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MORALITY BEFORE KNOWLEDGE

The impact of land cover change on carbon stocks in a biocultural teak production landscape

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ABSTRACT

Background: Land cover change is one of the factors contributing to the increasing concentration of CO_2 in the atmosphere, with direct implications for the ecological and cultural sustainability of production landscapes shaped by long-term human–forest interaction. Monitoring land cover change and estimating carbon stocks are essential for supporting emission mitigation efforts at various spatial scales. This study analyzes the impact of land cover change on carbon stocks in Randublatung District, Central Java, a landscape historically managed as a teak production forest reflecting the interconnection between local livelihoods and ecosystem management, by integrating geographic information systems (GIS) and remote sensing data to assess land cover change and carbon stocks in Randublatung District during the 2013–2025 period using the Google Earth Engine (GEE) platform. **Methods:** This study employed the random forest (RF) algorithm for land cover classification, and carbon stock estimation was conducted using a Tier 2 approach based on carbon constants. **Findings:** Randublatung District is dominated by teak plantation forests. Forest cover expanded by 2,152.78 ha during 2013–2025, while settlement land, dryland agriculture, and paddy fields decreased sequentially by 1,042.30 ha, 595.57 ha, and 514.92 ha. These land cover changes are directly proportional to changes in carbon stocks, which increased by 200,636.08 tons, driven by a 211,790.81 tons increase from plantation forests, whereas other non-forest land-use classes experienced a decline. **Conclusion:** The increase in carbon stock indicates vegetation recovery or reforestation supporting climate change mitigation and illustrates how managed production landscapes can sustain both ecological function and community-based land use. **Novelty/Originality of this article:** The novelty of this study lies in the application of the Random Forest algorithm for carbon stock mapping at the sub-district level, as well as in its focus on teak production forest areas as a biocultural landscape, which have received relatively limited attention in carbon-related research.

KEYWORDS: carbon stock; land cover; land cover change, random forest.

1. Introduction

Climate change remains a global issue that has received significant attention. Climate change is caused by increasing atmospheric CO_2 concentrations as a result of the conversion of forests into non-forest land carried out by humans (Malik et al., 2024). In general, CO_2 is the dominant greenhouse gas (GHG) in the atmosphere and the main contributor (>50%) to global warming (Sahoo et al., 2021). Most of the CO_2 accumulated in the atmosphere originates from soil carbon reserves. These CO_2 emissions have been generated over the past 150–200 years as a result of increased mineralization of soil organic matter (SOM). This occurs due to land-use change from forest to non-forest areas. This process causes soil carbon to decompose more rapidly into CO_2, which is subsequently released into the atmosphere (García-Campos et al., 2022).

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Land cover serves as a tangible indicator of changes occurring on the Earth's surface. Changes in land cover affect various aspects of the Earth's surface, including climate, terrestrial ecosystems, biodiversity, and water balance. The impacts of land cover change on terrestrial ecosystems play a crucial role in the global carbon cycle and therefore constitute a major concern among researchers (Noi Phan et al., 2020). In the context of carbon dynamics, land cover change can influence the global carbon balance, as each type of land cover possesses a different capacity for carbon storage (Withaningsih et al., 2024). The conversion of forested land to non-forest land is inversely related to changes in carbon stocks; higher rates of forest conversion lead to a decline in stored carbon. Such conditions result in increased concentrations of CO_2 in the atmosphere, which in turn contribute to climate change (Lakshita & Rahayu, 2021).

According to the Intergovernmental Panel on Climate Change (2023), the Agriculture, Forestry, and Other Land Use (AFOLU) sector contributes approximately 22% of total global greenhouse gas (GHG) emissions. About half of the total CO_2 emissions from the AFOLU sector originate from land-use change and deforestation activities. This condition indicates that changes in land cover/land use play a significant role in storing or releasing carbon stocks on the Earth's surface, particularly in tropical forest land cover, which contains high carbon reserves (Grassi et al., 2022). Therefore, changes in tropical forest land cover will affect the global carbon balance.

On the other hand, forests play a crucial role in climate change mitigation. Forests not only act as sources of CO_2 emissions but also play an important role in absorbing (sinks) and storing (stocks) carbon in the form of biomass, dead organic matter, soil, and harvested wood products through the process of photosynthesis (Grassi et al., 2022). Carbon stored in aboveground and belowground biomass is estimated at approximately 296 gigatons (Gt), with 44% stored in plant biomass. Aboveground biomass consists of all living organisms and vegetation present in terrestrial ecosystems, such as trees, shrubs, and herbaceous plants (Piyathilake et al., 2022). Aboveground biomass strongly influences the carbon storage potential of ecosystems, which plays an important role in the global carbon balance (Sintayehu et al., 2020). Forest areas have carbon stock potential that is ten times greater than that of other vegetation types (Malik et al., 2024). Therefore, sustainable forest management is essential for mitigation, both in terms of avoiding emissions to the atmosphere and enhancing carbon sequestration from the atmosphere (Keith et al., 2024). Accordingly, land cover change is one of the main factors influencing carbon stock dynamics, as each land cover type has a different carbon storage capacity. Therefore, it is necessary to analyze the relationship between land cover change and carbon stocks to understand the impacts of land cover change on climate change mitigation.

Indonesia is a country that plays an important role in maintaining global climate balance. This is because Indonesia possesses tropical forests with the highest carbon reserves in the world (Adnan & Dadi, 2023). The forest area in Indonesia covers more than 60% of its total land area (Syakila et al., 2023). Forest land cover is dynamic and can change rapidly, with deforestation being one such change. Deforestation rates continue to fluctuate, either increasing or decreasing, as a result of human activities in land use, which have led to the loss or expansion of forest cover (Adnan & Dadi, 2023). In 2023–2024, Indonesian forests experienced deforestation of 0.17 million ha (KLHK, 2025). Deforestation in Indonesia occurs due to agricultural land conversion, forest fires, logging, and the use of fuelwood. Deforestation has a major impact on climate change related to increased CO_2 levels in the atmosphere. Substantially, activities such as forest protection, restoration, rehabilitation, and the management of forests and agricultural land serve as effective solutions for mitigating climate change (Adnan & Dadi, 2023).

