A NEW METHOD FOR IMPROVING THE ECOLOGICAL ENVIRONMENT INDEX BASED ON DOWNSCALING OF LAND SURFACE TEMPERATURE

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ABSTRACT:

In the process of urban construction and development, the ecological environment has always been an important consideration factor. How to quickly monitor the long-term ecological environment quality changes in large urban areas is currently one of the main research hotspots. With the continuous development of remote sensing intelligent cloud computing technology, the application of remote sensing methods to monitor urban ecological environment quality changes is becoming more efficient and convenient. Based on the remote sensing ecological index (RSEI) on the remote sensing intelligent cloud platform Google Earth Engine (GEE), this article innovatively proposes an improved remote sensing ecological index (DS-RSEI, Downscale-RSEI). Using the normalized difference vegetation index (NDVI) and land cover data (LULC), terrain data as auxiliary data, the method of moving window and principal component analysis is used to implement spatial downscaling of the heat components in the index, which increases the resolution of the original MODIS land surface temperature (LST) 1000-meter resolution product to 500 meters. When fusing with other images, it can supplement missing image details and improve the ability to evaluate the ecological spatial details of complex urban blocks.Through a comparative analysis of the RSEI index and the DS-RSEI index proposed in this article, it can be seen that DS-RSEI can express the details of ecological environment changes better in complex blocks.

1. INTRODUCTION

The United Nations' SDG 11.3 sub-target mentions strengthening inclusive and sustainable urbanization in all countries by 2030. Therefore, we need to focus not only on the social and economic levels of cities but also on changes in urban ecological quality. For major cities, it is essential to objectively evaluate the quality of the ecological environment and get the accurate trend of its change and development, which can provide effective support for monitoring ecological environment quality changes and assessing the sustainable development capacity of cities.

Based on the PSR framework, Xu proposed the RSEI (Risk-Screening Environmental Indicator) using remote sensing data, which is based on the four dimensions of greenness, wetness, dryness, and warmth. The four components are combined into an index by the method of PCA (Principal Component Analysis). Many scholars achieve the evaluation of the ecological environment in different regions by this method.(Boori and Choudhary et al., 2021; Chen and Huang et al., 2023) Previous studies typically used Landsat satellite remote sensing image datasets with a spatial resolution of 30 meters. MODIS data is used relatively less due to its lower spatial resolution. However, high spatial resolution data like Landsat have a lower temporal resolution, and factors such as cloud cover and other climatic conditions can render the image data unavailable. This leads to uneven seams in composite quarterly remote sensing ecological indices and significant discrepancies in data on both sides of the stitched remote sensing images. This greatly affects the accuracy of environmental assessment results. Therefore, this study used various integrated MODIS remote sensing data products and improved the spatial resolution of the warmth index to develop DS-RSEI (Down-Scaled improved Remote Sensing Ecological Index). This study evaluated the improvement of the overall regional ecological environment assessment results and the assessment results of sampled areas with different land cover types. A comparison between DS-RSEI and RSEI revealed that this method enhanced the ability to identify ecological spatial details in the index. Subsequently, the DS-RSEI index was applied to assess the ecological environment status of Beijing from 2001 to 2021.

2. METHODS

2.1 Calculation of the DS-RSEI

2.1.1 DS-RSEI Index acquisition: The DS-RSEI remote sensing ecological index consists of four indicator components: greenness, humidity, dryness, and heat. The greenness indicator is represented by the NDVI (Normalized Difference Vegetation Index). NDVI utilizes the characteristics of reflected red light and near-infrared bands in remote sensing imagery to capture vegetation features. It is widely used due to its ease of acquisition and strong accuracy in monitoring vegetation cover. In this study, the greenness indicator is extracted from the band values of the MOD13A1 dataset. The calculation formula is as follows:

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{1}$$

where ρ_{nir} = red light band in satellite sensors
ρ_{red} = near-infrared bands in satellite sensors

