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Research article

Comprehensive comparison of two models evaluating eco-environmental quality in Fangshan

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A R T I C L E I N F O

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A B S T R A C T

It is crucial to employ scientifically sound models for assessing the quality of the ecological environment and revealing the strengths and weaknesses of ecosystems. This process is vital for identifying regional ecological and environmental issues and devising relevant protective measures. Among the widely acknowledged models for evaluating ecological quality, the ecological index (EI) and remote sensing ecological index (RSEI) stand out; however, there is a notable gap in the literature discussing their differences, characteristics, and reasons for selecting either model. In this study, we focused on Fangshan District, Beijing, China, to examine the differences between the two models from 2017 to 2021. We summarized the variations in evaluation indices, importance, quantitative methods, and data acquisition times, proposing application scenarios for both models. The results indicate that the ecological environment quality in Fangshan District, Beijing, remained favorable from 2017 to 2021. There was a discernible trend of initially declining quality followed by subsequent improvement. The variation in the calculation results is evident in the overall correlation between the RSEI and EI. Particularly noteworthy is the significantly smaller correlation between EI and the RSEI in 2021 than in the other two years. This discrepancy is attributed to shifts in the contribution of the evaluation indices within the RSEI model. The use of diverse quantitative methods for evaluating indicators has resulted in several variations. Notably, the evaluation outcomes of the EI model exhibit a stronger correlation with land cover types. This correlation contributes to a more pronounced fluctuation in RSEI levels from 2017 to 2021, with the EI model's evaluation results in 2019 notably surpassing those of the RSEI model. Ultimately, the most prominent disparities lie in the calculation results for water areas and construction land. The substantial difference in water areas is attributed to the distinct importance assigned to evaluation indicators between the two models. Moreover, the notable difference in construction land arises from the use of different quantification methods for evaluation indicators. In general, the EI model has suggested to be more comprehensive and effectively captures the annual comprehensive status of the ecological environment and the multiyear change characteristics of the administrative region. On the other hand, RSEI models exhibit greater flexibility and ease of implementation, independent of spatial and temporal scales. These findings contribute to a clearer understanding of the models' advantages and limitations, offering guidance for decision makers and valuable insights for the improvement and development of ecological environmental quality evaluation models.

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1. Introduction

The evaluation of eco-environmental quality (EEQ) assesses the nature of the ecological environment and the results of the state of change in the eco-environment according to the specific requirements of human beings within a specific time and space [1] to reflect the degree of eco-environmental advantages and disadvantages at the ecosystem level. EEQ is crucial for understanding present conditions [2,3], identifying potential issues [4], and devising conservation measures [5].

The assessment of EEQ involves a holistic and complex process encompassing multiple disciplines, scales, and elements with a diverse range of assessment objectives. At present, some research concentrates on the overall ecological quality of watersheds [6–8], urban conglomerates [9], and cities [10], typically considering factors such as natural conditions, infrastructure, socioeconomic elements, and cultural aspects [11]. Another segment of study has focused on specific ecosystems, such as forests [12], wetlands [13], rangelands [14], wetlands [15] and rivers [16], characterizing environmental quality through the monitoring of habitat conditions and biological growth statuses [17,18]. However, this approach results in disparate evaluation criteria, posing challenges in comparing and analyzing results across studies. These challenges impede the establishment of widely applicable reference points and hinder the connection between evaluation outcomes and broadly applicable environmental protection strategies.

To standardize the assessment of EEQ on a national scale and to comprehensively analyze the ecological environmental conditions and dynamic patterns, the Ministry of Ecology and Environment of the People's Republic of China (MOE) promulgated a version of the Technical Criterion for Ecosystem Status Evaluation (trial implementation) in 2006, which was revised for the first time in 2015, to evaluate regional EEQ by the ecological index (EI) [19]. Since the release of the Technical Criterion, the EI has become one of the key indicators for assessing the quality of the ecological environment and is publicly released annually through the Ecological Environment Status Bulletin [20]. However, the EI model only proposes evaluation methods for municipal and above administrative areas, and the needed data are more numerous and difficult to obtain, causing many difficulties in obtaining the ecological environment quality of the study area quickly and hindering its widespread use in academic research.

To address the deficiencies of existing assessment models, scholars have conducted intensive research focused on two objectives: creating a more scientifically sound and locally relevant assessment system and developing a more efficient and precise assessment method. In response to the above objectives, the remote sensing ecological index (RSEI) was proposed to determine the ecological status of the study area [21]. The RSEI has also become the mainstream method for assessing ecological environment quality at this stage, and many scholars have used the RSEI and improved models to assess the spatial and temporal characteristics of EEQ over many years [22–25]. As two of the most widely accepted EEQ assessment models applicable, both models have been extensively applied in research and practical projects. However, there has been a notable absence of research examining the distinctions between the principles of the two models and the consequent errors in calculation results. The characteristics and application scenarios of these models have not been fully elucidated, and naturally, the rationale behind choosing a particular model has not been elucidated. These gaps inevitably undermine the credibility of evaluation results, underscoring the need for our research to address these issues.

In attempting to explicate the disparities between the two models and their respective application contexts, it becomes apparent that ecological quality does not lend itself to quantification in the same manner as metrics such as rainfall or green volume. Unlike these measurable indicators, which yield precise values for assessing model accuracy, ecological quality lacks a definitive benchmark for determining proximity to the "true" environmental condition. Therefore, we undertake an innovative analysis of the underlying principles of each model to elucidate differences in their calculation results. Through this approach, we aim to highlight both the strengths and limitations of these models in practical settings and provide clarity on their suitable applications. The primary objective of our study is to establish a foundation for selecting the most suitable model for evaluating ecological environment quality while offering valuable insights to improve and advance such assessment methodologies. Specifically, our research compares the fluctuations in calculation results produced by the two models over time, both at a holistic level and concerning different land use categories. Furthermore, we utilize correlation analysis to explore the relationship between calculation outcomes and variance across various land

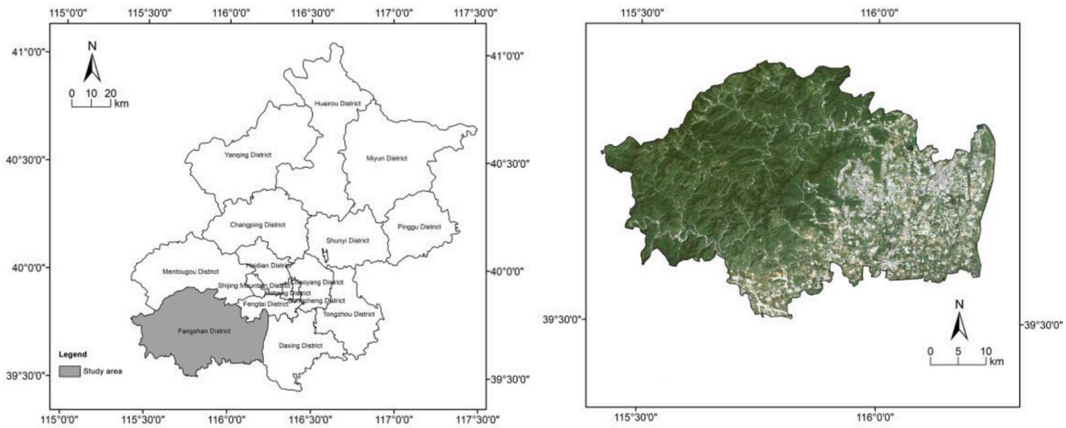

Fig. 1. Location of the study area.

use types. This allows us to discern patterns in variance concerning model indicators, quantification methods, data temporality, and delineate specific scenarios for model application.

2. Materials and methods

2.1. Study area

Fangshan District is situated in southwestern Beijing and ranges between 39°30′ and 39°55′ north latitude and 115°25′ and 116°15′ east longitude (Fig. 1). The district features a warm, mild, humid continental monsoon climate characterized by cold and dry winters and warm, rainy summers. Endowed with favorable natural conditions, Fangshan District boasts a total of 13 nature reserves [26].

The selection of Fangshan District as the research focus adheres to the principles of typicality and diversity. On the one hand, as a subordinate district of the city, Fangshan District represents the smallest research area where both the EI and RSEI models are applicable. Fangshan District also has the highest number of evaluation needs and objects, rendering it highly typical and significant for research. On the other hand, Fangshan District is positioned northwest of downtown Beijing and thus serves as an intermediate area between a highly developed zone and a forested area. This area encompasses urban, rural, and natural landscapes, and it features a diverse range of land use types and topographies, including plains, hills, and mountains. This diversity ensures a broad sample size for the study, facilitating a more comprehensive and equitable comparison of the calculations generated by various models.

2.2. Data acquisition

The data utilized in this research paper were processed as 10 m raster data through projection calibration and resampling. The data collection period for all the data was 2017~2021. Table 1 shows the specific data content and data sources used.

2.3. Method

Building upon the acknowledgment of spatial heterogeneity in EI, to further investigate the differences in their computed outcomes, graphical representations were generated for both models to follow up from the raster scale of the data. The method used in this study consists of three parts: EI modeling, RSEI modeling, and comparison of calculation results between the EI model and the RSEI model.

2.3.1. EI model

The EI model was developed with two primary objectives: (1) to assess the overall state of the eco-environment in the study area throughout the year and (2) to facilitate comparisons of ecological quality between different regions. To fulfill the first objective, the EI model considers the ecological background conditions by assessing the total amount of biology, vegetation resources, and the

Table 1
Data sources used in this study.

