

Surface Carbon Stock Estimation Using Geospatial-Based Stock Difference Method in Sungai Kakap District, Kubu Raya Regency

Agus Sudiro^{1*}, Paiman¹, Rosanti¹, Muhammad Haikal Parabi¹, Muhammad Aprizal¹

¹ Department of Geography Education, PGRI Pontianak University, Indonesia.

Received: July 2, 2026

Revised: August 7, 2026

Accepted: August 10, 2026

Published: October 31, 2026

Corresponding Author:

Agus Sudiro

agussalim_abuaisyah@yahoo.co.id

DOI: [10.29303/jppipa.v12i10.15912](https://doi.org/10.29303/jppipa.v12i10.15912)

 Open Access

© 2026 The Authors. This article is distributed under a (CC-BY License)



Abstract: Carbon stock assessment is a critical component of climate change mitigation, particularly in coastal areas experiencing rapid land-use change. This study aims to estimate aboveground carbon stocks, potential CO₂ emissions, and the economic value of carbon across various land use and land cover (LULC) types in Sungai Kakap District, Kubu Raya Regency, West Kalimantan, Indonesia. A geospatial stock-difference approach was used by integrating land use/land cover maps with carbon emission factors for each LULC category. Carbon stocks were calculated by multiplying the area of each land use class by its respective carbon density, while potential CO₂ emissions were estimated using the IPCC conversion factor (44/12). The economic value of carbon was determined using a carbon price of USD 5 per ton of CO₂. The study results show that the total aboveground carbon stock reached 3.197.198,96 tons of carbon, with an estimated potential emission of 11.723.062,86 tons of CO₂ and a total carbon economic value of USD 15.985.994,81. Mangrove ecosystems contributed the largest carbon stock (1.141.154,51 tons of C), followed by agricultural land (828.861,07 tons of C) and forest formations (620.751,79 tons of C). Consequently, mangroves also exhibit the highest CO₂ emission potential and carbon economic value among all land use classes. These findings highlight the strategic importance of mangrove and forest conservation while promoting sustainable land management to maintain carbon storage, reduce greenhouse gas emissions, and enhance the economic benefits of ecosystem services. Integrating geospatial analysis with carbon valuation provides a practical framework to support low-carbon development and evidence-based land-use planning in coastal landscapes.

Keywords: Carbon stock; CO₂ emissions; Geospatial analysis; Land use; Mangroves

Introduction

Although peatlands cover only 3% of the Earth's surface, they contribute approximately one-third of global soil carbon storage (Carless et al., 2021; Yu et al., 2011). Indonesia alone contributes 75%-80% of the world's carbon reserves. These reserves must be utilized to their full potential, one way being through carbon trading. Emissions from degraded peatlands have a significant global impact. Drained or burned peatlands are estimated to release 1.3 Gt of CO₂ annually, contributing 10% of greenhouse gas emissions from the

land-use sector (Carless et al., 2021; IUCN, 2017) and a significant portion of national greenhouse gas emissions in many countries (Joosten et al., 2012).

Climate change and global warming are currently a significant threat to the global ecosystem (Arredondo Trapero et al., 2023; Frimawaty et al., 2023; Hassan & Nile, 2021). The primary cause is increased greenhouse gas emissions due to increased development and massive industrialization. Temperatures in places inhabited by more than a fifth of humanity have risen by 1.5 degrees Celsius (C) above pre-industrial levels for at least one season (Javaherian et al., 2021). Global

How to Cite:

Sudiro, A., Paiman, P., Rosanti, R., Parabi, M. H., & Aprizal, M. (2026). Surface Carbon Stock Estimation Using Geospatial-Based Stock Difference Method in Sungai Kakap District, Kubu Raya Regency. *Jurnal Penelitian Pendidikan IPA*, 12(10), 1-12. <https://doi.org/10.29303/jppipa.v12i10.15912>

temperatures will continue to rise in the 21st century, averaging 3.7°C to 4.8°C, if no mitigation efforts are made to reduce greenhouse gases (IPCC, 2014).

Global warming is a major global issue today, with high global temperatures directly related to greenhouse gases (GHG) and high levels of carbon dioxide (CO₂) resulting from the combustion of fossil fuels (Hussein, 2022; Suardana et al., 2023), and the conversion of tropical forests to regional agricultural land (Hussein, 2022; Paustian et al., 2016). To combat or mitigate global warming, carbon stock estimation is necessary. Assessment of carbon stocks or biomass can provide an idea of the amount of CO₂ that forests and other plantations can remove from the atmosphere (Dahy et al., 2020; Issa et al., 2020).

Therefore, C exchange in peatlands and the atmosphere should be a primary concern for scientists in global climate change. The question is whether the amount of C stored belowground will be released in a warmer climate, causing further warming, or whether more C will be absorbed due to increased plant growth in a warmer climate. How do land-use changes, forest fires, and melting polar ice caps affect the magnitude and direction of carbon dioxide (CO₂) and methane (CH₄) exchange in the atmosphere (Pratiwi et al., 2022; Yu et al., 2011). Consequently, global climate change has had significant impacts on the micro and macro sectors of the global climate, including biodiversity loss, natural vegetation degradation, the loss of important natural ecosystem functions, and the disruption of local wisdom (Birhane et al., 2020). These questions remain challenging and require possible answers, which can be obtained from various research studies that have recently made significant progress.

The Kyoto Protocol under the United Nations Framework Convention on Climate Change (UNFCCC) and its Doha Amendment establish legally binding commitments for greenhouse gas (GHG) emission reductions among participating countries (Nations, 1998; UNFCCC, 2012, 2015). This international agreement has been complemented by updated carbon accounting guidelines, allowing countries to voluntarily report changes in carbon stocks associated with peatland drainage and rewetting as part of national CO₂ emission inventories (Hiraishi et al., 2014). This approach reflects the critical role of peatlands in the global carbon cycle and climate change mitigation (Hussain, 2024).

Carbon loss in peat ecosystems is not only caused by carbon emissions into the atmosphere as greenhouse gases, but also through carbon export in the form of Dissolved Organic Carbon (DOC) and Particulate Organic Carbon (POC) transported by hydrological systems. Therefore, peat carbon stock estimates must consider all carbon loss pathways to produce a more representative carbon balance. In this context,

strengthening the Measurement, Reporting, and Verification (MRV) system for global peat carbon stocks is an urgent need. Improving the accuracy of carbon inventories not only supports the formulation of climate change management and mitigation policies, but also provides more reliable data for global climate models to predict potential positive climate feedbacks triggered by peatland degradation (Purwanto et al., 2025; Zhang et al., 2018).

