

Spatiotemporal dynamics of surface water and eco-environmental responses in Thac Ba Reservoir, Vietnam: a remote sensing and machine-learning approach

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Abstract. This study examines surface-water dynamics and shoreline environmental responses in Thac Ba Reservoir, Vietnam, using a multi-source data integration and Random Forest classification framework. Landsat imagery, Sentinel-1 SAR (Synthetic Aperture Radar), Sentinel-2, terrain variables and hydrometeorological observations were used to analyse the benchmark years 2015, 2020 and 2025 under low-water and high-water conditions. The classification produced stable results, with overall accuracy ranging from 0.850 to 0.920 and Kappa coefficient values from 0.77 to 0.88. Under low-water conditions, water bodies expanded from 13,830.3 ha in 2015 to 16,916.9 ha in 2025, while terrestrial ecosystems decreased slightly. Semi-inundated ecosystems changed non-linearly, increasing between 2015 and 2020 and decreasing thereafter. Vegetation-related classes showed patterns that differed between hydrological states: under low-water conditions, vegetation structure varied within the exposed drawdown belt, whereas, under high-water conditions, sparse and moderate vegetation decreased and dense vegetation increased in more stable shoreline sectors. The results indicate that reservoir change in Thac Ba was expressed not only by variation in open-water extent, but also by adjustment of the drawdown belt and adjacent shoreline environments. The study demonstrates the value of integrating optical imagery, SAR backscatter and terrain information for mapping water-related and transitional classes in morphologically complex monsoonal reservoirs.

Key words:

Thac Ba Reservoir,
surface-water dynamics,
shoreline environmental
responses,
remote sensing,
Random Forest
classification

Introduction

Reservoirs are important components of inland-water systems and dynamic physical-geographical units. By impounding river valleys, they alter local hydrological regimes, reshape shoreline morphology and create new interfaces between permanent water, periodically exposed land and adjacent terrestrial environments. These effects are particularly pronounced in monsoonal regions, where strong seasonal contrasts in rainfall and runoff produce repeated expansion and

contraction of reservoir extent. As a result, reservoir change is expressed not only by variations in open-water area, but also by shifts in drawdown zones (the area of reservoir bed exposed when water levels fall), shoreline stability, sediment redistribution and the structure of littoral vegetation. Reservoirs should therefore be examined as integrated water–land systems in which hydrological regulation and landscape reorganization operate together (Vörösmarty et al. 2010; Ptak 2018; Ulibarri and Taeihagh 2018; Busker et al. 2019; Hou et al. 2022).

Satellite remote sensing provides an effective basis for analysing such systems. The long Landsat archive, in particular, enables the reconstruction of interannual and seasonal changes in surface water across lakes and reservoirs. Previous studies have shown that medium-resolution imagery is well suited to detecting long-term water dynamics in both natural and regulated inland-water environments (Donchyts et al. 2016; Pekel et al. 2016; Wang et al. 2018; Wang et al. 2019; Sogno et al. 2022). Remote sensing has also been widely applied to lake and reservoir studies concerned with water quality, surface temperature and other environmental properties, confirming its value for inland-water research beyond simple water delineation (Dörnhöfer and Oppelt 2016; Coluzzi et al. 2019; Tran et al. 2021; Albarqouni et al. 2022). For reservoirs, this broader perspective is important because water extent is influenced not only by climate variability, but also by storage regulation, operational decisions and shoreline topography.

A persistent methodological challenge lies in the interpretation of transitional shoreline zones. Threshold-based approaches, including fixed thresholds applied to NDWI and MNDWI, Otsu automatic thresholding and AWEI-based water extraction (Automated Water Extraction Index), have been widely used for delineating open-water surfaces because they are relatively simple and efficient (Otsu 1979; McFeeters 1996; Xu 2006; Ji et al. 2009; Feyisa et al. 2014). These methods are effective where the spectral contrast between water and non-water surfaces is clear. Their reliability may decrease, however, in heterogeneous littoral settings where shallow water, wet sediment, sparse vegetation, semi-inundated surfaces and stable terrestrial cover occur in close proximity or within mixed pixels. In such conditions, the most responsive parts of the reservoir margin are often also the most difficult to classify. Spectral indices such as NDVI, NDWI, MNDWI, LSWI and AWEI remain useful for identifying vegetation, open water and moisture-related surface conditions, but they do not always fully represent the continuous transition from permanent water to exposed draw-down surfaces and vegetated shoreline zones when used as stand-alone threshold variables (Rouse et al. 1973; Tucker 1979; Myneni et al. 1995; McFeeters 1996; Gao 1996; Xu 2006; Ji et al. 2009; Chandrasekar et al. 2010; Dong et al. 2014; Feyisa et al. 2014). This limitation is particularly relevant for reservoir margins, where hydrological fluctuation, shoreline

gradient and vegetation cover jointly influence the spectral and radar response of the surface.

Multi-source data integration can help address this problem by combining optical imagery, radar observations, terrain information and supervised classification within a common analytical framework. Instead of relying on a single spectral threshold, such an approach allows transitional classes to be interpreted from a broader set of predictors. Among supervised classification methods, Random Forest (an ensemble machine-learning method based on many decision trees) has been widely used for heterogeneous ecosystems and land-cover mosaics because it can handle non-linear class boundaries, correlated predictors and mixed spectral responses (Breiman 2001; Pal 2005; Belgiu and Drăguț 2016). It has been applied successfully in surface-water extraction, wetland and shoreline mapping and other heterogeneous land-cover contexts, including grassland management classification using combined Sentinel-1 and Sentinel-2 data (Acharya et al. 2019; Li et al. 2019; Bartold et al. 2024). For reservoir-margin analysis, this is relevant because open water, moist soil, semi-inundated vegetation and stable terrestrial cover may show overlapping optical responses, whereas radar backscatter and terrain position can provide additional information on moisture conditions and shoreline setting. Random Forest therefore provides a suitable classification framework for integrating optical, radar and terrain variables in the analysis of complex shoreline environments.

These methodological advances have been strengthened by cloud-based geospatial platforms. Google Earth Engine now allows large satellite archives to be processed efficiently with consistent routines for image compositing, index calculation and classification, making multi-temporal analysis more feasible for hydrological and environmental applications (Gorelick et al. 2017; Tamiminia et al. 2020; Ghosh et al. 2022; Yang et al. 2022; Vijayakumar et al. 2024). In Vietnam, remote sensing and geospatial methods have been applied increasingly to drought assessment, flash-flood analysis, precipitation evaluation, vegetation monitoring and other environmental problems in tropical and monsoonal settings (Trinh and Vu 2019; Kieu 2021; Kieu and Tran 2021; Nguyen and Nguyen 2025; Trinh et al. 2025; Tran et al. 2026). Reservoir studies in Vietnam have likewise demonstrated the usefulness of satellite data for analysing chlorophyll-a, water quality,

storage variation and shoreline effects associated with water-level fluctuation (Pham QV et al. 2019; Phan et al. 2020; Pham et al. 2022; Pham-Duc et al. 2022; Tran et al. 2021). Even so, most previous studies have addressed individual reservoir attributes separately rather than examining the coupled behaviour of water extent and shoreline transition zones within a single analytical framework.

