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Long-Term Spatiotemporal Dynamics of Forest Ecosystem Water Conservation and Management Zoning Based on Coupling Coordination Analysis in the Eastern Dabie Mountains, China

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Abstract

Forest ecosystem water conservation is an important ecohydrological regulating service for sustaining mountain watersheds under climate change. This study assessed water-conservation services in the eastern Dabie Mountains of China by integrating the InVEST Water Yield module under the Budyko framework, a Coupling Coordination Degree (CCD) model, and pixel-scale Theil–Sen, Mann–Kendall, and Ordinary Least Squares analyses. The study covered 1985–2024 through ten benchmark years (1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020, 2022, and 2024). Mean water-conservation capacity across the benchmark-year maps was 362.7 mm. The OLS slope was 1.40 mm/a, while the two-sided MK test was non-significant ($Z_{MK} = 0.54$, $p = 0.592$), indicating a weak positive tendency in the benchmark-year sequence. Year-to-year variation was closely associated with hydroclimatic conditions, with canopy interception, litter storage, soil-water storage, and flow attenuation providing process pathways within the model framework. Water-conservation capacity reached 534.4 mm in the wet 2020 benchmark year, declined to 268.2 mm during the 2022 drought, and recovered to 369.6 mm in 2024. Comparison with area-scaled official bulletin surface-water references for seven overlapping years yielded a mean absolute percentage error of 5.21% and absolute relative errors of 0.00%–17.62%. High-value service areas were concentrated in the central forested massif, whereas low-value and coordination-imbalance areas were more common along agricultural and urbanizing margins. The integrated framework links service intensity, coordination status, and historical tendency to support differentiated watershed management and to identify spatial contrasts together with benchmark-year hydroclimatic responses.

Keywords: forest ecosystem; water conservation; InVEST water yield model; spatiotemporal dynamics; coupling coordination degree; historical trends; eastern Dabie Mountains, China



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1. Introduction

Costanza et al. [1] established the theoretical foundation for valuing terrestrial ecosystem services and highlighted hydrological regulation as a key service for regional ecological security. As climate change intensifies and human disturbance expands, understanding the

spatiotemporal dynamics of forest ecosystem services has become central to ecohydrology and adaptive watershed management. Forests function as terrestrial water towers: they regulate runoff generation, enhance soil-water retention, attenuate flood peaks, and help sustain baseflow during dry periods [2]. In mountain watersheds, canopy foliage, organic litter, and porous soil form a multilayered ecohydrological system that intercepts precipitation, slows overland flow, and promotes infiltration and deep percolation. These processes can reduce flash-flood intensity, rainfall-driven soil erosion, and near-surface drying [2]. The associated moisture regulation may also lower wildfire susceptibility [3]. Quantifying forest water-conservation capacity is therefore essential for evaluating ecological-barrier functions and developing sustainable forest and watershed policies.

Sharp et al. [4] developed the InVEST Water Yield module within the Budyko water-energy balance framework. Because the module is spatially explicit, physically interpretable, and relatively economical in its data requirements, it has become a widely used tool for ecosystem-service assessment [5]. Zhou et al. [6] demonstrated its usefulness for evaluating forest water yield and water conservation under land-use change and climate variability. Recent mountain-basin applications have also used localized InVEST parameters to evaluate water-conservation services [7]. In the Dabie Mountains, ecosystem-service assessment has been linked with socioeconomic development to support regional interpretation [8]. Nevertheless, many mountain-forest studies rely on short time windows or isolated reference years, making it difficult to distinguish directional tendencies from hydroclimatic fluctuations. Assessments also often describe spatial patterns without integrating service intensity, functional coordination, and historical tendency into management-oriented zones.

The Dabie Mountains lie at the transition between subtropical and warm-temperate climates. They form a natural watershed barrier between the Yangtze and Huaihe river systems and constitute an important forest-biodiversity reservoir in central China. Previous studies have examined water conservation in the western Dabie Mountains, but a long-term, management-oriented assessment of the eastern forested massif remains limited.

To address this gap, this study evaluated forest water-conservation services across the 1985–2024 study period using ten benchmark years. The framework links (i) spatially explicit InVEST water-yield estimates, (ii) water-conservation service levels, (iii) CCD-based coordination diagnosis, and (iv) pixel-level historical tendencies. It was designed to separate persistent spatial structure from benchmark-year hydroclimatic variability and to translate the results into differentiated management priorities. The objectives were to (1) quantify benchmark-year water yield and water-conservation capacity; (2) examine precipitation–water-yield relationships and spatial heterogeneity among seven sub-watersheds; (3) diagnose coordination between service supply and human-development pressure; and (4) identify historical tendencies using Theil–Sen, MK, and OLS analyses, with particular emphasis on the sensitivity of the regional tendency to the exceptionally wet 2020 benchmark year.

2. Study Area

The eastern segment of the Dabie Mountains, also known as the Western Anhui Dabie Mountains, has an effective study area of 28,977.9 km² in the Lu'an–Anqing region (Figure 1). This effective area was used for water-yield aggregation, regional comparison, and subsequent water-conservation analysis. Elevation ranges from less than 50 m in the northern and southern plains to more than 1700 m in the central massif. The region lies in the warm-humid northern subtropical monsoon zone, with a mean annual temperature of approximately 12.5 °C and mean annual precipitation of approximately 1100 mm [9]. Rainfall is concentrated in the warm and monsoon seasons, particularly from May to September, and the dense river network responds strongly to this seasonal forcing. The

central mountain core is dominated by subtropical broadleaved and coniferous forests, with forest cover exceeding 65%, and supplies water to tributaries of the Yangtze and Huaihe systems.

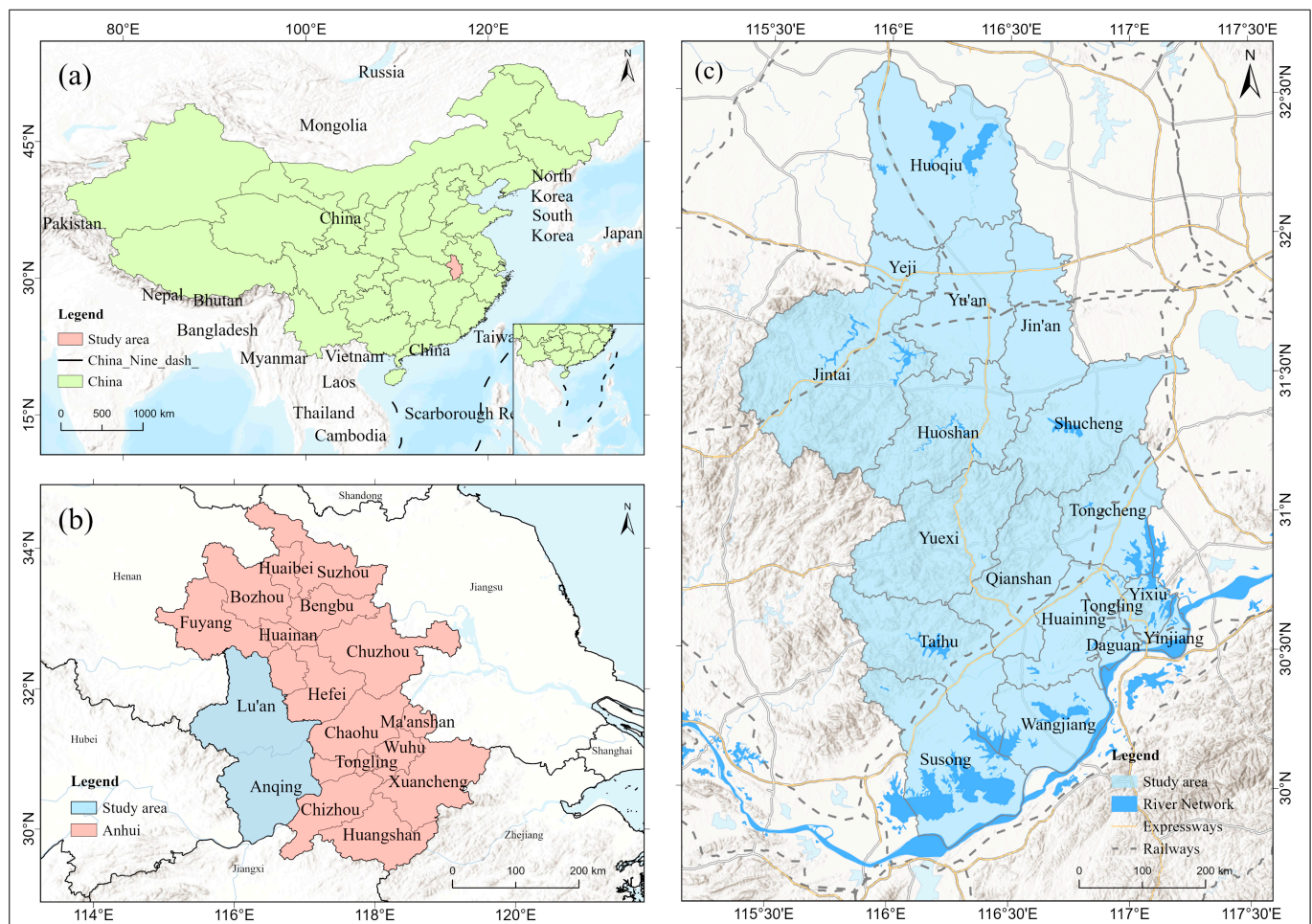


Figure 1. Overview map of the study area. (a) Entire China; (b) Anhui Province; (c) Study region and its hydrological network.

The study area has a well-developed river network and abundant water resources. The Shi River, Pi River, Dongfei River, Qi River, Xishui River, and Dawu River form the main drainage system. Forest cover has important hydrological implications: canopy and litter interception reduce rainfall energy and surface-flow velocity, thereby helping moderate flood peaks and soil erosion. Maintaining soil moisture and near-surface wetness may also reduce wildfire susceptibility [3]. By combining annual gridded climate forcing with regional water-resource statistics, this study characterizes watershed-scale water-conservation services. The available regional bulletins do not provide a consistently defined long-term discharge series for the longest river within the study area; therefore, river-specific discharge is not used in the analysis.

3. Materials and Methods

3.1. Data Sources and Spatial Harmonization

The study used land use/land cover (LULC), annual precipitation, annual reference evapotranspiration (ETo), soil properties, a DEM, watershed boundaries, and official water-resource bulletins [10] (Table 1). LULC data for 1985–2022 were obtained from GLC_FCS30D [11]. The 2024 layer was obtained from CLCD [12]. ArcGIS Pro 3.1.5 was

used for spatial preprocessing, watershed delineation, raster processing, and map production, and InVEST 3.14.3 was used for water-yield simulation. LULC and DEM inputs were prepared at 30 m, whereas climate and soil/root-depth inputs had approximately 1 km support and were aligned during preprocessing. Nearest-neighbor resampling was used for categorical layers and bilinear interpolation for continuous layers. Water-yield outputs were produced on the 30 m CGCS2000/3-degree Gauss–Krüger zone 38 grid (EPSG:4548), while water-conservation and service-level calculations used approximately 1 km geographic grids (EPSG:4490). Cross-year summaries were calculated with valid masks and native cell areas. No field instruments or laboratory devices were used. For the ASTER DEM, the archived record identifies NASA/USGS and the Geospatial Data Cloud access route, but the original download URL and access date were not retained.

