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# Quantifying the spatiotemporal coupling effects of Shrinkage development policy and climate change on surface runoff

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## Abstract

Against the backdrop of global climate change, the frequency and intensity of extreme precipitation events continue to increase, significantly heightening the importance of surface runoff prediction and management. At the same time, many megacities are attempting to reduce runoff risks by optimizing land-use patterns. However, existing research still lacks a comprehensive framework capable of conducting spatiotemporal coupling analyses between policy-driven landscape pattern changes and climate change. To clarify the contributions of these two factors to changes in runoff and their interaction mechanisms, this study developed an integrated analytical framework combining Random Forest (RF), the Patch-Generated Land-Use Simulation Model (PLUS), and the Soil and Water Assessment Tool (SWAT). The results indicate that: (1) Under the SSP1-2.6 scenario, the predicted monthly average runoff is the lowest, with a peak runoff of 11.68 $m^3/s$ in July; (2) The ecological conservation scenario is most effective at reducing runoff and mitigating water security risks; (3) The differences in runoff caused by different climate scenarios were significantly greater than those resulting from different land-use policy scenarios. The study indicates that a low-growth development strategy relying solely on land-use regulation is unlikely to effectively address the water security challenges posed by future climate change. This study provides a new framework for quantitatively assessing the coupling mechanisms among policy, landscape pattern, and climate change, and offers a scientific basis for strategic environmental assessment and water security management in rapidly transforming cities.


## Highlights

- An integrated framework was developed to quantify policy–climate impacts on runoff.
- Climate and landscape factors influencing runoff were identified and ranked using machine learning.
- Ecological protection scenarios achieved the lowest runoff and water-security risk.
- Climate-induced runoff changes were substantially larger than policy-driven land-use effects.
- Increased extreme precipitation under climate change offset or even reversed runoff reductions from degrowth policies.

# 1 Introduction

## 1.1 Dual Context of Climate Change and Urban Development Policy Transformation

With the intensification of global warming, the frequency of extreme hydrological events has increased worldwide. Under the combined influence of climate change and urban expansion, urban surface runoff has been significantly altered, leading to greater flooding risks and more complex and unpredictable hydrological processes (Sinha and Eldho et al., 2020; Rodrigues and Reis et al., 2019; Ajjur and Al-Ghamdi, 2022; Nerantzaki and Nikolaidis, 2020).

Today, as global cities move toward sustainable urban development, many megacities have shifted from extensive land expansion to shrinkage growth strategies that emphasize ecological protection, resource efficiency, and spatial optimization. Through policy interventions that limit sprawl, optimize land structure, and strengthen green infrastructure, these cities aim to mitigate flooding risks caused by extreme precipitation. However, the effectiveness of such locally implemented policy efforts is being severely threatened by the runoff-increasing effects of climate change.

## 1.2 Landscape Pattern: A Key Mechanism Reflecting the Indirect Effects of Policy on Runoff

The shrinkage development policy can indirectly influence surface runoff by altering urban land use and land cover (LULC). Numerous studies have demonstrated that urban development modifies the underlying surface through changes in LULC, thereby affecting runoff dynamics and generating variations across different temporal scales (Chen et al., 2017; Zhang and Liu et al., 2014; Lin and Huang et al., 2021; Zhang and Wang et al., 2021; He et al., 2021; Rodrigues and Reis, 2019; Ajjur and Al-Ghamdi, 2022; Lin and Chen, 2015). Thus, planning policies affect surface runoff through indirect pathways.

Landscape pattern refers to the spatial configuration of heterogeneous elements within natural ecosystems, reflecting the spatiotemporal interactions between natural and anthropogenic factors (Wu and Zhao, 2015; Dey and Mishra, 2017). It effectively captures LULC changes and serves as a critical and sensitive indicator for evaluating the effectiveness of land management and ecological protection policies (Herold et al., 2005; Uuemaa et al., 2013). For example, Wu and Zhao (2015) assessed the impact of urban expansion on Beijing's landscape patterns, demonstrating that landscape metrics can effectively capture the spatial effects of urbanization and LULC changes. Fu and Zhao (2005) further showed that variations in landscape composition and spatial distribution influence runoff generation, providing the scientific basis for using landscape pattern as a quantitative indicator of policy effects, as well as for comparing the relative contributions of policy and climate to runoff dynamics.

However, most existing studies focus on urban green spaces within cities, districts, or suburbs (Chen et al., 2017; Wang et al., 2020; Ju et al., 2023; Zhang et al., 2015), with limited research conducted at the watershed scale. Wu and Zhao (2015) found that the temporal dominance of different land use types in the Beijing-Tianjin-Hebei region may be influenced by urban planning and policy, indicating that landscape metrics at administrative or city scales may not fully capture the details of landscape evolution under urban expansion (Sun et al., 2020; He et al., 2021). Such limitations make it difficult to ensure the integrity and continuity of hydrological units, thereby constraining the study of runoff response mechanisms.

## 1.3 Unclear Runoff Response Mechanisms to Changes in Landscape Pattern under Climate Change

To comprehensively explore runoff dynamics, scholars often adopt multi-factor analyses. Zhang and Liu (2019) used the SPAC model to quantify the contributions of landscape and climate to runoff, finding

that their synergistic effects increase total runoff and the number of active groundwater days, with climate change having a higher contribution. Sheng and Liu (2023) analyzed rainfall–landscape–runoff interactions from 1958 to 2020, showing that annual precipitation is strongly correlated with runoff, while landscape pattern acts as the dominant factor driving drought–flood variability. These studies confirm that climate and landscape pattern are the primary drivers of runoff, although their relative dominance varies across scenarios and regions. Existing research has demonstrated that landscape pattern metrics and land cover types can influence surface runoff, revealing the extent of human impacts on the surface (Bin and Xu, 2024; Gao and He, 2020; Wang and Hou, 2023). However, few studies have investigated the response mechanisms of surface runoff to landscape pattern changes under a changing climate, which can reveal how anthropogenic factors, such as urban expansion, affect runoff (Ji et al., 2025).

## 1.4 Research Objectives and Scientific Contribution

At a time when floods have become the most significant climate-related disaster posing a global threat, according to a report by the Center for Research on the Epidemiology of Disasters (CRED), water security faces critical threshold risks, creating an urgent need to evaluate the effectiveness of development reduction policies in mitigating surface runoff. This study selected the Beiyun River Basin (Beijing section) as the study area. As a representative major Chinese city that has been among the first to enter a phase dominated by contraction policies and subject to strict water resource constraints, Beijing's strategies for development reduction hold exceptional regional urgency and global reference value for managing land use and landscape changes.

This study developed a runoff estimation framework integrating the Random Forest (RF) model, the SWAT model, and the PLUS model. It examined the spatiotemporal evolution of green space landscape patterns at the watershed scale, analyzed hydrological responses under different land cover and climate scenarios. The study aims to address the following questions: (1) How do green space landscape patterns evolve in complexity and uncertainty when urban development goals shift from expansion to shrinkage? (2) What are the relative contributions and combined effects of climate change and policy-driven land use changes on controlling surface runoff?

The ultimate contribution of this study lies in revealing the patterns of landscape pattern evolution in response to urban downsizing policies, as well as the multi-scenario response mechanisms of surface runoff to green space landscape pattern indices and climatic factors, thereby providing a basis for future urban sustainable development and policies addressing extreme weather events.

# 2 Research Materials and Methods

## 2.1 Study area and data

This study focuses on the North Canal Basin in Beijing, extending 89.4 km with a drainage area of 3,862 km², accounting for 23.6% of the city. Since 2014, Beijing has advanced stock-based development and

functional deconcentration, guided by the Beijing Urban Master Plan (2016–2035), which introduced the concept of shrinkage development—optimizing urban scale, reducing density, alleviating resource stress, and enhancing sustainability in line with SDGs 4, 8, 11, 13, and 15.

Beijing faces rising flood risks due to high population density and intensive infrastructure. The North Canal, which drains 90% of urban rainwater and sewage, is vital for flood control. Its basin supports about 13 million residents (70% of Beijing's total) and contributes over 80% of the city's GDP, making green space pattern and runoff regulation crucial for resilience. Considering Beijing's 2035 planning goals—reducing industrial and construction land while expanding ecological and residential areas—2035 was selected as the target year for runoff simulations under shrinkage development and climate scenarios.

Remote sensing data were obtained from the Geospatial Data Cloud Platform of the Chinese Academy of Sciences. Landsat 7 imagery (2008–2012) and Landsat 8 imagery (2013–2022), both at 30 m resolution, were used to ensure temporal consistency. Data sources for land cover driving factors are listed in Table 1.

