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Research Paper

Assessing the climate change impact on floodplain inundation map in the Chiang Mai municipality, upper Ping river basin of Thailand

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ABSTRACT

Coupling of water balance model and floodplain inundation model is developed to receive projected rainfall time series from two types of regional climate model (RCM). Providing Regional Climates for Impacts Studies (PRECIS) and Meteorological Research Institute (MRI) are RCM with resolution 0.2 x 0.2 degree (grid size 20 x 20 km) daily time step, from year 2015-2044. They are generated from ECHAM 4 climate models. Empirical quantile mapping is used for bias correction of projection rainfall that its adjustment factors are estimated from comparison between observed and past projection rainfall from base-time period, year 1985-2014. A floodplain inundation model is applied based on 1D rating curve approach. This model receives peak runoffs as results from the water balance model, and generate flood extent in flood plain and draw flood inundation map of Chiang Mai municipality with different return periods. These expected results show the increase of flood inundation extent as a consequence of climate change.

1. Introduction

The impact assessment studies of climate change in various basins different part of the world indicate changes in the amount of precipitation, its frequency and intensity affecting the magnitude and seasonal pattern of streamflow. Sharma and Babel (Sharma and Babel, 2013) use the rainfall-runoff model (HEC-HMS) to receive time series of future projection rainfall from ECHAM4/OPYC general circulation model (GCM) for upper Ping river basin after they are improved by bias-correction and spatial disaggregation. Simulated results suggest a decrease of 13-19 % in annual streamflow and a shift in seasonal streamflow pattern. For regional and national scale studies, GCMs are a common tool to generate future projection climate variables at a coarse scale. For local scale such as basin level, many studies have applied different bias-correction and downscaling approaches to improve the local patterns of climate variables. Regional climate models (RCMs) are commonly used to transform coarse resolution GCM data to the local scale. Sharma and Babel (Sharma and Babel, 2013) use Gamma-Gamma distribution for rainfall intensity correction and use disaggregation model based on multiplicative random cascade approach for downscaling. To reduce bias of RCM simulation from Providing Regional Climates for Impacts Studies (PRECIS) and ECHAM4 climate models, Boonrawd and Jothityangkoon (Boonrawd and Jothityangkoon, 2015a) use distribution mapping based on derived adjustment

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factors (AF), which is the ratio of observed and simulated rainfall depth for a given frequency of occurrence. They found that the combination of using seasonal AFs derived from monthly rainfall data for each month of all years, and AFs derived from all daily rainfall data and used to shift distribution of daily rainfall intensity provide the best improvement of simulated rainfall. Potential effect of both climate and land use change on the extreme flood for the upper Ping River Basin was studied by Jothityangkoon et al. (Jothityangkoon et al., 2013). A distributed rainfall–runoff model appropriate for extreme flood conditions is used to generate revised estimates of the Probable Maximum Flood (PMF). For mapping space-time flood extent of Chiang Mai floods, developed a coupling of a 1-D flood routing model and quasi 2-D floodplain inundation model to simulated temporal extent of flood area (Boonrawd and Jothityangkoon, 2015b). This rainfall-runoff model and inundation model is used to receive future projection rainfall after bias correction and to delineate flood map in this study. Wuthiwongyothin et al. (Wuthiwongyothin et al., 2017) assessed the effects of climate change of the upper Ping River basin by using future projection rainfall from the ECHAM5 and the CCSM3 global climate model (GCM) They found that averaged discharge of inflow to Bhumibol dam increase to 17.3 % from 5.25 to 6.36 billion m^3 at the end of the 21th century (2016-2099). Tangang (2017) presents simulation output of more than ten CMIPS Global Climate Model (GCMs) from Southeast Asia Regional Climate Downscaling Experiment/ Coordinated Regional Climate Downscaling Experiment (SEACLID/CORDEX). Simulated results show a tendency of wetting in the northern area of equator by the increasing frequency of projected rainfall intensity 20 and 50 mm/day for near, mid, and end-of-century, and the increase of projected annual maxima for daily rainfall and daily rainfall intensity with 10 year return period. In contrast, the drying tendency is clearly increased such as the increase of projected consecutive dry day.