Global forest biomass carbon stocks declined by approximately 0.5 Gt C yr⁻¹ between 2005 and 2010, primarily due to widespread deforestation and forest degradation (Forestry Economics and Policy Division, 2010). Indonesia also experienced substantial forest loss, with an estimated 0.63 million hectares of deforestation occurring between 2015 and 2016 (KLHK, 2018; Malik et al., 2023). These land-use changes contribute significantly to greenhouse gas emissions, along with emissions from the energy sector, accelerating the increase in atmospheric CO₂ concentrations. Atmospheric CO₂ is projected to reach 434.96 ppm by 2050, exceeding the 400 ppm threshold widely recognized as an important indicator of global climate change (Cahyono et al., 2022). Therefore, assessing carbon stock losses associated with land use and land cover change (LULC) is becoming increasingly important for climate change mitigation and sustainable land management (Lahiji et al., 2020). In Indonesia, numerous studies have quantified carbon sequestration and storage in various ecosystems, including natural forests (Darawan et al., 2022), production forests (Situmorang & Sugianto, 2016), urban green spaces (Dewantoro & Jatmiko, 2021), mangroves (Kusumaningtyas et al., 2022), and agroforestry systems (Latifah et al., 2018).

Estimation of forest biomass and carbon stocks has traditionally relied on field-based inventory methods, which involve direct measurements using sample plots (Batsaikhan et al., 2020; Nguyen & Nguyen, 2016b). While these methods offer high accuracy, they are time-consuming, labor-intensive, expensive, and often impractical for large or remote areas with complex terrain. Recent advances in Geographic Information Systems (GIS) and remote sensing have provided an efficient alternative by integrating spatial data with field observations to estimate biomass and carbon stocks across large landscapes. GIS facilitates the detection and monitoring of land use and land cover (LULC) changes over time and enables comprehensive assessments of ecosystem disturbances (Zhao et al., 2018). Furthermore, spatial modeling improves understanding of how these disturbances affect ecosystem services, supporting more effective carbon stock assessments and sustainable land management (Jiang et al., 2021).

Recent advances in Geographic Information Systems (GIS) and remote sensing have substantially improved the assessment of land use and land cover (LULC) dynamics and aboveground carbon stocks. Previous studies have shown that integrating geospatial techniques with remotely sensed data provides an effective approach to quantifying the impact of LULC changes on biomass and carbon storage (Purwanto, 2024; Purwanto et al., 2025). For example, simulation models incorporating annual LULC maps have been used to evaluate the effects of land cover transitions on vegetation biomass and carbon stocks (Liu et al., 2016; Malik et al., 2023). Similarly, remote sensing approaches based on multispectral imagery have successfully detected changes in LULC and aboveground vegetation carbon stocks, revealing significant decreases in vegetated area associated with land cover conversion (Masseti & Gil, 2020).

Geospatial technologies, particularly Remote Sensing (RS) and Geographic Information Systems (GIS), have become essential tools for rapid, cost-effective, and spatially explicit terrestrial biomass estimation over large areas. By integrating remote sensing data with spatial analysis, these technologies enable reliable assessments of above- and belowground biomass, thereby improving carbon stock estimation (Dahy et al., 2020). Consequently, the integration of RS and GIS provides a robust framework for accurate carbon monitoring and management. Compared with conventional field-based approaches, RS-GIS techniques offer broader spatial coverage, higher efficiency, and enhanced capabilities for large-scale biomass assessment, while creating new opportunities to advance carbon accounting and ecosystem monitoring (Dahy et al., 2020; Issa et al., 2020).

Method

Study Area

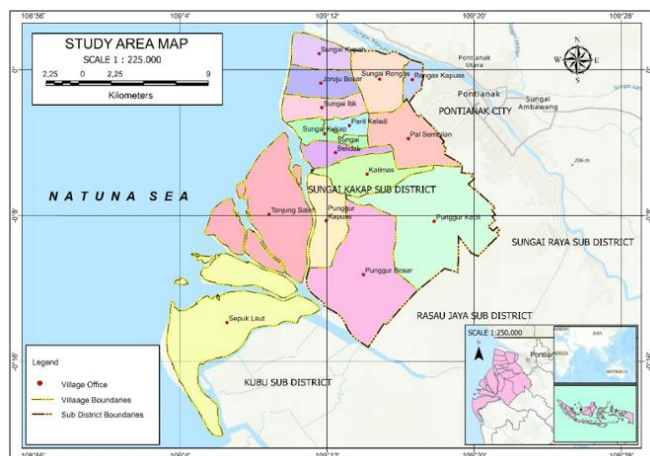


Figure 1. Study area

The research area is in the Sungai Kakap sub-district, Kubu Raya Regency. Sungai Kakap sub-district is astronomically located at 10° 35' E - 109° 58' E and 0° 44' N - 10° 1' N. Sungai Kakap Sub-District consists of 13 villages. The administrative area of the Sungai Kakap sub-district is 45.317 ha. The region of the research area can be seen in Figure 1.

Result and Discussion

Data Collection

The dataset used in this study consists of Sentinel-2A imagery acquired in 2025, a 2025 land use and land cover (LULC) map, and a 2024 Digital Elevation Model (DEM). The LULC dataset was generated by integrating the existing 2025 LULC map with land cover information interpreted from the 2025 Sentinel-2A imagery to improve classification accuracy.

Aboveground biomass estimation is based on remote sensing analysis using the fraction of Absorbed Photosynthetically Active Radiation (fAPAR), which represents the proportion of incoming photosynthetically active radiation absorbed by vegetation for photosynthesis. Because fAPAR is closely related to vegetation density and chlorophyll content, it is widely used as a proxy for biomass estimation through empirical linear regression models. In this study, fAPAR values are derived from the Normalized Difference Vegetation Index (NDVI), which is calculated using the following equation:

$$fAPAR = c + d * NDVI \quad (1)$$

Where: c and d are empirical coefficients commonly used in Southeast Asia (c=0.08 and d=1.075).

Normalized Difference Vegetation Index

NDVI is calculated based on the reflectance difference of the near-infrared band and the Sentinel 2A red band with the following formula:

$$NDVI = \frac{\text{Band 8} - \text{Band 4}}{\text{Band 8} + \text{Band 4}} \quad (2)$$

Where: Band 8 = Near Infrared (Near Infrared); Band 4 = Reflectance of the Red (Red); NDVI = Normalized Difference Vegetation Index. NDVI values range from +1.0 to -1.0, but values less than zero usually have no ecological significance, so the range of the index was cut from 0.0 to +1.0.

Leaf Area Index (LAI)

The Leaf Area Index (LAI) represents the ratio of leaf surface area to the corresponding ground surface

area and is a key biophysical parameter describing the structure of a vegetation canopy (Nguyen & Nguyen, 2016a; Purwanto et al., 2025). Because LAI is closely related to vegetation density, productivity, and photosynthetic capacity, it is widely used to estimate aboveground biomass, monitor vegetation dynamics, and assess crop and forest productivity (Nguyen & Nguyen, 2016a; Purwanto et al., 2025). LAI values typically range from 0 to above 6, with values below 1 indicating sparse vegetation with bare soil, values of 1 representing complete ground coverage by a single layer of leaves, and values greater than 1 indicating a multi-layered vegetation canopy.

In this study, LAI was estimated from satellite imagery using an empirical linear regression model that links spectral information obtained from remote sensing with LAI measurements obtained in the field. Specifically, this model establishes a relationship between the Normalized Difference Vegetation Index (NDVI) and LAI, allowing vegetation canopy characteristics to be estimated from satellite observations (Nguyen & Nguyen, 2016a). LAI is calculated using the following equation:

$$\text{LAI} = e + f * \text{DVI} \quad (3)$$

Where: e and f are the coefficients to be calculated by analyzing the relationship between NDVI and LAI.

