Interactive influence of climate variability and land-use change on blue and green water resources: a case study from the Ganjiang River Basin, China

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Abstract

The response of blue and green water to climate and land-use change in the Ganjiang River Basin (GRB) is evaluated, via the SWAT model that combines three scenarios (the land-use/land-cover (LULC), climate change, and integrated climate and LULC change scenarios) in the 2040s (2031–2050) and 2060s (2051–2070). The results indicate that, for the GRB, cropland, woodland, and grassland show a decreasing trend, while build-up and water areas show an increasing trend in terms of future land-use change. The climatic conditions projected using NORESM1-M model data under the RCP4.5 and RCP8.5 scenarios suggest, respectively, increases in precipitation (31.17 and 27.24 mm), maximum temperature (2.25 and 2.69 °C), and minimum temperature (1.96 and 2.58 °C). Under climate change conditions, blue water is estimated to decrease by up to 16.89 and 21.4 mm under RCP4.5 and RCP8.5, while green water is estimated to increase up to 19.14 and 20.22 mm, respectively. Under the LULC changes, blue water is projected to increase by up to 5.50 and 7.57 mm, while green water shows decreases of 4.05 and 7.80 mm for the LULC2035 and LULC2055 scenarios, respectively. Under the four combined LULC and climate change conditions (RCP4.5_2040s, RCP4.5_2060s, RCP8.5_2040s, and RCP8.5_2060s), blue water tends to decrease by 0.67, 7.47, 7.28, and 9.99 mm, while green water increases by 19.24, 20.8, 13.87, and 22.30 mm. The influence of climate variation on blue and green water resources is comparatively higher than that of the integrated impacts of climate and land-use changes. The results of this study offer a scientific reference for the water resources management and planning department responsible for scheduling water resource management plan in the GRB.

Key words: blue water, climate change, Ganjiang River, green water, land-use change, SWAT model

Highlights

- This study investigates the effects of climate changes and land-use changes on blue/green water.
- The NORESM1-M model data from the CMIP5 are combined with the SWAT model to analyse the influence of future climate changes on blue/green water.
- The CA–Markov model is applied to generate future land-use scenarios.
- Multiple climate and land-use scenarios are set to quantitatively analyse the changes of blue/green water.
INTRODUCTION

Climate variabilities and land-use changes have altered the hydrological process and influenced the spatiotemporal distribution of water resources (Shrestha & Wang 2020). Freshwater is vital for the maintenance of ecological equilibrium and the sustainable development of human activities (Zhang et al. 2019; Liang et al. 2020). Falkenmark & Rockstrom (2006) first proposed the concept of blue and green water. Blue water is tightly related to human requirements for agricultural irrigation, shipping, industrial production, and municipal water needs (Du et al. 2018; Liang et al. 2018). Green water is the foundation for plant growth, accounting for 80% of water resources used in global agricultural production (Liu et al. 2010; Xie et al. 2019). Climate change, which plays a crucial role in the hydrological cycle, can have a critical impact on the sustainable development of blue and green water (Oki & Kanae 2006; Zhang et al. 2012; Jiao et al. 2020; Yu et al. 2020). Iman et al. (2019) evaluated the effect of variations in climate on the spatiotemporal variation of blue and green water in the Bazoft Basin. Brij et al. (2019) integrated the Coupled Model Inter-comparison Project Phase 5 (CMIP5) and the SWAT model to investigate the potential effects of climate variation on blue/green water in the Upper Narmada River Basin. Yuan et al. (2019) used the SWAT model to estimate the blue water, green water flow, and green water storage under the effect of future climate changes. In addition, human activities including agricultural irrigation, construction of reservoirs, and industrial production can exert a critical effect on the water resources (i.e., blue and green water) of a basin (Li et al. 2021). Human activities indirectly affect the canopy interception, surface infiltration, evaporation, and soil water that are processes in the water cycle by changing the underlying surface conditions of the basin; this has a vital impact on the water balance in the basin (Liang & Ding 2012). Thus, the impacts of human activities and climate variations on the cycle of blue/green water resources are often intertwined (Chun et al. 2020). Human activities, such as industrial production, have also exacerbated global warming, thereby changing the spatiotemporal distribution of water resources (Siriwardena et al. 2006). Many in-depth studies have been conducted to investigate the double effects of climate variation and human activity on water resources. Huang et al. (2019) considered the interactive impacts of climate change and land use/land cover (LULC) on the global consumption of agricultural blue and green water. Therefore, simulating and projecting climate and LULC scenarios are significant for studying the spatiotemporal distribution and change rules of water resources in future research. This includes work like that of Akbar & Gheewala (2021), who studied the influence of climate and land-use changes on runoff in the Kunhar River basin, Pakistan.
Methods for studying the response of blue/green water to changes in climate and land use generally include watershed experiments, statistical analyses, and model simulation methods (Tian et al. 2020). Among these, hydrological models widely used such as SWAT (Wang et al. 2020), MPI-HM (Faramarzi et al. 2013), and SWIM (Gao et al. 2018) can simulate blue and green water at different spatiotemporal scales and combine meteorological and land-use change data to quantitatively analyse blue and green water. The SWAT model, which is a distributed hydrological model with a strong physical mechanism, has also been widely used given the broad applicability of its scale and parameter settings, which are efficient at simulating the effects of changes in climate and land use on blue/green water (see, e.g., Zhao et al. 2016; Yuan et al. 2019; Zhang et al. 2020). Zhao et al. (2016) utilized the SWAT model to investigate the interactive effects of climate variations and human activities on blue/green water in the Weihe River in China. Yuan et al. (2019) quantified the changes in blue water, green water flow, and green water storage under the influence of variations in climate in the Yangtze River source region in China. Zhang et al. (2020) evaluated the variations in characteristics of blue/green water in the upper Ganjiang River Basin (GRB) under historical climate and LULC changes. Although many studies have evaluated the influence of changes in climate or land use on blue/green water, there are relatively few studies on the possible effects of integrated future climate and land-use changes on blue/green water, especially on the response of blue/green water to future land-use change.

Thus, the main objective of this study was to investigate the independent and joint impacts of changes in climate and LULC on the spatiotemporal distribution pattern of blue/green water in the GRB. In the ‘Study areas and datasets’ section, the equidistant cumulative distribution function (EDCDF) was used to correct the bias of the NORESM1-M model data. In the ‘Methodology’ section, the cellular automata–Markov chain (CA–Markov) model was used to generate scenarios related to future land-use patterns. Finally, in the ‘Results’ section, blue and green water processes under disparate scenarios (e.g., climate change scenarios, land-use change scenarios, and combined LULC and climate change scenarios) were simulated using the SWAT model, and the impacts of future climate variations and LULC on blue/green water are analysed quantitatively.

