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Ecological Quality Assessment of the Semipalatinsk Nuclear Test Site Using RSEI Based on Sentinel-2 Data: A Comparison of 2020 and 2024 Summer Conditions

Zhandos Mukaliyev[1*], Zhazira Zhumatayeva[2]

[1] Department of Cartography and Geoinformatics, Faculty of Geography and Environmental Sciences, Al-Farabi Kazakh National University, Almaty 050040, Kazakhstan
[2] Department of Geography, Land Management and Cadastre, Faculty of Geography and Environmental Sciences, Al-Farabi Kazakh National University, Almaty 050040, Kazakhstan

Corresponding Author Email: mukaliyevz@gmail.com

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ABSTRACT

This study assesses the ecological quality of the Semipalatinsk Nuclear Test Site (SNTS) using the Remote Sensing Ecological Index (RSEI) based on Sentinel-2 satellite imagery for summer periods of 2020 and 2024. Four indicators, including Normalized Difference Vegetation Index (NDVI), Wetness, Land Surface Temperature (LST), and Normalized Difference Built-up and Soil Index (NDBSI), were integrated using principal component analysis (PCA). All datasets were resampled to a unified spatial resolution of 1000 m prior to analysis. The results show that the study area is predominantly characterized by moderate to high ecological quality. In 2020, the Excellent class covered 83.5% of the territory, while in 2024 this value decreased to 59.3%, accompanied by an increase in the Good class from 13.2% to 37.5%. Poor, Fair, and Moderate classes together account for less than 4% of the area in both years. These results indicate a redistribution of ecological conditions rather than widespread degradation. The findings demonstrate the applicability of RSEI for monitoring environmental conditions in post-nuclear landscapes and provide a baseline for future multi-temporal analysis.

1. INTRODUCTION

The Semipalatinsk Nuclear Test Site (SNTS), established on 21 August 1947, served as the primary nuclear weapons testing ground of the Soviet Union for more than four decades. Located in northeastern Kazakhstan, the site covers approximately 18,500 km² across parts of the former Semipalatinsk, Pavlodar, and Karaganda regions. Between 1949 and 1989, a total of 473 nuclear detonations were conducted, including atmospheric, surface, and underground tests. These activities resulted in extensive radioactive contamination affecting large areas of land and surrounding populations [1].

The environmental consequences of nuclear testing at the SNTS have been substantial and long-lasting. Nuclear explosions caused severe disturbances to vegetation cover, soil structure, and surface hydrological processes. In addition, long-lived radionuclides such as cesium-137, strontium-90, and plutonium isotopes persist in the environment and may influence ecosystem recovery processes. However, it is important to note that ecological conditions are shaped not only by historical contamination but also by natural factors such as climate variability, soil moisture, and vegetation dynamics [2].

Despite extensive research on radiation exposure and public health impacts, spatially explicit assessments of ecological conditions across the entire SNTS remain limited. Field-based ecological surveys are constrained by the large spatial extent and restricted access to certain areas. In this context, remote sensing provides an effective approach for monitoring environmental conditions over large territories in a consistent and repeatable manner.

One of the widely used approaches for integrated ecological assessment is the Remote Sensing Ecological Index (RSEI). The RSEI combines multiple environmental indicators into a single composite index using principal component analysis (PCA), enabling objective evaluation of ecological quality [3]. The index integrates four key components: the Normalized Difference Vegetation Index (NDVI), representing vegetation conditions; Wetness, reflecting surface moisture; Land Surface Temperature (LST), indicating thermal characteristics; and the Normalized Difference Built-up and Soil Index (NDBSI), representing surface dryness and soil exposure. The RSEI approach has been successfully applied in various environmental contexts, including urban environments, arid regions, post-mining landscapes, and river basins [4, 5].

Although previous studies have investigated environmental conditions in Kazakhstan and post-disturbance landscapes, the application of the RSEI framework to the SNTS remains limited. In particular, comparative analyses of ecological conditions across different years using consistent remote sensing data are scarce [6]. Therefore, this study aims to fill this gap by applying the RSEI method to Sentinel-2 satellite imagery and assessing ecological quality during the summer seasons of 2020 and 2024. The results provide a comparative evaluation of ecological conditions and contribute to the development of a baseline for future environmental monitoring of the SNTS.

2. MATERIALS AND METHODS

2.1 Study area

The Semipalatinsk Nuclear Test Site (SNTS) is located in northeastern Kazakhstan, centered approximately at 50.4 °N, 78.0 °E (Figure 1). The site covers an area of approximately 18,500 km² spanning the territories of the former Semipalatinsk (now East Kazakhstan), Pavlodar, and Karaganda oblasts. The terrain is predominantly flat to gently undulating steppe, with elevations ranging from approximately 150 to 500 m above sea level. The Irtysh River forms the northern boundary of the test site, while the Chagan River flows through the central test area. The city of Kurchatov (formerly Semipalatinsk-21), the former administrative center of the SNTS, is located on the northern site boundary [7].

The regional climate is strongly continental, characterized by hot and dry summers (mean temperatures of 25–35 ℃) and cold winters. Annual precipitation ranges from 200 to 300 mm, with most rainfall occurring in spring [8].

Natural vegetation is dominated by dry steppe communities, including grasses such as Stipa and Festuca, and drought-resistant shrubs of the genus Artemisia. Riparian vegetation, including willow and poplar, occurs along river valleys.

