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LAND COVER AND CARBON STORAGE IN A CERTIFIED SUSTAINABLE COMMUNITY FOREST IN SUMBEREJO VILLAGE, WONOGIRI, CENTRAL JAVA, USING LANDSAT DATA SERIES 2000, 2015 AND 2020

SUMMARY

The Indonesian Ecolabel Institute certified Sumberejo Village’s 426.19 hectares of community forest as the first to receive a certificate of sustainable community forest management in 2004 for the first 15 years until 2019. Some economic, socio-cultural, and ecological aspects of this community forest management have been studied, but not the extent of land cover and the amount of carbon storage capacity. Indeed, this data is crucial in determining the role of certified community forests in climate change mitigation. Therefore, the purpose of this study is to look at the changes in land cover and the amount of carbon storage in Sumberejo Village’s community forest as a result of certification. Landsat 7 satellite images from the year 2000, Landsat 8 satellite images from 2015, and Landsat 8 satellite images from the year 2020 were used to represent the state-of-the-art community forest before, during, and the end of the certification period, respectively. Using a combination of the forest canopy density model and carbon storage conversion at the national level, we analyzed land cover classes from 2000 to 2015 and from 2015 to 2020, representing changes in the initial and final phases. The SPOT image 2020 land cover classification was then used as training data for a supervised classification-

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maximum likelihood algorithm to classify the images for 2000, 2015, and 2020. The result showed that moderately dense forest dominated the investigated area in 2000, followed by open forest and high dense forest, with 398.58 ha, 83.53 ha, and 35.53 ha, respectively. Total Carbon storage 45,230.02 tons C during this period. In 2015, moderately dense forest increased by 516.63 ha, while open forest significantly decreased by 4.73 ha as a result of tree planting activity, and high dense forest decreased by 1.69 ha as a result of harvesting. Due to public awareness of the need to manage and conserve forests through methodical harvesting, the composition of land cover, as well as carbon storage, remained unchanged in 2020. This consistent condition of carbon storage ensures that the certification has a positive impact on climate change mitigation.

Keywords: Climate change mitigation; Canopy density model; Nationally carbon conversion; Indonesian Ecolabel Institute

INTRODUCTION

After Brazil and the Congo, Indonesia's tropical forests play an important role as the world's third-largest biodiversity site. Furthermore, tropical forests in Indonesia are one of the world's climate regulators, absorbing CO_2 gas from the atmosphere through photosynthetic processes and storing it as biomass (Arianasari et al., 2021); Nurrochmat and Abdulah, 2017). The role of forests as carbon sinks and stores is critical in mitigating the effects of greenhouse gases (GHGs) that cause global warming (Windarni et al., 2018). However, primary tropical forests in Indonesia have suffered massive degradation and deforestation. Between 2001 and 2019, Indonesia's tropical forests shrank by 9.5 million hectares (Butler, 2020). Illegal logging, forest fires, mining, and the transfer of forest functions to agricultural land are all factors that contribute to forest degradation and deforestation (Askar et al., 2018; Wahyuni and Suranto, 2021). Moreover, the high rate of forest destruction as a result of deforestation and forest degradation has drawn international attention. This is due to the fact that the issue not only causes forests loss in Indonesia but it also causes in an increase in GHGs emissions, which eventually leads to the accumulation of GHGs in the atmosphere. Land use, land-use change, and forestry (LULUCF) are the primary contributors to CO_2 emissions in Indonesia (Askar et al., 2018).

During the G-20 summit in Pittsburgh, Pennsylvania, USA, the Indonesian government addressed this critical issue. At the meeting, Indonesia pledged to cut GHGs emissions by 26% on its own, or 41% with international assistance, by 2020 (Bappenas, 2011). One of the Indonesian government's efforts to reduce GHGs is the issuance of Presidential Regulation No. 61 of 2011, which establishes a national action plan to reduce GHGs emissions in Indonesia. The regulation's action plan includes forest and land fire control, network and water systems management, forest and land rehabilitation, industrial crop forest development, private forest development, eradication of illegal logging, deforestation prevention, and community empowerment

(Arupa, 2014). One of the national action plans expected to play a significant role in reducing GHGs emissions is the development of private forests. A private forest, according to the Indonesian Ministry of Environment and Forestry, is defined as a forest that grows on land subject to property and other rights, has a minimum area of 0.25 ha, and is more than 50% devoid of timber crops and other plants (Fujiwara et al., 2018; Hardjanto and Patabang, 2019; Kurniawan et al., 2020). Additionally, experts in some related literature define private forests as forests that grow on property-rights-protected land and are composed of woody trees grown monoculture or in mixed stands, both self-planted and with government assistance (Kurniawan et al., 2020).

