HYDROLOGICAL PROCESSES
Hydrol. Process. **25**, 3437–3447 (2011)
Published online 4 April 2011 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/hyp.8072

The impacts of climate change on local hydrology and low flow frequency in the Geum River Basin, Korea

Jae H. Ryu,[1] Joo Heon Lee,[2]* Sangman Jeong,[3] Seon K. Park[4] and Kyuha Han[3]

[1] *Department of Biological and Agricultural Engineering, University of Idaho, Boise, ID 83702-7359, USA*
[2] *Department of Civil Engineering, Joongbu University, Geumsan, Chungnam-Do, Republic of Korea*
[3] *Department of Civil and Environmental Engineering, Kongju National University, Kongju, Republic of Korea*
[4] *Department of Environmental Science and Engineering, Severe Storm Research Center and Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Republic of Korea*

Abstract:

The climate sensitive analysis of potential climate change on streamflow has been conducted using a hydrologic model to identify hydrologic variability associated with climate scenarios as a function of perturbed climatic variables (e.g. carbon dioxide, temperature, and precipitation). The interannual variation of water resources availability as well as low flow frequency driven by monsoonal time shifts have been investigated to evaluate the likelihood of droughts in a changing climate. The results show that the timing shift of the monsoon window associated with future climate scenarios clearly affect annual water yield change of −12 and −8% corresponding to 1-month earlier and 1-month later monsoon windows, respectively. Also, a more severe low flow condition has been predicted at 0·03 m^3/s as opposed to the historic 7Q10 flow of 1·54 m^3/s given at extreme climate scenarios. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS climate change; low flow; frequency analysis; SWAT; hydrologic model; water resources management

Received 29 July 2010; Accepted 24 February 2011

INTRODUCTION

The potential consequences of climate change have received considerable attention internationally as studies increasingly demonstrate that a wide variety of natural resources, ecosystems, and populations will be affected by future climate variability and change. Recent studies show that the global climate cycle will intensify, creating more severe, frequent, and long-lasting droughts in many regions, resulting in threats to the reliability and quality of water resources, the stability of regional economies, and the sustainability of utility infrastructure (Frederick *et al*., 1997; NCAR, 2008). The variability of precipitation and temperature in eastern Asia, in particular, is of great interest because the annual rainfall occurring during the summer monsoon basically determines the water availability over the year. Additionally, extreme weather conditions during this period often contribute to drought conditions and consequently causes tremendous economic losses (Ryu *et al*., 2009b). These characteristics of the summer monsoon underline the importance of the climate change impact study on mitigating damages associated with uncertain future hydrologic events.

Many studies have been done to investigate long-term hydrologic variability associated with climate change. General circulation models (GCMs) are commonly utilized for regional climate simulation and/or local-scale forecasts under global warming scenarios. For instance, because of the timing change of precipitation and snowmelt in the Pacific Northwest in the United States, regional water resources management is increasingly facing challenges; thus, increased winter precipitation, reduced spring snowpack, and reduced summer streamflows have the potential to disrupt reliable water supplies (Monte *et al*., 2003; Whitely Binder, 2006). Based on the evidence of a larger proportion of snowmelt-driven streamflow volume during springtime due to temperature increase, Miller *et al*. (2003) also have indicated potential impacts of climate change on streamflow in California. Additionally, a number of investigations of international river basins have been conducted to estimate future availability of water and to develop new management strategies in the presence of climate change (Kim *et al*., 2008; Park *et al*., 2009, 2010).

The main goal of the previous studies, however, was to focus on hydrologic consequences of climate change scenarios so that the variability of daily to interannual environmental forcing is investigated. For instance, given the dominantly linear response of the GCMs, future perturbations of hydrologic cycles induced by climate change are identified and estimated to perceive discernible hydrometeorological changes at the regional scale over the next few decades. Relatively little attention was given to understanding the effect of climate change on local hydrology and low flow frequency analysis for the existing system (Ryu *et al*., 2009c).

In this article, the impacts of potential future climate change on the Geum River Basin, Korea, are first

* Correspondence to: Joo Heon Lee, Department of Civil Engineering, Joongbu University, Geumsan, Chungnam-Do, Republic of Korea. E-mail: leejh@joongbu.ac.kr

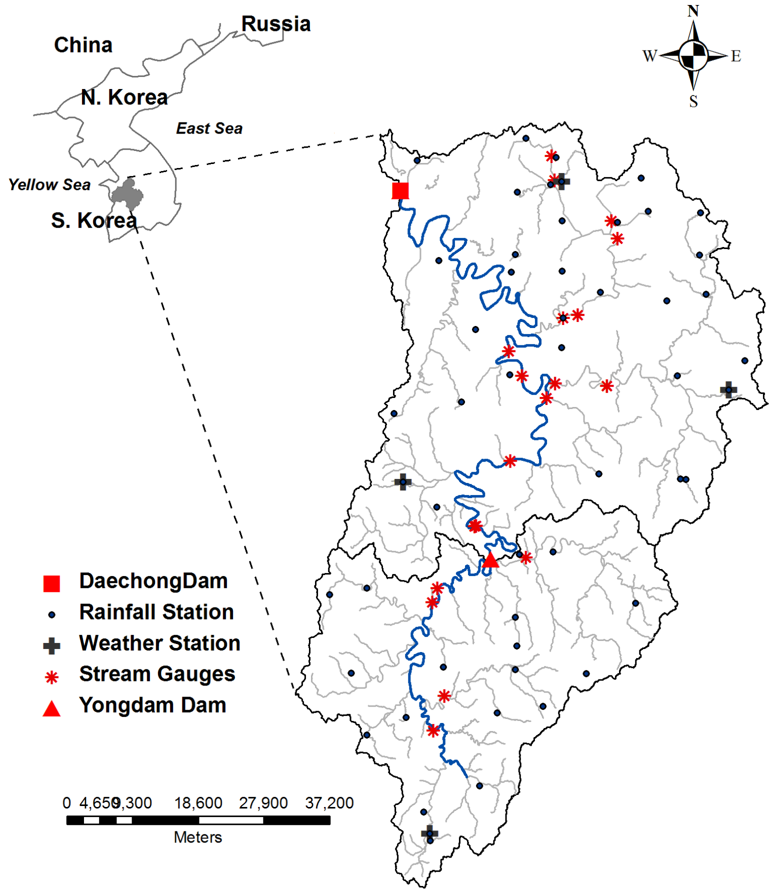

Figure 1. Map of the water system in the Geum River Basin

evaluated based on five different climate scenarios and then the low flow frequency analysis was conducted to evaluate the likelihood of drought in the future. For this purpose, hydrologic simulations associated with environmental forcing from several GCMs were applied to the basin, one of the most climate sensitive basins in Korea, and the 7Q10 (described later in low flow section) low flow statistics was computed to be used as a benchmark by which to evaluate future severe drought conditions induced by climate variability and change. As a result, this work will contribute to finding the missing link between climate science and system engineering, and facilitate interdisciplinary research activities to resolve climate change issues on sustainable water resources planning and management in a changing climate at the watershed scale.