Moisture content is derived using the Tasselled Cap transformation, which captures the moisture content in both soil and vegetation(Huang and Wylie et al., 2002; Kauth and Thomas, 1976; Ordoyne and Friedl, 2008). The Tasselled Cap transformation effectively reduces data redundancy and compresses information. The humidity index, represented by the wet component, accurately reflects the moisture content in soil and vegetation. In this study, the moisture index is obtained using the following formula:

$$WET = 0.1147\rho_1 + 0.2489\rho_2 + +0.2408\rho_3 + 0.3132\rho_4 \\ -0.3122\rho_5 - 0.6416\rho_6 - 0.5087\rho_7 \quad (2)$$

where $\rho_1 - \rho_7 =$ bands 1-7 of the MOD09A1 V6

To ensure an accurate calculation of the moisture index, it is essential to mask out water bodies before extracting the index. In this study, MNDWI (enhanced Modified Normalized Difference Water Index) is employed for water extraction and masking, which is computed using the following formula:

$$MNDWI = (\rho_{green} - \rho_{swir})/(\rho_{green} + \rho_{swir}) \quad (3)$$

where ρ_{green} = green light band in satellite sensor
ρ_{swir} = mid-infrared band in satellite sensor

This improved MNDWI helps differentiate water bodies from other land cover types, ensuring the reliability of the moisture index calculation.

The dryness index is determined by combining the IBI (Impervious Surface Index) and the SI (Soil Index) . Urban areas exhibit characteristics such as impervious surfaces and bare soil, necessitating the consideration of both indices simultaneously. This combined index provides a comprehensive measure of dryness in urban areas, accounting for both impervious surfaces and soil conditions. In this study, the dryness index is computed by synthesizing the results of the two indices using the following approach:

$$NDBSI = \frac{(IBS + SI)}{2} \quad (4)$$

among them, the calculation formulas of IBI and SI are as follows：

$$IBI = \frac{\frac{2\rho_{swir}}{\rho_{swir} + \rho_{nir}} - \left(\frac{\rho_{nir}}{\rho_{nir} + \rho_{red}} + \frac{\rho_{green}}{\rho_{green} + \rho_{swir}}\right)}{\frac{2\rho_{swir}}{\rho_{swir} + \rho_{nir}} + \left(\frac{\rho_{nir}}{\rho_{nir} + \rho_{red}} + \frac{\rho_{green}}{\rho_{green} + \rho_{swir}}\right)} \quad (5)$$

$$SI = \frac{(\rho_{swir} + \rho_{red}) - (\rho_{blue} + \rho_{nir})}{(\rho_{swir} + \rho_{red}) + (\rho_{blue} + \rho_{nir})} \quad (6)$$

where ρ_{nir} = near-infrared light band in satellite sensor
ρ_{swir} = mid-infrared band in satellite sensors
ρ_{green} = green light band in satellite sensors
ρ_{blue} = blue light band in satellite sensors
ρ_{red} = red light band in satellite sensors

In this study, heat is assessed using satellite remote sensing sensor data, specifically the MODIS LST (Land Surface Temperature) product. LST plays a significant role as an indicator of ecological environment changes and exhibits strong correlations with biomass, urban surface construction, and human comfort. It is a commonly utilized metric to investigate variations in the thermal environment of the Earth's surface, energy balance, and other related research topics (Neteler, 2010; Singh and Setia et al., 2015). The representation of heat in this study relies on the analysis of MODIS LST data.

2.1.2 Improved heat indicator : When utilizing MODIS remote sensing image data to extract ecological indices, it is important to consider the resolution differences among the component indicators. The greenness, moisture, and dryness indicators have a resolution of 500 meters, while the LST product data is captured at a resolution of 1000 meters. The MOD11A2 product provides an average LST value for an 8-day period within a 1200*1200 km grid. Each pixel value in MOD11A2 represents the simple average of all corresponding MOD11A1 LST pixels collected during that 8-day period. However, this averaging process results in the loss of spatial heterogeneity in thermal characteristics. Directly fusing the lower-resolution thermal component with the other indicators would decrease the resolution of the synthesized RSEI image, making it more challenging to discern spatial details of ecological conditions. To address this issue and enhance the resolution of the ecological index, a downscaling technique is applied, specifically targeting the optimization of the heat component(Xu and Wang et al., 2019).

