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Correcting streamflow bias considering its spatial structure for impact assessment of climate change on floods using d4PDF in the Chao Phraya River Basin, Thailand

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ABSTRACT

Study region: Chao Phraya River Basin (CPRB), the predominant basin located in Thailand.
Study focus: This study aims to ascertain the difference between spatial bias heterogeneity of streamflow in large river basins such as CPRB for a robust analysis. The upstream major dams and the outlet of the basin were examined with two-step bias correction and compared with a more practical bias correction only at the outlet of the basin. The former clarified that, due to the large effect of downstream bias, the upstream bias effect was considered negligible thus the two approaches resulted in similar future projections in the CPRB. Through this comparison, streamflow bias in the past and future climate experiments was corrected considering its spatial characteristics for robust assessments of quantitative impacts of climate change.
New hydrological insights for the region: A + 4 K warmer climate will increase the frequency of the 2011 flood in CPRB and enhance 100-year flood peak discharge by 1.1–1.6 times than the past climate (1961–2010). The future flood in the basin, which starts predominantly in September in the present climate, is likely to begin in September and August equally with a prolonged duration of floods around 10–50 days. The study region is likely expected to experience elevated flood volume, earlier flood occurrence, and longer flood duration which indicates that forthcoming floods will be more rigorous.

1. Introduction

The Chao Phraya River Basin (CPRB) is the principal river basin occupying 30% of Thailand's geographical extent and inhabiting 40% of the country's total population. It has been endowing livelihood, employment opportunities, and developing country's agronomics contributing to 66% of Gross Domestic Product (Abhishek et al., 2021; Gunawardana et al., 2021). This basin has been under continuous ramifications of floods, droughts, land subsidence, urbanization, increase in population, etc. especially affecting the lower delta region (Hogendoorn et al., 2018; Loc et al., 2020; Park et al., 2021). Over 3000 dams have been built in the CPRB since 1950 to store monsoon rains and increase agricultural potential during the dry season. Bhumibol and Sirikit Dams are the two substantially large dams, controlling 22% of the runoff from the total basin territory (Bond et al., 2018). Various episodic hydro-meteorological events have hit the CPRB in the past couple of decades such as floods in 2006, 2011, and 2021; droughts in 2015–2016, and 2019–2020, affecting millions of people and causing a large economic damage (Loc et al., 2020; Abhishek et al., 2021). As a result, for

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CPRB sustainability, knowing the influence of climate change and its effect on future extreme events is a prerequisite.

Innumerous studies have been carried out on climate change impact assessments on river discharge and water availability (Li et al., 2016; Hughes and Farinosi, 2020; Budhathoki et al., 2021; Casale et al., 2021; Jahandideh Tehrani et al., 2021). Environmental, ecological and socio-economic sectors, such as agriculture, industry, hydropower, and biodiversity protection, rely on the ability to estimate water availability under varying climatic circumstances and hydrological changes, both in the near and far future (Li et al., 2016; Didovets et al., 2020; Liu et al., 2021; Wannasin et al., 2021). According to regional impact assessments in Thailand, the country will experience a change in high-intensity rainfall falling between − 5% in the dry season to raising to 36.5% in the wet season annually (Champathong et al., 2013; Chaowiwat et al., 2019). Studies with several general circulation models (GCM) show that average annual discharge, as well as maximum annual flows, will surge up between 6.8% and 38.4% with rising rainfall in the CPRB towards to end of the 21st century (Kure and Tebakari, 2012; Hunukumbura and Tachikawa, 2012; Ligaray et al., 2015).

Despite reduced uncertainty in climate change projections at the global scale owing to compiled evidence (AR6), catchment-scale future change projections are still varied, which is possibly due to high uncertainty associated with the large impact of internal climate variability on extreme precipitation that cannot be captured with limited ensembles (Peel et al., 2015). Therefore, previous works on climate change impact assessments on floods in Thailand are limited to overall tendencies such as mean or variance, and hard to give a robust estimate of frequency changes in extreme with a limited sample size such as the 2011 flood event. To overcome this issue, huge ensembles covering the internal climate variability as much as possible are required for the impact assessments of extreme floods. The database for(4) Policy Decision making for Future climate change (d4PDF) has therefore been developed (Mizuta et al., 2017) with tens (50–100) of ensembles for 60-year simulation in the non-global warming, past (1951–2010), and future climates for + 1.5 K, + 2 K, and + 4 K degree increase in global mean temperature. The d4PDF has been employed in a variety of climate change impact studies looking into river discharge, floods, tropical cyclones, storm surges, etc. (Lavender et al., 2018; Mori et al., 2019; Tanaka et al., 2020; Ninomiya et al., 2021). Therefore, d4PDF has the potential of detecting future changes in extreme flood characteristics.

The d4PDF, however, still contains the model bias even after achieving such huge ensemble simulations (Tanaka et al., 2019; Watanabe et al., 2020) and hence, a prominent approach for addressing biases in GCM outputs is the quantile-quantile mapping (QQM) bias correction technique is used for enhancing the accuracy of climate forecasts and hydrological simulations (Piani et al., 2010; Tong et al., 2018). In this method, the GCM data of a grid cell is adjusted using the QQM, which links observation climate data from the same or surrounding grid cells and has been found to be very efficient at eliminating biases from climate model outputs while keeping shifts in climate frequency and variance (Ines and Hansen, 2006; Elshamy et al., 2009). Many streamflow impact assessments lag the correlation structure in their bias that needs to be considered (Maraun, 2016). This issue would be critical in the CPRB where approximately 80% of precipitation is consumed by evapotranspiration, i.e. runoff is considered a residual in terms of the water cycle (Wichakul et al., 2014; Zhao et al., 2022). Therefore, as an alternative, bias correction to GCM runoff data has been lately called to attention to reduce the uncertainty and results show improved river discharge calculations (Ibarra et al., 2021), in particular in Thailand or the Indochina peninsula (Duong et al., 2013; Ram-Indra et al., 2020a). However, it is still challenging due to the necessity of preparing reference runoff data that requires precise land surface simulations. A more direct approach, streamflow bias correction is considered in a few studies (Farmer et al., 2018), possibly due to the combination of small observation/simulation sample size, runoff bias heterogeneity, and human intervention such as dam control and/or irrigation. Due to the long record of streamflow observations and large ensemble climate simulations such as d4PDF, the sample size issue can be addressed. Nevertheless, the later factors need regional-scale analysis of bias structure in the selected river basin. After the spatial bias structure is clarified with rigorous discussions, streamflow bias correction could be adopted as a strategy. Although such a basin-specific approach is hard to apply uniformly to the entire globe, is crucial to compile regional studies for a comprehensive understanding as a whole.

This study aims to discuss robust streamflow bias correction in the CPRB considering spatial contrast in bias between upstream and downstream and to present impact assessments on floods using d4PDF. There is a unique topography of the CPRB where the inflows to the Bhumibol and Sirikit Dams represent upstream mountainous catchments. Hence, we explore the upstream GCM bias and the corrected inflows at the two major dams following to middle stream bias which is corrected at Nakhon Sawan, a major stream gauge in the downstream area. Additionally, we compare the two-step bias correction with the bias correction of simulated discharge only at Nakhon Sawan (single-step bias correction). Based on the general efficacy of the two-step bias correction and its performance in the CPRB, the bias-corrected d4PDF is applied in the basin to analyze its future floods in a + 4 K warming condition.

Therefore, this study explores a unique method of spatial bias correction of simulated discharge using large climate ensembles for probabilistic future floods projection in the basin to avoid drastic damage like in the 2011 Thailand Flood. Additionally, an insightful aspect on changes in reoccurrences, commencing month and time span of future floods due to the effects of climate change is elaborated in this study. This quantitative impact assessment based on huge ensemble climate simulations with robust bias correction can be advantageous for future flood risk assessment, damage estimations, and policymaking in the CPRB.

