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Optimal watershed management practices for the reduction of future non-point pollutants loads

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ABSTRACT

From a water quality perspective, adaptation to climate change means reducing pollutants (total phosphorus in this study) increased by climate change to the current state. In this study, best management practices (BMPs) are presented to maximize the cost-effective pollutant reduction effect for adapting to climate change. Multi-purpose optimization by direct driving of soil water assessment tool (SWAT) requires unrealistic simulation time. Therefore, in this study, after setting various BMPs scenarios based on the identification of BMPs applicable for each land use, TP reduction efficiency, and cost required for each scenario were databased. Using this database, multi-purpose optimization was performed without direct simulation of SWAT. The method proposed in this study significantly reduced the number of SWAT simulations and climate change adaptation in the upper reaches of Namgang Dam in Korea was possible with sufficient investigations with only 18 SWAT simulation results. The finally derived BMPs plans was displayed on a map so that the exact location of the BMPs facilities could be identified.

Keywords: Best management practice; Climate change; Multi-objective optimization; SWAT; Total phosphorus

1. Introduction

According to the report of the Intergovernmental Panel on Climate Change (IPCC), the global average temperature has risen by about 0.6°C due to climate change, and the annual average temperature in Korea has risen by about 1.1°C over the past 75 y. Of these, 0.7°C is estimated to be due to climate change. Climate change is affecting rainfall patterns as well as rising temperatures. Changes in the frequency and intensity of rainfall events due to climate change have been observed for decades [1,2], and have a significant effect on river flow and water quality. Sinha et al. [3] also published a study that the amount of nutrients discharged from rainfall changes will continue to increase in the 21st century. Eventually, climate change adversely affects water quality by affecting the increase in the emission of non-point sources. To clarify this phenomenon and to effectively manage watersheds, many researchers are studying the relationship between the change in precipitation and the emission of pollutants due to climate change [4–6].

Considering the impact of climate change for effective watershed management can be one direction, and securing clean river water quality at the present time is also one of the important watershed management directions. A number of researchers have studied ways to improve water quality by reducing point and non-point pollutants discharged into the river [7–14]. Lee et al. [13] developed a simple distributed hydrological model to optimized the installation location of low-impact development facilities and analyze the reduction effect of non-point sources in

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urban drainage areas. Cho et al. [14] analyzed the effect of LID facilities in terms of reducing non-point sources in urban area. These studies focus on urban areas, and studies were mainly conducted using EPA-SWMM. However, since cities occupy about 3% of the total area of Korea, there is a limit to managing urban non-point sources in terms of management of the entire watershed. Therefore, it is necessary to establish a strategy for managing non-point sources, including agricultural areas.

Most existing studies for watershed management have been conducted separately from the analysis of the adverse effects of climate change on water quality and the improvement of water quality at the present time. However, climate change is having an adverse effect on the whole world, including river water quality. In line with these social concerns, studies were conducted to analyze the degree of impact of climate change on river flow and water quality, and to explore ways to reduce pollutants such as suspended solids, total nitrogen, and total phosphorus increased due to climate change [15,16]. However, these studies have limitations in establishing a watershed management policy since financial aspects are not considered. The resources to be invested in reducing pollutants increased by climate change are inevitably limited. Therefore, measures to maximize cost efficiency should be investigated. Although studies on cost-effectiveness have been conducted by several researchers [17–24], most of these studies do not take into account climate change. The purpose of this study was to focus on cost-effectiveness and climate change considerations necessary for establishing watershed management policies. In other words, the investigation of cost-effective watershed management measures considering the impact of climate change is the most important part of this study different from other studies. This study attempts to investigate a watershed management plan that can restore river water quality, which is predicted to deteriorate due to climate change, to the present time, considering economic factors.

2. Materials and methods

2.1. Research procedure and study area

This study proposes a method of planning best management practice (BMPs) that can adapt to climate change. Adapting to climate change means installing BMPs appropriately to maintain water quality at the present time by removing pollutants increased by climate change. In this study, the water quality variable was set as total phosphorus (TP), one of the indicators used for watershed management in Korea.

Fig. 1 is a schematic diagram of the research procedure. The overall research procedure is as follows: (1) establish a soil water assessment tool (SWAT) model, (2) through simulation of current and future flow rates and water quality, we grasp the trend of changes in pollutants, (3) identify watershed MPs that can be used in climate change adaptation planning, and (4) investigate optimal installation alternatives for BMPs that can reduce TP loads increased due to climate change.

The study area is the upper basing of the Namgang Dam in Korea. The Namgang Dam upstream basin is an area requiring continuous watershed management since it has a great influence on the Namgang Dam Reservoir, which is used as the main water source in the Namgang downstream area, a metropolitan area. Of the total area of 2,281.72 km^2, forest areas consist of 73%, and rice farming areas, field farming areas, and urban areas account for 7%, 6%, and 4%, respectively (Fig. 2). Since this watershed is designated as a special zone for water source protection, urban development is strictly restricted.

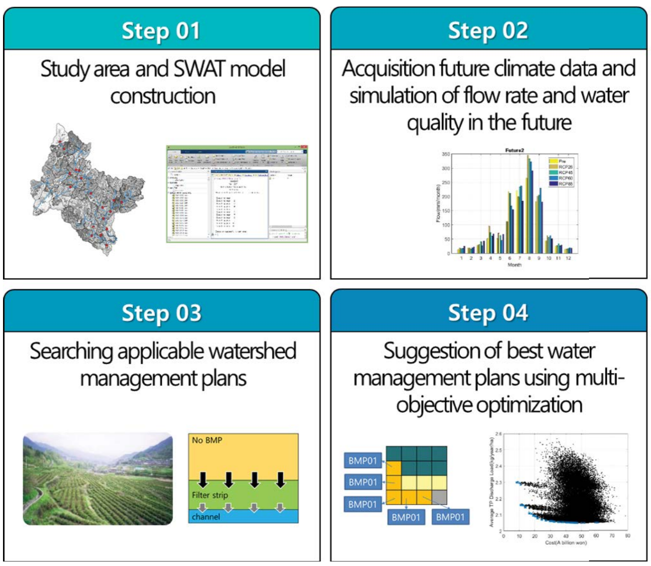

Fig. 1. Research procedure.

2.2. SWAT setup

SWAT can simulate the flow rate and water quality by reflecting the characteristics of soil and land use, and provides a simulation function of BMPs for controlling non-point sources. It is one of the general-purpose models suitable for achieving the purpose of this study. To construct SWAT, meteorological data, data on topographic characteristics of a watershed, and human activity factors that affect river flow and water quality are needed (Table 1). Meteorological data were prepared from four meteorological sites (Geochang, Namwon, Sangcheong, and Jinju) affecting the research basin. The data period is from 2005 to 2015. Daily rainfall, daily maximum and minimum temperature, daily relative humidity, and daily wind speed were collected in common at four sites, but solar radiation was collected only at Jinju site. The data on the topographic characteristics of the watershed were prepared by DEM, land use map, and soil map. SWAT constructs hydrologic response units (HRUs), which are the basic units for simulation of runoff and water quality, from the collected topographic data. A total of 467 HRUs were formed, of which 68 HRUs in paddy farming areas and 13 HRUs in field farming areas. The rest consisted of HRUs in forest areas.

