A Multi-Temporal Remote Sensing Approach to Quantify Land Cover Change and its Impact on Ecosystem Sustainability in Riau, Indonesia

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Abstract. This study analyzes land cover change in Riau Province from 2015 to 2024, focusing on deforestation and degradation as indicators of ecosystem sustainability. Landsat 8 OLI/TIRS and Landsat 9 OLI-2 imagery processed in Google Earth Engine (GEE), combined with MODIS hotspot data (MOD14A1) and socioeconomic indicators—Gross Regional Domestic Product (GRDP) and Open Unemployment Rate (OUR) from Statistics Indonesia (BPS)—were used to assess spatiotemporal patterns. The Normalized Difference Vegetation Index (NDVI) was applied with thresholds for deforestation (NDVI < –0.3) and degradation (–0.3 ≤ NDVI ≤ –0.1). Results show that 2015 was the most severe period, dominated by peatland fires, while 2019 recorded forest loss at a lower intensity and 2020–2024 indicated partial vegetation recovery linked to restoration efforts. Pelalawan, Indragiri Hilir, and Kampar were the most affected districts. Correlation analysis revealed that fire hotspots had the strongest association with land cover change, while economic and social indicators showed weaker relationships. Peatland fires remain the main driver of land degradation, emphasizing the need to strengthen fire management, peatland protection, and sustainable plantation governance to support Sustainable Development Goal (SDG) 15 on Life on Land, particularly the target of Land Degradation Neutrality (15.3.1) by 2030.
Keywords: deforestation, degradation, fire hotspot, NDVI, sustainable development, Riau.

1. Introduction

Sustainable development is a global agenda that aims to achieve a balance between environmental, social, and economic dimensions. This agenda is embodied in the 17 Sustainable Development Goals (SDGs) adopted by the United Nations in 2015. The SDGs call for collective action to eradicate poverty, protect ecosystems, and ensure that everyone enjoys peace and prosperity by 2030 [4]. At the national level, Indonesia has integrated the SDGs into its medium- and long-term development policies through the National Medium-Term Development Plan (RPJMN). This commitment affirms that economic development must go hand in hand with environmental protection and social justice, in accordance with the principle of SDG integration [4]. Against this backdrop, the context of sustainable development becomes increasingly important to analyze in regions facing high ecological pressure, such as Riau Province.

Riau Province is one of the regions with the most important terrestrial ecosystems in Indonesia, which includes tropical rainforests, peatlands, and high biodiversity. However, development pressures through land conversion for oil palm plantations, industrial timber plantations (HTI), and land conversion for settlements have led to serious environmental problems. Forest and land fires, especially in peatlands, have become a major disaster causing deforestation and high greenhouse gas emissions [8]. The peatland fires in Sumatra in 2015, for example, caused large-scale environmental, health, and economic losses [11]. These conditions not only resulted in the loss of forest cover but also had direct implications for the achievement of SDG 15 on terrestrial ecosystems, requiring a scientific approach to assess land change dynamics.

Remote sensing technology and Geographic Information Systems (GIS) offer essential tools for monitoring and addressing land degradation challenges. Optical and radar satellite data are widely used to observe land cover changes, detect fires, and map ecosystem conditions. Landsat-8 and Sentinel-2 have proven effective for detecting tropical peatland fires [6], while multi-source data (optical and radar) offer higher accuracy in monitoring peatlands [10]. On the other hand, GIS plays an important role in spatial analysis, ranging from overlay techniques, spatial modeling, to conservation planning. Research by Wildayana [2] integrates remote sensing data with GIS to identify socio-economic factors causing peatland degradation, while Han et al. [9] emphasize the use of spatial data in evaluating SDG indicators. Thus, the use of spatial data not only highlights ecological aspects, but also links ecosystem dynamics to broader socio-economic factors.

Previous studies in Sumatra show that peat ecosystem degradation is not solely triggered by ecological factors but also by socio-economic and governance variables. Carbon emission estimates from peat fires have been extensively studied using an approach that integrates remote sensing and GIS [11]. In addition, mapping of tropical forest carbon stocks using optical satellite imagery and LIDAR, as well as studies of land degradation for SDG indicator 15.3.1, show that spatial methods can serve as a tool for measuring SDG achievement [5], [7]. More specifically, the dynamics of deforestation and degradation are also influenced by social and economic variables. Variables such as the Open Unemployment Rate (OUR) reflect social pressure on land use [14], Gross Regional Domestic Product (GRDP) is related to the expansion of land-based sectors and regional economic growth [16], [17], while the number of hotspots is the main proxy for measuring the intensity of fires that directly impact forest and land degradation [15].

Based on this context, this study focuses on analyzing changes in land cover and terrestrial ecosystems in Riau Province for the period 2015–2024. The study aims to analyze the dynamics of deforestation and degradation using a Google Earth Engine-based Normalized Difference Vegetation Index (NDVI) approach, identify degradation hotspots and their contributing variables, examine the relationship between land cover change and social, economic, and environmental indicators, and evaluate its implications for the achievement of SDG 15. From an academic perspective, this research strengthens the methodology of remote sensing-based ecosystem monitoring in the context of SDGs [3]. From a practical perspective, the results of this research provide relevant spatial data for sustainable development planning and support evidence-based policies for local governments in accordance with Bappenas guidelines.

2. Research Method

This study uses a quantitative approach based on spatial and statistical analysis to examine the dynamics of deforestation, degradation, and their relationship with social, economic, and environmental indicators. The unit of analysis consists of regencies and cities in Riau Province for the period 2015–2024. This approach was chosen because it enables the integration of satellite data and statistical indicators to provide a more comprehensive picture of land cover change. The main data were obtained from Landsat 8 OLI/TIRS and Landsat 9 OLI-2 satellite images accessed through the Google Earth Engine (GEE) platform. These data were used to calculate vegetation indices and analyze changes in land cover. Information on hotspots was obtained from MODIS Thermal Anomalies/Fire (MOD14A1) products for 2015, 2019, and the 2020–2024 period. Meanwhile, the administrative boundary map of districts and cities in Riau Province was obtained from the Central Bureau of Statistics (BPS) as the basis for spatial analysis of area division. The socioeconomic indicators were also sourced from BPS. The economic indicator used is the Gross Regional Domestic Product (GRDP) at Constant 2010 Prices (ADHK) for the Agriculture, Forestry, and Fisheries sector, hereafter referred to as GRDP_agri, while the social indicator is the Open Unemployment Rate (OUR), referred to as Unemp_rate. These indicators were selected to represent economic and social pressures on land use and ecosystem changes.

The analysis of land cover changes in the study area was conducted using the Normalized Difference Vegetation Index (NDVI) analysis method on the Google Earth Engine (GEE) platform. NDVI was chosen for its ability to detect variations in biomass and vegetation density both temporally and spatially. The NDVI calculation formula is as follows:

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \qquad (1)$$

where,

NIR : spectral reflectance values in the near-infrared channel

RED : spectral reflectance value in the red band

The NDVI index produces values between –1 and +1, where values close to +1 indicate healthy and dense vegetation, while values close to –1 indicate conditions without vegetation or damaged vegetation. Thus, NDVI calculations provide a quantitative basis for assessing vegetation changes over time.

