Future projections and uncertainty assessment of precipitation extremes in the Korean peninsula from the CMIP5 ensemble

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Abstract
Projections of changes in extreme climate are sometimes predicted by multi-model ensemble methods that combine forecasts from individual simulation models using weighted averaging. One method to assign weight to each model is the Bayesian model averaging (BMA) in which posterior probability is used. For the cases of extreme climate, the generalized extreme value distribution (GEVD) is typically used. We applied the approach of GEV-embedded BMA to a series of 35 years of the annual maximum daily precipitation data (both historical data and data gathered from simulation experiments for future periods) over the Korean peninsula as simulated by the models in the Coupled Model Intercomparison Project Phase 5 (CMIP5). Simulation data under two Representative Concentration Pathway (RCP) scenarios, namely RCP4.5 and RCP8.5, were used. Observed data and 17 CMIP5 models for 12 grid cells in Korea have been examined to predict future changes in precipitation extremes. A simple regional frequency analysis of pooling observations from three stations in each cell was employed to reduce the estimation variance and local fluctuations. A bias correction technique using the regression-type transfer function was applied to these simulation data. Return levels spanning over 20 and 50 years, as well as the return periods relative to the reference years (1971–2005), were estimated for two future periods, namely Period 1 (2021–2050) and Period 2 (2066–2095). From these analyses, relative increase observed in the spatially averaged 20-year (50-year) return level was approximately 23% (16%) and 45% (36%) in the RCP4.5 and RCP8.5 experiments, respectively, by the end of the 21st century. We concluded that extreme rainfalls will likely occur two times and four times more frequently in the RCP4.5 and RCP8.5 scenarios, respectively, as compared to in the reference years by the end of the 21st century.

KEYWORDS
climatic change, global climate model, heavy rainfall, multimodel simulation, Taylor diagram, weighted averaging
1 | INTRODUCTION

Heavy rainfall occurs frequently over the Korean peninsula during the warm season from late June through early September in association with synoptic disturbances, typhoons, or convective changes within the air masses over the region. Previous studies (Jung et al., 2002; Choi et al., 2010; Park et al., 2011) have reported an increase in observed extreme precipitation in Korea. Boo et al. (2006), Im et al. (2011), Seo et al. (2015), and Cha et al. (2016) predicted increasing changes in the future in the form of extreme rainfall over Korea using a regional projection model. However, their findings were based on a single simulation model, which limited confidence in them and suggested an ensemble approach based on multiple models to be more appropriate for reliable results.

Ahn et al. (2016) and Kim et al. (2019) also studied future changes in extreme precipitation over Korea using multiple regional climate models. They predicted that mean and extreme precipitation intensities over South Korea may increase in the future (2021–2100). Increasing extreme precipitation over South Korea is proportional to the increase in convective precipitation as compared to nonconvective precipitation. The study regions considered in the aforementioned studies (Seo et al., 2015; Ahn et al., 2016; Baek et al., 2017; Kim et al., 2019) were confined only to South Korea, whereas Kim et al. (2012) compared precipitation in South and North Korea using observation and reanalysis data sets. They found decreasing summer precipitation trends in North Korea, while opposite trends (i.e., increase) were observed in South Korea.

Ensemble methods of climatic projection have been proven to improve upon the systematic bias and to have fewer general limitations that are typically associated with single simulation models. Among the many ensemble methods, the approach we applied here was based on Bayesian model averaging (BMA), which determines static weights for each individual model using the posterior probability (Raftery et al., 2005; Sloughter et al., 2007). When prediction of extreme climatic events is the objective, generalized extreme value distribution (GEVD) is typically used as an assumed probability distribution in BMA. The GEVD encompasses all three possible asymptotic extreme value distributions predicted by the large sample theory. It is widely used to analyze univariate extreme values (Coles, 2001). In this study, we employed the approach by Zhu et al. (2013) in which seven regional climate models were used to project future extreme rainfall intensities. The method adopted by these researchers was a GEVD-embedded BMA, which is referred to as GEV-BMA here.

