Predicting long-term hydrological change caused by climate shifting in the 21st Century in the headwater area of the Yellow River Basin

Running head: Predicting hydrological change caused by climate shifting

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Content List

Abstract.....3
1 Introduction.....4
2 Materials and methods.....8
  2.1 Study area.....8
  2.2 Model description.....9
  2.3 Model input data.....9
  2.4 Model setup, calibration, and validation.....10
  2.5 Future climate scenarios.....11
  2.6 Statistical analysis.....13
3 Results.....14
  3.1 Model evaluation.....14
  3.2 Historical spatiotemporal characteristics of key hydrological components.....15
  3.3 Projected climate over the 21st century.....17
  3.4 Hydrological responses to projected climate change.....18
4 Discussion.....21
  4.1 Intense climate change and potential threats.....21
  4.2 Projected hydrologic changes and influencing climate factors.....22
  4.3 Implication.....24
  4.4 Limitations and uncertainties.....25
5 Conclusions.....26
6 Acknowledgments.....28
References.....30
Table captions.....35
Figure captions.....36

Abstract

The Qinghai-Tibetan Plateau (QTP) is one of the amplifiers of global climate change. The headwater area of the Yellow River Basin (HYRB) on the QTP is the dominant water source region for the whole Yellow River Basin (YRB). However, the sensitive responses of hydrological processes to the intensifying climate change are exerting high uncertainties to the water cycle in the HYRB. The aim of this study was to investigate the potential climate change under three Representative Concentration Pathways (RCP 2.6, 4.5, and 8.5) and their hydrological impacts in this region using the ensemble climate data from eight general circulation models (GCMs) and the Soil and Water Assessment Tool (SWAT). Compared to the baseline (1976–2015), the projected climate indicated a rise of 7.3–7.8% in annual precipitation, 1.3–1.9°C in maximum air temperature, and 1.2–1.8°C in minimum air temperature during the near future period (2020–2059), and an increment of 9.0–17.9%, 1.5–4.5°C, and 1.3–4.5°C in precipitation, maximum and minimum temperature, respectively, during the far future period (2060–2099). The well-simulated SWAT modeling results suggested that due to a wetter and warmer climate, annual average actual evapotranspiration (AET) would increase obviously in the future (31.9–35.3% during the near future and 33.5–54.3% during the far future), which might cause a slight decrease in soil water. Water yield would decrease by 16.5–20.1% during the near future period, implying a worsening water crisis in the future. Till the end of this century, driven by the increased precipitation, water yield would no longer continue to decrease, with a decline by 15–19.5%. Overall, this study can not only provide scientific

understanding of the hydrological responses to the future climate in both semi-arid and alpine areas, but also contribute to the decision support for sustainable development of water resources and protection of eco-environment in the HYRB.

Keywords: Climate change; Hydrological components; Representative Concentration Pathways; SWAT

1 Introduction

Global warming is one of the most important threats to human society. Indeed, it has already begun to threaten the sustainability of Earth's life support systems (Lubchenco, 1998). According to Intergovernmental Panel on Climate Change (IPCC) reports, the global average air temperature has increased by 0.85 °C from 1880 to 2012, and the situation might get worse as temperature are anticipated to rise by 1–5 °C by the end of the 21st century (Holden *et al.*, 2018; Lin *et al.*, 2018; Stocker *et al.*, 2013). Recent studies have pointed out that high-altitude regions, such as the Qinghai-Tibetan Plateau (QTP), were the amplifier of global climate change (Giorgi *et al.*, 2010; Jian *et al.*, 2014; Liu and Chen, 2015). Due to the high altitude, low temperature, and slow vegetation growth, the ecosystems in these regions are fragile and difficult to be repaired once damaged (Wang *et al.*, 2007). Thus, these regions are experiencing much more changes and uncertainties caused by the global climate change than other regions.

Global warming could affect the water resources and complicate their assessment and management (Christensen *et al.*, 2004; Oki and Kanae, 2006; Zhou *et al.*, 2011).

The increase of temperature has made the spatial and temporal variability of precipitation increase, which caused more frequent drought and flood events and more serious economic losses (Piao *et al.*, 2010; Trenberth *et al.*, 2014). Associated with global warming, the actual evapotranspiration (AET) has also changed significantly during the past several decades, resulting in the loss of soil water and runoff (Berg *et al.*, 2017; Donnelly *et al.*, 2017). Coles *et al.* (2017) assessed trends in climatological and hydrological variables of hillslopes on Great Plains, and found that snowmelt-runoff and spring soil water content all decreased. In the future, a warming climate would accelerate multiphase water transformation processes and increase the uncertainty of water cycle prediction, preventing us from making firm statements (Meaurio *et al.*, 2017; Wu *et al.*, 2016; Zhang *et al.*, 2016). Liu *et al.* (2017) examined the impacts of 1.5 and 2 °C global warming on water cycle and indicated drier springs, and more severe floods over long return periods (25 and 50 years) for Yiluo and Beijiang River catchment.Yang *et al.* (2014) reported that the weakened water vapor exchange led to less precipitation in the monsoon-impacted southern and eastern Plateau, but the warming enhanced land evaporation. An in-depth understanding of the future climate change impacts on water cycles is hence of great significance for the water resource management and associated policy formulation, which has also been an important concern in the field of global change studies.

