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Carbon Stocks Estimation Using the Stock Difference Method of Various Land Use Systems Based on Geospatial in Kualan Watershed

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Abstract: Indonesia controls 75%-80% of the world's carbon stocks, so the amount of carbon stocks must be utilized optimally. This study aims to determine carbon stocks, potential emissions, and economic value of carbon stocks in each land use. The method used is secondary data analysis and field checking. The data collected were Sentinel 2A acquisitions in 2020 and 2022, Digital Elevation Model (DEM), and land use land cover in 2020-2023. Data analysis used SNAP and ArcGIS 10.8. The tool used for data analysis is spatial analysis map algebra. The results showed mixed dryland agriculture has the most extensive carbon stock, at 2,614,178 tons/ha, with potential emissions of 9,585,320 tons/ha. The most minor carbon stock is in mining land use, which is 0 tons/ha with potential emissions of 0 tons/ha. The highest C02 value in USD is the forest land use group. In the Secondary Dryland Forest, Secondary Swamp Forest, and Plantation Forest groups, it is 17,517,400.50 USD, while the lowest is mining land use, which is 0 USD. Overall, the CO2 value of land use in the study area is 34,246,314.45 USD. Integrating remote sensing data analysis and field surveys in geospatial technology is one of the new approaches to studying carbon stocks and CO2 emissions in topsoil from various land uses. By utilizing geospatial technology, efforts to estimate carbon stocks on the surface are easier and faster.

Keywords: Carbon stock; Estimation; Geospatial; Land use; Watershed

Introduction

Although peatlands cover only 3% of the earth's surface, they account for about one-third of all soil carbon storage on a global scale (Carless et al., 2021; Yu et al., 2011). With Indonesia accounting for 75%-80% of the world's carbon stocks, these stocks must be utilized to the fullest extent possible, such as through carbon trading. Emissions from degraded peatlands are of global significance. Drained or burned peatland landscapes are estimated to release 1.3 Gt CO_2 annually, accounting for 10% of greenhouse gas emissions from the land use sector (Carless et al., 2021; IUCN, 2017) and a major share of national greenhouse gas emissions in many countries (Joosten et al., 2012).

Climate change and global warming have been the cause of significant threats to global ecosystems (Trapero et al., 2023; Frimawaty et al., 2023; Hassan & Nile, 2021). The recent increase in greenhouse gas emissions resulting from massive human social development and industrialization is one of the primary emissions causing climate change. Temperatures in places inhabited by more than one-fifth of humanity have increased by 1.5 degrees Celsius (C) above pre-industrial levels by at least one season (Javaherian et al., 2021). Without mitigation efforts to reduce greenhouse

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gases, global temperatures will continue rising in the 21st century, with an average increase of 3.7°C to 4.8°C (IPCC, 2014).

Global warming is one of the issues in the world today, as seen by the high temperature of the earth, which is directly related to greenhouse gases. Peatlands on land store a massive carbon (C) source and are located a few meters from the atmosphere. Small amounts of carbon dioxide (CO2) and other greenhouse gases (GHGs) in the atmosphere are now widely recognized as the leading cause of global warming (Hussein, 2022; Suardana et al., 2023). Most of them are caused by the burning of fossil fuels and the conversion of tropical forests into regional agricultural land (Hussein, 2022; Paustian et al., 2016). Carbon stock estimation is a critical component to combat global warming. Biomass assessments can give an idea of the amount of CO2 that can be removed from the atmosphere by forests and other plantations (Dahy et al., 2020; Issa et al., 2020).

Therefore, the exchange of C in peatlands and the atmosphere should be a primary concern for scientists in global climate change. It is a question of whether the amount of C stored below the soil surface will be released in a warmer climate, causing it to warm further. Alternatively, more C is absorbed due to increased plant growth in warmer climates.

