Contrasting Ecosystem Quality Outcomes: An Analysis Spanning Three Decades Across the Protected, Ancestral, and Reforestation Zones of the Magbando Watershed, Occidental Mindoro, Philippines

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Abstract *Effective management of watersheds with overlapping conservation and ancestral land designations requires robust monitoring. This study assesses more than 35 years of spatiotemporal ecosystem quality dynamics in the Magbando watershed, Mindoro Island, which contains the Mts. Iglit-Baco Natural Park (an ASEAN Heritage Park) and the Buhid-Bangon ancestral domain. Using cloud-based remote sensing, the research employed the Remote Sensing Ecological Index (RSEI), which integrates greenness (NDVI), dryness (NDBSI), wetness (LSM), and heat (LST) via Principal Component Analysis to provide a holistic ecological assessment.*

The results reveal that zones under indigenous and formal protection have the highest ecological quality. Ancestral domains ranked highest (peak RSEI 0.717: good), followed by overlapping protected/ancestral areas (0.656: good) and protected areas alone (0.624: good). Conversely, ecological health declined significantly in other zones, with lands under the National Greening Program (NGP) registering a lower "moderate" quality (0.597) and unprotected areas showing the lowest values (0.519).

These findings strongly suggest that traditional indigenous land management practices within the Buhid-Bangon domain are more effective at maintaining long-term ecosystem integrity than the studied government-led reforestation program. The results challenge conventional top-down restoration approaches and highlight the vital role of Indigenous Peoples as effective environmental stewards. Further field validation is needed to investigate the specific land-use practices driving these outcomes and to better integrate indigenous knowledge into national conservation and restoration strategies.

Keywords: ecological quality, ancestral domain, protected areas, National Greening Program, Google Earth Engine

Introduction

Properly managed watersheds offer crucial ecosystem services that significantly benefit human well-being. These vital natural systems provide communities with essentials such as food and water production. They also deliver regulating services like flood control and soil conservation, offer supporting services through processes like nutrient cycling, and contribute cultural services (Yang et al. 2019).

Ecological quality is a measure of ecosystem integrity, health, and resilience. This encompasses components, structure, and function of such ecosystems. It is a reflection of how stable and adaptable the ecosystem is, which is a critical factor for the survival and development of human societies (Ma et al 2020, Torrez et al 2023).

Watersheds offer a variety of crucial ecosystem services, including providing water, regulating climate, conserving soil, supporting primary productivity, and maintaining biodiversity (Flotemersch et al, 2016). Unfortunately, these vital systems are facing significant degradation due to climate change and human activities. This deterioration manifests as problems like water shortages, declining water quality, loss of biodiversity, and desertification (Caldwell et al. 2012).

Therefore, comprehensive spatio-temporal assessments of watersheds are essential. These assessments help pinpoint specific parts of the whole watershed that require protection and management interventions (Paetzold et al., 2010). A holistic approach to evaluating these ecosystems is necessary to inform conservation, protection, and management strategies (Hu and Xu, 2018; Zhu et al., 2020), emphasizing the need for tools that can track changes in ecological quality across both space and time.

While comprehending, assessing, and tracking environmental shifts across various ecosystems can be challenging, remote sensing technology offers an efficient solution. This technology enables the effective evaluation and monitoring of changes through its high-throughput and periodic data collection capabilities (Liu et al., 2020, Israel et al. 2024). Moreover, remote sensing provides detailed insights into ecosystem features and components that are often difficult to measure directly on the ground (Shan et al., 2020).

The Remote Sensing Ecological Index (RSEI) offers a robust method for evaluating the ecological health of watersheds and river basins. It accomplishes this by integrating four essential remote sensing-derived variables: greenness (NDVI), wetness (LSM), dryness (NDBSI), and heat (LST) (Xu, 2013; Gao et al., 2021; Yuan et al., 2021).

This versatility makes the RSEI an objective and adaptable tool for monitoring ecological conditions over time and across vast areas (Xu et al., 2019; Gao et al., 2020). Consequently, it has been widely used in recent research to assess the ecological quality of watersheds and river ecosystems, delivering a high-yield output for evaluating environmental conditions (Yao et al., 2022).

This study uses remote sensing datasets to evaluate the ecological quality of the Magbando watershed in Occidental Mindoro, Philippines. The watershed is a complex landscape containing several significant, overlapping land designations. It is home to Mounts Iglit-

Bako Natural Park—a designated ASEAN Heritage Park (1984) and a protected area under the ENIPAS Act of 2018—and the Buhid-Bangon Ancestral Domain. Furthermore, the area includes over 9,000 hectares of reforestation sites through the National Greening Program. The study specifically aims to assess and compare the ecological quality across these protected, ancestral, and reforestation zones, particularly in their areas of overlap.

Methodology

Study Site

The Magbando watershed is located between 120.970790° E 12.428670° N and 121.310694° E and 12.849878° N and measures around 56016.82 hectares. It covers the municipalities of Sablayan, Rizal and San Jose in the province of Occidental Mindoro and small portions of the municipalities of Bongabong and Mansalay in the province of Oriental Mindoro. The figure below shows the location map of the study site.