Carbon Stock Identification

Aboveground carbon stocks were estimated by integrating spatial land use and land cover (LULC) data with the corresponding carbon density values assigned to each land use category. The carbon stock for each land use class was calculated by multiplying its area by its respective carbon density factor. Because this study focused exclusively on aboveground biomass, belowground biomass and soil organic carbon were excluded from the analysis. The estimated carbon stocks were then converted to carbon dioxide equivalents ($\text{CO}_2\text{-eq}$) using the molecular weight conversion factor 44/12, as recommended by the Intergovernmental Panel on Climate Change. The calculation of aboveground carbon stocks and $\text{CO}_2\text{-eq}$ was performed using the following equations (Baasansuren et al., 2019)

$$\text{Carbon Stock} = \text{Lulc area (ha)} * \text{emission factor} \quad (4)$$

$$\text{CO}_2 = 3.67 * \text{Carbon Stock} \quad (5)$$

Satellite Image Interpretation

The satellite imagery used in this study was Sentinel 2A, downloaded for free from the website <https://www.sentinel-hub.com/>, obtained in 2024. After review, L2A imagery with a resolution of 30m x 30m and 30% cloud cover was selected. SNAP and ArcGIS 10.8 were used to process and interpret Sentinel 2A imagery.

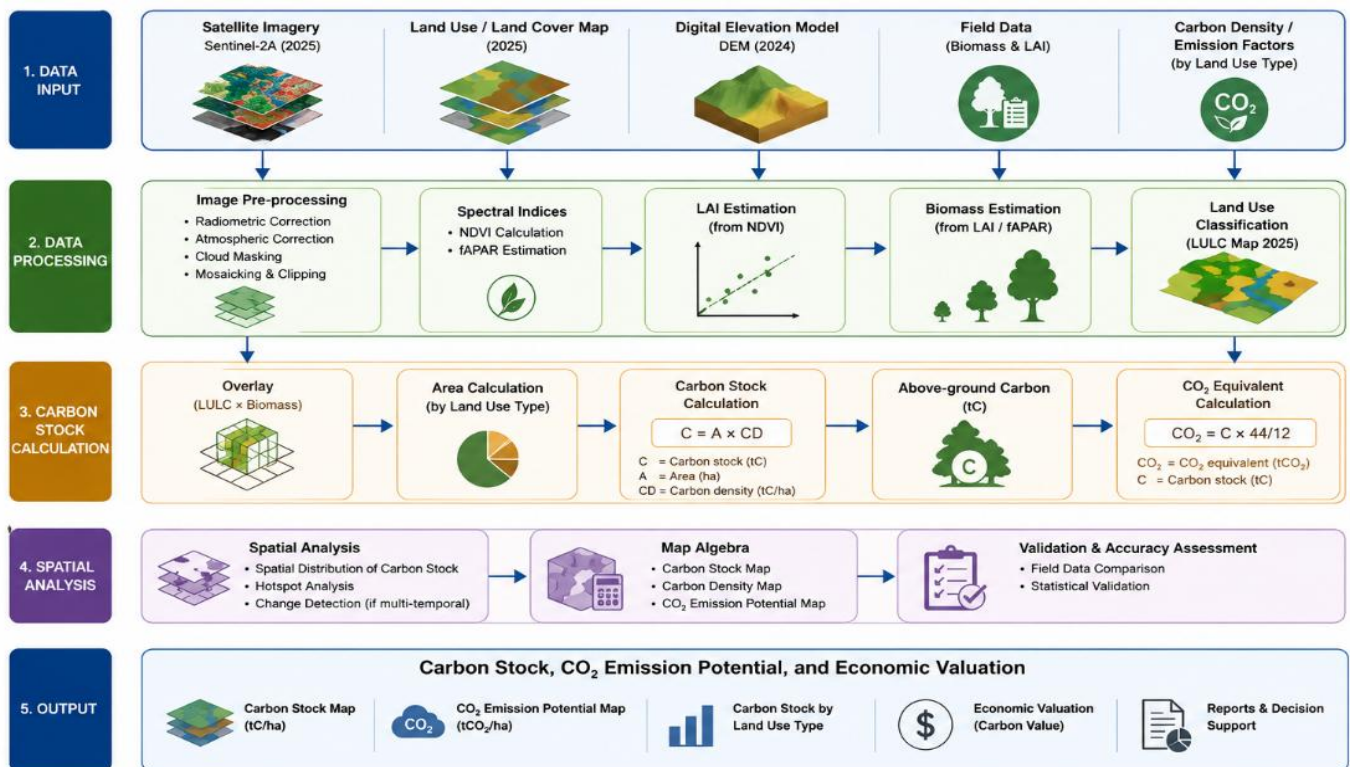


Figure 2. Framework for carbon stock calculating from various land use systems (Note: This diagram was created using AI ChatGPT)

SNAP was used for image processing, while ArcGIS 10.8 software was used to map land use and land cover and to calculate biomass and carbon stocks in the study area across various land use variations.

Spatial analyses were performed using ArcGIS 10.8, employing the Spatial Analyst extension and Map Algebra to integrate and process multiple spatial datasets for aboveground carbon stock estimation (ESRI, 2021). Statistical analyses were conducted to quantify the relationships between vegetation characteristics and carbon stocks. Pearson correlation analysis was first applied to evaluate the relationships among the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and carbon stock values across different land use and land cover (LULC) classes. Next, regression analysis was performed to determine the extent to which vegetation indices explain the spatial variability of aboveground carbon stock and to account for the spatial distribution between vegetation indices and carbon stock (Comber et al., 2024; Fotheringham et al., 2009; Oshan et al., 2019).

Result and Discussion

fAPAR

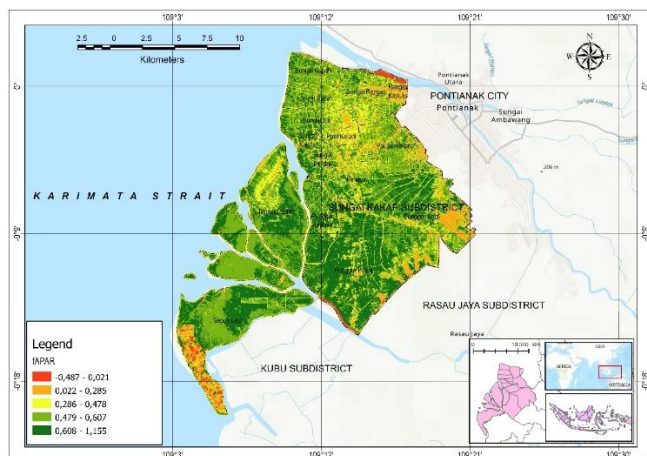


Figure 3. fAPAR distribution in the Kualan Subwatershed

Vegetation biomass estimation in this study is based on a linear relationship between biomass and the Fraction of Absorbed Photosynthetically Active Radiation (fAPAR). The fAPAR parameter describes the fraction of photosynthetically active radiation absorbed by the vegetation canopy to support the photosynthesis process. The fAPAR values obtained ranged from 0.49–1.15 with an average of 0.53, indicating a relatively high level of solar radiation absorption by vegetation in most of the study area. Ecologically, an increase in the fAPAR value indicates an increase in the efficiency of solar energy absorption by the canopy, which is correlated with high chlorophyll content, leaf area index (LEI), and

primary productivity of vegetation. Therefore, areas with high fAPAR values tend to have greater biomass than areas with low fAPAR values. The spatial distribution of fAPAR values in the study area is shown in Figure 3.

