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Aboveground Spatiotemporal Carbon Storage Model in the Changing Landscape of Jatigede, West Java, Indonesia

Susanti Withaningsih [1,2,3,*], Annas Dwitri Malik [3] and Parikesit Parikesit [1,2,3]

1 Sustainability Science Program, Graduate School, Universitas Padjadjaran, Jl. Dipati Ukur No. 35, Bandung 40132, Indonesia
2 Department Biology, Faculty of Mathematics and Natural Sciences Natural Science, Universitas Padjadjaran, Jl. Raya Bandung–Sumedang Km. 21, Andir 45363, Indonesia
3 Center for Environment and Sustainability Science, Universitas Padjadjaran, Jl. Sekeloa Selatan 1 No. 1, Bandung 40132, Indonesia
* Correspondence: susanti.withaningsih@unpad.ac.id; Tel.: +62-22-250-2176

Abstract: Land use and land cover (LULC) change is the variable with the maximum influence on carbon storage in terrestrial ecosystems, due to a fundamental alteration of the ecosystem, structure, function, and variability over time. Understanding the dynamics of aboveground carbon stocks in underway constructions and urban expansions is crucial to provide a basis for land use management and planning. The objective of this study was to analyze the spatiotemporal dynamics of aboveground carbon storage and assess how the LULC change is affected by human intervention, as well as how aboveground carbon stocks respond to these changes in the tropical highland landscape of Jatigede. In this study, changes in aboveground carbon stocks were investigated between 2014 and 2021 by using the integrated valuation of ecosystem services and tradeoffs (InVEST) model. The results revealed that the total aboveground carbon stock decreased between 2014 and 2021. Forests showed the greatest decline in the aboveground carbon stock in terms of space. The primary cause of the reduction in the aboveground carbon stock was the conversion of vegetated land to agricultural and urban land cover. The aboveground carbon stock change was also caused by the continuing construction, which resulted in the extension of construction zones. However, an increase in the aboveground carbon stock was mostly observed in mixed gardens that were close to forest areas. The preservation of mixed gardens as a tree-based agroforestry system can be suggested for enhancing the aboveground carbon stock, as mixed gardens play a significant role in carbon storage in the midst of the increasingly massive deforestation due to the expansion of urban areas.

Keywords: aboveground; carbon; dynamics; land use changes; InVEST model

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1. Introduction

Atmospheric mean temperature increases of 1.4–2.0 °C by 2050 and 1.8–3.7 °C by 2070 are predicted under different future climate change scenarios [1]. Over time, this condition may have an effect on the Earth's ecosystems, endangering people and other living things [2]. Global warming is mainly caused by an increase in greenhouse gas concentrations in the atmosphere, and CO_2 is considered one of the largest contributors to this climate phenomenon [3,4]. Changes in some environmental factors in the long run denote climate change. These changes have an impact on the agriculture industry, animals, the hydrological cycle, wind patterns, rainfall distribution, and plant growth and development, and since plants are the primary producers on Earth, the entire food chain will be affected as well [5]. The Paris Agreement's goal, which states that efforts should be made to prevent the rise in global average temperature to 1.5 °C above preindustrial levels and to keep it well below 2 °C, reflects the increased ambition of the international climate policy [6]. Sequestering the carbon concentrated in the atmosphere to the

Earth's terrestrial ecosystems might be the key aspect in mitigating the increase in global temperatures [7].

Given its strong relationship with both the productivity of terrestrial ecosystems and climate control, carbon storage is a crucial indication of the functioning of ecosystem services [8]. In order to remove a significant amount of CO_2 from the atmosphere, it is practical to ensure that it is absorbed by the physiological system, where it is first stored as biomass through photosynthesis and then becomes a component of the soil [9,10]. It is widely known that forests have the potential to store high amounts of carbon in terrestrial ecosystems. Because of their high resilience and reduced risk of the quick release of carbon into the atmosphere, trees and soil in forests that are maintained well have been found to have significant potential for sequestering carbon [11,12]. Carbon sequestration services are more prominent in some tropical regions because of the high plant diversity and massive carbon storage provided by tropical rainforests [2,13,14]. About 37% of the estimated 1150 Gt of carbon stored in forests worldwide comes from tropical forests [15,16].

Land use and land cover (LULC) change is the variable with the maximum influence on carbon storage in terrestrial ecosystems, due to a fundamental alteration in the ecosystem, structure, function, and variability over time [17]. Between 2000 and 2030, the loss of carbon in living biomass from the habitat loss caused by urban expansion is estimated to be 299–633 million tons C and the emission to the atmosphere is expected to be around 1.9 gigatons C [18], which is slightly lower than the urban carbon emitted due to energy consumption [19]. A change from the forest landscape to non-vegetated land would obviously release carbon into the atmosphere and reduce the carbon storage in terrestrial ecosystems, which would, in turn, increase the CO_2 concentration in the atmosphere [20]. Therefore, carbon storage valuation in terrestrial ecosystems is a prominent issue since carbon stocks tend to vary in different types of land use and land cover. Moreover, the spatial and temporal dynamics of LULC change interactions and their resultant shaping of the ecosystem service supply potential in dynamic landscapes continue to be essential aspects in evaluating carbon sinks in such ecosystems over time [21].

Relying only on field inventory data through destructive sampling to estimate plant biomass and the carbon stored is not efficient and consumes a lot of time and resources. Non-destructive methods, such as the allometric equation to estimate biomass, remote sensing, and spatial modeling, are more effective in evaluating the carbon storage in such ecosystems over large areas. With the development of remote sensing and geographic information systems, many scholars have developed tools for estimating carbon storage based on land use and land cover (LULC). These include the Carnegie–Ames–Stanford approach (CASA), which is frequently used in net primary productivity (NPP) estimation, especially for various types of vegetation in North America [22]; the carbon exchange between vegetation, soil, and atmosphere (CEVSA) model, which requires further high-degree technical analysis of CO_2 assimilation and stomatal conductance based on soil, water and climate factors for carbon sequestration assessment [23]; and the land utilization and capability indicator (LUCI), which provides more detailed carbon storage information for each soil type and LULC combination but cannot split this into each carbon pool [24,25]. The integrated valuation of ecosystem services and tradeoffs (InVEST) is a sophisticated, up-to-date, and easily accessible model for evaluating the dynamics of carbon storage in terrestrial ecosystems over time or the ecosystem service assessment [10,26,27]. The InVEST carbon storage and sequestration model performs better when studying and evaluating how climate change and LULC change affect carbon storage [28,29]. The InVEST model provides spatially explicit data (using spatial data), resulting in spatial and statistical data in terms of tons of carbon sequestered [30]. Such a model is effective in evaluating carbon storage in the landscape using carbon pool and LULC change data [31]. Therefore, this is a powerful model for providing carbon storage dynamics over a large landscape for spatiotemporal analysis [24].

