



Ecohydrological niches and water-table thresholds of riparian vegetation associations under long-term environmental flows

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Abstract. Ecohydrological assessments of regulated dryland rivers have largely focused on aggregate vegetation responses, such as vegetation cover or greenness, whereas the spatial organization of vegetation at the association level and its coupling with hydrological gradients remain poorly resolved. Using the lower Tarim River, where environmental flows have been implemented continuously since 2000, as a case study, we combined field surveys, multi-source remote-sensing imagery, and groundwater data to establish a spatially continuous 10 m vegetation-association baseline for 2025, distinguishing 13 representative riparian vegetation associations. Among six classifiers evaluated using spatial block cross-validation, XGBoost achieved the highest performance, with an overall accuracy of 80 %. Using this association-level baseline, we developed an integrated hydrogeographic framework to quantify vegetation differentiation across three interrelated dimensions representing longitudinal environmental-flow conveyance, lateral distance from the river, and water-table depth. The vegetation associations exhibited pronounced differentiation across these dimensions. Most *Populus euphratica*- and *Tamarix*-related associations had their main distribution centres at intermediate water-table depths of approximately 4–6 m, whereas the *Phragmites australis* wetland association was concentrated under shallower groundwater conditions. With increasing water-table depth, vegetation composition progressively shifted towards drought-tolerant shrub and desert-herb associations. Association-specific realized groundwater niches further revealed empirical compositional transition zones around water-table depths of approximately 4 and 6 m, representing shifts in community organization rather than universal physiological thresholds or groundwater optima. Longitudinal zonation and lateral differentiation further showed that association patterns



35 reflected the interconnected influences of downstream water delivery, river proximity, and groundwater accessibility. Together,
these results characterize the present-day ecohydrological organization of riparian vegetation under a hydrological regime
shaped by a quarter-century of environmental-flow releases. By advancing environmental-flow assessment from aggregate
vegetation responses to spatially explicit association-level ecohydrological organization, this study provides a finer ecological
framework for identifying hydrologically differentiated vegetation units and supporting spatially differentiated environmental-
40 water management and riparian restoration in regulated dryland rivers.

1 Introduction

Riparian ecosystems in arid inland river basins depend strongly on limited surface-water and groundwater resources that vary
markedly in space and time. Declining river discharge, falling groundwater levels, and weakened floodplain connectivity can
reduce plant-available water, leading to riparian vegetation degradation, simplification of community structure, and loss of
45 ecosystem functions (Ahring and Steward, 2012; Kløve et al., 2014). This dependence is particularly pronounced in hyper-arid
regions, where precipitation is insufficient to meet plant evapotranspiration demand and riparian forests, wetlands, and deep-
rooted plant communities rely partly or persistently on groundwater, forming typical groundwater-dependent ecosystems
(GDEs) (Eamus et al., 2015; Eamus and Froend, 2006; Otoo et al., 2025). Consequently, under the combined pressures of
climate change and increasing water-resource development, maintaining or restoring hydrological connectivity among rivers,
50 groundwater, and riparian vegetation through managed water allocation has become a major challenge in dryland river
restoration worldwide (Kløve et al., 2014; Otoo et al., 2025).

Environmental flows are an important management tool for restoring ecological processes in regulated rivers and sustaining
riparian ecosystems. Their purpose is not simply to increase the volume of water released to a river, but to provide an
ecologically appropriate flow regime in terms of magnitude, timing, duration, and other flow characteristics needed to sustain
55 ecological processes (Acreman and Dunbar, 2004; Virkki et al., 2022). Environmental flows have been applied to restore
riparian processes in the Colorado River Delta and to support river–floodplain–wetland ecosystems in the Murray–Darling
Basin (Shafroth et al., 2017; Swirepik et al., 2016). However, ecological responses to environmental flows are strongly spatially
heterogeneous: comparable water releases may produce contrasting outcomes depending on local groundwater conditions,
hydrological connectivity, and vegetation requirements (Rivaes et al., 2017). Evidence from the Tarim River further indicates



60 that restoration efficiency depends not only on the total amount of water delivered but also on the timing and periodicity of water conveyance relative to vegetation growth and groundwater responses (Liu et al., 2022). Consequently, environmental-flow management increasingly requires a process-based understanding of how released water is redistributed within the river–groundwater–vegetation system and how different ecological units respond to that redistribution.

The lower Tarim River provides a representative example of environmental-flow management in a hyper-arid inland river
65 system. During the late twentieth century, intensive water-resource development in the upper and middle reaches substantially reduced downstream discharge, resulting in prolonged channel desiccation, groundwater decline, and severe degradation of desert riparian vegetation dominated by *Populus euphratica* and *Tamarix* spp. (Chen et al., 2006). Since 2000, a series of ecological water-conveyance events has been implemented to restore river connectivity, promote groundwater recharge, and improve hydrological conditions in the lower riparian corridor (Chen et al., 2026, 2010). Long-term monitoring has
70 demonstrated substantial groundwater recovery and improvements in vegetation cover and growth following these releases, although the hydrological and ecological effects generally weaken with increasing distance from the river and vary among locations (Hao and Li, 2014; Xu et al., 2007). Over the past two decades, restoration effects have been evaluated primarily using groundwater dynamics, vegetation cover, normalized difference vegetation index (NDVI), land-cover change, and responses of dominant species (Bao et al., 2017; Hao and Li, 2014). Nevertheless, recovery has not been spatially uniform,
75 and improvements in groundwater conditions and vegetation greenness do not necessarily indicate complete regeneration of riparian communities (Glenn et al., 2017; Hao and Li, 2014). After approximately a quarter-century of environmental flows, how the present-day riparian ecosystem is organized at the finer level of vegetation-association composition and how these associations occupy different hydrological settings remain poorly resolved.

A vegetation association represents a relatively homogeneous plant-community unit characterized by a consistent floristic
80 composition, physiognomy, and habitat conditions (Theurillat et al., 2021). Compared with aggregate metrics such as vegetation cover or greenness, an association-level perspective therefore retains explicit information on species composition and community organization. This distinction is particularly relevant in groundwater-dependent riparian ecosystems, where hydrological alteration can modify not only vegetation extent but also species composition and the spatial distribution of plant communities along gradients of river proximity and water availability (Ding et al., 2017; Vanderhoof et al., 2019). In the lower



85 Tarim River, however, previous assessments have largely characterized ecological responses using vegetation cover, remotely sensed greenness, dominant species such as *Populus euphratica*, or relatively broad vegetation types (Halik et al., 2019; Liu et al., 2024). Consequently, a continuous association-level spatial baseline capable of distinguishing *Populus*-dominated mixed communities, *Tamarix* shrub–herb assemblages, wetland associations, and halophytic associations across the entire riparian corridor remains lacking. Such information is needed to advance environmental-flow assessment from determining whether
 90 vegetation has increased towards understanding how community composition is spatially organized under different hydrological conditions.

Reliable association-level analysis first requires accurate spatial identification. In hyper-arid riparian landscapes, vegetation is typically sparse and spatially heterogeneous, while trees, shrubs, herbs, non-photosynthetic vegetation, and highly reflective bare surfaces may occur within the same moderate-resolution pixels, increasing spectral mixing and classification (Daryaei et al., 2020; Guo et al., 2021). Moreover, vegetation communities sharing dominant species may exhibit similar spectral characteristics, making single-date optical imagery insufficient for resolving subtle differences in community composition. Multi-season observations can exploit differences in phenological trajectories and thereby improve vegetation-community separability (van Deventer et al., 2019; Liu et al., 2026), while Sentinel-2 red-edge and shortwave-infrared bands provide additional sensitivity to vegetation condition and moisture-related properties (van Deventer et al., 2022). Sentinel-1 synthetic
 95 aperture radar (SAR) observations provide complementary structural information to optical imagery, and image-texture metrics can further characterize spatial heterogeneity in vegetation structure and patch organization (Lechner et al., 2022; Mohammadpour et al., 2022). The fusion of optical and SAR observations therefore offers a means of reducing classification uncertainty arising from spectral similarity and landscape heterogeneity (Bartsch et al., 2024). In the present study, however, remote-sensing classification serves primarily to establish an association-level spatial baseline; the central scientific objective
 100 is to use this baseline to resolve the spatial ecohydrological differentiation of vegetation associations under long-term environmental flows.

The spatial organization of desert riparian vegetation is closely linked to the redistribution of environmental water within the river–groundwater system. River water recharges adjacent aquifers through channel infiltration, while the groundwater response generally weakens with increasing distance from the channel (Zeng et al., 2016). Longitudinal position, distance from



110 the river, and water-table depth therefore represent three interrelated hydrogeographic dimensions of downstream water delivery, lateral recharge, and groundwater accessibility to vegetation. In the lower Tarim River, groundwater depth has been identified as a major control on vegetation distribution, community structure, and species diversity (Chen et al., 2006; Li et al., 2013). Previous studies generally indicate favorable vegetation conditions at groundwater depths of approximately 2–4 m and increasingly pronounced ecological transitions around 4–6 m, although responses vary among species and plant functional types (Hao et al., 2010; Ling et al., 2015). However, these relationships have rarely been examined at the vegetation-association level.

