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## Decoupling the effects of climate, topography, land use, revegetation, and dam construction on streamflow, sediment, total nitrogen and phosphorus in the Yangtze River Basin

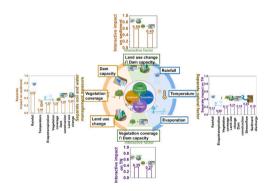
Yinan Ning <sup>a,b,c</sup>, Joao Pedro Nunes <sup>b</sup>, Jichen Zhou <sup>a,b,c</sup>, Jantiene Baartman <sup>b</sup>, Coen J. Ritsema <sup>b</sup>, Yunqing Xuan <sup>d</sup>, Xuejun Liu <sup>c</sup>, Lihua Ma <sup>a,\*</sup>, Xinping Chen <sup>a</sup>

- <sup>a</sup> Interdisciplinary Research Center for Agriculture Green Development in Yangtze River Basin, College of Resources and Environment, Southwest University, Chongqing 400715. China
- <sup>b</sup> Soil Physics and Land Management Group, Wageningen University and Research, Wageningen, Netherlands
- <sup>c</sup> State Key Laboratory of Nutrient Use and Management, College of Resources & Environmental Sciences, National Academy of Agriculture Green Development, China Agricultural University, Beijing 100193, China
- <sup>d</sup> Faculty of Science and Engineering, Bay Campus, Swansea University, Fabian Way, Swansea SA1 8EN, UK

#### HIGHLIGHTS

- Sediment discharge decreased, TN rose, streamflow and TP were stable (1980–2020).
- These trends were aligned with dam construction, revegetation and land use change.
- Dam construction combined with land use change contributed 46 % to these indicators.
- Revegetation combined with dam construction multiplied their individual impacts.

#### G R A P H I C A L A B S T R A C T



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## ABSTRACT

Evaluating changes in streamflow, sediment, and nutrient fluxes, as well as quantifying their influencing factors, is crucial for regional water resource protection. While the relationships between major influencing factors and these indicators have been widely studied, the quantitative contributions of the separate and interactive effects of these influencing factors have not been fully explored. This study quantitatively evaluated the changing characteristics of streamflow, sediment discharge, total nitrogen (TN) and total phosphorus (TP), as well as the separate and interactive effects of various major influencing factors such as—rainfall, temperature, evaporanspiration (ET), revegetation, dam construction, and land use change—by applying the GeoDetector method to account for their spatial heterogeneity and contributions. Our findings reveal that the influence of these factors has gradually intensified over time, with dam construction and land use change emerging as the most significant contributors to changes in sediment discharge and TN, respectively. Notably, the interactive effects between dam

E-mail address: malh@swu.edu.cn (L. Ma).

 $<sup>^{\</sup>star}$  Corresponding author.

capacity and vegetation cover on streamflow and sediment discharge was twice as strong as their separate impacts, highlighting the effectiveness of integrating dam construction with reforestation to control erosion and sediment transport. Similarly, the interaction of dam capacity and land use change had a 1.5 times greater impact on TN and TP than their separate effects, indicating that reducing fertilizer application at the source and in the meantime implementing direct interception measures are more effective ways to control water pollution. These findings provide a solid foundation for policymakers to develop integrated water management strategies targeting multiple factors simultaneously, that address both water quantity and quality concerns in the Yangtze River Basin and similar regions.

#### 1. Introduction

Water resources are essential for socio-economic development, ecosystem health, and human society survival. Since the mid-20th century, streamflow altered in 24 % of world's large rivers and sediment flux in 53 % of the world's rivers decreased significantly (Lehner et al., 2011; Li et al., 2020). Alongside these changes, total nitrogen (TN) and total phosphorus (TP) have increased around 35 % for world rivers from 1970 to 2020, becoming primary drivers of nutrient transport to sea (Seitzinger et al., 2010; Yin et al., 2023b). These shifts highlight the importance of streamflow, sediment discharge, TN and TP as key indicators for analyzing the impact of influencing factors on water quantity and quality within watersheds (Dey et al., 2021; Wang et al., 2022; Wijk et al., 2024). Water quantity has been shown to be affected by increasing temperature and irregular precipitation (Dahl et al., 2021; IPCC, 2023; Li and Quiring, 2021), and strongly contradictory relationships between water quantity and quality have been discovered (Dey et al., 2021; Zhang et al., 2016). In addition, a lot of human activities, like land use change, dam construction, revegetation makes these conflicts exacerbated through influencing streamflow discharge, sediment and nutrients generation and transportation (Das et al., 2021; Syvitski et al., 2022; Valente et al., 2021). Therefore, to understand the factors behind the changes in water quantity and quality, it is not only necessary to quantify the impact of separate factors, but also to consider the interactions between them.

In the study of attribution analysis of water quantity and quality, process-based and statistics-based approaches have received considerable attention, each offering unique strengths and limitations (Murphy, 2020; Tian et al., 2023). Process-based approaches primarily include hydrology only models (e.g., Water Erosion Prediction Project (WEPP), (Flanagan et al., 2007)), water quality only models (e.g., QUAL2Kw, (Pelletier et al., 2006)), integrated hydrology and water quality models (e.g., Soil and Water Assessment Tool (SWAT), (Neitsch et al., 2011)) and machine learning models (e.g., Long short-term memory (LSTM), (Mohammed et al., 2022)). A key advantage of these models lies in their ability to decouple the impacts of various influencing factors by designing different scenarios (Arias et al., 2018; Dadaser-Celik, 2024). Although these models have a large analysis potential, their application requires a large amount of input and measured data, which make them challenging to implement in large, complex watersheds (Devia et al., 2015; Keller et al., 2023; Ye et al., 2020). The statistics-based approaches, such as correlation analysis (Das et al., 2020), regression analysis (Zhang et al., 2019), redundancy analysis (Liu et al., 2022b; Wu et al., 2021b) and trend analysis (Chai et al., 2017), offer an alternative with lower data demands and simpler application. Recent advancements, such as partial correlation analysis can effectively decouple the influence of single climatic factors by controlling for others (Mao et al., 2024; Zhou et al., 2022). Structural equation modeling (SEM), on the other hand, introduces latent variables and multiple causality pathways, allowing a comprehensive examination of interactions between factors (Li et al., 2024; Meng et al., 2022). Despite these advances, statisticsbased approaches may lack the spatial and temporal resolution needed to accurately capture the complex interactions among influencing factors (Camara et al., 2019; Cheng et al., 2022). The Geodetector method, a statistical approach based on spatial heterogeneity, can handle largescale spatial data and assess factor interactions, has recently been widely used in social and ecological research to assess the effects of both separate factors and their interactions on dependent variables (Liu et al., 2023; Tegegne et al., 2023; Wang et al., 2021; Wang, 2017).