Large parts of the SNTS are characterized by sparsely vegetated or disturbed surfaces, particularly within former test zones. These environmental conditions are influenced by a combination of historical disturbances and natural factors such as aridity, soil properties, and climatic variability [7].

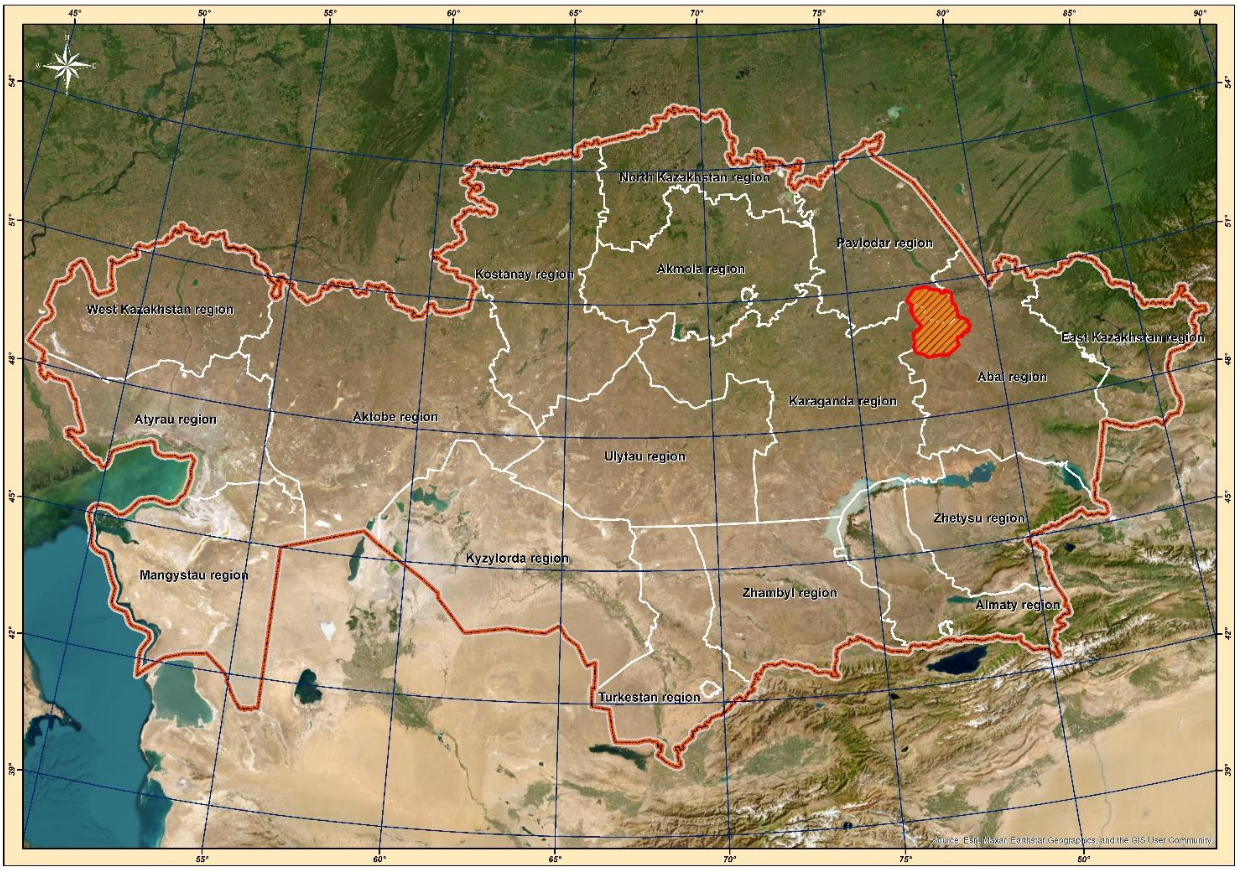

Figure 1. Geographic location of the study area within Kazakhstan, including the Semipalatinsk Nuclear Test Site (SNTS)

2.2 Data sources

Satellite data from Sentinel-2 and Landsat 8 were used to derive the input indicators for the RSEI model. Sentinel-2 Level-2A surface reflectance imagery from the COPERNICUS/S2_SR_HARMONIZED collection was used for the calculation of NDVI, Wetness, and NDBSI. Data were selected for the summer growing seasons (1 June to 31 August) of 2020 and 2024 to ensure temporal consistency.

To ensure data quality, scenes were filtered using a cloud cover threshold of less than 10%. Cloud masking was performed using both the QA60 band and the Scene Classification Layer (SCL), allowing the removal of clouds, cirrus, cloud shadows, and other low-quality pixels. The filtered image collections were composited using pixel-wise median aggregation to generate spatially continuous seasonal composites.

Landsat 8 Collection 2 Tier 1 Level-2 data (LANDSAT/LC08/C02/T1_L2) were used for LST derivation, as Sentinel-2 does not include thermal infrared bands. The same seasonal filtering (June–August) was applied for both 2020 and 2024. Cloud and shadow masking were performed using the QA_PIXEL band, with pixels flagged as dilated cloud (bit 1), cloud shadow (bit 3), snow (bit 4), or cloud (bit 5) excluded from analysis. The median composite of the thermal band (Band 10, ST_B10) was used to estimate LST [8, 9].

All data processing, including filtering, masking, compositing, and index calculation, was conducted within the Google Earth Engine (GEE) cloud computing platform, which enables efficient processing of large-scale geospatial datasets and is widely applied in ecological monitoring studies [2, 8].