2. Material and methods

2.1. Study area

The CPRB, (99°000 E–101°300 E, 13°150 N–17°000 N) is considered to be the largest river basin situated in Thailand which spans about a length of 1352 km and a drainage area of 170,000 km^2 from the Shan plateau in the northwest part of Thailand reaching to the south to the Gulf of Thailand. The Ping (36,018 km^2), Wang (11,708 km^2), Nan (34,557 km^2), and Yom (24,720 km^2) are the four major tributaries in the basin. Fig. 1 shows that from the Northern Mountain territories, the Ping and Wang tributaries amalgamate with the Nan and Yom tributaries at Nakhon Sawan province which is the middle part of CPRB, and forms the Chao Phraya River. The river then runs down and passes through Ayutthaya and Bangkok (capital) provinces before releasing to the Gulf of Thailand.

The climate in the basin is hot and humid, affected by an Asian tropical monsoon in the north and mild throughout the year in the south which is faced with the marine climate. The basin comprises two seasons, January to April is considered to be the dry season whereas May to December is considered to be the wet season. The monthly average temperature in the basin is 22–28 °C with slight

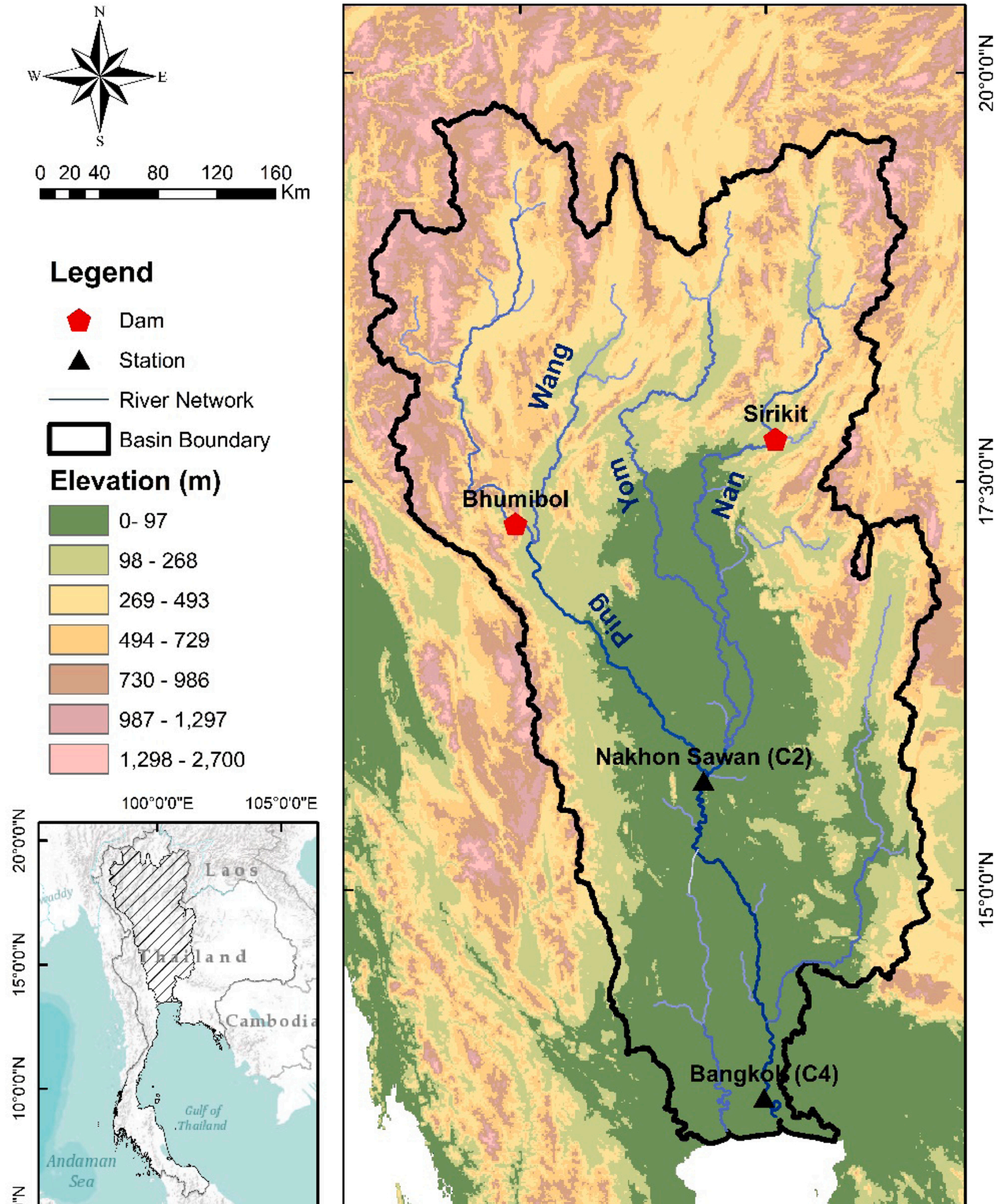

Fig. 1. Study area of the Chao Phraya River Basin.

changes. Average rainfall of 1220 mm in the northern mountains, 1360 mm in the central and 1875–2000 mm in the southern area occurs in the basin, out of which 85% of the rainfall and increasing the river discharge happens during the monsoon season (May to December). The water quantity in CPRB changes promptly with seasons with approximately ten times the difference between wet and dry seasons. The basin experiences peak discharge during September and October.

People in Thailand typically reside in the floodplains since the area is suitable for farming and agriculture. The central provinces receive a huge quantity of water practically every year due to their steep terrain and extensive forests (60%of area) in the upper CPRB, causing floods in low-lying regions along the Yom and Nan Rivers. In 2011 a great catastrophic flood-hit Thailand with the people residing in the low-lying areas of the Chao Phraya River was vastly affected. Around 2 million people were affected with a fatality of 400 people. Tentatively, 1400 mm of rainfall occurred alone in the wet season of 2011, resulting from flood-hit five typhoons and depressions that hit the northern part of the CPRB. Over 3000 dams have been built in the CPRB since 1950 to store monsoon rains and increase agricultural potential during the dry season. The Bhumibol and Sirikit Dams are the two huge dams in Ping River and Nan River respectively, whose purpose is hydropower generation, irrigation, flood control, and salinity intrusion management. During the mid of April 2011, 45% of Bhumibol and 51% of Sirikit dam were filled, which increased to 95% on both dam reservoirs by 05 October and 14 September 2011 (Komori et al., 2012; Mateo et al., 2014; Loc et al., 2020; Park et al., 2021).

In October 2011, Nakhon Sawan received a peak discharge of 4686 m^3/s. Approximately USD 46.5 billion of economic damage and loss ravaged Thailand during the 2011 flooding (Sayama et al., 2015).

2.2. Data

2.2.1. Observed data

The observed inflow at the Bhumibol and Sirikit Dams is provided by the Electricity Generating Authority of Thailand (EGAT). The one at the C2 station (Nakhon Sawan) was collected from the Royal Irrigation Department (RID). Table 1 shows the details of the data collected and its sources for the CPRB study.