Table 1. Input datasets, spatial support, and processing roles.

No.	Data Source	Data Type	Resolution/Support	Primary Purpose
1	GLC_FCS30D (1985–2022) [11]; CLCD (2024) [12]	30-m land-cover products	30 m; EPSG:4548 for InVEST alignment	LULC classes for benchmark years
2	China gridded climate products: annual precipitation [13]; reference evapotranspiration [14]	Annual precipitation and reference-ETo rasters	Approximately 1 km; EPSG:4548	P(x) and ETo/PET forcing for the water-yield simulations
3	China soil-property dataset for land-surface modeling [15]	Soil texture, organic matter, and root-restricting depth	Approximately 1 km; EPSG:4548	SAN, SIL, CLA, OM, and root-restricting depth
4	HWSD v1.2-derived soil database [16]; available-soil-water-capacity method [17]	Plant-available water content (PAWC)	Original approximately 1 km; PAWC1 model input aligned to 30 m	PAWCv fraction for AWC calculation
5	ASTER Global DEM (NASA/USGS), accessed through Geospatial Data Cloud	DEM and terrain derivatives	30 m; EPSG:4548	Flow accumulation, slope, and TWI
6	Project-derived parameter and processing layers	Flow-velocity coefficient, Ks/Kmin, TWI_min	30 m intermediate layers; Retention output approximately 1 km EPSG:4490	Water-conservation attenuation factors
7	Anhui Water Resources Bulletins, 2000, 2005, 2010, 2015, 2020, 2022, and 2024 [10]	Regional reference water-resource amount	Sub-basin/regional statistics	External consistency check for modeled water yield

The technical workflow comprised five linked phases: (1) multi-source data preprocessing and spatial harmonization; (2) InVEST water-yield simulation for ten benchmark years; (3) water-conservation-capacity calculation; (4) water-conservation service-level classification; (5) CCD diagnosis, benchmark-year trend analysis, and management zoning. The input–output relationships are shown in Figure 2. LULC denotes land use/land cover, *ETo* reference evapotranspiration, *PET* potential evapotranspiration, *PAWCv* plant-available water content expressed as a fraction, *AWC* effective plant-available water storage, *Kc* the crop coefficient, *Z* the year-specific seasonal constant, *TWI* the topographic wetness index, *Ks* the saturated-conductivity indicator, and *v* the flow-velocity coefficient. Water yield *Y* was used to calculate water-conservation capacity; the resulting WC surfaces supported service-level classification, CCD diagnosis, sub-watershed summaries, benchmark-year trend analysis, and management zoning.

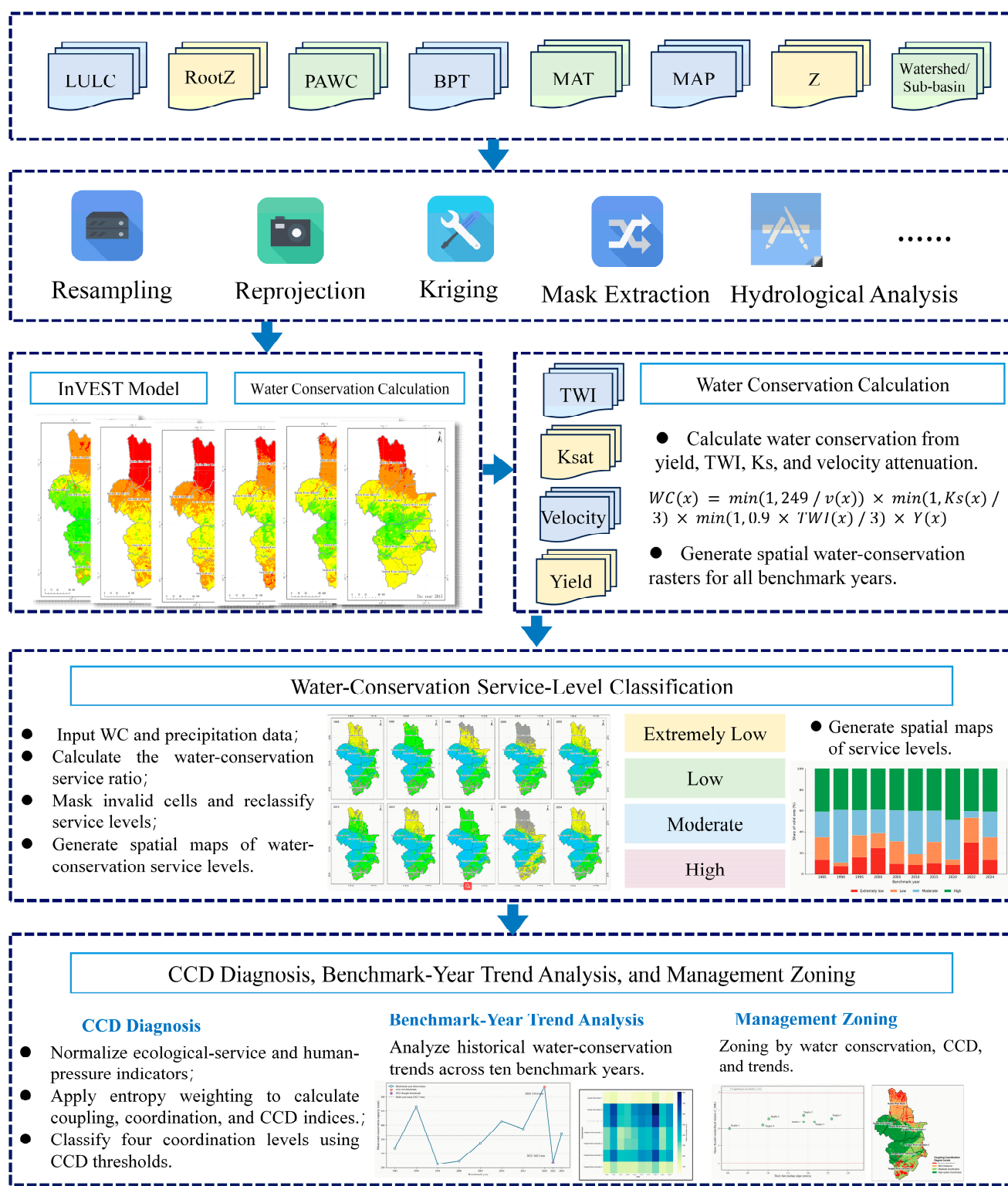


Figure 2. Research workflow for forest water-conservation service assessment across ten benchmark years spanning 1985–2024. Abbreviations: InVEST, Integrated Valuation of Ecosystem Services and Trade-offs; LULC, land use/land cover; PAWC, plant-available water content; BPT, biophysical parameter table; MAT, mean annual temperature; MAP, mean annual precipitation; Z, seasonal constant; RootZ, root-zone depth; TWI, topographic wetness index; Ksat, saturated hydraulic conductivity; Yield, water yield; Velocity, flow-velocity coefficient; WC, water-conservation capacity; CCD, coupling coordination degree; MK, Mann–Kendall. Colored icons distinguish schematic input and processing-product roles; the ellipsis denotes additional preprocessing operations, and no overlap changes the analytical sequence. OLS is ordinary least squares.

3.2. InVEST Water Yield Module

The InVEST Water Yield module estimates annual water yield within the Budyko water–energy balance framework [4]. Spatial outputs were generated for ten benchmark years spanning the 1985–2024 study period. The same ten observations were used for pixel-level Theil–Sen, MK, and OLS analyses, so the reported slopes describe changes across the benchmark-year sequence while retaining the actual calendar-year spacing. This application follows recent basin-scale studies that use localized InVEST parameterization for water-conservation assessment [7].

Input-layer preprocessing:

- (1) Land cover: The 1985–2022 layers used the fine GLC_FCS30m classification system, including broadleaved forests, needle-leaved forests, shrubland, and grassland. The 2024 CLCD layer contains 9 land cover classes.
- (2) Precipitation and *PET*: Annual precipitation rasters were prepared from the 1 km gridded climate product [13]. Reference evapotranspiration was estimated from gridded temperature data using the Hargreaves method and aggregated to the annual scale [14]. These precipitation and *ET₀* layers supplied the *P(x)* and *PET* forcing for the water-yield calculations. For the model runs used here, the water-yield simulations read the precomputed reference-ET rasters associated with each benchmark year; the present study did not recompute these rasters. Hargreaves describes the upstream estimation route, whereas FAO-56 Penman–Monteith is identified as a future cross-check when the required meteorological observations are available.

Here *ET₀* (*ET₀*) is reference evapotranspiration, *R_a* is extraterrestrial radiation, and *T_{mean}*, *T_{max}*, and *T_{min}* are mean, maximum, and minimum air temperature, respectively. Temperature is expressed in °C; when *R_a* is expressed as equivalent evaporation depth, *ET₀* is obtained in the corresponding daily depth unit and monthly values are summed to annual *ET₀*.

$$ET_0 = 0.0023 \times R_a \times (T_{mean} + 17.8) \times (T_{max} - T_{min})^{1/2} \quad (1)$$

- (3) Root-restricting layer depth: Root-restricting depth was obtained from the China soil-property dataset DBS_PDEP_2000.tif [15] and expressed in mm. It limits the soil depth available to the vegetation rooting zone.
- (4) Plant-available water content (PAWC): Soil sand, silt, clay, and organic-matter percentages were used in the available-soil-water-capacity calculation [17]. The HWSD-derived soil database supplied the corresponding soil attributes [16]. PAWC was first calculated as a percentage and then divided by 100 to obtain *PAWC_v*, the dimensionless fraction supplied to InVEST.

In Equation (2), *SAN*, *SIL*, *CLA*, and *OM* denote sand, silt, clay, and organic-matter contents (%), respectively, and *PAWC_v* is plant-available water content expressed as a fraction. The effective plant-available water storage used by the Budyko calculation is $AWC(x) = PAWC_v(x) \times \min[RD(x), root_depth(L_x)]$, where *RD* is root-restricting depth (mm), *root_depth* is the vegetation-class rooting depth (mm), and *L_x* is the LULC class at cell *x*. *AWC* is therefore expressed in mm, whereas *PAWC_v* is dimensionless.

$$PAWC_v = [54.509 - 0.132 \times SAN - 0.003 \times SAN^2 - 0.055 \times SIL - 0.006 \times SIL^2 - 0.738 \times CLA + 0.007 \times CLA - 2.688 \times OM + 0.501 \times OM^2]/100 \quad (2)$$

- (5) Watershed Delineation: Seven sub-watersheds were delineated across the Yangtze and Huaihe divide (Figure 3): Huaihe Sub-basin 1, Huaihe Sub-basin 2, Huaihe Sub-basin 3, Yangtze Sub-basin 1, Yangtze Sub-basin 2, Yangtze Sub-basin 3, and Yangtze Sub-basin 4.

