Integrated modelling system with UNCERTAINTYanalysis for reservoir water quality management in a reclamation RIVER BASIN[[1]](#footnote-2)†

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ABSTRACT

A developedintegrated modelling system with the uncertainty analysis (Monte Carlo simulation and generalized likelihood uncertainty estimation) was used to evaluate the effect of uncertainty sources on long-term water quality and develop river basin management measures to meet the specified water quality criteria based on the predicted probability of occurrence in the reclamation river basin. The results of deterministic integrated modelling system without the uncertainty analysis showed that the HwaongReservoir water quality for total phosphorus(T-P) (0.094 mg L-1) in 2022 would meet the reservoir water quality standard (0.1 mg L-1). However, the water quality prediction for theHwaong Reservoir in 2022 using the integrated modelling system with the uncertainty analysis showed that only 28% would meet the T-P water quality standard, indicating that to meet the water quality standard with a 90% level of confidence, further river basin management measures should be applied in addition to the construction of planned wastewater treatment plants and treatment wetlands. The developed integrated modelling system with the uncertainty analysis was demonstrated to be advantageous because it can allow modellers to make useful decisions about whether a river basin management plan can meet specified waterquality criteria based on the probability of occurrence.

KEYWORDS: uncertainty analysis;integrated modelling system;river basin management measure; treatment wetland; Monte Carlo simulation; GLUE.

RÉSUMÉ

Le système de modélisation intégrée a été développé en combinant leprogramme-FORTRAN de simulation hydrologique avec le programme de simulationde la qualité de l'eau. Ce système de modélisation intègre l'analyse d'incertitude (simulation de Monte Carlo et estimation de l'incertitude de vraisemblance généralisée),et a été proposé pour évaluer l'effet des sources d'incertitude sur la qualité de l'eau à long terme et d'élaborer des mesures de gestion des bassins hydrographiques pour répondre à la qualité de l'eau spécifiée par des critères basés sur la probabilité prédite d'occurrence dans le bassin ou la rivière est remise en état. Les résultats du système déterministe de modélisation intégrée sans l'analyse de l'incertitude ont montré que la qualité de l'eau du réservoirHwaongpour le phosphore total (actuellement 0,094 mg L-1) serait conforme en 2022 à la norme de qualité de l'eau applicable à un réservoir (0,1 mg L-1). Cependant, le résultat de prédiction de la qualité de l'eau en 2022 obtenu en appliquant le système de modélisation intégrée à l'analyse d'incertitude a montré que seulement 28 % serait conforme à la norme de qualité de l'eau de TP. Ceci indique que pour satisfaire à la norme de qualité de l'eau avec une confiance de 90 %, des mesures de gestion complémentaires des bassins doivent être appliquées, en plus de la construction d'usines et de zones humides de traitement des eaux usées. Il a été démontré que le système de modélisation intégrée couplée à l'analyse d'incertitude peut permettre aux modélisateurs de prendre des décisions utiles si le plan de gestion du bassin de la rivière peut répondre aux critères spécifiés qualité de l'eau en fonction de la probabilité d'occurrence.

Mots clés :analyse d'incertitude ; système de modélisation intégrée ; mesure de gestion des bassins fluviaux ; zone humide de traitement ; simulation de Monte Carlo; GLUE.

INTRODUCTION

Most of estuarine reservoirs in South Korea have been forcedto deal with the eutrophication problem that is caused by nutrient discharge from the surrounding areas. Methods to effectively control the eutrophication problem have attracted a great deal of interest. It is wellknown that reservoir eutrophication management should be implemented on a river basin scale (Cooke *et al.*, 1993) because of the complex interactions between a water body and surrounding region (Somlyody and Wets, 1988).

Various river basin management measures can be available for managing a reservoir eutrophication problem. A general approach for identifying the best set of management measures is to implement a computer simulation model to describe the relationship between a given river basin management measure at a specific location and the resulting reservoir water quality (Crowder *et al.*, 1985).

For the practical application, the computer model first should be calibrated using observed data and then used to examine the impact of various river basin management scenarios on the future behaviour of the system. Research has demonstrated that reliable results from a computer model can only be obtained if the input data and parameter values are known with some accuracy (Eckhardt*et al.*, 2003). Research has also shown that the uncertainty in water quality modelling is inevitably high because of uncertainties in the model structure, the model parameters and the future behaviour of the system caused by natural variability (Beck, 1987; Annan, 2001; Mu *et al.*, 2008; Mu *et al.*, 2013). Somestudies show the importance of model parameter uncertainty and its impact on model output (Cheng *et al.*, 2014; Lin *et al.*, 2014; Xue*et al.*, 2014; Leta*et al.*, 2015).If a river basin management plan is to meet specified water quality criteria, an uncertainty analysis associated with model parameters and future behaviour such as pollutant loads and climate change should be conducted (National Research Council (NRC), 2001).

During the last several decades uncertainty analysis has received special attention (particularly in hydrological, ecological and climate modelling) and several methods have been developed and implemented to investigate the impacts of different types of uncertainty sources on the predictions of numerical models (Todini, 2008; Singh *et al.*, 2010; Shojaei*et al.*, 2015). Monte Carlo-based methods such as Bayesian analysis (Starrfelt and Kaste, 2014; Wellen*et al.*, 2014; Li *et al.*, 2015), Markov Chain Monte Carlo (MCMC)(Yang *et al.*, 2008; Cheng *et al.*, 2014; Zheng and Han, 2015) and the Generalized Likelihood Uncertainty Estimation method(GLUE) (Beven and Binley, 1992;Beven and Freer, 2001; Beven and Binley, 2013) are prominent among the methods used to conduct uncertainty analysis.