Against this background, we integrated field surveys conducted in 2024–2025, multi-source Sentinel imagery, and groundwater data to develop a 10 m vegetation-association map of the lower Tarim River for 2025 and to examine association-level spatial differentiation along longitudinal, lateral, and groundwater gradients. The principal advance of this study is to move 120 ecohydrological assessment of the lower Tarim River from broad vegetation responses to spatially explicit vegetation-association organization. Specifically, we establish an association-level 10 m spatial baseline and link it to three interconnected hydrogeographic dimensions representing downstream environmental-flow conveyance, lateral river influence, and groundwater accessibility. This framework enables association-specific groundwater niches and compositional transition zones to be evaluated at the landscape scale. Specifically, this study addresses three questions: (1) How accurately can representative 125 vegetation associations be mapped using multi-source remote-sensing predictors and spatial block cross-validation? (2) How are vegetation associations spatially differentiated along longitudinal river position, distance from the river, and groundwater depth? (3) What empirical groundwater-depth niches and compositional transition zones characterize the different vegetation associations?

2 Study area and data acquisition

130 2.1 Study area

The study area is located along the main riparian corridor of the lower Tarim River in the eastern Tarim Basin, Xinjiang,



northwestern China (Fig. 1), extending from Daxihaizi Reservoir to Taitema Lake. It represents a typical arid inland-river ecosystem. The region has a warm-temperate hyper-arid continental climate, with mean annual precipitation of less than 50 mm and annual potential evaporation of approximately 2,500-3,000 mm (Mamat et al., 2019). Because evaporative demand greatly exceeds precipitation, regional water availability depends primarily on environmental flows in the river channel and associated groundwater recharge (Chen et al., 2010). The terrain is generally flat and is dominated by floodplains, abandoned channels, natural levees, and aeolian dunes. Groundwater is therefore a key hydrological control on the growth, regeneration, and succession of desert riparian vegetation.

Since 2000, environmental-flow releases have been implemented from Daxihaizi Reservoir, located at the upstream end of the lower Tarim River, and conveyed downstream along the river channel toward Taitema Lake, substantially altering river-flow regimes, water-table depth, and riparian vegetation patterns. These long-term hydrological changes have contributed to the development of a typical GDE, characterized by a spatial transition from *Populus euphratica* forests and *Tamarix* shrublands near the river to halophytic vegetation in more distal areas. The persistent hydrological gradients established under long-term environmental-flow management make the lower Tarim River an appropriate natural setting for investigating the spatial differentiation of vegetation associations and their ecohydrological responses.

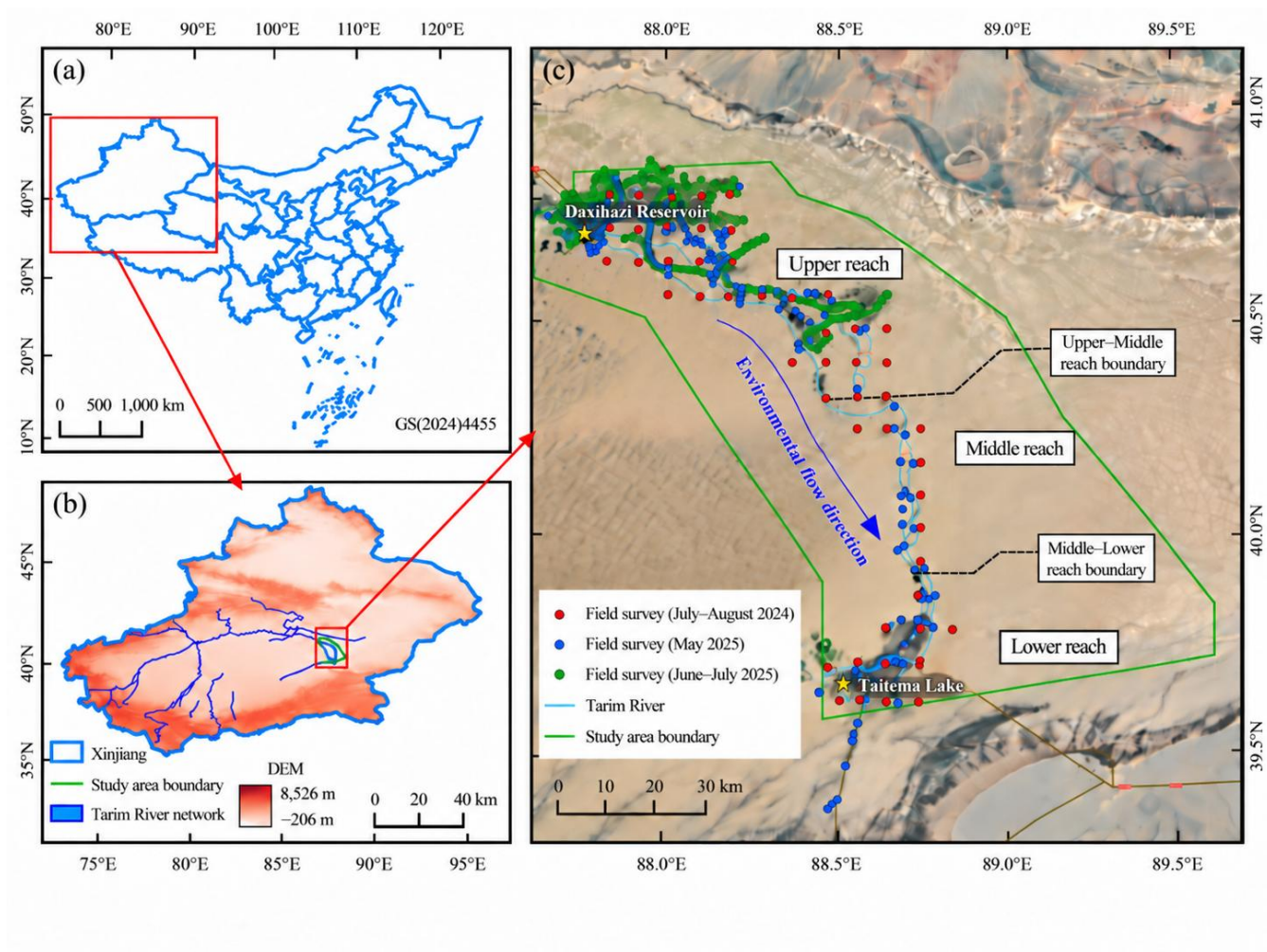


Figure 1: Location of the study area in the lower Tarim River and distribution of field surveys. (a) Location of Xinjiang within China; (b) location of the study area within Xinjiang, showing the digital elevation model (DEM), Tarim River network, and study area boundary; (c) distribution of the three field surveys.

150 2.2 Field surveys and identification of vegetation associations

To establish an association-level vegetation classification scheme and obtain reliable training and validation samples, three field surveys covering the entire study area were conducted during 2024–2025 (Fig. 1c). The first survey was carried out at July and August 2024 using a $0.1^\circ \times 0.1^\circ$ grid-based sampling design and included 50 georeferenced sampling sites to



155 characterize baseline vegetation composition and spatial distribution. The second survey, conducted from at May 2025, focused
on vegetation characteristics during the spring phenological stage and included 488 georeferenced sampling sites within the
riparian corridor. The third survey was conducted at June and July 2025 during the peak growing season and included 1,201
georeferenced sampling sites, with additional sampling in low-lying and wetland areas to improve sample representation across
vegetation associations. In total, 1,739 georeferenced sampling sites from the three field surveys were used in this study. These
field observations provided the primary reference information for vegetation-association identification and the development
160 of the reference dataset used for subsequent classification and accuracy assessment.

At each site, information on species composition, dominant species, vegetation cover, community structure, and habitat
conditions were recorded, together with low-altitude unmanned aerial vehicle (UAV) imagery and field photographs to support
visual interpretation. Following the classification principles of the Vegetation of China, vegetation associations were identified
primarily based on perennial dominant and community-forming species, together with community structure and habitat
165 characteristics (Guo-Hong et al., 2020; Ke et al., 2020). Seasonal variation in species occurrence among the three surveys was
considered during classification, and short-lived or seasonal species were used as supplementary rather than diagnostic
information. Accordingly, 13 representative vegetation associations were defined as the target classes in this study.
Representative field photographs of these associations are shown in Fig. 2. The field-survey dataset has been publicly released
(Chen et al., 2025) and provides the basis for developing the association-level classification scheme and evaluating
170 classification accuracy.