This gap is evident in Thac Ba Reservoir in northern Vietnam. Thac Ba is a morphologically complex multi-island reservoir with a highly indented shoreline, numerous narrow inlets, shallow marginal sectors and a broad seasonal fluctuation belt. These characteristics create a fragmented littoral landscape in which permanent water, exposed drawdown surfaces, semi-inundated areas and terrestrial cover are closely interwoven. Such spatial complexity makes the reservoir a suitable case for physical-geographical analysis, but it also increases classification difficulty. Existing studies related to Thac Ba have mainly focused on selected reservoir properties, such as chlorophyll-a and storage variation, while broader regional work has pointed to the need for improved monitoring of surface-water conditions and management in the surrounding area (Pham et al. 2019; Takami 2022; Kieu et al. 2023). A spatially integrated assessment of how surface-water dynamics, semi-inundated zones and vegetation-related shoreline responses interact within the same reservoir-margin system is still lacking.

In this study, the term “eco-environmental responses” is used in a specific and operational sense. It refers to shoreline environmental responses expressed through changes in semi-inundated zones, vegetation condition and transitions among permanent water, seasonally exposed surfaces and stable terrestrial cover. This usage is appropriate for a remote-sensing investigation because such responses can be identified from combinations of spectral, radar and terrain variables, even where detailed field ecological measurements are limited. In a reservoir setting, these responses are part of the geographical expression of repeated water-level fluctuation within the littoral zone. The term is therefore used here to describe remotely sensed and spatially explicit shoreline responses, rather than species-level ecological processes or floristic community change.

Against this background, the present study investigates the spatiotemporal dynamics of surface water and shoreline environmental responses in Thac Ba

Reservoir using a multi-source data integration and machine-learning approach. The analysis is based primarily on Landsat imagery for the benchmark years 2015, 2020 and 2025, supported by Sentinel-1 SAR (Synthetic Aperture Radar), Sentinel-2 imagery, terrain variables and hydrometeorological information. The study has three objectives: (1) to quantify changes in the principal landscape units of Thac Ba Reservoir under contrasting low-water and high-water conditions; (2) to examine the spatial pattern of semi-inundated and vegetation-related classes as indicators of shoreline environmental response; and (3) to evaluate the usefulness of a Random Forest-based classification framework for mapping water-related and transitional classes in a morphologically complex reservoir. By addressing these objectives, the study contributes to the physical-geographical interpretation of regulated reservoir landscapes in monsoonal environments and provides a stronger basis for spatial monitoring of shoreline change in Thac Ba Reservoir.

Location, data and methodology

Study area

Thac Ba Reservoir is located in northern Vietnam, within the Chay River basin. The reservoir was formed after the impoundment of the Chay River for the Thac Ba hydropower scheme, which was completed in 1971 and has been in operation since 1972. Besides hydropower generation, the reservoir contributes to seasonal flow regulation, dry-season water storage and downstream flood moderation. It therefore represents an important engineered water body and a dynamic physical-geographical unit in the middle reaches of the Chay River system (Takami 2022; Kieu et al. 2023). The location of the study area is shown in Figure 1.

Thac Ba Reservoir has a complex planform and shoreline configuration. The water surface is commonly reported at ~23,400 ha, and the reservoir contains more than 1,300 islands and hill-islands distributed across a highly indented system of embayments, narrow inlets and branching flooded valleys. Its longitudinal extent exceeds 60 km. The surrounding terrain is dominated by low hills and dissected slopes typical of the northern Vietnamese

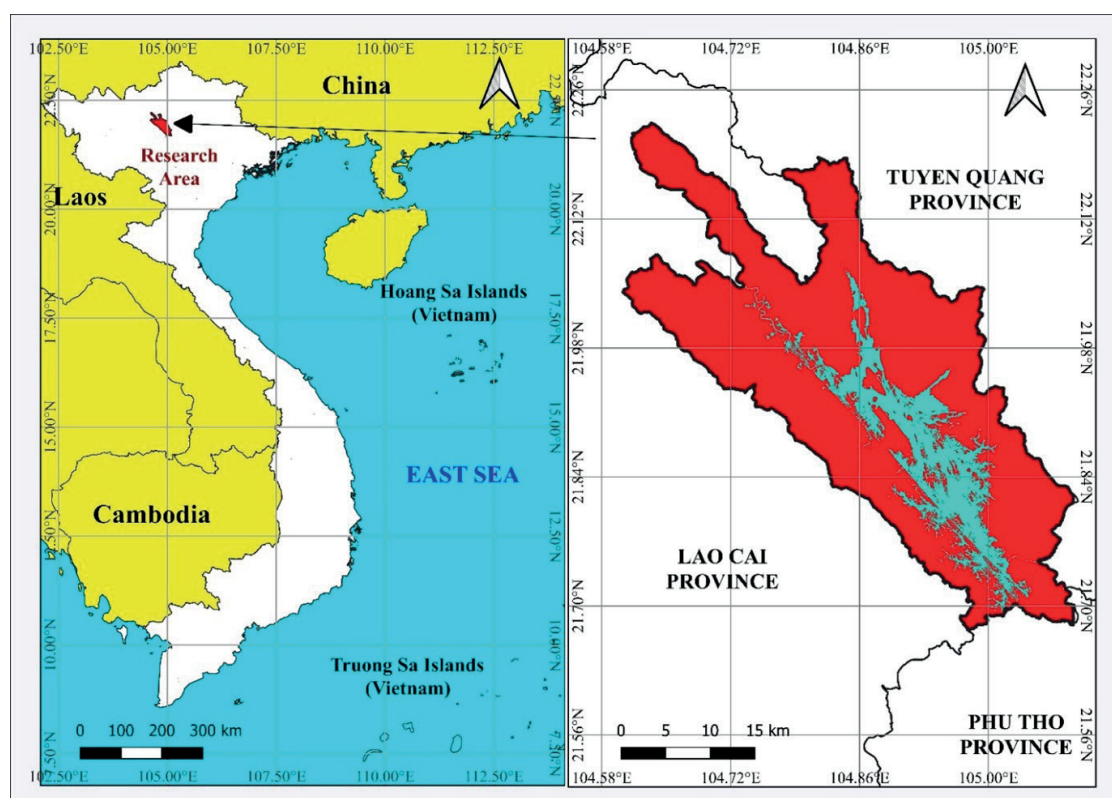


Fig. 1. Location of the study area

midland belt. Around the central lake sector, elevations commonly range between 100 and 200 m, while higher terrain occurs toward the surrounding mountain margins. This combination of flooded valleys, insular hilltops, gently sloping reservoir edges and irregular shorelines produces a fragmented littoral zone in which permanent water, seasonally exposed surfaces, semi-inundated vegetation and stable terrestrial cover occur in close spatial proximity.

