

Article

Coupled PLUS and SWAT Model Assessment of Streamflow Response to Climate Change and Human Interventions in Arid Alpine Regions: A Case Study of the Zamu River, China

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Abstract: Climate change and human interventions have exerted a long-term influence on variations in continental streamflow. Despite this, the precise mechanisms by which these factors regulate the change in streamflow remain inadequately understood, especially in arid alpine regions, due to the limited number of observations which exacerbates difficulties in comprehensively assessing streamflow alterations. Consequently, assessing the impacts of climate change and human interventions on streamflow is a challenge in data-scarce regions. Here, using the Zamu River as an example, we analyzed streamflow changes in arid alpine regions using a method that integrates the Patch-generated Land Use Simulation model, the Soil and Water Assessment Tool, and the Coupled Model Intercomparison Project Phase 6. Our analysis highlighted that climate change primarily drove streamflow variations in the Zamu River, accounting for over 80% of the observed contributions. This influence was further amplified by the effects of future climate and changes in land use and land cover, resulting in increased streamflow. Additionally, precipitation emerged as the main factor driving the rise in streamflow. These findings emphasize the significant impact of climate change on water cycles in arid alpine regions and underscore the necessity for tailored water resource management strategies to ensure sustainable regional development and effective climate change adaptation.

Keywords: streamflow; climate change; land use/cover change; SWAT model; arid alpine region



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1. Introduction

Arid alpine regions are highly vulnerable to climate and hydrological changes [1–3]. These regions have fragile water resources and are prone to frequent extreme hydrological events; the complexity of river streamflow variations in these areas surpasses that observed in other global regions [2,4]. Recent years have witnessed profound and sustained transformations in the global hydrological cycle, driven both by climate change and human intervention [5–7]. Historical reconstructions of global streamflow data have indicated a significant increasing trend in river streamflow since the last century [8–10]. These impacts have been particularly pronounced and significantly amplified in arid alpine regions [11,12].

Separating the contributions of climate change and human intervention to streamflow is challenging [13–15]. Arid alpine regions, which serve as sources for many major rivers and provide essential water supplies to surrounding drylands, are particularly affected by these factors. However, traditional hydrological analyses are limited by insufficient flow

measurement instruments, short or intermittent flow records, and restrictive data-sharing policies, hindering our understanding of the causes of flow changes in these regions [16,17]. To address this issue, there is an urgent need for research on hydrological processes in arid alpine regions [16–18].

Using hydrological conceptual models to distinguish the effects of different drivers on streamflow changes is a valuable methodological approach [12,19,20]. Currently, hydrological models such as Variable Infiltration Capacity (VIC), the Distributed Hydrology Soil Vegetation Model (DHSVM), Hydrologiska Byråns Vattenbalansavdelning (HBV), and the Soil and Water Assessment Tool (SWAT) have been extensively utilized to examine the effects of hydrological processes [21–25], offering significant insights into the interactions between climate change, land use/land cover change (LUCC), and hydrological processes. The SWAT model is particularly widely used for its capability to integrate multiple climates and LUCC scenarios while simulating distributed hydrological processes. Its effectiveness is especially notable in the hydrological processes of arid alpine regions [24–27].

Current research on streamflow drivers in arid alpine regions often overlooks the combined impact of climate change and LUCC on streamflow. Instead, studies typically focus on either the isolated impacts of climate change [28–30] or the effects of a single climate model and LUCC [31]. This limitation hinders our understanding of streamflow changes and complicates effective water resource management [4]. While recent studies have increasingly integrated climate models [32–34] to predict future climate impacts and human interventions, this approach has primarily been applied in humid areas [18,34]. In contrast, there remains a dearth of research in arid alpine regions, where observational data are scarce.

The main objectives of this study were to (1) develop a methodological framework for attributing variations in streamflow to both climate change and human interventions in arid alpine environments, (2) analyze the streamflow evolution characteristics under different climate change scenarios and human disturbances, and (3) identify the primary factors influencing streamflow in arid alpine regions. The findings are anticipated to provide theoretical foundations for the management and sustainable use of water resources in arid alpine regions, enhance the maintenance of regional hydrological balance, and assist in mitigating the effects of climate change.

2. Methods and Materials

2.1. Study Area

To investigate the streamflow dynamics in arid alpine regions, we selected the Zamu River (ZMR) in northwest China as our study area (Figure 1). This basin features significant elevation differences and a distinct vertical zonation. The area of the basin is approximately 851 km², with the main land use/cover change (LUCC) types being grassland (47%) and forest (18%). The elevation within the basin ranges from 1996 m to 4805 m, with the terrain generally higher in the west and lower in the east. The landscape is primarily composed of mountains and river valley basins, featuring significant elevation differences and distinct vertical zonation. The dominant soil types are Eutric Leptosols and Gelic Leptosols, with a soil moisture around 5%. The basin experiences a typical continental temperate arid to semi-arid climate, characterized by complex and variable meteorological and hydrological conditions, and the annual average temperature fluctuates between 2 °C and 8 °C, with potential evaporation between 2000 mm and 3000 mm, and annual precipitation from 237 mm to 628 mm, resulting in complex meteorological and hydrological conditions. The average annual streamflow is approximately 6.5 m³/s [35]. Recently, both climate change and anthropogenic factors have influenced streamflow patterns in the ZMR [36], but the specific causes of these changes remain unclear. Thus, we chose this study area to explore streamflow variations in similar environments.

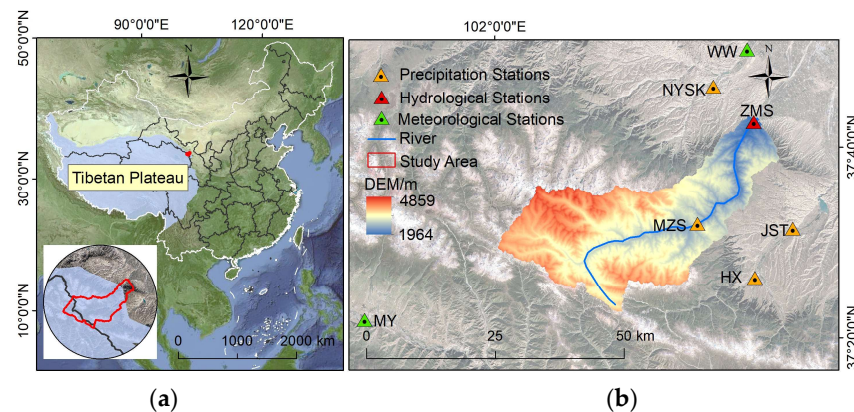


Figure 1. Location of the ZMR basin. (a) describes the location of the ZMR basin in China. (b) illustrates the environmental context of the ZMR basin, where DEM stands for Digital Elevation Model. The abbreviations used in the diagram are provided in Supplementary Materials Table S1.

2.2. Methods

2.2.1. Research Method

To clarify streamflow dynamics in arid alpine regions under various climate change scenarios and human disturbances, we employed an integrated research method that combines the PLUS model, SWAT model, and CMIP6 projections. This method effectively distinguishes between the impacts of climate change from those caused by human interventions in these environments. We quantified streamflow variations across different climate and disturbance scenarios, identified the key factors influencing changes in streamflow, and proposed adaptive management strategies (Figure 2).

2.2.2. Data Sources

The data for this study primarily comprised remote sensing imagery, reanalysis products, hydrological station observations, CMIP6 model projections, and socio-economic statistics, and these were used for LUCC and streamflow simulations. In the PLUS model, we selected two economic factors (Economic density and Night light data), eight natural factors (Altitude, Slope gradient, Distance from the river, Soil type, Soil depth, Average annual precipitation, Annual average temperature, and Vegetation coverage), four social factors (Population density, Distance from railway, Distance from road, and Distance from main residential areas), and one limiting factor (Qilian Mountain National Nature Reserve) as driving variables. The LUCC data were obtained from the Resource and Environment Science Data Center (<http://www.resdc.cn>, accessed on 25 June 2022), specifically the China Land Use Status Remote Sensing Monitoring Database for the years 1990, 2000, 2010, and 2020. In the SWAT model, the daily streamflow data were obtained from the observations at the Zamusi (ZMS) hydrology station, while daily precipitation data were sourced from six rain and precipitation stations, including Maozangsi (MZS), Haxi (HX), Longgou (LG), and Wushaoling (WSL). Daily temperature data were retrieved from the Daily Values of the China Surface Climatological Data Dataset V3.0 (<https://data.cma.cn/>, accessed on 10 January 2020), with data from the Wuwei (WW) and Menyuan (MY) stations. For climate change assessment, we selected three emission scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5) from four GCMs in the CMIP6 dataset (<https://esgf-node.llnl.gov/projects/cmip6/>, accessed on 10 June 2024). Detailed information regarding the data sources and preprocessing methods can be found in the Supplementary Materials. All data were extracted using masking, projection transformations, and resampling procedures. The projection coordinate system used was GCS_WGS_1984, with a spatial resolution of 30 m × 30 m.

