

Selection of representative GCM scenarios preserving uncertainties

Jae-Kyoung Lee and Young-Oh Kim

ABSTRACT

Climate change studies usually include the use of many projections, and selecting an essential number of projections is very important, because using all Global Climate Model (GCM) scenarios is impossible in practice. Furthermore, the climate change impact assessment is often sensitive to the choice of GCM scenarios. This study suggests that selecting the best-performing scenarios based on a historical period should be avoided in nonstationary cases like climate change, and then proposes a new approach that can preserve the uncertainty, that all scenarios contain. The new approach groups all GCM scenarios into several clusters, and then selects a single representative scenario among member scenarios of each cluster, based on their skill scores. The proposed approach is termed 'selecting the principal scenarios', and applied to select five principal GCM scenarios for the South Korean Peninsula, among 17 GCM scenarios of the 20C3M emission scenario. The uncertainty preservation is measured with the maximum entropy theory. The case study presents that the principal scenarios preserve the full range of total uncertainty, compared to less than 65% for the best scenarios confirming that preserving uncertainty with the principal scenarios is more adequate, than selecting the best-performed scenarios, in climate change studies.

Key words | climate change uncertainty, cluster analysis, entropy, GCM scenario selection, principal scenario

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INTRODUCTION

Since climate change studies are the process of forecasting an uncertain future, 'uncertainty' is most definitely a keyword of all climate change assessments. According to the four assessment reports published by the Intergovernmental Panel on Climate Change (IPCC), of which the first report was published in 1990 (IPCC 1990), projected temperatures are on a continuous increasing trend on average in East Asia (including the Korean Peninsula), and uncertainties in accordance with climate change have also increased, due to the large range of temperature rise year after year. The greater the

level of uncertainty, the more difficult it has become to project what may happen in the future. Furthermore, since climate change studies are conducted in various steps, using Global Climate Models (GCMs), Regional Climate Models, downscaling techniques, and rainfall-runoff models, the uncertainty is all the more amplified. Although previous studies recognized such uncertainties, studies have only quantified and shown the uncertainties in each step of the climate change assessments using a form of sensitivity analysis (Katz 2001; Kay *et al.* 2009; Prudhomme & Davies 2009; Chen *et al.* 2011; Poulin *et al.* 2011; Zhang *et al.* 2011).

According to existing studies, of all the uncertainties that are generated from climate change assessments, uncertainties from GCM scenarios are known to be the greatest

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(Wolock & McCabe 1999; Wilby & Harris 2006; Kay *et al.* 2009; Prudhomme & Davies 2009; Chen *et al.* 2011). Therefore, it is inevitable that future water resource projections will be much impacted by which GCM scenario is used. In the review of existing studies, using only one with a few different initial conditions or a small number of multiple GCM scenarios was recommended, to project and assess the impact of climate change. It is not convincing that a single GCM scenario selected at present would occur some decades in the future. On the other hand, one may employ all the GCM scenarios provided by IPCC to cover more possibilities in the future, but this would be an impractical alternative to decision-making in practice, even if it were possible for research purposes. Therefore, it is necessary to select several scenarios, to show the possible number of cases, to the maximum extent possible.

Until now, standard criteria for selecting climate change scenarios have not been obvious. GCM scenarios were selected depending on arbitrary means, or the subjective judgment of the researcher. For example, climate impact assessments have been mainly conducted using a GCM scenario developed by their own country, or using high-resolution GCM scenarios. The most objective method of selecting a GCM scenario is to compare performances of various GCM scenarios during a certain past period (i.e. baseline simulation), and to select the GCM scenario with the best accuracy, which implies the assumption that the best projection occurs 100% of the time, but the others never occur. One may assign a different weight to each scenario, to create a combined scenario, but it is considered that all GCM scenarios in the 4th Assessment Report of IPCC (2007) have equal possibilities of occurrence, due to lacking information to make reliable estimates of which are more or less likely to occur. Moreover, the nonstationarity concept in climate change implies that the future would not be a repetition of the past, and thus some best-performed GCM scenarios could not explain the uncertainties of all GCM scenarios in the future.

The purpose of this study is to propose a new approach for selecting some representative GCM scenarios (called the 'principal' scenarios). Here we underline preserving the uncertainty the IPCC GCM scenarios show. Using the maximum entropy (ME) theory, this study also quantifies the uncertainty of the selected GCM scenarios, to prove the principal scenarios that attempt to preserve the whole

range of uncertainty of all GCM scenarios are more effective than the 'best' individual scenarios. Finally, based on the proposed approach, this study proposes some GCM scenarios that are more appropriate for future water resources management in the Korean Peninsula.

A NEW APPROACH FOR THE SELECTION OF REPRESENTATIVE GCM SCENARIOS

As mentioned in the introduction, this study proposes selecting the 'principal' scenarios which best represent the uncertainty range of all IPCC GCM scenarios, rather than the 'best' scenarios which performed best in the past, with respect to a certain accuracy measure. The best scenario approach would be unconvincing, because the best scenarios selected based on a historical period may not perform well in the future (Raisanen 2007), due to the 'non-stationary' climate, where the key statistics of hydro-climate variables are a function of time, and thus the future would not be a repetition of the past. Furthermore, the uncertainty in climate change assessment is generally huge, and thus characterized as 'deep uncertainty' (United Kingdom Climate Impacts Programme (UKCIP) 2003), where even likelihoods of future scenarios are generally unknown. Therefore, in such a nonstationary world, preserving future uncertainty should be more focused on deep uncertainty. In this study, the principal scenario approach consists of two steps: first, 'clustering' scenarios; and then, 'selecting' a representative scenario from each cluster.