To detect changes in land cover over time, this study does not only use a single NDVI value, but also calculates the delta NDVI (ΔNDVI). This change is obtained by comparing the NDVI value in the analysis period with the NDVI value in the baseline period, using the following formula:

$$\Delta NDVI = NDVI_t - NDVI_{t-1} \qquad (2)$$

where,

$NDVI_t$: NDVI value from satellite imagery in the analysis period

$NDVI_{t-1}$: NDVI value from satellite imagery in the baseline period

Based on the analysis results $\Delta NDVI$, land cover change is classified into two main categories, namely deforestation and forest degradation, using different thresholds. Deforestation is defined as the total loss of tree cover, which is classified for areas with the most drastic decline in vegetation. To identify this category, an $\Delta NDVI$ threshold of less than 0.3 is used. This value was selected based on a study by Demir and Dursun (2023), which showed that this threshold is the most effective and accurate value for separating extreme vegetation changes (such as burned areas) from seasonal variations or minor disturbances [1]. Meanwhile, forest degradation is defined as a gradual and non-permanent decline in forest quality or density. This category was chosen to provide a more comprehensive picture, as not all forest damage results in total loss. To identify degradation, a more lenient threshold is used, namely a $\Delta NDVI$ value between -0.3 and -0.1. This range allows the study to capture areas that have suffered significant damage, such as from selective logging, but have not been completely lost. With this classification, the study can more accurately distinguish the ecological impacts of total forest cover loss from a decline in vegetation quality.

The analysis period was divided into three stages: 2015 to assess the impact of forest fires with a baseline average of 2010–2014, 2019 to assess the impact of fires with a baseline of 2016–2018, and 2020–2024 to assess vegetation recovery trends with a baseline of 2019. The image data processing was carried out in GEE, including cloud masking, annual composite creation, vegetation index calculation, and deforestation and degradation classification. The processed data was exported to QGIS for overlaying with district/city administrative maps and thematic map creation, while tabular analysis and correlation were performed using Microsoft Excel. This stage ensured that the results obtained were not only spatial but also had a quantitative dimension that could be further tested.

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To examine the relationship between land cover change and social, economic, and environmental indicators, this study uses Pearson's correlation analysis. Environmental indicators are represented by the number of fire hotspots (from MODIS), which have been empirically proven to be closely correlated with forest fires and land degradation [15], [16]. Economic indicators are represented by GRDP_agri, which reflects regional economic growth dynamics and is closely related to the expansion of land-based sectors such as plantations and forestry [14], [17]. Meanwhile, social indicators are represented by the Unemp_rate as a measure of social pressure on land use, given that labor dynamics have an influence on changes in forest and land use patterns [14]. This analysis aims to identify the significance of forest fires in influencing deforestation and degradation, while evaluating their relationship with regional socioeconomic conditions. Thus, the methodological approach used not only focuses on biophysical conditions but also integrates social and economic dimensions as part of a sustainable development analysis framework.

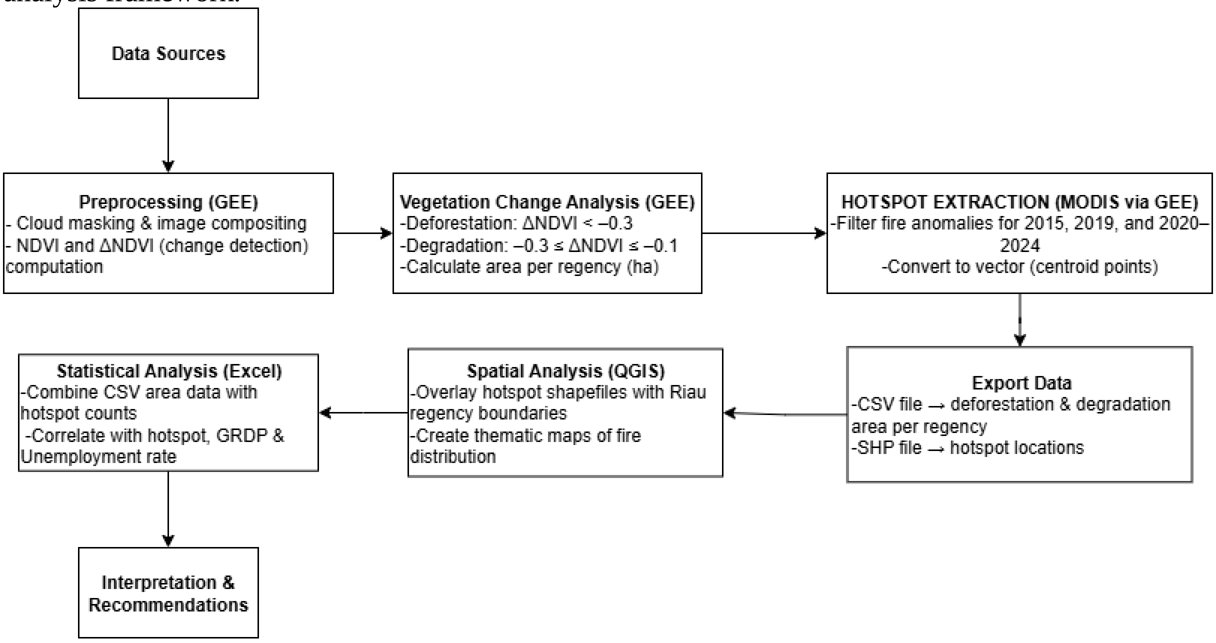


Figure 1. Workflow of Data Processing and Analysis for Land Cover Change and Correlation Assessment.

3. Result and Discussion

3.1. General Description of Land Cover Change

The analysis of land cover change in Riau Province shows varying dynamics of deforestation and degradation across the study period (Figure 1). The year 2015 represented the most severe phase of forest damage, largely driven by large-scale peatland fires. During this period, degradation exceeded deforestation, indicating that most of the damage reflected a decline in vegetation quality rather than a complete loss of forest cover. Although vegetation remained in many areas, ecosystem quality had deteriorated sharply. By 2019, forest damage remained significant but with lower intensity. Degradation continued to dominate over deforestation. This reflects a shift in disturbance patterns, where ecosystem pressure persisted, though not as intense as in 2015. In the 2020–2024 period, the results indicated a gradual trend of vegetation recovery. Deforestation became relatively limited, while degradation still occurred but at smaller scales. This suggests ongoing vegetation regeneration and the positive effects of peatland restoration efforts. Nevertheless, the recovery remains partial, as peat ecosystems continue to be highly vulnerable to renewed disturbances.

