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Article

A New Way for Incorporating GCM Information into Water Shortage Projections

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Abstract: Climate change information is essential for water resources management planning, and the majority of research available uses the global circulation model (GCM) data to project future water balance. Despite the fact that the results of various GCMs are still heterogeneous, it is common to utilize GCM values directly in climate change impact assessment models. To mitigate these limitations, this study provides an alternative methodology, which uses GCM-based data to assign weights on historical scenarios rather than to directly input their values into the assessment models, thereby reducing the uncertainty involved in the direct use of GCMs. Therefore, the real innovation of this study is placed on the use of a new probability weighting scheme with multiple GCMs rather than on the direct input of GCM-driven data. Applied to make future projections of the water shortage in the Han River basin of Korea, the proposed methodology produced conservative but realistic projection results (15% increase) compared to the existing methodologies, which projected a dramatic increase (144%) in water shortage over 10 years. As a result, it was anticipated that the amount of water shortages in the Han River basin would gradually increase in the next 90 years, including a 57% increase in the 2080s.

Keywords: water resources management; water balance; Global Circulation Model (GCM); climate change; water shortage

1. Introduction

An accurate water balance projection is essential to a successful water resources planning for an uncertain future, especially in a nonstationary world [1]. Water balance projections simply calculate the difference between the total water demand and the total supply capability for a basin. When the demand exceeds the supply, water shortage occurs. To be systematic, short- and medium-range water resource planning alternatives, which can reduce potential water shortages, should be established under a predefined long-range water resource plan encompassing at least 20 years. For such a long-range time scale, the impacts of climate change cannot be ignored.

This study began with a broad review of studies that focused on water balance projection methodologies reflecting climate change impacts. Most studies utilized multiple general circulation model (GCM) climate change scenarios, and the average number of GCM scenarios used in these water balance projection studies ranges from four to five. For instance, some studies relied on only a single GCM scenario [2–4], whereas Islam *et al*. [5] applied the most number of GCM scenarios, which is 12 in total. In terms of water shortage calculation, water balance analysis models have been commonly used with GCM-driven streamflow scenarios. Thus, most studies that project future water balance have been using GCM-driven runoff series as water supply scenarios. They also used multiple GCM scenarios to overcome the heterogeneity that arises from GCMs. Moreover, various water balance analysis models have been utilized, which include CalSim II [6], WEAP [7,8], CALVIN [3], WRAP [9], Mospa [10], Sibuc [11], IQQM [12], Riverware [13], and WSM [14]. In Korea, the K-WEAP and the K-MODSIM models have been popularly employed for water balance analysis, and there have been several efforts to incorporate GCM scenarios into water balance analysis to reflect future climate change impact [15–17]. Thus, most studies made use of different models for their own purposes.

The assessment of future water resources using GCM-driven streamflow, which is the general analysis framework of most previous studies, would provide an evaluation of possible climate change impacts. However, there are two possible problems to be considered when GCM-driven streamflow scenarios are used for water balance analysis. First, Korea, for example, has established its own national water resource plan based on historical data. Although it is imperative that the impacts of climate change on long-range water resources be considered, an inconsistency in methodologies may occur if historical runoff data are suddenly substituted with GCM-driven runoff scenarios. Furthermore, it would be risky to establish water resource plans based on the results of GCM-driven scenarios when they are directly inputted into the water balance analysis models because of the heterogeneity and uncertainty that arise from GCMs.

This paper describes a new alternative approach that uses GCM climate information by assigning weights to historical runoff scenarios rather than directly inputting GCM-driven runoff into water balance models. By maintaining most of the existing water balance analysis framework, the proposed methodology is able to mitigate the risk created by the uncertainty of GCM-driven values.

The remainder of this paper is organized in the following manner. The first section demonstrates the previous methodology for water shortage projection. The next section describes the new water shortage projection methodology, which incorporates climate change impacts and compares it to the previous methodology. The application of this approach is described in the following section. The application results are analyzed by comparing them with the results of the previous methodology, and future water shortage projection results in each future period are presented. This paper concludes with a summary of the results and a discussion of possible avenues for further studies.

2. Materials and Methods

2.1. Previous Methodology

2.1.1. Water Vision 2020: The National Water Resources Planning Report in Korea

In general, most countries have established their own long-term water resources plans. In Korea, the long-term water resources plan is established every 20 years and updated every 5 years. The current plan entitled "*Water Vision 2020*" was established in 2001 and updated in 2011. Water balance analysis predicts possible water shortages by calculating the balance between water supplies—Such as surface runoff, reservoir storage, and groundwater—And multiple water demands, including municipal, agricultural, and industrial demands. In this regard, water balance analysis is one of the core parts of the long-term water resources plan. A rainfall-runoff model calculates the conversion of rainfall into runoff using the observed rainfall data. Afterward, a water balance model estimates the amount of water shortages using this calculated runoff data as fundamental water supply.

In the case of Korea, the water shortage for each watershed is calculated every five days because agricultural water demands temporally vary during the farming season. When it comes to a model used in Water Vision 2020, the TANK model, a conceptual rainfall-runoff model that is composed of multiple tanks laid vertically, and the K-WEAP model (briefly introduced in Section 2.4) have been officially applied as the rainfall-runoff model and the water balance model, respectively. Water Vision 2020 [18] declared that the water shortage of the Korean Peninsula will amount to 862 million m^3 in 2020 (Table 1).

Table 1. Water shortage projection of previous studies in Korea.

Report	Water Vision 2020 [a]	The Strategic Report [b]
Target year	2020	2040s (2031 ~ 2060)
Maximum water shortage (10^6 m^3)	862	3300

Notes: The same water demand scenario was applied to both reports. [a] "*Water Vision 2020* (*2006–2020*)", which is the national water resources plan in Korea, used the observation-driven flow in 1967–2003 as water supply scenarios [19]; [b] The Strategic Report, "*Adaptation to Climate Change in Future Water Resources Management*", used a fine resolution RCM-driven runoff series in 2031–2060 as water supply scenarios.

2.1.2. An Example of Water Balance Analysis Using Climate Change Information

Studies on climate change impacts have sporadically been conducted in Korea since the mid-1990s. However, "*The Strategic Report*," which is the first national report on water resources planning that considered climate change, was published based on the research [15]. The Strategic Report estimated the future water balance of the Korean Peninsula, taking into consideration climate change information, as shown in Table 1, but there remained two issues to be resolved.

