RESEARCH PAPER

UTILIZATION OF REMOTE SENSING DATA IN DETERMINING THE THRESHOLD VALUE OF URBAN ECOLOGICAL QUALITY INDEX IN BANDUNG CITY, WEST JAVA, INDONESIA

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ABSTRACT. Bandung City has the highest land conversion rate in Indonesia and was named a city with a moderate environmental quality index status in 2022. This status has been exacerbated by the diminishing green spaces in the city due to rapid urbanization. Conducting ecological assessments has become increasingly important, one approach being the utilization of remote sensing data. Remote sensing data, specifically Landsat 8 OLI/TIRS, processed to derive the RSEI (Remote Sensing Ecological Index) based on the PCA value of PC1, requires further development. Several limitations of the RSEI in assessing ecological quality, such as the subjectivity of remote sensing data, the use of equal interval methods for index classification, and the inability to validate the results, are the focus of development in this study. Based on these weaknesses, the RSEIT offers advancements in integrating actual data to support RSEI, determining index thresholds, and enabling model validation. The findings of this study demonstrate that: (1) ecological issues such as floods, waste accumulation, and landslides are the most prevalent problems in the study area; (2) compared to RSEI, which relies solely on remote sensing data, RSEIT is a model that can be validated with actual data. During the dry and rainy seasons, it achieves threshold values of 0.474 and 0.566, respectively, demonstrating a model performance accuracy exceeding 70%. The average validation results show an overall accuracy of 83.34%, a sensitivity of 78.55%, and a specificity of 87.50% across both seasons; and (3) urban centers, characterized by extensive surface hardening, minimal vegetation, and numerous ecological issues, predominantly fall under the poor RSEIT category, especially during the dry season. In contrast, suburban areas with higher proportions of green space and fewer ecological problems are largely classified under the good RSEIT category, particularly during the rainy season. This study can be further enhanced by refining the threshold aspects and strengthening actual data collection through the involvement of various stakeholders with expertise in ecology.

KEYWORDS: remote sensing, Landsat 8 OLI/TIRS, Bandung City, RSEIT, threshold, seasonal differences

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INTRODUCTION

Urbanization, which has resulted in the degradation of green spaces and a decline in ecological quality, has created a sense of urgency for urban ecological monitoring. In general, the concept of urban ecology refers to the dynamics and reciprocal activities that occur between biotic and abiotic in urban ecosystems. Urbanization is one of the contexts that greatly affects urban dynamics, and Bandung City is no exception. An increase in population that is not matched by the availability of facilities will have its own consequences for the ecological environment and will ultimately be destructive (Ary et al. 2018). When compared to other cities in Indonesia, research by Widiawaty et al. (2019) indicates that Bandung City has the highest rate of land-use conversion in the country. Meanwhile, the ecological footprint of the regional area in Bandung City is 0.04 or <1, which signifies that the natural carrying capacity of Bandung City has been exceeded or is in deficit relative to the needs of its population (Muchtar et al. 2024). This condition has led to challenges such as air quality issues, waste management, water quality concerns, and the insufficient extent of green open spaces that do not meet national standards.

In terms of ecological spatial aspects specifically in green open space study, Budiman et al. (2014) research on changes in green open space in Bandung City in 1991, 2000, and 2013 showed a change in pattern, where in 1991 green open space tended to cluster in the periphery, while in 2000 and 2013 it became randomly spread due to the development of built-up land that increasingly intervened in the periphery of Bandung City. Meanwhile, research by Kustiwan and Ladimananda (2012) reported a decrease from 14.41% in 2004 to 10.56% in 2020. These changes were attributed to the increasing demand for residential land, public facilities, and industrial centers. Rapid population growth, coupled with industrial expansion, rising population density, and increased motor vehicle use, significantly impacts environmental quality (Lestiani et al. 2013). The spatial aspect plays a crucial role in ecological assessment, which can be conducted, among other methods, through remote sensing.

In ecological assessment, Indonesia generally employs environmental quality evaluation methods that are locally regulated under the Environmental Quality Index (IKLH - Indeks Kualitas Lingkungan Hidup). The IKLH integrates assessments of air, water, soil, and seawater quality indices (Ministry of Environment and Forestry of the Republic of Indonesia 2022). The methodology includes field monitoring and laboratory analysis of observation samples. According to the 2022 IKLH report, Bandung City achieved an environmental quality index score of 55.70, categorized as moderate. However, as noted by Suprayogi et al. (2013), the implementation of the IKLH has yet to incorporate spatial analysis for each variable used. Meanwhile, according to the 2022 Regional Environmental Management Performance Information Document (IKPLHD- Dokumen Informasi Kinerja Pengelolaan Lingkungan Hidup Daerah) of Bandung City, which is regulated by the local government, there are five priority environmental issues that are the primary focus of the regional administration. These include land conversion and usage, degradation of water and air quality, disaster risk management, and improving efficiency in waste management (Environmental Office Bandung City 2022)

Remote sensing is one field that can offer solutions to assess environmental quality. Satellite imagery, which has the ability to record the earth's surface in wide coverage at various scales can be an option for labor and cost efficiency. Remote sensing products in the form of satellite images themselves have the ability to extract ecological variables such as vegetation, water, air, and soil (Caio et al. 2015; Kwok 2018; Reza and Abdullah 2011). In the assessment of ecological quality, Xu (2013) introduced the Remote Sensing Ecological Index (RSEI), which integrates four environmental indicators greenness index, moisture index, dryness index, and land surface temperature using satellite image data to monitor ecological conditions. These indicators are analyzed through principal component analysis (PCA) on the first principal component (PC1) and classified into five classes using the equal interval method. However, Wang et al. (2023) argued that the RSEI remains probabilistic and cannot be universally implemented due to the varying characteristics of Earth's surface regions.

Several studies in Indonesia have applied RSEI-based approaches to assess ecological quality, such as those conducted by Dai et al. (2023) along the Jakarta-Bandung High-Speed Railway corridor, Indrawati et al. (2020) in Semarang City, and Giofandi et al. (2024) in Pekanbaru City. These studies highlight the limitations noted by Wang et al. (2023), including the absence of field validation and continued reliance on probabilistic methods. This condition underscores the need to integrate actual input data that reflects field conditions into RSEI outputs, enabling the establishment of threshold values and direct field validation of the results.

The determination of thresholds using field data can enhance the objectivity of outcomes, as actual data collected from the field can aid in identifying real-world conditions that satellite imagery may fail to detect. Furthermore, determining thresholds based on actual data also improves the effectiveness of results, particularly those derived from validation processes (Palapa and Maramis 2014). In line with this statement, research by (Henrys and Jarvis 2019) highlights that remote sensing data, when supported by primary field data, can provide better objectivity. One analysis method used in determining threshold values is the receiver operating characteristic (ROC), where the ROC curve evaluates binary data within "good" and "poor" categories, formulated based on sensitivity and specificity values, which can be used to determine the cut-off threshold (Obuchowski et al. 2005).

Bandung City is currently experiencing a decline in its ecological dynamics, as indicated by the IKPLHD document, which highlights the need for the city to address five priority ecological issues. Meanwhile, the environmental quality index in Bandung City in 2022 reached 55.70, categorized as moderate. The reduction in green zones within the city exacerbates this situation. This condition presents an opportunity in this study to enhance the capability of the RSEI in modeling ecological conditions by integrating existing ecological data with remote sensing data (RSEI) to develop a threshold-based ecological modeling framework (RSEIT). RSEIT has been developed by integrating actual data with remote sensing data (RSEI), determining ecological index thresholds, and validating the accuracy of RSEIT. In 2023, Bandung City implemented this model during both the dry and rainy seasons.

MATERIALS AND METHODS

Study Area

This research was conducted in Bandung City, West Java Province. Bandung City is astronomically at 6°50'10"S - 6°54'50"S and 107°35'52"E - 107°41'54"E, with an area of 167.31 km2. Bandung City borders West Bandung Regency and Bandung Regency on the north side, Cimahi City on the west side, and Bandung Regency on the east and south sides. Bandung City has a geographical position with unique characteristics because it is located in a basin surrounded by hills and mountains. This results in the average temperature of Bandung City being 23.6 °C, which is classified as low for the average temperature in Indonesia (Lestiani et al. 2013).