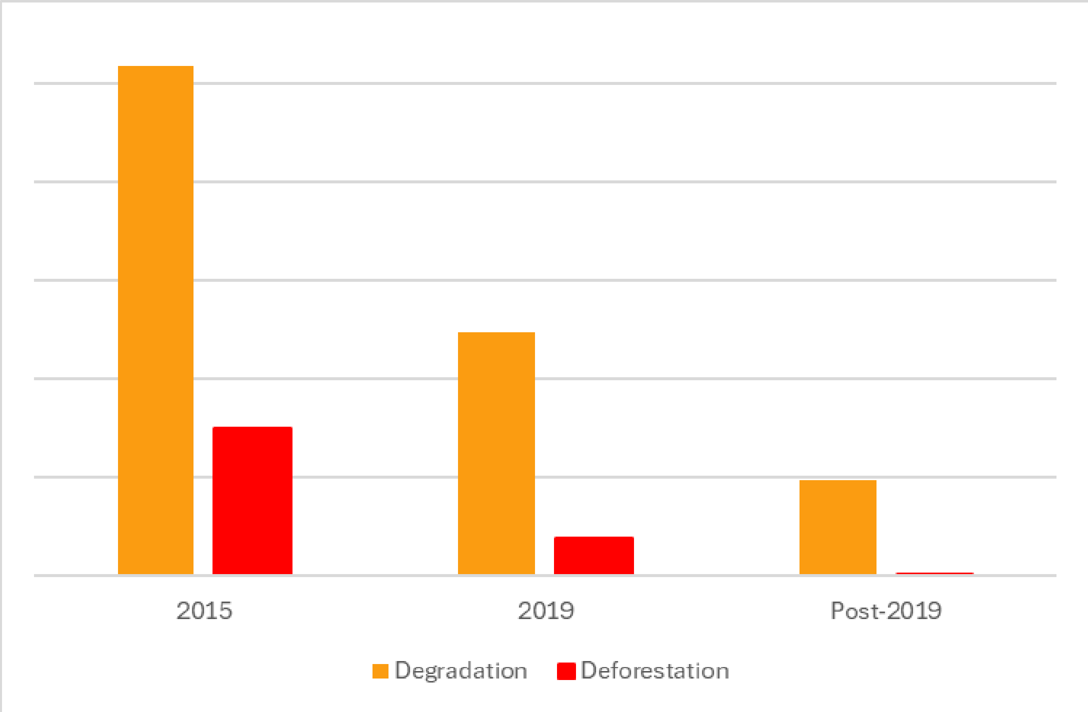
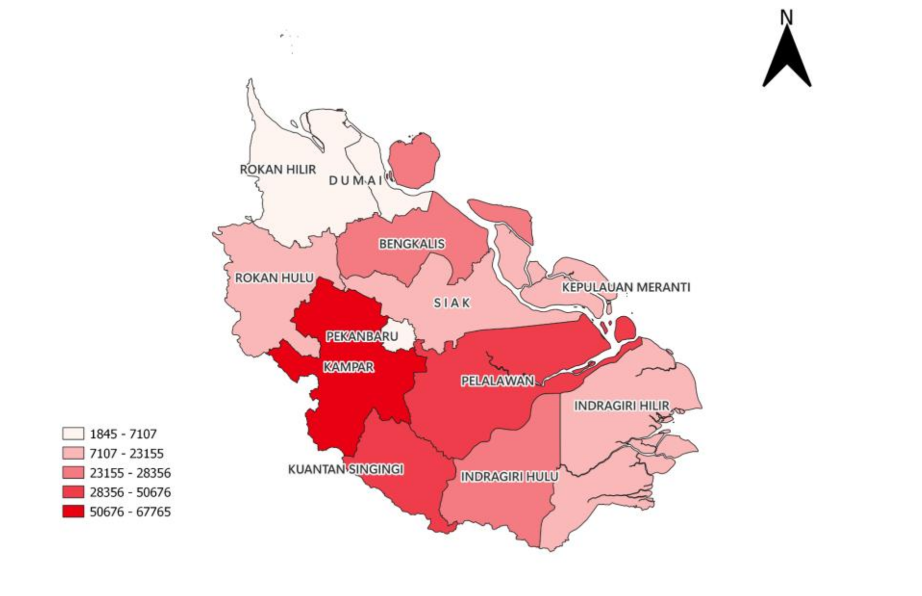


Figure 2. Comparison of deforestation and degradation areas in Riau Province in three analysis periods (2015, 2019, and post-2019).

3.2. Spatial Analysis of Land Cover Change

To provide a spatial overview, thematic maps were generated to illustrate the distribution of deforestation across districts and cities in Riau (Figure 2). In 2015, the largest deforestation occurred in Kampar District (approximately 67,764 hectares), followed by Pelalawan and Kuantan Singingi, reflecting the impact of widespread forest and peatland fires. Areas with dense plantation and peat ecosystems tended to be deforestation hotspots. In 2019, Pelalawan recorded the highest deforestation (around 20,561 hectares), followed by Indragiri Hilir and Siak. This pattern corresponds to the dominance of oil palm and industrial forest plantations (HTI) that increased fire risks, while urban areas such as Pekanbaru and Dumai experienced relatively low rates of forest loss. These results confirm that agriculture-based economic structures remain major drivers of ecosystem degradation. After 2019, deforestation decreased sharply across most districts, aligning with the decline in hotspot numbers and indicating that restoration and fire management policies had begun to take effect. However, Indragiri Hilir remained under persistent land pressure, reflecting ongoing vulnerability in peat-dominated areas.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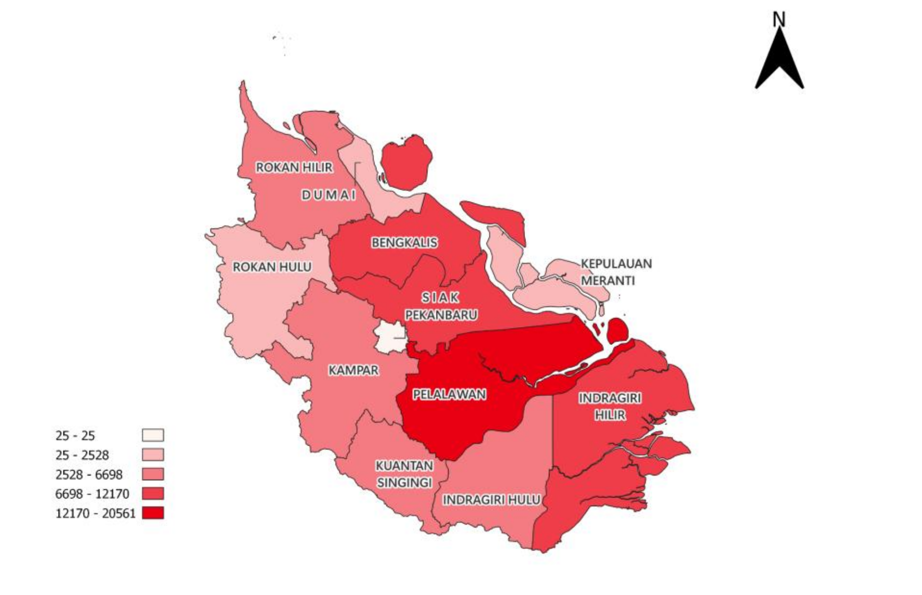
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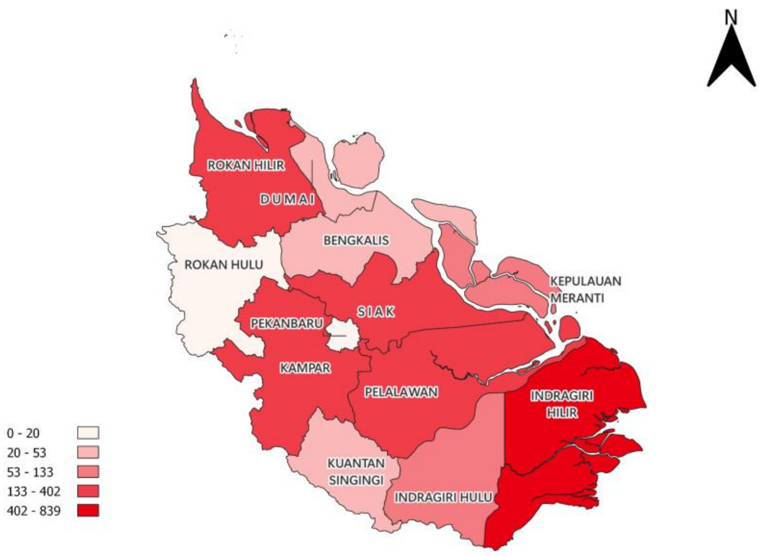
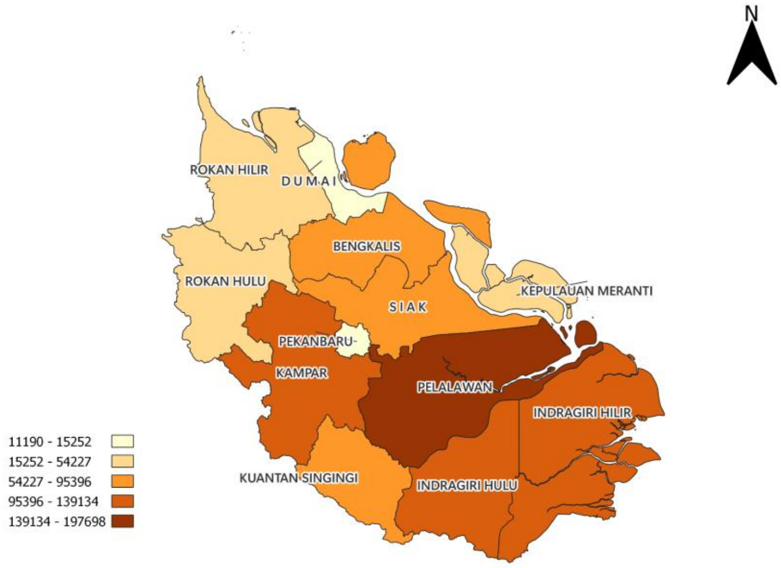


