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Forecasting 100-year changes of streamflow in the Mun River Basin (NE Thailand) under the HAPPI experiment using the SWAT model

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ABSTRACT

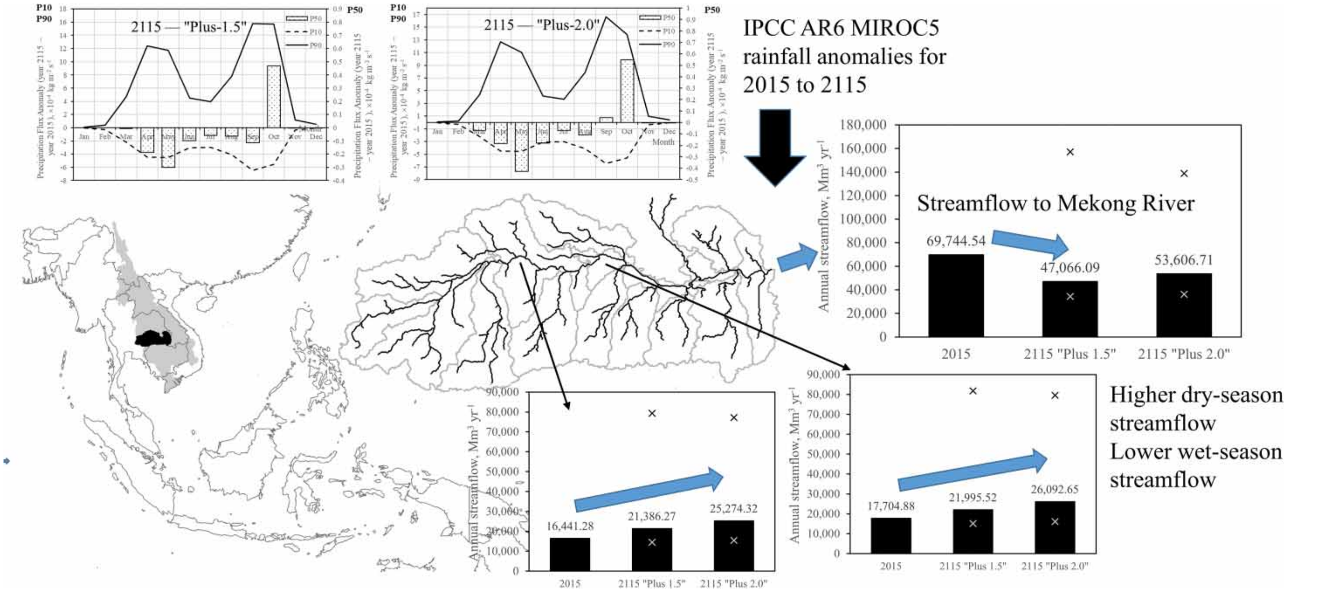
The Lower Mekong River is one of the significant rivers nurturing people on the Southeast Asian mainland. Its tributaries include the Mun River (NE Thailand), which often experiences extreme water events. In this study, the streamflow change in the year 2115 was simulated by relying on the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) experiment and the Model for Interdisciplinary Research on Climate, version 5 (MIROC5) climate model for average global warming of 1.5 °C (Plus1.5) and 2.0 °C (Plus2.0) above pre-industrial levels and compared with the base year in 2015 for the Mun River Basin. The Soil–Water Assessment Tool (SWAT) was used for the streamflow simulation. The results showed an increasing air temperature against lowering rainfall and relative humidity (except for the post-monsoon months), suggesting overall rain suppression in response to the warming climate. The median projected annual streamflow to the Mekong River in 2115 decreased for both 'Plus1.5' (−32.5%, median) and 'Plus2.0' (−23.1%, median). However, increasing annual streamflow could be found only in the middle part. Seasonal streamflow changes revealed a different spatiotemporal response to climate change resulting in inconsistent streamflow changes across the basin. The adaptive measures for the middle part should be focused on flooding control, whereas the upper and the lower parts should be against drought.

Key words: HAPPI, IPCC AR6, Lower Mekong River, MIROC5, Mun River, SWAT

HIGHLIGHTS

- IPCC AR6 HAPPI predicts overall rain suppression in response to the warming climate across the Mun River Basin.
- The projected streamflow to the Mekong River in 2115 declines for both warming scenarios.
- Positive annual streamflow anomalies could be found in the middle part.
- In this middle part, we found higher dry-season streamflow and less wet-season streamflow.
- Upper and lower parts tend to be drought-prone.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Southeast Asia is one of the regions most vulnerable to climate change, which is attributed to its heavy reliance on agriculture for livelihoods, high poverty incidence, and experiencing more intense heat waves, droughts, floods, and tropical cyclones (Asian Development Bank 2009). Climate change was ranked among Southeast Asia's top three security concerns. The most severe climate impacts of concern in the year 2021 were floods, followed by loss of biodiversity, sea-level rise, heatwaves, rainfall-induced landslides, and drought (ISEAS-Yusof Ishak Institute 2021). The impact of climate change on water resources must be addressed to promote adaptive ability, especially for those vulnerable groups living in this region. The Mekong River is the longest in mainland Southeast Asia, and it also has the largest drainage area. It flows from the Tibet Plateau, across China, along the Thai-Laos PDR boundary, across Cambodia and Vietnam before discharging to the South China Sea. Despite warming trends that have been consistently projected in the Mekong River region (Eastham *et al.* 2008; Kingston *et al.* 2011), recent studies on forecasting hydrological responses to climate change showed high uncertainty in projections of discharge among various climate models. The high uncertainties in annual river discharges range from −5.4 to +4.5% (Kingston *et al.* 2011). This uncertainty could be attributed to complexities in land dynamics and the individual model structure.

In the 2015 Paris Agreement, the Conference of the Parties of the United Nations Framework Convention on Climate Change (UNFCCC) targets the increase in the global average temperature to below 2 °C above pre-industrial levels and pursues efforts to limit the rise to 1.5 °C (UNFCCC 2015). The UNFCCC invited the Intergovernmental Panel on Climate Change (IPCC) to provide a special report on the impacts of global warming of 1.5 °C above pre-industrial levels (SR1.5) (Mitchell *et al.* 2017). The SR1.5 relies on the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI-MIP) project, providing a framework for generating climate data illustrating impacts on natural hazards corresponding to 1.5 and 2 °C warming (Mitchell *et al.* 2017). The experiment under HAPPI uses the RCP2.6 to provide the model boundary condition for the 1.5 °C scenario and a combination of RCP2.6 and RCP2.5 for the 2 °C scenario (Mitchell *et al.* 2017). The recent IPCC Annual Report 6 (AR6) was confident that global warming of 1.5 and 2 °C will be exceeded during the 21st century unless there is a profound reduction in greenhouse gases (IPCC 2021). The continued warming will intensify variability in monsoon precipitation and the severity of wet and dry events (IPCC 2021).

Recently, the HAPPI protocols have inspired many research studies that emphasized the effects associated with the UNFCCC targets. Wehner *et al.* (2018) adopted the HAPPI protocols and projected more frequent and more intense tropical cyclones. Seneviratne *et al.* (2018) reported comparative changes in temperature and water cycle extremes between both the 1.5 °C and the 2.0 °C warming scenarios and those among different regions in the world. Nevertheless, their study did not include the Southeast Asian (SEA) region. Lee *et al.* (2018) pointed out that under the HAPPI protocols, a stronger Asian monsoon could result in heavier precipitation and devastating impacts on humans and ecosystems over the Indian sub-continent eastwards to Southeast Asia and East Asia. Paltan *et al.* (2018) simulated a global river that flowed under the HAPPI experiment and illustrated an overall wetter future in South Asia and Southeast Asia. A limited study focuses on the impacts of the climate changes in the sub-basin scale of the Greater Mekong River Region by considering local land–sea–atmosphere complexity.

The Mun River Basin is part of the Greater Mekong River Basin, and it discharges approximately 10% of the runoff into the Lower Mekong River at the Pakse station (Kingston *et al.* 2011). Water from the Mun River to the Lower Mekong River has significantly driven socio-economic development in this region, including agriculture, energy, and fishery sectors. Therefore, high runoff variability associated with climate change can affect social security at national to regional scales (Eastham *et al.* 2008; Västilä *et al.* 2010). Recent monitoring-based studies have pointed out high exposure and vulnerability to extreme water events in the Mun River Basin. Prabnakorn *et al.* (2018, 2019a) reported that the rice cultivation in this basin had been regularly faced with drought, resulting in low yields. They expect that the yield losses will become substantial in the future with rising temperatures. Moderate to high drought vulnerability was also likely mainly due to low adaptive capacity (Prabnakorn *et al.* 2019a). Prabnakorn *et al.* (2019b) also report that the flooding in the Mun River Basin has been frequent, particularly in the upper and the middle parts. In contrast, the flooding in the lower part was less often but of extended duration (Prabnakorn *et al.* 2019b).

Previous studies on the effects of climate change on hydrological processes in the Mun River Basin reached inconsistent conclusions. Artlert & Chaleeraktrakoon (2013) studied long-term meteorological characteristics in the Mun-Chi-Mekong River Basins. They found increases in the annual maximum daily rainfall in the middle Mun River Basin but decreasing trends in the upper and lower basins. Furthermore, consecutive dry days (CDD) could increase in the Chi and eastern Mun River Basins (Artlert & Chaleeraktrakoon 2013). Consistent with the long-term trend, the climate simulations for the Mun River Basin in the year 2030 using HadCM3 and GCM3 models showed an increasing annual maximum daily rainfall in the middle region (Artlert & Chaleeraktrakoon 2013). The A1B and A2 scenarios increase CDD across the basin (Artlert& Chaleeraktrakoon 2013). These findings could imply a lowering of streamflow in the upper and lower Mun River basin. Li & Fang (2021) simulated streamflow for the Mun River under RCP2.6, 4.5, and 8.5. Their simulation resulted in increasing streamflow in the wet season (10.5, 20.1, and 23.3%, respectively) and slightly declining trends in the dry season (1.1–37.2%).