The Yangtze River (YR), the longest river in Asia and third-longest in the world, plays a vital role in transporting streamflow, sediment, and nutrients from the Eurasian continent to the East China Sea (Wu et al., 2019; Yang et al., 2023). Over the past several decades, the Yangtze River Basin (YRB) has profoundly affected by extensive human activities, including rapid urbanization, dam construction and afforestation (Yan et al., 2021; Yunus et al., 2022). As a result, the streamflowsediment relationship in this region, which the upstream section of the YRB historically accounted for roughly half of the streamflow and 60 % of the sediment contribution to the river, has altered (Valentin et al., 2015; Zhou et al., 2020). Nutrient fluxes from this region to the East China Sea have been a topic of concern, with studies showing increased dissolved inorganic nitrogen and phosphate since the mid-20th century (Dai et al., 2011). The TN and TP in this region, has undergone significant temporal changes, the initial period (1950-1979) is characterized by steady changes, rapid growth from 1980 to 2002, and a stable flux from 2003 to 2020 (Wang et al., 2020a; Yang et al., 2023). Although these studies have demonstrated the change trends for streamflowsediment relationships and nutrients flux and the anthropogenic impacts (especially distinguish sources of these nutrients) on these changes (Deng et al., 2021; Li et al., 2022a; Zhang et al., 2021), there is a lack of research that quantify the separate and interactive effects of specific factors, and also the exact influence of streamflow and sediment discharge on nutrients. To address this issue, this study aims to assess the separate and interactive impacts of main influencing factors under the climate change category (e.g., rainfall, temperature, evapotranspiration (ET)), and those related to human activities (e.g., vegetation cover, dam capacity, and hydrological connectivity (calculated based on topography and land use), on the changes of streamflow, sediment, TN and TP in the YRB from 1980 to 2020. Specifically, this investigation (1) evaluates the change trends of streamflow, sediment discharge, TN and TP by using the Mann-Kendall (M-K) test method; (2) unravels the separate impacts of considering influencing factors on these indicators by using the factor detector approach of the Geodetector method; and (3) quantifies the interactive impacts of those influencing factors on these indicators by using the interaction detector approach of the Geodetector method.

## 2. Materials and methods

## 2.1. Study area

The Yangtze River is the longest river in China, spanning the area of 1.8 million  $\rm km^2$  (Fig. 1). There are two distinct climatic zones in the YRB: the plateau climate in the upstream source region, characterized by long durations of sunshine, strong solar radiation, cold temperature, and dry conditions; and the subtropical monsoon climate in other regions, featuring distinct four seasons with cold winters and hot, humid summers (Li et al., 2022b). The annual average temperature in the source region fluctuates in the range of  $-10\,^{\circ}\mathrm{C}$  to  $10\,^{\circ}\mathrm{C}$ , while outside this area, the annual average temperature typically ranges from 16  $^{\circ}\mathrm{C}$  to 18  $^{\circ}\mathrm{C}$ 

(Chen et al., 2022). In addition, the YRB receives abundant amount of rainfall, with an average annual precipitation of around 1067 mm, although its distribution across the region is uneven, with the southeast receiving more than the northwest (Wang et al., 2018a). Since the mid-1980s, in order to coordinate the uneven temporal and spatial distribution of water resources caused by the uneven distribution of precipitation, a series of soil and water management measures have been implemented in the region, such as vegetation restoration, dams and reservoirs construction, which have affected the local streamflow-sediment relationship (Chen et al., 2016; Dai et al., 2016).

#### 2.2. Methods

The main methodology of this study comprises three parts that are employed to assess the complex impacts of driving factors on water quantity, inlcuding:1) the M–K trend test and M–K mutation test are used to analyze the spatial-temporal variations of streamflow, sediment discharge, TN, and TP; 2) the factor detector of the Geodetector is used to quantify the separate effects of key influencing factors on those indicators; and 3) utilizing the interaction detector of the Geodetector to quantify the interactive effects of influencing factors on those indicators.

#### 2.2.1. Data

Table 1 describes the data used in this study. The spatial distribution of monitoring stations of streamflow, sediment discharge, TN, and TP is shown in Fig. 1. By comparing the seven interpolation methods, Lopes et al. (2023) found that the spline interpolation showed the best performance for data with random gaps. In this study, we also employed the spline interpolation method to interpolate the station data onto regular raster grids with a resolution of 1 km. Other raster data that had different resolutions were resampled onto the 1 km resolution grids using the nearest resampling method in ArcGIS, which performed well with a relative error (RE) of 6.0 % according to (Tan et al., 2015).

Among the influencing factors considered in this study (Fig. 2), the effect of land use change is represented by the Index of Connectivity (IC), which is the probability of a unit amount of substances reaching the channel or sink from the source through catchment hillslopes (Borselli et al., 2008). The  $IC_i$  for a given grid cell i is calculated according to the following equation:

**Table 1**Data collected and used in the study.

Factors	Data source	Description
Digital elevation model (DEM)	Hole-filled seamless SRTM data V4 (http://srtm.csi.cgiar.org)	Resolution: 90 m
Streamflow and sediment discharge	Hydrology Yearbook of the People's Republic of China	Annual streamflow and sediment discharge from 1980 to 2020.
TN and TP	Resource and Environment Science and Data Center (htt ps://www.resdc.cn/)	Annual TN and TP from 1990 to 2010
Rainfall	Resource and Environment Science and Data Center (htt ps://www.resdc.cn/)	Annual rainfall from 1980 to 2020. Resolution: 1 km
Temperature	Resource and Environment Science and Data Center (htt ps://www.resdc.cn/)	Annual temperature from 1980 to 2020.
ET	Martens et al. (2017) https://gmd.copernicus. org/articles/10/1903/2017/	Annual ET from 1980 to 2015. Resolution: 1 km
Normalized Difference Vegetation Index (NDVI)	National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.	Annual NDVI from 1980 to 2020. Resolution:5 km
Location and capacity of dams	Global Reservoir and Dam (GRanD) Database (https://sed ac.ciesin.columbia.edu/d ata/collection/grand-v1/se ts/browse)	
Land use	Yang and Huang (2021) https://zenodo.org/recor d/5816591	Annual land use from 1985 to 2020. Resolution: 30 m
C factor	National Earth System Science Data Center (http://www.ge odata.cn/)	Resolution: 30 m Annual C factor from 1982 to 2020.