(c)

Figure 3. Map of the spatial distribution of deforested land area with three analysis periods: (a) 2015 compared to the 2010–2014 average, (b) 2019 compared to the 2016–2018 average, and (c) the 2020–2024 period compared to 2019.

The spatial pattern of forest degradation in Riau Province also varied across periods (Figure 3). In 2015 (Figure 3a), degradation was extensive, with the highest concentrations in Pelalawan and Kampar—each exceeding 130,000 hectares—consistent with large peat fires that caused severe vegetation loss across eastern and southern Riau. Urban areas such as Pekanbaru and Dumai showed relatively low degradation, confirming that vegetation damage was concentrated in fire-prone peatland regions. By 2019 (Figure 3b), the extent of degradation had declined but remained considerable. Pelalawan again recorded the highest degradation, followed by Indragiri Hilir and Siak (75,000–96,000 hectares), while Kampar showed a notable reduction. This shift indicates that the degradation center moved eastward, dominated by peat and oil palm plantation zones, highlighting plantation expansion and unsustainable land management as key contributors. During 2020–2024 (Figure 3c), a positive trend emerged with a significant decline in degradation across most districts. Indragiri Hilir still recorded the largest degraded area (about 28,000–35,000 hectares), but this was much lower than before. Kampar and Pelalawan exhibited signs of vegetation regeneration, indicating the success of peatland restoration efforts. However, residual degradation in peat areas suggests that recovery remains uneven and ecosystems continue to be susceptible to new fires.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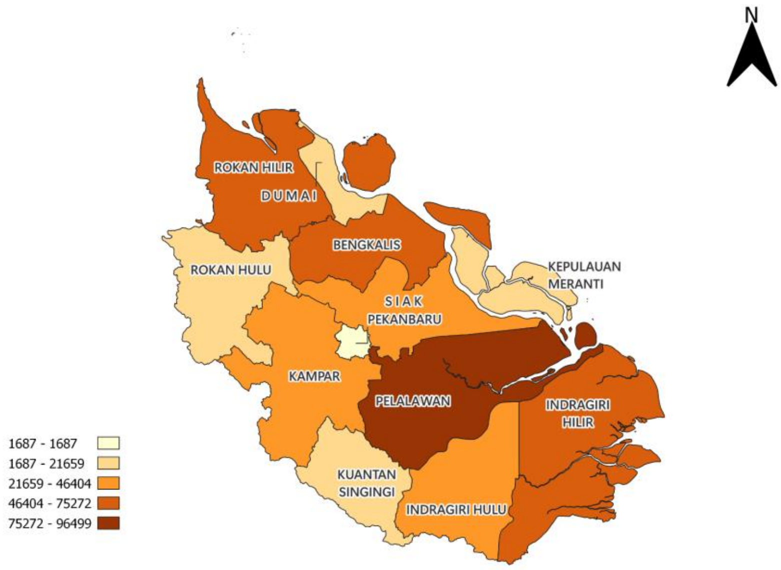
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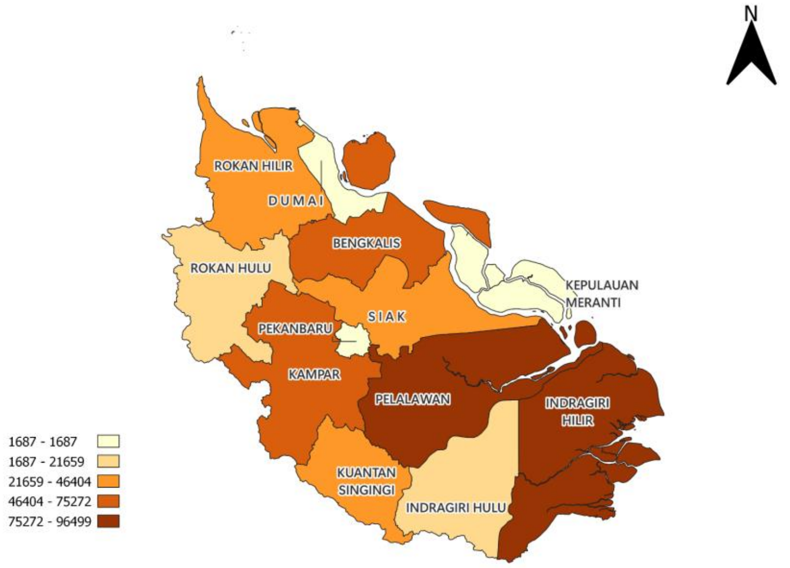


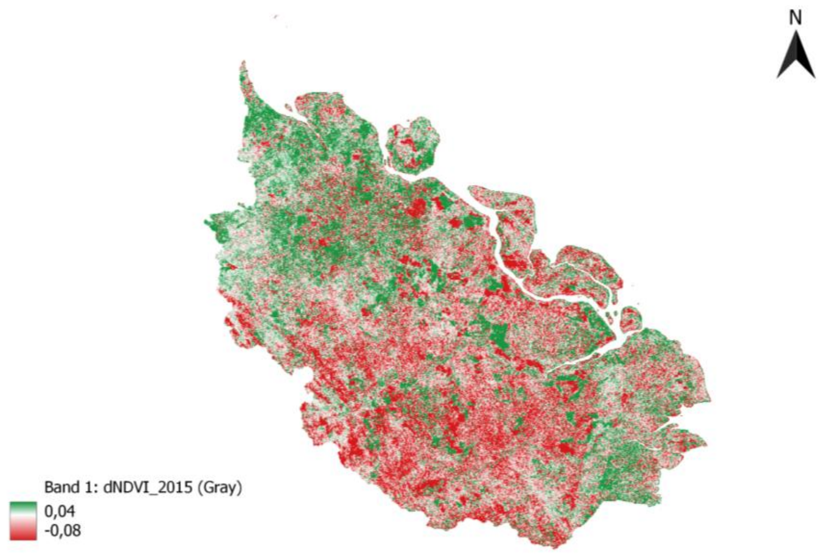
(c)

Figure 4. Spatial distribution map of degraded land area with three analysis periods: (a) 2015 compared to the 2010–2014 average, (b) 2019 compared to the 2016–2018 average, and (c) 2020–2024 compared to 2019.

