

Applicability of SWAT-GL in the Jinghe River Basin, Xinjiang, and Spatiotemporal Distribution Characteristics of Blue and Green Water

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Abstract

To analyze the sensitivity characteristics of glacier meltwater-fed hydrological processes in the arid Jinghe River Basin of Xinjiang to climate and land use, and to propose targeted control and adaptive measures, this study applies the SWAT-GL model to overcome the limitations of the traditional SWAT (Soil and Water Assessment Tool) model in simulating glacier meltwater-fed basins, systematically analyzes the spatiotemporal evolution patterns of blue and green water, and constructs a SWAT-GL-FLUS (Future Land-Use Simulation)-CMIP6 (Coupled Model Intercomparison Project Phase 6) multi-model coupling framework to predict spatiotemporal changes in blue and green water under future scenarios and propose adaptive management strategies. The results show that: (1) The R^2 and NSE values of the SWAT-GL model during the calibration/validation periods are both >0.7 , indicating improved accuracy compared with the traditional SWAT model, with good consistency between simulated and observed runoff. (2) Blue water accounts for 52% of the basin and shows no significant interannual trend, while green water accounts for 48% and increases synchronously with precipitation; spatially, blue water decreases from upstream to downstream, while green water is low upstream, fluctuates in the midstream, and is high downstream, with significant differences in the spatial distribution characteristics of blue and green water among different hydrological year types. (3) Under future climate scenarios, precipitation increases, temperature follows the pattern of “high carbon > medium carbon > low carbon,” blue water decreases, and green water increases, while the spatial distribution continues the pattern of decreasing blue water and increasing green water, with a significant driving effect under the high-carbon scenario.

Full Text

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Applicability of SWAT-GL in the Jinghe River Basin, Xinjiang, and Spatiotemporal Distribution Characteristics of Blue and Green Water

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Abstract: To analyze the sensitivity characteristics of glacier-meltwater-supplied hydrological processes in the arid Jinghe River Basin of Xinjiang to climate and land use, and to propose targeted regulation and adaptive measures, this study applied the SWAT-GL model to overcome the simulation limitations of the traditional SWAT (Soil and Water Assessment Tool) model in glacier-meltwater-fed basins. The spatiotemporal evolution patterns of blue and green water were systematically analyzed, and a multi-model coupling framework of SWAT-GL-FLUS (Future Land-Use Simulation)-CMIP6 (Coupled Model Intercomparison Project Phase 6) was constructed to predict spatiotemporal changes in blue and green water under future scenarios and to propose adaptive management strategies. The results show that: (1) During the calibration/validation periods of the SWAT-GL model, both R^2 and NSE were > 0.7 ; compared with the traditional SWAT model, the accuracy was improved, and the simulated runoff agreed well with the observed runoff. (2) Blue water accounted for 52% of basin water and showed no significant interannual trend, while green water accounted for 48% and increased synchronously with precipitation; spatially, blue water decreased from “upstream to downstream,” whereas green water showed a pattern of “low upstream—fluctuating midstream—high downstream,” with significant differences in the spatial distribution characteristics of blue and green water among different hydrological years. (3) Under future climate scenarios, precipitation increases, and temperature follows the order “high carbon $>$ medium carbon $>$ low carbon”; blue water decreases while green water increases, and the spatial distribution continues the pattern of “decreasing blue water and increasing green water,” with a pronounced high-carbon driving effect.

Keywords: SWAT-GL model; blue water; green water; spatiotemporal distribution; Jinghe River Basin

Global ecological security and the water-resources crisis are becoming increasingly severe. As key fragile zones of the Earth system, arid regions have land-surface process evolutions that exert broad impacts on the water cycle of inland river basins and on regional ecological security[1]. The Sixth Assessment Report of the IPCC (Intergovernmental Panel on Climate Change) clearly states that global warming caused by human activities has profoundly altered the spatiotemporal distribution of precipitation and has intensified variability in the water cycle of inland river basins in arid regions[2]. Blue water specifically refers to water resources present in surface runoff and groundwater systems, whose ultimate transformation pathway is expressed as a direct supply function for human social production and daily life. Green water mainly refers to evapotranspiration (ET) formed from rainfall and water resources stored in unsaturated soil layers and vegetation canopy structures; this type of water completes its ecological cycling process through vegetation transpiration[3]. In evaluation systems for traditional hydrological response mechanisms and basin water-

resources management research, long-term attention has focused on blue-water storage within basin systems, while relatively insufficient attention has been paid to green-water resources. To overcome the limitations of traditional assessment models, Falkenmark first systematically defined the conceptual framework of blue water and green water in 1995, providing a new cognitive dimension for water-resources evaluation[4]. Common blue- and green-water assessment models include SWAT (Soil and Water Assessment Tool)[5], VIC (Variable Infiltration Capacity)[6], and SWIM (Soil and Water Integrated Model)[7]. Among them, the SWAT model has a relatively long development history and comparatively comprehensive design modules, enabling it to represent the physical mechanisms of the water cycle and to accurately evaluate blue- and green-water resources[8]. Han Ziyang et al.[3] used multi-source geographic data and analyzed the spatiotemporal changes in blue- and green-water resource security based on the SWAT model. Qi Wenhua et al.[9], from the perspective of supply-demand balance, quantified the blue- and green-water resources of the Tumen River Basin based on the SWAT model. Li Wenting et al.[10] analyzed the spatiotemporal distribution of blue and green water in the Ganjiang River Basin in typical years using the SWAT model. Hordofa et al.[11], from the perspective of climate change, modeled and evaluated the Meki River in Ethiopia using the SWAT+ model.

Although the SWAT model has made significant progress in studies of runoff evolution and the spatiotemporal characteristics of blue- and green-water change, some shortcomings remain in research on the glacier module. The accuracy of the SWAT model in simulating glacier meltwater in arid regions still needs improvement, and glacier meltwater is, for many ...

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is an important component of runoff in alpine basins; however, the glacier module in the SWAT model is relatively simple in terms of parameterization and simulation, and still cannot effectively simulate the dynamic influence mechanism by which glacier meltwater contributes to runoff generation in a basin[12].

The method proposed by Luo et al.[13] in 2013, which integrates volume-area scaling into SWAT, has become one of the important extension approaches for simulating glacier hydrological processes. Most existing methods represent glacier dynamics in SWAT by coupling it with an external glacier model, or use static glacier-melt approaches that do not simulate glacier retreat. SWAT-GL is an open-source glacier module developed by Timo Schaffhauser's team at the Technical University of Munich. It includes a mass-balance module and a

glacier-evolution module for simulating glacier dynamics, and has shown good applicability in South Tyrol, Italy[14].