How land use change, fires, and ice sheet melt affect the magnitude and direction of carbon dioxide (CO2) and methane (CH4) exchange with the atmosphere (Pratiwi et al., 2022; Yu et al., 2011). As a result, climate change has brought significant impacts to the micro and macro sectors of the climate world, including loss of biodiversity, destruction of natural vegetation, and loss of important natural ecosystems and their services, as well as local wisdom (Birhane et al., 2020). These questions remain challenging and require possible answers that can be obtained from various research studies that have recently made significant progress.

The Kyoto Protocol 2008, an agreement within the United Nations (UN) Framework Convention on Climate Change and the 2012 Doha Amendment, committed its parties to internationally binding greenhouse gas emission reduction targets (Agricul & Series, 2012). Therefore, updated international carbon accounting regulations mean that peatland soils, and in particular changes in carbon stocks as a result of activities related to drainage and rewetting of wetlands, can be voluntarily considered for CO2 emissions reporting (Hiraishi et al., 2014; Hussein, 2022).

In addition to emissions, carbon loss in peatlands can also occur in the form of dissolved organic carbon and particulate organic carbon. Therefore, accurate assessments, including improved measurement, reporting, and verification of global peat carbon stocks, are needed to support the governance of mental inventories and also to inform global climate change models, including predicting potential positive climate feedback from degraded peatlands (Gallego-Sala et al., 2018).

Between 2005 and 2010, the carbon in the world's forest biomass will decline by 0.5 Gt annually. This reduction was mainly due to a reduction in forest area worldwide (Forestry Economics and Policy Division, 2010). Also, between 2015 and 2016, it is estimated that forests in Indonesia experienced 0.63 million hectares of deforestation (KLHK, 2018; Malik et al., 2023). Carbon emissions originate from the coal energy sector and this figure is expected to continue to rise until it reaches 434.96 parts per million (ppm) by 2050, where the increase in carbon could exceed 400 ppm is categorized as a global phenomenon (Cahyono et al., 2022). Investigating the potential loss of valuable ecosystem components due to LULC changes is critical (Lahiji et al., 2020). Several studies in Indonesia have analyzed the potential of various ecosystems to sequester carbon, for example in state 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).

In recent years, various studies related to biomass estimation have been conducted. Some standard methods, such as making and counting standard cells directly from the field, are used (Batsaikhan et al., 2020; Nguyen & Nguyen, 2016). This method has high accuracy but is time-consuming, costly, labor-intensive, and difficult to apply in distant places and complicated terrain conditions. The recent rapid development of Geographic Information Systems and Remote Sensing combined with field investigation is applied to determine forest carbon stocks, which is considered a new approach. Geographic Information Systems (GIS) provide an opportunity to identify LULC changes over time and comprehensively detect specific disturbances of ecosystem services (Zhao et al., 2018). In addition, spatial models provide a more precise explanation of how disturbances impact ecosystem services (Jiang et al., 2021).

Studies on LULC change and aboveground carbon stock measurements can vary using remote sensing and GIS. Several previous studies focused on uncovering the significant impacts of LULC change on carbon stocks using GIS and remote sensing approaches. A general simulation model for carbon stock dynamics incorporating annual maps was conducted to analyze the effect of LULC changes on vegetation biomass and carbon stocks (Liu et al., 2016; Malik et al., 2023). Assessment of LULC changes and aboveground vegetation carbon stocks using multispectral data in a remote sensing-based methodology showed a relevant decrease in vegetated areas (Ahmad et al., 2023; Massetti & Gil, 2020; Samuel, 2020).

Geospatial technologies, including Remote Sensing (RS) and Geographic Information Systems (GIS), offer the means to enable rapid assessment of terrestrial biomass over large areas in a timely and cost-effective manner, making above- and below-ground estimates possible (Dahy et al., 2020; Katkani et al., 2022; Trivedi et al., 2022). Therefore, applying an integrated RS-GIS approach for precise carbon management is essential. The use of RS and GIS in large-scale aboveground biomass estimation provides good alternatives, insights, challenges, opportunities, and future trends compared to conventional approaches (Dahy et al., 2020; Issa et al., 2020).

