

# Assessment of future water resources and water scarcity considering the factors of climate change and social–environmental change in Han River basin, Korea

Soojun Kim · Byung Sik Kim · Hwandon Jun ·  
Hung Soo Kim

Published online: 19 July 2014  
© Springer-Verlag Berlin Heidelberg 2014

**Abstract** Water resources are influenced by various factors such as weather, topography, geology, and environment. Therefore, there are many difficulties in evaluating and analyzing water resources for the future under climate change. In this paper, we consider climate, land cover and water demand as the most critical factors affecting change in future water resources. We subsequently introduce the procedures and methods employed to quantitatively evaluate the influence of each factor on the change in future water resources. In order to consider the change in land cover, we apply the Multi-Regression approach from the cellular automata-Markov Chain technique using two independent variables, temperature and rainfall. In order to estimate the variation of the future runoff due to climate change, the data of the SRES A2 climate change scenario were entered in the SLURP model to simulate a total of 70 years, 2021–2090, of future runoff in the Han River basin in Korea. However, since a significant amount of uncertainties are involved in predicting the future runoff due to climate change, 50 sets of daily precipitation data from the climate change scenario were

generated and used for the SLURP model to forecast 50 sets of future daily runoff. This process was used to minimize the uncertainty that may occur when the prediction process is performed. For future water balance analysis, the future water demand was divided into low demand, medium demand and high demand categories. The three water demand scenarios and the 50 daily runoff scenarios were combined to form 150 sets of input data. The monthly water balance within the Han River basin was then calculated using this data and the Korean version of Water Evaluation and Planning System model. As a result, the future volume of water scarcity of the Han River basin was predicted to increase in the long term. It is mostly due to the monthly shift in the runoff characteristic, rather than the change in runoff volume resulting from climate change.

**Keywords** Climate change · Water scarcity · SLURP model · WEAP · Water balance

## 1 Introduction

Water resources are influenced by various factors such as weather, topography, geology and environment. Therefore, we experience numerous difficulties when evaluating and analyzing water resources. This stems from our lack of a scientific understanding of the many land, atmospheric, and ocean processes as well as the various impacts of our population explosion on the availability of adequate water resources for our health, environment, and economic well-being (Sivakumar 2011). In particular, despite the fact that predicting and evaluating future water resources is crucial for water resource planning, there is a limit to the credibility or accuracy of the results due to the high uncertainty. The climate change due to global warming, in particular, is

---

S. Kim  
Columbia Water Center, Columbia University, New York, USA

B. S. Kim  
Kangwon National University, Samcheok, South Korea

H. Jun (✉)  
Department of Civil Engineering, Seoul National University of  
Science and Technology, 172 Gongreung 2-dong, Nowon-gu,  
Seoul 139-743, South Korea  
e-mail: hwjun@snut.ac.kr

H. S. Kim  
Department of Civil Engineering, Inha University, Incheon,  
South Korea

a critical factor when predicting and evaluating future water resources. According to the Synthesis Report of the IPCC Fourth Assessment Report (2007), global warming is clearly evidenced by the rise of the earth's average temperature and sea water temperature, widespread melting of snow and glaciers, and the rise of the earth's sea level, which has been observed and measured. By the 2050s, freshwater availability in Central, South, East and South-East Asia, particularly in large river basins, is projected to decrease.

Extreme climate events have an effect on various fields such as agriculture, public enterprises, transportation, water supply, and the economy. Hence, the overall stability of society can be compromised by extreme climate conditions (Kunkel et al. 1999). Evidence of climate change and the increase in the frequency and magnitude of floods in various regions around the world have been made apparent in various studies over the last several decades. Studies regarding the effects of climate change on water resources have been undertaken frequently since the mid-1980s. Gleick (1986) studied the effects of global warming on water resources within the Sacramento basin. Miller and Russell (1992) and Cooley et al. (1992) evaluated the effects of climate change on runoff and water supply. Bronstert et al. (1999) carried out a study similar to that of McCabe and Wolock (1999), which studied the effects of climate change on the snow melting in the western region of the US. Hamlet and Lettenmaier (1999) studied the change in water resources in the Columbian River basin. Roald et al. (2003) calculated the average annual runoff and the average seasonal runoff in Norway based on the climate change scenario. Applying the SWAT model to the upper Mississippi River basin, Jha et al. (2004, 2006) evaluated the effects of climate change on runoff while Stewart et al. (2005) studied the temporal changes of runoff characteristics in the Northwest region of the US instigated by climate change. Many studies regarding changes in runoff characteristics caused by climate change are currently being undertaken. A good example is a study done by Andersson et al. (2006), which analyzed the effects of the change in runoff depending on the climate change and development scenarios. Kyoung et al. (2011) assessed the dynamic characteristics of monthly rainfall in the Korean Peninsula under climate change.

Researchers have also simultaneously evaluated the changes in runoff characteristics and water balance due to climate change. In those studies, they developed water balance models and applied their models to different regions in order to explore the effects of climate change. For example, Gleick (1987) applied his model to the Sacramento basin, and Yates and Strzepek (1998) as well as Guo et al. (2002) performed similar studies for the Nile River of Egypt and China, respectively. To explore the

effect of climate change and urbanization on the runoff characteristics, Franczyk and Chang (2009) performed continuous runoff simulations using AVSWAT-X for a highly and rapidly urbanized area. Cuo et al. (2010) considered the effects of mid-twenty-first century climate and land cover change simultaneously on the hydrology of the Puget Sound basin. In addition, Purkey et al. (2008) employed the WEAP (Water Evaluation and Planning System) model on the Sacramento River basin and confirmed its applicability. Obeysekera et al. (2011) took climate change into account when analyzing flood control and the vulnerability of the water management system in south Florida. As stated here, efforts to evaluate water resources whilst taking climate change into account are currently in progress.

Global climate change influences changes in hydrometeorological characteristics such as spatio-temporal change as well as quantitative change. Social–environmental change, such as land cover change and population growth, impacts the hydrological system. For example, flow in an area in which precipitation tends to decrease due to climate change and in which the impermeable layer tends to increase due to urbanization, would be greatly decreased in the dry season. In this situation, the increasing of water demand due to population growth would aggravate the water scarcity in the area. Therefore it is possible to estimate the water scarcity quantitatively when the above processes are understood and analyzed.

So far, most studies regarding the impact of climate change on water resources have focused on the change of hydrological aspects such as rainfall and runoff. Various drought indices taking hydrological and meteorological factors into account have been developed and applied in the assessment of regional drought severity. The social–environmental changes in a basin that have resulted from anthropogenic activity, however, has been overlooked for this reason. The impact of climate change on the regional drought severity can be different depending on the social–environmental change. For this reason, it is necessary to develop a methodology and process that is able to quantitatively assess the water scarcity by considering both climate change and social–environmental changes in the basin. In addition, a predictive scenario-based assessment should be performed for the quantitative estimation of an uncertain future.

In this paper, we propose procedures and methods to quantitatively analyze the future water supply by considering not only climate change, but also future changes in land cover as well as changes in water demand. In order to do so, we adopt the A2 scenario based on the SRES AR4 and the RegCM3 regional climate models (RCMs). These models are especially useful for considering the climate change which has been occurring globally. For considering

the regional change, we used the cellular automata (CA)-Markov Chain to obtain the change of land cover in the future. Future daily runoff simulations were then performed. Based on the climate change and water demand scenarios developed in this study and the forecasted future daily runoff, the water balance analysis was carried out to evaluate the impact of the change of land cover, climate and water demand on future water resources. Finally the procedure and methods developed were applied to the Han River basin in Korea to examine their applicability.

## 2 Methodology and analysis procedure

Evaluating the effects that climate change and land cover have on water resources requires many complicated procedures and involves considerable uncertainties. In this study, we developed procedures to predict the amount of water considering the climate change and the change of land cover.

First, daily precipitation data were generated by the Nonstationary Markov Chain Model using the monthly series from the A2 scenario of the RegCM3 RCM provided by the Korean Meteorological Agency. To overcome the uncertainties resulting from the climate change and the generation of daily precipitation, 50 sets of daily precipitation data were generated.

