

Article

Surface Inundation Gradients and Lagged Fractional Vegetation Cover Responses of *Populus euphratica* Oliv. Forests to Ecological Water Conveyance in the Lower Tarim River, China

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Abstract

To quantify the spatial and lagged associations between ecological water conveyance and fractional vegetation cover (FVC) in *Populus euphratica* Oliv. forests, we integrated Landsat imagery (1995–2025), conveyance records, groundwater observations, and multi-period random forest classifications in the lower Tarim River. Newly formed or expanded surface water was mapped within dynamic annual response windows and characterized by annual surface inundation expansion area, multi-year inundation frequency, and distance from forest pixels to recurrently inundated water surfaces. These metrics were related to FVC using Theil–Sen trends and Lag 0–Lag 3 correlations. After 2010, reservoir releases, annual surface inundation expansion area, and groundwater conditions generally improved. Mean FVC increased by 0.182 percentage points per year, with improvement and degradation interspersed spatially. Relatively low- to moderate-frequency inundation was associated with pronounced positive FVC trends, and FVC improvement was concentrated within 0–0.5 km of recurrently inundated water surfaces. Associations of FVC with reservoir releases, groundwater depth, and annual surface inundation expansion area were strongest after 2–3 years. Together, these surface inundation metrics complement reservoir-release and groundwater records and support spatially differentiated monitoring of FVC changes in *P. euphratica* forests.

Keywords: *Populus euphratica*; forest hydrology; ecological water conveyance; surface inundation; inundation frequency; fractional vegetation cover; lagged response



Academic Editor: Pengtao Yu

Received: 22 August 2026

Revised: 10 September 2026

Accepted: 16 September 2026

Published: 19 September 2026

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1. Introduction

Runoff regulation, groundwater decline, and insufficient lateral recharge threaten riparian forests, wetlands, and ecological corridors. Environmental flows and ecological water conveyance are therefore used to maintain river connectivity and restore riparian habitats [1–3]. The lower Tarim River, between the Taklimakan and Kuruk deserts, forms an important ecological barrier that supports oasis stability and regional ecological security [4]. As the dominant riparian tree species in this corridor, *Populus euphratica* Oliv. plays an important role in maintaining riparian vegetation. Under scarce precipitation and intense

evaporation, *P. euphratica* forest growth depends mainly on river inflow, groundwater availability, and episodic surface-water recharge [5,6]. Ecological water conveyance is therefore particularly important for maintaining water availability and supporting *P. euphratica* forest recovery in the lower Tarim River.

Since 2000, ecological water conveyance has promoted hydrological restoration and *P. euphratica* habitat improvement in the lower Tarim River [7]. However, delivered water volume alone does not explain the spatial heterogeneity of forest recovery. Existing evaluations generally combine water-input, hydrological-response, and vegetation-recovery indicators [8–11]. Reservoir releases and conveyance duration describe delivery intensity but not whether water reaches side channels, floodplains, or forest patches. Groundwater depth characterizes subsurface conditions at monitored locations [12], whereas fractional vegetation cover (FVC) and the normalized difference vegetation index (NDVI) describe vegetation outcomes without locating surface-water access [13]. A recent meta-analysis also showed that *P. euphratica* responses vary under different water-management conditions [14]. However, existing studies have mainly focused on water availability or hydrological conditions, while the spatial accessibility of conveyed surface water, particularly its expansion extent, recurrence, and proximity to *P. euphratica* forests, remains insufficiently quantified. A key unresolved issue is how the spatial distribution of conveyed surface water is associated with spatial variation in *P. euphratica* forest FVC.

Recent studies have examined this forest–water relationship at complementary scales. Plot comparisons linked inundation to understory microclimate, soil conditions, and drought-related physiology of *P. euphratica* [15]. Tree-ring analyses related radial growth and drought resilience to hydrothermal conditions and groundwater depth [16]. Terrestrial light detection and ranging (LiDAR) surveys associated stand structure and regeneration with groundwater, soil moisture, and salinity [17], while Landsat phenology analysis showed that climatic and hydrological effects varied with groundwater depth [18]. Unmanned aerial vehicle (UAV) surveys can complement satellite observations by providing finer-scale information on riparian canopy structure, channel morphology, and habitat characteristics [19]. Research in another river system found nonlinear vegetation responses across inundation-frequency classes [20]. These studies reveal multiple forest responses to water availability, but mainly focus on physiological, structural, phenological, or hydrological responses, while regional-scale studies linking conveyed surface-water accessibility to long-term forest FVC change remain limited.

Surface inundation represents the intermediate spatial process between water delivery and forest response. Ecological water conveyance can restore terminal lakes, wetlands, and riparian moisture conditions [21,22], while floodwater expansion and vegetation response have been used to evaluate environmental-flow outcomes [23]. In the lower Tarim River, newly formed or expanded surface water during ecological water conveyance response periods indicates lateral expansion beyond established water bodies. Annual surface inundation expansion area characterizes expansion extent, multi-year inundation frequency characterizes recurrence, and distance from forest pixels to recurrently inundated water surfaces characterizes proximity to potential recharge sources [24,25]. Together, these metrics provide spatial information that complements release and groundwater records. At the landscape scale, Landsat-based spectral indices such as the Modified Normalized Difference Water Index (MNDWI) provide established approaches for mapping surface water [26]. The Joint Research Centre (JRC) Global Surface Water dataset provides a consistent reference for long-term surface-water occurrence [27].

We integrated Landsat imagery from 1995 to 2025 with reservoir releases, ecological water conveyance dates, groundwater depth observations, and multi-period *P. euphratica* classifications. Three questions guided the analysis: (1) how far and how often surface

water expanded during ecological water conveyance response periods; (2) how forest FVC varied along inundation-frequency and distance gradients; and (3) whether FVC responses were delayed relative to reservoir releases, groundwater depth, and annual surface inundation expansion area. This framework provides a spatial basis for identifying forest areas with limited surface-water accessibility and evaluating spatial variation in *P. euphratica* forest responses to ecological water conveyance.

2. Materials and Methods

2.1. Study Area and Data Sources

The lower Tarim River is located in the eastern Tarim Basin, Xinjiang, China. The region has a temperate continental arid climate, with a mean annual temperature of approximately 10 °C, annual precipitation of 20–50 mm, and annual potential evaporation of 2429–2910 mm [28]. Natural surface-water recharge capacity is weak. The growth of *P. euphratica* forest is mainly affected by river inflow, groundwater depth, and episodic surface-water recharge [24,29]. Influenced by upstream inflow changes and water-resource development, the runoff regime in the lower reaches is strongly regulated by human activities. Ecological water conveyance has therefore become an important hydrological process for maintaining riparian water conditions and restoring *P. euphratica* forest [30]. This study focused on the *P. euphratica* forests in the lower Tarim River and analyzed FVC changes from 1995 to 2025 using the long-term Landsat record, which covers the pre-conveyance baseline before 2000 and the subsequent ecological water-conveyance period, together with surface inundation patterns and their spatial associations with forest responses. The location of the study area, main river channels, and land-cover background in 2025 are shown in Figure 1.

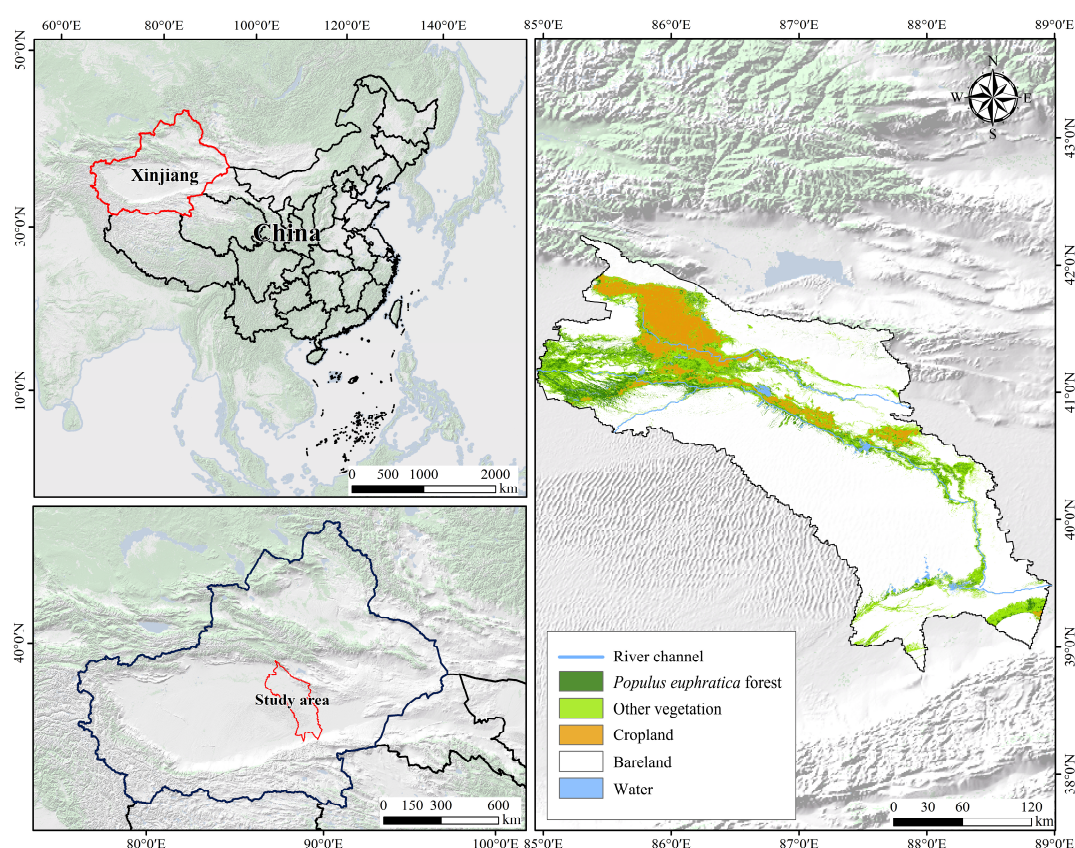


Figure 1. Location of the study area and spatial background of major surface types in 2025. Note: The national location map was based on the standard map of China (approval number: GS(2024)0650).

This study used Landsat 5/7/8/9 surface reflectance imagery, ecological water conveyance records, groundwater depth data, Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) data, JRC Global Surface Water, World Wildlife Fund (WWF) HydroSHEDS (Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales) river-channel vectors, and visually interpreted samples (Table 1) [27,31,32]. Landsat imagery was processed on the Google Earth Engine (GEE) platform, including cloud and cloud-shadow removal, reflectance scaling, band harmonization, and cross-sensor consistency correction for Operational Land Imager (OLI) imagery [33,34]. Detailed image selection, annual compositing, and preprocessing parameters are provided in Table S1. Ecological water conveyance dates were used to determine the dynamic observation windows, while reservoir releases and groundwater depth data from three monitoring transects were used for hydrological response analysis. No ecological water conveyance occurred in 2008, and groundwater depth observations were unavailable for that year.