Method

Study Area

The administrative research area is located in the Kulan sub-watershed of Ketapang Regency. Astronomically it is located between 109°5'0"-110°37'30" East and 0°21'33"-0°30'0" LS. The research area is traversed by the Kualan River. Kualan Sub Watershed has an area of 1534.93 km² and covers nine villages including Kualan Hulu, Merawan, Semandang Kiri, Balai Pinang Hulu, Balai Pinang, Butuh Bosi, Kualan Hilir, Sekucing Kualan, Lebak Hilir.

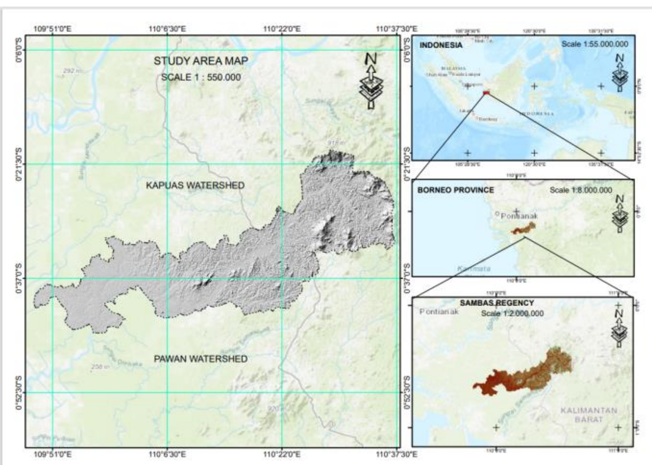

Figure 1. Study area

Data Collection

Data collection includes among others Sentinel 2A acquired in 2020 and 2022, and Digital Elevation Model (DEM) land use land cover in 2020-2023. Land use land cover data in this study was obtained from two sources, namely Sentinel 2A images in 2020, 2021, and 2022 with land use land cover maps of the research area in 2020, 2021, and 2022.

In remote sensing, biomass is strongly influenced by the fAPAR index on satellite images with a linear regression function, where fAPAR is the solar radiation absorbed by plants through photosynthesis through chlorophyll. The fAPAR index is determined based on the relationship between vegetation indices called Normalized Difference Vegetation Index (NDVI) which is expressed by the formula:

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

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:

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

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)

According to Nguyen et al. (2016), the leaf area index (LAI) is the ratio of upper leaf surface area to ground surface area (for broadleaf canopies) or the projection of conifer needle surface area to ground surface area (for coniferous trees) for a given unit area. Nguyen et al. (2016) said, LAI can be used to estimate biomass, vegetation dynamics, or harvest estimation. The range of LAI values is 0 to 6 or higher. A value of less than one indicates the presence of bare soil between vegetated patches, while an LAI value of one indicates that there is one layer of leaves completely covering one unit of ground surface area. A layered canopy with multiple leaf layers per unit of soil surface area is indicated by LAI values greater than 1.

A linear regression technique that aims to connect sensor reflectance data to field measurements of LAI can be used to generate LAI from satellite pictures. According to the following formula, such an approach can connect the fractional cover detected on the ground to the reflectance band of the sensor or a vegetation index like the NDVI (Nguyen & Nguyen, 2016).

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

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

Carbon Stock Identification

Carbon stock identification is done by calculating the land use area multiplied by the carbon emission factor for each land use. As discussed in the scope of the study, this research only focuses on above-ground biomass. Therefore, the amount of carbon and CO2 will be calculated using the formula:

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

$$CO_2 = 3.67 * \text{Carbon Stock} \tag{5}$$

Satellite Image Interpretation

The satellite imagery used in this study is Sentinel 2A downloaded for free from the website https://www.sentinel-hub.com/ acquired in 2020-2022. After review, L2A imagery with 30m x 30m resolution and 30% cloud cover was selected. To process and interpret the Sentinel 2A imagery using SNAP as well as ArcGIS 10.8. SNAP was used for image processing, while ArcGis10.8 software was used to map land use land cover as well as to calculate biomass and carbon stock in the study area at different land use variations.