Next, we used the SLURP model to simulate 50 sets of daily runoff data of 2020–2090. Given those sets of daily precipitation data, we estimated the range of daily runoff values, instead of a single value of daily runoff. It is clear that there are a significant amount of uncertainties in predicting future daily precipitation and daily runoff if a single set of daily precipitation data is used for the runoff simulation. However, it is also clear that if 50 sets of daily precipitation data are used for the runoff simulation and, based on that, the range of daily runoff values for water balance analysis is estimated, the prediction uncertainties

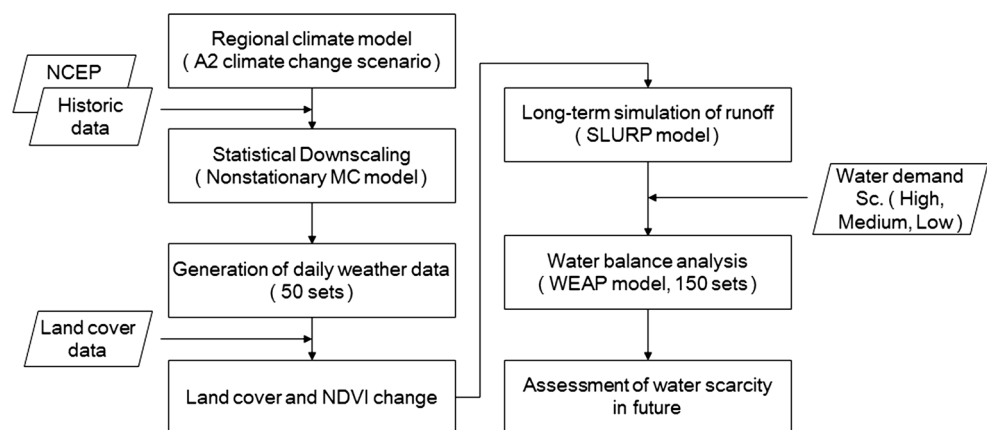
will be minimized, especially compared to the case of a single value of daily runoff used. Thus, the estimated water scarcity will be proposed by the range of daily runoff values and this will make the estimation more reliable. We understand that even 50 sets of daily precipitation data may not be enough to consider many aspects of the prediction uncertainties in the future daily runoff and this issue will remain even if we generate and use a greater number of sets of daily precipitation data (e.g., 100 or more). However, 50 sets of daily precipitation data will be enough to generate the statistical parameters and the possible range of the future daily runoff to estimate the future water scarcity. Again, it is much more reasonable to estimate the future water scarcity in a range of values, and not a single value, to minimize the involved uncertainties.

Thirdly, three water demand scenarios, namely high demand, medium demand, and lower demand, which are from the Long-term Comprehensive Water Resources Plan of 2006, were combined to form 150 sets by referring to 50 sets of daily runoff from the SLURP simulation. Finally, the K-WEAP analyzes water balance to estimate the water scarcity based on the 150 sets. The suggested procedure is shown in Fig. 1.

### 2.1 Climate model and downscaling

The RegCM3 model is the middle-range climate model developed by the International Center of Theoretical Physics and in 2004, its methodology and usage was revealed. The RegCM3 model was developed on the basis of the MM5 (Mesoscale Model version 5th, <http://users.ictp.it/RegCNET/>). Hydrostatic model uses the Sigma coordinate and the Arakawa B grid coordinate for the vertical and horizontal coordinates, respectively. The model’s major methods of physical parameterization were the Grell cumulus parameterization (Grell 1993 ), CCM3 radiation process, and the non-local vertical diffusion for the planetary boundary layer process. Generally, RCM uses

**Fig. 1** A schematic drawing of the analysis procedures for this study



GCM data as the initial condition. The simulation begins when the model gives the localized forcing such as the surface weather condition and lateral boundary condition to climate components within RCM domain. Depending on the size of the RCM domain and resolution, the amount of computation may increase significantly (Kwon et al. 2008).

The SRES scenarios are presented by the four families (A1, A2, B1, and B2) and six scenario groups (IPCC 2007). Among the SRES scenarios, the A2 scenario is a very heterogeneous world with a continuously increasing global population and regionally oriented economic growth that is more fragmented and slower than in other scenarios (Nakicenovic et al. 2000). In this study, we adopted the RegCM3 RCM and focused on the SRES A2 scenario because it provides an important clue to researchers interested in extreme events as the worst case scenario.

Kwon and Kim (2009) combined the Markov Chain, a stochastic model, with a statistical downscaling model and developed the Nonstationary Markov Chain Model. In order to create a relationship between the four parameters of the Nonconditional Markov Chain and to link external factors, a regression analysis is used. The four stochastic parameters are the probability of transitioning from no-rain to rain ( $a$ ), the probability of transitioning from rain to rain ( $b$ ), both  $a$  and  $b$  are found in the transition matrix  $P_{tr}$ , the  $\alpha$  scale parameter and the  $\beta$  shape parameter, both belonging to the Gamma probability distribution used for simulating precipitation.

$$P_{tr} = \begin{bmatrix} 1-a & a \\ b & 1-b \end{bmatrix}, \quad P(X) = \frac{\alpha^\beta X^{\beta-1} e^{-\alpha X}}{\Gamma(\beta)}. \quad (1)$$

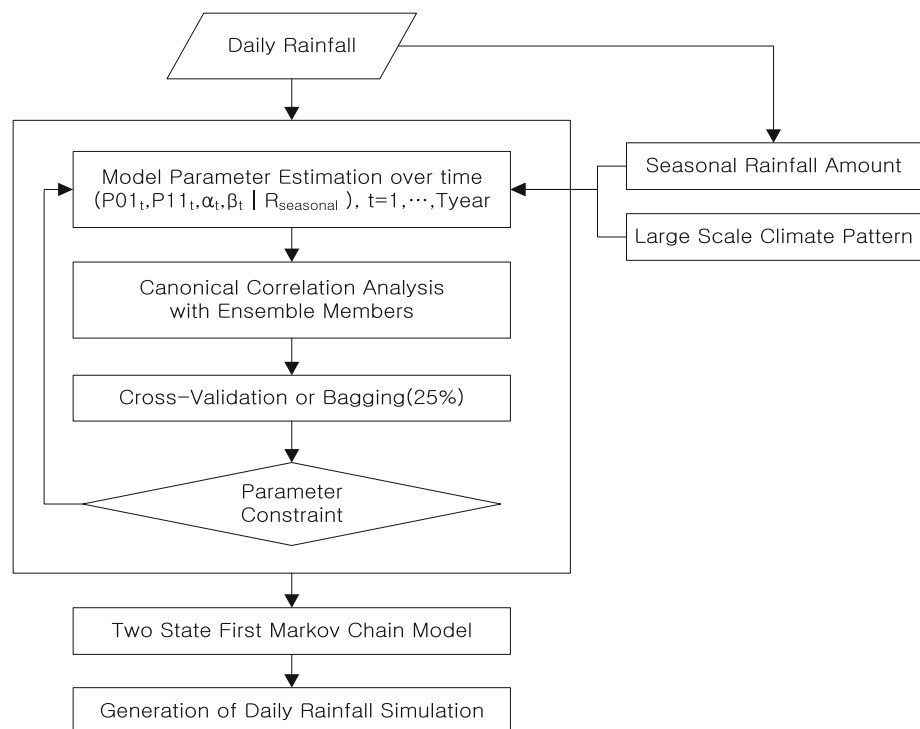
Thus, four seasonal values must be dynamically generated for each stochastic parameter. Using those generated stochastic parameters, daily rainfall data are produced by the Nonstationary Markov Chain Model. The downscaling process by the Nonstationary Markov Chain Model is as shown in Fig. 2.

## 2.2 Methods for the prediction of land cover change

The Markov Chain Model, which can reflect the change in trend of the land cover change, and the CA-Markov method that combines the CA (cellular automata) model (Clarke et al. 1997), were applied to predict the change in future land cover. The Markov Chain model is not only calculated easily from the digital image as well as the GIS data of the grid basis, but also has the advantage of efficiently reflecting the change in trends from the current land cover. A cellular automata model, which is a non-linear dynamic model, consists of a regular grid of land cover cells, each of which can be updated synchronously in discrete time steps according to a local and identical interaction rule.

Climate change may trigger weather changes such as temperature variation and change of rainfall intensity, and has a potential effect on the types, quantity, and

**Fig. 2** Flowchart of Nonstationary Markov Chain Model (by Kwon and Kim 2009)



distribution of vegetation in the basin (Ministry of Science and Technology, Korea 2006). In general, vegetation change can be estimated by the change in the Normalized Difference Vegetation Index (NDVI). Thus, future vegetation change can be predicted through the prediction of the future NDVI which can be built by a regression analysis between temperature–rainfall and NDVI. After analyzing the correlation between temperature and rainfall and the current NDVI, the future NDVI can be estimated by Eq. (2) which is established from a regression equation for each type of land cover.

$$NDVI_{fu,i} = f(T_i, P_i), \quad (2)$$

where  $fu$ ,  $i$ ,  $T_i$ ,  $P_i$  denotes future, monthly (the NDVI time unit) temperature and precipitation, respectively.

### 2.3 Water demand scenario

In Korea, the Long-term Comprehensive Water Resources Plan is established for a period of 10 years. In recent plans established in 2006 (Ministry of Construction and Transportation, Korea 2006), which considered social and economic trends and designated 2020 as the targeted time goal, water demand scenarios were classified into three groups: high demand, medium demand and low demand in regards to domestic use, industrial use and irrigation use (see Table 1).

### 2.4 SLURP for runoff simulation and WEAP for water balance analysis

In order to analyze the influence of climate change on the basin's water resources, it is necessary to reflect the climate change scenarios such as the GCM or RCM, as well as using the evapotranspiration, which is important for the runoff analysis. It is also necessary to account for the change in land cover and to consider the physical changes in the basin, which is reflected in GIS data. In this study, the SLURP model (Kite 2007), which offers the advantage of considering the climate change, including dam, land cover and vegetation change, was selected.

SLURP ([www.wrpllc.com/books/slurp.html](http://www.wrpllc.com/books/slurp.html)), which is a daily runoff model, requires geomorphological parameters, time-series data, and physical parameters for the simulation. Runoff simulation relies on aggregated simulation area (ASA), which is similar to real subbasin area. For each ASA, the water balance analysis is first performed vertically. Then, a river routing procedure is implemented between ASAs to obtain runoff hydrographs at the outlet.