Over the past few decades, Indonesia, as a developing country, has seen a notable increase in its population and in urban expansion that have had an impact on both urban and rural regions, especially Java, the fastest-growing island [32]. With this increase in the urban landscape, natural ecosystems endure significant pressure. Land use conversion to built-up areas, such as industrial, residential, and agricultural land, at the expense of natural ecosystems is the most prominent issue in the majority of developing urban areas [33]. A reduction in the regulation of ecosystem services, such as carbon sequestration, is generally caused by the conversion of the natural landscape to agricultural land, both for commercial and for subsistence purposes, and this trend is exacerbated by the increased area of construction land [34]. In the past decade, a tropical highland landscape that is situated in Jatigede, Sumedang Regency, West Java, has experienced forest cover degradation. These land deteriorations include alterations of protected forests and production forests of 7817 ha between 2015 and 2017, which conflicts with the regional planning of Sumedang Regency [35]. In recent years, the national strategic project of the Jatigede Reservoir and Hydropower Plant, which is expected to produce 110 MW of electricity and raw water for agriculture irrigation, has likely significantly degraded the forest cover. In turn, the carbon sequestration potential of vegetated ecosystems in this area would likely be diminished. Determining the relationship between LULC change and carbon storage in this area is crucial since changing LULC classes have different impacts on carbon stocks [36], and this large-scale construction is still underway. This study focuses on analyzing the spatiotemporal dynamics of the aboveground carbon storage in the tropical highland landscape of Jatigede between 2014 and 2021 and assessing how the LULC change is affected by human intervention, as well as how aboveground carbon stocks respond to these changes, by using the InVEST model for the assessment of the carbon storage capability and resilience of the landscape to the undergoing rapid LULC change.

2. Materials and Methods

2.1. Study Area

This study was conducted in Jatigede Subdistrict, which is situated in Sumedang, West Java, Indonesia. Sumedang Regency is dominated by an agricultural area that consists of rainfed rice fields, irrigated rice fields, plantations, mixed gardens, and upland fields [37]. Before the Jatigede Reservoir was built, 53.93% of the land around it was used for agriculture, while 46.07% was for non-farmland use. Following the building of the Jatigede Reservoir, agricultural land use dropped from 44.36% to 9.56% [38]. Regarding livelihood, most of the residents of Jatigede Subdistrict work in the agricultural sector, either as farmers or as farm laborers. This is related to the condition of the region, which supports the agricultural sector. A small number of others work in the government, industrial, trade, and self-employed sectors. The study area is presented in Figure 1.

2.2. Data Collection

Field measurements and geographic information system (GIS) measurements were conducted in this integrated approach in order to aggregate primary and secondary data. The primary data of carbon storage were collected from the direct inventory of a tree stand's diameter at breast height (DBH) and tree height. Purposive sampling was used to sample and quantify the tree stands in the research region, while taking topographic, climatic, and safety considerations into account. The sample size of 30×30 m^2 corresponds to a pixel size of about 30 m in medium-resolution satellite imagery. The secondary data consisted of the worldwide geographical distribution of agricultural yields of all commodities in Jatigede in ton/ha, such as sweet potato, maize, groundnut, banana, cassava, and rice. These data were considered as biomass of nontimber plants in the study area and were converted to the mass of carbon/carbon contents. The agricultural yields were obtained from Global Agro-ecological Zones+ (GAEZ+) data on global crop yields [39]. Medium-resolution multispectral satellite imageries were downloaded from the United States Geographical Survey (USGS) website (earthexplorer.usgs.gov, accessed on 3 October 2023 and 25 February 2024) and were analyzed using ArcMap 10.6.1 software. The satellite imagery data required for spatial analysis, including the reference years of data obtained, are detailed in Table 1.

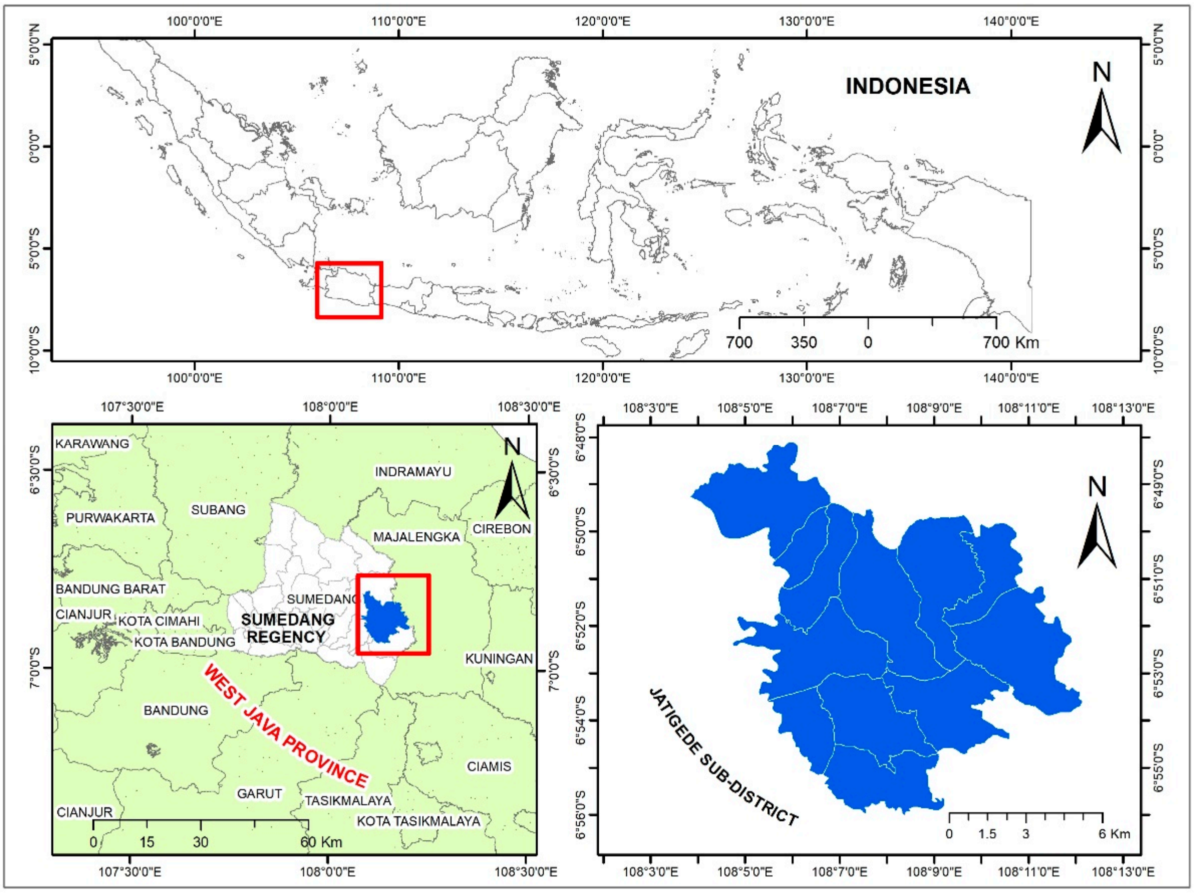

Figure 1. Map of the study area location in Jatigede Subdistrict in West Java, Indonesia.

Table 1. Satellite imagery data used in this study.

Year	Data	Imagery Date	Bands	Resolution (m)	Source
2014	Landsat 8 OLI TIRS C2 L1	5 August 2014	Multispectral	30	https://earthexplorer.usgs.gov (accessed on 25 February 2024)
2021	Landsat 8 OLI TIRS C2 L1	5 June 2021	Multispectral	30	https://earthexplorer.usgs.gov (accessed on 3 October 2023)

2.3. Methods

2.3.1. Preprocessing

Satellite imagery correction was required to reduce atmospheric disturbance. The preprocessing consisted of two steps, namely radiometric calibration and atmospheric correction. All preprocessing steps were executed in the Semiautomatic Classification Plugin (SCP), which is integrated in the QGIS 3.16 spatial analysis data software. The free QGIS plugin called SCP makes it easier to convert satellite images to reflectance, which improves the state of the Earth's surface by decreasing atmospheric disturbance. In all steps of calibration and correction, dark-object subtraction (DOS1) was applied.