2.2.2. d4PDF data

The d4PDF is created by the joint project of the Meteorological Research Institute of Japan Meteorological Agency, Atmosphere and Ocean Research Institute of the University of Tokyo, Disaster Prevention Research Institute of Kyoto University, National Institute of Environmental Study, Japan Agency for Marine-Earth Science and Technology (JAMSTEC), and University of Tsukuba (http://search.diasjp.net/en/dataset/d4PDF_RCM_3D_Plev) in order to project the future climates at various global warming levels by running numerous climate simulations using a high-resolution global atmospheric model AGCM-3.2 at a 60-km resolution and then dynamically downscaling with a regional atmospheric model at a 20-km resolution around Japan (Mizuta et al., 2017). Hence the global climate experiment was used in this. For both experiments, four climate scenarios: the non-global warming, the past, 2-degree/4-degree warmer climates were employed. In this study, the boundary conditions were based on Mizuta et al. (2017) where the past climate simulation was driven by the observed sea surface temperatures (SST) and sea ice for 60 years from 1951–2010 with 100 variations of small perturbation comparable to observation errors yielding 6000-year data in total (hereinafter, past climate experiment); the future climate simulation was driven by six representatives of the projected SST patterns (see Table 2) from CMIP5 (Mizuta et al., 2017) with the same perturbation setting and performed for 60 years yielding 5400-year data (Mizuta et al., 2017; Ishii and Mori, 2020). These SST models have been used in several studies around the globe for climate change projections for various applications. Chen et al. (2022) study the future variation of extreme precipitation from Southern China to North-East Asia using the d4PDF data. Yang et al. (2018) assess the past and future storm surges in the Korean peninsula. Similarly, using d4PDF data, the future flood risks on significant river basins of Japan along with its economic damage were analyzed (Tanaka et al., 2020, 2021). Apart from wide global implementation, these six SST models have been used in the nearby region, the Mekong river basin which is a transboundary basin in East and Southeast Asia for the assessment of uncertainty in water resources and projection of flood inundation (Try et al., 2020; Meema et al., 2021). Based on these, this study uses the most-widely used the combination of the past climate experiment and the 4-degree rise scenario in global mean temperature (hereinafter, the 4-degree rise experiment) (Mizuta et al., 2017; Mori et al., 2019) to explore the impact of the most severe temperature increase on flooding in the CPRB.

2.3. Overall methodology

The overall methodology opted in the study is shown in Fig. 2. This study simulates streamflow through river routing simulations from runoff outputs of d4PDF (the details are described below). The most controversial point of this approach is neglecting spatial bias structure in climatic variables as well as runoff. Hence, this study proposes to incorporate bias correction for upstream dam inflows at

Table 1
Details of the data used in the Chao Phraya River Basin.

Station ID	Station Name	Type	Location	Frequency	Duration	Source
BB	Bhumibol	Dam Inflow	Ping	Daily	1965–2011	EGAT, Thailand
SK	Sirikit	Dam Inflow	Nan	Daily	1974–2011	EGAT, Thailand
C2	Nakhon Sawan	Discharge	Chao Phraya	Daily	1979–2017	RID, Thailand

Another requirement for hydrological modeling other than hydro-meteorological data is topographic data.

Table 2
AGCMs selected and their details used in the study (Mizuta et al., 2017).

SST Model	Driving GCM	Institute	Country
CC	CCSM4	National Centre for Atmospheric Research,	USA
GF	GFDL CM3	Geophysical Fluid Dynamics Laboratory	USA
HA	HadGEM2-AO	National Institute of Meteorological Research	Korea
MI	MIROC5	Univ. Tokyo and Japan Agency for Marine-Earth Science and Technology (JAMTEC)	Japan
MP	MPI-ESM-MR	Max Planck Institute for Meteorology	Germany
MR	MRI-CGCM3	Meteorological Research Institute	Japan

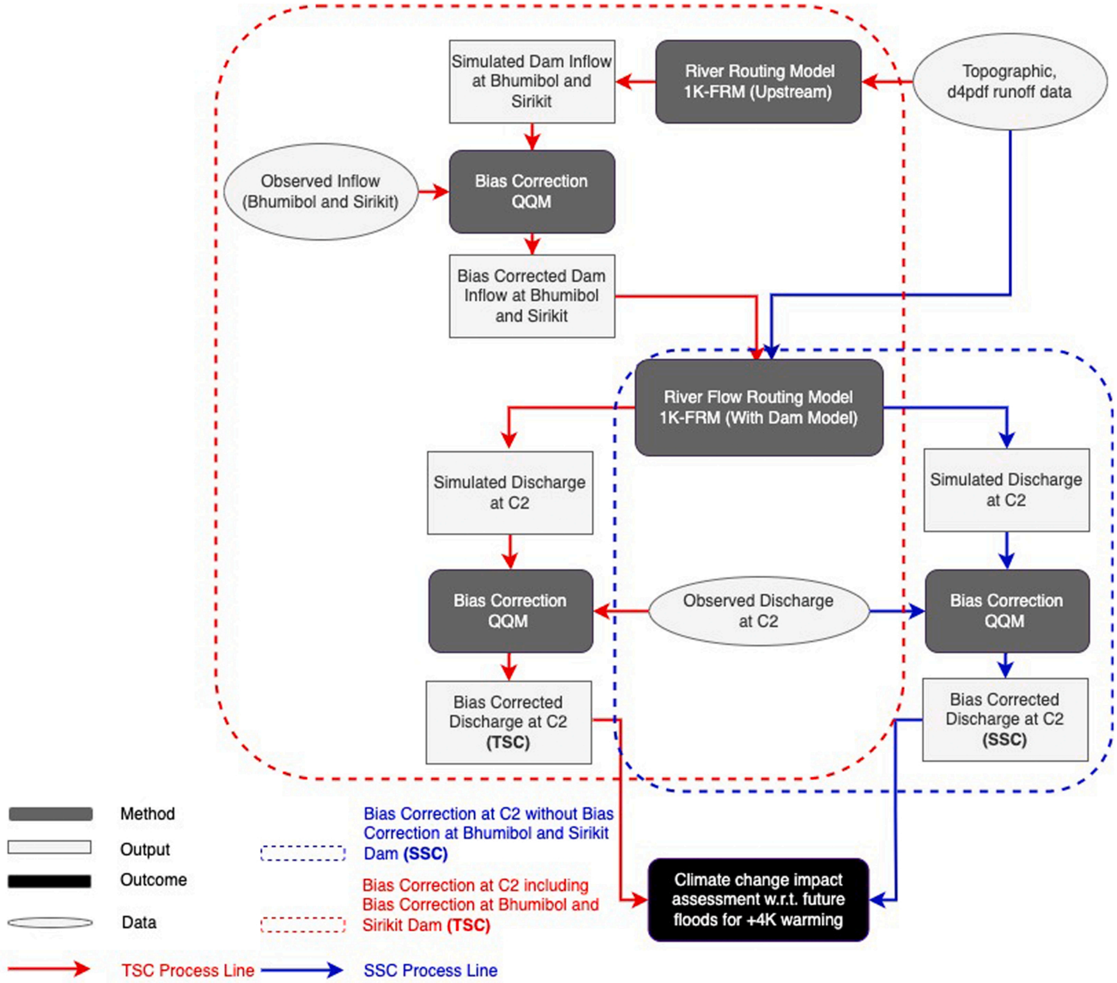

Fig. 2. Overall methodological framework opted in the study basin. The light gray oval box represents the data used in the study; dark gray rectangular box represents the method opted in the study; light gray box represents the model outputs; and black box represents the outcome and arrow represents the respective method flowlines of the study.

BB and SK before the direct correction at the downstream station (hereinafter, Two-Step Correction (TSC)) as shown in the red-colored dotted box. As a far more straightforward alternative, we also test the blue-colored dotted box which shows the bias correction at C2 without bias correction at two upstream dams of the basin (hereinafter, Single-Step Correction (SSC)). Indeed, SSC is a commonly used bias correction method by quantile mapping. We then compare the results of the two approaches and examine how enough effective SSC is compared to TSC as a more complicated method. We opt for this validation because CPRB contains contrasting basin climates between upstream and midstream areas. Bias-corrected streamflow data at C2 was then analyzed to evaluate the impact of climate change on flood peak/volume, its duration, and the starting season. The details of the methodological steps are shown in the following sections.

