

Article

Dual-Spatial-Scale Assessment of Watershed Water Yield Responses to Land-Use Change in the Upper Yangtze River Basin

Wenxian Guo ¹, Xuyang Jiao ¹, Yong Niu ^{2,*} and Hongxiang Wang ¹

¹ College of Water Conservancy, North China University of Water Resources and Electric Power, Zhengzhou 450045, China; guowenxian@ncwu.edu.cn (W.G.); 201604632@stu.ncwu.edu.cn (X.J.); wanghongxiang@ncwu.edu.cn (H.W.)

² National Engineering Laboratory for Lake Pollution Control and Ecological Restoration, Institute of Lake Ecology and Environment, Chinese Research Academy of Environmental Sciences, Beijing 100012, China

* Correspondence: 13603966272@163.com; Tel.: +86-156-3823-5613

Abstract

Understanding how land change affects water yield is essential for sustainable land management and water security. However, previous studies often rely on a single model or spatial scale, limiting their ability to capture fine-scale land-surface heterogeneity and basin-integrated hydrological processes; consequently, cross-scale consistency in water-yield patterns and drivers remains unresolved. This study developed a dual-spatial-scale framework for the Upper Yangtze River Basin. The Patch-generating Land-Use Simulation (PLUS) model projected land patterns for 2030, the Integrated Valuation of Ecosystem Services and Tradeoffs Annual Water Yield (InVEST-AWY) model mapped grid-scale water yield, the Soil and Water Assessment Tool (SWAT) model simulated sub-basin hydrological responses, and Geodetector identified dominant drivers. Their integration links local land transitions with basin-scale hydrological consequences under consistent scenarios, thereby overcoming the limitations of single-model assessments. Results showed that high water-yield areas were concentrated in the eastern and central basin, while the two scales exhibited similar spatial patterns but locally different magnitudes and trends. Built-up land under urban development was 7.96% greater than under ecological protection. Climatic variability increased runoff by 2115.33 m³/s under ecological protection, while precipitation dominated water-yield variation, with explanatory powers of 0.81 and 0.67 at the grid and sub-basin scales, respectively. These findings advance understanding of scale-dependent responses and support land optimization and watershed planning.

Keywords: SWAT model; InVEST-AWY model; PLUS model; multi-scenario simulation; water yield services

Academic Editor: Lei Wang

Received: 16 June 2026

Revised: 27 July 2026

Accepted: 31 July 2026

Published: 2 August 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\) license](https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Water resources are fundamental to human well-being, socioeconomic development, and ecosystem stability. Since the twentieth century, climate change has substantially altered the global water cycle and increased the frequency and intensity of hydrological extremes, including floods and droughts [1,2]. At the same time, urbanization, agricultural expansion, and ecological restoration have continuously reshaped land-use and land-cover (LULC) patterns, thereby modifying precipitation interception,

evapotranspiration, soil infiltration, groundwater recharge, and surface runoff [3]. Water-yield services reflect the capacity of terrestrial ecosystems to regulate and supply water through these interconnected hydrological processes and constitute an important component of watershed ecosystem services [4,5]. Their stability is closely related to ecosystem resilience [6] and supports agricultural irrigation, hydropower generation, fisheries, tourism, and regional water security [7]. However, the combined effects of climate variability and intensive human activities have increased the mismatch between water supply and demand and intensified the spatial heterogeneity of water availability [8]. Accurately identifying the spatiotemporal response of water yield to climate and LULC change is therefore essential for land-use optimization, ecological conservation, and watershed water-resource management.

Water yield assessment has gradually developed from empirical estimation and statistical analysis toward spatially explicit ecosystem-service evaluation, process-based hydrological simulation, and future scenario analysis. Distributed and semi-distributed hydrological models can describe runoff generation, evapotranspiration, groundwater processes, and channel routing and are widely used to assess the hydrological consequences of climate and LULC change. The Soil and Water Assessment Tool (SWAT), for example, provides a physically based representation of the watershed hydrological cycle and is suitable for evaluating temporal dynamics and integrated responses at the hydrological response unit and sub-basin scales [9]. The Variable Infiltration Capacity model and the Hydrological Simulation Program—Fortran model also account for spatial heterogeneity, although their applications may be constrained by computational demand, parameterization, input-data quality, and spatial discretization [10,11]. In parallel, ecosystem-service models have become increasingly important for mapping the spatial distribution of water-related services. The Integrated Valuation of Ecosystem Services and Tradeoffs Annual Water Yield model (InVEST-AWY) estimates annual water yield within a Budyko-based water-balance framework and can efficiently generate spatially continuous grid-scale results [12]. However, its annual equilibrium formulation simplifies seasonal hydrological variability, water storage, groundwater dynamics, and channel routing. In addition, future hydrological responses increasingly require spatially explicit projections of LULC change. Cellular automata models, including the CA-Markov model, the Future Land-Use Simulation model, and the Patch-generating Land-Use Simulation (PLUS) model, have been widely used for this purpose [13–16]. By integrating a Land Expansion Analysis Strategy and a multi-type Random Patch Seeds mechanism, PLUS can identify land-expansion drivers and reproduce the emergence and evolution of multiple LULC patches [17,18]. These methodological developments have improved the representation of water-yield patterns, future land-use trajectories, and their potential hydrological consequences.

The Upper Yangtze River Basin has abundant water resources, complex topography, pronounced climatic and ecological gradients, and intensive human activities, and it plays a critical role in regional ecological security and socioeconomic development [19]. Rapid urban growth, infrastructure construction, agricultural adjustment, and ecological restoration have altered regional LULC patterns and increased the difficulty of coordinating development with ecosystem conservation [20]. Currently, the research on water yield has gradually evolved from the application of a single model to model comparison, multi-model integration, multi-scenario prediction, and assessment at different spatial scales. Process-based hydrological models are increasingly being combined with ecosystem service and land-use simulation models, not only for assessing historical hydrological changes but also for analyzing the potential impacts of future changing environments. At the same time, researchers are paying more attention to the differences in model structure, spatial units, and data requirements, as these differences may affect the judgment of estimates of water yield services [21,22]. With the advancements and integration of remote

sensing technology, distributed hydrological modeling, ecosystem service assessment, and land-use simulation, the research on comprehensive assessment of changes in water yield and its climate and anthropogenic driving factors has been promoted. These studies have substantially improved the understanding of water-yield dynamics in large and environmentally heterogeneous river basins. Nevertheless, three limitations remain. First, many studies rely on a single model or a single spatial unit, which cannot simultaneously retain fine-scale land-surface heterogeneity and represent basin-integrated hydrological processes. Second, grid-based and sub-basin-based results are often evaluated separately; therefore, the consistency of their spatial patterns, change magnitudes, and dominant drivers remains insufficiently understood. Third, future LULC simulation, water-yield assessment, climate–LUCC attribution, and driver identification are frequently conducted as separate analytical tasks, limiting the ability to trace how alternative development strategies are translated into land-use transitions, hydrological responses, and spatially differentiated water-yield effects. These shortcomings are particularly important in the Upper Yangtze River Basin, where strong environmental gradients and rapid land-use transitions may amplify scale-dependent responses.

In view of these issues, this study developed a comprehensive dual-spatial-scale framework for assessing historical and future water yield changes in the Upper Yangtze River Basin. The SWAT model is used to simulate hydrological processes and water yield at the sub-basin scale, while InVEST-AWY is applied to map spatially continuous annual water yield at the grid scale. The PLUS model generates LULC patterns under the urban development and ecological protection scenarios for 2030, and the projected LULC data are used as consistent scenario inputs for both water-yield models. A scenario-comparison method is then employed to separate the effects of climatic variability and LUCC on runoff, and Geodetector is used to identify the explanatory power and interactions of the principal natural and socioeconomic drivers at both spatial scales. We hypothesize that water-yield patterns are broadly consistent across the two spatial scales, whereas their response magnitudes and dominant drivers vary because of differences in spatial aggregation and hydrological process representation. On this basis, this study aims to: (1) characterize the spatiotemporal evolution of water yield from 2000 to 2020 at the grid and sub-basin scales; (2) assess water-yield responses under alternative development scenarios in 2030; (3) quantify the relative effects of climate variability and LUCC on watershed runoff; and (4) identify scale-dependent differences in the dominant controls of water-yield heterogeneity. The integrated framework links future LULC scenarios and local water-yield patterns with basin-scale hydrological responses, providing complementary cross-scale information for land-use management and water-resource planning in the Upper Yangtze River Basin.

2. Study Area and Data

2.1. Study Area

The Yangtze River, a vital river in China and globally, supports significant economic, cultural, and ecological functions, including being a major grain production area [23]. The basin is governed by a subtropical monsoon climate, with mean annual temperature ranging from approximately 0 to 17 °C from the Tibetan Plateau to the Sichuan Basin, mean annual precipitation of about 1045 mm, annual actual evapotranspiration of approximately 450–490 mm, and more than 60% of annual precipitation concentrated in summer, with July generally being the hottest and wettest month and winter being comparatively cold and dry [24].

This study focuses on the Upper Yangtze River Basin (Figure 1), covering an area of 1013,809.4 km² and comprising diverse landscapes such as urban, rural, and mountainous regions. The basin contains both ecologically sensitive headwater and mountainous areas

and densely populated regions undergoing rapid urbanization and land-use transformation. Meanwhile, ecological restoration and land-protection policies have increased the need to balance regional development with the conservation of forests, grasslands, and water resources. Strong spatial differences in precipitation, topography, vegetation, and human disturbance also lead to considerable heterogeneity in runoff generation and water yield, making the basin suitable for examining water-yield responses to LUCC across different spatial scales. The Yichang (YC) hydrological station in the basin is the exit station of the basin and an important hydrological station in the upper reaches of the Yangtze River. The progression of urbanization has increasingly disturbed the aquatic ecosystems in the Upper Yangtze River Basin. Therefore, understanding the spatiotemporal distribution of water yield in this region is essential for protecting its ecological integrity and supporting sustainable development.

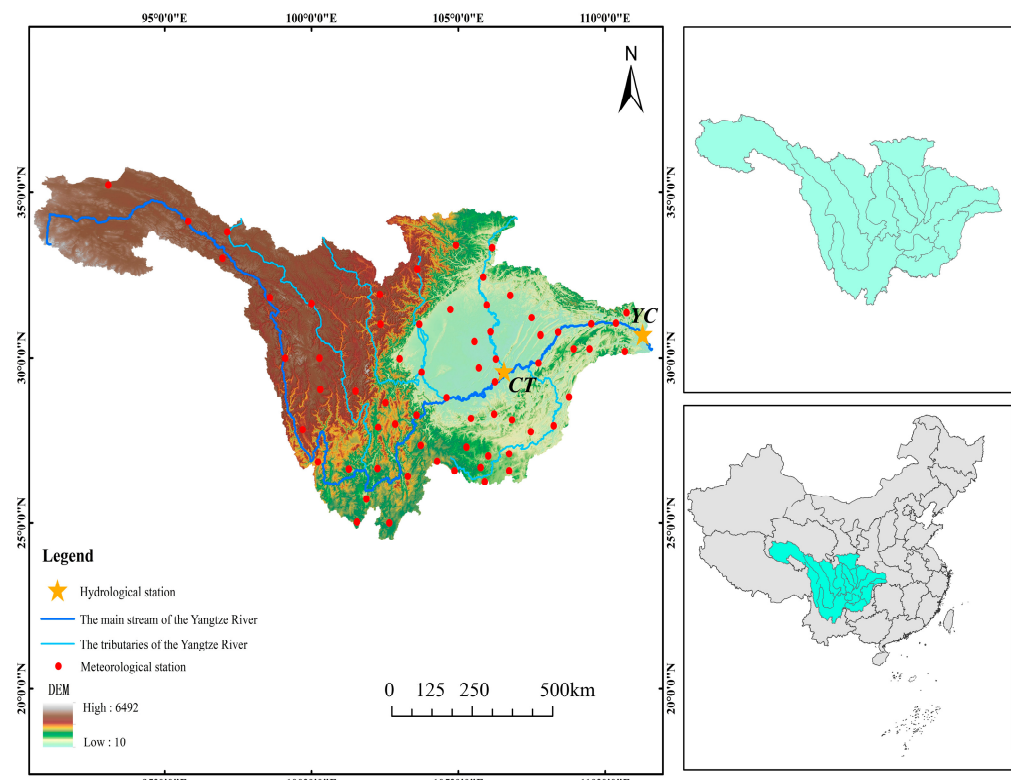


Figure 1. Location of the study area.

