Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-14

DOI: *10.15244/pjoes/219361* ONLINE PUBLICATION DATE: 2026-06-15

Original Research

Ecological Environment Assessment Based on Remote Sensing: A Case Study of Hangzhou, China

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Received: 24 November 2025
Accepted: 15 March 2026

Abstract

Timely monitoring of urban ecological environments is essential for sustainable development. This study addresses the need to understand the complex internal mechanisms of ecological quality change, especially when indicators present contradictory trends. It evaluates the spatiotemporal evolution of ecological quality in Hangzhou, China, from 2016 to 2024, to identify the specific drivers of its improvement. The study utilized Landsat 8 data processed on the Google Earth Engine platform. Four key indicators were extracted: greenness (NDVI), wetness (WET), dryness (NDBSI), and heat (LST). These indicators were then integrated using Principal Component Analysis (PCA) to construct the comprehensive Remote Sensing Ecological Index (RSEI). The findings reveal that Hangzhou's mean RSEI increased by 8.07%, rising from 0.5249 in 2016 to 0.5710 in 2024. This overall enhancement was marked by a 9.55% expansion of the "Excellent" ecological grade area. Spatially, the city maintained a stable "southwest-high, northeast-low" ecological gradient. This ecological gain presents a significant finding. The improvement was not driven by an increase in greenness. The city-wide mean NDVI remained stable with a 0.15% decrease. Instead, the RSEI increase was caused by the mitigation of human-induced stress. This is evidenced by a sharp 17.55% decrease in dryness (NDBSI) and a 9.77% decrease in heat (LST). Hangzhou's ecological progress was achieved by alleviating urban pressures, such as the heat island effect and impervious surface impacts, rather than by expanding vegetation. This study validates the RSEI's utility for capturing complex improvements in mature urban ecosystems.

Keywords: monitoring of ecological environment quality, remote sensing ecological index, Google Earth engine, Landsat-8

Introduction

The ecological environment is the foundation for human survival and development. It not only supplies essential natural resources but also provides the basic conditions that underpin sustainable societal progress. In recent decades, rapid global urbanization has driven economic growth. However, this process has also placed immense pressure on regional ecological systems. The expansion of impervious surfaces, alteration of land use, and intensification of human activity can lead to habitat degradation, biodiversity loss, and a decline in

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overall environmental quality [1, 2]. Consequently, the timely and accurate monitoring of ecological quality has become a fundamental task. It is no longer merely a scientific endeavor but also an indispensable prerequisite for supporting ecological protection, fostering sustainable land management, and ensuring long-term economic growth. Effective monitoring provides the data necessary for evidence-based policymaking and adaptive management [3].

International research on ecological monitoring has a long history. For instance, the United States established an environmental impact assessment system as early as the 1960s. This was followed by efforts to create integrated indices, such as the "Total Environmental Quality Index" proposed by the Canadian Department of Environmental Protection in 1974, which sought to combine factors like atmosphere, water, and soil. With the launch of Earth observation satellites, such as Landsat in the 1980s, remote sensing technology introduced powerful new possibilities for ecological monitoring. Early remote sensing studies frequently relied on single indicators, such as the Normalized Difference Vegetation Index (NDVI) for greenness or Land Surface Temperature (LST) for urban heat. Recent studies have further suggested that temperature variations can significantly influence vegetation productivity, indicating that LST reflects not only the thermal environment but also ecological functioning and stress [4]. This approach, however, proved to be a significant limitation. Recent studies have also reported that the relationship between vegetation indices and LST can be nonlinear across large regions, which further highlights the difficulty of interpreting ecological conditions using any single indicator in isolation [5]. A single metric is often unable to represent the full range of regional ecological conditions. It can only capture one specific facet of a complex, interacting ecosystem. Therefore, relying on a single indicator makes it challenging to obtain a comprehensive understanding of overall ecological quality [3, 6].

In response to this clear limitation, researchers sought to develop composite indices. These multi-indicator frameworks are advantageous because they "communicate complex information by combining multiple measures into a single indicator" [7]. A composite index can provide a more holistic snapshot of environmental system health. This allows for robust comparisons over time and provides clear, actionable information for policymakers. In China, an early official framework was the Ecological Index (EI) introduced by the Ministry of Environmental Protection in 2006. A significant methodological advancement occurred when Xu Hanqiu proposed the Remote Sensing Ecological Index (RSEI) in 2013. The RSEI is a comprehensive index constructed by integrating four factors that are crucial to terrestrial ecological health: greenness (NDVI), wetness (WET), dryness (NDBSI), and heat (LST). A key strength of the RSEI model is its objectivity. Instead of relying on subjective weighting methods like the Analytic Hierarchy Process, the RSEI employs Principal Component Analysis (PCA). PCA is an objective method that determines the relative weight of each of the four indicators based on the data's inherent variance. This automated weighting allows the index to adapt to different regional environments and avoids the subjectivity of expert-defined models, making it a highly robust and replicable tool [7].

The RSEI model has been widely validated and applied. Its effectiveness has been demonstrated in diverse settings, including the assessment of ecological quality in mining areas, arid basins, and, increasingly, complex urban environments [8, 9]. A recent review highlights that the RSEI and its derivatives have become pivotal in broadening the analytical frameworks for assessing urban quality, particularly with the rise of advanced remote sensing technologies [3]. Recent studies have successfully leveraged the Google Earth Engine (GEE) platform, as this study does, to conduct long-term RSEI analyses in major cities. For example, a 2024 study on Wuhan, China, used GEE and RSEI to analyze ecological trends from 1990 to 2020. That study concluded that human geographic factors, such as population density and GDP, were the main drivers of spatial differentiation in ecological quality [10]. Recent city-scale studies suggest that land-use change can be a major driver of vegetation dynamics, and in some settings its influence may exceed that of climate variability. These studies also report that NDVI trajectories are often linked to urban land expansion and ecological protection policies [11]. This growing body of work demonstrates that analyzing the drivers of RSEI change in urban agglomerations is an important current research topic.

