Impacts of climate change on hydrological regimes in the Jinsha River Basin, China

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Abstract

The flow regime is of vital importance for the sustainable development of both human society and aquatic biota. Alterations in natural streamflow will modify the stability and biophysical distribution of river conditions, causing a series of adverse ecological and economic consequences. Climate change has been proven to pose potential threats to ecosystems; however, few studies have been conducted to quantify the variations between the flow regime of a future period and pristine natural flow specifically. This study investigates the future impacts induced by the changing climate in the Jinsha River Basin, which is known as the “Asian Water Tower” due to its rich hydroelectric energy resources. The SWAT model is used and calibrated to predict future streamflow. Seven GCMs from NASA NEX-GDDP with one ensemble average under two RCPs (RCP4.5 and RCP8.5) are used for both the NFP (2040s) and the FFP (2080s). The Indicators of Hydrologic Alteration (IHA) software and the river regime index (RRI) are used to assess the potential flow alterations of the Jinsha River. The results show that Pr, Tmax and Tmin all denote increasing trends, with the temperature trends being more obvious. For interannual alterations in flow regimes, most IHA values show moderate and high changes in all predicted conditions. In

regard to the intra-annual changes, the results of the RRI show that river flow tends to be more concentrated in wet seasons than in cold seasons and denote evident seasonality and transience with advanced overall peaks of the river system. These findings together indicate that the flow patterns may have noticeable changes corresponding to the natural river regime.

Keywords: Climate change; SWAT; GCM; RCP; Indicators of Hydrologic Alteration; River regime index; Hydrological regimes; Jinsha River

1. INTRODUCTION

The maintenance of natural hydrologic variability is essential in conserving native riverine biota and the integrity of river ecosystems (Richter, Baumgartner, Braun & Powell, 1998) because rivers can provide a wide range of positive functions for humankind (Costanza, 2003; Gao, Booij & Xu, 2009; Molden & Bos, 2005; Torabi & Kløve,2013). While streamflow variability is considered the primary driver of the riverine ecosystem's function and structure (Poff et al., 1997), alterations of natural streamflow regimes can modify the distribution and availability of riverine habitat conditions (Poff et al., 1997). This further hinders the sustainable development of human society, including infrastructure construction, economic growth, food security, and energy consumption (Brown, Zhang, Mcmahon, Western, &Vertessy, 2005; Ma, Yang, Tan, Gao, & Hu, 2010; Nagy, Lockaby, Kalin, & Anderson, 2012), and causes adverse consequences for native biota and endangered species (Bunn & Arthington, 2002). Climate change has the potential to substantially alter river flow regimes (Arnell & Gosling, 2013). Changing temperatures and rainfall rates intensify hydrological processes (Huntington, 2006) and may further trigger alterations in streamflow (Reshmidevi, Kumar, Mehrotra, & Sharma, 2018); temperature can influence streamflow by altering the evapotranspiration ability of a stream, while changes in precipitation can directly disturb the runoff of certain river basins simultaneously (Patterson, Lutz, & Doyle, 2013; Wang& Hejazi, 2011). Therefore, a comprehensive assessment is urgently needed to understand the impacts caused by climate change on natural flow regimes, especially at the watershed scale.

A common approach to studying climate impacts on water resources is using global climate model (GCM) projections of the future climate (Brown, Ghile, Laverty, & Li, 2012). The fifth phase of the Climate Model Intercomparison Project (CMIP5) (Taylor, Stouffer, & Meehl, 2012), designed to advance our knowledge of climate variability and climate change, has been widely applied in the field of future climate impacts and has been established as stable and reliable (Cao & Yin, 2020; Sunde, He, Hubbart, & Urban, 2017). The three main sources of uncertainty in modeling climate trends are scenario uncertainty, model uncertainty, and internal climate variability (Deser, Philips, Bourdette, & Teng, 2010; Evin et al.,2019); the choice of downscaling methods and bias-correcting techniques can also introduce new, nonnegligible uncertainties (Chen, Haerter, Hagemann, & Piani, 2011; Hagemann et al.,2011; Teutschbein & Seibert, 2012). With these factors in mind, to avoid further introducing new uncertainties in the current study, we choose 7 GCMs, after referring to existing studies (Chen, Xu, Xu, &, Yao, 2014; Siew, Tangang, & Juneng, 2014; Xin, Zhang, Zhang, Wu, & Fang, 2013), from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset, which was developed by the National Aeronautics and Space Administration (NASA) and verified to be robust even in topographically complex regions (Jain, Salunke, Mishra, Sahany. & Choudhary, 2019; Sun & Cao, 2017), with which to perform this study.

A hydrological model is a mediator between hydrological theories and the practices of the real world (Babel & Choudhary, 2013); by far, using GCM output as the hydrological model input has largely assisted and advanced the process of projecting future streamflow, which seems to be essential and necessary to better understand the potential effects of a changing climate on hydrologic and fluvial regimes (Zhang, Su, Hao, Xu, Yu, Wang, & Tong, 2015). The SWAT hydrological model is a conceptual and spatially distributed model coupling several different components, including climatic inputs, crop growth and yield, hydrological cycling, representation of management practices, erosion processes and resulting sediment transport, and pollutant (nutrient, pesticide, and pathogen) cycling and transport (Tan, Gassman. Yang, & Haywood, 2020; Zhai, Zhang, Wang, Xia, & Liang, 2014), and has been proven to be applicable to the Yangtze River watershed (Chen, Chen, Li, & Shen, 2019; Wang, Zhang, Wang, Wu, & Zhang, 2018). In this study, the SWAT model, integrated with the ArcGIS graphical user interface, is used at a daily timestep to assess the impacts of climate change on hydrologic and riverine regimes in the upper Jinsha River.