The Jinghe River Basin in Xinjiang is a typical arid inland glacier-fed basin, characterized by the vertically differentiated hydrological pattern of “runoff generation in the mountains and water consumption on the plains.” The glacier area of the basin is 96.2 km^2 , and the annual glacier recharge is $0.96 \times 10^8 \text{ m}^3$, accounting for 20.6% of the total river runoff. At present, studies on water resources in the Jinghe River Basin of Xinjiang mostly focus on runoff simulation, soil moisture, and ecological risk assessment[15–18], while systematic research on the spatiotemporal differentiation of blue and green water driven by glacier-recharge processes remains lacking. Against this background, this study: (1) applies the SWAT-GL model to the Jinghe River Basin, verifies its simulation advantages over the traditional SWAT model, improves the accuracy of long-series runoff simulation, and provides technical support for glacier hydrological simulation in arid regions; (2) reveals the spatiotemporal distribution characteristics of blue and green water under the basin’s “glacier-valley-basin” geomorphic units, laying a scientific foundation for optimizing the spatial allocation of regional water resources; and (3) constructs a SWAT-GL-FLUS (Future Land-Use Simulation, FLUS)–CMIP6 (Coupled Model Intercomparison Project Phase 6) multimodel coupling framework to quantitatively project the evolution of blue and green water under future climate scenarios, thereby providing practical reference for ensuring water-resource security in arid regions.

1 Data and Methods

1.1 Overview of the Study Area

The Jinghe River Basin has a total length of 114 km. It is located in Bortala Mongolian Autonomous Prefecture, Xinjiang, on the northern foot of the Borohoro Mountains, a branch of the Tianshan Mountains, and on the southwestern margin of the Junggar Basin (Fig. 1). The basin has a temperate continental climate. Its precipitation is derived from water-vapor transport from the Arctic Ocean and the Atlantic Ocean. The mean annual temperature is 7.8°C , annual precipitation is 102.2 mm, and evaporation is 1512.6 mm. The basin terrain exhibits a three-part distribution pattern, high in the south and low in the north: the southern part consists of glacier recharge areas such as the Borohoro Mountains; the central part is a piedmont inclined plain, where the fan-edge zone has deep, fertile soils and constitutes the core agricultural area of the basin; and the northern part borders Ebinur Lake, with lacustrine plains widely distributed with mobile dunes, saline-alkali flats, and marsh wetlands.

1.2 Data Sources

1.2.1 Digital elevation model data The elevation data (DEM) required by the SWAT model were obtained from the Geospatial Data Cloud platform of the Computer Network Information Center, Chinese Academy of Sciences

(<http://www.gscloud.cn>). The 2022 ASTER GDEM data for the Jinghe River Basin at 30 m resolution were used, and the planar projection coordinate system was uniformly set to WGS_1984_UTM_Zone_44N.

1.2.2 Meteorological and hydrological driving data Considering the scarcity of meteorological stations in the Jinghe River Basin, the strong heterogeneity of the underlying surface, and the spatial precipitation caused by vertical zonality

Note: The basemap was prepared using the standard map of the Ministry of Natural Resources; the map approval number is GS(2019)3266. No modifications were made to the basemap boundaries. The same applies below.

Fig. 1 Schematic diagram of Jinghe River Basin

To address the problem of uneven distribution, the CN05.1 dataset was selected. Based on measured meteorological data from the Jinghe station, the data were corrected using the multi-year mean ratio and spatial relationship correction method, thereby reducing accuracy errors caused by scale mismatch (Fig. 1)^[19]. Daily-scale elements for 1961–2022, including air temperature, humidity, wind speed, precipitation, and solar radiation, were extracted, and monthly runoff data from the Jinghe hydrological station were used as the basis for model calibration and validation.

1.2.3 Soil Distribution in the Jinghe River Basin

The spatial heterogeneity of soil physical properties constitutes the intrinsic linkage mechanism for differences in runoff generation and confluence processes among hydrological response units in the SWAT model. This study used the 1 km-resolution Harmonized World Soil Database Version 1.2 (HWSD V1.2), jointly developed by the Food and Agriculture Organization of the United Nations (FAO) and the International Soil Reference and Information Centre (ISRIC), as the soil dataset (Fig. 2)^[20].

Fig. 2 Schematic diagram of soil distribution in the Jinghe River Basin

Visible legend: Jinghe River Basin; weakly developed gray calcic soil; weakly developed black calcic soil; weakly developed chestnut calcic soil; clay-illuviated calci-accumulation soil; clay-illuviated gypsic soil; transitional sandy soil; gleyic black soil; calcareous alluvial soil; loose gleyic soil; loose saline soil; calcareous sandy soil; water-frozen thin-layer soil; water bodies.

1.2.4 Land-Use Distribution and Glacier Data in the Jinghe River Basin

This study used the 2022 China Multi-period Land Use Remote Sensing Monitoring Dataset (CNLUCC) to extract land-use attributes and carry out first-level classification and reclassification (Fig. 3). To adapt to the SWAT-GL glacier module, the initial glacier outline data from the Randolph Glacier Inventory

and the global glacier ice-thickness dataset published by Farinotti et al. were selected as the basic inputs for the glacier module^[21-22]. Based on the DEM of the study area and glacier-outline vector data, the glacier-covered elevation range was determined to be 3235.6–4330 m. In the ArcGIS 10.2 platform, this elevation range was evenly divided into 10 elevation bands according to elevation slices (Elevation Slice, ES) (ES1–10);

Fig. 3 Land use distribution map of the Jinghe River Basin

Visible legend: Jinghe River Basin; glacier; lakes; bare land; high-coverage grassland; medium-coverage grassland; low-coverage grassland; rural land; urban land; construction land; forest land; cultivated land.

through spatial overlay analysis, glacier raster values were assigned and updated into the SWAT crop database. Parameters such as ice thickness, glacier area, and ice water equivalent for each elevation band were imported into the SWAT-GL configuration file, completing construction of the model's glacier module.

1.3 Research Methods

1.3.1 Introduction to the Principles of SWAT-GL

The SWAT model can be used to analyze the spatiotemporal distribution of blue and green water resources, and can effectively simulate runoff under the influences of different soil conditions, land-use types, climate scenarios, and human activities^[23]:

$$SW_t = SW_0 + \sum_{i=1}^t (P - Q_s - ET - W - Q_{gw}) \quad (1)$$

where SW_t is the final soil water content at time t (mm); SW_0 is the initial water content (mm); P is precipitation (mm); Q_s is surface runoff (mm); ET is evaporation (mm); W is infiltration at the bottom of the soil profile and lateral flow (mm); and Q_{gw} is groundwater content (mm).

SWAT-GL is a glacier-improved version of SWAT. By discretizing glaciers through elevation slices (ES), it overcomes the limitations of the traditional fixed elevation band (Elevation Band, EB) approach and enables glacier-change simulation based on Δh .

1.3.2 Mass-Balance Model

The mass-balance calculation is combined with the existing snow-based calculation (snom.f). The mass balance can be expressed as:

$$EW_t = EW_{t-1} - M_t (1 - \beta_f) - S_t + C_t \quad (2)$$

where EW_t is the ice water equivalent on day t (mm H_2O); M_t is the melt rate (mm $H_2O \cdot d^{-1}$); S_t is the sublimation rate (mm $H_2O \cdot d^{-1}$); C_t is the accumulation rate (mm $H_2O \cdot d^{-1}$); and β_f denotes the refreezing factor of meltwater.

1.3.3 Glacier Evolution Model

Changes in ice thickness are stronger in low-altitude areas (ablation zones) and smaller in accumulation zones. The standardization of ES is based on flow

the minimum and maximum glacier elevations within the region:

$$E_{norm,i} = \frac{E_{max} - E_i}{E_{max} - E_{min}} \quad (3)$$

where $E_{norm,i}$ is the normalized elevation of ES_i ; E_{max} and E_{min} denote the maximum and minimum glacier elevations (m), respectively; and E_i is the actual elevation of ES_i .

