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*Research Article*

# Assessing Watershed Health Using Long-Term Moderate Resolution Imaging Spectroradiometer (MODIS)-Derived Vegetation Dynamics in the Upper Citarum Watershed

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**Abstract:** Rapid land-use/land-cover (LULC) change, vegetation degradation, and increasing anthropogenic pressures have reduced the ecological stability of many tropical watersheds, creating a need for practical approaches to long-term environmental monitoring. Although watershed health is commonly evaluated using hydrological, ecological, and water-quality indicators, the application of long-term satellite-derived vegetation dynamics within the Reliability–Resilience–Vulnerability (RRV) framework remains limited. This study applied the RRV framework to assess vegetation-based watershed health in the Upper Citarum Watershed (UCW), Indonesia, using MODIS MOD13Q1 Normalized Difference Vegetation Index (NDVI) data (250 m) during the dry season (June–September) from 2000 to 2020. Reliability-Resilience-Vulnerability were integrated into a Watershed Health Index (WHI) using a geometric mean. Correlation and threshold sensitivity analyses were conducted to evaluate land-cover relationships and framework robustness. The mean dry-season NDVI of the UCW was 0.60, with higher values in mountainous forested areas than in urbanized regions. Vegetation greenness declined during 2002–2003, 2006–2007, and 2015–2016, corresponding to major El Niño and positive Indian Ocean Dipole (IOD) events. Ciwidey exhibited the highest WHI (0.80), whereas Cikapundung had the lowest (0.34). Forest cover was positively associated with Reliability, Resilience, and WHI, while built-up areas showed the opposite relationship. Although NDVI threshold selection affected absolute indicator values, the spatial pattern and sub-watershed ranking remained stable, demonstrating framework robustness. Compared with conventional NDVI analysis, the proposed RRV–NDVI framework captures vegetation persistence, recovery capacity, and degradation severity, providing a practical and transferable approach for long-term vegetation-based watershed health assessment in data-limited tropical watersheds.

**Keywords:** MODIS NDVI; Reliability-Resilience-Vulnerability; Upper Citarum watershed; Vegetation-Based watershed health

## 1. Introduction

A watershed is an integrated ecosystem in which hydrological, geomorphological, and ecological processes continuously interact to regulate water availability, environmental quality, and ecosystem sustainability (Musy & Higy, 2011). A watershed's health reflects its ability to maintain ecological stability and provide sustainable ecosystem services under both natural and anthropogenic pressures (Flotemersch et al., 2016; Vollmer et al., 2022). Stable hydrological conditions, adequate vegetation cover, balanced infiltration–runoff processes, and strong ecological recovery capacity characterize a healthy watershed. Conversely, LULC change, deforestation, urbanization, and climate variability degrade watershed conditions by reducing ecological resilience and increasing hydrological vulnerability.

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Various studies have assessed watershed health using multi-indicator approaches involving hydrology, water quality, geomorphology, habitat, and socio-economic variables (Hoque et al., 2012; US Environmental Protection Agency, 2012). Although these approaches provide comprehensive evaluations, they require extensive and continuous datasets that are often unavailable, particularly in developing countries. Consequently, a simpler yet reliable watershed health assessment approach based on consistently available long-term remote sensing observations.

Vegetation plays a fundamental role in maintaining watershed health because it regulates infiltration, evapotranspiration, runoff generation, erosion control, and sediment retention (Ahn & Kim, 2017; Griffith et al., 2002). Therefore, long-term vegetation dynamics provide a meaningful basis for assessing the health of vegetation-based watersheds. In this study, vegetation-based watershed health is operationally defined as the condition of watershed vegetation evaluated through its long-term persistence, recovery capacity, and degradation resistance. Although watershed health is inherently multidimensional, the proposed framework specifically evaluates its vegetation dimension using long-term NDVI dynamics as a practical proxy with explicit spatial representation (Ellison et al., 2017; Huete et al., 2002; Pettorelli et al., 2005). Accordingly, the proposed framework should be interpreted as a vegetation-based watershed health assessment rather than a comprehensive assessment encompassing the hydrological, geomorphological, water quality, and biological dimensions of watershed health (Ahn & Kim, 2017; Flotemersch et al., 2016).

The RRV framework has been widely applied in drought assessment, water quality evaluation, watershed hydrology, and climate-related environmental studies since its introduction by Hashimoto et al. (1982) (Babaousmail et al., 2024; Chanda et al., 2014; Maity et al., 2013; Sung et al., 2018). In watershed health assessment, Hoque et al. (2012), Hoque et al. (2014), Hoque et al. (2016), Hazbavi and Sadeghi (2017), Sadeghi and Hazbavi (2017), Hazbavi et al. (2018), Hazbavi et al. (2019), Zeng et al. (2020), and Chamani et al. (2023) demonstrated the applicability of the RRV framework using hydrological, water-quality, climatic, and ecological indicators. However, applications integrating long-term remotely sensed vegetation dynamics, particularly NDVI, for vegetation-based watershed health assessment in tropical watersheds remain limited. NDVI has been widely used to monitor vegetation greenness, biomass productivity, and long-term ecosystem dynamics (Abbaszadeh Tehrani et al., 2022; Chen et al., 2012; Wu et al., 2015). Although NDVI primarily represents vegetation greenness rather than overall ecosystem integrity and may saturate under dense tropical forests, it remains suitable for evaluating long-term vegetation dynamics and landscape responses to environmental pressures and LULC change (Didan, 2015; Pettorelli et al., 2005).

Most watershed health studies applying the RRV framework rely on hydrological, water quality, or climate indicators. The application of long-term satellite-derived vegetation dynamics to characterize watershed reliability, resilience, and vulnerability remains limited, particularly in tropical watersheds experiencing rapid LULC change. Therefore, this study investigates the potential of long-term MODIS NDVI to assess the health of vegetation-based watersheds. Although other remote sensing products, such as EVI, LAI, NPP, evapotranspiration, and soil moisture, are also available (Huete et al., 2002), NDVI was selected because it provides the longest consistent global record since 2000, has been extensively validated, and is well suited for multidecadal vegetation monitoring (Didan, 2015; Pettorelli et al., 2005). Unlike NDWI and MNDWI, which detect surface water conditions (McFeeters, 1996; Xu, 2006), NDVI is more appropriate for representing long-term vegetation persistence, recovery, and degradation within the proposed RRV framework (Didan, 2015; Pettorelli et al., 2005). Future studies may integrate vegetation and water-related indices to provide a more comprehensive ecohydrological assessment (Pedzisai et al., 2022).

The UCW, located in West Java, Indonesia, represents one of the most critical watersheds in the country and has been designated as a national priority watershed in the Indonesian National Medium-Term Development Plan (RPJMN) 2020–2024. Rapid urbanization, conversion of vegetated land into built-up areas (Sapan et al., 2022; Syabila et al., 2026), declining infiltration zones, erosion, flooding, drought occurrences, and water quality degradation have increasingly threatened the ecological stability of the watershed (Hanifa et al., 2020; Junengsih et al., 2017; Juniarti, 2020). These pressures have resulted in substantial spatial disparities in vegetation-based watershed health among sub-watersheds, particularly between densely urbanized regions and relatively preserved upland areas. Understanding the spatial and temporal dynamics of vegetation conditions is therefore essential for identifying environmentally degraded areas and supporting sustainable watershed management. Since the Reliability–Resilience–Vulnerability (RRV) framework relies heavily on the definition of satisfactory and unsatisfactory system conditions, a threshold determination procedure based on long-term dry season NDVI conditions is applied in this study and is described in detail in the Methods section.