2.3.1. River flow routing model

1 K-FRM, a distributed river flow routing model with a spatial resolution of 10 km was used in this study (https://hywr.kuciv.kyoto-u.ac.jp/products/1K-DHM/1K-DHM.html). To convert the runoff generated by a land surface model (SiBUC) embedded in the GCM into a river discharge, this kinematic wave model is used where all the rectangular units channel the water downstream based on flow direction. The continuity equation for each rectangular unit is shown in Eq. (1).

$$\frac{\partial Q}{\partial t}+\frac{\partial A}{\partial x}=q_L(x,t) \tag{1}$$

where, t: time; x: distance from the rectangular unit's top (m); A: cross-sectional area (m^2); Q: discharge (m^3/s); $q_L(x,t)$: the lateral inflow per unit length of channel unit given as d4PDF runoff generated by MRI AGCM 3.2 (m^3/s).

MRI-AGCM 3.2 outputs 3-hour averaged surface and baseflow runoff, both of which were added as $q_L(x,t)$ in the continuity equation Eq. (1). The one-dimensional momentum Manning's equation was used to route the water which regulates the open channel flow characteristics.

$$Q = \alpha A^m \tag{2}$$

$$\alpha = \frac{\sqrt{i_0}}{n}\left(\frac{1}{B}\right)^{m-1} \tag{3}$$

where, i_0: slope; n: Manning's roughness coefficient; m is the river cross-sectional parameter (=5/3); the model parameters of the flow model B which is the width of flow is determined by $B = aS^c$, Here, S is the catchment area at the calculated points, and $a = 1.06$ and $c = 0.69$ are constant parameters. The value of n is determined to be 0.03 $m^{-1/3}$ s for the channel when the catchment area at the calculated point is larger than 250 km^2 and 11.0 $m^{-1/3}$ s for the slope when the catchment area is smaller than 500 km^2 (Tachikawa et al., 2011; Duong et al., 2013). The topological dataset is hydrological data and maps based on 30-second digital elevation and flow direction data, Shuttle Elevation Derivatives at Multiple Scales (HyDroSHEDS) (Lehner, 2005) upscaled at 10-km spatial resolution for the flow routing model 1 K-FRM (Duong et al., 2013). The downstream area of the Yom River (see Fig. 2) is frequently flooded in the middle stream area, which was expressed by applying the following linear reservoir model to downstream cells:

$$\frac{dS}{dt}=I-Q \tag{4}$$

$$S = kQ \tag{5}$$

where S is the flooded storage, I is the upstream inflow discharges to a target cell, Q is the river discharge considering the delay due to inundation around the cell, k is the model parameters indicating the delay of flood peaks between inflow I and river discharge Q.

Duong et al. (2013) used 1 K-FRM to compare the changes in flow for the past and future climate under changing climate for the Indochina Peninsula. In order to well represent the spatially distributed topography of the Chao Phraya River Basin, this flow routing model was successfully used by Wichakul et al. (2013) and Hunukumbura and Tachikawa (2012).

2.3.2. Dam operation

The monthly operations of the Bhumibol (1.3 billion m^3) and Sirikit (0.9 billion m^3) dams were modeled to store water during the wet season and release it during the dry season based on Wichakul et al. (2013), which estimated normal downstream water resources demands as 200 m^3/s for the Bhumibol dam and 250 m^3/s for the Sirikit dam. Further, during the wet season, the amount of water discharged was governed by a minimum/maximum reservoir storage capacity and spillway capacity. When reservoir storage was less than maximum, both dams released roughly 15% and 30% of the natural inflow to sustain downstream flow. Due to the limited storage capacity of the dam, they must entirely release the water when a dam's storage capacity approaches its limit (6000 m^3/s and 3200 m^3/s for the Bhumibol and Sirikit dams, respectively).

2.3.3. Bias correction

Numerous studies have used QQM for GCM bias correction for a variety of climatic variables (Mishra and Herath, 2011, 2015; Bennett et al., 2014). These studies targeted a single model ensemble and corrected its bias from observation data with comparable record lengths. Such procedures become complicated when multiple ensembles are available like d4PDF used due to far larger sample size than observation data. There are several possible ways of bias correction, particularly for the selection of model quantiles to compare with observation ones: each ensemble, aggregation of all members, a median member as a baseline, and an arbitrary ensemble as a baseline. Chen et al. (2019) investigated the difference in performance among them and verified that the median ensemble-based correction showed robust performance. A similar approach was applied by Tanaka et al. (2020) that estimated the median of d4PDF ensembles at each percentile as a baseline to compare with observation ones. Hence, in this analysis, the same method was employed: the median of 100 ensembles is calculated in order to identify the bias correction factors.

The QQM procedures are formulated as follows:

$$R_i = \frac{F_{\mathrm{obs}}^{-1}\left(F_{\widetilde{X}_{\mathrm{raw},i}}\left(\widetilde{x}_{\mathrm{raw},i}\right)\right)}{\widetilde{x}_{\mathrm{raw},i}} \tag{6}$$

where, R_i is the bias correction factor for i-th order statistics of the target variable $(i = 1, 2, \ldots, 60)$; $\widetilde{x}_{\mathrm{raw},i}$ is the median of a target streamflow variable among 100 ensembles; $F_{\widetilde{X}_{\mathrm{raw},i}}(x)$ is its empirical cumulative probability; $F_{\mathrm{obs}}^{-1}(P)$ is the inverse function of the empirical cumulative probability P of the observation data for the target variable. Unambiguously, the bias correction factors are determined such that among 100 ensembles of 60-year data, the cumulative probability of their median match that of observation as for the target variable. As described in the results and discussions, the target variables are wet (May to December) and dry (January to April) season total inflows and the flood volume (total volume over 2000 m^3/s) at C2, all of which are annual data. Then, the raw simulation daily discharge at the day d in the i-th rank year for the target variable, $Q_{\mathrm{raw},i}(t)$ is corrected to $Q_{\mathrm{bc},i}(d)$ by:

$$Q_{\mathrm{bc},i}(d) = \quad R_i Q_{\mathrm{raw},i}(d) \tag{7}$$

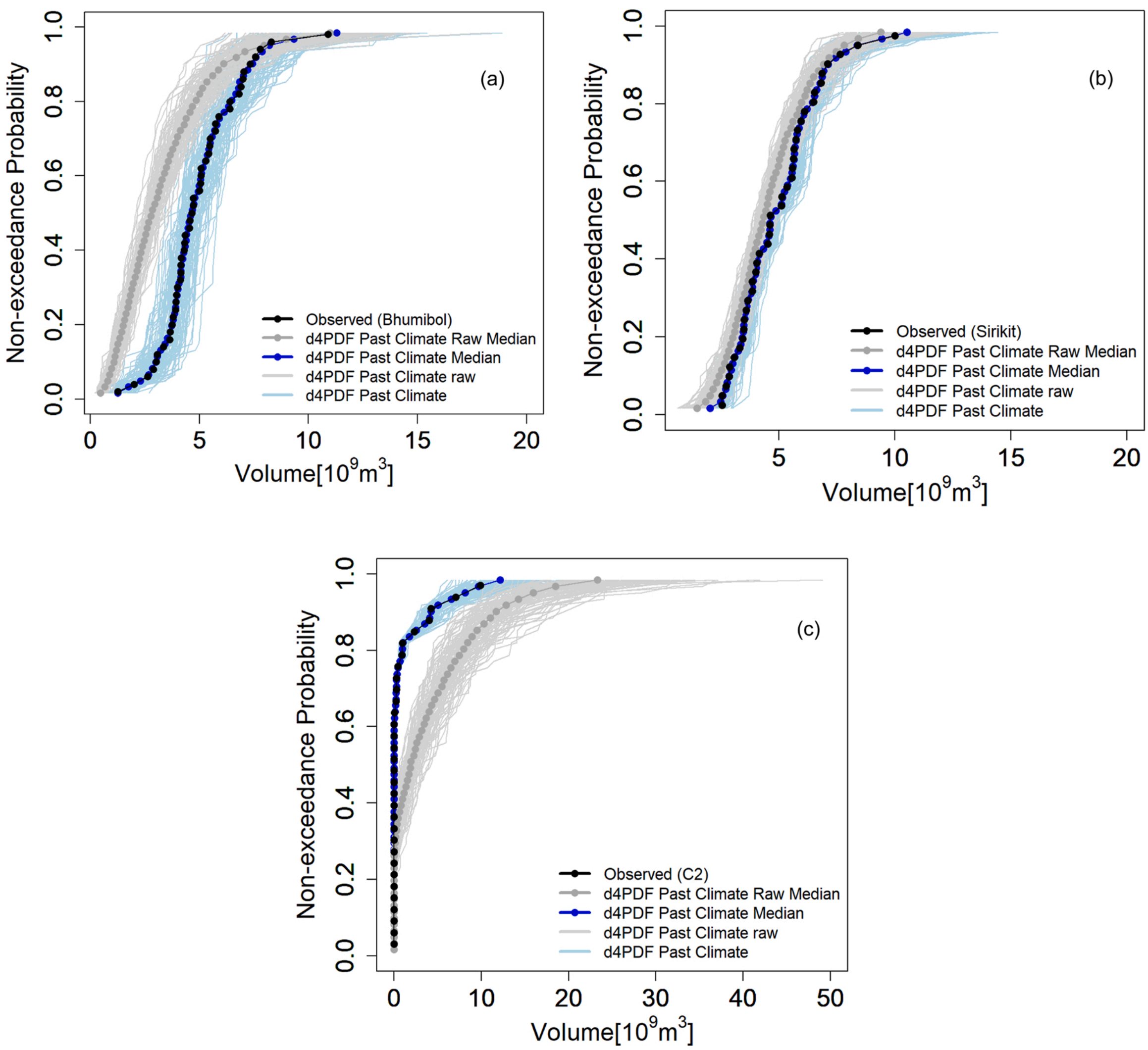

Fig. 3. Cumulative probability plot of observed (black dots), raw (light-gray lines), and corrected (light-blue lines) ensemble for wet season volume at (a) Bhumibol, (b) Sirikit, and (c) for flood volume at C2. The gray dots show the median of raw ensembles as a baseline of bias correction. The median of corrected ensembles (blue dots) perfectly matches observation data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Results and discussions

3.1. Past climate simulation

The raw d4PDF runoff data for 100 ensembles were first used in the river flow routing simulation with 1 K-FRM. The simulated 100 ensemble dam inflows to BB and SK were sorted and for each dam, their median was calculated at each percentile as a baseline to calculate the bias ratio by Eq. (6). Fig. 3(a) and (b) show the cumulative probability plot of d4PDF dam inflows before/after bias correction. The raw d4PDF data (gray) are underestimated in comparison to the observed data (black) for both dams. After the bias correction, the median of corrected data (blue) should match the observation and as the result, each corrected ensemble spreads around the observation plot. The corrected daily inflow data was again input to 1 K-FRM to simulate downstream river discharge with dam operations and middle stream inundation as described above.

The cumulative plot at C2 is shown in Fig. 3(c). As per RID, the downstream part of the CPRB has a discharge capacity of 2000 m^3/s over which flooding occurs. Thereby, the bias correction at the C2 station is done for the total amount of discharge over 2000 m^3/s (hereinafter, flood volume). After streamflow simulations with bias-corrected dam inflows, it is found that in contrast to the dam inflows, downstream river discharge overestimated the observed data, which implies that middle stream runoff was overestimated. As demonstrated here, the final output of river discharge is often affected by spatial heterogeneity of runoff (or its original climate) bias, even resulting in the opposite direction; therefore, we suspected that the presence of bias correction at upstream dams (SSC or TSC) will affect the future projections of downstream streamflow. Therefore, this study further investigated its impact as a case study in the CPRB.

The magnitude of bias in wet-season streamflow volume for the inflows at the upstream dams and middle stream river discharge at C2 was compared in Fig. 4. It shows that bias in the Bhumibol dam is higher than in the Sirikit dam. We can also observe that the bias in the wet-season volume at C2 is much larger than the bias in Bhumibol, and Sirikit dams as well as their total, indicating that the

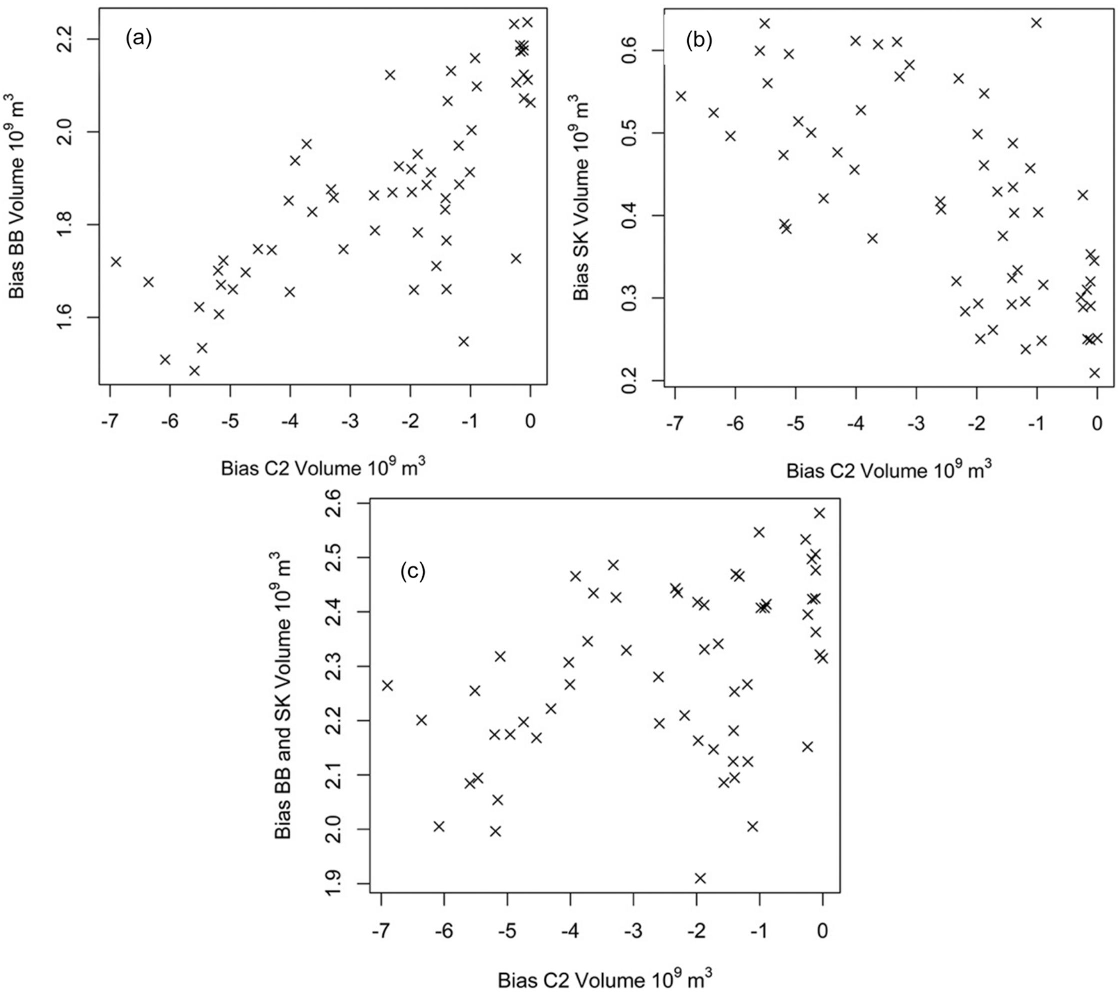

Fig. 4. Scatter plot between bias of wet-season volume in the (a) Bhumibol and (b) Sirikit dams and (c) their total with respect to that at C2.

