Addressing heterogeneities in climate change studies for water resources in Korea

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Without exception, global warming affects the water resources in Korea. Several climate change projects have been initiated for future water resources assessment but have produced very different projections with a significant range of heterogeneities. Therefore, it is necessary to develop a standard procedure and scheme that can reduce this heterogeneity. In this study, we first examine all general circulation model (GCM) scenarios available at the IPCC Data Distribution Centre. The six A1B GCM scenarios are then selected (such as INM, CCCma, MPI_MIUB, UKMO, NIES and NCAR) for a climate change assessment of water resources in Korea. A modified version of a reliability ensemble average (M-REA) has been proposed as a multi-model ensemble weighting scheme that can combine the heterogeneous scenarios. When applied to the six A1B GCM scenarios, M-REA projected that Korea on an average will experience a 9.43% increase in precipitation in the year 2037.

Keywords: Climate change, ensemble, heterogeneities, water resources.

Introduction

ALTHOUGH there is a debate about whether global warming has been caused by an increase of greenhouse gases or by natural variability, global warming as an observed phenomenon cannot be ignored. In the last decade, as in other parts of the world, the presence of global warming in the Korean Peninsula has become considerably obvious. On an average, the surface temperature increased by ~1.5°C over the last century[1] and the sea surface level rose by 1.8 mm/year during the last 40 years. The annual precipitation gradually increased although its trend is not yet statistically significant, while the number of annual rainy days has reduced by 14% over the past 20 years and the rainfall intensity has increased by 18% (ref. 2). It is interesting that the annual precipitation in the northern part of the Korean Peninsula (North Korea) shows an opposite trend compared to the southern part of the Korean Peninsula (South Korea) because the annual precipitation in North Korea has decreased gradually. This might be the reason why North Korea has recently been facing more frequent and severe droughts, severely affecting its agricultural production. Some meteorologists in Korea have proposed that a change has taken place in the pattern of the Korean monsoon, called 'Jangma', during the summer months; Jangma was not able to migrate upward to the northern part of the Korean Peninsula, causing a decrease in precipitation in North Korea.

In Korea, many climate change studies have been made and significant differences between the studies have been reported. The present study provides a broad review of the results, analyses how heterogeneous the studies are and proposes methodologies that can handle the model heterogeneities.

Climate change studies

Although climate change studies for water resources in Korea were launched in the mid-1990s, most projects and studies began after 2000. We found that there are totally 38 project reports and 64 research papers available on climate change relevant to hydrology and water resources in Korea. They are classified into three subjects, projection, assessment and adaptation (Table 1). All the reports and papers address future projection because the assessment and adaptation need to be based on a projection. It is interesting that only 3% of the research papers deal with the adaptation issue whereas it was dealt with in half the project reports. This implies that adaptation techniques have not been intensively studied. It is to be noted that, of the US$ 400 million invested for the entire climate change R&D, less than 3% was invested for the development of adaptation strategies. This section briefly introduces major climate change projects conducted in Korea over the last decade.

The Ministry of Construction and Transportation[3] examined the potential effects of global warming on a water

Table 1. Ratio of the climate change reports (38) and papers (64) in Korea that deal with each subject

	Projection (%)	Assessment (%)	Adaptation (%)
Project reports	100	50.0	50.0
Research papers	100	66.7	3.0

100% represents all the reports or papers that handle the corresponding subject.

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resources system in Korea. Assuming a doubling in CO_2 concentration, basin-scale scenarios for precipitation and other hydrometeorological variables were generated from the existing general circulation model (GCM) results using a simple stochastic downscaling technique. Specifically, the existing outputs of five GCMs including CCC, GFDL, GISS, UKMO and GFDL-R30 were used to consider the uncertainty scenario and the maximum, average and minimum of these five GCM results were then considered, which were denoted as $2CO_2$–high, $2CO_2$–average and $2CO_2$–low scenarios respectively for each month. The generated temperature and precipitation scenarios were incorporated into the NWS-PC hydrologic model to generate the corresponding streamflow scenarios over the Geum river basin in Korea for the period 2001–2100. A reservoir simulation model for Daecheong dam in the Geum river basin was developed using the object-oriented simulation environment, STELLA. For each streamflow scenario, the performance of the reservoir was assessed in terms of reliability, resilience and vulnerability.

