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1	Identifying how future climate and land use/cover changes impact
2	streamflow in Xinanjiang Basin, East China
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11 Graphical Abstract



13 Abstract

12

14 Climate and land use/cover changes are the main factors altering hydrological regimes. To 15 understand the impacts of climate and land use/cover changes on streamflow within a specific 16 catchment, it is essential to accurately quantify their changes given many possibilities. We 17 propose an integrated framework to assess how individual and combined climate and land 18 use/cover changes impact the streamflow of Xinanjiang Basin, in East China, in the future. Five 19 bias-corrected and downscaled General Circulation Model (GCM) projections are used to 20 indicate the inter-model uncertainties under three Representative Concentration Pathways 21 (RCPs). Additionally, three land use/cover change scenarios representing a range of tradeoffs between ecological protection (EP) and urban development (UD) are projected by Cellular 22 23 Automata - Markov (CA-Markov). The streamflow in 2021-2050 is then assessed using the 24 calibrated Soil and Water Assessment Tool (SWAT) with 15 scenarios and 75 possibilities. 25 Finally, the uncertainty and attribution of streamflow changes to climate and land use/cover changes at monthly and annual scale are analyzed. Results show that while both land use/cover 26 27 change alone and combined changes project an increase in streamflow, there is a disagreement 28 on the direction of streamflow change under climate change alone. Future streamflow may 29 undergo a more blurred boundary between the flood and non-flood seasons, potentially easing the operation stress of Xinanjiang Reservoir for water supply or hydropower generation. We 30 31 find that the impacts of climate and land use/cover changes on monthly mean streamflow are 32 sensitive to the impermeable area (IA). The impacts of climate change are stronger than those 33 induced by land use/cover change under EP (i.e., lower IA); and land use/cover change has a 34 greater impact in case of UD (i.e., higher IA). However, changes in annual mean streamflow 35 are mainly driven by land use/cover change, and climate change may decrease the influence 36 attributed to land use/cover change.

37

38 Key words: multiple scenarios, climate change, land use/cover change, streamflow response,
39 uncertainty, attribution.

41 **1. Introduction**

42 Efficient water resource management calls for a thorough understanding of changes in 43 hydrological regime. Streamflow, as a primary component of the hydrological cycle, is widely 44 believed to be affected mainly by climate and land use/cover changes (Alaoui et al., 2014; Ning 45 et al., 2016; Abera et al., 2019). Climate change indirectly affects streamflow through changes 46 in temperature, precipitation, and evaporation (Ruelland et al., 2012; Ahn and Merwade, 2014; Guo et al., 2019). Land use/cover change can significantly alter canopy interception, infiltration 47 48 and evapotranspiration, which may eventually change the runoff volume, peak flow and flow routing time (Molina-Navarro et al., 2014; Zhang et al., 2017; Umair et al., 2019). Determining 49 50 the individual or combined hydrological consequences of climate and land use/cover changes is a key for implementing effective measures for adaptation to climate change and for 51 52 understanding the patterns of water use under different land use/cover policies (Wang et al., 53 2018; Clerici et al., 2019; Trolle et al., 2019).

Numerous studies have investigated the effects of climate change on streamflow (Gao et 54 al., 2015; Chase et al., 2016). Particularly, since the publication of the Fifth Assessment Report 55 56 of the Intergovernmental Panel on Climate Change (Cubasch et al., 2013), many studies have 57 widely applied General Circulation Model (GCM) projections of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to quantify how climate change impacts streamflow 58 59 (Neupane et al., 2015; Eisner et al., 2017; Zheng et al., 2018). Results indicate that changes in streamflow show strong spatial variability under different Representative Concentration 60 61 Pathways (RCPs). For example, Shrestha et al. (2018) found that RCP8.5 and RCP4.5 were

responsible for a 19.5% and 24% decrease in future streamflow, respectively, in Thailand; but Wen et al. (2018) reported increases in streamflow along with the increasing temperature and precipitation under RCP2.6, RCP4.5, and RCP8.5 in the future, in southeast China. Another issue is the low resolution of GCM projections. Previous studies agree that the raw GCMs is too coarse to accurately describe the hydrological processes at regional scales (Chen and Frauenfeld, 2014; Sun et al., 2016; Guo et al., 2019), and thereby the conclusions on streamflow regime changes might not be reliable.

69 However, the extent to which streamflow responds to land use/cover change has not been 70 fully investigated, and this response varies between catchments and between scenarios. Due to 71 the acceleration of urbanization, the area of urban land has significantly increased, and 72 consequently the area of impermeable surface has expanded, causing a sharp increase in 73 streamflow at both long-term and short-term scales (Suriya and Mudgal, 2012; Li et al., 2018; 74 Zhang et al., 2018). Ecological protection projects, e.g., the "Grain for Green" in China (Zhang 75 et al., 2016), were initiated to increase the areas of forest and grassland, potentially resulting in 76 an increase in vegetation coverage and a decline in surface streamflow (Zuo et al., 2016; Wang 77 et al., 2019a; Yang et al., 2019). Some findings, however, have suggested that forest transforming to farmland and grassland could cause increases in mean annual streamflow (Shi, 78 79 2013). Accordingly, determining not only the impact of climate change on hydrology but also 80 how different land use/cover management policies affect streamflow is vital for better managing 81 water resources.

82 Recently, the joint effects of climate and land use/cover change on hydrology have been a main research focus (Liu et al., 2009; Kim et al., 2013; Zhang et al., 2017). Results show the 83 84 complex and non-additive interactions between streamflow and climate and land use/cover 85 change. Some studies found that streamflow alteration involved the superposition of the effects 86 of climate and land use/cover changes, and land use/cover change was a dominant factor (Liu 87 et al., 2009; Yin et al., 2017b), while some revealed that climate change was more dominant 88 (Kim et al., 2013; Woldesenbet et al., 2018); Other studies also reported that climate change 89 and land use/cover change each contributed 50% to streamflow variation (Wei et al., 2010). 90 The abovementioned studies argue that the effects of climate and land use/cover changes on streamflow vary spatially. To understand the impacts of climate change and land use/cover 91 92 management on streamflow, it is essential to accurately assess future changes within a specific 93 catchment under diverse conditions. Nevertheless, few studies have attempted to combine 94 varying land use/cover with varying climatic conditions for an uncertain future. Thus, an in-95 depth study on streamflow response to multiple climate and land use/cover change scenarios is needed. 96