Therefore, to curb the rate of forest loss and greenhouse gas (GHG) emissions, the Government of Indonesia has committed to reducing emissions by 29% (unconditionally) and 41% (conditionally or with international assistance) through the Forest and Other Land Use (FOLU) Net Sink 2030 policy program (Asdak, 2023). Forest and Land Rehabilitation (FLR) as the main strategy to achieve the FOLU Net Sink 2030 target needs to be emphasized to enhance carbon sequestration. However, one of the major challenges in implementing this policy is the limited availability of up-to-date and consistent spatial data at the local level. Most carbon inventories are still conducted through field surveys, which require substantial time and cost. Thus, the application of remote sensing and Geographic Information Systems (GIS) approaches serves as an effective solution for providing rapid, extensive, and accurate spatial data. Satellite image–based analysis offers opportunities for periodic monitoring of land cover changes, which can be used to predict fluctuations in carbon stocks over time and to assess the effectiveness of implemented mitigation policies (Ambarwulan et al., 2022). Therefore, accurate and up-to-date land cover mapping at the sub-district level is essential to effectively monitor these changes and to support sustainable development, planning, and natural resource management.

The development of Geographic Information Systems (GIS) has created opportunities to identify and monitor changes over time (Malik et al., 2024). Studies on land cover change and aboveground carbon stocks are conducted by integrating GIS and remote sensing approaches. This research utilizes remote sensing data to map land cover and monitor land cover changes over time using Landsat 8 OLI imagery as the dataset. The study employs GIS by utilizing Google Earth Engine (GEE) for geospatial analysis. GEE is a cloud-based platform that integrates large volumes of remote sensing data from various sources and provides high-performance computing services to support efficient and user-friendly satellite image processing. The advantages of GEE include large storage capacity, high processing power, and flexibility in applying various analytical approaches (Loukika et al., 2021).

Randublatung is one of the districts in Blora Regency with the largest forest area managed by Perhutani. Randublatung District is located at an elevation of 40–200 meters above sea level, with undulating topography that supports the growth of teak (Tectona grandis) (Rahutama et al., 2024). Teak forests in this area have high economic and ecological value, as their timber is profitable and also functions as a long-term carbon sink. Land use is dynamic along with regional development and continuous population growth. During the period 2014–2024, the Blora area, including Randublatung District, experienced land use changes due to human activities such as the conversion of forest land to non-forest land (Rahutama et al., 2024). These changes can affect the magnitude of aboveground carbon stocks, as the carbon sequestration capacity differs among land cover classes. Therefore, spatial analysis of land use change and its impact on carbon stocks in Randublatung is important to determine the level of carbon loss or gain during the period 2013–2025.

Land cover change is closely associated with changes in carbon stock, as reported in several previous studies. Rahman et al. (2023) and Achmad et al. (2023) conducted land cover classification using the Maximum Likelihood algorithm, and their findings indicated a decrease in carbon stock due to forest conversion. Malik et al. (2024) also applied the Maximum Likelihood algorithm for land cover classification and reported a decline in carbon stock in Rancakalong District as a result of the reduction in mixed garden area, which represents the dominant land cover type in the region. Similarly, the study by Withaningsih et al. (2024) demonstrated a decrease in carbon stock in Jatigede, West Java, caused by the conversion of forest to non-forest land, using the same classification approach.

However, most of these studies still employed conventional methods, namely the Maximum Likelihood algorithm, for land cover classification. This algorithm has limitations in handling the spectral complexity of various land cover types. Therefore, this study was conducted to address this gap by applying the Random Forest (RF) algorithm as a land cover classification method. Based on the study conducted by Loukika et al. (2021), the use of the RF algorithm for land cover classification achieved a high accuracy of 94.85%.

Moreover, most previous studies have predominantly focused on national or regional scales. At present, studies examining the impacts of land cover change on carbon stocks at the local level, particularly in Randublatung Subdistrict, remain very limited. This area has distinct characteristics, as it is dominated by teak production forests managed by Perum Perhutani and features close interactions with agricultural land and community settlements. These conditions generate land cover change patterns that differ from those in natural forest areas, thereby necessitating specific research to understand the dynamics of carbon stocks. Therefore, this study is conducted to address this gap, aiming to analyze the impacts of land use change on carbon stocks in Randublatung Subdistrict during the 2013–2025 period using a GIS-based approach and remote sensing data. This research is expected to contribute empirical references on carbon dynamics in plantation forest ecosystems and to serve as a basis for evaluating sustainable forest management to support the achievement of national emission reduction targets. In addition, this study may provide a foundational analytical framework that can be replicated in other areas with similar characteristics, thereby supporting efforts to develop more accurate local-level spatial carbon databases.

2. Methods

2.1 Research location

This research was conducted in Randublatung District (Figure 1), located in Blora Regency, Central Java, with a total area of 23,601.76 ha. Most of Blora Regency consists of production forest areas dominated by teak stands managed by Perum Perhutani, with the largest teak forest cover located in Randublatung District. The selection of this research location was based on the characteristics of Randublatung as a teak production forest area experiencing a high level of land-use change.