Brown and King, 2003 (Brown & King, 2003) proposed both that streamflow should meet the needs of human demands and that the conservation of freshwater biodiversity for the environment is a legitimate use of the river, which highlights the importance of evaluating flow variability from an ecological perspective. To date, more than 171 hydrologic metrics have been proposed to summarize various aspects of the flow regime (Olden & Poff, 2003)). One common hydrologic metric is the Indicators of Hydrologic Alteration (IHA), first developed by Richter, Baumgartner, Powell, &, Braun (1996), which has been extensively used to characterize the impact of regulation on flow regimes. The Nature Conservancy integrated the indicators into one user-friendly software program to facilitate their application by scholars (IHA V7-1). With the aim of setting streamflow-based river management targets combining the concepts of hydrologic variability and aquatic ecosystem integrity, the range of variability approach (RVA) was further proposed (Richter, Baumgartner, Wigington,& Braun, 1997). This approach has been proven to be a practical and effective means to assess the degree of hydrologic alterations, and it has been applied to many river basins around the world (Richter et al.,1998; Koel & Sparks, 2002; Shiau & Wu, 2004). In addition, Torabi (Torabi & Kløve, 2013) developed a dimensionless index called the river regime index (RRI) to quantify river flow regimes that are independent of magnitude conditions, such as units of discharge, which proved to be useful for studying environmental flow alterations and allocations.

Located in the upper region of the Yangtze River, the Jinsha River Basin (JRB), known as the “Water Tower of China”, is the largest hydropower production region in

China (Li, Lu, Yang, Chen, & Lin, 2018). The river supports many freshwater fish species in the Palearctic zone (Sun& Cao, 2008) due to its complicated natural environment and thus its high diversity of fish habitats. Significant effects of global warming on glacier retreat and permafrost degradation have been confirmed over the JRB (Lutz. Immerzeel . Shrestha, & Bierkens, 2014), and the area will further incur large-scale and possibly irreparable regional hydrological disturbances (Wu, Yen, Arnold, Yang, & Srinivasan, 2020). However, to the best of our knowledge, few studies have focused on the pure effects of climate change on the pristine riverine regime, while numerous studies have focused on the combined and separated influences of climate change and human activity on hydrological and riverine regimes over the regulated JRB (Chen, Gao, & Zeng, 2017; Zhang, Cai, Yang, Yi, & Yang, 2020; Zhang, Yan, Yue, & Xu, 2019).

The main objectives of this study are: (1) quantify the predicted alterations in the climate over the JRB; (2) further investigate the changes in river regimes under different future climate scenarios and periods in the JRB; (3) gain insight into the changes in hydrological regimes over different timescales via the joint use of the IHA and RRI; (4) fill the gaps in previous studies and provide a new and intensive view through which scholars and policy-makers can better investigate and properly make decisions.

2. STUDY AREA AND DATA

2.1 Study Area

The Jinsha River Basin (JRB), which includes the Jinsha River and its largest tributary, the Yalong River, covers a vast drainage area of 502 000 km^2 (27.8% of the entire basin area of the Yangtze River) (Huang, Gao, Yang, & Yi, 2018), provides an annual discharge approximately 38% that of the Yangtze River (~140 billion m^3) (Li et al., 2018), and serves as an important section connecting and maintaining the source area to the mainstream of the Yangtze River. The climate components in the JRB show both great spatial variability (precipitation ranges from approximately 300 mm upstream to >1,300 mm downstream (Li et al.,2018), the annual minimum temperature occurs in the upstream region (-5.6 °C), and the maximum temperature occurs in the downstream region (21.9 °C) (Wu et al., 2020)) and temporal heterogeneity (the flood season, from June to September, accounts for more than 70% of the precipitation (Chen et al., 2019)) as a result of the combined effects of the monsoon climate and the extremely varied terrain. The streamflow of the JRB is jointly affected by the melting of the snowbelt covering the source area of the Yangtze River and the flow induced by precipitation in the watershed (Xiong, Li, & Chen, 2020); these factors are influenced more by climate change than by anthropogenic activities. Therefore, it is a typical place to study the natural evolution of river regime alterations.

2.2 Data

To drive the SWAT hydrological model, spatial and temporal data must be collected to represent the climatic and physical characteristics over the target watershed. In this study, the 90 × 90 m SRTM (Shuttle Radar Topography Mission) DEM was downloaded from the International Scientific and Technical Data Mirror Site (http://www.gscloud.cn), the land use/cover map data were derived from the Resources and Environment Data Center of the Chinese Academy of Sciences with a 100-m spatial resolution in 1980, and the soil map data were obtained using the Harmonized World Soil Database, HWSD v1.1 from the International Institute for Applied System Analysis (IIASA) with standard depths of 0–30 cm and 30–100 cm, which were further recalculated by the Soil–Plant–Atmosphere–Water model (SPAW) software.

