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Remote Sensing of Mangrove Health and Vulnerability in Tolongano

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ABSTRACT

Mangrove ecosystems play an important role in protecting coastal areas from erosion, waves, and other environmental disturbances. However, increasing anthropogenic pressures, including aquaculture expansion, settlement development, and land-use conversion, threaten their sustainability. Previous studies have commonly assessed mangrove health or vulnerability separately, providing limited insight into the relationship between ecosystem condition and potential threats. This study addresses this gap by integrating the Soil Adjusted Vegetation Index (SAVI) and Multi-Criteria Decision Analysis (MCDA) to evaluate mangrove health, spatial vulnerability, and their relationship in Tolongano Village, South Banawa Sub-district, Central Sulawesi. The integration of SAVI and MCDA offers a novel framework for identifying healthy mangrove areas that remain exposed to significant anthropogenic pressures.Using Landsat 8/9 imagery, land-use data, and field validation at 45 sampling points, mangrove health was classified into healthy (72.78 ha; 52.47%), moderate (32.82 ha; 23.66%), and unhealthy/degraded (33.11 ha; 23.87%) categories. Classification accuracy was high, with an Overall Accuracy of 97.78% and a Kappa coefficient of 0.98. Vulnerability analysis showed that 87.40% of the mangrove area was categorized as very highly vulnerable, mainly due to the proximity of aquaculture ponds. Correlation analysis produced a weak negative relationship ($r = -0.2390$) between mangrove health and vulnerability. The results indicate that healthy mangrove stands may still face substantial future threats. The SAVI–MCDA approach provides a practical tool for conservation prioritization, coastal spatial planning, and long-term mangrove management.

Keywords : mangrove forests, vegetation health, vulnerability, remote sensing, SAVI, weighted overlay.

1. INTRODUCTION

Advances in remote sensing technology have significantly improved the monitoring of mangrove ecosystems through the use of multi-temporal satellite imagery. Landsat 8 and Landsat 9 provide continuous Earth observation data with adequate spatial and temporal resolution for large-scale ecosystem assessment. Recent studies have demonstrated the effectiveness of satellite-based vegetation indices for monitoring mangrove condition and detecting ecosystem degradation in coastal environments (Vasquez et al., 2024; Putri et al., 2025). However, most previous studies have focused either on assessing mangrove vegetation health or on evaluating vulnerability caused by anthropogenic pressures. As a result, the spatial relationship between ecosystem health and vulnerability remains insufficiently understood, particularly in coastal areas experiencing rapid land-use change.

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The Normalized Difference Vegetation Index (NDVI) has been widely used to evaluate vegetation condition, but its performance may be affected by soil background reflectance in sparsely vegetated areas. Therefore, this study employs the Soil-Adjusted Vegetation Index (SAVI), which incorporates a soil correction factor and is considered more suitable for mangrove environments characterized by exposed sediments, mudflats, and shallow water surfaces (Simarmata et al., 2021). To complement vegetation health assessment, this study integrates SAVI with Multi-Criteria Decision Analysis (MCDA), a spatial decision-support approach that enables the incorporation of multiple anthropogenic pressure indicators, including proximity to settlements, aquaculture ponds, and agricultural land. Although both methods have been widely applied independently, studies integrating SAVI-derived mangrove health information with MCDA-based vulnerability assessment remain limited, particularly in post-disaster coastal landscapes of Indonesia.

This study therefore offers a novel contribution by developing an integrated SAVI–MCDA framework to simultaneously assess mangrove health and spatial vulnerability, enabling the identification of areas that are currently healthy but exposed to high anthropogenic pressures and future degradation risks. Such information is important for supporting evidence-based conservation planning, rehabilitation prioritization, and sustainable coastal management.

Accordingly, the objectives of this study are: (1) to assess mangrove vegetation health using the Soil-Adjusted Vegetation Index (SAVI); (2) to evaluate mangrove vulnerability based on anthropogenic pressure factors using a Multi-Criteria Decision Analysis (MCDA) approach; and (3) to analyse the spatial relationship between mangrove health and vulnerability in Tolongano Village, South Banawa Sub-district, Donggala Regency, Central Sulawesi.