The results of the 2015 NDVI delta analysis against the 2010–2014 average show a predominance of red in almost the entire Riau region, especially in the east and south, which are dominated by peatlands (Figure 4a). This red color indicates a sharp decline in vegetation due to large forest and land fires that occurred that year. In contrast, areas colored white were relatively few, indicating limited areas with stable vegetation conditions. Green colors were still found, although in small numbers and more concentrated in the northern region and areas with low disturbance levels. These conditions confirm that 2015 was the period with the most severe ecosystem damage throughout the analysis period.

In 2019, the NDVI delta results compared to the 2016–2018 average showed slightly better conditions than in 2015 (Figure 4b). Red still dominates in the east, especially in the districts of Pelalawan, Indragiri Hilir, and Siak. However, its distribution is more localized than in 2015. On the other hand, white areas were seen to be expanding, indicating an increase in areas with stable vegetation. In addition, green areas began to appear more frequently, especially in the western part, such as Kampar and Kuantan Singingi, indicating vegetation regeneration in several areas. Thus, although the 2019 fires still had a significant impact, especially on peat ecosystems, signs of vegetation recovery began to appear in several areas.

The 2020–2024 period shows the most positive changes (Figure 4c). Green colors are increasingly widespread in various regions, especially in central and western Riau, indicating a more noticeable recovery of vegetation. White areas dominate most of the map, indicating that many areas are stable with no significant changes. However, red still appears in several locations, particularly in Indragiri Hilir and parts of Pelalawan, representing residual degradation in peatland areas. Overall, these results show a clear trend of vegetation recovery after the major fires, although the recovery is not yet completely uniform and still leaves vulnerabilities in peatland areas.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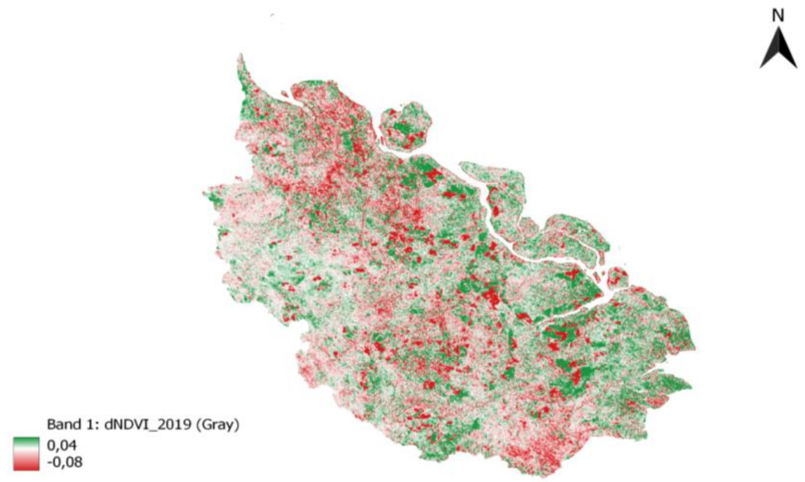
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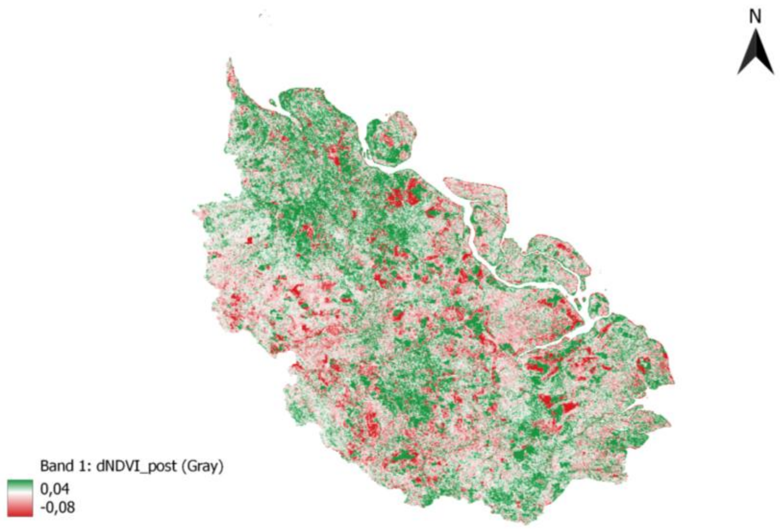


(c)

Figure 5. Map of land cover change distribution in Riau Province based on NDVI delta for three analysis periods: (a) 2015 compared to the 2010–2014 average, (b) 2019 compared to the 2016–2018 average, and (c) 2020–2024 compared to 2019.

These findings have important implications for the achievement of SDG 15, particularly indicator 15.3.1 on Land Degradation Neutrality. The dominance of degradation over deforestation shows that the main challenge is not only the loss of forest cover, but also the widespread decline in vegetation quality. The recovery trend in the 2020–2024 period is a positive sign that peatland restoration and fire prevention efforts are beginning to show results. However, uneven recovery and the vulnerability of peatland ecosystems indicate the need for stronger policy interventions, including fire control, peatland protection, and sustainable plantation management. These efforts are key to ensuring that Riau can contribute to the achievement of the 2030 sustainable development targets.

3.3. Correlation between Land Cover Change and Economic, Social, and Environmental Indicators

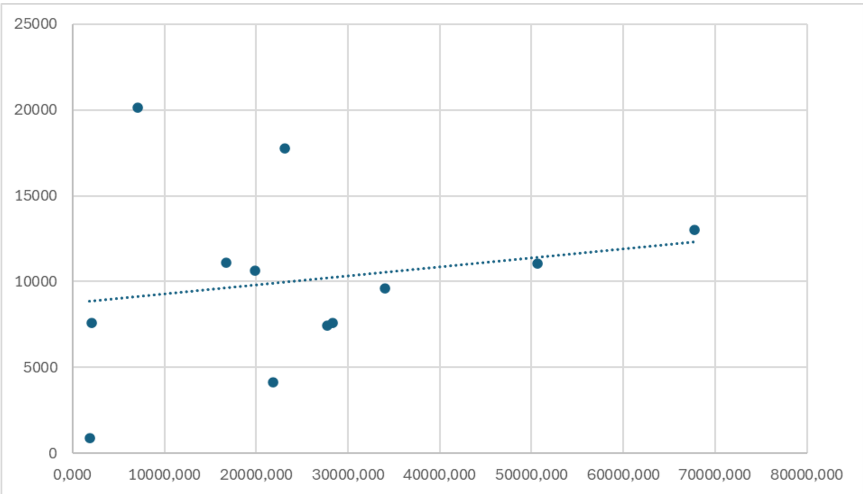
Correlation analysis was conducted to understand the relationship between deforestation and economic, social, and environmental indicators in Riau Province during three observation periods, namely 2015, 2019, and 2020–2024. The interpretation of the correlation coefficient (r) was based on its direction and strength, while its significance was determined through the p-value with a significance level of 5%.