Table 1. Main datasets and sources used in this study.

Data Type	Dataset	Time Range	Spatial Resolution	Data Source	Main Purpose
Remote sensing imagery	Landsat Collection 2 Level-2 Surface Reflectance imagery	1995–2025	30 m	United States Geological Survey (USGS)/Google Earth Engine	Land-cover classification, FVC retrieval, and surface inundation extraction
Topographic data	SRTM digital elevation model	Not applicable	30 m	National Aeronautics and Space Administration (NASA)/USGS	Elevation and slope features
Surface water data	JRC Global Surface Water	1984–present	30 m	European Commission Joint Research Centre	Stable water identification and hydrological corridor constraint
River channel data	WWF HydroSHEDS river channel vector data	Not applicable	Vector	WWF HydroSHEDS	River-distance calculation and buffer analysis
Ecological water conveyance data	Reservoir releases from Daxihaizi Reservoir and water conveyance start and end dates	2000–2025	Annual	Tarim River Basin Management Bureau	Water conveyance intensity analysis and dynamic observation window determination
Groundwater depth data	Groundwater depth data from three monitoring transects	2000–2020	Annual	Compiled from Chen Yongjin’s published data	Groundwater depth change analysis
Sample data	Visually interpreted samples from Google Earth high-resolution imagery	Multiple periods	Sub-meter to meter-scale (Google Earth); 30 m (Landsat)	Google Earth/interpretation of typical-year Landsat imagery	Classification training and validation

The analytical workflow is shown in Figure 2 and includes multi-source data preprocessing, derivation of surface inundation metrics, *P. euphratica* forest FVC retrieval, and response analysis.

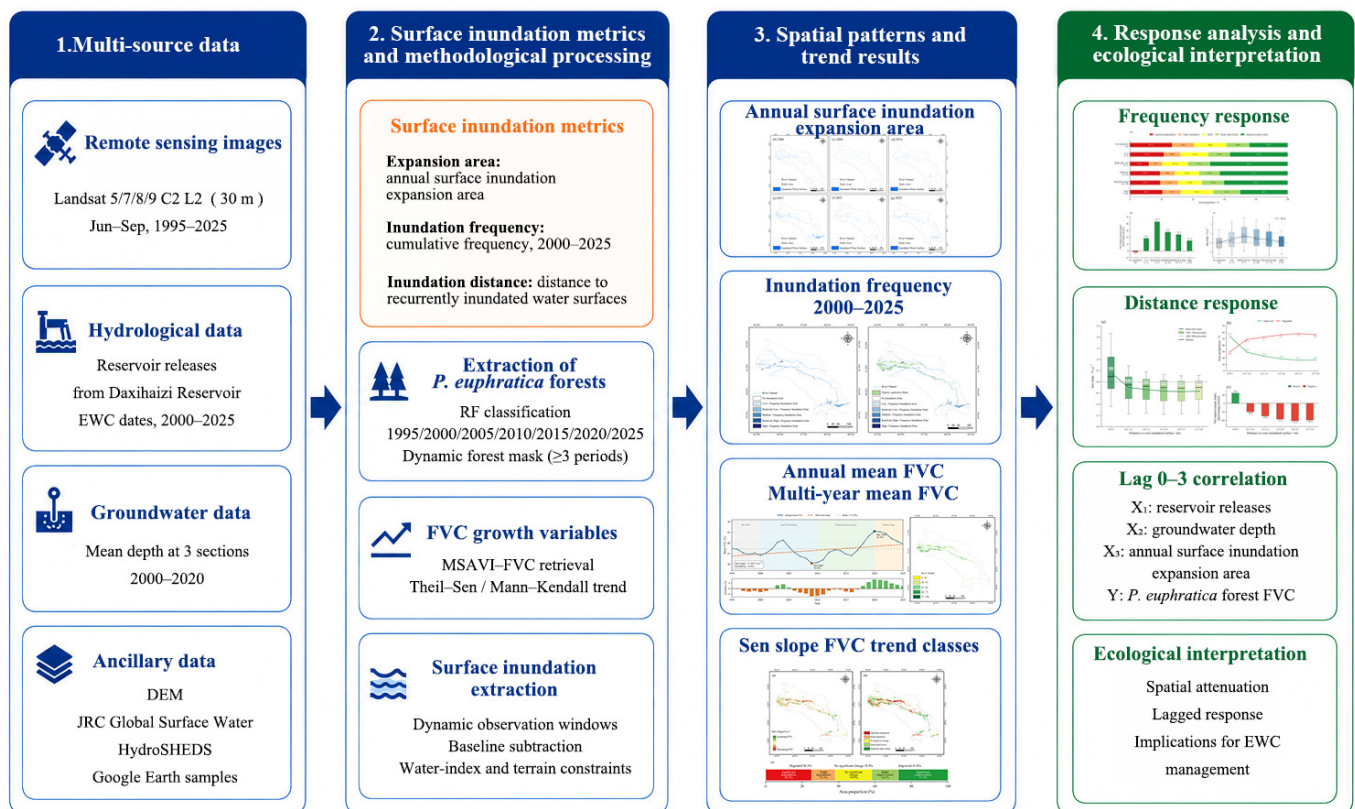


Figure 2. Analytical workflow for mapping surface inundation and evaluating *P. euphratica* forest FVC responses.

2.2. Multi-Temporal Consensus *P. euphratica* Forest Mask Construction and FVC Estimation

2.2.1. *P. euphratica* Forest Classification and Multi-Temporal Consensus Mask Construction

Random forest (RF) is widely used in remote-sensing classification because of its robustness and ability to handle complex, heterogeneous predictors [35,36]. Based on Landsat imagery, four land-cover classes, including *P. euphratica* forest, other vegetation, cultivated land, and bare land, were extracted for 1995, 2000, 2005, 2010, 2015, 2020, and 2025. A 5-year interval was adopted to provide regularly spaced classification observations across the study period for constructing the multi-temporal consensus *P. euphratica* forest mask. Water bodies were identified with the assistance of MNDWI and JRC Global Surface Water data [26,27]. The classification features included spectral bands, NDVI, enhanced vegetation index (EVI), MNDWI, normalized burn ratio (NBR), land surface water index (LSWI), shortwave infrared texture, DEM, and slope [37–41]. These features were selected to provide complementary information on vegetation greenness, surface water and moisture conditions, spectral texture, and topography, thereby supporting the separation of the four land-cover classes. The equations, spectral bands, and variables of the remote-sensing indices are summarized in Table 2. Landsat imagery information and scene inventory are provided in Table S2 and Supplementary Data S1, respectively.

Training samples were obtained from field samples, Google Earth historical imagery, and Landsat interpretation for typical years, and stable samples were selected to build a multi-period sample library [42]. Up to 1000 samples per class were randomly divided into training and validation sets (70:30, seed = 42). Five-fold spatial block cross-validation at 1, 3, and 5 km scales was additionally conducted to evaluate the influence of spatial dependence [43,44]. A separate RF classifier with 200 trees was trained for each classification year using corresponding Landsat imagery and samples. RF parameters and validation settings are summarized in Table S3. The RF model was evaluated using confusion matrices, includ-

ing overall accuracy (OA), kappa coefficient, producer's accuracy (PA), and user's accuracy (UA), where PA represents the proportion of reference samples correctly classified for each class and UA represents the proportion of classified samples that agree with reference data, indicating class-specific omission and commission errors [45,46]. RF outputs were refined using MNDWI, JRC water data, cropland constraints, vegetation-index thresholds, and non-vegetated masks. Sample statistics are provided in Table S4 and Figure S1. To reduce single-period classification errors, pixels identified as *P. euphratica* forest in ≥ 3 periods were retained in the multi-temporal consensus mask [47], while 2025 cropland and built-up land were excluded to reduce anthropogenic effects. Sensitivity of the consensus criterion was assessed using ≥ 2 , ≥ 3 , and ≥ 4 periods, and classification continuity was evaluated using adjacent-period spatial overlap rates [48].

Table 2. Remote-sensing indices used for land-cover classification.

Index	Formula	Variables
NDVI	$NDVI = \frac{NIR - Red}{NIR + Red}$	Red, NIR
EVI	$EVI = 2.5 \times \frac{NIR - Red}{NIR + 6 \times Red - 7.5 \times Blue + 1}$	Blue, Red, NIR
MNDWI	$MNDWI = \frac{Green - SWIR1}{Green + SWIR1}$	Green, SWIR1
NBR	$NBR = \frac{NIR - SWIR2}{NIR + SWIR2}$	NIR, SWIR2
LSWI	$LSWI = \frac{NIR - SWIR1}{NIR + SWIR1}$	NIR, SWIR1

Note: NIR, near-infrared; SWIR1, shortwave infrared 1; SWIR2, shortwave infrared 2. For Landsat 5/7, Blue = B1, Green = B2, Red = B3, NIR = B4, SWIR1 = B5, and SWIR2 = B7; for Landsat 8/9, Blue = B2, Green = B3, Red = B4, NIR = B5, SWIR1 = B6, and SWIR2 = B7.

2.2.2. FVC Retrieval and Endmember Determination

Within the multi-temporal consensus *P. euphratica* forest mask, Landsat imagery acquired during the June–September growing season was selected each year to generate annual median composites. Given the sparse canopy of the lower Tarim riparian forest, annual FVC was used to characterize long-term vegetation-cover dynamics [49]. The modified soil-adjusted vegetation index (MSAVI) was used to reduce the influence of soil background, and FVC for *P. euphratica* forest from 1995 to 2025 was retrieved based on the dimidiate pixel model [50,51]. The dimidiate pixel model assumes that each pixel contains mixed information from vegetation and bare soil, and FVC is estimated by scaling the observed MSAVI between vegetation and soil endmembers.

The FVC was calculated as follows [52]:

$$FVC = \frac{MSAVI - MSAVI_{soil}}{MSAVI_{veg} - MSAVI_{soil}} \times 100 \quad (1)$$

where $MSAVI_{soil}$ and $MSAVI_{veg}$ represent the MSAVI values of the bare-soil and full-vegetation endmembers, respectively. To ensure the comparability of multi-year FVC estimates, unified endmember values were used in this study. Within the valid area of the multi-temporal consensus *P. euphratica* forest mask after excluding cropland and built-up areas in 2025, the 5th and 95th percentiles of MSAVI were extracted for each year to determine the soil and vegetation endmembers while reducing the influence of extreme pixel values. The median values of these multi-year percentiles were then used as robust global estimates of the bare-soil and full-vegetation endmembers, respectively [53].