Land Use Land Cover

The results of the Land Use/Land Cover (LULC) classification show that the study area is dominated by Other Agriculture covering an area of 27,629 ha or 47.2% of the total area. The next largest land cover is Rice Paddy covering an area of 12,354 ha (21.1%), followed by Mangrove covering an area of 6,713 ha (11.5%), Forest Formation covering an area of 5,524 ha (9.4%), and Oil Palm covering an area of 3,057 ha (5.2%). Meanwhile, land cover classes with smaller proportions include Aquaculture (1,636 ha; 2.8%), River, Lake, and Ocean (889 ha; 1.5%), Non-Forest Natural Vegetation (503 ha; 0.9%), and Other Non-Vegetation (180 ha; 0.3%). The land use and land cover classification of the study area can be seen in the Table 1.

Table 1. Land use land cover Sungai Kakap

Lan Use Land Cover	Area_ha	%
Forest Formation	5.524	9.4
Mangrove	6.713	11.5
Non Forest Natural Vegetation	503	0.9
Other Agreculture	27.629	47.2
Other Non Vegetation	180	0.3
Aquaculture	1.636	2.8
River, Lake, Ocean	889	1.5
Oil Palm	3.057	5.2
Rice Paddy	12.354	21.1

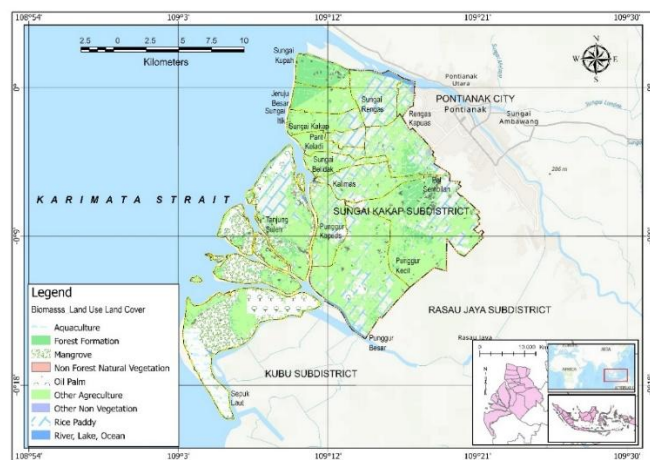


Figure 4. Land use land cover in the Sungai Kakap sub-district

This composition shows that the landscape of the study area is dominated by agricultural land use, while natural ecosystems are still maintained, especially in the form of forests and mangroves. The dominance of agricultural land indicates high intensity of cultivation

activities, while the presence of forests and mangroves plays a crucial role in maintaining ecological functions, including carbon storage, biodiversity protection, and hydrological cycle regulation. LULC information is a crucial component in spatial analysis because land cover distribution directly influences ecosystem dynamics, environmental change, and natural resource management (Mashala et al., 2023; Wang et al., 2023). For more details of the land use and land cover classification of the study area can be seen in Figure 4.

Normalized Difference Vegetation Index (NDVI)

The results of the Normalized Difference Vegetation Index (NDVI) analysis show that NDVI values in the study area ranged from 0.42 to 1.00, with an average value of 0.46. Most areas had NDVI values in the range of 0.41–0.64, indicating a predominance of moderate to high-density vegetation cover. An NDVI value closer to 1 indicates denser, healthier vegetation with higher photosynthetic activity, while a lower value reflects sparser vegetation or areas with non-vegetation land cover. With an average NDVI of 0.46, the vegetation conditions in the study area can generally be categorized as moderately dense, reflecting the dominance of agricultural land, rice fields, and some forested and mangrove areas. These findings indicate that NDVI is able to represent the greenness and vigor of vegetation, making it an important parameter in biomass analysis, vegetation productivity, and carbon stock estimation (Huang et al., 2021). For more details of the Kuala sub-watershed land use land cover can be seen in Figure 5.

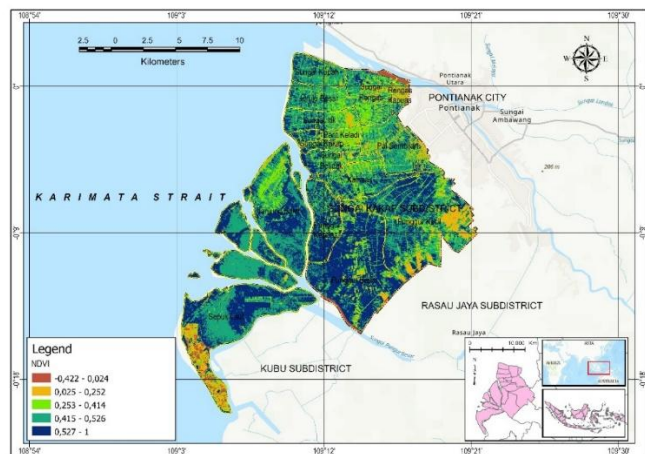


Figure 5. Index NDVI in the Sungai Kakap sub-district

However, in very dense vegetation canopies, NDVI can experience saturation, so that increases in biomass or leaf area index (LAI) are not always accompanied by a proportional increase in NDVI. Therefore, NDVI is more effective in describing vegetation greenness than in estimating biomass in areas with very dense vegetation cover (Mutanga et al., 2023; Yan et al., 2025).

Leaf Area Index (LAI)

The results of statistical analysis show that the Leaf Area Index (LAI) values in the study area ranged from -0.71 to 3.03, with an average value of 1.28. In general, the LAI value describes the level of vegetation canopy development, where a higher LAI value indicates a greater leaf surface area covering an area, thereby increasing the vegetation's ability to absorb solar radiation for photosynthesis. Low to negative LAI values in this study generally represent water bodies, built-up areas, and open land with very little or no vegetation cover. Conversely, high LAI values are found in areas with dense vegetation, such as forests, mangroves, and plantations, which are characterized by high canopy density and greater biomass potential.

Thus, the distribution of LAI values indicates variations in vegetation canopy structure that influence primary productivity and biomass accumulation in the study area (Lv et al., 2024). The results of the LAI index analysis of the study area can be seen in Figure 6.

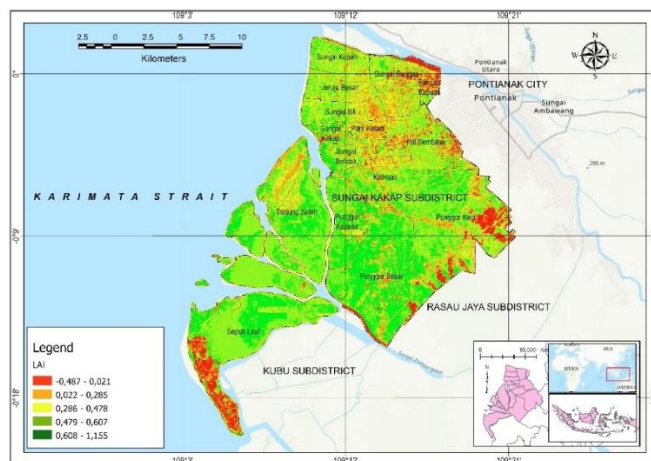


Figure 6. Index LAI in the Sungai Kakap sub-district

The negative LAI values observed in this study resulted from an empirical regression model used to estimate LAI from vegetation indices. These values correspond to non-vegetated surfaces, such as water bodies, built-up areas, and bare land, where the model extrapolates beyond the physical range of LAI. Because LAI is not physically negative, these values are interpreted as representing the absence of vegetation (Mthembu et al., 2023).