Study area

The Geum River Basin is located in the midwest Korea and has a drainage area of about 9810 km^2 measured at Daechong Dam (Figure 1). The climate of the basin is dominated by the monsoon system and water resources depend largely on the precipitation that occurs during the summer season (June–August). The annual average temperature and precipitation are about 20 °C and 1200 mm, respectively. During typical summer months, heavy rain, humid weather, and wind contribute more than 60% of the annual precipitation. Intensified rain accompanied by tropical cyclones in the region creates flooding, thereby generating tremendous economic losses. This mechanism is reversed during the winter months (December–March). Wind arises from the northeast and originates in the vast anticyclonic circulation over Siberia and brings cold temperature and dry weather. Consequently, the quantity of precipitation that occurs during the monsoon season defines wet/drought conditions so that such a complex climate characteristic makes it difficult to provide accurate climate and hydrologic forecasts.

In addition to the complexity of regional climate system, there are many other water-related issues, including fish flow requirements, water quality control, and increased water demands due to regional population growth, revolving around among the local stakeholders. An adaptive water resources management under uncertain future climate, therefore, is further highlighted to minimize the impacts caused by future extreme drought events.

METHODOLOGY

Climate models and uncertainty

The GCMs are the primary tool for understanding past climate variations and predicting future climate conditions associated with various boundary conditions and environmental forcing, including the initial conditions between atmosphere and sea surface, the amount of solar energy, and the concentrations of anthropogenic gases and particles in the atmosphere. Although there is the tendency of the monsoonal circulation to result in increased precipitation in summer and it is likely warming well above the global mean in East Asia, many aspects of tropical climatic responses, such as cloud physics and atmosphere–ocean interaction, are still not fully understood (Christensen *et al*, 2007). Uncertainty inherent in estimating greenhouse gas (e.g. carbon dioxide—hereafter CO_2) emissions and concentrations is also controversial in the sense that the Intergovernmental Panel on Climate Change (IPCC) scenario, such as IS92a, predicts CO_2 emission under average development and growth projection, considering no adaptive policies for emission mitigation. Furthermore, economists claim that all GCMs currently available do not take into account the policy and economic dimensions of climate change. Thus, the carbon technology improvement is not implemented into the modelling block needed to bring CO_2 into equilibrium.

The comprehensive boundaries of climate change issues, such as pros and cons of individual GCMs in region-specific applications, uncertainties embedded into particular GCMs, discussion of feasible range of CO_2 emission scenarios, and a global/regional climate impact studies, are complex in the different levels of output and cost between developed and developing countries. For the scope of this article, therefore, hydrologic responses and low flow frequency associated with uncertain future climate are solely highlighted to evaluate how climate-driven environmental variables (e.g. CO_2, temperature, and precipitation) affect local hydrology in the Geum River Basin over the next few decades

Climate scenarios

Many scenarios with a combination of CO_2 levels and other environmental factors (e.g. sea surface temperature) are considered and employed in a hydrology model to project future hydrometeorological conditions driven by environmental forcing, such as precipitation and temperature associated with various greenhouse gas scenarios. Two different approaches are most common for indicating the impacts of climate change on the adequacy of local water resources. The application of the coupled climate–hydrologic models to evaluate the potential consequences of climate change is one approach. This approach combines the hydrologic models with the output from GCMs and CO_2 scenarios in GCMs to simulate future runoffs for large-scale simulations (Lettenmaier *et al*., 1999). Alternatively, the climate adjustments associated with climate scenarios are also commonly used. The idea of this approach is to reflect the differences in climate change that characterize the control and analogue periods into the natural streamflow so that flow reconstructions, consequently, are induced by climate change (Frederick, 1993). In this study, a combination of these two methods is utilized to create climate scenarios. Thus, although the meteorological data adjustment is implemented into a hydrologic model to simulate streamflows, the adjustment values are solely derived from GCMs (Christensen *et al*., 2007).

Four scenario families are listed in the IPCC report to represent a broad range of scenarios associated with economic activities, population levels, and energy consumption in the future. Although it appears that both A1B (balanced) and A2 (low energy consumption and high population growth) are most likely representing regional population trends, governments' long-term economic policies, and the rapid development of internet technologies in this study area, scenario A1B has been adopted to generate regional climate scenarios because A1B-based GCMs predict more rigorous climate variability for the next few decades. Based on A1B scenarios, the report provides the regional average of temperature and precipitation projections (2080–2099) using a multi-model data set (MMD) from a set of 21 regional climate models (RCMs) for eight land regions, including Africa, Europe, Asia, North America, Central and South America, Australia and New Zealand, polar regions, and small islands. Those scenarios developed for Asian region are adopted to create the five climate scenarios. Note that the 15-year period from 1981 to 1995 was selected to represent the baseline scenario and the concentration of 330 parts per million by volume (ppmv) for CO_2 level was applied for this study.

A total of five regional climate scenarios were created to identify hydrologic responses to future climate change. For the adjustments of changed climate, the additive and multiplicative technique is utilized for temperature and precipitation, respectively. For instance, Scenario 2 (shown in Table I) simulates July hydrographs using climate forcing, which is a combination of adding daily increases of temperature by 3·3 °C and multiplying precipitation by a factor of 0·42 (−58%) to the baseline scenario. This method applies to all intraseasonal precipitation and temperature shifts over the 15-year baseline simulation periods, in combination with the $1{\cdot}5 \times CO_2$ levels for Scenarios 2–4 and a doubling CO_2 ($2 \times CO_2$) levels for Scenario 5, respectively.