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2. MATERIALS AND METHODS

Study Location and Data Collection

This study was conducted in Tolongano Village, South Banawa Sub-district, Donggala Regency, Central Sulawesi Province. The study area covers approximately 10.51 km² with a population of 1,585 inhabitants and a population density of 151 persons km^{-2}. Spatial data processing and field verification were conducted from March to May 2026.

Primary data included field coordinates collected using a Garmin GPSMAP 65s Global Positioning System (GPS), aerial observations acquired using a DJI Mini 4 Pro drone, visual assessments of mangrove canopy conditions, and photographic documentation. Secondary data consisted of cloud-free Landsat 8 Operational Land Imager (OLI) and Landsat 9 OLI-2 imagery

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obtained through Google Earth Engine (GEE), national mangrove ecosystem boundary data provided by the Directorate General of Forestry Planning, Ministry of Forestry, and high-resolution PlanetScope imagery used for manual interpretation of settlements, aquaculture ponds, and rice fields. Spatial analysis was performed using ArcGIS Pro version 3.3, Google Earth Engine (GEE) cloud-computing platform, and Microsoft Excel 2021 for statistical processing.

Analysis of the Vegetation Health Index using SAVI

Mangrove vegetation health was assessed using the Soil-Adjusted Vegetation Index (SAVI). Although the Normalized Difference Vegetation Index (NDVI) is widely used for vegetation monitoring, SAVI was selected because it incorporates a soil adjustment factor that minimizes the influence of soil background reflectance. This characteristic is particularly important in mangrove ecosystems where exposed mudflats, sediment surfaces, and shallow standing water may affect spectral responses and reduce NDVI accuracy. Consequently, SAVI provides a more reliable representation of vegetation condition in heterogeneous coastal environments. SAVI was calculated using Landsat 8/9 Near-Infrared (Band 5) and Red (Band 4) reflectance values according to:

$$SAVI = ((NIR - Red) / (NIR + Red + L)) * (1 + L)$$

where L is the soil background adjustment factor, set at 0.5 to compensate for medium vegetation density conditions. The next stage involves classifying *the Soil Adjusted Vegetation Index* (SAVI) based on the resulting value ranges, namely:

Table 1. SAVI classification ranges (Hawari, 2025)

No	SAVI Value	Land Condition
1	-0.71	No Vegetation
2	-0.29 - 0.26	Low
3	0.26 – 0.66	Medium
4	0.66–0.99	High
5	0.99 – 1.38	Very High

Mangrove Vulnerability Analysis

Mangrove vulnerability was assessed using a Multi-Criteria Decision Analysis (MCDA) framework. Vulnerability was determined based on four indicators: mangrove vegetation health (SAVI), distance from aquaculture ponds, distance from settlements, and distance from rice fields. Anthropogenic pressure indicators were derived using Euclidean Distance analysis and classified into five vulnerability classes using buffer intervals of 250 m, 500 m, 750 m, 1000 m, and >1250 m.

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The Mangrove Vulnerability Index (MVI) was generated using the Equal Weighted Overlay method in ArcGIS Pro. Each criterion was assigned an equal weight of 25%. Equal weighting was adopted because no empirical evidence or previous local studies were available to justify assigning greater importance to one pressure factor over another. Furthermore, all selected variables represent major and relatively comparable drivers of mangrove vulnerability in the study area. The equal-weight approach is commonly recommended in exploratory spatial assessments to reduce subjective bias and ensure methodological transparency (Busra Ayan et al., 2023):

*MVI = [25% * SAVI_Score] + [25% * Distance_to_Fish_Ponds] + [25% * Distance_to_Settlements] + [25% * Distance_to_Rice_Fields]*

Field Validation and Correlation Analysis

Field validation employed a stratified random sampling approach to ensure representation across all vegetation health classes. A total of 45 validation points were collected, consisting of 15 points from each health category (healthy, moderate, and degraded). At each sampling point, geographic coordinates, canopy cover conditions, vegetation density, dominant species composition, and photographic evidence were recorded. Observations were subsequently compared with SAVI-derived classifications to evaluate classification accuracy.The reliability of the classification results was assessed using a confusion matrix, from which User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA), and the Kappa coefficient were calculated. An Overall Accuracy greater than 85% and a Kappa coefficient greater than 0.80 were considered indicative of strong classification performance (Novianti et al., 2024). Furthermore, a spatial, pixel-based Pearson correlation analysis (r) was carried out to determine the direction of the relationship and the strength of the association between the vulnerability index values and the physical health of the mangrove canopy in the field. (Mukaka, 2012)