2.2.3. FVC Trend Test and Growth Class Classification

Based on annual FVC data, the Theil–Sen median slope estimator was used to estimate the rate of change in FVC, and the Mann–Kendall test was used to determine trend

significance [54,55]. Their non-parametric nature enables robust trend analysis without assuming data normality. The calculation formula is as follows [56]:

$$\beta = \text{median}\left(\frac{FVC_j - FVC_i}{j - i}\right), j > i \quad (2)$$

where β represents the rate of change in FVC, expressed in percentage points per year; FVC_i and FVC_j represent the FVC values in years i and j , respectively. $\beta > 0$ indicates improvement, whereas $\beta < 0$ indicates degradation. *P. euphratica* forest growth was classified into five levels (Table 3) based on existing vegetation trend classification methods [57–59] and the percentage unit and cumulative change magnitude of FVC over 1995–2025. The threshold sensitivity test showed that the pixel-level consistency between the alternative schemes and the scheme used in this study ranged from 90.66% to 95.57%, and the main recovery/degradation patterns remained stable (Table S5).

Table 3. Classification criteria for FVC growth classes of *P. euphratica* forest.

Growth Level	Judgment Conditions
Significant degradation	$\beta < -0.45$ and $p < 0.05$
Slight degradation	$-0.45 \leq \beta < -0.15$, or $\beta < -0.45$ and $p \geq 0.05$
Stable	$-0.15 \leq \beta \leq 0.15$
Slight improvement	$0.15 < \beta \leq 0.45$, or $\beta > 0.45$ and $p \geq 0.05$
Significant improvement	$\beta > 0.45$ and $p < 0.05$

Note: β is the annual change rate of FVC, expressed in percentage points per year. Thresholds of 0.15 and 0.45 percentage points per year correspond to cumulative changes of approximately 4.5 and 13.5 percentage points over a 30-year period, respectively.

2.3. Surface Inundation Extraction and Frequency Calculation During Ecological Water Conveyance

2.3.1. Dynamic Observation Windows and Surface Inundation Extraction

Based on the GEE platform, annual water bodies were identified from Landsat imagery from 2000 to 2025. The annual surface inundation expansion area during the ecological water-conveyance response period was defined as the area of newly formed or expanded surface water detected at least once during the response period after excluding water already present during the pre-conveyance baseline period. Dynamic observation windows were constructed from the recorded start and end dates of individual water-conveyance events from Daxihaizi Reservoir (Table S6). For years with multiple water-conveyance events, event-specific observation windows were defined and combined for annual surface inundation extraction. For regular events, the baseline period was defined as the month preceding the start of water conveyance, and the response period extended from the start date to 75 days after gate closure. For short-duration events (≤ 20 days), the image search window was extended to reduce omission errors caused by the temporal resolution and limited availability of Landsat imagery [60].

Water bodies were identified using an integrated thresholding method based on MNDWI, NDVI, NIR, SWIR1, and brightness index [26,61–64]. Background water bodies in the baseline period and multi-year stable water bodies from JRC Global Surface Water [27] were then excluded to extract newly formed or expanded surface inundation areas during the response period. The core discrimination thresholds, targeted controls for vegetation, wet soil or bare land, bright surfaces, and shadows, and representative visual verification examples are provided in Table S7 and Figure S2 [65].

2.3.2. Surface Inundation Frequency Calculation and Classification

Binary surface inundation layers from 2000 to 2025, excluding 2008 when no ecological water conveyance occurred, were accumulated pixel by pixel to obtain the surface inundation frequency during ecological water conveyance response periods:

$$F = \sum_{i \in Y} I_i$$

$$Y = \{2000, 2001, \dots, 2025\} \setminus \{2008\}$$

where F represents the surface inundation frequency during ecological water conveyance response periods, and I_i represents the binary surface inundation layer in year i . When newly formed or expanded surface water occurred in a pixel in a given year, I_i was assigned a value of 1; otherwise, it was assigned a value of 0.

For mapping and group comparison, six inundation-frequency classes were defined to represent increasing recurrence intensity and facilitate spatial comparisons (Table 4). The ≥ 3 -year threshold was used to identify recurrently inundated areas and reduce the influence of occasional one- or two-year inundation occurrences; its spatial sensitivity was evaluated across thresholds from ≥ 3 to ≥ 6 years (Table S8). Pixel-level frequency values were retained for subsequent statistical analyses.

Table 4. Classification criteria for surface inundation frequency during ecological water conveyance response periods.

Frequency	Surface Inundation Class
0	No surface inundation area
1–2	Low-frequency surface inundation area
3–5	Relatively low-frequency surface inundation area
6–10	Moderate-frequency surface inundation area
11–15	Relatively high-frequency surface inundation area
16–23	High-frequency surface inundation area

2.4. Analysis of *P. euphratica* Forest Growth Responses to Surface Inundation

2.4.1. Differences in *P. euphratica* Forest Growth Among Inundation Frequency Classes

According to Table 4, *P. euphratica* forest pixels were classified into six inundation-frequency classes ranging from no inundation to high-frequency inundation. The proportions of FVC growth classes, Sen slope, and net improvement index (improved pixel proportion minus degraded pixel proportion) were calculated for each class. Differences among groups were evaluated using the rank-based Kruskal–Wallis test, which does not require a normality assumption and is suitable for comparing multiple independent groups, followed by Mann–Whitney U tests with Benjamini–Hochberg false discovery rate (FDR) correction to control the increased risk of false positives from multiple pairwise comparisons [66–68]. To account for spatial dependence among neighboring 30 m pixels, Global Moran’s I was calculated for block-median Sen slopes at 500 m, 1 km, and 2 km scales using rook contiguity and 999 permutations [69]. Robustness of inundation-frequency comparisons was further assessed using spatial block-cluster bootstrap analysis at five spatial scales (500 m, 1 km, 2 km, 3 km, and 5 km) with 2000 replicates to derive 95% confidence intervals [70].

2.4.2. Growth Responses of *P. euphratica* Forest Along Inundation Distance Gradients

Pixels with inundation frequency ≥ 3 during 2000–2025 were defined as recurrently inundated areas, and the Euclidean distance from each pixel within the multi-temporal consensus *P. euphratica* forest mask to the nearest recurrently inundated water surface was calculated. This threshold was used to identify areas with repeated inundation signals and

reduce the influence of occasional surface water occurrence and short-term ponding on the distance-based analysis. With reference to the reported concentration of riparian vegetation within 3 km of the river channel in the lower Tarim River [71], a 0–3 km distance range was adopted for descriptive analysis of proximity to recurrently inundated areas. This range was divided into six equal 0.5 km intervals to balance spatial detail and the number of pixels available within each class. Multi-year mean FVC, Sen slope, the proportion of each growth class, and the net improvement index were then calculated within each distance gradient to compare changes in *P. euphratica* forest growth across distance gradients.

2.4.3. Time-Lagged Correlation Analysis

Lagged correlations over 0–3 years were examined between reservoir releases from Daxihaizi Reservoir (X_1), mean groundwater depth across the three monitoring transects (X_2), annual surface inundation expansion area during response periods (X_3), and annual mean FVC of *P. euphratica* forest (Y). Pearson correlations between $X_i(t)$ and $Y(t+k)$ were calculated for $k = 0-3$, with all observations and lagged pairs involving 2008 excluded. Spearman correlations and linearly detrended Pearson correlations were additionally calculated to assess robustness [72]. The optimal lag was defined as that with the largest absolute Pearson correlation coefficient, and R^2 was used to compare association strength. Linear regression was used to illustrate the relationships between each water-related variable and FVC at its optimal lag.

Use of Generative AI

Generative AI tools were used solely for English translation and language polishing during manuscript preparation. They were not used for study design, data acquisition, data processing, statistical analysis, interpretation of results, or the generation of data and figures. All AI-assisted text was reviewed and verified by the authors, who take full responsibility for the content of the manuscript.

3. Results

3.1. Hydrological Processes and Surface Inundation Patterns Under Ecological Water Conveyance

3.1.1. Variations in Ecological Water Releases and Groundwater Depth

Since the implementation of ecological water conveyance in 2000, reservoir releases to the lower Tarim River have shown distinct temporal changes (Figure 3a). For descriptive comparison, the study period was divided into three stages according to temporal changes in reservoir releases: the early conveyance stage (2000–2009), enhanced conveyance stage (2010–2020), and recent stage (2021–2025). During 2000–2009, reservoir releases were generally low and showed substantial interannual variability. After 2010, reservoir releases increased markedly [73], with the mean release increasing from $2.27 \times 10^8 \text{ m}^3$ during 2000–2009 to $5.62 \times 10^8 \text{ m}^3$ during 2010–2020. Over the same period, the mean groundwater depth across the three monitoring transects decreased from 5.71 m to 4.55 m, indicating an overall improvement in groundwater conditions (Figure 3b). During 2021–2025, reservoir releases remained at a medium-to-high level, and interannual variability weakened.

3.1.2. Annual Variations in Surface Inundation Area During Ecological Water Conveyance

The annual surface inundation expansion area showed distinct stage-based variation from 2000 to 2025 (Figure 4a). During 2000–2009, excluding 2008 when no ecological water conveyance occurred, the mean surface inundation expansion area was approximately 193.3 km^2 , with substantial interannual fluctuations. It increased to 451.0 km^2 during 2010–2020, with the highest values occurring during 2016–2019 and a peak of 820.3 km^2 in 2017. During 2021–2025, the mean surface inundation expansion area decreased to 342.2 km^2 . To illustrate spatial variation across the three conveyance stages, 2000 and 2004

were selected for the early conveyance stage, 2014 and 2017 for the enhanced conveyance stage, and 2021 and 2025 for the recent stage (Figure 4b–g). The representative maps showed substantial differences in the extent and spatial distribution of inundated water surfaces both among and within stages, with the most extensive inundation occurring in 2017 and relatively localized inundation in 2004 and 2014. Overall, surface-water expansion increased after 2010 but remained highly variable among years.