Bandung City climatologically has two seasons a year and has a tropical climate. The division of the seasons is divided into two ranges: April to September, which is the dry season, and October to March, which is the rainy season. Bandung City has unique physical characteristics because it is surrounded by mountains and is located in a basin area. Morphologically, Bandung City is dominated by flat to sloping morphology and sloping to steep on the north side with elevations ranging from 645 to 1820 meters above sea level. This makes areas that are at low elevations with flat to gentle slopes find many built-up land objects, such as settlements, public facilities, and industrial areas, as well as green land, especially rice fields, while in areas that tend to be high with steep slopes, more green land is found, such as forests and plantations. Figure 1 illustrates the research location, featuring object samples and a false-color composite of Landsat 8 imagery in Bandung City. The composite constructed using near-infrared, red, and green bands, highlights vegetation, built-up areas, and inundated objects (wet rice fields). Each square depicted on the map represents observed objects in the field, where ecological conditions are significantly influenced by these surface features.

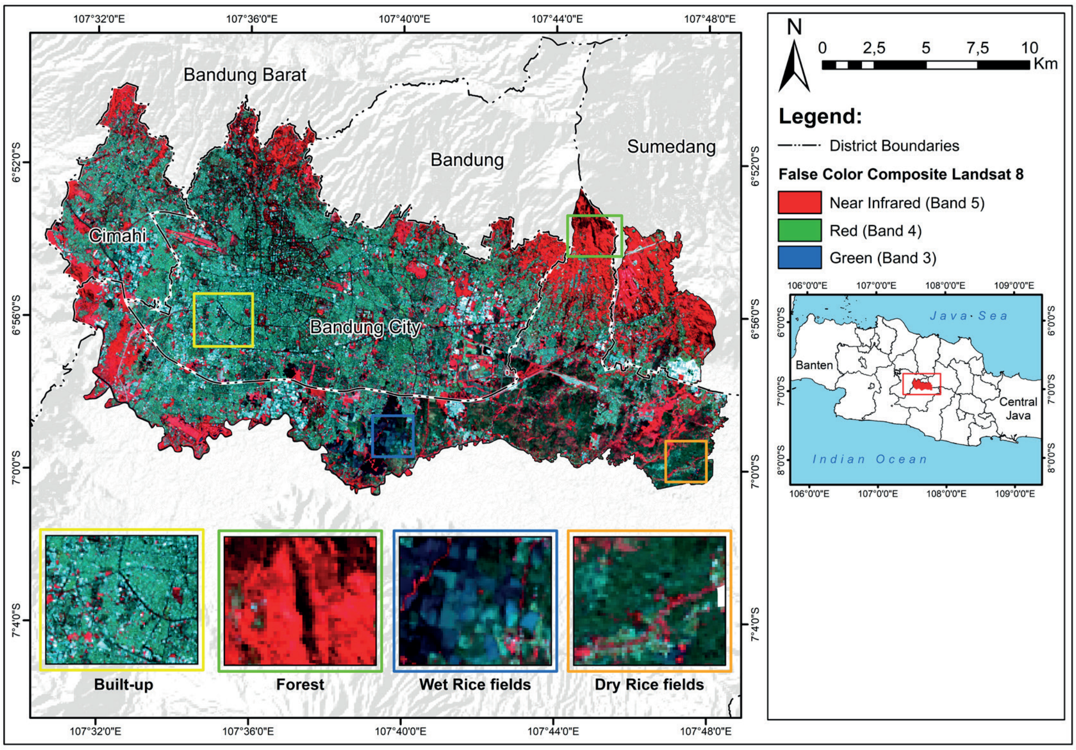

Fig. 1. Study area at Bandung City, West Jawa, Indonesia

Data Source

The data used in this study include remote sensing data in the form of Landsat 8 OLI/TIRS images to build RSEI data, 30 field interview data, and 20 data belonging to the Indonesian National Disaster Management Agency (https://bnpb.go.id/) on ecological issues and disaster event data around the research area, hereinafter referred to as actual data. The Landsat 8 OLI/TIRS image recorded in 2023 used in this study was sourced from the United States Geological Survey (https://www.usgs.gov/). To obtain more comprehensive results, the data was divided into two recording times, namely during the dry season and during the rainy season. The dry season recording was acquired on September 6, 2023, and the wet season was acquired on May 24, 2023, both in path/row 122/065. When choosing the recording time, apart from considering the season, researchers also considered the percentage of cloud cover, where the cloud cover contained in both recording times was below 20%.

Remote Sensing Ecological Index (RSEI)

RSEI was first introduced in 2013 and first applied to the study of ecological change in Tzhangingchow, Fujian Province (Xu 2013). Xu (2013) introduced a remote sensing ecological index (RSEI) that integrates four environmental indicators through satellite image data in the form of greenness index, moisture index, dryness index, and surface temperature to monitor ecological quality (Eq. 1-4). The purpose of RSEI is to test the ability of remote sensing imagery to monitor ecological quality quickly and objectively, which can be visualized. The capabilities of the RSEI-based index itself can be further developed, especially in urban ecological areas (Firozjaei et al. 2021; Wang et al. 2020).

Table 1. RSEI indicator formula

Indicators	Formula	No.
Greenness (NDVI)	$NDVI = (B5 - B4) / (B5 + B4)$	(1)
Moisture (Wetness Index)	$Wet = (0.1511 \times B2) + (0.1972 \times B3) + (0.3283 \times B4) + (0.3407 + B5) - (0.7117 \times B6) - (0.4559 \times B7)$	(2)
Dryness (NDBSI)	$NDBSI = \frac{IBI + SI}{2}$ $IBI = \frac{(B5 + B4) - (B5 - B2)}{(B5 + B4) + (B5 - B2)}$ $SI = \frac{2B6/(B6 + B5) - [B5/(B5 + B4) + B3/(B3 + B6)]}{2B6/(B6 + B5) + [B5/(B5 + B4) + B3/(B3 + B6)]}$	(3)
Surface Temperature (LST)	$L\lambda = ML \times Qcal + AL - Oi$	(4)

Source: (Niu and Li 2020; Seddon et al. 2016; Xu and Zhang 2013; Yue et al. 2019a)

NDVI is a method that can be used to view vegetation cover at various scales by utilizing near and red infrared channels (Seddon et al. 2016; Xu and Zhang 2013). Many studies have found that NDVI is sensitive to low vegetation cover, including urban areas with high building density (Li et al. 2017; H. Wang et al. 2015). NDVI in the RSEI study itself can be used to represent greenness indicators using the near infrared and red bands.

The wetness indicator in RSEI can be represented by the wetness index (WET), where WET is obtained through tassel cap transformation (TCT) to indicate the level of moisture in vegetation and soil objects (Niu and Li 2020). NDBSI in the appearance of field objects symbolizes the influence of urbanization flows and human activity factors that create drought, represented by the level of land development and soil openness. These factors will cause a drought due to the conversion of green land, which causes the deterioration of environmental quality (Yue et al. 2019b). NDBSI is composed of two indices, namely soil index (SI) and Index-based Built-up Index (IBI). LST in Landsat 8 OLI/TIRS imagery is obtained through the thermal channel in band 10, which can be used to represent surface temperature indicators. To obtain LST data, the first step is to convert the digital number (DN) into radians at the top of the atmosphere (ToA).

The four RSEI indicators need to go through a normalization process to avoid non-uniform value ranges; for example, the NDVI value, which is in the range of -1 - 1 is different from the LST value, which has units of °C, so a normalization process is needed to change the value range on each indicator to 0 - 1 with the following equation (Eq. 5-6):

$$NI = (I - Imin) / (Imax - Imin) \tag{5}$$

$$NI = (Imax - I) / (Imax - Imin) \tag{6}$$

where NI is the normalized value, I is the calculated indicator value, Imin is the minimum value of the indicator and Imax is the maximum value of the indicator (Xu, 2013). In the normalization formula number 5 is used for NDVI and WET indicators, while formula number 6 is used for NDBSI and LST indicators to avoid negative correlation, especially for NDVI indicators.

