Technology and Society Perspectives (TACIT) Vol. 4, No. 2, July-October 2026, pages 666–682

Spatial Analysis of Land Cover Change and Its Impact on Carbon Stocks in Majalengka Regency, West Java, Indonesia

Sodikin[1*], Joel Osei-Asiamah[2]

[1]*Universitas Terbuka, Banten, Indonesia*
[2]*University of South Africa, Pretoria, South Africa*

ARTICLE INFO

Article history:
Received: 03 September 2026
Revised: 29 September 2026
Accepted: 06 October 2026

DOI:
10.61100/tacit.v4i2.379

Keywords:
Land Cover, Carbon Stock, Google Earth Engine, Dynamic World, Remote Sensing

This work is licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License

ABSTRACT

This study aims to analyze land cover dynamics and carbon stock changes from 2017 to 2024 and to identify spatial patterns of carbon loss and gain. The analysis utilized Google Dynamic World – based on Sentinel-2 imagery – on the Google Earth Engine platform at a 10-meter resolution. Land cover was analyzed for the years 2017, 2021, and 2024 across eight classification categories. Temporal composites were generated using the mode method, followed by ground-truthing to verify the accuracy of the interpretation against actual field conditions. Carbon stocks were calculated based on the area of each land cover class and specific carbon stock constants, while spatial changes were determined by calculating the difference in carbon values between years at the pixel level. The results indicate that tree cover and agriculture are the dominant land cover types. The area of tree cover increased from 63,434.59 ha in 2017 to 65,114.72 ha in 2021, before declining to 60,716.49 ha in 2024. Carbon stocks rose to 11,733,128.29 tonnes of C in 2021 and subsequently fell to 11,061,552.19 tonnes of C in 2024. These findings provide a spatial basis for vegetation protection, the management of land cover changes, and the prioritization of rehabilitation efforts to support climate change mitigation in Majalengka Regency.

ABSTRAK

Penelitian ini bertujuan menganalisis dinamika tutupan lahan dan perubahan cadangan karbon selama 2017–2024 serta mengidentifikasi pola spasial kehilangan dan peningkatan karbon. Analisis menggunakan Google Dynamic World berbasis citra Sentinel-2 pada platform Google Earth Engine dengan resolusi 10 m. Tutupan lahan dianalisis pada 2017, 2021, dan 2024 menggunakan delapan kelas. Komposit temporal dibentuk menggunakan metode mode, kemudian dilakukan ground truthing untuk mengonfirmasi kesesuaian hasil interpretasi dengan kondisi lapangan. Cadangan karbon dihitung berdasarkan luas setiap kelas tutupan lahan dan konstanta stok karbon, sedangkan perubahan spasial ditentukan dari perbedaan nilai karbon antartahun pada tingkat piksel. Hasil menunjukkan bahwa pepohonan dan pertanian merupakan tutupan dominan. Luas pepohonan meningkat dari 63.434,59 ha pada 2017 menjadi 65.114,72 ha pada 2021, kemudian menurun menjadi 60.716,49 ha pada 2024. Cadangan karbon meningkat menjadi 11.733.128,29 ton C pada 2021, lalu menurun menjadi 11.061.552,19 ton C pada 2024. Temuan ini menyediakan basis spasial untuk perlindungan vegetasi, pengendalian perubahan tutupan lahan, dan penentuan prioritas rehabilitasi dalam mendukung mitigasi perubahan iklim di Kabupaten Majalengka.

1. INTRODUCTION

Land cover change is a form of environmental change with direct consequences for ecosystem functions, carbon balance, and regional sustainability (Zhao et al., 2023; Yuan & Chen, 2024). The conversion of natural vegetation into agricultural land, plantations, settlements, or infrastructure can alter the structure and composition of land cover while simultaneously affecting the ecosystem's carbon storage capacity (Xu et al., 2023). Land use and land cover change (LULCC) is a critical component of terrestrial carbon dynamics, as such changes can lead to either the release or reduction of carbon stocks stored in biomass and soil (Sleeter et al.,

* *Corresponding author, email address: sodikinn@ecampus.ut.ac.id*

2018). In Indonesia, while uncertainties regarding LULCC-related carbon emission estimates persist, various approaches and modeling products indicate that land-use change remains a significant source of carbon. Pressure on land cover is intensifying due to population growth, urban expansion, infrastructure development, agricultural intensification, and changes in spatial functions (Herrmann et al., 2020). These pressures are particularly evident in Majalengka Regency, where regional development has increased demands for agricultural, residential, industrial, and transportation land. Previous research in Majalengka Regency reported substantial changes in land cover between 2011 and 2021, including a reduction in agricultural land, particularly irrigated rice fields and dryland farms (Adrian et al., 2023). These changes indicate that Majalengka is experiencing significant land-cover dynamics that may affect ecosystem functions, including carbon storage. The conversion of vegetated and agricultural areas into built-up areas can reduce the amount of carbon stored in terrestrial ecosystems, whereas the maintenance or expansion of woody vegetation can contribute to carbon retention. Therefore, the continuing changes in land cover in Majalengka Regency provide an important context for examining the implications of spatial development and land conversion for regional carbon stocks.

Although previous studies have examined land-cover and land-use changes in Majalengka Regency, the emphasis has primarily been on identifying the extent and spatial patterns of land-cover conversion. For example, Adrian et al. (2023) analyzed land-cover changes in Majalengka using Google Earth Engine, but the implications of these changes for the spatial distribution of carbon stocks were not explicitly quantified. Consequently, there remains a need to link multitemporal land-cover dynamics with spatially explicit changes in carbon storage. Addressing this gap is important because changes in land-cover composition do not affect carbon stocks uniformly; transitions involving high-carbon vegetation may produce substantially different carbon consequences from changes among low-carbon land-cover classes. This study extends previous land-cover assessments by integrating Google Dynamic World data, Google Earth Engine-based multitemporal analysis, and land-cover-specific carbon-stock constants. This integration enables land-cover changes to be translated into quantitative estimates of carbon stocks and provides spatial information on areas experiencing carbon loss and carbon gain. The approach therefore provides an additional dimension to conventional land-cover change assessment by explicitly examining its implications for regional carbon storage.

Conversely, an increase in vegetation cover—particularly woody vegetation characterized by high and relatively stable biomass—has the potential to enhance carbon accumulation through photosynthesis and carbon storage in both biomass and soil. These dynamics demonstrate that land cover change should be understood not merely as a physical or spatial transformation of a region, but also as a process that influences carbon balance and environmental quality. The magnitude of changes in carbon stocks depends heavily on the direction, extent, intensity, and duration of land-cover changes (Shuai et al., 2024). For instance, converting forests or dense vegetation into built-up areas can result in a greater loss of carbon stocks compared to transitions between land-cover types with relatively similar vegetation structures. The relationship between land-cover change and carbon stock dynamics has been widely used to evaluate the ecological consequences of spatial changes, particularly regarding ecosystem alterations driven by urbanization, agricultural expansion, deforestation, and vegetation rehabilitation. Advances in remote sensing technology enable the multitemporal monitoring of land-cover changes; when combined with biomass data or carbon storage factors, these technologies allow for the spatial estimation of changes in carbon stocks. This approach is increasingly vital in tropical regions, which are experiencing rapid land-use changes while playing a crucial role in global carbon storage. Consequently, analyzing land-cover changes in relation to carbon stocks provides a more comprehensive picture of the ecological impacts of spatial changes and serves as a foundation for formulating strategies for conservation, ecosystem rehabilitation, and land management that support climate change mitigation.

Multitemporal monitoring of land-cover change requires data with broad spatial coverage and temporal consistency. Remote sensing offers an effective approach, while Google Earth Engine (GEE) facilitates the processing of vast amounts of satellite data via cloud computing, eliminating the need to download entire datasets locally (Phiri et al., 2020; Kumar & Mutanga, 2018). This platform is widely used to analyze land-cover and vegetation changes and to generate spatiotemporal information with high accuracy. In addition, the Google Dynamic World product provides consistent 10-m land-cover information derived from Sentinel-2 imagery, enabling detailed characterization of land-cover dynamics across multiple periods (Brown et al., 2022). Integrating these capabilities with carbon-stock estimation can provide spatially explicit information that is not obtained from conventional land-cover change analysis alone.

