Author response to the reviews of the paper “Simulating warming climate scenarios with intentionally biased bootstrapping and its implications for precipitation”

(Manuscript # gmd-2016-188)

Taesam Lee

Line 53. White space missing

Reply: The space is added accordingly.

Line 58 Clausis-Clapeyron -> Clausius Clapeyron

Reply: The word has been modified accordingly as Clausius-Clapeyron. Note that the author do not remove ‘–‘ mark between two name because this relation has been popularly employed as is.

Line 152 Sigma2 = E(X^2) – (EX)^2
Shouldn’t it be Sigma2 = E(X2) – E(X)^2 ? Please check

Reply: The author checked the equation once again and find no error in the equation. It is right with E(X^2).

Figure 3 legend caption. What are the red crosses? Please explain how are defined the boxes, the whiskers, the line in the boxes.

Reply: The caption has been modified accordingly with adding the sentence as below.
“Boxes indicate the interquartile range (IQR), and whiskers extend to +/-1.5IQR. The horizontal lines inside the boxes depict the median of the data. Data beyond the fences (+/-1.5IQR) are indicated by a plus symbol (+), which represent outliers.”

Figure 4 legend caption. Please explain how are defined the boxes, the whiskers, the line in the boxes.

Reply: The caption has been modified accordingly with adding the sentence as below:
Boxes indicate the interquartile range (IQR), and whiskers extend to +/-1.5IQR. The horizontal lines inside the boxes depict the median of the data. Data beyond the fences (+/-1.5IQR) are indicated by a plus symbol (+), which represent outliers.

Author response to the reviews of the paper “Simulating warming climate scenarios with intentionally biased bootstrapping and its implications for precipitation”

(Manuscript # gmd-2016-188)

Taesam Lee

Reviewer #1

D. Defrance (Referee)

This article presents a statistical method to determine local climate change from global observations. With this approach, the Intentionaly Biased Bootstrapping (IBB) and some hypothesis, the author estimates the future temperature and precipitation at a local point. The article is clearly divided into several parts: a good description of the method, the complete procedure to permit to everyone to use easily it and a good application on the South Korea to validate the method with a good description of the results. The methodology is precisely described but some information will permit to improve the comprehension. I suggest to publish this article in GMD with minor revision. The different remarks and suggestions are described below.

Reply: The author appreciates this reviewer's generous comment. The author tried his best efforts to improve the manuscript. Hope this improvement is satisfactory to this reviewer.

Some questions

Line 31: To specify that the temperature from GCM is relatively accurate as you mention in the conclusion

Line 54: In some places, such as the Sahel, the increasing in temperature results from global warming but also from feedback related to the reduction of precipitations. It is perhaps too generalist to assert that everywhere the increasing in temperature will be followed by an increasing in precipitation with the self-order of magnitude. Can this depend on the type of precipitation or the origin (e.g. monsoon system or stratiform precipitation) ?

Reply: The proposed IBB method does not postulate that the temperature increase means the increase of precipitation. The method employs the empirical relation between temperature and precipitation. When an observed temperature increases and an observed precipitation decreases, the same reverse relation can be reproduced through the proposed IBB method. The author considers that the proposed method is not physical-based method so that the type of precipitation cannot be taken into consideration.

Line 78: In the methodology, some hypothesis must be mentioned: - The method is only based on the temperature mean. If in the future the extremes of temperature increases (warmest and coldest), the method does not take this into consideration. - For the precipitation, the evolution is in relation with only the temperature evolution in the methodology and the meso-scale change is not supported.

The author really appreciates this reviewer's insightful comment. No physical mechanisms can be included. This limitation was discussed at the conclusion section.

“The proposed IBB method is not a physical-based method but a statistical simulation

approach in which a physical mechanism of precipitation cannot be taken into consideration. Substantial modification might be required to accommodate this mechanism."

Line 160: for the block bootstrapping technique to simulate the temperature, I would like a better description of the method with one or two sentences because it is easier to read the entire method rather than reading into the references.

Reply: The author totally agrees with this reviewer's comment. Simple sentences were added accordingly as follows:

"Bootstrapping is a random sampling with replacement and block bootstrapping is to resample blocks. Each block contains a set of predictor and predictand like a regression. Here, temperature and precipitation can be set as a block and they act as predictor and predictand, respectively."

The author hopes that this modification is satisfactory to this reviewer

Line 191: Data description, you describe the available data (74 locations) and you give 1283 mm a year but you select 54 datasets with a good hypothesis (> 30 years available data). Is the precipitation mean the same with the only 54 datasets? I suggest to insert directly the selected datasets in the beginning of the paragraph with the hypothesis and the annual mean.

Reply: The author appreciate this reviewer's detailed comment. Official annual mean precipitation of South Korea (1283mm) is announced by KMA, not calculated from the current study. The sentence was modified accordingly as follows:

"In the current study, weather stations that record temperature and precipitation in South Korea (54 locations) and that are managed by the Korea Meteorological Administration (KMA) and whose length is more than 30 years were employed. South Korea is located in Far East Asia and has a mean annual precipitation of 1283 mm from KMA."

The author hopes that this modification is satisfactory to this reviewer

Line 250: you very accurately write that the test period is relatively short and not enough of high values of annual temperature. Did you tested a longer test period with a short validation period e. g. 20 years test period 1976-1997 and validation period 1998-2008 ?

Reply: The author really appreciates this reviewer's pinpointing comment. 20 years was also tested with no difference from the current test. 15 years (the test period that has been used in the current study) and 20 years are not much different in analyzing the long-term change.

Line 335: In the conclusion, the limits of the method in terms of variability of extremes should be recreated. This limit associated with IBB can still be disturbing for some applications such as extreme floods. Figure 3 and 4, there are many data on it and it is not easy to analyse it for the reader. Maybe to classify the stations by order of error could permit to better interpret the results. I am not a good example to suggest to you a good representation of the results.

Reply: The author really appreciates this reviewer's insightful comment. The authors consider that long-term variability of hydrological extremes can be derived from the IBB method when it is related with other variables such as precipitation. But no physical mechanisms can be included as this reviewer pointed in the previous comment. This limitation and possible extension were discussed at the conclusion as follows:

"The proposed IBB method is not a physical-based method but a statistical simulation approach in which a physical mechanism of precipitation cannot be taken into consideration. Substantial modification might be required to accommodate this mechanism. Also, a possible extension of the current study must be on analyzing the future variation of hydrological extreme events (e.g. extreme floods). If a long-term variation of hydrological extreme events is related with precipitation, one can derive the variation from the IBB method."

Hope this reviewer satisfactory to this modification.

Technical notes

Line 58: 1 hour intensity

Reply: It was modified as 'the intensity of hourly precipitation'. Hope this modification is satisfactory to this reviewer.

Line 64: for this paragraph, a reference could be appreciated

Reply: A reference is added accordingly.

Line 98: local linear smoothing (Cai, 2001)

Reply: It was modified as 'local linear regression'.

Line 208: but employed in comparison ? Can you use validation ?

Reply: The author appreciates this reviewer's detailed comment. 'validation' was used now according to this reviewer's comment.

Author response to the reviews of the paper "Simulating warming climate scenarios with intentionally biased bootstrapping and its implications for precipitation"

(Manuscript # gmd-2016-188)

Taesam Lee

Reviewer #2

M. A. Ben Alaya (Referee)

In this paper, the author presents a statistical non parametric resampling approach called intentionally biased bootstrapping (IBB) to simultaneously simulate temperature and precipitation at a single site taking into account the increase of the temperature according to observed global warming data. The manuscript is well organized and the methodology is adequate, reasonable and clearly presented. The problematic and the application are of great interest for GMD. Hence I suggest to publish this paper. However, there are a few statements that don't entirely ring true, and I'd like the author to address these a bit more carefully. Also, drawbacks of the proposed method should be mentioned and discussed.

Reply: The author appreciates this reviewer's generous comment. The author tried his best efforts to improve the manuscript. Hope this improvement is satisfactory to this reviewer.

Below I list relatively minor points that could be addressed with some small revisions to the text and a few more figures:

1- Line 31: "The temperature variable is the most reliable of the GCM outputs". I'm not sure that this statement is true.

Reply: The author really appreciates this reviewer's detailed comment. The sentence was modified accordingly as:
"The temperature variable is more reliable than other variables in GCM outputs."

2- Line 57: I agree that moisture availability increases at the same rate with warming through the Clausius-Clapeyron (C-C) relation. Nevertheless this does not guarantee that precipitation intensity should also increase at the same rate, this presumably assumes stationarity of precipitation efficiency.