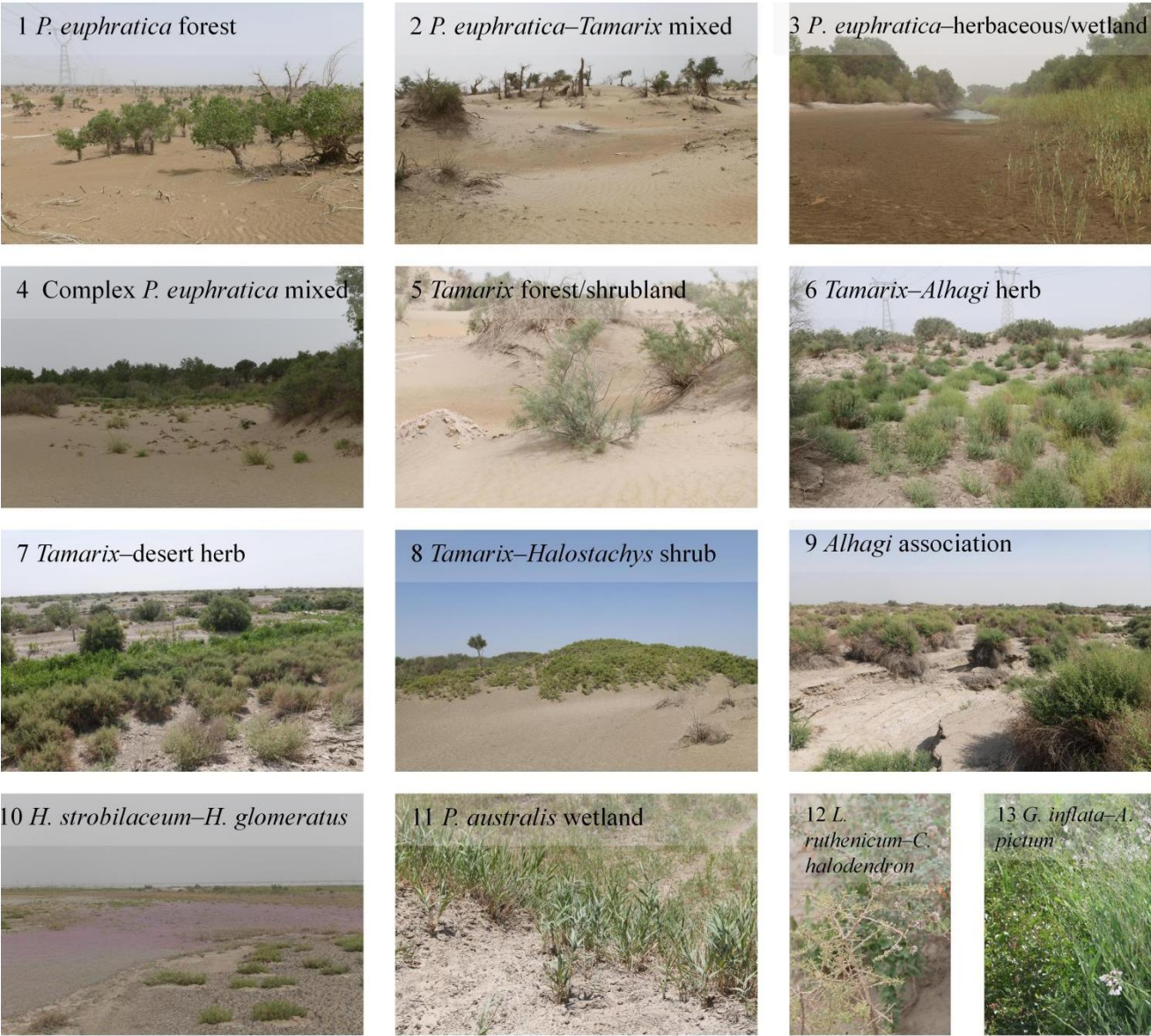


Figure 2: Representative field photographs of the 13 vegetation associations identified in the lower Tarim River. Numbers 1–13 correspond to the association labels shown in each photograph and are used consistently throughout the manuscript.

2.3 Multi-source remote-sensing data and feature construction

175 Using the Google Earth Engine (GEE) cloud-computing platform, we integrated Sentinel-2 optical imagery and Sentinel-1



dual-polarization SAR data acquired throughout 2025 to construct an initial multi-source remote-sensing feature set at 10 m spatial resolution. A total of 28 candidate predictors were derived to characterize variation among vegetation associations in spectral properties, vegetation condition, moisture status, seasonal dynamics, canopy structure, and spatial texture (Table 1). The optical feature set included four reflectance bands (Blue_Band, Green_Band, Red_Band, and NIR_Band), three red-edge bands (Red_Edge_1, Red_Edge_2, and Red_Edge_3), and the normalized difference red-edge index (NDRE), where NIR refers to the near-infrared spectral region. Two shortwave-infrared (SWIR) bands (SWIR_1 and SWIR_2) and the normalized difference water index (NDWI) were included to characterize vegetation and surface moisture conditions. To represent seasonal vegetation dynamics, six phenological features were derived from the annual Sentinel-2 time series, i.e., Spring_NDVI, Summer_NDVI, Autumn_NDVI, Winter_NDVI, NDVI_Max, and NDVI_Std.

Sentinel-1 dual-polarization SAR data were used to derive five features based on vertical-transmit/vertical-receive (VV) and vertical-transmit/horizontal-receive (VH) backscatter, i.e., VV_Mean, VH_Mean, VV_Std, VH_Std, and VV_VH_Ratio. These features provide complementary information on vegetation structure and radar backscatter characteristics. In addition, six grey-level co-occurrence matrix (GLCM) texture metrics, i.e., angular second moment (ASM), contrast, correlation, variance, inverse difference moment (IDM), and entropy, were calculated from the near-infrared band to characterize spatial heterogeneity in vegetation patches and canopy organization. All feature layers were standardized to a spatial resolution of 10 m and co-registered to ensure spatial consistency among data sources. These 28 candidate predictors were subsequently evaluated for redundancy and predictive relevance before classification modelling (Sect. 3.1).

Table 1: Initial 28 candidate remote-sensing features before feature screening

Feature group	Feature	Data source	Definition / description	Main ecological or physical relevance
Phenological and vegetation-growth features	Spring_NDVI	Sentinel-2	Seasonal NDVI representing vegetation greenness during spring	Characterizes spring vegetation growth and seasonal phenological status



	Summer_NDVI	Sentinel-2	Seasonal NDVI representing vegetation greenness during summer	Characterizes peak-season vegetation growth and canopy greenness
	Autumn_NDVI	Sentinel-2	Seasonal NDVI representing vegetation greenness during autumn	Reflects late-season vegetation activity and senescence
	Winter_NDVI	Sentinel-2	Seasonal NDVI representing vegetation greenness during winter	Reflects dormant-season background and persistent vegetation signals
	NDVI_Max	Sentinel-2	Maximum NDVI derived from the annual time series	Represents annual maximum vegetation greenness and productivity
	NDVI_Std	Sentinel-2	Standard deviation of NDVI over the annual time series	Represents intra-annual variability in vegetation greenness
Red-edge physiological features	Red_Edge_1	Sentinel-2	Reflectance in the first red-edge band	Sensitive to vegetation chlorophyll and physiological condition
	Red_Edge_2	Sentinel-2	Reflectance in the second red-edge band	Characterizes differences in vegetation vigor and canopy condition
	Red_Edge_3	Sentinel-2	Reflectance in the third red-edge band	Provides information on vegetation chlorophyll and canopy structure
	NDRE	Sentinel-2	Normalized Difference Red Edge Index	Sensitive to vegetation chlorophyll content and physiological status
Moisture- and drought-related	SWIR_1	Sentinel-2	Reflectance in the first shortwave-infrared band	Sensitive to vegetation and surface moisture conditions



features	SWIR_2	Sentinel-2	Reflectance in the second shortwave-infrared band	Characterizes moisture stress and dry surface conditions
	NDWI	Sentinel-2	Normalized Difference Water Index	Represents vegetation/surface moisture conditions and water availability
SAR backscatter features	VV_Mean	Sentinel-1	Mean VV-polarized backscatter	Characterizes surface roughness, vegetation structure, and moisture-related scattering
	VH_Mean	Sentinel-1	Mean VH-polarized backscatter	Sensitive to vegetation volume scattering and structural complexity
	VV_Std	Sentinel-1	Standard deviation of VV-polarized backscatter	Represents spatial variability in co-polarized radar response
	VH_Std	Sentinel-1	Standard deviation of VH-polarized backscatter	Represents spatial variability in cross-polarized radar response
	VV_VH_Ratio	Sentinel-1	Ratio between VV- and VH-polarized backscatter	Enhances structural differences among vegetation and surface-cover types
Texture features	NIR_ASM	Sentinel-2 NIR	Angular second moment derived from the NIR-band GLCM	Represents local uniformity and textural homogeneity
	NIR_Contrast	Sentinel-2 NIR	Contrast derived from the NIR-band GLCM	Measures local spectral contrast and spatial heterogeneity
	NIR_Correlation	Sentinel-2 NIR	Correlation derived from the NIR-band GLCM	Represents spatial dependence among neighboring pixels
	NIR_Variance	Sentinel-2 NIR	Variance derived from the NIR-band GLCM	Quantifies local variability in NIR reflectance



	NIR_IDM	Sentinel-2	Inverse difference moment	Represents local homogeneity and smoothness
		NIR	derived from the NIR-band GLCM	
	NIR_Entropy	Sentinel-2	Entropy derived from the NIR-	Characterizes textural complexity and spatial disorder
		NIR	band GLCM	
Basic spectral reflectance features	Blue_Band	Sentinel-2	Reflectance in the blue band	Provides basic spectral information on vegetation and surface background
	Green_Band	Sentinel-2	Reflectance in the green band	Characterizes vegetation reflectance and surface-cover differences
	Red_Band	Sentinel-2	Reflectance in the red band	Sensitive to chlorophyll absorption and vegetation condition
	NIR_Band	Sentinel-2	Reflectance in the near-infrared band	Sensitive to vegetation biomass, canopy structure, and vigor

2.4 Topographic and groundwater data

195 Topographic information was obtained from the Copernicus Digital Elevation Model (Copernicus DEM, GLO-30, <https://dataspace.copernicus.eu/explore-data/data-collections/copernicus-contributing-missions/collections-description/COP-DEM>, accessed 10/07/2026), with a native spatial resolution of 30 m. The DEM was reprojected to the World Geodetic System 1984 / Universal Transverse Mercator Zone 45N (WGS 1984 / UTM Zone 45N) and resampled onto the common 10 m analysis grid using bilinear interpolation to ensure spatial alignment with the Sentinel-based remote-sensing layers. This resampling

200 was performed solely for grid matching and did not increase the inherent spatial information of the original 30 m DEM. The processed DEM ranged from 804.7 to 849.7 m above sea level and was used to characterize subtle topographic variation and its potential influence on local water redistribution.

