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RESEARCH ARTICLE

Exploratory of Ecological Quality from Remote-Sensing Ecological Index and Drought Hazard in Pekalongan Regency, Indonesia

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Abstract

Climate change has intensified environmental hazards, including floods, landslides, and droughts, with Pekalongan Regency, Indonesia, emerging as a vulnerable region facing these multifaceted challenges. While flood-related studies dominate existing study, drought impacts remain understudied, despite their growing prevalence. Current climate hazard assessments in Pekalongan's adaptation plans rely heavily on historical data, limiting their predictive accuracy. This study addresses these gaps by developing a Remote Sensing Ecological Index (RSEI) model to evaluate ecological quality and its association with drought hazards, aligning with climate-resilient development objectives. The study employs Landsat imagery to construct RSEI using four key indicators: NDVI (greenness), WET (wetness), NDBSI (dryness), and LST (heat). Drought hazard data were derived from 2023 disaster records provided by Pekalongan's Regional Disaster Management Agency (BPBD). Statistical analysis using chi-square tests examined the relationship between RSEI components and drought hazard classes.Results demonstrate that RSEI's first principal component (PC1) effectively captures spatial ecological patterns, with southern regions (notably Petungkriyono's tropical rainforest) exhibiting "good" to "excellent" conditions, while northern urbanized areas score lower ("fair" to "poor"). PC1 shows a statistically significant association with drought hazard, unlike PC2 or PC3, suggesting its utility as a drought vulnerability indicator. However, the chi-square approach only identifies categorical relationships without quantifying effect strength or direction, highlighting methodological limitations.
This study contributes to climate adaptation science by validating RSEI's applicability for drought assessment in tropical coastal regions. Future study should incorporate ordinal regression or spatial modeling to enhance predictive capability. The findings support evidence-based policymaking for targeted mitigation in Pekalongan Regency and similar vulnerable regions, emphasizing the integration of ecological monitoring into climate adaptation frameworks.

Keywords: RSEI, ecological quality, drought hazard, chi-square, climate change

1. Introduction

Climate change has emerged as one of the most pressing global challenges of our time, with far-reaching impacts on natural systems and human communities. Scientific evidence demonstrates that rising global temperatures or global boiling are intensifying various natural disasters, including floods, droughts, extreme storms, and landslides (Adamopoulos et al., 2024; Frame et al., 2020; Moustafa et al., 2023). These climate-related hazards have caused significant damage across multiple sectors, particularly affecting coastal and marine ecosystems, water resources, agricultural productivity, and public health systems. In the Indonesian context, the marine and coastal sector has been identified as particularly vulnerable, with Central Java Province representing a critical area of concern (BAPPENAS, 2021). Within this region, Pekalongan Regency stands out as a priority area for climate action due to its unique combination of environmental sensitivity and socioeconomic importance (BAPPEDA Provinsi Jawa Tengah, 2023).

Pekalongan Regency is an interesting area to study climate change in Indonesia. This area is one of the bustling urban areas on the economically important northern coastal corridor of Java (Pantura), productive agricultural land, but still has one of the last remaining tropical rainforests on the island in the Petungkriyono area (Mardiansjah et al., 2021; Woelansari et al., 2020). However, this diverse landscape faces growing threats from climate change impacts, particularly coastal inundation and prolonged drought conditions (Riyatmoko and Sanjoto, 2022; Sarah et al., 2021). These environmental stresses threaten not only the region's ecological balance but also its economic stability and community livelihoods, making Pekalongan Regency an ideal case study for examining climate adaptation strategies. Studies related to climate change disasters in Pekalongan Regency are mostly still about floods, especially tidal floods, such as the study by Pratama (2019) and Wahyuddin et al. (2023), even though this region also experiences other disasters such as drought (Fariz et al., 2022; Gradiyanto and Parmantoro, 2025).

