



# Future Changes in Water Availability Due to Climate Change Projections for Huong Basin, Vietnam

Quan V. Dau<sup>1</sup> · Kittiwet Kuntiyawichai<sup>2</sup> · Adebayo J. Adeloye<sup>1</sup> 

Received: 27 March 2020 / Accepted: 13 October 2020 / Published online: 17 October 2020  
© Springer Nature Switzerland AG 2020

**Abstract** The main aim of this study is to assess the water availability in the Huong River Basin, Central Vietnam under the impacts of climate and population changes. Regarding the climate change impacts assessment, two options were adopted to produce fine scale climate projections over the river basin. First, coarse scale projections of rainfall and temperature by the HadCM3 General Circulation Model (GCM) were downscaled statistically using the Statistical Downscaling Model (SDSM). The second approach used bias-corrected dynamically downscaled output of HadGEM3-RA Regional Climate Model (RCM). The HEC-HMS hydrologic model was used for simulating the rainfall-runoff response in association with climate forcing. Finally, water availability was evaluated using the Water Evaluation and Planning (WEAP) model by taking into account plausible population changes within the river basin. The results showed that the future temperature will rise by 0.2 to 3.5 °C and annual rainfall will increase by 1 to 8%. Water shortages in 2080s were non-existent if population projections were ignored, which is to be expected given the projected increase in rainfall. When projected population increases were considered, however, there were unmet urban water demands in districts that were previously self-sufficient. However, the shortages remain very small relative to the gross domestic demand that they give no cause for alarm. The big message here is that the hydrology of the Huong River Basin in Vietnam will cope with the most severe projected climate to meet its agricultural and domestic water supply obligations well into the future.

## Highlights

- Temperature and rainfall are both projected to rise in the Huong River Basin.
- Simulated water shortage was small for the projected climate.
- Population changes accentuated water scarcity within the Basin.

---

✉ Adebayo J. Adeloye  
a.j.adeloye@hw.ac.uk

<sup>1</sup> Institute for Infrastructure and Environment, Heriot-Watt University, Edinburgh EH14 4AS, UK

<sup>2</sup> Faculty of Engineering, Khon Kaen University, Khon Kaen 40002, Thailand

**Keywords** Climate change · Water availability · Water shortage · GCM/RCM · Downscaling technique

## 1 Introduction

Adequate water and sanitation for all is one of the Sustainable Development Goals (SDGs) targets that the Vietnamese government is fully committed for national development (MPI 2018). With mean annual rainfall of 1960 mm and 2360 rivers, Vietnam can be considered rich in surface water resources in terms of runoff capacity to cater for its water supply and other needs (Nguyen-Tien et al. 2018; Nguyen et al. 2020). The estimated total annual surface water resources in the country is  $840 \times 10^9$  m<sup>3</sup> (Sagris et al. 2017); however, much of this water (around  $524 \times 10^9$  m<sup>3</sup>) derives from the runoff from the neighboring countries (i.e.  $1.2 \times 10^6$  km<sup>2</sup> area located outside the border of Vietnam (Nong et al. 2020)) and only  $316 \times 10^9$  m<sup>3</sup> comes from the direct rainfall in Vietnam. With the total area of 331,230.8 km<sup>2</sup>, almost half of the country (44.5%) is dominated by forest in which the main hydrologic abstractions are evapotranspiration and infiltration. The United Nation's FAO showed that groundwater resources in Vietnam are estimated at  $63 \times 10^9$  m<sup>3</sup> (Sagris et al. 2017), which is much smaller than the surface water resources, with 50%, 40%, and 10% of storage capacity distributed in the central, northern, and southern regions, respectively.

Based on the Vietnam Development Report in 2011 (World-Bank 2011), the water resources utilized for agriculture, domestic, aquaculture and industry in Vietnam were estimated at 82%, 3%, 11% and 5%, respectively. However, due to financial constraints and the attendant lack of physical infrastructure to harness the vast water resources, uneven distribution of the monsoon rainfall across the country and the prolonged dry season, Vietnam is frequently affected by water shortage especially during the dry season (typically from January to August) when the runoff is only about 15 to 30% of the annual total. Another feature of the water resources situation in Vietnam is the major disparity in accessing the improved water supply and hygiene facilities between the urban and rural areas. In 2011, about 73.8% of households in Vietnam were able to access both improved water sources and sanitation facilities, whereas, the proportion in the poorest quintile enjoying such facilities was just 35.4% (Tran et al. 2016). This means that about two-third of poor households had no access to clean water. Irrigation in Vietnam currently consumes almost 82% of the total water production withdrawal (Nguyen et al. 2020) and this proportion is likely to grow if the irrigation potential of approximately 9.4 million hectares is fully developed. Currently, only approximately 27% of this potential irrigation area is being irrigated.

Climate change is another major threat for sustaining water resources in Vietnam. Kuntiyawichai et al. (2017) revealed that being situated along coastline areas in the tropical monsoon belt, Vietnam is considerably influenced by the effects of climate change comprising of tropical cyclones, floods, droughts, and landslides. Average annual temperature in the South coast has increased significantly by 0.28 °C in last 10-year (Ngo-Duc 2014), and has been increasing at a rate of  $0.26 \pm 0.1$  °C per decade since the 1970s (Nguyen et al. 2014). Meanwhile, another report prepared by the Ministry of Natural Resources and Environment (MONRE) in 2012 suggested that average temperature in Vietnam has soared high to 1.0 °C in the last recent years (MONRE 2012). Increasing rainfall and temperature would significantly change the hydrological system and threaten the livelihoods of people. Therefore, it is essential to fully assess the water resources situations in Vietnam, particularly for the central region that

is very prone to severe natural disasters on an annual basis, and hence, likely to be most hit by extreme weather events associated with projected climate change.

Notwithstanding the importance of this river basin, there are still very limited number of studies carried out on the impacts of climate change on hydrological regimes and water allocations in central Vietnam. Most of the recent studies were merely focused on climate change adaptation or flood risks assessment. For example, Sen et al. (2020) employed a FAO's resilience framework to measure households resilience in response to the effects of climate change. Trinh et al. (2018) combined a binary logit and multivariate probit models to examine different factors influencing farmers' decision on climate change adaptation. Recently, various studies involving numerical modelling/simulation were carried out to understand flood risk and damages in the central region (Dau et al. 2017; Dau and Kuntiyawichai 2020; Mai and De Smedt 2017; Nguyen et al. 2013); however, studies assessing sufficiency in water allocation for the region are still very few. Thus, the need for comprehensive assessment of a region's water resources as a precursor to the development of robust adaptation and mitigation strategies for climate change effects in the central region of Vietnam is necessary.

Indeed, studies on the impact of climate change on water allocation have become very popular worldwide. Pickard et al. (2017) used Bayesian statistical modeling to compare domestic water demand for each county within the contiguous United States based on the four IPCC Supplemental Report on Emission Scenarios (SRES), i.e. A1b, A2, B1, and B2 scenarios. They estimated that water demand will exceed the 2010 levels by about 50% in 2090 for all four scenarios compared, particularly in the States of California, Texas, and isolated portions of the Mid-West, Southeast, and Mid-Atlantic. Sun et al. (2018) evaluated agricultural water demand under future climate change in the Loess Plateau of Northern Shaanxi, China. The results exhibited a downward trend of the irrigation water requirement under the RCP8.5 (−0.9%), RCP4.5 (−0.77%), and RCP2.6 (−0.3%) scenarios. Kiniouar et al. (2017) assessed water demands for domestic, industrial and irrigation sectors in the Kébir-Rhumel Basin, Algeria, for 30 years (2007–2037) using the Water Evaluation And Planning (WEAP) system with projections of population and irrigated crop lands. They concluded that reducing the drinking water consumption by a mere 5% could save about  $37 \times 10^6$  m<sup>3</sup> of water resources over a 30-year period.

With this goal, this study seeks to carry out an assessment of the water availability under projections of future climate emission scenarios. Climate models under the Coupled Model Inter-comparison Project – phase 3 (CMIP3) were compared to the CMIP5 for understanding hydrological response to meteorological forcing. They were downscaled individually using a statistical downscaling analysis with an attempt to improve biases from models. Water allocation was then assessed using a coupled hydrologic rainfall-runoff model HEC-HMS (Hydrologic Engineering Center–Hydrologic Modeling System) and WEAP water allocation model. The focus was on irrigation and domestic water consumptions, these being the two main sectors of consumptive water use in Vietnam, and hence, for which it is crucial to establish the additional impacts of human activities especially in the central region of Vietnam.

