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Research Article

Agri-Environmental Assessment of Land-Cover Dynamics, Ecological Pressure, and Economic–Ecological Decoupling in Konaweha Watershed

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Abstract

Watershed transformation poses a challenge for maintaining agricultural production while sustaining ecological functions, particularly in tropical regions where economic activities are strongly dependent on natural resources. This study aimed to (i) analyze economic dynamics in the agriculture, forestry, and fisheries sectors of Konawe Regency; (ii) quantify land-cover change and spatial ecological pressure in the Konaweha Watershed; and (iii) assess the relationship between sectoral economic growth and ecological change using the Tapio decoupling framework. A quantitative observational approach integrated Landsat 8 and Sentinel-2 imagery, Random Forest classification using Google Earth Engine, GIS-based hotspot analysis, Forest Loss Rate (FLR), Land Use Pressure Index (LPI), aggregate ecological change (ΔC), and constant-price GRDP for 2014, 2019, and 2024. The classification achieved overall accuracy above 87%. Secondary dryland forest declined by 54,712 ha, while plantations expanded by 59,205 ha (123.1%), indicating substantial land transformation toward anthropogenic production systems. The extent of ecologically functional land-cover classes declined by 16.16% during 2014–2024, with ecological-pressure hotspots concentrated in the middle and lower watershed. Sectoral GRDP increased from IDR 944.69 to 1,947.22 billion, while Tapio analysis indicated absolute decoupling across all observation periods (2014–2019, 2019–2024, and 2014–2024). The findings demonstrate persistent ecological degradation alongside economic growth and provide an integrated basis for watershed assessment, sustainable land management, and resource planning.

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1. Introduction

Agri-environmental assessment is increasingly important for understanding the interaction between economic development and ecological sustainability, particularly in developing regions where agriculture, forestry, and fisheries remain strongly dependent on natural resources.

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Watersheds function as interconnected land–water systems that regulate hydrological processes, support agricultural production, and sustain ecosystem services. However, rapid land-cover change associated with agricultural expansion, plantation development, and infrastructure growth can alter watershed functions and ecological resilience (de Groot et al., 2002; Costanza et al., 2017; Hasan et al., 2020; Viana et al., 2022). Previous studies have shown that such changes can modify ecosystem-service provision and landscape functionality, creating persistent challenges for sustainable watershed management (Weldemariam et al., 2024).

From a geophysical perspective, watershed sustainability depends strongly on land-cover configuration because vegetation structure influences infiltration, runoff generation, sediment transport, and water-regulation functions. Conversion of forest and other ecologically functional land to agricultural or built-up uses can increase surface runoff and reduce hydrological stability, thereby affecting water regulation and agricultural sustainability (Lu et al., 2004; Aneseyee et al., 2022; Mersha et al., 2024; Anggraheni et al., 2025). These relationships indicate that watershed sustainability assessment requires spatially explicit characterization of land-cover transformation and ecological pressure rather than assessment of economic or environmental conditions in isolation.

The socioeconomic dimension is equally important because watershed-dependent production is embedded in regional economic structures. In Indonesia, agriculture, forestry, and fisheries contribute substantially to regional economic activity while remaining vulnerable to land degradation and hydrological instability (Christiaensen & Martin, 2018; Kasim et al., 2026). At the same time, structural economic transformations also influence land use patterns in rural areas (Anderson & Ponnusamy, 2023). Nevertheless, ecological and economic conditions are frequently evaluated separately, limiting understanding of whether economic growth is accompanied by proportional ecological degradation. Recent studies have emphasized the value of integrating ecological change with economic indicators to better evaluate sustainability and resource-use relationships (Ureta et al., 2021; Velasco-Munoz et al., 2022).

The Konaweha watersheds provides a relevant case for examining these interactions because it functions simultaneously as a production landscape and a hydrological regulation system. Previous studies have documented substantial land-cover transformation, including forest conversion to plantations and agricultural land, and have linked these changes to hydrological and ecological consequences (Baco et al., 2011a; Marwah, 2014; Taufik et al., 2021; Jasman et al., 2023; Maladeni et al., 2023). However, the existing literature remains fragmented in three respects. First, land-cover and ecological changes have rarely been evaluated through spatially differentiated watershed zones to identify where ecological pressure is concentrated. Second, the integration of spatial ecological change with the economic performance of the agriculture, forestry, and fisheries sectors, represented by regional Gross Regional Domestic Product (GRDP), remains limited. Third, the economic–ecological relationship has rarely been quantified at the watershed scale using a decoupling framework.

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Consequently, existing studies provide evidence of land transformation, ecological impacts, and economic dynamics, but offer limited integrated assessment of how geophysical conditions and sectoral economic performance jointly shape watershed sustainability.

Although previous studies have documented substantial hydrological and land-cover changes in the Konaweha region, their integration into watershed sustainability assessment remains limited. First, land-cover and ecological changes have rarely been evaluated through spatially differentiated watershed zones to identify where ecological pressure is concentrated. Second, spatial ecological changes have not been systematically linked to the economic perfo to rmance of the agriculture, forestry, and fisheries sectors, represented by regional GRDP. Third, the economic–ecological relationship has rarely been quantified at the watershed scale using a decoupling framework. Although decoupling analysis has been widely applied in energy and emissions studies (Tapio, 2005; Ortega-Ruiz et al., 2020; Wang et al., 2023; Jing et al., 2024), its application to integrated watershed-scale economic–ecological assessment remains limited. This limitation is particularly relevant because changes in land cover can modify ecosystem-service exchanges and consequently affect watershed management (Regueiro-Ferreira & Alonso-Fernández, 2022; Sun et al., 2025; Kasim et al., 2026)). Consequently, existing studies provide evidence of land transformation, ecological impacts, and economic dynamics, but do not yet provide a sufficiently integrated assessment of how geophysical conditions and sectoral economic performance jointly influence watershed sustainability.

Recent advances in remote sensing, machine learning, and GIS provide the technical basis for addressing these gaps through spatially explicit watershed assessment. Multitemporal satellite imagery and Random Forest classification enable consistent characterization of land-cover dynamics, while GIS-based spatial statistics can identify localized concentrations of ecological pressure (Phan et al., 2020; Shafizadeh-Moghadam et al., 2021; Tesfaye et al., 2024; Bill et al., 2024; Rynkiewicz et al., 2025). When combined with ecological pressure indicators and sectoral economic data, these tools allow watershed performance to be evaluated simultaneously from geophysical and socioeconomic perspectives rather than through separate assessments. This integration provides a basis for linking spatially differentiated ecological conditions with sectoral economic dynamics and for evaluating their relationship through economic–ecological decoupling (Sun & Ongsomwang, 2023).

In light of this, this study presents a combined agro-environmental evaluation approach for watershed sustainability that integrates multi-temporal remote sensing imagery, a Random Forest-based classification method for detecting land-cover changes, GIS-based spatial diagnostic analysis, ecological pressure indicators, and economic sector analysis. Fundamentally, this approach links geophysical evidence—reflected in land-cover changes, ecological pressures, and spatial hotspot patterns—with socio-economic evidence reflected in the GRDP of the agriculture, forestry, and fisheries sectors and their linkages to environmental changes. By leveraging recent advances in ecosystem service assessment and land-use change analysis—which largely focus on detailed spatial

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descriptions of environmental changes and their impacts on human well-being and resource management (de Groot et al., 2020; Azadi et al., 2021; Admasu et al., 2023)—this study contributes to the literature on watershed sustainability in three specific aspects. First, it integrates spatial ecological-pressure assessment with economic–ecological decoupling to evaluate whether sectoral economic growth occurs alongside proportional ecological degradation. Second, it extends conventional land-cover change assessment by combining machine-learning classification with hotspot diagnostics to identify intra-watershed concentrations of ecological pressure. Third, it brings these geophysical and socioeconomic dimensions together within a watershed-scale assessment framework, providing an operational basis for linking observed environmental change with economic dynamics and supporting sustainability-oriented watershed planning and management.