First, the continuity of the existing water balance analysis methodology, that is, the methodology of the current national plan, was not considered. The Strategic Report utilized rainfall data from a single RCM, while the typical national water resources plans, Water Vision 2020, used the observed rainfall data as an input variable as mentioned above. Moreover, The Strategic Report suddenly changed the rainfall-runoff model from the TANK (used in Water Vision 2020) to the Semi-Distributed Land Use-Based Runoff Processes (SLURP) which has made the discrepancies in methodology larger. The TANK is a conceptual rainfall-runoff model, whereas the SLURP is a semi-distributed model that makes use of graphical data input and a graphical display of output. Both models simulate vertical water balance for runoff calculation, but the SLURP routes runoff from each element to the outlet. In this regard, the TANK is computationally less intensive, whereas the SLURP can produce spatial maps of runoff. Although the SLURP model has some advantages for spatial representation, this inconsistency in the use of a hydrologic model can mask a fair and effective comparison between different methodologies.

The other issue was the lack of reflection of the uncertainty that arises from climate change scenarios. The Strategic Report used rainfall data from a single RCM called RegCM3 under an A2 emission scenario. However, the projected monthly rainfall series from various GCMs provided by the Intergovernmental Panel on Climate Change (IPCC) lead to highly heterogeneous results [19], as shown in Figure 1. Given that these uncertainties are rather noticeable, a national water resources plan based on a single GCM scenario seems unrealistic. Moreover, the direct use of GCM datasets through hydrologic and water balance models could be risky in practice because GCMs are still highly uncertain despite the fact that many climate change studies rely on their direct use.

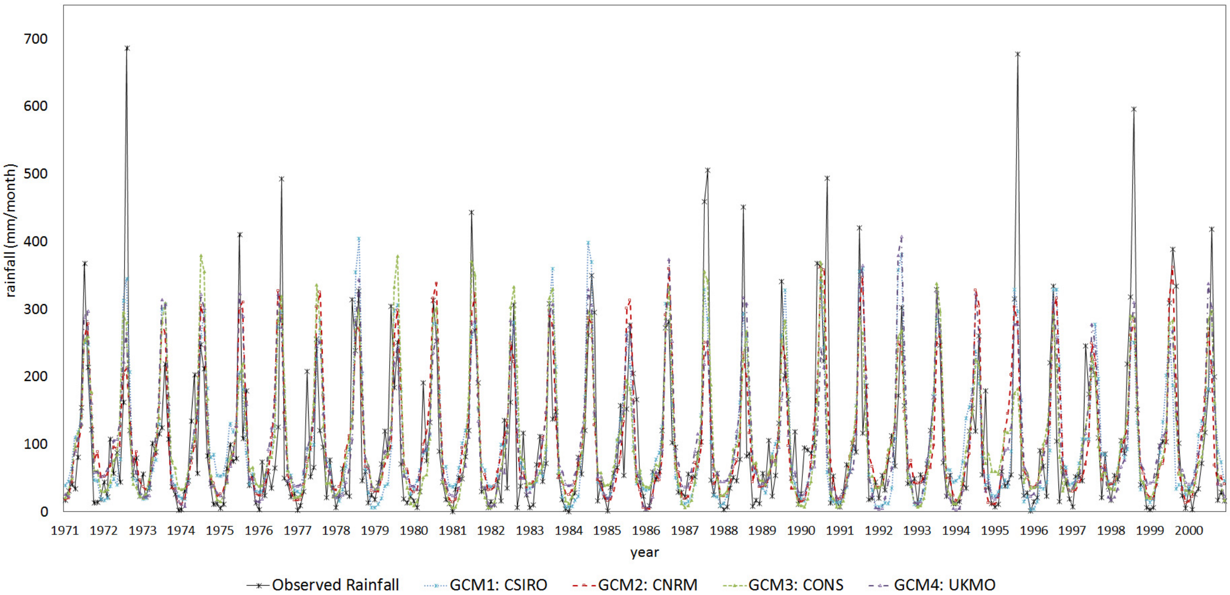


Figure 1. Time series plots of the observed and simulated monthly rainfall of four GCMs under the A2 scenario for the Korean Peninsula.

2.2. New Approach

2.2.1. Overview

This study has proposed a new alternative approach to solve these two problems, which are the discontinuity of the existing water balance analysis methodology for the current national water resources management plan and the direct use of GCM projection values, which involves a huge uncertainty. To ensure the continuity of the existing methodology, the TANK model which has been used for "*Water Vision*," the national water resources management plan, was used as a rainfall-runoff model. Second, by considering the runoff series driven by observed rainfall time series (rather than GCM) as an input climate variable for the water balance model, the continuity of the methodology could be maintained. In addition, four GCM datasets under the AR4 A2 emission scenario were used to consider the uncertainty that arises from GCMs. Then, GCM information was incorporated to estimate the likelihood of observation-driven runoff scenarios to minimize the risks when GCM values are directly utilized. The proposed methodology assigns more probability to an observation-driven scenario, which is closer to a GCM scenario.

2.2.2. Weighting Scheme

In this study, a nonparametric *K*-nearest neighbor (*K*-nn) algorithm [20–22] was used as a weighting scheme for clustering/sampling objects based on the closest training samples. This algorithm has been widely applied because of its simple and useful scheme to weight the contribution of the neighbors so that the closer neighbors can contribute more to the expectation than the more distant ones [20].

2.2.3. Procedure

The procedure is described as follows. Suppose that there are m years (e.g., 30 years of available GCM data in a target period) of the runoff series simulated by inputting GCM data (hereinafter GCM-driven flow) where the runoff series simulated by inputting historical observed rainfall data (hereinafter observation-driven flow) can be obtained. In the case of the ith year of the target period, this study selects K number of nearest neighbors to a given GCM-driven flow of the ith year among a whole annual series of observation-driven series, and inputs these K series into a water balance model to estimate the water shortage value of the ith target year. Here, the metric distance to be compared is the total sum of monthly flows for nine months (from October to the following June), that is, the non-flood season in Korea. Scenario selecting and weighting schemes are based on the *K*-nn algorithm. By calculating the weighted average value across the selected K series, the water shortage value (S_i) of the ith year of the target period can be obtained. The weight of the jth nearest series (w_j) can be estimated using the following equation (1):

$$w_j = \frac{1/j}{\left(\sum_{j=1}^{K} 1/j\right)} \tag{1}$$

where $j = 1$ represents the nearest neighbor while $j = k$ represents the kth nearest neighbor.

The aforementioned steps are repeated from the first year to the last year of the target period, and the whole procedure is carried out using all GCMs.