WEAP (“Water Evaluation And Planning system”, [www.weap21.org/](http://www.weap21.org/)) is a user-friendly software tool that takes an integrated approach to water resources planning. Freshwater management challenges are increasingly

**Table 1** Establishment of scenarios for estimating future water demand [Long-term Comprehensive Water Resources Plan (2006–2020)]

Use	Demand categories	Scenarios
Domestic use	High demand	Current diminishing water demand and up to 50 % water-saving are taken into consideration
	Medium demand	Current diminishing water demand and up to 70 % water-saving are taken into consideration
	Low demand	Current diminishing water demand and maximum degree of water-saving are taken into consideration
Industrial use	High demand	Demand necessitated by 4.0 % economic growth
	Medium demand	Demand necessitated by 3.5 % economic growth
	Low demand	Demand necessitated by 3.0 % economic growth
Irrigation use	High demand	Maintenance of maximum area of rice field for food security; cultivated acreage of 1,773,000 ha in 2013
	Medium demand	Plan that considers current agricultural environment: Comprehensive Plan for Agriculture and Rural Communities; cultivated acreage of 1,731,000 ha in 2013
	Low demand	Diminishment of rice field acreage due to the opening of rice market is taken into consideration

common. Allocation of limited water resources between agricultural, municipal and environmental uses now requires the full integration of supply, demand, water quality and ecological considerations. The Water Evaluation and Planning system, or WEAP, aims to incorporate these issues into a practical yet robust tool for integrated water resources planning. WEAP is developed by the Stockholm Environment Institute's US Center. In this study, we used K-WEAP which is the Korean version of WEAP. K-WEAP is a model developed by KICT (Korea Institute of Construction Technology), which is one of the Korean government-funded institutes and has been used for water balance analysis for 5 large watersheds and 117 mid-size watersheds since 2006. The model, which is operated by the basic principles of water balance analysis, can be applied to the water demand–supply system of farming areas, a single small basin, or complex river basins. In addition, it can deal with wide-ranging issues: analysis of water demand by usage, water-saving, water right and priorities in distribution, river water and groundwater simulation, reservoir operation, hydroelectric power generation, tracking of pollutants, and analysis of water necessary for the eco-system.



### 3 Runoff simulation and water scarcity under climate change

#### 3.1 Han River basin

In this study, to evaluate the influence of climate change on the basin's water circulation elements and water resources system and to verify the applicability of the suggested procedure, the Han River basin was chosen as the target water basin. Being the largest water basin in Korea and located near the major urban areas including Seoul, it serves as the social and economic center. Also, there are many large scale multi-purpose dams being operated which are important water sources that produce the water supply of the major cities such as Seoul, the province of Gyeonggi and the province of Gangwon.

The Han River basin is located in the mid region of the Korean Peninsula. It spreads across the north latitude  $36^{\circ}30'–38^{\circ}55'$  and the east latitude  $126^{\circ}24'–129^{\circ}02'$ . As the largest river that penetrates the capital Seoul, it is divided (predominantly) into the Northern Han River sphere and the Southern Han River sphere. It is the premiere river of South Korea with a drainage area of  $26,365 \text{ km}^2$  (including the  $8,455 \text{ km}^2$  region in North Korea), river length of  $481.7 \text{ km}$ , and a basin shape factor of  $0.119$ . There are 21 rainfall stations and 4 major dams in the basin (shown in Fig. 3).

#### 3.2 Precipitation and runoff simulation

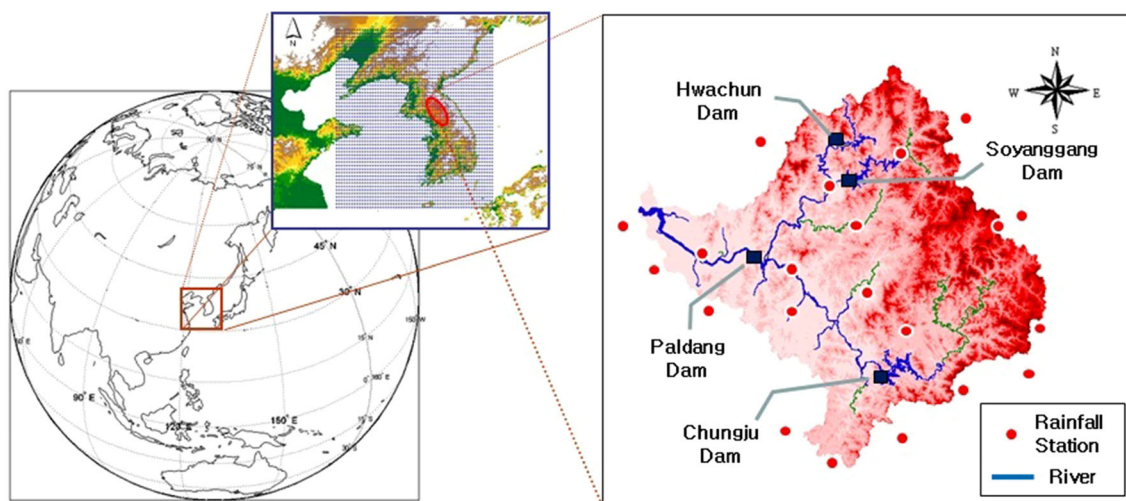
##### 3.2.1 Daily precipitation simulation

The forecasted daily precipitation data were organized into the annual precipitation and represented by both subbasin

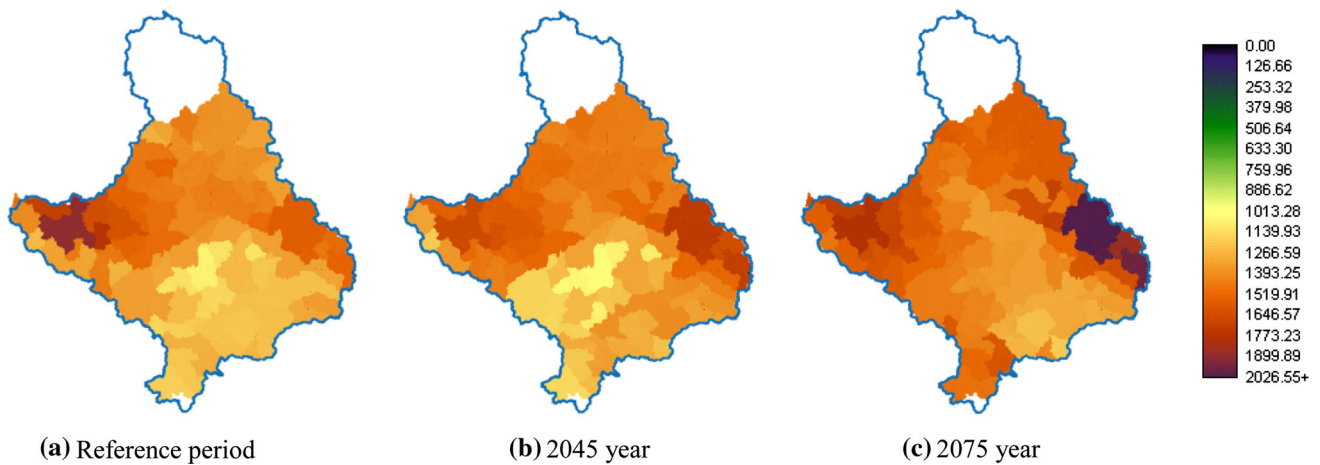
and period within the Han River basin (Fig. 4). Due to climate change, the annual precipitation will increase while the characteristic of the precipitation's spatial distribution showed that the variation by subbasin was deepening. In particular, the change in the annual precipitation in comparison to the past is  $-2.4$  to  $3.0 \%$ . However, monthly variation of precipitation will increase to  $-30$  to  $70 \%$ , predicting that the vulnerability in the maintenance of the water supply would increase immensely (shown in Table 2).

