Ukrainian Journal of Remote Sensing
journal homepage: www.ujrs.org.ua

https://doi.org/10.36023/ujrs.2026.13.3.310

UDC 528.88:504.064.2(477.72)"2013/2025"

Assessment of Spatio-temporal Dynamics of the Remote Sensing Ecological Index (RSEI) based on Landsat 8 Data: A Case Study of Kherson Region, Ukraine (2013–2025)

M. A. Tymchyshyn* https://orcid.org/0000-0003-2966-4794

State environmental inspectorate of Ukraine, Novopechersky lane 3, building 2, Kyiv, 01042, Ukraine

This scientific paper presents a comprehensive assessment of the spatio-temporal dynamics of the ecological state of the Kherson region from 2013 to 2025, with a particular focus on the consequences of the full-scale military aggression by the Russian Federation. Amidst intensive hostilities, the destruction of critical infrastructure, and global climate challenges, objective geospatial monitoring of the natural environment is a crucial task for documenting damages and forecasting the region's future development.

The study is based on the use of modern geographic information systems and remote sensing data. Using the Google Earth Engine cloud computing platform and an archive of multispectral satellite imagery from Landsat 8 OLI/TIRS, the Remote Sensing Ecological Index (RSEI) was calculated. This index comprehensively integrates four key biophysical indicators: greenness (based on the Normalized Difference Vegetation Index, NDVI), wetness (Wet), dryness (based on the Normalized Difference Build-up and Soil Index, NDBSI), and land surface temperature (LST). The application of Principal Component Analysis (PCA) allowed these indicators to be mathematically combined into a single standardized index, where the first principal component (PC1) explains the highest proportion of the total spatial data variance. This indicates that the first principal component (PC1) successfully captures the vast majority of the variance among the four input indicators, which is a basic premise of the RSEI methodology.

The results of the cartographic and statistical analyses revealed a sharp, unprecedented deterioration in the ecosystem health of the study region in 2025 compared to retrospective data from previous years. A critical drop in the average RSEI value was established – from 0.381 in the relatively stable year of 2021 to 0.205 in 2025. The spatial assessment demonstrated that the area of territories classified as being in a state of ecological crisis (the «Terrible» category, with an index ranking from 0 to 0.2) more than doubled: from 26% of the region's total area in 2021 to a critical 60% in 2025.

The sharp drop in RSEI spatially aligns with the large-scale hydrological transformations caused by the destruction of the Kakhovka Dam; however, this indicator also reflects the synergistic impact of intense hostilities, fires, the cessation of irrigation, and climate anomalies. Kakhovka Dam destruction led to the catastrophic destruction of the hydrographic network, the disappearance of water supply sources for vital agricultural lands, and the disruption of life-support systems in urbanized areas. The only exception against the general backdrop of the ecological catastrophe is the recorded local natural restoration of the old Dnipro riverbed ecosystem, which is gradually returning to its historical state that preceded massive anthropogenic intervention and river regulation in the 1950s.

In conclusion, the synergistic impact of continuous large-scale hostilities, the destruction of established ecosystem links, and the exacerbation of global climate change shape an extremely bleak forecast. Further degradation of the soil and vegetation cover and the depletion of water resources create a high risk of transforming a significant part of the Kherson region into a territory unfit for safe living, agriculture, and socio-economic functioning.

Keywords: Remote Sensing Ecological Index (RSEI), Google Earth Engine, ArcGIS, remote sensing data, Landsat 8, Kherson region.

© M. A. Tymchyshyn. 2026

1. Introduction

Currently, global changes in environmental conditions are taking place in the world. The same is happening in Ukraine at the regional level. A significant question arises as to how we can assess these changes. Since the mid-20th century, with the beginning of the development of remote sensing, it has become possible to remotely assess the state of the natural environment (Kamran & Yamamoto, 2023).

Despite the existence of various remote sensing indices, such as the Normalized Difference Vegetation Index (NDVI) (Greenness), normalized difference bare soil index (NDBSI) (Dryness), the Tasseled Cap Wetness method (Wetness) and the surface temperature of the Earth's surface LST (Heat), To overcome the limitations of single ecological indicators, Xu (2013) proposed integrating them into a comprehensive Remote Sensing Ecological Index (RSEI) using Principal Component Analysis (PCA), which preserves the majority of the original variables' variance and avoids subjective weight assignment (Xu, 2013).

RSEI is a comprehensive indicator for quantifying the quality of the ecological environment, which integrates

*Corresponding author / Автор для кореспонденції: M.A. Tymchyshyn / M.A. Тимчишин / tymchyshyn.m.a@gmail.com

This is an Open Access article under the CC BY licenses (http://creativecommons.org/licenses/by/4.0/)
Стаття опублікована на умовах відкритого доступу за ліцензією CC BY (http://creativecommons.org/licenses/by/4.0/)

four key ecological indicators using the principal component analysis (PCA) method (Tuan & Thu, 2025).

These four components reflect the main factors of the ecosystem:

• Greenness: Usually measured by the Normalized Difference Vegetation Index (NDVI) (Tuan & Thu, 2025; Li et al., 2024; 5. Xu et al., 2019).

• Wetness: Reflects the moisture content of the soil and vegetation (the Wetness component of the Tasseled Cap transformation) (Tuan & Thu, 2025; Li et al., 2024).

• Dryness: Represented by the Building and Soil Index (NDBSI or NDSI), which shows the impact of human activities and bare soil (Tuan & Thu, 2025; Li et al., 2024).

• Heat: Determined by land surface temperature (LST) (Tuan & Thu, 2025; Li et al., 2024).

In modern conditions, there are automation tools for manipulating remote sensing data. One of these tools is the Google Earth Engine environment. GEE eliminates the need for local loading of satellite data and allows cloud computing using JavaScript. Of the above, GEE is ideally suited for calculating the RSEI index (Li et al., 2024).

A number of scientists have developed the topic of calculating and applying the remote sensing ecological index.