2.3. Study Basin

The proposed methodology was applied to the Han River basin located at the center of the Korean Peninsula (Figure 2). The area of the Han River is approximately 26,200 km^2, which is 23% of the national territory, and the total length of the basin is approximately 481 km. Prior to the construction of a number of major dams, the river was known for its huge coefficient of river regime, with a ratio between the maximum and the minimum amount of flow of 1:390. The annual mean precipitation and runoff based on a 30-year period from 1978 to 2007 are 1260 mm and 17.4 billion m^3, respectively. Because of the monsoon climate, 62% of the annual precipitation occurs during the three-month flood season from late June to late September. The Han River basin is occupied by several types of land covers, such as urban, paddy fields, farms, forests, grassland, wetlands, barren, and water, but more than 70% of the basin is covered with forests. The major soil type in the basin (as of 2001) is lithosol, which typically has a shallow overburden and lacks horizon development because of the steep slopes.

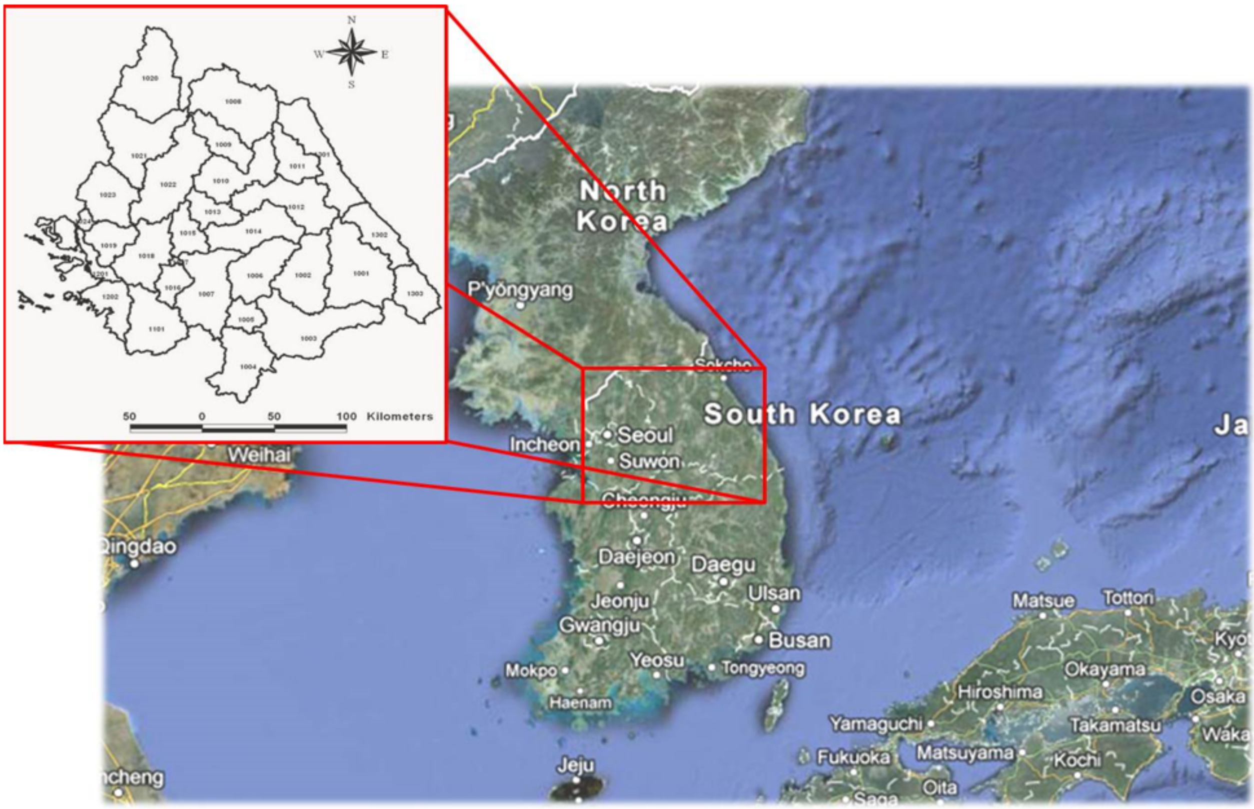


Figure 2. Han River basin, Korea.

2.4. Water Balance Model

The K-WEAP water resources management model was used to project potential water shortages for each sub-watershed of the Han River basin. The K-WEAP model was developed through a cooperation between the Korea Institute of Construction Technology (KICT) and the Stockholm Environment

Institute—Boston Center (SEI-B). Before becoming officially adopted in Water Vision 2020, the K-WEAP was tested by several studies to prove its applicability and efficiency [23]. A linear program, built in the model, is applied to solve water allocation problems at each time step by maximizing the satisfaction of water demands subject to supply priorities, demand site preferences, and other constraints (see [24] for details). Figure 3 presents a snapshot of the Han River basin's water allocation network realized in the K-WEAP model.