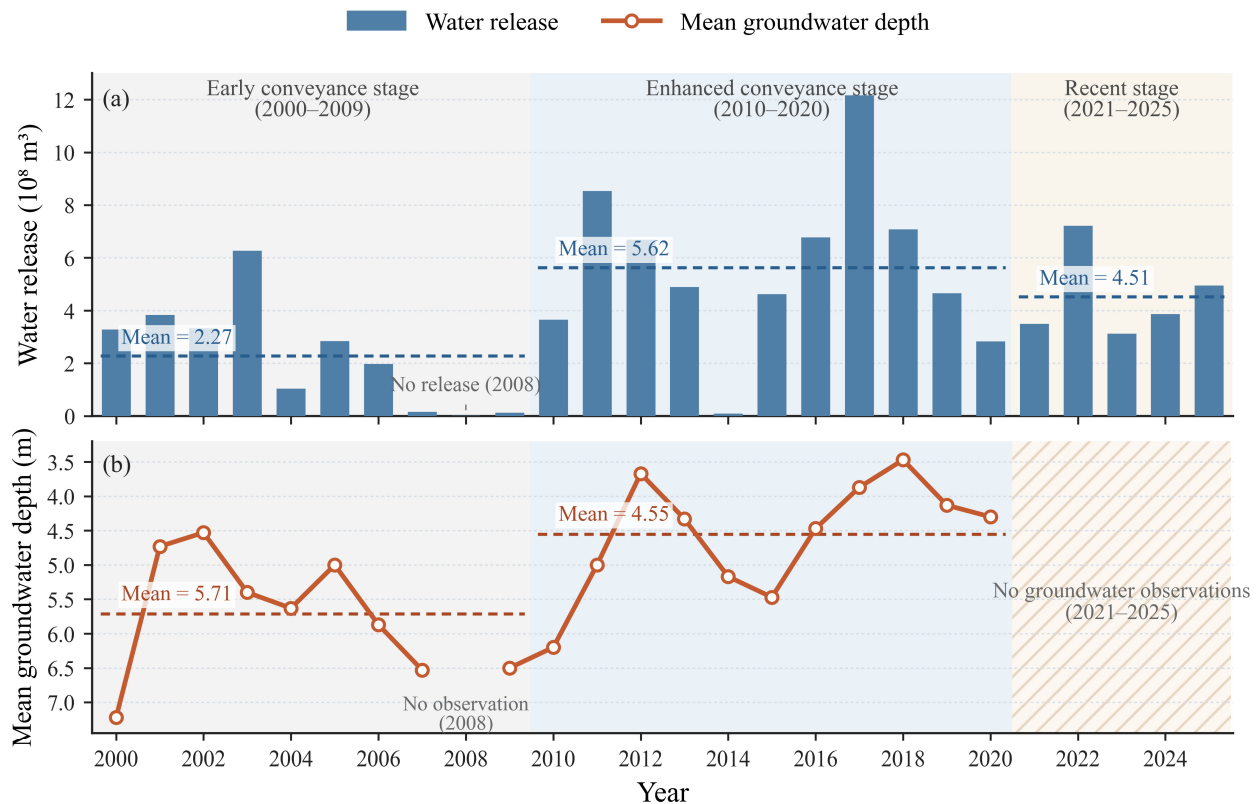


Figure 3. Dynamic changes in ecological reservoir releases and mean groundwater depth in the lower Tarim River. Note: (a) Changes in ecological reservoir releases to the lower Tarim River from 2000 to 2025, represented by releases from Daxihaizi Reservoir; (b) changes in mean groundwater depth from 2000 to 2020. Groundwater depth represents the annual mean values of three typical monitoring transects: Yingsu, Kaerdayi, and Yiganbujima. Groundwater depth from 2021 to 2025 is not shown due to data availability limitations.

3.1.3. Spatial Patterns of Surface Inundation Frequency

Surface inundation frequency reflects the multi-year recurrence of newly formed or expanded surface water during ecological water conveyance response periods. Annual surface inundation expansion maps for 2000–2025 are provided in Figure S3, showing interannual variation in inundation extent and spatial distribution. From 2000 to 2025, surface inundation frequency showed a clear channel-constrained pattern. High-frequency and relatively high-frequency inundation areas were mainly concentrated in the main river channel, locally connected side channels, and terminal water-collecting areas. Low- to moderate-frequency inundation areas extended along the downstream river channel, lateral shallow channels, and terminal areas, whereas desert areas far from the river channels were rarely inundated (Figure 5a). Low-frequency and relatively low-frequency inundation areas dominated the inundated area, accounting for 54.1% and 18.7%, respectively, whereas relatively high-frequency and high-frequency areas accounted for only 6.7% and 2.0%, respectively (Figure 5). Overall, recurrent inundation was concentrated along the river network, while high-frequency inundation occupied a relatively small proportion of the

inundated area. The overlay of the multi-temporal consensus *P. euphratica* forest mask with surface inundation frequency showed that detected surface inundation overlapped 487.7 km² of the valid *P. euphratica* forest analysis area, accounting for 18.2% (Figure 5b). Among the *P. euphratica* forest areas where surface inundation was detected, 88.5% occurred within the low- to moderate-frequency inundation classes.

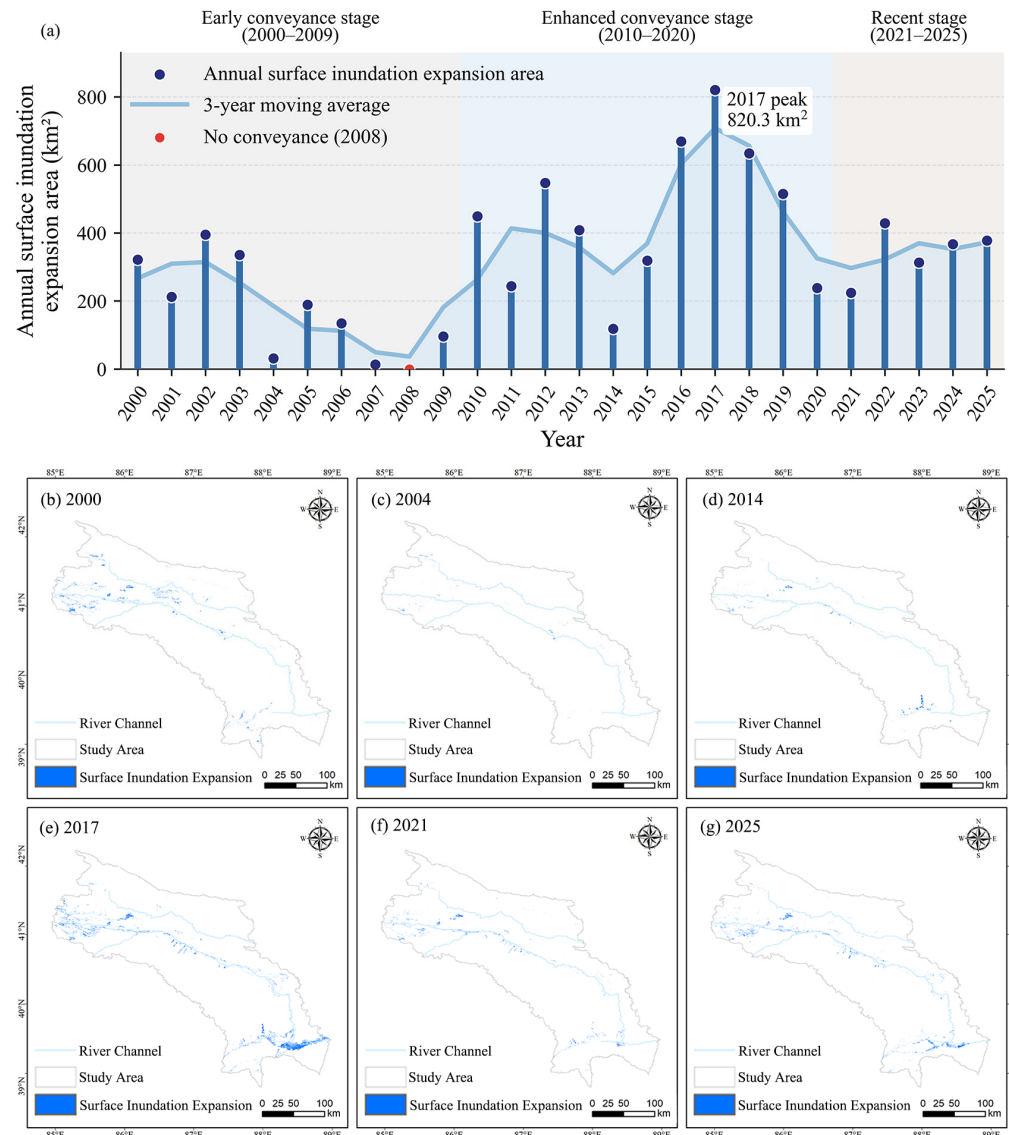


Figure 4. Annual surface inundation expansion area from 2000 to 2025 and spatial distributions in representative years across three ecological water-conveyance stages: (a) annual variation in surface inundation expansion area; (b–g) spatial distributions in 2000, 2004, 2014, 2017, 2021, and 2025, respectively.

3.2. Characteristics of FVC Changes in *P. euphratica* Forest

3.2.1. Accuracy Assessment and Spatial Consistency Evaluation of Random Forest Classification

The seven-period random forest classification results showed that the overall accuracy (OA) ranged from 84.6% to 89.5%, and the kappa coefficient ranged from 0.795 to 0.860. The mean OA and kappa coefficient were 88.0% and 0.840, respectively (Table 5). The producer's accuracy (PA) of *P. euphratica* forest ranged from 73.3% to 82.8%, and the user's accuracy (UA) ranged from 73.3% to 81.2%, with mean values of 78.4% and 76.4%, respectively. Five-fold spatial-block cross-validation at 1, 3, and 5 km yielded mean OA values across the seven periods of 83.0%, 81.5%, and 80.7%, and corresponding mean kappa

coefficients of 0.772, 0.750, and 0.737 (Table S9). Together, these assessments support the use of the classification results for consensus mask construction. The ≥ 3 -period criterion required repeated identification of pixels as *P. euphratica* forest to reduce the influence of single-period classification errors; threshold sensitivity results are presented in Table S10. The spatial overlap rate of *P. euphratica* classification results between adjacent periods ranged from 59.83% to 86.71%, with a mean value of 73.22% (Table S11), indicating spatial consistency alongside inter-period differences.

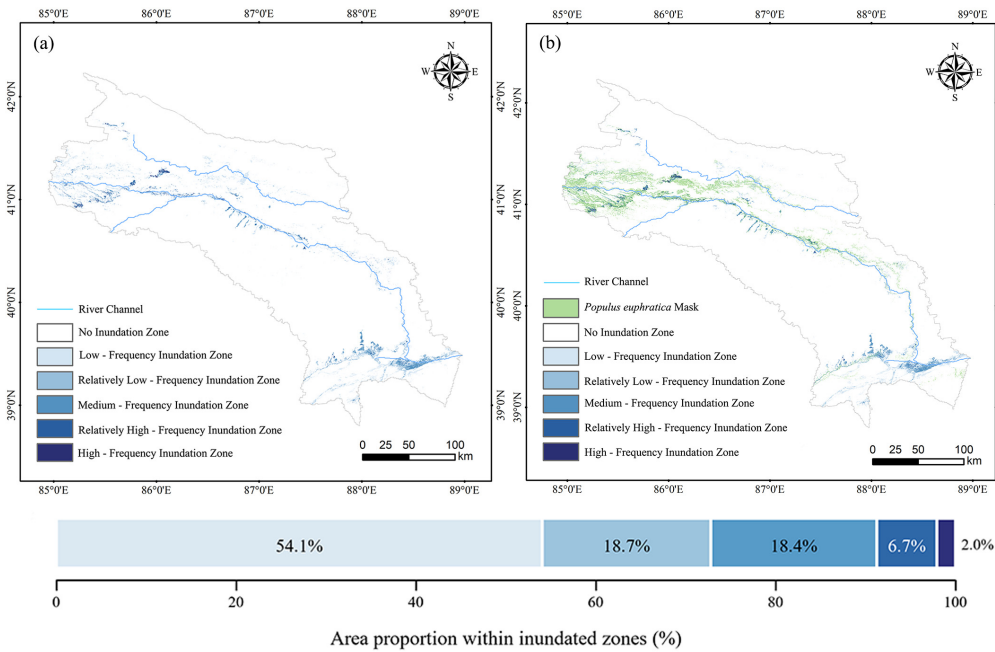


Figure 5. Surface inundation frequency during ecological water conveyance response periods from 2000 to 2025 and its spatial relationship with the multi-temporal consensus *P. euphratica* forest mask: (a) surface inundation frequency during ecological water conveyance response periods from 2000 to 2025; (b) spatial relationship between surface inundation frequency and the multi-temporal consensus *P. euphratica* forest mask.

