Biosystems Diversity

ISSN 2519-8513 (Print)
ISSN 2520-2529 (Online)
Biosyst. Divers.

Procrustean analysis of the set of spectral indices reveals the transformations in plant community hemeroby and functional structure induced by anthropogenic disasters

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Article info

Received 09.02.2025
Received in revised form 15.03.2025
Accepted 21.04.2025

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Tutova, H., Lisovets, O., Kunakh, O., & Zhukov, O. (2025). Procrustean analysis of the set of spectral indices reveals the transformations in plant community hemeroby and functional structure induced by anthropogenic disasters. Biosystems Diversity, 33(2), e2528. doi:10.15421/012528

This study presents an integrated remote sensing approach for assessing the ecological consequences of the destruction of the Kakhovka Reservoir in Southern Ukraine. The methodology combines spectral vegetation indices, principal component analysis, and Procrustean analysis to evaluate spatial and functional transformations in vegetation cover following a large-scale anthropogenic disaster. The approach was applied to floodplain ecosystems on Khortytsia Island and adjacent areas using satellite imagery from the Sentinel-2 mission for the years 2022 and 2024. A set of twenty-nine spectral indices, sensitive to vegetation density, pigment composition, water conditions, and soil properties, was employed to identify patterns in plant community dynamics and environmental change. Principal component analysis was utilized to identify the dominant axes of spectral variability, while Procrustean rotations facilitated the detection of significant spatial shifts over time. The results demonstrated strong correlations between changes in vegetation patterns and key ecological indicators, including hemeroby, naturalness, species richness, and functional diversity. Two primary ecological trends were identified. The first trend is associated with ecosystem degradation due to anthropogenic pressure, characterized by increasing hemeroby, a decline in naturalness, and reductions in both functional evenness and functional divergence. The second trend reflects the internal reorganization of plant communities under near-natural conditions, where increases in projective cover and species richness occur alongside a decrease in functional richness. Spectral indices, such as the normalized difference vegetation index, the normalized difference chlorophyll index, the red-edge vegetation index, the normalized difference tillage index, and the normalized difference water index, have proven particularly effective in detecting both degradation and successional processes. This study demonstrates that satellite-based spectral indices can serve as reliable proxies for assessing the functional structure and ecological condition of vegetation. The proposed methodology provides an effective tool for spatially explicit and timely environmental monitoring, thereby supporting evidence-based decision-making in post-disaster landscape management, including the question of restoring water bodies or conserving newly formed floodplain ecosystems. This approach has broad applicability for long-term ecological monitoring, restoration planning, and adaptive management in regions impacted by significant anthropogenic transformations.

Keywords: nature protection; innovative projects; monitoring; bioindication; environmental impact assessment; geographic information systems; remote sensing data.

Introduction

A comparison of various time periods using individual spectral indices is frequently employed to evaluate landscape dynamics. This approach is particularly effective for assessing disturbances caused by human activities. Certain spectral indices exhibit high sensitivity to fire-induced changes, particularly in an event's immediate aftermath. This methodology enables the detection of both abrupt and gradual changes, effectively distinguishing them from background variability. Utilizing long-term remote sensing data and spectral indices allows the documentation of the disturbance event and the monitoring of ecosystem recovery. This capability significantly enhances the value of this method for analysing anthropogenic impacts over the long term (Hislop et al., 2018). Analysing time series of spectral indices is regarded as a crucial tool for evaluating landscape dynamics resulting from urbanization (Fan et al., 2017). The normalized difference vegetation index (NDVI) is a widely used metric for detecting disturbances in the structure of vegetation cover. NDVI can identify spatial variations in vegetation density and structure, encompassing natural and artificial green spaces (Gascon et al., 2016). NDVI has proven to be highly effective in detecting changes in vegetation cover, particularly across various climates. The NDVI-differencing method, which involves comparing the index between images from two different periods, enables the detection of changes in the direction of vegetation degradation and growth. While NDVI may sometimes be less accurate than other vegetation indices, it has demonstrated superior results in certain cases, depending on the vegetation type and its spectral behaviour. This underscores that NDVI remains one of the most reliable indicators of changes in vegetation structure, especially when basic and rapid monitoring is necessary (Rokni & Musa, 2019). The NDVI is a valuable tool for detecting general changes in vegetation. However, other indices may be more effective for precisely monitoring specific disturbances in vegetation structure (Marques et al., 2024). The NDVI has been shown to have limited effectiveness for land cover classification compared to other, less common, or newer indices. In contrast, greater accuracy was achieved using the original indices formed by combining different Sentinel-2 channels, particularly those based on the formula (A–B)/(A+B+C). This finding confirms that the effectiveness of these indices significantly depends on the specific characteristics of the landscape, the phytocoenotic structure, and the phenological changes in vegetation cover. Therefore, relying solely on NDVI is insufficient. While NDVI remains a useful benchmark, it is not universally the best indicator, and its application should be reevaluated in the context of more flexible and adaptive approaches to multispectral data analysis (Pesaresi et al., 2024). The various vegetation indices exhibit a strong correlation in areas with homogeneous vegetation cover, making it appropriate to assess dynamics based on one of these indices (Li et al., 2025). In such conditions, soil reflection is either negligible or consistent, and the vegetation cover creates a uniform canopy that minimizes the influence of background factors (Mukiibi et al., 2024). Consequently, most vegetation indices exhibit statistical similarity and yield comparable values, allowing any of them to be used to assess changes in vegetation over time. However, when coverage decreases or heterogeneity in community structure emerges, this mutual correlation diminishes. For accurate analysis, selecting the index more judiciously becomes essential, considering the background signal and spectral characteristics (Payero et al., 2004). Specific spectral indices may be helpful in assessing the transformation of various homogeneous landscape surface types, including agricultural land (Qin et al., 2021), rock (Pereira et al., 2023), and water (Montero et al., 2023).