3. RESULT AND DISCUSSION

Analysis of Mangrove Forest Health

Based on the Soil Adjusted Vegetation Index (SAVI) spatial analysis, the total area of the mangrove forest ecosystem in Tolongano Village is 138.71 hectares. The ecosystem is characterized by three distinct health categories (Table 2). The "Healthy" category dominates the area, spanning 72.78 ha (52.47% of the total ecosystem), reflecting dense canopy cover and robust chlorophyll activity. The "Moderate" category serves as an ecological transition zone covering 32.82 ha (23.66%). The "Unhealthy" or degraded category accounts for 33.11 ha (23.87%).

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Table 2. Distribution of mangrove forest health category areas based on SAVI analysis

No	**SAVI Value Range**	**Health Category**	**Area (ha) / Percentage (%)**
1	-0.015 – 0.23	Unhealthy	33.11 Ha (23.87%)
2	0.23 – 0.46	Moderate	32.82 Ha (23.66%)
3	0.46 – 0.74	Healthy	72.78 Ha (52.47%)
Total Ecosystem Area			138.71 Ha (100.00%)

Validation testing using 45 empirical field control points yielded an overall classification accuracy of 97.78% with a Kappa coefficient of 0.98. Only a single sample point from the "Moderate" class was misclassified as "Unhealthy" by the automated extraction model.

Anthropogenic Pressure Metrics.

Proximity mapping identifies aquaculture development as the dominant spatial stressor along the Tolongano coastline. A total of 68.49% (95.01 ha) of the mangrove ecosystem sits within a high-risk buffer zone less than 250 meters from active fish pond embankments (Table 3). In contrast, direct spatial pressure from residential settlements is lower, with 10.08% (13.98 ha) located within the critical <250 m zone, while the remaining areas are distributed at distances of 750 to 1,000 m (27.31%) and over 1,250 m (25.87%). Wetland agricultural pressure (rice fields) is concentrated furthest inland, with 54.66% (75.82 ha) located more than 1,250 m away from the mangrove boundaries.

Table 3. Distribution of mangrove area by threat risk distance zoning

Buffer Distance (m)	**Risk Level**	**Area Relative to Settlements (ha)**	**Area Relative to Fish Ponds (ha)**	**Area Relative to Rice Fields (ha)**
< 250	Very High	13.98 (10.08%)	95.01 (68.49%)	0.74 (0.53%)
250–500	High	21.88 (15.77%)	28.78 (20.75%)	13.26 (9.56%)
500–750	Medium	29.09 (20.97%)	10.76 (7.76%)	26.99 (19.46%)
750–1,000	Low	37.88 (27.31%)	4.17 (3.00%)	21.90 (15.79%)
> 1250	Very low	35.88 (25.87%)	0.00 (0.00%)	75.82 (54.66%)

Mangrove Vulnerability Index (MVI)

The composite spatial modeling (MVI)—which integrates vegetation health and anthropogenic distance parameters via Weighted Overlay analysis—reveals that 121.23 ha (87.40%) of the ecosystem falls into the "Very High Vulnerability" tier. The remaining 17.48 ha

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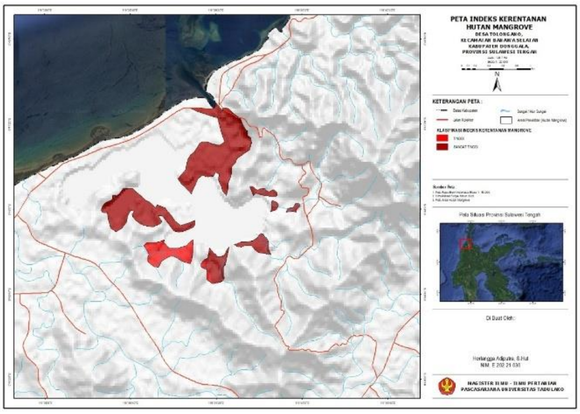
(12.60%) is classified as "High Vulnerability." No mangrove stands fall within low or negligible vulnerability classes.

