indicated a good performance of the horizontal distribution throughout the season (Fig. 1b).

The MIROC5 model overestimated precipitation throughout most of the year, except for the autumn season, by up to 22% (Fig. 1c). The spatial correlation coefficient was very low, owing to the coarse grid spacing of MIROC5 to reproduce spatial variation. Although both correction methods improved the spatial distribution of precipitation, CDFDM data still gave a dry bias in winter and wet bias in the other seasons (Fig. 1c). The Taylor diagram...
shown in Fig. 1d indicated that the CDFDM greatly improved the reproducibility of annual precipitation, but the performance of seasonal precipitation was not as good. GSA data showed an overestimation of 12−18% for precipitation in every season. Although the three other GCMs had different biases to those of MIROC5, the CDFDM generally showed a slight warm bias and relatively low observed seasonal variation. GSA data showed very good seasonal reproducibility for both temperature and precipitation. However, there was an overestimation of precipitation.

3.2 Averaged monthly variation over Japan

We also compared the monthly variation of temperature and precipitation averaged over Japan (Fig. 2). Both CDFDM and GSA data generally removed the warm bias of MIROC5. Future temperature rises in Japan under RCP8.5 were almost constant throughout the seasons in MIROC5: an approximate 1.6°C rise in the near future and 4.1°C warming by the end of the century. Both corrected datasets followed the future changes of MIROC5. The seasonal change in precipitation showed peaks in July and September, while the first peak occurred in June and the second was too small in MIROC5. An early precipitation peak was also reported by Kusunoki and Arakawa (2015), possibly associated with the representation of the Baiu-front. Winter precipitation in the CDFDM was underestimated, as shown in Fig. 1. This was particularly remarkable in the coastal area of the Sea of Japan (figure not shown), which may contribute to the lower standard deviation for the spatial pattern for precipitation (Fig. 1d). The seasonal precipitation distribution in the GSA data was generally consistent with the observations, but overestimation was found throughout the year. As originally projected by MIROC5, the corrected precipitation seemed to increase during the winter season in the near future and then, increase almost every season by the end of the century. The response of precipitation due to climate change derived from the four GCMs showed large variability by seasons. The direction of changes calculated by GCMs in each month were generally followed by both correction methods.

3.3 Projected temporal sequence

In addition to seasonal changes, we compared the temporal sequence from past to the future. Figure 3 shows temperature and precipitation anomalies averaged over the land area of Japan. After 2006, only RCP8.5 results were shown. The temperature deviation of the GSA data was similar to the GCM results before correction for all GCMs. On the other hand, CDFDM data did not coincide with the timeseries of original GCMs, especially for MIROC5. Future changes in precipitation were not linear but complex (Fig. 3b). Nevertheless, in general, an increasing tendency was found as
generally eliminated. However, SDII after applying GSA was from GCMs, which led to an overestimation of the number of (Fig. 5). A major cause of this was the drizzle effect inherited as a precipitation related index. Original GCMs reproduced compared to those between individual GCMs and RCPs.

In the near and far future, the ranges of SU derived from corrected climate data for 1981–2005 must be warmer than actual observed value if the seasonal progression in the GCM did not ried out in each percentile regardless of original date. The seasonal changes in precipitation along the Sea of Japan. The accuracy of seasonal variation may be further improved by constructing the CDF in seasonal or monthly time windows if allowed by the CDFDM, a correction function was constructed by comparing the mean value after CDFDM correction would be different from theeling values from 1967 to 2005. Japan’s temperature has already shown a warming trend (Fig. 3a), which has been characterized by a frequent updating of the statistics describing historical records of annual temperatures (JMA 2019). As the historical data were corrected using observations that included this warming trend, the CDF of observations from 1980 to 2018, with corresponding modeled values from 1967 to 2005. The CDFDM correction and the observation (Fig. 3) may show some information was improved, deviation of the relationship between seasonal climate and GSA in past and future scenarios over various time scales. It is meaningful to recognize the source of error and the limitations of each BC method to ascertain appropriate use in risk assessment and further improve the correction methods.