For the Northeast region of Thailand, the National Master Plan for Water Resource Management for the years 2018–2037 set the development direction toward enhancing water productivity for the agricultural sector and fulfilling future consumption demands in special economic zones (National Water Committee 2019). The National Water Committee (2019) claimed that adverse effects from climate change are recurring more often and becoming more intensified. Water retention and scavenging have been introduced to provide water security during the dry period. Integrated water administration has been encouraged to improve individual adaptive abilities to extreme water events, including drought and flood. Soil–water conservation practices have also been incorporated into the master plan. To attain the objectives of the master plan and cope with the extreme water events, the effects of future climate changes on the hydrological processes in this region have to be deliberated.

In response to the Paris Agreement's goal of limiting global warming to well below 2 °C, preferably to 1.5 °C, compared with pre-industrial levels, our studies employ the climate data for the year 2115 under the HAPPI experiment to investigate the possible effects of climate change on the water runoff in the Mun River Basin. Both 1.5 and 2 °C scenarios are considered. The studied outputs illustrate the magnitude of the future extreme water events as indicated from 100-year projected changes in the simulated 2115 surface runoff compared with the baseline in 2015. The results provide comparative evidence of the changes in surface water budgets that will enable policymakers to understand the spatial characteristics and magnitudes of the hydrohazard across the Mun River Basin.

This manuscript first introduces the research methodology, including data collection, preparation, data treatment, and streamflow simulation using the Soil–Water Assessment Tool (SWAT) model. In the results and discussion section, we present the results from model calibration and validation. Later climate change and streamflow change projections (annual and seasonal) in 2115 are presented and discussed.

2. METHODOLOGY

2.1. Study area

The Mun River Basin is part of the Lower Mekong Sub-Basin, which is located in Northeast Thailand. It has a total watershed area of 71,060 km^2, discharging approximately 9,563–45,534 Mm^3 (years 2006–2016 at the 50120 hydrological stations, 38.6 km from the confluence of the Mekong River; data acquired from the Department of Water Resource) annually to the Mekong River. The climate is influenced by the SEA monsoon system – prevailing southwesterly winds inducing the rainy season from July to October and northeasterly winds generating the winter season from December to February. Tropical cyclones generally develop in the Pacific Ocean and likely bring along high convective rainfall to the region from August to October (Hydro-Informatics Institute 2018). Mean rainfall increases from west to east from 870 mm yr^{-1} in the western or upper part to 1,758 mm yr^{-1} in the eastern or lower part (see Figure 1). The lowest streamflow months are from April to May, and the high-water months are September to November. River discharges at the monitoring stations referred to in this study are detailed in Table 1.

The dominant soil type across the Mun River Basin is yellowish or reddish sandy loam. The soil in the upper region is a more clayey texture and has higher organic content than the lower part (Wu *et al.* 2019). The upper basin is characterized by undulated highland. Land use here is mainly for cultivating field crops (sugarcane, maize, cassava, etc.) and orchards. Slopes complex soil type is often found (8.2%), resulting in high flow velocity and soil erosion. Several large dams (Lam Takhong Dam, Mun Bon Dam, Lam Sae Dam, Lam Nang Rong Dam, and Lam Phra Phleong Dam) and reservoirs have been constructed to retain sufficient water for cultivation and consumption next dry season.

In the middle part of the basin, brownish silty loam soil is dominant (9.8%), and it exhibits poor drainage, low fertility, and a pH of 5.0–6.0. The basin is flat, and rice fields predominate. Furthermore, there is a salt rock formation in the Lam Choengrai sub-basin and the Lam Sa Thaet sub-basin, resulting in high water salinity, especially in the dry season (Bridhikitti *et al.* 2020). The main Mun River is meandering due to high water flow but low velocity. Since it has poorly draining soil and no major dams, this zone has historically been flood-prone.

The lower basin is also potentially flood-prone due to the influxes of the Chi River and the Mekong River. Rice fields and rubber plantations predominate the basin. Soil with loamy texture and medium to low fertility (7.7%) and soil with a sandy layer topped

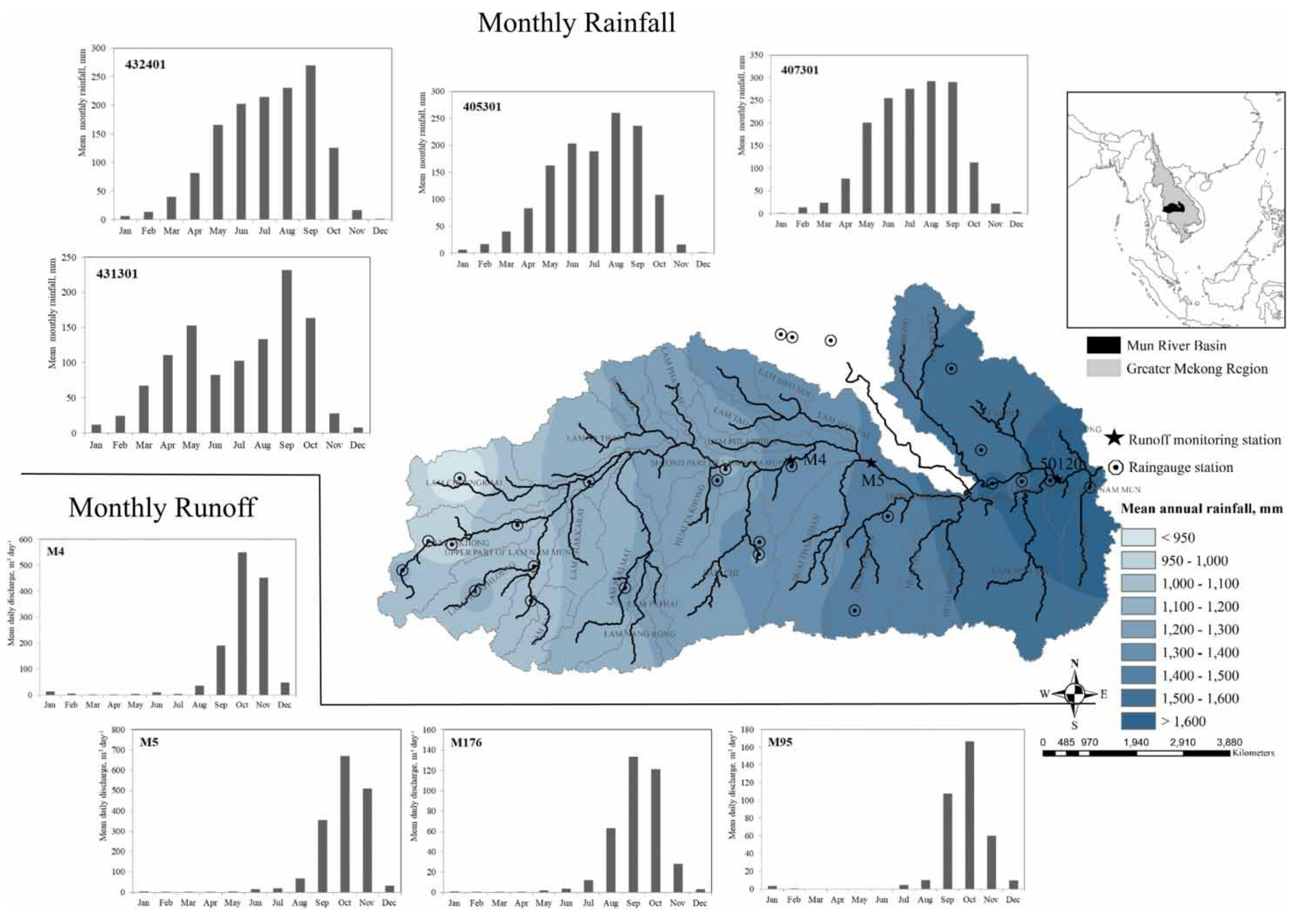


Figure 1 | Annually and monthly cumulative rainfall at the selected rain gauge stations and RID monthly discharges distributed across the Mun River Basin.

Table 1 | River discharges at the hydrological stations in years 2006–2016

Hydrological stations	SWAT sub-basins (see Figure 2)	Sub-basins	Average daily discharge, m^3 day^{-1} (minimum, maximum)			
			Driest month		High-water month	
M4	Sub-basin 8	Huai Aek, Lam Phang Su, Lam Sa Thaet, The 2nd part of the Mun River Basin, Huai Ta Khong, Lam Phlappha	Mar	1.0 (0, 9.1)	Oct	566.6 (160.6, 1,239)
M5	Sub-basin 5	The 2nd part of the Mun River Basin	Mar	8.1 (0.3, 26.9)	Oct	1,015.5 (196.8, 2,255.7)
50120	Sub-basin 9	Huai Tung Lung, The lower part of the Mun River Basin, Lam Dom Noi	Feb	317.8 (94.1, 665)	Oct	2,491.3 (749, 4,131.3)

over a clayey layer (6.7%) are often found. One large dam in Lam Dome Noi, Sirindhorn Dam, and three dams in the main Mun River (Hua Na Dam, Rasi Salai Dam, and Pak Mun Dam) were installed to secure sufficient water in the dry season.