Various methods have been proposed and utilized to disentangle climate change impacts on watershed hydrology (Zhang *et al.*, 2018), such as paired catchment approach, hydrological modelling approach, conceptual approach, empirically statistical method, and hydrological sensitivity method (Gao *et al.*, 2016; Zhang *et al.*, 2017). Because hydrological models relate model parameters directly to physically observable land surface characteristics, this method can effectively extract a significant amount of information from limited existing data (Yang *et al.*, 2017). Lu *et al.* (2018) used Variable Infiltration Capacity (VIC) model and RegCM4 and found that evapotranspiration would increase by 10–60% in the source regions of Yellow and Yangtze rivers due to the temperature rise. Recently, a common approach for assessing future hydrological conditions is to use General Circulation Model (GCM) projections in combination with hydrological models (Chen *et al.*, 2012). The Soil and Water Assessment Tool (SWAT), a physical-based, semi-distributed, and bio-physical model, is suitable to investigate the response of simulated streamflow to climate change, especially with the help of projected climate data from various GCMs (Arnold *et al.*, 1998; Zhao *et al.*, 2018). For example, using SWAT and outputs from 20 GCMs to estimate the potential hydrological changes, Neupane *et al.* (2019) found that the mean annual streamflow would decrease under the worst-case Representative Concentration Pathways (RCP) 8.5 during the 2080s in the Suwannee River Basin in the United States.

The headwater area of the Yellow River Basin (HYRB) on the QTP is the source region of the Yellow River, the second largest river in China. The HYRB is crucial to the Yellow River Basin (YRB), as it contributed nearly 40% water to the whole YRB with an area of only about 16% (Chu *et al.*, 2018). It was reported that the HYRB is one of the high-altitude regions with the richest biodiversity in the world (Guo *et al.*, 2004). Therefore, the specific ecosystem in this region is valuable and critical for the YRB, and even for the whole globe. The unique geographical location and climate conditions make the ecosystem of the HYRB fragile and sensitive to environmental changes (Sun *et al.*, 2019; Zhang *et al.*, 2013; Zhou *et al.*, 2005). In the context of global climate change, the HYRB is experiencing a much more intense climate change and associated effects, thus greatly increasing the uncertainties of water resources in this region. The annual average flow of the HYRB has decreased over the past 50 years (Cuo *et al.*, 2013). What is worse, the runoff in the 1990s suffered a serious decrease and the zero-flow days at the most upstream gauging station (Huangheyan station) increased (Chen *et al.*, 2007; Hu *et al.*, 2011; Zhang *et al.*, 2004), which, in long term, could influence the ecological environment and socio-economic development in the HYRB (Lin *et al.*, 2012). Besides, due to the characteristics of water shortage in semi-arid areas, comprehensive research including climate and hydrology needs to be used to evaluate possible strategies in order to make these areas less affected by the changing climate (Patel *et al.*, 2020).Thus, accurately assessing the potential impacts of climate change on the key hydrological processes in the HYRB is an urgent and important task for water resources management.

Our modeling result will provide a proper perspective for investigating the main influencing climate factors of the hydrological components, which is not only useful for people to formulate suitable strategies and policies in semi-arid area, but also key to the sustainable development of the eco-environment in the YRB. With this in mind, the goal of the present study was to assess the hydrological responses to the future projected climate in the HYRB during the near-future period (2020–2059) and far-future period (2060–2099). The assessment was made for three RCP scenarios (RCP 2.6, 4.5, and 8.5) using an ensemble of eight downscaled GCMs and SWAT modeling. The specific objectives were: (1) to validate the suitability and performance of the SWAT model in simulating the hydrological processes in the HYRB; (2) to predict the characteristics of air temperature and precipitation from CMIP5 GCMs under the above three scenarios; and (3) to investigate the spatiotemporal patterns of the key hydrological components (including AET, soil water, and water yield) over the whole basin and across the 21st Century. The outcomes of this study are anticipated to provide a good scientific basis for the sustainable management of the HYRB.

2 Materials and methods

2.1 Study area

The HYRB, well known as the 'water tower' of the Yellow River basin, is located in the Qinghai Province and the northeastern part of the QTP with an area of 118,000 km^2, accounting for 16.2% of the YRB (Figure 1). The average annual precipitation (based on observations over the period 1956–2015) is approximately 497 mm and the average annual temperature is about 1.8°C. The average annual runoff (based on observations over the period 1956–2012) is 19,800,000,000 m^3, which is as much as about 42% of the runoff of the Yellow River Basin in the corresponding period. In comparison with the middle and lower reaches, the upper reach of the HYRB is less affected by anthropogenic activities. So, the response of hydrological components to climate change could be reflected objectively in the HYRB.

2.2 Model description

The SWAT model was developed by the United States Department of Agriculture, Agricultural Research Service (USDA-ARS), and has been widely used to predict the impact of climate change and land use change on water, sediment, and chemical components (Arnold *et al.*, 1998). The hydrological components in the SWAT is based on the water balance equation (Gassman *et al.*, 2007):

$$SW_t = SW + \sum_{i=1}^{t} \left(R_i - Q_i - ET_i - P_i - QR_i \right) \quad (1)$$

where SW is the soil water content, *i* is the time t (days) for the simulation period, R (mm), Q (mm), ET (mm), P (mm), and QR (mm) are the daily amounts of precipitation, runoff, evapotranspiration, percolation, and return flow, respectively. Hydrological Response Unit (HRU) is the basic unit in SWAT. The HRU is defined as a unique aggregation of land use, soil properties, management, and terrain slope (Flügel, 2010; Patel and Srivastava, 2013). In the modeling process, we facilitated the elevation band to discretize the topographic effects of temperature and precipitation into snow melting and runoff (Hartman *et al.*, 1999).