SWAT setup and calibration

As a hydrologic model, the Soil and Water Assessment Tool (SWAT) is used to simulate streamflow not only because this model is commonly used in many watersheds (Gassman *et al*., 2007), but also because SWAT provides a wide range of flexibility for model formulation and calibration processes. The SWAT (Arnold *et al*., 1998) is a semi-distributed and time continuous watershed simulation model, which is developed to address the impact of management and climate on water supplies, sediment, and agricultural chemical yields in watersheds and larger river basins. In SWAT, a watershed is delineated into sub-watersheds that are then further discretized into a series of hydrologic response units (HRUs), which are spatially identified as unique soil–landuse combination areas.

The digital elevation model (DEM), 15 arc-second (1 : 250 000 scale), is employed for topographic relief

Table I. Five climate scenarios to simulate hydrographs

Scenario	Climate parameter	January	February	March	April	May	June	July	August	September	October	November	December
1	CO_2 (ppm)	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5	×1·5
2[a]	Temperature (°C)	3·3	3·3	3·3	3·3	3·3	3·3	3·3	3·3	3·3	3·3	3·3	3·3
	Precipitation (%)	−13	−13	−13	−13	−13	−58	−58	−58	−13	−13	−13	−13
3[a]	Temperature (°C)	5·4	5·4	4·6	4·6	4·6	5·0	5·0	5·0	5·0	5·0	5·0	5·4
	Precipitation (%)	−13	−13	−13	−13	−58	−58	−58	−13	−13	−13	−13	−13
4[a]	Temperature (°C)	5·4	5·4	4·6	4·6	4·6	5·0	5·0	5·0	5·0	5·0	5·0	5·4
	Precipitation (%)	−13	−13	−13	−13	−13	−13	−58	−58	−58	−13	−13	−13
5[b]	CO_2 (ppm)	×2	×2	×2	×2	×2	×2	×2	×2	×2	×2	×2	×2
	Temperature (°C)	5·4	5·4	4·6	4·6	4·6	5·0	5·0	5·0	5·0	5·0	5·0	5·4
	Precipitation (%)	−35	−35	−30	−30	−30	−58	−58	−58	−18	−18	−18	−35

[a] Scenario 1 is incorporated into each scenario.
[b] An extreme drought condition.

Table II. The initial values and parameter ranges for SWAT calibration

Parameter	Description (input file)	Units	Initial value	Final estimate	Value used in literature	Range of values	
						Typical[a]	Possible[a]
AlphaBF	Baseflow recession constant (gw)	None	0·98	0·92	0·01[a], 1·0[b], 0·035[c]	0·1–1	0·04–1
CN2	Curve number II for soil moisture condition (mgt)	None	60	57	49·3[b], 1·0[d]	35–98	0–100
EPCO	Plant uptake compensation factor (hru)	None	1·0	0·8	0·0882[d], 0·6[e]	0·01–1	0–1
ESCO	Soil evaporation compensation factor (hru)	None	0·95	0·2	0·95[f], 0·1[e]	0·01–1	0·10–1
GW_DELAY	Groundwater delay time (gw)	Days	31	0·018	1[a], 150[g], 260[b], 31[f], 47[d]	—	0–400[c]
GW_REVAP	Groundwater 'revap' coefficient (gw)	None	0	0·12	0·02, 0·03[b,e], 0·02[f], 0·2[c]	0·02–0·2	0·02–0·2
GWQMN	Threshold depth for baseflow to occur (.gw)	mm	0	1,087	37·365[d], 5000[c]	—	0–5000
SOL_AWC	Soil available water capacity (sol)	mm	0·16	0·19	0·18[a]	0·01–0·25	0–1

[a] Ahl *et al*. (2008).
[b] Van Liew and Garbrecht (2003).
[c] Tobin and Bennett (2009).
[d] Muleta and Nicklow (2005).
[e] Santhi *et al*. (2001).
[f] Jha *et al*. (2006).
[g] Wu and Xu (2006).

mapping, watershed delineations and modelling, and flow direction computing. And, land use maps of the year of 1995 and 1 : 250 000 soil maps obtained from Water Management Information System (WAMIS, http://wamis.go.kr/eng/; accessed 5 November 2010) of the Ministry of Land, Transport and Maritime Affairs are utilized (not shown in the article). For the potential evapotranspiration (ET) and hydrograph routing, the Penman–Monteith equation (Monteith, 1965) and Muskingum method (McCarthy, 1938) are used. Additional physical mechanism of runoff processes is well documented in a series of publications (Arnold *et al*., 1998).

To identify hydrologic responses to increased CO_2 incorporated into climate scenarios, evaporation of water from the soil into the atmosphere through plant photosynthesis is evaluated. The relation dynamics between CO_2 and environmental variables used for hydrologic simulation in SWAT are explained by the Penman–Monteith equation for ET (Stonefelt *et al*., 2000). The net radiation data are increased appropriately to incorporate the level of CO_2 into hydrologic simulation. The net radiation as CO_2 increase results in facilitating ET processes, causing a decrease in surface runoff (Stonefelt *et al*., 2000). Note that concentrations of CO_2 in climate scenarios range from 495 to 660 ppmv by assuming atmospheric CO_2 concentration of 330 ppmv for the baseline scenario as the reference.

The model calibration and validation periods are 1 January 1981 to 31 December 1991 and 1 January 1992 to 31 December 1995, respectively. The first water year (1 October 1981 to 30 September 1982) is utilized as a 'warm-up' period to stabilize the simulation runs for SWAT. Although many observed streamflow data are readily available at some interior locations (Figure 1), simulated streamflow at the Daechong Dam are evaluated to measure the strength of relationship between the observed and simulated streamflow for the climate impact study. An automatic calibration tool built in the model is utilized to find the best parameter set during the calibration period. For statistical measurements of model performances at the calibration streamflow gauges, the correlation coefficient (R) and Nash–Sutcliffe efficiency (E) (Nash and Sutcliffe, 1970) were selected to compare the model simulations from SWAT to observed streamflow. Eight of the SWAT parameters were calibrated based on guidelines given in Neitsch *et al*. (2005), and the summary of input parameters and range values for the calibration of SWAT is listed in Table II.

