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AN EXPLORATION OF THE DATA ON GLOBAL WARMING POTENTIAL AND ITS CORRELATES FOR THE CITY OF NAGA AND THE PROVINCE OF CAMARINES SUR

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ABSTRACT: *This study examined tree cover loss and its socio- economic factors in Naga City and Camarines Sur, Philippines, highlighting the urgent need to monitor forest changes amid rapid environmental shifts. Traditional ground- based methods in the region face limitations due to fragmented geography and limited resources. To address this, satellite imagery from Global Forest Watch (GFW) was used to assess tree cover loss from 2000 to 2020. The study introduced the Forest Cover Performance Index (FCPI) to compare forest conservation performance across local government units. This index was correlated with the Cities and Municipalities Competitiveness Index (CMCI), focusing on pillars like Economic Dynamism, Government Efficiency, Infrastructure, and Resiliency. Statistical analyses included Pearson correlation and non- parametric tests, with significance set at $p < .05$. Results showed a loss of over 14, 854 hectares of tree cover, producing carbon emissions equivalent to 8, 140.41 kilotonnes of CO_2 e, known as the Global Warming Potential (GWP). Tree cover gains during the same period were minimal. Significant positive correlations were found between FCPI and the CMCI pillars of Economic Dynamism ($p = .048$) and Infrastructure ($p < .001$), especially with sub- indicators such as Financial Deepening, Employment Generation, Local Economic Growth, Size of Local Economy, Productivity, and Safety- compliant Businesses. Conversely, educational infrastructure showed a significant negative correlation with FCPI. These findings highlight the usefulness of remote sensing for environmental monitoring, reveal the extent of forest loss and its climate impact, and emphasize the importance of economic and infrastructure development as key drivers of deforestation. The study recommends integrating environmental considerations into local development plans, prioritizing forest protection, strengthening monitoring systems, improving data quality, and institutionalizing the FCPI as a policy tool for informed decision- making.*

Keywords: *Forest carbon emission, Global warming potential, Tree cover, Climate change*

INTRODUCTION

Remote sensing involves collecting measurements and making observations from afar, without direct physical contact. An early example is sonar, developed over a century ago, which mapped the ocean floor by measuring how long it took sound waves to travel and reflect back. This enabled the calculation of distance and aided in interpreting the ocean's shape and depth.

Another common method is satellite imagery, along with photos taken from airplanes or drones. These methods analyze how objects reflect light to identify and examine features on the Earth's surface, including vegetation, water, and buildings. When sunlight hits an object, some light is reflected while some is absorbed, depending on the material. The reflected visible light appears to us as color. For example, chlorophyll in plants reflects green light while absorbing red and blue, which are used in photosynthesis. This is why most plants look green. White reflects all light, while black absorbs it, which explains why wearing black on hot days feels warmer.

Every object has a unique reflectance, or its ability to reflect light. High-resolution images can capture this property. Using spectral signature detection techniques, it is possible to distinguish between different materials. For example, the reflectance of real grass differs from that of synthetic grass, enabling identification through image analysis.

In Naga City and Camarines Sur, agencies like the Department of Environment and Natural Resources and the Sagip Kalikasan Task Force are tasked with environmental protection. However, limited personnel and resources make it hard to monitor remote or rugged areas. This not only impacts enforcement but also restricts data collection. Field surveys, while helpful, cannot fully assess forest conditions in inaccessible regions.

Remote sensing provides an effective way to address these challenges. With satellite imagery and aerial surveys, it becomes possible to evaluate forests over vast, difficult-to-access areas with greater precision. In addition to mapping, remote sensing can identify patterns of deforestation and environmental stressors, offering valuable insights for resource management and conservation.

This study focused on describing the current condition of forests in Naga City and Camarines Sur and identifying the factors related to that state. It aimed to evaluate the current state of forests in these areas and investigate the factors that influence forest health. Understanding how specific variables relate to forest health can lead to better decision-making and more effective management practices.

To address the first objective, satellite imagery was used to assess forest conditions. Key indicators, including vegetation cover, forest health, and temporal changes, were analyzed to establish a baseline for monitoring. The study also measured tree cover loss and its equivalent Global Warming Potential (GWP), highlighting the environmental impact of deforestation. For the second objective, the study investigated human-driven and environmental stressors related to economic activity. By linking these with observed forest conditions, it identified patterns that contribute to degradation or sustainability. This provided insights into the causes of tree cover loss and its broader ecological and socio-economic effects, helping to improve understanding of forest dynamics to support informed policymaking and enhance conservation efforts in Naga City and Camarines Sur.

The research also examined the relationship between forest cover and local economic competitiveness. It investigated how the Forest Cover Performance Index (FCPI) related to aspects of the Cities and Municipalities Competitiveness Index (CMCI), such as economic dynamism, government efficiency, infrastructure, and resiliency. Understanding these links can help shape policies on sustainable land use, climate response, and conservation.

This study, however, was limited in scope to examining tree cover loss and GWP data, along with their related factors, for the City of Naga, the various municipalities, and the component city of the Province of Camarines Sur. The main goal was to produce a detailed report on deforestation in these areas and to investigate possible socio-economic links. Due to this specific focus, certain limitations were unavoidable. While every effort was made to ensure the data and methods' reliability and relevance, the following constraints were recognized.

Limitations Related to Data Characteristics

The study faced several data-related limitations. Temporal inconsistencies in GFW data, caused by changing algorithms and sensor upgrades from 2000 to 2020, affected year-to-year comparability. The 30-meter resolution and tree cover definition may have missed small-scale disturbances. A critical limitation of the GFW dataset is its inability to distinguish between different types of tree cover. The Hansen et al. (2013) dataset defines a tree based solely on structural criteria (height ≥5 meters regardless of crown diameter, or height 3–5 meters with a minimum crown diameter of 5 meters), with no differentiation between natural forests and plantation forests (e.g., oil palm, rubber, or timber plantations), native tree species and introduced/ exotic species, primary (old-growth) forests and secondary regrowth, or natural regeneration and human-led reforestation efforts.

This means that when the data reports tree cover gain, it cannot be assumed to signify ecological restoration or biodiversity conservation. A gain could equally represent the expansion of a monoculture plantation, which offers significantly different ecosystem services (carbon storage, habitat provision, water regulation) than a naturally regenerating forest. Similarly, tree cover loss in one area might be partially offset by plantation establishment elsewhere, but the dataset cannot determine whether such replacement is ecologically equivalent.