Statistical Correlation Analysis



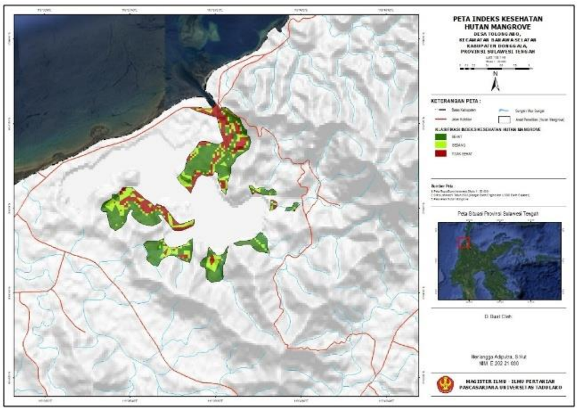
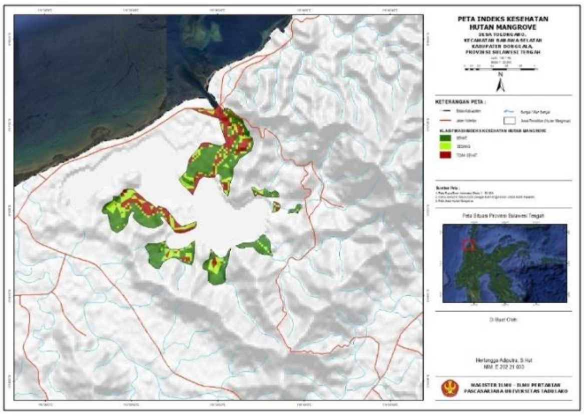


Figure 1. Mangrove Forest Vulnerability Index **Figure 2.** Mangrove Forest Health Index



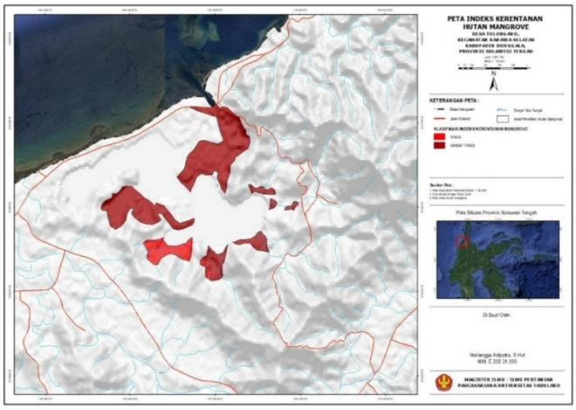


Figure 3. Mangrove Forest Health Distribution **Figure 4**. Mangrove Forest Vulnerability Distribution

A pixel-by-pixel spatial Pearson correlation test between the composite vulnerability layer and the actual canopy health index values yielded a weak negative correlation coefficient:

r = -0.2390, p < 0.01$$

The spatial breakdown reveals that within the 121.23 ha classified as "Very High Vulnerability," a sub-total of 60.76 ha contains vegetation stands that are currently classified as physically "Healthy." (Partama et al., 2024).

DISCUSSION

The spatial and statistical patterns observed in Tolongano Village expose a critical ecological paradox: a weak, negative correlation (r = -0.2390$, p < 0.01$) showing that highly

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vulnerable spatial zones still host physically healthy, dense mangrove canopies. This indicates that canopy greenness alone is a poor indicator of long-term ecosystem security. Instead, it highlights an *ecological lag effect*, where structurally intact forests are currently facing severe, latent environmental stress that has not yet triggered visible canopy dieback.

The spatial distribution of vulnerability within mangrove forests is strongly structured by zonation, with landward and upper-zone mangroves consistently identified as more vulnerable to stress-induced mortality than seaward fringe populations (Gauthey et al., 2022; , Duke et al., 2022), Saintilan et al., 2022). Yet these landward zones may support dense, structurally complex canopies under ambient conditions, as they are often dominated by mature trees that have established over decades of relatively stable environmental conditions. Gauthey et al. explicitly noted that landward mangroves at the Gulf of Carpentaria site were "more likely to experience extreme water stress during the die off event because of greater baseline level of water stress of landward mangroves and greater exposure to the effects of the sea level drop," yet these same trees had green canopies prior to the event (Gauthey et al., 2022) .