1.3.4 Blue/green water calculation method The SWAT model can directly estimate the composition and availability of blue and green water[24]. Blue water consists of sub-basin water yield ($WYLD$) and deep aquifer recharge (DA_RCHG); green water includes actual evapotranspiration (ET) and soil water storage (SW). The green-water coefficient is the ratio of green water to total water and is used for blue/green water assessment[25]. The core calculation formulas are:

$$GW = ET + SW \quad (4)$$

$$BW = WYLD + DA_RCHG \quad (5)$$

$$GWC = \frac{GW}{GW + BW} \quad (6)$$

where GW is the green-water resource amount (mm); BW is the blue-water resource amount (mm); and GWC is the green-water coefficient.

1.3.5 FLUS model and driving data Dynamic evolution of land use in the FLUS model is jointly driven by natural environmental and socioeconomic factors. The FLUS model integrates the spatiotemporal dynamic characteristics of cellular automata (CA) with the nonlinear mapping capability of artificial neural networks (ANN). By integrating multiple driving factors, it realizes multi-scenario simulations of land-use change. Its prominent features are its ability to handle complex interactions and its adoption of an adaptive inertia mechanism to optimize simulation convergence[26].

1.3.6 Construction of the Delta statistical downscaling model Delta statistical downscaling is an efficient bias-correction scheme advocated by the U.S. National Assessment Center (NAC). Owing to its advantages of requiring relatively few selected parameters and having strong applicability, it has been widely used in both academic research and practice. By mapping the difference characteristics between historical observational data and gridded Global Climate Model (GCM) data—precipitation as relative change and temperature as absolute change—onto future model scenarios, it can estimate climatic element values under different emission pathways[26].

$$\alpha_{s,M} = \overline{\alpha_{obs,M}} / \overline{\alpha_{h.GCM,M}} \quad (7)$$

$$\sigma_{s,M} = \sigma_{obs,M} / \sigma_{h.GCM,M} \quad (8)$$

where $\overline{\alpha_{obs,M}}$ is the monthly mean of the observational data at each meteorological station during the historical observation period; $\overline{\alpha_{h.GCM,M}}$ is the monthly mean of the corresponding GCM grid; $\sigma_{obs,M}$ is the monthly standard deviation of the observational data at each meteorological station during the historical observation period; and $\sigma_{h.GCM,M}$ is the monthly standard deviation of the corresponding GCM grid.

$$\alpha'_{f.GCM,M} = (\alpha_{f.GCM,M} - \overline{\alpha_{f.GCM,M}}) \cdot \sigma_{s,M} + (\overline{\alpha_{f.GCM,M}} \cdot \alpha_{s,M}) \quad (9)$$

where $\alpha'_{f.GCM,M}$ is the corrected future GCM monthly data; $\alpha_{f.GCM,M}$ is the monthly mean of the corrected future GCM.

1.4 SWAT-GL simulation and evaluation

1.4.1 Construction of the SWAT-GL model After extraction in ArcGIS, the Jinghe River Basin covered 1820.15 km². It was divided into 10 elevation bands, 42 sub-basins (Fig. 4), and 392 hydrological response units, with each hydrological response unit uniquely mapped to a specific ES unit. Considering the time scale of runoff and the influence of human activities, and also to allow all hydrological processes in the initial simulation period to transition from their initial state to equilibrium, the warm-up period of SWAT-GL in this study was set to 4 years, i.e., 1971-1974; the calibration period was 1975-1998; and the validation period was 1999-2022.

Fig. 4 Sub-basin division results of Jinghe River Basin

1.4.2 Evaluation of the SWAT-GL model The calibration and validation of the model in this study were carried out using SWAT-GL combined with the SUFI-2 algorithm in Python, considering the synergistic effects of multiple parameters and conducting a comprehensive uncertainty analysis[27]. Based

on the SWAT model technical manual and related research results, this study first screened 20 key hydrological parameters with significant influence on runoff simulation, and conducted sensitivity analysis and calibration of SWAT model parameters. In combination with the sensitivity-analysis results, 15 parameters with relatively large influence on runoff were selected to complete parameter calibration and determine the optimal model parameter combination. On the basis of SWAT model calibration, the SWAT-GL model was progressively calibrated using a trial-and-error method. Meanwhile, four glacier-module parameters specific to the model— $f_{frze.gl}$, $f_{accu.gl}$, $GLMFMX.gl$, and $GLMFMN.gl$ —were incorporated. After each parameter adjustment, the model was run, the simulated runoff was compared with the observed runoff, and the model evaluation indicators were used to judge the sim...

the fitting performance, with iterative optimization conducted until the optimal parameter combination was determined, thereby ensuring that the model simulation accuracy met the requirements of this study. Model accuracy was evaluated using the Nash-Sutcliffe efficiency coefficient (NSE) [28] and the coefficient of determination (R^2). Simulation accuracy was assessed with NSE and R^2 , referring to the evaluation system of Moriasi et al. [29], with monthly-scale $NSE \geq 0.65$ adopted as the criterion for an acceptable model [30].

2 Results and Analysis

2.1 Simulation Validation and Analysis Based on SWAT-GL

Using the long-series monthly observed runoff data from the hydrological station at the Jinghe River mountain outlet, model validation was completed (Table 1), and the optimal parameter values are shown in Table 2. For the traditional SWAT model, the calibration-period results were $NSE = 0.01$ and $R^2 = 0.53$, and the validation-period results were $NSE = 0.04$ and $R^2 = 0.45$, neither meeting the acceptable standard. For the SWAT-GL model, the calibration-period results were $NSE = 0.75$ and $R^2 = 0.82$, and the validation-period results were $NSE = 0.80$ and $R^2 = 0.84$; both indicators were > 0.65 , and the simulated runoff agreed well with the observed runoff (Table 1, Fig. 5). In summary, SWAT-GL can significantly improve the accuracy of runoff simulation in arid regions, shows good applicability in the Jinghe River basin, and can support basin hydrological simulation and the statistical calculation of blue- and green-water resources.

Tab. 1 Evaluation results of Jinghe River runoff simulation

Period	Model	NSE	R^2
Calibration period (1975-1998)	SWAT model	0.01	0.53
Calibration period (1975-1998)	SWAT-GL model	0.75	0.82
Validation period (1999-2022)	SWAT model	0.04	0.45
Validation period (1999-2022)	SWAT-GL model	0.80	0.84
Entire period (1975-2022)	SWAT model	0.03	0.49

Period	Model	<i>NSE</i>	<i>R</i> ²
Entire period (1975–2022)	SWAT-GL model	0.78	0.83

As shown in Fig. 6, the glacier area in the study area first increased and then decreased with rising elevation, reaching a peak at 3722 m above sea level. Under the influence of climate warming and human activities, glacier area continued to shrink during the simulation period; high-elevation areas are sensitive zones for glacier mass balance and exhibit nonlinear responses to climate warming, with faster ablation rates. The glaciers of the Jinghe River basin are undergoing systematic shrinkage across all elevation belts, and the risk of ablation of high-elevation glaciers requires focused attention.