Based on the conceptual relationship between vegetation condition and watershed function, the following hypotheses are proposed: H1: Sub-watersheds with higher and more stable NDVI values will exhibit higher levels of reliability and resilience, as well as lower levels of vulnerability; H2: Watersheds dominated by vegetated LULC will have higher watershed health index values than watersheds dominated by built-up areas; and H3: H3: Long-term NDVI dynamics can reveal spatial differences in vegetation-based watershed health associated with LULC change and climate variability. This study aims to assess vegetation-based watershed health in the UCW using a RRV framework based on long-term MODIS-derived NDVI data from 2000 to 2020. This study evaluates the spatiotemporal dynamics of dry-season vegetation conditions, assesses vegetation-based watershed health across sub-watersheds using RRV indicators, and examines the relationship between vegetation-based watershed health and LULC characteristics. The findings of this study are expected to provide a practical and spatially explicit framework for monitoring the health of vegetation-based watersheds and support ecological restoration and sustainable watershed management in tropical regions.

## 2. Methods

### 2.1 Study Area

This research was conducted in the Upper Citarum Watershed (UCW) with an area of 1,790 km$^2$ which includes the Regency and City of Bandung, Cimahi City, West Bandung Regency, Subang, Garut, and Sumedang. Astronomically, this research area is located at coordinates 6°43’-7°15’S and 107°30’-108°E. A series of mountains, including Tangkuban Perahu in the north and Patuha–Malabar, Krenceng, and Mandalawangi in the south, surround the watershed. The boundaries of the UCW are determined based on the location of the discharge station that serves as the watershed outlet, namely the Citarum-Nanjung discharge station with station number 2-16-4-2. The station is located in Nanjung Village, Batujajar District, Bandung Regency, West Java, at an elevation of 654 meters above sea level, at coordinates 06°56’501” South Latitude and 107°32’155” East Longitude.

The UCW was selected because it represents a highly heterogeneous tropical watershed characterized by strong gradients in topography, vegetation cover, urbanization, and LULC dynamics. It experiences a tropical monsoon climate with annual rainfall ranging from 1,500 to 3,500 mm and elevations from approximately 650 to over 2,400 m above sea level. The watershed contains forests, plantations, agricultural land, rice fields, built-up areas, and water bodies. Volcanic geology not only contributes to fertile soils but also increases susceptibility to erosion and land degradation when vegetation cover declines. These diverse environmental conditions make the UCW an appropriate case study for evaluating vegetation-based watershed health under varying ecological and anthropogenic pressures.

The catchment boundaries were delineated using a DEM-based hydrological analysis and subsequently verified against the official watershed dataset provided by the River Basin Organization (BBWS). Minor discrepancies were manually adjusted to ensure consistency with official watershed boundaries. Third-order catchments were selected because they provide an appropriate balance between spatial detail and computational efficiency, resulting in 173 catchments grouped into six sub-watersheds (Figure 1 and Table 1).

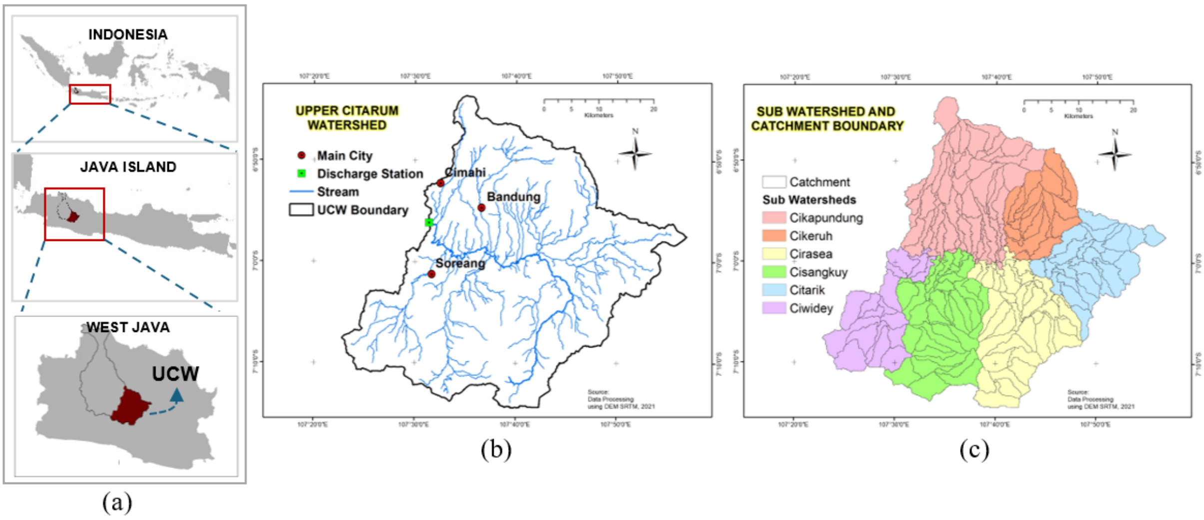



**Figure 1** The study area: (a) Indonesia – Java Island – West Java location, (b) Upper Citarum Watershed (UCW) location with main cities and stream network, and (c) six sub-watersheds and catchments delineated using a DEM-based hydrological analysis and subsequently verified using the official watershed boundary dataset provided by the River Basin Organization (BBWS)

**Table 1** Sub-watershed area as the analysis unit

| No. | Sub-watersheds | Area ($km^2$) | Number of catchments |
|---|---|---|---|
| 1 | Cikapundung | 444.7 | 44 |
| 2 | Cikeruh | 188.5 | 16 |
| 3 | Cirasea | 351.7 | 36 |
| 4 | Cisangkuy | 333.9 | 32 |
| 5 | Citarik | 250.0 | 27 |
| 6 | Ciwidey | 220.7 | 18 |
| | Total area | 1,790 | 173 |

The six sub-watersheds exhibit contrasting LULC characteristics, ranging from highly urbanized areas in Cikapundung and Cikeruh to forest- and plantation-dominated landscapes in Ciwidey and Cisangkuy, while Cirasea and Citarik represent transitional conditions. This variability provides suitable conditions for evaluating the health of vegetation-based watersheds across different disturbance levels.

The RRV indicators were first calculated at the catchment level as the fundamental hydrological unit and subsequently aggregated to the sub-watershed level using arithmetic averages. This multiscale approach captures local vegetation dynamics while enabling broader spatial comparisons of vegetation-based watershed health.