97 The Xinanjiang is the main water source for riverside residents in Anhui and Zhejiang 98 provinces. Studies investigating climate change in Xinanjiang Basin have noted that the annual 99 streamflow showed an obvious increasing trend during a historical period due to the heavy rains 100 and mountainous terrain (Zheng et al., 2015; Pan et al., 2018). In recent years, land use/cover 101 in this basin has undergone dramatic changes because of urbanization and specific land 102 use/cover policies; however, few studies have investigated how land use/cover change has

103 affected streamflow. A better understanding of streamflow response driven by climate and land 104 use/cover changes in Xinanjiang Basin would be beneficial for flood defense and hydropower 105 utilization of Xinanjiang Reservoir. We aim to systematically investigate the individual and 106 combined effects of climate and land use/cover changes on future streamflow in Xinanjiang 107 Basin. Specifically, the Bias Correction and Spatial Disaggregation daily (BCSDd) downscaled 108 CMIP5 GCM projections and land use maps simulated by the Cellular Automata - Markov 109 (CA-Markov) model are employed to drive a Soil and Water Assessment Tool (SWAT) 110 hydrological model and to project streamflow under diverse scenarios. Then, the streamflow 111 uncertainty is evaluated at various levels using the fuzzy extension principle, while the individual and combined effects of climate and land use/cover changes on streamflow are 112 113 analyzed with the relative change rate (RCA) and contribution rate.

114 **2** Materials and methods

115 **2.1 Study area**

116 The Xinanjiang is the upstream part of the Qiantang River located in eastern China and has a total length of 323 km with an area of 11,503 km², as shown in Fig. 1. Three tributaries, 117 118 the Hengshui River, the Shuaishi River, and the Lian River, flow into the main stream of 119 Xinanjiang. The average annual temperature in Xinanjiang Basin is between 15.4 °C and 120 16.4 °C, whereas the average annual precipitation is between 1280 mm and 1700 mm. The basin 121 is dominated by a typical subtropical humid monsoon climate. The wet season (March to July) 122 accounts for approximately 74% of the annual streamflow, while the dry season (from August 123 to February) takes up the remaining 26%. Various landscapes, such as plains and mountains, are spatially distributed in the basin. Forest and grassland are the most widely distributed types,
and cultivated land is concentrated at the periphery of urban land. Xinanjiang Reservoir is
located downstream of Xinanjiang Basin, and is the first domestically designed and constructed
reservoir in China, used mainly for hydropower generation for East China Region including
Shanghai, Jiangsu, Anhui, and Zhejiang provinces, as presented in Fig. 1.



130

129

Fig. 1. Geographic location of Xinanjiang Basin.

131 **2.2 Data collection**

The observed meteorological data from 1976 to 2005 here are obtained from the National Meteorological Information Center of China (http://data.cma.cn) and these data comprise the daily precipitation, temperature, solar radiation, wind speed, and relative humidity, which are collected at nine hydrometric stations including Ningguo, Huangshan, Linan, Qimen, Tunxi, Chunan, Jinhua, Yiwu, and Quzhou, as shown in Fig. 1. The GCM climate projections are provided by the Earth System Grid Federation (https://esgf-node.llnl.gov), and these data include the daily precipitation and average, maximum and minimum temperature in 1976-2005 139 and 2021-2050. Five Coupled Model Inter-comparison Project Phase 5 (CMIP5) GCMs, 140 namely Cnrm-cm5, Gedl-esm2m, Ipsl-cm5a-lr, Miroc-esm-chem, and Noresm1-m are used due 141 to their good performance in climate simulation in China (Wen et al., 2018; Yang et al., 2019). 142 More details on GCMs can be found in Supplementary information A1. 143 Geospatial data includes digital elevation model (DEM), land use/cover and soil map data. 144 The DEM map at 90 m resolution used for defining streams and boundaries of sub-basins is 145 provided by the Geospatial Data Cloud of China (http://www.gscloud.cn). The 30 arc-second soil map is originally derived from the Cold and Arid Regions Sciences Data Center at Lanzhou 146 147 (http://westdc.westgis.ac.cn). Land use/cover maps at a 1km resolution for 1995, 2005 and 2015 from the Resource and Environment Data Cloud Platform of China (http://www.resdc.cn) are 148 149 used to estimate the effect of land use/cover change over this period. The land use/cover here 150 is reclassified into six classes for the SWAT model, namely forest, grassland, cultivated land, 151 urban land, water body, and unused land.

The Zhejiang Design Institute of Water Conservancy & Hydro-electric Power provides the
monthly inflow of Xinanjiang Reservoir from 1976 to 2005.

154 **2.3 Methodology**

We propose an integrated and systematic framework to assess how future climate and land use/cover changes impact streamflow using Xinanjiang Basin as a case study. This approach combines 1) scenario design involving individual and combined climate and land use/cover change; 2) climate and land use/cover change projection, where GCM projections are downscaled by the BCSDd method, and land use/cover maps are simulated by the CA-Markov model; 3) streamflow response modelling under uncertainty; 4) streamflow assessment including uncertainty, monthly and annual attribution analysis. In this study, the baseline is in the period of 1976-2005 and the future is in the period of 2021-2050. We assume that there were no significant changes in land use/cover before 2005, and therefore use the land use/cover in 1995 as the representative land use/cover in the baseline period. Regarding to the land use/cover change scenarios, we use the land use/cover in 2025 as the representative land use/cover in the future period.

167 2.3.1 Scenario design

We select three RCP scenarios to assess how different emission scenarios impact streamflow, namely RCP2.6, RCP4.5 and RCP8.5. These three scenarios represent the low, medium and high emission of greenhouse gases, respectively, which are named according to their total radiative forcing in 2100 relative to pre-industrial values (+2.6, +4.5 and +8.5 W/m², respectively).

Three land use/cover scenarios that represent a range of tradeoffs between ecological protection and urban development are proposed to identify how different land use/cover policies affect streamflow, namely Historical Trend (HT), Ecological Protection (EP) and Urban Development (UD) scenarios. The three scenarios all assume that future land use/cover demands are based on the historical trend, but vary with specific characteristics of each scenario. (1) HT Scenario. This scenario emphasizes there would be no interventional policy made for land use/cover changes in the future. (2) EP Scenario. This scenario also aims to maintain a greater vegetation coverage rate
and develop the ecological land (forest and grassland) area, which forbids the transformation
of the ecological land to other land use/cover types. It is generally used to represent future land
use/cover with a low impermeable area (IA).

(3) UD Scenario. In contrast with the EP scenario, this scenario not only requires the urban
land not to be transformed to other land use/cover types, but also encourages the other types to
be converted to urban land. To some extent, this scenario reflects the current maximum
economic profit and ignores ecological protection. It is generally used to represent future land
use/cover with a high IA.