Against this backdrop, this study selects Hangzhou as its research area. Hangzhou is located on the southern wing of the Yangtze River Delta (YRD) urban agglomeration and is an important city where the regional integration strategy is being implemented. Changes in Hangzhou's ecological environment are not only relevant to local high-quality development but are also associated with the ecological environment and economic development of other cities in the YRD region. From the perspective of topography and urban configuration, Hangzhou is highly representative. The southwestern part is dominated by mountainous and hilly terrain with high vegetation coverage, serving as an important ecological barrier. In contrast, the northeastern part consists mainly of plains with dense river networks and concentrated construction land, resulting in a clear spatial gradient in ecological quality. Over the past decade, with the advancement of rapid urbanization, construction land has continued to expand and land-use types have changed rapidly.

The increase in impervious surfaces has intensified ecological pressure, which is mainly reflected in the intensification of the urban heat island effect and the compression of ecological space. Therefore, achieving a dynamic balance between rapid urbanization and ecological environment protection has become a practical challenge that Hangzhou must address. In response to these issues, during the study period, particularly since 2016, Hangzhou has continuously promoted the implementation of green infrastructure and the construction of "sponge city" initiatives. On the one hand, the city has optimized its urban green space system and increased green space area. On the other hand, it has strengthened water body protection and shoreline restoration and imposed stricter ecological controls and spatial constraints, in an effort to mitigate the negative effects caused by the heat island effect and impervious surfaces. Against this background, selecting Hangzhou as the study area is both representative and practically meaningful. The city combines strong urbanization pressure, a distinct ecological gradient, and sustained governance intervention, which provides an ideal setting for identifying the internal mechanisms of ecological quality improvement.

While many studies correlate RSEI changes with external drivers, a gap often persists in understanding the internal mechanisms of RSEI change. Moreover, recent work has noted that vegetation recovery is jointly shaped by natural environmental conditions and policy intervention, implying that greenness trends alone may not fully represent policy-driven ecological improvement [12]. This is especially true when different ecological indicators present contradictory trends, such as stable greenness existing alongside improving overall ecological quality. Beyond its scientific value, this study has practical implications for urban ecological planning and sustainability-oriented governance. The results suggest that, in a mature and highly urbanized environment, overall ecological quality can improve even when greenness remains stable, because the key gains may come from alleviating human-induced stress reflected in heat and dryness indicators. This provides a management-relevant perspective for evaluating policy outcomes, as it shifts attention from greenness increase alone to the effectiveness of interventions that mitigate the urban heat island effect and impervious-surface-related pressure. In this sense, RSEI and its component indicators can support evidence-based ecological protection strategies by identifying where ecological stress is concentrated and by tracking whether targeted governance measures translate into measurable improvements over time. The findings also offer transferable experience for other fast-growing cities facing similar trade-offs between development and ecological protection. When greenness is relatively stable, relying on a single vegetation index may underestimate policy-driven progress, whereas a composite assessment can better capture improvements achieved through stress reduction in the urban core. Therefore, cities implementing green infrastructure and sponge-city-type initiatives may benefit from using RSEI-based monitoring to prioritize interventions in high-pressure built-up areas and to evaluate whether planning and control measures effectively reduce thermal and dryness stress, rather than focusing solely on expanding vegetation cover. This study aims to address this gap by not only quantifying RSEI changes but also dissecting the specific contributions of the four component indicators.

Materials and Methods

Overview of the Study Area

Hangzhou is located in the northern part of Zhejiang Province on China's southeastern coast and serves as the provincial capital as well as a core city of the Yangtze River Delta urban agglomeration. The municipality covers 16,850 km² and governs 10 districts, 2 counties, and 1 county-level city. Its main urban area lies on the southern edge of the Hangjiahu Plain, with a landscape that rises in the southwest and slopes down toward the northeast. The western part of the city is dominated by the Tianmu Mountain range, while the east is characterized by low-lying plains interlaced with river networks [13]. Hangzhou has a subtropical monsoon climate with four distinct seasons, abundant rainfall, and mild temperatures. The mean annual temperature is approximately 17.8°C, and average yearly precipitation reaches about 1,450 mm [14]. The city is traversed by a dense water network, most notably the Qiantang River, which is known for its tidal bore. It also possesses significant natural and cultural resources, such as West Lake, a UNESCO World Cultural Heritage site. These geographical and cultural features shape the ecological conditions of the region and provide a unique background for environmental assessment [13]. Socioeconomic development in Hangzhou has accelerated in recent years, with the city undertaking major national and international events such as the G20 Summit and preparations for the Asian Games. In 2020, administrative divisions were adjusted, and by 2021, the urban area had expanded to 8,289 km². Over the past decade, the urban population increased from 7.04 million in 2012 to 10.20 million in 2021, while the urbanization rate rose from 74.3% to 83.6% [15]. Rapid urban expansion and economic growth have inevitably placed pressure on the ecological environment, underscoring the need for systematic monitoring and assessment [15]. Fig. 1 shows the digital elevation model (DEM) of the study area.

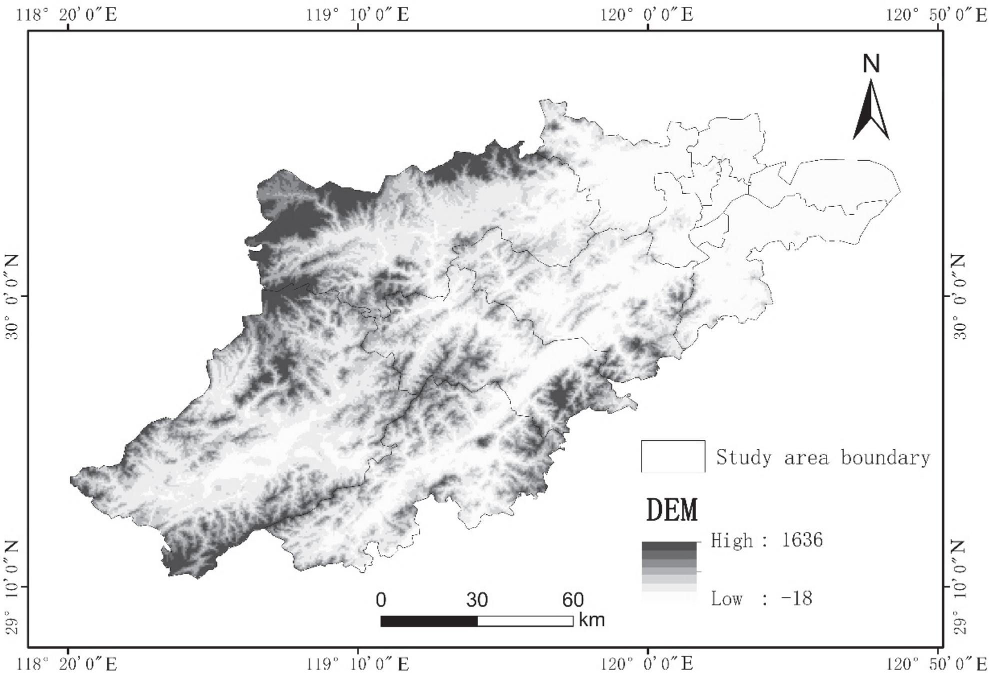

Fig. 1. Topographic map of Hangzhou.