2.2. Data Sources

This study utilized LULC data and driving-factor data, with their sources and spatial resolutions detailed in Table 1. LULC data for 2000, 2010, and 2020, with a spatial resolution of 30 m, were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences. Slope was treated as a derived topographic variable and calculated from the Digital Elevation Model (DEM) using the Slope tool in ArcGIS 10.2 rather than being obtained as an independent dataset. Long-term climatic and hydrological data, including daily precipitation, maximum and minimum temperatures, sunshine duration, relative humidity, wind speed, and average daily streamflow, were collected from the Yichang Hydrological Station and multiple meteorological stations in the Upper Yangtze River Basin. The data were obtained from the China Meteorological Administration, the Yangtze River Water Resources Commission, the National Meteorological Information Center, and the National Tibetan Plateau Data Center [25]. Specifically, streamflow data were provided by the Yangtze River Water Resources Commission, while meteorological data were obtained from the China Meteorological Administration.

Table 1. Description of driver factor data.

Category	Data	Year (S)	Original Resolution	Sources
Land dataset	LULC	2000, 2010, 2020	30 m	https://www.resdc.cn/
Natural environmental data	DEM	2020	1000 m	https://www.resdc.cn/
	Temperatures	2020	1000 m	https://www.resdc.cn/
	Precipitation	2020	1000 m	https://www.resdc.cn/
	Soil type distribution	2020	1000 m	https://www.resdc.cn/
	Distance from river	2020	30 m	Based on ArcGIS10.2 Euclidean distance calculation
Socioeconomic data	Population density	2020	1000 m	https://www.resdc.cn/
	GDP	2020	1000 m	https://www.resdc.cn/
	Distance from primary road	2020	30 m	Based on ArcGIS10.2 Euclidean distance calculation
	Distance from secondary road	2020	30 m	Based on ArcGIS10.2 Euclidean distance calculation
	Distance from tertiary road	2020	30 m	Based on ArcGIS10.2 Euclidean distance calculation

3. Methodology

3.1. Technical Framework

This study evaluates the spatiotemporal changes in water resources and analyzes the dynamic patterns of water yield in the Upper Yangtze River Basin by examining the impacts of LULC and climatic factors. Initially, the SWAT model was utilized to simulate the hydrological cycle within the basin and estimate the spatial distribution of water yield at the sub-basin scale from 2000 to 2020. Subsequently, the InVEST-AWY model was employed to assess the spatial distribution of water yield at the grid scale over the same period. The PLUS model predicted LULC in 2030 under two scenarios: Urban Development (UD) and Ecological Protection (EP). The predicted LULC data were integrated into the SWAT and InVEST-AWY models to simulate future water yield distributions under the two LULC scenarios at both grid and sub-basin scales, thereby combining their complementary capabilities in spatial assessment and hydrological process simulation [21]. Finally, attribution analysis quantified the impacts of human activities and climate change on runoff and identified key factors influencing water yield services at both scales using Geodetector risk and interaction detectors [26]. Figure 2 outlines the detailed technical workflow of this study.

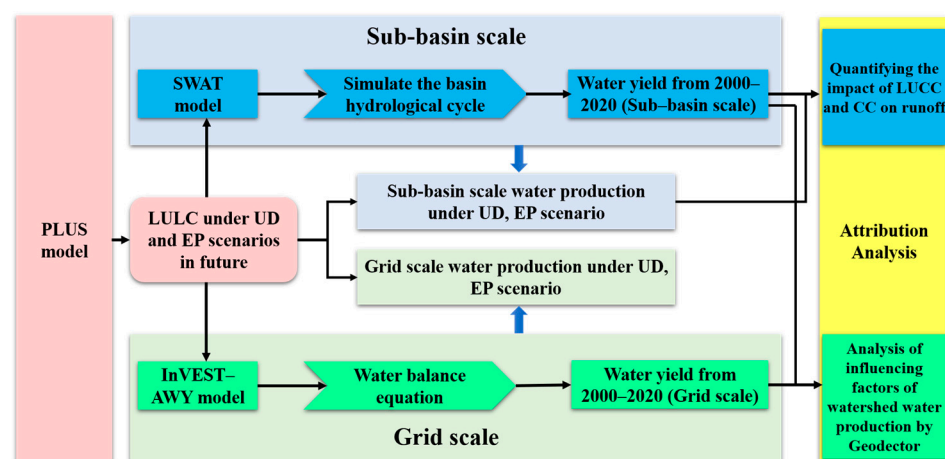


Figure 2. Methodological framework.

3.2. PLUS Model Framework and Implementation

The PLUS model, a CA model, utilizes the Land Expansion Analysis Strategy (LEAS) framework and the multi-type Random Seed (CARS) mechanism. It identifies driving factors of land expansion and landscape change through two main modules: a LEAS and a CARS [27]. In the LEAS module, the PLUS model employs a Random Forest Regression (RFR) algorithm to derive the development probabilities for each LULC type based on LULC data from two periods. The RFR algorithm was preferred because it can capture nonlinear relationships and interactions between multiple driving factors and land expansion while providing the development probability of each LULC type [28]. The PLUS model employs a decreasing threshold rule for generating patch seeds, progressively constraining the growth of LULC patches through an iterative process. Cells with higher probabilities change first, governed by this threshold. The PLUS model uses the RFR algorithm to establish relationships between LUCC and driving factors, which are then used to predict development probabilities for each LULC type. In this study, the PLUS model considered the following natural and social factors for predicting LUCC:

Natural Factors: (1) Elevation (DEM): Digital Elevation Model data representing terrain height and topographic variation; (2) Slope: Slope data calculated from DEM, indicating the steepness of the terrain; (3) Precipitation: Annual precipitation data reflecting water availability and climatic conditions; (4) Temperature: Annual average temperature data representing climatic conditions; (5) Soil Type: Soil type data indicating soil characteristics and suitability across different regions; (6) Distance to Rivers: Distance to major rivers calculated using Euclidean distance in ArcGIS 10.2, representing water source accessibility.

Social Factors: (1) Population Density: Data on population density within the region, reflecting the intensity of human activities; (2) GDP: Data on regional Gross Domestic Product, indicating the intensity of economic activities and development level; (3) Distance to Major Roads: Distance to major roads calculated using ArcGIS, representing transportation accessibility and infrastructure development.

The PLUS model uses the Random Forest Regression algorithm to determine the influence weights of these driving factors on LUCC. These factors are integrated with the model's roulette competition mechanism to simulate the spatial distribution and dynamics of LULC types within mixed cells. The performance of the PLUS model is evaluated using accuracy metrics such as the Kappa coefficient, Overall Accuracy (OA), and Figure of Merit (FoM) [29].

3.2.1. Performance Evaluation of the PLUS Model in LULC Prediction

LULC data from 2010 and 2015 were used to simulate the LULC in 2020, and the simulation results were compared with the actual 2020 LULC data to verify the applicability of the PLUS model. As shown in Table 2, the simulated 2020 LULC data achieved a Kappa coefficient of 0.89 and an Overall Accuracy of 0.92, indicating high simulation accuracy. The Mean Relative Error (MeanRE) of 0.315 and Modified Figure of Merit (McFom) of 0.390 suggest minimal information loss and accurate predictions of LUCC.

Table 2. Simulation accuracy of LULC in 2020 based on PLUS model.

Land Type	Actual Coverage	Simulated Coverage	User's Accuracy	Producer's Accuracy	OA	Kappa	FOM
Cropland	38.00%	37.74%	0.903	0.903	0.929	0.898	0.180
Forest	48.12%	48.43%	0.941	0.941			
Grassland	7.68%	7.32%	0.943	0.942			
Water	3.26%	3.20%	0.858	0.856			
Construction Land	2.85%	3.01%	0.635	0.636			
Unused Land	0.12%	0.30%	0.961	0.959			

3.2.2. Scenario Development for Future LULC Simulation

Based on the LUCC characteristics in the study area from 2010 to 2020 and future regional development plans, two scenarios were established to simulate future LULC demands: Urban Development (UD) and Ecological Protection (EP).

(1) Urban Development Scenario (UD): In this scenario, the probability of converting cropland, forest, and grassland to built-up land increases by 50%, while the probability of converting built-up land to other types (except cropland) decreases by 50% [30]. This scenario reflects intensified LUCC driven by urban expansion, increasing the demand for built-up land and reducing other LULC types. Rapid urban development may significantly reduce cropland and forest areas, decrease ecosystem service functions, and weaken ecological resilience.

(2) Ecological Protection Scenario (EP): This scenario integrates the “Overall Plan for the Protection and Restoration of Important Ecosystems in China (2021–2035)” [31] and considers the study area’s environmental conditions to protect ecosystems and biodiversity. Under this scenario, the probability of converting forest and grassland to built-up land is reduced by 50%, and the probability of converting cropland to built-up land is reduced by 30%. Meanwhile, the probability of converting built-up land to forest is increased by 20%, and habitat degradation is strictly prohibited. Water bodies are designated as constraints to restrict LULC conversions [32]. This scenario emphasizes the priority of protecting natural ecosystems and biodiversity, aiming to maintain ecosystem health by reducing land development. This scenario emphasizes prioritizing natural ecosystems and biodiversity, aiming to limit built-up land expansion, increase forest and grassland areas, enhance ecosystem service functions, and improve ecological resilience.

Traditional methods for adjusting transition matrices to constrain LUCC at large spatial scales often lead to inaccuracies. Considering the study area’s scale, the Markov-chain method was applied to adjust transition probabilities between LULC types under the two scenarios [33]. Table 3 presents the transition probability matrix between different land-use types under the two scenarios. Each row represents the probability that a specific land-use type (as indicated by the row) will transition to other types (as indicated by the columns) in the next period.

Table 3. The development probability of different classes in different scenarios.

Scenario	a	b	c	d	e	f
Urban development scenario	90.22%	4.37%	1.96%	0.42%	3.01%	0.001%
	2.72%	94.03%	2.76%	0.16%	0.30%	0.001%
	1.22%	3.12%	94.85%	0.22%	0.24%	0.004%
	3.43%	1.45%	2.82%	90.94%	0.63%	0.007%
	11.13%	0.90%	0.51%	0.44%	87.02%	0.001%
	0.04%	0.38%	3.08%	0.50%	0.03%	95.98%
Ecological protection scenario	91.71%	4.45%	1.99%	0.43%	1.42%	0.01%
	2.72%	94.22%	2.76%	0.16%	0.10%	0.04%
	1.22%	3.12%	94.93%	0.22%	0.08%	0.42%
	3.43%	1.45%	2.82%	90.97%	0.63%	0.71%
	10.88%	2.15%	1.02%	0.87%	85.06%	0.01%
	0.03%	0.38%	3.08%	0.50%	0.03%	95.98%

Note: a–f represent Cropland, Forest, Grassland, Water, Construction Land, Unused Land.

3.3. SWAT Model

The Soil and Water Assessment Tool (SWAT) is a physically based semi-distributed hydrological model. It can simulate hydrological cycles, sediment transport, crop growth, and the movement and transformation of chemicals (such as nutrients and pesticides) in a watershed on daily, monthly, or yearly time scales [34]. The SWAT model simulates watershed runoff using detailed hydrological processes based on physical and empirical equations, incorporating actual watershed data. This provides a comprehensive tool for assessing and managing watershed water resources.

3.3.1. SWAT Model Construction

All raster data were projected to WGS_1984_Albers before model construction. The DEM, projected to WGS_1984_Albers with units in meters, was first imported into the SWAT model. Additionally, real river network data of the watershed were loaded to assist the model in generating a more accurate watershed stream network. For watershed delineation in SWAT, a threshold drainage area of 500,000 hectares was selected with reference to previous SWAT applications in the Upper Yangtze River Basin [35] and to balance spatial detail with computational efficiency, with the Yichang hydrological station designated as the watershed's main outlet. Based on this threshold, the study area was divided into 98 sub-basins (Figure 3).

The Hydrological Response Unit (HRU), the fundamental computational unit in SWAT, is defined by the unique combination of land-use/cover (LULC), soil type, and slope characteristics. It divides the watershed into homogeneous areas to simulate hydrological processes and capture spatial heterogeneity. LULC data for 2020 were extracted for the upper Yangtze River basin, projected to WGS_1984_Albers, and reclassified into six SWAT categories: cropland, forest, grassland, water bodies, built-up land, and unused land. Soil data were obtained from the Harmonized World Soil Database (HWSD). Due to significant topographic variation, slopes were classified into two groups using a threshold of 10%. By integrating LULC, soil, and slope data, 473 HRUs were generated. To enhance model efficiency, less influential categories were excluded with an area threshold of 10%. The selection of these thresholds aims to balance computational efficiency and the full representation of spatial heterogeneity, and refers to the parameter selection of predecessors in this study area [35]. Although more detailed segmentation can capture more details, the current setup has been proven to effectively represent key hydrological processes and generate reliable simulation results at the basin scale.