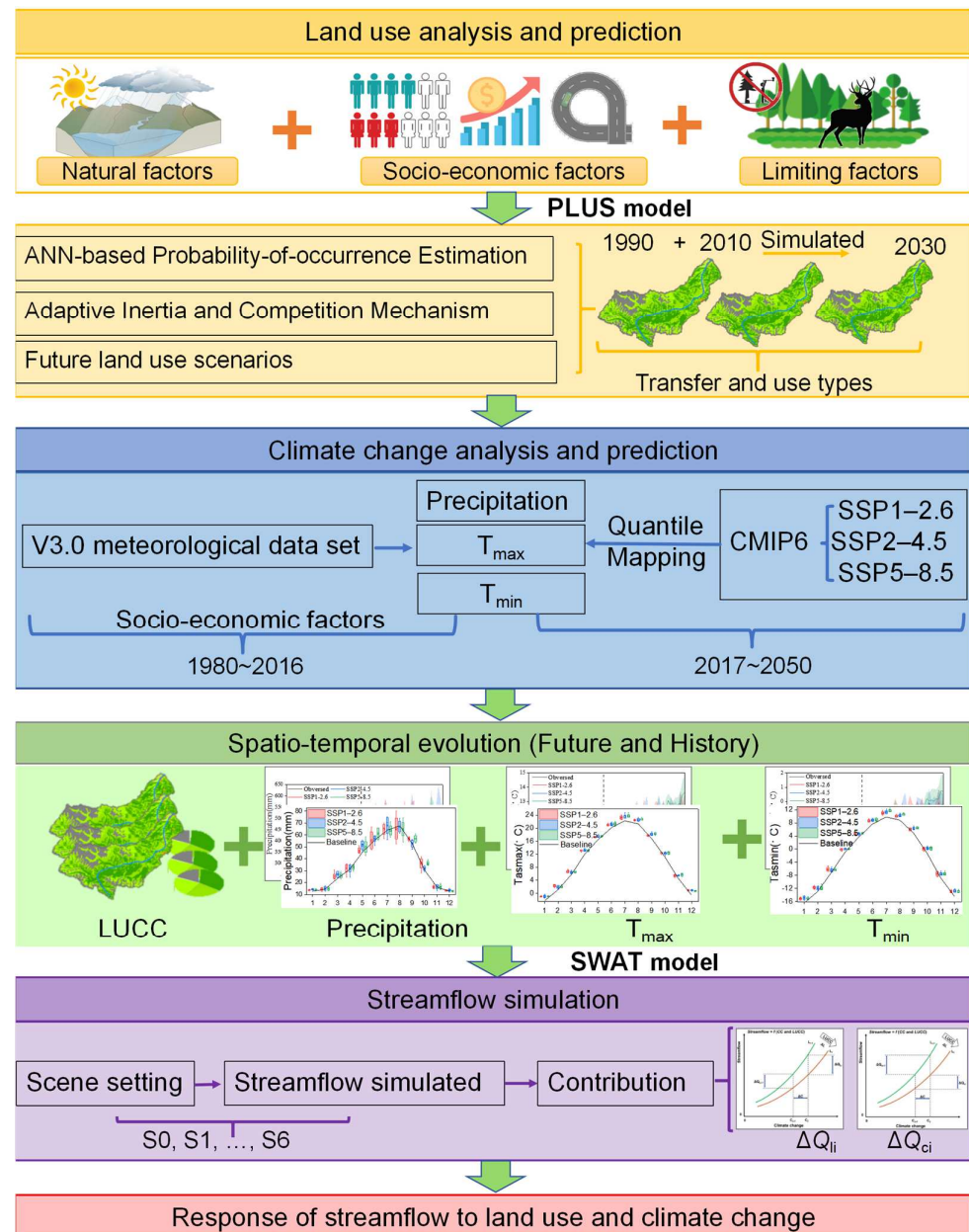


Figure 2. Streamflow research method. Note: The abbreviations illustrated in the diagram are defined in Table S1 of the Supplementary Materials.

2.2.3. Approaches to LUCC Measurement and Simulation

The PLUS model (Version 1.3.5) is used to predict future LUCC scenarios, incorporating the land expansion strategy analysis module (LEAS) along with the cellular automata model using multi-class random patch seeds (CARS) [37]. Known for its advanced simulation capabilities, the PLUS model is widely applied in urban planning, agricultural land management, and ecological conservation [37,38]. We utilized 30 m × 30 m LUCC data to classify the ZMR basin into seven land use types: Cultivated Land (CL), Forest Land (FL), Water Body (WB), Urban Land (UrL), Unutilized Land (UnL), High-Cover Grassland (HCG), Medium-Cover Grassland (MCG), and Low-Cover Grassland (LCG). The PLUS model was used to simulate LUCC for the years 2000, 2010, and 2020. The simulated results were then compared with observed data to assess the model's applicability and validate its accuracy. The simulated results for 2010 were validated against actual LUCC data. Between 1990 and 2010, the major land use changes in the basin occurred in forest land, high-cover grassland, medium-cover grassland, and unutilized land, which together accounted for

more than 95% of the total change in land area. Specifically, 3.25 km² of forest land was converted to other land use types, with 74.33% of it transitioning to high-cover grassland. Additionally, 2.64 km² of high-cover grassland was converted to other land use types, with 84.68% transitioning to forest land. Furthermore, 2.04 km² of medium-cover grassland was converted to other land use types, with 39.31% transitioning to high-cover grassland. Lastly, 1.22 km² of unutilized land was converted to other land use types, with 90.70% transitioning to medium-cover grassland. Further details regarding the model composition, parameter settings, and verification processes can be found in the Supplementary Materials (Test S1, Tables S3 and S4).

To assess LUCC dynamics over an extended timeframe in the study area, a LUCC transition matrix is applied to illustrate the evolving change among various LUCC categories from the start to the conclusion of the study period [39,40]. The formulation of this matrix is presented in Equation (1), as follows.

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \quad (1)$$

where S represents the area (km²) and n represents the total number of LUCC types, while i and j correspond to the LUCC types at the start and conclusion of the study period, respectively.

2.2.4. Streamflow Modeling Methods

The SWAT model was employed to simulate streamflow in watersheds [24]. This model is built on the water balance equation and is known for requiring fewer input parameters, providing superior spatial visualization, and yielding more reliable simulation results compared to other hydrological models [24,41,42]. The water balance equation used in the SWAT model is as follows.

$$SW_t = SW_0 - SW_s \quad (2)$$

$$SW_s = \sum_{i=1}^t (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad (3)$$

where SW_t represents the water content of the soil's water content at the end of the period, while SW_0 denotes the soil's water content at the start of the period. SW_s signifies the cumulative value of the differences among precipitation (R_{day}), surface streamflow (Q_{surf}), evapotranspiration (E_a), soil profile infiltration into the vadose zone (W_{seep}), and groundwater regression flow (Q_{gw}) over the time period t . All these physical quantities are measured in millimeters (mm).

In the SWAT model (Version 10.2), Sequential Uncertainty Fitting version 2 was selected, and 230 Hydrological Response Units (HRU) were established with a 5% threshold. The calibration period (1985–2000) and validation period (2001–2016) were established.

Through sensitivity analysis, eleven parameters significantly influencing flow were identified for calibration (Table S2). To comprehensively assess the simulation performance of the model, we employed a suite of metrics to evaluate the accuracy of the simulation, such as the following: the Nash–Sutcliffe Efficiency (NSE) to assess the model's goodness-of-fit, the Coefficient of Determination (R^2) to measure the model's ability to explain the variability in the data, the Kling–Gupta Efficiency (KGE) which takes into account bias, variance, and correlation, and the Percentage Bias ($PBIAS$) to gauge the degree of deviation

between the model's predictions and observed values [42,43]. The relevant formulas (4)–(7) for each metric are as follows:

$$NSE = 1 - \frac{\sum_{i=1}^n (S - M)^2}{\sum_{i=1}^n (S - \bar{M})^2} \quad (4)$$

$$R^2 = \frac{[\sum_{i=1}^n (M - \bar{M})(S - \bar{S})]^2}{\sum_{i=1}^n (M - \bar{M})^2 (S - \bar{S})^2} \quad (5)$$

$$KGE = 1 - \sqrt{(R - 1)^2 + \left(\frac{\sigma_s}{\sigma_o} - 1\right)^2 + \left(\frac{\bar{M}}{\bar{S}} - 1\right)^2} \quad (6)$$

$$PBIAS = \frac{\sum_{i=1}^n (M - S)}{\sum_{i=1}^n S} \times 100\% \quad (7)$$

where M represents the simulated value at time i , and $\bar{M}$ denotes the simulated average value at time i . S_i is the measured value at time i , with $\bar{S}$ being the measured average value at time i . All units are expressed in m^3s^{-1} . The number of time periods is denoted by n , R is the correlation coefficient, σ_s is the standard deviation of the simulated values, and σ_o is the standard deviation of the measured values. Improved simulation performance is indicated by efficiency coefficients (i.e., NSE , R^2 , KGE) approaching 1 and $PBIAS$ values nearing 0.