This paper assesses the impacts of climate change on maximum annual discharges in the upper Ping River of Thailand and focusing on the future expansion of flood inundation in community area of Chiang Mai municipality and its vicinity, which is an initial step to develop possible flood hazard map (Osti et al., 2008).

2. Study area and RCM data

The Upper Ping River catchment is located in the north of Thailand. The river flows southward through the valley of Chiang Mai. The catchment area upstream of stream gauge station P1 (Navarat Bridge) and P68 (Ban Nam Tong) are 6,350 and 6,430 km^2, respectively (Boonrawd and Jothityangkoon, 2015b). The flood study area covers about half of Chiang Mai municipality (40.2 km^2) and two districts (Pa Daet, 25 km^2 and Nong Hoi, 3.67 km^2) which lie on the floodplain of the Upper Ping River.

Observed flood inundation area

The observed flood inundation area from past floods was defined based on relationship between flood level at P1 and flood depth measured in the city during past flood events. Flood warning system for Chiang Mai city was set up in the form of flood hazard maps by Civil Engineering Natural Disaster Research Unit (CENDRU) (CENDRU, 2013). Inundation areas were divided into seven zones depending on upstream referenced water level at P1 (see **Table 1** and **Fig. 1**).

RCM data and observed rainfall

Two sets of time series of projection rainfall are generated from Providing Regional Climates for Impacts Studies (PRECIS) and Meteorological Research Institute (MRI) which receives input data from ECHAM4 climate models with resolution 0.2 x 0.2 degree (grid size 20x20 km.) daily time step, baseline period from year 1985-2014 (30 years) and future projection period from year 2015-2044 (30 years). The simulation covers the Intergovernmental Panel on Climate Change (IPCC) emission scenarios A2 and B2. For this study, only A2 is selected (Boonrawd and Jothityangkoon, 2015a). Japan Meteorological Agency (JMA) developed operational forecast model for a quasi-equilibrium experiment under a doubled atmospheric CO_2 condition called MRI-AGCM 3.1S version (AR4) (high-resolution atmosphere-only general circulation models, AGCMs). Baseline periods of projected rainfall are divided into 3 periods: past (1979-2006), near future (2015-2039), far future (2075-2099) (Koontanakulvong et al., 2015). A 30 year time's series (1985 - 2014) of observed daily rainfall from selected 42 rain gauges over the Upper Ping River basin is used to compare with projected rainfall from RCMs.

3. Methodology

To construct a map of floodplain inundation, the flowchart of 7 main steps is presented in **Fig. 2** and each step is explained in details in the following sub-section.

3.1 Derived AFs

The method of higher-skill bias corrected RCM data or empirical quantile mapping is operated based on derived adjustment factors (AF), which is the ratio between observed and simulated rainfall for a given frequency of occurrence. Correcting only the monthly mean precipitation can distort the relative variability of the inter-monthly precipitation distribution, and may adversely affect other moments of the probability distribution of daily precipitations. For bias correction test, the complexity of derived AFs is added in 5 method (Boonrawd and Jothityangkoon, 2015a).

