Russian Journal of Earth Sciences Online ISSN: 1681-1208

District-Level RSEI Patterns and Ecological Heterogeneity in the Minsk Region, Belarus

B. Zhao[1,*], S. Song[1], and C. Jiang[1]

[1] Belarusian State University, Minsk, Belarus
* **Correspondence to:** Bochao Zhao, geozhao@outlook.com

Abstract: Assessing ecological environment quality at the administrative-unit scale is important for understanding regional landscape differentiation and ecological dynamics in temperate regions. This study used the Remote Sensing Ecological Index (RSEI), derived from Landsat 8/9 growing-season imagery processed in Google Earth Engine, to examine district-level spatiotemporal patterns and ecological heterogeneity in the Minsk Region, Belarus, during 2016–2025. Annual RSEI maps were generated to characterize spatial patterns, intra-district variability, and temporal tendencies. Mean district-level RSEI values ranged from 0.539 to 0.682, showing clear spatial differentiation among districts. Higher values were generally associated with forest-dominated and semi-natural landscapes, whereas agriculturally transformed and urbanized districts showed lower values and greater internal heterogeneity. Temporal trends were predominantly negative but weak. The results indicate that average ecological conditions alone are insufficient for characterizing district-level ecological environment quality and confirm the usefulness of RSEI for detecting subtle ecological contrasts in temperate Eastern European landscapes.

Keywords: ecological environment quality, spatial heterogeneity, spatiotemporal analysis, administrative units, landscape structure, remote sensing, RSEI, Minsk Region

Citation: Zhao B., Song S., and Jiang C. (2026), District-Level RSEI Patterns and Ecological Heterogeneity in the Minsk Region, Belarus, *Russian Journal of Earth Sciences*, 26, ES4006, EDN: QDKTLQ, https://doi.org/10.2205/2026es001144

1. Introduction

Assessing ecological environment quality is an important task in physical geography and environmental science because it reflects the combined effects of land-surface processes, landscape structure, and human–environment interactions. At regional and administrative-unit scales, such assessment is especially relevant for identifying spatial differentiation and internal landscape heterogeneity. Traditional field-based observations remain indispensable, but their limited spatial coverage and discontinuous temporal records restrict their use for long-term regional comparison. Remote sensing therefore provides an effective basis for spatially continuous monitoring of land-surface ecological conditions. In Belarus, ecological environment quality is closely related to land-resource structure, territorial planning, agricultural development, and sustainable environmental management, which have been widely discussed in previous geographical and geoecological studies [*Loginov and Struk*, 2009; *Pirozhnik et al.*, 2009; *Sokolov*, 2017; *Vitchenko et al.*, 2009].

Ecological environment quality can be described using many indicators, including vegetation activity, surface moisture, land-surface temperature, land-cover composition, artificial surfaces, wetlands, disturbed land, and landscape diversity. Belarusian regional assessment systems also use broader environmental, resource, and management indicators to evaluate ecological development [*Dubianok et al.*, 2022]. However, individual indicators usually represent only one dimension of ecological conditions. For regional remote-sensing assessment, a composite index is therefore needed to integrate vegetation, moisture, dryness, and thermal information within a consistent spatial framework.

Research Article

Received: January 24, 2026
Accepted: June 22, 2026
Published: October 28, 2026

Copyright: © 2026. The Authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

The Remote Sensing Ecological Index (RSEI) proposed by Xu et al. integrates greenness, wetness, dryness, and heat components through principal component analysis (PCA), avoiding subjective weighting and producing a synthetic indicator of land-surface ecological conditions [*Xu et al.*, 2018, 2019]. Early and widely cited RSEI applications demonstrated its capacity to detect spatial and temporal ecological changes related to population growth, impervious-surface expansion, watershed transformation, and regional land-use change [*Xiong et al.*, 2021; *Yuan et al.*, 2021; *Zhang et al.*, 2022]. These studies established RSEI as a practical framework for combining multiple land-surface ecological dimensions into a single remote-sensing-based index.

Subsequent methodological studies further improved the robustness of the RSEI framework. These works addressed issues such as index construction, modified ecological indicators, incorporation of additional ecological information, forest structure and quality, and the temporal stability of RSEI time-series analysis [*Liu et al.*, 2022; *Liu et al.*, 2023; *Luo et al.*, 2025; *Ning et al.*, 2020; *Wang et al.*, 2023; *Yang et al.*, 2022; *Zheng et al.*, 2022]. These improvements are important because RSEI values may be affected by normalization strategy, PCA orientation, indicator selection, land-cover composition, and interannual image conditions. Therefore, although RSEI is useful for integrated ecological assessment, its results require careful interpretation within a specific geographical and land-cover context.

RSEI has also been applied in a wide range of geographical settings, including urban systems, agricultural and oasis regions, mining areas, arid river basins, and large watershed or ecological corridor systems [*An et al.*, 2022; *Chen et al.*, 2023; *Gan et al.*, 2024; *Gao et al.*, 2020; *Geng et al.*, 2022; *Gong et al.*, 2023; *Maimaitituersun et al.*, 2025; *Yang et al.*, 2023]. These studies show that RSEI can capture ecological contrasts associated with vegetation dynamics, surface dryness, thermal stress, urbanization, and human disturbance. At the same time, they indicate that RSEI should not be treated as a complete substitute for comprehensive environmental assessment, because it does not directly measure biodiversity, soil contamination, water quality, ecosystem services, or below-ground ecological processes.

Two limitations remain important for geographical and landscape-ecological applications. First, many RSEI studies focus on short- or medium-term comparisons, whereas analyses capable of identifying persistent spatial patterns over a decadal period remain less common. Second, RSEI results are often interpreted at pixel or whole-region scales, while administrative units are usually treated only as statistical containers. This is problematic because districts are internally heterogeneous landscape systems composed of forests, croplands, wetlands, settlements, and disturbed land. Mean RSEI values may therefore obscure internal spatial variability caused by land-use mosaics, fragmentation, and transitional zones between dominant land-cover types.