In terms of the combined climate and land use/cover change scenarios, we assemble RCPs with HT as HTs (i.e., HT2.6, HT4.5, and HT8.5); EP as EPs (i.e., EP2.6, EP4.5, and EP8.5); UD as UDs (i.e., UD2.6, UD4.5, and UD8.5). Thus, different scenarios, 15 in total, are designed based on different climate and land use/cover changes. Accordingly, there are in total 75 possibilities by coupling 15 scenarios and 6 GCMs projections (5 GCM models and 1 multimodel ensemble means).

195 **2.3.2 Bias correction of future climate data**

To address the low-resolution problem of raw GCM projections at regional scales, the BCSDd method (Thrasher et al., 2012) is applied to establish empirical relationships between GCM-resolution climate variables and local climate and to reproduce the regional climate features. Generally, the BCSDd method includes two steps: 1) Bias correction. Both daily raw GCM projections and observations are first re-gridded to a certain coarse resolution by the 201 inverse distance weighted (IDW) method (Mito et al., 2011). The bias-corrected value for a raw 202 daily GCM projection is obtained by using the Cumulative Distribution Function (CDF) for the 203 GCM and observation to determine the same quantile associated with the projection. 204 Particularly, bias correction covers a common time period for observations and GCM. 2) Spatial 205 downscaling. The daily bias-corrected values are spatially disaggregated to a high-resolution 206 grid by the sonographic mapping system (SYMAP) interpolating (Shepard, 1984). The high-207 resolution value is then used to calculate the correction factors between the observations and 208 high-resolution GCM projections, specifically, multiplication for precipitation and plus for 209 temperature. Further, the index of root mean squared error (RMSE), mean of bias (MBIAS), standard deviation of bias (SBIAS), and correlation coefficient (R) are used to examine the 210 211 accuracy of the downscaled results of the BCSDd method. Note that the low the MBIAS, 212 SBIAS, and RMSE values are, the better the results, whereas a larger R are preferable. The 213 details on statistic variable equations can be found in Supplementary Materials A2.

214

2.3.3 CA-Markov land use/cover modelling

Land use/cover models are commonly divided into three categories, namely quantitative, space and combination models. The CA-Markov model (Zhao et al., 2019) linking CA (a space model) and Markov Chain (a quantitative model) is adopted to project the land use/cover change in this study. The Markov model (Sang et al., 2011) describes the likelihood of change from one state to another based on a transition probability matrix achieved with the following equation in the Markov Chain process:

$$S_{t+1} = P \times S_t \tag{1}$$

where S_t and S_{t+1} are the land use/cover status at time of t and t+1, respectively; P is the transition probability matrix in a state that is calculated as follows:

$$P = \begin{vmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{vmatrix}$$
(2)

223 where $\sum_{i=1}^{n} P_{ij} = 1$, $0 \le P_{ij} \le 1$, P_{ij} is the transition probability from land use/cover type *i* to

224 type j; and n is the number of land use/cover types in the target area.

Due to lack of spatial parameters, the Markov Chain model is unable to identify the spatial variability in land use/cover (Firozjaei et al., 2019). By adding an element of spatial contiguity as well as information on the likely spatial distribution of transitions to Markov chain analysis, the CA model makes it possible to simulate spatial and temporal evolution of land use/cover using the CA-Markov model. The CA model can be defined as follows:

$$S_{t+1} = f\left(S_t, N\right) \tag{3}$$

230 where N is the cellular field; and f is the transition rule of the cellular states.

There are two cores in the CA-Markov model, the transition probability matrix from baseline to potential land use/cover change for Markov and the suitability map built according to the driving force analysis of land use/cover change for CA, and their combination contributes to a better land use/cover simulation. To distinguish the differences on land use/cover between scenarios, constraint maps under different scenarios were expressed using the Boolean map, with suitable transformation areas coded with one and others coded with zero (Behera et al., 2012). Then, the sub-suitability maps coupled with the constraint maps are prepared as the final suitability map for different scenarios. In this study, we use the land use/cover in 2025 as the representative land use/cover in the future period. Details on the specific processes of CA-Markov modelling land use/cover in 2025 under different scenarios can be found in Supplementary materials A3. Before prediction, the Kappa index (Mitsova et al., 2011) is adopted to gauge the degree of agreement between the simulated and observed land use/cover map. The land use/cover simulation is acceptable if Kappa>0.4.

244 2.3.4 SWAT hydrological model

Hydrological modelling methods are widely used to quantify the effects of climate and 245 246 land use/cover change (Woldesenbet et al., 2018). The Variable Infiltration Capacity (Liang et al., 1994), SWAT (Arnold et al., 1998), Hydrologic Simulation Program-Fortran (Deliman et 247 248 al., 1999) and Water Erosion Prediction Project (Flanagan et al., 2001) are the commonly used 249 hydrological models, among which the SWAT model has been successfully used in studies 250 associated with climate change and land use/cover change. It is evident that the SWAT model 251 has yielded high accuracy for short/long-term simulations of yearly and monthly mean 252 streamflow (Zuo et al., 2016; Anand et al., 2018; Bhatta et al., 2019). Thus, we use the SWAT 253 model to project future streamflow under diverse scenarios. In the SWAT model, a catchment will be divided into several sub-basins and then partitioned into hydrological response units 254 255 (HRUs) according to the same land use/cover and soil type. The water flow in each HRU is 256 simulated based on the water budget formula. See more details in Arnold et al. (1998).

In this study, ArcSWAT2012 running on an ArcGIS 10.2 platform is used for watershed
 delineation and sub-basin discretization. The Xinanjiang Basin is divided into 121 sub-basins

259 and multiple HRUs according to the land use/cover, soil types, and slope classes. The slope of 260 Xinanjiang Basin with a range from 0 to 10% is accounted for more than 90% of the whole 261 basin. The procedures of parameter calibration, verification, and sensitivity analysis in the 262 SWAT model can be conducted by the SWAT Calibration and Uncertainty Programs (SWAT-263 CUP) (Abbaspour et al., 2007). The sensitivity analysis of the parameters is determined by the 264 t-statistics and the p-value. A larger absolute value of t-statistics and a smaller value of the p-265 value correspond to a more sensitive parameter. The coefficients of determination (R^2) (Woldesenbet et al., 2017) and Nash-Sutcliffe efficiency (NSE) (Dile et al., 2016) are used to 266 267 quantify the goodness of model performance. The performance of hydrological simulation is considered to be acceptable if $R^2 > 0.5$ or NSE>0.5. 268

Discharge data during the period of 1976-2005 at one hydrological station (presented in Fig.1) located at upper dam site of Xinanjiang Reservoir is used for model sensitivity analysis, calibration and validation. First, under the land use/cover of 1995 and driven by the observed meteorological data during 1975-2005, the SWAT model is calibrated and validated on a monthly scale in 1976-1995 and 1996-2005. Further, the individual and combined effects of climate change and land use/cover change on streamflow are evaluated using the SWAT model.

