RESEARCH PAPER

ASSESSMENT OF REMOTE SENSING APPROACH FOR URBAN ECOLOGICAL QUALITY EVALUATION IN PEKANBARU CITY, RIAU PROVINCE INDONESIA

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ABSTRACT. There are obstacles in estimating environmental dynamics behind its convenience, beginning with the development of effective policies for sustainable urban development. The objectives of this research were to comprehend the ability and performance of ecological indices integration and to identify the spatial distribution of changes from 2018 to 2021 in Pekanbaru City, Riau province, Indonesia. This study employed remote sensing data to create ecological parameters including the build-up index, vegetation index, soil index, and moisture index, as well as principal component analysis to generate ecological index integration. The findings indicate a correlation of over 90% among these parameters from 2018 to 2021. Overall, there has been a significant decrease in the ecological quality index's high-quality categories, such as good and excellent, covering a total of 19.6% over 127 km^2. Conversely, the poor ecological quality category increased to 2.2%, encompassing an area of 15 km^2, up from the initial 21.2% covering 122 km^2. Additionally, the fair and moderate categories also experienced increases of 4% and 13.4%, respectively, reaching 28 km^2 and 84 km^2. The study area's ecological quality is largely affected by increased anthropogenic activities, leading to a drastic decrease in the presence of ecological quality in the good and excellent categories. The importance of spatial planning is emphasized to incorporate aspects of ecological assessment rather than solely focusing on increasing economic activity. This outcome can be used to respond to the concept of sustainable development by caring for the ecological environment, particularly in urban areas, and mitigating ecological damage.

KEYWORDS: Assessment, urban ecology, remote sensing, geographic information system, ecosystem, ecological modelling, restoration, sustainability

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INTRODUCTION

Environmental ecology is one of the scientific disciplines that examine alterations in land configuration resulting from human spatial activities, with the objective of managing environmental quality dynamics (Wiyono and Sunarto 2016). Human activity has had a considerable direct and indirect impact on natural landscapes by growing built-up areas (L. Sun et al. 2021). One of the planning scientists' goals is to develop policies that may improve environmental ecological quality monitoring by incorporating sustainable development into community spatial planning (Xu et al. 2019). Sustainable community development may be carried out in several stages by paying more attention to remote sensing (Zheng et al. 2022).

The concept of urban ecology that we aim to develop focuses on environmental quality through a regional characteristics approach, environmental comfort, and human ecology (J. Wang et al. 2022). One crucial aspect of the viability of urban ecology is considering the physical qualities of urban environments that are conducive to sustaining ecological systems (Liu and Shi 2019; Yu et al. 2022). The potential for ecological vulnerability is determined by the characteristics of the stratified ecosystem (C. Sun et al. 2020), and addressing this vulnerability can involve a series of intellectual conceptual flows, such as ecological vulnerability zoning (Amri et al. 2017).

When external demands exceed an ecosystem's carrying capacity, a state of instability arises, threatening ecosystem development and resilience (Liao and Jiang 2020). This explains why the assessment of ecological quality serves not only as scientific evidence for conservation (Bobby Rahman et al. 2019) but also as a valuable starting point for addressing sustainable development and impartiality towards industries inflicting environmental damage.

Numerous theorists and practitioners in urban ecology have explored the impact of land development on urban ecological environments using remote sensing data (Safitri and Giofandi 2019; Giofandi et al. 2020). An obvious advantage of environmental monitoring is the constituent elements of primary analytical methods, such as drought index, greenness index, humidity and ecosystem heat (Muhlisin et al., 2021). However, certain thresholds may face data restrictions on specific indicators and challenges in defining the hierarchy. According to research by (X. Wang et al. 2018; Shi and Li 2021), different vegetation densities with the corresponding vegetation indices can serve as environmental ecological quality variables, containing three aspects: changes in external disturbances, production capacity, and the impact of human social and economic development.

The evaluation of ecological quality aims to assess the state of the environment and the ecosystem health. It aids in understanding the impact of various factors on vegetation coverage and the overall ecological conditions (Y. G. Gao et al. 2022). In this study, the Remote Sensing Ecological Index (RSEI) is used to assess the ecological quality in Pekanbaru City, Riau province, Indonesia. RSEI, a model utilizing remote sensing data, combines multiple index factors to provide a quick and easy evaluation of regional ecological quality. RSEI avoids the artificial setting of weights by using the contribution rate of each index to the first principal component. It facilitates an objective coupling of indices and provides a comprehensive assessment of the ecological environment (Jiang et al. 2020). RSEI has been proven effective in analyzing ecological quality changes across various areas, and its reliability and applicability make it a suitable choice for regional ecological quality assessment (Shi and Li 2021).