For the purposes of this study, this limitation means that the Forest Cover Performance Index (FCPI) should be interpreted strictly as a measure of tree cover quantity, not forest quality or ecological integrity. While the FCPI usefully tracks whether LGUs are maintaining or losing tree cover overall, it cannot determine whether that cover represents biologically diverse, resilient forest ecosystems or simplified agricultural tree crops. This distinction is crucial for policymakers: maintaining tree cover through plantations is not the same as conserving natural forests, and the two should not be conflated in environmental planning or performance assessment.

Additionally, CMCI indicators depend on self-reported data from local governments, which may introduce bias or inaccuracies.

Limitations Related to the Scope and Focus of the Analysis

The study faced limitations in scope and focus. It excluded the 'Innovation' pillar of the CMCI from the analysis. The Innovation pillar, which measures local government units' capacity for innovation through indicators like digitalization, local patents, and technology adoption, was introduced by the Department of Trade and Industry only in 2022. Since this study's timeframe covers 2000-2020, Innovation pillar data are unavailable for most of the period. Including only post-2020 Innovation data would create a temporal mismatch with the tree cover loss data and would be methodologically inappropriate for correlation analysis spanning two decades.

It is important to emphasize, however, that the absence of the Innovation pillar does not undermine the validity or completeness of the findings presented. The four pillars that were analyzed represent the core aspects of local competitiveness that have been consistently measured throughout the study period.

Moreover, correlation analysis showed associations but did not prove causation, which leaves open the possibility of unmeasured confounding factors. Also, the results were limited to Naga City and Camarines Sur, reducing their general applicability.

Simplified Representation of Complex Dynamics

The analysis simplified the complicated relationship between forest cover and socio-economic indicators. While it provided valuable insights, the statistical methods used couldn't fully reflect the complex interactions driving environmental change and growth.

Addressing these limitations offers valuable opportunities for future research. Extending the temporal scope of data collection, adding more socio-economic indicators such as the 'Innovation' pillar, and using more advanced analytical methods like multivariate analysis or structural equation modelling could provide deeper insights into the complex interactions between environmental and socio-economic factors. Additionally, incorporating qualitative data through field studies or stakeholder interviews could offer contextual insights that quantitative analysis alone might miss. By considering these approaches, future studies can develop a more comprehensive understanding of the factors influencing global warming potential and create more targeted strategies for environmental management and policymaking.

METHODOLOGY

This study combined geospatial, demographic, and economic data to evaluate forest cover and its drivers in Naga City and Camarines Sur.

Data Sources

The main data source was Global Forest Watch (GFW), an open-access platform launched in 2014 by the World Resources Institute. GFW offers near-real-time satellite-based forest-monitoring tools. Three datasets were used:

- Tree Canopy Cover (TCC) from Hansen et al. (2013), with a 5-meter height threshold and 30-meter resolution.
- Tree Cover Height (TCH) from Potapov et al. (2020), using a 3-meter height threshold and 20–25% canopy cover.
- Tropical Tree Cover (TTC) from Brandt et al. (2022), with 10-meter resolution and variable definitions that combine height and canopy diameter.

These datasets were accessed via the GFW interactive map. Data included forest extent in 2010, tree cover loss from 2010 to 2023, tree cover gain from 2000 to 2020, percentage of remaining forest, and related CO_2 emissions (Global Warming Potential). Additional data were obtained from the 2020 Census of Population and Housing (Mapa, 2022) and the Cities and Municipalities Competitiveness Index (CMCI), developed by the National Competitiveness Council and the Department of Trade and Industry. CMCI scores were based on five equally weighted pillars: economic dynamism, government efficiency, infrastructure, resiliency, and innovation, each with 10 sub-indicators.

It should be noted that the GFW dataset defines tree cover based solely on structural criteria and does not differentiate between natural forests, plantations, or other forest types. This study uses the dataset as intended by its creators, as a measure of tree cover extent and change over time, while recognizing that it does not address forest quality or ecological composition.

Data Processing and Preparation

Relevant datasets were downloaded, filtered, and cleaned to remove duplicates and format inconsistencies. Data specific to Naga City and municipalities in Camarines Sur were retained. Adjustments were made to account for water bodies (e.g., Lake Buhi and Lake Bato) that GFW reported separately. The GFW and CMCI datasets were merged using municipality names as the key.

Microsoft Excel (Office 365 Build 16.0.18706.42301) was utilized for data management, calculations, and visualizations. Excel's RANK.AVG() function was used to prepare data for correlation analysis. The Statistics Kingdom website provided the Shapiro-Wilk test to evaluate the data's normality.

Analytical Framework

Forest Cover Performance Index (FCPI)

The FCPI was calculated as the ratio of average annual tree cover loss (2000–2020) to the initial forest cover in 2000. A score of 100 indicated no loss. This standardized measure, based on Yale's Environmental Performance Index (EPI), allowed for comparisons across LGUs.

Correlation Analysis

Pearson correlation was employed to analyze linear relationships between geographic or economic variables and tree cover loss. Shapiro-Wilk tests were conducted to evaluate the distribution of the variables.

For normally distributed data, Pearson's r was used. Conversely, Spearman's ρ and Kendall's τ were employed when the data were non-normal to examine monotonic relationships. These tests evaluated correlations between FCPI and CMCI pillars and sub-indicators. Statistical significance was defined as $p < .05$. For significant findings, 95% confidence intervals were calculated using Fisher's Z-transformation.

This multi-source, statistically rigorous approach allowed for a thorough analysis of forest trends and their socio-economic factors in the study area, establishing a solid basis for the findings and policy recommendations.

RESULTS AND DISCUSSIONS

To enable accurate monitoring of trees in urban areas, agricultural lands, and open-canopy and dry-forest ecosystems, Brandt et al. (2022) derived tropical tree cover data from multi-temporal convolutional neural network models applied to Sentinel optical and radar imagery at 10-meter and half-hectare resolutions. This dataset shows that approximately 357,422 hectares are under tropical tree cover in Camarines Sur and the City of Naga, with 322,757 hectares (90.31%) classified as forest, 11,381 hectares (3.18%) as grassland, 9,642 hectares (2.70%) as settlement, 6,382 hectares (1.79%) as wetland, 5,366 hectares (1.50%) as cropland, and 1,894 hectares (0.53%) as other types of tree cover.