275

2.3.5 Methods for streamflow change analysis

a) Fuzzy extension principle

As multiple drivers involve many uncertainties, identifying the uncertainty and range of predicted streamflow is beneficial for water management. Fuzzy set theory is able to handle uncertainty problems, especially one of which is associated with a lack of information at hand. In this study, we use the fuzzy extension principle (Wambura et al., 2015) to evaluate the uncertainty in streamflow. The method uses a horizontal line, namely fuzzy alpha-level cut $(\alpha$ -cut), to describe the elements belonging to a particular certainty level from the membership function. The membership level may take any value ranging from zero to one:

$$\mu_{A}(x) = \begin{cases} 0 & \text{if } x \le a \\ \frac{x-a}{b-a} & \text{if } a < x \le b \\ \frac{c-x}{c-b} & \text{if } b < x \le c \\ 0 & \text{if } x \ge c \end{cases}$$
(4)

where $\mu_A(x)$ is the degree of membership of x in fuzzy subset A, $\mu_A(x)=0$ means no membership and $\mu_A(x)=1$ represents full membership; a and c stand for the lower and upper bounds, respectively, and b is the core of the fuzzy number.

287 The α -cut is the certainty level, which ranges between zero and one (Gonzalez et al., 288 1999). In general, a high α -cut corresponds to a higher confidence degree and a lower 289 uncertainty level. Assume that the α -cut is assigned as 0%, 50% and 100%, the corresponding 290 uncertainty levels will be 100%, 50% and 0%, respectively.

b) Relative change rate

The RCA (Wen et al., 2018) is defined as the ratio of changes in the outcome variable before and after considering the influence factors to the standard deviation of the outcome variable, which can directly compare the relative contribution on outcome variable between different influence factors. Thus, the RCA is a powerful tool to provide a better understanding of how different influence factors alter streamflow at monthly scale, and it can be calculated by the following formula:

$$\alpha_i = \begin{vmatrix} d_i \\ D_i \end{vmatrix}$$
(5)

$$D_{i} = \sqrt{\frac{1}{N} \sum_{j=1}^{N} \left(Q_{ij} - \overline{Q_{i}} \right)^{2}}$$
(6)

$$d_i = \overline{Q_i} - \overline{q_i} \tag{7}$$

where α_i is the RCA of the mean monthly streamflow of the *i*th month, D_i is the standard deviation of the mean monthly streamflow of the *i*th month, d_i is the difference in mean annual streamflow of the *i*th month between the basic and future periods, Q_{ij} is the mean monthly streamflow in different years in the baseline, $\overline{Q_i}$ and $\overline{q_i}$ are the mean annual streamflow of the *i*th month in the baseline and future period, respectively; *N* is the number of years.

304 c) Contribution rate

305 When one driving factor varies and another remains constant, the simulation results show 306 the effects of the variable factor on the hydrological components (Yin et al., 2017a). The 307 contribution rate can be used to directly separate the effects of climate and land use/cover changes on streamflow (Qiang et al., 2016). We use RCP2.6 and HT as an example here. The 308 difference in streamflow between RCP2.6 ($Q_{RCP2.6}$) and the baseline (Q_b) can be regarded as 309 310 the effect of RCP2.6 on streamflow change. Similarly, the difference in streamflow between HT2.6 ($Q_{HT2.6}$) and HT (Q_{HT}) can be regarded as the effect of RCP2.6 on streamflow change. 311 Therefore, the impacts of RCP2.6 ($\Delta Q_{RCP2.6}$) on streamflow should be calculated by the 312 313 following formula:

$$\Delta Q_{RCP2.6} = \frac{(Q_{RCP2.6} - Q_b) + (Q_{HT2.6} - Q_{HT})}{2}$$
(8)

Furthermore, the effects of HT (ΔQ_{HT}) on streamflow can be determined by applying the difference between HT (Q_{HT}) and the baseline (Q_o) or between HT2.6 ($Q_{HT2.6}$) and HT $(Q_{RCP2.6})$:

$$\Delta Q_{HT} = \frac{(Q_{HT} - Q_b) + (Q_{HT2.6} - Q_{RCP2.6})}{2}$$
(9)

The difference between streamflow in HT2.6 and the baseline represents the combined effects of RCP2.6 and HT on streamflow change. We find the combined effects ($\Delta Q_{HT2.6}$) are equal to the sum of the individual effects.

$$\Delta Q_{HT2.6} = Q_{HT2.6} - Q_b = \Delta Q_{RCP2.6} + \Delta Q_{HT} \tag{10}$$

Hence, the percentage contributions of RCP2.6 ($\eta_{RCP2.6}$) and HT (η_{HT}) to the variations in streamflow can be calculated as follows:

$$\eta_{RCP2.6} = \frac{\Delta Q_{RCP2.6}}{\Delta Q_{RCP2.6} + \Delta Q_{HT}} \times 100\%$$
(11)

$$\eta_{HT} = \frac{\Delta Q_{HT}}{\Delta Q_{RCP2.6} + \Delta Q_{HT}} \times 100\%$$
(12)

322 The quantitative contribution of the other climate and land use/cover change scenarios can323 also be determined by the above principle.

324 **3. Results**

325 **3.1 Climate change under varying scenarios**

We used the BCSDd method to correct and downscale the GCM temperature and precipitation during the period of 1976-2005 and 2021-2050 in Xinanjiang Basin. Table 1 shows the evaluation indexes between the raw and BCSDd downscaling of GCM projections

from 1976 to 2005. It is clear that BCSDd downscaling can significantly correct the GCM temperature and precipitation. Specifically, all the performance indexes for precipitation are improved. For temperature, the values of RMSE and SBIAS are reduced by 0.42-1.10 °C and 0.32-0.71 °C, respectively, while the value of R is increased by 0.01-0.02; due to the bias correction of daily historical probability distribution function, the value of MBIAS is expected to be 0.

Table 1 Comparison of the evaluation indexes between the raw and BCSDd downscaling of GCMs from1976 to 2005.