To assess the spatio-temporal dynamics of the ecological state in arid and sandy regions, a number of scientists have successfully adapted remote sensing methods. Sun et al. used the Particular Remote Sensing Ecological Index (PRSEI) on the example of the Beijing-Tianjin sand source region. Yao et al. used the classic RSEI index to assess the quality of the ecological environment in the Hotan oasis, Xinjiang. Cen et al., in their work, focused on new indices: The Arid Region Remote Sensing Ecological Index (ARSEI) and the Composite Remote Sensing Ecological Index (CoRSEI), in order to compare them with the traditional remote sensing ecological index (RSEI) in the Tarim River Basin from 2000 to 2023 (Sun et al., 2025; Yao et al., 2022; Cen et al., 2025).

A crucial tool for modern researchers, as in our work, is the use of the Google Earth Engine platform. Zhang et al. applied the Google Earth Engine platform using the remote sensing ecological index to conduct dynamic monitoring of environmental quality on the Loess Plateau from 2000 to 2020 (Zhang et al., 2022). Lu et al. used the GEE platform to calculate the RSEI index and assess the environmental quality of an urban agglomeration (Lu et al., 2025). Wang et al. used the GEE platform to assess the environmental condition of the Lhasa–Nyingchi Expressway using a modified remote sensing environmental index (Wang et al., 2024). Airiken & Li used the GEE platform to conduct dynamic monitoring and analyze the driving forces of environmental quality on the Tibetan Plateau (from 2000 to 2022), and to construct a remote sensing environmental index (RSEI) (Airiken & Li, 2024). Du et al. assessed the ecological condition of Tibetan alpine meadows in Gannan. In their work, the authors used remote sensing ecological indicators, including the calculation and analysis of the remote sensing ecological index (Du et al., 2024). Ariken et al. analyzed the consistency of urbanization processes and the ecological environment in the Yanqi Basin from 2000 to 2018. The authors used data from multiple remote sensing sources, as a result of which they calculated the remote sensing ecological index (Ariken et al., 2020).

Liao & Jiang conducted an assessment of spatiotemporal variations in the quality of the eco-environment in China. The authors calculated and created a model of the remote sensing ecological index of China using four components: wetness, greenness, dryness, and heat. Liao & Jiang conducted the RSEI knowledge granulation. A method was proposed to assess the relative contribution of each ecological component using information entropy methods (Liao & Jiang, 2020).

The Kherson region (Ukraine) was chosen as the research area. It is one of the heavily war-affected territories in our country, in which there are combat clashes in the Russian-Ukrainian full-scale war. The region is a high priority for future post-war recovery. As a result of the destruction of the Kakhovka reservoir dam during military operations, an uncontrolled water leak occurred, which flooded urbanized lands, thereby causing ecosystem degradation, which has signs of ecocide in this region (Chernogor et al., 2024). It is crucial to compare the situation in peacetime from 2013 to 2021, as well as in wartime in 2025.

A scientific paper was published in Ukraine, which considered the use of the RSEI index to assess the ecological state of the Lviv region. Lei used the Google Earth Engine environment (Lei, 2023). Although RSEI was initially popularized in Asian research, its universal biophysical components make it highly effective for assessing environmental degradation in European landscapes, including the agricultural steppe zones of Ukraine. The author used data from the Landsat 8 satellite and data from the MODIS sensor in his work. The results of this study confirmed the efficiency of using cloud-computing platforms to process large volumes of remote sensing data for regional ecological assessments. The study confirmed the effectiveness of using GEE to assess the ecological state of Ukrainian regions, but the difference between our work and the work of this author is the definition of a different study area, which, in our opinion, is relevant during the war and subsequent post-war recovery. The time period was more complete, namely, I used data for 2013, 2017, 2021, and 2025. I used data exclusively from the Landsat 8 satellite. I developed an optimized JavaScript script that allows us to automate the calculation process and adapt it to any vector layer (Shapefile).

The purpose of the paper is to quantitatively assess spatiotemporal changes to evaluate the long-term environmental transformations of the territory, with a critical focus on the ecological degradation following the onset of the full-scale invasion.

2. Materials and Methods

2.1. Study Area

Kherson region (Ukraine) was selected as the study area (Fig.1.). The description of the area was taken from the Ecological Passport of Kherson region for 2023.

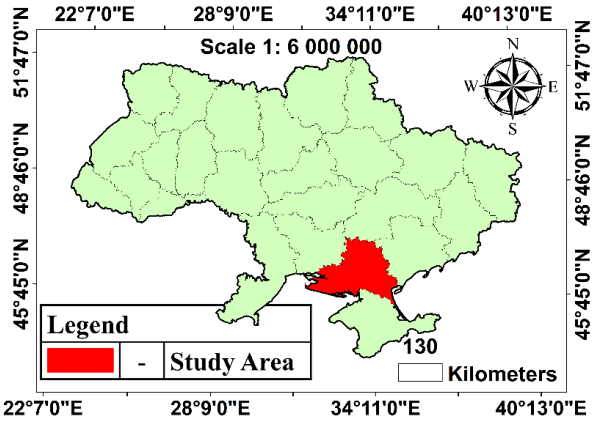

Fig. 1. Kherson Region as Study Area

The territory of the Kherson region is located in the Black Sea Lowland. Some heights of the region reach 50–60 meters above sea level. The region is located in the south of Ukraine within the Steppe zone and is washed by the Black Sea and the Sea of Azov, as well as the Syvash (The Rotten Sea).

As of 2023, water bodies occupy 29.1 thousand hectares. The hydrographic network of the region is represented by the Dnieper (200 km within the region), Ingulets (180 km), and five small rivers (123.5 km).

As of January 1, 2023, the total area of the Kherson region was 2850.17 thousand hectares, of which 2162.29 thousand hectares fall on the temporarily occupied territory. The land fund of the Kherson region is 2846.1 thousand hectares, of which: 1968.4 thousand hectares are occupied by agricultural lands (69.1% of the total land fund area); 152 thousand hectares are forests and other forested areas (5.3%); 725.7 thousand hectares are other lands (25.6%).