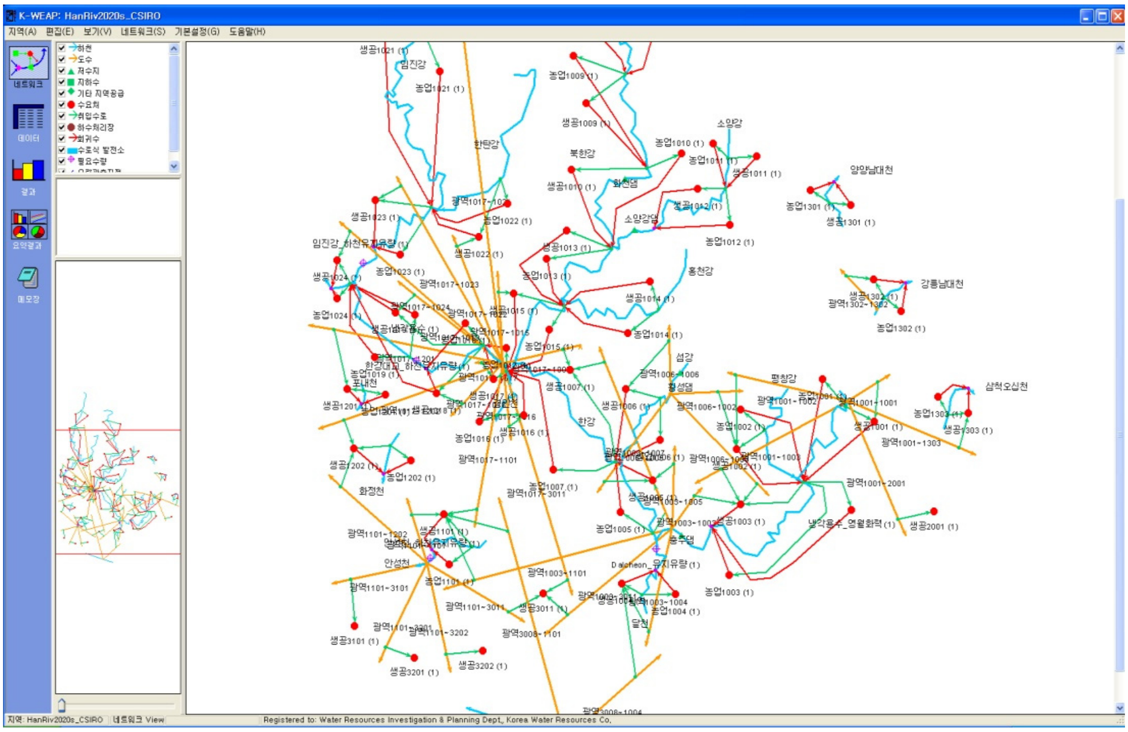


Figure 3. Schematic network of the Han River basin, the K-WEAP model.

2.5. Climate Change Scenarios

To take into account GCM uncertainty, this study utilized four GCM datasets under an A2 emission scenario from IPCC AR4: CSIRO, CNRM, CONS, and UKMO (Table 2). Although recent studies on climate change projection use RCP (representative concentration pathways) scenarios from IPCC AR5, which is up-to-date climate change information, we preferred to use the former dataset—A2 emission scenario from IPCC AR4—for an exhaustive comparison with the current national water resources management plan of Korea. The A2 emission scenario is used here under the assumption that there will be radical climate change due to the continuously increasing population and a very heterogeneous world. These four GCM datasets were selected based on the research that addresses a selection of principal GCM scenarios [25]. Lee [25] provided principal scenarios that reflects overall uncertainty across multiple GCM datasets. Thus, the selected GCM datasets can preserve most of the uncertainty even though all of the GCM datasets available are not used. According to Kim and Lee [20], those GCMs were known to more suitably represent the Korean rainfall patterns in the low-flow (non-flood) period (October to June), along with better performance on temperature. The GCM data on monthly temperature and precipitation were downloaded from the IPCC data distribution center [26]. Figure 4 illustrates the monthly precipitation and its standard deviation of both the observed data and the CSIRO: MK3.0 GCM hindcast precipitation data.

As shown in this figure, the GCM mean series follow well those of the observed data, while the GCM standard deviation series tend to underestimate those of the observed data.

Table 2. GCMs used in this study.

No.	Model (Agency: Version)	Abbreviation	Country	Resolution (km)	
				Atmosphere	Ocean
1	CSIRO: MK3.0	CSR	Australia	192 × 96	192 × 189
2	CNRM: CM3	GNR	France	128 × 64	182 × 152
3	CONS: ECHO-G	MIU	Germany/Korea	96 × 48	128 × 117
4	UKMO: HadCM3	UKC	United Kingdom	192 × 144	360 × 216

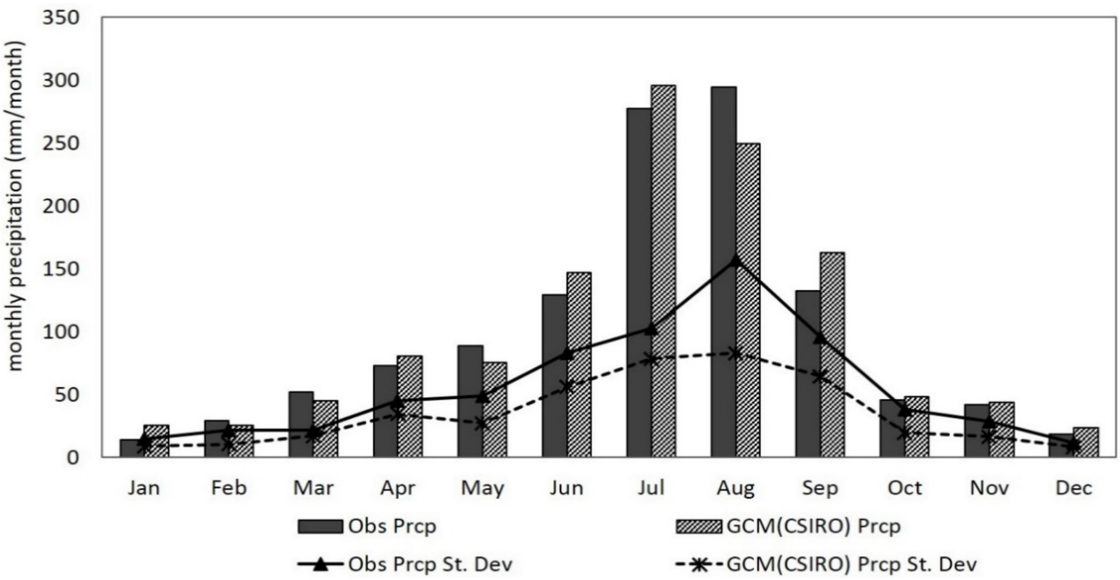


Figure 4. Mean monthly precipitation and standard deviation of observed and GCM-simulated series (1971–2000).

However, these GCM data should be spatially downscaled to local scale and temporally disaggregated to daily series to be used as an input forcing data of the TANK model. Hence, these GCM data are spatially downscaled and temporally disaggregated by Bae *et al*. [27]. They spatially downscaled the GCM data using the cyclostationary empirical orthogonal function (CSEOF) and multi-linear regression analysis, and temporally disaggregated from monthly to daily series using a weather generator called WXGEN [27].

2.6. Bias Correction

The GCM-driven flows usually contain a systematic bias [28], which should be corrected before being applied to a water balance model. This study employed a quantile mapping (QM) technique, which has been frequently applied to correct the bias of flow series [10,29,30], and is based on a bias correction technique for the downscaled GCM output described by Wood *et al*. [31]. Unlike a simple bias correction method such as the delta method, which applies a constant correction factor for all events within a single duration (e.g., a month), the QM determines correction factors by mapping hindcast/historical

GCM-driven flows to observation-driven flows through the empirical distribution of variables, and same correction factors are applied to the projected future GCM-driven flows of the target period. In other words, the non-exceedance probability of the future GCM value is mapped in the empirical distribution of the GCM hindcast dataset with a duration that is similar to the observed dataset [28]. Then, future GCM values are corrected through the Equation (2) as follows. More details about the QM technique are described on Wiley [28].

$$Z_i = F_{oi}^{-1}\left(F_{si}\left(\hat{Y}_i\right)\right) \tag{2}$$

where $\hat{Y}_i$ is the projected future GCM value, Z_i is the bias-corrected value, $F_{si}(\cdot)$ is the empirical CDF of the GCM hindcast data set, and $F_{oi}(\cdot)$ is the empirical CDF of the observed dataset.