**Table.1.** Data sources of land use driving factors in Beijing

| Data Type | Name | Data Source |
|---|---|---|
| Natural Geographic Factors | Elevation | Geospatial Data Cloud(gscloud.cn) |
| | Slope | Generated from elevation |
| | Aspect | Generated from elevation |
| Socioeconomic Factors | Population Density | Resource and Environment Science and Data Center resdc.cn |
| | Per Capita GDP | |
| Accessibility Factors | Highways | National Geographic Information Resource Catalogue Service System webmap.cn |
| | Primary Roads | |
| | Secondary Roads | |
| | Tertiary Roads | |
| | Railways | |
| | Water Systems | Open Street Map OpenStreetMap |
| | Residential Areas | National Geographic Information Resource Catalogue Service Systemwebmap.cn |
| | District Governments | National Bureau of Statistics |

Daily runoff data was provided by the Beijing Water Authority. Meteorological data was sourced from the National Meteorological Science Data Center (https://data.cma.cn/). Soil data were obtained from the China Soil Dataset (v1.1) within the Harmonized World Soil Database (HWSD). The meteorological data used in the SWAT model included daily precipitation and maximum/minimum temperatures under three Shared Socioeconomic Pathways (SSPs) from CMIP6: SSP1-2.6, SSP2-4.5, and SSP5-8.5.

## 2.2 Identifying Landscape Pattern Characteristics Using Fragstats Software

Landscape pattern analysis in this study was conducted across three hierarchical levels—patches, landscape types, and the overall landscape—using quantitative landscape metrics to describe the composition, spatial configuration, and temporal evolution of green spaces. Land use maps were generated from Landsat remote sensing data obtained from the Geospatial Data Cloud Platform of the Chinese Academy of Sciences, and processed in ENVI 5.3 and ArcGIS. Following the Chinese Land Use Classification Standard (GB/T21010–2017), land cover was categorized into cropland, forestland, grassland, water bodies, built-up areas, and unused land. The metrics were calculated using Fragstats 4.2.1 (McGarigal & Marks, 1995). Indices with unclear ecological significance, threshold dependency, or poor statistical performance—such as edge depth, contrast, and similarity—were excluded. After screening, 30 class-level and 37 landscape-level metrics were retained, from which seven representative indicators were selected for detailed examination. These included the percentage of landscape (PLAND), largest patch index (LPI), mean fractal dimension (FRAC_MN), patch cohesion (COHESION), division index (DIVISION), contagion (CONTAG), and Shannon's diversity index (SHDI), which together reflect the spatial characteristics and diversity of the landscape structure.

## 2.3 Research Framework Development

The integrated framework proposed in this study, illustrated in the figure below, consists of three main components:(1)Mechanism analysis using the Random Forest (RF) model: Identifying how landscape pattern indices and climate factors influence runoff dynamics.2Future land use prediction with the PLUS model: Projecting land use under three development scenarios for 2035 based on land cover trends from 2008 to 2022.3Runoff prediction using the SWAT model: Constructing the SWAT model based on daily meteorological data from 2008 to 2022 and hydrological data from 2010 to 2020 to predict future surface runoff under different development and climate scenarios.

### 2.3.1 Identifying the Drivers of Runoff Changes

Random Forest (RF) is an ensemble learning method using multiple parallel decision trees with nonlinear fitting. To align landscape indices with hydrological processes, we assumed each index remained constant within a year. Runoff was set as the dependent variable, with 70% of samples for training and 30% for testing. Variable importance was measured by %IncMSE, where higher values indicate stronger influence.

The Pearson Correlation Coefficient is a widely used indicators for assessing correlation, ranging from −1 to + 1. A value of -1 indicates a perfect negative correlation, + 1 indicates a perfect positive correlation, and 0 indicates no linear relationship. In this study, Pearson correlation analysis is first used to exclude redundant landscape pattern and climate indices that exhibit high autocorrelation and do not provide additional information. Subsequently, the Random Forest model is employed to rank the importance of climate factors (e.g., rainfall, solar radiation, average relative humidity) and anthropogenic factors (landscape type level indices, overall landscape level indices) in influencing runoff in the North Canal Basin (Beijing section). Further analysis focuses on the mechanisms through which indices with an importance ranking exceeding 10% impact runoff, offering deeper insights into their roles in hydrological processes.

## 2.3.2 The PLUS (Patch-generating Land Use Simulation) model

The PLUS (Patch-generating Land Use Simulation) model is a patch-generation land cover change simulation model developed by the HPSCIL@CUG Laboratory of China University of Geosciences. It is based on raster data and comprises two primary models: the LEAS module and the CARS module. This model enables the dynamical simulation of patch-level changes across various land cover types.

In this study, the PLUS model is used to predict land cover changes under four different scenarios based on observed trends in land cover type from 2008 to 2022. The method primarily consists of the following steps:

Thirteen driving factors were converted into raster datasets in ArcGIS, and land cover maps for 2008, 2012, 2016, and 2020 were preprocessed and imported into the LEAS module. A random forest algorithm with 30 trees and a 0.1 sampling rate quantified the relationship between land expansion and its driving factors, generating development probability maps. The CARS module (neighborhood size = 3) was then used to simulate land cover transitions from 2016 to 2020, while the Markov Chain module estimated land demand for 2020, with iterative adjustments of conversion rules and weights to improve accuracy (Table 2).

**Table.2. Neighborhood weight factor parameter table**

| Land Use Type | Cropland | Forestland | Grassland | Water bodies | Built-up areas | Unused land |
|---|---|---|---|---|---|---|
| Neighborhood weight factor | 0.186 | 0.067 | 0.020 | 0.516 | 0.493 | 0.012 |
| Based on the calibrated model, future land use patterns for 2035 were simulated under three development scenarios for the North Canal Basin (Beijing section): | | | | | | |

(1) Inertial Development Scenario: This scenario reflects land cover evolution trends from 2008 to 2020, projecting future changes driven solely by natural and socio-economic factors through linear regression

of land demand, and represents a continuation of the city's current expansion trajectory.

(2) Cropland Protection Scenario: This scenario emphasizes stock-based development by designating cropland and built-up land that remained unchanged from 2008 to 2020 as long-term stable zones. Conversion probabilities from cropland to other land types were reduced by 70%, while those from built-up areas to other categories were reduced by 40%.

(3) Ecological Protection Scenario: Guided by the principles of the Beijing Urban Master Plan (2016–2035), this scenario identifies stable cropland, forestland, and water bodies that persisted across all years (2008–2020) as permanent ecological zones with restricted conversion. In this scenario, the probability of forestland, grassland, and water bodies converting to built-up areas was reduced by 50%, and cropland-to-built-up conversion by 30%, representing the transition from urban expansion to shrinkage development.

## 2.3.3 The SWAT model

The SWAT model, developed by the USDA Agricultural Research Service in the early 1990s, is a distributed hydrological model designed for watershed-scale and long-term simulations. The modeling process involves four steps: (1) extracting watershed topography from DEM data and defining the catchment threshold; (2) setting watershed outlets and hydrological stations, dividing the basin into sub-basins; (3) integrating land cover, soil, and slope data to generate Hydrological Response Units (HRUs); and (4) creating soil and meteorological databases. The model then simulates runoff for each HRU, which is aggregated to estimate total watershed runoff.

HRUs are the smallest computational units formed by spatial elements with similar hydrological characteristics. In this study, based on the DEM data of the North Canal Basin, the study area is divided into 21 sub-basins, which are further subdivided into 139 HRUs.

This study selects daily rainfall (mm), daily average temperature (℃), daily average relative humidity (%), daily average wind speed (m/s), and daily solar radiation (MJ/m²) data from nine meteorological stations in the study area for the 15-year period spanning 2008 to 2022. The meteorological data used in this study is sourced from the National Meteorological Science Data Center (https://data.cma.cn/). To construct the meteorological database for the SWAT model, a weather generator is employed to input precipitation and temperature data. Since this study has access to relatively complete observed data, wind speed, relative humidity, and solar radiation data are all directly derived from measurements.

According to the regulations of the Beijing Water Authority, only limited daily flow data from hydrological stations are available for the study area. Consequently, this study uses daily runoff data from 2010 to 2020, covering periods aligned with shifts in urban development goals: expansion (2010–2013), the stock-based development (2014–2016), and shrinkage development (2017–2020). Previous research have indicated that the accuracy of monthly-scale runoff simulation using SWAT is superior to daily-scale runoff simulation. Therefore, the simulation in this study focuses on monthly-scale runoff, with a simulation period of 11 years (2010–2020), a calibration period of 6 years (2011–2016), and a validation

period of 4 years (2017–2020), with 2010 serving as the model warm-up period. This timeline reflects transitions between urban development goals and captures runoff variations associated with land use changes under different development strategies.

## 2.4 Runoff Simulation Under Different Climate and Policy Scenarios

Based on the SWAT hydrological model, daily precipitation data and daily maximum/minimum temperature data from CMIP6's three Shared Socioeconomic Pathways (SSPs)—SSP1-2.6, SSP2-4.5, and SSP5-8.5—are employed. After supplementing other meteorological data with the weather generator, a comprehensive meteorological database for the North Canal Basin (Beijing section) is established. Based on land cover data under the three SSP scenarios, the study simulates two types of future scenarios for runoff prediction in the North Canal Basin (Beijing section) for the year 2035 to separately explore the effects of land utilization and climate change on surface runoff. The two scenario types are: (1) Landscape pattern is treated as the variable, with all other factors held constant, while the climate scenario is set to SSP2-4.5; and (2) The climate scenario is treated as the variable, with land cover set to the inertial development scenario, and all other variables held constant.