The hydrological regime of Thac Ba Reservoir is strongly seasonal. During the dry season, water levels decline markedly, commonly falling to ~46–52 m a.s.l. and marginal surfaces are exposed at the foot of islands and along gently sloping shores. During the wet season and subsequent storage period, water levels rise substantially and may reach ~57–58 m a.s.l., inundating low-lying shoreline sectors and reactivating semi-inundated belts around the reservoir margin. This seasonal displacement of the water line is directly relevant to the present study because it produces a wide drawdown zone, strong contrasts in surface moisture and repeated transitions between aquatic, semi-inundated and terrestrial conditions.

Climatically, the reservoir lies within the monsoonal regime of northern Vietnam. The Chay River

basin has a rainy season from May to October and a dry season from November to April. Mean annual rainfall generally ranges approximately from 1,500 to 2,000 mm, with a multi-year average of ~1,800 mm, while mean annual air temperature is ~22–23 °C. Rainfall is concentrated in the wet season, and the largest rainfall events commonly occur in July and August. This seasonal structure provides the climatic basis for the intra-annual fluctuation of reservoir extent and supports the selection of late dry-season and peak wet-season satellite images in the present analysis.

From a physical-geographical perspective, Thac Ba Reservoir can be considered a water–land system in which hydrological regulation repeatedly alters the spatial relationship among permanent water, drawdown surfaces, semi-inundated zones and more stable terrestrial areas. Previous studies have shown that satellite data are suitable for monitoring selected reservoir-related variables in Thac Ba, including chlorophyll-a, suspended sediment concentration and storage-related variation (Pham et al. 2019; Takami 2022). However, the multi-island morphology of the reservoir and the pronounced seasonal displacement of the littoral zone make it suitable for

an integrated assessment of surface-water dynamics and shoreline environmental responses. The main shoreline and geomorphological features of Thac Ba Reservoir are presented in Figure 2.

Data sources

This study used multi-source satellite imagery, terrain data and hydrometeorological observations to analyse surface-water dynamics and shoreline environmental responses in Thac Ba Reservoir. Landsat Collection 2 Level-2 imagery was used as the principal optical dataset because it provides atmospherically corrected surface reflectance and a consistent medium-resolution archive for interannual comparison. Landsat 8 images were used for the benchmark years 2015 and 2020, while Landsat 8/9 images were used for 2025. Sentinel-2 MSI Level-2A imagery was used (Multi Spectral Instrument) as a complementary optical source to support the interpretation of shoreline geometry and transitional

reservoir-margin features. Because Sentinel-2 data became available only after mid-2015, they were used mainly as supplementary information for 2015 and more fully for 2020 and 2025.

Sentinel-1 GRD (Ground Range Detected) C-band SAR imagery was included to provide radar information on water surfaces, moist drawdown areas and semi-inundated shoreline zones. The analysis used VV and VH backscatter layers (the strength of the radar signal reflected back to the sensor). Terrain conditions were represented by the Copernicus DEM GLO-30 (a digital elevation model), from which elevation and slope variables were derived. Hydrometeorological observations, including reservoir water level, rainfall and air temperature, were used to describe the hydrological background of the selected image periods. Reference and validation data were compiled from high-resolution Google Earth imagery and field observations. The main datasets used in the study are summarized in Table 1.

Monthly rainfall records for the benchmark years were aggregated by hydrological season and by the

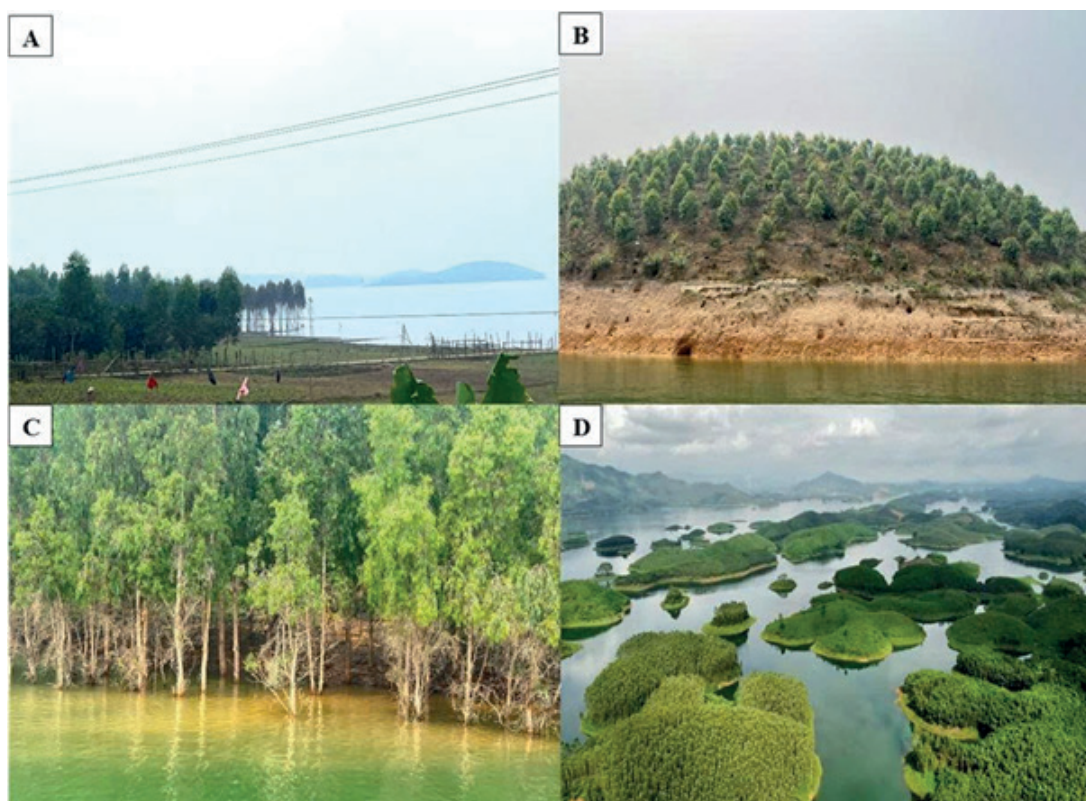


Fig. 2. Field photographs of geomorphological and shoreline features of Thac Ba Reservoir: (A) Irregular shoreline and reservoir edge; (B) Exposed drawdown surface; (C) Semi-inundated vegetation; (D) Island/hill-island morphology

two image-selection windows used in this study. The dry season was defined as November–April and the wet season as May–October. The late dry-season image window corresponded to March–May, which includes the transition from late dry-season to early wet-season conditions, while the peak wet-season image window corresponded to August–October. These rainfall data were used to characterize the hydro-climatic setting of the benchmark years and were not included as pixel-level predictors in the Random Forest classification. Seasonal rainfall characteristics are presented in Table 2.