Private forests are one type of community involvement that helps to mitigate climate change by absorbing and storing CO_2 in crops. According to Askar et al. (2018); Ivando et al. (2019), private forests can be relied on to reduce GHGs emissions due to their ability to absorb and store CO_2. However, one of the major challenges in maximizing the role of private forests is ensuring the sustainability of private forest management (Kurniawan et al., 2020). Therefore, a mechanism capable of overcoming the sustainability issues associated with private forest management in Indonesia is required. The sustainable community-based forest management (SCBFM) certification program is one mechanism that is expected to be able to address these issues (Mindawati et al., 2006).

This certification program has successfully increased awareness, knowledge, and recognition of the concept of forest management, including private forests, by meeting three aspects of sustainable development: economic, social, and ecological aspects (Rametsteiner and Simula, 2003; Yuwono, 2008). In 2004, the Indonesian Ecolabel Institute (LEI) certified the 426.19 hectares of community forest in Sumberejo Village, Wonogiri Subdistrict, as the first private forest to have received a certificate of sustainable community forest management (Yuwono, 2008). Several studies have themes related to sustainable community forest management in Sumberejo Village, including people's perception of the SCBFM program (Yuwono, 2008), private forest management performance (Anen, 2017), the history of development and acquisition of private forest ecolabel certification (Purwanto, 2015), gender-based private forest management (Kunretno, 2013), farmers' local wisdom in rehabilitating critical land in Sumberejo Village (Ekawati, 2006), financial analysis of private forest farming on several broad strata of land ownership in Sumberejo Village (Jariyah et al., 2003), and contribution of private forests to farmers' household income and village economy (Ichwandi et al., 2007).

Those researches have been only discussed private forest management in terms of economic, socio-cultural, and ecological in general, with no studies on the extent of land cover and the amount of carbon stored as one of the roles of certified sustainable community forest in Sumberejo Village in climate change mitigation. Factually, data on the extent of land cover and the amount of carbon stored before and after the certification program is critical for determining how important private forests' roles in mitigating climate change are. This study aims to examine the state of land cover and the amount of carbon stored in private forests before and after certification in Sumberejo Village. This evidence is important as the foundation for continuing the community forest certification program. Furthermore, the finding is expected to be taken into account by stakeholders, especially the central government (The Ministry of Environment and Forestry) and local governments (Wonogiri Regency Regional Government and Central Java Provincial Government), when developing policies to reduce GHGs emissions in the context of climate change mitigation.

MATERIAL AND METHODS

Study area

Sumberejo Village, Batuwarno Subdistrict, Wonogiri District, Central Java Province was the site of this study (Figure 1). The research site was selected with purpose, with private forests in Sumberejo Village being the first private forest in Indonesia to receive sustainable community-based forest management certification from LEI in 2004. This village has a land area of 546 ha and is located between 7°32' and 8°15' South Latitude and from 110°41' to 111°18' East Longitude. This area has an elevation of about 274 meters above sea level and is mostly mountainous with a fairly steep land slope (> 40%), with 55 percent of the land being choppy to hilly and 15 percent flat to choppy.

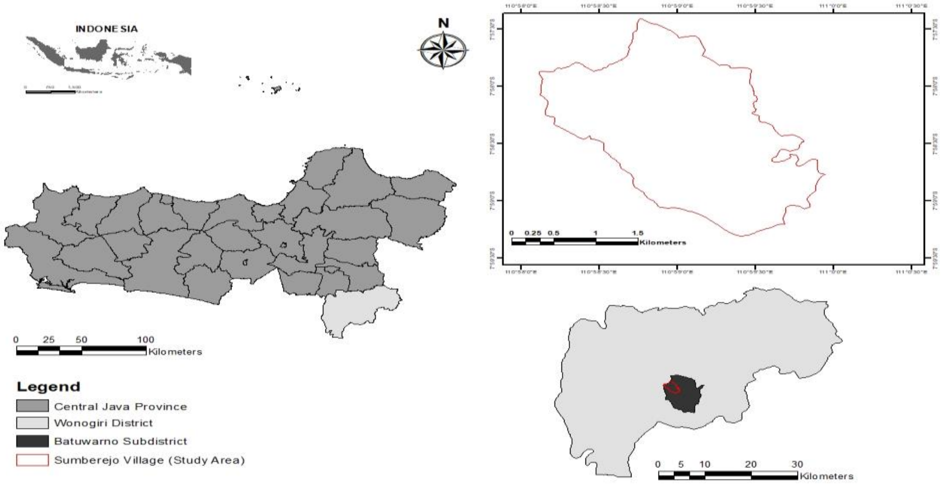


Figure 1. The study area is in Sumberejo Village, Batuwarno Subdistrict, Wonogiri Regency, Central Java Province, Indonesia