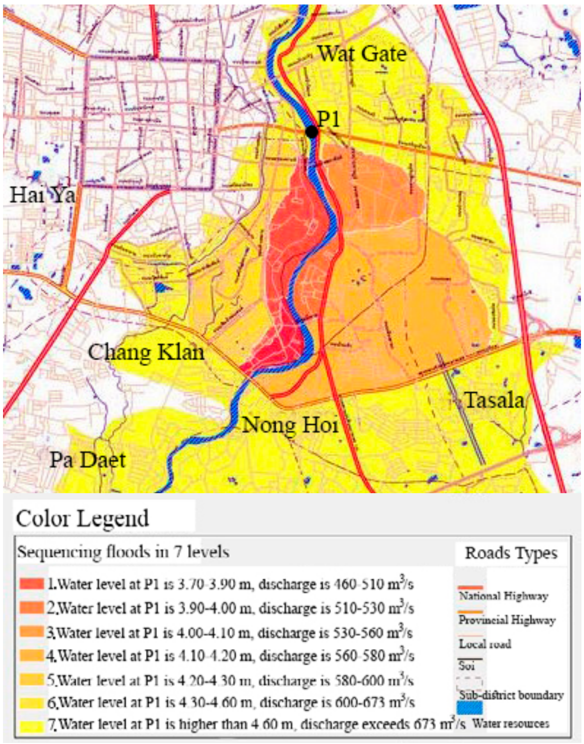

Fig. 1. Observed flood inundation area by Civil Engineering Natural Disaster Research Unit (CENDRU).

Table 1 Observed flood inundation area from past floods.

Observed flood (m^3/s)	Water level at P1 (m)	Inundation area (km^2)	Return period (year)
510	3.90	0.353	7.90
530	4.00	1.259	9.15
560	4.10	1.761	11.40
580	4.20	2.689	13.25
600	4.30	6.505	15.40
673	4.60	8.138	26.80

Method 1: AFs are derived from all daily rainfall data and used to shift distribution of daily rainfall intensity (daily AFs for daily).
Method 2: temporal scaling of input rainfall data is changed from daily to monthly (monthly AFs for monthly).
Method 3: is similar to Method 2, the difference is AFs are used to adjust distribution of daily rainfall (monthly AFs for daily).
Method 4: seasonal AFs are derived from monthly rainfall data for each month of all years and used to shift distribution of monthly rainfall of each month (seasonal monthly AFs for monthly).
Method 5: is the combination of Method 4 for the first step and Method 1 for the second step (seasonal monthly AFs for monthly+ daily AFs for daily).

(Boonrawd and Jothityangkoon, 2015a) found that the Method 5 provides the best derived AFs compare to the other methods. An example of testing results from the Method 5 is shown in **Fig. 3** for PRECIS rainfall and **Fig. 4** for MRI rainfall. For calibration step, AFs are estimated from observed and simulated rainfall from RCM rainfall during 1982-1996 (15 years). For verification step, these estimated AFs are used to correct RCM rainfall during 1997-2011 (15 years) and compare to observed rainfall in the same verified period. For further testing in this study, the Method 5 is used to derive AFs for many locations of available observed rainfall. Finally, this method is used to d

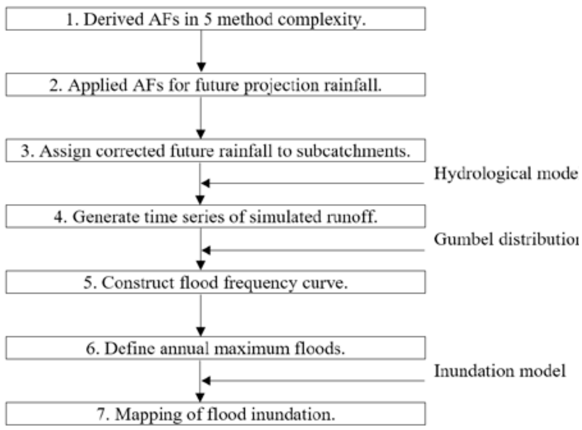

Fig. 2. Flowcharts for constructing a map of floodplain inundation.

3.2 Application of AFs for future projection rainfall

AFs are estimated again using the whole historical data (1982-2011, 30 years) for each grid. These AFs are used for bias correction of future projection rainfall at all grids of RCM data.

3.3 Assignment of corrected future rainfall to subcatchments.

A time series of corrected future rainfall from a grid that give the shortest distance between the centroid of RCM grid and the subcatchment is assigned to the subcatchment.