Table 5. Accuracy assessment of random forest classification models for different years.

Year	OA (%)	Kappa	<i>P. euphratica</i> PA (%)	Other Vegetation PA (%)	Cultivated Land PA (%)	Bare Land PA (%)	<i>P. euphratica</i> UA (%)	Other Vegetation UA (%)	Cultivated Land UA (%)	Bare Land UA (%)
1995	84.6	0.795	78.3	71.0	89.9	99.0	73.5	73.6	93.5	97.7
2000	89.2	0.856	82.8	77.6	95.6	98.3	78.0	80.5	97.6	97.7
2005	89.0	0.856	81.0	77.3	97.6	98.3	75.8	79.9	99.4	99.0
2010	86.7	0.822	73.6	74.7	99.0	98.0	74.1	74.5	98.3	98.3
2015	87.4	0.832	73.3	78.2	96.3	98.7	73.3	76.6	97.6	99.4
2020	89.5	0.860	81.7	79.8	97.0	98.4	78.9	80.6	98.3	99.4
2025	89.5	0.860	78.2	79.7	99.3	97.7	81.2	75.7	99.0	99.0
Mean	88.0	0.840	78.4	76.9	96.4	98.3	76.4	77.3	97.7	98.6

3.2.2. Interannual Variation and Spatial Distribution of FVC in *P. euphratica* Forest

The annual mean FVC of *P. euphratica* forest showed pronounced interannual variation and distinct temporal changes from 1995 to 2025, with a multi-year mean of 37.29%. The overall Theil–Sen slope was 0.182 percentage points per year, and the Mann–Kendall test indicated a significant long-term increasing trend ($p = 0.041$) (Figure 6). Annual mean FVC reached its minimum in 2009 (30.42%), increased overall thereafter, and reached a maximum of 45.54% in 2020, followed by a decline toward 2025.

Spatially, multi-year mean FVC was mainly distributed in strips and patches along the lower Tarim River. The study area was dominated by low to moderate FVC values

(30%–60%). Areas with FVC above 60% were mainly distributed in the western part of the study area and in some near-channel areas, whereas patches with FVC of 75%–100% were limited in extent and spatially fragmented. Overall, multi-year mean FVC exhibited substantial spatial variation across the *P. euphratica* forest.

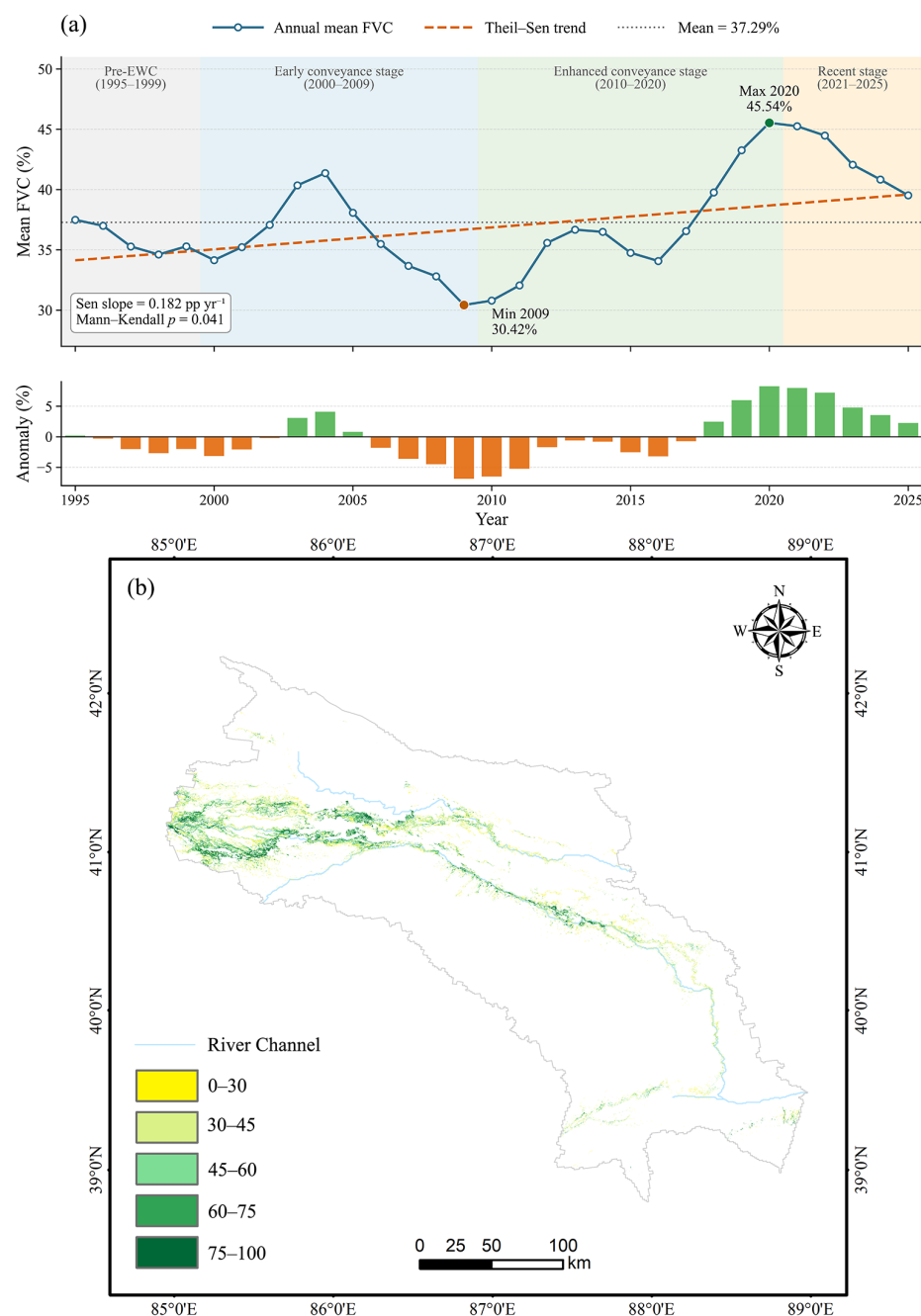


Figure 6. Interannual variation in annual mean FVC and spatial distribution of multi-year mean FVC in *P. euphratica* forest from 1995 to 2025. Note: (a) The interannual variation and anomalies of annual mean FVC within the multi-temporal consensus *P. euphratica* forest mask. The orange dashed line represents the Theil–Sen trend line, and the gray dashed line represents the multi-year mean value from 1995 to 2025. (b) The spatial distribution of multi-year mean *P. euphratica* forest FVC. The unit of FVC is %.

3.2.3. FVC Change Trends, Growth Classes, and Area Proportions of *P. euphratica* Forest

From 1995 to 2025, FVC trends of *P. euphratica* forest in the lower Tarim River showed substantial spatial variation, with increasing and decreasing areas interspersed along the

river corridor (Figure 7a). Increasing areas were mainly distributed in the western part of the study area, the southeastern river corridor, and areas near the terminal reaches, whereas decreasing areas were mainly concentrated in the central riparian zone and the west-central transition zone. Based on the Sen slope and Mann–Kendall significance test, FVC trends of *P. euphratica* forest were classified into five growth classes (Figure 7b). Area statistics showed that improved areas accounted for 41.8%, degraded areas accounted for 38.3%, and areas with no significant change accounted for 19.9% (Figure 7). Overall, improved areas slightly exceeded degraded areas, while improvement, degradation, and no significant change were all widely distributed across the *P. euphratica* forest.

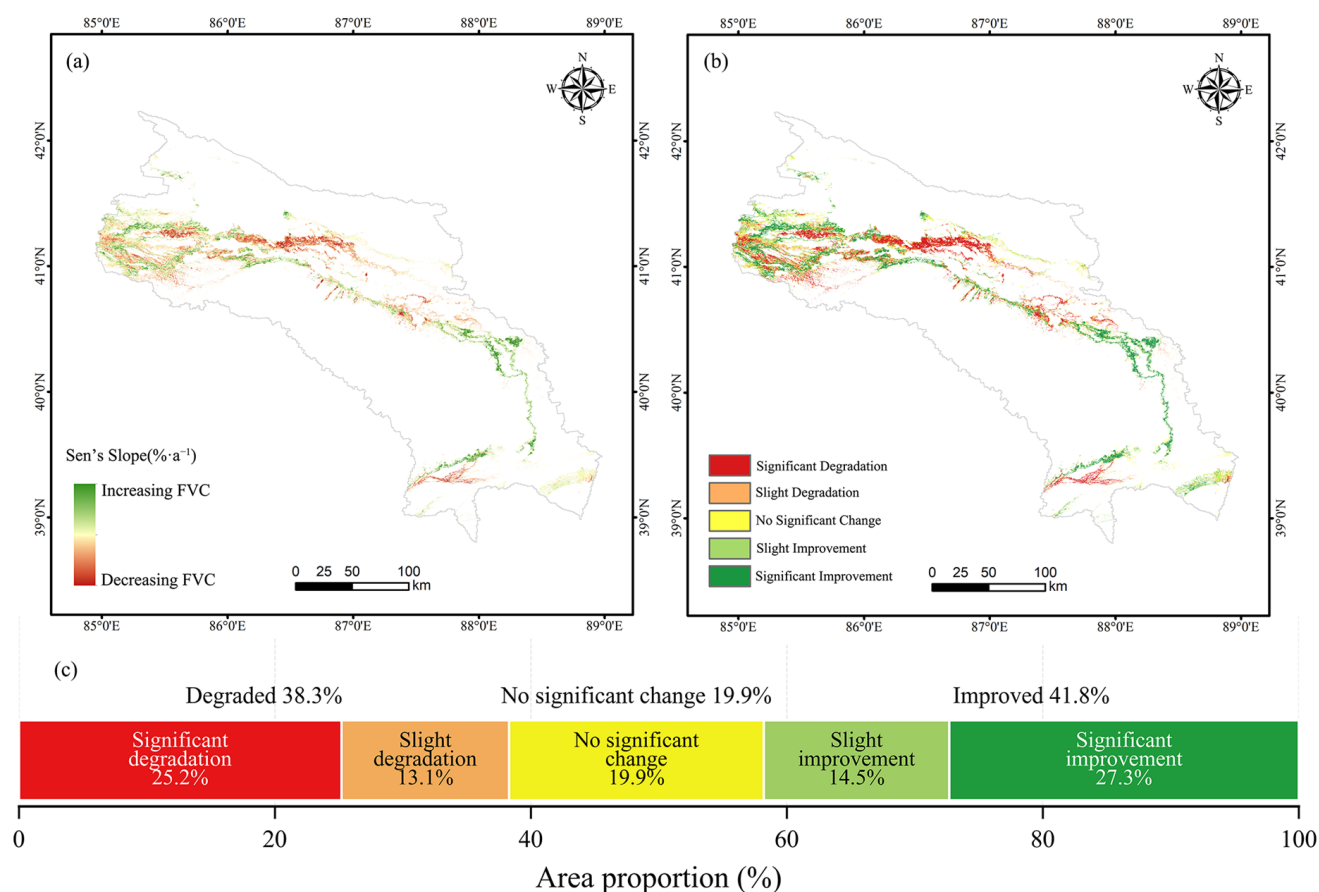


Figure 7. Spatial patterns of FVC change trends, growth classes, and area proportions of *P. euphratica* forest. Note: (a) The spatial distribution of the Theil–Sen slope, expressed in percentage points per year, (b) the spatial distribution of FVC growth classes of *P. euphratica* forest, and (c) the area proportions of the five FVC growth classes of *P. euphratica* forest. The horizontal bar shows the area proportions of the five growth classes.