In addition to meteorological data and topographical data, there are influences from human activities as factors affecting flow rate and water quality. Therefore, when building SWAT, these factors should be reflected in

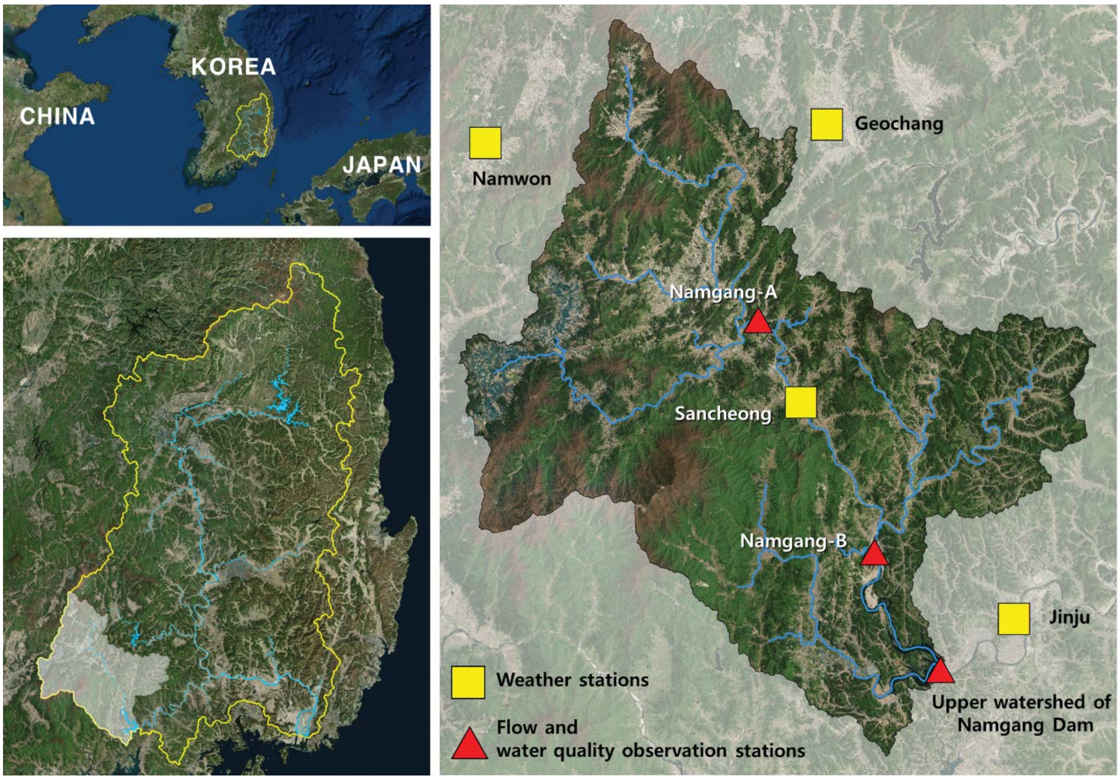

Fig. 2. Study area.

Table 1
Model input data

Data type	Scale	Period	Source
Precipitation	Daily	2005–2015	Korea Meteorological Administration (KMA)
Maximum and minimum temperature	Daily	2005–2015	KMA
Relative humidity	Daily	2005–2015	KMA
Wind speed	Daily	2005–2015	KMA
Solar radiation	Daily	2005–2015	KMA
DEM	30 m by 30 m	–	National Geographic Information Institute (NGII)
Land use map	30 m by 30 m	–	Ministry of Environment
Soil map	30 m by 30 m	–	NGII
Effluent of Environmental Facility	Monthly	2015	Gyeongsangnam-do [25]
Water-intake for living and industrial water	Monthly	2015	Gyeongsangnam-do [25]
Water-intake for agricultural water	Monthly	–	Lee et al. [26]
Non-point source discharge load per unit area	–	2015	Gyeongsangnam-do [25] and NIER [27]

order to accurately simulate the flow rate and water quality generated in the watershed. Factors influencing river flow and water quality by human activities such as flow rate and quality of effluent water from basic environmental facilities, agricultural water consumption, water intake, fertilizer sprayed on agricultural land, and livestock were investigated, and these factors were reflected in the model. First, the flow rate and water quality discharged from the water treatment facility and the amount of water intake from the water intake facility were collected by referring to Gyeongsangnam-do [25]. For the use of agricultural water, the data used by Lee et al. [26] were applied.

Since the emission of non-point source pollutants varies depending on land use, the basic unit data for each land use presented by the National Institute of Environmental Research (NIER) [27] was used. In the case of agricultural land, fertilizers are added, so there is a limit to calculating non-point sources based on land use and soil characteristics. Therefore, it was additionally considered that phosphorus fertilizer is added once a year, and in mid-April

[24]. In addition to agricultural land, some of the pollutants generated from livestock are introduced into the river along with rainfall runoff and affect the river water quality. Since the inflow path is similar to the non-point source, it was assumed that untreated pollutants generated from livestock were introduced into the river in the form of a non-point source.

Finally, river flow and water quality data were collected for parameter estimation of the constructed model. In order to manage the total amount of water pollution, river flow, and water quality data observed by NIER at 8 d intervals at Namgang-A and Namgang-B sites were used. In addition, the flow rate observation data of the Upper watershed of Namgang Dam was used as the daily flow rate flowing into the Namgang Dam, and the monthly water quality observation data of Jinyang Lake was used as the water quality observation data at the outlet of the basin.

The traditional model parameter correction process is performed through a trial and error method, which depends on the understanding of the model and watershed hydrological structure to determine the reliability of the parameter estimation results. In this study, in order to alleviate these difficulties, a module that automatically performs correction was constructed by linking MATLAB and SWAT. The procedure for parameter calibration is as follows: (1) modify the parameters that affect flow rate and water quality in SWAT is driven, the result value of river flow is extracted from "output.rch", (2) evaluate the simulation results using Kling–Gupta efficiency (KGE), and (3) repeat the above-described steps until the KGE approaches 1.0 (Fig. 3).

The KGE used to evaluate the model results is a model evaluation index developed by Gupta et al. [28], and was developed to reflect the root mean square error and the model efficiency coefficient at the same time [Eqs. (1) and (2)].

$$\text{KGE} = 1 - \text{ED} \tag{1}$$

$$\text{ED} = \sqrt{\left(r-1\right)^2 + \left(\alpha-1\right)^2 + \left(\beta-1\right)^2} \tag{2}$$

where r is the linear correlation coefficient between the observed data and the simulated data, α is the ratio of the standard deviation of the observed data and the standard deviation of the simulated data, and β is the ratio of the mean of the observed data and the mean of the simulated data. The closer the KGE value is to 1.0, the better the simulated data reproduce the observed data.

2.3. Future climate data

The Korea Meteorological Administration provides simulated outputs for the present period (1985–2005) and future period (2006–2100) produced using the combination of HadGEM2-AO and HadGEM3-RA climate models (https://www.climate.go.kr). Before using future data, it is necessary to check whether the simulated outputs for the current period are the same as the actual observed statistics. If the statistics are not similar, it is difficult to make any sense to simulate future flow rates and water quality using simulated outputs from climate models. In this study, bias correction was performed to increase the reliability of climate model outputs. Various studies are being conducted for bias correction: a method of correcting bias using extreme value statistics [29], a method of correcting bias using mean and variance [30,31], and a method of correcting bias based on distribution type [32], and many more.

