

POST-BREACH LANDSCAPE TRANSFORMATION OF THE FORMER KAKHOVKA RESERVOIR BED

NATALIIA I. MAGAS

Department of Ecology and Environmental Technologies, Admiral Makarov National University of Shipbuilding, 9 Heroes of Ukraine Avenue, Mykolaiv 54007, Ukraine

ORCID: <https://orcid.org/0000-0002-2579-1465>

**Corresponding author email: nataly.magas@gmail.com*

Received: 7th June 2026, **Accepted:** 8th July 2026

ABSTRACT

The destruction of the Kakhovka Hydropower Plant dam in June 2023 caused rapid drainage of one of the largest reservoirs in Ukraine and exposed an extensive reservoir bed that began to develop as a new post-disturbance landscape mosaic. This study assesses the post-breach landscape transformation of the former Kakhovka Reservoir bed using multi-temporal Sentinel-2 and Landsat 8/9 satellite data processed in Google Earth Engine. The analysis combines a five-class surface-type classification, monthly structural dynamics, transition-matrix analysis for 2023–2025, an author-proposed Degradation State Difference Index (DSDI), and statistical evaluation of vegetation-moisture-temperature relationships. Five surface types were identified: residual water bodies, dry sandy-detrital surfaces, flat dry muddy surfaces, wet or waterlogged surfaces, and surfaces with a distinct vegetation signal. Between 19 August 2023 and 19 August 2025, the area of residual water decreased from 312.7 km² to 136.2 km², while surfaces with a distinct vegetation signal increased from 265.4 km² to 1315.7 km². The dominant transition pathway was the conversion of flat dry muddy surfaces to surfaces with a distinct vegetation signal, covering 540.7 km². DSDI indicated a substantial reduction in highly degraded surfaces, with DSDI ≥ 0.50 decreasing from 1067.7 km² in summer 2023 to 127.9 km² in summer 2025. Nevertheless, large areas remained exposed to residual thermal and moisture stress. In 2025, Spearman correlations between NDVI and NDMI, NDVI and LST, and NDMI and LST were 0.89, -0.64, and -0.71, respectively. The DSDI-NDMI relationship also showed a strong negative association (Spearman $\rho = -0.94$), indicating that the integrated degradation signal decreased with increasing surface moisture. The results show that the former reservoir bed should not be interpreted only as a degraded surface, but as a rapidly reorganising post-reservoir landscape mosaic combining initial vegetation establishment, potential surface stabilisation and persistent ecological risks.

Keywords: Kakhovka Reservoir; reservoir-bed exposure; landscape transformation; vegetation establishment; DSDI; remote sensing.

INTRODUCTION

Large reservoirs are simultaneously hydrological infrastructures and landscape systems. They regulate water storage, sediment retention, riparian gradients, aquatic and wetland habitats, and local surface-energy exchange. When a reservoir is suddenly drained or its dam is removed or destroyed, the ecological response cannot be reduced to a simple loss of water surface. A formerly aquatic area becomes an exposed reservoir bed in which sediments, residual channels, waterlogged depressions, bare surfaces and new vegetation patches begin to interact. Studies of dam removal and reservoir drawdown show that such systems often follow nonlinear trajectories controlled by hydrological connectivity, sediment texture, topography, seed availability, moisture gradients, climatic conditions and ecological trade-offs (Auble *et al.*, 2007; Bellmore *et al.*, 2019; Shafroth *et al.*, 2002; Stanley & Doyle, 2003).

The ecological interpretation of exposed reservoir beds is particularly important because early vegetation colonisation may simultaneously indicate recovery and mask continuing risks. On the one hand, spontaneous revegetation can stabilise fine sediments, reduce surface erosion, increase roughness, lower surface temperature and create conditions for further habitat development. On the other hand, newly exposed sediments may remain vulnerable to drying, cracking, dust mobilisation, secondary salinisation and thermal stress. Evidence from exposed reservoir beds and dam-removal contexts confirms that initial vegetation development is often rapid but strongly heterogeneous, and that early successional communities do not necessarily represent complete ecological restoration (Auble *et al.*, 2007; Prach *et al.*, 2019; Shafroth *et al.*, 2024).

Remote sensing provides an effective basis for studying these processes at landscape scale, especially where field access is limited. Water and moisture indices such as NDWI and MNDWI are widely used to delineate open water and wet surfaces (McFeeters, 1996; Xu, 2006), while NDVI and related vegetation indices remain central for detecting vegetation cover and vigour (Tucker, 1979). NDMI and short-wave infrared information support the interpretation of moisture conditions (Gao, 1996), and Landsat thermal data allow the assessment of land-surface temperature. Cloud-based platforms such as Google Earth Engine have made it possible to process dense multi-temporal satellite series and derive spatially consistent indicators for large areas (Gorelick *et al.*, 2017). In addition, global surface-water products have demonstrated the value of long-term satellite archives for analysing water occurrence, disappearance and persistence (Pekel *et al.*, 2016).

The destruction of the Kakhovka Hydropower Plant dam in June 2023 created one of the largest recent cases of abrupt reservoir-bed exposure in Europe. The event caused both downstream flooding and rapid drainage of the reservoir, with severe environmental, hydrological and socio-economic consequences. The broader environmental consequences were rapidly discussed in scientific assessments and commentary (Naddaf, 2023; Stone, 2024; UNEP, 2023; Vyshnevskiy *et al.*, 2023) and were later synthesised in an integrated analysis of environmental effects (Shumilova *et al.*, 2025). These studies are essential for understanding the disaster as a whole, but they also underline the need for more detailed spatial analysis of the former reservoir bed as a newly formed landscape system.

Several recent studies have begun to address this need. Pichura *et al.* (2024) analysed the natural and climatic transformation of the Kakhovka Reservoir after dam destruction using Sentinel-2, Sentinel-3 and Landsat 8/9 data, emphasising microclimatic and water-scarcity consequences. Operational satellite geomonitoring documented flooding and drainage processes during the first post-breach months (Lischenko & Filipovych, 2024), while Kozlova *et al.* (2024) mapped post-breach water occurrence and its spatial variability. Dovhanenko *et al.* (2024) characterised the dried-up zone as a heterogeneous environment

with variable relief, soil properties, moisture conditions and early vegetation development. Vyshnevskiy & Shevchuk (2024) described natural processes in the area of the former reservoir, including rapid overgrowth and hydrological variability. Lischenko *et al.* (2025) mapped spatiotemporal transformations of the former reservoir bed using Sentinel-2 imagery and surface-water occurrence analysis. Kuzemko *et al.* (2025) combined field surveys and remote sensing to document the initial stages of revegetation and habitat formation, demonstrating that the former reservoir bed contains newly formed terrestrial habitats, including wetland-related and woody vegetation types. Together, these studies show that the Kakhovka case is not only a hydrological disaster, but also a large-scale case of post-disturbance landscape formation.

Despite this progress, several research gaps remain. Existing work has often focused either on water-surface loss, hydrological consequences, general environmental damage or botanical evidence of revegetation. Less attention has been paid to the integration of surface-type typology, monthly landscape-structure dynamics, transition pathways, degradation-state assessment and statistical vegetation-moisture-temperature relationships within a single remote-sensing framework. In particular, the former reservoir bed needs to be analysed as a spatially heterogeneous landscape mosaic rather than as a binary water-versus-land object or a uniformly degraded surface.

This study addresses that gap by combining Sentinel-2 and Landsat 8/9 data in Google Earth Engine to assess the post-breach landscape transformation of the former Kakhovka Reservoir bed. The analysis integrates five components: a five-class surface-type classification, monthly percentage dynamics of surface structure, a transition matrix for 2023–2025, an author-proposed Degradation State Difference Index (DSDI), and statistical analysis of relationships among vegetation, moisture, dryness and surface temperature. The aim of this study was to assess the post-breach landscape transformation of the former Kakhovka Reservoir bed by quantifying changes in water extent and surface-type structure, identifying the main transition pathways associated with vegetation establishment on the exposed reservoir bed, and determining where residual degradation risks persisted during 2023–2025.

MATERIALS AND METHODS

The study area corresponds to the historical bed of the former Kakhovka Reservoir within its pre-breach water-surface boundary. The reservoir was created in 1956 as part of the Dnipro cascade and functioned as a major water-management and landscape-forming system in southern Ukraine. Before the dam breach, it was used for industrial and drinking water supply, irrigation, energy production, navigation, fishing and recreation. In addition, the reservoir supported aquatic, wetland and riparian ecosystems. After the destruction of the Kakhovka Hydropower Plant dam in June 2023, the study area changed from a large water body into a newly exposed reservoir bed with rapidly developing terrestrial, wetland and residual aquatic components.