Based on this, the paper evaluates remote sensing by proposing the combined use of several indices, such as NDBI (Build-up index), SAVI (Vegetation index), NDSI (Soil index), and NDMI (Moisture Index), amalgamated into an Ecological Index to measure urban ecological quality. The effectiveness of the ecological system is gauged by an objective ecological index based on a multidimensional and multi-method long-time series approach spanning from 2018 to 2021. This study seeks to address the following questions: (i) whether spatial factors can explain the capability and efficacy of integrated ecological indices in the context of environmental management, and (ii) whether ecological indices can be classified and explained concerning changes in spatial distribution. These findings aim to improve the urban ecology evaluation system for restoration success, offering enduring insights for construction ecology practitioners in the research area.

MATERIALS AND METHODS

Study Area

Pekanbaru City is one of the fastest-growing areas on the island of Sumatra, especially when compared to other cities. In the 2020 population census, researchers conducted a temporally spanning ecological quality assessment covering a total area of approximately 402.32 km^2, with a total population of 983,356 individuals (BPS 2021). Given the increasing urban and economic expansion, it is vital to assess spatial aspects to comprehend the environmental dynamics (Giofandi and Sekarjati 2020), and spatial-temporal ecological evolution in Pekanbaru City (Fig. 1).

Data Sources and Pre-Processing

This observation utilizes multi-temporal remote sensing data acquired by Landsat 8 Operational Land Imager (OLI) in June 2018 and July 2021. The selection of the acquisition date is based on the availability of satellite imagery with the least cloud cover and the use of the same month to minimize seasonal differences at the observation site. Pekanbaru is located on the Landsat 8 OLI image line for study area 127/060 using the World Geodetic System 1984 – Universal Transverse Mercator 47 South projection at 30 m resolution. The data was downloaded from the United States Geological Survey platform (www.earthexplorer.usgs.gov), which is OpenSources, to obtain ecological index maps for 2018 and 2021. Before further processing the image, the first step is pre-processing using remote sensing software with processing specifications including radiometric calibration chosen to convert the digital number (DN) value of the multispectral band to the reflectance value of the Earth's surface, and atmospheric correction using the Fast Line of sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) approach as the data process to reduce the effects of weather and cloud cover. The next step is to crop the image based on the observation location.

Vegetation index, soil condition index, moisture index, and human activity index from Landsat 8 OLI image are the selected bands for developing an index adapted to the Landsat image channel, retrieved, and used as a reference for band calculation to obtain remote sensing dataset values such as Normalized Difference Build-up Index (NDBI), Normalized Difference Soil Index (NDSI), Normalized Difference Moisture Index (NDMI), and Soil Adjusted Vegetation Index (SAVI). The SAVI index is an algorithm that improves upon the Normalized Difference Vegetation Index (NDVI) by mitigating the impact of background soil on canopy brightness. The vegetation line equation (representing vegetation with uniform density and a consistent background) is derived through the estimation of canopy reflectance using a first-order photon interaction model, which simulates the interaction between the canopy and the ground layer. In addition, the indicators for the ecological index were selected based on the representation of the ecological environment, which includes vegetation, moisture, presence of buildings, and soil condition, which are the characteristics of the urban environment. Finally, an ecological index is created, which is geometrically combined with the previous indicators to reflect and evaluate the ecological quality of the city.

The ecological index is formed from four components: NDBI, NDSI, SAVI, and NDMI. These components are analyzed using the Principal Component Analysis (PCA) method to form an equation, along with the eigenvalue contribution rate, which indicates the ability of principal components (PCs) to explain the characteristics of the data. The PCA method aims to simplify the observed variables by reducing their dimensions, achieved by eliminating correlations between independent variables by transforming the original variables into new uncorrelated ones. It is assumed that k principal components are created from the p variables (with $k \leq p$), where these principal components are linear combinations of the original p

