Available online at www.sciencedirect.com

ScienceDirect

Journal of Environmental Sciences 2010, 22(6) 840–845

JOURNAL OF ENVIRONMENTAL SCIENCES
ISSN 1001-0742
CN 11-2629/X
www.jesc.ac.cn

Predicting the impacts of climate change on nonpoint source pollutant loads from agricultural small watershed using artificial neural network

Eunjeong Lee[1], Chounghyun Seong[1,*], Hakkwan Kim[2], Seungwoo Park[1,2], Moonseong Kang[1,2]

1. Department of Landscape Architecture and Rural Systems Engineering, Seoul National University, Seoul 151-921, Korea. E-mail: tweety45@snu.ac.kr
2. Research Institute for Agricultural & Life Sciences, Seoul National University, Seoul 151-921, Korea

Received 02 October 2009; revised 24 December 2009; accepted 06 January 2010

Abstract

This study described the development and validation of an artificial neural network (ANN) for the purpose of analyzing the effects of climate change on nonpoint source (NPS) pollutant loads from agricultural small watershed. The runoff discharge was estimated using ANN algorithm. The performance of ANN model was examined using observed data from study watershed. The simulation results agreed well with observed values during calibration and validation periods. NPS pollutant loads were calculated from load-discharge relationship driven by long-term monitoring data. LARS-WG (Long Ashton Research Station-Weather Generator) model was used to generate rainfall data. The calibrated ANN model and load-discharge relationship with the generated data from LARS-WG were applied to analyze the effects of climate change on NPS pollutant loads from the agricultural small watershed. The results showed that the ANN model provided valuable approach in estimating future runoff discharge, and the NPS pollutant loads.

Key words: artificial neural network; climate change; LARS-WG; nonpoint source pollution; runoff

DOI: 10.1016/S1001-0742(09)60186-8

Introduction

From the recent Intergovernmental Panel on Climate Change (IPCC) 4th Assessment Report, the increase of global average temperature for the end of the 21st century (2090–2099) relative to 1980–1999 would be 0.3–6.4°C, and a rise in global average sea level of about 18–59 cm would be expected at the 21st century (IPCC, 2007). Global warming not only causes increasing atmospheric water vapor content, changing precipitation patterns, intensity and extremes, and changing soil moisture and runoff, but also affects water quality and exacerbates many forms of water pollution such as nutrients, sediments, and pathogens with possible negative impacts on ecosystems and human health (Bates et al., 2008). The effects of these pollutants, called as nonpoint source (NPS) pollutants which caused by rainfall, are well documented in the other studies (Carpenter et al., 1998; Novotny and Olem, 1994).

Controlling NPS pollution is important to improve water quality. However, the control of NPS pollutions is difficult because they are affected by rainfall runoff which has great temporal and spatial variations. More accurate estimation of runoff and NPS pollutions is required to manage water quality, and make plans for future strategies to be applied at watershed. For that purpose, numerous watershed simulation models are used today. Many of the commonly used watershed models are based on physical theories and require lots of input data, meteorological, geomorphic data and so on, and great efforts are needed. However the commonly used weather generators to simulate a future climate data, LARS-WG (Long Ashton Research Station-Weather Generator) and WGEN (A Model for Generation Daily Weather Generator), only generate precipitation, maximum and minimum temperature and solar radiation on a daily basis. Thereby, there are lack of data to simulate the detailed hydrologic models.

The artificial neural network (ANN) algorithm, which is a non-linear black-box model, would seem to be a useful alternative for modeling the runoff. The advantages of an ANN model are that it is able to represent nonlinearity by means of a smaller number of parameters and that there are no prior assumptions regarding the processes involved (Kang et al., 2006). The ANN is widely used in river flow prediction, and rainfall-runoff relationship (Hsu et al., 1995; Dawson and Wilby, 2001; Kisi, 2004), ANN applications in hydrology were reviewed by the ASCE Task Committee (2000a, 2000b).

This study aims to predict NPS pollutant loads from agricultural small watershed when rainfall pattern becomes different by climate change. The future rainfall data are generated by stochastic weather generator, and the ANN

* Corresponding author. E-mail: fpdlsao2@snu.ac.kr

model to simulate runoff discharge from rainfall data is developed. The NPS pollutant loads are calculated from load-discharge relationship driven by long-term monitoring data.