Model calibration and validation are vitally important to ensure the accuracy of later use of the model. Taking both data continuity and a study period with little or no human disturbances into consideration, 27 meteorological stations with observed climate data, including daily precipitation, solar radiation, relative humidity, wind speed and maximum and minimum daily air temperature, were selected from which to gather data from the period 1964-1986 over the JRB from the National Climate Center of China Meteorological Administration (http://data.cma.cn/), as depicted in orange points in **Figure 1**. Data preprocessing was performed by interpolating missing meteorological data with data from neighboring timeseries or stations. The Pingshan Hydrological Station is located downstream of the junction of the mainstream Jinsha River and its tributary, the Yalong River, and is the exit control station at which the Jinsha River enters the Yangtze River. Thus, we chose Pingshan Station as the location for the model calibration. The daily streamflow data, available from 1964 to 1986, were supported by the Chinese Water Year Book of Jinsha River, Yangtze River Basin. The average annual runoff at Pingshan Station is 4443 m^3/s, with maximum and minimum values of 28600 m^3/s and 760 m^3/s, respectively. Regarding future climate variables, the NEX-GDDP was chosen for this study. Based on bias-corrected spatial disaggregation (BCSD) downscaling technology, NEX-GDDP is a high-resolution (0.25°longitude×0.25°latitude) dataset providing precipitation (Pr) and maximum and minimum air temperature (Tmax and Tmin) on a daily scale, comprising 21 GCMs on a global scale from CMIP5 under RCP4.5 and RCP8.5 from the historical period of 1950-2005 to the future period of 2006-2100. An official and detailed explanation can be found at https://cds.nccs.nasa.gov/nex-gddp/. Detailed descriptions of the GCMs and RCPs used in this study are provided in **Table 1** and **Table 2**. We further selected 33 NEX-GDDP grids with the conditions of being both representative and having efficient calculation methods; see the green points in **Figure 1**.

[Insert Table 1, Table 2, and Figure 1 here]

3. METHOD

Dividing the streamflow time series into two spans, the “baseline or natural period” and the “impacted period”, is a general approach for quantifying the relative contributions of climate change and anthropogenic influences (Liu, Huang, Shao, & Cheng, 2020; Obeysekera, Irizarry, Park, Barnes, & Dessalegne, 2011). Based on this classification theory, we define three timespans: the historical period (1970s) (HP), near-future period (2040s) (NFP) and far-future period (2080s) (FFP); only climate change and variability are taken into consideration in these periods.

3.1 SWAT

The Soil and Water Assessment Tool (SWAT) (Arnold, Srinivasan, Muttiah, & Williams, 1998) is used in this study for the purpose of calibrating and validating the historical streamflow at Pingshan Station and then predicting the future streamflow as it is influenced only by climate change. Thus, with respect to different sets of precipitation and temperature under various climate conditions, the corresponding responses of the target watershed are developed.

The calculation process of the swat model is as follows: First, the SWAT partitions the study basin into multiple subunits by delineating the watershed, and then the land area in a subbasin is further divided into smaller hydrologic response units (HRUs) that possess unique combinations of soil attributes, slope and land use properties based on thresholds defined by the user. Thereafter, the simulated hydrological components are aggregated toward the outlet of the basin through its network of streams.

The components simulated by the SWAT model in the hydrological cycle are based on the water balance equation:

$$SW_t = SW_{init} + \sum_{i=1}^{t} \left(R_{day}(i) - Q_{surf}(i) ¿ - E_a(i) - W_{seep}(i) - Q_{gw}(i) \right) ¿ \quad (1)$$

where SW_t and SW_{init} are the final and initial soil water content (mm), respectively; t is the simulation period in days; $R_{day}(i)$ is the total amount of rainfall on day i(mm); $Q_{surf}(i)$ is the surface runoff (mm); $E_a(i)$ is the evapotranspiration (mm); $W_{seep}(i)$ is the percolation portion entering the vadose zone through the soil profile (mm); and $Q_{gw}(i)$ is the return flow (mm).

The modified soil conservation service (SCS) curve number method is used in the SWAT to estimate streamflow. In addition, in the current study, the Penman-Monteith method is used to assess evapotranspiration within the basin. The accuracy of the model was checked by calibrating and validating the observed streamflow records versus the predicted data using the SUFI–2 algorithm via SWAT–CUP (Calibration and Uncertainty Programs) (Abbaspour, Vejdani, & Haghighat, 2007). Due to our study purpose, namely, investigating the pure effects of climate change as well as the inadequateness of measured streamflow data, the entire study period is divided into spin-up (1964-1966), calibration (1967-1976) and validation (1977-1986) periods based on daily timesteps. The performance of the model was measured using the coefficient of determination (R^2) and using Nash–Sutcliffe model efficiency coefficient (NSE) (Nash & Sutcliffe,1970) statistics against the recorded and predicted data based on the evaluation ratings proposed by Moriasi. (Moriasi, Arnold, Liew, Bingner, Harmmel, & Veith, 2007). The statistics are expressed as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n} \left(R_i^{obs} - R_i^{¿} \right)^2}{\sum_{i=1}^{n} \left(¿ R_i^{obs} - R_i^{\overline{obs}} \right)^2 ¿} \tag{2}$$

$$R^2 = ¿¿ \tag{3}$$

where R_i^{obs} and $R_i^{¿}$ are the observed and simulated data for the ith point, respectively; and $R_i^{\overline{obs}}$ and $R_i^{\bar{¿}}$ are the mean values of the observed and simulated data, respectively. For both NSE and R^2, perfect agreement between the observed and simulated data is achieved when the values are 1.

