Jurnal Ilmu Kehutanan
https://jurnal.ugm.ac.id/v3/jik/
ISSN: 01264451 (print); EISSN: 2477375 (online)

Geospatial Modeling of Carbon Emission Reduction Achievement in Siak Regency, Riau Province

Pemodelan Geospasial Capaian Penurunan Emisi Karbon di Kabupaten Siak, Provinsi Riau

Amaliyah Putri[1], Ris Hadi Purwanto[1], & Emma Soraya[1]*

[1]Faculty of Forestry, Universitas Gadjah Mada, Jalan Agro No. 1, Bulaksumur 55281, Yogyakarta, Indonesia
*Email: esoraya@ugm.ac.id

RESEARCH ARTICLE

DOI: 10.22146/jik.v19i1.14262

MANUSCRIPT:
Submitted : 25 June 2024
Revised : 15 November 2024
Accepted : 20 Desember 2024

KEYWORD
Green Siak Policy,
LULC change model,
CA-Markov, carbon mapping,
InVEST model

ABSTRACT

The Siak Regency implemented the Green Siak Policy in 2016 to commit to reducing carbon emissions. This research aimed to assess land use and land cover (LULC) changes from 2016 to 2023 and make projections for 2030, quantify carbon stocks by LULC type, and estimate CO_2 emissions associated with the implementation of the Green Siak Policy. This research classified LULC using Landsat imagery. It employed the CA-Markov to project land cover in 2030 using eight driving factors: elevation, temperature, rainfall, population density, distance from roads, burned areas, state forest areas, and evidence likelihood. This research assessed carbon stocks using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model and calculated CO_2 emissions based on changes in LULC and peat decomposition. The findings revealed a slight reduction in total carbon stock from 1,232.52 MtC in 2016 to 1,232.12 MtC in 2023, with annual CO_2 emissions of 1.4 $MtCO_2e$. Projections indicated an increase in carbon stock, expected to reach 1,232.27 MtC by 2030, with anticipated annual emissions of 1.398 $MtCO_2e$ from 2023 to 2030. While the Green Siak Policy targeted a decrease in emissions of 23.28 $MtCO_2e$/year by 2030, the results indicated that the Regency achieved merely 0.03% of its target.

KATA KUNCI
Kebijakan Siak Hijau,
model perubahan lahan,
CA-Markov, pemetaan karbon,
model InVEST

INTISARI

Kabupaten Siak menginisiasi Kebijakan Siak Hijau tahun 2016 untuk menunjukkan komitmen dalam mengurangi emisi karbon. Penelitian ini bertujuan untuk membuat model proyeksi tutupan lahan, estimasi simpanan karbon dan emisi CO_2 *di Kabupaten Siak yang terkait dengan implementasi Kebijakan Siak Hijau. Citra* Landsat *digunakan untuk klasifikasi tutupan lahan tahun 2016-2023. Proyeksi tutupan lahan tahun 2030 dilakukan dengan model CA-Markov. Delapan faktor pendorong yang digunakan yaitu ketinggian, suhu, curah hujan, kepadatan penduduk, jarak dari jalan, area terbakar, kawasan hutan, dan* evidence likelihood. *Simpanan karbon dianalisis menggunakan model* Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST). *Emisi* CO_2 *dihitung berdasarkan emisi dari perubahan tutupan lahan dan dekomposisi gambut. Hasil menunjukkan total simpanan karbon mengalami penurunan dari 1.232,52 MtC pada tahun 2016 menjadi 1.232,12 MtC pada tahun 2023. Selama tujuh tahun, perubahan tutupan lahan menyebabkan emisi* CO_2 *sebesar 1,4* $MtCO_2e$*/tahun. Estimasi simpanan karbon di Siak tahun 2030 adalah 1.232,27 MtC, dan emisi* CO_2 *pada tahun 2023-2030 sebesar 1,398* $MtCO_2e$*/tahun. Kabupaten Siak diperkirakan dapat menurunkan emisi karbon pada sektor kehutanan dan lahan gambut tahun 2030 sebesar 0,03% dari target 23,28* $MtCO_2e$*/tahun.*

Introduction

The Indonesian government is committed to reducing greenhouse gas (GHG) emissions as part of its Nationally Determined Contribution (NDC). Riau Province is instrumental in achieving these GHG reduction targets, as it contains extensive peatlands estimated at 53 million hectares and state forest areas totaling 54 million hectares (KLHK 2022a). The province's initiatives to align with the Medium-Term Development Plan (RPJMD) have formulated an action plan for GHG mitigation across 12 regencies (KLHK 2022a). A notable example is Siak Regency, which implemented a comprehensive set of these action plans and was designated a "green regency" in 2016 to promote the sustainable use and conservation of natural resources. Siak is the only regency in Riau Province to adopt a green policy following Siak Regent Regulation No. 22 of 2018, later reinforced by Regional Regulation No. 4 of 2022.

The Siak Government introduced the Green Siak Policy in 2016, yet there has been no evaluation regarding the effectiveness of this policy in reducing greenhouse gas (GHG) emissions. Conducting such an evaluation is crucial, as one of the policy's primary goals is to achieve a 22.7% reduction in GHG emissions by 2030 based on the 2018 baseline (Governor of Riau 2022) across five key sectors: forestry and peatland, agriculture, energy and transportation, industry, and waste (Regent of Siak 2018). The Enhanced Nationally Determined Contributions (NDC) document (Government of Indonesia 2022) indicated that changes in land use and land cover (LULC), along with peatland and forest fires, are the primary sources of GHG emissions in Indonesia, accounting for 50.13% of the national total. Consequently, monitoring LULC changes is essential since reductions in emissions related to forestry and peatland play a vital role in meeting national GHG targets.

Greenhouse gas (GHG) emissions primarily comprise water vapor (H_2O), carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), ozone (O_3), and fluorinated gases (Yoro & Daramola 2020). Notably, CO_2 contributes to 80-90% of total anthropogenic emissions globally (Smoot & Baxter 2003), making it a strong indicator for overall GHG emissions in this analysis. This research aimed to assess land use and land cover (LULC) changes from 2016 to 2023 and make projections for 2030, quantify carbon stocks by LULC type, and estimate CO_2 emissions associated with the implementation of the Green Siak Policy.

Methods

Research Area

Siak Regency, located in Riau Province on Sumatra Island, spanned an area of 837,779 ha and was geographically positioned between 100°54'21" E to 102°10'59" E longitude and 01°16'30" N to 00°20'49" N latitude, as presented in Figure 1. This research was conducted from October 2023 to May 2024.

Research Materials

This research used data from various sources (Table 1), including the Landsat 8 OLI/TIRS images for 2016, 2020, and 2023 obtained from Google Earth Engine. Moreover, a cloud-masking process was applied to acquire cloud-free images suitable for analysis.

LULC Classification and Accuracy Assessment

This research generated LULC maps utilizing supervised classification through the maximum likelihood method. This classification technique is widely recognized in remote sensing and geospatial analysis as an effective approach for LULC mapping (Blissag et al. 2024). The resulting LULC maps comprised ten categories: dry land forests, mangrove forests, peat swamp forests, plantation forests, open areas, plantations, settlements, paddy fields, shrubs, and water bodies (Figure 2). Direct field surveys and high-resolution imagery from the Google Earth platform validated the 2023 LULC map. A stratified random sampling method was adopted to select samples, treating each LULC class as a distinct stratum, with a minimum of 50 sample points allocated per class (Lillesand et al. 2015). In total, 530 sample points were distributed throughout the research area. The accuracy assessment utilized an error or confusion matrix, followed by calculating overall accuracy and the Kappa coefficient, with a target threshold set at ≥ 85%. The 2023 LULC, with ≥ 85% accuracy level, served as a reference for classifying Landsat images from 2016 and 2020.