GCM scenarios clustering

The scenario clustering step groups the entire set of GCM scenarios used into several clusters, according to only the statistical properties of each GCM scenario not a GCM structure, because even GCMs have different scenarios under identical research. Among many cluster analysis methods, the characteristic-based K-means cluster analysis method is able to cluster the data, after reducing the dimensionality (e.g. the number of data) of higher-order time series, such as GCM scenarios, using only statistical characteristics (Wang & Smith 2006). In this study, the uncertainties are assumed to all be captured with six statistical characteristics (i.e. average

for the total period, average for each month, standard deviation for the total period, standard deviation for each month, trend for each month, and lag-1 autocorrelation). In other words, it is assumed that the GCM scenarios in the same cluster classified by the characteristic-based K-means cluster method, are statistically the most similar.

Selection of representative scenarios from each cluster

The second step of the principal scenario approach selects a representative scenario from each cluster, by evaluating the performance of GCM scenarios belonging to each cluster. In this step, the choice of a selection measure should first be determined. Previous studies utilized various measures, such as bias (Wilks 2005; Gleckler *et al.* 2008), root mean square error (Murphy 1996; Wilks 2005; Gleckler *et al.* 2008; Pitman & Perkins 2008; Reichler & Kim 2008; Winter & Nychka 2009; Chiew *et al.* 2009), correlation (Epstein & Murphy 1989; Murphy 1989), brier score (Raisanen & Palmer 2001), relative entropy (Kleeman 2002; Shukla *et al.* 2006), potential predictability (Ma & Cao 1999; Boer 2004; Boer & Lambert 2008), and Taylor diagram (Taylor 2001).

In this study, the probability density function (PDF) method (Perkins *et al.* 2007), which compares PDFs of GCM scenarios and observations, was adopted, because the overall likelihood of the tested scenarios is more important than time-to-time matching with the observed series. If PDFs of both scenarios of a GCM and a corresponding observed series are identical, the skill score becomes one. The skill score of the PDF method is calculated as follows (refer to Figure 1):

$$\text{Skill score} = \sum_{i=1}^n \min(p_{X_{GCM}}(x_i), p_{X_{Obs}}(x_i)) \quad (1)$$

where x_i is the value of the i th quantile, $p_{X_{GCM}}(\bullet)$ is the empirical PDF of scenarios of a GCM for a historical period, $p_{X_{Obs}}(\bullet)$ is the empirical PDF of the observed series, and n is the total number of quantiles.

ME for uncertainty quantification

Introduced by Shannon (1948), entropy was utilized to quantify uncertainties of random variable X with probabilities p . In the field of hydrology, for example, there exist a number of studies (e.g. Singh 1997; Koutsoyiannis 2005; Deng &

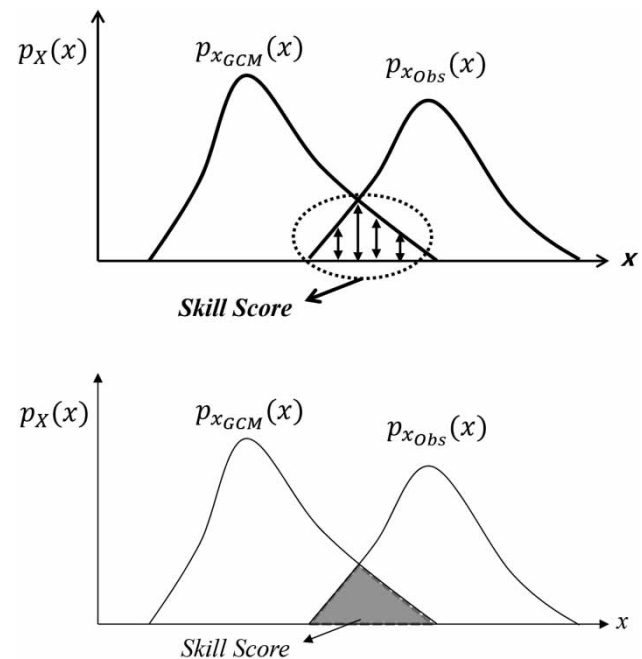


Figure 1 | Illustration of the PDF method.

Pandey 2008; Gay & Estrada 2010). Jaynes (1957) further extended the Shannon's entropy theory to the 'ME', to maximize uncertainty subject to given available information. A basic equation of the ME is as follows (Jaynes 1957):

$$\max_p H(X) = - \sum_{i=1}^N p_X(x_i) \ln p_X(x_i) \quad (2)$$

subject to

moment – consistency constraint:

$$\sum_{i=1}^N p(x_i) f_k(x_i) = y_k, \quad (k = 1, 2, \dots, m)$$

normalization constraint: $\sum_{i=1}^N p_X(x_i) = 1, \quad (p_X(x_i) \geq 0)$

where H is the entropy of X , X is the random variable with probabilities p , x is the value of X , $p_X(\bullet)$ is the probability mass function of X , $f_k(\bullet)$ is the moment constraint, N is the sample size, K is the number of moments. After applying the Lagrangian multiplier to Equation (2) under unconstrained conditions, the estimated $p_X(x)$ can be expressed as

$$p_X(x_i) = \frac{\exp[-\sum_{k=1}^m \lambda_k f_k(x_i)]}{\sum_{i=1}^N \exp[-\sum_{k=1}^m \lambda_k f_k(x_i)]} \quad (3)$$

where λ_k is the weight of constraint $f_k(\cdot)$ in k th moment. In Equation (3), because the probability $p_X(x)$ of the ME is not in closed form, numerical analysis techniques are required to estimate parameter λ and probability $p_X(x)$.

The above ME theory implies that the distribution with the largest entropy should be chosen if nothing is known about a distribution except the given information. For example, when values of a maximum and a minimum are given, the uniform distribution has the ME. In this study, the ME theory was applied to quantify the uncertainty of the selected projections. More specifically, the selected scenarios provide the maximum and minimum values and Equation (3) calculates the entropy of the selected scenarios as the uncertainty measure.