2.2. Data collection

Datasets used as inputs to the SWAT include a digital elevation model (DEM), surface runoff, reservoir operation, land use, soil properties, and meteorological characteristics. The datasets are detailed below.

SRTM DEM (Shuttle Radar Topography Mission Digital Elevation Model) has a spatial resolution of 1 arc-second (~30 m). The DEM was acquired for 2018 from the United States Geological Survey (USGS).

Daily runoff from the years 2006 to 2016 was acquired from the Royal Irrigation Thailand (RID) and the Department of Water Resources (DWR) for one inlet from the Chi River (RID E20A station) and three monitoring stations for model calibration and validation in the Mun River Basin. The stations were M4 (RID) – the 2nd part of the Mun River Basin, M5 (RID) – the 2nd part of the Mun River Basin, and 50120 (DWR) – the lower part of the Mun River Basin to the Mekong River (see Figure 1).

The release rate and operational information of seven large dams were acquired from the RID and the Electricity Generating Authority of Thailand (EGAT). These details include monthly storage, monthly outflow, monthly consumption, reservoir surface area, the volume of water needed, initial reservoir volume, initial sediment concentration, median particle diameter, and hydraulic conductivity of the reservoir bottom. The reservoirs (see Figure 2) are Lam Takhong Dam, Mun Bon Dam, Lam Sae Dam, Lam Nang Rong Dam, Lam Phra Phleong Dam, and Sirindhorn Dam. Their monthly outflow

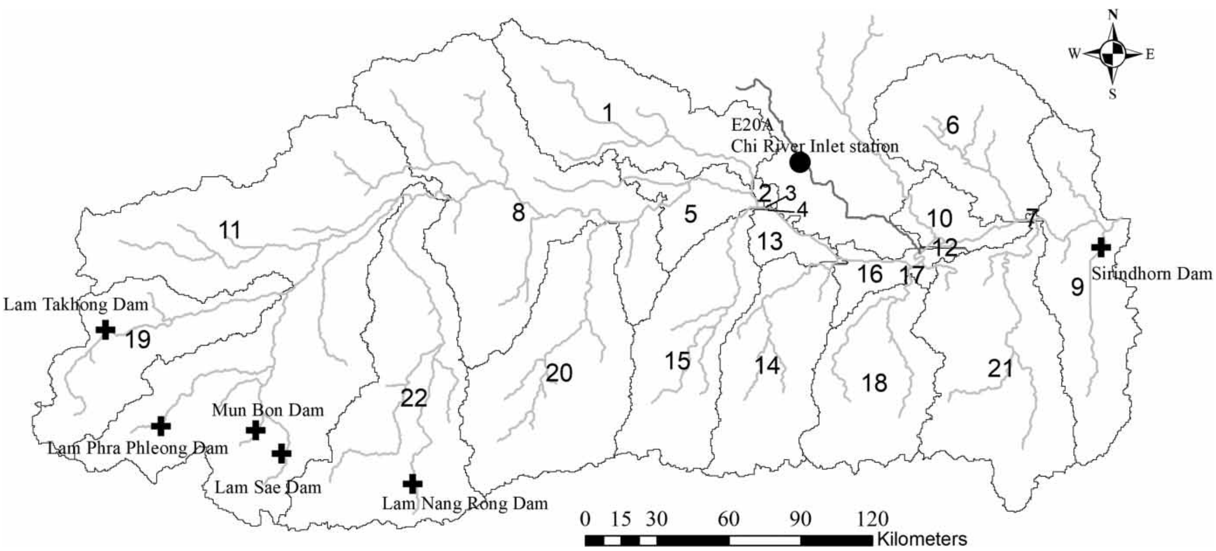


Figure 2 | The 22 SWAT sub-basins and locations of the Chi River inlet station and the dams referred to in this study.

was used in model calibration and validation. This study, however, did not include the operational data for the three in-stream dams (Hua Na Dam, Rari Salai Dam, and Pak Mun Dam) in the 3rd part and lower part of the Mun River.

Land-use data for 2015–2016 were utilized and were acquired from the Land Development Department (LDD), Thailand, as a polygon shapefile and later converted to raster format. Land-use attribution follows SWAT codes, which are URBN (built-up land), RICE (paddy field), AGRR (field crops), AGRL (integrated farm, horticulture), RUBR (perennial crops), ORCD (orchard), PAST (pasture and farmhouse), WETL (aquatic plant), WATR (aquaculture land, water body), and FRST (forest lands).

A polygon shapefile soil map and user soil look-up table were developed based on the soil series database acquired from the LDD, Thailand. A total of 90 soil series was included.

Daily meteorological data at 13 stations (see Figure 1) were acquired from the Thai Meteorology Department (TMD) from 2006 to 2016. The data included rainfall, maximum temperature, minimum temperature, relative humidity (RH), and wind speed.

2.3. Simulated climate data

Climate data were simulated from the HAPPI Tier-1 experiments in this study, comprising three scenarios – All-Hist, Plus1.5, and Plus2.0. The 'All-Hist' scenario was based on observed sea surface temperature from 2006 to 2015 resulting in approximately 0.8 °C warmer than the pre-industrial level (Chevuturi *et al.* 2018). The 'Plus1.5' scenario was 1.5 °C warmer than the pre-industrial level, exhibiting boundary conditions from the representative concentration pathway (RCP) 2.6 of the Coupled Model Inter-comparison Project Phase 5 (CMIP5). The 'Plus2.0' scenario was 2.0 °C warmer than the pre-industrial level, having a weight combination of RCP2.6 and RCP4.5 (Mitchell *et al.* 2017).

The Model for Interdisciplinary Research on Climate, version 5 (MIROC5) climate model, contributing to HAPPI, was chosen for the climate simulations. The model was developed by the Atmosphere and Ocean Research Institute (University of Tokyo), the National Institute for Environmental Studies, and the Japan Agency for Marine-Earth Science and Technology (JAMSTEC). The MIROC5 couples with atmosphere, ocean, land surface, and sea-ice models (Watanabe *et al.* 2010). The atmosphere components include spectral dynamical core, radiation, cumulus convection, cloud and cloud microphysics, turbulence, and aerosols. The ocean component includes general circulation and physical parameterization. The land component includes lakes, river routing, snow, and ice albedo. Climate products used in this study were precipitation flux (Pr), minimum near-surface air temperature (Tasmin), maximum near-surface air temperature (Tasmax), near-surface RH (Hurs), and having a grid resolution of 150×150 km on a daily basis (Shiogama 2019). Sixty ensemble members for the 'All-Hist' scenario for the year 2015 (run101 to run160) and 100 members for the 'Plus1.5' scenario and the 'Plus2.0' scenario each for the year 2115 were used for the analysis in this study. The simulated climate parameters were acquired from the National Energy Research Scientific Computing Center (NERSC), U.S. Department of Energy portal via https://portal.nersc.gov/c20c/data.html.

Bias correction for the grid simulation in 2115 was implemented using point measurements at the 13 meteorological stations. First, residuals of the subtraction of the observed minimum temperature, maximum temperature, RH, and rainfall flux for the year 2015 from the simulated 'All-Hist' scenario in 2015 were distributed for each daily simulation. Later, the distributed residuals were added to the projected 'Plus1.5' and 'Plus2.0' scenarios, creating 60,000 possible members. Finally, the probability distribution of the bias-corrected members for the year 2115 was created, and values at 10th, 50th, and 90th percentiles were used for the SWAT analysis.

2.4. SWAT simulation

The SWAT is a hydrological model designed to address water quality and quantity under various land–water management, climate scenarios, land-use changes, and agricultural practices (Kheereemangkla *et al.* 2016; Mohammed *et al.* 2018; Shrestha *et al.* 2018). The SWAT has been widely used to investigate the hydrological response to environmental changes, including the watersheds in Northeast Thailand. Kheereemangkla *et al.* (2016) applied the SWAT to investigate the impacts of various land management scenarios for the Chi River Basin. Similarly, Akter & Babel (2012) employed the SWAT to assess water quality in connection with land uses, and their findings could be helpful for sustainable land management. Shrestha *et al.* (2018) focused their study on the small sub-watershed of the Songkhram River in NE Thailand. Effects on the streamflow and water quality were assessed using the SWAT model simulation.

The SWAT can be interfaced with ArcGIS, ArcSWAT, providing flexible applications. In this study, ArcSWAT 2012.10.24 software (acquired online from https://swat.tamu.edu/software/arcswat/) interfaced with ArcGIS 10.5 simulated the streamflow under the projected climate scenarios. In the watershed delineator, a total of 22 sub-basins and 147 hydrologic response units (HRUs) were obtained. The streamflows simulated for sub-basin 8, 5, and 9 were calibrated and validated with those observed at M4, M5, and 50120, respectively (see Figure 1). A total of 66,689.75 km^2 SWAT watershed was created, covering 93.85% of the Mun River watershed area. In HRU analysis, the slope was classified to 0–2, 2–5, and >5%. Threshold values for the HRU module were 10% land-use percentage over the sub-basin area, 10% soil class percentage over land-use areas, and 10% slope class percentage over the soil area. The HRU analysis showed dominant HRUs for each sub-basin, as detailed in Table 2. Among these HRUs, we usually found RICE (68%) and AGRR (21%), flat terrain of 0–2% slope class (81%), and the soil series of Re (fine-loamy, mixed, subactive, isohyperthermic Aeric Kandisquults, 44%), Kt (fine-loamy, siliceous, isohyperthermic typic (Oxyaquic) Kandiustults, 23%), and SC – slope complex (18%).