Data type	Model	Index	Source
Land cover data	EI (Ecological Index) model	AI (abundance index)	Sentinel-2 10 m land use/land cover time series of the world [27].
NDVI(normalized difference vegetation index) data		VCI (vegetation coverage index)	MOD13Q1 data by MODIS (https://modis.gsfc.nasa.gov/data/dataprod/mod13.php).
Water resources data		WNDI (water network density index)	Water Resources Bulletin of Fangshan District (https://www.bjfsh.gov.cn/zwgk/qswj/ywdt_1390/bmdt_1391/tjdc_1410/tjgb_1411/201909/P020190918638373343401.pdf; https://www.bjfsh.gov.cn/zwgk/qswj/ywdt_1390/bmdt_1391/tzgg_1405/202203/P020220322556960354826.pdf; https://www.bjfsh.gov.cn/zwgk/qswj/ywdt_1390/bmdt_1391/tzgg_1405/202301/P020230119362460386455.pdf).
Soil erosion data		LSI (Land stress index)	Soil and Water Conservation Bulletin of Beijing and Fangshan District (https://www.bjfsh.gov.cn/zwgk/qswj/ywdt_1390/bmdt_1391/tjdc_1410/tjgb_1411/201901/P020190102559845578868.pdf; https://swj.beijing.gov.cn/zwgk/stbcgb/202011/P020201119583946044001.pdf; https://www.bjfsh.gov.cn/zwgk/qswj/ywdt_1390/bmdt_1391/tzgg_1405/202212/P020221213366973316986.pdf).
Environmental quality data		PLI (pollution load index)	Beijing Fangshan Yearbook 2018–2022 (https://www.shujuku.org/fangshan-statistical-yearbook.html).
Landsat-8 Multispectral remote sensing image data	RSEI (remote sensing ecological index) model	Wet (wetness) NDVI LST (land surface temperature) NDBSI (normalized difference build-up and soil index)	United States Geological Survey (USGS, https://glovis.usgs). The data collection time was July 10, 2017, August 17, 2019, and September 7, 2021

abundance of water resources. Simultaneously, the degree of stress on the ecological environment can be gauged by examining the erosion of land resources, the extent of air pollution, and incidents of ecological degradation and environmental pollution. The specific calculation method is as follows [19]:

$$EI = 0.35 \times AI + 0.25 \times VCI + 0.15 \times WNDI + 0.15 \times (100\text{-}LSI) + 0.10 \times (100\text{-}PLI) + ELI \quad (1)$$

where the EI can range from 0 to 100, AI is the abundance index, VCI is the vegetation coverage index, WNDI is the water network density index, LSI is the land stress index, PLI is the pollution load index, and ELI is the environmental limitation index. Table 2 shows the detailed calculation methods used.

To fulfill the second objective, a unified assessment system and grading rules were established, which allow for the calculation and comparison of independent assessment results for each administrative region, subsequently integrating them into the ecological environment quality assessment dataset. The EI can be categorized into levels of Excellent, Good, Moderate, Poor, and Worst, with classification thresholds set at 75, 55, 35, 20, and 0, respectively.

Due to the constraint of data statistical units, the computation results of this method are predominantly presented as evaluation scores for counties, provinces, and ecological regions. Ouyang Ling et al. attempted to assess the ecological environment using the ecological environment status index and accomplished spatial mapping [28]. In this study, the evaluation results of the EI model were visualized using a methodology inspired by its mapping approach, in which the ecological environment status index was extracted for each raster.

2.3.2. RSEI model

The RSEI model employs remote sensing inversion to comprehend the assessment framework for regional ecological conditions. This model is constructed based on four major indicators, using the NDVI, wetness (Wet), land surface temperature (LST), and normalized difference build-up and soil index (NDBSI) as indicators reflecting the superiority or inferiority of ecological conditions [29]. Thematic information enhancement techniques are used to obtain information on the distribution of vegetation and its biomass, the degree of surface exposure, and other subsurface information to characterize EEQ. The model uses principal component analysis to synthesize ecological information and normalize the data based on extreme values, thus standardizing the data. We mainly refer to the RSEI calculation method proposed by Xu in the comparative study of EI and RSEI models [30], and did not mask the water body. Equations (2) and (3) show the calculation formula [21,30]:

$$RSEI_0 = 1\text{-}\{\mathrm{PC1}[NDVI, Wet, LST, NDBSI]\} \quad (2)$$

$$RSEI = (RSEI_0 - RSEI_{0\_min})/(RSEI_{0\_max} - RSEI_{0\_min}),\ 0 \leq RSEI \leq 1 \quad (3)$$

where PC1 [NDVI, Wet, LST, NDBSI] is the first principal component information obtained after the principal component transformation, and selecting PC1 aids in avoiding subjective weighting bias during the calculation process (refer to Table 3 for details). $RSEI_0$ is the initial ecological index; $RSEI_{0\_max}$ and $RSEI_{0\_min}$ are the maximum and minimum values of the initial ecological index, respectively.

The RSEI (values range from 0 to 1) is categorized into five grades at 0.2 intervals [31]. These grades denote ecological conditions as poor, relatively poor, moderate, good, or excellent, aligning with the grading rules proposed in the EI model. This alignment has been consistently applied in subsequent RSEI studies, facilitating meaningful comparisons between the two models.

2.3.3. Difference calculation

2.3.3.1. Calculation of the difference between the two model assessments. Given that the numerical ranges of the EI and RSEI differ, attempting to forcibly standardize them into the same dimensional range may result in data dimensionality reduction, potentially

Table 2
The EI model evaluation index calculation formula is as follows [19].

Index	Calculation Formula	Formula Remarks
AI	$AI = A_{bio} \times$ (0.35 × woodland+0.21 × rangeland+0.28 × water areas+0.11 × farmland+0.04 × construction land+0.01 × unused land)/ total area	A_{bio}: normalization coefficient with a reference value of 511.2642131067; Area unit: km^2.
VCI	$VCI = A_{veg} \times \left(\frac{\sum_{i=1}^{n} P_i}{n}\right)$	P_i: Mean of the monthly maxima of NDVI from May to September; n: number of pixels in the region; A_{veg}: normalization coefficient with a reference value of 0.0121165124.
WNDI	$WNDI$=((A_{riv} × river length/total area + A_{lak} × water area/total area + A_{res} × water resources/total area)/3	A_{riv}, A_{lak}, A_{res} are normalized coefficient with reference values of 84.3704083981, 591.7908642005, 86.3869548281; Length unit: KM; Area unit: km^2; Unit of water resources: 10^6 m^3.
LSI	$LSI = A_{ero}$ × (0.4 × heavily eroded area+0.2 × moderately eroded area+0.2 × construction land area+0.2 × other land stress)/total area	A_{ero}: normalization coefficient with a reference value of 236.0435677948; Area unit: km^2.
PLI	PLI=(0.2 × A_{COD} × COD emission+0.2 × A_{NH3} × ammonia nitrogen emission) / total annual precipitation+(0.2 × A_{SO2} × SO_2 emission+0.1 × A_{YFC} × smoke (dust) emission+0.2 × A_{NOX} × nitrogen oxides emission+0.1 × A_{SOL} × solid waste disposal) / total area	A_{COD}, A_{NH3}, A_{SO2}, A_{YFC}, A_{NOX}, A_{SOL} are normalized coefficient with reference values of 4.3937397289, 40.1764754986, 0.0648660287, 4.0904459321, 0.5103049278, 0.0749894283; Unit of waste emission or disposal: t; Total annual precipitation unit: mm; Area unit: km^2.

Table 3
Principal component analysis of the RSEI.

Indicator	2017				2019				2021			
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
NDVI	0.650	0.432	0.559	0.280	0.677	0.245	0.655	0.229	0.630	0.529	0.535	0.190
Wet	0.165	0.146	−0.663	0.715	0.130	0.252	−0.512	0.811	0.147	0.099	−0.559	0.810
NDBSI	−0.462	−0.362	0.496	0.640	−0.476	−0.494	0.489	0.539	−0.418	−0.342	0.633	0.554
LST	−0.581	0.813	0.043	0.008	−0.546	0.795	0.264	0.007	−0.637	0.770	−0.015	0.012
Eigenvalues	0.011	0.002	0.001	0.000	0.018	0.003	0.001	0.000	0.015	0.003	0.001	0.000
Percent of EigenValues/%	76.114	16.136	7.159	0.591	81.611	11.998	5.952	0.439	75.976	17.352	6.284	0.389

obscuring the intrinsic quality information of the ecological environment embedded in the values. As both models share a common 5-level classification grading method, the evaluation grading results serve as the calculation index, and the difference (ΔE) is employed to gauge the disparity between the two models. Furthermore, to assess the fluctuations in eco-environmental quality from 2017 to 2019, the difference between the two models was compared with the difference in fluctuation ($\Delta E_{m\text{-}n}$). Equations (4) and (5) were used to calculate this indicator:

$$\Delta E = EI\ Levels\text{-}RSEI\ Levels \quad (4)$$

$$\Delta E_{m\text{-}n} = EI\ Levels_m\text{-}EI\ Levels_n\text{-}(RSEI\ Levels_m\text{-}RSEI\ Levels_n) \quad (5)$$

where ΔE ranges from −1 to 1, and the grading results of the visible EI and RSEI exhibit a higher degree of consistency. When the absolute value of ΔE equals 2, a general difference emerges in the graded results, and when the absolute value of ΔE surpasses 2, the graded results are considerably distinct. Here, EI $Levels_m$ and EI $Levels_n$ denote the ecological and environmental quality grades of EI in years m and n, respectively. Similarly, RSEI $Levels_m$ and RSEI $Levels_n$ represent the ecological and environmental quality grades of the RSEI in years m and n, respectively. A $\Delta E_{m\text{-}n}$ greater than 0 indicates that, compared with the RSEI, the EI demonstrates less deterioration in the quality of the ecological environment or more improvement in the quality of the ecological environment. Conversely, when ΔEm-n is less than 0, the opposite is suggested.

2.3.3.2. Correlation analysis between the calculated results of the model and the calculated differences. Correlation analysis was employed to explore the relationships among EI and RSEI values, ΔE, and the correlations between multiyear fluctuations and $\Delta E_{m\text{-}n}$. Using SPSS software, a correlation analysis was performed to assess the associations by calculating and comparing the Pearson correlation coefficients. The Pearson correlation coefficient ranges from 0 to 1, where 1 indicates a perfect positive correlation and 0 indicates no correlation. Additionally, the correlations can be categorized into extremely strong, strong, moderate, weak, and extremely weak, with classification thresholds set at 0.8, 0.6, 0.4, 0.2, and 0, respectively.