The main features of the CDFDM included a warm bias and inferior reproducibility of seasonality in the present climate. In the CDFDM, a correction function was constructed by comparing the CDF of observations from 1980 to 2018, with corresponding modeled values from 1967 to 2005. Japan’s temperature has already shown a warming trend (Fig. 3a), which has been characterized by a frequent updating of the statistics describing historical records of annual temperatures (JMA 2019). As the historical data were corrected using observations that included this warming trend, the CDF of observations from 1980 to 2018, with corresponding modeled values from 1967 to 2005. The CDFDM correction and the observation (Fig. 3) may show some information was improved, deviation of the relationship between CDFDM correction and the observation (Fig. 3) may show some improvements.

Fig. 4. Number of summer days (SU) in which the maximum temperature in excess of 25°C in the seven subregions of Japan for the past (upper), near future (middle) and far future (lower). The acronyms NJ, NP, EJ, EP, WJ, WP, and SI indicate the Japan Sea side of northern Japan, Pacific Ocean side of northern Japan, Japan Sea side of eastern Japan, Pacific Ocean side of eastern Japan, Japan Sea side of western Japan, Pacific Ocean side of western Japan, and the Southern Islands, respectively (see Supplement 1). Cross marks show the observations. The length of each box and bar reveal the range of values derived from the four GCMs. In the middle and lower panels, boxes and error bars reveal the range for RCP 2.6 and 8.5, respectively.

a common feature of the four GCMs. The CDFDM precipitation change rate was almost the same as that of the original GCMs. However, the GSA data showed a larger increase than all GCMs 1.4–4.3 times at the end of the 21st century.

3.4 Daily temperature and precipitation indices
To examine the magnitude of uncertainties owing to the selection of GCMs, RCPs, and the BC method, a comparison of the daily temperature index was carried out in seven subregions of Japan. Figure 4 shows the change in the number of summer days (SU), which was defined as the annual number of days with daily maximum temperature > 25°C. SU for the past period was underestimated by all GCMs in all subregions. The small range of SU derived from BC procedures indicated that uncertainty due to the selection of GCMs was almost eliminated in the past period. In the near and far future, the ranges of SU derived from corrected data were similar to those derived from the original GCM. This is because SU is directly reflected by the temperature increase of each GCM. The difference in range between RCP2.6 and RCP8.5 was small in the near future. Furthermore, there was no significant difference between ranges derived from the two BC data. This implied that the major uncertainty source in SU during the near future came from the selection of GCMs. On the other hand, at the end of the 21st century, SU varied significantly depending on the RCPs. SU was expected to increase by 12–40 and 40–95 days at the end of the 21st century under RCP2.6 and RCP8.5, respectively. Our results were consistent with the partitioning uncertainty analysis by Howkins and Sutton (2009). Regarding other climate change indices (CCI) related to temperature, such as the number of frost days and the growing season, it was confirmed that the change indices (CCI) related to temperature, such as the number of days with daily precipitation in excess of 1 mm.

underestimated, especially in eastern and western Japan, while GSA data tended to overestimate total precipitation (Figs. 1 and 2). SDII seemed to increase with global warming under the CDFDM, with the small variation due to the selection of GCM. GSA data also showed an increasing trend when comparing precipitation intensity in the past period, but the intensity was still lower than observations even in the future projection. The difference in SDII between the two BC methods was larger than the RCP difference in the near future. Large uncertainty due to the BC method was found in other indices related to precipitation, especially in the precipitation extremes (figure not shown).

4. Discussion
Several systematic features were found by comparing CDFDM and GSA in past and future scenarios over various time scales. It is meaningful to recognize the source of error and the limitations of each BC method to ascertain appropriate use in risk assessment and further improve the correction methods.