The pixel-wise median compositing strategy, applied independently to each year's filtered collection, ensured full spatial coverage across the entire 18,500 km² study area for both 2020 and 2024, with no data gaps remaining after processing.

The main characteristics of the satellite data used in this study, including data source, processing level, spatial resolution, temporal period, cloud-cover threshold, and derived indicators, are summarized in Table 1.

Table 1. Characteristics of satellite data used in the study

Parameter	Sentinel-2	Landsat 8
Google Earth Engine collection	COPERNICUS/S2_SR_HARMONIZED	LANDSAT/LC08/C02/T1_L2
Processing level	Level-2A Surface Reflectance	Collection 2 Tier 1 Level-2
Spatial resolution	10–20 m	30 m
Temporal period	June 1 – August 31, 2020 and 2024	June 1 – August 31, 2020 and 2024
Cloud cover threshold	<10% per scene	<10% per scene
Scenes used (2020)	43	14
Scenes used (2024)	48	16
Indicators derived	NDVI, Wetness, NDBSI	LST
Compositing method	Pixel-wise median	Pixel-wise median
Spatial coverage after compositing	Complete	Complete

Notes: NDVI: Normalized Difference Vegetation Index, NDBSI: Normalized Difference Built-up and Soil Index.

2.3 Calculation of ecological indicators

The Normalized Difference Vegetation Index (NDVI) was calculated from the Sentinel-2 median composite using the standard formula:

$$NDVI = \frac{B8 - B4}{B8 + B4} \quad (1)$$

where, B8 is the near-infrared band (842 nm, 10 m spatial resolution) and B4 is the red band (665 nm). NDVI values range from –1 to +1, with higher values indicating denser and more photosynthetically active vegetation. In the SNTS, NDVI reflects spatial variability in vegetation cover influenced by environmental conditions such as soil properties, moisture availability, and climatic variability [7].

Wetness was derived using the tasseled cap transformation adapted for Sentinel-2:

$$\begin{aligned} Wetness = {} & 0.1509B2 + 0.1973B3 \\ & + 0.3279B4 + 0.3406B8 \\ & - 0.7112B11 - 0.4559B12 \end{aligned} \quad (2)$$

where, B2, B3, B4, B8, B11, and B12 correspond to the blue, green, red, near-infrared, and shortwave infrared bands. Higher wetness values indicate increased surface and soil moisture conditions [9].

LST was derived from Landsat 8 thermal infrared data (Band 10, ST_B10) using the Collection 2 Level-2 scaling factors:

$$LST = DN \times 0.00341802 + 149.0 - 273.15 \quad (3)$$

where, DN is the digital number of the thermal band. The resulting LST values represent surface temperature conditions during the summer composite period. Higher LST values indicate increased thermal stress and are typically associated with bare or sparsely vegetated surfaces [10].

The Normalized Difference Built-up and Soil Index (NDBSI) was calculated from Sentinel-2 data as a composite of the Soil Index (SI) and the Built-up Index (BI):

$$SI = \frac{(B11+B4)-(B8+B2)}{(B11+B4)+(B8+B2)} \quad (4)$$

$$BI = \frac{(B11+B3)-(B8+B4)}{(B11+B3)+(B8+B4)} \quad (5)$$

$$NDBSI = \frac{SI+BI}{2} \quad (6)$$

where, SI is the Soil Index, BI is the Built-up Index, and NDBSI is the average of these two components. Higher NDBSI values indicate greater surface bareness and soil exposure, which are characteristic of degraded or unvegetated terrain. NDBSI is particularly sensitive to extensive bare ground and disturbed soils found in the core test areas of the SNTS.

Higher NDBSI values indicate greater surface bareness and soil exposure, characteristic of degraded or unvegetated terrain. NDBSI is particularly sensitive to the extensive bare ground and disturbed soils found in the core test areas of the SNTS [3, 7].

Before RSEI computation, all indicators were normalized to the (0, 1) range using min–max normalization:

$$X_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

where, X_{norm} is the normalized value of a given indicator, x is the original pixel value of the indicator, and x_{min} and x_{max} represent the minimum and maximum values of the corresponding indicator, respectively.

The normalized indicators were then integrated using PCA. To ensure consistency and reduce spatial noise, all datasets were resampled to a common spatial resolution of 1000 m prior to PCA. This aggregation improves the stability of covariance estimation and enhances the robustness of the resulting components [2].

The PCA loadings of the ecological indicators used for RSEI construction are presented in Table 2. Since PC1 loads positively on degradation indicators (LST and NDBSI) and negatively on ecological quality indicators (NDVI and Wetness), the index was calculated as:

$$RSEI = 1 - PC1_{norm} \quad (8)$$

Table 2. Principal component analysis (PCA) loadings of ecological indicators used for RSEI construction

Indicator	PC1 Loading
NDVI	-0.72
Wetness	-0.65
LST	+0.68
NDBSI	+0.74

Note: RSEI: Remote Sensing Ecological Index, NDVI: Normalized Difference Vegetation Index, LST: Land Surface Temperature, NDBSI: Normalized Difference Built-up and Soil Index.

This transformation ensures that higher RSEI values correspond to better ecological quality.

Finally, the RSEI was classified into five categories using the equal interval method:

- Poor (0–0.2)
- Fair (0.2–0.4)
- Moderate (0.4–0.6)
- Good (0.6–0.8)
- Excellent (0.8–1.0)

For mapping and statistical analysis, these classes were reclassified into integer values (0–5).