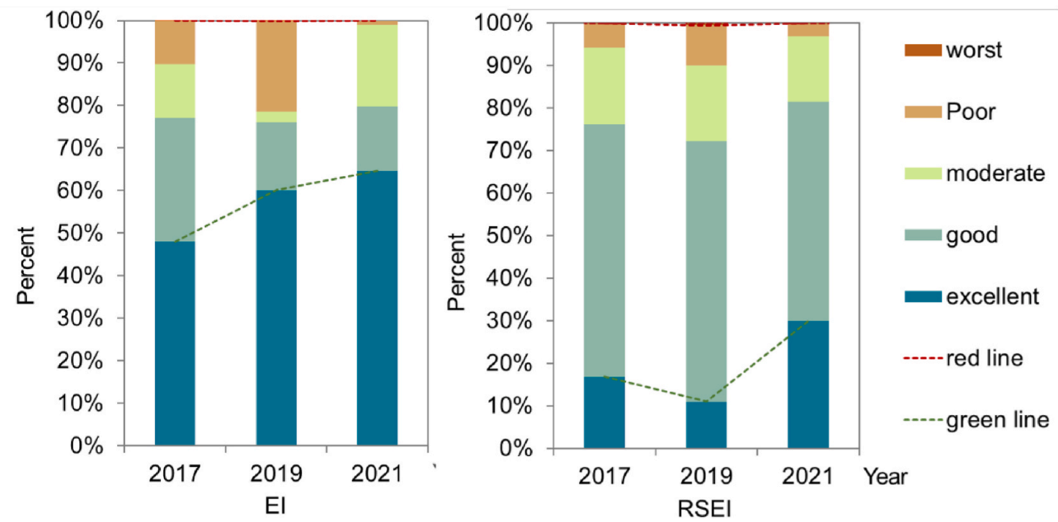

Fig. 2. The percentage of EI and RSEI level areas from 2017 to 2021.

3. Results

3.1. Evaluation results of the EEQ based on two models

3.1.1. Overall evaluation results

Based on the ecological environment assessment and the remote sensing ecological index model calculations, the average EI values for Fangshan District, Beijing, in 2017, 2019, and 2021 were 67.153, 66.715, and 73.230, respectively. Correspondingly, the average RSEI values were 0.678, 0.649, and 0.718 for the same years. In accordance with the grading standards of both models, Fangshan District clearly maintained a good ecological environment from 2017 to 2021.

As indicated by the grading results (refer to Fig. 2), the ecological environment quality of Fangshan District from 2017 to 2021 predominantly fell within the "good" and "excellent" categories, all surpassing 70 % of the total area. Between 2017 and 2021, the category with the smallest geographical coverage was consistently classified as "worst". The areas with the "worst" EI levels accounted for 0.015 %, 0.066 %, and 0.000 % of the total area in 2017, 2019, and 2021, respectively. Moreover, the areas with the "worst" RSEI values were slightly greater, at 0.154 %, 0.515 %, and 0.116 %, respectively, in the same years. Notably, all these proportions remained below 0.6 %. The multiyear trend indicates an initial increase followed by a subsequent decrease, as indicated by the red trend line. In 2017, 2019, and 2021, the proportions of areas with "excellent" EI levels in Fangshan District were 47.005 %, 60.070 %, and 64.595 %, respectively. This was markedly higher than the percentages of 16.857 %, 10.997 %, and 29.940 % observed in the RSEI results. The change trend of the proportion of areas with "excellent" EI levels gradually increases, while the RSEI results initially decrease and then increase, as depicted by the green trend line. The "excellent" area of the two models exhibits notable differences both in terms of proportion and in terms of the multiyear fluctuation trend.

Based on the spatial distribution of the multiyear EEQ calculated by the two models, the western part of the Fangshan District consistently exhibited significantly better conditions than did the eastern part (refer to Fig. 3). The areas characterized by poor and worst EEQs are primarily concentrated in the central construction and development zones in the eastern part of the district. The EEQs in these areas have shown substantial fluctuations and irregular distributions over the years. In contrast, the EEQs in the western mountainous areas are predominantly assessed as good or excellent, and they have maintained relative stability over several years. However, it is noteworthy that the excellent area calculated by the EI model is notably larger than that calculated by the RSEI model. The RSEI model's results primarily indicate good ecological conditions, with a significant increase in the excellent area observed only in 2021.

3.1.2. Detailed change results

Fig. 4 illustrates that from 2017 to 2021, the change trends in EI and RSEI levels were relatively consistent, displaying an initial weakening followed by improvement compared to the more intricate transition process of the RSEI. Between 2017 and 2021, there was a general degree of transfer between EI grades, accounting for 30.530 % of the total area. This transfer comprised 39.732 % of the total population in the period from 2017 to 2019 and 27.614 % of the total population from 2019 to 2021. The overall degree of change between RSEI grades was more pronounced, covering 36.014 % of the area. Most of these fluctuations occurred during the period from

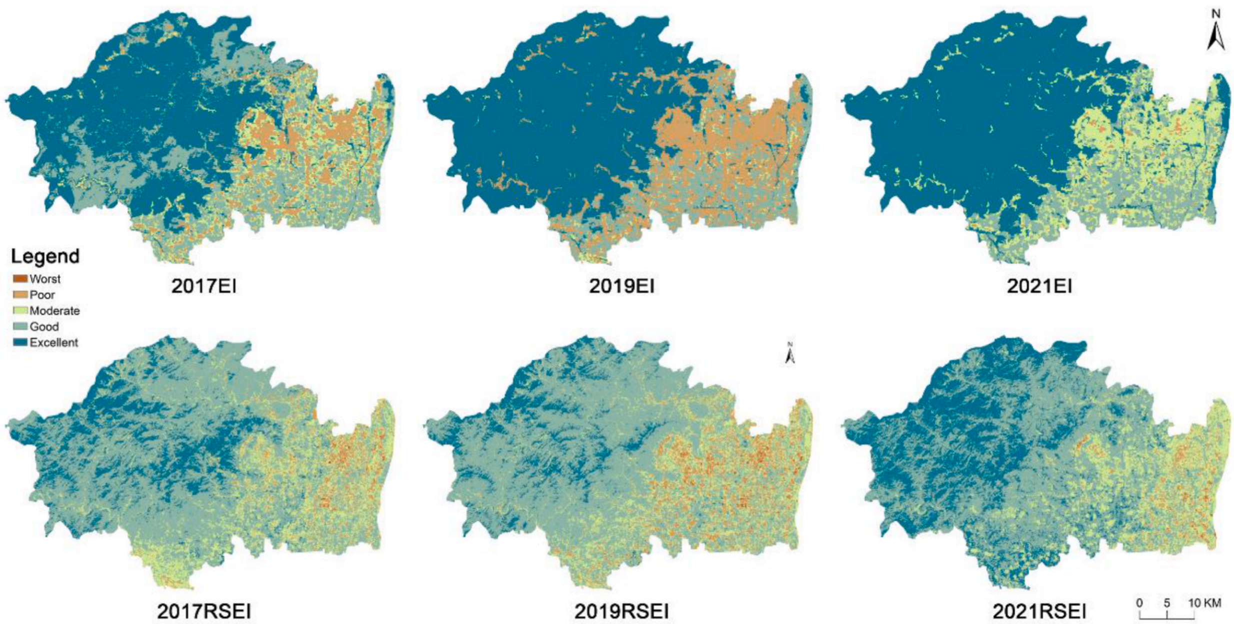

Fig. 3. Spatial distribution of EI and RSEI levels from 2017 to 2021.

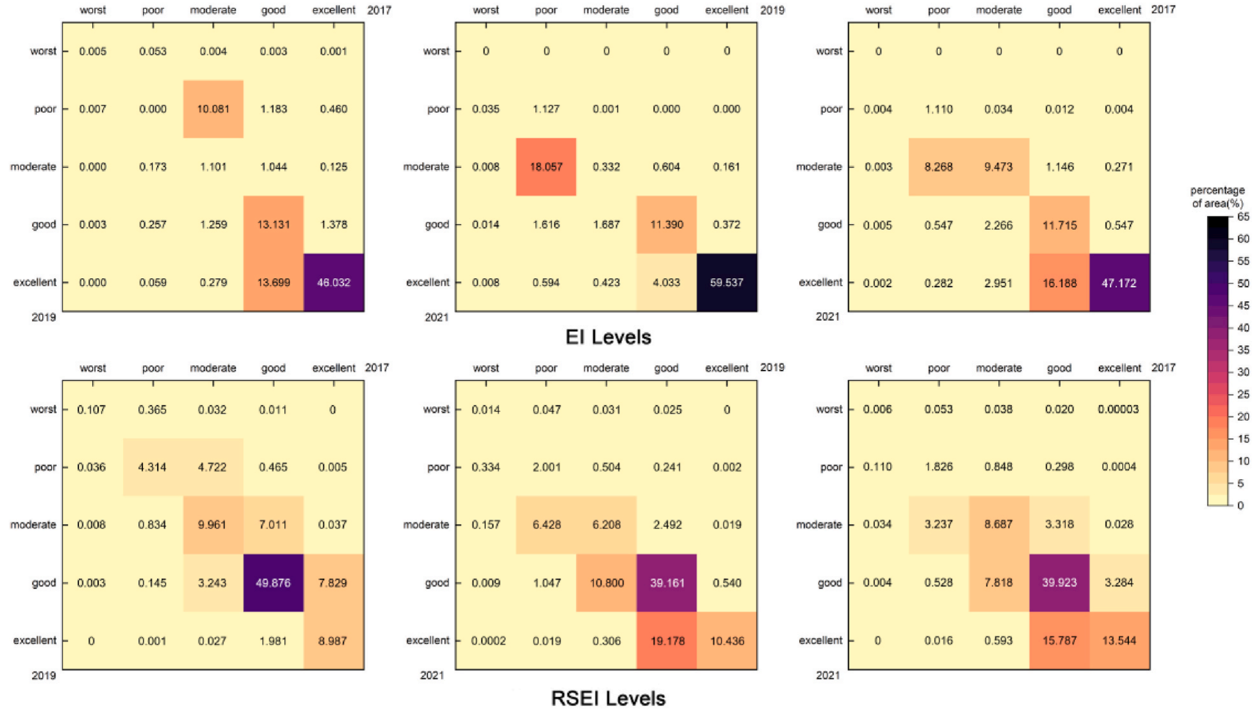

Fig. 4. 2017–2021 transition matrix of the EI and RSEI levels.