The Ministry of Environment[4] developed a regional climate model called SNURCM and applied a chained modelling procedure to evaluate climate change impacts on the Geum river basin from 2030 to 2049. Five GCM-driven climate change scenarios (called CSIRO (GCM name – Mk3.0), GFDL (CM2.1), CCSR (MIROC 3.2 hires), ECMWF (ECHAM5) and NCAR (CCSM3)) were downscaled to a 20×20 km scale using SNURCM and were incorporated to the *abcd* monthly water balance model. Note that the name inside parenthesis represents a GCM name that has been developed by the centre name in front of the parenthesis. A simulation model built in the STELLA environment is used to evaluate system sensitivity to changes in streamflow. An optimization model using sampling stochastic dynamic programing was then used to identify potential operational alternatives and recommend the adaptations available in the basin.

The Ministry of Science and Technology[5] examined the historical hydrometeorological time series through a trend analysis and projected a long-term variability of the future climate. Detailed future climate projections from ECHO-G based on the A2 and B2 emission scenarios were incorporated into RegCM3 to generate regional future climate projections. These climate projections were incorporated into the PRMS hydrologic model to generate the corresponding runoff scenarios for the Geum river basin for the period 2021–2050.

Climate change projects for water resources

This section compares results of climate change assessment studies in Korea to examine their degree of heterogeneity. A summary of major studies is shown in Table 2.

Most of the projects followed a typical chained modelling procedure for climate change. GCMs based on emission scenarios provided the future climate projection, whereas the results from GCMs were downscaled to generate the future river flows using several hydrologic models for water resources planning. However, the final results were heterogeneous because the selection of scenarios and models varied significantly. For example, although studies C, E and G were carried out in the same basin, their runoff projections varied and their projection ranges were large.

Selection of GCM scenarios

One hundred and forty eight GCM scenarios from 23 GCMs of 15 countries were available at the IPCC Data Distribution Centre (www.ipcc-ddc.org) as a result of the 4th IPCC assessment. However, we have studied only the A1B GCM scenarios and calculated monthly average precipitation and temperature from GCM grids that covered the Korean Peninsula. The GCM scenarios were then compared with observed values for a period from January 2001 to December 2007 (Figure 1). As in other parts of the world, for the Korean Peninsula, the GCM performed significantly better in the temperature simulation than in the precipitation simulation. Furthermore, it was found that all GCMs do not capture the summer monsoon pattern that causes the three-month flood season in Korea while the models generally perform relatively better in the precipitation simulation for the other seasons from October to the following June (called the low flow period hereafter). Therefore, in this study, the A1B GCM scenarios (Table 3) are employed for the nine-month low flow period.

The accuracy of each GCM was measured with the model efficiency[6] which becomes 100% when it is perfectly simulated. Table 4 reports model efficiencies of the A1B scenarios. Since all the scenarios performed well in the temperature simulation, in this study there were finally six GCM scenarios – (INM (CM3), CCCma (CGCM3), MPI_MIUB (ECHAM5), UKMO (HadCM3), NIES (MIROC) and NCAR (PCM)) – that produce the best model efficiencies in the precipitation simulation provided that the model efficiencies are larger than 80% in the temperature simulation. Note that the selected six GCMs such as INM, CCCma, MPI_MIUB, UKMO, NIES and NCAR projected increases of precipitation for the Korean Peninsula by –8.41%, 4.90%, 3.00%, 14.51%, –6.43% and –3.43% respectively.

Dealing with heterogeneities: multi-model ensemble weighting schemes

Several questions need to be answered: which of the many future projections we should follow and what kind of scenarios we should employ for our future adaptation

Table 2. Comparison of climate change assessment studies in Korea

	A	B	C	D	E	F	G
Basin	Korean Peninsula	Geum river basin	Geum river basin	Yongdam dam	Geum river basin	Yongdam* dam basin	Yongdam dam basin
GCM		IRSHAM96 based on MRI	CCC, GFDL, etc.	YONU CGCM	CCSM3, ECHAM5, etc.	YONU CGCM	ECHO-G
Future projection		30-year (1966–95)	100-year (2001–100)	20-year (2030–49)	20-year (2030–49)	20-year (2030–49)	30-year (2021–50)
Emission scenario	$2CO_2$	$1CO_2$, $2CO_2$	$1CO_2$, $2CO_2$	$1CO_2$, $2CO_2$	B1, A1B	$1CO_2$, $2CO_2$	A2, B2
RCM					SNURCM		RegCM3
Grid size		20 km × 20 km	Different		60 km, 20 km		60 km, 20 km
Time step	Annual	Daily	Monthly	Daily	Monthly	Monthly	Daily
Hydrologic model	Deterministic model	IRSHAM96	NWS-PC	SLURP	*abcd* model	TANK	PRMS
Changes of precipitation	–17–35%	Decrease in $2CO_2$	–5–13%	–18–7.2%	–12.5%		0–30%
Changes of runoff	–30–40%	Increase in flood and drought	–13–7%	20–40%	8.5%	Increase in flood	–10%

*Note that Yongdam dam is located in the Geum River basin.