The recent development of Pekalongan's Regional Climate Change Adaptation Action Plan in 2024 represents an important step forward, but reveals significant methodological limitations. Current approaches to hazard and risk assessment remain constrained by traditional administrative-boundary frameworks, which fail to capture the complex spatial dynamics of climate impacts. While these conventional methods offer advantages in terms of cost-effectiveness and operational simplicity, they suffer from several critical weaknesses. Most notably, their heavy reliance on historical disaster data renders them particularly inadequate for regions with limited observational records, and their coarse spatial resolution prevents the identification of localized vulnerability patterns. These limitations highlight the urgent need for more sophisticatd assessment tools that can provide spatially explicit, timely, and accurate information for climate adaptation planning.

Remote sensing technology has emerged as a powerful alternative for environmental monitoring and climate risk assessment. This is because remote sensing involves data collection without direct physical contact with the target object (Bariadi and Saepuloh, 2025) , so that several phenomena such as drought in an area can be identified quickly through image transformation of Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI) (Bhowmik and Bhatt, 2024; Serban and Maftei, 2025). Among various remote sensing approaches, the Remote Sensing Ecological Index (RSEI) has demonstrated particular promise as a comprehensive tool for environmental quality evaluation in both urban, watershed and coastal areas (Gao et al., 2021; Sidiq et al., 2024; Xu and Jin, 2024). By integrating four key indicators namely greenness (NDVI), wetness (WET), heat (LST), and dryness (NDBSI), RSEI provides a multidimensional assessment of ecosystem health and resilience (Zhang et al., 2024). While RSEI has been successfully applied in urban and watershed contexts, its potential for drought hazard identification in tropical regions like Pekalongan Regency remains largely unexplored, representing a significant gap in current study and practice. Although RSEI builders can indicate drought as well, especially NDVI and LST (Mistry and Suryanarayana, 2023; Sholihah et al., 2016).

This study aims to address these study gaps through two primary objectives. First, it seeks to develop and validate an RSEI-based ecological quality assessment model specifically tailored for Pekalongan Regency using Landsat satellite imagery Second, this study will systematically examine hypotheses regarding the relationship between environmental quality indicators derived from RSEI and drought hazard patterns observed across the region. The findings are expected to make several important contributions to both academic study and practical climate adaptation efforts, which are also in line with climate resilient development programs.

2. Method

2.1. Study Location

This study was conducted in Pekalongan Regency, Central Java Province, Indonesia (Figure 1). Pekalongan was chosen as the study area because it has a high level of vulnerability to the impacts of climate change, not only floods and tidal floods but also droughts. Based on land cover, this area consists of urban, rural, agricultural land and forests. Based on landform, the northern region is mostly fluviomarine plains and the southern region is volcanic mountain slopes and a few structural hills.