In previous studies, auxiliary data were employed to downscale the thermal data and subsequently extract the RSEI index. A commonly used approach involves downscaling LST using NDVI auxiliary data.(Xu and Wang et al., 2019) By establishing a linear regression relationship between LST and NDVI, a higher-resolution LST data image can be obtained. In this study, the DS-RSEI approach is proposed to improve the remote sensing ecological index, with a particular focus on optimizing the heat component. The downscaling methodology is adapted and refined based on previous research(Zakšek and Oštir, 2012). Multiple auxiliary data, including NDVI, land cover data, and topographic data are utilized to downscale the thermal component of the index. Techniques such as moving window and principal component analysis are applied to reduce the original MODIS LST 1000m resolution product to a 500m resolution product. This novel approach of incorporating multiple auxiliary data and employing principal component analysis and the moving window method for downscaling represents a significant improvement in enhancing the ecological remote sensing index, as depicted in Figure 1. Compared to the use of a single auxiliary data, such as NDVI, the proposed downscaling method demonstrates superior performance. Additionally, downsizing NDVI using the correlation between NDVI and LST can enhance the correlation between LST and NDVI, indirectly strengthening the contribution of the NDVI greenness component in the RSEI remote sensing index. The results indicate that when merged with the three other 500m resolution images, the downscaled LST image can complement missing details in the overall image, thereby improving the ability to assess the spatial intricacies of ecological conditions within complex urban areas. It provides a more accurate representation of the details pertaining to ecological environmental changes in the analysis of large-scale complex blocks.

Initially, multiple auxiliary datasets were resampled to a resolution of 500m and subjected to PCA to select the most influential principal components. Previous studies have shown high correlations among NDVI, land cover data, terrain data, and other variables. Directly correlating these datasets with LST can result in redundant information. To overcome this, PCA was employed to transform these potentially correlated variables into independent principal components. The top-ranking principal components were then chosen as the auxiliary dataset, which was obtained from Google Earth Engine.

The results of PCA for the auxiliary dataset were subsequently resampled to a resolution of 1000m. This resampling was necessary to match the spatial resolution of LST before applying the regression equation. In this study, the auxiliary data were resampled to 1000m resolution for comparison.

The regression equation was then applied using a moving window analysis. Due to the local dependency of the correlation between each principal component and LST, it was not feasible to search the entire area of interest for the regression equation when aiming to narrow down the range of large-area LST. Instead, a regression equation was established for each pixel based on the principal component and LST values within a moving window. The size of the moving window was determined through testing, and a 7x7 square moving window was utilized.

Based on the regression equation, the LST at a 500m spatial resolution was estimated. Once the regression equation was determined, it was applied to the principal components with a spatial resolution of 1000m. By using the corresponding high-resolution values of the auxiliary data, an estimation of LST at the same resolution was obtained.

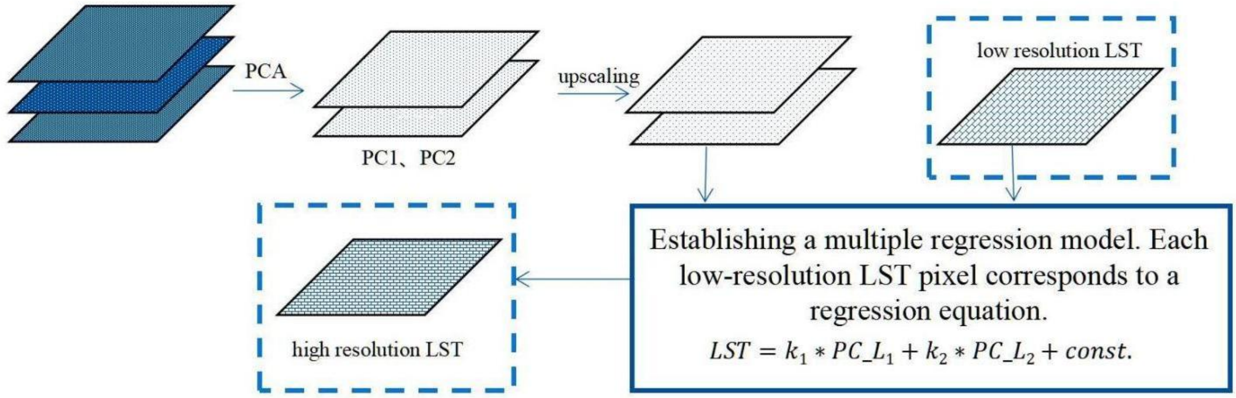

Figure 1. down-scale processing.

