Case Study

Use of Regional Climate Models for Proxy Data over Transboundary Regions

M. T. Vu[1]; S. V. Raghavan[2]; and S.-Y. Liong[3]

Abstract: The sharing of water resources across transboundary regions between countries has long been a political problem. Sharing of data among countries is also a significant impediment for both planning and research purposes. In the context of climate change, it is necessary to know about possible future climatic changes and their potential impacts that would be especially crucial to water resources management. This requires data for hydrological modeling and data management, as in the case of river basins. This paper presents a study over the course of the Da River, which flows from China (upstream) to Vietnam (downstream), and it is assumed that rainfall data from China are not available. To overcome data limitation, regional climate model outputs are used as proxy data for this upstream region to study changes over the downstream Da River. The Weather Research and Forecasting (WRF) model was used as the regional climate model, driven by the European reanalysis data for the baseline period of 1961–1987 for a domain covering the transboundary areas, at a resolution of 25 km. Precipitation outputs from this model were used as inputs to the hydrological model and soil and water assessment tools (SWAT) to calibrate/validate the model at data-available gauging station sites. The initial results of this study imply that the regional climate model (RCM) data proxies serve as a good alternative to assess water resources over transboundary regions and are useful tools for assessing future climate changes and their impacts at subregional and local scales. **DOI:** 10.1061/(ASCE)HE.1943-5584.0001342.

Author keywords: Transboundary; Regional climate model (RCM); Proxy data; Water resource management.

Introduction

International river basins that include political boundaries of two or more countries cover 45.3% of the Earth's land surface, host approximately 40% of the world's population, and account for approximately 60% of global rivers (Wolf et al. 2005). Due to different governmental policies, conflicts arise in the sharing of water resources, more frequently when the advantage is higher for the upstream country using these water resources. The problem of water resource management arises when no data are available due to poorly managed observing stations, lack of technology and resources, and wartime and financial limitations. Data availability is also an issue when data sharing is difficult between countries that have no formal data sharing agreement. Research by Lu and Siew (2006) showed that dam constructions in China have been affecting water discharge and sediment flux over the lower Mekong River during the past decades. For example, when the availability of water resources needs to be assessed over northern Vietnam, the data for the upstream region that lies over the southern part of China are not available. This poses a strong limitation as the water quantity over the downstream Vietnam depends on the flow from the upstream China. This is a clear case of a transboundary problem. Thus, this paper describes an approach to overcome transboundary data requirement issues in managing water resources by using the outputs from climate models as inputs to hydrological models.

The use of hydrological models in river catchments for climatological applications requires data with high spatial resolutions of forcing meteorological fields, such as rainfall and temperature. The hydrological models are sensitive to biases in the forcing data (Berg et al. 2012) because they are generally calibrated against observational data. Due to coarse resolution, climate estimates derived from global climate models (GCMs) are not useful for impact studies, in this case, hydrological processes (Mearns et al. 2001; Allen and Ingram 2002; Forest et al. 2002). Data from high-resolution regional climate models (RCMs) are used as inputs to hydrological models for impact studies (Teutschbein and Seibert 2010) because information obtained from the GCMs is too coarse. Many studies have utilized RCMs to study hydrological flow (González-Zeas et al. 2012; Im et al. 2010; Ma et al. 2010). Most of these studies applied bias-correction methods to the RCM outputs as an intermediary coupling step (Hay et al. 2002; González-Zeas et al. 2012). However, bias-correction methods require robust station data, which are very difficult or sometimes even impossible to obtain over data-sparse areas or transboundary regions. Therefore, the use of the direct output from RCMs for regional hydrological studies is still utilized (Graham et al. 2007a, b; Wood et al. 2004).

There are uncertainties associated in the downscaling of climate models; those uncertainties that propagate into hydrological models when climate model outputs are used as inputs. Some studies have found that uncertainties in climate change impacts on water resources are primarily due to the uncertainty in precipitation inputs

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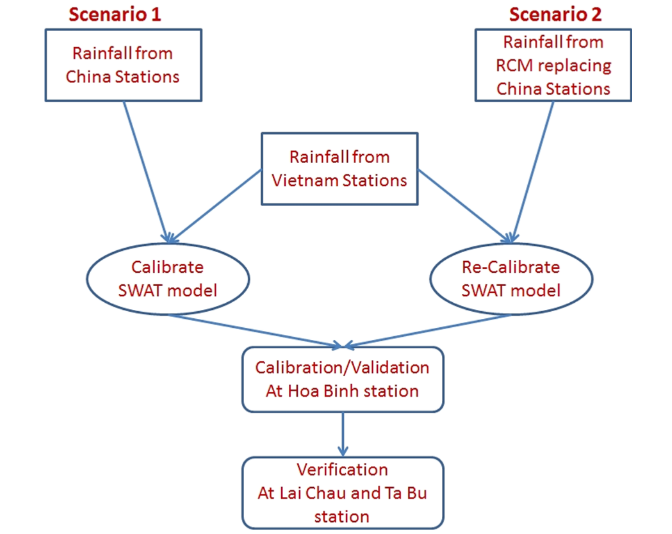

Fig. 1. Schematization of study workflow

and less because of uncertainties in greenhouse gas emissions, in climate sensitivities, or in hydrological models themselves (IPCC 2007). The uncertainty in precipitation inputs to the hydrological model have been addressed in many other studies. Strauch et al. (2012) used ensemble rainfall for uncertainty analysis in their SWAT streamflow study, in which they applied four different inputs of precipitation: (1) point data from available stations, (2) smoothed version of gauge data derived from moving averages, (3) spatially distributed data from the Thiesson polygon, and (4) tropical rainfall measuring mission radar data. The results enhanced the level of confidence in simulation results, particularly for data-poor regions. Similar studies can be found in Cho et al. (2009), Georgakakos et al. (2004), and Lopes (1996).