2.2.5. Methods for Processing Climate Models

CMIP6 includes more than 50 climate models from 14 countries [44]. Based on the research by Wang et al. on the arid alpine region of China [44–46], we considered model data from multiple countries, resolution differences, and data availability when selecting climate models. As a result, we identified four CMIP6 climate models (GCMs) that are particularly suitable for the arid alpine region of northwest China and cover the full historical and future periods: EC-Earth3-veg, FGOALS-g3, GFDL-ESM4, and IPSL-CM6A-LR. These models have been validated to accurately simulate the complex climatic conditions of arid alpine regions, particularly with respect to precipitation [44–46]. For emission scenarios, we referred to prior studies [44–46] and selected data from three scenarios—SSP1–2.6, SSP2–4.5, and SSP5–8.5—representing low, medium, and high emission levels, respectively (Table 1).

To enhance the accuracy of the research, we performed bias correction on the datasets and applied a multi-model equal-weighted averaging method to obtain the multi-model ensemble (MME). The bias-corrected datasets reflect change in climate variability and atmospheric means. Data were collected for two periods (i.e., the historical period (1985–2017) and the future projection period (2018–2050)). This methodology ensures that future stream-flow projections account for both historical climate variability and anticipated change under different emission scenarios.

Precipitation, maximum temperature ($T_{\max}$), and minimum temperature ($T_{\min}$) data from four General Circulation Models (GCMs) selected from CMIP6 were spatially down-scaled to a resolution of $0.5^\circ \times 0.5^\circ$ using the angular distance weighting interpolation method [17,34]. Subsequently, quantile mapping (QM) was applied to correct for deviations, with the correction effectiveness assessed through a Taylor diagram [47,48].

The QM method establishes a transfer function by leveraging the cumulative probability distribution functions derived from the observed and simulated data within the historical period to calibrate the simulated values for future periods [47,48]. When applied to precipitation and temperature correction, the QM method demonstrated high perfor-

mance by substantially reducing system biases during the verification period, thereby providing more accurate and reliable predictive outcomes.

$$Y = F_o^{-1} \left[F_{b,n} \left(X_{f,n} \right) \right] \quad (8)$$

where Y represents the corrected value. F_o denotes the empirical cumulative distribution function (CDF) of the observed data, while $F_{b,n}$ refers to the empirical CDF of model n during the historical period. $X_{f,n}$ represents the original data from model n for the prediction period.

Table 1. Information of 4 GCMs from CMIP6.

GCMs	Institutions	Lon. × Lat.
FGOALS_g3	The Institute of Atmospheric Physics, Chinese Academy of Sciences (CAS)	2° × 2°
GFDL_ESM4	Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Research (USA)	1.25° × 1.0°
IPSL_CM6A_LR	Institut Pierre-Simon Laplace (IPSL)	2.5° × 1.25°
EC-Earth3_veg	European EC-Earth Consortium (Europe)	0.703° × 0.703°

2.2.6. Setting of Simulation Scenarios

To thoroughly evaluate the effects and relative contributions of climate change and LUCC on the hydrological processes of the ZMR, seven distinct scenarios were delineated [23,34,49]. These scenarios utilized meteorological data from two historical periods (1985–2000 and 2001–2016) and future projections (2017–2050), coupled with LUCC data from the year 1990, 2010, and 2030 (Table 2).

Table 2. Scenario setting and basis.

Scenario	Description	Climate	Land Use	Symbol
S0	Basic scenario	1985–2000	1990	$Q_{I_1}^{c_1}$
S1	Climate scenario	2001–2016	1990	$Q_{I_1}^{c_2}$
S2	LUCC scenario	1985–2000	2010	$Q_{I_2}^{c_1}$
S3	Comprehensive scenario	2001–2016	2010	$Q_{I_2}^{c_2}$
S4	Future climate scenario	2017–2050 (i.e., SSP1–2.6, SSP2–4.5, and SSP5–8.5)	2010	$Q_{I_2}^{c_{3-1.26}}$
S5	Future LUCC scenarios	2001–2016	2030	$Q_{I_3}^{c_2}$
S6	Future comprehensive scenario	2017–2050 (i.e., SSP1–2.6, SSP2–4.5, and SSP5–8.5)	2030	$Q_{I_3}^{c_{3-1.26}}$

Scenario S0 (Basic scenario): Utilizes meteorological data from 1985 to 2000 alongside LUCC data from 1990, serving as a reference point for comparative analysis.

Scenario S1 (Climate scenario): Substitutes the baseline meteorological data with records from 2001 to 2016 to isolate the effects of climate change on watershed hydrological components.

Scenario S2 (LUCC scenario): Updates LUCC data to 2010 while retaining the baseline meteorological data to assess the impact of LUCC on hydrological components.

Scenario S3 (Comprehensive scenario): Employs meteorological data from 2001 to 2016 and LUCC data from 2010 to evaluate the combined effects of climate change and LUCC on hydrological components.

Scenario S4 (Future climate scenario): Builds on Scenario S3 by incorporating future meteorological projections from 2017 to 2050 to investigate the impact of future climate change on hydrological components.

Scenario S5 (Future LUCC scenarios): Expands upon Scenario S3 by integrating future LUCC projections for 2030 to analyze the effects of anticipated LUCC on hydrological components.

Scenario S6 (Future comprehensive scenario): Advances Scenario S3 by incorporating both future meteorological projections (2017–2050) and future LUCC data (2030) to forecast the response of hydrological components to the combined influence of future climate change and LUCC.

2.2.7. Analytical Approaches for Attributing Streamflow Variations

To elucidate the intricate nonlinear relationship arising from the interaction between LUCC and climate change, we adopted the method proposed by Yang et al. (2017) [50] to estimate the contribution of each factor to the change in streamflow, distinguishing the individual contributions of LUCC and climate change, followed by attribution analysis. The method utilized formulas given as (9)–(13):

$$\Delta Q_{ci} = \frac{1}{2} \left[\left(Q_{li}^{ci+1} - Q_{li}^{ci} \right) + \left(Q_{li+1}^{ci+1} - Q_{li+1}^{ci} \right) \right] \quad (9)$$

$$\Delta Q_{li} = \frac{1}{2} \left[\left(Q_{li+1}^{ci+1} - Q_{li}^{ci+1} \right) + \left(Q_{li+1}^{ci} - Q_{li}^{ci} \right) \right] \quad (10)$$

$$\Delta Q_i = \Delta Q_{ci} + \Delta Q_{li} = Q_{li+1}^{ci+1} - Q_{li}^{ci} \quad (11)$$

$$Q_{ci} = \frac{\Delta Q_{ci}}{\Delta Q_i} \quad (12)$$

$$Q_{li} = \frac{\Delta Q_{li}}{\Delta Q_i} \quad (13)$$

where i and $i + 1$ correspond to the data for the current and previous periods, respectively, ΔQ_{li}^{ci} represents the contribution of the combined i -th period climate data and i -th period LUCC data to streamflow, ΔQ_{ci} denotes the contribution of climate change to streamflow, ΔQ_{li} represents the contribution of LUCC to streamflow, ΔQ_i indicates the combined contribution of LUCC and climate change to streamflow, Q_{li} represents the contribution rate of LUCC to streamflow, and Q_{ci} represents the contribution rate of climate change to streamflow.

3. Results

3.1. LUCC Simulation Verification and Process Analysis

3.1.1. LUCC Simulation Verification

The PLUS model was used to simulate LUCC for the years 2000, 2010, and 2020. The simulation accuracy was evaluated using Overall Accuracy (OA) and the Kappa coefficient, with values close to 1 indicating high precision. The simulated LUCC for 2000, 2010, and 2020 were compared with the actual LUCC data; the OA for the three periods were 90.35%, 93.62%, and 92.32%, respectively, and the Kappa coefficients were 0.85, 0.90, and 0.88. These high values demonstrate the satisfactory accuracy of the simulation, and Figure 3 confirms the robust applicability of the PLUS model for this study. The calibrated PLUS model was then used to simulate land use changes for 2030 (Figure 3a).