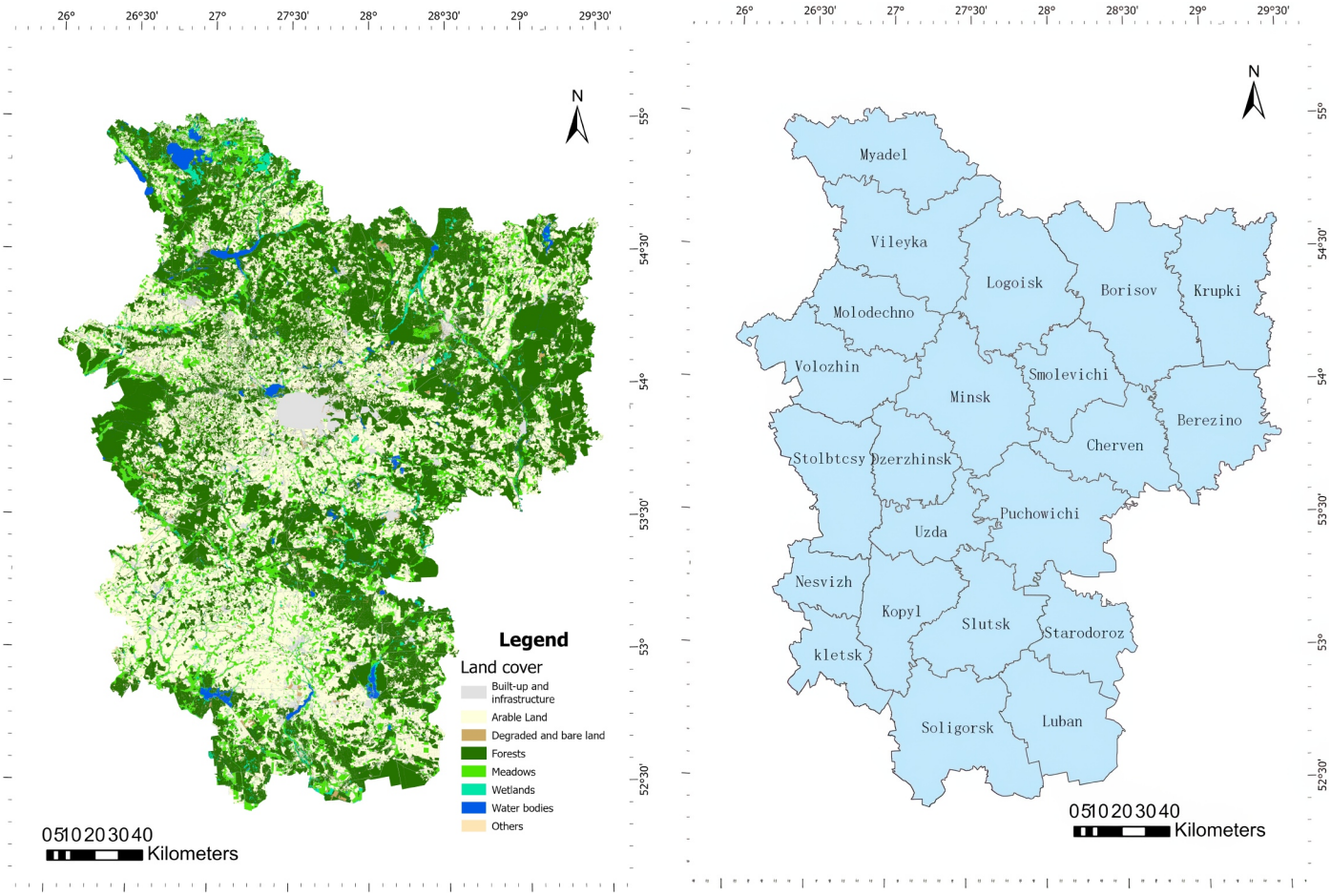
The Minsk Region of Belarus is suitable for such an assessment because it forms a transitional landscape zone between more forest-dominated northern areas and more intensively cultivated southern agricultural landscapes. Its mixed land-use structure, including forests, croplands, grasslands, wetlands, water bodies, and urbanized areas, provides a practical basis for comparing both average ecological conditions and intra-district heterogeneity. Official land-resource statistics indicate pronounced contrasts among agricultural lands, forest complexes, and built-up zones within the region [*Land Resources Register of the Republic of Belarus*, 2025]. Previous studies have examined agricultural and soil-agroclimatic potential, anthropogenic pressure, agricultural land changes, and soil-cover structure in the Minsk Region [*Chernysh and Chervan*, 2020; *Chervan and Romanova*, 2021; *Kolmykov and Avdeev*, 2020, 2021]. However, these studies do not provide a spatially continuous, multi-year remote-sensing assessment of ecological environment quality across all districts.

This study therefore investigates district-level spatiotemporal patterns and spatial heterogeneity of ecological environment quality in the Minsk Region during 2016–2025 using Landsat-based RSEI. The objectives are to map annual RSEI patterns, compare mean ecological environment quality among districts, quantify intra-district RSEI variability

as an indicator of landscape heterogeneity, and describe temporal tendencies over the ten-year period. The study contributes to Belarusian geoecological research by linking a standardized remote-sensing index with administrative-unit comparison and land-cover-based interpretation.

2. Materials and Methods

The Minsk Region is located in central Belarus and represents a suitable area for district-level ecological environment assessment (Figure 1). Situated within the East European Plain, it is characterized by predominantly flat and gently undulating terrain, with elevations generally ranging from about 150 to 300 m above sea level. The region forms a transitional landscape zone between more forest-dominated northern areas and more intensively cultivated southern agricultural landscapes. Its land-cover structure includes croplands, forests, grasslands, wetlands, water bodies, and urbanized areas, which makes it appropriate for analyzing both regional spatial differentiation and intra-district ecological heterogeneity. The climate is temperate continental, with a mean annual air temperature of about 6–7 °C and annual precipitation of approximately 600–700 mm, much of which falls during the warm season. Administrative districts were used as the basic spatial units for statistical analysis. Previous land-resource and regional studies indicate pronounced contrasts among agricultural areas, forest complexes, soil-cover conditions, and built-up zones in the Minsk Region [*Chernysh and Chervan*, 2020; *Chervan and Romanova*, 2021; *Kolmykov and Avdeev*, 2020, 2021; *Land Resources Register of the Republic of Belarus*, 2025].



(a) (b)

Figure 1. Land cover and administrative districts of the Minsk Region, Belarus: (a) land-cover distribution; (b) administrative districts.

The main remote-sensing data were Landsat 8 OLI/TIRS Collection 2 Level-2 products for 2016–2025 and Landsat 9 OLI-2/TIRS-2 Collection 2 Level-2 products from 2022 onward. These products provide atmospherically corrected surface reflectance and land-surface temperature data suitable for constructing the greenness, wetness, dryness, and heat components of RSEI. Landsat 8 and Landsat 9 data were used together because Collection 2 Level-2 products are processed within a consistent radiometric framework. Optical surface reflectance bands were scaled using the official Collection 2 scale factors and offsets, and the thermal band was converted to land-surface temperature in degrees Celsius.

For each year, images acquired from May to September were selected to represent growing-season ecological conditions. This seasonal window was used instead of a single fixed month because cloud contamination and uneven image availability in humid temperate regions can reduce spatial completeness and create unstable annual estimates. Pixels flagged as clouds, cloud shadows, cirrus, dilated clouds, and snow/ice in the QA_PIXEL band were masked. For each year, valid images were combined using a median composite. Pixels with fewer than three valid observations during the May–September period were excluded to reduce the influence of residual cloud contamination and incomplete annual coverage.

Administrative district boundaries were used for zonal statistics. Land-cover data were used to calculate the proportions of major land-cover classes, including forests, croplands, grasslands, wetlands, water bodies, artificial surfaces, and disturbed or transitional land within each district. These land-cover data were not used to construct RSEI directly, but served as contextual information for interpreting spatial patterns, district-level differences, and intra-district heterogeneity.

Ecological environment quality was evaluated using the Remote Sensing Ecological Index (RSEI) proposed by *Xu et al.* [2018, 2019]. Following the standard RSEI framework, four indicators were selected: greenness, wetness, dryness, and heat. Greenness was represented by the Normalized Difference Vegetation Index (NDVI):

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}},$$

where ρ_{NIR} and ρ_{Red} are the surface reflectance values of the near-infrared and red bands, respectively.