$$IC_i = log_{10} \left( \frac{D_{up,i}}{D_{dn,i}} \right) = log_{10} \left( \frac{\overline{W_i S_i} \sqrt{A_i}}{\sum \frac{d_i}{W_i S_i}} \right)$$
 (1)

where:  $\overline{W}$  denotes the average weight of up-slope contributing area; S is the average slope gradient of contributing area (m m<sup>-1</sup>); A is the upslope contributing area (m<sup>2</sup>);  $d_i$  (m) is the distance along the steepest

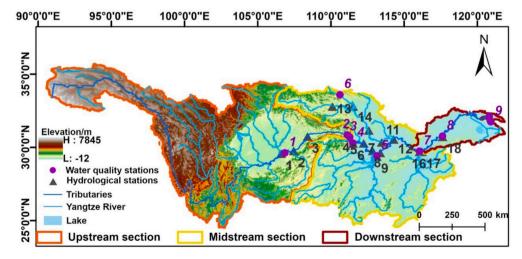


Fig. 1. The map of the YRB including the elevation, river networks, and the hydrological and water quality monitoring stations used in the study. Water quality stations: Upstream section: 1. Cuntan, 2. Huanglingmiao, 3. Yichang; Midstream section: 4. Zhicheng, 5. Chenglingji, 6. Wuguan; Downstream section: 7. Jiujiang, 8. Datong, 9. Xuliujing. Hydrological stations: Upstream section: 1. Cuntan 2. Qingxichang 3. Wanxian 4. Huanglingmiao 5. Yichang; Midstream section: 6. Zhicheng 7. Shashi 8 Jianli 9. Chenglingji 10. Luoshan, 11. Xiantao, 12. Hankou, 13. Baihe, 14. Huangjiagang, 15. Huangzhuang; Downstream section: 16. Jiujiang 17. Hukou, 18. Datong.

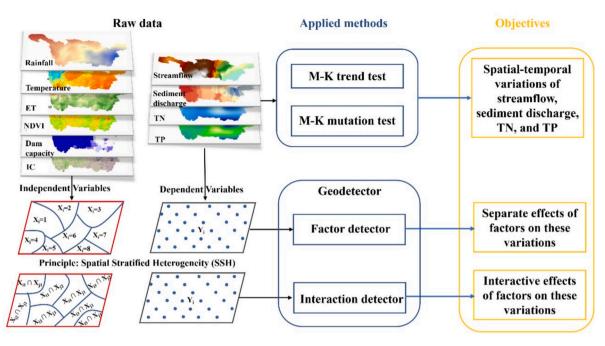


Fig. 2. The main components and workflow of the study.

downslope direction from the  $i_{th}$  pixel to the first downslope stream pixel;  $W_i$  is the weight factor of the  $i_{th}$  pixel;  $S_i$  is the slope of the  $i_{th}$  pixel. For the W factor, we used the C factor in USLE-RUSLE models given by the National Earth System Science Data Center (http://www.geodata. cn/) as the alternative value (Borselli et al., 2008). C (Cover-Management Factor) is used to represent the impact of vegetation coverage and management measures on soil erosion, and it has been found to be the most sensitive factor to soil erosion in the USLE-RUSLE model (Guo et al., 2015; Risse et al., 1993).

#### 2.2.2. Mann-Kendall test

The non-parametric Mann-Kendall (M-K) test was used to analyze the spatio-temporal variations of streamflow, sediment discharge, TN, and TP (Kendall, 1990; Modi and Chintalacheruvu, 2024; Wu et al., 2020). The method is briefly summarized as follows: For a given time series  $\{x_i\}$  (i=1,2,...n), the statistic S can be estimated following Eqs. (2) and (3) below, which is an indicator of whether there is a positive/increase or negative/decrease trend in the time series. The significance of the trend can be evaluated using the Z statistic that is linked to S (Eq. 2).

$$S = \sum_{i=1}^{n} \sum_{j=1}^{i-1} sgn(x_i - x_j)$$
 (2)

$$sgn(x_i - x_j) = \begin{cases} -1 \ x_i < x_j \\ 0 \ x_i = x_j \\ 1 \ x_i > x_j \end{cases}$$
(3)

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \tag{4}$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & S > 0\\ 0 & S = 0\\ \frac{S+1}{\sqrt{Var(S)}} & S < 0 \end{cases}$$
 (5)

When  $\mid Z \mid$  is 1.96 and 2.32, the sequence passes 95 % and 99 % significance tests, respectively (Kristo et al., 2017).

Further, we made use of the M-K mutation test to analyze the change points of these indicators (Kendall, 1990). The calculation was done

using the following formulas:

$$S_k = \sum_{i=1}^k r_i \ (k = 2, 3, ..., n)$$
 (6)

$$r_i = \begin{cases} 1 \ x_i > x_j \\ 0 \ x_i \le x_j \end{cases} \ (j = 1, 2, ..., i - 1)$$
 (7)

$$EV(S_i) = \frac{i(i-1)}{4} \tag{8}$$

$$Var(S_i) = \frac{i(i-1)(2i+5)}{72} \tag{9}$$

$$UF_i = \frac{S_i - EV(S_i)}{\sqrt{Var(S_i)}} \ (i = 1, 2, ..., n)$$
 (10)

where,  $x_i$  is the hydrological series with sample length n,  $S_k$  is the number of  $x_i > x_j$  in the sample sequence,  $EV(S_i)$  represents the expected value of  $S_i$ ,  $Var(S_i)$  is the variance of  $S_i$ , and  $UF_i$  is the statistical variables. For a significance level  $\alpha$ , the critical value of the normal distribution is  $U_{\alpha/2}$ . If  $UF_i < U_{\alpha/2}$ , it means that the change trend is not significant, and vice versa.  $UB_i$  as the negative value of the reverse sequence of  $UF_i$  if the change trend of the original sequence is significant, the intersection of  $UF_i$  and  $UB_i$  can be determined as the change point (Menna and Waktola, 2022; Xiang et al., 2021a).