1 Materials and methods

1.1 Study watershed

The Baran watershed, located in Hwaseong City in Gyunggi-do, Korea, has been monitored since 1996, hydrologic and water quality data have been collected on biweekly basis. The HP#6, an agricultural sub-watershed, was selected for estimating future NPS loads. The study watershed has a drainage area of 384.8 ha, with 51% forest, 20% urban, 19% paddy, and 10% the remainder consisting of cropland and some water (Fig. 1).

The water levels have been measured by two types of water level gauge, float- and pressure-type, and measured water level data were converted to stream flow rates using stage-discharge relationship equation which derived from discharge measurements. Figure 2 shows daily streamflow hydrograph at the HP#6 gauging station from 1996 to 2004. An exponential load-discharge relationship was applied to calculate daily SS, TN, and TP loads at the watershed outlet. The load-discharge relationships were established for SS, TN, and TP using data collected during the study period (Table 1). These relationships are commonly used to determine NPS loads because that well represent the variation of water quality due to runoff discharge even if that are based on the assumption that there are no landuse changes and NPS discharge characteristics in watershed.

1.2 Generation of future climate data

LARS-WG model is a stochastic weather generator which can be used for the simulation of weather data at a single site (Racsko et al., 1991; Semenov et al., 1998) and for the assessment of climate change impacts. These

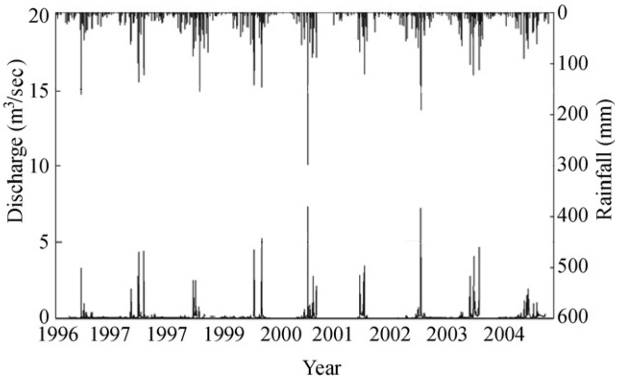

Fig. 2 Daily streamflow hydrograph at the HP#6 gauging station.

data are in the form of daily time-series for a suite of climate variables, namely, precipitation (mm), maximum and minimum temperature (°C) and solar radiation ($\times 10^6$ J/(m^2·day)). LARS-WG is based on modeling of dry and wet periods, precipitation is modeled independently for each wet day. The temperature and radiation are conditioned on wet or dry status of the day (Semenov and Barrow, 1997). Semi-empirical distributions were used for precipitation, duration of wet and dry spells and radiation (Semenov et al., 1998), which are more flexible for representing local weather conditions.

Climate change scenario used in present study was based on the output from the Hadley Centre Climate Model (HadCM3) included in LARS-WG model. The HadCM3 was used to predict climate change for the IPCC 3rd and 4th Assessment Reports, and has been widely used in other studies for impact assessment. The IPCC SRES (Special

Table 1 Load-discharge relationship at HP#6

Station	Item	Load-discharge relationship	R^2
HP#6	SS (kg/day)	SS = $0.0003 \times Q^{1.4778}$	0.885
	TN (kg/day)	TN = $0.0367 \times Q^{0.8104}$	0.923
	TP (kg/day)	TP = $0.0009 \times Q^{0.8901}$	0.847

TN: total nitrogen; TP: total phosphorous.