Forest Cover Performance Index as Tree Cover Proxy

Tree cover across cities and municipalities in Camarines Sur varies greatly in both size and type. Forests are the main form of tree cover in most areas, supplemented by grasslands, settlements, wetlands, croplands, and other small vegetation types.

To enable comparison between cities and municipalities without being biased by differences in their land sizes or the advantage of larger, more forested areas, the approach used by the Yale Center for Environmental Law & Policy in developing the Environmental Performance Index (EPI) was adopted. Instead of using multiple factors to create an index similar to the EPI, this study used a simplified version that considers tree cover loss as the ratio of the average annual tree cover loss over 20 years, from 2000 to 2020, to the forest cover extent in 2000. This results in an index score where 100 indicates no tree cover loss, and lower scores indicate worse performance. This measure will be called the Forest Cover Performance Index (FCPI). Table 1 shows the FCPI for municipalities and cities in Camarines Sur, ranked from the LGU with no tree cover loss in the last 20 years, i.e., FCPI of 100.00, to the LGU with the most loss, Ragay, with an FCPI of 65.61.

Table 1 is based on GFW tree cover data from 2000 to 2020, using a threshold of greater than 30%. This means that for an area to be considered as having tree cover, more than 30% of the land must be covered by tree canopies.

Table 1. Forest Cover Performance Index for the Cities and Municipalities in the Province of Camarines Sur (2000-2020)

Rank	Name of LGU	FCP Index
1	Camaligan	100.00
2	Gainza	100.00
3	Cabusao	96.83
4	Milaor	96.54
5	Magarao	95.06
6	Nabua	94.03
7	Canaman	92.42
8	Caramoan	90.03
9	Sipocot	89.82
10	San Jose	89.60
11	Bula	89.22
12	Tigaon	86.30
13	Garchitorena	86.05
14	Sagnay	85.03
15	Ocampo	84.89
16	Siruma	84.83
17	Presentacion	84.76
18	Pamplona	84.53
19	Del Gallego	81.95
20	Lupi	81.46
21	Iriga City	80.77
22	Bato	80.28
23	Tinambac	79.87
24	Libmanan	79.48
25	Balatan	79.14
26	Pili	79.03
27	Goa	78.90
28	Bombon	78.87
29	Baao	78.52
30	Buhi	77.10
31	Pasacao	76.50
32	Lagonoy	75.45
33	San Fernando	73.18
34	Naga City	71.60
35	Minalabac	68.19
36	Calabanga	67.99
37	Ragay	65.61

For example, in a 1-hectare area, at least 0.3 hectares should be covered by tree canopy, which is measured by the vertical projection of the tree canopies onto the ground, including foliage and branches that form a cover over the land surface. In this dataset, a tree was defined by both height and crown diameter. Woody vegetation taller than 5 meters, regardless of crown diameter, or between 3 and 5 meters with a minimum crown diameter of 5 meters, was considered a tree, with no distinction between plantation and non-plantation trees. It is important to note that between 2000 and 2020, improvements were made to the data collection methods. The original baseline was the tree canopy cover dataset developed by Hansen et al. (2013), which was likely the best available spatial data on forest changes, based on 30-meter-resolution imagery. It had global coverage, spanned multiple decades, and was updated annually. Improvements to the algorithm introduced in 2015 enhanced loss detection. Additionally, improved sensors on Landsat 8 allowed for better detection of tree cover loss. The baseline used available images from Landsat 5 and 7 in 2013 and from Landsat 8. Therefore, comparisons of data between years should be approached with caution, if possible.

Loss and Gain of Tree Cover

Between 2000 and 2020, the Province of Camarines Sur lost about 13,640 hectares of tree cover. That amount is larger than the combined land areas of the City of Naga and the neighboring towns of Milaor, Gainza, and Camaligan. This can be visualized by imagining removing all trees and vegetation covering at least 9 square meters of soil in a 30-square-meter block throughout Naga and the three municipalities.

A Pearson correlation analysis was performed to explore the relationship between geographic size and average annual tree cover loss across two cities and 35 municipalities in the province. The findings show a strong, positive correlation, $r(35) = .89$, $p < .001$, indicating that larger local government units tend to experience more tree cover loss. Because the p-value (1.21×10^{-13}) is extremely small, the correlation is highly significant, suggesting the relationship is very unlikely due to chance.

The cities of Naga and Iriga showed

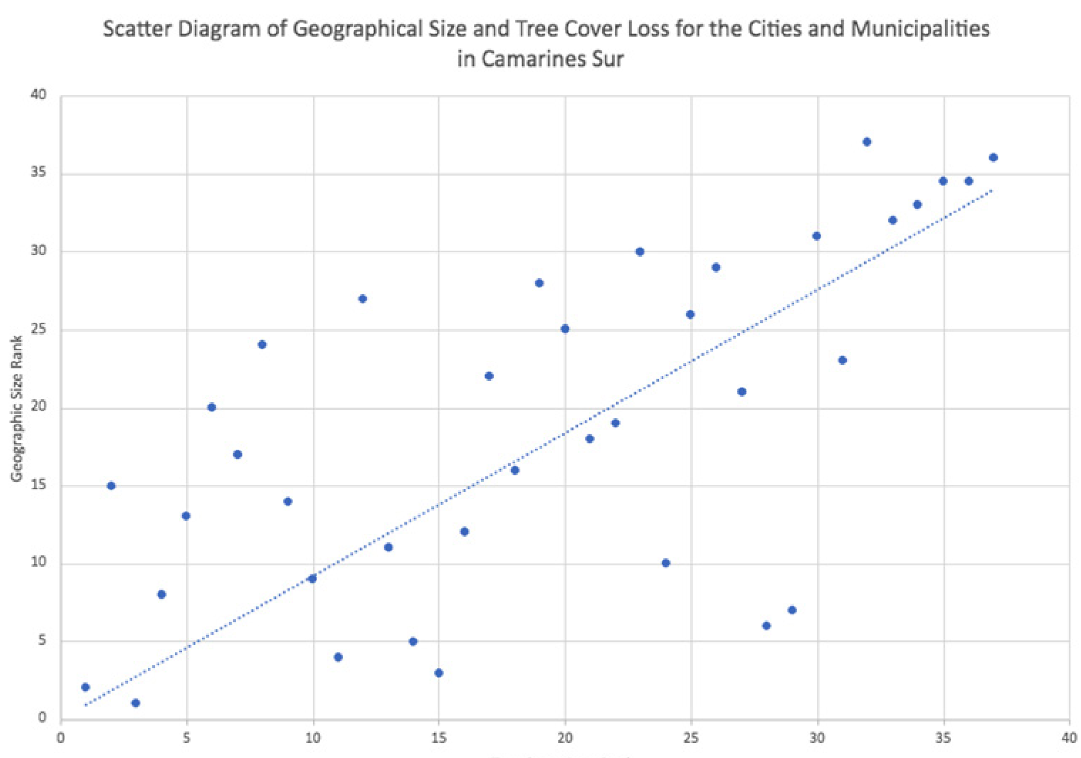

Figure 1. Scatter diagram of the tree cover loss rank of the LGUs against their geographic size rank, with a regression line showing a positive linear relationship