3.2 Indicators of Hydrologic Alteration (IHA)

The Indicators of Hydrologic Alteration (IHA) program is employed in this study to investigate and measure the degree of change in the riverine ecosystem between the target timeseries. The IHA program is one of the most commonly used tools for assessing hydrological changes in certain river flows over recent years (Papadaki et al., 2016), and it provides a comprehensive analysis of streamflow characteristics with 33 hydrological indicators based on the following aspects: (1) magnitude of monthly water conditions, (2) magnitude and duration of extreme annual flows, (3) timing of extreme annual conditions, (4) frequency and duration of high and low pulses, and (5) rate and frequency of water condition changes (detailed information on all these indicators can be found in the user manual of the IHA) (Poff et al., 1997; Poff &

Zimmerman, 2010). Although the IHA is based on data collected from a single point (for instance, a hydrological station or dam), it can reflect hydrologic conditions and processes over a wide and long area of the target river (Richter et al., 1998). These indicators focus on descriptors of the flow regime that are thought to be important to the biological and physical aspects of a river (Richter et al.,1996); thus, IHA can systematically assess the fluvial alterations comparing the pre- and postimpact periods.

However, many studies have indicated that the IHA parameters are intercorrelated and somewhat redundant (Olden & Poff, 2003); thus, principal component analysis (PCA) (Jolliffe, 2005) is employed to reduce this redundancy and simplify the environmental flow assessments (Yang, Cai, & Herricks, 2008).

In conjunction with the IHA, the range of variability approach (RVA) (Richter et al., 1997) is widely used to further quantify the degree of hydrological alterations (DHA) using the natural, predevelopment variation in the IHA parameter values as a reference to define the extent of alteration of natural flow regimes. In this study, the degree of hydrologic alterations, defined as Eq. (4), is calculated as follows with the RVA for each individual selected IHA:

$$DAH_i = \left| \frac{F_o - F_e}{F_e} \right| \times 100 \tag{4}$$

where i is the DAH of the i[th] IHA; F_o is the frequency of the projected period, which is equal to the ratio of observed years that fall into the target range of the RVA to the total number of observed years; and F_e is the expected frequency, which is equal to the number of values in the category during the preimpact period multiplied by the ratio of postimpact years to preimpact years. A DAH_i value lower than 33 represents no alteration or slight alter ation, a value of 33-67 represents moderate alteration and a value higher than 67 represents high alteration.

3.3 River regime index (RRI)

To further investigate the intra-annual variations on a monthly timescale, a general dimensionless index, the river regime index (RRI) (Torabi & Kløve, 2013), is used to study the impacts of future climate change on the river systems. The steps taken to calculate the RRI are as follows.

First, the concept of the unit river should be defined and the total annual river flow is rescaled to 100 million cubic meters (MCMs). The unit river allows users to assess the alterations directly by comparing the proportion of monthly runoff to annual runoff without considering the differences in unit or magnitude among various target locations or time spans; this greatly simplifies the calculation process and also allows the user to focus on the differences themselves. The rescaled monthly data will be obtained by multiplying by the factor η using Eq. (5) as follows:

$$\eta = \frac{U}{Q_o} \tag{5}$$

where U is the flow scaling unit (usually 100 million cubic meters or 100% per year) and Q_o is the original annual average flow of the given river.

Then, the concept of the monthly river regime point (MRRP) is developed for quantifying the skewed degree between the impacted river and the unimpacted river. If the unit discharge is smaller or larger than the even discharge of a “uniform regulated river” (8.333 MCMs per month), MRRP will increase from 0; the extreme situation (dry river) will be reached when the MRRP equals 100 MCMs per month. Overall, there are three models used to calculate the MRRP per month; Torabi (Torabi & Kløve, 2013) suggested that Model 2 is the best option due to it being fairly symmetrical around the minimum point and highly sensitive to flow variations. Thus, we only introduce Model 2 to preserve simplicity of presentation.

$$\text{I}f\ 0 \le Q \le 8.333: MRRP = -12 \times Q + 100 \tag{6}$$

$$\text{I}f\ 8.333 < Q \le 13.333: MRRP = +12 \times Q - 100 \tag{7}$$

$$\text{I}f\ 13.333 < Q \le 100: MRRP = 0.46 \times Q + 53.85 \tag{8}$$

Finally, the river regime index (RRI) can be obtained after all the MRRPs are derived using the equation as follows:

$$RRI = \sum_{n=1}^{23} MRRP(n)\,(n = 1, 2, \ldots, 12) \tag{9}$$

where *n* is the number of the month. The RRI in this study is calculated using the Excel calculator developed by Torabi (Torabi & Kløve, 2013).

4. RESULTS

4.1 Performance of the SWAT hydrological model

The NSE was selected as the objective function, and the widely used SUFI-2 algorithm was employed to execute the calibration and validation process within the SWAT-CUP software, which was developed to rate parameters automatically and efficiently. **Figure 2** clearly summarizes the performance of the SWAT model, from which we can see that both the calibration (1964-1976, first three years was set as a spin-up period) and validation (1977-1986) periods gained satisfying results on the daily scale according to the standards of Moriasi et al.,2007. The NSE and R^2 are larger than 0.75 for both the calibration (NSE=0.80, R^2=0.81) and validation periods (NSE=0.78, R^2=0.80). In addition, the PBIAS for both periods are lower than 10% (calibration: 6.4%, validation: 6.4%). These results together illustrate that the SWAT model built in this study has the ability to reconstruct the observed runoff fairly well. Thus, the calibrated SWAT model was further used to explore future hydrologic responses corresponding to future climate variables, as described in the following sections.