##### 3.2.2 Prediction of land cover change

As mentioned in the previous paragraph the change in land cover was predicted using the CA-Markov technique. The Idrisi Kilimanjaro module, which are useful for applying the technique ([www.clarklabs.org](http://www.clarklabs.org)), were used for estimating the transition probability and transition area matrices from the images at different times. A transition area matrix contains the number of pixels that are expected to change to a land cover class from another class over a certain time period. The land cover was separated into urban, barren, wetland, grass, forest, paddy, and crop from the Water Management Information System (WAMIS, <http://www.wamis.go.kr>) in Korea. The transition probability matrix is calculated from the land cover class and a pixel in a land cover is updated by the CA-Markov process during a time period (shown in Fig. 5). A land cover map from 2005 was used to calibrate the maps every 5 years during the time period 1975–2000. The maps were used to project land cover up to the year 2055. Since the land cover has been surveyed every 5 years, the future land cover is predicted every fifth year. Also, “0.0” is used as the assign value for



**Fig. 3** Study area (Han River basin)



**Fig. 4** Change of precipitation depth due to climate change (unit mm)

**Table 2** The variance of monthly rainfall due to the impacts of climate change (unit mm)

	Reference	2031–2060	Variance	2061–2090	Variance
Jan	22.8	38.5	15.7 (+69 %)	36.7	14.0 (+61 %)
Feb	31.3	35.2	3.9 (+1 %)	33.2	1.9 (+6 %)
Mar	50.8	39.3	−11.5 (−23 %)	37.9	−12.8 (−25 %)
Apr	75.1	108.2	33.1 (+44 %)	103.1	28.1 (+37 %)
May	89.7	114.1	24.4 (+27 %)	109.3	19.6 (+22 %)
June	150.5	110.2	−40.3 (−27 %)	105.8	−44.8 (−30 %)
July	253.5	194.1	−59.4 (−23 %)	221.1	−32.4 (−13 %)
Aug	241.6	187.1	−54.4 (−23 %)	211.9	−29.6 (−12 %)
Sept	125.9	179.2	53.3 (+42 %)	203.9	78.0 (+62 %)
Oct	41.3	38.6	−2.7 (−7 %)	40.5	−0.8 (−2 %)
Nov	39.3	36.3	−3.0 (−8 %)	37.7	−1.6 (−4 %)
Dec	23.3	37.9	14.6 (+63 %)	38.8	15.6 (+67 %)
Annual rainfall	1,144.8	1,118.5	−26.3 (−2 %)	1,179.8	35.0 (+3 %)

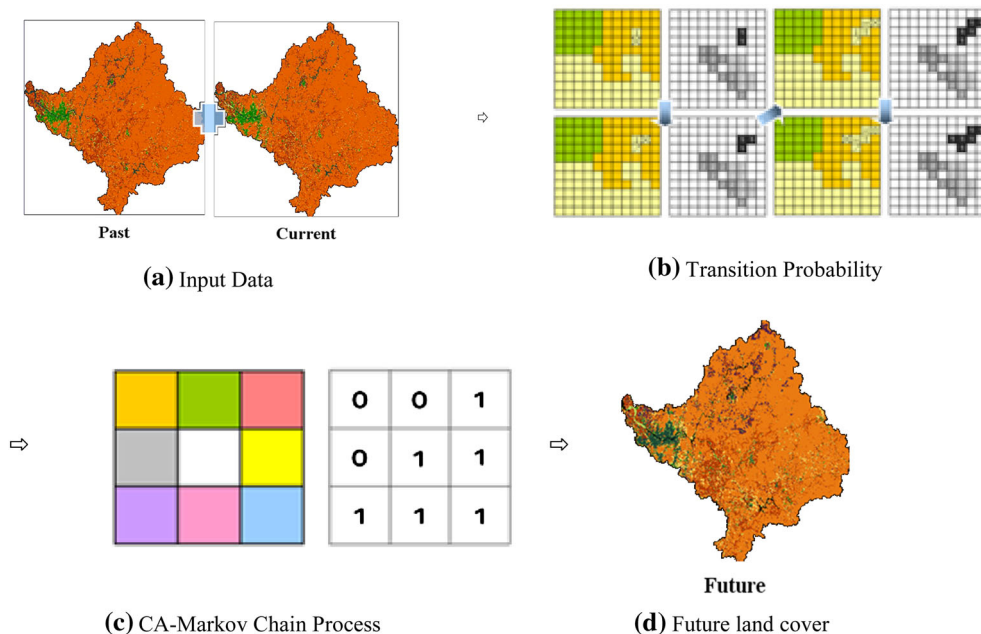
the background cells and “0.15” is the value for the proportional error of the data to make the accuracy of the prediction about 85 %. After completing the predictions of the future land cover of the Han River basin, it was found that the change in land cover is negligible during the prediction period and after the year 2020, land cover in the basin remains almost the same (about 86 %). This includes the rates of water, urban land area, barren land area, wetland area, grass area and forest area (Fig. 6).

Additionally, the Multi-Regression analysis of the NDVI and weather data was executed to forecast the future NDVI. The precipitation factor, which is sensitive to the degree and change in flux, is selected as the weather data. Data from NOAA/AVHRR are used to build the NDVI. In Table 3, the regression equations of NDVI estimated from temperature and precipitation for seven land covers are shown. The coefficients of determination of comparing the simulated NDVI from the regression equations to the observed NDVI were larger than 0.8.

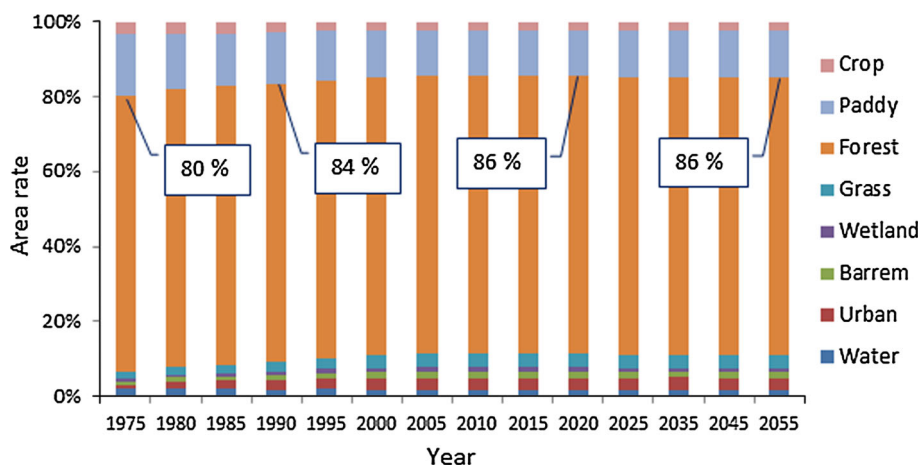
### 3.2.3 Runoff simulation

A rainfall–runoff model to simulate runoff in the basin was set up using SLURP. A Digital Elevation model was used with 1:25,000 topographic maps from the Korea National Geography Institute. Soil maps and land cover maps were used from the WAMIS ([www.wamis.go.kr](http://www.wamis.go.kr)). The weather data required by the model are daily average and dew point temperatures, relative humidity, wind speed, the daily total number of hours of sunshine, and daily precipitation. The daily data was collected for the years 1974–2006 from WAMIS. The calibration was performed at Hwachun Dam and Chungju Dam (shown in Fig. 3) during 2 years (2000–2001) and the result is shown in Table 4. The Nash–Sutcliffe efficiency (1970) was improved significantly from 0.254 to 0.440 at Hwachun Dam and from −0.381 to 0.520 at Chungju Dam. The result of validation during 2001–2006 is shown in Fig. 7. The built-up model was considered to be applicable for modeling in the basin.

**Fig. 5** Procedure to predict land cover change from CA-Markov Chain



**Fig. 6** Prediction of future land cover in the Han River basin



**Table 3** The forecasted NDVI by land cover class

Land cover	Estimated regression equation	R <sup>2</sup>
Urban	$NDVI_{fu,i} = -0.00032 + 0.00017 \times P_i + 0.0114 \times T_i + 0.41$	0.882
Barren	$NDVI_{fu,i} = -0.00011 + 0.000235 \times P_i + 0.0134 \times T_i + 0.46$	0.852
Wetland	$NDVI_{fu,i} = -0.00083 + 0.000232 \times P_i + 0.0116 \times T_i + 0.35$	0.860
Grass	$NDVI_{fu,i} = -0.00011 + 0.000178 \times P_i + 0.0151 \times T_i + 0.53$	0.886
Forest	$NDVI_{fu,i} = -0.00100 + 0.000072 \times P_i + 0.0165 \times T_i + 0.62$	0.813
Paddy	$NDVI_{fu,i} = -0.00011 + 0.000229 \times P_i + 0.0137 \times T_i + 0.50$	0.875
Crop	$NDVI_{fu,i} = -0.00001 + 0.000187 \times P_i + 0.0150 \times T_i + 0.51$	0.861

Using SLURP, 50 sets of daily runoff data from 2021 to 2090 were generated. To demonstrate the result of the rainfall–runoff simulations, the Paldang Dam in the Han River was selected and the observed data were collected as well to make a comparison between the observed and generated data. The data period of “Present” is from 1974

to 2005 and the one of “Future” is from 2021 to 2090 (shown in Fig. 8).

Figure 8a shows the box-plots for the monthly runoff obtained from 50 sets of the daily runoff during the 70 years. The higher variation is found from July to September, which is expected since that period coincides with



**Table 4** The runoff calibration results of the SLURP model

Calibration	Hwachun Dam		Chungju Dam	
	Before 2000–2001	After 2000–2001	Before 2000–2001	After 2000–2001
Computed mean flow (m <sup>3</sup> /s)	23.513	52.375	187.09	199.45
Historical mean flow (m <sup>3</sup> /s)	54.408	54.408	197.65	197.65
Standard error	−30.894	−2.032	−0.559	11.803
Nash–Sutcliffe efficiency	0.254	0.440	−0.381	0.520

the Monsoon season in Korea. Also, the flow-duration analysis was carried out based on three classes, namely, “Upper”, “Median”, and “Lower”, of the generated data. To perform this analysis, we ranked the 50 sets of the daily runoff by its values for every day during the 70 years and obtained the values of the daily runoff at 5, 50, and 95 %, for “Upper”, “Median”, and “Lower”, respectively. We then performed the flow-duration analysis on the selected 356 daily runoff data for each class. The obtained flow-duration curves are displayed with the current (present)

flow-duration curve based on the observed data (shown in Fig. 8b).

