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Risk Screening Environmental Indicators Model Change Based on Spectral Transformation Around New Yogyakarta International Airport

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ABSTRACT

The development of New Yogyakarta International Airport (NYIA) in Temon sub-district is aimed at improving the progress of the surrounding region, where the construction has an impact on the increase in built-up land of 572.38 hectare (2013–2017) and 268.67 hectare (2017–2023) which is potentially a decrease in the environmental quality index. The purpose of the research was to analyze changes in the environmental quality index Risk Screening Environmental Indicators (RSEI) of 2013, 2017 and 2024 around NYIA. The research designs used quantitative approaches with scoring approaches, while research methods used spectral transformation and Principal Component Analysis transformation. The research has limited the use of Landsat 8 image data as a primary data source with a spatial resolution of 30 meters, where the image has not yet been able to deliver the results of the research with a high degree of exhaustion. The originality of the research is the identification of changes in the environmental quality index that are correlated with changes in built-up land and vegetation coverage. The results of the study showed a decrease in the RSEI values, where high-level RSEIs decreased by about 295.17 hectare (2013–2017) and 1720.91 hectare (2017–2024), in addition there was an increase in the area of low-level RSEI by about 122.33 hectare (2013–2017) and 1898.79 hectare (2017–2024). The decline in RSEI in the area study has been correlated with increased built-up land and decreased vegetation area, with built-up land increasing by 572.38 hectare (2013–2017) and 269.97 hectare (2017–2024), besides decreasing vegetation areas by 137.82 hectare (2013–2017), and 97.34 hectare (2017–2024). The study concluded that there was a decrease in the environmental quality index, where increased built-up land and decreased vegetation area were influential factors. This research opens up further research opportunities to predict the environmental quality index with the cellular automata model.

Keywords: environmental quality, remote sensing, land cover change.

INTRODUCTION

The development of public infrastructure is aimed at improving services to the community so that it can improve the well-being and economy of the region (Syahza et al., 2019; Thacker et al., 2019). Infrastructure development activities are always undertaken in different sectors of life in a uniform manner in order to increase the prosperity of the population. Infrastructure development will have an impact on the improvement of other buildings as needed, thereby affecting the increase in built-up land that could potentially lead to a decrease in environmental quality (Sanjoto, 2020; Sidiq et al., 2022). The development of public infrastructure that could potentially have an impact on the surrounding area is NYIA in Kulon Progo district, Daerah Istimewa Yogyakarta (DIY) Province. NYIA is a development of the previous airport which is difficult to develop due to land constraints which causes less optimal visits of foreign tourists. Besides, the development of NYIA also aims to boost the economy of the region which has relatively slow development compared to other districts and cities in the DIY Province (Kadarisman, 2019; Utami et al., 2021).

The land cover change around NYIA could potentially lead to environmental problems, such as declining biodiversity indices, potential droughts due to reduced vegetation coverage, food imbalances due to agricultural land conversion, loss of natural landscape and soil erosion, and deforestation of environmental balancing vegetation (Majidi et al., 2019; Zamroni et al., 2021). Growth of built-up land around NYIA has so far been observed rapidly, with the year 2013-2017 increasing to 572.38 hectares and an increase of 268.67 hectares (2017–2023) such as hotels, commercial buildings, infrastructure and settlements (Utami et al., 2021; Sidiq et al., 2024). Growth of built-up land has been impacted by a decrease in agricultural land of 418,07 hectares (2013–2017) and 153,57 hectares (2017–2023) (Utami et al., 2021; Sidiq et al., 2024). Development in the region is expected to continue to increase with the emergence of some open land that has been prepared for development. Therefore, based on the data change of land cover, time series can potentially against a decrease of the environmental quality index, this is because most of the NYIA development area corresponds to vegetation and agricultural land that have a contribution to the quality of environment in the region. Further monitoring of the environmental quality index was carried out in 2013, 2017 and 2024, where the selection of the year was based on the development of the NYIA at the research site, 2013 as the base year because at that time the discourse of development and development activities of NYIA did not appear, next year 2017 was taken because in that year the construction of NYIA started which had an impact on the increase of the built-up land, while the election of 2024 was taken to know the index of quality of environment exists, where already a lot of improvement of the built-up land is potentially on the decrease in the environment quality index around NYIA. Monitoring of environmental quality indices can be leveraged using remote sensing technology with the RSEI method (Xu et al., 2019; Zheng et al., 2022).

The problem-solving approach in this study is through monitoring of environmental quality indices in time series (2013, 2017 and 2024) around NYIA by utilizing remote sensing technology through RSEI approach with parameters greenness index, humadity index, dryness index and heat index to obtain a model of change in environment quality at the research site. The aim of this study was to compile a time series environmental quality index model around NYIA that can be used as input in development planning and environmental management around the NYIA. The novelty of this research is the use of RSEI methods based on data raster method principal component analysis (PCA). The results of the research can be used as one of the controls of the regional planning policy in the coming years around NYIA so that the expected economic sector improvement does not affect the decline in environmental quality in the region.

METHODOLOGY

Research sites

The research area is located in the sub-district that borders directly with the Temon sub-district which is the NYIA site, where there are 7 sub-districts that are the research site. The following picture shows a map of the location of the study (Fig. 1).

Data source

The satellite image data used in this study is Landsat 8 time series image from the Google Earth Engine (GEE) with the data set category is surface reflectance collection 2. This dataset contains atmospherically corrected surface reflectance and land surface temperature derived from the data produced by the Landsat 8 sensors. The acquisition image consists of 2013, 2017 and 2024; to avoid the impact of seasonal differences, the satellite image period chosen was the month of March-October which is the rainy season (Zhu et al., 2021). After the selected time period, the next pre-processing was cloud and cloud shadow removal using the QA (pixel_qa) band bit mask technique, so that the satellite image used represented the condition of a time period (Yan et al., 2022), where it helps the mapping process in tropical regions that are covered by many clouds, such as Indonesia (Amalia et al., 2024).

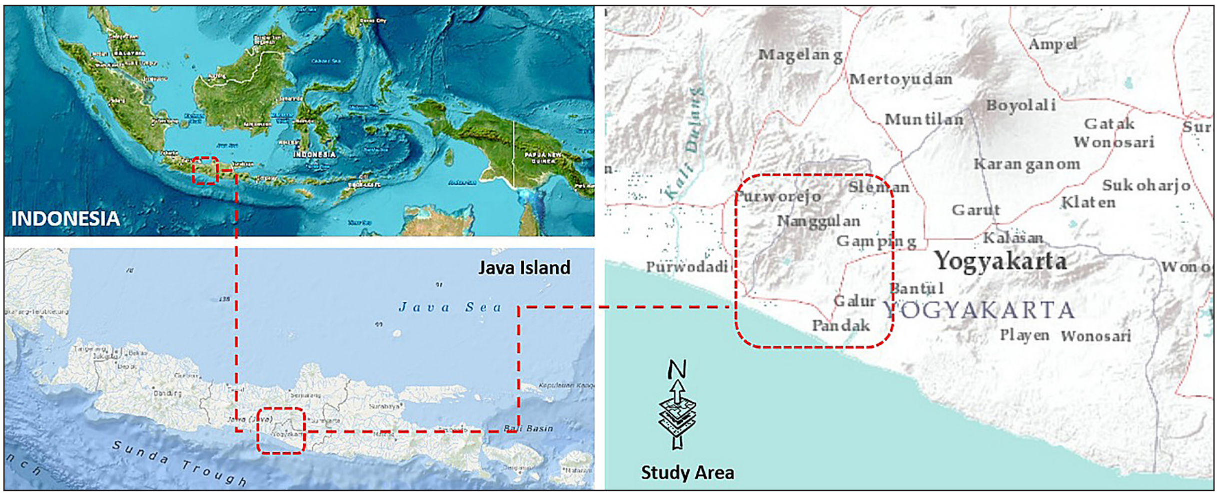

Figure 1. Research sites

Data processing

Risk screening environmental indicators parameters RSEI is the environmental quality index used in this study, which includes 4 parameters. These parameters are very close to the quality of the natural ecological environment namely greenness, humidity, dryness and heat (Hu and Xu, 2018; Liu and Zhang, 2024). The representation and methods of calculation of each ecological factor used in RSEI are described as follows.