For details on each of the calibration parameters, the readers are referred to the literature (Neitsch *et al*., 2005).

Low flow (7Q10 flow)

In general, 7Q10 flow has been utilized as an indicator to define the low flow for regulatory water quality control. The United States Environmental Protection Agency (USEPA) defines the 7Q10 flow as the 'lowest 7-day average flow that occurs (on average) once every 10 years' (USEPA, 2009). Since the 7Q10 flow

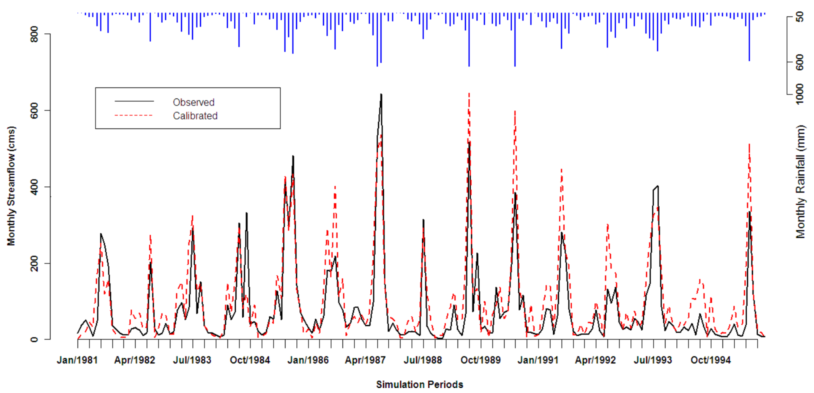

Figure 2. Comparison of observed *versus* simulated monthly average streamflow at the Daechong Dam after calibration

determines minimum instream flow requirements, a low 7Q10 estimate under uncertain future climate can provide useful insights for water managers to alter system operations to meet their demand targets associated with future climate variability and change. To identify the sensitivity of 7Q10 flow against abrupt future climate, frequency analysis is necessary. Based on the literature review, Gumbel has proposed that the third asymptotic distribution of the extreme (smallest) value is one of the most accepted theoretical probability distribution functions for a low flow study (Gumbel, 1958). Later, many scientists suggested that other distributions, such as the generalized extreme value type III (GEV3), the lognormal, and Pearson distributions (Matalas, 1963; Loganathan, 1985; Tasker, 1987), are also acceptable. The parameters of these distributions, however, should be estimated from several statistical methods. Deininger and Westfield (1969) have accomplished estimation of the parameters of GEV3 using four different methods, including (1) the method of moment, (2) an order statistic approach (later L-moment), (3) an observed flow-based method, and (4) a technique based on the sequential least squares and a Fibonacci search, which is a new method introduced by them. They concluded that the fourth estimation method is more acceptable estimates than the other methods, even if it requires highly computational work. Tasker (1987) also examined the performance of parameter estimation for two hypothetical distributions (log-Pearson III and Weibull) by the bootstrap method and suggests that these two distributions are acceptable for the low flow frequency study. Later, based on a regional probability plot correlation coefficient (PPCC) test, Vogel and Kroll (1989) recommended the 2- and 3-parameter lognormal (LN2 and LN3) and log-Pearson type III (LP3) distribution for low flow study, but Önöz and Bayazit (1999) recommended the GEV3 by examining the fit of various probability distributions to low flows at 16 European rivers. More recently, Pearson type III and the 3-parameter lognormal distributions have been recommended by the literature (Kroll and Vogel, 2002; Ames, 2006). For low flow frequency in the study basin, three probability distributions, including (1) GEV3, (2) LN3, and (3) LP3, are selected and three parameter estimation techniques, L-moment (Hosking and Wallis, 1997), the quantile method (Stedinger, 1980), and the method of moment (Stedinger *et al.*, 1993), are applied to fit GEV3, LN3, and LP3 distribution, respectively. More details in statistical justification can be found in the Appendix.

RESULTS AND DISCUSSIONS

Calibration results

Figure 2 shows hydrograph comparisons for the Geum River Basin during simulation periods (1 January 1981 to 31 December 1995) to measure how the calibrated model predicts streamflows against the observed flows. The key hydrologic parameters shown in Table II were adjusted until the simulated flow was nearly equal to the observed flow during calibration processes. Overall, the calibrated flows match observed flows well, but the magnitude of peaks during the summer monsoon (June–August) is somewhat different from the observed flow in particular years, such as July 1986 and 1992 (Figure 2). However, the statistical results show that the model predicted the streamflow at the gage station reasonably because the correlation coefficient (R) and Nash–Sutcliffe efficiency (E) are 0·9 and 0·7, respectively.

Exceedance probability is also a good measure to evaluate how well the model performs to simulate a wide range of streamflows, from low to high flows through normal flows. Although calibrated flows agreed very well with the observed high flows, the simulation overestimates discharge associated with months with normal flows. Outperformance of high flows against normal and low flows in SWAT does not necessarily guarantee that the model exhibits superior results during wet periods because sometimes the simulation consistently overpredicts streamflow during the summer monsoon (Figure 3). Nonetheless, since the overall model performance for streamflow simulation shows satisfactory statistical results, it is considered as a suitable hydrologic model for the long-term climate impact study in the basin.

Climate change scenario output

A total of five climate scenarios are routed into the SWAT model to generate climate sensitive streamflows for the next few decades (2080–2099). All simulations