Quantile delta mapping (QDM) was used in this study (Fig. 4). QDM is an improved version of the quantile mapping method that performs bias correction assuming that the climate model outputs are stationary. This method uses the cumulative probability density function (CDF) of each of the current observation data, the current simulation data, and the future simulation data to perform bias correction reflecting the relative change over time. In this study, the

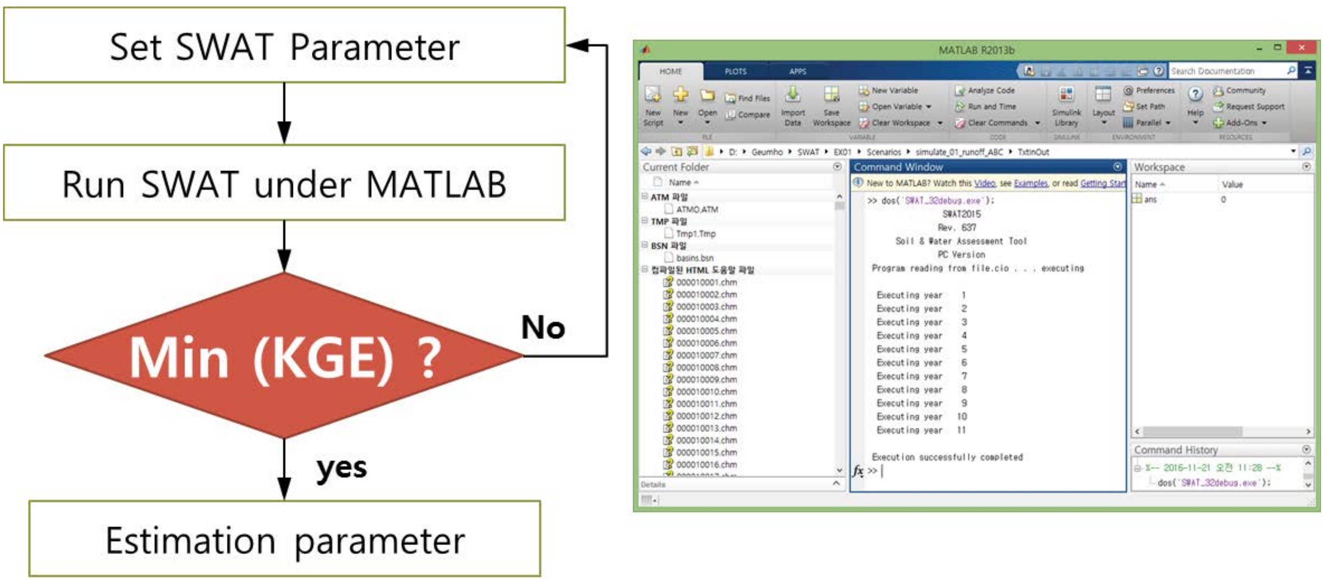

Fig. 3. Parameter calibration using SWAT-MATLAB integrated module.

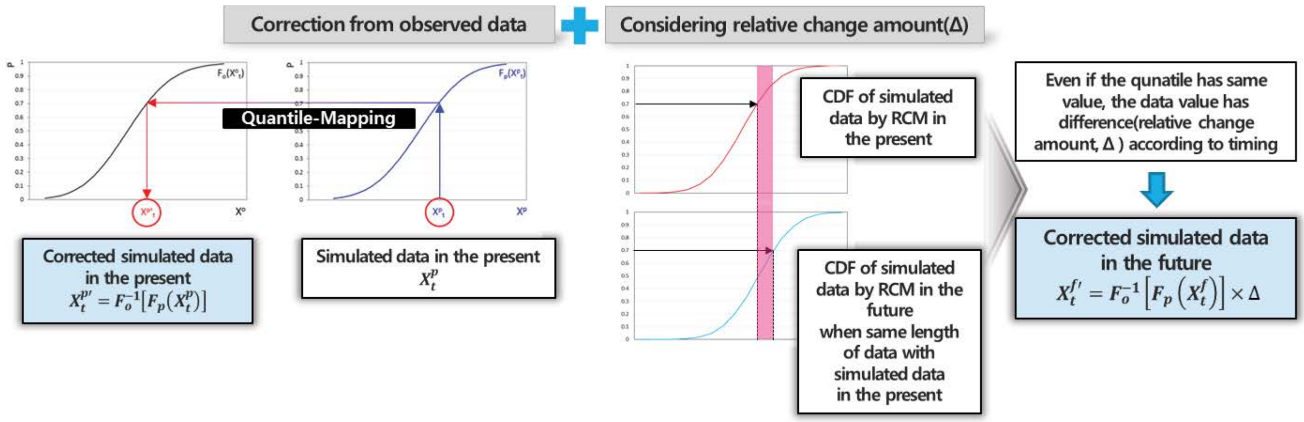

Fig. 4. Schematic diagram for applying QDM to climate model outputs.

observation period and the current period are from 1981 to 2005. That is, the observed CDF and the current CDF were calculated using data for 25 y. The CDF for 2020, the future period, was calculated using data for 25 y from 2008 to 2032. In 2021, the CDF was calculated using 25 y data from 2009 to 2033. In this way, the non-stationarities of climate change that change over time are taken into account.

Climate change model outputs performed by bias correction in this study are precipitation, maximum, and minimum temperature, relative humidity, and wind speed for each of the four representative concentration pathways (RCP) scenarios. These outputs are used as input data for SWAT. In the case of precipitation, the rainfall days in the climate model outputs were first corrected, and then bias correction for rainfall depth was performed. Fig. 5 shows the results of bias correction at Jinju site. It can be found that the bias correction was well performed for both precipitation and maximum temperature (Figs. 5a and c). In addition to Jinju site, Geochang, Namwon, and Sancheong sites achieved the similar results. The results of bias correction of future outputs are shown in Figs. 5b and d. Winter precipitation is projected to be similar to the present. However, precipitation in summer is projected to increase significantly. The maximum temperature tends to increase gradually regardless of the season.

Among the SWAT input data, solar radiation that is not provided by the climate model was produced by sing a regression equation that produces solar radiation using rainfall, maximum and minimum temperature, relative humidity, and wind speed.

2.4. Method for optimal implementation of BMPs for adapting to climate change

2.4.1. BMPs types

When looking at the Namgang Dam basin, the effect of non-point pollutants generated in cites on water quality is insignificant, and non-point pollutants generated from agricultural activities are expected to have a great influence on river water quality. In order to select BMPs applicable to agricultural land, it is necessary to understand the characteristics of agricultural land in Korea. Korea's agricultural land is largely divided into a paddy farming area and a field farming area. Since rice fields are filled with water and rice is grown, the types of BMPs that can be applied are limited. Since a field is a place where crops are planted and farmed without filling with water, the types of BMPs that can be applied may be more diverse than that of paddy fields. Reflecting the characteristics of agricultural land, BMP, called fertilizer input control, was applied to rice fields, and fertilizer input control and filter strip were applied to fields.

The fertilizer input control applied to the paddy field and the field at the same time reduces the amount of fertilizer input for crop cultivation. Fig. 6a is a conceptual diagram showing fertilizer movement in SWAT. When fertilizer is added, some fertilizer is discharged out of the watershed through surface runoff, and part of it remains in the soil layer. Therefore, it is possible to control the amount of pollutants discharged out of the watershed by managing the amount of fertilizer that is input.

The vegetative filter strip is located between the river and the agricultural land and serves to filter sediments, organic matter, nutrients, and so on discharged through stormwater (Fig. 6b). It is not appropriate to apply a filter strip since rice paddies trap water and grow crops. Therefore, the filter strip was applied only to the field.