The relationship between NDVI and LAI in the field plots based on linear regression analysis can be seen in the following Table 2. The relationship between NDVI and LAI in the field plots based on linear regression analysis can be seen in the following Figure 7.

Based on the correlation diagram shown, the relationship between the Normalized Difference Vegetation Index (NDVI) and the Leaf Area Index (LAI) shows a very strong positive correlation. This is evident

from the distribution of observation points, which follow a linear regression line (red line) with relatively small deviations. As the NDVI value increases from approximately 0.15 to 0.60, the LAI value also increases consistently, from approximately 0.30 to nearly 1.90. This pattern indicates that the higher the level of vegetation greenness, as represented by the NDVI, the greater the leaf area per unit land area, as expressed by the LAI (Qiao et al., 2024).

Table 2. LAI and NDVI Values of the Field Plots

NDVI	LAI
-0.030752	-0.060578
0.33266	0.80891
0.512291	143.607
0.491271	135.168
0.506516	141.253
0.525327	149.026
0.601096	183.807
0.554726	161.813
0.613805	190.283
0.497292	137.549
0.569743	168.675
0.614286	190.532
0.584618	175.711
0.561717	164.978
0.539861	155.245
0.442574	116.885
0.509537	142.481
0.265922	0.618279
0.485714	132.995
0.281745	0.661862
0.15651	0.340414
0.345876	0.848915
0.487327	133.623
0.525418	149.064
0.364732	0.907418
0.255332	0.589633
0.447677	118.724
0.481785	131.473
0.309856	0.741711
0.528912	150.542
0.511379	143.234
0.290351	0.68597
0.214497	0.482863
0.561041	16.467
0.270782	0.631565
0.379964	0.955954
0.451749	120.205
0.214823	0.483692
0.465453	125.267
0.527631	149.999
0.494574	136.471
0.431127	11.282

The linear relationship shown in the graph indicates that the NDVI is a good predictor of LAI over the range of observed vegetation values. Although there are slight

deviations at very low NDVI values (near zero), overall, the observation points are very close to the regression line. This indicates that variations in LAI can be largely explained by changes in NDVI, thus ensuring a good regression model for estimating LAI based on spectral information from satellite imagery.

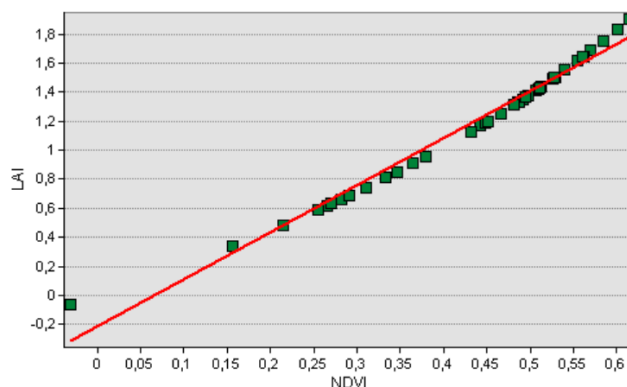


Figure 7. Correlation between LAI and NDVI

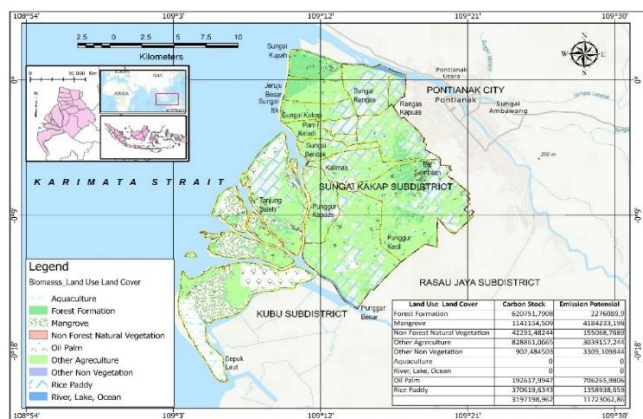
Based on some of the above conditions ranging from NDVI, LAI, and fAPAR, the carbon biomass and CO₂ reserves can be estimated. With the capabilities of GIS technology and Remote Sensing systems, this process will be easier to do and save costs and energy. The following is the estimation of carbon stock in the Sungai Kakap Sub-District (Mthembu et al., 2023).

Biophysically, these results align with the characteristics of both parameters. NDVI represents the level of photosynthetic activity and greenness of vegetation through differences in red and near-infrared (NIR) reflectance, while LAI describes the total leaf area, which plays a role in radiation interception, transpiration, and photosynthesis. Therefore, increasing canopy density and vegetation biomass generally increases NDVI while simultaneously increasing LAI. However, in very dense vegetation, this relationship can become nonlinear due to the phenomenon of NDVI saturation, when increases in biomass are no longer accompanied by significant increases in NDVI. In the presented graph, this saturation phenomenon is not yet clearly visible because the maximum NDVI value is still in the range of ± 0.60 , so the linear relationship can still be maintained (Bajocco et al., 2024; Yan et al., 2025).

Overall, the graph shows that the obtained NDVI-LAI relationship model is sufficiently representative of the vegetation conditions at the study site. This strong positive correlation supports the use of NDVI as a simple and effective indicator for LAI estimation, particularly in vegetation monitoring studies, biomass estimation, land productivity, and carbon stocks using remote sensing data (Pu et al., 2024).

Table 3. Carbon Stock and Emission Potential CO₂

Land Use Land Cover	Area(ha)	Emission Factor	Carbon Stock (ton/ha)	Emission Potential
Forest Formation	5.523,833	112,377	620.751,7908	2.276.089,9
Mangrove	6.712,674	170	1.141.154,509	4.184.233,198
Non Forest Natural Vegetation	503,254	84,036	42.291,48244	155.068,7689
Other Agreculture	27.628,702	30	82.8861,0665	3.039.157,244
Other Non Vegetation	180,497	5	902,484503	3.309,109844
Aquaculture	1.636,458	0	0	0
River, Lake, Ocean	888,888	0	0	0
Oil Palm	3.057,428	63	192.617,9947	706.265,9806
Rice Paddy	12.353,988	30	3.70.619,6343	1.358.938,659
Sum			3.197.198,962	11.723.062,86

**Figure 8.** Carbon stock and emission potential of Sungai Kakap sub-district

Based on Table 3, the total surface carbon stock in the study area reached 3.197.198,96 tons of C, which is equivalent to a potential emission of 11.723.062,86 tons

of CO₂ if all of the carbon reserves were released into the atmosphere due to land use changes or ecosystem degradation. The large potential emissions indicate that the study area plays a significant role as a carbon sink and as a significant source of emissions if land conversion occurs. This calculation follows the conversion of carbon to carbon dioxide using a factor of 44/12 (3.67), which is commonly used in greenhouse gas inventories (Murdiyarso et al., 2023).