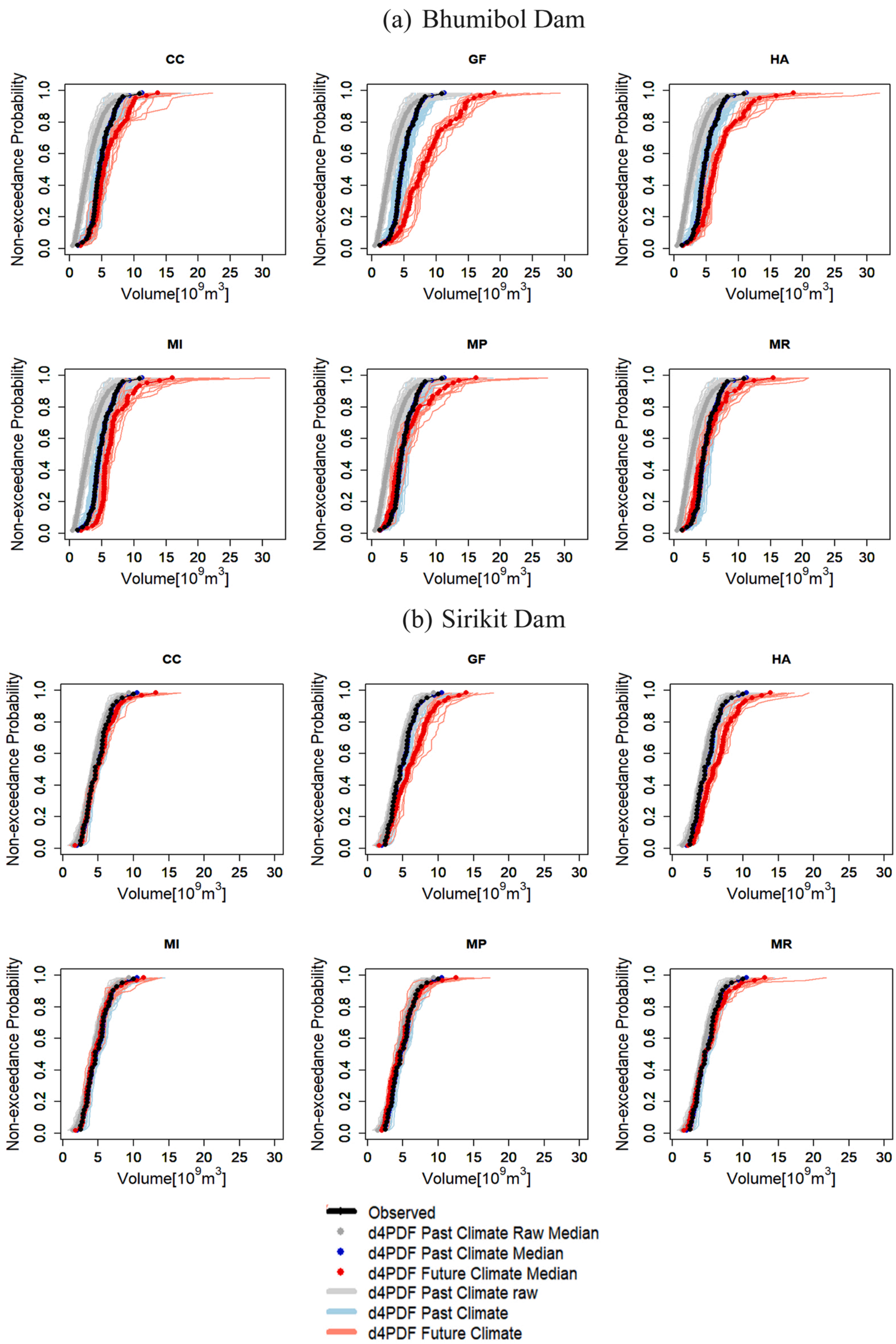

Fig. 5. Cumulative probability plot of observed (black dots), raw (light-gray lines), corrected (light-blue lines), and projected future (light-red lines) ensemble for wet season volume at (a) Bhumibol, (b) Sirikit. The gray dots show the median of raw ensembles as a baseline of bias correction. The median of corrected ensembles (blue dots) perfectly matches observation data. The median of the future ensembles (red dots) shows an increasing trend. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

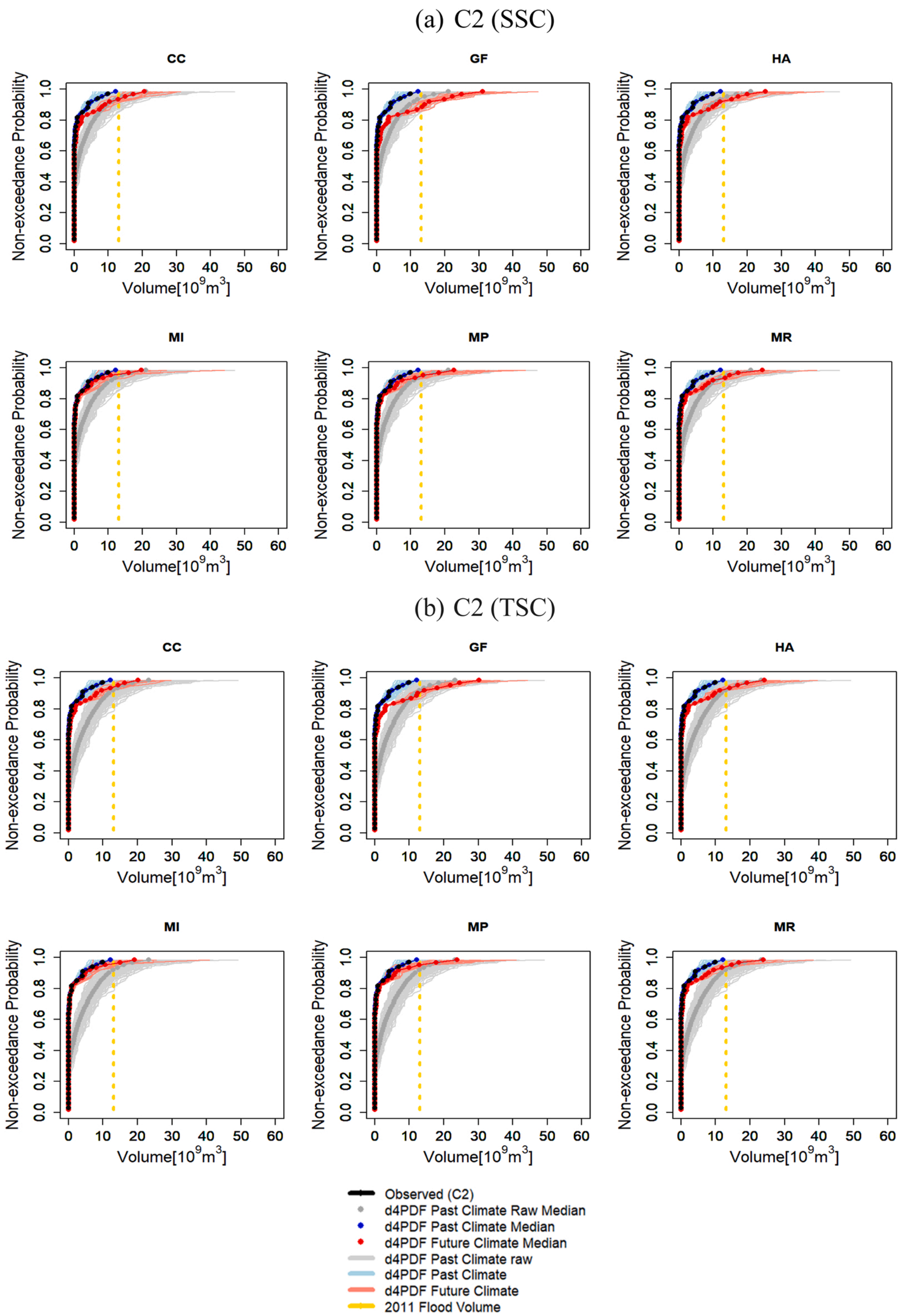

Fig. 6. Cumulative probability plots of observed (black dots), raw (light-gray lines), corrected (light-blue lines), projected future (light-red lines) ensemble and 2011 flood volume (yellow dotted lines) for flood volume at C2 (a) SSC, (b) TSC. The gray dots show the median of raw ensembles as a baseline of bias correction. The median of corrected ensembles (blue dots) perfectly matches observation data. The median of the future ensembles (red dots) shows an increasing trend. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

upstream bias correction at the dams does not contribute significantly to the future projection of downstream discharge in this particular river basin. This is verified by applying both SSC and TSC to future projections below.