Based on these gaps, this study aims to assess watershed sustainability by integrating geophysical and socioeconomic evidence through three specific objectives: (1) to analyze the economic dynamics of the agriculture, forestry, and fisheries sectors in Konawe Regency as the socioeconomic dimension of watershed performance; (2) to quantify land-cover change and evaluate spatial ecological pressure within the Konaweha Watershed using integrated landscape indicators as the geophysical dimension; and (3) to assess the relationship between sectoral economic growth and ecological change using the Tapio decoupling framework to determine whether economic expansion is accompanied by proportional ecological degradation. Together, these objectives are designed to provide an integrated evidence base for sustainability assessment and management of land and natural resources within the Konaweha Watershed.

2. Material and Methods

2.1 Study Area: Konaweha Watershed as an Agri-Environmental System

This research was conducted in the Konaweha watershed, Southeast Sulawesi, Indonesia, covering an area of approximately 678,908 ha. This watershed covers the main area of Konawe Regency as well as small parts of Kolaka, North Kolaka, East Kolaka, South Konawe, and Kendari City. The complete geographic location of the Konawe River Basin is presented in Figure 1.

In this study, the Konaweha watershedis treated as an integrated agricultural-environmental system (land-water-production system), where hydrological processes, land-use dynamics, and natural resource-based economic activities interact within a single physical system unit. The Konaweha Watershed boundary was delineated using the 30-m Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), which was subsequently used to define the spatial extent of the watershed-based land-cover analysis. This delineation ensured that the ecological and spatial analyses were consistently conducted within the same hydrologically defined watershed unit.

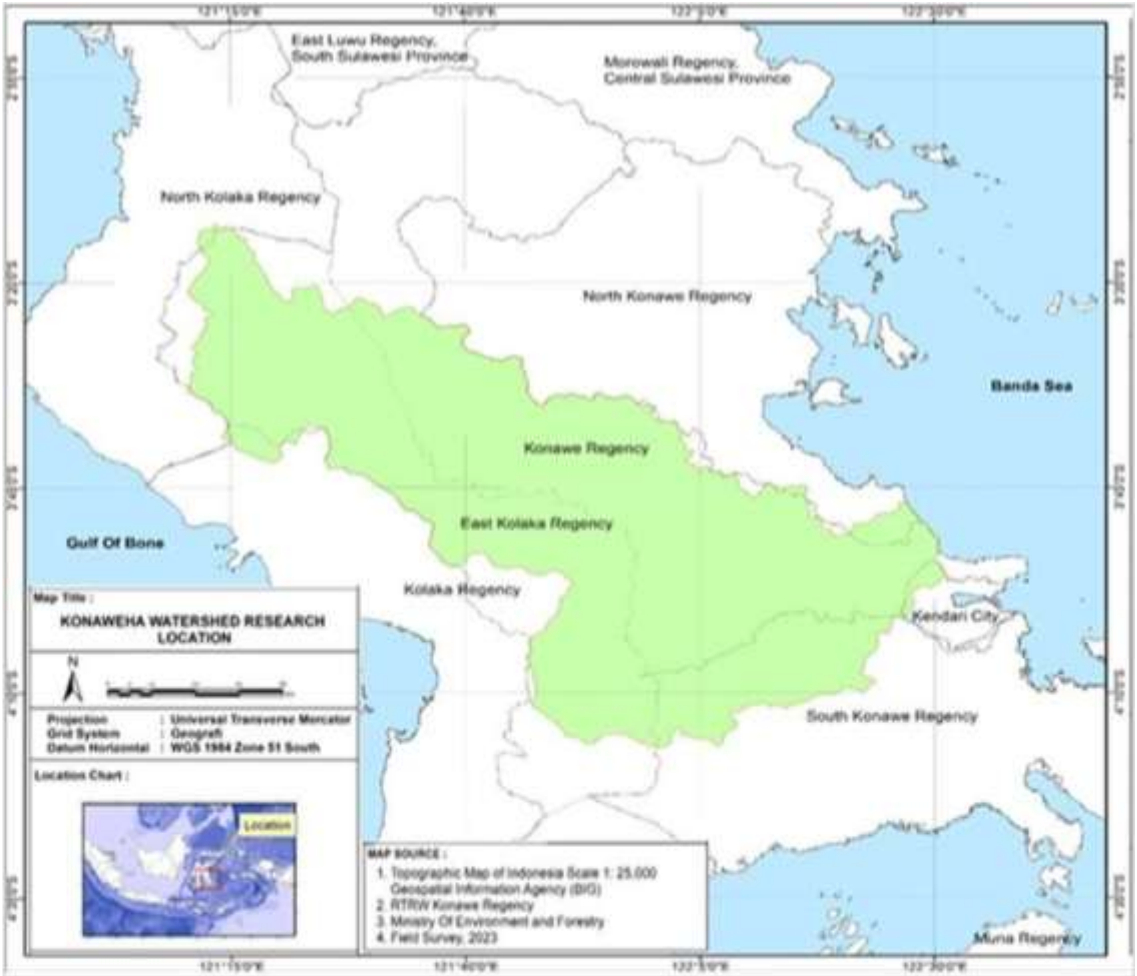

Figure 1. Konaweha watershed.

The GRDP-based economic analysis used Konawe Regency as the administrative economic unit because it represents the dominant production area associated with the Konaweha Watershed. The analysis therefore uses Konawe Regency GRDP as a socioeconomic proxy for the dominant economic area associated with the watershed, rather than as a spatially aggregated watershed-level GRDP. Accordingly, the economic and ecological datasets retain their respective administrative and hydrological boundaries, and their decoupling relationship is interpreted as a temporal system-level association rather than as a spatially equivalent comparison.

For the purpose of descriptive stratification, watersheds are categorized into hydrological zones (upstream, midstream, and downstream) based on their relative positions along the drainage network derived from a DEM, extending from the headwaters to the watershed outlet. This zonal division serves solely to structure the spatial interpretation of ecological pressures and is not treated as an independent variable in spatial modeling.

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2.2 Research Design: System-Based Quantitative Framework

This study employs a quantitative observational design based on an integrated agri-environmental systems approach, which combines remote sensing-based land cover analysis, machine-learning land-cover classification, ecological pressure assessment, hotspot-based spatial diagnostics, and sectoral economic evaluation using GRDP data. The analysis is conducted at three temporal points: 2014 (T_1), 2019 (T_2), and 2024 (T_3), representing medium-term system dynamics. All satellite images are selected from the dry season period to minimize atmospheric bias and phenological variability.