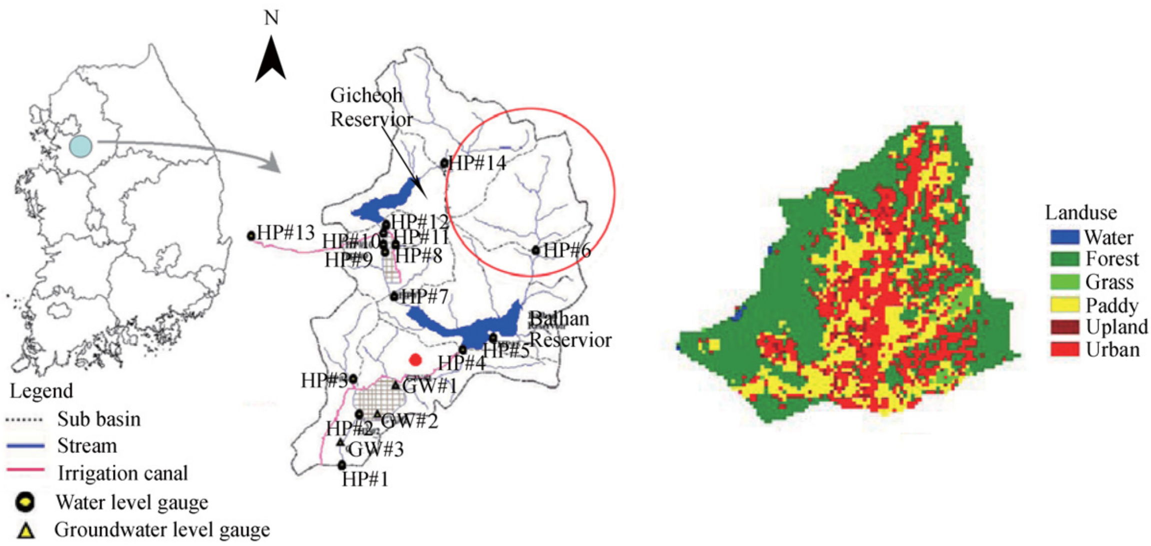

Fig. 1 Monitoring network and landuse of Baran study watershed.

Report on Emission Scenarios A1B scenario (IPCC, 2000), which assumes globalization with strong economic growth and technological emphasis balanced across all sources (i.e., the lower middle range of growth in CO_2 emissions) and most coincides with the reality, was selected to simulate future climate.

The meteorological data such as maximum and minimum temperature, rainfall, and solar radiation from 1973 to 2008 were obtained from the Suwon National Weather Station located approximately 8 km northwest of the study watershed.

1.3 Artificial neural network

The artificial neural network (ANN) model consists of an input layer, a hidden layer, an output layer, and connections between them (Fig. 3). The corresponding architecture for back-propagation learning in incorporating both the forward and the backward phases of the computation involved in learning process. The learning mechanism of this back-propagation network is a generalized delta rule that performs a gradient descent on the error space to minimize the total error between the actual calculated values and the desired ones of an output layer during modification of connection strengths.

ANNs with one hidden layer are commonly used in hydrologic modeling since these networks are considered to provide enough complexity to accurately simulate nonlinear-properties of the hydrological processes (Wu et al., 2009).

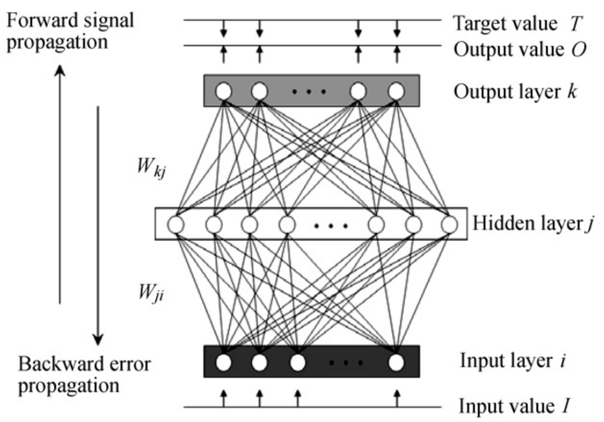

Fig. 3 Structure of multilayer neural network.

Table 3 Results of estimating future NPS loads (ton/yr)

	SS	TN	TP
2011–2030	148.4	15.2	0.8
2046–2065	351.4	20.7	1.2
2080–2099	281.1	19.0	1.1

2 Results and discussion

2.1 Generation of future climate data

The meteorological data, daily maximum and minimum temperature, rainfall, and solar radiation from Suwon National Weather Station, were used as input data of LARS-WG to generate future climate data caused by climate changes. To determine if there are any statistically-significant differences between the observed and synthetic data, Q-test was performed. Because the synthetic data probability distributions are close to the long-term observed distributions for the site in question, 300 of years of synthetic weather data were generated. Table 2 shows statistical characteristics of observed and simulated data. The parameters derived from input data were well estimated.