In 2015, the correlation between deforestation area and socioeconomic and environmental variables showed a relatively weak and insignificant relationship. The correlation between deforestation and the gross domestic product (GDP) of the agricultural sector was 0.190 ($p = 0.5539$), indicating a positive but insignificant relationship. This suggests that increased agricultural economic activity was not directly related to increased deforestation during that period. Conversely, the social variable, namely the Open Unemployment Rate (OUR), shows a negative correlation with deforestation of –0.292 ($p = 0.3575$). This negative direction illustrates that an increase in unemployment is not directly related to the expansion of deforestation. This phenomenon is consistent with the characteristics of 2015, where massive forest and land fires were the dominant factors causing forest cover loss, rather than community activities or local labor. Meanwhile, the environmental variable, namely the number of hotspots, has a moderate positive correlation with deforestation ($r = 0.359$; $p = 0.2512$), but is not statistically significant. This correlation value indicates a relationship between an increase in hotspots and the extent of deforestation, although it is not yet statistically significant. This finding is consistent with the conditions in 2015, when large forest fires caused severe haze in Riau, making the relationship between hotspots and land cover change ecologically relevant.

Table 1. Pearson Correlation Matrix (r and p-values) Between Deforestation Area and Selected Socioeconomic and Environmental Variables in 2015.

	Deforest_area	GRDP_agri	Unemp_rate	Fire_hotspot
Deforest_area	1,0000	0,1902	-0,2918	0,3594
		(0,5539)	(0,3575)	(0,2512)
GRDP_agri	0,1902	1,0000	-0,2235	0,3550
	(0,5539)		(0,4850)	(0,2576)
Unemp_rate	-0,2918	-0,2235	1,0000	0,0826
	(0,3575)	(0,4850)		(0,7986)
Fire_hotspot	0,3594	0,3550	0,0826	1,0000
	(0,2512)	(0,2576)	(0,7986)	

Note: Values in parentheses indicate p-values. (*) denotes statistical significance at the 5% level.



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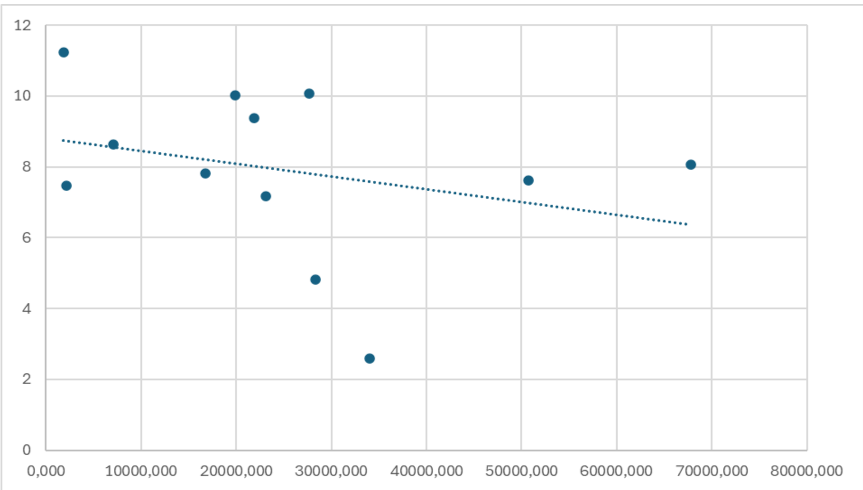

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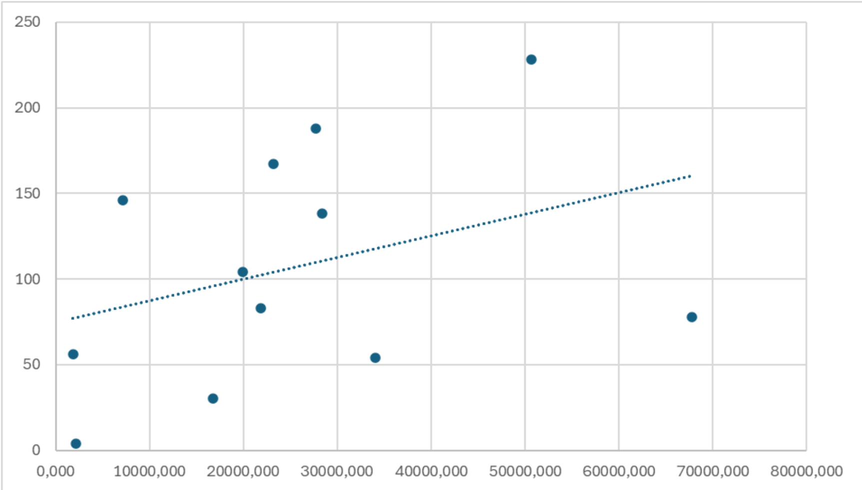

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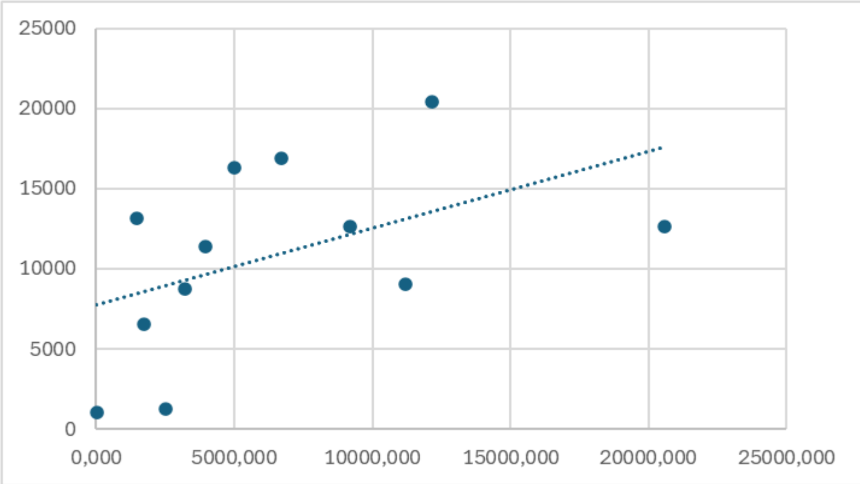
Figure 6. Scatter plots illustrating the relationships between deforestation area and key variables: (a) GRDP_agri, (b) Unemp_rate, and (c) Fire_hotspot for the year 2015.

In 2019, the pattern of relationships between variables changed significantly compared to 2015. The correlation between deforestation and agricultural GRDP increased to 0.479 (p = 0.1149), indicating a stronger positive direction, although not yet significant at the 5% level. This direction of relationship indicates that land-based economic activities are beginning to play a greater role in forest cover change in Riau. Meanwhile, the correlation between deforestation and TPT showed a value of –0.122 (p = 0.7044), remaining negative and insignificant, indicating that social factors do not yet have a real influence on the dynamics of deforestation. Environmental variables showed the most prominent results. The correlation between deforestation and the number of hotspots reached 0.877 (p = 0.0002) and was statistically significant. This value indicates a very strong and significant positive relationship, confirming that the 2019 forest and land fires were the main cause of forest cover degradation and loss in Riau. Although the area burned in 2019 was smaller than in 2015, the high concentration of fires in peatland areas made their impact on the ecosystem much more serious. Thus, environmental factors were the main determinants of deforestation this year, far exceeding social and economic influences.