2.3 Data Sources and Preprocessing

The spatial data used in this study consisted of Landsat 8 OLI/TIRS and Sentinel-2 MSI imagery obtained through the United States Geological Survey (USGS) and Copernicus Programme, respectively, and a 30-m-resolution SRTM-DEM used for watershed delineation (Earth Resources Observation and Science Center, 2020). Satellite imagery was selected for the three observation years (2014, 2019, and 2024) from the dry-season period to minimize seasonal and phenological variability. Landsat 8 OLI/TIRS and Sentinel-2 MSI were used as complementary multispectral data sources to support land-cover discrimination across the observation periods, with sensor selection determined by data availability for each observation year. Because the two sensors provide imagery at different spatial resolutions, their inputs were processed within a common spatial analysis framework before classification. Post-classification comparison was then used to assess multi-temporal land-cover change, providing a consistent basis for comparison across observation periods. The satellite imagery and DEM were accessed and processed using Google Earth Engine (GEE) (Gorelick et al., 2017), a cloud-based geospatial computing platform widely used for land-cover change studies and environmental analysis because of its efficiency and scalability (Phan et al., 2020; Shafizadeh-Moghadam et al., 2021; Tesfaye et al., 2024). Sectoral economic data were obtained from the BPS-Statistics Indonesia of Konawe Regency, using GRDP data for 2014, 2019, and 2024 from the corresponding regional statistical publications (BPS-Statistics Indonesia Konawe Regency, 2017, 2022, 2025).

Preprocessing steps included atmospheric correction and cloud masking to improve image spectral quality, followed by multi-temporal median compositing of the selected dry-season observations for each observation year. The median composite was used to reduce residual pixel-level variability among image acquisitions within each observation period and to provide a representative seasonal image for subsequent analysis. The resulting composites were then cropped to the watershed boundary. Topographic correction was subsequently performed using the C-correction method to minimize the influence of relief on reflectance values. Spectral features such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), were derived from the multispectral imagery, while elevation and slope were derived from the SRTM-DEM (Sun &

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Ongsomwang, 2023; Rynkiewicz et al., 2025). The resulting multi-temporal datasets were subsequently used as inputs for Random Forest land-cover classification.

These procedures produce a consistent basis for multi-temporal land-cover classification and change analysis. This integrative approach also aligns with previous research showing that the combination of remote sensing, machine learning, and spatial analysis can improve the accuracy of landscape change detection and the assessment of its ecological impacts (Biedemariam et al., 2022; Admasu et al., 2023; Mersha et al., 2024).

2.4 Land-Cover Classification and System Representation

Land cover classification was performed using the Random Forest algorithm (500 trees) in GEE, which has been widely adopted for remote sensing-based land-cover mapping because of its ability to integrate multiple spectral and topographic predictor variables (Phan et al., 2020; Sun & Ongsomwang, 2023). The Random Forest model classified each pixel into predefined land-cover classes using multispectral reflectance, vegetation and water indices, and terrain attributes as predictor variables.

The input variables used include multispectral reflectance, NDVI, NDWI, and topographic variables derived from the SRTM-DEM, including elevation and slope. This combination of spectral and topographic predictors has been applied in machine-learning-based land-cover mapping to improve class discrimination across heterogeneous landscapes (Shafizadeh-Moghadam et al., 2021; Rynkiewicz et al., 2025).

The resulting land-cover classes consisted of forests, agriculture, plantations, settlements, and water bodies/wetlands. Model validation was conducted using stratified random sampling and evaluated using Overall Accuracy, Producer Accuracy, and User Accuracy, with validation based on high-resolution image interpretation and field data (Sari et al., 2021; Admasu et al., 2023).

2.5 Quantification of Land-Cover Change

Land-cover change was analyzed using a post-classification area comparison approach, in which multi-temporal comparison classification maps were compared to identify changes among land-cover classes through a transition matrix. This approach produces three main outputs: (i) absolute area change for each class, (ii) proportional change to the total watershed area, and (iii) an inter-class transition matrix to explicitly represent land conversion dynamics.

Post-classification comparison was used because it enables land-cover changes to be quantified from independently classified maps, thereby providing a consistent basis for comparison across observation periods despite differences in sensor characteristics and acquisition conditions. The transition matrix was subsequently used to identify the direction and magnitude of conversions among land-cover classes and to provide the basis for calculating the ecological pressure indicators described in the following subsection.

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2.6 Spatial Hotspot Analysis

Spatial hotspot analysis was conducted to identify the geographic concentration of land-cover-derived ecological pressure within the Konaweha Watershed. The analysis was conducted after FLR and LPI were calculated for the spatial observation units, allowing the spatial distribution of ecological pressure to be evaluated across the watershed rather than only as an aggregate watershed value.

The Getis–Ord Gi* statistic, a local spatial autocorrelation statistic, was used to identify spatial clusters of relatively high and low ecological-pressure values. For each spatial observation unit, the FLR and LPI values derived from land-cover transitions were evaluated in relation to neighboring observations. The Gi* statistic determines whether high or low values are spatially concentrated rather than randomly distributed across the study area. Spatial relationships among observations were incorporated through the spatial-weight structure used in the GIS analysis, allowing neighboring observations to contribute to the local Gi* statistic. Positive Gi* z-scores indicate statistically concentrated clusters of high ecological-pressure values (hotspots), whereas negative z-scores indicate clusters of relatively low ecological-pressure values (coldspots) (Kumar et al., 2024; Velástegui-Montoya et al., 2025).

The resulting hotspot patterns were used to identify areas where land-cover-derived ecological pressure was spatially concentrated and to support the interpretation of spatial heterogeneity across the watershed. Hydrological zoning into upstream, middle, and downstream areas was used only to facilitate interpretation of the resulting spatial patterns and was not treated as an independent variable in the spatial analysis. Aggregate ecological change (ΔC) was not included in the Gi* analysis because it represents a watershed-level temporal measure of aggregate ecological change and was used separately as an input to the subsequent Tapio decoupling analysis.

2.7 Ecological Pressure Indicators

Ecological pressure was quantified using two spatial indicators derived from multi-temporal land-cover change analysis: the Forest Loss Rate (FLR) and the Land Use Pressure Index (LPI). Both indicators were calculated for spatial observation units within the Konaweha Watershed to characterize the spatial distribution of forest-loss and land-conversion pressure. The FLR represents the proportion of forest area lost relative to the initial forest extent and is calculated as:

$$FLR = \frac{F_{t2} - F_{t1}}{F_{t1}} \ x \ 100 \quad (1)$$

where Ft1 and Ft2 represent forest area within each spatial observation unit at the initial and final observation periods, respectively. The LPI measures the proportion of larea converted from selected natural and semi-natural categories to anthropogenic land uses and is formulated as:

$$LPI = \frac{A_c}{A_t} \ x \ 100 \quad (2)$$

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where A_c denotes the land-cover area converted into anthropogenic land uses within each spatial observation unit and A_t represents the corresponding area of the observation unit.

In this study, shrubland, primary dryland forest, secondary dryland forest, secondary mangrove forest, secondary swamp forest, and rice fields were defined as ecologically functional land-cover categories because of their contributions to hydrological regulation, ecological productivity, erosion control, biomass storage, and watershed ecological stability. FLR and LPI were therefore used as spatially distributed diagnostic indicators of forest-loss and land-conversion pressure, respectively, and their spatial values were subsequently used in the Getis–Ord Gi* hotspot analysis. In contrast, aggregate ecological change (ΔC) was calculated separately as a watershed-level temporal measure and served as the principal ecological variable in the subsequent decoupling analysis.

2.8 Ecological-Economic Linkage Variable

GRDP from the agriculture, forestry, and fisheries sector is used as a proxy for natural resource–based economic output at the Konawe Regency administrative level. The unit of analysis for GRDP was Konawe Regency for each observation period (2014, 2019, and 2024), which represents the dominant production area associated with the Konaweha Watershed. Within the analytical framework, GRDP is interpreted as a monetary representation of production intensity within the land–water system rather than as a conventional macroeconomic indicator. All GRDP data are expressed in constant prices to ensure temporal comparability.