2.3.2. Land Use and Land Cover Classification

LULC classification was conducted for the satellite products of both imagery dates (2014 and 2021). The Landsat OLI 8 data allow image enhancement in the pan-sharpened process to produce a higher-resolution image. To obtain LULC classification maps, the maximum likelihood–supervised classification was applied in ArcMap 10.6.1. On each satellite imagery that represented the LULC classes, a certain number of training samples were selected (buildings/settlements, forests, upland fields, paddy fields, mixed gardens, bare lands, and water bodies). Recommendations of the Ministry of Forestry and Environment and Regional Planning Agency of Sumedang for the remote sensing technique for medium-resolution satellite imaging data were followed in choosing this nomenclature variant of LULC classes. Training samples in the multispectral image data were determined, assisted by ground-truthing on the research site and Google Earth satellite imagery. The number of training datasets and their distribution in each LULC class are presented in Tables 2 and 3. The best combination of spectral bands that could be applied in this study for Landsat 8 OLI was band 4–3-2 [40]. Moreover, the band combination for false color (5-4-3) was the best band combination to map the vegetation covers in the study area. Tree leaves contain a lot of chlorophyll, which makes them stronger in absorbing red light from the infrared spectrum, making the false color band combination the most suitable for vegetation cover mapping [41]. Subsequently, an accuracy evaluation was carried out to reduce LULC classification mistakes due to the sampling technique and the possibility of pixel values in the imaging data being misinterpreted. All random training sample points were taken from the result of image classification, and stratified random sampling was used in the accuracy assessment. The area-based proportion for each LULC class using the overall expected standard error of 0.014 was applied for both LULC maps, which resulted in 51 sample points on the 2014 LULC map and 50 sample points on the 2021 LULC map. The producer's accuracy, the user's accuracy, and the overall accuracy, along with the kappa coefficient, were calculated in the Accuracy Assessment of Thematic Maps (AcaTaMA), which is also integrated in QGIS 3.16. The higher the accuracy of kappa, the higher the accuracy of the LULC mapping (>85%) [10].

Table 2. The number of training samples for the 2014 LULC classification.

Class Name	Area (m^2)	Count
Forests	3,319,568.373	3688
Water bodies	59,244.24933	66
Buildings/settlements	281,645.0885	313
Mixed gardens	5,663,479.708	6293
Paddy fields	3,423,530.412	3804
Dryland	3,477,032.264	3863
Bare lands	189,613.258	211

Table 3. The number of training samples for the 2021 LULC classification.

Class Name	Area (m^2)	Count
Forests	1,318,722.53	1465
Built-up areas	15,023.65651	17
Buildings/settlements	2,365,091.795	2628
Water bodies	6,671,714.647	7413
Paddy fields	128,032.3131	142
Bare lands	94,210.19243	105

2.3.3. Vegetation Index Mapping

The direct biomass and carbon stock inventory of tree stands were extrapolated from the plot scale to the landscape scale using a vegetation index distribution map. Finding the index value of the vegetation cover that was present at the research location was another helpful application of this index. The Normalized Difference Vegetation Index (NDVI) is the most widely used spectral vegetation index. Landsat 8 OLI image data were transformed into a raster map with the values of the vegetation index in order to determine the present condition of the vegetation in the study area. The NDVI was used in this study to obtain data on the canopy and vegetation coverage, which was then represented on a map of the distribution of vegetation [42]. In this study, the most recent available Landsat 8 OLI multispectral imagery was used to generate the NDVI. The multispectral image's NDVI is a partition of the red and near-infrared bands, which correspond to bands 5 and 4 in Landsat 8 OLI. The following formula was used to obtain the NDVI map:

$$NDVI = (NIR - RED)/(NIR + RED) \tag{1}$$

where *NDVI* is the Normalized Difference Vegetation Index, *NIR* is spectral band number 5 (near infrared) in Landsat 8 imagery, and *RED* is spectral band number 4 (red) in Landsat 8 imagery. A map of the NDVI distribution was generated after being processed in the Raster Calculation feature of ArcMap 10.6.1 software. The NDVI ranges between −1.0 and 1.0, where negative values indicate an area of water bodies or open area and positive values represent some area with vegetation [43]. An area of vegetation is said to have increased photosynthetic activity if its NDVI value is higher [44].

2.3.4. Biomass and Carbon Stock Inventory

In this study, due to the significant impact of LULC changes on deforestation and considering that vegetation is the most active carbon reservoir in the carbon cycle, only the vegetation's aboveground biomass was assessed [45]. Non-destructive sampling was conducted in the study area. Sample plots with a size of 30×30 m^2, similar to the pixel size of Landsat 8 OLI (~30 m), were distributed across 50 sampling points in the study area. This sampling size was based on the calculation of a 1% proportion of the total vegetated area at the study site. In each sample plot, the species were identified and the diameter at breast height (DBH) and the tree height were measured. In this non-destructive sampling technique, an allometric equation was used to estimate tree biomass. This allometric equation and the coefficient developed by [46] were used since the most significant predictive factors for aboveground biomass estimation in most tropical wet regional areas are tree height, wood density, and diameter at breast height. The wood density of all tree species measured at the study site was obtained from the Global Wood Density Database [47]. The allometric model is as follows:

$$\mathrm{AGB} = 0.0509 \times \rho \times \mathrm{DBH}^2 \times \mathrm{T} \tag{2}$$

where AGB is the aboveground biomass of trees in kilograms (kg), DBH is the diameter of trees measured at breast height in meters (m), ρ is the wood density of all measured trees in grams/cubic centimeters (g/cm^3), and T is the height of the measured trees in meters (m).

2.3.5. Carbon Stock Model Development

The total biomass was multiplied by 0.46 as the default value for the carbon content in living biomass [48]. Using correlation analysis, carbon stocks from field observations were projected to the landscape scale. Before conducting the analysis, Kolmogorov–Smirnov and Shapiro–Wilk normality tests were performed for both the NDVI variable and the field carbon inventory variable to make sure that all the data were normally distributed. Regression analysis using a single explanatory variable was chosen to determine the relationship between NDVI values and carbon stock measurements conducted in the field. The NDVI value distribution map was the independent variable (X) in the regression model, and the plot-level carbon stock inventory was the dependent variable (Y). To make sure that the distribution of plot-level carbon stock data mirrored the trend of the NDVI, a scatterplot of the NDVI values between the carbon stock measured in every permanent plot was created. The regression analysis was executed using IBM SPSS Statistics 26 software. The simple linear regression equation $Y = a + bX$ was generated in the regression analysis, where a determination coefficient (R^2) of more than 50% would represent a strong correlation between both variables in the regression analysis. Using the carbon stock model obtained from the equation, a raster calculation analysis was used to generate the carbon model distribution map of the study area in GeoTIFF image format. In the output maps, each grid cell of a region's carbon concentration was informed based on the carbon density pool measured on the permanent plots, which took the concentration of aboveground carbon into account.