## 2.2 Conceptualization of the RRV framework

This study adopts the RRV framework as the primary methodological basis for assessing vegetation-based watershed health using long-term NDVI dynamics. The RRV framework was originally introduced by Hashimoto et al. (1982) to evaluate the performance of water resource systems under uncertain watershed health conditions using three indicators: reliability, resilience, and vulnerability. Reliability refers to the probability of a system remaining in a satisfactory condition, Resilience represents the system's capability to recover after failure, and Vulnerability describes the magnitude or severity of failure consequences (Hashimoto et al., 1982;

Maity et al., 2013). The framework relies on long-term time-series analysis to identify satisfactory and unsatisfactory system states based on predefined threshold values, thereby enabling the evaluation of temporal watershed dynamics and degradation responses (Chanda et al., 2014; Zeng et al., 2020). The calculation formulas for reliability, resilience, and vulnerability can be explained as follows.

$$\text{Reliability} = 1 - \frac{\sum_{j=1}^{M} d_{(j)}}{T} \tag{1}$$

$$\text{Resilience} = \left\{ \frac{1}{M} \sum_{j=1}^{M} d_{(j)} \right\}^{-1} \tag{2}$$

$$\text{Vulnerability} = \frac{1}{M} \sum_{i=1}^{T} \left\{ \left[ \frac{NDVI_{obs\,(i)} - NDVI_{thr\,(i)}}{NDVI_{thr\,(i)}(i)} \right] \times H \left[ NDVI_{obs\,(i)} - NDVI_{thr\,(i)} \right] \right\} \tag{3}$$

Where,
$d_{(j)}$ : duration of the jth failure event
$M$ : number of failure events
$T$ : total number of time intervals
$NDVI_{obs(i)}$ : observed NDVI value at time i
$NDVI_{thr(i)}$ : NDVI threshold representing satisfactory vegetation condition
$H[.]$: Heaviside function that ensures that only failed events are included in the
The vulnerability calculation.

In this study, a failure event is defined as one or more consecutive observations in which the NDVI falls below the predefined satisfactory threshold. Reliability represents the probability that the vegetation condition remains above the threshold, Resilience describes its recovery following disturbance, and Vulnerability represents the severity of vegetation degradation during failure events. Accordingly, the proposed framework evaluates vegetation-based watershed health represented by long-term vegetation dynamics rather than comprehensive watershed health. Because NDVI observations exhibit temporal dependence associated with vegetation phenology and seasonal climate variability, the resulting RRV indicators should be interpreted as descriptive measures rather than independent probabilistic measures. Future studies should integrate hydrological, geomorphological, water quality, and ecological indicators to achieve more comprehensive watershed health assessments.

### 2.3 NDVI: Landscape indicator

In this study, NDVI was adopted as a landscape-based ecological indicator within the RRV framework to represent vegetation-based watershed health. Within this framework, the terms *"healthy" and "unhealthy" refer* to operational vegetation-condition states defined relative to the selected NDVI threshold rather than absolute measures of overall watershed health. Although watershed health is inherently multidimensional, NDVI is used to evaluate its vegetation dimension because it effectively represents long-term vegetation responses to environmental stress and LULC change, while acknowledging that comprehensive watershed health assessment also requires hydrological, climatic, and water-quality indicators.

NDVI data were obtained from the MOD13Q1 Version 6.1 Terra Vegetation Indices product with a spatial resolution of 250 m and a temporal resolution of 16 days (https://modis.gsfc.nasa.gov/data/dataprod/mod13.php). MODIS was selected because it provides continuous observations since 2000 and incorporates compositing procedures that substantially reduce cloud contamination and atmospheric noise (Didan, 2015; Huete et al., 2002). Although Landsat offers finer spatial resolution, its longer revisit interval and greater cloud susceptibility limit its suitability for continuous two-decade vegetation monitoring in tropical regions. Therefore, this study prioritizes temporal consistency over spatial detail. Vegetation condition strongly influences watershed hydrological and ecological processes, including infiltration, runoff regulation, and erosion control (Ahn & Kim, 2017; Hasani et al., 2023). Consequently, higher NDVI values generally indicate healthier vegetation and better vegetation-based watershed health, whereas lower values indicate vegetation degradation (Hazbavi & Sadeghi, 2017; Sadeghi et al., 2019). Nevertheless, NDVI reflects vegetation greenness rather than overall ecosystem integrity and should therefore be interpreted as an indicator of vegetation condition rather than comprehensive watershed function.

We used dry-season NDVI observations (June–September) from 2000 to 2020 because vegetation stress is more apparent under limited water availability and cloud contamination is generally lower than during the wet season (Nazarova et al., 2020; Prudente et al., 2020). Accordingly, dry-season imagery provides more stable spectral responses for long-term vegetation monitoring.

To reduce short-term vegetation fluctuations and residual atmospheric noise, the RRV threshold was determined using the average dry-season NDVI (Cao et al., 2018; Eklundh & Jönsson, 2015). Seasonal averaging provides a more stable representation of long-term vegetation dynamics (Fayech & Tarhouni, 2021; Mehmood et al., 2024). Because ecologically meaningful thresholds vary across vegetation types, elevation, and climate, a uniform operational threshold was adopted to ensure methodological consistency throughout the watershed. Dry-season vegetation is generally more sensitive to hydrological stress and land degradation (Gessesse & Melesse, 2019; Van Hoek et al., 2016; Wang et al., 2016), making dry-season NDVI suitable for distinguishing satisfactory and unsatisfactory vegetation conditions within the RRV framework (Mallick et al., 2021; Mondal et al., 2017). Therefore, the selected threshold should be interpreted as a methodological reference rather than a universal ecological boundary for comparative long-term assessment.

### 2.4 Calculation of watershed health index

The Watershed Health Index (WHI) was calculated as the geometric mean of the standardized reliability, resilience, and vulnerability indicators. In this study, WHI represents a composite indicator of vegetation-based watershed health derived from long-term NDVI dynamics rather than a comprehensive measure of overall watershed health. The geometric mean was selected because it prevents high performance in one indicator from fully compensating for poor performance in another, thereby preserving the multidimensional characteristics of the watershed condition.

Reliability and Resilience were standardized using Equation (4), whereas Vulnerability was standardized using Equation (5) (Sadeghi et al., 2019).

$$C_s = (C_i - C_{min})/(C_{max} - C_{min}) \tag{4}$$

Meanwhile, the negative vulnerability index is standardized using the following equation:

$$C_s = (C_{max} - C_i)/(C_{max} - C_{min}) \tag{5}$$

where $C_s$ is the standardized indicator value, $C_i$ is the observed indicator value, and $C_{\max}$ and $C_{\min}$ represent the maximum and minimum indicator values, respectively.

The standardized indicators were then combined using the geometric mean as follows:

$$WHI = \sqrt[3]{Reliability \times Resilience \times Vulnerability} \tag{6}$$

We applied equal weighting because reliability, resilience, and vulnerability represent the three fundamental dimensions of the RRV framework and have been treated equally in previous watershed health studies (Hazbavi et al., 2019). The resulting WHI values were classified into five watershed health classes: 0.00–0.20, Very Unhealthy; 0.21–0.40, Unhealthy; 0.41–0.60, Moderately Healthy; 0.61–0.80, Healthy; and 0.80–1.00, Very Healthy.