GCM		Precipitation (mm)			Temperature (°C)				
GCM		RMSE	R	MBIAS	SBIAS	RMSE	R	MBIAS	SBIAS
Nanam 1 m	Raw	10.16	0.10	0.39	10.16	2.37	0.97	-0.89	2.20
Noresini-in	BCSDd	5.86	0.80	-0.11	5.86	1.58	0.98	0.00	1.58
Miroa asm sham	Raw	9.76	0.07	1.16	9.69	2.61	0.97	1.60	2.06
Whoe-esm-chem	BCSDd	5.90	0.79	-0.12	5.90	1.75	0.98	0.00	1.76
Insl om5a lr	Raw	9.84	0.09	0.89	9.80	2.08	0.97	-0.60	1.99
ipsi-eni3a-n	BCSDd	6.23	0.78	-0.11	6.23	1.66	0.98	0.00	1.66
Gedl esm?m	Raw	9.81	0.11	1.07	9.75	2.72	0.96	-1.36	2.36
Gedi-esili2ili	BCSDd	7.17	0.72	-0.13	7.17	1.65	0.98	0.00	1.65
Corm om5	Raw	10.60	0.10	-0.80	10.57	2.64	0.97	-1.85	1.88
Chinii-chii3	BCSDd	6.05	0.79	-0.15	6.05	1.54	0.98	0.00	1.54
Multi-model	Raw	8.65	0.17	0.54	8.63	1.71	0.98	-0.62	1.59
ensemble means	BCSDd	4.98	0.84	-0.12	4.98	1.27	0.99	0.00	1.27

337	Fig. 2 shows the temperature and precipitation over Xinanjiang Basin in 1971-2005 and
338	2021-2050. The mean annual temperature in the baseline period is 16.32 °C, while that in the
339	future varies under different GCM projections. The mean annual temperatures of the Noresm1-
340	m, Ipsl-cm5a-lr and Miroc-esm-chem models are significantly increased by 0.07-3.86 $^\circ$ C under
341	RCPs, the Gedl-esm2m model are slightly decreased by 0.09-0.40 °C relative to the baseline

period. The Cnrm-cm5 model has the exception that the mean annual temperature decreases under RCP2.6, but increases under RCP4.5 and RCP8.5. Not surprisingly, the mean annual temperature is expected to increase with increasing radiation intensity for all GCM projections, and the multi-model ensemble means under RCPs (solid markers) may experience an increase in mean annual temperature ranging from 0.76°C to 1.20 °C. Additionally, Xinanjiang Basin has four distinct seasons both in the baseline and future periods. The differences in monthly temperature among RCPs are not significant.

349 The mean annual precipitation in 1976-2005 is 1598.61 mm, and will probably increase 350 by 2.40-3.24% in 2021-2050. The multi-model ensemble range in monthly precipitation is 351 narrow and similar. However, the error bar indicating the multi-model ensemble range in 352 monthly temperature shows the larger uncertainty under RCPs. Although GCMs do not all 353 project an increased mean annual precipitation with increasing radiation intensity, the multi-354 model ensemble means anticipates positive increases in the mean annual precipitation by 44.07-355 45.08 mm under RCPs. There is a non-uniform distribution of mean monthly precipitation in 356 Xinanjiang Basin. The precipitation in spring and summer accounts for 72.93% of the total 357 precipitation in 1976-2005, and 72.03-72.72% in 2021-2050.



Fig. 2 Mean (a) annual temperature and precipitation, monthly (b) temperature and (c) precipitation averaged over Xinanjiang Basin projected by downscaled CMIP5 GCMs under different RCPs in 2021-2050. The error bars indicate the multi-model ensemble range.

358 **3.2 Land use/cover change under varying scenarios**

Here, the land use/cover map of 2015 was first predicted using the maps of 1995 and 2005. The simulated map of 2015 was compared to the observed map of 2015 to evaluate the reliability of the CA-Markov model, which was acceptable with a Kappa value of 0.68 for Xinanjiang Basin. Then, the CA-Markov model was applied to simulate the land use/cover changes under the three scenarios in 2025, as shown in Fig. 3.

364 By comparing the land use/cover simulation results of Xinanjiang Basin in 2025 relative to those in 1995, we can see that the spatial distributions of land use/cover under the three 365 366 scenarios differ significantly. Under HT, the areas of forest, cultivated land and water body 367 decrease from 1995 to 2025, while the areas of the other land use/cover types are all increased 368 to varying degrees ranging from 43.84% to 516.28%. Under EP, forest and grassland are still 369 the two dominant land use/cover types, contributing to a total increase of 5.48%. The area of 370 water body declines slightly, and cultivated land has a large reduction of 51.70%. The urban 371 area increases largely owing to the changeover of forest and cultivated land. Under UD, a sharp 372 increase in urban land is observed with a value of 192.68%. The urban area increases largely 373 due to the conversion of forest, grassland, and cultivated land. Overall, the areas of forest and 374 grassland under EP are predicted to undergo the largest proliferation among all scenarios, while 375 the area of urban land is the lowest. In contrast, the area of urban land under UD is obviously 376 larger than those under the other two scenarios, while the areas of forest and grassland are the 377 lowest. Land use/cover under HT has undergone changes because of urbanization following the 378 historical trend, but less urbanization occurs than that under UD.



Fig. 3. Projected land use/cover maps in 2025 under (a) HT, (c) EP, and (e) UD scenarios, and proportions of area of each land use type under (b) HT, (d) EP, and (f) UD scenarios.

380 **3.3 Sensitivity analysis, calibration and validation results of SWAT model**

The results of global sensitivity analysis using SWAT-CUP are listed in Table 2, based on their ranking. ESCO, GW_DELAY, SURLAG, CH_S2, CH_K2, GWQMN, CN2, SLSUBBSN, SOL_Z, CANMX, SOL_AWC, and OV_N are the first 12 high sensitivity parameters for the simulated streamflow. Soil evaporation compensation factor 'ESCO' ranked the first, much higher than others. Table 2 shows that parameters representing groundwater return flow, soil properties, ground water, and surface runoff are sensitive. Therefore, accurate estimation of these parameters is important for streamflow.