The average annual air temperature for 2023 was 12.4–12.7°C, which is 1.8°C above the climatic norm. The annual amount of precipitation was 442–509 mm, or 102% of the annual norm. (Ecological Passport of Kherson region for 2023, 2024).

2.2. Methodology

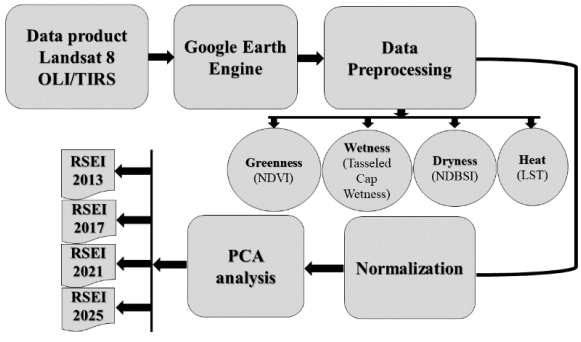

Fig. 2. Methodology flowchart

The Google Earth Engine (GEE) cloud platform was used to conduct the study, which allows processing large amounts of satellite data. The input data were Landsat 8 satellite images (OLI/TIRS sensors) of the Collection 2 Level 2 (Surface Reflectance) processing level, which had already undergone atmospheric correction. The time range of the study covers the period from 2013 to 2025 (from 01 June to 30 September).

For data preprocessing, scaling of values (Scale Factors) for optical and thermal channels was applied according to the product specification. To eliminate atmospheric interference, the cloud and shadow masking function based on the QA_PIXEL quality channel was applied using bitwise operations.

Since the RSEI index is intended to assess the ecological state of land, water bodies were excluded from the analysis. For this purpose, the Modified Normalized Differential Water Index (MNDWI, Equation 1) was calculated (Xu, 2006; Acharya et al., 2018; Yuan et al.,2021). Pixels with an MNDWI value ≥ 0.2 were classified as water and masked (excluded from the analysis). Values < 0.2 were retained for further calculations. This threshold was selected empirically to appropriately exclude shallow waters and the waterlogged zones of the Dnipro floodplains. The final image was formed by calculating the median value (median composite) for each pixel, which allowed for minimizing noise.

$$\boldsymbol{MNDWI} = (Green - SWIR) / (Green + SWIR), \quad (1)$$

where Green and SWIR are spectral channels of the Landsat 8 satellite.

Calculation of ecological indicators

The RSEI (Remote Sensing Ecological Index) is based on four component indicators (Equation 2 from Xu et al., 2019 and Lei, 2023) that reflect key aspects of environmental quality.

$$\boldsymbol{RSEI} = f(Greenness, Wetness, Dryness, Heat). \quad (2)$$

1. Greenness Index: Calculated using the Normalized Difference Vegetation Index (NDVI) (Equation 3), which serves as a widely used proxy for vegetation vigor and greenness, though it may saturate in dense forest canopies (Xu et al., 2019).

$$\boldsymbol{NDVI} = (NIR - Red) / (NIR + Red), \quad (3)$$

where NIR and RED are the spectral channels of the Landsat 8 satellite.

2. Wetness Index: Obtained by Tasseled Cap Transformation (Equation 4). For the Landsat 8 sensor, empirical coefficients proposed in (Baig et al.,2014) were used. Due to the pre-masking of water, this index reflects the moisture of soil and vegetation, and not open water bodies. It should be noted that the Wetness index is a proxy and can be influenced by shadows or soil characteristics, which is a recognized limitation of the Tasseled Cap method. Before calculating Wetness, a scale factor (0.0000275x – 0.2) was applied to the Level-2 bands. The coefficients proposed by Baig et al. were used as a generally accepted approximation, which is a standard practice in RSEI studies, while acknowledging the limitations of transferring them to SR (Surface Reflectance) data. Empirical coefficients for Landsat 8 were derived by Baig et al. (2014) based on statistical analysis of simulated reflectance data.

$$\boldsymbol{Wetness} = 0.1511(Blue) + 0.1973(Green) + 0.3283(Red) + 0.3407(NIR) - 0.7117(SWIR1) - 0.4559(SWIR2), \quad (4)$$

where Blue, Green, Red, NIR, SWIR1 and SWIR2 are the spectral channels of the Landsat 8 satellite.

3. Dryness Index: Represented by the NDBSI (Normalized Difference Built-up and Soil Index) (Equation 5), which is the arithmetic mean between the built-up index (IBI) (Equation 6) and the soil index (SI) (Equation 7). This allows for the consideration of both

anthropogenic load (building) and open soils (Tuan & Thu, 2025).

$$\boldsymbol{NDBSI} = (IBI + SI)/2. \quad (5)$$

$$IBI = \frac{\frac{2(SWIR1)}{(SWIR1+NIR)} - \left[\frac{NIR}{(NIR+RED} + \frac{Green}{(Green+SWIR1)}\right]}{\frac{2(SWIR1)}{(SWIR1+NIR)} + \left[\frac{NIR}{(NIR+RED} + \frac{Green}{(Green+SWIR1)}\right]}. \quad (6)$$

$$SI = \frac{(SWIR1+Red)-(NIR1+Blue)}{(SWIR1+Red)+(NIR1+Blue)}. \quad (7)$$

where SWIR1, NIR, Red, Green, Blue are the spectral channels of the Landsat 8 satellite.

4. Heat Index (Heat): Calculated based on the land surface temperature (LST). The atmospherically corrected Surface Temperature product (ST_B10 band) was used. Quality control was conducted through cloud masking using the QA_PIXEL band; an additional ST_QA filter was not applied in order to preserve maximum spatial coverage. TIRS 1 thermal channel was used to degrees Celsius (Equation 8) (USGS Landsat 8 Level 2, Collection 2, Tier 1, 2026)

$$\boldsymbol{LST} = (DN * 0.00341802 + 149.0) - 273.15), \quad (8)$$

where: DN is the pixel value from the TIRS 1 channel (Digital Number) of the Landsat 8 satellite; 0.00341802 is the scale factor; 149.0 is the offset; 273.15 is the constant for converting from Kelvin to Celsius.