The meteorological database was constructed to include data for the weather generator, precipitation, maximum and minimum temperatures, wind speed, relative humidity, and solar radiation. The WGEN_CFSR_World model was selected as the weather generator. Solar radiation was derived from the calculation of sunshine hours, while the other data were obtained from observed measurements. The meteorological data, spanning from 1980 to 2019 on a daily scale, were sourced from the China Meteorological Data Service Center (<http://data.cma.cn>). Following data preparation, the SWAT model was run for the period from 1 January 1980, to 31 December 2019, with 1980–2003 as the calibration period and 2004–2019 as the validation period. A three-year warm-up period was included within this timeframe, and simulations were run on a monthly scale. Simulation results were input into SWAT-CUP for calibration and validation to improve model accuracy.

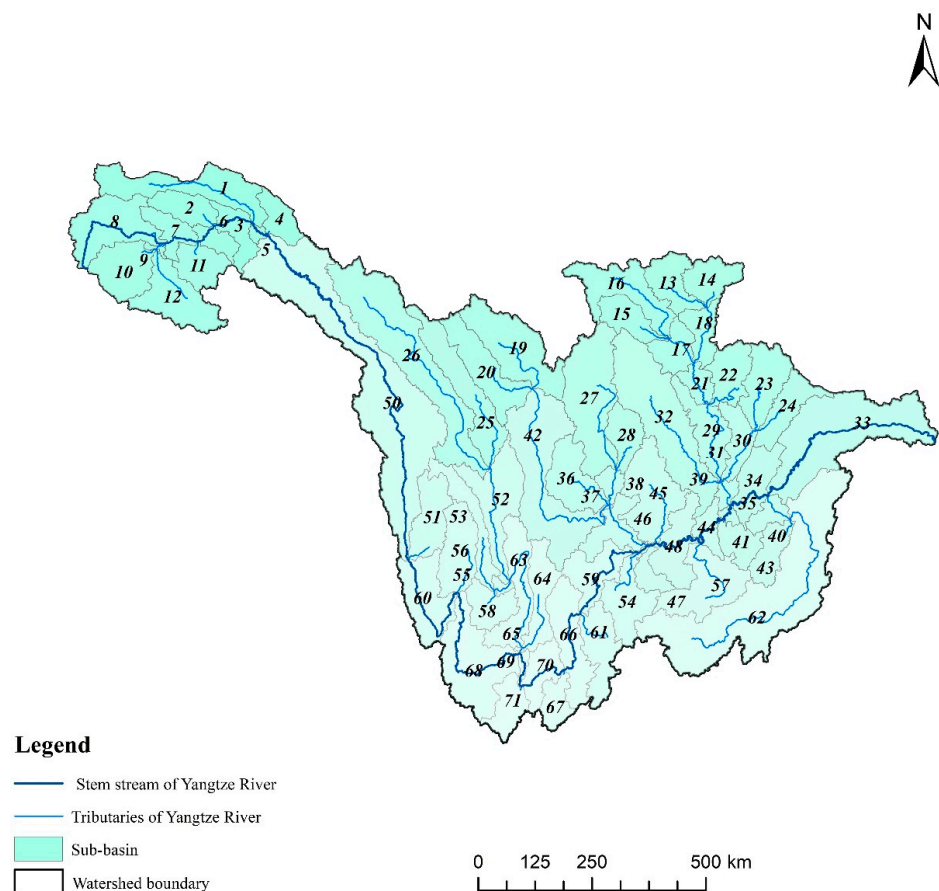


Figure 3. Simulated river network and sub-basin division.

3.3.2. Model Calibration and Performance Evaluation of SWAT

Calibration and validation of the SWAT model were performed using the Sequential Uncertainty Fitting version 2 (SUFI-2) within the SWAT Calibration and Uncertainty Program (SWAT-CUP) [36]. Sensitive parameters of the SWAT model were selected based on relevant literature [37,38] and adjusted to the study area's specific conditions. The initial ranges for these parameters were defined based on recommended values from SWAT documentation and previous studies in similar basins. Through an iterative process of sensitivity analysis and manual adjustment, the parameters were calibrated by comparing simulated outputs with observed streamflow data. The calibration and validation of all parameters listed in Table 4 were conducted using observed monthly streamflow data from the Yichang hydrological station, a key controlling outlet in the upper mainstream

of the Yangtze River. The final selected parameters are listed in Table 4. Initial parameter values were fitted through multiple iterations, with 500 simulations per iteration. After each iteration, optimal parameter ranges were refined by intersecting ranges from previous iterations to obtain final parameter values.

The performance of the model was evaluated using the recommended SWAT metrics—Nash–Sutcliffe efficiency (NSE), coefficient of determination (R^2)—and the calculation formula used followed [39]. Simulated flow data from the calibration period were compared with observed runoff data from the Yichang station. Upon achieving satisfactory agreement between simulated and observed values, and meeting evaluation criteria, the same parameters were applied to the validation period for runoff simulation.

Table 4. Parameter calibration results and sensitivity analysis.

Input Parameter	Parameter Description	t-Stat	p-Value	Initial Range	Optimal Parameter Selection
R_CN2.mgt	SCS runoff curve number.	7.11	0	−5–5	−0.54
V_ALPHA_BF.gw	Baseflow alpha factor.	20.42	0	0–1	0.79
V_GW_DELAY.gw	Groundwater delay time.	−0.49	0.62	30–450	71.744
V_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur.	0.62	0.53	0–500	225.94
V_ESCO.bsn	Soil evaporation compensation factor.	2.28	0.02	0–1	0.311
R_SOL_AWC().sol	Available water capacity of the soil layer.	−0.6	0.54	−3–3	2.23
V_HRU_SLP.hru	Average slope steepness.	2.52	0.01	0–1	0.38
V_REVAPMN.gw	Threshold depth of water in the shallow aquifer for “revap” or percolation to the unsaturated zone.	1.44	0.14	190–579	231.09
R_SOL_K().sol	Saturated hydraulic conductivity.	2.55	0.01	−3–3	2.43
V_CH_N2.rte	Manning’s “n” value for the main channel.	−1.14	0.25	0–0.3	0.23
R_SOL_Z().sol	Depth of soil layer.	0.99	0.32	−0.5–5	0.12
V_GW_REVAP.gw	Groundwater “revap” coefficient.	0.04	0.96	0.02–2	1.19
V_CANMX.hru	Maximum canopy storage.	1.48	0.14	0–100	15.94
R_SOL_ALB().sol	Soil albedo.	−0.01	0.99	0–0.25	0.001
R_SOL_BD().sol	Soil bulk density.	2.56	0.01	−0.5–2.5	0.57
V_CH_K2.rte	Effective hydraulic conductivity in the main channel.	−5.52	0	5–200	162.58
V_SURLAG.bsn	Surface runoff lag time.	−1.8	0.07	0.05–24	21.53
V_TIMP.bsn	Snowpack temperature lag factor.	−0.25	0.8	0.01–1	0.84
V_SMFMX.bsn	Maximum melt rate for snow on 21 June.	−1.15	0.24	0–20	17.31
V_SMTMP.bsn	Snow melt base temperature.	−0.93	0.35	−10–10	8.09
V_BIOMIX.mgt	Biological mixing efficiency.	0.05	0.95	0–1	0.94
V_SFTMP.bsn	Snowfall temperature.	0.45	0.65	−10–10	1.64

3.3.3. Sub-Basin Water Yield Simulation Based on SWAT Model

The water production volume we selected refers to the net water volume that leaves the sub-basin and leads to runoff, representing a key parameter of sustainable water resource management [20]. After calibrating the SWAT model, the optimal parameters are reintroduced for further simulation. The water yield (WYLD) (mm) in SWAT is calculated by Equation (1).

$$WYLD = SR + LF + GD - TL - PA \quad (1)$$

where SR , LF , GD , TL and PA , respectively, stand for surface runoff (mm), lateral flow (mm), groundwater discharge (mm), transmission losses (mm) and pond abstractions (mm)

3.4. InVEST-AWY Model

The InVEST-AWY model estimates the relative contribution of various landscape components to annual water yield by considering different LULC types, meteorological data, topography, and soil characteristics. This provides insights into how changes in LULC patterns affect annual surface water yield [40]. The model's input data include average annual precipitation, average annual reference evapotranspiration, root restricting layer depth, plant available water content (PAWC), LULC types, watershed and sub-watershed vectors, biophysical table, Z parameter, among others [41]. The formula provided for calculating annual water yield using the InVEST-AWY model is based on the average annual precipitation and the Budyko curve, and it is applied to each pixel as follows:

$$Y_{(x)} = \left(1 - \frac{AET_{(x)}}{P_{(x)}}\right) \cdot P_{(x)} \quad (2)$$

where $Y_{(x)}$ represents the annual water yield for pixel x ; $AET_{(x)}$ is the actual evapotranspiration for pixel x ; $P_{(x)}$ is the actual precipitation of pixel x .

The equations provided describe the calculation of vegetation evapotranspiration using the Budyko framework under equilibrium assumptions for LULC:

$$\frac{AET_{(x)}}{P_{(x)}} = 1 + \frac{PET_{(x)j}}{P_{(x)}} - \left[1 + \left(\frac{PET_{(x)j}}{P_{(x)}}\right)^{\omega}\right]^{\frac{1}{\omega}} \quad (3)$$

where $PET_{(x)}$ represents the potential evapotranspiration for LULC type j on pixel x , $\omega_{(x)}$ is related to plant-available water content (AWC), precipitation, and Z parameter, calculated as:

$$\omega_{(x)} = \frac{AWC_x}{P_x} \cdot Z \quad (4)$$

where Z is a dimensionless coefficient reflecting the equilibrium relationship between effective moisture and expected precipitation, with a value range of 1 to 30, representing the seasonal characteristics that affect precipitation distribution [42]. The plant-available water content (AWC) is defined as:

$$AWC_x = \min(\text{soil_depth}, \text{root_depth}) \times PAWC \quad (5)$$

$$\begin{aligned} PAWC = & 54.509 - 0.132SSAN - 0.003(SSAN)^2 - 0.055SSIL \\ & - 0.006(SSIL)^2 - 0.738CCLA + 0.007(CCLA)^2 \\ & - 2.688OM + 0.501(OM)^2 \end{aligned} \quad (6)$$

where PAWC represents the plant available water capacity, calculated based on soil type and soil physical properties through a nonlinear pedotransfer function model; SSAN is the percentage of sand content (%); SSIL is the percentage of silt content; CCLA is the percentage of clay content (%); OM is the percentage of organic matter content (%).

The biophysical parameters mainly involve the maximum root depth of plants in each LULC class, which was determined according to the recommended values in the literature and the InVEST user guide [43]. The Z parameter was initially constrained to a range of 0.5–3.0 based on previous regional studies [44,45] and calibrated using a one-factor iterative search with an interval of 0.1. For each candidate Z value, the pixel-scale annual water yield was aggregated over the Upper Yangtze River Basin and compared with the observed annual runoff at the Yichang hydrological station after streamflow was converted into runoff depth. The mean absolute relative error between the simulated and

observed annual runoff was used as the primary evaluation criterion, and the Z value producing the minimum error was selected. The minimum error of 4.9% was obtained when Z was 1.1; therefore, this value was adopted for the subsequent simulations. The InVEST model requires remote-sensing data to have a uniform spatial coordinate system and resolution. Therefore, all remote-sensing data were resampled and reprojected using ArcGIS 10.2 software. A consistent grid size of 1000 m was applied throughout the simulation, determined based on the resolution of the original input data sources. Finally, the InVEST model's water-yield module was used to simulate and analyze the spatiotemporal changes in water yield in the Upper Yangtze River Basin for 2000, 2010, and 2020.

3.5. Quantitative Analysis of Runoff Changes Due to Climate and LULC Transformations

Climate change and LUCC transformation are assumed to be independent factors in this study. The quantitative impact analysis on runoff was conducted by integrating relevant literature [30,46] with the specific conditions of this study to establish an appropriate framework for quantifying the effects of climate change and LUCC. In this study, the term “climate change” primarily refers to historical climatic variability rather than future projections. Key meteorological parameters considered include precipitation, temperature, wind speed, and solar radiation, which are essential components of the SWAT model's meteorological inputs and directly influence evapotranspiration, snowmelt, and runoff generation processes. Meteorological data from the periods 1980–2003 and 2004–2019 were used to represent two distinct climate periods, while LULC data for 2020, and projected data for 2030 under UD and EP scenarios, represented three different LULC patterns. The calibrated SWAT model was applied to six scenarios, combining the two climate periods with the three LULC patterns. A one-factor-at-a-time statistical technique was used to attribute changes in runoff, quantifying the impacts of climate and LUCC by comparing scenarios where only one factor was varied.