2.3 Model input data

The monthly streamflow data observed over the period 1970–2010 at the

Tangnaihai gaging station were provided by the Yellow River Conservancy Commission of the Ministry of Water Resources (http://www.yrcc.gov.cn/). Meteorological data observed over the period 1951–2015 at 16 stations, including daily maximum temperature (TMAX), minimum temperature (TMIN), precipitation, wind speed, solar radiation, and relative humidity, were provided by the Data Center of the China Meteorological Administration (CMA, http://data.cma.cn/). The input data also included digital elevation model (DEM), soil type, and land use. The 90 m × 90 m Shuttle Radar Topography Mission (SRTM) DEM were used to extract the flow direction and accumulation, create streams, delineate the watershed, and calculate the subbasin parameters. Land use data of the year 1980 (1 km × 1 km) and soil data with a 1:1 million scale were provided by the Ecological and Environmental Science Data Center for West China (http://westdc.westgis.ac.cn). Land use data were reclassified into seven major classes including mid-density and sparse grassland (56.9%), dense grassland (19.0%), barren or sparsely vegetated land (14.4%), forest (7.3%), water bodies (2.8%), cropland (0.4%) and urban, industrial and residential land (0.03%).

2.4 Model setup, calibration, and validation

The HYRB was divided into 157 subbasins based on DEM and digital stream network information, and the subbasins were further divided into 2205 HRUs using a threshold of 5% for each of land use, soil class, and slope. The monthly streamflow data from the Tangnaihai gauging station at the watershed outlet was used to calibrate and validate the SWAT model. In this study, SWAT-CUP (Calibration and Uncertainty

Procedures) was used to identify the set of parameters based on the sensitivity analysis and generate the optimized values of the parameters (Abbaspour *et al.*, 2007; Andrianaki *et al.*, 2019; Xu *et al.*, 2009) (listed in Table 2). The Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm was adopted for the parameter optimization in this study (Yang *et al.*, 2008). The monthly streamflow data were available for 40 years (1971–2010), from which a twenty-year (1981–2000) record of monthly streamflow was used to calibrate the model, and the other twenty-year (1971–1980 and 2001–2010) record was used for validation. We used a series of numeric criteria to evaluate the model performance, including the Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), and percentage bias (PBIAS). Details of these are presented in Appendix 1.

2.5 Future climate scenarios

In this study, eight General Circulation Models (GCMs) were selected for climate change projections. The data were downloaded from the ESGF's website (http://pcmdi9.llnl.gov/). Details of the data sources used in this study are presented in Table 1. The daily data sets (precipitation, maximum and minimum temperatures) of the above three GCMs were selected under RCP 2.6, 4.5, and 8.5 scenarios (representing a very low forcing scenario, medium stabilization scenario, and very high emission scenario, respectively) to predict the future climate scenarios. Two future periods were considered to study the temporal change of hydrological components: near future: 2020–2059 and far future: 2060–2099. The impacts of climate change on hydrological components were investigated by comparing the yearly and monthly difference between the baseline (1976–2015) and the future projections from the model outputs. Specifically, we used absolute changes to evaluate future maximum and minimum temperature, and relative changes to evaluate future precipitation, AET, soil water, and water yield.

Before implementing the GCM output data in SWAT modeling, it is necessary to downscale the raw data to get a fine resolution (Wilby *et al.*, 2002). In this study, we used bilinear interpolation to obtain high-resolution data that could be used in hydrological models (Bae *et al.*, 2015; Sun *et al.*, 2016); see Appendix 2 for details. Then we used a simple bias correction method to correct the downscaled data. The correction of precipitation used the relative change between the monthly observed and simulated data of the historical period (1971–1990), while temperature used the monthly absolute change for the historical period. These biased climate data were calculated as follows:

$$P_{fm} = \left(1 + \alpha_m\right) \times P_{fm0} \tag{2}$$

$$\alpha_m = \frac{P_{hm} - P_{hm0}}{P_{hm0}} \tag{3}$$

$$T_{fm} = \beta_m + T_{fm0} \tag{4}$$

$$\beta_m = T_{hm} - T_{hm0} \tag{5}$$

where m is the month m, P_{fm} and T_{fm} are the corrected GCMs precipitation and temperature, P_{fm0} and T_{fm0} are initial GCMs precipitation and temperature, P_{hm} and T_{hm} are GCMs precipitation and temperature data in historical period, P_{hm0} and T_{fm0} are CMA precipitation and temperature data.

The GCMs data were evaluated by comparing with the CMA data during the historical period (1986–2005) (Figure 2). Although the downscaling procedure for precipitation underestimated some peaks, the downscaled data were generally consistent with the CMA-based observations, with R^2 being 0.87 (Figure 2a). For the monthly maximum and minimum temperatures, the downscaled data were in much closer agreement with the observed data than the case for monthly precipitation, as shown in Figure 2b and c. The R^2 between monthly temperature (maximum and minimum) derived from the downscaled GCMs and CMA exceeded 0.95 (0.96 for maximum and 0.98 for minimum). Generally, both the simulated downscaled precipitation and the temperature values were in close agreement with the observed ones, suggesting that the real climate conditions of the study area (HYRB) could be fairly accurately reflected by the downscaled climate data derived from the GCMs.