For economic purposes, the carbon value of various land uses can be calculated. According to the Institute for Forest Inventory and Planning, Natural Resources and Environmental Policy, if the cash price of 1 ton of CO₂/hectare is \$5, then the total payment amount can be calculated as follows:

$$\text{Total payment amount} = \text{Amount of CO}_2 * \text{Unit price (USD/ton CO}_2\text{)} \quad (6)$$

Table 4. Market Value of Carbon from Different Land Uses

Land Use Land Cover	Carbon Stock (Ton/ha)	Unit	CO ₂ (USD) Value
Forest Formation	62.0751,7908	5	3.103.758,954
Mangrove	1.141.154,509	5	5.705.772,543
Non Forest Natural Vegetation	42.291,48244	5	211.457,4122
Other Agreculture	828.861,0665	5	4.144.305,333
Other Non Vegetation	902,484503	5	4.512,422515
Aquaculture	0	5	0
River, Lake, Ocean	0	5	0
Oil Palm	192.617,9947	5	963.089,9735
Rice Paddy	370.619,6343	5	1.853.098,172
Sum	3.197.198,962		15.985.994,81

Based on each land use class, mangrove forests are the largest carbon sink, with a carbon stock of 1.141.154,51 tons of carbon dioxide (C), potential emissions of 4.184.233,20 tons of CO₂, and the highest economic value of USD 5.705.772,54. This high value reflects the ability of mangrove forests to store carbon in biomass and sediment, making them a crucial ecosystem for climate change mitigation (Ceanturi et al., 2024; Slamet et al., 2020).

Other agricultural land ranks second with a carbon stock of 828.861,07 tons of carbon dioxide (C), potential

emissions of 3.039.157,24 tons of CO₂, and an economic value of USD 4.144.305,33. Although the carbon stock per hectare is lower than that of forests and mangroves, the dominant land area still contributes significantly to the total carbon stock (Arifanti et al., 2024; Slamet et al., 2020).

Furthermore, forest formations have a carbon stock of 620.751,79 tons of carbon, with potential CO₂ emissions of 2.276.089,90 tons and an economic value of USD 3.103.758,95. This indicates that forest areas still

play a vital role as natural carbon sinks and have high economic value if maintained.

For rice fields, the carbon stock reached 370.619,63 tons of carbon, with potential CO₂ emissions of 1.358.938,66 tons and an economic value of USD 1.853.098,17. Meanwhile, oil palm plantations store 192.617,99 tons of carbon, generating potential CO₂ emissions of 706.265,98 tons, and having an economic value of USD 963.089,97. Both land uses contribute significantly to the region's carbon stocks, although they remain lower than those of forest and mangrove areas.

On the other hand, non-forest natural vegetation only contributes 42.291,48 tons of C, with a potential emission of 155.068,77 tons of CO₂ and an economic value of USD 211,457.41. Land without vegetation has a very small carbon stock, namely 902,48 tons of C, with a potential emission of 3.309,11 tons of CO₂ and an economic value of USD 4.512,42, while ponds (aquaculture) and water bodies (rivers, lakes, seas) do not store carbon stocks above the surface so they do not contribute to the potential emission or economic value of carbon.

Conclusion

Based on estimates, the total carbon stock across all land uses in the study area reached 3.197.198,96 tons of carbon, equivalent to potential emissions of 11.723.062,86 tons of CO₂ if all of this carbon were released into the atmosphere due to land-use change. Using a carbon price of USD 5 per ton of CO₂ equivalent, the total economic value of carbon stocks reached USD 15.985.994,81. This value indicates that the ecosystems in the study area not only serve an ecological function as carbon sinks but also possess significant economic value in the context of carbon trading and payment for environmental services schemes. Mangrove and forest ecosystems are the largest carbon reservoirs, while also possessing the highest potential CO₂ emissions and carbon economic value compared to other land uses. Therefore, efforts to maintain these ecosystems are a key strategy in climate change mitigation. Conservation of forested areas and mangroves needs to be prioritized through preventing land conversion, rehabilitating degraded land, and ecosystem-based management to maintain carbon reserves and minimize emissions.

Acknowledgments

The authors are appreciative of Kemenristekdikti for offering chances and financial support for grants for scientific study

Author Contributions

Conceptualization: Sudiro, A., Paiman, Rosanti; methodology: Sudiro, A., Paiman, Rosanti; investigation: Sudiro, A., Paiman, Rosanti; writing—original draft preparation: Sudiro, A., Paiman, Rosanti; writing—review and editing: Sudiro, A.,

Paiman, Rosanti; Parabi, M., H., Aprizal, M; visualization: Sudiro, A., Paiman, Rosanti; Parabi, M., H., Aprizal, M. All authors have read and agreed to the published version of the manuscript.

Funding

This research was funded by Ke-menristekdikti.

Conflicts of Interest

The authors declare no conflict of interest in this research.

References

- Arifanti, V. B., Candra, R. A., Putra, C. A. S., Asyhari, A., Gangga, A., Ritonga, R. P., Ilman, M., Anggoro, A. W., & Novita, N. (2024). Greenhouse Gas Fluxes of Different Land Uses in Mangrove Ecosystem of East Kalimantan, Indonesia. *Carbon Balance and Management*, 19(1), 17. <https://doi.org/10.1186/s13021-024-00263-3>
- Arredondo Trapero, F. G., Guerra Leal, E. M., & Kim, J. (2023). Effectiveness of the Voluntary Disclosure of Corporate Information and Its Commitment to Climate Change. *Global Journal of Environmental Science and Management*, 9(4), 1033–1048. <https://doi.org/10.22034/gjesm.2023.04.25>
- Baasansuren, J., Fukuda, M., Ngarize, S., Osako, A., Pyrozhenko, Y., Shermanau, P., & Federici, S. (2019). 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. IPCC Switzerland.
- Bajocco, S., Ferrara, C., Savian, F., Ginaldi, F., Puletti, N., Crecco, L., Bregaglio, S., & Chianucci, F. (2024). LAI: an R Package to Estimate LAI from Normalized Difference Vegetation Index. *SoftwareX*, 27, 101776. <https://doi.org/10.1016/j.softx.2024.101776>
- Batsaikhan, B., Lkhamjav, O., Batsaikhan, G., Batsaikhan, N., & Norovsuren, B. (2020). Carbon Stock Estimation Using Remote Sensing Data and Field Measurement in Haloxylon Ammodendron Dominant Winter Cold Desert Region of Mongolia. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 3, 9–17. <https://doi.org/10.5194/isprs-annals-V-3-2020-9-2020>
- Birhane, E., Ahmed, S., Hailemariam, M., Negash, M., Rannestad, M. M., & Norgrove, L. (2020). Carbon Stock and Woody Species Diversity in Homegarden Agroforestry Along an Elevation Gradient in Southern Ethiopia. *Agroforestry Systems*, 94, 1099–1110. <https://doi.org/10.1007/s10457-019-00475-4>
- Cahyono, W. E., Joy, B., Setyawati, W., & Mahdi, R. (2022). Projection of CO₂ Emissions in Indonesia. *Materials Today: Proceedings*, 63, S438–S444.