2.2 Index Fusion Method

PCA (Principal Component Analysis) is a statistical analysis method that reduces the dimensionality of a dataset. It utilizes an orthogonal transformation to transform the observed values of potentially correlated variables into a set of linearly uncorrelated variables, known as principal components. PCA is not a conventional weighted sum method. In this study, the improved DS-RSEI index values are represented as a result of applying PCA.

$$DS - RSEI = f(Wet, NDVI, NDBSI, LST) \tag{7}$$

3. RESULTS

3.1 Comparison of remote sensing ecological index results with and without sharpening LST

In this study, the thermal component of the remote sensing ecological index was enhanced through a process called sharpening, and the resulting downscaled image was referred to as DS-RSEI (DownScale-RSEI). The ecological environment evaluation results of DS-RSEI and the original RSEI compare and validated using overall and local samples from the images. Figure 2 and Table 1 compare the average values of RSEI and DS-RSEI over multiple years and the percentage differences. The results consistently showed that the mean value of DS-RSEI was higher than that of RSEI, with a percentage increase ranging from 0.68% to 4.16%. Based on this, we further divide the region into smaller areas to conduct a comparative analysis of the two ecological indices and evaluate the practicality of the DS-RSEI index.

The visual representation in Figure 3 illustrates that the downscaled 500m LST image utilizes a 4:1 pixel ratio compared to the original 1000m LST image. Consequently, the DS-RSEI image at a resolution of 500 meters more effectively captures the ecological environment's intricate spatial and temporal details. This discrepancy is also reflected in the outcomes of the RSEI environmental index. To further investigate the optimization and improvement effects of LST downscaling on the results, this study focused on samples from five distinct land cover types: impervious surfaces(a), densely built-up urban areas(b), non-densely built-up urban areas(c), non-densely vegetated areas(d), and densely vegetated areas(e). A comparative analysis was conducted to examine the impact of downscaled LST on the ecological environment index across different land cover types.
The selected samples consisted of 0.1°*0.1° square areas representing typical urban land covers. These samples encompassed five distinct areas: densely vegetated mountainous areas in the northwest of Beijing, Ta Zhao Village near Fangshan District in the southwest of Beijing (characterized by low-rise buildings and vegetation, belonging to non-densely vegetated areas), the densely built-up area of HuiLongguan Town and its surroundings, the vicinity of the Capital International Airport, and the central urban area of Beijing. These diverse sample areas allowed for examining the impact of resolution increase on the ecological environment index across different land cover types.
The results for selected sample areas (Figure 3 and Table 2) show that for areas with dense vegetation cover and rural regions with moderate vegetation cover, the increase in resolution has little effect on the results. The notable differences were observed in areas with complex urban layouts and intricate ecological environments, where the DS-RSEI index exhibited an upward trend compared to the RSEI index. For instance, the Beijing Capital International Airport encompassed a significant area of impervious surfaces composed of dense buildings and roads, but it also contained pockets of vegetation cover. The RSEI index failed to display the high values of the green cover area effectively. In contrast, the downscaled results of DS-RSEI optimized the representation of spatial details relative to the original RSEI, accurately capturing the variations in ecological environment changes. In complex terrain environments, particularly areas with more built-up land than vegetation, DS-RSEI successfully identified green patches, such as small green areas near the airport and green building areas within urban clusters. Therefore, the improved ecological environment index

demonstrated enhanced capabilities in identifying and monitoring complex urban environmental conditions and areas with significant differences.

	2001	2005	2009	2013	2017	2021
RSEI	0.591	0.596	0.553	0.574	0.591	0.591
DS-RSEI	0.599	0.604	0.576	0.595	0.595	0.600
Percentage Difference (%)	1.35	1.34	4.16	3.66	0.68	1.52

Table 1. The mean values of DS-RSEI and RSEI indices in the time series.