Building the RSEI model: Before conducting the principal component analysis (PCA), all four indicators were normalized. To avoid the influence of extreme values (outliers) on the data distribution, robust normalization based on percentiles (2% and 98%) was applied instead of the standard Min-Max method. Values that exceeded these limits were clamped to the range [0, 1].

The indicators were integrated using the principal component analysis (PCA). The covariance matrix was calculated with a spatial resolution (scale) of 500 meters to ensure representativeness of the sample. A 500-meter scale was used as a statistical sampling step for calculating the covariance matrix to optimize cloud computing. The final index was retained at a 30-meter resolution. The first principal component (PC1), which accumulates the largest share of the data variance, was selected to form the index. The obtained PC1 was inverted (1 – PC1), since high values of the components «Dryness» and «Heat» negatively affect ecological quality. The final RSEI index was also normalized within [0, 1] using the 2nd and 98th percentiles. The obtained values were classified into 5 levels of ecological status with a step of 0.2: Terrible (0–0.2), Less than normal (0.2–0.4), Normal (0.4–0.6), Better than normal (0.6–0.8), and Good (0.8–1.0).

3. Results and Discussion

In order to confirm the reliability of the calculations, it is necessary to conduct a PCA principal component analysis. Table 1 below shows the contribution of the components to the variance (in percentages).

It was decided, for greater reliability, to set PC1 as the principal component, since this component has the greatest contribution to the variance. Accordingly, for 2013 – 87.614%; 2017 – 87.82%; 2021 – 87.006%; 2025 – 81.5%.

Table 1. Component contribution to variance (PCA)

2013				
Indicator	**PC1**	**PC2**	**PC3**	**PC4**
Contribution to variance (%)	87.614	6.7	4.6	1.06
2017				
Indicator	**PC1**	**PC2**	**PC3**	**PC4**
Contribution to variance (%)	87.82	6.937	4.268	0.97
2021				
Indicator	**PC1**	**PC2**	**PC3**	**PC4**
Contribution to variance (%)	87.006	7.84	4.2	0.95
2025				
Indicator	**PC1**	**PC2**	**PC3**	**PC4**
Contribution to variance (%)	81.5	11.14	5.78	1.55

The analysis of eigenvectors (Table 2) revealed a clear ecological interpretation of the principal component (PC1). As shown empirically in Table 2, the calculated eigenvectors demonstrated a consistent polarity across all studied years: Greenness and Wetness exhibited negative loadings, while NDBSI and LST showed positive loadings. This statistical result justifies the inversion (1 – PC1). An example from work: for 2013 – Greenness (NDVI) – (–0.5), Wetness – (–0.64); 2017 – Greenness (NDVI) – (–0.509), Wetness – (–0.687); 2021 – Greenness (NDVI) – (–0.51), Wetness – (–0.5); 2025 – Greenness (NDVI) – (–0.47), Wetness – (–0.64), respectively. At the same time, the indicators of anthropogenic load NDBSI and LST have positive values, namely: for 2013 Dryness (NDBSI) – 0.42, Heat (LST) – 0.399; for 2017 Dryness (NDBSI) – 0.298, Heat (LST) – 0.425; for 2021 Dryness (NDBSI) – 0.59, Heat (LST) – 0.36; for 2025 Dryness (NDBSI) – 0.51, Heat (LST) – 0.33. This polarity of PC1 values indicates that high values correspond to the deteriorated ecological state of the territory. Given this, to calculate the final RSEI index, where 1 corresponds to the best ecological state, the inversion RSEI = 1 – PC1 was applied. After that, we got the results we needed.

Table 2. Coefficients (Loadings) for PC1

2013			
Indicator	**Value (PC1)**	**Type of Indicator**	**Mark**
Greenness (NDVI)	–0.5	«Good»	Minus (–)
Wetness	–0.64	«Good»	Minus (–)
Dryness (NDBSI)	0.42	«Bad»	Plus (+)
Heat (LST)	0.399	«Bad»	Plus (+)
2017			
Indicator	**Value (PC1)**	**Type of Indicator**	**Mark**
Greenness (NDVI)	–0.509	«Good»	Minus (–)
Wetness	–0.687	«Good»	Minus (–)
Dryness (NDBSI)	0.298	«Bad»	Plus (+)
Heat (LST)	0.425	«Bad»	Plus (+)
2021			
Indicator	**Value (PC1)**	**Type of Indicator**	**Mark**
Greenness (NDVI)	–0.51	«Good»	Minus (–)
Wetness	–0.5	«Good»	Minus (–)
Dryness (NDBSI)	0.59	«Bad»	Plus (+)
Heat (LST)	0.36	«Bad»	Plus (+)
2025			
Indicator	**Value (PC1)**	**Type of Indicator**	**Mark**
Greenness (NDVI)	–0.47	«Good»	Minus (–)
Wetness	–0.64	«Good»	Minus (–)
Dryness (NDBSI)	0.51	«Bad»	Plus (+)
Heat (LST)	0.33	«Bad»	Plus (+)

Fig. 3, 4 shows maps of the calculated RSEI index for 2013, 2017, 2021, and 2025.

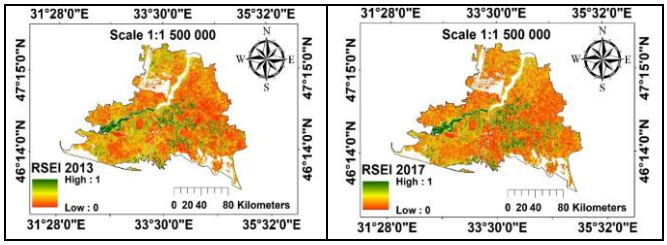

Fig. 3. Maps of the calculated remote sensing ecological index of the Kherson region for 2013, 2017

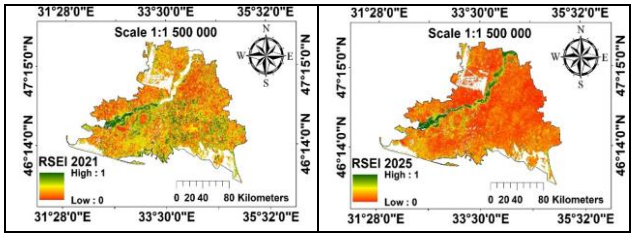

Fig. 4. Maps of the calculated remote sensing ecological index of the Kherson region for 2021 and 2025

The results are clearly shown in the graph Fig. 5.

