

Prediction of the Impact of Climate Change and Land Use Change on Flood Discharge in the Song Khwae District, Nan Province, Thailand

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Abstract: One of the main challenges in the world is adaptation to the impacts of climate change, and it is important to understand which impacts will take place in each region. Thailand endures substantial damage from floods every year and needs accurate measurement to mitigate flood disaster predicted under the looming scenario of climate change. The predicted impacts of climate change on flood discharge need to consider land use changes in the future, especially in developing countries because of their vulnerabilities to economic growth. The objective of this study was the quantitative predictions of the impacts of climate change and land use changes on flood discharge, using two simulation models at one watershed in the Song Khwae District, Nan Province, Northern Thailand. This study has three steps: (1) predictions of future land uses (14 scenarios having different proportion of forest cover), (2) calculation of 3.3 and 10-year return period rainfall for the period of 2006-2016 and 2040-2050, and (3) comparisons of average daily discharge from 3.3 and 10-year return period rainfall in 14 land use patterns. The results showed that although climate change will decrease the average daily discharge from the 3.3 and 10-year return period rainfall, discharge from future rainfall that has a 10-year return period, where land use patterns limit forest areas to less than 45%, will be greater than present levels. These quantitative predictions can lead to cost-benefits performance analysis and contribute to positive adaptation to climate change.

Keywords: Climate change; Adaptation; Land use; Flood; CLUEs; SWAT.

Introduction

Climate change is one of the biggest issues in the world today. The Intergovernmental Panel on Climate Change (IPCC) is warning the opposite risk, increasing flood discharge and food shortage caused by drought in the Asian region (Mach et al., 2014). Kundzewicz et al. (2014) also pointed out that the global impacts of climate change on flood discharge are not equal to the impacts at the local scales and necessitate knowledge of the future risk in each region. He further mentioned that predictions of the impacts of climate change on

flood discharge at the basin scale are limited mostly in developed countries, such as in Europe and North America. In Japan, Wada et al. (2005) evaluated flood and drought risk that will be driven by changes in the rainfall pattern, which are one of the impacts of climate change. They revealed that in some regions, flood risk will increase, while in other regions, the risk of drought will be strengthened. As part of the efforts in developing countries, Perera et al. (2015) analyzed flood risk under climate change in Nepal. Their results showed increasing flood discharge, and a seasonal shift in its occurrences.

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To predict the impacts of climate change on flood discharge, an understanding of land use changes as a factor should also be considered. It is well known that forests have an ability to mitigate the maximum flood discharge by retaining excess rainwater. Therefore, forest lands and bare lands respond differently to heavy rainfall. Wolfersberger et al. (2015) described that developing countries preferentially tend to undergo significant land use changes in a short period. In addition to urbanization and population increases, Lambin et al. (2011) suggested that with the economic growth in developing countries, land uses in the countryside are affected because of increasing food export. It is predicted that land uses in local regions in developing countries will be different from their current states when the impacts of climate change occur. Thus, it is important to consider land use changes under the condition of climate change.

Thailand, one of the countries in the southeast Asia region, faces flood disaster during every rainy season (May to October). From August to December in 2011, an extensive flood disaster caused tremendous damage over much of Thailand, with 752 human fatalities (Komori et al., 2012). To mitigate flood disaster, the Thai government has been promoting forest conservation since the 1980s (Leblond, 2014) based on research results that show flood disaster at low elevation attributed to a loss of forests at high elevation area. Also, there are some projects ongoing in Thailand to identify adaptive methods to mitigate flood disaster under the condition of climate change. Some research has focused on the flood risk. For example, Amnatsan et al. (2009) assessed the flood risk under climate change in Nan Province, while Wangpimool et al. (2013) evaluated the impacts of land use changes on flood disaster. However, there are no studies that analyze the impacts of both climate change and land use changes.

The objective of this study was to quantitatively predict the impacts of climate change and land use changes on flood discharge, using two simulation models at one watershed in the Song Khwae District, Nan Province, Northern Thailand.