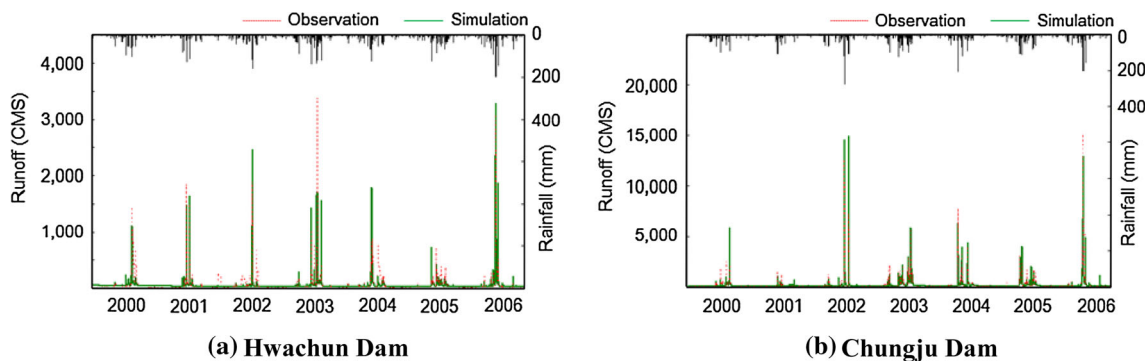
From the comparison between the generated and observed monthly runoff, it is found that the future monthly runoffs are generally higher than the observed, except in July. In particular, in August and September, the runoff may increase to almost twice that of the observed. The flow-duration analysis confirms this conclusion as well. Thus, due to climate change, the magnitude of the future monthly runoff may increase, especially during the Monsoon season.

As a result of comparing the generated runoff by sub-basins in order to confirm the spatial variation of the runoff due to climate change, it was evident that the deviation of the runoff by subbasin was deepening (shown in Fig. 9).

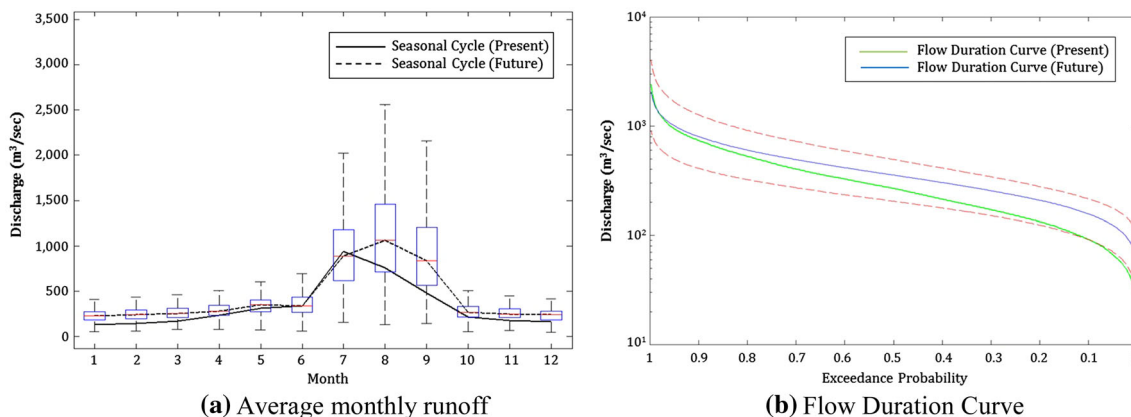
### 3.3 Water balance and water scarcity analysis

#### 3.3.1 Water demand analysis

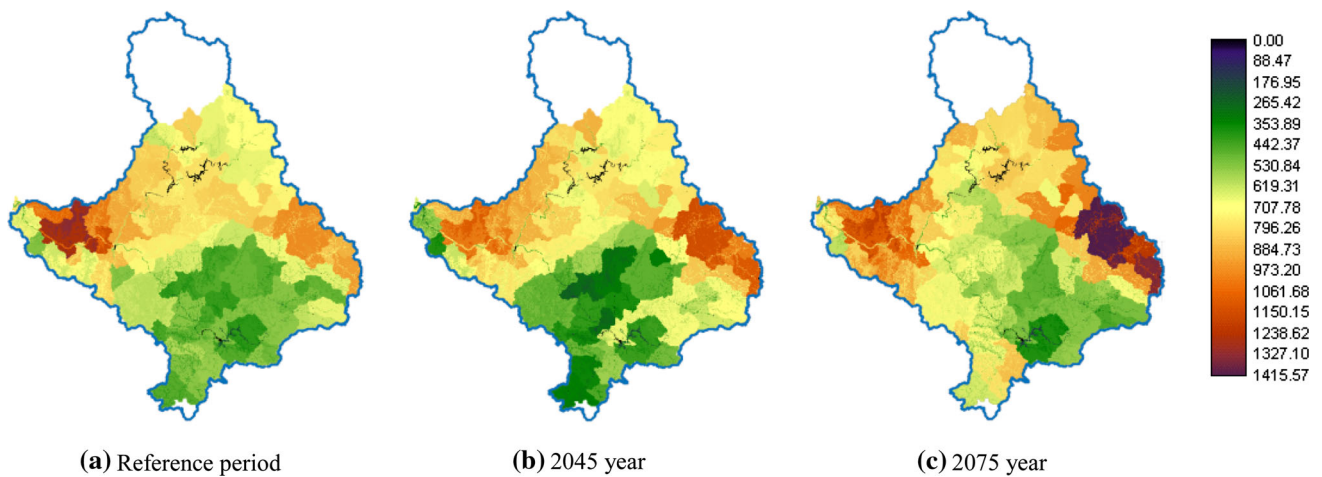
In this study, using the RegCM3 RCM under SRES A2 climate change scenario, the water demand scenarios (high



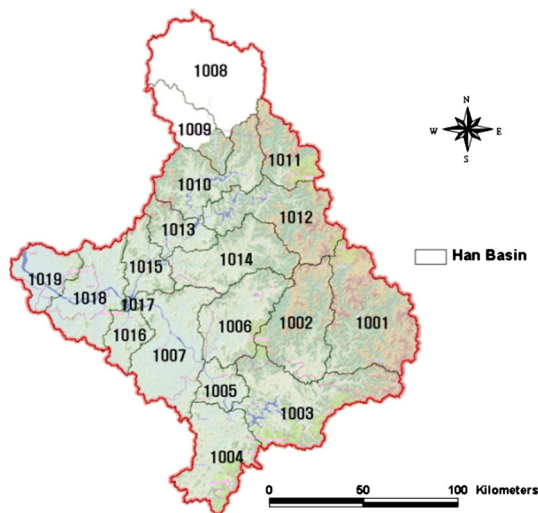
**Fig. 7** The runoff validation results of the SLURP model



**Fig. 8** Comparison of the simulated and historical monthly runoff and duration curve at Paldang Dam



**Fig. 9** Spatial variation of the generated runoff by subbasins (unit mm)



**Fig. 10** Target subbasins for evaluating water scarcity

demand, standard demand, low demand) based on the future predictions presented by the Long-term Comprehensive Water Resources Plan (2006) were developed and subsequently used to form the three climate change–water demand scenarios as shown in Table 5.

50 sets of the daily runoff data generated by the SLURP model based on the A2 climate change scenario and three water demand scenarios are combined (A2-high demand, A2-medium demand, A2-low demand), making a total of 150 input data sets for the K-WEAP model. The 19 subbasins of the Han River basin are shown in Fig. 10.

Also, the water supply and demand network of the basins on the K-WEAP model are shown in Fig. 11. This network consists of 17 rivers, 38 diversions, 4 reservoirs, 67 demand sites, 100 transmission links and 63 return flows. Using the K-WEAP model, the long-term water

balance analysis was performed to estimate the amount of water scarcity for the entire basin and for each subbasin in the future.