STUDY AREAS AND DATASETS

Study region

The GRB is in Jiangxi Province, China (24°31′–28°45 N and 113°54′–116°58 E), covering an area of 83,500 km² (Figure 1). It is the largest water system in the Poyang Lake basin and one of the most important tributaries of the Yangtze River. The entire area accounts for 51% of the entire Poyang Lake basin that is a continuous part of Ganzhou, Ji’an, Pingxiang, Yichun, and other regions. The GRB includes six land-use types: woodland, cropland, grassland, build-up land, water area, and bare land. The main land-use types in the basin are woodland and cropland and account for 65.89 and 24.72%, respectively, of the total area of the basin. The terrain of the basin has a high and low elevation in the south north, respectively, as a steppe. The dominant soil types in the basin are typical strong leachate and artificial dry tillage. The GRB has a subtropical humid monsoon climate with four distinct seasons; of these, the rainy season is long and summers are hot and rainy. The annual mean precipitation in the GRB is approximately 1,600 mm, and its average temperature is approximately 17.8 °C. The annual average blue water in GRB is 900–1,000 mm; the annual average green water is between 800 and 900 mm. In terms of spatial distribution, the blue water decreased from north to south, and the green water decreased from east to west.

Datasets

The inputs for the SWAT model included a digital elevation model (DEM) and land use, soil type, and meteorological data. This study used a 90 × 90 m grid DEM (https://www.gscloud.cn/). The meteorological data (temperature, precipitation, wind speed, solar radiation, and relative humidity) came from 12 meteorological stations in the GRB and were downloaded from https://data.cma.cn/; any missing data were adjusted for using linear interpolation. Future climate data obtained from the NORESM1-M model (https://esgf-node.llnl.gov/) were bias-corrected and downscaled using the EDCDF method (Li et al. 2010; Yang et al. 2020). The land-use data taken from the Resource and Environment Science and Data Centre (http://www.resdc.cn/) had a resolution of 30 m. The basic geographic information data of railway, highway, and expressway are derived from the National Basic Geographic Information System of China (http://www.ngcc.cn/). The soil data were derived from the World Soil Database (HWSD) and could be applied directly to the SWAT model. The monthly runoff data for the Waizhou hydrological station came from statistics in the GRB Hydrological Yearbook. Table 1 lists the sources of the data.
The framework used to evaluate the influence of climate variations and land-use changes on blue/green water (Figure 2) includes four primary parts: (1) the construction of the SWAT model and analysis of its calibration using hydrological observations; (2) the use of the EDCDF method to bias-correct and downscale the NORESM1-M model data and obtain the future precipitation and temperature data; (3) the use of the CA-Markov model to project future land-use types in the GRB based on a variety of natural and socioeconomic data; and (4) the establishment of multiple land-use and climate change scenarios and quantitative analysis of the spatiotemporal variations in blue/green water in different scenarios.

**Figure 1** | The location of the GRB.

**Table 1** | Inventory of input data used in this study

| Data        | Description                                           | Resolution | Sources                                      |
|-------------|-------------------------------------------------------|------------|----------------------------------------------|
| Topography  | Digital elevation model                               | 90 m       | Geospatial Data Cloud                        |
| Land use    | Land-use type data for 1995, 2005, and 2015           | 30 × 30 m  | Resource and Environment Data Cloud Platform |
| Meteorology | Including 12 weather stations in the GRB              | Daily      | National Meteorological Information Center   |
| Future      | Daily temperature and precipitation for the period    | 1,000 m    | Downscaled global climate model data from CMIP5 |
| climate     | 2030–2070                                             |            |                                              |
| Soil        | Detailed soil compositions                            | 1:1,000,000| Cold and Arid Regions Science Data Center at Lanzhou |
| Streamflow  | Streamflow data for the period 1960–2016              | Daily      | Ganjiang Hydrological Yearbook               |

**METHODOLOGY**

The framework used to evaluate the influence of climate variations and land-use changes on blue/green water (Figure 2) includes four primary parts: (1) the construction of the SWAT model and analysis of its calibration using hydrological observations; (2) the use of the EDCDF method to bias-correct and downscale the NORESM1-M model data and obtain the future precipitation and temperature data; (3) the use of the CA-Markov model to project future land-use types in the GRB based on a variety of natural and socioeconomic data; and (4) the establishment of multiple land-use and climate change scenarios and quantitative analysis of the spatiotemporal variations in blue/green water in different scenarios.
Projecting the future climate using the EDCDF method

Considering that the NORESM1-M model uses large-scale, low-resolution data and that there is a large deviation between the output results and the measured data, this study bias-corrected and downscaled output from CMIP5 using the EDCDF method developed by Li et al. (2010). The cumulative distribution functions of the historical and future simulated values of the climate elements are constructed by EDCDF using the difference between the climate variables temperature and precipitation. This study used bias-corrected climate projection outputs as SWAT model input data to allow an evaluation of the potential effects of future changes in climate on blue/green water.

Predicting LULC changes using the CA–Markov model

The CA–Markov model consists of a CA filter (Wei et al. 2014), Markov chain (Xia 2021), and multi-criteria evaluation methods (Montgomery & Dragičević 2016). The model fully integrates the spatial dynamic simulation ability of a CA model with the long-term predictive capacity of a Markov model that can simulate dynamic changes in land use in a comprehensive way (Nouri et al. 2014). This study used the CA–Markov model to simulate and predict the distribution of land-use types in the GRB in 2035 and 2055. The specific steps were as follows:

1. Data pre-processing: the land-use distribution map was converted into the ASCII code format, then imported into the software IDRISI and converted it into the RST data format; the Fuzzy module was used to standardize the elevation, slope, highway, motorway, railway, river constraint data.

2. Construction of land transfer probability matrix: the land transfer probability and transfer area matrixes of the study area for the period 1995–2005 were obtained using the Markov module to overlay the land-use data measured in the GRB in 1995 and 2005, respectively. The internal time and time period are both 10 years, and the proportional error is 0.15.

3. Construction of the suitability atlas: water areas and construction land were set as the limiting factors, and elevation, slope, distance from water area, railways, highways, motorways, and rivers were set to the limiting conditions. This allowed the conversion of different land-use types in the basin to be constrained and restricted. In addition, this study used the MCE module to generate a suitability atlas for different land-use types and applied the Collection Edit module to merge the different suitability atlases into one.

4. Creating future land-use projections: this study set the land-use distribution in 2005 as the starting year and combined the land-use suitability atlases for the period 1995–2005 with the land-use transfer probability matrix to simulate the distribution of land uses in the GRB in 2015. The study then repeated this but set the land-use pattern in 2015 as the
starting year. The land-use patterns for 2035 and 2055 were thus simulated by integrating the land-use transfer probability matrix with the land-use suitability atlas.

