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Uncertainty Analysis of SWAT Model using Monte Carlo Technique and Ensemble Flow Simulations

몬테카를로 기법과 앙상블 유량모의 기법에 의한 SWAT 모형의 불확실성 분석

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ABSTRACT

수학적 모델은 수량과 수질의 예측을 위해 현장 조사의 대안으로 사용되어지며 이러한 모델의 사용과 실측에 불확실성이 존재하게 된다. 불확실성에 대한 많은 연구들이 진행되어 왔으나 시나리오에 의한 모델링 과정에서 발생하는 불확실성에 대한 연구는 미흡한 실정이다. 본 연구에서는 산림이 농경지와 목초지로의 변화에 따른 시나리오를 설계한 후 시나리오 적용에 따른 SWAT (Soil and Water Assessment Tool) 매개변수의 불확실성을 분석하고자 하였다. 몬테카를로 기법 (Monte Carlo simulation)을 이용하여 각 매개변수별 1,000개의 난수를 발생하였으며 앙상블 유량모의 기법을 이용하여 미국 Alabama주 카하바강 상류 (50,967ha)를 대상으로 각 난수별 100개의 유량을 통해 불확실성을 분석하였다. 분석 결과 산림지역이 농경지와 목초지로 변화되었을 때 유출량이 증가하는 것으로 분석되었으며, 임야가 목초지 보다 농경지로 변화되었을 때 유출량은 더욱 증가하는 것으로 나타났다. 각 시나리오별 SWAT 매개변수의 불확실성은 AWC (Available water capacity), CN (Curve number), GWREVAP (groundwater re-evaporation coeffeicient), REVAPMN (minimum depth of water in shallow aquifer for re-evaporation to occur)순으로 크게 나타났으며, Ksat (Saturated hydraulic conductivity)와 ESCO(Soil evaporation compensation factor)는 유출량의 변화에 큰 영향을 미치지 못하는 것으로 분석되었다. 토지피복별 산림 면적이 클 경우 불확실성이 크게 나타나 산림이 목초지와 농경지로 변함에 따라 불확실성은 감소하는 것으로 나타났다.

Keywords: Uncertainty; monte carlo technique; ensemble flow simulation; land use change

I. INTRODUCTION

The analysis of uncertainty associated with the utility of simulation models is an important consideration in the development of watershed management plans. Modeling uncertainty should be rigorously addressed in development and application of models, especially when stake holders are affected by the decisions contingent upon model-supported analyzes (NRC, 2001).

The common modeling approach entails the {calibrate → validate → predict} process. Calibration of a simulation model for a given watershed will reduce, but not totally remove, modeling uncertainties associated with both structure of the model and parameter estimates. Even with the best model structure, parameter estimation contains residual uncertainty (Beck, 1987) that propagates forward into model predictions and evaluation of effectiveness of management practices. Although the literature is replete with sensitivity analysis and uncertainty analysis methods (Spear and Hornberger, 1980; Beven and Binely, 1992; Spear et al., 1994), implications of uncertainty

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associated with model predictions have not been widely endorsed in the decision making process mainly as a result of large uncertainty estimates.

The argument, however, is that if the goal of a modeling study is to examine the impact of management scenarios on study area, it may be neither practical nor necessary to incorporate large uncertainty of absolute predictions in the decision making process. It would be perhaps more feasible (and more desirable) to communicate and implement uncertainty of estimated effectiveness of management practices rather than uncertainty of absolute predictions (Zhang and Yu, 2004).

The impact of modeling uncertainties on evaluation of management scenarios has not been addressed sufficiently, as studies have generally focused on uncertainty of point predictions. In this paper, a Monte Carlo-based probabilistic approach is utilized (i) to analysis the uncertainty; (ii) to examine the effect of long-term water flow impacts in scenarios by land use change using a distributed watershed model, SWAT; and (iii) to quantify the impact of input parameters uncertainty in the each land use scenario using ensemble flow simulation.