Reply: The author totally agrees with this reviewer's comment. The sentence was circumvented as follows:
" From the Clausius-Clapeyron (C-C) relation, saturation vapor pressure increases by 6-7% for each 1°C increase in temperature and rainfall intensity also increase in a similar rate with warming (Trenberth and Shea, 2005)."

3- The proposed approach is based on the assumption that only the mean of observed temperature changes in the future, and assumes a static variance in the future. This assumption should be mentioned. Indeed the proper reproduction of the temporal variability is a very important issue, because a poor representation of the temporal variability could leads to a poor representation of extreme events.

Reply: The author really appreciates this reviewer's insightful comment. The limitation and its possible development is discussed at the conclusion section as the below. Hope this modification is satisfactory to this reviewer.

"The proposed IBB method is conditioned and assumed only on the mean temperature change. A further scheme can be developed to consider changes of multiple variables with classifying the conditions of interested variable."
For the relation of the temporal variability and extreme events, the author consider that this reviewer's comment can be true but not always as far as this reviewer's viewpoint. Further study relates on this issue can be studied.

4- Line 166: "Unlike for the case of temperature, there is no variance reduction in the resampled precipitation data because the precipitation data are not conditionally resampled"; I'm not sure that this statement is true. The existence of dependence between precipitation and temperature which motivates this work implies the existence of a concordance in the ranks of these variables. In the case of dependence there will always be some reduction in the variability of precipitation using the IBB technique. I ask the author to verify this fact by comparing the observed variance and the simulated one in the case of precipitation.

Reply: The author really appreciates this reviewer's insightful comment. The author compared the observed variance with the simulated one for all the 54 stations. No significant variance reduction was observed and even some stations (15 stations) present variance inflation (i.e. simulated variance is bigger than the observed variance). Therefore, the author consider that the statement can be true but with a little less certainty. The sentence was modified as:
"not much significant variance reduction is expected in the resampled precipitation data because the precipitation data are not conditionally resampled."

5- The proposed approach is not appropriate to simulate change in extreme events, indeed as it is the case for most resampling approach the IBB technique suffers from the inability to simulate values that are more extreme than those observed.

Reply: The author really appreciates this reviewer's insightful comment. The authors consider that long-term variability of extremes can be derived from the IBB method when it is related with other variables such as precipitation. But it might be limited since no physical mechanisms can be included. This limitation and possible extension were discussed from this reviewer and the other reviewer's comment at the conclusion as follows:

"The proposed IBB method is not a physical-based method but a statistical simulation approach in which a physical mechanism of precipitation cannot be taken into consideration. Substantial modification might be required to accommodate this mechanism. Also, a possible extension of the current study must be on analyzing the future variation of hydrological extreme events (e.g. extreme floods). If a long-term variation of hydrological extreme events is related with precipitation, one can derive the variation from the IBB method."

Simulating climate warming scenarios with intentionally biased bootstrapping and its implications for precipitation

Taesam Lee

Dept. of Civil Engr., ERI, Gyeongsang National University,

501 Jinju-daero, Jinju, Gyeongnam, 660-701, South Korea

Corresponding Author: Taesam Lee, Ph.D.
Gyeongsang National University, Dept. of Civil Engineering
501 Jinju-daero, Jinju, Gyeongnam, 660-701, South Korea
Tel) +82-55-772-1797
Fax) + 82-55-772-1799
Email) tae3lee@gnu.ac.kr

Abstract

The outputs from GCMs provide useful information about the rate and magnitude of future climate change. The temperature variable is more~~the most~~ reliable ~~of the GCM outputs~~than other variables in GCM outputs. However, hydrological variables (e.g., precipitation) from GCM outputs for future climate change possess an uncertainty that is too high for practical use. Therefore, a method, called intentionally biased bootstrapping (IBB), that simulates the increase of the temperature variable by a certain level as ascertained from observed global warming data is proposed. In addition, precipitation data was resampled by employing a block-wise sampling technique associated with the temperature simulation. In summary, a warming temperature scenario is simulated and the corresponding precipitation values whose time indices are the same as the one of the simulated warming temperature scenario. The proposed method was validated with annual precipitation data by truncating the recent years of the record. The proposed model was also employed to assess the future changes in seasonal precipitation in South Korea within a global warming scenario as well as in weekly time scale. The results illustrate that the proposed method is a good alternative for assessing the variation of hydrological variables such as precipitation under the warming condition.

1. Introduction

The complex influence of human actions on the climate system is well represented through global climate models (GCMs). A number of GCMs demonstrate variations in the large-scale atmospheric circulation and related changes in hydrometeorological variables (Allen and Ingram, 2002; Held and Soden, 2006; Lenderink and Van Meijgaard, 2008). It has been generally accepted that to quantify the range of possible changes in the hydrological cycle (such as precipitation and evaporation) is harder than in temperature (Allen and Ingram, 2002). Furthermore, hydrological variables vary much more in space and time than temperature and difficult to correctly simulate.

The relationship between temperature and precipitation has been studied in literature in order to predict the future variations of precipitation under the global warming condition. From the Clausius-Clapeyron (C-C) relation, saturation vapor pressure increases by 6-7% for each 1ºC increase in temperature and rainfall intensity ~~should~~ also increases ~~at the same rate~~in a similar rate with warming (Trenberth and Shea, 2005). Lenderink and Van Meijgaard (2008) presented that the intensity of hourly precipitation exhibit a C-C relation for summer while showing super C-C scaling for winter.

These relations are only focused on very short time scale (not more than daily) or generally retrieved from GCM outputs. The behavior of mean precipitation over long-term period such as months and seasons is difficult to predict as temperature increases. It might be beneficial if one could derive the behavior of long-term mean precipitation under warming condition or the range of possible changes (IPCC, 2013).

Therefore, a simple method that simulates temperature from observed data is proposed in the current study while increasing temperature up to a certain level as a warming scenario. In addition, precipitation is simulated by employing a block-wise resampling technique (Srinivas and Srinivasan, 2000) associated with the temperature simulation. The resampled covariate, precipitation, forcing the warming condition in a certain level is obtained from the simulation. The proposed approach allows assessing the impact of precipitation as temperature increases with a current climate horizon.

The paper is organized as follows. In the next section, the fundamental mathematical background related to bias bootstrapping modeling is presented. The employed data and application methodology are described in section 3. The validation study of the proposed IBB approach is shown in section 4. The results assessing the long-term evolution of seasonal precipitation with simulating weekly temperature and precipitation data are illustrated in section 5. Finally, the summary and conclusions are presented in section 6.

2. Methodology

In order to simulate warming scenario, i.e. increasing mean temperature, up to a certain level, the observed data must be sampled with different combination. Intuitively, warmer temperature values are more likely to be resampled among the observations if the mean is increased. Therefore, the proposed method in the current study is to resample the observed data by fixing the mean temperature increment in the resampled dataset by weighting the probability of selection according to its magnitude (see Figure 1~~Figure 1~~). In addition, the block bootstrapping with precipitation was employed to assess the changes in these variables as temperature increases.

2.1. Intentionally Biased Bootstrapping (IBB)

Bootstrapping (also known as resampling from observed data with replacement) is a statistical method for creating replica datasets from the original data to assess the variability of the quantities of interest without analytical calculation (Davison and Hinkley, 1997; Davison et al., 2003; Ouarda and Ashkar, 1995). This bootstrapping technique has been extended to simulate time series of hydrometeorological variables (Beersma and Buishand, 2003; Lall et al., 1996; Lall and Sharma, 1996; Lee and Ouarda, 2011, 2010; Mehrotra and Sharma, 2005). In the current study, the intentionally bias bootstrapping (**IBB**) technique is employed so that the mean of the resampled datasets are varied as needed to simulate a global warming scenario.

IBB was proposed by Hall and Presnell (1999) as a class of weighted bootstrapping techniques in order to reduce bias or variance as well as to render some characteristic equal to a predetermined quantity. A good example of IBB is the adjustment of Nadaraya-Watson kernel estimators to make them competitive with local linear ~~smoothing~~regression (Cai, 2001). In the current study, IBB was employed to simulate the temperature data from observation by bootstrapping under the constraint of increasing mean value, which indicates warming. The conceptual background of IBB has been employed to simulate future climates of weather analogs (Orlowsky et al., 2010; Orlowsky et al., 2008). In the current study, a IBB method with easy manipulation to simulate increased temperature data is proposed. The mathematical description of the proposed IBB method is the following.