[Insert Figure 2]

4.2 Climate change projections

Figure 3 shows the three climate variables (Pr (mm), Tmax (°C), and Tmin (°C)) during the timeseries from 2030 to 2089, corresponding to the two RCPs obtained from each downscaled climate model provided by NASA NEX-GDDP and their ensemble mean values over the targeted JRB. Compared with the apparent upward skewness of the projected temperature extremes, the trends of the multimodel projections of future precipitation are less obvious. The upward tendency in Pr of both RCPs is not as obvious as the trends in both Tmax and Tmin. Regarding individual model performance, it is quite clear that ISP-CM5A-MR provides the highest temperature fluctuation, while INMCM4 shows the lowest; moreover, there is no obvious stand-out model for the Pr projections.

[Insert Figure 3]

The annual monthly changes in mean precipitation (Δmm) and air temperature (calculated as the average of Tmax and Tmin) (Δ°C) based on the NASA NEX-GDDP dataset over the JRB are depicted in **Figure 4**. Projected changes for both NFP and FFP, compared with HP, corresponding to the seven GCMs and one ensemble mean under two representative greenhouse gas emission scenarios (RCP4.5 and RCP8.5) are contained in groups in **Figure 4**; each plot has a similar form but differs in the x- and y- coordinate scales. In general, the monthly changes in temperature under RCP8.5 are larger than those under RCP4.5, but a similar changing trend is not clear in terms of NFP and FFP; however, both of the RCPs and the temporal scales seem to devote the same contributions to the alterations of precipitation. It is easy to see that the various FFP ranges under RCP8.5 are much wider than are the other three combinations in regard to the changes in one single plot; however, the changing patterns of temperature are usually more obvious than those of precipitation. The temperature outputs from each GCM under the two RCPs all denote increscent values, while the conditions in precipitation are much more complex because negative values exist in cold months. It is worth noting that during the NFP, the negative precipitation values are mainly concentrated in November and December, whereas October also denotes nonnegligible negative values in the FFP, which may suggest that the decreasing trend in precipitation will occur earlier in each year in the late 21th century over the JRB. The ensemble mean values for the projected change in the mean annual precipitation/temperature in the basin under the RCP4.5 scenario in the NFP and FFP are 1.60 mm/8.20°C and 1.74 mm/8.97°C, respectively, while the corresponding values under the RCP8.5 scenarios are 1.58 mm/8.47°C and 2.12 mm/10.71°C, respectively. The conditions above demonstrate that there are variabilities nested inside GCMs despite the similar changing patterns, and these differences would be amplified with larger emission pathways and longer time scales.

[Insert Figure 4]

4.3 Climate change impacts on hydrologic indicators

The climate variables derived from the 7 GCMs with one ensemble mean under two greenhouse gas emission scenarios served as inputs to the well-calibrated SWAT model; then, the projected streamflow was simulated as the output. After obtaining the future streamflow, the IHA and RRI were further utilized to analyze the alterations of inter- and intra-annual hydrologic and river regimes over the JRB.

4.3.1. Interannual changing patterns in the JRB

To avoid redundancy in the IHA, PCA was first performed on SPSS software to filter trivial indicators. We eliminated the number of zero days (for no no-flow days appear over the JRB) and the magnitude of monthly water conditions (these will be further discussed using the RRI) group to ensure a positive definite matrix. Then, based on the scree test, five indicators were finally selected from the original indicator set: annual minimum 30-day means, annual maximum 90-day means, Julian date of each annual 1-day maximum, mean or median duration of low pulses (days) and mean or median duration of high pulses (days). These five indicators are from the IHA parameter groups 2, 3, and 4 and together represent the magnitude, duration, timing, and frequency of extreme water conditions and high and low pulses over the JRB. The radar plot (**Figure 5**) clearly shows the distribution of each DHA of the five IHAs corresponding to each GCM and one ensemble model under the two emission scenarios.

[Insert Figure 5]

Generally, the value of the DHA during the FFP is quite larger than that during the NFP, while the same phenomenon is not obvious under the two RCPs over the same impacted period. For individual IHAs, high degrees of alterations are found in all GCMs for the indicator of high pulse duration, which may induce an adverse impact on the bed load transport, channel sediment textures, and duration of substrate disturbance. For the 90-day maximum indicator, high alterations still exist in all GCMs under both RCPs (6 GCMs show 100, INMCM4 shows 87). However, the remaining indicators do not show similar changing patterns. Six of the seven GCMs showed high DHAs in the 30-day minimum for the FFP under both RCPs, while five of the seven showed high DHAs in NFP under RCP4.5, and only three of the seven showed high DHAs in NFP under RCP8.5. Moreover, great variations can be found in regard to the DHA of the date of the flow maximum as well as for the low pulse duration. High, moderate, and low alterations all exist in all GCM-RCP combinations for low pulse duration, while for the date of the flow maximum, only moderate and low alterations are shown in FFP under RCP8.5, with the rest of the combinations also covering the full range of alteration.