#### 2.2.3. Geodetector method

The Geodetector is a quantitative method widely used to quantify the separate impact of each factor on dependent variables (factor\_detector) and the effects of interactive factors on dependent variables (interaction\_detector) (Venkatesh et al., 2022; Wang et al., 2024a). The method is based on the principle of spatial stratified heterogeneity (SSH), which posits that if independent variables significantly influence the dependent variable, their spatial distribution should be comparable (Wang, 2017; Whetton et al., 2017) (Fig. 2). By identifying and measuring SSH between independent and dependent variables, Geodetector uses ANOVA to test their relationships without being influenced by collinearity among independent variables (Qiao et al., 2022; Wang, 2017).

The impact of independent variables on the dependent variable is quantified using the q value, calculated as follows:

$$q = 1 - \frac{\sum\limits_{h=1}^{L} N_h \sigma^2_h}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{11}$$

$$SSW = \sum_{h=1}^{L} N_h \sigma^2_h \tag{12}$$

$$SST = N\sigma^2 \tag{13}$$

where, h means the subregions of those variables and ranges from 1 to L;  $N_h$  and N are the number of units in subregion h and the total area;  $\sigma$  is the variance of the dependent variable. SSW and SST are the within sum of squares and the total sum of squares. The range of q is [0, 1], with values closer to 1 indicating the greater the influence of independent variables on the dependent variable, and vice versa.

In this study, based on previous research, we analyzed the separate impacts of climate and anthropogenic factors—such as rainfall, temperature, ET, NDVI, dam capacity, and IC—on streamflow and sediment discharge, which are known to be significantly influenced by these variables (Al-Ghorani et al., 2021; Yin et al., 2023b; Zhang et al., 2023b). For TN and TP, in addition to the previously mentioned factors, we also analyzed the separate effects of streamflow and sediment discharge, as they are the main carriers of these nutrients (Zhang et al., 2022) (Fig. 2).

The interaction detector is used to evaluate the interactive effects between distinct independent variables on dependent variables by overlaying the subregions of the interactive factors and recalculating the q values. For streamflow and sediment discharge, we set four interactive groups based on their relevance to key influencing factors and existing

studies: (1) rainfall  $\cap$  temperature, representing the combined impacts of climate variability on hydrological processes (Chen et al., 2024; Zhang et al., 2023a); (2) NDVI  $\cap$  dam capacity, reflecting the influence of vegetation dynamics and reservoir regulation as critical soil and water management measures (SWM) (Li et al., 2023); (3) NDVI  $\cap$  slope, indicating the effectiveness of terraced fields in controlling soil erosion (Cao et al., 2021; Nie et al., 2024); and (4) dam capacity  $\cap$  IC, capturing the multiple-scale impacts of human interventions on hydrology and sediment transport processes (Chen and Wang, 2019; Zhao et al., 2020). For TN and TP, in addition to the above groups, we included the interaction between streamflow and sediment discharge to represent the impact of soil erosion on nutrient fluxes in the YRB (Yin et al., 2023b).

#### 3. Results

#### 3.1. Spatio-temporal variation analysis

#### 3.1.1. Spatio-temporal analysis of streamflow, sediment, TN and TP

The trends in the time series of annual streamflow, sediment discharge, TN, and TP from 1980 to 2020 are shown in Fig. 3a–c, where they are further grouped into the upper, middle, and lower sections of the YRB, respectively. Across all three sections, no significant changes were found in streamflow (P > 0.1), whereas the sediment discharge decreased considerably by  $>\!80$ % (P < 0.01), with the upstream region experiencing the most substantial decline (from 540  $\times$  10 $^6$  t to 50  $\times$  10 $^6$  t). On the other hand, TN has shown significant upward trends in all three regions (P < 0.01), while TP only increased significantly in the downstream section during 1998–2010 (P < 0.01).

The results of the combinatorial M-K trend analysis for annual streamflow and sediment discharge, TN and TP at stations located in the upstream, midstream, and downstream sections can be categorized into

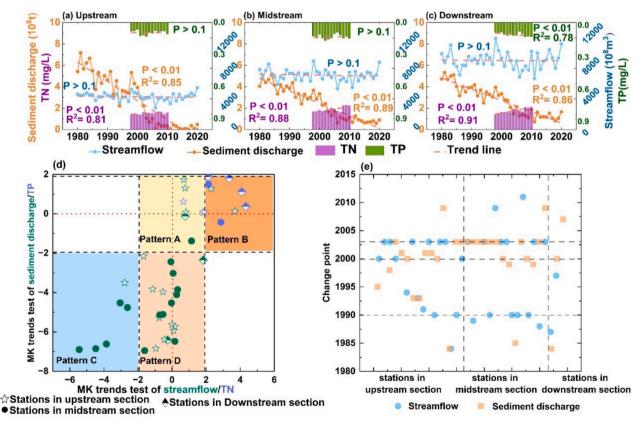


Fig. 3. Spatiotemporal variations and trend analyses of streamflow, sediment discharge, TN and TP in the YRB during 1980–2020. (a–c) annual streamflow, sediment discharge, TN, and TP in the upstream, midstream, and downstream sections of the YRB, (d) results of MK trend analysis for these indicators, (e) change points identified for streamflow and sediment discharge.

four patterns, A, B, C, and D, each reflecting different combinations of significant change trends (Fig. 3d). Pattern A: this pattern includes stations where streamflow, sediment discharge, TN, and TP all remain stable, showing no significant trends. Three water quality stations in the upstream section fall into this pattern; Pattern B: in this pattern, streamflow and TN show increasing trends, while sediment discharge and TP remain stable. This group consists of two upstream hydrological stations and all the midstream and downstream water quality stations; Pattern C: this pattern is characterized by decreasing trends in both streamflow and sediment discharge. It includes six hydrological stations, with 83 % of them located in the midstream section; Pattern D: stations in this pattern do not exhibit any significant change in streamflow but show a substantial decrease in sediment discharge. This group includes 20 hydrological stations. Each pattern highlights the spatial and temporal variability in how streamflow, sediment discharge, TN, and TP have changed across the YRB, providing insight into the underlying factors driving these trends.