This study assesses the uncertainties in a different way by applying two different inputs of precipitation to the SWAT hydrological model: (1) using point data from available stations, and (2) substituting point data from the upstream part of the river basin by direct output data from an RCM. The objective in this study is to simulate the hydrological processes under climatological conditions with missing data from the upstream for a transboundary river basin between China (upstream) and Vietnam (downstream). All the inputs for the semidistributed hydrology model, SWAT, were obtained from many available sources (described in section "Spatial Data as Input to SWAT Model"). The RCM WRF model was used to downscale the European reanalysis data ERA40, which provide the required boundary forcing under the current climate conditions. The two main climate variables, precipitation and temperature, were compared with the gridded observation data and station data, for benchmarking. The authors aim to estimate parameter uncertainty analysis for the SWAT model using the parameter solution procedure (ParaSol) (van Griensven and Meixner 2006). These data were then used as proxies over the data-sparse region at the upstream catchment to simulate the river flow at the downstream. The idea behind this work is to assess how suited RCM outputs are as proxies for hydrological applications over data-sparse regions so that their usefulness can be adequately harnessed for future climate impact studies spanning such data-lacking areas. The study methodology is shown in Fig. 1.

Materials and Methods

Study Region

The Da River originates from the Yunnan Province in China and flows downstream through mountainous regions, crosses the border between China and Vietnam, and joins as a tributary of the Red River in Vietnam. The Da River has a total catchment area of about 53,000 km^2, 48% of which lies in China's territory, 2% in the Lao People's Democratic Republic (PDR), and 50% in Vietnam. This can be seen in Fig. 2(a). The Da River spans a total length of 1,010 km, of which 570 km is in Vietnam, and a population of 1.3 million people live in this region. The total annual precipitation ranges between 1,000 and 2,300 mm per annum (Nguyen et al. 2013). The Da River has a high annual average discharge of 1,770 m^3/s, recorded at Hoa Binh station. During the main flood season (June–October), the total flow volume accounts for approximately 78% of the annual flow volume. Flood occurs heavily because of very high rainfall concentrations over the steep topography and narrow valleys, leading to very high peak floods of approximately 5,000 m^3/s during extreme events. Therefore, the basin has a very high potential for hydropower. Due to its importance in the Vietnam hydropower system, the Da River is always listed as the first in hydropower generation.

The need for climate-based studies comes in the backdrop of the water resources management. The main issue is what impacts will occur if dams constructed in China affect the amount of water flowing into Vietnam.

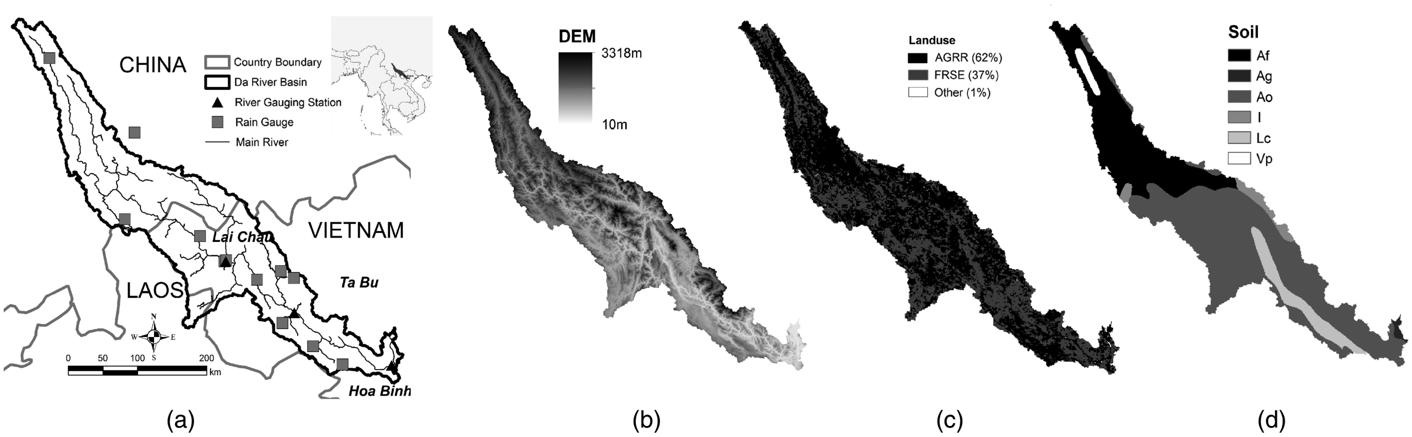

Fig. 2. (a) Da River basin and station locations; (b) DEM; (c) land use; (d) soil

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Model

Hydrological Model SWAT

SWAT is a river basin scale model, developed by the USDA's Agriculture Research Service in the early 1990s. It has been designated to work for large river basins. Its purpose is to quantify the impact of land management practices on water, sediment, and agriculture chemical yields with varying soil, land use, and management conditions (Arnold and Fohrer 2005). In this study, the soil conservation service (SCS) curve number procedure (USDA-SCS 1985) was used to estimate the surface runoff in the SWAT model. In order to calculate the potential evapotranspiration (PET), numerous methods have been developed (Neitsch et al. 2005). Three of these methods that have been used frequently in the SWAT model are the Penman-Monteith (PM) method (Monteith 1965; Allen 1986), the Priestley-Taylor method (Priestley and Taylor 1972), and the Hargreaves method (Hargreaves et al. 1985). Although the PM method remains the most reliable and widely used method for many agriculture studies (Shukla et al. 2014), it requires a number of inputs such as solar radiation, air temperature, relative humidity, and wind speed (some of which were not available for this study). Therefore, the Hargreaves method was selected for computing PET because it requires only maximum, minimum, and mean air temperature variables as input. In the SWAT model, the land area in a subbasin was divided into what are called *hydrological response units (HRUs)*. In other words, an HRU is the smallest portion that combines different land use and soil type by overlaying their spatial map. All processes such as surface runoff, PET, lateral flow, percolation, soil erosion, nitrogen, and phosphorous are usually carried out for each HRU.

Regional CLIMATE Model—WRF

Developed at the National Center for Atmospheric Research (NCAR) in the United States, the WRF model has found wide applications in climate research and in weather forecasting. The model incorporates advanced numeric and data-assimilation techniques, a multiple-nesting capability, and numerous state-of-the-art physics options. For this study, the WRF model was simulated over the period spanning 1961–1990. A 25-km, one domain configuration was adopted for WRF, which was forced by the ERA40 reanalysis data at the model's lateral boundaries. In terms of physics, the Kain-Fritsch scheme (Kain 2004) was used for the cumulus convection scheme. The Yonsei University (YSU) scheme (Hong et al. 2006) was used for the planetary boundary layer. The Thompson scheme (Thompson et al. 2004) was used for the explicit moisture physics parameterization and rapid radiative transfer model GCM applications (RRTMG) (Iacono et al. 2008) were applied for both long- and short-wave radiations. The NOAH (Ek et al. 2003) land surface scheme was implementation for surface hydrology. The physics options were chosen from different parameterization sensitivity studies performed previously that best represented the climate of the region. The WRF model outputs, precipitation, and surface temperature were benchmarked against gridded observations and station data when available. These WRF outputs were then used as inputs to the SWAT hydrological model.