3.4 Generation of time series of simulated runoff.

A hydrological model used in this study is an adaptation of a sub-catchment based distributed water balance model developed by Jothityangkoon et al. (2013). The model has two components: a hillslope runoff generation model and a distributed flood routing model. The hillslope water balance model contains a number of parameters, which are measured or derived a priori from climate, soil and vegetation data or streamflow recession analyses. Based on the dynamics of water balance concept, discharges from each subcatchment are generated from 2 different runoff generation processes: saturation excess runoff and subsurface runoff. The catchment area upstream of P1 is divided into 62 subcatchments. The routing model based on a configuration of channel storages in parallel and series using constant averaged flow velocity (49.5 km/day), estimated from time lag of observed hydrographs within the catchment. This model is applied to receive runoff fr k

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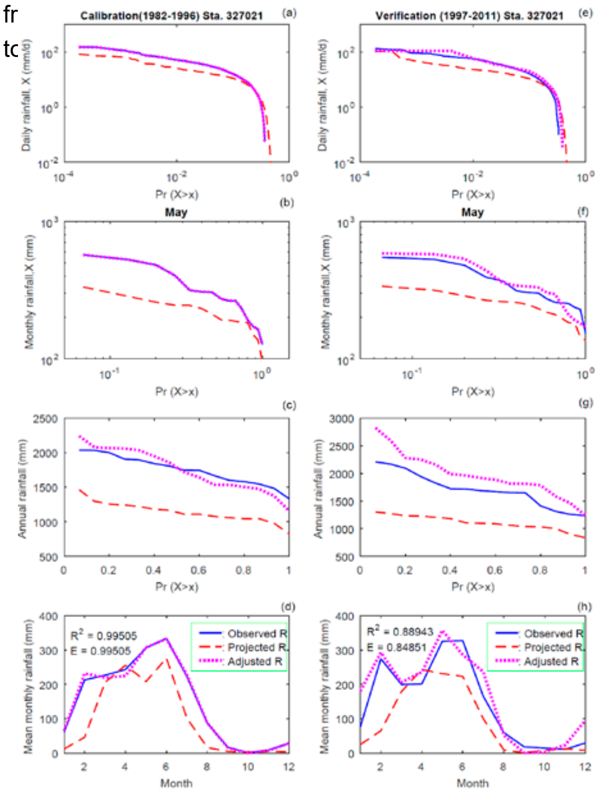


Fig. 3. Input rainfall from PRECIS (Method 5), Comparison of observed, projected and adjusted rainfall at Sta. 327021, for calibrated results (a) to (d) and for validated results (e) to (h), consisting of exceedance probability of observed, projected and adjusted data (daily, monthly annual and mean monthly rainfall).

3.5 Construction of flood frequency curve.

Annual maximum of observed or simulated runoff is estimated from a time series of observed or simulated daily runoff and results from frequency analysis of the annual maximum are plotted in Gumbel distribution paper.

3.6 Defining annual maximum floods

The Extreme Value Type I distribution or Gumbel distribution is used to fit the observed or simulated annual maximum runoff. For a given specific return period, annual maximum flood can be estimated.

3.7 Mapping of flood inundation

Flood at specific return period is converted to flood level by using simulated rating curve for a compound channel developed by Jothityangkoon (Jothityangkoon et al., 2013) Flat level of water surface is assumed and used to define intersection point between water surface and floodplain. At the same time, the shape or cross section of floodplain is estimated based on trial and error