Methods

The methodological framework consisted of five steps: image selection and preprocessing; derivation of spectral, radar and terrain variables; multi-source data integration; supervised classification; and spatiotemporal analysis of reservoir-margin landscape units. The workflow was implemented for the benchmark years 2015, 2020 and 2025 under low-water and high-water conditions (Figure 3).

Image selection and preprocessing

For each benchmark year, satellite images were selected for two hydrological states. Late dry-season

Table 1. Summary of datasets used in this study

Data source	Product / type	Spatial resolution	Study period	Variables used
Landsat 8/9	Collection 2 Level-2	30 m	2015, 2020, 2025	Surface reflectance, land-surface temperature, spectral indices
Sentinel-2 MSI	Level-2A	10-20 m, resampled to 30 m	2015*, 2020, 2025	B2, B3, B4, B8, B11, B12; water and vegetation indices
Sentinel-1 SAR	GRD, C-band	10 m, resampled to 30 m	2015, 2020, 2025	VV and VH backscatter
Reservoir hydrometeorological observations	Water-level and meteorological records	Daily / monthly	2015-2025	Water level, rainfall, air temperature
Copernicus DEM	GLO-30	30 m	Static	Elevation, slope, terrain derivatives
Training and validation data	Point / polygon samples	Sample-based	2015, 2020, 2025	Water bodies, semi-inundated ecosystems, terrestrial ecosystems, bare soil / built-up surfaces

For 2015, Sentinel-2 data were limited to post-launch acquisitions in the second half of the year.

Table 2. Seasonal rainfall characteristics in the Thac Ba Reservoir area for the benchmark years used in this study (mm).

Year	Annual rainfall	Dry season, Nov–Apr	Wet season, May–Oct	Late dry-season window, Mar–May	Peak wet-season window, Aug–Oct
2015	1808.9	238.7	1570.2	299.6	740.2
2020	1579.1	239.0	1340.1	198.5	717.6
2025	3617.5	289.6	3327.9	540.1	1738.8
Mean	2335.2	255.8	2079.4	346.1	1065.5

Rainfall data were provided by the Viet Bac Regional Hydrometeorological Station.

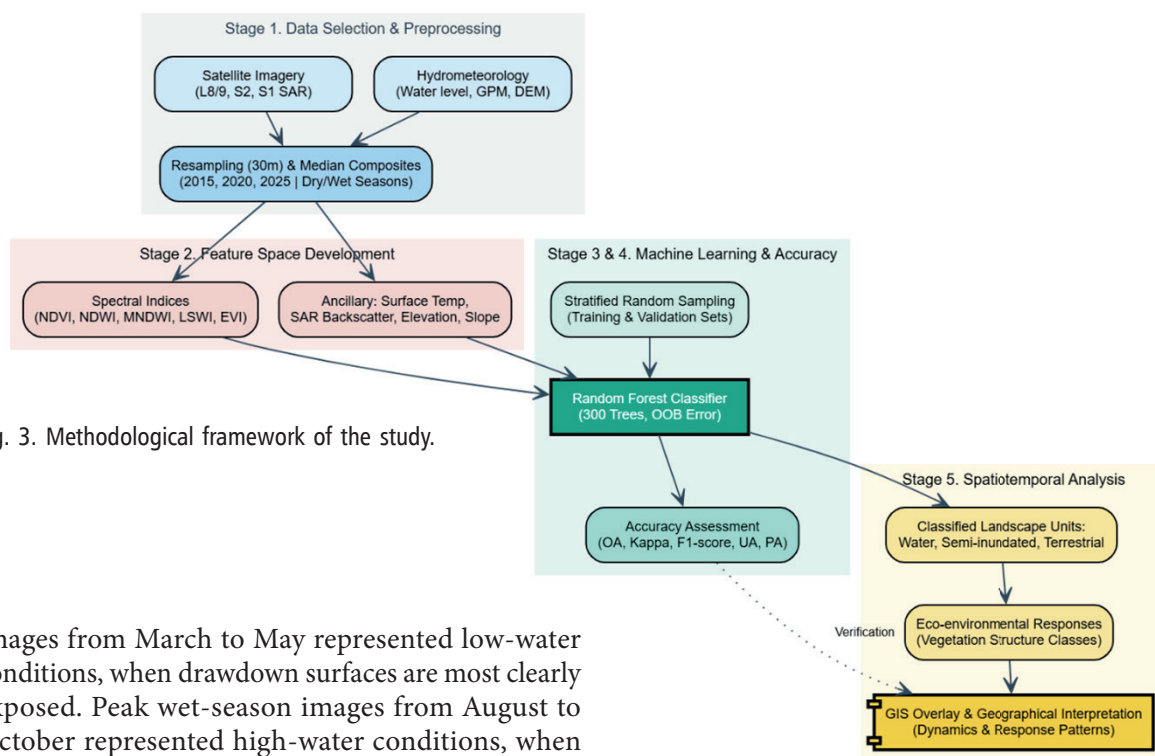


Fig. 3. Methodological framework of the study.

images from March to May represented low-water conditions, when drawdown surfaces are most clearly exposed. Peak wet-season images from August to October represented high-water conditions, when reservoir inundation approaches its seasonal maximum. This seasonal design allowed comparison between reduced and expanded water conditions.

Landsat Collection 2 Level-2 surface reflectance was used as the primary optical dataset. Landsat 8 images were used for 2015 and 2020, whereas Landsat 8/9 images were used for 2025. Cloud and cloud-shadow pixels were masked using the quality-assurance layers supplied with the image products. Median seasonal composites were generated for each year-season subset to reduce residual cloud contamination, atmospheric noise and short-term surface anomalies (Gorelick et al. 2017; Tamiminia et al. 2020; Ghosh et al. 2022).

Sentinel-2 MSI Level-2A images were used as complementary optical data for shoreline interpretation. Sentinel-1 GRD C-band SAR data were processed in Google Earth Engine using standard preprocessing steps, including thermal noise removal, radiometric calibration and terrain correction. VV and VH backscatter coefficients were converted to decibel units. All optical, radar and terrain predictors were resampled to a common 30-m grid, using the Landsat grid as the spatial reference for interannual comparison.

Spectral, radar and terrain variables

Spectral indices were calculated to represent vegetation, open water and surface moisture conditions. For Landsat 8/9, the Blue, Green, Red, Near-Infrared and Shortwave Infrared bands correspond to B2, B3, B4, B5 and B6, respectively. For Sentinel-2, the corresponding bands were B2, B3, B4, B8 and B11. The indices were used as predictor variables in the classification.

