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# Effect of biophysical conditions on standing and soil carbon storage in various land uses in Gunung Mas, Central Kalimantan, Indonesia

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**Abstract.** *Lindiani P, Sundawati L, Suwarna U. 2023. Effect of biophysical conditions on standing and soil carbon storage in various land uses in Gunung Mas, Central Kalimantan, Indonesia. Biodiversitas 24: 4493-4502.* One of the human activities that accelerates climate change is degradation and deforestation, which can lead to new land use in the form of palm oil plantations and agroforestry. Both of these land uses have the potential to store carbon, which can be optimized if the influencing factors are known. This study aims to estimate the potential for carbon storage in palm oil and agroforestry plantations in Gunung Mas, Central Kalimantan, Indonesia, and to analyze the effect of biophysical conditions such as topography, soil fertility, and stand density on the potential for carbon storage. The research was conducted in palm oil plantations (POP) and agroforestry areas categorized as agroforestry with forestry and palm oil plantation commodities (AG-SS), as well as agroforestry consisting of forestry, palm oil, and fruit crops (AG-SSB). Sample plots were determined through purposive sampling with 30 plots for each land use. The research results show significant differences in aboveground carbon (AGC), soil organic carbon (SOC), and total carbon storage among the three land uses. The largest total AGC was in AG-SS (66.24 ton.ha$^{-1}$), while the lowest AGC was observed in POP (48.15 ton.ha$^{-1}$). The greatest SOC was recorded in AG-SSB (2163.21 ton. ha$^{-1}$), followed by POP (1922.12 ton.ha$^{-1}$) and AG-SS (1846.72 ton.ha$^{-1}$). The highest total carbon storage was measured in AG-SSB (2223.36 ton.ha$^{-1}$), followed by POP (1970.27 ton.ha$^{-1}$), and the lowest in AG-SS (1912.96 ton.ha$^{-1}$). Biophysical factors, including topography, soil fertility, and stand density, influenced carbon storage in each land use. Topography and stand density factors significantly influenced AGC, while soil fertility factors significantly affected SOC and total carbon storage in all three land uses.

**Keywords:** Aboveground carbon, agroforestry, palm oil plantation, SEM-PLS soil organic carbon

## INTRODUCTION

The Intergovernmental Panel on Climate Change, or IPCC (2021), states that the average temperature of the Earth's surface has increased by 1.5°C in two decades. Increasing air temperature is one of the critical characteristics of climate change. One of the human activities that accelerates climate change is degradation and deforestation, which leads to increased carbon emissions in the atmosphere. According to Houghton et al. (2012), carbon emissions from deforestation account for 20%-26% of total carbon emissions. Moreover, degradation and deforestation are the causes of the reduced forests carbon storage. This is supported by the study of Suberi et al. (2018), which indicates that the total carbon storage in harvested forests is 41.55% less than in unharvested forests.

Degradation and deforestation activities have taken place in Indonesia. The data from the Ministry of Environment and Forestry (2018) shows that the area of deforestation in Indonesia during 2017-2018 reached 439,439 ha. Pervasive deforestation involves converting forests into agricultural land, especially palm oil plantations. Wicke et al. (2011) stated that the forest area converted to palm oil plantations in Indonesia from 1975-2005 increased by 5,400,000 ha. Apart from palm oil plantations, forest conversion to agricultural land has led to a new land use termed agroforestry, which involves combining forestry crops with agricultural crops, plantations, and livestock (Wulandari et al. 2019).

One of the regions facing degradation and deforestation challenges in Indonesia is Gunung Mas, Central Kalimantan, Indonesia, which has a considerable forest area and the potential for carbon storage. However, this potential becomes threatened by the rise of the forest to palm oil plantation conversion. The introduction of palm oil commodities has prompted land use changes, transforming what were once rubber forests into agroforestry lands that incorporate forestry commodities such as rubber or *Sengon*, along with palm oil and fruit crops. Such land use alternations inevitably impact the carbon stored in Gunung Mas. According to Besar et al. (2020), palm oil plantations and agroforestry lands have smaller carbon storage potential than primary or secondary forests.

