Desalination and Water Treatment
www.deswater.com
doi: 10.1080/19443994.2014.996010

57 (2016) 670–683
January

Taylor & Francis
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Development of water quality forecasting system with ensemble stream prediction method in the Geum River Basin, Korea

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Received 2 August 2013; Accepted 10 March 2014

ABSTRACT

The accurate prediction of the water quality of a river is very important in identifying instream flow and water supply requirements and solving relevant environmental problems. The purpose of the study is to develop a water quality forecasting system for the Geum River in Korea. The water quality forecasting system was composed with the Streamflow Synthesis and Reservoir Regulation (SSARR) for watershed runoff simulation and Qual2E for calculation of river quality. The SSARR model was improved by applying the Optimal Linear Correction method and was also used to predict probabilistic streamflow with the ensemble stream prediction. The water quality forecasting system was validated with data measured at the Geum River Basin in 2007 and 2008. As the results, it was found that the proposed model simulated the values of BOD, T-N, and T-P within acceptable reliability. The developed system will contribute to various prediction of water, and improvement of current water quality management practice.

Keywords: Water quality forecasting system; SSARR; Qual2E; Ensemble stream prediction

1. Introduction

Water security is standing out as one of the major issues in the world as the severity of damages and losses caused by extreme weather events (e.g. drought, flood, typhoon, etc.) are increasingly becoming intense and frequent. It is important to establish management policies that can manage uncertain and limited water resources effectively. Thus, simulation methods are required to precisely analyze rainfall–runoff relations in a basin and produce highly reliable information for streamflow prediction.

In Korea, real-time streamflow predictions have been studied to secure immediate utilization for flood control. However, there have been relatively little attention and few studies on streamflow prediction for a long-term period. Therefore, various studies and researches are required to identify how to predict long-term streamflow which is essential to facilitate water supply and reservoir management for long-term basis in Korea. One of the most important challenges for the long-term prediction is to reflect and improve

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1944-3994/1944-3986

meteorological and hydrological uncertainty that significantly affects streamflow prediction.

Since the ensemble streamflow prediction (ESP), one of probabilistic streamflow prediction methods was developed by the California–Nevada River Forecast Center (RFC) of National Weather Service (NWS), it has been used in many studies to forecast probabilistic prospects for water supply in river basins. Actually, the need of probabilistic forecasting in hydrology was addressed, and the ESP method was introduced by compiling a number of short and long term studies [1]. The ESP method was applied for forecasting inflow of a dam or streamflow [2–4], and was also used to improve a runoff model [5].

Meanwhile, as industrialization and urbanization have increased river pollutants by deteriorating the self-purification properties of water sources, water pollution problems have become one of the serious issues. Water quality simulation methods are essentially required to precisely forecast and effectively improve water quality in a river. Downstream reaches of dams are affected by tributaries' runoff and water quality as well as dams' releases. Most of the river basins located in tributaries are ungauged, and, therefore, runoff in the river basin is very uncertain.

The purpose of the current study is to develop a water quality forecasting system for the Geum River in Korea. The ESP method was applied to the Streamflow Synthesis and Reservoir Regulation (SSARR) model to estimate probabilistic streamflow in each tributary of the Geum River Basin. The Optimal Linear Correction (OLC) was used as a post-processing to improve the accuracy of the estimated streamflow. The SSARR model was validated by the measured data and was integrated with the Qual2E model using Visual Basic to simulate water quality for lower reaches of the Geum River located downstream of the Daecheong Dam. A model-driven graphical user interface (GUI) was designed as to effectively collect the data required for analysis and to secure convenience of the analysis.

The water quality forecasting system uses release of the Daecheong Dam determined by dam operators and water quality measured at the dam. The system also uses the runoff scenarios of tributaries that are estimated by the ESP method and water quality measured at each of the tributaries. The water quality forecasting system was validated with data measured at the Geum River Basin in 2007 and 2008. The water quality forecasting system developed in the study would be helpful in decision-making process by providing the various profiles of water quality based on the runoff scenarios of tributaries.

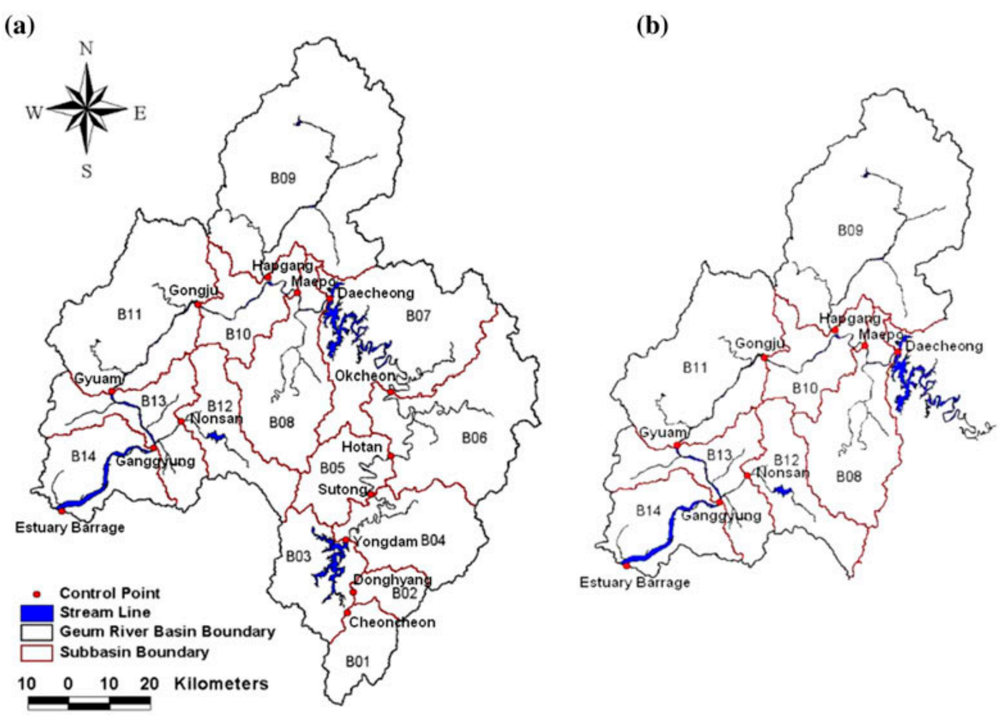

Fig. 1. Map of the Geum River Basin. (a) Full site map and (b) SSARR model segment.

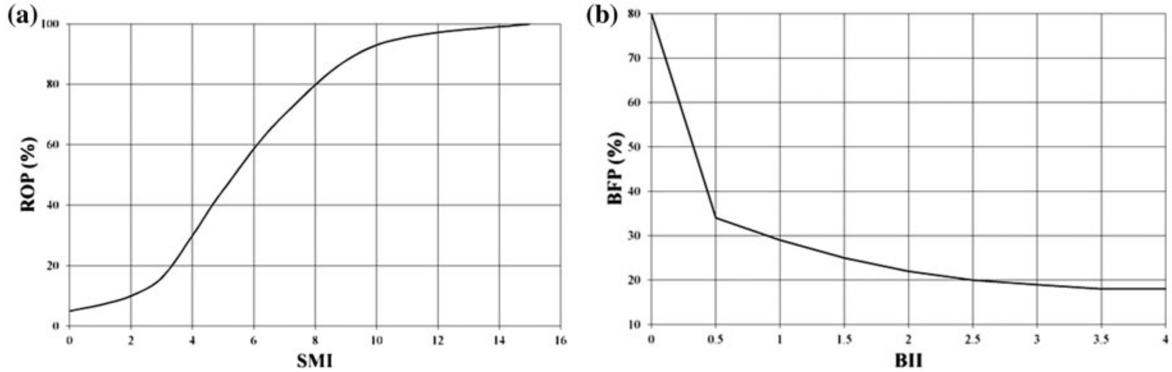

Fig. 2. Model parameters of the SSARR. (a) SMI-ROP and (b) BII-BFP.