Geographical conditions and geological structures with layered/folded limestone have created the impression that this area is earthy rock. The topography is undulating and hilly, with layered limestone dominating the soil structure. In addition, this area is dominated by the association of a soil type of

Mediterranean acid brown lithosol made from a parent of medier tufvolcan with volcanic physiography and hill folds. Furthermore, the solum soil is very thin, with only a small amount of soil visible on the rock's sidelines. Sumberejo Village has a dry climate, with an average annual rainfall of 2,108 mm and 160 rainy days per year. Drought is frequently caused in this area by the uneven distribution of rain and low rainfall.

Data collection and image pre-processing

Satellite imageries from the multi-temporal Landsat 7 (ETM) year 2020 and Landsat 8 (OLI) year 2015 and 2000 were downloaded from the United States Geological Survey (USGS) - Earth Explorer website. Each image used in this study was chosen with the base overcast cover, high deception of the scene, highest satellite picture quality, and accessibility in mind (Emran et al., 2016). Other data used include the Sumberejo Village vector boundary, SPOT images for 2020, and Google Earth images from 2021 (Table 1).

Table 1. The data collected, the date of acquisition, and the sources

Data	Acquisition Date	Sources
Landsat 8, Path/Row 119/65, spatial resolution 30 m	23/08/2020	USGS[1]
Landsat 8, Path/Row 119/65, spatial resolution 30 m	25/07/2015	USGS[1]
Landsat 7, Path/Row 119/65, spatial resolution 30 m	09/09/2000	USGS[1]
Google Earth Image	2021	Google Earth
SPOT Image	2020	LAPAN[2]
Sumberejo Village Boundary	2021	BIG[3]

[1]USGS= United States Geological Survey, [2]LAPAN= Lembaga Antariksa dan Penerbangan Nasional / National Aeronautics and Space Administration, [3]BIG = Badan Informasi Geospasial / Geospatial Information Agency.

All satellite images are USGS L1T results automatically referred to and geometrically corrected to the World Geodetic System (WGS84) datum (Storey et al., 2014). The images are projected in GeoTiff format using the Universal Transverse Mercator framework (zone UTM 49 South). Then, as suggested by Young et al. (2017), radiometric corrections are made using the open-source software Quantum GIS (QGIS) to reduce atmospheric effects that may interfere with data processing. Every one of the seven groups of Landsat images was converted to BIL format before being processed by the FCD Mapper Ver.2 program, with supports from CEOS, TIFF/GEO TIFF, and BMP or BSQ/BIL format. Landsat images can be reprocessed to reduce commotion, for example, atmospheric, water, cloud, cloud shadow, and slope shadow impacts using the pass 1 and 2 steps on Forest Canopy Density (FCD) Ver.2 as proposed by Rikimaru et al. (2002). We can distinguish and exclude the appearance of water, cloud, cloud shadow, slope shadow, and atmospheric effects such as haze and cloud-free mosaic in satellite images by using noise-reduction normalization in

FCD Mapper Ver.2. Finally, we limit the coverage of satellite imagery to Sumberejo Village's vector boundaries.

Land cover classification, land cover changes, and carbon stock analysis

In terms of land cover classification, we used the National Standardization Agency's (Badan Sandardisasi Nasional, BSN) land cover change order framework: SNI-Standard Nasional Indonesia No. 7645-2010. Therefore, we divided the land cover class into four classes based on FCD Mapper Ver. 2, namely non-forest (<10%), open forest (10–40%), moderately dense forest (40–70%), and dense forest (>70%). In addition, this study focuses on two critical issues: deforestation and degradation. Deforestation is defined as a change in land cover from forest to non-forest and open forest, whereas degradation is defined as a change from dense forest to moderately dense forest. We use the method developed by Garai et al. (2018) to calculate the percentage of LULCC using the following formula (Equation 1):

$$CP = \frac{*PLULCA - PLULCA}{PLULCA} \text{x} 100\ \% \quad [1]$$

Where:
CP = Change in percentage (%)
*PLULCA = Present Land Use and Land Changes Area
PLULCA = Previous Land Use and Land Changes Area

Moreover, we recognized land use and determined the spaces of each land cover class, and the absolute carbon stock of each land cover class could be assessed using the carbon stock change approach for the national scale of the corresponding land cover class (Tosiani, 2015). In addition, Table 2 depicts the FCD classification at the national level based on land cover class, identified land use, and carbon storage used in this study.