3.2. Future impact assessment

3.2.1. Bhumibol and Sirikit dam inflows

Fig. 5 shows the same plot as Fig. 3 (the Bhumibol and Sirikit dam inflows) adding the bias-corrected future projections for the six SST ensembles (red) in wet season volume. The dry season volume analysis was also done in the study to compare the bias of dam operation. The future discharge volume is going to be magnified in both dams during the wet season period. The intensification of the future volume is higher in the Bhumibol dam than in the Sirikit dam. There is a slight increase or almost similar future trend in Sirikit dam whereas for the Bhumibol dam the future volume is going to enlarge. The mean increase ratio for 100-year volume for the six SST ensembles is likely going to be between 1.3 and 1.5 times the past climate for the Bhumibol dam whereas 1.2–1.4 times the past climate for the Sirikit dam. Fig. 5 it shows that for both Bhumibol and Sirikit dams the future volume (red) is higher than the past (blue). In both the cases, the cumulative probability higher than 0.9 for all SST ensembles shows greater volume than in the past. This indicates that future dam operation rules (such as rule curves) need updates to avoid an adverse effect on downstream flooding.

3.2.2. C2 station

Fig. 6 shows the future changes in flood volume at C2 with (a) SSC and (b) TSC respectively. In both cases, all SST ensembles show a clear increasing trend (red). As for the bias correction approach, both SSC and TSC showed a similar trend. The mean increase ratio for 100-year volume for the six SST ensembles is likely going to be between 1.1–1.5 times times the past climate by SSC and 1.1–1.6 times the past climate by TSC. The downstream of the C2 station is dominated by many industrial and agricultural areas. This increase in future flood volume might alter downstream activities drastically.

Due to the large C2 bias in the future climate similar to the past climate the upstream dam bias correction was insignificant in this particular case study. However, in general, the TSC is more prominent and robust as it tries to reduce the bias correction uncertainty with multi-step corrections; therefore, we opt for the TSC bias correction for further analysis of flood characteristics in the study.

The bias correction of discharge is one of the main considerations of this study. Studies show that the land surface model generates runoff data which incorporates the direct effect of land cover in GCM simulation techniques. As a result, the bias correction of runoff and river discharge in GCMs may adapt to different types of land cover settings which is to a greater degree effective than the bias correction of precipitation (Mizushima et al., 2019; Ram-Indra et al., 2020a, 2020b). The bias correction of the discharge method with an adequate statistical performance taking into account non-stationary conditions is an effectual method for the estimation of future discharge (Manee et al., 2016).

3.3. Future flood characteristics

3.3.1. Return period

The annual maximum peak discharge and flood volume at each return period at C2 are shown in Fig. 7. The maximum discharge is going to be higher than in the past climate experiment. More severe floods are likely to occur more frequently, i.e., less return period. The figure shows that approximately 70-year return period event was corresponding to the 2011 Thailand Flood discharge whereas

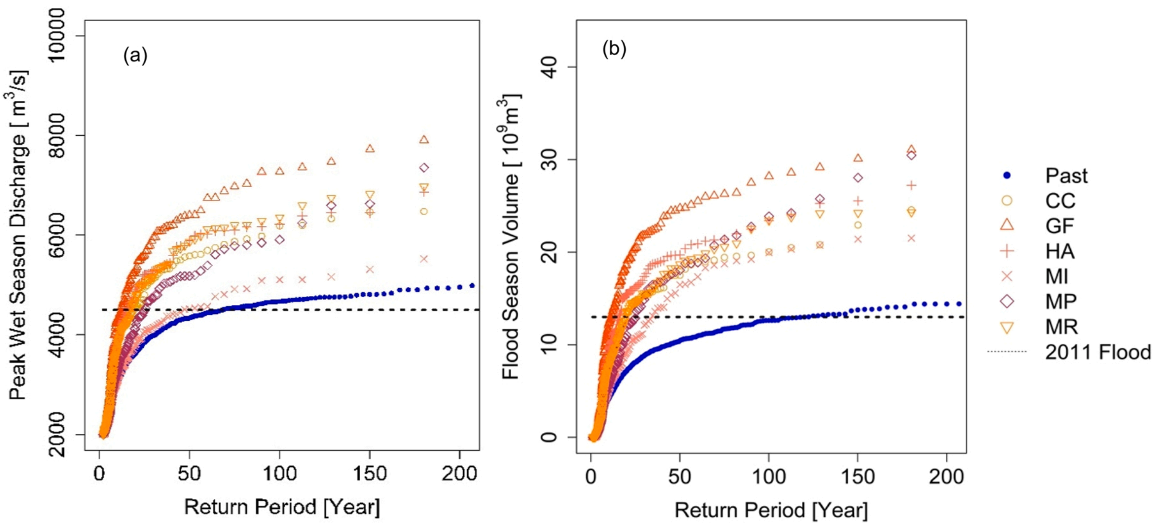

Fig. 7. (a) Peak discharge and (b) flood volume at each return period for wet season in past climate and 6 SST ensembles of 4-degree rise experiments at C2.

tentatively 120-year return period total volume was corresponding to the 2011 Thailand Flood. We can also observe that the peak discharge may be slightly increased whereas for the same or less return period the volume of the flood is going to be huge. It also shows that a reduced return period of similar or higher discharge and volume than the 2011 Thailand Flood in all the SST members is expected in the future in the CPRB. The 100-year return period flood is likely to be more 1.1–1.6 times in the future as shown in Table 3. This implies frequency of the floods is also likely to increase, and a future higher volume of floods will result in severe economic damage than in the past.

Similar studies in the basin show that the increase in future discharge is expected to be between 28% and 40% (Tebakari et al., 2012; Ponpang-Nga and Techamahasaranont, 2016) in overall agreement with this study showing 10–60% increase. In addition, the mean monthly discharge in the basin is likely to increase in all the months, and the flood risk in the future projection periods increases, according to a flood frequency analysis utilizing the annual maximum daily flow record according to Wichakul et al. (2015) in the CPRB. Kotsuki et al. (2014) also suggested that at the C2 station, there will be an increased annual runoff due to the increase in precipitation.

3.3.2. Shift in flood onset

The change of flood is also assessed in terms of a shift in flood (over 2000 m^3/s) onset in Fig. 8, indicating that typical, i.e., the most frequent starting month will be expanded from predominantly September in the past climate (blue) to both August and September equally (and even June and July at certain frequencies). Among the six SST ensembles, MI shows relatively a similar pattern to the past climate, corresponding to the closer future change ratio of peak discharge in Fig. 7(a). Table 3 shows that there is an increase in discharge for the 6 SST ensemble with respect to the return period in the CPRB. This implies that the projected shift in flood occurrence month in Fig. 8 is caused by the overall increase in annual maximum discharge. This undeniably shows that longer and early occurrence of floods is likely to happen in all SST members. Previously there were rare occurrences of floods during June and July whereas in the future, frequent flood events are likely to turn up during these months too. Similar results can be observed where the occurrence of floods in the future is starting from the month of June in the basin (Kitpaisalsakul et al., 2016). Therefore, planning for adaptation for different crops cultivation especially rice which is a major source of income for people residing in Chao Phraya would be an urgent need.