2.6 Statistical analysis

In this study, the unitary linearity regress method was used to fit the relation between variables. The prediction model of the univariate linear regression analysis method is as follows:

$$Y_t = a x_t + b \tag{6}$$

$$b = \frac{\sum Y_i}{n} - a\frac{\sum x_i}{n} \tag{7}$$

$$a = \frac{n\sum x_i Y_i - \sum x_i \sum Y_i}{n\sum x_i^2 - \left(\sum x_i\right)^2} \tag{8}$$

where x_t represents the value of independent variable in t period, Y_t represents the value of dependent variable in t period, a and b represent the parameter of linear regression equation.

We also used Mann-Kendall nonparametric rank test to analyze the trend of hydrological and meteorological elements (Kendall and MauriceG, 1979). The rank correlation test for two sets of observations $X = x_1, x_2, \dots x_n$ and $Y = y_1, y_2, \dots y_n$ is formulated as follows. The statistic S is calculated as follows:

$$S = \sum_{i<j} a_{ij} b_{ij} \tag{9}$$

where

$$a_{ij} = sgn(x_j - x_i) = \begin{cases} 1 \, x_i < x_j \\ 0 \, x_i = x_j \\ -1 \, x_i > x_j \end{cases} \tag{10}$$

and b_{ij} is similarly defined for the observations in Y. Under the null hypothesis that X and Y are independent and randomly ordered, the statistic S tends to normality for large n, with $E(S) = 0$ and variance given by:

$$var(S) = \frac{n(n-1)(2n+5)}{10} \tag{11}$$

The significance of trends is tested by comparing the standardized test statistic Z with the standard normal variate at the desired significance level. Z is calculated as:

$$Z = \begin{cases} \dfrac{(S-1)}{\sqrt{var(S)}} \, S > 0 \\ 0 \, S = 0 \\ \dfrac{(S+1)}{\sqrt{var(S)}} \, S < 0 \end{cases} \tag{12}$$

$|Z| \geq 1.64$ means that the confidence level in the current test is more than 95%

($p<0.05$).

3 Results

3.1 Model evaluation

A visual comparison of the monthly simulated streamflow values against the monthly observed streamflow values for the calibration (1981–2000) and validation (1971–1980 and 2001–2010) periods is shown in Figure 3. Although there were three peak flows (e.g., 1981, 1983, and 1999) underestimated and two peak flows (e.g. 1995 and 2007) overestimated during extreme high-water years, the monthly streamflow simulations generally matched well with the observations. The results from the statistical evaluation were presented in Table 3. For the calibration period, the model performed efficiently with the NSE of 0.85, R^2 of 0.86, and PBIAS of -0.3%. As for the validation periods, the NSEs were 0.87 and 0.82, R^2 were 0.88 and 0.89, and PBIAS were -0.3% and 11.3% for validation period I (1971–1980) and validation period II (2001–2010), respectively. Based on the performance ratings of assuming typical uncertainty in observations given by Pereira *et al.* (2016), the streamflow simulation in this study could be evaluated as 'good' ($|PBIAS| \leq 15\%$, $0.8 \leq NSE$, and $R^2 \geq 0.85$). These results indicate that the SWAT model performed well in the HYRB and can be used to investigate the future climate change impacts on hydrological processes.

3.2 Historical spatiotemporal characteristics of key hydrological components

Figure 4 showed that the average annual AET was about 292 mm during 1976–2015, with a range of 250 mm in 1997 to 329 mm in 2012. SD (standard deviation) of AET was 19.46 mm, which means AET fluctuated greatly during the study period. The linear fitting results showed that AET in the whole region increased significantly with a rate of 0.93 mm/yr, which was due to the increase of precipitation and temperature in this region (Figure S1). Spatially, in comparison with the northwestern part, the southeastern part of the basin had a higher AET value (Figure 5 a). From 1976 to 2015, AET increased mainly in the southeast, central and western parts of the basin, and the change in most areas is significant. While it decreased slightly in the northeast (Figure 5 d and g). Table 4 showed that 84.2% of the basin experienced increased AET with a rate ranging from 0.1 to 2.0 mm/yr, with significant increasing portion detected for 74.0%.

The basin-average soil water approximately amounted to 120 mm during 1976–2015 (Figure 4). During the study period, the minimum soil water was 116 mm, which appeared in 1988, and the maximum value was 126 mm, which appeared in 1983. Soil water in the whole region showed a slightly decreasing trend with a rate of 0.05 mm/yr during the 40-year period. Soil water showed an increasing gradient from the northwest to the southeast with a range of 0 to 578 mm (Figure 5 b). There was abundant rainfall and high coverage grassland in the southeast, which could increase the retention time of rainwater on the land surface and increase the infiltration of rainwater, so the soil water in this area was higher. Figure 5 h showed that the area with decreased soil water was greater than the increased one, and we could also find the same result from Table 4.

Water yield refers to the capacity of a catchment to supply water (Arnold *et al.*, 1998). The average water yield in study area was 205 mm with a range of 147 to 305 mm during 1976–2015 (Figure 4). The SD of water yield was 35.65 mm, and the linear fitting results showed that the water yield decreased by 0.02 mm/yr, and the downward trend was insignificant. From Figure 5 c, we found that water yield of the basin had obvious spatial heterogeneity, that is, water yield of the eastern and southern region was much higher than that in the western and northern area. During the study period, water yield mainly showed a decreasing trend in the south of basin (about 51.8% of the whole basin), while the western and northern regions showed an increasing trend (48.2% of the whole basin) (Figure 5 i and Table 4). Besides, there was no statistical significance in the trend of water yield in both increasing and decreasing areas.