388 Table 2 Parameter sensitivity analysis and calibration results for the SWAT model.

Deverseter	Description	Sensitivity	analysis	Calibration			
Parameter	Description	<i>t</i> - statistics	<i>p</i> -value	Min	Max	Optimal	
v_ESCO	Soil evaporation compensation factor	-4.22	0	-1.00	1.00	0.40	
r_GW_DELAY	Groundwater delay time (days)	-3.01	0	-120.00	100.00	-54.00	
v_SURLAG	Surface water lag	-2.7	0.01	0.05	30.00	3.05	
v_CH_S2	Average slope of the main channel in the sub-basin (m/m)	2.23	0.03	-0.20	0.10	0.07	
v_CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/h)	2.04	0.04	-0.20	0.10	0.01	
r_GWQMN	Threshold depth of water in the shallow aquifer required for return flow (mm)	-2.02	0.04	0.00	2.00	1.40	
v_CN2	SCS runoff curve number for moisture condition II	-1.62	0.11	-0.20	0.20	-0.16	
r_SLSUBBSN	Average slope length	-1.4	0.16	0.00	100.00	50.00	
v_SOL_Z	Soil depth (mm)	1.34	0.18	-	-	-	
v_CANMX	Maximum storage capacity(mm)	1.33	0.19	0.00	0.10	0.07	
v_SOL_AWC	Base flow alpha factor (mm/mm)	1.01	0.31	-	-	-	
v_OV_N	Manning's "n" value for overland flow	0.91	0.36	0.01	1.00	0.11	

389 The SWAT model was calibrated and validated on a monthly scale in 1976-1995 and 1996-390 2005, respectively. Results show that the observed and SWAT simulated discharge fit well with 391 values of R²=0.92 and NSE=0.93 for the calibration period, and R²=0.90 and NSE=0.92 for the 392 validation period. The hydrological model captures the low flows and some peaks very well, in 393 particular the highest peak. The simulated and observed inflow of Xinanjiang Reservoir over 394 the period 1976-2005 for calibration and validation can be found in Supplementary materials 395 A4. The derived parameter values obtained from calibration and confirmation analyses were 396 incorporated with the SWAT database for further simulations.

397 **3.4 Streamflow response modeling under multiple scenarios**

398 We then projected the long-term (2021-2050) streamflow under climate change alone, land use/cover change alone, and their combination using the calibrated SWAT model and 75 399 400 possibilities. Two widely used methods in mainstream literatures, Mann-Kendall-Sen (MK-Sen) 401 trend test (Mann, 1945; Kendall, 1975) and Pettitt test (Pettitt, 1979) were adopted to analyze 402 the trends and abrupt changes of the streamflow time series in this study, respectively. The test 403 principle and results are provided in Supplementary materials A5-A6. These results show that 404 almost every annual streamflow series show an increasing trend during 2021-2050, and only 405 some possibilities have a significant increasing trend at 5% significance level. It can be found 406 that streamflow abruptly changed around 2030s in Xinanjiang Basin in the future. The predicted 407 streamflow at annual and monthly scales are shown in Fig. 4.

408 **3.4.1 Under varying climate change scenarios**

409 In 1976-2005, the mean annual streamflow is 334.86 m³/s with a frequent fluctuation between dry and flood years. The mean annual streamflow in 2021-2050 is 334.32-356.35 m³/s, 410 411 with a variation of -0.16-6.42% relative to that in 1976-2005. All GCMs show an increasing 412 trend in future streamflow under RCPs except the Miroc-esm-chem model under RCP2.6. This 413 result occurs because the Miroc-esm-chem model sees the most pronounced warming with 414 minimal rainfall under RCP2.6; thus, evapotranspiration increases, resulting in a decrease in streamflow. The annual streamflow has a slight fluctuation between dry and flood years, and 415 416 especially for the multi-model ensemble means. This result indicates that the mean GCM 417 projections will underestimate the probability of extreme flood and drought events.

418 Fig. 4 (b) shows an uneven distribution of mean monthly streamflow is expected in 419 Xinanjiang Basin in both 1976-2005 and 2021-2050. In the flood periods from March to August, the mean streamflow is 541.77 m³/s and the total streamflow accounts for 80.89% of the total 420 421 streamflow in a year in 1976-2005. In 2021-2050, the difference in streamflow between dry and 422 wet years might decline. In the flood periods, the mean streamflow is decreased by 0.73-6.70% 423 compared to that in 1976-2005, while the total streamflow in this period accounts for 74.06-424 76.56% of the total streamflow, with a decline of 5.35-8.45%. Meanwhile, an increase in the 425 monthly streamflow is observed in the dry periods and the mean streamflow is 159.18-184.87 426 m^3 /s with an increase of 24.40-44.48% relative to that in 1976-2005; while the total streamflow 427 in this period accounting for the total streamflow in a year is also increased by 22.67-35.77%. 428 Overall, it is evident that a more blurred boundary between dry and wet periods may occur in

the future. All GCMs project similar streamflow under RCPs at the monthly scale, which
indicates that the streamflow in Xinanjiang Basin is affected mainly by precipitation rather than
by temperature.

432 **3.4.2 Under varying land use/cover change scenarios**

433 Fig. 4 (c) and (d) show the annual and monthly streamflow variations under land use/cover 434 change. The streamflow shows a similar increasing trend over the period of 2021-2050 under 435 three land use/cover change scenarios, with a mean annual streamflow of 347.89-354.32 m³/s. The areas of urban land use/cover significantly expand under UD, resulting in a sharp increase 436 437 in IA, and the mean annual streamflow in 2021-2050 increases by 5.81% relative to that in 1976-2005. Because land use/cover has undergone dramatic changes due to urbanization during 438 439 2005-2015, the urban land increases under HT but its increase is still lower than that under UD. 440 Therefore, the mean annual streamflow under HT is lower than that under UD with a variation 441 of 4.00%. In EP, the vegetation coverage is the highest, but the mean annual streamflow is the 442 lowest with a variation of 3.89%.

The maximum monthly streamflow is expected to decline by 55.78-90.32 m³/s in June, which is similar to the pattern under climate change. The UD scenario has the largest monthly streamflow in June, indicating that a flood crisis might be induced by urban development. Additionally, an increase in the monthly streamflow is expected in the dry periods, and the minimum monthly streamflow in December is predicted to increase by 248.32-249.19 m³/s. Overall, it is evident that a more blurred boundary can be observed between the flood and nonflood seasons under land use/cover change. The different distribution characteristics of monthly 450 streamflow under land use/cover change can be divided into two periods. The monthly 451 streamflow from January to June under UD is higher than that under the other two scenarios; 452 in contrast, the monthly streamflow from August to December under UD is smaller than that 453 under both HT and EP. Therefore, land use/cover change can affect not only the amount of 454 annual average, but also the timing of streamflow in Xinanjiang Basin.