Multitemporal assessment of land cover and carbon stocks can therefore provide both scientific and practical information for understanding the environmental consequences of landscape change. Scientifically, this study provides a spatially explicit approach for linking land-cover dynamics with changes in carbon stocks using a consistent 10-m spatial dataset. Practically, the resulting information can support the identification of areas experiencing carbon loss and carbon gain and provide a spatial basis for vegetation conservation, land-cover management, and climate-change mitigation planning. This study aims to analyze land-cover dynamics and changes in carbon stocks in Majalengka Regency, West Java, during the 2017–2024 period using Google Dynamic World and Google Earth Engine. Specifically, the study analyzes land-cover changes in 2017, 2021, and 2024, estimates carbon stocks associated with each land-cover class, and identifies the spatial distribution of carbon loss and carbon gain resulting from land-cover changes. By integrating these components, the study provides spatially explicit evidence of how land-cover dynamics are associated with changes in carbon storage and offers information that can complement existing land-cover assessments for spatially targeted environmental management in Majalengka Regency.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

2.1 Land Use and Land Cover Change

Land use and land cover are two distinct but closely related concepts. Land use refers to the purpose, function, activities, and management of land by humans, such as agriculture, settlements, forestry, industry, and infrastructure. In contrast, land cover refers to the physical and biophysical characteristics covering the Earth's surface, such as trees, vegetation, water bodies, built-up areas, bare land, and other surface-cover types that can be identified through remote sensing. Thus, land use emphasizes the function and human activities associated with land, whereas land cover describes the physical condition of the Earth's surface (Yuan & Chen, 2024; Rimal, 2019; Mirici, 2024).

In this study, Google Dynamic World empirically represents land cover rather than land use directly. Dynamic World is a land-cover classification product based on Sentinel-2 imagery that identifies Earth's surface into land-cover classes at a spatial resolution of 10 m (Brown et al., 2022). The classes used in this study include water, trees, grass, flooded vegetation, crops, shrub/scrub, built-up areas, and bare ground. Although some classes, such as crops and built-up areas, are closely associated with particular human activities or land uses, the Dynamic World classification primarily represents observable surface-cover characteristics, rather than the underlying purpose, function, or management system of the land. Therefore, the Dynamic World results in this study are referred to as land-cover classes.

This distinction is important because the terms land use and land cover should not be used interchangeably. In the empirical analysis, the terms land cover, land-cover class, and land-cover change are used when referring specifically to the Dynamic World classification. Meanwhile, the term land use and land cover change (LULCC) is retained within the broader conceptual framework to describe interactions among human activities, land functions, and changes in Earth's surface characteristics. Accordingly, changes identified from Dynamic World are interpreted as land-cover changes, while their implications for land functions and environmental management are discussed within the broader LULCC framework.

Land Use and Land Cover Change (LULCC) is the process of altering the Earth's surface characteristics resulting from interactions between biophysical factors and human activities. Such changes may involve the conversion of forested areas into agricultural land, settlements, or infrastructure, as well as shifts between vegetation types. LULCC not only alters the spatial structure of a region but also affects ecosystem functions, including vegetation productivity, hydrological cycles, biodiversity, and carbon cycles (Yuan & Chen, 2024). From a landscape ecology perspective, land cover is a key factor determining a region's capacity to provide ecosystem services. Woody vegetation cover—particularly forests—generally possesses a higher carbon storage capacity than open land, built-up areas, or low-biomass vegetation cover (Rimal, 2019; Mirici, 2024).

The relationship between land-cover change and carbon is dynamic. Increased vegetation cover can enhance biomass accumulation and carbon stocks, whereas vegetation loss or conversion to low-biomass land can reduce carbon stocks. Therefore, changes in land-cover composition can alter carbon storage capacity at the landscape level. In this study, land-cover changes identified through Dynamic World provide the empirical basis for analyzing spatial changes in carbon stocks using carbon-stock constants assigned to each land-cover class.

2.2 Carbon Stock and Ecosystem Carbon Storage

Ecosystem carbon refers to carbon stored within various ecosystem components, primarily vegetation biomass, soil organic matter, and other organic materials. In the context of land cover change, the amount of stored carbon is significantly influenced by vegetation type, biomass density, productivity, and the extent of disturbance and land-use change. Land cover characterized by more complex vegetation structures generally exhibits a higher carbon storage capacity compared to land cover dominated by non-vegetated surfaces (Fryer, 2021). Conceptually, the carbon stock of a region can be calculated by linking the area of each land-cover class to the average carbon stock value per unit area. This approach allows spatial changes in land cover to be translated into quantitative changes in carbon stocks. In this study, this principle is applied by assigning a carbon stock constant to each land-cover class and then multiplying that value by the area of the respective class. A similar approach is widely used in spatial analyses of the relationship between land-use/land-cover change and carbon, as it enables carbon estimation at the landscape scale using remote sensing data (Waleed, 2024). Consequently, changes in total carbon stock can be understood as the aggregate result of changes in the extent and composition of land-cover classes. Converting a class with high carbon stock to one with low carbon stock results in carbon loss, whereas a shift toward cover with higher carbon storage capacity can yield a carbon gain. This framework allows for the evaluation of carbon changes not only in terms of total values but also based on their spatial distribution.

2.3 Relationship Between Land Cover and Carbon Dynamics

The theoretical relationship between land cover and carbon stocks is based on the principle that different land cover types possess different carbon storage capacities. In this study, the tree cover class exhibits the highest carbon stock constant, whereas open land and built-up areas have substantially lower values. These differences indicate that changes in land cover composition can directly influence the estimated carbon storage capacity of the study area. The carbon stock constants applied in this study were derived from Kurniawati (2021), who estimated carbon stocks associated with different land-use and land-cover categories using the ICLEI Greenhouse Gas (GHG) Calculator approach. The values adopted in the present study include 169.7 tonnes C/ha for tree cover, 120.0 tonnes C/ha for inundated vegetation, 30.0 tonnes C/ha for shrubs, 10.0 tonnes C/ha for agriculture, 5.0 tonnes C/ha for built-up areas, 4.5 tonnes C/ha for grass, 2.5 tonnes C/ha for open land, and 0 tonnes C/ha for water. These values correspond broadly to carbon coefficients for forest, wetland/mangrove-related vegetation, shrubland, agricultural land, grassland, built-up land, open land, and water reported in the reference study. Kurniawati (2021), for example, reported 169.7 tonnes C/ha for secondary dryland forest, 120 tonnes C/ha for secondary mangrove forest, 30 tonnes C/ha for shrubland, 10 tonnes C/ha for dryland agriculture, 5 tonnes C/ha for built-up land, 4.5 tonnes C/ha for grassland, and 2.5 tonnes C/ha for open land.

The application of these constants to Majalengka is considered reasonable for a land-cover-based spatial assessment because the study uses broad land-cover categories that are functionally comparable to those for which the coefficients were originally developed. In particular, the dominant vegetated class in Majalengka represents woody vegetation, while the other classes represent agricultural, shrub, grass, open, built-up, and water surfaces. These categories have broadly comparable differences in biomass and carbon-storage capacity, with woody vegetation generally storing considerably more carbon than agricultural, grass, built-up, or open surfaces. Moreover, the coefficients originate from an Indonesian study and are expressed in the same unit (tonnes C/ha), making them operationally compatible with the land-cover area data used in this study. The use of a common coefficient framework also facilitates consistent comparison of carbon-stock changes among land-cover classes and across observation periods

Nevertheless, the transfer of carbon stock constants from Surabaya to Majalengka involves an important source of uncertainty. The two regions differ in environmental setting, vegetation composition, land-management practices, biomass density, soil characteristics, and landscape structure. In addition, the 169.7 tonnes C/ha coefficient used for the tree-cover class was originally associated with secondary dryland forest in Kurniawati (2021), whereas the Dynamic World "trees" class used in this study may encompass a broader range of woody vegetation types. Similarly, the 120 tonnes C/ha coefficient is associated with secondary mangrove forest in the reference study, whereas the Dynamic World flooded vegetation class does not necessarily represent mangrove ecosystems exclusively. Therefore, these constants should not be interpreted as direct measurements of actual carbon density in every location within Majalengka. Instead, they function as standardized coefficients for estimating relative and spatially explicit carbon-stock differences associated

with land-cover transitions.