While palm oil plantations and agroforestry lands exhibit lower potential for carbon storage than primary or secondary forests, these two land uses possess distinct carbon storage capacities. This variation in potential arises due to the spatial distribution of these land uses, leading to differences in biophysical conditions. Furthermore, carbon storage potential is influenced by various factors, such as topography encompassing elevation and slope, stand density, stand age, composition, and vegetation structure (Oliver and Morecroft 2014; Bayat et al. 2021; Shiferaw et al. 2022; Sukartono et al. 2023). Another contributing factor to carbon storage potential is soil fertility. As van der Sande et al. (2018) noted, enhanced soil fertility can elevate productivity and biomass stocks, impacting above and below-ground carbon stores.

Research addressing the factors influencing carbon storage is imperative to optimize carbon potential by understanding these effects. Several studies, such as those by Sattler et al. (2014), Sun et al. (2015), and Nero and Opoku (2022), underscore the significant influence of topography on carbon storage. Sang et al. (2013) and van der Sande et al. (2018) have explored the pronounced impact of soil fertility, particularly soil, organic carbon on carbon storage. Additionally, some studies discuss the effect of stand density on carbon storage (Teshome et al. 2020; Joshi et al. 2021; Darmawan et al. 2022). However, despite existing research, a dearth of studies concurrently elucidate the impact of the three factors on carbon storage, particularly within palm oil plantations and agroforestry in Gunung Mas, Central Kalimantan. Hence, this study aims to: (i) estimate carbon storage potential in palm oil plantations and agroforestry within Gunung Mas, Central Kalimantan, and (ii) analyze the effects of biophysical conditions encompassing topography (altitude and slope), soil fertility, and stand density on carbon storage potential.

## MATERIALS AND METHODS

### Study area

The study was carried out in Gunung Mas District, Central Kalimantan Province, Indonesia (Figure 1). The topography of Gunung Mas comprises lowlands to the south and hills to the north, with slopes ranging from 8-15°. The climate of Gunung Mas is tropical, characterized by temperatures ranging between 27-28°C. Gunung Mas District comprises 12 sub-districts, with the study explicitly conducted in Manuhing (1°21′44.28″S, 113°22′42.6″E) and Rungan Barat (1°14′9.6″S, 113°15′46.8″E) subdistricts.

Land use patterns within these sub-districts encompass both forested and non-forested areas. Agricultural crops, including palm oil plantations, predominantly occupy non-forested land areas. Some portions of these lands are allocated for fruit cultivation as supplementary crops. It is a common practice for individuals to integrate forestry crops with agriculture through agroforestry systems. This research was conducted within community-owned Palm Oil Plantations (POP) and agroforestry lands. Agroforestry is further divided into agroforestry with forestry and palm oil commodities (AG-SS) and mixed agroforestry involving forestry, palm oil, and fruit crops (AG-SSB).

### Procedures

The data employed encompass both primary and secondary sources. Primary data was obtained through field measurements and direct observations, while secondary data was collected through literature reviews from diverse sources. Estimating Aboveground Carbon Storage (AGC) involves calculating the biomass of trees, poles, saplings, understorey, and litter. Additionally, Soil Organic Carbon storage (SOC) was determined using soil C-organic data and bulk density.