The ecological-economic interaction is represented by the change in GRDP (ΔGRDP) and total ecological system change (ΔC). ΔGRDP captures economic dynamics, while ΔC reflects aggregate changes in the selected ecologically functional land-cover categories derived from multi-temporal land-cover change analysis. These variables constitute the core inputs for the subsequent decoupling analysis between economic growth and ecological pressure.

2.9 Decoupling Analysis: System Efficiency Approach

The relationship between economic growth and ecological pressure is analyzed using the Tapio Decoupling Elasticity model, a widely adopted framework for assessing the coupling relationship between economic development and environmental stress (Regueiro-Ferreira & Alonso-Fernández, 2022; Wang et al., 2023; Sun et al., 2025). The decoupling elasticity index (D) measures the responsiveness of ecological pressure change relative to economic growth.

Economic and ecological changes are computed as follows (Tapio, 2005; Jing et al., 2024):

$$\Delta GRDP = \frac{GRDP_{t2} - GRDP_{t1}}{GRDP_{t1}} \ x\ 100 \quad (3)$$

$$\Delta C = \frac{C_{t2} - C_{t1}}{C_{t1}} \ x\ 100 \quad (4)$$

The decoupling elasticity index is defined as:

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$$D = \frac{\Delta C}{\Delta GRDP} \tag{5}$$

where D represents the elasticity of ecological pressure relative to economic growth.

The classification of decoupling states follows Tapio (2005): $D < 0$ indicates absolute decoupling; $0 \leq D < 0.8$ indicates relative decoupling; $0.8 \leq D \leq 1.2$ indicates coupling; and $D > 1.2$ indicates negative decoupling.

To improve statistical robustness and reduce estimation uncertainty, a non-parametric bootstrap resampling procedure with 1,000 iterations was applied simultaneously to ΔGRDP and ΔC. This approach is widely used in environmental and socio-economic modelling to approximate sampling distributions under minimal parametric assumptions (Aggarwal, 2015; Dash et al., 2023). The procedure generates 95% confidence intervals for D, thereby enhancing the reliability and inferential stability of the decoupling results.

2.10 Data Integration Framework

All variables are described within an integrated systems framework consisting of land-cover dynamics (L), ecological pressures (S), and economic outputs (P). Land-cover dynamics represent changes in land cover and land use over time, while ecological pressures, represented by FLR, LPI, and total system change (ΔC), serve as aggregate ecological indicators. Economic outputs are linked to sectoral GRDP derived from agriculture, forestry, and fisheries activities.

These components are conceptualized as interconnected land–water socio-ecological systems operating within a hydrologically connected watershed framework, reflecting the interactions between landscape transformation, ecological pressures, and resource-based economic activities. This analysis adopts a system aggregation approach without explicit spatially distributed modeling.

2.11 Computational Tools

Image processing and land-cover classification were conducted using Google Earth Engine, while spatial visualization and descriptive inspection were performed using QGIS 3.30. Statistical analyses, decoupling calculations, and uncertainty estimation were carried out in R (version 4.x; R Foundation for Statistical Computing, Vienna, Austria) using the randomForest and boot packages.

2.12 Methodological Validity

This methodology adheres to international standards for land cover change analysis (Lu et al., 2004), economic-environmental decoupling evaluation (Tapio, 2005), and economics-based socio-ecological assesement approaches (de Groot et al., 2020). The secondary datasets and their sources are explicitly documented in the "Data Sources and Preprocessing" subsection. Land-cover validation was performed through a combination of high-resolution image interpretation and field data. No synthetic data manipulation was performed, and all procedures were designed to ensure full reproducibility.

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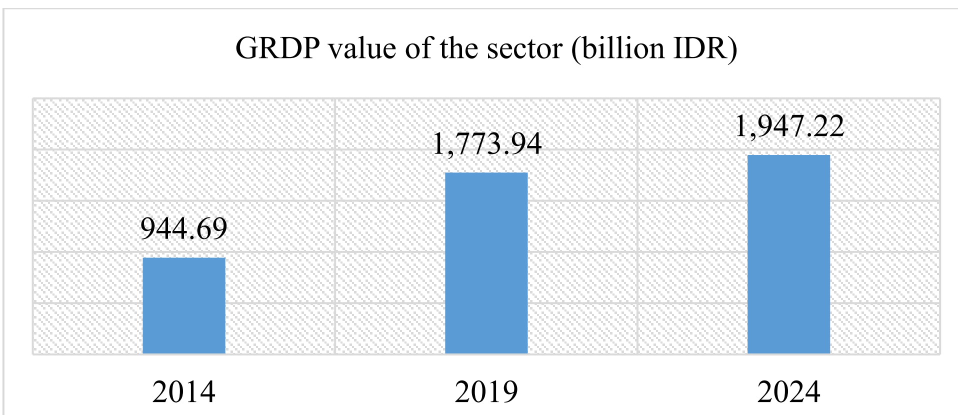
3. Results and Discussion

3.1 Economic Dynamics of the Agriculture, Forestry, and Fisheries Sector

The agriculture, forestry, and fisheries sectors in Konawe Regency represent one of the most fundamental components of the region's natural resource-based economy. This sector comprises several subsectors with distinct production characteristics, including: (a) food crops, (b) seasonal and perennial horticulture, (c) seasonal and perennial plantations, (d) livestock and agricultural services, (e) forestry and logging, and (f) capture and aquaculture fisheries. The structural differentiation among these subsectors provides an essential framework for assessing the performance of natural resource economic engineering, particularly in relation to production capacity, land utilization, and environmental carrying capacity within the Konaweha Watershed system.

The economic analysis used constant-price GRDP data for 2014, 2019, and 2024 to characterize medium-term sectoral growth dynamics. The quantitative results are presented in Figures 2–4, which display the GRDP values, sectoral contributions, and growth rates of the agriculture, forestry, and fisheries sectors.



Source: BPS-Statistics Indonesia Konawe Regency (2017, 2022, and 2025)

Figure 2. GRDP value of the agriculture, forestry, and fisheries sector in Konawe Regency 2014–2024.

Figure 2 indicates that the agriculture, forestry, and fisheries sector in Konawe Regency has shown a substantial increase in GRDP value over the past decade. Constant-price GRDP data reveal that the sector's output rose from IDR 944.69 billion in 2014 to IDR 1,773.94 billion in 2019, and further to IDR 1,947.22 billion in 2024. This nearly twofold increase during the first half of the period reflects strong growth momentum driven by agricultural land expansion, productivity improvements, and supportive regional policies. However, the growth rate slowed between 2019 and 2024, suggesting emerging constraints related to land carrying capacity, forest cover degradation, and market fluctuations. Overall, the figure highlights that while the natural resource-based sector remains a