Accordingly, the resulting carbon-stock estimates should be interpreted as land-cover-based modeled estimates rather than direct measurements of ecosystem carbon stocks. The principal strength of this approach lies in its ability to consistently represent the spatial and temporal implications of land-cover change for carbon storage across the entire study area. However, local variation in biomass, species composition, vegetation structure, soil organic carbon, and management practices may cause actual carbon stocks to differ from the assigned coefficients. This uncertainty is particularly relevant when interpreting absolute carbon-stock values and should be considered when comparing the estimates with field-based carbon measurements. Future research should therefore incorporate field measurements of biomass and carbon pools in Majalengka to develop locally calibrated coefficients and reduce uncertainty in carbon-stock estimation.

$$\text{Carbon Stock} = \Sigma \left(\text{Area of Land Cover Class} \times \text{Carbon Stock Constant}\right)$$

Consequently, an increase in the area of classes with high carbon capacity raises the estimated regional carbon stock, while an increase in the area of classes with low carbon capacity tends to lower it. This framework also explains why changes in forest or tree cover areas have a relatively greater impact on total carbon stock changes compared to changes in classes with low carbon stock values.

Carbon changes resulting from Land Use and Land Cover Change (LULCC) do not always occur linearly. A region may experience a carbon gain during a specific period due to increased vegetation, followed by a carbon loss in a subsequent period caused by deforestation, development, or changes in land function.

2.4 Remote Sensing for Land Cover and Carbon Assessment

Remote sensing offers an effective approach for identifying and monitoring land cover changes over large areas across multiple time periods. Satellite imagery enables consistent recording of Earth's surface characteristics, allowing for the comparison of spatial changes between periods. Advances in remote sensing technology—specifically the use of Sentinel-2 imagery with 10-meter spatial resolution—provide opportunities to detect land cover changes at a finer scale than lower-resolution global products.

The Google Dynamic World product was developed using Sentinel-2 imagery and provides global land cover classification at a 10-meter resolution. This product generates land cover class probability data and class labels suitable for multitemporal analysis. Dynamic World is designed to generate land cover information consistently and has the capability to create composites based on specific time intervals (Brown et al., 2022).

The use of multitemporal data is also crucial because land cover is a phenomenon subject to temporal change, and a single pixel may exhibit classification variations due to atmospheric conditions, cloud cover, seasonality, or changes in surface conditions. Consequently, a temporal composite approach can yield a more stable representation of land cover. In this study, Dynamic World data were composited using the mode method for the periods of 2017, 2021, and 2024, such that the most frequently occurring class for each pixel served as the land cover representation for that period.

2.5 Google Earth Engine as a Spatial Analysis Platform

Google Earth Engine (GEE) is a cloud computing platform that enables the processing of large volumes of remote sensing data without the need to download the entire dataset locally. This capability is highly relevant for land-cover change research, as analyses can be performed on spatiotemporal datasets covering extensive geographic areas. The integration of GEE with Sentinel-2 and Dynamic World collections allows for data selection, temporal compositing, land-cover mapping, area calculation, carbon estimation, and change analysis to be conducted within a single computing environment (Brown et al., 2022).

In this study, GEE serves as the platform for acquiring and processing Dynamic World data, generating temporal composites, calculating the area of each land-cover class, estimating carbon stocks, and producing spatial information regarding carbon gain and carbon loss. This cloud-based approach enhances analysis efficiency and enables consistent processing of multitemporal data.

2.6 Spatial Dynamics of Carbon Gain and Carbon Loss

Spatial analysis of carbon stock changes is essential because carbon changes are not uniformly distributed

across a region. Two areas experiencing the same magnitude of land-cover change may result in different changes in carbon stocks if the specific land-cover types involved differ. Therefore, identifying carbon gain and carbon loss based on location is crucial for understanding the ecological consequences of land-cover change. Theoretically, carbon loss occurs when a pixel or area transitions from a class with relatively high carbon stocks to one with lower carbon stocks. Conversely, carbon gain occurs when land-cover change results in increased carbon storage capacity. This spatial approach allows for the detailed identification of locations experiencing carbon stock loss or gain, thereby serving as a basis for determining priorities regarding conservation, rehabilitation, and spatial management.

Research on the relationship between land-use/land-cover change (LULCC) and carbon indicates that land-cover changes can significantly impact carbon fluxes at both regional and global scales. Forest changes, particularly deforestation and reforestation, are key components of carbon flux changes resulting from land-use change (Grassi, 2022; Qin, 2024).

The relationship among land-use and land-cover change (LULCC), land-cover composition, and carbon dynamics provides an integrated conceptual framework for this study. LULCC alters the composition and spatial configuration of land-cover classes, which in turn determines the relative distribution of areas with different carbon-storage capacities. Changes from high-carbon vegetation classes, particularly tree cover, toward lower-carbon classes such as built-up areas, agriculture, grass, or open land are therefore expected to reduce estimated carbon stocks, whereas transitions toward woody or other higher-carbon vegetation classes can increase carbon storage. These changes in carbon storage are not only reflected in the total amount of carbon at the landscape level but also generate spatially heterogeneous patterns of carbon loss and gain. Thus, the conceptual pathway of LULCC → changes in land-cover composition → differences in carbon-storage capacity → carbon loss or gain → spatial distribution of carbon changes forms the theoretical basis for the empirical analysis conducted in this study. Empirically, this framework is operationalized by identifying land-cover classes from multitemporal Google Dynamic World data, quantifying changes in the area of each class, assigning class-specific carbon-stock constants, and calculating carbon-stock differences between observation periods at the pixel and landscape levels. The resulting spatial patterns are then used to identify locations where changes in land cover are associated with carbon loss or carbon gain. In this way, the analysis moves beyond describing land-cover change alone by explicitly linking observed spatial transformations to their estimated implications for carbon-storage capacity.

3. RESEARCH METHOD

3.1 Study Area

The study was conducted in Majalengka Regency, West Java Province, Indonesia. The unit of analysis encompassed the entire administrative area of Majalengka Regency. Spatial analysis was performed using raster data with a 10-meter resolution. In addition to the regency level, the results of the carbon stock change analysis were interpreted based on sub-district administrative boundaries to identify the spatial distribution of carbon loss and carbon gain. The map of the study area is presented in Figure 1.

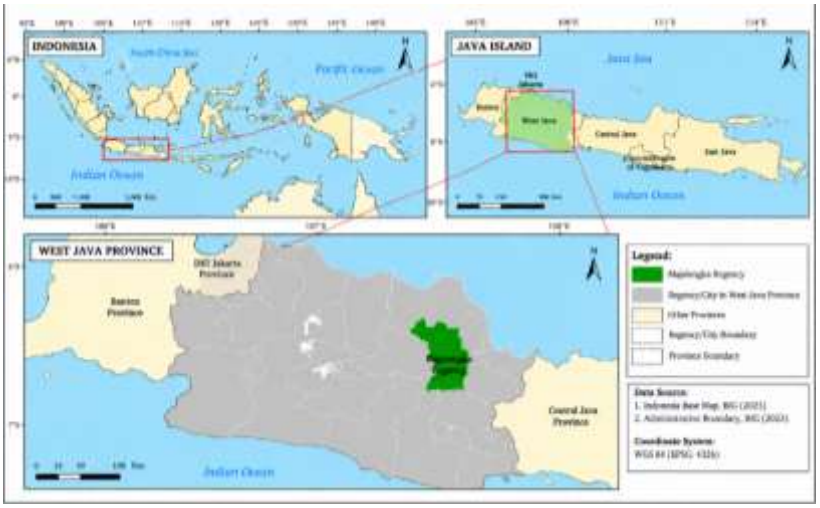


Figure 1. Studi Area

The primary data source for this study is Google Dynamic World Version 1, accessed via the Google Earth Engine (GEE) platform. Dynamic World is a land cover product based on Sentinel-2 imagery with a spatial resolution of 10 meters. The data were used to obtain land cover information for three observation periods: 2017, 2021, and 2024. Although the Dynamic World dataset comprises nine classes, the "snow and ice" class was excluded from this study as it is irrelevant to the tropical characteristics of Majalengka Regency. Consequently, the study utilized eight land cover classes: water, trees, grass, flooded vegetation, crops, shrub/scrub, built-up areas, and bare ground. In addition to the imagery, administrative boundary data for Majalengka Regency and its sub-districts were used as supplementary data to define the study area and present spatial results. Carbon stock constants were applied to estimate carbon reserves based on land cover classes; the constants used in this study are presented in Table 1.

Table 1. Carbon stock constants by land cover class

Land Cover Classes	Dynamic World Code	Carbon Stock Constant (ton C/ha)
Water	0	0,0
Trees	1	169,7
Grass	2	4,5
Inundated vegetation	3	120,0
Agriculture	4	10,0
Shrubs	5	30,0
Built-up area	6	5,0
Open land	7	2,5

The research equipment consists of a computer or laptop with internet access, used to run the Google Earth Engine Code Editor. GEE is utilized for image processing, temporal compositing, classification, area calculation, carbon stock estimation, change analysis, spatial visualization, and result export.