3.3. Surface Inundation Patterns and *P. euphratica* Forest Growth Responses

The preceding results showed that ecological water conveyance was accompanied by changes in reservoir releases, groundwater conditions, and surface inundation, while *P. euphratica* forest FVC exhibited substantial temporal and spatial variation. To link these hydrological changes with forest responses, this section examines FVC variation across inundation-frequency and distance gradients and further compares its temporal associations with reservoir releases, groundwater depth, and annual surface inundation expansion area.

3.3.1. Differences in FVC Growth of *P. euphratica* Forest Among Different Surface Inundation Frequency Classes

To analyze the relationship between surface inundation frequency and *P. euphratica* forest growth, the composition of FVC growth classes, net improvement index, and Sen slope distribution were calculated for different inundation-frequency classes (Figure 8). In no-inundation areas, degraded pixels slightly exceeded improved pixels, resulting in a net improvement index of -1.7 percentage points. Improved pixels generally showed higher proportions in inundated areas than in no-inundation areas, with relatively low-frequency inundation showing the highest improvement proportion (63.0%) and net improvement index (42.7 percentage points) (Figure 8a,b). However, the improvement proportion decreased to 47.2% in high-frequency inundation areas, indicating weaker improvement than in relatively low- and moderate-frequency classes.

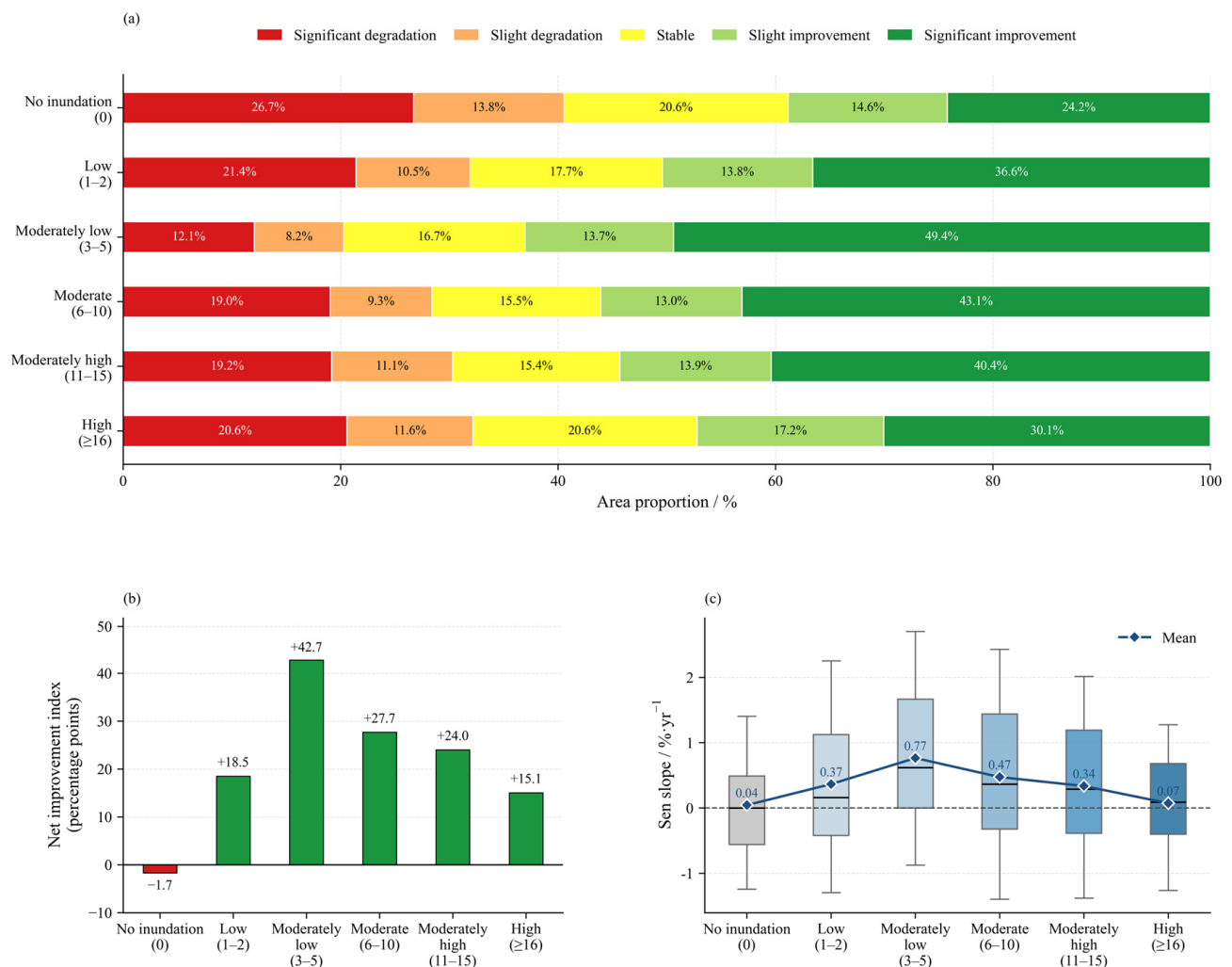


Figure 8. FVC growth response characteristics of *P. euphratica* forest under different surface inundation frequency classes. Note: (a) Composition of FVC growth classes of *P. euphratica* forest under different surface inundation frequency classes; (b) net improvement index under different surface inundation frequency classes; (c) differences in Sen slopes among different surface inundation frequency classes. The box represents the interquartile range (25th–75th percentiles), the horizontal line inside the box represents the median, the whiskers represent the range from the 10th to the 90th percentile, the blue diamond represents the mean, and the dashed line represents a Sen slope of 0.

The Sen slope distribution showed a similar non-monotonic pattern (Figure 8c). The highest mean Sen slope occurred in relatively low-frequency inundation areas (0.77 percent-

age points per year), followed by moderate-, low-, and relatively high-frequency classes (0.47, 0.37, and 0.34 percentage points per year, respectively), whereas high-frequency inundation areas showed a much lower value (0.07 percentage points per year), close to that of no-inundation areas. Differences among inundation-frequency classes remained significant after FDR correction ($p < 0.001$; Tables S14 and S15).

Global Moran's I values of 0.892, 0.844, and 0.764 at 500 m, 1 km, and 2 km, respectively, confirmed positive spatial dependence in FVC trends (Table S16). Spatial block-cluster bootstrap results showed that the higher improvement trends in relatively low- and moderate-frequency inundation classes than in no-inundation and low-frequency classes were consistent across block scales from 500 m to 5 km, whereas contrasts involving the high-frequency class varied with scale (Table S17). These results indicate that the main between-class pattern was robust to spatial aggregation.

3.3.2. Growth Responses of *P. euphratica* Forests Along Inundation Distance Gradients

To assess how *P. euphratica* forest growth varied with distance from inundated water surfaces, pixels inundated at least three times during 2000–2025 were used to define the reference inundation surface. The distance from each *P. euphratica* forest pixel to the nearest inundated water surface was calculated and divided into six gradients from 0–0.5 km to 2.5–3.0 km. The Sen slope, proportions of improved and degraded pixels, and net improvement index were then calculated for each distance gradient (Figure 9).

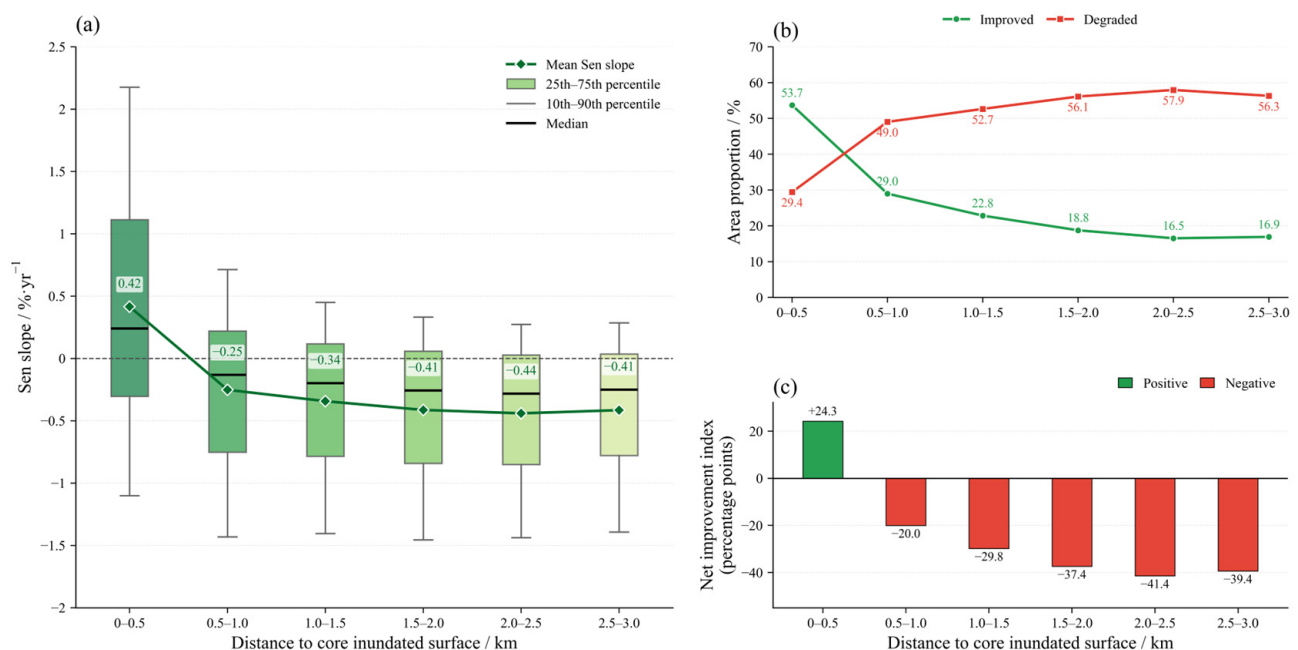


Figure 9. Growth response characteristics of *P. euphratica* forest along distance gradients from inundated water surfaces. Note: (a) Sen slope distribution under different distance gradients; (b) area proportions of improved and degraded classes; (c) net improvement index. The box represents the interquartile range (25th–75th percentiles), the whiskers represent the range from the 10th to the 90th percentile, the dot represents the mean, and the dashed line represents a Sen slope of 0.