Wetness was derived from the tasseled-cap wetness component for Landsat 8 OLI and Landsat 9 OLI-2 surface reflectance data:

$$\mathrm{WET} = 0.1511\rho_{\mathrm{Blue}} + 0.1973\rho_{\mathrm{Green}} + 0.3283\rho_{\mathrm{Red}} + 0.3407\rho_{\mathrm{NIR}} - 0.7117\rho_{\mathrm{SWIR1}} - 0.4559\rho_{\mathrm{SWIR2}}.$$

Dryness was represented by the Normalized Difference Built-up and Soil Index (NDBSI), calculated as the average of the Soil Index (SI) and the Index-based Built-up Index (IBI):

$$\mathrm{NDBSI} = \frac{\mathrm{SI} + \mathrm{IBI}}{2}.$$

Heat was represented by land surface temperature (LST) derived from the thermal infrared information in Landsat Collection 2 Level-2 products. Together, NDVI, WET, NDBSI, and LST characterize vegetation condition, surface moisture, exposed or built-up surfaces, land-use intensity, and thermal environment.

To make the indicators comparable, NDVI, WET, NDBSI, and LST were normalized to the range 0–1 using min–max scaling:

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}},$$

where X_i is the original value of a given indicator, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of that indicator in the study area for a given year, and X_i' is the normalized value.

Principal component analysis (PCA) was applied to the four normalized indicators separately for each annual May–September composite. The first principal component (PC1), which explained the largest proportion of total variance, was used as the basis for RSEI construction. Because the sign of PC1 is mathematically arbitrary, the ecological direction of PC1 was checked for each year. Higher NDVI and WET values were interpreted as better ecological conditions, whereas higher NDBSI and LST values represented stronger dryness, exposed or built-up surfaces, and thermal stress. When the PC1 loadings were opposite to this expected direction, PC1 was multiplied by −1 before final normalization. The annual RSEI was then calculated as:

$$\mathrm{RSEI} = \frac{\mathrm{PC1}_{\mathrm{adj}} - \mathrm{PC1}_{\mathrm{adj,min}}}{\mathrm{PC1}_{\mathrm{adj,max}} - \mathrm{PC1}_{\mathrm{adj,min}}},$$

where $\mathrm{PC1}_{\mathrm{adj}}$ is the direction-adjusted first principal component, and $\mathrm{PC1}_{\mathrm{adj,min}}$ and $\mathrm{PC1}_{\mathrm{adj,max}}$ are its minimum and maximum values in the study area for a given year. Annual PCA loadings and variance contributions were examined to confirm whether PC1 consistently represented a meaningful ecological gradient.

Annual RSEI maps were generated for 2016–2025. The values therefore represent growing-season ecological conditions rather than single-date observations or full calendar-year averages. To improve consistency, the same seasonal window, data source, quality-masking procedure, indicator formulas, normalization strategy, PCA workflow, PC1 orientation rule, and final rescaling procedure were applied to all years.

District-level statistics were calculated by aggregating pixel-based RSEI values within administrative boundaries. Mean RSEI was used to characterize average ecological environment quality, whereas the spatial standard deviation of RSEI was used as an indicator of intra-district heterogeneity. Temporal tendencies were assessed using linear regression of annual mean RSEI values for each district:

$$\overline{\mathrm{RSEI}}_{d,t} = \alpha_d + \beta_d t + \varepsilon_{d,t},$$

where $\overline{\mathrm{RSEI}}_{d,t}$ is the mean RSEI of district d in year t, α_d is the intercept, β_d is the annual RSEI trend slope, and $\varepsilon_{d,t}$ is the residual term. Given the relatively short ten-year period, these slopes were interpreted as descriptive temporal tendencies rather than definitive evidence of long-term ecological change.

Land-cover composition was used to support interpretation of the RSEI patterns. The proportions of major land-cover classes were compared with district-level mean RSEI, intra-district RSEI standard deviation, and temporal trend slopes. Spearman correlation analysis was used to evaluate associations between land-cover composition and RSEI metrics. The reliability and regional interpretability of the results were assessed from three perspectives: ecological consistency of PCA loadings, spatial plausibility of RSEI patterns in relation to land cover, and agreement with previous Belarusian and regional studies on land resources, anthropogenic pressure, agricultural land dynamics, soil-cover structure, and ecological development [*Chernysh and Chervan*, 2020; *Chervan and Romanova*, 2021; *Dubianok et al.*, 2022; *Kolmykov and Avdeev*, 2020, 2021; *Loginov and Struk*, 2009; *Pirozhnik et al.*, 2009; *Sokolov*, 2017; *Vitchenko et al.*, 2009]. The overall workflow is summarized in Figure 2, and the annual RSEI map series for 2016–2025 is shown in Figure 3.

3. Results

The annual PCA results confirmed the ecological consistency of RSEI construction during 2016–2025 (Table 1). PC1 explained 75.42–87.72 % of the total variance, indicating that the first component captured the dominant ecological gradient in all years. After sign adjustment, NDVI and WET contributed positively to the final RSEI, whereas NDBSI and LST contributed negatively. Therefore, higher RSEI values consistently indicated better ecological environment quality. Since the index was derived from growing-season composites and normalized within the study area, RSEI should be interpreted as a relative indicator of ecological conditions in the Minsk Region rather than an absolute environmental quality score.