### 3.3.2 Water scarcity analysis

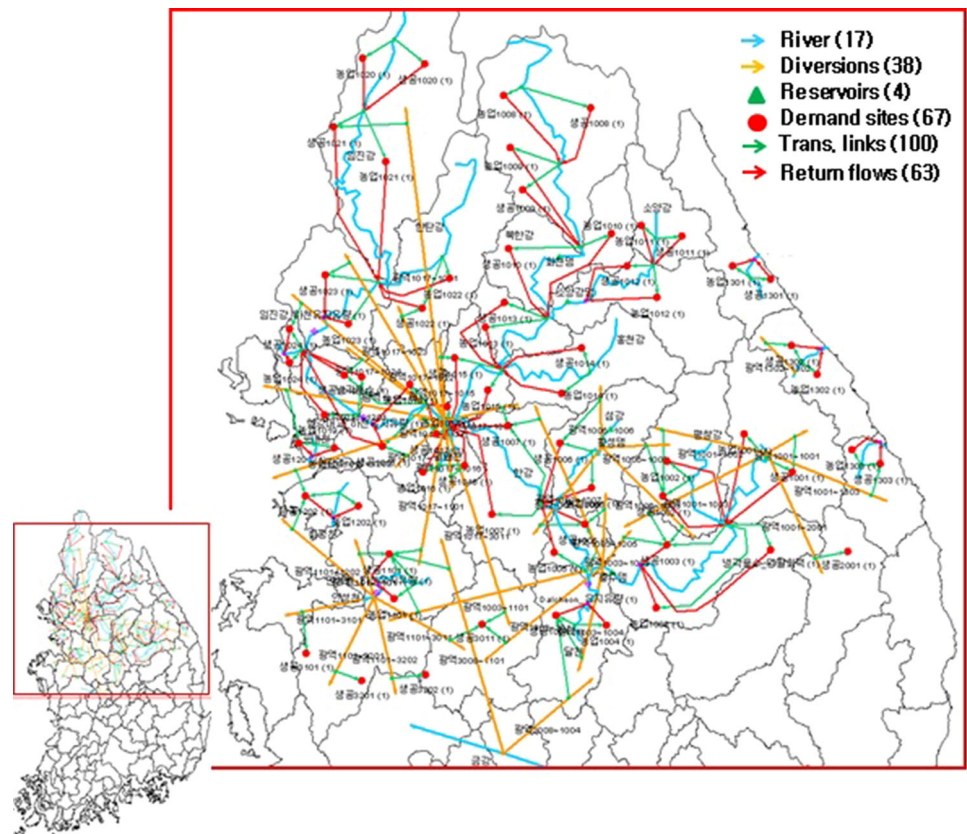
As a result of the predictions of water scarcity, which is displayed in the water scarcity trend graph shown in Fig. 12 one can see how the level of water scarcity in the basin changes. In the graphs, the range can be noted as the water scarcity range calculated by the 50 sets of water scarcity while the average is the value calculated from 50 sets of the water scarcity yearly.

In order to explore whether there is a change trend in the long term when comparing the water scarcity with its reference period (2020–2030), the moving average method was applied to the annual average value of the calculated water scarcity level. The calculated water scarcity, after applying a 10 year moving average filter, shows that the Han River basin's water scarcity would increase in the long term in every climate change–water demand scenarios we considered.

As shown in Fig. 13, in each scenario, the water scarcity increased by approximately 2.2–2.7 times in target period I (2021–2060) and 2.7–3.4 times in target period II (2061–2090) when compared to the water scarcity in the reference period (2020–2030).

In order to examine the spatial distribution of the future water scarcity within the Han River basin, the scarcity within each subbasin was estimated (Fig. 14). The ratio of water scarcity within each subbasin to the total water scarcity of the Han River basin within the target period is presented in Fig. 14 and the figures in parenthesis are the volume of each subbasin's water scarcity.

**Fig. 11** The water supply network of the Han River basin built in K-WEAP



Compared to the water scarcity of the reference period, the number of the subbasins suffering from the water scarcity will increase and the amount of the water scarcity for each subbasin will increase. Also, during target period II (2061–2090), the water scarcity will deepen within the majority of the basins.

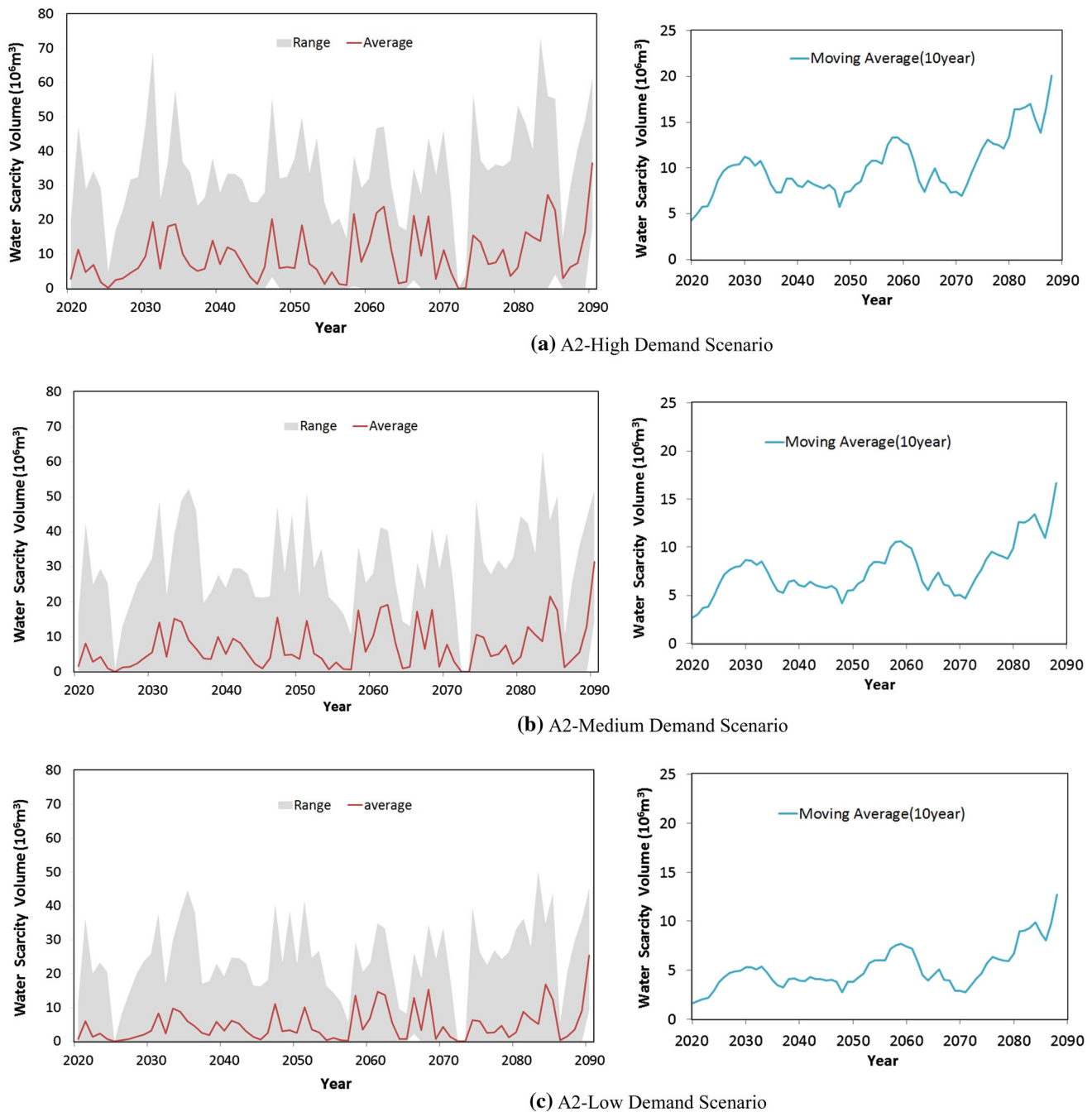
In particular, the water scarcity seemed to be deepening in the mid-lower basin compared to the upper basin of the Han River. Also, it is expected that there will be greater scarcity in the high demand scenario than the low demand scenario.

### 3.3.3 Discussions

Climate change and land-cover change are very important factors for estimating the runoff in a basin. Here, land-cover is caused by change in the social environment such as urbanization. The interaction between climate change and land-cover change is not considered directly in this paper. However the NDVI is a factor that is affected by both climate change and land-cover change. As a result, the NDVI provides an indirect connection between the two. In the case of the Han River basin, there will not be little change after the year 2020 as an already developed area.

In order to examine the cause of the water scarcity, the amount of runoff within each target period and the water demand for each usage (domestic and industrial use, irrigation use) was examined. As a result, it was affirmed that the future monthly fluctuation in precipitation (refer to Table 2) is influencing the water scarcity for the month of June as shown in Fig. 15. Also, the water scarcity was deepening due to the excess and deficiency of the irrigation use, which requires the water supply the most in June, more so than the domestic and industrial use which requires a steady water supply throughout the year. The irrigation use is separated into rice farming use and dry-field farming use, where in rice farming a steady amount of water is continuously needed for the growth of rice after rice planting in April and May. In the case of dry-field farming, because the most water is needed in June, it is evident that throughout the year the irrigation use is needed most in June. As shown in Table 6, based on a comparison of the average of runoff and water demand for each month within each target period, there is a high possibility that a problem with the supply and demand for water would occur in June due to the climate change.

In addition to the irrigation use as one of the causes of the water scarcity, we have found three more reasons resulting in water scarcity during the target period.



**Fig. 12** Water scarcity and moving average trends (from 50 sets of the water scarcity data)

- (I) As the runoff characteristic of the rainy season shifts from July–September to August–October, the volume of water scarcity relatively increased in June since water demand in June is the largest.
- (II) During target period I (2031–2060), as the amount of runoff decreased overall [in Fig. 16(-right), the middle value of the box plot is decreasing] the increase in water scarcity was showing.
- (III) While target periods I and II may show similar runoff characteristics [Fig. 16(left)], the variation of the monthly runoff during target period II is much higher than the same variation during target period I [Fig. 16(right)], so that there are instances of the water scarcity deepening in the second target period. By viewing the box plot in Fig. 16(right), it can be confirmed that the declination of the target period 2061–2090 is increasing even more.