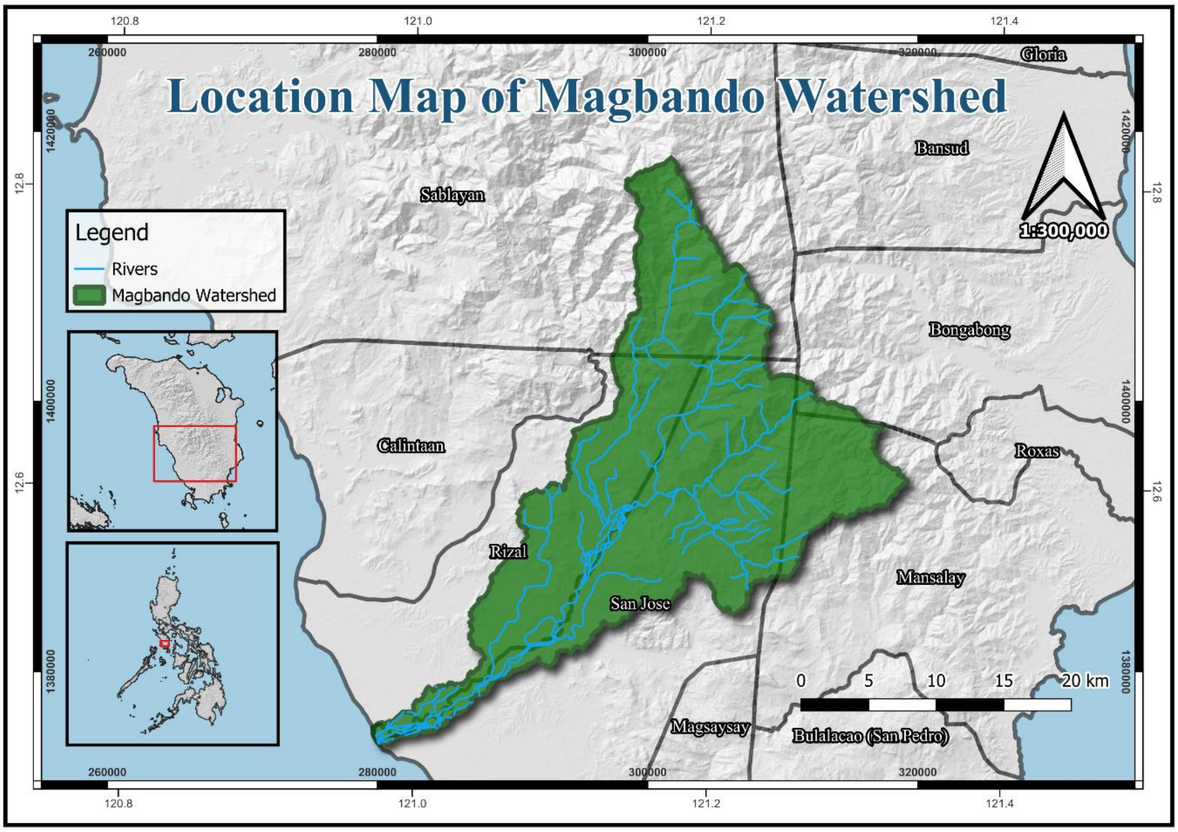

Figure 1. Location map of Magbando Watershed

The watershed peaks at around 2314 meters above sea level and more than 65% of the total area is situated above 18% slope. Most of the watershed experiences Type I based from the Modified Corona Classification System, which means that there are two pronounced seasons, dry from November to April, and wet during the rest of the year, with maximum rain period is from June to September.

Satellite Imagery Collection and Acquisition

The collection and acquisition of satellite imagery were performed within the Google Earth Engine (GEE) platform. Satellite images from Landsat 5, 7, and 8 were used in this study. With datasets already containing atmospherically corrected surface reflectance and land surface temperature datasets present in the GEE catalog, this eliminates the need for image pre-processing. Mosaics were generated within the months of January to May for each of the years of 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, 2019, 2022, and 2025. Cloud masking was also performed within the GEE interface. Various bands in satellite images were used to generate the inputs for the RSEI computation, such as Blue, Green, Red, Near-Infrared (NIR), Shortwave Infrared 1 (SWIR 1), Shortwave Infrared 2 (SWIR 2). These bands were selected because of their effectiveness in capturing different aspects of the landscape, like vegetation health, land surface characteristics, and water bodies, (Xu et al., 2018). The specific wavelengths of the bands for each satellite used are listed in Tables 1 and 2.

Table 1. List of spectral bands used from images obtained by Landsat 5 and 7 and their corresponding wavelength ranges and descriptions

Band Name	**Wavelength Range (µm)**	**Description**
SR_B1	0.45-0.52	Band 1 (blue) surface reflectance
SR_B2	0.52-0.60	Band 2 (green) surface reflectance
SR_B3	0.63-0.69	Band 3 (red) surface reflectance
SR_B4	0.77-0.90	Band 4 (near infrared) surface reflectance
SR_B5	1.55-1.75	Band 5 (shortwave infrared 1) surface reflectance
SR_B7	2.08-2.35	Band 7 (shortwave infrared 2) surface reflectance

Table 2. List of spectral bands used from images obtained by Landsat 8 and their corresponding wavelength ranges and descriptions

Band Name	Wavelength Range (μm)	Description
SR_B2	0.452-0.512	Band 2 (blue) surface reflectance
SR_B3	0.533-0.59	Band 3 (green) surface reflectance
SR_B4	0.636-0.673	Band 4 (red) surface reflectance
SR_B5	0.851-0.879	Band 5 (near infrared) surface reflectance
SR_B6	1.566-1.651	Band 6 (shortwave infrared 1) surface reflectance
SR_B7	2.107-2.294	Band 7 (shortwave infrared 2) surface reflectance

Generation of Remote Sensing Ecological Index Indicators

The indicators used in the generation of the RSEI are heat, dryness, wetness, and greenness which correspond to LST, NDBSI, LSM, and NDVI, respectively. These are derived from the satellite images obtained using Google Earth Engine and are based on the pressure-state-response framework using principal component analysis (PCA) (Hu and Xu, 2018; Xu et al., 2018; Hu and Xu 2019). The indicators are summarized in the table below.