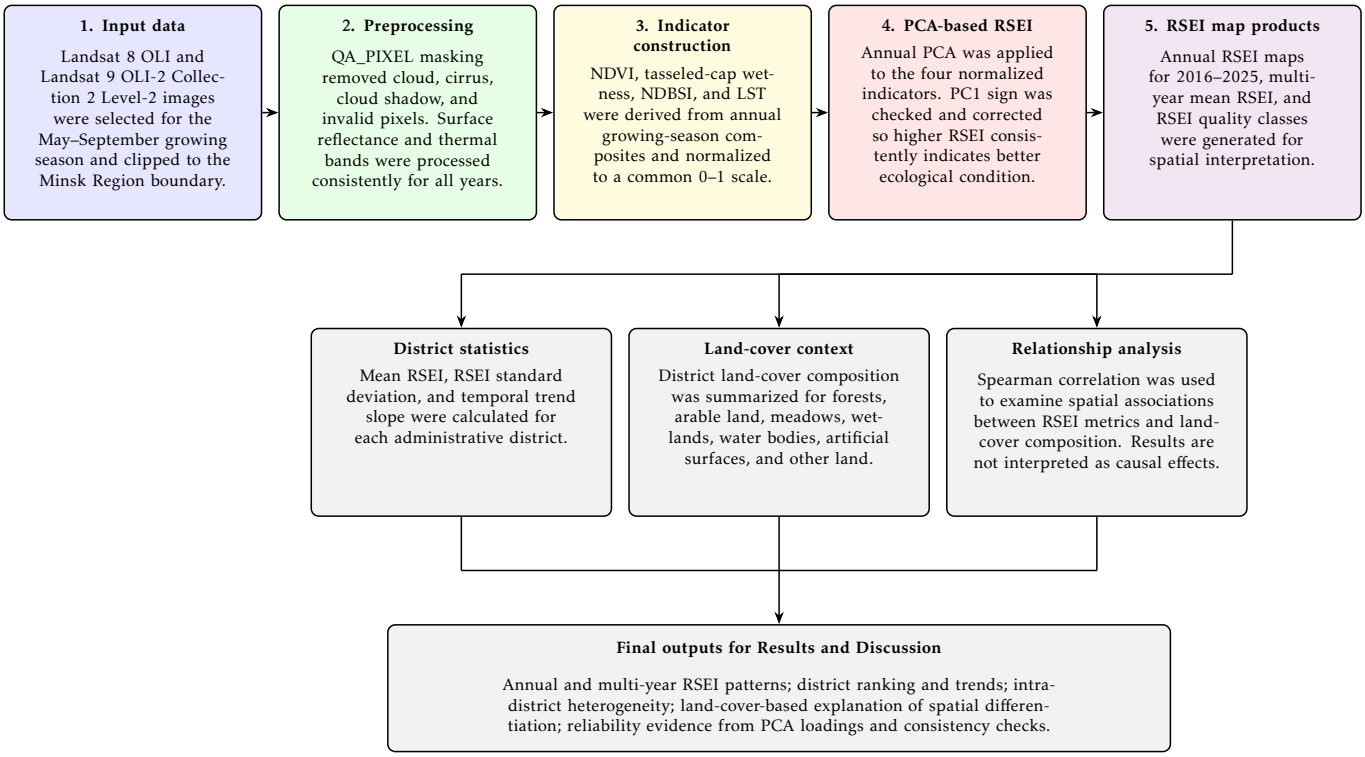


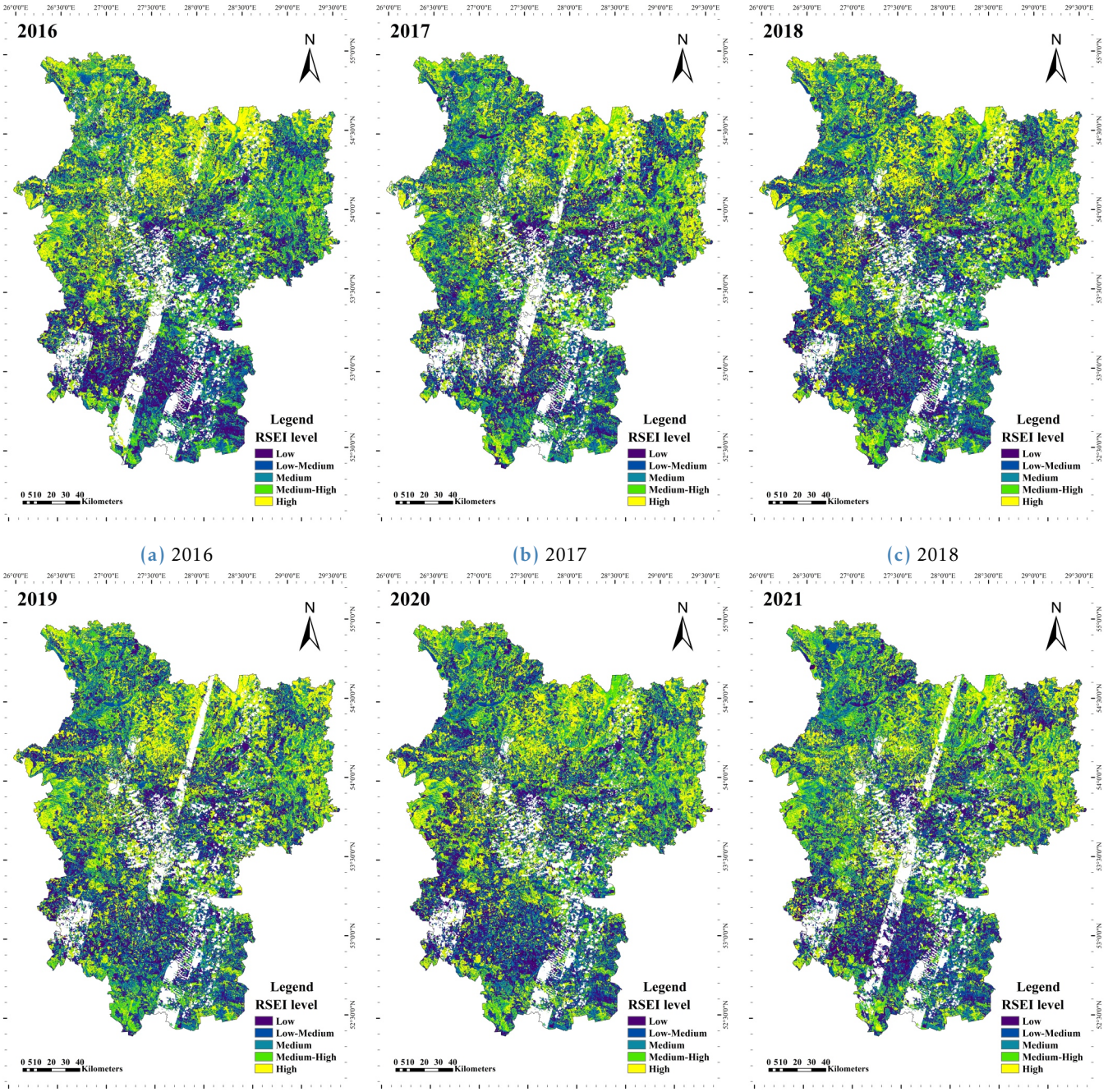
Figure 2. Workflow of data processing, RSEI construction, and spatiotemporal analysis in this study. Study area: Minsk Region, Belarus. Data: Landsat 8/9 Collection 2 Level-2, 2016–2025.

Table 1. Annual PCA loadings and variance contribution of PC1 used for RSEI construction, 2016–2025

Year	Raw images	NDVI loading	WET loading	NDBSI loading	LST loading	PC1 variance explained (%)	Sign adjusted
2016	100	0.357	0.604	−0.587	−0.405	79.34	Yes
2017	92	0.302	0.496	−0.712	−0.395	75.42	Yes
2018	103	0.355	0.550	−0.683	−0.323	84.22	Yes
2019	110	0.274	0.571	−0.701	−0.328	85.02	Yes
2020	103	0.299	0.521	−0.734	−0.317	81.71	Yes
2021	97	0.382	0.537	−0.716	−0.232	83.93	Yes
2022	203	0.301	0.539	−0.743	−0.259	85.14	Yes
2023	219	0.358	0.524	−0.646	−0.424	84.70	Yes
2024	221	0.375	0.543	−0.698	−0.277	87.72	Yes
2025	190	0.327	0.555	−0.721	−0.256	82.30	Yes

Annual RSEI maps revealed clear spatial differentiation in ecological environment quality across the Minsk Region (Figure 3). Relatively high RSEI values were mainly distributed in the northern, northeastern, and northwestern parts of the region, where forest complexes, lake–wetland systems, and less intensively transformed landscapes are common. Lower values occurred more frequently in central and southern agricultural districts and in areas affected by urbanization, transport infrastructure, and intensive land use. This pattern indicates that RSEI distribution was closely linked to the regional landscape mosaic and land-cover composition.