4.3.2. Intra-annual changing patterns of the JRB

Further monthly river regime alterations were investigated using RRI. Torabi proposed three virtual river models (the uniform regulated river, the dry river, and the tetra-seasonal river) based on the concept of the unit river, in which the uniform regulated river means the discharge is 8.33 MCMs per month, the dry river indicates 100 MCMs of annual flow all occurring during 1 month while the other months have 0 MCM of flow, and the tetra-seasonal river is located between these two virtual rivers; the tetra-seasonal river has four classical seasons of 3 months each and 100% of the annual river flow is distributed as 10% (3.33 MCMs), 20% (6.66 MCMs), 30% (10 MCMs) and 40% (13.33 MCMs) for the dry, semidry, semiwet and wet seasons, respectively. According to these three suppositional rivers, we define four classes using the values mentioned above: 0-3.33 MCMs, 3.33-8.33 MCMs, 8.33-13.33 MCMs, and 13.33-100 MCMs, aiming to quantify the overall river regime alteration patterns relative to the HP. As an increase to a higher value level indicates that the streamflow tends to be more concentrated, and the extreme case will be a dry river, the increase to a lower value level indicates that a more even river regime occurs. The average percent frequency of each combination of GCM-RCPs, responding to the four ranges of scaled discharge, is clearly demonstrated in **Figure 6**, from which we can see that although individual combinations show different degrees, the gross trend is rather obvious. More than 40% of the scaled monthly discharge values are found to be lower than 3.33 MCMs, except for the far-future period under RCP8.5, in which the lowest percent frequency appears between the range of 8.33-13.33 MCMs and all the combinations share the same trends. Under RCP4.5 in both periods, river discharge seems more concentrated in the 0-3.33 range than it does over the HP; on the contrary, the values under RCP8.5 in the far future are relatively even, with the most scaled discharge values appearing in the 3.33-8.33 and 13.33-100 ranges. Distinct differences are found in the two lower ranges (0-3.33 and 3.33-8.33), with a more than 20% increase in the 0-3.33 range and an approximately 6% reduction in the 3.33-8.33 range compared with the historical period.

[Insert Figure 6]

The monthly alterations for each model are depicted in **Figure 7,** and the changing RRI values with respect to the HP are arranged in Table 3. Obviously, all GCM-RCP combinations show quite different patterns for July and August compared to the historical period; the scaled discharge of projected streamflow in all GCMs under both RCPs is much larger than that of the historical period. The apex of all plots appeared in the FFP under RCP8.5, except for the trend predicted by the model Nor-ESM1-M, in which the peak appears in the 2040s under RCP8.5. Under RCP4.5, no protruding difference can be found between the NFP and FFP, which may certify that the influence of the RCP can be magnified as time passes and that the higher RCP can also have large impacts on the same time stage. In addition to the magnitude of the peak value, the timing of the peak value of each model under all combinations generally occurs earlier than that of the reference period; however, for some models (such as INMCM4), the discharge pattern appears to be ahead of the historical period as a whole. The hydrograph types representing the scaled discharge in the future periods are generally higher and sharper in summer and autumn and lower and smoother in spring and winter, meaning that the streamflow predicted by GCMs is plausibly more concentrated than that seen in historical records.

[Insert Table 3 and Figure 7]

For the ΔRRI values summarized in **Table 3**, the average value of each combination consists of the results of the changing climate, since the higher RCP and the farther period shows the larger variations, and vice versa. This finding means that the intra-annual flow regime of the JRB tends to be seasonal and ephemeral under high RCPs in the FFP. In terms of individual GCMs, the reverse results can be found in BCC-CSM1.1 and IPSL-CM5A-MR under RCP4.5, while INMCM4 and Nor-ESM1-M show opposite values under both RCPs. We owe these findings to the different internal structures of each model; this underlines the necessity of using multiple climate models when studying climate change and its impacts.

5. DISCUSSION

With the aid of GCMs, we simulated future climate variables in the JRB. As seen from the M-K test results shown in **Table 4**, for the average temperature, all GCMs under the two RCPs show significant upward trends; the rainfall under both RCPs also exhibits an upward trend in the future. There are exceptions: the rainfall of IPSL-CM5A-MR under RCP8.5 shows a significant downward trend, while two GCMs show nonsignificant trends under both RCPs. The results show that the JRB is becoming warmer and wetter, which is overall consistent with the results of previous work (Qin et al., 2019; Yuan, Xu, & Wang, 2018). The hydrological model is also a source of uncertainty according to the case study by Chen (Chen et al., 2017), who compared the three prevalent hydrological models, SWAT, VIC, and HBV, and confirmed that the SWAT simulation results were the closest to the average performance of the three models, meaning that SWAT contains the least uncertainty. Therefore, SWAT was chosen, and the streamflow of the JRB was proven to be aptly simulated. The increasing precipitation and temperature values may cause increased melt and evaporation of mountain glaciers (Zhang et al., 2018); as a result, runoff in the JRB also depicts an upward trend in both future time periods. According to the results of the M-K test, all GCMs under both RCPs during the NFP and FFP depict significant upward trends, except IPSL-CM5A-MR, and the results are relatively reasonable, as its rainfall also shows an abnormal trend as mentioned above. This finding is in accordance with the findings of previous studies (Su, Huang, Zeng, Gao, & Jiang, 2017). This indicates that there are large uncertainties that exist in the IPSL-

CM5A-MR model, which may not be sufficiently suited for the prediction of climatic variables in the JRB, or at least should not be used alone. Further, in addition to the inherent model differences, we cannot neglect to discuss the special location of Pingshan Station. Pingshan Station lies at the watershed outlet and thus serves as the control station of the JRB. The combined uncertainties coming from the upper area of the watershed, the variety of topography and the inhomogeneous climate variables together contribute to the large uncertainty seen in the future flow projections of Pingshan Station. In addition, one phenomenon that is fairly common, but of little concern, is that the parameter values of the fixed hydrological models can be altered along with future climate scenarios (Deshmukh& Singh, 2019). Thus, it is unsurprising when different predicted streamflow results are obtained as long as the overall trend is consistent.

