Future streamflow assessment in the Haihe River basin located in northern China using a regionalized variable infiltration capacity model based on 18 CMIP5 GCMs

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ABSTRACT

The impact of future climate change on streamflow is assessed in the Haihe River basin (HRB) by the Variable Infiltration Capacity (VIC) model, using the outputs from 18 general circulation models (GCMs) of the Coupled Model Inter-comparison Project Phase 5 (CMIP5). Three Representative Concentration Pathway (RCP) scenarios have been used, including RCP2.6, RCP4.5, and RCP8.5. Based on the model parameters calibration in six catchments in the HRB and parameter regionalization, the hydrological simulation for the whole HRB denotes good performance of the VIC model. Taking the period 1961–1990 as a baseline period, the outputs from the GCMs indicate that the HRB will become warmer and wetter in the 21st century (2010–2099). There might be an increasing trend for the streamflow in the HRB under future climate change scenarios. For example, in the 2050s (2040–2069), the streamflow may increase by 12%, 28%, and 24% under the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. Monthly, the highest and lowest increase in streamflow is in dry and wet seasons, respectively. Spatially, the increasing trend for streamflow in the north HRB is higher than that in the south HRB. The uncertainty from the GCMs and climatic scenarios should be further focused.

INTRODUCTION

The hydrological cycle process and water resources system have been extensively influenced by climate change (Vorosmarty et al. 2000; Zhang & Wang 2007; IPCC 2014). Streamflow is the key component of the hydrological cycle and is the most important source of water for human society. In the last several decades, due to the impact of climate change and human activities, observed streamflow has changed over the world, e.g. United States, Canada, China, Europe, and Australia (Lins & Slack 1999; Douglas et al. 2000; Zhang et al. 2001, 2007; Stahl et al. 2010). There was high confidence in the increase of temperature and a probable change of precipitation in the future which would lead to an impact on the hydrological cycle and water resources (Vorosmarty et al. 2000; Bao et al. 2012b; IPCC 2014).

As one of the 10 largest basins in China, the Haihe River basin (HRB) is the political, cultural, and transport center of China (Ren et al. 2007). The regional population, total grain yield, and gross domestic product (GDP) represent 10%, 12%, and 14% of the national total, respectively. Recently, water resources scarcity has become a major critical challenge for local socioeconomic development (Liu & Xia 2004). The water resources per capita in HRB are only 1/7 of the average in China and 1/27 of the average in the world (Ren et al. 2007). More serious is that during the last
several decades, the observed precipitation and streamflow have decreased across the HRB (Gong et al. 2004; Zhang et al. 2007; Yang & Tian 2009; Cong et al. 2010). Therefore, it was essential to assess the impact of future climate change on the streamflow using scenarios from global atmospheric general circulation models (GCMs) to predict future water supplies for water resources planning and management.

Generally, the future water resources under the impact of climate change is assessed by the following stages: (1) projecting future regional climatic scenarios by downscaling the outputs from GCMs; (2) calibrating the parameters of the hydrological model with observed hydro-climatic data; and (3) assessing future water resources using calibrated hydrological model and downscaled climatic scenarios (Xu 1999). Based on this methodology, the impact of climate change on water resources was studied in many basins over the world (Arnell 1999; Chiew & McMahon 2002; Bae et al. 2011; Nóbrega et al. 2011; Setegn et al. 2011; Sun et al. 2011; Vaze et al. 2011; Wang et al. 2012; Guimberteau et al. 2013). In Europe, Arnell (1999) studied the effects of climate change by the 2050s on hydrological regimes at a spatial resolution of 0.5 × 0.5°, using a macro-scale hydrological model and four climate change scenarios, and pointed out that there would be a general reduction in annual runoff in southern Europe, and an increase in the north. In Australia, Chiew & McMahon (2002) presented the likely impacts of climate change on runoff in the more populated and important agricultural regions, by comparing the water fluxes simulated by a hydrologic model using present climate data and greenhouse-enhanced climate scenarios in 2030, such as the annual runoff in southeast Australia could decrease by up to 20%. In Africa, Setegn et al. (2011) investigated the impact of climate change on the hydroclimatology of the Lake Tana Basin in Ethiopia, using 15 GCMs and the SWAT model. In Asia, Wang et al. (2012) assessed the impact of climate change on water resources, using the Variable Infiltration Capacity (VIC) model and the Providing Regional Climate for Impact Studies (PRECIS) model, and pointed out that annual runoff over China as a whole would probably increase by approximately 3%–10% by 2050.