Materials and Methods

Study Area

The watershed in the Song Khwae District in Nan Province, northern Thailand was selected as the study area. As of 2016, in northern Thailand, 46% of the local population worked in the agricultural and fishery sectors (Thai National Statistical Office, 2016). Furthermore,

crop yields are increasing because of improvements in agricultural techniques (Suzuki et al., 2014). The main crop in this region is maize, which is one of the five major crops (rice, sugar cane, cassava and oil palm and maize) in Thailand. For the most parts, double cropping systems with maize are dominant, with rainy season cropping and dry season cropping (November to April).

In northern Thailand, Nan Province, especially, has a lot of agricultural land used for maize. The area of the province is 11,472.1 km², and agricultural land accounts for 57%, which is the second largest crop area in northern Thailand. The areas under maize cultivation are more than twice that for sugar cane and cassava (Thai National Statistical Office, 2013). Because of the intensity of cultivation, a lot of forest lands has changed to crop lands, and bare lands can be seen after harvesting of the maize.

Nan River, which has a channel length of 740 km and a watershed area of 13,130 km² flows through the middle of the province. A tributary of the Nan River, which has 612 km² watershed area and flows in the Song Khwae District, was selected as the target watershed for this research. This watershed also suffered extensive damage from floods in 2011. Discharge from the tributaries was observed by the Royal Irrigation Department, Thailand (RID). Land use data prepared by the Land Development Department (LDD) shows that the forest areas in this watershed increased from 2010 to 2016. The significant potential for land use changes in the future and the limited missing data relative to other watersheds were the main reasons why this watershed was selected.

Data Sources

The GIS data used for running the land use simulation models, including the location of villages, rivers and roads, were obtained from the Japan International Cooperation Agency (JICA). The Digital Elevation Model (DEM) was downloaded from the United States Geological Survey (USGS). The soil map was acquired from the “Thailand on disk Soil View 2.0”, while the population map was acquired from East View Land Scan. The LDD provided land use data in raster map format for 2010 and 2016. All raster data was used in 30 m horizontal and vertical resolution.

For rainfall and other meteorological data, the Thai Meteorological Department (TMD) supplied daily data of temperature (Celsius), relative humidity (%) and wind speed (m/s) data covering the period from April 1, 1993, to March 31, 2016. As no organization had daily solar radiation data, observation of solar radiation

(MJ/m²) was conducted at Thung Chang from October 16, 2016, to September 26, 2017. To align the period of data between solar radiation and others, observed solar radiation data from Chang Mai (Tanaka et al., 2008) was also utilized. Figure 1 shows the target watershed in the Nan Province and the locations of Nan River and observatories.

Daily rainfall data (mm) from April 1, 1993, to March 31, 2016 observed by RID at the Song Khwae observatory and daily discharge data (m³/s) at the N65 observatory were used for the hydrological simulations. To predict the impacts of climate change on flood discharge, daily rainfall and other meteorological data for 2040–2050 generated by Watanabe et al. (2014) were used. Their data is created under the RCP4.5 and RCP8.0 downscaling scenarios, and RCP4.5 was applied to this study due to the limitation of available data set for the predictions of impacts of climate change in RCP8.5 scenario.

Land Use Change Simulation

The Conversion of Land Use and its Effects at small regional extent (CLUEs) model was used in this study to simulate the future land use scenarios in the target watershed in 2050. This model was developed to simulate land use change using empirically quantified relationships between land uses and its driving factors (Veldkamp et al., 1996). In contrast to other land use simulation models, CLUEs can deal with multiple land use types simultaneously and can be applied at any scale, from continental level to sub-national level (Verburg et al., 2004). Zhang et al. (2016) adopted the CLUEs model to predict spatial distribution of green manures in crop lands and orchards in 2020 in the Pinggu District, Beijing, China. They developed two scenarios using CLUEs: Scenario 1: promotion of green manures spreading in orchards; and Scenario 2: promotion of simultaneous green manures planting in orchards and crop lands. Verburg et al. (2002) examined the accuracy of the CLUEs model in Sibuyan Island, the Philippines, and the Klang-Langat watershed in Malaysia. They concluded that CLUEs can easily be applied to wide range of study areas and land use change situations and pointed out that there are some limitations to simulating land use dynamics in areas without land use change history.

