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Enhanced understanding of dominant drivers of Water Yield change across China through the improved coupled carbon and water model

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Abstract: The rapid environmental changes, including climate change, escalating atmospheric CO_2 concentration ([CO_2]), and vegetation dynamics, have been significantly impacting hydrological processes. Accurately quantifying their contribution to water yield (WY) has become a significant challenge in water resource management and climate adaptation studies. Therefore, this study improved the coupled carbon and water (CCW) model integrating dynamic water use efficiency (WUE) to quantify the CO_2-physiological feedback; furthermore systematically investigated the causes for WY change during 1982-2017 in China using a scenario analysis method based on the improved CCW model. The results showed that the effects on WY from changes in climate, vegetation, and [CO_2] exhibited a significant regional variability. Climate change (especially precipitation change) emerged as the dominant driver, directly affecting over 70% of China's land area. The vegetation change was the second largest factor, especially in central China, where vegetation change led to a general decrease in runoff. The effect of the escalating [CO_2], which reduced transpiration by inducing stomatal closure, was relatively small. Spatial analysis aligned with isohyetal lines further revealed that vegetation change and [CO_2] exerted greater influence within the 400–1600 mm precipitation range. In addition, the elasticity analysis showed that the sensitivity ranking of impact factors is precipitation ($\varepsilon P = 1.55$) > [CO_2] ($\varepsilon CO_2 = 0.55$) > NDVI ($\varepsilon NDVI = -0.44$) for the whole China. Historically, NDVI change has exceeded precipitation and [CO_2] impacts on runoff in some regions due to its higher relative change; however, CMIP6 SSP585 projections indicate that accelerating [CO_2] rise (2.34% yr^{-1}) will amplify its hydrological effect to a +1.29% annual WY increase by 2100, surpassing vegetation influences. This study provided theoretical support for water resource management and offered new perspectives for climate change adaptation strategies, vegetation restoration, and water resource management.

Keywords: the coupled carbon and water (CCW) model; runoff change; climate change; vegetation change; increasing atmospheric CO_2 concentrations; attribution analysis

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Plain language: Climate change, rising CO_2, and vegetation dynamics are reshaping global water cycle, but their impacts remain unclear. We improved the coupled carbon and water model to analyze China's water yield (WY) changes (1982–2017). Our results showed that climate change was the dominant driver nationally, vegetation/ CO_2 most affected in 400-1600 mm precipitation zones. Projections indicate CO_2 may increase WY 1.3% annually by 2100, surpassing other drivers. This work informs sustainable water management.

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1 Introduction

The global environment has been undergoing rapid changes, impacting hydrological processes through climate change, escalating atmospheric CO_2 concentration [CO_2], and vegetation dynamics. Notably, China has experienced a visible greening trend in recent decades, prompting a heightened focus on ecological and water resource concerns (Chen et al., 2019). Investigating the influence of vegetation changes on runoff has thus emerged as a pivotal research area, aligning with China's increasing emphasis on environmental sustainability. Understanding the intricate interplay among vegetation dynamics, climate change, and [CO_2] within the water cycle, particularly concerning runoff, holds significant promise for informing future water resource management strategies and ecosystem preservation initiatives and offering valuable insights for climate change adaptation endeavors (Ogutu et al., 2021; Yang et al., 2019).

Climate change directly affects runoff by altering precipitation patterns, temperature regimes, and radiation levels (Ban et al., 2023; Li et al., 2022). It also indirectly influences runoff dynamics by altering vegetation phenology (Liu et al., 2024). Vegetation, in turn, plays a key role in the hydrological cycle by influencing root water uptake, canopy transpiration, rainfall interception, and soil infiltration processes (Hoek Van Dijke et al., 2022; Shi et al., 2022; Yang et al., 2023; Zhang et al., 2022a). Additionally, rising [CO_2] affects transpiration by influencing vegetation photosynthesis, thus indirectly impacting hydrological processes (Wei et al., 2024; Zhou et al., 2023). Although recent studies have attempted to separate the impacts of vegetation from climate using ecohydrological models, the results remain inconsistent (Fu et al., 2023; Yang et al., 2020). Some research suggested that climate change had a more significant direct impact on runoff (Liu et al., 2024; Yang et al., 2021; Zhai and Tao, 2017, 2021), while others highlighted the comparable or even dominant role of vegetation change and [CO_2] in runoff dynamics (Li et al., 2020b; Wang et al., 2021;

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Zhou et al., 2023). Therefore, further research is needed to disentangle the complex effects of climate, vegetation, and [CO_2] change on runoff.

Several methods have been employed to separate the effects of climate, vegetation, and [CO_2] change on runoff change, including paired catchment experiments, statistical methods, and modeling approaches (Zeng et al., 2020). Given that annual water yield (WY) equates to runoff through negligible soil water storage changes, these methodological evaluations directly inform WY attribution frameworks (Zhang et al., 2022c). The paired catchment experiment method, though classical, is limited to small-scale watersheds and is less applicable to larger regions (Peng et al., 2016). Statistical methods, while helpful in identifying correlations, lack a physical basis and are insufficient for explaining the underlying mechanisms of runoff changes (Chen et al., 2022). Modeling approaches, which are broadly categorized into conventional hydrological models and ecohydrological models, provide a more systematic framework for attribution analysis. Conventional hydrological models tend to focus on runoff simulation and often oversimplify the effects of vegetation and [CO_2], potentially underestimating their impacts on runoff (Zhai and Tao, 2021). Ecohydrological models, which consider both hydrological and vegetation processes, can better separate the effects of climate, vegetation, and [CO_2], but are often computationally demanding and limited in their spatial applicability (Jiao et al., 2017; Ma et al., 2023). Among these modeling approaches, the Budyko framework, widely used to separate climate change effects on runoff, quantifies water balance through the aridity index (PET/precipitation) and incorporates a catchment-specific parameter "n" representing integrated land surface characteristics (e.g., vegetation, soil, topography) (Zhang et al., 2022b, 2016a). However, existing studies typically attributed temporal changes in "n" solely to vegetation change (Tan et al., 2024; Xue et al., 2022; Zhou et al., 2023) or correlated "n" with vegetation indices (e.g., NDVI) through multivariate regression (Liu et al., 2024; Tan et al., 2023)—might not accurately reflect the true impact of vegetation change. This is because the approach oversimplifies the role of "n"

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by conflating vegetation effects with confounding factors (e.g., CO_2-induced stomatal adjustments, and climate change), as regression-based methods inherently fail to disentangle covarying drivers, thereby obscuring whether "n" changes originate from vegetation dynamics, CO_2-physiological feedbacks, or multi-factor synergies (Gan et al., 2021). While some studies incorporated [CO_2] effects via PET adjustments instead of actual evapotranspiration, this indirect approach conflates CO_2-driven PET changes with other meteorological drivers (e.g., radiation, wind) and propagates parameter uncertainties (e.g., "n"), obscuring [CO_2]'s independent impact on runoff (Liu et al., 2024).