Otherwise, there was a small quantity of studies focused on future climate change impact in the HRB. Based on a 1.2 °C increase of temperature and 1% increase of precipitation, Ying & Huang (1997) using the Watbal model found that the annual runoff would decrease by 4.7% in the HRB during the next 20–50 years. Yuan et al. (2005) studied the future water resources in the HRB using the VIC model combining with PRECIS and concluded that the mean annual runoff would tend to decrease by 3.4% and 8.8% under A2 and B2 scenarios, respectively. Although the impact of future climate change on water resources has been assessed by several previous studies in the HRB, there are some shortages and several questions need further discussion. First, few GCMs have been used by the previous studies. For example, only one GCM was used by Yuan et al. (2005). Because of the limitation of the performance for climate simulation, the uncertainty resulting from GCMs is the biggest source of the model chain for the hydrological projection (Dobler et al. 2012). Based on the previous research, the future climate projection from the multi-model ensemble is more reasonable than a single GCM (Zhou & Yu 2006; Xu et al. 2007). Therefore, the more GCMs are used, the better results will be obtained. Second, the previous studies mainly focused on the typical catchment scale because the parameters of the hydrologic model were calibrated in the sub-catchments. The hydrological simulation in the ungauged basins is a critical challenge for hydrologists. For example, Yuan et al. (2005) constructed the hydrological model for the HRB, by the average values of calibrated model parameters in two small sub-catchments. So, how to assess future streamflow for the entire HRB using reasonable regionalized hydrological model? These questions will be further discussed in this study. The primary objective of this study is to investigate the impact of future climate change on the streamflow in the HRB, using the VIC model and 18 GCMs. The remaining sections of this paper are organized as follows: the study area and dataset are summarized in the section ‘Study area and dataset’; the brief introductions of the climate change impact assessment, the VIC model, and parameter regionalization are expressed in the section ‘Methodology’; the changes of hydro-climatic variables in the HRB during the 21st century are described in the section ‘Results’; the results and conclusions are discussed and summarized in the following sections.
STUDY AREA AND DATASET

Study area

The HRB located at northern China (112°–120°E, 35°–43°N) is the densely populated political, cultural, and transport center of China (Figure 1). The northern boundary is the Mongolian Plateau; the western and southern boundary is the Yellow River; and the eastern boundary is the Bohai Sea. With a basin area of 317,800 km², representing 3.3% of the national total, the HRB is one of the 10 largest basins in China. The western and northern parts are mountain areas which are 189,400 km² (60%), and the eastern and southern parts are plain with areas of 128,400 km² (40%). Encompassing Beijing (the capital of China), Tianjin (one of the four municipalities of China), Shijiazhuang (the capital of Hebei province), and another 23 large and medium cities, there were 0.132 billion residents and 55.92 million
ton total grain yield within the watershed in 2005, and the watershed’s 2005 GDP was about 2,140 billion RenMinBi (RMB) yuan, representing 10%, 12%, and 14% of the national total, respectively.

The HRB has a continental monsoon climate. The annual mean temperature is 9.6 °C, and the total annual precipitation is about 530 mm. The precipitation in the flood season (June–September) generally contributes to 70%–85% of the total annual precipitation; meanwhile, the annual precipitation decreases from south to north, from the coastal zone to the inland area. Impacted by the intensity and impact range of subtropical high over the northern Pacific in summer, annual variability of precipitation is very significant in the HRB. For example, the annual precipitation is more than 800 mm in the wet year, but it is only about 350 mm in the drought year. That leads to a very high frequency of flood and drought in the HRB.

**Observed data**

There are 38 standard meteorological stations with daily precipitation, and daily mean, maximum, and minimum temperature data in and around HRB (Figure 1). The longest available data period is from 1951 to 2017, and most stations have data for more than 60 years. The high-quality data in these 38 stations are maintained according to the standard methodology of the China Meteorological Administration, which applies data quality control before releasing these data.

There are 312 rain gauges with daily precipitation and six hydrological stations with daily streamflow (from the Year Book of Hydrology China, published by the Bureau of Hydrology China). Six hydrological stations in the HRB are used to calibrate model parameters (Figure 1). The detailed information of the six hydrological stations is expressed in Table 1. Using the inverse distance weighting method, the precipitation and temperature data at the stations are interpolated into grid data as the input for the hydrological model (Zhang & Wang 2007).

The soil data are extracted from the Food and Agriculture Organization (FAO) two-layer 5-minute 16-category global soil texture maps (FAO et al. 2013). In this dataset, the soil is classified into 16 categories, the first 12 kinds of which are used in this study. The land cover data are obtained from the University of Maryland’s 1 km Global Land Cover data, including 14 kinds of land cover types (Hansen et al. 2000). The Digital Elevation Model (DEM) data are obtained from the Shuttle Radar Topography Mission (SRTM) 90 m DEM Digital Elevation Database.

**GCM data**

The precipitation and temperature data in 1961–2100 are obtained from 18 GCMs, based on Phase 5 of the Coupled Model Inter-comparison Project (CMIP5). The data are available in the Program for Climate Model Diagnosis and Intercomparison (PCMDI) (IPCC 2013). The basic information of the 18 GCMs is shown in Table 2. In order to cover different social–economic development scenarios, three greenhouse gas emission scenarios termed ‘Representative Concentration Pathways’ (RCPs; Moss et al. 2010; Meinshausen et al. 2011) are used in this study, including RCP2.6, RCP4.5, and RCP8.5. All of the data have been interpolated onto a common 0.25° x 0.25° grid by the National Climate Center, China (Xu & Xu 2012a, 2012b). For the model ensemble, the arithmetic mean was used.