The Normalized Difference Vegetation Index (NDVI) was calculated as:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

NDVI was used to represent vegetation greenness and density (Rouse et al. 1973; Tucker 1979; Myneni et al. 1995). The Normalized Difference Water Index (NDWI) was calculated as:

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (2)$$

NDWI was used to support open-water detection (McFeeters 1996). The Modified Normalized Difference Water Index (MNDWI) was calculated as:

$$MNDWI = \frac{Green - SWIR}{Green + SWIR} \quad (3)$$

MNDWI improves the separation of open water from moist non-water surfaces (Xu 2006). The Land Surface Water Index (LSWI) was calculated as:

$$LSWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (4)$$

LSWI was used to indicate vegetation and land-surface moisture conditions in the fluctuating shoreline zone (Chandrasekar et al. 2010; Dong et al. 2014; Mohammed et al. 2024). The Enhanced Vegetation Index (EVI) was calculated as:

$$EVI = 2.5 \times \frac{NIR - Red}{NIR + 6Red - 7.5Blue + 1} \quad (5)$$

EVI was included to represent vegetation structure in denser shoreline and upper-slope sectors (Huete et al. 2002).

In addition to spectral indices, the predictor set included Landsat-derived land-surface temperature, Sentinel-1 VV and VH backscatter, elevation and slope. Elevation and slope were derived from the Copernicus DEM GLO-30. Reservoir water level, rainfall and air temperature were used for hydrological interpretation and were not included as pixel-level predictors.

Multi-source data integration and Random Forest classification

The classification framework was based on multi-source data integration. Landsat, Sentinel-2, Sentinel-1 and DEM-derived variables were resampled to the same spatial grid and organized as predictor layers. The predictor stack included optical reflectance, spectral indices, land-surface temperature, SAR backscatter and terrain variables.

A Random Forest classifier was used to map reservoir-margin landscape units because it is suitable for multi-class remote-sensing classification in heterogeneous land-cover settings and can handle non-linear relationships among correlated predictors (Breiman 2001; Pal 2005; Belgiu and Drăguț 2016). The model was implemented with 300 decision trees, and the number of variables considered at each split was set to the square root of the total number of predictors. During model development, we monitored for out-of-bag error (an internal Random Forest error estimate calculated from data withheld from each individual tree), whereas final accuracy assessment was based on independent validation samples.

The final classification scheme included three principal classes: water bodies, semi-inundated ecosystems and terrestrial ecosystems. Bare soil and built-up surfaces were identified during sample interpretation but were merged with terrestrial ecosystems in the final classification because they occupied limited and fragmented areas and were not the main focus of the shoreline analysis.

The semi-inundated ecosystems class represented seasonally water-affected land within the reservoir fluctuation belt. It was characterized by intermediate water- and moisture-index values, positive vegetation-index values, radar responses distinct from open water and dry terrestrial surfaces and a topographic position close to the seasonal shoreline. This class included areas affected by periodic inundation, residual moisture and semi-inundated vegetation.

A separate vegetation-related classification was applied to the non-water component of the shoreline. Vegetated surfaces were grouped into sparse, moderate and dense vegetation using vegetation indices, moisture-related indices and classification outputs. These classes were used to examine shoreline vegetation structure under low-water and high-water conditions.

Sampling strategy and accuracy assessment

Training and validation samples were compiled using a stratified sampling design by class, benchmark year and hydrological condition. This design ensured representation of both extensive classes and spatially fragmented shoreline classes. Training and validation samples were prepared independently.

A total of 1,200 validation samples were used for accuracy assessment, with 200 samples for each year-season subset. For 2015 and 2020, validation samples were interpreted mainly from contemporaneous high-resolution Google Earth imagery. For 2025, validation samples were derived from Google Earth imagery and field observations collected during the image-acquisition period.

Classification accuracy was assessed from confusion matrices for each benchmark year and hydrological condition. The metrics included overall accuracy (OA), Kappa coefficient (κ – a statistical measure of classification agreement beyond chance), user's accuracy (UA), producer's accuracy (PA) and F1-score.

Overall accuracy was calculated as:

$$OA = \frac{\sum_i x_{ii}}{N} \quad (6)$$

where x_{ii} is the number of correctly classified validation samples in class i , and N is the total number of validation samples.

The Kappa coefficient was calculated as:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \quad (7)$$

where p_o is the observed agreement and p_e is the expected agreement by chance.

User's accuracy and producer's accuracy were calculated as:

$$UA = \frac{TP}{TP + FP} \quad (8)$$

$$PA = \frac{TP}{TP + FN} \quad (9)$$

where TP , FP and FN denote true positives, false positives and false negatives, respectively.

The F1-score was calculated as:

$$F1 = \frac{2 \times UA \times PA}{UA + PA} \quad (10)$$

Spatiotemporal analysis

Spatiotemporal change was analysed at two levels. First, the areas of water bodies, semi-inundated ecosystems and terrestrial ecosystems were calculated from the low-water classifications of 2015, 2020 and 2025. Low-water classifications were used for interannual comparison because the drawdown zone and shoreline transition belt are most clearly expressed during this period. Second, vegetation-related classes were analysed under both low-water and high-water conditions to compare shoreline vegetation structure between contrasting hydrological states.

Class areas were calculated in hectares from the number of classified 30-m pixels. Each pixel represented 900 m², equivalent to 0.09 ha. Inter-period change was expressed as absolute area change and percentage change. Percentage change ($\Delta\%$) was calculated as:

$$\Delta\% = \frac{A_{t2} - A_{t1}}{A_{t1}} \times 100 \quad (11)$$

where A_{t1} and A_{t2} are the class areas at the initial and subsequent benchmark years, respectively.

Spatial interpretation was conducted by comparing classified maps, water-extent layers, vegetation-related classes and DEM-derived terrain information. Shoreline environmental responses were interpreted as spatial changes in reservoir-margin landscape units associated with repeated water-level fluctuation.

Results

Classification accuracy

The Random Forest classification produced consistent accuracy across the six year-season subsets. Overall accuracy ranged from 0.850 to 0.920, and Kappa coefficient values ranged from 0.77 to 0.88 (Table 3). The highest classification accuracy was obtained for the 2020 high-water subset, whereas the lowest value was recorded for the 2015 low-water subset.

The class-specific F1-scores ranged from 0.83 to 0.94. Water bodies showed F1-scores between 0.86 and 0.93, while semi-inundated ecosystems showed F1-scores between 0.85 and 0.94. The terrestrial ecosystems class had F1-scores between 0.83 and 0.91. These values indicate that the three principal landscape units were mapped with sufficient consistency for subsequent spatiotemporal analysis.

Changes in principal landscape units under low-water conditions

The areas of the principal landscape units under low-water conditions are presented in Table 4. Their spatial distribution in 2015, 2020 and 2025 is shown in Figure 4, and the corresponding area trends are shown in Figure 5.