2.2 Spatiotemporal Distribution of Blue- and Green-Water Resources

2.2.1 Interannual and Monthly Variation Characteristics of Blue and Green Water Based on the 1975–2022 time-series analysis (Fig. 7), the blue- and green-water resources of the Jinghe River basin fluctuated markedly from year to year. Annual precipitation in the basin was 54–231 mm (multi-year mean 119 mm); blue-water resources were 147–380 mm (multi-year mean 234 mm), accounting for 52% of total water resources; and green-water resources were 169–262 mm (multi-year mean 219 mm), accounting for 48%. Within the year, blue and green water showed a unimodal seasonal evolution. Precipitation from May to August constituted the wet season, with a peak of 17 mm in May. Blue water was concentrated from March to August, accounting for 95% of the annual total, while green water was concentrated from April to September, accounting for 78%. The M-K test showed that annual precipitation and green-water amount exhibited significant increasing trends (slopes of 1.833 and 0.5736, respectively; $P < 0.05$), whereas the change in blue water was not significant. Precipitation is the core dominant factor governing the allocation of blue and green water in the basin.

Tab. 2 Final parameter values of SWAT-GL models

Parameter name	Parameter definition	Final optimized value
f_frze.gl	Refreezing factor	0.03
f_accu.gl	Accumulation factor	0.13
GLMFMX.gl	Ice melt factor on June 21 / (mm H ₂ O · °C ⁻¹ · d ⁻¹)	32.17
GLMFMN.gl	Ice melt factor on December 21 / (mm H ₂ O · °C ⁻¹ · d ⁻¹)	−62.00
CN2.mgt	SCS runoff curve number	27.00

Parameter name	Parameter definition	Final optimized value
TLAPS.sub	Temperature lapse rate / ($^{\circ}\text{C} \cdot \text{km}^{-1}$)	-8.29
PLAPS.sub	Precipitation lapse rate / ($\text{mm} \cdot \text{km}^{-1}$)	55.40
ALPHA_BF.gw	Baseflow α factor / d	0.06
GW_DELAY.gw	Groundwater recharge delay time / d	41.00
GWQMN.gw	Threshold water level of the shallow aquifer for groundwater flow into the main channel / mm	8.90
ESCO.hru	Soil evaporation compensation factor	0.80
SMTMP.bsn	Snowmelt base temperature / $^{\circ}\text{C}$	2.02
SMFMX.bsn	Snowmelt factor on June 21 / ($\text{mm} \cdot ^{\circ}\text{C}^{-1} \cdot \text{d}^{-1}$)	10.79
SMFMN.bsn	Snowmelt factor on December 21 / ($\text{mm} \cdot ^{\circ}\text{C}^{-1} \cdot \text{d}^{-1}$)	16.98
TIMP.bsn	Snowpack temperature lag factor	0.43
SURLAG.bsn	Surface runoff lag coefficient	4.59
CH_N2.rte	Manning' s coefficient for the main-channel bed	1.70
CH_K2.rte	Effective hydraulic conductivity of the main-channel bed / ($\text{mm} \cdot \text{h}^{-1}$)	0.12
SOL_K.sol	Saturated hydraulic conductivity of soil / ($\text{mm} \cdot \text{h}^{-1}$)	-2.69

2.2.2 Spatial Distribution Characteristics of Blue and Green Water

Based on the simulation results of the SWAT-GL model, the Jinghe River basin was divided into 42 sub-basins, and the blue- and green-water resources of each sub-basin from 1975 to 2022 were calculated; the spatial distribution character-

Fig. 5. Time series plot with in-figure legend: observed values, simulated values, precipitation; annotations: $NSE = 0.75$, $R^2 = 0.82$; $NSE = 0.80$, $R^2 = 0.84$. Axes: monthly runoff ($\text{m}^3 \cdot \text{s}^{-1}$), precipitation/mm, year.

Figure 1: Fig. 5. Time series plot with in-figure legend: observed values, simulated values, precipitation; annotations: $NSE = 0.75$, $R^2 = 0.82$; $NSE = 0.80$, $R^2 = 0.84$. Axes: monthly runoff ($\text{m}^3 \cdot \text{s}^{-1}$), precipitation/mm, year.

Fig. 6. Variation of glacier volume with altitude; in-figure legend: initial glacier volume, simulated final volume. Axes: glacier volume/ 10^8 m^3 , altitude/m.

Figure 2: Fig. 6. Variation of glacier volume with altitude; in-figure legend: initial glacier volume, simulated final volume. Axes: glacier volume/ 10^8 m^3 , altitude/m.

istics are shown in Fig. 8. Blue-water resources showed a decreasing trend from upstream to downstream. The upstream glacier area had the highest blue-water storage, whereas in the downstream plain area, where agricultural and construction land are concentrated, blue-water consumption was large and resources were relatively scarce (Fig. 8a). Green-water resources exhibited a pattern of “low upstream—fluctuating in the midstream—locally high downstream.” In the upstream area, green water was slightly higher only in some glacier areas because of evapotranspiration; in the midstream, green water fluctuated markedly under the influence of underlying-surface heterogeneity; and downstream, green water increased significantly under the combined effects of human activities and vegetation cover.

Fig. 5 Monthly mean simulated and observed runoff at the Jinghe River outlet hydrological station, 1975–2022

Fig. 5 Monthly mean runoff measured and simulated values at Jinghe River outlet hydrological station from 1975 to 2022

Fig. 6 Variation of glacier volume with altitude in the Jinghe River Basin

Fig. 6 Variation of glacier volume with changes in altitude in Jinghe River Basin

2.3 Spatiotemporal distribution characteristics of blue and green water in the Jinghe River Basin in typical years

2.3.1 Determination of typical years

The annual runoff anomaly percentage (Run-off Anomaly Percentage, RP) can serve as an intuitive indicator for evaluating wet and dry conditions in a basin. According to the RP threshold values specified in the *Standard for Hydrological Information and Hydrological Forecasting* (GB/T 22482-2008), hydrologi-

Fig. 7. Interannual and intra-annual variation characteristics of blue and green water; in-figure legend: blue water, green water, precipitation. Subplots: (a) interannual variation; (b) intra-annual variation. Axes: water resources/mm, precipitation/mm, year, month.

Figure 3: Fig. 7. Interannual and intra-annual variation characteristics of blue and green water; in-figure legend: blue water, green water, precipitation. Subplots: (a) interannual variation; (b) intra-annual variation. Axes: water resources/mm, precipitation/mm, year, month.

cal years can be classified into three categories: wet, normal, and dry (Table 3). Given that the Jinghe River Basin is an arid-region basin recharged by glacier meltwater, the runoff anomaly percentage can comprehensively reflect the multiple recharge effects of precipitation and glacier meltwater. Therefore, a correlation framework between blue water and green water was established to reveal their allocation patterns. The year 1988 (29.68%) was selected as the typical wet year, 1990 (0.05%) as the typical normal year, and 2014 (−23.08%) as the typical dry year, so as to comprehensively investigate the spatiotemporal variation characteristics of blue- and green-water resources under typical year types.