APPLICATIONS AND RESULTS

Performance of IPCC GCM scenarios

In this study, GCM scenarios were selected to study the climate change impact on water resources for the South Korean Peninsula. The South Korean Peninsula is located in a temperate climate region at 33–43 degrees north latitude and 124–132 degrees east longitude, and its total area is 99,646 km² (Korea Institute for National Unification 2009). The annual average precipitation in the regime is 1,314.21 mm/year over the past 40 years (1970–2009), and its standard deviation is 247.26 mm/year. Its annual average temperature is 12.36 °C, maximum monthly average temperature is 27.71 °C, and minimum monthly average temperature is –4.80 °C.

To enhance the understanding of climate phenomenon, and improve the simulation technique with computers, several advanced countries developed GCMs to project the future climate, and suggested the results from GCMs to the international society. For a typical example, the IPCC 4th Report (AR4 hereafter) offers 148 GCM scenarios, based on a total of six emission scenarios (1PTO2X, 1PTO4X, COMMIT, SRES A1B, SRES A2, and SRES B1) and two baseline simulations (20CM3 and P1_cntrl) from 25 GCMs of 15 countries that were used in the AR4. The centers (and the corresponding scenarios) providing GCM scenarios are BBC and LAGS (China), BCCR (Norway), GISS, NCAR and GFDL (USA), INGV (Italy), INM (Russia), IPSL and CNRM (France), CSIRO (Australia), MPI-M (Germany),

MIUB, METRI and M&D (Germany and Korea), CCCma (Canada), MRI and NIES (Japan), and UKMO (UK).

This study tested 71 AR4 GCM scenarios for the South Korean Peninsula. These consist of scenarios based on the 20C3M emission scenario before 2000 (from January 1970 to December 1999), and scenarios based on the SRES A2 (economic growth oriented) and B1 (environment oriented) emission scenarios after 2000 (from January 2001 to December 2009). Selected GCM scenarios were directly downloaded from the IPCC Data Distribution Centre (www.ipcc-dds.org), and in each GCM scenario, monthly average precipitation and temperature for Korea were calculated as a simple average of the GCMs grid values that include the South Korean Peninsula. This study dealt with monthly average precipitation and temperature time series instead of the annual time series because the hydrological characteristic in the summer season (two-thirds of total precipitation occurs) of the Korean Peninsula is very distinct from that of the winter season. As shown in Figure 2(a) and 2(b), the simulated monthly average precipitation of the AR4 GCMs based on 20C3M and A2 & B1 emission scenarios, are very heterogeneous. As a result, none of those scenarios capture the summer monsoon pattern during the three-month flood season from mid-June to mid-September, when two-thirds of the annual precipitation falls. Therefore, it was concluded that the use of the AR4 GCM was still inadequate for flood mitigation purposes. On the other hand, some GCM scenarios performed well in precipitation during the nine-month dry season, which suggested that these GCM scenarios can be utilized for water supply purposes (refer to Table 1). Simulated monthly average temperature of the AR4 GCMs however, follows the general pattern of observations well (Figure 3(a) and 3(b)), underestimating the observations consistently, by about 3 °C, on average.

Like the majority of the climate change assessment studies (Taylor 2009; Shukla *et al.* 2006; Perkins *et al.* 2007; Gleckler *et al.* 2008; Climate Impacts Group 2009), the selection procedure was carried out based on the 20C3M emission scenario, because the projection period (i.e. 10 years) of the SRES A2 & B1 emission scenarios is too short for testing GCMs. Therefore, this study mainly utilizes 17 GCMs of the 20C3M emission scenario. It is interesting to examine how the best GCMs are based on the PDF method from 20C3M or the other emission scenarios. As shown in Figure 4, for