Greenness index

Vegetation is a very important factor in representing the quality of the ecological environment in a region (22). The greenness index is expressed by the normalized difference vegetations index (NDVI) which can represent the spread of density and vegetation coverage (Islam et al., 2021). The NDVI formula is defined as follows:

$$NDVI = (\rho NIR - \rho R)/(\rho NIR + \rho R) \tag{1}$$

ρNIR is the reflectance of the near-infrared band on remote sensing data, and ρR is the reflection of the infrared band upon remote sensor data. In Landsat 8 data, they relate to the fifth and fourth bands respectively.

Humidity index

Humidity index can represent vegetation and soil water levels. In this study, humidity parameters used the wetness index of tasseled cap transformation (Chen et al., 2023). Wetness index can also be used to estimate environmental impacts, such as drought and flooded vegetation (Dzakiyah and Saraswati, 2020; Ticehurst et al., 2022). The formula used to calculate the wetness index with Landsat 8 images is as follows:

$$\begin{aligned} Wet = {} & 0.1511\rho B + 0.1972\rho G + 0.3283\rho R + 0.3407\rho NIR - \\ & - 0.7117\rho SWIR1 - 0.4559\rho SWIR2 \end{aligned} \tag{2}$$

Processing wetness index using several Landsat 8 image bands, including ρB, ρG, ρR, ρNIR, $\rho SWR1$, and $\rho SWR2$ are the reflectances of the blue, green, red, near-infrared, shortwave infrared 1, and shortwave infrared 2 bands.

Dryness index

The high intensity of built-up land or impervious surface and bare soil can have a negative impact on the ecological environment (Anthony et al., 2024). This can be represented by drying of soil which can be calculated by combining the index-based built-up index (IBI) and the normalized bare soil index (SI) using the method the normalized difference soil index (NDBSI) (Zhou and Liu, 2022). This index uses many bands, including NIR, SWIR1 and SWIR2 that are capable of discriminating impervious surfaces from other objects, as well as sensitive to soil moisture dynamics (Bidgoli et al., 2020; Fariz and Faniza, 2023). The formula used by NDBSI is as follows:

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

IBI and SI are the index-based built-up index and normalized bare soil index. The specific formulas used to calculate these indices were as follows:

$$\begin{aligned} BI = {} & \{2\rho SWIR1/(\rho SWIR1 + \rho NIR) - \\ & - [\rho NIR/(\rho NIR + \rho R) + \rho G/(\rho SWIR1 + \rho G)]\} \cdot \\ & \cdot \{2\rho SWIR1/(\rho SWIR1 + \rho NIR) + \\ & + [\rho NIR/(\rho NIR + \rho R) + \rho G/(\rho SWIR1 + \rho G)]\} \end{aligned} \tag{4}$$

$$SI = [(\rho SWIR1 + \rho R) - (\rho NIR + \rho B)]/ /[(\rho SWIR1 + \rho R)+(\rho NIR + \rho B)] \quad (5)$$

There are several bands used for NDBSI processing, including: ρB, ρG, ρR, ρNIR, $\rho SWR1$, and $\rho SWR2$ are the reflectances of the blue, green, red, near-infrared, shortwave infrared 1, and shortwave infrared 2 bands.

Heat index

Heat index can be represented in land surface temperature (LST), where LST in this study involves emissivity and in Celsius units. The calculation of the land surface emissivity adopted the vegetation cover method and the fractional vegetation cover was calculated using the NDVI (Sekertekin and Bonafoni, 2020). The formula for calculating LST is as follows:

$$L = gain \times DN + bias \quad (6)$$

$$Tb = K2/\ln(K1/L6 + 1) \quad (7)$$

$$pv = [(NDVI - NDVImin)/ /(NDVImax - NDVImin)]2 \quad (8)$$

$$\varepsilon = 0.004 \times pv + 0.986 \quad (9)$$

$$LST = Tb/[1 + ((\lambda Tb)/\rho)\ln(\varepsilon)] - 273.15 \quad (10)$$

where: L is radians temperature, and Tb is the brightness temperature; DN is the gray value of the data pixel, and gain and bias are the band gain value and bias values, respectively, which can be obtained using the image header; $K1$ and $K2$ are calibration parameters, which can be obtained by referring to the user manual. ε is the land surface emissivity, which was calculated by applying a threshold to the *NDVI*; pv is the fractional vegetation cover; *NDVI* is the normalized difference vegetation index, and *NDVImin* is the minimum value of the *NDVI*, which represents the *NDVI* value of completely bare soil or areas with no vegetation cover. *NDVImax* is the maximum value of the *NDVI*, which represents the *NDVI* value of pure vegetation pixels; *LST* is the land surface temperature, and ρ = 1.438 × 10−2 mK; λ is the center wavelength of the thermal infrared band, where: λTM = 11.435 μm and $\lambda TIR1$ = 10.900 μm.

Risk screening environmental indicators processing

RSEI is built on the basis of principal component analysis (PCA) transformation. All parameters are represented in indices, such as NDVI, Wetness, NDBSI and LST processed in PCA analysis. The specific formula used to calculate the *RSEI* was as follows:

$$RSEI = f(NDVI, Wet, LST, NDBSI) \quad (11)$$

PCA is an image transformation that rotates the axis of the original feature space coordinate system to a new orthogonal axis called principle axes by maximizing data variance (Alganci, 2019). Use of PCA to synthesize several indicators to avoid bias caused by subjective factors in the degradation process (Chen et al., 2023). However, before to the PCA process, all RSEI parameters (NDVI, Wet, NDBSI, LST) were normalized in intervals (0–1) (Li et al., 2023). The normalization process aims to harmonize the weight of each parameter, given that every parameter has a different range of values, this process uses the following formula:

$$NIi = (Ii-Imin)/(Imax-Imin) \quad (12)$$

where: NI_i is the result of normalized processing of the index, and I_i, I_{min}, and I_{max} are the values of the ith pixel of the index, the minimum value, and the maximum value.