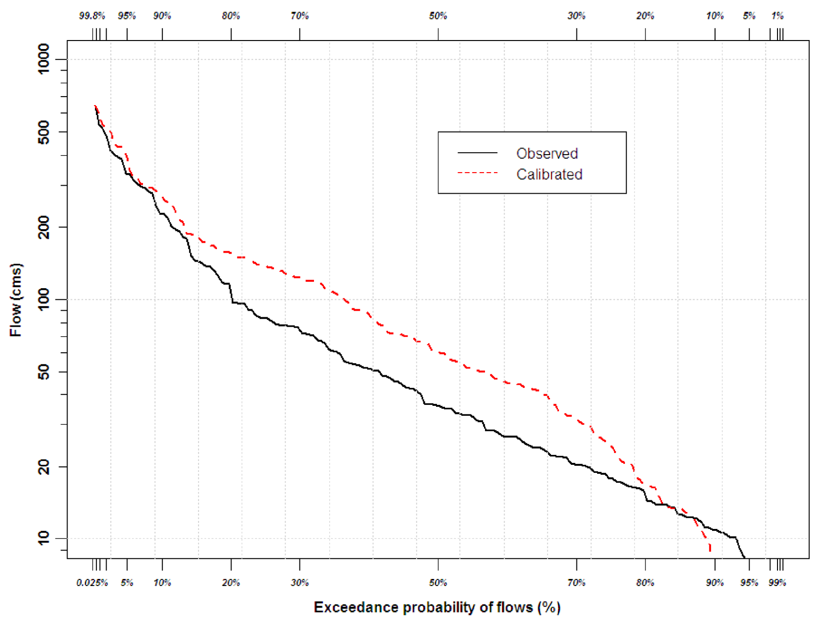

Figure 3. Exceedance probability of observed and simulated flow after calibration over the calibration period at the Daechong Dam

Table III. Relative changes of streamflow (m^3/s) associated with five different climate change scenarios

Month	Baseline scenario	Scenarios				
		1	2	3	4	5[a]
January	19	4 (−79)	5 (−74)	14 (−26)	13 (−32)	9 (−53)
February	29	12 (−59)	16 (−45)	27 (−7)	27 (−7)	14 (−52)
March	46	47 (2)	61 (33)	53 (15)	50 (9)	32 (−30)
April	54	97 (80)	62 (15)	53 (−2)	54	39 (−28)
May	47	74 (57)	63 (34)	23 (−51)	60 (28)	41 (−13)
June	93	163 (75)	53 (−43)	50 (−46)	139 (49)	48 (−48)
July	270	288 (7)	96 (−64)	94 (−65)	99 (−63)	90 (−67)
August	228	242 (6)	83 (−64)	211 (−7)	83 (−64)	78 (−66)
September	158	139 (−12)	129 (−18)	137 (−13)	53 (−66)	116 (−27)
October	45	48 (7)	45	45	43 (−4)	39 (−13)
November	28	42 (50)	46(64)	46 (64)	44 (57)	40 (43)
December	24	8 (−67)	19 (−21)	24	23 (−4)	17 (−29)
Annual(%)		6	−15	−12	−8	−32

Unit in parenthesis is percent (%).
[a] Doubling carbon dioxide ($2 \times CO_2$) and all other scenarios with $1{\cdot}5 \times CO_2$

have been conducted with the same calibrated parameter so that only the consequence of climate change affects the hydrographs. Table III shows relative changes of streamflow simulation associated with five different climate change scenarios. Most of the scenarios project a decrease in streamflow during the dry season, including December, January, and February (DJF). Note that the only simulation of Scenario 1 with increased CO_2 ($1{\cdot}5 \times CO_2$) resulted in an average increase in annual streamflow of 6%, but the magnitude of change varied from season to season.

All scenarios except Scenario 1 are simulated with a combination of an increase in temperature and CO_2 and a gradual decrease of precipitation up to −58%. Precipitation of −58% during a typical monsoon resulted in a large magnitude of change in seasonal variations and produced −15% of annual average flow. It is noteworthy that significant streamflow reduction occurs in all winter months for all scenarios and some gains occur in some months, especially March.

Effects of a possible time shift during the monsoon season on streamflow variability associated with significant precipitation decrease (−58%) are also examined. Scenarios 3 and 4 represent a possible 1-month time shift forward and backward, respectively, and Scenario 2 has no shift applied. Thus, although the months of the typical summer monsoon are defined as a period of June through August, the monsoon window has been redefined as May, June, and July (MJJ) for Scenario 3 and July, August, and September (JAS) for Scenario 4. Interestingly, the results show that Scenario 3 produced maximum monthly flow reduction in July (−65%) and annual flow reduction of 12%, while Scenario 4 produced maximum reduced streamflow of 66% in September and annual reduction of

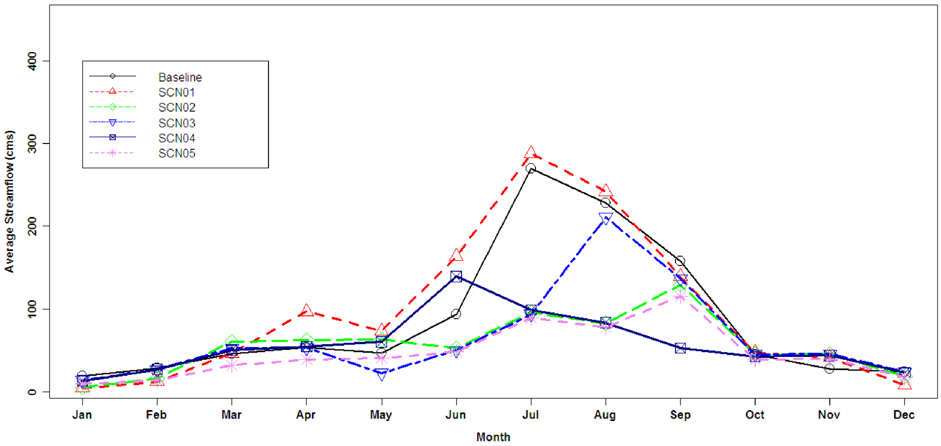

Figure 4. Comparison of baseline *versus* simulated monthly average streamflows from seven different climate scenarios