Table 2. Forest canopy density classification based on land cover class, identified land use and carbon storage at the national level

Forest Canopy Density	Land Cover Class	Identified Land Use	Carbon storage (Ton of Carbon ha^{-1})
<10%	Non – forest	Open land	2.5
10 – 40%	Open forest	Mixed dry land agriculture	30.00
40 – 70%	Moderately dense forest	Plantation forest	98.38
>70%	High dense forest	Secondary forest	98.84

Sources: Rikimaru et al. (2002); Sadono et al. (2020); Tosiani (2015).

FCD Mapper Ver.2 was used to analyze tree canopy density in forested land to simplify the land cover classification process. According to Rikimaru et al. (2002), the condition of forest vegetation is assessed based on canopy density. Using this methodology, FCD Mapper Ver.2 computed four records, namely the

Advanced Vegetation Index (AVI), Bare Soil Index (BI), Shadow Index (SI), and Thermal Index (TI). We created an FCD map for 2000, 2015, and 2020 using FCD Mapper Ver.2, which communicated in rate for each pixel. Table 3 shows the important equations and calculations used by the FCD model for the records. All lists and FCD were determined using FCD Mapper Ver.2 programming.

Table 3**.** Formulas and algorithms used to calculate indices in Forest Canopy Density Mapper

Index		Formula or Algorithm
VI		
	NDVI	= (NIR – Red/NIR + Red)
	AVI	= $[NIR \times (256\text{-}Red) \times (NIR - Red) + 1]^{1/3}$, $(NIR - Red)>0$
	ANVI	= This index is derived from NDVI and AVI by PCA
BI		= [(SWIR1 + Red) – (Blue + NIR) / (SWIR1 + Red) + (Blue + NIR)] × 100 + 100
SI		= $[(256 - Blue) \times (256 - Green) \times (256 - Red)]^{1/3}$
TI		= This index is calibrated from the thermal data band
FD		= This index is calculated from the first principal component of VI and BI
SSI		= This index is calibrated for the forested land
FCD		= $(VD \times SSI + 1)^{1/2} - 1$

Note: Landsat bands: Visible bands = Blue, Green, Red; NIR = Near Infrared; SWIR = Shortwave Infrared Indices: VI = Vegetation Index; NDVI = Normalize Difference Vegetation Index; AVI = Advance Vegetation Index; ANVI = Advanced Normalize Vegetation Index; BI = Bare Soil Index; TI = Thermal Index; VD = Vegetation Density; SSI = Scaled Shadow Index; FCD = Forest Canopy Density.
Sources: Mon et al. (2012); Pujiono et al. (2019); Rikimaru et al. (2002).

Later, the training data was compiled from the results of the land cover classification analysis using FCD Mapper Ver.2 and SPOT Images. We used a supervised classification-maximum likelihood classification (MLC) algorithm to classify images for years 2000, 2015, and 2020 based on the training data. To reduce the salt and pepper effect caused by spectral effects variability, post-classification smoothing was performed using a 3 x 3 m – pixel majority filter. Finally, image classification was converted to vector format in order to make measuring the area of each type of land cover classification easier.

Accuracy assessment

The accuracy was determined by comparing each QGIS land cover classification result with Google satellite imagery, previously geotagged data, socio-economic and boundary surveys. If the reference data is incorrect, the assessment findings show that many errors occur during the land cover classification procedure (Negassa et al., 2020). Producer accuracy, as defined in Equation 2, is map correctness from the map maker's perspective (the producer). This is the method by which genuine elements on the ground are frequently accurately displayed on the planned guide or the possibility that a specific land front of space on the ground is named. It is also the number of reference locations precisely separated by the total number of reference locations for that class.

$$PA = \frac{TPC}{TPCR} \quad [2]$$

Where:
PA = Producer Accuracy
TPC = Total number of pixels in classification
TPCR = Total number of pixels in classification from reference data (i.e., total row)