On the basis of the PCA results, the first component, PC1, integrates various ecological factors and contains information about some of the ecological index values, so it can be used to estimate ecological environmental quality. The higher the PC1 value, the better the quality of the environment. However, PC1 results sometimes show reverse results, so the following calculations need to be done (Zheng et al., 2022):

$$RSEI0 = 1-\{RSEI\} \quad (13)$$

Furthermore, to facilitate further analysis, the end result of the RSEI is normalized so that it has a range (0–1) (Li et al., 2023). The closer the value to 1, the better the ecological condition, while the closer it is to the value of 0, the worse the ecologic condition (Fig. 2) (Hu and Xu, 2018; Liu and Zhang, 2024). The formula for normalizing *RSEI* is as follows:

$$RSEIf = (RSEI0-RSEI0\_min)/ /(RSEI0\_max-RSEI0\_min) \quad (14)$$

RESULT AND DISCUSSION

RSEI parameters processing results

The environmental quality index at the research site is obtained from the results of the processing of the RSEI time series in 2013, 2017 and 2024 for monitoring the changes in the quality of the environment as an impact of the development of NYIA. The processing uses 4

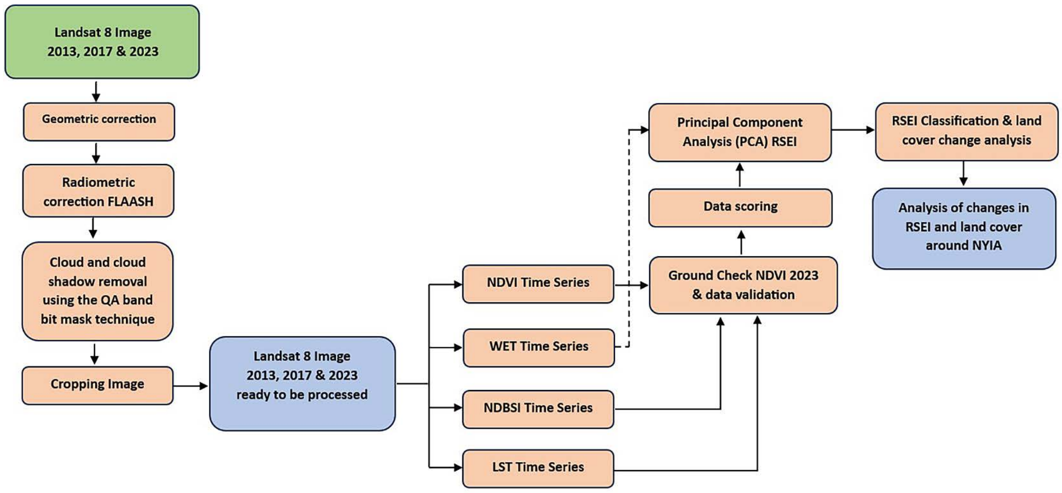

Figure 2. Research flow chart

parameters with processing the spectral transformation of Landsat 8 image data, including greenness index, humidity index, dryness index and heat index, from which each index can provide thematic information related to the environment quality at the study site. Here are the results of RSEI parameter processing with spectral transformation of Landsat 8 time series image data.

Greenness index

The NDVI level of greenery in the study area is presented with a value of -1–1 for each pixel, where pixel values -1–0 are non-vegetation objects (water, soil and built-up), whereas pixel value 0–1 is vegetation, where the larger the value indicates the higher the level of vegetation density (Spadoni et al., 2020; Zhang et al., 2023). NDVI time series processing results showed an increase in the area of non-vegetation objects from 2013–2017 with an area of 1416.70 hectares and an increase of 329.83 hectares (2017–2024). The increase in the object is largely due to the development of the NYIA which affects the increase in other built-up land around it, where increases in built-up land converting vegetation and agricultural land influence the decline in RSEI values at the research site (Zhang et al., 2024). Further from the value of the NDVI time series shows there was a decrease in the area of low-density vegetation from 2013–2017 with an area of 1758.80 hectares and the vegetation of moderate density from 2017–2024 with a area of 721.61 hectares, where based on the type of objects of vegetation with low density – moderate are mixed gardens. On the basis of on the value of the NDVI, time series will influence the decrease in the RSEI value at the research site due to the increase in built-up land and decreased coverage and vegetation density at the study site.

The following Table 1 and Figure 3 shows the value and distribution of the spatial greenness index at the research site (Chen et al., 2022; Silva et al., 2024).

Humidity index

The humidity index in the RSEI parameter is treated with a wetness index that indicates the level of water content in the soil and vegetation,

Table 1. NDVI time series processing results

No.	NDVI value	Vegetation density level	Area (hectares)				
			2013	2013–2017	2017	2017–2024	2024
1	-0.0783–0.0018	Non vegetation	103.01	+1416.70	1519.73	+329.83	1849.56
2	0.0019–0.2770	Low	10902.32	-1758.80	9143.48	+408.81	9552.29
3	0.2780–0.3521	Moderate	12367.74	+237.97	12605.71	-721.61	11884.10
4	0.3531–0.5136	High	14514.86	+104.15	14619.01	-17.03	14601.98
Total			37887.93	–	37887.93	–	37887.93

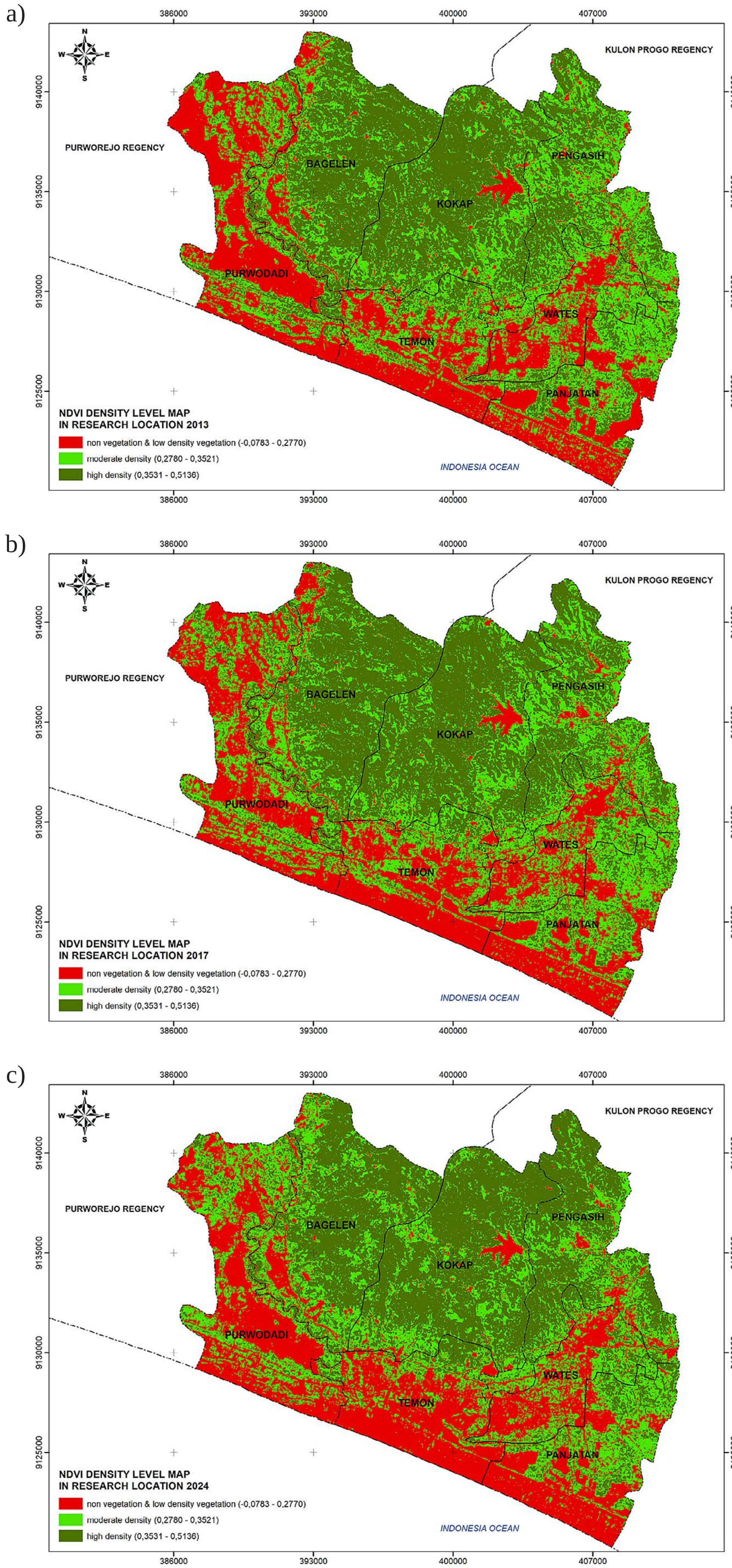

Figure 3. NDVI density level time series: (a) 2013, (b) 2017, (c) 2024

where the higher value of the index indicates high water content so it has a low threat of drought (Xu et al., 2022). The result of the processing of the wetness index time series at the site of the study has a value interval of -1.093–0.532 for each pixel, where the larger the pixel value indicates a high level of humidity, and the lower the pixels value (minus) indicates the area is dry. The results of the wetness index processing at the research site in 2013, 2017 and 2024 showed that most of the area has high humidity with the largest area in 2017 with an area of 16601.81 hectares. This is due to the area with high density vegetation cover in the Bagelen sub-district, Pengasih sub-district and Kokap sub-district resulting in a high water content. The humidity level of the area from 2013 to 2024 was relatively dynamic, with an area decrease of approximately 1864.69 hectares compared to the area with high moisture levels from 2017 to 2024, while areas with very low humidities increased by about 1043.70 hectares between 2017 and 2024 and areas with low levels increased to about 851.52 hectares.