The coupled carbon and water (CCW) model integrates hydrological and ecological processes by mechanistically linking vegetation dynamics to water and carbon fluxes through remote sensing-driven parameterization (Li et al., 2024b; Zhang et al., 2021b, 2022c). Unlike the Budyko framework's empirical parameter "n"—which conflates vegetation effects with unaccounted catchment characteristics—CCW explicitly resolves vegetation impacts through two distinct pathways: (1) structural effects—quantified by NDVI-modulated canopy absorption of photosynthetically active radiation (FPAR) that captures changes in energy partitioning due to vegetation greening; and (2) physiological adjustments—represented by biome-specific variations in underlying water-use efficiency (UWUE) and vapor pressure deficit (VPD)-mediated regulation of evapotranspiration (ET). In the model, GPP is estimated from light-use efficiency theory (ε_{pot} × FPAR × PAR× Rs × Ts × Ws), and ET is mechanistically coupled to GPP via UWUE—a physiologically grounded parameter representing ecosystem-level carbon–water trade-offs, calibrated against global FLUXNET observations (Zhang et al., 2016b), which encapsulates ecosystem-level carbon–water trade-offs. By contrast, Budyko's empirical "n" aggregates these distinct vegetation controls into a single catchment-scale parameter, obscuring their individual hydrological impacts.

Nevertheless, the original CCW model, while robust in capturing vegetation-climate interactions, does not account for CO_2-induced physiological changes, specifically long-term enhancements in water-use efficiency (WUE) resulting from elevated [CO_2] (Adams et al., 2020; Li et al., 2023). This omission limits its ability to isolate [CO_2] fertilization effects from climate and LULC (land use and land cover) changes, a gap particularly problematic in regions like China, where CO_2-driven WUE improvements may offset or amplify vegetation greening impacts on runoff.

Therefore, we aim to improve the CCW model by incorporating dynamic WUE responses to [CO_2], building on the biome-specific UWUE framework. Furthermore, by integrating CO_2-dependent WUE adjustments into the ET-GPP coupling, our improved model explicitly partitions runoff changes into three causal drivers: (1) climate change (eg. precipitation, temperature, and so on), (2) vegetation structural changes (NDVI, and land use and land cover (LULC)), and (3) CO_2-physiological effects (stomatal optimization).

2 Methods and Data

2.1 Data sources and processing

Four main datasets were employed in the improved CCW model: vegetation data (NDVI), climate data (precipitation, temperature, shortwave radiation, vapor pressure deficit, and atmospheric pressure), land use and land cover (LULC), and [CO_2]. The monthly NDVI dataset used in this study (Table 1) was derived from a daily 0.05° gap-free NDVI dataset in China (https://doi.org/10.6084/m9.figshare.c.7002225.v1) (Li et al., 2024a), which was developed from the NOAA's daily NDVI dataset, applying effective data recognition and spatiotemporal gap-filling techniques. The dataset spans 1981–2023 and provides a spatial resolution of 0.05°, and we used bilinear interpolation to generate the dataset with a spatial resolution of 0.1°.

Climate data (Table 1), including precipitation, air temperature, surface downward shortwave radiation, relative humidity, and atmospheric pressure, were sourced from

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the China Meteorological Forcing Dataset (CMFD) at the National Tibetan Plateau Data Center (TPDC) of the Institute of Tibetan Plateau Research, Chinese Academy of Sciences (He et al., 2020). The dataset spans 1979–2018 and provides a spatial resolution of 0.1° and temporal resolutions at 3-hour, daily, monthly, and annual scales. As the dataset did not provide vapor pressure deficit (VPD), we calculated VPD using the method from Howell and Dusek (1995), based on atmospheric pressure, temperature, and relative humidity.

LULC data (Table 1) were obtained from the Zhang et al. (2024) global dataset, which provides consistent multi-temporal global LULC maps at 30 m spatial resolution for 1985–2022. The dataset includes 35 fine-resolution LULC types. For the purposes of this study, and to facilitate LULC change analysis, we merged these 35 LULC types into 17 types using the IGBP classification, based on the method by Yang et al. (2017). Four primary LULC types—cropland, forest, grassland, and bare land—were determined following the method described by Mu et al. (2013). The data were resampled to the 0.1° spatial resolution, ensuring compatibility for modeling within the modified CCW framework.

[CO_2] data were sourced from the Mauna Loa Observatory (MLO), Hawaii (20°N, 156°W) (http://cdiac.esd.ornl.gov/ftp/trends/co2/ maunaloa.co2), with yearly observations used to represent national [CO_2] levels due to the minimal spatial variation in [CO_2] across China (Table 1). These datasets were then used to drive the improved CCW model.

In this study, the hydrological data for model validation from 145 hydrological stations (Fig. 1), each with at least 15 years of continuous data since 1982, was collected from the Hydrological Bureau of the Ministry of Water Resources of China (https://www.mwr.gov.cn/english/). Annual runoff data were calculated from the daily runoff and the catchment area controlled by each hydrological station.

Table 1. Hydrology, climate, and vegetation data for the improved CCW model

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Dataset	Original Resolution (spatial/temporal)	Period	Reference
NDVI	0.05° ×0.05° (daily)	1981 - 2023	(Li et al., 2024a)
Landcover	30m×30m (5-year)	1985 - 2022	(Zhang et al., 2024)
Climate	0.1° ×0.1° (monthly)	1979 - 2018	(He et al., 2020)
[CO_2]	yearly	1959 - 2023	Mauna Loa Observatory, Hawaii
Streamflow	daily	1982 - 1995 (or later)	On-site streamflow records and the regional flow summary reports of government

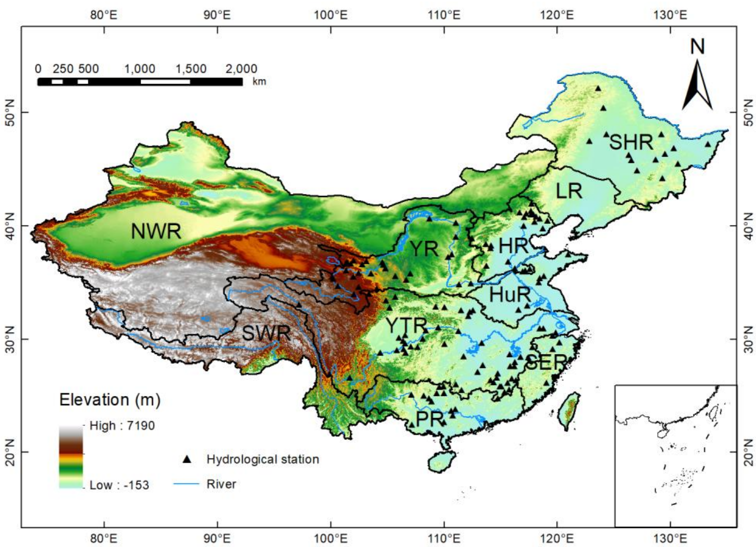

Figure 1. The geographic location and topography of the study area, where the black triangles mark the location of the hydrological gauging stations for model evaluation. Ten river basins considered in this study are: Songhua River basin (SHR), Liao River basin (LR), Hai River basin (HR), Huai River basin (HuR), Yangtze River basin (YZR), Yellow River basin (YR), Pearl River basin (PR), Southeast Rivers (SER), Southwest Rivers (SWR) and Northwest Rivers (NWR).