The results showed that FVC improvement of *P. euphratica* forest generally decreased with increasing distance from inundated water surfaces. Improvement was most concentrated within the 0–0.5 km range, where the mean Sen slope was 0.42 percentage points per year, improved pixels accounted for 53.7%, degraded pixels accounted for 29.4%, and the net improvement index was +24.3 percentage points. Beyond 0.5 km, the proportion of

improved pixels decreased, while the proportion of degraded pixels increased. Overall, the strongest FVC improvement was observed within the 0–0.5 km distance band.

3.3.3. Lagged Responses of *P. euphratica* FVC to Hydrological and Inundation Variables

Correlations of FVC in the *P. euphratica* forest with hydrological factors and surface inundation metrics were strongest at lags of 2–3 years (Table 6). Reservoir releases were significantly positively correlated with FVC at lags of 2–3 years. Groundwater depth was significantly negatively correlated with FVC at lags of 0–3 years, with the strongest correlation occurring at a 2-year lag. Surface inundation expansion area was significantly positively correlated with FVC at lags of 2–3 years. Spearman and detrended analyses supported reservoir releases at Lag 2, groundwater depth at Lag 1–2, and surface inundation expansion area at Lag 2–3, whereas support for the other significant Pearson relationships was weaker (Table S12). Overall, the lagged correlation between surface inundation expansion area and FVC was relatively stable, suggesting that a lag of 2–3 years is appropriate for characterizing associations between *P. euphratica* forest growth and ecological water conveyance and surface inundation. Figure 10 further illustrates the lagged relationships among the three water-related variables and FVC. At their optimal lags, annual surface inundation expansion area at Lag 3 had an R^2 of 0.433, compared with 0.281 for reservoir releases at Lag 3 and 0.449 for groundwater depth at Lag 2.

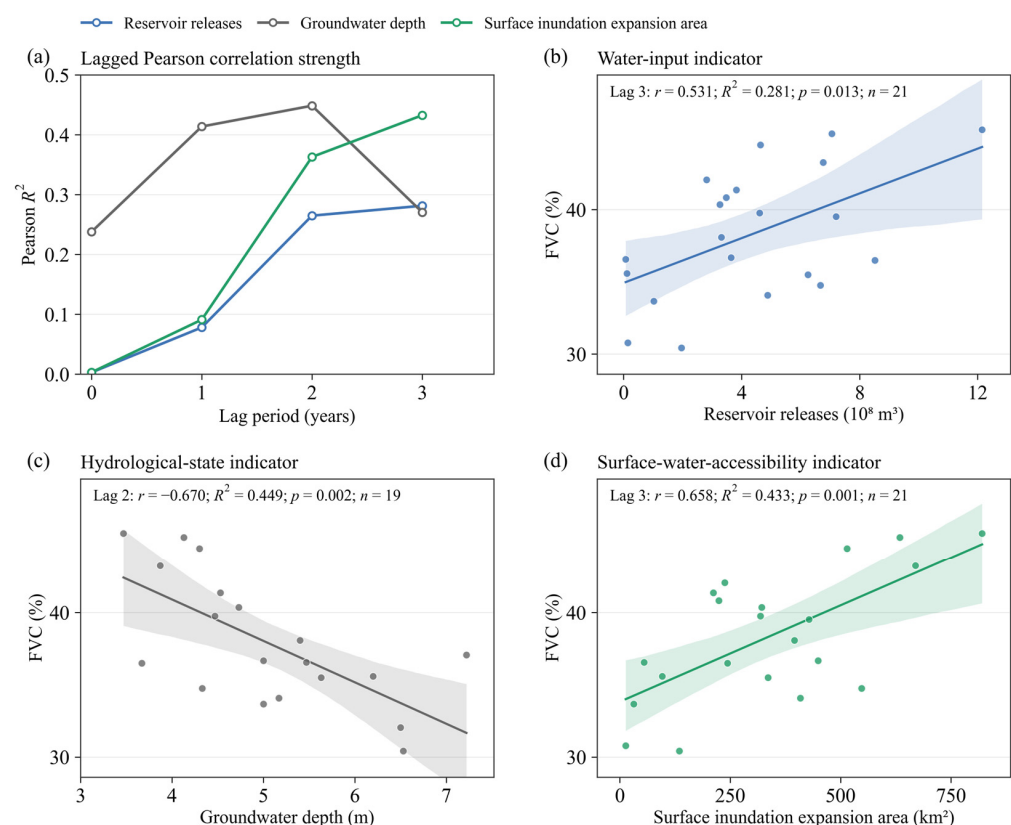


Figure 10. Lagged relationships between water-related indicators and annual mean FVC of *P. euphratica* forest. Note: (a) Squared Pearson correlation coefficients (R^2) for the relationships between reservoir releases, groundwater depth, surface inundation expansion area, and FVC under different lag periods; (b–d) linear relationships between each indicator and FVC at the optimal lag period. Each indicator value in year t was paired with FVC in year $t + k$. All observations and lagged pairs involving 2008 were excluded.

Table 6. Lagged correlations of hydrological factors and surface inundation expansion area with annual mean FVC of the *P. euphratica* forest.

Variable	Lag 0	Lag 1	Lag 2	Lag 3	Optimal Lag Period
X_1	0.054 ns ($p = 0.798$)	0.279 ns ($p = 0.196$)	0.515 * ($p = 0.014$)	0.531 * ($p = 0.013$)	Lag 3
X_2	−0.488 * ($p = 0.029$)	−0.643 ** ($p = 0.003$)	−0.670 ** ($p = 0.002$)	−0.520 * ($p = 0.022$)	Lag 2
X_3	0.056 ns ($p = 0.791$)	0.302 ns ($p = 0.162$)	0.603 ** ($p = 0.003$)	0.658 ** ($p = 0.001$)	Lag 3

Note: X_1 , reservoir releases from Daxihaizi Reservoir; X_2 , mean groundwater depth across the three monitoring transects; X_3 , annual surface inundation expansion area during response periods. Values are Pearson r , with p values in parentheses. Spearman and detrended results are provided in Table S12. * $p < 0.05$; ** $p < 0.01$; ns, not significant. Lag 0 indicates the current year, and Lag 1–Lag 3 indicate lags of 1–3 years. The optimal lag corresponds to the largest absolute r .

4. Discussion

4.1. Surface-Water Accessibility and *P. euphratica* Forest Responses

Annual surface inundation expansion area was not fully synchronized with reservoir releases (Figures 3 and 4), indicating that changes in water input were not directly translated into proportional changes in lateral surface-water expansion. Riparian forest restoration assessments commonly combine water input, groundwater conditions, channel connectivity, and vegetation indicators [30]. Reservoir releases and conveyance duration quantify engineering water input [8], whereas groundwater observations and vegetation or land-cover indicators primarily characterize subsurface conditions and ecological outcomes [4,13,19,74]. Hydrological connectivity controls whether released water can move from the main channel into side channels and floodplain areas [75], thereby shaping where surface inundation occurs within the riparian corridor.

Surface inundation frequency and distance further revealed spatial differences in surface-water accessibility to *P. euphratica* forest. Recurrent inundation was concentrated along the river network, while stronger FVC improvement occurred near recurrently inundated water surfaces. Annual surface inundation expansion area, multi-year inundation frequency, and distance from forest pixels to recurrently inundated water surfaces represent complementary dimensions of surface-water extent, recurrence, and proximity. Together, these metrics characterize surface-water expansion and accessibility gradients and help identify areas where FVC improvement remains limited [9,76,77]. A broader comparison of conventional hydrological, connectivity, vegetation, and plot-based indicators with the three surface-inundation metrics is provided in Table S13.

4.2. FVC Patterns Across Inundation-Frequency, Distance, and Lag Gradients

FVC improvement in *P. euphratica* forest did not vary monotonically with surface inundation frequency. Relatively low-frequency areas showed the highest improvement proportion (63.0%), a net improvement index of 42.7 percentage points, and a mean Sen slope of 0.77 percentage points per year, whereas the mean Sen slope decreased to only 0.07 percentage points per year in the highest-frequency class (Figure 8; Tables S14 and S15). Relatively low- to moderate-frequency inundation showed pronounced positive FVC trends, whereas FVC improvement was generally weaker in the highest-frequency class, although the magnitude of this contrast varied across spatial scales. Surface inundation can improve water availability and drought-related physiological conditions of *P. euphratica* [15], but increasing inundation frequency does not necessarily favor FVC improvement [20]. Differences in soil salinity and local stand conditions may partly contribute to the observed FVC patterns under high-frequency inundation [78–81]. Distance gradients showed a corresponding spatial pattern. Within 0–0.5 km of recurrently inundated water surfaces,

53.7% of forest pixels showed improvement, and the mean Sen slope reached 0.42 percentage points per year, whereas FVC improvement weakened with increasing distance (Figure 9). Shorter distances to recurrently inundated surfaces indicate greater potential surface-water accessibility, while shallow infiltration and localized groundwater rise may increase root-zone water availability [5,82], although these relationships may also vary with channel morphology, topography, soil conditions, and subsurface flow paths. Taken together, the frequency and distance gradients suggest that proximity to the main channel, connected side channels, and recurrently inundated surfaces is associated with greater water accessibility and stronger FVC improvement.

Temporal variation in FVC further indicated that FVC changes lagged behind hydrological variations. Annual mean FVC showed a declining phase before 2009 and subsequently increased, reaching its maximum in 2020. The increasing FVC trend followed a period of enhanced surface inundation during 2016–2019 and generally improved groundwater conditions. Lagged correlations showed that associations of FVC with reservoir releases, groundwater depth, and annual surface inundation expansion area were strongest after approximately 2–3 years (Table 6; Table S12; Figure 10). The observed lag indicates close temporal associations between hydrological variations and FVC dynamics. Interannual climatic variability may represent an additional background influence on FVC dynamics. Together with the frequency and distance gradients, these results suggest a spatial–temporal association pattern linking surface-water accessibility and groundwater conditions to subsequent FVC improvement (Figure 11).