The increase in areas with very low and low humidity levels from 2017–2024 at the research site may be due to the change in land cover from vegetation to built-up land that mostly occurs around NYIA, such as hotels, dining houses, supermarkets and other built-up land. On the basis of the value of the wetness index time series will influence the decrease of the RSEI value at the research site because there is an increase in areas with very low and low humidity levels (Xu et al., 2022). The following Table 2 and Figure 4 show the value and distribution of the spatial wetness index at the research site.

Dryness index

The dryness index parameters were obtained from the processing of the normalized difference soil index (NDBSI) to provide information on the drought level at the research site. The level of drought is one of the parameters of environmental quality that relates to the availability of water in an area to meet the needs of living creatures. The result of the NDBSI time series processing showed a pixel value of 1.979–8.682 with a classification of very low-high, where the higher the value of the pixel represents the higher level of drought. On the basis of the results of the 2024 NDBSI processing, most of the area has a low drought level with an area of 19377.41 hectares, then there is an area with a moderate drought rate with a area of 14213.17 hectares. The drought levels in the study area are mostly low and moderate, where this is mostly due to the area that is widely used for agricultural land so requires a large supply of water resources, besides that most areas are high plains with close vegetation cover so that has a potential high water resources. In general, the drought rate in the area study from 2013–2024 is quite dynamic, where from 2017–2024 there has been an increase in high drought area with an area of 2412.08 hectares, but the area with a low drought level has also experienced an increase of approximately 10786.30 hectares. On the basis of NDBSI values, the time series will influence the increase in RSEI values at the research site because there is an increase in the areas with low drought levels at the study site (Liu et al., 2023). The following Table 3 and Figure 5 show the value and spatial distribution of the dryness index at the research site.

Heat index

Parameter heat index describes the conditions of the surface temperature of the soil in the study area, where the higher surface temperature indicates the lower level of environmental quality. The phenomenon of rising surface temperature will affect the increase of microclimate which causes environmental conditions to become more uncomfortable. The heat index as the RSEI parameter is obtained from the land surface

Table 2. Wetness index time series processing results

No.	Wet index value	Humidity level	Area (hectares)				
			2013	2013–2017	2017	2017–2024	2024
1	-1.093–(-0.389)	Very low	3960.88	-2396.20	1564.68	+1043.70	2608.38
2	-0.390–(-0.247)	Low	7648.45	-301.63	7346.82	+851.52	8198.34
3	-0.248–(-0.136)	Moderate	11111.84	+1262.80	12374.61	-30.53	12344.08
4	-0.137–0.532	High	15166.76	+1435.10	16601.81	-1864.69	14737.13
Total			37887.93	–	37887.93	–	37887.93

a)

b)

c)