The use of conventional vegetation indices, in particular NDVI, to evaluate the impacts of environmental disasters, such as the destruction of the Kakhovka Dam, is supported by several key factors (Pichura et al., 2025). These indices are straightforward to calculate, easy to interpret, and are grounded in a well-established methodological framework that facilitates rapid responses in situations with limited access to field research (Hamel et al., 2009). Conventional indices exhibit high sensitivity to variations in vegetation cover, soil moisture, and biomass status. This is crucial for identifying degradation processes such as soil erosion, decreased vegetation productivity, or secondary colonization of bare areas (Piedallu et al., 2019). In the case of the Kakhovka Reservoir, these indices enabled researchers to quickly assess the structure of the new vegetation cover, identify regions with satisfactory or critical vegetation activity, and analyse the spatial dynamics of phytomass recovery (Dzyba & Kyriienko, 2024). Conventional indices can be integrated with temperature and humidity metrics to create a composite index, allowing for a more comprehensive characterization of ecosystem conditions in the post-disaster period. Their application is justified for immediate assessments and long-term monitoring of environmental changes resulting from large-scale anthropogenic interventions (Pichura et al., 2025). NDVI can demonstrate the dynamics of vegetation cover expansion during the revegetation of reservoir bottoms; however, its capacity to distinguish between the characteristics of various types of vegetation cover is limited. The monitoring of complex landscape systems necessitates the assessment of the dynamics of heterogeneous land cover types through a set of spectral indices sensitive to the characteristics of vegetation, soil, and water surfaces (Lausch et al., 2025). The destruction of the Kakhovka Dam has had significant consequences for floodplain ecosystems, which consist of a combination of water bodies and land areas, some of which are covered with various types of vegetation, while others may lack vegetation entirely, such as riverbanks or dried-up riverbeds (Didukh et al., 2024). Relying on one or more vegetation indices alone is insufficient to adequately assess the dynamics of the landscape cover in the affected area. Anthropogenic pressure significantly impacts the physiological condition of plants (Zinnert et al., 2013). Therefore, it is advisable to utilize spectral indices responsive to their health status (Młynarczyk et al., 2022).

A detailed understanding of the spatial dynamics of vegetation expansion in areas exposed due to the removal of water cover as a result of the disaster is essential. This analysis should consider the functional aspects of the forming communities. Additionally, it is scientifically and practically essential to address which plant groups are establishing themselves in the newly emerged dry land following the dam's destruction. These communities may consist primarily of native plant species or may be dominated by invasive species. The conservation status of the area and subsequent management strategies will depend on this distinction. Experts hold varying opinions regarding the future of this area. One perspective supports converting the land back into reservoirs to aid irrigation for the surrounding farmland and enhance shipping activities. Conversely, another viewpoint suggests that the natural floodplain ecosystems and the original water regime of the Dnipro River could be restored in this region. The area, which was initially created and subsequently devastated by environmental disaster, has the potential to transform into a significant ecological reserve, preserving the unique flora and fauna of the floodplain forests in Ukraine's steppe zone. The trajectory of the developing vegetation cover may provide insights into selecting the most viable alternative for the future.

The objectives of this article are as follows: 1) to evaluate the dynamics of floodplain ecosystems influenced by anthropogenic impacts; 2) to determine the correlation between observed patterns of variability in spectral indices and the functional state of vegetation cover; 3) to ascertain the feasibility of indicating the level of hemeroby (human influence) or naturalness of vegetation cover based on remote sensing data.

Material and methods

On June 6, 2023, the destruction of the Kakhovka Dam resulted in severe damage to the Kakhovka Reservoir. To evaluate the alterations in land cover within the impacted region, we examined images of the southern section of Khortytsia Island alongside the adjacent waters of the Dnipro River, captured one year prior to the disaster (August 24, 2022) and one year post-disaster (August 18, 2024). We used Sentinel-2B Level-2A imagery, which encompasses 13 spectral channels (B1–B12, including B8A). It has a 10-meter resolution for channels B2 (Blue), B3 (Green), B4 (Red), and B8 (NIR); 20 meters for channels B5–B7, B8A, B11, and B12; and 60 meters for channels B1, B9, and B10. For our analysis, the images were reclassified to a consistent resolution of 10 meters. We assessed land cover features by utilising 29 spectral indices (Kunakh et al., 2025). The set of indices (NDVI, GNDVI, GLI, NDGCI, NDRE, RedEdge NDVI1/2, and RENDVI) effectively captures both quantitative aspects (like density and Leaf Area Index [LAI]) and qualitative factors (including pigment content and the physiological state of plants) of vegetation cover. These indices are crucial for monitoring productivity, stress, and phytomass degradation over large areas, particularly illustrated by the landscape alterations following the destruction of the Kakhovka Reservoir. In this study, several spectral indices are vital for assessing the ecological conditions of the aquatic environment as they indicate the presence of open water and the quality of aquatic vegetation cover. Notably, the Normalized Difference Water Index 1 (NDWI1) helps identify water surfaces by contrasting green and near-infrared spectral ranges. Its enhanced version, the Modified Normalized Difference Water Index (MNDWI), improves water detection in the presence of aquatic vegetation or suspended solids by using the Short-Wave Infrared (SWIR) channel. Simultaneously, the Land Surface Water Index (LSWI), Normalized Difference Infrared Index (NDII), and NDWI2 (also referred to as the Normalized Difference Moisture Index, NDMI) all respond sensitively to the moisture levels in vegetation and soil (Yakovenko et al., 2023)princ. This sensitivity makes them popular tools for evaluating water stress, especially in agroecosystems and wetlands. Furthermore, the Normalized Difference Turbidity Suspended Matter (NDTSM) index aids in estimating the concentration of suspended solids in water, serving as a vital indicator of turbidity and human impact. The NDChla index is used to estimate chlorophyll-a levels, which can indicate eutrophication or significant phytoplankton growth. A separate group includes indices that pertain to saline conditions, such as SVSI and NDI, which indicate salinity's secondary effects through changes in pigment levels and vegetation structure. Another important index is the RBNDVI, a three-component metric integrating atmospheric exposure, vegetation features, and soil salinity. In conclusion, the AC_Index facilitates the estimation of aerosol and organic matter levels in coastal waters, which is crucial for detecting pollution. Therefore, specialised spectral indices aimed at evaluating aquatic environments deliver a thorough overview of various conditions, such as humidity, the presence of water bodies, pollution levels, eutrophication, and salinity. These data plays a key role in tracking changes related to hydrological and human-induced transformations. Among the spectral indices examined in this study, several targeted indices help characterize soil cover properties, including bareness, surface structure, moisture content, salinity, and iron oxide concentrations. Significantly, the Normalized Difference Bare Soil Index (NDBaI) can automatically detect areas with bare soil, indicating vegetation degradation or ongoing erosion. The Normalized Difference Tillage Index (NDTI), which utilises two shortwave infrared (SWIR) channels, is particularly sensitive to moisture levels and micro-relief changes. This feature enables it to distinguish between treated and untreated soil and to identify features that heighten erosion risks. The NDI index indicates the level of salinity at the soil surface, crucial for observing degraded regions or those affected by irrigation. The Rock Index (RI) distinguishes surface types using the ratio of visible to shortwave infrared (SWIR) reflectance, aiding in the identification of mineral variations, especially in dry and open areas. The NDIO index highlights the presence of ferrous oxides, allowing for an evaluation of soil chemistry and signs of hydrothermal alterations. The NDWI2, NDII, and LSWI indices, typically employed for assessing moisture in vegetation, also respond well to soil moisture, notably in bare regions where infrared wavelengths are prominent in the spectral response. These selected indices provide a thorough evaluation of soil cover, taking into account its physical structure, moisture content, chemical makeup, and extent of bareness. This assessment is vital for identifying degradation processes, spatial variability, and assessing human impacts on ecosystems. The procedure is described in more detail in the protocol (Kunakh et al., 2025).