455 **3.4.3** Under varying combined climate and land use/cover change scenarios

456 Fig. 4 (e) and (f) present the annual and monthly streamflow variations under combined climate and land use/cover changes. The streamflow shows an increasing trend over the period 457 458 2021-2050 under combined scenarios, with a mean annual streamflow of 335.92-364.07 m³/s, 459 and has an annual variation of 0.32-8.72% compared with that in 1976-2005. The mean annual 460 streamflow under UDs is the largest, followed by that under HTs and EPs. Moreover, the 461 alteration characteristics of annual streamflow are similar under different land use/cover 462 changes. Regarding the same land use/cover change, the annual mean streamflow is not 463 sensitive to increasing radiation intensity, and the annual fluctuation varies between the dry and 464 flood year. The annual streamflow under the combined climate and land use/cover change is 465 consistent with that under climate change alone, although the mean value is lower than that of 466 individual land use/cover influence, and higher than that of individual climate change influence. In the flood seasons from April to July, the streamflow accounts for the total streamflow 467 468 decrease by 2.97-9.55% relative to that in 1976-2005. However, there is a disagreement on the 469 direction of streamflow change in this period. The mean streamflow is 593.30-627.65 m³/s with 470 a decline of 1.42-6.82% under HTs and EPs, but the mean streamflow is changed by -2.52-3.40% 471 under UDs. A significant increase of 25.91-65.94% occurs in the non-flood seasons from 472 October to January. This result also demonstrates that in the future under combined climate and 473 land use/cover changes, a more blurred boundary between the flood and non-flood seasons may 474 be expected. Then, we compared the streamflow between the combined scenarios and climate 475 change alone and land use/cover change alone. A similar distribution pattern of monthly 476 streamflow with that under individual land use/cover change can be observed. The monthly 477 streamflow under UDs from January to June is higher than that under both EPs and HTs, while 478 the monthly streamflow under UDs from August to October is lower. Under the same land 479 use/cover change conditions, no significant difference can be detected among RCPs, which is 480 similar to that under climate change alone. These results indicate that complex and non-additive 481 interactions exist between streamflow and climate change and land use/cover change.



Fig. 4. Mean annual and monthly streamflow in Xinanjiang Basin in 2021-2050 under (a)-(b) climate change, (c)-(d) land use/cover change, and (e)-(f) combined climate and land use/cover change. The error bars indicate the multi-model ensemble range.

482 **4. Discussion**

483 **4.1 Uncertainty analysis of streamflow**

We used the fuzzy extension principle method to describe the streamflow uncertainty. The uncertainties at various levels resulted from the uncertainties or ranges in the GCM projections and land use/cover information in our study. Here the uncertainty in streamflow was computed at the α -cut values of 0%, 25%, 50%, and 75%, therefore the corresponding uncertainty levels were 100%, 75%, 50%, and 25%, respectively.

489 As shown in Fig. 5, the maximum variation in monthly streamflow occurs in October, and 490 ranges from 125.17 to 258.40 m³/s, while the minimum variation is observed in November and 491 December, with a value of 26.72-32.86 m³/s. The results show that annual streamflow in the baseline (1976-2005) is 334.86 m³/s, and in the future (2021-2050), the mean annual streamflow 492 under all scenarios is projected to be $345.69 \text{ m}^3/\text{s}$. The baseline streamflow exceeds the upper 493 494 bounds in the flood seasons in March and June and the lower bounds in the non-flood seasons from September to December. The streamflow is concentrated mainly from April to July in 495 496 both the baseline and the future periods. However, the future streamflow migrates from April 497 to May and from June to July, resulting in a lower and more uniformly distributed streamflow 498 in the flood seasons. This result corresponds to the phenomenon that GCM projections may 499 underestimate the probability of extreme flooding (Malhi et al., 2009; Pervez and Henebry, 500 2014; Supharatid, 2015). In addition, the increased streamflow in the main non-flood seasons 501 from October to December, with a significant value of 24.35-96.09%, contributes to a more 502 blurred boundary between the flood and non-flood seasons. This result means that operating 503 Xinanjiang Reservoir for water supply or hydropower generation might be easier in the future.



Fig. 5. Uncertainties of streamflow.

504 **4.2** Attributing streamflow change to climate and land use/cover change

505 In this study, we first analyzed the individual and joint contributions of climate and land use/cover change to mean monthly streamflow change in Xinanjiang Basin. We used the multi-506 507 model ensemble means to eliminate the inter-model uncertainties under different RCPs. The 508 RCA of streamflow attributed to climate change, land use/cover change, and combination is 509 defined as the ratio of the change in streamflow under RCPs, land use/cover change (i.e., HT, 510 EP, and UD) and combined conditions (i.e., HTs, EPs, UDs) in 2021-2050 relative to that in 511 1976-2005 to the standard deviation of streamflow in 1976-2005, respectively. The results are 512 shown in Fig. 6.

513 Overall, climate change is one of the primary factors that influences the variation in 514 streamflow. Although streamflow shows an increasing trend with increasing radiation intensity 515 relative to the baseline streamflow, the RCA under RCPs is not sensitive to radiation intensity.

516	The maximum mean RCA occurs under RCP2.6, followed by that under RCP8.5 and RCP4.5.
517	The impacts of climate change on streamflow are mainly realized through increased
518	precipitation and temperature with a mean RCA of 0.34, 0.33, and 0.33 under the effects of
519	RCP2.6, RCP4.5 and RCP8.5, respectively. In addition, the streamflow is concentrated mainly
520	from May to July, it is less affected by climate change and thus has a lower bound of < 0.18
521	compared with that in the other months, especially in the non-flood seasons from September to
522	October. Wen et al. (2018) and Wang et al. (2019b) also had the similar conclusion when
523	evaluating the future streamflow variation induced by RCPs in southeastern China.
524	Furthermore, we find that streamflow induced by HT or EP has similar changes to that
525	affected by climate change, with a mean RCA of 0.32 and 0.33, respectively; however, the
526	streamflow under UD has a lower mean value of 0.20. As we mentioned before, the land
527	use/cover in Xinanjiang Basin has undergone dramatic changes because of the sharp increase
528	in urbanization. In this case, the UD with strong urbanization is more consistent with the
529	baseline than the HT in terms of monthly streamflow. Zhang and Wei (2012) indicated that the
530	decreasing forest reduces evaporation and interception, and causes increases in soil water
531	content and groundwater re-charge, finally resulting in an increase in low flow. However, the
532	streamflow under EP slightly increases due to the combined effects of the decreased forestland
533	and increased grassland in our study.

The streamflow is less affected in non-flood seasons from September to October under UDs, which is similar to that under the effect of only UD; however, the streamflow is significantly altered in this period under the effects of HTs or EPs, which is similar to that under climate change alone. Accordingly, the combined impacts of climate and land use/cover changes on mean monthly streamflow are sensitive to IA. The impacts of climate change are stronger than those induced by land use/cover change under EP (i.e., lower IA), and land use/cover change has a greater impact in the case of UD (i.e., higher IA). The lack of observed significant changes in streamflow between HTs and EPs demonstrates that an increase in vegetation coverage does not contribute to the streamflow variation as much as IA does in Xinanjiang Basin.