The GLUE method introduced by Beven and Binley (1992) is a well-known stochastic framework that is widely used in environmental simulation models to evaluate the distribution of predicted variables and to characterize their plausible ranges of fluctuations. GLUE uses a likelihood measure to judge how close the model performance is to the reality with the given parameter set. By adopting a strategy similar to Monte Carlo simulation and Bayesian updating, GLUE is able to identify the parameters' posterior distributions, which can be used for future predictions under uncertainty (Yu *et al.*, 2014). The GLUEmethod has been recently used to analyze the impact of model parameter uncertainty on flood inundation models (Aronica*et al.*, 2012; Jung and Merwade, 2012),a rainfall-runoff model (Mirzaei*et al.*, 2015) and a river basin model (Uniyal*et al.*, 2015).

Inthe study reported herein, an integrated modelling system that combines the Hydrological Simulation Program-FORTRAN (HSPF) with the Water Quality Analysis Simulation Program (WASP) was developed to evaluate the effect of river basin management measures on reservoir water quality in a reclamation river basin. This integrated modelling system was integrated with Monte Carlo simulation and the GLUE based probabilistic approach to estimate the effect of three uncertainty sources (i.e., model parameters, point source (PS) pollutant loads and climate data) on changes in long-term water quality.To demonstrate the usefulness of theintegrated modelling system (including the uncertainty analysis via Monte Carlo simulation and GLUE)a practical application was undertaken to estimate the level of uncertainty and the probability of occurrence in water quality prediction and to evaluate whether the river basin management plan can meet the specified waterquality criteria in the reclamation river basin.

METHODOLOGY

Case study river basin

The Hwaong Reservoir river basin is located in the Gyeonggi Province on the west coast of the Korean peninsula (Figure 1). The mean annual precipitation and temperature for 2008–2012were 1,620 mm and 12.3°C, respectively.The 23,600hariver basin is composed of 7% urban, 24% agricultural, 43% forested and 26% new polder lands. The Hwaong Polder Project began in 1991 and sea dike (9.8km) construction was completed in 2002, resulting in 6,012ha of reclaimed tideland with 4,082ha of the area used as new farmland and 1,730ha allocated to a freshwater reservoir. This large-scale polder project is expected to mitigate flooding problems in the coastal area and secure 54 million metric tons of water resources per year, as well as increase food production.However, the future condition of water quality in the new reservoir has been questioned by environmental activist groups. Precautionary actions and comprehensive researchare being implemented to prevent potential water quality problems.

Figure 1.Study river basin and river basin management plans

Integrated modelling system

In this study the integrated modelling system was used to simulateriver basin loading, receiving water quality and wetland performance, and thereby evaluate the effect of river basin management measures on reservoir water quality. The integrated modelling system was composed of three major models: 1)HSPF, a well-known comprehensive river basinloading model (Bicknell *et al.*, 2001);2) WASP, a widely used program to simulate water quality in reservoirs (Ambrose *et al.*, 1993); 3) BASINS, a multipurpose environmental analysis system for river basin and water quality studies (U.S. Environmental Protection Agency (USEPA), 2001). In this project, BASINS was modified to incorporate the WASP and NPS-WET (Non-Point Source Pollution Control Wetland model),which was developed by previous research (Ham, 2005), in addition to the built-in HSPF. Modules to estimate the PS pollutant load were developed and then linked with the integrated modelling system.

Figure 2.Flowchart of integrated modelling system

Monitoring data and model calibration

Streamflow rate and water quality observed at the monitoring site of ST0 (Figure 1) in the river basinwere used to calibrate the river basin loading model (HSPF), and reservoir water quality observed from nine monitoring sites in the Hwaong Reservoir were used to calibrate thereceiving water quality model (WASP).The sampling scheme applied to all monitoring pointsinvolved grab sampling at monthly or biweekly intervals from January through December 2012. Routine chemical analyses of water samples by using the Standard Methods (American Public Health Association (APHA), 1998) included total suspended solids (TSS), chemical oxygen demand (COD), ammonia-nitrogen (NH3-N), nitrite-nitrogen (NO2-N), nitrate-nitrogen (NO3-N), total nitrogen (T-N), soluble reactive phosphorus (PO4-P) and total phosphorus (T-P).

Graphical methods (time series plots and scattergrams) and statistical measures were used to evaluate the model performance based on the observed data.By using a single goodness-of-fit measure for model evaluation is inappropriate due to its limitations. Therefore, three statistical measures were used to evaluate the goodness-of-fit: coefficient of determination (r2), Nash-Sutcliff efficiency (NSE) (Nash and Sutcliffe, 1970) and root mean square error (RMSE).Eq. 1 defines the Nash-Sutcliff efficiency (NSE):

(1)

where and are the observed and predicted values, respectively, is the mean of the observed values and *n* is the number of samples. The NSE can range from -∞ to 1, with 1 indicating a perfect fit.