The analysis of change points in streamflow and sediment discharge at each hydrological station reveals that these mutations are primarily concentrated around the years 1990, 2000, and 2003 (Fig. 3e, Table A.1-4). In 1990, following the introduction of SWM, significant changes in streamflow were observed at two upstream stations and four midstream stations. In approximately 2000, during the implementation of the "Grain to Green" project, three stations in the upstream and midstream sections experienced a sudden change in streamflow. Concurrently, two stations in these areas and one in the downstream section showed notable alterations in sediment discharge. The year 2003 marked the most concentrated occurrence of change points, coinciding with the commencement of the TGR operation. Based on the identified change points, the study period was divided into four distinct periods: P1: 1980-1990, P2: 1991-2000, P3: 2001-2003, and P4: 2004-2020. Throughout these periods, streamflow remained relatively across all regions, with a noticeable increase in TN (Fig. A.1a). In contrast, sediment discharge decreased significantly in all regions, while TP exhibited relatively stable (Fig. A.1b).

#### 3.1.2. Spatio-temporal analysis of driving factors

Rainfall, temperature, evapotranspiration, NDVI, dam capacity, and IC are considered as the primary natural and anthropogenic factors in this study that have influenced the streamflow, sediment discharge, TN and TP in the YRB from 1980 to 2020 (Fig. A.2). Analysis of the spatiotemporal variations of these factors reveal that rainfall is the only factor without a significant temporal trend over the period, but it exhibits considerable spatial variability. The highest multi-year average rainfall was recorded in the midstream section (1402.5 mm). In contrast, the multi-year average temperature in this region increased significantly during this same period, rising from 11.5 °C to 12.7 °C, with the multiyear average temperature in the downstream section being twice that in the upstream section. Evapotranspiration (ET) trends over the study period mirrored those of temperature, showing a significant growth rate of 1.18 mm/y. The spatial distribution of ET, like that of rainfall, was highest in the midstream section, accounting for about 40 % of the rainfall in this region (556.9 mm). NDVI also showed a significant increase, from 0.41 to 0.45, probably due to the implementation of the 'Grain to Green' project, with the highest multi-year average NDVI value observed in the midstream section (0.48). Additionally, dam capacity in the YRB increased significantly during this period. Before 2000, most dams were constructed in the midstream section, and then the emphasis shifted to the upstream area, resulting in an additional dam capacity of  $2.39 \times 10^{12} \text{ m}^3$ , with the TGR contributing 84 %. The IC, which is mainly affected by land use change, decreased significantly during 1980-2020, with the highest multi-year average IC value observed in the upstream section (-3.28). During this period, the main changes of land use were: 30 % of the cultivated land concentrated in the upstream and midstream sections was converted to forest and grassland; at high elevations in the upstream section, 91.5 % of this region has been

converted to forest and grassland; in the midstream section,  $59\,\%$  of the forest has been degraded to farming; urban expansion mainly occurred in the downstream section, with the urban area increasing by  $12.2\,\%$  (Table A.2).

# 3.2. Impacts of separate and interactive driving factors on streamflow and sediment discharge

Fig. 4a-b show the contribution of each influencing factor on streamflow and sediment discharge of the entire YRB over four periods (P1 to P4). Among them, rainfall was found to have the greatest impact on streamflow (60 %) and sediment discharge (50 %) in each period. Temperature, as another natural factor, showed the smallest contribution among all the driving factors (<10 %). ET was the factor that has the greatest impact on streamflow, besides rainfall. Its influence on streamflow increased from 28 % (P1) to 38 % (P4), which was much greater than the influence on sediment discharge (22%). Compared with the natural factors, the influence of human activities on streamflow and sediment discharge, as represented by NDVI, dam capacity, and IC, was more complex. Among them, IC, as a factor reflecting land use changes, was the most significant anthropogenic factor affecting streamflow and sediment discharge in all periods and reached its maximum in P4 (29% for streamflow and 33 % for sediment discharge). The effects of the other two anthropogenic factors, NDVI and dam capacity, were found to have greater influence on sediment discharge than on streamflow, and their influences on streamflow and sediment discharge increased in each period and were highest in P4. In P4, the contribution of NDVI and dam capacity on streamflow was 23 %, while the influence of NDVI on sediment discharge was 26 %, and the influence of dam capacity on sediment discharge was 31 %.

Across different regions in space, the influence of each factor on streamflow and sediment discharge in the upstream, midstream, and downstream sections varies significantly (Fig. 4c–e). Among them, rainfall, ET, and NDVI showed the highest influence in the midstream section, while the upstream section was least affected, which is consistent with the spatial distribution of these factors (Fig. A.2). The influence of IC was more prominent in the upstream and midstream sections, similar to how land use changes in the upper and middle areas are more environmentally sustainable compared to those in the downstream area (Fig. A.2). The contribution of dam capacity to streamflow and sediment discharge varies significantly across distinct time periods. In P1, dams were mainly constructed in the upstream section. In P2, the focus of dam construction transferred from the upstream section to the midstream section. In P3, the focus of dam construction shifted to the upstream section again.

As a representative of natural factors, the influence of rainfall  $\cap$ temperature on streamflow and sediment discharge reached 70 % in the entire YRB during 1980-2020 (74 % for streamflow and 65 % for sediment discharge) (Fig. 5a-b). Similarly, as a representative of human activities during the study period, dam capacity ∩ IC also exhibited a substantial impact on streamflow (53 %) and sediment change (59 %), which increased gradually from P1 to P4, reaching approximately 60 % in P4. As a combination of biological and engineering measures, the influence of NDVI \(\cap \) dam capacity on streamflow and sediment discharge in the YRB was higher than the single factor during 1980-2020. With the development of afforestation and dam construction during this period, the interaction between these two factors increased from 40 % in P1 to 50 % in P4. NDVI ∩ slope, which represents the impacts of terraces, contributed 28 % to streamflow and 23 % to sediment discharge, with P3 identified as its main action period (30 % for streamflow and 24 % for sediment discharge).

By analyzing the effects of these interactive factors in each region, the results show that the influence of rainfall  $\cap$  temperature and NDVI  $\cap$  slope in the midstream section is slightly greater than that in other regions; both interaction factors related to dam construction contribute the most in the upstream region (Fig. 5c–e).