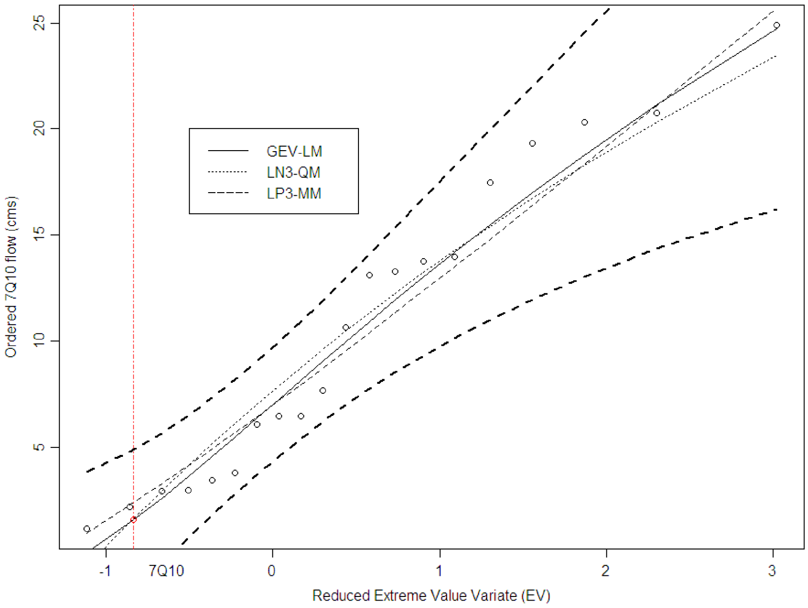

Figure 5. Comparison of three theoretical distributions (GEV-LM, LN3-QM, LP3-MM) with three-parameter estimation techniques for low flow frequency at 95% confidence level

8%. This result implies that annual flow reduction due to the time shift of 1 month during a typical monsoon generally contributes to a change in annual water yield. Scenario 5 represents an extreme drought case; a significant precipitation reduction has been applied to all months with an additional decrease (−58%) during the summer monsoon (Table I). An annual flow reduction is obvious and monthly variations are also noticeable. Perhaps the most interesting cases on water management under uncertain climate are the seasonal change streamflow reduction with diverse climate scenarios, including warmer conditions (Scenario 1), a time shift of the summer monsoon (Scenarios 2–4), and the worst case scenario of a severe drought (Scenario 5). Comparison of the baseline *versus* simulated monthly average streamflows from five different climate scenarios are shown in Figure 4.

From a hydrologic perspective, the summer monsoon system impacts the transition from periods of high to low seasonal flows depending on the magnitude of rainfall during the summer monsoon, so it is very valuable to measure water availability during this period. Knowing water availability under uncertain climate, especially during the summer monsoon, will help system managers provide extra flood control volumes when high flows are expected, store more water at the beginning of a drawdown season when less than average flows are expected, and encourage wise water use during unseasonably dry summer months. The results from climate scenarios produce quantitative estimates of the effects of climate change on streamflow, which is a major water resource to meet all regional water demand targets, including agricultural irrigation, hydropower production, municipal and industrial demand, and environmental flows.

Low flow (drought) frequency output

Figure 5 illustrates a comparison of the 7Q10 streamflow against the Gumbel reduced variable (EV). The 7Q10 streamflow at above the upstream dam during the summer monsoon has been used for a low flow frequency analysis. For parameter estimation, the

L-moment, quantile method, and the method of moment were applied to fit three theoretical distributions: (1) Gumbel's extreme value type III (GEV-LM), (2) the three-parameter lognormal (LN3-QM), and (3) log-Pearson type III (LP3-MM), respectively. Simple correlation coefficients were computed for goodness-of-fit and it is concluded that all three methods are acceptable because of a high correlation coefficient (>0·98). Confidence limits for the events (low flow) suggested by Kite (1975) were also applied to provide useful insights for water managers, who may utilize this analysis to mitigate impacts caused by droughts. Note that the upper and lower dotted lines are established from LN3, parameters being estimated from the observed data by the quantile method and those lines indicate a wide range of uncertainty for LN3 distribution at 95% confidence level. The vertical dotted line represents the 7Q10 low flow driven by uncertain future climate scenarios. Although all three distributions show satisfactory goodness-of-fit, it appears that LN3-QM is the most plausible model because of better fit as it moves toward low flows (Figure 5).

As a result, the magnitude of the 7Q10 low flow from LN3-QM model as opposed to the historic 7Q10 flow during the summer monsoon is greater because those values are computed as 0·03 and 1·54 m^3/s, respectively.

CONCLUSIONS AND FUTURE WORKS

The objective of this study was to examine the effects of climate change on local hydrology and low flow frequency. The SWAT model was utilized to measure hydrologic response to uncertain future climate along with several different climate scenarios, including CO_2 and temperature increase as well as precipitation decrease. Calibration and validation processes were also carried out to evaluate the model's performance. A useful statistic, such as the Nash–Sutcliffe efficiency (E), was computed to evaluate the performance of the hydrologic simulations and then climate-sensitive hydrographs were generated with the input of all combinations of the perturbed climate variables.

In this study, climate change projections in the Geum River Basin are calculated by five different climate scenarios derived from regional climate projections described in the IPCC report (Christensen *et al.*, 2007). Since climate change is expected to further exacerbate existing water shortages, a low flow frequency study is also conducted using a reduced amount of precipitation with temperature increases of 3·3–5·4 °C. Because extreme hydrologic events (drought) are determined by the amount of precipitation during the summer monsoon, drought-prone climate scenarios are applied to SWAT to investigate future problems involving extreme low flow events. Three theoretical distributions, including GEV, LN3, and LP3 with appropriate parameter estimation techniques, are applied to the low flow frequency study. The results show that the decreased precipitation contributes to the streamflow reduction, which is obvious in a hydrologic sense. It is noteworthy that the time shift of 1 month during a typical monsoon contributes to seasonal variation in the average monthly flows. The result shows that the 7Q10 flow driven by the worst case climate scenario as opposed to the historic 7Q10 flow imply that water manager should be aware of future hydrologic changes in the basin.

Water resources in many watersheds are exacerbated by rapid demographic and economic development. The Geum River Basin, in particular, has a heavy and increasing stress due to ongoing water conflicts (Ryu *et al.*, 2009a), therefore the impact of climate change on sustainable water resources management is of great concern. The GCMs provide many climate scenarios and scientific evidences that show that global warming and climate change could potentially have adverse impacts on water resources, the environment, and socioeconomic activities. However, there is still a missing link between climate and social science disciplines, which need to better communicate 'what we know and what to do now' in order to address as many questions as possible related to climate change in human dimensions. The results from this study will help bridge the gap among interdisciplinary water research activities, especially for studies of the impacts of climate variability and change on regional water management.