[Insert Table 4]

Using the IHA and RRI, the multitemporal-scale variations of the hydrological regimes are discussed in this study. Previous studies aimed at this area mainly investigated historical changes and considered the combined effects of both reservoirs and climate change; our study can provide a new interpretation angle for the existing work. Yin (Yin, Xu, Tian, & Yang, 2014) used 32 IHA indexes to analyze the altered natural characteristics of hydrological regimes undergoing construction of dams and reservoirs based on the measured historical daily flow series at the Pingshan, Zhutuo, and Cuntan hydrological stations in the JRB. He found that compared with the other stations, the hydrological situation at the Pingshan station is affected the most by the cascading operations of reservoirs. Furthermore, the streamflow in the dry season (from December of a given year to April of the following year) is increasing, and the degree of variation in low-flow events is higher. We found that the future flow will be more concentrated in the wet seasons. Yin's (Yin et al., 2014) conclusion, which is contrary to the conclusions of our study, highlights the storage and replenishment functions of cascade reservoirs, which can be reasonably used to prevent and control future extreme risks. Similarly, Zhou (Zhou, Huang, Zhao, & Ma, 2020) also found that the flow duration curves of the JRB under the regulation of cascade reservoirs showed a declining trend in the high-flow section and an increasing trend in the low-flow section, further illustrating the huge impacts the construction and operation of cascade reservoirs have on the flow regimes. Referring to our current work, however, relevant departments should reasonably attach importance to the planning of the role of hydraulic structures in softening the potential impact of future climate changes on the hydrological regime of the watershed, and further efforts should be made to deepen this understanding.

The JRB, in addition to its abundant hydropower resources, also serves as one of the most biodiverse regions of China and as the connecting area for fishes between the Qinghai-Tibet Plateau and the river plain; the JRB possesses many unique fishes that can only be found locally (Wu & Wu, 1990). Thus, determining the changing hydrological regimes under a plausible warmer and wetter JRB will not only have profound significance at the economic and decision-making levels but will also provide a scientific basis for environmental impact assessments. In this study, overall, upward trends are found in the annual minimum 30-day means, annual maximum 90-day means, and high pulse duration in the JRB, threatening the structure of aquatic ecosystems by abiotic vs. biotic factors, river channel morphology, and physical habitat conditions. In addition, large uncertainties exist in the date of maximum flow and low pulse duration, which may influence the spawning cues for migratory fish and alter their behavioral mechanisms. Numerous studies have affirmed that climate change and anthropogenic activities have already caused declines in aquatic biota in the JRB (Wang et al., 2019; Zhang et al., 2018). Overall, climate change is one of the most severe threats to stream fishes (Woodward, Perkins, & Brown, 2010) because the increase in air temperature will shift the water temperature, and the alterations of hydrological regimes will eventually change the habitat conditions of freshwater species as well. Moreover, changes in the magnitude and duration of annual extreme water conditions can influence sediment transport. Studies have found that (Hu et al., 2019; Liu et al., 2014) the sediment flux from the Yangtze River suffers a downward trend. Sediment plays an important role in forming the geomorphology and geology of an area and can affect the geomorphologic evolution of river channels, deltas, and estuaries. Thus, the loss of sediment may challenge the sustainability of the development of a river delta, pose a threat to the safety of cities and, obviously, menace the habitats of aquatic life. The JRB may also suffer further loss of sediment ascribed to the changing climate; hence, water managers should take this latent risk into consideration when handling watershed planning and management issues. All of these findings highlight that the straightforward clarification of future altered hydrological regimes will assist in the protection of ecological diversity.

Agreeing with Qin (Qin et al., 2019) and Chen (Chen et al., 2019), we also found that no negligible changing patterns occurred in the intra-annual flow regimes: the peak values will arrive sooner than the traditional timing, and the river flow seems to be more centralized in wet seasons than in cold ones. This finding suggests that the future river regime of the JRB will be more concentrated and the magnitude of the freshet will be more obvious, requiring flood-control authorities to pay more attention to these flood-prone seasons. Thus, special attention should be paid to the supervision of future wet-season hydrological situations, and the reservoirs should be reasonably adjusted and planned according to future flood control risk.

6. CONCLUSIONS AND PROSPECTS

6.1 Conclusions

Climate change is likely to substantially alter river flow regimes (Arnell & Gosling, 2013); quantifying the alterations of river flow regimes will be paramount for evaluating climate change risks related to freshwater and will further assist in the maintenance of essential ecosystem goods and services. However, when facing pressing river management issues, the complex, dynamic river regime is often regarded as simplistic and static for the sake of simplicity (Arthington, Bunn, Poff, & Naiman, 2006). The temporal variations in river flows are capable of determining the structure and function of a riverine ecosystem and the adaptations of its biota (Arthington et al.,2006). Thus, the plausible multitemporal changing patterns under multicombinations of GCM-RCPs in the upper Jinsha River Basin.are investigated in this study.