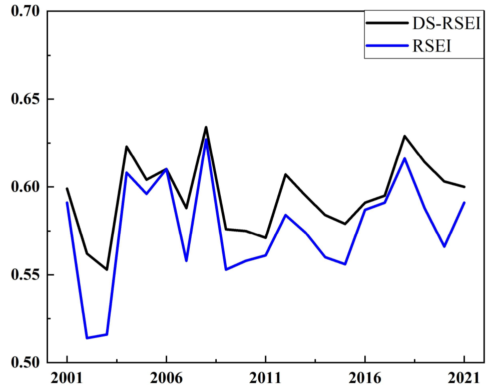

Figure 2. Comparison of the mean values of DS-RSEI and RSEI indices in the time series.

	a	b	c	d	e
land cover type	intensive vegetation area	non-intensive vegetation area	non-intensive building area	intensive building area	highlight impervious surface area
DS-RSEI result	0.711	0.512	0.378	0.300	0.311
RSEI result	0.714	0.491	0.350	0.281	0.280

Table 2. Comparison of index results for five land cover types.

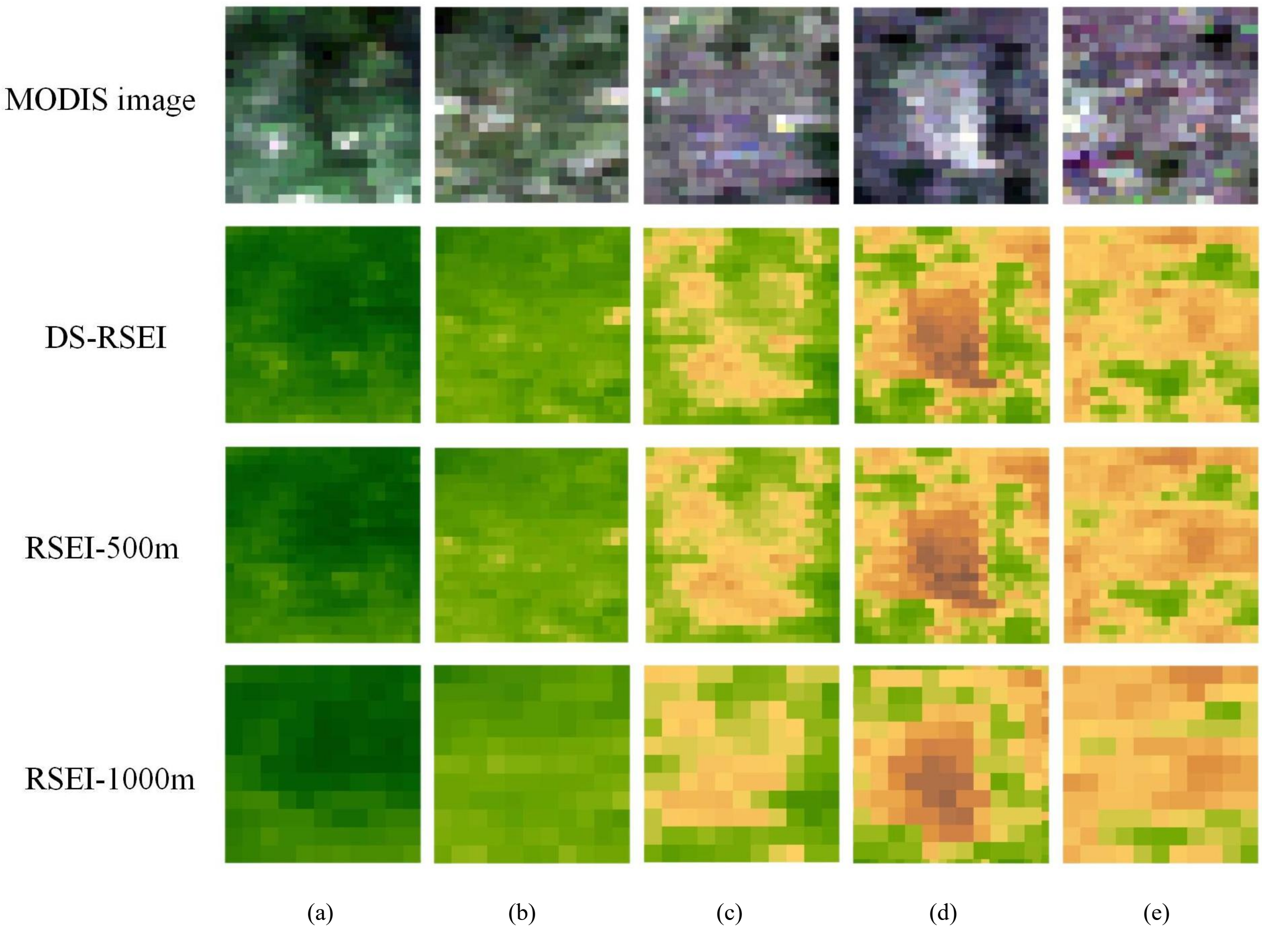

Figure 3. Comparison of index results for five land cover types.