Data

Spatial Data as Input to SWAT Model

Due to the inability to acquire sufficient input data from the upstream region, most of the input data were obtained from a suite of open sources that are available to the research community. The digital elevation model (DEM) [Fig. 2(b)] was taken from the National Aeronautics and Space Administration's (NASA's) shuttle radar topography mission (SRTM) three-arc second (approximately 90 m), where the digital elevation data was obtained on a near-global scale to generate the most complete high-resolution digital topographic database of the Earth (Farr and Kobrick 2000). The land-use map was taken from the 2000 global land cover (GLC). For this case study, the authors assumed that the 2000 GLC would be similar to the study period from 1961 to 1990 because the GLC map for this part of the world is very limited and the 2000 GLC was the only one available. This is the most recent version of the database available until now, which can be accessed at the USGS website (USGS 2014). Similar methods have been mentioned by van Griensven et al. (2007) and Oeurng et al. (2011). The land use for the Asia region was downloaded and cropped to the study area. The land use was classified into six different categories of which the agricultural land-row crops (AGRR) and forest evergreen (FRSE) cover a majority area of 62.7% and 37%, respectively [Fig. 2(c)]. The soil map was taken from the digital soil map of the world provided by the Food and Agricultural Organization (FAO) (FAO 2003) at a 1:5.000.000 scale, in the geographic projection (latitude–longitude) intersected with a template containing water-related features (e.g., coastlines, lakes, glaciers, and double-lined rivers). There are approximately 23 soil types with a spatial resolution of 10 km and soil properties for two layers (layer 1: 0–30 cm depth; layer 2: 30–100 cm depth). The cropped region for the Da River basin includes six types, as shown in Fig. 2(d).

Gauging Station Data

Besides the spatial data required for the SWAT model setup, some meteorological data were available for this study over the upstream China portion of the river (under one of the authors' collaborative projects) from three of the nearest stations to the basin. Meteorological and discharge data from the Vietnam region was obtained from the Institute of Meteorology, Hydrology, and Climate Change (IMHCC) under the Ministry of Natural Resources and Environment (MONRE), Vietnam. In Vietnam, nine rainfall stations and three river gauging stations on the Da River main stream were used in this study. All data collected were on daily scales. The Hoa Binh gauging station, which is the control station for the Da River catchment, was used for model calibration [Fig. 2(a)]. The other two gauging stations in Vietnam, Lai Chau (120 km from the boundary of China and Vietnam) and Ta Bu (in the middle of Lai Chau and Hoa Binh), were used to verify the model performance. The locations of these rainfall stations and the three river gauging stations are shown in Fig. 2(a).

Observed Data

ECMWF-ERA40 Data Set. The ERA40 is a global atmospheric analysis of many observations and satellite data available for the period spanning 1957–2002. The analyses were produced every 6 h daily at 00Z, 06Z, 12Z, and 18Z h. The atmospheric model was run with 60 levels in the vertical and spatial resolution of 2.5×2.5°C. ERA40 has been used extensively by several climate modelers for simulating regional climates (Heikkilä et al. 2011; Rockel et al. 2008; Boe et al. 2007). They are also increasingly important for validating long-term model simulations, for helping develop a seasonal forecasting capability, and for establishing the climate of ensemble prediction system (EPS) forecasts. These data sets have also been documented by (Uppala et al. 2005). This reanalysis data set was used in this study to evaluate the performances of RCM WRF over the climate from 1961 to 1990.

CRU Data Set. The RCM results were compared with the 0.5×0.5°C climatic research unit (CRU) gridded observed precipitation and temperature data set CRU TS 3.21, made available through the

Table 1. Sensitivity Analysis Ranking of 10 Most Sensitive Parameters in the SWAT Model to Streamflow in This Case Study

Sensitivity analysis order	Parameter	Description	Parameter range
1	Cn2	Moisture condition II curve number	35–98
2	Alpha_Bf	Baseflow recession constant	0–1
3	Ch_K2	Effective hydraulic conductivity in main channel	−0.01–500
4	Surlag	Surface runoff lag coefficient	1–24
5	Ch_N2	Manning *n* value for the main channel	−0.01–0.3
6	Blai	Maximum potential leaf area index for land cover	0–8
7	Sol_Awc	Available water capacity	0–1
8	Esco	Soil evaporation compensation factor	0–1
9	Canmx	Maximum canopy storage	0–100
10	Gwqmn	Threshold water level in shallow aquifer for base flow	0–5,000

British atmospheric data center (BADC). Details of this data set can be found in Harris et al. (2014).

SWAT Model Parameter Selection and Uncertainty Analysis

The model calibration was based on the 10 most sensitive parameters, specified by Latin hypercube (LH) one factor at a time (OAT) sampling (van Griensven and Meixner 2006). This method samples the full range of all parameters, using LH design and the precision of OAT sampling to ensure that the changes in each model output could be attributed to the changed parameter. The LH-OAT design has been coupled with the SWAT model for sensitivity analysis. Model parameters were analyzed based on the performance of its output compared with observed data and the model itself. In the SWAT model, there are 27 flow parameters with their default bounds (Winchell et al. 2007). In this study, the 10 most sensitive parameters of the available 27 options were analyzed because the streamflow is the main focus (Table 1).

Model calibration and estimation of both parameters were performed using the ParaSol method. Parasol is a built-in autocalibration tool created by van Griensven and Meixner (2007) for *ArcSWAT version 2005*. ParaSol is a method that performs optimization and uncertainty analysis for complex hydrology models. ParaSol operates using a parameter search method for model parameter optimization followed by a statistical method that was performed during the optimization to provide parameter uncertainty bounds and the corresponding uncertainty bounds on the model outputs. The ParaSol method aggregates objective functions (OFs) into a global optimization criterion (GOC), minimizes these OFs or a GOC using the shuffled complex evolution method (SCE-UA) algorithm and performs uncertainty analysis with a choice between two statistical concepts. The SCE-UA (Duan et al. 1992) method is based on a synthesis of all the best functions from many other existing methods, consisting of the genetic algorithm (GA), simplex method (Nelder and Mead 1965), controlled random search (Price 1987), competitive evolution (Holland 1975), and the newly developed concept of complex shuffling. SCE-UA conducts a global minimization of a single function for up to 16 parameters. This method is also applicable for nonlinear optimization problems.