## 2.5 Model Accuracy Validation

To evaluate the accuracy of the model's predictions, two performance indicators were used: the coefficient of determination ($R^2$) and the Nash-Sutcliffe efficiency coefficient (ENS). The $R^2$ value ranges from 0 to 1, while the ENS value can range from negative infinity to 1. A value of $R^2$ and ENS closer to 1 indicates better model performance and a higher degree of fit between simulated and observed values.

# 3 Results

## 3.1 Landscape pattern evolution characteristics

Based on five landscape type-level indices and two overall landscape-level indices, which accurately capture the dynamic changes in green space landscape patterns, this study analyzed the spatiotemporal evolution characteristics of the North Canal Basin (Beijing section). The key findings are as follows:

(1) The continuous expansion of built-up areas and forestland has encroached upon large amounts of cropland, resulting in a sustained decline in both the area and dominance of cropland. In contrast, the area and dominance of built-up areas and forestland have steadily increased.

(2) The connectivity of built-up areas and forestland is relatively high, with fragmentation steadily decreasing. Conversely, the connectivity of cropland has been decreasing annually, accompanied by a corresponding increase in its fragmentation.

(3) The shape complexity of each land use type has continuously changed. Notably, water bodies consistently exhibit the highest shape complexity throughout the study period.

(4) From an overall landscape perspective, both landscape fragmentation and complexity have shown a gradual decline, suggesting a trend towards a more stable landscape configuration in the region..

## 3.2 Drivers of runoff change

### 3.2.1 Driver Screening Results

After excluding the indices with high correlation among landscape pattern indices and climate factors, the final variables for the next step of analysis are shown in Table 3.

**Table.3.** Final variables after screening high correlation data

| Implicit variable | Type | |
|---|---|---|
| TA0 | Anthropogenic Factors | Overall Landscape-Level Indices |
| AREA_MN0 | | |
| PAFRAC0 | | |
| LSI0 | | |
| COHESION0 | | |
| RPR0 | | |
| SHAPE_MN1 | | Landscape Type-Level Indices |
| CONTIG_MD1 | | |
| hAREA_AM2 | | |
| CIRCLE_AM2 | | |
| PAFRAC2 | | |
| LPI3 | | |
| AREA_MN3 | | |
| COHESION3 | | |
| FRAC_MD4 | | |
| CONTIG_MD4 | | |
| TE5 | | |
| FRAC_MN5 | | |
| PAFRAC5 | | |
| CLUMPY5 | | |
| SHAPE_MN6 | | |
| PAFRAC6 | | |
| Precipitation | Natural Factors | Climate |
| Average wind speed | | |
| Solar radiation | | |
| Average relative humidity | | |

## 3.2.2 Results of Identifying the Key Drivers of Runoff Change

The top three factors influencing runoff changes are all natural factors, aligning with previous research conclusions that natural factors are the primary drivers of runoff variation. Among these, precipitation has the greatest impact on runoff, being the only variable with a %IncMSE value exceeding 15%, accounting for 17.07% of the total importance. Solar radiation and average relative humidity follow, contributing for 12.03% and 11.94% of the importance, respectively. The fourth and fifth most influential indices are the patch cohesion index and the perimeter-area fractal dimension, derived from the overall landscape-level indices, each accounting for 12.03% and 11.94%, respectively. The combined importance of all other indices is less than 10%.

For further analysis, factors with an importance share exceeding 10% were extracted. Since natural factors and runoff operate on a daily time scale, while the two overall landscape-level indices are annual, the time scale of all variables was standardized to an annual basis for consistency. The results are shown in Fig. 5.

Among natural factors, precipitation and average relative humidity show a positive correlation with runoff, while solar radiation exhibits a negative correlation. Regarding the overall landscape-level indices, patch cohesion and perimeter-area fractal dimension are positively correlated with runoff. The perimeter-area fractal dimension (i.e., patch shape complexity) is positively correlated with runoff. Therefore, maintaining continuous and intact green spaces with simple patch shapes and minimizing fragmentation of green areas can positively impact runoff reduction.

# 3.3 PLUS Model Simulation Results

Using the 2020 land cover data and using the development probability maps for various land cover types from 2016 to 2020, the PLUS software simulates the land cover maps for the North Canal Basin (Beijing section) in 2035 under three scenarios (Fig. 6). The calculation results of landscape pattern factors are shown in Table 4. The proportion of landscape types in the overall landscape (PLAND) visually reflects the land use distributions. The calculated PLAND results for 2035 under the three scenarios reveal no significant differences in the area proportions of land use types. Compared to the 2020 built-up land proportion (50.18%), the projected increase is minimal, consistent with the trend of a steady rise in built-up land observed between 2016 and 2020.

**Table.4.** Calculation results of the proportion of landscape types to the overall landscape area (PLAND) in 2035 (%)

| Landscape Type | Inertial Development Scenario | Cropland Protection Scenario | Ecological Protection Scenario |
|---|---|---|---|
| Cropland | 0.6639 | 2.1647 | 2.0784 |
| Forestland | 45.2251 | 45.5617 | 46.4535 |
| Grassland | 0.4812 | 0.4835 | 0.4839 |
| Water bodies | 0.5565 | 0.7277 | 0.7 |
| Built-up areas | 53.068 | 51.0572 | 50.2789 |
| Unused land | 0.0053 | 0.0053 | 0.0053 |

The two anthropogenic factors with the greatest impact on runoff are patch cohesion (COHESION) and perimeter-area fractal dimension (PAFRAC), with the calculation results summarized in Table.5 and Fig. 7. Under all three scenarios, both patch cohesion (connectivity) and perimeter-area fractal dimension (shape complexity) show a declining trend. In the inertial development scenario, patch cohesion remains the highest, indicating the strongest connectivity, while patch shape exhibits the greatest complexity. Conversely, in the ecological protection scenario, patch cohesion is comparatively the weakest, and the patch shape is less complex than in the other two scenarios.

**Table.5.** Calculation results of human factors with the greatest impact on runoff

| Overall Landscape-Level Indices | Inertial Development Scenario | Cropland Protection Scenario | Ecological Protection Scenario |
|---|---|---|---|
| COHESION | 99.8861 | 99.8797 | 99.8783 |
| PAFRAC | 1.4357 | 1.425 | 1.3965 |

# 3.4 SWAT Model Calibration and Validation

After fitting tests, the simulated runoff process in the North Canal Basin (Beijing section) based on land cover data from 2011 to 2016 was compared with observed runoff trends. At the Yulinzhuang station, during the calibration period, both $R^2$ and ENS were 0.84. For the validation period in each year, the $R^2$ values ranged from 0.59 to 0.60, and the ENS values ranged from 0.55 to 0.57. This result further demonstrates that the model provides good predictive accuracy for the study area. With both $R^2$ and ENS exceeding 0.5, the finding confirms that the model performs well at the monthly scale in the study area and can provide reliable hydrological simulation data.

# 3.5 Runoff responses under different landscape pattern scenarios

# 3.5.1 Monthly average runoff of Yulinzhuang station under different landscape pattern scenarios

The calibrated SWAT model was used to simulate runoff changes in 2035 under different scenarios. The runoff simulation results are shown in Fig. 11. The analysis indicate that the monthly runoff trends and peak values are nearly identical under all three scenarios, with the peak consistently occurring in July.

**Table.6.** Monthly average runoff of Yulinzhuang station under different landscape pattern scenarios

| Time | SSP2-4.5precipitation (mm) | Monthly runoff($m^3/s$) | | |
|---|---|---|---|---|
| | | Inertial Development Scenario | Ecological Protection Scenario | Cropland Protection Scenario |
| 2035/1 | 1.69 | 0 | 0 | 0 |
| 2035/2 | 9.85 | 0.1423 | 0.1418 | 0.1408 |
| 2035/3 | 7.28 | 0.5934 | 0.5904 | 0.586 |
| 2035/4 | 54.14 | 1.094 | 1.086 | 1.07 |
| 2035/5 | 73.53 | 2.608 | 2.602 | 2.589 |
| 2035/6 | 92.66 | 9.652 | 9.597 | 9.564 |
| 2035/7 | 716.53 | 65.92 | 65.84 | 65.72 |
| 2035/8 | 217.77 | 37.54 | 37.52 | 37.56 |
| 2035/9 | 169.53 | 39.26 | 39.28 | 39.38 |
| 2035/10 | 0.06 | 9.974 | 10 | 10.08 |
| 2035/11 | 3.11 | 4.301 | 4.291 | 4.336 |
| 2035/12 | 3.02 | 1.582 | 1.594u | 1.614 |

The peak flow in the inertial development scenario reaches the highest at 65.92 $m^3/s$, slightly higher by 0.08 $m^3/s$ compared to the cropland protection scenario, and 0.2 $m^3/s$ higher than the ecological protection scenario. Overall, the monthly runoff in the inertial development scenario is marginally higher than in the other two scenarios, while the ecological protection scenario exhibits the lowest monthly runoff across all three scenarios. These findings suggest that while land cover changes influence watershed runoff, they may not be the primary factor driving runoff variation, a conclusion consistent with previous research.