A novelty of this study is its comparison between the CMIP3 and CMIP5 models, thus representing a radical departure from current focus on the use of ensembles of CMIP5 that does not test how far the climate change science has evolved. Additionally, the application of bias-correction with double-gamma distribution for high resolution RCM model would be useful for similar studies in the region and elsewhere. Furthermore, the integrated hedging policy and rule curves for reservoir operation in the WEAP model provides a proven, robust operating policy for managing water scarcity for tempering system vulnerability. Lastly, the

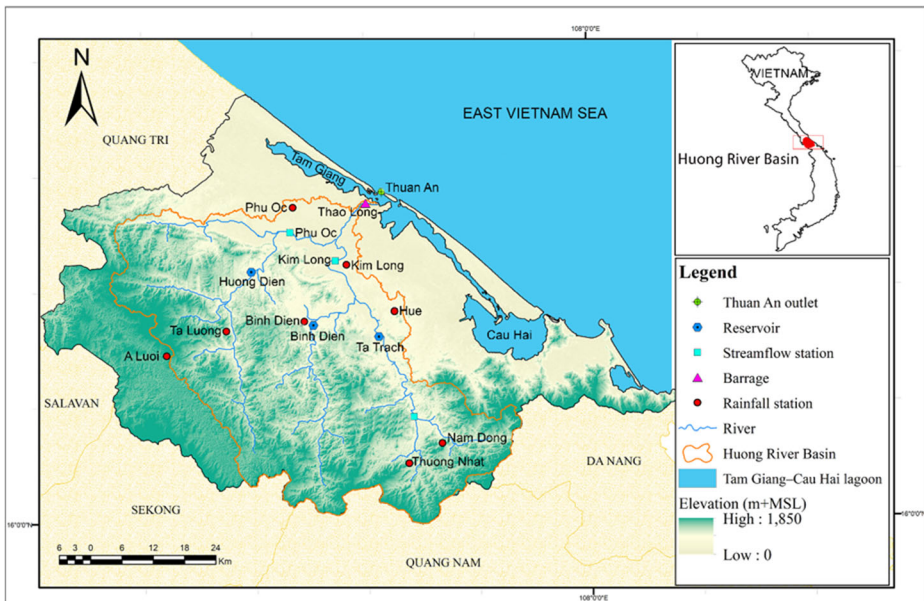
outcomes would serve the MONRE in central region of Vietnam in the effective planning for water resources allocation locally within the country or elsewhere.

## 2 Study Area

This research focuses on the Huong River Basin located in Thua Thien Hue Province, Vietnam at latitude 16 - 17°N and longitude 107 - 108°E (Fig. 1). The basin covers a total area of 2830 km<sup>2</sup> with altitudes varying between 150 m and 1850 m above Mean Sea Level (MSL). It comprises three major reservoirs, namely, Huong Dien, Binh Dien, and Ta Trach, located respectively on the Bo, Huu Trach, and Ta Trach tributaries.

ed and operated by the MONRE. Of these, the Huong Dien reservoir built in 2009 is the largest, with a total capacity of  $820.66 \times 10^6$  m<sup>3</sup>. Binh Dien reservoir also built in 2009 has a capacity of  $423.68 \times 10^6$  m<sup>3</sup> and like the Huong Dien reservoir serves flood control, power generation, irrigation and tourism needs. The Trach reservoir is much newer, coming into operation at the end of 2014, has a capacity of  $420.5 \times 10^6$  m<sup>3</sup> and serves similar purposes like the other two. Along the coast, the basin encompasses the largest lagoon in Vietnam, namely, Tam Giang – Cau Hai with a total surface area of 220 km<sup>2</sup> and 68 km in length. Runoff from upstream discharges into the lagoon through the Thao Long barrage before entering the sea. The Thao Long barrage has a total length of 480.5 m and contains of 15 sluice gates, each having a width of 30 m. The population in the study area was about  $1.087 \times 10^6$  in 2009; this is expected to increase to  $1.287 \times 10^6$  in 2034 based on government's projections (GSO 2017).

As a consequence of the direct effect of the North-Western Pacific Ocean typhoon in the area, the Huong River Basin is commonly influenced by severe and extreme weather events (Lindegaard 2018). For example, the area has the highest rainfall in the Central region of Vietnam, with mean annual rainfall that ranges from 2500 to 3500 mm during the short



**Fig. 1** The Huong River Basin in Thua Thien Hue Province, Vietnam

rainy season that lasts from September to December. During this period, rainfall usually occurs in short and heavy bursts, causing erosion to the upper parts and flooding at downstream locations. The remainder of the year is the dry season when little or no rain falls. The mean annual discharge of the Huong River also varies widely between  $0.040 \text{ m}^3/\text{s}/\text{km}^2$  in the lowland coastal area to  $0.080 \text{ m}^3/\text{s}/\text{km}^2$  in the mountainous areas (UNESCO-IHP 2004).

In terms of temperature, average annual temperature can range from 21 to 26 °C with the highest recorded temperature of 41.3 °C at Hue station. Average humidity observed during the period 2002 to 2016 is approximately 87%; the lowest recorded value is 78% (June) and the highest value is 93% in December.

### 3 Materials and Methods

#### 3.1 Data Collection

Daily rainfall, maximum and minimum temperatures spanning 1977 to 2014, and streamflow data from 2009 to 2014 were obtained from the Thua Thien Hue Hydrology and Meteorology Center (TTHMC). There are eight rainfall stations in the basin (i.e., A Luoi, Binh Dien, Thuong Nhat, Nam Dong, Hue, Kim Long, Ta Luong, and Phu Oc), and four streamflow measurement stations (i.e., Binh Dien, Kim Long, Phu Oc, and Thuong Nhat). Land use and soil type data were obtained from the Ministry of Natural Resources and Environment (MONRE 2019). Population census data were obtained from the General Statistics Office (GSO 2017) and used to estimate the gross domestic water demands. To project the population data to future time horizons, the approach being used by the Thua Thien Hue Department of Statistic (DoS) was applied as shown in Eq. (1):

$$P_t = P_{2009} (1 + r)^{t-2009} \quad (1)$$

where,  $P_t$  is the projected population in year  $t$ ,  $P_{2009}$  is the population observed in the baseline year 2009, and  $r$  is percentage population growth rate ( $= 1.15\%$ ). The baseline year was taken as 2009 when two of the reservoirs went into operation.

For climate data projections, the third generation UK Hadley Centre GCM model (HadCM3) after statistical downscaling and the RCM model HadGEM3-RA with appropriate bias correction were used. HadCM3 has a coarse spatial resolution with ( $2.5^\circ \times 3.75^\circ$ ), while the spatial resolution for HadGEM3-RA is much finer at  $0.44^\circ \times 0.44^\circ$ . There has been very limited studies carried out to determine the best climate models for the central region of Vietnam. Indeed, climate change assessments in Vietnam are still based on the projection scenarios of the IPCC SRES, i.e., A1F1, B2 and B1, and as approved by the MONRE in June 2006. It is, therefore, timely that considerations of state-of-art GCM and RCM model outputs in water resources availability investigations are implemented in the Huong River Basin. In this regard, both HadCM3 and HadGEM3-RA have been suggested by recent studies (e.g., Dau et al. 2017; Dau and Kuntiyawichai 2015) as potential candidates for representing the climate in the basin. In particular, the HadCM3 model is more suitable for Southeast Asia region where monsoon climate dominates, and this appropriateness can pertain for the central region of Vietnam as well (Khoi and Hang 2015; Shrestha et al. 2016). On the other hand, HadGEM3-RA model complies with the protocol of the Coordinated Regional Climate

Downscaling Experiment (CORDEX), that was also projected specifically for Asia finer resolutions. Therefore, the two models would be expected to have a strong potential in representing climate conditions in Vietnam. As a consequence of the abovementioned reasons, they were selected for this study.

In terms of radiative forcing, emission scenario A2, a very heterogeneous world scenario, and Representative Concentration Pathway (RCP) 8.5, a scenario of comparatively high greenhouse gas (GHG) emission, were considered for HadCM3 and HadGEM3-RA models, respectively. For Vietnam, the growth of population and industry will lead to high concentration of greenhouse gases (GHGs) at the end of the twenty-first century (Shrestha et al. 2016); therefore, projection for high emission scenarios would be necessary for this region.

### 3.2 Statistical Downscaling of GCM Model Output

As alluded to in the foregoing Section, the output of the  $2.5^\circ \times 3.75^\circ$  coarse resolution by HadCM3 is unsuited for meaningful water resources assessment without downscaling. To downscale the projected climate forced with SRES A2 scenario, the relatively much easier downscaling approach was used (Khan et al. 2006). This was accomplished using the Statistical Downscaling Model (SDSM), which is a multiple regression-based approach that relates the local climate (e.g., temperature, precipitation, humidity, etc.) as predictand to large scale atmospheric weather variables as predictors. For specifying the appropriate predictor variables applied for model calibration, the National Center for Environmental Prediction (NCEP) reanalysis predictors during the period of 1977 to 2001 were selected. The predictors were analyzed using correlation analysis and partial correlation analysis to represent the potential utilization of predictor and predictand relationships. Higher correlation values imply a higher degree of association (Wilby and Dawson 2013). Rainfall was modeled as a *conditional process* because the amount of rainfall depends on wet-day occurrence while the temperature was modeled as an *unconditional process*. Full details about the SDSM are provided by Wilby et al. (1999); it essentially involves seven processes, namely quality control, screen variable, transforms variable, calibrate model, weather generator, scenario generator, and results comparison.

Consequently, projections for fixed time horizons in the future, i.e., the 2020s (2016–2040), 2050s (2046–2070) and 2080s (2075–2099), were produced from model output for comparison with the 25-year baseline period (1977–2001). You may note that the period 1977–2001 was selected as a baseline period for this study due to the availability of observations and also due to the limitation of the NCEP predictor variables between 1960 and 2001.

### 3.3 Bias Correction Using Quantile Mapping of RCM Outputs

In general, downscaled climate data from RCM are biased due to limited process understanding and insufficient spatial resolution. It is therefore essential to post-process these data in order to correct the bias as much as possible before using the downscaled data for climate impacts assessment (Christensen et al. 2008). There are several bias correction methods, including delta change approach, multiple linear regression, analogue method, local intensity scaling, quantile mapping, etc. In this study, a quantile mapping (QM) method was used because of its many advantages, such as: (1) its ability to correct over the entire statistical distribution of the downscaled variable; (2) its use of the double gamma distribution for better representation of extreme events; (3) its use of distribution fitting which makes possible extrapolation beyond the observed range, which is very useful when both extreme events and variability are important; and (4) wet/dry state dependent

temperature correction. Its limitations include that climate signal can be altered; correction increments are the same as in the current climate; and extreme values are restricted to those in the observed. For the current study, these limitations are not thought to significantly outweigh advantages; consequently, the QM approach was used.