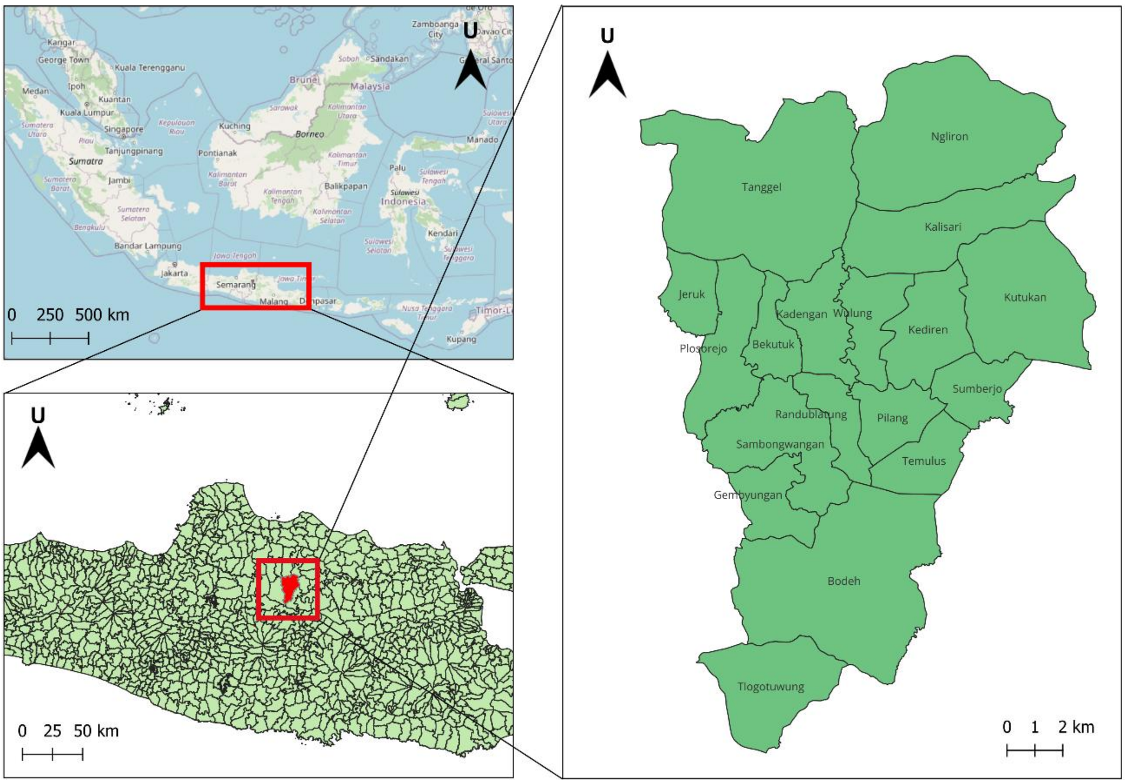

Fig. 1. Research location map

Based on land cover maps of Blora Regency in 2014 and 2024, Randublatung has undergone changes in teak forest cover, rice fields, dryland agriculture, and settlements (Rahutama et al., 2024). These conditions have the potential to affect the balance of carbon stocks, making this area relevant for further investigation.

2.2 Data methods

The tools used in this study included a laptop, the Google Earth Engine (GEE) platform, QGIS, and Microsoft Excel. The data employed in this study consisted of secondary data, namely Landsat 8 OLI satellite imagery from 2013 and 2025 obtained through the GEE platform (Table 1). Several considerations underlie the selection of Landsat 8 imagery,

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including its high temporal consistency, the fact that Landsat 8 Surface Reflectance Tier 1 imagery has been geometrically, radiometrically, and atmospherically corrected, and its 30 m spatial resolution, which is suitable for interpreting land cover classes at the sub-district scale.

Table 1. Secondary data information

Parameter	Data	Spatial Resolution	Data Format	Source
Land Cover 2013	Landsat 8 OLI	30	Landsat 8 Surface Reflectance Tier 1	code.earthengine.com
Land Cover 2025	Landsat 8 OLI	30	Landsat 8 Surface Reflectance Tier 1	code.earthengine.com
Area of Interest (AOI)	Administrative boundary of Randublatung	-	*.shp	gadm.org/data.html
Carbon Stock Constant	Carbon constants for each land cover class	-	-	Tosiani (2015)

The methodology employed in this study adopts a remote sensing–based approach using the Google Earth Engine (GEE) platform to process satellite imagery data. GEE functions as a repository for extensive remote sensing datasets. It integrates a multipetabyte catalog of satellite imagery and geospatial data with planetary-scale analytical capabilities (Pande et al., 2024). The data processing stages in this study are illustrated in a flowchart (Figure 2).

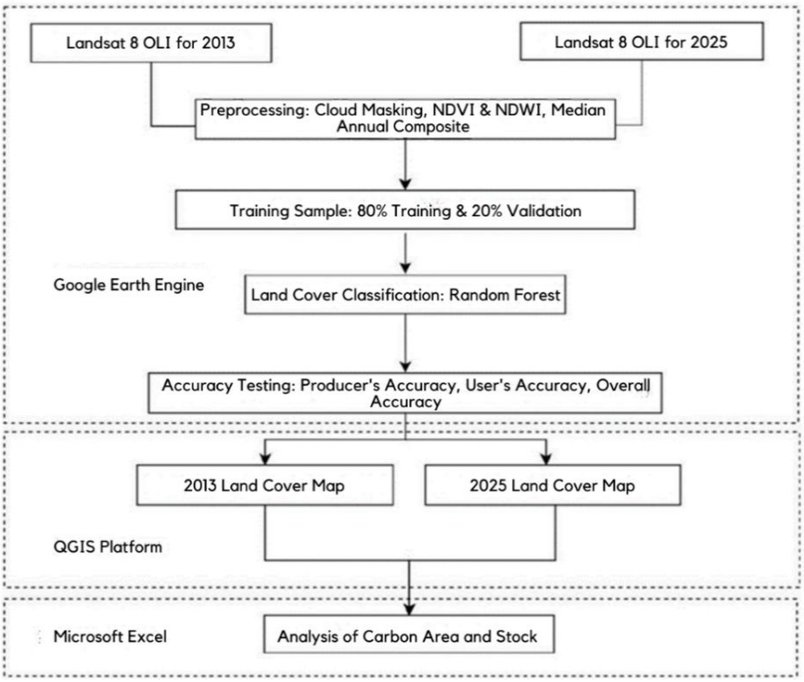

Fig. 2. Research methodology flowchart

2.2.1 Pre-processing and additional variables

At this stage, image filtering was conducted based on the Randublatung administrative boundary, acquisition time, and cloud cover of less than 30%. Subsequently, cloud and cloud shadow masking were applied to remove pixels affected by clouds and their shadows. Images from each year were then composited using a median annual composite to produce annual images with reduced cloud interference. Previous studies have demonstrated that this method yields more accurate results in similar analyses (Tesfaye et al., 2024).

$$NDVI = \frac{(B5-B4)}{(B5+B4)} \quad \text{(Eq. 1)}$$

$$NDVI = \frac{(B3-B5)}{(B3+B5)} \quad \text{(Eq. 2)}$$

This study required additional variables, namely the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI), to improve land cover classification accuracy. NDVI was derived from the normalized difference between the near-infrared (NIR, Band 5) and red (Band 4) bands, while NDWI was calculated from the normalized difference between the green (Band 3) and near-infrared (Band 5) bands, as shown in Equations 1 and 2. The combination of spectral bands and indices was used as input variables in the classification process.