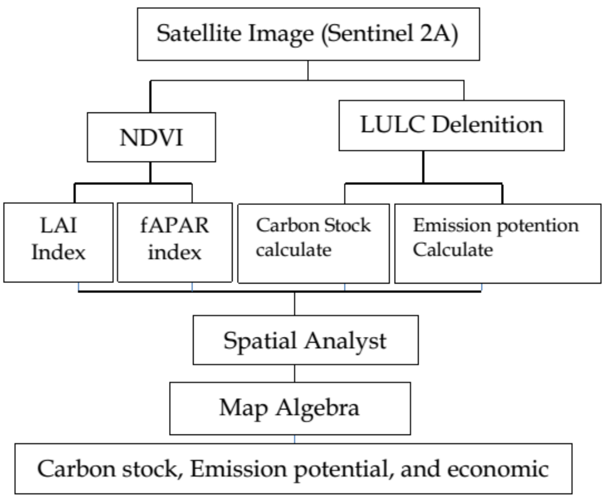

Figure 2. Framework for carbon stock calculating from various land use systems

The analysis in the study used ArcGIS 10.8, a spatial analyst tool using Map Algebra, a spatial statistical tool in the form of correlation and modeling spatial relationship, namely Regression Weighted Regression (GWR). Correlation analysis is used to measure the relationship between variables, where in this study the variables used are the value of the vegetation index (NDVI) used and the value of carbon content in each land use and leaf area index (LAI). Regression analysis measures how much the independent variable can explain the dependent variable, from the value of the vegetation index used and the value of carbon content in each land use.

Result and Discussion

fAPAR

In remote sensing, biomass is strongly influenced by the fAPAR index on satellite images with a linear regression function, where fAPAR is the solar radiation absorbed by plants through photosynthesis through chlorophyll. The maximum fAPAR value is 1.15 and the minimum is 0.09 and the average fAPAR value is 0.89. Based on the fAPAR value, it can be concluded that the greater the fAPAR value, the greater the solar radiation absorbed by plants. This will certainly have a major effect on the amount of chlorophyll and or green leaves. The results of the fAPAR analysis implemented in the form of a map can be seen in Figure 3.

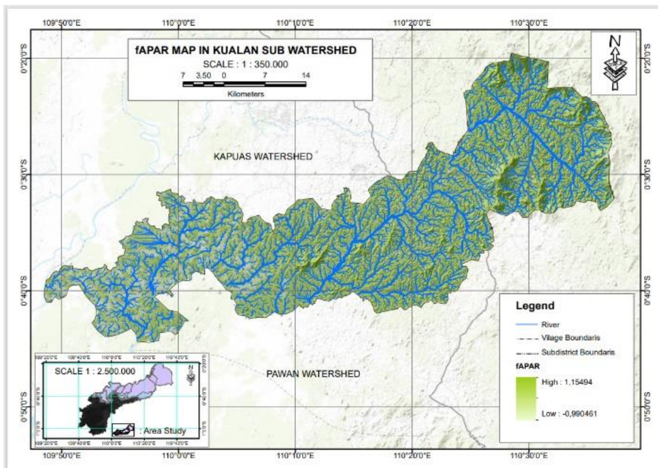

Figure 3. fAPAR distribution in the Kualan Subwatershed

The results of research Nguyen et al. (2016) conducted in Bach Ma National Park, Thua Thien Hue Province are much different from the results of the research conducted by the authors. The results of the analysis obtained a maximum fAPAR value was 0.7 and a minimum was -0.2, while the results of the research conducted by the authors were the maximum fAPAR value of 1.15 and a minimum of 0.09. This difference is likely due to the dense plant conditions in the Kualan sub-watershed, as also indicated by the larger leaf area index (LAI) when compared to the study (Nguyen & Nguyen, 2016)

Land Use Lan Cover

The first interpretation and analysis carried out is by using guided analysis. Based on that method the land use land cover of the study area is forest plantation, secondary swamp forest, secondary dryland forest, plantation, mixed dryland farming, swamp shrubs,

shrubs, rice fields, mining, settlement, and cleared land. The area of each land use land cover can be seen in Table 1.