In the three LULC modes (L1, L2, and L3), the changes in river runoff caused by climate change are denoted as ΔQ_{C1} , $\Delta Q_{C2(UD)}$ and $\Delta Q_{C3(EP)}$. Similarly, under the two different climatic conditions (C1 and C2), the changes in hydrological processes due to LUCC are represented by $\Delta Q_{L1(EP)}$, $\Delta Q_{L2(EP)}$, $\Delta Q_{L1(UD)}$ and $\Delta Q_{L2(UD)}$. Detailed scenario settings and parameter explanations are provided in Table 5.

Table 5. Scenario setting.

Scenario	Meteorological Data	LULC Data	Value of Simulation
S1	1980–2003	2020	ΔQ_{C1}^{L1}
S2	1980–2003	2030UD	ΔQ_{C1}^{L2}
S3	1980–2003	2030EP	ΔQ_{C1}^{L3}
S4	2004–2019	2020	ΔQ_{C2}^{L1}
S5	2004–2019	2030UD	ΔQ_{C2}^{L2}
S6	2004–2019	2030EP	ΔQ_{C2}^{L3}

The formulas provided are used to quantify the impacts of LULC activities and climate change under the UD and EP scenarios:

(1) Under the UD Scenario. The impact of LULC activities $\Delta Q_{L(UD)}$ and climate change $\Delta Q_{C(UD)}$ are calculated as follows:

$$\Delta Q_{L(UD)} = \frac{1}{2} (\Delta Q_{L1(UD)} + \Delta Q_{L2(UD)}) = \frac{1}{2} [(\Delta Q_{C1}^{L2} - \Delta Q_{C1}^{L1}) + (\Delta Q_{C2}^{L2} - \Delta Q_{C2}^{L1})] \quad (7)$$

$$\Delta Q_{C(UD)} = \frac{1}{2}(\Delta Q_{C1} + \Delta Q_{C2(UD)}) = \frac{1}{2}[(\Delta Q_{C2}^{L1} - \Delta Q_{C1}^{L1}) + (\Delta Q_{C2}^{L2} - \Delta Q_{C1}^{L2})] \quad (8)$$

(2) Under the EP Scenario. The impact of LULC activities $\Delta Q_{L(EP)}$ and climate change $\Delta Q_{C(EP)}$ are calculated as follows:

$$\Delta Q_{L(EP)} = \frac{1}{2}(\Delta Q_{L1(EP)} + \Delta Q_{L2(EP)}) = \frac{1}{2}[(\Delta Q_{C1}^{L3} - \Delta Q_{C1}^{L1}) + (\Delta Q_{C2}^{L3} - \Delta Q_{C2}^{L1})] \quad (9)$$

$$\Delta Q_{C(EP)} = \frac{1}{2}(\Delta Q_{C1} + \Delta Q_{C2(EP)}) = \frac{1}{2}[(\Delta Q_{C2}^{L1} - \Delta Q_{C1}^{L1}) + (\Delta Q_{C2}^{L3} - \Delta Q_{C1}^{L3})] \quad (10)$$

3.6. Geodetector

Geodetector is a statistical method for detecting spatial heterogeneity and assessing the relationships between driving factors by comparing the spatial distributions of independent and dependent variables [47]. Geodetector consists of four main components: Risk Detector, Factor Detector, Ecological Detector, and Interaction Detector [27]. The Factor Detector assesses the spatial heterogeneity of the dependent variable and evaluates the influence of driving factors. The Interaction Detector identifies the interaction effects among different factors on the dependent variable [48]. This study utilizes the Factor Detector and Interaction Detector to explore the explanatory power of various driving factors on water yield, quantified by the q -value. The calculation formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST} \quad (11)$$

where h represents the strata of variable Y or factor X , such as categories or regions, N_h and N denote the number of units in stratum h and the entire region, respectively, σ_h^2 and σ^2 are the variances of Y within stratum h and the entire region, SSW is the sum of squared deviations within strata, and SST is the total sum of squared deviations for the entire region.

4. Results

4.1. LUCC Analysis Under UD and EP Scenarios

This study simulated LULC in the upper Yangtze River basin for 2030 under two scenarios, as shown in Figure 4. The results indicate significant LUCC from 2020 to 2030 between the two scenarios. Under the 2030 UD scenario, the most notable changes compared to 2020 occurred in built-up land, forest land, and cultivated land. Built-up land increased by 2102.73 km² (16.63%), forest land by 7774.72 km² (2.19%), and cultivated land by 3094.62 km² (1.45%). In the 2030 EP scenario, the most significant changes compared to 2020 were in forest land, grassland, and unused land. Forest land increased by 8382.08 km², with a change rate of about 2.36%. Grassland decreased by 7144.40 km², approximately −1.95%, and unused land decreased by 2402.92 km², about −4.87%. Notable differences in land type distribution were also observed between the two scenarios. For instance, in the 2030 UD scenario, grassland area was 6900.32 km² less than in the 2030 EP scenario, representing a 1.92% decrease. Unused land in the 2030 UD scenario increased by 3524.36 km² (7.51%), and built-up land showed the largest change, increasing by 1088.48 km² (7.96%).

Spatially, the overall distribution of LULC types differs slightly between the scenarios, with differences being subtle. Overall, cultivated land is primarily distributed in

patches across the central and eastern flat areas; forest land is mainly found in the central and southern regions of the upper Yangtze River basin, showing broad and continuous coverage. Grassland is scattered, mainly concentrated in the peripheral and high-altitude areas of the study region. Built-up land is densely clustered along the main and tributary channels of the Yangtze River, though its overall area remains relatively small. Under the EP scenario, built-up land expansion is limited to existing urban areas from 2020 to 2030. Forest land expands noticeably but shows fragmented growth, while grassland and unused land areas decrease significantly, contributing to the increased forest area. Conversely, the UD scenario shows significant expansion of built-up land, particularly in the central and eastern parts of the study area, mainly as outward extensions of existing urban areas. Forest and grassland areas decrease and become more fragmented, while cultivated land also increases, exhibiting a patch-like distribution.

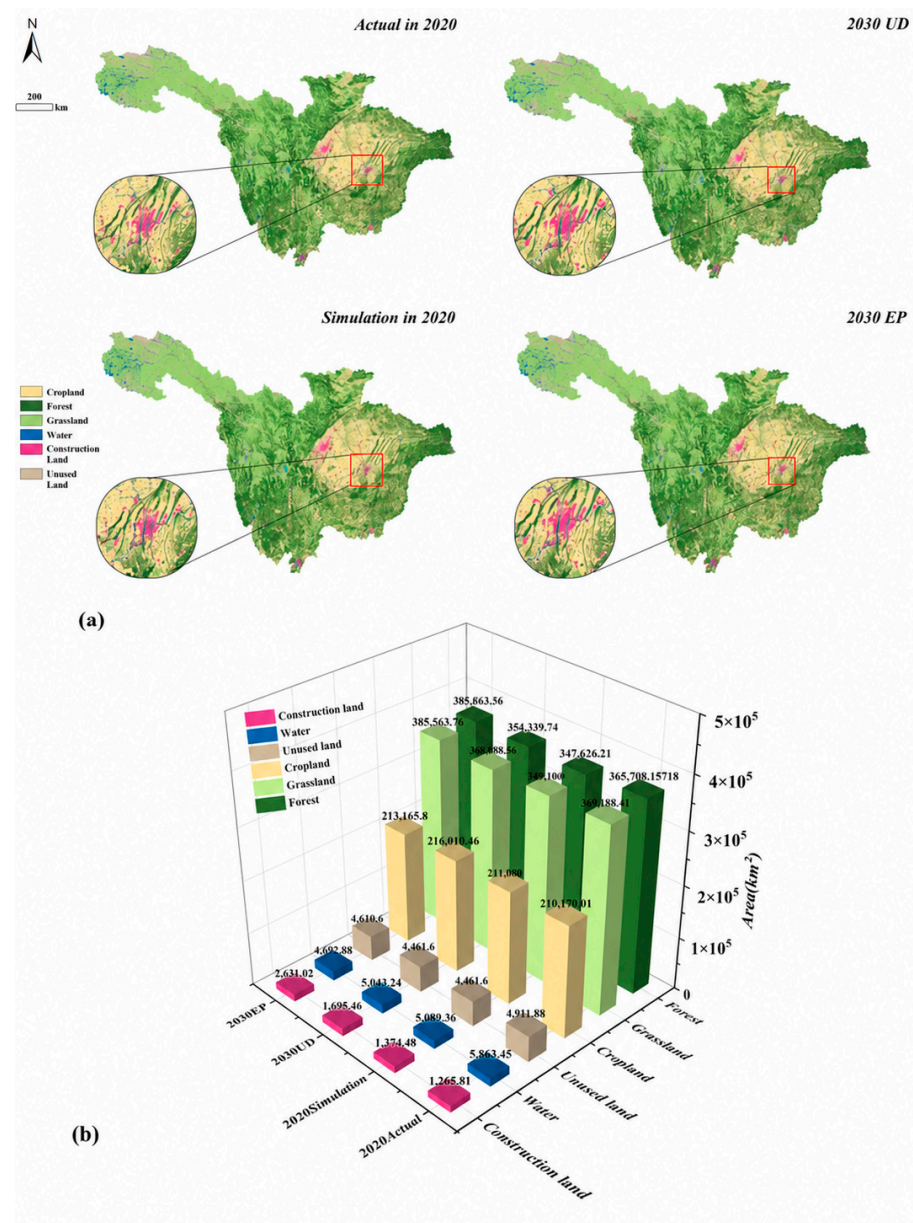


Figure 4. (a) Comparison of simulated LULC structures under four scenarios; (b) area distribution of LULC structures across multiple scenarios.

4.2. Spatiotemporal Variations in Water Yield in the Upper Yangtze River Basin

4.2.1. Spatial Expression of Water Yield Heterogeneity Across Scales

This study employed the InVEST-AWY model at the grid scale and the SWAT model at the sub-basin scale to estimate the ecosystem water yield services of the basin. The SWAT model was calibrated using SWAT-CUP, which considers simulation results reliable if the coefficient of determination (R^2) is above 0.5 and the Nash–Sutcliffe efficiency (NSE) exceeds 0.5. As shown in Figure 5, the SWAT model achieved an R^2 of 0.92 and an NSE of 0.85 during the calibration period (1980–2003), and an R^2 of 0.77 and an NSE of 0.72 during the validation period (2004–2019). All values exceeded the recommended thresholds, indicating satisfactory model performance in simulating the hydrological processes of the basin. Additionally, the uncertainty analysis from the SUFI-2 algorithm showed satisfactory performance, with a P-factor of 0.82 and an R-factor of 0.68 during the calibration period, indicating that the model captured a high proportion of the observed data within the prediction uncertainty bounds. Similar uncertainty performance was maintained during the validation period.

Figure 6 shows the spatial distribution of water yield at both grid and sub-basin scales in 2000. At the grid scale, higher water yields were observed in the northern and central regions, whereas lower yields were found in the southwestern and eastern regions. At the sub-basin scale, most areas showed high water yield, with only a few sub-basins exhibiting lower yields. In 2010, the distribution pattern of water yield showed some changes. At the grid scale, high-yield areas expanded, though the overall pattern remained similar to 2000. At the sub-basin scale, the sub-basins in the western and northern regions had higher water yields, while the central and eastern sub-basins showed a decrease. By 2020, high-yield areas at the grid scale further expanded, particularly in the northern and central regions. At the sub-basin scale, most areas maintained high water yield, though some sub-basins in the western and eastern regions showed declines. From 2000 to 2020, increasing urbanization contributed to an upward trend in water yield at the grid scale, expanding high-yield areas in the eastern basin. Meanwhile, low-yield areas in the central and western regions contracted, and previously water-scarce areas experienced improved water availability. Conversely, at the sub-basin scale, water yield initially increased and then declined, with spatial patterns similar to those at the grid scale but with notable differences. For example, in the southeastern basin, the grid scale exhibited a gradual annual increase in water yield, whereas the sub-basin scale showed a significant annual decrease.