lower-than-average tree cover loss across all LGUs. This is probably because cities started with less tree cover than municipalities, as urban development has replaced much of their natural forests. With fewer forests to begin with, cities have less potential for additional tree cover loss compared to municipalities with larger rural and forested areas. A Pearson correlation analysis was performed to confirm this and to examine the relationship between the amount of forest cover and the average yearly tree cover loss for the LGUs in the province. The results reveal a strong, positive correlation, $r(35) = .90$, $p < .001$, indicating that LGUs with more forest cover tend to lose more trees. Since the p-value (1.71×10^{-14}) is extremely small, the correlation is highly significant, meaning the relationship observed is unlikely due to chance. The cities of Naga and Iriga ranked 28th and 14th in terms of existing tree cover size, based on the 2000 baseline.

The direct relationship between the geographic size of cities and municipalities and the corresponding tree cover loss is illustrated in Figure 1. The LGUs were ranked from largest to smallest, with the largest ranked first and the smallest 37th. Similarly, the LGU with the greatest tree cover loss was ranked first, while the LGU with the least tree cover loss was ranked 37th. It is evident that those with high geographic area rankings also tend to have high tree cover loss rankings.

Tree cover loss results in an equivalent carbon dioxide emission, or a Global Warming Potential (GWP), measured in kilotons of CO2e. The 14,854 hectares of tree cover lost in Camarines Sur over the past two decades equates to 8,140.41 kt of CO2e. To put this into perspective, according to EPA-420-F-23-014 by the Office of Transportation and Air Quality (EPA, 2023), the average annual tailpipe CO2 emissions of a typical passenger vehicle are about 4.6 metric tons. Tree cover loss in Camarines Sur is comparable to the tailpipe emissions from 1,769,565 passenger cars in a single year.

To provide further context, Ritchie and Rosado (2025) estimated that the average annual carbon footprint of an individual in the Philippines is 1.3 metric tons. This means that the GWP for the tree cover loss in Camarines Sur over the last 20 years is equivalent to the carbon footprint of 6,261,854 people, which is three times the combined population of the entire City of Naga and the Province of Camarines Sur.

Despite the province's significant tree cover loss, there is a small gain of up to 751 tons of CO2 sequestration. Although this only accounts for 0.01% of the total loss, it is still worth noting. Figure 2 illustrates what this tiny gain involves.

The primary contributors to the increase in tree cover for Camarines Sur are the municipalities of Del Gallego (11%), Lupi (10%), Libmanan (9%), Sipocot (9%), Goa (7%), Ragay (6%), Tinambac (4%), Garchitorena (4%), and Siruma (4%). Other municipalities account for the remaining 36%, but only in small amounts. These same municipalities also contribute the largest losses of tree cover. In any case, it is important to note that tree cover loss in the province continues to surpass tree cover gain, with loss rates far exceeding gains by more than 100%. Without significant intervention and sustainable management practices, this downward trend is likely to continue, jeopardizing the region's long-term ecological health. Urgent action is needed to balance these efforts with measures that address the root causes of tree cover loss.

From a policy perspective, it will be helpful to investigate the factors that have contributed to recent gains in tree cover. These gains may result from natural forest regeneration, or they could be attributed to deliberate reforestation and tree-planting efforts, which have been actively supported by schools, civic organizations, and local communities. There are many initiatives aimed at restoring forest cover and increasing green spaces, but the current data does not distinguish between natural regrowth and plantation-type trees. Policymakers and environmental planners can more effectively evaluate the effectiveness of these initiatives if data are available to distinguish natural regrowth from the product of active intervention. This, in turn, could help refine strategies for future environmental activities and land-use planning efforts, ensuring that resources are directed to achieve the greatest impact.

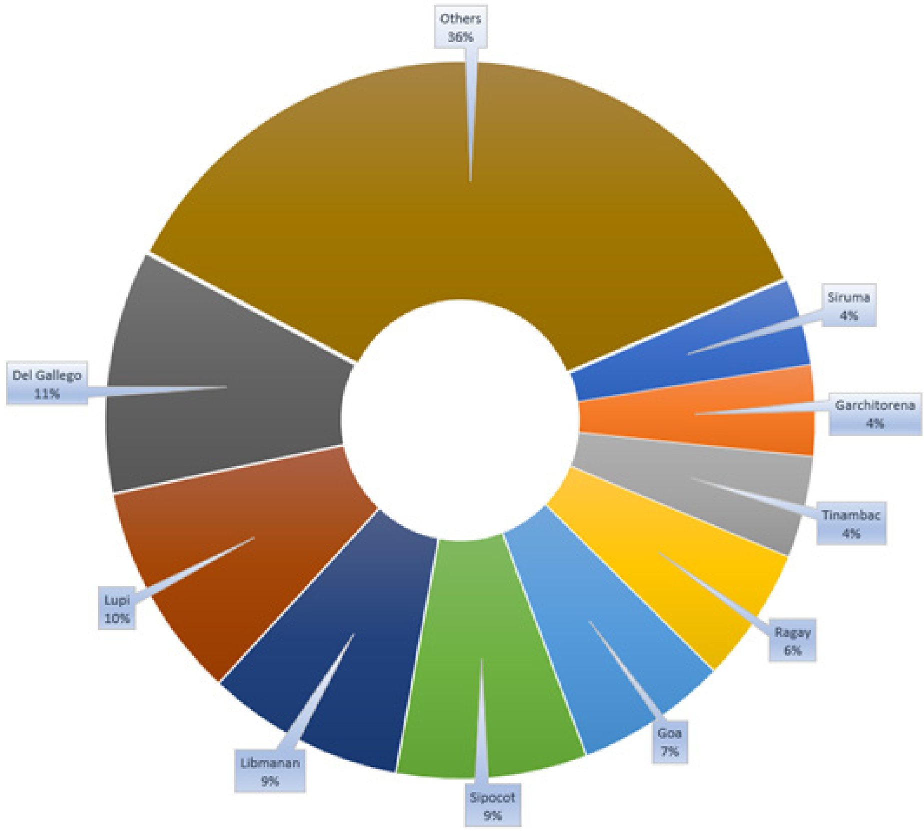

Figure 2. Gain of 751 tons of CO2e in Camarines Sur and the contributing municipalities for the positive increase in tree cover