The QM method assumes that for the downscaled data to be valid, its cumulative distribution function (CDF) must be the same as that of the observed data. For this reason, the QM method is often referred to as Distribution-Based Scaling (DBS) (Yang et al. 2010). Thus, to bias-correct, specific quantiles from the empirical CDF of the downscaled are equated to similar quantiles of the observed leading to the determination of a quantile function for correcting the bias.

For rainfall, the frequency distribution of the rainfall intensity is assumed to follow the 2-parameter gamma density function (Yang et al. 2010):

$$f(x) = \frac{\left(\frac{x}{\beta}\right)^{\alpha-1} \exp\left(\frac{-x}{\beta}\right)}{\beta \Gamma(\alpha)} ; x, \alpha, \beta > 0 \tag{2}$$

where,  $\alpha$  is the shape variable,  $\beta$  is the scale variable, and  $\Gamma(x)$  is the inverse gamma function. To ensure that extremes are well modelled, the rainfall distribution can be separated into two parts, the low and moderate rainfall intensities (<95% non-exceedance probability), and extreme rainfall intensity (>95% exceedance probability). The resulting distribution is hereafter referred to as the double gamma distribution with two sets of parameters –  $\alpha, \beta$  (for the low to moderate intensities) and  $\alpha_{95}, \beta_{95}$  for the extremes – which were estimated from observation and the HadGM3-RA outputs during the period 1977 to 2001. Maximum likelihood estimation (MLE) was preferred for estimating the distribution parameters.

Once parameterized, the DBS correction of the future rainfall projections of the HadGM3-RA model was obtained using (Yang et al. 2010):

$$\begin{cases} P_{DBS} = F^{-1}(\alpha_{obs}, \beta_{obs}, F^{-1}(P^*, \alpha_{RCM}, \beta_{RCM})) \\ P_{DBS} = F^{-1}(\alpha_{obs,95}, \beta_{obs,95}, F^{-1}(P^*, \alpha_{RCM,95}, \beta_{RCM,95})) \end{cases} \tag{3}$$

where subscript *obs* denotes parameters estimated from observed data, and *RCM* denotes parameters estimated from global climate model data,  $F^{-1}$  is the inverse of the gamma distribution CDF,  $P^*$  is daily rainfall from HadGEM3-RA outputs, 95 is the percentile of rainfall intensity.

For the temperature, since this is more symmetrically distributed, it was described by the normal distribution function:

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{4}$$

where,  $\mu$  is mean of the daily temperature,  $\sigma$  is standard deviation, and  $f(x)$  is the CDF.

The DBS correction for temperature then becomes:

$$T_{DBS} = F^{-1}(\sigma_{obs}, \mu_{obs}, F^{-1}(T^*, \sigma_{RCM}, \mu_{RCM})) \tag{5}$$

where,  $T^*$  is daily temperature from HadGEM3-RA outputs, and all other symbols are as previously defined.

### 3.4 Rainfall–Runoff Simulations

Rainfall-runoff modelling to estimate catchment's response to weather forcing was achieved using the HEC-HMS developed by the US Army Corps of Engineers. HEC-HMS uses the input watershed meteorological data and control specifications to calculate hydrographs throughout the river basin. The HEC-HMS model was selected since it has been extensively used worldwide, with its capability in analyzing flood frequency, flood warning system planning, and stream restoration, etc. In addition, the selected model was also recently suggested by the TTHMC for simulating rainfall-runoff processes in the Huong River Basin (personal communication, June 2017).

There are four major constituents in HEC-HMS, namely baseflow separation, runoff volume computation, direct runoff, and flow routing (Feldman 2008). HEC-HMS employs the Soil Conservation Service–Curve Number (SCS–CN) loss method to estimate the rainfall excess from rainfall events. The SCS-CN was originally developed for use on small agricultural watersheds but has been applied to rural, forest and urban watersheds (Mishra and Singh 2003). To route the rainfall excess into runoff hydrograph, the Snyder unit hydrograph method was used (Dau et al. 2017). Baseflow recession analysis was used to characterize the subsurface flow while the in-stream translation or routing of hydrograph was achieved using the Muskingum routing method.

There are three river gauging stations, namely, Phu Oc, Binh Dien and Ta Trach, situated in the river basin (Fig. 2). In detail, both Binh Dien and Ta Trach stations have only recorded flow measurement, whereas Phu Oc station has only water level data. Therefore, the daily flow measured at Binh Dien during 2010 to 2011 and 2012 were used for model calibration and validation, respectively. For Ta Trach station, the observed daily flow during September to October 2014 was used for calibration, while the period November to December 2014 was used for validation.

### 3.5 Water Availability Assessment

The water availability assessment was performed using the WEAP model, a water resources evaluation and planning tool developed by the Stockholm Environment Institute (Sieber and

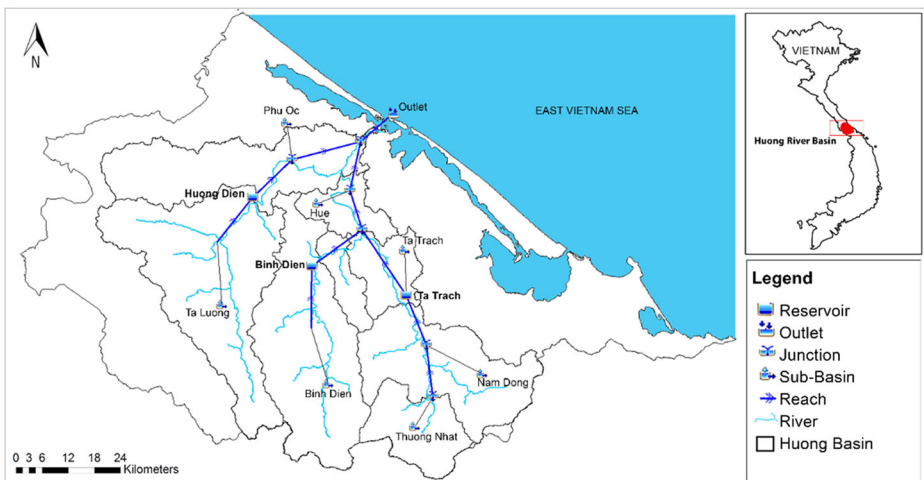


Fig. 2 HEC-HMS schematic diagram for the Huong River Basin



Purkey 2011). The model is designed to support water resources planning and management by representing the water allocations between agricultural, municipal and environment uses, which usually requires a full integration of supply, demand, water quality, and ecological considerations. The WEAP model has been used widely for solving various water-related problems (Dau et al. 2018; Faour and Fayad 2014; Momblanch et al. 2019; Tena et al. 2019). Based on its demonstrated capability, the decision was made to use the WEAP model for this study.

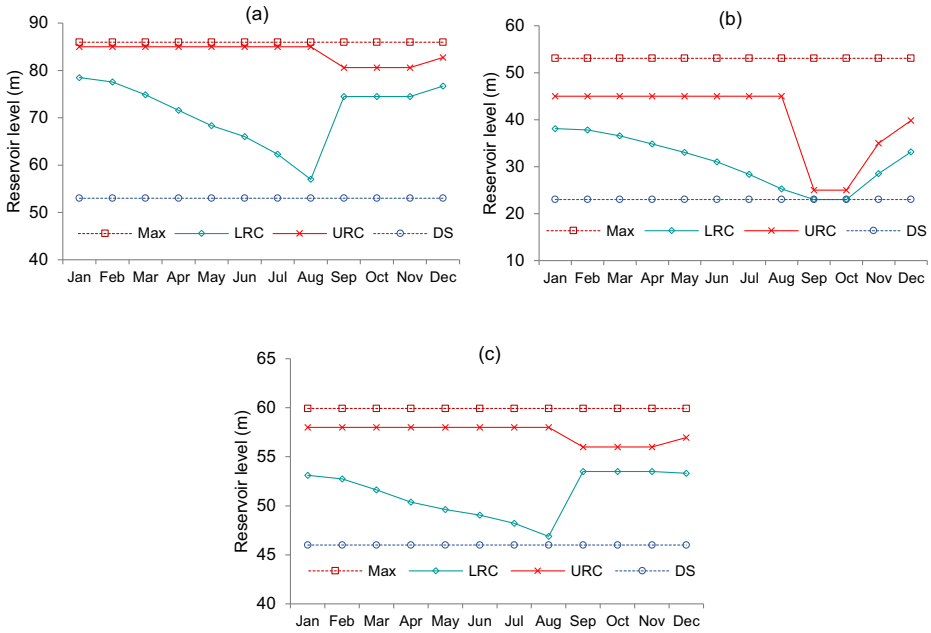
The MABIA (MAitrise des Besoins d'Irrigation en Agriculture) irrigation method based on the *dual*  $K_c$  method (Allan et al. 1998) was used in WEAP to estimate the actual evapotranspiration, and hence, irrigation requirements and its scheduling, crop growth and yields, soil water dynamics, etc. The  $K_c$  is divided into *basal* crop coefficient ( $K_{cb}$ ) and the soil evaporation coefficient ( $K_e$ ). The  $K_{cb}$  is ratio of the crop evapotranspiration ( $ET_c$ ) to reference evapotranspiration ( $ET_o$ ), when topsoil is dry that direct evaporation is almost gone but water is present from the root zones to the crops for transpiration to continue (Allan et al. 1998). When the soil becomes wetter or close to saturation following rainfall or irrigation, evaporation dominates the evapotranspiration process and the value of  $K_e$  will be increased. In general, the actual evapotranspiration  $ET_c$  is estimated by multiplying  $K_{cb}$ ,  $K_e$  and  $ET_o$ .