### 2.5 Correlation analysis between RRV and LULC

Pearson correlation analysis was performed to examine the relationships between LULC composition and RRV indicators, including the Watershed Health Index (WHI), for 173 catchments. LULC data were obtained from (Marko et al., 2021, 2025). Vegetation dynamics are closely related to land-cover change (Foley et al., 2005; Lambin et al., 2003). Therefore, the present analysis specifically evaluates the association between LULC composition and vegetation-based watershed health derived from NDVI. The percentages of forest, bush-grass, dry agricultural land, rice fields, plantations, and built-up areas were correlated with the reliability, resilience, vulnerability, and WHI values using Pearson correlation. All variables were aggregated at the catchment level before the analysis. Because LULC strongly influences NDVI, the observed relationships should be interpreted as ecological associations rather than evidence of direct causality or independent validation of the RRV framework.

The Pearson's formula used is:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{7}$$

where:
$r$ = Pearson correlation coefficient
$X_i$ = percentage of LULC species in the $i^{th}$ catchment
$Y_i$ = RRV or WHI indicator value in the $i^{th}$ catchment
$\bar{X}$ = average LULC percentage
$\bar{Y}$ = average RRV or WHI indicator value
$n$ = number of catchments or sub-watersheds

### 2.6 Sensitivity Analysis

A one-at-a-time (OAT) sensitivity analysis was conducted to evaluate the robustness of the RRV-based WHI to uncertainty in the NDVI threshold (Pianosi et al., 2016; Saltelli & Annoni, 2010). The threshold was varied by ±10% and ±20% from the baseline value to represent moderate and large deviations, respectively. Reliability, resilience, vulnerability, and WHI were recalculated for each scenario to assess the stability of vegetation-based watershed health estimates. This analysis exclusively focuses on threshold uncertainty because threshold selection is a key component of the RRV framework. Other uncertainty sources, including spatial resolution, temporal aggregation, and data quality, were beyond the scope of this study and should be considered in future research.

The model sensitivity was calculated as follows:

$$SI = \frac{WHI_i - WHI_b}{WHI_b} \times 100\% \tag{8}$$

where $SI$ is the sensitivity index, $WHI_i$ is the WHI under the $i$-th threshold scenario, and $WHI_b$ is the baseline WHI. Larger absolute SI values indicate greater model sensitivity, whereas values close to zero indicate a stable model response.

## 3. Results and Discussion

### 3.1 Spatiotemporal Dynamics of Dry-Season NDVI

The MODIS-derived dry-season NDVI (June–September) during 2000–2020 indicates generally moderate to high vegetation greenness across the UCW (Table 3). Forest exhibited the highest NDVI values, followed by bush-grass, dry agricultural land, rice fields, and plantations, whereas built-up areas consistently showed the lowest NDVI values (Table 4). These patterns indicate that vegetation density strongly reflects differences in land-cover characteristics and provides the basis for subsequent vegetation-based watershed health assessment.

**Table 3** Monthly mean NDVI values based on MODIS images for 2000–2020.

| Month | Average | Minimum | Maximum | Standard Deviation |
|---|---|---|---|---|
| June | 0.632 | 0.067 | 0.893 | 0.168 |
| July | 0.630 | 0.096 | 0.970 | 0.161 |
| August | 0.590 | 0.128 | 0.880 | 0.162 |
| September | 0.540 | 0.141 | 0.865 | 0.162 |
| Average | 0.600 | 0.110 | 0.900 | 0.160 |

Note: Statistics were calculated using MODIS MOD13Q1 dry-season observations (June–September) from 2000 to 2020

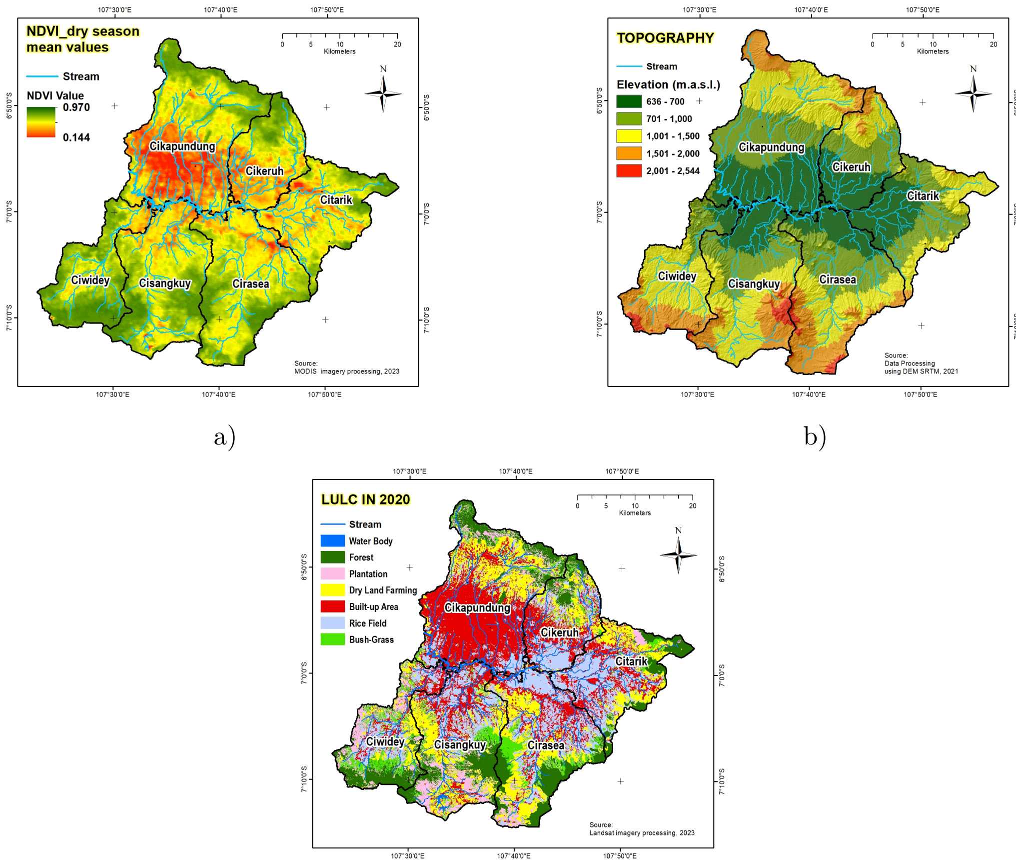
**Table 4** NDVI values for each LULC type based on MODIS images in the dry season of 2000–2020

| LULC Type | Minimum | Maximum | Mean | Range | Std. Deviation |
|---|---|---|---|---|---|
| Forest | 0.59 | 0.90 | 0.81 | 0.31 | 0.08 |
| Bush-Grass | 0.52 | 0.94 | 0.80 | 0.42 | 0.11 |
| Plantation | 0.20 | 0.88 | 0.77 | 0.68 | 0.09 |
| Dry-land farming | 0.25 | 0.83 | 0.54 | 0.58 | 0.15 |
| Rice Fields | 0.13 | 0.88 | 0.51 | 0.75 | 0.21 |
| Built-Up Area | 0.16 | 0.23 | 0.19 | 0.07 | 0.02 |
| Water Body | -0.19 | 0.52 | 0.15 | 0.71 | 0.18 |

Note: Statistics were calculated using MODIS MOD13Q1 dry-season observations (June–September) from 2000 to 2020

Spatially, high NDVI values were consistently observed in the northern and southern mountainous areas dominated by forests and plantations, whereas lower values were observed in the urbanized central watershed (Figure 2). Vegetation greenness gradually declined from June to September, reflecting increasing dry-season water stress, whereas forested uplands remained relatively stable throughout the observation period.