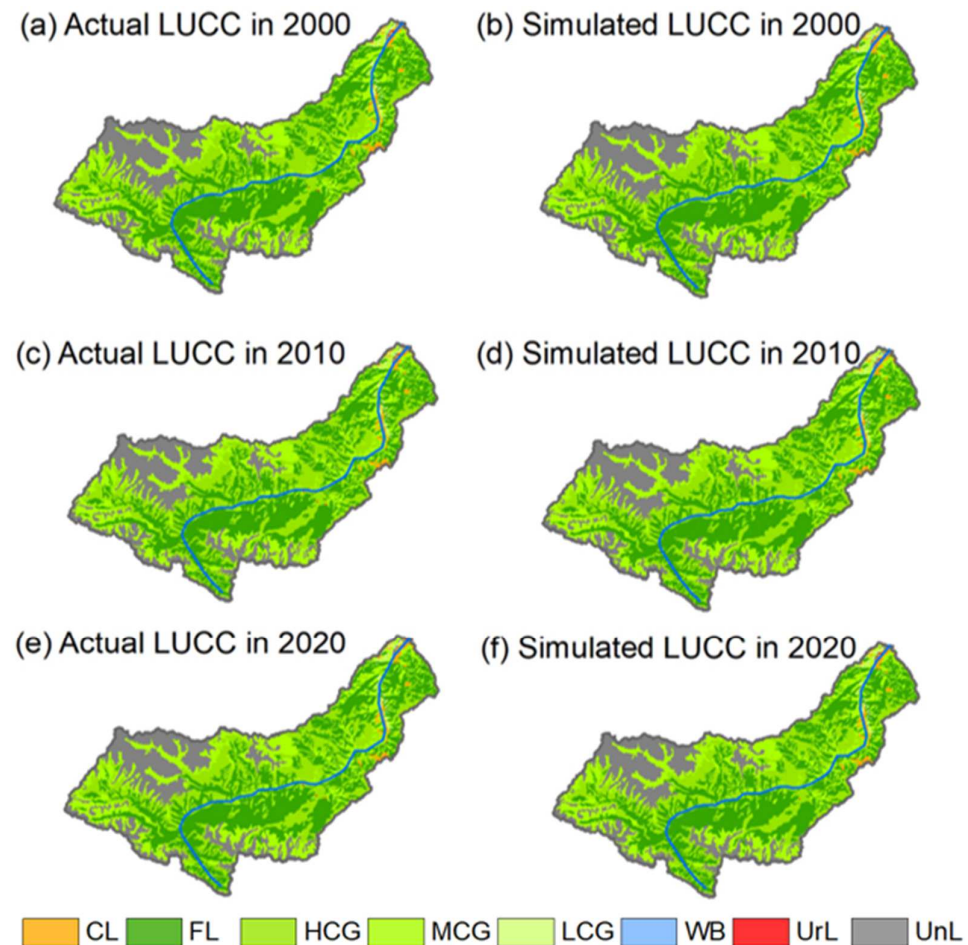


Figure 3. Status and simulated LUCC type in 2000, 2010, and 2020. Note: The abbreviations CL, FL, WB, UrL, UnL, HCG, MCG, and LCG represent cultivated land, forest land, water body, urban land, unutilized land, high-cover grassland, medium-coverage grassland, and low-cover grassland, respectively.

3.1.2. Process of LUCC

The spatial distribution of LUCC patterns in the ZMR displays significant variability. Unused land clusters in the higher altitudes to the northwest, while construction land is dispersed along the lower-altitude eastern riverbanks. Grass land and forest land interweave throughout the basin, with water bodies flowing from northwest to northeast (Figure 4a). The primary land cover in the ZMR consists of forest land (33.88% to 34.00%), high-cover grassland (23.90% to 24.11%), and medium-coverage grassland (22.26% to 22.44%). From 1990 to 2030, notable changes primarily occurred in forest land, grassland, and unused land, which together represent over 95% of the total land area change (Figure 4b).

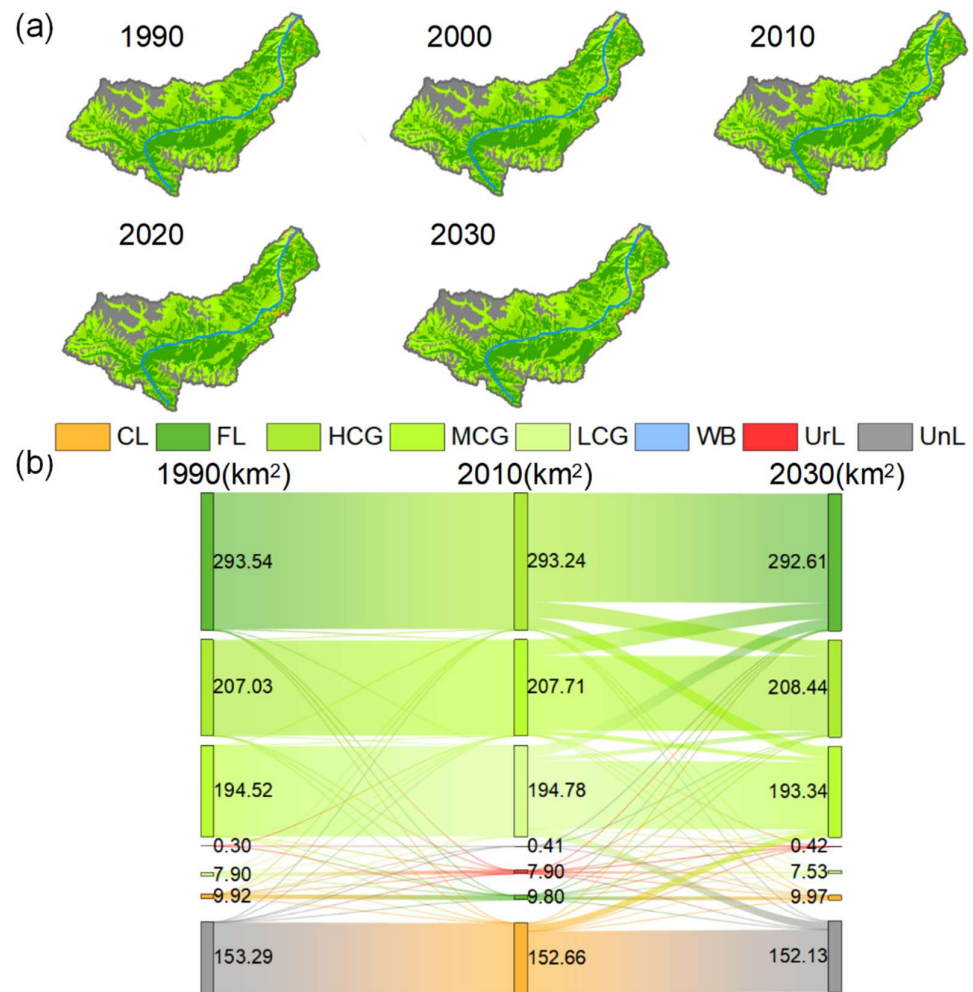


Figure 4. LUCC in the ZMR from 1990 to 2030. (a) represents the spatial distribution of land use in ZMR from 1990 to 2030. (b) represents the land use change in ZMR from 1990 to 2030. Note: Abbreviations have the same meanings as in the caption of Figure 3.

3.2. Simulation and Validation of Hydrometeorological Data

3.2.1. Streamflow Simulation Verification

The SWAT model was driven by daily precipitation and temperature inputs, with its parameters calibrated and validated through the utilization of monthly streamflow records obtained from the Zamusi hydrological station. Figure 5 illustrates the evaluation of monthly streamflow simulation performance assessment for the calibration period (1985 to 2000) and the validation period (2001 to 2016) for the Zamu River. The calibration results had an $NSE = 0.8$, $R^2 = 0.79$, and $PBIAS = 5.6\%$, while the validation results had an $NSE = 0.73$, $R^2 = 0.7$, and $PBIAS = 10.8\%$. The streamflow simulation at the Zamusi hydrological station met the criteria of $NSE \geq 0.7$, $R^2 \geq 0.7$, and $PBIAS \leq 20\%$. The KGE values for the calibration and validation periods were recorded as 0.88 and 0.81, respectively. The simulated streamflow process aligns closely with the observed streamflow, particularly showing high consistency between simulated and measured base flow values (Figure 5a). During the calibration period, the scatter points of simulated vs. observed values are mostly near the 1:1 line, indicating that the simulation values accurately reflect reality. Although the scatter points during the validation period are slightly more dispersed than during calibration, most points still cluster around the 1:1 line, suggesting a high confidence in the simulation results (Figure 5). Overall, the model's simulation results effectively reflect actual conditions, demonstrating satisfactory performance.