	1	0.07	0.05	0.03	0.03	0.02	0.16	0.09	0.07	0.05	0.09	0.07	0.05	0.19	0.17	0.15	
	2	0.18	0.21	0.18	0.16	0.18	0.02	0.15	0.19	0.15	0.15	0.18	0.14	0.05	0.01	0.06	1
	3	0.54	0.56	0.53	0.44	0.46	0.16	0.50	0.53	0.50	0.50	0.52	0.49	0.21	0.23	0.20	
	4	0.28	0.30	0.30	0.19	0.21	0.00	0.25	0.27	0.28	0.25	0.27	0.27	0.05	0.06	0.07	0.8
	5	0.01	0.01	0.01	0.02	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.09	0.10	
	6	0.18	0.16	0.18	0.13	0.14	0.08	0.16	0.14	0.16	0.16	0.14	0.16	0.10	0.09	0.11	0.6
RCA	7	0.17	0.17	0.18	0.19	0.20	0.20	0.16	0.15	0.17	0.15	0.15	0.16	0.15	0.15	0.16	
	8	0.37	0.40	0.38	0.36	0.38	0.12	0.35	0.38	0.35	0.34	0.37	0.34	0.07	0.10	0.08	0.4
	9	1.04	1.09	1.08	1.10	1.13	0.65	1.00	1.04	1.03	0.97	1.02	1.01	0.47	0.55	0.52	
	10	0.77	0.73	0.77	0.78	0.78	0.49	0.75	0.71	0.76	0.73	0.70	0.75	0.47	0.43	0.50	0.2
	11	0.09	0.11	0.11	0.26	0.25	0.24	0.10	0.12	0.11	0.10	0.12	0.11	0.12	0.12	0.12	0.2
	12	0.29	0.27	0.37	0.19	0.19	0.19	0.29	0.27	0.37	0.28	0.26	0.36	0.28	0.25	0.36	
		RCP2.6	RCP4.5	RCP8.5	HT	EP	QU	HT2.6	HT4.5	HT8.5	EP2.6	EP4.5	EP8.5	UD2.6	UD4.5	UD8.5	0

Fig. 6. Monthly RCA of streamflow attributed to climate change, land use/cover change, and combined climate and land use/cover change effects in Xinanjiang Basin.

544 We then quantified the contribution of climate and land use/cover changes impacting 545 streamflow at the mean annual scale. The results listed in Table 3 show that the joint climate 546 and land use/cover changes cause an increase in the mean annual streamflow of $6.35-13.61 \text{ m}^3/\text{s}$. The mean annual streamflow is expected to increase under both climate change alone and land 547 548 use/cover change alone, but under the combined conditions it is lower than that of individual 549 land use/cover influence, and higher than that of individual climate change influence. These 550 results are because the complex and non-additive interactions between streamflow and climate 551 change and land use/cover change in the future. Changes in mean annual streamflow will be 552 mainly driven by land use/cover change, and climate change might weaken the influence on streamflow attributed to land use/cover change. Specifically, the land use/cover change leads 553 554 to an increase in annual streamflow by $7.32-13.83 \text{ m}^3/\text{s}$, with a contribution of 101.60-115.37%, 555 while the climate change decreases the annual streamflow by 0.22-0.99 m³/s, with a contribution ranging from -15.37% to -1.60%. RCP8.5 has smaller effects in decreasing the 556 557 influence on streamflow attributed to land use/cover change than does RCP2.6 and RCP4.5. 558 However, under different catchments, different break points, different methods or even 559 different time periods, the results may be different. The dominant effects of land use/cover 560 change found in our study is consistent with the study by Berihun et al. (2019) and Yang et al. 561 (2012), who both found that land use/cover change had a more pronounced effect than climate 562 change on mean annual streamflow in Ethiopia and China, respectively. The opposite was found 563 by Shrestha et al. (2018) in Thailand, and by El-Khoury et al. (2015) in Canada, who reported 564 that climate variability had a greater effect than land use/cover change on annual streamflow 565 response.



Scenarios	HT2.6	EP2.6	UD2.6	HT4.5	EP4.5	UD4.5	HT8.5	EP8.5	UD8.5
Climate change (%)	-13.55	-14.67	-7.86	-14.09	-15.37	-8.14	-3.30	-3.64	-1.60
Land use change (%)	113.55	114.67	107.86	114.09	115.37	108.14	103.30	103.64	101.60
Total (%)	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

567 **5 Conclusions**

This study implemented a systematic framework consisting of scenarios design, climate and land use/cover change projection, streamflow response modelling and assessment, to quantify and characterize future streamflow variations in Xinanjiang Basin attributed to the individual and combined effects of climate and land use/cover changes. The main conclusions are summarized as follows:

(1) Climate in 2021-2050 was projected to be wetter and almost warmer relative to that in
1976-2005 in the target region. The areas of forest and grassland under EP were projected to
undergo the largest proliferation among all scenarios from 1995 to 2025, while the area of urban
land was the lowest; the land use/cover change under UD was on the contrary of that under EP.
The land use/cover under HT would undergo dramatic changes following the historical trend,
but experience less urbanization than that under UD.

(2) While both land use/cover change alone and combined changes projected an increase in streamflow (relative change: 3.89-5.81%, and 0.32-8.72%), there was a disagreement on the direction of streamflow change under climate change alone (relative change: -0.16-6.42%). The increased streamflow in the main non-flood seasons from October to December contributed to a more blurred boundary between the flood and non-flood seasons, which might potentially ease the operation stress of Xinanjiang Reservoir for water supply or hydropower generation. 585 (3) The impacts of climate change and land use/cover change on mean monthly streamflow was sensitive to IA: climate change was the dominant factor when the IA was smaller under 586 587 HT and EP, whereas the land use/cover change was more dominant when the IA was larger 588 under UD. However, changes in the mean annual streamflow were mainly driven by land 589 use/cover change, and climate change might decrease the influence on streamflow attributed to 590 land use/cover change. The contribution of climate change to decrease annual streamflow was 591 -15.37-1.60%, while the contribution of land use/cover change to increase was 101.60-115.37%. 592 This study contributes to a better understanding the possible effects of climate and land 593 use/cover changes on streamflow in Xinanjiang Basin and can therefore benefit greatly decision 594 makers to design and implement possible adaptation actions for reservoir operations under 595 environmental changes including both climate and land use/cover changes. Moreover, the 596 approach of this study is beneficial for evaluating the combined effects of climate and land 597 use/cover changes on basin hydrology and can be applied to other regions encountering similar 598 pressures from environmental changes.

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