From a long-term perspective (Figure 3), Ciwidey and Cisangkuy exhibited gradual increases in NDVI with slopes of 0.0004 and 0.0008, respectively, indicating improved vegetation conditions over the 2000–2020 period. However, synchronous NDVI declines occurred during 2002–2003, 2006–2007, and 2015–2016, likely associated with strong El Niño (Erasmi et al., 2009; Qian et al., 2019) and positive Indian Ocean Dipole (IOD) events (D'Arrigo & Smerdon, 2008) across Southeast Asia, intensifying drought stress and reducing vegetation productivity (Wang et al., 2016). Similar drought-induced vegetation responses have also been reported in the Citarum Watershed using MODIS-derived vegetation and drought indicators (Dimyati et al., 2024), highlighting the climatic sensitivity of vegetation dynamics in the UCW. Nevertheless, confirming a direct causal relationship would require additional hydroclimatic observations. Overall, these results indicate that vegetation dynamics are jointly influenced by climate variability and LULC change, emphasizing the need for ecological rehabilitation and sustainable land management, particularly in the Cikapundung sub-watershed where vegetation conditions remain consistently degraded. These NDVI dynamics provide the basis for the subsequent RRV analysis, in which catchments with consistently high NDVI are expected to exhibit higher reliability, those with faster post-disturbance vegetation recovery have higher resilience, and those experiencing prolonged vegetation decline have greater vulnerability.




a) b)

c)

**Figure 2** Spatial distribution of the mean dry-season NDVI (a), elevation (b), and land-use/land-cover (LULC) (c) in the Upper Citarum Watershed. The maps highlight forested uplands with consistently high vegetation greenness, an urban core characterized by low NDVI, an agricultural transition zone with moderate vegetation conditions, and a degraded central watershed associated with intensive anthropogenic LULC change

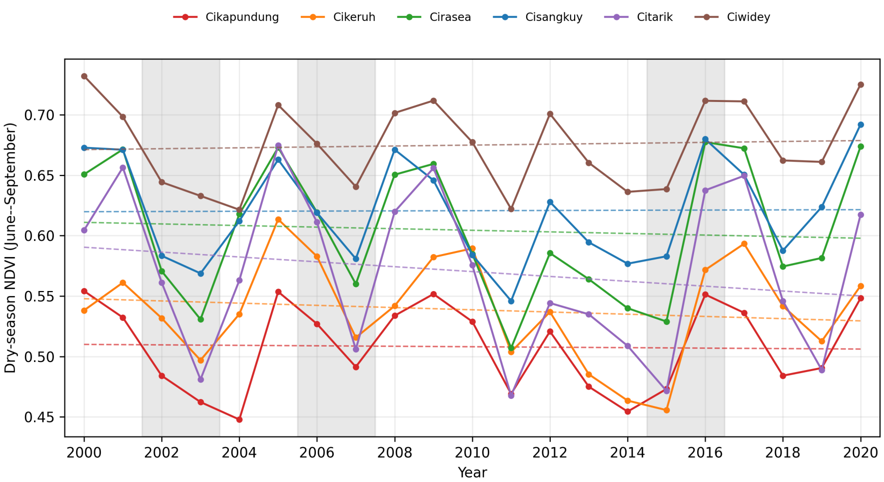



**Figure 3** Annual dry-season NDVI (June–September) of the six sub-watersheds in the Upper Citarum Watershed from 2000 to 2020. Shaded areas indicate periods influenced by concurrent El Niño and positive Indian Ocean Dipole (IOD) events (2002–2003, 2006–2007, and 2015–2016), which are associated with reduced rainfall and green vegetation across Indonesia. The dashed lines represent the linear NDVI trends for each sub-watershed.

### 3.2 Vegetation-based watershed health assessment

Table 5 summarizes the average Watershed Health Index (WHI) values for the six sub-watersheds, revealing considerable spatial variation in vegetation-based watershed health across the UCW. The reported WHI values represent vegetation-based watershed health derived from long-term NDVI dynamics rather than comprehensive watershed health. The relatively narrow range of normalized vulnerability values reflects the min–max normalization procedure and should not be interpreted as identical vulnerability levels among sub-watersheds. Ciwidey exhibited the highest WHI (0.80), supported by high reliability (0.81), resilience (0.75), and vulnerability (0.98), whereas Cikapundung showed the lowest WHI (0.34) due to low reliability and resilience despite moderate vulnerability. Cikeruh also displayed relatively poor watershed health (WHI = 0.41), whereas Cirasea and Cisangkuy showed the same WHI (0.65), indicating relatively good vegetation-based watershed health. Citarik represents an intermediate condition (WHI = 0.55). Overall, Ciwidey, Cisangkuy, and Cirasea exhibited better vegetation-based watershed health than Cikapundung and Cikeruh (Figure 4).

Figure 5 reveals clear spatial differences in watershed health among the six sub-watersheds based on the proportion of catchments within each WHI class. Ciwidey exhibits the most favorable condition, with 83.3% of its catchments classified as Very Healthy and no catchments in either the Healthy or Moderate classes, indicating a watershed dominated by highly stable vegetation conditions. Cisangkuy (43.8%) and Cirasea (36.1%) also show relatively high proportions of Very Healthy catchments, although both retain a mixture of lower health classes, reflecting greater spatial heterogeneity. In contrast, Cikapundung and Cikeruh have the highest proportions of Very Unhealthy catchments (56.8% and 41.2%, respectively), indicating widespread ecological degradation. Citarik exhibited the most balanced distribution among the five WHI classes, reflecting an intermediate watershed condition with substantial opportunities for ecological improvement. Overall, the stacked percentage chart clearly demonstrates that watershed health is highly heterogeneous across the Upper Citarum Watershed, with healthy sub-watersheds dominated by very healthy catchments, whereas very unhealthy catchments predominate degraded sub-watersheds.