The precision from a user's point of view, as shown in Equation 3, is referred to as user accuracy. The User accuracy essentially tells us to know how frequently the class on the map will be available on the ground. In addition, the commission error is supplemented by the user accuracy, with user accuracy equaling 100% commission error. The user accuracy is determined by dividing the total number of correct classifications for a given class by the total number of rows.

$$UA = \frac{TPC}{TPCR} \quad [3]$$

Where:
UA = User Accuracy
TPC = Total number of pixels in classification
TPCR = Total number of pixels in classification from reference data (i.e., total column)

Furthermore, Equation 4 demonstrates how overall accuracy was used to compute a precision proportion for the entire image across all classes present in the characterized image. Overall accuracy, which determines the extent of pixels accurately ordered, can be used to depict the aggregate accuracy of the map for all the classes.

$$OA = \frac{SDE}{TAP} \quad [4]$$

Where:
OA = Overall Accuracy
SDE = Sum of diagonal elements
TAP = Total number of accuracy sites pixels (total column)

The kappa statistics value represents a percentage of the arrangement of classification and reference data (Mishra et al., 2020; Wang et al., 2012). Cohen (1968) classified kappa values were divided into six categories, ranging from 0 to 1: 0 denoted a low probability of correctness. There was a slight chance of accuracy between 0.10 and 0.20, a fair chance of accuracy between 0.21 and 0.40, a moderate chance of accuracy between 0.41 and 0.60, a substantial chance of accuracy between 0.61 and 0.80, and a nearly perfect chance of accuracy between 0.81 and 0.99. A Kappa accuracy value of 50 % to 90% is regarded as adequate (RSPO, 2017). A value of more than 0.6 Kappa coefficients is considered excellent precision. A Kappa coefficient greater than 0.6 indicates that the translation result is precise enough for remote sensing and that no reevaluation is necessary. The flowchart in Figure 2 summarizes the methods used to assess changes in forest cover and carbon storage.