Data Platform and Source

This study utilized the Google Earth Engine (GEE) cloud computing platform for all data acquisition processing and analysis. GEE provides a multi-petabyte catalog of geospatial datasets. It also offers planetary-scale analysis capabilities. These features facilitate large-scale and long-term ecological monitoring.

The RSEI model was constructed exclusively from the Landsat 8 OLI/TIRS Collection 2 dataset. This data is provided by the U.S. Geological Survey (USGS). This specific data product was chosen because it provides a consistent and co-registered set of multispectral and thermal data. These data come from the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Using a single unified data source ensures high internal consistency among the four ecological indicators. This approach also eliminates the methodological uncertainties associated with sensor fusion or data resampling [16]. Peer-reviewed studies have successfully validated the use of GEE and Landsat time series for RSEI assessment [17-19]. The specific Landsat 8 bands used to derive RSEI indicators are detailed in Table 1.

Data Acquisition and Preprocessing on GEE

The entire workflow was executed on the GEE platform [20]. The primary data was sourced from the image collection. This Collection 2 Level 2 product provides analysis-ready data [21]. The OLI bands are processed to Surface Reflectance (SR), and the TIRS band is processed to Surface Temperature (ST) [17]. This automated preprocessing replaces traditional manual radiometric calibration and atmospheric correction [20]. We selected two study periods to align with the 2016 and 2024 timeframes. For each period, a filter was applied to select images from the summer season. This season (June 1st to August 31st) was chosen to capture the peak of vegetation vigor [22]. A subsequent filter was applied to limit the data collection to the administrative boundaries of Hangzhou. Following this, a single representative image was generated for each study year. This was achieved by applying a median composite function to all cloud-free pixels within the summer date range [23]. This method produces a robust cloud-free composite image. This approach is superior to traditional mosaicking [23]. Finally, the administrative boundary of Hangzhou was used to clip the composite images. Water bodies were masked out using a water mask to ensure the RSEI analysis focused exclusively on terrestrial ecological quality [22].

Ecological Indicator Generation

The RSEI model integrates four key ecological indicators, commonly referred to as greenness, wetness, dryness, and heat [24]. All four indicators were calculated using Landsat 8 OLI/TIRS bands as specified in the following sections.

Table 1. Landsat 8 OLI/TIRS bands used for RSEI construction.

Landsat 8 Band	Band Name	Spectral Range (μm)	Resolution (m)	RSEI Indicator (s)
Band 2	Blue	0.45-0.515	30	WET, NDBSI
Band 3	Green	0.525-0.600	30	WET, NDBSI
Band 4	Red	0.630-0.680	30	NDVI, WET, NDBSI
Band 5	Near-Infrared (NIR)	0.845-0.885	30	NDVI, WET, NDBSI
Band 6	Shortwave Infrared 1 (SWIR1)	1.560-1.660	30	WET, NDBSI
Band 7	Shortwave Infrared 2 (SWIR2)	2.100-2.300	30	WET
Band 10	Thermal Infrared 1 (TIRS)	10.6-11.2	100 (resampled to 30)	LST

$$NDVI = \frac{(\rho_{NIR} - \rho_{\text{Red}})}{(\rho_{NIR} + \rho_{\text{Red}})} \tag{1}$$

Where ρNIR is the reflectance of Band 5, and ρRed is the reflectance of Band 4 [24].

The wetness indicator measures the moisture content of soil and vegetation. This study employed the wetness component (WET) derived from the Tasseled Cap Transformation (TCT). The calculation used the established coefficients for Landsat 8 OLI Surface Reflectance [25].

$$\text{WET}=0.1511\rho_{Blue}+0.1973\rho_{\text{Green}}+0.3283\rho_{\text{Red}} +0.3407\rho_{\text{NIR}}-0.7117\rho_{\text{SWIR1}}-0.4559\rho_{\text{SWIR2}} \tag{2}$$

The dryness indicator reflects the "drying" effect of impervious surfaces and bare soil. It is represented by the Normalized Difference Built-up and Soil Index (NDBSI). This index is a composite of the Soil Index (SI) and the Index-based Built-up Index (IBI) [26].

$$NDBSI = \frac{(SI + IBI)}{2} \tag{3}$$

The SI and IBI components were calculated for Landsat 8 bands as follows [26]:

$$SI = \frac{((\rho_{SWIR2} + \rho_{Red}) - (\rho_{NIR} + \rho_{Blue}))}{((\rho_{SWIR2} + \rho_{Red}) + (\rho_{NIR} + \rho_{Blue}))} \tag{4}$$

$$IBI = \frac{2\rho_{SWIR1}/(\rho_{SWIR1} + \rho_{NIR}) - [\rho_{NIR}/(\rho_{NIR} + \rho_{Red}) + \rho_{Green}/(\rho_{Green} + \rho_{SWIR1})]}{2\rho_{SWIR1}/(\rho_{SWIR1} + \rho_{NIR}) + [\rho_{NIR}/(\rho_{NIR} + \rho_{Red}) + \rho_{Green}/(\rho_{Green} + \rho_{SWIR1})]} \tag{5}$$

Where ρ_{Blue} (Band 2), ρ_{Green} (Band 3), ρ_{Red} (Band 4), ρ_{NIR} (Band 5), ρ_{SWIR1} (Band 6) and ρ_{SWIR2}(Band 7) are the respective band reflectances.

The heat indicator reveals the surface thermal environment. This study derived Land Surface Temperature (LST) directly from the thermal band provided in the Landsat 8 Level 2 product. This band is already atmospherically corrected and processed by the USGS. The digital number (DN) values were converted to Kelvin (K) using the scaling factors provided. They were then converted to Celsius (°C) for analysis. This direct-use method replaces the complex manual radiative transfer calculations [27].

$$LST(°\text{C}) = (ST_{B10} * 0.00341802 + 149.0) - 273.15 \tag{6}$$

Where STB10 represents the pixel value of the Surface Temperature band.