3.3.3. Duration of flood

As the result, flood duration, defined as the total number of days when daily discharge is over 2000 m^3/s at C2, is likely to be longer in the 4-degree rise climate (red) compared to past climate (blue) as shown in Fig. 9. On average, the flood used to occur approximately 70 days annually during the past which will shoot up between 80–120 days annually in the future based on SST members. This means in the future the flood duration is going to be extended by 10–50 days on average. Higher flood volume, early occurrence of flood, and prolonged duration of flood show the future is going to be more intensive and persistent. During the 2011 Thailand Flood, the floods lasted from 3 weeks to 3 months depending on the various provinces which affected a large population giving a threat to the capital city (Jular, 2011). Frequent floods and prolonged duration will affect the economic, social, and environmental aspects of the basin and influence a large population depending on the CPRB for their sustainability (Abhishek et al., 2021). Therefore, understanding the past flood characteristics to be prepared for future flood damage is essential (Komori et al., 2012).

4. Conclusions

The CPRB in Thailand is strategically located in the heart of Southeast Asia's mainland, making it one of the most vulnerable to the effects of climate change due to increased floods. Despite the obvious necessity for revealing its impact, a single solid answer to this question is hard to obtain due to the large catchment area in a contrasting climate and geography with human interventions such as streamflow control. This gives challenges to climate simulations, bias correction, and hydrological modeling. Climate simulation challenges have been addressed recently with large ensemble experiments such as the d4PDF; however, the bias correction of such large ensembles for multiple climate variables or unobservable runoff is a far more challenging task. On these backgrounds, in this study, we explored the applicability of streamflow bias correction considering its spatial bias heterogeneity for the d4PDF datasets and assessed the impacts on future floods due to a 4-degree rise in global mean temperature corresponding to the end of the 21st century in the Representative Concentration Pathway (RCP) 8.5 scenario.

To achieve this, large ensemble runoff data from d4PDF was translated into streamflow using the 1-km Flow Routing Model (1 K-FRM) customized in the CPRB with the dam operation module for the two major upstream dams: the Bhumibol and Sirikit dams as well as a simple representation of middle stream overflow using a validated linear reservoir model. The bias of the obtained dam inflows was identified and corrected using the QQM method and then the bias-corrected dam inflows were used in 1 K-FRM again to obtain the discharge at C2 with upstream bias eliminated and middle stream bias remained. These results were compared with the observed river discharge at C2 and corrected. This TSC approach is considered to realize robust bias removal even if the bias is in the opposite direction between upstream and middle stream catchments as demonstrated in this study. Due to the large biases present in the middle stream catchment (revealed as bias at C2 in the TSC approach), the upstream bias correction is nominal which implies similitude results between the multi-step bias correction and a simpler bias correction at C2 in the case of d4PDF, which was also verified by comparing the future projections with both bias corrections. However, this might not be the case in other large basins, and it might be interesting to see the effect which helps to reduce the uncertainty that lies in the model. Results show that the future flood volume with respect to both the spatial bias correction techniques are expected to increase with respect to the past. Furthermore, the impact assessment in the future floods shows that in the future the floods are going to be more prominent, and their profound effect will be

Table 3
Increase in discharge and rate of increase (RI) with respect to past return period based on TSC for 6 SST ensembles in the CPRB (increasing ratios are shown in the brackets).

Year-Flood	Past [m^3/s]	CC [m^3/s] (RI)	GF[m^3/s] (RI)	HA[m^3/s] (RI)	MI [m^3/s] (RI)	MP [m^3/s] (RI)	MR [m^3/s] (RI)
50	4336.8	5581.4 (1.3)	6397.4 (1.5)	5880.8 (1.4)	4518.1 (1.1)	5180.9 (1.2)	5864.2 (1.4)
100	4668.4	6185.6 (1.3)	7270.2 (1.6)	6216.1 (1.3)	5103.9 (1.1)	5910.4 (1.3)	6358.8 (1.4)
200	4955.1	6603.0 (1.3)	7924.9 (1.6)	6899.8 (1.4)	5564.0 (1.1)	7507.9 (1.5)	7177.6 (1.5)
500	5267.6	7821.6 (1.5)	9017.6 (1.7)	8088.7 (1.5)	6483.3 (1.2)	9002.3 (1.7)	7615.4 (1.5)

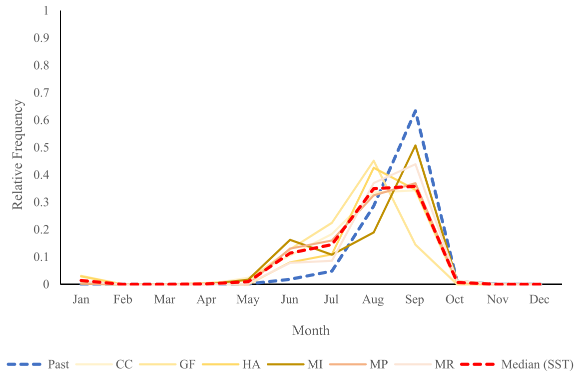

Fig. 8. Starting period of the flood in the past and 6 SST future members in the CPRB (the blue dashed line shows the past climate experiment; light solid lines show each SST ensemble; the red dashed line shows the 4-degree rise experiment) at C2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

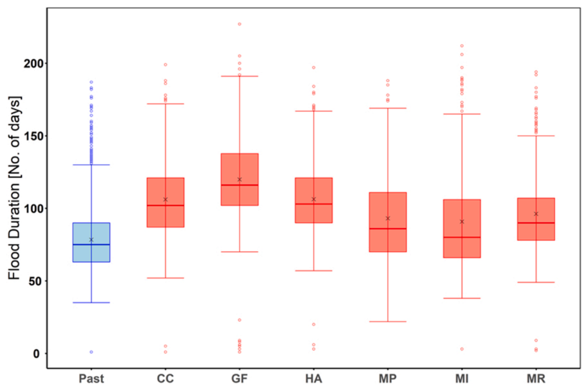

Fig. 9. Duration of floods in past and 6 future SST members in the CPRB (blue: past climate experiment; red: 4-degree rise experiments) at C2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

much higher than the 2011 flood in Thailand in both SSC and TSC bias correction techniques. Elevated flood volume, earlier flood occurrence, and longer flood duration indicate that forthcoming floods will be more rigorous. The increase in 100-year floods by 1.1–1.6 times with a larger duration exceeded by 10–50 days with respect to the past climate is observed in this study. There is an urgent need for climate change adaptation to avoid future ravishing economic, social, and environmental destructions like or higher than the 2011 Thailand flood.

Consequently, hydrological extremes such as floods are caused by several factors in addition to climate change such as local vulnerability and/or spatial heterogeneity of people and property which is not considered in this study; consequently, flood volume change cannot perfectly explain resulting inundation and economic damage. In particular, literature still lacks knowledge about such social factors being a barrier to quantitative flood risk assessment in Southeast Asian countries (Leitold et al., 2021) compared to Europe or the United States where flood damage estimation procedures are manualized, which will be investigated further for future research.

CRediT authorship contribution statement

Aakanchya Budhathoki: Conceptualization, Methodology, Modeling experiments, Analysis, Visualization, Writing – original draft. **Tomohiro Tanaka**: Supervision, Conceptualization, Methodology, Modeling experiments, Resources, Writing – review & editing. **Yasuto Tachikawa**: Supervision, Conceptualization, Methodology, Resources, Review.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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