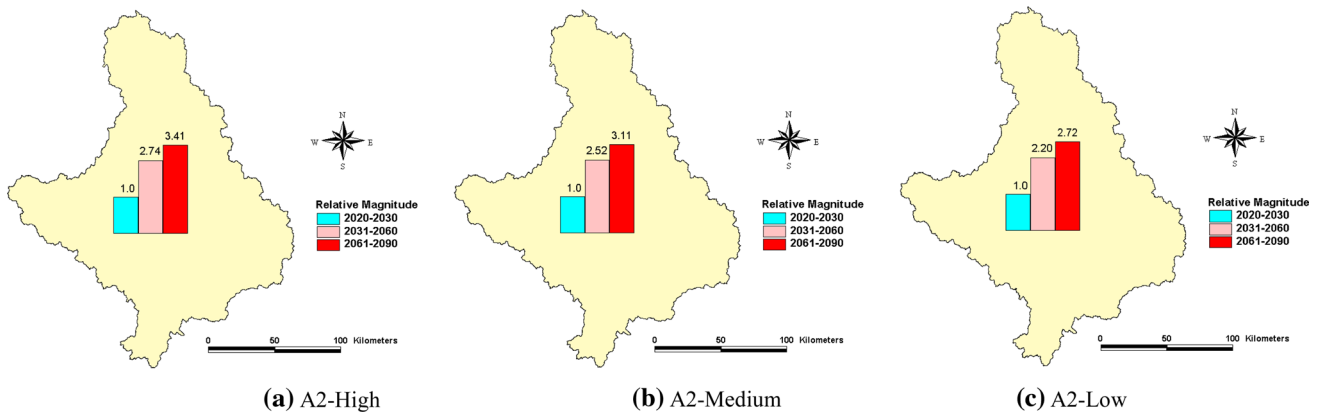


Fig. 13 Increase in water scarcity for the target years by the scenarios

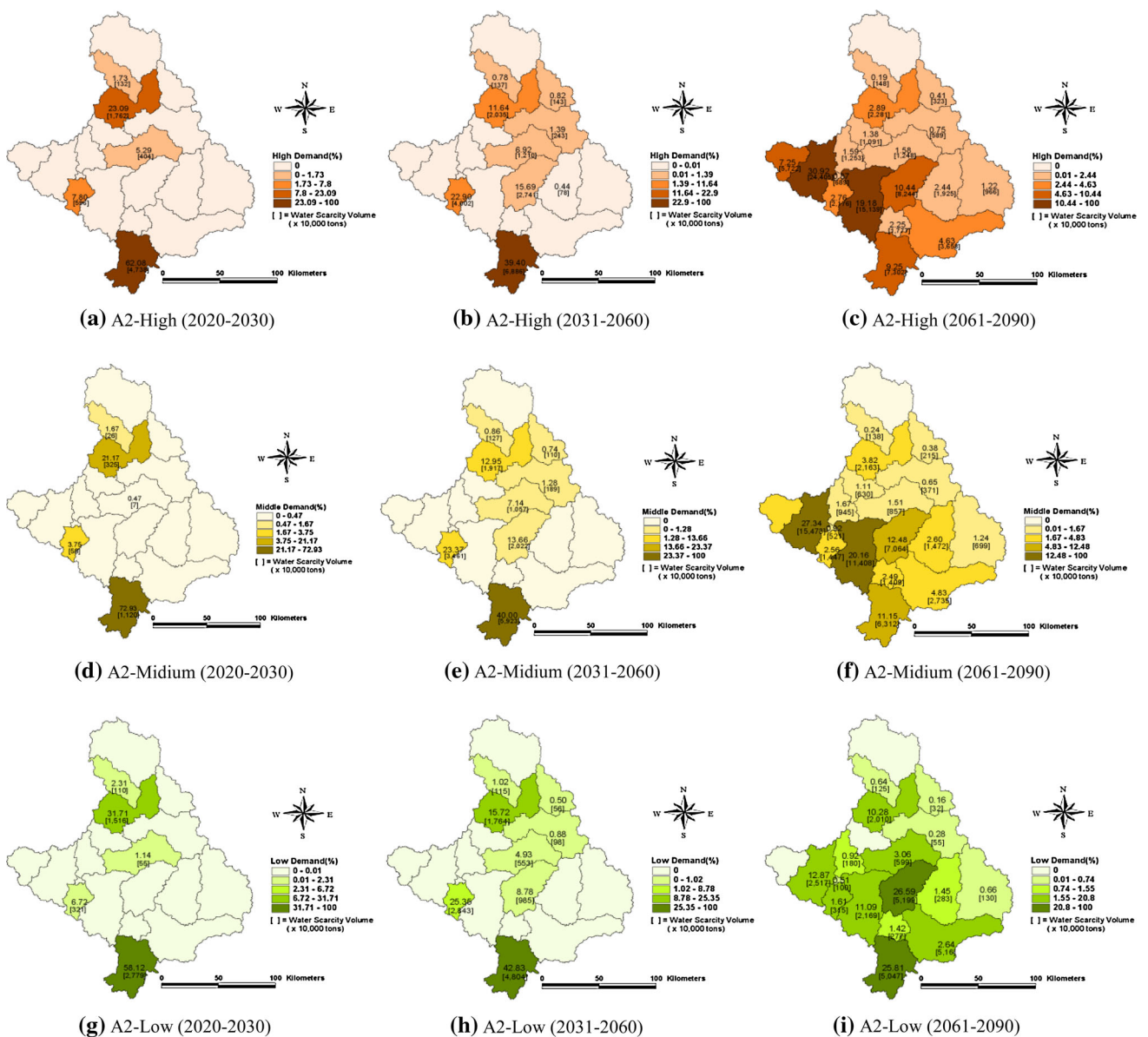
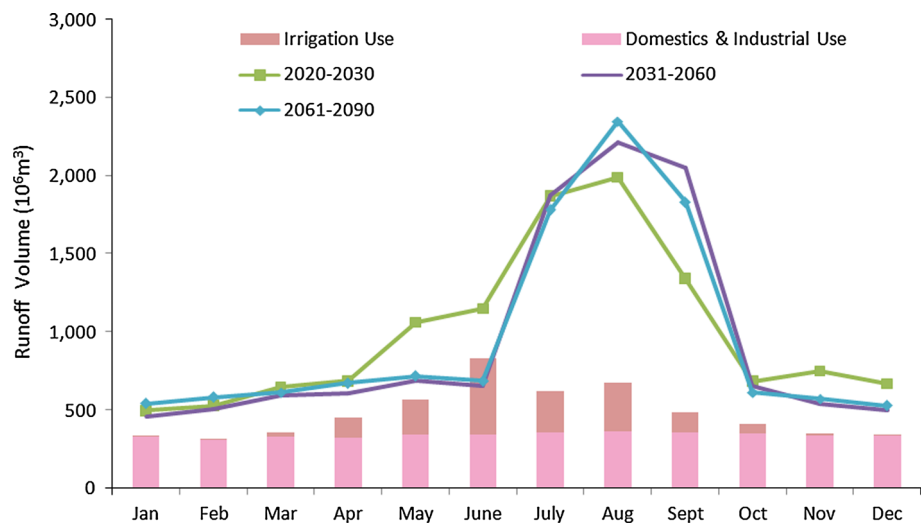


Fig. 14 The share of water scarcity by each sub-basin



**Fig. 15** Change in monthly runoff and demand with respect to the target periods

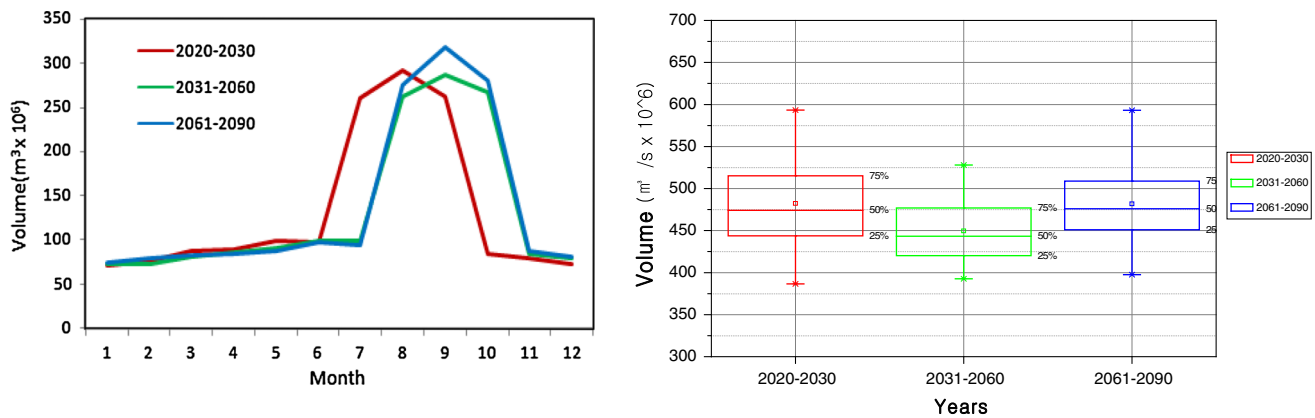


**Table 5** The developed scenarios under consideration of climate change and future water demand

Climate change scenario	Water demand scenarios		Climate change–water demand scenarios
	Scenarios	Demand categories	
A2	High demand	Domestic use Industrial use Irrigation use	A2-high demand
	Medium demand	Domestic use Industrial use Irrigation use	A2-medium demand
	Low demand	Domestic use Industrial use Irrigation use	A2-low demand