Normalization of RSEI Construction

The four indicators (NDVI, WET, NDBSI, LST) possess different dimensions and scales. They cannot be directly integrated. Therefore, a min-max normalization was applied to each indicator. This process scales all four indicators to a uniform range of 0 to 1.

$$Nl = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{7}$$

Where *NI* is the normalized value of an indicator. I is the original pixel value. I_{min} and I_{max} are the minimum and maximum values of that indicator within the study area.

Following normalization, Principal Component Analysis (PCA) was performed within the GEE platform. The four indicators were derived in GEE using a consistent preprocessing workflow, including cloud masking and seasonal compositing, to ensure

Table 2. Principal component analysis of indicators for 2016 and 2024.

Year	Indicator	PC1	PC2	PC3	PC4
2016	NDVI	-0.60933865	-0.36341098	0.45419458	0.53883776
	WET	-0.38319344	0.76792127	0.43101308	-0.27872464
	LST	-0.55441204	-0.22729109	0.77934588	-0.18326493
	NDBSI	-0.41772774	-0.47599174	-0.02355831	-0.77355051
	Eigenvalue	0.047	0.009	0.007	0.002
	Contribution Rate of Eigenvalue	78.06	14.29	7.26	0.39
2024	NDVI	-0.59764888	-0.36828327	0.44692447	0.55447430
	WET	-0.33688216	0.73403727	0.51365337	-0.28958575
	LST	-0.59677441	-0.29502518	0.73236858	-0.14302687
	NDBSI	-0.41615684	-0.48838187	-0.00741483	-0.76696913
	Eigenvalue	0.039	0.008	0.004	0.001
	Contribution Rate of Eigenvalue	80.21	12.81	6.65	0.34

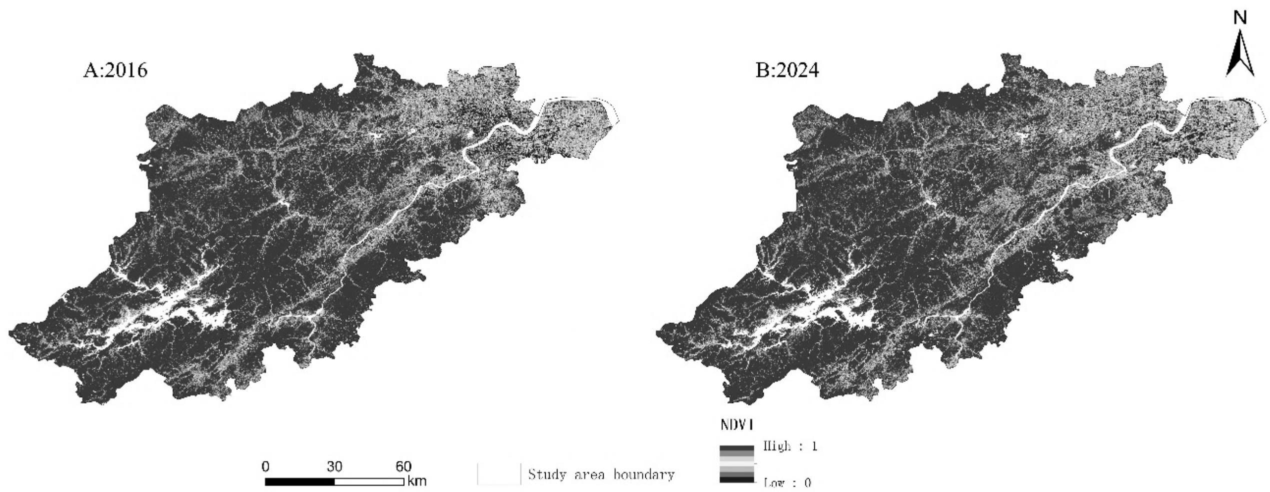

Fig. 2. Normalization results of Greenness indicators for 2016 and 2024.

reliable inputs. Following normalization, PCA was performed on the stacked four-indicator image using the centered covariance matrix of the normalized variables. The eigenvectors of this covariance matrix define the loadings of each indicator, and PC1 is the linear combination of NDVI, WET, NDBSI, and LST that explains the maximum variance. The direction of PC1 was determined by the indicator loadings. When PC1 is negatively associated with ecological quality, as indicated by negative loadings of the four indicators in Table 2, PC1 was inverted to form the initial index as RSEI′ = 1 − PC1. The resulting RSEI′ was then rescaled to 0-1 using the same min-max normalization to obtain the final RSEI. PCA is an objective method that integrates the four indicators. It determines their respective weights based on the data's inherent variance.

The first principal component (PC1) typically concentrates most of the information from the four indicators. The PC1 loadings were examined. Greenness (NDVI) and wetness (WET) are positive ecological factors. In contrast, dryness (NDBSI) and heat (LST) are negative factors. As detailed in Table 2, the PCA results showed that all four indicators (NDVI, WET, LST, and NDBSI) had negative loadings for both 2016 and 2024. This indicates that PC1 itself is negatively correlated with ecological quality. Therefore, the initial RSEI' (RSEI prime) was calculated by inverting PC1. This RSEI' value was then normalized again using the min-max method (Formula (7)). This step produced the final Remote

Table 3. Statistical summary of NDVI in Hangzhou for 2016 and 2024.

Year	Minimum	Maximum	Mean	Standard Deviation
2016	0	1	0.7866	0.512
2024	0	1	0.7854	0.509

Table 4. Statistical summary of WET in Hangzhou for 2016 and 2024.