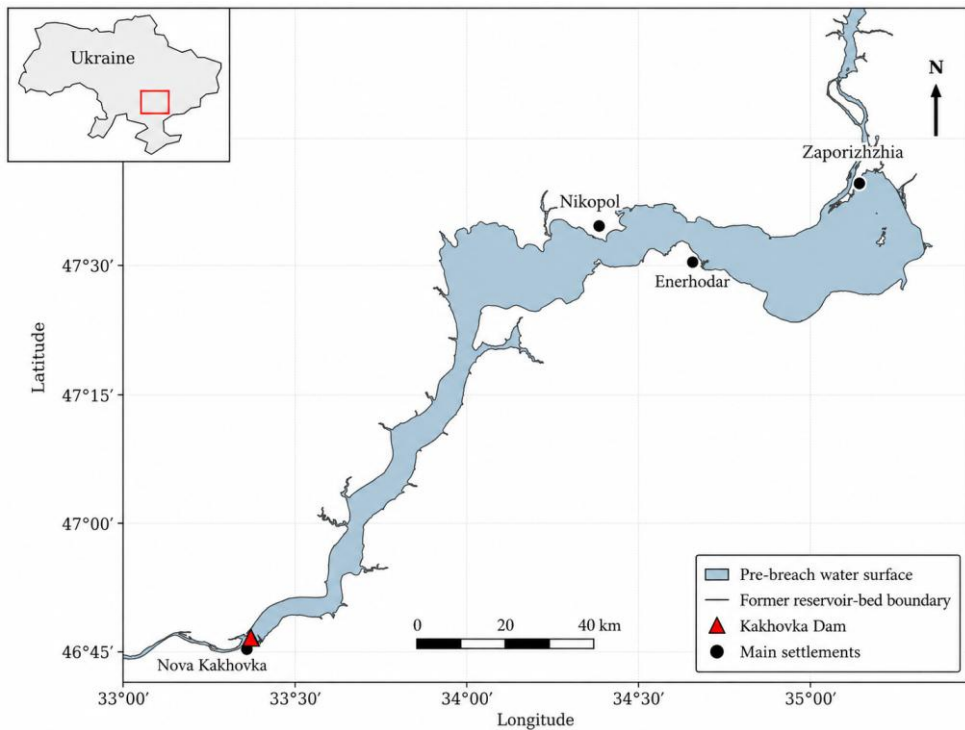
Prior to the breach, the Kakhovka Reservoir was one of the largest artificial water bodies in Ukraine. At the normal retention level, its water-surface area was approximately 2155 km², with a total volume of about 18.2 km³ and a useful storage volume of approximately 6.8 km³. The reservoir extended for about 240 km, with a width ranging from 3 to 23 km, an average depth of 6–8 m and a maximum depth of up to 26 m. These morphometric characteristics emphasise the exceptional spatial scale of the post-breach reservoir-bed exposure and justify the use of satellite-based monitoring for landscape-scale assessment.

A single digital boundary of the former reservoir bed was used as the area of interest for all calculations. The boundary covers approximately 2136 km². In subsequent thematic maps, this same outline is referred to as the study area boundary. Using the same spatial frame for all image composites, area calculations and transition matrices ensured comparability among dates, months and years. Small differences between the geometric boundary area and the sum of raster-classified areas may result from pixel resolution, masking, cloud-free data availability and the area-calculation procedure in Google Earth Engine.

The spatial context of the study area is shown in Figure 1. The map presents the pre-breach water-surface extent, the former reservoir-bed boundary used as the study area, the Kakhovka Dam location and the main settlements that frame the spatial interpretation of the post-breach transformation.

Fig. 1: Study area within the former Kakhovka Reservoir bed, southern Ukraine.

The blue polygon represents the pre-breach water surface, while the grey line indicates the former reservoir-bed boundary used as the study area for all calculations. The Kakhovka Dam location and main settlements are shown for spatial orientation; the inset indicates the location of the study area in Ukraine.



Source: author's mapping based on the former reservoir-bed boundary and satellite data.

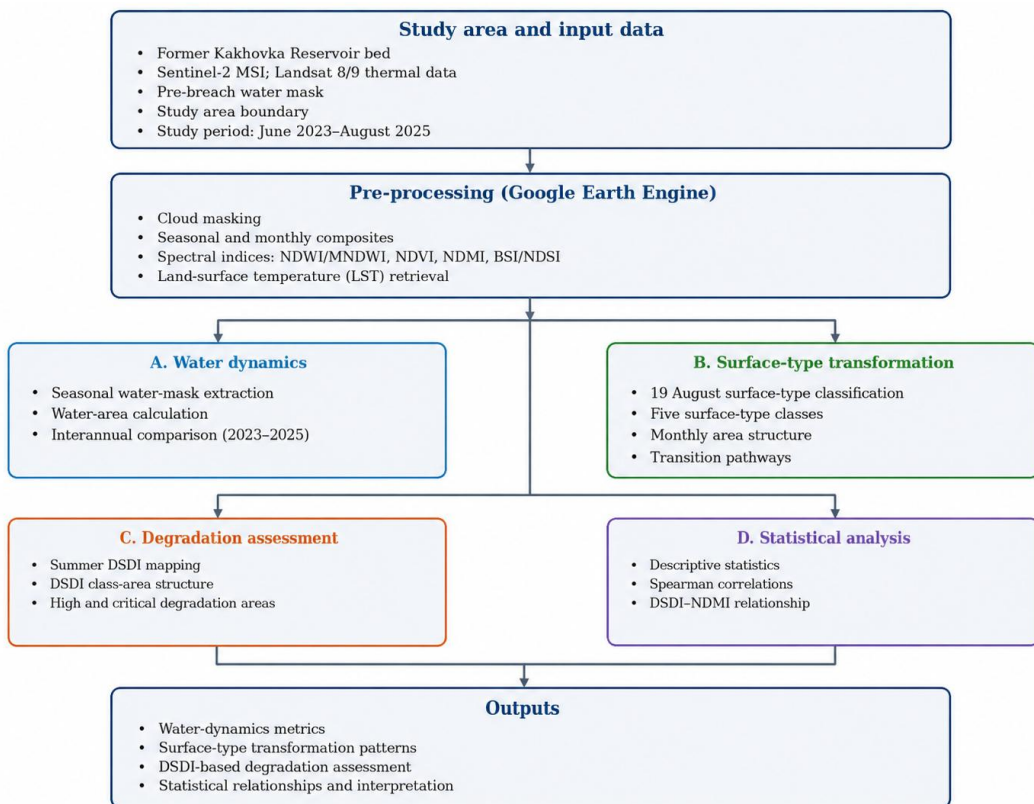
The remote-sensing workflow combined Sentinel-2 Surface Reflectance data (European Space Agency (ESA), 2025) and Landsat 8/9 Collection 2 Level-2 data (USGS, 2025). Sentinel-2 imagery was used to detect residual water, wet surfaces, vegetation, bare sediments and surface dryness. Landsat 8/9 thermal data were used to derive land-surface temperature (LST). All data processing was carried out in Google Earth Engine (Gorelick *et al.*, 2017), including image filtering, cloud masking, index calculation, median compositing, surface-type classification, area estimation and export of statistical tables.

The temporal design included two complementary levels. First, three control observations were used for detailed interannual comparison: 19 August 2023, 19 August 2024 and 19 August 2025. The same calendar date was selected to minimise phenological differences and to represent comparable stages of the growing season after the initial drainage. Second, monthly composites from June 2023 to August 2025 were used to analyse early post-breach structural dynamics and seasonal variability. This monthly period covers the initial transformation after drainage and two subsequent growing seasons, but it is not intended to represent long-term successional stabilisation. Monthly summaries were calculated at a coarser analysis scale for computational stability over the entire large study area, whereas the control-date classification was used for more detailed area and transition estimates.

The overall analytical workflow is summarised in Fig. 2. The scheme separates the input data and pre-processing stage from the four main analytical branches: water dynamics, surface-type transformation, DSDI-based degradation assessment and statistical analysis.

Fig. 2: Workflow of the satellite-based assessment of post-breach landscape transformation in the former Kakhovka Reservoir bed.

The scheme summarises the input data, pre-processing steps, analytical branches and final outputs used to assess water dynamics, surface-type transformation, DSDI-based degradation patterns derived from summer composites, and statistical relationships.



Source: author's design based on the analytical workflow implemented in Google Earth Engine.

The index set was selected to represent the main biophysical dimensions of the exposed reservoir bed. NDWI and MNDWI were used to identify open water and very wet surfaces. NDVI was used to characterise vegetation cover and identify surfaces with a distinct vegetation signal. NDMI represented surface and vegetation moisture. BSI and NDSI were used as indicators of bare, dry or potentially saline sediment surfaces, while LST represented thermal stress. Table 1 summarises the satellite data and analytical indicators used in the study.

Table 1: Satellite data, indices and analytical purpose used in the study.

Data / indicator	Spatial resolution / basis	Analytical purpose in this study
Sentinel-2 Surface Reflectance	10-20 m multispectral data	Water detection, vegetation, moisture, dryness and surface-type classification
Landsat 8/9 Level-2	Thermal product used for LST estimation	Land-surface temperature and thermal-stress assessment
NDWI / MNDWI	Green, NIR and SWIR Sentinel-2 bands	Residual water and wet-surface detection
NDVI	Red and NIR Sentinel-2 bands	Vegetation cover and identification of surfaces with a distinct vegetation signal
NDMI	NIR and SWIR Sentinel-2 bands	Surface and vegetation moisture conditions
BSI / NDSI	Visible, NIR and SWIR Sentinel-2 bands	Bare, dry or potentially saline sediment signal
LST	Landsat 8/9 thermal data	Surface overheating and thermal stress
DSDI	Author-proposed composite index	Integral assessment of degradation state of exposed reservoir-bed surfaces

Source: prepared by the author based on Sentinel-2 and Landsat 8/9 processing in Google Earth Engine.

A five-class surface-type classification was developed to describe the major components of the post-breach landscape mosaic. The classes were defined not as formal soil or botanical units, but as remote-sensing surface types that can be consistently identified from Sentinel-2 spectral information. The classification combined water indices, NDVI, BSI and a simple brightness measure calculated from the green, red and near-infrared bands. The rules were applied in a hierarchical manner: open water and vegetation-related surfaces were identified first, followed by dry sandy-detrital, wet or waterlogged and flat dry muddy surfaces.

The decision rules in Table 2 should be interpreted as operational thresholds developed for the former Kakhovka Reservoir bed and the selected Sentinel-2 composites. They provide reproducible separation of the dominant surface types, but they do not replace field-based geomorphological, pedological or geobotanical classification. In particular, the class ‘surfaces with a distinct vegetation signal’ identifies areas with vegetation cover detectable by Sentinel-2 using the adopted NDVI threshold. It does not identify a particular successional stage and does not provide information on species composition, community structure, habitat quality or the relative contribution of native and non-native taxa.