Groundwater depth (GWD) data for 2025 were derived from long-term groundwater monitoring in the lower Tarim River and



205 supplemented by a spatially continuous regional groundwater dataset developed in previous research (Liu et al., 2024). The
2025 GWD dataset was spatially aligned with the common 10 m analysis grid to ensure consistency with the remote-sensing
layers. It was used to characterize groundwater gradients and analyse the ecohydrological responses of vegetation associations.

3 Methods

The overall methodological framework, encompassing data acquisition, vegetation-association mapping, hydrogeographic
gradient analysis, and ecohydrological interpretation, is illustrated in Fig. 3.

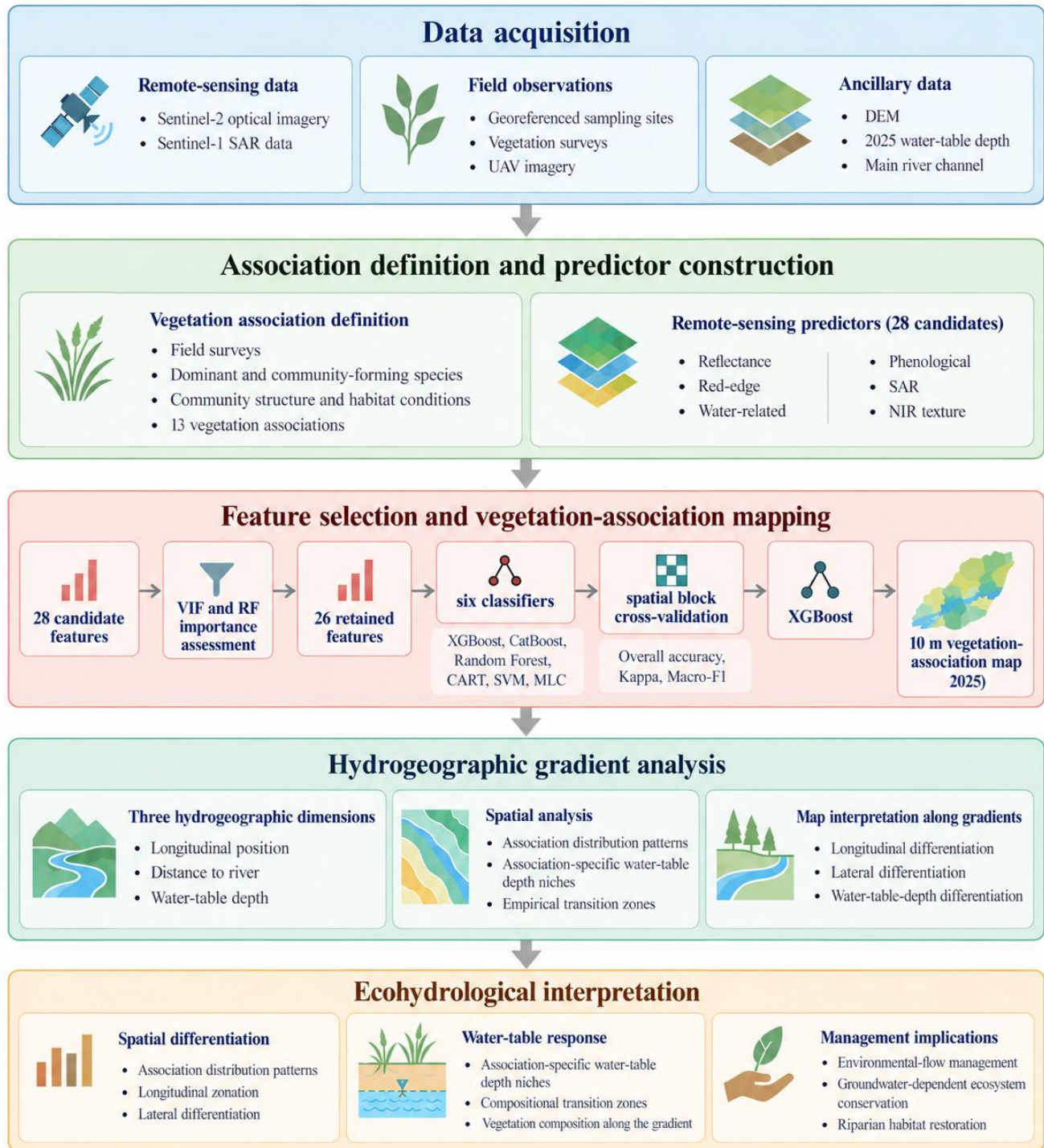


Figure 3: Analytical framework integrating field observations, multi-source remote sensing, predictor screening, vegetation-



association classification, hydrogeographic-gradient analysis, and ecohydrological interpretation.

3.1 Feature selection and variable optimization

To assess redundancy among the 28 candidates remote-sensing predictors, stratified random samples were selected from the reference dataset described in Sect. 2.2, and feature values were extracted from the corresponding 10 m pixels. These sampled values were used to construct the predictor matrix for multicollinearity assessment. For each feature i , the variance inflation factor (VIF) was calculated as

$$VIF_i = \frac{1}{1 - R_i^2} \quad (1)$$

where R_i^2 is the coefficient of determination obtained by regressing the i th predictor against all remaining predictors. Larger VIF values indicate stronger multicollinearity. A VIF threshold of 10 was adopted to identify substantial multicollinearity, following commonly used diagnostic conventions (Dormann et al., 2013; O'Brien, 2007). However, VIF was treated as a diagnostic criterion rather than an automatic exclusion rule, because correlated remote-sensing predictors may contain complementary information relevant to vegetation-association discrimination. To assess their predictive relevance, the relative importance of all 28 candidate predictors was quantified using mean decrease in impurity (MDI) derived from a Random Forest (RF) classifier. Feature selection jointly considered VIF magnitude and RF-based predictive importance.

3.2 Vegetation-association mapping and accuracy assessment

To compare the performance of different classification algorithms for fine-scale vegetation-association mapping in an arid riparian environment, six classifiers were implemented: XGBoost, CatBoost, RF, Classification and Regression Tree (CART), Maximum Likelihood Classification (MLC), and linear Support Vector Machine (linear SVM). The same screened remote-sensing predictor set was used consistently across all six classifiers to maintain a common predictor space for model comparison. Following the feature-screening procedure described in Sect. 3.1, 26 numerical remote-sensing predictors were retained. For each georeferenced reference sample, values of these predictors were extracted from the corresponding 10 m raster pixel to construct the predictor matrix, with the associated mapping class serving as the response label. The reference



dataset comprised 16 mapping classes, including 13 vegetation-association classes and three non-vegetation or artificial land-cover classes, i.e., (bare land, permanent water, and artificial or shelterbelt forest.

235 Because nearby reference samples are spatially autocorrelated, random sample-level partitioning may yield overly optimistic estimates of predictive performance. We therefore used five-fold spatial block cross-validation for model evaluation (Roberts et al., 2017; Valavi et al., 2019). Using the projected geographic coordinates of the reference samples, the spatial extent covered by the samples was divided into a regular 5×5 grid, producing up to 25 non-empty spatial blocks. Each reference sample was assigned to the grid cell containing its geographic location. The spatial blocks, rather than individual samples, were then
 240 randomly allocated to five folds using a prefixed random seed. In each iteration, approximately 80 % of the spatial blocks were used for model training and the remaining 20 % for validation, with all samples within each block assigned to the same subset. Because sample numbers varied among spatial blocks, the actual training-to-validation ratio at the sample level could differ among folds. Classification performance was evaluated using overall accuracy (*OA*), Cohen's kappa coefficient (*k*), and the macro-averaged F1 score (*Macro-F1*).

$$OA = \frac{\sum_{k=1}^K n_{kk}}{N} \quad (2)$$

$$k = \frac{p_o - p_e}{1 - p_e} \quad (3)$$

$$Macro-F1 = \frac{1}{K} \sum_{k=1}^K \frac{2P_k R_k}{P_k + R_k} \quad (4)$$

245 where $K=16$ is the number of mapping classes, n_{kk} is the number of correctly classified samples in class k , N is the total number of validation samples, p_o is the observed agreement, p_e is the agreement expected by chance, and P_k and R_k are the precision and recall for class k , respectively. These complementary metrics were used to assess overall agreement and classification performance across classes, thereby avoiding reliance on a single accuracy measure (Congalton, 1991; Foody, 2002). The three metrics were calculated for each held-out validation fold and then averaged across the five folds to obtain the final cross-
 250 validation performance. The best-performing classifier was subsequently refitted using the full reference sample set and applied to the 2025 remote-sensing feature stack to generate the final 10 m vegetation-association map of the lower Tarim River.



3.3 Hydrogeographic gradient analysis and characterization of groundwater-depth niches

Based on the final vegetation-association map, the main river channel, and water-table-depth data, three interrelated hydrogeographic gradients were constructed to characterize the longitudinal, lateral, and groundwater-related differentiation of vegetation associations. The longitudinal gradient represented downstream position along the lower Tarim River from Daxihaizi Reservoir to Taitema Lake. The total along-channel length of the main river was divided into three approximately equal-length sections, defined as the Upper, Middle, and Lower reaches, respectively. These zones therefore represent relative positions along the environmental-flow conveyance pathway rather than administrative or geomorphological boundaries.

The lateral gradient was quantified as the shortest Euclidean distance from each vegetation pixel to the nearest segment of the main river channel, hereafter referred to as distance to river (DTR). Each pixel was therefore assigned according to its minimum distance to the river, irrespective of river-bank side. DTR was grouped into five intervals: 0–1, 1–2, 2–5, 5–10, and >10 km. The water-table-depth gradient was divided into five classes: 0 – 2, 2 – 4, 4 – 6, 6 – 8, and >8 m. For each vegetation association, the number of 10 m pixels occurring within each longitudinal zone, DTR interval, and water-table-depth class was calculated. These counts were normalized by the total number of mapped pixels of the corresponding association to obtain within-association proportions (%). Heatmaps were subsequently generated to visualize how each association was distributed along the longitudinal, lateral, and water-table-depth gradients.