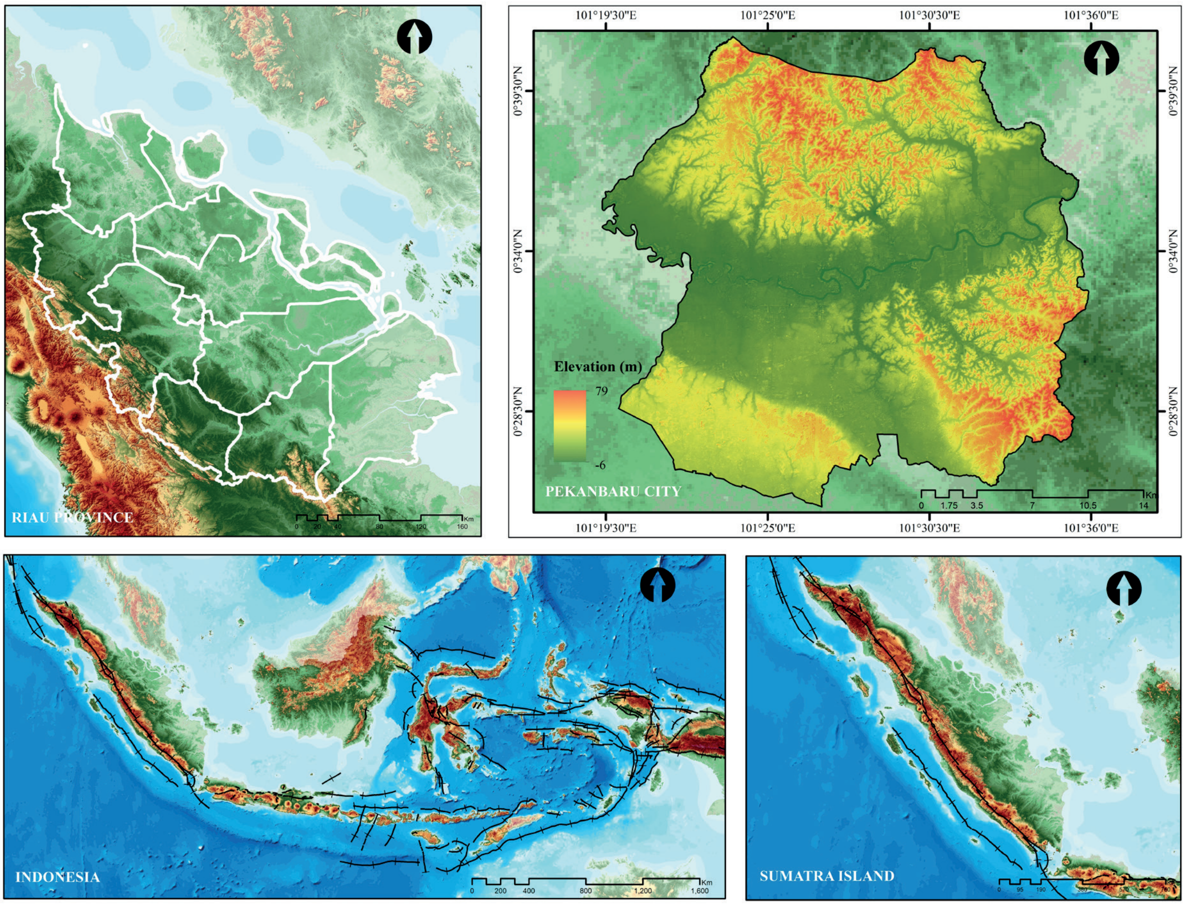


Fig. 1. Research site

variables. The advantages of the PCA method include the removal of correlations without losing a significant amount of information about all variables. PCA analysis was conducted using Minitab 21 software.

Development of Ecological Index Remote Sensing Data

The ecological index based on remote sensing is developed to quantify ecological quality by integrating four ecological factors: SAVI, NDBI, NDSI, and NDMI. These factors were selected based on a review of existing research (Jiang et al. 2020; Lian et al. 2022). Firstly, the dynamics of land use change, particularly in urban settings, alter the conditions and procedures of ecological study. Changes in landscape conditions initially influenced by human activities are obtained. As a result, the NDBI technique can be used to demonstrate the expansion of human activities under environmental conditions. Secondly, the vegetation indicator aims to reflect the environment and the quality of the ecological habitat as a green condition, while the soil condition is represented by the NDSI algorithm chosen to explain the ecological condition. In response to ecological changes, the NDMI method provides complete information on surface climatic change circumstances, such as air humidity.