Under low-water conditions, the water-body class increased from 13,830.3 ha in 2015 to 15,475.1 ha in 2020 and 16,916.9 ha in 2025, corresponding to a net increase of 22.32%. Semi-inundated ecosystems increased from 3,909.3 ha in 2015 to 5,319.1 ha in 2020, then decreased to 4,177.6 ha in 2025. Their 2025 extent remained slightly higher than that recorded in 2015. Terrestrial ecosystems

Table 3. Classification accuracy of the Random Forest model for the benchmark years and hydrological conditions.

Year	Hydrological condition	Overall accuracy	Kappa coefficient	F1-score: water bodies	F1-score: semi-inundated ecosystems	F1-score: terrestrial ecosystems
2015	Low-water	0.850	0.77	0.86	0.85	0.83
	High-water	0.860	0.79	0.88	0.87	0.84
2020	Low-water	0.880	0.82	0.89	0.89	0.84
	High-water	0.920	0.88	0.91	0.94	0.91
2025	Low-water	0.885	0.83	0.89	0.90	0.86
	High-water	0.915	0.87	0.93	0.91	0.90

Table 4. Changes in the principal landscape units of Thac Ba Reservoir under low-water conditions, 2015–2025

Landscape unit	Area 2015 (ha)	Area 2020 (ha)	Area 2025 (ha)	Change 2015–2020 (%)	Change 2020–2025 (%)	Net change 2015–2025 (%)
Water bodies	13,830.3	15,475.1	16,916.9	11.89	9.32	22.32
Semi-inundated ecosystems	3,909.3	5,319.1	4,177.6	36.06	-21.46	6.86
Terrestrial ecosystems	102,199.9	99,145.4	98,845.1	-2.99	-0.30	-3.28

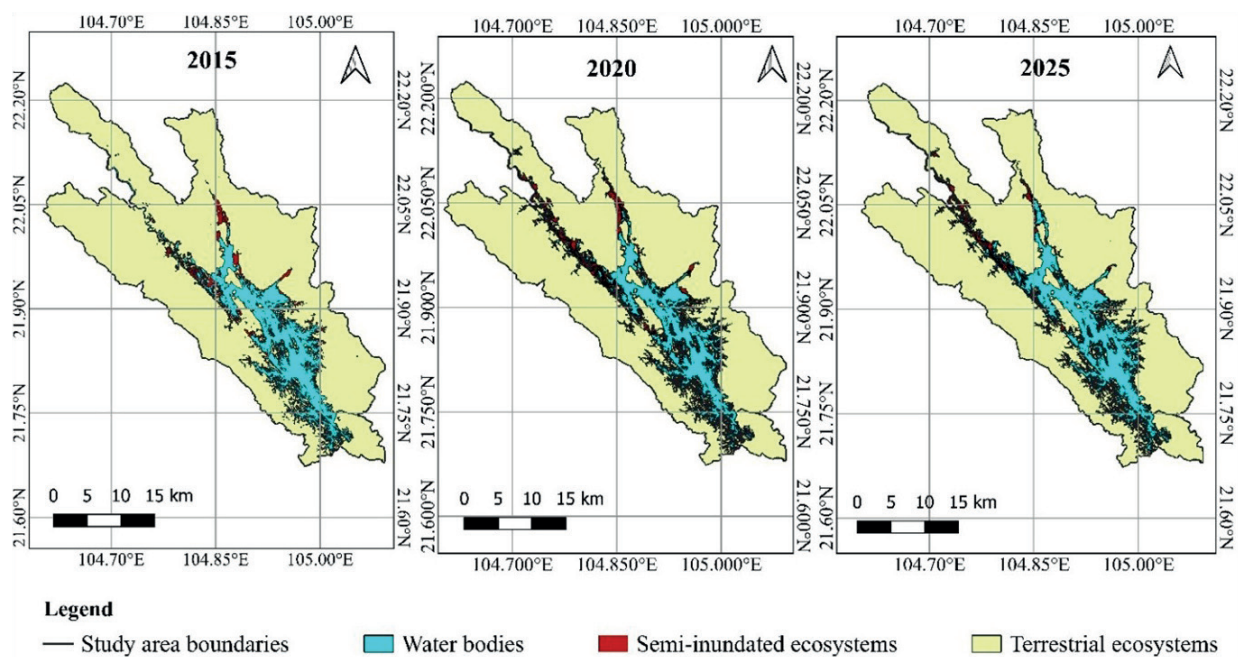


Fig. 4. Spatial distribution of water bodies, semi-inundated ecosystems and terrestrial ecosystems in Thac Ba Reservoir under low-water conditions in 2015, 2020 and 2025

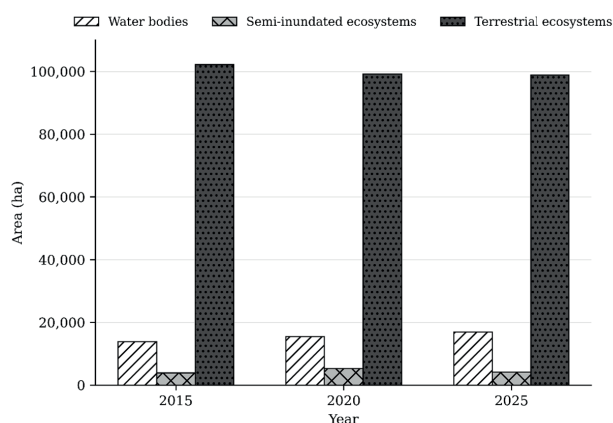


Fig. 5. Changes in the area of water bodies, semi-inundated ecosystems and terrestrial ecosystems in Thac Ba Reservoir under low-water conditions, 2015–2025

decreased from 102,199.9 ha in 2015 to 98,845.1 ha in 2025, with a net decrease of 3.28%.

The spatial pattern in Figure 4 shows that water bodies were concentrated along the main reservoir axis and branching flooded valleys. Semi-inundated ecosystems occurred mainly around reservoir margins, island-foot slopes and shallow embayments. Terrestrial ecosystems remained dominant in the surrounding upland and more stable shoreline sectors.

Vegetation-related classes under low-water and high-water conditions

Vegetation-related classes were analysed separately under low-water and high-water conditions. The area statistics are presented in Table 5, and their spatial distribution is shown in Figure 6.

Under low-water conditions, sparse vegetation decreased continuously from 7,634.8 ha in 2015 to 5,855.6 ha in 2025. Moderate vegetation decreased markedly between 2015 and 2020, then increased again by 2025, reaching 84,125.9 ha. Dense vegetation increased from 12,708.6 ha in 2015 to 36,091.1 ha in 2020, then decreased to 13,041.2 ha in 2025.

Under high-water conditions, water bodies increased from 17,715.6 ha in 2015 to 21,060.9 ha in 2025. Sparse vegetation and moderate vegetation both decreased through the study period. Sparse vegetation declined by 32.45%, while moderate vegetation declined by 45.65%. Dense vegetation showed the opposite trend, increasing from 57,590.6 ha in 2015 to 73,580.7 ha in 2025.