II. MODEL, APPLICATION WATERSHED AND DATA

1. Watershed model

The SWAT model (Arnold et al., 1998) is a physically based, distributed parameter, watershed-scale model. It divides the study watershed into sub-basins and identifies smaller homogeneous areas within each sub-basin called hydrologic response units (HRU) (Arnold et al., 1998; Neitsch et al., 2001). All model calculations are performed at the HRU level. SWAT uses a modification of the SCS curve number method (USDA Soil Conservation Service, 1972) or Green and Ampt infiltration method (Green and Ampt, 1911) to compute surface runoff volume for each HRU. Moreover, SWAT has the capability to evaluate the relative effects of different management scenarios on water quality, sediment, and agricultural chemical yield in large, ungaged basins. Major components of the model include weather, surface runoff, return flow, percolation, evapotranspiration (ET), transmission losses, pond and reservoir storage, crop growth and irrigation, ground water flow, reach routing, nutrient and pesticide loads, and water transfer.

SWAT was selected in this study as the model that would be used to analysis the uncertainty in a complex watershed with various soils, land use and scenarios over a long period of time. Also, the physically based SWAT model uses input data that is readily available, computes efficiently, and makes it possible for users to study long-term impacts (DiLuzio et al., 2002; Neitsch et al., 2002a). The model can be used to simulate a single watershed or a system of hydrologically connected multiple watersheds. A watershed must first be divided into sub-basins and then HRUs for each sub-basin evaluated based on the land use and soil distributions (DiLuzio et al., 2002).

AVSWAT was developed as an extension of ArcView GIS entirely in avenue and is dependent on the spatial analyst and the dialog designer extensions. Without leaving the user-friendly ArcView GIS environment, the user can has available a complete set of tools for watershed delineation and definition, enabling the user to edit the hydrological and agricultural management inputs and execute and calibrate the model.

2. Monte Carlo Simulation (MCS)

In MCS analysis, the effect of uncertainty in model parameter P on output O is estimated by repeated simulations using randomly selected parameter values. Effects of uncertain knowledge of one or more parameter values can be reliably estimated using MCS analysis. MCS analysis has been reported to be the most robust method for estimating uncertainty in water quality models (Hession et al., 1996) and is commonly selected as a standard for comparing against other methods (Yu et al., 2001). The accuracy of output uncertainty estimates depends on the number of model simulations performed and on the adequacy of the assumed parameter distribution (Haan, 2002). The number of model simulations should be sufficiently large to reliably estimate the probability distribution of the output variables (Gardner and O'Neill, 1983).

3. Watershed and data

The Cahaba River is an important resource for the state from a variety of viewpoints. It is a major municipal water supply for the Birmingham metropolitan area, and is also used for the disposal of domestic and industrial wastewater. The Cahaba River is the third largest tributary to the Alabama River in the Mobile River basin. It extends for 308 ㎞ from its headwaters in St. Clair County northeast of Birmingham to its confluence with the Alabama River southwest of Selma. The drainage area lies entirely within the state of Alabama, and encompasses approximately 470,000 ha including portions of St. Clair, Jefferson, Shelby, Bibb, Tuscaloosa, Perry, Chilton, and Dallas Counties. Elevation in the watershed ranges from 335.3 m in Shelby County to 30.5 at the confluence with the Alabama River.

The targeted upper Cahaba River including St. Clair, Jefferson and Shelby County in this study is an important resource for the state. The type of land-use in the watershed is mostly forest (63 %), agricultural crop area (14 %), urban (9 %), pasture (7 %), and the remainder including water (7 %). The geomorphologic characteristics of flow total length, slope, watershed area 157 ㎞, 0.62 and 509.7 ㎢, respectively.

Modeling in this study was used 30 m resolution DEM, Soil map by STATSGO and land use map for 1:250,000 watersheds were used for the watershed model (www.aces.edu/waterquality/gis_data). Stream flow data for model calibration were obtained by USGS (waterdata.usgs.gov/al) which are (1) Cahaba at Camp Coleman, (2) Cahaba River near Mountain Brook and target outlet, (3) Cahaba River at Caldwell Ford Bridge. Fig. 1 shows location of weather and water flow measurement station in watershed.