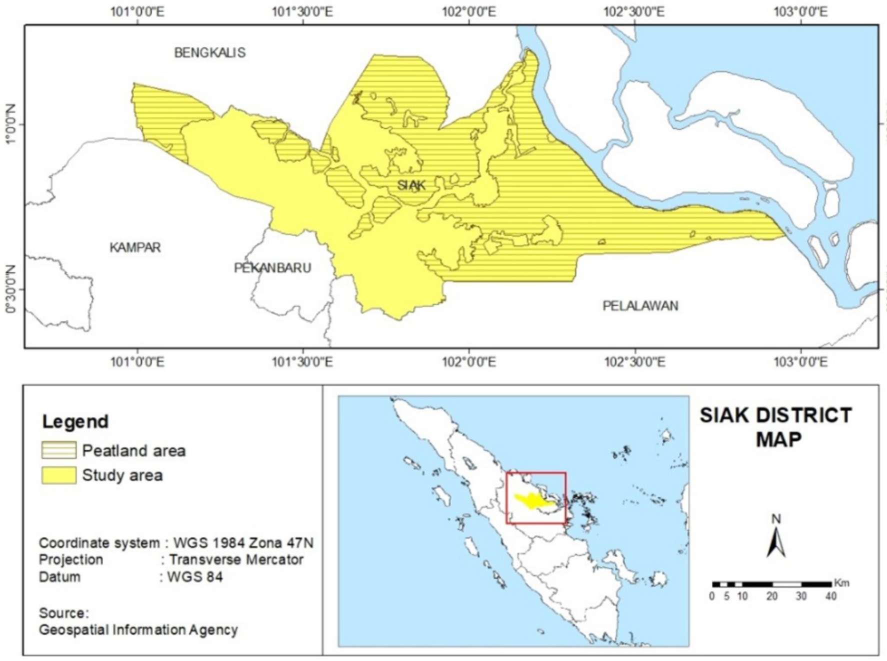


Figure 1. The map of Siak Regency

Table 1. Data Types and Their Sources for This Research

No.	Data type	Source
1	Landsat-8 OLI TIRS	https://earthengine.google.com/
2	Digital Elevation Model (DEM)	Geospatial Information Agency https://tanahair.indonesia.go.id/
3	Temperature	https://dataonline.bmkg.go.id/
4	Rainfall	https://dataonline.bmkg.go.id/
5	Population density	Badan Pusat Statistik Kabupaten Siak
6	Distance from road	Geospatial Information Agency https://tanahair.indonesia.go.id/
7	Distance from river	Geospatial Information Agency https://tanahair.indonesia.go.id/
8	Burned area	Dirjen Planologi Kehutanan dan Tata Lingkungan, KLHK
9	State forest area	Geospatial Information Agency https://tanahair.indonesia.go.id/

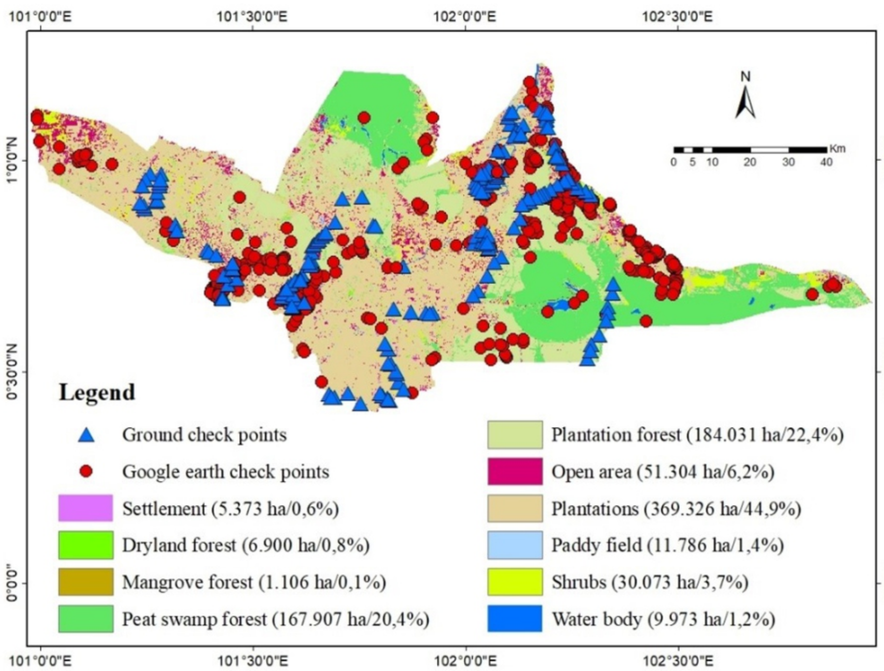


Figure 2. LULC map and ground checkpoints

Forest canopy density was assessed through overlay analysis of LULC and Normalized Difference Vegetation Index (NDVI) maps. The NDVI data processed using Google Earth Engine and illustrated in Figure 3 indicated vegetation health and density, directly impacting carbon storage capacity. These characteristics highlighted the importance of differentiating canopy density levels. Furthermore, the LULC map was overlaid with peatland distribution to distinguish various types of plantation forests and to identify Acacia species on peatlands and Eucalyptus species on mineral soils.

LULC Change Driving Factors

Several driving factors—such as elevation, slope, rainfall, temperature, distance from roads and rivers, burned areas, population density, state forest areas, and evidence likelihood—have significantly influenced changes in land use and land cover (LULC). Evidence likelihood was applied to transform categorical variables, such as transitions between land cover classes, into numerical values (Leta et al. 2021). Additionally, driving factor standardization was conducted using fuzzy set membership functions in IDRISI Selva software, enabling the conversion of diverse measurement units of the factor layers into comparable suitability values (Eastman 2012). The correlation strength between each driving factor and LULC change was evaluated using Cramer's V value. Factors demonstrating a moderate or stronger influence were identified by a Cramer's V value exceeding 0.10 (Akoglu 2018) and were included in the transition model. The calculation of the Cramer's V value relied on the following formula:

$$V = \sqrt{\frac{X^2}{N\,(m-1)}}$$

which X^2 = chi-square; N = population size of the driving factor and land cover change (spatial units/grid cells); m = number of columns in the contingency table.