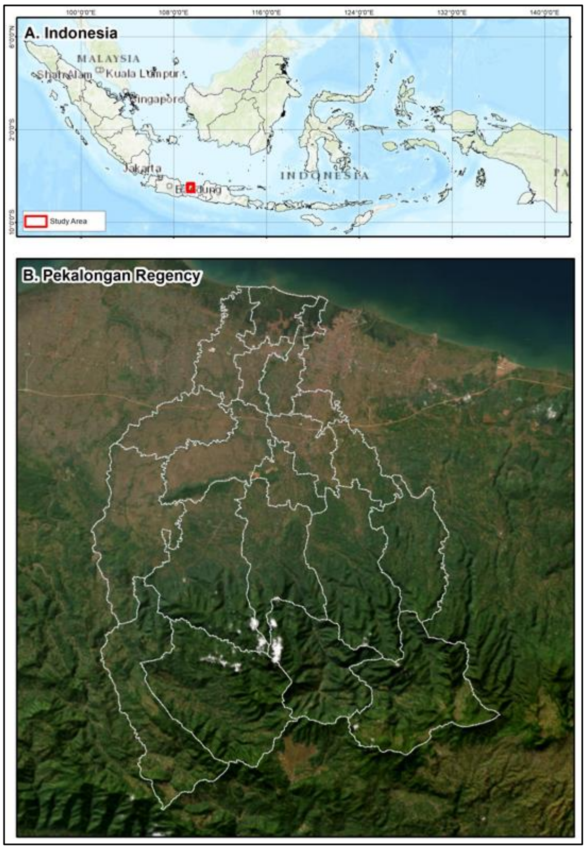

Fig 1. Location study

2.2. Data Collection and Preprocessing

This study incorporated secondary administrative boundary data from BAPPEDA Jawa Tengah to support the spatial analysis. The primary remote sensing analysis was conducted using Google Earth Engine (GEE) platform (code.earthengine.google.com). We acquired Landsat 8 Level 2, Collection 2, Tier 1 surface reflectance data (Path 120/Row 65) from USGS, specifically targeting the dry season period from July 1 to October 31, 2023. This temporal selection was based on two key considerations namely the El Niño event in 2023 which exacerbates drought conditions throughout Indonesia, and the dry season period which is common in Central Java Province (Aristiana, 2023; Sanjaya et al., 2024).

Cloud cover and cloud shadow masking was implemented using the QA_PIXEL band quality assessment approach (Yan et al., 2022), a critical preprocessing step given Indonesia's tropical climate with persistent cloud cover (Fariz et al., 2024). This process ensured that only clear-sky pixels were included in subsequent analyses.

2.3. Remote Sensing Ecological Index (RSEI) Analysis

1. Parameter Extraction and Calculation

The Remote Sensing Ecological Index (RSEI) integrates four key ecological indicators derived from satellite imagery: greenness, humidity, dryness, and heat. These indicators are calculated using spectral indices and transformations as described below:

- **Greenness Index (NDVI)**
  Vegetation health is represented using the Normalized Difference Vegetation Index (NDVI), which reflects vegetation density and vigor. It is calculated using the formula:

$$NDVI = (\rho NIR - \rho Red) / (\rho NIR + \rho Red)$$

where ρNIR and ρRed correspond to the reflectance of Landsat 8 bands 5 and 4, respectively (Islam et al., 2021).

- **Humidity Index (Wetness)**
  The wetness index represents soil and vegetation moisture and is derived from the tasseled cap transformation. The equation applied for Landsat 8 data is:
  $$Wet = 0.1511\rho Blue + 0.1972\rho Green + 0.3283\rho Red + 0.3407\rho NIR - 0.7117\rho SWIR1 - 0.4559\rho SWIR2$$
  This method is effective in identifying drought-prone or flooded areas (Chen et al., 2023; Dzakiyah and Saraswati, 2020).
- **Dryness Index (NDBSI)**
  Surface dryness is quantified by combining the Index-Based Built-Up Index (IBI) and the Soil Index (SI), forming the Normalized Difference Built-Up and Soil Index (NDBSI):
  $$NDBSI = (IBI + SI) / 2$$
  The IBI is defined as:
  $$IBI = [2\rho SWIR1/(\rho SWIR1 + \rho NIR) - (\rho NIR/(\rho NIR + \rho Red) + \rho Green/(\rho SWIR1 + \rho Green))] / [2\rho SWIR1/(\rho SWIR1 + \rho NIR) + (\rho NIR/(\rho NIR + \rho Red) + \rho Green/(\rho SWIR1 + \rho Green))]$$
  and the SI is calculated as:
  $$SI = [(\rho SWIR1 + \rho Red) - (\rho NIR + \rho Blue)] / [(\rho SWIR1 + \rho Red) + (\rho NIR + \rho Blue)]$$
  This index effectively represents urbanization and bare soil exposure (Fariz and Faniza, 2023; Liu et al., 2024; Sidiq et al., 2024)
- **Heat Index (LST)**
  Land Surface Temperature (LST) is derived from the thermal band and corrected for emissivity using NDVI-derived vegetation cover. The following steps are used:
  $$L = gain \times DN + bias$$
  $$Tb = K2 / \ln(K1 / L + 1)$$
  $$Pv = [(NDVI - NDVImin) / (NDVImax - NDVImin)]^2$$
  $$\varepsilon = 0.004 \times Pv + 0.986$$
  $$LST = Tb / [1 + (\lambda \times Tb / \rho) \times \ln(\varepsilon)] - 273.15$$
  where K1 and K2 are calibration constants, ε is land surface emissivity, and λ is the wavelength of the thermal band. This method captures spatial variations in surface heating (Sekertekin and Bonafoni, 2020).