Treatment wetlands construction scenario

For diffuse pollution control, the construction of treatment wetlands at the mouths of the three main streams were considered in this study (Figure 1) because approximately 80% of the pollutant loading from the river basin was transported to the Hwaong Reservoir by the three main streams (the Namnyang, Jaan, and Eoeun). The total area of wetlands under consideration was 264 ha (wetland-1, 65 ha; wetland-2, 102 ha; wetland-3, 97 ha), which was about 1.1% of the total river basin area (Figure 1). The wetland model calibrated using observed data from an experimental site was used to evaluate the nutrient removal rate and effluent concentration of constructed wetlands.Results from the HSPF and wetland modelswere used as input data into the reservoir water quality model in the integrated modelling system.

Monte Carlo simulation

One of the most popular methods by which the effect of uncertainty is incorporated into numerical models is the use of randomized methods based on Monte Carlo simulation techniquesin which input data are randomly sampled from underlying probability distributions. The Monte Carlo method for the uncertainty analysis of model input data is quite simple in principle. The application procedure generally includes the following steps. First, the important input data which are needed to carry out the uncertainty analysis must be identified. Second, the uncertainty ranges and shapes of probability density functions of the selected input data should be prescribed. Third, Monte Carlo simulation is carried out and a new set of input data from specified probability distributions and ranges (which are typically based on field measurements or prior knowledge) is randomly generated. Fourth, the given model is run to generate the result using the set of input datagenerated. Finally,these procedures are repeated until statistical information on the model outputs is derived.

GLUE analysis

The GLUE analysis was undertaken with the identified sensitive parameters from one-factor-at-a-time (OAT) sensitivity analysis technique. The GLUE methodology is based on recognition of the importance of the set of parameters to produce the behaviour of the system, not individual parameters. The acceptable model realizations (i.e. behaviour set) obtained from Monte Carlo simulations are given a likelihood weight according to observed data and a likelihood function. Several choices for an appropriate likelihood function can be obtained from Beven and Freer (2001).

A likelihood measure based on the NSE criterion with shaping factor *N* is defined by Eq.2 (Freer and Beven, 1996):

(2)

where is the likelihood of parameter set given the observed data. The quantities and refer to the error variance between model simulations and observed data, and the variance of the observed data, respectively. For *N*=1, in Eq. 2 is the well-known NSE that is often used for calibration of hydrologic and water quality models.

Parameter sets that result in likelihood values below a certain threshold (NSE  0) are termed 'non-behavioural' and are eliminated from further consideration. The remaining 'behavioural' parameter sets are assigned recalled likelihood weights. Therefore, the likelihood measure can be rewritten as Eq. 3:

(3)

For each simulation from a random parameter set, a likelihood weight is obtained using Eq. 3. Then, these weights are rescaled by dividing each individual weight by their total sum. The rescaled likelihood weights are used to construct a cumulative distribution for the output of interest, which can be used to estimate the uncertainty bounds associated with the output by computing its quantiles.

Updating the likelihood distribution as more data become available may be achieved by the application of Bayes equation in the form of Eq. 4:

(4)

where is a prior likelihood for the parameter set, is the likelihood calculated using the set of observed variables, is the posterior likelihood for the simulation of givenand is a scaling constant calculated such that the cumulative value of equals unity.

Uncertain input data and uncertainty analysis

Uncertainty enters the application of models through a variety of routes, such as model structure uncertainty, model parameter uncertaintyand natural stochasticity. The uncertain input data considered in the present study included 1) water quality model parameter values that had uncertainty after calibration due to the unstable water body of a newly constructed estuarine reservoir; 2) climate data and predicted PS pollutant loads that can change significantly with time.

The uncertainty analysis was performed to investigate the effect of various uncertain input data on the reservoir water quality prediction for 2022. Using GLUE likelihood weights and behaviour parameter sets computed from the Bayes Theorem (Eq. 4) a likelihood distribution was updated and a cumulative GLUE likelihood was generated for the uncertainty analysis of model parameters.

Monte Carlo simulation was performed to investigate the effect of future behaviour uncertainty (particularly climate data and predicted PS pollutant loads) on the output. In the uncertainty analysis of climate data, it was assumed that the future weather condition would be the same as any of the existing climate data sets from the last 40 years. Therefore a climate data set was randomly selected from among the 40 sets of annual climate data. In the uncertainty analysis of predicted PS pollutant loads, the mean and standard deviation of the PS pollutant loads prediction error (predicted PS pollutant loads – actual PS pollutant loads) were assumed to be 0 and 20% of the predicted PS pollutant loads, respectively. This assumption was based on other completed polder reclamation project studies in similar settings to the study area in the present research (Lee *et al.*, 2014). To generate likelihood weights of combineduncertainty sources, likelihood weights of three uncertainty sources were first multiplied together and the product divided by their total.

RESULTS AND DISCUSSION

Calibration and prediction of the integrated modelling system without the uncertainty analysis

Before making future predictions of water quality in the Hwaong Reservoir(Figure 1), the integrated modelling system that incorporated the HSPF and WASP modelswas calibrated using observed data (TablesI and II). The outputs of the calibrated HSPF and WASP models are shown in Figures 3and4 and in Table III.These resultsdemonstrated that the HSPF and WASP modelswere well calibrated. The outputs from the two models matchedthe observed data reasonably well.The boundary condition of the reservoir water quality model (WASP) was estimated accurately by the river basin loading model of HSPF. This result contributed to improve the calibration result of the WASP model significantly. The results of the HSPF and WASP models showed that the average concentrations of T-N and T-P in the Hwaong Reservoir were 0.76 and 0.049 mg L-1, respectively.