Table 2. Forest Canopy Density Classification Based on NDVI Values

No.	NDVI Values	Canopy density class
1	NDVI ≤ 0	Open area or water body
2	0 < NDVI ≤ 0,4	Open canopy
3	0,4 < NDVI ≤ 0,6	Medium canopy
4	0,6 < NDVI ≤ 1	Closed canopy

Source: Aquino et al. (2018)

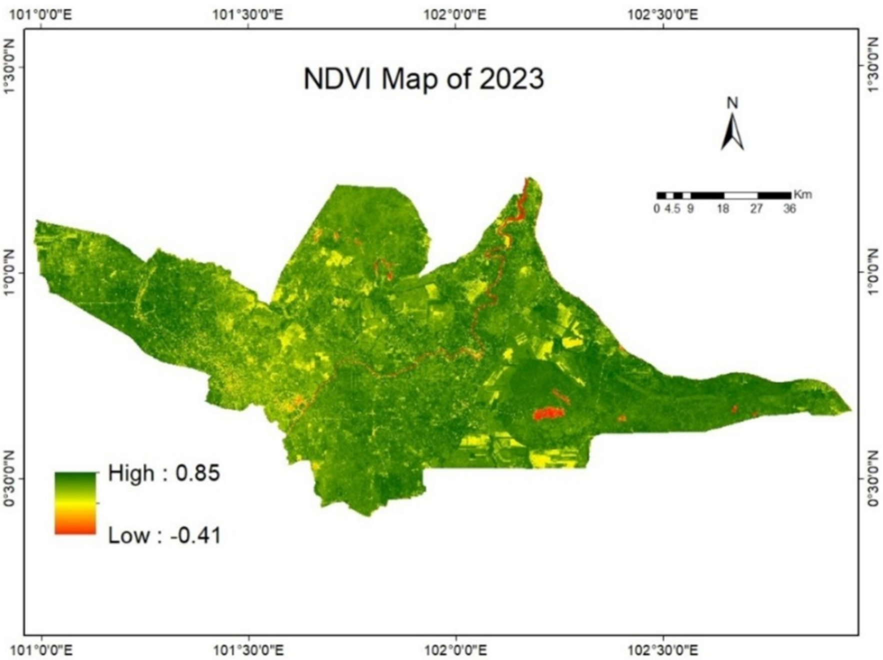


Figure 3. The distribution of NDVI in Siak Regency in 2023

LULC Change Prediction and Model Validation

A spatial model for LULC change was developed utilizing the CA-Markov process within the Land Change Modeler (LCM) module of IDRISI Selva software. This model comprises several key stages: change analysis, transition potential modeling, change prediction, and validation. LULC changes between 2016 and 2020 were identified in the change analysis stage, resulting in data and maps for each LULC class. The subsequent stage involved determining transition potentials and defining six sub-models of LULC change, namely deforestation, degradation, ecosystem enhancement, reforestation, succession, and agriculture or plantation. Following this, the Markov Chain model was employed to quantitatively assess the likelihood of pixel transitions between classes, resulting in a transition matrix (Darvishi et al. 2020; Bachri et al. 2024; Verma et al. 2024). The multi-layer perceptron neural network method executed each transition sub-model, yielding accuracy rates and skill measure values. The skill measure calculations were conducted following the formula outlined by Kumar & Agrawal (2023):

$$S = [A - E(A)] / [1 - E(A)]$$

which E(A) = expected accuracy; A = measured accuracy.

The expected accuracy was calculated using the following formula:

$$E(A) = 1 / (T + P)$$

which T = the number of transitions in the sub-model; P = persistence classes in the sub-model.

The 2016 and 2020 LULC maps were utilized to simulate the LULC for 2023. This process included implementing a validation module to evaluate the accuracy of the predicted map by comparing it to a reference image from 2023. The model was deemed valid and suitable for generating a 2030 LULC prediction when the Kappa value fell within the 'very good' category (≥ 0.7).

Carbon Stock Estimation using InVEST

The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model for carbon storage and sequestration was utilized to estimate carbon stocks. Data on various carbon pools were gathered through a literature review, as outlined in Table 3. Biomass values were converted into carbon stocks using a conversion factor of 0.47 (IPCC 2006). The calculations assumed that changes in above-ground biomass (AGB) resulting from land use and land cover (LULC) transitions also influenced other biomass components.

Table 3. Carbon pools associated with different LULC types

No.	LULC	AGB (ton/ha)	Rooot: Shoot ratio			Sources
			BGB	DW	LI	
1	Dryland forest closed canopy	367	0.212	0.330	0.027	(Uryu et al. 2008; Krisnawati et al. 2015; IPCC 2019)
2	Dryland forest medium canopy	264	0.212	0.330	0.027	
3	Dryland forest open canopy	73	0.207	0.330	0.027	
4	Mangrove forest closed canopy	187	0.212	0.748	0	(Uryu et al. 2008; Krisnawati et al. 2014; IPCC 2019)
5	Mangrove forest medium canopy	140	0.212	0.748	0	
6	Mangrove forest open canopy	37	0.207	0.748	0	
7	Peat swamp forest closed canopy	281	0.212	0.239	0.023	(Uryu et al. 2008; Krisnawati et al. 2015; IPCC 2019)
8	Peat swamp forest medium canopy	234	0.212	0.239	0.023	
9	Peat swamp forest open canopy	62	0.207	0.239	0.023	
10	Acacia plantation forest	104	0.325	0.239	0.023	
11	Eucalyptus plantation forest	64	0.325	0.330	0.027	(Latifah & Sulistiyono 2013; IPCC 2019)
12	Open area	0	Nd	Nd	Nd	(Uryu et al. 2008)
13	Plantations	48.1	0.325	Nd	Nd	(KLHK 2022b)
14	Paddy field	10	0.236	Nd	Nd	
15	Shrubs	60.39	0.236	Nd	0.111	(Afentina et al. 2022; KLHK 2022b)

Remarks: AGB = Above ground biomass; BGB = Below ground biomass; DW = Deadwood; LI = Litter; Nd = No data.

Soil organic carbon (SOC) in mineral soils was estimated using the IPCC (2019) with a default value of 52 tC/ha. For peatland soil carbon stock, the estimation was calculated using the following formula provided by Wahyunto et al. (2005):

$$C_{PeatSoil} = B \times A \times D \times \%C$$

which B = bulk density of peat soil (gr/cc) (see Table 4); A = peatland area (m^2); D = peat depth (m) %C = Carbon content/C-organik (%).

Total carbon stocks for each LULC class were calculated using the following formula:

$$C_{LULC} = A \times (C_{AGB} + C_{BGB} + C_{DW} + C_{LI} + C_{SOC})$$

which A = area of LULC class (ha); C_{AGB}, C_{BGB}, C_{DW}, C_{LI}, C_{SOC} = carbon stocks in each carbon pool (ton/ha).

CO_2 Emission Calculation

CO_2 emission was estimated based on changes in LULC and peat decomposition rates. The emissions resulting specifically from LULC change were calculated using the following formula:

$$E_{LULC} = (Ct2 - Ct1)/(t2 - t1) \times (-CF)$$

which E_{LULC} = CO_2 emission from LULC changes (t CO_2/year); Ct1 = carbon stocks at early year (tC); Ct2 = carbon stocks at late year (tC); t1 = early year; t2 = late year; FK = conversion factor of C to CO_2 (3.67).

CO_2 emissions from peat decomposition were calculated solely for areas experiencing deforestation and degradation in peat swamp forests. The formula used for the calculation was presented as follows:

$$E_{PD} = A \times EF_{PD} \times CF$$

which E_{PD} = CO_2 emission from peat decomposition (tCO_2/year); A = area of deforestation and degradation of peat swamp forest (ha); EF_{PD} = emission factor of peat decomposition (tC/ha/year).