2. RSEI Computation

The construction of the Remote Sensing Ecological Index (RSEI) involves the integration of four remote sensing-based ecological indicators NDVI, Wetness, NDBSI, and LST. These indicators are first normalized using **min-max normalization** to ensure they are on a comparable scale. The normalization formula is:

NIi=Ii−IminImax−IminNI_i = \frac {I_i - I_{min}}{I_{max} - I_{min}}NIi=Imax−IminIi−Imin

where NIiNI_iNIi is the normalized value, IiI_iIi is the original value of the index, and IminI_{min}Imin and ImaxI_{max}Imax are the minimum and maximum values of that index, respectively (Li et al., 2023).

Following normalization, Principal Component Analysis (PCA) is employed to synthesize the four indicators into a single composite index. PCA transforms the original feature space into a new set of orthogonal axes called principal components that maximize the variance of the data. This transformation effectively integrates the information content of all indicators without assigning subjective weights (Alganci, 2019; Chen et al., 2023). Principal Component Analysis (PCA) was constructed using SAGA GIS software.

The first principal component (PC1) is typically used as it accounts for the largest portion of the total variance and captures the dominant patterns of ecological conditions in the study area. However, in some cases, a higher PC1 score may correspond to poorer ecological conditions. To correct this, the initial RSEI score (RSEI0RSEI_0RSEI0) is inverted as follows:

RSEI0=1−PC1RSEI_0 = 1 - PC1RSEI0=1−PC1

This adjustment ensures that higher RSEI values consistently represent better ecological quality (Zheng et al., 2022). Subsequently, the RSEI0RSEI_0RSEI0 values are normalized again to the [0, 1] range to produce the final RSEI (RSEIfRSEI_fRSEIf), which is calculated using:

RSEIf=RSEI0−RSEI0minRSEI0max−RSEI0minRSEI_f = \frac{RSEI_0 - RSEI_{0_{min}}}{RSEI_{0_{max}} - RSEI_{0_{min}}}RSEIf=RSEI0max−RSEI0minRSEI0 −RSEI0min

This final normalization step is essential to standardize the index for further analysis and comparison across spatial and temporal scales (Li et al., 2023). In the final RSEI, values approaching 1 indicate superior ecological conditions, while values near 0 suggest environmental degradation (Hu and Xu, 2018; Sidiq et al., 2024). This study did not conduct separate validation processes, like similar RSEI studies by Sidiq et al. (2025) and Muhaimin et al (2024), because all RSEI components were derived from pre-processed satellite data (radiometrically and geometrically corrected) using scientifically established physical/statistical parameters (NDVI, LST, wetness, NDBSI). As RSEI represents a relative composite index without absolute reference values, direct field validation against ground-truth data remains methodologically challenging.

3. Drought Hazard Assessment and Statistical Analysis

Drought hazard assessment incorporated historical drought event records from Pekalongan's Regional Disaster Management Agency (BPBD) for 2023. Hazard levels were classified based on both frequency and impact severity of drought events.

The relationship between RSEI-derived ecological quality and drought hazard patterns was examined using chi-square test of independence. This non-parametric approach was selected because:

(1) both variables (RSEI classes and drought hazard levels) are ordinal, and

(2) the test appropriately assesses whether the distribution of drought hazards differs across RSEI categories without assuming linear relationships.

3. Result

3.1. Ecological quality from RSEI

Principal Component Analysis (PCA) was applied to four remote sensing indicators, namely NDVI, WET, LST, and NDBSI. The eigenvector matrix shows that the first principal component (PC1) captures the majority of the ecological variance (Table 1). Although the percentage of eigenvalue is not explicitly stated, the magnitude of the loadings in PC1 indicates that it concentrates most of the information across the indicators.