After the four indicators are normalized, the data is ready to be analyzed through PCA. PCA is an analysis that has the ability to identify important variables, where PCA excels in eliminating the impact of the collinearity of the four indicators that make up RSEI (Seddon et al. 2016). PCA analysis in RSEI is used to integrate four indicators that have been normalized and weighted based on the contribution of each index to the value in PC1 (Zhu et al. 2020).

Actual Data Acquisition

The actual data used to find the RSEI threshold value and modeling validation totaled 50 data points, divided into 30 interview data points and 20 disaster event data points throughout 2023. Both interview data and disaster event data serve to provide information on ecological issues, both natural and human-induced. The actual data primarily functions to assess the performance of the RSEI model through ROC AUC analysis and model validation while also determining the threshold value. These data are further categorized into two subsets: training data and validation data, with a distribution of 70% and 30%, respectively. The 50 actual data points will be used for analysis to determine the threshold value and validation, ultimately enabling the determination of the RSEIT interval, particularly the boundary between the good and poor RSEIT classes.

This study used interviews to assess how residents of Bandung City view their local ecological conditions. A total of 30 respondents were selected with specific criteria, such as (1) being more than 17 years old; (2) having a length of stay in the research location of at least 10 years; and (3) having a minimum education of high school. In relation to the area, the respondents were determined randomly but still considered the geographical conditions of the surveyed area so that the output results were more optimal and reflected the actual conditions.

The disaster event data sourced from the Indonesian National Disaster Management Agency (https://bnpb.go.id/) is publicly available. The website provides information regarding the locations of disaster occurrences in the year 2023. Based on this data, 20 regions were selected, but these regions were not included in the interview process.

Determination of Thresholds and Validation Assessment

Receiver Operating Characteristic (ROC) is an analysis often used to measure the performance of a model (Mas et al. 2013). ROC works by utilizing actual and predicted data pairs in the form of contingency tables and area under the curve or (AUC). The contingency table is composed of four categories of paired table results, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN) (Fig. 2). Meanwhile, AUC is the area under the curve, AUC is used to assess the accuracy performance of actual data which has a value range of 0-1. If the AUC value is <0.5, it means that the tested model has low accuracy and indicates that the model is poor (Fawcett 2006; Zou et al. 2007).

		Prediction	
		Positive (0)	Negative (1)
Actual	Positive (0)	True Positive (TP)	False Positive (FP)
	Negative (1)	False Negative (FN)	True Negative (TN)

Fig. 2. ROC contingency

In this study, the results of RSEI modeling will be analyzed using ROC curves that utilize 70% of training data to generate an AUC value, which is then validated by utilizing 30% of actual data. Training and validation data appear in binary form, where the data is categorized as good (no ecological problems) with code "0" and categorized as poor (there are ecological problems) with code "1". The binary data will be analyzed together with the RSEI modeling that has been made to get the threshold value. In connection with the validation of the ROC curve, an analysis of overall accuracy, sensitivity, and specificity is used (Eq. 7-9):

$$Sensitivity\,(TPR) = \frac{TP}{TP + FN} \tag{7}$$

$$1 - Specificity\,(FPR) = \frac{FP}{FP + FN} \tag{8}$$

$$OverallAccuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

Sensitivity indicates the ability of the RSEIT model to detect true positive cases (TP), in which case the RSEIT class is good; specificity indicates the ability of the model to detect true negative cases (TF), in which case the RSEIT class is poor; and overall accuracy indicates the ability of the model to detect all cases.

RESULTS

Components of RSEI

RSEI indicators collected in 2023 using Landsat 8 OLI/TIRS imagery in both seasons can be categorized into two components, which are positively correlated (NDVI and WET) and negatively correlated (NDBSI and LST). In the NDBSI and LST indicators in the normalization process, the values are reversed. This approach aims to avoid the negative correlation of the NDVI and WET indicators so that the 1-RSEI$_0$ calculation process is not carried out. The normalization results seen in (Fig. 3) show that the highest NDVI and WET are in the periphery of the research area. This is because the area has green land cover, both in the form of stands and non-stands. In the NDBSI and LST indicators, due to the reversal in the normalization process, areas that have high values tend to be green land, like the NDVI and WET indicators, where high values should be in the built-up land zone.

The mean values formed in the two seasons shown in (Fig. 4) each have different means in NDVI, WET, and LST, but the same mean value occurs in the NDBSI indicator. The NDVI, WET, and LST indicators differ by 0.02, 0.04, and 0.03, respectively, while the NDBSI has no difference in value. From the overall mean value of RSEI indicators, indicators other than NDVI have a correlation that is not aligned with the influence of the season. The higher NDVI indicator in the dry season may be due to the influence of the rainy season causing inundation in the green zone area in the southeast of the study area, so the ability of NDVI in the rainy season cannot detect plants in the area.

The PCA results shown in (Table 2) show that PC1 in both seasons has a value above 80%, which indicates PC1 has higher information compared to PC2, PC3, and PC4, where PC1 in the dry season has a higher percentage than the rainy season. In line with this, research by Niu and Li (2020) showed that the higher characteristics of PC1 compared to other PCs can be used as a basis for the formation of the RSEI index. The NDVI indicator appears less

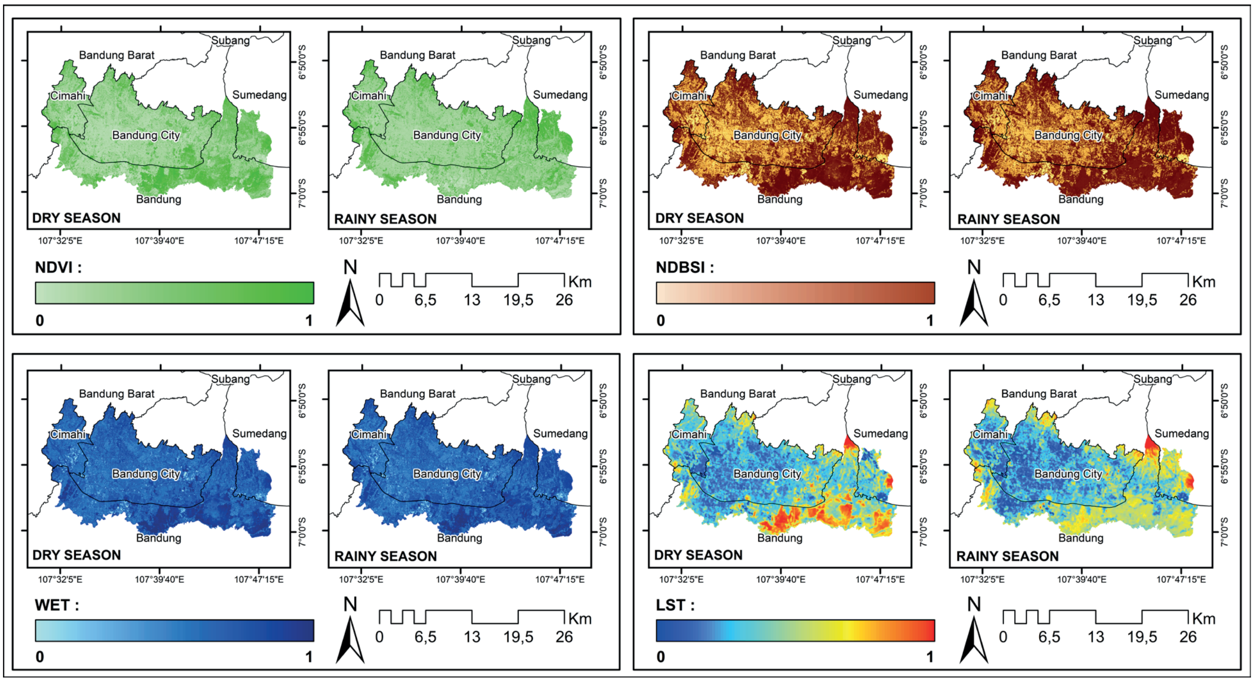

Fig. 3. RSEI indicator map (NDVI, WET, NDBSI, and LST)