2.2.2 Land cover classification

The classification of land cover classes in this study refers to the SNI 7645-1 standard, which includes settlements, dryland agriculture, paddy fields, and plantation forests (Badan Standardisasi Nasional, 2014). Prior to the image classification process, training samples were generated by creating polygons based on visual interpretation of RGB composite imagery, and each polygon was assigned a "classification" attribute according to the land cover classes used in this study. In this study, the number of samples for each class was set at 500 pixel samples to ensure balance and to avoid bias resulting from differences in sample size. This principle is explained by Weitkamp & Karimi (2023), who state that balanced sample sizes for each class result in higher accuracy. In addition, a larger number of samples generally leads to higher accuracy; however, beyond a certain threshold, further increases do not significantly improve accuracy (Weitkamp & Karimi, 2023). Therefore, the selection of 500 samples per class was considered representative. The training samples were randomly divided into 80% for training and 20% for validation. This proportion refers to the study conducted by Mohammed & Alsunosi (2022), which reported that an 80:20 split produced relatively high accuracy, with a value of 0.87.

In this study, land cover classification was performed using a supervised method with the Random Forest (RF) algorithm. The RF algorithm operates by repeatedly constructing multiple decision trees using the predefined training samples (Jamei et al., 2022). The RF algorithm has several advantages, including: the ability to effectively handle noisy data and outliers; higher accuracy compared to other algorithms such as Support Vector Machine (SVM), k-Nearest Neighbour (kNN), or Maximum Likelihood Classification (MLC); the capability to manage complex data and a large number of variables; and fast and efficient computational processing because RF selects only the most important variables (Noi Phan et al., 2020). These considerations formed the basis for selecting the RF algorithm in this study. There are two main parameters used, namely ntree (number of decision trees) and mtry (number of variables). This study set the ntree value to 200, referring to several previous studies that reported the optimal ntree range to be between 100 and 500, while the mtry value used the default setting, namely the square root of the total number of variables used in the model (Loukika et al., 2021).

2.2.3 Accuracy assessment

The subsequent stage is accuracy assessment to determine the accuracy of the classification results. The classification outcomes were validated using a confusion matrix to calculate Overall Accuracy (OA), Producer's Accuracy (PA), and User's Accuracy (UA). Validation data were used to evaluate the accuracy of the model. These accuracy results were employed to assess whether the classification outcomes are suitable for land use change analysis. OA indicates the proportion of reference data that were correctly classified. Its value is calculated by dividing the total number of correctly classified pixels by the total number of pixels in the sample. UA reflects the reliability of the map from the perspective of map users. Its value is calculated by dividing the number of correctly identified pixels in a particular class by the total number of pixels classified as that class. This measure describes the proportion of pixels classified as a given class on the map that truly belong to that class under actual conditions. Meanwhile, PA explains the accuracy of the map from the perspective of the map producer. Its value is determined by dividing the number of pixels correctly classified for a particular class by the total number of pixels that actually belong to that class. This measure indicates the proportion of pixels of a given class that were successfully classified correctly (Mulkal et al., 2024).

2.2.4 Area and carbon stock analysis

The classification results were converted into area data for each class (ha) using the ee.Image.pixelArea() function in GEE. Carbon stock values were obtained by multiplying the area by the carbon stock constant (Table 2) for each land cover class, as shown in Equation 3. This method was selected because it is more efficient and practical for spatial analysis at national and regional scales.

Table 2. Carbon constants for each land cover class

Land cover class	Constant (ton C/ha)	Source
Settlement	4	Juknis PEP RAD GRK, 2013
Dryland agriculture	10	Juknis PEP RAD GRK, 2013
Paddy field	2	Juknis PEP RAD GRK, 2013
Plantation forest	98.38	Litbanghut, 2014

(Tosiani, 2015)

This study employed a Tier 2 carbon estimation approach, in which the carbon constants have been adjusted to national and regional conditions, thereby providing more accurate results. The carbon constant values were obtained from the Carbon Sequestration and Emission Activities Book, which has been adapted to the biophysical conditions and land cover types in Indonesia (Tosiani, 2015).

$$\text{Carbon stock} = \left[\mathrm{X}\left(\frac{ton\ C}{ha}\right) \times \mathrm{Y}\ (\mathrm{ha})\right] \qquad \text{(Eq. 3)}$$

The carbon constants differ among land cover classes to reflect variations in vegetation structure, biomass density, and land management characteristics. Forest areas were assigned higher carbon density values than agricultural land, paddy fields, and settlements due to their greater biomass accumulation capacity. Therefore, the use of Tier 2 carbon constants is considered more representative of Indonesian conditions than the default global values provided by the IPCC Tier 1 approach. Carbon stock was calculated by multiplying the carbon constant by the area of each land cover class (Equation 3).