The operational thresholds were refined iteratively by comparing the classified outputs with Sentinel-2 true-colour and false-colour composites and the corresponding spectral-index layers across representative parts of the former reservoir bed and the three control dates. Because independent field reference data were unavailable, this procedure was treated as a visual and spectral consistency assessment rather than a formal classification-accuracy assessment.

Table 2: Decision rules used for remote-sensing interpretation of surface types.

Surface type	Main spectral decision rules	Landscape-ecological interpretation
Residual water bodies	MNDWI > 0.20 or NDWI > 0.50	Open water and persistently inundated depressions within the former reservoir bed.
Dry sandy-detrital surfaces	NDWI < 0; MNDWI < 0.10; NDVI < 0.35; BSI > 0.15; brightness > 0.18	Light, dry and weakly vegetated bare surfaces, often more exposed to heating and potential deflation.
Flat dry muddy surfaces	NDWI < -0.15; NDVI < 0.40; BSI from -0.05 to 0.20; brightness criterion; excluding water, wetland, sandy and vegetation classes	Fine-grained exposed bottom sediments forming the main bare-sediment class after drainage.
Wet or waterlogged surfaces	NDWI from -0.20 to 0.45; MNDWI from -0.15 to 0.35; NDVI < 0.40; BSI < 0.25 or NDWI > 0.05	Moist mudflats, shallow depressions and waterlogged surfaces with high residual moisture.
Surfaces with a distinct vegetation signal	NDVI ≥ 0.50	Areas where Sentinel-2 data indicate clearly expressed vegetation cover on newly exposed reservoir-bed surfaces. This is a remote-sensing vegetation class rather than a botanical or successional classification.

Source: classification rules developed by the author and implemented in Google Earth Engine.

For integral assessment of surface degradation, this study proposes the Degradation State Difference Index (DSDI). The index was designed specifically for newly exposed reservoir-bed surfaces where degradation cannot be represented by a single factor. It combines four normalised components: dryness or potential salinity, moisture deficit, surface overheating and vegetation deficit. The index was used as a comparative spatial indicator of degradation state rather than as a universal normative index.

The DSDI was calculated as $DSDI = 0.35 \times C_{dry} + 0.25 \times C_{moisture} + 0.25 \times C_{thermal} + 0.15 \times C_{vegetation}$, where C_{dry} is the normalised dryness/potential-salinity component derived from NDSI, $C_{moisture}$ is the inverse NDMI-based moisture component, $C_{thermal}$ is the normalised LST component, and $C_{vegetation}$ is the inverse NDVI-based vegetation component. All components were scaled to the 0–1 range and clipped to avoid the influence of extreme values. Higher DSDI values indicate stronger combined degradation signals, whereas lower values indicate better moisture, vegetation and thermal conditions. NDSI was not interpreted as a direct measurement of sediment salinity; it was used as a spectral proxy

for bright, dry and potentially saline surfaces, because similar spectral responses may also result from low surface moisture, sediment mineralogy and surface crusting.

The weights were assigned according to the expected ecological role of each component in an exposed reservoir-bed environment. Dryness and potential salinity received the highest weight because newly exposed bottom sediments are particularly sensitive to drying, surface crusting and secondary salinisation. Moisture deficit and thermal stress were treated as equally important limiting factors, while vegetation deficit was included as an indicator of weak biological stabilisation. Because DSDI is an author-proposed index, its interpretation is restricted to relative comparison within the study area and period; further sensitivity testing and field validation would be needed before broader transfer to other systems.

Because the DSDI weights were assigned through expert judgement, a sensitivity check was performed to assess whether the main temporal interpretation depended on the selected weighting scheme. The baseline DSDI was compared with four alternative formulations: equal weighting of all components, increased emphasis on dryness/potential salinity, increased emphasis on moisture and thermal stress, and increased emphasis on vegetation deficit. For each formulation, the agreement with the baseline DSDI was evaluated using Spearman rank correlation, and the share of sampled summer pixels exceeding the threshold of 0.5 was compared for 2023, 2024 and 2025. This test was used as a robustness check of the direction of change rather than as a recalibration of the index.

For cartographic interpretation, the normalised DSDI range from 0 to 1 was divided into four equal-width operational intervals: low degradation, $0.00 \leq \text{DSDI} < 0.25$; moderate degradation, $0.25 \leq \text{DSDI} < 0.50$; high degradation, $0.50 \leq \text{DSDI} < 0.75$; and critical degradation, $0.75 \leq \text{DSDI} \leq 1.00$. These intervals were introduced to support consistent relative spatial and temporal comparison within the study area. They should not be interpreted as regulatory, normative or field-calibrated degradation thresholds.

Surface-class areas were calculated for each control date and for monthly composites. For the monthly structural analysis, percentages were calculated from the valid classified area in each month to reduce the influence of cloud masking and minor variations in valid image coverage. A transition matrix was produced by cross-tabulating the classified surfaces observed on 19 August 2023 and 19 August 2025. This matrix allowed identification of both transformation pathways, such as the conversion of exposed sediments to vegetation-related surfaces, and persistence pathways, such as stable residual water or stable dry sediment classes.

Statistical analysis was performed at two levels. First, descriptive statistics were calculated for NDVI, NDMI, NDSI, LST and DSDI. Second, Spearman rank correlation was used to evaluate relationships among vegetation cover, moisture, dryness, thermal conditions and integrated degradation state. Spearman correlation was chosen because remote-sensing indices over heterogeneous post-disturbance surfaces often have non-normal and nonlinear distributions. For the statistical relationship analysis, the correlation matrix was calculated from the pooled summer pixel sample for 2023–2025, while the DSDI-NDMI relationship was visualised for the 2025 summer pixel sample using individual pixels and binned median values. Because DSDI was derived from NDVI, NDMI, NDSI and LST, correlations involving DSDI were interpreted as an internal consistency check rather than as independent validation.

RESULTS

The results are organised in four connected steps. The surface-type classification first quantifies the shift from a continuous reservoir surface to a differentiated post-reservoir mosaic. Monthly structure then separates early post-breach reorganisation from seasonal variability. The transition matrix identifies the surface types that supplied new vegetation-related areas and those that remained hydrologically or sedimentologically persistent. Finally, DSDI and statistical analyses evaluate whether the mapped changes are accompanied by coherent moisture, vegetation and thermal gradients.

At the three control dates, the most pronounced change was the reorganisation of the former reservoir bed from water and open sediments towards vegetation-related surfaces (Table 3). On 19 August 2023, residual water still occupied 312.7 km², while flat dry muddy surfaces and dry sandy-detrital surfaces together covered 1385.5 km². By 19 August 2025, residual water had decreased to 136.2 km², and the combined area of the two main dry sediment classes had declined to 650.8 km². This reduction of exposed sediment surfaces was accompanied by a major increase in surfaces with a distinct vegetation signal, from 265.4 km² to 1315.7 km². Thus, the main landscape signal was not simply reservoir desiccation, but the rapid redistribution of surface types within the exposed reservoir bed.

Table 3: Surface-type areas in the former Kakhovka Reservoir bed at control late-summer dates.

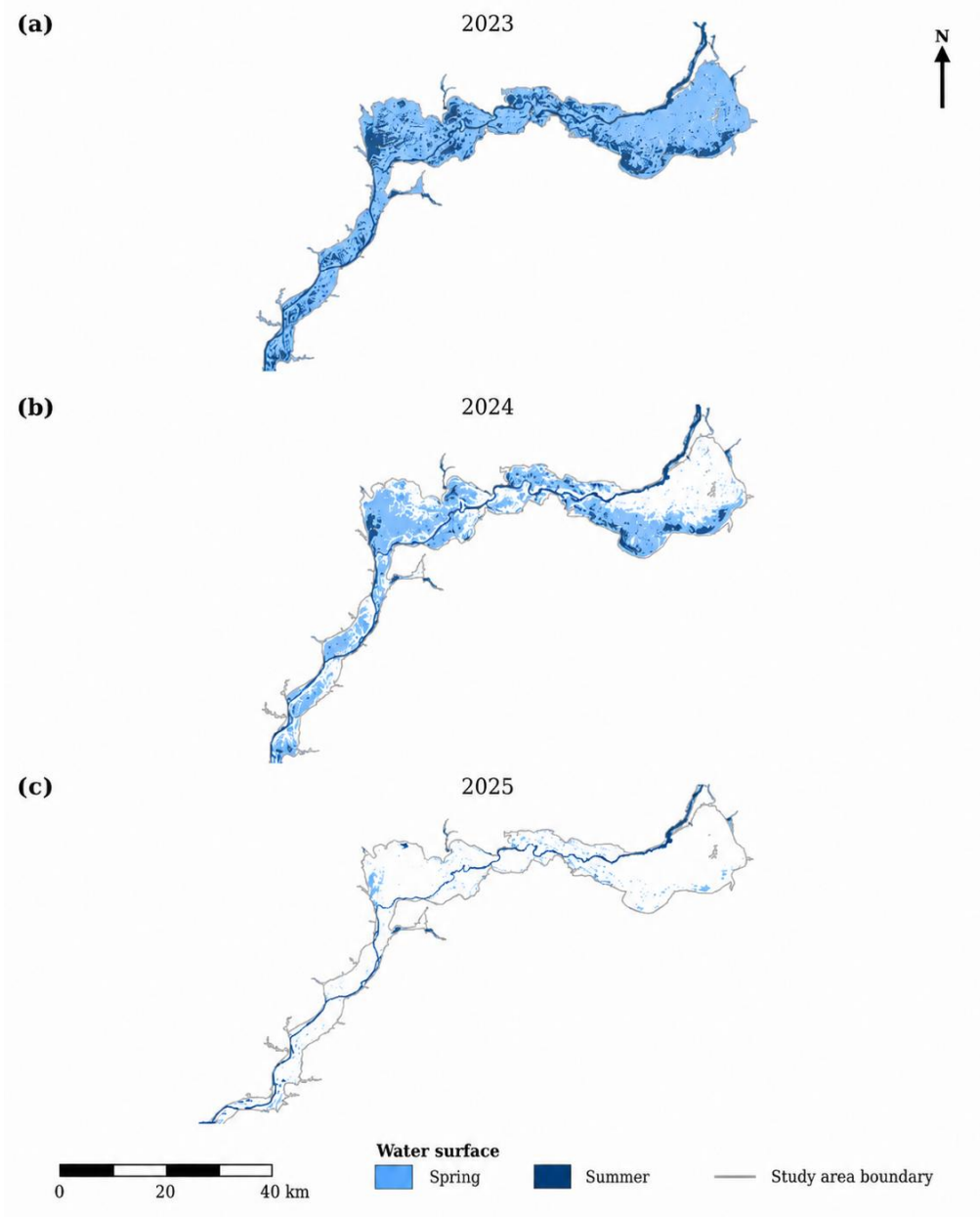
Surface type	19 Aug 2023, km ²	19 Aug 2024, km ²	19 Aug 2025, km ²	Change 2023–2025, km ²
Residual water bodies	312.7	125.2	136.2	-176.5
Dry sandy-detrital surfaces	593.8	290.7	342.6	-251.2
Flat dry muddy surfaces	791.7	435.5	308.2	-483.5
Wet or waterlogged surfaces	178.4	92.9	39.3	-139.1
Surfaces with a distinct vegetation signal	265.4	1197.8	1315.7	+1050.3

Source: calculated by the author from Sentinel-2 classification results in Google Earth Engine.