Table 1. Land Use Land Cover Kualan Watershed

Land Use Land Cover	Area	Percentage
Shrubs	1466.20	0.97
Swamp Shrubs	3481.54	2.29
Secondary Dryland Forest	15644	10.30
Secondary Swamp Forest	20545.36	13.52
Forest Plantation	6853.1	4.51
Settlements	153.87	0.10
Plantation	9046.58	5.95
Mining	2807.58	1.85
Mixed Dryland Farming	87139.27	57.36
Rice Fields	68.75	0.05
Cleared Land	4712.43	3.10
Sum	151918.68	100.00

Based on the data in Table 1, it is known that the most extensive land use land cover is mixed dryland farming, with an area of 87139.27 ha (57.36%), while the smallest is rice fields with an area of 68.75 ha (0.05%). For more details of the Kualan sub-watershed land use land cover can be seen in Figure 4.

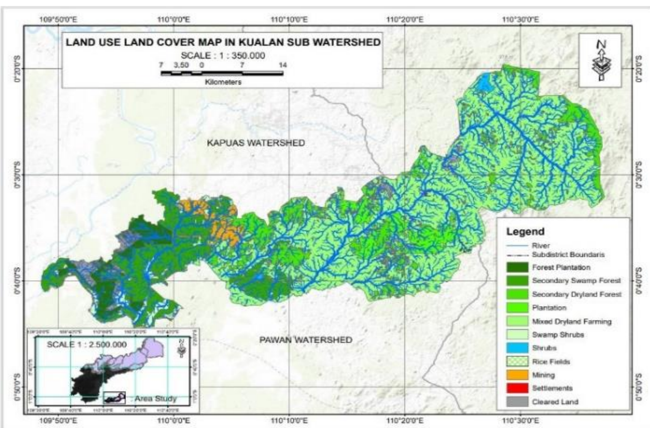

Figure 4. Land use land cover in the Kualan Watershed

Normalized Difference Vegetation Index (NDVI)

The NDVI vegetation index was processed and calculated using SNAP and ArcGIS 10.8. Based on the results of the Normalized Difference Vegetation Index (NDVI) analysis, it is known that the NDVI value ranges from 0.41-1. When viewed from the results of the analysis, most of the NDVI of the study area has values ranging from 0.62-0.78 and 0.78-1. The average NDVI obtained is 0.72. This is reasonable because the study area is 41.36% forest plantations, swamps, plantations, and mixed agriculture. Therefore, trees can grow well, resulting in high NDVI values. The results of NDVI interpretation and analysis of the study area can be seen in Figure 5, farming, with an area of 87139.27 ha (57.36%), while the smallest is rice fields with an area of 68.75 ha (0.05%). For more details of the Kualan sub-watershed land use land cover can be seen in Figure 4.

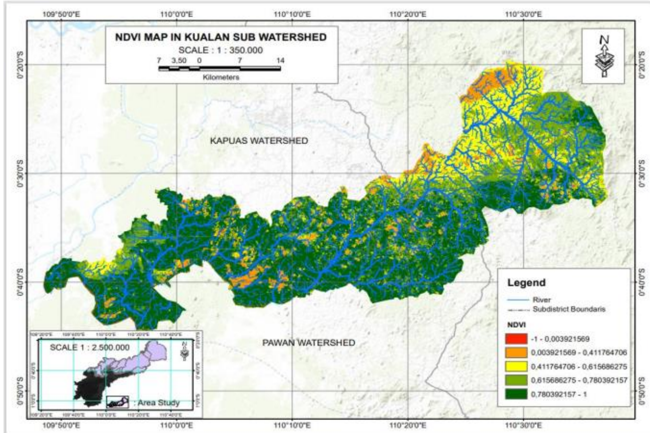

Figure 5. Index NDVI in the Kualan Watershed

In studies conducted (Goswami et al., 2015; Nguyen & Nguyen, 2016), the NDVI of natural forests or perennial plants fluctuated from 0.5 to 0.8. When compared with NDVI values determined from remote sensing imagery in the index, the values are quite similar (Nguyen & Nguyen, 2016).