3.2 Evaluation Results of Ecological Environment Status

Based on the scoring criteria specified in the "Standards" and considering the proportional distribution of different index levels, this study classifies the RSEI ecological index within the range of [0,1] into four distinct groups. These levels are arranged in ascending order: 0-0.4 corresponds to the "Poor" level, 0.4-0.6 corresponds to the "Moderate" level, 0.6-0.8 corresponds to the "Good" group, and 0.8-1 corresponds to the "Excellent" class. The proportion chart illustrating these levels is depicted in Figure 5.

The RSEI value in Beijing is derived through PCA (principal component analysis) of four key indicators. The results of the PCA analysis are presented in Table 3. From 2001 to 2021, with a sampling interval of four years, PC1 exhibits a contribution rate ranging from 79.41% to 87.78%. This indicates that PC1 captures over 79% of the information and effectively represents the comprehensive information of the four indicator components. Among these components, Wet and greenness (NDVI) are positive values, while warmth (LST) and dryness (NDBSI) are negative values. The opposing contributions of these two types of components imply their contrasting effects on the ecological environment. Previous research has demonstrated that humidity and greenness positively impact the ecological environment, whereas warmth and dryness negatively impact the environment. The annual mean results of DS-RSEI are provided in Table 1. This suggests that the overall ecological quality of Beijing has remained relatively stable, slightly above average, throughout the period from 2001 to 2021. In Figure 4, it can be observed that the NDVI values were relatively low in 2001 and 2009, falling below 0.7. These values reached a trough in 2009 and subsequently showed a gradual increase, indicating a declining trend in urban greening rates from 2001 to 2009 and a steady and gradual improvement in urban greening rates after 2009. The humidity index remained relatively steady, with an average value of approximately 0.48, peaking in 2013. The aridity index experienced a peak in 2009 due to a notable increase in construction land between 2005 and 2009, followed by a subsequent recovery. The heat index reached its highest points in 2009 and 2021 while remaining relatively low in other years, displaying a significant correlation with LST and NDVI.

Year	PC1 Contribution (%)	NDVI	LST	WET	NDBSI
2001	79.41	0.691	0.481	0.091	-0.532
2005	85.16	0.676	0.428	0.163	-0.577
2009	85.24	0.679	0.430	0.150	-0.576
2013	87.78	0.663	0.438	0.097	-0.599
2017	83.79	0.681	0.449	0.073	-0.574
2021	79.46	0.634	0.505	0.054	-0.583

Table 3. loadings of the four variables to the first principal component.

Figure 6 visually portrays the DS-RSEI (DownScale-RSEI) image of Beijing across multiple years, offering a clearer depiction of the spatial and temporal variations in the city's ecological environment quality. The central area of the city exhibits a higher concentration of yellow spots, which gradually expands over the years, indicating concentrated land development and utilization in the central and southern regions. In contrast, the western and northern parts of the city feature extensive green patches, predominantly comprised of mountains and forests, signifying a higher level of ecological environment quality. The overall trend showcases a decline followed by an improvement, with a certain degradation of the ecological environment observed from 2001 to 2009, and subsequent continuous enhancement since 2012, pointing to a positive advancement of the ecological environment in Beijing as a whole. The DS-RSEI remote sensing ecological index facilitates a more intuitive analysis of the spatiotemporal transformations in a region's ecological environment, enabling the identification of its ecological characteristics in space and the examination of changes in the ecological index over time.