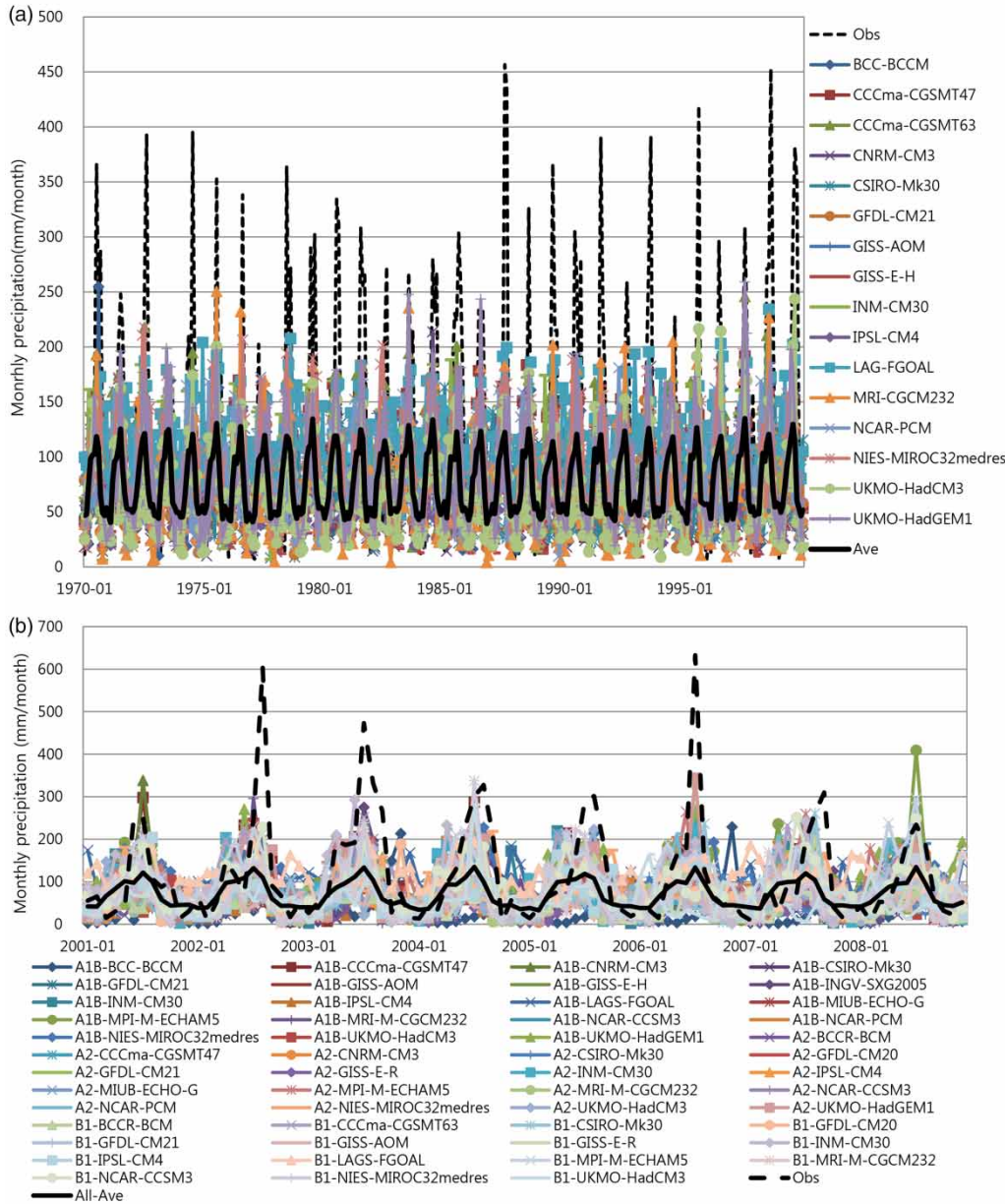


Figure 2 | Simulated monthly average precipitation time series of various GCMs (bold black line: observations, bold black dotted line: average of GCM scenarios). (a) Time series of monthly average precipitation (based on 20C3M emission scenario): Jan. 1970–Dec. 1999. (b) Times series of monthly average precipitation (based on A2, B1, and A1B emission scenarios): Jan. 2001–Dec. 2009.

example, the selection of the best GCMs varies significantly between the emission scenarios: the third-ranking GCM, UKMO-HadCM3 in 20C3M, is ranked the 16th and the 12th in A1B and A2, respectively, while the best GCM in A1B is ranked the sixth in 20C3M. This fact would be a symbol of non-stationarity, although a short length in A1B and A2 would also cause the sampling uncertainty. In other words, Figure 4 warns

the best selection based on a certain period may be meaningless, in different periods in the climate change era.

Bias correction of GCM scenarios

Climate change impact assessments attempt to quantify the future risks to water resource systems, particularly at regional

Table 1 | Key statistics of simulated monthly average precipitation and temperature for four emission scenario cases

		20C3M	Obs ¹	A1B	A2	B1	Obs ²
(a) For the whole year							
Precipitation (mm/month)	Average	77.67	108.9	75.16	73.69	78.40	111.68
	Standard deviation	27.93	98.79	27.33	29.16	28.13	119.16
Temperature (°C/month)	Average	12.23	12.23	9.74	9.09	9.56	12.64
	Standard deviation	9.41	9.05	9.28	9.63	9.19	8.85
(b) For the dry season							
Precipitation (mm/month)	Average	68.83	58.81	62.95	61.32	66.51	53.36
	Standard deviation	24.26	42.15	21.04	23.13	21.13	41.21
Temperature (°C/month)	Average	3.83	7.09	4.43	3.58	4.27	7.63
	Standard deviation	6.62	6.38	6.52	6.78	6.38	6.30

Obs¹: from Jan. 1970 to Dec. 1999, Obs²: from Jan. 2001 to Dec. 2009.

and catchment scales. However, it is well known that GCM rainfall scenarios are biased at both the spatial and temporal scales (Xu & Singh 2004; Anandhi *et al.* 2011). Although improving the GCMs to simulate the meteorological characteristics in the Korean Peninsula is the best way, utilizing a proper bias correction is much simpler and easier than that process. Therefore, GCM scenarios should be bias corrected using a proper bias correction method, to project the future water resources accurately. When the IPCC GCM scenarios for the study area were compared with the corresponding observed series for a historical period (January 1960–December 1999), we realized that the biases of GCMs used are generally constant during the dry season (from October to next following May), while those during the flood season (from June to September) are generally proportional to the corresponding GCM values. Therefore, this study employed additive and multiplicative bias correction equations, as follows:

$$\text{The flood season: } P_{cor} = P_p \times \frac{\overline{P_{Obs}}}{\overline{P_h}} \quad (4)$$

$$\text{The dry season: } P_{cor} = (P'_p \times \sigma_{Obs}) + \overline{P_{Obs}}; \quad P'_p = \frac{P_p - \overline{P_p}}{\sigma_p} \quad (5)$$

where P is the precipitation, P_{cor} is the corrected precipitation of GCMs, P_p is the projected precipitation of GCMs, $\overline{P_{Obs}}$ is the average of the observed precipitation, $\overline{P_h}$ is the average of the simulated precipitation of GCMs for the historical period, $\overline{P_p}$ is the average of the projected precipitation of GCMs, σ_{Obs} is the standard deviation of the observed precipitation, and σ_p is the standard deviation of the projected precipitation of GCMs.