3.3 Projected climate over the 21^{st} century

The downscaled data were analyzed for the two future time periods: near future (2020–2059) and far future (2060–2099). The future bias-corrected scenarios RCP 2.6, RCP 4.5, and RCP 8.5 were then compared with the observed climate data from the historical period (1976–2015).

Figure 6 showed that during the near future period, the annual increases in precipitation were found to be 7.3%, 7.6%, and 7.8% under RCP 2.6, RCP 4.5, and

RCP 8.5, respectively. The annual precipitation was projected to continuously increase in the HYRB under three RCPs during the far future period. From the Table 5, we found that the CV (coefficient of variation) of far future period precipitation was higher than that of near future period precipitation. Figure 7 (a) showed that the precipitation in the HYRB mainly concentrated from May to September every year during the historical period. The rainfall in the study area would increase in every month, while the changes in monthly projected rainfall showed large differences (Figure 7 b). The precipitation increased most obviously in January and November. In particular, it was anticipated to increase by 63% and 63.3% in these two months under RCP 8.5 scenario during the far future period. These results indicated that the future precipitation changes had temporal heterogeneity under different scenarios.

Both annual and monthly temperatures showed a significant warming trend across the HYRB (Figure 6 and Figure 7). Under RCP 2.6, the increment of temperature was similar during the near future and far future periods. Under RCP 4.5 scenario, the maximum temperature increased by 1.6 °C and the minimum temperature increased by 1.5 °C in the near future period. The maximum temperature and minimum temperature increased by 2.6 °C and 2.4 °C respectively in the far future period. The HYRB was projected to experience the warmest period at the end of this century under RCP 8.5, in which period the maximum temperature and minimum temperature were expected to increase by 4.5 °C. Table 5 indicated that the CV of far future period temperature was higher than that of near future period temperature. Figure 7 (a) showed that the maximum values of the maximum and minimum temperature in the

HYRB appear in July and the minimum values appear in January. The maximum temperature increased the most in October (by 5.2 °C), and the minimum temperature increased the most in March (by 6.4 °C), which occurred in the RCP 8.5 scenario at the end of this century (Figure 7 c and d).

3.4 Hydrological responses to projected climate change

We analyzed the effects of climate change on several key hydrological components in the HYRB, including actual evapotranspiration (AET), soil water, and water yield. Figure 8 and Figure 9 showed the annual and monthly change, respectively, of the future AET, soil water, and water yield.

Figure 8 indicated that AET was sensitive to climate change. During the near future period, the increment of AET in the three RCPs was similar, ranging from 31.9% to 35.3%. During the far future period, AET continued to increase, with the most dramatic increase under RCP 8.5 scenario, which might be related to obvious increase of precipitation and temperature in the HYRB. From the Figure 9 (a), we found that the AET in historical period reached its maximum in July. During the near future and far future period, AET showed an increasing trend (Figure 9 b). AET was projected to increase greatly in March, April, October, and November, and the maximum increment occurred under RCP 8.5 scenario at the end of this century, with a change rate of 174%. Figure 10 showed the spatial changes of AET compared with historical periods. The AET of the whole basin would increase in the future, while it increased more obviously in the eastern and southern part of the basin, indicating more water loss in this region in the future. Compared with RCP 2.6 and RCP 4.5, AET increased most under RCP 8.5, which was related to the different temperature changes under the three scenarios.

Soil water decreased slightly during near future period, by 3.1% in RCP 2.6 scenario, 6.1% in RCP 4.5, and 8.5 scenarios (Figure 8). By the end of this century, soil water decreased more obviously, by 13.3% under RCP 8.5 scenario compared with base period, which could affect the absorption of water by vegetation The monthly variation of soil water was shown in Figure 9 (c). Under different scenarios, soil water decreased most obviously in April and May. The change of soil water was similar to that of temperature, which meant that although the rainfall increased in this region, the increase of ET due to raise of temperature played a greater role. Figure 11 showed that the decrease of soil water was predicted to be mainly in the west, middle and export areas of the basin, while it would increase slightly in the southeastern region. Compared with the near future period, the increment of soil water in southeast may decrease during the far future period, and even turn to a decrease.

Under the combined effects of increased temperature and variations in precipitation, the water yield showed a decrement of 16.5–20.1% during the near future period (Figure 8). At the end of this century, due to the increase of precipitation, the water yield would be no longer continuously reduced, and the decline rate was similar to that the near future period (15–19.5%). Table 6 indicated that water yield had a larger range of variation and correlation than AET and soil water. Figure 9 (a) showed that during the base period, the lowest level of water yield occurred in January, and then increased sharply in May. Water yield peaked in July and decreased after September. From Figure 9 (d), we found that the water yield in February, March and November showed an obvious increasing trend compared with the historical period. The highest change was in February, with a change rate of 39.1–129%. The relative changes were also obvious because of the small value of absolute water yield in winter. Besides, water yield was projected to decrease from May to August in each scenario. Figure 12 was the change of water yield during two future periods. We found that water yield in most HRUs would decrease under three RCPs, which was related to the obvious increase of AET. The water yield was predicted to increase only in a few areas, mainly distributed in the southeast of the basin, with the variation range of 1–70 mm. Compared with the near future period, the decline of water yield at the end of this century was reduced, which might be caused by the increase of rainfall.