3.2 Data Collection Techniques

This This research employs secondary data collection techniques based on remote sensing and geospatial data. Primary data were obtained via the Google Earth Engine catalog, enabling the entire processing workflow to be cloud-based. Dynamic World data were collected for the administrative area of Majalengka Regency across three observation periods: 2017, 2021, and 2024. To enhance the stability of land cover information and mitigate the impact of anomalous pixels, a temporal composite approach was utilized. The 2017 period was constructed using data from 2016–2018, the 2021 period using data from 2020–2022, and the 2024 period using data from 2023–2024. The years 2017, 2021, and 2024 were selected to represent three observation periods that enable the characterization of medium-term land-cover changes during 2017–2024. The varying lengths of the temporal windows were determined by the availability and continuity of Google Dynamic World data during the respective observation periods. The use of multi-year temporal composites based on the mode method was intended to reduce the influence of transient land-cover variations, seasonal fluctuations, atmospheric disturbances, and classification inconsistencies in individual observations. Consequently, the resulting land-cover classes represent dominant and relatively persistent conditions during each observation period rather than momentary conditions at a specific date.

This approach also helps smooth short-term land-cover fluctuations that could otherwise produce apparent or spurious changes in multitemporal analysis. However, the use of multi-year composites may obscure brief or temporary land-cover changes and therefore may not capture all short-term transitions. Accordingly, the results should be interpreted primarily as representing relatively persistent land-cover changes at the scale of the observation periods rather than annual or short-term land-cover dynamics. Data for each period were composited using the mode method, which identifies the most frequently occurring land-cover class for each pixel throughout the respective observation period. In cases where pixels lacked values in the primary composite, a supplementary composite spanning 2015–2024 was used as a fallback to minimize the occurrence of missing pixels. Following the compositing process, the snow/ice class was excluded because it is not relevant to the tropical characteristics of Majalengka Regency. The resulting land-cover data were then clipped to the administrative boundaries of Majalengka Regency to ensure that the analysis was confined to the study area. Furthermore, field verification (ground truthing) was conducted in

July 2026 using 100 validation points selected through stratified sampling to assess the correspondence between the image-based land-cover interpretation and actual field conditions. The accuracy assessment comparing the interpreted land-cover classes with field observations yielded an overall accuracy of 85%.

3.3 Data Analysis Technique

Land cover mapping was conducted using the Google Dynamic World product on the Google Earth Engine platform. Dynamic World label data served as the source for land cover class information. Following the creation of temporal composites using the mode method, land cover maps were generated for the years 2017, 2021, and 2024. The eight land cover classes utilized were water, trees, grass, flooded vegetation, crops, shrub/scrub, built-up areas, and bare ground. Each class was assigned a numerical code ranging from 0 to 7. These codes were used for spatial analysis, area calculation, and the identification of inter-period changes. The area of each land cover class was calculated based on pixel area using the pixel area function in Google Earth Engine. Pixel areas were converted from square meters to hectares by dividing the value by 10,000. Area calculations were performed using the following equation:

$$A_i = \sum_{j=1}^{n} \frac{P_j}{10.000}$$

Note:
Ai = area of land cover class i (ha);
Pj = area of pixel j (m^2);
10,000 = conversion factor from m^2 to hectares.

Land cover change was analyzed by comparing land cover maps across different periods. The primary analysis focused on the 2017–2024 period, while 2021 served as an intermediate period to illustrate temporal dynamics. Changes in land cover classes were identified using a combination of class codes from the initial and final years. Change codes were calculated using the following equation:

$$C = (LC_{t1} \times 10) + LC_{t2}$$

Note:
CC = land cover change code;
LCt1 = land cover class in the initial year;
LCt2 = land cover class in the final year.

Carbon stock estimation was conducted by associating each land cover class with the carbon stock constant value listed in Table 1. Each pixel was assigned a carbon stock value corresponding to its land cover class and then multiplied by the pixel area in hectares. The total carbon stock for a given land cover class was calculated using the following equation:

$$C_i = A_i \times K_i$$

Meanwhile, the total carbon stock for the entire area is calculated using:

$$C_{total} = \sum_{i=1}^{n} (A_i \times K_i)$$

Note:
Ci = carbon stock of land-cover class i (tonnes C);
Ai = area of land-cover class i (ha);
Ki = carbon stock constant for land-cover class i (tonnes C/ha);
Ctotal = total carbon stock of the study area (tonnes C).

Carbon stock estimation was conducted by associating each land-cover class with the fixed carbon

stock constant values presented in Table 1. Each pixel was assigned a carbon stock value corresponding to its land-cover class and then multiplied by its pixel area in hectares. The total carbon stock for each land-cover class was calculated by multiplying the area of the respective class by its corresponding carbon stock constant, while the total carbon stock of the study area was obtained by summing the estimated carbon stocks across all land-cover classes. This approach assumes that areas belonging to the same land-cover class have a relatively homogeneous carbon stock density represented by a single fixed coefficient (tonnes C/ha). Therefore, the estimated values represent spatially modeled carbon stocks based on land-cover characteristics rather than direct measurements of actual carbon stocks in the field. The approach also assumes that differences in carbon storage among locations within the same land-cover class are sufficiently represented by the assigned class-specific coefficient. The estimation primarily represents the carbon stock associated with the land-cover classes and does not constitute a direct measurement of individual carbon pools in the field. Consequently, variations in biomass density, vegetation structure, species composition, soil organic carbon, dead organic matter, and other carbon pools within the same land-cover class are not explicitly quantified unless they are implicitly represented by the adopted carbon stock constant. Accordingly, the resulting carbon stock values should be interpreted as land-cover-based estimates rather than direct field measurements of total ecosystem carbon stocks.

Carbon stock change is calculated by comparing carbon stock values between periods. Absolute change is calculated using:

$$\Delta C = C_{t2} - C_{t1}$$

To determine the rate of change in the average carbon stock per year, the equation is used:

$$\Delta C_{annual} = \frac{C_{t2} - C_{t1}}{t_2 - t_1}$$

Description:
ΔC = change in carbon stock (tonnes C);
Ct1 = carbon stock in the initial year;
Ct2 = carbon stock in the final year;
t2−t1 = observation time interval (years).

A negative carbon change value indicates a loss of carbon stock, whereas a positive value indicates an increase in carbon stock. In addition to calculating the total change in carbon stock, a spatial analysis was conducted to identify the distribution of carbon loss and carbon gain. The carbon stock change value for each pixel was calculated based on the difference between the carbon values for 2024 and 2017:

$$\Delta C_{pixel} = C_{2024} - C_{2017}$$

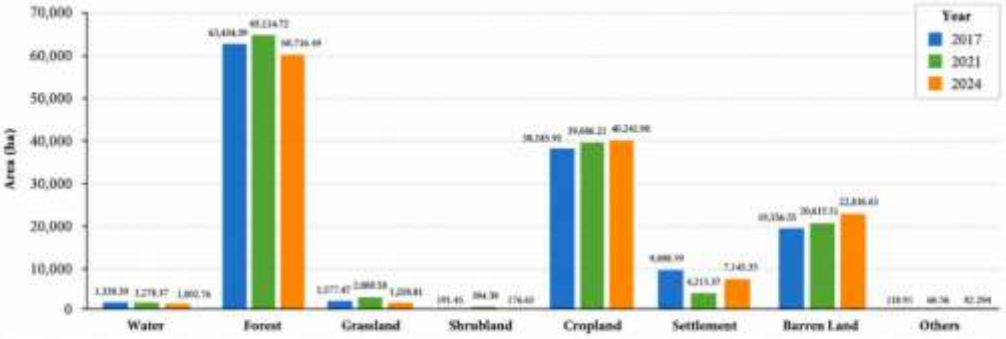
Negative values indicate pixels experiencing a loss of carbon stocks, whereas positive values indicate an increase in carbon stocks.

4. DATA ANALYSIS AND DISCUSSION

4.1 Spatial Dynamics of Land Use and Land Cover Change

The dynamics of land use and land cover serve as a key indicator for characterizing changes in the environmental conditions of a region (Dofee, 2024). Such changes arise from the interaction between biophysical factors and human activities—including the expansion of settlements, intensified agricultural activity, infrastructure development, and shifts in land-use functions. Visualizations of the multi-temporal land-change analysis for Majalengka Regency (covering the years 2017, 2021, and 2024) are presented in Figure 2.