The above equations were applied to the precipitation scenarios of each GCM, month by month. Table 2 reports averages and standard deviations over all the GCM scenarios, before and after the bias correction, compared with the observation. Note that Equations (4) and (5) were calibrated using the period from January 1960 to December 1979, while the verifications shown in Table 3 were based on the period from January 1980 to December 1999.

Selection of representative GCM scenarios

This section illustrates how to select five representative GCM scenarios for the South Korean Peninsula. One can select the five best, or the five principal scenarios, as described in the following two subsections.

(1) Five best GCM scenarios

The five best-performed GCM scenarios were selected using the PDF selection method. The selection was carried out with the 20C3M emission scenario from January 1980 to December 1999, and applied to the GCM precipitation scenarios only when their skill scores in temperature exceeded 80%. The resulting five best scenarios (and their skill scores) include MRI-CGCM232 (Germany), UKMO-HadCM3 (UK), UKMO-HadGEM1 (UK), CNRM-CM3 (France), and BCCR-BCM (China).

(2) Five principal GCM scenarios

The characteristic-based K-mean method was applied to the 17 IPCC GCM scenarios, based on the 20C3M emission

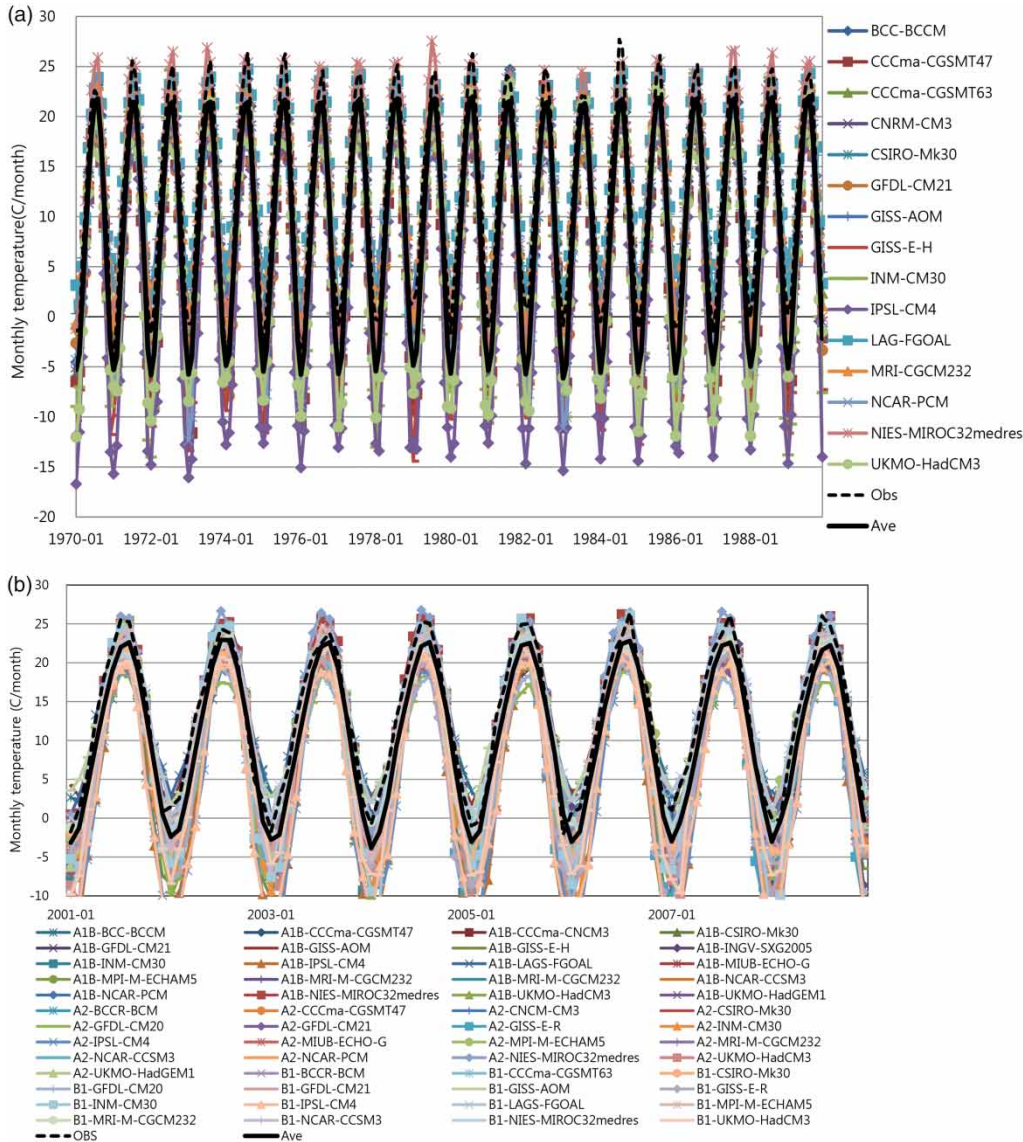


Figure 3 | Simulated monthly average temperature time series of various GCMs (bold black line: observations, bold black dotted line: average of GCM scenarios). (a) Time series of monthly average temperature (based on 20C3M emission scenario): Jan. 1970–Dec. 1999. (b) Time series of monthly average temperature (based on A and B emission scenarios): Jan. 2001–Dec. 2009.

scenario. Table 4 presents the resulting five clusters, their member GCMs, and their overall averages and standard deviations, among the six statistical characteristics used in the cluster analysis. It is obvious in Table 4 that the averages and standard deviations are very heterogeneous over the clusters. A single scenario was then selected from each cluster, in the same way as the PDF method for the selection of five best scenarios. The above two-step selection procedure finally resulted in the five principal scenarios, namely MIUB-ECHO-G (Germany/Korea), MPI-ECHAM5 (Australia), GISS-AOM (USA), MRI-

CGCM232 (Germany), and CSIRO-Mk30 (Australia). Table 5 compares the best and principal GCM scenarios for the South Korean Peninsula. The two approaches share MRI-CGCM232, while four out of the five GCMs in each approach are different.