Water availability was then estimated by considering the water balance of inflows taken from hydrological model (HEC-HMS), crop evapotranspiration, and water demands for both irrigation and domestic consumptions. The first five districts presented in Table 1 are located in the downstream part of the river basin and are supplied from the three main reservoirs, while the remaining four upstream districts rely on direct water abstraction from the river. The water released by the three reservoirs is governed by their prevailing rule curves as suggested by MONRE and the dam operators (Fig. 3).

Referring to the WEAP model setup (see Fig. 4 for a schematic diagram), competing demand sites and catchments, reservoir filling and hydropower generation, and flow requirements are allocated water according to demand priorities. In this case, a priority rule is useful in representing a system of water rights, and helpful during water shortage so that higher priorities are satisfied as fully as possible before lower priorities are considered (Sieber and Purkey 2011). In WEAP, the priority index ranges from 1 to 99, with the lower value indicating higher priority and vice versa. For example, if a reservoir filling has low priority (99), then it will only fill if water remains after serving all other higher priority demands. Meanwhile, if priorities are the same, shortage will be equally shared between all the demands.

**Table 1** Irrigation and domestic water demand for the Huong River Basin

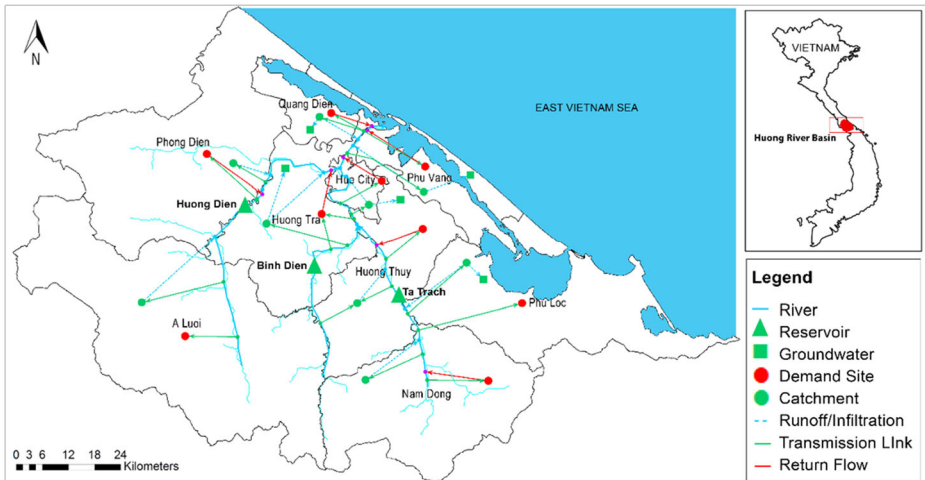
District	Irrigation water demand ( $\times 10^6$ m <sup>3</sup> )	Domestic water demand ( $\times 10^6$ m <sup>3</sup> )	
		Baseline	With the projected population in 2080s
Hue	26.54	26.56	55.85
Quang Dien	102.90	0.40	0.85
Phong Dien	202.04	0.25	0.52
Phu Vang	189.77	1.68	3.53
Huong Tra	115.20	6.16	12.94
Aluoi	86.72	0.27	0.58
Huong Thuy	78.27	5.07	10.66
Nam Dong	23.02	0.14	0.30
Phu Loc	162.51	0.39	0.83
Total	987	41	86



**Fig. 3** Reservoir rule curves at (a) Binh Dien, (b) Ta trach, and (c) Huong Dien, where *Max* is reservoir capacity, *LRC* is lower rule curve, *URC* is upper rule curve, *DS* is reservoir dead storage

### 3.6 Criteria for Model Performance

Three common statistical indices were evaluated to assess the goodness-of-fit for model simulations. These are the Nash-Sutcliffe coefficient ( $N_s$ ), the coefficient of determination ( $R^2$ ), and root mean square error ( $RMSE$ ), as presented in Eqs. (6), (7), and (8), respectively.



**Fig. 4** WEAP schematic diagram for the Huong River Basin

$$N_a = 1 - \frac{\sum_{i=1}^n (X - Y)^2}{\sum_{i=1}^n (X - \bar{X})^2} \tag{6}$$

$$R^2 = \left[ \frac{\sum_{i=1}^n (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum_{i=1}^n (X - \bar{X})^2 \sum_{i=1}^n (Y - \bar{Y})^2}} \right]^2 \tag{7}$$

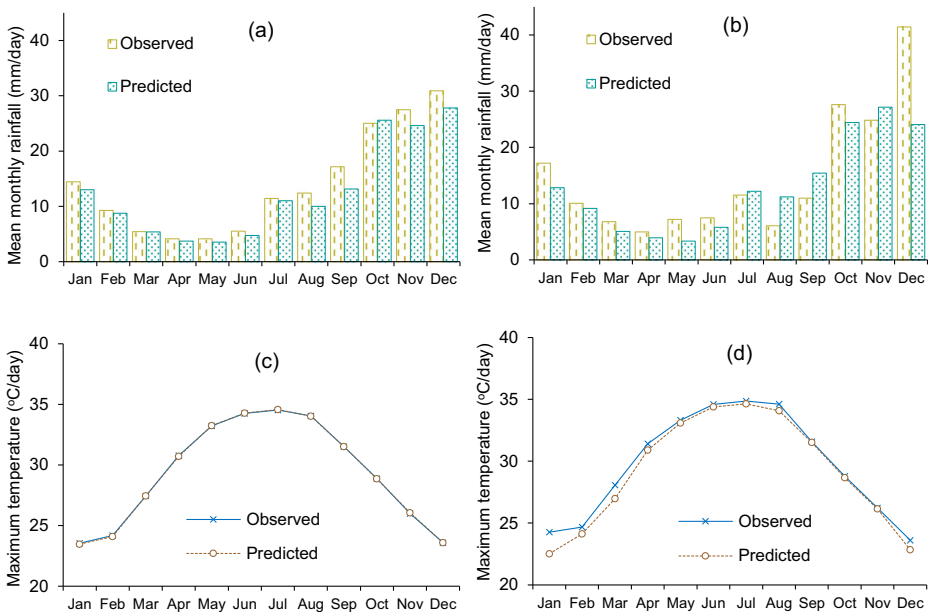
$$RMSE = \left[ \frac{1}{n} \sum_{i=1}^n (Y - X)^2 \right]^{\frac{1}{2}} \tag{8}$$

where,  $X$  is observed data;  $\bar{X}$  is mean of observed data;  $Y$  is simulated data;  $\bar{Y}$  is mean of simulated data;  $n$  is total number of data. Indices  $N_a$  and  $R^2$  were used for the assessment of the climate projections while all three indices were used rainfall-runoff modelling assessment.

## 4 Results and Discussions

### 4.1 Climate Change Assessment under GCM Model with Statistical Downscaling

The outcomes of the statistically downscaled climate are summarized in Fig. 5a, b for rainfall and Fig. 5c, d for temperature. These demonstrate that the mean monthly rainfall and



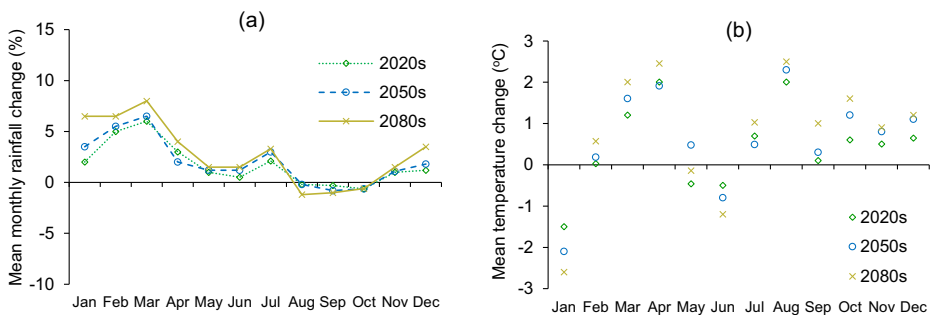
**Fig. 5** The results of calibration (a, c) and validation (b, d) for mean monthly rainfall and maximum temperature at Hue station using SDSM model

temperature for the observed and modelled data are in good agreement, both during calibration and validation. The relevant statistical indices evaluated for Hue station lend further support to the good performance evidence, with the  $R^2$  value varying from 0.88 to 0.99, and  $RMSE$  value ranging between 3.72 and 0.05 for both monthly rainfall and temperature variables.