Fifteen SWAT parameters (see Table 3) were calibrated, and they involved groundwater (.gw), land and water management practices (.mgt), HRU diversity feature (.hru), soil characteristics (.sol), and diversity of physical processes at the watershed level (.bsn). SWAT calibration was processed using the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) with the Sequential Uncertainty Fitting (SUFI) method. The calibration was done for the years 2006–2013 with a 2-year warm-up period. The validation was

Table 2 | Details on the SWAT sub-basins in this study

SWAT sub-basin	Sub-basin areas (Ha)	Dominant HRU land use/soil series[a]/% slope (% area covered)	Mun River sub-basin
1	415,825	RICE/Re/0–2 (52.90%)	Lam Tao, Lam Sieo Noi, Lam Sieo Yai
2	9,100	RICE/Re/0–2 (74.16%)	Lam Sieo Yai, The 3rd part of the Mun River Basin
3	100	RICE/Ac/0–2 (100%)	The 3rd part of the Mun River Basin
4	225	PAST/Ac/0–2 (56.28%)	The 3rd part of the Mun River Basin
5	126,775	RICE/Re/0–2 (47.21%)	The 2nd part of the Mun River Basin
6	355,475	RICE/Re/0–2 (38.05%)	Lam Se Bok
7	1,900	RICE/Kt/0–2 (34.02%)	The 3rd part of the Mun River Basin, The lower part of the Mun River Basin
8	797,500	RICE/Re/0–2 (65.65%)	Huai Aek, Lam Phang Su, Lam Sa Thaet, The 2nd part of the Mun River Basin, Huai Ta Khong, Lam Phlappha
9	389,475	RICE/Kt/0–2 (26.18%)	Huai Tung Lung, The lower part of the Mun River Basin, Lam Dom Noi
10	99,425	RICE/Kt/0–2 (20.67%)	Lam Se Bai, The 3rd part of the Mun River Basin
11	1,313,000	AGRR/SC/>5 (40.46%)	Lam Choeng Krai, Lam Phraphloeng, Lam Chakkarat, Lam Sa Thaet
12	1,125	FRST/Ac/0–2 (39.66%)	The 3rd part of the Mun River Basin
13	57,275	RICE/Re/0–2 (74.97%)	The 3rd part of the Mun River Basin
14	337,575	RICE/Re/0–2 (60.66%)	Huai Samran
15	362,150	RICE/Re/0–2 (74.95%)	Huai Thap Than
16	81,150	RICE/Re/0–2 (60.20%)	The 3rd part of the Mun River Basin
17	50	ORCD/Kt/0–2 (50.43%)	Huai Khayung
18	320,675	RICE/Re/0–2 (35.19%)	Hua Tha, Huai Khayung
19	338,700	AGRR/SC/5–9999 (26.99%)	Lam Takhong
20	524,250	RICE/Re/0–2 (52.26%)	Lam Chi
21	527,075	RICE/Kt/0–2 (42.18%)	Lam Dom Yai
22	610,150	RICE/Re/0–2 (25.28%)	Lam Plai Mat, Lam Pathai, Lam Nang Rong

[a]Re, fine-loamy, mixed, subactive, isohyperthermic Aeric Kandisquults; Kt, fine-loamy, siliceous, isohyperthermic typic (Oxyaquic) Kandiustults; Ac, mixed, isohyperthermic Fluventic Endoaquepts (Haplustepts); SC, slope complex.

Table 3 | 15 SWAT parameters and their initial values used in this study

SWAT parameters	Description	Unit	Ranges	Sub-basin 9			Sub-basin 5			Sub-basin 8		
				Best-fitted	Calibrated value	Sensitive rank	Best-fitted	Calibrated value	Sensitive rank	Best-fitted	Calibrated value	Sensitive rank
A_ALPHA_BF.gw	Baseflow alpha factor	day^{-1}	0.2–0.9	0.40	0.80	12	0.42	1.00	7	0.58	1.16	12
V_GW_DELAY.gw	Groundwater daily time	Days	60–350	82.2	82.2	8	99.0	99.0	13	84.4	84.4	10
V_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	mm H_2O	1,100–3,300	1,665	1,665	2	1,745	1,745	11	1,611.6	1,611.6	9
V_GW_REVAP.gw	Groundwater 'revap' coefficient	Unitless	0.0–0.3	0.27	0.27	14	0.24	0.24	10	0.20	0.20	5
V_REVAPMN.gw	Threshold depth water in the shallow aquifer for 'revap' or percolation to the deep aquifer to occur	mm H_2O	0–800	411.2	411.2	6	411.8	411.8	2	409.8	409.8	11
A_RCHRG_DP.gw	Deep aquifer percolation fraction	Days	0–1.0	0.26	0.52	1	0.34	0.68	3	0.29	0.58	1
V_CN2.mgt	Initial SCS runoff curve number for moisture condition II	Unitless	−0.2–0.1	0.09	33.7–63.7	4	0.17	33.7–63.7	6	0.10	33.7–63.7	13
A_EPCO.hru	Plant uptake compensation factor	Unitless	0.1–1.0	0.63	1.26	5	0.68	1.36	12	0.55	1.10	15
A_ESCO.hru	Soil evaporation compensation factor	Unitless	0.4–0.9	0.58	1.16	9	0.59	1.18	5	0.53	1.06	7
R_SOL_AWC.sol	Available water capacity of the soil layer	mm H_2O mm^{-1} soil	−20–70	0.61	3.1–135	15	0.60	3.1–135	1	0.55	3.1–135	2
R_SOL_K.sol	Saturated hydraulic conductivity	mm hr^{-1}	−31–40	1.17	30–40	10	1.40	30–40	15	1.15	30–40	6
A_SURLAG.bsn	Surface runoff lag time	Days	1–24	2.17	4.34	13	1.57	3.14	9	1.31	2.62	8
A_CH_N2.rte	Manning's n valve for the main channel	Unitless	0.1–0.3	0.10	0.20	7	0.10	0.20	8	0.15	0.30	3
A_CH_K2.rte	Effective hydraulic conductivity in main channel alluvium	mm hr^{-1}	40–75	60.1	120.2	3	63.2	126.4	14	61	121	14
A_ALPHA_BNK.rte	Baseflow alpha factor for bank storage	Days	0.1–0.5	0.20	0.40	11	0.20	0.40	4	0.25	0.50	4
Target SWAT sub-basins				9, 10, 11, 12, 17, 18, 19, 21, 22			1, 6, 7, 8, 13, 14, 15, 16, 20			2, 3, 4, 5		

from 2012 to 2016 with a 2-year warm-up period. Model performance was evaluated using the coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), percentage of observations covered by the 95% prediction uncertainty, (*P*-Factor), and percent bias (PBIAS) measuring the average tendency of the simulated data to be larger or smaller than the observations. The positive PBIAS value indicates model underestimation, and the negative value indicates model overestimation.

2.5. Data analysis

Changes in the rainfall, RH, and surface air temperatures from 2015 to 2115 were estimated by subtracting the simulated values at 10th, 50th, and 90th percentiles for 2115 from those observed for 2015. The estimating changes in streamflow also applied similar approaches using the SWAT-derived streamflow in 2015 and 2115. Median values (50th) for the changes were discussed and compared with the previous studies, whereas the 10th–90th range implies model uncertainty. Both annual and monthly changes in the streamflow were discussed. Furthermore, different streamflow responses on the climate changes among the sub-basins were also reported. The findings were later discussed for possible mitigation measures to cope with hydro-hazards attributed to climate change.

3. RESULTS AND DISCUSSION

3.1. Calibration and validation of the SWAT model

From Table 3, the parameters (top 5) responding to high model sensitivity for streamflow in the observing sub-basins (5, 8, 9) were groundwater parameters, which are deep aquifer percolation fraction (RCHRG_DP.gw), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN.gw), threshold depth water in the shallow aquifer for 'revap' or percolation to the deep aquifer to occur (REVAPMN.gw), and groundwater 'revap' coefficient (GW_REVAP.gw). As implied from the high sensitivity of SWAT groundwater parameters (.gw), the shallow aquifer and deep percolation zone were major contributors to the streamflow variation of the Mun River Basin. Furthermore, soil permeability, soil hydraulic conductivity, and channel characteristics also responded significantly to the streamflow as implied from the high sensitivity of runoff curve number (CN2.mgt), an available water capacity of the soil layer (SOL_AWC.sol), effective hydraulic conductivity in the main channel alluvium (CH_K2.rte), Manning's n valve for the main channel (CH_N2.rte), and baseflow alpha factor for bank storage (ALPHA_BNK.rte). The SOL_AWC.sol had a role to play in the streamflow in the middle part of the Mun River Basin (sub-basins 5 and 8), whereas its role in the lower part was not significant ($p>0.05$).

Figure 3 shows observed and SWAT-simulated streamflows at three hydrological stations. From Table 4, high R^2 (0.76–0.85 and 0.68–0.82 for calibration and validation, respectively) and NS coefficient (0.75–0.83 and 0.55–0.78, respectively) between the observed and the simulated for sub-basin 5 (represented by the M5 station), sub-basin 8 (M4), and sub-basin 9 (50120) suggest high goodness of fit. The fraction of observation covered the 95% prediction uncertainty (*P*-Factor) was $\geq$0.84, and it was in an acceptable range. However, the validated *P*-Factor for sub-basin 8 was low (0.52). Overall negative PBIAS indicates that the average tendency of the simulated data was higher than the observations for the Mun River Basin.