The CLUEs model predicts future land use scenarios based on four input data and one optional setting: (1) spatial policies and restrictions; (2) land use type specific conversion settings; (3) land use requirements; and (4) location characteristics for required input data,

and neighbour settings for an optional setting. Land use conversions are expected with the highest “preference” for the specific type of land use at that moment in time. This “preference” is determined by a binomial logit model calculated following:

$$\log\left(\frac{1 - P_i}{P_i}\right) = \beta_o + \beta_1 X_{1,i} + \dots + \beta_n X_{n,i} \quad (1)$$

where P_i is the occurrence probability of land use types on grid-cells i and independent variables (X) are the location factors, meaning biophysical or socio-economic characteristics of grid-cells i such as elevation and population etc. The coefficients (β) are estimated with a maximum likelihood estimation using the actual land use information.

In this study, the validation of the CLUEs model was examined with the actual land use maps in 2010 and 2016. Land use types in these two maps were classified as “forest”, “crop”, “orchard” and “others”. As location factors to obtain the logistic regression models, eight biophysical and socio-economic characteristics were applied: (1) population; (2) elevation; (3) slope; (4) aspect; (5) distance to city; (6) distance to village; (7) and (8) distance to road and to river. However, there were some areas where land use changes happened from 2010 to 2016 that the logistic regression model could not express. But, these represented changes that could not be seen in the land use change history. Therefore, in this validation, land use change restrictions were applied, and those areas were designed as “no change will occur in this validation period”. Finally, in order to consider the effects of neighbourhood land use types, neighbour settings were used in this simulation. The validation results gave a kappa coefficient (κ) value of 0.86 representing very good agreement, and precisions of each land use type: forest, crop, orchard, others, were 0.96, 0.91, 0.68, and 0.98, respectively. These values indicate that the CLUEs model can be applied in this target watershed to predict future land use scenarios.

To consider the impacts of land use changes on flood discharge, 13 scenarios having different proportions of forest area were simulated. Based on the proportion of forest areas in 2016 (70%), its value was changed to 8, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60 and 80% in the simulated land use scenarios in 2050 (12 scenarios). In addition to them, a business as usual scenario (BAU scenario) was prepared. In the BAU scenario, land use changes from 2010 to 2016 were retained until 2050 (75% forest area). The same logistic regressions with validation were used for all these simulations. No restricted areas were applied. In the simulations of the

12 scenarios, the areas of land use type “orchard” was increased by 200.25 ha each year, which is the same value as between 2010 and 2016, while “others” was not changed because of its small proportion in 2016. The rest of the areas was occupied by “crop” land.

Scale of Target Rainfall

To consider the impacts of climate change on flood discharge, return periods for the rainfall from 2006 to 2016 (current rainfall) and from 2040 to 2050 (future rainfall) were calculated. Return period is the average length of time in years for an event, such as floods or large rainfall, calculated using data from past events. Return period (T) exceeding x_p , which is the expectation value at the return period of T , is expressed as:

$$T = \frac{1}{1 - F(x_p)}, F(x_p) = 1 - \frac{1}{T} \quad (2)$$

where $F(x_p)$ is the occurrence probability of X not exceeding x_p . The occurrence probability of X follows a probability distribution function $f(x)$.

$$F(x_p) = \int_{-\infty}^{x_p} f(x) dx \quad (3)$$

In determining the best probability distribution function $f(x)$ for the current and future rainfall, six probability distributions: (1) normal distribution; (2) log-normal distribution; (3) Gumbel distribution; (4) log-Gumbel distribution; (5) exponential distribution; and (6) generalized pareto distribution, were plotted against each yearly maximum rainfall. After that, each plot was compared with the plotting position formula for the goodness of fit tests. Standard Least-Square Criterion (SLSC) was used to determine the best probability distribution.