Year	Minimum	Maximum	Mean	Standard Deviation
2016	0	1	0.6415	0.427
2024	0	1	0.6436	0.431

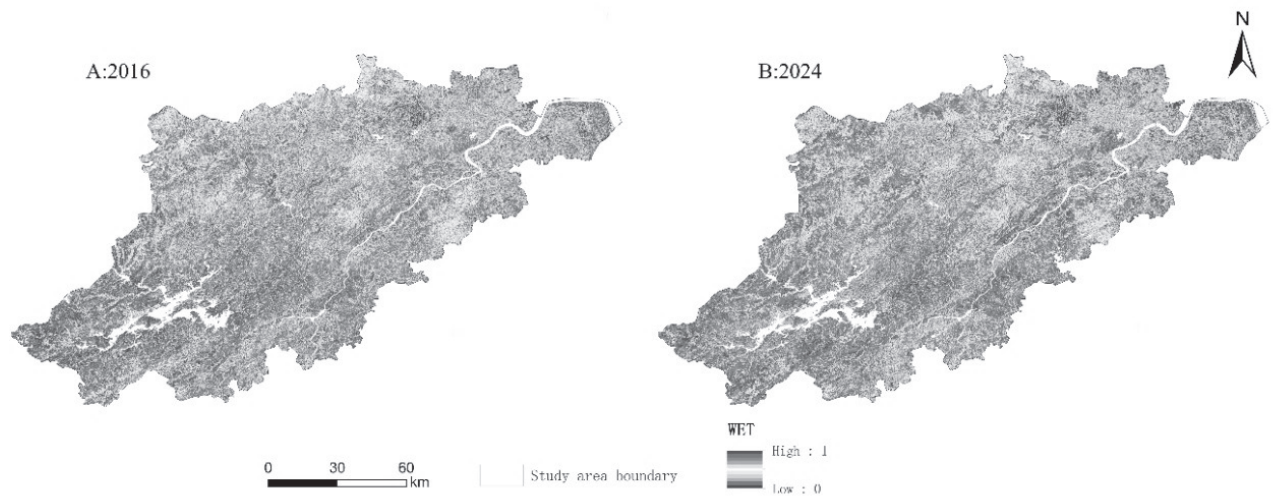

Fig. 3. Normalization results of Wetness indicators for 2016 and 2024.

Sensing Ecological Index (RSEI). The final RSEI is a comprehensive index scaled from 0 to 1. Higher values represent better ecological environmental quality [28].

$$RSEI' = 1 - PC1 \tag{8}$$

$$RSEI = \frac{RSEI' - RSEI'_{min}}{RSEI'_{max} - RSEI'_{min}} \tag{9}$$

Although the index construction is deterministic once the annual composites are generated, some uncertainty may still arise from pixel availability under cloud masking and from spatial heterogeneity. This uncertainty is mitigated by using a consistent preprocessing workflow and standardized PCA-based integration.

Results

Ecological Indicators Analysis in Hangzhou

Table 2 shows that the eigenvalue contribution rates of the first principal component (PC1) were exceptionally high, at 78.06% in 2016 and 80.21% in 2024. The PC1 column showed that all four indicators, including greenness (NDVI), wetness (WET), heat (LST), and dryness (NDBSI), had negative loadings in both 2016 and 2024.

As shown in Table 3, the mean of the greenness indicator for Hangzhou was 0.7866 in 2016 and 0.7854 in 2024, and the standard deviations for Hangzhou were 0.512 in 2016 and 0.509 in 2024. Over the eight years, the mean of the greenness indicator for Hangzhou decreased by 0.15%, and the standard deviation declined by 0.59%. Fig. 2 shows that greenness was higher in southwestern Hangzhou and lower in the northeastern areas spatially.

Table 4 shows that the mean of the wetness indicator for Hangzhou was 0.6415 in 2016 and 0.6436 in 2024, and the standard deviations for

Table 5. Statistics of NDBSI in Hangzhou for 2016 and 2024.

Year	Minimum	Maximum	Mean	Standard Deviation
2016	0	1	0.4346	0.223
2024	0	1	0.3697	0.206

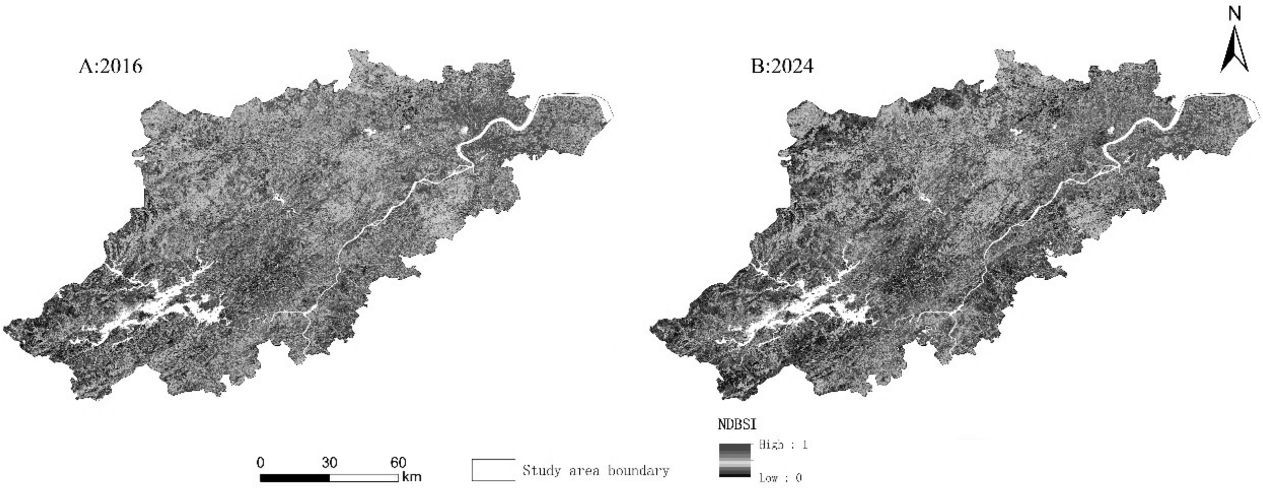

Fig. 4. Normalized results of Dryness factors for 2016 and 2024.

Table 6. Statistics of LST in Hangzhou for 2016 and 2024.