Results and Discussion

LULC Maps and Accuracy Assessment

The accuracy assessment of the 2023 LULC map demonstrated a high level of reliability, reflected by a Kappa value of 0.88 and an overall accuracy of 89%. These figures indicate an almost perfect agreement, as both surpassed the 85% threshold (Pal & Ziaul 2017; Khwarahm et al. 2021; Shabani et al. 2022). An overlay analysis of the LULC map with NDVI and peatland distribution maps revealed 17 distinct land cover classes. However, water bodies and settlements were excluded from further analysis, as they did not significantly impact LULC change or carbon stocks in Siak Regency. Consequently, only 15 LULC classes were retained for further examination (Figure 4).

LULC Change Driving Factors

The Cramer's V test indicated that the distance from rivers, slopes, and burned areas had a weak influence on LULC change, as reflected by Cramer's V values of less than 0.10 (see Figure 5). The consistent water availability throughout the research area and the prevalence of peatland with existing canal systems explain the weak correlation between distance from rivers and LULC change. However, this research suggested that including canals as a factor could enhance future studies, especially considering the extensive peatland management in Siak Regency (Dadap et al. 2021). The relatively flat landscape, covering 77% of the area or 644,854 ha, resulted in a minimal impact of slope on LULC change. Although the model excluded distance from rivers and slopes, it retained the burned area to account for the recurring nature of fire-related disturbances in the regency.

Table 4. Bulk density and carbon content of peat soil

No.	Peat depth (m)	Bulk density (gr/cc)	Carbon content (%C)
1	0 - < 1	0.2794	27.74
2	1 - < 2	0.2794	28.55
3	2 - < 3	0.2794	29.75
4	3 - < 6	0.1716	34.18
5	≥ 6	0.1716	38.20

Source: Yunardy (2015)

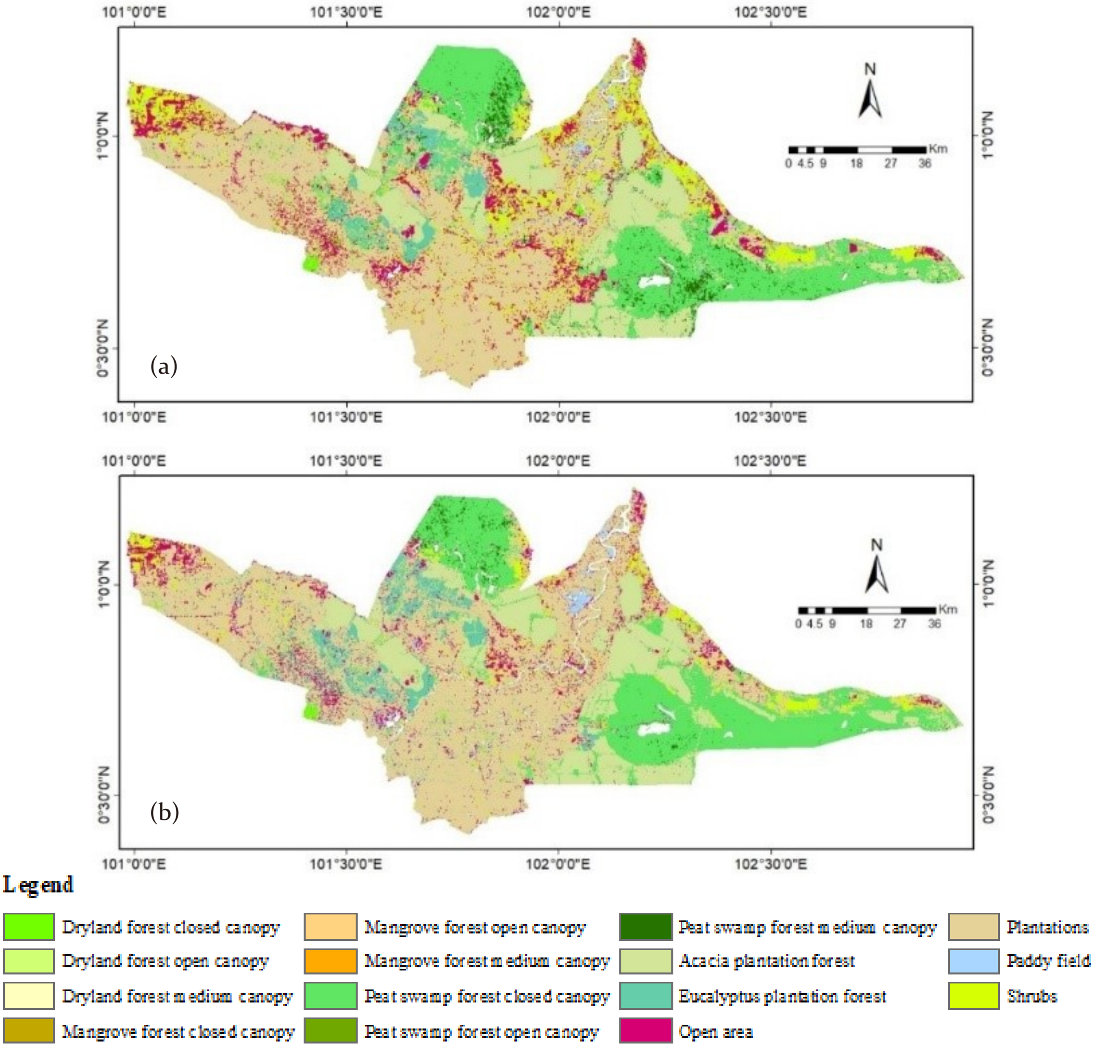
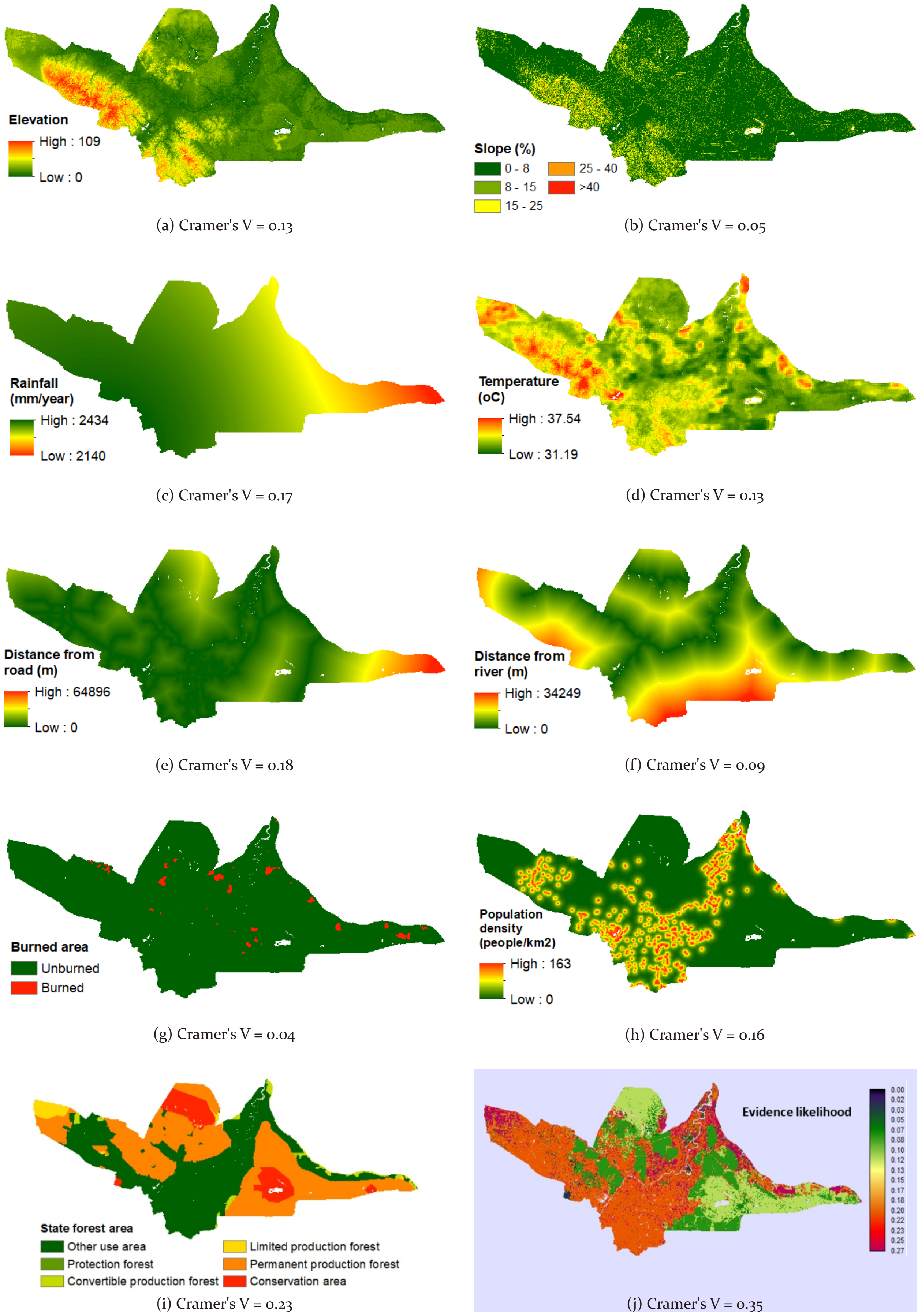