2.2 The improved CCW model

The original Coupled Carbon and Water (CCW) model (Zhang et al., 2016b) is a data-driven, remote sensing-based model that effectively integrates carbon and water dynamics to estimate monthly gross primary productivity (GPP) and evapotranspiration (ET). This model, which is particularly carbon-centric, derives ET from GPP constrained by underlying water-use efficiency (UWUE) parameters, which were calibrated using global FLUXNET data (Zhang et al., 2016b; Zhou et al., 2014). Despite

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its simpler structure, the CCW model achieves accuracy comparable to more complex process-based models in ET estimation. The essential components of the CCW model are represented as:

$$GPP = APAR \times \varepsilon = PAR \times FPAR \times \varepsilon_{pot} \times R_s \times T_s \times W_s \qquad (1)$$

where APAR is the absorbed photosynthetically active radiation (MJ m^{-2}), which is calculated as the product of incident photosynthetically active radiation (PAR) and the fraction of PAR absorbed by vegetation (FPAR), and PAR is typically assumed to be 45% of the total shortwave radiation (Running et al., 2000); FPAR is determined by the normalized difference vegetation index (NDVI) (Sims et al., 2005); ε is the realized light-use efficiency (g C MJ^{-1}), which is calculated by multiplying the potential light-use efficiency (ε_{pot}) and environmental scalars for diffuse radiation (Rs), temperature (Ts), and moisture stress (Ws). This formulation ensures that GPP estimates reflect the influence of radiation, temperature, and moisture limitations on photosynthetic activity.

In this study, we improve the CCW model by incorporating dynamic water use efficiency (WUE) instead of static UWUE. This enhancement addresses the limitations of the original model, particularly its inability to adapt to environmental changes such as varying [CO_2] and vapor pressure deficit (VPD). WUE's estimation method is estimated using the WEC (Water Efficiency and Carbon) equation proposed by Cheng et al. (2017). The final formula for calculating WUE is:

$$WUE = \frac{C_a \times P_a}{1.6\left(VPD + g_1\sqrt{VPD}\right)}[1 - exp(-k * LAI)](1 - f_i) \qquad (2)$$

where C_a is atmospheric CO_2 concentration (mol(CO_2) mol^{-1}(air)); Pa is atmospheric pressure (kPa); VPD is vapor pressure deficit (kPa); g_1 is an empirical parameter of the Ball stomatal conductance model; k is the radiation extinction coefficient, typically set at 0.6, describing how light is absorbed by the canopy; LAI is the leaf area index; and f_i is a factor representing nonproductive water use (such as evaporation from soil and canopy interception). This equation provides a dynamic estimate of WUE, considering the effects of environmental factors like VPD, CO_2 concentration, atmospheric pressure,

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and canopy structure (LAI). The factor 1−exp(−k×LAI) accounts for light interception by the canopy.

In order to ensure the consistency of NDVI and LAI trends, we calculated LAI using NDVI (Gutman and Ignatov, 1998) instead of LAI dataset:

$$\begin{cases} LAI = -2ln(1 - f_{NDVI}) \\ f_{NDVI} = \dfrac{NDVI - NDVI_0}{NDVI_1 - NDVI_0} \end{cases} \tag{3}$$

where $NDVI_0 = 0.04$, $NDVI_1 = 0.52$

Evapotranspiration (ET) is then calculated as the ratio of GPP to WUE:

$$ET = \frac{GPP}{WUE} \tag{4}$$

This modification allows the model to estimate ET using dynamic WUE, replacing the static UWUE from the original model. The dynamic nature of WUE enhances the model's ability to simulate ecosystem water use across different environmental conditions and vegetation types.

Finally, the water yield (WY) is calculated as the difference between precipitation (P) and ET:

$$WY = P - ET \tag{5}$$

On an annual scale, WY is assumed to be approximately equal to runoff, as changes in soil water storage over long periods (one year or longer) are considered negligible. Thus, the attribution of WY can also be considered as the attribution of runoff.

2.3 Attribution analysis framework

To explore the combined and individual effects of climate, vegetation, and [CO_2] change on water yield (WY), four scenarios were designed based on data from 1982 to 2017 (Table 2). Scenario 1 (Actual) aimed to validate the improved CCW model and estimate the combined effects of climate, vegetation, and [CO_2] change on WY by

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allowing all variables to vary from 1982 to 2017. Scenario 2 (Vegetation Change) focused on estimating the direct effects of vegetation change on WY by allowing vegetation variables (NDVI and LULC) to vary while keeping climate and [CO_2] fixed at 1982 levels. In this case, the trend in WY obtained reflects the impact of vegetation change alone. Scenario 3 (Climate Change) aimed to estimate the direct effects of climate change on WY by allowing climate variables (precipitation, temperature, relative humidity, solar radiation, and atmospheric pressure) to change, while fixing vegetation and [CO_2] at 1982 levels. This scenario helps isolate the effects of climate change on WY. Scenario 4 ([CO_2] Change) was designed to estimate the direct effects of [CO_2] change on WY by varying [CO_2] levels from 1982 to 2017, while climate and vegetation variables were fixed at 1982 levels. The resulting WY trend reflects the impact of [CO_2] change alone.

Table 2. Scenario designs in the improved CCW model for WY attribution. LULC: Land use and land cover types; NDVI: Normalized difference vegetation index; TMP: Temperature; SRAD: Shortwave radiation; VPD: Vapor pressure deficit.

Scenarios	**Vegetation**		**Climate**					**CO_2**	**Purposes**
	LULC	NDVI	P	T	RH	Srad	Pa	CO_2	
S1 (baseline)	▲	▲	▲	▲	▲	▲	▲	▲	Validating the improved CCW model and estimating the combined effects of climate, vegetation, and CO_2 change.
S2 (vegetation)	▲	▲	△	△	△	△	△	△	Estimating the direct effects of vegetation change.
S3 (climate)	△	△	▲	▲	▲	▲	▲	△	Estimating the direct effects of climate change.