2. Methodology

2.1. Target basin

The study area is the Geum River Basin that is located in the Republic of Korea and has an area of 17,537.00 km^2. There have been in-depth investigations and field surveys carried out for eight years from 2003 to 2010 in the Geum River Basin to obtain highly reliable hydrologic data. The Geum River Basin was divided herein into 14 sub-basins based on major runoff and water quality control points, long-term water supply, and comprehensive basin development.

Fig. 1(a) shows the 14 sub-basins of the Geum River Basin as determined herein. The sub-basins can be divided into two areas: upstream area (B01–B07) and downstream area (B08–B14) of the Daecheong Dam. As runoff of the upstream areas is regulated by the Daecheong Dam, release of the dam was used in current study. On the other hand, the runoff of the downstream area was simulated by the SSARR model in the study (Fig. 1(b)), which will be described in Section 2.2.

2.2. Streamflow prediction

2.2.1. Basin streamflow model

The SSARR model was used herein as a long-term streamflow prediction model to evaluate the effects of reservoir operation on a basin [6]. In Korea, the SSARR model has been used in water resources management practices since it was developed by the United States Army Corps of Engineers (USACE) in 1956 and, subsequently, upgraded to a Windows-based GUI program. The model was successfully employed in large rivers (e.g. the Columbia River in the US [7], the Mekong River in Vietnam [8], and so on [9–11].

Relationship between soil moisture index (SMI) and runoff percent (ROP), which is the most sensitive parameter in the SSARR model determines total runoff rate [3]. Relationship between Base Flow Infiltration Index (BII) and Base Flow Percent (BFP) separates

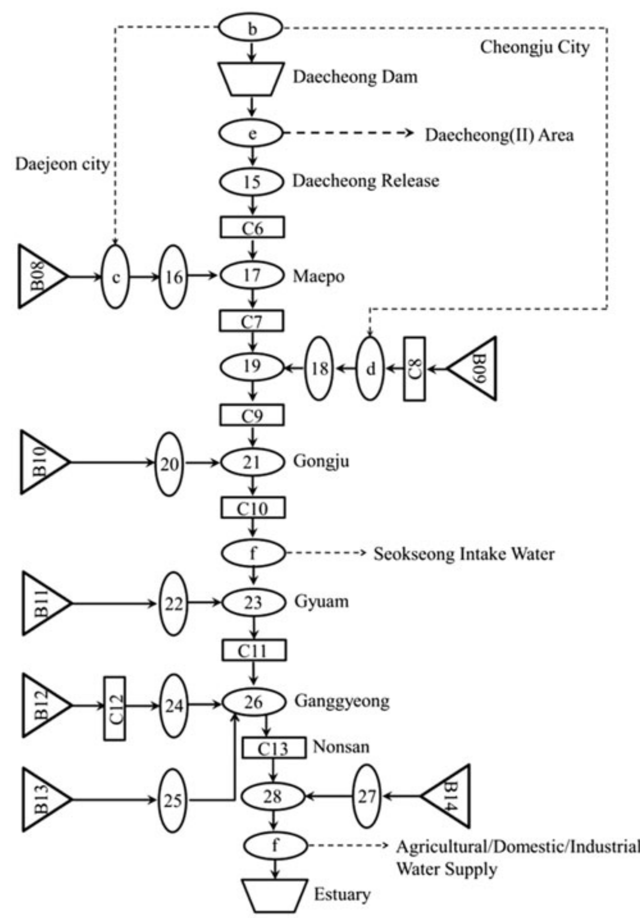

Fig. 3. Schematic diagram for catchment and runoff distribution.

total runoff calculated from the SMI and ROP into direct runoff and base flow. Surface–Subsurface Separation (S–SS) separates direct runoff into surface runoff and subsurface runoff. The S–SS is important to analyze in terms of flood control the characteristics of short-term runoff during the occurrence of a flood. Parameters used in this study include SMI–ROP, BII–BFP, and S–SS, which had been validated based on streamflow data observed in the Geum River for the period 1983 through 2006 [3]. The calculated parameters, including SMI–ROP and BII–BFP, must be calibrated to be used as initial parameters at the time of simulation in the form of graphs (Fig. 2). In this study, it was assumed that the calibration of the calculated parameters with a year period could produce initial parameters at the time of simulation. Modeling and analysis procedures started with the collection of input data, including rainfall, temperature, type of water supply, intake volume, and dam discharge. Rainfall–runoff relations for each divided basin were characterized by parameters, and then corrected by comparing estimated runoff results and observed runoff results. Runoff was calculated in the SSARR model based on the runoff system in the Geum River Basin as shown in Fig. 3.

2.2.2. OLC

The applicability of OLC has been proven in theoretical studies. Especially, the OLC was used to improve simulation accuracy of the SSARR model [12]. The OLC is a post-processing procedure to further improve the accuracy of the SSARR model even if the model alone is considered sufficiently reliable. The improvement of such accuracy requires lots of time and efforts due to difficulties in estimating complicate parameters (SMI–ROP, BII, BFP, etc.) of the SSARR model and compiling input data. The correction or combination of estimated or simulated results is one of the most common methods to enhance the accuracy of estimation in the field of economics. There are a number of studies underway to apply these combination approaches to meteorological estimation. The approaches include Multi-model Ensemble and Multi-model Super Ensemble (MSE), in which arithmetic and weighted averages are computed, respectively, from the estimation of several climate models [13–15].

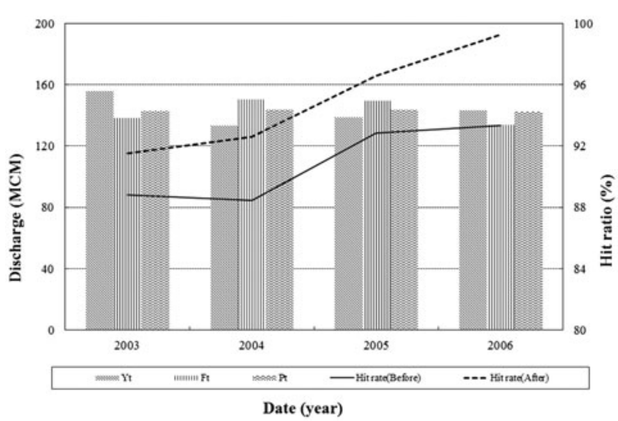

Fig. 4. Results of analysis using the OLC method.

The OLC was introduced to show that estimated or simulated results could be corrected in a simple linear regression equation [16]. A mean squared error between the estimated result F and the observed result Y over a certain period of time consists of three components as shown in Eq. (1) below [17]:

$$\mathrm{MSE} = (\bar{Y} - \bar{F})^2 + (S_F - \rho S_Y)^2 + (1 - \rho^2) S_Y^2 \tag{1}$$

where $\bar{Y}$ and $\bar{F}$ are the average of observed and estimated results, respectively; S_F and S_Y are the standard deviation of the observed and estimated results, respectively; and ρ is a coefficient of correlation between the two results, ranging between −1 and 1.