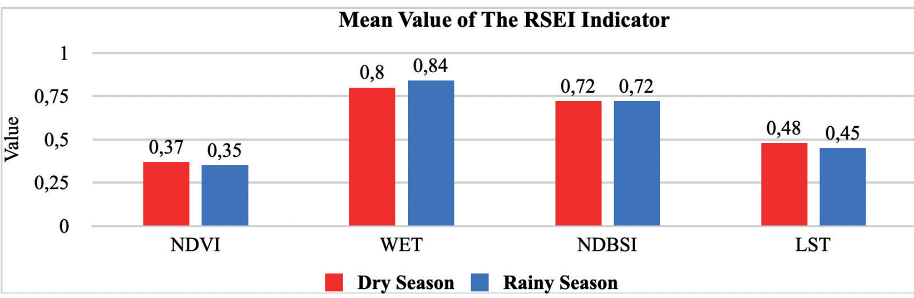

Fig. 4. RSEI indicator mean value diagram

aligned with seasonal conditions. The use of the NIR band in the NDVI algorithm tends to produce higher NDVI during the dry season because the wavelengths in the band are absorbed by water objects. This is because many rice fields and wetlands on the southeast side of Bandung City are waterlogged during the rainy season and overgrown with vegetation during the dry season.

Actual Data Acquisition Results

Bandung City has 5 types of ecological problems throughout 2023 that are considered to interfere with community activities, where problems in the form of flooding are dominant in the region with a percentage of 40%, followed by waste problems by 10%, landslides by 8%, and heat island effect and earthquakes each by 2%. Of the total 5 problems, there is a total of 62% of data indicating that the ecology has a poor status. Meanwhile, 38% of the data states that the ecological conditions in the region are classified as safe because they have never experienced ecological disturbances, especially disasters. Fig. 5 below illustrates the spatial distribution of the actual data collection.

The spatial distribution of ecological issues in Bandung City, particularly flooding, is widespread across the central area, as well as the southern and southeastern parts. Flooding often occurs due to rainwater runoff from elevated areas and the overflow of rivers passing through the study area, such as the Citarum River, especially during the rainy season. The flooding problem in the urban center and the southern parts of Bandung City is primarily caused by extensive surface sealing, which reduces the land's ability to absorb water. In contrast, flooding in the southeastern area, which is predominantly

Table 2. PCA analysis result

PC	Percent of Eigenvalues (%)	
	Dry Season	Rainy Season
PC1	81,61%	80,55%
PC2	13,33%	11,20%
PC3	4,35%	7,50%
PC4	0,70%	0,73%

Source: Primary data Processing

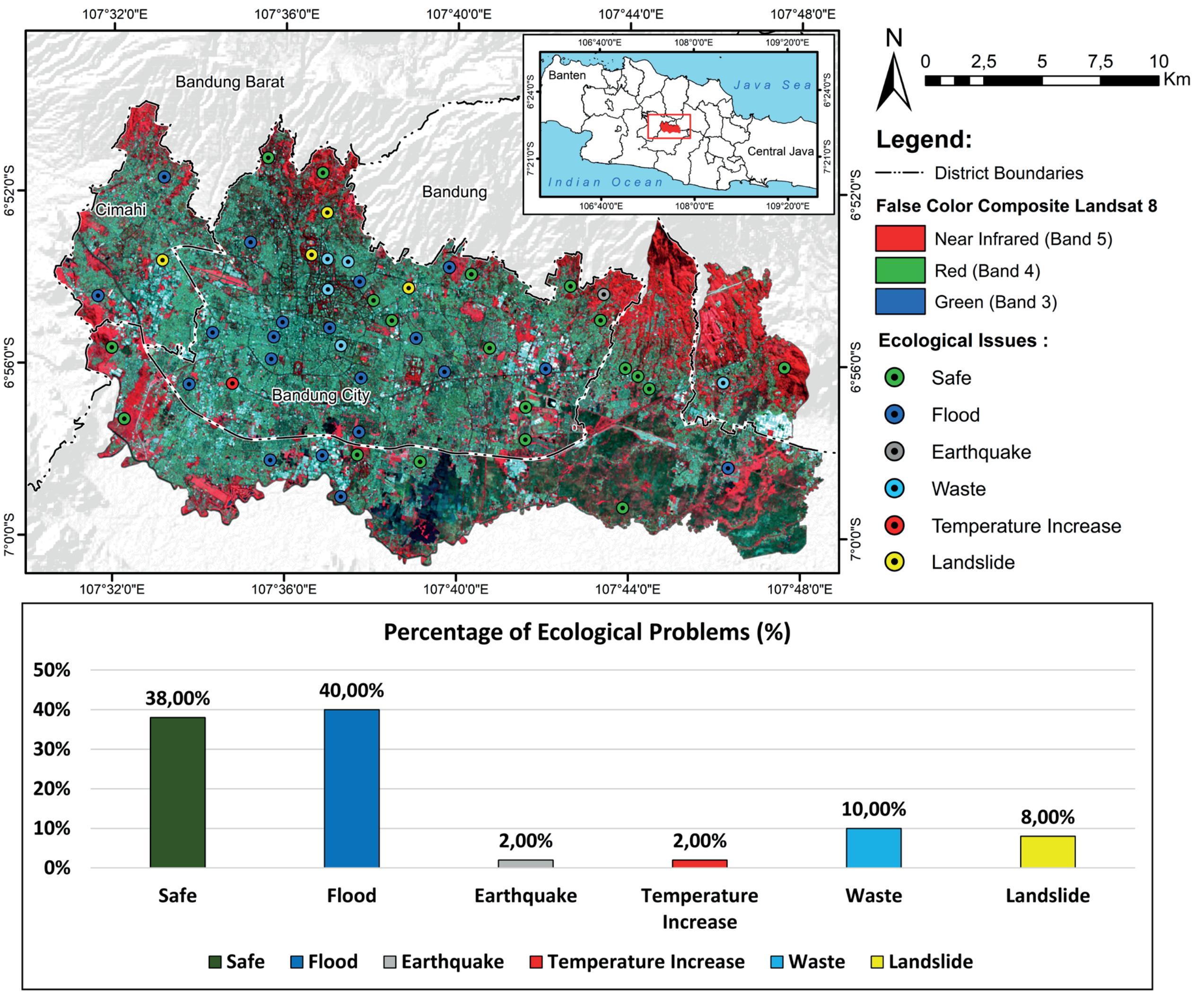

Fig. 5. Respondent distribution map and ecological problem statistics

agricultural land with flat topography, is mainly caused by waterlogging due to soil saturation and low porosity, preventing the land from absorbing and draining water efficiently. Waste management issues in Bandung City have intensified following the closure of the Sarimukti landfill due to a fire, making it difficult for residents to manage domestic waste, leading to the accumulation of trash in residential areas. This situation results in visible waste piles along roadsides and in front of homes. Landslide issues occur in the higher-elevation areas with sloping terrain. Unstable soil conditions, exacerbated by land-use changes from vegetation to residential areas, compromise soil stability. The loss of plant roots, which serve to bind the soil, and the creation of built-up land increase the surface load, further destabilizing the area. The heat island effect persists in the urban center of Bandung City, caused by the high building density in the area without adequate green spaces. Additionally, the scarcity of green zones and tree planting programs contributes to air pollution, along with the prevalence of roads and motor vehicle emissions. Although earthquakes are rare, the Lembang Fault in the northern region poses a potential threat to the safety of residents.

Determination of Threshold Value

The threshold value was determined by utilizing mean RSEI data in PC1 on built-up land and actual data. The built-up land data was used to obtain the mean value of the RSEI index in 2023 for each neighborhood. The data used as field samples is presented in binary form, where the data is categorized as good (no ecological problems) with code "0" and categorized as poor (ecological problems exist) with code "1". Both data will be analyzed together through ROC-AUC curve analysis to determine the threshold value.