Tree Cover Loss and the Competitiveness Index

The Cities and Municipalities Competitiveness Index (CMCI) evaluates each city or municipality's competitiveness through a total score. A higher score indicates greater competitiveness. This score is derived from five main areas: economic dynamism, government efficiency, infrastructure, resiliency, and innovation. However, innovation data have not been collected before 2022 and will therefore be excluded from this study, which covers the 20-year period from 2000 to 2020. Each of these areas, known as pillars of the CMCI, includes several factors, and the scores depend on both the actual data submitted by the respective local government units and their completeness.

To examine the relationship between the FCPI and various components of the CMCI, either parametric or nonparametric correlation analyses were conducted, depending on the data's normality. A Shapiro-Wilk test indicated that CMCI scores were not normally distributed ($W = 0.8719$, $p = .000533$). Therefore, Spearman's rank correlation and Kendall's tau were used. The correlation between FCPI and CMCI was not statistically significant, $\rho = -0.182$, $t(35) = -1.093$, $p = .282$, Kendall's $\tau = -0.237$, suggesting no meaningful association between forest cover performance and overall competitiveness.

Regarding the relationship between FCPI and the CMCI Resiliency pillar, the data also did not support the assumption of normality ($W = 0.7400$, $p < .001$). Results showed a non-significant positive correlation, $\rho = 0.089$, $t(35) = 0.527$, $p = .602$, with Kendall's $\tau = 0.111$, indicating no substantial relationship between resiliency and forest cover performance.

In contrast, Government Efficiency scores were roughly normally distributed ($W = 0.980$, $p = .850$). A Pearson's correlation was performed, showing a negative but non-significant relationship with FCPI, $r(35) = -0.283$, $p = .090$, 95% CI [–0.56, 0.05]. While the direction indicated that higher government efficiency might be linked to lower forest cover performance, the evidence was not strong enough to confirm this trend statistically.

For the Economic Dynamism pillar, which did not meet the normality assumptions ($W = 0.7700$, $p < .001$), a moderate and statistically significant positive correlation with FCPI was found using Spearman's method, $\rho = 0.328$, $t(35) = 2.05$, $p = .048$, 95% CI [0.004, 0.589]. However, Kendall's τ indicated a weak negative association ($\tau = -0.207$), revealing inconsistencies between the correlation measures and suggesting that the relationship may be sensitive to the method used.

Finally, the Infrastructure pillar also violated normality ($W = 0.7900$, $p < .001$). While Kendall's τ showed no meaningful association ($\tau = -0.015$), Spearman's ρ indicated a statistically significant and moderate-to-strong positive relationship, $\rho = 0.597$, $t(35) = 4.405$, $p < .001$, 95% CI [0.323, 0.780]. This suggests that LGUs with better infrastructure performance also tended to have better forest cover outcomes. These are summarized in Table 2 below.

Table 2. Results of Statistical Tests Conducted to Assess the Relationship of FCPI and CMCI

Statistical Parameter	FCPI & CMCI	FCPI & Resiliency	FCPI & Gov't Efficiency	FCPI & Economic Dynamism	FCPI & Infrastructure
Normality	Non-normal (W = 0.8719, p = .000533)	Non-normal (W = 0.7400, p < .001)	Normal (W = 0.980, p = .850)	Non-normal (W = 0.7700, p < .001)	Non-normal (W = 0.7900, p < .001)
Correlation Method	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Pearson's r	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ
Correlation Coefficient	ρ = –0.182, τ = –0.237	ρ = 0.089, τ = 0.111	r = –0.283	ρ = 0.328, τ = –0.207	ρ = 0.597, τ = –0.015
t-statistic	–1.093	0.527	-1.74†	2.05	4.405
p-value	0.282	0.602	0.09	0.048	< .001
95% Confidence Interval	[–0.51, 0.16]	[–0.25, 0.41]	[–0.56, 0.05]	[0.004, 0.589]	[0.323, 0.780]
Significance (p < .05)	No	No	No (marginal)	Yes (weak)	Yes (high)

The analysis examined the relationship between tree cover loss, measured by the Forest Cover Performance Index (FCPI), and four pillars of the Cities and Municipalities Competitiveness Index (CMCI): Resiliency, Government Efficiency, Economic Dynamism, and Infrastructure. Innovation, the fifth CMCI pillar, was excluded because data were insufficient before 2022. The results showed no statistically significant relationship between FCPI and either Resiliency or Government Efficiency, indicating that any weak correlations observed were probably due to chance and were not further explored.

However, significant links were found between FCPI and both Economic Dynamism and Infrastructure. These results support the idea that land-use changes driven by economic growth and infrastructure development contribute to forest cover loss. Economic dynamism—defined by business activity, investment, and urban expansion—was connected to deforestation through higher land demand. Similarly, infrastructure projects often require clearing forested areas, leading to habitat fragmentation and ecological damage.

Despite the observed correlations, inconsistencies between Spearman's ρ and Kendall's τ indicate that the relationship varies across different components. For example, some aspects of economic dynamism may promote deforestation, while others could support sustainable urban planning. Likewise, the environmental impact of infrastructure development can differ based on its type and implementation. These findings highlight the need to break down CMCI pillars to analyze their individual factors, providing a clearer understanding of how economic and infrastructural forces affect forest cover change. Such insights are crucial for shaping policies that balance development with ecological sustainability.

FCPI and the Drivers of Economic Dynamism

Economic dynamism fuels the steady expansion of businesses and industries, leading to more job opportunities. This indicator links the local economy's output and productivity with available resources. As centers of economic activity, localities become focal points for business growth and employment, making these developments clearly visible within the community. In the CMCI, economic dynamism includes several factors: active establishments, costs of doing business, cost of living, employment creation, financial deepening, local economic growth, the size of the local economy, presence of business and professional organizations, productivity, and safety-compliant businesses.