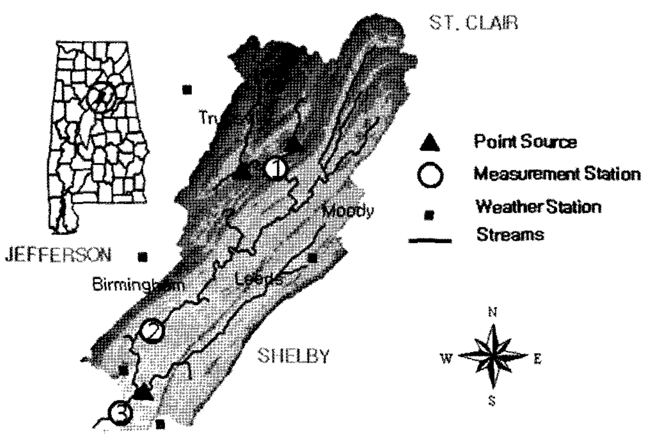


Fig. 1 Location of weather and Water flow measurement station in watershed

III. METHODOLOGY

Uncertainty in model parameter values was introduced based on probability distributions and Monte Carlo sampling, and ensemble flow simulations were generated by SWAT for evaluation through land use change within watershed of interest. A measure of the dispersion in the ensemble flow simulations was used to quantify the uncertainty of the flow simulations. This section describes the land use changing method and the features of the methodology employed for the uncertainty analysis through Monte Carlo and flow ensemble technique.

The steps involved in the execution of the uncertainty analysis with the distributed hydrologic model are:

(1) calibration and validation of the SWAT model based on adequate reproduction of observed stream flows at watershed gauged locations to establish model credibility;

(2) flow modeling of land use changed by land-use suitability mapping and analysis

(3) generation of ensemble simulated flows for watershed in a Monte Carlo experiment sampling from the input probability distributions parameter;

(4) computation of uncertainty for changing land use scenario in watershed;

The model was calibrated and validated for flow simulation using the observed data from the period Jan 1993 - Dec 1998. Land use suitability mapping and analysis was performed to evaluate the flow impact and uncertainty measurement by land use change. Uncertainty analysis was applied from 1996 to 1998 with the same watershed.

Land-use suitability mapping and analysis is one of the most useful applications of GIS for spatial planning and management (Malczewski, 2004). The analysis aims at identifying the most appropriate spatial pattern for future land uses according to specify requirements, preferences, or predictors of some activity (Collins et al., 2001). In general, the GIS-based land suitability analysis assumes that a given study area is subdivided into a set of basic unit of observations such as polygons or rasters. Then, the land-use suitability problem involves evaluation and classification of the areal units according to their suitability for a particular activity.

This study considered altitude and slope as the factors for land-use suitability analysis, because the factors are important to develop the other land use for economic profit and topographical condition. Forest in the study watershed was changed to agricultural area and pasture for each scenario considering current developing condition of the study watershed. Therefore, the same area of forest was transmitted to agricultural area and pasture by 10, 30 and 50 percent.

MCS analysis involves sensitivity analysis to identify the model parameters that have the most influence on predicted outputs, generating a probability distribution of those parameters, running the model using each realization of the model parameter, and generating a probability distribution of model outputs to quantify output uncertainty (Yoon, 1994; Ham et al., 2007). Model parameters identified from the instructions for the calibration of the SWAT model, as given in the user's manual, are known for the most sensitive parameters (Neitsch et al., 2001). Therefore, the parameters considered for uncertainty analysis in this study are GWREVAP (groundwater re-evaporation coefficient), REVAPMN (minimum depth of water in shallow aquifer for re-evaporation to occur), AWC (Available water capacity), Ksat (Saturated hydraulic conductivity), ESCO (Soil evaporation compensation factor), GWQMN (Minimum depth of water in soil for base flow to occur), and CN (Curve number). The values of parameters used were within the range suggested in the SWAT user's manual (Neitsch et al., 2001).

These parameters were assumed to be uniformly distributed, and 1,000 random values were obtained based on range of each parameter distribution. Therefore, each parameter was generated with 100 ensemble flow by each scenario.