2.4.2. Multi-objective optimization for adopting climate change

For effective climate change adaptation, it is necessary to maximize the reduction effect of BMPs. However, there are limitations in applying BMPs. If the TP reduction efficiency of BMPs is increased for adaptation to climate change, the required cost (installation and maintenance cost) increases accordingly, so a multi-purpose optimization technique is needed to find a compromise that can exhibit the maximum TP reduction effect at a low cost. In the multi-purpose optimization technique, the TP load and required cost are calculated by applying various BMPs for each HRU in the SWAT. At this time, if the TP reduction effect against cost is not maximized, a series of simulation process for changing the type of BMPs applied for each HRU are repeated. That is, if there are 3 BMPs that can be

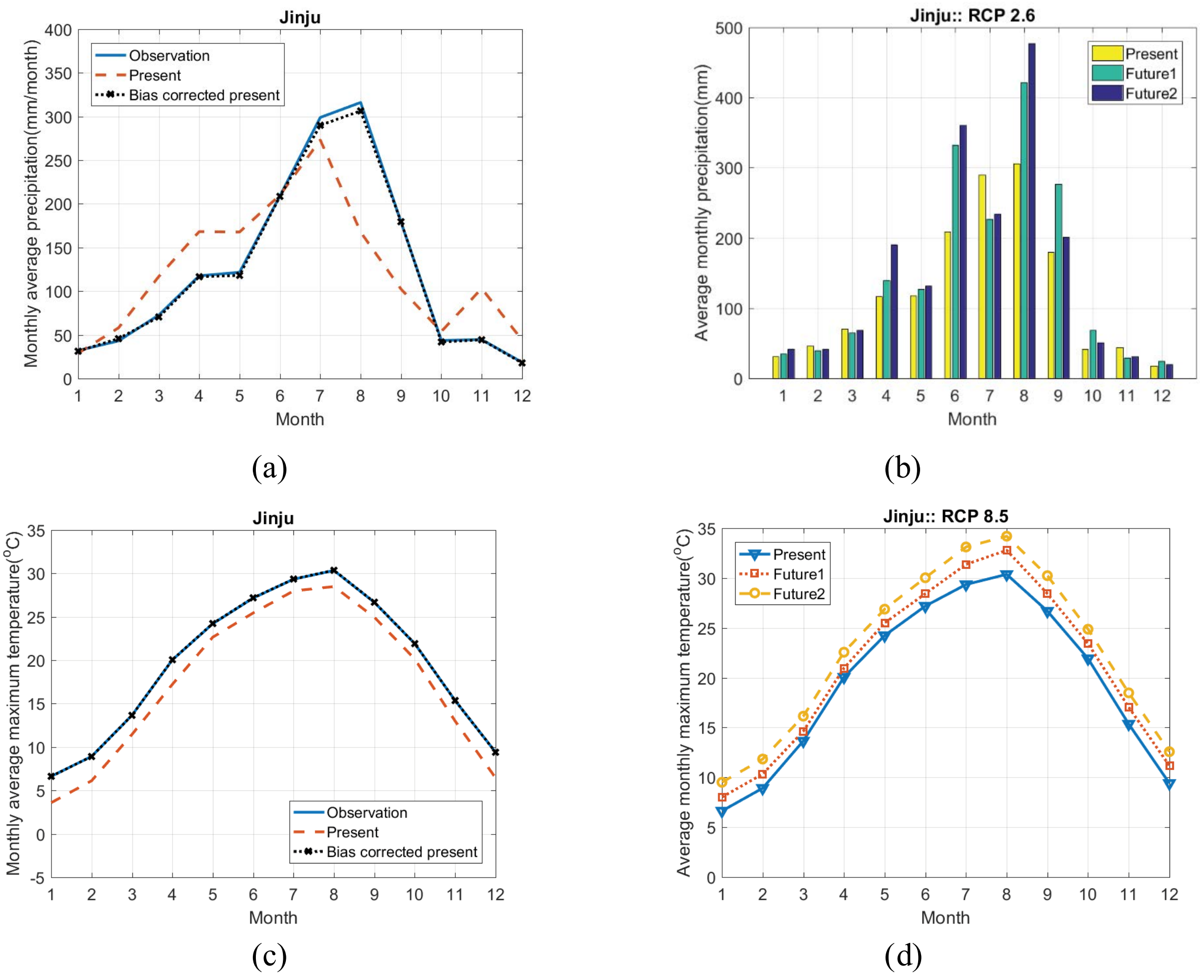

Fig. 5. Bias-correction of climate model outputs at Jinju site: precipitation in the (a) present, (b) future and maximum temperature in the (c) present, (d) future.

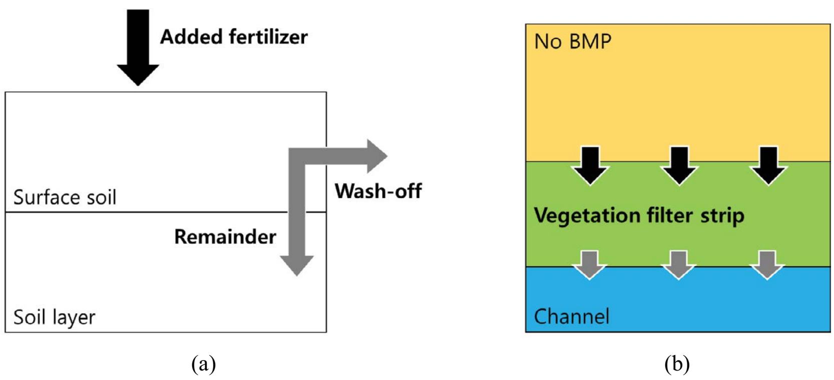

Fig. 6. Diagrams of applicable BMPs: (a) fertilizer and (b) vegetation filter strip.

applied to 5 HRUs, up to 1,024 SWAT runs are required for multi-purpose optimization. In other words, the number of simulations increases exponentially as the number of HRUs and the type of BMPs applied increases. In this study, in order to reduce the number of simulations and simulation time for multi-purpose optimization, a BMPs database (hereinafter, BMPs DB) that can be applied to the watershed was constructed through SWAT pre-simulations. Using the BMPs DB constructed in this way, the effect of reducing TP load vs. cost is evaluated (Fig. 7).

Multi-purpose optimization is performed in MATLAB using BMPs DB and natural TP loads (SWAT pre-simulation

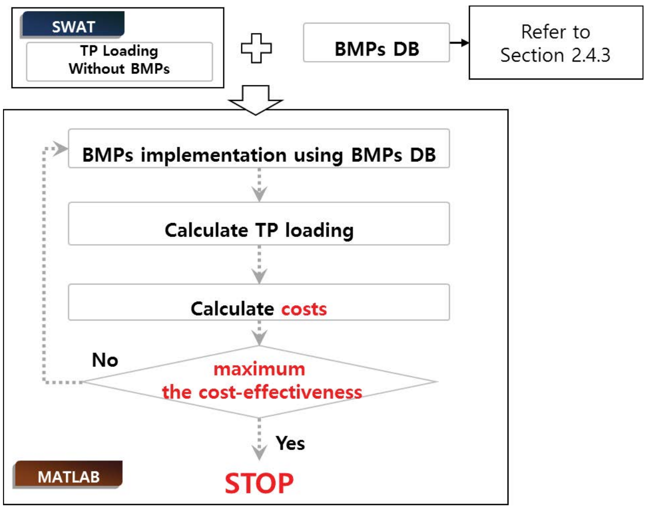

Fig. 7. Multi-objective optimization method.

results). Different BMPs scenarios are applied for each HRU, and TP load for BMP application is calculated by multiplying TP load in natural state by TP reduction efficiency for BMPs application. At the same time, the cost of application to the BMPs scenario is calculated. By changing the BMPs scenarios applied for each HRU, the application plan that most reduces the TP load compared to cost is searched using Eqs. (3) and (4).

$$f_{\text{op},1} = \sum_{X=1}^{N} P_X \times R_X \tag{3}$$

$$f_{\text{op},2} = \sum_{X=1}^{N} C_X \times a_X \tag{4}$$

Here, N in the total number of applied HRUs, P_X is the TP load in the natural state of a specific HRU, R_X is the TP reduction efficiency of the applied BMP that can be referenced from the BMPs database, C_X is the cost per unit area required for applying the BMP scenario, and a_X is the BMPs scenario application area. Eq. (3) is the TP load for applying the BMPs scenario. The better the TP load reduction efficiency of BMP is, the smaller the TP load is, but the required cost increases as the capacity of BMP increases. A plan that can compromise Eqs. (3) and (4) can be said to be a BMP application plan that maximizes the TP reduction effect compared to cost.