The $\kappa$ coefficient is usually used to examine the consistency of simulated and observed images and is applied mostly to verify the precision of land-use simulations (Memarian et al. 2012). This study applied the $\kappa$ coefficient to examine the accuracy of using the CA–Markov model to predict land use in the GRB. The formula used to make this calculation was as follows:

$$
\kappa = \frac{P_0 - P_c}{1 - P_c}
$$

where $P_0$ is the proportion of the grid that was correctly simulated and $P_c$ is the grid proportion simulated correctly in a random case and represents the proportion of grids simulated correctly under an ideal classification.

**SWAT model**

The SWAT model was developed by the Agricultural Research Service of the United States Department of Agriculture (USDA) (Lai et al. 2012). It includes simulations of the hydrological cycle, soil erosion processes, and a pollution load sub-model that can project the influence of various factors in the future (Zhao et al. 2010). The process of applying the SWAT model is as follows: first, the research area was segmented into several sub-basins in line with topographic factors, the distribution of the river network, and other factors related to the basin. Following this, the hydrological response units (HRUs) were divided according to the thresholds set for land-use type, soil type, slope, and a runoff yield calculated separately for each HRU. Finally, the total runoff of the outlet section was obtained using confluence calculus.

The accuracy of the hydrological model was improved effectively by adjusting the model parameters. The SWAT calibration and uncertainty programmes (SWAT-CUP) were applied to calibrate the parameters of the SWAT model (Wang et al. 2019). This study set 1960–1964 as the warming period, 1965–1990 as the calibration period, and 1991–2016 as the validation period. Runoff observation data from the Waizhou hydrological station was applied to calibrate and validate the outputs of the SWAT model. This study used the coefficient of determination ($R^2$) and Nash–Sutcliffe efficiency (NSE) coefficients to assess the precision of the SWAT model (Rong et al. 2021). It is generally accepted that $R^2$ and NSE values should be greater than 0.5 for the monthly SWAT calibration results to be considered credible (Awan & Ismaeel 2014).

The quantity of blue/green water can be calculated using the output results for each hydrological variable in the SWAT model (Zang & Liu 2013) as follows:

$$
B_W = W_{YLD} + D_{A,RCHG}
$$

$$
G_W = E_T + S_W
$$

where $B_W$ is the quantity of blue water, $G_W$ is the quantity of green water, $W_{YLD}$ is the water yield from the sub-basin, $D_{A,RCHG}$ is the amount that the deep aquifer was recharged, $E_T$ is the actual evapotranspiration level, and $S_W$ is soil moisture.

**LULC and climate change scenarios**

This study designed three scenarios to quantify the response of blue/green water to future variations in climate and LULC in the GRB (Table 2). The baseline uses meteorological data from 1975 to 2015 and land-use data from 2015. Scenario 1 considers only the effect of variations in climate; scenario 2 reflects only the impact of changes in LULC; and scenario 3 considers the impacts of changes in both climate and LULC. Each scenario is compared with the baseline period to show the change of blue/green water.

| Future scenario | Date of LULC data | Dates of climate data | Descriptions of the scenarios |
|-----------------|------------------|-----------------------|-------------------------------|
| Scenario 1      | 2015             | 2030–2070             | Impacts of changes in climate |
| Scenario 2      | 2035 and 2055    | 1975–2015             | Impacts of changes in LULC    |
| Scenario 3      | 2035 and 2055    | 2030–2050 and 2050–2070 | Impacts of changes in both climate and LULC |
RESULTS

Projections of future changes in climate

The results for the deviations from the NORESM1-M model outputs are listed in Table 3, which shows that the performance of the model improved significantly by correcting the deviations. The relative deviations in monthly precipitation ranged from 0.18 to 17.29%; all of these were less than 20%. Meanwhile, the correction effect is also satisfactory in terms of the temperature data. The absolute deviation of the simulated maximum temperature was between −0.27 and 1.55 °C, and that of the minimum temperature was between 0.96 and 1.81 °C; both of these are within 2 °C. Yang et al. (2018) evaluated the performance of the EDCEF method in China and found that the mean RMSE of bias-corrected precipitation is decreased to 38.82 mm, while that of the raw model is about 56 mm. And the mean RMSE of bias-corrected temperature varies from 0.98 to 4.58 °C, which is obviously less than those of the raw models (1.53–16.38 °C). These results indicate that the EDCDF method can effectively reduce the deviation between data from the original model and observations.

This study used bias-corrected NORESM1-M model data to project the temperature and precipitation in the GRB for the period 2030–2070. Compared with the baseline, the annual precipitation and maximum and minimum temperatures in the GRB showed an increasing trend in the future, changing by 31.17 mm, 2.25, 1.96 °C, and 27.24 mm, 2.69, and 2.58 °C, respectively, under the RCP4.5 and RCP8.5 scenarios (Table 4). The increase in future precipitation levels was more obvious under RCP4.5, while the increase in future temperature was more obvious under RCP8.5. The changes in monthly precipitation show that the monthly average precipitation has an increasing trend under the RCP4.5 and RCP8.5 scenarios (Figure 3). The highest precipitation levels were observed in June. Similarly, the monthly maximum and minimum temperatures present

Table 3 | Comparison of results of correcting deviations in precipitation and temperature data

| Month | Precipitation | Corrected precipitation | Relative error | Maximum temperature | Corrected maximum temperature | Absolute error | Minimum temperature | Corrected minimum temperature | Absolute error |
|-------|---------------|-------------------------|----------------|--------------------|-------------------------------|----------------|---------------------|-------------------------------|----------------|
| 1     | 64.60         | 78.11                   | 17.29          | 10.61              | 9.95                          | −0.66          | 2.97                | 3.93                          | 0.96           |
| 2     | 105.96        | 100.87                  | −5.05          | 11.35              | 11.37                         | 0.02           | 4.52                | 6.18                          | 1.65           |
| 3     | 156.26        | 174.80                  | 10.61          | 16.02              | 15.76                         | −0.27          | 8.66                | 10.22                         | 1.56           |
| 4     | 223.09        | 201.12                  | −10.92         | 22.06              | 23.00                         | 0.94           | 14.21               | 15.23                         | 1.02           |
| 5     | 245.20        | 237.09                  | −3.42          | 26.90              | 28.24                         | 1.33           | 18.98               | 20.23                         | 1.26           |
| 6     | 242.34        | 253.70                  | 4.48           | 29.95              | 31.50                         | 1.55           | 22.01               | 23.69                         | 1.68           |
| 7     | 130.25        | 130.49                  | 0.18           | 33.63              | 34.92                         | 1.29           | 24.09               | 25.69                         | 1.60           |
| 8     | 134.59        | 119.49                  | −12.63         | 33.27              | 34.77                         | 1.50           | 24.08               | 25.89                         | 1.81           |
| 9     | 95.82         | 96.38                   | 0.58           | 29.24              | 30.68                         | 1.45           | 20.59               | 22.38                         | 1.79           |
| 10    | 81.62         | 73.10                   | −11.65         | 24.34              | 25.44                         | 1.10           | 15.46               | 16.46                         | 1.00           |
| 11    | 60.88         | 54.64                   | −11.43         | 18.54              | 19.11                         | 0.57           | 9.54                | 10.46                         | 0.92           |
| 12    | 43.88         | 42.24                   | −3.89          | 13.10              | 13.46                         | 0.35           | 4.20                | 5.43                          | 1.23           |