3. RESULT

3.1 Spatial distribution of ecological indicators

The spatial distributions of NDVI, Wetness, LST, and NDBSI across the SNTS for the summer season of 2024 are presented in Figures 2-5. These indicators represent complementary aspects of ecological conditions, including vegetation cover, moisture availability, thermal characteristics, and surface dryness.

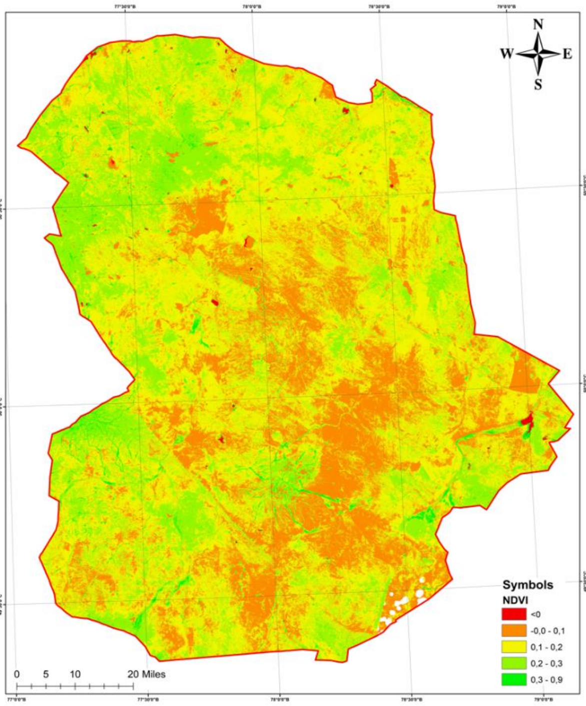

Figure 2. Normalized Difference Vegetation Index **(**NDVI) distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2020

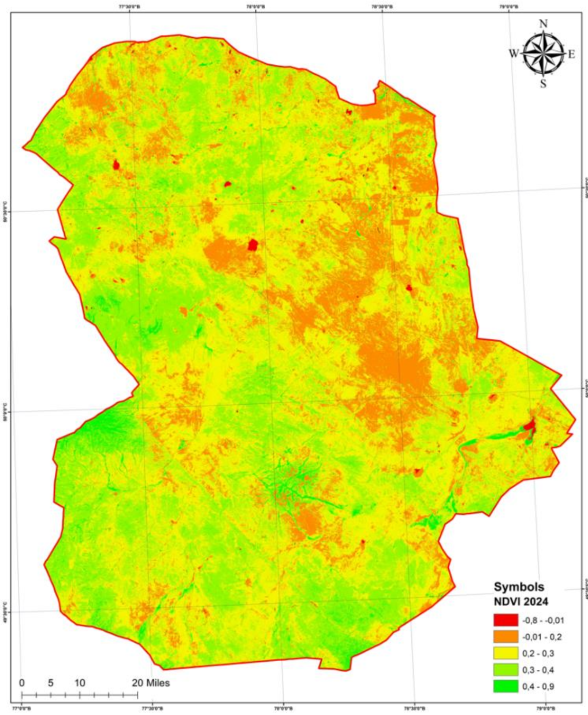

Figure 3. Normalized Difference Vegetation Index (NDVI) distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2024

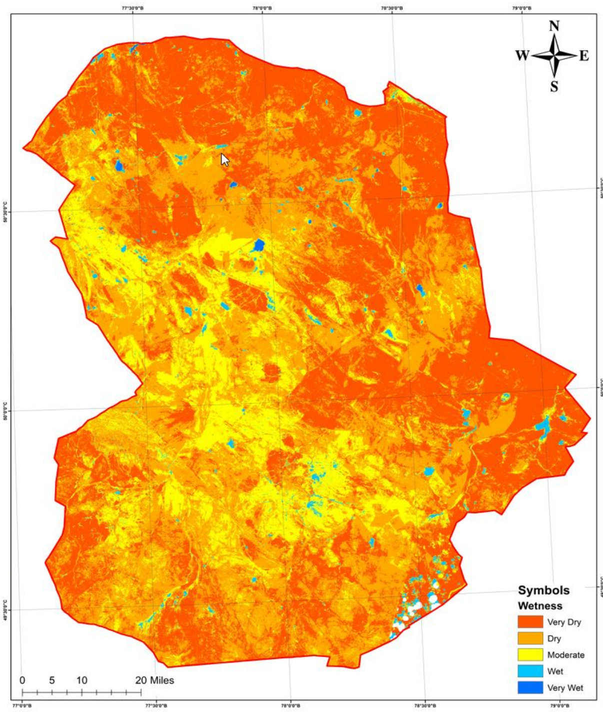

Figure 4. Wetness distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2020

NDVI values across the SNTS ranged from near zero in the central parts of the test site to moderate values (0.3–0.5) in peripheral steppe areas and along the Irtysh River corridor. Lower NDVI values were primarily observed in the central testing zones, including the Experimental Field area, where vegetation cover remains sparse. This spatial pattern reflects the combined influence of environmental factors such as soil properties, moisture availability, and climatic conditions [7, 11].

The Wetness distributions for 2020 and 2024 are presented in Figures 4 and 5, respectively.