Seasonal water masks were used to quantify the hydrological contraction of the former reservoir independently from the five-class surface-type classification (Fig. 3). These masks represent water-surface extent derived from water-index thresholds for spring, summer and autumn composites and should therefore be interpreted as remote-sensing estimates rather than design or morphometric reservoir-area values. The results show an abrupt decrease from 2082 km² in spring 2023 to 279 km² in summer 2023 and 155 km² in autumn 2023. A temporary seasonal increase was observed in spring 2024, when the mapped water surface reached 774 km², followed by a decline to 194 km² in summer and 139 km² in autumn. In 2025, the seasonal water surface remained much smaller and relatively stable, decreasing from 139 km² in spring to 124 km² in summer and 116 km² in autumn. In contrast, the single-date surface-type classification treats residual water as one class within a broader landscape typology; minor differences between seasonal water-mask areas and the residual-water class should therefore be interpreted as methodological differences rather than inconsistencies.

Fig. 3: Seasonal dynamics of water-surface contraction within the former Kakhovka Reservoir in 2023–2025.

Panels (a–c), arranged vertically, show the spatial distribution of spring and summer water masks for 2023, 2024 and 2025, respectively. The grey outline indicates the former reservoir-bed boundary used as the study area. Spring 2023 represents the pre-breach reference state, whereas subsequent seasons show post-breach residual water bodies. Seasonal water masks document hydrological contraction, while the single-date five-class classifications quantify landscape structure and surface-type transitions.



Source: calculated by the author using Sentinel-2 data in Google Earth Engine.

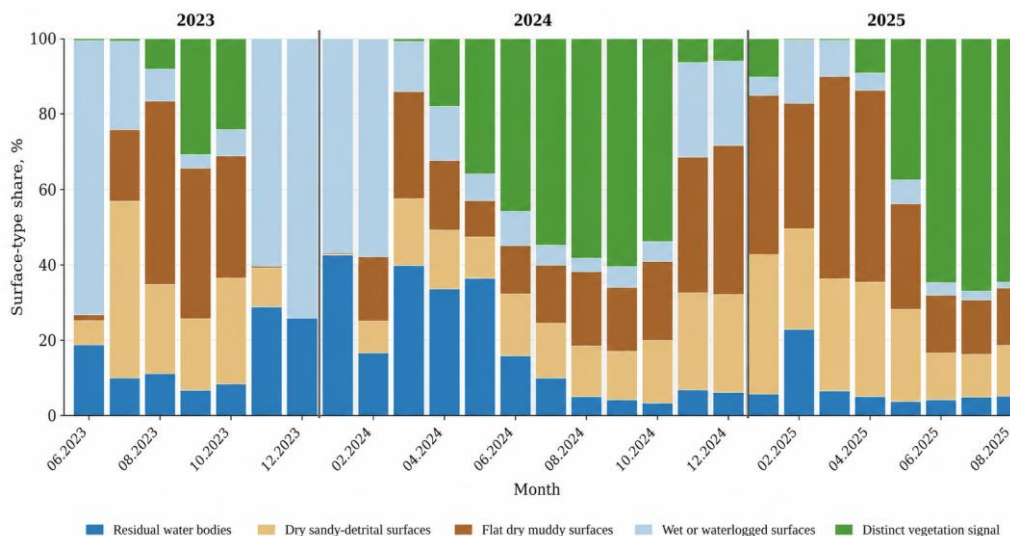
Monthly surface-type dynamics were analysed from June 2023 to August 2025, covering the initial post-breach phase and two subsequent growing seasons. This period is sufficient to characterise early reorganisation of the exposed bed, but not long-term successional stabilisation. The monthly results are therefore used to assess short-term landscape-structure dynamics and seasonal variability.

Fig. 4 extends the interpretation beyond the three late-summer control dates. Because monthly shares were calculated relative to the valid classified area, the diagram emphasises internal landscape structure rather than variations in cloud-free coverage. Wet and waterlogged surfaces were most prominent during the first months after drainage and during wetter or transitional periods, whereas vegetation-related surfaces became more prominent during the 2024 and 2025 growing seasons.

The monthly sequence also shows that vegetation expansion was spatially uneven. Dry sandy-detrital and flat dry muddy classes persisted in several months, and short-term fluctuations in wet or dry classes may reflect both real changes in surface moisture and the timing of cloud-free Sentinel-2 observations.

Fig. 4: Monthly percentage structure of surface types in the former Kakhovka Reservoir bed from June 2023 to August 2025.

Shares are calculated from the valid classified area in each monthly Sentinel-2 composite. Thicker vertical separators distinguish the three calendar years. The figure characterises early post-breach landscape-structure dynamics and seasonal variability rather than long-term successional trends.

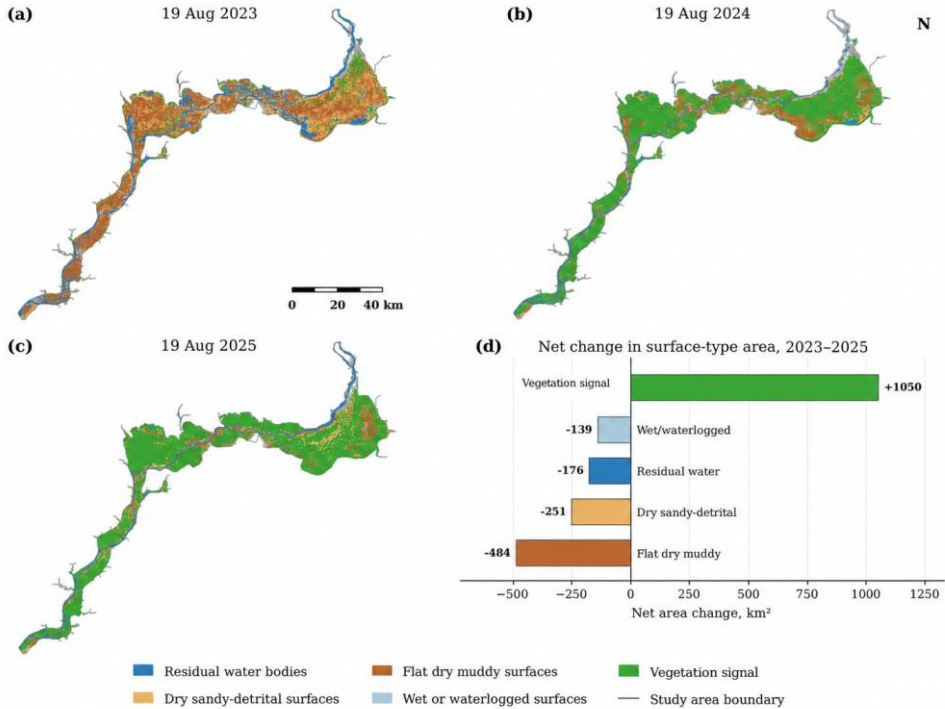


Source: calculated by the author from Sentinel-2 classification results in Google Earth Engine.

The control-date classifications are presented together with net class-area changes in Fig. 5. This layout separates spatial pattern from quantitative change: panels (a–c) show the mapped surface-type mosaic, whereas panel (d) highlights the net gain or loss of each surface class between 19 August 2023 and 19 August 2025.

Fig. 5: Surface-type classification and net area changes within the exposed bed of the former Kakhovka Reservoir, 19 August 2023–19 August 2025.

Panels (a–c) show the five-class Sentinel-2 surface-type classification for 19 August 2023, 19 August 2024 and 19 August 2025. Panel (d) summarises net area changes between 19 August 2023 and 19 August 2025; values are rounded to the nearest square kilometre. In panel (d), ‘Vegetation signal’ refers to surfaces with a distinct vegetation signal. The grey outline indicates the former reservoir-bed boundary used as the study area. All map panels are shown at the same scale.



Source: calculated by the author from Sentinel-2 classification results in Google Earth Engine.

Area changes establish the overall direction of reorganisation, but they do not identify the source classes of new vegetation-related areas. The transition matrix (Table 4) therefore provides a more diagnostic view. The largest pathway was the conversion of flat dry muddy surfaces to surfaces with a distinct vegetation signal, covering 540.7 km². Because flat muddy sediments were the dominant exposed class in the first post-breach season, this pathway suggests that a large share of fine-grained deposits retained or accumulated sufficient moisture to support vegetation establishment.