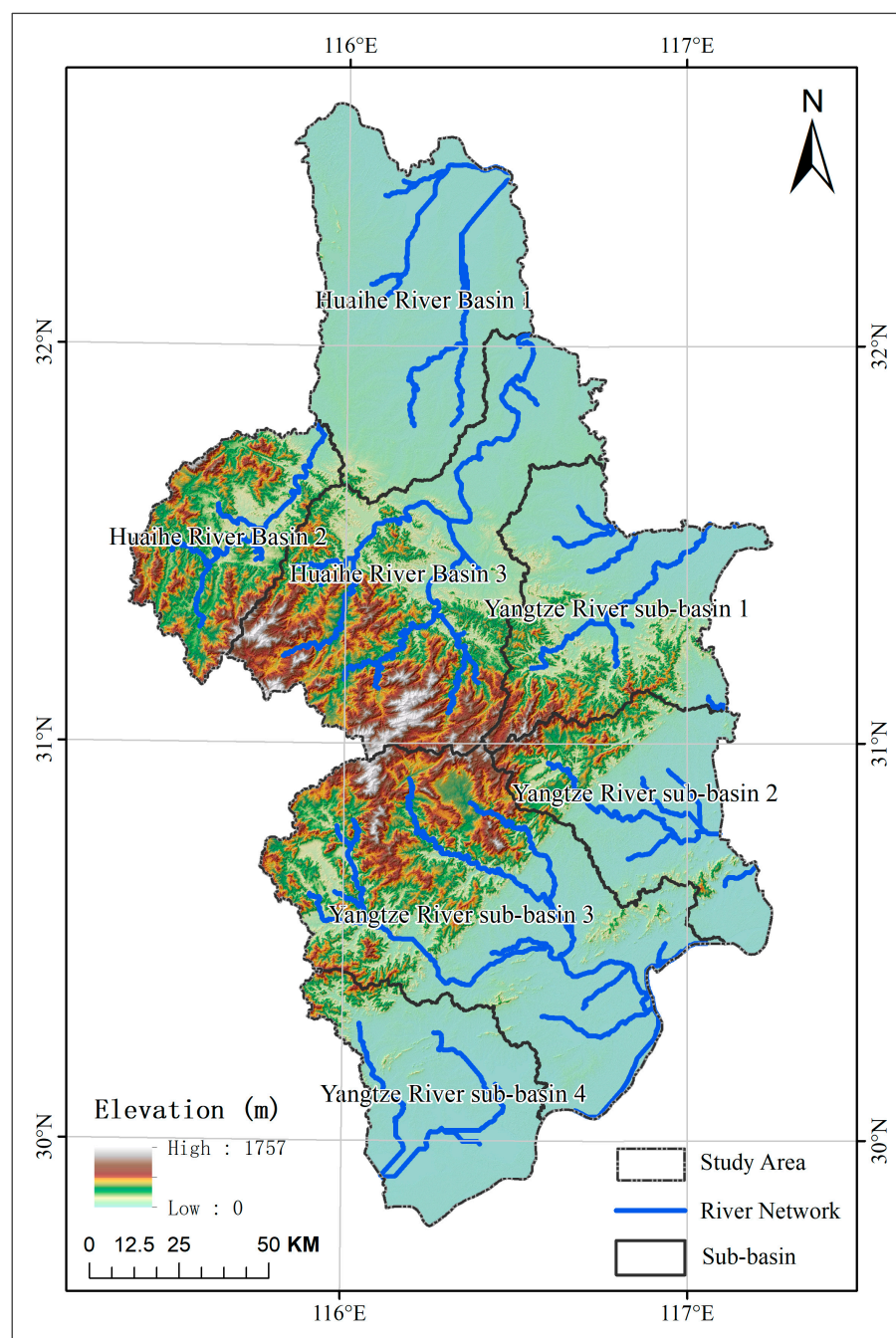


Figure 3. Map of the seven sub-watersheds.

- (6) Z value: Seasonal constant Z set to 13 based on regional runoff calibration.
- (7) Biophysical parameter table: Lucode, LULC_veg, root_depth, and K_c were assigned by land-cover class. The parameter values used are listed in Table 2.

The InVEST water-yield equations use Fu's Budyko curve to represent the water–energy relationship [18]. Annual evapotranspiration follows a rational-function formulation [19]. The spatially explicit water-balance uncertainty framework is described by Hamel and Guswa [20]. The equations are:

Table 2. Biophysical parameter table of the study area, compiled by the authors from the run-specific model parameter tables.

Lucode	Description	LULC_Veg	Root_Depth (mm)	Kc
10	Rainfed cropland	1	1850	0.750
11	Herbaceous cover cropland	1	2000	0.610
20	Irrigated cropland	1	1850	0.720
51	Open broadleaved forest	1	1000	1.100
52	Closed evergreen broadleaved forest	1	1000	0.965
61	Open deciduous broadleaved forest (0.15 < fc < 0.4)	1	1000	1.100
62	Closed deciduous broadleaved forest (fc > 0.4)	1	3500	1.008
71	Open evergreen needle-leaved forest (0.15 < fc < 0.4)	1	3500	1.008
72	Closed evergreen needle-leaved forest (fc > 0.4)	1	3500	1.008
82	Closed deciduous needle-leaved forest (fc > 0.4)	1	3500	1.008
121	Evergreen shrubland	1	3500	1.008
130	Grassland	1	3500	1.008
150	Sparse vegetation (fc < 0.15)	1	3500	1.008
181	Swamp	1	2000	1.008
182	Marsh	1	2000	0.965
183	Flooded flat	1	1000	1.055
190	Impervious surfaces	0	500	0.350
200	Bare areas	0	500	0.450
210	Water body	0	10	1.000

where x denotes a raster cell; $Y(x)$ is annual water yield, $P(x)$ is annual precipitation, $AET(x)$ is actual evapotranspiration, $PET(x)$ is potential evapotranspiration, $AWC(x)$ is effective plant-available water storage, Z is the year-specific seasonal constant, and $\omega(x)$ is the dimensionless Budyko shape parameter. P , AET , PET , AWC , and Y are expressed in mm, whereas $PAWC_v$ is a dimensionless fraction. In the water-yield calculation, $P = 0$ represents a zero-input boundary condition, while ω and Z are supplied model parameters.

$$Y(x) = [1 - AET(x)/P(x)] \times P(x) \quad (3)$$

$$AET(x)/P(x) = 1 + PET(x)/P(x) - [1 + (PET(x)/P(x))^{\omega(x)}]^{1/\omega(x)} \quad (4)$$

$$\omega(x) = Z \times AWC(x)/P(x) + 1.25 \quad (5)$$

Regional consistency validation: Modeled InVEST water-yield volumes were compared with an area-scaled reference derived from the official Anhui Water Resources Bulletins for seven overlapping benchmark years (Table 3). Because the bulletins report province-wide surface-water resources, the reference value was calculated as $V_{ref}(y) = V_{bulletin,surface}(y) \times A_{study}/A_{province}$, where $A_{study} = 28,977.9 \text{ km}^2$ and $A_{province} = 140,100 \text{ km}^2$. The comparison used signed error, absolute relative error,

bias, MAE, RMSE, MAPE, and Pearson correlation. This comparison evaluates regional consistency between modeled and reference magnitudes.

Table 3. Comparison of modeled InVEST water yield with area-scaled official bulletin surface-water references (10^8 m^3).

Year	Modeled Water Yield (10^8 m^3)	Bulletin Provincial Surface-Water Amount (10^8 m^3)	Area-Scaled Reference (10^8 m^3)	Signed Error (M – R) (10^8 m^3)	Absolute Relative Error (%)
2024	167.29	810.94	167.73	−0.44	0.26
2022	115.98	476.72	98.60	17.37	17.62
2020	248.94	1193.72	246.91	2.03	0.82
2015	175.84	850.19	175.85	−0.01	0.00
2010	190.24	876.27	181.25	8.99	4.96
2005	146.85	672.20	139.04	7.82	5.62
2000	122.95	554.62	114.72	8.23	7.17

3.3. Forest Water-Conservation Calculation

Water-conservation capacity $WC(x)$ (mm) was calculated from water yield together with the topographic wetness index (TWI), saturated-conductivity indicator (K_s), and flow-velocity attenuation factors, following the MEP/NDRC-based processing framework [21]. The calculation was:

$$WC(x) = \min(1, 249/v(x)) \times \min(1, K_s(x)/3) \times \min(1, 0.9 \times TWI(x)/3) \times Y(x) \quad (6)$$

Here $v(x)$ is the land-cover-specific flow-velocity coefficient listed in Table 4; $K_s(x)$ is the saturated-conductivity indicator; $TWI(x)$ is the dimensionless topographic wetness index; and $Y(x)$ and $WC(x)$ are water-yield and water-conservation depths (mm), respectively. The three $\min()$ terms are dimensionless attenuation factors and can be written as $K_{min} = \min(1, K_s/3)$, $TWI_{min} = \min(1, 0.9 \times TWI/3)$, and $Vel_{min} = \min(1, 249/v)$.

Table 4. Flow-velocity coefficients used in the water-conservation calculation.

Land Class Code	Land Use Type	Flow Velocity Coefficient (v)
1	Cultivated Land	800
2	Forest Land	200
3	Grassland	400
4	Water Body	2012
5	Construction Land	2012
6	Unused Land	1500

K_s was derived from soil texture and organic-matter layers using the soil pedotransfer relationship $K_s = 1930 \times (Q_s - Q_{33})^{\gamma} (3 - \gamma)$, where $\gamma = 1/B$ and $B = [\ln(1500) - \ln(33)]/[\ln(Q_{33}) - \ln(Q_{1500})]$. Q_{33} , Q_{1500} , and Q_s denote volumetric water-content estimates at 33 kPa, 1500 kPa, and saturation, respectively. The final conductivity attenuation factor was $K_{min} = \min(1, K_s/3)$. TWI was calculated from 30 m terrain derivatives as $\ln[(FA + 1) \times 30 / \tan(\beta)]$, where FA is the flow accumulation in cells, 30 is the cell size in meters, and β is the local slope angle. A small positive tangent was used for zero-slope cells. The flow-velocity values in Table 4 follow the land-cover coefficient convention

used in the calculation; v has the same coefficient convention and units as the constant 249 in the attenuation term. [22]

3.4. Coupling Coordination Degree (CCD) Model

The CCD model was used to quantify the interaction between forest ecohydrological service supply and human-development pressure. Service indicators were normalized to form the service subsystem U_1 , and disturbance/development indicators were normalized to form the pressure subsystem U_2 . Entropy weighting was used to determine indicator weights, and the two subsystem coefficients were set to $\alpha = \beta = 0.5$. Both U_1 and U_2 are dimensionless composite indices scaled to $[0, 1]$. The coupling degree C is defined as:

$$C = 2 \times [(U_1 \times U_2)/(U_1 + U_2)^2]^{1/2} \quad (7)$$

The comprehensive coordination index T represents the weighted combined development level. Here α and β are the subsystem coefficients, $\alpha + \beta = 1$, and the entropy-weighting procedure uses normalized indicator values z_{ij} to calculate $p_{ij} = z_{ij}/\sum_i z_{ij}$, $e_j = -[1/\ln(n)]\sum_i p_{ij} \ln(p_{ij})$, and $w_j = (1 - e_j)/\sum_j (1 - e_j)$. Each subsystem index is then calculated as $U_k = \sum_j w_j z_{kj}$.

$$T = \alpha \times U_1 + \beta \times U_2 \quad (8)$$

$$D = (C \times T)^{1/2} \quad (9)$$

Here $D \in [0, 1]$ is the CCD, C is the coupling degree, and T is the comprehensive coordination index. The square-root exponent denotes the arithmetic square root of $C \times T$. Before aggregation, pressure indicators in U_2 were reverse-coded where necessary so that higher U_2 represented lower pressure or better ecological condition. The thresholds in Table 5 link the CCD classes to differentiated ecological-management actions.