3. Results and Discussion

3.1 Land cover change in Randublatung 2013 and 2025

Land cover refers to biophysical conditions that include features observable on the Earth’s surface, such as vegetation, buildings, roads, communication infrastructure, and others. Land cover change denotes alterations in the physical form of the Earth’s surface over a certain period. This process is dynamic and has significant impacts on the environment, economy, and society of a region (Mandala et al., 2024). Measurement of land cover change over a specific time period can be conducted by analyzing satellite imagery acquired at different times (Lakshita & Rahayu, 2021). The output of satellite image analysis is a land cover map that presents the classification of each land cover type. Accurate and up-to-date land cover change maps are crucial for sustainable management. A comprehensive understanding of land cover dynamics not only provides an overview of past changes but also assists in designing sustainable land resource management strategies to maintain the essential functions of a landscape.

The preparation of land cover maps was carried out using the GEE platform. Prior to analysis, the results of land cover classification must undergo accuracy assessment to determine the level of map precision. The classification results were validated using a confusion matrix to calculate OA, PA, and UA. A confusion matrix is a tabular representation used to evaluate the performance of a classification model. It provides details of predicted and actual classes, enabling the calculation of various accuracy metrics (Sultana & Inayathulla, 2022). The confusion matrix illustrates how many pixels are correctly classified and how many are misclassified. Rows in Table 3 represent the classification or model prediction results, while columns represent reference data or actual conditions. PA indicates the extent to which field classes are correctly identified by the classification. UA indicates the extent to which the classification results correspond to actual field conditions. OA indicates the overall accuracy of the entire classification. The results of the confusion matrix and the accuracy assessment of land cover classification in Randublatung District are presented in Table 3. Through this accuracy assessment, the reliability of the classification results can be confirmed before further spatial analysis is conducted.

Table 3. Confusion matrix results and accuracy assessment of land cover classification

Land cover class	Settlement	Dryland agriculture	Paddy field	Planted forest	Total	UA (%)
(a) Year 2013						
Settlement	97	3	1	1	102	98
Dryland agriculture	2	114	2	0	118	95
Paddy field	0	2	86	0	88	96
Planted forest	0	1	0	106	107	99
Total	99	120	89	107	415	388
PA (%)	95	96	97	99	-	-
OA (%)	97					
(a) Year 2025						
Settlement	86	3	0	0	89	94
Dryland agriculture	5	95	0	1	101	97
Paddy field	0	0	90	3	93	1
Planted forest	0	0	0	105	105	96
Total	91	98	90	109	388	288
PA (%)	97	94	97	1	-	-
OA (%)	97					

Accuracy assessment was conducted using three parameters: PA, UA, and OA. Each land cover class in 2013 produced PA and UA values ranging from 95% to 99%, with an overall accuracy of 97%. These values indicate that the 2013 image classification results have high precision and reliability, with minimal classification errors. As shown in Table 3, the plantation forest class has the highest accuracy values, with PA of 99% and UA of 99%, indicating that this object is the easiest to identify based on its spectral characteristics. Minor errors occurred in the settlement and dryland agriculture classes, which may be confused with each other due to similar tone and texture in the imagery. These results are comparable to the 2025 land cover classification, which produced PA and UA values ranging from 94% to 100%, with an overall accuracy of 97%. This figure indicates that the 2025 classification results are also very good and consistent with those of 2013. The highest accuracy is observed in the plantation forest class, with a PA of 100% and a UA of 96%. The settlement and dryland agriculture classes experienced slight classification errors due to spectral similarity between the two classes.

According to research conducted by Ambarwulan et al. (2022), the recommended minimum accuracy standard is 80%. Based on this statement, the accuracy assessment results in this study indicate that the classification method used, namely Random Forest, is capable of identifying each land cover class very well, so that the classification results are reliable for land cover change analysis and carbon stock estimation in Randublatung District in 2013 and 2025. The land cover maps of Randublatung District for 2013 and 2025 are presented in Figure 3.

Randublatung District has a total area of 23,601.76 ha, which is divided into four land cover classes, namely settlements, dryland agriculture, paddy fields, and plantation forests. Based on the land cover maps of Randublatung District, plantation forests are observed to dominate the area. Plantation forest cover in both 2013 and 2025 predominates in the southern and northern parts of the district. This is consistent with environmental protection and management plan/*rencana perlindungan dan pengelolaan lingkungan hidup (RPPLH)* data, which indicates that the largest forest land cover area in Blora Regency is located in Randublatung District (Blora Regency Environmental Agency, 2024).

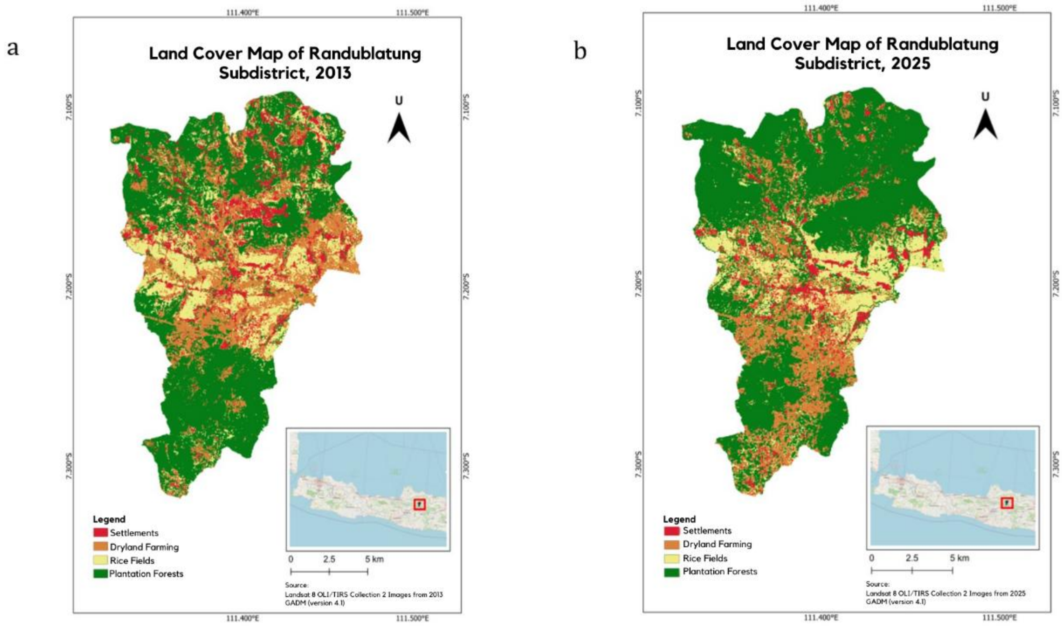

Fig. 3 (a) Land cover map of Randublatung District in 2013; (b) Land cover map of Randublatung District in 2025