Figure 4. LULC maps for the reference years 2016 (a) & 2023 (b)

Prediction and Validation of the 2023 LULC Map

This research utilized maps from 2016 and 2020 to generate a prediction map for 2023 using LCM. The transition sub-models demonstrated an average accuracy rate ranging from 66.42% to 72.52%, with skill measures varying between 0.42 and 0.68, as shown in Table 5. These findings align with the observations made by Gibson et al. (2018), which indicated that accuracy rates for transition sub-models fell between 36% and 89%. The variation in the accuracy of the transition sub-model can be attributed to the differential impact of the driving factors on each transition, with LULC changes grouped into sub-models based on common driving variables (Hasan et al. 2020; Solaimani & Darvishi 2024). Notably, the agriculture or plantation category exhibited the lowest accuracy rate and skill measure, indicating that the chosen driving factors had a limited impact on this sub-model. Overall, the accuracy rates and skill measures reflect the degree to which driving factors influence land cover change (Gibson et al. 2018).

This research produced the 2023 LULC prediction map by calculating the transition probability matrix from the 2016 and 2020 LULC maps. This matrix quantified the likelihood of each LULC class transitioning into another, forming the basis for simulating and validating the 2023 predictions. The outcomes of the prediction model were deemed valid, evidenced by a Kappa accuracy of 0.84, which falls within the excellent category. This result aligns with the recommendation from Leta et al. (2021) that a prediction model can be considered validated when the Kappa value surpasses 0.70. Following the



(a) Cramer's V = 0.13 (b) Cramer's V = 0.05

(c) Cramer's V = 0.17 (d) Cramer's V = 0.13

(e) Cramer's V = 0.18 (f) Cramer's V = 0.09

(g) Cramer's V = 0.04 (h) Cramer's V = 0.16

(i) Cramer's V = 0.23 (j) Cramer's V = 0.35

Figure 5. The maps of LULC change's driving factors

Table 5. Accuracy rate and skill measure of transition sub-model

No.	Transition sub-model	x̄ Accuracy rate (%)	x̄ Skill Measure
1	Deforestation	66.42%	0.59
2	Degradation	71.44%	0.68
3	Ecosystem enhancement	72.52%	0.54
4	Reforestation	68.46%	0.63
5	Succession	71.33%	0.66
6	Agriculture/plantation	65.98%	0.42

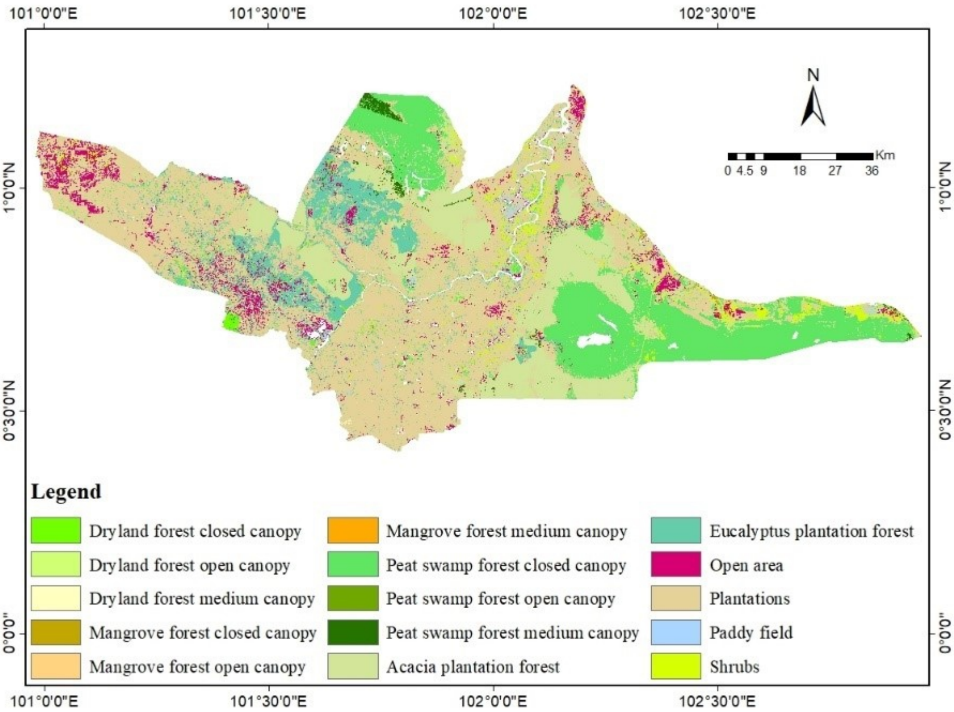


Figure 6. The predicted 2030 LULC map

validation process, the model was employed to forecast the 2030 LULC map, illustrated in Figure 6.

LULC Change Analysis of 2016, 2023, and 2030 Data

The three largest LULC types in Siak Regency were plantations, peat swamp forest closed-canopy, and Acacia plantation forest as presented in Figure 7. Plantations represented the most extensive land use, expanding significantly from 304,622 ha (37%) in 2016 to 369,326 ha (45%) in 2023 and were projected to reach 376,248 ha (46%) by 2030. This rapid growth reflected different developmental activities in the sector by private companies, partnerships, plasma programs, and self-managed systems (Hafni 2017). The area of peat swamp forest closed-canopy, a part of the largest LULC classes, showed a slight decrease over time while Acacia and Eucalyptus plantation forests expanded significantly. It was also observed that open areas and shrublands decreased substantially probably due to land fires. Moreover, most burned peatland areas since 2016 were unproductive lands, such as wet shrubs and open areas (Rossita et al. 2023).