Comparison of the best and the principal GCM scenarios in uncertainty

This study also quantified uncertainties of various sets of scenarios, such as all, the best, and the principal scenarios

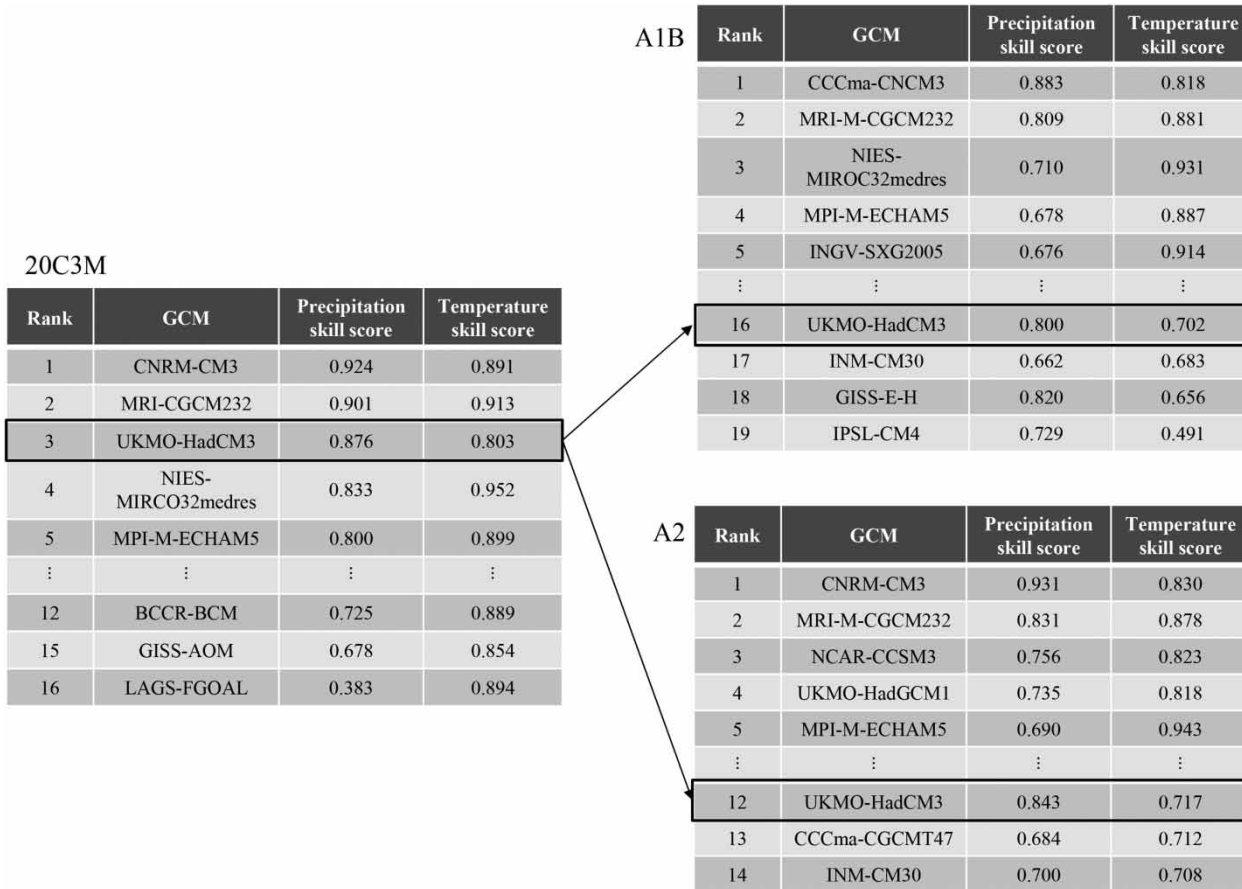


Figure 4 | Skill rank changes between 20C3M, A1B, and A2 emission scenarios.

Table 2 | Statistics over all the GCM scenarios, before and after the bias correction

Statistics	Observation	Bias corrected	Raw
Average (mm/month)	110.52	110.50	73.71
Standard deviation (mm/month)	102.28	80.04	31.03

sets, using ME. Since a GCM scenario is a time series, where values vary as a function of time, it is necessary to represent the simulation with a single summary statistic, before the

ME is applied. In this study, we adopt average or standard deviation of each GCM scenario over time as the summary statistics. As a result, all, the best, and the principal scenarios sets have 17, 5, and 5 summary statistics, respectively. Among the summary statistics, their maximum and minimum values are denoted ‘a’ and ‘b’, respectively. The equation of ME is then expressed as:

$$H(X) = - \int_a^b f_X(x) \ln f_X(x) dx \tag{6}$$

Table 3 | Statistics of the bias correction method for the calibration and verification period

Statistics	Calibration (1960–1979)			Verification (1980–1999)		
	Obs	Bias corrected	Raw	Obs	Bias corrected	Raw
Average (mm/month)	105.72	105.72	72.12	110.52	110.50	73.71
Standard deviation (mm/month)	95.62	95.62	47.26	102.28	80.04	31.03

Table 4 | Result of the cluster analysis for the South Korean Peninsula

Cluster	GCM members	Average (mm/month)	Standard deviation (mm/month)
1	MIUB-ECHO-G	124.13	109.02
2	CCCma-CGSMT47, GISS-E-H, MPI-M-ECHAM5	103.25	80.52
3	GISS-AOM	139.91	140.79
4	BCCR-BCM, CCCma-CGSMT63, CNRM-CM3, GFDL-CM21, INM-CM30, NIES-MIROC32medres, LAGS-FGOAL, IPSL-CM4, MRI-CGCM232, NCAR-PCM, UKMO-HadCM3, UKMO-HadGEM1	109.78	93.62
5	CSIRO-Mk30	82.42	61.54