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S4 (CO_2)	△	△	△	△	△	△	△	▲	Estimating the direct effects of CO_2 change.

Note: The symbol "▲" denotes a changing input variable over time, whereas the symbol "△" represents a fixed input variable at the level of the initial year (1982).

The relative contributions of climate, vegetation, and [CO_2] to changes in WY were calculated using the following formula:

$$\begin{cases} RC_{vegetation} = \dfrac{trend_{vegetation}}{|trend_{vegetation}| + |trend_{climate}| + |trend_{CO2}|} \times 100\% \\ RC_{climate} = \dfrac{trend_{climate}}{|trend_{vegetation}| + |trend_{climate}| + |trend_{CO2}|} \times 100\% \\ RC_{CO2} = \dfrac{trend_{CO2}}{|trend_{vegetation}| + |trend_{climate}| + |trend_{CO2}|} \times 100\% \end{cases} \quad (6)$$

where $trend_{vegetation}$, $trend_{climate}$, and $trend_{CO2}$ represent the changes in water yield (WY) resulting from vegetation, climate, and [CO_2] changes, respectively, as calculated in each scenario; the relative contributions ($RC_{vegetation}$, $RC_{climate}$, and RC_{CO2}) are expressed as percentages, indicating the proportion of each factor's influence on the overall changes in WY.

At each grid point, the absolute values of the relative contributions of each factor (vegetation, climate, and [CO_2]) are compared. For each grid point, we identify the most significant contributor to water yield (WY) changes by comparing the relative contributions of each factor. If the absolute values of the relative contributions of two factors do not exceed 5%, then these two factors are considered joint significant contributors to the changes in WY at that grid point (Ma et al., 2024; Saltelli et al., 2007). This approach helps to highlight areas where the impacts of multiple factors are closely intertwined and both play a critical role in influencing water yield, suggesting that their combined effects are comparable in magnitude. In these cases, the relative contribution of each factor is not significantly stronger than the other, indicating that their combined influence on WY is equally important at the local scale.

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The scenario analysis previously conducted revealed the relative contributions of climate, vegetation, and [CO_2] to WY changes. However, these contributions arise from both the intrinsic rate of change of each factor and the sensitivity of runoff to those changes (the elasticity coefficient) (Yang and Yang, 2011). To gain a deeper understanding of the changes in WY, we employ elasticity coefficients to quantify its sensitivity to individual factor. We specifically focused on precipitation because, despite not always having the highest sensitivity, it is integral to the hydrological cycle and essential for assessing water yield (WY) under various climate change scenarios (Liu et al., 2017). The elasticity of runoff refers to the variation in runoff depth resulting from a 1% increase in each climatic variable (Xu et al., 2014). The absolute value of elasticity reflects the sensitivity of runoff to various influencing factors. In other methods, elasticity coefficients are typically calculated using an analytical expression based on instantaneous changes in runoff corresponding to variations in a given factor in a specific year (Fu et al., 2023; Liu et al., 2017; Yang and Yang, 2012). However, in our study, we applied scenario-based analysis over the period of 1982 to 2017. This extended temporal window allowed us to better account for the long-term effects and interactions of multiple factors influencing WY. So we vary each factor (precipitation, NDVI, and [CO_2]) by 1% relative to the baseline scenario S1 across the entire 1982-2017 period. We then calculated the annual average runoff values from the adjusted sequence and compared them with the average original baseline runoff values. The difference between these two values, divided by the average baseline runoff value, gave us the runoff change rate:

$$\frac{\Delta R_x}{R_x} = \frac{WY_{mean_x} - WY_{mean_x}}{WY_{mean_x}} \tag{7}$$

Mathematically, the elasticity coefficient is defined as the runoff change rate divided by 1%, and the formula is as follows:

$$\varepsilon_x = \frac{\frac{\Delta R_x}{R_x}}{\frac{\Delta x}{x}} = \frac{\frac{\Delta R_x}{R_x}}{1\%} \tag{8}$$

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Generally, while the scenario analysis above has identified which factors are most influential based on their relative contributions, the elasticity coefficients allow us to explain why these factors are critical by demonstrating their respective impacts on WY through sensitivity analysis. This dual approach—combining both the changes in the factors and their elasticities—provides a more comprehensive understanding of the drivers behind the observed changes in WY, ensuring that the results of the scenario analysis are both meaningful and robust.

3 Results

3.1 Changes in hydrometeorological variables

Fig. 2 demonstrates the trends of annual precipitation, air temperature, relative humidity, atmospheric pressure, solar radiation, and NDVI across China during 1982-2017. Annual precipitation change exhibited a clear spatial distribution pattern, specifically decreases in central China, including the middle reaches of the Yellow River and the Yangtze River basins, and increases in the northwest and southeast. Air temperature exhibited a consistent warming trend across China. In contrast, relative humidity generally decreased across most China. Atmospheric pressure remained relatively stable. Regarding solar radiation, decreases were in northern China, while an increase was in southern regions. The decreasing solar radiation in northern China is likely due to increased aerosol concentrations (Liang et al., 2024). NDVI showed a significant increasing trend, which indicates an overall enhancement in vegetation growth across China. This trend was especially prominent in central and eastern regions, including the Yellow River Basin and the Yangtze River Basin. In these regions, LULC changes, such as afforestation and agricultural practices, likely contributed to the observed increases in NDVI (Chen et al., 2019).

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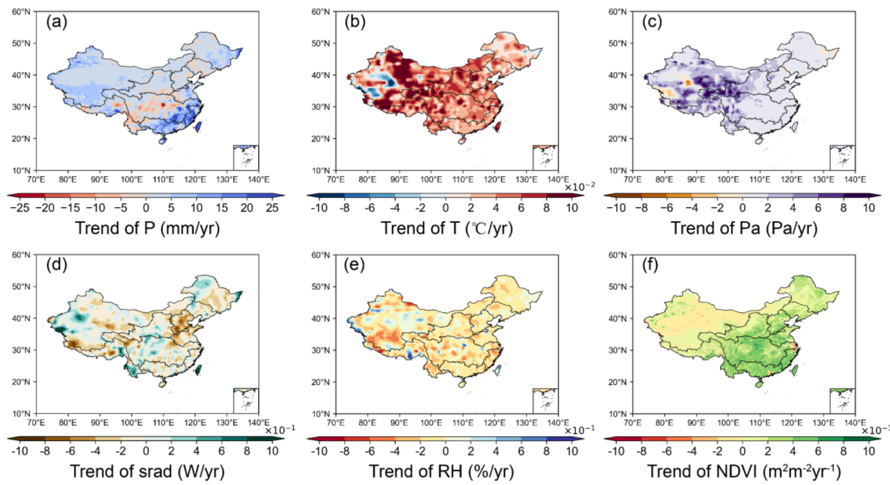

Figure 2. Spatial patterns of trends in annual climatic and vegetation variables during 1982–2017. (a) precipitation (mm/yr); (b) air temperature (°C/yr); (c) Atmospheric pressure (Pa/yr); (d) shortwave radiation ($W/m^2/yr$); (e) relative humidity (%/yr); (f) NDVI (yr^{-1}).