Spectral indices used to reduce the dimensionality of the trait space underwent principal component analysis (Eastman and Fulk, 1993). Principal component analysis (PCA) predominantly uncovers key patterns that highlight the crucial characteristics of landscape cover, including the ratio of vegetated to non-vegetated areas and the comparison of land to water (Zymaroieva et al., 2019). These types of land cover are clearly differentiated and comprise a large portion of the imagery. In instances where land cover changes are minimal (like forest fires or total loss of water bodies), the overall patterns of landscape structure tend to overshadow smaller-scale alterations in land cover. To identify these smaller spatial patterns, the variability linked with principal components 1 and 2 was extracted from spectral index values. This extraction involved performing linear regressions of the spectral indices with respect to PC 1 and PC 2. The residuals from these regression analyses were then analysed through a secondary principal component analysis. The results of the PCA on the residuals were further analysed using Procrustes analysis using the vegan library (Oksanen et al., 2022). The Procrustes function in this library adjusts one configuration to achieve maximum similarity with another by minimizing the sum of squared differences. The Protest function assesses the significance of nonrandomness between two configurations. Procrustes rotation is commonly employed to compare ordination results. Here, the solutions derived from analysing the principal components of the residuals from the regression of spectral indices on the primary principal components are compared. The standard deviation of the correlation coefficients and the statistical significance of the deviation of the correlation coefficients from the null alternative were estimated using the bootstrap procedure (Lee & Rodgers, 1998; Li et al., 2011).

The study explores the relationship between shifts in spatial patterns, as determined by Procrustean analysis, and indicators of hemeroby, naturalness, species richness, functional diversity indices, and the projective cover of plant communities (Lisovets et al., 2024). The functional structure of these plant communities was assessed during the first year following the disaster. A total of 146 vascular plant species were recorded across 135 locations. The methodology for describing plant communities and calculating functional diversity indices is detailed in the accompanying protocol.

Results

The primary principal component analysis identified two principal components with eigenvalues greater than one (Table 1). The spatial patterns of the spectral indices for 2022 and 2024 are remarkably similar. Principal Component 1 reflects the variability in vegetation density, while Principal Component 2 is sensitive to the spectral characteristics of both the aquatic environment and land (Fig. 1).

Table 1
Primary analysis of the principal components of spectral indices and the analysis of the principal components of the residuals from the regression dependencies of spectral indices on the scores of the first two principal components (loadings exceeding 0.2 are displayed)

Index	Primary analysis of the principal components				Residual PCA							
	2022		2024		2022				2024			
	PC1, λ=19.5	PC2, λ=6.6	PC1, λ=18.5	PC2, λ=7.4	PC1, λ=11.2	PC2, λ=6.8	PC3, λ=5.3	PC4, λ=2.5	PC1, λ=12.0	PC2, λ=5.4	PC3, λ=4.7	PC4, λ=3.0
AC_Index	–	–	–	–	–	–	–	0.30	–0.23	–	–	–
BIG2	–	–	–	–	–	–	0.29	–	–	–	0.40	–
GLI	–	–	–	0.22	–	0.25	0.24	–	–	–0.24	0.34	–
GNDVI	0.22	–	0.22	–	–0.28	–	–	–	–0.27	–	–	–
LSWI	0.21	–	0.22	–	–	–0.31	–	–	–	0.38	–	–
MNDW	–	0.25	–	0.25	0.22	–0.22	–	–	0.26	–	–	0.20
NBRI	0.21	–	0.21	–	0.22	–0.21	–	–	0.26	–	–	–
NDBaI	–	0.33	–	0.33	–	–0.31	–	–	–	–	–	0.37
NDChla	–	0.30	–	0.33	–	0.34	–	–	–	–0.32	–	–
NDGCI	0.22	–	0.22	–	–0.28	–	–	–	–0.26	–	–	–
NDI	–	–	–0.20	–	–	0.34	–	–	–	–0.38	–	–
NDII	–	0.24	–	0.24	0.23	–0.21	–	–	0.26	–	–	–
NDIO	–	–0.36	–	–0.35	–	–	0.27	–	–	–	0.25	–
NDNIRBlue	–	–0.32	–	–0.32	–	0.31	–	–	–	–0.28	–	0.21
NDRE	0.22	–	0.23	–	–	–	–0.22	–	–	–	–0.32	0.35
NDREI	0.22	–	0.22	–	–	–	–0.37	–	–	–	–0.30	–
NDTI	0.22	–	0.21	–	–	–	–	–0.36	–	0.28	–	–0.28
NDTSM	0.22	–	0.22	–	–0.24	–	0.20	0.22	–0.23	–	0.24	–
NDVI	0.22	–	0.22	–	–0.28	–	–	–	–0.27	–	–	–
NDWI1	–0.22	–	–0.23	–	–	–	0.29	–0.44	–	–	0.22	0.38
NDWI2	–	0.36	–	0.32	–	–0.22	0.30	–	–	0.31	0.21	–
RBNDVI	0.22	–	0.22	–	0.22	–	–0.29	–	0.23	–	–	–
RedEdge_NDVI1	0.23	–	0.23	–	–0.24	–	–	–	–0.27	–	–	–
RedEdge_NDVI2	0.23	–	0.23	–	–0.28	–	–	–	–0.28	–	–	–
REDI	0.21	–	0.21	–	–	–	–0.21	–	–	–	–	–
RENDVI	0.23	–	0.23	–	–	–	–	–	–	–	–0.27	0.35
RI	0.21	–	0.21	–	0.22	–0.21	–	–	0.26	–	–	–
SIPI	0.22	–	0.23	–	–	–	–	0.46	–	–0.25	–	–0.39
SVSI	–	–0.35	–	–0.33	–	–0.20	0.25	–	0.21	–	0.24	–