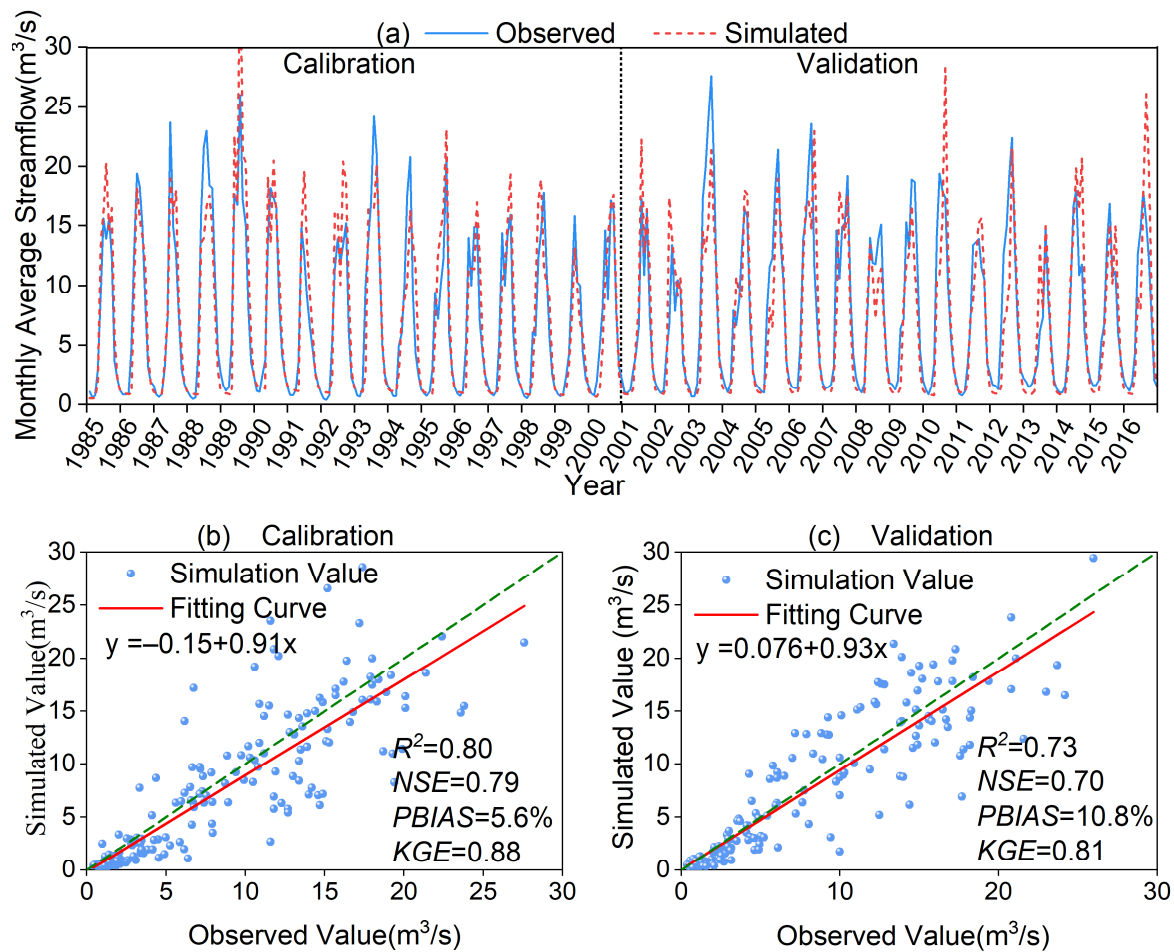


Figure 5. Observed and simulated monthly streamflow in the ZMR. (a) illustrates the comparison between SWAT-simulated streamflow and the monthly observational data from the Zamusi Hydrological Station spanning the period 1980–2016. (b) displays a scatter plot of observed versus simulated streamflow during the calibration phase, while (c) shows the same comparison for the validation phase. Note: The green dashed line represents the 1:1 line.

3.2.2. Validation of GCMs Simulation Results

As shown in Figure 6, the Taylor diagram represents the performance and error of the meteorological model after correction. The closer the meteorological element values to the observed data, the better the simulation performance. The simulated values for the maximum (Figure 6b) and minimum temperatures (Figure 6c) closely matched the observed values across different GCM models, whereas the accuracy of precipitation simulation (Figure 6a) was marginally lower. Notably, the MME exhibited the highest agreement with observed data, outperforming individual models. The MME model demonstrated strong simulation capabilities, with monthly correlation coefficients for precipitation, $T_{\max}$, and $T_{\min}$ of 0.78, 0.98, and 0.99, respectively. Thus, the MME model's results are deemed more reliable for projecting future meteorological change.

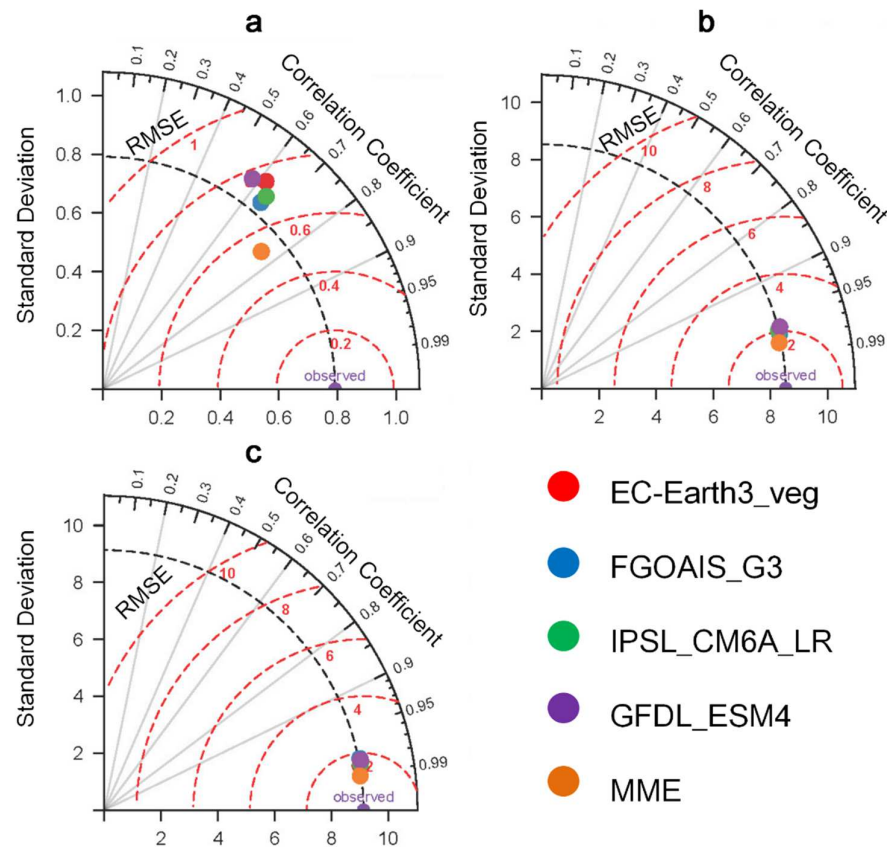


Figure 6. Taylor diagram of monthly precipitation, with $T_{\max}$ and $T_{\min}$ simulation results under different GCM models. (a) Simulation results for monthly precipitation. (b) Simulation results for $T_{\max}$. (c) Simulation results for $T_{\min}$.

3.3. Change in Climate and Hydrological Variables

3.3.1. Change in Precipitation

From 1985 to 2016, the annual average precipitation in the ZMR varied between 320 mm and 540 mm, with averages of 431.30 mm (1985–2000) and 435.55 mm (2001–2016), showing a historical trend of a 0.7 mm increase per decade. For 2017–2050, precipitation is projected to rise across all SSP scenarios (Figure 7a), with annual averages of 439.94 mm (SSP1–2.6), 455.75 mm (SSP2–4.5), and 449.17 mm (SSP5–8.5). The SSP5–8.5 scenario predicts the highest increase at 4.81 mm per decade, compared to 3.88 mm for SSP2–4.5 and 2.32 mm for SSP1–2.6, reflecting relative increase rates of 5.58%, 4.77%, and 3.41%, respectively.

The monthly precipitation from May to October is heavily concentrated, accounting for approximately 73% of the annual total (Figure 7b). Significant increases occur from March to July and September to October, with changes ranging from 1.58 to 4.51 mm, while other months see minor increases (<1 mm). Notably, January, March, May, and October show relative increases exceeding 10%, with October and May contributing most to the annual total. In SSP1–2.6 and SSP5–8.5, October accounts for 40.85% and 24.75% of the annual increment, while May contributes 28.66% in SSP2–4.5.

3.3.2. Change in Temperature

From 1985 to 2016, the watershed's annual average $T_{\max}$ and $T_{\min}$ were 10.75 °C and −2.26 °C, respectively (Figure 7). Between 2017 and 2050, projected increases in $T_{\max}$ and $T_{\min}$ under SSP scenarios range from 0.29 °C/decade to 0.33 °C/decade for $T_{\max}$ and 0.32 °C/decade to 0.38 °C/decade for $T_{\min}$. This indicates that as radiative forcing intensifies, $T_{\min}$ is expected to rise more than $T_{\max}$ annually.