Among an n number of observations x_i, where i=1,…,n, assume resampling the observations with replacement (i.e. bootstrapping) by increasing the mean of the simulated data by as much as Δ_μ; this implies that higher values have a higher probability of being resampled and lower values have lower selection probability. This IBB can be achieved by assigning different weights $S_{i,n}$ according to the magnitudes of the observations as

$$S_{i,n} = i/n \tag{1}$$

Note that this assigned weight $S_{i,n}$ plays a role in the selection probability for the observed data in the IBB procedure after scaling and adjusting it.

The mean of the resampled data is

$$\tilde{\mu} = \frac{1}{\Psi}\sum_{i=1}^{n} S_{i,n} x_{(i)} \tag{2}$$

where $x_{(i)}$ represents the i^{th} increasing ordered value and $\Psi = \sum_{i=1}^{n} S_{i,n}$. The amount of the mean increase δ_{μ} is

$$\delta_{\mu} = \tilde{\mu} - \hat{\mu} = \frac{1}{\Psi}\sum_{i=1}^{n} S_{i,n} x_{(i)} - \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

To obtain different values of δ_{μ},the weights can be generalized with the weight order (r) as

$$\tilde{\mu}(r) = \frac{1}{\Psi_r}\sum_{i=1}^{n} S_{i,n}^{r} x_{(i)} \tag{4}$$

where $\Psi_r = \sum_{i=1}^{n} S_{i,n}^{r}$. The difference is

$$\delta_{\mu}(r) = \tilde{\mu}(r) \quad \hat{\mu} = \frac{1}{\Psi_r}\sum_{j=1}^{n} S_{j,n}^{r} x_{(j)} - \frac{1}{n}\sum_{j=1}^{n} x_j \tag{5}$$

Once the magnitude of the mean increase is given (e.g., temperature increase) as Δ_{μ}, the weight order 'r' is estimated accordingly. For example, when the temperature change is obtained from the GCM outputs and this change is supposed to be propagated into a specific location and a finer time scale, the selection of the weight order can be performed using a meta-heuristic optimization technique with the objective function as

$$\text{Minimize } [\Delta_\mu - \delta_\mu(r)]^2 \tag{6}$$

In the current study, the harmony search (HS) was used for the meta-heuristic optimization. The performance of the HS in hydrological applications is well reviewed in the literature (Geem et al., 2001; Lee and Geem, 2005, 2004; Lee and Jeong, 2014a; Mahdavi et al., 2007; Yoon et al., 2013a). Note that if $r > 0$, then $\delta_\mu(r) > 0$, which implies a global warming scenario; if $r < 0$, then $\delta_\mu(r) < 0$, which implies a global cooling scenario. When $r < 0$, lower values are resampled more frequently than are higher values. causing the mean of the resampled data to decrease. Furthermore, if *r* goes to infinity then the maximum of the observations is always selected, and if *r* goes to negative infinity, only the minimum is chosen.

In the IBB procedure, the adjusted scaled weight $\eta_i = S_{i,n}^r / \Psi_r$ is the probability that each i^{th} data point is subject to be selected. In the case of *n*=30, the weights for *i*=1,…,*n* are shown in Figure 2~~Figure 2~~ with the weight order of *r*=0.5. The figure presents that the probability of being selected (i.e., η_i) is between approximately 0.01 for the lowest values and 0.05 for the highest order values of approximately 0.05 to lead positive bias in the resampled data (e.g., 1.0℃ increase). For example, if the number of the simulation is 100 and η_i=0.05, then the data point will be selected 5 times. A different probability implies a different number of selection for each data point. Subsequently, a different number of selections may lead to variation changes, called variance reduction or inflation. This issue is dealt with in the following section.

2.2. Variance reduction and inflation

Because of the biased selection of higher values, the variance of the resampled data results is reduced (Lee and Jeong, 2014a; Lee and Ouarda, 2010; Lee et al., 2010a; Salas and Lee, 2010; Sharif and Burn, 2006). The estimated variance of the simulated data with IBB is

$$\tilde{\sigma}^2(r) = \sum_{j=1}^{n} \frac{S_{j,n}^r}{\Psi_r} x_{(j)}{}^2 - \tilde{\mu}^2 \qquad (7)$$

Note that the variance in Eq. (7) is based on $\sigma^2 = E(X^2) - (EX)^2$. The difference of the variance is

$$\delta_{\sigma^2}(r) = \hat{\sigma}^2 - \tilde{\sigma}^2(r) \qquad (8)$$

where $\hat{\sigma}^2$ is the sample variance of the observed data. To overcome the reduction of the variance in IBB, a random perturbation can be applied to the resampled data X_R as

$$X_R{}^* = X_R + \sqrt{\delta_{\sigma^2}(r)}\varepsilon \qquad (9)$$

where ε is a random variable with a normal distribution $N(0,1)$. Subsequently, the mean and variance of the perturbed data are

$$\hat{\mu}_{R^*} = \tilde{\mu} \qquad (10)$$

$$\hat{\sigma}_{R^*}^2 = \tilde{\sigma}^2 + \delta_{\sigma^2}(r) = \tilde{\sigma}^2 + \hat{\sigma}^2 - \tilde{\sigma}^2(r) = \hat{\sigma}^2 \qquad (11)$$

2.3. Block bootstrapping

Bootstrapping is a random sampling with replacement and block bootstrapping is to resample blocks. Each block contains a set of predictor and predictand like a regression. Here, temperature and precipitation can be set as a block and they act as predictor and predictand, respectively.~~resample random samples~~

When the temperature presumably increases by a certain degree, it is interesting to note how the other weather variables vary. For example, if the temperature is increased by 1°C, the greatest concern in climate research will be how the precipitation will change.

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To address this question, the block bootstrapping technique for the precipitation variable is adapted (Carlstein et al., 1998; Lee et al., 2010b). Once the temperature is resampled from the observed data at certain times using IBB, the observed precipitation data from the same time are considered (see Figure 2). Unlike for the case of temperature, ~~there is no variance reduction in~~ not much significant variance reduction is expected in the resampled precipitation data because the precipitation data are not conditionally resampled. This block bootstrapping technique is popularly employed in multivariate weather simulations (Lee and Jeong, 2014b; Lee et al., 2012).~~.~~

2.4. Overall Simulation Procedure

The overall simulation procedure of temperature and precipitation data is described in this section. Simple schematic presentation of the procedure is shown in Figure 1~~Figure 1~~.

Let x_i, y_i (i=1,…,n) be the observed temperature and precipitation data, respectively. Suppose that the simulation length is the same as the record length (i.e. n) and100 series need to be simulated.

(a) Assume that the increased overall temperature mean is known as Δ_μ .

(b) Estimate the weight order (r) from meta-heuristic algorithm (here, Harmony Search) with the objective function of Eq.(6) from the observed temperature data.

(c) Resample the temperature data from the observations with the probability of $S^{r}_{i,n}$ for i^{th} largest data (i=1,…, n).

(d) Assume that k^{th} largest temperature data $x_{(k)}$ is resampled from step (3) and its corresponding time index of (k) is ‘j’. Note that (k) indicates the k^{th} largest value and j indicates the j^{th} time-index value. Then, j^{th} precipitation data, y_j, is resampled simultaneously.

(e) Apply Eq.(9) to the resampled temperature data from step(3) (say, $x_{(k)} + \sqrt{\delta_{\sigma^2}(r)\varepsilon}$), if the variance inflation is chosen.

Note that the current procedure is explained for the case of no seasonal variability due to simplicity. In other words, the explained procedure above must be applied at each week or each month for weekly or monthly data. The detailed description of the proposed method for the case of monthly precipitation data with the full record is provided in the supplementary material (Supplement A).

3. Data description and application methodology

In the current study, 54 weather stations that record temperature and precipitation in South Korea ~~(74 54 locations)~~ with more than 30 years of record length and that are managed by the Korea Meteorological Administration (KMA) ~~and whose length is more than 30 years~~ were employed. South Korea is located in Far East Asia and has a mean annual precipitation of 1283 mm from KMA. This country is climatologically influenced by the Siberian air mass during winter and the Maritime Pacific High during summer. Most of the annual precipitation in South Korea falls during the rainy season from June to September due to the occurrence of tropical cyclones, extratropical cyclones, fronts and other weather systems. Because the orographic area in South Korea is heterogeneous and large, the rainfall in South Korea has large spatial and temporal variability (Park et al., 2007; Yoon et al., 2013b). The water resource control system, including climate change, is an important aspect of this study due to the seasonal and spatial variability of rainfall in this country.

Datasets shorter than 30 years of data were excluded, after which a total of 54 datasets were employed. The data were extracted from the KMA website (http://www.kma.go.kr/). Most of the time spans are approximately 33 years, from 1976 to 2008.