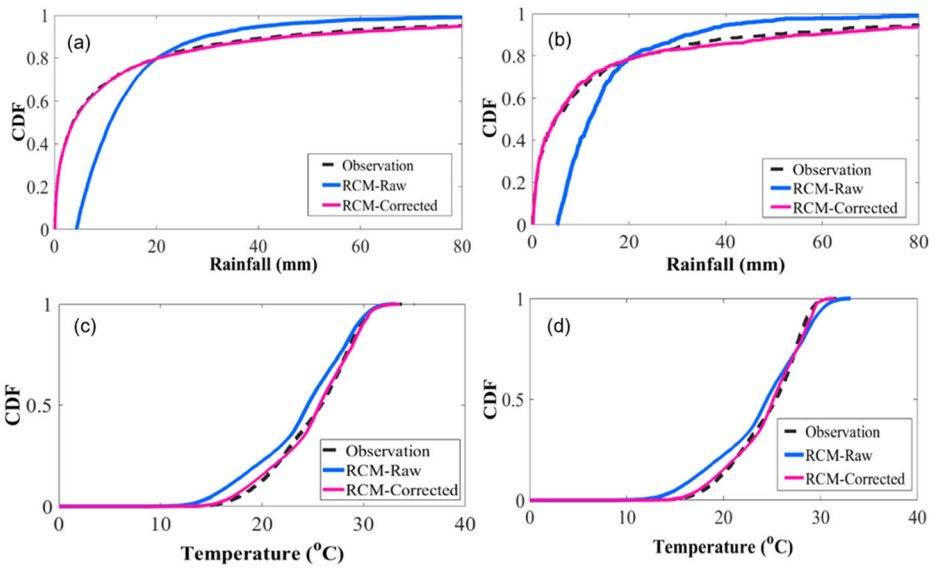
With the downscaling model shown to be satisfactory for the baseline, the model was applied to similarly downscale the future climate projections. Figure 6a shows the projected changes in mean monthly rainfall, from where it is clear that these will increase throughout the year except during the rainy season (August – October) when slight decreases in rainfall are projected. What is also clear from Fig. 6 is that the increased wetness will be sustained well into the end of the Century. Indeed, by 2080s, rainfall increase of up to 8% is likely in February–March, with more modest but still significant increases in the other dry season months. These projected rises in dry season rainfall are a welcome development as they signify improved water security in the basin. The temperature projections shown in Fig. 6b are signifying changes of  $-2.5$  to  $+2.5$  °C depending on the time of the year. The temperature reductions occur during January, May and June, with January recording the highest decline. Rises in temperature projected for the other months are a sink of water by causing evapotranspiration and other consumptive demands for water to increase. It is therefore a threat to future water security but whether or not these effects are sufficient to annul the effects of the increased rainfall-runoff will become clearer when the water availability situation is evaluated with the WEAP model. Nonetheless, the above observations agree with other independent studies. For example, MONRE (2012) and Schmidt-Thome et al. (2015) found that rainfall at the end of the twenty-first century in the Huong River Basin will increase by 2 to 10% and temperature will also increase by 2.5 to 3.7 °C.

#### 4.2 Climate Change under RCM Model with DBS Bias Correction

The DBS was calibrated using the 1997 to 2001 data and validated using the 2002 to 2005 data. The empirical cumulative distribution functions (CDFs) for the raw and bias-corrected output of the RCM during calibration and validation are compared with that of the historical climate data in Fig. 7 from which it is clear that the DBS bias correction approach has been very effective in reducing the huge bias associated with the raw RCM output. This observed good performance was well supported by the evaluated performance indices with the  $R^2$  ranging from 0.76 to 0.95, and  $N_a$  varying from 0.69 to 0.95 for both rainfall and temperature projections.



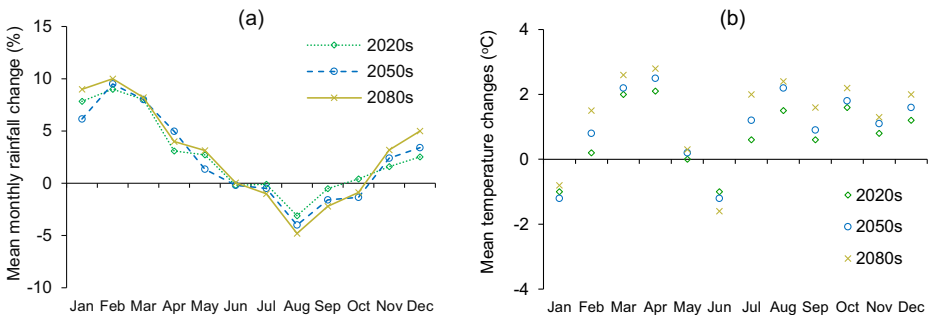
**Fig. 6** Mean monthly of the (a) rainfall and (b) temperature changes under A2 scenario downscaled by SDSM model



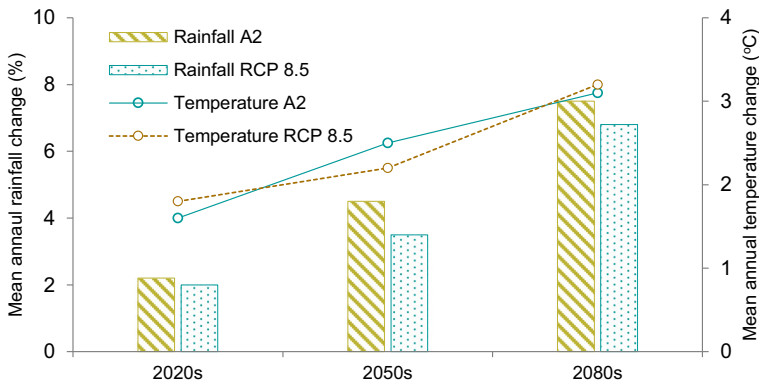
**Fig. 7** Cumulative distribution function (CDF) of daily rainfall and temperature for (a, c) calibration and (b, d) validation using QM approach at Hue station

Once the bias-correction has been performed satisfactorily for the historical period, the projection for future climate was done accordingly. However, rather than using the A2-CMIP3 emissions scenario, the high GHG emission scenario RCP8.5-CMIP5 was used. Figure 8a shows that the rainfall is likely to increase during the dry season from January to May similarly to the A2 scenario, with the highest increase of 10% occurring in February. As also was the case with the A2, the rainy season is drier with RCP8.5 much drier with up to 5% reduction in average August rainfall compared to the baseline situation. Although different baseline periods were used here (1977 to 2001) compared to the shorter period used for the A2-CMIP3 analysis (1977 to 1990), which could have affected the obtained changes, it is also possible that differences in grid resolutions of the climate models can result in differences in model outputs. The temperature changes shown in Fig. 8b exhibit a similar pattern to that of the A2 scenario although as was the case with rainfall, the obtained changes were slightly different.

To reveal further the differences in the magnitude of the projected changes (as opposed to the trends) by the two approaches, Fig. 9 compares the average annual projected changes in



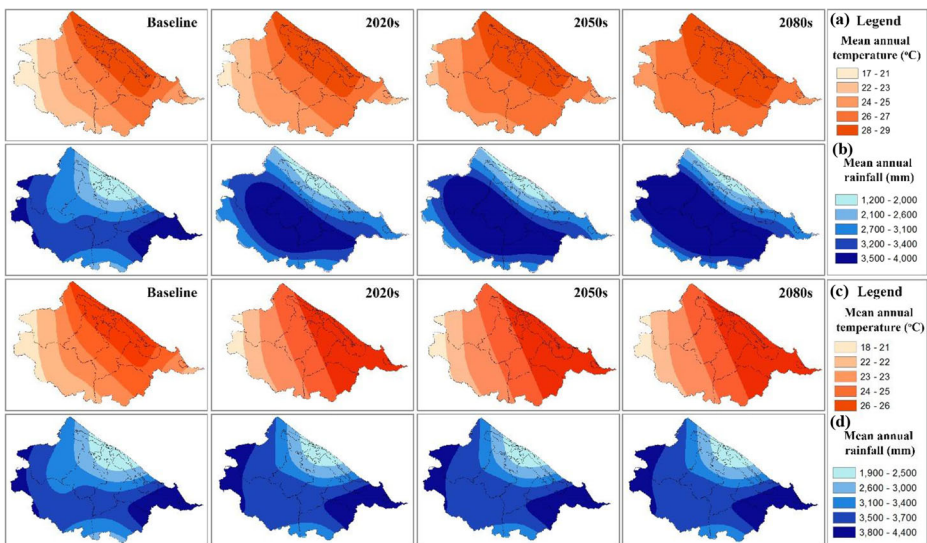
**Fig. 8** Mean monthly of the (a) rainfall and (b) temperature changes under RCP 8.5 scenario based on bias-correction method



**Fig. 9** Mean annual rainfall and temperature changes under A2 and RCP 8.5 scenarios

both the precipitation and temperature. As shown in the figure, both approaches are projecting increasing annual rainfall in the future, which rises by about 8% at the end of the Century when compared with the baseline. What is also noticeable in Fig. 9 is that the A2-CMIP3 scenario has projected higher annual rainfall increase than the RCP8.5-CMIP5 scenario. A recent study conducted by Onyutha et al. (2016) for Lake Victoria in Africa showed that projection changes in the rainfall extremes from the RCP8.5-CMIP5 were lower than those of the A2-CMIP3. Similarly for the lower emission scenarios, Mirgol and Nazari (2018) also found that rainfall in the Qazvin Province, Iran under projection of RCP2.6-CMIP5 was lower than B2-CMIP5. Thus, although the seasonal trends in the rainfall changes were similar, the significantly lower precipitation during the rainy season for the RCP8.5 has resulted in its annual total rainfall change being lower than that of the A2 scenario.