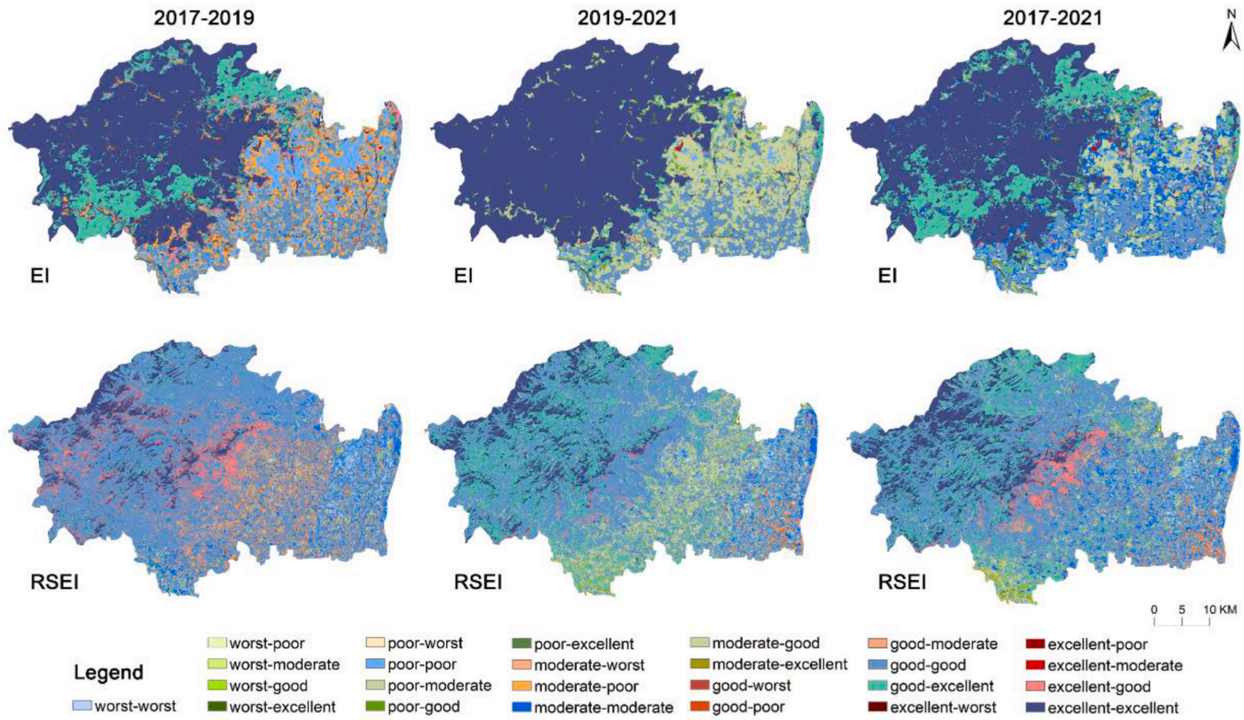

Fig. 5. Spatial distribution of EI and RSEI levels from 2017 to 2021. Note: Orange–red indicates a deterioration in EEQ, green indicates improvement, and blue indicates no change in EEQ. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

2019 to 2021, constituting 42.179 % of the area, while the change was less severe from 2017 to 2019, accounting for 26.755 % of the area.

Specifically, the changes in EI levels from 2017 to 2019 primarily resulted from the transition from moderate to poor and from good to excellent. Similarly, the changes from 2019 to 2021 were concentrated in these four grades, but all of these changes indicated an improvement in the ecological environment. The area transitioning from poor to moderate was 36027.790 ha, and the area shifting from good to excellent was 8046.910 ha.

The changes in RSEI levels exhibited a more intricate pattern characterized by a pronounced downward trend in ecological environment quality levels from 2017 to 2019. Primarily, the moderate, good, and excellent grades all decreased by one level each, with corresponding changes of 9420.920 ha, 13988.290 ha, and 15619.930 ha, respectively. Conversely, from 2019 to 2021, the quality of the ecological environment significantly improved. The poor, moderate, and good grades all advanced by one grade each, encompassing a change area of 12826.060 ha, 21549.460 ha, and 38263.940 ha, respectively.

Fig. 5 shows that from 2017 to 2021, the EI levels that remained unchanged were predominantly excellent and good. The western part of Fangshan District was mostly consistently excellent, while the eastern part remained primarily in the stable good category. Between 2017 and 2019, the enhancement of the ecological environment from good to excellent was mainly concentrated in the western region. Conversely, from 2019 to 2021, the eastern region primarily transitioned from poor to moderate.

The RSEI levels that remained constant between 2017 and 2021 were predominantly excellent and good. Areas with consistently good RSEI levels were more evenly distributed across Fangshan District, with stable excellent areas concentrated in the western fringes of the district, gradually expanding toward the center. From 2017 to 2019, the degradation of ecological environmental quality occurred mainly in the east-central region, forming a southwest–northeast trending belt across Fangshan District. However, this situation reversed to some extent from 2019 to 2021, with an improvement in the quality of the ecological environment in that region. Consequently, from 2017 to 2021, this zonal change zone became less prominent, with only a small area in the central region experiencing a decrease in quality, while the ecological environment in the southern corner exhibited significant improvement.

3.2. Comparative results of the two models

3.2.1. Comparison of EEQ evaluation results

As indicated in Table 4, in 2017, 2019, and 2021, the proportions of the region with ΔE values equal to −1 to 1 were 96.135 %, 95.168 %, and 96.652 %, respectively. The proportion of the area with an absolute value of ΔE greater than 2 did not exceed 0.3 %, suggesting a high overall consistency in the classification results of the two models. In 2017 and 2021, the proportions of areas with ΔE values of 0 and 1 were similar (both approximately 40 %). However, in 2019, the proportion of the area with ΔE equal to 1 increased to 52.629 %, with only 36.266 % of the areas having identical evaluation results. In this year, most of the land showed higher EI grading results than RSEI levels.

Fig. 6 clearly shows that areas with positive and zero ΔE values are concentrated in the western part of Fangshan District and the eastern fringe areas, while most other areas in the east exhibit negative values. In 2019, the number of regions with ΔE equal to 1 increased significantly in the western region, correlating with a decrease in the number of regions with ΔE equal to 0, leading to the data results presented in Table 4. The topography and natural conditions in Fangshan District contributed to the western part being a relatively pristine nature reserve, with human activities and construction primarily concentrated in the eastern part of the region. By combining this information with the spatial distribution law of the model calculation results in Section 3.1, the difference between the calculation results of the two models may be related to the land use type.

3.2.2. Comparison of EEQ fluctuation results

A comparison of the results of the two models over the years indicates that the proportion of the area with $\Delta E_{m\text{-}n}$ equal to −1 to 1 is greater than 95 % (as shown in Table 5). The closer the value is to 5 or -5, the smaller the area proportion is, indicating more consistent fluctuations reflected by the EI and RSEI models.

In general, the proportion of areas with a value less than 0 in $\Delta E_{2021\text{-}2017}$ (20.771 %) was less than that of areas with a value greater than 0 (26.204 %), indicating that EI exhibited a stronger trend of improving the quality of the ecological environment than did RSEI

Table 4
Table of statistical data for ΔE values from 2017 to 2021.

ΔE	Year					
	2017		2019		2021	
	area (ha)	percent (%)	area (ha)	percent (%)	area (ha)	percent (%)
−3	19.770	0.010	0.350	0.0002	2.150	0.001
−2	3042.240	1.525	254.120	0.127	743.350	0.373
−1	24016.790	12.037	12515.730	6.273	20878.280	10.464
0	92008.550	46.114	72359.810	36.266	92004.910	46.112
1	75787.780	37.984	105007.970	52.629	79960.980	40.076
2	4263.900	2.137	8385.670	4.203	5614.860	2.814
3	382.660	0.192	990.570	0.496	293.150	0.147
4	2.280	0.001	9.750	0.005	26.290	0.013

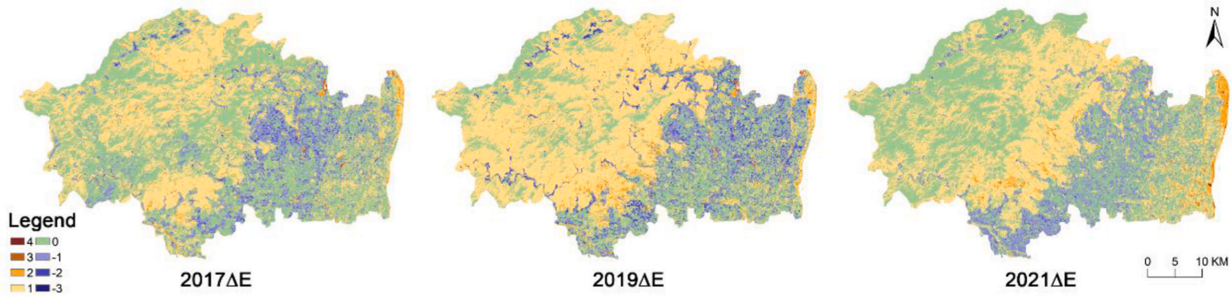

Fig. 6. Spatial distribution characteristics of ΔE.

Table 5
Statistical table of Δ Em-n from 2017 to 2021.