Table 4 | Annual mean changes in precipitation and temperature for the period 2030–2070

| The entire GRB | Baseline period (1975–2015) Mean | Future period (2030—2070) RCP4.5 Mean | Variation | RCP8.5 Mean | Variation |
|----------------|-----------------------------------|----------------------------------------|-----------|-------------|-----------|
| Precipitation (mm) | 1,648.18                        | 1,679.35                               | 31.17     | 1,675.42    | 27.24     |
| Maximum temperature (°C) | 22.83                          | 25.08                                  | 2.25      | 25.52       | 2.69      |
| Minimum temperature (°C) | 14.65                          | 16.61                                  | 2.06      | 17.23       | 2.58      |
the same change trend under the two scenarios, with both showing the smallest increase in spring and the largest increase in summer.

**Predicting future changes in LULC**

This study used the observed land-use data from 2015 in the GRB to evaluate the accuracy of the CA–Markov model. The land use simulated for 2015 had a $\kappa$ coefficient of 0.95, which was determined using the Crosstab module (Figure 4); the latter has a good spatial simulation effect. In addition, analysis of the accuracy of simulated and observed land use for 2015 (Table 5) indicated that the former generally captured the characteristics of land-use patterns in the GRB. The accuracies of the values for cropland, grassland, water areas, and build-up land were relatively high, at 90.10, 97.22, 92.31, and 91.64%, respectively. However, the accuracy of the value for woodland was lower, with a value of 71.35%; this was due to woodlands being greatly influenced by natural factors and human activities (Zhang et al. 2017). The evolution of these rules is changeable which leads to low simulation accuracy. However, the results did indicate that the CA–Markov model can be utilized to

**Figure 3** | Changes in precipitation and temperature in different months during the future period simulated in this study.

**Figure 4** | (a) Observed LULC for 2015 and simulated LULC for (b) 2015, (c) 2035, and (d) 2055.
predict future land-use patterns in the GRB. Therefore, in this study, it was applied to simulate land use in 2035 and 2055 in the GRB (Figure 4).

The dynamic attitude of land use in the GRB in 2015, 2035, and 2055 (Table 6) revealed that woodland areas accounted for the largest proportion (65.89%) of the land cover in the LULC2015; cropland came second, accounting for 24.74% of the land cover, and grassland was third and accounted for 5.11% of the land cover. During the 2015–2035 period, cropland, woodland, and grassland land cover showed a decreasing trend, while build-up land and water areas showed an increasing trend. In terms of the speed at which land-use types were changing; the single dynamic attitude of build-up is 4.94% with the highest annual growth rate compared to other land-use types. In addition, the area of cropland showed a −0.16% change, while those of forest lands and grasslands were −0.12 and −0.41%, respectively; this indicated no significant decreasing trend. During the period 2035–2055, the amount of build-up land and water areas in the basin will increase further, while the amount of cropland, woodlands, and grassland will decrease further, principally because the change in land-use trends from 2015–2035 was maintained by the land-use trend used for the 2035–2055, as simulated by the CA–Markov model.

Evaluation of the SWAT model
The SUFI-2 algorithm (Nilawar & Waikar 2019) in SWAT-CUP was applied to analyse the sensitivity of 10 parameters in the calibration of the SWAT model calibration (Table 7). The parameters CH_K2, ALPHA_BF, CN2, and CH_N2 are more sensitive in the GRB than the others. Figure 5 presents the calibration and validation results for data from the Waizhou hydrological station in the GRB. It shows that for the SWAT model calibration period, the NSE and $R^2$ were 0.93 and 0.94, respectively, while they were 0.90 and 0.93, respectively, for the period. All the indicators in the calibration and validation periods met the standard of $R^2 > 0.6$ and an NSE > 0.5 (Awan & Ismaeel 2014). This indicates that the SWAT model is satisfactory and has good applicability in GRB. Because of this, it can be utilized to simulate the spatiotemporal distribution of blue/green water under the effects of changes in climate and land use.

Impacts of future changes in climate on blue and green water resources
In this section, the effects of climate change alone on blue/green water are evaluated for two time periods the 2040s (2031–2050) and the 2060s (2051–2070) under the RCP4.5 and RCP8.5 (Table 8 and Figure 6). The meteorological data used for the

Table 5 | Comparison and precision test of simulated land-use patterns in the GRB in 2015

| Land-use type | Actual land-use structure in 2015 | Simulated land-use structure in 2015 | Comparison accuracy (%) |
|---------------|----------------------------------|----------------------------------|-------------------------|
|               | Area (km²)                       | Proportion (%)                   | Area (km²)              | Proportion (%) |                       |
| Cropland      | 19,940.1                         | 24.74                            | 20,403.93               | 25.32          | 90.10                 |
| Bare land     | 10.23                            | 0.01                             | 24.18                   | 0.02           | 94.21                 |
| Woodland      | 53,097.3                         | 65.89                            | 51,735.08               | 64.2           | 71.35                 |
| Grassland     | 4,115.99                         | 5.11                             | 3,956.69                | 4.91           | 97.22                 |
| Build-up      | 1,951.76                         | 2.42                             | 2,320.83                | 2.88           | 91.64                 |
| Water area    | 1,468.85                         | 1.82                             | 2,143.54                | 2.66           | 92.31                 |

Table 6 | Changes of land-use types in the GRB for the period 2015–2055

| Land-use type | 2015 km² | 2035 km² | 2055 km² |
|---------------|----------|----------|----------|
|               | %        | %        | %        |
| Cropland      | 19,940.1 | 19,302.64| 17,603.68|
| Bare land     | 10.23    | 8.31     | 15.57    |
| Woodland      | 53,097.3 | 51,829.6 | 48,909.7 |
| Grassland     | 4,115.99 | 3,778.82 | 3,278.85 |
| Build-up      | 1,951.76 | 3,879.26 | 8,300.89 |
| Water area    | 1,468.85 | 2,143.54 | 2,477.39 |

|               | 2015–2035 Dynamic degree (%) | 2035–2055 Dynamic degree (%) |
|---------------|-----------------------------|-------------------------------|
| Cropland      | – 0.16                      | – 0.44                        |
| Bare land     | – 0.94                      | 3.47                          |
| Woodland      | – 0.12                      | – 0.28                        |
| Grassland     | – 0.41                      | – 0.66                        |
| Build-up      | 4.94                        | 5.70                          |
| Water area    | 2.24                        | 3.07                          |