Fig. 7 Interannual and intra-annual variation characteristics of blue and green water in the Jinghe River Basin

Fig. 7 Interannual and intra-annual variation characteristics of blue and green water in Jinghe River Basin

Fig. 8 Distribution characteristics of multi-year average blue and green water in the Jinghe River Basin from 1975 to 2022

- (a) Multi-year average blue-water amount
- (b) Multi-year average green-water amount
- Legend: blue and green water resources/mm
 - Blue water: <100, 100–150, 150–200, 200–250, >250
 - Green water: <75, 175–200, 200–225, 225–250, 250–275, 275–300
- Scale: 0–30 km

Table 3 Classification criteria for hydrological annual types

Grade	Runoff anomaly percentage/%	Annual type
1	$RP > 20$	Wet year

Grade	Runoff anomaly percentage/%	Annual type
2	$10 < RP \leq 20$	Moderately wet year
3	$-10 < RP \leq 10$	Normal year
4	$-20 < RP \leq -10$	Moderately dry year
5	$RP \leq -20$	Dry year

2.3.2 Temporal variation characteristics of blue and green water resources in typical years

In the Jinghe River Basin, blue and green water resources differ markedly among wet, normal, and dry years (Fig. 9). Blue water decreases synchronously with declining precipitation: blue water in wet years is twice that in dry years. The difference in green water is relatively small; green water in wet years is 0.81 times that in dry years, and in dry years green water exceeds blue water by 49 mm. The green-water coefficient is highest in dry years (57.18%) and lowest in wet years (44.88%). This pattern indicates that, as hydrological conditions become drier, the allocation proportion of green water within total water resources increases.

Fig. 9 Water resources in different annual types in the Jinghe River Basin

- Left axis: water-resource amount/mm
- Right axis: green-water coefficient/%
- X-axis: annual type; wet year, normal year, dry year
- Legend: precipitation; blue water; green water; green-water coefficient
- Green-water coefficient labels: 44.88, 48.17, 57.18

2.3.3 Spatial distribution of blue and green water resources in typical years

In the Jinghe River Basin, blue water decreases from the upstream glacier area to the downstream plain area (Fig. 10). The upstream glacier area exceeds 250 mm and serves as the core recharge source. In wet years, the upstream non-glacier area is approximately 250–320 mm, the midstream area approximately 160–250 mm, and the downstream area approximately 80–130 mm. In normal years, all zones are essentially consistent with the multi-year average. In dry years, the downstream area is below 80 mm. Green water, by contrast, shows nonlinear variation: in wet years, the downstream plain area reaches 220–260 mm, higher than the upstream area; in normal years, all zones agree with the multi-year average; in dry years, the upstream area is approximately 180–270 mm and the midstream area approximately 140–210 mm. The decreasing trend

of blue water is obvious, whereas the spatial distribution of green water is more balanced; in dry years, the proportion of green water increases.

2.4 Evaluation of the fit of future climate and future land-use projections

2.4.1 Simulation, validation, and analysis of future land-use change

This study used the FLUS model to carry out simulation and prediction of the evolution of the land-use pattern in Jinghe County. Using the measured land-use data for 2010 as the baseline, the land-use status in 2020 was simulated. Confusion-matrix analysis showed that the Kappa coefficient reached 0.95, higher than the high-accuracy threshold of 0.75, indicating excellent simulation performance and strong reliability. According to the overall territorial spatial plan of Jinghe County, a policy scenario dominated by cultivated-land protection was set. Using the two phases of land use in 2010 and 2020, the land use in 2050 was further simulated (Fig. 11). Based on territorial spatial planning control in Jinghe County and the constraints of water-resource carrying capacity in arid regions, the pattern of the core land classes in the basin will tend to stabilize after 2050. This treatment can effectively strip out interference from land-use fluctuations and focus on the driving effects of climate scenarios on blue and green water.

Under the cultivated-land protection scenario, compared with 2020, construction land in 2050 continues to expand by 54.79%, the largest increase among all land-use types, followed by an increase of 48.85% in cultivated land. It is estimated that the grassland area in Jinghe County will decrease by 9.41% in 2050, while unused land and forest land will decrease by 7.64% and 2.78%, respectively. The expansion of construction land is most pronounced in the downstream plain area of the Jinghe River Basin.

2.4.2 Simulation, validation, and analysis of future climate change

Linear interpolation was used to downscale data from five CMIP6 models (Table 4). SSP1-RCP2.6 (low-carbon pathway), SSP2-RCP4.5 (medium-carbon pathway), and SSP5-RCP8.5 (high-carbon pathway) were adopted (hereafter abbreviated as SSP126, SSP245, and SSP585). Using 1979–1999 as the baseline period, a correction field was constructed, and Delta values were used to correct the data for 2000–2014 (validation period) and 2023–2100 (future period). The spatial resolution was unified to

- (a1) Blue water resources in wet years
- (a2) Blue water resources in normal years
- (a3) Blue water resources in dry years
- (b1) Green water resources in wet years
- (b2) Green water resources in normal years
- (b3) Green water resources in dry years

Legend: Blue and green water resources / mm

- <100
- 100-150
- 150-200
- 200-250
- >250
- <175
- 175-200
- 200-225
- 225-250
- 250-275
- 275-300
- >300

Scale: 0-30 km

Fig. 10 Distribution characteristics of blue and green water resources in different annual types in Jinghe River Basin

(a) Land use in 2010

(b) Land use in 2020

(c) Land use under the cultivated-land protection scenario in 2050

Legend: cultivated land; forest land; grassland; water area; construction land; unused land

Scale: 0-80 km

Fig. 11 Spatiotemporal evolution of land use in Jinghe County from 2010 to 2050

Tab. 4 Basic information of selected CMIP6 models

Model name	Institution / country	Resolution
ACCESS-CM2	ARCCSS / Australia	$1.25^{\circ} \times 1.875^{\circ}$
ACCESS-ESM1-5	CSIRO / Australia	$1.25^{\circ} \times 1.875^{\circ}$
MIROC6	MIROC / Japan	$1.4^{\circ} \times 1.4^{\circ}$
MRI-ESM2-0	MRI / Japan	$1.125^{\circ} \times 1.125^{\circ}$
NESM3	NUIST / China	$0.5^{\circ} \times 0.5^{\circ}$

$0.25^{\circ} \times 0.25^{\circ}$, and the multi-model ensemble average (MME) method was introduced to improve the reliability of precipitation and temperature simulations. The Taylor diagram evaluation shows that the simulated correlation coefficient for monthly precipitation is 0.7-0.8, with the MME reaching 0.85; the MME correlation coefficients for maximum and minimum air temperature both reach 0.99, markedly outperforming the individual models (Fig. 12).

2.5 Estimating the future spatiotemporal distribution of blue and green water in the Jinghe River Basin

2.5.1 Analysis of future changes in climate data

In this study, land-use prediction data for 2050 from the FLUS model and meteorological data from the CMIP6-MME model were used to drive the SWAT-GL model. The years 2023–2100 were divided into the near term (2023–2048), mid term (2049–2074), and far term (2075–2100). As shown in Fig. 13a, under the SSP126, SSP245, and SSP585 scenarios, precipitation in the basin generally shows an increasing trend, and the amplitude of deviation increases. By 2100, the annual mean increases are $0.21 \text{ mm} \cdot \text{a}^{-1}$, $0.23 \text{ mm} \cdot \text{a}^{-1}$, and $0.30 \text{ mm} \cdot \text{a}^{-1}$, respectively; SSP585 has the largest increase and fluctuation, while SSP126 has the smallest. Fig. 13b shows that the increase in daily maximum temperature gradually expands with each period, displaying a significant gradient pattern: warming is $0.97\text{--}3.22 \text{ }^{\circ}\text{C}$ in the near term, $1.39\text{--}4.98 \text{ }^{\circ}\text{C}$ in the mid term, and $1.44\text{--}6.66 \text{ }^{\circ}\text{C}$ in the far term. Under the SSP585 scenario, far-term warming is 21%–43% higher than in the historical period, making the warming effect the most pronounced.