Table 5 | The best five and principal GCM scenarios for the South Korean Peninsula, and their skill scores

Set	GCM (Nation)	Skill score for precipitation	Skill score for temperature
Best 5 GCM scenarios	MRI-CGCM232 (Germany)	0.797	0.914
	UKMO-HadCM3 (UK)	0.781	0.804
	UKMO-HadGEM1 (UK)	0.765	0.900
	CNRM-CM3 (France)	0.762	0.891
	BCCR-BCM (China)	0.761	0.889
Principal GCM scenarios	MIUB-ECHO-G (Germany/Korea)	0.726	0.820
	MPI-M-ECHAM5 (Germany)	0.747	0.900
	GISS-AOM (USA)	0.680	0.854
	MRI-CGCM232 (Germany)	0.797	0.914
	CSIRO-Mk30 (Australia)	0.650	0.869

subject to

$$\text{normalized constraint: } \int_a^b f_X(x) dx = 1$$

The optimum of the above constrained optimization problem is

$$\begin{aligned} H_{opt} &= - \int_a^b f_X(x) \ln f_X(x) dx \\ &= - \int_a^b \frac{1}{b-a} \ln \frac{1}{b-a} dx = - \ln(b-a) \end{aligned} \quad (7)$$

H_{opt} measures the uncertainty of all, the best, and the principal scenarios sets, when the time average on the time standard deviation is employed, as summarized in Table 6. When the average is used as the summary statistic, ME (=4.052) of the principal scenarios approach fully covers the uncertainty all GCM scenarios contain (i.e. the total uncertainty), but the best five scenario approach (ME = 2.474) covers only 61.07% of the total uncertainty.

Table 6 | Results of the ME for various sets of the selected GCM scenarios

Range	GCM scenarios		
	All scenarios	Principal scenarios	Best 5 scenarios
(a) Summary statistic = average			
max	139.913	139.913	117.038
min	82.418	82.418	105.163
ME	4.052	<i>4.052 (100%)</i>	2.474 (61.07%)
(b) Summary statistic = standard deviation			
max	140.790	1,409.790	100.804
min	61.542	61.542	84.505
ME	4.373	<i>4.373 (100%)</i>	2.791 (63.83%)

Italics: simulations close to the ME of all.

When the standard deviation is used as the summary statistic, ME (=4.373) of the principal scenarios also covers the whole range of the total uncertainty but ME (=2.791) of the best five scenarios occupies only 63.83%. Our results confirm that the principal GCM scenarios approach is

Table 7 | Ratios of observations that are included in all, the best five, and the principal scenario sets for A1B, A2, and B1 emission scenarios

GCM scenarios	A1B	A2	B1
All	87.50%	76.56%	68.75%
Best 5	51.56%	53.13%	53.13%
Principal	76.56%	60.94%	56.25%

superior to the best five scenarios approach, in terms of the uncertainty preservation. Table 7 shows that the ratio (76.56% in A1B, 60.94% in A2, and 56.25% in B1 emission scenario) of observations in the principal scenarios is larger than the best five scenarios, in all emission scenarios.

CONCLUSION

The issue of how to select representative GCM scenario is dealt with, when many scenarios are available. This study warns that selecting the best-performing scenarios based on a historical period should be avoided in nonstationary cases like climate change, and then proposes a new approach that can preserve the uncertainty that all scenarios contain. The new approach groups all GCM scenarios into several clusters, and then selects a single representative scenario among member scenarios of each cluster, based on their skill scores. The proposed approach is termed 'selecting the principal GCM scenarios', and is applied to select five principal GCM scenarios for the South Korean Peninsula, among 17 GCM scenarios of the 20C3M emission scenario. The uncertainty preservation is measured with the ME theory. It is learnt from our case study that:

1. GCMs that perform well for the 20C3M historical period often do not perform well for other emission scenarios in the future, which confirms that selection of the best GCMs based on a historical period should be avoided;
2. the principal GCM scenarios preserve 100% of the total uncertainty, while the best GCM scenarios preserve less than 65%; and
3. five GCMs, namely MIUB-ECHO-G, MPI-M-ECHAM5, GISS-AOM, MRI-CGCM232, and CSIRO-Mk30, are proposed as the representative GCMs for climate change impact assessments in the South Korean Peninsula. In future, therefore, national water resources plans coping

with climate change should be established on the basis of these five GCM scenarios.

Selecting an essential number of scenarios among the many scenarios available is very important, because using all the scenarios is impossible in practice. The proposed approach can be applied to any GCM scenario selection that is dominated by nonstationarity with large uncertainty.

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REFERENCES

- Anandhi, A., Frei, A., Pierson, D. C., Schneiderman, E. M., Zion, M. S., Lounsbury, D. & Matonse, A. H. 2011 [Examination of change factor methodologies for climate change impact assessment](#). *Water Resources Research* **47**, W03501.
- Boer, G. J. 2004 [Long time-scale potential predictability in an ensemble of coupled climate models](#). *Climatic Dynamics* **23**, 23–44.
- Boer, G. J. & Lambert, S. J. 2008 [Multi-model decadal potential predictability of precipitation and temperature](#). *Geophysical Research Letters* **35**, L05706.
- Chen, J., Brissette, F., Poulin, A. & Leconte, R. 2011 [Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed](#). *Water Resources Research* **47**, W12509.
- Chiew, F. H. S., Teng, J., Vaze, J. & Kirono, D. G. C. 2009 [Influence of global climate model selection on runoff impact assessment](#). *Journal of Hydrology* **379**, 172–180.
- Climate Impacts Group 2009 *The Washington Climate Change Impacts Assessment: Evaluating Washington's Future in a Changing Climate*. University of Washington, Seattle, Washington, USA.
- Deng, J. & Pandey, M. D. 2008 [Cross entropy quantile function estimation from censored samples using partial weighted moments](#). *Journal of Hydrology* **363**, 18–31.
- Epstein, E. S. & Murphy, A. M. 1989 [Skill scores and correlation coefficients in model verification](#). *Monthly Weather Review* **117**, 572–581.
- Gay, C. & Estrada, F. 2010 [Objective probabilities about future climate are a matter of opinion](#). *Climatic Change* **99**, 27–46.