In Eq. (1), the first term represents the systematic error of a prediction approach (or a model) (i.e. the mean bias of the estimated results), and the second term represents the range in which the estimation results fail to reproduce the variability of the observed results (i.e. the regression bias of the estimated results). The last term represents the unique variability of the observed results (i.e. target phenomena), which are irrelevant to the estimated results. The first and second terms of Eq. (1) could be eliminated by the OLC in equations as shown below [16]:

$$Y_t = \hat{a} + \hat{b} F_t \tag{2}$$

$$P_t = \hat{a} + \hat{b} F_t \tag{3}$$

where Y_t and F_t are observed and estimated results, respectively, at the time of t; P_t is the corrected result of estimation at the time of t; and $\hat{a}$ and $\hat{b}$ are an intercept and slope of the linear regression model, respectively.

The analysis of estimates obtained from the observed results in a linear regression model with corresponding time series Y_t and F_t will give Eq. (2). If a proper prediction approach has been employed, the solutions of the equation will be $\hat{a} = 0$ and $\hat{b} = 1$. If there is only an average bias in the model, the solutions must be $\hat{a} = -\mathrm{bias}$ and $\hat{b} = 1$. As there is,

Table 1
Procedure for the ESP

Step 1	Step 2	Step 3	Step 4
Historical streamflow data	Current basin conditions	ESP scenarios	ESP probability
Determine initial parameters for runoff simulation through the past one-year calibration	Apply current basin conditions, including water uses (e.g. municipal water, industrial water, crop water, withdrawal, etc.), temperature, etc	Produce as many runoff scenariosas the number of historical rainfall events by year	Present monthly ESP probability for each station point by analyzing runoff outputs using statistical probability methods

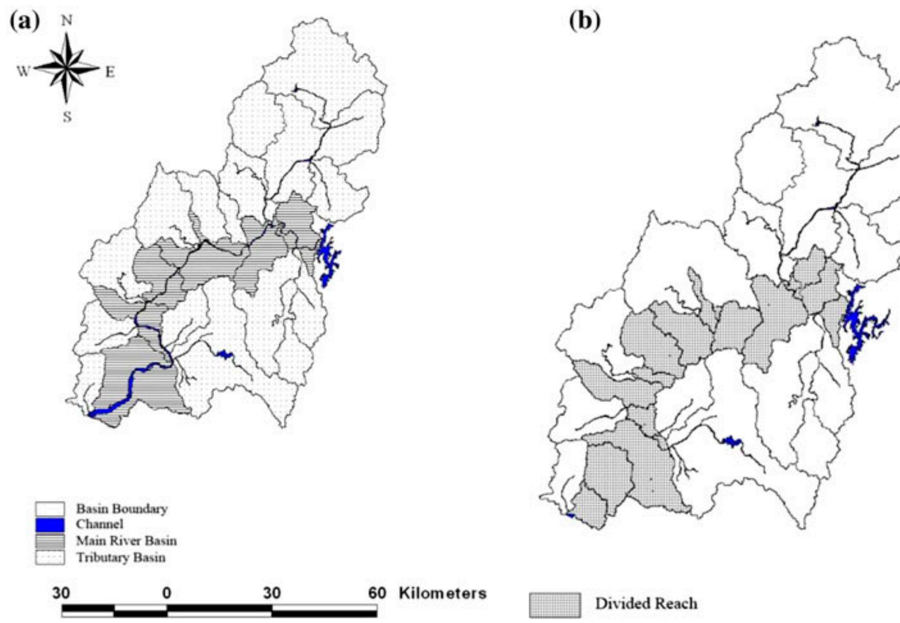

Fig. 5. Classification of the main river basins and reaches. (a) Main river basins and (b) Reach boundary.

Table 2
Information about tributaries downstream of the Daecheong Dam

Tributary	Length (km)	Area (km^2)	Areal ratio
Gap	33.53	648.87	Sub-basin 08 × 0.864
Miho	39.13	1,855.35	Sub-basin 09 × 1.000
Daegyo	19.06	65.75	Sub-basin 10 × 0.157
Jungan	29.60	161.71	Sub-basin 11 × 0.145
Yugu	15.70	282.60	Sub-basin 11 × 0.254
Ji	17.80	250.66	Sub-basin 11 × 0.221
Geum	14.70	165.19	Sub-basin 13 × 0.283
Suksung	12.10	145.78	Sub-basin 13 × 0.261
Nonsan	21.45	667.16	Sub-basin 12 + Sub-basin 13 × 0.261
Gilsan	11.40	113.68	Sub-basin 14 × 0.213

however, a regression bias as well as an average bias in typical models, $\hat{b}$ is not 1 in most cases. It should be noted that both average and regression biases will be affected by the correction during the application of the OLC [12]. The application of the solutions of $\hat{a}$ and $\hat{b}$, which are calculated from Eq. (2) to Eq. (3) will give the OLC model. With the estimated result F_t at a certain time in the future, the corrected result P_t for the corresponding period of time can be calculated in Eq. (3).

The OLC was used herein to improve the accuracy of simulation at Gongju. Given the seasonal characteristics of runoff in Korea, the corrections were made in equations that varied with different months ranging from January to December. The value of $\hat{a}$ and $\hat{b}$ in the OLC model are estimated by the measured data in 2003 to 2006, and validated with the measured data in 2007 and 2008. Fig. 4 shows the "hit rate", describing the success rate of an effort of the results corrected by the OLC in January. The comparison of runoff results observed in Gongju, estimated in the SSARR model, and corrected by the OLC indicated that the simulated runoff corrected by the OLC was far closer to the actually measured runoff than the runoff estimated in the SSARR model, which suggested that the OLC would considerably improve the accuracy of simulated results as shown in Eq. (4) below:

$$\text{Hit rate } (\%) = 100 - |\, 100 - Q_{min}/Q_{max} \times 100 \,| \quad (4)$$

where Q_{min} and Q_{max} are determined from the comparison of Y_t and F_t, and Y_t and P_t, respectively.

Table 3
Discharge coefficient

	$V = aQ^b$		$h = cQ^d$		
Reach	a	b	c	d	Roughness
1	0.0313	0.59	0.0935	0.4907	0.027
2	0.088	0.4164	0.0927	0.4873	0.027
3	0.1089	0.3831	0.1376	0.3982	0.027
4	0.0744	0.3741	0.1693	0.3876	0.027
5	0.0234	0.5516	0.4837	0.2807	0.027
6	0.1326	0.3363	0.2372	0.3222	0.027
7	0.1506	0.3112	0.2485	0.3449	0.027
8	0.0367	0.4653	0.4084	0.3138	0.027
9	0.0426	0.4624	0.4342	0.238	0.027
10	0.005	0.7206	1.7049	0.1079	0.027
11	0.0028	0.7567	3.2566	0.0427	0.026
12	0.0023	0.7762	3.6809	0.0421	0.026
13	0.0019	0.7482	3.6809	0.0421	0.025
14	0.001	0.7545	4.345	0.0251	0.025
15	0.0006	0.7746	5.2256	0.0117	0.025
16	0.0005	0.7567	6.9449	0.0255	0.025

2.2.3. Ensemble streamflow prediction

The ESP is a prediction approach to combine overall basin conditions, including snowfall, soil moisture, temperature, water demand, dams, reservoirs, rivers, etc., with reproducible rainfall events, and thereby