Fig. 12 Taylor diagram after bias correction of each model

Visible legend: MIROC6, ACCESS-CM2, MRI-ESM2-0, ACCESS-ESM1-5, NESM3, MME.

Panels: (a) Monthly-scale precipitation; (b) Monthly-scale maximum temperature; (c) Monthly-scale minimum temperature.

Axes/labels: standard deviation; root-mean-square error; correlation coefficient.

Fig. 13 Trend analysis of precipitation and temperature under different scenarios from 2023 to 2100

Legend: historical period; SSP126; SSP245; SSP585.

Panels: (a) 2023–2100 precipitation; (b) 2023–2100 maximum temperature.

Axes/labels: precipitation/mm; temperature/ $^{\circ}\text{C}$; year; historical period; near term; mid term; far term.

Note: The shaded area represents the standard-deviation range.

2.5.2 Temporal changes in blue and green water in the Jinghe River Basin under future scenarios

The dynamic prediction results for blue and green water under different scenarios in the Jinghe River Basin are shown in Fig. 14. During the historical baseline period (1975–2022), the mean annual blue-water amount was 234.03 mm. Affected by the reduction in glacier-melt recharge, the mean annual blue-water amounts under the future SSP126, SSP245, and SSP585 scenarios decrease to 182.90 mm, 174.64 mm, and 170.32 mm, respectively. Among them, SSP585 shows the fastest decline, decreasing by 63.71 mm relative to the historical period, with a reduction of 27.2%. The mean annual green-water amount in the historical period was 219.43 mm. Under the three future scenarios, the mean

annual green-water amounts increase to 270.64 mm, 279.96 mm, and 306.23 mm, respectively, presenting a gradient of “high carbon > medium carbon > low carbon” ; SSP585 exhibits the largest increase, rising by 86.80 mm, with an increase of 39.6%. The core driver is the intensification of evapotranspiration caused by warming under high carbon emissions, confirming the strong driving effect of the high-carbon pathway on the regional water cycle.

2.5.3 Spatial changes in blue and green water in the Jinghe River Basin under future scenarios

Warming drives a decrease in blue water from the upper reaches to the lower reaches of the basin, with the most significant decline occurring in the upstream glacier meltwater area (Fig. 15). In the near term, blue water under the SSP126 scenario decreases gently along the river course, while the medium- and high-carbon scenarios show similar magnitudes of change. In the mid-term, SSP126 still shows a gentle decline, whereas under the medium- and high-carbon scenarios, high-blue-water areas increase in the middle reaches. In the long term, blue water in the glacier regions under all three scenarios decreases sharply, and glacier ablation leads to insufficient blue-water recharge across the entire basin. Green water in each sub-basin continuously increases from upstream to downstream and from the near term to the long term, with the magnitude of increase showing a gradient of SSP585 > SSP245 > SSP126. This trend is consistent with the conclusion of Zhan Mingyue [31] that, under CMIP6 scenarios, the increase in basin green-water volume is most significantly affected by temperature. The further intensification of climate extremes under the SSP585 scenario aggravates the process of green-water growth.

3 Discussion

3.1 Applicability of the SWAT-GL model in the Jinghe River Basin

By embedding glacier mass-balance and evolution modules, the SWAT-GL model performs excellently in long-series monthly runoff simulation in the Jinghe River Basin. The NSE values in both the calibration and validation periods are greater than 0.75, indicating a significant improvement in accuracy compared with the traditional SWAT model, and the model can effectively support simulation of basin hydrological processes and accounting of blue and green water resources. The main deficiency of the model is that it somewhat underestimates extreme runoff peaks during the high-flow season (June–August). The core reason is that the model’s ablation algorithm is based on the degree-day factor method, which assumes a linear relationship between ablation amount and positive accumulated temperature. This method cannot fully characterize nonlinear glacier ablation in arid-region summers driven by extreme high temperatures and strong radiation, nor the flood-peak process caused by the superposition of short-duration heavy precipitation and pulsed meltwater, resulting in overly smoothed simulated flood peaks. Overall, the SWAT-GL model has good applicability in the study area.

3.2 Spatiotemporal allocation characteristics of blue and green water resources and their driving mechanisms

The blue and green water resources of the Jinghe River Basin exhibit significant spatiotemporal heterogeneity. At the interannual scale, blue water is dominated by precipitation but shows no significant trend, while green water increases significantly with precipitation; the basin water cycle is shifting from “blue-water dominance” to “joint blue-water-green-water driving.” At the intra-annual scale, the blue-water peak is synchronized with the snowmelt-glacier ablation period, whereas the green-water peak lags behind precipitation, reflecting the nonlinear response of vegetation transpiration to climate change [32]. Analysis of typical years shows that the green-water coefficient in dry years is significantly higher than that in wet years, indicating that vegetation feedback mechanisms associated with soil moisture are strengthened under drought conditions and highlighting the ecological resilience of green water under an arid background. Although precipitation differences between wet and dry years are relatively small, blue water fluctuates sharply; this is mainly due to the nonlinear regulation of blue water by glacier meltwater, whereas green water is buffered by the soil-vegetation system and therefore has greater stability. In terms of spatial distribution, blue-water resources in the Jinghe River Basin exhibit a stepwise decreasing gradient of “upstream glacier area-middle-reach transition zone-downstream plain area.” This differentiation is dominated by glacier meltwater recharge, precipitation distribution, and terrain slope, and the upstream high-altitude glacier area is the core recharge source of blue water in the basin. Green-water resources show a pattern of “low values upstream-fluctuation in the middle reaches-down ...

Legend: SSP126; SSP245; SSP585

(a) Multi-scenario blue-water changes

(b) Multi-scenario green-water changes

Fig. 14 Dynamic prediction of blue and green water under multiple scenarios from 2023 to 2100

Figure panel labels: SSP126; SSP245; SSP585; SSP126; SSP245; SSP585. Rows: near term; medium term; long term. North arrow. Scale: 0-30 km. Legend: blue and green water resources / mm; <100; 100-150; 150-200; 200-250; >250; <175; 175-200; 200-225; 225-250; 250-275; 275-300; >300.

Fig. 15 Distribution characteristics of blue and green water under different scenarios

a pattern of “localized high values in the reaches,” jointly regulated primarily by elevation gradients—temperature and evapotranspiration—and land-use types, namely oasis vegetation cover. Watershed water-resource management must take into account differences in vertical zonality, establish a three-dimensional management system of “glacier protection-ecological water replenishment-green-

water regulation,” and, based on the coordinated allocation of blue and green water, focus on preventing and controlling the risk to downstream blue-water supply caused by glacier melting while adapting to the green-water dependence of oasis agriculture.