Monthly, $T_{\max}$ and $T_{\min}$ peak in July, ranging from 23.30 °C to 27.76 °C and 10.99 °C to 11.92 °C, respectively. The lowest values occur in March, ranging from −1.40 °C to −0.96 °C

for $T_{\max}$ and -15.09°C to -14.89°C for $T_{\min}$. July experiences the largest temperature increases, with $T_{\max}$ rising by 1.12°C to 1.58°C and $T_{\min}$ by 1.22°C to 1.93°C , contributing 8.94% to 11.11% and 8.76% to 11.88% of the annual increments, respectively. In contrast, March shows the smallest increases. Overall, warming in spring is less pronounced than in other seasons across all the emission scenarios.

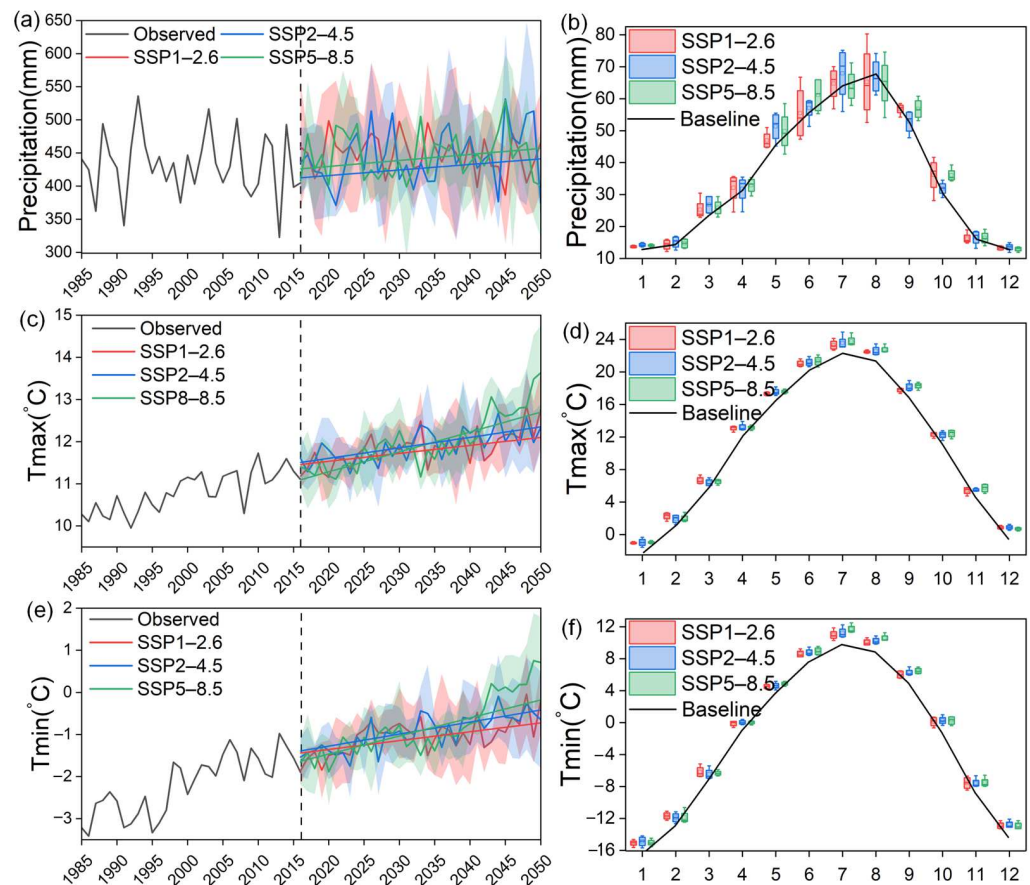


Figure 7. Annual and monthly change in precipitation (a,b), $T_{\max}$ (c,d), and $T_{\min}$ (e,f) from 1985 to 2050 in the ZMR. The 95% uncertainty bands are shown in the shaded region.

3.4. Response of Hydrological Factors to Climate Change and LUCC

3.4.1. Response of Annual Streamflow to Climate Change and LUCC

The ZMR's future streamflow is anticipated to experience an upward trend due to the influence of both climate change and alterations in LUCC, with an increase of 12.25% to 15.10% compared to historical periods (Figure 8a). The SSP5–8.5 predicts the highest increase at $0.32\text{ m}^3/\text{s}$ per decade, followed by SSP2–4.5 at $0.29\text{ m}^3/\text{s}$ and SSP1–2.6 at $0.26\text{ m}^3/\text{s}$.

During the historical period (1985–2016), streamflow rose by $0.21\text{ m}^3/\text{s}$ due to climate change, with $0.04\text{ m}^3/\text{s}$ from LUCC and $0.25\text{ m}^3/\text{s}$ from their combined effects (Table 3); climate change contributed to 84% and LUCC 16%. For the future period (2017–2050), the projected streamflow increases are $1.07\text{ m}^3/\text{s}$, $1.14\text{ m}^3/\text{s}$, and $1.25\text{ m}^3/\text{s}$ under SSP1–2.6, SSP2–4.5, and SSP5–8.5, respectively. LUCC is expected to contribute an additional $0.25\text{ m}^3/\text{s}$.

The combined effects of climate change and LUCC are expected to result in increases in river streamflow by $1.31\text{ m}^3/\text{s}$, $1.39\text{ m}^3/\text{s}$, and $1.50\text{ m}^3/\text{s}$, respectively, with climate change accounting for 81% to 83% of these increases. Overall, climate change remains the dominant influence on streamflow changes, significantly outpacing the effects of LUCC both historically and in future projections.

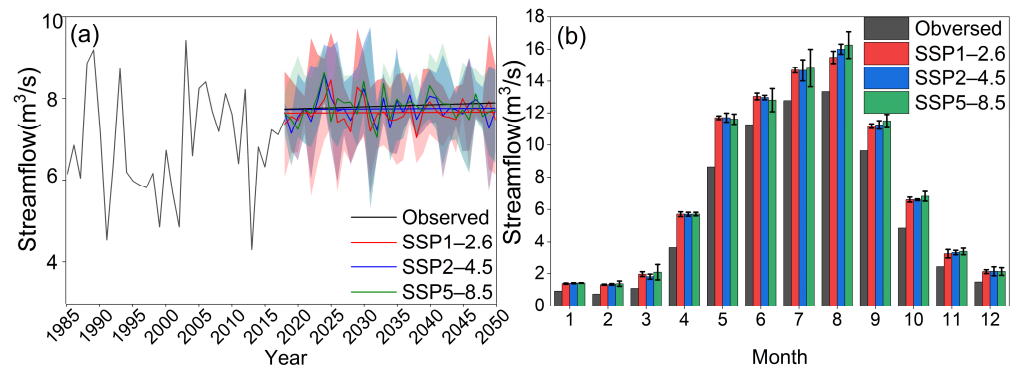


Figure 8. Annual (a) and monthly (b) change in streamflow from 1985 to 2050 in the ZMR. The 95% uncertainty bands are shown in the shaded region.

Table 3. Annual streamflow change in ZMR basin under different scenarios.

Scenario	Climate	LUCC	Streamflow (m ³ /s)	Streamflow Change		
S0	1985–2000	1990s	6.49			Percent (%)
S1	2001–2016	1990s	6.69	Q_{C_1}	0.21	84.00
S2	1985–2000	2010s	6.52	Q_{I_1}	0.04	16.00
S3	2001–2016	2010s	6.73	ΔQ_1	0.25	100
S4	2017–2050 (SSP1–2.6)	2010s	7.72	$Q_{C_2-1.26}$	1.07	81.30
	2017–2050 (SSP2–4.5)	2010s	7.79	$Q_{C_2-2.45}$	1.14	82.01
	2017–2050 (SSP5–8.5)	2010s	7.91	$Q_{C_2-5.85}$	1.25	83.67
S5	2001–2016	2030s	6.90	$Q_{I_2-1.26}$	0.25	18.70
				$Q_{I_2-2.45}$	0.25	17.99
				$Q_{I_2-5.85}$	0.25	16.33
S6	2017–2050 (SSP1–2.6)	2030s	8.04	$\Delta Q_2-1.26$	1.31	100
	2017–2050 (SSP2–4.5)	2030s	8.12	$\Delta Q_2-2.45$	1.39	100
	2017–2050 (SSP5–8.5)	2030s	8.23	$\Delta Q_2-5.85$	1.5	100

3.4.2. Response of Monthly Streamflow to Climate Change and LUCC

Under future climate scenarios, streamflow is projected to increase across all months, with significant growth rates exceeding 35% from February to May. March shows the highest growth rate, ranging from 79.2% to 90.66%, while May experiences the largest absolute increase in streamflow, from 2.97 to 3.07 m³/s (Figure 8). For June to September, streamflow rises above 1.5 m³/s, although higher baseline flows result in growth rates of below 20%. Seasonal variations indicate that the largest increases occur in summer, with SSP1–2.6, SSP2–4.5, and SSP5–8.5 showing increases of 5.4%, 6.05%, and 7.39%, respectively, compared to historical averages.