The water quality in the Hwaong Reservoir was still good in2012due to the dilution effect from sea water introduced specifically for this purpose. Sea water introduction to the reservoir appeared to be very effective in terms of reservoir water quality management measure. However, the reservoir is no longer available as a freshwater resource until the sea water introduction is stopped.

Table I. Adjusted parameters for calibration of the HSPF model

Table II. Adjusted parameters for calibration of the WASP model

Figure 3. HSPF calibration result using observed data from monitoring station ST0

Figure 4. WASP calibration result using observed data from the Hwaong Reservoir

Table III. Comparison of observed and simulated data for calibration

The calibrated integrated modelling system was used to predict the future water quality in the Hwaong Reservoir for the scheduled completion time of 2022. The population was assumed to increase at a rate of 1.5% based on the average growth rate in Gyeonggi Province. Pollutant loading,except additional loadings from new farmland and planned industrial complexes in polder areas, was assumed to remain at the same level as in 2012. The parameters of theriver basinloading model(HSPF)and receiving water quality model (WASP) were the same as those used for the 2012 simulation. The climate data wereextracted from the 2012 data set (1,220 mm of rainfall) as these data were similar to the average precipitation pattern for the last 40 years (1,270 mm of rainfall). To reduce pollutant loadings from the given river basin, several river basin management measureswere planned. Only WWTP (wastewater treatment plant) construction was,however,considered as a river basin management measure for the prediction of future water quality in this study. Two WWTPs (WWTP-1 in Zone II, treating 15,000 metric tons day-1; WWTP-2 in Zone V, treating 16,000 metric tons day-1) and fifteen small-scale wastewater treatment systems (each treating fewer than 500 metric tons day-1) were planned and are being constructed in the river basin to reduce PS pollutant loads from the river basin (Figure 1).

The simulation result show that the mean concentrations of T-N and T-P in the Hwaong Reservoir in2022 (without-WETLAND scenario) were predicted to be 2.14and 0.111 mg L-1, respectively. This result means that the Hwaong Reservoir was predicted to be in a state of eutrophication, mainly due to excessive pollutant loads from the river basin.

If 264ha of treatment wetlands were constructed (simulated by the with-WETLAND scenario), the predicted concentrationsof T-N and T-P in the Hwaong Reservoir would be 1.98 and 0.094 mgL-1, respectively. Thus, water quality was predicted to improve by 7.5%in terms of reduced T-N and by 15.3% in terms of reduced T-P compared to the without-WETLAND scenario. These results demonstrated that the deterministic integrated modelling was useful for evaluating the impact of river basin management scenarios on future water quality in a future river basin conditions. If the goal of a modelling study is to examine the impact of river basin management scenarios on water quality of a study area, the deterministic integrated modelling system without the uncertainty analysis may be practical.In such cases, evaluation of the impacts of management scenarios would not be inhibited by the uncertainty of model output.

Figure 5. Deterministic reservoir water quality prediction result without- and with-WETLAND scenario (i.e., the construction of treatment wetlands)

Results of the GLUE analysis

Before the model parameter uncertainty analysis was conducted, the GLUE analysis was conducted using the sensitive parameters identified with the OAT sensitivity analysis technique to estimate GLUE likelihood weights and behaviour parameter sets. The range for each parameter shown in Table IVwas based on the range of appropriate values found in the literaturesuch as the WASP user manual (Ambrose *et al.*, 1993) and other studies(USEPA, 1985; Wu *et al.*, 1996). A uniform distribution function over a chosen range was used to define a standard prior distribution, and 20,000 model parameter sets were randomly generated from their specified ranges. By using parameter set, model simulations were performed for 2012 when observed water quality data were collected. Likelihood weights of the simulation for daily output variables were computed by applying Eq. 3,resulting in9,100 acceptable parameter sets. Likelihood weights were rescaled by dividing each individual weight by their total sum to obtain confidence intervals (CI).

Table IV. WASP model parameters used in the GLUE analysis

Observed and calibrated data, best-fit data, andthe 90% confidence interval bounds from the GLUE analysis are shown in Figure 6 and Table V. Lower and upper bounds of range (90% CI) in Table V refer to the 5th and 95th percentiles of the cumulative likelihoods, respectively, while the median represents the 50th percentile. Data in TableV highlight an interesting observation that the GLUE method estimated the NSE value of best-fit parameter sets to be higher than the deterministic model estimates for both T-N and T-P concentration. For example, the NSE value of best-fit parameter sets obtained from the GLUE method for the T-N concentration was 0.845 mg L-1, compared to 0.832 mg L-1 from the deterministic modelling.This result demonstratesthat even though the model was well calibrated with the observed data set, there could exist other better parameter sets (i.e., sets havinghigher NSE values), indicating that deterministic modellingcan have possibly a risk to over- or under-estimating the future water quality in some cases.