3.3 Policy implications and adaptive management of blue-green water changes under future scenarios

The evolution of the blue-green water pattern under different future carbon-emission scenarios poses new requirements for water-resource management in arid regions. In response to the water-source risks of the traditional blue-water-dependent irrigation model, optimization of agricultural planting structure should be promoted; drought-tolerant crops should be popularized in light of the rising share of green water; water-saving irrigation technologies should be widely adopted; and priority should be given to ensuring domestic water use and key ecological water use. In accordance with the spatial differentiation characteristics of blue and green water, an integrated watershed-wide governance system of “upstream conservation-midstream regulation-downstream water saving” should be established. In the upstream area, glacier ecological protection should be strengthened to maintain the core recharge function of blue water; in the midstream area, sponge-city technologies should be promoted to mitigate the disturbance of construction-land expansion to the green-water cycle; and in the downstream area, a joint blue-green water dispatching mechanism should be established, using inter-basin water transfer and rainwater harvesting and storage to compensate for blue-water deficits. Based on the conclusion that a low-carbon pathway can significantly slow the decline of blue water, water-resource carrying capacity should be taken as a hard constraint on industrial layout, and differentiated water pricing and carbon-tax policies should be used to compel industries to transform toward low-water-consumption and low-carbon models, thereby reducing at the source the impact of climate change on the watershed water cycle.

4 Conclusions

Based on the SWAT-GL model, this study systematically analyzed the hydrological processes and the spatiotemporal allocation characteristics of blue and green water resources in the Jinghe River Basin from 1975 to 2022. The main conclusions are as follows:

- (1) Compared with the traditional SWAT model, the SWAT-GL model demonstrated good capability for long-term monthly runoff simulation in the Jinghe River Basin, with $NSE = 0.75/0.80$ for the calibration/validation periods. In particular, in simulating glacier mass balance in high-elevation areas, it reproduced the nonlinear variation of glacier volume with elevation and the systematic shrinkage characteristics under the background of climate warming.

- (2) The blue and green water resources in the Jinghe River Basin exhibit significant spatiotemporal heterogeneity. Interannually, blue water accounts for 52% and shows no significant trend, while green water accounts for 48% and increases with precipitation; within the year, the blue-water peak matches snowmelt, whereas green water lags behind precipitation. Spatially, blue water

decreases from upstream to downstream, while green water presents a pattern of “low in the upstream reaches—fluctuating in the middle reaches—locally high in the downstream reaches.” In dry years, the green-water coefficient increases by 12.3% compared with wet years, indicating stronger green-water stability.

- (3) Under different future carbon-emission scenarios, blue-water resources show a decreasing trend, while green-water volume shows an increasing trend. Spatially, the pattern continues in which blue water decreases from upstream to downstream and green water increases continuously; moreover, the magnitudes of change in both blue and green water exhibit a gradient characterized by high-carbon scenario > medium-carbon scenario > low-carbon scenario.

References

- [1] Meng Xianyong, Wang Hao, Lei Xiaohui, et al. Simulation, validation and analysis of hydrological components of the Jing and Bo River Basin based on the SWAT model driven by CMADS[J]. *Acta Ecologica Sinica*, 2017, 37(21): 7114-7127.
- [2] Sun Ying. Impact of human activities on the climate system: an interpretation of Chapter III of the WG I report of IPCC AR6[J]. *Transactions of Atmospheric Sciences*, 2021, 44(5): 654-657.
- [3] Han Ziyang, Meng Jijun, Zou Yi. Spatio-temporal variation analysis of blue-green water safety in the middle reaches of the Heihe River Basin based on the SWAT model[J]. *Acta Ecologica Sinica*, 2024, 44(15): 6473-6486.
- [4] Falkenmark M. Eco-conflicts—the water cycle perspective[J]. *Environmental and Conflict Project, Occasional Report*, 1995, 14: 31-47.
- [5] Zhao Anzhou, Zhao Yuling, Liu Xianfeng, et al. Impact of human activities and climate variability on green and blue water resources in the Weihe River Basin of Northwest China[J]. *Geographical Science*, 2016, 36(4): 571-579.
- [6] Huang Yiting, Yang Xiaoli, Wu Fan, et al. Response of blue and green water to climate and land-use change in the Hekouzheng-Longmen Region[J]. *China Rural Water and Hydropower*, 2024, 66(3): 24-33.
- [7] Zhang Shulan, Zhang Haijun, Wang Yanhui, et al. Influence of vegetation type on hydrological process at landscape scale in the upper reaches of Jinghe Basin[J]. *Geographical Science*, 2015, 35(2): 231-237.

- [8] Zhang Jie, Jia Shaofeng. Study on difference of blue-green water in Huangshui Basin and green water under different types of land use based on SWAT model[J]. *Journal of Water Resources and Water Engineering*, 2013, 24(4): 6–10.
- [9] Qi Wenhua, Jin Yihua, Yin Zhenhao, et al. Analysis of blue and green water scarcity based on the SWAT model in the Tumen River Basin[J]. *Acta Ecologica Sinica*, 2023, 43(8): 3116–3127.
- [10] Li Wenting, Yang Xiaoli, Ren Liliang. Effects of climate and land-use changes on blue and green water in the Ganjiang River Basin[J]. *Water Resources Protection*, 2022, 38(5): 166–173, 89.
- [11] Hordofa A T, Leta O T, Alamirew T, et al. Climate change impacts on blue and green water of Meki River Sub-Basin[J]. *Water Resources Management*, 2023, 37(6): 2835–2851.
- [12] Omani N, Srinivasan R, Smith P K, et al. Glacier mass balance simulation using SWAT distributed snow algorithm[J]. *Hydrological Sciences Journal – Journal des Sciences Hydrologiques*, 2017, 62(4): 546–560.
- [13] Luo Y, Arnold J, Liu S, et al. Inclusion of glacier processes for distributed hydrological modeling at basin scale with application to a watershed in Tianshan Mountains, Northwest China[J]. *Journal of Hydrology*, 2013, 477: 72–85.
- [14] Schaffhauser T, Tuo Y, Hofmeister F, et al. SWAT-GL: A new glacier routine for the hydrological model SWAT[J]. *Journal of the American Water Resources Association*, 2024, 60(3): 755–766.
- [15] Li Jiaqiang, Chen Yaning, Li Weihong, et al. Variation features of precipitation and runoff of the middle-small rivers in the northern piedmont of the Tianshan Mountains: A case of Jinghe River[J]. *Arid Land Geography*, 2010, 33(4): 615–622.
- [16] Zhang Jinyan, Wu Zhaopeng, Yu Hui, et al. Spatiotemporal variation of soil nutrients during the oasisification process in the Jinghe River Basin in an arid region[J]. *Chinese Journal of Agricultural Resources and Regional Planning*, 2020, 41(2): 252–260.
- [17] Ren Manli. Research on runoff simulation in Ebinur Lake Basin based on SWAT model[D]. Urumqi: Xinjiang University, 2013.
- [18] Wang Yuejian. Study on changes in water resources of lake-basin watersheds in arid areas and their influence on ecological security: A case study of the Ebinur Lake Basin in Xinjiang[D]. Urumqi: Xinjiang University, 2018. [Wang Yuejian. Study on the Influence of the Change of Water Resources and Its Impact on Ecological Security in the Arid Region: An Example of Ebinur Lake Basin in Xinjiang[D]. Urumqi: Xinjiang University, 2018.]
- [19] Luo Yingxue, Xu Changchun, Chu Zhi, et al. Application of CN05.1 meteorological data in watershed hydrological simulation: a case study of the Kaidu

River Basin in Xinjiang[J]. *Advances in Climate Change Research*, 2020, 16(3): 287-295. [Luo Yingxue, Xu Changchun, Chu Zhi, et al. Application of CN05.1 meteorological data in watershed hydrological simulation: A case study in the upper reaches of Kaidu River Basin[J]. *Climate Change Research*, 2020, 16(3): 287-295.]