The validation study was performed with annual dataset to present the performance of the proposed model with truncating recent years as 1994-2008. The truncated data was not used in simulation but employed in ~~comparison~~validation. Also, a case study was applied with the weekly dataset of the 54 stations in South Korea. In the application study of the proposed IBB procedure in section 5, (1) 0.5°C and 1.0°C increases in the mean weekly temperature were assumed; (2) weekly temperature datasets were simulated using the assumed temperature increase; (3) weekly precipitation datasets were also simulated along with the weekly temperature dataset as a block. Note that the simulation does include not a gradual change, such as a trend, but the overall mean change. We simulated the weekly time scale so that the data spanned a long enough period to provide a summary of weather statistics and a short enough period to reflect the temporal variability. Furthermore, the observed weekly datasets of temperature and precipitation were aggregated into seasonal time scale data, and the aggregated seasonal data were used to present the seasonal variations in precipitation as temperature increases.

Note that although we simulated the temperature with a specific condition of increase (e.g. +0.5 °C or +1.0°C), no such restriction was placed on the precipitation, allowing one to determine whether there is any change in precipitation with the condition of increasing temperature. One hundred series were simulated with the same time span as the observations.

4. Validating IBB model with annual data

To further obtain the credibility of the proposed IBB model, we validated the model with truncating the last 15 years (1994-2008) of the annual mean temperature and precipitation data over South Korea. The last truncated 15 years were set as the validation period while the rest of the preceding years as the test period. The dataset of the test period was employed in simulation while the dataset of the validation period is only used in comparison to check how much the proposed model performs. Among others, annual scale data is employed to easily illustrate the performance of the proposed IBB model. At first, some mathematical terms need to be defined to explain the validation procedure as follows.

$$D\mu_p^{obs} = \mu p_V - \mu p_T \tag{12}$$

$$D\mu_p^{IBB} = \mu p_{IBB} - \mu p_T \tag{13}$$

where μp_V and μp_T are the mean annual precipitation over the validation years and over the test period, respectively, while μp_{IBB} is the annual mean precipitation of the IBB simulated data with the record length of the validation years. The same denotation as the precipitation variable is taken for the temperature variable as μT_V, μT_T, μT_{IBB}, $D\mu_T^{obs}$, and $D\mu_T^{IBB}$.

The validation procedure is (1) to truncate the 15 years (1994-2008) of annual temperature and precipitation for each station; (2) to estimate the mean differences of the annual temperature and precipitation between the validation period (1994-2008) and the test period (1976-1993), $D\mu_T^{obs}$ and $D\mu_p^{obs}$, respectively; (3) to perform the IBB simulation with the annual precipitation and temperature of the test period conditioned on the estimated mean differences of the temperature between two periods (i.e. $D\mu_T^{obs}$) for each station; and (4) to compare the estimated mean differences of the observed precipitation (i.e. $D\mu_p^{obs}$) with the mean differences between the IBB simulated precipitation and the precipitation for the test period (i.e. $D\mu_p^{IBB}$).

The annual mean temperature differences between the validation period and the test period at each station is presented in Figure 3~~Figure 3~~ for the IBB simulated data ($D\mu_T^{IBB}$, boxplot) and the observed data ($D\mu_T^{obs}$, circle). The figure indicates that the IBB model fairly well simulates the temperature data as much as it was intended, except few stations that shows high increase especially with more than one-degree increase (e.g. stations 6 and 7). Note that the employed test period is relatively short and not enough number of high values of annual temperature is included during the test period and this might result the underestimation of the intended temperature increase.

In Figure 4~~Figure 4~~, the annual mean precipitation of the observation over the validation period (μp_V, filled blue circle) and the test period (μp_T, filled red triangle) as well as the IBB simulation (μp_{IBB}, boxplot) is illustrated. The result indicates that the observed mean precipitation over the validation period (μp_V) presents higher than the mean for the test period (μp_T) in most of the stations. The IBB simulated data reflects this tendency showing higher mean precipitation than the mean precipitation of the test period though its magnitude shows some difference.

The mean of the observed annual precipitation for the validation period at each station and the mean of one hundred IBB simulated data is presented in Figure 5~~Figure 5~~. The top panel presents that the simulated data fairly well reproduce the observed mean of annual precipitation for the validation period (1994-2008). The observed mean difference ($D\mu_p^{obs}$) of the annual precipitation between the test period (1976-1993) and the validation period shown at the bottom panel of Figure 5~~Figure 5~~ fairly matches with the one of the IBB simulated data ($D\mu_p^{IBB}$). Rather high variability at the difference is inevitable due to relatively small record length for both the test period and the validation period. Overall, the validation study implicates that the proposed IBB approach can simulate the future evolution of annual precipitation over South Korea.

In Figure 6~~Figure 6~~, the spatial distribution of the differences for the annual mean precipitation is presented with the observed data (i.e. $D\mu_p^{obs}$) and with the IBB simulated data ($D\mu_p^{IBB}$). High increase of annual mean precipitation in the north and south part of the country and small increase and slight decrease in the south part shown in the observed data (left panel) is well reflected in the IBB simulated data (right panel) except that the increase is shown from the IBB simulated data (right panel) in the left south part of the country is not shown in the observed data. Overall, the figure indicates that the spatial pattern of the annual mean precipitation difference from the observed data (see the left panel) is similar to the one from the IBB simulated data (see the right panel).

5. Precipitation changes according to assumed temperature increase

Figure 7~~Figure 7~~ shows the results of the fitted IBB model for the Buan station, located at 35º 44' N and 126º 43' E. The top panel (Figure 7~~Figure 7~~(a)) shows the estimated weight order of each week for the mean temperature data employing the HS meta-heuristic algorithm with the objective function of Eq. (6) while assuming a 0.5℃ increase. The estimated values range from 0.2 to 1.3. The mean and standard deviation of the observed and theoretical results (see Eqs. (2) and (7)) with a 0.5℃ mean increase are shown in Figure 7~~Figure 7~~(b) and (c), respectively. The predominant annual cycle of the mean weekly temperature is seen in the mean statistics, as shown in Figure 7~~Figure 7~~(b), while the annual cycle of the standard deviation (equivalent to the square root of variance) is not as prominent as the annual cycle of the mean (see Figure 7~~Figure 7~~(c)). Note that the weight order and the standard deviation (see Figure 7~~Figure 7~~(a) and (c)) are highly negatively correlated. In other words, when the standard deviation is small (e.g., at approximately the 23rd week), the weight order is high and vice versa. This result is intuitive in that if the variance is great, the corresponding temperature values differ greatly from each other. Subsequently, the weights of the large values to be selected are not necessarily much different from the weights of the low values in such a case, which induces a low weight order. In Figure 7~~Figure 7~~(c), the variance difference between the observed and theoretical data, as defined in Eq. (8), is shown with a dotted line. This variance difference is inflated to the resampled data, as in Eq. (9). This inflation procedure is optional in assessing the overall trend of annual mean precipitation data regarding climate warming scenarios. However, it might be helpful when the purpose of the study is to evaluate an overall variation of extreme precipitation statistics.

The statistics of the simulated data from IBB with the condition of a 0.5°C degree mean temperature increase are shown as a boxplot in Figure 8~~Figure 8~~; the statistics of the observed data are shown in the same figure with dotted lines and cross marks. The mean increases by exactly 0.5°C, as intended, and the standard deviation (square root of variance) is well preserved through the variance inflation process (see Eq. (8)). The minima and maxima of the mean weekly temperatures are increased.

Shown in Figure 9~~Figure 9~~(a) are the mean differences between the simulated and observed weekly precipitation with the conditions of 0.5°C and 1.0°C increases at the Buan station. The differences are not significant at the 5% level. However, the mean differences are continuously positive from the 30th to 40th week, which is during the summer season. This result indicates that a seasonal effect on the precipitation change must exist. Therefore, we also extended our study to a seasonal time scale. The mean precipitation differences of all 54 stations are shown for 0.5°C and 1.0°C increases in Figure 9~~Figure 9~~(b) and (c), respectively. Both plots show a decrease in autumn and increases in the other seasons.

For a 1.0°C temperature increase, 61%, 24%, and 45% of the employed stations show a significant increase in mean precipitation for the winter, spring, and summer seasons, respectively. In contrast, the mean temperature decreases during the autumn season. Approximately 30% of the stations experience a significant change in the mean precipitation at the 5% level given a 1.0°C temperature increase. The detailed information is provided in Table 1.