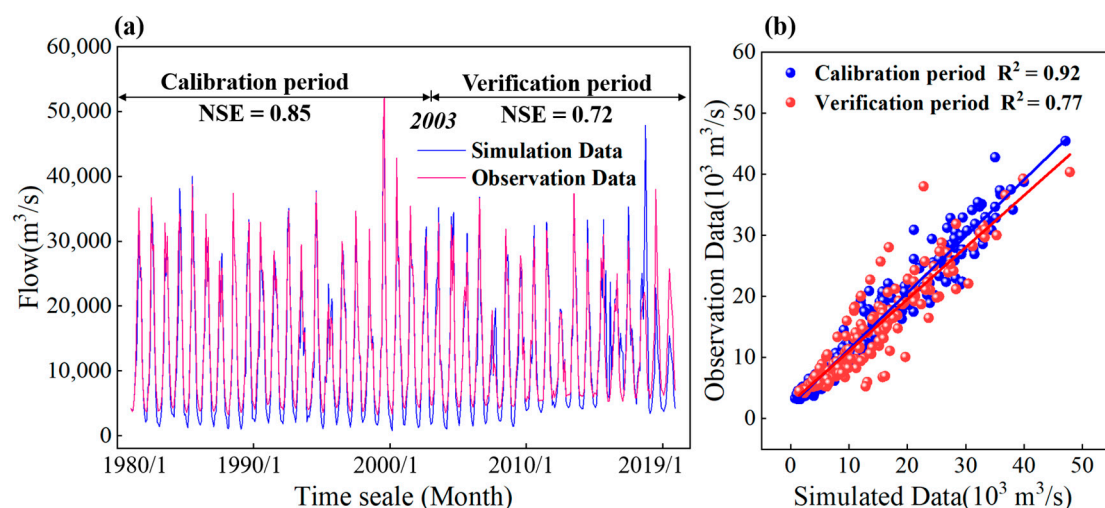


Figure 5. (a) Comparison of the monthly traffic values simulated and observed during the calibration and verification period at the YC station. (b) Correlation plots of observed and simulated flows during YC station calibration and verification.

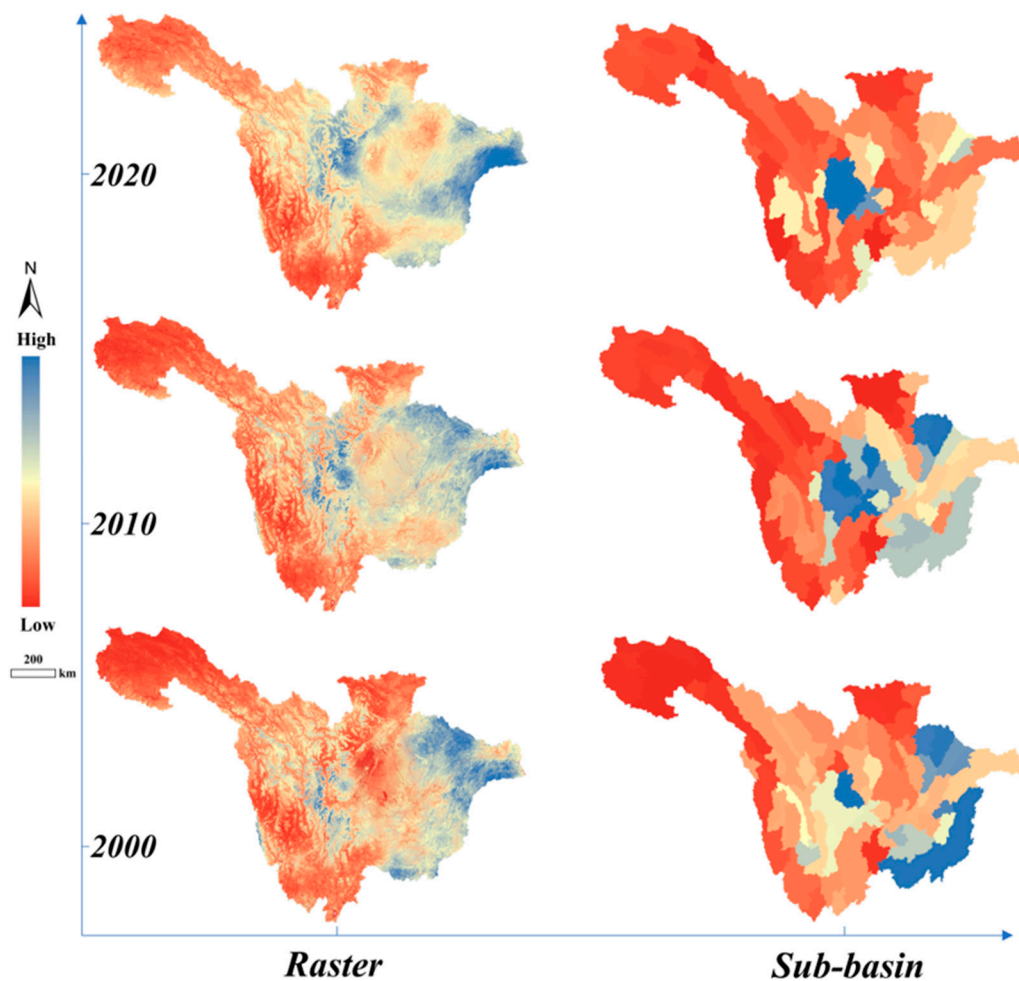


Figure 6. Spatial distribution of water yield at the raster scale and sub-basin scale from 2000 to 2020.

4.2.2. Impact of LUCC on Water Yield Under Different Scenarios

LUCC critically influence water yield in river basins. This study explores the impact of LUCC under different scenarios on water yield within the basin. Figure 7 shows that under the UD scenario, grid-scale changes in water yield are minimal in the western and southern parts of the study area. In contrast, significant urban expansion in the central and eastern regions has increased high-water-yield areas around urban zones. Conversely, water yield from forest and grassland areas decreased. At the sub-basin scale, changes in water yield are more pronounced. Urban construction and expansion in the western basin have enhanced water yield in previously low-yield areas due to increased human exploitation of water resources. Conversely, in the central basin, the conversion of forest and grassland into cropland has reduced the overall water yield capacity.

Under the EP scenario, the overall distribution of water yield at both grid and sub-basin scales shows little difference compared to the UD scenario. This similarity suggests that low construction levels in the western basin have not significantly altered the water yield distribution in barren lands. However, effective ecological protection measures have slightly increased the areas of forest and grassland in the central and eastern regions, contributing to a modest rise in water yield. The future changes in LULC will not alter the distribution pattern of high-water-yield areas. At two scales, high-water-yield areas are

still concentrated in the Sichuan Basin and the Chongqing region. The establishment of ecological protection zones has enhanced water resource accumulation in these areas. Further implementation of ecological protection measures is expected to expand high-water-yield areas, particularly in ecological restoration zones. Furthermore, at the sub-basin scale, the average annual water production in the UD scenario in 2020 was 7.96% higher than that in the EP scenario. This indicates that, compared with the ecological protection strategy of enhancing water-retention capacity through vegetation, the UD strategy increases water yield primarily through the expansion of impervious surfaces, which reduces infiltration and promotes surface runoff. However, while increasing water yield, the expansion of impervious surfaces may also increase peak discharge and flood risk, reduce groundwater recharge, and disrupt watershed hydrological regulation and ecosystem organization.

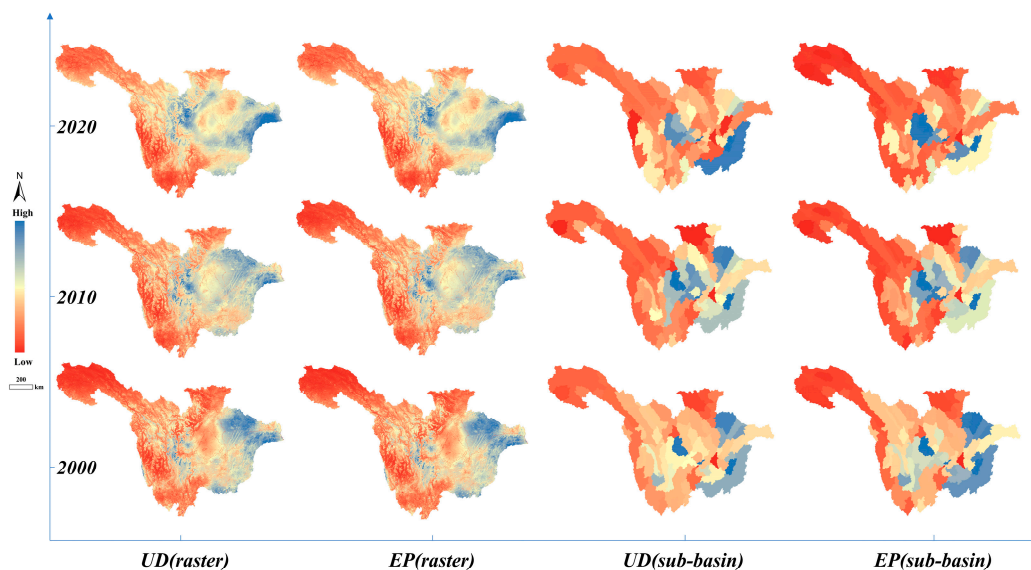


Figure 7. Spatial distribution of water yield under UD and EP scenarios at two scales (raster scale and sub-basin scale) under different climatic conditions.

4.3. Attribution Analysis of Watershed Water Yield

4.3.1. Impacts of LUCC and CC on Watershed Runoff

Within the watershed water cycle, runoff represents the portion of precipitation remaining after evapotranspiration, infiltration, and water-storage processes. Therefore, it can serve as a quantitative indicator of the magnitude of regional water yield. This study utilized simulated data instead of observed data to compare the effects of climate change (CC) and future LUCC on runoff in the upper Yangtze River basin at the sub-basin scale. Runoff was simulated using the SWAT model under six hypothetical scenarios, applying separation Equations (7)–(10) to assess the contributions of LUCC and CC to runoff variations.

As shown in Figure 8, under the 2030 EP scenario, LUCC significantly increased runoff in January (1700.425 m³/s) and February (1584.485 m³/s) but decreased it notably in May (−2760.58 m³/s), June (−3427.38 m³/s), and October (−2117.53 m³/s). CC contributed to overall increases in runoff during spring (notably March at 2675.13 m³/s) and autumn (especially in August at 10,587.47 m³/s and September at 2694.575 m³/s), while significantly reducing runoff in summer (particularly in July at −2018.77 m³/s). Under the 2030 UD scenario, LUCC significantly increased runoff in January (641.785 m³/s), February (750.915 m³/s), May (678.645 m³/s), and June (1337.87 m³/s), but decreased it notably in October

($-1288.79 \text{ m}^3/\text{s}$) and November ($-1124.3 \text{ m}^3/\text{s}$). CC led to significant runoff increases from January to June but substantial reductions from July to October, particularly in August ($-5718.67 \text{ m}^3/\text{s}$). Seasonal comparisons show that both LUCC and CC increased runoff in spring (EP: $763.065 \text{ m}^3/\text{s}$; UD: $487.245 \text{ m}^3/\text{s}$) and autumn (EP: $1817.42 \text{ m}^3/\text{s}$; UD: $-325.76 \text{ m}^3/\text{s}$), but reduced it in summer (EP: $-4705.78 \text{ m}^3/\text{s}$; UD: $890.815 \text{ m}^3/\text{s}$). Spring and autumn are characterized by high water yield periods where LUCC and CC markedly enhance runoff. In contrast, summer, typically a low-water-yield period, shows reductions in runoff, particularly pronounced in July and August. Winter generally exhibits minimal impact, though positive contributions from LUCC and CC in December (EP: $1219.9 \text{ m}^3/\text{s}$; UD: $10.255 \text{ m}^3/\text{s}$) and January (EP: $1700.425 \text{ m}^3/\text{s}$; UD: $641.785 \text{ m}^3/\text{s}$) suggest some increase in runoff during this season. Overall, under the 2030 EP scenario, the impacts of LUCC and CC on runoff are relatively balanced, increasing in spring and autumn while reducing in summer. Conversely, the 2030 UD scenario shows greater increases in spring and winter, with notable reductions during the low-flow periods of summer. Annually, the contribution of CC to runoff increase under the 2030 EP scenario ($2115.33 \text{ m}^3/\text{s}$) far exceeds that of LUCC ($-398.51 \text{ m}^3/\text{s}$), while in the 2030 UD scenario, contributions are more balanced (LUCC: $223.72 \text{ m}^3/\text{s}$; CC: $141.38 \text{ m}^3/\text{s}$).

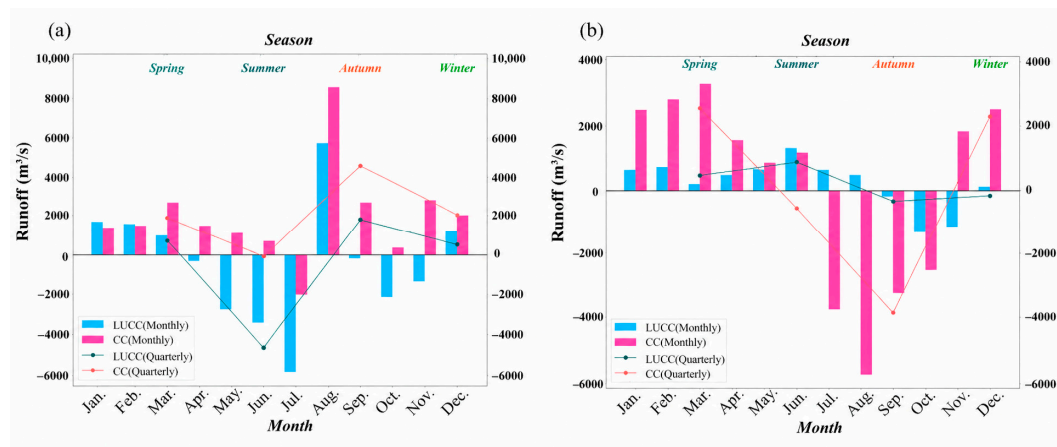


Figure 8. Monthly (seasonal) runoff changes caused by CC and LUCC: (a) EP scenario, (b) UD scenario.