Three values were considered for each parameter (low, medium and high). Parameter values were varied one at a time covering all different possible combinations of parameters (Table 1). Based on the sensitivity analysis,

Table 1 The parameter value for calibration in SWAT model

Parameter	Definition	Optimized value	Range of parameter values used for modeling		
			Low	Medium	High
AWC	Available water capacity	0.09	0.08	0.12	0.16
ESCO	Soil evaporation compensation factor	0.80	0.01	0.50	1.00
GWQMN	Min. depth of water in soil for base flow to occur	57	50	100	200
CN	Curve number	CN-2	CN-2	CN	CN+2

simulated flow was found to be relatively insensitive to the parameters GWREVAP and REVAPMN and they were, therefore, excluded from the calibration procedure.

Ensemble flow simulations were generated for current land use and changing land use by introducing model parameters through random sampling from prescribed probability distributions within a Monte Carlo simulation framework. Watershed modeling using the Monte Carlo simulations began approximately 3 years prior to the beginning of target period for using the same initial states at the beginning of the watershed model for generating the ensemble flow.

A normalized measure of the dispersion in the flow ensemble was selected, indicating the influence of the parametric uncertainty on the uncertainty in flow simulations. This measure, termed R_Q, was defined at each time step as the difference between the 90th and 10th percentile ensemble flow values normalized by the median ensemble flow value.

$$R_Q = \frac{Q_{90} - Q_{10}}{Q_{50}} \tag{1}$$

This measure is suitable for comparing ensemble dispersion among different scenarios and flow simulation locations, and it is independent of the shape of the ensemble values at each period. The measure was computed for each time step over the selected scenarios, with the value at the time of maximum dispersion (i.e. maximum difference between Q90 and Q10), represented as $R_Q^{\max}$, reported for each scenario and each uncertainty case at the identified locations. An analogous measure, termed $R_C^{\max}$, was computed based on the ensemble of cumulative flows for each event (Carpenter and Georgakakos, 2004).

Ⅳ. RESULTS AND DISCUSSION

1. Model calibration

The calibration tool incorporated in AVSWAT allows the user to perform global changes on input parameters that are commonly modified during the calibration process (Neitsch et al., 2002b). Users can change the value of calibration parameters, run SWAT for the scenario, and then compare the scenario results to those in the original default simulation or those generated by other scenarios.

In this study, the trial-and-error method was adopted for model calibration and the parameter values were varied one at a time to cover all possible combinations of the parameters. Parameter values were adjusted from the initial estimates given in the model within the acceptable ranges (Neitsch et al., 2002a) to achieve the desired proportion.

For each constituent of interest, model performance is qualitatively evaluated with time series plots and quantitatively evaluated using three model performance statistics. The coefficient of determination (R^2) and RMSE were used to quantitatively assess the ability of the model to replicate temporal trends (daily and monthly) in measured data. The model was calibrated using the observed data from 1993 through 1998 in terms of flow on a daily basis. R^2 is the ratio of the mean square error of the predictions to the total mean square error of the observations. While lower values of R^2 (i.e. those close to zero) mean a poorer model prediction, values closer to 1.0 represent a more accurate prediction (Santhi et al., 2001).

Some studies indicated that the success of a calibration process is highly dependent on the objective function chosen as a calibration criterion (Gupta et al., 1998; Sorooshian and Gupta, 1995). The most commonly used calibration criterion is the sum of squared errors between observed and simulated model responses. In this study, a root mean square of errors (RMSE), which measures the generalized standard deviation between observed and simulated values, is primarily used and it is given in Eq. (2):

$$RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} (O_i - S_i)^2} \tag{2}$$

where O_i and S_i are observed and simulated watershed values, respectively, and N is the total number of data. The RMSE ranges between 0 and infinity and for a perfect match, it should be equal to 0, in which case O_i and S_i assume the same value.