Leaf Area Index (LAI)

The next step was to determine the actual LAI of each standard plot in the field. The LAI map was interpreted from satellite images by reconnecting NDVI and LAI as formula (2) with linear regression analysis: LAI = 0.65 + 36.7059 * NDVI with R2 = 0.025. The results of the statistical analysis showed that the average value of the LAI index on the image was 32. The maximum value of the LAI index obtained on the image was 41.8 and the minimum value was -35.8. The smallest LAI values are represented as mine sites, settlements, and vacant land, while land covered by dense vegetation with large biomass has high LAI index values. The results of the LAI index analysis of the study area can be seen in Figure 6.

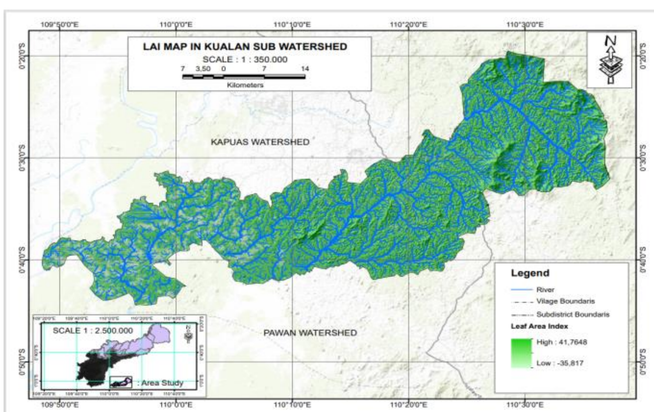

Figure 6. Index LAI in the Kualan Watershed

The LAI values of land use land cover ranged from -35.8 to 41.7. More details about the relationship between NDVI and LAI index in the sample plots can be seen in Figure 6. As can be seen, the NDVI and LAI index have a positive correlation with R2 0.0255. This means that the more trees there are, the more bio-mass there is.

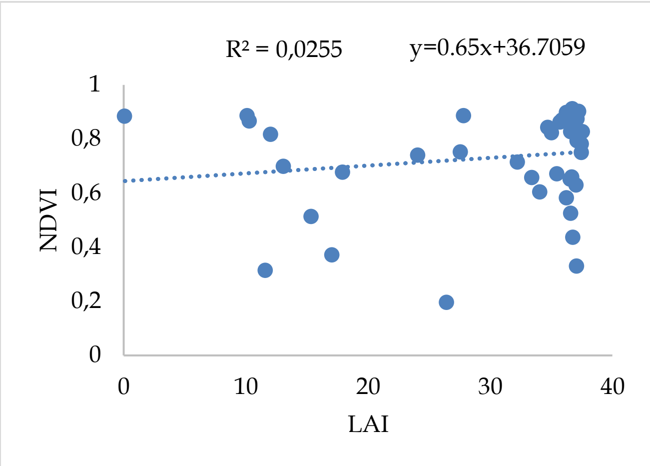

Figure 7. Correlation Between LAI and NDVI

The standard plotting in determining LAI in the land use land cover of the Kualan sub-watershed can be seen in Figure 8.