For the climate change impacts on NPS loads, three time periods were considered as scenarios: 1973–2008 (baseline), 2011–2030, 2046–2065, and 2080–2099. The future daily climate data of three time periods were generated based on HadCM3 SRES A1B scenario using validated parameters. According to climate change, a rise in mean maximum and minimum temperature, a gradual increase in precipitation, and a decrease in solar radiation would be expected to occur.

2.2 ANN model calibration and validation

The ANN model was developed to simulate the daily discharge rate. Among the four factors generated by LARS-WG model, the rainfall strongly influences runoff, but minimum and maximum temperature and solar radiation have little effects on it. It leads to a problem that there were insufficient nodes in input layer of ANN model, because only the rainfall data could be used as input data of ANN model. To solve it, a simple moving average method was considered and window length (K) was determined by the Pearson correlation coefficient between observed discharge data and moving average. The simple moving average is simply the average of the last K rainfall data. The final K was 2, 3, and 4.

Table 2 Result of LARS-WG Q-test (monthly mean values)

Item		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rainfall (mm)	Obs	27.3	23.9	57.7	85.9	91.3	158.5	265.4	265.4	158.6	69.4	46.6	27.0
	Sim	22.1	23.5	44.6	76.9	95.7	136.8	323.3	279.6	139.8	49.8	46.9	23.1
Min temp (°C)	Obs	–7.2	–5.4	0.3	5.9	11.4	17.0	21.2	21.5	15.9	8.5	1.5	–4.6
	Sim	–7.6	–5.6	–0.4	5.6	11.5	17.1	21.5	21.8	16.0	8.4	1.4	–4.7
Max temp (°C)	Obs	2.4	4.7	11.0	17.2	22.4	26.2	28.7	29.4	25.5	19.7	12.1	5.1
	Sim	2.1	4.6	10.4	17.7	22.7	26.6	28.7	29.7	25.8	20.0	12.0	4.9
Solar radiation	Obs	7.7	10.2	12.5	15.0	16.7	15.8	13.2	14.0	12.9	10.7	8.0	7.0
($\times 10^6$ J/(m^2·day))	Sim	7.8	10.4	12.9	15.5	16.7	15.8	12.9	13.7	13.1	11.4	8.1	7.0

Obs: observed; Sim: simulated.

The hydrologic data from 1996 to 2000 were used for the calibration and the data from 2001 to 2004 were used for the validation.

The following function was proposed:

$$Q(t) = function\{R(t - 1), R(t), R_{mv_2}(t), R_{mv_3}(t), R_{mv_4}(t)\}$$

where, $Q(t)$ (m^3/sec) is the daily discharge rate at time t (day), R(t–1), $R(t)$ (mm) is the rainfall at time t–1 and t, and $Rmv_i(t)$ is the i-term moving average of rainfall at time t.

The node number of hidden layer was determined by comparing the total error that sum of differencesbetween observed and simulated discharge. Total error showed the smallest value at the hidden layer that has 14 nodes. Figure 4 shows the results of calibration and validation. The runoff discharge for HP#6 watershed was well reproduced by the ANN model, with the determination coefficients (R^2) of 0.9048 for calibration and 0.7494 for validation.