To further characterize association-specific groundwater-depth niches, the final vegetation-association map was spatially overlaid with the water-table-depth raster. Water-table-depth values were extracted for all valid vegetation pixels, while non-vegetation classes and pixels with missing or invalid water-table-depth values were excluded. For each vegetation association, the mean, median, and 2.5th and 97.5th percentiles of water-table depth were calculated. The interval between the 2.5th and 97.5th percentiles was used to represent the empirical groundwater-depth niche range, thereby reducing the influence of extreme values while retaining the central 95 % of the observed distribution. Association-specific niche ranges and central tendencies were then compared across the water-table-depth gradient to characterize niche differentiation. Approximate shifts in association composition around specific water-table depths were interpreted as empirical compositional transition zones rather than universal physiological thresholds.



4 Results

4.1 Remote-sensing feature screening and classification performance

Feature screening revealed marked differences in redundancy among the 28 candidate remote-sensing predictors (Fig. 4a).

Summer_NDVI and Spring_NDVI exhibited exceptionally high VIF values of 902.29 and 897.03, respectively, substantially exceeding those of the other predictors and indicating particularly strong redundancy within the candidate feature set. Several other predictors also showed elevated VIF values, but their redundancy was less pronounced than that of Summer_NDVI and Spring_NDVI. Predictive relevance was further evaluated using RF-derived MDI for the 28 candidate predictors (Fig. 4b). Summer_NDVI and Spring_NDVI ranked as the two least important predictors, with relative contributions of 1.09 % and 0.76 %, respectively. Considering their exceptionally high redundancy together with their limited predictive contribution, these two predictors were excluded. The remaining 26 predictors, representing complementary spectral, red-edge, moisture-sensitive, phenological, SAR, and texture information, were retained for subsequent vegetation-association classification.

Using this common 26-predictor feature set, the six classifiers were subsequently evaluated using five-fold spatial block cross-validation (Table 2). Classification performance varied substantially among these algorithms. XGBoost achieved an *OA* of 0.80, a kappa coefficient of 0.78, and a *Macro-F1* score of 0.80, followed by CatBoost (0.78, 0.77, and 0.78, respectively) and RF (0.77, 0.75, and 0.76, respectively). CART showed lower performance, with an *OA* of 0.65, a kappa coefficient of 0.63, and a *Macro-F1* score of 0.65, whereas MLC and linear SVM yielded the lowest *OA* values, at 0.55 and 0.54, respectively. Overall, the three ensemble-learning classifiers showed consistently higher performance across the three evaluation metrics than CART, MLC, and linear SVM, with XGBoost yielding the highest values and therefore being selected to generate the final vegetation-association map.

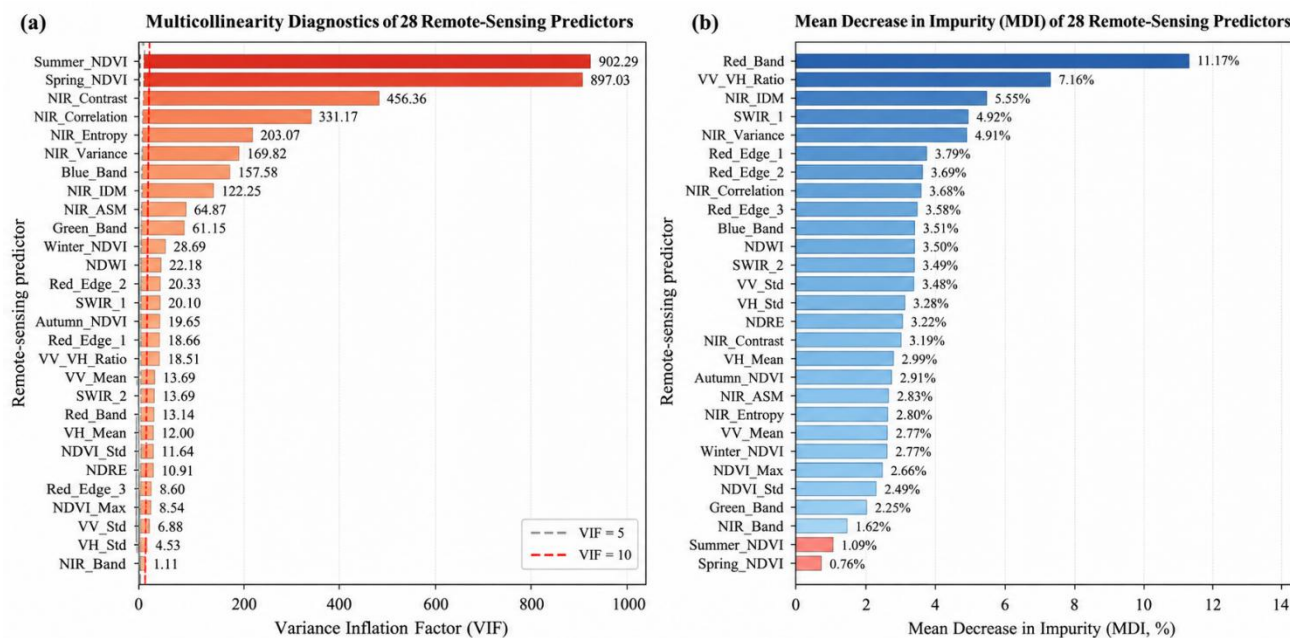


Figure 4: Remote-sensing feature screening based on predictor redundancy and importance. (a) VIFs of the 28 candidate predictors. (b) Random Forest MDI for the same predictors.

Table 2: Five-fold spatial cross-validation performance of the six classification algorithms.

Model	<i>OA</i>	Kappa	<i>Macro-F1</i>
CatBoost	0.78	0.77	0.78
RF	0.77	0.75	0.76
CART	0.65	0.63	0.65
MLC	0.55	0.52	0.51
Linear SVM	0.54	0.51	0.50
XGBoost	0.80	0.78	0.80

4.2 Spatial distribution of vegetation associations in the lower Tarim River

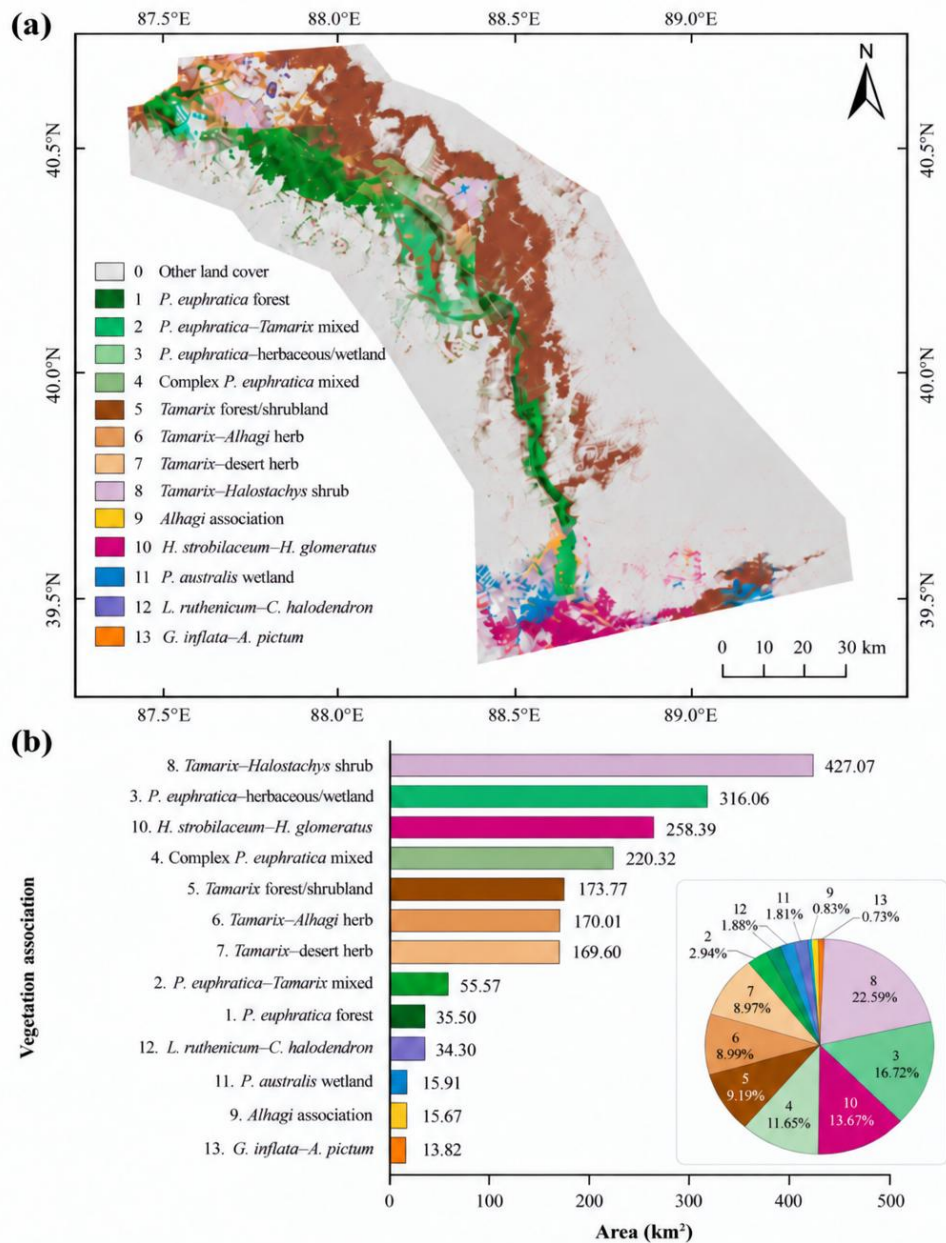
Based on the 26 screened remote-sensing predictors, the best-performing XGBoost classifier was used to generate the 2025



vegetation-association map of the lower Tarim River (Fig. 5a). The original classification contained 16 mapping classes, including 13 vegetation associations and three additional land-cover classes (bare land, permanent water, and artificial or shelterbelt forest). For visualization and vegetation-area analysis, these three non-target classes were merged into a single “other land cover”.