**Table 1** Information of the six catchments in the HRB

<table>
<thead>
<tr>
<th>Hydro-stations</th>
<th>Longitude (°E)</th>
<th>Latitude (°N)</th>
<th>P (mm)</th>
<th>T (°C)</th>
<th>Ep/P</th>
<th>Drainage area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sandaohezi</td>
<td>117.7</td>
<td>41.0</td>
<td>422</td>
<td>7.27</td>
<td>2.21</td>
<td>17,100</td>
</tr>
<tr>
<td>Taolinkou</td>
<td>119.1</td>
<td>40.1</td>
<td>650</td>
<td>7.38</td>
<td>1.35</td>
<td>5,060</td>
</tr>
<tr>
<td>Zhangjiafen</td>
<td>116.8</td>
<td>40.6</td>
<td>454</td>
<td>9.12</td>
<td>2.17</td>
<td>8,506</td>
</tr>
<tr>
<td>Zhongtangmei</td>
<td>114.9</td>
<td>38.9</td>
<td>506</td>
<td>11.82</td>
<td>2.08</td>
<td>3,480</td>
</tr>
<tr>
<td>Weishui</td>
<td>114.1</td>
<td>38.0</td>
<td>611</td>
<td>9.72</td>
<td>1.61</td>
<td>5,387</td>
</tr>
<tr>
<td>Guantai</td>
<td>114.1</td>
<td>36.3</td>
<td>559</td>
<td>13.15</td>
<td>2.02</td>
<td>17,800</td>
</tr>
</tbody>
</table>

P is the multi-year annual precipitation; T is the multi-year annual mean temperature; Ep is the multi-year annual pan evaporation; and Ep/P is the aridity index.
<table>
<thead>
<tr>
<th>No.</th>
<th>Name of GCMs</th>
<th>Institution</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Beijing Climate Center Climate System Model version 1 (BCC-CSM1-1)</td>
<td>BCC, China Meteorological Administration</td>
<td>China</td>
</tr>
<tr>
<td>2</td>
<td>Beijing Normal University Earth System Model (BNU-ESM)</td>
<td>The College of Global Change and Earth System Science (GCCESS), BNU</td>
<td>China</td>
</tr>
<tr>
<td>3</td>
<td>Flexible Global Ocean-Atmosphere-Land System Model-grid version 2 (FGOALS-g2)</td>
<td>State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, and Tsinghua University</td>
<td>China</td>
</tr>
<tr>
<td>4</td>
<td>The First Institution of Oceanography Earth System Model (FIO-ESM)</td>
<td>The First Institution of Oceanography, State Oceanic Administration (SOA), Qingdao</td>
<td>China</td>
</tr>
<tr>
<td>5</td>
<td>Goddard Institute for Space Studies Model E version 2 with Russell ocean model (GISS-E2-R)</td>
<td>Goddard Institute for Space Studies, National Aeronautics and Space Administration</td>
<td>USA</td>
</tr>
<tr>
<td>6</td>
<td>Goddard Institute for Space Studies Model E version 2 with Hycoml ocean model (GISS-E2-H)</td>
<td>Goddard Institute for Space Studies, National Aeronautics and Space Administration</td>
<td>USA</td>
</tr>
<tr>
<td>7</td>
<td>The Community Climate System Model version 4 (CCSM4)</td>
<td>National Center for Atmospheric Research</td>
<td>USA</td>
</tr>
<tr>
<td>8</td>
<td>Geophysical Fluid Dynamics Laboratory Climate Model version 3 (GFDL-CM3)</td>
<td>Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration</td>
<td>USA</td>
</tr>
<tr>
<td>9</td>
<td>Geophysical Fluid Dynamics Laboratory Earth System Model version 2 with Generalized Ocean Layer Dynamics (GOLD) code base (GFDL-ESM2G)</td>
<td>Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration</td>
<td>USA</td>
</tr>
<tr>
<td>10</td>
<td>Geophysical Fluid Dynamics Laboratory Earth System Model version 2 with Modular Ocean Model version 4.1 (GFDL-ESM2M)</td>
<td>Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration</td>
<td>USA</td>
</tr>
<tr>
<td>11</td>
<td>Meteorological Research Institute Coupled General Circulation Model version 3 (MRI-CGCM3)</td>
<td>Meteorological Research Institute</td>
<td>Japan</td>
</tr>
<tr>
<td>12</td>
<td>Model for Interdisciplinary Research on Climate Earth System, version 5 (MIROC5)</td>
<td>Atmosphere and Ocean Research Institute (AORI), National Institute for Environmental Studies (NIES), Japan Agency for Marine-Earth Science and Technology, Kanagawa (JAMSTEC)</td>
<td>Japan</td>
</tr>
<tr>
<td>13</td>
<td>Model for Interdisciplinary Research on Climate Earth System (MIROC-ESM)</td>
<td>Atmosphere and Ocean Research Institute (AORI), National Institute for Environmental Studies (NIES), Japan Agency for Marine-Earth Science and Technology, Kanagawa (JAMSTEC)</td>
<td>Japan</td>
</tr>
<tr>
<td>14</td>
<td>Centre National de Recherches Météorologiques Climate Model version 5 (CNRM-CM5)</td>
<td>CNRM/Centre European de Recherche et Formation Avances en Calcul Scientifique</td>
<td>France</td>
</tr>
<tr>
<td>15</td>
<td>Institute Pierre Simon Laplace Climate Model 5A-Low Resolution(IPSL-CM5A-LR)</td>
<td>Institute Pierre Simon Laplace</td>
<td>France</td>
</tr>
<tr>
<td>16</td>
<td>Max-Planck Institute Earth System Model-Low Resolution (MPI-ESM-LR)</td>
<td>Max-Planck Institute for Meteorology</td>
<td>Germany</td>
</tr>
<tr>
<td>17</td>
<td>Canadian Earth System Model version 2 (CanESM2)</td>
<td>Canadian Centre for Climate Modeling and Analysis</td>
<td>Canada</td>
</tr>
<tr>
<td>18</td>
<td>Commonwealth Scientific and Industrial Research Organization Mark Climate Model version 3.6 (CSIRO-Mk3-6-0)</td>
<td>CSIRO in collaboration with the Queensland Climate Change Centre of Excellence</td>
<td>Australia</td>
</tr>
</tbody>
</table>
METHODOLOGY