Comparison between the two hydrological conditions shows that vegetation-related classes varied more irregularly under low-water conditions. Under high-water conditions, the decrease in sparse and moderate vegetation and the increase in dense vegetation were more consistent across the three benchmark years.

Table 5. Changes in vegetation-related classes under low-water and high-water conditions

Season	Vegetation class	Area 2015 (ha)	Area 2020 (ha)	Area 2025 (ha)	Change 2015–2020 (%)	Change 2020–2025 (%)	Net change 2015–2025 (%)
Low-water	Water bodies	13,830.3	15,475.1	16,916.9	11.89	9.32	22.32
	Sparse vegetation	7,634.8	6,642.4	5,855.6	-13.00	-11.85	-23.30
	Moderate vegetation	85,765.9	61,730.9	84,125.9	-28.02	36.28	-1.91
	Dense vegetation	12,708.6	36,091.1	13,041.2	183.99	-63.87	2.62
High-water	Water bodies	17,715.6	20,703.5	21,060.9	16.87	1.73	18.88
	Sparse vegetation	7,867.6	5,612.2	5,314.4	-28.67	-5.31	-32.45
	Moderate vegetation	36,765.8	25,416.6	19,983.5	-30.87	-21.38	-45.65
	Dense vegetation	57,590.6	68,207.3	73,580.7	18.43	7.88	27.77

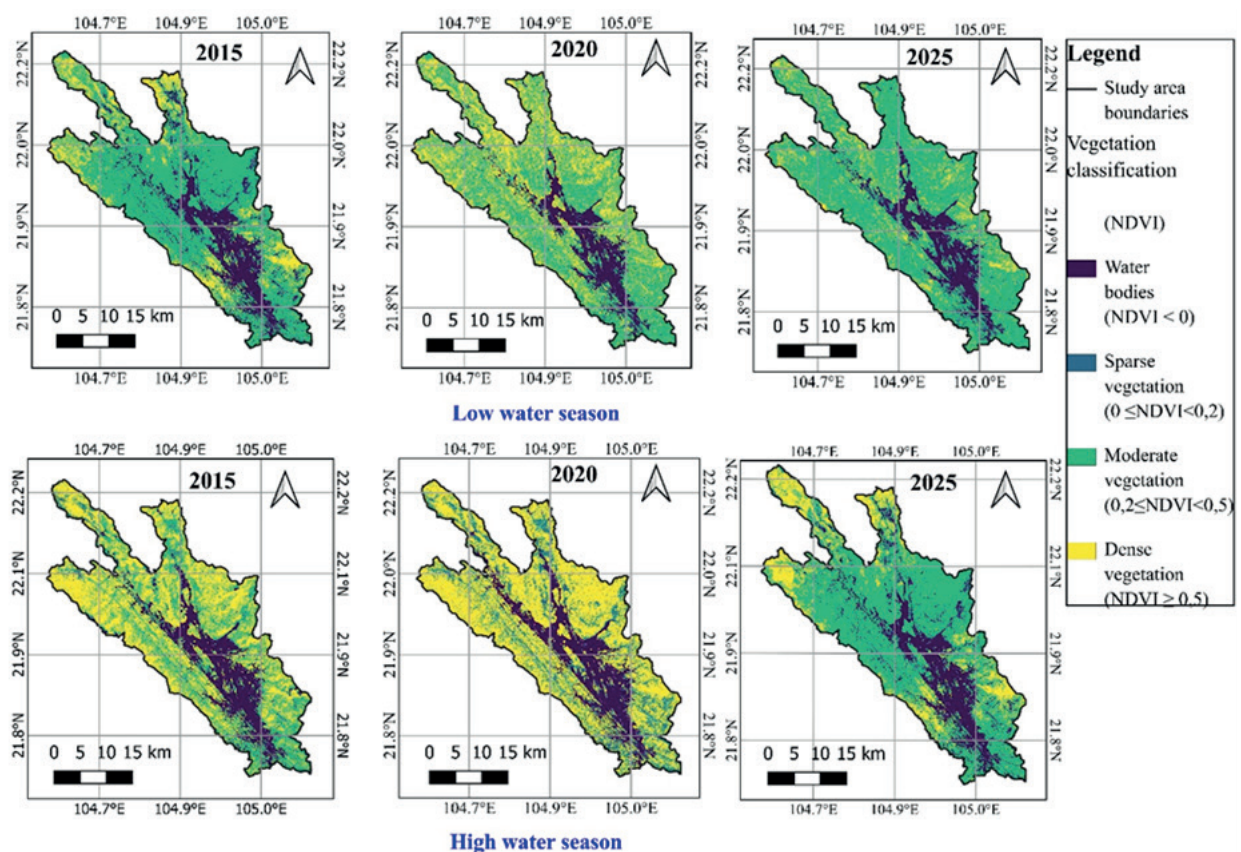


Fig. 6. Spatial distribution of vegetation-related eco-environmental classes in Thac Ba Reservoir under low-water and high-water conditions

Discussion

Reservoir-margin reorganization under contrasting hydrological conditions

The results show that changes in Thac Ba Reservoir during the study period were expressed not only by variation in open-water extent, but also by changes in the structure of the reservoir margin. Under low-water conditions, the water-body class increased between 2015 and 2025, while terrestrial ecosystems decreased slightly. The semi-inundated class showed a non-linear pattern, increasing between 2015 and 2020 and then decreasing by 2025. This pattern indicates that the reservoir margin functioned as a fluctuating transition zone rather than as a fixed boundary between water and land.

The low-water classifications provide a useful basis for interpreting shoreline adjustment because the drawdown belt is most clearly exposed during

this period. In Thac Ba Reservoir, island-foot slopes, shallow embayments and narrow flooded valleys are widespread. Under such conditions, small vertical differences in water level may produce relatively large horizontal changes in marginal surfaces. The larger mapped water extent in 2025 corresponds with the very wet conditions recorded for that year, although reservoir extent also reflects antecedent storage, inflow, operational regulation and local shoreline morphology. Similar interactions between hydro-climatic variability and reservoir management have been reported in studies of lake and reservoir surface-water dynamics (Busker et al. 2019; Hou et al. 2022; Sogno et al. 2022).

The behaviour of the semi-inundated class further illustrates the sensitivity of the shoreline transition belt. Its expansion in 2020 and subsequent contraction in 2025 suggest that seasonally water-affected surfaces changed in response to the combined influence of water-level fluctuation and local topographic setting. This is consistent with the physical setting of Thac Ba Reservoir, where

fluctuating water levels intersect a highly irregular shoreline and numerous low-gradient marginal sectors. The semi-inundated belt therefore forms an important spatial expression of reservoir-margin adjustment.

Vegetation-related shoreline responses

The vegetation-related results differed between low-water and high-water conditions. Under low-water conditions, sparse vegetation declined continuously, whereas moderate and dense vegetation changed more strongly between benchmark years. This variability reflects the heterogeneous character of the exposed drawdown belt, where vegetation structure is influenced by exposure duration, residual moisture and local topographic position.