Significant changes in land use and land cover (LULC) occurred in China during 1982-2017, as illustrated in Fig. 3. Although the overall percentage distribution of major land cover types, namely grasslands, forests, croplands, and bare lands, remained relatively stable, these four categories dominated the landscape, with most changes concentrated within them. Notably, the transitions among these categories were characterized by mutual conversions, particularly from bare land to grasslands (Fig. 3). Spatially, the changes exhibited distinct regional patterns. In southern China, LULC changes were mainly characterized by the conversion of land to forests and grasslands. In contrast, the northeastern regions exhibited more complex transformations, with some areas shifting to bare land and croplands (Fig. 3).

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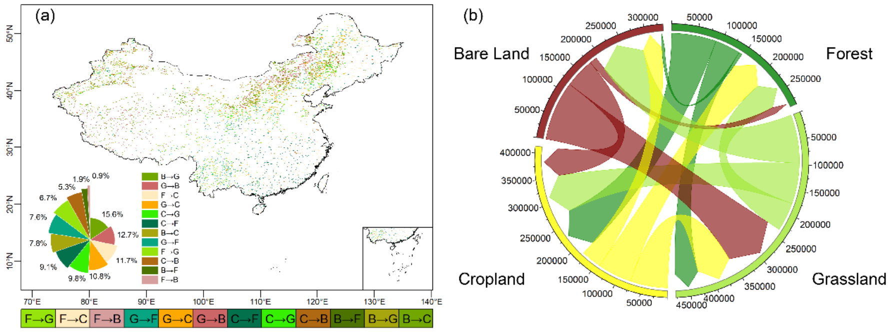

Figure 3. Land use and land cover (LULC) changes from 1982 to 2017. (a) Spatial pattern distribution of LULC change; (b) Chord diagram of LULC conversion flows (unit: km^2), where directional arrows represent transitions between land types (originating type → current type), with chord widths proportional to the converted areas. The figure illustrates the converted areas and does not include the unchanged regions.

3.2 Performance of the improved CCW model

As shown in Fig. 4a, the observed annual water yield (WY) and the simulated annual WY by the improved CCW model showed strong linear correlations ($R^2 = 0.7$), with the regression line slope being 1.45, R^2 being 0.7, and RMSE being 12.49 mm/year. It indicates that the model provides a reliable representation of the observed trends.

The estimated annual WY trends had distinct spatial patterns (Fig. 4b), which closely aligned with that of precipitation. Specifically, decrease trends in WY occurred in the central regions of the Yellow River Basin and the middle section of the Yangtze River Basin, while increase trends were found in other regions, with the southeast exhibiting the highest rate of increase.

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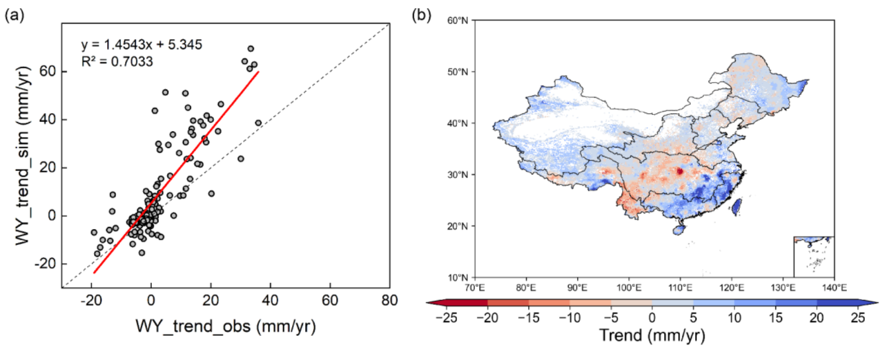

Figure 4. (a) Validation of simulated WY trend using the improved CCW model; (b) Spatial distribution of WY trends under scenario S1(actual situation) during 1982–2017.

3.3 Attribution analysis of annual WY changes

Fig. 5 shows the distribution of WY changes caused by climate, vegetation, and [CO_2] changes, integrating both absolute magnitude (Fig. 5a-c) and relative dominance (Fig. 5d-f) of their contributions. Climate-driven WY changes exhibited marked spatial heterogeneity, with absolute increases exceeding 15 mm/yr in southeastern China (Fig. 5a), corresponding to 60-90% relative contributions (Fig. 5d). Central basins showed contrasting declines of 0-6 mm/yr under climate forcing, while northeastern transitional zones displayed mixed positive/negative absolute changes (Fig. 5a) despite maintaining 40-70% relative climate dominance (Fig. 5d). This spatial heterogeneity aligned with precipitation change patterns (Fig. 2a).

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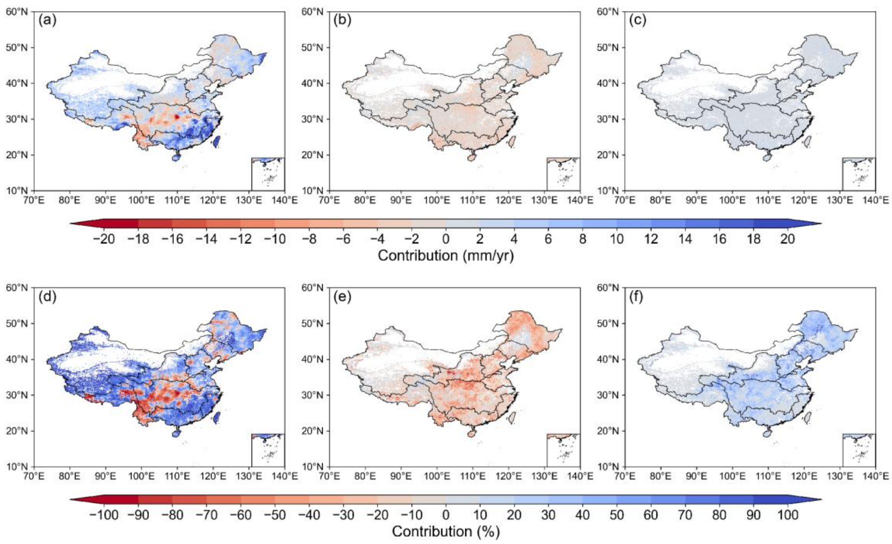

Figure 5. The absolute contributions of (a) climate, (b) vegetation, and (c) [CO_2], and the relative contributions of (d) climate, (e) vegetation, and (f) [CO_2] to changes in WY trends for 1982-2017.