Assessing future streamflow under climatic change scenarios

The impact of climate change on the streamflow is defined by the proportional change of simulated variables, by comparing their values with outputs from GCMs in the climate change scenarios to their values with outputs from GCMs in the baseline. The relative streamflow change (ΔRe) in future scenarios compared to it in the baseline period is expressed as follows:

\[ \Delta R_{\text{Re}} = \frac{R_{\text{FG}} - R_{\text{BG}}}{R_{\text{BG}}} \times 100\% \]  

(1)

where \( R_{\text{FG}} \) is simulated average annual streamflow using data in future scenarios from GCMs, and \( R_{\text{BG}} \) is simulated average annual streamflow using data in the baseline period from GCMs. The changes of streamflow are calculated for three periods: 2020s (2010–2039), 2050s (2040–2069), and 2080s (2070–2099), compared to the baseline (1961–1990) from the 20th century experiment runs.

A brief introduction of the VIC model

The VIC model is used for the simulation of streamflow in the HRB. VIC is a semi-distributed macro-scale hydrological model and could balance both the water and surface energy budgets within the grid cell (Liang et al. 1994, 1996; Dan et al. 2012). The key characters of the VIC model are the representation of multiple land cover types, spatial variability of soil moisture capacity, soil water moving between the three soil layers, surface flow considering both infiltration excess and saturation excess, and nonlinear baseflow. With refined description of hydrologic process on land surface and finer performance of streamflow simulation, the VIC model was applied in a number of catchments over the world (Abdulla et al. 1996; Lohmann et al. 1998; Su et al. 2005; Xie et al. 2007; Zhu & Lettenmaier 2007).

In the VIC model, surface runoff generated from the upper two soil layers was accounted for based on the variable soil moisture capacity curve, which was described by the Xinanjiang model, in order to represent the sub-grid spatial variability in soil moisture capacity (Zhao et al. 1980; Zhao 1992). That was expressed as follows:

\[ W = W_{\text{mm}}(1 - (1 - A)^{1/b}) \]  

(2)

where \( W \) and \( W_{\text{mm}} \) are the point and maximum point soil moisture capacity, respectively, the unit is mm; \( A \) is the fraction of area for which the soil moisture capacity is less than \( W_{\text{m}} \); and \( b \) is the soil moisture capacity shape parameter. Since the top thin soil layer has a very small water holding capacity, the surface runoff, \( Q_S \) (the unit is mm) within each time step, is calculated for the entire upper layer (layer 1 and layer 2) as follows:

\[ Q_S = \begin{cases} PE - (W_m - W_0), & PE + W \geq W_{\text{mm}} \\ PE - (W_m - W_0) + W_m \left(1 - \frac{PE + W}{W_{\text{mm}}}\right)^{1+b}, & PE + W < W_{\text{mm}} \end{cases} \]  

(3)

where \( PE \) is precipitation minus evapotranspiration; \( W_m \) is soil moisture capacity of the calculated grid and could be estimated by the soil porosity and the thickness of the second soil layer (d2); and \( W_0 \) is the soil moisture at the previous time step; the unit of these parameters is mm.

Using the Arno model formulation (Franchini & Pacciani 1991; Todini 1996), baseflow (subsurface runoff, \( Q_b \)) from the third soil layer is expressed as follows:

\[ Q_b = \begin{cases} D_3 D_m \theta_5 / W_S \theta_S, & 0 \leq \theta_5 \leq W_S \theta_S \\ D_3 D_m \theta_5 + \left(D_m - D_3 D_m / W_S \theta_S\right) \left(\theta_5 - W_S \theta_S / \theta_5 - W_S \theta_S\right)^2, & \theta_5 > W_S \theta_S \end{cases} \]  

(4)

where \( D_m \) is the maximum subsurface flow, the unit is mm; \( D_S \) and \( W_S \) are the fractions of \( D_m \) and maximum soil moisture of the third layer (\( \theta_5 \)), respectively, which is defined by the soil porosity and the thickness of the third soil layer (d3); and \( \theta_5 \) is the current soil moisture of the third layer. The baseflow recession curve is linear and nonlinear when \( \theta_5 \) is below and above a threshold (\( W_S \theta_S \)), respectively.

There are six parameters in the VIC model needing to be calibrated: the three baseflow parameters: \( D_m, W_S, \) and \( D_S \); the variable soil moisture capacity curve parameter, \( b \); and
two parameters, \( d_2 \) and \( d_3 \), that control the thickness of the second and third soil layer, respectively, the unit of \( d_2 \) and \( d_3 \) is m. The three baseflow parameters are non-sensitive for model calibration (Demaria et al. 2007). In order to reduce the interdependence of model parameters, they are directly estimated by soil properties (Bao et al. 2015). The other three parameters are optimized by two objectives: Nash–Sutcliffe coefficient (Nsc, Nash & Sutcliffe 1970) and relative error (Re), which are defined as follows:

\[
\text{Nsc} = 1 - \frac{\sum (Q_{\text{obs}} - Q_{\text{sim}})^2}{\sum (Q_{\text{obs}} - \bar{Q}_{\text{obs}})^2}
\]

\[
\text{Re} = \frac{R_{\text{obs}} - R_{\text{sim}}}{R_{\text{obs}}} \times 100\%
\]

(5)

where \( Q_{\text{obs}} \) and \( Q_{\text{sim}} \) are the observed and simulated streamflow, respectively; \( \bar{Q}_{\text{obs}} \) is the mean value of \( Q_{\text{obs}} \); and \( R_{\text{obs}} \) and \( R_{\text{sim}} \) are the observed and simulated average annual runoff, respectively.