In PC1, NDVI (0.508), LST (0.518), and NDBSI (0.585) had strong positive loadings, while WET (−0.363) contributed negatively. This pattern is consistent with ecological interpretations where NDVI and WET indicate vegetation and moisture, while NDBSI and LST reflect degradation and heat stress. Components PC2 to PC4 presented more mixed loadings, indicating residual or less interpretable variance. Following previous studies (Xiong et al., 2021; Wang et al., 2019b), the first principal component was selected to construct the Remote Sensing Ecological Index (RSEI) due to its dominant explanatory power and clear ecological relevance.

Table 1. Eigenvector matrix

Principal component	NDVI	WET	LST	NDBSI
PC1	0.51	-0.36	0.52	0.58
PC2	0.29	-0.73	-0.59	-0.18
PC3	-0.43	0.01	-0.45	0.78
PC4	-0.69	-0.58	0.41	-0.13

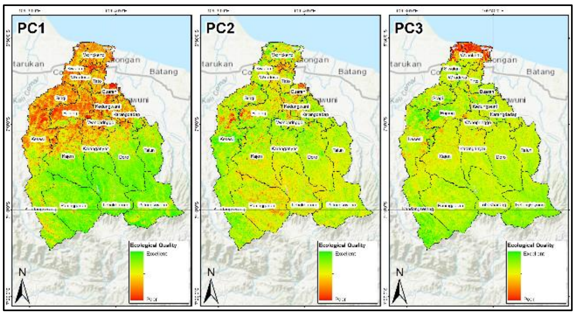

Fig 2. RSEI from PC1, PC2 and PC3

As illustrated in Figure 2, the spatial distribution of ecological quality derived from PC1 analysis reveals distinct regional patterns. Areas demonstrating good to excellent ecological conditions are predominantly concentrated in the southern regions, while fair to poor ecological quality zones are primarily distributed across northern territories. This spatial pattern aligns with findings by Xiong et al. (2024), who established a significant correlation between land cover characteristics and RSEI-derived ecological quality distribution patterns. The observed distribution shows that PC1 values closely reflect the land cover configuration across the study area, compared to PC2 and PC3. PC1's superior performance is evident in its consistent ecological interpretability (positive loading for NDVI/WET, negative for NDBSI/LST) and significant drought hazard association (χ^2=20.10, $p<0.05$), unlike PC2-PC4 which showed neither theoretical coherence nor statistical significance.

The northern regions are characterized by predominant urban settlements, interspersed with rural residential areas and flood-prone zones, contributing to diminished ecological quality scores. In contrast, the southern districts exhibit superior ecological conditions, largely attributable to mixed plantation systems and forested landscapes. Notably, the Petungkriyono sub-district in the southern highlands contains one of Java's last remaining tropical rainforest ecosystems. This conservation area serves as a critical habitat for endangered flora and fauna species, including the Javan hawk-eagle (*Nisaetus bartelsi*), further underscoring its exceptional ecological value within the region's environmental matrix (Ambarwati et al., 2023; Setiawan et al., 2020).

Building upon the RSEI analysis derived from PC1 (ranging from 0 to 1), we classified the ecological quality into five distinct categories: poor (0–0.2), fair (0.2–0.4), moderate (0.4–0.6), good (0.6–0.8), and excellent (0.8–1.0) (Chen et al., 2023; Sidiq et al., 2024). This stratification allows for a more nuanced assessment of environmental conditions across Pekalongan Regency.