4.3.2. Analysis of Driving Factors of Watershed Water Yield Based on Geodetector

Water yield in the upper Yangtze River basin was analyzed as the dependent variable, with impacts of various driving factors assessed using line density and Euclidean distance. Independent variables included natural factors (slope, elevation, temperature, evapotranspiration, precipitation, soil) and social factors (population, GDP). Indicator data were discretized using the natural breaks method, reclassified, and analyzed with the Geodetector tool to quantify the influence of driving factors on water yield. Results indicated that all independent variables had p -values less than 0.01, confirming the statistical significance of their q -values.

As shown in Figure 9a,b, precipitation is the primary driving factor at both scales, contributing most to water yield with weights of 0.81 at the grid scale and 0.67 at the sub-basin scale. Temperature (TEM) and evapotranspiration (EVP), both natural factors, also significantly influence water yield at both scales, with weights of 0.29 and 0.27 at the sub-basin scale and 0.22 and 0.26 at the grid scale, respectively. Elevation (DEM) and slope (SLOPE) have moderate or smaller impacts at both scales, suggesting that terrain plays a role in water yield but is not a primary driver. Social factors like GDP and population (POP) have minor influences at both scales, underscoring that natural factors, particularly precipitation, are the main drivers of water yield in the basin.

Interaction detector results (Figure 9c,d) indicate that combined effects of dual factors on spatial variations in water yield are similar at both scales, often exceeding the influence of individual factors, demonstrating bi-factor and nonlinear enhancements. In the upper Yangtze River basin, interactions between precipitation and other factors exhibit high explanatory power for spatial variations in water yield, often exceeding 60%. Specifically, interactions between precipitation and population density explain 83% at the grid scale and 68% at the sub-basin scale, while interactions between precipitation and GDP explain 82% and 67%, respectively. This suggests that spatial heterogeneity in water yield is significantly enhanced under consistent precipitation depth when there are spatial variations in population density and GDP, indicating that human activities will increasingly influence the spatial distribution of water yield. The interaction between evapotranspiration and elevation has a significantly higher impact than most other bi-factor interactions, suggesting that the interplay between evapotranspiration and elevation will further expand the spatial distribution differences in water yield within the basin.

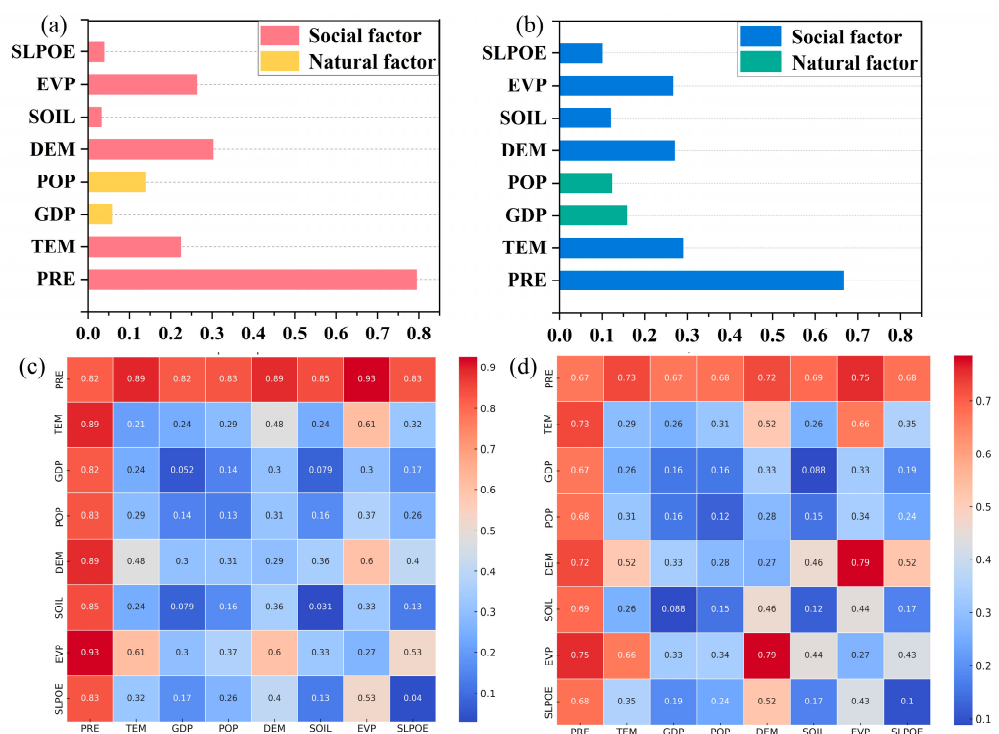


Figure 9. Influence of different watershed factors on the spatial heterogeneity of water yield: (a) raster scale, (b) sub-basin scale. Interaction effects of water yield driving factors: (c) raster scale, (d) sub-basin scale. Note: TEM stands for temperature, POP stands for population, PRE stands for precipitation, and EVP stands for evapotranspiration.

5. Discussion

5.1. Uncertainty Analysis and Study Limitations

This study used the PLUS model to simulate LULC distributions under different future scenarios and incorporated the resulting LULC data into the SWAT and InVEST models to estimate water yield at the sub-basin and grid scales, respectively. These widely used models support watershed planning, ecological assessment, and environmental management, but each has limitations. The PLUS model simulates LUCC by evaluating the contribution of driving factors within the LEAS framework; however, factor selection is partly subjective and may not fully reflect policy influences. The InVEST-AWY model does not explicitly represent complex subsurface processes, and its outputs are sensitive to the Z parameter and biophysical table values, which are often derived from the

literature or expert judgment [49]. The SWAT model requires extensive soil, meteorological, and parameter inputs, and different parameter combinations may affect simulation results. In addition, spatial aggregation introduced by the 500,000 ha sub-basin threshold and 10% HRU threshold may underestimate local heterogeneity in topography and land cover. Although these settings balance computational efficiency and model stability, they may simplify fine-scale hydrological processes.

A further source of uncertainty arises from treating climate variability and LUCC as independent drivers in the attribution analysis. In reality, climate variability may influence vegetation conditions and land-use transitions, while LUCC can alter evapotranspiration, surface roughness, albedo, and local hydroclimatic processes. Therefore, the estimated contributions should be interpreted as scenario-based effects under a simplifying independence assumption rather than as fully coupled causal effects. In addition, because the LULC outputs of the PLUS model are used as inputs to the SWAT and InVEST models, uncertainty in future land-use projections may propagate through the integrated modeling framework. Differences in spatial resolution, process representation, and parameterization may further contribute to uncertainty in the final water-yield estimates.

The PLUS model's performance in simulating 2020 LULC was evaluated with a Kappa coefficient of 0.89 and an Overall Accuracy of 0.92. SWAT model simulations achieved an R^2 of 0.92 and an NSE of 0.85, indicating close agreement between simulated and observed data. The Z parameter of the InVEST-AWY model was calibrated against observed runoff, providing an additional check on the consistency of the annual water-yield estimates. These evaluations support the reliability of the individual model components, although the integrated framework cannot be independently validated as a whole under future conditions because corresponding observations are unavailable. It should be noted that the model was calibrated at a monthly time step, which may lead to uncertainty in capturing daily scale extreme hydrological events. Although the overall performance metrics meet recommended standards, the smoothing effect of monthly aggregation can reduce sensitivity to peak flows. Alternative sub-basin and HRU thresholds may alter the representation of local heterogeneity and the magnitude of simulated responses. However, their influence on basin-scale spatial patterns and relative differences among scenarios is expected to be limited, and this uncertainty was not quantitatively assessed in the present study. Future research could incorporate multi-time-scale calibration, finer temporal and spatial resolutions, and systematic threshold sensitivity analyses to further evaluate the robustness of the modeling framework.

The LULC data for future water yield simulations at grid and sub-basin scales were based on PLUS model predictions; however, future climate change impacts were not considered, as meteorological and precipitation data were historical. In reality, besides human activities, climate change is also a critical factor influencing water yield in the basin. Future climate data can be simulated using machine learning models, such as transformers, LSTM, and random forests, trained on historical meteorological data. Alternatively, future climate changes can be modeled using various tools provided by the Coupled Model Intercomparison Project Phase 6 (CMIP6) [50]. Future studies should integrate dynamically consistent climate and land-use scenarios to account for their potential interactions and feedbacks, thereby providing a more realistic assessment of future water-yield changes and their driving mechanisms.

5.2. Comparative Analysis of Water Yield Simulations at Grid and Sub-Basin Scales

In the Upper Yangtze River Basin, water yield simulated using the InVEST model at the grid scale ranged from 0 to 1730.64 mm in 2000, 0 to 1706.51 mm in 2010, and 0 to 2028.66 mm in 2020. Comparatively, the SWAT model at the sub-basin scale showed water yield ranges of 211.36 to 715.31 mm in 2000, 226.83 to 747.25 mm in 2010, and 240.31 to

866.39 mm in 2020. The differences in spatial and temporal water yield distributions between the two scales are due to different modeling and calculation approaches: the grid scale represents spatial variation at the individual-cell level, whereas the sub-basin scale averages water yield within each sub-basin. The resulting differences in magnitude therefore reflect both spatial aggregation and the distinct hydrological process representations of the two models. Overall, water yield trends show an increase from west to east across the basin. The study finds that water retention in forest areas remains consistently high, while water yield capacity in large portions of cultivated and urban areas in the central basin has declined over time. The northwestern region, characterized by plateau terrain and extensive bare land, exhibits low water yield capacity due to its alpine climate, resulting in scarce water resources and a fragile ecological environment. Water yield and its variability have been focal points in ecological research. Topography plays a critical role in water yield processes within the watershed, as factors like slope, aspect, elevation, and terrain complexity affect surface runoff, infiltration, evaporation, and groundwater recharge [51]. Results indicate a general negative correlation between water yield capacity and elevation in the Upper Yangtze River Basin.

Water yield capacity varies significantly among different land cover types, influenced by land cover, soil characteristics, vegetation conditions, and human activities [52]. Forest areas typically exhibit lower water yield capacity but strong water retention functions; stable vegetation and soil structures enhance infiltration and reduce runoff variability [53]. In contrast, grasslands and farmlands have moderate water yield capacity with significant seasonal variability [54]. Urban areas, with extensive impervious surfaces, exhibit increased water yield due to reduced evapotranspiration, leading to rapid surface runoff and elevated flood risk [55]. Wetlands, known for their unique water storage and regulation functions, can store water during high levels and release it during low levels, exhibiting strong water regulation capacity; they also play a significant role in pollutant removal and water quality improvement [56]. Bare and desert areas generally have low water yield capacity due to loose soil structures and poor infiltration; although precipitation can quickly form surface runoff, the total water yield remains limited due to typically low rainfall [57].

This study comprehensively simulates and evaluates water yield at both grid and sub-basin scales, leveraging the strengths of different models to represent spatiotemporal water yield services. The grid scale is modeled using the InVEST-AWY model, known for its global applicability and flexibility, providing high-resolution spatial details that capture variations in water yield at smaller scales [58]. The sub-basin scale employs the SWAT model, a traditional distributed hydrological model that divides the basin into multiple sub-basins. By integrating various meteorological and hydrological data within the basin and refining the modeling process through iterative simulations, the model accurately simulates the hydrological cycle of each sub-basin [59]. This approach helps identify differences between sub-basins and provides more precise numerical simulations, although it lacks the fine detail of the grid scale. Future research could further strengthen the assessment of cross-scale consistency through a more systematic comparison of the InVEST-AWY and SWAT simulations. Such efforts would provide additional evidence for the interoperability of multi-scale model results and support a more integrated understanding of water-yield dynamics.

5.3. Influence of Anthropogenic Activities and Climate Change on Water Yield in River Basins

Climate change has a more pronounced impact on water yield than LUCC. Studies separating the contributions of LULC and climate change to river runoff in the upper Yangtze River basin show that climate change generally has a higher contribution to runoff variations at both monthly and seasonal scales compared to LUCC. At the monthly

scale, the difference in runoff attributed to climate change compared to human activity exceeds 2000 m³/s in more than half of the months. Geodetector analysis of driving factors reveals that climate factors are the dominant drivers of water yield, with precipitation significantly explaining the spatial heterogeneity of water yield in the upper Yangtze River basin more than other factors. The importance of meteorological factors to basin water resources is confirmed by other studies. For instance, research indicates that precipitation patterns and temperature variations in the Yangtze River basin significantly influence extreme hydrological events, such as floods and droughts, underscoring the critical role of meteorological factors in water resource management [60]. A study using multi-source remote sensing data analyzed changes in surface water area in India, finding that meteorological factors such as precipitation and evaporation significantly influence the dynamics of water bodies, directly affecting agricultural and ecosystem sustainability [61].