As one of the targets of current rainfall to examine the impacts of climate change and land uses change on flood discharge, a rainfall event in 2011 (122.4 mm/day) that caused tremendous damage all over Thailand was selected. Based on the probability distribution for current rainfall, the return period X for a 122.4 mm/day rainfall was calculated. Then, rainfall Y in future rainfall having the same return period X was obtained as a target future rainfall from the probability distribution of the future rainfall.

Flood Discharge Simulation

For hydrological simulations, the Soil and Water Assessment Tool (SWAT) model (Abbaspour et al., 2015) was applied in this study. It is a continuous time model that operates on a daily time step (Neitsch

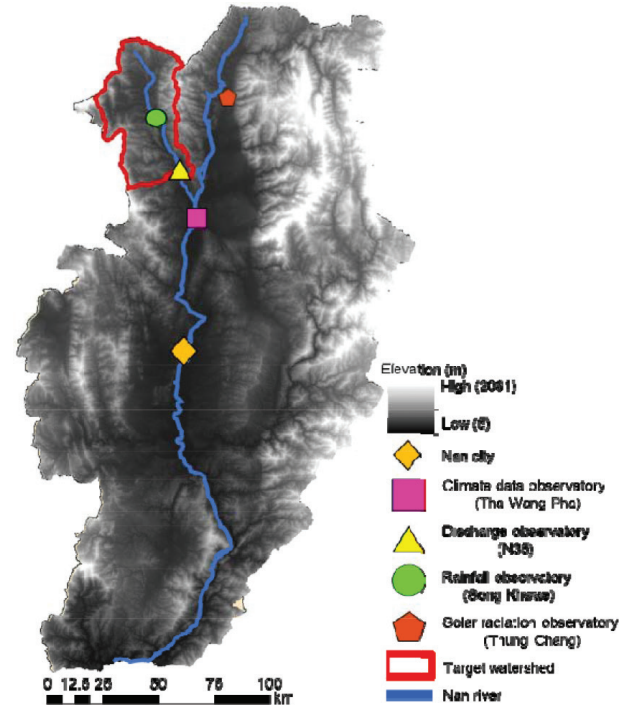


Figure 1: DEM of target watershed in Nan Province, showing data points.

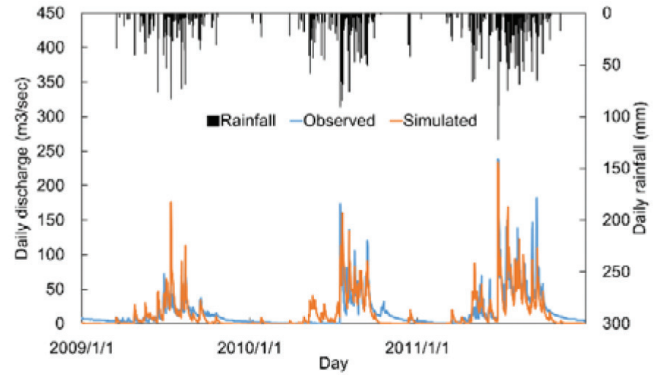


Figure 2: Results of calibration (2009) and validation (2010-11).

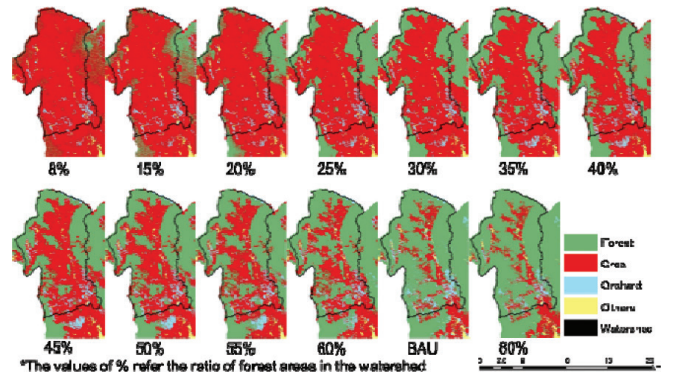


Figure 3: Results of CLUEs simulations.