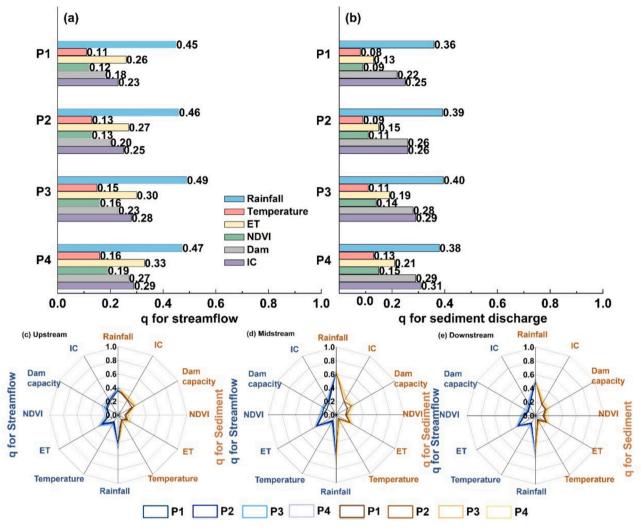


Fig. 4. Contributions of separate factors to streamflow and sediment discharge in the YRB during four periods. (a–b) factor detector analysis in the entire YRB; (c–e) factor detector analysis in the upstream section, midstream section, and downstream section respectively.

## 3.3. Impacts of separate and interactive driving factors on TN and TP

The impacts of rainfall, ET, NDVI, IC, dam capacity, streamflow, and sediment discharge on TN and TP vary significantly from P2 to P4 across the entire YRB (Fig. 6a–b). Streamflow and sediment discharge, as the main carriers of nitrogen and phosphorus, play a dominant role among these influencing factors. The influence of streamflow on TN was greater than that on TP, and it remained basically stable during each period, accounting for 25 % for TN and 15 % for TP. However, the influence of sediment discharge on TP was about 1.8 times greater than that on TN, and its contribution to TN and TP increased gradually from P2 to P4, reaching 19 % for TN and 34 % for TP in P4. Three anthropogenic factors, NDVI, IC, and dam capacity, also showed increased influence on TN and TP over time. Among them, IC contributed the most, with an impact of 23 % on TN and 26 % on TP in P4. Rainfall and ET, as the main influencing factors of streamflow and sediment discharge, showed <10 % direct influence on TN and TP.

The contribution of each separate influencing factor to TN and TP in different regions aligns with the spatial distribution of each factor (Fig. 6c–e). Rainfall and streamflow contributed the most in the downstream section, 1.5 times more than in the upstream section, where they had the least effect. However, sediment discharge, dam capacity, and IC showed the highest influence on TN and TP in the upstream section and the least influence in the downstream section. Only NDVI and ET exhibited the most influence on TN and TP in the midstream section.

The impacts of the four interaction groups considered in this study on TN and TP increased over time across the entire YRB (Fig. 7a–b). Notably, the interaction between streamflow and sediment discharge, which represents non-point source pollution, exhibited the highest impact, accounting for approximately 40 %. The second most influential group is dam capacity  $\cap$  IC, with its influence on TN increasing from 31 % to 37 % and on TP rising from 34 % to 40 %. Another set of interacting factors related to dam capacity, the impact of NDVI  $\cap$  dam capacity on TN and TP, rose to 30 % in P4. NDVI  $\cap$  slope, the group with the smallest contribution among the selected factors, had approximately 22 % influence on TN and 24 % influence on TP.

Results from the sub-regional analysis indicated that the impacts of streamflow  $\cap$  sediment discharge and NDVI  $\cap$  slope on TN and TP were most significant in the midstream section, approximately 1.4 times that in the downstream section. The other two interaction groups, NDVI  $\cap$  dam capacity and dam capacity  $\cap$  IC, both demonstrated the greatest impact on the upstream section, followed by the midstream section (Fig. 7c–e).

#### 4. Discussion

## 4.1. Spatio-temporal variations of streamflow, sediment discharge, TN and TP

The spatio-temporal variation trends of streamflow, sediment

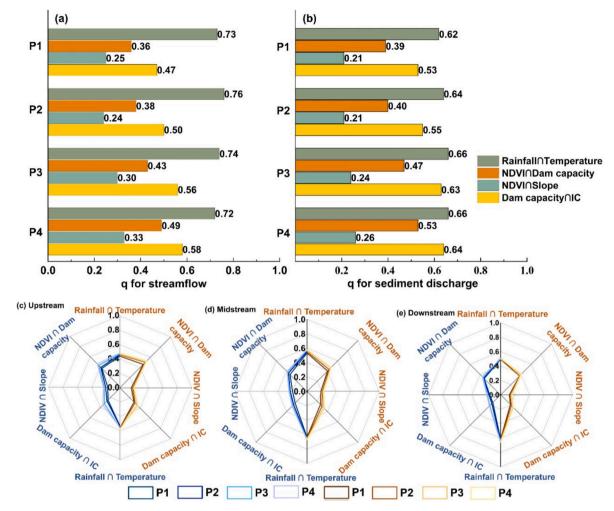


Fig. 5. Contributions of interactive factors to streamflow and sediment discharge in the YRB during four periods. (a–b) interaction detector analysis in the entire YRB; (c–e) interaction detector analysis in the upstream section, midstream section, and downstream section respectively.

discharge, TN, and TP in the YRB during 1980–2020 are inconsistent (Fig. 3a–c). Notably, streamflow did not exhibit significant changes, while sediment discharge decreased significantly (Ghosh and Muñoz-Arriola, 2023; Peng et al., 2022; Wang et al., 2020b). However, there was a notable rise in TN across the basin from 1998 to 2009, while TP saw a significant increase mainly in the downstream regions, consistent with Tong et al. (2017). Furthermore, The change points of streamflow and sediment discharge, though varying in stations, were concentrated in 1990, when a large number of SWM began to be implemented, in 1999, when the project of returning farmland to forest and grassland was initiated, and in 2003, when the TGR began operating (Fig. A.3) (Zhang et al., 2020).

## 4.2. Impacts of separate and interactive driving factors on streamflow, sediment, TN and TP

Unlike most previous studies, which primarily identified the negative correlation between those SWM measures, such as vegetation restoration, dam construction, land use change, and streamflow-sediment through enhanced infiltration and rainfall interception (Berio Fortini et al., 2023; Hu et al., 2021; Khurram et al., 2023), this study quantifies the contributions of key SWM measures, as well as their interactions, to streamflow and sediment discharge. While IC, primarily representing land use change, was identified as a significant factor influencing sediment discharge in this study, previous research has highlighted reservoir construction as the dominant factor controlling