The development of the ecological index involves several key processes, starting with the selection of ecological environmental characteristics and concluding with the integration of the ecological index. The physical ecological quality of the existing conditions in the study area is represented by four ecological parameters: SAVI, NDBI, NDSI, and NDMI. These parameters include the ecological quality of vegetation on the soil surface regarding greenery, human activity levels from the building perspective, soil conditions, and humidity conditions (Table 1). The comprehensive ecological indicator was then developed using the PCA regression. In this case, the following formula is employed to calculate the integrated ecological index with four ecological factors for ecological evaluation.

Table 1. Case studies and used methods

No	Formula	Parameter	Source
1	$NDBI = \dfrac{SWIR - NIR}{SWIR + NIR}$	Build-up Index	(Zha et al. 2003)
2	$NDSI = \dfrac{BSI + NDISI}{2}$	Soil Index	(Deng et al. 2015)
3	$SAVI = \dfrac{NIR - RED}{NIR + RED + L}(1 + L)$	Vegetation Index	(Huete, 1988)
4	$NDMI = \dfrac{NIR - SWIR}{NIR - SWIR}$	Moisture Index	(B.-C. Gao, 1995)

Ecological Index Integration

The four normalized ecological parameters generated from the previous technique are critical in this study since they can be used to construct a comprehensive ecological index that incorporates information from the four parameters. The PCA regression was used to create the ecological composite index. As one of the multidimensional technical approaches, PCA can eliminate the effect of collinearity among distinct variables (Xu et al. 2019; Liao and Jiang 2020; Hao et al. 2022). PCA captures the most information from all factors and is utilized to construct an ecological index image. The ecological index can be expressed by equation (1):

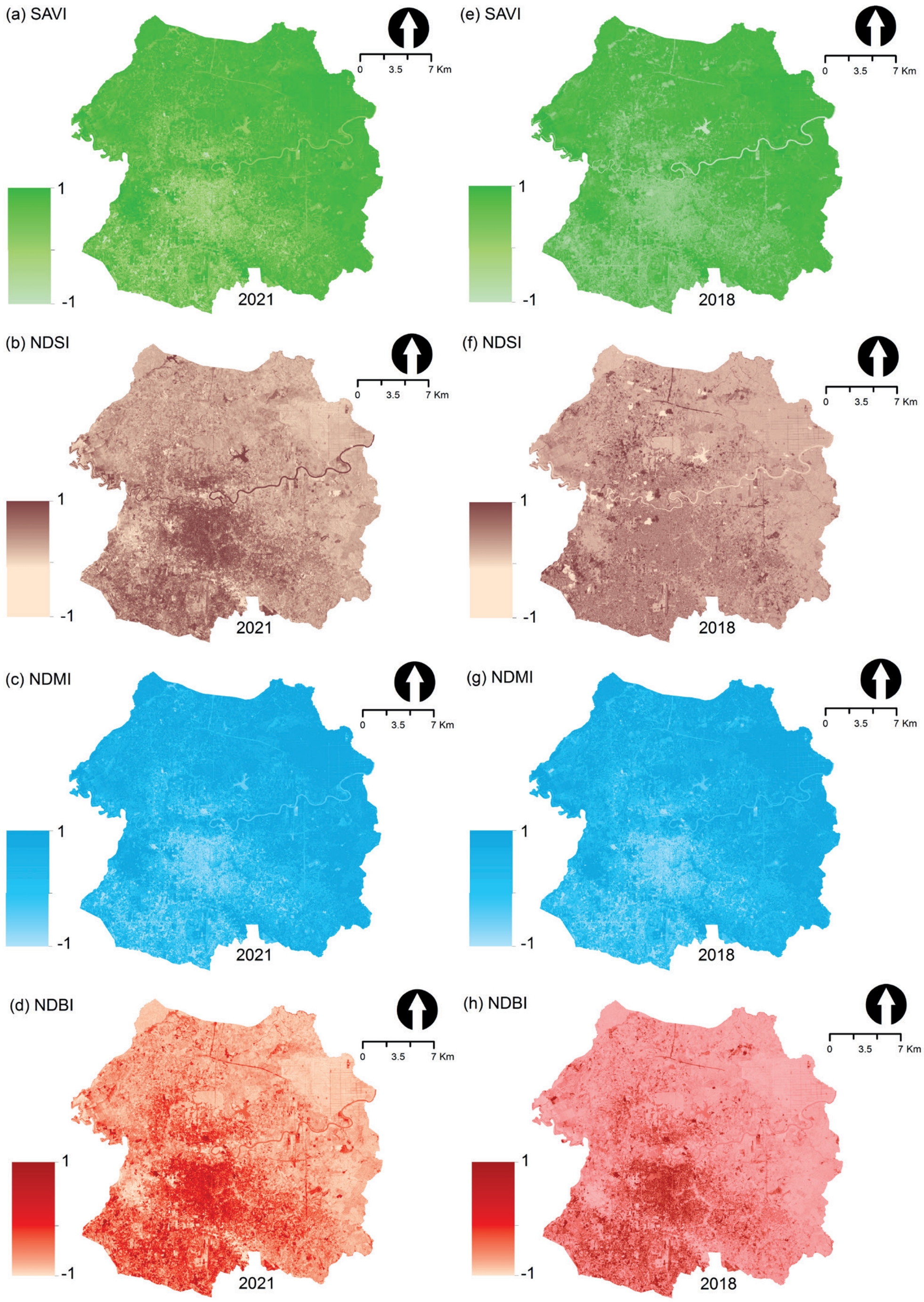
$$Ecology\ Index = f\,(NDBI, NDSI, SAVI, NDMI) \tag{1}$$