Table 3. IPCC AR4 GCM list

Nation (centre)	GCM	Emission scenario
China (BCC)	CM1	A1B, B1
Norway (BCCR)	BCM 2.0	A2
USA (GISS)	AOM	A1B, B1
	E-H	A1B
	E-R	A1B, A2, B1
USA (NCAR)	CCSM3	A1B, A2, B1
	PCM	A1B, A2
USA (GFDL)	CM2.0	A1B, A2, B1
	CM2.1	A1B, A2, B1
Italy (INGV)	SXG2005	A1B
Russia (INM)	CM3.0	A1B, B1
France (IPSL)	CM4	A1B, A2, B1
Australia (CSIRO)	Mk3.0	A1B, A2, B1
Germany (MPI-M)	ECHAM5-OM	A1B, A2, B1
Germany/Korea (MIUB METRI M&D)	ECHO-G	A1B, A2
Canada (CCCma)	CGCM3(T47)	A1B, B1
	CGCM3(T63)	A1B, B1
Japan (MRI)	CGCM2 3.2	A1B, A2, B1
Japan (NIES)	MIROC 3.0 hires	A1B, B1
	MIROC 3.2 medres	A1B, A2, B1
UK (UKMO)	HadCM3	A1B, A2, B1
	HadGEM1	A1B, A2

strategy. To help answer these questions, we present some methodologies for dealing with multiple, heterogeneous scenarios that are common in global warming studies. Specifically, we attempt to combine various scenarios to effectively produce a single summary series of these scenarios with multi-model ensemble (MME) weighting schemes[7–9].

Reliability ensemble average

The simplest way to combine multiple model outputs is to assign an equal weight to each model and take an arithmetic average of the model outputs. When information was available on individual models, such as past model performances, unequal weights were assigned to each model using this information (model accuracy) to combine the model series[10–15].

Giorgi and Mearns[11] proposed a weighting scheme to combine temperature projections from multiple GCMs. They considered model consistency as well as model accuracy, which is given by

$$R_i = \left\{ \left[\frac{\varepsilon_T}{\text{abs}(B_{T,i})} \right]^m \left[\frac{\varepsilon_T}{\text{abs}(D_{T,i})} \right]^n \right\}^{[1/(m \times n)]}, \tag{1}$$

where R_i is the weight on the ith GCM, ε_T the difference between the maximum and the minimum temperatures among the 10-year moving averages, $B_{T,i}$ the bias for the simulated temperature series of the ith GCM during a historical period, $D_{T,i}$ the difference between ΔT_i and the average of ΔT_i values over the GCMs, and ΔT_i is the average change between the simulated and the projected temperature series. The first and second terms on the right side of eq. (2) represent the model accuracy and