2.4.3. BMPs DB construction

As described in section 2.4.2 (Multi-objective optimization for adopting climate change), when performing multi-purpose optimization for climate change adaptation, a BMPs DB should be established to save the number of simulations and simulation time. The BMPs DB consists of TP reduction efficiency for each BMPs scenario and the required cost of the applied BMPs scenario. Fig. 8 shows a method for building a BMPs DB.

After calculating the TP load through SWAT simulation applying a specific BMP scenario to all HRUs with the same land use, the reduction efficiency for a specific BMP scenario is calculated by comparing it with the TP load in the natural state. TP reduction efficiency and be calculated by applying this method to all BMP scenarios

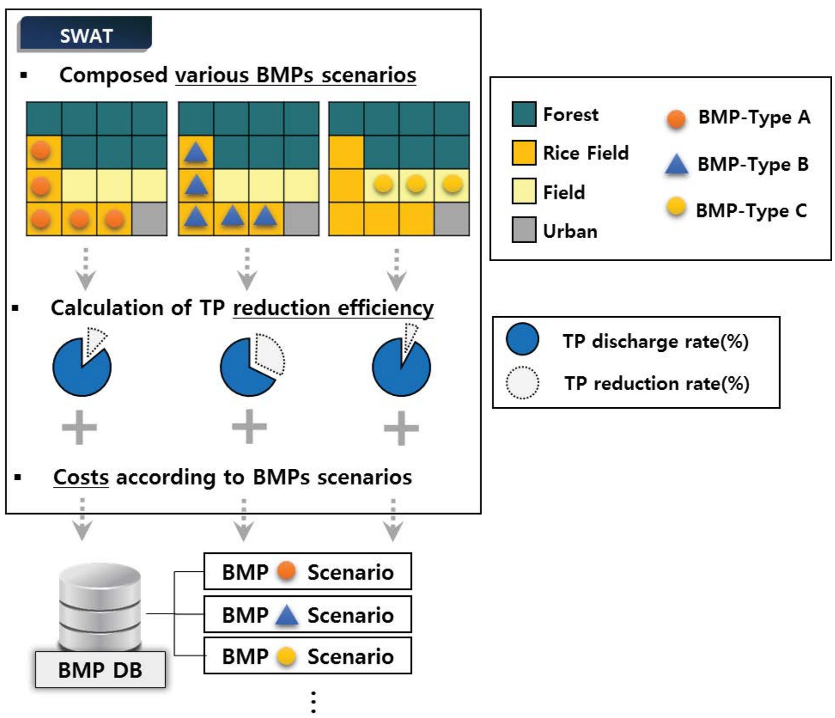

Fig. 8. Construction method of BMPs DB.

applicable to the watershed. These results are combined to form a BMP database.

In this study, BMPs scenarios are applied to rice fields and fields. Scenarios applied to paddy fields are there fertilizer control: (1) existing input, (2) 10% reduction, and (3) 20% reduction. Two types of BMPs can be applied in duplicate to the field: control of fertilizer and vegetation filter strip. The amount of fertilizer is divided into three types as in the rice field, and the filter strip is composed of five scenarios based on capacity. The "FILTER_RATIO", which determines the capacity of the filter strip in the SWAT, is the ratio of the area of the watershed to the area of the filter strip. Area ratios generally range from 30 to 60 [33]. In this study, scenarios were classified into area ratios of 0, 30, 40, 50, and 60.

Since the cost required for each BMPs scenario varies depending on the area of the BMP, the cost per unit area of the BMP was converted into a DB. As for the cost of fertilizer control, the campaign cost to reduce the amount of fertilizer was considered. The campaign cost was assumed to be the same as the campaign cost required to reduce non-point sources by 10% [34]. The initial cost of the filter strip consists of land purchase cost and facility installation cost. The land purchase cost was applied to the official land price of the field farming area in the upper reaches of the Namgang Dam. ME [35] provides the initial and maintenance costs required to apply various BMPs. With this reference, the installation cost and maintenance cost of the filter strip were calculated. Table 2 shows the cost for the BMP application area.

3. Results and discussion

3.1. Flow and water quality in the present and the future

To simulate current and future flow rates and water quality, it is necessary to calibrate the parameters of the established SWAT model. Only by calibrating the parameters of SWAT so that the observed flow rate and water quality can be reproduced well, reliability can be ensured in the simulation results of future flow rates and water quality. Figs. 9–11 shows the SWAT parameter correction results.

Looking at the simulation results of the flow rate, it can be found that the observed data and the simulated data are similar in the rainy summer season, but the flow rate is underestimated in the dry winter season. In particular, in the spring of 2014, the flow rate was underestimated. However, since the KGE, which is the model performance evaluation index, is all above 0.8, it can be said that the constructed model is suitable for flow simulation. In the case of TP load, there is a tendency to overestimate the load in winter when the observed load is small, but the model performance evaluation index KGE was calculated as 0.7650 for Namgang-A, 0.8463 for Namgang-B, and 0.7313 for upper watershed Namgang Dam. Therefore, it can be said that the model is well established in terms of load.

When simulating the future flow rate and water quality of the upper reaches of the Namgang Dam, future data are input in the case of meteorological data, but the simulation was performed assuming that the environmental infrastructure such as the amount of water intake the amount of agricultural water and the amount of discharge of environmental infrastructure are the same as present.

Data from 1981 to 2005 were used for the current period to confirm the trend of changes in flow rate and water quality, and the future period was divided into Future1 (2026–2050) and Future2 (2051–2075) for comparison with the current period. Figs. 12 and 13 compare monthly flow rates and water quality under RCP scenarios. In particular, the flow rate tends to increase in summer. Since the flow rate and precipitation are directly related to each other; it can be seen that the flow rate increases significantly during the summer, when precipitation is increasing. In Future1 of the RCP 2.6 scenario, the flow rate is projected to increase by 19.0% compared to the present. The TP load is also showing a trend of increasing overall. In the RCP scenario, the TP load of Future1 is projected to increase by 7.5% compared to the present.

Table 3 shows the necessity of climate change adaptation plan along with the rate of change of TP loads by future period for each RCP scenario. In Future1 in RCP 6.0 and Future2 in RCP 8.5, the TP load is projected to decrease from the present. In that case, there is no need to perform multi-purpose optimization for adaptation to climate change. In the other cases, since the TP load is projected to increase compared to the present, multi-purpose optimization for adaptation to climate change is required. In this study, multi-purpose optimization was performed for the RCP 8.35 scenario where the TP load increases the most in Future1, which is the relatively near future.