Finally, the value of the ecological quality images can be compared between different years. Therefore, the higher the ecological index value, the higher the ecological quality, and vice versa (Chen et al. 2020).

RESULTS

Capabilities and Performance of the Ecological Index Integration

Four ecological parameters are integrated by PCA, from 2018 and 2021 (Fig. 2). According to the PCA results of the four parameters used, the first principal component (PC1) has the highest contribution rate from the eigenvalues in 2018 and 2021, exceeding 76 %. The first PCA component typically explains more than 80% of the dataset characteristics, and is used to represent the ecological index (Yue et al. 2019). This indicates that PC1 represents the primary information and characteristics of the dataset (Table 2). Therefore, the results derived from PC1 can effectively contain most of the information from the four parameters.



Source: Primary data processing

Fig. 2. Four parameters index (SAVI, NDSI, NDMI, NDBI) from 2018 and 2021

Table 2. Remote sensing ecological index calculation based on Landsat 8 OLI

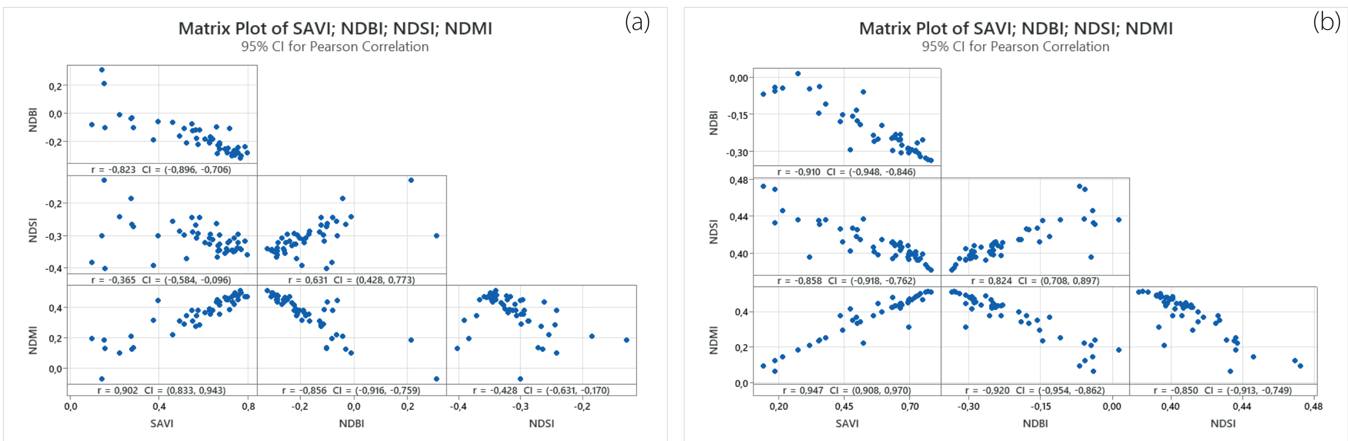
Year	Indicator	PC 1	PC 2	PC 3	PC 4
2021	SAVI	-0,508	-0,181	-0,517	0,665
	NDBI	0,500	0,392	-0,765	-0,106
	NDSI	0,484	-0,865	-0,132	0,031
	NDMI	-0,509	-0,255	-0,361	-0,739
	Eigenvalues	3,656	0,1973	0,0938	0,0523
	Eigenvalue contribution rate	91,4%	4,9%	2,3%	1,3%
2018	SAVI	-0,522	-0,383	-0,491	0,582
	NDBI	0,548	-0,056	-0,804	-0,224
	NDSI	0,373	-0,874	0,310	0,021
	NDMI	-0,536	-0,293	-0,127	-0,781
	Eigenvalues	30,510	0,7373	0,1181	0,0936
	Eigenvalue contribution rate	76,3%	18,4%	3%	2,3%