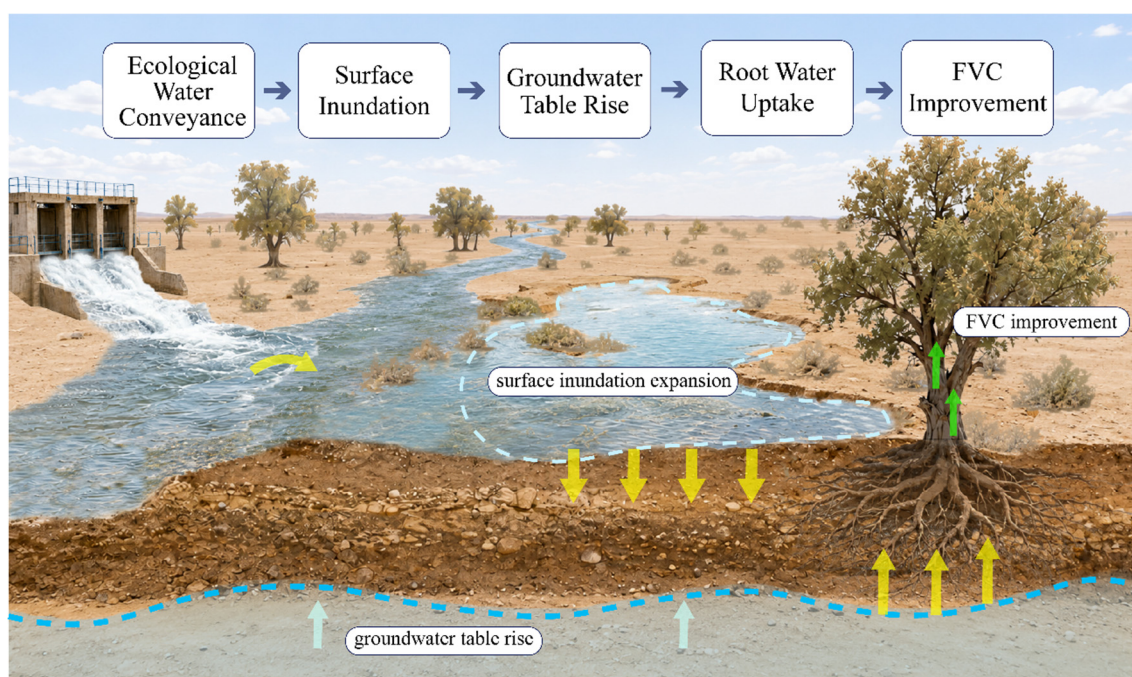


Figure 11. Conceptual pathway linking ecological water conveyance, surface inundation, groundwater recharge, root-zone water availability, and FVC improvement of *P. euphratica* forest.

4.3. Implications for Riparian Forest Monitoring and Water-Conveyance Management

The combined inundation-frequency, distance, and lag patterns provide a practical basis for spatially differentiated forest monitoring and water-conveyance management. Areas with declining FVC that remain uninundated and are located more than 0.5 km from recurrently inundated water surfaces should be prioritized for field verification to determine whether limited FVC improvement is associated with hydrological disconnection, salinity, stand condition, land use, or classification uncertainty. Where hydrological disconnection is

confirmed, reconnection of side channels or floodplains, removal of local flow obstructions, shallow-gully linkage, and adjustment of conveyance duration can be evaluated as site-specific measures [83,84]. Relatively low-to-moderate inundation frequencies may provide useful reference conditions for intermittent water delivery, whereas high-frequency areas require additional consideration of channel position, root-zone aeration, salinity, and local stand conditions. Accordingly, water-conveyance management should account for hydrological processes and spatial differences in ecological water demand [85,86]. The observed 0–0.5 km response band, relatively low-to-moderate inundation frequencies, and 2–3-year lag provide empirical reference ranges for future monitoring and field validation in the lower Tarim River. Long-term evaluation should integrate water delivery, groundwater conditions, surface-water accessibility, and measurable forest responses [87].

4.4. Measurement Limits and Validation Priorities

Several sources of uncertainty may affect the interpretation of our results. At the 30 m spatial resolution of Landsat, narrow channels, shallow water, wet sandy surfaces, sparse vegetation, and mixed land–water pixels may affect the delineation of surface-inundation boundaries, particularly in small side channels and low-frequency inundation areas [88]. Differences in the number and seasonal distribution of cloud-free Landsat observations among years may also affect the detection of short-lived inundation events. The multi-temporal consensus *P. euphratica* forest mask may be influenced by inter-class spectral confusion and by the choice of temporal-consensus threshold, which may in turn affect the mapped forest extent [49]. Future studies could further evaluate this sensitivity using independent forest inventories or higher-resolution observations. FVC represents fractional vegetation cover and therefore cannot directly characterize individual-tree vitality, biomass, regeneration, or ecosystem productivity. The pixel-level Mann–Kendall classifications were not adjusted for spatial field significance, so their mapped distributions and area proportions were interpreted mainly as descriptive representations of local FVC trend patterns, while regional statistical significance was interpreted with consideration of spatial dependence among neighboring pixels. In addition, climatic variability was not explicitly incorporated into the lagged analyses, and therefore, the observed associations between ecological water conveyance and FVC dynamics may also reflect concurrent climatic influences. Groundwater observations were limited to three monitoring transects and may not fully capture the spatial variability of groundwater conditions across the lower Tarim River. Given that *P. euphratica* stand structure and regeneration vary along groundwater, soil-moisture, and salinity gradients [17], and its phenological response also varies with groundwater depth [18], future studies could combine Sentinel-2 or higher-resolution imagery with UAV surveys, while expanding groundwater monitoring and incorporating soil-moisture, salinity, and repeated tree-level observations. These combined observations would improve the validation of surface-inundation mapping and FVC responses and strengthen understanding of the links among surface inundation, groundwater conditions, root-zone water availability, and FVC dynamics.

5. Conclusions

Based on long-term Landsat imagery from 1995 to 2025, this study combined annual surface inundation expansion area, multi-year inundation frequency, and distance from forest pixels to recurrently inundated water surfaces to evaluate *P. euphratica* forest responses to ecological water conveyance in the lower Tarim River. The main conclusions are as follows.

- (1) During ecological water-conveyance response periods from 2000 to 2025, newly formed or expanded surface water showed clear temporal and spatial variation. After

2010, reservoir releases and annual surface inundation expansion area generally increased, although their annual variations were not fully synchronized. Multi-year high-frequency inundation areas were mainly distributed along the main channel, connected side channels, and low-lying terminal areas.

- (2) *P. euphratica* forest FVC showed an overall fluctuating upward trend from 1995 to 2025, with a multi-year mean of 37.29% and a Theil–Sen slope of 0.182 percentage points per year. The increasing trend was significant according to the Mann–Kendall test. At the pixel scale, improvement, stability, and degradation coexisted, indicating pronounced spatial heterogeneity in FVC change.
- (3) Surface-inundation frequency and distance were associated with distinct patterns of *P. euphratica* forest FVC response. Relatively low- to moderate-frequency inundation areas showed stronger FVC improvement than the high-frequency class. FVC improvement was most concentrated within 0–0.5 km of recurrently inundated water surfaces and weakened markedly beyond 0.5 km.
- (4) Associations of *P. euphratica* forest FVC with reservoir releases, groundwater depth, and annual surface inundation expansion area were strongest at lags of 2–3 years. Annual surface inundation expansion area, multi-year inundation frequency, and distance from forest pixels to recurrently inundated water surfaces characterize surface-water accessibility in terms of extent, recurrence, and proximity. Together, these metrics complement reservoir-release and groundwater records and provide spatial information for long-term monitoring and evaluation of *P. euphratica* forest recovery under ecological water conveyance.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f17091117/s1>, Table S1: Landsat image screening and preprocessing parameters; Table S2: Summary of Landsat imagery used to construct the seven land-cover classification composites; Table S3: Random forest parameters and validation framework for the seven classification periods; Table S4: Statistics of random forest classification samples and capped sample pixels; Table S5: Sensitivity test of FVC growth classification under different threshold schemes; Table S6: Annual start and end dates of ecological water conveyance in the lower Tarim River; Table S7: Decision rules, targeted error sources, and supporting evidence for surface inundation extraction; Table S8: Sensitivity analysis of recurrent inundation threshold selection; Table S9: Five-fold spatial block cross-validation results for random forest classification across seven periods; Table S10: Sensitivity of the multi-temporal consensus *P. euphratica* forest mask to the occurrence criterion; Table S11: Spatial consistency assessment of multi-period *P. euphratica* classification results between adjacent periods; Table S12: Robustness checks for lagged correlations between hydrological variables and FVC of *P. euphratica* forest; Table S13: Comparison of conventional indicators and surface inundation metrics for characterizing growth responses of *P. euphratica* forest; Table S14: Sen slope statistics of *P. euphratica* FVC among surface inundation frequency classes; Table S15: Pairwise comparisons of Sen slopes among surface inundation frequency classes after FDR correction; Table S16: Global Moran’s I assessment of spatial autocorrelation in FVC trends; Table S17: Robustness assessment of inundation-frequency differences using spatial block-cluster bootstrap analysis; Figure S1: Spatial distribution of random forest classification samples; Figure S2: Local visual inspection examples of newly formed or expanded surface inundation extraction in representative years; Figure S3: Annual spatial distribution of surface inundation expansion during ecological water conveyance response periods from 2000 to 2025; Supplementary Data S1: Complete scene-level inventory of the 788 Landsat images used in this study, including acquisition date, scene ID, WRS path/row, cloud cover, image role, compositing information, and preprocessing parameters.

Author Contributions: Conceptualization, J.W. and M.W.; methodology, J.W., Z.Y., F.M. and G.C.; software, J.W. and Z.Y.; validation, Z.Y., F.M., Y.H. and X.H.; formal analysis, J.W. and F.M.; investigation, J.W., Z.Y., Y.H. and S.D.; resources, S.D. and G.C.; data curation, J.W., Y.H., S.D. and M.P.;

writing—original draft preparation, J.W.; writing—review and editing, Z.Y., P.J. and M.W.; visualization, J.W. and M.P.; supervision, P.J. and M.W.; project administration, M.W.; funding acquisition, Z.Y., G.C. and M.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Research Operation Fund of Xinjiang Yuli Desert Ecosystem Observation and Research Station and the Technical Challenge Project in Key Field of Xinjiang Production and Construction Corps (Grant No. 2024AB075).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors acknowledge the support provided by Google Earth Engine for the cloud-computing resources used in this study. During the preparation of this manuscript, the authors used ChatGPT-5 (OpenAI) for language polishing and improving the clarity of expression. The authors have reviewed and edited the output and take full responsibility for the content of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

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