sediment discharge (Jiang et al., 2023; Liang et al., 2024). Our results indicate that due to the construction of dams and reservoirs, the influence of them on decreasing sediment discharge increased from 19 % to 31 %, slightly lower than the impact of IC, which increased from 24 % to 33 %. This discrepancy may arise from the interconnected effects of reservoir construction on connectivity in the watershed and its indirect influence on land use changes represented by IC (Wu et al., 2023; Yi et al., 2022). For the interactive influence, we demonstrated that the interactive influence of rainfall and temperature on streamflow and sediment discharge is larger than their separate contributions. This can be attributed to their synergistic effects, where increasing rainfall enhances runoff generation, while rising temperatures intensify evaporation and alter snowmelt processes, collectively amplifying hydrological responses (Koneti et al., 2018; Qiu et al., 2021). Additionally, the spatial heterogeneity in climate factors across the YRB may further explain this. In regions where precipitation dominates, streamflow changes are more sensitive to rainfall variations, while in areas with higher temperature fluctuations, evapotranspiration-driven processes may play a greater role (Yin et al., 2023a; Zhang et al., 2015). Furthermore, we found that the interaction between NDVI and dam capacity had an effect on sediment discharge that was twice as large as the impact of these factors separately. Therefore, vegetation restoration in the reservoir area is an effective way to alleviate the regional economic and environmental losses that may be caused by the declining storage capacity of dams and reservoirs.

Consistent with the findings of Deng et al. (2023) and Behrouz et al.

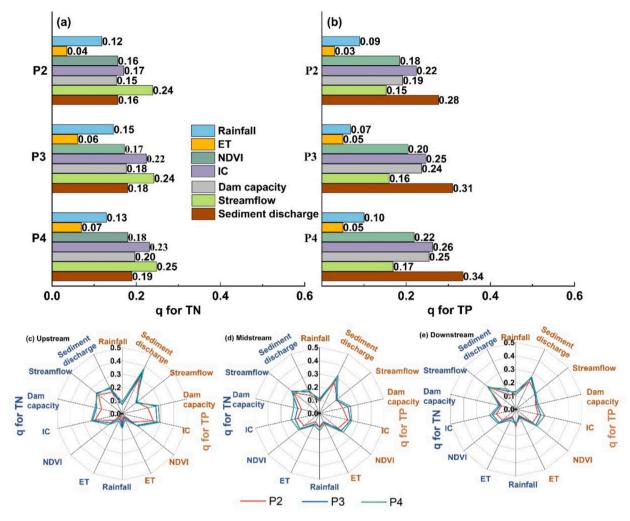


Fig. 6. Contributions of separate factors to TN and TP in the YRB during P2–P4. (a–b) factor detector analysis in the entire YRB; (c–e) factor detector analysis in the upstream section, midstream section, and downstream section respectively.

(2022), which indicated that environmental factors have a greater impact on TN than human activities, this study identifies streamflow as the most significant factor influencing TN, accounting for approximately 25 % of its variation. After the large-scale implementation of SWM, the influence of NDVI, IC, and dam capacity on TN also increased to around 20 % (Fig. 6). The interaction between dam capacity and IC—representing the combined impact of dam construction and land use changes—that has the most substantial effect on increasing TN, contributing about 35 % (Fig. 7). These results suggest that while SWM can control the transport of pollutants during the process, effective water quality management strategies must combine source reduction (land use changes) with process control (SWM).

In recent years, many countries have undertaken large-scale development to maximize resources utilization, particularly in large river basin such as the Nile, Amazon, Yangtze, Mekong and Indus (Cella-Ribeiro et al., 2017; Kansara and Lakshmi, 2022; Wang et al., 2024b). The dense human activities create complex impact by exerting a nonlinear superposition effect on the river water quantity and quality (Chen et al., 2021; Condé et al., 2019). For instance, Herut et al. (2023) demonstrated that reservoir construction along the Nile River significantly increased sediment deposition, which, in turn, affected nutrient fluxes to the Eastern Mediterranean. Similarly, Kayitesi et al. (2022), through a comparative analysis of 60 case studies in tropical regions, identified land use changes as a major driver influencing streamflow and sediment discharge. Even though these findings provide insightful information for the separate impacts of key factors on hydrologic or

nutrient fluxes, the interaction of multiple factors in real-world situations remains underexplored. Through the quantification of the separate and interactive impacts of major influencing factors on streamflow, sediment, TN, and TP, this study offers valuable insights for the development of management strategies within the watersheds that are facing climate change challenges and extensive soil and water management measures.

## 4.3. Limitations and uncertainties

Due to limitations in the historical records from the data source, the evapotranspiration data used in this study is only available up to 2015, and the TN and TP data are limited to the period from 1990 to 2010. Although the evapotranspiration data does not extend beyond 2015, trend analysis during the overlapping period (1980-2015) shows consistent patterns with other datasets that extending to 2020 (Su et al., 2023). This consistency suggests that the primary conclusions drawn from the overall analysis remain robust, even though the evapotranspiration data covers a shorter period. However, it is important to note that the temporal limitation of the TN and TP data may have influenced the findings of this study. For example, Liu et al. (2022a) reported a peak in TN and TP around 2003, followed by a decline during 2007-2016, a pattern that was not detected in this study. This difference may be the result of the data in this study were limited to the 1990-2010 period, which would lead to the absence of certain trends in the results. Nonetheless, the change point observed in 2003, coincides with the change

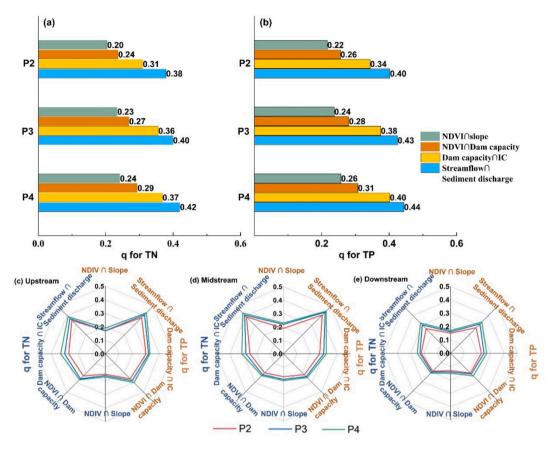


Fig. 7. Contributions of interactive factors to TN and TP in the YRB during P2–P4. (a–b) interaction detector analysis in the entire YRB; (c–e) interaction detector analysis in the upstream section, midstream section, and downstream section respectively.

point between P3 and P4 in this study, allowing us to reasonably infer the key factors influencing changes in TN and TP concentrations. From a spatial perspective, the limited number of monitoring stations across the extensive YRB presents another constraint. To address this, we interpolated these station data using the spline interpolation method, producing a spatially continuous dataset on 1 km raster grids. The spline interpolation has been demonstrated to perform well in handling random gaps in spatial datasets (Amirzehni et al., 2023; Hutchinson and Gessler, 1994; Li and Heap, 2014). This interpolation process inherently introduces uncertainty, particularly in regions with sparse monitoring points. Nevertheless, since our analysis primarily focuses on the results at upstream, midstream, and downstream sections, the potential impact of these uncertainties is reduced. Dong et al. (2023) demonstrated that nutrient fluxes at most monitoring stations within the same river section are almost stationary, with values varying primarily across upstream, midstream, and downstream sections. Furthermore, by analyzing water quality data from 1007 monitoring stations during 2016–2020, Liu et al. (2022b) identified anthropogenic activities, socioeconomic and land use as the main influencing factors of spatiotemporal variations in nutrient fluxes, which support the validity and credibility of our study results. To further validate and expand upon the findings of this study, future research should aim to acquire all data that cover a longer time span and more comprehensive spatial coverage.