2.3.6. InVEST Model Development

An open-source model called the integrated valuation of ecosystem services and tradeoffs (InVEST) modeling framework was used to map and value ecosystem services. For simulations of carbon dynamics using the InVEST carbon storage model, identical area pairs of LULC maps from successive dates and transition matrices for the carbon pool measured in between need to be provided [49]. The InVEST carbon storage model is a product of the Natural Capital Project, which is situated at Stanford University [26]. In this study, raster data from the LULC classification dates of 2014 and 2021 were used, and the aboveground carbon stocks were the only estimated carbon pool. The LULC and carbon pool datasets were created in order to fulfill the needs of the model, and these were the main sources of information used to calculate the amount of carbon stored in each grid cell. Land use codes, LULC class names, and aboveground carbon contents were all included in the matrix of datasets in comma-delimited (.csv) format. The raster imagery data obtained from the preceding extrapolation process's carbon stock calculation were transformed into numerical values of carbon density for every LULC class. Buildings/settlements and water bodies that have zero potential to store aboveground carbon stocks were represented by a zero value in the aboveground carbon pool column. To start modeling the existing aboveground carbon stock, all LULC raster images and .csv files were merged into InVEST 3.9.0 version software. Carbon storage distribution maps in a GeoTIFF file were included in the final output.

3. Results and Analysis

3.1. The Changes in LULC during 2014–2021

Based on the result of land use and land cover classification, the study area consists of seven land use and land cover types, namely buildings/settlements, forests, upland fields, paddy fields, mixed gardens, bare lands, and water bodies. The kappa coefficient for the classification result was 85.62% for the 2014 LULC and 90.32% for the 2021 LULC, which indicates excellent accuracy. The number of training sample points and the results of the accuracy test are presented in Tables 4 and 5. The spatial distribution of land use and land cover classes is presented in Figure 2. Land use and land cover changes between 2014 and 2021 in Jatigede are presented in Table 6. As seen in Table 6, upland fields were the main LULC type in 2014, followed by mixed gardens, which were the second-most common LULC type in 2014, accounting for 2599.08 ha (23%). Meanwhile, in 2021, mixed gardens and upland fields were the most common LULC types, accounting for 3495.06 ha (31%) and 3281.30 ha (29%), respectively. As shown in Table 1, the LULC detection analysis revealed that the LULC type that had declined the most was forests, with total declined areas of 1777.19 ha (74%). Meanwhile, paddy fields were the second-most declined LULC type, accounting for 459.32 ha (19%). In contrast, water bodies experienced the highest expansion between 2014 and 2021, with a total increased area of 1192.34 ha (94%). This trend was followed by mixed gardens, accounting for an increase of 895.98 ha (26%). In this study, forests and mixed gardens could be considered as vegetated areas, which was mainly attributed to vegetation that predominantly covered these LULC types. Vegetation covered 4999.31 ha (45%) of these areas in 2014, while it covered 4118.09 ha (37%) in 2021, indicating a decline of 881.21 ha (18%) in the vegetation cover. Both in 2014 and in 2021, the areas covered by vegetation were less than the non-vegetated areas in Jatigede.

Table 4. Confusion matrix for the 2014 LULC classification.

	Classes	Validation								
		Forests	Mixed gardens	Buildings/ settlements	Bare lands	Paddy fields	Upland fields	Total	User accuracy	Errors of omission
Reference data	Forests	9	1	0	0	1	0	11	0.81818	0.18182
	Mixed gardens	2	10	0	0	0	0	12	0.83333	0.16667
	Buildings/ settlements	0	0	1	0	1	0	2	0.5	0.5
	Bare lands	0	0	0	2	0	0	2	1	0
	Paddy fields	0	0	0	0	11	0	11	1	0
	Upland fields	0	0	0	0	2	11	13	0.84615	0.15385
	Total	11	11	1	2	15	11	51		
	Producer accuracy	0.82002	0.90806	1	1	0.72936	1		Overall accuracy	0.86113
	Errors of omission	0.17998	0.09194	0	0	0.27064	0		Kappa coefficient	0.82448

Table 5. Confusion matrix for the 2021 LULC classification.

	Classes	Validation									
		Forests	Water bodies	Buildings/ settlements	Mixed gardens	Paddy fields	Upland fields	Bare lands	Total	User accuracy	Errors of omission
Reference data	Forests	6	0	0	0	0	0	0	6	1	0
	Water bodies	0	6	0	0	0	0	0	6	1	0
	Buildings/ settlements	0	0	1	0	0	1	0	2	0.5	0.5
	Mixed gardens	0	0	0	13	0	0	0	13	1	0
	Paddy fields	0	0	0	0	7	2	0	9	0.77778	0.22222
	Upland fields	0	0	0	0	1	11	0	12	0.91667	0.08333
	Bare lands	0	0	0	0	0	0	3	3	1	0
	Total	6	6	1	13	8	14	3	51		
	Producer accuracy	1	1	1	1	0.84748	0.86547	1		Overall accuracy	0.93347
	Errors of omission	0	0	0	0	0.15252	0.13453	0		Kappa coefficient	0.90327

From 2014 to 2021, LULC conversion occurred at a different rate, depending on the type of LULC (Table 7). Forests were mainly converted to mixed gardens and upland fields. Mixed gardens were mainly converted to upland fields and water bodies. The decrease in paddy fields was mainly attributed to the conversion of this LULC type to upland fields, water bodies, and mixed gardens. Conversely, the increase in water bodies was mainly attributed to conversion from paddy fields, mixed gardens, and bare lands. The expansion of water bodies mainly occurred at the expense of agricultural lands in the study area. The expansion of bare lands was commonly due to conversion from mixed gardens and paddy fields. The increase in upland fields was mainly attributed to conversion from paddy fields, mixed gardens, and forests. The highest LULC conversion observed was from forests to mixed gardens, accounting for 1268.37 ha (53%), followed by conversion from upland fields to paddy fields, accounting for 704.46 ha (24%). Undoubtedly, conversions across LULC types have an impact on the composition and dynamics of ecosystems, as well as variance in the total carbon storage.