**Table 5** Average RRV and WHI values for each sub-watershed

| No. | Sub-watershed | Rel | Res | Vul | Rel_std | Res_std | Vul_std | WHI |
|---|---|---|---|---|---|---|---|---|
| 1 | Cikapundung | 0.31 | 0.29 | 3.89 | 0.32 | 0.28 | 0.77 | 0.34 |
| 2 | Cikeruh | 0.37 | 0.34 | 1.17 | 0.37 | 0.32 | 0.93 | 0.41 |
| 3 | Cirasea | 0.58 | 0.53 | 0.13 | 0.59 | 0.52 | 0.99 | 0.65 |
| 4 | Cisangkuy | 0.61 | 0.57 | 0.20 | 0.62 | 0.56 | 0.99 | 0.65 |
| 5 | Citarik | 0.46 | 0.42 | 0.35 | 0.48 | 0.42 | 0.98 | 0.55 |
| 6 | Ciwidey | 0.80 | 0.75 | 0.29 | 0.81 | 0.75 | 0.98 | 0.80 |

Figure 6 illustrates the spatial distribution of RRV and WHI for each catchment. The RRV indicators further explain these spatial differences. Ciwidey consistently exhibited the highest reliability and resilience, indicating stable vegetation conditions and strong recovery following disturbance, whereas Cikapundung showed the lowest values, reflecting persistent vegetation degradation associated with intensive urbanization and LULC change. Vulnerability was generally low across most sub-watersheds, although Cikapundung was the only sub-watershed containing catchments classified as Very Unhealthy, highlighting its priority for ecological restoration and watershed management.

Unlike the average NDVI, which represents general vegetation greenness, the RRV framework captures vegetation persistence (Reliability), recovery following disturbance (Resilience), and degradation severity (Vulnerability). Consequently, catchments with similar mean NDVI values may exhibit different RRV and WHI values due to differences in long-term vegetation dynamics.

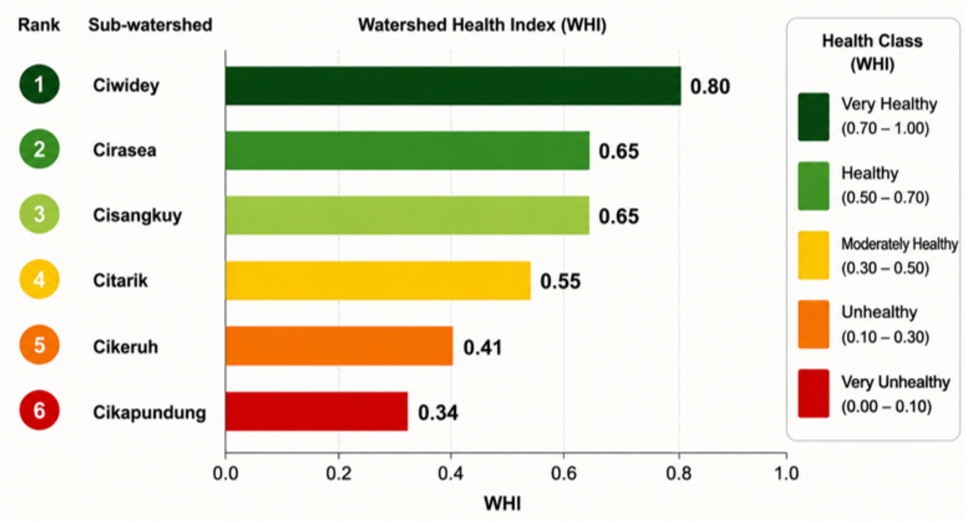



**Figure 4** Ranked watershed health index (WHI) of six sub-watersheds

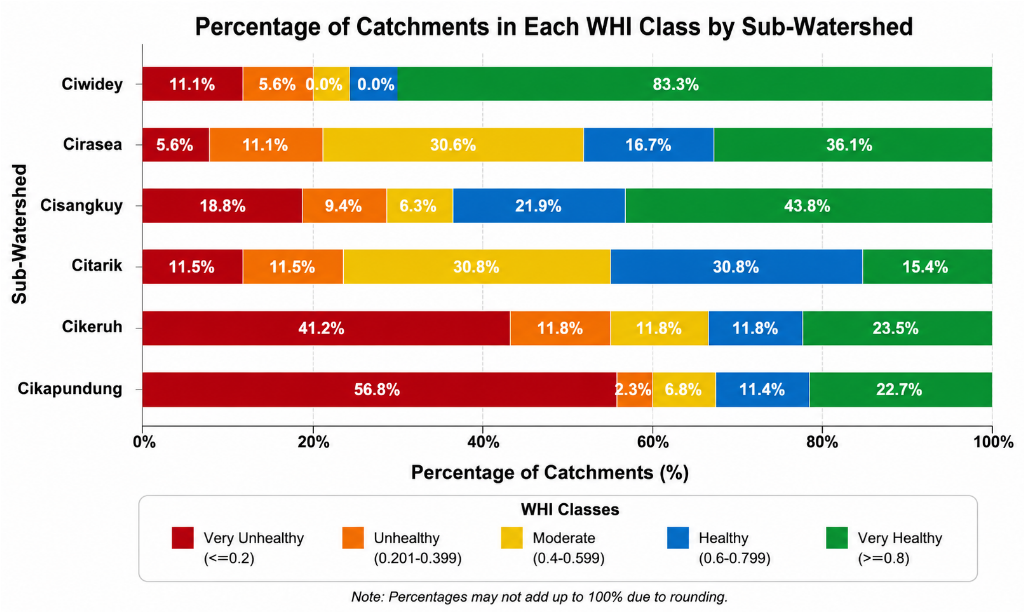



**Figure 5** Percentage of Catchments in Each WHI Class by Sub-Watersheds

### 3.3 Correlation between the RRV indicator and LULC

The correlation analysis (Figure 7) shows that the Watershed Health Index (WHI) and the RRV indicators exhibit distinct relationships with different LULC types. WHI was strongly and positively correlated with forest ($r = 0.65$; $p < 0.01$), plantation ($r = 0.60$; $p < 0.01$), and bush–grass ($r = 0.59$; $p < 0.01$), indicating that vegetation-dominated catchments generally have better vegetation-based watershed health. Dry farming also showed a moderate positive correlation ($r = 0.37$; $p < 0.01$). In contrast, the built-up area exhibited a very strong negative correlation with WHI ($r = -0.89$; $p < 0.01$), whereas the rice field showed a weak negative correlation ($r = -0.26$; $p < 0.01$) and the water body was not significantly correlated ($r = -0.10$; $p = 0.17$). These relationships are ecologically consistent because vegetation enhances infiltration, reduces runoff, and limits soil erosion; however, they should be interpreted as ecological associations rather than independent validation because NDVI and LULC are intrinsically related.

Reliability and resilience were generally higher in catchments dominated by forest, plantation, and bush-grass, indicating greater vegetation persistence and recovery following climatic or hydrological stress. Conversely, built-up area was consistently negatively correlated with both indicators, indicating lower watershed capacity to maintain stable vegetation conditions and recover after disturbance in more urbanized areas. Vulnerability showed the opposite pattern, increasing with the built-up area and decreasing with the vegetated LULC, indicating that vegetation mitigates degradation severity by supporting infiltration, runoff regulation, and water storage.