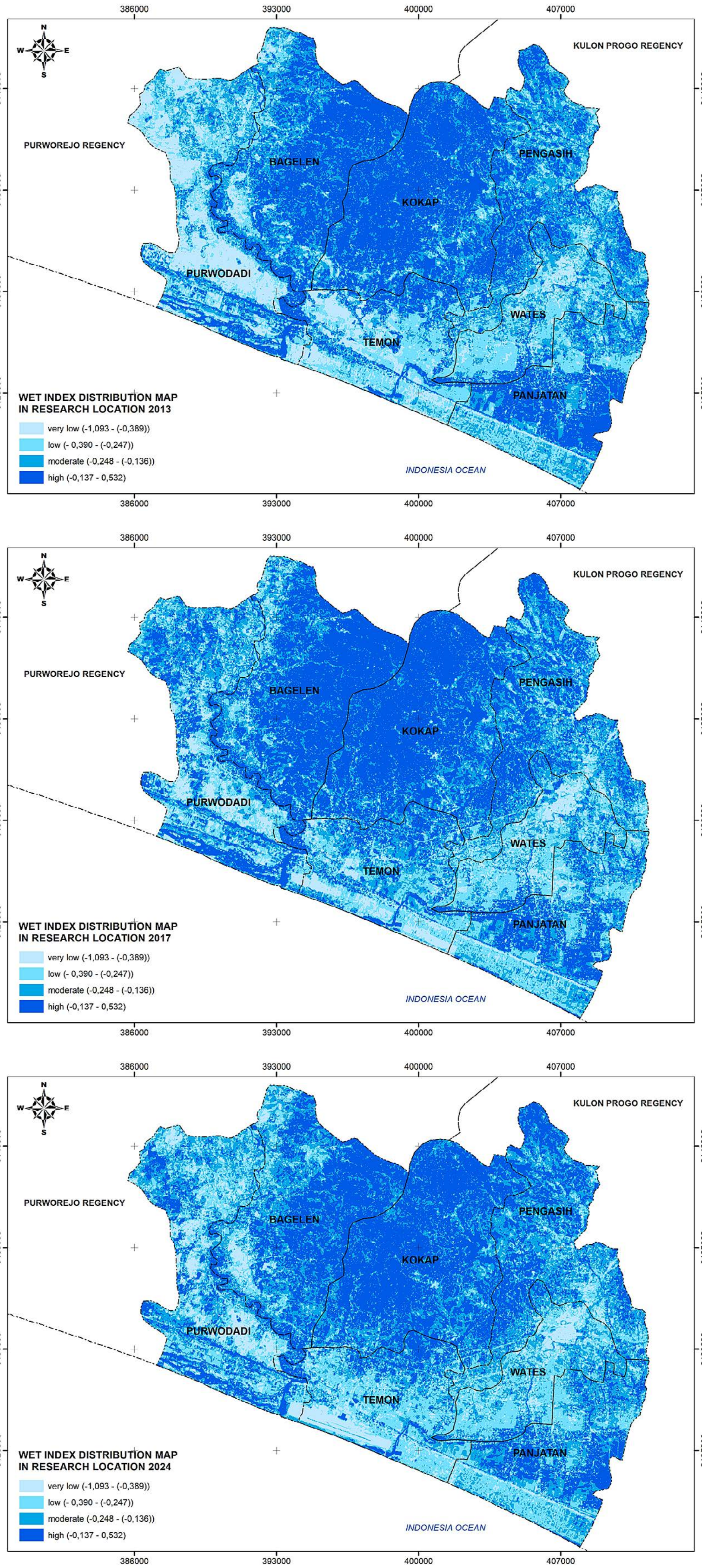

Figure 4. Wetness index time series: (a) 2013, (b) 2017, (c) 2024

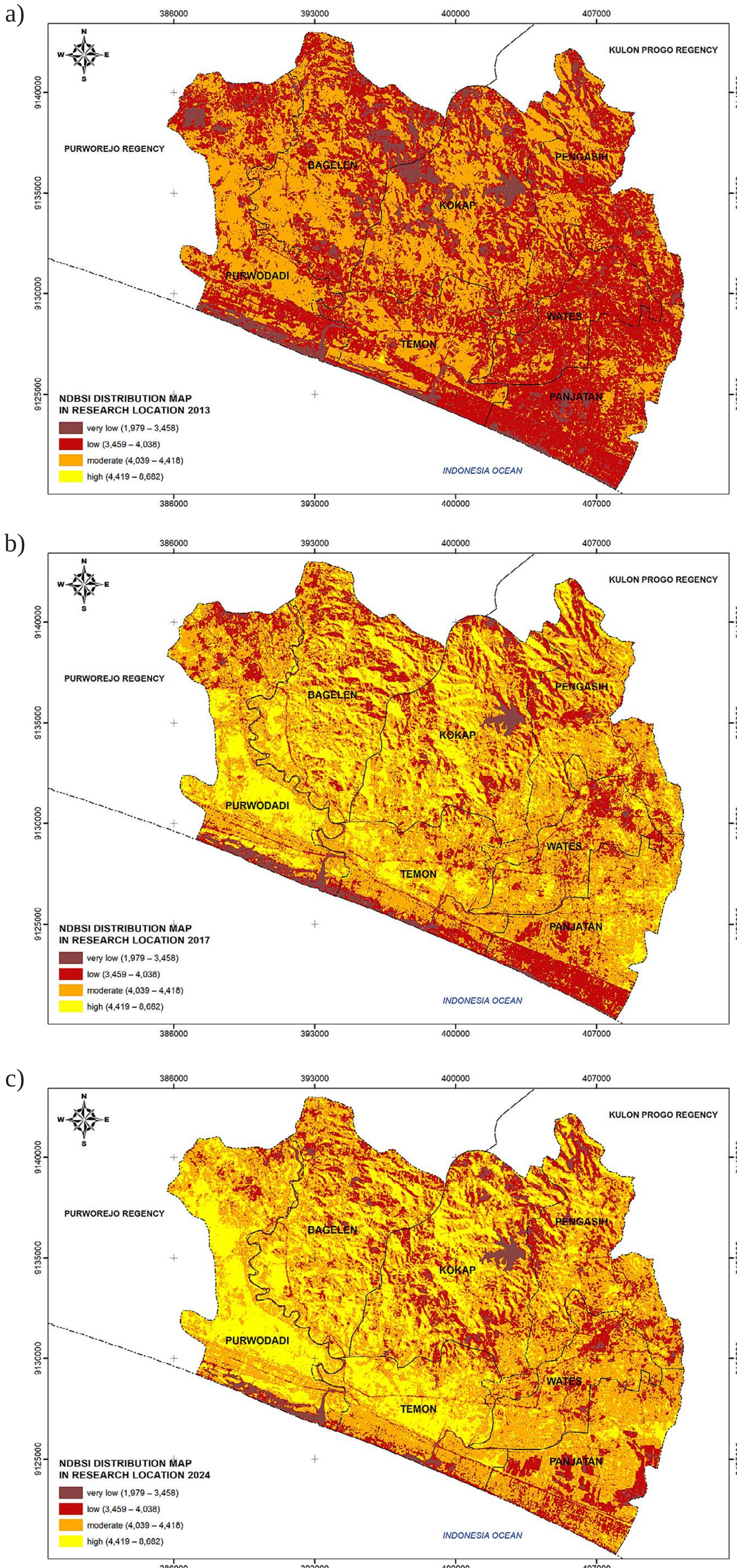

Figure 5. Dryness index time series: (a) 2013, (b) 2017, (c) 2024

Table 3. NDBSI time series processing results

No.	NDBSI value	Drought level	Area (hectares)				
			2013	2013–2017	2017	2017–2024	2024
1	1.979–3.458	Very low	2792.90	-83.39	2709.51	-239.15	2470.36
2	3.459–4.038	Low	7461.71	+1129.40	8591.11	+10786.30	19377.41
3	4.039–4.418	Moderate	16992.33	+180.07	17172.4	-2959.23	14213.17
4	4.419–8.682	High	10640.99	-1226.1	9414.91	+2412.08	11826.99
Total			37887.93	–	37887.93	–	37887.93

temperature (LST) processing results using the thermal band on the Landsat 8 image to produce the surface temperature value in celsius units at each pixel value. The LST time series processing result has an interval value of 28.27–32.01 °C, where for 2024 most areas have a moderate LST value (30.478–30.944 °C) with an area of 15571.21 hectares, and a low LEST value (30.084–30.477 °C), with a area of 11949.25 hectares. The increase in the area of high LST occurred in the 2013-2017 interval with an increase of 544.47 hectares and increased again from 2017–2024 with a size of 452.02 hectares.

In addition, there has been an increase in the size of the medium LST area from 2017–2024 to the area of 3515.02 hectares. However, there is a decrease in the area area of the LST very low from the year 2017–2024, about 1527.37 hectares and low LST with the decreased area of about 2440.39 hectares. The time series data showed that there was an increase in LST from 2013–2024 which affected the increase in the microclimate at the research site, where the increase of LST is due to the decrease in the vegetation area that turned into built-up land especially around NYIA (Xu et al., 2023). On the basis of the value of the LST time series will have an impact on the decline in the RSEI value at the study site because of the increased area with high LST. The following Table 4 and Figure 6 show the value and distribution of the spatial heat index at the study site.

RSEI change analysis

RSEI is processed using the PCA method using 4 parameters, including greenness index, humidity index, dryness index and heat index Landsat 8 time series image processing results in 2013, 2017 and 2024. The processing result of the time series can provide information about changes in the quality of the environment around NYIA, the processing output of RSEI has a value of 0–1 for each pixel of the image, where the higher the pixel value indicates that the location has better environmental quality, whereas if pixel values are lower, then it shows that the environment quality is worse. On the basis of the results of the processing, RSEI showed most of the study area in 2024 has a high environmental quality index with an area of 10994.71 hectares, but the size of the area has decreased compared to 2017 with the area area of 12715.65 hectares and has a further decrease from 2013 with the surface area of 13010.79 hectares.

On the basis of the spatial distribution of the area that suffered the decrease of the value of the index is mostly in the area of Temon sub-district that has land cover change from the development of NYIA. The values of the RSEI time series from the year 2013–2024 showed there was a decline in the index of high quality in the study area, where the decline can be caused by various factors, including decreased vegetation area, increased microclimate, reduced potential of water

Table 4. LST time series processing results

No.	LST value	LST level	Area (hectares)				
			2013	2013–2017	2017	2017–2024	2024
1	28.273–30.083	Very low	7808.35	+102.44	7911.29	-1527.37	6383.92
2	30.084–30.477	Low	14384.07	+5.57	14389.64	-2440.39	11949.25
3	30.478–30.944	Moderate	12708.67	-652.48	12056.19	+3515.02	15571.21
4	30.995–32.010	High	2986.34	+544.47	3530	+452.02	3983.55
Total			37887.93	–	37887.93	–	37887.93