Table 3. List of indices their corresponding descriptions

Index	Acronym	Description
Normalized difference vegetation index	NDVI	An assessment of the greenness and density of an area (Corresponds to greenness) (Xu et al., 2018; Lin et al., 2019)
Index-based built-up index	IBI	A comprehensive indicator for detecting built-up characteristics in remote sensing data. It's been established that higher IBI values correlate with higher Land Surface Temperature (LST) and lower Normalized Difference Vegetation Index (NDVI) values. (Xu, 2008; Zheng et al., 2022)
Soil index	SI	Highlights regions with little to no plant cover, suggesting possible deforestation or land abandonment across the study area. (Hu and Xu, 2019)
Normalized differential build-up and	NDBSI	Serves as an indicator of human-induced land pressures, being derived from a combination of the IBI and SI. (corresponds to dryness) (Hu and Xu, 2019; Zheng et al.,

Index	Acronym	Description
bare soil index		2022)
Land surface temperature	LST	Reflects shifts in temperature as a result of environmental pressures and alterations.(corresponds to heat) (Qi et al., 2019; Hu and Xu, 2019)
Land surface moisture	LSM	Reflects alterations in humidity and wetness in response to environmental shifts. (corresponds to wetness) (Hu and Xu, 2019)
Remote Sensing Ecological Index	RSEI	A composite indicator, RSEI reflects the ecological health of an ecosystem. It synthesizes data from NDVI, NDBSI, LST, and LSM to show how ecosystems are affected by human interventions, environmental status, and climate. (Xu et al., 2018)

Normalized difference vegetation index

Often used to gauge vegetation cover in various ecosystems, the NDVI (Xu and Zhang, 2013; Lin et al., 2019) provides crucial insights. It has a strong correlation with aspects like plant biomass, leaf area, and the general extent and vigor of plant growth in a given region (Goward et al., 2002). Equation 1 shows the formula for NDVI.

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} \tag{1}$$

Normalized differential build-up and bare soil index

The expansion of urban areas and human activities has transformed natural landscapes into built structures and exposed soil, leading to increased dryness and a decline in ecological quality. To comprehensively measure this dryness, the Normalized Difference Built-up and Bare Soil Index (NDBSI) was developed.

It integrates both the Built-up Index (IBI), represented by Equation (2), and the Soil Index (SI), represented by Equation (3), to fully capture the extent of dryness as shown in Equation (4).

$$IBI = \frac{\left\{\frac{2\rho SWIR1}{\rho SWIR1 + \rho NIR}\right\} - \left[\frac{\rho NIR}{\rho NIR + \rho RED} + \frac{\rho GREEN}{\rho GREEN + \rho SWIR1}\right]}{\left\{\frac{2\rho SWIR1}{\rho SWIR1 + \rho NIR}\right\} + \left[\frac{\rho NIR}{\rho NIR + \rho RED} + \frac{\rho GREEN}{\rho GREEN + \rho SWIR1}\right]} \tag{2}$$

$$SI = \frac{[(\rho SWIR1 + \rho RED) - (\rho NIR + \rho BLUE)]}{[(\rho SWIR1 + \rho RED) + (\rho NIR + \rho BLUE)]} \quad (3)$$

$$NDBSI = \frac{IBI + SI}{2} \quad (4)$$

Land surface temperature

To incorporate the impact of heat and temperature on an ecosystem's ecological quality, Land Surface Temperature (LST) values were generated Band 6 from Landsat 5 TM & Landsat 7 ETM+ and bandsets 10 and 11 from Landsat 8 OLI/TIRS . We performed a series of calculations, utilizing properties like solar irradiance and vegetation (as detailed in Equations 5-8), to derive the necessary information from the Landsat 8 TIRS data (Hu and Xu, 2019). The final LST index is represented by Equation (9).

$$L_\lambda = M_L Q_{cal} + A_L \quad (5)$$

$$T_b = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda + 1}\right)} \quad (6)$$

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \quad (7)$$

$$\epsilon = mP_v + n \quad (8)$$

$$T = \frac{T_{sensor}}{\left[1 + \lambda * \frac{T_{sensor}}{\rho}\right] ln * \varepsilon} \quad (9)$$

Land surface moisture

The wetness component, which quantifies land surface moisture from both soil and vegetation cover, is represented by Equation (10). This component was specifically derived using the Tasseled Cap Transformation adapted for Landsat 8 (OLI) imagery (Baig et al., 2014).

$$LSM = (0.1511\rho_{Blue}) + (0.1973\rho_{Green}) + (0.3283\rho_{Red}) + (0.3407\rho_{NIR}) + (-0.7117\rho_{SWIR1}) + (-0.4559\rho_{SWIR2}) \tag{10}$$

Before conducting Principal Component Analysis (PCA), values from the four calculated variables were normalized to a range of [0, 1]. This crucial step was necessary because each indicator had different units and ranges (Xu, 2008), ensuring they could be accurately compared.

The final satellite images used for PCA were then projected into the WGS 84 UTM Zone 51N (EPSG:326541) coordinate reference system (CRS).

Remote Sensing Ecological Index

The Remote Sensing Ecological Index (RSEI) is created by combining four different environmental indices using Principal Component Analysis (PCA). Specifically, it's represented by the first principal component (PC1) derived from this analysis (Geng et al., 2022).

This approach is highly effective for evaluating an environment's ecological quality because each variable's influence on the RSEI is determined by its loading onto PC1, meaning it's not affected by human biases (Xu et al., 2018). The RSEI itself is mathematically defined by Equation (11).

$$RSEI = PCA\big(f(LSM, LST, NDBSI, NDVI)\big) \tag{11}$$

The PCA results were normalized to a scale of 0 to 1. This normalized index is then categorized into five distinct tiers, with each tier representing an increment of 0.2. The table below summarizes interpretations of RSEI results (Yue et al, 2019; Zhu et al., 2020).