Table 5. CCD classification scheme and corresponding ecological-management implications.

CCD Range (D)	Coordination Level	Spatial Feature Description	Conditional Ecological Governance Implication
[0.70, 1.00]	High-quality Coordination	Core forested massif with dense canopy and intact soil	Strict conservation; monitor forest-cover loss, road expansion, and riparian continuity
[0.50, 0.70)	Moderate Coordination	Ecological transition belts around the central mountain core	Buffer maintenance and close-to-nature forestry; monitor fragmentation and soil infiltration
[0.40, 0.50)	Mild Imbalance	Agricultural plains and sub-basin margins with landscape fragmentation	Targeted restoration and riparian/soil-water conservation; monitor land conversion and runoff response
[0.00, 0.40)	Severe Imbalance	Urbanized or highly disturbed fringes with impervious-surface pressure	Priority land-use control and ecological engineering; monitor impervious expansion and streamflow response

3.5. Benchmark-Year Trend Analysis and Robustness Checks

All trend analyses used the ten benchmark-year water-conservation surfaces for 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020, 2022, and 2024. These observations span the 40-year period from 1985 to 2024 and are irregularly spaced, with $n = 10$. Regional and sub-watershed means were calculated after masking no-data cells, and the actual calendar years were used in all trend calculations. (1) Theil–Sen slope estimator [23]: the median of

all pairwise slopes was calculated using the actual calendar-year difference, so the unit is mm/a and the 2020 and 2022 observations use their actual temporal spacing:

$$\beta = \text{Median}\{(WC_j - WC_k)/(t_j - t_k)\}, \forall 1 \leq k < j \leq n \quad (10)$$

Here WC_j and WC_k are water-conservation values at benchmark years t_j and t_k , respectively; t_j and t_k are calendar years, $n = 10$ for the primary analysis, and β is expressed in mm/a. A positive β indicates an increasing benchmark-year tendency, whereas a negative β indicates a declining tendency. The estimator is robust to individual extreme values in principle, while the limited number of irregular observations makes the result sensitive to benchmark-year selection.

(1) Mann–Kendall (MK) non-parametric test [24]: the test evaluates whether the ordered benchmark-year values show a monotonic tendency. The statistic S is calculated as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(WC_j - WC_k) \quad (11)$$

The sign function $\text{sgn}(\theta)$ equals 1 when $\theta > 0$, 0 when $\theta = 0$, and -1 when $\theta < 0$. If tied values occur, the tie-corrected variance is $\text{Var}(S) = [n(n-1)(2n+5) - \sum t(t-1)(2t+5)]/18$, where t denotes the size of each tied group; the no-tie expression is the special case used when no ties occur.

$$\text{Var}(S) = [n \times (n-1) \times (2n+5)]/18 \quad (12)$$

The standardized Mann–Kendall statistic Z_{MK} is defined as:

$$Z_{MK} = (S - 1)/\sqrt{\text{Var}(S)} \ (S > 0); 0 \ (S = 0); (S + 1)/\sqrt{\text{Var}(S)} \ (S < 0) \quad (13)$$

At $\alpha = 0.05$, two-sided normal-approximation p values were used, with $|Z_{MK}| \geq 1.96$ as the 5% significance threshold. The benchmark-year observations were evaluated in chronological order, and their irregular calendar intervals were retained in the slope calculations. With $n = 10$, the MK statistic summarizes monotonic tendency across the benchmark-year sequence. The sub-watershed results are summarized in Table 6 and discussed in Section 4.2.

Table 6. Benchmark-year water-conservation statistics and historical tendencies for the seven sub-watersheds.

Sub-Watershed	Mean WC (mm)	Min (Year; mm)	Max (Year; mm)	OLS (mm/a)	Sen (mm/a)	Z_{MK}	p	5% sig.
Huaihe River Basin 1	90.0	2000; 41.9	2020; 175.0	0.33	0.04	0.00	1.000	No
Huaihe River Basin 2	520.8	2000; 346.3	2020; 806.9	1.98	1.89	0.36	0.721	No
Huaihe River Basin 3	492.7	2000; 346.6	2020; 712.1	1.41	1.02	0.54	0.592	No
Yangtze River sub-basin 1	354.1	1995; 224.8	2020; 528.1	2.13	2.59	0.54	0.592	No
Yangtze River sub-basin 2	355.0	1995; 244.6	2020; 504.8	1.66	1.89	0.72	0.474	No
Yangtze River sub-basin 3	464.1	2022; 359.6	2020; 657.7	1.69	2.16	0.36	0.721	No
Yangtze River sub-basin 4	197.0	2022; 142.2	2020; 287.0	0.79	0.87	0.18	0.858	No

(2) Pixel-level Ordinary Least Squares (OLS) slope matrix: OLS was fitted to each pixel using the actual calendar years to characterize the spatial distribution of historical linear tendencies across the ten benchmark-year surfaces. The resulting slope matrix provides a spatial measure of the direction and magnitude of change represented by the selected benchmark years.

$$\text{Slope} = [n \times \sum(t_i \times WC_i) - \sum t_i \times \sum WC_i] / [n \times \sum(t_i^2) - (\sum t_i)^2] \quad (14)$$

Here t is the calendar year, and WC is the corresponding water-conservation value. Using calendar year t preserves the actual time intervals from 1985 to 2024.

4. Results and Analysis

4.1. Water-Yield Simulation and Spatial Distribution

The benchmark-year water-yield results showed clear year-to-year variation associated with hydroclimatic conditions across the 40-year study period. As shown in Figure 4, water-yield depth and precipitation covaried, and their relationship is presented in the lower panel. Modeled watershed water-yield volumes were $115.98 \times 10^8 \text{ m}^3$ in the 2022 drought benchmark year and $248.94 \times 10^8 \text{ m}^3$ in the wet 2020 benchmark year, compared with $146.95 \times 10^8 \text{ m}^3$ in 1985 and $167.29 \times 10^8 \text{ m}^3$ in 2024. In 2020, the mean water-yield depth was 859.055 mm over 28,977.9 km², corresponding to 24,893,632,673 m³; volume = depth $\times$ area, therefore confirming $248.94 \times 10^8 \text{ m}^3 = 24.894 \times 10^9 \text{ m}^3$. Across the ten observations, the exploratory OLS relation was water-yield depth (mm) = $0.8188 \times$ precipitation (mm) $- 560.3$ ($n = 10$, $R^2 = 0.372$, Pearson $r = 0.610$, two-sided $p = 0.061$), summarizing the co-variation between precipitation and modeled water-yield depth. Across the seven overlapping years, comparison with the area-scaled official surface-water references yielded MAPE = 5.21% and Pearson $r = 0.995$, indicating good regional consistency. The 2022 comparison had the largest absolute relative error (17.62%; signed error $17.37 \times 10^8 \text{ m}^3$), likely because drought conditions amplify spatial contrasts in precipitation and runoff, while area scaling of province-wide statistics provides only a coarse representation of local drought responses.

Water-yield depth displayed pronounced geographic non-stationarity across the study area (Figure 5). High water-yield zones (>700 mm) were concentrated in the central high-elevation massifs, where monsoon precipitation and steep topography are prominent, whereas lower values (<300 mm) occurred mainly in northern low-elevation agricultural and urban plains.

4.2. Spatiotemporal Evolution of Forest Water-Conservation Services

Combining water yield with TWI , K_s , and flow-velocity attenuation produced water-conservation surfaces that were spatially consistent with forest-cover density (Figure 6). High-value areas (>500 mm) corresponded mainly to closed evergreen broadleaved forests (Lucode 52) and closed deciduous broadleaved forests (Lucode 62) in the central mountain core. This pattern indicates a spatial association between forest structure and modeled water-conservation capacity.

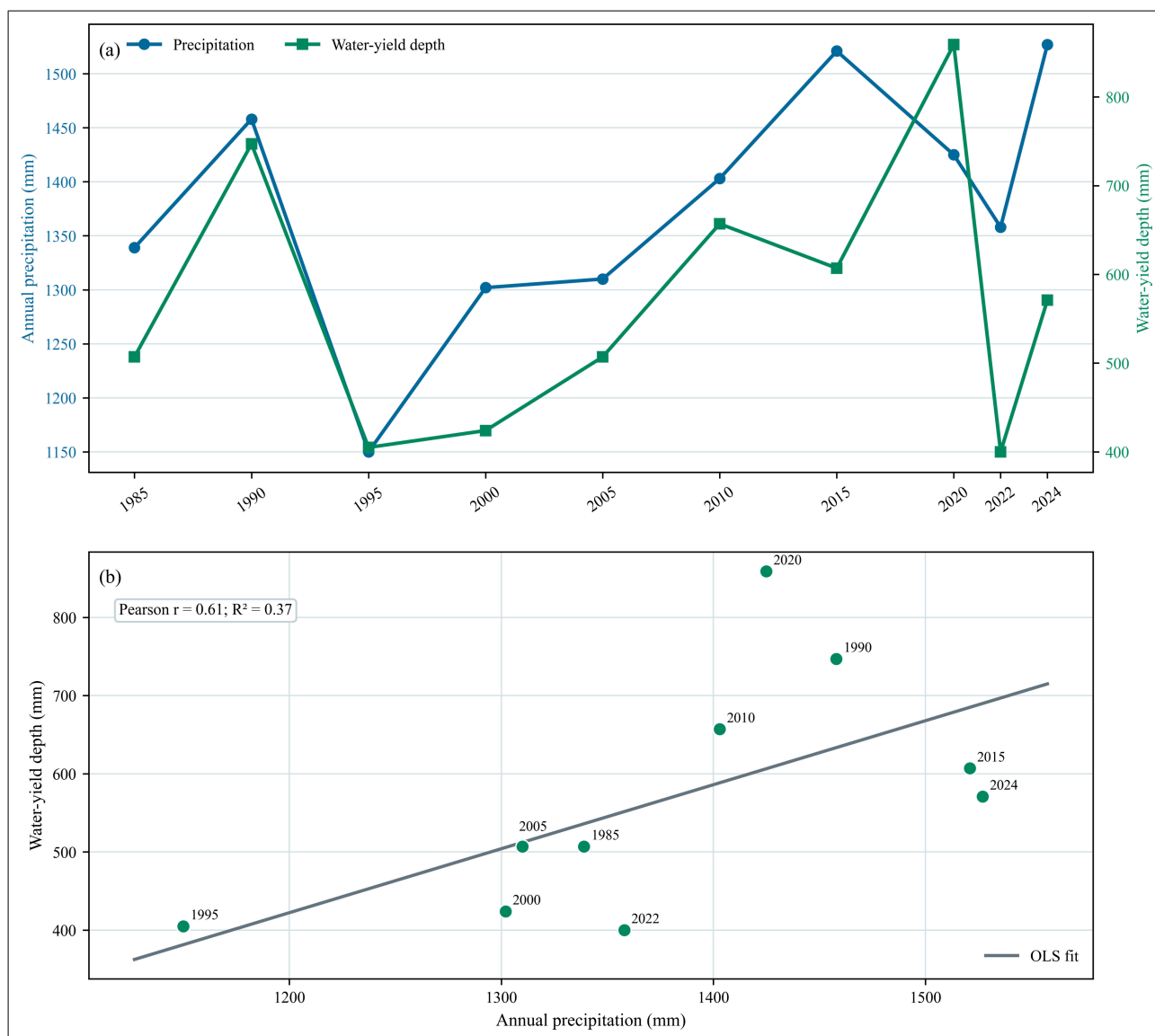


Figure 4. Benchmark-year variation and precipitation–water-yield relationship. (a) Annual precipitation and water-yield depth; (b) precipitation–water-yield scatterplot and OLS fit. The ten observations span 1985–2024.