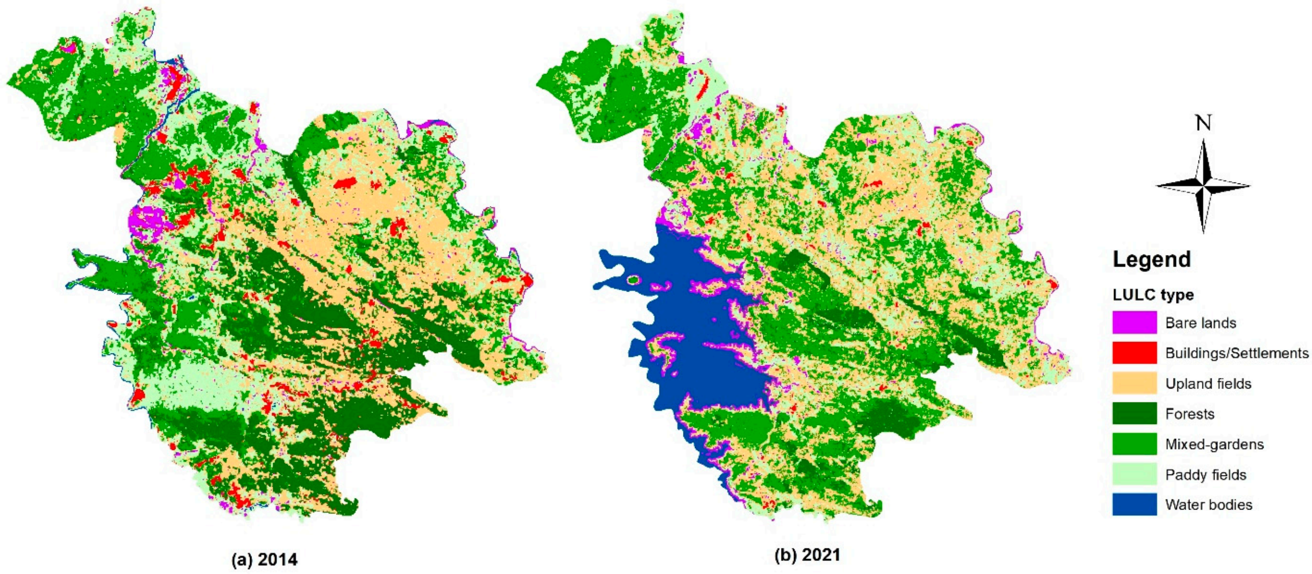

Figure 2. Land use and land cover changes in Jatigede during 2014–2021.

Table 6. Land use and land cover change trends during 2014–2021.

LULC Type	2014 (ha)	2021 (ha)	2014 (%)	2021 (%)	Area Change (ha)	Area Change (%)
Bare lands	263.31	451.11	2%	4%	187.80	42%
Buildings/settlements	453.39	67.70	4%	1%	−385.69	−85%
Upland fields	2935.22	3281.30	26%	29%	346.07	11%
Forests	2400.22	623.04	22%	6%	−1777.19	−74%
Mixed gardens	2599.08	3495.06	23%	31%	895.98	26%
Paddy fields	2421.01	1961.69	22%	18%	−459.32	−19%
Water bodies	71.04	1263.38	1%	11%	1192.34	94%

Table 7. Land use and land cover conversion matrix during 2014–2021.

		LULC 2021 (ha, %)						
	LULC Types	Bare Lands	Buildings/ Settlements	Upland Fields	Forests	Mixed Gardens	Paddy Fields	Water Bodies
LULC 2014 (ha, %)	Bare lands	61.14, 23%	0.70, 0.3%	51.62, 20%	1.75, 0.7%	11.20, 4%	99.02, 38%	37.89, 14%
	Buildings/ settlements	12.02, 3%	59.98, 13%	233.38, 51%	5.18, 1%	49.06, 11%	57.26, 13%	36.50, 8%
	Upland fields	79.67, 3%	2.94, 0.1%	1432.35, 49%	15.41, 0.5%	600.19, 20%	704.46, 24%	100.20, 3%
	Forests	38.79, 2%	0.16, 0.01%	384.58, 16%	550.72, 23%	1268.37, 53%	76.05, 3%	81.55, 3%
	Mixed gardens	109.97, 4%	1.11, 0.04%	503.19, 19%	34.49, 1%	1290.90, 50%	239.51, 9%	419.91, 16%
	Paddy fields	135.22, 6%	2.81, 0.1%	674.19, 28%	13.23, 0.5%	274.53, 11%	761.23, 31%	559.78, 23%
	Water bodies	14.30, 20%	0, 0%	2.00, 3%	2.23, 3%	0.81, 1%	24.15, 34%	27.55, 39%

3.2. The NDVI Cover during 2014–2021

As shown in Figure 3, dense vegetation was found to be the most dominant NDVI cover category in Jatigede, both in 2014 and in 2021. The highest value of the NDVI decreased over time between 2014 and 2021, which indicates a decrease in the greenness index over time. The highest NDVI value found in 2014 was around 0.89. Meanwhile, the highest value of the NDVI found in 2021 was around 0.86. An NDVI value above 0.1 can be considered to indicate vegetation cover, and the higher the value of the NDVI, the denser the vegetation cover in a typical area [50]. NDVI values between 0 and 0.1 represent bare soil/rocks, and water bodies typically have an NDVI value below 0 [50]. As shown in Figure 4, dense vegetation was calculated to cover an area of around 7429 ha in 2014 compared to 6213 ha in 2021, indicating a decrease in dense vegetation. The moderate vegetation cover decreased from 3490 ha in 2014 to 3192 ha in 2021. A decrease in the sparse vegetation (agriculture) cover was also observed from 2014 (224 ha) to 2021 (188 ha). Meanwhile, unevenly distributed bare soil/rocks showed an increase in area between 2014 (20 ha) and 2021 (41 ha). Water bodies represented the highest expansion in Jatigede, with an area increase of 1530 ha over time between 2014 and 2021. Mostly, the water body area increased at the expense of the dense vegetation cover during 2014–2021.

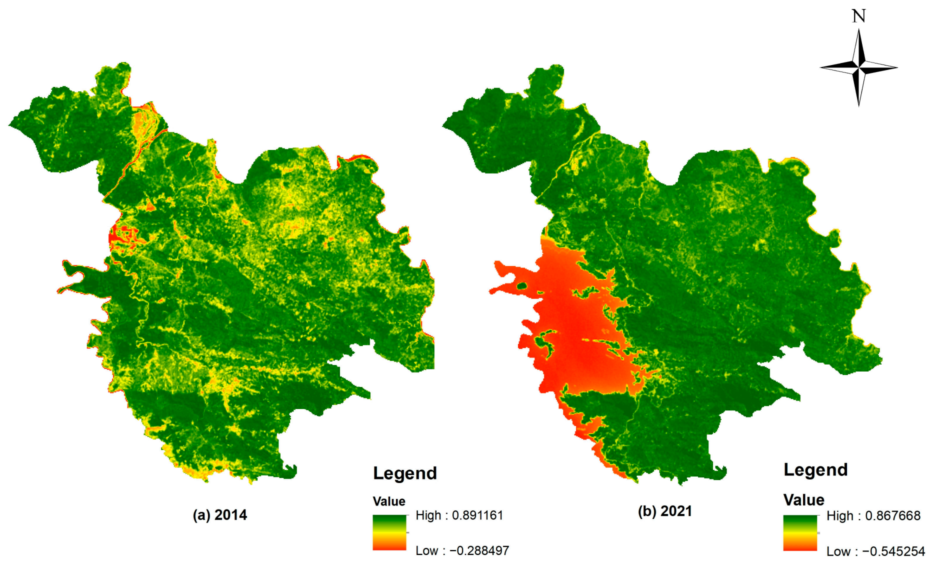

Figure 3. Time-series NDVI in Jatigede during 2014–2021.