Year	Area (ha)							
	Water	Forest	Grassland	Shrubland	Cropland	Settlement	Barren Land	Others
2017	1,338.39	63,434.59	1,577.47	191.45	38,185.91	9,498.59	19,356.55	118.91
2021	1,278.37	65,114.72	2,088.58	394.39	39,686.21	4,215.37	20,615.51	66.56
2024	1,002.76	60,716.49	1,258.81	176.65	40,241.90	7,145.35	22,836.63	82.294

Source: Analysis results from Google Earth Engine (GEE)

Note: Land cover classification is based on the Dynamic World dataset (Google)

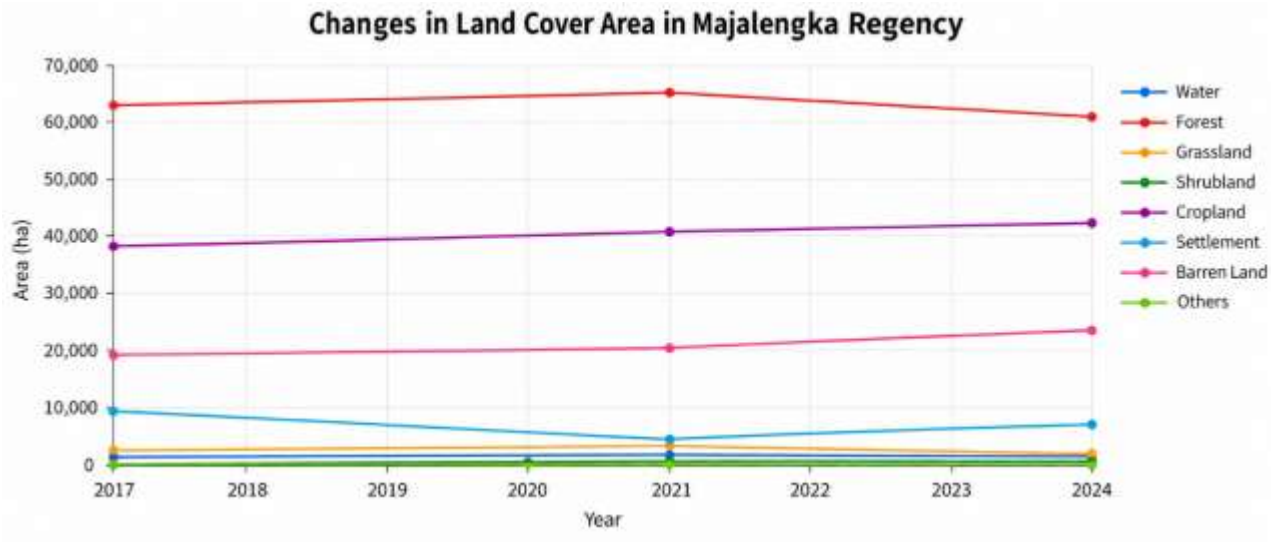
Figure 2. Spatial changes in land cover area in Majalengka Regency.

Figure 2 illustrates the dynamics of land cover in Majalengka Regency during the 2017–2024 period. While forest and agricultural classes remained the dominant land-cover types, several classes underwent significant changes. Forest area increased from 63,434.59 ha in 2017 to 65,114.72 ha in 2021, before declining to 60,716.49 ha in 2024. Conversely, agricultural land steadily expanded from 38,158.91 ha to 40,241.90 ha, and built-up areas grew from 19,256.55 ha to 22,806.83 ha. The approximately 18.4% increase in built-up areas between 2017 and 2024 indicates a trend of urban expansion within the study area. The observed changes in land cover are likely associated with increasing development pressure in Majalengka Regency, particularly through urban expansion, infrastructure development, agricultural land conversion, and changes in spatial functions. Majalengka is part of the broader Rebana Triangle development corridor, which has increased demand for land for settlements, transportation, industrial activities, and supporting infrastructure. Previous research in Majalengka reported substantial land-cover changes between 2011 and 2021, including a reduction in agricultural land, particularly irrigated rice fields and dryland farms (Adrian et al., 2023). These findings provide an important local context for interpreting the increase in built-up areas observed in the present study.

The development of Kertajati International Airport represents an important infrastructure-related process in the transformation of land cover in Majalengka. Previous spatial-temporal research documented changes in paddy fields, settlements, and dryland areas associated with land acquisition and airport development in several villages surrounding the airport area. Such infrastructure development can increase accessibility and stimulate subsequent changes in surrounding land functions, particularly through the development of settlements, transportation facilities, and other supporting activities. These processes provide a plausible local context for the expansion of built-up areas identified in this study, although the present analysis does not directly quantify the causal contribution of individual infrastructure projects.

The expansion of built-up areas from 19,256.55 ha in 2017 to 22,806.83 ha in 2024 should therefore not be interpreted solely as a consequence of general population growth. Rather, it may reflect the combined effects of infrastructure-led regional development, urban expansion, and changes in the function of surrounding agricultural and vegetated areas. At the same time, the increase in agricultural land observed in this study does not necessarily contradict previous evidence of agricultural land loss. Land-cover transitions may occur simultaneously in different parts of the regency, resulting in a non-linear spatial pattern. Agricultural areas may expand through conversion from other land-cover classes while agricultural land in other locations is converted into settlements, infrastructure, or other uses. Thus, the net increase in agricultural area represents the balance of multiple spatial transitions rather than the absence of agricultural land conversion. The dynamics of the tree-covered class further demonstrate the non-linear nature of land-cover change. Tree-covered areas increased from 63,434.59 ha in 2017 to 65,114.72 ha in 2021 but subsequently declined to 60,716.49 ha in 2024. The increase during 2017–2021 may reflect vegetation recovery, land-cover succession, or changes in land management, whereas the subsequent decline indicates that this increase was not sustained through 2024. However, because the present study does not explicitly model the driving factors of tree-cover change, the specific contribution of development, agricultural expansion, vegetation recovery, or other processes cannot be quantitatively separated. The observed pattern should therefore be interpreted as the spatial outcome of multiple interacting land-cover processes.

These findings are consistent with broader research indicating that land-cover changes are strongly influenced by human activities, particularly agricultural expansion and urbanization (Song et al., 2018). In Majalengka, the simultaneous expansion of built-up and agricultural areas, together with fluctuations in tree and shrub cover, demonstrates that land-cover transformation does not follow a single linear trajectory. Instead, different land-cover transitions occur simultaneously across the landscape in response to development pressure, agricultural dynamics, infrastructure development, and local land-management processes. Meanwhile, the water body class decreased from 1,338.70 ha to 1,050.76 ha. The shrubland class fluctuated, dropping from 9,405.89 ha to 4,215.37 ha in 2021 before rising again to 7,148.25 ha in 2024. These fluctuations demonstrate that land-cover changes do not follow a linear path and can be influenced by both land-use dynamics and environmental conditions. Overall, the expansion of agricultural and built-up areas, coupled with the reduction in tree cover by 2024, indicates increasing pressure on land resources. The expansion of built-up areas can exert both direct and indirect pressure on natural and agricultural landscapes (Vliet, 2019). From an environmental perspective, these land-cover transitions are important because changes between vegetation-dominated and built-up or other low-carbon classes can alter the carbon storage capacity of the landscape. Conversion from vegetation with relatively high carbon-storage capacity to built-up areas may contribute to carbon loss, whereas vegetation recovery or expansion can increase carbon storage. The observed land-cover dynamics therefore provide an important spatial context for interpreting the carbon-stock changes presented in the following section. In particular, the increase in built-up areas and the decline in tree-covered areas after 2021 are relevant to understanding the reduction in total carbon stocks observed in 2024. Details regarding land cover changes in Majalengka Regency are presented in Figure 3.