The service ratio $r(x) = WC(x)/P(x)$ was classified into four levels using the function-level reclassification thresholds: Extremely Low for $0 \leq r < 0.05$, Low for $0.05 \leq r < 0.10$, Moderate for $0.10 \leq r < 0.20$, and High for $0.20 \leq r \leq 0.70$. No-data and invalid cells were excluded from the area summaries. Figure 7 shows the spatial distribution of the four classes. High-level service areas were concentrated in the forested mountain core, whereas drought-related contraction of higher levels was most evident in peripheral and human-dominated areas.

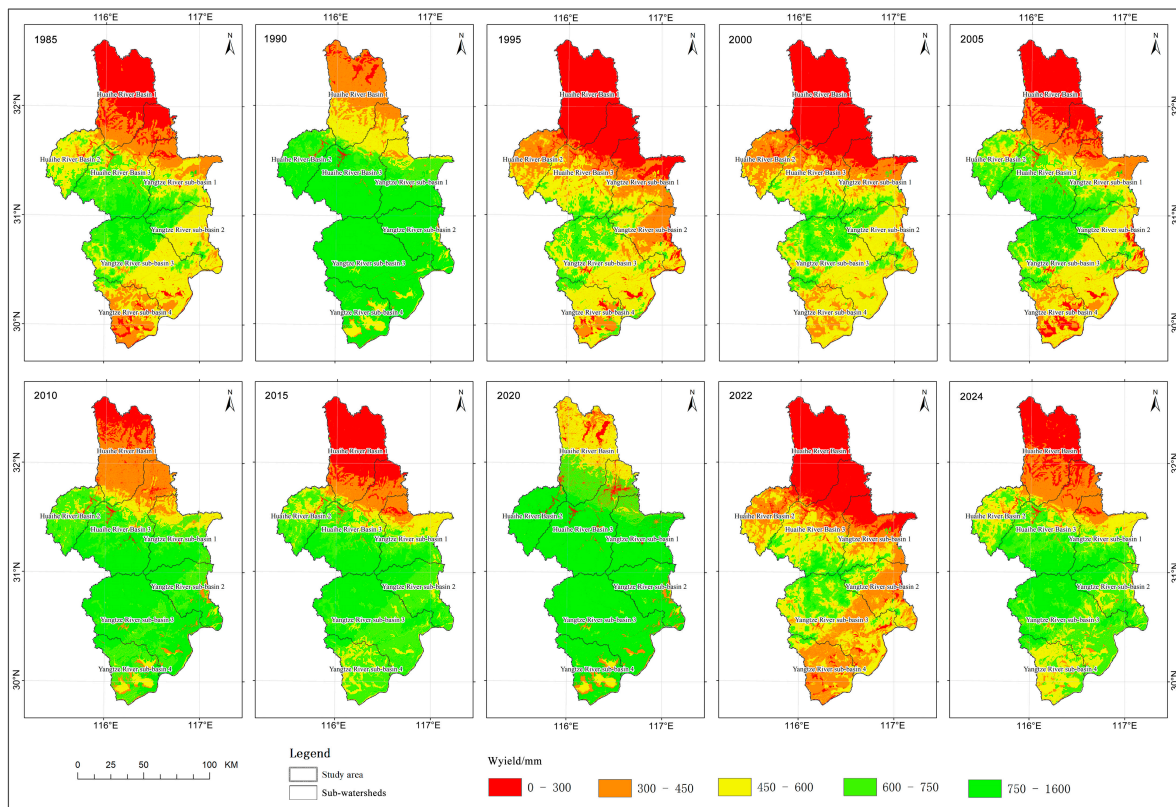


Figure 5. Spatial distribution of benchmark-year water-yield depth across the study area from 1985 to 2024. All panels use the same unit (mm) and a common legend.

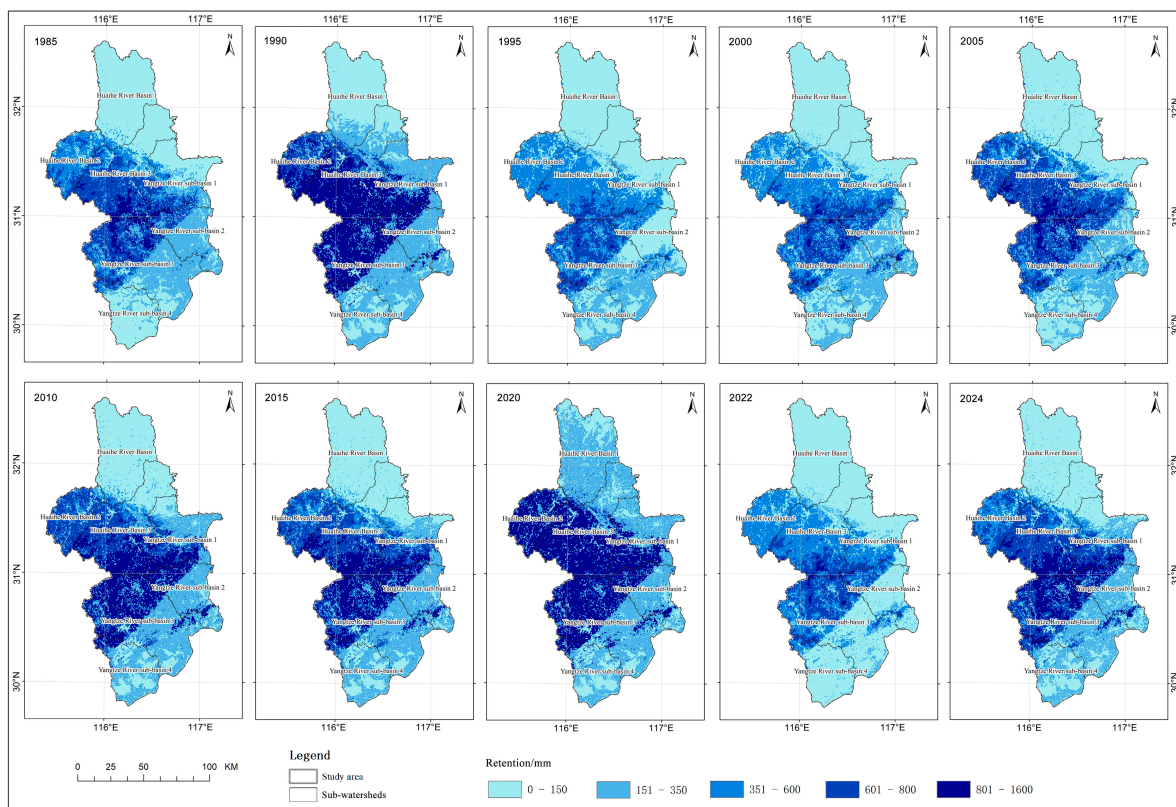


Figure 6. Spatial distribution of benchmark-year water-conservation capacity (mm). High values identify areas where precipitation-driven water yield is further attenuated by forest, soil, and topographic factors.

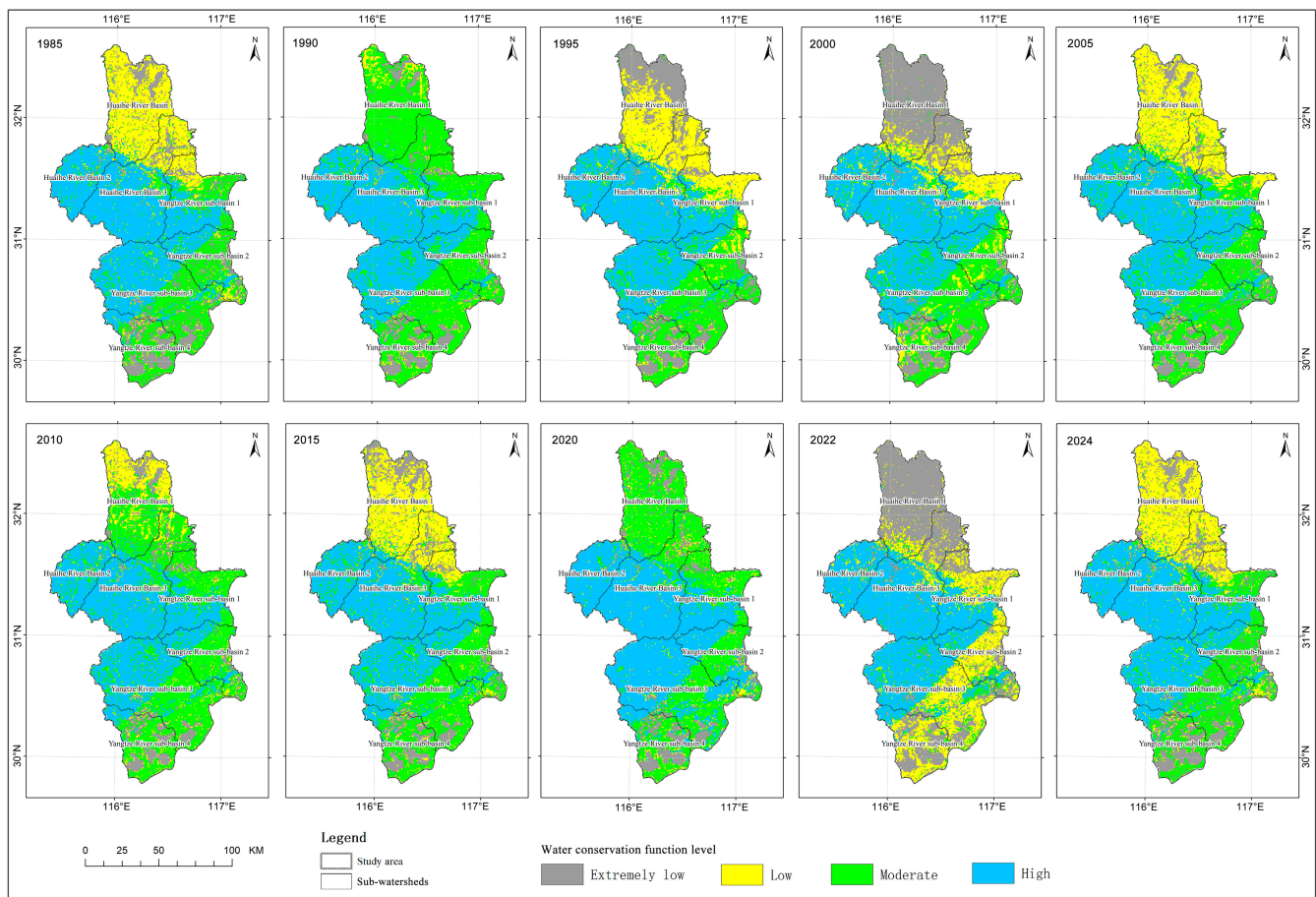


Figure 7. Spatial distribution of four water-conservation service levels across the ten benchmark years from 1985 to 2024. Extremely Low, Low, Moderate, and High classes are shown with a common enlarged legend.