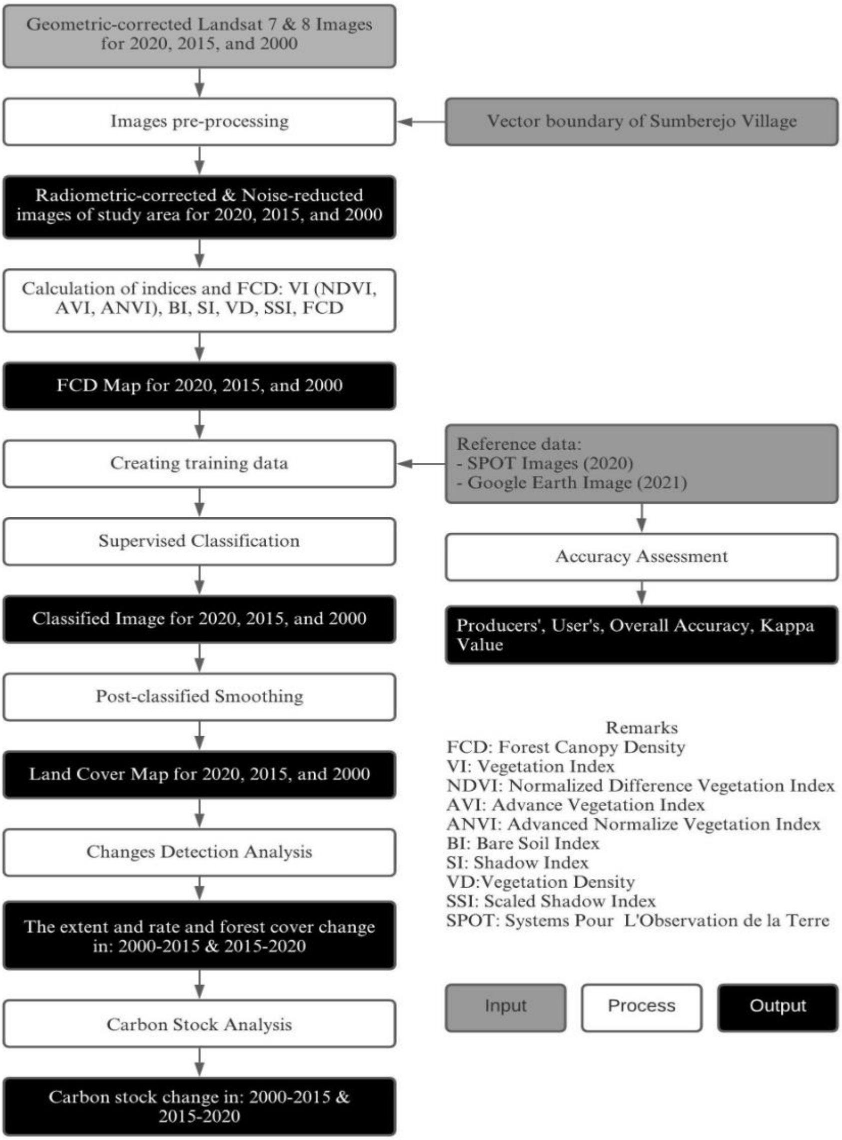


Figure 2. Flowchart of the method used to assess changes in forest cover and carbon storage in Sumberejo Village's community forest

RESULTS AND DISCUSSION

Land cover and changes for the years 2000, 2015 and 2020

Based on the obtained forest land cover, the majority of the areas (77%) consisted of moderately dense forests in 2000, with sporadic open forest areas in some places. Interestingly, this year, there are still many high dense forests, despite accounting for only about 7% of the total forest area (Figure 3). From 2000 to 2015, the open forest category decreased by 78.80 ha (94.34%) from 83.53 ha to 4.73 ha, and the high dense forest decreased by 33.84 ha (95.24 %) from 35.53 ha to 1.69 ha. In contrast, the area of moderately dense forest increased by 118.05 ha (29.62 %) from 398.58 ha to 516.63 ha. The decline in open forest area between 2000 and 2015 was most likely caused by regional tree planting, as well as an increase in forest stand density over time, transforming the open forest category into a moderately thick forest category. The opposite situation occurred in the high dense forest category, with the area of this category decreasing by 95.24 % between 2000 and 2015 due to a high level of tree harvesting activity in the high dense forest category by the community, resulting in the high dense forest transforming from a high dense forest to moderately dense forest (Figure 4).

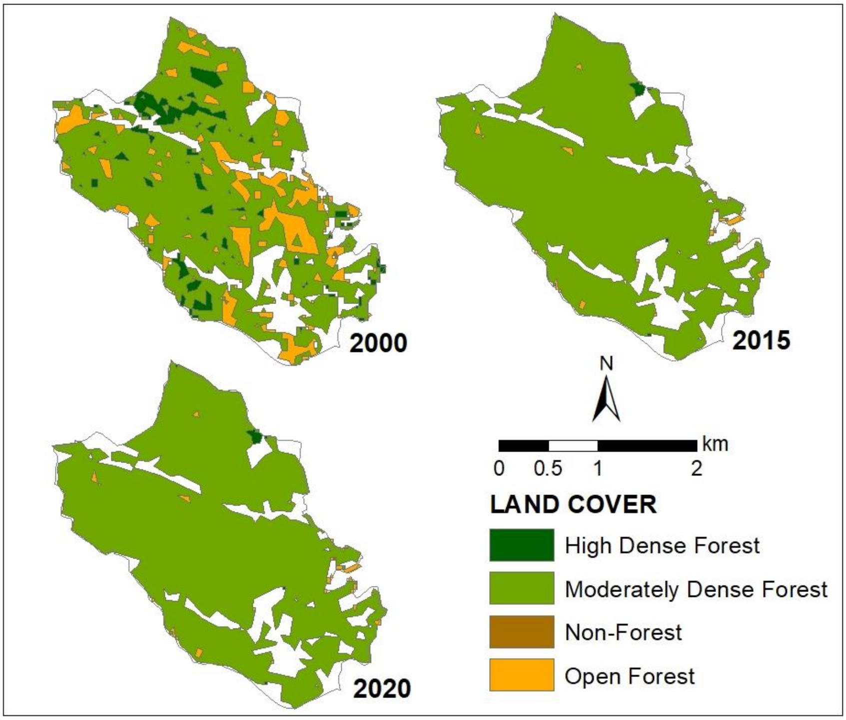


Figure 3. Changes in land cover in the investigated area of Sumberejo Village's community forest from the years 2000 on the left, 2015 on the middle, and 2020 on the right

In 2015, the condition of the forest changed over time. This year, the Sumberejo Village community forest is more dominated by moderately dense forest, accounting for 99% of the total area. This condition shows that after certification, forest density in Sumberejo Village community forest tends to be uniform. It is because there is a possibility that the community will harvest and replant the forest at the same time. There are several places in the form of open forest and high dense forest with a fairly small area, which may be influenced by the level of community need to sell wood.