The % Bias is defined as the relative percentage difference between the average simulation and measured data time series over n time steps and is given Eq. (3):

$$\%Bias = \frac{100 \times (\sum_{i=1}^{n} S_i - \sum_{i=1}^{n} O_i)}{\sum_{i=1}^{n} O_i} \tag{3}$$

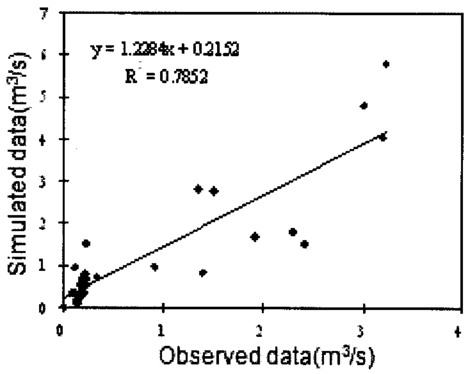
Fig. 2 compare the observed stream flows with the simulations for the data periods used for the calibration at three measured points in the watershed. The statistics of R^2, RMSE and % Bias were shown in table 2. And the statistics of R^2 were 0.79, 0.74 and 0.86 in (a), (b) and (c), which are final outlet, respectively (Fig. 2). The simulation results showed good agreement with the observed data.

2. Scenario Application

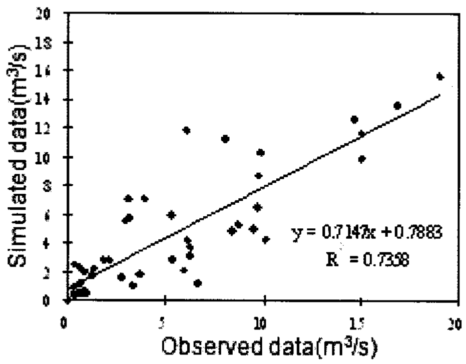
Land use was changed considering this study watershed covered with mainly forest and the watershed model was run to analyze flow in the each changed land use. To investigate the impact of changing flow in response to land use change, we simulated the stepwise transition from initial forest condition in the watershed to crop and pasture area (current, 10 %, 30 % and 50 % of watershed area covered with forest). Land use by each scenario was replaced using land-use suitability analysis.

Fig. 3 shows the land use change aspect that forest of green color area are becoming gradually yellow, crop area and light blue, pasture area by changing percent.

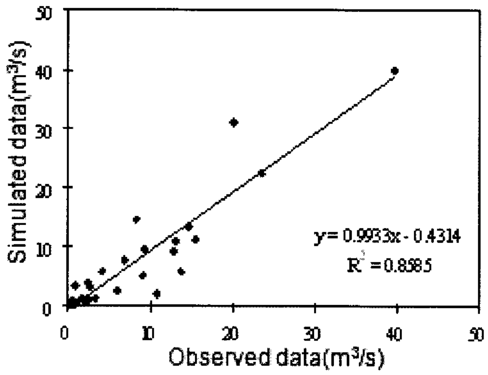
To investigate flow impact of uniform land use, land use change was executed in forest, crop area and pasture like as Table 3.



(a) Cahaba at Camp Coleman



(b) Cahaba River near Mountain Brook

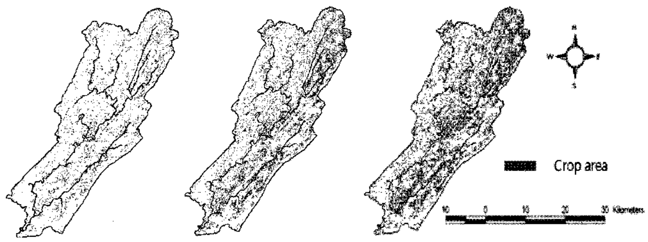


(c) Cahaba River at Caldwell Ford Bridge (Final outlet)

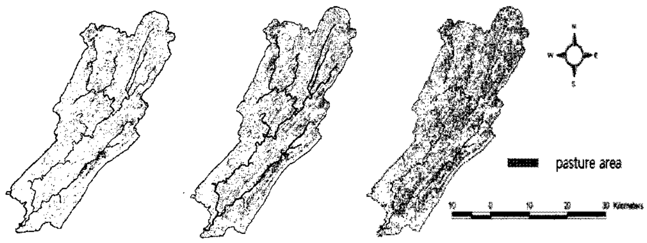
Fig. 2 Results of flow calibration in study watershed