The use of field data to determine threshold values yields objective results in the development of the RSEI model into RSEIT. Actual field data helps identify real-world conditions that cannot be captured by satellite imagery. Furthermore, determining the threshold based on real conditions produces results that accurately represent the actual field situation through the validation process conducted (Palapa and Maramis 2014). In line with this statement, the study by (Henrys and Jarvis 2019) indicates that remote sensing data supported by primary field data provides better objectivity. One of the analyses used to determine threshold values is the receiver operating characteristic (ROC) curve, which can test binary data in good and poor categories, formulated based on sensitivity and specificity values, and can be used to generate the cut-off threshold value (Obuchowski et al. 2005). In this context, RSEIT is not only a model but also has the capability to be validated both in terms of model performance and based on actual field conditions.

The AUC value, which shows the performance of the model as shown in (Fig. 6), shows that in the dry season and rainy season, both obtained AUC values of 0.732 and 0.734, respectively. According to research by Carter et al. (2016), predicting a model with an ROC that obtains an AUC value of > 0.7 can be considered logical, especially if only a small sample is used. Through this statement, it can be interpreted that the resulting model has the ability to separate RSEI into good and poor classes. Furthermore, to determine the consistency of the performance of the ROC AUC model, it is necessary to conduct a validation test.

The threshold value formed from the analysis obtained a value of 0.4737 in the dry season and 0.5662 in the rainy season. The cutoff value or threshold value is the determinant of good and poor class boundaries in RSEIT modeling which is used as a reference in the moderate class. Determining the threshold value in this study will certainly produce a different spatial distribution, where Xu (2013) set the value of the moderate class at 0.4 with the equal interval method.

ROC curve validation, as shown in (Table 3), uses three assessments in the form of an overall accuracy value, a

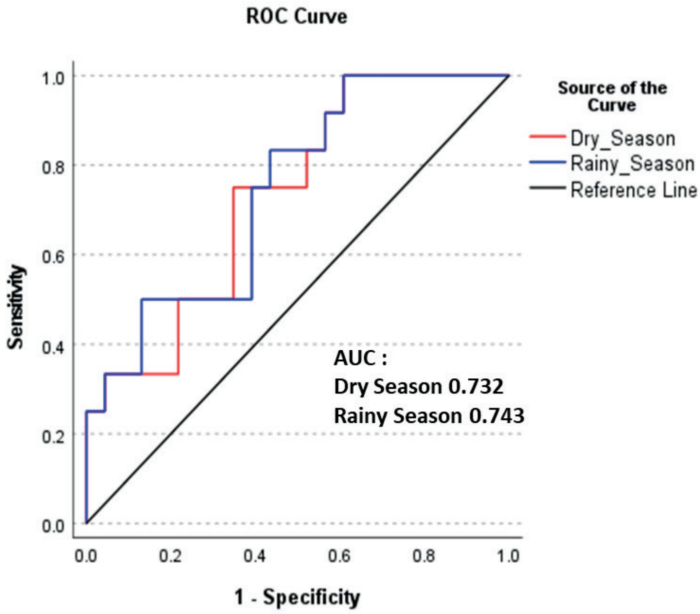

Fig. 6. ROC curve analysis results

Table 3. Results of threshold analysis and validation test

Season	Threshold	Overall Accuracy	Sensitivity	Specificity
Dry Season	0.474	80.00%	71.40%	87.50%
Wet Season	0.566	86.67%	85.70%	87.50%

Source: Primary data processing

sensitivity value, and a specificity value obtained through 30% of the validation data. The overall accuracy value formed in both seasons is greater than 80%. This value can be interpreted as indicating that the resulting model can predict good and poor classes with an accuracy above 80% in the field. The sensitivity value is a value that shows the ability of the model to detect true cases (TP). In this case, the RSEIT class is good, with an ability level of 71.40% in the dry season and 85.70% in the rainy season. Meanwhile, the specificity value used to measure the model's ability to detect true negative cases (TN), in this case the RSEI class is poor, which in both seasons shows an ability of 87.50%.

Threshold Value Based Ecological Index Classification (RSEIT)

The RSEIT classification uses 5 classifications to measure ecological quality in Bandung City, namely very poor, poor, moderate, good, and very good classes. The difference in threshold values between the rainy season and the dry season greatly affects the spatial distribution of RSEIT in each class. Further, (Table 4) shows the RSEI class interval.

In general, the RSEIT intervals formed in both seasons show a higher difference than the interval determined by Xu (2013) of 0.4 in the moderate class. The difference between the RSEI classification applied by Xu (2013) and the RSEIT classification is 0.074 in the dry season and 0.166 in the rainy season. In the very poor, poor, good, and very good classes, the equal interval method is still utilized. In both the dry and wet seasons, the very poor and poor classes used intervals of 0.237 and 0.283, respectively, while the good and very good classes used intervals of 0.176 and 0.145, respectively. The equal interval classification is still used in these classes because RSEIT only looks for thresholds in the moderate class. The interval scale set in the RSEIT classification in the moderate class has a higher value compared to RSEI, which will cause differences in spatial distribution and area in each class.

The spatial distribution of RSEIT in both seasons shown in (Fig. 7) shows a different distribution pattern in both seasons, where in the dry season the distribution in all classes is more varied than in the rainy season. The poor and very poor classes have almost the same distribution in both seasons, where the distribution tends to be centered

Table 4. Class interval RSEIT

Classification	Dry Season Interval	Rainy Season Interval
Very Poor	> 0.236	< 0.282
Poor	0.237 - 0.473	0.283 - 0.565
Moderate	0.474 - 0.648	0.566 - 0.710
Good	0.649 - 0.825	0.711 - 0.855
Very Good	0. 825 <	0.855 <