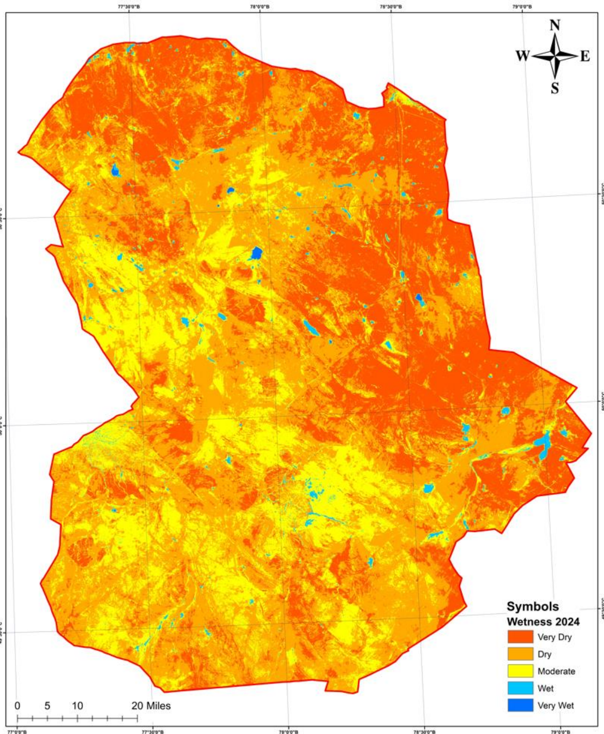

Figure 5. Wetness distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2024

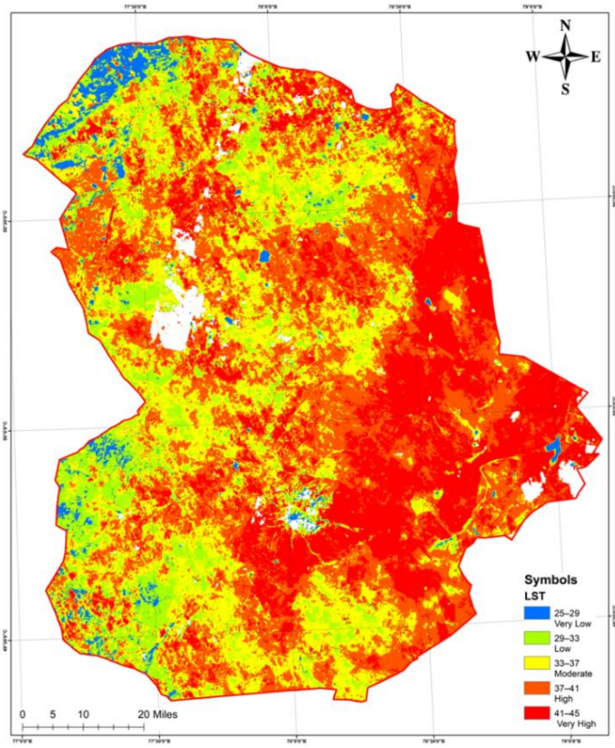

Figure 6. Land Surface Temperature (LST) distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2020

The Wetness index exhibited generally low values across most of the SNTS, consistent with the arid continental climate of the region. Slightly higher Wetness values were observed along the Irtysh River floodplain and in localized depressions where moisture accumulation occurs. These patterns indicate spatial variability in soil and surface moisture conditions [9].

The LST distributions for 2020 and 2024 are shown in Figures 6 and 7, respectively.

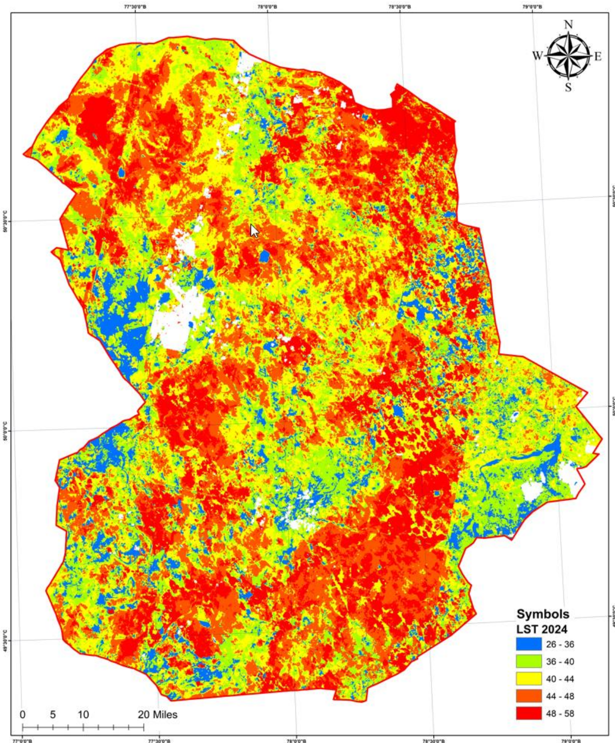

Figure 7. Land Surface Temperature (LST) distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2024