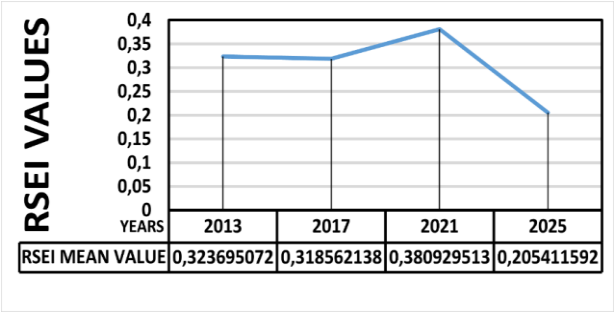

Fig. 5. Average value of the RSEI index of Kherson region for 2013, 2017, 2021 and 2025.

According to the results of the average value of the RSEI index, there was a fluctuating situation with minimal changes during 2013 and 2017. The situation became better in 2021. But in 2025, as a result of the ecocide caused by the Russian troops by blowing up the dam of the Kakhovka reservoir and, in general, global changes in environmental conditions, the situation had a sharply negative impact on the ecological situation in the Kherson region, as can be seen in the graph Fig. 5 for 2025. It is worth noting that due to its location in the steppe zone and arid climate, the region has lower average index values, which is an unfavorable indicator for environmental components.

Table 3. Standard Deviation RSEI

2013	2017	2021	2025
0.261719	0.262426	0.265197	0.212608

To evaluate the spatial variability and statistical dispersion of the environmental conditions, the standard deviation (Table 3) of the RSEI values was calculated. During the period prior to the full-scale invasion, this indicator remained stable and relatively high: 0.262 in 2013, 0.262 in 2017, and 0.265 in 2021. Such high variance indicates significant spatial heterogeneity of the ecological conditions in the Kherson region, reflecting a sharp contrast between arid steppes, built-up areas, and ecologically vigorous zones (such as irrigated agricultural lands and floodplains). However, in 2025, a notable decrease in the standard deviation to 0.213 was recorded. Coupled with the critical drop in the overall mean index value, this reduction in variability indicates a massive ecological homogenization of the landscape. As a result of the Kakhovka Dam destruction, the loss of irrigation systems, and general ecosystem degradation, the territory lost its contrasting moistened zones and transitioned into a significantly more uniform area characterized by poor ecological quality.

Table 4. Statistical significance, standard deviation, and 95% Confidence Interval of the regional Mean RSEI (2013–2025)

Year	Sample Size (N pixels)	Mean RSEI	Standard Deviation (SD)	Standard Error of Mean (SEM)	95% Confidence Interval (CI)
2013	~ 29,900,111	0.324	0.262	0.000048	0.3240 ± 0.00009
2017	~ 29,900,111	0.318	0.262	0.000048	0.3180 ± 0.00009
2021	~ 29,900,111	0.3809	0.265	0.000048	0.3809 ± 0.00009
2025	~ 29,900,111	0.2054	0.213	0.000039	0.2054 ± 0.00008

Table 4 presents the statistical evaluation of the regional mean RSEI values across the observation years. To address the high spatial variance indicated by the standard deviation (SD ranging from 0.213 to 0.265), the Standard Error of the Mean (SEM) and 95% Confidence Intervals (CI) were computed. Because the analysis leverages pixel-level data across the entire Kherson region, the sample size (N) for each composite is exceptionally large, comprising approximately 29.9 million pixels. This vast volume of spatial data reduces the SEM to near zero (≤ 0.000048).

As detailed in Table 4, the baseline ecological conditions prior to the full-scale invasion demonstrated typical inter-annual fluctuations, with mean RSEI values of 0.324 in 2013, 0.318 in 2017, and reaching 0.381 in 2021. Conversely, the mean RSEI in 2025 plummeted to 0.2054. The calculated 95% confidence intervals for these means are remarkably narrow (e.g., ± 0.00009). The complete absence of overlap between the pre-invasion intervals and the 2025 interval provides definitive statistical proof. It confirms that the sharp decline observed in 2025 is not a product of random spatial noise or typical climatic variance, but represents a statistically significant, systemic biophysical shock to the regional landscape.

RSEI index classification The territories of the Kherson region were classified and divided according to the following values – 5 levels of ecological status with a step of 0.2: Terrible (0–0.2), Less than normal (0.2–0.4), Normal (0.4–0.6), Better than normal (0.6–0.8) and Good (0.8–1.0).

Table 5 shows the calculated areas of qualitative indicators by year for 2013, 2017, 2021 and 2025.

Table 5. Areas of classified territory in km^2 for 2013, 2017, 2021 and 2025

Classification area in sqare kilometers					
Range	**Quality**	**2013**	**2017**	**2021**	**2025**
0	Masked area	3723,45	3648,33	3760,36	3071,84
0–0,2	Terrible	9502,4	9657,96	7077,43	16152,2
0,2–0,4	Less than normal	6613,08	7080,89	6240,71	4710,13
0,4–0,6	Normal	3449,2	2982,95	5203,36	1384,45
0,6–0,8	Better than normal	1749,83	1487,53	2457,14	615,387
0,8–1	Good	1872,11	2052,42	2171,08	976,106
Total sq km		26910,1	26910,1	26910,1	26910,1

For a clearer understanding of the situation, it is worth focusing on the percentages of areas of classified territories for 2013, 2017, 2021, and 2025 (Table 6).