$\Delta E_{m\text{-}n}$	Year					
	2017～2019		2019～2021		2017～2021	
	area (ha)	percent (%)	area (ha)	percent (%)	area (ha)	percent (%)
−5	0.940	0.0005	0	0	0.050	0.00003
−4	47.410	0.024	2.130	0.001	3.130	0.002
−3	854.270	0.428	127.670	0.064	118.140	0.059
−2	3422.150	1.715	1864.600	0.935	2271.780	1.139
−1	24815.370	12.437	49435.190	24.777	39050.150	19.572
0	112263.710	56.266	115735.440	58.006	105797.140	53.025
1	53464.020	26.796	26547.720	13.306	46642.870	23.377
2	4306.970	2.159	4713.170	2.362	5136.110	2.574
3	325.230	0.163	1051.430	0.527	480.990	0.241
4	23.670	0.012	46.410	0.023	23.430	0.012
5	0.230	0.0001	0.210	0.0001	0.180	0.0001

from 2017 to 2021. An area of $\Delta E_{2019\text{-}2017}$ less than 0 accounted for 14.605 %, which was less than that of the area greater than 0 (29.129 %), suggesting that, from 2017 to 2019, compared with the fluctuations in ecological environmental quality shown by the RSEI, the EI indicated greater deterioration of ecological environmental quality. An area of $\Delta E_{2021\text{-}2019}$ less than 0 accounted for 25.776 %, which was more than the area greater than 0 (16.218 %), indicating that, from 2019 to 2021, compared with the fluctuations in eco-environmental quality shown by the RSEI, the EI demonstrated more improvement in eco-environmental quality.

As shown in Fig. 7, areas with positive $\Delta E_{2019\text{-}2017}$ values are mainly concentrated in the central part of Fangshan District, while areas with negative values are mainly distributed in the east. $\Delta E_{2021\text{-}2019}$ exhibited a different trend, with positive areas mainly concentrated in the eastern part of Fangshan District and negative areas mainly distributed in the western part.

3.3. Correlation analysis between the results of the model calculations and the differences in calculations

The relationships between EI and between the RSEI and ΔE were explored through Pearson correlation analysis (Fig. 8). The results showed that the EI and RSEI were significantly positively correlated from 2017 to 2021, and the correlation between the EI and RSEI in 2017 and 2019 was greater than 0.7. However, in 2021, the correlation coefficient was slightly smaller. In 2017 and 2019, both the EI and RSEI were positively correlated with ΔE; however, in 2021, only the EI was positively correlated with ΔE, while the RSEI was

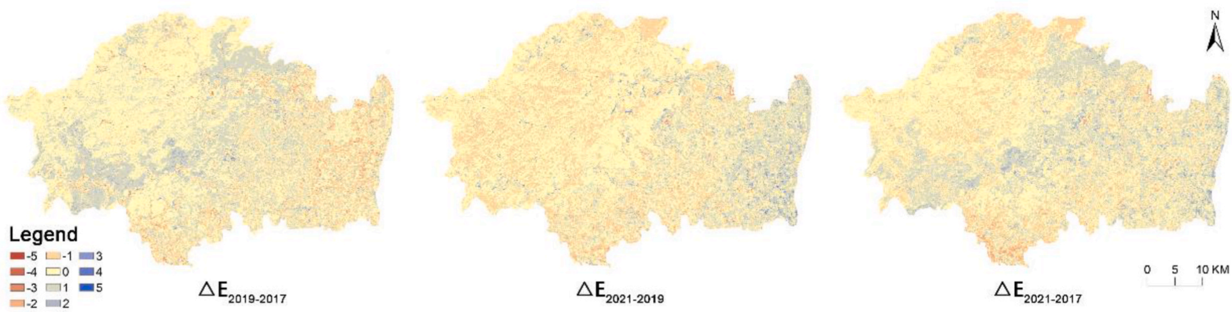

Fig. 7. Spatial distribution characteristics of $\Delta E_{m\text{-}n.}$

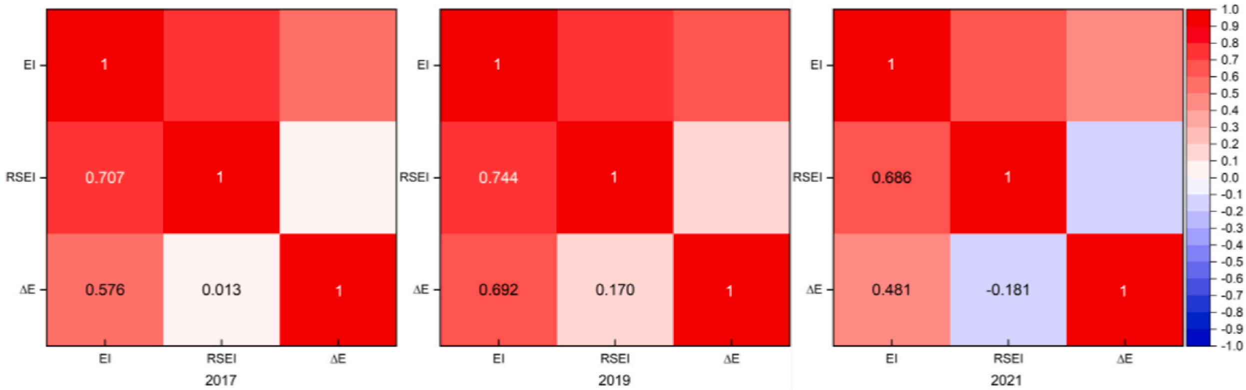

Fig. 8. Correlation analysis of EI, the RSEI and ΔE.

negatively correlated with ΔE. The absolute values of the Pearson coefficients of EI and ΔE in all years were much greater than those of RSEI and ΔE, and both were positive. This indicates that the magnitude of ΔE was more correlated with the EI, and ΔE also showed an increasing trend with increasing EI.

Correlation analysis was conducted between the fluctuations in the multiyear evaluation results and the differences in fluctuations between the two models (Fig. 9). The difference in EI between the mth and the nth year was expressed as $EI_{m\text{-}n}$, and the difference in RSEI between mth and the nth year was expressed as $RSEI_{m\text{-}n}$. From the results, it can be observed that the correlation analysis results reflected in 2017~2019 and 2019–2021 are relatively similar. First, the correlation between the fluctuation results reflected by the two models is weak, with the Pearson coefficient being approximately 0.2. Second, $EI_{m\text{-}n}$ was significantly positively correlated with $\triangle E_{m\text{-}n}$, and $RSEI_{m\text{-}n}$ was negatively correlated with $\triangle E_{m\text{-}n}$. Finally, the absolute value of the correlation between $EI_{m\text{-}n}$ and $\triangle E_{m\text{-}n}$ was greater than that between $RSEI_{m\text{-}n}$ and $\triangle E_{m\text{-}n}$, which is similar to the correlation between the calculated results and differences obtained each year.

3.4. *Model evaluation results and land cover types*

According to the results, the difference between the evaluation results of the two models may be correlated with the land cover type. First, the evaluation results of the EI and RSEI under each land cover type were determined. Table 6 shows that the difference between the minimum and maximum values of the EI level of each land cover type is 0~2, and the difference between the minimum and maximum values of the RSEI level is obviously larger, with the evaluation results of other land uses except woodland being distributed in five grades.

Second, the average EI grades of each land cover type greatly differed, and the average values of woodland, water areas, rangeland, farmland, construction land, and unused land gradually decreased in order. In contrast, the RSEI shows the same decreasing trend except water areas, where the average value of water areas is lower than that of farmland, but the values are very close.

Finally, the standard deviation of the EI level of each land cover type was significantly lower than that of the RSEI, especially the standard deviation of woodland and water areas. Taken together, these three results suggest that the evaluation results of the EI are more related to the land cover type, the evaluation results within each type exhibit little difference, and the ecological environment

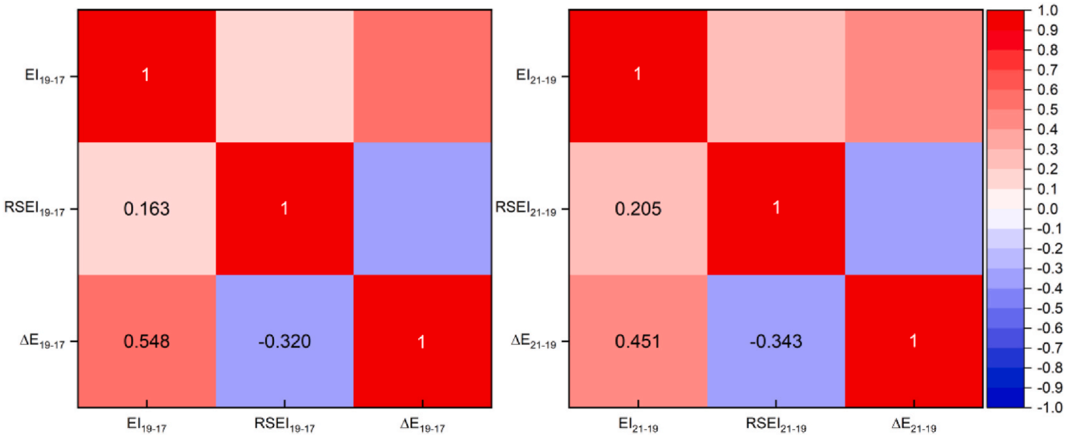

Fig. 9. Correlation analysis of $EI_{m\text{-}n}$, $RSEI_{m\text{-}n}$ and $\Delta E_{m\text{-}n}$.

Table 6
Statistics of EI levels and RSEI levels for each land cover type from 2017 to 2021.