The purpose of this study was to predict future changes in precipitation extremes in the Korean peninsula and to assess uncertainty in the predictions from the Coupled Model Intercomparison Project Phase 5 (CMIP5) models using the GEV-BMA method and to use a bias correction (BC) technique. We focused on the intensity of annual maximum daily precipitation under two global warming scenarios (Representative Concentration Pathways; Moss et al., 2010), namely RCP4.5 and RCP8.5.

2 | DATA AND SIMULATION MODELS

We used four data sets comprising annual maximum daily precipitation (AMP1) observations, historical data, and future simulation data for two periods. Three periods were considered in data analysis: observation and historical data from 1971 to 2005 (Period 0), future data from 2021 to 2050 (Period 1), and from 2066 to 2095 (Period 2).

In the process of GEV-BMA, we required standard grids because the resolution of CMIP5 models varies, as presented in Table S1. For that standard, grids of $2\degree \times 2\degree$ are set as shown in Figure 1 that covered the Korean peninsula with 12 grid cells. The red triangle in Figure 1 depicts the center of the cell. Table S1 lists model names, institutes, and resolutions of the 17 CMIP5 models considered in this study. Figures S1 and S2 are grid and resolution maps of the models.

Time series values for annual maxima of the observed daily precipitation for 35 years (1971–2005) in South and North Korea were obtained from the Korean Meteorological Administration (KA, 2010). Table S2 presents a
summary of the statistics of the observations. Some missing data from the early years for some stations in North Korea were estimated using a formula obtained by comparing the APHRODITE (Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation, v1101; Yatagai et al., 2009) reanalysis data and observations for non-missing years (Lee et al., 2017). For more robust and reliable analysis (Kendon et al., 2008; Zhu et al., 2013) and for a regional frequency analysis based on observation, three stations were selected in each cell of Figure 1. Therefore, 105 (3 stations × observation, three stations were selected in each cell of their correlation were widely distributed between each location. The figures display that BMA weights before the BC were concentrated in a few simulation models, while they were distributed less prominently after the BC. This may be attributable to the criterion of the BC and of weight assignment being similar in the sense that they were both based on the difference between observation and historical data.

Figure S6 shows the Taylor diagram (Taylor, 2001) obtained from simulation models. The Taylor diagram quantifies the degree of correspondence between the modeled and observed behaviors, in terms of correlation coefficient, the ratio of the normalized root mean-squared errors (RNRMSE), and the normalized standard deviation (NSD). After the BC, simulation models exhibited NSD that was similar to that of the observations (around 60), with a high correlation (around 0.99). On the other hand, simulation models before the BC had fairly low NSD (below 40) and larger RNRMSE, while their correlations were widely distributed between approximately −0.1 and 0.85. This illustrates the usefulness of the BC in building a multimodel ensemble, as pointed out by Christensen et al. (2008) and Ratnam et al. (2019).

Figure S7 shows boxplots of the ratios (γ) of among-model SDs over within-model SDs (see Equation (14) in

For historical data, AMP1 for 35 years (1971–2005; Period 0) was obtained from historical experiments from each simulation model. Future data for the two periods of 30 years, 2021–2050 (Period 1) and 2066–2095 (Period 2), were obtained using CMIP5 models.

The scenarios considered in this study were the RCP4.5 and RCP8.5. The RCPs were designed to accommodate a wide range of possibilities, while integrating social and economical development factors consistent with specific radiative forcing paths. The estimated radiative forcing values by year 2100 are 4.5 W m⁻² and 8.5 W m⁻² in the RCP4.5 and RCP8.5 scenarios, respectively.

3 | METHODS

The GEVD is widely used to analyze univariate extreme values. Assuming the data on annual maxima of daily precipitation in this study followed an approximate GEV distribution, the parameters were estimated by the L-moments method (Hosking, 1990). Estimates of extreme quantiles of the annual maximum distribution were useful to assess any changes in the extremes. It was obtained by the formula known as the return level associated with the return period (Coles, 2001). For example, a 20-year (50-year) return level was computed as the 95th (98th) quantile of the fitted GEVD (see Supporting Information for details).