2.3 Estimation of future NPS loads

The future NPS loads, summation of daily loads during the year, were calculated from simulated discharge rate data on a daily basis and load-discharge relationship equations each NPS pollutants such as SS, TN, and TP in Table 1. The results of estimation of future NPS loads are provided in Table 3. The most of NPS loads were expected to be discharged from small watershed in 2046–2065. These results were caused by several intensive rainfall events. As shown in Table 4, the maximum and mean amount of rainfall in 2046–2065 is higher than in 2080–2099 from May to October. Because the NPS loads were calculated from load-discharge relationship which is expressed in exponential form (Table 1), several heavy rainfall events have resulted in huge amount of NPS loads. The annual mean SS loading in 2080–2099 (281.1 tons/yr) was 1.89 times greater than that in 2011–2030 (148.4 tons/yr), and the nutrient loads in 2080–2099 increased to 1.25 times for total nitrogen and 1.38 times for total phosphorous compared with that in 2011–2030 (Table 3). The results of this study were compared with other studies because there are no true values to compare with simulated values for future. According to Chang et al. (2001), the change of future mean annual nutrient loads were estimated to range

Table 4 Characteristics of generated weather data from LARS-WG

Month		2011–2030				2046–2065				2080–2099			
		Min temp (°C)	Max temp (°C)	Rainfall (mm)	Solar radiation (× 10^6 J/(m^2·day))	Min temp (°C)	Max temp (°C)	Rainfall (mm)	Solar radiation (× 10^6 J/(m^2·day))	Min temp (°C)	Max temp (°C)	Rainfall (mm)	Solar radiation (× 10^6 J/(m^2·day))
Jan	Min	–19.5	–7.1	0.0	0.2	–17.6	–5.4	0.0	0.2	–15.2	–2.8	0.0	0.2
	Mean	–4.8	4.9	1.1	7.4	–3.0	6.7	1.6	7.2	–0.4	9.3	1.4	7.0
	Max	11.8	17.8	28.8	14.1	13.8	19.4	41.6	13.6	16.5	22.0	44.6	13.2
Feb	Min	–17.0	–6.4	0.0	0.4	–14.5	–4.1	0.0	0.4	–11.6	–1.3	0.0	0.4
	Mean	–3.2	6.8	0.7	10.0	–0.8	9.3	1.1	9.7	2.0	12.1	1.5	9.5
	Max	8.2	21.4	30.0	17.8	10.7	23.7	38.5	17.8	13.3	26.4	53.6	17.4
Mar	Min	–11.0	–2.0	0.0	0.2	–8.9	0.0	0.0	0.2	–7.3	1.8	0.0	0.2
	Mean	1.4	12.1	2.4	11.7	3.3	13.9	1.9	12.2	4.6	15.2	2.1	12.1
	Max	14.1	24.9	94.3	22.4	15.9	26.7	68.0	23.4	17.0	27.8	77.4	23.4
Apr	Min	–3.5	4.6	0.0	1.2	–1.7	6.4	0.0	1.3	–0.5	7.6	0.0	1.3
	Mean	6.7	18.0	3.2	14.1	8.5	19.8	3.4	14.7	9.8	21.1	3.5	14.7
	Max	18.8	30.9	133.2	26.2	20.6	32.6	138.5	27.5	21.9	33.9	147.9	27.5
May	Min	2.7	11.8	0.0	1.1	4.4	13.6	0.0	1.2	5.6	14.8	0.0	1.2
	Mean	12.4	23.4	2.9	16.2	14.2	25.1	3.1	17.3	15.4	26.4	2.7	17.1
	Max	21.1	33.2	97.6	29.4	23.1	35.1	112.2	30.5	24.4	36.4	100.0	30.8
Jun	Min	9.0	17.5	0.0	1.2	11.0	19.6	0.0	1.2	12.3	20.8	0.0	1.2
	Mean	18.4	27.7	4.0	16.4	20.6	29.9	5.9	16.3	21.9	31.2	5.4	16.8
	Max	25.3	36.6	172.0	31.3	27.4	38.7	275.3	30.8	28.8	40.0	254.8	31.9
Jul	Min	15.3	23.5	0.0	0.7	17.4	25.4	0.0	0.6	18.7	26.7	0.0	0.6
	Mean	23.1	30.4	9.1	13.4	24.9	32.3	17.1	11.9	26.2	33.6	15.4	12.4
	Max	28.5	38.6	376.7	30.0	30.2	40.4	726.7	27.6	31.6	41.7	656.7	28.7
Aug	Min	10.7	21.7	0.0	1.2	12.9	23.9	0.0	1.1	14.7	25.7	0.0	1.2
	Mean	23.0	30.8	11.4	13.2	25.1	33.0	17.5	12.4	26.9	34.7	15.0	13.1
	Max	28.5	37.6	298.1	26.3	30.7	39.6	491.1	24.1	32.5	41.4	429.0	25.3
Sep	Min	3.6	15.9	0.0	0.5	5.4	17.5	0.0	0.5	7.1	19.2	0.0	0.5
	Mean	17.1	26.8	4.4	12.8	19.3	29.0	7.3	12.6	21.0	30.7	5.6	13.0
	Max	26.1	35.4	217.3	24.6	28.4	37.6	365.6	23.7	30.1	39.4	282.1	24.7
Oct	Min	–3.5	7.9	0.0	0.1	–2.4	9.0	0.0	0.1	–0.4	10.9	0.0	0.1
	Mean	9.9	21.1	1.9	10.6	11.0	22.2	2.2	11.0	12.8	24.0	1.9	11.2
	Max	21.3	31.1	117.3	20.8	22.8	32.6	166.1	21.1	24.5	34.3	131.6	21.7
Nov	Min	–13.2	–3.4	0.0	0.3	–11.4	–1.5	0.0	0.3	–9.1	0.8	0.0	0.3
	Mean	2.9	13.5	1.7	7.6	4.5	15.0	1.4	8.1	6.8	17.3	2.0	7.7
	Max	16.7	24.9	83.6	16.0	17.9	26.1	78.8	16.8	20.0	28.2	92.6	16.7
Dec	Min	–21.8	–6.5	0.0	0.1	–19.5	–4.3	0.0	0.1	–17.4	–2.1	0.0	0.1
	Mean	–2.8	7.0	0.9	6.8	–0.4	9.3	1.1	6.7	1.6	11.4	1.3	6.6
	Max	10.7	18.4	40.7	12.2	12.8	20.6	36.9	12.3	15.0	22.7	52.3	11.9