**Parameters regionalization in ungauged catchments**

In order to apply the VIC model for the entire HRB, parameter regionalization is studied by six catchments in the HRB (Figure 1). The details of the six hydrological stations in the HRB are shown in Table 1. The VIC model is firstly calibrated in the six catchments at a 0.25° spatial and daily temporal resolution. The model parameters for the ungauged regions are estimated by an integrated parameter regionalization methodology, considering both the spatial proximity and physical similarity (Oudin et al. 2008; Zhang & Chiew 2009; Bao et al. 2022a). Then, the hydrological regime for the whole HRB could be simulated. In order to describe the catchment characteristics, nine physical descriptors are used for regionalization: annual precipitation (\( P \)), annual mean temperature (\( T \)), aridity index (\( E_p/P \), where \( E_p \) is pan evaporation), leaf area index (\( \text{LAI} \)), the vegetation root depth (\( \text{Depth} \)), saturated hydraulic conductivity of the top layer soil (\( T-\text{ksat} \)) and bottom layer soil (\( B-\text{ksat} \)), and the ratio of field capacity to saturated soil moisture of the top layer soil (\( T-\text{sf} \)) and bottom layer soil (\( B-\text{sf} \)). For each ‘ungauged catchment’, the weights of other donor catchments are estimated by the combination of physical distance and spatial distance.

During the physical distance estimation, the physical descriptors of the catchment are all normalized, as a result of the different units and scales. The physical weight (\( w_p \)) of each donor catchment is estimated by the inverse physical distance between the donor catchments and the ‘ungauged catchment’ for each normalized catchment descriptor. Equally, the spatial weight (\( w_s \)) of each donor catchment is estimated by the inverse spatial distance between the donor catchments and the ‘ungauged catchment’. The integrated weight (\( w_i \)) of each donor catchment is estimated by the sum of physical and spatial weight. The model parameters in the ‘ungauged catchment’ are estimated as follows:

\[
p_0 = \sum_{i=1}^{k} p_i \times w_i
\]

(6)

where \( p_0 \) and \( p_i \) are the model parameters in the ‘ungauged catchment’ and donor catchments, respectively. Then, the streamflow could be simulated with \( p_0 \) in the ‘ungauged catchment’ and for the whole HRB.

**RESULTS**

**Historical simulation of streamflow for the whole HRB**

Based on the model calibration in six catchments in the HRB, the model parameters in 615 grids of the HRB with 0.25° spatial resolution are estimated using the integrated parameter regionalization methodology (Figure 2). The highest and lowest values for the parameter \( b \) (\( d_2 \)) are 0.23 (1.18 m) in the northeast HRB and 0.17 (0.8 m) in the southwest HRB, respectively. On the contrary, higher values for the parameter \( d_3 \) are located in the southwest HRB, and the east HRB has a lower parameter \( d_3 \). A majority of parameters \( b \), \( d_2 \), and \( d_3 \) belongs to 0.18–0.2 m, 0.8–0.92 m, and 0.23–0.32 m, respectively.

The prediction in ungauged basins is a critical challenge for hydrologists. Generally, regionalization has greater uncertainty than calibration for streamflow simulation. With the estimated model parameters in the 615 grids, the streamflow is simulated for the whole HRB. In the six gauged catchments in the HRB, the regionalization
Figure 2 | The estimated parameters $b$ (a), $d_2$ (b), and $d_3$ (c) by regionalization. (The unit of $d_2$ and $d_3$ is m).
methodology has little worse results compared to the calibration methodology (Table 3). Taking the Sandaohezi catchment as an example, the Nsc (Re) values are 0.82 (−6.8%) and 0.80 (11.2%) by the calibration and regionalization, respectively. The values of Nsc and Re could be used to assess the performance of the hydrological model for rainfall-runoff forecasting in gauged basins (National Standard of the People’s Republic of China 2008). The four intervals such as \( Nsc > 0.9, 0.9 \geq Nsc \geq 0.7, 0.7 > Nsc \geq 0.5, \) and \( 0.5 > Nsc \) mean excellent, good, pass, and fail of the results, respectively. Out of the six catchments, the Nsc values based on the regionalization methodology are higher than 0.5 and 0.7 in six and four catchments, respectively. The Re value less than 20% means that the result is acceptable. And the Re value less than 10% means that the simulated streamflow is excellent (Bao 2009). Out of the six catchments, the Re values based on the regionalization methodology are less than 20% and 10% in six and three catchments, respectively. Figure 3 shows simulated monthly streamflow both by calibration and regionalization in the Sandaohezi and Zhongtangmei catchment. The hydrograph denotes good performance of the VIC model with the regionalization methodology. Overall, the accuracy of the regionalized VIC model is acceptable for hydrological simulation in the whole HRB.