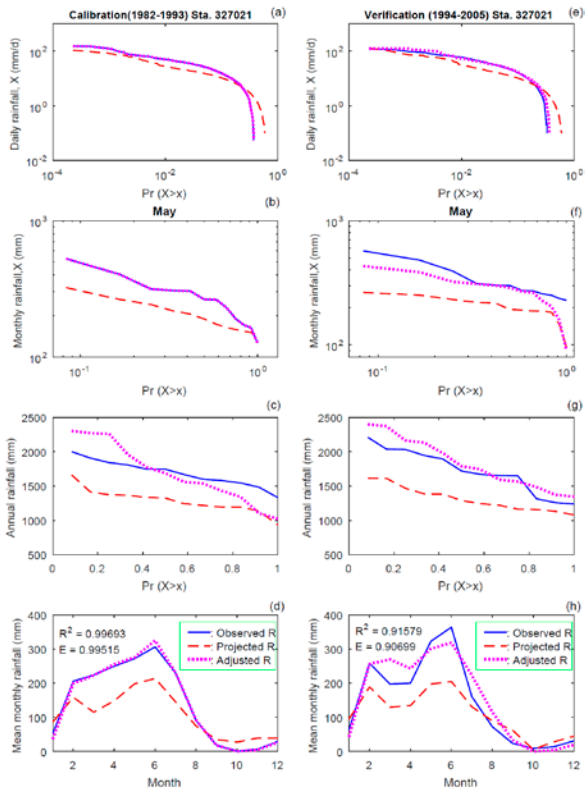


Fig. 4. Input rainfall from MRI (Method 5), Comparison of observed, projected and adjusted rainfall at Sta. 327021, for calibrated results (a) to (d) and for validated results (e) to (h), consisting of exceedance probability of observed, projected and adjusted data (daily, monthly annual and mean monthly rainfall).

between estimated and observed flood extent in **Fig. 1**. For each river cross section with estimated rating curve and the shape of floodplain, the distance of flood extent from the main channel for any flood magnitudes is calculated and use to draw flood map.

4. Results and Discussion

Return period of observed annual maximum flood in the fourth column of **Table 1** shows that the return period of maximum observed flood for flood warning is about 27 years. By using derived AF based on Method 5 (combination of seasonal monthly AFs for monthly data and daily AFs for daily data), exceedance probability of annual and mean monthly projected rainfall are shifted close to observed rainfall (**Figs. 3, 4(b), (c), (f), (g)**). For intra-annual variability, adjusted mean monthly rainfall has a good agreement with observed mean monthly rainfall for both PRECIS and MRI, calibration and validation period, coefficient of determination (R^2) > 0.89 and Nush-Sutcliffle efficient (E) > 0.84.

Figure 5 and **Table 2** present observed and simulated annual maximum flood from different input rainfall. Simulated annual maximum flood from the water balance model with receiving observed rainfall similar to observed runoff for all return periods. Although, the time series of past projected rainfall from PRECIS and MRI are improved by bias correction using AFs, when the model receives past projected rainfall, simulated annual maximum is about 22-24 % for PRECIS and 31-35 % for MRI higher than simulated flood from observed rainfall. Due to climate change, if the model receives future projected rainfall, simulated annual maximum flood is about 31-35 % for PRECIS and 94-104 % for MRI, higher than simulated flood from observed rainfall (**Table 2**).

Table 2 Annual maximum flood from different methods.

Return period (year)	Observed Max. Q (m^3/s)	Simulated annual maximum flood from (m^3/s)		
		Observed rainfall	Past projected R	
			PRECIS	MRI
10	524	542	649	696
25	663	664	806	869
50	754	754	923	998
100	843	844	1,038	1,125

Return period (year)	Observed Max. Q (m^3/s)	Simulated annual maximum flood from (m^3/s)		
		Observed rainfall	Future projected R	
			PRECIS	MRI
10	524	542	706	1,014
25	663	664	866	1,298
50	754	754	985	1,509
100	843	844	1,103	1,718

In term of flood inundation area, future projected rainfall gives about 89.5, 20.8, 10.2, 7.0 % increase for PRECIS and 91.2, 30.4, 22.1, 21.5 % increase for MRI of inundation area compare to past flood area for 10, 25, 50 and 100 years return period, respectively (**Table 3**). Flood inundation maps and its boundary are presented in **Fig. 6** for PRECIS input and in **Fig. 7** for MRI input.

Table 3 Flood inundation area.