This pattern is consistent with the findings of Hickey et al. at Mangrove Bay, Australia, where NDVI was used as a proxy for canopy condition over a 29-year period, revealing oscillating patterns of canopy area correlated with the Southern Oscillation Index (SOI) (Hickey et al., 2021). The study demonstrated that mangroves at aridity range-limitswhere trees are small in stature and forests small in aare particularly susceptible to climate variability, yet their canopy greenness may appear adequate during inter-El Niño periods (Hickey et al., 2021). The temporal heterogeneity of canopy condition highlighted by Hickey et al. underscores that a snapshot of canopy greenness is an unreliable indicator of long-term ecosystem security (Hickey et al., 2021).

The overwhelming dominance of aquaculture ponds within the immediate <250 m buffer zone (68.49%) aligns with broader regional trends across Southeast Asia. Massive conversion of mangrove interiors to brackish water aquaculture often termed the "Blue Revolution" has historically been the primary driver of mangrove loss in nations like the Philippines, Vietnam, and elsewhere in Indonesia (Richards & Friess, 2016). The close proximity of these active ponds threatens the Tolongano mangroves with progressive habitat fragmentation, severe disruption of localized tidal hydrology, and chemical runoff from pond discharges.

By utilizing the SAVI algorithm, this study successfully muted the spectral background noise from wet coastal mudflats, verifying high reliability (97.78% accuracy, Kappa = 0.98). This methodological success matches international remote sensing frameworks where modified vegetation indices are prioritized over standard NDVI in highly reflective intertidal zones (Proisy

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et al., 2018). While previous local models relied heavily on internal vegetation conditions (Partama et al., 2024), integrating external landscape-level stressors (MVI) creates a clearer early-warning metric. The fact that 60.76 ha of healthy forest is sitting in a very high vulnerability zone means these areas should be prioritized for immediate conservation zoning before degradation becomes irreversible.

4. CONCLUSSION

The conclusions that can be drawn from this study are as follows:

1. The health index of the mangrove forest area at the study site is predominantly in the ‘healthy’ and ‘moderate’ categories. This indicates that the mangrove vegetation remains in good condition and well-maintained, with a percentage of 50 per cent or above.
2. The vulnerability of the mangrove forests is predominantly in the ‘very high’ category, covering an area of 121.23 ha, or 87.40 per cent of the total mangrove area of 138.7 ha. Meanwhile, the ‘high’ category covers an area of 17.48 ha, or 12.60 per cent. This indicates that the majority of the mangrove area is in a vulnerable state due to anthropogenic disturbances (settlements, fish ponds and rice fields).
3. The relationship between vulnerability and mangrove health indicates that a high level of vulnerability does not always correlate directly with poor vegetation health, with a correlation coefficient (r) of -0.2390. Most areas classified as ‘very vulnerable’ actually still exhibit good health conditions. This suggests that the vulnerability index used in this study is influenced not only by vegetation conditions but also by various environmental pressures that could potentially threaten the future sustainability of the mangrove ecosystem.
4. The current distribution of mangrove forest vulnerability in Tolongano village, South Banawa sub-district, comprises ‘very high’ and ‘high’ vulnerability levels, whilst the distribution of mangrove health comprises ‘healthy’, ‘moderate’ and ‘unhealthy’ categories.

RECOMMENDATIONS

The recommendations arising from this study are as follows:

1. There is a need to improve the sustainable management and protection of mangrove areas, particularly in regions with a very high level of vulnerability. Controls on land-use change, coastal zone planning, and monitoring of settlement, aquaculture and agricultural activities around mangrove forests need to be strengthened to reduce anthropogenic pressure on mangrove ecosystems.

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2. There is a need to raise awareness and encourage active participation in safeguarding the sustainability of mangrove forests through conservation, rehabilitation and the environmentally friendly utilisation of coastal resources. Community involvement is expected to support the sustainability of the ecological and economic functions of mangrove ecosystems.
3. This research can serve as a basis for formulating coastal zone management policies and determining conservation priorities. Areas with a very high level of vulnerability should be the primary focus of rehabilitation programmes and efforts to mitigate the impacts of human activities.
4. Develop an analysis of mangrove vulnerability by incorporating additional biophysical and environmental parameters, such as coastal erosion, tidal fluctuations, salinity, water quality, changes in the shoreline, population density, and climate change factors. Furthermore, the use of satellite imagery with higher spatial resolution and more comprehensive weighting methods.

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