et al., 2011). SWAT uses spatially distributed data on topography, soils and land uses to simulate daily flood discharge against the input rainfall (Douglas-Mankin et al., 2010). In its calculations, the watershed is divided spatially into sub-watersheds, and further subdivided into lumped, non-spatial hydrologic response units (HRUs) having similar landscape characteristics. The SWAT model has been used in a lot of studies, for example, Abbaspour et al. (2015) used the SWAT model to build a hydrological model of Europe at the sub-basin level and monthly time intervals, while Baker et al. (2013) analyzed whether the observed land cover change within the River Njoro watershed can be casually linked to hydrological alternations with the SWAT model. In this study, maximum flood discharge from target current and future rainfall were calculated.

To apply the SWAT model in the study area, calibration with observed data in 2009 and validation with observed data in 2010-11 were examined using the land use map from 2010. In this calibration, SWAT-CUP software (Abbaspour et al., 2007) was used to find appropriate parameters to express the hydrological responses in the target watershed. The Nash-Sutcliffe (NS) coefficient was used as the criteria for the goodness of fit tests. Figure 2 shows the calibration and validation results. The NS coefficient was 0.80 and the simulated discharge from the target rainfall in 2011 was 233.9 m³/s, which almost fit with the observed discharge of 239.2 m³/s. Then, with the same parameters, another validation was examined using the land use map from 2016 to verify that the SWAT model can simulate discharge in any land use scenarios.

To obtain results considering the temporal distribution of precipitation, some rainfall samples were created by raising the amount of current and future rainfall. Daily rainfall with 120, 140, 160, 180 and 200% of the value of the target rainfall, (i.e., 122.4 mm/day for current rainfall and Y mm/day for future rainfall) were selected. Insufficient samples were obtained from the lower raising rates (i.e., 120% and 140%), while the larger raising rates (i.e., 180% and 200%) were unrealistic. Therefore, in this study, raising rate of 160% was applied. Then, all daily rainfall that satisfies that condition was substituted into 122.4 mm/day in the current rainfall period and into Y mm/day in the future rainfall period. Then, SWAT calculated discharge from these rainfall one by one. If there were more than two daily rainfall in one year, the daily rainfall that caused the maximum discharge was used for the simulation.

SWAT calculated the discharge from all rainfall samples (current and future) with 14 land use patterns

(13 scenarios and the actual land use in 2016). All input data for current (2006-16) was based on observation and for future (2040-50) was from model calculation as described above. For the predictions of impacts of climate change on flood discharge, the Mann-Whitney U test was used to examine the discharge from current and future rainfall in the same land use patterns. The antecedent precipitation index (API) was used for the discussion, which is expressed as:

$$API = \sum_{i=1}^n a_i \times R^i \quad (4)$$

where n is day, a_i is coefficient and R^i is daily rainfall i days before (mm/day). API for the 10, 20 and 30 days before the rainfall ($i = 10, 20, 30$) was calculated. Finally, discharge from current and future rainfall in different land use patterns were compared to predict the impacts of climate change and land use changes.

Results and Discussion

Land Use Change Simulation

Figure 3 shows the results of the CLUEs model simulating 13 land use scenarios in 2050. It was readily apparent that the lower the proportion of forest areas, the more crop lands expand. Forest areas found in the 8% and 15% scenarios are located in the relatively higher elevation areas, which isn't suitable for agriculture. Based on the effects of this initial location, "orchard" may increase around lower elevation areas and near the "others" in the 8-60% and BAU scenarios.

Return Period

Yearly maximum current rainfall follows log-Gumbel distribution (blue line: SLSC = 0.022), while yearly maximum future rainfall follows log-normal distribution (red line: SLSC = 0.036). It is apparent that climate change has an effect on changing rainfall patterns (Figure 4). For yearly maximum future rainfall, the variance becomes larger than for current rainfall, i.e., more extremely large and small rainfall events will tend to occur during 2040-50 rather than during 2006-16.