Estimated Carbon Stocks in Different LULC

Siak Regency has extensive peatlands that store significantly more carbon than mineral soils. In peat soils, carbon is distributed uniformly from the surface to the deeper layers, whereas in mineral soils, its concentration is primarily confined to the top 0-30 cm (Agus et al. 2011). A substantial portion of the carbon in peatlands is found in the soil (Verwer & Meer 2010), which makes these areas particularly vulnerable to carbon loss due to deforestation. The total carbon stocks in Siak Regency comprised approximately 5% plant biomass and 95% soil organic carbon.

Peat swamp forests with a closed canopy had the

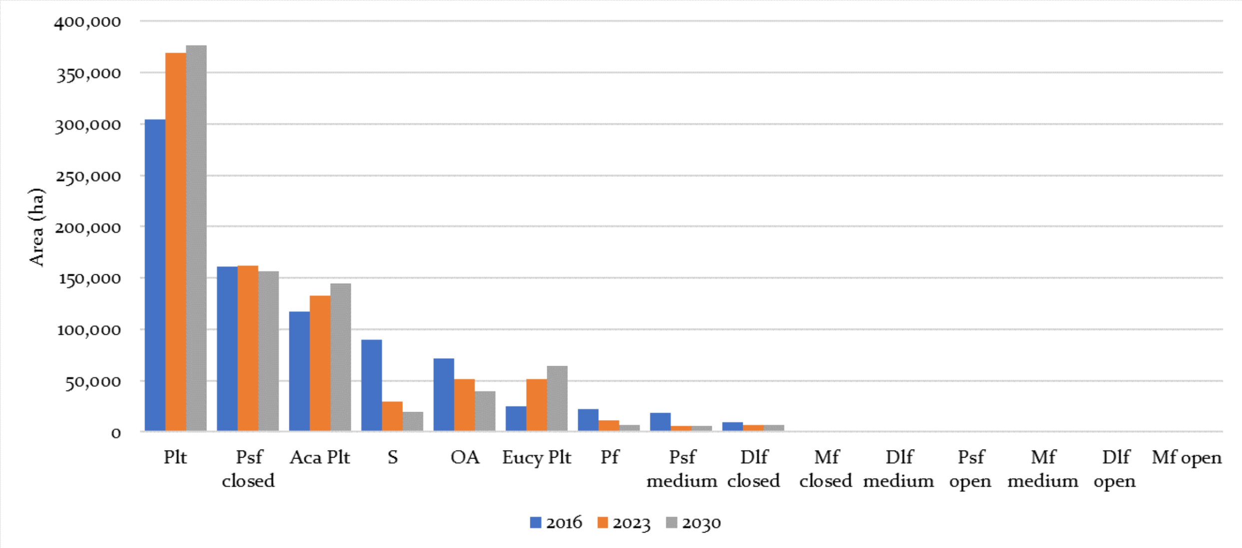


Figure 7. LULC area of Siak Regency (Dlf = Dryland forest; Mf = Mangrove forest; Psf = Peat swamp forest; Aca Plt = Acacia Plantations; Eucy Plt = Eucalyptus Plantations; OA = open area; Pf = Paddy field; S = Shrubs).

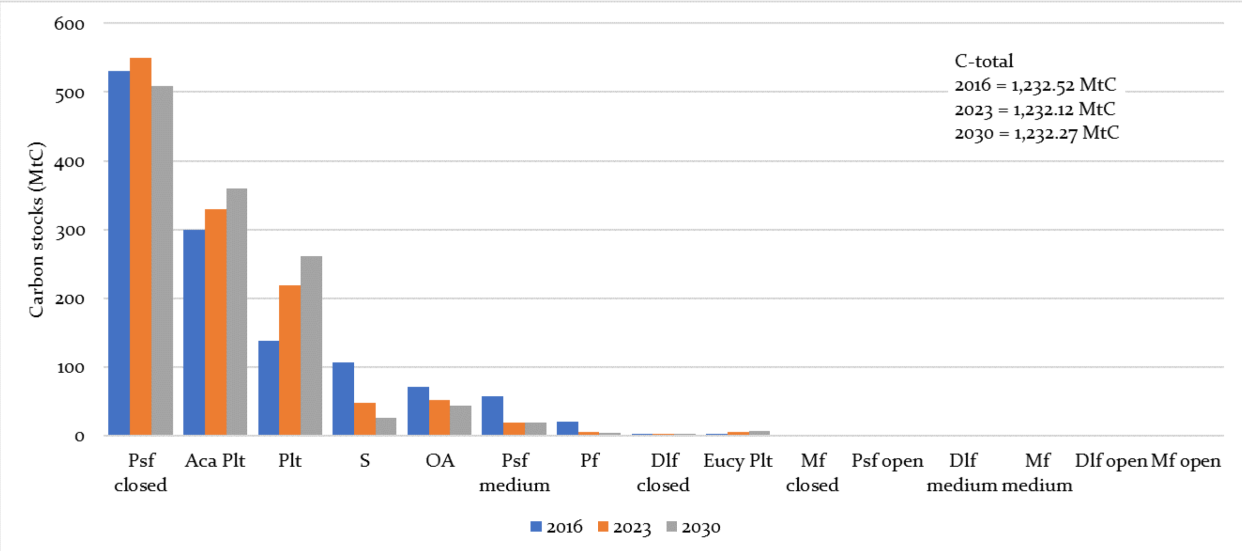


Figure 8. Estimated carbon stocks in different LULC (Dlf = Dryland forest; Mf = Mangrove forest; Psf = Peat swamp forest; Aca Plt = Acacia Plantations; Eucy Plt = Eucalyptus Plantations; OA = open area; Pf = Paddy field; S = Shrubs).

highest carbon stocks despite covering a smaller area than plantations due to their greater carbon density. The trend was possible because high-density forests exhibited the most significant carbon density among all LULC types (Warren et al. 2017; Verma et al. 2024). In 2016, total carbon stocks reached approximately 1,232.52 MtC, slightly decreasing to 1,232.12 MtC by 2023, but they are projected to rise to 1,232.27 MtC by 2030. Land use and land cover (LULC) changes have decreased total carbon stocks between 2016 and 2023. As illustrated in Figure 8, the most significant losses in carbon stocks during this period occurred in shrubland and peat swamp forests characterized by medium canopy cover. While carbon stocks experienced increases in peat swamp forests with closed canopies, Acacia plantation forests, and other plantations, these gains were insufficient to counterbalance the losses, leading to an overall reduction in total carbon stocks by 2023 compared to 2016. Nevertheless, projections indicate a net increase in carbon stocks from 2023 to 2030. The deforestation of peat swamp forests closed-canopy has contributed to the decline in carbon stocks. However, the growth of Acacia and other plantations was projected to lead to a higher total carbon stock by 2030.