3.2. Climate change projection in 2115 compared with the 2015 base year

The changes in climate parameters in 2115 compared with the 2015 base year were projected under the HAPPI experiment and the MIROC5 climate model. Their anomalies are illustrated in Figure 4.

3.2.1. Air temperature

The 'Plus1.5' scenario showed an increase in the maximum temperature in the range of 1.06 °C (median) in October to 2.69 °C (median) in January and an increase in the minimum temperature from 0.48 °C (median) in November to 1.67 °C (median) in January. The 'Plus2.0' scenario showed an increase in the maximum temperature from 1.44 °C (median) in September to 3.06 °C (median) in January and increases in the minimum temperature from 1.05 °C (median) in November to 2.07 °C (median) in June.

Based on long-term observations, climate change trends toward warming across Thailand have been documented in many reports. Vongvisessomjai (2010) found an increasing maximum temperature from 1951 to 2007. Sharma & Babel (2014) found increasing numbers of warm days and warm nights and decreasing numbers of cold days and cold nights from 1961 to 2002 in western Thailand. Artlert & Chaleeraktrakoon (2013) reported an increase in the annual maximum number of CDD from 1961 to 1990. Furthermore, studies of future simulated air temperature reported in the work of Li & Fang (2021) also found a corresponding warming trend for the Mun River Basin (Li & Fang 2021).

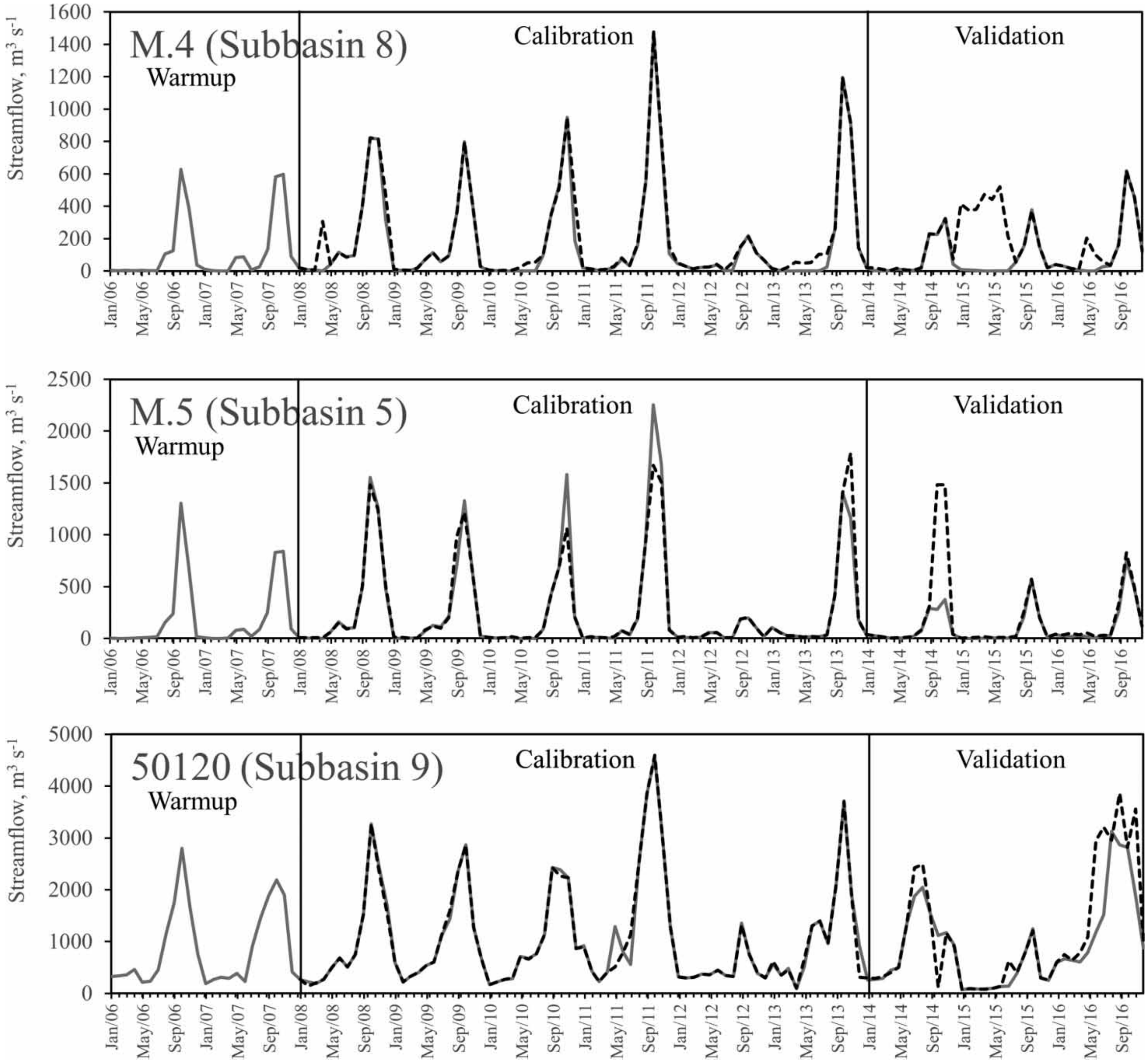


Figure 3 | Observed (solid gray line) and best-simulated (black dash line) streamflow for calibration (years 2006–2013) and validation (years 2014 to 2016).

Table 4 | SWAT model performance for calibration (the year 2006–2013, 2-year warm-up) and validation (the year 2014–2016, 2-year warm-up)

	Calibration/validation		
SWAT-CUP parameters	**Sub-basin 8**	**Sub-basin 5**	**Sub-basin 9**
R^2	0.85/0.80	0.76/0.68	0.84/0.82
NSE	0.76/0.78	0.75/0.55	0.83/0.76
P-Factor	0.88/0.52	0.84/0.87	0.96/0.87
PBIAS	−12.1/−11	−6.3/−13.7	−3.1/−13.1

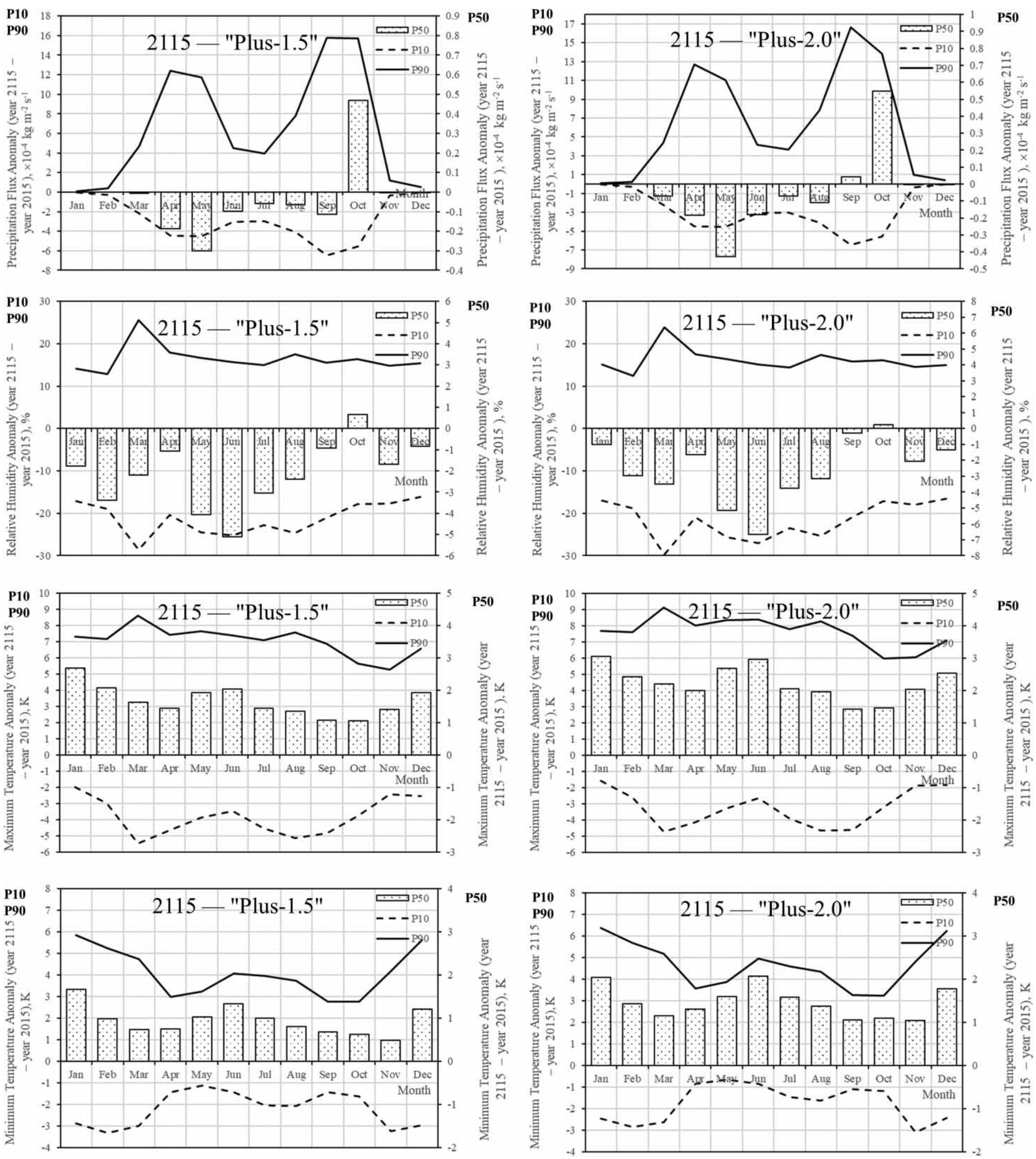


Figure 4 | Anomalous monthly HAPPI MIROC5 humidity, temperature (minimum and maximum), and precipitation flux for the simulated 1.5 °C warming scenario (Plus1.5) and the simulated 2.0 °C warming scenario (Plus2.0) in the year 2115 as compared with the 'All-Hist' scenario in the year 2015.