Return period (year)	Flood inundation area (km^2)				
	Past floods	Future rainfall : PRECIS		Future rainfall : MRI	
		area	Increase (%)	area	Increase (%)
10	0.895	8.493	89.47	10.208	91.24
25	7.677	9.692	20.79	11.030	30.40
50	9.010	10.036	10.23	11.563	22.08
100	9.621	10.339	6.95	12.258	21.51

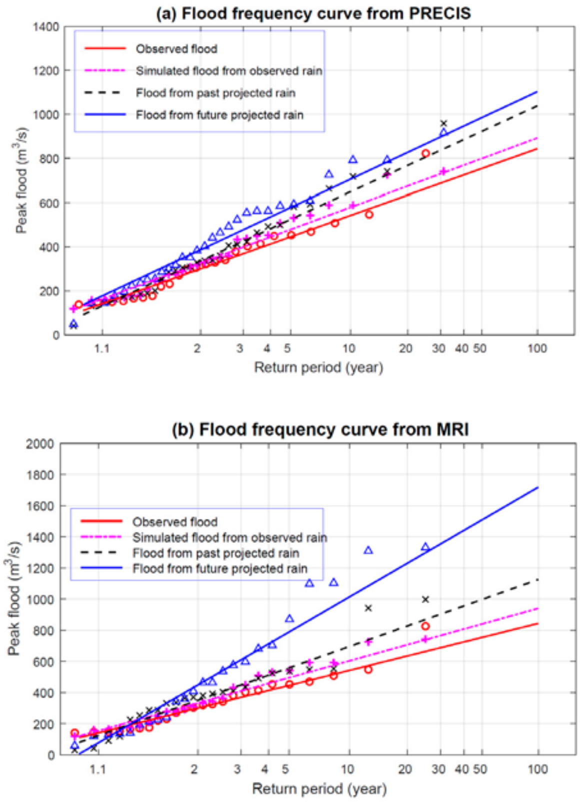
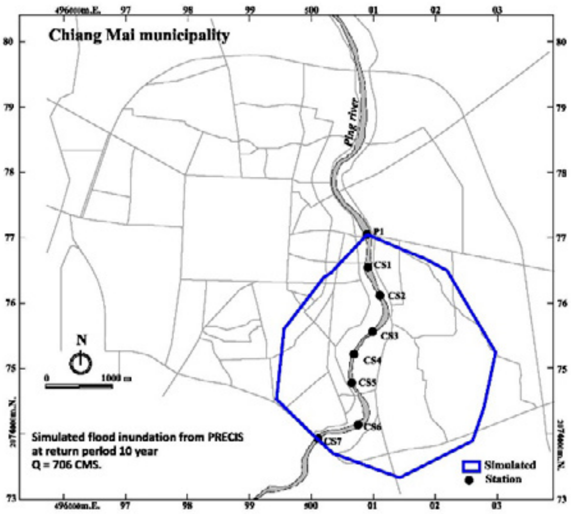
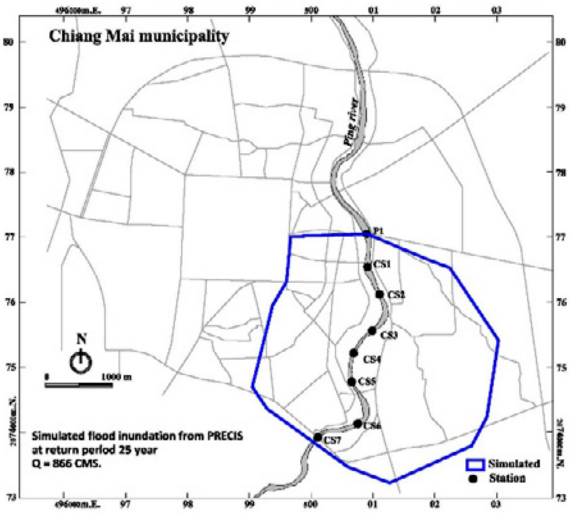


Fig. 5. Comparison of flood frequency curve between observed floods, simulated annual maximum flood from observed rain, past projected rain and future projected (a) input rainfall from PRECIS, (b) input rainfall from MRI.