4 Discussion

4.1 Intense climate change and potential threats

Our study found that the climate in HYRB would become wetter in terms of the changes of precipitation, especially during far future period under the RCP 8.5 scenarios. The rainfall was projected to increase by 7.3–7.8% for the near future period and 9.0–17.9% for the far future period. Increased precipitation will have a positive effect on AET, soil water, and water yield in study area. The result of the increases in precipitation was generally in line with Feng *et al.* (2016) and Li *et al.* (2008). Compared with summer (June, July, and August), the monthly dynamics of precipitation in other months was more obvious, which may affect the monthly variation of hydrological components in HYRB.

For temperature, the results suggested an increase in both maximum and minimum temperature in the future, and this increasing trend of future temperature is consistent with that in the historical period (Figure S1). During the near future period, the raises of temperature were projected to be substantially similar under RCP 2.6, RCP 4.5, and RCP 8.5, indicating that the different emissions scenarios would not lead to significantly different temperature responses. However, the increase in temperature began to diverge under different emission scenarios during the far future, since the temperature increase was generally 3 °C more under RCP 8.5 than under RCP 2.6. Furthermore, Figure 7 showed that projected increment of maximum temperature were slower than that of minimum temperature, which is consistent with most areas around the world and might lead to a decline in diurnal temperature range (DTR) and considerably affect the growth of vegetation (Donat *et al.*, 2013; Feng *et al.*, 2018; Morak *et al.*, 2013). According to the fifth assessment report (AR5) of IPCC, the simulation results showed that the global average temperature rise could reach 2.6–4.8 °C by the end of the 21st century (Stocker *et al.*, 2013), with the temperature projected to increase more at higher elevations and latitudes (Hu *et al.*, 2014; Luo *et al.*, 2019). Previous studies have shown that the temperature changes in the Qinghai-Tibetan Plateau region and the polar regions were more severe than that in other areas (Gao *et al.*, 2012; Overland *et al.*, 2014). As it is climatically sensitive and ecologically fragile, the HYRB region and its environment have been significantly affected by climate change. For example, the wetland ecosystem in the HYRB plays an irreplaceable role in water source conservation, run-off adjustment, and biodiversity maintenance. Climate change will make future efforts to restore and manage wetlands more complex (Erwin, 2008). Consequently, the increasing temperature may cause serious disturbances to the ecological structure and degradation of ecosystem functions, posing a threat to the safety of ecosystems in the middle and lower reaches of the Yellow River Basin.

4.2 Projected hydrologic changes and influencing climate factors

Quantifying the influence of climate factors on hydrological processes is essential for water resources management, especially in semi-arid region. The AET was projected to increase by 31.9–35.3% for the near future period and up to 33.5–54.3% for the far future period, which was relative to the combined influence of precipitation and temperature. While as for monthly change, the increase in AET in May, June, July, and August was less than other periods. This was due to the reason that the change in precipitation in same period was small, although the temperature increment was similar to other periods. Therefore, the change in temperature made the AET in whole area increase, but the monthly scale change of AET would be greatly affected by precipitation. The warm and wet climate could lead to a downward trend in soil water in the future. The raise of rainfall might have a positive effect on soil water, but the increment of AET due to temperature would result in a decreasing trend of it. Also, due to severe temperature rise, soil water was predicted to continue to decline during far future period, which meant that in the study area, temperature dominated changes in soil water.

The water yield would reduce by 16.5~20.1% for the near future period, which may imply that the HYRB would be under a severe water stress during the mid-century period. The magnitude of the decline in water yield obtained from this study was a little higher than that from Lin *et al.* (2012), who reported a decrease of about 9.5% (2020s) under the A2 scenario in the HYRB. We found that the water yield showed a decreasing trend from May to August both in two periods. The decline of water yield was due to the increase in AET caused by warming, even if the precipitation was also raising during the same period. So the increase in ET would be the main cause for water yield decrease. Meng *et al.* (2016) found that runoff in the HYRB decreased by about 20% in the 2000s, during which precipitation contributed for 3% to the runoff reduction, while the increase in AET accounted for 97%. Besides, due to strong warming over the region, AET has been playing an increasingly important role in influencing runoff changes in recent decades. In the end of this century, driven by the increased precipitation, water yield would no longer continue to decrease, with a decline by 15–19.5% for the far future period. Hence the variation of temperature would dominate the changes in water yield in the HYRB, while rainfall can affect it to some extent.

4.3 Implication

The climate warming has been regarded as an undoubted fact and could further exert adverse effects on the soil water yield, which can alert decision makers for the potential risks, including drought. For example, the reduction of water yield in May to August due to the increment of temperature in the HYRB could be an indicator of reduced water availability in the growing season. Therefore, there was a concern about steady water supply for industrial purposes and crop irrigation not only in the HYRB, but also in the whole Yellow River Basin. Besides, the raising AET and the resulting decline of soil water, especially in irrigation period (May to August), would cause an increasing potential of water stress on crop growth and a resulting increase in water demand for irrigation. Therefore, the reduction in water yield in the HYRB and the increase in irrigation demand require watershed managers to pay attention to the more effective water-use schemes and optimizing effective water-saving irrigation equipment.