LUCC is closely linked to human development strategies. In China, rapid economic growth driven by the reform and opening-up policy has led to urban expansion encroaching on forests and grasslands, posing significant threats to watershed water resources [62]. Studies have shown that under human intervention, LULC changes exhibit irreversible trends; the expansion of impervious surfaces not only alters the distribution of groundwater resources but also affects evapotranspiration processes [63]. However, since the implementation of the “Green is Gold” ecological protection strategy in China in 2017, the ecological environment within the basin has begun to slowly recover, and water resource security has been enhanced [62]. This study used the PLUS model to predict LULC in 2030 under two scenarios and simulated water yield at both grid and sub-basin scales. The results indicate that while the UD and EP scenarios do not significantly alter water yield at the grid scale, they considerably affect the spatial distribution of water yield at the sub-basin scale. While the direct impact of human activities on watershed water resources is less significant than that of climate change, increased human intervention exacerbates global climate change, increasing the frequency of extreme climate events and further altering the spatial distribution of watershed water resources [64].

6. Conclusions

This study simulated the spatiotemporal distribution of water yield in the Upper Yangtze River Basin at grid and sub-basin scales and assessed the spatial patterns of water yield for 2020. It also projected LUCC for 2030 under UD and EP scenarios using the PLUS model. Differences between the future LULC scenarios and the actual 2020 LULC were analyzed, followed by an evaluation of the spatial distribution patterns of water yield under the UD and EP scenarios. The dual-scale framework provides complementary information for identifying local spatial heterogeneity and supporting basin-scale water-resource management. The key conclusions are as follows:

(1) LULC Differences Across Future Scenarios: Significant differences in LULC were observed among the future scenarios. In the UD scenario, built-up land increased by 7.96% compared to the EP scenario. Grassland area decreased by 1.92%, while cultivated land increased by 1.38% relative to EP. Despite variations in the extent of land types under different scenarios, forests, grasslands, and cultivated lands remain the dominant LULC types across the basin.

(2) Distinct Differences in Water Yield Across Scales: The spatiotemporal distribution of water yield at both grid and sub-basin scales showed significant differences, though their overall patterns were similar: high-water-yield areas were mainly concentrated in the eastern and central parts of the basin, while low-water-yield areas were primarily located in the western and northern parts. From 2000 to 2020, water yield generally increased at the grid scale, whereas at the sub-basin scale, it initially increased and then decreased.

(3) **Impact of Human Development Strategies on Water Yield at the Sub-Basin Scale:** Human development strategies had a significant impact on water yield at the sub-basin scale. Under both UD and EP scenarios, changes in water yield at the grid scale were minimal. In the UD scenario, water yield increased in the western and eastern parts of the basin, while some central regions experienced a decline in water-yield capacity. In the EP scenario, water yield remained low in the western part of the basin but improved in the central and southeastern regions, with most other areas showing a slight decrease compared to 2020. These spatial differences indicate that land-use management and ecological protection measures should be adapted to local water-yield conditions rather than applied uniformly across the basin.

(4) **Climate Change as the Dominant Factor Influencing Water Yield:** Under the EP scenario, climate change significantly increased runoff (+2115.33 m³/s), whereas LUCC reduced runoff (−398.51 m³/s). Under the UD scenario, the overall effects of climate change and LUCC were relatively small (+141.38 and +223.72 m³/s, respectively), although climate change exerted a stronger influence during wet months. Geodetector analysis further identified precipitation as the dominant driver of water yield at both scales, with explanatory powers of 0.81 at the grid scale and 0.67 at the sub-basin scale. These findings highlight the importance of precipitation variability in future water-resource management. Future research should further examine the interactions between climate change and LUCC.

Author Contributions: W.G.: Acquisition of Funds, Management of Projects, Resources, Research, and Supervision; X.J.: The stages involved in this process include conceptualization, data curation, formal analysis, investigation, methodology, original draft writing, and editing. Y.N.: Acquisition of Funds and Project Management. H.W.: Visualization, Research, and Formal Evaluation. and all authors commented on previous versions of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Henan Provincial Higher Education Key Scientific Research Project Programme (23ZX012 & 24ZX007); 2025 Henan Provincial Natural Science Foundation (252300421334); 2025 Henan Provincial Outstanding Youth Science Foundation (252300421049); Foreign Scientist Studio for Eco-hydrological Effects and Regulation of the Yellow River Basin of Henan Province (GZS2026012).

Data Availability Statement: Section 2.2 and Table 1. The processed datasets and model outputs generated during this study are available from the corresponding author upon reasonable request.

Acknowledgments: Thanks to the data from the Resources and Environment Center of the National Forestry and Land Administration and the data platform of the China Meteorological Network and other related open platforms for your support.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Liu, J.G.; Li, D.L.; Chen, H.; Wang, H.; Wada, Y.; Kummu, M.; Gosling, S.N.; Yang, H.; Pokhrel, Y.; Ciais, P. Timing the first emergence and disappearance of global water scarcity. *Nat. Commun.* **2024**, *15*, 7129. <https://doi.org/10.1038/s41467-024-51302-z>.
2. Reichstein, M.; Riede, F.; Frank, D. More floods, fires and cyclones—Plan for domino effects on sustainability goals. *Nature* **2021**, *592*, 347–349. <https://doi.org/10.1038/d41586-021-00927-x>.
3. Ke, X.L.; Wang, L.Y.; Ma, Y.C.; Pu, K.P.; Zhou, T.; Xiao, B.Y.; Wang, J.H. Impacts of strict cropland protection on water yield: A case study of Wuhan, China. *Sustainability* **2019**, *11*, 184. <https://doi.org/10.3390/su11010184>.
4. Li, P.; Chaubey, I.; Muenich, R.L.; Wei, X.M. Evaluation of freshwater provisioning for different ecosystem services in the Upper Mississippi River Basin: Current status and drivers. *Water* **2016**, *8*, 288. <https://doi.org/10.3390/w8070288>.

5. Wang, P.; Xu, M. Dynamics and interactions of water-related ecosystem services in the Yellow River Basin, China. *J. Geogr. Sci.* **2023**, *33*, 1681–1701. <https://doi.org/10.1007/s11442-023-2148-0>.
6. Yang, J.; Xie, B.P.; Zhang, D.G.; Tao, W.Q. Climate and land use change impacts on water yield ecosystem service in the Yellow River Basin, China. *Environ. Earth Sci.* **2021**, *80*, 72. <https://doi.org/10.1007/s12665-020-09277-9>.
7. Yan, Y.; Liu, Z.Y.; Chen, X.H.; Huang, L.Y. Stability of water yield in watersheds. *Sci. China Earth Sci.* **2024**, *67*, 483–496. <https://doi.org/10.1007/s11430-023-1206-4>.
8. Chen, X.; Lin, S.Y.; Tian, J.; Wang, Y.J.; Ye, Y.X.; Dong, S.N.; Gong, X.L.; Lin, Q.L.; Zhu, L.Y. Simulation study on water yield service flow based on the InVEST-Geoda-Gephi network: A case study on Wuyi Mountains, China. *Ecol. Indic.* **2024**, *159*, 111694. <https://doi.org/10.1016/j.ecolind.2024.111694>.
9. Pignotti, G.; Rathjens, H.; Cijin, R.; Chaubey, I.; Crawford, M. Comparative analysis of HRU and grid-based SWAT models. *Water* **2017**, *9*, 272. <https://doi.org/10.3390/w9040272>.
10. Hamman, J.J.; Nijssen, B.; Bohn, T.J.; Gergel, D.R.; Mao, Y.X. The Variable Infiltration Capacity model version 5 (VIC-5): Infrastructure improvements for new applications and reproducibility. *Geosci. Model Dev.* **2018**, *11*, 3481–3496. <https://doi.org/10.5194/gmd-11-3481-2018>.
11. Yan, C.A.; Zhang, W.C. Effects of model segmentation approach on the performance and parameters of the Hydrological Simulation Program–Fortran (HSPF) models. *Hydrol. Res.* **2014**, *45*, 893–907. <https://doi.org/10.2166/nh.2014.182>.
12. Wei, P.J.; Chen, S.Y.; Wu, M.H.; Deng, Y.F.; Xu, H.J.; Jia, Y.L.; Liu, F. Using the InVEST model to assess the impacts of climate and land use changes on water yield in the upstream regions of the Shule River Basin. *Water* **2021**, *13*, 1250. <https://doi.org/10.3390/w13091250>.
13. Pan, T.S.; Zuo, L.J.; Zhang, Z.X.; Zhao, X.L.; Sun, F.F.; Zhu, Z.J.; Liu, Y.C. Impact of land use change on water conservation: A case study of Zhangjiakou in Yongding River. *Sustainability* **2021**, *13*, 22. <https://doi.org/10.3390/su13010022>.
14. Pasquier, U.; Vahmani, P.; Jones, A.D. Quantifying the city-scale impacts of impervious surfaces on groundwater recharge potential: An urban application of WRF–Hydro. *Water* **2022**, *14*, 3143. <https://doi.org/10.3390/w14193143>.
15. He, C.Y.; Zhang, J.X.; Liu, Z.F.; Huang, Q.X. Characteristics and progress of land use/cover change research during 1990–2018. *J. Geogr. Sci.* **2022**, *32*, 537–559. <https://doi.org/10.1007/s11442-022-1960-2>.
16. Fu, F.; Deng, S.M.; Wu, D.; Liu, W.W.; Bai, Z.H. Research on the spatiotemporal evolution of land use landscape pattern in a county area based on CA-Markov model. *Sustain. Cities Soc.* **2022**, *80*, 103760. <https://doi.org/10.1016/j.scs.2022.103760>.
17. Yuan, L.; Xu, J.; Feng, B.R. Evaluation and prediction of carbon storage in the Qinghai-Tibet Plateau by coupling the GMMOP and PLUS models. *Sustainability* **2024**, *16*, 5776. <https://doi.org/10.3390/su16135776>.
18. Xu, L.F.; Liu, X.; Tong, D.; Liu, Z.X.; Yin, L.R.; Zheng, W.F. Forecasting urban land use change based on cellular automata and the PLUS model. *Land* **2022**, *11*, 652. <https://doi.org/10.3390/land11050652>.
19. Xie, Z.Q.; Zhang, Y.; Fang, Z.Q. High-quality development evaluation and spatial evolution analysis of urban agglomerations in the middle reaches of the Yangtze River. *Sustainability* **2022**, *14*, 14757. <https://doi.org/10.3390/su142214757>.
20. Chen, D.; Jiang, P.; Li, M. Assessing potential ecosystem service dynamics driven by urbanization in the Yangtze River Economic Belt, China. *J. Environ. Manag.* **2021**, *292*, 112734. <https://doi.org/10.1016/j.jenvman.2021.112734>.
21. Cong, W.; Sun, X.; Guo, H.; Shan, R. Comparison of the SWAT and InVEST Models to Determine Hydrological Ecosystem Service Spatial Patterns, Priorities and Trade-Offs in a Complex Basin. *Ecol. Indic.* **2020**, *112*, 106089. <https://doi.org/10.1016/j.ecolind.2020.106089>.
22. Decsi, B.; Ács, T.; Jolánkai, Z.; Kardos, M.K.; Koncsos, L.; Vári, Á.; Kozma, Z. From Simple to Complex—Comparing Four Modelling Tools for Quantifying Hydrologic Ecosystem Services. *Ecol. Indic.* **2022**, *141*, 109143. <https://doi.org/10.1016/j.ecolind.2022.109143>.
23. Huang, H.; Zhang, B.; Cui, Y.Q.; Ma, S.Q. Analysis on the characteristics of dry and wet periods in the Yangtze River Basin. *Water* **2020**, *12*, 2960. <https://doi.org/10.3390/w12112960>.
24. Li, Y.; Yan, D.H.; Peng, H.; Xiao, S.B. Evaluation of precipitation in CMIP6 over the Yangtze River Basin. *Atmos. Res.* **2021**, *253*, 105406. <https://doi.org/10.1016/j.atmosres.2020.105406>.
25. Ma, Z.Q.; Xu, J.T.; Zhu, S.Y.; Yang, J.; Tang, G.Q.; Yang, Y.J.; Shi, Z.; Hong, Y. AIMERG: A new Asian precipitation dataset (0.1°/half-hourly, 2000–2015) by calibrating the GPM-era IMERG at a daily scale using APHRODITE. *Earth Syst. Sci. Data* **2020**, *12*, 1525–1544. <https://doi.org/10.5194/essd-12-1525-2020>.
26. Ma, X.Y.; Liu, S.S.; Guo, L.; Zhang, J.Z.; Feng, C.; Feng, M.Y.; Li, Y.L. Evolution and Analysis of Water Yield under the Change of Land Use and Climate Change Based on the PLUS-InVEST Model: A Case Study of the Yellow River Basin in Henan Province. *Water* **2024**, *16*, 2551. <https://doi.org/10.3390/w16172551>.