3. Results

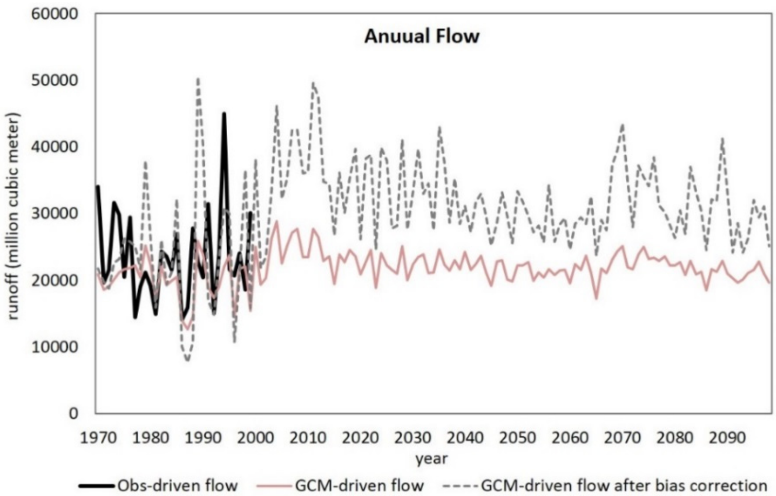
3.1. Flow Projections

The daily precipitation and potential evaporation projections in the basin scale were inputted into the TANK rainfall-runoff model, which was officially utilized in the development of Water Vision 2020 in Korea. The GCM-driven daily flow series for 130 years (1970–2099) were simulated by the TANK model using the downscaled precipitation and potential evaporation, and they were bias-corrected. A 100-year flow series (2000–2099) was corrected based on a 30-year control period (1970–1999). Figure 5 presents the annual flow series of observation-driven flow, the GCM-driven flow without bias correction (CSIRO MK3.0 GCM model), and the GCM-driven flow with bias correction. As shown in Figure 5, without bias correction, the annual mean value and the variation of the GCM-driven flow were somewhat underestimated than the observation-driven flow in the historical period. However, after the QM-based bias correction, both the annual mean value and the variation of the GCM-driven flow were reliably realized as to those of the observation-driven flow.

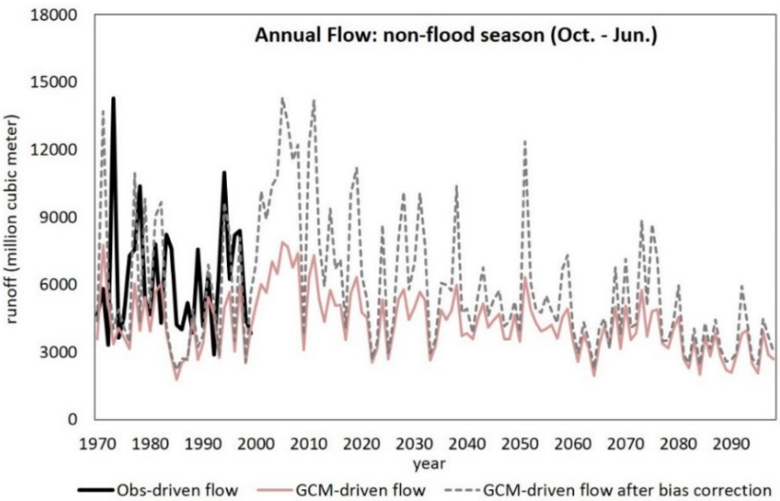
Figure 6 shows the monthly pattern of the bias-corrected GCM-driven flow, averaged over the four GCMs, in the Han River basin in four time periods: the basis (1967–2003), 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099). In the 2020s, as shown in Figure 6, whereas a dramatic increase of flow is anticipated for the flood season, a moderate decrease is anticipated for the fall and winter seasons (October—January), which is in accordance with Figure 5b, which shows a decreasing trend for 2020s. Moreover, this decreasing trend in the low-flow season lasts until the 2080s. Given that water shortage is mainly affected by the low-flow season, we only focused on this non-flood annual series of GCM-driven flow in this study.

3.2. Water Shortage Projections

A set of time series of observation-driven flows for 37 years from 1967 to 2003 was inputted into the K-WEAP water balance analysis model. Note that the GCM-driven flow projections were not directly inputted but rather utilized to assign a weight to each yearly scenario of the 37-year observation-driven flows. In other words, the closest seven observation-driven flow scenarios to the value of the given year of each GCM-driven flow are selected through the *K*-nn technique. Then, using Equation (1), the corresponding weights of the selected seven scenarios were estimated, and these weights were used to calculate the weighted average of the seven water shortages values driven by the seven selected flows. Consequently, zero weight was assigned to each of the remaining 30 scenarios, that is, not used in the analysis of the given year. This procedure was repeated for the four GCMs, and the final water shortage projection in the projection year was calculated as the average of the four GCM results. In this study, it is assumed that the water demand for the year 2020, estimated by Water Vision 2020, remains constant throughout the entire projection period. Table 3 summarizes the average water shortage (AWS) in the Han River basin in three future periods, such as the 2020s, 2050s, and 2080s. Moreover, Figure 7 presents a trend of water shortage projections, which is the AWS toward the end of the 21st century. It was anticipated that the amount of water shortages in the Han River basin would gradually increase over the next 90 years, and water shortages would increase up to 56% on average (ranging from 33% to 78%) in the 2080s compared to the current water shortage amounts projected by Water Vision 2020.



(**a**)



(**b**)

Figure 5. Annual flow comparison of observation-driven flow, GCM-driven flow (without bias correction), and GCM-driven flow after bias correction: (**a**) total annual flow; (**b**) non-flood season flow.