The spatial distribution of seasonal mean precipitation differences is presented in Figure 10~~Figure 10~~ given the condition of a 1℃ temperature increase. An increasing pattern of precipitation during winter (see Figure 10~~Figure 10~~(a)) can be seen over the South Korea peninsula. Notably, the eastern and southern coastal areas undergo a significant increase with a 95% confidence interval (±5.38). Note that the significance interval at each station is different because the variances between stations are different. The detailed significance interval for each station is provided in Table 2. During spring (see Figure 10~~Figure 10~~(b)), the northern part of the country shows an increasing pattern while the southwestern and southeastern parts show decreasing patterns, but their magnitudes are not significant (±15.04). The summer precipitation (see Figure 10~~Figure 10~~(c)) undergoes a significant increase in the southwest area of the country (±29.94). In contrast to the other seasons, a significant decrease in mean precipitation occurs during autumn (see Figure 10~~Figure 10~~(d)) throughout the country, especially over the eastern coastal area. The same spatial pattern of seasonal mean precipitation can be observed given the condition of a 0.5℃ temperature increase, as in the case of a 1.0℃ temperature increase, with little significant change (see Figure 11~~Figure 11~~).

The spatial distributions of seasonal precipitation changes seem to be related to the flow direction of the seasonal air mass. In South Korea, winter is influenced primarily by the Siberian air mass with prevailing northwesterly winds, while summer is hot and humid with southeasterly winds.

6. Summary and Conclusions

A simple method is proposed (1) to simulate precipitation given the condition of a mean temperature increase derived from the observations and (2) to address the problem of how the precipitation vary while the temperature is increased through global warming. The results illustrated that a simple IBB technique for the temperature variable incorporating block sampling of precipitation can achieve this objective.

The presented technique is valuable because hydrometeorological variables such as precipitation and discharge are difficult to model with current GCMs, while the temperature prediction is relatively accurate. The proposed method can be extended to other hydrometeorological variables as well as other applications, including studies at the global scale. The limit of the proposed method is that the temperature increase is limited since employed data is observational. One possibility for allowing a greater temperature increase than that from the observations is to include neighboring, similar stations or seasons. The author believes that the proposed model can be a good surrogate or competitor in GCM-based climate change impact assessments of hydrometeorological variables.

The proposed IBB method is not a physical-based method but a statistical simulation approach in which a physical mechanism of precipitation cannot be taken into consideration. Substantial modification might be required to accommodate this mechanism. The proposed IBB method is conditioned and assumed only on the mean temperature change. A further scheme can be developed to consider the changes of multiple variables with classifying the conditions of interested variable. ~~Also, a~~Another possible extension of the current study must be on analyzing the future variation of hydrological extreme events (e.g. extreme floods). ~~If~~When a long-term variation of hydrological extreme events is related with precipitation, the proposed IBB method ~~one can~~ can be used to derive the variation ~~from the IBB method~~.

7. Code and Data Availability

All the employed code can be provided upon the request to the author of the current study. The employed precipitation and temperature data over South Korea can be downloaded from the KMA website http://www.kma.go.kr/weather/climate/past_cal.jsp .

Acknowledgements

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Table 1. Mean precipitation difference of the observed and simulated data for seasonal data over all the employed stations in South Korea in case of +1.0 ºC mean temperature increase.

	Mean Diff					Mean Diff			
Station	Winter	Spring	Summer	Autumn	Station	Winter	Spring	Summer	Autumn
1	**11.2**	**14.3**	20.2	-12.0	28	2.6	12.1	9.6	-4.1
2	3.2	**22.4**	4.5	0.0	29	**4.4**	**20.6**	**50.4**	-3.8
3	11.0	5.0	21.5	**-17.2**	30	**5.5**	11.7	30.0	-4.2
4	1.6	**15.7**	**38.1**	-2.3	31	**4.4**	**19.2**	15.8	-4.7
5	1.5	11.9	3.9	-6.2	32	4.2	**15.9**	18.0	-2.0
6	1.7	10.1	**28.5**	-2.0	33	**6.6**	**16.4**	**46.1**	-4.2
7	1.7	8.2	16.8	-2.3	34	**9.5**	9.5	**32.6**	**-7.1**
8	3.2	**22.3**	33.6	-3.1	35	**6.4**	1.7	**44.1**	-6.8
9	2.3	**19.1**	**15.0**	-4.9	36	5.1	-4.2	**52.1**	**-9.4**
10	**9.8**	6.7	21.4	**-16.3**	37	**5.6**	7.4	**39.9**	**-9.4**
11	2.8	**18.8**	**30.3**	-3.3	38	**9.2**	-4.3	**53.8**	-3.1
12	5.3	10.8	**32.9**	-7.2	39	**9.6**	-3.2	**65.0**	-5.6
13	**5.1**	3.5	21.5	**-9.3**	40	**11.5**	-9.9	**82.2**	-6.5
14	**9.8**	1.2	28.8	-4.5	41	**9.1**	4.2	**33.3**	**-7.4**
15	**6.6**	-0.9	11.5	**-5.1**	42	**9.6**	-11.5	**61.2**	**-8.1**
16	**5.9**	-1.0	**32.6**	**-7.5**	43	4.2	12.9	**42.7**	-3.0
17	**10.2**	-9.3	26.7	0.6	44	**6.3**	**20.2**	**33.8**	-2.6
18	**8.2**	-1.7	**50.2**	-4.5	45	**12.9**	8.8	10.5	**-7.9**
19	**13.2**	-2.7	23.4	0.8	46	**5.8**	**11.2**	19.4	-3.8
20	**9.8**	-4.3	33.1	-0.7	47	3.1	**14.3**	**56.3**	**-7.0**
21	**8.1**	-15.4	12.4	-4.5	48	**7.1**	-2.4	14.8	**-4.7**
22	**7.8**	-6.0	**52.3**	-2.3	49	**9.0**	3.4	**68.4**	**-5.9**
23	**11.4**	-17.5	19.7	**-12.6**	50	4.2	2.1	31.6	-2.3
24	1.9	11.2	21.1	0.1	51	**8.9**	5.5	**39.5**	-3.2
25	2.3	8.6	21.8	-2.4	52	**8.6**	8.0	**78.2**	-1.5
26	2.3	8.8	13.4	0.8	53	**16.4**	6.0	28.8	-4.1
27	2.5	9.3	26.0	-2.9	54	**10.5**	20.9	23.2	1.7
Mean confidence interval						±5.38	±15.04	±29.94	±7.01
# of Significant Stations (percent)						33 (61%)	13 (24%)	25 (46%)	16 (30%)

Table 2. Confidence interval for mean precipitation difference of the observed and simulated data for seasonal data.

Station	Winter	Spring	Summer	Autumn	Station	Winter	Spring	Summer	Autumn
1	10.7	12.4	28.4	13.6	28	3.89	14.15	32.45	6.08
2	3.7	13.2	29.0	5.1	29	4.71	14.76	31.49	6.34
3	12.7	10.3	29.6	14.2	30	5.24	14.79	30.39	5.55
4	3.7	14.6	34.7	7.6	31	4.08	14.26	27.61	7.45
5	3.6	12.0	25.9	7.8	32	4.25	14.31	28.31	7.09
6	4.0	12.0	25.3	5.6	33	5.00	15.87	31.29	8.08
7	3.6	14.0	25.9	7.7	34	5.62	13.73	25.75	6.06
8	4.1	13.7	26.4	6.4	35	4.86	12.44	30.64	6.93
9	4.1	14.8	27.1	8.6	36	5.61	12.53	27.52	7.52
10	8.9	10.5	26.7	11.4	37	5.32	12.89	26.21	7.28
11	4.8	14.5	23.0	7.0	38	5.12	13.53	32.37	5.46
12	5.5	15.2	30.7	6.4	39	5.15	15.64	34.46	6.45
13	4.6	13.1	24.6	5.2	40	5.27	20.28	37.15	6.87
14	8.2	12.9	30.9	6.7	41	4.80	20.76	29.50	5.57
15	4.8	12.1	23.6	4.5	42	5.20	21.00	35.75	7.88
16	5.6	12.5	26.9	6.3	43	4.45	15.73	26.47	6.16
17	7.2	15.7	30.1	6.9	44	5.23	14.63	26.25	5.11
18	5.2	15.4	31.9	5.7	45	8.23	11.25	24.05	7.16
19	6.9	20.1	35.1	8.7	46	4.30	10.81	24.10	4.29
20	6.0	19.3	34.3	7.5	47	4.60	11.30	25.36	4.91
21	4.6	15.7	26.5	6.1	48	4.80	11.24	23.40	4.32
22	5.0	19.5	30.1	6.9	49	5.81	12.41	34.88	5.73
23	5.4	22.6	39.4	8.4	50	5.38	14.71	33.37	5.54
24	3.6	17.3	27.5	8.3	51	4.73	15.29	30.09	6.00
25	3.6	13.1	30.8	6.6	52	6.32	17.35	41.62	7.15
26	4.0	13.5	28.2	6.9	53	7.70	29.41	44.00	11.16
27	3.3	13.5	27.7	4.6	54	7.56	23.95	42.12	9.89