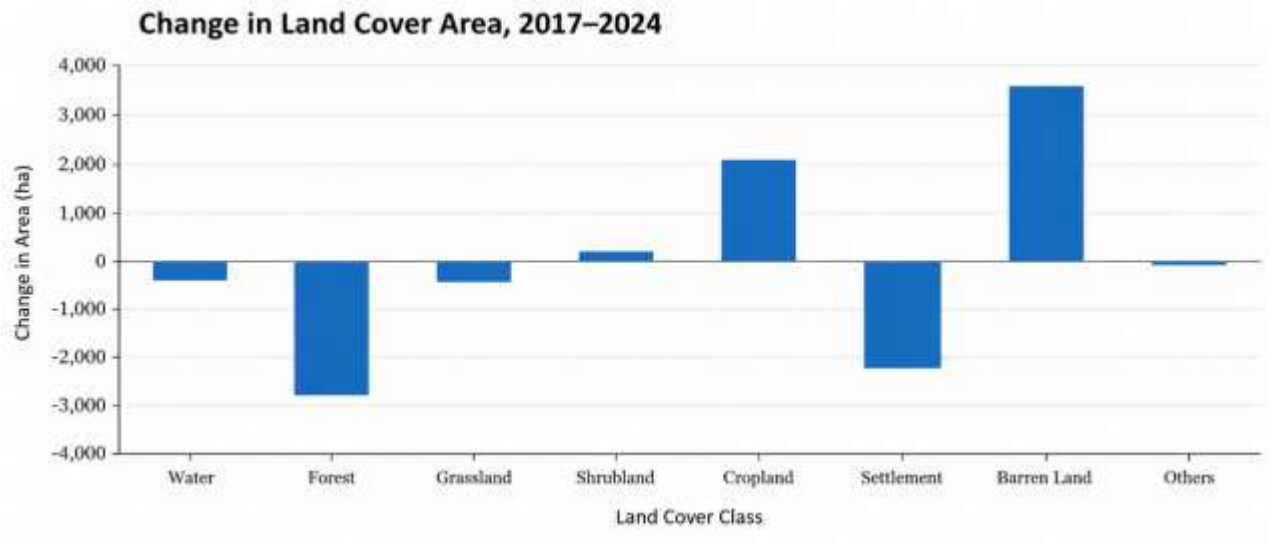


Figure 3. Changes in land cover area in Majalengka Regency

4.2 Changes in Carbon Stocks in Majalengka Regency

Based on the results of the multitemporal analysis, changes in carbon stocks in Majalengka Regency during the 2017–2024 period are classified into categories ranging from very high loss to very high gain. The spatial distribution of these analysis results is presented in Figure 4.

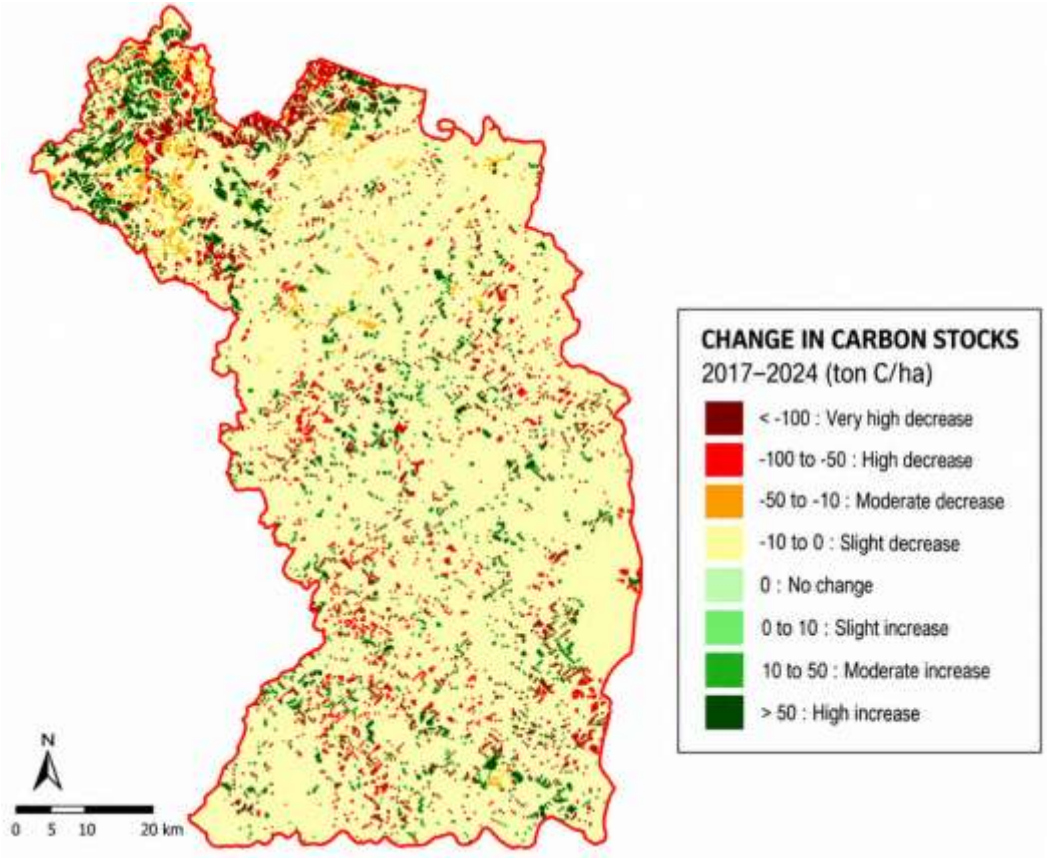


Figure 4. Changes in carbon stocks in Majalengka Regency

Figure 4 reveals that changes in carbon stocks in Majalengka Regency during the 2017–2024 period were spatially heterogeneous. The relationship between land-cover transitions and carbon-stock changes can

be explained by the differences in carbon-stock constants assigned to each land-cover class. The tree class has the highest carbon-stock constant at 169.7 tonnes C/ha, followed by inundated vegetation at 120.0 tonnes C/ha, shrubs at 30.0 tonnes C/ha, agriculture at 10.0 tonnes C/ha, built-up areas at 5.0 tonnes C/ha, grass at 4.5 tonnes C/ha, and open land at 2.5 tonnes C/ha, while water is assigned a value of zero. Consequently, transitions from tree-covered areas to built-up, agricultural, shrub, grass, or open-land classes have the potential to generate carbon loss because land with relatively high carbon-storage capacity is replaced by classes with lower assigned carbon values. In contrast, transitions from lower-carbon classes toward tree or other higher-carbon vegetation classes result in carbon gains. The increase in built-up areas provides an important context for interpreting the observed carbon losses. Between 2017 and 2024, built-up areas increased from 19,256.55 ha to 22,806.83 ha, while tree-covered areas declined from 65,114.72 ha in 2021 to 60,716.49 ha in 2024. Although the present analysis does not provide a transition matrix that quantitatively identifies the exact source and destination of every changed pixel, the combination of increasing built-up land and declining tree cover indicates a potentially important pathway for carbon loss.

In particular, where tree-covered pixels were converted into built-up areas, the difference between the tree carbon constant and the built-up carbon constant would produce a substantial negative carbon change. Similar carbon losses would occur where tree-covered areas were converted into agricultural, shrub, grass, or open-land classes, although the magnitude would depend on the specific transition. Carbon gains, in contrast, are spatially associated with areas where land-cover conditions shifted toward classes with greater carbon-storage capacity. For example, conversion from agricultural land, grass, shrub, or open land toward tree-covered areas would increase the estimated carbon stock because the receiving class has a higher carbon-stock constant. Such transitions may represent vegetation recovery, natural succession, rehabilitation, or changes in land management.

However, because the present study estimates carbon stocks from land-cover classes rather than directly measuring biomass or carbon pools in the field, the observed carbon gain should be interpreted as an increase in estimated land-cover-based carbon storage rather than direct evidence of measured biomass accumulation. Most of the area was dominated by the low-loss class (-10 to 0 tons C/ha), whereas moderate to very high losses were distributed across specific locations, particularly in the northern, central, and southern parts of the study area. Conversely, increases in carbon stocks are indicated by green-colored areas, which are generally associated with vegetated regions. This pattern demonstrates that changes in land cover and vegetation conditions influence carbon stock dynamics (Chang, 2022). Areas experiencing higher carbon loss require attention in land management, while areas showing carbon gains should be preserved to support ecosystem functions related to carbon storage (Song et al., 2018; Verstegen, 2019). Further details regarding carbon stock changes in Majalengka Regency are presented in Figure 5.