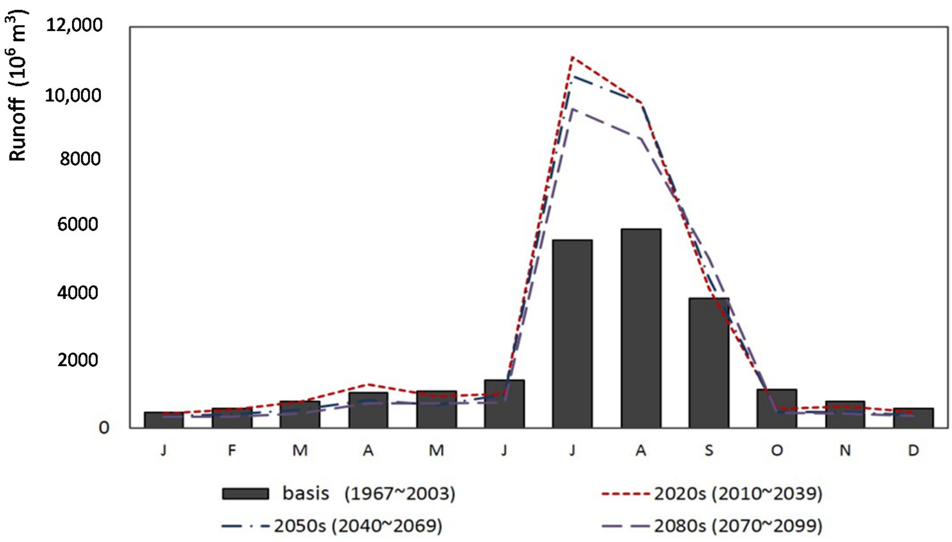


Figure 6. Monthly flow variations in the projections for the Han River basin, Korea.

Table 3. The average water shortage projections in the Han River basin (unit: 10^6 m^3).

Water Vision 2020 [a] **(Target Year: 2020)**	**Future Projection**			
	GCM Models	**2020s**	**2050s**	**2080s**
42.0	CSIRO: MK3.0	42.3	49.6	55.8
	CNRM: CM3	47.1	55.7	72.8
	UKMO: HadCM3	52.9	70.9	74.6
	CONS: ECHO-G	51.6	59.8	60.6
Average **(increase ratio from the current)**		48.5 **(15% ↑)**	59.0 **(40% ↑)**	65.4 **(56% ↑)**

Note: [a] Water Vision 2020 used the observation-driven flow in 1967 ~ 2003 as water supply scenarios [19].

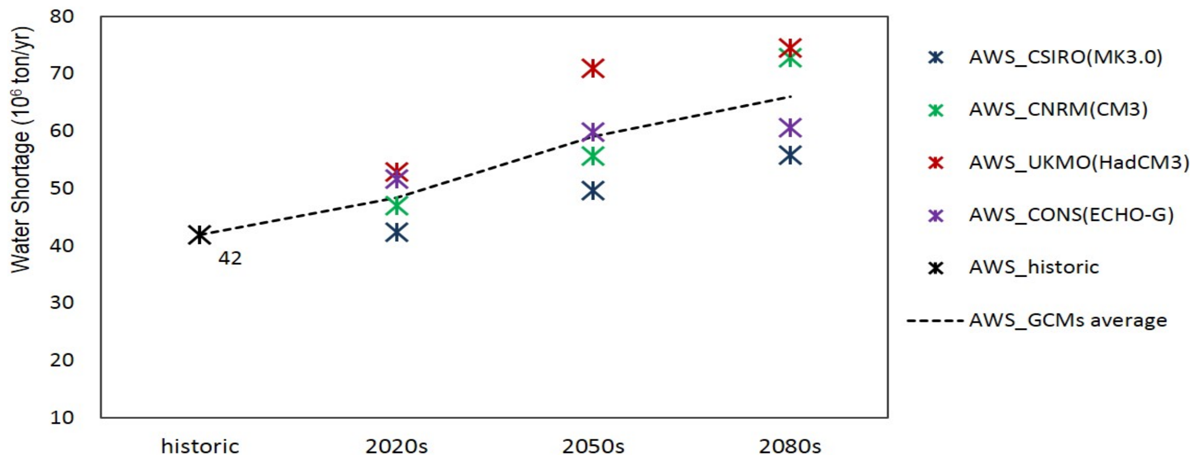
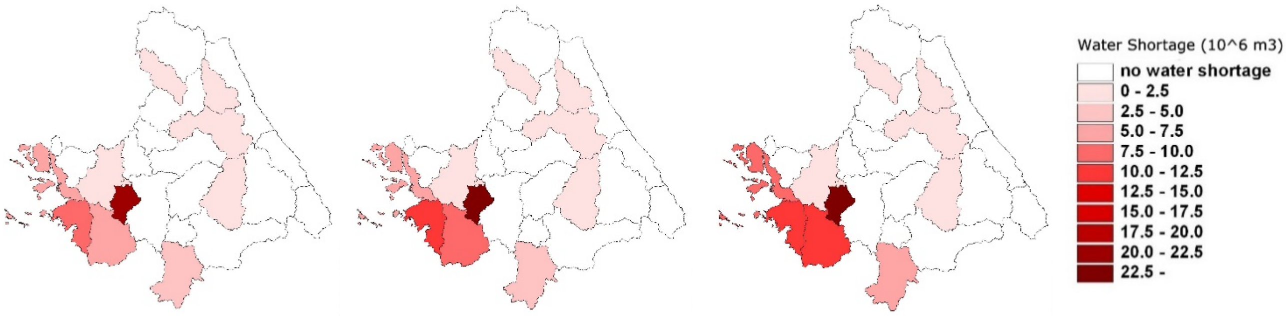


Figure 7. Trend of water shortage projections in the Han River basin: 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099).

Figure 8 illustrates schematically the amount of water shortages in each sub-watershed, warning that the downstream areas where the capital city of Korea, Seoul, is located would be vulnerable to future water shortages.



(**a**) (**b**) (**c**)

Figure 8. Average water shortage in each sub-watershed of the Han River basin (unit: 10^6 m^3/year) (**a**) 2020s; (**b**) 2050s; (**c**) 2080s.

3.3. Comparison with the Previous Methodology

This study compared the proposed methodology with the previous methodology, the GCM value input method (described in Section 2.2), which directly inputs the values of GCM-driven flows into the K-WEAP model. For fair comparison, both methodologies began with the same GCM selections for consistency. Therefore, the only difference between the two methodologies is whether the GCM-driven data were directly inputted into the K-WEAP model while the other settings remained constant. Note that the Strategic Report, an example of the GCM value input method, used only a single RCM scenario. Thus, it is different from the GCM value input method described in this section.