3.2. BMPs DB

Before applying the multi-purpose optimization of BMPs for climate change adaptation, a BMPs DB was constructed to save the number of simulations and simulation time. In this study, the natural state without BMP was set as a default, and all cases of BMPs that can be applied by

Table 2
Implementation cost according to BMPs type

BMPs types	Case	Initial cost ($/ha)		Maintain cost ($/ha/y)	
		Rice forming area	Field forming area	Rice forming area	Field forming area
	Default	–	–	–	–
Fertilizer	10% reduction from default	–	–	5.00	5.83
	20% reduction from default	–	–	10.00	11.67
Filter strip	Depend on BMP capacity	–	379,200	–	1,854

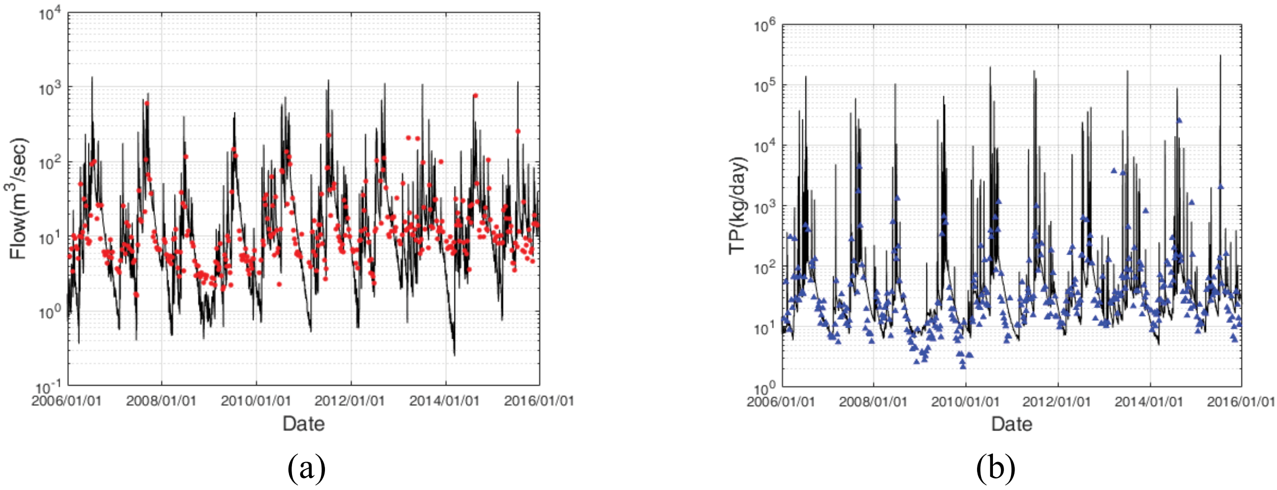

Fig. 9. Calibration result in Namgang-A: (a) flow and (b) TP loading.

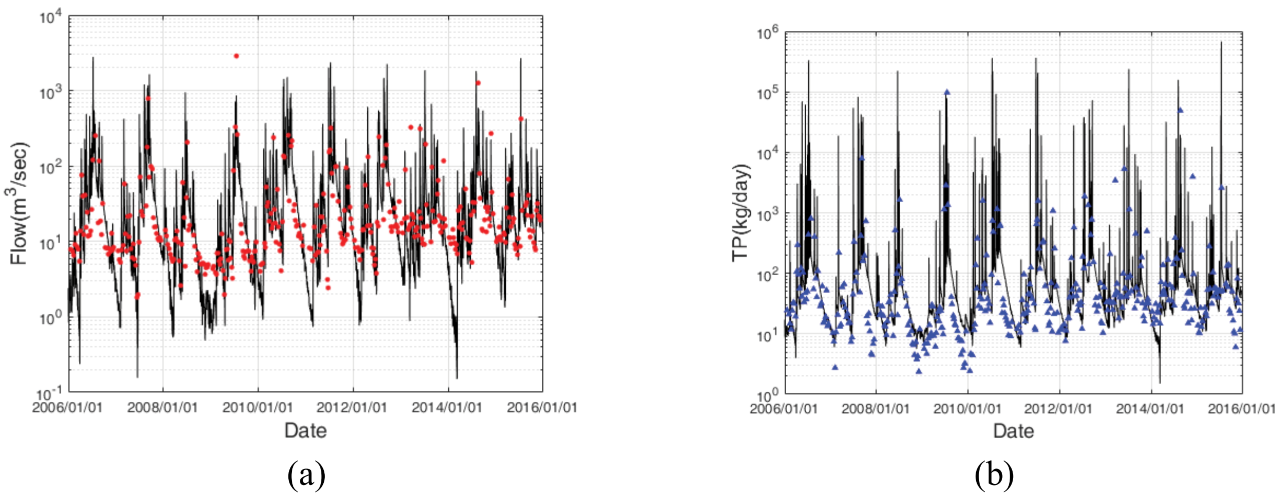

Fig. 10. Calibration result in Namgang-B: (a) flow and (b) TP loading.

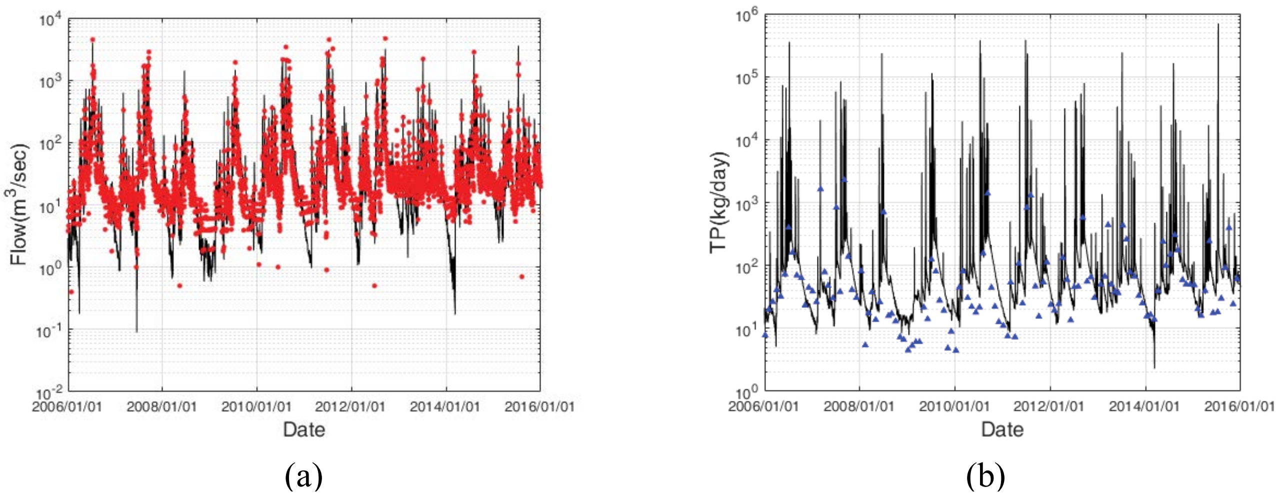

Fig. 11. Calibration result in upper watershed of Namgang Dam: (a) flow and (b) TP loading.