Future scenarios for mean temperature and precipitation

Mean temperature

All the 18 GCMs indicate an obvious increasing trend for annual mean temperature in the HRB under future climate change scenarios (Figure 4(a)). Temporally, the highest increase and variability among the 18 GCMs and three scenarios are in the 2080s, followed by the 2050s, and then the 2020s. In the 2020s, the mean annual temperature change is almost the same under the three climatic scenarios. The 50th percentile values of the annual mean temperature change are 1.207, 1.211, and 1.324 °C, in RCP2.6, RCP4.5, and RCP8.5, respectively. In the 2050s and 2080s, the highest annual mean temperature increase is under RCP8.5, followed by RCP4.5, and then RCP2.6. In the 2050s, the 50th percentile values of the annual mean temperature change are 1.552, 2.094, and 2.838 °C, in RCP2.6, RCP4.5, and RCP8.5, respectively. In the 2080s, the 50th percentile values of the annual mean temperature change may reach 1.448, 2.366, and 4.669 °C, in RCP2.6, RCP4.5, and RCP8.5, respectively.

The relative change of the temperature in the 21st century varies monthly (Figure 5). Except for a few GCMs, the temperature will increase in all 12 months, with the highest and lowest increasing trend in winter and spring, respectively. Taking the 2050s as an example, in January,
the 50th percentile values of the monthly mean temperature change are 1.797, 2.147, and 3.135 °C in RCP2.6, RCP4.5, and RCP8.5, respectively. Otherwise, in May, the 50th percentile values of the monthly mean temperature change are only 1.443, 1.744, and 2.533 °C in RCP2.6, RCP4.5, and RCP8.5, respectively. The uncertainty of the monthly mean temperature change in colder seasons is higher than that in warmer seasons. In the 2050s under the RCP 8.5 scenario, the interval of the mean temperature change is 4.894 °C (from 0.653 to 5.547 °C) and 3.112 °C (from 1.473 to 4.585 °C) in January and July, respectively.

Figure 6 illustrates the spatial distribution of the annual mean temperature change by the ensemble mean of 18 GCMs in the 21st century compared to the baseline period over the HRB. Generally, the annual mean temperature will increase in every grid of the HRB. The increasing trend in the northern HRB is higher than that in the southern HRB. For example, in the 2050s under the RCP 4.5 scenario, the annual mean temperature might increase over 2.25 °C in the northern HRB, but it would only increase less than 2.0 °C in the southern HRB. This is consistent with the results by IPCC (2014), i.e. the increase in temperature at higher latitudes is greater than that at lower latitudes. The temporal and spatial change in annual mean temperature is consistent with the results by Xu & Xu (2012a).

Precipitation

Most of the GCMs show an increase in annual precipitation in the 21st century (Figure 4(b)). By contrast to the annual mean temperature change, it is not clear which scenario has a highest increasing trend for annual precipitation. The variability of precipitation in the HRB is rather complicated, including many impacting factors: El Niño-Southern Oscillation (ENSO), the Pacific decadal oscillation (PDO), the interdecadal Pacific oscillation (IPO), and global warming. In the China eastern monsoon region, the natural variability contribution to the influence of precipitation accounts for about 70% and anthropogenic forcing, i.e. greenhouse gas emission impact is about 30% (Xia et al. 2016). That means, for precipitation change, the impact of natural variability is more important than the impact of climate change caused by carbon dioxide emissions due to anthropogenic forcing. Therefore, it is difficult to investigate which RCP scenario has a bigger precipitation change. The uncertainty of future precipitation change is relatively greater than the uncertainty of future temperature change. In the 2020s,
the highest annual precipitation increase is under RCP2.6 (the 50th percentile value is 8.055%), followed by RCP8.5 (the 50th percentile value is 5.37%), and then RCP4.5 (the 50th percentile value is 4.635%). But the 2050s show opposite results, i.e. the highest annual precipitation increase is under RCP4.5, followed by RCP8.5, and then RCP2.6. The 50th percentile values of annual precipitation change are 13.69%, 11.515%, and 7.77%, under RCP4.5, RCP8.5, and RCP2.6, respectively. In the 2080s, annual precipitation changes among different scenarios are similar to annual
mean temperature changes. The highest annual precipitation increase is under RCP8.5, followed by RCP4.5, and then RCP2.6. From the 2020s to 2080s, the uncertainty of annual precipitation change will become higher among different GCMs. For example, under RCP4.5, the highest (lowest) change of precipitation is 13.27% (−6%), 28.5% (−7.92%), and 33.39% (−9.37%) in the 2020s, 2050s, and 2080s, respectively.

The relative change of monthly precipitation for the 21st century is expressed in Figure 7. Generally, most months show an increase in precipitation, with the highest and lowest increasing trend in dry and wet seasons, respectively. For example, in the 2050s under the RCP8.5 scenario, the precipitation may increase by 33.6% in January, but it will only increase by 9.82% in July. Meanwhile, the uncertainties in wet months are lower than that in dry months. For example, in the 2050s under the RCP8.5 scenario, the highest and lowest values of precipitation changes are 125.6% and −4.01% in January, but the highest and lowest values of precipitation changes are 36.59% and −18.82% in July. This is mainly because of the uneven intra-annual distribution of monthly precipitation in the HRB. The precipitation during June to September accounts for 70%–85% of the total annual precipitation. Multi-year average monthly precipitation is 152 and 3.3 mm in July and January, respectively. With a same absolute precipitation change, the relative change in January is much higher than that in July.