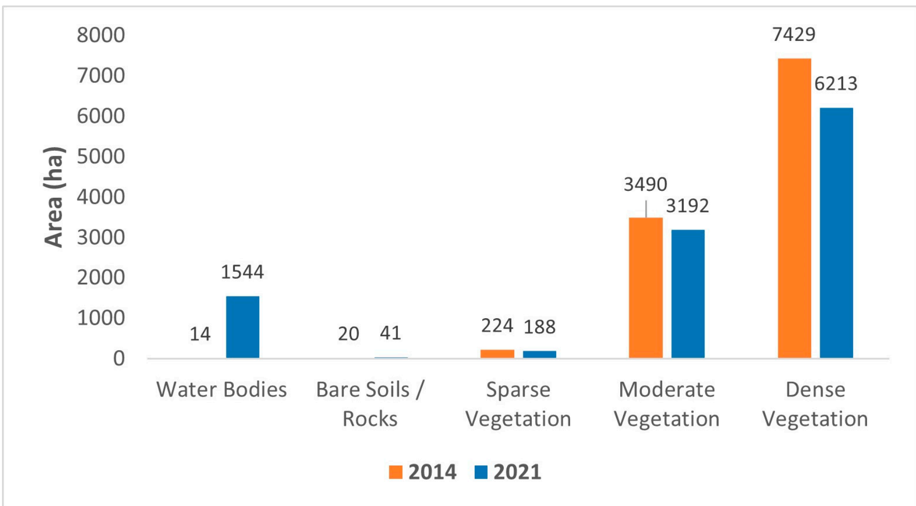

Figure 4. Analysis of the area covered by each category of the NDVI in Jatigede.

3.3. The Aboveground Carbon Stock Dynamics during 2014–2021

Kolmogorov–Smirnov and Shapiro–Wilk normality tests presented a normal distribution of the NDVI and field inventory of aboveground carbon stock data. The results showed that all NDVI data and aboveground carbon field inventory data were normally distributed (Table 8). The results of simple linear regression analysis showed a strong positive correlation between the field measurement of aboveground carbon stock and the NDVI (Figure 5). The analysis revealed a determination value of 92.85%, which suggests that the field carbon stock can be determined by 92.85% of NDVI data, while 7.15% is most likely influenced by other parameters. A significant positive correlation means that an increase in the NDVI will be followed by an increase in the aboveground carbon stock in the study area. The LULC class with the greatest potential for carbon storage was determined with the use of the InVEST carbon model. The InVEST spatial model identified that the highest aboveground carbon stock value in the study area was 2.02 tons, both in 2014 and in 2021 (Figure 6). The maximum value of carbon stock could be identified in the vegetated area. Meanwhile, the lowest aboveground carbon stock value was identified in buildings/settlements, bare lands, and water bodies since these LULC classes do not have the potential to hold aboveground carbon stock. Changes or LULC conversions in Jatigede between 2014 and 2021 were detected, and these resulted in a decrease in the aboveground carbon stock. The total aboveground carbon stock in 2014 was 187,073 tons and that in 2021 was 166,866 tons. Every LULC class had a different potential for aboveground carbon stocks (Figure 7). In 2014, the highest aboveground carbon stock was discovered in forests, contributing 23.26 ton/ha of carbon stock, followed by mixed gardens, which had an aboveground carbon stock of 23.16 ton/ha. Other agricultural lands, such as upland fields and paddy fields, had aboveground carbon stocks of 13.61 ton/ha and 13.02 ton/ha, respectively. Meanwhile, in 2021, the highest carbon stock potential was found in mixed gardens, at 22.53 ton/ha. This was followed by forests, which contributed 21.85 ton/ha of aboveground carbon stock; upland fields, at 15.03 ton/ha of aboveground carbon stock; and paddy fields, at 13.04 ton/ha of aboveground carbon stock. Since it is believed that buildings/settlements, bare lands, and water bodies lack the capacity to store aboveground carbon over an extended period, the aboveground carbon stock of these LULC classes was considered as zero for both 2014 and 2021.

Table 8. The results of the normality test on the NDVI and field carbon inventory data.

Test	Number of Samples	Asymptotic Significance (2-Tailed)	α	Description
Kolmogorov–Smirnov Shapiro–Wilk	50	0.2 0.458602	0.05	Normally distributed Normally distributed

The InVEST statistical model indicated that the study area's aboveground carbon stock decreased by 20,207 tons between 2014 and 2021. The change in the aboveground carbon stock for every LULC class between 2014 and 2021 is presented in Table 9. The aboveground carbon stock significantly decreased in the forest LULC class. The carbon density decreased from 23.26 ton/ha to 21.85 ton/ha. Mixed gardens also experienced a decrease in the carbon stock, going from 23.16 ton/ha to 22.53 ton/ha. However, the aboveground carbon stocks in upland fields and paddy fields increased, from 13.61 ton/ha to 14.03 ton/ha for upland fields and 13.02 ton/ha to 13.04 ton/ha for paddy fields. Compared to other LULC classes, vegetated areas are expected to have a higher potential aboveground carbon stock. Forests and mixed gardens can be classified as vegetated areas because of the predominance of vegetation stand coverage seen in both these LULC classes. The total aboveground carbon stores in forests and mixed gardens were substantially greater than those in other LULC classes, as Figure 7 illustrates. The forest cover was expected to have a higher aboveground carbon stock compared to other agricultural areas, such as paddy fields and upland fields, for both 2014 and 2021. However, as one of the types of agricultural areas, mixed gardens were identified to have significantly higher aboveground carbon stocks (22.53 ton/ha) than forests (21.85 ton/ha) in 2021. As shown in Table 6, mixed gardens were the largest LULC class in both 2014 and 2021, which is significantly larger than the forests class. Moreover, a massive decrease in the forest cover in 2021 resulted in a significant reduction in the aboveground carbon stock in this LULC class.

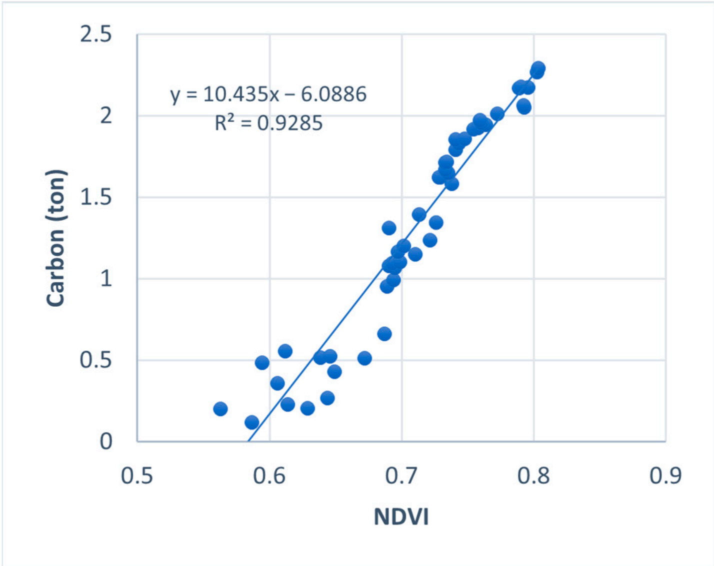

Figure 5. Simple linear regression analysis between the field inventory of carbon and the NDVI.