Methodology

The experimental study consisted of four steps:

1. Setup of the SWAT model for the Da River basin.
2. Calibration and validation of the SWAT model using observed daily rainfall data from China (though limited) and Vietnam. In this step, the reference station was the Hoa Binh gauging station on the downstream edge of the Da River. The calibration and validation periods were 1961–1980 and 1981–1987, respectively, with the first year used as warm-up. The Lai Chau and Ta Bu stations were the two stations at which the verification of the SWAT-simulated discharge were done to establish model performance. All model simulations were performed at daily temporal scales. This was considered as Scenario 1.
3. Substitute rainfall over China with the output data from the regional climate model WRF, with the data being bilinearly interpolated to the same locations and recalibrated. This was considered as Scenario 2.
4. Perform uncertainty analysis and compare with the results from both scenarios

The Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970) and the coefficient of determination R^2 were used as the benchmarking indices for the simulation of runoff.

Results

Regional Climate Model Output

For the discussion of results in this paper, the simulations of the WRF model driven by ERA40 data are referred to as WRF/ERA. The WRF/ERA output was validated against the CRU data and also using the station data from Vietnam (interpolated using the Kriging method).

Spatial Simulation of Surface Temperature

Fig. 3(a) represents the interpolation of station data for temperature from the Vietnam territory, while Figs. 3(b and c), which are gridded data sets, show those from both China and Vietnam. When compared to gridded observations [Fig. 3(b)], the simulated temperature of WRF/ERA [Fig. 3(c)] agrees well in terms of its spatial distribution. The east-west gradient is also resolved well when comparing WRF/ERA results with gridded observations, although the CRU data set is coarser at 50 km than with the 25-km run of the WRF model. The advantage of the 25-km finer resolution of WRF/ERA is that it was able to resolve the high topography at the Hoang Lien Son mountain chain [represented by declining temperatures for the range represented by the circle in Figs. 3(a and c)], which is absent in the coarser gridded data of 50-km CRU observations.

Spatial Simulation of Precipitation

Unlike temperature, precipitation is more difficult to simulate because it is highly variable in space and time. Fig. 4(a) displays the interpolated station data for precipitation over the Vietnam territory, while Figs. 4(b and c) are gridded data sets showing China and Vietnam. The WRF/ERA model [Fig. 4(c)] is able to reproduce the heavy rainfall (about 4.5–5 mm/day) over the border of China and Vietnam, as found in the station data set (~6 mm/day) [Fig. 4(a)], while CRU exhibits less rainfall (3.5–4 mm/day) in its spatial distribution [Fig. 4(b)]. The difference between the interpolated station data [Fig. 4(a)] and the gridded observation data [Fig. 4(b)] is approximately 35%. This could be due to the coarse-gridded CRU data set, in which the local rainfall affected by the mountainous region might not be captured correctly. The WRF/ERA shows an average value of precipitation in the midrange between two observation data sets, indicating that it was able to

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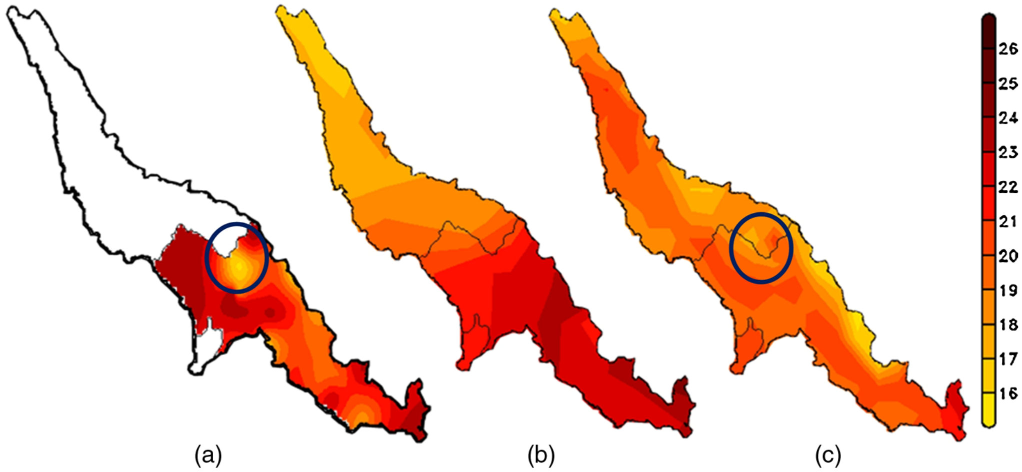

Fig. 3. Annual average surface temperature (°C): (a) station; (b) CRU; (c) WRF/ERA

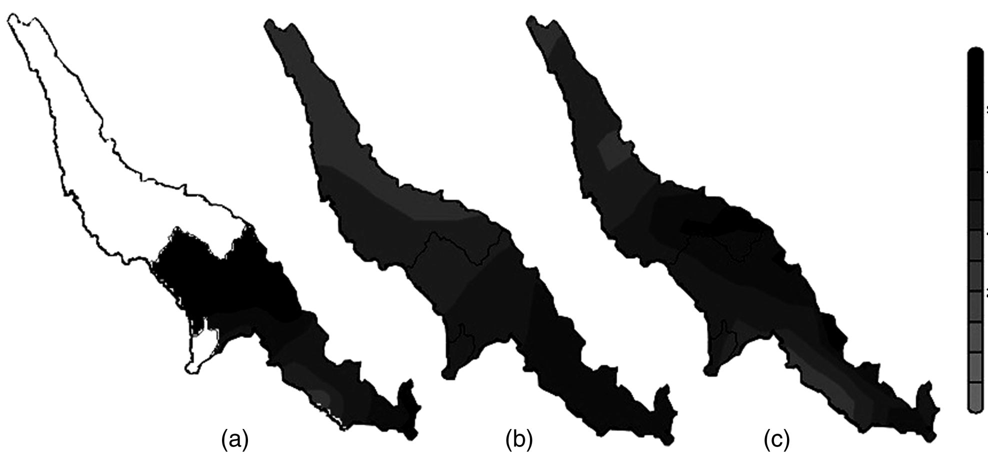

Fig. 4. Annual average precipitation (mm/day): (a) station; (b) CRU; (c) WRF/ERA

capture the average rainfall over this area well. Overall, the east-west and south-north gradient of rainfall are represented well by the WRF model when compared with observations.