At the district level, mean RSEI values for 2016–2025 ranged from 0.539 to 0.682 (Table 2). The highest values occurred in Logoisk, Myadel, Borisov, and Krupki, whereas



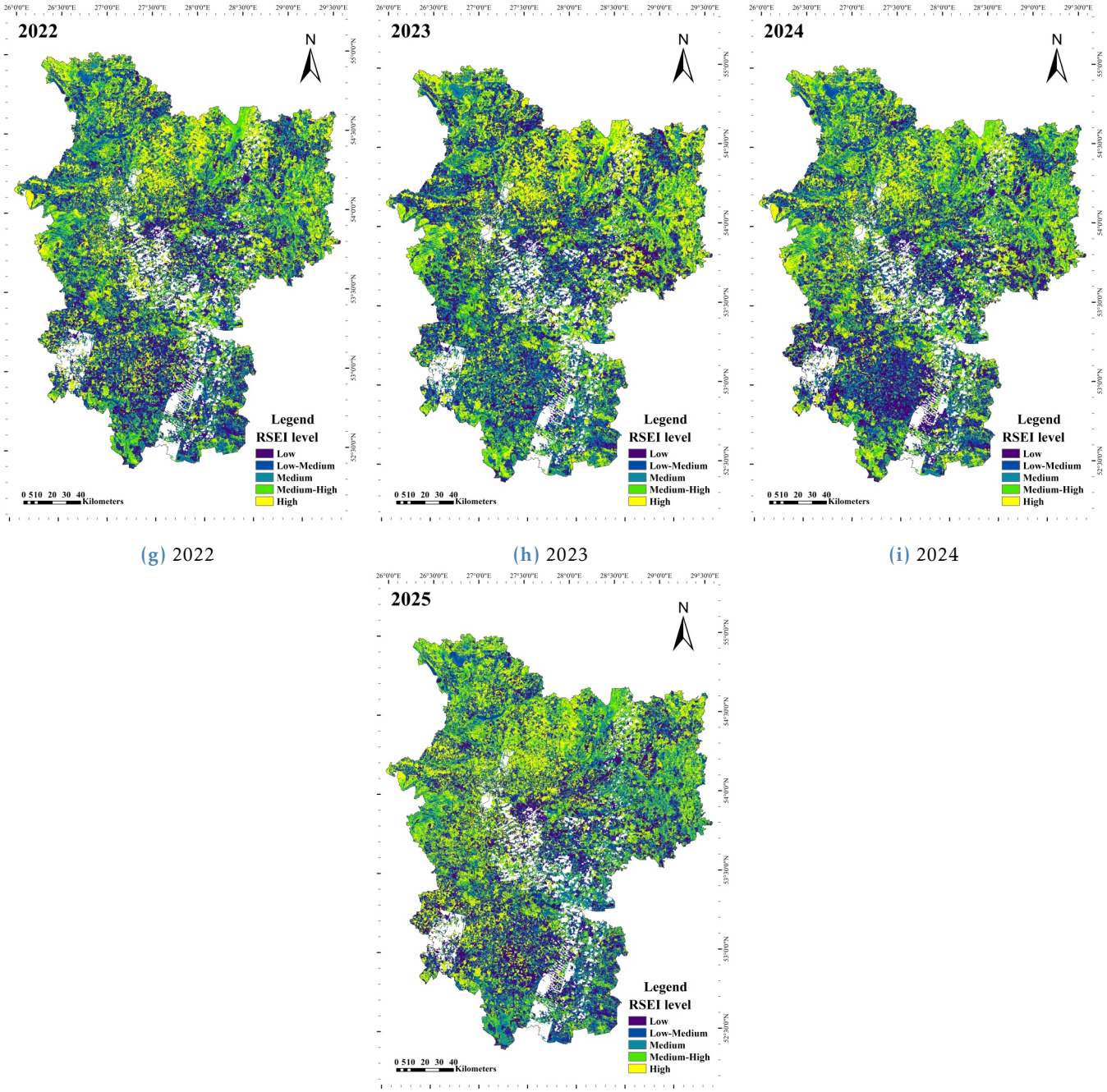
(a) 2016 (b) 2017 (c) 2018

(d) 2019 (e) 2020 (f) 2021

Figure 3. Spatial distribution of annual Remote Sensing Ecological Index (RSEI) values in the Minsk Region during 2016–2025 (part 1/2).

the lowest values were found in Slutsk, Nesvizh, and Kopyl. These contrasts correspond to the regional transition from more forested and semi-natural northern landscapes to more agriculturally transformed southern districts. The ten-year mean pattern shown in Figure 4 confirms that this spatial hierarchy remained broadly stable despite interannual variation.

Intra-district spatial heterogeneity, represented by the mean annual standard deviation of RSEI, also varied substantially among districts. Higher heterogeneity was observed in Nesvizh, Slutsk, Minsk, Kopyl, and Smolevichi, whereas lower values occurred in Myadel, Logoisk, Krupki, and Vileyka. This result shows that mean RSEI alone does not fully characterize district-level ecological environment quality, because districts with similar average values may differ strongly in internal spatial structure. Temporal trend slopes



(g) 2022 (h) 2023 (i) 2024

(j) 2025

Figure 3. (continued) Spatial distribution of annual Remote Sensing Ecological Index (RSEI) values in the Minsk Region during 2016–2025 (part 2/2).

included both positive and negative values, but their magnitudes were generally small. The slopes were therefore interpreted as descriptive tendencies rather than statistically confirmed evidence of ecological degradation or improvement.

Land-cover composition provided the main context for interpreting district-level RSEI differences (Table 3). Districts with higher mean RSEI generally had larger forest proportions and lower cropland coverage. Logoisk, Krupki, and Borisov combined high forest coverage with high RSEI values, whereas Myadel showed high RSEI under a semi-natural structure with low cropland and relatively large wetland and water areas. In contrast, Nesvizh, Slutsk, and Kopyl had high cropland proportions and lower mean RSEI values. However, land-cover composition did not explain all variation. Starodorozhsky, for

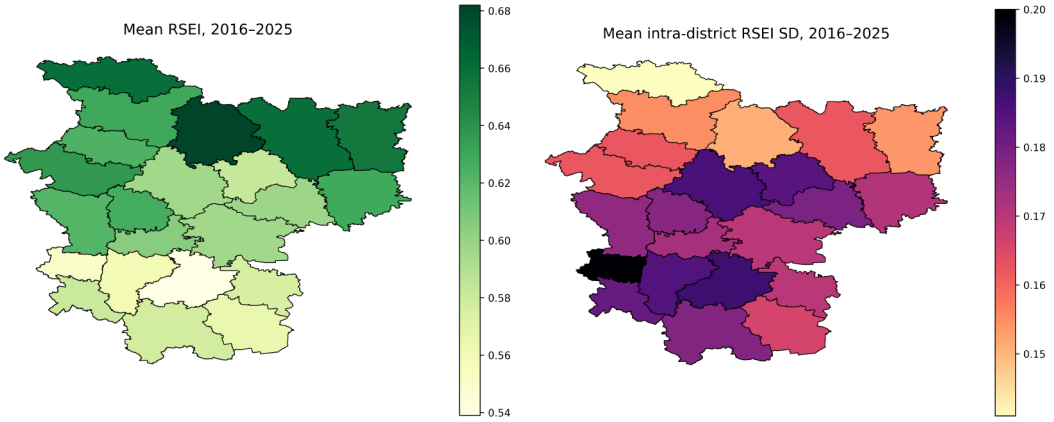


Figure 4. District-level ecological environment quality in the Minsk Region during 2016–2025: (a) mean RSEI; (b) mean intra-district RSEI standard deviation.

example, had high forest coverage but relatively low mean RSEI, suggesting that vegetation condition, soil moisture, land management, patch configuration, and interannual variability also affected district-level RSEI. Therefore, these relationships should be interpreted as spatial associations rather than deterministic causal mechanisms.