From this result, the return period of 122.4 mm/day rainfall in 2011 became 3.3 years under current rainfall. Under future rainfall, yearly maximum rainfall of the same return period, 3.3 years, was 125.8 mm/day. To predict the impacts from larger yearly maximum rainfall, the 10-year return period was also analyzed. Yearly maximum current rainfall in the 10-year return period was 176.4 mm/day, while yearly maximum future

rainfall was 220.5 mm/day. The number of rainy days that meet the condition are shown in Table 1.

Table 1: Rainfall days that meet condition and rainfall samples for simulations

Return period	3.3 years		10 years	
	Current	Future	Current	Future
Rainfall that meets condition	17	6	9	4
Rainfall samples for simulations	10	6	7	4

Flood Discharge Simulation

Figure 5 shows the average discharge from the 3.3-year return period rainfall by the SWAT model in the 14 land use patterns simulated by CLUES. This result indicates that the average discharge from future rainfall (red line) was less than that from current rainfall in all land use patterns. The Mann-Whitney U test shows that the differences of average daily discharge between current and future rainfall in all land use patterns met the 5% significance level. However, Perera et al. (2013) simulated the impacts of climate change on flood risk in Nepal and concluded that significant increases in the magnitude and frequency of high discharge were indicated in the near future and future compared to the present, which is the opposite of this result. The simulation results were different between Nan Province and Nepal because the impacts of climate change will vary widely from region to region (Kundzewicz et al., 2014). Therefore, it is important to analyze each region. In Nan Province, it can be said that the impacts of climate change will decrease the average discharge in the 3.3-year return period rainfall. In addition, as the proportion of forest areas decreases, it could be seen that average daily discharge from both rainfall was increasing. This result also can be seen in the study of Wangpimool et al. (2013), which showed that reforestation was useful in reducing the flow in the upper-basin in Nan Province. This could be attributed to the effects of forests mitigating the maximum discharge by storing rainfall temporarily, and/or greater amounts of evapotranspiration from the forest areas.

Similar to the previous results, there were two tendencies. Firstly, although the comparisons of average daily discharge from current rainfall with that from future rainfall in the same land use patterns didn't reach the 5% significance level under the Mann-Whitney U test, climate change reduced the average daily discharge. Secondly, increases in discharge with decreasing areas

could be seen for the average daily discharge from the 10-year return period rainfall. In this case, additionally, the differences between average daily discharge from current and future rainfall were becoming smaller as forest areas decreased. It is broadly held that forests are more effective with smaller scale rainfall events and have less power to mitigate floods during larger scale rainfall events, which contradicts with this result. It could be assumed that insufficient rainfall samples (four

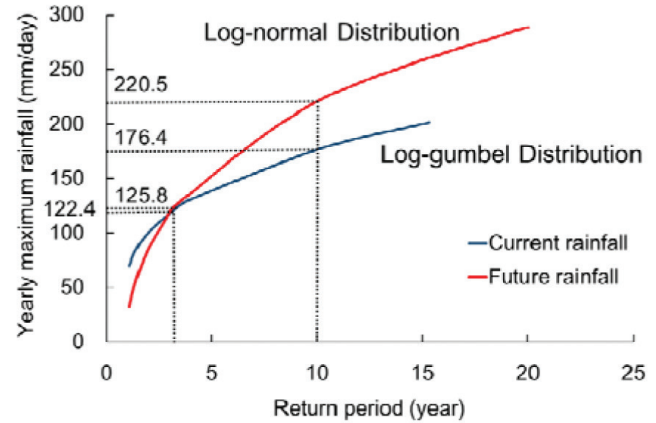


Figure 4: Return period of yearly maximum rainfall against current and future rainfall.

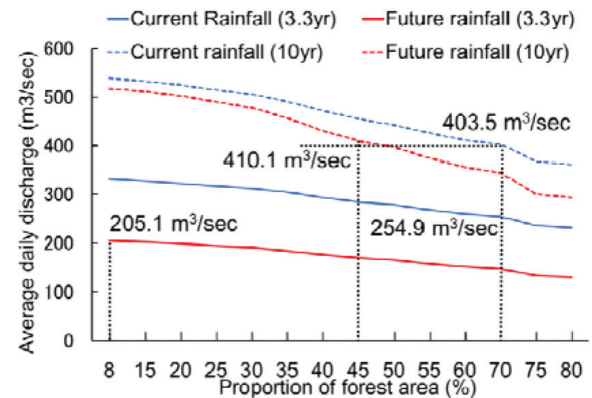


Figure 5: Results of SWAT simulations.