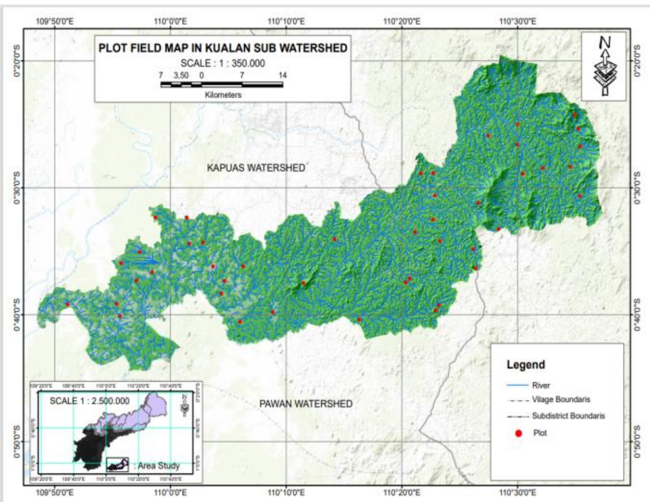

Figure 8. Plot location in land use land cover

The relationship between NDVI and LAI in the field plots based on linear regression analysis can be seen in the table 2. 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 Kualan watershed.

Table 2. LAI and NDVI Values of the Field Plots

Point	LAI	NDVI	No	LAI	NDVI
1	0.10539	0.884024	23	37.1539	0.794383
2	36.7059	0.659888	24	24.0907	0.739531
3	27.6036	0.752151	25	10.293	0.867562
4	36.7986	0.436964	26	36.9338	0.877866
5	10.1228	0.885714	27	37.5623	0.826456
6	37.4913	0.751142	28	35.7394	0.86293
7	36.734	0.91224	29	13.0878	0.699465
8	27.8639	0.886188	30	26.4436	0.196937
9	36.7327	0.864364	31	17.0741	0.370886
10	35.0571	0.824112	32	37.0881	0.896647
11	34.0919	0.605286	33	37.0175	0.8802
12	32.2511	0.715736	34	37.1315	0.875244
13	33.4323	0.658411	35	11.5987	0.315484
14	36.2758	0.897422	36	36.2595	0.582109
15	34.7484	0.843125	37	36.6152	0.827016
16	35.9267	0.87002	38	36.6283	0.525251
17	12.0598	0.816393	39	17.9409	0.67756
18	37.0454	0.629682	40	36.5613	0.651498
19	15.351	0.512797	41	37.487	0.781736
20	36.9473	0.883629	42	35.4677	0.671742
21	36.8143	0.868509	43	37.2825	0.90226
22	36.4007	0.88087	44	37.0992	0.33072

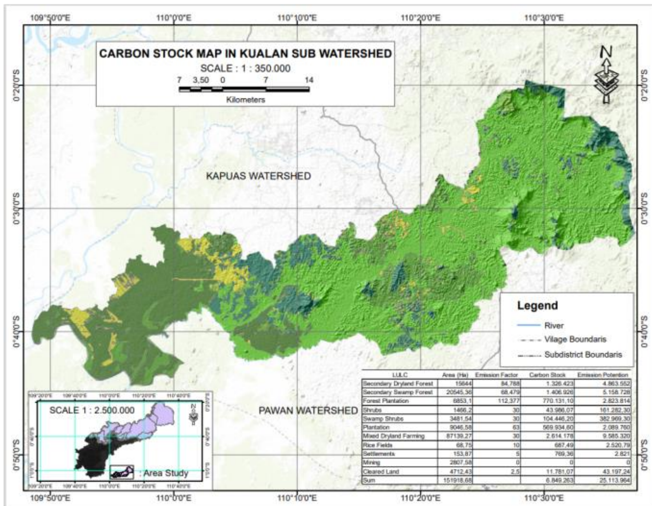

Figure 9. Carbon stock and emission potential of Kualan Watershed

Based on the results of the calculation, the carbon stock is broadly divided into three, namely carbon stock in forest land use, which includes Secondary Dryland Forest, Secondary Dryland Forest, Forest Plantation, cultivated land use including plantation, mixed dryland farming, rice fields, scrub swamp land, and non-cultivated land includes settlement, mining and cleared land. Carbon stock analysis of different land uses averaged 3,424,631.5 to/ha. The largest carbon stock is mixed dryland farming, which is 2,614,178 tons/ha, with potential emissions of 9,585,320 tons/ha. The least carbon stock is in mining land use at 0 to/ha with potential emissions of 0 tons/ha.