The relationship between FCPI and indicators of economic dynamism was analyzed using the same approach as previously described. These indicators included establishments, cost of doing business, cost of living, employment generation, local economic growth, size of the local economy, presence of professional and business organizations, productivity, and safety-compliant businesses. Normality testing with the Shapiro-Wilk test showed that none of the datasets followed a normal distribution. All variables exhibited significant skewness and leptokurtosis, with several extreme outliers identified, which justified the use of non-parametric statistical methods.

Active establishments exhibited a weak, non-significant negative correlation with FCPI ($\rho = -0.107$, $p = .528$). The cost of doing business showed a moderate, significant positive correlation ($\rho = 0.349$, $p = .034$), indicating that areas with higher forest cover might face higher operational costs, possibly due to sustainable practices.

The cost of living showed a weak, non-significant link ($\rho = 0.084$, $p = .620$). Employment generation had a strong, significant positive relationship ($\rho = 0.583$, $p < .001$), indicating that green sectors may drive job creation. Financial deepening also displayed a significant positive correlation ($\rho = 0.546$, $p < .001$). These are summarized in Table 3 below.

Table 3. Results of Statistical Tests Conducted to Assess the Relationship Between FCPI and 5 Indicators of Economic Dynamism (Active Establishments, Cost of Doing Business, Cost of Living, Employment Generation, Financial Deepening)

Statistical Parameter	Active Establishments	Cost of Doing Business	Cost of Living	Employment Generation	Financial Deepening
Normality	Not normal ($W = 0.79$, $p < .001$)	Not normal ($W = 0.74$, $p < .001$)	Not normal ($W = 0.43$, $p < .001$)	Not normal ($W = 0.49$, $p < .001$)	Not normal ($W = 0.69$, $p < .001$)
Correlation Method	Kendall's Tau, Spearman's ρ	Kendall's Tau, Spearman's ρ	Kendall's Tau, Spearman's ρ	Kendall's Tau, Spearman's ρ	Kendall's Tau, Spearman's ρ
Correlation Coefficient	$\tau = -0.138$, $\rho = -0.107$	$\tau = 0.432$, $\rho = 0.349$	$\tau = 0.090$, $\rho = 0.084$	$\tau = 0.823$, $\rho = 0.583$	$\tau = 0.805$, $\rho = 0.546$
t-statistic	-0.637	2.201	0.501	4.247	3.853
p-value	0.528	0.034	0.62	< 0.001	< 0.001
95% Confidence Interval	[-0.417, 0.225]	[0.028, 0.604]	[-0.246, 0.397]	[0.319, 0.763]	[0.269, 0.739]
Significance ($p < .05$)	No	Yes	No	Yes	Yes

Local economic growth exhibited a moderate to strong positive correlation with FCPI ($\rho = .60$, $p < .001$), supported by both parametric and nonparametric analyses. The size of the local economy also showed a strong positive correlation ($\rho = .70$, $p < .001$), suggesting that larger economies may better support forest cover. The presence of professional and business organizations was weakly and non-significantly related to FCPI ($\rho = .10$, $p = .550$). Meanwhile, productivity was strongly and significantly associated with FCPI (ρ = .63, p < .001), as was the number of safety-compliant businesses (ρ = .73, p < .001), indicating that more forested areas may promote safer, more productive business environments. These are summarized in Table 4 below.

Table 4. Results of Statistical Tests Conducted to Assess the Relationship Between FCPI and 5 Indicators of Economic Dynamism (Local Economic Growth, Size of Local Economy, Presence of Professional and Business Organizations, Productivity, and Safety-Compliant Businesses)

Statistical Parameter	Local Economic Growth	Size of Local Economy	Prof. & Business Orgs.	Productivity	Safety-Compliant Businesses
Normality	Not normal (W = 0.759, p < .001)	Not normal (W = 0.303, p < .001)	Not normal (W = 0.460, p < .001)	Not normal (W = 0.370, p < .001)	Not normal (W = 0.660, p < .001)
Correlation Method	Pearson, Spearman, Kendall's Tau	Spearman, Kendall's Tau	Spearman,	Kendall's Tau, Spearman's ρ	Kendall's Tau, Spearman's ρ
Kendall's Tau	Spearman, Kendall's Tau	Spearman, Kendall's Tau	τ = 0.090, ρ = 0.084	τ = 0.823, ρ = 0.583	τ = 0.805, ρ = 0.546
Correlation Coefficient	r = 0.448 ρ = 0.597 τ = 0.829	ρ = 0.700 τ = 0.990	ρ = 0.100 τ = 0.147	ρ = 0.630 τ = 0.913	ρ = 0.730 τ = 1.063
t-statistic	4.401	5.723	0.603	4.835	6.328
p-value	0.005, < .001	< .001	0.550	< .001	< .001
95% Confidence Interval	[0.145, 0.674] [0.338, 0.772]	[0.479, 0.832]	[-0.230, 0.412]	[0.390, 0.790]	[0.530, 0.850]
Significance (p < .05)	Yes	Yes	No	Yes	Yes

Taken together, these findings emphasize the complex and multi-layered nature of economic dynamism. The variation in correlation strength highlights the need for targeted policies that foster financial access, job creation, and sustainable business practices. While the results indicate that economic growth and environmental sustainability are not inherently opposed, more research is needed to understand causal mechanisms and regional differences. A comprehensive and integrated approach will be crucial for achieving balanced, inclusive, and environmentally responsible development.

FCPI and the Drivers of Infrastructure

Infrastructure is an indicator that measures the availability and quality of physical and digital assets that support mobility, connectivity, and essential services. Infrastructure allows businesses and industries to operate efficiently and grow sustainably. It is reflected in improved transportation, utilities, and digital connectivity. A well-developed infrastructure improves accessibility, lowers transaction costs, and attracts investments. In the CMCI, infrastructure includes several factors, such as accommodation capacity, availability of basic utilities, distance to a port, education infrastructure, financial technology capacity, health, information technology capacity, local government investment, road network, and transport vehicles.

The relationship between FCPI and the infrastructure indicators was analyzed using the same approach as previously described. Since data for accommodation capacity, availability of basic utilities, distance to a port, education infrastructure, and financial technology capacity significantly deviated from normality according to Shapiro-Wilk tests (all p-values < .001), non-parametric tests were used throughout the analysis. Spearman's rank correlation and Kendall's Tau measured the strength and direction of the relationships.