APPENDIX

Low flow frequency analysis

Extreme value type III distribution. In low flow frequency analysis for drought, Gumbel's third asymptotic distribution (Gumbel, 1958) of the smallest value is widely used because type III distribution has a lower bound. This type of asymptotic distribution for maxima, which is commonly used for flood frequency analysis, is given as (Jenkinson, 1969; Stedinger *et al.*, 1993)

$$F(x) = \exp\left[-\exp\left(-\frac{x-\zeta}{\alpha}\right)\right],\ k = 0 \qquad \text{(A1a)}$$

$$F(x) = \exp\left\{-\left[1-\frac{k(x-\zeta)}{\alpha}\right]^{1/k}\right\},\ k \neq 0 \qquad \text{(A1b)}$$

where ζ, $\alpha > 0$, and k are location, scale, and shape parameters, respectively. The shape parameter k determines the types, including types I, II, and III corresponding to $k = 0$, $k > 0$, and $k < 0$, respectively. Type II has an upper bound $[x < (\zeta + (\alpha/k))]$ when $k > 0$, while type III has a lower bound $[x > (\zeta + (\alpha/k))]$ when $k < 0$. Since low flow (drought) is opposite from high flow (flood), their relationship is symmetric. The symmetry principle of the generalized extreme value (GEV) distribution for mimima (e.g. drought) can be written (Önöz and Bayazit, 1999)

$$F(x) = 1 - \exp\left[-\exp\left(-\frac{x-\zeta}{\alpha}\right)\right],\ k = 0 \qquad \text{(A2a)}$$

$$F(x) = 1 - \exp\left\{-\left[1 - \frac{k(x-\zeta)}{\alpha}\right]^{1/k}\right\},\quad k \neq 0 \tag{A2b}$$

Type III has a lower bound $\left[x \geq -\left(\zeta + \frac{\alpha}{k}\right)\right]$ when $k > 0$.

In terms of parameter estimation, the L-moment approach based on the ordered sample is convenient and efficient (Hosking and Wallis, 1997). To estimate the parameters of GEV3 for minima, the formulas are derived by the method of the probability-weighted moments (PWMs) (Önöz and Bayazit, 1999)

Three-parameter lognormal. Another method used for low flow frequency analysis in this study is the three parameter lognormal (LN3) method using an improved fitting procedure introduced by Stedinger (1980). The cumulative distribution function of LN3 is

$$F(x) = \Phi\left[\frac{\{\ln(x-\tau) - \mu_y\}}{\sigma_y}\right] \tag{A3}$$

where $\Phi[\bullet]$ is the cumulative distribution function of the standard normal distribution, and μ_y, σ_y and τ are mean, standard deviation, and location parameter, respectively (Hoshi *et al.*, 1984). A location parameter τ is normally estimated by the various methods. The parameter estimation of τ for LN3 is obtained by the quantile method (Stedinger, 1980).

Log-Pearson type III (LP3). Ames (2006) demonstrates 7Q10 streamflow estimates using log-Pearson type III method. This method is recommended by the American Society of Civil Engineers for low flow studies (ASCE, 1980). The probability density function of LP3 can be represented as

$$f(x) = \frac{\lambda^{\beta}(x-\zeta)^{\beta-1}e^{-\lambda(x-\zeta)}}{\Gamma(\beta)} \tag{A4}$$

where, λ, β, and ζ are parameters for LP3 and the method of moments is applied for parameter estimations (Stedinger *et al.*, 1993).

ACKNOWLEDGEMENTS

This project is supported by multiple funding sources. Jae H. Ryu and Sangman Jeong received support from the National Emergency Management Agency of Korea (NEMA-08-NH-05) as part of the Drought Information System for National Disaster Reduction. Seon K. Park received support from the Ministry of Environment, Korea, under the National Comprehensive Measures against Climate Change Program (No. 1700-1737-322-210-13) and from the Ministry of Education, Science and Technology, Korea, through the National Research Foundation grant (No. 2009-0093464). Additionally, Jae Ryu, University of Idaho, was supported by the NSF Idaho EPSCoR Program and by the National Science Foundation under award number EPS-0814387.

REFERENCES

Ahl RS, Woods SW, Zuuring HR. 2008. Hydrologic calibration and validation of SWAT in a snow-dominated Rocky Mountain Watershed, Montana, USA. *Journal of the American Water Resources Association* **44**(6): 1411–1430.

Ames DP. 2006. Estimating 7Q10 confidence limits from data: a bootstrap approach. *Journal of Water Resources Planning and Management* **132**(3): 204–208.

Arnold JG, Srinivasan R, Muttiah RS, Williams JR. 1998. Large area hydrologic modeling and assessment, Part I: model development. *Journal of the American Water Resources Association* **34**(1): 73–89.

ASCE. 1980. Characteristics of low flows. Task committee on low-flow evaluation methods, and needs of the committee on surface water hydrology of the hydraulics division. *American Society of Civil Engineers* **106**(5): 717–731.

Deininger RA, Westfield JD. 1969. Estimation of the parameters of gumbel's third asymptotic distribution by different methods. *Water Resources Research* **5**(6): 1238–1243.

Frederick KD. 1993. Climate change impacts on water resources and possible responses in the MINK region. *Climatic Change* **24**(1–2): 93–115.

Frederick KD, Major DC, Stakhiv EZ. 1997. *Climate Change and Water Resources Planning Criteria*. Kluwer Academic Publishers: Dordrecht, The Netherlands; 313 pp.

Gassman PW, Reyes MR, Green CH, Arnold JG. 2007. The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASAE* **50**(4): 1211–1250.

Gumbel EJ. 1958. Statistical theory of floods and droughts. *Journal of the Institution of Water Engineers* **12**(3): 157–184.

Hoshi K, Stedinger JR, Burges SJ. 1984. Estimation of log-normal quantiles: monte carlo results and first-order approximations. *Journal of Hydrology* **71**(1–2): 1–30.

Hosking JRM, Wallis JR. 1997. *Regional Frequency Analysis*. Cambridge University Press: New York.

Christensen JH, Hewitson B, Busuioc A, Chen A, Gao X, Held I, Jones R, Kolli RK, Kwon W-T, Laprise R, Magaña Rueda V, Mearns L, Menéndez CG, Räisänen J, Rinke A, Sarr A, Whetton P. 2007. Regional Climate Projections. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds.). Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA.

Jenkinson AF. 1969. *Statistics of extremes*. Technical Note 98. World Meteorological Organisation, Geneva.