Table 2. District-level RSEI statistics and temporal trends in the Minsk Region from 2016 to 2025

District	Mean RSEI 2016–2025	Mean RSEI SD 2016–2025	RSEI trend slope per year	Min annual RSEI mean	Max annual RSEI mean
Berezino	0.629	0.171	−0.0017	0.591	0.654
Borisov	0.660	0.162	−0.0047	0.613	0.710
Cherven	0.598	0.179	−0.0040	0.568	0.640
Dzerzhinsk	0.627	0.177	−0.0016	0.596	0.669
Kletsk	0.581	0.182	0.0012	0.536	0.642
Kopyl	0.560	0.185	0.0042	0.505	0.616
Krupki	0.654	0.154	−0.0017	0.600	0.682
Logoisk	0.682	0.151	−0.0032	0.632	0.730
Luban	0.565	0.166	0.0020	0.536	0.613
Minsk	0.596	0.186	−0.0016	0.555	0.638
Molodechno	0.624	0.162	0.0001	0.580	0.678
Myadel	0.660	0.141	−0.0024	0.608	0.704
Nesvizh	0.551	0.200	−0.0003	0.511	0.600
Puchowichi	0.597	0.170	−0.0025	0.561	0.619
Slutsk	0.539	0.188	0.0019	0.478	0.594
Smolevichi	0.583	0.184	−0.0031	0.548	0.631
Soligorsk	0.577	0.178	−0.0007	0.528	0.623
Starodorozhsky	0.576	0.170	0.0015	0.532	0.636
Stolbtsy	0.622	0.176	−0.0017	0.589	0.669
Uzda	0.605	0.173	−0.0028	0.565	0.642
Vileyka	0.630	0.155	−0.0015	0.580	0.677
Volozhin	0.637	0.162	−0.0013	0.607	0.685

Note: Mean RSEI represents the average annual district-level RSEI value from 2016 to 2025. Mean RSEI SD represents the average intra-district standard deviation of RSEI and is used as an indicator of spatial heterogeneity. The RSEI trend slope was calculated from a linear regression of annual mean RSEI against year and is expressed in RSEI units per year.

Table 3. District-level land-cover composition within the mapped classified area in the Minsk Region

District	Artificial (%)	Cropland (%)	Grassland (%)	Forest (%)	Wetlands (%)	Water (%)	Other (%)	Shannon H
Berezino	3.77	24.77	8.71	58.33	0.54	0.71	3.17	1.169
Borisov	4.64	20.88	10.04	52.56	3.38	0.84	7.67	1.390
Cherven	4.38	35.30	11.34	45.73	0.19	1.43	1.63	1.249
Dzerzhinsk	7.91	41.71	10.14	35.14	0.46	0.53	4.11	1.349
Kletsk	5.84	45.82	16.62	24.47	0.68	1.35	5.22	1.412
Kopyl	6.18	51.58	17.55	18.81	0.88	2.02	2.97	1.358
Krupki	3.53	23.27	9.87	56.44	0.58	1.29	5.01	1.245
Logoisk	4.98	22.94	8.39	56.43	0.41	0.40	6.46	1.239
Luban	4.96	37.90	9.89	41.60	0.57	2.11	2.98	1.326
Minsk	10.58	38.46	9.23	31.13	0.82	2.33	7.46	1.509
Molodechno	8.86	35.18	13.82	34.50	0.52	0.77	6.35	1.463
Myadel	4.14	16.09	19.79	41.15	6.77	7.86	4.20	1.627
Nesvizh	8.24	59.88	14.80	10.74	0.73	0.85	4.77	1.256
Puchowichi	5.20	28.47	12.26	42.87	3.00	1.00	7.20	1.472
Slutsk	6.42	49.43	15.74	22.89	0.95	0.89	3.68	1.361
Smolevichi	9.13	38.53	7.62	38.16	0.58	1.32	4.67	1.380
Soligorsk	4.56	31.66	15.50	33.20	3.10	2.10	9.87	1.578
Starodorozhsky	4.36	22.67	14.05	52.66	2.26	0.97	3.03	1.323
Stolbtsy	5.02	27.69	11.85	50.52	0.54	0.69	3.67	1.288
Uzda	5.34	33.93	14.08	42.70	0.64	0.76	2.56	1.326
Vileyka	4.55	23.27	13.74	47.86	1.20	3.30	6.08	1.441
Volozhin	6.56	31.78	12.25	41.54	0.94	0.34	6.59	1.408

Note: Percentages use the sum of the eight source land-cover class areas within each district as the denominator. Bare/disturbed land and shrub/transitional vegetation are combined as Other. H is calculated from the seven unrounded class fractions using natural logarithms. Displayed percentages may differ slightly from 100% because of rounding.

The relationships between land-cover composition and RSEI metrics are visualized in Figure 5 and quantified in Table 4. Forest proportion was positively correlated with mean RSEI, whereas cropland proportion showed a stronger negative correlation. The forest–cropland balance had the strongest positive relationship with mean RSEI, confirming that the main district-level gradient was structured by the contrast between forested and cultivated landscapes. Artificial surface proportion was negatively but not significantly related to mean RSEI, indicating that urbanized land did not dominate the district-wide average pattern at this spatial scale.

The correlation results also showed that land-cover composition was more strongly related to intra-district RSEI heterogeneity than to mean RSEI. Cropland proportion was strongly positively correlated with mean intra-district RSEI standard deviation, whereas forest proportion showed a negative relationship. Artificial surface proportion was also positively correlated with heterogeneity, while the Shannon land-cover diversity index was not significant. This indicates that internal ecological contrast was controlled less by overall land-cover diversity than by the dominance of specific land-cover types, especially cropland, forest, and artificial surfaces. Associations between land-cover composition and temporal RSEI trends were weaker and should be interpreted cautiously because they were based on a ten-year annual series and do not imply direct causal effects.

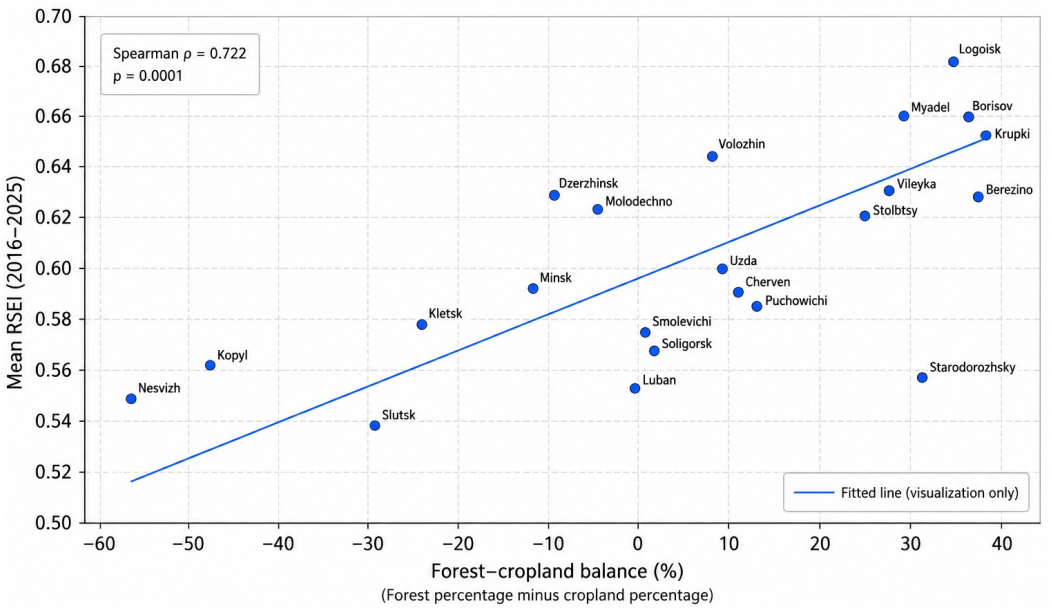


Figure 5. Relationship between forest–cropland balance and district-level mean RSEI in the Minsk Region during 2016–2025.