The concentrations for T-N and T-P reported in Table Vshowed that the predictedconcentrations from the GLUE method were lower than those from the deterministic modelling.The concentrations of T-N and T-P from the GLUE method were predicted to be 0.67 and 0.045 mg L-1 respectively,compared to 0.76and 0.049 mg L-1, respectively, from the deterministic modelling. This result indicates that deterministic modelling can be well fit for the purpose of predicting future water quality. Due to uncertainty associated with model parameters and other inputs, however, it is necessary that the model incorporate uncertainty analysis whenthe model is applied to evaluate the ability of ariver basin management plan to meet a specific water quality standard.Therefore, estimated GLUE likelihood weights and behaviour parameter sets linked with the integrated modelling system were used for the uncertainty analysis of model parameters and other inputs.The integrated modelling system under uncertainty is possibly more reliable at predicting the future water quality.

Figure 6. Model output probability distribution resulting from WASP model parameters

Table V. Summary of the GLUE analysis result

Results of the integrated modelling system with the uncertainty analysis

GLUE and Monte Carlo simulations were performed to evaluate the effects of model parameters and future behaviour uncertainty (particularly climate data and predicted PS pollutant loads) on the output, respectively. Figure 7 shows cumulative likelihood distributions of three uncertainty sources in simulations without the treatment wetland construction scenario (without-WETLAND) in the integrated modelling system (Figure 2). All three uncertainty sources largely affect the model output. Among the three uncertainty sources, the model parameter uncertainty was the most significant contributor to overall output uncertainty, compared to the uncertainty of climate data and predicted PS loads.

Figure 7. Model output probability distribution resulting from various uncertainty sources

Figure 8. Comparison of confidence intervals among various uncertainty sources

From the cumulative distribution of each uncertainty source (Figure 7), 90% confidence intervals (from 5th to 95thpercentiles of the cumulative distribution)were estimated (Figure 8).Figure 8 shows that the concentrations of T-N and T-P inthe Hwaong Reservoir would be in the range of 1.30–3.16mg L-1and 0.091–0.173 mg L-1, respectively, with a 90% probability without the wetland construction scenario (without-WETLAND) under combined uncertainty sources.

The simulations predicted that the concentrations of T-N and T-P in the Hwaong Reservoir would be less than 2.84 and 0.163 mg L-1, respectively, with 90% confidence and only 11% would meet the T-P reservoir water quality standard (0.1 mg L-1) in 2022under combined uncertainty sources (Figure 7). This result suggests the conclusion that although WWTPs are constructed in the river basin to control the point source pollutant loads, the Hwaong Reservoir will, nevertheless, be in a state of eutrophication in 2022.

Evaluation of a river basin management measureusing the integrated modelling system with the uncertainty analysis

The water quality prediction result for the Hwaong Reservoir using the integrated modelling system indicated that river basin pollutant loads should be reduced to meet the specified water quality criteria;thus, the construction of treatment wetlands was considered as an additional river basin management measure.Treatment wetlands are commonly used for controlling the pollutant loads from non-point sources; thus,constructing wetlands to abate the pollutant loads from non-point sources has received much attention (e.g., Kadlec and Knight, 1996; Mitsch and Gosselink, 2000; Nairn and Mitsch, 2000).

The computational procedure described previously was performed to quantify the uncertainty associated with both model simulations and the estimated effectiveness of a specific river basin management measures(construction of treatment wetlands). Figure 9 depicts the cumulative likelihood distribution of average daily T-N and T-P concentrations.

The with-WETLAND scenario predictedimproved overall reservoir water quality, compared to that predicted by the without-WETLAND scenario.If treatment wetlands were applied for the pollution control of non-point sources, the predicted T-N and T-P concentrations in the Hwaong Reservoir would be (with 90% probability) in the range of 1.15–2.82 mg L-1 and 0.079–0.143 mg L-1, respectively, (Table VI), and less than 2.57 and 0.135 mg L-1, respectively, with 90% confidence (Figure 9).

The predicted water quality of the Hwaong Reservoir in 2022 using integrated modelling with the uncertainty analysis showed that only 28% would meet the T-P water quality standard (0.1 mg L-1) for the agricultural reservoir (Figure 9) although 264 ha of treatment wetlands were constructed (with-WETLAND scenario).In contrast, theresults of deterministic modelling without the uncertainty analysis show that the HwaongReservoir water quality for T-P (0.094 mg L-1) in 2022 would meet the reservoir water quality standard.This result indicate that in order to meet the water quality standard with a 90% level of confidence, additional river basin management measures should be applied beyond the construction of treatment wetlands and WWTP.Furthermore, the uncertainty analysis associated with model parameters and future behaviour can be recommended if the goal of a modelling study is to develop river basin management plans to meet specified water quality criteria.

Figure 9. Cumulative distribution of predicted the Hwaong Reservoir water quality simulated using the without-WETLAND and with-WETLAND scenarios

Table VI. Summary of the Hwaong Reservoir water quality predicted using the integrated modelling system with the uncertainty analysis

CONCLUSIONS

An integrated modelling system that included Monte Carlo simulation and a GLUE-based probabilistic approach was developed as a computational procedure for predicting reservoir water quality by incorporating uncertainty and developingriver basin management measures to meet the specified water quality criteria based on the predicted probability of occurrence.