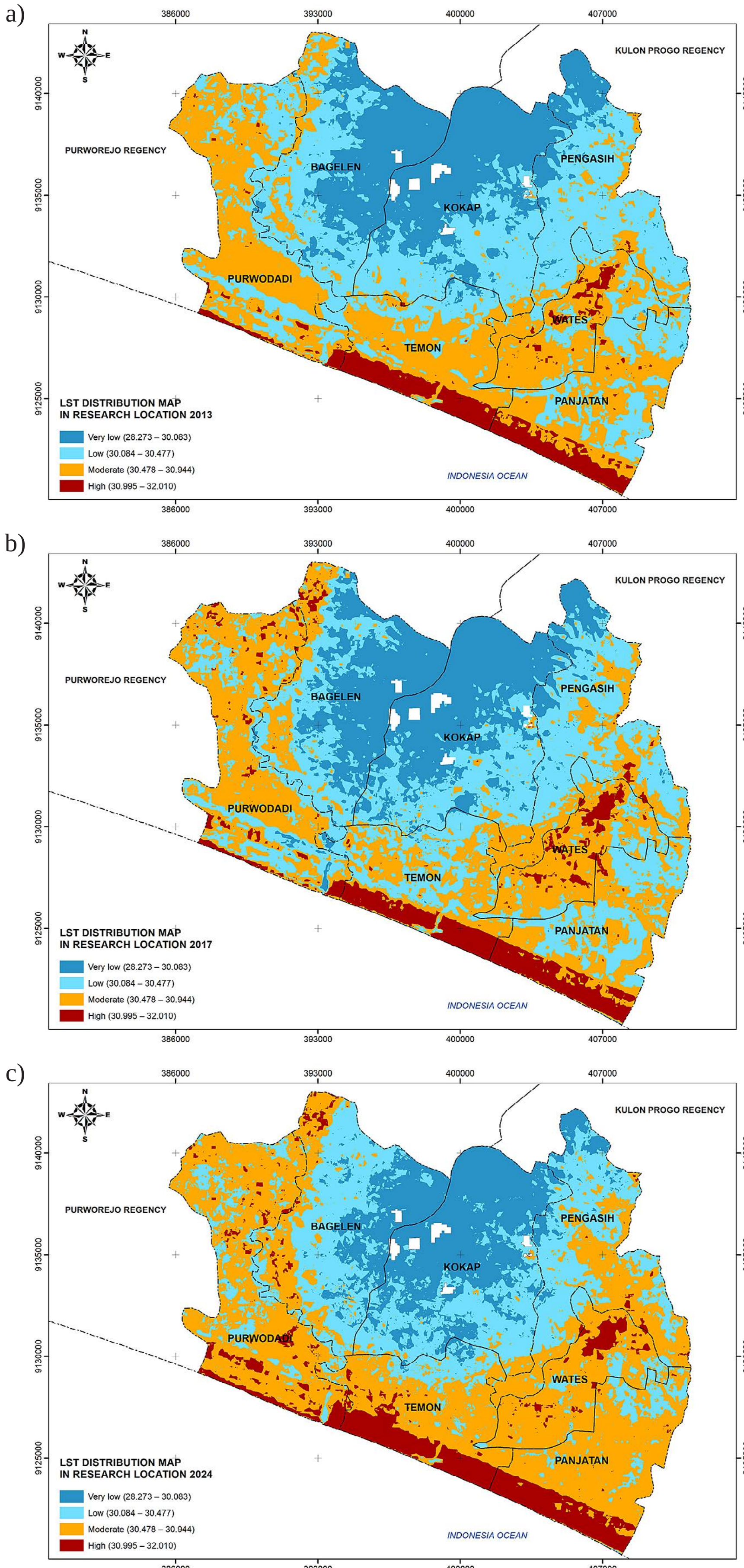

Figure 6. LST value time series: (a) 2013, (b) 2017, (c) 2024

resources and various other factors. Furthermore, f the results of processing RSEI time series also showed a wide increase in the areas with very low and low quality index, which from 2013–2017 increased about 122.33 hectares and increased another 1898.79 hectares from 2017–2024. The increase in the area is mostly in the southern part of the study area, such as Temon and Panjatan sub-districts, which in recent years have land cover change. An increase in the areas with a low environmental quality index will affect the decline in air quality, water quality, soil quality and potential disasters, such as flooding, landslides, improved microclimate, land subsidance and a variety of other potential disaster (Liu and Zhang, 2024). Thus, it is necessary to regularly monitor the quality of the environment around NYIA so that land cover change can always be controlled and can be immediately reversed if there is an extreme decrease in the quality index. The following Tables 5 and 6, Figures 7 and 8 present the time series environment quality index at the research site.

Land cover change to RSEI

According to the results of the processing RSEI time series, there was a decrease in high quality index area and an increase in the areas with low quality index, so it can be concluded that the study area experienced a decline in environmental quality from the year 2013–2024. The decrease in the environmental quality index mostly occurred in the Temon sub-district, which is a NYIA development area, as evidenced by the decline in the NDVI and the increase in the LST in the region. The decline in the value of RSEI in a region is influenced by various factors, including an increase in the cultivated land and a decrease in the vegetation area that serves as an environmental balancer (Chen et al., 2022; Gong et al., 2023). This phenomenon also occurred in the study area, where there was an increase in built-up land, increasing by 572.38 hectares (2013–2017) and 269.97 hectares (2017–2024). The increase in built-up land is correlated with a decrease in the area of the very high and high environmental

Table 5. RSEI time series processing results

No.	RSEI value	RSEI level	Area (hectares)				
			2013	2013–2017	2017	2017–2024	2024
1	0–0.343	Very low	541.09	+99,70	640.97	+223.26	864.05
2	0.344–0.0496	Low	3925.33	+20.63	3945.96	+1452.53	5398.49
3	0.497–0.601	Moderate	9370.01	+399.76	9769.77	-213.37	9556.40
4	0.602–0.707	High	13010.79	-295.17	12715.62	-1720.91	10994.71
5	0.708–1	Very high	9027.71	-228.92	8798.79	+251.49	9050.28
Total			37887.93	–	37887.93	–	37887.93