Source: Primary data processing

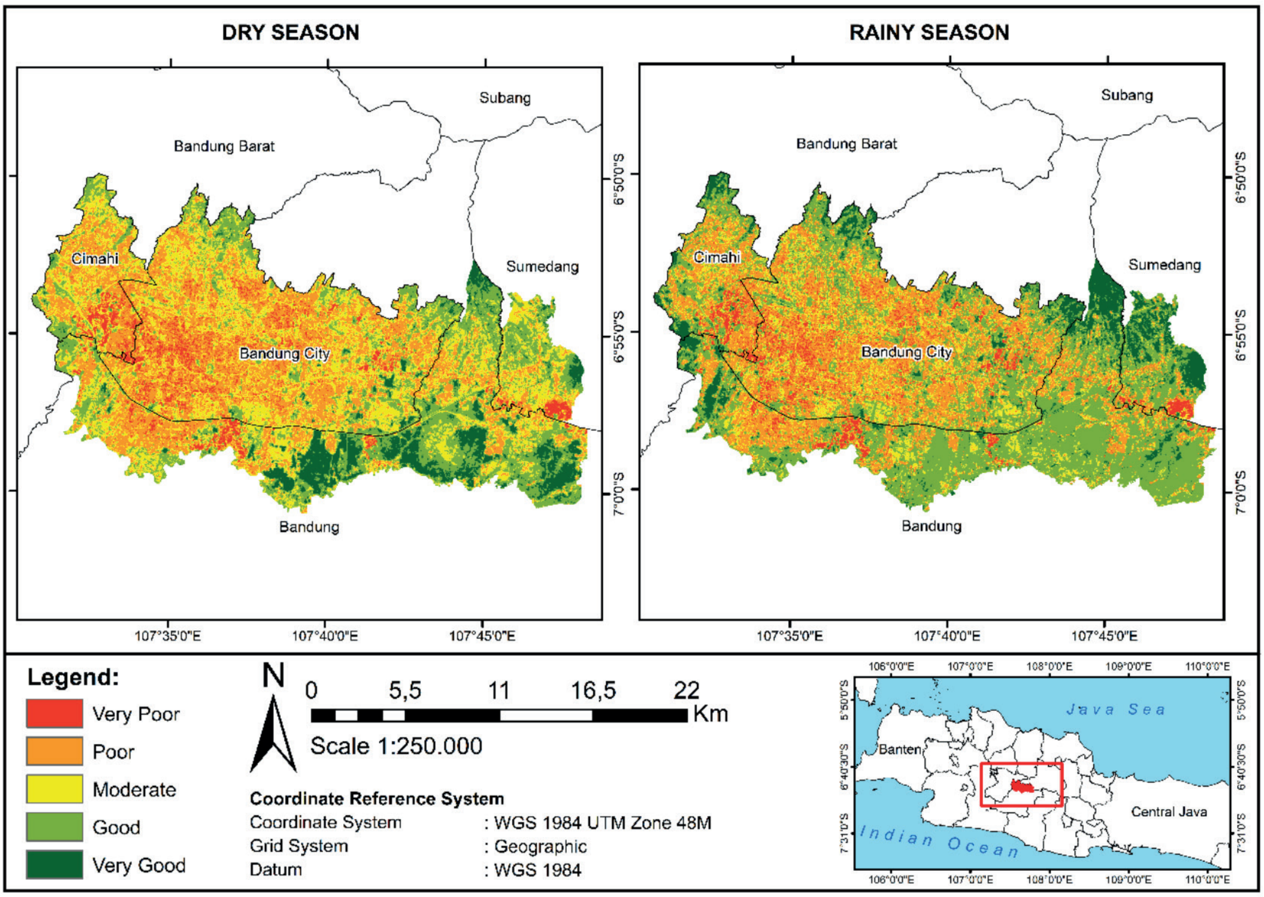

Fig. 7. RSEIT spatial distribution map

in the central area of Bandung City, where there is a lot of built-up land such as settlements, public facilities, and industrial areas. The moderate class in both seasons shows the clearest difference between all classes; in the dry season, the moderate class tends to be evenly distributed in the research area, while in the rainy season, the moderate class tends to be very small. In the good and very good classes, in general, the distribution is on the outskirts of Bandung City, which is found in many green land objects such as forests, plantations, and rice fields. But specifically, it can be seen that the distribution of good and very good classes is more concentrated during the rainy season, even in urban areas of Bandung City.

The percentage of RSEIT area displayed in (Fig. 8) shows that the seasonal factor responded to the spectral value of image data and, when integrated with 50 actual data points, shows logical results in each RSEIT class area. In line with this statement, research by Indrawati et al. (2020) stated that seasonal factors greatly affect the ecological index formed. RSEIT statistics show that the very poor and poor classes will be wider during the dry season with a difference in area of 0.05% and 3.13%, respectively, while the good and very good classes will tend to be wider during the rainy season with a difference in area of 41.72% and 1.14%, respectively. On the other hand, the moderate class is widely higher during the dry season than during the rainy season with a difference of 15.32%.

The formation of spatial distribution patterns and the extent of the RSEIT area can be viewed from the aspect of the season that affects the NDVI and WET indicators, as well as the aspect of the threshold value. In terms of seasonal influence, NDVI and WET indicators associated with vegetated green zones will be higher during the rainy season. This is in line with statements in previous studies, where ecological quality is strongly influenced by the presence of vegetation; the higher the vegetation cover, the better the ecological condition of the area (Cheng and He 2019; Su et al. 2022). In the aspect of threshold values that reflect actual conditions in the field, it proves that the concentration of ecological problems in urban areas makes poor and very poor index classes tend to be formed in urban areas, while good and very good classes tend to be formed in urban peripheries.

DISCUSSION

Remote sensing is currently one of the most important elements in assessing ecological quality. The ability of remote sensing data to provide spatial and temporal resolution is a distinct advantage for examining large areas, such as the area used in this study. RSEI is one method that can currently be used to analyze urban ecological quality. Xu (2013) introduced RSEI, which uses basic data in the form of remote sensing data that integrates four environmental indicators using PCA. PCA on PC1 is the basis for forming five RSEI classes with an equal interval model. Niu and Li (2020) shows that the higher characteristics of PC1 compared to other PCs can be used as the basis for the formation of the RSEI index. A total of 5 classes broken down based on equal interval calcification does not pay attention to actual conditions in the field. In line with this, Wang et al. (2023) research states that RSEI still has weaknesses, such as the fact that the fact that the resulting output is still probabilistic and cannot be applied in general. Furthermore, in several similar studies, RSEI was not validated, meaning that actual field conditions were not taken into account. Compared to RSEI, RSEIT has the ability to determine threshold values through ROC AUC analysis, and its results can be tested through overall accuracy, sensitivity, and specificity calculations.

Research on ecological indices based on the Remote Sensing Ecological Index (RSEI) is generally similar across different regions, with minimal variation in methods and results, as assessments rely solely on indicators derived from remote sensing data. Several studies on RSEI in Indonesia and Asia, such as those by Dai et al. (2023) on the Jakarta-Bandung High-Speed Railway in Indonesia, Indrawati et al. (2020) in Semarang City, dan Giofandi et al. (2024) in Pekanbaru City, as well as studies in Asia by Diep et al. (2024) in Chan Tho City, Vietnam dan Zhang et al. (2024) in Wuhan City, China, generally conclude that ecological quality assessments remain limited to the RSEI approach without further development using additional data or methods. Specifically, these studies indicate that areas with high RSEI quality are often located in regions with high elevations, steep slopes, abundant vegetation, low temperatures, and low humidity. Conversely, areas with poor ecological quality are typically found in regions dominated by urbanized, built-up land, characterized by flat topography, sparse vegetation, low humidity, and high temperatures. This condition highlights that RSEI-based ecological assessments focus solely on four physical environmental variables derived from remote sensing sensors, with the eigenvalue relationships (particularly on PC1) serving as a benchmark to determine the extent to which each RSEI variable contributes to the overall ecological quality.

In fact, for the ecological assessment of Bandung City in 2023 across both seasons, areas with high (good) ecological index values do not always align with being free from ecological issues based on actual data. For example, the northern region of Bandung City (Figure 5), which is still lush, heavily vegetated, and sparsely populated, faces ecological challenges such as earthquake and landslide threats due to its steep terrain and proximity to the Lembang Fault. To address this, the RSEIT model enhances the capabilities of the RSEI algorithm by incorporating actual data, determining threshold values through ROC curve analysis in conjunction with RSEI data, and conducting model validation tests to evaluate the extent

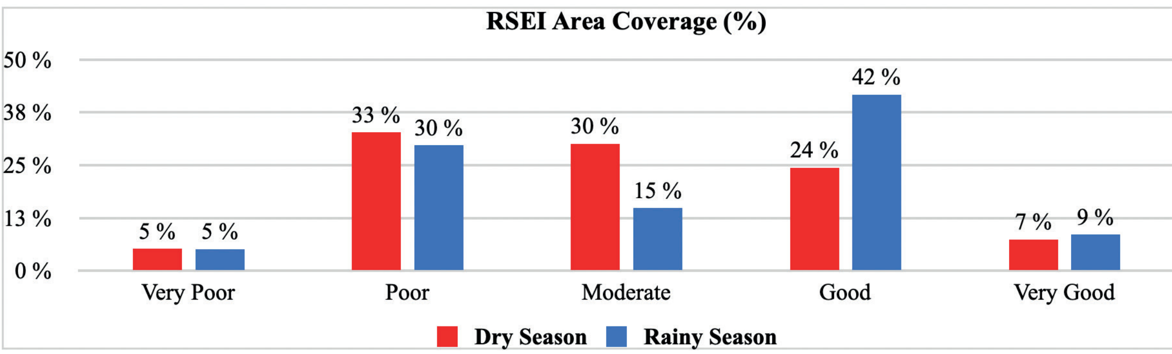

Fig. 8. RSEIT area coverage diagram

to which the RSEIT model represents factual conditions. This approach offers an alternative for producing ecological quality assessments (RSEIT) that better reflect actual field conditions, particularly in areas with high index values that still face ecological challenges and vice versa.