In the meantime, except for non-forest classes, there was no change in forest land cover categories between 2015 and 2020. This situation arose as a result of public awareness of the importance of maintaining and preserving forest stands through planned harvesting in order to avoid changing the forest land cover category. Meanwhile, the shift in the non-forest class was caused by the non-forest class's tree planting.

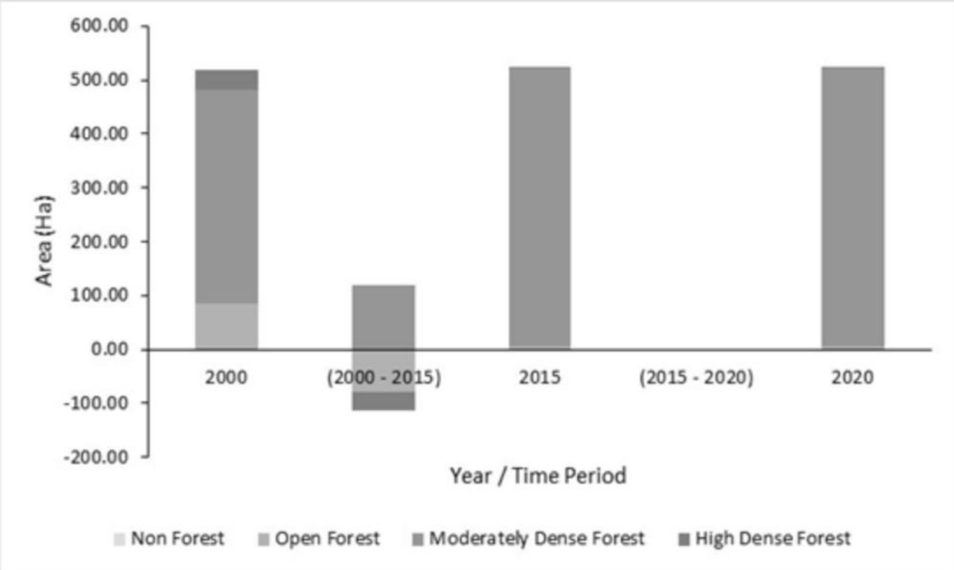


Figure 4. Stacked histogram of land cover and its changes in the investigated area of Sumberejo Village's community forest for the periods of 2000–2015 and 2015–2020

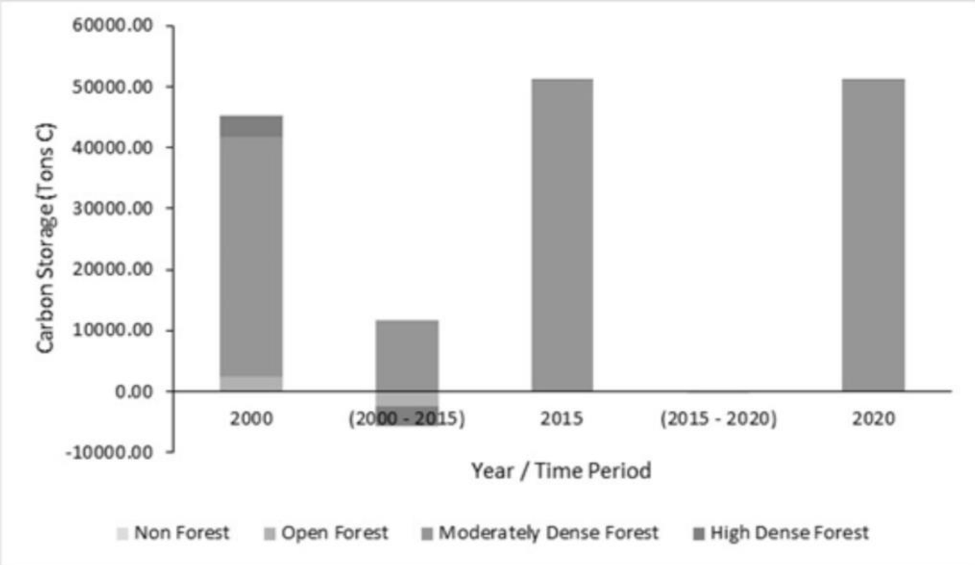
Carbon storage and changes for the years 2000, 2015, and 2020