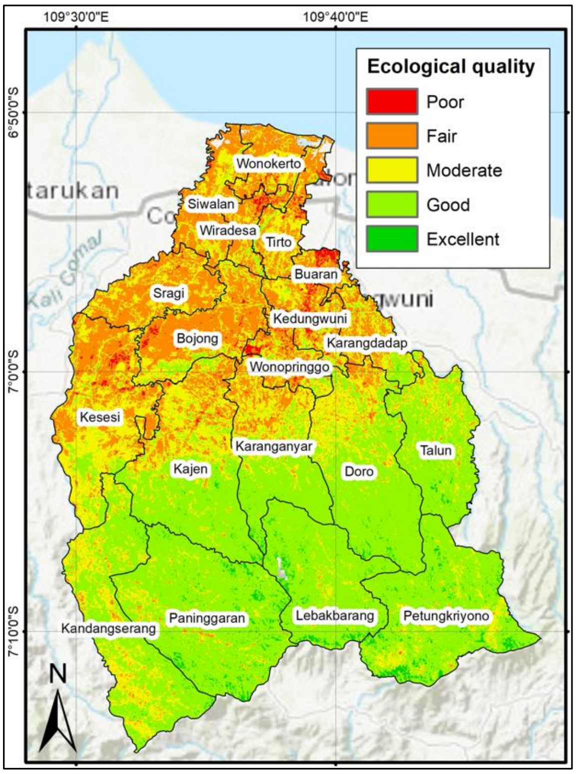

Fig 3. Ecological quality (RSEI) from PC1

At the district level, our evaluation revealed that Pekalongan Regency is predominantly characterized by fair ecological quality, with nine districts falling within this category: Buaran, Sragi, Bojong, Wiradesa, Siwalan, Wonokerto, Kedungwuni, Tirto, and Wonopringgo (Figure 3). These areas, characterized by mixed land use and moderate human activity, reflect transitional ecological conditions due to their location along Java Island's main coastal transportation and economic corridor (Buchori et al., 2022; Ula and Tijan, 2020). A subset of four districts—Kesesi, Karangdadap, Karanganyar, and Kajen—exhibited moderate ecological quality, suggesting relatively balanced enviromnral conditions with localized areas of improvement. Notably, six districts—Kandangserang, Doro, Talun, Paninggaran, Petungkriyono, and Lebakbarang—were classified as good, highlighting their superior ecological integrity. These areas, particularly Petungkriyono, are distinguished by their forested landscapes and lower levels of human disturbance, reinforcing the critical role of conservation efforts in maintaining regional biodiversity and ecosystem resilience. This spatial stratification underscores the variability in environmental quality across Pekalongan Regency and provides a foundation for targeted policy interventions aimed at enhancing ecological sustainability in more vulnerable districts.

3.2. Drought hazard and RSEI

The drought hazard classification was constructed from drought event records in 2023, incorporating both frequency and impact severity data. Villages/kelurahan exhibiting higher drought frequency and greater impacts were classified into the "very high" hazard category.