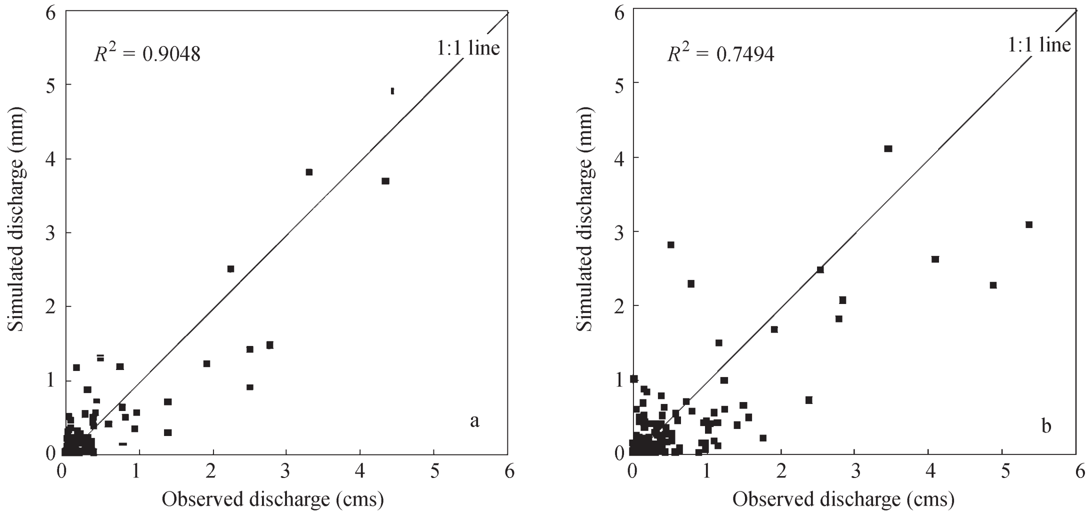

Fig. 4 Results of calibration (a) and validation (b).

from –22.4% to 186.6% for nitrogen and from –22.4% to 218.8% for phosphorous caused by climate change in six watersheds of the Susquehanna River Basin. Holmberg et al. (2006) reported that the fluxes of total organic carbon, TN, and TP were increased range from 4% to 26% with the high change scenario at two watersheds in Finland. Therefore, the results of this study were considered reasonable even though simple comparison of results of these studies has many limitations.