## 3.5.2 Monthly Average Runoff at Yulinzhuang Station under Different Climate Scenarios

Significant differences are observed in the monthly runoff of the North Canal Basin (Beijing section) under different climate scenarios. Under the SSP1-2.6 climate scenario, the overall runoff is the lowest, with only January, February, March, and April slightly higher than the other two climate scenarios, and December slightly higher than the SSP5-8.5 scenario. The peak runoff occurs in July, reaching 11.68 $m^3/s$. The SSP5-8.5 scenario shows intermediate runoff levels, with the peak also occurring in July at 20.72 $m^3/s$. Under the SSP2-4.5 scenario, the runoff is the highest overall, with the peak still occurring in July at 65.92 $m^3/s$, more than three times the runoff of the SSP5-8.5 scenario and nearly six times that of the SSP1-2.6 scenario. Unlike the other two scenarios, the trend in the SSP2-4.5 scenario demonstrates a clear bimodal pattern. After the peak flow in July, there is a decrease in August, followed by a slight increase in September, resulting in the second highest monthly runoff in 2035 under the SSP2-4.5 scenario. These findings underscore the dominant role of rainfall in influencing runoff variation.

**Table.7.** Monthly average runoff at Yulinzhuang station under different climate models

| Time | Monthly runoff($m^3/s$) | | | precipitation(mm) | | |
|---|---|---|---|---|---|---|
| | SSP1-2.6 | SSP2-4.5 | SSP5-8.5 | SSP1-2.6 | SSP2-4.5 | SSP5-8.5 |
| 2035/1 | 0.003327 | 0 | 0.0003599 | 2.12 | 1.69 | 2.89 |
| 2035/2 | 0.6509 | 0.1423 | 0.2646 | 26.14 | 9.85 | 2.93 |
| 2035/3 | 1.859 | 0.5934 | 0.005541 | 11.25 | 7.28 | 3.7 |
| 2035/4 | 1.906 | 1.094 | 0.00755 | 66.17 | 54.14 | 3.14 |
| 2035/5 | 1.027 | 2.608 | 1.594 | 37.73 | 73.53 | 34.23 |
| 2035/6 | 4.025 | 9.652 | 8.953 | 55.01 | 92.66 | 56.36 |
| 2035/7 | 11.68 | 65.92 | 20.72 | 106.73 | 716.53 | 234.56 |
| 2035/8 | 7.593 | 37.54 | 13.36 | 130.14 | 217.77 | 92.66 |
| 2035/9 | 0.9644 | 39.26 | 6.636 | 2.85 | 169.53 | 30.23 |
| 2035/10 | 1.923 | 9.974 | 3.368 | 17.34 | 0.06 | 20.61 |
| 2035/11 | 1.106 | 4.301 | 1.133 | 30.69 | 3.11 | 4.25 |
| 2035/12 | 1.431 | 1.582 | 0.3797 | 0 | 3.02 | 4.1 |

# 4 Discussion

4.1 **Predict the Impact of urban development policy shifts on landscape pattern evolution trends to inform planning and policy-making**

Our findings indicate that, under the assumption of continuous urban expansion (the inertial development scenario), simulated surface runoff is higher than that in the farmland conservation scenario, and both exceed the results under the ecological conservation scenario. Notably, the reduction in simulated net runoff under the ecological conservation scenario is 2.5 times greater than that under the farmland conservation scenario compared to the inertial development scenario. This highlights the significant benefits of shifting from expansion-focused to sustainability-oriented urban development policies in reducing surface runoff. Against the backdrop of shifting urban development objectives, urban planning policies play a crucial role in shaping landscape patterns. As found by (Wu and Zhao et al., 2015), during the early stages of Beijing's urbanization, landscape fragmentation and irregularity increased, consistent with the typical effects of urban expansion on landscape patterns. However, after 1990, this trend shifted toward more organized development, indicating that urban planning policies can effectively mitigate chaotic landscape changes and align with urban development objectives. These findings also suggest that the landscape's response to urban expansion varies across different spatiotemporal scales. The relative dominance of different land uses within a city evolves over time and may be influenced by urban planning, policies, or other socioeconomic factors. Consequently, a general understanding of landscape indicators at the regional or urban scale may fail to reveal the subtle landscape dynamics driven by urban expansion. For example, as urban development goals shift from expansion to contraction, land-use patterns adjust in response to policy changes, leading to a reduction in the total built-up area. The distribution and proportions of various land-use types also change, which is reflected in landscape pattern indices.

Landscape pattern indices not only track changes in land cover but also provide deeper insights into how urban development policies influence land-use transitions. This study screened hydrologically relevant landscape pattern indicators to clarify the mechanisms by which landscape patterns and climate influence runoff in the Northern Canal Basin (Beijing section), thereby laying the foundation for future runoff predictions under climate change and providing a scientific basis for establishing a high-quality green space development system and formulating sustainable policies.

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# 4.2 Differentiated Responses of Surface Runoff to Different Green Space Types

Our simulation results show that surface runoff is higher under the farmland conservation scenario than under the ecological conservation scenario. This confirms that green spaces such as forests and grasslands are more effective than cropland in reducing surface runoff. Furthermore, surface runoff under both the cropland conservation and ecological conservation scenarios is lower than that under the business-as-usual scenario, highlighting the critical role of green spaces in enhancing urban water

security. Different types of green spaces have varying effects on surface runoff (Lian and Hung, 2019). Hydrological modeling has demonstrated that runoff in the Hai River Basin is highly sensitive to changes in vegetation cover (Chang and Liu et al., 2024); vegetation restoration reduces total runoff while increasing baseflow. In scenarios where farmland is converted to forest and grassland, both total runoff and surface runoff decrease, and conversion to forest exhibits higher water-generating potential than conversion to grassland. Green spaces play a crucial role in maintaining the stability of urban ecosystems. In-depth research on the relationship between green spaces and surface runoff is essential for enhancing urban water security, promoting sustainable socioeconomic development, and building high-quality green space systems. Based on the findings of this study, combined with a runoff prediction framework, guidance can be provided for the rational classification and spatial planning of urban green spaces in the future.

## 4.3 Strengths and Limitations

Although this study makes valuable contributions, it still faces some limitations and uncertainties. The land cover data used in this study encompass six generalized land cover types, whereas the SWAT model classifies land cover using a more detailed classification system. Therefore, simulation results based on generalized data may differ from those obtained using land cover data with a finer classification. Furthermore, future land cover changes are influenced by numerous natural and anthropogenic factors, adding considerable complexity and uncertainty. The future land cover change projections generated by the PLUS model may contain errors; future research could explore methods to improve the model's accuracy in this regard. Furthermore, the SWAT model was calibrated using data from 2010 to 2020, a relatively short time period. Due to limited available runoff data, it was not possible to use longer historical data for model calibration, which may affect the model's accuracy. Furthermore, although a large number of CMIP6 experimental models are available, this study only referenced models used in similar regions reported in the literature and did not comprehensively evaluate their suitability for the Northern Canal Basin (Beijing section), which introduces potential uncertainty into the simulation results. This study focused specifically on surface runoff in the Beijing section of the Northern Canal Basin under the influence of relevant urban development policies. To more comprehensively assess the impact of urban development policies on surface runoff and their application in development decision-making in other regions, future research could incorporate social development indicators—such as shared socioeconomic pathways and the Sustainable Development Goals—and apply them to runoff forecasting to better support policy planning.

# 5 Conclusion

This study proposed an analytical framework that employs a calibrated SWAT hydrological model to simulate runoff variations in the Beijing section of the North Canal Basin in 2035 under different land-cover development scenarios—namely inertial development, farmland protection, and ecological protection—and three climate scenarios (SSP1–2.6, SSP2–4.5, and SSP5–8.5). The framework was used

to analyze how green-space landscape patterns evolve and influence runoff in response to shifts in urban development objectives.

The main findings are as follows: Our results confirm that simulated surface runoff decreases sequentially from the inertial development scenario to the farmland protection and ecological protection scenarios, underscoring the critical role of green spaces in enhancing urban water security. Moreover, forests and grasslands were found to be more effective than croplands in reducing surface runoff. Precipitation was identified as the primary driver influencing runoff variations, while among anthropogenic factors, the landscape-level patch cohesion index exerted the greatest impact on runoff.

Under scenarios with varying policy intensities, the inertial development scenario exhibited the highest peak discharge (65.92 $m^3/s$), while the ecological protection scenario showed the lowest value (65.72$m^3/s$), indicating that land-use policy orientation can effectively mitigate runoff peaks and optimize monthly runoff distribution. However, the differences among climate scenarios were even more pronounced: the peak discharge under the SSP2–4.5 scenario (65.92 $m^3/s$) was nearly six times that of SSP1–2.6 (11.68 $m^3/s$), demonstrating that precipitation variation plays a dominant role in runoff formation.

These results reveal that although ecological protection and shrinkage development policies can significantly improve surface runoff conditions, their positive hydrological effects are being rapidly undermined by the increasing frequency of intense rainfall events under climate change. When precipitation exceeds the basin's storage and regulation capacity, the runoff reduction effect induced by policy measures may be entirely offset.

Therefore, the significance of shrinkage development policies for maintaining urban water security lies not merely in reducing runoff volume during individual events but in providing a controllable mitigation pathway under climate-dominated conditions. This finding suggests that strengthening ecological spatial constraints, enhancing surface permeability, and optimizing the configuration of green spaces remain key strategies for coping with future climate uncertainties and mitigating flood risks.

## Declarations

# Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have influenced the work reported in this paper.

# Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Xiangbo Liu and Yue Lai. The first draft of the manuscript was written by

Xiangbo Liu, Yue Lai and Zimeng Li. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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# Figures

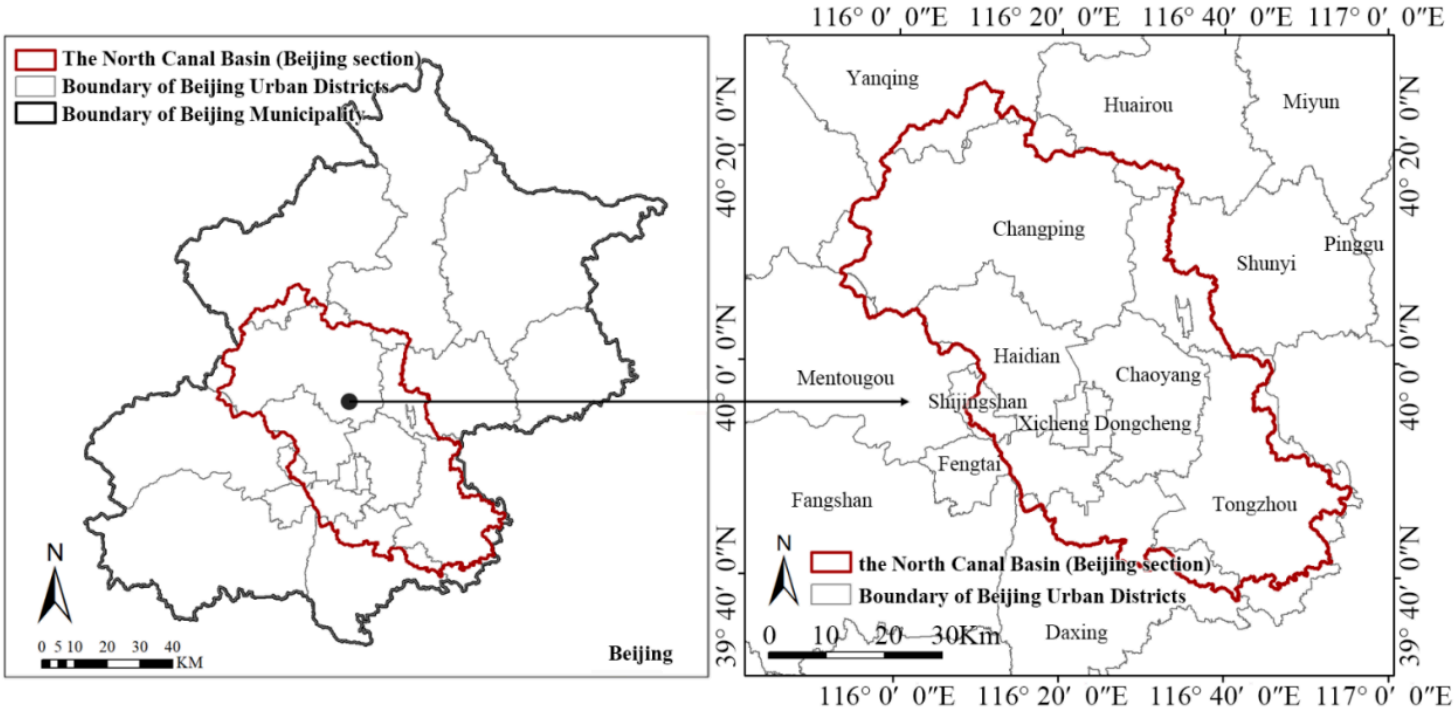



**Figure 1**

Geographical location of the North Canal Basin

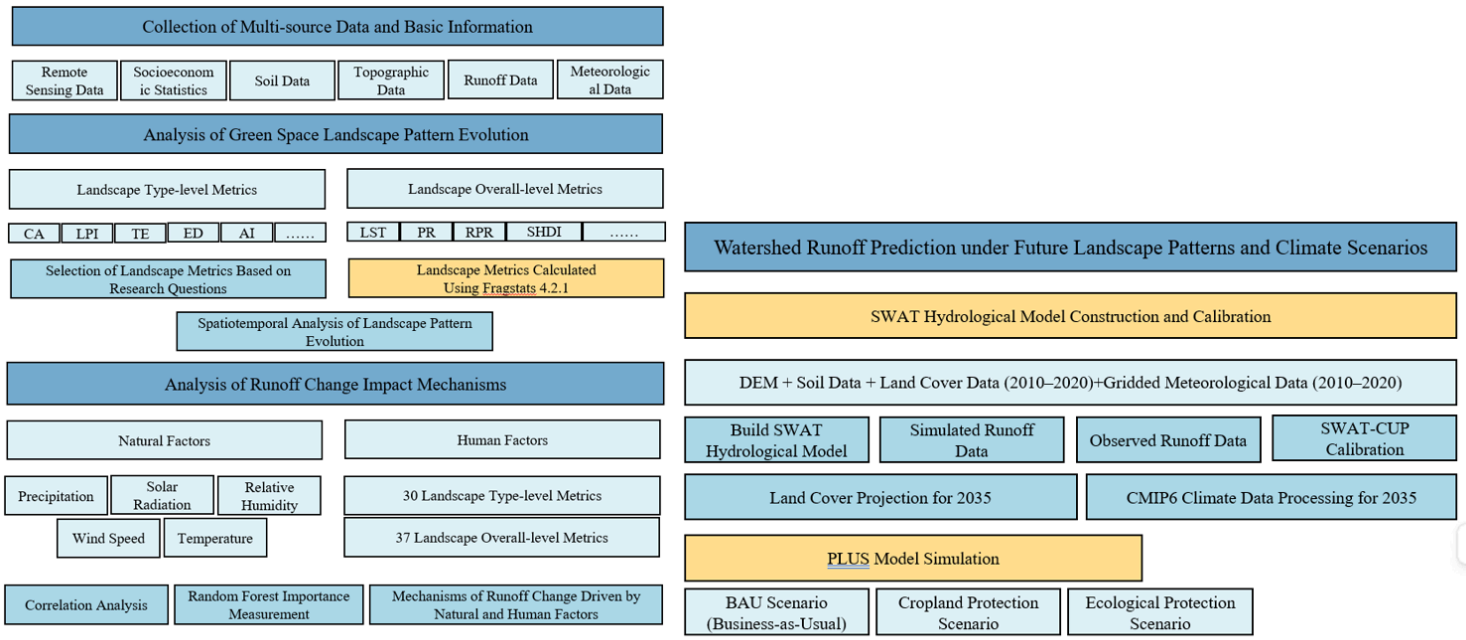



**Figure 2**

Integrated framework for runoff estimation

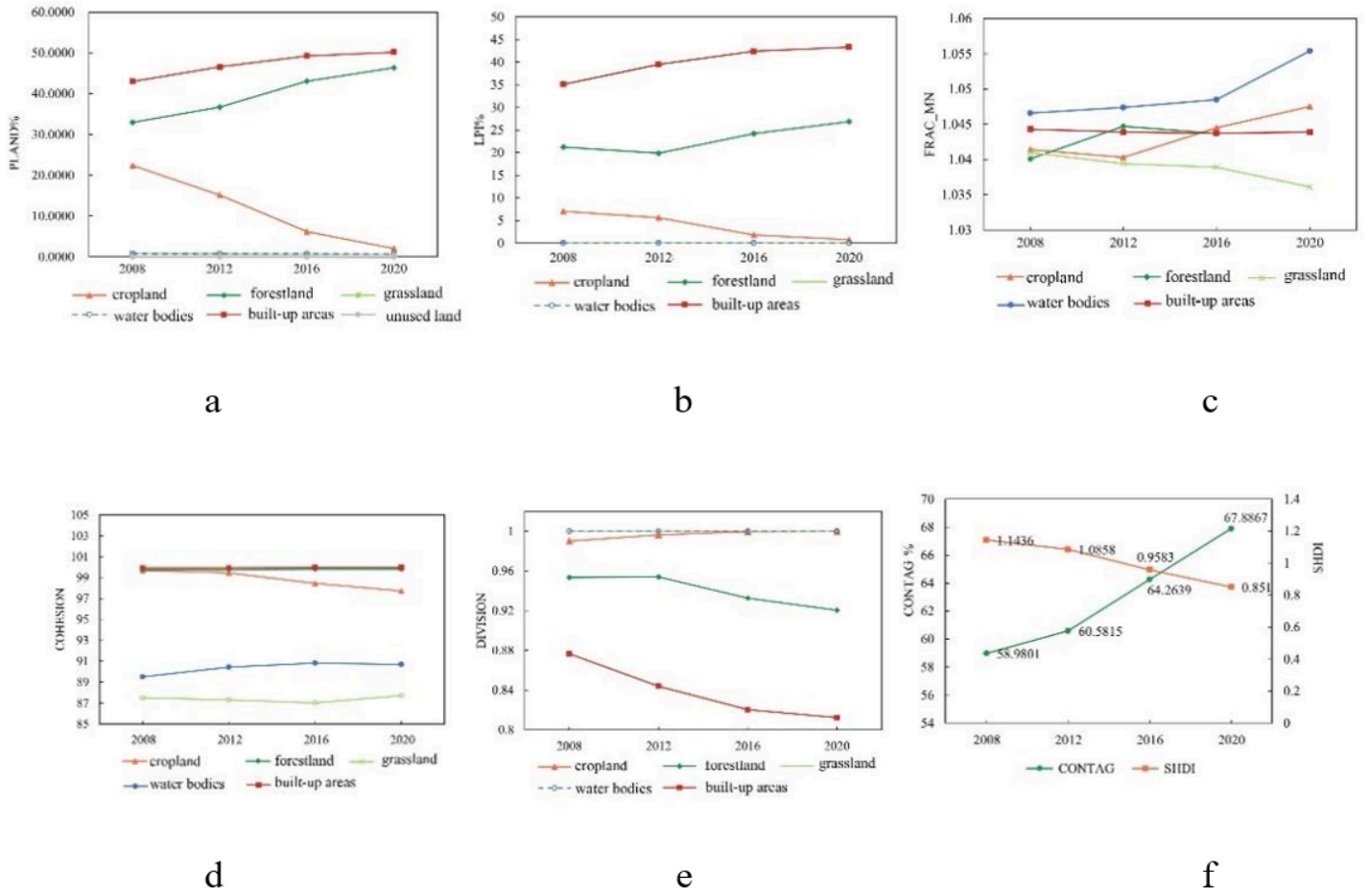


**Figure 3**

Trends in Landscape Pattern Indices of the North Canal Basin (Beijing Section)