The 13 vegetation associations covered a total area of 1890.54 km², whereas the combined “other land cover” covered 8055.49 km². Among the vegetation associations, the *Tamarix*–*Halostachys* shrub association (association 8) had the largest mapped area (427.07 km²; 22.59 % of the total vegetation area), followed by the *P. euphratica*–herbaceous/wetland association (association 3; 316.06 km²; 16.72 %), the *H. strobilaceum*–*H. glomeratus* association (association 10; 258.39 km²; 13.67 %), and the complex *P. euphratica* mixed association (association 4; 220.32 km²; 11.65 %) (Fig. 5b). Together, these four associations accounted for 64.63 % of the mapped vegetation area. In contrast, the *G. inflata*–*A. pictum*, *Alhagi*, and *P. australis* wetland associations had the smallest mapped extents, each covering less than 20 km².

Spatially, *P. euphratica*-dominated associations were concentrated primarily along the river corridor, whereas *Tamarix*-dominated associations generally occupied broader areas farther from the main channel. Several herbaceous and halophytic associations showed more localized distributions, with the *H. strobilaceum*–*H. glomeratus* and *P. australis* wetland associations concentrated mainly in the lower reach and terminal-lake region. Overall, the mapped associations formed a distinct river-to-desert spatial mosaic, providing the spatial basis for subsequent analysis along the longitudinal, lateral, and water-table-depth gradients.



320 **Figure 5: Spatial distribution and area composition of the 13 vegetation associations in the lower Tarim River in 2025. (a) Vegetation-association map. (b) Mapped areas of the 13 vegetation associations, with an inset pie chart showing their relative proportions.**

4.3 Differentiation in empirical groundwater-depth niches among vegetation associations



The 13 vegetation associations showed clear differentiation along the water-depth gradient (Fig. 6). Their groundwater-depth distributions were characterized using the mean, median, and central 95% range (2.5th–97.5th percentiles) of water-table depth extracted from the final vegetation-association map. These distributions represent empirical realized groundwater niches rather than physiological optimum ranges, because they reflect the spatial co-occurrence of mapped vegetation associations and groundwater conditions within the study area.

P. euphratica-related (vegetation associations 1-4) were generally distributed under shallow to intermediate groundwater conditions. Among them, the *P. euphratica*-herbaceous/wetland (vegetation association 3) occurred under the shallowest groundwater conditions, with a median water-table depth of approximately 3.4 m. The median water-table depths of *P. euphratica* forest (vegetation association 1), *P. euphratica*-*Tamarix* mixed (vegetation association 2), and complex *P. euphratica* mixed (vegetation association 4) were centred mainly around 4–5 m.

Tamarix-related (vegetation associations 5-8) showed a broader range of groundwater conditions. The median water-table depths of *Tamarix* forest/shrubland (vegetation association 5), *Tamarix*-*Alhagi* herb (vegetation association 6), and *Tamarix*-*Halostachys* shrub (vegetation association 8) were all between approximately 4.5 and 5.5 m. The *Tamarix*-desert herb (vegetation association 7) occurred under the deepest groundwater conditions among the *Tamarix*-related associations, with a median water-table depth close to 6 m.

Herbaceous and halophytic (vegetation associations 9-13) occupied distinct groundwater niches. The *P. australis* wetland (vegetation association 11) was concentrated mainly where the water table was shallower than 4 m. The *H. strobilaceum*-*H. glomeratus* (vegetation association 10) exhibited the narrowest water-table-depth range, indicating a relatively constrained empirical groundwater niche. By contrast, the *Alhagi* association (vegetation association 9), *L. ruthenicum*-*C. halodendron* mixed shrub (vegetation association 12), and *G. inflata*-*A. pictum* (vegetation association 13) occurred predominantly under intermediate groundwater conditions.

Overall, vegetation associations exhibited a distinct pattern of empirical groundwater-depth niche differentiation. Water-table depths shallower than approximately 4 m were more strongly associated with wetland vegetation and some *P. euphratica*-dominated associations; intermediate conditions of approximately 4–6 m contained the main distribution centres of several *Populus* and *Tamarix* associations; and depths greater than approximately 6 m were increasingly occupied by drought-tolerant

shrub and desert-herb assemblages. The approximately 4 and 6 m boundaries are therefore interpreted as empirical compositional transition zones rather than universal physiological thresholds or groundwater optima.

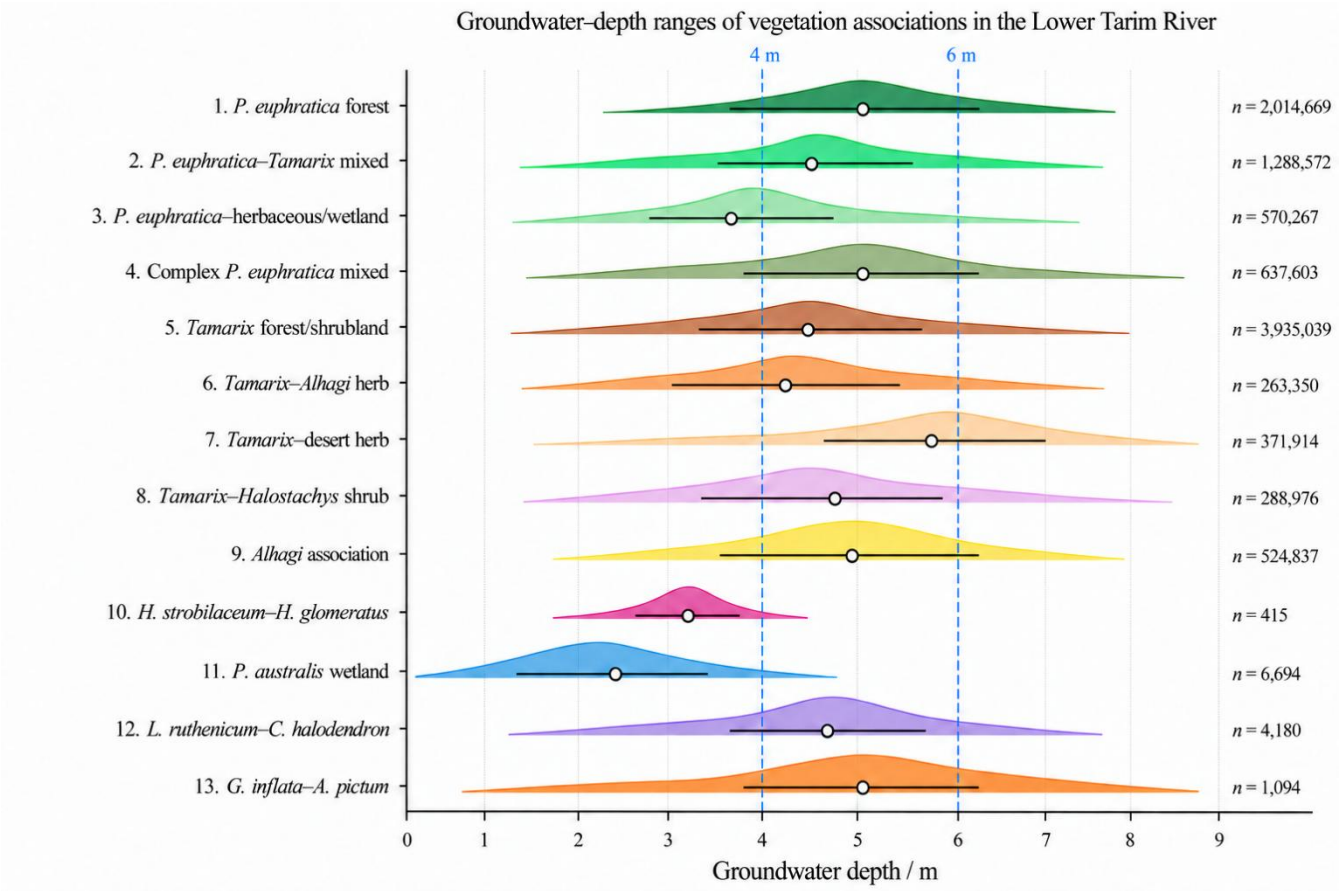


Figure 6: Water-table-depth distributions and ecohydrological niche differentiation of the 13 vegetation associations in the lower Tarim River. Blue horizontal lines indicate the observed Water-table-depth range of each association, with vertical ticks marking the median and orange circles indicating the mean. Values of n denote the number of valid vegetation pixels used to characterize the groundwater-depth distribution of each association.