Source: Primary data processing

The primary components explaining the dynamic variations in the index values of the first four main component ecological elements from 2018 and 2021 can be examined using the information provided in (Table 2). Among the four factors, SAVI, NDBI, and NDMI contributed the most absolute value. The SAVI parameter contributed to the index reaching -0.522 in 2018, which then increased to -0.508 in 2021. The NDBI parameter contributed to the index reaching 0.548 in 2018, which then declined to 0.500 in 2021. Meanwhile, the NDMI parameter contributed to the index reaching -0.536 in 2018, which then increased to -0.509 in 2021. A drawback of sensitivity to the scaling of variables is found in PCA. If the variables are not on the same scale, the results can be skewed, and only linear relationships in the data may be captured. Non-linear relationships are not suitable for capture by PCA.

Correlation analysis is necessary to determine the relationship between variables in 2018 and 2021. If the correlation coefficient is positive, it indicates a unidirectional relationship, while a negative coefficient signifies a non-unidirectional correlation (opposite direction). In this study, we used the Pearson correlation method because of the interval-ratio scale data. (Fig. 3) shows that the correlation between parameters in 2018 has the same sign as the correlation in 2021. This indicates that the correlation results between parameters align with the ecological meaning expressed by each of the four parameters, thus confirming the applicability. and effectiveness of the ecological index for the assessment of ecological quality. This finding is in line with the research by (Hui et al. 2021), which states that the ecological index has a significant positive correlation with ecological quality.

(Fig. 3-a) shows the correlation between the four parameters (SAVI, NDBI, NDSI, and NDMI) in 2018, while (Fig. 3-b) represents the correlation in 2021. It is evident from the graph above that NDSI and NDBI do not correlate with SAVI and NDMI. NDSI and NDBI have a negative association with the SAVI, but a positive correlation with the NDMI. Between 2018 and 2021, the correlation coefficient between SAVI and NDMI exceeds 90%, indicating\ a strong relationship between them. This finding is consistent with the results of (Y. G. Gao et al. 2022), who found that the average value of the Ecological Index increased in the Wugong Mountain region from 2015 to 2019, with the greenness and humidity indices positively impacting ecological quality. Meanwhile, \NDBI correlates negatively with NDMI but positively with NDSI, while NDSI has a negative correlation with NDMI.



Source: Primary data processing

Fig. 3. Correlations among four parameters

Ecological Quality Classification and Spatial Change from 2018 to 2021

In Pekanbaru City, the ecological quality is generally higher in the suburbs and lower in the center/core area. Areas with poor environmental quality are becoming more common, particularly in the center of Pekanbaru. Meanwhile, decent environmental quality continues to degrade and is mostly found on the outskirts of Pekanbaru (Fig. 4).

The classification of the ecological index utilizing remote sensing is divided into five sorts of landscapes: poor, fair, moderate, good, and excellent. In this study, the images were classed into five levels of ecological quality based on the mean and standard deviation. (Fig. 5) and (Table 3) present the results of the ecological quality classification in Pekanbaru City from 2018 to 2021. Based on the processed data, there was a considerable decrease in the value of the ecological quality index Between 2018 and 2021, there was an increase in the proportion of 0.212% with an area