		Farmland		Woodland		Rangeland		Water areas		Construction land		Unused land	
		EI levels	RSEI levels	EI levels	RSEI levels	EI levels	RSEI levels	EI levels	RSEI levels	EI levels	RSEI levels	EI levels	RSEI levels
2017	Minimum	3	1	5	2	3	1	5	1	1	1	1	1
	Maximum	4	5	5	5	5	5	5	5	3	5	3	5
	Mean	3.892	3.702	5.000	4.474	4.748	4.202	5.000	3.295	2.524	3.029	1.977	2.406
	Standard deviation	0.311	0.568	0.000	0.516	0.435	0.516	0.000	0.715	0.499	0.729	0.288	0.583
2019	Minimum	3	1	5	2	4	1	5	1	1	1	1	1
	Maximum	4	5	5	5	5	5	5	5	3	5	2	5
	Mean	3.856	3.611	5.000	4.364	4.946	4.079	5.000	3.228	2.013	2.763	1.600	2.153
	Standard deviation	0.351	0.596	0.000	0.512	0.226	0.495	0.000	0.756	0.112	0.779	0.490	0.550
2021	Minimum	3	1	5	2	4	1	5	1	2	1	2	1
	Maximum	4	5	5	5	5	5	5	5	4	5	3	5
	Mean	3.954	3.898	5.000	4.502	4.980	4.378	5.000	3.739	2.944	3.257	2.425	2.843
	Standard deviation	0.210	0.715	0.000	0.514	0.139	0.566	0.000	0.590	0.231	0.699	0.494	0.656

quality of each cover type has a clear cascading relationship. In contrast, the RSEI evaluation results exhibited little correlation with land cover type, and the cascading relationship between the ecological environment quality and each cover type was weak.

Based on the statistics of the difference between the two models for each land cover type in each year (as shown in Table 7), some notable patterns emerge. Rangeland consistently exhibited the highest proportion of area, with ΔE values primarily concentrated at approximately 0 and 1. In 2017 and 2019, the areas with ΔE values equal to 1 and 0, respectively, were comparable, but in 2019, the proportion of ΔE equal to 1 notably surpassed that of ΔE equal to 0. This discrepancy contributed to the distinct overall statistical results of ΔE in 2019 compared to those in the other two years. The second-largest land cover type, construction land, predominantly features ΔE values of 0 and -1. The proportions of these two areas remain relatively similar over multiple years.

The analysis (see Fig. 10) examined the proportion of land cover types in each ΔE value. Notably, water areas and construction land exhibited relatively high proportions of areas with substantial differences. When the ΔE in Fangshan District is 4 or 3, indicating that the ecological environmental quality reflected by the EI significantly surpasses the RSEI evaluation results, these areas predominantly comprise water bodies. Conversely, when ΔE is less than 0, denoting that the quality of the ecological environment reflected by the EI

Table 7
Statistics of the proportion of each land cover type area from 2017 to 2021.

ΔE		Percent of area (%)					
		Farmland	Woodland	Rangeland	Water areas	Construction land	Unused land
2017	−3	0	0	0	0	0.010	0.0001
	−2	0.022	0	0	0	1.491	0.012
	−1	1.288	0	1.519	0	9.132	0.098
	0	10.592	1.582	25.032	0.019	8.729	0.160
	1	3.953	1.673	30.395	0.412	1.546	0.004
	2	0.210	0.024	1.405	0.480	0.017	0
	3	0.003	0.001	0.051	0.137	0	0
	4	0	0	0.0001	0.001	0	0
	Total	16.068	3.280	58.402	1.049	20.925	0.275
2019	−3	0	0	0	0	0.022	0.0004
	−2	0.004	0	0	0	3.828	0.012
	−1	1.212	0	0.008	0	8.938	0.066
	0	9.368	1.555	10.666	0.013	8.308	0.076
	1	4.058	2.482	44.656	0.353	0.479	0.004
	2	0.401	0.060	2.764	0.386	0	0
	3	0.013	0.001	0.100	0.168	0	0
	4	0	0	0.0001	0.0004	0	0
	Total	15.057	4.097	58.193	0.920	21.575	0.158
2021	−3	0	0	0	0	0.001	0.0003
	−2	0.020	0	0	0	0.345	0.007
	−1	2.785	0	0.056	0	7.573	0.050
	0	8.556	0.413	27.510	0.069	9.519	0.046
	1	2.671	0.392	34.166	0.768	2.066	0.012
	2	0.424	0.006	2.008	0.334	0.040	0.002
	3	0.038	0.00002	0.086	0.023	0	0
	4	0	0	0.013	0.0005	0	0
	Total	14.495	0.811	63.839	1.195	19.543	0.117

Fig. 10. The proportion of land cover type area affected by each ΔE value from 2017 to 2021.

is inferior to that of the RSEI evaluation, the majority of these areas are construction land. Additionally, areas with E equal to 2 or 1 are predominantly rangelands. The ΔE of woodland was mostly concentrated from 0 to 1, reflecting relatively consistent evaluation results between the two models. The area with a ΔE equal to 0 in farmland constituted the highest proportion, while the other grades exhibited varying distributions.

4. Discussion

4.1. Explanations for the discrepancy

4.1.1. Evaluation indicators and their importance

Both the EI and RSEI models consider the condition of surface vegetation. However, the EI model views the ecological environment as a composite entity composed of multiple elements, and it integrates various ecological resources and ecological and environmental conditions. The comprehensive ecological indicators introduced by the RSEI reflect the characteristics of the Earth's surface. These indicators exhibit high correlation within their areas of focus but do not take environmental factors into account. Therefore, when assessing ecological environment quality, the RSEI model tends to focus on "ecology" while neglecting "environment" [32].

However, the RSEI model shows stronger potential in terms of model content improvement. In addition, thematic ecological zone assessment models have been developed based on generic models, including the ecological function assessment model for ecological function zones, the urban ecological environment quality assessment model, and the nature reserve protection status assessment model. In addition, the researcher was unable to modify the evaluation model according to the evaluation needs and the characteristics of the research subjects. The RSEI model is much more adjustable than the other models, and many scholars have adapted the RSEI model to the study of different geographical areas. For example, in semiarid areas, the indices can be adjusted to include the wet, growth-stage-based drought vulnerability index (GDVI), desertification index (DI), and salinity index (SI) to suit regional characteristics such as poor vegetation growth and prominent land desertification [33]. For wetland ecosystems, surface temperature is replaced with aquatic vegetation indicators for assessment [34].

Furthermore, there is a large difference between the two evaluation models in terms of determining the importance of evaluation indicators, and compared with the fixed weights of the EI model, the RSEI model shows strong flexibility and uncertainty, which leads to different trends in the overall evaluation results of the EI and RSEI. Table 3 shows that among the PC1 components from 2017 to 2021, the absolute contribution to the NDVI was the highest in 2017 and 2019, and the absolute contribution to the LST was the highest in 2021. This is related to the fact that both the EI and RSEI were positively correlated with ΔE in 2017 and 2019, and only the EI was positively correlated with ΔE in 2021. According to the formula for calculating ΔE, the higher the EI level or the lower the RSEI level is, the smaller the ΔE value, which is closer to the correlation results presented in 2021. The correlation between 2017 and 2019 (see Fig. 8) can be interpreted as indicating a very high correlation between EI and the RSEI, which was stronger than that between EI and the RSEI in 2021; thus, RSEI and ΔE also exhibited positive correlation trends in 2017 and 2019. Changes in and differences in the importance of evaluation indicators lead to changes in the difference trends of evaluation results between the EI and RSEI models.

On the other hand, disparities in evaluation indicators and their respective importance may contribute to variations in assessing water ecological quality between the two models. In the EI model, when calculating the abundance index, water areas had the second highest weight, surpassed only by woodlands, with a weight of 0.28. Consequently, the calculation results suggest that the ecological environment quality is excellent for aquatic areas. However, the RSEI model is designed to eliminate the impact of extensive water areas in its calculation, making it more suitable for terrestrial environments. When evaluating the greenness, humidity, heat, and dryness of water bodies, although the humidity evaluation yields favorable results, the absence of a high greenness evaluation results in a moderate ecological quality grade for water patches in Fangshan District. Therefore, it is essential to discuss whether the same method can be employed to evaluate both land and water bodies in the subsequent assessment of ecological environmental quality. If distinct evaluation indicators are applied to assess the two parameters, further exploration is needed to determine how to unify the evaluation criteria.

4.1.2. Quantitative methods of evaluating indicators

The EI model primarily quantifies the evaluation indices through classification and assignment, while the RSEI model directly quantifies the quality of the ecological environment based on the smallest spatial unit of high-resolution continuous data. This leads to the observation that when discussing the relationship between the evaluation results of the two models and the land cover type in Section 3.4, the correlation between the EI levels and the land cover type is stronger. The evaluation results of each raster for the cover type are very similar. Specifically, excluding the MOD13Q1 NDVI data (with a spatial resolution of 250 m, which is too coarse compared to the 30 m spatial resolution of multispectral remote sensing images) used to calculate VCIs, the remaining data were classified and assigned, significantly weakening the heterogeneity and diversity of the evaluation area. This approach significantly diminishes the heterogeneity and diversity of the evaluation area.

Additionally, the areas with $\triangle$E values of -3 and -2 are predominantly built-up land. For these land cover types, the average AI of the EI model is 20.451, the average VCI is 52.227, and the average NDVI of the RSEI model is 0.663. Both the VCI and NDVI are vegetation condition evaluation factors of the two models, and the scores are high, which contradicts the ecological environment quality level reflected by the land cover condition evaluation factor AI of the EI model. Furthermore, it is evident from Fig. 6 that the majority of these construction lands are situated in the transitional zone between the construction land and the surrounding vegetation. The RSEI presents a more gradual numerical transition than does the clear clustering division of the EI model. Therefore, land cover type data and remote sensing images reflect inconsistent surface characteristics, resulting in RSEI levels being much greater than EI levels.