Table 2. Pearson Correlation Matrix (r and p-values) Between Deforestation Area and Selected Socioeconomic and Environmental Variables in 2019.

	Deforest_area	GRDP_agri	Unemp_rate	Fire_hotspot
Deforest_area	1,0000	0,4793	-0,1225	0,8773
		(0,1149)	(0,7044)	(0,0002)*
GRDP_agri	0,4793	1,0000	-0,5375	0,5041
	(0,1149)		(0,0715)	(0,0947)
Unemp_rate	-0,1225	-0,5375	1,0000	-0,1016
	(0,7044)	(0,0715)		(0,7535)
Fire_hotspot	0,8773	0,5041	-0,1016	1,0000
	(0,0002)*	(0,0947)	(0,7535)	

Note: Values in parentheses indicate p-values. (*) denotes statistical significance at the 5% level.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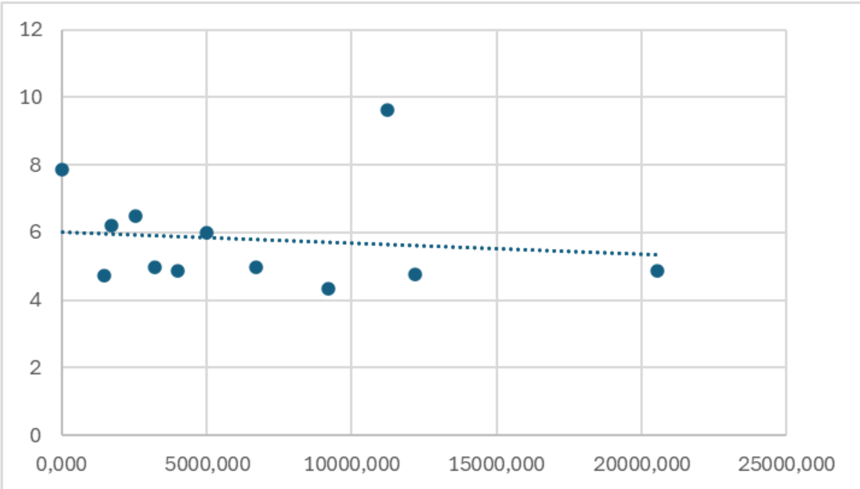
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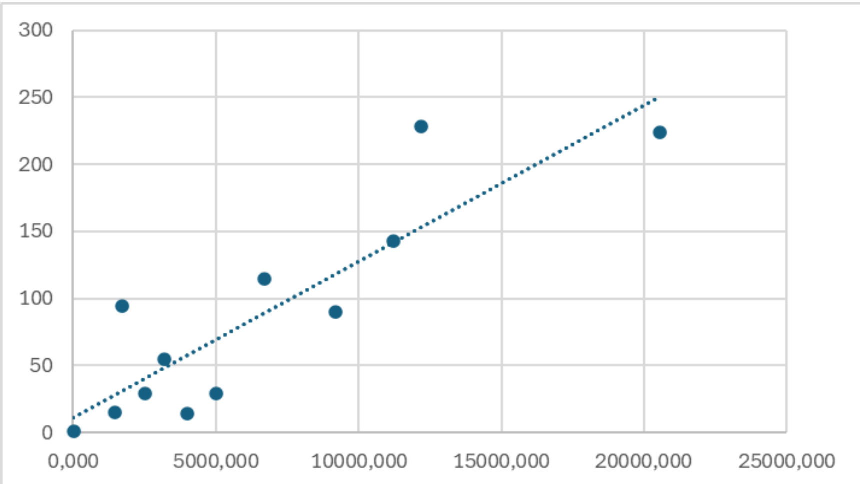
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(c)

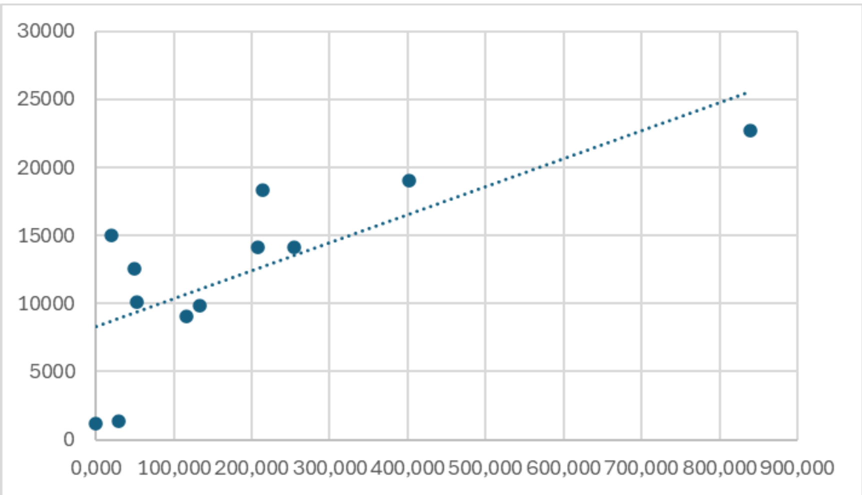
Figure 7. Scatter plots illustrating the relationships between deforestation area and key variables: (a) GRDP_agri, (b) Unemp_rate, and (c) Fire_hotspot for the year 2019.

In the 2020–2024 period, the relationship pattern shifted again. The correlation between deforestation and agricultural sector GRDP increased sharply to 0.742 ($p = 0.0057$) and was significant at the 5% level. This indicates that economic growth in Riau after 2019 is positively and significantly correlated with increased deforestation, suggesting that regional economic expansion is still heavily dependent on the exploitation of natural resources and land. Rising global commodity prices, especially for palm oil, as well as post-pandemic economic recovery programs, have also encouraged new land clearing activities. Meanwhile, TPT has a moderate negative correlation with deforestation ($r = –0.483$; $p = 0.1121$) but is not significant. This negative direction can be interpreted as meaning that when unemployment rates decline, land-based economic activities increase, but this relationship is not statistically significant. Unlike previous years, the number of hotspots actually showed a weak and insignificant positive correlation ($r = 0.280$; $p = 0.3788$). This indicates that although fires still occur, their contribution to deforestation has decreased substantially. This achievement reflects the effectiveness of policies to control forest and land fires, restore peatlands, and improve land use governance. Thus, during this period, deforestation was influenced more by economic factors and non-fire land use than by environmental factors such as hotspots.