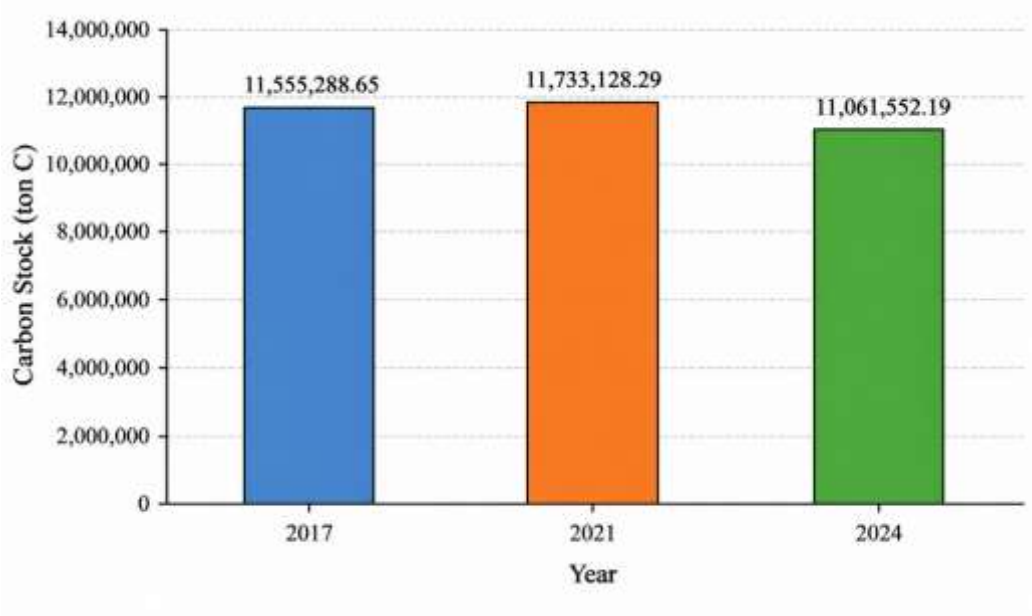
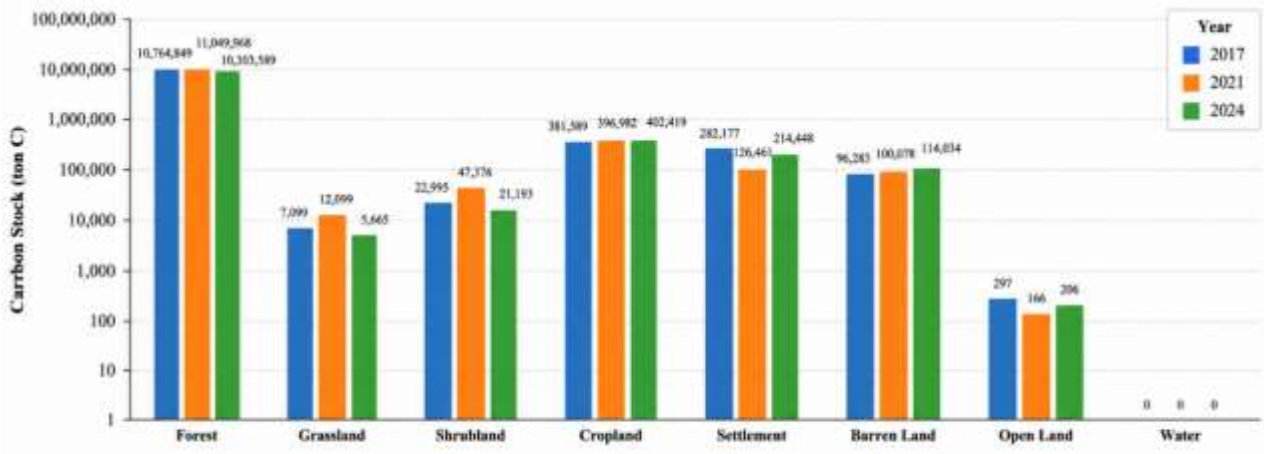


Figure 5. Carbon stocks in Majalengka Regency in 2017, 2021, and 2024.

Figure 5 shows that carbon stocks in Majalengka Regency fluctuated between 2017 and 2024. Carbon stocks increased from 11,555,288.65 tonnes C in 2017 to 11,733,128.29 tonnes C in 2021—an increase of approximately 1.54%—before declining to 11,061,552.19 tonnes C in 2024, a decrease of about 5.72% compared to 2021. Overall, carbon stocks in 2024 were approximately 4.27% lower than in 2017. This decline indicates a reduction in carbon storage capacity, which may be linked to changes in land cover and vegetation biomass (Gitima, 2025). Studies in Indonesia indicate that land-cover changes can significantly alter carbon storage; increases in forest cover or vegetation rehabilitation tend to boost carbon stocks, whereas vegetation conversion can lead to carbon loss (Sadono et al., 2020; Sumarlin et al., 2021). Similar findings have been reported in East Kalimantan, where land-use changes were shown to potentially cause carbon loss and impact ecosystem sustainability (Verstegen et al., 2019). Consequently, the 2021–2024 period warrants attention—particularly in areas experiencing changes in vegetation cover—as the decline in carbon stocks may signal increasing pressure on the ecosystem's function as a carbon store. The temporal pattern of total carbon stocks further supports the relationship between land-cover transitions and carbon dynamics. Total carbon stocks increased from 11,555,288.65 tonnes C in 2017 to 11,733,128.29 tonnes C in 2021, before declining to 11,061,552.19 tonnes C in 2024. The increase during 2017–2021 indicates that carbon gains associated with transitions toward higher-carbon land-cover classes outweighed carbon losses during this period. Conversely, the decline between 2021 and 2024 suggests that transitions toward lower-carbon classes, particularly in areas experiencing vegetation reduction and built-up expansion, outweighed carbon gains during the later period. Thus, changes in total carbon stocks represent the cumulative effect of multiple land-cover transitions occurring across the landscape.

Carbon stocks categorized by land-cover class are presented in Figure 6.



Year	Carbon Stock (ton C)							
	Forest	Grassland	Shrubland	Cropland	Settlement	Barren Land	Open Land	Water
2017	10,764,849	7,099	22,995	381,589	282,177	96,283	297	0
2021	11,049,968	12,099	47,376	396,982	126,461	100,078	166	0
2024	10,303,589	5,665	21,193	402,419	214,448	114,034	206	0

Figure 6. Carbon stocks by land cover class in Majalengka Regency in 2017, 2021, and 2024.

Figure 6 shows that forests are the largest contributor to carbon stocks in Majalengka Regency, accounting for 10,764,849 tonnes of C in 2017, rising to 11,049,968 tonnes of C in 2021, and subsequently declining to 10,303,589 tonnes of C in 2024. This significant contribution highlights the importance of woody vegetation cover in maintaining carbon stocks. Changes in land cover and vegetation conditions are known to influence carbon stock dynamics; an increase in forest cover can lead to greater carbon storage, whereas the loss of vegetation cover can result in a decline in carbon stocks (Sadono et al., 2020; Verstegen et al., 2019). Meanwhile, carbon stocks in agricultural and built-up areas showed an increase during the observation period, whereas the grass, inundated vegetation, and shrub categories exhibited fluctuations. These patterns indicate that changes in carbon stocks are influenced not only by the extent of land cover but also by vegetation characteristics and land-use changes. Thus, forests remain a strategic component in maintaining Majalengka Regency's carbon storage capacity.

5. CONCLUSION, IMPLICATION, SUGGESTION, AND LIMITATIONS

This study demonstrates that land cover in Majalengka Regency underwent substantial spatial and temporal changes during 2017–2024, particularly through the expansion of agricultural and built-up areas and the decline in tree cover after 2021. Built-up areas increased from 19,256.55 ha in 2017 to 22,806.83 ha in 2024, while tree-covered areas decreased from 65,114.72 ha in 2021 to 60,716.49 ha in 2024. Correspondingly, estimated carbon stocks increased from 11,555,288.65 tonnes C in 2017 to 11,733,128.29 tonnes C in 2021, before declining to 11,061,552.19 tonnes C in 2024. The tree-covered class remained the dominant contributor to carbon stocks. Spatially, carbon losses and gains were unevenly distributed and concentrated in specific locations. These findings demonstrate that integrating Google Earth Engine, Dynamic World, multitemporal land-cover analysis, and land-cover-based carbon estimation can provide spatial information to support the monitoring of changes in carbon-storage capacity in Majalengka Regency.

The carbon-loss hotspots identified in Figure 4 can serve as a basis for prioritizing field verification, conservation, rehabilitation, and periodic monitoring. Areas with high tree cover and carbon stocks should be maintained to prevent further carbon loss, while locations showing relatively high carbon losses can be considered initial targets for rehabilitation and vegetation recovery assessments. The expansion of built-up areas should also be considered in spatial planning, particularly in locations overlapping with declining vegetation cover. Thus, the spatial information presented in Figures 4–6 can support more targeted land management and periodic carbon monitoring in Majalengka Regency.