The main features of the CDFDM included a warm bias and inferior reproducibility of seasonality in the present climate. In the CDFDM, a correction function was constructed by comparing the CDF of observations from 1980 to 2018, with corresponding modeled values from 1967 to 2005. Japan’s temperature has already shown a warming trend (Fig. 3a), which has been characterized by a frequent updating of the statistics describing historical records of annual temperatures (JMA 2019). As the historical data were corrected using observations that included this warming trend, the corrected climate data for 1981–2005 must be warmer than actual measurement. This warm bias could be reduced by improving the selection of the reference period. Furthermore, correction was carried out in each percentile regardless of original date. The seasonal mean value after CDFDM correction would be different from the observed value if the seasonal progression in the GCM did not match observations. In other words, seasonal variation of BC data closely followed the original GCM outputs. Underestimation of corrected winter precipitation for MIROC5 based on CDFDM, was largely associated with the reproducibility of seasonal changes in precipitation along the Sea of Japan. The accuracy of seasonal variation may be further improved by constructing the CDF in seasonal or monthly time windows if allowed by the amount of observed data. If the reproducibility of seasonal climate information was improved, deviation of the relationship between CDFDM correction and the observation (Fig. 3) may show some improvements.
After applying the trend-preserving approach, the GSA reproduced temperature well. On the other hand, this method suggested an excessive amount of precipitation. This was largely due to the assumption of a Gaussian distribution used to describe daily precipitation. The frequency of daily precipitation is generally higher at weak intensities. If the corrected precipitation became negative, precipitation was further adjusted to 0 mm. The mean precipitation was, therefore, overestimated by applying the Gaussian distribution. Our results indicate that an appropriate choice of BC methods is important to avoid unnecessary uncertainties in climate projections. When it is unclear which BC method to employ, the use of different BC methods could be a solution to consider possible future ranges. To apply the GSA to precipitation, application of a transformation of variables (e.g., Box and Cox 1964) can be considered, but discussion of these methodologies is beyond the scope of this paper.

For both BCs, the precipitation amounts were adjusted through the BC procedure, which, in turn, affected reproducibility of the lengths of dry and wet spells and the number of wet days. As these values were not directly corrected but incidentally adjusted through BC procedure, we must carefully interpret consecutive dry or wet spells in corrected projections (Maraun et al. 2017). The fundamental approach for climate impact assessment includes procedures to select appropriate climate models and BC methods, according to the representativeness of relevant climate aspects (Maraun and Widmann 2018). In contrast, our dataset could be employed as common climate scenarios for organized adaptation planning in various sectors. Under this procedure, the appropriateness of the chosen BC method may depend on the type of target sector. When we can identify improper use of the BC method, we could adopt another method. If it is not clear whether the BC method is appropriate, we may check the robustness of the obtained results by comparing them to those collected using different BC methods. In addition, we would consider different land–sea distributions obtained from GCMs and observations. Generally, the amplitude of temperature fluctuations over land is greater than that above sea. As Japan has a complex topography, we should carefully check the representation of the Japan archipelago in each GCM. For example, we should not select a GCM, in which the Japan Sea is not adequately represented, as the sea is essential for determining the winter climate in Japan. To make effective and credible impact assessments, further research into appropriate GCM selection methods, with consideration of uncertainty, is required. Nevertheless, we note that BC cannot reproduce sub-grid variabilities or events in which the climate model does not capture the relevant processes (Maraun et al. 2017).

5. Conclusions

We developed new climate scenarios and compared the derived results using different BC methods. CDFDM showed excellent improvement in terms of the spatial distribution of climatological annual mean temperature and precipitation, and the seasonal variations in the corrected data closely followed the original GCM. This approach showed a slight warm bias attributed to the selection of the reference period. GSA successfully reproduced the observed features for temperature including the seasonal variation. The amount of precipitation after BC was overestimated by 12–18% in every season, which was associated with an inappropriate assumption of the probability distribution.

According to the selected four GCMs, daily mean temperature and precipitation over Japan in the near future (2026–2050) would increase by 1.1–2.7°C and 1.3–6.4%, respectively, relative to 1981–2005. In this period, selection of the GCM was the main source of uncertainty for the temperature-related CCI, while the precipitation-related CCI was remarkably different between the BC methods. According to the GCMs, at the end of 21 century (2076–2100), daily mean temperature and precipitation are expected to increase by 3.4–6.1°C and 2.8–12.1%, respectively. There is a dependency on RCPs and GCMs as the major source of uncertainty in projected daily temperature indices, while the uncertainty owing to the selection of BC methods is relatively small. In spite of the existence of large variability due to the selection of GCMs, SDII was considered to increase across the region, which was remarkable in the southern region of Japan. Again, large uncertainty was found due to BC methods for the daily precipitation indices.

Our results indicated the BC methods are also a source of uncertainty in climate risk assessments (Izumi et al. 2017). In addition to the use of different GCMs and RCPs, the appropriate choice of BC or the use of different BC methods is encouraged for local climate change mitigation and adaptation planning.

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Supplement

Supplement 1: Area classification map used in Figs. 4 and 5.

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