4.4 Spatial differentiation of vegetation associations along three interrelated hydrogeographic gradients

Based on the 2025 vegetation-association map, the distributions of the 13 associations were compared across three interrelated hydrogeographic gradients: longitudinal river position (upper, middle, and lower reaches), lateral distance to river (0–1, 1–2,



2–5, 5–10, and >10 km), and water-table depth (0–2, 2–4, 4–6, 6–8, and >8 m). Within-association proportions were calculated to quantify the share of each association occurring within each gradient interval and to characterize its present-day spatial differentiation (Fig. 7a–c).

Along the longitudinal river gradient (Fig. 7a), vegetation associations showed pronounced reach-scale differentiation. Most associations were concentrated in the upper reach, where *P. euphratica* forest (vegetation association 1), *P. euphratica*–*Tamarix* mixed (vegetation association 2), *Tamarix*–*Alhagi* herb (vegetation association 6), *Alhagi* association (vegetation association 9), *L. ruthenicum*–*C. halodendron* mixed shrub (vegetation association 12), and *G. inflata*–*A. pictum* (vegetation association 13) had their highest within-association proportions in the upper reach. The complex *P. euphratica* mixed (vegetation association 4) and *Tamarix* forest/shrubland (vegetation association 5) were concentrated mainly in the middle reach. In contrast, the *H. strobilaceum*–*H. glomeratus* (vegetation association 10) and *P. australis* wetland (vegetation association 11) occurred predominantly in the lower reach and terminal-lake region.

Along the lateral distance-to-river gradient (Fig. 7b), the associations exhibited clear spatial zonation. *P. euphratica* forest (vegetation association 1), *P. euphratica*–herbaceous/wetland (vegetation association 3), and *Alhagi* association (vegetation association 9) had their highest within-association proportions within 0–1 km of the river. *Tamarix* forest/shrubland (vegetation association 5) occurred predominantly at distances of 5–10 km, whereas the *L. ruthenicum*–*C. halodendron* mixed shrub (vegetation association 12) and *G. inflata*–*A. pictum* (vegetation association 13) were concentrated mainly in areas more than 10 km from the river.

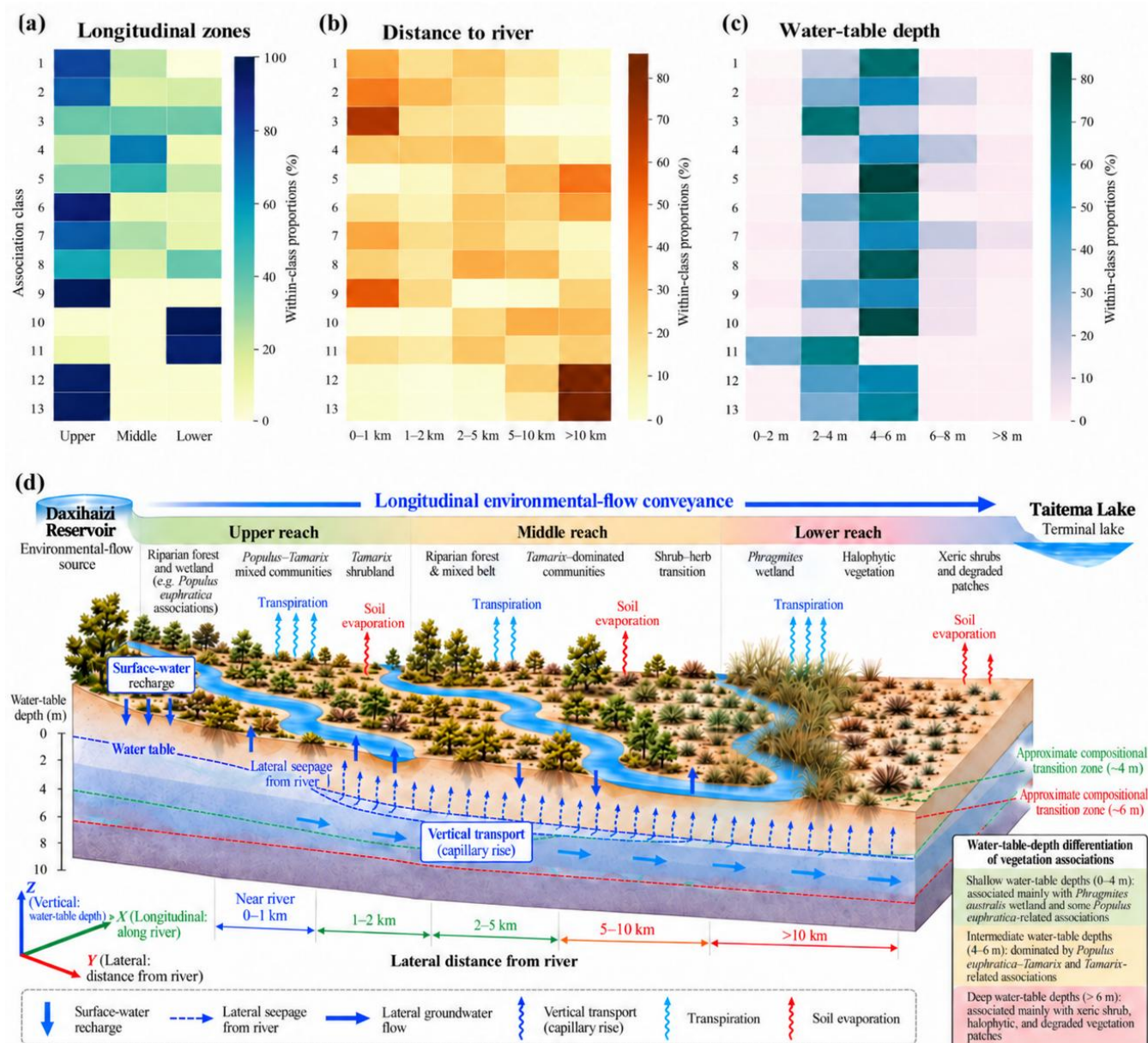
The water-table-depth gradient further revealed distinct groundwater niche differentiation among associations (Fig. 7c). The *P. australis* wetland (vegetation association 11) had its highest within-association proportion under shallow groundwater conditions of 0–2 m. Several *Populus*, *Tamarix*, shrub, and halophytic associations showed relatively high proportions within the 4–6 m interval, whereas deeper groundwater classes contained increasing proportions of some drought-tolerant shrub and desert-herb associations. Because these values represent within-association spatial proportions, a high proportion within a particular water-table-depth class indicates the present-day concentration of an association rather than a physiological groundwater optimum.

Taken together, the three interrelated hydrogeographic dimensions (Fig. 7d) describe complementary aspects of the present-



385

day spatial organization of vegetation associations in the lower Tarim River. Longitudinal position captures reach-scale differentiation, distance to river reflects lateral zonation, and water-table depth characterizes groundwater-related niche differentiation. The conceptual model in Fig. 7d synthesizes these observed spatial patterns together with hydrological processes that may contribute to their formation. It should therefore be interpreted as a conceptual ecohydrological framework rather than as a quantitative test of the independent or joint causal effects of environmental-flow delivery, lateral seepage, and groundwater depth.



390 **Figure 7: Spatial differentiation of riparian vegetation associations along three hydrogeographic gradients in the lower Tarim River.**
 (a) Longitudinal distribution across the upper, middle, and lower reaches; (b) distribution along the distance-to-river gradient; (c)
 distribution along the water-table-depth gradient; and (d) conceptual model illustrating longitudinal environmental-flow conveyance,
 lateral river – groundwater connectivity, water-table-depth differentiation, and associated vegetation patterns.



5 Discussion

5.1 Ecohydrological value of association-level vegetation mapping

The primary advance of the mapping component is therefore not the comparison among classifiers itself, but the establishment of a spatially continuous 10 m association-level ecological baseline capable of distinguishing communities that would otherwise be merged within broad vegetation classes (Daryaei et al., 2020; Guo et al., 2021). In this study, a 26-predictor multi-source remote-sensing feature set was used to distinguish 13 vegetation associations at 10 m resolution. Among the six classifiers evaluated using spatial block cross-validation, XGBoost achieved the highest overall accuracy (80 %), indicating that association-level mapping is feasible despite the strong spectral and structural heterogeneity of the lower Tarim River. The remote-sensing predictors represented complementary spectral, phenological, moisture-sensitive, SAR, and texture information; however, because no feature-source ablation experiment was conducted, the individual contribution of each information domain cannot be isolated. Accordingly, the principal value of the classification framework lies not in demonstrating a universally superior classifier or a quantified advantage of multi-source fusion, but in providing a spatially continuous association-level baseline for subsequent ecohydrological analysis.

More importantly, association-level mapping revealed groundwater-related differentiation that would be obscured if vegetation were represented only by broad physiognomic groups or dominant species. Previous studies have shown that riparian communities may occupy distinct positions along hydrological gradients (Ding et al., 2017; Loheide II and Gorelick, 2007; Zhu et al., 2012). In the present study, associations sharing the same dominant genus nevertheless exhibited contrasting groundwater-depth distributions. For example, the *P. euphratica*–herbaceous/wetland association was concentrated under comparatively shallow groundwater conditions, whereas the *P. euphratica*–*Tamarix* mixed association was centred at greater water-table depths. Similar differentiation among *Tamarix*-dominated associations further indicates that community composition contains ecohydrological information beyond dominant-species identity. These differences represent empirical realized groundwater niches derived from the present-day spatial co-occurrence of vegetation and groundwater conditions, rather than physiological optimum ranges.

Association-level mapping therefore extends remote sensing from representing vegetation presence or cover towards



delineating spatially explicit ecological units that can be related to groundwater conditions. Although the 10 m spatial resolution cannot fully eliminate mixed-pixel effects in small or structurally complex patches, the resulting map provides a landscape-scale framework for identifying association-specific ecohydrological differentiation and for linking vegetation composition with hydrological gradients in groundwater-dependent dryland riparian ecosystems.