27. Zhang, J.P.; Wang, J.; Chen, Y.H.; Huang, S.D.; Liang, B.Y. Spatiotemporal variation and prediction of NPP in Beijing-Tianjin-Hebei region by coupling PLUS and CASA models. *Ecol. Inform.* **2024**, *81*, 102620. <https://doi.org/10.1016/j.ecoinf.2024.102620>.
28. Xu, X.L.; Wang, S.Y.; Rong, W.Z. Construction of ecological network in Suzhou based on the PLUS and MSPA models. *Ecol. Indic.* **2023**, *154*, 110740. <https://doi.org/10.1016/j.ecolind.2023.110740>.
29. Gao, Z.Q.; Tao, F.; Wang, Y.H.; Zhou, T. Potential ecological risk assessment of land use structure based on MCCA model: A case study in Yangtze River Delta Region, China. *Ecol. Indic.* **2023**, *155*, 110931. <https://doi.org/10.1016/j.ecolind.2023.110931>.
30. Dan, D.; Xi, C.; Zhou, H.J.; Wan, Z.Q.; Xia, Y.Y.; Na, W. Quantitative impacts of climate change and human activities on runoff in the Huolin River catchment. *J. Water Clim. Change* **2022**, *13*, 3851–3866. <https://doi.org/10.2166/wcc.2022.223>.
31. Shi, X.; Wu, L.; Zheng, Y.Q.; Zhang, X.; Wang, Y.J.; Chen, Q.; Sun, Z.Y.; Nie, T.Z. Dynamic estimation of mangrove carbon storage in Hainan Island based on the InVEST-PLUS model. *Forests* **2024**, *15*, 750. <https://doi.org/10.3390/f15050750>.
32. Guo, Q.; Lai, X.; Jia, Y.; Wei, F. Spatiotemporal pattern and driving factors of carbon emissions in Guangxi based on geographic detectors. *Sustainability* **2023**, *15*, 15477. <https://doi.org/10.3390/su152115477>.
33. Marey, A.; Wang, L.Z.; Goubran, S.; Gaur, A.; Lu, H.; Leroyer, S.; Belair, S. Forecasting urban land use dynamics through patch-generating land use simulation and Markov chain integration: A multi-scenario predictive framework. *Sustainability* **2024**, *16*, 10255. <https://doi.org/10.3390/su162310255>.
34. Wang, Q.F.; Qi, J.Y.; Wu, H.; Zeng, Y.; Shui, W.; Zeng, J.Y.; Zhang, X.S. Freeze-thaw cycle representation alters response of watershed hydrology to future climate change. *Catena* **2020**, *195*, 104767. <https://doi.org/10.1016/j.catena.2020.104767>.
35. Sun, F.Y.; Mejia, A.; Che, Y. Disentangling the contributions of climate and basin characteristics to water yield across spatial and temporal scales in the Yangtze River Basin: A combined hydrological model and boosted regression approach. *Water Resour. Manag.* **2019**, *33*, 3449–3468. <https://doi.org/10.1007/s11269-019-02310-y>.
36. Abbaspour, K.C.; Rouholahnejad, E.; Vaghefi, S.; Srinivasan, R.; Yang, H.; Klove, B. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *J. Hydrol.* **2015**, *524*, 733–752. <https://doi.org/10.1016/j.jhydrol.2015.03.027>.
37. Samadi, S.Z. Assessing the sensitivity of SWAT physical parameters to potential evapotranspiration estimation methods over a coastal plain watershed in the southeastern United States. *Hydrol. Res.* **2017**, *48*, 395–415. <https://doi.org/10.2166/nh.2016.034>.
38. Franco, A.C.L.; de Oliveira, D.Y.; Bonumá, N.B. Comparison of single-site, multi-site and multi-variable SWAT calibration strategies. *Hydrol. Sci. J.* **2020**, *65*, 2376–2389. <https://doi.org/10.1080/02626667.2020.1810252>.
39. Zaibak, I.; Meddi, M. Simulating streamflow in the Chelif basin of west northern Algeria using the SWAT model. *J. Earth Syst. Sci.* **2022**, *131*, 25. <https://doi.org/10.1007/s12040-021-01777-x>.
40. Valencia, J.B.; Guryanov, V.V.; Mesa-Diez, J.; Tapasco, J.; Gusarov, A.V. Assessing the effectiveness of the use of the InVEST Annual Water Yield model for the rivers of Colombia: A case study of the Meta River Basin. *Water* **2023**, *15*, 1617. <https://doi.org/10.3390/w15081617>.
41. Zhao, L.L.; Shen, Y.J.; Liu, M.Z.; Wang, Y.X.; Li, Y.L.; Pei, H.W. The impacts of land use changes on water yield and water conservation services in Zhangjiakou, Beijing's upstream watershed, China. *Sustainability* **2023**, *15*, 11077. <https://doi.org/10.3390/su151411077>.
42. Dennedy-Frank, P.J.; Muenich, R.L.; Chaubey, I.; Ziv, G. Comparing two tools for ecosystem service assessments regarding water resources decisions. *J. Environ. Manag.* **2016**, *177*, 331–340. <https://doi.org/10.1016/j.jenvman.2016.03.012>.
43. Yang, H.F.; Nie, S.A.; Deng, S.Q.; Zhou, H.; Zhou, X. Evaluation of water yield and its driving factors in the Yangtze River Basin, China. *Environ. Earth Sci.* **2023**, *82*, 429. <https://doi.org/10.1007/s12665-023-11113-9>.
44. Zhang, X.; Zhang, G.S.; Long, X.; Zhang, Q.; Liu, D.S.; Wu, H.J.; Li, S. Identifying the drivers of water yield ecosystem service: A case study in the Yangtze River Basin, China. *Ecol. Indic.* **2021**, *132*, 108304. <https://doi.org/10.1016/j.ecolind.2021.108304>.
45. Guo, Q.; Yu, C.X.; Xu, Z.H.; Yang, Y.; Wang, X. Impacts of climate and land-use changes on water yields: Similarities and differences among typical watersheds distributed throughout China. *J. Hydrol. Reg. Stud.* **2023**, *45*, 101294. <https://doi.org/10.1016/j.ejrh.2022.101294>.
46. Guo, W.X.; Hong, F.T.; Yang, H.; Huang, L.T.; Ma, Y.C.; Zhou, H.T.; Wang, H.X. Quantitative evaluation of runoff variation and its driving forces based on multi-scale separation framework. *J. Hydrol. Reg. Stud.* **2022**, *43*, 101183. <https://doi.org/10.1016/j.ejrh.2022.101183>.
47. Guo, W.X.; Yu, L.; Huang, L.T.; He, N.; Chen, W.X.; Hong, F.T.; Wang, B.; Wang, H.X. Ecohydrological response to multi-model land use change at watershed scale. *J. Hydrol. Reg. Stud.* **2023**, *49*, 101517. <https://doi.org/10.1016/j.ejrh.2023.101517>.
48. Wang, H.; Xu, Y.; Wei, X. Rural resilience evaluation and influencing factor analysis based on geographical detector method and multiscale geographically weighted regression. *Land* **2023**, *12*, 1270. <https://doi.org/10.3390/land12071270>.

49. Chen, J.Z.; Kasimu, A.; Rehemani, R.; Wei, B.H.; Han, F.Q.; Zhang, Y. Temporal and spatial variation and prediction of water yield and water conservation in the Bosten Lake Basin based on the PLUS-InVEST model. *J. Arid Land* **2024**, *16*, 852–874. <https://doi.org/10.1007/s40333-024-0101-4>.
50. Kumar, T.V.L.; Vinodhkumar, B.; Rao, K.K.; Chowdary, J.S.; Osuri, K.K.; Desamsetti, S. Insights from the bias-corrected simulations of CMIP6 in India's future climate. *Glob. Planet. Change* **2023**, *226*, 104137. <https://doi.org/10.1016/j.gloplacha.2023.104137>.
51. Chen, W.X.; Zeng, J.; Li, N. Change in land-use structure due to urbanisation in China. *J. Clean. Prod.* **2021**, *321*, 128986. <https://doi.org/10.1016/j.jclepro.2021.128986>.
52. Geng, X.L.; Wang, X.S.; Yan, H.M.; Zhang, Q.; Jin, G. Land use/land cover change induced impacts on water supply service in the upper reach of Heihe River Basin. *Sustainability* **2015**, *7*, 366–383. <https://doi.org/10.3390/su7010366>.
53. Ellison, D.; Futter, M.N.; Bishop, K. On the forest cover–water yield debate: From demand- to supply-side thinking. *Glob. Change Biol.* **2012**, *18*, 806–820. <https://doi.org/10.1111/j.1365-2486.2011.02589.x>.
54. Wang, S.A.; Fu, B.J.; Piao, S.L.; Lu, Y.H.; Ciais, P.; Feng, X.M.; Wang, Y.F. Reduced sediment transport in the Yellow River due to anthropogenic changes. *Nat. Geosci.* **2016**, *9*, 38–41. <https://doi.org/10.1038/NGEO2602>.
55. Xu, T.; Xie, Z.Q.; Jiang, F.S.; Yang, S.Q.; Deng, Z.T.; Zhao, L.; Wen, G.Z.; Du, Q.Y. Urban flooding resilience evaluation with coupled rainfall and flooding models: A small area in Kunming City, China as an example. *Water Sci. Technol.* **2023**, *87*, 2820–2839. <https://doi.org/10.2166/wst.2023.149>.
56. Haque, A.; Ali, G.; Badiou, P. Event-based analysis of wetland hydrologic response in the Prairie Pothole Region. *J. Hydrol.* **2022**, *604*, 127237. <https://doi.org/10.1016/j.jhydrol.2021.127237>.
57. Zhang, C.; Wu, C.S.; Peng, Z.D.; Kuai, S.Y.; Zhang, S.H. Synergistic effects of changes in climate and vegetation on basin runoff. *Water Resour. Manag.* **2022**, *36*, 3265–3281. <https://doi.org/10.1007/s11269-022-03199-w>.
58. Hamel, P.; Guswa, A.J. Uncertainty analysis of a spatially explicit annual water-balance model: Case study of the Cape Fear Basin, North Carolina. *Hydrol. Earth Syst. Sci.* **2015**, *19*, 839–853. <https://doi.org/10.5194/hess-19-839-2015>. Corrigendum in *Hydrol. Earth Syst. Sci.* **2015**, *19*, 855. <https://doi.org/10.5194/hess-19-855-2015>.
59. Pandi, D.; Kothandaraman, S.; Kuppusamy, M. Simulation of water balance components using SWAT model at sub catchment level. *Sustainability* **2023**, *15*, 1438. <https://doi.org/10.3390/su15021438>.
60. Fang, J.; Kong, F.; Fang, J.Y.; Zhao, L. Observed changes in hydrological extremes and flood disaster in Yangtze River Basin: Spatial-temporal variability and climate change impacts. *Nat. Hazards* **2018**, *93*, 89–107. <https://doi.org/10.1007/s11069-018-3290-3>.
61. Surjibhai, A.S.; Nath, R.; Singh, S.; Swarnkar, S.; Patra, B. Unravelling surface water dynamics in semi-arid central Indian region for sustainable agricultural practices. *Environ. Monit. Assess.* **2024**, *196*, 827. <https://doi.org/10.1007/s10661-024-12955-x>.
62. Pan, W.H.; Wang, S.Y.; Wang, Y.; Yu, Y.J.; Luo, Y.Y. Dynamical changes of land use/land cover and their impacts on ecological quality during China's reform periods: A case study of Quanzhou city, China. *PLoS ONE* **2022**, *17*, e0278667. <https://doi.org/10.1371/journal.pone.0278667>.
63. Mengistu, T.D.; Chung, I.; Kim, M.G.; Chang, S.W.; Lee, J.E. Impacts and implications of land use land cover dynamics on groundwater recharge and surface runoff in East African watershed. *Water* **2022**, *14*, 2068. <https://doi.org/10.3390/w14132068>.
64. Haddeland, I.; Heinke, J.; Biemans, H.; Eisner, S.; Flörke, M.; Hanasaki, N.; Konzmann, M.; Ludwig, F.; Masaki, Y.; Schewe, J.; et al. Global water resources affected by human interventions and climate change. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 3251–3256. <https://doi.org/10.1073/pnas.1222475110>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.