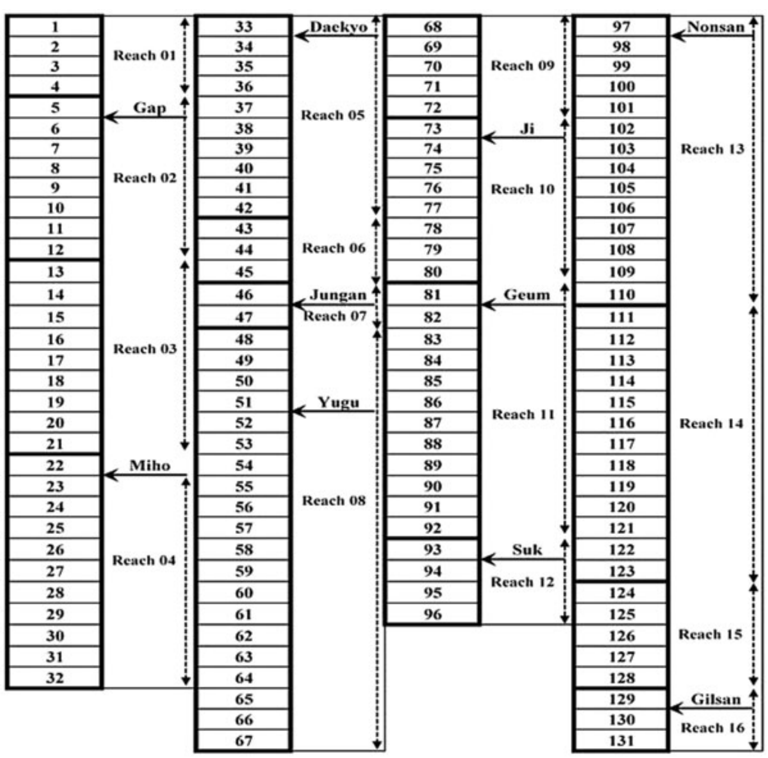

Fig. 6. Flow chart for the water quality model (as used herein).

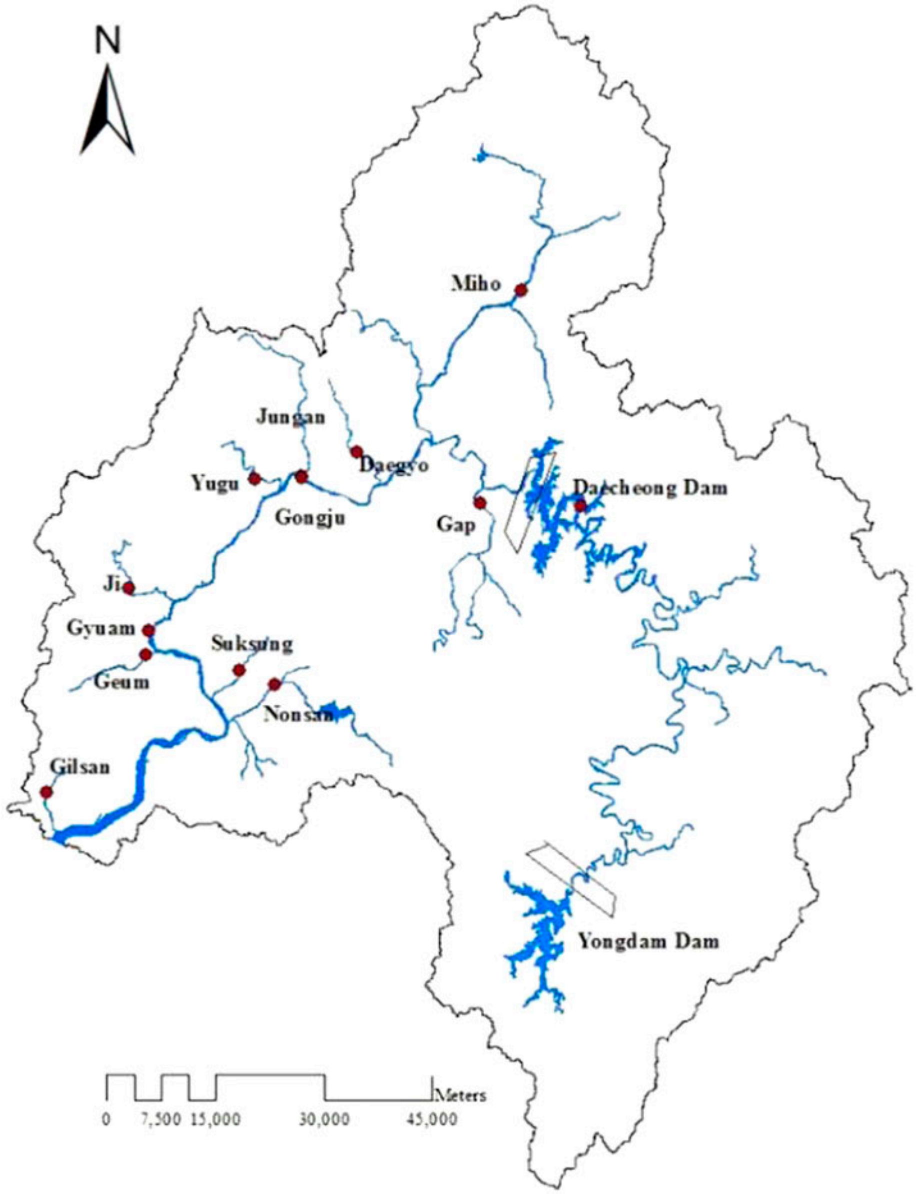

Fig. 7. Major tributaries and water quality monitoring points in the Geum River Basin.

enable the probabilistic prediction of time series data. The possibility of probabilistic prediction is dependent on the selection of appropriate probability distribution for runoff scenarios under the assumption that the historical meteorological events represent future phenomena, in other words, will be recurrent in the future. A probabilistic statistical analysis considers only the probability of exceedance (or non-exceedance), regardless of the chronological order of hydrologic events, to analyze ungrouped entire data that have been created through an empirical frequency analysis.

In this study, the frequency of entire annual ESP results was analyzed without being grouped in a plotting position formula, which is a graphical analysis to estimate exceedance probability by examining fitness of a sample to a specific probability distribution on the probability paper. Out of many conventional plotting position formulas, a formula was restructured herein as a general formula [18]. A formula that was proposed by Weibull was used to analyze at-site frequency by probabilistic plotting [19]. A linear regression analysis was also used herein to obtain a regression equation from data plotted on a probability

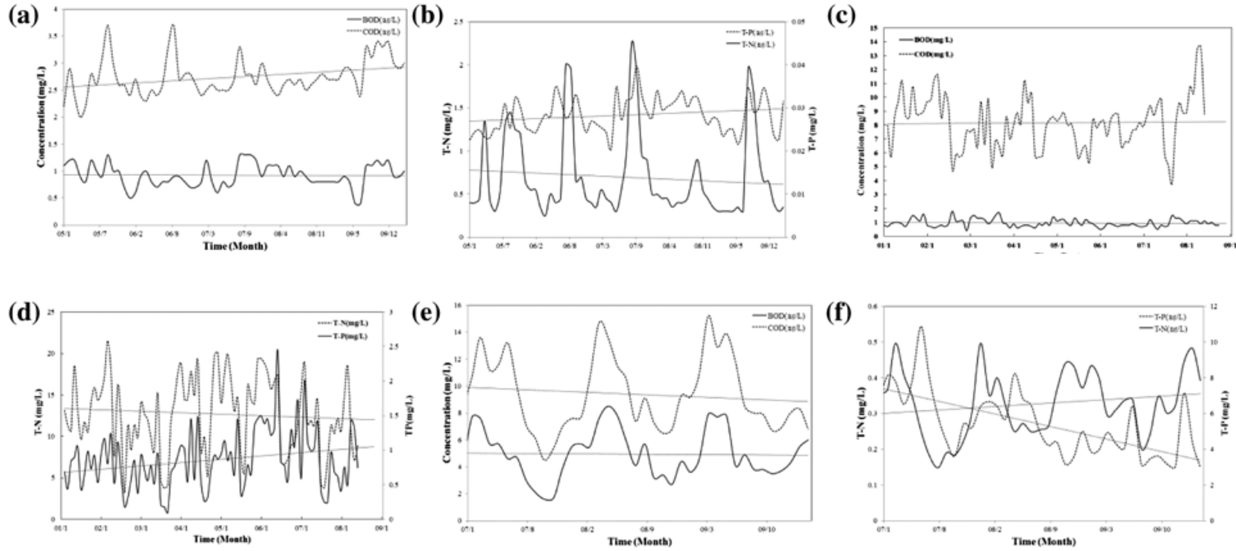

Fig. 8. Measured water quality of Geum River and tributaries for the recent 5 years. (a) BOD and COD in Daecheong Dam, (b) T-N and T-P in Daecheong Dam, (c) BOD and COD in Gap stream, (d) T-N and T-P in Gap stream, (e) BOD and COD in Miho stream, and (f) T-N and T-P in Miho stream.

paper to linearize probability distribution. Table 1 shows the ESP procedure for streamflow prediction.