Table 2 Performance of hydrological modelling

Location	R^2	RMSE (m^3/s)	% Bias
Cahaba at Camp Coleman	0.78	0.35	14.5
Cahaba River near Mountain Brook	0.74	2.60	-12.2
Cahaba River at Caldwell Ford Bridge	0.86	6.34	10.6



(a) Replacing crop area by 10, 30 and 50 % of forest



(b) Replacing pasture area by 10, 30 and 50 % of forest

Fig. 3 Result Maps of by changing land use

Table 3 Summary of area for application of land use change (unit: ha)

Scenarios		Forest	Agricultural crop area	Urban	Pasture	Others
Current		31922	7082	4477	3441	4045
Crop	10 %	28843	10160	4477	3441	4045
	30 %	22584	16419	4477	3441	4045
	50 %	16030	22974	4477	3441	4045
Pasture	10 %	28843	7082	4477	6519	4045
	30 %	22584	7082	4477	12777	4045
	50 %	16030	7082	4477	19333	4045

Fig. 4 presents the simulated monthly mean runoff in watershed by current land use, forest replace to crop and forest to pasture. When replacing crop area by forest, amount of flow were increased with mean ratio, 1.7, 9.6 and 16 percent in the crop 10, 30 and 50 percent, respectively. In case of replacing pasture area, amount of flow were increased with 1.5, 3.3 and 5.5 percent by each changing ratio (Table 4).

Overall, flow of replacing crop area and pasture were higher than current land use condition. The results indicate that the flow of the forest cropped were higher than that of the pasture treatment by 0.2, 6.3, and 10.5 percent at the ratio of 10, 15, and 20 percent, respectively.

Bosch and Hewleet (1982) reviewed results from 94 experiments throughout the world, most of them dealing with deforestation. The observational data scatters over

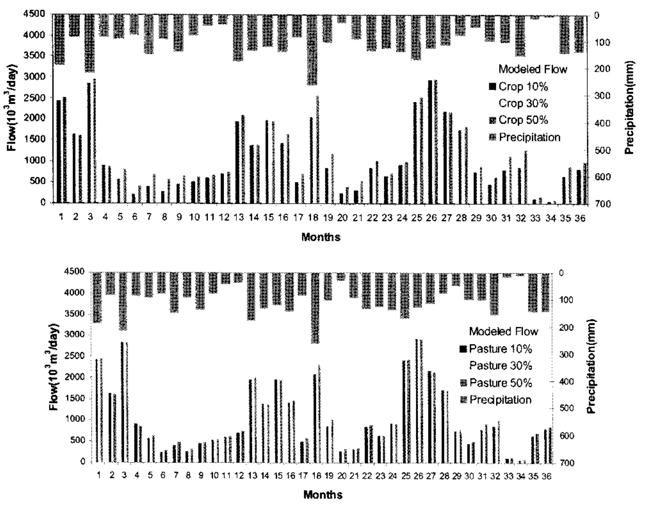


Fig. 4 Monthly mean flow results maps of by scenarios of changing land use

Table 4 Summary of monthly mean flow results maps of by scenarios of changing land use

Scenarios		1996		1997		1998	
		m³/s	m³/d	m³/s	m³/d	m³/s	m³/d
Current		11.02	952.22	12.74	1077.34	13.07	1128.91
Crop	10 %	11.20	967.48	12.70	1097.08	13.27	1146.52
	30 %	12.03	1039.69	13.80	1192.28	14.21	1227.96
	50 %	12.73	1099.75	14.70	1269.93	14.97	1293.60
Pasture	10 %	11.17	965.02	12.70	1097.63	13.25	1144.48
	30 %	11.34	979.44	12.98	1121.86	13.45	1162.11
	50 %	11.53	996.02	13.36	1154.65	13.68	1181.54
Precipitation		1276.61		1537.7		1189.49	

wide ranges. Bosch and Hewleet (1982) concluded that 'reductions in forest cover of less than 20 %··· apparently cannot be detected by measuring stream flow'. In case of crop area in this study, the flow was increased with about 10 percent from area changing ratio 30 %.