- <https://doi.org/10.1016/j.matpr.2022.04.091>
- Carless, D., Kulesa, B., Booth, A. D., Drocourt, Y., Sinnadurai, P., Street-Perrott, F. A., & Jansson, P. (2021). An Integrated Geophysical and GIS Based Approach Improves Estimation of Peatland Carbon Stocks. *Geoderma*, 402, 115176. <https://doi.org/10.1016/j.geoderma.2021.115176>
- Ceanturi, A., Tuahatu, J. W., Lokollo, F. F., Supusepa, J., Hulopi, M., Permatahati, Y. I., Lewerissa, Y. A., & Wardiatno, Y. (2024). Mangrove Ecosystems in Southeast Asia Region: Mangrove Extent, Blue Carbon Potential and CO₂ Emissions in 1996–2020. *Science of the Total Environment*, 915, 170052. <https://doi.org/10.1016/j.scitotenv.2024.170052>
- Comber, A., Harris, P., & Brunsdon, C. (2024). Multiscale Spatially Varying Coefficient Modelling Using a Geographical Gaussian Process GAM. *International Journal of Geographical Information Science*, 38(1), 27–47. <https://doi.org/10.1080/13658816.2023.2270285>
- Dahy, B., Issa, S., Ksikisi, T., & Saleous, N. (2020). Geospatial Technology Methods for Carbon Stock Assessment: A Comprehensive Review. *IOP Conference Series: Earth and Environmental Science*, 540(1), 12036. <https://doi.org/10.1088/1755-1315/540/1/012036>
- Darawan, A. A., Ariyanto, D. W. I. P., Basuki, T. M., Syamsiyah, J., & Dewi, W. S. I. H. (2022). Biomass Accumulation and Carbon Sequestration Potential in Varying Tree Species, Ages and Densities in Gunung Bromo Education Forest, Central Java, Indonesia. *Biodiversitas Journal of Biological Diversity*, 23(10). <https://doi.org/10.13057/biodiv/d231016>
- Dewantoro, B. E. B., & Jatmiko, R. H. (2021). Estimation of Aboveground Carbon Stock Using SAR Sentinel-1 Imagery in Samarinda City. *International Journal of Remote Sensing and Earth Sciences*, 18(1), 103–116. <https://doi.org/10.30536/j.ijreses.2021.v18.a3609>
- Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2009). Geographically Weighted Regression. *The Sage Handbook of Spatial Analysis*, 1, 243–254. <https://doi.org/10.4135/9780857020130.n13>
- Frimawaty, E., Ilmika, A., Sakina, N. A., & Mustabi, J. (2023). Climate Change Mitigation and Adaptation Through Livestock Waste Management. *Global Journal of Environmental Science and Management*, 9(4), 691–706. <https://doi.org/10.22035/gjesm.2023.04.03>
- Hassan, W. H., & Nile, B. K. (2021). Climate Change and Predicting Future Temperature in Iraq Using CanESM2 and HadCM3 Modeling. *Modeling Earth Systems and Environment*, 7, 737–748. <https://doi.org/10.1007/s40808-020-01034-y>
- Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M., & Troxler, T. G. (2014). *2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands*. IPCC, Switzerland.
- Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A Commentary Review on the Use of Normalized Difference Vegetation Index (NDVI) in the Era of Popular Remote Sensing. *Journal of Forestry Research*, 32(1), 1–6. <https://doi.org/10.1007/s11676-020-01155-1>
- Hussein, A. (2022). Carbon Stock Potential across Different Land Covers in Tropical Ecosystems of Damota Natural Vegetation, Eastern Ethiopia. *Applied and Environmental Soil Science*, 2022. <https://doi.org/10.1155/2022/8414027>
- Issa, S., Dahy, B., Ksikisi, T., & Saleous, N. (2020). A Review of Terrestrial Carbon Assessment Methods Using Geo-Spatial Technologies with Emphasis on Arid Lands. *Remote Sensing*, 12(12), 2008. <https://doi.org/10.3390/rs12122008>
- IUCN. (2017). *Peatlands and Climate Change*. IUCN.
- Javaherian, M., Ebrahimi, H., & Aminnejad, B. (2021). Prediction of Changes in Climatic Parameters Using CanESM2 Model Based on Rcp Scenarios (Case Study): Lar Dam Basin. *Ain Shams Engineering Journal*, 12(1), 445–454. <https://doi.org/10.1016/j.asej.2020.04.012>
- Jiang, H., Wu, W., Wang, J., Yang, W., Gao, Y., Duan, Y., Ma, G., Wu, C., & Shao, J. (2021). Mapping Global Value of Terrestrial Ecosystem Services by Countries. *Ecosystem Services*, 52, 101361. <https://doi.org/10.1016/j.ecoser.2021.101361>
- Joosten, H., Tapio-Biström, M.-L., & Tol, S. (2012). *Peatlands: Guidance for Climate Change Mitigation Through Conservation, Rehabilitation and Sustainable Use*. Food and Agriculture Organization of the United Nations Rome.
- Kusumaningtyas, M. A., Kepel, T. L., Solihuddin, T., Lubis, A. A., Putra, A. D. P., Sugiharto, U., Ati, R. N. A., Salim, H. L., Mustikasari, E., & Heriati, A. (2022). Carbon Sequestration Potential in the Rehabilitated Mangroves in Indonesia. *Ecological Research*, 37(1), 80–91. <https://doi.org/10.1111/1440-1703.12279>
- Lahiji, R. N., Dinan, N. M., Liaghati, H., Ghaffarzadeh, H., & Vafaeinejad, A. (2020). Scenario-Based Estimation of Catchment Carbon Storage: Linking Multi-Objective Land Allocation with InVEST Model in a Mixed Agriculture-Forest Landscape. *Frontiers of Earth Science*, 14, 637–646. <https://doi.org/10.1007/s11707-020-0825-1>
- Latifah, S., Muhdi, M., Purwoko, A., & Tanjung, E. (2018). Estimation of Aboveground Tree Biomass Toona Sureni and Coffea Arabica in Agroforestry