Furthermore, the spatial distribution of the projected climate is shown in Fig. 10, where the higher temperatures are towards the eastern part of the basin whereas the wetter areas are

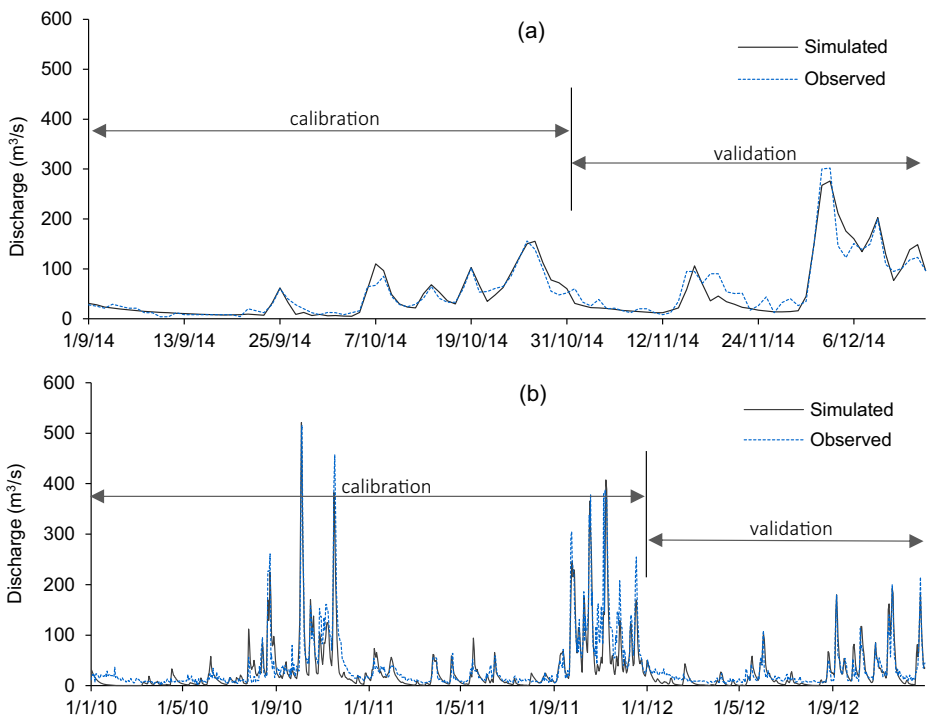


**Fig. 10** Spatial distribution of mean annual temperature and rainfall (a, b) downscaled by SDSM model under A2 scenario, and (c, d) bias corrected by QM under RCP8.5 scenario

confined in the central part of the basin. The spatial patterns of the temperature and rainfall for RCP8.5-CMIP5 bear resemblance to those observed for the A2-CMIP3 scenario.

### 4.3 Evaluation of the Hydrological Model HEC-HMS

The performance of the hydrological model is shown in Fig. 11, where the observed and simulated hydrographs are compared for both the calibration and validation periods. Focusing on the HEC-HMS model, initial values of the model parameters were taken from recent studies in the basin (Mai and De Smedt 2017; Nguyen et al. 2013) and were adjusted manually during the calibration process to produce good fits with the observed streamflow. These include the Curve Number (CN) varying from 60 to 75, lag time ( $t_p$ ) ranging from 7 to 10 h, baseflow ( $Q_0$ ) fluctuating between 15 and 30  $m^3/s$ , and Muskingum variables ( $K$  ranging from 1 to 4 h and  $x$  equal to 0.25). Statistical indices as presented previously were used to evaluate the performance of the HEC-HMS in simulating flows and hence the best estimates of the parameters. The results indicated a good model performance for the rainfall-runoff process along the Huong River Basin. In addition, the goodness-of-fit indices obtained during the calibration and validation are at: Phu Oc station ( $R^2=0.85$  and 0.86, respectively,  $N_a=0.78$  and 0.84, respectively); Binh Dien station ( $R^2=0.84$  and 0.85, respectively,  $N_a=0.77$  and 0.83, respectively); and Ta Trach station ( $R^2=0.91$  and 0.94, respectively,  $N_a=0.89$  and 0.91, respectively). In comparison to the calibration results of other studies (Abdo et al. 2009; Mai and De Smedt 2017; Nguyen et al. 2013), it can be stated that HEC-



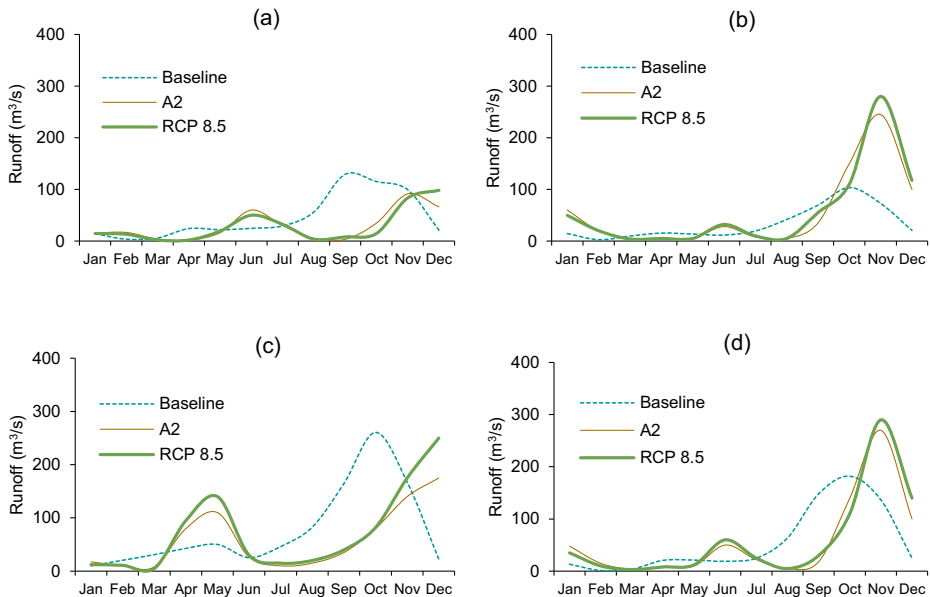
**Fig. 11** The calibrated and validated results of the HEC-HMS model at (a) Ta Trach and (b) Binh Dien stations

HMS is satisfactorily suited for hydrological simulations in order to understand the runoff response due to rainfall in the study area.

#### 4.4 Climate Change Impacts on Runoff

With the HEC-HMS satisfactorily calibrated and validated, the model was forced with the climate-change perturbed rainfall and temperature data to derive the catchment response. The end-of-Century responses are summarized in Fig. 12 which compares the mean monthly runoff for the climate change situations with the baseline hydrology. In general, the trend in the projected runoff agrees with the trend in the projected rainfall. Thus, the runoff during dry period (January – May) was generally higher than the baseline runoff because the rainfall behaved similarly. This increment has been previously noted by Dau and Kuntiyawichai (2020) indicating that mean annual rainfall for the dry period will increase by about 5 to 15%, 5 to 20%, and 5 to 25% at the Ta Trach, Huong Dien, and Binh Dien reservoirs, respectively. The rainfall was projected to decrease during June to September by both CMIP3 and CMIP5 projections and this decrease is translated to lower runoff during these months. The significant rise in the runoff from October onwards is a direct consequence of the projected rainfall increase and the relatively lower temperature rises, which would have also lowered the evapotranspiration in the basin.

The runoff situation shown in Fig. 12 exhibits distinct seasonality which at first sight might connote potential water security issues in the basin. However, in terms of surface water availability, the runoff has not changed much (Mean Annual Runoff difference is 10% and 5% for RCM and GCM, respectively). Dau et al. (2017) suggested future runoff in the Huong Basin will increase by more than 10% under RCP8.5 scenario using the HadGEM3-AO climate model. The seasonality of the runoff is what can be tempered by reservoirs, and the



**Fig. 12** Climate change impacts on future runoffs in the (a) Ta Trach, (b) Huu Trach, (c) Bo, and (d) Huong rivers in 2080s



three reservoirs in the basin, if effectively operated, will smoothen out this seasonality in river flow and thus temper any potential water shortages in the basin.

#### 4.5 Determination of Water Availability Using WEAP Model

The WEAP model forced with the simulated weather and runoff data was used to evaluate water demand conditions for each district in the Huong River Basin. Both irrigation and domestic water needs (Table 1) were considered for each district, with a prioritization given to irrigation as mentioned earlier in the priority rule. This means that in each time period, effort will first be made to meet the irrigation water demands and only the remainder, if any, is allocated to domestic water supply.

In general, effort is made to keep the reservoir state between the upper and lower rule curves when the full demand can be met. If the reservoir storage falls below the lower rule curve, hedging or deliberate water rationing kicks in. The hedging factor used is 0.8. WEAP allows this hedging factor to be applied to only the starting storage volume without considering the (unknown) inflow during the ensuing period. The WEAP simulation carried out in this study also adopted this approach. The three reservoirs are essentially parallel and to enhance their combined yield, total desired water (or demand) was apportioned to each reservoir based on its available storage space at the start of the period and the anticipated inflow, i.e., the Space Rule (Bower et al. 1962). A similar approach was described recently by Adeloje and Dau (2019) and Adeloje et al. (2019) in the Beas-Sutlej Basin, India, although rather than apply the hedging factor to the water in storage, they applied it directly to the demand.

The outcome of the water availability simulations for the end-of-Century is summarized in Table 2. The results in Table 2 do not include urban population projections, a case that will be discussed in the next section. As expected, most all the downstream districts using water from the reservoirs did not experience water shortages under the GCM or RCM climate projections. The increased runoff that would result from the projected future climate by both climate models, coupled with the integrated operation of the three reservoirs for meeting the downstream demands as argued previously, have ensured the perfect performance of the reservoirs. There were, however, water shortages at the upstream districts that rely solely on direct river abstraction. For example, there was a total shortage of  $50 \times 10^6 \text{ m}^3$  with the GCM climate projections in the 2080s, whilst the corresponding shortage for the RCM was  $40 \times 10^6 \text{ m}^3$ .