The deterministic integrated modelling system without uncertainty analysis (Monte Carlo simulation and GLUE)was used to simulateriver basin loading, receiving water quality and wetland performance to evaluate the effect of river basin management measures on reservoir water quality. The calibrated integrated modelling system was then used to predict the HwaongReservoir water quality. The results show that although wastewater treatment plants were constructed in the reclamation river basin to control the point source pollutant loads, the Hwaong Reservoir was predicted to be in a state of eutrophication in 2022. However, if 264 ha of treatment wetlands werealso constructed (a situation simulated in the with-WETLAND scenario) as a river basin management measure, the HwaongReservoir water quality for T-P (0.094 mg L-1) in 2022 would meet the Korean water quality standard for T-P in reservoirs (0.1 mg L-1).

The integrated modelling systemwith the uncertainty analysis also predicted that the Hwaong Reservoir would be in a state of eutrophication in 2022 although WWTPs were constructed. If 264 ha of treatment wetlands (as simulated in the with-WETLAND scenario) wereconstructed for the pollution control of non-point sources, only 28% would meet the T-P water quality standard for agricultural reservoirs.However, the HwaongReservoir water quality for T-P would meet the reservoir water quality standard when the deterministic integrated modelling system without the uncertainty analysis was used. This result indicates that to meet the water quality standard with a 90% level of confidence, further river basin management measures should be applied in addition to the construction of planned WWTPs and treatment wetlands.

In our study, the proposed integrated modelling system with the uncertainty analysiswas demonstrated to be very useful for estimating the level of uncertainty and the probability of occurrence in water quality prediction. The advantage of the integrated modelling system with uncertainty analysis was that it can allow modellers to make useful decisions about whether a river basin management plan can meet specified water-quality criteria based on the predicted probability of occurrence.

REFERENCES

Ambrose RB, Wool TA, Martin JL. 1993. *The Water Quality Analysis Simulation Program, WASP5 version 5.10. Part A: Model Documentation*. Environmental Research Laboratory, U.S. Environmental Protection Agency, Office of Research and Development, Athens, GA, USA.

American Public Health Association (APHA). 1998. *Standard Methods for the Examination of Water and Wastewater (20thed.)*. Washington, DC, USA.

Annan JD. 2001. Modelling under uncertainty: Monte Carlo methods for temporally varying parameters. *Ecological Modelling***136**: 297–302.

Aronica GT, Candela A, Fabio P, Santoro M. 2012. Estimation of flood inundation probabilities using global hazard indexes based on hydrodynamic variables. *Physics and Chemistry of the Earth Parts A/B/C***42-44**: 119–129. DOI: 10.1016/j.pce.2011.04.001.

Beck MB. 1987. Water quality modelling: A review of the analysis of uncertainty. *Water Resources Research***23**(8):1393–1442.

Beven KJ, Binley A. 1992. The future of distributed models: model calibration and uncertainty prediction. *Hydrological Processes***6**: 279–298.

Beven KJ, Binley A. 2013. GLUE: 20 years on. *Hydrological Processes***28**(24): 5897–5918. DOI: 10.1002/hyp.10082.

Beven KJ, Freer J. 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modeling of complex environmental systems using the GLUE methodology.*Journal ofHydrology***249**: 11–29.

Bicknell BR, Imhoff JC, Kittle JL, Donigian AS,Johanson RC. 2001. *Hydrological Simulation Program-FORTRAN (HSPF): User's Manual for Release 12*. Environmental Research Laboratory, U.S. Environmental Protection Agency, Athens, GA, USA.

Cheng QB, Chen X, Xu CY, Reinhardt-Imjela C, Schulte A. 2014. Improvement and comparison of likelihood functions for model calibration and parameter uncertainty analysis within a Markov chain Monte Carlo scheme.*Journalof Hydrology***519**: 2202–2214. DOI: 10.1016/j.jhydrol.2014.10.008.

Cooke GD, Welch EB, Peterson SA,Newroth PR. 1993.*Restoration and Management of Lakes and Reservoirs, 2nd edn.*CRC Press, New York, NY, USA.

Crowder BM, Pionke HB, Epp DJ, Young CE. 1985. Using CREAMS and economic modelling to evaluate conservation practices: An application. *Journal of Environmental Quality***14**: 428–434.

Eckhardt K, Breuer L,Frede H. 2003. Parameter uncertainty and the significance of simulated land use change effects. *Journal of Hydrology***273**: 164–176.

Freer J,Beven KJ. 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach. *Water Resources Research***32**(7): 2161–2173.

Ham JH. 2005. *Nonpoint Source Pollution Control using Constructed Wetlands and Integrated Watershed Modelling*. PhD thesis, Department of Rural Engineering, Konkuk University, Seoul, Korea.

Jung Y,Merwade V. 2012. Uncertainty Quantification in Flood Inundation Mapping Using Generalized Likelihood Uncertainty Estimate and Sensitivity Analysis. *Journal of Hydrologic Engineering***17**(4): 507–520. DOI: 10.1061/(ASCE)HE.1943-5584.0000476.

Kadlec RH, Knight RL. 1996. *Treatment wetlands*. CRC Press: Boca Raton, FL, USA.

Lee CH, Lee BY, Chang WK, Hong SG, Song SJ, Park JS, Kwon BO, KhimJS. 2014. Environmental and ecological effects of Lake Shihwa reclamation project in South Korea: A review. *Ocean & Coastal Management***102**(B): 545–558.

Leta OT, Nossent J, Velez C, Shrestha NK, Griensven A, Bauwens W. 2015. Assessment of the different sources of uncertainty in a SWAT model of the River Senne (Belgium).*Environmental Modelling & Software***68**: 129–146. DOI: 10.1016/j.envsoft.2015.02.010.