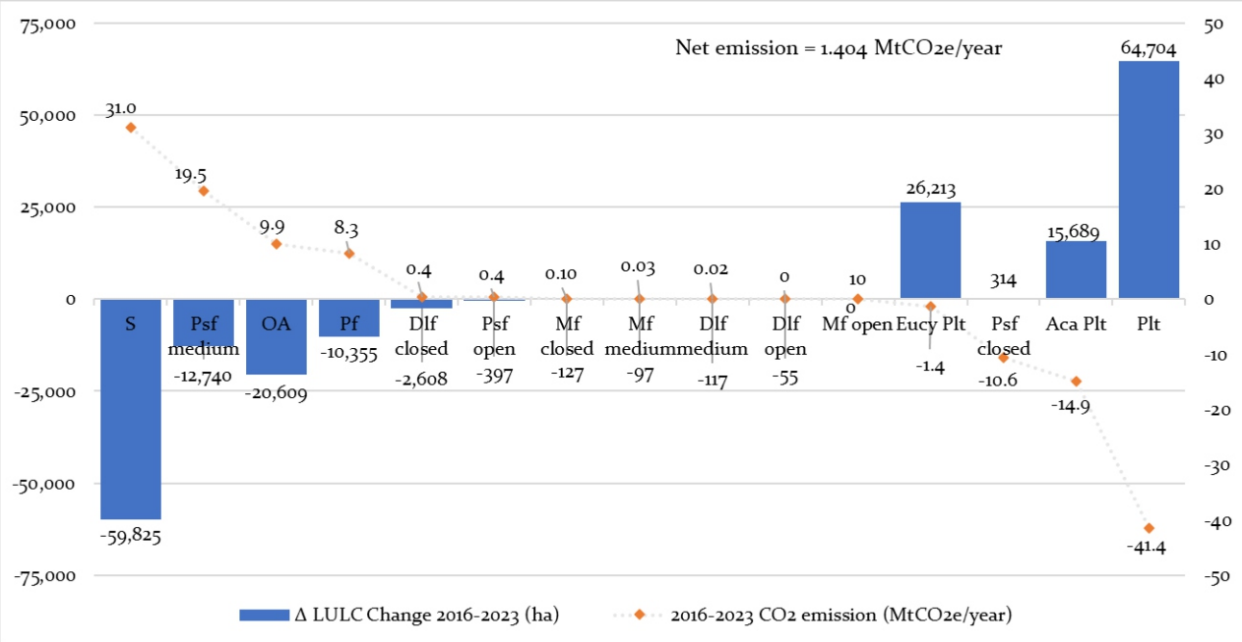


Figure 9. LULC Change and CO2 emission in 2016-2023 (Dlf = Dryland forest; Mf = Mangrove forest; Psf = Peat swamp forest; Aca Plt = Acacia Plantations; Eucy Plt = Eucalyptus Plantations; OA = open area; Pf = Paddy field; S = Shrubs).

CO_2 Emission from Green Siak Policy Implementation

LULC changes, particularly the conversion of forested areas to non-forest uses, have significantly contributed to CO_2 emissions, exacerbating global warming and climate change. These emissions were linked to carbon stock loss in vegetation and peat decomposition. Research findings indicate that net emissions in Siak Regency averaged 1.404 $MtCO_2e$ per year from 2016 to 2023, as illustrated in Figure 9. This value was substantially higher than the 0.23 $MtCO_2e$ per year estimated for the same timeframe by Global Forest Watch (2024). Due to the absence of a specific greenhouse gas (GHG) emissions baseline for Siak Regency, this study adopted the GHG reduction target set for Riau Province, 102.58 $MtCO_2e$ per year based on the 2018 baseline (Governor of Riau, 2022). The regency aims to reduce GHG emissions by 22.7% by 2030, translating to a reduction of 23.28 $MtCO_2e$ annually.

The findings indicated that CO_2 sequestration predominantly occurred in plantations, Acacia plantation forests, peat swamp forests closed-canopy, and Eucalyptus plantation forests from 2016 to 2023. In contrast, other LULC types were associated with CO_2 emissions (see Figure 9). The decline in vegetation resulted in CO_2 emissions from aboveground carbon stocks and soil, particularly in peatland, likely due to various activities, including land clearing, drainage, peat fires, and the decomposition of peat organic matter (Hayati et al. 2022). The projected net annual CO_2 emissions between 2023 and 2030 are estimated at 1.398 $MtCO_2e$, indicating a slight decline from the 1.404 $MtCO_2e$ recorded between 2016 and 2023. Furthermore, the Green Siak scenario anticipates that the Siak Regency will achieve a reduction in annual CO_2 emissions at a rate of 0.006 $MtCO_2e$ by 2030. This research indicates that land use and land cover (LULC) changes in the forestry and peatland sectors could contribute to a carbon emission reduction of approximately 0.03% of the overall targeted reduction of 22.7%.

The projection indicated that from 2023 to 2030, the loss of peat swamp forests with closed canopies resulted in the highest CO_2 emissions with an estimated output of 22.05 $MtCO_2e$ per year, as illustrated in Figure 10. In contrast, the most significant CO_2 sequestration during this timeframe, totaling 22.02 $MtCO_2e$ per year, was attributed to plantations. However, despite their potential for carbon sequestration, expanding plantation areas, particularly on peatland, raised environmental concerns. Practices such as burning, logging, drainage, and fertilization associated with peatland

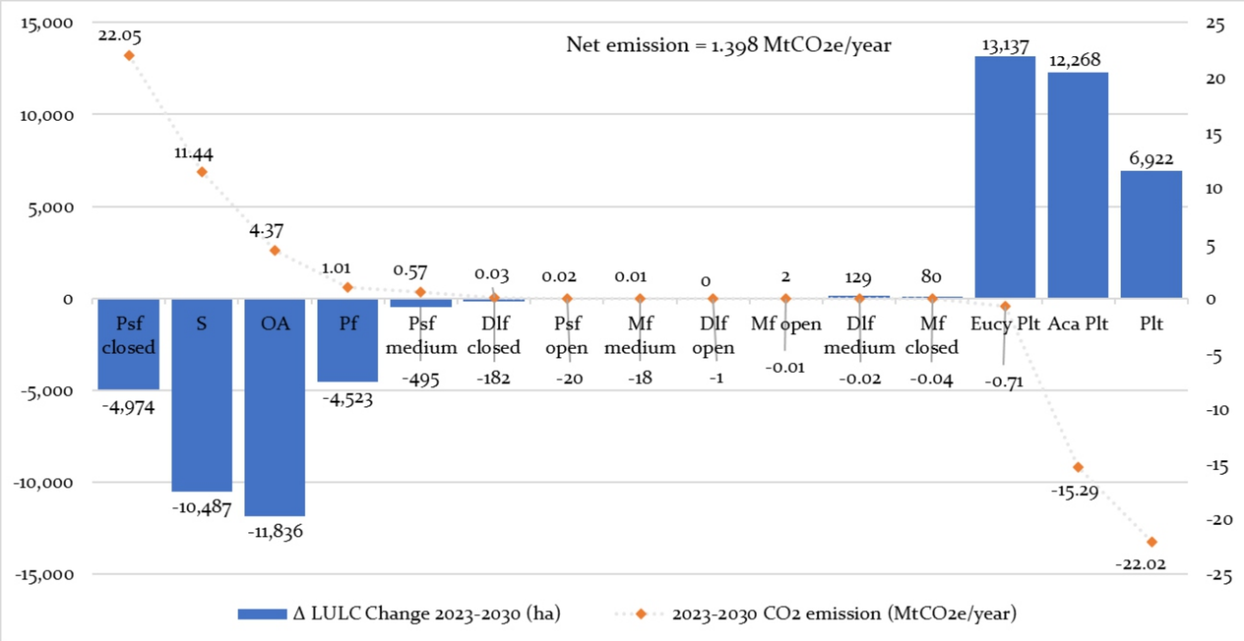


Figure 10. Projection of LULC change and CO2 emission in 2023-2030 (Dlf = Dryland forest; Mf = Mangrove forest; Psf = Peat swamp forest; Aca Plt = Acacia Plantations; Eucy Plt = Eucalyptus Plantations; OA = open area; Pf = Paddy field; S = Shrubs).

clearing accelerated the decomposition of soil organic matter, consequently leading to increased CO_2 emissions (Hayati et al. 2022). This finding aligned with the observations of Krisnawati et al. (2015), which indicated that disturbances in peat swamp forests can exacerbate soil organic carbon losses, further contributing to emissions over time.