The regional means for the ten benchmark years were 317.3, 465.1, 262.9, 273.6, 334.5, 413.5, 387.4, 534.4, 268.2, and 369.6 mm in chronological order from 1985 to 2024. Using actual calendar years, the complete sequence produced OLS = 1.40 mm/a, Theil–Sen = 1.85 mm/a, $S = 7$, $Z_MK = 0.54$, and $p = 0.592$. A leave-one-out check for the wet 2020 benchmark year yielded OLS = -0.09 mm/a, Theil–Sen = 0.53 mm/a, $S = 2$, $Z_MK = 0.10$, and $p = 0.917$. Together, these estimates show a weak positive regional tendency in the complete benchmark-year sequence and sensitivity of its magnitude to the inclusion of the exceptionally wet observation. Figure 8 displays the ten benchmark-year observations and their multi-year mean without fitting a trend line.

The seven sub-watersheds showed clear differences in water-conservation capacity (Table 6; Figures 9 and 10). Huaihe River Basin 1 had the lowest mean capacity (90.0 mm; minimum 41.9 mm in 2000; maximum 175.0 mm in 2020; OLS = 0.33 mm/a, Theil–Sen = 0.04 mm/a, $Z_MK = 0.00$, $p = 1.000$). Huaihe River Basin 2 had the highest mean (520.8 mm; minimum 346.3 mm in 2000; maximum 806.9 mm in 2020; OLS = 1.98 mm/a, Theil–Sen = 1.89 mm/a, $Z_MK = 0.36$, $p = 0.721$), followed by Huaihe River Basin 3 (492.7 mm; minimum 346.6 mm in 2000; maximum 712.1 mm in 2020; OLS = 1.41 mm/a, Theil–Sen = 1.02 mm/a, $Z_MK = 0.54$, $p = 0.592$). Yangtze River sub-basin 1 had a mean of 354.1 mm (minimum 224.8 mm in 1995; maximum 528.1 mm in 2020; OLS = 2.13 mm/a, Theil–Sen = 2.59 mm/a, $Z_MK = 0.54$, $p = 0.592$), and sub-basin 2 had a mean of 355.0 mm (minimum 244.6 mm in 1995; maximum 504.8 mm in 2020; OLS = 1.66 mm/a, Theil–Sen = 1.89 mm/a, $Z_MK = 0.72$, $p = 0.474$). Yangtze

River sub-basin 3 averaged 464.1 mm (minimum 359.6 mm in 2022; maximum 657.7 mm in 2020; OLS = 1.69 mm/a, Theil–Sen = 2.16 mm/a, $Z_{MK} = 0.36$, $p = 0.721$), while sub-basin 4 averaged 197.0 mm (minimum 142.2 mm in 2022; maximum 287.0 mm in 2020; OLS = 0.79 mm/a, Theil–Sen = 0.87 mm/a, $Z_{MK} = 0.18$, $p = 0.858$). None of the seven two-sided MK tests were significant at $\alpha = 0.05$. The common 2020 maximum and the low values in 2022 indicate that the cross-sub-watershed differences are embedded in strong benchmark-year hydroclimatic variability.

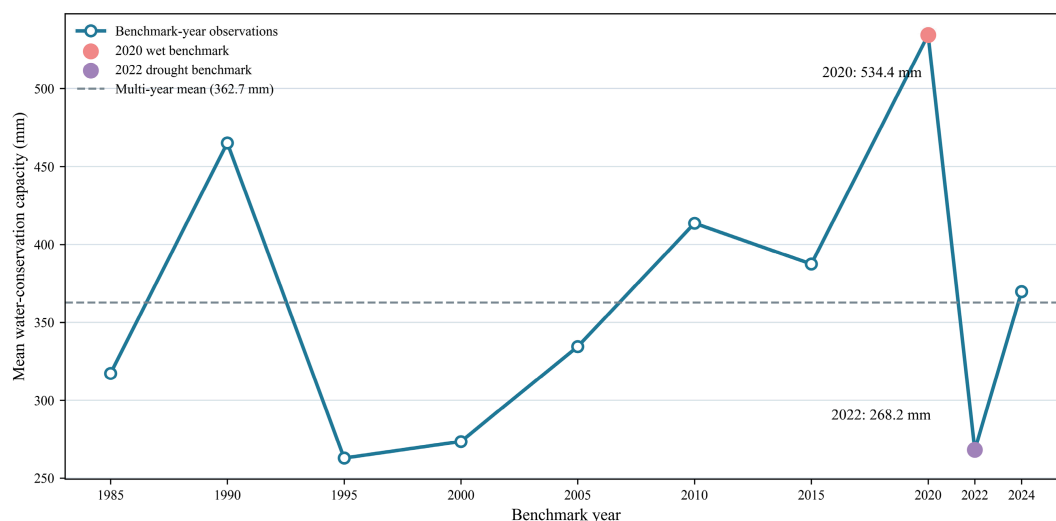


Figure 8. Benchmark-year variation in mean water-conservation capacity across the 40-year study period (1985–2024). The line connects the ten benchmark-year observations and the dashed line indicates their multi-year mean; no fitted trend line is shown.

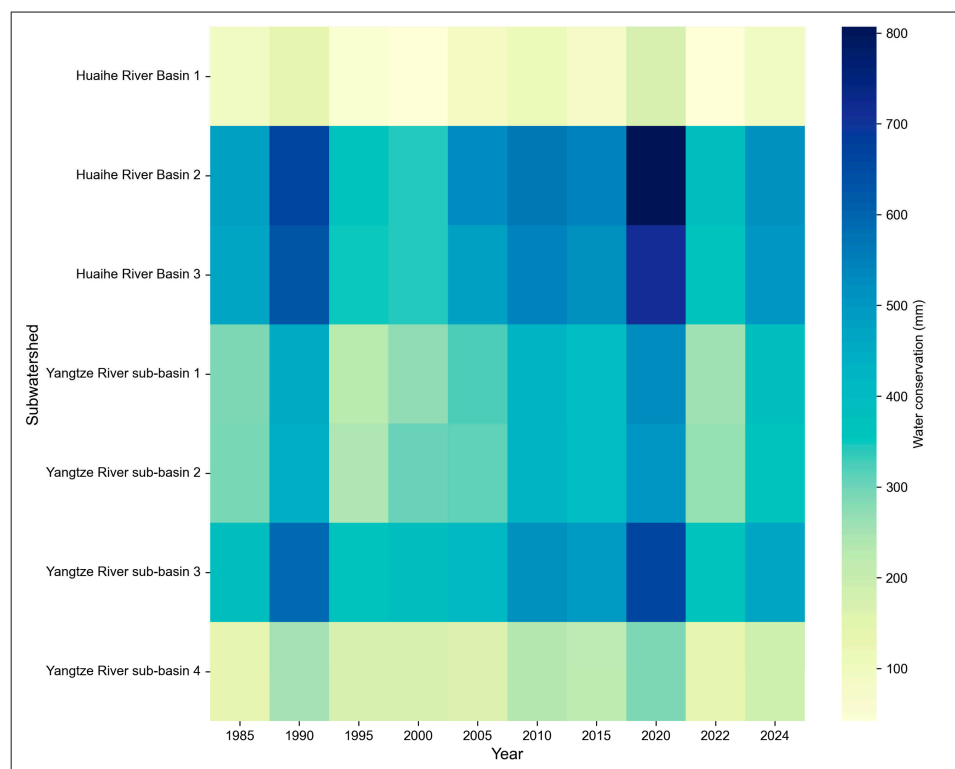


Figure 9. Heatmap of benchmark-year water-conservation capacity across the seven sub-watersheds. Rows identify sub-watersheds and columns identify benchmark years, allowing spatial contrasts and drought-year changes to be read directly.

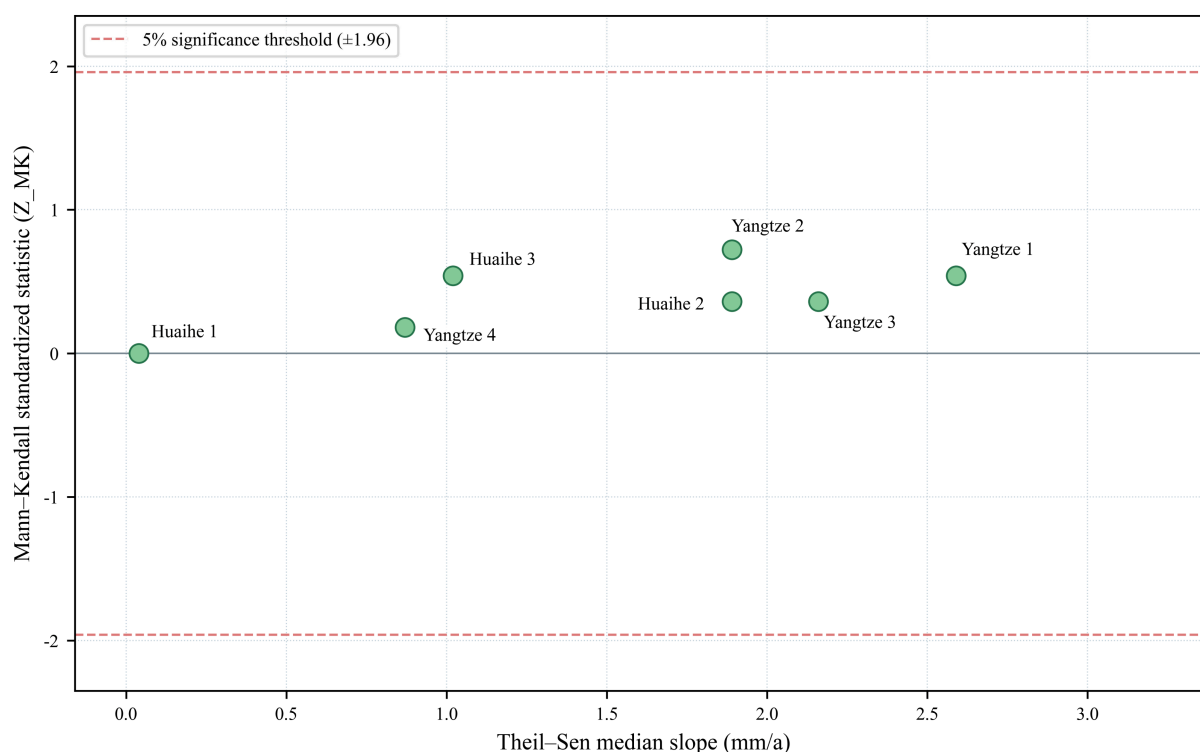


Figure 10. Joint sub-watershed trend diagnosis based on Theil–Sen median slopes (mm/a) and Mann–Kendall standardized statistics (Z_{MK}) across the ten benchmark years. Dashed lines mark the two-sided 5% thresholds (± 1.96); all points remain within them.