It should be recognized that only annual streamflow, sediment discharge, TN, and TP in the YRB were used in this study; hence, no seasonal variability was accounted for. Liu et al. (2022c) revealed that streamflow and sediment discharge in the YRB from July to September accounted for >80 % of the whole year. During the same period, TN and TP were also high and showed the highest levels in July (Wang et al., 2011; Wu et al., 2021a). Among these factors, streamflow and sediment discharge, which are mainly affected by natural factors, were found to

be influenced about 15 % more by climate change in summer than in other seasons (Yang, 2021). Although fertilizer application is the most important source of nitrogen and phosphorus in the YRB, climatic factors also have the greatest impact on TN and TP due to farmland erosion caused by heavy rainfall in the summer (Chong et al., 2022). In addition to the uneven distribution of climatic factors within a year, the impact of human activities also shows seasonal characteristics (Asmal, 2000; Hu et al., 2012). In particular, the operation of dams has exact storage and release times, and the resulting water level changes are highly related to the sediment discharge, TN, and TP in their control area (Hu et al., 2012).

Another limitation of the dataset is that this study utilized reservoir data from the Global Reservoir and Dam (GRanD) database, which was last updated in 2011 and includes 6862 dams (Penny Beames and Anand, 2011). While GRanD provides valuable information for globalscale studies, it does not capture many smaller reservoirs or recently constructed dams (Du et al., 2022). This limitation is pronounced in the YRB, where over 61,000 reservoirs had been built by 2016, with many more under construction or planned (Song et al., 2023; Wang et al., 2018b). However, the dominant influence of the Three Gorges Reservoirs (TGR), which has been operated in 2003, has been operated in 2003 (Guo et al., 2023; Tang et al., 2018; Xiang et al., 2021b). While smaller reservoirs may contribute to regional variations, the TGR has a far greater cumulative effect, potentially mitigating concerns about the exclusion of recently constructed dams or smaller reservoirs in the GRanD dataset. Future studies should consider utilizing newer global datasets, such as the Global Dam Watch (GDW) dataset (Lehner et al., 2024), or developing region-specific inventories to better capture the cumulative and localized impacts of all reservoirs.

Geodetector can effectively, quickly, and objectively quantify the separate and interactive contribution of influencing factors to dependent variables based on spatial distribution data (Wang, 2017). However the method relies heavily on prior knowledge, and the selection of independent variables directly or indirectly affects the contribution results (Kalisa et al., 2023; Sun and Xie, 2022). In this study, we synthesized insights from similar research to identify six key factors-rainfall, temperature, ET, NDVI, dam capacity, and IC- that capture the main influences on streamflow, sediment discharge, TN and TP (Jiu et al., 2019; Kalisa et al., 2023). While these factors account for major natural and anthropogenic influences, they do not explicitly distinguish between point and non-point source pollution However, some pollution influences are indirectly captured through variables like NDVI, which reflects non-point source effects associated with land use changes, and IC, which represents broader land management impacts. This indirect consideration allows us to capture the broader impacts of soil and water management measures without isolating separate pollution sources.

Future research should consider more specific pollution indicators and influencing factors to comprehensively understand the changes in water quantity and quality. Additionally, analysis on monthly and seasonal scales would enhance understanding of the dynamic processes influencing water quantity and quality.

#### 5. Conclusion

Based on the streamflow, sediment discharge, TN, and TP data series in the YRB from 1980 to 2020, we found a significant reduction in sediment discharge and an increase in TN, while streamflow and TP remained relatively stable. The changing points of these trends were concentrated in 1990, 1999, and 2003, which coincided with the timeline of the large-scale construction of SWM, returning farmland to forest and grassland, and the construction of the Three Gorges Reservoir in this region. Furthermore, the separate effects of ET, NDVI, dam capacity, and IC on those indicators increased over time, peaking during the period 2004–2020. The interactive impact of NDVI  $\cap$  dam capacity, representing major SWM in the YRB, on sediment discharge was two times greater than that of any single factor. Moreover, beyond the impact of streamflow ∩ sediment discharge, which showed a greatest influence on TN and TP (>40 %), the interaction between dam capacity and IC, representing land use changes and major engineering measures, also significantly influenced TN and TP, contributing over 30 %.

By overcoming the complexities coming from the compounded positive and negative impacts of climate change and human activities on streamflow, sediment discharge, TN, and TP, this study finds that combining dam construction with vegetation restoration can effectively prevent soil erosion at the source and reduce sediment discharge, and changing land use (reducing fertilizer application at the source) and implementing direct interception measures (dam construction) are effective ways for controlling water pollution.

These results will help policymakers arrange suitable water resource management measures to combat climate change and contribute to achieving sustainable development goals. Incorporating seasonal and longer-term datasets in future research could further refine our understanding and enhance the strategic management of these measures.

### CRediT authorship contribution statement

Yinan Ning: Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation. Joao Pedro Nunes: Writing – review & editing, Supervision, Project administration, Methodology. Jichen Zhou: Writing – review & editing, Methodology, Data curation. Jantiene Baartman: Writing – review & editing, Supervision. Coen J. Ritsema: Writing – review & editing, Supervision, Project administration. Yunqing Xuan: Writing – review & editing. Xuejun Liu: Writing – review & editing, Supervision, Funding acquisition. Lihua Ma: Writing – review & editing, Supervision, Funding acquisition. Xinping Chen: Supervision, Funding acquisition, Conceptualization.

#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: NING Yinan reports financial support was provided by China Scholarship Council.

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#### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.178800.

#### Data availability

Data will be made available on request.

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