Vegetation-mediated WY reductions reached 0-6 mm/yr (Fig. 5b), accompanied by 0-60% relative contributions (Fig. 5e). These effects originated from enhanced evapotranspiration through land-use changes and NDVI-based greening, particularly pronounced in central China. Specific regions in the Yangtze, Yellow, and northeastern rivers showed vegetation-driven relative contributions reaching 40-60% (Fig. 5e). [CO_2] effects generated limited direct absolute impacts (<5 mm/yr, Fig. 5c) but exerted 10-40% relative influences (Fig. 5f) through stomatal closure mechanisms. This process partially counteracted vegetation-related WY losses in transitional climates like northeastern China, where competing drivers created complex ecohydrological interactions (Fig. 5d-f).

Fig. 6 illustrated the spatial distribution of WY trend drivers over the past four decades. Climate change was the dominant factor of WY variation in more than 70% regions, mainly in the Northwest, Southwest, Southeast, Pearl River basins, and other parts of the Yangtze and Yellow River basins. Vegetation changes ranked as the secondary control, dominating WY changes in parts of the Yangtze, Yellow, Songhua,

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Liao, and Hai Rivers. Remarkably, it was shown that the region where vegetation and [CO_2] had the dominant influence mainly distributes within precipitation ranges of 400–1600 mm. CO_2-induced effects were least influential at a national scale. This three-tiered hierarchy—climate changes as the primary forcing, vegetation changes as the secondary control, and [CO_2] effects as a localized modifier—reveals how hydrological regimes govern the spatial succession of dominant drivers across China's diverse ecohydrological gradients.

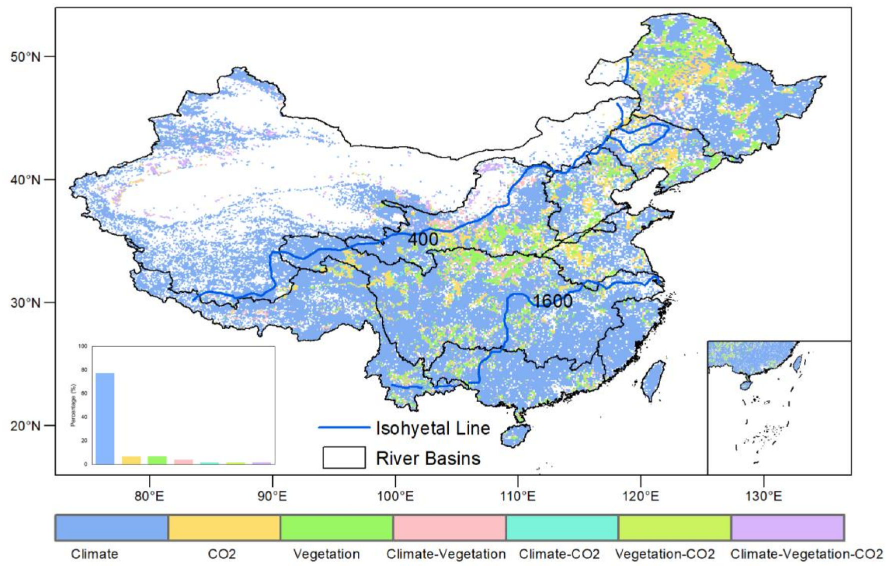

Figure 6. Spatial distributions of dominant factors controlling WY change. Driving factors include climate, vegetation, and [CO_2]. Climate: Areas where climate (e.g., precipitation, temperature) is the dominant factor influencing WY change; CO2: Areas where [CO_2] is the primary driver of WY change; Vegetation: Areas where vegetation changes (e.g., NDVI, LULC) primarily drive WY changes. Climate-Vegetation: Areas where both climate and vegetation jointly influence WY; Climate-CO2: Areas where both climate and [CO_2] jointly contribute to WY change; Vegetation-CO2: Areas where vegetation changes and [CO_2] jointly control WY; Climate-Vegetation-CO2: Areas where the combined effect of climate, vegetation, and [CO_2] jointly controls WY change. Additionally, the approximate isohyetal line shown in the figure were derived based on annual precipitation data from 1982 to 2017.

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3.4 Elasticity of WY to main variables

The sensitivity of WY to precipitation (εP), NDVI (εNDVI), and [CO_2] (εCO_2) exhibits distinct spatial patterns in (Fig. 7). Nationally averaged elasticity coefficients showed that a 10% increase in precipitation, [CO_2], and NDVI altered WY by 15.5% (εP=1.55), 5.5% (εCO_2=0.55), and -4.4% (εNDVI=-0.44), respectively, indicating that, in terms of the sensitivity of runoff to changes in each factor, the ranking was precipitation > [CO_2] > NDVI.

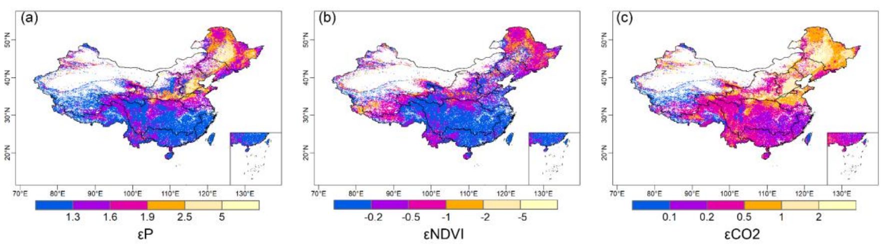

Figure 7. Spatial distribution of elasticity coefficients of WY relative to changes in hydrological variables such as (a) annual precipitation, (b) NDVI, and (c) [CO_2].

The elasticity coefficients of precipitation (εP), [CO_2] (εCO_2), and vegetation (|εNDVI|) all exhibited a coherent latitudinal decline across China's river basins, showing systematically higher sensitivity in northern regions than southern counterparts. Quantitatively, εP decreased from 2.09 in the Songhua River basin to 1.15 in the Southeastern Basin, accompanied by similar reductions in |εNDVI| (from 0.76 to 0.13) and εCO_2 (from 1.08 to 0.16) (Table 3).

A distinct abrupt transition zone in elasticity coefficients was identified around 33°N, closely aligning with China's traditional North-South physiographic divide. Around the zone, elasticity coefficients exhibited an abrupt decline from the Yellow River Basin to the Yangtze River Basin. Specifically, the Yellow River Basin showed higher sensitivities to precipitation (εP=1.87), [CO_2] (εCO_2=0.86), and NDVI (εNDVI=-0.53), which were approximately 1.4, 2.8, and 2.8 times greater, respectively, than those in the Yangtze River Basin (εP=1.31, εCO_2=0.31, εNDVI=-0.19).