Function protest estimates the significance of the Procrustes statistic and uses a correlation-like statistic derived from the symmetric Procrustes sum of squares. The total inconsistency observed in the patterns characterized by the principal components (m212 = 0.55) suggests notable differences in vegetation structure configurations across years. The correlation coefficient of 0.67 indicates a moderately high level of similarity. The statistical significance ($P < 0.001$) confirms that the observed similarity between the configurations is not random but exhibits a significant systematic nature. The spatial patterns estimated by Residual PCA revealed a substantial discrepancy between years (m212 = 0.96) and a significantly lower correlation of 0.20 ($P < 0.001$). This may suggest that the residual variations (deformations not accounted for by the primary model) have undergone significant changes over the years. The shift in residual PC1 indicates areas that have been exposed due to reservoir drainage (Fig. 2).

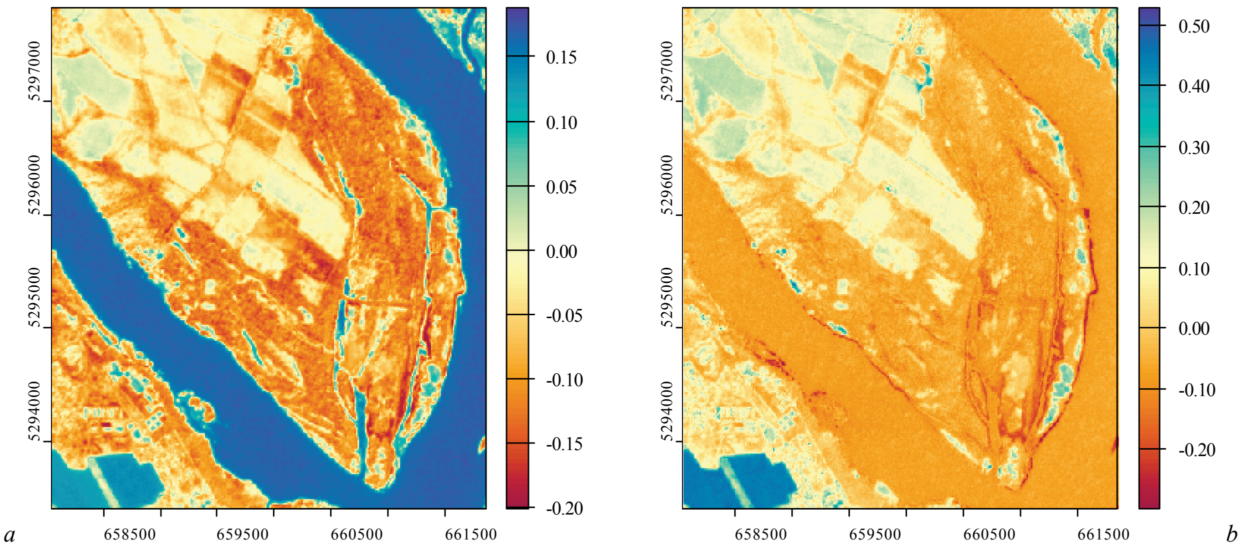


Fig. 1. Variation of the Procrustes shifts of the primary principal components 1 (*a*) and 2 (*b*) in geographical space

Positive values of this shift denote areas devoid of vegetation, while negative values indicate regions that have been freed from the water mirror and where terrestrial vegetation has proliferated. The shift in residual PC1 was primarily influenced by spectral indices such as NDNIRBlue, NDChla, and REDI (Fig. 3). Residual PC1 and residual PC2 were statistically significantly correlated ($r = 0.62$, $P < 0.001$), indicating similar spatial patterns. A positive shift in residual PC2 signified areas lacking vegetation cover following the reservoir drawdown, whereas a negative shift indicated regions with significant changes in vegetation cover. The shift in residual PC2 was mainly attributed to spectral indices such as NDTI, NDBaI, NDII, and MNDW. Residual PC3 exhibited no correlation with residual PC1 ($r = –0.15$, $P = 0.10$) but was positively correlated with residual PC2 ($r = 0.25$, $P = 0.003$). Positive shifts in residual PC3 indicated plant communities that were not significantly impacted by the decrease in water level after the reservoir was removed, while negative shifts indicated floodplain areas that were significantly affected by the water level reduction. The shift in residual PC3 was primarily influenced by spectral indices such as NBRI, NDTSM, RBNDVI, and NDREI. Residual PC4 was positively correlated with both residual PC1 ($r = 0.43$, $P < 0.001$) and residual PC2 ($r = 0.23$, $P = 0.008$) but showed no correlation with residual PC3 ($r = 0.03$, $P = 0.74$). The positive shift in residual PC4 indicated predominantly tree communities that were not significantly affected by the removal of the reservoir. Conversely, a negative shift in residual PC4 indicated wetland communities that were significantly impacted by the lowering of water levels in floodplain ecosystems. The shift in residual PC4 was primarily influenced by spectral indices such as NDIO, GLI, NDWI1, and NDChla.