Lin K, Liu P, He Y,Guo S. 2014. Multi-site evaluation to reduce parameter uncertainty in a conceptual hydrological modeling within the GLUE framework.*Journal ofHydroinformatics***16**(1): 60–73. DOI: 10.2166/hydro.2013.204.

Li S, Xiong L, Li HY, Leung R, Demissie Y. 2015. Attributing runoff changes to climate variability and human activities: uncertainty analysis using four monthly water balance models.*Stochastic Environmental ResearchAnd Risk Assessment* DOI: 10.1007/s00477-015-1083-8.

Mirzaei M, Huang YF, El-Shafie A, Chimeh T, Lee J, Vaizadeh N, Adamowski J. 2015. Uncertainty analysis for extreme flood events in a semi-arid region.*Natural Hazards***78** (3): 1947–1960 DOI: 10.1007/s11069-015-1812-9.

Mitsch WJ, Gosselink JG. 2000. *Wetlands*. John Wiley & Sons: New York, NY, USA.

Mu J, Khan S, Gao Z. 2008. Integrated water assessment model for water budgeting under future development scenarios in Qiantang river basin of China.*Irrigation and Drainage***57**(4): 369–384. DOI: 10.1002/ird.366.

Mu J, Khan S, Liu Q, Xu D, Xu J, Wang W. 2013. A stochastic approach to analyse water management scenarios at the river basin level.*Irrigation and Drainage***62**(4): 379–395. DOI: 10.1002/ird.1753

Nairn RW,Mitsch WJ. 2000. Phosphorus removal in created wetland ponds receiving river overflow. *Ecological Engineering***14**: 107–126.

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

National Research Council (NRC). 2001. *Assessing the TMDL approach to water quality management. Committee to access the Scientific Basis of the Total Maximum Daily Load Approach to Water Pollution Reduction*. Water Science and Technology Board, Division of Earth and Life Studies. Washington, DC.

Shojaei M,Nazif S,Kerachian R. 2015. Joint uncertainty analysis in river water quality simulation: a case study of the Karoon River in Iran. *Environmental Earth Sciences***73**: 3819–3831. DOI: 10.1007/s12665-014-3667-x.

Singh A, Mishra S, Ruskauff G. 2010. Model averaging techniques for quantifying conceptual model uncertainty.*Ground Water***48**: 701–715.

Somlyody L, Wets R. 1988. Stochastic optimization models for lake eutrophication management. *Operations Research***36**(5): 660–681.

Starrfelt J, Kaste O. 2014. Bayesian uncertainty assessment of a semi-distributed integrated catchment model of phosphorus transport.*Environmental Science: Processes &Impacts* **16**: 1578–1587. DOI: 10.1039/C3EM00619K.

Todini E. 2008. A model conditional processor to assess predictive uncertainty in flood forecasting.*International Journal of River Basin Management***6**: 123–137.

Uniyal B, Jha MK, Verma AK. 2015. Parameter Identification and Uncertainty Analysis for Simulating Streamflow in a River Basin of Eastern India. *Hydrological Processes***29** (17): 3744–3766. DOI: 10.1002/hyp.10446.

U.S. Environmental Protection Agency (USEPA). 1985. *Rates, Constants, and Kinetics Formulations in Surface Water Quality Modelling(second edition)*, EPA/600/3-85/040. Office of Research and Development, Athens, Georgia, USA.

U.S. Environmental Protection Agency (USEPA). 2001. *Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) Version 3.0 User's Manual*, EPA 823-8-01-001. Office of Water , Washington, D.C., USA.

Wellen C, Arhonditsis GB, Long T, Boyd D. 2014. Quantifying the uncertainty of nonpoint source attribution in distributed water quality models: A Bayesian assessment of SWAT's sediment export predictions.*Journal of Hydrology***519**: 3353–3368. DOI: 10.1016/j.jhydrol.2014.10.007.

Wu RS, Sue WR, Chen CH, Liaw SL. 1996.Simulation model for investigation effect of reservoir operation on water quality.*Environmental Software***11**(1-3): 143–150.

Xue C, Chen B, Wu H. 2014. Parameter Uncertainty Analysis of Surface Flow and Sediment Yield in the Huolin Basin, China. *Journal of Hydrology Engineering***19**(6): 1224–1236. DOI: 10.1061/(ASCE)HE.1943-5584.0000909.

Yang J, Reichert P, Abbaspour KC, Xia J, Yang H. 2008.Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China.*Journal of Hydrology***358**: 1–23. DOI: 10.1016/j.jhydrol.2008.05.012.

Yu JJ, Qin XS, Larsen O. 2014. Uncertainty analysis of flood inundation modelling using GLUE with surrogate models in stochastic sampling. *Hydrological Processes***29** (6): 1267–1279. DOI: 10.1002yhyp.10249.

Zheng Y, Han F. 2015. Markov Chain Monte Carlo (MCMC) uncertainty analysis for watershed water quality modeling and management. *Stochastic Environmental ResearchAnd Risk Assessessment* DOI: 10.1007/s00477-015-1091-8.