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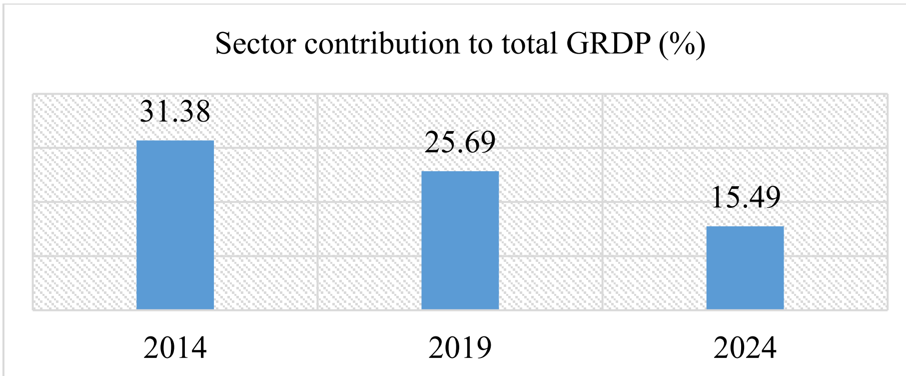
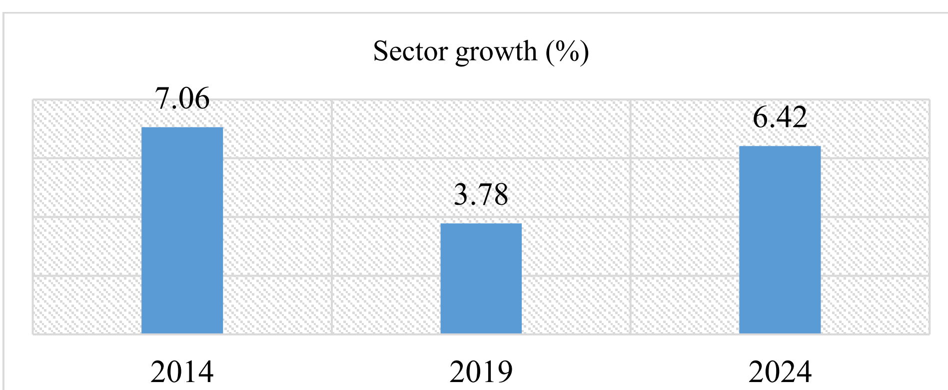
critical pillar of the regional economy, concerns about efficiency and sustainability are becoming more prominent, particularly within the context of managing the Konaweha Watershed as both an ecological and economic system.



Source: BPS-Statistics Indonesia Konawe Regency (2017, 2022, and 2025)

Figure 3. Contribution of the agriculture, forestry and fisheries sectors to the total GRDP of Konawe Regency 2014-2024.

Figure 3 shows that the contribution of the agriculture, forestry, and fisheries sector to Konawe Regency's total GRDP has declined significantly over the past decade. In 2014, the sector accounted for 32.38% of total GRDP, decreasing to 25.69% in 2019 and further dropping to only 15.49% in 2024. This steady decline reflects a structural transformation in the regional economy, where growth is increasingly driven by secondary and tertiary sectors—particularly manufacturing, trade, and services—which have expanded more rapidly than the primary sector. Although the agriculture-based sector continues to play a crucial role in employment and rural livelihoods, its relative contribution to the overall economy has weakened, suggesting a gradual shift from a resource-dependent structure toward a more diversified and industrialized regional economy.



Source: BPS-Statistics Indonesia Konawe Regency (2017, 2022, and 2025)

Figure 4. Growth rate of the agriculture, forestry and fisheries sector in Konawe Regency 2014-2024.

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As seen in Figure 4, the growth rate of the agriculture, forestry, and fisheries sector in Konawe Regency has fluctuated over the past decade. In 2014, the sector recorded a relatively high growth rate of 7.06%, driven by agricultural expansion, favorable climate conditions, and policy support for primary production. However, growth slowed to 3.78% in 2019, reflecting emerging constraints such as declining land productivity, environmental pressures, and limited technological innovation. In 2024, the growth rate recovered slightly to 6.42%, indicating a partial recovery driven by increased productivity and adaptive management efforts. Overall, these fluctuations indicate that while the sector remains resilient, its growth is increasingly sensitive to ecological conditions and market dynamics, emphasizing the need for sustainable resource engineering and integrated watershed management.

The observed trends in the agriculture, forestry, and fisheries sector of Konawe Regency indicate a dual dynamic: increasing sectoral output coupled with a decreasing contribution to total regional GRDP. This pattern reflects the ongoing structural transformation in the regional economy, with the industrial and service sectors growing faster than the primary sector. A similar trajectory has been reported in developing regions undergoing economic diversification, where agriculture gradually shifts from being the dominant engine of growth to serving as a foundation supporting broader economic development (Chrisendo et al., 2021; Anderson & Ponnusamy, 2023).

From an economic and environmental perspective, this dynamic may reflect a gradual transition from an extensive growth model, which relies primarily on land expansion, to a more intensive growth model that emphasizes productivity improvements and management adaptation. Although sectoral output continues to increase, the observed growth slowdown during 2019–2024 suggests emerging constraints related to land availability, ecological pressures, and market volatility. This trend is consistent with the resource-use efficiency approach, which seeks to maintain economic productivity while reducing ecological pressures (Hasddin, 2019; Azadi et al., 2021).

The fluctuating growth trajectory also demonstrates the sector's sensitivity to environmental and economic pressures. Periods of slower growth may be associated with declining land productivity, rainfall variability, and commodity price volatility, while subsequent recovery phases indicate adaptive responses in agricultural management and production systems. A similar pattern has been observed in watershed-based agricultural areas, where technological adaptations and conservation practices contribute to maintaining production under changing environmental conditions (Viana et al., 2022; Anggraheni et al., 2025).

Despite its declining contribution to total GRDP, the agriculture-based sector remains crucial for employment, food security, and watershed stability in the Konaweha region. Land-use changes in watersheds directly affect hydrological processes, including runoff, sedimentation, and ecosystem services (Baco et al., 2011b; Jasman et al., 2023). Therefore, sustainable land management practices—such as the implementation of agroforestry, contour-based cultivation, and conservation-oriented

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irrigation—remain important to balance agricultural productivity with ecological ecosystems (Andono et al., 2014; Maladeni et al., 2024).

3.2 Land-Cover Change and Spatial Distribution of Agricultural and Forest Areas

Land-cover change in the Konaweha Watershed was assessed for three observation years—2014, 2019, and 2024. The classification results comprised 12 main land-cover classes: primary dryland forest, secondary dryland forest, secondary mangrove forest, secondary swamp forest, shrubland, plantations, mixed dryland agriculture, savanna/grassland, rice fields, settlements, water bodies, and aquaculture ponds. The spatial distribution of these land-cover classes across the watershed is presented in Figures 5, 6, and 7, respectively, while their corresponding area distribution is summarized in Table 1.