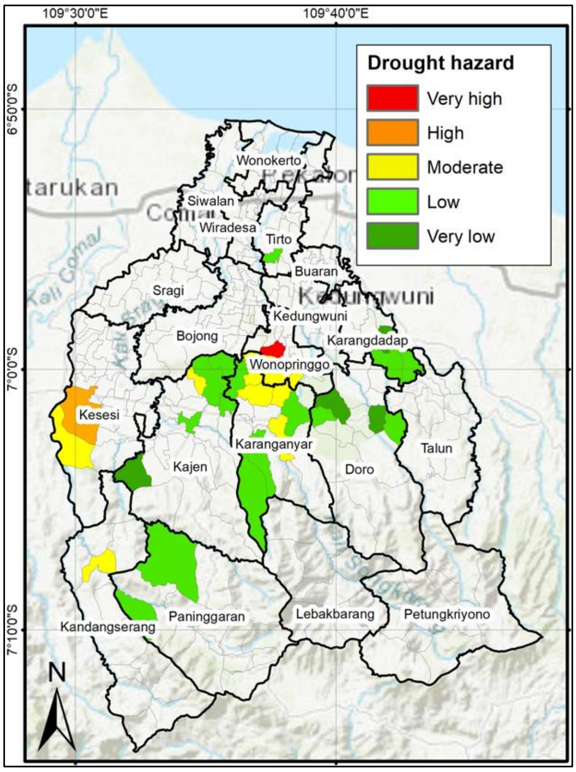

Fig 4. Drought hazard

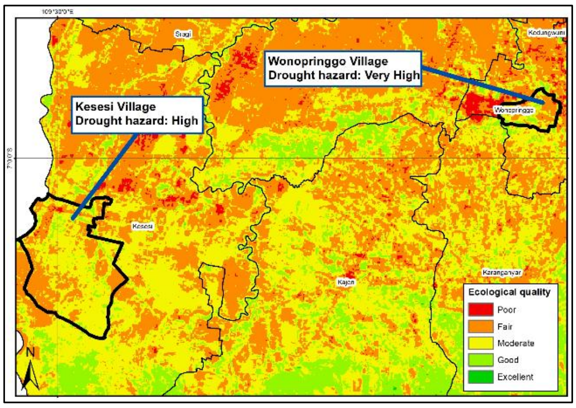

Fig 5. Overlay between RSEI and villages with high and very high drought hazard

In Pekalongan Regency's 285 villages/kelurahan, the majority (255) were classified as drought-free areas. Notably, Kesesi Village (Kesesi District) was identified as high drought hazard, while Wonopringgo Village (Wonopringgo District) represented the very high hazard category (Figure 4 & Figure 5). To examine the relationship between RSEI and drought hazard, we employed zonal statistics to calculate mean RSEI values for each village/kelurahan, followed by chi-square analysis. Areas without drought hazard were intentionally included in the analysis to maintain data integrity.

The chi-square test results for RSEI components revealed in Table 2. The analysis demonstrated that only PC1-derived RSEI showed a statistically significant association with drought hazard levels (χ^2 = 20.10, df = 10, p = 0.028), suggesting its potential as an ecological indicator for drought vulnerability. In contrast, neither PC2 (χ^2 = 2.39, p = 0.792) nor PC3 (χ^2 = 1.99, p = 0.850) exhibited meaningful correlations with drought patterns during the study period.

Table 2. Chi-square between RSEI and drought hazard

RSEI Variable	Chi-Square	df	p-value	Interpretation
PC1	20.1	10	0.028	Significant
PC2	2.39	5	0.792	No relationship
PC3	1.99	5	0.85	No relationship

While these findings indicate a relationship between PC1-based RSEI and drought hazard, several methodological limitations warrant consideration. First, the chi-square approach only identifies categorical associations without quantifying relationship strength or direction. Second, the PCA-derived RSEI components may contain inherent biases depending on the original ecological indicator distributions and data structures. Third, the ordinal drought hazard classification might not fully capture the complex spatiotemporal dynamics of drought conditions. We therefore recommend complementary analyses, such as ordinal regression or spatial modeling approaches, to develop a more comprehensive understanding of these ecological–climate interactions. This study should also be expanded by developing the RSEI using more recent satellite imagery, such as Landsat 9, which offers enhanced radiometric resolution and temporal consistency to improve ecological monitoring accuracy (Fariz et al., 2025; Ghasempour et al., 2023). The advancement of such studies is crucial not only for supporting ecological quality monitoring but also for providing a scientific basis to assess climate change hazards in Indonesia and other vulnerable regions globally.

4. Conclusion

This study demonstrates that the first principal component (PC1) of the Remote Sensing Ecological Index (RSEI) serves as the most representative indicator for assessing ecological quality in Pekalongan Regency. The spatial distribution of PC1-derived RSEI reveals clear regional patterns, with southern areas exhibiting superior ecological conditions (good to excellent) compared to the northern regions (fair to poor), a finding consistent with established land cover characteristics. Statistical analysis between RSEI and drought hazard confirms that only PC1 shows a significant association with drought hazard levels, while PC2 and PC3 demonstrate no meaningful correlations.

However, these results should be interpreted with caution, as the chi-square analysis merely indicates an association without elucidating the direction or strength of the relationship. The limitations of this approach underscore the need for more sophisticated statistical methods, such as ordinal regression or spatial modeling, to better quantify these ecological-climate interactions. Future study should focus on integrating these advanced techniques to enhance the predictive capacity of RSEI for drought vulnerability assessment, ultimately supporting more targeted climate adaptation strategies in vulnerable regions.

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