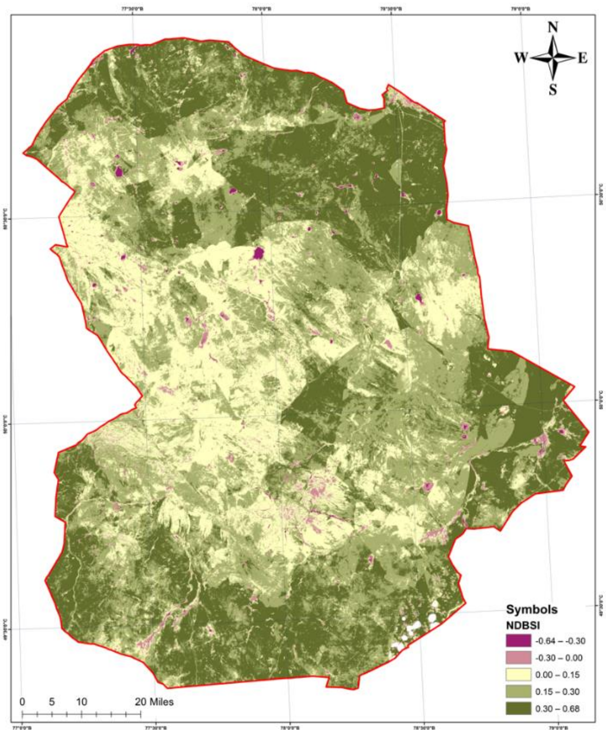

Figure 8. Normalized Difference Built-up and Soil Index (NDBSI) distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2020

LST values during summer ranged from approximately 25 ℃ in vegetated and moist areas to over 40 ℃ in bare and sparsely vegetated zones. Higher temperatures were observed in the central parts of the test site, where surface exposure is greater. These thermal patterns are consistent with reduced vegetation cover and increased surface dryness [8, 10].

The NDBSI distributions for 2020 and 2024 are presented in Figures 8 and 9, respectively.

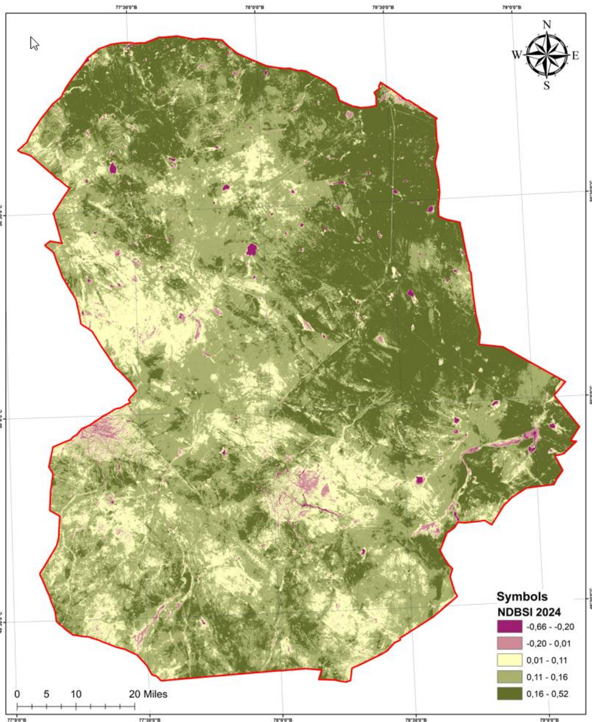

Figure 9. Normalized Difference Built-up and Soil Index (NDBSI) distribution in Semipalatinsk Nuclear Test Site (SNTS), summer 2024

NDBSI values indicate that a large proportion of the SNTS is characterized by bare or sparsely vegetated surfaces. Higher NDBSI values were concentrated in central areas, while lower values were observed in steppe-covered regions and near river systems. This distribution highlights the spatial variability of land surface conditions and potential degradation processes [3, 7].

Overall, the combined spatial patterns of the four indicators consistently identify the central parts of the SNTS as areas with less favorable ecological conditions, while peripheral regions and riverine zones exhibit relatively improved environmental characteristics.

3.2 Remote Sensing Ecological Index spatial distribution and classification

The spatial distribution of the RSEI for 2020 and 2024 is presented in Figures 9 and 10. The results reveal a heterogeneous pattern of ecological quality across the SNTS, reflecting spatial variability in environmental conditions and land surface characteristics [12].

Areas classified as Poor ecological quality are limited and primarily concentrated in the central part of the study area (Figures 10 and 11). These zones are characterized by low vegetation cover, elevated LST, and high surface dryness.

The Fair and Moderate classes are also limited in extent and occur mainly in transitional zones between central and peripheral areas, indicating intermediate ecological conditions [13].

The Good class is widely distributed, particularly in peripheral regions and along riverine zones such as the Irtysh River, where higher soil moisture and vegetation density are observed.

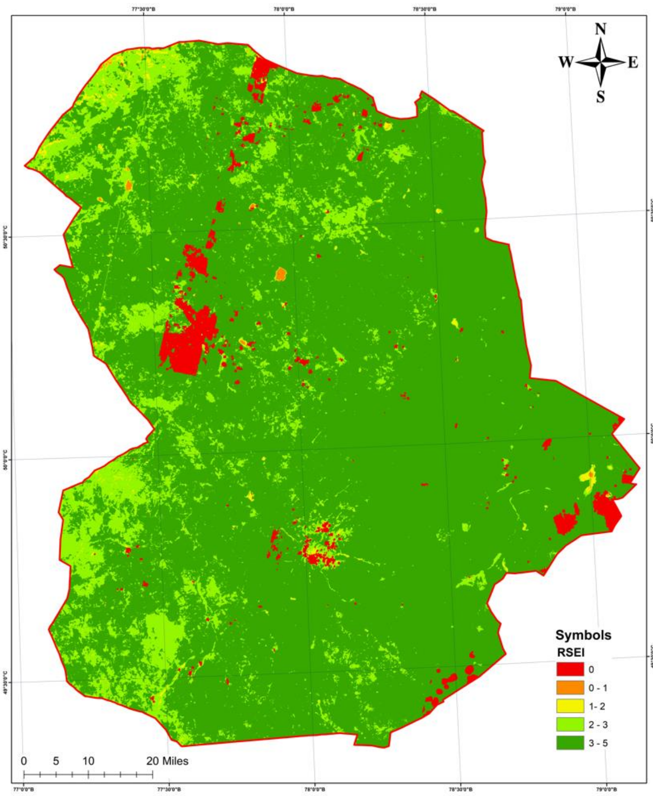

Figure 10. Remote Sensing Ecological Index (RSEI) classification of Semipalatinsk Nuclear Test Site (SNTS), summer 2020