3.2.2. Atmospheric water

In the dry season from November to March, the median simulated climate in the year 2115 showed slightly changing monthly rainfall, -0.07×10^{-4} to 0 kg m^{-2} s^{-1} (-0.6 to 0 mm day^{-1}), from the base year (2015) in both 'Plus1.5' and 'Plus2.0' scenarios (see Figure 4). The median estimate rainfall greatly declined in the pre-monsoon month of May, -0.301×10^{-4} kg m^{-2} s^{-1}

(-2.6 mm day^{-1}) for the 'Plus1.5' scenario and -0.427×10^{-4} kg m^{-2} s^{-1} (-3.7 mm day^{-1}) for the 'Plus2.0' scenario. Increasing median estimated rainfall from the base year could be pronounced in the post-monsoon month of October, $+0.468\times10^{-4}$ kg m^{-2} s^{-1} ($+4.0$ mm day^{-1}) for the 'Plus1.5' scenario and $+0.548\times10^{-4}$ kg m^{-2} s^{-1} ($+4.7$ mm day^{-1}) for the 'Plus2.0' scenario. Additionally, a slightly increased rainfall could also be found in September under 'Plus2.0'. Furthermore, the large difference between the 10th and 90th predictions indicates high uncertainties and potential to precipitation extremes in 2115 pre-monsoon months (April and May) and the post-monsoon months (September and October).

As shown in Figure 4, the RH in 2115 could decline from the base year in both dry and pre-monsoon months. The median RH substantially decreased in May (−4.05% for the 'Plus1.5' scenario and −5.15% for the 'Plus2.0' scenario) and June (−5.10% for the 'Plus1.5' scenario and −6.66% for the 'Plus2.0' scenario). The median RH slightly increased in October (0.64% for the 'Plus1.5' scenario and 0.25% for the 'Plus2.0' scenario).

Previous historical data analyses in the literature using the datasets from 1953 to 2006 resulted in diverse conclusions on rainfall trends. Similar to our finding, the drying trend and the decline in annual precipitation across the country were reported in the work of Vongvisessomjai (2010). Under the extreme climate change scenario (RCP8.5), the negative annual cumulative rainfall (−10 to −20 mm) was projected in the Mun River Basin (Amnuaylojaroen 2021). Nonetheless, wetter trends in the Mun River Basin were reported in Lacombe *et al.* (2013), indicating increases in the dry-season rainfall, both intensity and frequency. Simulated rainfalls in the work of Li & Fang (2021) also showed high temporal variations in the rainfall projections. They found increasing trends in January (dry), May (pre-monsoon), August (monsoon), and December (dry). However, there were inconsistent trends among the 2030s, 2060s, and 2080s in the other months. Generally, in both rainy and dry seasons, the projected rainfall under RCP2.6 and RCP4.5 increased during the 2060s and 2080s but decreased during the 2030s (Li & Fang 2021). Kiguchi *et al.* (2021) also discussed significant variations in the projected rainfall and temperature among general circulation models (GCMs) for Southeast Asia. Thus, the uncertainty of streamflow simulations could be substantial.

3.3. Streamflow change projection in 2115

3.3.1. Annual streamflow

The projected annual streamflow is illustrated in Figure 5. The median streamflow in 2115 under 'Plus1.5' to the Mekong River (sub-basin 9) was estimated to be 47,066 Mm^3 yr^{-1}, which is −32.5% lower than the 2015 base flow (69,744 Mm^3 yr^{-1}). The 'Plus2.0' median streamflow to the Mekong River was slightly higher than that of the 'Plus1.5', which is 53,607 Mm^3 yr^{-1} and −23.1% of the base flow. The decline in the streamflow to the Mekong River was also found in the Songkhram River sub-basin in the Lower Mekong River Basin, NE Thailand. Shrestha *et al.* (2018) simulated climate changes using Regional Climate Models under IPCC AR5 RCPs of RCP4.5 and RCP8.5. They showed that climate change is responsible for a −19.5 to −24% decline in annual streamflow in the 2020s, 2050s, and 2080s for the Songkhram River sub-basin. Inconsistently, Li & Fang (2021) projected streamflow in the Mun River Basin based on IPCC CMIP5. They found increasing annual streamflow to the Mekong River from 2020 to 2093 by +10.5, +20.1, and +23.2 under RCP2.6, RCP4.5, and RCP8.5, respectively.

In previous studies, simulated streamflows in the Lower Mekong River reached consistent conclusions on significant flow variations. Thompson *et al.* (2013) employed a MIKE-SHE model to simulate future streamflow under a 2 °C increase in the global mean. There is high variation among seven GCMs, ranging from −20.6 to +16.5% at the Ubon Station, NE Thailand. The annual streamflow change under 2 °C at another nearby station at the Lower Mekong River, Pakse, ranged from −17.8 to +6.5% (Kingston *et al.* 2011).

The decline in projected annual streamflow in 2115 was pronounced in the upper part and lower part of the Mun River Basin. As shown in Figure 5, sub-basin 11 in the upper part (Lam Choeng Krai, Lam Phraphloeng, Lam Chakkarat, Lam Sa Thaet) and sub-basin 18 in the lower part (Hua Tha, Huai Khayung) exhibited the greatest decrease in the streamflow from the 2015 base year for both 'Plus1.5' (−68.4 and −59.0%, respectively) and 'Plus2.0' (−58.0 and −60.0%, respectively).

Despite the decline in the Mun River's outflow to the Mekong River, the increase in streamflow in the middle part of the basin (sub-basins 5 and 8) was projected. As shown in Figure 5, The annual simulated median streamflow in the year 2115 under the 'Plus1.5' warming scenario in this region was higher than the 2015 base flow of +30.1% in sub-basin 8 (21,386 Mm^3 yr^{-1}) and +24.2% in sub-basin 5 (21,996 Mm^3 yr^{-1}). A higher annual streamflow in the year 2115 in this region is expected under the 'Plus2.0' warming scenario. The estimated median streamflow for sub-basin 8 increased +53.7% (25,274 Mm^3 yr^{-1}), sub-basin 5 is +47.4% (26,092 Mm^3 yr^{-1}), and sub-basin 13 is +3.3% (33,243 Mm^3 yr^{-1} decision-aid tools).