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Table 3. Elasticity Coefficients of Runoff to Precipitation, NDVI, and CO_2 in Different Watersheds

Dataset	εP	εNDVI	$εCO_2$
Songhua River basin	2.09	-0.76	1.08
Hai River basin	2.13	-0.44	1.12
Yellow River basin	1.87	-0.53	0.86
Yangtze River Basin	1.31	-0.19	0.31
Huai River basin	1.64	-0.18	0.63
Pearl River basin	1.25	-0.17	0.25
Southeast Rivers	1.15	-0.13	0.15

Note: Some LULC types were excluded from the analysis. Due to many missing data points, the Liao River, Southwest, and Northwest river basins were also omitted.

4 Discussion

4.1 Strength of the attribution analysis framework

To address limitations in current methods for analysing the effects of climate, vegetation, and [CO_2] on runoff changes, we developed an attribution analysis framework based on the improved CCW model. This framework has been improved in three aspects. Firstly, the explicit and mechanistic integration of vegetation dynamics and [CO_2] effects overcomes the oversimplifications inherent in conventional approaches. Traditional Budyko-based frameworks often attribute vegetation effects to temporal variations in the parameter "n" by either statistically regressing "n" against vegetation proxies such as NDVI (Liu et al., 2024; Tan et al., 2023) or simplistically equating "n" to vegetation effects (Li et al., 2020b; Zhou et al., 2023). Such approaches conflate structural vegetation changes (e.g., leaf area index) with physiological adjustments (e.g., CO_2-induced stomatal closure), thereby obscuring the independent roles of vegetation dynamics and [CO_2]. For example, while rising [CO_2] levels directly reduce stomatal conductance and transpiration, Budyko-based studies often misinterpret this effect as part of the "n" parameter's variability, erroneously attributing it to vegetation changes (Zeng et al., 2020). In contrast, our framework mechanistically separates these pathways: structural modifications are distinguished from CO_2-driven

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stomatal physiological responses, resolving contradictions in prior findings where vegetation greening was reported to both mitigate (Zeng et al., 2018) and exacerbate (Farley et al., 2005) runoff changes.

Secondly, unlike Budyko-based methods that indirectly represent [CO_2] impacts through adjustments to potential evapotranspiration (PET)—a practice conflating [CO_2] effects with meteorological drivers like radiation and wind—our framework explicitly quantifies CO_2's physiological influence on actual evapotranspiration (AET) by mechanistically modeling its role in stomatal conductance and water-use efficiency (WUE). Elevated [CO_2] reduces stomatal aperture, directly suppressing transpiration while enhancing carbon assimilation. For example, our results show that reduction in transpiration due to CO_2-driven stomatal closure offsets water losses, a mechanism entirely masked in Budyko frameworks where [CO_2] effects are ambiguously embedded in PET adjustments or erroneously attributed to vegetation structural changes via the "n" parameter (Liu et al., 2024).

Thirdly, while numerous studies have conducted runoff attribution analysis at the basin scale (Liu et al., 2024, 2017; Yang et al., 2022), our grid-scale approach transcends the spatial constraints of fixed watershed boundaries by resolving regional heterogeneity in hydrological drivers. Conventional basin-aggregated methods obscure critical intra-basin differences—for instance, our analysis reveals that grids in the upper Yangtze River basin, where precipitation change dominates runoff trends, necessitate climate scenario-based water resource planning. In contrast, mid-basin grids with significant NDVI-driven greening exhibit pronounced WY reductions, highlighting the need for vegetation management strategies that restrict excessive afforestation in water-sensitive areas (Sun et al., 2022; Yang et al., 2021). By decoupling analysis from rigid watershed boundaries, our framework enables targeted strategies such as restricting reforestation in water-stressed grids or selecting CO_2-adapted vegetation species, thereby aligning management actions with localized climate-vegetation-hydrology interactions.

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4.2 New insights into attribution analysis

Our findings highlighted climate change as the dominant driver of water yield (WY) changes (contributing >70%), consistent with other assessments (Table 4), yet reveal critical regional divergences. Climate impacts dominated in the Northwest and Southwest River Basins, as well as parts of the Yangtze, Yellow, Southeast, and Pearl River Basins, while vegetation and [CO_2] effects prevailed in central China (parts of the Yangtze, Yellow, Songhua, Liao, and Hai River basin)—a spatial pattern slightly distinct from earlier studies. Although previous studies identified human activities as the primary driver in some northern basins (Liao, Hai, and Yellow River Basins) (Yang et al., 2022), their long-term study (1965-2018) diluted the gradually strengthening vegetation signals after 2000 mentioned in other studies (Liu et al., 2017; Sun et al., 2023) through time-averaging. Our findings now confirm the emerging importance of vegetation dynamics in southern basins like the Yangtze through our symmetric 1982-2017 study period.

Table 4. Comparative studies of the contribution of climate variability and vegetation to runoff changes.

Reference	Study region	Study period	Method/Model	Driving factors
(Wei et al., 2024)	Global	1981-2020	Trendy phase 11 +ROF	Climate change
(Liu et al., 2024)	Global	1984-2010; 2000-2100	Improved Budyko	Precipitation
(Zhou et al., 2023)	Global	1850-2014; 2015-2100	Improved Budyko + CMIP6	Land surface changes
(Tan et al., 2023)	Global	2003-2016; 1982-2016	Improved Budyko	Effective precipitation
(Yang et al., 2022)	China	1965-2018	Budyko	P: Northwest river basin, Southwest river basin, Yangtze river basin, Southeast river basin, and Pearl river basin; n: Liaohe river basin, Haihe river basin, Yellow river Basin, Songhuajiang river basin, and Huaihe river basin
(Zhang et al., 2022c)	Yangtze River	2001-2018	CCW Model	Climate variability
(Chen et al., 2022)	Six river basins in China	1982-2015	Gray Relational Analysis (GRA)	Precipitation

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(Zhai and Tao, 2021)	China	1982-2015	VIC Model	Climate change
(Li et al., 2020a)	Yihe River	1960-2013	SWAT+WRF	Climate variability
(Shen et al., 2017)	China	1960-2010	Budyko	Underlying surface change (n): the Songhua Basin, the Liaohe Basin and the Haihe Basin; Climate change: in other basins.