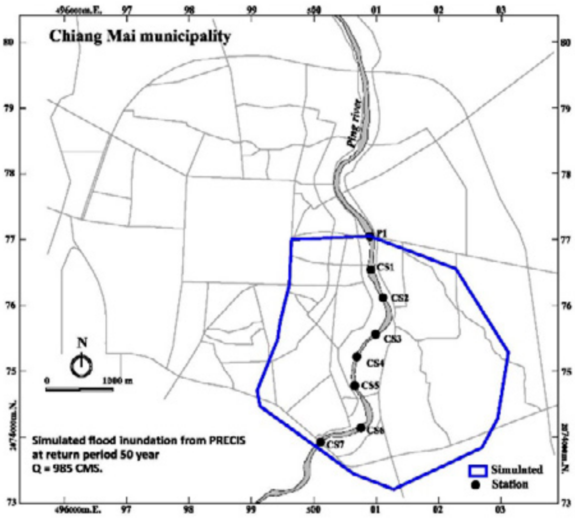
(a) Future rainfall from PRECIS, Q=706 m^3/s (T= 10 year)



(b) Future rainfall from PRECIS, Q=866 m^3/s (T= 25 year)



(c) Future rainfall from PRECIS, Q=985 m^3/s (T= 50 year)



(d) Future rainfall from PRECIS, Q=1,103 m^3/s (T= 100 year)

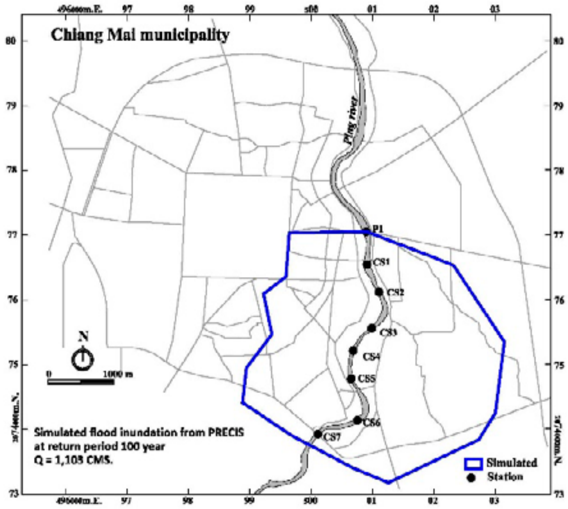
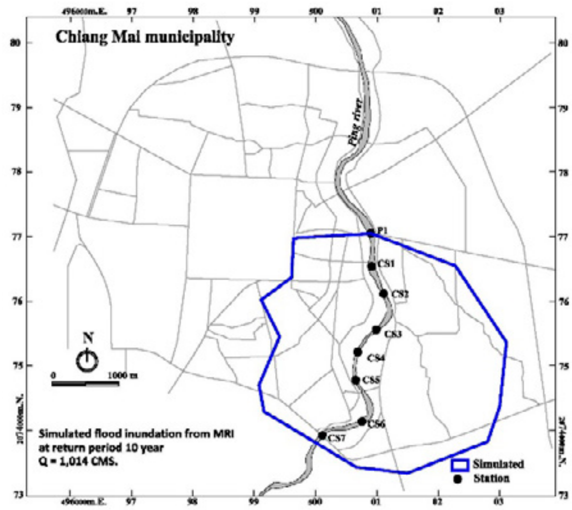
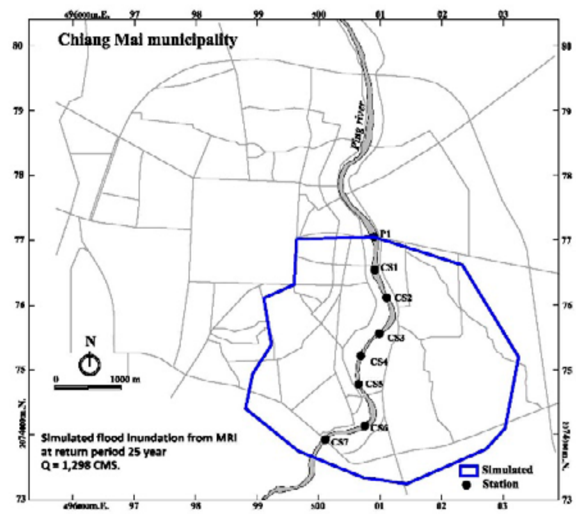


Fig. 6. Boundary of simulated flood inundation from PRECIS at return period (a) 10 year (b) 25 year (c) 50 year and (d) 100 year.