Many semi-arid regions have the characteristics of water shortage, fragile natural resources, obvious climate change, and great social pressure (Krol *et al.*, 2006). Integrated studies including climatology and hydrology are required to evaluate possible strategies to make semi-arid areas less susceptible to current and changing climate. Our modeling study provided a proper perspective for investigating the main influencing climate factors of the hydrological components in semi-arid area. This is certainly informative and valuable for people who are interested in the modeling research related to water cycles and its response to climate change, and a better understanding of climatic and hydrological changes in semi-arid areas is highly required to formulate specific and suitable strategies in water resources management

(Shen *et al.*, 2019). Besides, climate change dominated the hydrological shifts in alpine region (Yang *et al.*, 2019). Considering the co-effects of both climate and land cover changes on the hydrological cycle, such a headwater area with minimal disturbance by human activities is suitable for diagnosing the historical changes without the challenge of disentangling the land cover changes. In general, although this research is a case study, out results can not only be helpful for understanding the hydrological responses to climate change in semi-arid areas and alpine areas, but also demonstrates the necessity to predict future climate and water cycle changes at local areas, especially when seeking decision support, which can help managers to develop adaptive strategies to mitigate risks and benefit the public.

4.4 Limitations and uncertainties

The soil type, land use, and anthropogenic activities have a great influence on hydrological components, and this may lead to over/under-estimation of the hydrological components. Besides, previous studies have indicated that high-altitude catchments would experience more complex hydrological changes because of the important role of glaciers, snowmelt, and freeze-thaw process of soil in the water balance (Wang *et al.*, 2015), while we did not take these processes into account in this study because of the model simulation ability. In the future, we will carry out relevant researches. Furthermore, there are inherent uncertainties in the GCMs processes (Zhou *et al.*, 2015). Although out study adopted the arithmetic ensemble averages from the hydrological model outputs that are driven by the eight GCMs to address this uncertainty, due to the complexities involved in the climate change phenomenon, accurately predicting future climate change is very difficult (Knutti and Sedláček, 2012).

5 Conclusions

In this study, we investigated the projection of future climate and its impacts on key hydrological components in the HYRB. The SWAT was calibrated and evaluated for the HYRB. The model performed successfully with satisfactory NSE, R^2, and PBIAS values. Temporally, AET showed an significantly increasing trend during 1976–2015, while soil water and water yield decreased slightly. Spatially, these key hydrological components exhibited a substantial heterogeneity. The precipitation projections indicated that there would be a slight increase of 7.3–7.8% during the near future period and an increase by 9.0–17.9% during the far future period. The climate projections showed a warming of 1.3–1.9 °C for the near future period and 1.5–4.5 °C for the far future period for the maximum temperature. The corresponding values for the minimum temperature were 1.2–1.8 °C and 1.3–4.5 °C. And the projected changes in the maximum temperature were slower than those in the minimum temperature in January, February, March, November, and December. Due to the wetter and warmer climate, AET was predicted to increase dramatically under three RCPs, and there would be an increment in the whole basin compared with historical period. As for soil water, there would be a slight decline of 3.1–6.1% during the near future period and a decrease of 4.2–13.3% during the far future period. The spatial changes would be much complicated, but soil water in most HRUs would show a decreasing trend mainly caused by warming. The synergistic effect of the climate change would result in a 16.5–20.1% reduction in water yield during the near future period. In the end of this century, driven by the increased precipitation, water yield would no longer continue to decrease, with a decline by 15–19.5%. So in the HYRB, the variation of temperature would dominate the changes in water yield in the HYRB, while rainfall can affect it to some extent. Besides, the obvious reduction of water yield from May to August would lead to more severe water crisis not only in study area, but also in the whole Yellow River basin.

Our study examined the spatiotemporal hydrological dynamics in the HYRB under future climate change conditions. The prediction facilitates the development and implementation of an effective water management plan in advance to minimize potential negative water resources issues in the Yellow River basin. To achieve even more reliable results, future research should consider other factors besides climate change, such as land use changes and increased CO_2 concentrations due to human activities. We will address this in our future studies.

6 Acknowledgments

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Appendix 1. Model performance assessment

To measure the model performance, the Nash-Sutcliffe Efficiency (NSE) (Mandeville *et al.*, 1970), the coefficient of determination (R^2) , and the percentage bias (PBIAS) were used in this study. These criteria were calculated as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{m.i} - Q_{s,i})^2}{\sum_{i=1}^{n} (Q_{m.i} - Q_{m,avg})^2} \tag{5}$$

$$R^2 = ¿¿¿ \tag{6}$$

$$PBIAS = \frac{\sum_{i=1}^{n} (Q_{s.i} - Q_{m,i})}{\sum_{i=1}^{n} Q_{m.i}} \times 100\% \tag{7}$$

where $Q_{m.i}$ and $Q_{s,i}$ are measured and simulated streamflow at each time step i; $Q_{m,avg}$ and $Q_{s,avg}$ are the mean measured and simulated streamflow; and n is the number of time steps.

The NSE describes the explained variance for the observed values over time that is accounted for by the model (Green and Griensven, 2008). The PBIAS measures the average difference between observation and simulation. The closer NSE and R^2 are to 1, and PBIAS to 0, the better the SWAT model performs.

Appendix 2. Bilinear interpolation downscaling method

Bilinear interpolation, as an extension of linear interpolation, is used to interpolate functions of two variables (e.g., x and y) on a rectilinear 2D grid in mathematics (*https://en.wikipedia.org/wiki/Bilinear_interpolation*). The method is described as follows:

Suppose get the value of the unknown function f at point $P=(x,y)$. It's assumed that we know the value of the four points of the function f at $Q_{11}=(x_1,y_1)$, $Q_{12}=(x_1,y_2)$' $Q_{21}=(x_2,y_1)$' $Q_{22}=(x_2,y_2)$ (Figure S2).