Year	Minimum	Maximum	Mean	Standard Deviation
2016	0	1	0.3776	0.216
2024	0	1	0.3440	0.207

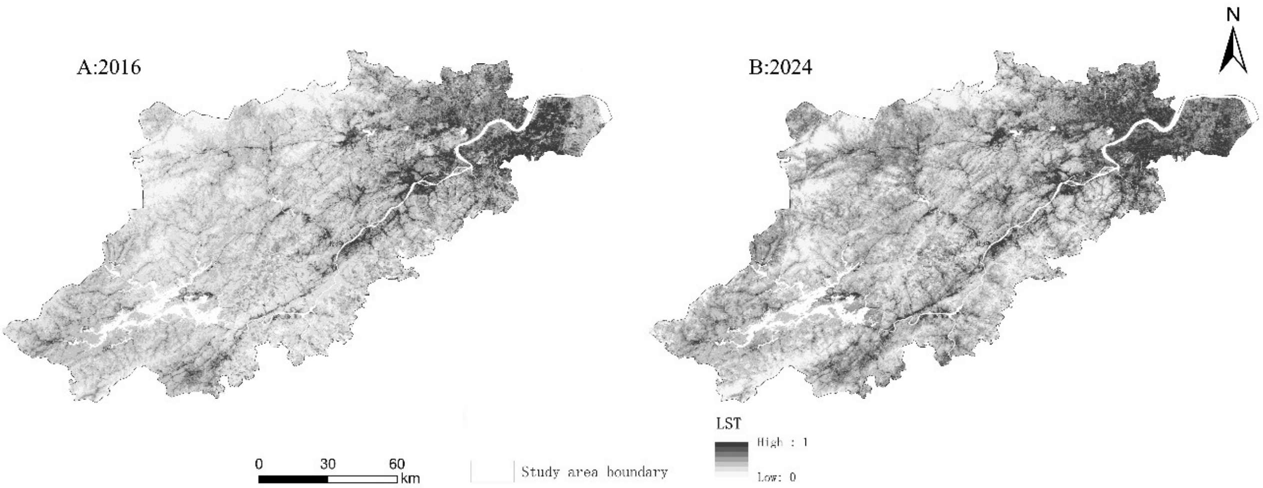

Fig. 5. Normalized results of Heat factors for 2016 and 2024.

Hangzhou were 0.427 in 2016 and 0.431 in 2024. Over the eight years, the mean of the wetness indicator for Hangzhou increased by 0.33%, and the standard deviation increased by 0.93%. As can be seen in Fig. 3, the wetness was higher in southwestern Hangzhou and lower in the northeastern areas spatially.

Table 7. Statistics of RSEI in Hangzhou for 2016 and 2024.

Year	Minimum	Maximum	Mean	Standard Deviation
2016	0	1	0.5249	0.313
2024	0	1	0.5710	0.325

Table 8. Area and proportion of each ecological grade in Hangzhou for 2016 and 2024.

Proportion of RSEI Grade Areas	Year 2016		Year 2024	
	Proportion	Area（km²）	Proportion	Area（km²）
Poor	3.76%	633.56	2.96%	498.76
Fair	8.02%	1351.37	7.42%	1250.27
Moderate	15.07%	2539.26	12.65%	2131.53
Good	50.10%	8441.85	44.37%	7476.35
Excellent	23.05%	3883.93	32.60%	5493.10

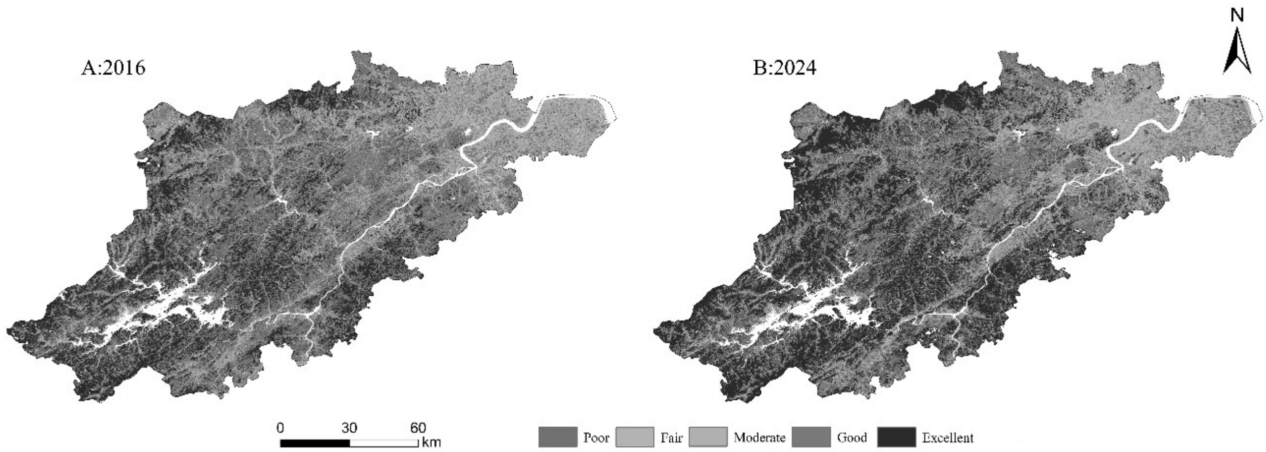

Fig. 6. RSEI ecological environment quality maps for 2016 and 2024.

According to Table 5, the mean of the dryness indicator for Hangzhou was 0.4346 in 2016 and 0.3697 in 2024, and the standard deviations for Hangzhou were 0.223 in 2016 and 0.206 in 2024. Over the eight years, the mean of the dryness indicator for Hangzhou decreased by 17.55%, and the standard deviation declined by 8.25%. As presented in Fig. 4, the dryness was lower in southwestern Hangzhou and higher in the northeastern areas spatially.

As shown in Table 6, the mean of the heat indicator for Hangzhou was 0.3776 in 2016 and 0.3440 in 2024, and the standard deviations for Hangzhou were 0.216 in 2016 and 0.207 in 2024. Over the eight years, the mean of the heat indicator for Hangzhou decreased by 9.77%, and the standard deviation declined by 4.35%. From Fig. 5, it is clear that the heat was lower in southwestern Hangzhou and higher in the northeastern areas spatially.

Spatio-Temporal Changes in the Ecological Environment of Hangzhou

According to Table 7, the mean RSEI for Hangzhou was 0.5249 in 2016 and 0.5710 in 2024, and the standard deviations for Hangzhou were 0.313 in 2016 and 0.325 in 2024. Over the eight years, the mean RSEI for Hangzhou increased by 8.07%, and the standard deviation increased by 3.69%.