- System of Simalungun, North Sumatra, Indonesia. *Biodiversitas Journal of Biological Diversity*, 19(2), 620–625.
<https://doi.org/10.13057/biodiv/d190239>
- Liu, J., Sleeter, B. M., Zhu, Z., Heath, L. S., Tan, Z., Wilson, T. S., Sherba, J., & Zhou, D. (2016). Estimating Carbon Sequestration in the Piedmont Ecoregion of the United States from 1971 to 2010. *Carbon Balance and Management*, 11, 1–13.
<https://doi.org/10.1186/s13021-016-0052-y>
- Lv, F., Sun, K., Li, W., Miao, S., & Hu, X. (2024). Estimation of Leaf Area Index across Biomes and Growth Stages Combining Multiple Vegetation Indices. *Sensors*, 24(18), 6106.
<https://doi.org/10.3390/s24186106>
- Malik, A. D., Arief, M. C. W., Withaningsih, S., & Parikesit, P. (2023). Modeling Regional Aboveground Carbon Stock Dynamics Affected by Land Use and Land Cover Changes. *Global Journal of Environmental Science and Management*.
<https://doi.org/10.22035/gjesm.2024.01>
- Massetti, A., & Gil, A. (2020). Mapping and Assessing Land Cover/Land Use and Aboveground Carbon Stocks Rapid Changes in Small Oceanic Islands' Terrestrial Ecosystems: A Case Study of Madeira Island, Portugal (2009–2011). *Remote Sensing of Environment*, 239, 111625.
<https://doi.org/10.1016/j.rse.2019.111625>
- Mthembu, N., Lottering, R., & Kotze, H. (2023). Forest, Crop and Grassland Leaf Area Index Estimation Using Remote Sensing: A Review of Current Research Methods, Sensors, Estimation Models and Accomplishments. *Applied Sciences*, 13(6), 4005.
<https://doi.org/10.3390/app13064005>
- Mutanga, O., Masenyama, A., & Sibanda, M. (2023). Spectral Saturation in the Remote Sensing of High-Density Vegetation Traits: A Systematic Review of Progress, Challenges, and Prospects. *ISPRS Journal of Photogrammetry and Remote Sensing*, 198, 297–309.
<https://doi.org/10.1016/j.isprsjprs.2023.03.010>
- Nguyen, H. K. L., & Nguyen, B. N. (2016a). Mapping Biomass and Carbon Stock of Forest by Remote Sensing and GIS Technology at Bach Ma National Park, Thua Thien Hue province: Xây dựng bản đồ sinh khối và trữ lượng carbon rừng bằng công nghệ viễn thám và GIS tại vườn quốc gia Bạch Mã, tỉnh Thừa Thiên Huế. *Journal of Vietnamese Environment*, 8(2), 80–87.
<https://doi.org/10.13141/jve.vol8.no2.pp80-87>
- Nguyen, H. K. L., & Nguyen, B. N. (2016b). Mapping Biomass and Carbon Stock of Forest by Remote Sensing and GIS Technology at Bach Ma National Park, Thua Thien Hue province. *Journal of Vietnamese Environment*, 8(2), 80–87.
<https://doi.org/10.13141/jve.vol8.no2.pp80-87>
- Oshan, T. M., Li, Z., Kang, W., Wolf, L. J., & Fotheringham, A. S. (2019). mgwr: A Python Implementation of Multiscale Geographically Weighted Regression for Investigating Process Spatial Heterogeneity and Scale. *ISPRS International Journal of Geo-Information*, 8(6), 269.
<https://doi.org/10.3390/ijgi8060269>
- Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-Smart Soils. *Nature*, 532(7597), 49–57.
<https://doi.org/10.1038/nature17174>
- Pratiwi, Y., Rejo, A., Fariani, A., & Faizal, M. (2022). Modelling for Estimation Carbon Stocks in Land Cover Using A System Dynamic Approach (Case Study: Prabumulih City, South Sumatera, Indonesia). *Jurnal Manajemen Hutan Tropika*, 28(3), 221. <https://doi.org/10.7226/jtftm.28.3.221>
- Pu, J., Yan, K., Roy, S., Zhu, Z., Rautiainen, M., Knyazikhin, Y., & Myneni, R. B. (2024). Sensor-Independent LAI/FPAR CDR: Reconstructing a Global Sensor-Independent Climate Data Record of MODIS and VIIRS LAI/FPAR from 2000 to 2022. *Earth System Science Data*, 16(1), 15–34.
<https://doi.org/10.5194/essd-16-15-2024>
- Purwanto, A. (2024). Carbon Stocks Estimation Using the Stock Difference Method of Various Land Use Systems Based on Geospatial in Kualan Watershed. *Jurnal Penelitian Pendidikan IPA*, 10(11), 8602–8611.
<https://doi.org/10.29303/jppipa.v10i11.6818>
- Purwanto, A., Paiman, & Mustikarani, W. (2025). An Assessment of High Carbon Stock and High Conservation Value Approaches in Mandor Nature Reserve Based on Geospatial. *IOP Conference Series: Earth and Environmental Science*, 1462(1), 12022. <https://doi.org/10.1088/1755-1315/1462/1/012022>
- Qiao, K., Zhu, W., Xie, Z., Wu, S., & Li, S. (2024). New Three Red-Edge Vegetation Index (VI3RE) for Crop Seasonal LAI Prediction Using Sentinel-2 Data. *International Journal of Applied Earth Observation and Geoinformation*, 130, 103894.
<https://doi.org/10.1016/j.jag.2024.103894>
- Situmorang, J. P., & Sugianto, S. (2016). Estimation of Carbon Stock Stands Using EVI and NDVI Vegetation Index in Production Forest of Lembah Seulawah Sub-District, Aceh Indonesia. *Aceh International Journal of Science and Technology*, 5(3), 126–139. <https://doi.org/10.13170/aijst.5.3.5836>
- Slamet, N. S., Dargusch, P., Aziz, A. A., & Wadley, D. (2020). Mangrove Vulnerability and Potential Carbon Stock Loss from Land Reclamation in Jakarta Bay, Indonesia. *Ocean & Coastal Management*, 195, 105283.
<https://doi.org/10.1016/j.ocecoaman.2020.105283>

- Suardana, A. A. M. A. P., Anggraini, N., Nandika, M. R., Aziz, K., As-syakur, A. R., Ulfa, A., Wijaya, A. D., Prasetyo, W., Winarso, G., & Dewanti, R. (2023). Estimation and Mapping Above-Ground Mangrove Carbon Stock Using Sentinel-2 Data Derived Vegetation Indices in Benoa Bay of Bali Province, Indonesia. *Forest and Society*, 7(1), 116–134. <https://doi.org/10.24259/fs.v7i1.22062>
- Yan, K., Gao, S., Yan, G., Ma, X., Chen, X., Zhu, P., Li, J., Gao, S., Gastellu-Etchegorry, J.-P., & Myneni, R. B. (2025). A Global Systematic Review of the Remote Sensing Vegetation Indices. *International Journal of Applied Earth Observation and Geoinformation*, 139, 104560. <https://doi.org/10.1016/j.jag.2025.104560>
- Yu, Z., Beilman, D. W., Frolking, S., MacDonald, G. M., Roulet, N. T., Camill, P., & Charman, D. J. (2011). Peatlands and Their Role in the Global Carbon Cycle. *Eos, Transactions American Geophysical Union*, 92(12), 97–98. <https://doi.org/10.1029/2011EO120001>
- Zhang, H., Piilo, S. R., Amesbury, M. J., Charman, D. J., Gallego-Sala, A. V., & Väliranta, M. M. (2018). The Role of Climate Change in Regulating Arctic Permafrost Peatland Hydrological and Vegetation Change Over the Last Millennium. *Quaternary Science Reviews*, 182, 121–130. <https://doi.org/10.1016/j.quascirev.2018.01.003>
- Zhao, Z., Liu, G., Mou, N., Xie, Y., Xu, Z., & Li, Y. (2018). Assessment of Carbon Storage and Its Influencing Factors in Qinghai-Tibet Plateau. *Sustainability*, 10(6), 1864. <https://doi.org/10.3390/su10061864>