Ultimately, the variance in the quantitative methods of the evaluation indicators might indirectly explain the greater number of regions with $\triangle$E values equal to 1 than with $\triangle$E values equal to 0 in 2019. The primary reason for this phenomenon lies in the fact that in 2019, more than 40 % of the rangeland area had a $\triangle$E equal to 1, which is a significantly greater proportion than that of other areas with $\triangle$E values. The evaluation results from Section 3.1 indicate a clear pattern of deterioration and subsequent improvement in the ecological environment quality in Fangshan District, which is particularly evident in the RSEI calculations. The average RSEI for rangeland mirrors this trend (see Table 6). However, the rangeland in the EI model experienced a substantial improvement in ecological environment quality (from good to excellent) from 2017 to 2019, and the evaluation results in 2019 and 2021 were relatively similar, with EI levels ranging from 4 to 5. Upon comparing the EI results with the calculation results of each evaluation index, it was observed that the area essentially aligned with the heavily eroded area in 2017. Hence, the quantitative method of the EI model's evaluation index determines the consistency of the evaluation results for each land cover type over the years, despite the actual situation where the same cover type may experience substantial fluctuations in ecological environment quality. The RSEI indicated a significant deterioration in the ecological environment quality in Fangshan District in 2019, but due to limitations in the quantification method, the EI model could not reflect the pronounced degradation in rangeland. As a result, there were substantial differences in the calculation results in 2019; this underscores that the fluctuations reflected by the EI model are moderate within a certain range and that classification-assigned evaluation models will encounter similar issues.

4.1.3. Data acquisition time

The EI model uses the statistical unit of 'year' to reflect the annual average condition of the eco-environment, which can weaken the contingency of the assessment results due to the short time intervals of the data; however, it cannot assess the quality of the eco-environment on a smaller time scale, such as seasonal, monthly, weekly, or daily, while the RSEI can reflect the assessment of the quality of the eco-environment on a periodic basis due to the short time interval of remote sensing data collection and easy availability [35]. The most sensitive evaluation index to temporal changes is the ecological environment's vegetation conditions, particularly during the vegetation growing season (May to September), when the monthly NDVI values undergo significant fluctuations [36,37]. To address this challenge, the EI model suggests capturing the annual vegetation status by considering the average value of the monthly maximum MOD13Q1 NDVI data from May to September. Conversely, the RSEI model predominantly opts for summer images in its calculations [38]. However, the specific month for image acquisition is not strictly defined due to constraints related to image acquisition channels and quality.

Table 8
Table of statistical differences in the NDVI between the EI and RSEI models from 2017 to 2021.

Year	Percentage of area (%)			
	NDVI of the EI model > NDVI of the RSEI model	NDVI of the EI model = NDVI of the RSEI model	NDVI of the EI model < NDVI of the RSEI model	Total
2017	36.295	8.033×10^{-5}	63.705	100
2019	32.415	4.820×10^{-5}	67.585	100
2021	53.512	5.355×10^{-5}	46.488	100

In the calculation for Fangshan District, remote sensing images were obtained in July 2017, August 2019, and September 2021. The value range of the MOD13Q1 NDVI data was adjusted to 0 to 1, and a comparison was made between the NDVI values reflected by the EI model and the RSEI model in the past three years (refer to Table 8). In 2017 and 2019, the NDVI values of the EI model were greater than those of the RSEI model in more regions. However, in 2021, the situation presented an opposite scenario. In Beijing, the average NDVI in August is the highest, and the NDVI from July to September follows a pattern of initially increasing and then decreasing, with the average NDVI in September being the lowest among the three months [39,40]. Consequently, variations in the data acquisition time may contribute to changes in the calculation results of the RSEI model.

Nevertheless, it is crucial to note that this factor is not the primary reason for the variance between the two models. In 2017 and 2021, the proportions of areas with $\triangle$E were relatively similar, and the calculated results of the EI model in 2019 were significantly greater than those of the RSEI model, contradicting the disparity in the NDVI results between the two models. While the RSEI model might experience differences in results due to differences in data acquisition times, these changes are not substantial enough to significantly impact the differences in the calculation results of the two models. Therefore, despite the comprehensive elimination of time-related errors by the EI model, compared with the influence of the importance of the evaluation index and the quantitative method, the error is considered negligible. Thus, whether the EI model must employ such a complex NDVI calculation method and whether it is appropriate to integrate continuous data and classification assignment data when optimizing the evaluation model are topics worthy of further consideration.

4.2. *Situations to which the model applies*

Here, we discuss the applicable scenarios of these two models based on the observed differences. The EI model is well suited for governmental management departments to assess the ecological and environmental quality of counties, provinces, and specialized ecological zones; it effectively captures comprehensive annual ecological and environmental conditions as well as multiyear changes in administrative areas. The performance of the EI model facilitates the quantification of the effectiveness of ecological and environmental restoration and protection efforts. Furthermore, it facilitates comparisons of ecological and environmental quality across identical administrative regions, thereby aiding informed decision-making and policy implementation. However, it is less apt for portraying the spatial distribution of ecological and environmental conditions within a given region.

The RSEI model is not restricted by spatial scale and is well suited for depicting the spatial variation in EEQ across different study areas [41]. The model allows for the examination of short-term fluctuations and long-term evolution of EEQ within a region, enabling the exploration of driving factors behind spatial and temporal characteristics; this, in turn, facilitates the prediction of future EEQ trends and the development of corresponding control measures to ensure eco-environmental safety.

4.3. *Strengths and limitations*

The novelty of this study lies in its comprehensive examination of the differences in principles and calculation results between the commonly used EI and RSEI models for EEQ evaluation. The identification of these distinctions provides valuable insights into potential applications for each model. This research addresses a gap in the comparative analysis of these models, offering a foundation for future model selection by elucidating their characteristics and potential calculation errors.

While our method effectively assesses the disparities and traits of the two models, it is essential to acknowledge certain limitations. The choice of Fangshan District as the study area provides valuable insights, but the impact of the evaluation scale on the calculation results should be considered. Future studies could expand the research scale from the grid level to include administrative districts at the county level or higher for a more comprehensive discussion. Additionally, subsequent research may exclude external factors such as climate to better understand the influence of spatial scale on model calculations. Comparisons across multiple study areas of similar scale could further delineate calculation differences between the two models in various contexts.

5. Conclusions

In this study, we computed the differences in the multiyear calculation results and fluctuation patterns of the EI and RSEI models in Fangshan District. We analyzed these differences across ecological environmental quality grades, examined their relationships with land cover types, and explored the impacts of spatiotemporal scale differences in evaluation indicators, importance, quantitative methods, and representations. The characteristics of the evaluation models were summarized, and potential application scenarios were proposed. The key conclusions are as follows:

(1) Both models indicate that Fangshan District of Beijing maintained a good ecological environment from 2017 to 2021, exhibiting a trend of initial deterioration followed by improvement in the quality of the ecological environment. There is some consistency in the grading results of the two models, with the proportion of regions having absolute ΔE values greater than 2 not exceeding 0.3 %. However, the correlation between the EI and RSEI in 2017 and 2019 was stronger than that in 2021, which was attributed to changes in the contributions of the RSEI model evaluation indicators.
(2) The areas with substantial differences between the two models are primarily water areas and construction land. The significant difference in the evaluation of water areas is influenced by the utilization of different evaluation indicators, while the notable difference in the evaluation of construction land is attributed to distinct quantitative methods for evaluation indicators.

(3) The variance in index quantification methods is a key factor contributing to the disparities between the models. Consequently, the calculation results of the EI model reveal a clear cascading relationship between the quality of the ecological environment of each cover type. The evaluation results of the EI are more closely associated with land cover types, leading to a more pronounced overall shift between RSEI classes. Additionally, an unusually high proportion of areas with ΔE equal to 1 in 2019 compared to the other two years can be attributed to these differences.
(4) The EI model is suitable for evaluating national, provincial, and municipal administrative regions, offering a comprehensive assessment capturing annual status and multiyear changes. The RSEI, which is not constrained by spatial or temporal scales, is adept at studying short-term fluctuations and long-term evolution within a region. In comparison, the RSEI is simpler, more implementable, and adaptable to geographical conditions. These findings provide insights into the strengths and limitations of each model, guiding decision makers in terms of their optimal use in different contexts and contributing to the ongoing refinement and development of EEQ assessment models.

Data availability statement

The data that support the findings of this study are available upon request from the authors.