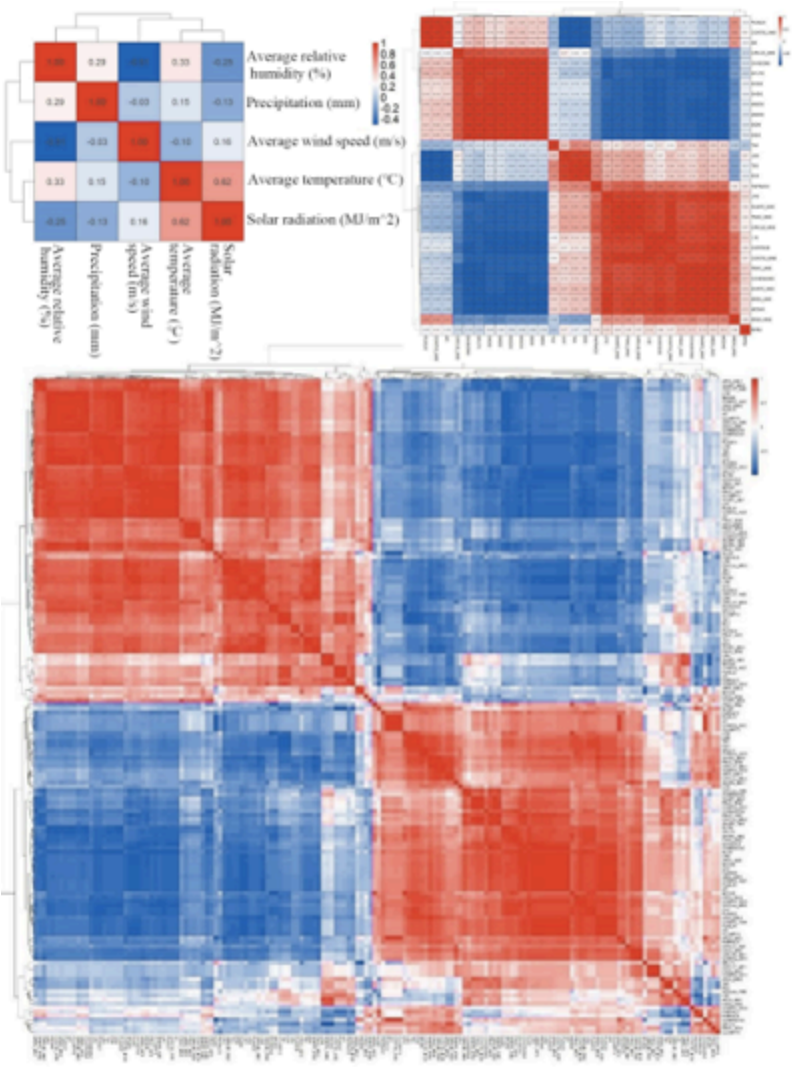



**Figure 4**

Heat map of Pearson correlation coefficient for Drivers of runoff change

(a)Heat map of Pearson correlation coefficient for landscape type level index (b)Heat map of Pearson correlation coefficient for overall landscape level index (c) Heat map of Pearson correlation coefficients of climate factors

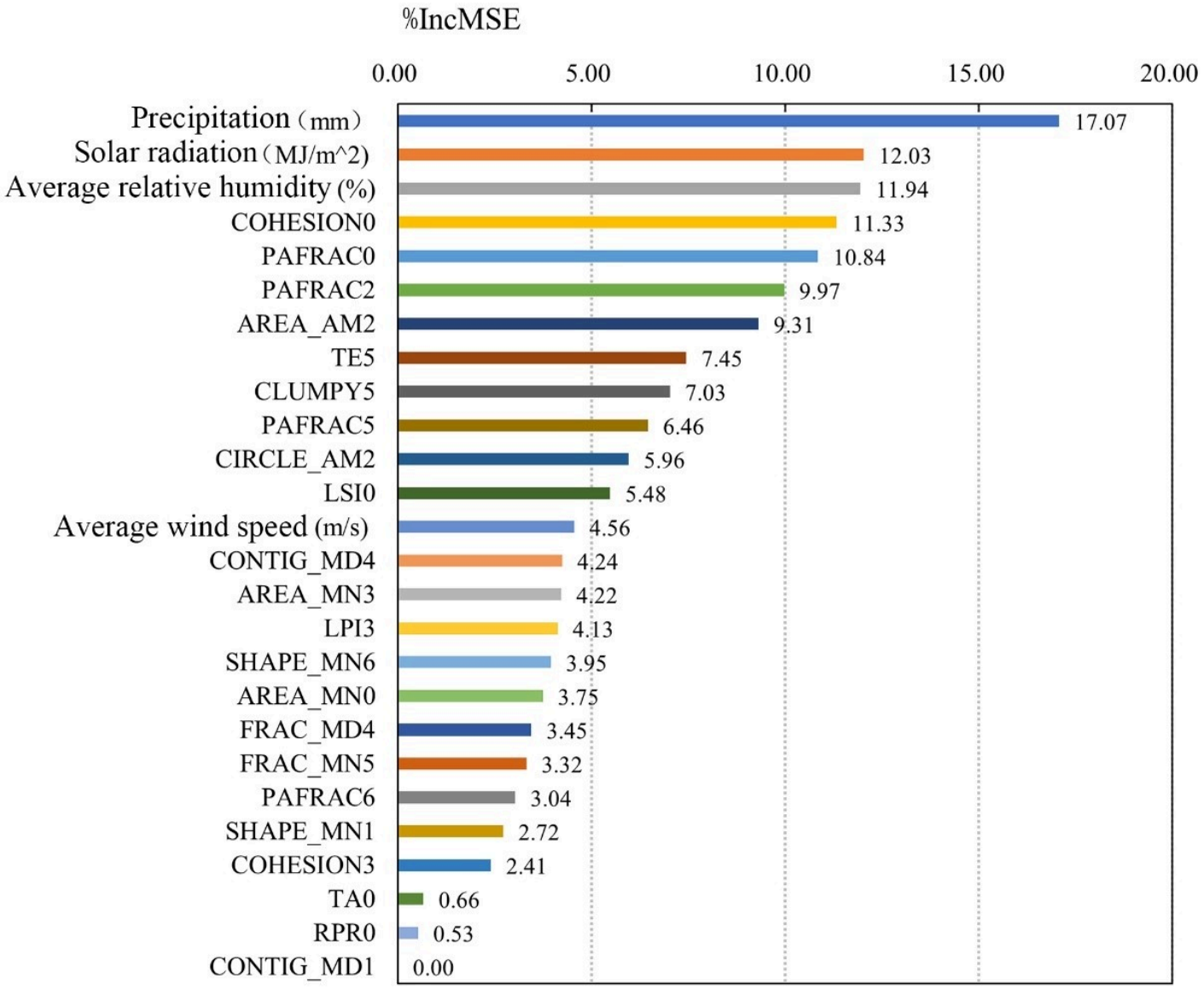
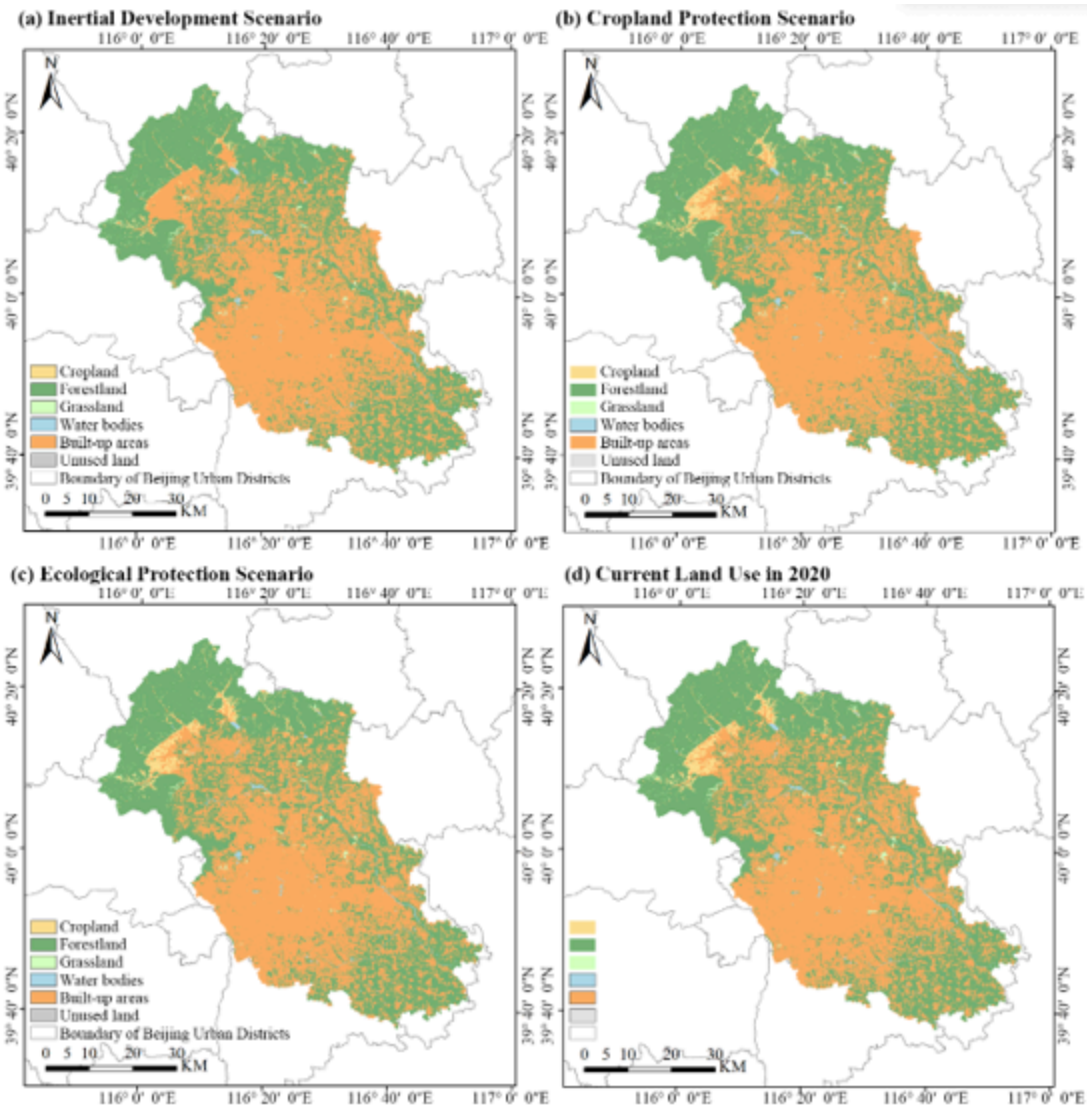