Elasticity analysis (Section 3.4) revealed distinct sensitivities of WY to environmental drivers: precipitation exhibited the highest elasticity coefficient for the whole China (εP = 1.55), followed by CO_2 (εCO_2 = 0.55) and NDVI (εNDVI = -0.44). However, spatial analysis showed that vegetation and [CO_2] collectively dominated WY changes in 400–1600 mm/yr precipitation zones, despite their lower sensitivity rankings. This apparent contradiction stemmed from the interplay between elasticity and the magnitude of driver change. In the 400–1600 mm/yr precipitation zones, NDVI displayed high spatial heterogeneity (Fig. 8), whereas precipitation fluctuated within a narrower relative range. Consequently, vegetation's stronger spatiotemporal variability amplified its hydrological influence, overriding its lower elasticity. Similarly, CO_2's historical impact was constrained by its slow accumulation rate (0.49%/yr), yet its relatively high elasticity positions it as a latent driver.

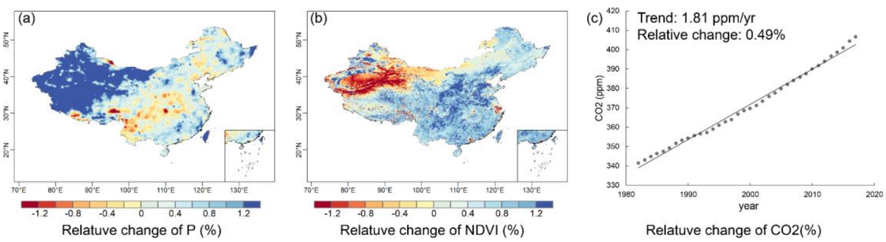

Figure 8. Spatial distribution of relative changes of different variables: (a) annual precipitation, and (b) NDVI.

This historical constraint, however, belied CO_2's transformative potential under intensified forcing scenarios. CMIP6 SSP585 projections indicate [CO_2] will rise at 2.34%/yr—nearly fivefold faster than historical rates (Cheng et al., 2022). At this trajectory, CO_2's elasticity would drive a +1.29% annual WY increase, eclipsing both vegetation greening effects and even surpassing precipitation-driven changes in some regions. Such reversal underscores the imperative to prioritize [CO_2] in long-term water management, particularly in 400–1600 mm/yr precipitation zones.

4.3 Uncertainty in attribution analysis

This study provides valuable insights into the relationship between water resources management and environmental changes, which can guide environmental management strategies. However, several limitations exist that need to be addressed in future work to improve the accuracy and robustness of the results.

Firstly, the improved CCW model does not account for the variation and specific values of f_i, assuming f_i is 0. In reality, f_i represents the ratio of interception evaporation to total evaporation, and in regions with abundant vegetation, f_i is not zero. Despite this, considering the small change of f_i in the current year (Zhao et al., 2022), its influence on runoff trends is negligible in our study (Cheng et al., 2017). However, future work should prioritize its calculation to improve the precision of WY estimates.

Secondly, the complex interrelationships among climate, vegetation, and [CO_2] cannot be fully disentangled. Vegetation exhibits tight biophysical interactions and feedback with climate, making it difficult to separate the impacts of climate change, vegetation dynamics, and [CO_2] on hydrological responses. Changes in vegetation, such as NDVI, reflect a combination of climate change, human activities (e.g., reforestation and irrigation), and natural vegetation growth. Additionally, vegetation greening in upwind regions can increase atmospheric moisture, potentially enhancing precipitation downwind (Zhang et al., 2021a), which may counteract some of the negative impacts of increased evapotranspiration on local WY. Although the climate data used in our model may implicitly capture some of these feedbacks, they cannot be explicitly separated in this analysis. Consequently, our results represent an attempt to estimate the direct first-order net impacts of climate, vegetation greening, and [CO_2] increase on WY (Zhang et al., 2021b). Future research should adopt more

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comprehensive models that consider soil-vegetation-atmosphere interactions to better differentiate the contributions of each driving factor to WY.

Thirdly, the improved CCW model does not incorporate certain human activities, such as dam construction and water extraction, which should be incorporated in future studies. Our research also excludes water bodies and built-up land. While urbanization can increase flood risks due to the growing proportion of impervious surfaces (Wasko and Sharma, 2017), these land-use changes represent a small portion of China's land area.

Finally, the future impact of vegetation greening on hydrological dynamics will depend on projected climate warming and drying trends, the persistence of vegetation greening, [CO_2] changes, and the complex feedbacks between climate, soil, and vegetation. These interactions require long-term study, and future research will involve more extensive monitoring to better capture these evolving dynamics.

5 Conclusions

In this study, we improved the CCW model incorporating dynamic water use efficiency (WUE) calculation to explicitly represent CO_2-physiological feedback on water yield. This mechanistic improvement enabled comprehensive national-scale assessment quantifying the relative contributions of climate forcing, vegetation structural changes, and CO_2-driven stomatal regulation to water yield (WY) dynamics in China. The main conclusions are as follows:

The improved CCW model effectively simulated WY variations in most basins under increased [CO_2] scenarios, demonstrating its applicability and reliability in modeling WY changes.

Climate change, particularly variations in precipitation, emerged as the primary driver influencing WY, displaying significant regional disparities in its effects. Vegetation changes constituted the second most critical factor, predominantly resulting in WY reduction, notably in central China. While the effect of CO_2-induced stomatal closure on WY was comparatively minor. Spatial analysis aligned with isohyetal lines further revealed that vegetation change and [CO_2] exerted greater influence within the 400–1600 mm precipitation range.

The elasticity analysis of WY indicated that northern basins exhibit higher sensitivity to influencing factors, whereas southern basins demonstrate relatively lower elasticity. Specifically, the absolute elasticity coefficients for the whole China were ranked in descending order as follows: precipitation > [CO_2] > NDVI. Thus, accelerating [CO_2] rise (2.34% /yr under SSP585) will amplify its hydrological role, potentially elevating CO_2-driven WY increases to +1.29% annually by 2100, surpassing climate and vegetation impacts.

These insights provide a nuanced understanding of regional hydrological responses, essential for sustainable water resource management under changing environmental conditions.

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Data Availability Statement

Datasets used for driving models were obtained from different sources described in Table 1. All the data related to our results in this study can be found online: the NDVI data (https://doi.org/10.6084/m9.figshare.c.7002225.v1); the climate data (https://www.tpdc.ac.cn/zh-hans/data/8028b944-daaa-4511-8769-965612652c49/); the land use and land cover (LULC) data (https://zenodo.org/records/8239305) (Liu et al., 2023); and the [CO_2] (http://cdiac.esd.ornl.gov/ftp/trends/co2/maunaloa.co2), except for the streamflow records for hydrological gauging stations, which are available upon reasonable request.

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Author contributions

HS designed the study, developed the model code, did the simulation experiments, and wrote the first draft of the paper. HY designed the research and edited the manuscript. CL provided feedback on the results and edited the manuscript.

Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

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