Procrustes rotations 1 and 4 exhibited positive correlations with functional evenness, divergence, and naturalness, while showing negative correlations with hemeroby (Table 2). In contrast, Procrustes rotations 2 and 3 were positively correlated with projective vegetation cover and species richness, but negatively correlated with functional richness.

Discussion

The Kakhovka Reservoir, constructed in 1956, effectively obliterated the floodplain ecosystems of the lower Dnipro River by triggering a shift from a lotic (flowing) to a lentic (still water) hydrological regime. This transition disrupted the natural riverbed cleansing processes that were previously driven by annual floods. The expansion of the water surface area, compared to the river's original channel, resulted in increased evaporation and a corresponding rise in the concentration of dissolved salts. The reduced flow velocity due to the enlarged water surface also led to water overheating, thereby accelerating eutrophication – particularly exacerbated by the continuous runoff of fertilizers and pesticide residues from agricultural lands, as well as the discharge of domestic and industrial wastewater into the Dnipro River. In many regions, dam deconstruction and the restoration of natural hydrological regimes and native floodplain vegetation are recognized as essential practices for ecological restoration. However, these interventions must be meticulously planned, considering environmental, social, and economic contexts. The intentional destruction of the dam by Russian forces represents an act of environmental barbarism and has precipitated a large-scale ecological disaster. The collapse of the Kakhovka Reservoir resulted in the rapid drainage of the water body, leading to the death of approximately 95,000 tons of fish and the loss of spawning grounds for over 40 fish species. The flooding of protected areas, such as Velykyi Luh, has caused the destruction of unique and irreplaceable ecosystems. (Shumilova et al., 2025).

Remote sensing data facilitated the assessment of the effective width and length of the dam breach, as well as the dynamics of water discharge from the reservoir over the 30 days following the disaster. The initial volumetric discharge was estimated at approximately 57,000 m^3/s, which is about 28 times higher than the average flow rate of the Dnipro River. Within 30 days, the water level in the reservoir had decreased by 12.6 meters, resulting in an almost complete depletion of its volume, which originally totalled 20.4 km^3 (Yi et al., 2025). The exposed bottom of the drained reservoir, which had accumulated over 83,000 tons of heavy metals, has become a significant source of environmental pollution. Toxic elements such as lead, cadmium, and nickel are now being released into the environment through surface runoff and wind erosion, posing serious risks to both human and animal health (Shumilova et al., 2025). The depletion of the reservoir has led to the total loss of the aquatic ecosystem, widespread fish mortality, and the eradication of essential spawning grounds. This impact is especially detrimental to rare and endangered species, such as sturgeon, whose survival relies on these vital habitats (Chernogor et al., 2024). The disaster also changed the hydrological regime of the area. The water level in the former reservoir is now directly influenced by the discharge volumes from the upstream Dnipro Hydroelectric Power Station. During periods of high water flow, significant portions of the former reservoir bed become temporarily inundated once again (Vyshnevskyi and Shevchuk, 2024a). The reduction in water surface area has led to the formation of a network of river branches and shallow lakes, where water temperature is now predominantly influenced by weather conditions. Remote sensing data indicate that the Dnipro Reservoir, located upstream, continues to significantly impact the thermal regime of the main river channel. In spring, the release of cold bottom-layer water from the reservoir results in persistently low temperatures in the downstream section of the river, extending as far as 150 km from the Zaporizhzhia Dam. This prolonged cooling can affect aquatic biota, particularly by altering the timing of fish spawning (Vyshnevskyi and Shevchuk, 2024b).