3. Uncertainty analysis results

To quantify the impact of input parameters uncertainty, 1,000 Monte Carlo simulations were performed for each land use type. The parameters are GWREVAP, REVAPMN AWC, Ksat, ESCO, GWQMN, and CN. The values of parameters used were within the range suggested in the SWAT user's manual. For each parameters and land use change, 1,000 flow ensembles were generated with watershed model.

The ensembles of the cumulative flow and dispersion of uncertainty measure for the parameters CN and AWC among the input parameters in Fig. 5 shows compare the simulated stream flows with 10th, 90th and 50th percentile ensemble flow. Fig. 6 presents the measures of parameters, CN and AWC uncertainty for each land use scenarios.

$R_Q^{\max}$ and $R_C^{\max}$ were calculated to quantify uncertainty through Eq. (1). The results uncertainties of parameters indicate that the values of R_C and R_Q were great in order AWC, CN, GWREVAP and REVAPMN (Table 4). It was found that the parameter Ksat, ESCO and GWQMN were almost not uncertain from the uncertainty analysis results.

R_C values of current land use in study watershed were bigger with 0.27, 0.4, 0.03 and 0.02 than those after land use changing. Also, $R_Q^{\max}$ values were bigger except CN and REVAPMN of changing pasture. But, these magnitudes of current land use and scenarios with changing pasture and crop area are a very small amount considering residual uncertainty (Beck, 1987), namely, modeling uncertainty in current land use. Therefore, the simulation of management scenarios is possible like effectiveness of management practices reported by Zhang and Yu (2004). Also, it is to be noted if forest area relatively bigger than that of pasture and crop area in some watershed, uncertainty of modeling result could be great. In uncertainty analysis of scenarios, $R_C^{\max}$ values were increased by increasing land use change ratios in crop and pasture, and $R_C^{\max}$ is higher at the large amount of precipitation than relatively small precipitation.

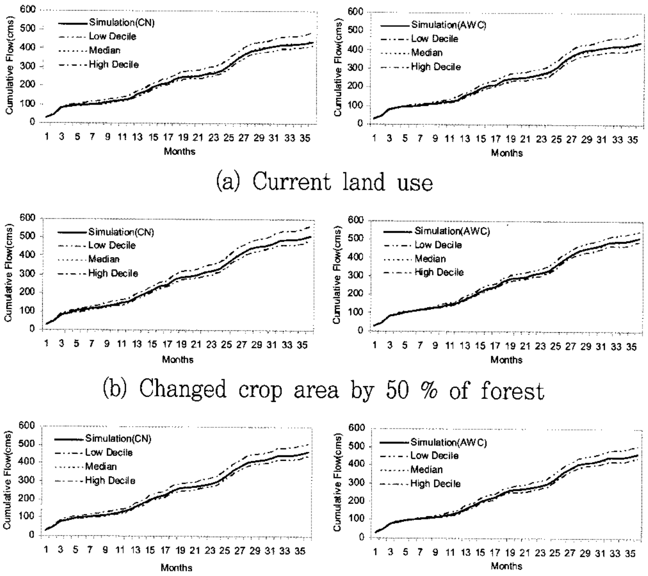
From preceding research for SWAT model parameters, CN and ESCO parameters are most sensitive for runoff (White and Chaubey, 2005) and the parameters GWREVAP and REVAPMN are not sensitive (Kannan et al., 2003). However, uncertainty of GWREVAP and REVAPMNG is larger than that of ESCO in the results of uncertainty analysis of this study. And the simulated flow was found to be relatively low affectation to the parameters Ksat and ESCO, and they were excluded from the results.