Table 4. RSEI values and their interpretation

RSEI Value Range	Interpretation
0 - 0.2	Poor
0.2 - 0.4	Fair
0.4 - 0.6	Moderate
0.6 - 0.8	Good
0.8 - 1.0	Excellent

Generating Zones in the Watershed

The protected, ancestral, and reforestation zones were initially identified within the watershed. The boundaries of Mts. Iglit-Bako Natural Park were obtained from the Biodiversity Management Bureau of the Department of Environment and Natural Resources (DENR-BMB), while the boundaries for the areas within the National Greening Program were obtained from the Forest Management Bureau of the same department (DENR-FMB). On the other hand, the boundaries for the Buhig-Bangon ancestral domain were acquired from the National Commission on Indigenous People. These layers were then overlaid in GIS software and were found to have intersections with one another, generating more zones within the watershed. These zones are summarized in the table below while the figure shows the location of these different zones in the watershed.

Table 5. Management zones within the watershed

Zone	Description
PA only	Mts. Iglit-Bako Natural Park only
CADT only	Buhig-Bangon ancestral domain only
NGP only	National Greening Program areas only
CADT x NGP only	National Greening Program areas within Buhig-Bangon ancestral domain
PA x NGP only	National Greening Program areas within Mts. Iglit-Bako Natural Park
PA x CADT only	Parts of Buhig-Bangon ancestral domain within Mts. Iglit-Bako Natural Park`
PA x CADT x NGP	Areas that are all part of the Mts. Iglit-Bako Natural Park, Buhig-Bangon ancestral domain, and National Greening Program areas at the same time
Outside PA x CADT x NGP	Areas outside the management zones in the watershed

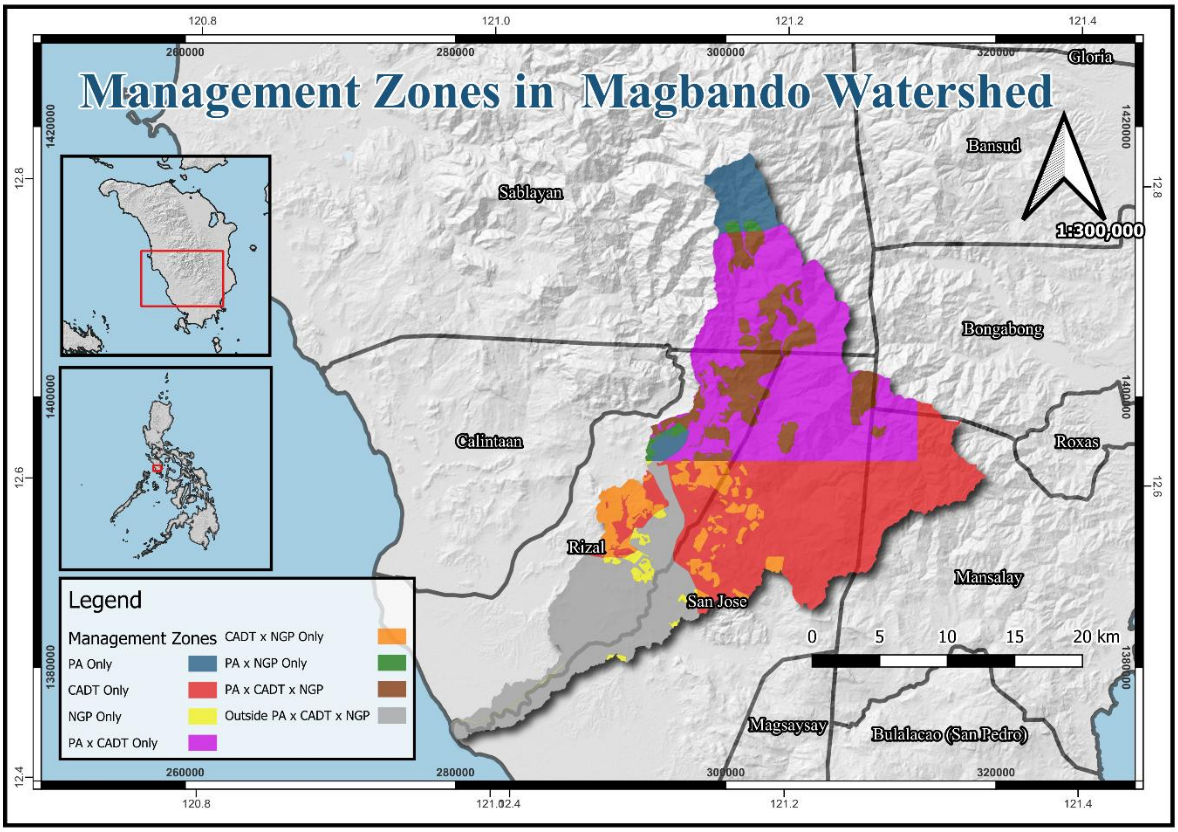

Figure 2. Management zones in Magbando watershed

Zonal Statistics

RSEI values within the different management zones were observed and plotted. Zonal means were computed for each zone for each year mentioned earlier to observe trends in the ecological quality within the different regions. These means were then tabulated and plotted to observe differences.

Results and Discussion

RSEI-Based Ecological Environment Evaluation

In the Magbando watershed, the first principal component (PC1) consistently captures the vast majority of ecological information, making it a robust foundation for building the Remote Sensing Ecological Index (RSEI). Over the period from 1989 to 2025, PC1 accounted for an average of 88.64% of the total variance from all four indicators. The component's contribution peaked in 1998 at 92.68% and was lowest in 2013 at 76.77%. An analysis of the component loadings reveals a stable pattern: greenness (NDVI) and humidity (LSM) consistently exerted a positive influence, while heat (LST) and dryness (NDBSI) had a negative impact. Greenness, with an average loading of 0.50, contributed slightly more than humidity (0.44), while dryness, with an average loading of -0.61, had a greater negative impact than heat (-0.35). Therefore, using PC1 to construct the RSEI is a practical and objective method that avoids the potential bias of subjective weighting. The table below shows the summary of the results of the principal component analysis for the watershed.