Table 6. Percentages of classified area in % for 2013, 2017, 2021 and 2025

Classification area in %					
Range	**Quality**	**2013**	**2017**	**2021**	**2025**
0	Masked area	13,8366	13,5575	13,9738	11,4152
0–0,2	Terrible	35,3117	35,8898	26,3003	60,0227
0,2–0,4	Less than normal	24,5748	26,3131	23,191	17,5032
0,4–0,6	Normal	12,8175	11,0849	19,3361	5,14472
0,6–0,8	Better than normal	6,50252	5,52778	9,13094	2,28683
0,8–1	Good	6,95691	7,62696	8,0679	3,62729
Total %		100	100	100	100

According to the results, we have an example of a change in values for certain years. Masking area, where we used the MNDWI index and No Data. A decrease of several percent (Table 6) in 2025 is visible, which was 11.4152% (11% approx.). The situation with intervals between 0 and 0.2 was stable in 2013 and 2017, then in 2021, the situation improved. In 2025, during wartime due to ecocide from the Russian army and global changes, the TERRIBLE indicator became astronomical, namely 60.0227% (60% approx.), which clearly shows how the quality of the territory deteriorated. If compared to 2021, then more than 2 times.

The situation with environmental indicators 0.2–0.4 (LESS THAN NORMAL) was declining, in 2017 it increased, and since 2021 it has decreased. And for 2025, it is clear that most of the territory has shifted to the TERRIBLE state. The NORMAL state with a range of 0.4–0.6 shows that compared to 2013 and 2017, the situation improved in 2021, and sharply worsened in 2025. The BETTER THAN NORMAL state, with a ranking of 0.6–0.8, shows the same trend as the NORMAL state. In 2021, the situation improved, and in 2025, it sharply worsened. The GOOD state with a ranking of 0.8–1 shows a gradual increase from 2013 to 2021, and in 2025, the situation sharply worsened.

Discussion

Since the PCA was calculated separately for each year, the absolute RSEI values reflect the relative ecological state within a specific season. To mitigate this discrepancy, fixed classification intervals (0.2) were applied, which allows for the assessment of structural shifts in area distributions, and the direct comparison of absolute mean values should be interpreted as a general trend rather than a linear magnitude.

An important factor influencing the Greenness and Wetness indicators is interannual meteorological variability. Fluctuations in precipitation during the summer months among 2013, 2017, and 2021 explain part of the background RSEI dynamics. However, the unprecedented drop in 2025 goes well beyond the typical climatic fluctuations of the region.

An important limitation of this study is that RSEI inherently provides a macro-level regional assessment. While NDBSI is a universally accepted proxy for dryness within the standard RSEI framework, local variations in land cover – such as the difference between bare agricultural soil after harvesting, sandy areas (e.g., Oleshky Sands), and urban asphalt – add a degree of uncertainty to the physical interpretation of this component. Since the «dryness» of these surfaces can vary significantly depending on their nature, future studies would benefit from further land-cover-specific calibration to account for these heterogeneous local conditions.

A fundamental limitation of this study is that the RSEI framework evaluates biophysical parameters without accounting for land-cover transitions. Prior to the full-scale invasion, approximately 70% of the Kherson region was utilized for agriculture, representing one of the largest irrigated areas in Ukraine. The severe drop in RSEI in 2025 largely reflects the destruction of irrigation infrastructure and the massive abandonment of croplands. While the RSEI mathematically records the reduction in moisture and crop biomass as ecological «degradation», from a broader ecosystem perspective (e.g., SDG 15.3.1), the transition from intensive, water-depleting agriculture to natural steppe vegetation can be classified as recovery. Therefore, the calculated drop in the index should be interpreted as a massive «biophysical shock» to the established landscape structure rather than absolute ecological destruction.

Furthermore, the temporal resolution of satellite data introduces inter-annual variability. Landsat 8 operates on a 16-day revisit cycle, which, restricted by cloud cover, may yield only 3 to 5 clear observations per spring-summer season for any given pixel. Consequently, the available cloud-free observations for different parts of the region within the same year might capture different phenological phases and weather conditions. Although median composites were applied to mitigate this noise, the random spatial distribution of clouds means that inter-annual variations in sensing dates remain a source of uncertainty. Future assessments would benefit from multi-year time-series analysis to smooth out phenological and data-availability variances.

4. Conclusions

The current situation with the assessment of the ecological state of the Kherson region is extremely difficult. The constant aggression of the Russian Federation on the territory of the Kherson region worsens the ecological state of the territory every day. Analysis of the maps showed that in 2025, the situation

is worse than in 2021. The only improvement on the 2025 map is associated with the natural restoration of the ecosystem of the old Dnieper River to its state before anthropogenic intervention in the 1950s. The sharp drop in RSEI spatially aligns with the large-scale hydrological transformations caused by the destruction of the Kakhovka Dam; however, this indicator also reflects the synergistic impact of intense hostilities, fires, the cessation of irrigation, and climate anomalies. This overall degradation is clearly reflected in the average values of the RSEI index, which fell from 0.381 in 2021 to 0.205 in 2025. According to the territorial classification, the «Terrible» ecological state (ranking 0–0.2) expanded to cover 60.0% of the area in 2025, indicating a severe ecological crisis. The forecasts remain highly pessimistic. The ongoing military aggression combined with global climate change creates a high risk of transforming a significant part of the territory into an uninhabitable zone.

Disclosure of AI use. In the process of conducting research and preparing the manuscript, the author used the large language model Google Gemini 3 Pro. The tool acted as a technical assistant and consultant at the stages:

1. Software development: assistance in writing, debugging and optimizing JavaScript scripts for the Google Earth Engine environment, in particular the implementation of the PCA algorithm.

2. Text preparation: providing recommendations on structuring the work, describing the methodology and improving the academic style of presentation.

The author carried out a full check of the generated code and text, verified the results obtained and bears sole responsibility for the content of this publication.

Data availability and integrity. The JavaScript code for Google Earth Engine developed for this study has been deposited in the Zenodo repository with a reserved DOI to ensure long-term accessibility and reproducibility of the results. The code will be publicly available upon acceptance of the manuscript for publication. The data can be provided by the author upon reasonable request.

Conflicts of Interest. The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements. The author is grateful to the reviewers and editors for their valuable comments, recommendations, and attention to the work.