First, linear interpolation is performed in the x-direction:

$$f(R¿¿1)\approx\frac{x_2-x}{x_2-x_1}f(Q¿¿11)+\frac{x-x_1}{x_2-x_1}f(Q¿¿21)¿¿¿ \qquad (2)$$

where, $R_1=(x,y_1)$,

$$f(R¿¿2)\approx\frac{x_2-x}{x_2-x_1}f(Q¿¿12)+\frac{x-x_1}{x_2-x_1}f(Q¿¿22)¿¿¿ \qquad (2)$$

where, $R_2=(x,y_2)$.

Then, linear interpolation is performed in the y-direction:

$$f(P)\approx\frac{y_2-y}{y_2-y_1}f(R¿¿1)+\frac{y-y_1}{y_2-y_1}f(R¿¿2)¿¿ \qquad (3)$$

Finally, the desired estimate of $f(x,y)$:

$$f(x,y)\approx\frac{f(Q¿¿11)}{(x_2-x_1)(y_2-y_1)}(x_2-x)(y_2-y)+\frac{f(Q¿¿21)}{(x_2-x_1)(y_2-y_1)}(x-x_1)(y_2-y)+\frac{f}{(x_2-} \qquad (4)$$

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Table captions

Table 1. Information of the eight General Circulation Models (GCMs) used in this study.

Table 2. Calibrated parameter values for the headwater area of the Yellow River Basin.

Table 3. Evaluation of model performance in monthly streamflow simulation at the Tangnaihai gaging station during the twenty-year (1981–2000) calibration and twenty-year (1971–1980, 2001–2010) validation periods.

Table 4.Area percentage of the changing trends of the three key hydrological components during 1976–2015.

Table 5. Variations in annual precipitation, maximum air temperature (TMAX), and minimum air temperature (TMIN) during the near future (NF, 2020–2059) and far future (FF, 2060–2099) periods under RCP 2.6, RCP 4.5, and RCP 8.5 compared with the baseline period (1976–2015). CV denotes the coefficient of variation of model annual averages.

Table 6. Variations in annual AET, soil water, and water yield during the near future (NF, 2020–2059) and far future (FF, 2060–2099) periods under RCP 2.6, RCP 4.5, and RCP 8.5 compared with the baseline period (1976–2015). CV denotes the coefficient of variation of model annual averages.

Figure captions

Figure 1. The location and brief description of the headwater area of the Yellow River Basin, China.

Figure 2. Comparison of observed and GCM-derived (a) monthly precipitation, (b) maximum and (c) minimum temperature in the HYRB during 1986 and 2005.

Figure 3. Monthly streamflow simulation at the Tangnaihai gaging station during the calibration period (1981–2000) and the validation periods (1971–1980, 2001–2010).

Figure 4. Temporal changes in annual AET (actual evapotranspiration), water yield, and soil water during 1976–2015. SD means standard deviation.

Figure 5. Spatial distributions of (a-c) annual mean key hydrological components, (d-f) annual trends of key hydrological components, and (g-i) probability density distribution of trends in the HYRB during 1976–2015 on the Hydrologic Response Unit (HRU) level. "///" indicates that the trend has passed the significance test ($p<0.05$).

Figure 6. Ensemble values of annual mean precipitation, maximum and minimum air temperature under three RCPs during the future period of 2020–2099. The blue, green, and red lines represent the historical period, near future (NF, 2020–2059), and the far future (FF, 2060–2099) periods, respectively. The shading area denotes the ±1 standard deviation range of model annual

averages.

Figure 7. (a) Monthly mean precipitation, maximum and minimum air temperature during baseline period (1976–2015). (b) Projected changes in ensemble monthly mean precipitation, (c) maximum and (d) minimum air temperature during the near future (NF, 2020–2059) and far future (FF, 2060–2099) periods under RCP 2.6, 4.5, and 8.5 relative to baseline.

Figure 8. Ensemble values of annual mean AET (actual evapotranspiration), soil water, and water yield under three RCPs during the future period of 2020–2099. The green and red lines represent the near future (NF, 2020–2059) and the far future (FF, 2060–2099) periods, respectively. The shading area denotes the ±1 standard deviation range of model annual averages.

Figure 9. (a) Monthly AET (actual evapotranspiration), soil water and water yield during the baseline period (1976–2015) and the projected monthly changes in (b) AET, (c) soil water, and (d) water yield during the near future (NF, 2020–2059) and the far future (FF, 2060–2099) periods under the RCP 2.6, 4.5, and 8.5 relative to baseline in the HYRB.

Figure 10. The difference of AET (actual evapotranspiration) between near future (2020–2059) and historical period, far future (2060-2099) and historical period under the RCP 2.6, 4.5, and 8.5.

Figure 11. The difference of soil water between near future (2020–2059) and historical period, far future (2060–2099) and historical period under the RCP 2.6, 4.5, and 8.5.

Figure 12. The difference of water yield between near future (2020–2059) and historical period, far future (2060–2099) and historical period under the RCP 2.6, 4.5, and 8.5.

Figure S1. Temporal changes in annual precipitation, maximum temperature, minimum temperature, wind speed, relative humidity, and solar radiation in the headwater area of the Yellow River Basin (HYRB) during 1966–2015.

Figure S2. Bilinear-interpolation schematic diagram.