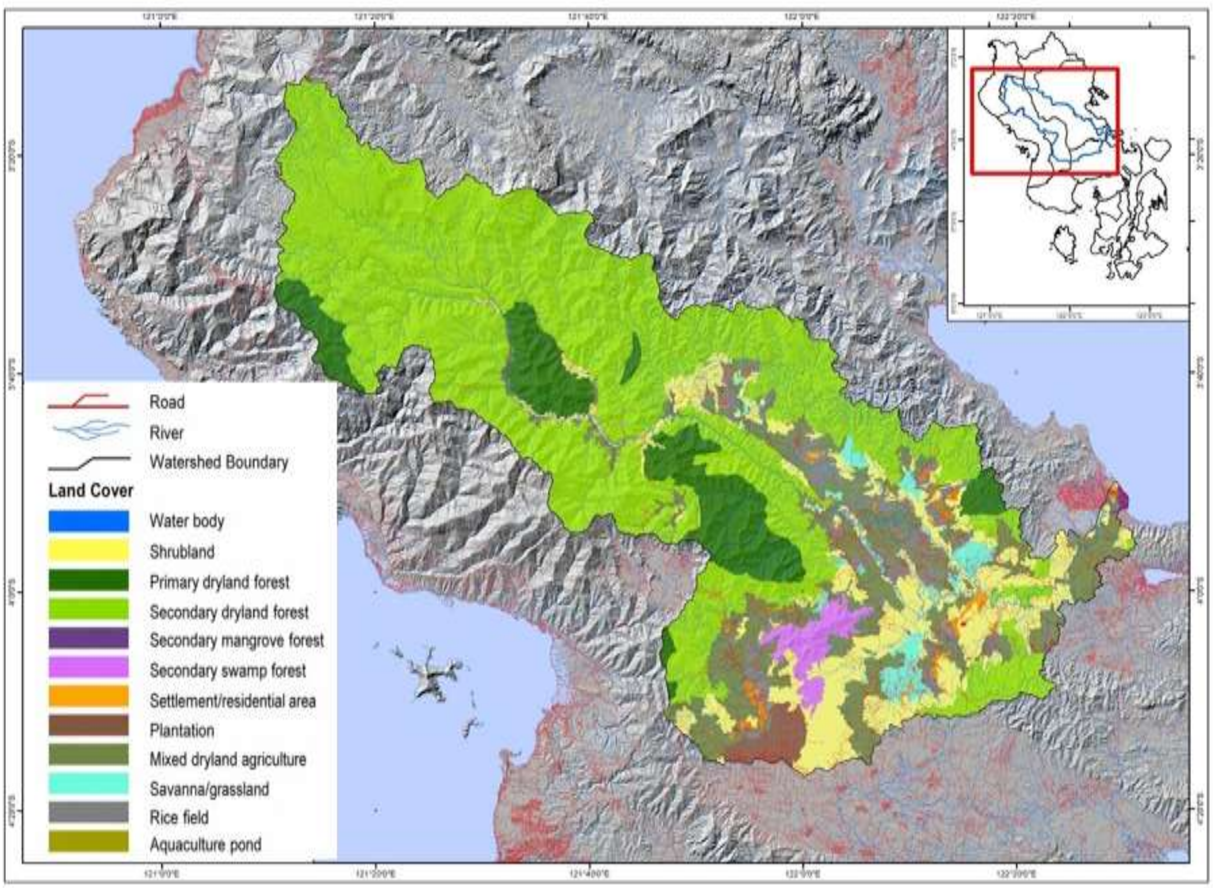

Figure 5. Spatial distribution of land-cover classes in the Konaweha Watershed, 2014.

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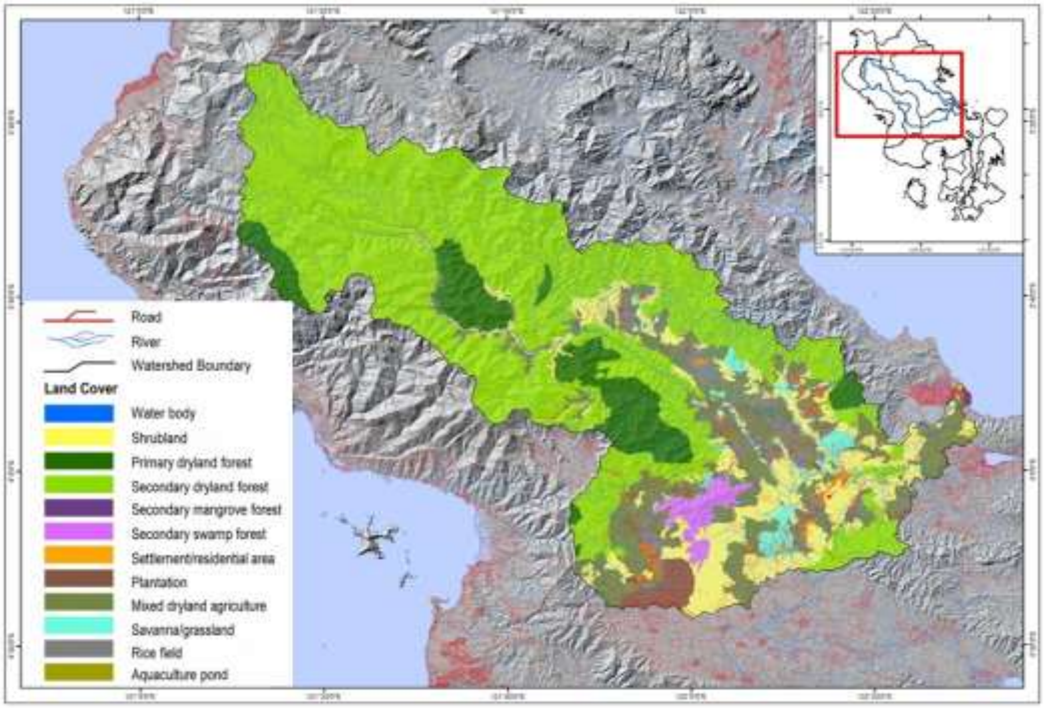

Figure 6. Spatial distribution of land-cover classes in the Konaweha Watershed, 2019.

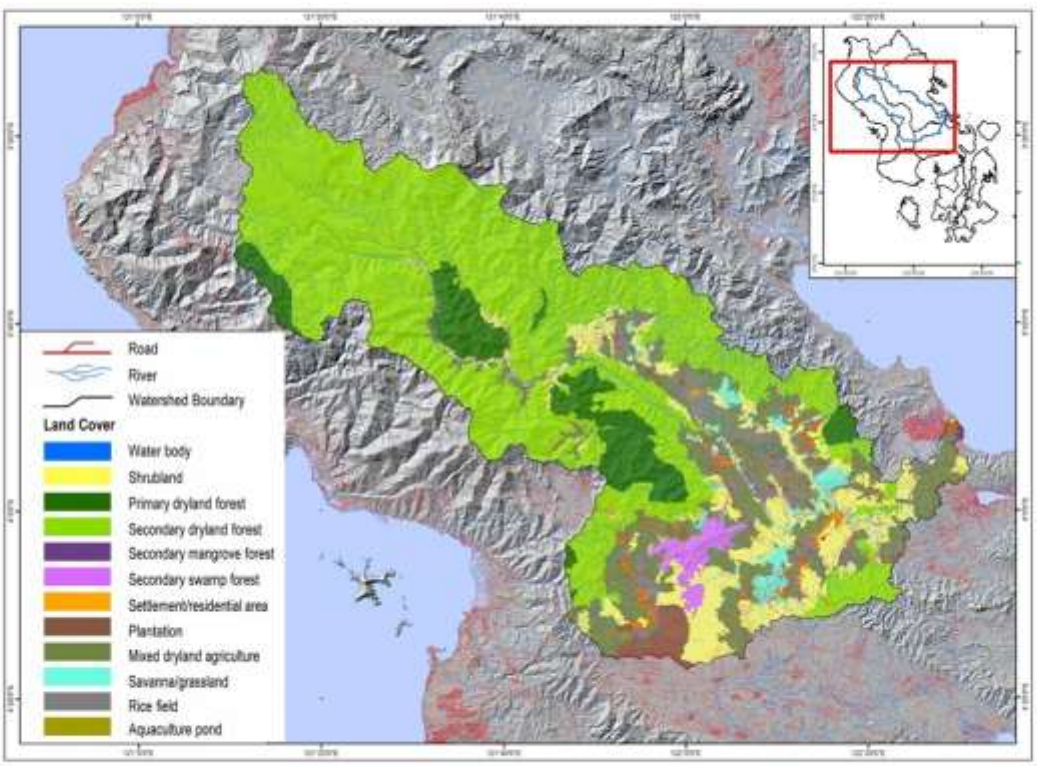

Figure 7. Spatial distribution of land-cover classes in the Konaweha Watershed, 2024.