Table 3. Carbon Stock and Emission Potential CO_2

LULC	Area (Ha)	Emission Factor	Carbon Stock	Emission Potential
Shrubs	1467	30	43986	161282
Swamp Shrubs	3482	30	104446	382969
Secondary Dryland Forest	15644	84.788	1326423	4863552
Secondary Swamp Forest	20545	68.479	1406926	5158728
Forest Plantation	6853	112.377	770131	2823814
Settlements	154	5	769	2821
Plantation	9047	63	56993406	2089760
Mining	2808	0	0	0
Mixed Dryland Farming	87139	30	2614178	9585320
Rice Fields	69	10	687	2521
Cleared Land	4712	2,5	11781	43197
Sum	151919		6849263	25113964

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

Total payment= CO2 amount*unit Price (USD/ton CO2) (5)

Table 4. Market Value of Carbon from Different Land Uses

LULC	Carbon Stock (ton/ha)	Unit	CO_2 (USD) value
Shrubs	43986	5	219.930
Swamp Shrubs	104446	5	522.231
Secondary Dryland Forest	1326423	5	6.632.115
Secondary Swamp Forest	1406926	5	7.034.630
Forest Plantation	770131	5	3.850.656
Settlements	769	5	3.847
Plantation	56993406	5	2.849.673
Mining	0.00	5	0,00
Mixed Dryland Farming	2614178	5	13.070.890
Rice Fields	687	5	3.437
Cleared Land	11781	5	58.905
Sum			34.246.314

Based on Table 3, it can be seen that the C02 value in USD that has a high value is the forest land use group. In the Secondary Dryland Forest, Secondary Swamp Forest, and Forest Plantation the total is 17,517,400.50 USD, while the lowest is land use in mining which is 0 USD. Overall, the CO2 value of land use in the study area is 34,246,314.45 USD.

Conclusion

The integration of remote sensing data analysis and field surveys in geospatial technology is one of the new approaches in the study of carbon stocks and CO2 emissions in topsoil from various land uses. By utilizing geospatial technology, efforts to estimate carbon stocks on the surface are easier and faster. The results of carbon stock estimation on land use land cover in the form of forests are on average high. This condition can be used as a reference to be oriented toward carbon stock management and is an important basis for determining the price of CO2 from each type of land use, especially forests, for the carbon commercial market domestically and globally. Broadly speaking, carbon stock is divided into three, namely carbon stock in forest land use, which includes Secondary Dryland Forest, Secondary Dryland Forest, Forest Plantation, cultivated land use including plantation, mixed dryland farming, rice fields, scrub swamp land, and non-cultivated land includes settlement, mining and cleared land. Carbon stock analysis on different land uses averaged 3,424,631.5 to/ha. The largest carbon stock is mixed dryland farming, which is 2,614,178 tons/ha, with potential emissions of 9,585,320 tons/ha. For least carbon stock is in mining land use of 0 to/ha with potential emissions also 0 tons/ha. C02 value in USD which has a high value is the forest land use group. In the Secondary Dryland Forest, Secondary Swamp Forest, and Forest Plantation the total is 17,517,400.50 USD, while the lowest is land use in mining which is 0 USD. Overall, the CO2 value of land use in the study area is 34,246,314.45 USD. So with these results, a geospatial approach can provide an effective solution for monitoring and managing carbon stocks and carbon emissions.

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Author Contributions
Ms. Sulha has contributed to the mapping of carbon stocks, potential emissions, and the economic value of CO2.

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Conflicts of Interest
The authors declare that there is no conflict of interest regarding the publication of this paper.

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