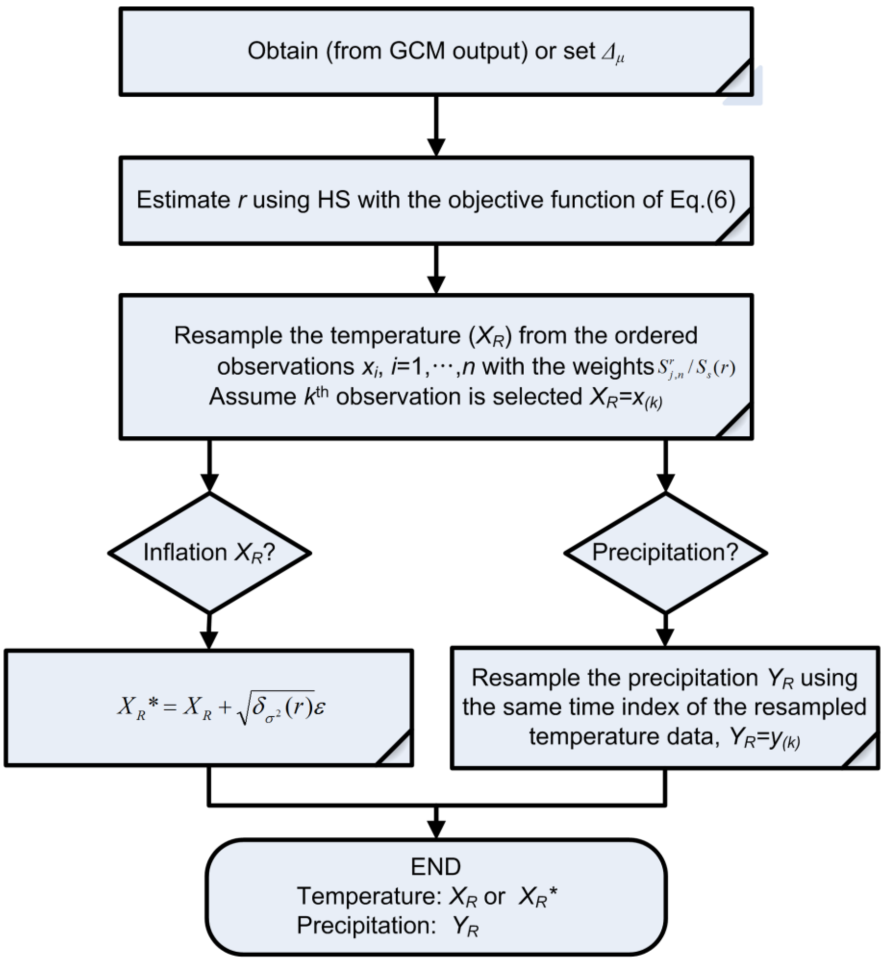


Figure 1. Procedure for the proposed simulation IBB method of temperature and precipitation data.

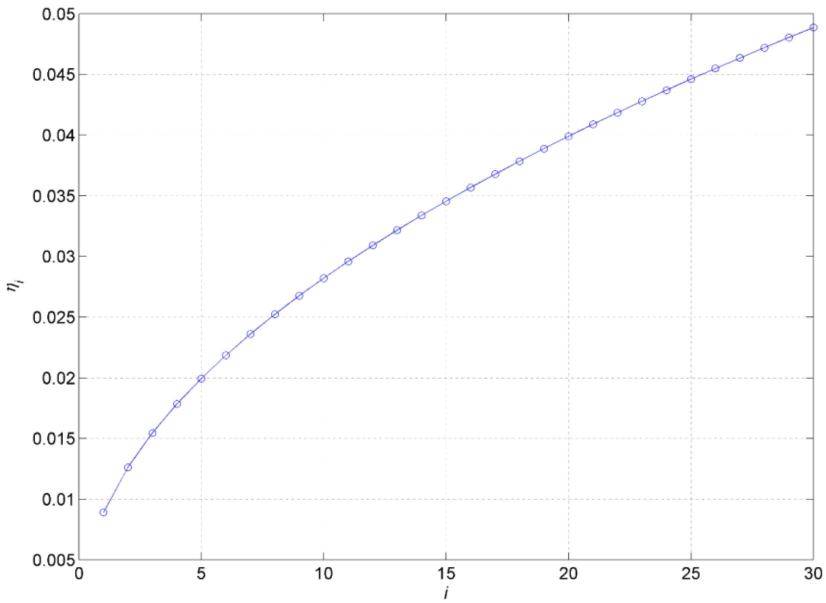


Figure 2. Example of the adjusted scaled weights (η_i) vs. order numbers in the case of n=30 and order weight r=0.5. Note that η_i is the probability of being selected and increases as the order is increased, so that higher values are subject to being selected more often than are lower values, leading to a positive bias.

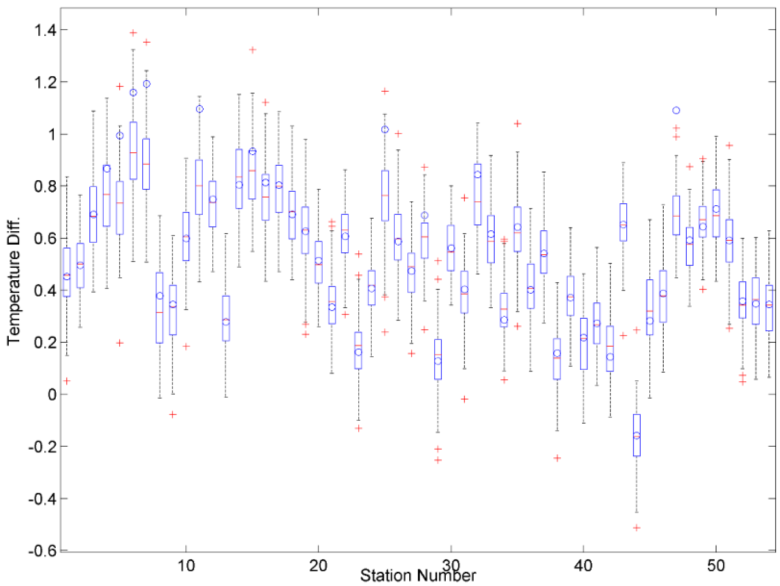


Figure 3. Annual mean temperature difference between the validation period (1994-2008) and the test period (1976-1993) for each station for the IBB simulated data (boxplot) and the observed data (circle). Boxes indicate the interquartile range (IQR), and whiskers extend to +/-1.5IQR. The horizontal lines inside the boxes depict the median of the data. Data beyond the fences (+/-1.5IQR) are indicated by a plus symbol (+), which represent outliers.

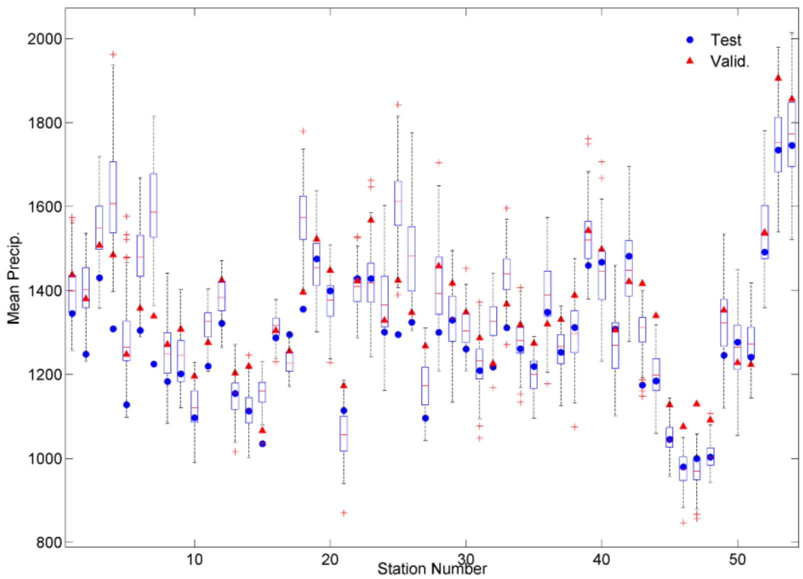


Figure 4. Annual mean precipitation of the IBB simulation (boxplot) and the observation over the validation period (filled blue circle) as well as the test period (filled red triangle) conditioned with the temperature change (see Figure 3~~Figure 3~~). Note that the observed mean precipitation over the validation period (1994-2008) (see the red triangles) shows mostly higher than the mean over the test period (1976-1993) (see the blue circles). Also, the IBB simulated precipitation (boxplot) reflects this tendency showing higher than the mean precipitation of the test period (blue circles). Boxes indicate the interquartile range (IQR), and whiskers extend to +/-1.5IQR. The horizontal lines inside the boxes depict the median of the data. Data beyond the fences (+/-1.5IQR) are indicated by a plus symbol (+), which represent outliers.