Table 7 | Parameters CH_K2, ALPHA_BF, CN2, and CH_N2 in the SWAT model calibration period

| Parameter | CH_K2 | ALPHA_BF | CN2 | CH_N2 |
|-----------|-------|----------|-----|-------|
| Value     |       |          |     |       |

Table 8 | Changes of land-use patterns in the GRB for the period 2015–2055

| Land-use type | 2015 km² | 2035 km² | 2055 km² |
|---------------|----------|----------|----------|
|               | %        | %        | %        |
| Cropland      | 19,940.1 | 19,302.64| 17,603.68|
| Bare land     | 10.23    | 8.31     | 15.57    |
| Woodland      | 53,097.3 | 51,829.6 | 48,909.7 |
| Grassland     | 4,115.99 | 3,778.82 | 3,278.85 |
| Build-up      | 1,951.76 | 3,879.26 | 8,300.89 |
| Water area    | 1,468.85 | 2,143.54 | 2,477.39 |

|               | 2015–2035 Dynamic degree (%) | 2035–2055 Dynamic degree (%) |
|---------------|-----------------------------|-------------------------------|
| Cropland      | – 0.16                      | – 0.44                        |
| Bare land     | – 0.94                      | 3.47                          |
| Woodland      | – 0.12                      | – 0.28                        |
| Grassland     | – 0.41                      | – 0.66                        |
| Build-up      | 4.94                        | 5.70                          |
| Water area    | 2.24                        | 3.07                          |
RCP4.5 and RCP8.5 scenarios drove the calibrated SWAT model, while keeping the land use for the baseline period (LULC2015) unchanged. The annual average changes in blue/green water are listed in Table 8, which show that the blue water decreases, under the two scenarios, to different magnitudes compared to the baseline period. The blue water decreased by 16.89 and 21.4 mm, respectively, under the RCP4.5 and RCP8.5 scenarios. In general, the decline in blue water under RCP4.5 was less than it was under RCP8.5; this was likely due to the increase in future precipitation being higher under the former than the latter. This indicated that the amplitude of the change in blue water was directly affected by the change in precipitation, which was a result similar to those of Zhang et al. (2011) and Lv et al. (2019).

Table 7 | Parameters used in the SWAT model

| Sensitivity sequencing | Parameter | Description | Parameter scale | Fitted value |
|------------------------|-----------|-------------|-----------------|--------------|
| 1                      | CH_K2     | Main channel hydraulic conductivity | 5–130          | 129.63       |
| 2                      | ALPHA_BF  | Base flow recession constant | 0–1            | 0.75         |
| 3                      | CN2       | SCS runoff curve number for moisture condition II | –0.2–0.2 | 0.01         |
| 4                      | CH_N2     | Main channel Manning coefficient | 0–0.3          | 0.21         |
| 5                      | GW_REVAP  | Evaporation coefficient | 0–0.2          | 0.19         |
| 6                      | SOL_AWC   | Available water capacity of the soil layer | –0.2–1 | 0.71         |
| 7                      | SOL_K     | Soil saturation conductivity | –0.8–0.8 | 0.32         |
| 8                      | ESCO      | Soil evaporation compensation factor | 0.8–1 | 0.96         |
| 9                      | GW_DELAY  | Groundwater delay time | 30–450         | 93.42        |
| 10                     | GWQMN     | Threshold water level in shallow aquifer for base flow | 0–2 | 1.30         |

Figure 5 | Comparative analysis of monthly runoff data for the calibration and validation periods of the model used in this study.
green water showed an increasing trend in the future. The annual increase in green water reached 20.22 mm under the RCP8.5 scenario, which was higher than that under RCP4.5 (19.14 mm). Thus, the higher the concentration of emissions under a particular RCP scenario was, the more obvious the increase in green water. This was mainly because the increase in the concentration of CO2 emissions would lead to corresponding increases in temperature and evapotranspiration (Mengistu et al. 2021), which in turn would lead to further increases in green water.

The spatial distribution patterns of blue and green water under the climate scenarios are presented in Figure 6. Compared to the baseline, the blue water is projected to decrease by 0.04–24.75 and 0.26–27.34 mm, respectively, under the RCP4.5 and RCP8.5 scenarios. The highest decreases in blue water were seen in the northern and southern regions of the GRB, while the lowest decreases were seen in its eastern and western regions. In contrast, the green water was projected to increase by 0.32–26.07 and 0.29–27.32 mm, respectively, under the RCP4.5 and RCP8.5 scenarios. The highest increases in green water were observed in the northern and southern regions of the basin, while the lowest changes were seen in its central and southern regions. Precipitation is the main source of blue water, and temperature is the key factor in affecting green water. Therefore, changes in the spatiotemporal distribution of precipitation and temperature affect the distribution of blue and green water.

### Impacts of the future changes in LULC on blue and green water resources

In this section, the impacts of changes in LULC alone on blue and green water are assessed for two time periods: the 2040s (2031–2050) and the 2060s (2051–2070) under two LULC change scenarios (LULC 2035 and LULC2055), keeping the meteorological data from the baseline (1975–2015) unchanged. The annual average of blue water showed a rising trend by the 2040 and 2060s under future LULC scenarios (Table 9), increasing by 5.50 and 7.57 mm under the LULC2035 and

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**Table 8** | Future changes in blue and green water in the GRB under the RCP4.5 and RCP8.5 climate change scenarios

| Scenario        | Blue water (mm) | Change in blue water (mm) | Green water (mm) | Change in green water (mm) |
|-----------------|-----------------|---------------------------|------------------|--------------------------|
| RCP4.5 Climate  | 942.75          | – 16.89                   | 864.68           | 19.14                    |
| RCP8.5 Climate  | 938.24          | – 21.4                    | 865.76           | 20.22                    |

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**Figure 6** | Simulated effect of changes in climate on blue and green water in the GRB.

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LULC2055 scenarios, respectively, mainly due to the increase in build-up land and the decrease in woodland in the basin. For the 2040s and the 2060s, the single dynamic attitude of build-up land was 4.94 and 5.7%, respectively; this showed a relatively high growth trend, while the dynamic attitude of woodland, which was −0.12 and −0.28% for the two periods, respectively, demonstrated a decreasing trend. The expansion of build-up land and the reduction of woodland will reduce infiltration and evaporation, which will eventually result in an increase in surface runoff (Giri et al. 2018). In contrast to this, the change in green water showed a decreasing trend under future LULC change scenarios, falling in general by 4.05 and 7.80 mm under the LULC2035 and LULC2055 scenarios, respectively. For the 2040 and 2060s, respectively, the single dynamic attitude of cropland was −0.16 and −0.44%, while the single dynamic attitude of grassland was −0.41 and −0.87%, all of which showed a decreasing trend. The reductions in cropland, woodland, and grassland areas will reduce evapotranspiration in the basin, thereby leading to a reduction in green water.