The ESP method was applied herein to the model according to the procedure as shown in the table. As mentioned above, a probabilistic statistical analysis considers only the probability of exceedance (or non-exceedance), regardless of the chronological order of hydrologic events, to analyze entire ungrouped data that have been created through an empirical frequency analysis. In this study, annual ESP results were classified, without being grouped, into a cumulative probability density function of the entire data from 1984 to 2007 as the probability of runoff prediction in a basin. Also, it was ensured that a cumulative probability would simply be estimated by ranking monthly runoff results in a descending order considering the number of data [20].

2.3. Water quality model

2.3.1. Estimation of runoff for main river basins

Fig. 5(a) is the main river basin located downstream of the Daecheong Dam. Discharges for the main river basins were estimated by the basin areal ratio method [21] given by Eq. (5). Table 2 shows the areal ratios of the main river basins closed to tributaries.

$$Q = \frac{A}{A_0} \times Q_0 \tag{5}$$

where Q is specific discharge from a reference basin (m^3/s); A is the catchment area of a reference basin (km^2); A_0 is total catchment area (km^2); and Q_0 is reference flow (m^3/s).

2.3.2. Hydraulic and water quality coefficients

The section for simulation with the Qual2E model is in the range from the Daecheong Dam to the Geum River. The estuarine dam located at the outlet of the Geum River Basin was used herein as the target section for a simulation analysis, and the Qual2E was used as a water quality model. And 14 reaches and 131 elements (as shown in Figs. 5(b) and 6) were identified considering major channels and tributaries as shown in Fig. 5(a). As seen in the figure, major tributaries consist of streams, including Gap, Miho, Daegyo, Jungan, Yugu, Ji, Geum, Suksung, Nonsan, and Gilsan.

A discharge coefficient method was used herein to identify the relationship between flow volume and flow velocity, and flow volume and water depth, so as to analyze water quality in the Geum River Basin. Table 3 shows parameters derived based on the hydraulic cross section of the reaches ranging from the lower area of the Daecheong Dam to its estuary. The discharge coefficients in Table 3 were determined from hydraulic simulation with measured data and those are calibrated and verified.

It was ensured that water quality parameters would include water temperature, BOD, COD, algae,

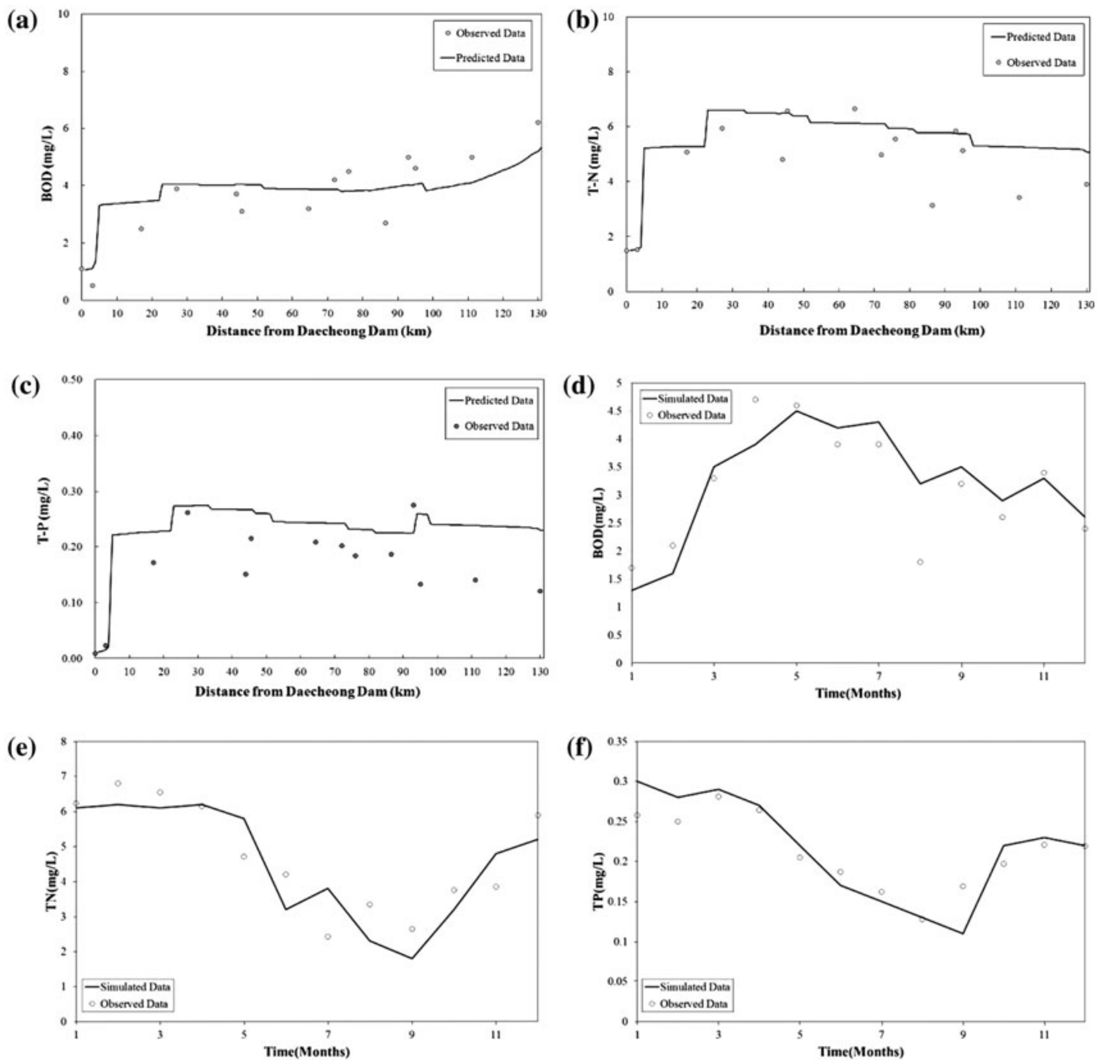

Fig. 9. Calibration results of the Qual2E model (BOD, T-N, T-P). (a) BOD according to distance, (b) T-N according to distance, (c) T-P according to distance, (d) BOD according to time, (e) T-N according to time, and (f) T-P according to time.