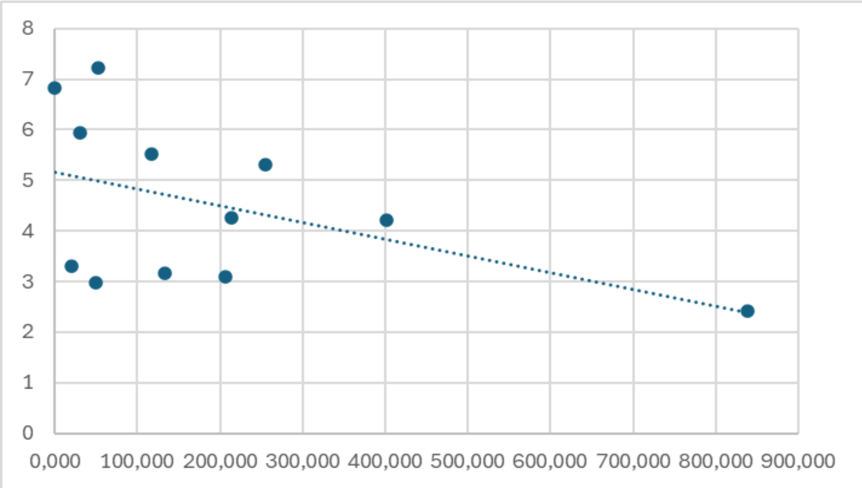
Table 3. Pearson Correlation Matrix (r and p-values) Between Deforestation Area and Selected Socioeconomic and Environmental Variables for 2020-2024.

	Deforest_area	GRDP_agri	Unemp_rate	Fire_hotspot
Deforest_area	1,0000	0,7421	-0,4825	0,2796
		(0,0057)*	(0,1121)	(0,3788)
GRDP_agri	0,7421	1,0000	-0,6666	0,2627
	(0,0057)*		(0,0179)*	(0,4094)
Unemp_rate	-0,4825	-0,6666	1,0000	-0,0145
	(0,1121)	(0,0179)*		(0,9643)
Fire_hotspot	0,2796	0,2627	-0,0145	1,0000
	(0,3788)	(0,4094)	(0,9643)	

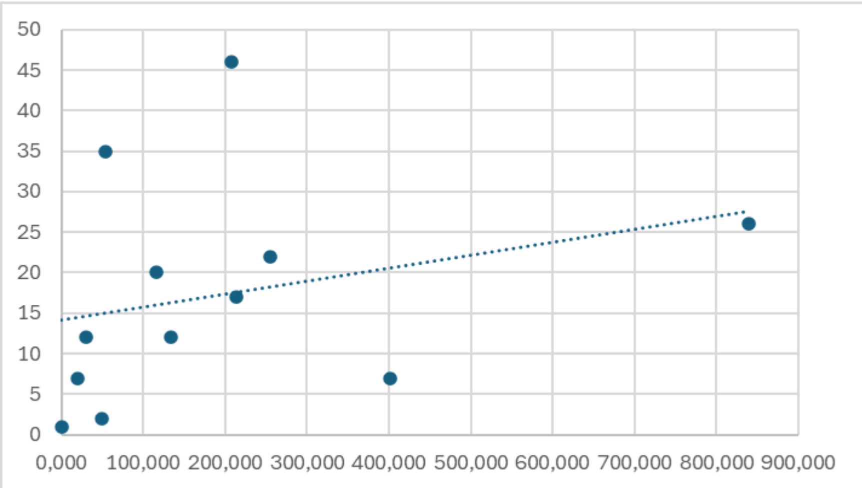
Note: Values in parentheses indicate p-values. (*) denotes statistical significance at the 5% level.



(a)



(b)



(c)

Figure 8. Scatter plots illustrating the relationships between deforestation area and key variables: (a) GRDP_agri, (b) Unemp_rate, and (c) Fire_hotspot for the year 2020-2024.

The results of the correlation analysis show a shift in the dominant factors affecting deforestation in Riau Province over time. In 2015 and 2019, deforestation was mainly triggered by environmental factors, particularly forest and land fires. However, in the 2020–2024 period, the significant relationship shifted towards economic factors, where GRDP growth in the agricultural sector was strongly associated with increased deforestation. These findings indicate that pressure on forest cover in Riau has shifted from ecological disasters to land-based economic activities. Therefore, controlling deforestation requires more than just fire mitigation; it requires structural transformation in the direction of regional economic development. An approach oriented towards a green economy and sustainable practices is needed so that economic growth no longer increases pressure on terrestrial ecosystems.

4. Conclusion

Land cover change in Riau Province during the period 2015–2024 was dominated by ecosystem degradation rather than total deforestation. The most severe environmental damage occurred in 2015 and 2019, driven by extensive forest and peatland fires, particularly in peat-rich districts such as Pelalawan, Indragiri Hilir, and Siak. These events caused large-scale vegetation loss and carbon release, marking critical setbacks for land sustainability. However, the 2020–2024 period showed signs of partial recovery, reflecting the impact of intensified restoration and fire management policies. Despite this progress, peatland areas remain highly vulnerable, continuing to experience degradation due to recurrent burning and unsustainable land-use practices. The correlation analysis further revealed that environmental variables—especially fire hotspots—had the strongest association with land cover change, while economic (GRDP) and social (open unemployment rate) variables showed weaker or negative relationships. This indicates that environmental pressures remain the dominant drivers of land degradation in Riau, particularly those linked to fire and peatland instability. Meanwhile, the emerging positive correlation between GRDP and land degradation in the post-2019 period suggests a gradual shift toward economically driven land pressure, primarily from the expansion of the agricultural sector.

These findings have significant implications for the achievement of Sustainable Development Goal (SDG) 15: Life on Land, particularly indicator 15.3.1 on Land Degradation Neutrality (LDN). The predominance of degradation over deforestation indicates that the key challenge in Riau extends beyond forest loss to encompass declines in ecosystem productivity and quality, especially in peatland ecosystems. Achieving LDN therefore requires an integrated approach that addresses both environmental restoration and economic transformation. Recent national policies have played an important role in mitigating degradation. The establishment of the Peat and Mangrove Restoration Agency (BRGM) and the inclusion of peatland restoration targets in the National Medium-Term Development Plan (RPJMN) 2020–2024 demonstrate strong institutional commitment to recovery [13]. Furthermore, Presidential Instruction No. 3 of 2020 on forest and land fire control directs ministries, agencies, and local governments to implement coordinated fire management, early warning systems, and peat-based landscape governance [12]. At the same time, sustainability certification schemes such as ISPO (Indonesian Sustainable Palm Oil) represent steps toward improving plantation governance. However, these efforts must be strengthened, expanded, and consistently enforced to ensure that Riau's land systems progress toward long-term ecological resilience and neutrality.

To accelerate the achievement of SDG 15.3.1 and ensure sustainable land recovery, several integrated and long-term strategies are recommended:

- Strengthen fire monitoring and early warning systems, particularly in high-risk peat districts, through advanced remote sensing technologies and community-based fire surveillance.
- Enhance peatland protection and restoration by enforcing land-use regulations, rehabilitating degraded areas, and maintaining high water tables to prevent reoccurring fires.
- Promote sustainable plantation management by accelerating ISPO certification, enforcing spatial compliance, and providing technical and financial assistance to smallholders.
- Institutionalize inter-agency coordination among BRGM, MoEF, and regional governments to support integrated landscape management and cross-sectoral data sharing.
- Integrate remote sensing–based monitoring into provincial planning systems to track progress toward the Land Degradation Neutrality (LDN) target.

Achieving Land Degradation Neutrality by 2030 in Riau Province ultimately depends on consistent policy implementation, transparent land governance, and sustained collaboration among national and local institutions. Without continued commitment, the ecological recovery achieved in recent years may remain fragile, undermining both local environmental sustainability and Indonesia's contribution to the global SDG 15 agenda.

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