Table 1. Land-cover of the Konaweha watershed in 2014, 2019, and 2024.

Land cover	Area (ha)			Change Dynamics	
	2014	2019	2024	2014-2019	2019-2024
Water body	1,700	1,700	1,700	0	0.00
Shrubland	60,096	52,567	47,972	-7,529	-4,595.00
Primary dryland forest	91,288	90,789	90,803	-499	14.00
Secondary dryland forest	221,211	180,806	166,499	-40,405	-14,307.00
Secondary mangrove forest	7,212	6,571	6,105	-641	-466.00
Secondary swamp forest	19,231	17,522	17,445	-1,709	-77.00
Settlement/residential area	5,922	7,607	8,986	1,685	1,379.00
Plantation	48,077	89,802	107,282	41,725	17,480.00
Mixed dryland agriculture	101,835	111,405	111,641	9,570	236.00
Savanna/grassland	98,780	95,009	94,801	-3,771	-208.00
Rice field/ricefield	23,317	24,766	25,262	1,449	496.00
Aquaculture pond	239	364	412	125	48.00
Konaweha Watershed	678,908	678,908	678,908		

Land-cover classification results show substantial structural transformation in the Konaweha River Basin during 2014–2024, particularly through the decline of secondary dryland forest and the expansion of plantations. Secondary dryland forest decreased by 54,712 ha, from 221,211 ha in 2014 to 166,499 ha in 2024, whereas plantation area increased by 59,205 ha, from 48,077 ha to 107,282 ha over the same period. These changes demonstrate a substantial restructuring of the watershed land-cover composition, with the decline of several natural and semi-natural land-cover classes occurring alongside the expansion of anthropogenic land-cover classes. The spatial distribution of these changes across the three observation years is shown in Figures 5–7, while the corresponding area dynamics are reported in Table 1. The spatial concentration of land-cover change in the hydrologically connected middle and lower reaches further indicates that ecological degradation is associated with infrastructure accessibility, irrigation development, and regional economic integration. Similar patterns have been reported across tropical watersheds, where agribusiness expansion is associated with deforestation and ecological degradation (Hasan et al., 2020; Admasu et al., 2023; Faoziyah et al., 2024).

The reduction of secondary dryland forests cover has important implications for watershed ecological stability. Previous studies in the Konaweha Watershed have linked declining forest cover to increased surface runoff, decreased infiltration, decreased baseflow stability, and higher flood vulnerability (Tanika et al., 2017). This study extends these findings by demonstrating that ecological degradation occurs unevenly across spatially interconnected land systems, rather than as isolated land-cover transitions. Intensive conversion in the Wawotobi, Unaaha, and Pondidaha Districts indicates that downstream agricultural accessibility and infrastructure expansion accelerate the

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accumulation of ecological pressures, while fragmentation along river corridors in upstream areas such as Lambuya and Asinua indicates the emergence of ecological instability despite relatively higher remaining forest cover.

The integration of the FLR, LPI, and aggregate ecological system change (ΔC) provides a more comprehensive representation of the dynamics of ecological pressures in the watershed. Rather than describing land-cover change solely through areal statistics, these indicators conceptualize ecological degradation as a spatially differentiated system of pressures across interconnected hydrological units. The strongest ecological pressure occurred during 2014–2019 ($\Delta C = -11.81\%$), coinciding with rapid plantation expansion and agricultural conversion, followed by a slower but persistent decline during 2019–2024 ($\Delta C = -5.30\%$). While this slowdown may indicate a partial stabilization of the land conversion process, the persistence of negative ΔC values suggests that regional economic growth remains partially linked to ecological degradation. A comparable transition pattern has been identified in recent decoupling-based environmental studies (Wang et al., 2023; Jing et al., 2024).

Spatial hotspot analysis further revealed significant intra-basin heterogeneity in the distribution of ecological pressures. Conversion hotspots are concentrated in the middle and lower reaches of the district, where transportation networks, irrigation systems, and agribusiness investments serve as spatial accelerators of land-cover transformation. These findings suggest that watershed degradation is shaped not only by land cover conversion itself but also by the spatial organization of socio-economic development within hydrologically connected areas. These findings suggest that watershed transformation in Konaweha reflects interconnected ecological and socio-economic processes operating across hydrologically connected areas.

3.3 Decoupling Between Economic Growth and Environmental Degradation

The analysis of the relationship between sectoral economic growth and environmental degradation was conducted using the Economic–Ecological Decoupling Analysis (Integrated Approach) based on the Tapio Decoupling Elasticity Model (Tapio, 2005; Jing et al., 2024). This approach allows quantification of the extent to which economic growth in the agriculture, forestry, and fisheries sectors can be separated from ecological pressures in the Konaweha watershed. This analysis supports the evaluation of the environmental efficiency of natural resource systems and the economic–ecological trade-offs.

Sectoral GRDP growth ($\Delta GRDP$) was calculated using constant-price GRDP data for the agriculture, forestry, and fisheries sector of Konawe Regency for 2014, 2019, and 2024, using Equation (3). Konawe Regency was used as the administrative economic unit, while the ecological analysis was conducted within the hydrologically delineated Konaweha Watershed. Thus, $\Delta GRDP$ represents temporal economic change at the Konawe Regency level and serves as a socioeconomic proxy for the dominant economic area associated with the watershed, rather than as a spatially aggregated watershed-level economic measure. The calculation results are presented in Table 2.

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Table 2. Sectoral economic growth (ΔGRDP).

Period	Initial GRDP (IDR billion)	Final GRDP (IDR billion)	Growth (%)
2014–2019	944.69	1,773.94	87.76
2019–2024	1,773.94	1,947.22	9.77
2014–2024	944.69	1,947.22	106.15

The analysis reveals a period of robust economic expansion from 2014 to 2019, followed by a deceleration in growth during 2019–2024. Cumulatively, the regional economy expanded by 106.15 % over the 2014–2024 period, reflecting sustained long-term growth despite the recent slowdown.

Ecological pressure was quantified based on changes in natural and semi-natural land-cover within the watershed. The analyzed categories included shrubland, primary dryland forest, secondary dryland forest, secondary mangrove forest, secondary swamp forest, and rice fields, representing ecologically functional land-cover contributing to hydrological regulation, biomass productivity, and ecosystem stability.

For the aggregate ecological change (ΔC), six ecologically functional land-cover classes were considered within the watershed: shrubland, primary dryland forest, secondary dryland forest, secondary mangrove forest, secondary swamp forest, and rice fields. These classes were included in the aggregate because they represent land-cover associated with hydrological regulation, ecological productivity, erosion control, biomass storage, and watershed ecological stability. Other land-cover categories—including settlements, plantations, aquaculture ponds, savanna/grassland, and water bodies—were retained in the land-cover inventory but excluded from the ΔC calculation. The aggregate extent of these six classes was calculated for each observation year, and the resulting changes were used to derive ΔC following Equation (4), as presented in Table 3.