Jha M, Arnold JG, Cassman PW, Giorgi F, Gu RR. 2006. Climate change sensitivity assessment on upper mississippi river streamflows using SWAT. *Journal of the American Water Resources Association* **42**(4): 997–1016.

Kim U, Kaluarachchi JJ, Smakhtin V. 2008. Generation of monthly precipitation under climate change for the Upper Blue Nile River Basin, Ethiopia. *Journal of the American Water Resources Association* **44**(5): 1231–1247.

Kite GW. 1975. Confidence limits for design events. *Water Resources Research* **11**(1): 48–53.

Kroll CN, Vogel RM. 2002. Probability distribution of low streamflow series in the United States. *Journal of Hydrologic Engineering* **7**(2): 137–146.

Lettenmaier DP, Wood AW, Palmer RN, Wood EF, Stakhiv EZ. 1999. Water resources implications of global warming: a U.S. regional perspective. *Climatic Change* **43**(3): 537–579.

Loganathan GV. 1985. Frequency analysis of low flows. *Nordic Hydrology* **17**(2): 129–150.

Matalas NC. 1963. *Probability distribution of low flows*. Professional Paper 434-A. U.S. Geological Survey Washington, DC.

McCarthy GT. 1938. The unit hydrograph and flood routing. *Conference North Atlantic Division*, US Army Corporation of Engineers.

Miller NL, Bashford KE, Strem E. 2003. Potential impacts of climate change on california hydrology. *Journal of the American Water Resources Association* **39**(4): 771–784.

Monte PW, Parson EA, Hamlet AF, Keeton WS, Lettenmaier DP, Mantua NJ, Miles EL, Peterson DW, Peterson DL, Slaughter R, Snover AK. 2003. Preparing for climate change: the water, salmon, and forests of the pacific northwest. *Climatic Change* **61**(1–2): 45–88.

Monteith JL. 1965. *The State and Movement of Water in Living Organisms, XIX Symposium Society for Experimental Biology*. Swansea, Cambridge University Press: Cambridge.

Muleta MK, Nicklow JW. 2005. Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. *Journal of Hydrology* **306**(1–4): 127–145.

Nash JE, Sutcliffe JV. 1970. River flow forecasting through conceptual models: part I—a discussion of principles. *Journal of Hydrology* **10**(3): 282–290.

NCAR. 2008. Climate Research. The National Center for Atmospheric Research. http://www.ncar.ucar.edu/research/climate/ [accessed: 2 January 2009].

Neitsch SL, Arnold JG, Kiniry JR, Williams JR. 2005. Soil and water assessment tool theoretical documentation, Version 2005. USDA-ARS Grassland, Soil and Water Research Laboratory. Temple, Texas. http://www.brc.tamus.edu/swat/doc.html [accessed 1 November 2006].

Önöz B, Bayazit M. 1999. GEV-PWM model for distribution of minimum flows. *Journal of Hydrologic Engineering* **4**(3): 289–293.

Park G-A, Ahn S-R, Lee Y-J, Shin H-J, Park M-J, Kim S-J. 2009. Assessment of climate change impact on the inflow and outflow of two agricultural reservoirs in Korea. *American Society of Agricultural and Biological Engineers* **52**(6): 1869–1883.

Park MJ, Park JY, Shin HJ, Lee MS, Park GA, Jung IK, Kim SJ. 2010. Projection of future climate change impacts on nonpoint source pollution loads for a forest dominant dam watershed by reflecting future vegetation canopy in a Soil and Water Assessment Tool model. *Water Science and Technology* **61**(8): 1975–1986.

Ryu JH, Palmer RN, Jeong S, Lee JH, Kim Y-O. 2009a. Sustainable water resources management–conflict resolution framework. *Journal of the American Water Resources Association* **45**(2): 485–499.

Ryu JH, Palmer RN, Wiley MW, Jeong S. 2009b. Mid-range streamflow forecast based on climate modeling-statistical correction and evaluation. *Journal of the American Water Resources Association* **45**(2): 355–368.

Ryu JH, Jeong SJ, Park SK, Lee JH, Han KH. 2009c. Application of SWAT to climate-driven low flow (drought) frequency analysis. *5th International SWAT Conference, August 3–7*, Boulder, Colorado.

Santhi C, Arnold JG, Williams JR, Dugas WA, Srinivasan R, Hauck LM. 2001. Validation of the SWAT model on a large river basin with point and non-point sources. *Journal of the American Water Resources Association* **37**(5): 1169–1187.

Stedinger JR. 1980. Fitting log normal distributions to hydrologic data. *Water Resource Research* **16**(3): 481–490.

Stedinger JR, Vogel RM, Efi F-G. 1993. In *Handbook of Hydrology*, Maidment D (ed). McGraw-Hill: New York; 18·12–18·13.

Stonefelt MD, Fontaine TA, Hotchkiss RH. 2000. Impacts of climate change on water yield in the Upper Wind River Basin. *Journal of the American Water Resources Association* **36**(2): 321–336.

Tasker GD. 1987. A Comparison of methods for estimating low flow characterisics of streams. *Journal of the American Water Resources Association* **23**(6): 1077–1083.

Tobin KJ, Bennett ME. 2009. Using SWAT to model streamflow in two river basins with ground and satellite precipitation data. *Journal of the American Water Resources Association* **45**(1): 253–271.

USEPA. 2009. DFLOW: a tool for low flow analysis in water quality models and tools. United States Environmental Protection Agency, Washington, DC, 5 March 2009. (http://epa.gov/waterscience/models/dflow/flow101.htm) [accessed: 10 January 2010].

Van Liew MW, Garbrecht J. 2003. Hydrologic simulation of the little washita river experimental watershed using SWAT. *Journal of the American Water Resources Association* **39**(2): 413–426.

Vogel RM, Kroll CN. 1989. Low-flow frequency analysis using probability-plot correlation coefficients. *Journal of Water Resources Planning and Management* **115**(3): 338–357.

Whitely Binder LC. 2006. Climate change and watershed planning in Washington state. *Journal of the American Water Resources Association* **42**(4): 915–926.

Wu K, Xu YJ. 2006. Evaluation of the applicability of the SWAT model for coastal watersheds in Southern Louisiana. *Journal of the American Water Resources Association* **42**(5): 1247–1260.