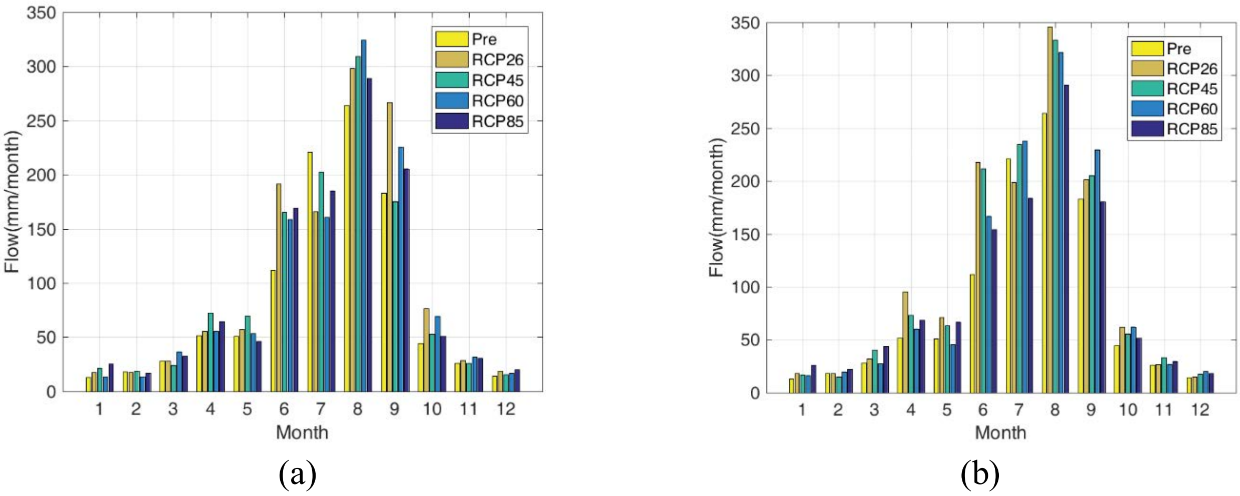

Fig. 12. Monthly flow under RCP scenarios in upper watershed of Namgang Dam: (a) Future1 and (b) Future2.

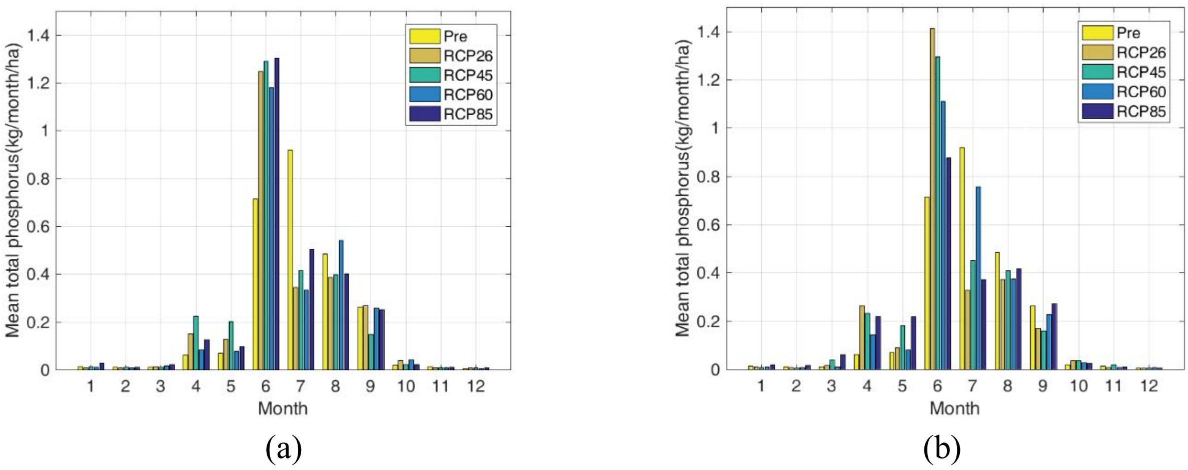

Fig. 13. Monthly TP loading under RCP scenarios in upper watershed of Namgang Dam: (a) Future1 and (b) Future2.

land use were composed as scenarios. This is summarized in Table 4.

Fig. 14a shows the mitigation efficiency of the three scenarios applied to the paddy area. Scenario 1 has no BMP applied, and Scenario 2 and 3 are scenarios in which the amount of fertilizer is reduced by 10% and 20%, respectively. Fig. 14b shows the reduction efficiency of 15 scenarios applied to field areas. Similar to the rice field, Scenario 1 is the case where none of the BMP is applied. Scenario 15 is the largest combination of BMPs applicable to field areas. In other words, this is a scenario in which the amount of fertilizer is reduced by 20% and FILTER_RATIO of the filter strip is set to 30.

3.3. Multi-objective optimization result for adapting to climate change

Multi-purpose optimization of watershed management for adaptation to climate change was performed targeting the RCP 8.5 scenario in which the TP load increased the most in Future1, which is the relatively near future. Fig. 15 shows the results of multi-purpose optimization of BMPs under the RCP 8.5 scenario. The black circle (●) in Fig. 15 shows all the analyzed alternatives to search for the optimal BMP application, and the blue star (★) is the most effective alternatives for reducing TP load in a given budget. A total of 174 alternatives for reducing TP load in a given budget. A total of 174 alternatives marked with a blue star were presented. It can be seen that as the cost of BMPs increases, the TP load decreases. However, if more than \$8 million is invested, it can be seen that the reduction rate of the TP load decreases. This in turn means that no matter how much money is invested, the effect will not satisfy our expectations if it exceeds a certain level. Among the alternatives searched for adaptation to climate change, the most economical alternative can be said to be the plan marked with a yellow square in Fig. 15. This is because adapting to climate change means returning the increased TP load due to climate change to the current level. BMPs can be applied beyond that, but in such cases, they are applied beyond the purpose (i.e., maintaining current water quality), which means that additional review of the budget and manpower used to reduce the TP load is required.

Fig. 16 shows the alternative BMPs selected for climate change adaptation presented in Fig. 15 on a map. Mapping of all alternatives (star (★) in Fig. 15) for adaptation to climate change, including the corresponding alternative, is possible. Through mapping, it is possible to identify where in the watershed where alternatives to apply BMPs explored through multi-purpose optimization are applied. In Fig. 16, the patches marked green (R #01) is the rice field. These patches mean that the amount of fertilizer added is maintained. Rice fields marked with dark pink (R #02) were planned to reduce fertilizer by 10%. Patches marked in purple (F #07) are fields. It was planned to reduce the amount of fertilizer by 10% and install a filter strip with an area ratio of 60.

Since multi-purpose optimization uses the SWAT pre-simulation results, it is necessary to verify whether the same results can be obtained through the actual SWAT simulation. Among the many alternatives explored through this study, the BMPs scenarios used in Fig. 16 were applied to SWAT to simulate the TP load. As a result of verification (Fig. 17), it was found that the proposed BMPs scenario was similar to the simulation result of SWAT. Through this, it can be recognized that it is appropriate to perform multi-purpose optimization using the method presented in this study.