There was a high probability that the simulation model was biased systematically. To solve this problem, one can apply the bias-correction technique that constructs a transfer function to match the observations and historical data well. Among the various statistical BC methods available (Maraun and Widmann, 2018), we employed the regression-type transfer function (TF) approach by Piani et al. (2010), using the R package, “qmap”, developed by Gudmundsson et al., 2012. Table S3 lists the transfer functions considered in this study. Parameters in the TF were estimated by the least squares method. The obtained TF was applied to the simulation data for future periods. One feature of the TF method is that it still allows the application of the BMA method, as per the approach by Zhu et al. (2013). It produces unequal weights, as shown in Figures S3 and S5, so that BMA may retain its advantage.

Over the past few decades, ensemble forecasts based on global climate models have become an important part of climate forecast due to their ability to help reduce uncertainty in prediction. Among the many ensemble methods, the BMA combines the forecast distribution of different models and builds a weighted predictive distribution from them (e.g., Sloughter et al., 2007; Wang et al., 2012; Niu et al., 2018; Shin et al., 2019). In a climate change study of extreme rainfall, Zhu et al. (2013) employed the GEV distribution in a BMA framework, where the weight of each forecast model was calculated by comparing reanalysis data and the historical data from a simulation model. In this study, we followed the BMA framework proposed by Zhu et al. (2013), while using equal priors.

4 | RESULTS

4.1 | Uncertainty in multimodels

Figure S3 shows histograms of spatially averaged BMA weights for simulation models before and after BC. Figures S4 and S5 show the histograms of weights for each location. The figures display that BMA weights before the BC were concentrated in a few simulation models, while they were distributed less prominently after the BC. This may be attributable to the criterion of the BC and of weight assignment being similar in the sense that they were both based on the difference between observation and historical data.

Figure S6 shows the Taylor diagram (Taylor, 2001) obtained from simulation models. The Taylor diagram quantifies the degree of correspondence between the modeled and observed behaviors, in terms of correlation coefficient, the ratio of the normalized root mean-squared errors (RNRMSE), and the normalized standard deviation (NSD). After the BC, simulation models exhibited NSD that was similar to that of the observations (around 60), with a high correlation (around 0.99). On the other hand, simulation models before the BC had fairly low NSD (below 40) and larger RNRMSE, while their correlations were widely distributed between approximately −0.1 and 0.85. This illustrates the usefulness of the BC in building a multimodel ensemble, as pointed out by Christensen et al. (2008) and Ratnam et al. (2019).

Figure S7 shows boxplots of the ratios (γ) of among-model SDs over within-model SDs (see Equation (14) in
the Supporting Information). They are drawn for 20-year and 50-year return levels for the two RCPs and the three periods. The high value of this ratio shows more variation between the different models relative to the variation within each model. We observed that the ratios for future simulations (γ ≈ 1.5 on median) were about three times higher than those for historical data (γ ≈ 0.5 on median). In addition, variations in γ for Period 2 and for RCP8.5 were slightly higher than those for Period 1 and for RCP4.5, respectively.

4.2 Projected future changes in precipitation extremes

The projected changes in rainfall extremes were determined relative to the 1971–2005 reference periods; these were expressed in terms of the corresponding changes in return periods for rainfall extremes simulated in the reference period.

Figure 2 shows boxplots of 20-year return levels for future periods (p1 from 2021 to 2050 and p2 from 2066 to 2095) obtained from CMIP5 multimodel ensembles under RCP4.5 and RCP8.5 scenarios over the Korean peninsula. “hist” and “nbc” denote the historical data and no bias correction (BC), respectively.

Figure 3 shows the contour plot for the 20-year and 50-year return levels from the two scenarios for Periods 1 and 2. A notable difference is observable in extreme rainfall by two RCP scenarios for Period 2, while no such difference can be observed for Period 1. The northern part and southern part of Korea show noticeable differences in extreme precipitation. Moreover, we found out that the coefficient of variations for the 20-year and 50-year return levels in the southern part were higher than those in the northern part. This may be because the occurrence of extreme rainfall in the southern part was related to more sources or variables than in the northern part (Ahn et al., 2016; Cha et al., 2016; Kim et al., 2019).