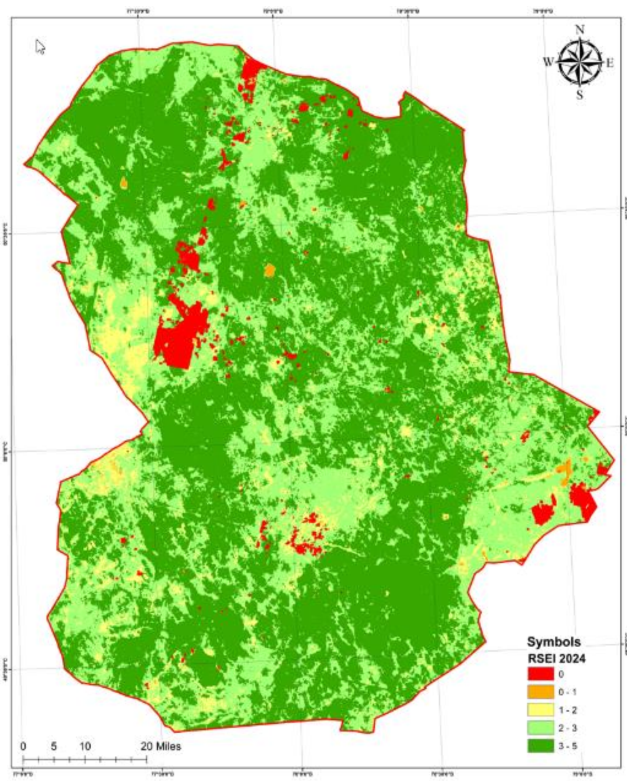

Figure 11. Remote Sensing Ecological Index (RSEI) classification of Semipalatinsk Nuclear Test Site (SNTS), summer 2024

The Excellent class occupies a significant portion of the territory in both years, especially in areas with relatively stable environmental conditions and lower surface disturbance.

3.3 Quantitative analysis of Remote Sensing Ecological Index classes

The quantitative distribution of RSEI classes for 2020 and 2024 is presented in Table 3.

Table 3. Remote Sensing Ecological Index (RSEI) class distribution in 2020 and 2024

Class	2020 Area (km²)	2020 (%)	2024 Area (km²)	2024 (%)
Poor	475.7	2.6	451.96	2.6
Fair	17.0	0.1	5.46	0.03
Moderate	109.7	0.6	110.12	0.6
Good	2427.3	13.2	6489.37	37.5
Excellent	15337.2	83.5	10269.72	59.3

The analysis of the results shows significant changes in the distribution of ecological quality classes between 2020 and 2024.

The proportion of areas classified as Excellent decreased from 83.5% in 2020 to 59.3% in 2024. At the same time, the Good class increased from 13.2% to 37.5%, indicating a redistribution of ecological conditions.

In contrast, the Poor, Fair, and Moderate classes remained relatively stable, collectively accounting for less than 4% of the total area in both years.

These results suggest that the observed changes are primarily associated with variations in surface conditions and environmental factors, rather than large-scale degradation.

4. DISCUSSION

The RSEI [13] assessment of the SNTS for the summer seasons of 2020 and 2024 reveals clear spatial contrasts in ecological conditions across the study area. The results indicate that areas with lower ecological quality are primarily concentrated in the central parts of the site, while relatively better conditions are observed in peripheral and riverine zones [11]. These patterns reflect the combined influence of environmental factors, including land surface properties, moisture availability, and climatic conditions [14].

Although the spatial distribution of lower RSEI values corresponds to historically disturbed areas, it is important to note that RSEI does not directly measure radioactive contamination. Instead, it captures integrated ecological responses observable at the surface, such as reduced vegetation cover, increased surface temperature, and higher soil exposure. Therefore, the observed patterns should be interpreted as indicators of environmental condition rather than direct measures of contamination [15].

The radar chart (Figure 12) illustrates the characteristic profiles of ecological indicators for different RSEI classes. The plotted values represent mean normalized values of NDVI, Wetness, LST, and NDBSI for each class. Areas classified as Poor exhibit high LST and NDBSI values combined with low NDVI and Wetness, reflecting unfavorable surface conditions. In contrast, the Good class is characterized by higher NDVI and Wetness values, indicating more stable ecological conditions. The Moderate class shows intermediate characteristics between these two extremes.

The observed spatial patterns are also influenced by regional climatic conditions. The SNTS is located in a semi-arid zone, where high summer temperatures and limited precipitation naturally result in relatively low vegetation density and moisture availability. As a result, even areas not subject to significant disturbance may exhibit moderate ecological quality. This highlights the importance of considering background environmental conditions when interpreting RSEI results [16].