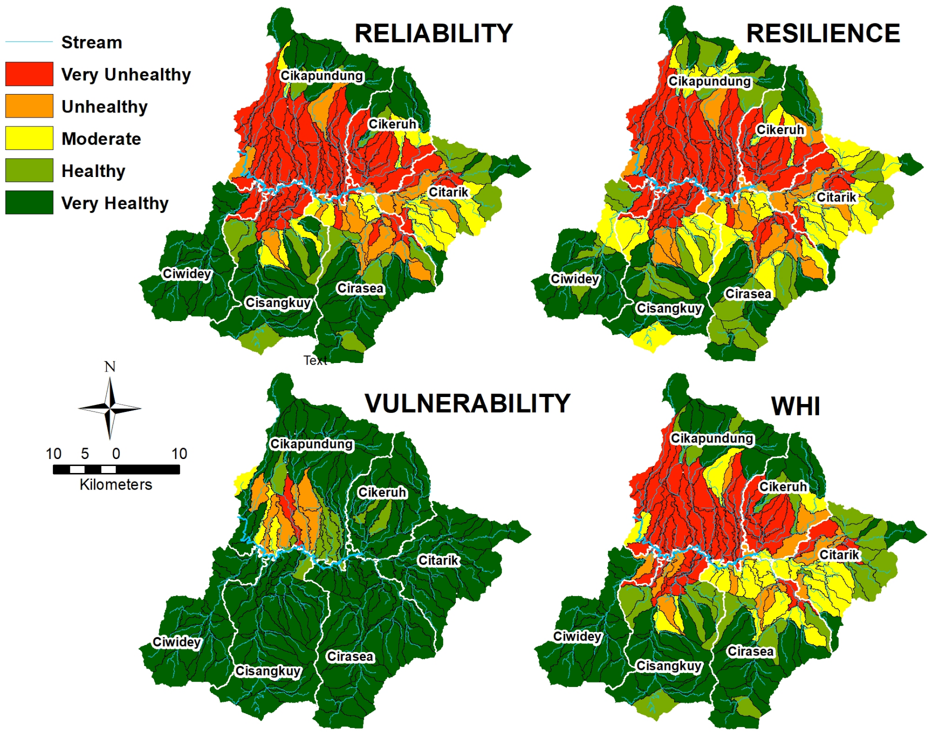
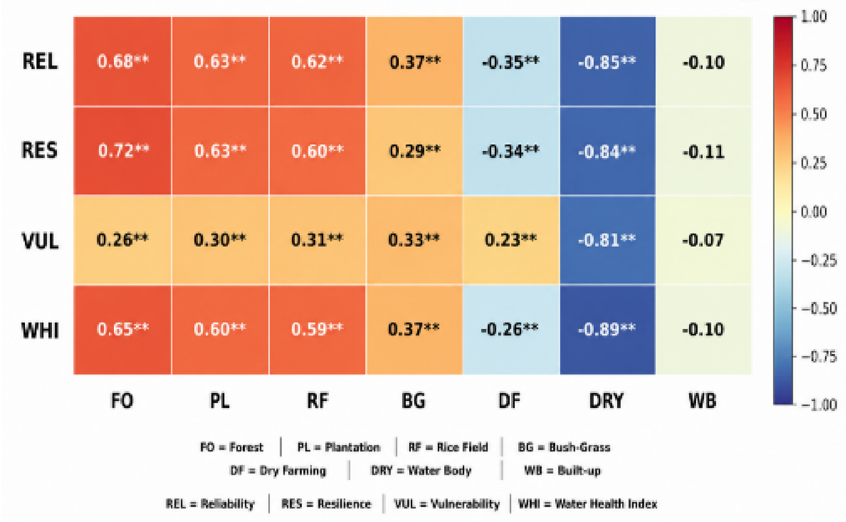



**Figure 6** Spatial distribution of reliability, resilience, vulnerability, and vegetation-based Watershed Health Index (WHI). The Cikapundung and Cikeruh sub-watersheds are priority restoration zones.

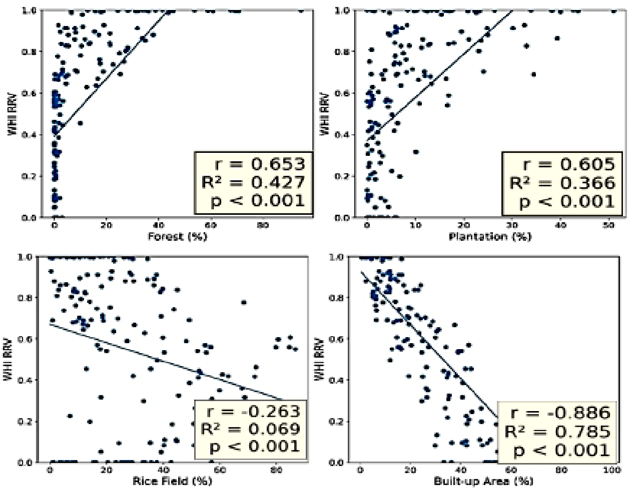
These findings agree with previous studies demonstrating that vegetation enhances infiltration, sustains baseflow, reduces runoff, and improves watershed hydrological functioning (Ellison et al., 2017; Filoso et al., 2017), whereas urbanization increases impervious surfaces, accelerates runoff, and reduces infiltration (McGrane, 2016; Salvadore et al., 2015). Overall, the positive relationships between vegetated LULC and reliability, resilience, and WHI confirm that land-cover composition is a key driver of vegetation-based watershed health. Therefore, watershed management should prioritize vegetation conservation and restoration, particularly in upstream and recharge areas, while limiting urban expansion and promoting sustainable land management practices. The integration of RRV and LULC analysis also provides a practical framework for the assessment and management of vegetation-based watershed health.

This study employed NDVI to evaluate long-term vegetation dynamics within the RRV framework. The observed relationships between NDVI-derived watershed health and LULC characteristics demonstrate that vegetation greenness provides a useful proxy for vegetation persistence, recovery capacity, and degradation over time. Although NDWI (McFeeters, 1996) and MNDWI (Xu, 2006) are valuable remote sensing indices for detecting surface water extent and moisture conditions, they were not selected because they do not directly characterize long-term vegetation dynamics, which constitute the basis of the proposed RRV assessment. Nevertheless, watershed health is influenced by the interactions between vegetation and hydrological processes.

Therefore, future studies should integrate NDVI with NDWI, MNDWI, and other ecohydrological indicators, such as soil moisture, evapotranspiration, precipitation, and streamflow, to provide a more comprehensive assessment of watershed health under changing climate and LULC conditions.




(a)




(b)

**Figure 7** (a) Correlation heatmap of Reliability, resilience, Vulnerability, WHI, and LULC and (b) selected scatterplots: WHI vs. forest, WHI vs. built-up area, WHI vs. plantation, and WHI vs. rice field. The built-up area has a strong negative correlation with WHI.

The present findings confirm that satellite-derived vegetation information can effectively represent spatial variations in the ecological conditions of watersheds. Remote sensing and GIS have similar applications to support watershed conservation and environmental management by providing spatially explicit information for identifying priority areas and guiding management strategies (Eng et al., 2019; Gunawan et al., 2013).