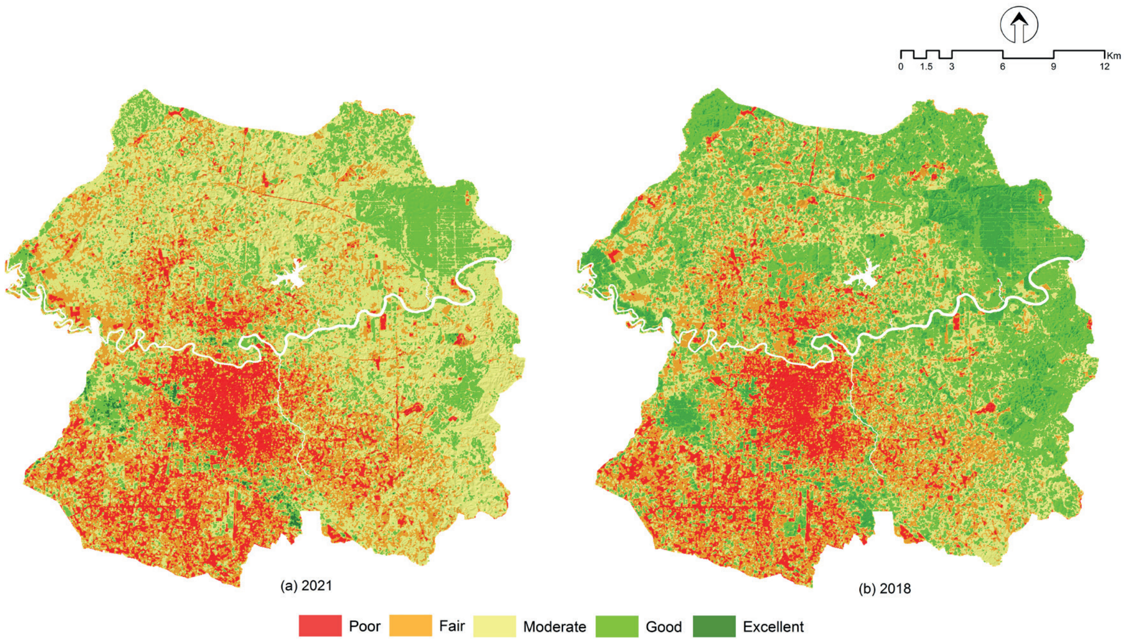


Fig. 4. Ecological index changes of Pekanbaru

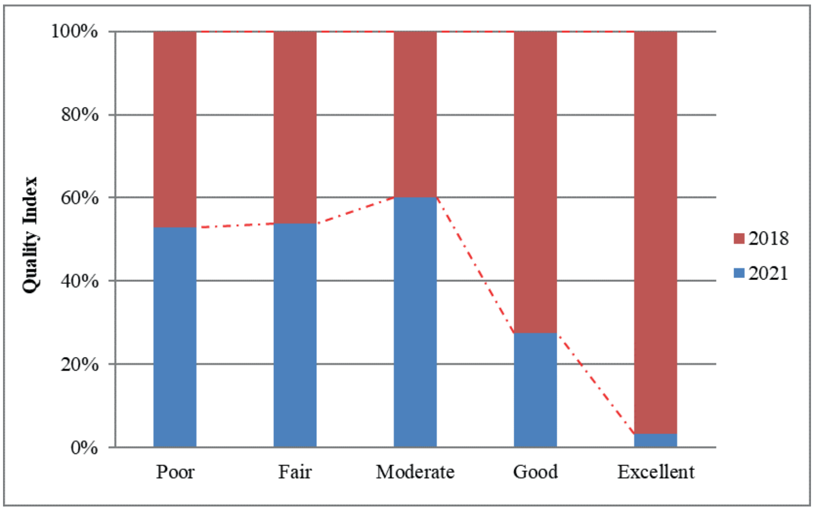


Fig. 5. Percentage accumulation chart of ecological index

Table 3. Remote sensing ecological index calculation based on Landsat 8 OLI

Quality Index	2021		2018	
	Area (Km²)	Percentage (%)	Area (Km²)	Percentage (%)
Poor	137	21.2	122	19
Fair	192	30.3	164	26.3
Moderate	249	38.9	165	25.5
Good	61	9.4	161	24.9
Excellent	1	0.2	28	4.3

Source: Primary data processing

of 137 km^2 in the category of poor ecological quality from the initial proportion of 0.190% with an area of 122 km^2 in 2018. Meanwhile, the proportion of the excellent category declined significantly from 0.043% with an area of 28 km^2 to 0.002% with an area of just 1 km^2.

DISCUSSION

The advantages of remote sensing can depict the ecological quality of the area at amicro level, and the spatial distribution of the ecological index through remote sensing can aid in understanding environmental ecological patterns. The analysis results of the four ecological index indicators via remote sensing and PC1 correlation have a high contribution rate of eigenvalues exceeding 90% in 2021. This study framework is oriented toward assessing changes in ecological configurations in urban areas through site-specific implementation, optimizing multi-temporal remote sensing data to understand changes in ecological landscapes in a sustainable manner.