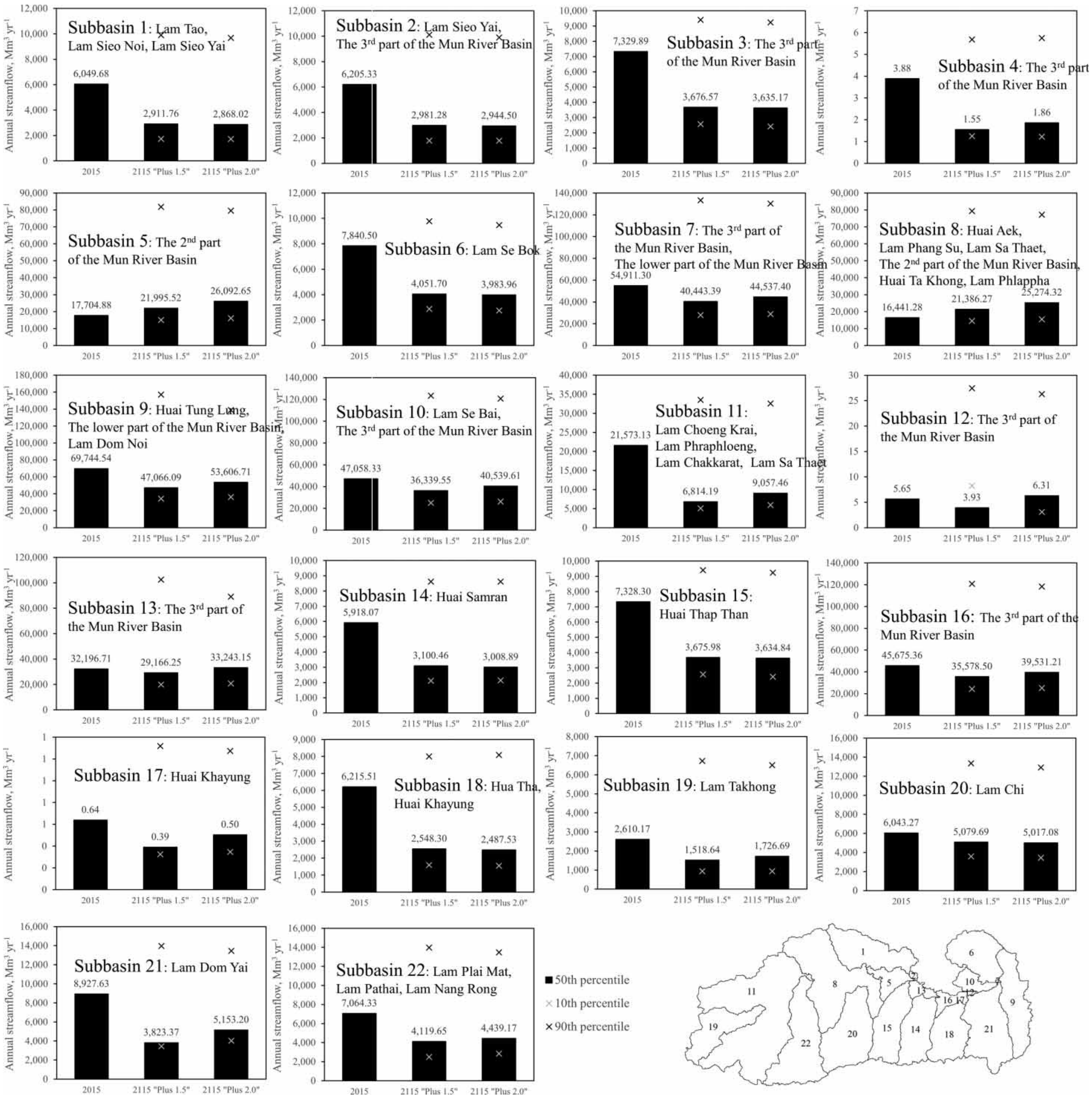


Figure 5 | Annual cumulative streamflow in 2015 (from Royal Irrigation Department) and 2115 simulated under 'Plus1.5' and 'Plus2.0' warming scenarios.

In the middle part of the Mun River Basin, the increasing median streamflow estimated for the sub-basins 5 and 8 corresponded well with increasing rainfall trends reported in the previous literature. Artlert & Chaleeraktrakoon (2013) reported spatial differences in rainfall changes in the Mun and Chi River Basins using UK HadCM3 and Canadian GCMs climate models under different emission scenarios in IPCC AR4. The model simulated an increase in the annual maximum daily rainfall changes of the 100-year return period in the middle Mun River Basin in the 2030s (+3.43 to +32.85 mm from the 1991–2007 base year) and decreasing trends for the upper and the lower parts (Artlert & Chaleeraktrakoon 2013). Nonetheless, their results showed high variations among the climate model simulations, with potential for severe impacts on floods and droughts in the basin (Artlert & Chaleeraktrakoon 2013).

3.3.2. Monthly streamflow

As shown in Figure 6, the projected monthly streamflow under the 'Plus1.5' warming scenario in the upper part of the Mun River Basin reveals possible drought in 2115, as decreasing streamflows are expected for most of the year. In sub-basin 19 (Lam Takhong), the median streamflow declines from −25.1% in October to −92% in February but increases in September (+35%). In sub-basin 11 (Lam Choeng Krai, Lam Phraphloeng, Lam Chakkarat, Lam Sa Thaet), the drought is more pronounced for the entire year, and the median streamflow changes can range from −9.6% in March to −97% in June to July. Under the 'Plus2.0' warming scenario, the dry-season drought is less pronounced, with increasing streamflow that could be found in January (+13.5% for sub-basin 19 and +41.1% for sub-basin 11) and February (+38.1% for sub-basin 11).

In the middle part of the Mun River Basin in the dry season from November to April in 2115, the streamflow under the 'Plus1.5' warming scenario was higher than that of the 2015 base year. As shown in Figure 6, the estimated median dry-season streamflow in 2115 increased from +13.2 to +87.3% in this region. The dry-season increasing streamflow could also be found for 10th and 90th percentile climate projections (see Figure 6). Conversely, in the rainy season from June to August, monthly streamflow was expected to decline −3.6 to −55.3%. In September, when the monsoon was fully developed, the median streamflow in the middle Mun River Basin in 2115 suddenly increased from the base year (2015), which was +101.3% for sub-basin 5 and +120.2% for sub-basin 8. Under the 'Plus2.0' warming scenario (Figure 6), the projected median streamflow in the year 2115 also exhibited higher streamflow in the dry season and lower streamflow in the wet season. The decline in rainy-season median streamflow was expected from July to October (−6.1 to −40.1% for sub-basins 5 and 8). The dry-season streamflow increased significantly and was even higher than the projected under the 'Plus1.5' scenario. The projected median streamflow rose 80.8% (sub-basin 5) and 88.9% (sub-basin 8) in November to 250% (sub-basin 5) and 248.4% (sub-basin 8) in January. The finding expects drought mitigation in the dry season but higher flooding potential, especially in September for the middle basin.

Under the 'Plus1.5' warming scenario, the lower part of the Mun River Basin (sub-basin 9) was expected to have a monthly streamflow reduction in the year 2115, except for January. The decline was from −16.1% in February (dry season) to −71.4% in June (rainy season). This finding indicates possible severe drought, especially in the dry season, and significantly lower streamflow to the Mekong for the entire year of 2115. An increase in dry-season streamflow under the 'Plus2.0' warming scenario was expected to last longer than projected under the 'Plus1.5' scenario. The increasing median streamflow from the base year 2015 to the year 2115 was likely to be from January (+69.6%) to April (+22.1%). The decline in median streamflow was

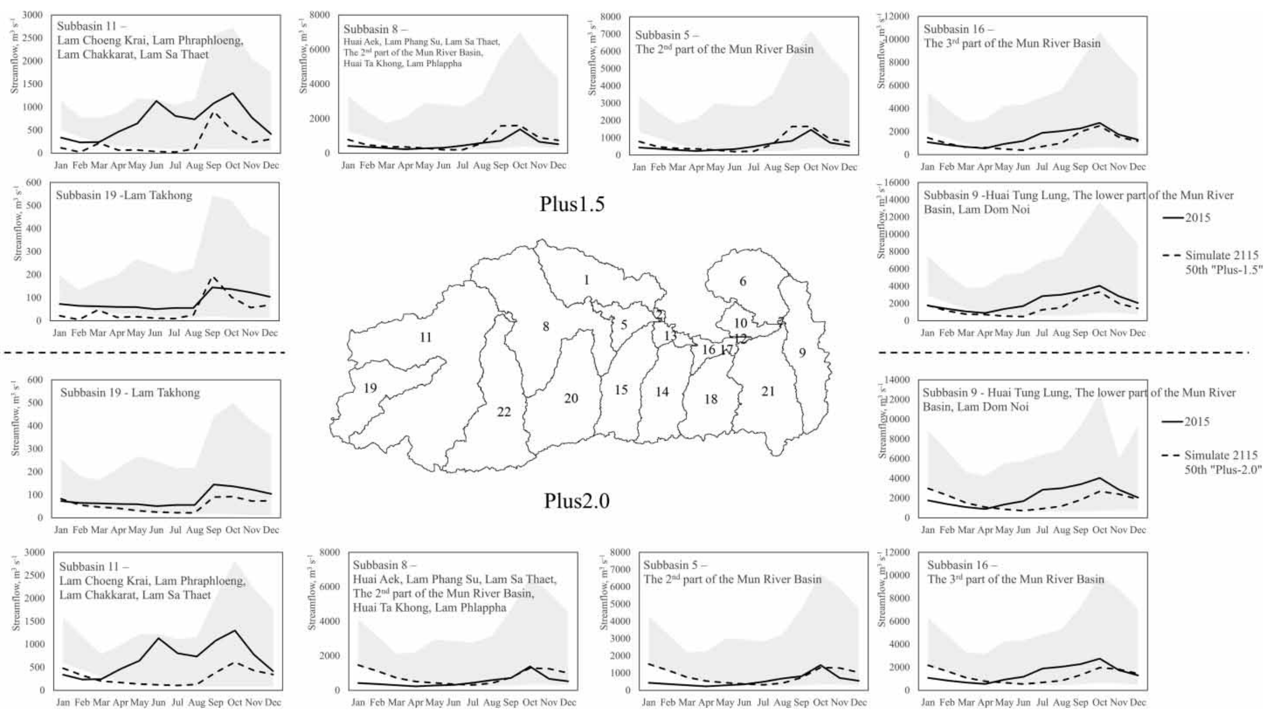


Figure 6 | Simulated monthly streamflow in 2015 (base year), shown in dashed line, and simulated streamflow in years 2115 under 'Plus1.5' and 'Plus2.0' scenarios, shown in solid line (a gray area indicates 10th–90th prediction interval).

expected for eight consecutive months from May (−35.6%) to December (−8.96%), with the greatest drop being in July (−67.3%). Li & Fang (2021) also projected a −1.1 to −37.2% decline in dry-season streamflow in the Mun River Basin from 2020 to 2093 under the CMIP5 climate projection. Shrestha *et al.* (2018) simulated future streamflow in the Songkhram River sub-basin in the Lower Mekong River Basin using Regional Climate Models under RCP4.5 and RCP8.5. They reported a decline in the streamflow of −21 to −34.5% in the 2080s during both dry and rainy seasons. The decreasing streamflow in the dry season could be induced by accelerating evaporation due to warm temperature (Li & Fang 2021). Eastham *et al.* (2008) projected rainfall in 2030, and they found a decreasing trend in NE Thailand, which experienced a high level of water stress.

Our finding that climate change under 'Plus2.0' warming induces more streamflow in the dry season and less streamflow in the rainy season across the Mun River Basin agreed well with the conclusions in Kingston *et al.* (2011). They showed increasing flows during April and June (pre-monsoon) and decreasing flows during July and August (fully developed monsoon) at the Chi-Mun discharge station. However, there are various conclusions on the projected streamflow for the Mun River. Västilä *et al.* (2010) projected increasing water levels and flood duration in the Lower Mekong floodplains from 2010 to 2049, and they expected positive impacts on ecosystems.