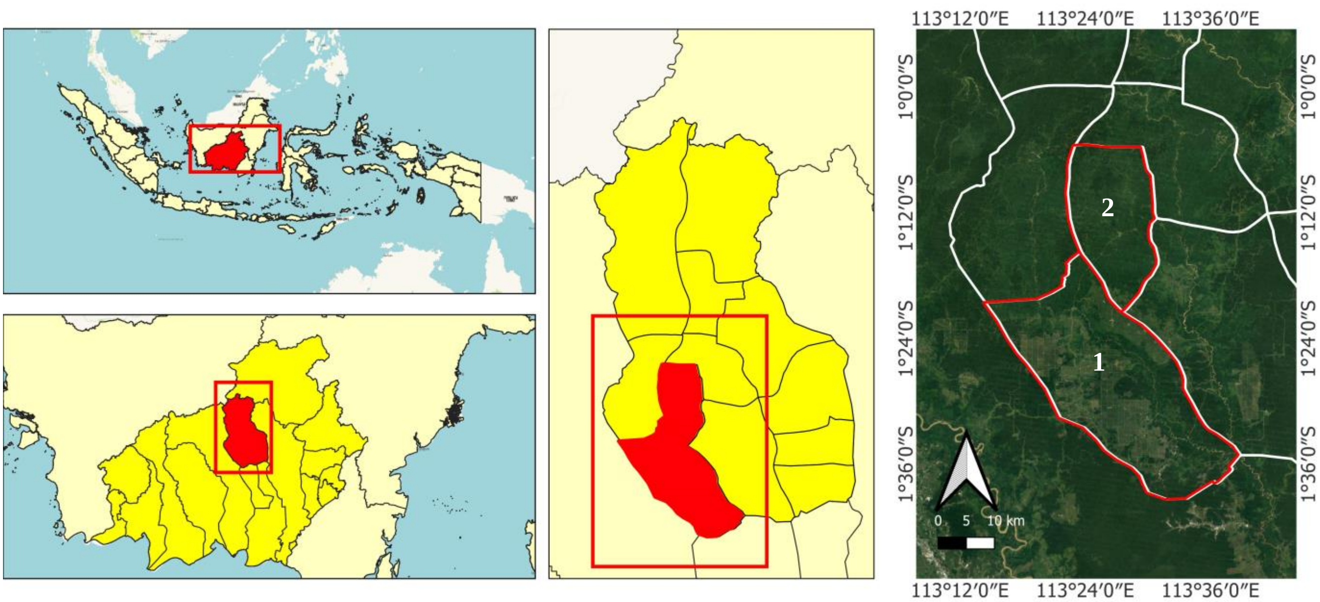


**Figure 1.** The research locations are in Manuhing (1) and Rungan Barat (2) subdistricts, Gunung Mas, District, Central Kalimantan Province, Indonesia

*Plot sample*

Sample plots were selected through purposive sampling, considering criteria like land use type, plant commodities present, and accessibility to the location. Each land use type had 30 sample plots. For AG-SS and AG-SSB, the plot shape adhered to SNI 7724:2011 standards, comprising a square plot with dimensions of 2 × 2 $m^2$ (understorey and litter), 5 × 5 $m^2$ (stakes), 10 × 10 $m^2$ (poles), and 20 × 20 $m^2$ (trees). POP plots were circular, with a 0.04 ha area and 11.29 m radius (BSN 2011).

*Aboveground biomass measurement*

Biomass measurement was conducted using both destructive and non-destructive methods. The destructive method involved cutting all aboveground plant parts. The understorey and litter from the sample plots were weighed to determine their total weight. A 100 g sample was taken from each understorey and litter collection, then dried in an oven at 85°C until a constant dry weight was attained. The biomass of understorey and litter was calculated using the following equation (BSN 2011):

$$Biomass\ (kg) = \frac{Dry\ weight\ of\ the\ example\ (kg)}{Wet\ weight\ of\ the\ example\ (kg)} \times Total\ wet\ weight\ (kg)$$

The non-destructive approach entailed measuring the diameter at breast height (DBH) 1.3 m above the ground using a tape measure and tree height measured through a laser range finder. The obtained diameter and height values were put into the allometric equation to estimate the biomass (Table 1).

*AGC estimation*

The acquired biomass data was subsequently applied to the following equations (BSN 2011):

$$Carbon\ storages\ (kg) = \sum biomass\ (kg) \times 0.47$$

$$Carbon\ storages\ (ton.ha^{-1}) = \frac{Carbon\ storages\ (kg)}{1000} \times \frac{1000}{Plot\ area\ (m^2)}$$

*SOC estimation*

Soil sampling involved the utilization of both disturbed and undisturbed methods. The undisturbed method employed ring samples, while the disturbed method utilized a composite approach by collecting 250 g from two different points within each sample plot. These samples were subsequently analyzed in the laboratory to ascertain their physical and chemical properties. The results of this testing, particularly C-organic and bulk density, were used to estimate carbon storage by using the following equation (BSN 2011):

$$SOC = SDt \times BDt \times COt$$

Where:

SOC : Represents soil organic carbon ($g.cm^{-2}$)

SDt : Stand for soil depth (cm), BDt indicates bulk density ($g.cm^{-3}$),

COt : Represents C-organic content (%).