Table 4. Spearman correlations between land-cover composition and district-level RSEI metrics

Variable X	Variable Y	Spearman's ρ	p-value	Significance
Forest percentage	Mean RSEI, 2016–2025	0.659	0.0009	***
Cropland percentage	Mean RSEI, 2016–2025	−0.712	0.0002	***
Artificial surface percentage	Mean RSEI, 2016–2025	−0.350	0.1108	ns
Wetland percentage	Mean RSEI, 2016–2025	−0.112	0.6184	ns
Water percentage	Mean RSEI, 2016–2025	−0.313	0.1556	ns
Other disturbed/transitional land percentage	Mean RSEI, 2016–2025	0.336	0.1262	ns
Forest–cropland balance	Mean RSEI, 2016–2025	0.722	0.0001	***
Forest percentage	Mean intra-district RSEI SD, 2016–2025	−0.675	0.0006	***
Cropland percentage	Mean intra-district RSEI SD, 2016–2025	0.837	< 0.0001	***
Artificial surface percentage	Mean intra-district RSEI SD, 2016–2025	0.540	0.0094	**
Land-cover diversity index	Mean intra-district RSEI SD, 2016–2025	−0.042	0.8516	ns
Forest percentage	RSEI trend slope, 2016–2025	−0.525	0.0122	*
Cropland percentage	RSEI trend slope, 2016–2025	0.474	0.0257	*
Artificial surface percentage	RSEI trend slope, 2016–2025	0.244	0.2728	ns

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ns = not significant. "Mean intra-district RSEI SD" represents spatial heterogeneity within districts, not interannual variability.

4. Discussion

The spatial differentiation of ecological environment quality in the Minsk Region was mainly associated with land-cover structure. Higher RSEI values were concentrated in

northern, northeastern, and northwestern districts with larger forest, wetland, or semi-natural components, whereas lower values occurred more often in southern agricultural districts. This pattern indicates that district-level ecological environment quality was structured primarily by the forest–cropland balance rather than by administrative location alone. The positive association between forest proportion and mean RSEI and the negative association between cropland proportion and mean RSEI are ecologically plausible, because forests usually maintain more stable vegetation cover, higher moisture conditions, and weaker thermal stress, while croplands show stronger seasonal vegetation dynamics and periodic soil exposure. These relationships, however, should be interpreted as spatial associations rather than direct causal effects.

A central result is the distinction between average ecological environment quality and intra-district spatial heterogeneity. Nesvizh, Slutsk, Kopyl, Minsk, and Smolevichi showed relatively high RSEI variability, indicating strong internal contrasts in land-surface ecological conditions, whereas forest-dominated districts such as Myadel, Logoisk, Krupki, and Vileyka were more spatially homogeneous. Cropland proportion was strongly positively correlated with intra-district RSEI standard deviation, while forest proportion showed a negative relationship. Artificial surfaces also contributed to heterogeneity, although their relationship with mean RSEI was weaker. The non-significant relationship between Shannon land-cover diversity and RSEI heterogeneity suggests that internal ecological contrast was controlled less by overall land-cover diversity than by the dominance of specific land-cover types, especially cropland, forest, and artificial surfaces.

Temporal trends in district-level RSEI during 2016–2025 were weak and spatially differentiated. Negative slopes were more common than positive slopes, but their magnitude was small. Therefore, the results should not be interpreted as evidence of strong regional ecological degradation. In forest-dominated districts, negative slopes may reflect interannual variation in vegetation condition, moisture availability, thermal conditions, or image-composite characteristics rather than direct forest degradation. Likewise, slight positive slopes in agriculturally dominated districts should not be interpreted as confirmed ecological restoration, because annual RSEI in cropland landscapes is sensitive to crop phenology, soil exposure, management timing, and seasonal weather conditions.

The administrative-unit application of RSEI provides a practical framework for comparing ecological environment quality, internal heterogeneity, and temporal tendencies across districts. However, RSEI remains a remote-sensing-based proxy of land-surface ecological condition, not a complete measure of ecosystem health. It does not directly quantify biodiversity, soil contamination, water quality, ecosystem services, or below-ground processes. District-level correlations are also affected by aggregation and should not be transferred directly to pixel-level or causal interpretations. In addition, annual RSEI values in this study represent May–September growing-season conditions, and annual PCA with min–max normalization makes the index relative to the study area and year-specific data distribution. Landsat spatial resolution may miss small landscape elements and fine urban–rural transitions, while ten-year trend slopes cannot be formally attributed to climatic, land-management, or socio-economic drivers. Future research should integrate longer time series, climatic and land-management data, soil and biodiversity information, and field observations.

5. Conclusions

This study assessed district-level spatiotemporal patterns and spatial heterogeneity of ecological environment quality in the Minsk Region, Belarus, using Landsat 8/9 growing-season composites and RSEI for 2016–2025. PCA results supported the ecological consistency of RSEI construction: PC1 explained 75.42–87.72 % of total variance, with positive contributions from NDVI and WET and negative contributions from NDBSI and LST.

The results showed clear spatial differentiation among districts. Mean RSEI values ranged from 0.539 to 0.682, with higher values generally occurring in forest-dominated

and semi-natural northern districts and lower values in more agriculturally transformed southern districts. Intra-district heterogeneity also varied substantially, with mean RSEI standard deviation ranging from 0.141 to 0.200, confirming that average RSEI alone is insufficient for characterizing district-level ecological environment quality.

Land-cover composition was closely associated with RSEI patterns. Forest proportion was positively correlated with mean RSEI, whereas cropland proportion was negatively correlated with mean RSEI and positively correlated with intra-district RSEI heterogeneity. Temporal trends were generally weak and should be interpreted as descriptive tendencies rather than definitive evidence of ecological degradation or improvement. Overall, combining RSEI with administrative-unit analysis and land-cover interpretation can support regional geoecological assessment in mixed temperate landscapes.

AI Use Statement. During the preparation of this work we used ChatGPT (OpenAI) and Gemini (Google) for English language editing and bibliographic formatting during manuscript preparation. We did not adequately verify the bibliographic output before submission. We apologize for this oversight and accept responsibility for the errors. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

An M., Xie P., He W., et al. Spatiotemporal change of ecologic environment quality and human interaction factors in three gorges ecologic economic corridor, based on RSEI // Ecological Indicators. — 2022. — Vol. 141. — P. 109090. — https://doi.org/10.1016/j.ecolind.2022.109090

Chen N., Cheng G., Yang J., et al. Evaluation of urban ecological environment quality based on improved RSEI and driving factors analysis // Sustainability. — 2023. — Vol. 15, no. 11. — P. 8464. — https://doi.org/10.3390/su15118464

Chernysh A. F. and Chervan A. N. Erosion-prone agrolandscapes of Belarus: soil erosion control and territorial land-use planning // Erosion and Channel Processes. Collection of Scientific Papers. Issue 7. — Moscow : Moscow State University Publ., 2020. — P. 338–356. — (In Russian).