Comparatively, climate change significantly impacts streamflow variation more than LUCC (Figure 9). Historically, LUCC's effect on streamflow was minimal, not exceeding 0.1 m³/s, with negative contributions noted in March and September. Climate change negatively affected streamflow from June to July, while positively influencing other months.

In the future, LUCC will contribute slightly more to monthly streamflow but will not surpass $1.0 \text{ m}^3/\text{s}$. Overall, climate change will dominate streamflow increases throughout most of the year, especially from July to October, with the greatest contributions in spring (May) and summer (July).

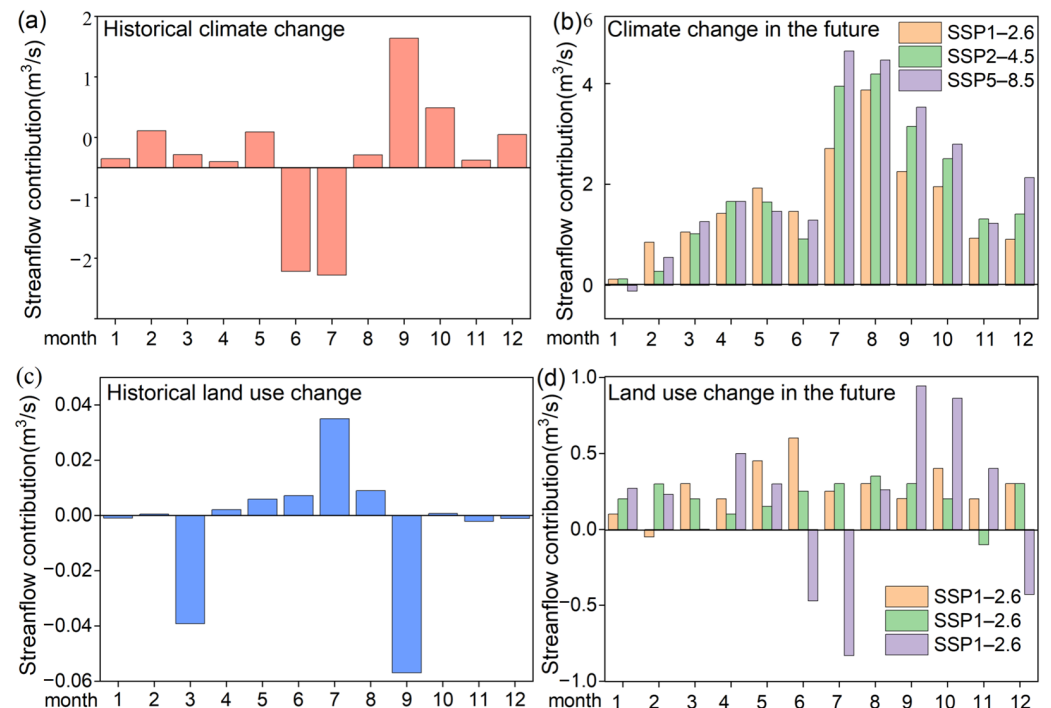


Figure 9. Change in monthly streamflow impacted by climate change and LUCC. (a) The impact of historical climate change alone on monthly scale streamflow change. (b) The impact of historical LUCC alone on monthly scale streamflow variations. (c) The impact of future climate change alone on monthly scale streamflow change under different scenarios. (d) The impact of future LUCC alone on monthly scale streamflow change under different scenarios.

3.4.3. Correlation Detection Between Streamflow and Climate Change

The analysis highlights a positive correlation between precipitation and streamflow throughout the year (Figure 10), with the most significant effects observed from June to October. While precipitation consistently enhances streamflow, $T_{\max}$ exhibits a mixed relationship, with a negative correlation from May to August and a positive one in the other months, peaking in March and April and declining in May and June. $T_{\min}$ shows a strong positive correlation with streamflow from February to April and October to December, but a notable negative correlation occurs in May and June. While temperature tends to reduce streamflow during late spring, precipitation remains the dominant factor influencing streamflow, leading to an upward trend year-round despite seasonal fluctuations.

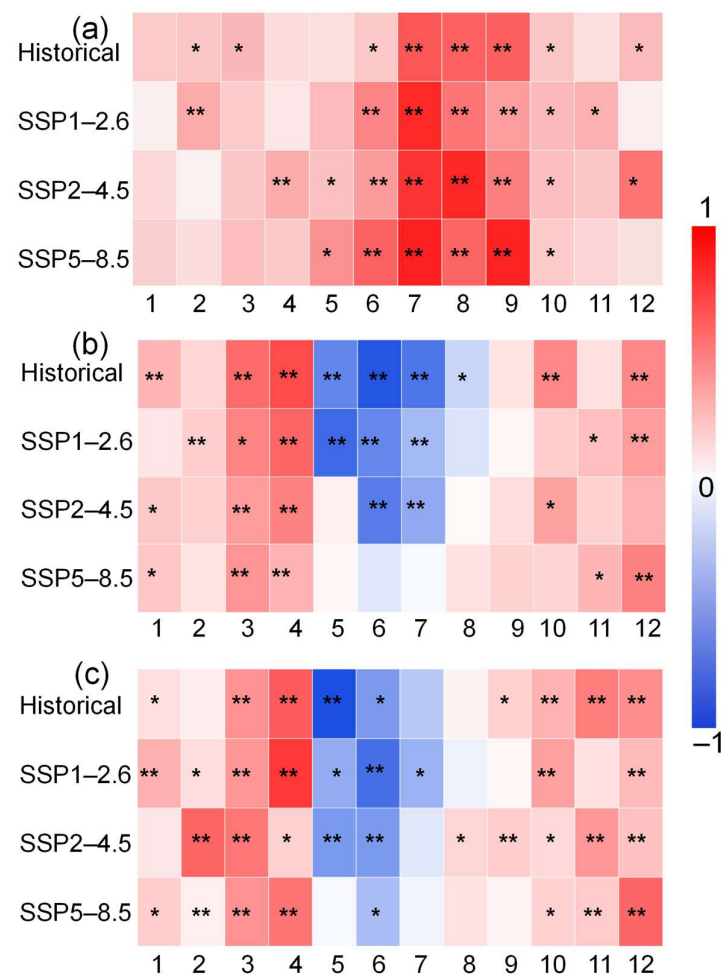


Figure 10. Heat map illustrating the correlation between monthly streamflow and precipitation (a), T_{max} (b), and T_{min} (c). Note: Single asterisks * represent statistical significance with $p < 0.05$, whereas double asterisks ** indicate a higher level of significance with $p < 0.01$.

4. Discussion

4.1. Causes of Climate Change Impact on Streamflow

Global warming is intensifying the hydrological cycle in vulnerable arid alpine regions. Average temperatures in these areas have risen by $0.032\text{ }^{\circ}\text{C}$ annually, with notable increases in recent decades [51,52]. Due to the low renewability of water systems [1], these regions are particularly susceptible to climate change, resulting in disrupted precipitation patterns and altered glacier dynamics, which destabilize the water cycle [53,54]. This instability manifests as shifts in annual streamflow distribution and increased hydrological variability [55,56].

The effects of climate change on streamflow are anticipated to be substantial by the mid-century [55,56]. Projection scenarios indicate that increased temperatures and precipitation will lead to higher streamflow (Figures 7 and 8). These results align with previous studies on streamflow changes in Shiyang and Manas River basins in China and the East Azerbaijan basin in Iran [50,57].

Increased precipitation directly affects streamflow, while rising temperatures, on the one hand, increase evapotranspiration, and on the other hand, advance the timing of snowmelt, leading to complex impacts on streamflow [50,58]. Our study indicates that climate change accounts for over 80% of the streamflow change in the ZMR basin, primarily driven by significant increases in precipitation and rapid temperature rise. Specifically, precipitation is positively correlated with streamflow change throughout the year (Figure 10), with a more pronounced impact on streamflow change. The relationship between temperature and streamflow shows a positive correlation during the colder months and a negative

correlation during warmer seasons. This suggests that in colder months, higher temperatures promote snowmelt, thereby increasing streamflow, whereas in warmer months, increased evapotranspiration reduces streamflow. Overall, the impact of temperature on streamflow remains predominantly positive for the entire year.