Joint analysis of the Theil–Sen slope and MK statistic (Figure 10) showed positive Theil–Sen slopes in all seven sub-watersheds, ranging from 0.04 to 2.59 mm/a. The Yangtze sub-basins had the largest positive slopes (0.87–2.59 mm/a), whereas Huaihe sub-basins 2 and 3 were positive but smaller, and Huaihe sub-basin 1 was near zero. All seven Z_{MK} values remained within the ± 1.96 threshold, placing the sub-watershed tendencies below the two-sided 5% significance level with $n = 10$. Figure 10 summarizes the spatial differences in historical benchmark-year tendencies among the seven sub-watersheds, together with their corresponding MK statistics.

The 100% stacked bar chart in Figure 11 shows how water-conservation service levels varied across the valid raster area. High-service zones remained dominant, accounting for approximately 38.8%–48.6% of the valid area, whereas Extremely Low and Low zones expanded during the 2022 drought benchmark year. The class shares were calculated from the categorical service-level maps using valid masks and native cell areas.

4.3. Spatial Assessment of CCD and Management Zoning

The CCD spatial overlay (Figure 12) shows that high-quality coordination (42.42%) and moderate coordination (24.96%) together covered 67.38% of the study area. The four classes use the ranges [0.70, 1.00], [0.50, 0.70), [0.40, 0.50), and [0.00, 0.40), respectively, and their area shares sum to 100.00%. Coordinated classes were concentrated mainly in central forested sub-watersheds, whereas imbalance classes occurred more frequently along human-dominated peripheral lowlands. These patterns indicate a spatial gradient from intact forest-service cores to areas with stronger development pressure and provide a basis for differentiated watershed management.

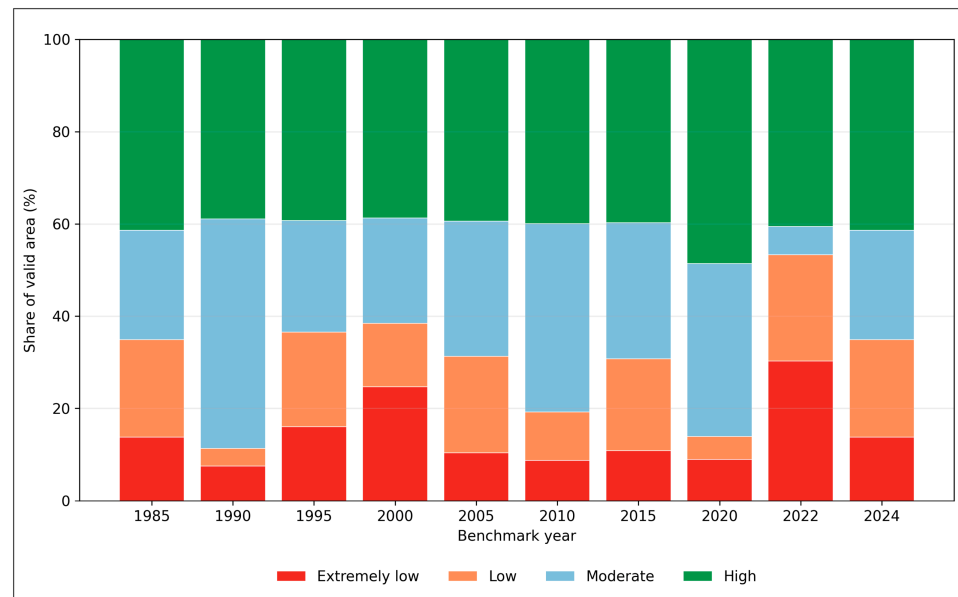


Figure 11. Composition of water-conservation service levels across the valid raster area for the ten benchmark years, shown as a 100% stacked bar chart.

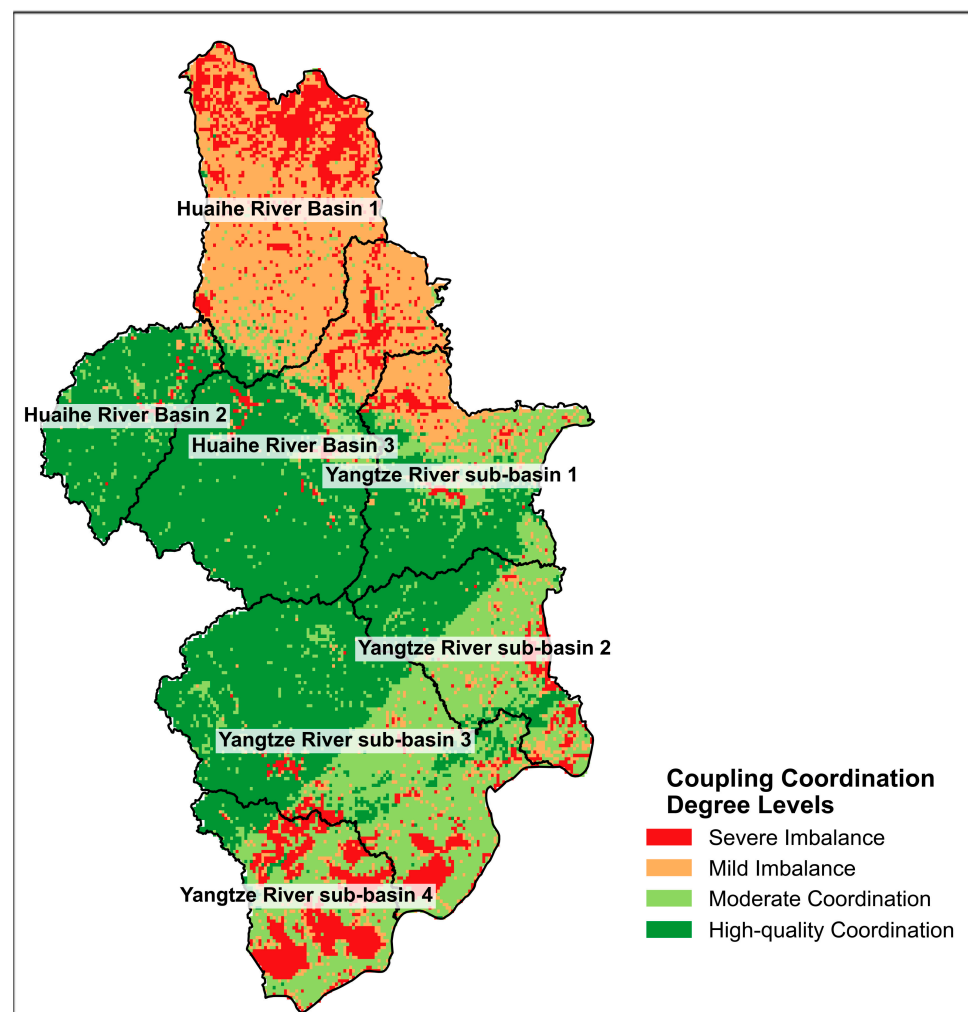


Figure 12. Spatial distribution of coupling coordination zones. The classes are high-quality coordination [0.70, 1.00] (42.42%), moderate coordination [0.50, 0.70) (24.96%), mild imbalance [0.40, 0.50) (20.64%), and severe imbalance [0.00, 0.40) (11.98%).

The pixel-level OLS slope matrix (Figure 13) uses the ten benchmark-year water-conservation surfaces and the actual calendar years to describe the spatial distribution of historical linear tendencies. Positive slopes were widespread in the central-eastern forest core, whereas localized negative slopes occurred along agricultural and urbanizing margins. The color scale represents the estimated historical slope in mm/a, providing a spatial basis for comparing benchmark-year changes and management priorities.

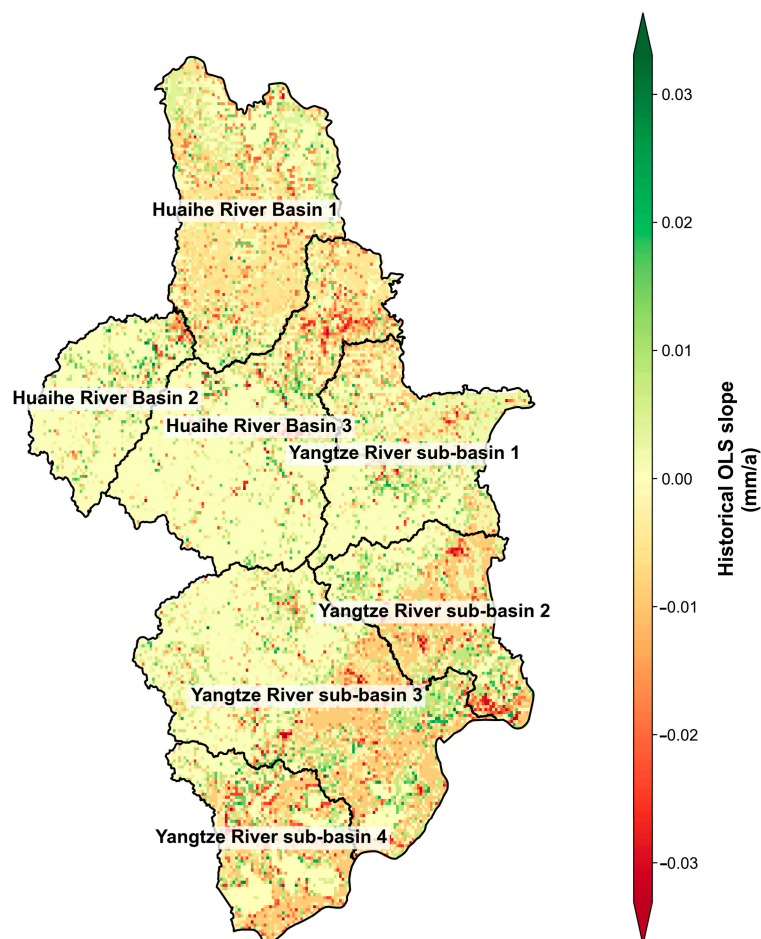


Figure 13. Pixel-level historical OLS trend-tendency matrix (slope, mm/a) estimated with actual calendar years from ten benchmark-year surfaces spanning 1985–2024.