**Table 2** Irrigation and domestic water shortages under projected RCP8.5 and A2 in 2080s

District	RCM and RCP8.5			GCM and A2		
	Irrigation ( $\times 10^6 \text{ m}^3$ )	Domestic ( $\times 10^6 \text{ m}^3$ )	Total ( $\times 10^6 \text{ m}^3$ )	Irrigation ( $\times 10^6 \text{ m}^3$ )	Domestic ( $\times 10^6 \text{ m}^3$ )	Total ( $\times 10^6 \text{ m}^3$ )
Hue	–	–	–	–	–	–
Quang Dien	–	–	–	–	–	–
Phong Dien	–	–	–	–	–	–
Phu Vang	–	–	–	–	–	–
Huong Tra	–	–	–	–	–	–
Aluoi	–	–	–	–	–	–
Huong Thuy	–	–	–	–	–	–
Nam Dong	5.40	0.039	5.44	6.90	0.042	6.94
Phu Loc	34.20	0.107	34.41	43.40	0.117	43.52
Total			40			50

**Table 3** Projected population for urban and rural areas in the mid- and end-century

District	Baseline		Mid Century		End Century	
	Urban	Rural	Urban	Rural	Urban	Rural
Hue	302,983	32,592	484,194	32,592	857,658	57,731
Quang Dien	9734	73,077	15,556	73,077	27,554	129,442
Phong Dien	6015	82,075	9613	82,075	17,027	145,380
Phu Vang	20,671	149,709	33,034	149,709	58,514	265,181
Huong Tra	7641	107,392	12,211	107,392	21,629	190,224
A Luoi	3272	19,294	5229	19,294	9262	34,176
Huong Thuy	13,497	82,625	21,569	82,625	38,206	146,354
Nam Dong	6303	36,218	10,073	36,218	17,842	64,153
Phu Loc	20,996	113,326	33,554	113,326	59,434	200,735
Total	391,112	696,308	625,032	696,308	1,107,126	1,233,377
	<b>1,087,420</b>		<b>1,321,340</b>		<b>2,340,502</b>	

However, compared to the gross demand, these shortages represent a mere 27% and 21%, respectively, and as argued by Adeloye et al. (2017) and Firing (1982), there is nothing to worry about because consumers should easily adapt.

#### 4.6 Water Availability Simulation under Socio-Economic (Population) Scenarios

According to the DoS, the population in Thua Thien Hue Province will continuously increase in the future as expressed by Eq. (1). The population is estimated to be about  $1.23 \times 10^6$  in 2020, with the majority (65%) being urban residents. The projected population for the district in the future is shown in Table 3, which has been split into urban and rural based on the current ratio. In accordance with Vietnamese Construction Standards 33:2006/BXD, the per capita water demand of 200 L/day must be met with at least 95% reliability while the rural population per capita demand of 100 L/day only carries a reliability of at most 90%. This gives a total water consumption of  $86 \times 10^6$  m<sup>3</sup>/year for the whole province at the end Century (Table 1).

The projected future populations, the associated demand as well the simulated water shortages by WEAP are summarized in Table 4 (see also Fig. 13). As seen in the Table, Nam Dong, Phu Loc and Huong Thuy districts that were previously self-sufficient are now experiencing water shortages due to the projected increase in their resident population. However, as was the case earlier when the gross (agricultural and domestic) demand was analyzed, the total shortage due to population expansion is modest and should be adaptable.

**Table 4** Domestic water shortage under projected population in the end-Century

District	Domestic water shortage ( $\times 10^6$ m <sup>3</sup> )			
	Without population		Within population	
	RCP 8.5	A2	RCP 8.5	A2
Huong Thuy	–	–	0.1167	0.1167
Nam Dong	0.0386	0.0421	0.0813	0.0813
Phu Loc	0.1073	0.1171	0.2260	0.2260
Other districts - (No shortage)				

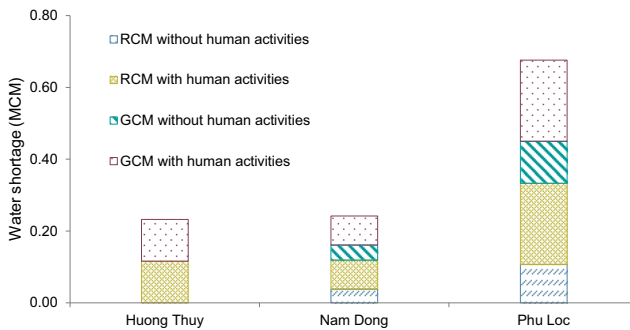


Fig. 13 Domestic water shortage with and without consideration of projected population

## 5 Conclusions

A water availability assessment under climate change impacts was carried out over the Huong River Basin. Climate outputs from GCM and RCM models were used as the forcing inputs for the HEC-HMS hydrological model to develop the runoff response of the basin to the different meteorological forcing scenarios. The result suggests that the basin is currently self-sufficient in water resources for its agricultural and domestic needs. When future projections of climate alone were incorporated, shortages were observed notably in the upper part of the basin that are not served by reservoirs while the downstream areas that are served by reservoirs (which help to smoothen the seasonality of the runoff) experienced no water shortages. However, when viewed in the context of the gross water demand, the total shortage was inconsequential as it can easily be adapted to. When population increases were incorporated, districts that were self-sufficient in domestic supply experience water shortages but as usual, these shortages were infinitesimal when compared to the gross domestic demand. This is good news for this basin in Vietnam because on the evidence of this research, there is sufficient water to cope even with most severe (and extreme) climate in the future.

The application of the statistical downscaling method presented in this study would be useful for further studies on climate studies, particularly in Southeast Asia. Nevertheless, there are some limitations emerging during this study, which need to be kept in mind, i.e.:

- the exclusion of groundwater resources from the study, although, as noted previously in the introduction, groundwater resources in Vietnam are not as many as surface water resources;
- the application of only one single scenario for each CMIP which could lead to a high uncertainty in projection, whereas the use of multi-model ensemble forced with different scenarios would enhance the reliability of the project future climate patterns;
- the insufficient observed data for model calibration and validation.

The above notwithstanding, however, that the conceptual framework developed for this study can be used as a template for other applications elsewhere around the world in managing water resources systems.

**Acknowledgements** The authors would like to thank the Department of Civil Engineering, Faculty of Engineering, Khon Kaen University in Thailand and the School of Energy, Geoscience, Infrastructure and Society (EGIS), Heriot-Watt University in the United Kingdom for their facilities used in conducting the study and preparing this manuscript.

**Availability of Data and Material** The datasets analyzed during the study are available from the corresponding author on request.

**Authors' Contributions** Conceptualization: [Quan V. Dau]; Methodology: [Quan V. Dau], [Kittiwet Kuntiyawichai], [Adebayo J. Adeloye]; Formal analysis and investigation: [Quan V. Dau], [Adebayo J. Adeloye]; Writing - original draft preparation: [Quan V. Dau]; Writing - review and editing: [Quan V. Dau], [Adebayo J. Adeloye]; Supervision: [Kittiwet Kuntiyawichai], [Adebayo J. Adeloye].

## Compliance with Ethical Standards

**Conflict of Interest** None.

**Code Availability** Quantile mapping MATLAB codes for climate downscaling are available from the corresponding author on request.

## References

- Abdo KS, Fiseha BM, Rientjes THM, Gieske ASM, Haile AT (2009) Assessment of climate change impacts on the hydrology of Gilgel Abay catchment in Lake Tana basin, Ethiopia. *Hydrol Process* 23:3661–3669. <https://doi.org/10.1002/hyp.7363>
- Adeloye AJ, Dau QV (2019) Hedging as an adaptive measure for climate change induced water shortage at the pong reservoir in the Indus Basin Beas River, India. *Sci Total Environ* 687:554–566. <https://doi.org/10.1016/j.scitotenv.2019.06.021>
- Adeloye AJ, Soundharajan B, Mohammed S (2017) Harmonisation of reliability performance indices for planning and operational evaluation of water supply reservoirs. *Water Resour Manag* 31:1013–1029. <https://doi.org/10.1007/s11269-016-1561-x>
- Adeloye AJ, Wuni IY, Dau QV, Soundharajan B-S, Kasiviswanathan KS (2019) Height–area–storage functional models for evaporation-loss inclusion in reservoir-planning analysis. *Water* 11(7):1413. <https://doi.org/10.3390/w11071413>
- Allan R, Pereira L, Raes D, Smith M (1998) Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56 vol 56. <http://www.fao.org/3/X0490E/x0490e00.htm>. Accessed 15 Dec 2018
- Bower TB, Hufschmidt MM, Reedy EW (1962) Operating procedures: their role in the design of water-resource systems by simulation analyses. In: Maass A, Hufschmidt MM, Dorfman R, Thomas HA, Marglin SA, Fair GM (eds) Design of water resources systems. Harvard University Press, Cambridge, pp 443–456
- Christensen JH, Boberg F, Christensen OB, LucasPicher P (2008) On the need for bias correction of regional climate change projections of temperature and precipitation *Geophys Res Lett* 35. <https://doi.org/10.1029/2008GL035694>
- Dau QV, Kuntiyawichai K (2015) An assessment of potential climate change impacts on flood risk in Central Vietnam. *Eur Sci J* 1:667–680 <http://eujournal.org/index.php/esj/article/view/6470>
- Dau QV, Kuntiyawichai K (2020) Identifying adaptive reservoir operation for future climate change scenarios: a case study in Central Vietnam. *Water Res* 47:189–199. <https://doi.org/10.1134/S009780782002013X>
- Dau QV, Kuntiyawichai K, Plermkamon V (2017) Quantification of flood damage under potential climate change impacts in Central Vietnam. *Irrig Drain* 66:842–853. <https://doi.org/10.1002/ird.2160>
- Dau QV, Kuntiyawichai K, Suryadi FX (2018) Drought severity assessment in the lower Nam Phong River basin, Thailand. *Songklanakarin J Sci Technol* 40:985–992. <https://doi.org/10.14456/sjst-psu.2018.99>
- Faour G, Fayad A (2014) Water environment in the coastal basins of Syria - assessing the impacts of the war. *Environ Processes* 1:533–552. <https://doi.org/10.1007/s40710-014-0043-5>
- Feldman AD (2008) Hydrologic modeling system HEC-HMS. Hydrologic engineering center, HEC 609 Second St. Davis, CA