Розкриття інформації про ШІ. У процесі проведення дослідження та підготовки рукопису автор використовував велику мовну модель Google Gemini 3 Pro. Інструмент виступав технічним помічником і консультантом на етапах:

1. Розроблення програмного забезпечення: допомога в написанні, налагодженні та оптимізації сценаріїв JavaScript для середовища Google Earth Engine, зокрема впровадження алгоритму PCA.

2. Підготовка тексту: надання рекомендацій щодо структурування роботи, опис методики та вдосконалення академічного стилю викладу.

Автор провів повну перевірку створеного коду та тексту, перевірив отримані результати та несе повну відповідальність за зміст цієї публікації.

Доступність даних. Код JavaScript для Google Earth Engine, розроблений для цього дослідження, було збережено в репозиторії Zenodo із зарезервованим DOI, щоб забезпечити довгострокову доступність і відтворюваність результатів. Код буде загальнодоступним після прийняття рукопису до публікації. Дані можуть бути надані автором за обґрунтованим запитом.

Конфлікти інтересів. Автор заявляє, що у нього немає відомих конкуруючих фінансових інтересів або особистих стосунків, які могли б вплинути на роботу, про яку йдеться в цій статті.

Подяки. Автор вдячний рецензентам і редакторам за цінні зауваження, рекомендації та увагу до роботи.

References

Acharya, T. D., Subedi, A., Yang, I. T., & Lee, D. H. (2018). Combining Water Indices for Water and Background Threshold in Landsat Image. *Proceedings*, 2(3), 143. doi:10.3390/ecsa-4-04902.

Airiken, M., & Li, S. (2024). The Dynamic Monitoring and Driving Forces Analysis of Ecological Environment Quality in the Tibetan Plateau Based on the Google Earth Engine. *Remote Sensing*, 16(4), 682. doi:10.3390/rs16040682.

Ariken, M., Zhang, F., Liu, K., Fang, C., & Kung, H. (2020). Coupling coordination analysis of urbanization and eco-environment in Yanqi Basin based on multi-source remote sensing data. *Ecological Indicators*, 114, 106331. doi:10.1016/j.ecolind.2020.106331.

Baig, M. H. A., Zhang, L., Shuai, T., & Tong, Q. (2014). Derivation of a tasselled cap transformation based on Landsat 8 at-satellite reflectance. *Remote Sensing Letters*, 5(5), 423–431. doi:10.1080/2150704X.2014.915434.

Cen, Y., He, L., He, Z., Luo, F., Zhao, Y., Gan, J., Bai, W., & Chen, X. (2025). Improving Remote Sensing Ecological Assessment in Arid Regions: Dual-Index Framework for Capturing Heterogeneous Environmental Dynamics in the Tarim Basin. *Remote Sensing*, 17(21), 3511. doi:10.3390/rs17213511.

Chernogor, L., Nekos, A., Titenko, G., & Chornohor, L. (2024). Ecological consequences of the catastrophic destruction of the Kakhovka reservoir dam. *Visnyk of V. N. Karazin Kharkiv National University. Series Geology. Geography. Ecology*, (61), 399–410. doi:10.26565/2410-7360-2024-61-32.

Du, Z., Ji, X., Liu, J., Zhao, W., He, Z., Jiang, J. … Gao, J. (2024). Ecological health assessment of Tibetan alpine grasslands in Gannan using remote sensed ecological indicators. *Geo-spatial Information Science*, 28(1), 246–264. doi:10.1080/10095020.2024.2311862.

Ecological Passport of Kherson region for 2023. (2024) Retrieved from https://mepr.gov.ua/diyalnist/napryamky/ekologichnyj-monitoryng/ekologichni-pasporty/.

Kamran, M., & Yamamoto, K. (2023). Evolution and use of remote sensing in ecological vulnerability assessment: A review. *Ecological Indicators*, 148, 110099. doi:10.1016/j.ecolind.2023.110099.

Lei, R. (2023). Assessment of changes in the quality of the environment in the Lviv region on the basis of environmental indices of remote sensing. *Urban Development and Spatial Planning*, (84), 132–144. doi:10.32347/2076-815x.2023.84.132-144 (In Ukrainian).

Li, G., Zhang, N., Cao, Y., Xia, Z., Bao, C., Fan, L., & Xue, S. (2024). Analysis of the temporal and spatial changes of ecological environment quality using the optimization remote sensing ecological index in the middle Yellow River Basin, China. *Earth Science Informatics*, 17(6), 5107–5122. doi:10.1007/s12145-024-01441-0.

Liao, W., & Jiang, W. (2020). Evaluation of the Spatiotemporal Variations in the Eco-environmental Quality in China Based on the Remote Sensing Ecological Index. *Remote Sensing*, 12(15), 2462. doi:10.3390/rs12152462.

Lu, F., Zhang, C., Cao, H., Wang, X., Zheng, T., & Huang, Z. (2025). Assessment of ecological environment quality and

their drivers in urban agglomeration based on a novel remote sensing ecological index. *Ecological Indicators*, 170, 113104. doi:10.1016/j.ecolind.2025.113104.

Sun, H., Huang, M., Lin, H., Ge, Y., Zhu, D., Gong, D., & Altan, O. (2025). Spatiotemporal dynamics of ecological environment quality in arid and sandy regions with a particular remote sensing ecological index: a study of the Beijing-Tianjin Sand source region. *Geo-spatial Information Science*, 1–20. doi:10.1080/10095020.2025.2541875.

Tuan, C. H., & Thu, H. N. T. (2025). Applying the Improved Remote Sensing Ecological Index (IRSEI) for urban ecological assessment in Ho Chi Minh City, VietNam. *IOP Conference Series Earth and Environmental Science*, 1539(1), 012008. doi:10.1088/1755-1315/1539/1/012008.

USGS Landsat 8 Level 2, Collection 2, Tier 1 (2026). Retrieved from: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_L2.