- Gleckler, P. J., Taylor, K. E. & Doutriaux, C. 2008 Performance metrics for climate models. *Journal of Geophysical Research* **113**, D06104.
- IPCC 1990 *First Assessment Report 1990: Working group II: Impacts assessment of climate change*. Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- IPCC 2007 *Climate change 2007: Synthesis report*. Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.
- Jaynes, E. T. 1957 Information theory and statistical mechanics. *The Physical Review* **106**, 620–630.
- Katz, R. W. 2001 *Techniques for Estimating Uncertainty in Climate Change Scenarios and Impact Studies*. Environmental and Societal Impacts Group Report, National Centers for Atmospheric Research.
- Kay, A. L., Davies, H. N., Bell, V. A. & Jones, R. G. 2009 Comparison of uncertainty sources for climate change impacts: flood frequency in England. *Climatic Change* **92**, 41–63.
- Kleeman, R. 2002 Measuring dynamical prediction utility using relative entropy. *Journal of Atmospheric Science* **59**, 2057–2072.
- Korea Institute for National Unification 2009 *The Outline of North Korea*. Korea Institute for National Unification Seoul, Korea.
- Koutsoyiannis, D. 2005 Uncertainty, entropy, scaling and hydrological stochasticity: 1. marginal distributional properties of hydrological processes and state scaling. *Hydrological Science Journal* **50**, 381–404.
- Ma, K. & Cao, J. 1999 Climatic noise and potential predictability of monthly mean temperature over China. *Meteorological Atmospheric Physics* **69**, 231–237.
- Murphy, A. H. 1989 Skill scores based on the mean-square error and their relationships to the correlation coefficient. *Monthly Weather Review* **116**, 2417–2424.
- Murphy, A. H. 1996 General decompositions of MSE-based skill scores: measures of some basic aspects of forecast quality. *Monthly Weather Review* **124**, 2353–2369.
- Perkins, S. E., Pitman, A. J., Holbrook, N. J. & McAneney, J. 2007 Evaluation of the AR4 climate models' simulated daily maximum temperature, minimum temperature, and precipitation over Australia using probability density functions. *Journal of Climate* **20**, 4356–4376.
- Pitman, A. J. & Perkins, S. E. 2008 Regional projections of future seasonal and annual changes in rainfall and temperature over Australia based on skill-selected AR4 models. *Earth International* **12**, doi:10.1175/2008EI260.1.
- Poulin, A., Brissette, F., Leconte, R., Arsenault, R. & Malo, J.-S. 2011 Uncertainty of hydrological modeling in climate change impact studies in a Canadian, snow-dominated river basin. *Journal of Hydrology* **409**, 626–636.
- Prudhomme, C. & Davies, H. 2009 Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 2: future climate. *Climatic Change* **93**, 197–222.
- Raisanen, J. 2007 How reliable are climate models? *Tellus* **59A**, 2–29.
- Raisanen, J. & Palmer, T. N. 2001 A probability and decision-model analysis of a multi-model ensemble of climate change simulations. *Journal of Climate* **14**, 3212–3226.
- Reichler, T. & Kim, J. 2008 How well do coupled models simulate today's climate? *Bulletin of American Meteorological Society* **89**, 303–311.
- Shannon, C. E. 1948 A mathematical theory of communication. *Bell System Technical Journal* **27**, 379–423.
- Shukla, J., Delsole, T., Fennessy, M., Kinter, J. & Paolino, D. 2006 Climate model fidelity and projections of climate change. *Geophysical Research Letters* **33**, L07702.
- Singh, V. P. 1997 The use of entropy in hydrology and water resources. *Hydrological Processes* **11**, 587–626.
- Taylor, K. E. 2001 Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research* **106** (D7), 7183–7192.
- United Kingdom Climate Impacts Programme 2003 *Climate adaptation: risk, uncertainty and decision-making*. UKCIP Technical Report, UKCIP, Oxford, UK.
- Wang, X. & Smith, K. 2006 Characteristic-based clustering for time series data. *Data Mining and Knowledge Discovery* **13**, 335–364.
- Wilby, R. L. & Harris, I. 2006 A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the River Thames, U.K. *Water Resources Research* **42**, W02419.
- Wilks, D. S. 2005 *Statistical Methods in the Atmospheric Sciences*, 2nd edn. Academic Press, New York.
- Winter, C. L. & Nychka, D. 2009 Forecasting skill of model averages. *Stochastic Environmental Research and Risk Assessment* doi:10.1007/s00477-009-0350-y.
- Wolock, D. M. & McCabe, G. J. 1999 Estimates of runoff using water-balance and atmospheric general circulation models. *Journal of American Water Resources Association* **35**, 1341–1350.
- Xu, C. Y. & Singh, V. P. 2004 Review on regional water resources assessment models under stationary and changing climate. *Water Resources Management* **18**, 591–612.
- Zhang, H., Huang, G. H., Wang, D. & Zhang, X. 2011 Uncertainty assessment of climate change impacts in the hydrology of small prairie wetlands. *Journal of Hydrology* **396**, 94–103.

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