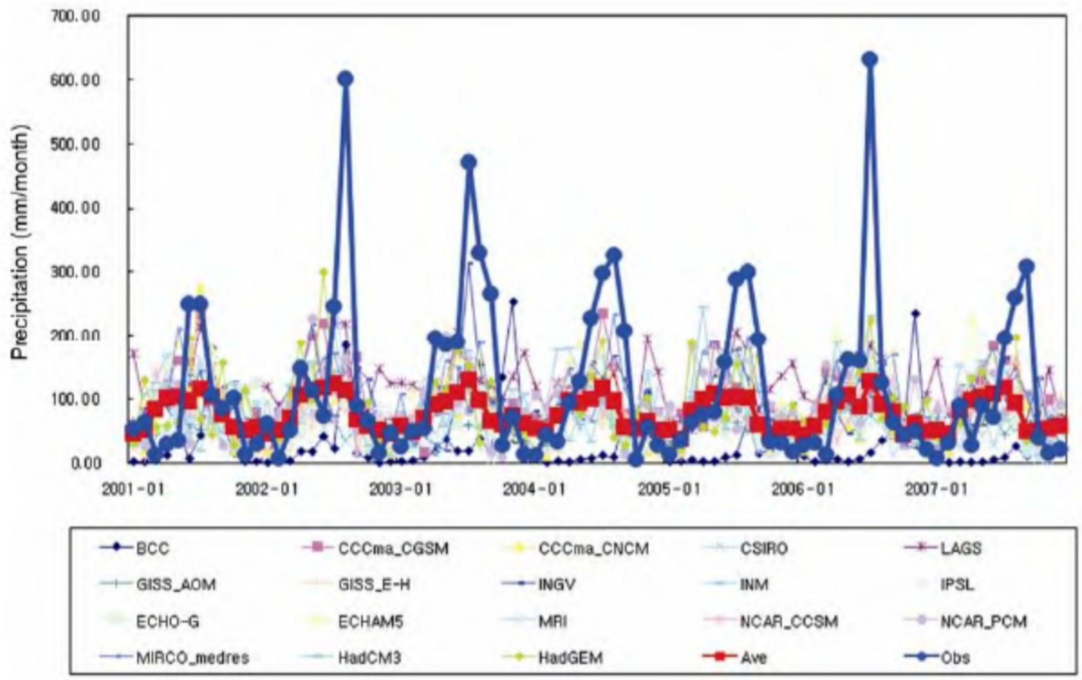

Figure 1. A1B GCM time series of monthly average precipitation for the Korean Peninsula. 'Ave' represents an ensemble average series of the GCM scenarios and 'Obs' represents the observed series.

Table 4. Model efficiencies (%) of the A1B GCM scenarios for the Korean Peninsula

Centre	GCM	Precipitation	Temperature
INM	CM3.0	0.02	0.87
CCCma	CGSM#_T47	–0.06	0.90
MPI_MIUB	ECHAM5	–0.10	0.90
UKMO	HadGEM1	–0.28	0.90
NIES	MIRCO 3.2 medres	–0.37	0.90
NCAR	PCM	–0.52	0.94
MRI	CGCM 2.3.2	–0.79	0.89
GISS	E-H	–0.81	0.86
INGV	SXG2005	–0.94	0.85
NCAR	CCSM3	–1.77	0.92
UKMO	HadCM3	–2.12	0.84
MPI_MIUB	ECHO-G	–2.28	0.84
CSIRO	Mk3.0	–6.54	0.87
GFDL	CM2.1	–0.19	0.71
IPSL	CM4	–1.12	0.61
BBC	CM1	–2.12	0.53
CCCma	CNCM3	–1.18	0.54
GISS	AOM	–2.50	0.75

the model consistency respectively. Because of the model consistency term, a model that projects differently from the average pattern of the other models has a small weight. In eq. (1), while Giorgi and Mearns[11] used temperature series to determine model weights, we employ in this study precipitation or a runoff series to calculate the weights.

Modified reliability ensemble average

The present study reveals two shortcomings of the reliability ensemble average (REA) and proposes an alternative called the M-REA (modified REA). First, R_i diverges if a model is unbiased because $B_{T,i}$ becomes zero. Second, the model accuracy is generally better measured using the root mean square error (RMSE) than using only the bias ($B_{T,i}$). RMSE reflects both the random and systematic error while the bias is only a measure of the systematic error. Therefore, assuming $m = n = 1$ in eq. (1), we modify eq. (1) slightly by substituting $B_{T,i}$ with the RMSE term.

$$R_i = \left[\frac{\varepsilon_T}{\mathrm{RMSE}_{T,i}}\right]\left[\frac{\varepsilon_T}{\mathrm{abs}(D_{T,i})}\right]$$

$$= \left[\frac{\varepsilon_T}{\sqrt{B_{T,i}^2 + \mathrm{Var}(T_i)}}\right]\left[\frac{\varepsilon_T}{\mathrm{abs}(D_{T,i})}\right], \quad (2)$$

where $\mathrm{RMSE}_{T,i}$ is the root mean square error for the simulated temperature series of the ith GCM during the historical period and $\mathrm{Var}(T_i)$ is the variance of the simulated temperature of the ith GCM during the historical period.