The outcomes of carbon storage were subsequently converted into ($ton.ha^{-1}$) using the following equation (BSN 2011):

$$SOC\ (ton.ha^{-1}) = SOC\ (g.cm^{-2}) \times 100$$

*Data on the measurement of land biophysical conditions*

Apart from carbon storage estimation, measurements were conducted on each sample plot to assess the biophysical characteristic of the land encompassing topography (elevation and slope), soil fertility (including C-organic content, total N-content, soil pH, and bulk density), and stand density. Soil fertility data were collected simultaneously with soil carbon sampling, whereas stand density was determined using the following equation (Rahman et al. 2018):

$$Stand\ density\ (individuals.ha^{-1}) = \frac{\sum vegetation\ in\ a\ plot}{plot\ area\ (ha)}$$

**Data analysis**

The data collected through field measurements and observations were subsequently subjected to Kruskal Wallis analysis to ascertain whether there were discrepancies in the amount of carbon stored across each land use. In cases where distinctions were identified, the Mann-Whitney test was employed. Furthermore, Structural Equation Modeling (SEM) using Partial Least Squares (PLS) analysis was executed to establish the credibility and consistency of factors influencing carbon storage. The software tools utilized for data analysis were IBM SPSS Statistics 25 and Smart PLS.

**Table 1.** Allometric equations for estimating biomass

| Stand type | Allometric equation models | Source |
|---|---|---|
| *Paraserianthes falcataria* (L.) I.C.Nielsen | $W = 0{,}2831\ D^{2{,}0630}$ | Siregar (2007) |
| *Musa* spp. | $W = 0{,}030\ D^{2{,}13}$ | Krisnawati et al. (2012) |
| *Eleaeis guineensis* Jacq. with high fronds > 1,3 m | $W = 0.003\ D^{2{,}761}$ | Muhdi et al. (2015) |
| *Eleaeis guineensis* Jacq. with high fronds < 1,3 m | $W = 0{,}0976\ H + 0{,}0706$ | Hairiah et al. (2011) |
| *Hevea brasiliensis* (Willd. ex A.Juss.) Müll.Arg. | $W = 0{,}0124\ D^{2{,}444}$ | Krisnawati et al. (2012) |
| *Shorea parvifolia* Dyer | $W = 0{,}09\ D^{2{,}58}$ | Krisnawati et al. (2012) |
| Arecaceae species | $W = \exp(-2{,}134 + 2{,}530 \ln(D))$ | Brown (1997) |
| Brached plants | $W = 0{,}11\rho(D)^{2{,}62}$ | Ketterings et al. (2001) |
| Unbrached plants | $W = \pi\rho D^2H/40$ | Hairiah et al. (2011) |

Note: W: Biomass ($kg.tree^{-1}$); D: DBH (cm); H: total tree height (cm); ρ: plant-specific gravity ($g.cm^{-3}$)

## RESULTS AND DISCUSSION

### Land biophysical conditions

The biophysical conditions investigated within this study encompassed stand density, topographical conditions, and soil fertility. Among these, the highest stand density was observed in AG-SS (445 individuals.ha$^{-1}$), while POP (274 individuals.ha-1) recorded the lowest stand density. The results indicate significant disparities in stand density in POP, AG-SS, and AG-SSB (P=0.00). Specifically, the stand density in POP significantly differed from AG-SS and AG-SSB (P=0.00), whereas the stand density in AG-SS and AG-SSB displayed no significant variance (P=0.92). Plant spacing differences and the vegetation volume present within each land use cause variations in stand density. Rodrigues et al. (2021) state that wider spacing tends to lower stand density. In the context of POP, the predominant spacing employed was 7 × 7 m, whereas AG-SS and AG-SSB employed smaller spacing due to incorporating an intercropping system involving forestry, agricultural, and palm oil crops. This intercropping system contributes to more vegetation in AG-SS and AG-SSB than POP, yielding a greater stand density (Hartoyo et al. 2022).

Altitudinal variations among POP, AG-SS, and AG-SSB were notably diverse. The elevation of AG-SS areas displayed a significant contrast from POP (P=0.01) and AG-SSB (P=0.03). However, the elevation of POP and AG-SSB exhibited no significant difference (P=0.57). Farmers need to take into account the determination of field elevation as it exerts an impact on plant growth rates. According to Sinha et al. (2018), elevated locations experience reduced temperature and humidity, hindering plant growth and nutrient absorption. In parallel to altitude, the slopes across the three land uses also exhibit disparities. The slope in POP tends to significantly differ from AG-SS (P=0.03) and AG-SSB (P=0.00), while the slope in AG-SS and AG-SSB showcase no significant difference (P=0.86). This slope factor greatly influences solar radiation receipt and the volume of water absorbed by plants. Consequently, *Sengon* plants tend to be found more commonly on a gently sloped terrain (8-15%) to facilitate enhanced water absorption. According to Haris et al. (2021), *Sengon* thrives on slopes below 8%, while palm oil is better suited for planting on slopes of 0-4% (Shanti and Nirmala 2018).