The map was classified into five grades based on RSEI: Poor (0-0.2), Fair (0.2-0.4), Moderate (0.4-0.6), Good (0.6-0.8), and Excellent (0.8-1.0). As shown in Table 8, in 2016, the areas classified as Poor, Fair, Moderate, Good, and Excellent were 633.56 km² (3.76%), 1351.37 km² (8.02%), 2539.26 km² (15.07%), 8441.85 km² (50.10%), and 3883.93 km² (23.05%) of the total area, respectively. In 2024, the areas classified as Poor, Fair, Moderate, Good, and Excellent were 498.76 km² (2.96%), 1250.27

km² (7.42%), 2131.53 km² (12.65%), 7476.35 km² (44.37%), and 5493.10 km² (32.60%) of the total area, respectively. From 2016 to 2024, the area with Poor, Fair, Moderate, and Good ratings decreased, while the area with Excellent rating increased. Fig. 6 illustrates a significant increase in the Excellent-rated area in southwestern Hangzhou, while the Poor-rated area contracted in the northeast; lower-grade areas were generally replaced by those with higher grades.

Discussion

Validation of the RSEI Model Construction

The PCA results are detailed in Table 2. The results validate the construction of the RSEI model in this study. The high contribution rates of PC1 (78.06% in 2016 and 80.21% in 2024) confirm its ability to represent the comprehensive information of the four indicators. The eigenvector loadings revealed the ecological meaning of PC1. As shown in Table 2, all four indicators (NDVI, WET, LST, and NDBSI) showed negative loadings for both 2016 and 2024. This indicates that the PC1 value itself is negatively correlated with ecological quality. Consequently, the RSEI' = 1 − PC1 transformation was necessary to ensure the final RSEI value was positively correlated with environmental quality [29].

Analysis of the Overall Improvement Trend in Ecological Quality

The main finding is that Hangzhou's ecological environment quality improved substantially from 2016 to 2024. Table 7 shows that the mean RSEI increased by 8.07%. As can be seen in Table 8, the "Excellent" area grew by over 1600 km². This improvement is very important when we compare it to the whole Yangtze River Delta (YRD) group of cities [30]. The YRD is growing very fast, and its ecology has changed in complex ways. The ecological environment quality in the YRD exhibited a decline followed by a recovery. The year 2016 seems to be an important time of change. It declined from 2011 to 2016, but showed a marked improvement from 2016 to 2021. This study found a strong 8.07% improvement in Hangzhou from 2016 to 2024. This finding aligns with the broader regional recovery observed after 2016, suggesting that the trend in Hangzhou was not an isolated phenomenon but rather indicative of the efficacy of regional ecological initiatives during this period. A city-level comparison within the YRD further supports this interpretation. Using MRSEI for 41 cities in the Yangtze River Delta urban agglomeration, Li et al. reported that the regional mean MRSEI showed only small fluctuations between 2016 and 2021. However, the city-level trends were clearly heterogeneous. In their trend results, Hangzhou showed a slight positive change, with an average slope of 0.00040, and Shanghai also showed a small positive slope of 0.00026. In contrast, several highly urbanized cities near the estuary and along the Yangtze River corridor showed negative trends, including Suzhou (−0.00352), Wuxi (−0.00192), Jiaxing (−0.00485), and Nantong (−0.00495). This comparison indicates that ecological quality change in the YRD is not uniform across cities. Importantly, although their assessment ends in 2021, it provides a city-level benchmark adjacent to the time window of this study. In this sense, the improvement observed in Hangzhou during 2016–2024 is consistent in direction with the "stable or slightly improving" group identified for 2016–2021, rather than with the "declining" group concentrated in the highly built-up core [31].

The year 2016 is an important mark. It was when the city hosted the G20 Summit and started big green projects, like the "Sponge City" program. The RSEI improved mainly because of the drops in LST and NDBSI. This result is consistent with the goals of "Sponge City" projects. Those projects use green spaces (UGS) to reduce the urban heat island effect and help more water soak into the ground. Other studies also show that green spaces work this way [32]. It is also possible to further explain why the improvements were mainly reflected in LST and NDBSI. These two indicators are closely related to the heat island effect and the pressure from impervious surfaces. Therefore, measures that modify surface conditions in built-up areas may influence them more directly. One type is green infrastructure. Expanding and optimizing urban green spaces, along with improved street-level greenery, can increase shading and enhance evapotranspiration, helping reduce surface heat. Another type is sponge city construction, whose key idea is to retain and infiltrate more rainfall locally. This includes permeable pavements, small retention and infiltration facilities, and more distributed runoff control. Such actions can weaken the dryness signal captured by NDBSI by improving near-surface moisture conditions and reducing the dominance of hardened surfaces. Water-related measures are also important in Hangzhou. Strengthening water body protection and restoring shoreline spaces can improve the local thermal and moisture environment, especially in dense areas near rivers and lakes. Overall, these actions are consistent with the observed pattern. At the city scale, greenness changed little, whereas heat and dryness decreased in built-up areas, which then contributed to the increase in RSEI. So, the 8.07% RSEI increase provides evidence that Hangzhou used special ecological actions to manage problems from city growth. This helped the whole area's ecology get better after 2016.

Spatial Differentiation of Ecological Quality and its Driving Factors

The spatial differentiation of ecological quality in Hangzhou is clear and consistent, defined by a southwest high, northeast low gradient. This pattern is driven by two primary factors: natural topography and human urbanization [33]. The southwestern region is dominated by the Tianmu Mountain range. This high-elevation, steep-slope terrain restricts development, which preserves high vegetation coverage with a mean NDVI greater than 0.78 and extensive water bodies with a mean WET greater than 0.64. This area functions as a stable, high-quality ecological source. Conversely, the northeastern region consists of low-lying plains, which are ideal for urban expansion. This area concentrates human activity, leading to the replacement of natural surfaces with impervious ones. This results in high ecological stress, characterized by high NDBSI, representing dryness, and high LST, representing urban heat. From 2016 to 2024, the four indicators did not change in the same way. The two positive indicators stayed almost the same at the city scale. NDVI was basically flat, with only a 0.15% decrease. WET also changed little, with a 0.33% increase. The two stress indicators showed the opposite pattern. NDBSI dropped by 17.55%, and LST dropped by 9.77%. This means the main improvement in Hangzhou did not come from more greenness. It came from weaker dryness and heat stress. This process also fits the spatial pattern. The southwest already had high NDVI and high WET, so its “room to improve” was limited. The northeast is the main built-up area, where NDBSI and LST were high, and where stress reduction can change the overall RSEI more clearly.