Annual Cycle

The annual cycle of temperature and precipitation at the Hoa Binh station between different data sets are displayed in Figs. 5(a and b), respectively. Both CRU and WRF/ERA were bilinearly interpolated to the station location and validated against the station data. In Fig. 5(a), it can be seen that the WRF/ERA was able to capture the annual cycle of temperature with higher values during summer months (Jun, Jul, Aug) and lower values during the winter (Dec, Jan, Feb). Fig. 5(b) exhibits the annual cycle of precipitation between the three data sets at the Hoa Binh station. The gridded

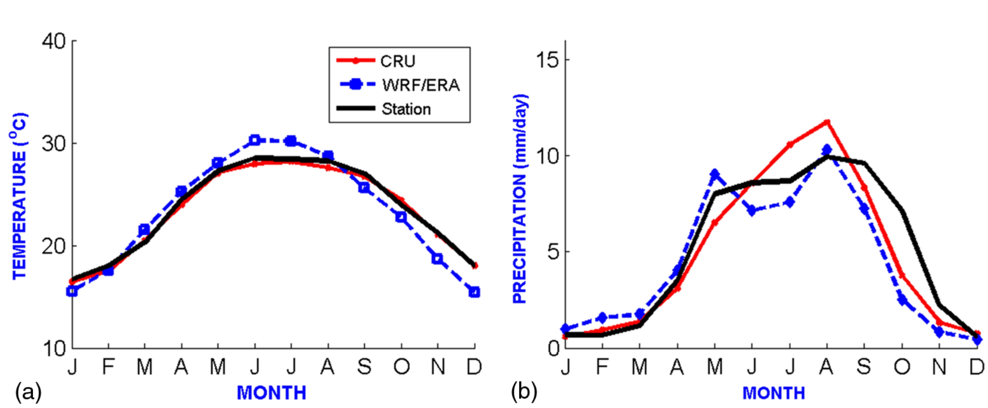

Fig. 5. Annual cycle at Hoa Binh station: (a) temperature; (b) precipitation

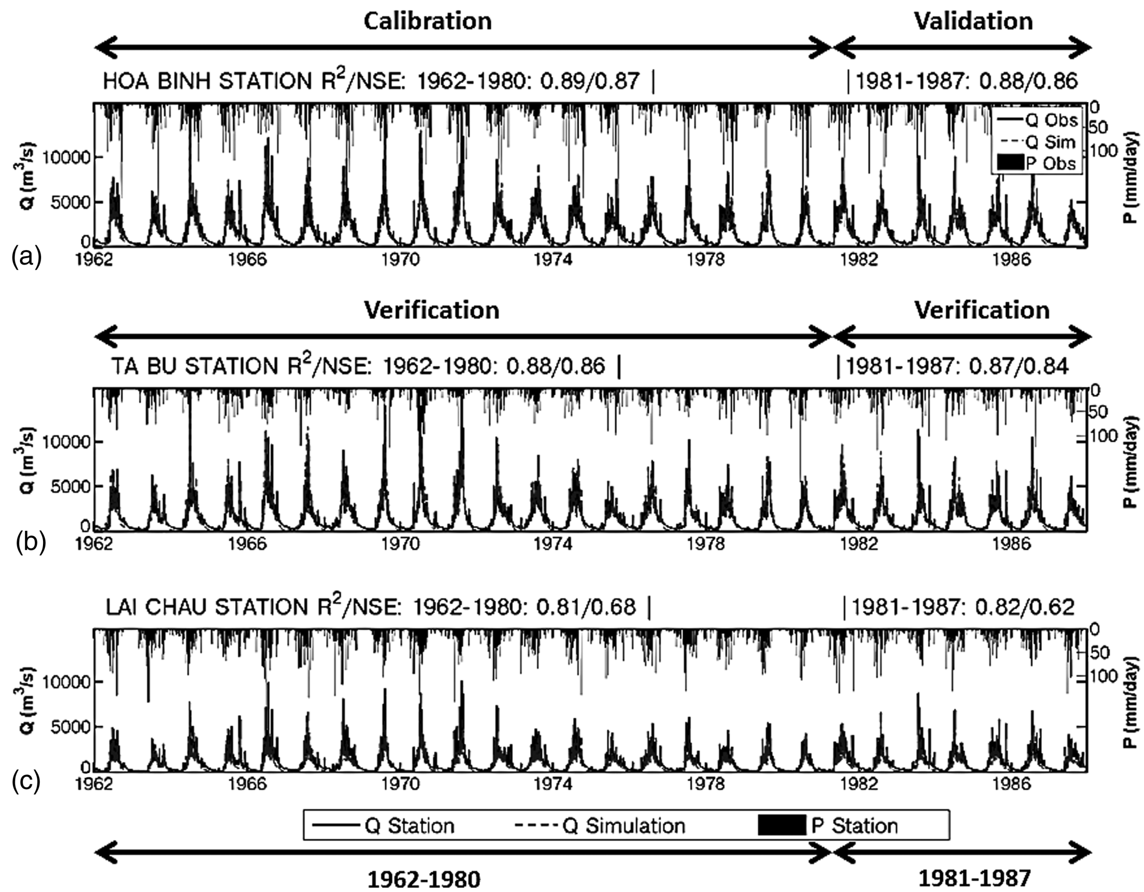

Fig. 6. Scenario 1 using observed rainfall from three China stations and observed rainfall from nine Vietnam stations; used as input to SWAT model to simulate stream flow at (a) Hoa Binh; (b) Ta Bu; (c) Lai Chau

CRU data, despite agreeing well on the temperature annual cycle against the station, show biases in precipitation when compared with station data. The annual cycle of precipitation of CRU displays a sharp increase in the highest rainfall peak in August, while station data show a gradual increase for the rainy season from May to September. The WRF/ERA indicates two peaks: a lower one in May and a higher one in August that coincides with the station and CRU data set. The discrepancy between the three data sets might be due to the coarse resolution of CRU and WRF/ERA or the varied topography over this mountainous area.