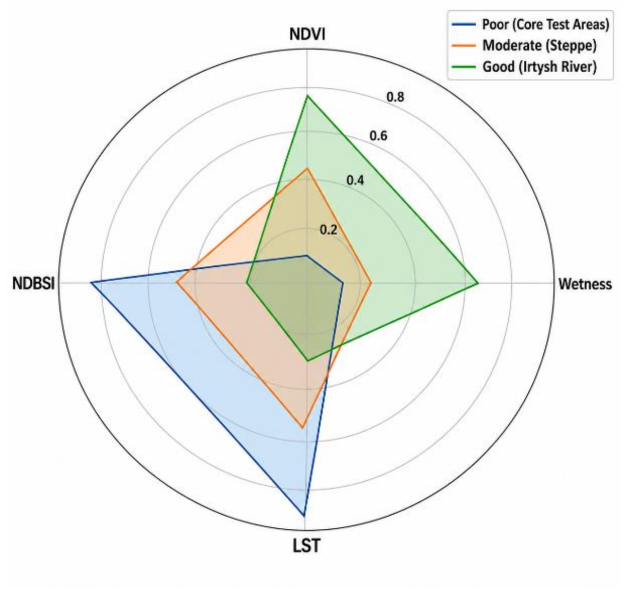

Figure 12. Radar chart showing the mean normalized values of NDVI, Wetness, LST, and NDBSI for different RSEI classes

Note: NDVI: Normalized Difference Vegetation Index, LST: Land Surface Temperature, NDBSI: Normalized Difference Built-up and Soil Index, RSEI: Remote Sensing Ecological Index.

The relatively higher ecological quality observed along the Irtysh River is consistent with the role of riparian zones as ecological refugia in semi-arid landscapes. Increased soil moisture and vegetation density in these areas contribute to lower surface temperatures and improved ecological indicators [17].

The spatial patterns identified in this study are broadly consistent with findings from previous remote sensing assessments of degraded and post-disturbance landscapes in Central Asia and arid regions. Similar spatial gradients of vegetation degradation have been observed in East Kazakhstan using NDVI and Landsat data, with the most pronounced deficits occurring in historically disturbed areas and relatively stable conditions along river corridors. This is consistent with the low NDVI and elevated NDBSI values observed in the central SNTS in the present study. RSEI effectively captures ecological gradients in desertification-prone arid environments, where the index is sensitive to the combined signal of sparse vegetation, dry soils, and elevated surface temperatures – conditions characteristic of the SNTS interior. The predominance of Good and Excellent classes in peripheral and riverine zones observed here is consistent with previous findings that riparian and low-disturbance areas consistently score higher in RSEI assessments across diverse landscape types [16]. Taken together, these comparisons support the validity of the RSEI approach for the SNTS and suggest that the observed ecological patterns reflect both the legacy of nuclear testing and the background constraints of the semi-arid steppe environment [18].

From a methodological perspective, the integration of Sentinel-2 and Landsat 8 data within the GEE platform proved effective for large-scale ecological assessment. The use of Sentinel-2 for vegetation, moisture, and surface condition indicators, combined with Landsat-derived LST, provides a balanced approach that leverages the strengths of both datasets [16, 19].

Several limitations should be acknowledged. First, the analysis represents seasonal conditions (summer periods of 2020 and 2024) and does not capture inter-annual variability. Second, the RSEI reflects only surface-observable ecological characteristics and does not directly quantify subsurface or radiological processes. Third, the absence of field validation introduces uncertainty in the interpretation of ecological classes.

Future research should focus on multi-temporal analysis and comparison with climatically similar reference areas to better distinguish between natural and disturbance-related ecological patterns.

5. CONCLUSION

This study presents an ecological quality assessment of the SNTS using the RSEI based on multi-source satellite data for the summer seasons of 2020 and 2024. By integrating NDVI, Wetness, LST, and NDBSI through PCA, the study provides a spatially explicit evaluation of environmental conditions across a large and complex post-disturbance landscape.

The results reveal clear spatial heterogeneity in ecological conditions across the SNTS. Areas with lower ecological quality are primarily concentrated in the central parts of the study area, while relatively improved conditions are observed in peripheral regions and along the Irtysh River. The quantitative analysis indicates a decrease in the proportion of the Excellent class and a corresponding increase in the Good class between 2020 and 2024, suggesting a redistribution of ecological conditions rather than a uniform trend of degradation.

The study highlights the effectiveness of the RSEI approach for integrated ecological assessment using remote sensing data. The combination of Sentinel-2 and Landsat 8 imagery within the Google Earth Engine platform provides a practical and scalable framework for large-area environmental analysis.

From an applied perspective, the results can support environmental monitoring and management efforts. Areas classified as Poor may be prioritized for detailed field investigation, Moderate areas for monitoring of ecological change, and Good areas – particularly along river systems – can serve as reference zones for comparatively stable environmental conditions.

This study provides a single-season baseline for future monitoring and demonstrates the potential of remote sensing methods for assessing ecological conditions in large and environmentally complex territories.

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NOMENCLATURE

RSEI	Remote Sensing Ecological Index
NDVI	Normalized Difference Vegetation Index
LST	Land Surface Temperature, ℃
NDBSI	Normalized Difference Bare Soil Index
SI	Soil Index
PCA	Principal Component Analysis
GEE	Google Earth Engine
SNTS	Semipalatinsk Nuclear Test Site
DN	Digital Number
B2, B3, B4, B8, B11, B12	Sentinel-2 Spectral Bands (Blue, Green, Red, Near-Infrared, SWIR1, SWIR2)
ST_B10	Landsat 8 Thermal Infrared Band