There is not a very clear spatial distribution of annual precipitation change by the ensemble mean of 18 GCMs in the 21st century compared to the baseline period over the HRB (Figure 8). Generally, the northern HRB has a higher increasing trend of precipitation than the southern part. Every grid of the HRB shows an increase of annual precipitation. In the 2020s, the northern HRB has a higher increasing trend of annual precipitation than the southern HRB under the RCP2.6 and RCP4.5 s but with opposite distribution under the RCP8.5 scenario. In the 2050s, the northern HRB has a higher increasing trend of annual precipitation than the southern HRB under the RCP4.5 and RCP8.5 scenarios, without a clear spatial distribution under the RCP2.6 scenario. In the 2080s, the northern HRB has a higher increasing trend of annual precipitation than the southern HRB under the RCP2.6 and RCP8.5 scenarios. The temporal and spatial change in annual precipitation is consistent with the results by Xu & Xu (2022a). They detected the climate changes in the 21st century China based on the projections of 11 climate models. The results indicated that the increasing precipitation in the northern regions would be significant and greater than that in the southern regions in China, and a remarkable increase was found in northwestern and northeastern China, where the changes were statistically significant. Spatially, the annual precipitation in south China (over 2,000 mm in some parts) is more than that in north China (less than 500 mm in some parts). Therefore, with the same absolute change, the relative change in north China will be much higher than that in south China. On the other hand, the simulation capacity of the GCMs is limited in the regions with heavy precipitation (i.e. southern China). The difference of precipitation projection among the different GCMs in the southern region is higher than that in the northern region. The variation of precipitation projection among different GCMs will be offset by the ensemble mean. The uncertainty in the precipitation projection is unavoidable, and further analyses are necessary with the development of GCMs.

**Impact of climate change on streamflow**

The results from the VIC model and most GCMs indicate that the streamflow will increase in the HRB under future climate change scenarios, i.e. the 50th percentile value of
each box in Figure 9 is positive. Similar to precipitation change, in the 2020s, the highest annual streamflow increase is under RCP2.6 (the 50th percentile value is 15.23%), followed by RCP8.5 (the 50th percentile value is 8.18%), and then RCP4.5 (the 50th percentile value is 6.25%). But the 2050s show opposite results, i.e. the highest annual streamflow increase is under RCP4.5, followed by RCP8.5, and then RCP2.6. The 50th percentile values of annual streamflow change are 27.57%, 24.03%, and 12.06% under RCP4.5, RCP8.5, and RCP2.6, respectively. In the 2080s,
the highest annual streamflow increase is under RCP8.5, followed by RCP4.5, and then RCP2.6.

Figure 10 shows the relative change of monthly streamflow for the 21st century. Most months show an increase in streamflow, with the highest and lowest increasing trend in dry and wet seasons, respectively. For example, in the 2050s under the RCP8.5 scenario, the streamflow may increase by 45.98% in January, but it will only increase by 22.17% in July. Meantime, the uncertainties in wet months are lower than those in dry months. For example, in the 2050s under the RCP8.5 scenario, the highest and lowest values of streamflow changes are 142.12% and −54.18% in January, but the highest and lowest values of streamflow changes are 82.21% and −43.66% in July. This is mainly because of the uneven intra-annual distribution of monthly streamflow in the HRB. With a same absolute streamflow change, the relative change in January is much higher than that in July.

The spatial distribution of annual streamflow change varies among different decades and scenarios (Figure 11). Every grid of the HRB shows an increase of annual streamflow. In the 2020s, the highest increase of annual streamflow is located in the northeast HRB. In the 2050s, the northern HRB has a higher increasing trend of annual streamflow than the southern HRB under the RCP4.5 and RCP8.5 scenarios, without a clear spatial distribution under RCP2.6 scenario. In the 2080s, the northern HRB has a higher increasing trend of annual streamflow than the southern HRB under the RCP2.6 and RCP8.5 scenarios.

DISCUSSION

Uncertainty analysis

The uncertainty of the impact of climate change on hydrological regime contains climate projections, downscaling methodology, and hydrological simulation (Xu 1999; Bae et al. 2011). Among the three processes, the highest uncertainty is from the climate projections, which include two aspects: different GCMs and different climate scenarios (Zhang & Wang 2007).

The highest uncertainty is from the different GCMs. From some GCMs, the streamflow may increase in the 21st century compared to that in the baseline period; however, the streamflow will decrease based on other GCMs. For example, in the 2020s under the RCP2.6 scenario, the streamflow will increase by 48.21% from the Geophysical Fluid Dynamics Laboratory Climate Model version 3 (GFDL-CM3), but it will decrease by 21.73% from the Goddard Institute for Space Studies Model E version 2 with Hycom1 ocean model (GISS-E2-H). Another important uncertainty is from the different climate scenarios. Taking the results from the Beijing Climate Center Climate System Model version 1 (BCC-CSM1-1) in the 2020s as an example, the streamflow will increase by 17%, 36.4%, and 7.17% under the RCP2.6, RCP4.5, and RCP8.5 scenario, respectively.