[20] Benavidez-Brook L, Taheripour F, Baldos U, et al. Updates in assessing soil organic carbon and their implications for evaluating land use change emissions[J]. *Environmental Research Communications*, 2026, 8(2): 025013.

[21] Pfeffer W T, Arendt A A, Bliss A, et al. The Randolph Glacier Inventory: A globally complete inventory of glaciers[J]. *Journal of Glaciology*, 2014, 60(221): 537-552.

[22] Farinotti D, Huss M, Furst J J, et al. A consensus estimate for the ice thickness distribution of all glaciers on Earth[J]. *Nature Geoscience*, 2019, 12(3): 168-173.

[23] Li Feng, Hu Tiesong, Huang Huajin. Research on the principle, structure, and application of the SWAT model[J]. *China Rural Water and Hydropower*, 2008, 50(3): 24-28. [Li Feng, Hu Tiesong, Huang Huajin. Research on the principle, structure and application of SWAT model[J]. *China Rural Water and Hydropower*, 2008, 50(3): 24-28.]

[24] Zhang Weibin, Zha Xiaochun, Ma Yugai. Spatio-temporal variation of blue-water and green-water resources in the source region of the Yellow River during 1961-2010[J]. *Bulletin of Soil and Water Conservation*, 2014, 34(6): 338-343. [Zhang Weibin, Zha Xiaochun, Ma Yugai. Spatio-temporal change of blue water and green water resources in source region of Yellow River during 1961-2010[J]. *Bulletin of Soil and Water Conservation*, 2014, 34(6): 338-343.]

[25] Kang Wendong, Ni Fuquan, Deng Yu, et al. Response of blue and green water in the Wujiang River Basin to climate and land-use change[J]. *Transactions of the Chinese Society of Agricultural Engineering*, 2023, 39(19): 131-140. [Kang Wendong, Ni Fuquan, Deng Yu, et al. Response of blue and green water to climate and land use changes: A study in the Wujiang River Basin, China[J]. *Transactions of the Chinese Society of Agricultural Engineering*, 2023, 39(19): 131-140.]

[26] Wang Baosheng, Liao Jiangfu, Zhu Wei, et al. Neighborhood weight setting for the FLUS model based on historical scenarios: a case study of land-use simulation for the Southern Fujian Golden Triangle urban agglomeration in 2030[J]. *Acta Ecologica Sinica*, 2019, 39(12): 4284-4298. [Wang Baosheng, Liao Jiangfu, Zhu Wei, et al. The weight of neighborhood setting of the FLUS model based on a historical scenario: A case study of land use simulation of urban agglomeration of the Golden Triangle of Southern Fujian in 2030[J]. *Acta Ecologica Sinica*, 2019, 39(12): 4284-4298.]

[27] Chen Aijiao. Impact of two statistical downscaling methods on projections of climate change in the northeastern Tibetan Plateau[D]. Xi'an: Northwest

University, 2021. [Chen Aijiao. Impact of Two Statistical Downscaling Methods on Projecting Climate Change in the Northeast Tibetan Plateau[D]. Xi'an: Northwest University, 2021.]

[28] Li Qian, Zhang Jing, Gong Huili. Hydrological simulation and parameter uncertainty analysis of the Guishui River Basin based on the SUFI-2 algorithm and the SWAT model[J]. Journal of China Hydrology, 2015, 35(3): 43-48. [Li Qian, Zhang Jing, Gong Huili. Hydrological simulation and parameter uncertainty analysis using SWAT model based on SUFI-2 algorithm for Guishuihe River Basin[J]. Journal of China Hydrology, 2015, 35(3): 43-48.]

[29] Moriasi D N, Arnold J G, Van Liew M W, et al. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations[J]. Transactions of the ASABE, 2007, 50(3): 885-900.

[30] Tian Haowei. Runoff response and adaptive countermeasures in the Jinghe River Basin under changing environments[D]. Shihezi: Shihezi University, 2023. [Tian Haowei. Runoff Response and Adaptive Measures in the Jinghe River Basin Under Changing Environments[D]. Shihezi: Shihezi University, 2023.]

[31] Zhan Mingyue. Study on the impact of vegetation greening in China on terrestrial evapotranspiration based on model data[D]. Nanjing: Nanjing University of Information Science & Technology, 2022. [Zhan Mingyue. Study on the Impact of Vegetation Greening in China on Terrestrial Evapotranspiration Based on Model Data[D]. Nanjing: Nanjing University of Information Science & Technology, 2022.]

[32] Nafees Ahmad H M, Sinclair A, Jamieson R, et al. Modeling sediment and nitrogen export from a rural watershed in eastern Canada using the soil and water assessment tool[J]. Journal of Environmental Quality, 2011, 40(4): 1182-1194.

Applicability of SWAT-GL and spatiotemporal distribution characteristics of blue and green water in the Jinghe River Basin, Xinjiang

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Abstract: This study applied the soil and water assessment tool (SWAT)-GL model to analyze the sensitivity of glacial meltwater-driven hydrological processes to climate and land use changes in the arid region of the Jinghe River Basin, Xinjiang, and to propose targeted control and adaptive measures. The SWAT-GL model overcomes the simulation limitations of the traditional SWAT model in glacial meltwater-supplied basins. It systematically analyzes the spatiotemporal evolution patterns of blue and green water and constructs a multi-model coupling framework integrating SWAT-GL, Future Land-Use Simulation, and Coupled Model Intercomparison Project Phase 6 to predict spatiotemporal changes in blue and green water under different scenarios and propose adaptive management strategies. The results indicate the following: (1) During the calibration and validation periods, the SWAT-GL model achieved R^2 and NSE values both greater than 0.7, demonstrating improved accuracy compared to the traditional SWAT model, with good agreement between simulated and observed runoff. (2) Blue water accounts for 52% of the basin's water resources, showing no significant interannual trend, whereas green water, accounting for 48%, increases in tandem with precipitation. Spatially, blue water decreases from upstream to downstream, whereas green water exhibits a pattern of low values upstream, fluctuations at midstream, and high values downstream. The model detected significant spatiotemporal differences in the distribution characteristics of blue and green water across different years. (3) Under future climate scenarios, precipitation increases, with temperatures following the order high-carbon>medium-carbon>low-carbon. Blue water is projected to decrease while green water increases, maintaining the overall spatial pattern of declining blue water and rising green water, with high-carbon scenarios exerting the strongest influence.

Keywords: SWAT-GL Model; blue water; green water; spatiotemporal distribution; Jinghe River Basin

Note: Figure translations are in progress. See original paper for figures.

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