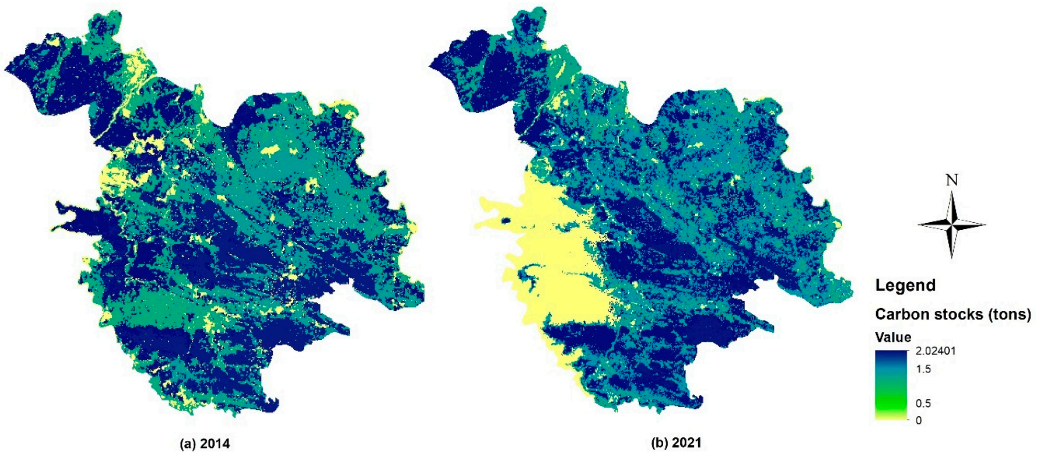

Figure 6. Spatial distribution of aboveground carbon storage dynamics in Jatigede during 2014–2021.

Table 9. Aboveground carbon stock change in the reference years.

LULC Classes	Year 2014 (tone/ha)	Year 2021 (tone/ha)	Change (tone/ha)
Forests	23.26	21.85	−1.41
Water bodies	0	0	0.00
Buildings/settlements	0	0	0.00
Mixed gardens	23.16	22.53	−0.63
Paddy fields	13.02	13.04	0.01
Upland fields	13.61	15.03	1.42
Bare lands	0	0	0.00

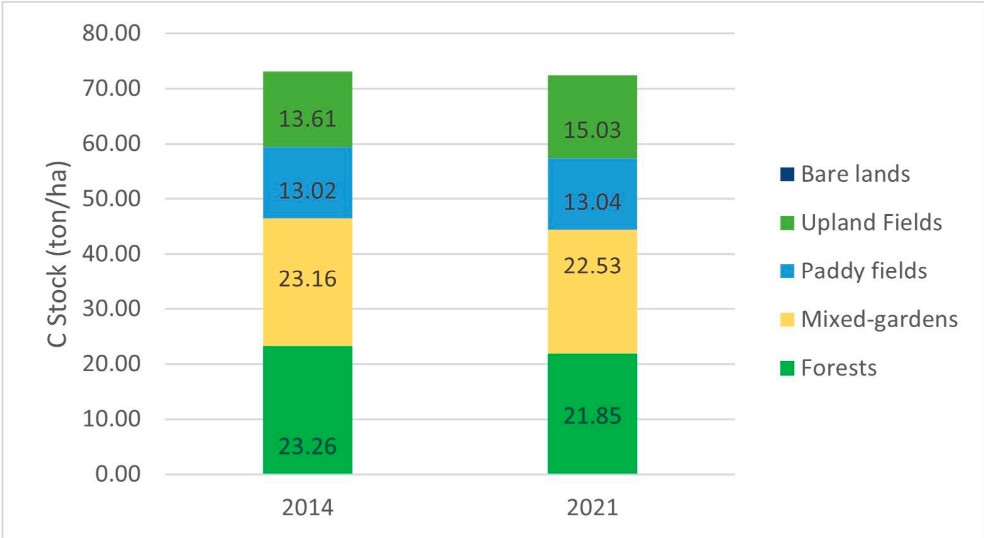

Figure 7. Aboveground carbon stock distribution in each LULC class.

4. Discussion

4.1. The Changes in the LULC in Jatigede between 2014 and 2021

This study developed a model based on the effect of land use and land cover changes on the aboveground carbon stock as one of regulatory ecosystem services on a spatial and temporal scale between 2014 and 2021. The land use and land cover change model discovered that forests are the most degraded land cover class in Jatigede, with a 1777.19 ha, or 74%, reduction between 2014 and 2021. Forests were mostly converted (1268.37 ha, 53%) to mixed gardens, followed by the conversion of 600.19 ha (16%) to upland fields. The visual features of forests and mixed gardens may have influenced the projected conversions between these land use and land cover classes, possibly resulting in a misclassification. While the mixed gardens in the research region may be viewed as an agroforestry system managed by local populations, which participate as forest buffer zones, forests and mixed gardens are visually comparable according to the remote sensing method used in this study. Because of their function as buffer zones around forest covers, limited agricultural activities were observed in such areas.

The NDVI also showed that the green density, which represents the vegetation cover, is not significantly different between forests and mixed gardens. The density and health of the vegetation cover gradually increased from the mixed-garden area to the forest area. This may occur because the rate of forest cover change caused by human activities in forests can be controlled. An increase in the percentage of forested area, including the agricultural model in the form of agroforestry, has a positive correlation with the increase in the ecosystem service percentage [51]. According to a study by [52], agroforestry techniques (e.g., home gardens and the production of trees and coffee) and natural forests both preserve a variety of woody vegetation in the agroforestry system. Agroforestry can be considered as one of methods of conserving the forest cover, while enhancing benefits to the local communities. The positive impacts of involving the community in managing forests on the environment, the biodiversity, and local communities' livelihood are more satisfactory than restoring degraded forests without involving the community [53].

Conversely, there was one land cover type that had the highest increase in area: water bodies were the only land cover that accounted for more than a 50% increase in area between 2014 and 2021. The results of land use and cover change analysis showed an increase of around 1192.34 ha (94%) in the water body area from 2014 to 2021. This increase in the water body area mostly occurred at the expense of paddy fields, which decreased by 559.78 ha, followed by the conversion of 419.91 ha of mixed gardens to water bodies. The expansion of water bodies, which resulted in a significant decrease in these two agricultural land covers (paddy fields and mixed gardens), was mainly caused by the strategic infrastructure project of the Jatigede Reservoir. This reservoir is known as a multipurpose rock-fill dam and covers more than 5000 ha around five subdistricts in Sumedang District [38], including Jatigede Subdistrict, where water bodies covered 1263.38 ha in 2021 according to this study's land use and land cover change detection. Construction began in 2007 and was completed in 2015, which coincided with the inundation of the reservoir [54]. The construction of the reservoir, especially during the land-clearing phase, resulted in the deterioration of some type of land use and land cover. The land use change analysis detected 263.31 ha of open areas or bare lands in 2014, which might be due to the land being cleared for many purposes, such as temporary access roads, quarrying, and soil banks. Between 2014 and 2021, the area of bare lands increased by 187.80 ha (42%). This implies that land clearing was escalated for the construction, which resulted in an increase in open area fragments in some locations. At present, the Jatigede Reservoir management is completing the necessary arrangements to start the construction of the reservoir's 110 megawatt turbines, which may contribute to the expanding bare lands in the study area in the future [55]. Many residents were required to relocate in 2015 because of the dam. It forced them to leave their agricultural land, resulting in a major decrease in paddy fields (by 495.32 ha) between 2014 and 2021. A study by [38] revealed that residents in a radius of 0–500 m from the reservoir, where rainfed rice fields were prevalent, experienced a moderate-to-high socio-economic change. Many farmers changed their livelihood to other occupations. Those among the local population who chose not to leave moved to a higher-altitude area not impacted by the construction, tilling their land to the season, resulting in an increase in upland fields in the Jatigede area by 346.97 ha between 2014 and 2021.