The RSEI is an integrated index, balancing the positive ecological factors of NDVI and WET against the negative human stress factors of NDBSI and LST. The city's overall mean RSEI increased by 8.07% from 2016 to 2024, showing a significant improvement in ecological quality. This temporal trend is directly linked to the spatial pattern. The stable, high-quality southwestern region acted as a consistent ecological baseline, but it was not the source of this improvement. The improvement was concentrated in the dynamic northeastern urban area. The mechanism for this improvement was not an increase in greenness; in fact, the city-wide NDVI mean remained flat, decreasing by only 0.15%. Instead, the improvement of RSEI was driven almost entirely by the successful mitigation of human stress factors. Specifically, the mean NDBSI decreased by 17.55%, and the mean LST decreased by 9.77%. This demonstrates that the overall ecological gain was achieved by alleviating pressure in the urban core, likely through policies like green infrastructure enhancement [34].

Driving Mechanism of Ecological Improvement: The “RSEI-NDVI” Paradox

A primary finding of this study is the significant 8.07% improvement in Hangzhou's mean RSEI, which increased from 0.5249 in 2016 to 0.5710 in 2024. This trend indicates a substantial enhancement of overall ecological quality. However, this improvement presents a counterintuitive finding when compared with the temporal data for the greenness indicator. During the same eight-year period, the mean NDVI decreased by 0.15%. This apparent contradiction of a rising RSEI ecological quality index with a flatlining NDVI vegetation index constitutes the RSEI-NDVI question. It challenges the conventional understanding that ecological improvement is not just about the expansion of vegetation cover [35].

The mechanism driving this paradox is elucidated by analyzing the full-spectrum composition of the RSEI. As a composite index, the RSEI's value is determined by the interplay of four factors, balancing the positive ecological components of NDVI and WET against the negative stress components of NDBSI and LST. The data from 2016 to 2024 clearly demonstrates that the 8.07% RSEI gain was not driven by the positive indicators. Instead, the improvement was almost entirely attributable to the successful alleviation of the negative human-induced stress factors [36]. This finding is directly supported by the indicator statistics and the PCA structure used to construct the RSEI. In Table 3 and Table 4, the city-wide mean of the two positive indicators changed very little from 2016 to 2024. The mean NDVI decreased from 0.7866 to 0.7854, and the mean WET increased only from 0.6415 to 0.6436. In contrast, Table 5 and Table 6 show much larger shifts in the two stress indicators. The mean NDBSI declined from 0.4346 to 0.3697, and the mean LST declined from 0.3776 to 0.3440. This imbalance in magnitude explains why the RSEI increased even when NDVI stayed flat. In addition, the PCA results confirm that the four indicators jointly determine PC1 and that the final index is obtained through the $RSEI' = 1 - PC1$ transformation. Since all four indicators have negative loadings in both years, the strong reductions in NDBSI and LST in 2024 shift PC1 in the direction that produces a higher RSEI after inversion. Therefore, the observed RSEI improvement mainly reflects the mitigation of dryness and heat stress, rather than an expansion of vegetation cover.

This finding provides a clear understanding of the observed ecological improvement: Hangzhou's progress was achieved not through measures like afforestation, but by alleviating ecological pressure in the city's core areas, thereby increasing the RSEI. This finding aligns with the spatial separation identified in the spatio-temporal analysis of RSEI and its component indicators. This sharp reduction in dryness and heat directly indicates that urban environmental policies were effective. These policies, such as green infrastructure enhancement, are designed to mitigate the impacts of impervious surfaces and the urban heat island effect. This paradox, therefore, validates the comprehensive nature of the RSEI. It also demonstrates that the index can capture improvements in urban livability and ecological resilience [37].

Conclusions

This study systematically evaluated the spatiotemporal evolution of ecological environment quality in Hangzhou, and constructed a Remote Sensing Ecological Index (RSEI) based on Landsat data from 2016 and 2024. The research has led to several key conclusions. First, the study confirms the RSEI model's applicability for a complex urban ecosystem. The model effectively integrated the four indicators of greenness, wetness, dryness, and heat. This was validated by Principal Component Analysis. The analysis showed that the first principal component (PC1) consistently concentrated over 78% of the total information from the four indicators. Second, the temporal analysis revealed a clear improvement in Hangzhou's overall ecological quality. The mean RSEI increased significantly by 8.07% from 0.5249 in 2016 to 0.5710 in 2024. This trend was marked by a substantial expansion of the “Excellent” grade ecological area. Spatially, the quality remains highest in the southwestern mountainous region. This area functions as a vital ecological barrier. However, the northeastern urban core also showed marked improvement. This demonstrates that Hangzhou has achieved a degree of balance between rapid urbanization and environmental protection. Finally, and most importantly, this study identified the specific mechanism driving this 8.07% improvement, which presents a counter-intuitive finding. The improvement was not driven by an increase in greenness. In fact, the city-wide mean NDVI remained flat with a negligible 0.15% decrease. Instead, the RSEI increase was almost entirely caused by the mitigation of negative human-induced stress factors. This was evidenced by a sharp 17.55% decrease in the dryness index (NDBSI) and a 9.77% decrease in the heat index (LST).

This central finding clarifies the observed ecological progress. Hangzhou's success was achieved by alleviating pressure in the urban core through policies that mitigated the urban heat island effect and controlled impervious surfaces. The study, therefore, provides a nuanced, quantitative validation that urban ecological quality can be significantly enhanced even when supporting vegetation cover remains stable. From a management perspective, this mechanism implies that balancing rapid urbanization and ecological protection should prioritize stress reduction in the built-up core, rather than relying solely on increasing greenness. In practical planning, interventions can be organized around the two dominant stress pathways identified in this study. For heat mitigation, green infrastructure should be strengthened in high-density areas through a more continuous urban green space network and improved street-level greenery, so that shading and evapotranspiration can reduce surface thermal pressure. For dryness and impervious-surface pressure, sponge-city-type measures should be further implemented, including permeable pavements and distributed runoff retention and infiltration facilities, to reduce the dominance of hardened surfaces and improve near-surface moisture conditions. In addition, water-related governance remains important in Hangzhou. Strengthening water body protection and promoting shoreline restoration can improve the local thermal and moisture environment, especially in river- and lake-adjacent built-up zones. Importantly, these measures should be guided by monitoring that tracks not only NDVI but also the stress indicators. Since the key gains observed in this study were reflected in NDBSI and LST, an RSEI-based assessment framework can help managers identify where stress is concentrated, prioritize interventions in high-pressure urban areas, and evaluate whether planning and control measures translate into measurable reductions in heat and dryness over time.

Conflict of Interest

The authors declare no conflict of interest.

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