Under high-water conditions, the pattern was more consistent. Sparse and moderate vegetation decreased, while dense vegetation increased over the study period. This contrast suggests a differentiation between lower shoreline sectors, which are more frequently affected by inundation and exposure, and higher or more stable sectors, where denser vegetation can persist. Similar hydrologically related contrasts in vegetation structure have been observed in wetland and reservoir-margin environments, where inundation frequency and surface moisture influence the spatial arrangement of vegetation and exposed surfaces (Palmer et al. 2015; Alwan and Aziz 2022; Bhaga et al. 2023).

In this study, the vegetation classes represent broad structural differences in vegetation density and surface condition detectable from remote sensing data. They are therefore useful for identifying landscape-scale shoreline responses, although they do not describe species composition or floristic community structure. This distinction is relevant for interpreting the results as spatial eco-environmental responses of the reservoir margin rather than as field-based ecological classification.

Contribution of multi-source data integration and SAR information

The classification results indicate that the integration of optical, radar and terrain variables was suitable

for mapping the principal reservoir-margin classes. Water bodies and semi-inundated ecosystems showed stable F1-scores across the year-season subsets. This is relevant for Thac Ba Reservoir because open water, wet sediment, sparse vegetation and semi-inundated vegetation often occur in close proximity and may produce overlapping optical responses.

Sentinel-1 SAR contributed complementary information for the interpretation of water and moisture-related surfaces. In the monsoonal setting of northern Vietnam, optical image availability may be limited by cloud cover, particularly during the wet season. SAR backscatter provides information on surface roughness, moisture condition and inundation state, which is useful for distinguishing open water, moist drawdown areas and semi-inundated surfaces. Radar observations have been widely used for water, wetland and soil-moisture monitoring in hydrologically variable environments (Dąbrowska-Zielińska et al. 2017; Li et al. 2019; Yang et al. 2022).

The analytical framework applied in this study was based on multi-source data integration. Landsat, Sentinel-2, Sentinel-1 and DEM-derived variables were resampled to a common grid and used jointly as predictor layers in the Random Forest classifier. This structure allowed optical, radar and terrain information to contribute to the discrimination of water-related and transitional shoreline classes without generating a separate fused image product.

Data reliability and uncertainty

The mapped changes need to be viewed in relation to the spatial resolution and consistency of the input datasets. The 30 m Landsat reference grid provided a common basis for comparison across the benchmark years, but narrow inlets, small islands and irregular shoreline edges are not fully resolved at this scale. Mixed pixels are likely in the semi-inundated belt, where shallow water, wet sediment and vegetation may occur within a single pixel. Such scale effects are common in medium-resolution studies of inland-water and shoreline dynamics (Wang et al. 2018; Wang et al. 2019; Zhang et al. 2022).

Sensor differences also affect the interpretation of shoreline classes. Sentinel-2 provides finer optical detail than Landsat, whereas Sentinel-1 measures radar backscatter rather than reflected solar radiation. Resampling these datasets to 30 m

maintained interannual comparability, but some fine-scale shoreline information was generalized. Harmonized Landsat–Sentinel products may improve future analyses, particularly where dense seasonal time series are required. In the present study, the Landsat archive provided the most consistent baseline for the three benchmark years, including 2015.

The hydrometeorological context helps interpret seasonal and interannual differences in mapped water extent. The high rainfall in 2025 is consistent with the larger mapped water area, but reservoir change also depends on inflow, water-level regulation and antecedent storage. A more detailed attribution of water-area change would require continuous water-level records, reservoir operation data and higher-frequency satellite observations.

The vegetation-related results also involve scale-dependent interpretation. Sparse, moderate and dense vegetation classes reflect spectral and structural differences observable from satellite data. They are appropriate for landscape-scale monitoring of shoreline condition, while species-level composition and vegetation succession require more detailed field surveys.

Practical implications and future research

The findings indicate that reservoir monitoring should include not only open-water extent but also semi-inundated zones and vegetation-related shoreline classes. These classes provide information on the drawdown belt and adjacent reservoir margin, especially in island-foot slopes, shallow embayments and low-lying shoreline areas where repeated inundation and exposure are common.

The approach is relevant to broader water and wetness monitoring. Satellite-based products such as the Copernicus High Resolution Layer Water and Wetness and wetland-oriented systems such as POLWET demonstrate the value of deriving spatial information on water occurrence, wetness and transitional environments from remote sensing data (Dąbrowska-Zielińska et al. 2016; Copernicus Land Monitoring Service 2025). At reservoir scale, similar information can support shoreline monitoring, drought assessment and water-resource management.

Future work should extend the benchmark-year approach to denser annual or seasonal time series. Higher-resolution optical data, harmonized Landsat–Sentinel products, longer-wavelength SAR observations and more systematic field validation would improve the interpretation of narrow shoreline sectors and semi-inundated vegetation. L-band radar data may be particularly useful for detecting inundation and moisture conditions beneath denser vegetation. Such developments would strengthen the analysis of links among reservoir hydrology, shoreline morphology and vegetation response in monsoonal water-land systems.

Conclusion

This study examined surface-water dynamics and shoreline environmental responses in Thac Ba Reservoir, Vietnam, using a multi-source data integration framework based on Landsat, Sentinel-1 SAR, Sentinel-2, terrain variables and hydrometeorological observations. The Random Forest classification produced stable results for the benchmark years 2015, 2020 and 2025, with overall accuracy ranging from 0.850 to 0.920 and Kappa coefficient values from 0.77 to 0.88.

The low-water classifications showed an expansion of water bodies from 13,830.3 ha in 2015 to 16,916.9 ha in 2025, together with a slight decrease in terrestrial ecosystems. Semi-inundated ecosystems changed non-linearly, increasing between 2015 and 2020 and decreasing thereafter. These results indicate that reservoir change was expressed not only by variation in open-water extent, but also by adjustment of the drawdown belt and adjacent shoreline units.

Vegetation-related classes showed different patterns under low-water and high-water conditions. Under low-water conditions, vegetation structure varied within the exposed drawdown belt. Under high-water conditions, sparse and moderate vegetation decreased, whereas dense vegetation increased in more stable shoreline sectors. This contrast confirms the importance of considering hydrological state when interpreting shoreline vegetation responses.

The study demonstrates the usefulness of integrating optical imagery, SAR backscatter and terrain information for mapping water-related and

transitional shoreline classes in a morphologically complex reservoir. The results also show the need for further work based on denser seasonal time series, harmonized Landsat–Sentinel products, longer-wavelength SAR data and more systematic field validation to improve the interpretation of shoreline transition processes in monsoonal reservoir environments.

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Disclosure statement

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Author contributions

Study design: TNHT; data collection: TLN; statistical analysis: TNHT; result interpretation: TNHT; manuscript preparation: QLK; literature review: QLK.

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