Regional skill scores

Dessai *et al.*[16] proposed the regional skill scores (called RSS) that incorporated the modified version based on Taylor[17]. RSS also consists of a model performance term that compares the GCM simulations with observations and a model convergence term that compares the GCM projections with the multi-model ensemble average. RSS is similar to M-REA, whereas the numerator of RSS differs from that of M-REA. RSS is given by

$$S = \left(\sqrt{S_{\text{performance}}} \times \sqrt{S_{\text{convergence}}}\right)^4,$$

$$S_{\text{performance}} = \frac{|\bar{x}_{\text{obs}}|}{\left[1/N \sum_{i=1}^{N} (x_{i,\text{mod}} - x_{i,\text{obs}})^2\right]^{1/2}},$$

$$S_{\text{convergence}} = \frac{|\bar{x}_{\text{ens}}|}{\left[1/N \sum_{i=1}^{N} (x_{i,j} - x_{i,\text{ens}})^2\right]^{1/2}}, \qquad (3)$$

where $S_{\text{performance}}$ is the accuracy of the historical GCM scenarios, $S_{\text{convergence}}$ the heterogeneity of the projected GCM scenarios, $x_{i,\text{mod}}$ the *i*th GCM simulations, $x_{i,\text{obs}}$ the *i*th observation, $x_{i,j}$ the *i*th simulation of the *j*th GCM scenario, $x_{i,\text{ens}}$ the ensemble average of the *i*th simulation, and $\bar{x}_{\text{ens}}$ the multi-model ensemble average. Note that RSS is identical to M-REA only when the performance term is used.

Bayesian model averaging

Recently, the use of Bayesian model averaging (called BMA) based on Bayesian theory has focused on the combining method. BMA overcomes the typical approach whereby the best model is selected among the possible competing models and the uncertainties are ignored or underestimated due to conditioning, on the entire ensemble of statistical models rather than only on a single best model[18]. The basic concept of BMA is given by

$$p(y \mid f_1, \ldots, f_k) = \sum_{k=1}^{K} \omega_k g_k(y \mid f_k)$$

$$g_k(y \mid f_k) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{y - \mu_k}{\sigma_k}\right)^2\right], \qquad (4)$$

where $p(y \mid f_1, \ldots, f_k)$ is the probability of observations required considering all GCM scenarios, y the observation, f the GCM scenario, K the number of GCM scenarios, $g_k(y \mid f_k)$ the probability distribution of the *k*th GCM scenario (the prior probability distribution), μ_k and σ_k the mean and standard deviations of the *k*th GCM scenario respectively, and ω_k the weight of the *k*th GCM scenario (the posterior probability). Weights ω_k were calculated using the expectation–maximization algorithm.

Application of multi-model ensemble weighting schemes

Study basin

The Geum river flows north westerly to about its midpoint, then flows south westerly for 395.9 km, before draining into an area of 9915.09 km^2 which occupies 10% of South Korea. The annual total precipitation of the Geum river basin is 1130.7 mm and more than 60% of the total precipitation occurs during the wet season in the months of July, August and September. The average annual runoff of the Geum river is 6627×10^6 m^3 and 73% of the total runoff occurs during the wet season. The river basin has two multipurpose dams: the Daecheong dam and the Yongdam dam (Figure 2). Located approximately 150 km upstream from the mouth of the Geum river, Daecheong dam is a water supply and flood control dam. The basin area of Daecheong dam is 4134 km^2, which is 42% of the Geum river basin. Yongdam dam was built in 2001 and is located 199.4 km upstream of Daecheong dam. The basin area of Yongdam dam is 930 km^2, which is only one-fifth as large as the drainage area of Daecheong dam.

Results and discussion

The selected six GCM scenarios were employed to test the proposed MME schemes using only the performance term for a low flow period from 2001 to 2007. Table 5 shows the resulting weights of each of the tested MME schemes assigned to the six GCMs and also the RMSE of each MME scheme. First, all the weighted averages of MME are superior to the simple average in RMSE and bias, which implies that MME is valuable to reduce heterogeneities. M-REA proposed in this study improves REA with respect to RMSE but not with respect to bias. Therefore, a choice between REA and M-REA depends on preference of the accuracy measure properties such as an unbiased perspective and efficiency. Note that M-REA considers INM as the second most important model whereas REA considers it as the least important. M-REA also produces results identical to RSS because only the performance term was used and both M-REA and RSS outperform the other schemes.

Table 6 reports M-REA and RSS assigned to different weights for a projection period where the convergence term is also included in both schemes. According to M-REA, which is the best MME scheme for the Korean Peninsula, it is anticipated that precipitation in Korea will increase by 9.43% in the year 2037.