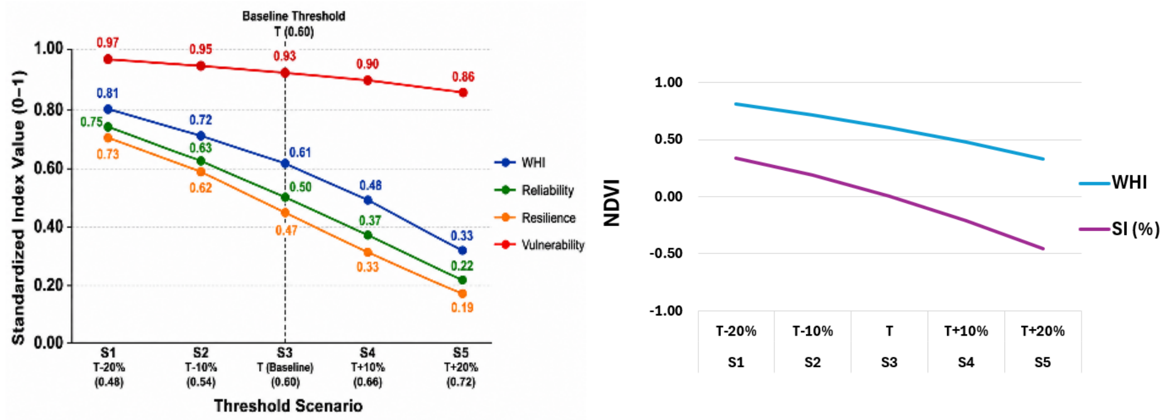
### 3.4 Sensitivity of the RRV-based WHI to NDVI threshold selection

Sensitivity analysis (Table 6 and Figure 8) indicates that NDVI threshold variations primarily affect the reliability and resilience components of the RRV framework. Reducing the threshold by 20% (NDVI = 0.48) resulted in the highest reliability, resilience, and WHI values, whereas increasing the threshold by 20% (NDVI = 0.72) produced the lowest values. This pattern indicates that a more restrictive threshold classifies fewer vegetation observations as healthy, thereby reducing the probability that the watershed remains in or recovers to a satisfactory condition. Conversely, a lower threshold classifies a larger proportion of observations as healthy, leading to improved system performance. In contrast, vulnerability changed only slightly, decreasing from 0.97 to 0.86 across all threshold scenarios. This finding indicates that the threshold variation has a much stronger influence on the frequency of healthy and unhealthy conditions than on the severity of vegetation degradation once the system enters an unhealthy state. Environmental modeling and uncertainty analysis studies have reported similar sensitivity to threshold selection (Pianosi et al., 2016; Saltelli & Annoni, 2010).

**Table 6** Scenarios of the sensitivity analysis of the NDVI threshold

| Scenario | Threshold | Reliability | Resilience | Vulnerability | WHI | SI (%) |
|---|---|---|---|---|---|---|
| S1 | T-20% | 0.75 | 0.73 | 0.97 | 0.81 | 0.33 |
| S2 | T-10% | 0.63 | 0.62 | 0.95 | 0.72 | 0.19 |
| S3 | T | 0.50 | 0.47 | 0.93 | 0.61 | 0.00 |
| S4 | T+10% | 0.37 | 0.33 | 0.90 | 0.48 | -0.21 |
| S5 | T+20% | 0.22 | 0.19 | 0.86 | 0.33 | -0.46 |

The Sensitivity Index (SI) further confirms that the response of WHI to threshold variation is gradual and nearly linear. Threshold changes of ±10% produced SI values ranging from 0.19 to −0.21, while changes of ±20% increased the response to 0.33 and −0.46. Despite these variations, no abrupt changes were observed around the baseline threshold (NDVI = 0.60), indicating that under moderate threshold variation, the proposed RRV framework remains reasonably robust. Furthermore, the larger SI magnitude under the +20% scenario indicates that increasing the threshold has a greater impact on watershed health assessment than decreasing it. This finding implies that selecting an excessively high threshold may lead to overly conservative estimates of watershed health by classifying a larger proportion of vegetation conditions as unhealthy.




(a) (b)

**Figure 8** Threshold sensitivity of the RRV components and the Watershed Health Index (WHI). (a) panel shows changes in standardized reliability, resilience, vulnerability, and WHI under five NDVI threshold scenarios, with the vertical dashed line indicating the baseline threshold (NDVI = 0.60). (b) panel presents the corresponding Sensitivity Index (SI) values across the threshold scenarios.

Based on these results, the baseline threshold of NDVI = 0.60, derived from the long-term dry-season average for 2000–2020, provides a balanced representation of vegetation conditions in the Upper Citarum Watershed. This threshold lies between two extreme conditions: the overestimation of watershed health under a lower threshold (WHI = 0.81) and the underestimation associated with a higher threshold (WHI = 0.33). At the baseline threshold, the resulting WHI of 0.62 provides a realistic representation of watershed health while maintaining stable model performance under threshold variation. These findings support the use of long-term average NDVI as a reference for representing normal vegetation conditions (Pettorelli et al., 2005). Overall, the results demonstrate that the proposed NDVI-based RRV framework provides stable watershed health assessments under threshold variations of up to ±20%, although future studies should further evaluate additional sources of uncertainty, including spatial resolution, sensor characteristics, and temporal aggregation methods, to improve the applicability of the framework across watersheds with different environmental and climatic conditions.

## 4. Conclusions

This study demonstrates that integrating long-term MODIS NDVI with the Reliability–Resilience–Vulnerability (RRV) framework provides a practical approach for assessing vegetation-based watershed health in the Upper Citarum Watershed (UCW). Analysis of the 2000–2020 dry-season NDVI time series revealed substantial spatial variation among sub-watersheds, reflecting differences in topography, LULC, and anthropogenic pressures. Ciwidey exhibited the highest WHI (0.80), supported by high Reliability and Resilience, whereas Cikapundung showed the lowest WHI (0.34), indicating persistent vegetation degradation associated with intensive urban development. Temporal NDVI declines during 2002–2003, 2006–2007, and 2015–2016 were consistent with El Niño and positive IOD-related drought events, highlighting the sensitivity of watershed vegetation to climate variability. Correlation analysis further showed that forests, plantations, and bush-grass were positively associated with Reliability, Resilience, and WHI, whereas built-up areas exhibited strong negative relationships, emphasizing the importance of vegetation in supporting watershed ecological functioning. Sensitivity analysis indicated that although WHI is affected by NDVI threshold selection, the model response remained consistent, supporting the use of the long-term dry-season NDVI threshold (0.60) for vegetation-based watershed health assessment in the UCW. This framework should be interpreted as an assessment of the vegetation dimension of watershed health, rather than a comprehensive evaluation of hydrological, geomorphological, water-quality, or biodiversity conditions. In addition, the correlation analysis indicates statistical associations rather than causal relationships, and the proposed framework has not yet been independently validated using hydrological observations or other ecological indicators. Future studies should integrate additional environmental indicators and independent validation datasets to improve the robustness and broader applicability of vegetation-based watershed health assessment. The proposed RRV–NDVI framework is transferable to other data-limited tropical watersheds where long-term hydrological and water-quality records are unavailable.

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## Author Contributions

**K. Marko**: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Original draft writing, Corresponding author.

**D. Sutjiningsih**: Conceptualization, supervision, methodology, writing, review and editing, and acquisition of funding.

**E. Kusratmoko**: Conceptualization, supervision, investigation, and curation of data.

**W. A. Prakoso**: Supervision

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