The spatial distribution of the annual of blue and green water under future changes in land use is presented in Figure 7. The blue water increases by 0.29–4.12 and 0.04–9.61 mm under the LULC2035 and LULC2055 scenarios, respectively. The increase in blue water is marked under the LULC2055 scenario, mainly because of the further expansion of build-up land and the further reduction of woodland and grassland from 2035 to 2055. These changes can lead to a continuous increase in surface runoff, which further increases the blue water. The maximum increase in blue water was observed in the northern and eastern regions of the basin, mainly because the area of construction land is high in this region. Compared with blue water, the green water decreased by 0.93–2.95 and 1.92–6.86 mm under the LULC2035 and LULC2055 scenarios, respectively. The decrease was greater under the latter. The highest decrease in green water was recorded in the northern region of the basin, while the lowest decrease was recorded in its southern and central regions. These results may have been the

| Scenario   | Blue water (mm) | Change in blue water (mm) | Green water (mm) | Change in green water (mm) |
|------------|-----------------|---------------------------|------------------|---------------------------|
| 2035-LULC  | 965.14          | 5.50                      | 841.49           | −4.05                     |
| 2055-LULC  | 967.21          | 7.57                      | 837.74           | −7.80                     |

Figure 7 | Simulated effect of changes in LULC on the blue and green water in the GRB.
result of main land-use type in the GRB being woodland; the changes in the distribution of woodland determined the spatio-temporal changes in blue and green water.

**Impacts of combined changes in climate and LULC on blue and green water resources**

The integrated influence of climate change (via the RCP4.5 and RCP8.5 scenarios) and land-use change (via the LULC2035 and LULC2055 scenarios) on blue/green water were also evaluated based on assessments of the individual effects of the former on the latter (Table 10; Figures 8 and 9). The changes in the mean annual of blue and green water under the effects of changes in both climate and land use are shown in Table 10. The results indicated that the blue water showed a decreasing trend under the four disparate scenarios. The blue water decreased by $-0.67$ and $-7.28$ mm under RCP4.5, $-7.47$ and $-9.99$ mm under RCP8.5, by the 2040 and 2060s periods, respectively. Furthermore, the blue water decreased more in the 2060s under both emission scenarios, although it decreased more under the RCP8.5 scenario under two time periods. In contrast, the green water increased by 19.24 and 13.87 mm under the RCP4.5 scenario, 20.8 and 22.30 mm under RCP8.5, by the 2040 and 2060s time periods, respectively. Similarly, the rate of increase of the green water in the 2060s was greater than it was in the 2040s under the same emission scenarios, although it increased more under RCP8.5 during two time periods. Compared with the influence of changes in land use or climate alone on blue and green water, their integrated impacts seem to be relatively weak. In addition, the effect of a change in climate on blue and green water is more significant overall (Woldesenbet et al. 2018).

The changes in the spatial distribution of the blue and green water under the combined effects of future changes in climate and land use are shown in Figures 8 and 9. The blue water changed $-9.9$ to $-0.02$, $-10.94$ to $-0.1$, $-8.9$ to $-0.01$, and $-9.8$ to $-0.09$ mm under the four disparate scenarios (RCP4.5_2040s, RCP4.5_2060s, RCP8.5_2040s, and RCP8.5_2060s),

**Table 10** | Changes in the areas of blue and green water under the combined effects of changes in climate and LULC in the GRB

| Scenario                | Blue water (mm) | Change in blue water (mm) | Green water (mm) | Change in green water (mm) |
|-------------------------|-----------------|----------------------------|-----------------|---------------------------|
| RCP4.5_2040s-Combined   | 958.97          | $-0.67$                    | 864.78          | 19.24                     |
| RCP8.5_2040s-Combined   | 952.17          | $-7.47$                    | 866.34          | 20.80                     |
| RCP4.5_2060s-Combined   | 952.36          | $-7.28$                    | 859.41          | 13.87                     |
| RCP8.5_2060s-Combined   | 949.65          | $-9.99$                    | 867.84          | 22.30                     |

**Figure 8** | Simulated effects of changes in climate and LULC on blue water in the GRB.
respectively. These results indicate that the greatest change in blue water was observed in the northern and southern regions of the basin, while the lowest change was observed in the eastern and western parts of its middle reaches. In comparison, the green water increased 0.29 to 27.32, 0.35 to 32.78, 0.26 to 24.59, and 0.31 to 29.5 mm under the four scenarios (RCP4.5_2040s, RCP4.5_2060s, RCP8.5_2040s, and RCP8.5_2060s), respectively. The maximum increase in green water was observed in the southwestern region of the middle reaches of the basin, while the minimum increase was observed in the southern and northern regions of the basin. The results indicated that the combined effects of changes in climate and land use on blue and green water have a trend similar to the impacts of climate change. They also showed that changes in land use had little effect on blue and green water.

**DISCUSSION**

The formulation and implementation of sustainable land and water resource management strategies in the GRB is based on being able to analyse the individual and joint effects of changes in climate and land use on the blue and green water in the area. This research used the NORESM1-M mode from the CMIP5, which has been widely applied in many studies of climate change (Nazari-Sharabian et al. 2019), to evaluate the impact of climate change in the GRB. The uncertainties related to climate change impact assessment include the future emission scenarios, climate models, and downscaling methods used. This study showed that the NORESM1-M mode using the RCP4.5 and RCP8.5 scenarios can be applied well in a region of China (Zhang et al. 2021). However, there are some other uncertainties that arise when only one climate model is used for such a purpose. Thus, data from multiple climate models should be considered to improve the accuracy of projections related to climate change.

This study used the improved CA–Markov model to simulate future land-use patterns in the GRB. The traditional CA–Markov model only considered the mathematical-statistical analysis method, not fully considering the restricting factors and conditions in the simulation process. This study selects water area and build-up areas as its restricting conditions. Meanwhile, natural factors (i.e., elevation and slope) and socioeconomic factors (i.e., the distances from railway, motorways, highways, rivers, and urban land) were selected as constraining factors (Aburas et al. 2017). Other natural factors such as soil type, groundwater, and other socioeconomic factors (i.e., density of residential areas, distribution of industrial areas, infrastructure, and the willingness of individual residents) may also impact land use. Unfortunately, these were not examined in this study due to the availability of these data on the patch scale only. Future work will focus on these directions.

The SWAT model has been applied extensively to the simulation of the blue and green water. To obtain the most accurate simulation from the model for the baseline period, it is necessary to evaluate the parameters of the former according to

![Figure 9](image_url)
observed data. Therefore, long-term hydrological observations are vital for evaluating the scope of the most sensitive parameters. In addition, because the SWAT model is based on physical data, it is data-intensive by nature. Therefore, any data missing from the model may result in an insufficient evaluation of the parameters of the latter and will ultimately lead to inaccurate simulations of the blue and green water. Precise and long-time series observations of climate data should provide the proper meteorological data that are required to estimate the blue and green water in basins with minimum uncertainty.