Figure 4 shows boxplots for the 20-year and 50-year return periods, as compared to the reference years (1971–2005) for future periods (p1 and p2) obtained by the BMA method under RCP4.5 and RCP8.5 scenarios over Korea. These plots indicate that the 20-year return periods for Period 2 (p2) and for RCP8.5 were shorter than those for Period 1 (p1) and for RCP4.5, respectively. Particularly, the return periods for 1971–2005 20-year extreme precipitation events have been projected to shorten to about 5 years for p2 under RCP8.5. We realize that a 1-in-20 year (1-in-50 year) annual maximum daily precipitation in the Korean peninsula will likely become a 1-in-10 (1-in-22) year and a 1-in-5 (1-in-12) year event in median by the end of the 21st century based on RCP4.5 and RCP8.5 scenarios, respectively, as compared to the observations from 1971 to 2005. This is similar to or projects more frequent precipitation than the results (1-in-11 and 1-in-6 years) reported by Kharin et al. (2013) globally for a 20-year return level. These findings indicate that both 20- and 50-year return periods will likely reduce to around half for RCP4.5 and to around one quarter for RCP8.5 by the end of the 21st century. This is similar or more frequent to the results obtained by
Seo et al. (2015) that were based on a single regional simulation model. The corresponding values of these boxplots are presented in Tables S6 and S7.

5 | DISCUSSION

We observed a scale discrepancy between the model grid and point observation, which may compromise the credibility of our results. Regional projections require fine resolution of the simulation models, whereas some of the CMIP5 models have coarse resolution. However, it is known that model-spread is one of the major sources of uncertainty in regional predictions (Hawkins and Sutton, 2009). A large number of model simulations can reduce this uncertainty and provide a robust projection (Kendon et al., 2008; Sillmann et al., 2013). As compared to regional climate models, a larger number of global
circulation models (GCMs) are available; therefore, multi-GCMs were fit in this study. Although a single GCM does not provide fine resolution, Figures S1 and S2 show that multi-GCMs of different scales may cover the study region with finer spatial structures. BC would not eliminate this problem due to the scale difference. To reduce this gap, three stations were selected in each grid cell of Figure 1, and 105 values for each cell were used.

The results presented in this study may depend excessively on observations and the BC method applied. The uncertainty due to the method selected to project changes in extremes was not clearly quantified in this study. More research is required to overcome this defect.

We computed the ratios ($\gamma$) of among-model over within-model SDs that are presented in Section 4. The ratios for future simulations were about three times higher than those for historical data. These larger ratios in the warming future may make the credibility of projected change in extremes questionable. Therefore, we need to develop a better way to reduce these ratios.

6 | SUMMARY

Projections of changes in extreme climate are usually predicted by multimodel ensemble methods, such as the BMA embedded with GEVD. The BMA is a popular method to combine forecasts from individual simulation models by weighted averaging and to characterize the uncertainty induced by simulation model structure. We applied this method to the annual maximum daily precipitation over the Korean peninsula as simulated by the CMIP5 models in historic and future experiments. Simulations were performed under two RCP scenarios, namely RCP4.5 and RCP8.5. The observed data and 17 CMIP5 models for 12 grid boxes in Korea were examined to predict the future changes in precipitation extremes. A BC technique was applied to these simulation data. The 20-year and 50-year return levels and return periods, relative to the reference years (1971–2005), were estimated by the BMA method for two future periods, namely Period 1 (2021–2050) and Period 2 (2066–2095).

From these analyses, relative increase in the observations of spatially averaged 20-year (50-year) return level was about 23% (16%) in the RCP4.5 experiment and about 45% (36%) in the RCP8.5 experiment by the end of the 21st century. For 20-year return level, this was about two times faster than the change in globally averaged value obtained by Kharin et al. (2013). We conclude that extreme rainfalls will likely occur two times and four times more frequently under the RCP4.5 and RCP8.5 scenarios, respectively, than in the reference years, by the end of the 21st century. The return levels for Period 2 were greater than those for Period 1, which indicates that there will likely be more extreme precipitation in Period 2 as compared to that in Period 1. This trend was more prominent for RCP8.5 than for RCP4.5.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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