Utilizing spatial and temporal characteristics of ecological status is crucial for enhancing accuracy and efficiency in assessment and monitoring. Several studies have developed design concepts using ecological indicators, diverse parameters, and systematic models to evaluate changes in ecological landscape configuration. This research is of great importance for developing an efficient model using a remote sensing approach for urban ecological quality assessment. This study derives from four various environmental parameters that can guide a simple, comprehensive ecological quality assessment. All the various parameters for the ecological quality index are easily available and applicable to other regions, facilitated by different databases. The ecological quality index needs four environmental parameters as an assessment input; all parameters are constructed from remote sensing data (Table 1). Overall parameters can be quickly calculated with Landsat images, and the urban ecological index is a key application of ecology from remote sensing.

The study discovered that the ecological condition in the Pekanbaru area had degraded over three years (Fig.4). This degradation is evidenced by a decrease in the vegetation index and normalized soil fluctuations, while SAVI, which mitigates the loss of vegetation index response, remains ineffective in altering vegetation canopy measurements (Indrawati et al. 2020). According to the correlation results, the SAVI indicator reflects the influence of surface vegetation on the ecological environment, specifically humidity and vegetation cover on soil quality, as well as the expansion of human activities as seen through changes in landscape use. The two indicators are negatively correlated, suggesting that the surface of vacant or construction landis not vast enough to harm the ecological environment. However, local climatic conditions (such as surface temperature and air humidity) are positively correlated in responding to environmental changes that occur and cause damage to the ecological environment. The indicators of ground surface moisture and heat were represented respectively by moisture and land surface temperature, which reveal climate changes responding to the ecosystem state alterations (Yue et al. 2019). Environmental quality is generally higher in the suburbs and lower in the city center or core area, with poor environmental quality becoming more common, especially in the Pekanbaru city center. Conversely, the "good" environmental quality category continues to deteriorate and is found mainly in the periphery of Pekanbaru. This shows how certain human activities harm the surrounding natural environment. As the impact of human activities on the natural environment increases, the complexity of the changes that occur intensifies.

The green indicator parameter represented by SAVI is employed in this study to measure the ecological state before and after changes in anthropogenic land surface functions. Meanwhile, humidity and building density are represented by NDMI and NDBI values, respectively, revealing climatic change as a response to changes in existing ecosystem circumstances. (Zhang et al. 2020) conducted a similar study with the same variables with the addition of land surface temperature. The utilization of results from the urban ecological quality index is rational and effective. This finding gives information about the dynamics of the environment from four ecological parameters, and the urban ecological quality evaluation index is expressed by the ecological index. Furthermore, the urban ecological quality index can be considered a four-aspect condition of urban ecology (such as soil condition, moisture, greenery, and human activities), a guide effective in helping a selected parameter with the assumption of ecological existence, and a tool to assess or evaluate the quality of urban ecology comprehensively.

There are some limitations to the assessment of the urban ecological quality index. Firstly, the medium-resolution data quality deteriorates information accuracy, necessary for the calculation of the ecological quality index. Regarding complex urban surface conditions using high-quality data (hyperspectral and high-resolution spatial imagery) provides more accurate information. Next, the observation time is relatively short, and it is necessary to conduct a long-term study, for instance of about 20 years. Such study will better explain the drivers that influence the ecological landscape dynamics by involving the factors (hydro climatology, anthropogenic influence, social economics, community mobility, and land use planning) that aim to determine the impact of surface activities. A combination of multiple remote sensing data sources, statistical data, geospatial data, and big data based on open sources can provide various types of data for research. Finally, the effect composition of the thermal environment should be studied in other metropolitan areas for proper decision-making in the management and protection of the sustainable ecological environment.

CONCLUSIONS

The results of the study obtained using the urban ecology approach revealed that the deteriorating trend. This is inextricably linked to the role of human land use in urban development, as well as the current state of land characteristics represented by soil index, moisture, and vegetation distribution. Given the complexity of the urban environmental system influenced by anthropogenic activities, research involving a longer time span is necessary to comprehensively understand the ecological spatial patterns. This condition has the potential to reduce the ecological index over the last three years while increasing the number of poorly categorized zones. The future handling required to be able to comprehend this challenge and establish a sustainable development concept that cares about the natural landscape, particularly in urban areas, as a kind of ecological harm anticipation and control. Further research is also needed to better understand the effects of ecological composition on the thermal environment in various situations and metropolitan areas.

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