The most notable conclusions of this study can be drawn as follows:

- First, the SWAT hydrologic model used in this study has been proven satisfying on the daily scale in both calibration and validation processes with NSE>0.75, R^2>0.80, and PBIAS<10%. The calibrated SWAT hydrologic model can grasp the main streamflow characteristics in the JRB, reproduce the hydrological process during the historical period accurately, and project the future river flow rationally. Thus, SWAT can be viewed as a reliable tool used to assist in the research of changing streamflow patterns under the context of global climate change; these findings are consistent with those of other studies (Musau et al., 2015; Zhang et al., 2016).
- Second, daily total precipitation, maximum daily air temperature, and minimum daily air temperature all have a growing trend; the fluctuation in daily total precipitation is more evident than those of maximum daily air temperature and minimum daily air temperature. The upward trend, therefore, seems to be somewhat inconspicuous. For annual monthly changes, the RCPs and temporal scales exert the same influence on precipitation, while temperature seems to be more influenced by RCPs than by the temporal scales. In addition, an anticipatory meteorological drought may occur in the winter in the late 2020s due to the early decline in precipitation and the increase in temperatures of great magnitudes.
- Third, the IHA and RRI were employed in this study to evaluate the alterations in hydrologic and river regimes from the inter- and intra-annual perspectives, respectively. No obvious changing patterns can be found in interannual alterations because the DHA varies among different GCMs. Most DHAs show moderate and high changes in the four GCM-RCP combinations, portending that the flow patterns may have large changes corresponding to the pristine river flow. For intra-annual variations, the river flow tends to be more concentrated in wet seasons than in cold seasons and denotes evident seasonality and transience with

the overall peaks of the river system advancing. Although the results computed from each GCM are slightly different, the overall results alert us that the potential changes under the context of climate change should not be ignored and should be seriously considered to be at least as urgent as the impacts of human activity. Hence, much attention should be paid to considering the design of hydraulic structures to reduce or eliminate the potential unfavorable impacts caused by global climate change. As the upper Yangtze River is a populous area with high ecological value, water managers and decision-makers should work to keep the postimpact distributions of river regimes as close to the preimpact distributions as possible (Richter et al., 1997) to avoid the evitable ecological changes threatening both humankind and biota.

6.2 Prospects

The approaches adopted in this study still have several limitations. In this study, we choose seven widely used GCMs and one ensemble mean under two typical RCPs and strove to predict the future climate comprehensively and reliably. However, as Tebaldi and Knutti 2007 pointed out, the mean processes of GCMs can produce spurious climate variables that may further influence the transmission of uncertainty in simulated streamflows (Stojkovic & Simonovic, 2020). Regarding the potential uncertainty nested in the choice of hydrologic model, SWAT has been proven to be trustworthy in numerous studies related to climate projection; thus, we consider it adequate to meet our objectives and assume that the associated uncertainty is equal in each projected output. In addition, the choice of bias-correction method can also introduce a new source of uncertainty (Hagemann et al., 2011; Teutschbein & Seibert, 2012). Consulting other related studies (Haro-Monteagudo, Palazón, & Beguería, 2020), we use no additive bias-correction approach to try to capture the transmission of the climate signal to the hydrological signal while preserving the variability between GCMs without inducing a new source of uncertainty. Determining the potential impacts caused by climate change on hydrologic and river regimes is the only objective matter in this study, so the uncertainty mentioned above is beyond our current research scope. We sincerely recommend that future research be carried out from the following aspects: 1) the uncertainty nested through the translation from the climate signal to the projected river flow can be further analyzed; 2) comparative studies referring to the pristine period can be conducted with a larger study area and with a longer study period; 3) changes in land use, reservoir-building and water allocation policy can be considered because the hydrological cycle is a dynamic, multi-input and multioutput nonlinear system.

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DATA AVAILABILITY

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

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TABLES

Table 1 Global climate models (GCMs) from the CMIP5 experiment used in this study.

Table 2 Description of the two representative concentration pathways (RCPs) used in this study (van Vuuren et al.,2011).

Table 3 The values of ΔRRI, comparing the historical period with two future periods under RCP4.5 and RCP8.5.

Table 4 The M-K test results of future precipitation, temperature, and streamflow.

FIGURE LEGENDS

Figure 1 Location of the study region and the hydrological and meteorological stations.

Figure 2 Simulated and observed discharge values at the Pingshan Output Station and the corresponding precipitation values for the calibration (1967-1976) and validation (1977-1986) periods. Both the discharge and precipitation values are shown on a monthly scale for better visual effects.

Figure 3 Average annual time series of the three climate variables [daily total precipitation, maximum daily air temperature (Tmax), and minimum daily air temperature (Tmin)] corresponding to the two RCPs as projected by each of the 7 GCMs and their ensemble mean between 2030 and 2089 averaged over the Jinsha River Basin (JRB).

Figure 4 Scatter plots of the monthly variations in mean precipitation and air temperature over the Jinsha River Basin between the reference and two future periods based on the 7 GCMs and their ensemble mean under the RCP4.5 and RCP8.5 emission scenarios.

Figure 5 Radar plots of the DHA of IHA corresponding to the near- and far-future periods under two RCPs by 7 GCMs and their ensemble average.

Figure 6 Histogram of the percent frequency of each range of scaled discharge between the historical period and the projected period related to 7 GCMs and their ensemble mean under two RCPs.

Figure 7 Scaled annual hydrograph obtained from the RRI model for 7 GCMs and their ensemble mean between the historical and future periods under two RCPs.