4.2. The Changes in LULC Effects on Aboveground Carbon Stocks

In 2014, the highest aboveground carbon stocks were identified in forests, which contributed 23.26 ton/ha of the aboveground carbon stock. Although the amount of forest cover was substantially smaller than that of other LULC classes combined, research by [27] showed that carbon storage is significantly higher in natural forests than in agricultural LULC classes. Furthermore, it has been demonstrated that sparse forests have a greater capacity than agricultural land to store carbon [56]. According to [57], there is a significant correlation between the degree of green density of plant growth, and carbon storage and sequestration. This study discovered that the greenest density is found in dense forests. However, the aboveground carbon stock in forests declined to 22.85 ton/ha in 2021. This declined aboveground carbon stock potential resulted in a higher aboveground carbon stock in mixed gardens (22.53 ton/ha) than that identified in the forest cover. In addition to the massive reduction in the forest cover from 2400.22 ha to 623.04 ha between 2014 and 2021, this prevalence is related to the nature and structure of these tree-based agricultural systems that have similarities with forests. The LULC change model identified that the forest cover was mostly converted to mixed gardens. A study by [58] found that the changing forest cover has less impact on biodiversity and ecosystem services than converting natural landscapes to agricultural or non-vegetated land uses (e.g., drylands, paddy fields, built-up areas, and bare lands).

In this study, after the LULC changes during 2014–2021, mixed gardens were found to be the largest contributor of the aboveground carbon stock. This increase was mainly due to the expansion of mixed gardens between 2014 and 2021. However, carbon stock measurements in mixed gardens may change due to the deposition of carbon during the harvesting of vegetation stands. Uncertainty may arise regarding the changes in aboveground carbon stores over time [59]. A study by [60] suggested that the carbon sequestration and stocks in many agricultural types may have been overestimated due to the possibility of offsets during harvesting. The higher carbon-storing capacity of mixed gardens compared to that of forests is attributed to the form and composition of the vegetation in this tree-based agricultural system. The findings regarding the potential of aboveground carbon stocks in mixed gardens were in line with the potential of other traditional agroforestry systems for carbon storage, which have higher values of carbon stocks and are significantly affected by the basal area of tree species [61]. A study by [62] also discovered that the carbon stocks in a small-scale agroforestry system are significantly correlated with the basal area, and the greater the tree density, the greater the carbon stocks.

Between 2009 and 2011, LULC changes resulted in the release of nearly 20,500 tons of aboveground carbon stocks. The decline in carbon stocks was mainly caused by LULC conversion from vegetated areas to agricultural and urban land cover. In the study area, a major conversion of forests to upland fields by 384.58 ha significantly depleted the aboveground carbon stocks in forests. Other studies have also revealed a decline in terrestrial carbon stocks due to LULC changes mainly attributed to the loss of vegetation cover [9,10,30,63]. The carbon storage and sequestration capacity decreased significantly over time as agricultural and urban land cover increased [64]. The decrease in the agricultural area has also significantly depleted the aboveground carbon stock potential. In the study area, the decline in the aboveground carbon stock potential in mixed gardens was considerably affected by the conversion of this vegetated agricultural land cover to reservoirs. Furthermore, in [65], the authors demonstrated that carbon stocks are significantly impacted by a shift from agricultural to urban areas. The carbon stock reduction is also related to the construction of the Jatigede Reservoir, which commenced in 2007. The research area's aboveground carbon stocks may have decreased as a result of this construction. According to LULC change data from 2014 to 2021, LULC conversion from mixed-garden and other agricultural land use classes caused a considerable expansion in bare lands and water bodies as a result of land clearing and inundation of the reservoir. The impacts of construction on terrestrial carbon stocks were also identified in [66], where the authors stated that road development has a substantial isotropic influence on carbon stocks, significantly decreasing them. This finding is also corroborated in [67], where the authors revealed that the increase in urban construction has an indirect impact on the increase in carbon emissions.

4.3. Strengths, Limitations, and Implications of This Study

In this study, information regarding the potential for carbon storage in various LULC classes may be obtained by creating a geographical distribution of aboveground carbon storage within those classes. The spatial dynamics of aboveground carbon stocks show how anthropogenic interventions, such as the expansion of constructions and agricultural management, cause aboveground carbon stocks to change over time within various LULC classes. By conducting the LULC change analysis using the maximum likelihood classification approach to the Landsat 8 satellite imagery, accurate land cover dynamics, that is, the increase or decrease in such land use classes' area because of the ongoing reservoir construction within seven years, can be comprehensively depicted in the form of an LULC map. The use of the InVEST model in this study offers a strong framework for measuring aboveground carbon stock and improving our comprehension of how changes in land use affect aboveground carbon dynamics.

Despite its strength, several limitations of this study should be acknowledged and, hopefully, can be addressed in further studies. It is necessary to conduct additional research on carbon stocks in other carbon pools, such as soil, litter, necromass, and belowground biomass. This research should make use of higher-resolution remote sensing data and increase the sample size at the plot level in order to map the dynamics of carbon sequestration and carbon stock potential in the research area across a range of land uses. There is limited access to the ongoing Jatigede hydropower blueprints and construction plans, and as the construction can be considered the main direct driver of the carbon stock dynamics at the study site, it is difficult to develop scenarios of LULC change in the future. Additionally, in order to assess regional carbon storage, this research examined the carbon stock of several LULC types based on the most active carbon pool in the terrestrial ecosystem. Because of this, it is believed that the carbon stock calculations were only estimates and further study is needed to improve the accuracy by accounting for seasonal fluctuations and conducting a local carbon estimate for each terrestrial ecosystem.

The results of this study are significant for Jatigede Subdistrict because they advance understanding about how LULC changes affect carbon stock in the region. The outcomes can help land management strategies and policies to reduce carbon emissions and protect important ecosystems. A notable finding in this research is the significant potential of tree-based agricultural systems to store carbon. Because of this, this type of agroforestry system requires suitable management techniques to increase carbon storage capacity and lower carbon emissions at the same time. Mixed gardens, a type of conservative farming practice, should be improved to support subsistence farming without compromising this agricultural landscape's ability to help mitigate climate change and sequester carbon.

5. Conclusions

This study incorporated the field measurement of aboveground carbon stocks into GIS and remote sensing methods to simulate the spatiotemporal dynamics of aboveground carbon stocks and analyze the impacts of agricultural expansion and ongoing construction on carbon stocks in Jatigede Subdistrict. The results reveal that the total aboveground carbon stocks decreased between 2014 and 2021. Spatially, the highest reduction in aboveground carbon stocks occurred in forests. The present study also further investigated the effect of land use and land cover change on the reduction in aboveground carbon stocks. The decline in the aboveground carbon stocks was mainly attributed to the land use and land cover conversion from vegetated areas to agricultural and urban land cover. In the study area, the conversion of mixed gardens as vegetated agricultural land cover to a reservoir had a significant impact on aboveground carbon stocks because mixed gardens store significant amounts of carbon. The ongoing construction, resulting in the expansion of the construction area, was also the main driver of aboveground carbon change. However, between 2014 and 2021, the increase in aboveground carbon stocks was mainly investigated in mixed gardens adjacent to forest areas. This trend made the mixed gardens the largest contributor of aboveground carbon stocks. Based on these results, in the midst of increasingly massive deforestation due to the expansion of urban areas, mixed gardens play a significant role in carbon storage and it is imperative to preserve this tree-based agroforestry system in the long term.

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