Future projections indicate that extreme precipitation events will lead to a more pronounced increase in streamflow. Both historical and future data show rising streamflow, but the future period (S4) is expected to be particularly affected by extreme precipitation in the Tibetan Plateau, along with observational biases from uneven meteorological station distribution and the limitations of CMIP6 models in simulating precipitation–altitude relationships in complex terrains.

4.2. Causes of LUCC Impact on Streamflow

LUCC in the ZMR basin significantly impacts streamflow dynamics. Grasslands and forests dominate the region (Figure 4). Human influence on surface conditions remains limited, aligning with findings from other arid regions like the Manas, Heihe, and Ili River basins, where environmental constraints restrict human impact [2,50].

The simulated scenario (S5) indicates an upward trend in streamflow linked to LUCC (Table 3). LUCC alters surface roughness and infiltration properties, indirectly influencing streamflow dynamics [59–61]. Urban expansion and increased impermeable surfaces decrease permeability, resulting in higher streamflow and reduced evapotranspiration post-rainfall [58,62]. Conversely, expanding grasslands, forests, and farmlands enhance moisture absorption and promote deeper water infiltration, which can lower streamflow through increased transpiration [59].

From 1990 to 2010, urban expansion and the reduction in grasslands increased impermeable surfaces, thereby raising streamflow. From 2010 to 2030, LUCC data showed declines in low-cover grasslands and forests, alongside increases in unused lands and high-cover grasslands (Figure 4). In cold, arid mountainous regions, warming and increased moisture have weakened vegetation's water retention capabilities, while more unused land reduces overall water storage, contributing to rising streamflow. Notably, LUCC changes from 2010 to 2030 are more pronounced than those from 1990 to 2010, resulting in a greater increase in streamflow under the S5 scenario compared to the S1 scenario.

4.3. Synergistic Effects of LUCC and Climate Change on Streamflow and Management Implications

Climate change and LUCC significantly affect streamflow, creating complex interactions that surpass the simple sum of their individual impacts. This research indicates that both historical and projected climate and human activity changes (scenarios S3 and S6) have greater effects on streamflow than any single factor (scenarios S1 and S2, S4 and S5). Importantly, future synergistic effects (S6) are expected to pose more significant challenges for watershed management than historical trends (S1).

In arid alpine regions, streamflow is particularly sensitive to climate change, with recent warming exacerbating these effects. While some arid mountainous areas experience increased moisture, broader desert regions confront warming and drying, accompanied by rising extreme temperatures [63,64]. This variability complicates the hydrological cycle [63,65]. Our case study shows that increased streamflow is driven by warming and enhanced precipitation. However, this rise in streamflow is unsustainable, as glaciers and snowmelt may not keep pace with precipitation [64]. Human activities, such as land reclamation and industrial processes, further modify land surfaces and increase water consumption [63]. Additionally, cross-regional water transfer projects disrupt natural streamflow processes and contribute to desertification.

It is worth noting that snowmelt is also one of the key factors influencing streamflow in arid and alpine regions [64]. Maintaining a certain level of snow cover can help to buffer the impact of climate change on streamflow. As temperatures rise, the melting rate of snow (especially seasonal snow) accelerates, leading to increased streamflow during the

warmer seasons. However, the increase in streamflow due to snowmelt is limited. As temperatures continue to rise, the snowline shifts upward, and the extent of snow cover decreases [50]. Once the snow cover is reduced to a level that can no longer effectively replenish streamflow, a “tipping point” is reached, beyond which further temperature increases will lead to a significant reduction in streamflow. At the same time, the reduction in snow cover also brings the potential risk of increased bare land exposure, which lowers the surface’s ability to retain precipitation, thereby increasing the frequency of extreme hydrological events. The complex effects of snow and ice meltwater on streamflow in arid alpine regions have been similarly observed by Yang et al. through the use of the SWAT model and the Budyko framework [50,58].

To tackle these challenges, accurately estimating streamflow in arid alpine regions is crucial for maintaining ecological base flows and a healthy watershed water cycle. Enhancing climate and hydrological monitoring, developing early warning systems, and maintaining long-term flow records are vital for effective water resource management (Figure 11).

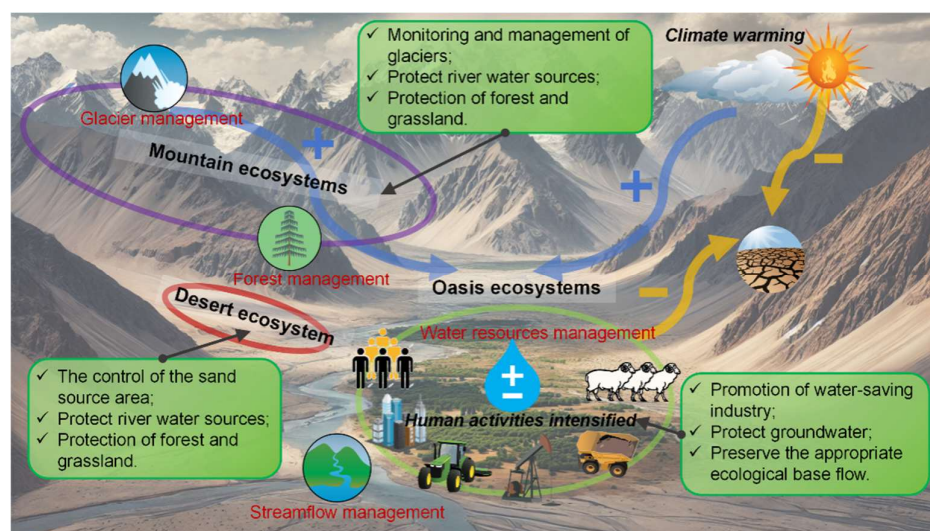


Figure 11. Streamflow suitability management in arid alpine regions.

4.4. Limitations

This study separated the effects of climate change and LUCC on streamflow, differentiating between individual factors and their interactions. It explored how these changes impact hydrological processes in arid alpine regions. However, the model could only generalize complex principles due to the unique hydrological processes in cold regions, failing to fully elucidate specific mechanisms [66]. The calibration of model parameters has introduced uncertainties and limitations to our study. From the streamflow simulation results (Figure 5) it can be seen that the overall trend in streamflow changes is consistent with the observed data, indicating that the streamflow curve settings are reasonable and that the simulation of baseflow is also relatively accurate. However, there are still discrepancies in the simulation of peak flows and the flood season, with differences in flood season simulations mainly arising from the setting of snowmelt-related parameters. The deviation in peak flow simulations is reflected in simulated values typically being lower than the observed values. This is partly due to the scarcity of upstream hydrological and meteorological stations leading to insufficient observational data, which makes it difficult to accurately capture streamflow characteristics. Additionally, in arid and cold mountainous areas, streamflow parameters are often set based on experience, and parameters automatically calibrated by the model may not fully reflect the actual conditions of the river. Therefore, model parameters need to be further improved by incorporating experiential knowledge and previous research [50]. Moreover, the impact of upstream hydropower stations on stream-

flow interception should also be considered [58]. Future research should address practical constraints like hydropower operations and ice–snow meltwater effects and improve the rationality of parameter settings to enhance simulations of hydrological processes [67–69]. Improving data resolution is crucial for accurate predictions, necessitating higher precision in remote sensing and field measurements. Integrating these efforts with a water–heat coupling model will clarify hydrological mechanisms in alpine areas and better represent their characteristics.

5. Conclusions

By combining the PLUS model, SWAT model, and CMIP6 predictions, we attributed the changes in streamflow in arid regions to climate change and human interventions, using the Zamu River Basin as a case study. This research contributes valuable insights to both academia and policy by addressing three key points. Firstly, it quantifies streamflow changes across various climate and human impact scenarios, showing that climate change drives over 80% of these alterations, with further intensification expected due to future climate impacts and LUCC. Secondly, our analysis highlights precipitation as the most significant climate factor affecting increased streamflow. Lastly, our findings emphasize the critical role of climate change in arid water cycles, underscoring the urgent need for improved streamflow management and the robust monitoring of meteorological and hydrological changes to tackle the challenges posed by climate change in these regions.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/land13122166/s1>, Test S1: Complementary methods, Test S2: Complementary tables, Test S3: References.

Author Contributions: Conceptualization, H.X., L.Y. and Q.F., methodology, H.X. and Y.S., software, H.X. and M.W., validation, L.Y., Y.S. and Q.F., formal analysis, H.X., L.Y. and Y.S., investigation, W.L. and Q.F., resources, H.X., L.Y. and Q.F., data curation, H.X. and Y.S., writing—original draft preparation, H.X., Q.F. and Y.S., writing—review and editing, H.X., Q.F., M.W. and W.H., visualization, H.X., L.Y. and W.L., supervision, L.Y., Q.F. and W.L., project administration, W.H. and X.Z., funding acquisition, X.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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