nitrogen and phosphorous-based substances, DO, etc. For the purpose of the correction of the model to improve its reliability of simulated results, actual values measured in the river were assumed herein as the values of reference water quality with no error. This aims at enhancing the accuracy of the model by adjusting such factors as response coefficient, which would affect the results of simulated water quality, to minimize gaps between natural events and results of mathematical analysis. A trial method, in which series of calculations are repeated until a difference between the measured results and the ones estimated from a model has reached the smallest wherever possible, was used herein for calibration process to determine parameters for the water quality model. Water quality data from the *Water Quality Monitoring Station* of the *Ministry of Environment* was used to calibrate parameters for the model; the water quality of a tributary is one of the most important factors affecting water quality in the main stream. Time series variations in main water quality items, including COD, BOD, T-N, and T-P at major water quality monitoring points in tributaries (Fig. 7) were analyzed from water quality data observed through the water quality monitoring network of the *Ministry of Environment*. The analysis results indicated that there were seasonal variations shown in tributaries and dams, and the water quality was periodically deteriorated during the occurrence of drought events as shown in Fig. 8. Other tributaries except the Daecheong, Gap, Ji and Suksung (as shown in Fig. 7) showed an increase in BOD, and T-N and T-P decreased in most of them. It was found that T-P

Table 4
Parameters calibrated by the Qual2E

Model parameters	Value	Model parameters	Value
UPTAKE BY NH_3 OXID	3.5	UPTAKE BY NO_2 OXID	1.2
PROD BY ALGAE	1.6	UPTAKE BY ALGAE	2
CONTENT OF ALGAE	0.085	CONTENT OF ALGAE	0.012
ALG MAX SPEC GROWTH RATE	1	ALGAE RESPIRATION RATE	0.1
HALF SATURATION CONST	0.04	HALF SATURATION CONST	0.04
LIN ALG SHADE CO	0.0088	NLIN SHADE	0.054
LIGHT FUNCTION OPTION	1	LIGHT SATURATION COEF	0.03
DAILY AVERAGING OPTION	1	LIGHT AVERAGING FACTOR	0.92
NUMBER OF DAYLIGHT HOURS	14	TOTAL DAILY SOLAR RADTN	354.8
ALGY GROWTH CALC OPTION	1	ALGAL PREF FOR NH_3-N	0.5
ALG/TEMP SOLR RAD FACTOR	0.45	NITRIFICATION INHIBITION COEF	10

was considerably increasing in Gap, Miho, and Nonsan, which accounted for the larger portion of the downstream area of the Daecheong Dam. These results and findings suggest that the water quality of tributaries caused an increase in BOD and T-P in the main stream.

Fig. 9 shows the calibration results of the Qual2E for three water quality items, including BOD, T-N, and T-P, to comparatively analyze their observed and simulated values. The (a)–(c) in Fig. 9 are the calibration results for the model by according to distance in April 2006, which show spatial variations. Similarly, the (d)–(f) in Fig. 9 are the calibration results for the model at the Gongju by the time in 2006. BOD and T-P were mostly well simulated in the model. Observed values for the T-N were abnormal within the range 80–100 km in Fig. 9(b), those errors might be caused by the inflow of other point pollutant sources or observation errors. Table 4 shows the parameters estimated in the study by calibration of the Qual2E.

2.4. System association or coupling

Fig. 10 shows the conceptual diagram for a hydrological integration model coupled or associated with water quality as developed herein. The model pursues the integrated processing of the following entire procedure: performing an SSARR to analyze the runoff process of pollutants; calculating pollutant loads to automatically create input data for a river water quality model; estimating inflow concentration for a river model to forecast the water quality of lakes; and forecasting water quality with a lake model for effective water quality management in the downstream area of the dam. Thus, it was ensured that the model was equipped with functions of interlinking with database systems, predicting ESP runoff, estimating discharge,

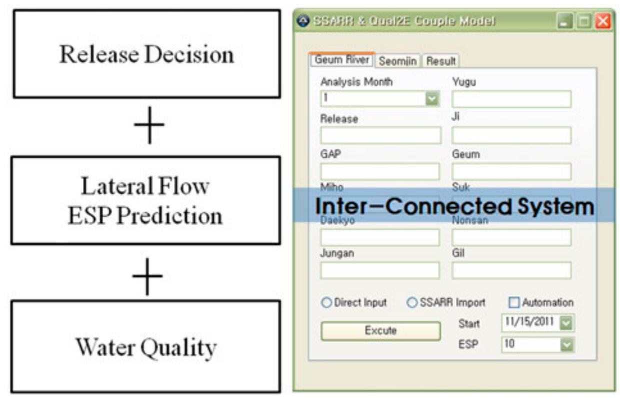

Fig. 10. System association or coupling.

and forecasting water quality. A number of hydrologic data was obtained from the interlinked database system to predict runoff in the ESP approach. Predicted runoff, including discharge determined through a decision-making process, was integrated into the model to forecast water quality. It was ensured that two different models serving different purposes would be so coupled or associated as to provide information for effective decision-making, and thereby facilitate a hydrologic modeling coupled or associated with water quality:

3. Results and discussion

Historical rainfall and temperature ensemble was entered into the SSARR model for the Geum River Basin to create streamflow prediction ensemble. With a warm-up period ranging from January 1 of the previous year (2006 in current study) to the time of prediction, observed rainfall and temperature was used in the SSARR model so that initial conditions, including soil moisture, temperature, river water level, and