**Figure 5**

Importance and Correlation of Driving Factors




## Figure 6

Simulation of land use types in the North Canal Basin (Beijing section) under different scenarios

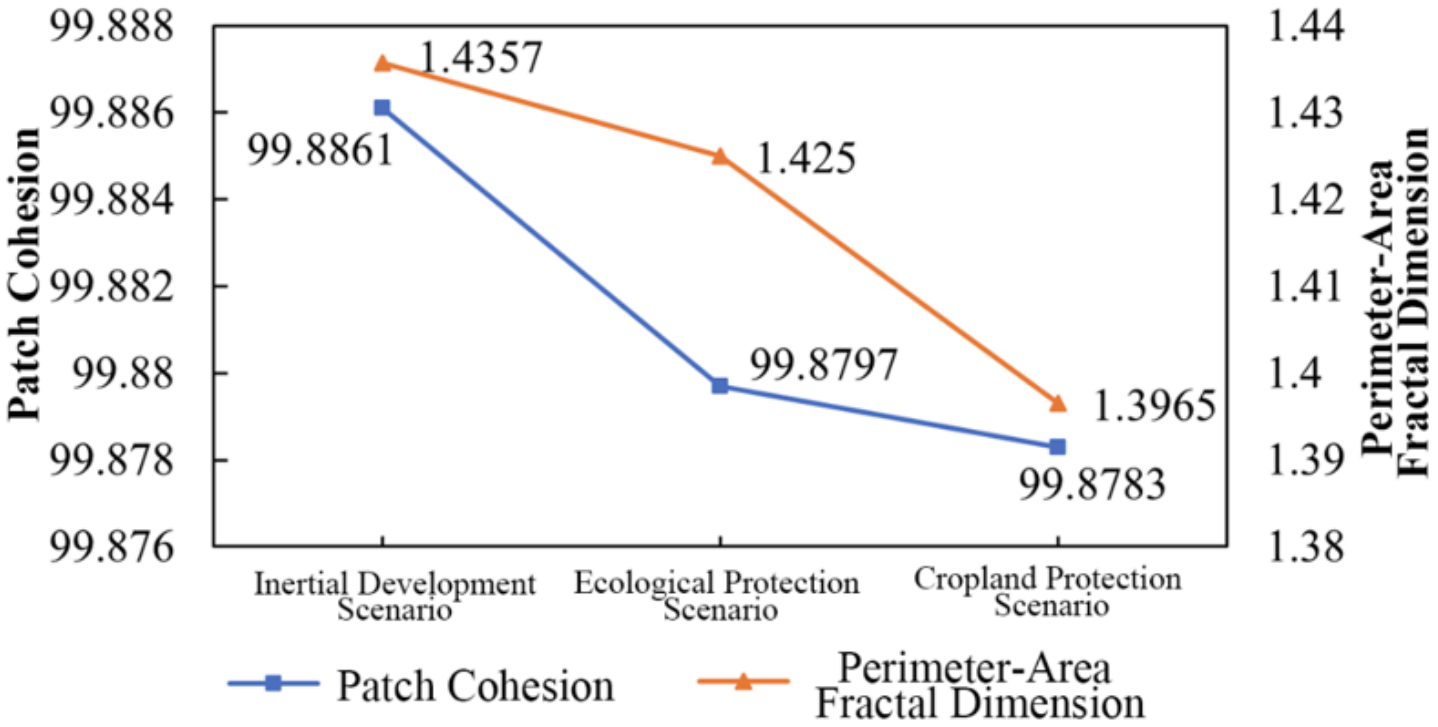
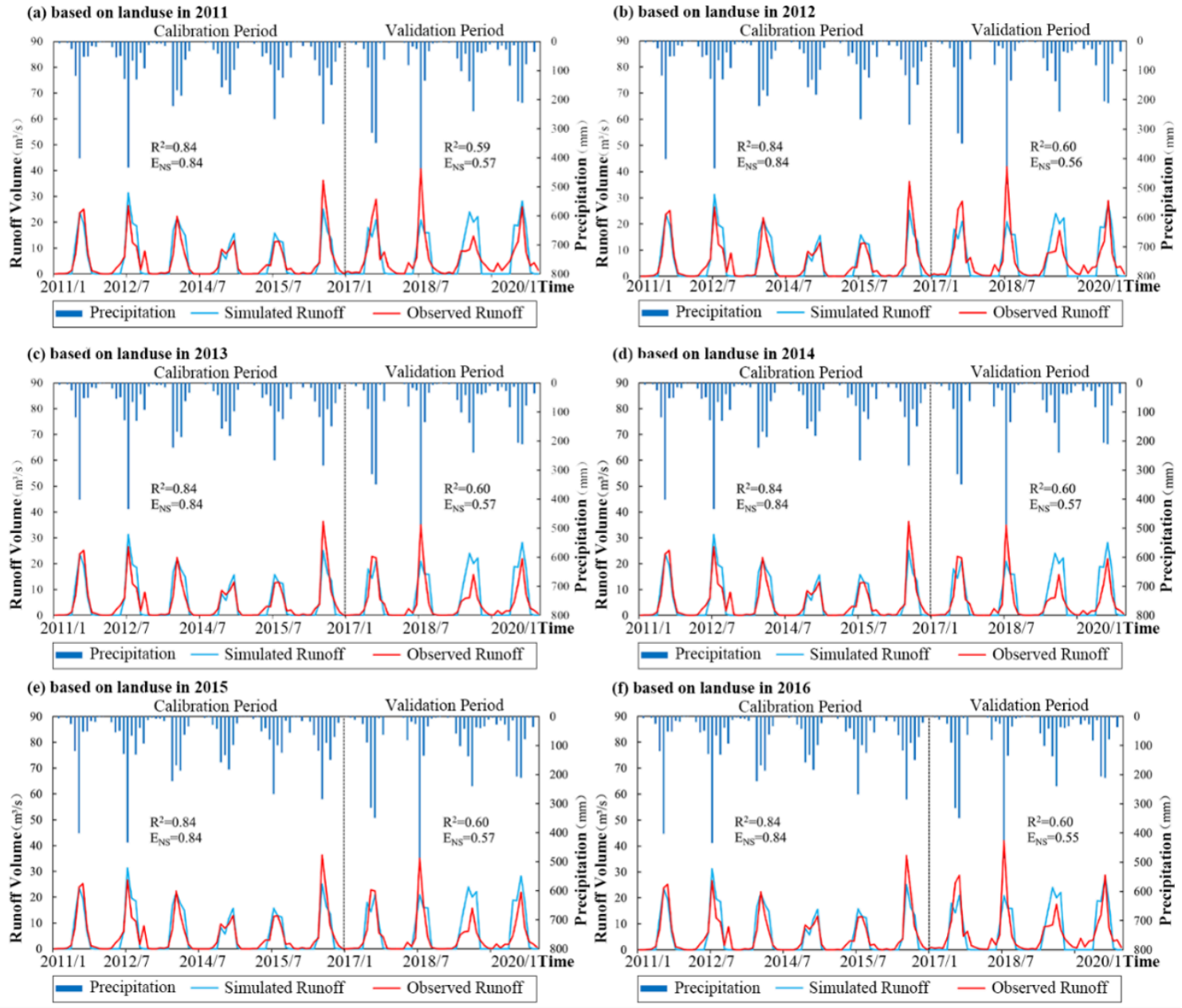