SWAT Simulations of Discharge

The precipitation and surface temperature outputs of WRF/ERA were used as inputs for the SWAT model. Two scenarios were carried out by calibration (1961–1980) and validation (1981–1987) by using different input data. These are discussed next.

Scenario 1 was a SWAT simulation with station data as inputs, and Scenario 2 was a SWAT simulation with RCM data as inputs. Uncertainty analysis between different inputs from different precipitation sources were carried out to compare the different runoff outputs. NSE and R^2 were used as comparing indices to quantify the quality of fit between streamflow outputs from both scenarios against observed streamflow at various locations. Probabilistic distribution of the output data was compared by applying the flow duration curve (FDC) technique. In addition, seasonal simulation of river discharges was assessed by using the annual cycle from the outputs of both scenarios.

Calibration and Validation Hydrology Model SWAT

Scenario 1. The SWAT model was simulated using inputs of rainfall from observed stations in China and Vietnam. The results for the daily time scale calibration at the Hoa Binh station for the 20-year period from 1961–1980 show that the NSE and R^2 agreement is calibration are quite good with values of 0.87 and 0.89, respectively (Fig. 6 and Table 2). This is taken as an indicator of very good performance, as such values have been obtained for hydrological modeling at daily time scale rainfall information (which are usually highly variable in space and time) compared with monthly time scales. The validation over a different period, 1981–1987, also holds well with nearly the same values for NSE and R^2. The benchmarking indices at Ta Bu and Lai Chau show values of R^2 of daily simulation are higher than 0.8, indicating good SWAT model performance.

Scenario 2. The SWAT model was also simulated using the WRF/ERA output of rainfall and temperature, bilinearly interpolated to upstream China station locations, as a proxy to replace observed station data. The SWAT simulations at Hoa Binh indicate that the R^2 and NSE values are less than Scenario 1, but they still indicate good SWAT model performance with calibration indices higher than 0.8 (Fig. 7 and Table 2). Ta Bu and Lai Chau locations also have slightly lesser values than Scenario 1. This suggests that although the benchmarking indices might be lower than when using observed station data, the RCM-derived outputs can be used as proxies, especially over regions where there is hardly any data available.

Table 2. Benchmarking Indices for Daily Discharge for Two Simulation Scenarios

	Scenario 1				Scenario 2			
	Calibration period		Validation period		Calibration period		Validation period	
Station	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Hoa Binh	0.89	0.87	0.89	0.87	0.83	0.81	0.79	0.77
Ta Bu	0.88	0.85	0.88	0.85	0.81	0.80	0.77	0.74
Lai Chau	0.81	0.69	0.82	0.64	0.60	0.46	0.53	0.34
Calibration period: 1961–1980 validation period: 1981–1987			—	—	—	—	—	—

Flow Duration Curve

The FDC is a cumulative frequency curve that shows the percentage of time during which specified discharges were equaled or exceeded in a given period (Searcy 1959). By using FDC, hydrological model simulations are able to show the distribution of high and low flow as compared with observed station (discharge gauge) data. The FDC of three gauging stations, Hoa Binh, Lai Chau, and Ta Bu, are displayed in Fig. 8 for both Scenario 1 (dashed curve) and Scenario 2 (dotted curve), for the calibration and validation periods. The SWAT model simulation for both scenarios shows similarities in FDC. Scenario 2 shows a better representation than Scenario 1 for the calibration process at Hoa Binh and Ta Bu stations for the medium discharge range [Figs. 8(a and c)]. For the validation process, the FDCs of both Scenarios 1 and 2 are very close to the measured station data FDC [Figs. 8(b and d)]. However, the high flow simulated by the hydrology SWAT model underestimated the station data at Lai Chau station for both calibration and validation [Figs. 8(e and f)]. This could be because Lai Chau is the first river gauging station to receive the water coming from China at the upstream part along the Da River [Fig. 2(a)], while the calibration and validation process for Hoa Binh took place at at the far end of the downstream part of the river. Therefore, the simulation at Lai Chau is not as good as that at Ta Bu (in the middle of Lai Chau and Hoa Binh stations) and Hoa Binh. In addition, Lai Chau is the collecting pot for the runoff coming from China, where the observed rainfall data is very limited compared with the denser network of rainfall stations covering Vietnam.

Annual Cycle of Discharge

In order to see the effect of seasonal interannual flow, the discharge annual cycle at the three different station locations considered is shown in Fig. 9 between observations of Scenarios 1 and 2.