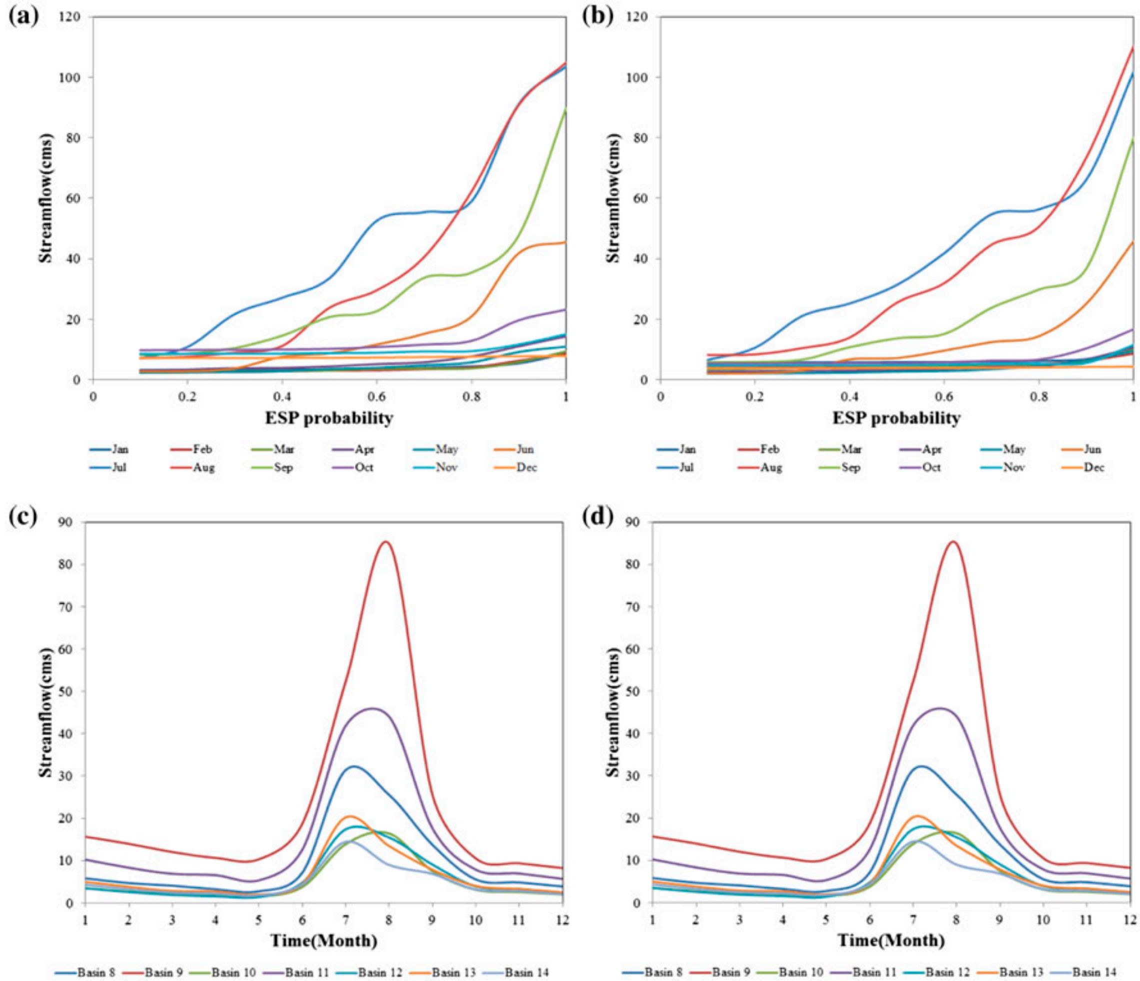

Fig. 11. Monthly runoff scenarios in sub-basins based on the ESP approach. (a) Streamflow in sub-basin 8 in 2007, (b) Streamflow in sub-basin 8 in 2008, (c) Streamflow for the basins for the ESP probability 0.5 in 2007, and (d) Streamflow for the basins for the ESP probability 0.5 in 2008.

snowfall, in the target basin at the time of prediction might be reflected in the simulation process. Water quality at Gongju in 2007 and 2008 was predicted from runoff calculated using the developed water quality forecasting model. Monthly water quality was simulated under normal conditions considering streamflow estimated for each tributary sub-basin with the ESP approach, and five year mean pollution loads recently observed by the *Ministry of Environment* to predict water quality items, including BOD, T-N, and T-P, at Gongju. Actual discharge from the Daecheong Dam in 2007 and 2008 was used as streamflow from upstream that was one of the important factors to perform a water quality simulation. The inflow of ten tributaries into the lower area of the Daecheong Dam was predicted with the ESP approach. Fig. 11 shows streamflow trends at monthly ESP probability in the sub-basin 8, and at the ESP probability of 0.5 for each sub-basin on the graphs. The calculated streamflow for each sub-basin was converted into inflow for each tributary using the areal ratios for each tributary system as shown in Table 2. With derived streamflow data as seen in Fig. 11, water quality was simulated and compared with measured data. All the procedures were automatically performed with the model.

Figs. 12–14 show the results of simulation as performed at Gongju in January to December in 2007 and 2008. Observed BOD was sometimes out of the ESP rank. However, since recent five-year mean water quality data in tributaries that lie within the range of the BOD prediction as estimated according to ESP weights were used herein, it can be judged that they simulated well measured values within allowable

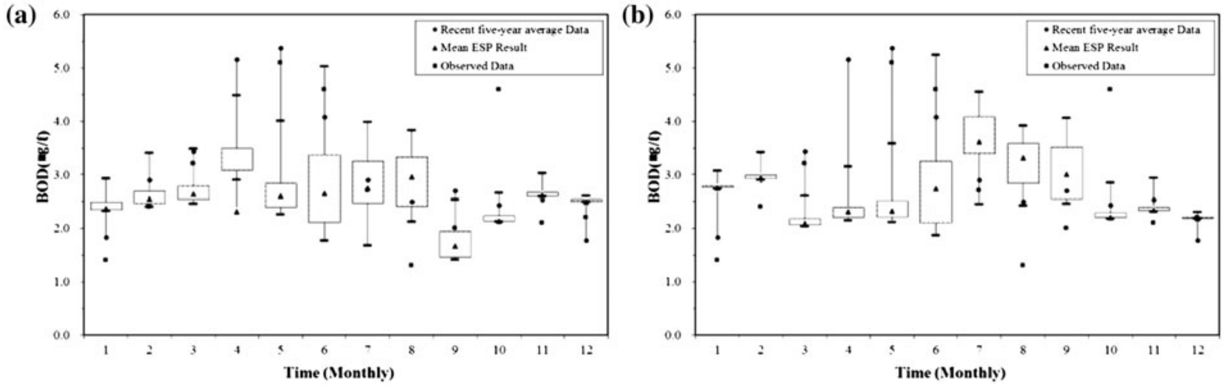

Fig. 12. Monthly BOD (as predicted using the ESP method). (a) BOD (2007) and (b) BOD (2008).

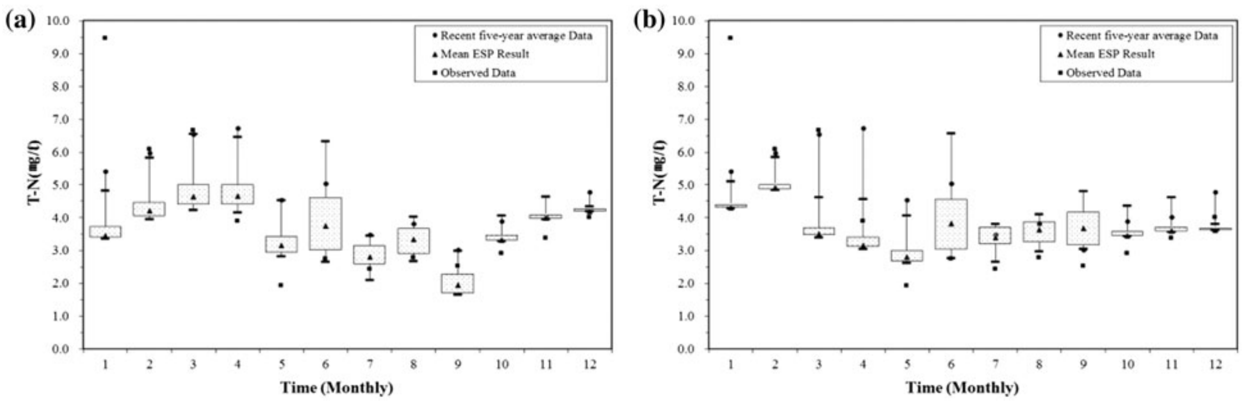

Fig. 13. Monthly T-N (as predicted using the ESP method). (a) T-N (2007) and (b) T-N (2008).

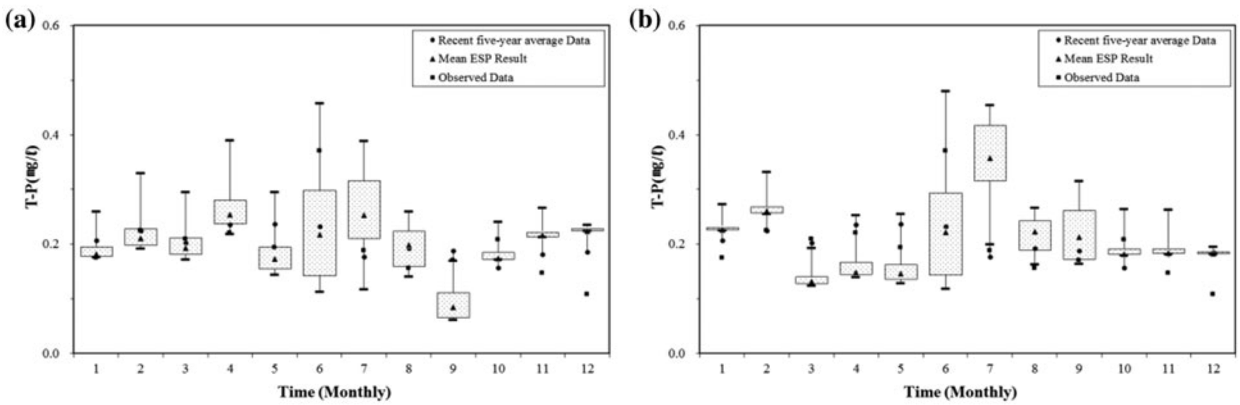

Fig. 14. Monthly T-P (as predicted using the ESP method). (a) T-P (2007) and (b) T-P (2008).

tolerance. Both observed and recent five-year observed T-N and T-P lay, on the whole, within the prediction range.