4. FURTHER DISCUSSION

4.1. Factors influencing inconsistent conclusions of climate change-induced rainfall and streamflow anomalies among climate models across the SEA region

The SEA region has two distinct geographic characteristics: the SEA mainland and archipelago. The Indian Ocean influences the region to the west and the Pacific Ocean to the east. Thus, air–sea fluxes could substantially promote air mass exchanges and cumulus formation. Therefore, different parameterizations among climate models could yield significantly diverse conclusions, particularly for this region. Juneng *et al.* (2016) investigated the performance of many climate models in simulating rainfall over SEA. They pointed out that the lack of air–sea interactions in the model could produce unrealistic anomalous responses to surface temperature. They also suggest further studies on the roles of convective rainfall and land surface interaction processes to improve the model predictability. In our study, we employed 60 ensemble members for the 'All-Hist' scenario for the year 2015 and 100 members for the 'Plus1.5' scenario and the 'Plus2.0' scenario each for the year 2115 to capture the diversity of model parameterizations under the HAPPI experiment. Significant variations in 10th–90th percentile values could imply high sensitivity on rainfall anomaly in response to the model parameterizations.

Dam and reservoir operations could have a role to play in the simulated streamflow. In this study, dam operation was included in the streamflow simulation but not for in-river dams (Hua Na Dam, Rari Salai Dam, and Pak Mun Dam) in the 3rd and lower parts of the Mun River. This could cause substantial uncertainty in projected streamflow, especially in the lower part of the Mun River. Such high variation associated with the dam effect was pronounced in the case of the Lower Mekong River. Lauri *et al.* (2012) conducted a streamflow simulation from 2032 to 2042 and found that the changes in streamflow in the Mekong River at Kratie (Cambodia) were from −11 to +15% for the wet season and −10 to +13% for the dry season. The effect of dam operation in the Mekong River is highly responsible for the streamflow variation, and it might override the impacts from climate change (Lauri *et al.* 2012).

4.2. Factors inducing differences in spatial response on rainfall and streamflow anomalies across the Mun River Basin

Geographical characteristics are highly responsive to the differences in hydrological budgets. Mountainous highlands lie along the western to the southern part of the basin, resulting in lower rainfall induced by the leeward effects of the southwesterly winds. The eastern part is often hit by tropical cyclones, seasonally visited from August to October (Hydro-Informatics Institute 2018). As climate change progresses, more frequent and intense tropical cyclones are expected (Wehner *et al.* 2018). This could partly contribute to there being more rainfall in the post-monsoon months (September and October) under both 'Plus1.5' and 'Plus2.0' across the Mun River Basin (see Figure 4). In September, simulated streamflow positive anomalies were also found in many sub-basins in the upper and middle parts (see Figure 6), and the tropical cyclones should play a role.

In the upper and lower part of the Mun River Basin, the decreasing annual streamflows were projected with a slightly different magnitude between those under 'Plus1.5' and 'Plus2.0' warming scenarios (see Figure 5). However, the conclusion is different for the middle part – sub-basins 5, 8, and 13 – where the streamflow tends to increase in the dry season and decrease in the wet season, except September. As shown in Figure 5, these sub-basins in the middle part are aligned in the main Mun River. This diverse pattern should be partly associated with long-term increasing rainfall trends, as increasing annual maximum daily rainfall at rain gauge stations in the middle part of the Mun and Chi Rivers was observed by Artlert & Chaleeraktrakoon (2013). Artlert & Chaleeraktrakoon (2013) also reported a consistent increase in the annual maximum number of CDD in the lower part of the Mun River Basin. Furthermore, saline soil predominant in the middle part induces a capillary rise of saline groundwater (Tatsuno *et al.* 2005), probably resulting in lower water infiltration and soil–water content, and higher surface runoff.

4.3. Proposed mitigation measures tackling hydrological hazards associated with climate change in the Mun River Basin

Our findings conclude that drought will be severe, especially for the upper and lower part of the basin under the 'Plus1.5' scenario, and confirm the dire requirement of water retention infrastructures, e.g., dams, reservoirs, and ponds, to maintain sufficient water in the dry period. Dam operation needs reliable and quantitative rainfall and streamflow forecasts for several months in advance to mitigate the effects of extreme water, both flooding and water shortages (Kiguchi *et al.* 2021). Smart farming and smart farmers are recommended to tackle the impacts of climate change for Thailand. Farmers should be educated and equipped with decision-making tools. As a result, farmland management and crop water requirements could become more sustainable (Kiguchi *et al.* 2021). Furthermore, the extended dry period could result in crop yield reduction. Therefore, drought-tolerant crop varieties and drought-mitigating agricultural technology are strongly recommended to maintain food security.

In the middle part of the basin, higher streamflow could be expected. The projected streamflow in the 3rd part of the Mun River Basin (sub-basin 16, see Figure 6) is likely to increase in the dry season (+14% in April to +35.4% in January) but decrease in the rest of the year. Presently, three in-river dams (Hua Na Dam, Rasi Salai Dam, and Pak Mun Dam) are installed in the mainstream between the middle and lower parts of the basin. Therefore, dam operation and other adaptive measures in this region are crucial to compromise imbalance streamflow between the middle and lower parts and mitigate hydro-hazards in response to long-term climate change. The possible adaptive measures recommended in this region include applications of various soil–water conservation measures in agricultural lands to minimize runoff-induced water quality degradation, soil loss/erosion, and sediment disasters during high flow events (Bridhikitti *et al.* 2021, 2022).

5. CONCLUSION

In this study, streamflow in the year 2115 in the Mun River Basin was simulated using the SWAT under average global warming of 1.5 °C (Plus1.5) and 2.0 °C (Plus2.0) above pre-industrial levels. This climate change scenario relies on the Project HAPPI, and the MIROC5 is employed. The 10th, 50th, and 90th percentiles of the simulated climate products in 2115 were created and reported from 60,000 possible members.

Monthly outflow from major reservoirs and daily inflow from the Chi River were used for the streamflow analysis. The simulation covered 66,689.75 km^2, 93.85% of the total Mun River watershed area, and consisted of 22 sub-basins and 147 HRUs. The SWAT model provides a coefficient of determination (R^2) of 0.76–0.85 and 0.68–0.82, NSE of 0.75–0.83 and 0.55–0.78, percentage of observations covered by the 95% prediction uncertainty (*P*-Factor) of 0.84–0.96 and 0.52–0.87, and PBIAS of −12.1 to −3.1 and −13.7 to −11.0 for calibration and validation, respectively.

The MIROC5 precipitable water and RH product estimate declined substantially in rainfall and humidity throughout the year 2115, except for the post-monsoon month of October under 'Plus1.5' and September to October under 'Plus2.0', when the anomalies were minimum or positive. Observing the negative corresponding air temperature and RH suggests that the warmer temperatures might generally suppress rainfall. Nonetheless, uncertainties associated with rainfall projection are substantial for the pre- and post-monsoon months.

The SWAT model showed a considerable decline in the median estimated annual streamflow in 2115 to the Mekong River for both 'Plus1.5' (−32.5%) and 'Plus2.0' (−23.1%) scenarios. The decline in annual streamflow was also expected in the upper part, which is the most significant reduction in sub-basin 11 (Lam Choeng Krai, Lam Phraphloeng, Lam Chakkarat, and Lam Sa Thaet). Positive streamflow anomalies, however, were expected in sub-basin 5 (the 2nd part of the Mun River Basin) and sub-basin 8 (Huai Aek, Lam Phang Su, Lam Sa Thaet, the 2nd part of the Mun River Basin, Huai Ta Khong, and Lam Phlappha) in the middle part of the Mun River Basin.

In the middle part of the Mun River Basin (sub-basins 5 and 8), the projected seasonal streamflow anomaly in 2115 under the 'Plus1.5' warming scenario was significantly positive (+13.2 to +87.3%) in the dry season from November to April. However, the projected streamflow in the rainy season declined (−3.6 to −55.3% from June to August), but in September. Under the 'Plus2.0' warming scenario, the projected dry-season streamflow anomaly in the year 2115 was expected to be positively higher than the projected under the 'Plus1.5' scenario. In the rainy season, the streamflow anomaly from the 2015 base year to 2115 was expected to decline for both 'Plus1.5' (−3.6 to −55.3% from June to August) and 'Plus2.0' (−6.1 to −40.1% from July to October).

In the upper and lower parts of the Mun River Basin, the projected streamflows under the 'Plus1.5' warming scenario declined (up to −97% in June–July for sub-basin 11) for most of the year 2115. The dry-season streamflow under the 'Plus2.0' warming scenario was expected to increase from the 2015 base year and even higher than the 'Plus1.5' warming scenario.

Based on the above evidence, drought could intensify with an extended period of low streamflow in the upper and lower basins, and adaptive measures against drought are strongly recommended. In the middle basin, drought risk could be less pronounced in the dry season, but severe flooding might occur in September. The difference in streamflow trends between the middle and lower parts of the basin requires proper reservoir/dam operation and other adaptive measures to compromise the imbalance water budgets and mitigate risk associated with the hydro-hazard. Future research for sustainable water resource development should focus on forecasting the streamflow, developing proxies for predicting extreme water events, and developing decision-aid tools for effective hydro-infrastructure operations and farmland management.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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