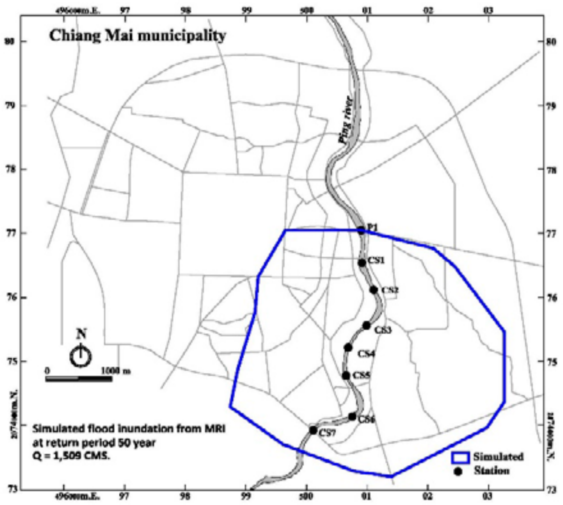
(a) Future rainfall from MRI, Q=1,014 m^3/s (T= 10 year)



(b) Future rainfall from MRI, Q=1,298 m^3/s (T= 25 year)



(c) Future rainfall from MRI, Q=1,509 m^3/s (T= 50 year)



(d) Future rainfall from MRI, Q=1,718 m^3/s (T= 100 year)

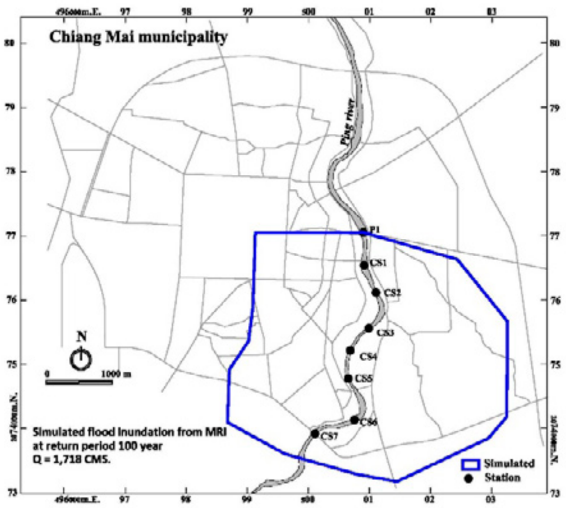


Fig. 7. Boundary of simulated flood inundation from MRI at return period, (a) 10 year, (b) 25 year, (c) 50 year and (d) 100 year.

5. Conclusion

To assess the impact of climate change, a time series of future projection rainfall from RCM rainfall models is used including PRECIS and MRI with bias correction. Combination of a water balance model and flood inundation model is linked to generate flood extent in flood plain and draw flood inundation map of Chiang Mai municipality. Simulated results show that the increase of flood inundation extent as a consequence of climate change. For bias correction method, adjustment factor based on empirical quantile mapping from a combination of seasonal monthly AF for monthly data and AFs for daily data is used to correct future projection rainfall from both PRECIS and MRI. By using a coupling of the distributed water balance model and floodplain inundation model to convert future projection rainfall from PRECIS to runoff and peak discharges and comparing to inundation area of past floods, the inundation area in Chiang Mai municipality is increased by 89.5, 20.8, 10.2 and 7.0 % with 10, 20, 50, 100 years return period, respectively. Similar trend occurs for MRI with higher percentage than PRECIS, increased by 91.2, 30.4, 22.1 and 21.5 % with 10, 20, 50, 100 years return period, respectively.

Limitation of this study is the use of projection rainfall from only two RCM outputs and using fixed landuse/ landcover. As being suggested by many studies of climate change impact, the use of more GCM, RCM and future IPCC scenario are required for decision-making processes in dealing with future uncertainty. However, it is expected that more RCM outputs are easily available in the future for this region. Integrated approach between climate change and land use change is recommended for future study.

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