In addition to forest land cover, Randublatung District also contains non-forest land cover, including settlements, dryland agriculture, and paddy fields. The dominance of teak plantation forests in Randublatung highlights the important role of the forestry sector in shaping the landscape structure of this region. The comparison of land cover maps of Randublatung District in 2013 and 2025 indicates significant changes in land cover conditions, particularly in the plantation forest class. In the southern area, plantation forest cover in 2013 is observed to have changed into dryland agriculture by 2025. Meanwhile, in the northern area, the conversion of non-forest land into plantation forest is evident. Specific information regarding the area of each land cover class in Randublatung District in 2013 and 2025 is presented in Table 4.

The analysis of land cover during the 2013–2025 period indicates that Randublatung District experienced significant land cover changes, particularly in plantation forest areas. The area of teak plantation forest managed by Perum Perhutani in Randublatung District increased, while non-forest land decreased over more than a decade. The plantation forest land cover class showed an increase from 49.7% in 2013 to 58.8% in 2025, with an additional area of 2,152.78 ha. The increase in plantation forest area is consistent with data from the Blora regency environmental protection and management plan/*rencana perlindungan dan pengelolaan lingkungan hidup (RPPLH)*, which reported a reduction in very critical and critical land areas in 2022. These conditions indicate a recovery of the ecological functions of forest areas. This phenomenon differs from many previous studies, which generally report a decline in forest area or the occurrence of deforestation in land cover change analyses. Therefore, the increase in plantation forest land cover in Randublatung needs to be further analyzed by considering policy, ecological, and socio-economic factors.

Table 4. Land cover area in Randublatung Subdistrict in 2013 and 2025

Land Cover Class	Area in 2013 (ha)	%	Area in 2025 (ha)	%	Area Difference (ha)
Settlement	2,796.18	11.8	1,753.88	7.4	-1,042.30
Dryland agriculture	4,599.39	19.5	4,003.82	17	-595.57
Paddy field	4,479.16	19	3,964.24	16.8	-514.92
Plantation forest	11,727.04	49.7	13,879.82	58.8	2,152.78
Total	23,601.76	100.0	23,601.76	100.0	-0.01

The expansion of plantation forests in Randublatung is closely linked to the efforts of the government and Perhutani in land rehabilitation and forest management. Over the past 12 years, the government has established various programs and regulations to address critical land in Blora Regency, including Randublatung District. Based on RPPLH data for Blora Regency, the reduction in critical land area in 2022 represents a tangible impact of the implementation of critical land rehabilitation programs carried out by the Blora Regency government. Land and forest rehabilitation/*rehabilitasi hutan & lahan (RHL)* activities are an integral part of the community-based forest management/*pengelolaan hutan bersama masyarakat (PHBM)* program implemented by Perhutani, in which Perhutani and local communities collaborate in forest management, land utilization, and forest product use. The implementation of the PHBM program in Randublatung, which has been in place since 2003, has been shown to reduce forest degradation and increase forest land cover through reforestation activities (Damayatanti, 2011).

In addition, another policy that supports the expansion of plantation forest areas is the special forest management area/*kawasan hutan dengan pengelolaan khusus (KHDPK),* which was established in 2022 with the aim of expanding community participation in forest management through social forestry schemes. KHDPK represents a strategic step in addressing the social, economic, and ecological conflicts that have burdened the state-owned enterprise Perhutani. Although the KHDPK policy has not yet fully contributed directly to changes in land cover during the research period, it has the potential to strengthen the recovery of ecological functions and improve forest management in the future. Therefore, the integration of these various policies has contributed to supporting the expansion of plantation forests in Randublatung.

In addition to policy factors, the biophysical conditions of the land constitute an important ecological factor determining the increase in plantation forest cover. Based on biophysical characteristics, Randublatung Subdistrict has lowland and hilly topography with elevations ranging from 40 to 200 m above sea level, slope gradients of approximately 0–40%, and an average annual rainfall of 1,291 mm. The area contains alluvial soil types (Dinas Lingkungan Hidup Kabupaten Blora, 2024). Lowland areas are generally utilized for agricultural activities and settlements, while hilly areas are dominated by production forests with teak stands managed by Perum Perhutani (Rahutama et al., 2024). This is consistent with the study conducted by Rathod et al. (2025), which explains that teak trees can grow at elevations of up to 1,200 m above sea level, with rainfall ranging from less than 900 mm to more than 2,500 mm. Teak grows well on deep, well-drained alluvial soils with relatively high calcium and phosphorus content. This indicates that the biophysical conditions of the land in this region optimally support teak growth. According to Santosa et al. (2020), teak stands have considerable biomass storage potential and therefore play an important role in carbon sequestration within production forest ecosystems. Thus, the expansion of plantation forest area in Randublatung Subdistrict is closely associated with the topographic conditions and biophysical characteristics of the land in this region.

In addition to policy and ecological factors, the socio-economic conditions of communities living around forest areas also contribute to the increase in plantation forest cover, as the expansion of plantation forests can also be explained from a socio-economic perspective. Through the forest village community-based management/*pengelolaan hutan bersama masyaraka (PHBM)* program, local communities are directly involved in forest management in collaboration with Perum Perhutani. Communities participate in planting and maintenance activities, as well as training and extension programs. Community involvement has fostered a sense of ownership over the forest, thereby strengthening local forest monitoring and protection (Damayatanti, 2011). This is consistent with the findings of Mutaqin et al. (2022), who reported that community involvement through social forestry schemes resulted in an increase in forest area of up to 50% of the total social forestry area. From an economic perspective, the PHBM program provides benefits to communities, including management rights over approximately 0.25 ha of land per forest village community institution/*lembaga masyarakat desa hutan (LMDH),* income from intercropping activities, and a 25% share of timber production revenues. These economic incentives encourage communities to maintain forest sustainability in order to ensure continued productivity, thereby contributing to increased forest cover (Damayatanti, 2011). Thus, the collaboration between well-targeted policy strategies, supportive ecological conditions, and community involvement in planting, maintenance, and forest management activities constitutes a set of factors that influence the expansion of plantation forests in Randublatung.