Carbon-stock estimation in this study relied on fixed carbon coefficients assigned to land-cover classes, which may not fully represent variations in biomass, vegetation structure, soil conditions, and other carbon components in the field. The use of mode-based temporal composites may also smooth or obscure short-term land-cover changes. In addition, Dynamic World classification may contain classification errors that affect carbon-stock estimation. Field validation was conducted in July 2026 using 100 validation points and achieved an overall accuracy of 85%; however, the validation was conducted outside the 2017–2024 observation period and was not accompanied by detailed reporting of metrics such as a confusion matrix, producer's accuracy, and user's accuracy. The study also did not directly measure biomass or carbon stocks and did not employ a land-cover transition matrix to quantify the contribution of individual transitions to carbon-stock changes. Therefore, the reported carbon values should be interpreted as land-cover-based estimates rather than direct measurements of ecosystem carbon stocks.

Future research should integrate field-based biomass and carbon measurements to develop carbon coefficients that better represent local environmental conditions. Validation should also be conducted using observations that are more temporally consistent with the satellite data and should include a confusion matrix and class-specific accuracy measures. The use of annual or seasonal data could improve the detection of land-cover changes that may be obscured by multi-year composites. In addition, developing a pixel-based land-cover transition matrix would enable the identification and quantification of specific transition pathways, such as conversion of tree-covered areas to built-up or agricultural land, that contribute to carbon losses. Integrating field measurements, higher-resolution remote-sensing data, and transition analysis could improve the accuracy of carbon-stock estimation and the spatial prioritization of carbon management in future studies.

REFERENCES

Adrian, A., Widiatmaka, W., Munibah, K., & Firmansyah, I. (2023). Pola spasial perubahan tutupan lahan/penggunaan lahan menggunakan Google Earth Engine di Kabupaten Majalengka. *Jurnal Pembangunan Wilayah dan Kota, 19*(4), 447–463. https://doi.org/10.14710/pwk.v19i4.46254

Brown, C. F., Brumby, S. P., Guzder-Williams, B., et al. (2022). *Dynamic World, near real-time global 10 m land use land cover mapping*. Scientific Data, 9, 251. https://doi.org/10.1038/s41597-022-01307-4

Chang, X., Xing, Y., Wang, J., Yang, H., & Gong, W. (2022). Effects of land use and cover change (LUCC) on terrestrial carbon stocks in China between 2000 and 2018. *Resources, Conservation and Recycling*. https://doi.org/10.1016/j.resconrec.2022.106333

Dofee, A. A., & Chand, P. (2024). Spatiotemporal dynamics of land use land cover patterns in the middle Omo-Gibe River Basin, Ethiopia: Machine learning, geospatial, and field survey integrated approach. *Modeling Earth Systems and Environment, 11*. https://doi.org/10.1007/s40808-024-02185-y

Fryer, J., & Williams, I. (2021). Regional carbon stock assessment and the potential effects of land cover

change.. *The Science of the total environment, 775*, 145815 . https://doi.org/10.1016/j.scitotenv.2021.145815

Gitima, G., Tadesse, T., Berhanu, Y., Kassie, M., Jakubus, M., & Teshome, M. (2025). Impacts of land use and land cover changes on carbon stocks (1992–2052) using geospatial technologies in Gena district, Southwest Ethiopia. *Scientific Reports, 15*. https://doi.org/10.1038/s41598-025-11558-x

Grassi, G., Conchedda, G., Federici, S., Abad Viñas, R., Korosuo, A., Melo, J., Rossi, S., Sandker, M., Somogyi, Z., Vizzarri, M., & Tubiello, F. (2022). Carbon fluxes from land 2000–2020: bringing clarity to countries' reporting. *Earth System Science Data*. https://doi.org/10.5194/essd-14-4643-2022

Herrmann, S., Brandt, M., Rasmussen, K., & Fensholt, R. (2020). Accelerating land cover change in West Africa over four decades as population pressure increased. *Communications Earth & Environment, 1*. https://doi.org/10.1038/s43247-020-00053-y

Jiang, Y., Ouyang, B., & Yan, Z. (2024). The response of carbon storage to multi-objective land use/cover spatial optimization and vulnerability assessment. *Sustainability*. https://doi.org/10.3390/su16062235

Kumar, L., & Mutanga, O. (2018). Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sensing, 10*, 1509.

Kurniawati, U. F. (2021). Dampak Perubahan Penggunaan Lahan Terhadap Besaran Stok Karbon di Kota Surabaya. *Jurnal Penataan Ruang, 16*(1), 54-58.

Mirici, M. E., & Berberoglu, S. (2024). Terrestrial carbon dynamics and economic valuation of ecosystem service for land use management in the Mediterranean region. *Ecol. Informatics, 81*, 102570. https://doi.org/10.1016/j.ecoinf.2024.102570

Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V., Murayama, Y., & Ranagalage, M. (2020). Sentinel-2 data for land cover/use mapping: A review. *Remote Sensing, 12*, 2291. https://doi.org/10.3390/rs12142291

Rimal, B., Sharma, R., Kunwar, R., Keshtkar, H., Stork, N., Rijal, S., Rahman, S., & Baral, H. (2019). Effects of land use and land cover change on ecosystem services in the Koshi River Basin, Eastern Nepal. *Ecosystem Services*. https://doi.org/10.1016/j.ecoser.2019.100963

Sadono, R., Pujiono, E., & Lestari, L. (2020). Land cover changes and carbon storage before and after community forestry program in Bleberan village, Gunungkidul, Indonesia, 1999–2018. *Journal of Sustainable Forestry, 40*, 134–144. https://doi.org/10.1080/21580103.2020.1801523

Shuai, Q., Xue, J., Dai, L., Huang, Y., Jin, D., Chen, Z.-X., Li, M., Shi, Z., & Chen, S. (2024). The effects of land use change on soil organic carbon stock in China: A meta-analysis with the empirical modeling approach. *Geoderma Regional*. https://doi.org/10.1016/j.geodrs.2024.e00774

Sleeter, B., Liu, J., Daniel, C., Rayfield, B., Sherba, J., Hawbaker, T., Zhu, Z., Selmants, P., & Loveland, T. (2018). Effects of contemporary land-use and land-cover change on the carbon balance of terrestrial ecosystems in the United States. *Environmental Research Letters, 13*. https://doi.org/10.1088/1748-9326/aab540

Song, X.-P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature, 560*, 639–643. https://doi.org/10.1038/s41586-018-0411-9

Sumarlin, D., Gusmayanti, E., & Anshari, G. Z. (2021). Analisis perubahan penggunaan lahan dan cadangan karbon sebagai indikator degradasi lingkungan di Kecamatan Sandai Kabupaten Ketapang. *Jurnal Ilmu Lingkungan, 19*(3), 576–581. https://doi.org/10.14710/jil.19.3.576-581

Verstegen, J. A., van der Laan, C., Dekker, S. C., Faaij, A. P. C., & Santos, M. J. (2019). Recent and projected impacts of land use and land cover changes on carbon stocks and biodiversity in East Kalimantan, Indonesia. *Ecological Indicators, 103*, 563–575. https://doi.org/10.1016/j.ecolind.2019.04.053

Vliet, V. J. (2019). Direct and indirect loss of natural area from urban expansion. *Nature Sustainability, 2*, 755–763.

Waleed, M., Sajjad, M., & Shazil, M. S. (2024). Urbanization-led land cover change impacts terrestrial carbon storage capacity: A high-resolution remote sensing-based nation-wide assessment in Pakistan (1990–2020). *Environmental Impact Assessment Review*. https://doi.org/10.1016/j.eiar.2023.107396

Qin, Z., Zhu, Y., Canadell, J., Chen, M., Li, T., Mishra, U., & Yuan, W. (2024). Global spatially explicit carbon emissions from land-use change over the past six decades (1961–2020). *One Earth*. https://doi.org/10.1016/j.oneear.2024.04.002

Xu, C., Zhang, Q., Yu, Q., Wang, J., Wang, F., Qiu, S., Ai, M., & Zhao, J. (2023). Effects of land use/cover change on carbon storage between 2000 and 2040 in the Yellow River Basin, China. *Ecological Indicators*.

https://doi.org/10.1016/j.ecolind.2023.110345

Yuan, J., & Chen, J. (2024). Disproportionate contributions of land cover and changes to ecosystem functions in Kazakhstan and Mongolia. *Scientific Reports, 14*. https://doi.org/10.1038/s41598-024-72231-3

Zhao, J., Liu, S., Wang, Z., Gao, H., Feng, S., Wei, B., Hou, Z., Xiao, F., Jing, L., & Liao, X. (2023). The impact of land use and landscape pattern on ecosystem services in the Dongting Lake Region, China. *Remote Sensing, 15*, 2228. https://doi.org/10.3390/rs15092228