Dry sandy-detrital surfaces also contributed substantially to vegetation establishment, with 322.5 km² converted to vegetation-related surfaces. This shows that plant colonisation was not limited to wet depressions or fine muddy deposits. However, 116.6 km² of dry sandy-detrital surfaces and 115.4 km² of flat dry muddy surfaces persisted, indicating zones that remained more exposed and potentially vulnerable to overheating, moisture deficit, surface crusting and wind erosion.

Other pathways represented persistence or redistribution among open sediment states rather than vegetation establishment. For example, transitions from flat dry muddy surfaces to dry sandy-detrital surfaces may reflect drying, increased brightness, sediment

redistribution or reduced surface moisture. Such persistent or increasingly dry areas represent priority zones for continued monitoring.

Table 4: Main transformation and persistence pathways between surface classes, 19 August 2023–19 August 2025.

Class in 2023	Class in 2025	Area, km ²	Process type	Interpretation
Flat dry muddy surfaces	Distinct vegetation signal	540.7	Vegetation establishment on muddy sediments	Largest transformation pathway; extensive vegetation establishment on fine-grained exposed sediments.
Dry sandy-detrital surfaces	Distinct vegetation signal	322.5	Vegetation establishment on dry surfaces	Vegetation establishment also occurred on exposed and potentially deflation-prone surfaces.
Distinct vegetation signal	Distinct vegetation signal	202.3	Persistence of vegetation signal	Persistence of vegetation cover detected on both control dates.
Dry sandy-detrital surfaces	Flat dry muddy surfaces	140.8	Redistribution among open sediments	Spectral and moisture changes within bare sediment classes.
Residual water bodies	Distinct vegetation signal	132.2	Shallow-water contraction and vegetation establishment	Conversion of former shallow-water zones to vegetation-related surfaces.
Flat dry muddy surfaces	Dry sandy-detrital surfaces	130.4	Increasing dryness or brightness	Possible drying, cracking or changes in exposed sediment properties.
Residual water bodies	Residual water bodies	126.6	Persistence of residual water	Stable elements of the residual hydrological framework.
Wet or waterlogged surfaces	Distinct vegetation signal	118.0	Vegetation establishment on wet surfaces	Consistent with the importance of moisture availability.
Dry sandy-detrital surfaces	Dry sandy-detrital surfaces	116.6	Persistence of dry surfaces	Areas where biophysical stabilisation remained limited.
Flat dry muddy surfaces	Flat dry muddy surfaces	115.4	Persistence of open muddy surfaces	Exposed sediments vulnerable to drying and overheating.

Source: calculated by the author from the 2023 and 2025 Sentinel-2 surface-type classifications.

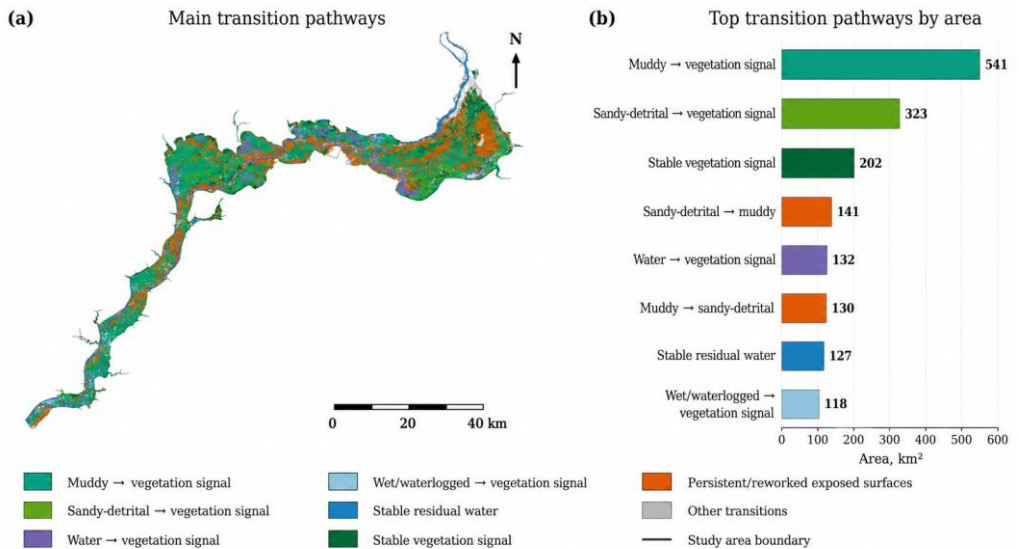
Overall, the transition matrix identifies three coexisting trajectories: vegetation establishment on exposed sediments, persistence of residual water in hydrologically stable depressions, and continued exposure of dry or muddy surfaces where biophysical stabilisation was slower. The former reservoir bed should therefore be interpreted as a mosaic

of vegetation establishment, hydrological persistence and residual risk rather than as a uniform restoration sequence.

To connect the tabular transition estimates with their spatial expression, the class-to-class transition matrix was aggregated into dominant transition groups (Fig. 6). This aggregation summarises the main pathways derived from the five-class classifications and does not introduce a new eight-class surface-type scheme. The group labelled persistent/reworked exposed surfaces combines persistent dry exposed classes and redistribution between dry sandy-detrital and flat dry muddy surfaces. Fig. 6 should therefore be read as a spatial and visual synthesis of Table 4 rather than as a replacement for the detailed transition table.

Fig. 6: Main transition pathways between surface types in the former Kakhovka Reservoir bed, 19 August 2023–19 August 2025.

Panel (a) shows the spatial distribution of dominant transition groups derived from the five-class Sentinel-2 surface-type classifications for the two control dates. Panel (b) ranks the largest transition pathways by area; values are rounded to the nearest square kilometre. The grey outline indicates the study area boundary.



Source: calculated by the author from Sentinel-2 classification results in Google Earth Engine.

The degradation-state analysis adds a complementary layer to the surface-type interpretation. The classification describes surface composition, whereas the author-proposed DSDI evaluates the intensity of combined degradation signals: dryness or potential salinity, moisture deficit, surface overheating and vegetation deficit. Areas with $DSDI \geq 0.50$ declined from 1067.7 km² in summer 2023 to 140.8 km² in summer 2024 and 127.9 km² in summer 2025, indicating a strong reduction in high integrated degradation values after the first post-breach season. Figure 7 summarises the spatial expression and class-area structure of this pattern.

Table 5 shows that this improvement was not equivalent to the disappearance of all stress factors. The area with $NDMI \leq 0.10$ decreased from 1761.6 km² in 2023 to 602.0 km² in 2024, but increased to 791.4 km² in 2025. Areas with $LST \geq 32$ °C also remained extensive on the analysed summer composites: 1766.7 km² in 2023, 943.9 km² in 2024 and 1659.1 km² in 2025. These values reflect both surface properties and year-specific meteorological

conditions, including air temperature, cloudiness, antecedent precipitation and surface-moisture availability. Interannual differences in the extent of high-LST surfaces should therefore not be interpreted solely as a consequence of landscape transformation.

The divergence between DSDI and individual stress indicators is analytically important. Expansion of vegetation-related surfaces can reduce the integrated degradation signal, but it does not necessarily remove the physical constraints imposed by summer heating and seasonal moisture deficit. The post-reservoir landscape therefore contains both areas of initial vegetation establishment and areas where ecological stability remains uncertain under dry and hot conditions.

Table 5: Summary DSDI and threshold-based degradation/stress indicators.

Indicator	Summer 2023	Summer 2024	Summer 2025	Interpretation
DSDI mean	0.50	0.30	0.33	Mean integrated degradation signal.
Area with DSDI ≥ 0.50 , km ²	1067.7	140.8	127.9	Area of high or critical degradation.
Area with DSDI ≥ 0.75 , km ²	0.0	0.0	0.0	Critical degradation threshold.
Area with NDMI ≤ 0.1 , km ²	1761.6	602.0	791.4	Moisture-deficit area.
Area with LST ≥ 32 °C, km ²	1766.7	943.9	1659.1	Surface overheating area.

Source: calculated by the author from Sentinel-2 and Landsat 8/9 data in Google Earth Engine.

Mean DSDI decreased from 0.50 in summer 2023 to 0.30 in summer 2024 and 0.33 in summer 2025. This confirms that the combined degradation signal was strongest during the first post-breach summer, although moisture-deficit and thermal-stress areas remained spatially extensive in 2025.

A sensitivity check was conducted to examine whether the interpretation of DSDI dynamics was dependent on the selected component weights (Table 6). This check was not used to redefine the DSDI formula, but to test whether the main degradation-reduction pattern remained stable under alternative weighting assumptions.

Table 6: Sensitivity check of DSDI weighting schemes based on monthly pixel samples.