Table 5. Results of principal component analysis from 1989 to 2025

Year	PCA Results				
	Loading of LSM	Loading of LST	Loading of NDBSI	Loading of NDVI	Percentage of Covariance Eigenvalue of PC1 (%)
1989	0.33	-0.35	-0.35	0.56	89.36
1992	0.45	-0.33	-0.63	0.53	87.67
1995	0.52	-0.24	-0.62	0.53	90.02
1998	0.50	-0.29	-0.62	0.54	92.68
2001	0.40	-0.33	-0.68	0.52	88.87
2004	0.51	-0.34	-0.62	0.50	87.01
2007	0.43	-0.32	-0.66	0.53	91.37
2010	0.49	-0.37	-0.60	0.52	90.59
2013	0.18	-0.32	-0.59	0.72	76.77
2016	0.45	-0.46	-0.65	0.40	90.87
2019	0.47	-0.43	-0.64	0.43	90.51
2022	0.46	-0.38	-0.69	0.41	87.18
2025	0.50	-0.43	-0.64	0.38	89.46
Average	0.44	-0.35	-0.61	0.50	88.64

It was observed that for the whole watershed, the RSEI values can be classified as mostly moderate (RSEI between 0.4-0.6) to good (RSEI between 0.4-0.6), with portions having fair classification (RSEI between 0.2-0.4) with the lowest recorded values for the average RSEI being in 1992 and 2007, measuring at 0.32 Many areas with low RSEI values were not able to reach a "good" RSEI values over the course of the period, most especially in the latter part of the study. The figures below show the maps of the RSEI values for year 2025 and the previous periods.

This may be attributed to human activities during and after the COVID-19 pandemic. Israel et al (2024) found that in other areas in the Philippines, forest degradation and deforestation is still rampant, with several drivers including: infrastructure development, timber extraction, small-scale mining, charcoal making, upland farming, and wildlife poaching.

In comparison, Soriano (2025), in their study, also used the RSEI to assess the ecological quality of Abra River Basin, and found that during the dry months, the mean RSEI for the river basin is at least 0.60, which is also considered good, which is a bit better than the Magbando watershed. Zhang et al (2024) also used RSEI to assess ecological quality of the Yanhe watershed in China and found an upward trend in the past 2 decades. They also observed similar results in the principal component analysis of the components in the index.

Meanwhile, Israel and Bantayan (2021) also made use of NDVI derived from satellite imagery to assess vegetation quality of protected areas, ancestral domain, and NGP areas. Their study found that highest NDVI values were consistently found within protected areas and ancestral domain of different areas in the Philippines.

The figures below show the map of the RSEI values for year 2025, the maps of RSEI for years 1989 to 2004, and the maps of RSEI for years 2007 to 2022.