The results indicate a decline in the aggregate extent of ecologically functional land-cover by 11.68% during 2014–2019, followed by a further decline of 5.08% during 2019–2024. Over the full 2014–2024 period, the aggregate extent decreased by 16.16%, equivalent to a net reduction of 68,269 ha. The smaller decline during 2019–2024 indicates a lower magnitude of aggregate ecological change than in the preceding period, although the negative ΔC across both intervals indicates continued contraction of the defined ecologically functional land-cover classes.

Tabel 3. Changes in natural and semi-natural land systems and aggregate ecological change.

Period	Initial Area (ha)	Final Area (ha)	ΔC (ha)	ΔC (%)
2014–2019	422,355	373,021	-49,334	-11.68
2019–2024	373,021	354,086	-18,935	-5.08
2014–2024	422,355	354,086	-68,269	-16.16

Finally, the Tapio decoupling elasticity model was used to evaluate the relationship between aggregate ecological system change (ΔC) and sectoral GRDP growth in the agriculture, forestry, and fisheries sectors. The results are presented in Table 4.

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Table 4. Decoupling analysis between aggregate ecological change (ΔC) and sectoral GRDP growth, 2014–2024.

Period	ΔC (%)	ΔGRDP (%)	*D*	Decoupling Category
2014–2019	-11.68	87.76	-0.1331	Absolute decoupling
2019–2024	-5.08	9.77	-0.5200	Absolute decoupling
2014–2024	-16.16	106.15	-0.1522	Absolute decoupling

Because the ecological and economic datasets have different spatial boundaries, the decoupling results are interpreted as a system-level temporal comparison rather than as a spatially equivalent watershed-level economic assessment. Ecological change (ΔC) was calculated within the Konaweha Watershed boundary, whereas sectoral GRDP for Konawe Regency was used as the socioeconomic proxy for the dominant production area associated with the watershed.

The results show that aggregate ecological system change (ΔC) remained negative across all observation periods, while sectoral GRDP increased. Accordingly, all three periods exhibited absolute decoupling, with D values of −0.1331, −0.5200, and −0.1522, respectively. The 2014–2019 period recorded the strongest sectoral GRDP growth (87.76%) alongside an 11.68% decline in ΔC, whereas growth slowed to 9.77% during 2019–2024 while ΔC declined by 5.08%. Over the full 2014–2024 period, sectoral GRDP increased by 106.15%, while ΔC declined by 16.16%.

These results indicate that economic growth in the agriculture, forestry, and fisheries sectors was not accompanied by a proportional increase in the aggregate ecological change measured in this study. However, the negative ΔC values indicate continued contraction of the defined ecologically functional land systems, so absolute decoupling should not be interpreted as an absence of ecological change.

The absolute decoupling observed across all periods indicates that economic growth occurred alongside a reduction in aggregate ecological change within the study framework. This pattern indicates a weakening of the proportional relationship between economic activity and ecological pressure, as economic expansion was not accompanied by a corresponding intensification of ecological change. Nevertheless, decoupling does not imply the absence of ecological transformation. The continued occurrence of land-system change indicates that environmental pressures remain relevant to watershed management and require sustained attention.

This pattern may reflect improvements in land-cover efficiency, adaptive management practices, technology adoption, or policy interventions related to environmental governance and resource management. Similar results have been reported in watershed systems and agriculture, where effective land management and institutional regulations contribute to reduced ecological pressure despite continued economic expansion (Admasu et al., 2023). These findings are also consistent with broader discussions on sustainable intensification and green growth, which emphasize the possibility of balancing economic development with environmental conservation under appropriate management conditions (Jing et al., 2024; Yu & Yang, 2024).

A comparable pattern of decoupling was recently reported by Kasim et al. (2026) in the Tiworo Watershed, Southeast Sulawesi, where absolute decoupling was also observed alongside sustained growth in the agriculture and fisheries sectors. However, while the Tiworo study primarily emphasized ecosystem service trade-offs and aggregate land-cover dynamics, this study expands the analytical application of decoupling analysis by integrating ecological pressure indicators (FLR, LPI, and ΔC), hotspot-based land transformation assessments, and machine learning-derived watershed classifications. This integration allows for a more spatially explicit interpretation of how ecological pressures are distributed across hydrologically connected watershed zones, thus strengthening the applicability of the decoupling approach to watershed assessment and land management planning in heterogeneous tropical landscapes.

The absolute decoupling observed during 2019–2024 indicates that economic growth was accompanied by a reduction in the magnitude of aggregate ecological change, despite the continued transformation of land-cover within the watershed. This pattern highlights the possibility of improving economic-ecological efficiency while ecological pressures remain present. Similar studies have emphasized that decoupling can represent an important transitional pathway toward more environmentally efficient development (Azadi et al., 2021; Mersha et al., 2024). However, the continued transformation of land-cover suggests that economic growth has not yet been fully separated from ecological change, underscoring the need for sustained efforts to strengthen environmental performance.

The lower magnitude of aggregate ecological change during the later period further indicates a reduction in the intensity of ecological transformation within the watershed. This trend may be related to adaptive responses such as rehabilitation efforts, the adoption of agroforestry, improved land management practices, or a shift toward less land-intensive agricultural activities. Similar patterns have been observed in other watershed systems where restoration measures and policy integration have contributed to lower ecological impacts while maintaining regional economic activity (Maladeni et al., 2024). However, the persistence of ecological transformation suggests that ecological stabilization in the Konaweha Watershed remains incomplete.

Furthermore, the decoupling index (D) provides a concise quantitative representation of the relationship between economic growth and ecological system change, allowing for clearer interpretation of environmental performance within the watershed system. This analytical approach offers a practical basis for evaluating whether regional economic expansion occurs concurrently with increasing or decreasing ecological pressures, thus supporting more evidence-based watershed planning and environmental management.

Overall, the findings suggest that sustainable economic growth in the Konaweha Watershed will depend on strengthened land-cover (and land use) planning, conservation-oriented agricultural practices, and watershed rehabilitation strategies. Improving the alignment between economic development and ecological capacity remains critical to maintaining long-term watershed resilience and mitigating future environmental stress in a rapidly transforming tropical landscape.

4. Conclusion

Overall, the Konaweha watershed experienced sustained economic growth alongside intensive land-cover transformation during 2014–2024, characterized primarily by the plantations expansion and the decline of natural and semi-natural land-cover, particularly secondary forests, while the growth of the agriculture, forestry, and fisheries sector slowed during the latter period. Spatial analysis further showed heterogeneous ecological pressures across the hydrologically interconnected watershed, with conversion hotspots concentrated mainly in the middle and lower reaches where agricultural and infrastructure-related activities were more intensive, indicating continued pressure on watershed ecological functions. The Tapio analysis indicated absolute decoupling across all examined periods, showing that economic growth was not accompanied by a proportional increase in the aggregate ecological change measured in this study; however, persistent negative ΔC values demonstrate that contraction of the defined ecologically functional land systems continued despite the decoupling condition. These findings indicate that economic development and ecological transformation in the Konaweha Watershed are not fully separated and that future agricultural and biosystem engineering strategies should prioritize spatially integrated watershed management, conservation-oriented agricultural intensification, and land-use planning that considers hydrological connectivity to maintain economic productivity while strengthening long-term ecological resilience.

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6. AI Writing Statement

The author used Grammarly as an AI-based writing aid solely for grammar checking, language editing, and enhancing manuscript clarity. All data processing, land-cover analysis, ecological pressure assessment, economic-ecological decoupling analysis, data interpretation, and scientific conclusions are the author own work.

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