- Fiering MB (1982) Estimates of resilience indices by simulation. *Water Resour Res* 18:41–50. <https://doi.org/10.1029/WR018i001p00041>
- GSO (2017) Part 1: data sources, methodology and projection results. General Statistics Office of Vietnam. [https://www.gso.gov.vn/default\\_en.aspx](https://www.gso.gov.vn/default_en.aspx). Accessed on December 01, 2019
- Khan MS, Coulibaly P, Dibike Y (2006) Uncertainty analysis of statistical downscaling methods. *J Hydrol* 319: 357–382. <https://doi.org/10.1016/j.jhydrol.2005.06.035>
- Khoi DN, Hang PTT (2015) Uncertainty assessment of climate change impacts on hydrology: a case study for the central highlands of Vietnam. In: Shrestha S, Anal AK, Salam PA, van der Valk M (eds) *Managing water resources under climate uncertainty: examples from Asia, Europe, Latin America, and Australia*. Springer International Publishing, Cham, pp 31–44. [https://doi.org/10.1007/978-3-319-10467-6\\_2](https://doi.org/10.1007/978-3-319-10467-6_2)
- Kiniouar H, Hani A, Kapelan Z (2017) Water demand assessment of the upper semi-arid sub-catchment of a Mediterranean basin. *Energy Procedia* 119:870–882. <https://doi.org/10.1016/j.egypro.2017.07.140>
- Kuntiyawichai K, Plermkamon V, Jayakumar R, Dau QV (2017) Climate change vulnerability mapping for the greater Mekong sub-region. *CMU J Nat Sci* 16:165–173. <https://doi.org/10.12982/CMUJNS.2018.0013>
- Lindegaard LS (2018) Adaptation as a political arena: interrogating sedentarization as climate change adaptation in Central Vietnam. *Glob Environ Chang* 49:166–174. <https://doi.org/10.1016/j.gloenvcha.2018.02.012>
- Mai DT, De Smedt F (2017) A combined hydrological and hydraulic model for flood prediction in Vietnam applied to the Huong River basin as a test case study. *Water* 9(11):879. <https://doi.org/10.3390/w9110879>
- Mirgol B, Nazari M (2018) Possible scenarios of winter wheat yield reduction of dryland Qazvin province, Iran, based on prediction of temperature and precipitation till the end of the century. *Climate* 6(4):78. <https://doi.org/10.3390/cli6040078>
- Mishra SK, Singh VP (2003) Soil conservation service curve number (SCS-CN) methodology. *Water Sci Technol Library* 42. <https://doi.org/10.1007/978-94-017-0147-1>
- Momblanch A, Papadimitriou L, Jain SK, Kulkarni A, Ojha CSP, Adeloje AJ, Holman IP (2019) Untangling the water-food-energy-environment nexus for global change adaptation in a complex Himalayan water resource system. *Sci Total Environ* 655:35–47. <https://doi.org/10.1016/j.scitotenv.2018.11.045>
- MONRE (2012) Climate change scenarios and sea level rise for Vietnam. Minister of Natural Resources and Environment, Hanoi <http://www.wimhacvn/files/doc/2017/CCS%20finalcompressedpdf> Accessed February 15, 2020
- MONRE (2019) Land use and soil type maps in Thua Thien hue province. Minister of Natural Resources and Environment, Vietnam <http://www.9monregovvn/wps/portal/english> Accessed May 20, 2018
- MPI (2018) Vietnam's voluntary national review on the implementation of the sustainable development goals. Department for Science, Education, Natural Resources and Environment, Ministry of Planning and Investment, Vietnam [https://sustainabledevelopmentun.org/content/documents/19967VNR\\_of\\_Viet\\_Nampdf](https://sustainabledevelopmentun.org/content/documents/19967VNR_of_Viet_Nampdf) Accessed February 20, 2020
- Ngo-Duc T (2014) 8 - climate change in the coastal regions of Vietnam. In: Thao ND, Takagi H, Esteban M (eds) *Coastal disasters and climate change in Vietnam* 175–198. <https://doi.org/10.1016/B978-0-12-800007-6.00008-3>
- Nguyen D, Nguyen HS, Le DT (2013) Application of model HEC-HMS and HEC-RAS for flood flow simulation of Huong River basin. *Hydrol Environ Sci* 42:12–17. <http://tapchikttv.vn/article/144>. Accessed 18 Jun 2017
- Nguyen DQ, Renwick J, McGregor J (2014) Variations of surface temperature and rainfall in Vietnam from 1971 to 2010. *Int Climate Climatol* 34:249–264. <https://doi.org/10.1002/joc.3684>
- Nguyen TT, Ngo HH, Gue W, Nguyen HQ, Luu C, Dang KB, Liu W, Zhang X (2020) New approach of water quantity vulnerability assessment using satellite images and GIS-based model: an application to a case study in Vietnam. *Sci Total Environ* 737:139784. <https://doi.org/10.1016/j.scitotenv.2020.139784>
- Nguyen-Tien V, Elliott RJR, Strobl EA (2018) Hydropower generation, flood control and dam cascades: a national assessment for Vietnam. *J Hydrol* 560:109–126. <https://doi.org/10.1016/j.jhydrol.2018.02.063>
- Nong D, Wang C, Al-Amin AQ (2020) A critical review of energy resources, policies and scientific studies towards a cleaner and more sustainable economy in Vietnam. *Renew Sust Energ Rev* 134:110117. <https://doi.org/10.1016/j.rser.2020.110117>
- Onyutha C, Tabari H, Rutkowska A, Nyeko-Ogiramoi P, Willems P (2016) Comparison of different statistical downscaling methods for climate change rainfall projections over the Lake Victoria basin considering CMIP3 and CMIP5. *J Hydro Environ Res* 12:31–45. <https://doi.org/10.1016/j.jher.2016.03.001>
- Pickard BR, Nash M, Baynes J, Mehaffey M (2017) Planning for community resilience to future United States domestic water demand. *Landsc Urban Plan* 158:75–86. <https://doi.org/10.1016/j.landurbplan.2016.07.014>
- Sagris T, Tahir S, Möller-Gulland J, Quang NV, Abbott J, Yang L (2017) Vietnam: hydro-economic framework for assessing water sector challenges. <https://www.2030wrg.org/wp-content/uploads/2017/08/Vietnam-Hydro-Economic-Frameworkpdf> Accessed May 15, 2019

- Schmidt-Thome P, Nguyen TH, Pham TL, Jarva J, Nuottimäki K (2015) Climate change in Vietnam. In: climate change adaptation measures in Vietnam: development and implementation 7-15. [https://doi.org/10.1007/978-3-319-12346-2\\_2](https://doi.org/10.1007/978-3-319-12346-2_2)
- Sen LTH, Bond J, Winkels A, Linh NHK, Dung NT (2020) Climate change resilience and adaption of ethnic minority communities in the upland area in Thừa Thiên-Huế province, Vietnam. *NJAS - Wageningen J Life Sci* 92:100324. <https://doi.org/10.1016/j.njas.2020.100324>
- Shrestha S, Deb P, Bui T (2016) Adaptation strategies for rice cultivation under climate change in Central Vietnam. *Mitig Adapt Strateg Glob Chang* 21:1–23. <https://doi.org/10.1007/s11027-014-9567-2>
- Sieber J, Purkey D (2011) WEAP, water evaluation and planning system. Stockholm Environment Institute, U.S. Center, Somerville
- Sun SK, Li C, Wu PT, Zhao XN, Wang YB (2018) Evaluation of agricultural water demand under future climate change scenarios in the loess plateau of northern Shaanxi, China. *Ecol Indic* 84:811–819. <https://doi.org/10.1016/j.ecolind.2017.09.048>
- Tena TM, Mwaanga P, Nguvulu A (2019) Hydrological modelling and water resources assessment of Chongwe River catchment using WEAP model. *Water* 11(4):839. <https://doi.org/10.3390/w11040839>
- Tran TTT, Jong-Koo L, Juhwan O, Hoang VM, Chul OL, Le TH, You-Seon N, Tran KL (2016) Household trends in access to improved water sources and sanitation facilities in Vietnam and associated factors: findings from the multiple indicator cluster surveys, 2000–2011. *Glob Health Action* 9:29434–29434. <https://doi.org/10.3402/gha.v9.29434>
- Trinh TQ, Rañola RF, Camacho LD, Simelton E (2018) Determinants of farmers' adaptation to climate change in agricultural production in the central region of Vietnam. *Land Use Policy* 70:224–231. <https://doi.org/10.1016/j.landusepol.2017.10.023>
- UNESCO-IHP (2004) Catalogue of rivers for Southeast Asia and the Pacific. [http://hywr.kuciv.kyoto-u.ac.jp/ihp/riverCatalogue/Vol\\_05/](http://hywr.kuciv.kyoto-u.ac.jp/ihp/riverCatalogue/Vol_05/). Accessed May 22, 2016
- Wilby RL, Dawson CW (2013) The statistical downscaling model: insights from one decade of application. *Int J Climatol* 33:1707–1719. <https://doi.org/10.1002/joc.3544>
- Wilby RL, Hay LE, Leavesley GH (1999) A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado. *J Hydrol* 225:67–91. [https://doi.org/10.1016/S0022-1694\(99\)00136-5](https://doi.org/10.1016/S0022-1694(99)00136-5)
- World-Bank (2011) Vietnam development report 2011. World Bank. <http://documents1.worldbank.org/curated/en/589341559130979599/pdf/Vietnam-Toward-a-Safe-Clean-and-Resilient-Water-System.pdf>. Accessed September 15, 2020
- Yang W, Andreason J, Graham LP, Olsson J, Rosberg J, Wetterhall F (2010) Distribution-based scaling to improve usability of regional climate model projections for hydrological climate change impacts studies. *Hydrol Res* 41:211–229. <https://doi.org/10.2166/nh.2010.004>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.