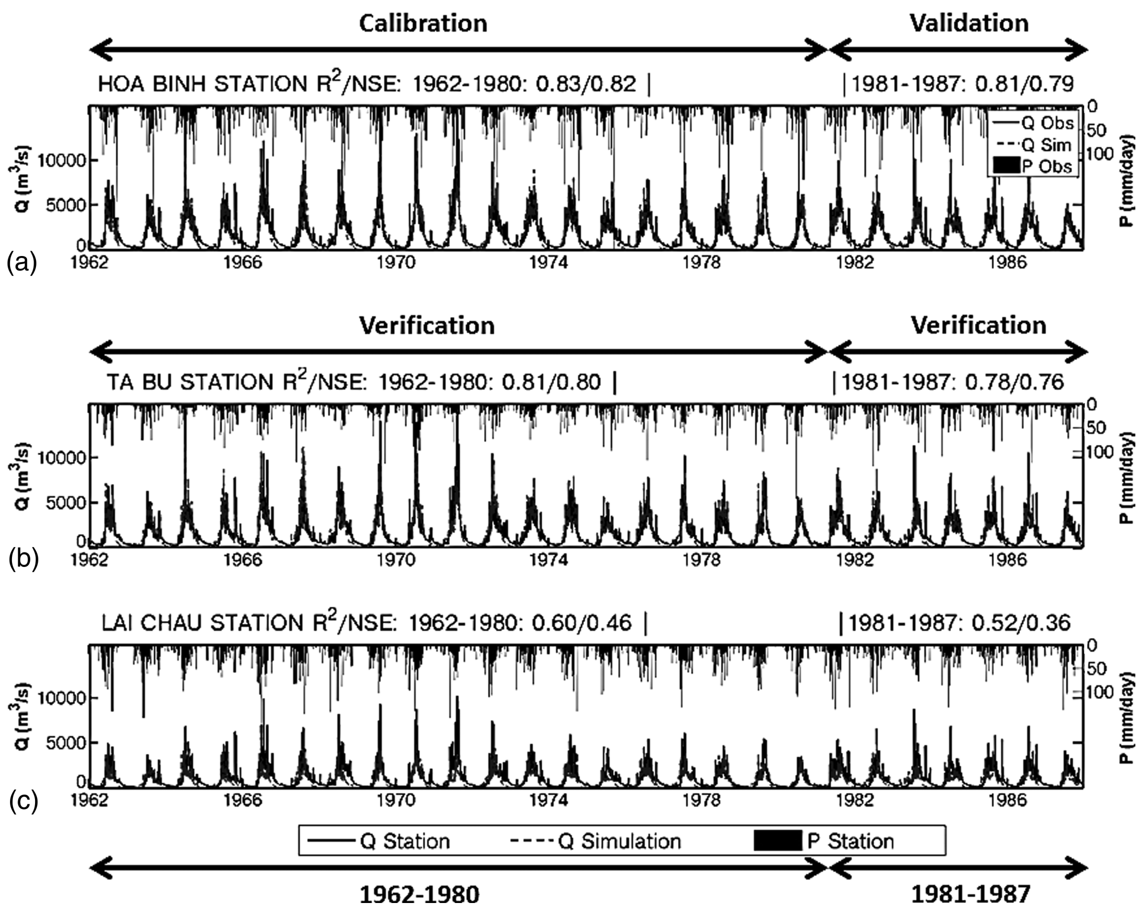

Fig. 7. Scenario 2 using WRF/ERA to replace rainfall from three China stations and remaining observed rainfall from nine Vietnam stations; used as input to SWAT model to simulate stream flow at (a) Hoa Binh; (b) Ta Bu; (c) Lai Chau

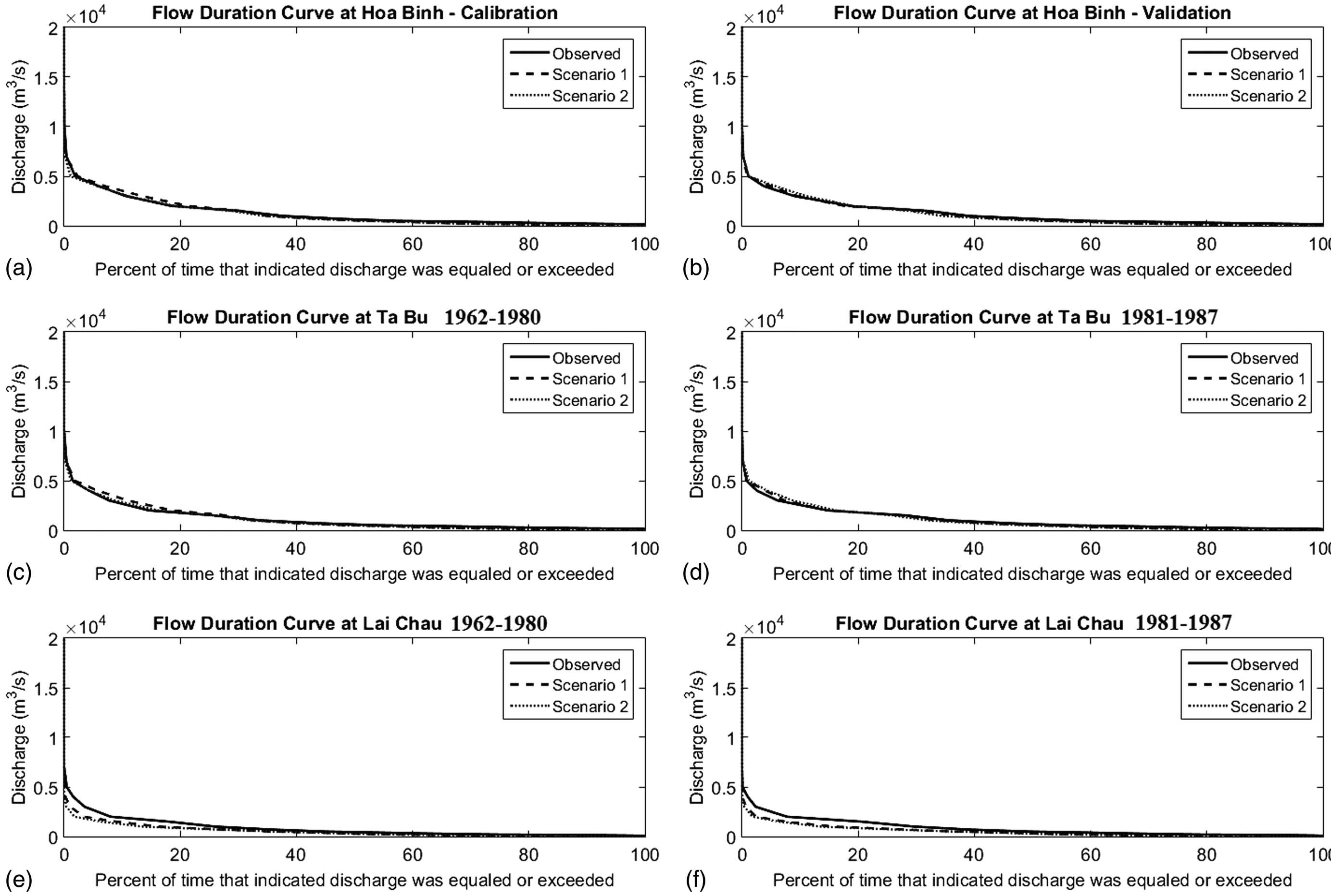

Fig. 8. FDC at three different locations: (a and b) calibration, validation at Hoa Binh; (c and d) calibration, validation at Ta Bu; (e and f) calibration, validation at Lai Chau