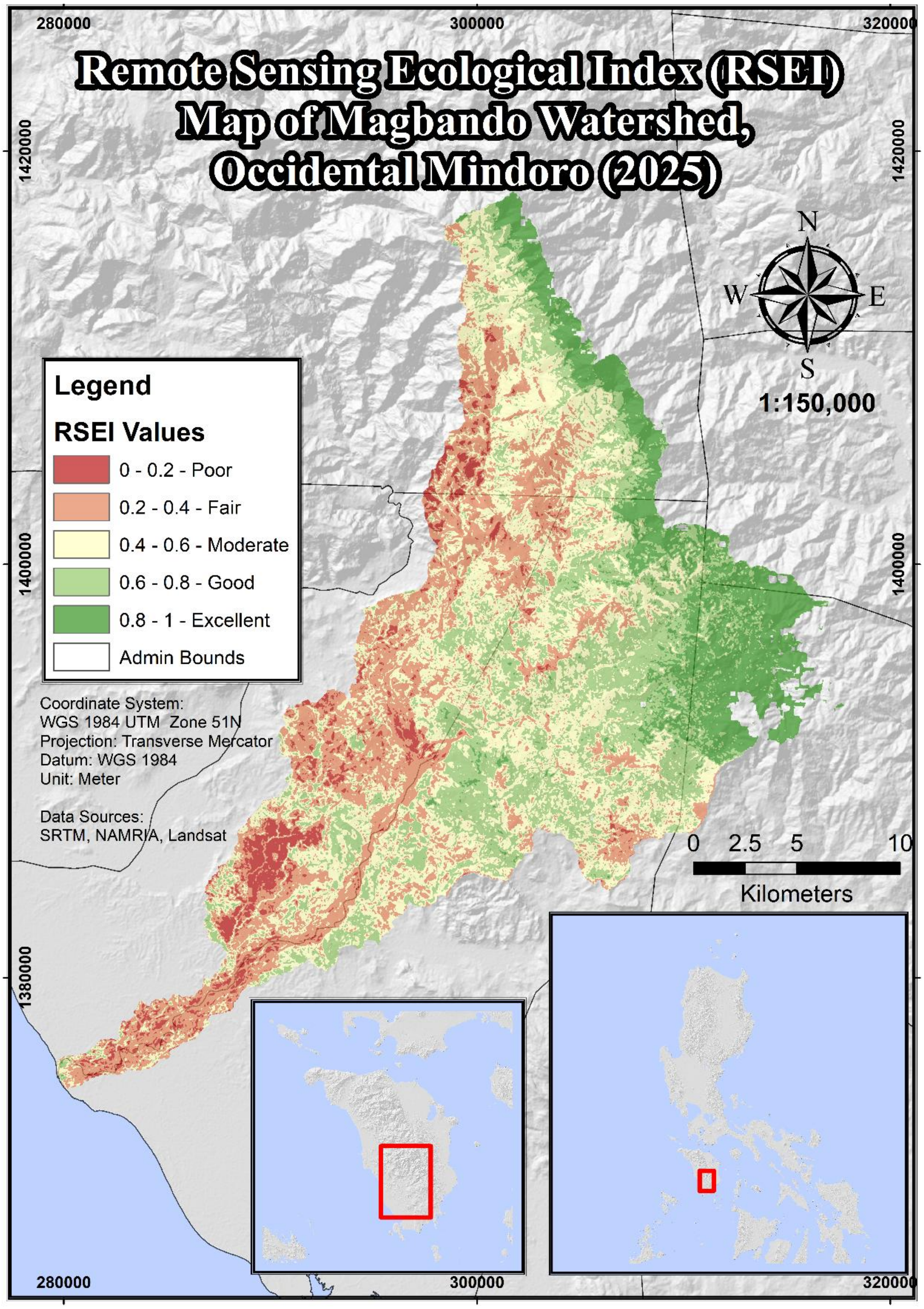

Figure 3. Map of Remote Sensing Ecological Index (RSEI) of Magbando watershed for year 2025

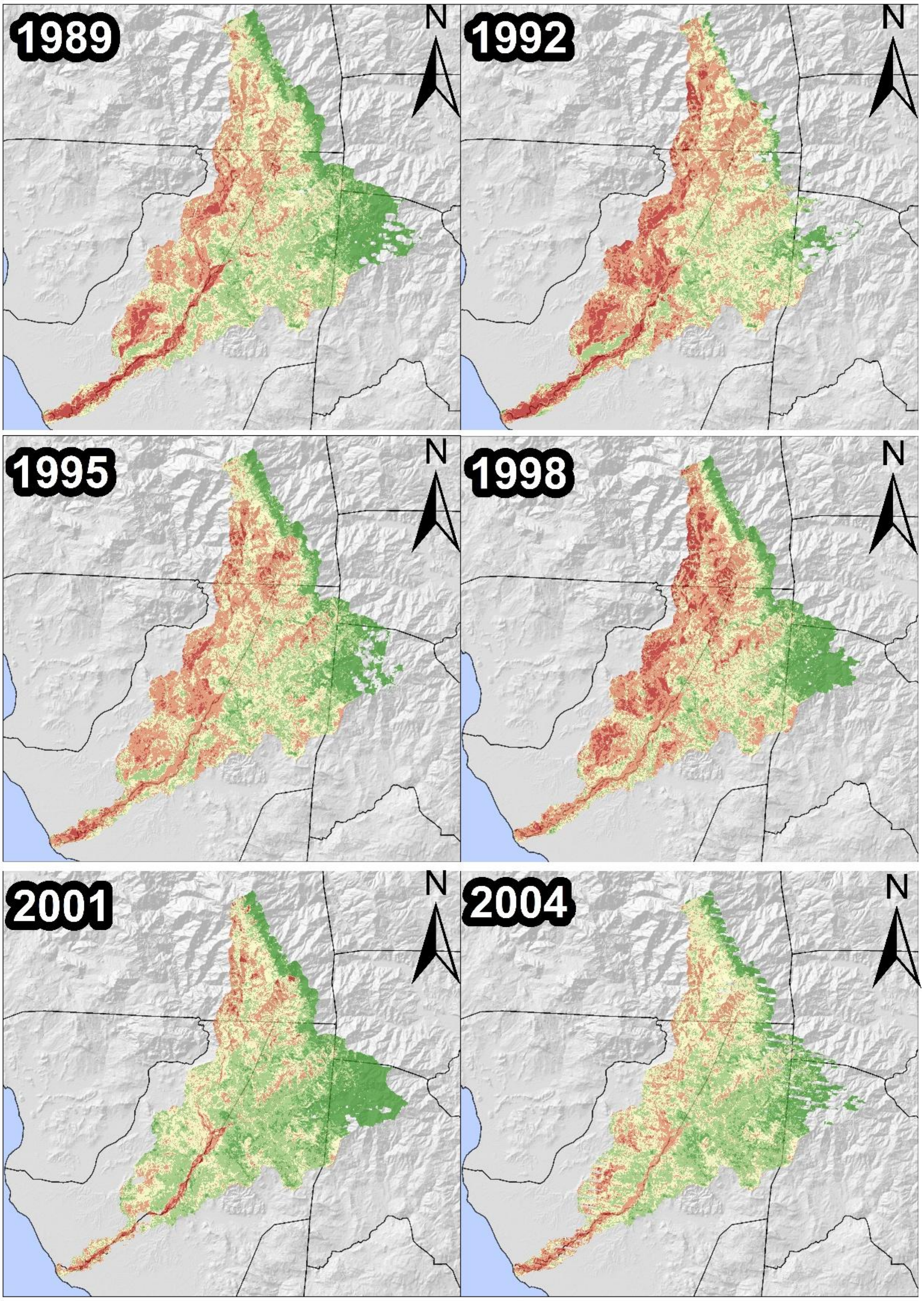

Figure 4. RSEI map of Magbando watershed for years 1989, 1992, 1995, 1998, 2001, and 2004