Chervan A. N. and Romanova M. L. Territorial planning of the use of meadow ecosystems on the example of the Pripyatsky Polesie using materials of multi-temporal space imaging // Regional systems of complex remote sensing of agrolandscapes: Proceedings of the III All-Russian Scientific and Practical Seminar. — Krasnoyarsk, 2021. — P. 26–31. — https://doi.org/10.52686/9785604524923_26 — (In Russian).

Dubianok S. A., Kulakou A. Y. and Kononchuk T. P. Methodology for developing and ranking the environmental development of the regions of the Republic of Belarus // Journal of the Belarusian State University. Ecology. — 2022. — No. 1. — P. 14–24. — https://doi.org/10.46646/2521-683x/2022-1-14-24 — (In Russian).

Gan X., Du X., Duan C., et al. Evaluation of ecological environment quality and analysis of influencing factors in Wuhan City based on RSEI // Sustainability. — 2024. — Vol. 16, no. 13. — P. 5809. — https://doi.org/10.3390/su16135809

Gao P., Kasimu A., Zhao Y., et al. Evaluation of the temporal and spatial changes of ecological quality in the Hami Oasis based on RSEI // Sustainability. — 2020. — Vol. 12, no. 18. — P. 7716. — https://doi.org/10.3390/su12187716

Geng J., Yu K., Xie Z., et al. Analysis of spatiotemporal variation and drivers of ecological quality in Fuzhou based on RSEI // Remote Sensing. — 2022. — Vol. 14, no. 19. — P. 4900. — https://doi.org/10.3390/rs14194900

Gong C., Lyu F. and Wang Y. Spatiotemporal change and drivers of ecosystem quality in the Loess Plateau based on RSEI: A case study of Shanxi, China // Ecological Indicators. — 2023. — Vol. 155. — P. 111060. — https://doi.org/10.1016/j.ecolind.2023.111060

Kolmykov A. V. and Avdeev A. N. Assessment of anthropogenic load on the territory of the Minsk Region of the Republic of Belarus // International Journal of Applied Sciences and Technology Integral. — 2020. — https://doi.org/10.24411/2658-3569-2020-10075 — (In Russian).

Kolmykov A. V. and Avdeev A. N. Production and soil-agroclimatic potential of agricultural organizations in Minsk Region // Bulletin of the Belarusian State Agricultural Academy. — 2021. — No. 3. — P. 191–200. — (In Russian).

Land Resources Register of the Republic of Belarus. — 2025. — URL: https://gki.gov.by/ru/activity_branches-land-reestr/ (visited on 01/01/2026).

Liu Y., Dang C., Yue H., et al. Comparison between modified remote sensing ecological index and RSEI // National Remote Sensing Bulletin. — 2022. — Vol. 26, no. 4. — P. 683–697. — https://doi.org/10.11834/jrs.20229338

Liu Y., Xu W., Hong Z., et al. Integrating three-dimensional greenness into RSEI improved the scientificity of ecological environment quality assessment for forest // Ecological Indicators. — 2023. — Vol. 156. — P. 111092. — https://doi.org/10.1016/j.ecolind.2023.111092

Loginov V. F. and Struk M. I. Environmental problems of regional development in Belarus // Izvestiya Rossiiskoi Akademii Nauk. Seriya Geograficheskaya. — 2009. — No. 3. — P. 24–36. — (In Russian).

Luo Z., Chai B. and Wang W. An improved RSEI-based evaluation for effective forest area by integrating forest structure and quality // Frontiers in Environmental Science. — 2025. — Vol. 13. — P. 1580169. — https://doi.org/10.3389/fenvs.2025.1580169

Maimaitituersun A., Yang H., Aobuliaisan N., et al. Assessing subtle changes in arid land river basin ecological quality: A study utilizing the PIE engine platform and RSEI // Ecological Indicators. — 2025. — Vol. 170. — P. 113035. — https://doi.org/10.1016/j.ecolind.2024.113035

Ning L., Jiayao W. and Fen Q. The improvement of ecological environment index model RSEI // Arabian Journal of Geosciences. — 2020. — Vol. 13, no. 11. — P. 403. — https://doi.org/10.1007/s12517-020-05414-7

Pirozhnik I. I., Martsinkevich G. I., Vlasov B. P., et al. Integrated geographical research for ensuring sustainable development of Belarus // Bulletin of Belarusian State University. Series 2: Chemistry. Biology. Geography. — 2009. — No. 3. — P. 53–57. — (In Russian).

Sokolov A. S. Regional features of natural environment transformation of Belarus and geoecological zoning of it // Scientific Notes of V. I. Vernadsky Crimean Federal University. Geography. Geology. — 2017. — Vol. 3(69), no. 3–1. — P. 228–239. — (In Russian).

Vitchenko A. N., Vlasov B. P. and Martsinkevich G. I. Landscape-ecological research as an implementation of the sustainable development strategy of Belarus // Bulletin of Belarusian State University. Series 2: Chemistry. Biology. Geography. — 2009. — No. 1. — P. 81–88. — (In Russian).

Wang Z., Chen T., Zhu D., et al. RSEIFE: A new remote sensing ecological index for simulating the land surface eco-environment // Journal of Environmental Management. — 2023. — Vol. 326. — P. 116851. — https://doi.org/10.1016/j.jenvman.2022.116851

Xiong Y., Xu W., Lu N., et al. Assessment of spatial-temporal changes of ecological environment quality based on RSEI and GEE: A case study in Erhai Lake Basin, Yunnan province, China // Ecological Indicators. — 2021. — Vol. 125. — P. 107518. — https://doi.org/10.1016/j.ecolind.2021.107518

Xu H., Wang Y., Guan H., et al. Prediction of ecological effects of potential population and impervious surface increases using a remote sensing based ecological index (RSEI) // Ecological Indicators. — 2018. — Vol. 93. — P. 730–740. — https://doi.org/10.1016/j.ecolind.2018.05.055

Xu H., Wang Y., Guan H., et al. Detecting ecological changes with a remote sensing based ecological index (RSEI) produced time series and change vector analysis // Remote Sensing. — 2019. — Vol. 11, no. 20. — P. 2345. — https://doi.org/10.3390/rs11202345

Yang W., Zhou Y. and Li C. Assessment of Ecological Environment Quality in Rare Earth Mining Areas Based on Improved RSEI // Sustainability. — 2023. — Vol. 15, no. 4. — P. 2964. — https://doi.org/10.3390/su15042964

Yang X., Meng F., Fu P., et al. Time-frequency optimization of RSEI: A case study of Yangtze River Basin // Ecological Indicators. — 2022. — Vol. 141. — P. 109080. — https://doi.org/10.1016/j.ecolind.2022.109080

Yuan B., Fu L., Zou Y., et al. Spatiotemporal change detection of ecological quality and the associated affecting factors in Dongting Lake Basin, based on RSEI // Journal of Cleaner Production. — 2021. — Vol. 302. — P. 126995. — https://doi.org/10.1016/j.jclepro.2021.126995

Zhang Y., She J., Long X., et al. Spatio-temporal evolution and driving factors of eco-environmental quality based on RSEI in Chang-Zhu-Tan metropolitan circle, central China // Ecological Indicators. — 2022. — Vol. 144. — P. 109436. — https://doi.org/10.1016/j.ecolind.2022.109436

Zheng Z., Wu Z., Chen Y., et al. Instability of remote sensing based ecological index (RSEI) and its improvement for time series analysis // Science of The Total Environment. — 2022. — Vol. 814. — P. 152595. — https://doi.org/10.1016/j.scitotenv.2021.152595