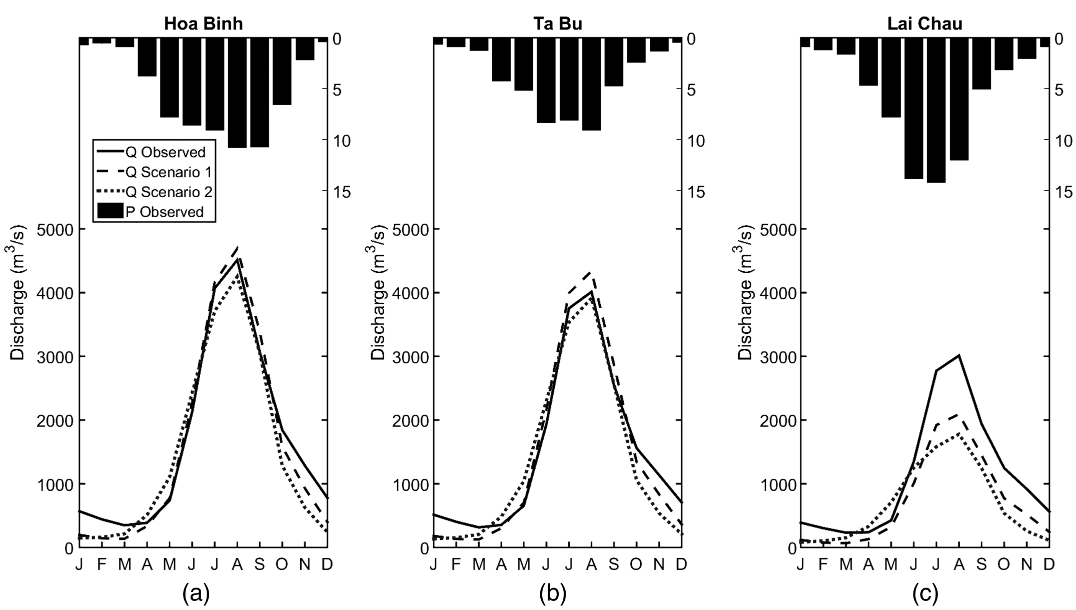

Fig. 9. Annual cycle of stream flow at three different locations: (a) Hoa Binh; (b) Ta Bu; (c) Lai Chau, for the study period 1961–1987

For Scenario 1, the discharge at Hoa Binh and Ta Bu stations are in close agreement with the station discharge data. Only at the Lai Chau location do both scenarios show underestimation. This implies that the SWAT-derived runoff using the station rainfall data from the Chinese upstream is not as good as the SWAT discharge over the downstream from Vietnam. This could be due to the study's consideration of only three rainfall stations in China (whatever was available for the study), whereas more stations (nine) were available from the Vietnam regions for this study. Similar results can be inferred for Scenario 2, which uses the WRF/ERA data as proxies. The simulations, therefore, are consistent in both scenarios because Scenario 2 substitutes RCM data at the same three stations in China, as considered in Scenario 1. The usefulness of the RCM data as proxies is made evident by this result.

Discussion and Conclusions

Discussion

The application of regional climate model data for hydrological studies has been practiced over the past few years owing to the "added value" in high-resolution climate simulations, compared with a coarse resolution from GCMs. Yet the transboundary study that adequately uses this RCM information is an extra bonus because it solves the issue of data sharing between countries, although the WRF model might not, in its entirety, be the best substitute for station data. The spatial distributions discussed previously are also not the only benchmarking factors that favor the use of the RCM data. It is first essential to note that significant uncertainties exist among the observations themselves. As only a small subset of available gridded observations are considered and compared in this paper, the real uncertainties may be large when studying catchments of this kind at high resolution. The available station records might also be prone to measurement and observational errors that might question the quality of data available. However, some station data help validate the climate model to some extent. What remains an important factor in climate research is the need for more dense and robust observations that would help to corroborate modeled data.

As mentioned previously, detailed evaluation of the simulation of the WRF model is not the focus of this paper. The authors understand that the spatial distributions alone are not sufficient in evaluating the RCM model, but a suite of other statistical metrics could add support to this exercise. Some of these metrics include assessing the biases, extremes, reproduction of annual cycles, probability density functions, and interannual variability. Similar research has been done by the authors and can be found in Vu et al. (2012) and Raghavan et al. (2012, 2014).

The differences in the WRF model results stem from the different rainfall intensities simulated by the model and can once again be attributed to the climate model physics and dynamics. It is clear that the uncertainties in the climate model–derived rainfall estimates also influence streamflow simulations. However, the annual/seasonal cycle is reasonably well reproduced, as this is crucial for stream flow assessments, which should be taken a good sign of WRF model simulations. Differences in the streamflow intensities are sort of model biases induced by the different rainfall outputs from the climate models that were used as inputs for driving the hydrological model. Since the overall present-day signature of the streamflow simulations was satisfactorily derived using the SWAT model, it also ensures that the RCM outputs can be used to assess future streamflow using the changes in future climate model–derived rainfall. What these results show is that there are greater uncertainty in the RCM simulations at subregional scales. This also suggests that even higher resolutions (of approximately 5–10 km) might be necessary to improve the simulations over such smaller areas, but this still supports the need for dense observational networks against which the WRF model performance can be further evaluated. Although further improvements might be necessary in the WRF model simulations, the results suggest that the climate model outputs are reasonably good to be used for streamflow simulations. This provides a first-cut understanding of the use of these outputs and their usefulness for hydrological studies, which have implications for the assessment of changes in hydrological responses in the future. Given that many RCM models will be used for climate projections, it falls to the modeling community to constrain uncertainties in RCM models, such as their physics and dynamics, incorporation of complex processes, atmospheric chemistry, and simulations of extreme events, to make climate projections more reliable and useful for impact studies. While these improvements are underway, an ensemble approach of using multiple GCM/RCM realizations for such studies will be more appropriate.

Conclusions

This paper presented an uncertainty analysis of hydrology over the Da River in Vietnam for a daily simulation over a 26-year period between 1961 and 1987 using the SWAT model across a transboundary region between China and Vietnam. The study assumed that the data from the upstream part of the river basin was not available; hence, the output from a regional climate model was used as proxy data. This method served as a novel methodology for river catchment when there is no information for the upstream area. Two scenarios were made: (1) using rainfall station from the upstream area (Chinese territory) as input to the hydrological model, and (2) substituting these station rainfall data with RCM outputs. Uncertainty analysis between the two scenarios indicates that, despite some uncertainties, the SWAT-simulated discharges using the RCM data were as good as those discharges simulated using station data. The results are significant and can be used for future climate studies when high-resolution, downscaled data may be available from RCMs, as the region under study is transboundary in nature and prone to large data-sharing issues. The use of the RCM as proxies, in such cases, is thus clearly established.

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