Weighting scheme	Weights: dry / moisture / thermal / vegetation	Spearman ρ with baseline	Summer sampled pixels ≥ 0.5 , 2023 (%)	Summer sampled pixels ≥ 0.5 , 2024 (%)	Summer sampled pixels ≥ 0.5 , 2025 (%)	Change 2023–2025 (pp)
Baseline DSDI	0.35 / 0.25 / 0.25 / 0.15	1.00	47.3	7.6	7.3	-40.0
Equal weights	0.25 / 0.25 / 0.25 / 0.25	0.98	80.2	15.1	13.2	-67.0
Dryness-emphasis	0.45 / 0.20 / 0.20 / 0.15	0.98	7.9	1.6	0.5	-7.4
Moisture-temperature emphasis	0.25 / 0.30 / 0.30 / 0.15	0.98	72.6	16.8	18.5	-54.1
Vegetation-emphasis	0.30 / 0.20 / 0.20 / 0.30	0.95	71.1	11.2	7.9	-63.2

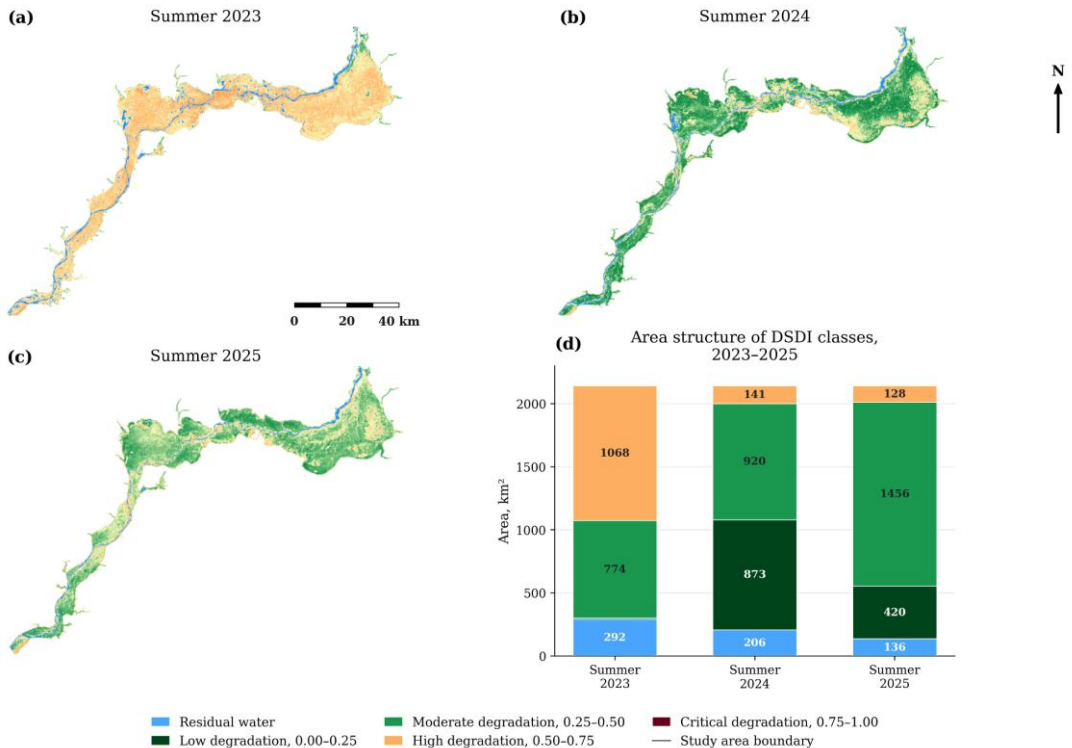
Source: calculated by the author from monthly DSDI pixel samples. High-score sampled pixels refer to the share of summer pixels with the respective DSDI formulation ≥ 0.5 ; pp – percentage points.

Changing the weights affected the absolute share of sampled pixels exceeding the 0.5 threshold, as expected, because each formulation changes the contribution of dryness, moisture, thermal stress and vegetation deficit. However, all alternative formulations retained strong rank agreement with the baseline DSDI and preserved the same main temporal signal: the share of high-degradation sampled pixels declined sharply after the first post-breach summer.

The robustness test supports the comparative use of the baseline DSDI. Although the alternative weighting schemes produced different absolute high-score shares, their rank similarity with the baseline remained high (Spearman $\rho \geq 0.95$), and all variants retained the same temporal signal: a substantial decline in high-degradation sampled pixels after 2023. This reduces the likelihood that the main DSDI interpretation is an artefact of a single weighting choice.

Fig. 7: Spatial distribution of DSDI degradation classes and class-area structure within the former Kakhovka Reservoir bed in the summer composites of 2023–2025.

Panels (a–c) show the classified DSDI maps, and panel (d) summarises the area structure of residual water and DSDI degradation classes for the same seasonal periods. Residual water is shown separately from the exposed-surface degradation classes. The class thresholds are operational equal-width intervals rather than normative criteria. The grey outline indicates the study area boundary.



Source: calculated by the author from Sentinel-2 and Landsat 8/9 data in Google Earth Engine.

To visualise the integrated degradation-state pattern, DSDI values were mapped for the summer composites of 2023, 2024 and 2025 (Fig. 7). Residual water bodies were displayed separately because open water was not interpreted as an exposed-surface degradation class. The four equal-width operational classes were low ($0.00 \leq \text{DSDI} < 0.25$), moderate ($0.25 \leq$

DSDI < 0.50), high ($0.50 \leq \text{DSDI} < 0.75$) and critical degradation ($0.75 \leq \text{DSDI} \leq 1.00$). Panel (d) summarises the class-area structure of residual water and DSDI classes. Because the critical class had zero mapped area in all three summer composites, the high-degradation segment in Fig. 7d corresponds, after rounding, to the $\text{DSDI} \geq 0.50$ areas reported in Table 5.

Table 7 clarifies the statistical relationships underlying the mapped patterns. The strongest and most ecologically consistent relationship was between vegetation and moisture: the NDVI-NDMI correlation increased from 0.47 in 2023 to 0.88 in 2024 and 0.89 in 2025. This suggests that, after the initial disturbance, vegetation became increasingly associated with wetter or moisture-retaining surfaces.

Temperature relationships provide a complementary interpretation. Negative NDVI-LST and NDMI-LST correlations show that vegetation cover and moisture were associated with lower surface temperatures, whereas dry and weakly vegetated surfaces remained more prone to heating. In 2025, these correlations reached -0.64 and -0.71, respectively. However, their interannual magnitude also reflects differences in weather and seasonal surface-moisture conditions.

The DSDI correlations were interpreted as internal consistency checks rather than independent validation, because NDVI, NDMI, NDSI and LST are index components. In the pooled 2023–2025 summer pixel sample (Figure 8a; $n = 32,448$), DSDI was strongly negatively correlated with NDVI and NDMI and positively correlated with NDSI and LST. The 2025 DSDI–NDMI scatter plot (Figure 8b; $n = 11,227$) further shows a monotonic decline in DSDI with increasing NDMI (Spearman $\rho = -0.94$), linking the integrated degradation signal directly to the surface-moisture gradient.

Table 7: Spearman correlations among key remote-sensing indicators.

Indicator pair	2023	2024	2025	Interpretation
NDVI-NDMI	0.47	0.88	0.89	Vegetation became increasingly associated with moisture availability.
NDVI-LST	-0.49	-0.44	-0.64	Vegetation-related surfaces were associated with lower surface temperatures.
NDMI-LST	-0.60	-0.61	-0.71	Moist surfaces were less prone to overheating.
DSDI-NDVI	-0.66	-0.95	-0.93	Higher vegetation corresponded to lower degradation signal.
DSDI-NDMI	-0.78	-0.88	-0.94	Moisture deficit was a central component of degradation.
DSDI-LST	0.82	0.62	0.81	Thermal stress contributed strongly to degradation-state differentiation.

Source: calculated by the author from random pixel samples of Sentinel-2 and Landsat 8/9 image stacks; Spearman rank correlation coefficient.

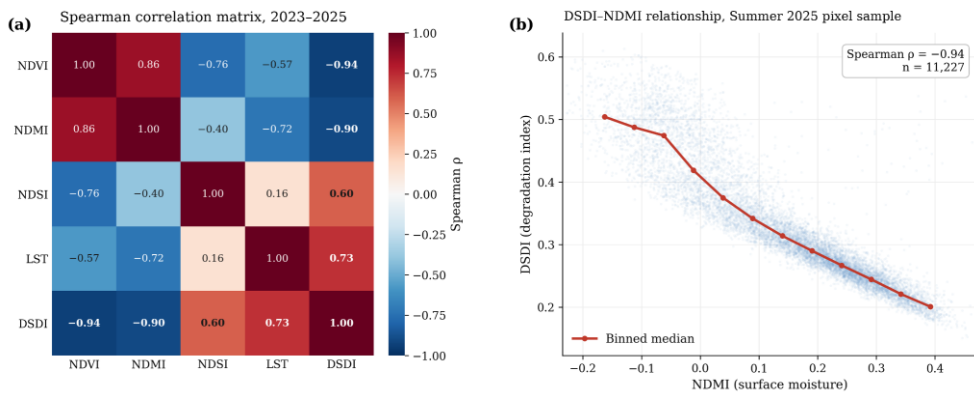
An exploratory multiple regression with LST as the response and NDVI, NDMI and NDSI as predictors showed increasing explanatory power, with R^2 values of 0.34, 0.41 and 0.52 for

2023, 2024 and 2025, respectively. This supporting analysis suggests that surface temperature became more closely related to vegetation cover, moisture and dryness as the post-reservoir mosaic developed; it should not be interpreted as causal evidence independent of meteorological conditions.

Additional lag-correlation analysis was not included as a main result. Although monthly data were available for June 2023–August 2025, the time series is short for robust lag analysis and is strongly affected by seasonality, cloud-free data availability and the abrupt initial disturbance. Lag-based analysis would require a longer monthly record and explicit meteorological predictors such as precipitation, air temperature and evapotranspiration.

Fig. 8: Statistical relationships among the surface indices and the Degradation State Difference Index (DSDI).

Panel (a) shows the Spearman rank-correlation matrix for NDVI, NDMI, NDSI, land-surface temperature (LST) and DSDI based on the pooled summer 2023–2025 pixel sample. Panel (b) shows the DSDI–NDMI relationship for the summer 2025 pixel sample; points represent individual pixels and the red line shows binned median values.



Source: calculated by the author from Google Earth Engine outputs.

DISCUSSION

Hydrological and meteorological context

Post-breach landscape dynamics were strongly modulated by Dnipro River discharge, spring flooding and year-specific weather. The seasonal water masks in this study show a pronounced temporary expansion of water-covered areas in spring 2024. This pattern is consistent with independent field and remote-sensing evidence that spring floods inundated large parts of the drained bed and replenished moisture in the bottom sediments (Kuzemko *et al.*, 2025; Pichura *et al.*, 2025). The estimates are not directly interchangeable because the studies used different dates, spatial procedures and classification thresholds, but all demonstrate that hydrological connectivity and floodwater redistribution were major controls on vegetation establishment.