5. Discussion

5.1. Long-Term Variation and Hydroclimatic Controls of Forest Water Conservation

Using ten benchmark-year maps over 1985–2024 provides a long-term perspective on forest water conservation while retaining interannual hydroclimatic variability. Regional water-conservation capacity averaged 362.7 mm, with benchmark-year values ranging from 262.9 mm in 1995 to 534.4 mm in 2020. The OLS slope (1.40 mm/a) and Theil–Sen slope (1.85 mm/a) were both positive, whereas the MK test was non-significant ($Z_{MK} = 0.54$, $p = 0.592$). These results indicate a weak positive tendency in the benchmark-year sequence, with year-to-year variation closely associated with hydroclimatic conditions. The pronounced maximum in 2020 and decline in 2022 show that moisture supply strongly influences the estimated service level. The long-term record therefore supports interpretation of persistent spatial patterns together with year-specific hydroclimatic responses.

The sequence from 2020 (534.4 mm) to 2022 (268.2 mm) and 2024 (369.6 mm) illustrates how hydroclimatic forcing shapes modeled water-conservation capacity. Canopy interception, litter storage, soil-water retention, topography, and flow attenuation provide

plausible pathways linking atmospheric inputs to the modeled service. Evidence from forest ecosystems also indicates that tree size and species diversity influence water holding by canopy, litter, and soil components [25]. The 2024 increase is interpreted as a recovery in modeled service under renewed moisture supply, while annual observations, controlled parameter experiments, and runoff measurements would help resolve the contribution of each process.

5.2. Spatial Heterogeneity and Forest Ecological-Barrier Functions

Spatial diagnostics revealed strong heterogeneity among sub-watersheds. High CCD values were concentrated in the central forested core. Water-conservation capacity exceeded 500 mm in high-elevation core sub-basins but was below 100 mm in Huaihe sub-basin 1. These spatial contrasts indicate that forest cover, elevation, topography, and precipitation jointly shape the distribution of ecosystem-service supply. Low-elevation peripheral sub-basins contained more imbalance patches, consistent with stronger agricultural and urban-development pressure. Such spatial differentiation is also relevant to regional water-security and ecological-planning assessments [26].

The spatial divide provides a useful management basis. In core mountain zones, intact forest cover is associated with stronger service supply and higher CCD classes. In fringe sub-basins, agricultural expansion, road construction, and growth of impervious surfaces can reduce infiltration and fragment habitats. Evidence from land-use pathway studies shows that climate–land-use interactions can alter water-conservation outcomes across management zones [27]. These pressure pathways should be evaluated with land-cover change, runoff observations, soil-hydraulic measurements, and sub-basin monitoring. Management at the sub-basin scale is therefore essential.

5.3. CCD-Based Multifunctional Forest-Watershed Management

Integrating service magnitude, CCD class, and the OLS historical-tendency matrix yields a conditional three-dimensional framework for multifunctional forest-watershed management. CCD serves as a screening indicator, while the trend layer, service magnitude, land-cover context, and field or remote-sensing observations jointly inform intervention priorities. The seven sub-watershed MK results provide a spatial diagnosis for prioritization, with slope direction and CCD class guiding the distinction between protection, buffer maintenance, and restoration actions.

- (1) Core forest ecological-protection zones (high-quality CCD [0.70, 1.00] and positive but non-significant benchmark-year tendency): These zones are located in central high-elevation massifs such as Huaihe sub-basin 2 and Yangtze sub-basin 2. Priorities include strict natural-forest protection, prohibition of commercial logging, and passive ecological fencing. Monitoring should focus on forest-cover loss, road expansion, riparian continuity, and changes in soil infiltration; detected deterioration should trigger a reassessment of management priorities.
- (2) Forest ecological-buffer maintenance zones (moderate CCD [0.50, 0.70] and no statistically significant benchmark-year tendency): These zones occur in mid-elevation mountain transition belts. Management should emphasize close-to-nature forestry, conversion of monoculture plantations toward mixed broadleaved–coniferous stands, and riparian forest buffers. Monitoring should track landscape fragmentation, canopy condition, soil organic matter, and stream-buffer continuity.
- (3) Priority ecological-restoration and land-use-control zones (mild imbalance [0.40, 0.50] or severe imbalance [0.00, 0.40], especially where the pixel-level OLS tendency is negative): These zones occur along urbanizing and agricultural fringes such as Huaihe sub-basin 1. Measures should combine cropland and impervious-surface control,

active reforestation on steep slopes, riparian buffering, bio-engineering soil and water conservation, and wetland restoration. Implementation should be evaluated using land-cover change, runoff observations, soil-hydraulic measurements, and sub-basin monitoring.

5.4. Model-Parameter Sensitivity and Uncertainty Assessment

Sensitivity analysis evaluated the effects of the seasonal constant Z , the crop coefficient K_c , and root depth. Varying Z from 10 to 16 changed total simulated runoff volume by less than 6.4%, and $Z = 13$, the relative error with respect to the regional bulletin reference series was the lowest. The relative errors for nearly all overlapping years were below 10%, except for the drought baseline year 2022, which reached 17.62%. Changing K_c and root depth by $\pm 15\%$ altered water-conservation estimates by less than 7.2%. These tests indicate that the principal conclusions are relatively stable within the tested parameter ranges, although parameter uncertainty should still be considered in local applications.

Uncertainty is associated mainly with the spatial resolution and parameterization of soil organic matter, PAWC, K_s , TWI , v , and the seasonal constant Z . The combination of 30 m LULC/DEM inputs and approximately 1 km meteorological and soil data also requires careful spatial harmonization. Trend interpretation reflects the ten irregularly spaced benchmark-year observations, their hydroclimatic contrast, annual autocorrelation considerations, year-specific Z settings, parameter-table differences among land-cover products, and the regional scale of the consistency assessment. Future work should incorporate annual forcing and FAO-56 Penman–Monteith ET_0 where observations permit [28]. Field measurements of K_s and PAWC, controlled parameter-sensitivity tests, and scenario-based land-use and climate projections would further strengthen the framework.

5.5. External Consistency Check, Contributions, and Limitations

Comparison with area-scaled official Anhui bulletin surface-water references [10] produced a bias of $6.29 \times 10^8 \text{ m}^3$, MAE of $6.41 \times 10^8 \text{ m}^3$, RMSE of $8.58 \times 10^8 \text{ m}^3$, MAPE of 5.21%, and Pearson $r = 0.995$ across seven overlapping years, indicating strong regional agreement in interannual variation. The largest absolute relative error occurred in the 2022 drought benchmark year (17.62%; signed error $17.37 \times 10^8 \text{ m}^3$). This higher deviation likely reflects the stronger spatial heterogeneity of drought precipitation and runoff response, together with differences between modeled water yield and province-wide surface-water accounting. Area scaling from province-wide statistics provides a coarse representation of local contrasts during a drought year. The comparison supports regional-scale consistency assessment, while local evaluation would benefit from gauged runoff and finer-scale reference data. The principal strength of the framework is its integration of service magnitude, spatial coordination, and historical tendency; its practical scope is regional prioritization and management diagnosis.

The temporal design defines the scope of the long-term comparison. The ten maps provide a 40-year context, and the regional slope summarizes the selected benchmark-year sequence. Its interpretation is conditioned by hydroclimatic forcing, year-specific Z settings, and parameter-table differences. Spatial contrasts and management diagnosis therefore provide the principal basis for interpreting the modeled service across the study area.

The results are consistent with Zhou et al. [6], who showed that ecosystem water conservation varies with climate and land-cover context. Lu and Lu [29] highlighted the usefulness of composite indicators for summarizing ecosystem-service variability. Recent research in the Dabie Mountains has likewise linked ecosystem services with socioeconomic development [8]. Studies of alternative land-use pathways emphasize that land-use context can reshape water conservation and should be considered in management planning [27].

Restoration-oriented watershed analyses also show that land-degradation pathways can modify water-conservation capacity [30]. The Lu'an case illustrates the relevance of ecological infrastructure and water-resource governance to regional planning [31]. Forest-plot evidence further indicates that tree size and species diversity affect water holding by canopy, litter, and soil components [25]. Soil-water studies identify hydroclimatic and vegetation controls on water storage and conservation capacity [32]. Regional water-security assessments provide a complementary framework for connecting ecological conditions with sustainable water management [26]. Integrated carrying-capacity analyses likewise show the value of combining water-resource, environmental, and development indicators for basin planning [33]. Huang et al. [34] examined the western Dabie Mountains during 1980–2018; the present study focuses on a different spatial segment and uses ten benchmark-year snapshots, so the numerical trend magnitudes are best interpreted as contextual cross-study evidence. Wang et al. [35] highlighted trade-offs between land-use intensity and ecosystem services in ecologically critical areas. The contribution of the present study is to combine service magnitude, coordination status, and historical tendency in a management-oriented framework. Relative to the process-based InVEST framework described by Sharp et al. [4], this workflow adds sub-watershed diagnosis and differentiated management zoning.

6. Conclusions

This study assessed forest water-conservation services in the eastern Dabie Mountains over 1985–2024 using ten benchmark-year maps and translated the results into a management framework based on service intensity, coupling coordination, and historical tendency. The design captures the long-term setting and benchmark-year variability, while the tendency analysis characterizes changes across the selected historical benchmark years. The main conclusions are as follows:

- (1) Core findings: Across the ten benchmark years spanning 1985–2024, mean forest water-conservation capacity was 362.7 mm. The complete sequence yielded an OLS slope of 1.40 mm/a and a Theil–Sen slope of 1.85 mm/a, with $Z_{MK} = 0.54$ and $p = 0.592$; the MK tendency was non-significant at $\alpha = 0.05$. The 2022 drought benchmark year reduced capacity to 268.2 mm, followed by recovery to 369.6 mm in 2024. This recovery is consistent with renewed hydroclimatic moisture supply and provides a basis for further assessment of forest-mediated buffering processes.
- (2) Framework contribution: High-quality and moderate coordination covered 67.38% of the area and were concentrated in central forested massifs. Integrating InVEST water-yield outputs, water-conservation surfaces, CCD diagnosis, and pixel-level historical tendency provides a framework for comparing spatial differences with benchmark-year hydroclimatic variability. The historical tendency layers provide spatial evidence for comparing benchmark-year changes and guiding regional management priorities.
- (3) Management implications: A differentiated forest-watershed strategy is recommended: strict passive protection in core forest massifs, close-to-nature mixed forestry and riparian buffering in transition zones, and active ecological restoration and land-use control in fringe imbalance zones. Annual observations, gauged runoff, field measurements, and future climate or land-use scenarios are needed to support subsequent validation and adaptive management.

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(Yuanyuan Tang); supervision, Y.T. (Yuanyuan Tang); project administration, Y.T. (Yuanyuan Tang). All authors have read and agreed to the published version of the manuscript.

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