**Table 6** The comparison of monthly volume of runoff and water demand during the target periods

	Runoff volume ( $10^6 \text{ m}^3$ )			Water demand volume ( $10^6 \text{ m}^3$ )		Marginal volume ( $10^6 \text{ m}^3$ )		
	2020–2030	2031–2060	2061–2090	Irrigation	Domestic and industrial	2020–2030	2031–2060	2061–2090
Jan	492.5	452.0	537.3	0.8	331.1	160.6	120.0	205.4
Feb	522.9	504.5	579.0	1.3	308.4	213.2	194.8	269.2
Mar	642.6	587.7	609.5	25.2	328.7	288.7	233.8	255.6
Apr	682.1	603.5	668.8	126.6	321.4	234.1	155.5	220.9
May	1,056.9	686.7	713.8	221.9	338.4	496.6	126.4	153.5
June	1,144.1	654.3	682.9	490.2	338.4	315.5	−174.3	−145.7
July	1,867.2	1,871.0	1,779.9	265.5	355.5	1,246.2	1,250.1	1,159.0
Aug	1,985.8	2,209.0	2,345.6	310.2	362.8	1,312.8	1,536.0	1,672.6
Sept	1,339.5	2,045.9	1,828.3	132.6	350.6	856.3	1,562.7	1,345.1
Oct	680.3	649.7	610.6	56.5	348.2	275.7	245.1	206.0
Nov	745.4	537.0	569.4	11.6	336.0	397.7	189.4	221.8
Dec	664.6	497.3	523.2	0.3	338.4	325.9	158.6	184.5



**Fig. 16** Comparison of the characteristics of the monthly runoffs for three periods

#### 4 Conclusions

In this study, in order to develop a methodology for evaluating changes in future water resources due to climate change, land cover change and water demand, we suggested a methodology consisting of various models and techniques. These models and techniques include the A2 climate change scenario of the RegCM3 climate model, the CA-Markov Chain technique, and SLURP. Also, while using the daily runoff data simulated from the SLURP model, a method to execute a water resources evaluation was presented which considers the basin's water supply situation using the K-WEAP model. The method employed depends on the climate change scenario. To reduce the uncertainty involved in predicting future daily precipitation and daily runoff, three climate change–water supply scenarios (A2-low, A2-medium, and A2-high water demands) were formed and for each scenario, 50 sets of daily precipitation and the corresponding daily runoff data were simulated to minimize the skewed values of the estimation. Using such procedures and methodologies, the water scarcity volume was estimated quantitatively while considering climate change and the change in basin characteristics (such as land cover and water demand) in the Han River basin. The result is that water scarcity seems to be deepening during the target periods. Finally, to investigate the cause of the water scarcity, we compared the monthly water scarcity and the monthly runoff in the basin. After investigating, we found that most of the water scarcity volume in the basin occurs in June when the water demand for irrigation use is at its highest. This is because the runoff characteristic of the rainy season shifts from July–September to August–October, which is affected by climate change.

By using the methodology suggested in this study, it is possible to generate predictions, for the purposes of future water resources planning, that takes climate change and change in basin characteristics into account, while

simultaneously minimizing the uncertainty that is inevitable in generating such predictions.

**Acknowledgments** This work was supported by the National Research Foundation of Korea (NRF) and Grant funded by the Korean government (MEST; No. 2011-0028564).

#### References

- Andersson L, Wilk J, Todd MC, Hughes DA, Earle A, Kniveton D, Layberry R, Savenije HG (2006) Impact of climate change and development scenarios on flow patterns in the Okavango River. *J Hydrol* 331:43–57
- Bronstert A, Burger G, Heidenreich M, Katzenmaier D, Kohler B (1999) Effect of climate change influencing storm runoff generation: basic considerations and a pilot study in Germany. In: Proceedings of the international RIBAMOD workshop, Wallingford
- Clarke KC, Hoppen S, Gaydos LJ (1997) A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environ Plan B* 24:247–261
- Cooley KR, Flerchinger GN, Wight JR, Hanson CL (1992) Effect of climate changes on water supplies managing water resources during change. *J Am Water Resour Assoc* 28:185–194
- Cuo L, Beyene TK, Voisin N, Su F, Lettenmaier DP, Alberti M, Richey JE (2010) Effects of mid-twenty-first century climate and land cover change on the hydrology of the Puget Sound basin, Washington. *Hydrol Process*. doi:10.1002/hyp.7932
- Franczyk J, Chang HJ (2009) The effects of climate change and urbanization on the runoff of the Rock Creek basin in the Portland metropolitan area, Oregon, USA. *Hydrol Process* 23(6):805–815
- Gleick PH (1986) Methods for evaluating the regional hydrologic impacts of global climatic changes. *J Hydrol* 88:97–116
- Gleick PH (1987) The development and testing of a water-balance model for climate impact assessment: modeling the Sacramento Basin. *Water Resour Res* 23:1049–1061
- Grell GA (1993) Prognostic evaluation of assumptions used by cumulus parameterizations. *Mon Weather Rev* 121:764–787
- Guo S, Wang J, Xiong L, Ying A, Li D (2002) A macro-scale and semi-distributed monthly water balance model to predict climate change impacts in China. *J Hydrol* 268:1–15
- Hamlet AF, Lettenmaier DP (1999) Effects of climate change on hydrology and water resources objectives in the Columbia River basin. *J Am Water Resour Assoc* 35:1597–1624

- IPCC (2001) Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge
- IPCC (2007) Climate Change 2007, the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change
- Jha M, Pan Z, Takle ES, Gu R (2004) Impacts of climate change on stream flow in the upper Mississippi River basin: a regional climate model perspective. *J Geophys Res* 109:D09105. doi:10.1029/2003JD003686
- Jha M, Arnold JG, Gassman PW, Giorgi F, Gu R (2006) Climate change sensitivity assessment on upper Mississippi River basin streamflows using SWAT. *J Am Water Resour Assoc (JAWRA)* 42(4):997–1016
- Jonathan IM, Graciana P, Kenneth MM (2004) Evaluation of the impact of climate change on hydrology and water resources in Swaziland: Part I. *Phys Chem Earth* 29:1181–1191
- Kite GW (2007) Manual for the SLURP hydrologic model version 12.7. HydroLogic-Solutions
- Kunkel KE, Andsager K, Easterling DR (1999) Long-term trends in extreme precipitation events over the conterminous United States. *J Clim* 12:2515–2527
- Kwon HH, Kim BS (2009) Development of statistical downscaling model using nonstationary Markov chain. *J Korea Water Resour Assoc* 42(3):213–225
- Kwon HH, Kim BS, Kim BK (2008) Analysis of precipitation characteristics of regional climate model for climate change impacts on water resources. *KSCE J Civ Eng* 28(5B):525–533
- Kyoung MS, Kim HS, Sivakumar B, Singh VP, Ahn KS (2011) Dynamic characteristics of monthly rainfall in the Korean Peninsula under climate change. *Stoch Environ Res Risk Assess* 25:613–625
- McCabe GJ, Wolock DM (1999) General circulation model simulations of future snowpack in the western United States. *J Am Water Resour Assoc* 35:1473–1484
- Miller JR, Russell GL (1992) The impact of global warming in river runoff. *J Geophys Res* 97:2757–2764
- Ministry of Construction and Transportation, Korea (2006) Long-term comprehensive water resources plan (2006–2020)
- Ministry of Science and Technology, Korea (2006) Technology for integrated basin-wide water budget analysis and water resources planning. Sustainable water resources research program, the 21st century frontier R&D program
- Nakicenovic N, Alcamo J, Davis G, Vries B, Fenhann J, Gaffin S, Gregory K, Grübler A, Jung TY, Kram T, Rovere ELL, Michaelis L, Mori S, Morita T, Pepper W, Pitcher H, Price L, Riahi K, Roehrl A, Rogner HH, Sankovski A, Schlesinger M, Shukla P, Smith S, Swart R, Rooijen S, Victor N, Dadi Z (2000) Special report on emissions scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, p 599
- Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models, Part I—a discussion of principles. *J Hydrol* 10:283–290
- Obeysekera J, Irizarry M, Park J, Barnes J, Dessalegne T (2011) Climate change and its implications for water resources management in south Florida. *Stoch Environ Res Risk Assess* 25:495–516
- Purkey DR, Joyce B, Vicuna S, Hanemann MW, Dale LL, Yates D, Dracup JA (2008) Robust analysis of future climate change impacts on water for agriculture and other sectors: a case study in the Sacramento Valley. *Clim Change* 87(Suppl 1):S109–S122
- Roald LA, Skaugen TE, Beldring S, Væringstad T, Engeset R, Førland EJ (2003) Scenarios of annual and seasonal runoff for Norway. EGS/AGU/EUG Joint Assembly, Nice, France
- Sivakumar B (2011) Global climate change and its impacts on water resources planning and management: assessment and challenges. *Stoch Environ Res Risk Assess* 25:583–600
- Stewart IT, Cayan DR, Dettinger MD (2005) Changes towards earlier streamflow timing across Western North America. *J Clim* 18:1136–1155
- Yates DN, Strzepek KM (1998) Modeling the Nile Basin under climate change. *J Hydrol Eng* 3(2):98–108