As BOD tended to rapidly increase with a rise in temperature in April, May, and June, the model should be corrected for the main stream of the Geum River from downstream of the Daecheong Dam to gradually increase discharge so that the predicted discharge would meet requirements for reference water quality.

The results of this study showed that care should be taken to estimate more reliable tributary streamflow and water quality, which, in turn, would require the selection of an appropriate methodology to calculate parameters well representing local conditions. To select a specific value from the range of water quality as forecasted under an ensemble scenario, in particular, it is recommended that a frequency distribution graph under the produced tributary runoff scenarios to classify, with a cumulative probability density function, the entire annual ESP data as a probability of runoff prediction in a basin without grouping those data. It's also recommended that weather forecasting data from the *Korea Meteorological Administration* be used to predict tributary runoff later. With regard to this, it can use the Croley's method [22] and the PDF ratio to improve the ESP approach [2,23].

4. Conclusion

The purpose of the study is to develop a water quality forecasting system for lower reach of the Geum River in Korea. ESP method that is a probabilistic analysis method and is used in the field of hydrological prediction practices was applied to SSARR model to estimate probabilistic streamflow for tributaries located in lower area of the Daecheong Dam. Qual2E model was used to calculate water quality for the downstream of the Daecheong Dam. Both SSARR and Qual2E models were associated into an integrated system to forecast water quality for the downstream of the Daecheong Dam. It is expected that the integrated system will enable the prediction of probabilistic water quality; the standardization of analysis procedures to provide fundamental solutions to problems linked to a lack of objectivity in simulated results; and the effective use of time, efforts, and money:

(1) In addition to the integration of both hydrological models and water quality models, the integrated system or model was designed as to be coupled with database; predict ESP runoff; estimate discharge; produce input data for water quality forecasting; estimate inflow concentration with a river model to predict the water quality of lakes; and predict water quality with a lake model.

(2) The application of the OLC model contributed to the improvement of the accuracy of the model. With the integrated system or model as developed herein, monthly water quality was simulated under normal conditions using data produced from the recent 5 year observed average pollutant loads at Gongju in 2007 and 2008. As a result, it was found that the recent 5 year observed BOD, T-N, and T-P at Gongju lay within the range of rank as classified according to ESP weights, which suggested that the integrated model simulated those observed data in consistence with measured data.

(3) It's judged that the use of weather forecasting data from the *Korea Meteorological Administration* in predicting tributary inflow and post-processing methods based on ESP weights should further be addressed in the future study to obtain more appropriate ESP probabilities.

References

[1] K.P. Georgakakos, R. Krzysztofowicz, Probabilistic and ensemble forecasting, J. Hydrol. 249 (2001) 1–196.

[2] D.I. Jeong, Y.O. Kim, Forecasting monthly inflow to Chungju Dam using ensemble streamflow prediction, J. Korean Soc. Civil Eng. 22 (2002) 321–333 (in Korean).

[3] J.M. Ahn, S.J. Lee, J.K. Kim, J.C. Kim, S.J. Maeng, D.H. Woo, Estimation of ESP probability considering weather outlook, J. Korean Soc. Water Qual. 27 (2011) 264–272 (in Korean).

[4] J.M. Ahn, Y.T. Hur, M.H. Hwang, G.H. Cheon, Study of stochastic techniques for runoff forecasting accuracy in Gongju basin, J. Korean Soc. Civil Eng. 31 (2011) 21–27 (in Korean).

[5] B.J. Harshburger, V.P. Walden, K.S. Humes, B.C. Moore, T.R. Blandford, A. Rango, Generation of ensemble streamflow forecasts using an enhanced version of the snowmelt runoff model1, J. Am. Water Resour. Assoc. 48 (2012) 643–655.

[6] USACE, The Streamflow Synthesis and Reservoir Regulation (SSARR) Model, U.S. Army Corps of Engineers North Pacific Division, Portland, OR, 1991.

[7] D.M. Rockwood, Columbia basin streamflow routing by computer, Trans. Am. Soc. Civil Eng. 126 (1961) 32–45.

[8] D.M. Rockwood, Application of stream-flow synthesis and reservoir regulation "SSARR" program to the lower Mekong River, The Use of Analog and Digital Computer in Hydrology Symposium, vol. 80, International Association of Scientific Hydrology, UNESCO, IAHS, 1968, pp. 329–344.

[9] S.J. Ahn, Y.S. Lee, Watershed runoff analysis by SSARR model, J. Korea Water Resour. Assoc. 22 (1989) 109–116 (in Korean).

[10] K.S. Ryoo, M.H. Hwang, S.J. Maeng, S.J. Lee, Analysis of runoff characteristics in the Geum River Basin using watershed management model, J. Korea Water Resour. Assoc. 23 (2007) 527–534 (in Korean).

[11] S.J. Lee, J.W. Noh, J.M. Ahn, J.C. Kim, Analysis of hydrologic geo-spatial information using runoff-management model, J. Korea Water Resour. Assoc. 11 (2009) 97–104 (in Korean).

[12] D.I. Jeong, J.K. Lee, Y.O. Kim, Improvement of the ensemble streamflow prediction system using optimal linear correction, J. Korea Water Resour. Assoc. 38 (2005) 471–483 (in Korean).

[13] K.P. Georgakakos, D.J. Seo, H. Gupta, J. Schaake, M.B. Butts, Towards the characterization of streamflow simulation uncertainty through multimodel ensembles, J. Hydrol. 298 (2004) 222–241.
[14] A.W. Wood, E.P. Maurer, A. Kumar, D.P. Lettenmaier, Long-range experimental hydrologic forecasting for the eastern United States, J. Geophys. Res. 107 (2002) 4429.
[15] F. Atger, Spatial and interannual variability of the reliability of ensemble-based probabilistic forecasts: Consequences for calibration, Mon. Weather Rev. 131 (2003) 1509–1523.
[16] H. Theil, Applied Economic Forecasting, North Holland Publishing Company, Amsterdam, 1971.
[17] P. Goodwin, Correct or combine? Mechanically integrating judgmental forecasts with statistical methods, Int. J. Forecasting 16 (2000) 261–275.
[18] C. Cunnane, Unbiased plotting positions—A review, J. Hydrol. 37 (1978) 205–222.
[19] W. Weibull, A statistical theory of strength of materials, Ingeniors Vetenskaps Akademien, Handlingar 151 (1939) 1–45.
[20] C.T. Haan, Statistical Methods in Hydrology, Iowa State Press, Ames, IA, 2002, pp. 30–31.
[21] S.A. Schumm, Evolution of drainage systems and slopes in Badlands at Perth Amboy, New Jersey, Geol. Soc. Am. Bull. 67 (1956) 597–646.
[22] T.E. Croley II, Using NOAA's new climate outlooks in operational hydrology, J. Hydrol. Eng. ASCE 1 (1996) 93–102.
[23] J.C. Kim, J.K. Kim, S.J. Lee, Improvement of mid/long-term ESP scheme using probabilistic weather forecasting, J. Korea Water Resour. Assoc. 44 (2011) 843–851 (in Korean).