Table I. Adjusted parameters for calibration of the HSPF model

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Parameter (Units) | Calibrated value |  | Parameter (Units) | | Calibrated value |
| Hydrology |  |  | Nutrients |  |  |
| LASN (in)  INFILT (in h-1)  AGWRC (day-1) | 6.74  0.47  0.069 |  | SQO (qty ac-1) | NH3  NO3  PO4 | 0.03  1.4  0.38 |
| UZSN (in)  KVARY (in-1)  INFEXP | 0.010  0.004  3.40 |  | POTFW (qty ton-1) | NH3  NO3  PO4 | 0.01  0.01  0.02 |
| INFILD (in)  INTFW  IRC (day-1) | 0.77  0.995  0.002 |  | POTFS (qty ton-1) | NH3  NO3  PO4 | 0.1  0.1  0.01 |
| LZETP  DEEPFR  BASETP | 0.77  0.995  0.002 |  | ACQOP (qty ac-1 d-1) | NH3  NO3  PO4 | 0.00  0.01  0.0008 |
| AGWETP  CEPSC (in)  PLS NSUR | 0.77  0.995  0.002 |  | SQOLIM (qty ac-1) | NH3  NO3  PO4 | 0.02  1.98  0.02 |
| Sediment |  |  | WSQOP (in hr-1) | NH3  NO3  PO4 | 0.5  0.5  0.5 |
| JSER (day-1)  KSER (day-1)  KGER (day-1)  KRER (day-1)  JGER (day-1) | 2.0  5.0  2.0  6.0  2.0 |

Table II. Adjusted parameters for calibration of the WASP model

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameter (Units) | Calibrated value |  | Parameter (Units) | Calibrated value |
| K12C (day-1)  K12T (-)  KNIT (mg O2/L)  K20C (day-1)  K20T (-)  KNO3 (mg O2/L)  K1C (day-1) | 0.113  1.04  1.12  0.247  1.01  1.93  2.41 |  | IS1 (ly/day)  KMNG1 (mg-N/L)  KMPG1 (mg PO4-P/L)  K1D (day-1)  NCRB (mg N/ mg C)  K71C (day-1)  K83C (day-1) | 219  0.112  0.053  0.089  0.134  0.119  0.315 |

Table III. Comparison of observed and simulated data for calibration

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Constituent | | Mean  observed  (m3/s, mg/L) | Mean  simulated  (m3/s, mg/L) | R2 | RMSE | NSE |
| HSPF | Flow  T-N  T-P | 3.08  9.90  0.644 | 2.87  10.40  0.691 | 0.96  0.86  0.92 | 0.74  1.57  0.126 | 0.92  0.63  0.71 |
| WASP | T-N | 0.60  0.041 | 0.66  0.045 | 0.94  0.95 | 0.15  0.008 | 0.83  0.85 |
| T-P |

Table IV. WASP model parameters used in the GLUE analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Parameter (Units) | Range |  | Parameter (Units) | Range |
| K12C (day-1) | 0.020 -0.340 |  | IS1 (ly/day) | 200.0 - 500.0 |
| K12T (-) | 1.000 - 1.080 |  | KMNG1 (mg-N/L) | 0.008 -0.235 |
| KNIT (mg O2/L) | 0.100 - 4.000 |  | KMPG1 (mg PO4-P/L) | 0.002 -0.053 |
| K20C (day-1) | 0.020 -0.400 |  | K1D (day-1) | 0.010 -0.200 |
| K20T (-) | 1.000 - 1.090 |  | NCRB (mg N/ mg C) | 0.020 -0.320 |
| KNO3 (mg O2/L) | 0.050 -2.000 |  | K71C (day-1) | 0.010 -0.140 |
| K1C (day-1) | 0.500 -3.600 |  | K83C (day-1) | 0.010 -0.350 |

Table V. Summary of the GLUE analysis result

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Constituent | Obs. | Deterministic  modelling |  | GLUE | | |
| Calibration |  | Best-fit | Median | Range (90% CI) |
| T-N (mg L-1) | 0.60 | 0.76 (0.832)a |  | 0.67(0.845)a | 0.73 | [0.59, 0.87] |
| T-P (mg L-1) | 0.041 | 0.049(0.834) |  | 0.045(0.916) | 0.054 | [0.046, 0.060] |

a concentration (NSE : Nash-Sutcliff efficiency coefficient)

Table VI. Summary of the Hwaong Reservoir water quality predicted using theintegrated modelling system with the uncertainty analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| River basin  management | Constituent | Deterministic  modelling | Uncertainty analysis | |
| Median | Range (90% CI) |
| without WETLAND  (mg L-1) | T-N | 2.14 | 1.95 | [1.30, 3.16] |
| T-P | 0.111 | 0.130 | [0.091, 0.173] |
| with WETLAND  (mg L-1) | T-N | 1.98 | 1.74 | [1.15, 2.82] |
| T-P | 0.094 | 0.110 | [0.079, 0.143] |
| Reduction  (%) | T-N | 7.5 | 10.8 | - |
| T-P | 15.3 | 15.4 | - |

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Figure 1

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Figure 2

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Figure 3

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Figure 4

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Figure 5

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Figure 6

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Figure 7

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Figure 8

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Figure 9

1. †Système de modélisationintégrée avec l'analyse de l'incertitude pour gestion de la qualité de l'eaud’un réservoirdans le cadre de l’aménagement d’un bassin versant. [↑](#footnote-ref-2)
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