4. Conclusions

It was confirmed that not only meteorological data such as precipitation and temperature, but also river flow and water quality changed due to climate change. In the case of the Namgang Dam upstream basin, it is projected that the summer flow rate and TP load will increase in the near future. The deterioration of river water quality due to climate change is a fact confirmed not only in this

Table 3
Rate of change of TP loads

Scenarios	Rate of change (%)	
	Future1	Future2
RCP 2.6	1.0	5.0
RCP 4.5	6.3	9.8
RCP 6.0	–0.9	6.8
RCP 8.5	7.5	–3.2

Table 4
BMP scenarios

Scenario Number	Description	Land use
R #1	No BMP	Rice farming area
R #2	Fertilizer 10% ↓	
R #3	Fertilizer 20% ↓	
F #1	No BMP	Field farming area
F #2	FILTER RATIO 60	
F #3	FILTER RATIO 50	
F #4	FILTER RATIO 40	
F #5	FILTER RATIO 30	
F #6	Fertilizer 10% ↓	
F #7	Fertilizer 10% ↓ + FILTER RATIO 60	
F #8	Fertilizer 10% ↓ + FILTER RATIO 50	
F #9	Fertilizer 10% ↓ + FILTER RATIO 40	
F #10	Fertilizer 10% ↓ + FILTER RATIO 30	
F #11	Fertilizer 20% ↓	
F #12	Fertilizer 20% ↓ + FILTER RATIO 60	
F #13	Fertilizer 20% ↓ + FILTER RATIO 50	
F #14	Fertilizer 20% ↓ + FILTER RATIO 40	
F #15	Fertilizer 20% ↓ + FILTER RATIO 30	

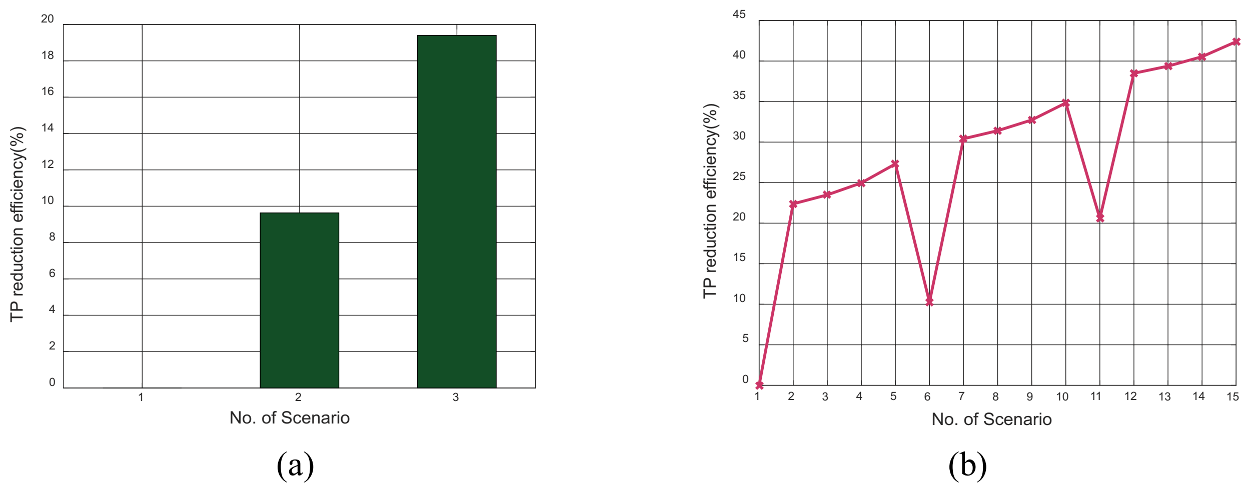

Fig. 14. TP loading reduction efficiency according to BMPs scenarios: (a) rice farming area and (b) field farming area.

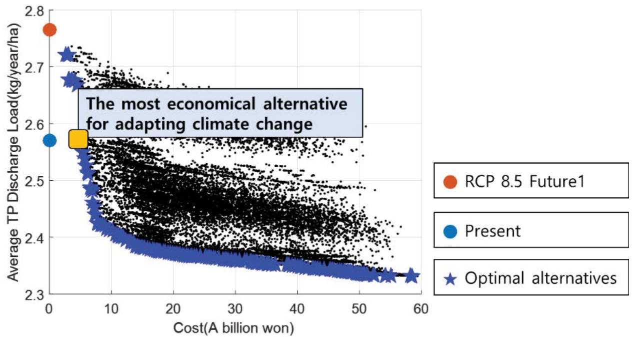

Fig. 15. Multi-objective optimization under RCP 8.5 scenario in Future1.

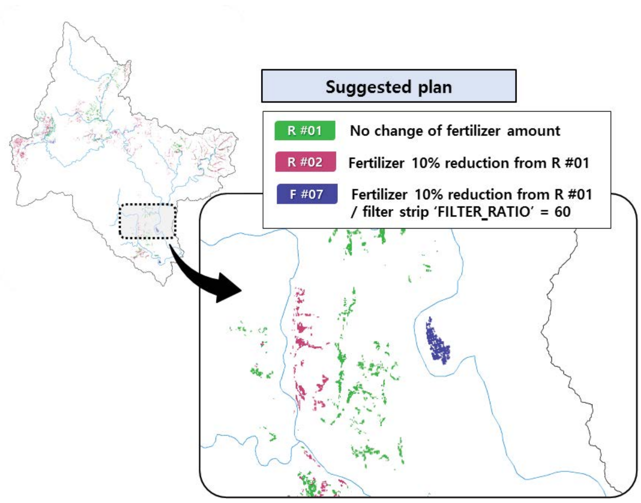

Fig. 16. Location of BMP alternatives in under basin Namgang Dam for TP reduction.

study, but also in previous study attempted to explore the alternative BMPs that can produce the maximum cost-effectiveness in reducing the TP load increased by climate change to the current level in the upper basin of Namgang Dam using SWAT. If multi-purpose optimization is performed using only SWAT, the number of simulations, and simulation time increase, resulting in poor utility. Taking this study as an example, three BMPs scenarios can be applied to 68 paddy areas, and 15 BMPs scenarios can be applied to 13 fields. It is practically impossible to perform multi-purpose optimization directly through SWAT simulation, considering the execution time. However, if the method proposed in this study is used, the number of SWAT simulations can be drastically reduced to 18 to perform multi-purpose optimization. In addition, since the BMPs scenarios explored through multi-purpose optimization can be visually expressed in the form of a map, they can be used more intuitively for watershed management.

In this study, BMPs for adaptation to climate change were different for each land use. It was set to reduce the amount of fertilizer previously input in the paddy area, and the amount of fertilizer and filter strip were considered in the field area. However, there are various types of BMPs

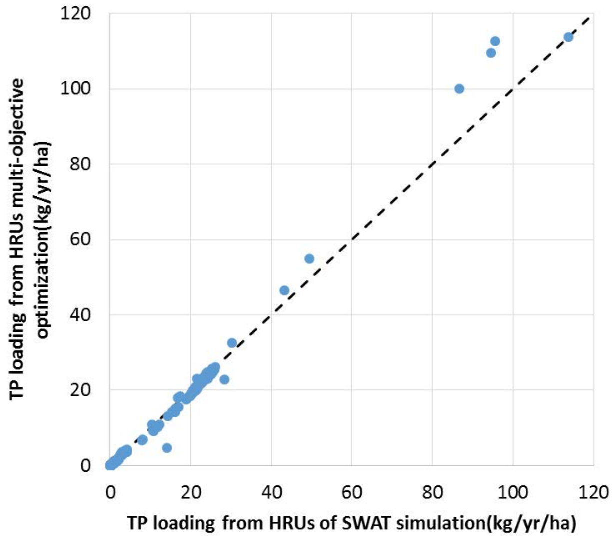

Fig. 17. Verification of multi-objective optimization for TP load reduction.

that can be applied in the watershed, and many studies have been conducted applying them [18,36–38]. Therefore, the characteristic analysis of BMPs should be additionally performed so that various types of BMPs can be considered. In addition, since this study is an analysis that considers only the impact of climate change, it is expected that it will be more useful in future watershed management countermeasures if the change in land use are considered in the future.

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