**Figure 7**

Calculation results of fractal dimension of patch cohesion and perimeter area




## Figure 8

Runoff fitting diagram of Yulinzhuang station in the North Canal Basin (Beijing section) (based on land use in 2011~2016)

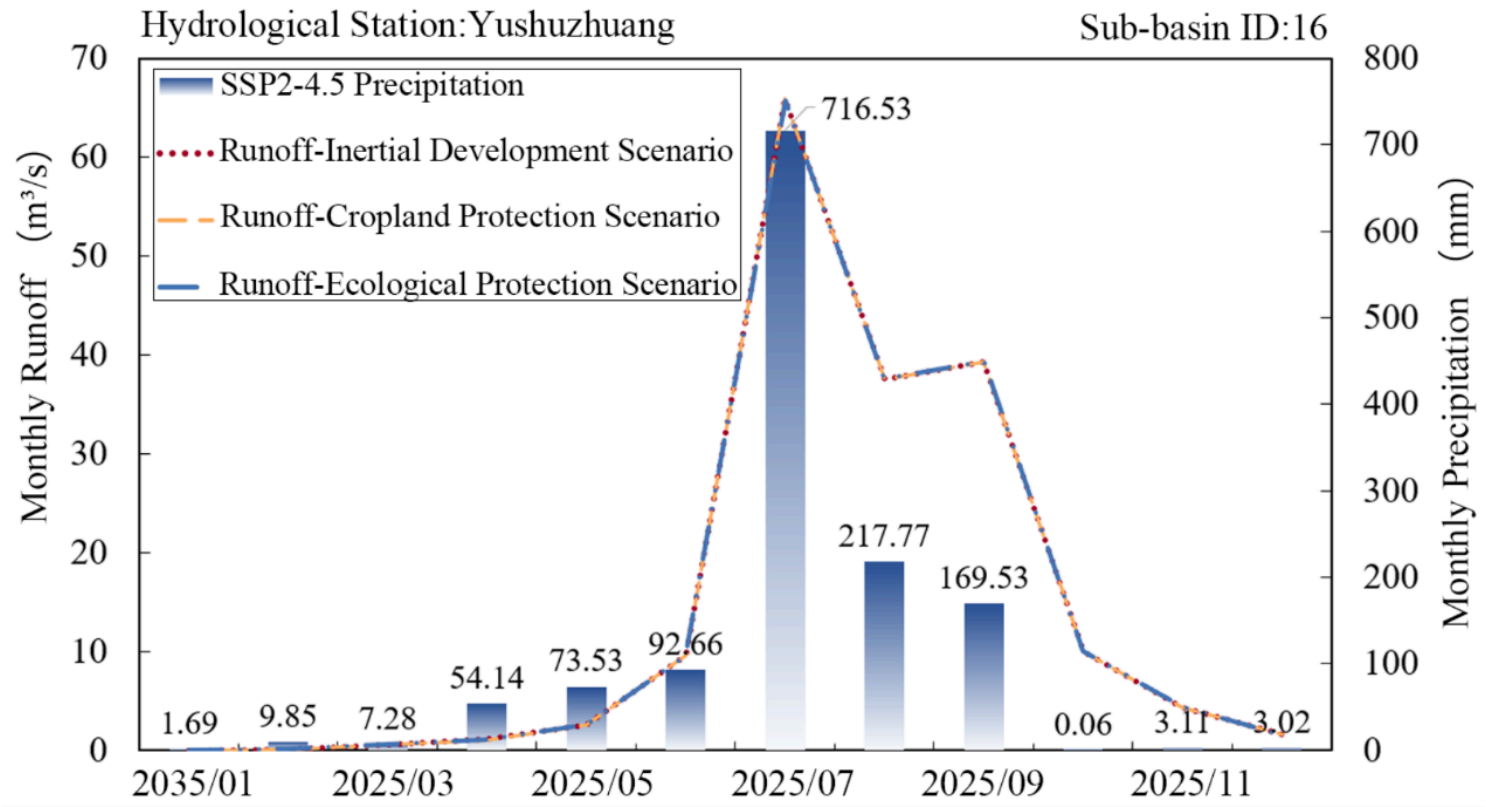



**Figure 9**

Monthly runoff simulation at Yulinzhuang station in 2035 under different land cover scenarios

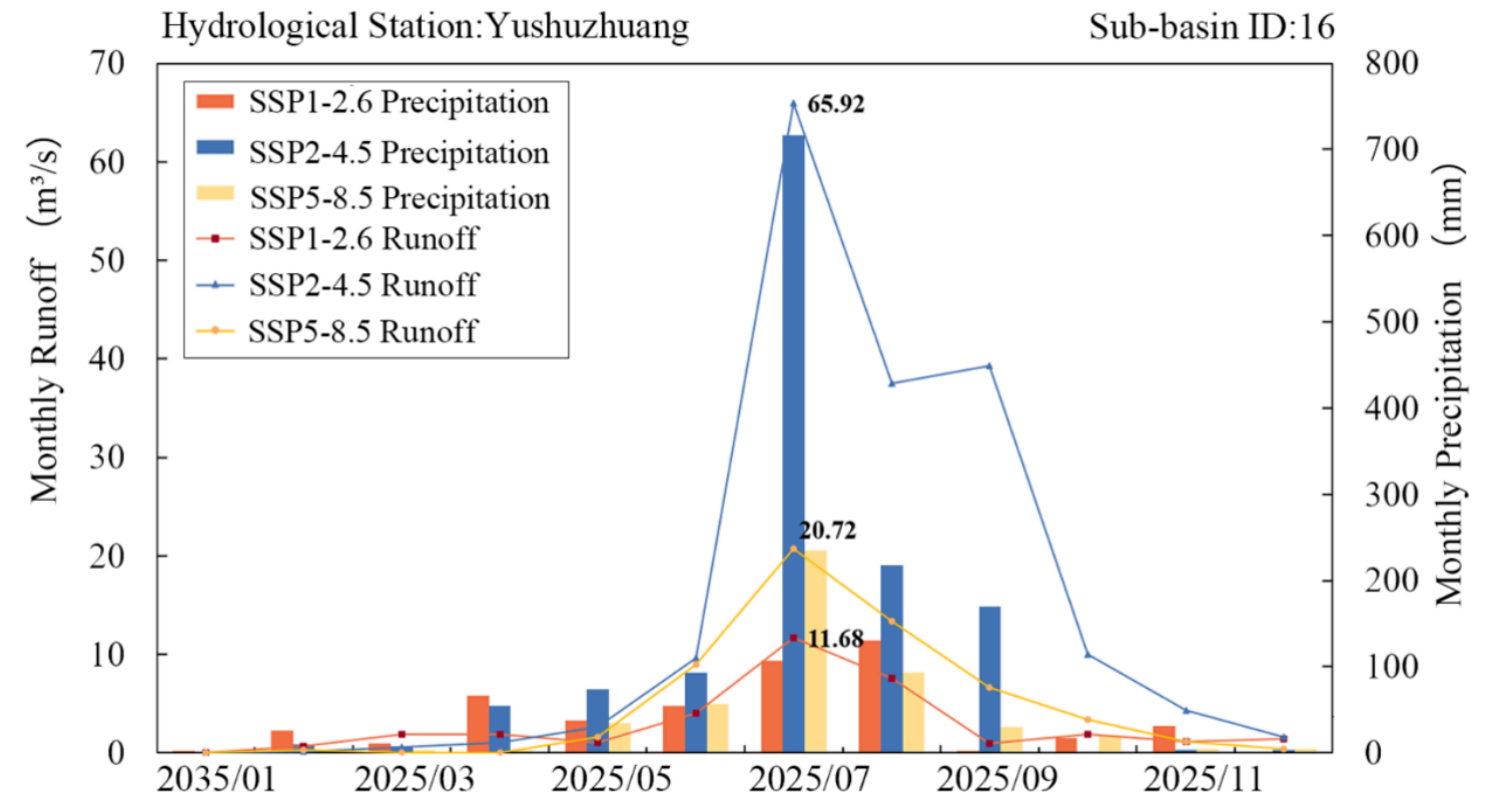



**Figure 10**

Monthly runoff simulation at Yulinzhuang station in 2035 under different climate model Scenarios