Conclusion

In conclusion, this research revealed notable changes in LULC over time, contributing to gains and losses in carbon stocks and CO_2 emissions. The projections indicated that Siak Regency achieved only a modest 0.03% of the targeted carbon emissions reduction by 2030. The Siak government needs to implement targeted land management strategies to achieve more significant carbon reduction goals and re-evaluate the emissions reduction targets, as current projections highlight a substantial disparity between the anticipated and actual outcomes.

References

Afentina, Patimaleh IB, Kurniadi. 2022. Above ground carbon stock across different land use types in Central Kalimantan Indonesia – First step toward redd implementation. Journal of Ecological Engineering **23**:170–180. Polskie Towarzystwo Inzynierii Ekologicznej (PTIE).

Aquino D do N, Neto OC da R, Moreira MA, Teixeira A dos S, de Andrade EM. 2018. Use of remote sensing to identify areas at risk of degradation in the semi-arid region. Revista Ciencia Agronomica **49**:420–429. Universidade Federal do Ceara.

Bachri S, Shrestha RP, Sumarmi, Irawan LY, Masruroh H, Prastiwi MRH, Billah EN, Putri NRC, Hakiki ARR, Hidiyah TM. 2024. Land use change simulation model using a land change modeler in anticipation of the impact of the Semeru volcano eruption disaster in Indonesia. Environmental Challenges **14**. Elsevier B.V.

Blissag B, Yebdri D, Kessar C. 2024. Spatiotemporal change analysis of LULC using remote sensing and CA-ANN approach in the Hodna basin, NE of Algeria. Physics and Chemistry of the Earth, Parts A/B/C **133**:103535.

Darvishi A, Yousefi M, Marull J. 2020. Modelling landscape ecological assessments of land use and cover change scenarios. Application to the Bojnourd Metropolitan Area (NE Iran). Land Use Policy **99**. Elsevier Ltd.

Gibson L, M€ Z, Palmer A, Mantel S. 2018. Future land cover change scenarios in South African grasslands e implications of altered biophysical drivers on land management. Heliyon **4**:693. Available from http://creativecommons.org/licenses/by/4.0/.

Government of Indonesia. 2022. Enhanced Nationally Determined Contribution Republic of Indonesia 2022.

Governor of Riau. 2022. Peraturan Gubernur Riau Tentang Rencana Pembangunan Rendah Karbon. Indonesia.

Hafni D. 2017. Estimasi Luas Kebakaran dan Emisi Karbon Akibat Kebakaran Hutan dan Lahan Gambut di Kabupaten Siak, Provinsi Riau. Tesis. Institut Pertanian Bogor, Bogor.

Hasan S, Shi W, Zhu X, Abbas S, Khan HUA. 2020. Future simulation of land use changes in rapidly urbanizing South China based on land change modeler and remote sensing data. Sustainability (Switzerland) **12**. MDPI.

IPCC. 2019. 2019 Refinement to the 2006 IPCC guidelines for National Greenhouse Gas Inventories Task Force on National Greenhouse Gas Inventories. Page (Buendia C, Tanabe E, Kranjc K, Baasansuren A, Fukuda J, Ngarize M, Osako S, Pyrozhenko A, editors). IPCC, Switzerland. Available from www.ipcc-nggip.iges.or.jp.

KLHK. 2022a. Rencana kerja Provinsi Riau. Seri-A FOLU Net Sink 2030 Nomor: A-14/Renja-Riau/09/2022.

KLHK. 2022b. Standar penghitungan penurunan emisi dan/atau peningkatan serapan gas rumah kaca untuk pelaksanaan Indonesia FOLU Net Sink 2030. Pusat Standardisasi Instrumen Ketahanan Bencana dan Perubahan Iklim. Kementerian Lingkungan Hidup dan Kehutanan.

Krisnawati H, Adinugroho WC, Imanuddin R, Hutabarat S. 2014. Estimation of Forest Biomass for Quantifying CO_2 Emissions. Research and Development Center for Conservation and Rehabilitation, Forestry Research and Development Agency – Ministry of Forestry, Bogor.

Krisnawati H, Imanuddin R, Adinugroho WC, Hutabarat S. 2015. Standard methods for estimating greenhouse gas emissions from forests and peatlands in Indonesia. Research, Development and Innovation Agency of the Ministry of Environment and Forestry, Bogor.

Latifah S, Sulistiyono N. 2013. Carbon sequestration potential in aboveground biomass of hybrid eucalyptus plantation forest. Jurnal Manajemen Hutan Tropika (Journal of Tropical Forest Management) **19**:54–62.

Regent of Siak. 2018. Peraturan Bupati Siak Tentang Siak Kabupaten Hijau. Indonesia.

Rossita A, Boer R, Hein L, Nurrochmat DR, Riqqi A. 2023. Peatland fire regime across Riau peat hydrological unit, Indonesia. Forest and Society **7**:76–94. Hasanuddin University.

Smoot LD, Baxter LL. 2003. Fossil fuel power stations—Coal utilization. Pages 121–144 Encyclopedia of Physical Science and Technology. Elsevier.

Solaimani K, Darvishi S. 2024. Comparative analysis of land use changes modeling based-on new hybrid models and CA-Markov in the Urmia lake basin. Advances in Space Research **74**:3749–3764. Elsevier Ltd.

Uryu Y et al. 2008. Deforestation, forest degradation, biodiversity loss and CO 2 Emissions in Riau, Sumatra, Indonesia One Indonesian Province's Forest and Peat Soil Carbon Loss over a Quarter Century and its Plans for the Future. Jakarta. Available from www.wwf.or.id.

Verma P, Siddiqui AR, Mourya NK, Devi AR. 2024. Forest carbon sequestration mapping and economic quantification infusing MLPnn-Markov chain and InVEST carbon model in Askot Wildlife Sanctuary, Western Himalaya. Ecological Informatics **79**. Elsevier B.V.

Wahyunto, Ritung S, Suparto, Subagjo H. 2005. Sebaran gambut dan kandungan karbon di Sumatera dan Kalimantan. Page (Suryadiputra I, Sutaryo D, editors). Wetlands International – Indonesia Programme dan Wildlife Habitat Canada, Bogor.

Warren M, Hergoualc'h K, Kauffman JB, Murdiyarso D, Kolka R. 2017, May 19. An appraisal of Indonesia's immense peat carbon stock using national peatland maps: Uncertainties and potential losses from conversion. BioMed Central Ltd.

Yoro KO, Daramola MO. 2020. Advances in Carbon Capture: methods, technologies and applications. Elsevier.

Yunardy S. 2015. Pemodelan spasial penggunaan lahan gambut berbasis mitigasi emisi karbon (Di kubah Gambut Merang Sumatera Selatan). Disertasi. Universitas Gadjah Mada, Yogyakarta.