CRediT authorship contribution statement

Fangqi Tan: Writing – original draft, Visualization, Software, Conceptualization. **Yuning Cheng:** Writing – review & editing, Funding acquisition, Conceptualization. **Yangyang Yuan:** Writing – review & editing, Conceptualization. **Xueyuan Wang:** Data curation. **Boqing Fan:** Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] L.H. Chai, D. Lha, A new approach of deriving indicators and comprehensive measure for ecological environmental quality assessment, Ecol. Indicat. 85 (2018) 716–728, https://doi.org/10.1016/j.ecolind.2017.11.039.
[2] M.S. Boori, K. Choudhary, R. Paringer, A. Kupriyanov, Eco-environmental quality assessment based on pressure-state-response framework by remote sensing and GIS, Remote Sens. Appl.: Society and Environment 23 (2021) 100530, https://doi.org/10.1016/j.rsase.2021.100530.
[3] H. Li, L. Dron, A new approach of deriving indicators and comprehensive measure for ecological environmental quality assessment, Ecol. Indicat. 85 (2018) 716–728, https://doi.org/10.1016/j.ecolind.2017.11.039.
[4] L. Zhang, H. Zhang, E. Xu, Information entropy and elasticity analysis of the land use structure change influencing eco-environmental quality in Qinghai-Tibet Plateau from 1990 to 2015, Environ. Sci. Pollut. Control Ser. 29 (13) (2022) 18348–18364, https://doi.org/10.1007/s11356-021-17978-2.
[5] Y. Yang, H. Li, C. Qian, Analysis of the implementation effects of ecological restoration projects based on carbon storage and eco-environmental quality: a case study of the Yellow River Delta, China, J. Environ. Manag. 340 (2023) 117929, https://doi.org/10.1016/j.jenvman.2023.117929.
[6] Z. Chen, J. Chen, C. Zhou, Y. Li, An ecological assessment process based on integrated remote sensing model: a case from Kaikukang-Walagan District, Greater Khingan Range, China, Ecol. Inf. 70 (2022) 101699, https://doi.org/10.1016/j.ecoinf.2022.101699.
[7] H. Li, S. Zhang, J. Zhang, W. Zhang, Z. Song, P. Yu, C. Xie, A framework for identifying priority areas through integrated eco-environmental risk assessment for a holistic watershed management approach, Ecol. Indicat. 146 (2023) 109919, https://doi.org/10.1016/j.ecolind.2023.109919.
[8] J. Xiong, X. Wang, D. Zhao, J. Wang, Spatiotemporal evolution for early warning of ecological carrying capacity during the urbanization process in the Dongting Lake area, China, Ecol. Inf. 75 (2023) 102071, https://doi.org/10.1016/j.ecoinf.2023.102071.
[9] Y. Zhang, J. She, X. Long, M. Zhang, Spatio-temporal evolution and driving factors of eco-environmental quality based on RSEI in Chang-Zhu-Tan metropolitan circle, central China, Ecol. Indicat. 144 (2022) 109436, https://doi.org/10.1016/j.ecolind.2022.109436.
[10] J. Sun, Y. Hu, Y. Li, L. Weng, H. Bai, F. Meng, T. Wang, H. Du, D. Xu, S. Lu, A temporospatial assessment of environmental quality in urbanizing Ethiopia, J. Environ. Manag. 332 (2023) 117431, https://doi.org/10.1016/j.jenvman.2023.117431.
[11] M. Yan, Y. Wang, Progress and prospects of regional ecological environment quality assessment, Journal of Ecology and Environment 21 (10) (2012) 1781–1788, https://doi.org/10.3969/j.issn.1674-5906.2012.10.025.
[12] S.M. Haq, M.S. Amjad, M. Waheed, R.W. Bussmann, J. Proćków, The floristic quality assessment index as ecological health indicator for forest vegetation: a case study from Zabarwan Mountain Range, Himalayas, Ecol. Indicat. 145 (2022) 109670, https://doi.org/10.1016/j.ecolind.2022.109670.
[13] A. Carletti, G.A.D. Leo, I. Ferrari, A critical review of representative wetland rapid assessment methods in North America, Aquat. Conserv. Mar. Freshw. Ecosyst. 14 (S1) (2004) S103–S113, https://doi.org/10.1002/aqc.654.
[14] A. Raj, L.K. harma, Spatial E-PSR modelling for ecological sensitivity assessment for arid rangeland resilience and management, Ecol. Model. 478 (2023) 110283, https://doi.org/10.1016/j.ecolmodel.2023.110283.
[15] M. Sedighkia, B. Datta, Monitoring ecological status of wetlands using linked fuzzy inference system-remote sensing analysis, Ecol. Inf. 74 (2023) 101971, https://doi.org/10.1016/j.ecoinf.2022.101971.
[16] O.S. Jakovljević, S.S. Popović, I.M. Živić, K.Z. Stojanović, D.P. Vidaković, Z.Z. Naunovic, J.Ž. Krizmanić, Epilithic diatoms in environmental bioindication and trout farm's effects on ecological quality assessment of rivers, Ecol. Indicat. 128 (2021) 107847, https://doi.org/10.1016/j.ecolind.2021.107847.
[17] P. Jurajda, O. Slavík, S. White, Z. Adámek, Young-of-the-year fish assemblages as an alternative to adult fish monitoring for ecological quality evaluation of running waters, Hydrobiologia 644 (2010) 89–101, https://doi.org/10.1007/s10750-010-0111-4.

[18] J. Wolfram, S. Stehle, S. Bub, L.L. Petschick, R. Schulz, Water quality and ecological risks in European surface waters–Monitoring improves while water quality decreases, Environ. Int. 152 (2021) 106479, https://doi.org/10.1016/j.envint.2021.106479.

[19] Ministry of Ecology and Environment of the People's Republic of China, Technical Criterion for Ecosystem Status Evaluation: HJ 192-2015, Beijing China Standard Press, 2015.

[20] Ministry of Ecology and Environment of the People's Republic of China, China ecological environment status Bulletin 2021 (Excerpt), Environ. Protect. 50 (12) (2022) 61–74, https://doi.org/10.14026/j.cnki.0253-9705.2022.12.009.

[21] H. Xu, The creation of urban remote sensing ecological index and its application, J. Ecol. 33 (24) (2013) 7853–7862.

[22] Z. Cai, Z. Zhang, F. Zhao, X. Guo, J. Zhao, Y. Xu, X. Liu, Assessment of eco-environmental quality changes and spatial heterogeneity in the Yellow River Delta based on the remote sensing ecological index and geo-detector model, Ecol. Inf. 77 (2023) 102203, https://doi.org/10.1016/j.ecoinf.2023.102203.

[23] X. Che, X. Zeng, C. Zhao, R. Qiu, L. Zhang, X. Hou, X. Hu, Analysis of ecological effects of road network based on remote sensing ecological index–Fuzhou City as an example, J. Ecol. 41 (12) (2021) 4732–4745, https://doi.org/10.5846/stxb202003260700.

[24] Z. Wang, T. Chen, D. Zhu, K. Jia, A. Plaza, RSEIFE: a new remote sensing ecological index for simulating the land surface eco-environment, J. Environ. Manag. 326 (2023) 116851, https://doi.org/10.1016/j.jenvman.2022.116851.

[25] B. Yuan, L. Fu, Y. Zou, S. Zhang, X. Chen, F. Deng, Z. Li, Y. Xie, Spatiotemporal change detection of ecological quality and the associated affecting factors in Dongting Lake Basin, based on RSEI, J. Clean. Prod. 302 (2021) 126995, https://doi.org/10.1016/j.jclepro.2021.126995.

[26] Y. Yang, L. Hu, Habitat quality assessment of nature conservation sites in Fangshan District, Beijing, Western Forestry Science 51 (4) (2022) 80–86, 0.16473/j.cnki.xblykx1972.2022.04.012.

[27] K. Karra, C. Kontgis, Z. Statman-Weil, J.C. Mazzariello, M. Mathis, S.P. Brumby, Global land use/land cover with Sentinel 2 and deep learning, in: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, IEEE, 2021, pp. 4704–4707, https://doi.org/10.1109/IGARSS47720.2021.9553499.

[28] L. Ouyang, H. Ma, Z. Wang, C. Lu, C. Wang, Y. Zhang, X. Yu, Dynamic evaluation of ecological and environmental conditions in the horqin sands based on remote sensing and geographic information data, J. Ecol. 42 (14) (2022) 5906–5921, https://doi.org/10.5846/stxb202004230977.

[29] X. Wang, X. Yao, C. Jiang, W. Duan, Dynamic monitoring and analysis of factors influencing ecological environment quality in northern Anhui, China, based on the Google Earth Engine, Sci. Rep. 12 (1) (2022) 20307, https://doi.org/10.1038/s41598-022-24413-0.

[30] H. Xu, A remote sensing index for assessment of regional ecological changes, China Environ. Sci. 33 (5) (2013) 889–897.

[31] H. Xu, M. Wang, T. Shi, H. Guan, C. Fang, Z. Lin, Prediction of ecological effects of potential population and impervious surface increases using a remote sensing based ecological index (RSEI), Ecol. Indicat. 93 (2018) 730–740, https://doi.org/10.1016/j.ecolind.2018.05.055.

[32] H. Xu, W. Deng, Analysis of the rationality of MRSEI index and its difference with RSEI index, Remote Sensing Technology and Applications 37 (1) (2022) 1–7, https://doi.org/10.11873/j.issn.1004-0323.2022.1.0001.

[33] J. Diwu, J. Mei, H. Yu, Y. Zhang, Y. Zhang, Construction and application of remote sensing ecological index in Semi-arid region, The Administration and Technique of Environmental Monitoring 34 (4) (2022) 21–26, https://doi.org/10.19501/j.cnki.1006-2009.2022.04.010.

[34] M. Jiang, J. Liu, W. Hou, H.Y. Sang, L. Zhai, An improved remote sensing ecological index construction and wetland monitoring application, Surveying and Mapping Science. 47 (7) (2022) 85–92, https://doi.org/10.16251/j.cnki.1009-2307.2022.07.012.

[35] X. Yang, F. Meng, P. Fu, J. Zhang, Y. Liu, Instability of remote sensing ecological index and its optimisation for time frequency and scale, Ecol. Inf. 72 (2022) 101870, https://doi.org/10.1016/j.ecoinf.2022.101870.

[36] Y. Xu, J. Yang, Y. Chen, NDVI-based vegetation responses to climate change in an arid area of China, Theor. Appl. Climatol. 126 (2016) 213–222, https://doi.org/10.1007/s00704-015-1572-1.

[37] X. Li, P. Shi, Sensitivity analysis of variation in NDVI, temperature and precipitation in typical vegetation types a across China, Chinese Journal of Plant Ecology 24 (3) (2000) 379–382.

[38] C. Sun, J. Li, Y. Liu, L. Cao, J. Zheng, Z. Yang, J. Ye, Y. Li, Ecological quality assessment and monitoring using a time-series remote sensing-based ecological index (ts-RSEI), GIScience Remote Sens. 59 (1) (2022) 1793–1816, https://doi.org/10.1080/15481603.2022.2138010.

[39] Q. Pan, W. Fan, H. Yu, F. Zhang, Y. Zhang, Temporal and spatial variation of normalized difference vegetation index and its influencing factors in Beijing, J. Beijing For. Univ. 34 (2) (2012) 26–33, https://doi.org/10.13332/j.1000-1522.2012.02.002.

[40] J. Liu, J. Wu, Z. Wu, M. Liu, Response of NDVI dynamics to precipitation in the Beijing–Tianjin sandstorm source region, Int. J. Rem. Sens. 34 (15) (2013) 5331–5350, https://doi.org/10.1080/01431161.2013.787505.

[41] L. Chen, C. Xu, J. Sun, Dynamic monitoring method of ecological environment quality based on big data technology, Ekoloji Dergisi 28 (108) (2019) 2111–2115, https://doi.org/10.1155/2022/9086946.