Table 4 and Figure 5 show the carbon storage levels for the years 2000, 2015, and 2020, with the amount of carbon storage stated in Tons C. The highest quantity of carbon storage in 2000 was found in moderately dense forest (39212.09), followed by high dense forest (3511.41) and open forest (2505.98). Moreover, the activities of forest certification started in 2004 caused the increase of moderately dense forest, about 11614.21 tons, and decreased was occurred in dense forest -3344.29 followed by open forest -2364.49 and non-forest -0.09 for the year of 2000-2015. In line with that, the moderated dense forest 50826.30 was increased and followed by high dense forest 167.12, open forest 141.98, and non-forest 0.45 in 2015. During the 2015-2020 period, the carbon storage of non-forest was decreased 0.23 ton, and the carbon storage quantity remained the same for the rest of the forest types. In 2020, the carbon storage status of all forests except the non-forest remained the same. However, the amount of carbon stored in non-forest areas was reduced and is now 0.23 tons.

Table 4. Carbon storage and changes in the investigated area of Sumberejo Village's community forest for the years 2000, 2015, and 2020

Land Cover Classes	Carbon stock (Tons C)		
	2000	2015	2020
Non-Forest	0.54	0.45	0.23
Open Forest	2,505.98	141.89	141.89
Moderately Dense Forest	39,212.09	50,826.30	50,826.30
High Dense Forest	3,511.41	167.12	167.12

Figure 5. Stacked histogram of carbon storage and its changes in the investigated area of Sumberejo Village's community forest for the time periods of 2000–2015 and 2015–2020



The certified sustainable community forest in Sumberejo village exhibits highly effective in the growth of carbon storage. Therefore, forest certification operations have a positive impact on the enhancement of forest carbon storage (Bettinger et al., 2017). The Sumberejo Village community forest, particularly the open forest space, has shrunk as a result of the locals collectively began planting more trees, resulting in a more fairly wooded forest region. Planting more trees, also known as afforestation and reforestation, could help to increase live-tree carbon storage in forests and carbon buildup in soils, as well as expand forestland and provide a variety of ecological services (Domke et al., 2020). In this case, increasing carbon storage was extremely beneficial in reducing carbon emissions, which caused climate change (Effendi, 2012). In the previous study conducted by Ulumuddin et al. (2005), developing countries received investment funding from industrialized countries to support programs that would reduce emissions, such as forestry projects that included activities to promote atmospheric carbon absorption. These activities were mostly carried out by expanding forest areas or preventing deforestation.

Furthermore, as the findings of this study showed, forest certification had primarily positive effects on the environment and society. However, Girolami and Arts (2018) found that certified harvest had a detrimental effect on biomass and tree carbon storage. When compared to pre-harvest reconstructed conditions, biomass was decreased by one-third, lowering potential commercial carbon storage values by 25-30%. In addition, Blackman et al. (2015) reported that Forest Stewardship Council (FSC) certification had a negative impact when compared to pre-harvest reconstructed stands, but not when compared to non-certified stands; hence the negative impact was moderate, which was only -0.50. Moreover, the forest certification in the private forest in Sumberejo village might have gained the same contribution as the previous study. In comparison to non-certified areas, FSC certification did not lower carbon emissions from logging activities. In line with that, another study revealed that FSC had no statistically meaningful impact on deforestation rates in forest management units in Mexico. The threshold of influence was set at 0 for this inquiry (Blackman et al., 2015).

CONCLUSIONS

Forest land-use changes in forest land use, such as forest degradation and deforestation, are significant contributors to carbon emissions and climate change. As a result, improving and maintaining forest land cover not only helps to mitigate the effects of global warming and climate change but also helps to improve societal and environmental services. Furthermore, obtaining forest certification is the most important thing to emphasize to improve forest land cover.

The amount of carbon stored in community forest woods in Sumberejo Village increased significantly between before and after certification. Between 2000 and 2015, land cover shifted from open forest and extremely thick forest cover classes to moderately dense forest cover classes, most likely as a result of increased forest density. Meanwhile, due to public awareness of the need to manage and conserve forests through methodical harvesting, there was no change in forest cover from 2015 to 2020. Changes in forest land cover had an impact on carbon storage in Sumberejo Village community forest woods, as predicted by forest land cover results.

To summarize, it is strongly recommended that additional private woods be certified in order to combat and mitigate the effects of global warming and climate change, as the residents have performed at the study site in a certified community forest of Sumberejo Village, which would increase the area's production and improve land cover. Forest certification has the potential to increase carbon absorption while also having a significant positive impact on climate change mitigation.

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