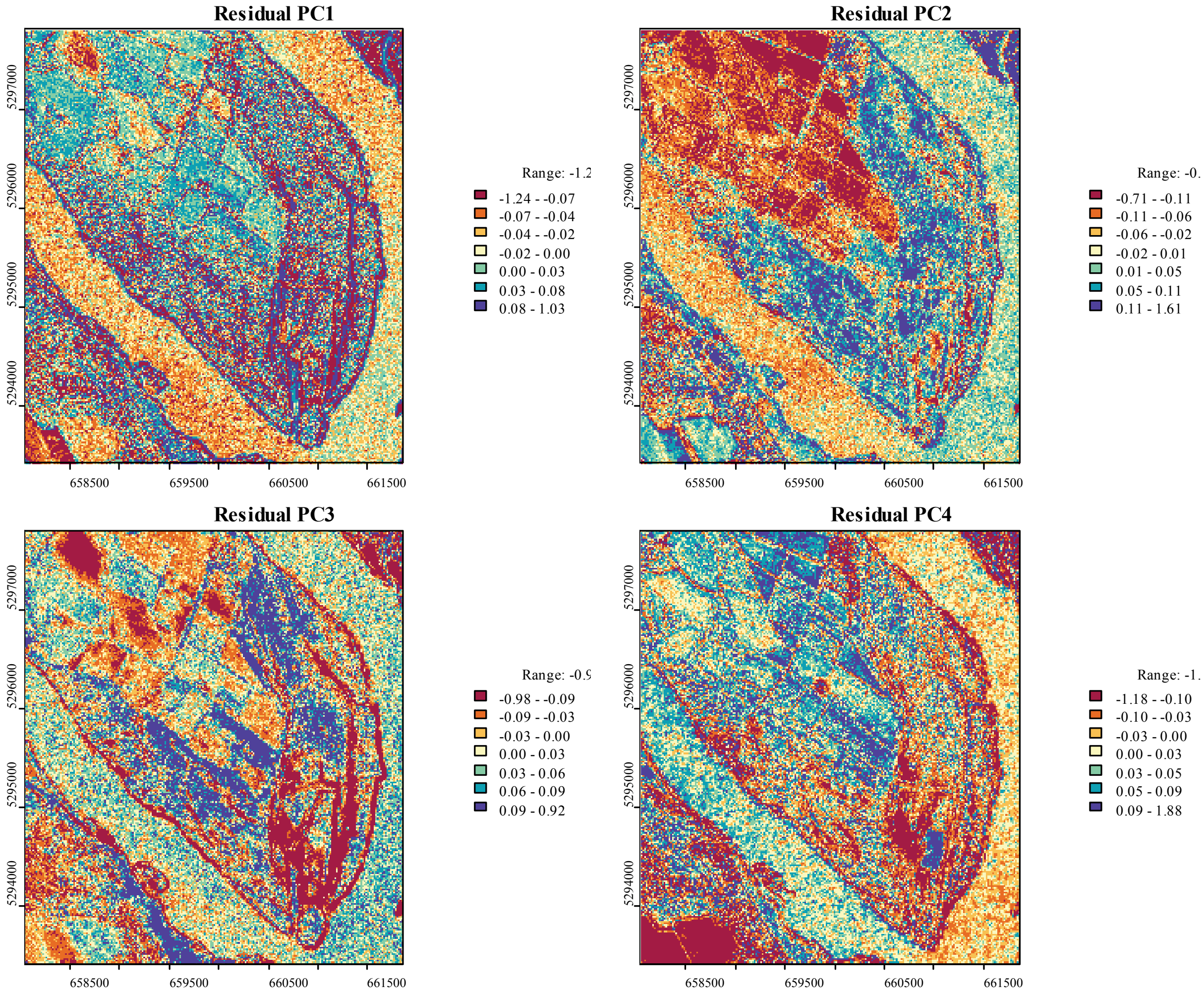
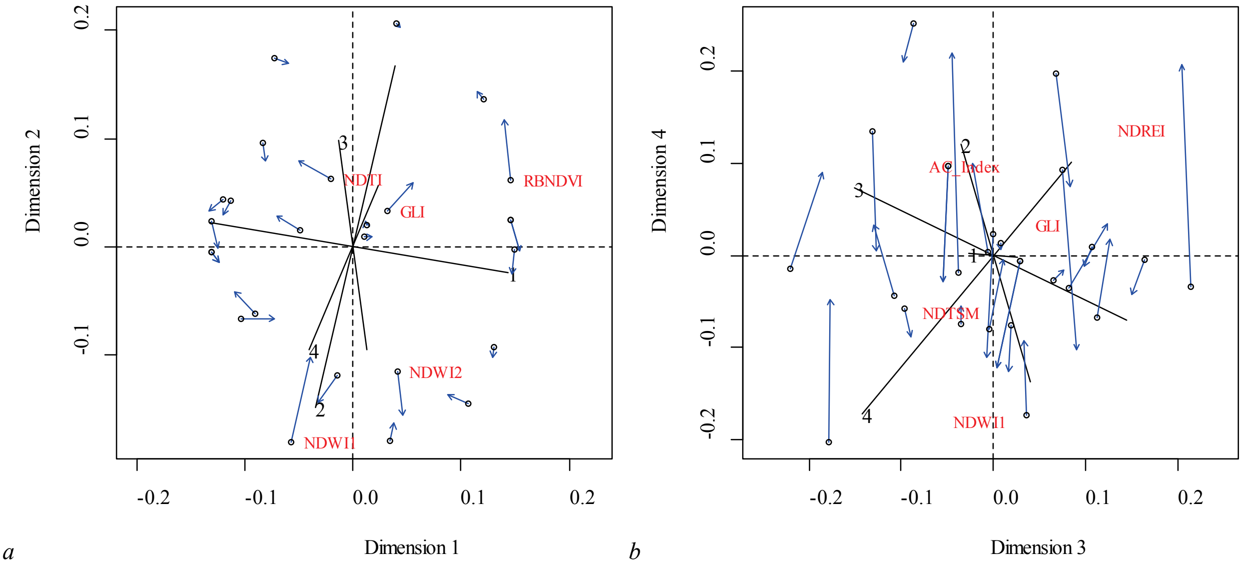


Fig. 2. Spatial variation of Residual PCA Procrustean shifts 1–4

The interaction of combined and cascading risks resulting from the destruction of the Kakhovka Dam, caused by Russian aggression, has significantly exacerbated the situation. This destruction has led to extensive environmental degradation and devastation, jeopardizing both human and ecological well-being, and exemplifies the defining characteristics of ecocide (Gan et al., 2024). Following the destruction of the Kakhovka Dam in June 2023, the exposed bottom of the former reservoir began to rapidly revegetate, with initially bare areas being colonized primarily by willows, particularly the hybrid *Salix* × *rubens*. Over the course of a year, a diverse mosaic of plant community types developed. In addition to the dominance of willows, *Populus nigra* was observed spreading, especially on sandy substrates. Species richness within the plant communities increased, with a total of 87 species of vascular plants, algae, and mosses recorded in the study plots. The emerging willow stands correspond to habitat type G1.11 (riverine willow forests), which is protected under the Bern Convention. The dynamics of natural revegetation reflect a unique process of ecological regeneration at the former reservoir site and underscore the high conservation value of these developments. If the reservoir were to be restored, these nascent floodplain ecosystems could be lost, necessitating a thorough assessment of the environmental and legal consequences of any future management decisions (Didukh et al., 2024).

The southern part of Khortytsia Island is characterized by floodplain ecosystems, whose diversity reflects the variety of ecosystem types found in the lower reaches of the Dnipro River. This area serves as an ideal natural laboratory for studying the consequences of the Kakhovka Reservoir's destruction. The decrease in water levels downstream of the Zaporizhzhia Dam following the disaster exposed riverbanks and resulted in the loss of floodplain water bodies within the central part of the island's floodplain system. Initial comparisons of spatial structures derived from principal component analysis (PCA) revealed only the most general patterns of landscape cover. As anticipated, in the immediate vicinity of the Zaporizhzhia Dam, key relationships between water bodies and land, as well as among major vegetation types, remained largely unchanged. To identify more subtle spatial patterns in the variability of vegetation cover, further analysis was conducted on the principal components of the residuals of spectral indices, after removing the dominant trends represented by the first two principal components. This approach facilitated the detection of finer-scale changes using remote sensing data.