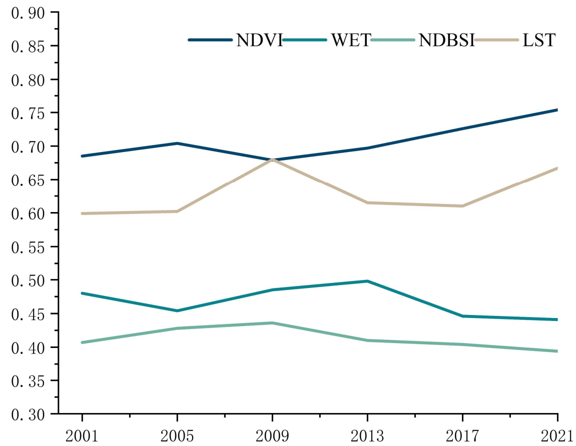

Figure 4. The normalized variation trend of each indicator component.

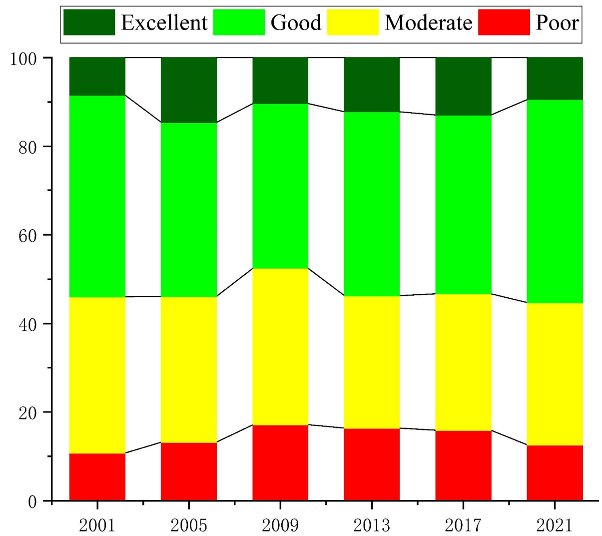

Figure 5. DS-RSEI ecological index grading results.

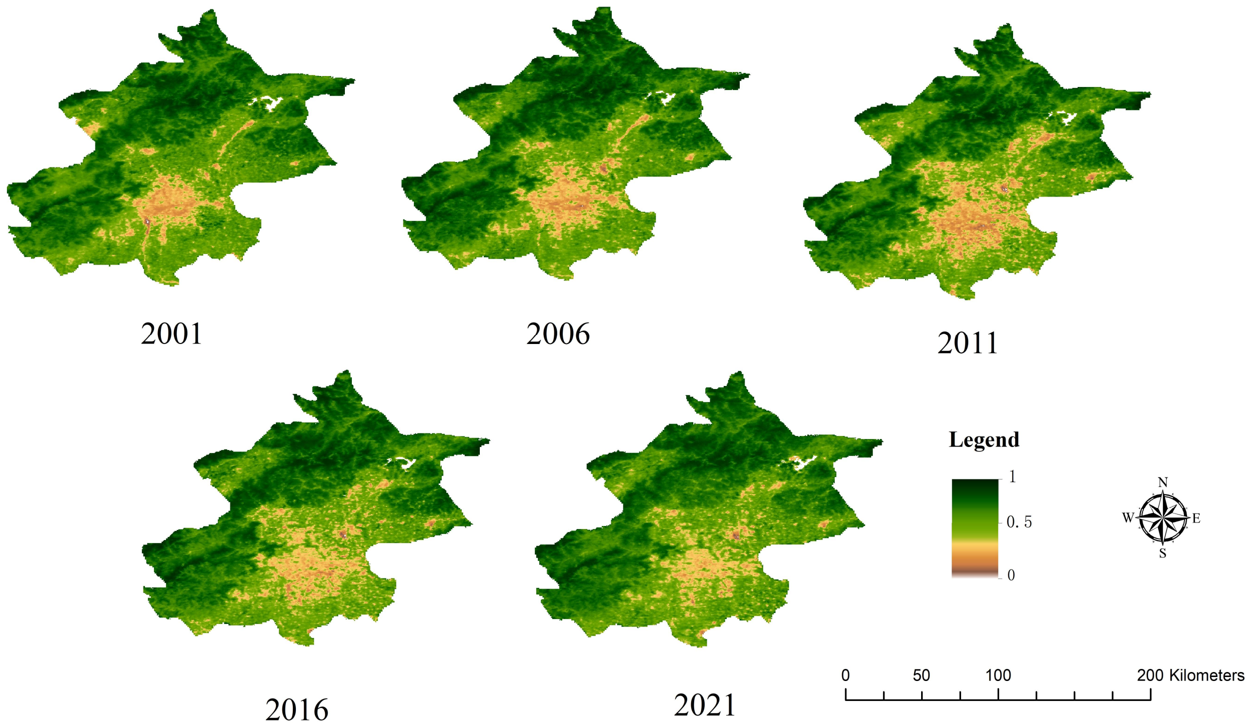

Figure 6. Time series DS-RSEI image.