3 Conclusions

This article presents the artificial neural network model developed to simulate the future runoff discharge using rainfall data. The future runoff discharge was used to calculate NPS loadings in the future using load-discharge relationship driven by long-term monitoring data. The LARS-WG model, a stochastic weather generator, was selected to generate the rainfall based on HadCM3 SRES A1B scenario that is one of the climate change scenarios. The best architectures of ANN model consisted of 5 input nodes, 14 hidden nodes, and 1 output node. The ANN model prediction capability was evaluated by comparing the simulated runoff discharge to the observed data in both calibration and validation procedures. There was an increase in NPS loads when climate scenario was adopted to generate future rainfall data reflecting climate change.

The non-parametric method, artificial neural network algorithm, can provide valuable approach for analyzing the runoff and water quality, even if there are many problems to estimate NPS loads affected by climate change because of lack of future data. And estimating future NPS loads is meaningful in that the results can be used to make long-range plans to manage water quality for watershed.

Acknowledgments

This research was supported by a grant (code number 4-5-3) from Sustainable Water Resources Research Center of 21st Century Frontier Research Program (50%) and Han River Basin Environmental Office and Han River Environment Research Center, Ministry of Environment (50%).

References

ASCE (American Society of Civil Engineers) Task Committee, 2000a. Artificial neural networks in hydrology I. *Journal of Hydrologic Engineering*, 5(2): 115–123.

ASCE (American Society of Civil Engineers) Task Committee, 2000b. Artificial neural networks in hydrology II. *Journal of Hydrologic Engineering*, 5(2): 124–132.

Bates B C, Kundzewicz Z W, Wu S, Palutikof J P (eds.), 2008. Climate Change and Water, Technical Paper of the Intergovernmental Panel on Climate Change. IPCC Secretariat, Geneva. 210.

Carpenter S R, Caraco N F, Correll D L, Howarth R W, Sharpley A N, Smith V H, 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological Applications*, 8(3): 559–568.

Chang H, Evans B M, Easterling D R, 2001. The effects of climate change on stream flow and nutrient loading. *Journal of the American Water Resources Association*, 27(4): 973–985.

Dawson D W, Wilby R L, 2001. Hydrological modelling using artificial neural network. *Progress in Physical Geography*, 25(1): 80–108.

Holmberg M, Forsius M, Starr M, Huttunen M, 2006. An application of artificial neural networks to carbon, nitrogen and phosphorous concentrations in tree boreal streams and impacts of climate change. *Ecological Modelling*, 195: 51–60.

Hsu K, Gupta H V, Sorooshian S, 1995. Artificial neural network modeling of the rainfall-runoff process. *Water Resources Research*, 31(10): 2517–2530.

IPCC (Intergovernmental Panel on Climate Change), 2000. IPCC Special Report, Emissions Scenarios. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC (Intergovernmental Panel on Climate Change), 2007. Summary for policymakers. In: Climate Change 2007: The

Physical Science Basis. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kang M S, Kang M G, Park S W, Lee J J, Yoo K H, 2006. Application of grey model and artificial neural networks to flood forecasting. *Journal of the American Water Resources Association*, 42(2): 473–486.

Kisi O, 2004. River flow modeling using artificial neural networks. *Journal of Hydrologic Engineering*, 9(1): 60–63.

Novotny V, Olem H, 1994. Water Quality: Prevention, Identification, and Management of Diffuse Pollution. Van Nostrand Reinhold, New York.

Racsko P, Szeidl L, Semenov M A, 1991. A serial approach to local stochastic weather models. *Ecological Modeling*, 57: 27–41.

Semenov M A, Barrow E M, 1997. Use of a stochastic weather generator in the development of climate change scenarios. *Climatic Change*, 35: 397–414.

Semenov M A, Brooks R J, Barrow E M, Richardson C W, 1998. Comparison of the WGEN and LARS-WG stochastic weather generators in diverse climates. *Climate Research*, 10: 95–107.

Wu C L, Chau K W, Li Y S, 2009. Methods to improve neural network performance in daily flows prediction. *Journal of Hydrology*, 372: 80–93.