Wang, X., Liu, Q., Jia, P., Huang, X., Yang, J., Mao, Z., & Shen, S. (2024). Highway Ecological Environmental Assessment Based on Modified Remote Sensing Index – Taking the Lhasa–Nyingchi Motorway as an Example. *Remote Sensing*, 16(2), 265. doi:10.3390/rs16020265.

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

Xu, H., Wang, Y., Guan, H., Shi, T., & Hu, X. (2019). Detecting Ecological Changes with a Remote Sensing Based Ecological Index (RSEI) Produced Time Series and Change Vector Analysis. *Remote Sensing*, 11(20), 2345. doi:10.3390/rs11202345.

Xu, H.Q.A. (2013). Remote sensing urban ecological index and its application. *Acta Ecol. Sin*. 33, 7853–7862.

Yao, K., Halike, A., Chen, L., & Wei, Q. (2022). Spatiotemporal changes of eco-environmental quality based on remote sensing-based ecological index in the Hotan Oasis, Xinjiang. *Journal of Arid Land*, 14(3), 262–283. doi:10.1007/s40333-022-0011-2.

Yuan, B., Fu, L., Zou, Y., Zhang, S., Chen, X., Li, F., Deng, Z., & Xie, Y. (2021). Spatiotemporal change detection of ecological quality and the associated affecting factors in Dongting Lake Basin, based on RSEI. *Journal of Cleaner Production*, 302, 126995. doi:10.1016/j.jclepro.2021.126995.

Zhang, J., Yang, G., Yang, L., Li, Z., Gao, M., Yu, C., Gong, E., Long, H., & Hu, H. (2022). Dynamic Monitoring of Environmental Quality in the Loess Plateau from 2000 to 2020 Using the Google Earth Engine Platform and the Remote Sensing Ecological Index. *Remote Sensing*, 14(20), 5094. doi:10.3390/rs14205094.

ОЦІНЮВАННЯ ПРОСТОРОВО-ЧАСОВОЇ ДИНАМІКИ ЕКОЛОГІЧНОГО ІНДЕКСУ ДИСТАНЦІЙНОГО ЗОНДУВАННЯ (RSEI) ЗА ДАНИМИ СУПУТНИКА LANDSAT 8: НА ПРИКЛАДІ ХЕРСОНСЬКОЇ ОБЛАСТІ, УКРАЇНА (2013–2025)

Тимчишин М. А. https://orcid.org/0000-0003-2966-4794

Державна екологічна інспекція України, провулок Новопечерський 3, к. 2, Київ, 01042, Україна

У науковій роботі здійснено комплексне оцінювання просторово-часової динаміки екологічного стану Херсонської області за період з 2013 по 2025 роки з особливим акцентом на наслідках повномасштабної військової агресії рф. В умовах інтенсивних бойових дій, руйнування критичної інфраструктури та глобальних кліматичних викликів, об'єктивний геопросторовий моніторинг навколишнього природного середовища є надзвичайно важливим завданням для фіксації збитків та прогнозування подальшого розвитку регіону.

Дослідження базується на використанні сучасних геоінформаційних технологій та даних дистанційного зондування Землі. За допомогою хмарної обчислювальної платформи Google Earth Engine та масиву архівних мультиспектральних супутникових знімків Landsat 8 OLI/TIRS було розраховано інтегральний індекс екологічного стану дистанційного зондування (RSEI). Цей індекс комплексно інтегрує чотири ключові біофізичні показники: зеленість (на основі нормалізованого відносного індексу рослинності, NDVI), вологість (Wet), сухість (на основі індексу оголеного ґрунту та забудови, NDBSI) та температуру земної поверхні (LST). Застосування методу аналізу головних компонент (PCA) дало змогу математично згорнути ці показники в єдиний стандартизований індекс, де перша головна компонента (PC1) пояснює найвищу частку загальної дисперсії просторових даних. Це підтверджує високу надійність та репрезентативність розробленої розрахункової моделі.

Результати картографічного та статистичного аналізів свідчать про різке, безпрецедентне погіршення стану екосистем досліджуваного регіону у 2025 році порівняно з ретроспективними даними попередніх років. Встановлено критичне падіння середнього значення індексу RSEI – з 0,381 у відносно стабільному 2021 році до 0,205 у 2025 році. Просторове оцінювання показало, що площа територій, які класифікуються як стан екологічної кризи (категорія «Terrible» з ранжуванням індексу від 0 до 0,2), зросла більше ніж удвічі: з 26% території області у 2021 році до критичних 60% у 2025 році.

Різке падіння RSEI просторово узгоджується з масштабними гідрологічними трансформаціями внаслідок руйнування Каховської ГЕС, проте цей показник також відображає синергетичний вплив інтенсивних бойових дій, пожеж, припинення зрошення та кліматичних аномалій. Знищення дамби Каховської ГЕС. призвів до катастрофічного руйнування гідрографічної мережі, зникнення джерел водопостачання для життєво важливих сільськогосподарських угідь та порушення систем життєзабезпечення урбанізованих територій. Єдиним винятком на загальному тлі екологічної катастрофи є зафіксоване локальне природне відновлення екосистеми старого річища Дніпра, яке поступово повертається до свого історичного стану, що передував масовому антропогенному втручанню та зарегулюванню річки у 50-х роках XX сторіччя.

У підсумку зроблено висновок, що синергетичний вплив безперервних масштабних воєнних дій, руйнування усталених екосистемних зв'язків та підсилення глобальних кліматичних змін формують вкрай невтішний прогноз. Подальша деградація ґрунтово-рослинного покриву та виснаження водних ресурсів створюють високий ризик трансформації значної частини Херсонської області у територію, яка є непридатною для безпечного життя, ведення сільського господарства та соціально-економічного функціонування.

Ключові слова: екологічний індекс дистанційного зондування (RSEI), Google Earth Engine, ArcGIS, дані дистанційного зондування, Landsat 8, Херсонська область.

Рукопис статті отримано 25.06.2026
Надходження остаточної версії: 10.09.2026
Публікація статті: 30.09.2026
Received 25.06.2026
Revised 10.09.2026
Accepted 30.09.2026