Table 4 reports a significant difference between the results from both methodologies. The GCM value input method anticipated an unrealistically huge increase (144%) in water shortage, while the proposed methodology produced a rather conservative result, that is, a 15% increase with an overall range of 1% to 26%. Whether or not the projection results of the proposed methodology are significantly different from those of the previous methodology was validated with a statistical hypothesis test: the two-tailed *t*-test was performed with the null hypothesis that there is no difference between the two population mean values. As a result, it turned out that the both methodologies have different mean values with all the four GCM scenarios (*i.e.*, all the null hypotheses were rejected with significance level of 0.05). Furthermore, in Table 4, the results produced by the GCM value input method show a huge heterogeneity between the GCMs. Although it is impossible to prove which methodology produces a better prediction because the future is uncertain, a 144% increase in 10 years seems extremely unlikely.

4. Conclusions

This study proposed a new methodology for water shortage projection under climate change impacts, which is essential to national water resources planning, to overcome the limitations of the GCM value input method that inputs GCM-driven flow directly. The new methodology uses GCM-driven flow scenarios to assign different weights to each observation-driven flow scenario rather than directly inputting GCM-driven flow scenarios into a water balance analysis model.

Table 4. The average water shortage projections for 2020s in the Han River basin (unit: 10^6 m^3).

Water Vision 2020 [a] **(Target Year: 2020)**	**Future Projection (Target Period: 2020s)**		
	GCM Models	**Proposed Methodology**	**Previous Methodology** [b]
42.0	CSIRO: MK3.0	42.3	63.5
	CNRM: CM3	47.1	17.4
	UKMO: HadCM3	52.9	137.6
	CONS: ECHO-G	51.6	192.2
Average **(increase ratio from the current)**		48.5 **(15% ↑)**	102.7 **(144% ↑)**

Notes: [a] Water Vision 2020 used the observation-driven flows in 1967 ~ 2003 as water supply scenarios [18]; [b] The previous methodology, the GCM value input method, inputted the GCM-driven flow directly into the K-WEAP model.

The proposed methodology was applied to project future water shortages in the Han River basin in Korea. The *K*-nn scheme selected seven observation-driven flows, which were most similar to the GCM-driven flows in the low-flow season. By calculating the weighted average values of the simulation results of the selected seven observation-driven flows, the water shortages of each target period were projected.

Compared to most previous studies, which assess climate change impacts on water resources by directly using GCM-driven flows, we have focused on how to provide reliable projection results for decision-makers in the water resources management field. As mentioned in the introduction, a radical change of methodology may confuse people with uncertain projection results. The comparison between the proposed method and the GCM value input method also showed a considerable difference in the projections. The results of the GCM value input method predicted a dramatic increase of 144% in the 2020s, which seems unrealistic. On the other hand, the proposed methodology used GCM-driven flows to assign different weights to each historical scenario rather than directly inputting them into a model so that we could reflect a more conservative climate change impact in water shortage projections, a 15% increase in the 2020s. Thus, this study successfully utilized observation-driven flow series as water supply scenarios and also reflected climate change impacts by assigning different weights to those observation-driven flows in accordance with the given GCM. The proposed methodology projected that the water shortage in the next 90 years in the Han River basin would gradually increase by 15%, 41%, and 57% in the 2020s, 2050s, and 2080s, respectively.

It is difficult to argue that the implementation of this conservative approach is the best way to assess climate change impacts. However, the blind use of GCM-driven flows should be reevaluated. Because the proposed methodology successfully reflected climate change impacts on water resources using GCM-driven flows, it may become one of the appropriate alternatives to be considered when addressing the impact of climate change. Nonetheless, as we proposed a rather conservative approach given that each annual water shortage value is projected within the limits of historical data, efforts to project extreme values beyond the observed record will be pursued in future studies.

In the near future, the current results of this study should be updated with the AR5 RCP scenarios that have been presented to the public in 2014 and are, thus, consequently being tested in Korea. The primary reason that we used the A2 emission scenario from AR4 was because of a consistent comparison, that is, because both Water Vision 2020 and the Strategic Report utilized the A2 emission scenario. Moreover, the QM technique was used to correct systematic bias on GCM datasets in this study. Other up-to-date bias correction schemes [32,33], however, can also be considered for future studies.

The assumption of a constant water demand until 2100 made in this study because of a consistency with Water Vision 2020. Note that the choice of the demand scenario used in Water Vision 2020 was a very valuable product that results from a long negotiation process between the Korean government and non-governmental organizations. However, the suitability of this future demand scenario should be re-studied and updated to be more realistic as a future study. For instance, Koutroulis *et al*. [34] developed a simple future water demand storyline based on future irrigation extension plans, population trends, *etc*. Above all, however, it needs to be reiterated that the main purpose of this study is to alert decision makers of the risk of the direct use of GCM-driven data without thorough analysis.

The proposed methodology is likely to be more useful for regions where the rainfall regime is highly variable and thus hard to find a consensus between GCMs. Korea, affected by the monsoon climate, belongs to this category. The proposed methodology may perform differently for other rainfall regimes such as semiarid regions.

To conclude, this approach could provide decision makers a reliable and realistic alternative for future water resources management plans. In addition, various approaches that take into consideration multiple variables, such as weighting factors, and project extreme water shortage values should be pursued in future studies.

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Author Contributions

Seung Beom Seo mainly contributed to the design and development of this manuscript under the supervision of Young-Oh Kim. Cho-Rong Kim contributed to the data collection and analysis.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Milly, P.C.D.; Betancourt, J.; Falkenmark, M.; Hirsch, R.M.; Kundzewicz, Z.W.; Lettenmaier, D.P.; Stouffer, R.J. Stationarity is dead: Whither water management? *Science* **2008**, *319*, 573–574.