In contrast to the increase in the area of plantation forests in Randublatung Subdistrict, non-forest land cover types, including settlements, dryland agriculture, and paddy fields, have experienced a decline in area. Over the past 12 years, the extent of settlements in Randublatung Subdistrict decreased from 11.8% in 2013 to 7.4% in 2025. This condition remains realistic when compared with data from the environmental protection and management plan/*rencana perlindungan dan pengelolaan lingkungan hidup (RPPLH)* of Blora Regency for 2024–2054, which reports a population growth rate of only 0.03 in Randublatung Subdistrict. Such a low growth rate indicates that the potential for settlement expansion is relatively limited, thereby reducing the likelihood of new settlement development. In addition to demographic factors, the reduction in settlement area may also be influenced by technical errors in image classification. Although the accuracy assessment yielded a very high value of 97%, minor classification errors may still occur. In the 2013 imagery, several areas of teak plantation forest affected by drought exhibited spectral characteristics similar to those of open land, which may have led to misclassification within the settlement class. By considering these factors, the observed decline in settlement area can still be regarded as scientifically acceptable.

Meanwhile, dryland agriculture and paddy fields, as the second and third largest land cover types after plantation forests, also experienced a reduction in area. The table shows that dryland agriculture decreased from 19.5% in 2013 to 17% in 2025, corresponding to a reduction of 595.57 ha. Similarly, paddy field area declined from 19% to 16.8%, with a decrease of 514.92 ha. An examination of the land cover maps for 2013 and 2025 indicates that most of the reduction in dryland agriculture and paddy fields resulted from land conversion into forest. As previously explained, the decline in dryland agriculture and paddy field areas is attributable to revegetation activities implemented through government-led forest and land rehabilitation programs.

Thus, land cover change in Randublatung Subdistrict during the period 2013–2025 reflects efforts to restore ecological functions, indicating the successful implementation of forest and land rehabilitation programs. Regular monitoring of forest cover in plantation forest areas is required to ensure that this positive trend is not merely temporary. In addition, KHDPK policies must be implemented with strong oversight, broad community involvement, and clear incentives in order to replicate this success in other regions. In light of these land cover changes, further analysis is required to understand how these dynamics affect carbon storage in Randublatung Subdistrict.

3.2 Impact of land cover area changes on carbon stock

Carbon stock refers to the amount of carbon dioxide (CO_2) absorbed and stored by vegetation in the form of living biomass, soil, and detritus (Joshi & Garkoti, 2025). Eighty percent of carbon in forest ecosystems is estimated to be stored above ground and forty percent below ground. Therefore, this study focuses on the calculation of aboveground carbon stocks. Carbon stock estimation is essential for improving environmental quality and mitigating climate change (Achmad et al., 2023). Understanding the distribution of aboveground carbon stocks helps assess the impact of land cover changes on the land's capacity to store carbon.

Land use change resulting from deforestation and forest degradation contributes to increased greenhouse gas (GHG) emissions (Li et al., 2024). Meanwhile, restoration activities and forest and land rehabilitation (RHL) have the potential to reduce GHG emissions through the process of photosynthesis (Li et al., 2024). Thus, land cover changes in a region can be said to influence the balance of carbon stocks stored by each land cover class (Lakshita & Rahayu, 2021). Therefore, monitoring changes in carbon stocks across different land cover classes is necessary as a reference for sustainable forest management planning at both global and local levels.

Based on the previous analysis, Randublatung District has experienced land cover changes during the 2013–2025 period, characterized by an increase in plantation forest areas and a decrease in non-forest land (settlements, dryland agriculture, and rice fields). These changes inevitably affect the magnitude of carbon reserves in each land cover class. Carbon stock estimation was obtained by multiplying the carbon constant by the area of each land cover class. From the calculations performed, the carbon stock values for each land cover class were obtained and are presented in Table 5.

Table 5. Carbon stock by land cover class in Randublatung District in 2013 and 2025

Land Cover Class	Carbon Constant (C t/ha)	Carbon Stock in 2013 (tons)	%	Carbon Stock in 2025 (tons)	%	Change in Carbon Stock (ton)
Settlement	4	11,184.71	0.9	7,015.53	0.5	-4,169.18
Dryland agriculture	10	45,993.90	3.8	40,038.18	2.8	-5,955.72
Paddy field	2	8,958.31	0.7	7,928.48	0.6	-1,029.83
Plantation forest	98.4	1,153,705.92	94.6	1,365,496.73	96.1	211,790.81
Total		1,219,842.84	100	1,420,478.92	100	200,636.08

Table 5 shows that each land cover class has a different carbon constant. Planted forests have a much higher carbon constant than other land cover classes. The magnitude of the carbon constant for planted forests will certainly have a significant impact on their carbon stock values. The carbon constants used in this study represent average carbon stocks for each land cover class derived from national inventories and previous studies across Indonesia (Tosiani, 2015). Differences in carbon constants among land cover classes reflect variations in vegetation biomass, which is influenced by stand structure, tree diameter, and wood density. Forest plantation areas generally exhibit higher biomass accumulation and consequently higher carbon storage capacity than agricultural land, paddy fields, and settlements. This finding is supported by Sintayehu et al. (2020), who reported a positive relationship between carbon stocks and functional diversity attributes, particularly wood density and tree diameter. Larger diameters and higher wood density contribute to greater biomass accumulation, resulting in increased carbon storage. Therefore, the higher carbon constants assigned to forested land cover classes are ecologically justified and reflect their greater capacity for carbon sequestration.