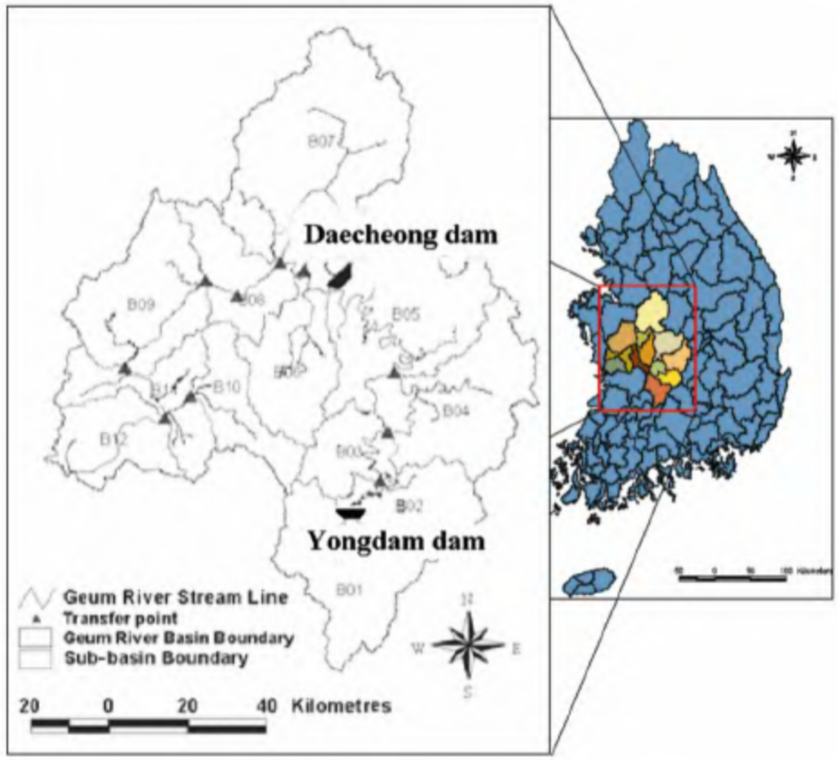

Figure 2. Location of the Geum river.

Table 5. Weights assigned by multi-model ensemble weighting schemes and the resulting RMSEs and biases for the calibration period

	Weights						RMSE (mm/month)	Bias (mm/month)
	INM	CCCma	MPI_MIUB	UKMO	NIES	NCAR		
REA	0.125	0.223	0.159	0.251	0.146	0.096	49.207	27.652
M-REA and RSS	0.158	0.197	0.153	0.193	0.154	0.146	48.853	29.440
BMA	0.150	0.230	0.125	0.221	0.145	0.128	49.067	29.671
Simple average	0.167	0.167	0.167	0.167	0.167	0.167	49.632	30.977

Table 6. Weights assigned by multi-model ensemble weighting schemes and the resulting precipitation projections for the year 2037

	Weights						Precipitation increase projection for 2037 (%)
	CM3.0	CGSM#_T47	ECHAM5	HadGEM1	MIROC3.2 medres	PCM	
REA	0.090	0.288	0.147	0.300	0.122	0.053	(+) 8.40
M-REA	0.153	0.238	0.143	0.191	0.145	0.130	(+) 9.43
BMA	0.164	0.312	0.141	0.062	0.191	0.130	(+) 14.00
RSS	0.124	0.290	0.148	0.143	0.179	0.116	(+) 9.51

Conclusion

Reviewing the projects and studies conducted for the climate change impact on water resources in Korea, we have found that most of the research results were significantly heterogeneous even when obtained from the same basin and they showed a wide range of heterogeneities through the typical climate change procedures. We also examined all the A1B GCM scenarios available at the IPCC Data Distribution Centre, and selected six GCM scenarios including INM, CCCma, MPI_MIUB, UKMO, NIES and NCAR and that were also based on the model efficiency and proposed them as the best GCM scenarios for the Korean Peninsula. To take care of uncertainty, we finally proposed an improved multi-model ensemble scheme called M-REA and compared it with the existing MME scheme. When applied to the six A1B GCM scenarios, M-REA projected that Korea will experience a 9.43% increase in precipitation on average in the year 2037. For future research, the present study will be extended to make a projection of streamflow and water shortage for basins in Korea.

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