5.2 Ecohydrological interpretation of spatial differentiation among vegetation associations

A key advance of this study is that association-level vegetation patterns were not interpreted against water-table depth alone, but within three interconnected hydrogeographic dimensions representing longitudinal environmental-flow conveyance, lateral river influence, and vertical groundwater accessibility. This multidimensional perspective reveals that similar groundwater conditions may support different association compositions depending on longitudinal position and river proximity, while associations sharing the same dominant genus can occupy contrasting hydrogeographic settings. The 2025 vegetation-association map revealed clear longitudinal and lateral differentiation across the lower Tarim River. Several *P. euphratica*-related associations had their highest within-association proportions in the upper reach and within the near-river corridor, whereas *Tamarix*-dominated, halophytic, and xeric shrub associations were increasingly represented farther from the river and towards the Middle and Lower reaches. These patterns are broadly consistent with the spatial attenuation of river-related groundwater recharge away from the main channel reported for the lower Tarim River (Xu et al., 2007; Zeng et al., 2016). However, distance to the present river channel should not be treated as a direct proxy for groundwater availability. Some associations occurring relatively far from the main channel were still associated with comparatively shallow groundwater, indicating that the present vegetation mosaic also reflects spatial heterogeneity in groundwater conditions and local hydrogeomorphic settings (Zeng et al., 2016).

Water-table depth provided a complementary dimension of association differentiation. Shallow groundwater conditions (<4 m) were associated mainly with *P. australis* wetland and the *P. euphratica*-herbaceous/wetland association, whereas several *Populus*-*Tamarix* and mixed woody associations had their main distribution centres between approximately 4 and 6 m. At greater depths (>6 m), drought-tolerant shrub and desert-herb associations became increasingly prominent. Previous studies in the lower Tarim River have similarly reported strong vegetation sensitivity to groundwater depth and relatively favourable



groundwater conditions within approximately 2–4 m for some riparian vegetation types (Hao et al., 2010; Li et al., 2013). However, the present results do not indicate that 4–6 m represents an optimal groundwater range. Instead, the changes in association composition around approximately 4 and 6 m suggest two empirical transition zones separating shallow-, intermediate-, and deeper-groundwater assemblages. These values should therefore be interpreted as compositional boundaries specific to the present dataset rather than universal physiological thresholds. Reported groundwater thresholds in the lower Tarim River also vary among reaches, vegetation types, and environmental settings (Han et al., 2015), further supporting this cautious interpretation.

The long history of environmental-flow releases provides an important hydrological context for these spatial patterns, but the 2025 vegetation map represents a single-period spatial snapshot rather than a reconstruction of vegetation change since 2000. Previous studies have shown that repeated environmental-flow releases can modify groundwater conditions and support riparian vegetation recovery (Hao and Li, 2014; Liu et al., 2022), but the present dataset cannot determine when individual associations became established or quantitatively attribute their current distributions to environmental-flow interventions. The observed association pattern is therefore best interpreted as the present-day ecohydrological configuration developed within a hydrological regime influenced by managed environmental flows, groundwater redistribution, and natural spatial heterogeneity. This association-level baseline provides a basis for future temporal comparisons of vegetation composition and ecohydrological change in the lower Tarim River.

5.3 Implications for targeted environmental-flow management in dryland rivers

The identification of association-specific groundwater niches extends previous groundwater – vegetation assessments from species- or greenness-based responses to community-compositional responses. A key management implication of this study is that environmental-flow assessment may benefit from considering association-specific vegetation patterns and their groundwater-depth relationships, rather than relying solely on total water delivery, vegetation greenness, or mean groundwater level. Environmental-flow management increasingly emphasizes maintaining ecologically relevant flow regimes and vegetation responses rather than maximizing water delivery alone (Acreman and Dunbar, 2004; Rivaes et al., 2017; Virkki et al., 2022). Our results show that associations sharing the same dominant genus, such as *Populus* or *Tamarix*, can be associated



with different groundwater-depth ranges and spatial positions. These contrasts indicate that dominant-species identity alone may not adequately represent the ecohydrological differentiation of riparian vegetation. In the lower Tarim River, near-channel *P. euphratica* and mesic associations were generally associated with relatively shallow groundwater conditions, whereas several drought-tolerant shrub and desert-herb associations occurred more frequently under deeper groundwater conditions.

These association-specific patterns suggest that applying a single groundwater-depth target uniformly across the river corridor may overlook substantial spatial heterogeneity in vegetation–groundwater relationships. They should, however, be regarded as empirical spatial references rather than prescriptive groundwater requirements. This interpretation is broadly consistent with recent efforts to optimize ecological water delivery in the Tarim River by considering interactions among water conveyance, groundwater conditions, and vegetation responses (Liu et al., 2022, 2024).

This association-based perspective may also be relevant to other regulated dryland rivers. Environmental-flow experiments in the Colorado River Delta have demonstrated strong spatial heterogeneity in groundwater and vegetation responses, while environmental-water planning in the Murray–Darling Basin recognizes that different vegetation and wetland targets may require different flow regimes (Shafroth et al., 2017; Swirepik et al., 2016). The transferable contribution of the present study is therefore not the approximately 4 and 6 m transition zones themselves, but the association-level framework linking vegetation composition with longitudinal position, distance to river, and groundwater conditions. Identifying the spatial distribution of target vegetation associations and the hydrological conditions with which they are currently associated may provide a more ecologically informative basis for restoration planning than uniform greening targets or a single groundwater-depth criterion.

6 Conclusions

Effective conservation of GDEs and environmental-flow management in arid and semi-arid regions require spatially explicit understanding of vegetation associations and their ecohydrological niches. By integrating field surveys, multi-source remote sensing, and groundwater data, this study developed a 10 m vegetation-association map of the lower Tarim River for 2025 and quantified association-level differentiation along interconnected hydrogeographic gradients. The main conclusions are as



follows.

- 490 (1) Association-level mapping resolved ecohydrological differences that are obscured by broader vegetation classifications. The integration of spectral, red-edge, moisture-sensitive, phenological, SAR, and texture information enabled the identification of 13 representative vegetation associations at 10 m resolution, with the best-performing model achieving an overall accuracy of 80 %. Compared with broad tree, shrub, and herbaceous classes, association-level mapping distinguished communities sharing the same dominant species but differing in accompanying species composition, thereby providing a finer spatial basis
- 495 for identifying association-specific ecohydrological niches.
- (2) Integrating longitudinal position, lateral distance from the river, and water-table depth revealed a multidimensional hydrogeographic organization of riparian vegetation associations, and spatial heterogeneity along the lower Tarim River. Natural vegetation covered 1890.54 km², with pronounced spatial heterogeneity among associations along the riparian corridor. In general, *P. euphratica*-related associations were concentrated along the river channel and in near-river areas, *Tamarix*-
- 500 related associations occurred more frequently in outer riparian and transitional zones, whereas wetland and halophytic associations were relatively concentrated in the lower reach, terminal-lake region, and local depressions. These patterns are consistent with spatial differences in downstream water delivery, river–groundwater connectivity, and groundwater availability across the riparian corridor.
- (3) Vegetation associations occupied distinct groundwater niches, with marked community turnover around water-table depths
- 505 of approximately 4 and 6 m. Shallow groundwater conditions (<4 m) were associated mainly with *P. australis* wetlands and *P. euphratica*–herbaceous/wetland associations, whereas several *Populus*–*Tamarix* and mixed woody associations were concentrated at 4–6 m. At greater water-table depths (>6 m), drought-tolerant shrub, desert-herb, and halophytic associations became increasingly prominent. Based on the groundwater-depth distributions, approximately 4 and 6 m therefore represent empirical association-turnover zones rather than universal physiological thresholds applicable to all associations or river
- 510 reaches.

Overall, our results show that environmental-flow assessment in drylands should move beyond total water delivery, vegetation cover, and uniform groundwater targets towards an association-specific perspective that accounts for spatial differences in hydrological requirements. The 2025 vegetation-association map provides a baseline for long-term monitoring, while the



proposed linkage among vegetation associations, spatial position, and hydrological conditions provides a basis for
515 differentiated ecological restoration and targeted environmental-water allocation in the lower Tarim River and other regulated
dryland river systems.

Data availability

Sentinel-1 and Sentinel-2 data and the Copernicus DEM GLO-30 are publicly available through the Copernicus Data Space
Ecosystem. The 2024 field-survey dataset is publicly available from the Global Change Research Data Publishing &
520 Repository (Chen et al., 2025; <https://doi.org/10.3974/geodb.2025.02.09.V1>)

Author contributions

X.C. and Q.L. contributed equally to this work. X.C. designed the study, conducted field surveys, compiled and processed the
data, performed the analyses, and prepared the original manuscript. Q.L. contributed to data curation, validation, and
manuscript review and editing. H.D. conceived the study and provided supervision. D.G. conceived and supervised the study
525 and acquired funding. Y.L., Q.J., and B.C. contributed to data curation, methodology, and validation. X.X. participated in the
field surveys and contributed to data collection. Y.B. and J.Y. contributed to methodological discussions and interpretation of
the results. P.D.M. and T.V.d.V. provided supervision, methodological guidance, and manuscript review and editing. All authors
reviewed and approved the final manuscript.

Competing interests

530 The authors have the following competing interests: At least one of the (co-)authors is a member of the editorial board of
Natural Hazards and Earth System Sciences.

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