4. DISCUSSION

Achieving precise representation of urban ecosystems through remote sensing imagery and monitoring the spatiotemporal changes of the ecological environment have always been key issues in the field of remote sensing technology. Since the introduction of the RSEI index, it has effectively addressed the transition from remote sensing images to ecological environment assessment.

Being the only city in the world to host both the Summer and Winter Olympics, Beijing witnessed a stable ecological environment that initially experienced a decline and then showed improvement during the planning and construction of the Olympic Village and its surrounding areas. This led to enhanced stability in the regional ecological environment. Evaluating Beijing's urban ecological environment over the past 20 years provides valuable guidance for the integrated development of the economy and ecology.Beijing is currently faced with transitioning, which involves multiple adjustments in industrial locations and optimization of the capital's functional space. The ecological environment evaluation method proposed in this study enables effective real-time monitoring of the urban ecological environment and facilitates long-term evaluation of environmental changes.

By utilizing remote sensing imagery, this study contributes to accurately assessing the dynamics of urban ecological systems and plays a crucial role in addressing the transition challenges faced by Beijing. It provides insights into the coupling development of the economy and ecological environment, facilitating the sustainable development of the city.

5. CONCLUSION

In this study, we propose an improved method for evaluating urban remote sensing ecological indices using MODIS data. We also address the limitations of MODIS surface temperature data and compare the improved DS-RSEI with the original RSEI through visual interpretation and statistical analysis. The results indicate that, relying on the more refined Land Surface Temperature (LST) data product, DS-RSEI effectively captures and analyzes detailed changes in the ecological environment, particularly in its improved ability to identify green spaces near artificial surfaces. It demonstrates a stronger capability in interpreting mixed pixel areas. Moreover, the evaluation results of the remote sensing ecological index in green coverage areas show no significant difference. DS-RSEI contributes to higher index values in areas with dense vegetation or surrounded by impervious surfaces.

Overall, this study provides an effective approach for real-time monitoring of urban ecological conditions and long-term evaluation of ecological environment changes. By utilizing remote sensing imagery, we can accurately assess the urban ecological system and its dynamics.

REFERENCES

Boori, M. S., Choudhary, K., et al., 2021: Spatiotemporal ecological vulnerability analysis with statistical correlation based on satellite remote sensing in Samara, Russia. *Journal of Environmental Management*, 285, 112138.

Chen, L., Huang, H., et al., 2023: Investigation on the spatial and temporal patterns of coupling sustainable development posture and economic development in World Natural Heritage Sites: A case study of Jiuzhaigou, China. *Ecological Indicators*, 146, 109920.

Huang, C., Wylie, B., et al., 2002: Derivation of a tasselled cap transformation based on Landsat 7 at-satellite reflectance. *International journal of remote sensing*, 23, 1741-1748.

Kauth, R. J.,Thomas, G., 1976: The tasselled cap--a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. LARS symposia, 159.

Neteler, M., 2010: Estimating daily land surface temperatures in mountainous environments by reconstructed MODIS LST data. *Remote sensing*, 2, 333-351.

Ordoyne, C.,Friedl, M. A., 2008: Using MODIS data to characterize seasonal inundation patterns in the Florida Everglades. *Remote Sensing of Environment*, 112, 4107-4119.

Singh, K. V., Setia, R., et al., 2015: Evaluation of NDWI and MNDWI for assessment of waterlogging by integrating digital elevation model and groundwater level. *Geocarto International*, 30, 650-661.

Xu, H., Wang, Y., et al., 2019: Detecting ecological changes with a remote sensing based ecological index (RSEI) produced time series and change vector analysis. *Remote Sensing*, 11, 2345.

Zakšek, K.,Oštir, K., 2012: Downscaling land surface temperature for urban heat island diurnal cycle analysis. *Remote Sensing of Environment*, 117, 114-124.