**CONCLUSIONS**

This study investigated the single and integrated influences of changes in climate and LULC on blue and green water resources in the GRB. The EDCDF was applied to downscale high-resolution climatic model outputs, while the CA-Markov model was utilized to project future land use in the GRB. The changes in blue and green water under multiple scenarios were simulated using the SWAT model.

The results showed that the SWAT model performed satisfactorily during both the process of calibration and validation. The $R^2$ and NSE values of the calibration were 0.94 and 0.93, respectively, and the $R^2$ and NSE values of the validation were 0.95 and 0.90, respectively. The simulated results for climate change scenarios in the GRB suggest that the blue water decreased by 16.89 and 21.4 mm, while green water increased by 19.14 and 20.22 mm, each respectively, under the RCP4.5 and RCP8.5 scenarios. The simulated results for future LULC scenarios showed that the blue water increased by 5.50 and 7.57 mm, respectively, under LULC2035 and LULC2055 scenarios, while green water decreased by 4.05 and 7.80 mm, respectively, under the LULC2035 and LULC2055 scenarios. The integrated effects of climate and land-use scenarios on blue and green water resources showed that the latter decreased by 0.67, 7.47, 7.28, and 9.99 mm, respectively, while green water increased by 19.24, 20.8, 13.87, and 22.30 mm, respectively, under four different scenarios (RCP4.5_2040s, RCP4.5_2060s, RCP8.5_2040s, and RCP8.5_2060s). This research revealed that the effect of climate change alone on blue and green water resources seems to be comparatively higher than the integrated impact of changes in both climate and LULC. Overall, climate adaptation management strategies should be implemented to reduce the negative influence of frequent extreme weather events.

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**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

**REFERENCES**

Aburas, M. M., Ho, Y. M., Ramli, M. F. & Zulfa, H. A. 2017 Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an analytical hierarchy process and frequency ratio. *International Journal of Applied Earth Observation and Geoinformation* 59, 65–78.

Akbar, H. & Gheewala, S. H. 2021 Impact of climate and land use changes on flowrate in the Kunhar River Basin, Pakistan, for the period (1992–2014). *Arabian Journal of Geosciences* 14 (8).

Awan, U. K. & Ismaeel, A. 2014 A new technique to map groundwater recharge in irrigated areas using a SWAT model under changing climate. *Journal of Hydrology* 519, 1368–1382.

Brij, K. P., Khare, D., Kawasaki, A. & Mishra, P. K. 2019 Climate change impact assessment on blue and green water by coupling of representative CMIP5 climate models with physical based hydrological model. *Water Resources Management* 33 (1), 141–158.

Chun, X., Qin, F. Y., Zhou, H. J., Dan, D., Xia, Y. Y. & Ulambadrakh, K. 2020 Effects of climate variability and land use/land cover change on the Daihai wetland of central Inner Mongolia over the past decades. *Journal of Mountain Science* 17 (12), 3070–3084.

Du, L. Y., Rajib, A. & Merwade, V. 2018 Large scale spatially explicit modeling of blue and green water dynamics in a temperate mid-latitude basin. *Journal of Hydrology* 562, 84–102.
Falkenmark, M. & Rockström, J. 2006 The new blue and green water paradigm: breaking new ground for water resources planning and management. Journal of Water Resources Planning and Management 132 (3), 129–132.

Faramarzi, M., Abbaspour, K. C., Ashraf Vaghefi, S., Farzaneh, M. R., Zehnder, A. J. B., Srinivasan, R. & Yang, H. 2013 Modeling impacts of climate change on freshwater availability in Africa. Journal of Hydrology 480, 85–101.

Gao, C., Lu, M., Yao, M. T. & Sun, Y. W. 2018 Applicability evaluation of the SWIM hydrological model in Wangjiaba region of China. Bulletin of Soil and Water Conservation 38 (1), 152–159.

Giri, S., Arbab, N. N. & Lathrop, R. G. 2018 Water security assessment of current and future scenarios through an integrated modeling framework in the Neshanic River Watershed. Journal of Hydrology 563, 1025–1041.

Huang, Z. W., Hejazi, M., Tang, Q. H., Vernon, C. R., Liu, Y. L., Chen, M. & Calvin, K. 2019 Global agricultural green and blue water consumption under future climate and land use changes. Journal of Hydrology 574, 242–256.

Iman, F. F., Farzaneh, M. R., Besalatpour, A. A., Salehi, M. H. & Faramarzi, M. 2019 Assessment of the impact of climate change on spatiotemporal variability of blue and green water resources under CMIP5 and CMIP6 models in a highly mountainous watershed. Theoretical and Applied Climatology 156 (1–2), 169–184.

Jiao, D. L., D., W., Lv, J. & Y. H. 2020 Effects of human activities on hydrological drought patterns in the Yangtze River Basin, China. Natural Hazards 104 (1), 1111–1124.

Lai, G. Y., Wu, D. Y., Zhong, Y. X., Zeng, F. H., Chen, J. & Zhang, W. L. 2012 Progress in development and applications of SWAT model. Journal of Hohai University (Natural Sciences) 40 (3), 243–251.

Li, H. B., Sheffield, J. & Wood, E. F. 2010 Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. Journal of Geophysical Research: Earth Surface 115, D10101.

Li, G. C., Chen, W., Li, R., Zhang, X. P. & Liu, J. L. 2021 Assessing the spatiotemporal dynamics of ecosystem water use efficiency across China and the response to natural and human activities. Ecological Indicators 126, 107680.

Li, G. F., Yang, H. F. & Ding, S. Y. 2012 The impacts of climate and land use changes on the runoff effects: case in the upper reaches of the Yihe River, the Yiluo River basin. Scientia Geographica Sinica 32 (5), 635–640.

Li, J. P., He, X. Y., Zeng, G. M., Zhong, M. Z., Gao, X., Li, X., Li, X. D., Wu, H. P., Feng, C. T., Xing, W. L., Fang, Y. L. & Mo, D. 2018 Integrating priority areas and ecological corridors into national network for conservation planning in China. Science of the Total Environment 626, 22–29.

Li, J., Liu, Q., Zhang, H., Li, X. D., Qian, Z., Lei, M. Q., Li, X., Peng, Y. H., Li, S. & Zeng, G. M. 2020 Interactive effects of climate variability and human activities on blue and green water scarcity in rapidly developing watershed. Journal of Cleaner Production 265, 121834.

Liu, J. G., Yang, H. & Hoff, H. 2010 Spatially explicit assessment of global consumptive water uses in cropland: green and blue water. Journal of Hydrology 384 (3), 187–197.