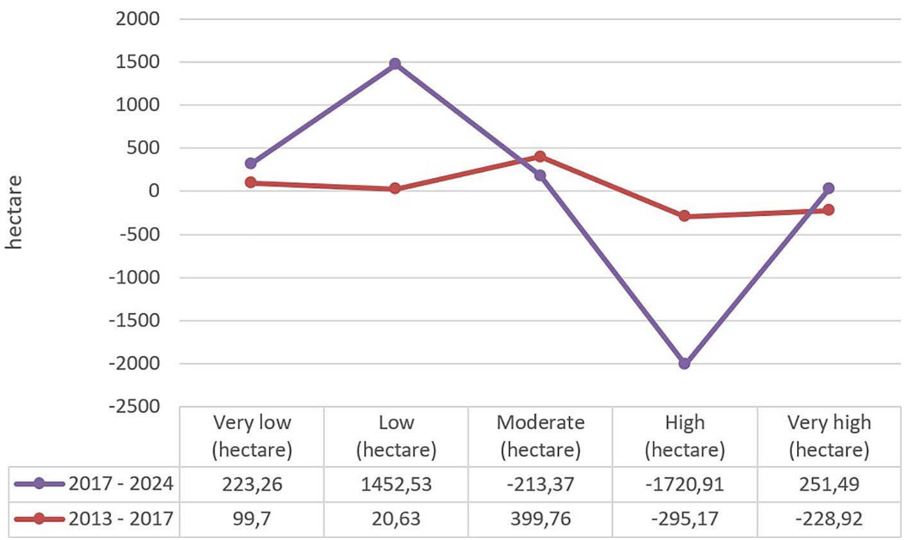

Figure 7. Graph of RSEI values changes time series

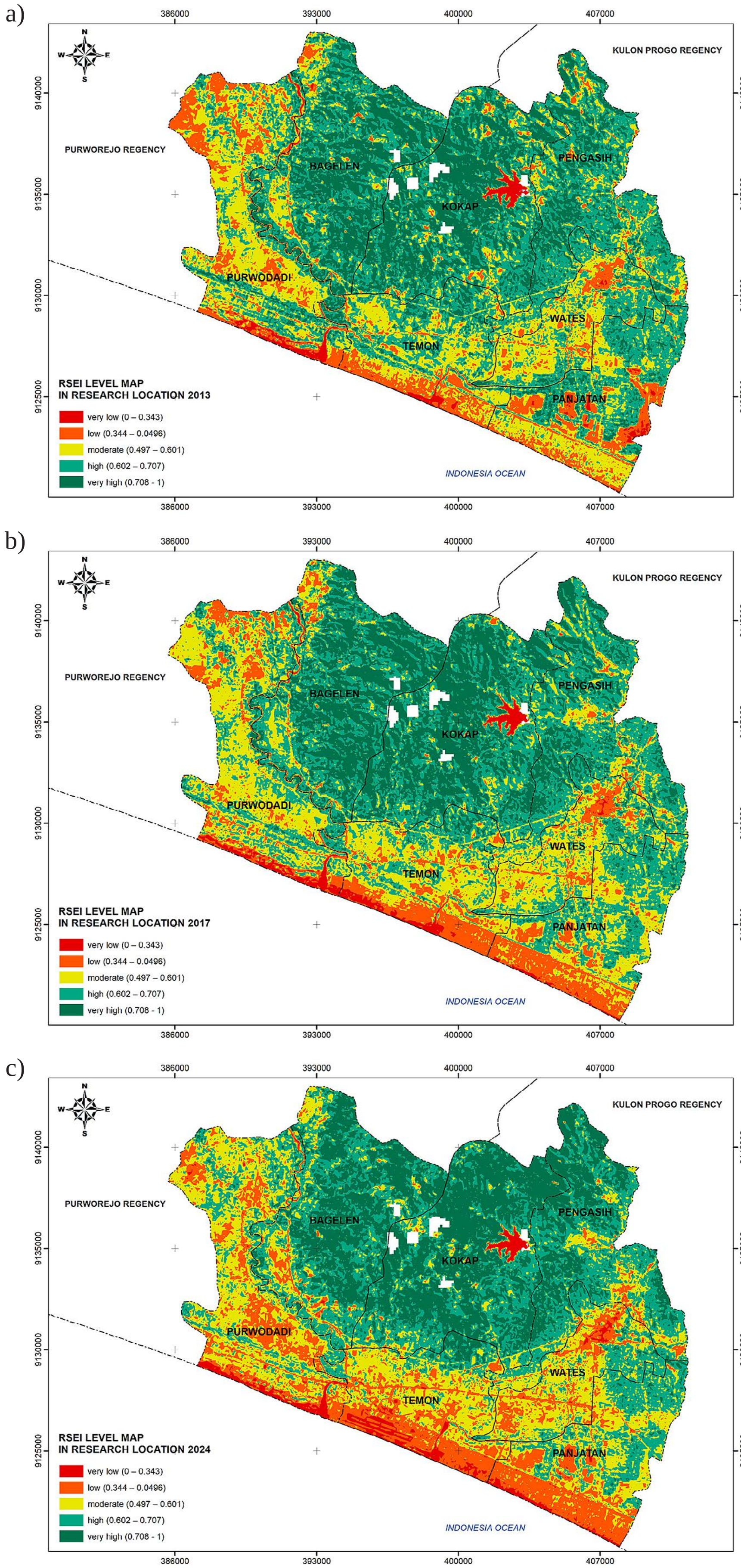

Figure 8. RSEI time series: (a) 2013, (b) 2017, (c) 2024

Table 6. RSEI change for each sub-district

No.	RSEI value	RSEI level	Area (hectares)				
			2013	2013–2017	2017	2017–2024	2024
Kokap sub-district							
1	0–0.343	Very low	134.32	-10.15	124.17	-12.08	112.09
2	0.344–0.0496	Low	140.37	-79.46	60.91	-1.74	59.17
3	0.497–0.601	Moderate	682.82	-242.72	440.10	-22.44	417.66
4	0.602–0.707	High	2512.62	+81.11	2593.75	-362.31	2231.44
5	0.708–1	Very high	3317.47	+247.22	3564.69	391.57	3956.26
Wates sub-district							
1	0–0.343	Very low	6.59	+9.77	16.36	+33.34	49.70
2	0.344–0.0496	Low	393.44	+84.28	477.72	+211.18	688.90
3	0.497–0.601	Moderate	1322.63	+115.62	1438.25	-45.56	1392.69
4	0.602–0.707	High	997.23	-183.25	813.98	-128.45	685.53
5	0.708–1	Very high	184.23	-26.42	157.81	-70.51	87.30
Pengasih sub-district							
1	0–0.343	Very low	0.93	+0.04	0.97	+0.68	1.65
2	0.344–0.0496	Low	174.35	-32.03	142.32	+29.13	171.45
3	0.497–0.601	Moderate	927.76	+65.78	993.54	-136.50	857.04
4	0.602–0.707	High	2717.22	+37.83	2755.05	-348.25	2406.80
5	0.708–1	Very high	1444.16	-71.62	1372.54	+454.94	1827.48
Panjatan sub-district							
1	0–0.343	Very low	89.85	-34.50	55.35	+75.25	130.60
2	0.344–0.0496	Low	951.86	+88.31	1040.17	+265.18	1305.35
3	0.497–0.601	Moderate	1350.41	+179.26	1529.67	-89.42	1440.25
4	0.602–0.707	High	1579.51	+28.80	1608.31	-182.53	1425.78
5	0.708–1	Very high	449.86	-261.87	187.99	-68.48	119.51
Purwodadi sub-district							
1	0–0.343	Very low	210.68	+44.68	255.36	-13.31	242.05
2	0.344–0.0496	Low	1356.07	-322.72	1033.35	+528.78	1562.13
3	0.497–0.601	Moderate	2697.20	+288.95	2986.15	-33.34	2952.72
4	0.602–0.707	High	1469.82	+141.62	1611.44	-347.73	1263.71
5	0.708–1	Very high	404.66	-152.53	252.13	-134.31	117.82
Bagelen sub-district							
1	0–0.343	Very low	10.49	-3.48	7.01	+0.76	0.77
2	0.344–0.0496	Low	192.08	-15.14	176.94	60.69	237.63
3	0.497–0.601	Moderate	790.53	-137.67	652.86	172.27	825.13
4	0.602–0.707	High	2441.58	-81.60	2359.98	104.37	2464.35
5	0.708–1	Very high	2825.95	+237.89	3063.84	-338.09	27.25.75

quality index which decreased by 524.09 hectares (2013–2017) and 1469.42 hectares (2017–2024).

In addition, the reduced vegetation cover also affects the decrease in the environmental quality index, as evidenced by the decreased area of vegetation from 2013–2017 with an area of 137.82 hectares and 97.34 hectares (2017–2024), where at the same interval of the year there was also an increase in the area with very low and low RSEI, as well as a decrease in areas of very high and high RSEIs in the study area. According to the results of such analysis, efforts are needed in limiting the growth of built-up land and reducing the area of vegetation to maintain environmental quality in the area study. The following Table 7 presents the time series data related to changes in land cover and RSEI in the area study (Fig. 9, Fig. 10).