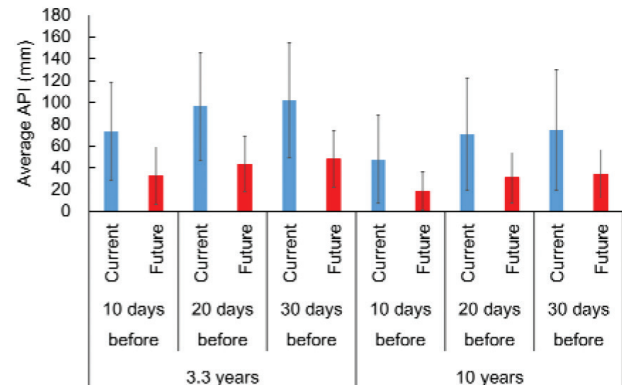


Figure 6: Plot of average APIs.

samples for future rainfall) was probably the reason for this disparity. In order to analyze the reasons for the lower average daily discharge from future rainfall than from current rainfall, average APIs of 10, 20 and 30 days before the 3.3 and 10-year return period rainfall were compared in Figure 6. All average APIs from current rainfall were larger than those from future rainfall. These differences showed statistical significance for the *t*-test at ($P < 0.05$ and $P < 0.1$ against the 3.3 and 10-year return period rainfall, respectively). It is possible that rainy days targeted for future rainfall might occur during drier conditions, and this could cause lower average daily discharge from future rainfall.

In addition, the reason why a 5% significance level in the U test was not observed for the average daily discharge in the 10-year return period rainfall could be due to the differences between the amounts of rainfall. The 10-year return period rainfall in the future was 44.1 mm larger than in the current situation, while the 3.3 years return period rainfall was only 3.4 mm larger. These differences may close the gaps between average daily discharge from current and future rainfall in the 10-year return period rainfall.

In predicting the impacts of climate change and land use changes against the 3.3-year return period rainfall, it was found that average daily discharge from future rainfall in the 8% scenario (i.e., 205.1 m³/s) was less than that from current rainfall in the 70% scenario (land use in 2016) (i.e., 254.9 m³/s). This indicates that future average daily discharge will not be above average daily discharge in the current situation, even if the forest areas are reduced to 8% in the watershed.

When viewed against the 10-year return period rainfall, average daily discharge from current rainfall in the 70% scenario (i.e., land use in 2016) was 403.5 m³/s, while that from future rainfall in the 45% scenario was 410.1 m³/s, which indicates that average daily discharge will be above that in the current situation. This indicates that the impacts of climate change decreasing average daily discharge will be counteracted by land use changes if the forest area is reduced to less than 45% in the watershed.

Conclusion

Multitier analysis considering climate change and land use changes could quantitatively predict their impacts on flood discharge. From the results, it could be concluded that even if crop lands increase to 50% of the target watershed, average daily discharge from 10-year return period future rainfall will not be larger

than that from current rainfall, and this can enable the economic development in the region. Moreover, this method can be applied to almost any locations as long as some simple input data to run the CLUEs and SWAT models are obtained.

Field work at the target watershed to ground truth the actual land use would contribute to more accurate simulations in the CLUEs model. Also, with longer duration future meteorological data, the predictions of impacts from larger return period rainfall (i.e., 15 years and more) can be examined using the SWAT model.

One limitation of this study centres on the difficulties in reflecting many factors. The combinations of CLUEs and SWAT can integrate hydrology, atmospheric, forest and land use factors, but other factors are also important such as policy decision for the land use changes. Also, the amount of discharge predicted in the results of the SWAT model cannot be equalled to the scale of the damage from floods. In order to do cost-benefit performance analysis, the amount of discharge needs to be transformed into the probable scale of damage.

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