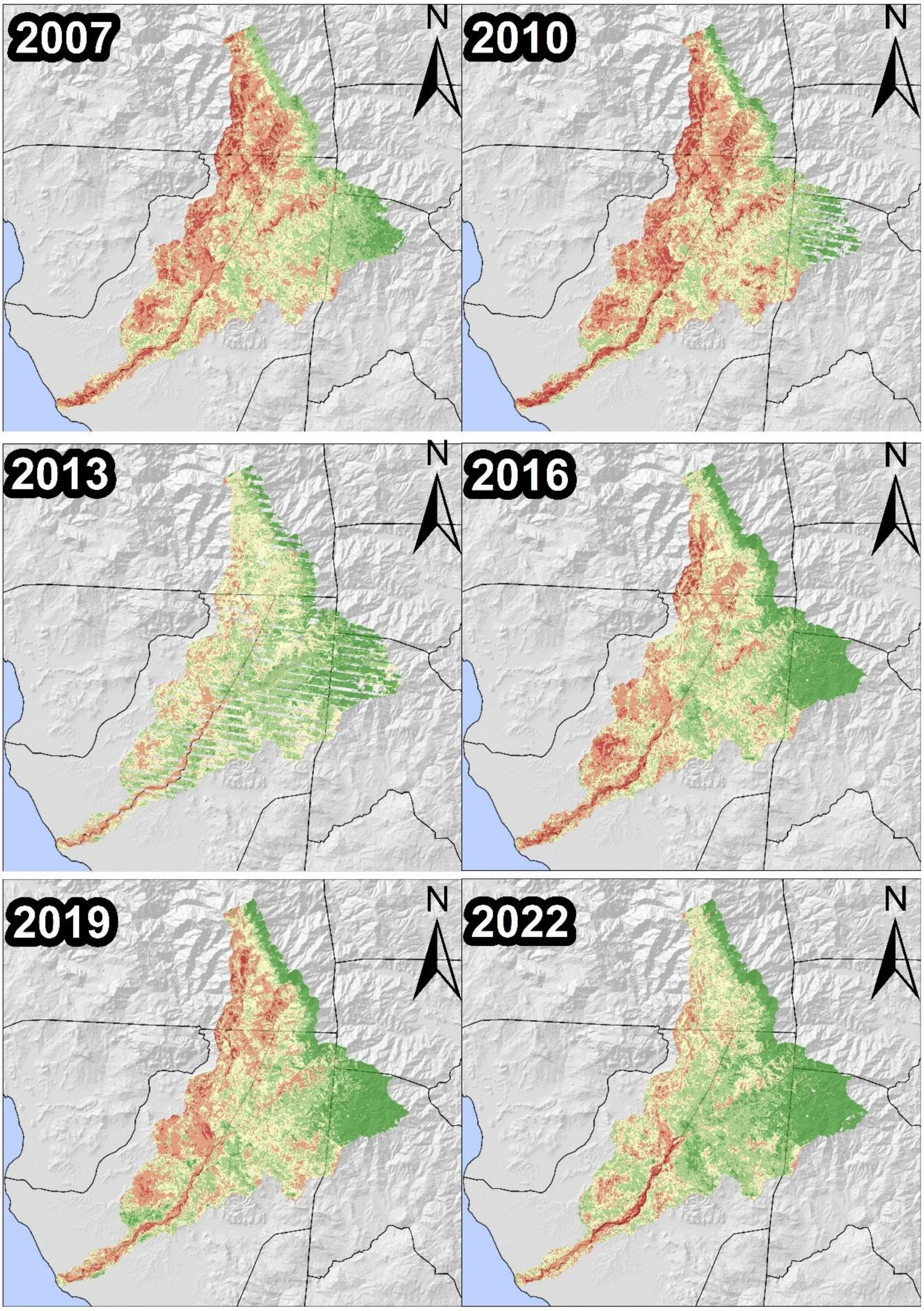

Figure 5. RSEI map of Magbando watershed for years 2007, 2010, 2013, 2016, 2019, and 2022

Comparing Zonal Averages of Different Management Zones

Analysis of zonal RSEI means revealed that areas within the ancestral domain only, protected areas only, and areas that are both part of the aforementioned zones were found to have the highest values, with the areas inside the ancestral domain having an average RSEI value of 0.62, with highest value of 0.71 observed in 2022. On the other hand, the areas part of the protected area only was observed to have an average RSEI value of 0.56, with highest value observed of 0.62 observed in 2016 and 2022. Meanwhile, regions part of both the protected areas and ancestral domain were also found to have a relatively high average RSEI value of 0.55, with highest value of 0.66 observed in 2022.

Areas within the implementation of the National Greening Program were observed to have relatively lower RSEI values before the implementation of the program in 2010, with the highest average RSEI value of 0.61 observed in 2001 within NGP areas inside the ancestral domain. Highest RSEI value within NGP areas were also observed within areas also inside the ancestral domain, peaking at 0.65 in 2016. NGP areas inside the ancestral domain were also found to have the highest average RSEI values among all zones with NGP, with an average value of 0.48. The table below shows the summary of mean RSEI values within different zones while the graph shows the trend of the values in the identified periods.