The favourable moisture conditions of winter and spring 2024 were followed by exceptionally warm and dry summer conditions. Pichura *et al.* (2025) reported July air temperatures of 40.5–42.0 °C in the study region and associated moisture depletion and vegetation stress. At the broader European scale, 2024 was the warmest year on record, and both spring and summer were record warm (Copernicus Climate Change Service, 2025). Consequently, the interannual differences in LST, moisture and vegetation-related surfaces

reflect both the evolving landscape structure and external hydrometeorological forcing. This limits any interpretation of the 2023–2025 sequence as a simple linear trajectory.

Landscape reorganisation, biological interpretation and future trajectories

The former Kakhovka Reservoir bed should be interpreted as a newly formed post-reservoir landscape mosaic rather than as a uniformly degraded surface. The principal post-breach change was not merely the disappearance of open water, but the rapid differentiation of the exposed bed into residual water bodies, wet or waterlogged depressions, dry sandy-detrital surfaces, flat dry muddy surfaces and surfaces with a distinct vegetation signal. These elements form an interacting spatial system in which hydrological persistence, substrate properties, seasonal moisture and vegetation establishment jointly determine landscape development. This interpretation is consistent with recent studies that emphasise the heterogeneity of the drained Kakhovka bed, the variable occurrence of residual water and the spatially uneven development of vegetation (Dovhanenko *et al.*, 2024; Lischenko *et al.*, 2025; Kuzemko *et al.*, 2025).

The five-class classification therefore functions as more than a descriptive land-cover map. It provides a simplified landscape typology for a highly dynamic post-disturbance area. Residual water bodies represent the remaining hydrological framework, whereas wet or waterlogged surfaces identify depressions and low-lying zones in which moisture accumulation may support wetland-related vegetation or more rapid vegetation establishment. Dry sandy-detrital and flat dry muddy surfaces represent exposed substrates with different likely responses to heating, desiccation, surface crusting, cracking and wind-driven particle mobilisation. Surfaces with a distinct vegetation signal indicate the development of spectrally detectable vegetation cover and possible initial surface stabilisation. Interpreting these classes together avoids a binary water-versus-land view and highlights the coexistence of hydrological persistence, biological establishment and residual environmental stress.

The transition analysis adds an important process-based dimension to this typology. The largest pathway, from flat dry muddy surfaces to surfaces with a distinct vegetation signal, suggests that fine-grained sediments may retain sufficient moisture to support vegetation establishment after their initial exposure. The substantial transition from dry sandy-detrital surfaces to the vegetation-signal class shows that vegetation establishment was not restricted to the most moisture-retaining substrates and that partial stabilisation also occurred on more exposed surfaces. At the same time, the persistence and interchange of muddy and sandy-detrital classes indicate that sediment reworking, drying and redistribution continued during the study period. These results complement the study by Kuzemko *et al.* (2025), which used field surveys and remote sensing to distinguish developing flora, vegetation and habitat types, including willow and poplar thickets, marsh vegetation and sparsely vegetated muddy, sandy and shell substrates. The present study does not classify botanical communities; instead, it quantifies broad remotely sensed surface types across the entire former reservoir bed and identifies the source classes of vegetation expansion through a transition matrix. The two approaches are therefore complementary: field observations provide species- and habitat-level interpretation, while the present framework provides landscape-scale spatial and temporal quantification through August 2025.

The vegetation signal should nevertheless be interpreted cautiously. The mapped class is a remote-sensing surface type rather than a floristic or successional classification. Sentinel-2 data can identify vegetation cover and spectral vigour but cannot determine species composition, community structure, dominance of native or non-native taxa, habitat quality or long-term ecological stability. The increase in vegetation-related surfaces should therefore be

interpreted as evidence of initial vegetation establishment and potential surface stabilisation, rather than as proof of a particular successional stage or complete ecosystem recovery. Early vegetation development may be rapid while remaining sensitive to subsequent drought, heat stress, sediment instability and changes in residual hydrological connectivity. Future field validation should assess species composition, projective cover and structural characteristics along the main moisture and substrate gradients, distinguish herbaceous, woody and wetland-related vegetation, evaluate the relative contribution of native and non-native taxa, and assign the developing vegetation to the principal community and habitat types.

Initial stabilisation and residual degradation risk therefore coexist within the same landscape. The marked reduction in areas with high DSDI values indicates that the strongest combined degradation signal was associated with the first post-breach season, when extensive newly exposed sediments were dry, weakly vegetated and thermally stressed. However, the persistence of dry sandy-detrital and muddy surfaces, together with areas of low NDMI and elevated LST in 2025, shows that the spread of vegetation did not eliminate moisture and thermal constraints. Some parts of the former reservoir bed are developing continuous vegetation cover, whereas other parts remain vulnerable to overheating, repeated drying, wind erosion, fire and potentially secondary salinisation. The NDSI-related component should be interpreted as a spectral signal of bright, dry and potentially saline surfaces rather than as a direct measurement of sediment salinity.

The author-proposed DSDI is useful in this context because it integrates the main stress dimensions expected for newly exposed reservoir-bed sediments: dryness or potential salinity, moisture deficit, surface overheating and vegetation deficit. It should nevertheless be treated as a comparative remote-sensing indicator rather than as a regulatory degradation standard. The equal-width class boundaries are operational thresholds introduced for consistent spatial and temporal comparison, not normative or field-calibrated criteria. The sensitivity analysis showed that the overall direction of temporal change was robust under alternative weighting schemes, which strengthens confidence in the comparative interpretation. Field-based validation and further testing in other exposed reservoir beds are still required before the index can be generalised beyond this case study.

The statistical relationships provide a biophysical explanation for the mapped mosaic. The strong positive NDVI-NDMI relationship indicates that vegetation establishment was closely structured by moisture availability, while the negative NDVI-LST and NDMI-LST relationships show that vegetation cover and surface moisture were associated with lower surface temperatures. Conversely, dry and weakly vegetated surfaces remained more prone to heating. The strong negative DSDI-NDMI relationship in 2025 further supports the internal consistency of the proposed degradation index with the observed moisture gradient, although this relationship is not an independent validation because NDMI contributes directly to DSDI. The exploratory regression results point in the same direction: the explanatory power of NDVI, NDMI and NDSI for LST increased from $R^2 = 0.34$ in 2023 to 0.41 in 2024 and 0.52 in 2025. This suggests that surface temperature became progressively more structured by the developing vegetation-moisture-sediment mosaic. These associations should not be interpreted as proof of causality, because interannual weather conditions also strongly influenced LST and moisture. Lag-correlation analysis was not included because the monthly record covers only the early post-breach phase and is strongly affected by seasonality, cloud-free data availability and the abrupt initial disturbance; a longer monitoring record with meteorological predictors would be required to identify delayed ecological responses reliably.

Future development is unlikely to follow a single uniform trajectory. Moisture-retaining fine sediments, residual channels and periodically flooded depressions are likely to continue

supporting vegetation establishment, whereas elevated sandy or repeatedly drying surfaces may remain vulnerable to overheating, moisture deficit, wind erosion and fire. Climate projections for Ukraine indicate a longer growing season, but a longer thermally suitable period does not guarantee stable vegetation where water availability is limiting (Krakovska *et al.*, 2024). Episodic floods may locally restore moisture, reconnect residual water bodies and redistribute vegetation, while warmer and drier periods may intensify stress and increase the instability of exposed sediments. The former reservoir bed should therefore be expected to remain a dynamic mosaic whose future condition depends on climatic variability, Dnipro discharge regulation, hydrological or engineering interventions and management decisions.

The findings have direct implications for adaptive management. A uniform strategy would be inappropriate because the area contains zones of vegetation establishment, persistent residual water and continuing degradation risk. Surfaces with a distinct vegetation signal should be protected from unnecessary disturbance where they contribute to sediment cover and potential stabilisation. Residual water bodies and wet or waterlogged surfaces form a hydrological framework for wetland-related vegetation and habitat development. Conversely, persistent dry sandy-detrital and muddy surfaces, especially where they coincide with high DSDI, low NDMI or elevated LST, require continued satellite monitoring, targeted field verification and, where necessary, measures to reduce disturbance and deflation risk. Management should therefore be spatially differentiated and periodically updated as hydrological connectivity, vegetation structure and surface conditions change.

Overall, the combined use of surface-type classification, monthly structural dynamics, transition analysis, DSDI assessment and vegetation-moisture-temperature statistics provides a transferable remote-sensing framework for other large exposed reservoir beds and rapidly changing post-disturbance landscapes where field access is limited. Continued observation is required to determine whether vegetation establishment develops into stable and diverse communities, whether residual dry-stress zones persist or expand, how the relative contributions of native and non-native taxa change, and how future climatic, hydrological or engineering decisions reshape the emerging landscape mosaic. Integration of satellite monitoring with repeated field surveys would provide the strongest basis for evaluating ecological trajectories and distinguishing temporary spectral greening from long-term ecosystem development.

CONCLUSIONS

The former Kakhovka Reservoir did not transform into a homogeneous degraded surface after the dam breach. Instead, it rapidly developed into a heterogeneous post-reservoir landscape mosaic composed of residual water bodies, dry sandy-detrital surfaces, flat muddy sediments, wet or waterlogged areas, and surfaces with a distinct vegetation signal. The principal post-breach process was therefore not only water loss, but also spatial reorganisation of the exposed reservoir bed.

The five-class surface-type classification showed a pronounced shift from exposed sediments to vegetation-related surfaces. Between 19 August 2023 and 19 August 2025, residual water decreased from 312.7 km² to 136.2 km², whereas surfaces with a distinct vegetation signal increased from 265.4 km² to 1315.7 km². The dominant transition was the conversion of flat dry muddy surfaces to the vegetation-related class, covering 540.7 km², followed by the transition from dry sandy-detrital surfaces, covering 322.5 km². These changes indicate extensive vegetation establishment on previously exposed sediments.