Results indicated that accommodation capacity had a very weak, negative, and nonsignificant correlation with FCPI (Spearman's ρ = −.062, p = .717). Similarly, the availability of basic utilities showed an almost negligible and nonsignificant correlation (ρ = .015, p = .932). The indicator for distance to port also displayed a weak and nonsignificant negative correlation (ρ = −.106, p = .534).

In contrast, educational infrastructure was the only indicator showing a statistically significant correlation. It exhibited a moderate-to-strong negative relationship with FCPI (Spearman's ρ = −.38, p = .021), indicating that higher levels of educational infrastructure were linked to lower FCPI scores. This finding was further corroborated by Kendall's Tau (τ = −.54) and a 95% confidence interval for ρ that did not cross zero [−.63, −.06], suggesting the result is unlikely due to chance.

Lastly, financial technology capacity also did not show a significant correlation with FCPI (ρ = −.15, p = .373), indicating no meaningful relationship between the two variables. These are summarized in Table 5 below.

Each of the remaining indicators of infrastructure, i.e., basic health infrastructure, Information Technology (IT) capacity, LGU investment, road network, and public transportation vehicles, exhibited significant right-skewness and leptokurtosis, with several outliers, confirming non-normal distribution.

Since the data were non-normal, Spearman's rank-order correlation and Kendall's tau were used to evaluate the strength and direction of the relationship between FCPI and each infrastructure variable. The correlations were weak and not statistically significant across all indicators. Results showed that for basic health infrastructure, Spearman's ρ was −0.10 (p = .548) and Kendall's τ was −0.17, with a 95% confidence interval from −0.41 to 0.23, indicating no meaningful association. Similarly, for Information Technology (IT) capacity, Spearman's ρ was −0.10 (p = .543), and Kendall's τ was −0.13, with a 95% confidence interval of −0.41 to 0.23, again suggesting a weak and non-significant relationship. For LGU investment, Spearman's ρ was −0.16 (p = .336), and Kendall's τ was −0.21, with a 95% confidence interval from −0.46 to 0.17, pointing to a small but statistically non-significant negative correlation. Regarding the road network, the analysis resulted in Spearman's ρ of 0.18 (p = .294) and Kendall's τ of 0.24, with a 95% confidence interval from −0.16 to 0.47, indicating a weak and non-significant positive correlation. Lastly, for public transportation vehicles, Spearman's ρ was 0.14

Table 5. Results of Statistical Tests Conducted to Assess the Relationship Between FCPI and 5 Indicators of Infrastructure (Accommodation Capacity, Availability of Basic Utilities, Distance to a Port, Education Infrastructure, Financial Technology Capacity)

Statistical Parameter	**Accommodation Capacity**	**Availability of Basic Utilities**	**Distance to Port**	**Education Infrastructure**	**Financial Technology Capacity**
Normality	Not normal (W = 0.36, p < .001)	Not normal (W = 0.84, p < .001)	Not normal (W = 0.59, p < .001)	Not normal (W = 0.60, p < .001)	Not normal (W = 0.62, p < .001)
Correlation Method	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ
Spearman's ρ	−0.062	0.015	−0.106	−0.38	−0.15
Kendall's τ	−0.060	0.033	−0.087	−0.54	−0.22
t-statistic	−0.365	0.086	−0.628	−2.41	−0.902
p-value	0.717	0.932	0.534	0.021	0.373
95% Confidence Interval	[−0.378, 0.268]	[−0.311, 0.337]	[−0.415, 0.226]	[−0.63, −0.06]	[−0.45, 0.18]
Significance (p < .05)	Not Significant	Not Significant	Not Significant	Significant	Not Significant

(p = .415), and Kendall's τ was −0.20, with a 95% confidence interval from −0.44 to 0.19, suggesting no significant relationship. These are summarized in Table 6 below.

Table 6. Results of Statistical Tests Conducted to Assess the Relationship Between FCPI and 5 Indicators of Infrastructure (Basic Health Infrastructure, Information Technology (IT) Capacity, LGU Investment, Road Network, and Public Transportation Vehicles

Statistical Parameter	Basic Health Infrastructure	IT Capacity	LGU Investment	Road Network	Public Transportation
Normality	Not normal (W = 0.67, p < .001)	Not normal (W = 0.89, p = .002)	Not normal (W = 0.64, p < .001)	Not normal (W = 0.35, p < .001)	Not normal (W = 0.55, p < .001)
Correlation Method	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ	Spearman's ρ, Kendall's τ
Spearman's ρ	−0.10	−0.10	−0.16	0.18	0.14
Kendall's τ	−0.17	−0.13	−0.21	0.24	−0.20
t-statistic	−0.61	−0.61	−0.97	1.06	0.83
p-value	0.548	0.543	0.336	0.294	0.415
95% Confidence Interval	[−0.41, 0.23]	[−0.41, 0.23]	[−0.46, 0.17]	[−0.16, 0.47]	[−0.44, 0.19]
Significant (p < .05)	No	No	No	No	No

These results showed that, in most cases, there was little to no statistically significant link between FCPI and different parts of infrastructure. Accommodation capacity, basic utilities, distance to port, financial technology capacity, basic health infrastructure, information technology capacity, LGU investment, road network, and public transportation vehicles all showed weak and non-significant connections with FCPI. In each case, both Spearman's rank correlation and Kendall's Tau indicated minimal relationships, with confidence intervals including zero, suggesting that any observed correlation was probably due to chance. Effect sizes for these variables were consistently small, reinforcing the lack of meaningful relationships. The only infrastructure indicator with a significant link to FCPI was educational infrastructure. A moderate negative correlation was seen (ρ = -0.38, p = .021), with a confidence interval [-0.63, -0.06] that did not include zero. The negative correlation indicates that as education infrastructure increases, FCPI tends to decrease. This finding calls for further research into possible underlying factors, such as land-use trade-offs between educational growth and forest conservation efforts. Overall, the results indicate that most infrastructure factors do not show a strong or consistent relationship with FCPI. While infrastructure development is vital for economic and social growth, its direct impact on forest cover performance seems limited in this dataset. Future studies might explore other variables, mediating factors, and a larger dataset to better understand how infrastructure development interacts with environmental sustainability.