Research areas that have ecological problems can be a measure of good or poor ecological quality. Through 50 actual data points for 2023 used as input to determine the threshold value, it was found that 62% of the study areas have ecological problems, with a ratio of 4 out of 5 problems directly connected to natural problems such as natural disasters. The distribution of areas with ecological problems also adjusts the physical characteristics of the area, such as flooding, waste, and the heat island effect, which tend to be clustered in urban areas that have low elevation in built-up land zones, while landslides and earthquakes tend to be scattered in upland areas with land cover dominated by green zones. These findings are field facts that can be utilized to test the extent to which remote sensing data can detect ecological conditions according to actual conditions through threshold analysis.

The ROC analysis value shown in the (Fig. 6) obtained an AUC value of > 0.7; this value can still be considered for use, especially if the sample used has a relatively small amount. The performance of the RSEIT model, which produces a threshold value of 0.4737 in the dry season and 0.5662 in the rainy season, needs to be tested for its application to 30% of the of the validation data. The threshold value used in the RSEIT index classification shows a higher value during the rainy season with a difference of 0.092; this is strongly influenced by the spectral response in the rainy season, where NDVI and WET indicators have an important role. During the rainy season, the level of wetness and greenness increases, especially in the training area. This is in accordance with the statement of Xu and Deng (2022), where ecological conditions are largely determined by the greenery element of vegetation. The results of the validation assessment on RSEIT data in both seasons showed an average value of overall accuracy, sensitivity, and specificity of 83.34%, 78.55%, and 87.50%, respectively. These results show that RSEIT has a capability of over 70% in its implementation in the field.

The spatial distribution of RSEIT in both seasons (Fig. 7) exhibits a distinct pattern, with a more varied distribution across all classes during the dry season compared to the rainy season. The poor and very poor classes have almost the same distribution in both seasons, where the distribution tends to be centered in the central area of Bandung City, where there is a lot of built-up land such as settlements, public facilities, and industrial areas.

The impervious surface in urban centers, without being balanced by green spaces such as city parks and vegetation planting, results in high values of NDBSI and LST, both of which are negatively correlated with RSEIT. Furthermore, based on actual data, this condition is exacerbated by the ecological issues commonly found in urban areas. The moderate class in both seasons shows the clearest difference between all classes, where in the dry season the distribution of the moderate class tends to be evenly distributed in the research area, while in the rainy season the distribution of the moderate class tends to be very small. In the good and very good classes, in general, the distribution is on the outskirts of Bandung City, which is found in many green land objects such as forests, plantations, and rice fields. The peripheral areas, which are often characterized by green zones, result in high values for the WET and NDVI variables, both of which show a positive correlation with RSEIT. Meanwhile, ecological issues are generally less prevalent in these peripheral areas. But specifically, the distribution of good and very good classes is formed during the rainy season, even in urban areas of Bandung City. Based on previous research, the spatial distribution of RSEIT is strongly influenced by land cover and land use, and the reflection of spectral values recorded on the sensor will adjust the recorded object (Yuan et al. 2021). In line with the spatial distribution formed, the RSEIT statistics of poor and very poor classes will be wider during the dry season, while the good and very good classes will tend to be wider during the rainy season. On the other hand, in the moderate RSEIT class, it tends to be higher during the dry season than during the rainy season. In line with this statement, according to research by Indrawati et al. (2020) in Semarang City, the ecological conditions formed are strongly influenced by the current seasonal conditions.

CONCLUSIONS

This research aims to determine the threshold value of the urban ecological quality index (RSEIT) in Bandung City in 2023. This research produced three findings that can be summarized: (1) Ecological problems are most prevalent in urban areas of Bandung City, where community activities are concentrated. Actual data shows that 63% of the study area experienced ecological problems mainly caused by nature. There are at least 3 main problems that occur, namely flooding, garbage, and landslides; (2) The RSEIT model obtained threshold values of 0.474 and 0.566 during the dry and rainy seasons, respectively. According to the ROC analysis, the RSEIT modeling demonstrated performance exceeding 0.7, classifying it as suitable for further validation testing. Additionally, the validation results for both seasons showed average values for overall accuracy, sensitivity, and specificity of 83.34%, 78.55%, and 87.50%, respectively, all exceeding 70%. These results directly indicate that the RSEIT model is capable of being validated based on actual field conditions, and (3) furthermore, urban centers with high surface imperviousness, limited vegetation, and prevalent ecological issues are predominantly classified under the poor category by RSEIT, especially during the dry season. In contrast, suburban areas, which maintain a higher proportion of green spaces and face fewer ecological problems, are more frequently classified under the good category, particularly during the rainy season.

Nevertheless, this study is still limited to a single threshold value for distinguishing between good and poor ecological quality (moderate class). The entire RSEIT classification system (very poor, poor, moderate, good, very good) should also employ threshold values supported by a set of qualified actual data. Although actual data sourced from disaster occurrence records and interviews can serve as references for factual condition information, it would be preferable for the data collection process to also involve other parties, such as academics and local policymakers, to enrich the data pool and provide more detailed information. Such involvement would enhance the RSEIT output in terms of model performance and validation, bringing it closer to reality.

REFERENCES

Ary M. F. A. A., Rondonuwu D. M., & Warouw, F. (2018). Kampung Susun Di Manado. Social Design. Jurnal Arsitektur DASENG, 7(2).

Budiman, A., Sulistyantara, B., & Zain, A. F. (2014). Deteksi Perubahan Ruang Terbuka Hijau Pada 5 Kota Besar Di Pulau Jawa (Studi Kasus : DKI Jakarta, Kota Bandung, Kota Semarang, Kota Jogjakarta, Dan Kota Surabaya). Jurnal Lanskap Indonesia, 6(1).

Caio C. de Araujo Barbosa, Atkinson, P. M., & Dearing, J. A. (2015). Remote sensing of ecosystem services: A systematic review. In Ecological Indicators (Vol. 52). https://doi.org/10.1016/j.ecolind.2015.01.007

Carter, J. V., Pan, J., Rai, S. N., & Galandiuk, S. (2016). ROC-ing along: Evaluation and interpretation of receiver operating characteristic curves. Surgery (United States), 159(6). https://doi.org/10.1016/j.surg.2015.12.029

Cheng, Z., & He, Q. (2019). Remote Sensing Evaluation of the Ecological Environment of Su-Xi-Chang 466 City Group based on Remote Sensing Ecological Index (RSEI). Remote Sensing Technology and Application, 34(3), 531–539.

Dai, X., Chen, J., & Xue, C. (2023). Spatiotemporal Patterns and Driving Factors of the Ecological Environmental Quality along the Jakarta–Bandung High-Speed Railway in Indonesia. Sustainability, 15(16), 12426. https://doi.org/10.3390/su151612426

Diep, N. T. H., Nguyen, N. T., Hieu, D. C., Huong, N. T. T., & Trang, D. H. (2024). Environmental Quality Monitoring Using Remote Sensing Ecological Index (RSEI) in Can Tho City, Vietnam. IOP Conference Series: Earth and Environmental Science, 1345(1). https://doi.org/10.1088/1755-1315/1345/1/012018

Environmental Office Bandung City. (2022). Performance Information Document Environmental Management Bandung City in 2022.