2. Christensen, N.S.; Wood, A.W.; Voison, N.; Lettenmaier, D.P.; Palmer, R.N. The effect of climate change on the hydrology and water resources of the Colorado River Basin. *Clim. Chang.* **2004**, *62*, 337–363.
3. Medellin-Azuara, J.; Harou, J.J.; Olivares, M.A.; Madani, K.; Lund, J.R.; Howitt, R.E.; Tanaka, S.K.; Jenkins, M.W.; Zhu, T. Adaptability and adaptations of California's water supply system to dry climate warming. *Clim. Chang.* **2008**, *87*, 75–90.
4. Minville, M.; Brissette, F.; Leconte, R. Impacts and uncertainty of climate change on water resource management of the Peribonka River System (Canada). *J. Water Resour. Plan. Manag.* **2010**, *136*, 376–385.
5. Islam, M.S.; Aramaki, T.; Hanaki, K. Development and application of an integrated water balance model to study the sensitivity of the Tokyo Metropolitan area water availability scenario to climate changes. *Water Resour. Manag.* **2005**, *19*, 423–445.
6. Vicuna, S.; Maurer, E.P.; Joyce, B.; Dracup, J.A.; Purkey, D. The sensitivity of California water resources to climate change scenarios. *J. Am. Water Resour. Assoc.* **2007**, *43*, 482–498.
7. Hoff, H.; Swartz, C.; Yates, D.; Tielborger, K. Water management under extreme water scarcity: Scenario analyses for the Jordan River Basin, using WEAP21. *Water Sav. Mediterr. Agric. Future Res. Needs* **2007**, *2*, 321–331.
8. Purkey, D.R.; Joyce, B.; Vicuna, S.; Hanemann, M.W.; Dale, L.L.; Yates, D.; Dracup, J.A. Robust analysis of future climate change impacts on water for agriculture and other sectors: A case study in the Sacramento Valley. *Clim. Chang.* **2008**, *87*, 109–122.
9. Wurbs, R.A.; Muttiah, R.S.; Felden, F. Incorporation of climate change in water availability modelling. *J. Hydrol. Eng.* **2005**, *10*, 375–385.
10. Fowler, H.J.; Kilsby, C.G.; Stunell, J. Modeling the impacts of projected future climate change on water resources in North-West England. *Hydrol. Earth Syst. Sci.* **2007**, *11*, 1115–1126.
11. Fujihara, Y.; Tanaka, K.; Watanabe, T.; Nagano, T.; Kojiri, T. Assessing the impacts of climate change on the water resources of the Seyhan River Basin in Turkey: Use of dynamically downscaled data for hydrologic simulations. *J. Hydrol.* **2008**, *353*, 33–48.
12. Kirono, D.G.C.; Podger, G.; Franklin, W.; Siebert, R. Climate change impact on rous water supply. *J. Aust. Water Assoc.* **2007**, *34*, 68–72.
13. Vano, J.A.; Scott, M.; Voisin, N.; Stockle, C.O.; Hamlet, A.F.; Mickelson, K.E.B.; Elsner, M.M.; Lettenmaier, D.P. Climate change impacts on water management and irrigated agriculture in the Yakima River Basin, Washington, USA. *Clim. Chang.* **2010**, *102*, 287–217.
14. Zhu, T.; Ringler, C. Climate change impacts on water availability and use in the Limpopo River Basin. *Water* **2012**, *4*, 63–84.
15. Kim, S.J.; Kim, B.S.; Jun, H.D.; Kim, H.S. The evaluation of climate change impacts on the water scarcity of the Han River Basin in South Korea using high resolution RCM data. *J. Korea Water Resour. Assoc.* **2010**, *42*, 295–308. (In Korean)
16. Kang, S.U.; Rieu, S.Y.; Cheong, T.S.; Ko, I.H. Evaluation water resources in Geum River Basin using generalized water budget analysis model. In Proceedings of the Korea Society of Civil Engineers Conference, Gwangju, Korea, 11 October 2006; Volume 10, pp. 1653–1656. (In Korean)
17. Choi, S.J.; Kim, J.H.; Lee, D.Y. Decision of the water shortage mitigation policy using multi-criteria decision analysis. *KSCE J. Civ. Eng.* **2012**, *16*, 247–253.

18. Ministry of Construction and Traffic. *National Water Resources Plan (2006–2020)*; Ministry of Construction and Transportation: Gwacheon, Korea, 2006. (In Korean)
19. Kim, Y.O.; Lee, J.K. Addressing heterogeneities in climate change studies for water resources in Korea. *Curr. Sci.* **2010**, *98*, 1077–1083.
20. Groves, D.G.; Yates, D.; Tebaldi, C. Developing and applying uncertain global climate change projections for regional water management planning. *Water Resour. Res.* **2008**, *44*, W12413.
21. Sharif, M.; Burn, D.H. Simulating climate change scenarios using an improved K-nearest neighbor model. *J. Hydrol.* **2006**, *325*, 179–196.
22. Yates, D. A Technique for generating regional climate scenarios using a nearest-neighbor algorithm. *Water Resour. Res.* **2003**, *39*, W1199.
23. Ministry of Construction and Traffic. *National Water Resources Security against Climate Change*; Ministry of Land, Transport and Maritime Affairs: Sejong Special Autonomous City, Korea, 2009. (In Korean)
24. Korea Institute of Construction Technology. *K-WEAP User Guide*; Korea Institute of Construction Technology: Goyang, Korea, 2005. (In Korean)
25. Lee, J.K. Scenario selection and uncertainty quantification for climate change impact assessments in water resources. In *Doctoral Dissertation*; Seoul National University: Seoul, Korea, 2013. (In Korean)
26. IPCC Data Distribution Centre: Climate Model Output—AR4 (2007): SRES Scenarios. Available online: http://www.ipcc-data.org/sim/gcm_monthly/SRES_AR4/index.html (accessed on 15 May 2015).
27. Bae, D.H.; Jung, I.W.; Lee, B.J. Outlook on variation of water resources in Korea under SRES A2 scenario. *J. Korean Water Resour. Assoc.* **2007**, *40*, 921–930. (In Korean)
28. Wiley, M.W. Analysis Techniques to Incorporate Climate Change Information into Seattle's Long Range Water Supply Planning. M.Sc. Thesis, University of Washington, Seattle, WA, USA, 2004.
29. Hamlet, A.F.; Lettenmaier, D.P. Effects of climate change on hydrology and water resources objectives in the Columbia River Basin. *J. Am. Water Resour. Assoc.* **1999**, *35*, 1597–1624.
30. Hashino, T.; Bradley, A.A.; Schwartz, S.S. Evaluation of bias-correction methods for ensemble streamflow volume forecasts. *Hydrol. Earth Syst. Sci.* **2007**, *11*, 939–950.
31. Wood, A.W.; Maurer, E.P.; Kumar, A.; Lettenmaier, D.P. Long-range experimental hydrologic forecasting for the Eastern United States. *J. Geophys. Res. Atmos.* **2002**, *107*, 4429–4443.
32. Ines, A.V.M.; Hansen, J.W. Bias correction of daily GCM rainfall for crop simulation studies. *Agric. For. Meteorol.* **2006**, *138*, 44–53.
33. Fabre, J.; Ruelland, D.; Dezetter, A.; Grouillet, B. Simulating past changes in the balance between water demand and availability and assessing their main drivers at the river basin scale. *Hydrol. Earth Syst. Sci.* **2015**, *19*, 1263–1285.
34. Koutroulis, A.G.; Tsanis, I.K.; Daliakopoulos, I.N.; Jacob, D. Impact of climate change on water resources status: A case study for Crete Island, Greece. *J. Hydrol.* **2013**, *479*, 146–158.

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