Randublatung Subdistrict plays an important role as the largest carbon reserve holder in Blora Regency due to its extensive forest area. Based on carbon stock data, Randublatung Subdistrict had a total carbon stock of 1,219,842.84 tons in 2013, which increased to

1,420,478.92 tons in 2025, with a net change of 200,636.08 tons. This indicates that land cover change has a direct influence on carbon stock dynamics in Randublatung Subdistrict. The increase in carbon reserves reflects the success of the RHL program, which has contributed to the expansion of plantation forest areas. In addition, this positive trend illustrates the contribution of Randublatung Subdistrict to national efforts in mitigating carbon emissions from the AFOLU sector. Thus, the management of plantation forests plays an important role as an instrument for carbon emission mitigation.

Changes in carbon stock in Randublatung Subdistrict are concentrated in plantation forest land cover. Plantation forests play an important role in mitigating climate change and achieving carbon neutrality (Babu et al., 2023). Forests play a crucial role in the global carbon cycle as carbon sinks, so even small changes within forest ecosystems can have significant impacts on the global carbon cycle (Yu & Song, 2023). Based on Table 5, the plantation forest land cover class contributed the largest share of carbon storage, amounting to 1,153,705.92 tons or 94.6% in 2013, which increased to 1,365,496.73 tons or 96% with an additional 211,790.8 tons. Meanwhile, non-forest land (settlements, dryland agriculture, and paddy fields) experienced a decline in carbon stock due to a reduction in the area of these three land cover classes. Carbon stock changes in settlement, dryland agriculture, and paddy field classes decreased sequentially by 4,169.18 tons, 5,955.72 tons, and 1,029.8 tons, respectively. These results are consistent with previous studies stating that carbon stocks in forest land are higher than those in non-forest land (Tadese et al., 2023). This variation is influenced by the constant values assigned to each land cover class. Land with dense vegetation, such as forests, has a greater carbon storage potential than land with sparse vegetation cover (Sahoo et al., 2021; Malik et al., 2024). In addition, these results are comparable to calculations using allometric equations conducted by Purnawan et al. (2023), who reported a carbon stock of 1,221,876 tons in plantation forests covering approximately ±12,249 ha. This demonstrates that carbon stock estimation using the Tier 2 approach and allometric equations yields comparable results, indicating that this approach provides sufficient accuracy.

These findings are consistent with a study by Cheng (2023) in China, which showed that plantation forest areas in China expanded by more than 50%, from 464,715 km^2 in 1990 to 903,099 km^2 in 2020. The expansion of plantation forests resulted in an increase in carbon stock from 675.6 ± 12.5 Tg C to 1,873.1 ± 16.2 Tg C. This increase was derived from the conversion of other land cover types (agricultural land, shrubland, and grassland) into plantation forests. Therefore, both the results of this study and the study in China indicate that the expansion of plantation forests has been proven to make a significant contribution to increasing aboveground carbon stocks.

Overall, the results of this study on the increase in carbon stock in Randublatung Subdistrict not only provide an overview of the biophysical conditions of the area but also have strategic implications for future forest management directions. The increase in carbon stock indicates that the RHL program and KHDPK policy have effectively contributed to the restoration of ecological functions while supporting the achievement of the FOLU Net Sink 2030 target. Thus, the results of this study can be used to evaluate the effectiveness of rehabilitation and climate change mitigation programs at the local level and serve as a reference for forest managers in formulating sustainable forest management plans that focus on maintaining a balance between environmental, economic, and social aspects.

3.3 Research limitations

This study has limitations in the analysis of carbon stock, as the calculations employed carbon constants derived from secondary data. These values do not fully represent actual field conditions and may therefore lead to discrepancies between the calculated results and real conditions. In addition, the carbon stock analysis only accounted for aboveground carbon pools, meaning that carbon stocks in other pools were not comprehensively estimated. Therefore, further research is required involving direct field-based biomass measurements to obtain local conversion factors that are more representative of the biophysical conditions of Randublatung. Moreover, it is necessary to calculate belowground carbon stocks to achieve a comprehensive estimation of carbon reserves. The use of high-resolution imagery such as Sentinel-2 or UAV (drone) data is recommended to map carbon stocks with higher accuracy.

4. Conclusions

This study monitored the impact of land cover change on carbon stock balance in Randublatung District from 2013 to 2025. The results demonstrate that changes in land cover area significantly influenced carbon stock dynamics in Randublatung District over the 12-year period. During 2013–2025, the area experienced a substantial increase in carbon stock amounting to 200,636.08 tons. Plantation forests, as the largest carbon storage component, had a major influence on the increase in carbon stock in Randublatung. The findings indicate that plantation forest area increased by 2,152.78 ha, resulting in an increase in carbon stock of 211,790.81 tons. Meanwhile, non-forest land (settlements, dryland agriculture, and paddy fields) decreased in area, leading to a reduction in carbon stocks within non-forest land cover classes. Settlement areas decreased by 1,042.30 ha, dryland agriculture by 595.57 ha, and paddy fields by 514.92 ha. The reduction in non-forest land area caused decreases in carbon stock in settlements, dryland agriculture, and paddy fields of 4,169.18 tons, 5,955.72 tons, and 1,029.83 tons, respectively. This indicates the presence of replanting activities on non-forest land. Overall, the results show that the expansion of plantation forests plays a crucial role in increasing carbon reserves. Therefore, RHL and KHDPK programs need to be optimized to support carbon emission mitigation efforts at both local and national levels.

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Author Contribution

The author is responsible for conceptualization, methodology, data collection, data analysis, interpretation of results, drafting of the original manuscript, review and editing, visualization, and the overall research process.

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Declaration of Generative AI Use

During the preparation of this work, the author used Scholar AI to assist in searching for and identifying relevant academic references. After using this tool, the author manually reviewed and selected the literature and assumes full responsibility for the accuracy and integrity of the final published content. The author also used ChatGPT to assist in reviewing journal articles. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the content of the publication.

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