Fawcett, T. (2006). An introduction to ROC analysis. Pattern Recognition Letters, 27(8). https://doi.org/10.1016/j.patrec.2005.10.010

Firozjaei, M. K., Fathololoumi, S., Kiavarz, M., Biswas, A., Homaee, M., & Alavipanah, S. K. (2021). Land Surface Ecological Status Composition Index (LSESCI): A novel remote sensing-based technique for modeling land surface ecological status. Ecological Indicators, 123. https://doi.org/10.1016/j.ecolind.2021.107375

Giofandi, E. A., Syahzaqi, I., Sekarjati, D., Putriana, A. M., Putti, H. M. D. M., & Sekarrini, C. E. (2024). Assessment Of Remote Sensing Approach For Urban Ecological Quality Evaluation In Pekanbaru City, Riau Province Indonesia. GEOGRAPHY, ENVIRONMENT, SUSTAINABILITY, 17(1), 28–35. https://doi.org/10.24057/2071-9388-2023-2640

Henrys, P. A., & Jarvis, S. G. (2019). Integration of ground survey and remote sensing derived data: Producing robust indicators of habitat extent and condition. Ecology and Evolution, 9(14). https://doi.org/10.1002/ece3.5376

Indrawati, L., Sigit Heru Murti, B. S., & Rachmawati, R. (2020). Integrated ecological index (IEI) for urban ecological status based on remote sensing data: A study at Semarang - Indonesia. IOP Conference Series: Earth and Environmental Science, 500(1). https://doi.org/10.1088/1755-1315/500/1/012074

Indrawati, L., Sigit Heru Murti, B. S., Rachmawati, R., & Aji, D. S. (2020). Effect of Urban Expansion Intensity on Urban Ecological Status Utilizing Remote Sensing and GIS: A Study of Semarang-Indonesia. IOP Conference Series: Earth and Environmental Science, 451(1), 012018. https://doi.org/10.1088/1755-1315/451/1/012018

Kustiwan, I., & Ladimananda, A. (2012). Pemodelan Dinamika Perkembangan Perkotaan dan Daya Dukung Lahan di Kawasan Cekungan Bandung. Tataloka, 14(2).

Kwok, R. (2018). Ecology's remote-sensing revolution. In Nature (Vol. 556, Issue 7699). https://doi.org/10.1038/d41586-018-03924-9

Lestiani, D. D., Santoso, M., Kurniawati, S., & Markwitz, A. (2013). CHARACTERISTIC OF AIRBORNE PARTICULATE MATTER SAMPLES COLLECTED FROM TWO SEMI INDUSTRIAL SITES IN BANDUNG, INDONESIA. Indonesian Journal of Chemistry, 13(3), 271–277. https://doi.org/10.22146/ijc.21287

Li, Y., Cao, Z., Long, H., Liu, Y., & Li, W. (2017). Dynamic analysis of ecological environment combined with land cover and NDVI changes and implications for sustainable urban–rural development: The case of Mu Us Sandy Land, China. Journal of Cleaner Production, 142, 697–715. https://doi.org/10.1016/j.jclepro.2016.09.011

Mas, J. F., Filho, B. S., Pontius, R. G., Gutiérrez, M. F., & Rodrigues, H. (2013). A suite of tools for ROC analysis of spatial models. ISPRS International Journal of Geo-Information, 2(3). https://doi.org/10.3390/ijgi2030869

Ministry of Environment and Forestry of the Republic of Indonesia. (2022). Indeks Kualitas Lingkungan Hidup.

Muchtar, H. S., Wijaya, I. N. S., & Setyono, D. A. (2024). Pembangunan Berkelanjutan Perkotaan Dalam Aspek Ekologi Kota Bandung. Planning for Urban Region and Environment Journal (PURE), 13(3), 193–204.

Niu, X., & Li, Y. (2020). REMOTE SENSING EVALUATION OF ECOLOGICAL ENVIRONMENT OF ANQING CITY BASED ON REMOTE SENSING ECOLOGICAL INDEX. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B3-2020, 733–737. https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-733-2020

Obuchowski, N. A., Blackmore, C. C., Karlik, S., & Reinhold, C. (2005). Fundamentals of clinical research for radiologists. American Journal of Roentgenology, 184(2). https://doi.org/10.2214/ajr.184.2.01840364

Palapa, T. M., & Maramis, A. A. (2014). Pemantauan Melalui Observasi Lapang, Pencitraan Satelit, dan SIG Tambang Talawaan-Tatelu. Prosiding Seminar Nasional Sains Dan Pendidikan Sains IX 2014, 594–601.

Reza, M. I. H., & Abdullah, S. A. (2011). Regional Index of Ecological Integrity: A need for sustainable management of natural resources. In Ecological Indicators (Vol. 11, Issue 2). https://doi.org/10.1016/j.ecolind.2010.08.010

Seddon, A. W. R., Macias-Fauria, M., Long, P. R., Benz, D., & Willis, K. J. (2016). Sensitivity of global terrestrial ecosystems to climate variability. Nature, 531(7593), 229–232. https://doi.org/10.1038/nature16986

Su, S., Zhaoning, G., Wenjing, Z., Yuan, Z., & Yifei, W. (2022). Change of vegetation coverage 560 and assessment of ecological environment quality in Beiyun River Basin. Acta Scientiae Circumstantiae, 42(1), 19–27.

Suprayogi, S., Tivianton, A., Nurchayati, W., & Mukarromah, D. (2013). Relevansi Spasial Indeks Kualitas Lingkungan Hidup dengan Pengetahuan Siswa akan Kesiapsiagaan Perubahan Lingkungan dan Iklim (Studi Kasus: SMU, SMP, SD sekitar Kota Yogyakarta, D.I. Yogyakarta). Prosiding Seminar Nasional Geografi UMS.

Wang, H., Liu, D., Lin, H., Montenegro, A., & Zhu, X. (2015). NDVI and vegetation phenology dynamics under the influence of sunshine duration on the Tibetan plateau. International Journal of Climatology, 35(5). https://doi.org/10.1002/joc.4013

Wang, J., Ma, J. L., Xie, F. F., & Xu, X. J. (2020). [Improvement of remote sensing ecological index in arid regions: Taking Ulan Buh Desert as an example]. Ying Yong Sheng Tai Xue Bao = The Journal of Applied Ecology, 31(11), 3795–3804. https://doi.org/10.13287/J.1001-9332.202011.011

Wang, Z., Chen, T., Zhu, D., Jia, K., & Plaza, A. (2023). RSEIFE: A new remote sensing ecological index for simulating the land surface eco-environment. Journal of Environmental Management, 326, 116851. https://doi.org/10.1016/J.JENVMAN.2022.116851

Widiawaty, M. A., Dede, Moh., & Ismail, A. (2019). ANALISIS TIPOLOGI URBAN SPRAWL DI KOTA BANDUNG MENGGUNAKAN SISTEM INFORMASI GEOGRAFIS. Seminar Nasional Geomatika, 3. https://doi.org/10.24895/sng.2018.3-0.1007

Xu, H. (2013). A remote sensing urban ecological index and its application. Acta Ecol, 7853–7862.

Xu, H., & Deng, W. H. (2022). Rationality analysis of MRSEI and its difference with RSEI. Remote Sensing Technology, 37, 1–7.

Xu, H., & Zhang, T. (2013). Assessment of consistency in forest-dominated vegetation observations between ASTER and Landsat ETM+ images in subtropical coastal areas of southeastern China. Agricultural and Forest Meteorology, 168. https://doi.org/10.1016/j.agrformet.2012.08.012

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

Yue, H., Liu, Y., Li, Y., & Lu, Y. (2019a). Eco-Environmental Quality Assessment in China's 35 Major Cities Based On Remote Sensing Ecological Index. IEEE Access, 7, 51295–51311. https://doi.org/10.1109/ACCESS.2019.2911627

Yue, H., Liu, Y., Li, Y., & Lu, Y. (2019b). Eco-environmental quality assessment in china's 35 major cities based on remote sensing ecological index. IEEE Access, 7. https://doi.org/10.1109/ACCESS.2019.2911627

Zhang, W., Zhang, W., Ji, J., & Chen, C. (2024). Urban Ecological Quality Assessment Based on Google Earth Engine and Driving Factors Analysis: A Case Study of Wuhan City, China. Sustainability (Switzerland) , 16(9). https://doi.org/10.3390/su16093598

Zhu, H., Wang, J. L., Cheng, F., Deng, H., Zhang, E. W., & Li, Y. X. (2020). [Monitoring and evaluation of eco-environmental quality of lake basin regions in Central Yunnan Province, China]. Ying Yong Sheng Tai Xue Bao = The Journal of Applied Ecology, 31(4), 1289–1297. https://doi.org/10.13287/J.1001-9332.202004.011

Zou, K. H., O'Malley, A. J., & Mauri, L. (2007). Receiver-operating characteristic analysis for evaluating diagnostic tests and predictive models. Circulation, 115(5). https://doi.org/10.1161/CIRCULATIONAHA.105.594929