This result is confirmed that although amount of uncertainty analysis of input parameter is large, the parameter

Table 5 Summary of measures of parameters uncertainty for each land use scenarios

	CN			AWC			GWREVAP			REVAPMN		
	R_Q^{max}	Flow	R_C^{max}	R_Q^{max}	Flow	R_C^{max}	R_Q^{max}	Flow	R_C^{max}	R_Q^{max}	Flow	R_C^{max}
Current	1.076	92954	0.273	2.080	179719	0.414	0.207	17894	0.030	0.097	8352	0.022
Crop 10 %	1.025	88566	0.258	1.911	165083	0.392	0.190	16373	0.028	0.092	7943	0.020
30 %	0.988	85339	0.237	1.259	108758	0.266	0.135	11681	0.022	0.079	6796	0.016
50 %	0.951	82199	0.226	0.907	78348	0.197	0.110	9538	0.019	0.070	6055	0.014
Pasture 10 %	1.056	91236	0.258	1.848	159627	0.381	0.178	15387	0.028	0.187	16150	0.023
30 %	1.140	98522	0.257	1.662	143564	0.339	0.152	13170	0.025	0.098	8458	0.019
50 %	1.194	103126	0.253	1.476	127532	0.299	0.122	10581	0.022	0.101	8715	0.018

* Flow (m^3/day) is difference amount of stream flow at RQ



(a) Current land use

(b) Changed crop area by 50 % of forest

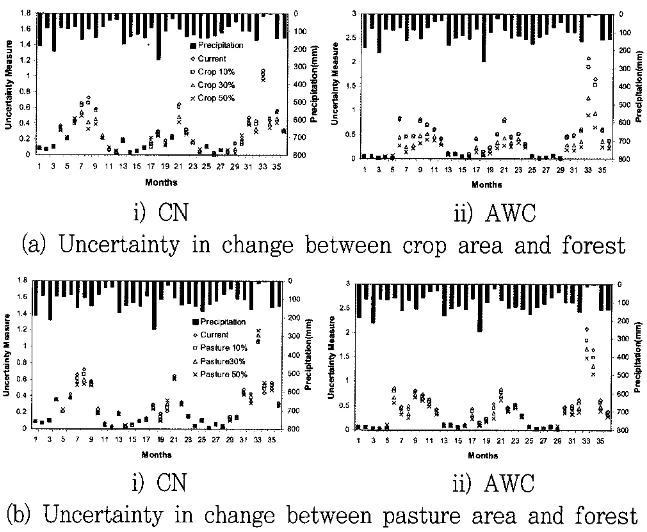
(c) Changed pasture area by 50 % of forest

Fig. 5 The ensembles of the cumulative flow and dispersion of uncertainty measure for the parameters CN and AWC (Low decile, Hight decile and Median are 10th, 90th and 50th percentile ensemble flow values)

would be rarely sensitive to output claimed by Lee (Lee et al., 2005).

V. CONCLUSIONS

The analysis of uncertainty associated with the utility of simulation models is an important consideration in the development of watershed management plans. In this paper, a Monte Carlo technique is utilized to analysis the uncertainty. 1,000 Monte Carlo simulations were performed to quantify the impact of input parameters for each land use scenario. Each 1,000 ensemble was generated with MCS results to analysis uncertainty using the SWAT model.



i) CN ii) AWC

(a) Uncertainty in change between crop area and forest

i) CN ii) AWC

(b) Uncertainty in change between pasture area and forest

Fig. 6 The measures of parameters, CN and AWC uncertainty for each land use scenarios

The model was calibrated using the observed data for periods (1993-1998). Calibration resulted in R^2 values of 0.74-0.86 in the three measurement stations. The simulated runoff values agreed well with the observed data.

This study simulated the stepwise transition from current land use in the watershed to crop and pasture area (current, 10 %, 30 % and 50 % of watershed area covered with forest) to investigate the impact of changing flow in response to land use change. The amount of flow when replacing forest by crop and pasture were higher than those of current land use. The amount of flow in replaced crop by same ratio was higher than those of replaced pasture.

Input parameters of SWAT model, which are GWREVAP, REVAPMN AWC, Ksat, ESCO, GWQMN, and CN, were used to analysis uncertainty by scenarios of land use change. The results uncertainties of parameters indicate that the values of RC and RQ were great in order AWC, CN, GWREVAP and REVAPMN in all scenarios. Uncertainty in large forest area relatively were higher than those of pasture and crop area.

Uncertainty of initial modeling was much greater than those of scenarios application. Therefore, if the uncertainties of initial modeling are minimized based on parameters of this study, it could be used in an effective manner to decide a political measures and devise a watershed management.

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