Lv, Y. T., Wang, X. R., Sun, C. Z. & Zhang, J. 2019 Study on the spatiotemporal variations of blue and green water resources in Xi River Basin using the SWAT model. Resources and Environment in the Yangtze Basin 28 (01), 39–47.

Memarian, H., Siva, K. B., Jamal, B. T., Christopher, T. B. S., Alias, M. S. & Karim, M. 2012 Validation of CA-Markov for simulation of land use and cover change in the Langat Basin, Malaysia. Journal of Geographic Information System 4 (6), 542–554.

Mengistu, D., Bewket, W., Dosio, A. & Panitz, H. J. 2021 Climate change impacts on water resources in the Upper Blue Nile (Abay) River Basin, Ethiopia. Journal of Hydrology 592, 125614.

Montgomery, B. & Dragićević, S. 2016 Comparison of GIS-based logic scoring of preference and multi-criteria evaluation methods: urban land use suitability: comparison of GIS-LSP and MCE methods. Geographical Analysis 48 (4), 427–447.

Nazar-Sharabian, M., Taheri-Jouy, M., Ahmad, S., Karakouzian, M. & Ahmadi, A. 2019 Water quality modeling of Mahabad Dam watershed–reservoir system under climate change conditions, using SWAT and system dynamics. Water 11, 394.

Nilawar, A. P. & Waikar, M. L. 2019 Impacts of climate change on streamflow and sediment concentration under RCP 4.5 and 8.5: a case study in Purna river basin, India. Science of the Total Environment 75 (11), 2307–2318.

Nourizadeh, L., Finlayson, B. L. & Mcmahon, T. A. 2006 The impact of land use change on catchment hydrology in large catchments: the comet river, central Queensland, Australia. Journal of Hydrology 326 (1), 199–214.

Tian, J., Guo, S. L., Liu, D. D., Chen, Q. H., Wang, Q., Yin, J. B., Wu, X. S. & He, S. K. 2020 Impacts of climate and land use/cover changes on runoff in the Hanjiang River basin. Acta Geographica Sinica 75 (11), 2307–2318.

Wang, Q. R., Liu, R. M., Men, C., Guo, L. J. & Miao, Y. X. 2019 Temporal-spatial analysis of water environmental capacity based on the couple of SWAT model and differential evolution algorithm. Journal of Hydrology 569, 155–166.

Wang, D., Liu, M. B., Chen, X. W. & Gao, L. 2020 Spatial and temporal variations of blue and green water resources in Shanmei Reservoir Watershed based on CMIP5 and SWAT. South–to–North Water Transfers and Water Science & Technology 1–15.
Wei, C. Z., Zheng, W. F. & Meng, Q. Y. 2014 Application of genetic neural network based on cellular automata in simulation and analysis of land use change. *Engineering of Surveying and Mapping* 23 (1), 45–49.

Woldesenbet, T. A., Elagib, N. A., Ribbe, L. & Heinrich, J. 2018 Catchment response to climate and land use changes in the Upper Blue Nile sub-basins, Ethiopia. *Science of the Total Environment* 644, 193–206.

Xia, Y. T. 2021 Applications of Markov chain in forecast. *Journal of Physics: Conference Series* 1848 (1).

Xie, Z. B., Zhu, K., Lu, F., Xu, Y. R. & Song, X. Y. 2019 Trend analysis for blue and green water resources in Chaobai river basin based on hydrologic cycle simulation. *Journal of China Hydrology* 39 (01), 44–49.

Yang, X. L., Wood, E. F., Sheffield, J., Ren, L. L., Zhang, M. R. & Wang, Y. Q. 2018 Bias correction of historical and future simulations of precipitation and temperature for China from CMIP5 models. *Journal of Hydrometeorology* 19 (3), 609–623.

Yang, X. L., Zhang, M. R., He, X. G., Ren, L. L., Pan, M., Yu, X. H., Wei, Z. W. & Sheffield, J. 2020 Contrasting influences of human activities on hydrological drought regimes over China based on high-resolution simulations. *Water Resources Research* 56 (6), 7.

Yu, B. Y., Wu, P., Sui, J., Ni, J. & Whitcombe, T. 2020 Variation of runoff and sediment transport in the Huai River – a case study. *Journal of Environmental Informatics* 35 (2), 138–147.

Yuan, Z., Xu, J. J. & Wang, Y. Q. 2019 Historical and future changes of blue water and green water resources in the Yangtze River source region, China. *Theoretical and Applied Climatology* 138, 1035–1047.

Zang, G. F. & Liu, J. G. 2015 Temporal and spatial differences of blue and green water in the Heihe River Basin in typical years. *Journal of Beijing Forestry University* 35 (03), 1–10.

Zhang, S. F., Hua, D. & Meng, X. J. 2011 Climate change and Its driving effect on the runoff in the ‘three-river headwaters’ region. *Acta Geographica Sinica* 66 (01), 13–24.

Zhang, A. J., Zhang, C., Fu, G. B., Wang, B., Bao, Z. X. & Zheng, H. X. 2012 Assessments of impacts of climate change and human activities on runoff with SWAT for the Huifa River Basin, Northeast China. *Water Resources Management* 26, 2199–2217.

Zhang, X. J., Zhou, Q. G. & Wang, Z. L. 2017 Simulation and prediction of land use change in three gorges reservoir area based on MCE-CA-Markov. *Transactions of the Chinese Society of Agricultural Engineering* 33 (19), 268–277.

Zhang, L. Y., Zheng, W. F., Yang, X. L., Zhang, M. R. & Yu, X. H. 2019 Temporal-spatial characteristics of drought in source region of Yellow River based on CMIP5 multi-mode ensemble and PDSI. *Water Resources Protection* 35 (06), 95–99.

Zhang, Y. F., Tang, C. J., Ye, A. Z., Zheng, T. H., Nie, X. F., Tu, A. G., Zhu, H. & Zhang, S. Q. 2020 Impacts of climate and land-use change on blue and green water: a case study of the Upper Ganjiang River Basin, China. *Water* 12, 2661.

Zhang, M. R., Yang, X. L., Ren, L. L., Pan, M., Jiang, S. H., Liu, Y., Yuan, F. & Fang, X. Q. 2021 Simulation of extreme precipitation in four climate regions in China by general circulation models (GCMs): performance and projections. *Water* 13, 1509.

Zhao, C. Y., Bie, Q. & Peng, H. H. 2010 Analysis of the niche space of picea crassifolia on the Northern Slope of Qilian Mountains. *Acta Geographica Sinica* 65 (01).

Zhao, A. Z., Zhao, Y. L., Liu, X. F., Zhu, X. F., Pan, Y. Z. & Chen, S. C. 2016 Impact of human activities and climate variability on green water and blue water resources in the Weihe river basin of Northwest China. *Scientia Geographica Sinica* 36 (04), 571–579.

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