Table 7. RSEI area changes, built-up land and vegetation 2013–2024

No	Information	Area (hectares)	
		2013–2017	2017–2024
1	Increase very low and low RSEI area	120.33	1675.79
2	Decline very high and high RSEI area	524.09	1469.42
3	Built-up area increase	572.38	268.97
4	Vegetation area decrease	137.82	97.34

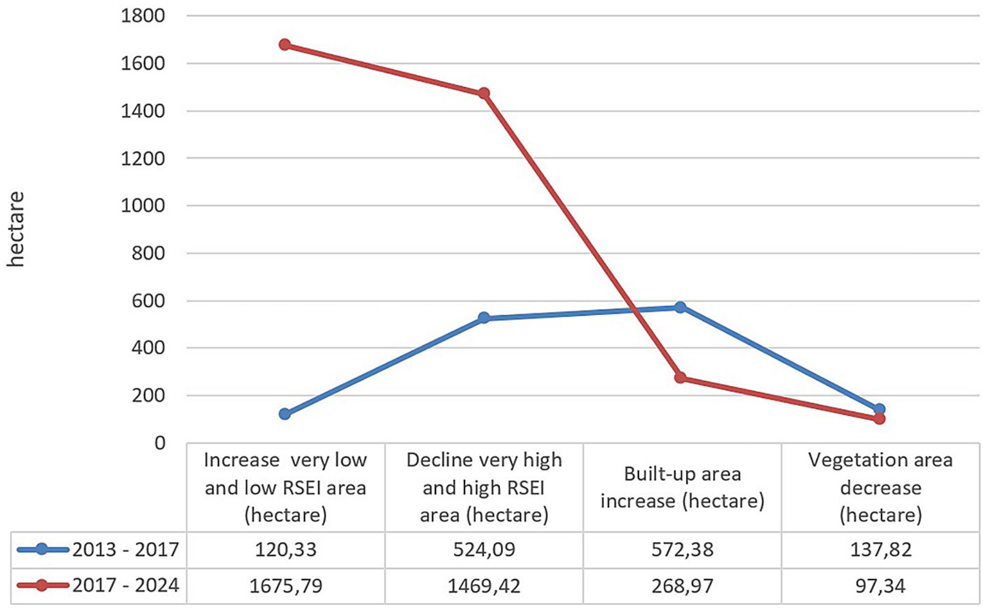

Figure 9. Graph of RSEI area change, built-up land and vegetation

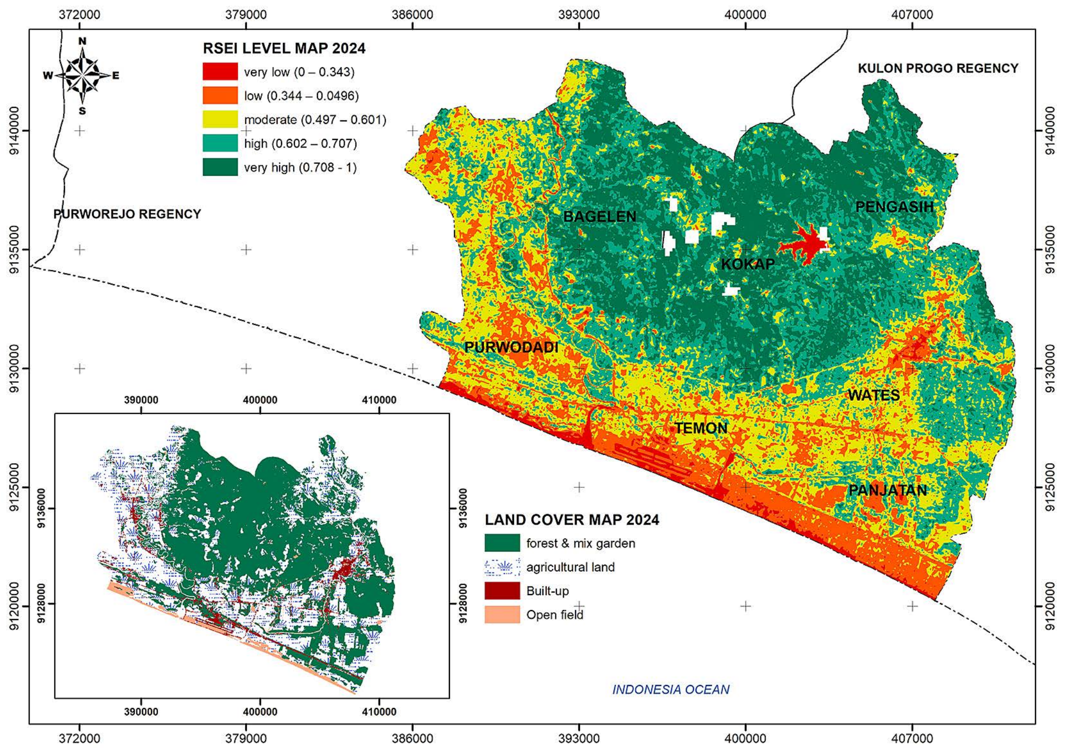

Figure 10. RSEI and land cover times series in the study area

DISCUSSION

The results of the research showed that there was a phenomenon of decrease in the environmental quality index around NYIA, which is seen from the increase in the value of RSEI of the low category and the decreased value of the high category. On the basis of the 4 parameters used in the calculation of RSEI, the greenness index of the result of the processing of NDVI gives a huge influence on the decline in index values, because the decrement of vegetation coverage will affect the declining value of other parameters of RSEI, such as the humidity index, drynees index and heat index (Liu et al., 2023). The phenomenon of decreased vegetation coverage that affects the decrease in the environmental quality index supports the previous research conducted in Anhui Province, China, wihch stated that vegetation damage in open mining affects its setting of the ecological quality index resulting in a loss of 104,000 yuan/year for the cost of carbon emissions, thus requiring harmonious regulation of coal mining in economic and environmental terms (Li et al., 2024). Further research located in the State of Paraíba, and Serra Negra do Norte Brazilian states that the associated levels of vegetation density influence the flux of solar radiation which affects the increase in the microclimate leading to a decrease in ecological quality (Liu et al., 2023).

Further, the decrease in the environmental quality index in 2024 around the NYIA is also due to the increase in built-up land, in the Temon sub-district that has increased 180,98 hectares. The increase in built-up land is more of a goods and services provider building that serves passengers on NYIA flights, including hotels, restaurants and transportation agencies. Increased built-up land has an impact on increased LST which has an effect on a decrease in the environmental quality index, according to a study by the Siliguri Municipal Corporation in north-eastern India which shows that increased urban-built-up footprint areas have an influence on the decline in high ecological function around the area, thus requiring ecological urban land-use planning (Mallick, 2024). In addition, the impact of increased built-up land on the decline in the environmental quality index also occurred in Chengdu-Chongqing urban China, where there was an increase in built-up land due to urbanization from 2000–2005 which affected the low quality index of the environment identified by the IRSEI model (Lei et al., 2024). Thus, based on comparisons with previous research result, there are similarities with the results of existing research that changes in coverage and the level of vegetation density have a major influence on the decrease of the environmental quality index in a region.

CONCLUSIONS

The results of the study showed that the majority of the survey area has a high environmental quality index (RSEI) with an area of 10994.71 hectares (2024), but there was a decrease in RSEI of the high category in the study area of about 295.17 hectares (2013–2017) and 1720.91 hectars (2017–2024). In addition, there was a great increase in RSEI category very low and low with an increase of 122.33 hectares from 2013–2017 and 1898.79 hectares (2017–2024). The decline in the environmental quality index in the study area (2013–2024) is due to the decline of the entire parameter values, including greenness index, humadity index, dryness index and heat index with varying rates of variation of values. The decline in RSEI in the area study was correlated with the increase in built-up land and decreased vegetation area, with built-up land increasing to 572.38 hectares (2013–2017) and 269.97 hectares (2017–2024). In addition, there was a decrease in vegetation areas of approximately 137.82 hectars (2013–2017) and 97.34 hectares. (2017–2024). Finally, the results of this research could be further developed to predict the environmental quality index in the next few years with the cellular automata model, where the results were used as guidelines in regional planning around NYIA.

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