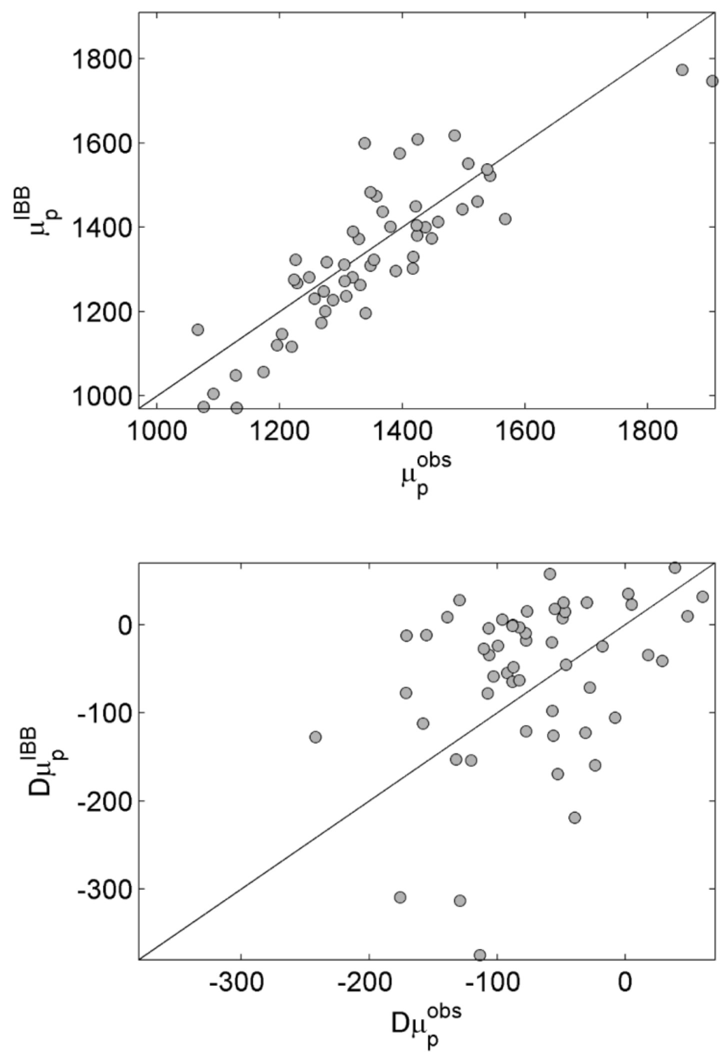


Figure 5. Annual mean precipitation (top panel) during the validation period (1994-2008) and its difference (bottom panel) with the test period (1976-1993) for the observed data (abscissa) and the IBB simulated data (ordinate) over all the employed stations in South Korea. For more details about the difference at the bottom panel, see Eqs. (12) and (13).

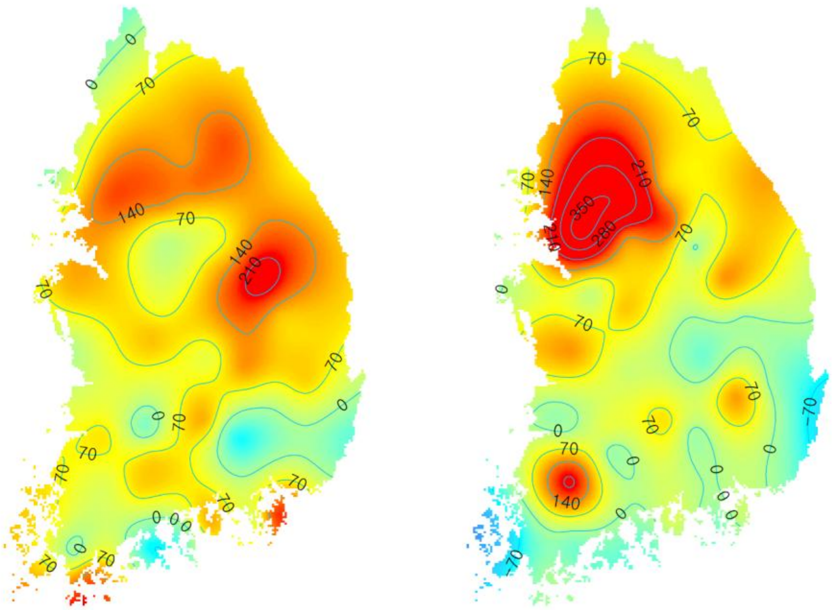


Figure 6. Spatial distributions of annual mean precipitation difference between the validation period (1994-2008) and the test period (1976-1993) for the observed data (left panel) and the IBB simulated data (right panel).

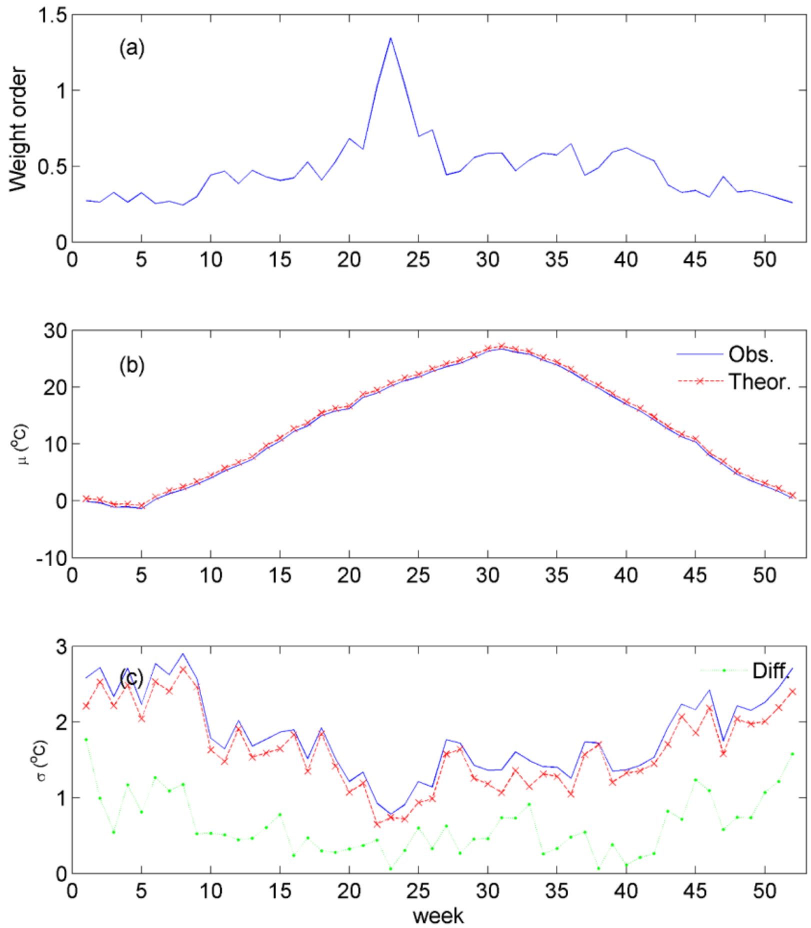


Figure 7. (a) Estimated weight order from HS and weekly statistics of (b) mean and (c) variance for the observed temperature data (solid line) and the theoretical statistics (dashed line with cross) using Eqs. (2) and (7) for Buan station. The weekly difference in variance between observation and theoretical (see Eq. (8)) is shown in panel (c) by a dotted line.