CONCLUSION

This study provided a thorough assessment of tree cover changes in Naga City and Camarines Sur, giving valuable insights into the scale, causes, and effects of deforestation. Using satellite imagery and remote sensing technologies, it overcame the limitations of traditional ground surveys, enabling a more detailed, accurate, and data-driven analysis of tree cover change across diverse and complex landscapes. From 2000 to 2020, the results showed a significant loss of over 14,854 hectares of tree cover, leading to carbon emissions comparable to those from about 1.77 million passenger vehicles annually. This widespread deforestation not only increased the region's vulnerability to climate change but also threatened local biodiversity and essential ecosystem services.

One of the study's main contributions was quantifying tree cover loss and its equivalent Global Warming Potential (GWP) in kilotons of CO_2 e, offering a tangible measure for evaluating environmental impact locally. Additionally, the introduction of the Forest Cover Performance Index (FCPI) allowed for standardized comparisons of forest conservation efforts across different LGUs, regardless of their size or initial forest cover. The study found that larger LGUs with more forest cover tended to have higher absolute tree cover losses, underscoring the need for targeted conservation strategies in those areas.

Beyond environmental implications, the study also examined the complex relationship between forest cover performance and socio-economic factors, especially through the lens of the Cities and Municipalities Competitiveness Index (CMCI). The analysis showed significant correlations between tree cover loss and economic metrics—particularly, higher rates of deforestation in regions with greater economic activity and infrastructure development. While some economic indicators, such as financial deepening, employment growth, and local economic expansion, had positive links with better forest cover performance, others, like basic educational infrastructure, had notable negative links. These findings suggest possible trade-offs between development and environmental sustainability and highlight the urgent need for policymakers to incorporate environmental considerations into economic and infrastructure planning to achieve a more sustainable balance between growth and conservation.

Although some municipalities reported slight improvements in tree cover, these were significantly insufficient to offset widespread losses. This underscores the need for stronger policy measures, restoration initiatives, and sustainable land-use strategies. The study also pointed out the importance of enhancing data quality to distinguish between natural forest regeneration and plantation-style tree cover, which is vital for accurately evaluating the success of reforestation efforts.

Policy Recommendations

This study offered evidence-based insights to support forest conservation efforts in Naga City and Camarines Sur. Several important policy recommendations arose from the findings.

- Forest protection and restoration must be prioritized. Local governments and environmental agencies should concentrate on reforestation, especially in areas experiencing high rates of deforestation. This involves supporting community-led initiatives, enforcing environmental laws, and providing financial incentives for conservation.
- Environmental sustainability should be integrated into economic planning. The connection between tree cover loss and economic activity emphasizes the need for development strategies that protect ecosystems. Policymakers should adopt sustainable land-use plans, promote green business practices, and invest in infrastructure.
- Strengthen remote sensing and data-driven monitoring. Satellite imagery and GIS tools are essential for tracking forest changes. LGUs should invest in real-time monitoring systems and collaborate with organizations like NASA and Global Forest Watch to access high-resolution data.
- A clearer understanding of forest cover dynamics is also necessary. Research should distinguish between natural regeneration and human-driven tree gains to guarantee that conservation efforts promote long-term ecological health and carbon storage.
- Community involvement is crucial for sustainable conservation. Local governments should promote community-led forest management and empower stakeholders like indigenous groups and farmers. Education campaigns can boost public awareness and engagement in forest stewardship.
- Greater collaboration among LGUs is

essential for regional forest management. Shared conservation strategies, combined resources, and aligned policies can enhance results across municipalities.

- The Forest Cover Performance Index (FCPI) should be adopted as an official policy tool. It can assist in resource allocation, influence incentives, and direct decision-making based on concrete forest results.

Given the rapid pace of deforestation, these actions need to be taken immediately. Incorporating forest conservation into broader development plans, enhancing monitoring systems, and engaging local communities can support a more sustainable future for the region.

Preserving forest cover is both an environmental and socio-economic priority. The future of Naga City and Camarines Sur depends on sustaining healthy forest ecosystems for present and future generations.

Future Research Directions

This study highlighted the relationship between tree cover loss and economic activity in Naga City and Camarines Sur, but its scope was limited. Future research should broaden the analysis, enhance data quality, and support stronger policy decisions. Including detailed land-use and land-cover data would help identify specific drivers of deforestation, such as agriculture, urban growth, and infrastructure development. Using refined time series datasets with consistent methods can enhance the accuracy of long-term trend analysis. Adding climate variables like temperature, rainfall, and extreme weather events would clarify how environmental conditions influence forest loss.

Spatial analysis techniques, such as spatial autocorrelation, can identify deforestation hotspots and better explain patterns of forest change. Moving beyond correlation, future studies should use regression models to predict tree cover loss and investigate causal relationships. Comparative studies involving other provinces or regions could help identify common trends and develop context-specific conservation strategies. Research should also evaluate the effectiveness of conservation efforts, including reforestation projects, protected areas, and community-based programs. Exploring governance, economic structures, and local participation can reveal social influences on forest outcomes. Additionally, analyzing the carbon sequestration capacity of forests and the ecosystem services they provide—such as biodiversity, water regulation, and disaster reduction—will emphasize their broader environmental and economic value.

Finally, future research should focus on using higher-resolution data or additional data sources that can differentiate between forest types. As this study notes, the GFW dataset's inability to tell natural forests apart from plantations limits the ecological interpretation of tree cover trends. Studies using LiDAR, hyperspectral imagery, or field validation could help determine whether the observed tree cover actually reflects forest restoration or just the growth of commercial tree crops. This distinction is crucial for accurately evaluating biodiversity, carbon storage, and long-term ecosystem resilience.

Incorporating the Innovation pillar of the CMCI will become feasible as more years of data are collected. Future research should assess whether LGUs with higher innovation capacity—reflected in digitalization, technology adoption, and innovation-friendly governance—show different forest cover outcomes compared to those evaluated solely on the four pillars analyzed here.

These research directions can enhance understanding of forest dynamics and promote more effective, evidence-based conservation strategies.

Concluding Remarks

This study emphasizes the urgent need for proactive, data-driven forest conservation strategies. By measuring tree cover loss, its environmental impacts, and the socio-economic factors associated with deforestation, the research offers valuable insights to guide policy decisions and local conservation efforts. The findings stress the importance of incorporating environmental sustainability into economic plans, improving monitoring systems, and involving communities in conservation initiatives. Moving forward, a balanced approach that supports both development and environmental protection will be crucial for the long-term health of the region's ecosystems and communities. By implementing evidence-based strategies and encouraging collaboration among stakeholders, Naga City and the Province of Camarines Sur can build a more sustainable and resilient future.

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