Year	Zonal RSEI Values							
	PA only	CADT only	NGP only	CADT x NGP only	PA x NGP only	PA x CADT only	PA x CADT x NGP	Outside PA x CADT x NGP
1989	0.57	0.63	0.38	0.46	0.39	0.56	0.45	0.38
1992	0.44	0.55	0.32	0.38	0.32	0.45	0.37	0.34
1995	0.58	0.60	0.39	0.41	0.40	0.52	0.41	0.39
1998	0.50	0.59	0.37	0.38	0.32	0.50	0.35	0.36
2001	0.60	0.72	0.62	0.61	0.54	0.61	0.52	0.52
2004	0.60	0.67	0.55	0.54	0.52	0.60	0.50	0.47
2007	0.47	0.56	0.41	0.38	0.32	0.47	0.47	0.38
2010	0.47	0.51	0.38	0.36	0.34	0.46	0.34	0.37
2013	0.61	0.68	0.58	0.56	0.55	0.63	0.55	0.52
2016	0.62	0.65	0.43	0.65	0.49	0.59	0.48	0.37
2019	0.56	0.64	0.46	0.44	0.38	0.57	0.43	0.45
2022	0.62	0.71	0.55	0.60	0.54	0.66	0.57	0.45
2025	0.60	0.61	0.47	0.44	0.48	0.58	0.46	0.38
Mean	0.56	0.62	0.45	0.48	0.43	0.55	0.46	0.41

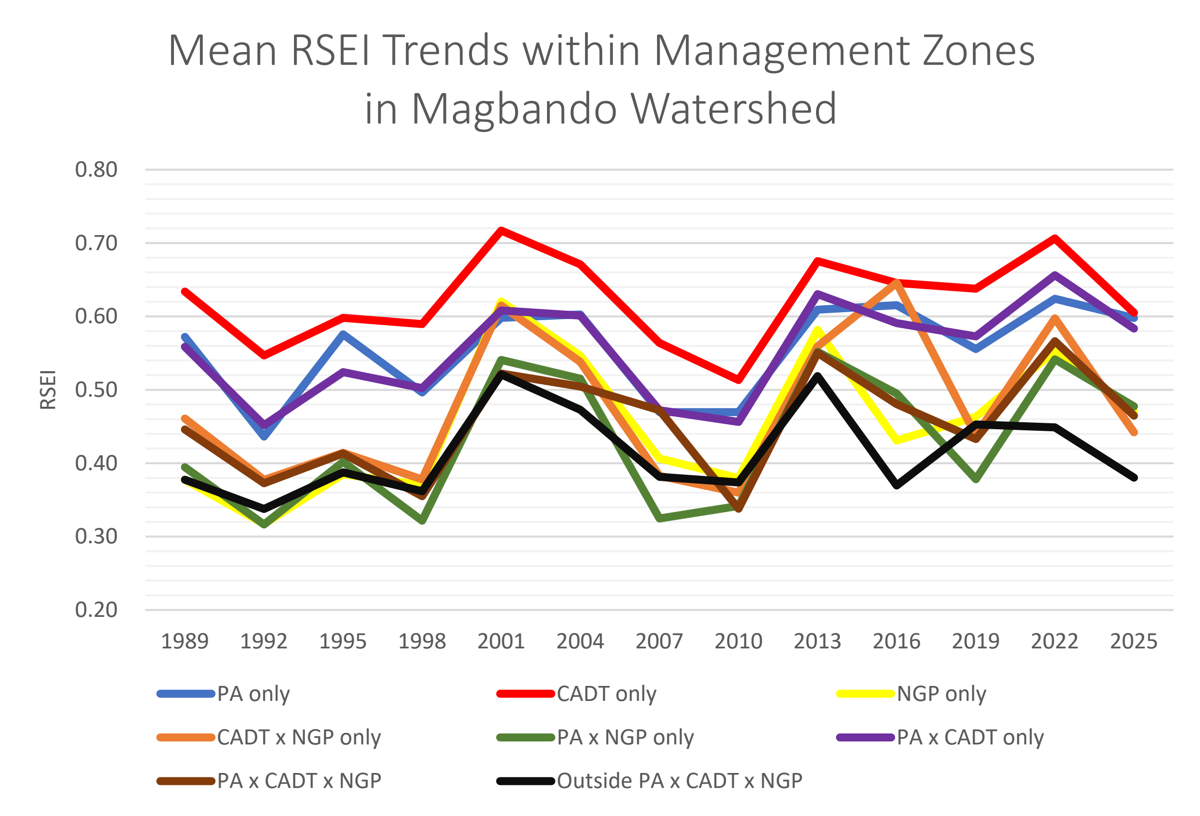

Figure 6. Mean RSEI Trends within Management Zones

Conclusion and Recommendation

Satellite data, especially when accessed through cloud platforms like Google Earth Engine (GEE), is highly effective for tracking shifts in a country's ecosystem quality. GEE, with its vast data repository, significantly simplifies the analysis of changes in vegetation cover over time. This platform streamlines the processing of large, time-series satellite imagery, eliminating the need for extensive local data storage.

The Remote Sensing Ecological Index (RSEI) model, which integrates four key sub-indices—Normalized Difference Vegetation Index (NDVI), Normalized Differential Build-up and Bare Soil Index (NDBSI), Land Surface Moisture (LSM), and Land Surface Temperature (LST)—offers a swift and precise method for evaluating and monitoring the ecological health of expansive areas like river systems and their watersheds. A significant advantage of RSEI is its objective weighting of each sub-indicator, ensuring an accurate reflection of the ecosystem's ecological status.

The application of the RSEI model shows that areas in the Magbando watershed under specific stewardship have the highest ecological quality. The purely ancestral domain exhibited the best conditions (average RSEI of 0.62), outperforming the purely protected area (0.56) and the zone where the two overlap (0.55). Even for National Greening Program sites, the highest mean RSEI value (0.51) was found where projects intersect with the ancestral domain. These findings contribute to an overall assessment of the watershed as having a moderate to good ecological quality.

The spatial variation in ecological quality across the area is influenced by factors such as human activity, weather patterns, physical landscape features, and the health of biological components. It's important to note that while the specific RSEI values derived for the Magbando watershed are unique to this area and shouldn't be directly applied elsewhere, the methodology itself is broadly applicable for assessing the ecological quality of other ecosystems. Further studies are highly encouraged to validate results generated from this study, especially studies that look at the specific management strategies within different programs. Continuous monitoring of our watersheds will ensure the continuous provision of the ecosystem services needed by human societies.

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