The proposed DSDI provided an integrated comparative assessment of degradation state. Areas with DSDI ≥ 0.50 decreased from 1067.7 km² in summer 2023 to 127.9 km² in summer

2025, and sensitivity testing supported the robustness of this temporal direction. The decline in DSDI should not be interpreted as complete ecological stabilisation, because extensive areas remained affected by thermal and moisture stress and the interannual LST pattern was also influenced by weather conditions.

The statistical analysis showed that development of the vegetation signal was closely associated with moisture availability and lower surface temperature. In 2025, Spearman correlations were 0.89 for NDVI-NDMI, -0.64 for NDVI-LST and -0.71 for NDMI-LST. The DSDI-NDMI relationship was also strong (Spearman $\rho = -0.94$), consistent with the central role of surface moisture in the emerging landscape mosaic.

An exploratory regression provided additional support for this interpretation, with the explanatory power of NDVI, NDMI and NDSI for LST increasing from $R^2 = 0.34$ in 2023 to $R^2 = 0.52$ in 2025. This relationship is comparative rather than causal and should be interpreted together with year-specific meteorological conditions.

The combined framework is suitable for continued monitoring of large exposed reservoir beds where field access is constrained. For the former Kakhovka Reservoir, the results support adaptive management that differentiates between zones of vegetation establishment and potential surface stabilisation, persistent residual water bodies, and areas of continued degradation risk. Field-based biological validation remains necessary to determine species composition, community structure, habitat quality and long-term ecosystem development.

ACKNOWLEDGEMENTS

The author acknowledges Admiral Makarov National University of Shipbuilding for organisational support. Satellite data processing was performed using Google Earth Engine.

CONFLICT OF INTEREST

The author declares no competing interests.

FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

DATA AVAILABILITY

The Sentinel-2, Landsat 8/9 and ancillary datasets used in this study are openly available through Google Earth Engine. Derived tables and processing scripts are available from the corresponding author upon reasonable request.

AUTHOR CONTRIBUTIONS

Nataliia I. Magas: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft preparation, writing – review and editing, visualization, and project administration.

REFERENCES

- Auble, G.T., Shafroth, P.B., Scott, M.L., Roelle, J.E., (2007). Early vegetation development on an exposed reservoir: implications for dam removal. *Environmental Management* 39(6), 806–818. <https://doi.org/10.1007/s00267-006-0018-z>.
- Bellmore, J.R., Pess, G.R., Duda, J.J., O'Connor, J.E., East, A.E., Foley, M.M., Wilcox, A.C., Major, J.J., Shafroth, P.B., Morley, S.A., Magirl, C.S., Anderson, C.W., Evans, J.E., Torgersen, C.E., Craig, L.S., (2019). Conceptualizing ecological responses to dam removal: If you remove it, what's to come? *BioScience* 69(1), 26–39. <https://doi.org/10.1093/biosci/biy152>.
- Copernicus Climate Change Service (C3S), (2025). *European State of the Climate 2024*. Copernicus Climate Change Service and World Meteorological Organization. Retrieved July 7, 2026, from: <https://climate.copernicus.eu/esotc/2024>.
- Dovhanenko, D.O., Yakovenko, V.M., Brygadyrenko, V.V., Boyko, O.O., (2024). Characteristic of the dried-up zone formed as a result of the breach of the Kahovka dam. *Biosystems Diversity* 32(2), 285–295. <https://doi.org/10.15421/012431>.
- European Space Agency (ESA), (2025). *Sentinel-2 mission and user documentation*. Retrieved May 24, 2026, from: <https://sentinels.copernicus.eu/>.
- Gao, B.-C., (1996). NDWI — A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* 58(3), 257–266. [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3).
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>.
- Kozlova, A., Lischenko, L., Andreiev, A., Lubskyi, M., Lysenko, A., (2024). Water occurrence mapping of Kakhovka Reservoir after the dam destruction. International Conference of Young Professionals *GeoTerrace* 2024, 1–5. <https://doi.org/10.3997/2214-4609.2024510066>.
- Krakovska, S., Shpytal, T., Chyhareva, A., Savchuk, S., Kryshtop, L., (2024). Climate characteristics of thermal periods in Ukraine until the end of the 21st century. Part II: growing season. Meteorology. Hydrology. *Environmental Monitoring* 2(6), 33–49. <https://doi.org/10.15407/Meteorology2024.06.033>.
- Kuzemko, A.A., Prylutskyi, O.V., Kolomytsev, G.O., Didukh, Ya.P., Moysiienko, I.I., Borsukevych, L.M., Chusova, O.O., Khodosovtsev, O.Ye., (2025). Initial stages of revegetation at the bottom of the drained Kakhovka Reservoir (Ukraine): synthesis of field surveys and remote sensing. *Ukrainian Botanical Journal* 82(5), 488–501. <https://doi.org/10.15407/ukrbotj82.05.488>.
- Lischenko, L., Filipovych, V., (2024). Operational satellite geomonitoring of the consequences of the destruction of the Kakhovka hydroelectric power plant dam. *Ukrainian Journal of Remote Sensing* 11(1), 21–31. <https://doi.org/10.36023/ujsr.2024.11.1.257>.
- Lischenko, L., Kozlova, A., Andreiev, A., (2025). Mapping of the spatiotemporal transformations of the former Kakhovka reservoir bed after dam destruction using Sentinel-2 satellite imagery. *Ukrainian Journal of Remote Sensing* 12(4), 29–37. <https://doi.org/10.36023/ujsr.2025.12.4.296>.
- McFeeters, S.K., (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing* 17(7), 1425–

1432. <https://doi.org/10.1080/01431169608948714>.

Naddaf, M., (2023). Ukraine dam collapse: what scientists are watching. *Nature* 618(7965), 440–441. <https://doi.org/10.1038/d41586-023-01928-8>.

Pekel, J.-F., Cottam, A., Gorelick, N., Belward, A.S., (2016). High-resolution mapping of global surface water and its long-term changes. *Nature* 540, 418–422. <https://doi.org/10.1038/nature20584>.

Pichura, V., Potravka, L., Dudiak, N., Bahinskyi, O., (2024). Natural and climatic transformation of the Kakhovka Reservoir after the destruction of the dam. *Journal of Ecological Engineering* 25(7), 82–104. <https://doi.org/10.12911/22998993/187961>.

Pichura, V., Potravka, L., Boiko, P., (2025). Climatic and hydrological conditions for the formation of vegetation cover in the drained Kakhovka reservoir's territory. *Ecological Engineering & Environmental Technology* 26(4), 357–373. <https://doi.org/10.12912/27197050/202227>.

Prach, K., Chenoweth, J., del Moral, R., (2019). Spontaneous and assisted restoration of vegetation on the bottom of a former water reservoir, the Elwha River, Olympic National Park, WA, USA. *Restoration Ecology* 27(3), 592–599. <https://doi.org/10.1111/rec.12915>.

Shafroth, P.B., Friedman, J.M., Auble, G.T., Scott, M.L., Braatne, J.H., (2002). Potential responses of riparian vegetation to dam removal. *BioScience* 52(8), 703–712. [https://doi.org/10.1641/0006-3568\(2002\)052\[0703:PRORVT\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2002)052[0703:PRORVT]2.0.CO;2).

Shafroth, P.B., Perry, L.G., Helfield, J.M., Chenoweth, J., Brown, R.L., (2024). Vegetation responses to large dam removal on the Elwha River, Washington, USA. *Frontiers in Ecology and Evolution* 12, 1272921. <https://doi.org/10.3389/fevo.2024.1272921>.

Shumilova, O., Sukhodolov, A., Osadcha, N., Oreshchenko, A., Constantinescu, G., Afanasyev, S., Koken, M., Osadchyi, V., Rhoads, B., Tockner, K., Monaghan, M.T., Schröder, B., Nabyvanets, J., Wolter, C., Lietytska, O., van de Koppel, J., Magas, N., Jähnig, S.C., Lakisova, V., Grossart, H.-P., (2025). Environmental effects of the Kakhovka Dam destruction by warfare in Ukraine. *Science* 387(6739), 1181–1186. <https://doi.org/10.1126/science.adn8655>.

Stanley, E.H., Doyle, M.W., (2003). Trading off: the ecological effects of dam removal. *Frontiers in Ecology and the Environment* 1(1), 15–22. [https://doi.org/10.1890/1540-9295\(2003\)001\[0015:TOTEEO\]2.0.CO;2](https://doi.org/10.1890/1540-9295(2003)001[0015:TOTEEO]2.0.CO;2).

Stone, R., (2024). Laid to waste. Ukrainian scientists are tallying the grave environmental consequences of the Kakhovka Dam disaster. *Science* 383(6678), 18–23. <https://doi.org/10.1126/science.adn7986>.

Tucker, C.J., (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment* 8(2), 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0).

UNEP, (2023). *Rapid Environmental Assessment of Kakhovka Dam Breach, Ukraine*. United Nations Environment Programme, Nairobi. Retrieved May 24, 2026, from: <https://wedocs.unep.org/handle/20.500.11822/43696>.

USGS, (2025). *Landsat 8/9 Collection 2 Level-2 Science Product documentation*. United States Geological Survey. Retrieved May 24, 2026, from: <https://www.usgs.gov/landsat-missions>.

Vyshnevskyi, V., Shevchuk, S., Komorin, V., Oleynik, Y., Gleick, P., (2023). The destruction of the Kakhovka dam and its consequences. *Water International* 48(5), 631–647.

<https://doi.org/10.1080/02508060.2023.2247679>.

Vyshnevskiy, V.I., Shevchuk, S.A., (2024). Natural processes in the area of the former Kakhovske Reservoir after the destruction of the Kakhovka HPP. *Journal of Landscape Ecology* 17(2), 147–164. <https://doi.org/10.2478/jlecol-2024-0014>.

Xu, H., (2006). Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing* 27(14), 3025–3033. <https://doi.org/10.1080/01431160600589179>.