The uncertainty from the downscaling methodologies contains dynamical downscaling and statistical downscaling.
The major sources of uncertainty in the hydrological simulation are mainly from the observed hydro-meteorological data, the model parameters calibration and regionalization, and the structure of the VIC model. Compared to the climate projections, the uncertainties from the downscaling methodologies and hydrological simulation are lower and will not be analyzed in this study (Nóbrega et al. 2011).

Figure 11 | The spatial distribution of annual streamflow change by the ensemble mean of 18 GCMs in the 21st century compared to the baseline period over HRB. (The unit in the figure is %).
Streamflow–precipitation–temperature relationship

Generally, the streamflow change has similar annual, monthly, and spatial characteristics to the precipitation change. Based on the numerous sensitivity analysis, the streamflow would increase with an increase of precipitation but would decrease when temperature increased (Bao et al. 2012b). The streamflow will decrease by 6.5% in HRB with a 2 °C increase in annual mean temperature. Meantime, the elasticity of streamflow to precipitation is almost 2.6, i.e. there is a 26% increase in streamflow with a 10% increase in precipitation. With a 2 °C increase in annual mean temperature and a 10% increase in annual precipitation, the streamflow will increase by 18% in the HRB (He et al. 2015). Due to the nonlinear response of streamflow to precipitation and temperature, the 18% change is a little less than 19.5% (2.6*10%−6.5%). In this study, in the 2050s under the RCP4.5 scenario, the 50th percentile values of annual mean temperature, precipitation, and streamflow are 2.09 °C, 13.69% and 27.57%, respectively. The 27.57% change in streamflow is also a little less than 29% (13.69% × 2.6−6.5%). Therefore, the results in this study from the simulations by the VIC model and 18 GCMs are consistent with the results from the previous sensitivity analysis.

Generally, the increases in annual precipitation and annual mean temperature in the northern HRB are higher than that in the southern HRB. The positive effect of precipitation on streamflow will be offset by the negative effect of the mean temperature. Therefore, the spatial distribution of streamflow change is less clear, i.e. the difference of streamflow change between the north and the south of HRB is less significant than that of precipitation change.

Comparison with previous studies

The hydrological model and outputs from GCMs are the two most important points for assessing the impact of climate change on hydrology and water resources. Compared to the previous studies, there are some improvements in this study. First, the hydrological model parameter estimation for the whole HRB in this study is more reasonable than that by Yuan et al. (2005). The model parameters were only calibrated in two small catchments located in the northwest HRB in Yuan et al. (2005); otherwise six catchments in different parts of the HRB were used in this study. On the other hand, Yuan et al. (2005) only regarded the average values of calibrated model parameters in the two catchments for the whole HRB; in contrast, the parameter regionalization methodology was used in this study.

Second, the future climatic scenarios are more reasonable in this study. Ying & Huang (1997) and Dan et al. (2012) only used the hypothetical climate change scenarios, which are set by the authors. That does not have the ability to indicate the future trends of temperature and precipitation. Using the hypothetical scenarios, it can only give the possible impact on hydrology, but cannot give future scenarios of hydrological variables. In recent studies, GCMs were regarded as the most important tool to indicate future climatic scenarios. But the uncertainty of GCMs is still very large. Therefore, more reasonable results will be obtained by more GCMs. Compared to only one GCM used by Yuan et al. (2005), 18 GCMs were used in this study.

Shortages of this paper

There are some shortcomings in this study. For example, more GCMs should be used, and more catchments could be calibrated. The quantitative uncertainty should be assessed, not only for GCMs and climatic scenarios but also for hydrological simulation and downscaling. Based on numerous previous studies, there is a significant impact of land use change on hydrology (Stehr et al. 2010; Nie et al. 2011). Therefore, future land use change scenarios should be considered when assessing future hydrological variables. Another important issue is regarding the impact of hydrological variables change on climate. For example, the irrigation has potential impacts on climate and streamflow (Guimberteau et al. 2012).

CONCLUSIONS

In order to predict future water supplies for water resources planning and management, the impact of climate change on streamflow has been assessed in the HRB. This is investigated by the regionalized VIC model using 18 GCMs.
forcing during the 21st century. First, the VIC model parameters are calibrated in six catchments in the HRB. Second, the model parameters in each grid of the HRB are estimated by the parameter regionalization methodology. Third, the hydrological projections are assessed by the VIC model and the outputs from the GCMs, which indicate that the HRB will become warmer and wetter in the 21st century. Generally, the streamflow might increase in the HRB under future climate change scenarios, compared to that in the baseline period (1961–1990). In the 2050s, the highest annual streamflow increase is under RCP4.5, followed by RCP8.5, and then RCP2.6. In the 2080s, the highest annual streamflow increase is under RCP8.5, and then RCP2.6. Most months show an increase in streamflow, with the highest and lowest increasing trend and uncertainty in dry and wet seasons, respectively. Spatially, the northern HRB has a higher increasing trend of annual streamflow than the southern HRB. In a way, the water shortage problem in the HRB might be relieved under future climate change scenarios.

ACKNOWLEDGEMENTS

This research is funded by several research programs: the National Key R&D Program of China (Grant Nos. 2017YFA0605002, 2017YFA0605004, 2016YFA0601501, and 2016YFC0401501); the National Natural Science Foundation of China (Grant Nos. 41961124007, 51779145, 41830863, and 51879162); and ‘Six top talents’ in Jiangsu province (Grant No. RJFW-031).

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