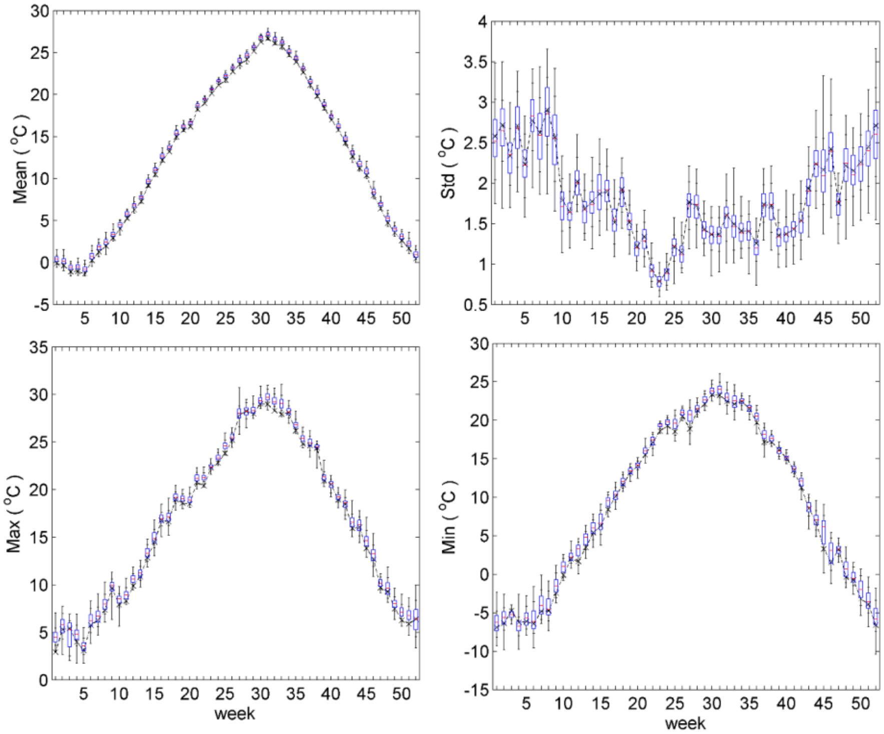


Figure 8. The statistics of the observed (dotted line with cross) and generated (boxplot) data for the weekly mean temperature using IBB with a 0.5°C temperature increase in Buan, South Korea. Boxes display the interquartile range (IQR), and whiskers extend to the extrema (i.e., maximum and minimum). The horizontal lines inside the boxes depict the median of the data. Note that the mean and maximum of the simulated data are increased significantly compared with the corresponding observed data, while the minimum of the simulated data is slightly increased and the standard deviation of the simulated data agrees with that of the observed data due to the variance inflation, as in Eq. (9).

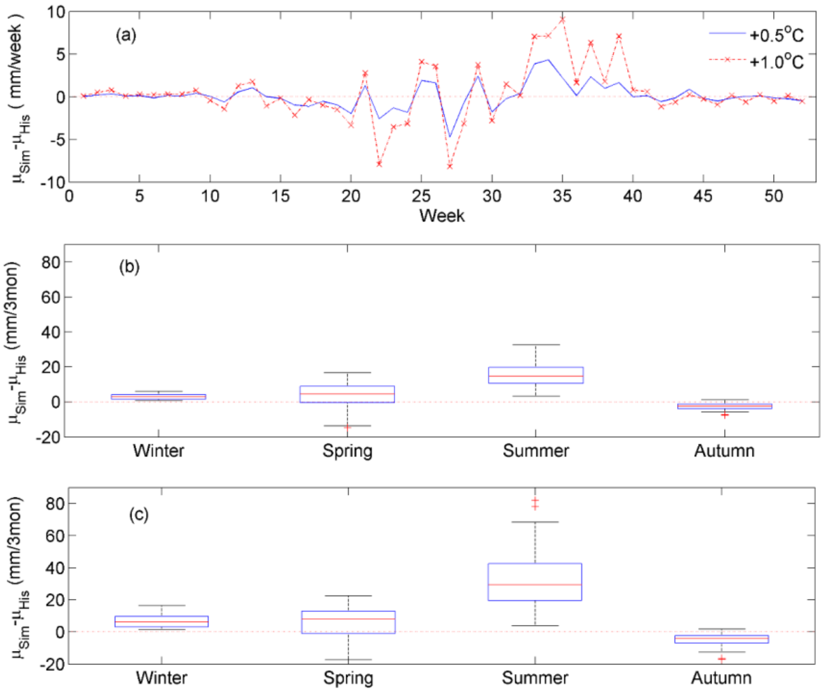
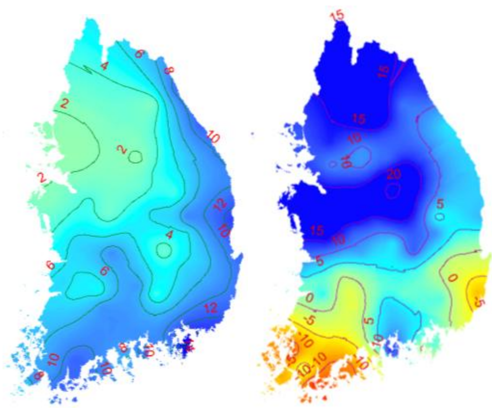
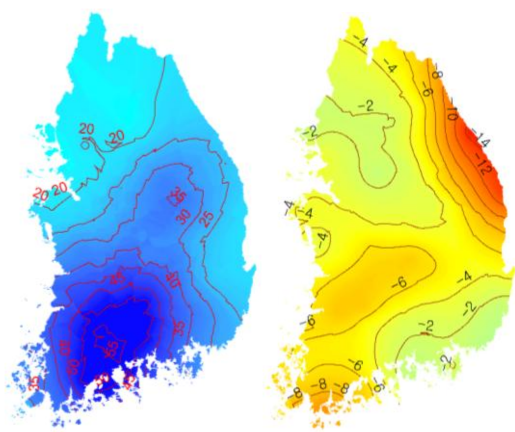


Figure 9. The mean precipitation differences of the observed and simulated data (a) for the weekly precipitation in Buan with a 0.5°C mean temperature increase, (b) for the seasonal precipitation of all 54 stations with a 0.5°C mean temperature increase and (c) for a 1.0°C mean temperature increase. Note that indicates the mean of the simulated precipitation data for weekly (a) or seasonal (b and c).

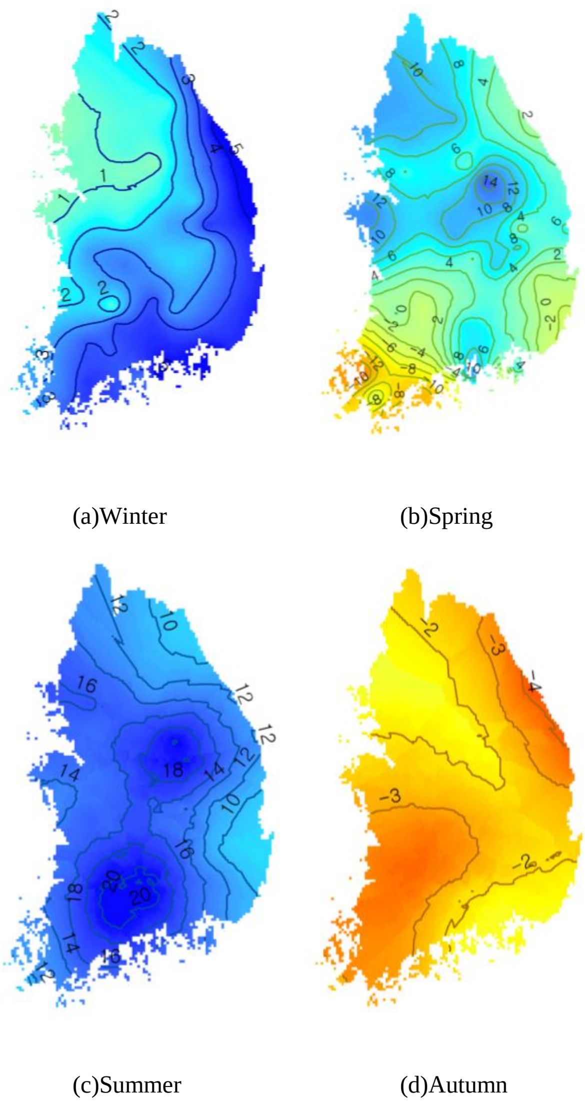


(a) Winter (b) Spring



(c) Summer (d) Autumn

Figure 10. Spatial distributions in South Korea of the mean difference in seasonal precipitation (mm) with a 1.0°C increase in mean temperature. Note that the scale for the summer distribution is different from the other seasons, the 95% significance intervals are different at each station and the mean values of the significance intervals are ±5.38, ±15.04, ±29.94, and ±4.84 for Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), and Autumn (September, October, November), respectively.



(a)Winter (b)Spring

(c)Summer (d)Autumn

Figure 11. Spatial distribution of mean difference of seasonal precipitation (mm) with 0.5^{o}C increasing mean temperature in South Korea. Note that the scale of summer is different from the other seasons and the 95% significance intervals are different at each station and the mean values of the significance intervals are ±5.38, ±15.04, ±29.94, and ±4.84 for Winter (December, January, February), Spring (March, April, May), Summer (June, July, August), and Autumn (September, October, November) respectively.