Shifts in land cover types occur within a complex landscape structure that includes both terrestrial and aquatic environments. Therefore, it is appropriate to utilize spectral indices that are sensitive to vegetation characteristics, aquatic conditions, and open land areas with minimal or no vegetation to detect such changes (Zhukov & Kunakh, 2025). To achieve this, a variety of spectral indices were applied. Principal Component Analysis (PCA) was employed to reduce the dimensionality of the feature space and to identify the dominant patterns of spectral variability within a single time frame. An equally important objective was to compare multidimensional spatial patterns across different dates to identify the primary trends in temporal landscape transformation. To achieve this, Procrustean analysis was employed. This method is traditionally used to compare the ordination results of biological communities; however, the outputs of Principal Component Analysis (PCA) of spectral indices are also, by their nature, ordination solutions. Procrustean analysis enables us to determine which spectral indices contribute most significantly to the rotation of spatial structures and to identify the specific geographic areas where these changes are most pronounced.



a *b*

Fig. 3. Variation of the Procrustes rotations of the residual principal components 1 and 2 (*a*) and 3 and 4 (*b*) in the space of spectral indices: the 5 spectral indices with the largest Procrustean shift are indicated

Procrustean rotations exhibit significant correlations with functional diversity indices, as well as with indicators of naturalness and hemeroby. This finding suggests that alterations in the naturalness and anthropogenic disturbance of plant communities are closely linked to changes in their functional composition, which can be detected using remote sensing data. Among the Procrustean solutions, Rotations 1 and 4 display nearly identical patterns of correlation with indices of functional diversity, naturalness, and hemeroby. These rotations reflect shifts in plant community organization associated with decreased naturalness, reduced functional evenness and divergence, and increased hemeroby. Such patterns are characteristic of anthropogenically transformed ecosystems. Under these conditions, ecosystems experience a loss of structural complexity, ecological stability, and historical continuity. This results in the dominance of species that are highly tolerant of disturbances and capable of colonizing unstable or degraded habitats. The decline in naturalness reflects the loss of the community's original structure, species composition, and ecological functions, leading to a simplified and homogenized vegetation cover. This phenomenon is often accompanied by the replacement of native species with ruderal or introduced taxa, which tend to be more resilient to environmental fluctuations and better adapted to disturbed environments such as agricultural lands, urban areas, or drained floodplains. A reduction in functional evenness indicates that species with similar adaptive traits dominate, resulting in an unbalanced utilization of ecosystem resources. In natural, stable ecosystems, each functional type occupies a distinct niche. However, under stressful conditions, many of these niches are lost or become redundant, favouring only those species that can withstand new environmental constraints. Similarly, a decline in functional divergence signifies that most species are clustered within a narrow spectrum of functional strategies. This limitation narrows the range of ecosystem functions that can be performed and diminishes the community's resilience to future disturbances or environmental changes.

Table 2
Correlation of Procrustes rotations and vegetation characteristics (only statistically significant correlation coefficients for $P < 0.05$ are shown)

Variable	Procrustes rotation 1	Procrustes rotation 2	Procrustes rotation 3	Procrustes rotation 4
Cover, %	–	0.34 ± 0.07	0.21 ± 0.08	–
Species	–	0.28 ± 0.06	0.21 ± 0.06	–
Functional evenness	0.33 ± 0.08	–	–	0.20 ± 0.10
Functional richness	–	–0.20 ± 0.09	–0.21 ± 0.09	–
Functional divergence	0.20 ± 0.09	–	–	0.27 ± 0.08
Naturalness	0.28 ± 0.08	–	–	0.21 ± 0.08
Hemeroby	–0.22 ± 0.08	–	–	–0.17 ± 0.09

Hemeroby, as an integrated indicator of anthropogenic impact, is on the rise due to the introduction of species characteristic of highly disturbed environments (Mykhailyuk et al., 2023). These species typically exhibit high ecological plasticity, short life cycles, and efficient dispersal mechanisms, and they are often annuals or non-native. Their establishment displaces species that are less tolerant of disturbance, further diminishing the naturalness and functional complexity of plant communities. Spectral indices such as NDNIRBlue, NDChla, REDI, NDIO, GLI, and NDWI1 serve as effective indicators of ecological changes. The NDNIRBlue index is a modified version of the traditional NDVI, in which the red spectral band is replaced by the blue band, thereby enhancing sensitivity to vegetation stress and dynamics related to disturbances. This adjustment increases sensitivity to low chlorophyll levels, allowing for more effective detection of stressed or degraded plants. The incorporation of the blue channel also improves the stability of the index in the presence of noise contamination or shadows, a particularly beneficial feature during the early stages of plant growth (Yang et al., 2004). NDChla is responsive to the content of plant pigments (Ha et al., 2017). REDI is highly sensitive to variations in chlorophyll content, making it an effective tool for detecting nutritional stress, aging, and pest damage (Addabbo et al., 2016). GLI shows the density of vegetation and its photosynthetic activity (Louhaichi et al., 2001). Therefore, spectral indices that reflect shifts in the hemeroby of plant communities primarily respond to changes in the physiological state of the photosynthetic system. NDIO is capable of detecting ferrous oxides that accompany hypoxic conditions in excess of water (Yazdi et al., 2013). The primary application of NDWI1 is the identification of lakes, rivers, and reservoirs in images. Additionally, NDWI1 can serve as an indicator of overall water turbidity (McFeeters, 1996). Spectral indices that respond to water-related conditions highlight the significance of water level fluctuations as a primary driver of vegetation dynamics.

Procrustes Rotations 2 and 3 also display similar correlation patterns with functional diversity indices. Unlike Rotations 1 and 4, these rotations are not sensitive to changes in hemeroby or naturalness. Instead, they reflect trends characterized by an increase in projective cover and species richness, accompanied by a decrease in the functional richness of plant communities. An increase in vegetation cover and species richness, accompanied by a decline in functional richness without changes in naturalness or hemeroby, suggests an internal structural reorganization of the community occurring under natural or near-natural conditions. In these instances, the ecosystem is not subjected to anthropogenic disturbances, maintains its compositional integrity, and is not colonized by ruderal or non-native species. The increase in projective cover may result from improved abiotic conditions, such as higher moisture availability, enhanced mineral nutrition, or increased light intensity. These factors stimulate biomass production in species that are already present or typical for the habitat. Additionally, species richness may increase due to the establishment of additional native species from the regional pool that are ecologically suited to the prevailing conditions, even if they are functionally similar to those already present. The observed decline in functional richness occurs because these new species do not introduce novel functional traits; rather, they replicate existing ecological strategies, such as similar life cycle durations, morphological features, or resource-use efficiencies. In this context, the ecosystem may appear denser and more species-rich, but its functional structure becomes increasingly uniform. This reduction in functional diversity may limit the community's capacity to perform a broad range of ecosystem functions and diminish its resilience to future environmental changes. The naturalness of the community is preserved, as its species composition remains consistent with the native environmental type. The lack of an increase in hemeroby indicates that the newly established species are not indicators of disturbance and do not undermine the ecological stability of the community. This phenomenon is typical of the early phases of successional stabilization or recovery following minor environmental changes, without compromising the natural character of the vegetation cover. These interpretations align with the patterns observed in the spectral indices.

These trends are represented by various spectral indices, including NDTI, NDBaI, NDII, and MNDWI, as well as NBRI, NDTSM, RBNDVI, and NDREI. Notably, NDTI and NDBaI exhibit heightened sensitivity to the characteristics of soil cover (Van Deventer et al., 1997). NBRI detects burned areas and vegetation loss due to fires (Seydi et al., 2021). NDII indicates the water content in vegetation and is utilized for drought assessment (Hardisky et al., 1983). The configuration of water bodies can be determined using MNDW (Xu, 2006). NDTSM estimates the total suspended matter in water bodies (Premkumar et al., 2021). The RBNDVI is a three-component index that has been shown to provide a superior method for assessing mixed vegetation and soil conditions. The B1 (coastal aerosol) channel is sensitive to aerosols and dust. Thus, its inclusion in the denominator helps normalize the effect of atmospheric exposure on reflectivity. The B5 red-edge channel allows for a more comprehensive evaluation of vegetation stress, including early signs of wilting, dryness, and salinity. By integrating soil, vegetation, and atmospheric information, the index enhances stability in arid and semi-arid regions, where other indices often demonstrate a diminished correlation with actual land cover. The index is employed for monitoring soil salinity, assessing vegetation cover in saline environments, and possesses an improved ability to differentiate between vegetation, bare soil, and saline areas (Wang et al., 2019). NDREI is highly sensitive to chlorophyll concentration and accurately reflects chlorophyll levels even in dense canopies. It is particularly effective for assessing nitrogen availability and is less dependent on cover density compared to NDVI or GNDVI.

The practical significance of this study lies in the development of an effective approach for monitoring the environmental impacts of anthropogenic disasters through the use of satellite imagery and spectral indices. The proposed methodology facilitates timely and spatially precise detection of changes in vegetation structure, particularly concerning hemeroby, naturalness, and the functional diversity of plant communities. This is especially valuable in situations where access to field observations is limited, as exemplified by the catastrophic destruction of the Kakhovka Reservoir. By utilizing spectral indices that are sensitive to water conditions, soil properties, and the physiological state of the plant photosynthetic system, this method enables the assessment of both degradation processes and the early stages of secondary succession. The findings can support evidence-based decision-making in environmental management, including the evaluation of whether to restore the reservoir or conserve the newly formed floodplain ecosystems. The study demonstrates the utility of Procrustes and principal component analyses in identifying spatial trends in ecological transformation, providing a promising toolkit for long-term environmental monitoring in regions affected by similar anthropogenic disturbances. The results hold practical significance for ecological assessment, spatial planning, biodiversity conservation, and the adaptive management of degraded landscapes.

Future research may concentrate on a comprehensive analysis of the spatial and temporal dynamics of successional processes in the region of the former Kakhovka Reservoir. This analysis will consider seasonal variability in spectral characteristics and the impact of climatic factors. A promising avenue for exploration is the integration of remote sensing data with soil survey results to investigate the relationships between soil chemical properties, the presence of toxicants, and the functional structure of plant communities. Special attention should be given to the role of invasive species in the development of new phytocoenoses on drained lands, as well as to the assessment of biodiversity in the context of phytosanitary risks. Further studies could also aim to develop integrated indices that incorporate vegetation, hydrological, and soil parameters, thereby enabling a more comprehensive evaluation of the ecological condition of post-disaster landscapes. The application of machine learning techniques and classification algorithms is also recommended to facilitate the automated mapping of vegetation types and to identify areas at high risk of degradation or with significant restoration potential.

Conclusion

This article presents a comprehensive approach to assessing changes in vegetation cover following the destruction of the Kakhovka Reservoir by integrating remote sensing spectral indices, principal component analysis, and Procrustes analysis. The study demonstrates that shifts in the spatial structure of plant communities are strongly correlated with levels of hemeroby, naturalness, and functional diversity. This underscores the ability of satellite data to capture both anthropogenic disturbances and natural successional processes. The rotations identified through Procrustes analysis revealed two distinct ecological trends. The first trend indicates ecosystem degradation due to anthropogenic pressure, characterized by increased hemeroby and reduced functional richness. The second trend reflects the internal restructuring of phytocoenoses within a natural context, driven by improved abiotic conditions. The application of spectral indices that are sensitive to water conditions, soil characteristics, and the physiological state of the plant photosynthetic system has facilitated the identification of ecologically significant indicators of vegetation change. This proposed methodology offers substantial practical value for long-term environmental monitoring, spatial planning, and informed management decisions concerning the future use of degraded landscapes. It is particularly useful in evaluating the choice between restoring the reservoir or preserving the newly formed floodplain ecosystems.

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