Soil fertility encompasses soil's physical, chemical, and biological properties that support plant growth and development. In the context of this study, a physical property examined was bulk density, indicating soil density. The increase in bulk density leads to a reduction in root length, diameter, and root mass density (Dal Ferro et al. 2014). Table 2 shows that the bulk density in the three land uses exhibited no significant difference (P=0.20). This may be attributed to the consistent soil depth of the samples utilized, according to Yang and Liu. (2023), bulk density is affected by soil depth, with deeper soil leading to higher bulk density values. The chemical properties of the soil observed in this study consisted of soil pH, C-organic content, and total nitrogen (N) -content. The pH values across the three land uses displayed no significant difference (P=0.60) as they all fall within the slightly acidic category. Similarly, C-organic and total N-content in the three land uses exhibited no significant difference. Nevertheless, a subtle disparity remained, with C-organic and total N-content in POP slightly higher than AG-SS and AG-SSB (Table 2). This variation can be attributed to land management practices, such as implementing more intensive fertilization in POP than the other two land uses.

### Aboveground biomass (AGB)

Carbon dioxide absorbed by the stands is subsequently sequestered as biomass. Apart from stands, biomass is also present in the understorey and necromass such as litter. The combined biomass in the stands, understorey, and litter is categorized as aboveground biomass (AGB). In the case of POP, the largest biomass contribution originated from standing biomass (96.43 ton.ha$^{-1}$), followed by litter (0.66 ton.ha$^{-1}$) and understorey (0.33 ton.ha$^{-1}$). The total AGB in POP was 97.22 ton.ha$^{-1}$. The understorey biomass in POP is notably limited due to routine weeding practices undertaken by farmers to maintain the quality of palm oil tree growth. The findings of this AGB study for POP surpassed those of Asari et al. (2013), who reported AGB in POP in Selangor, Malaysia, 47.19 ton.ha$^{-1}$. Similarly, the AGB outcomes for POP exceeded those of Khasanah et al. (2015), who indicated AGB for POP on mineral soils across various Indonesian regions as 5.35 ton.ha$^{-1}$.

Similarly, in the case of AG-SS and AG-SSB, the largest biomass proportion originated from stands, namely 139.90 ton.ha$^{-1}$ (AG-SS) and 126.58 ton.ha$^{-1}$ (AG-SSB). Notably, there was a significant in the litter biomass between AG-SS and AG-SSB, with values of 0.31 ton.ha$^{-1}$ and 0.41 ton.ha$^{-1}$, respectively. Likewise, understorey biomass for both land uses was 0.72 ton.ha$^{-1}$ in AG-SS and 0.99 ton.ha$^{-1}$ in AG-SSB. The cumulative AGB in AG-SS was 140.93 ton.ha$^{-1}$, while AG-SSB was 127.98 ton.ha$^{-1}$. Comparatively, Nur et al. (2022) reported a distinct AGB value of 336.37 ton.ha$^{-1}$, which differs from the results of this study. Consequently, concerning the AGB in the AG-SS and AG-SSB, this study's findings were smaller than those reported by Nur et al. (2022).

Table 3 shows the difference in AGB values for POP (97.42 ton.ha$^{-1}$), AG-SS (140.93 ton.ha$^{-1}$), and AG-SSB (127.98 ton.ha$^{-1}$). Based on the Kruskal Wallis test, the AGB values between each land use were significantly different (P=0.00). Variations in AGB values occur due to differences in the vegetation composition quantity, diameter, and stand density (Sukartono et al. 2023). POP constitutes monoculture land exclusively composed of palm oil vegetation (*Elaeis guineensis* Jacq.), whereas AG-SS and AG-SSB encompass diverse vegetation. AG-SS includes two vegetation types, namely *Sengon* (*Paraserianthes falcataria* (L.) I.C.Nielsen) and palm oil (*E. guineensis*), while AG-SSB encompasses 20 vegetation types predominantly *Sengon*, palm oil, *Cempedak* (*Artocarpus interger* (Thunb.) Merr.), banana (*Musa* sp.), and *Paken* (*Durio kutejensis* (Hassk.) Becc.).

Despite AG-SSB's diverse vegetation, the resultant biomass is lower than the AG-SS. This can be attributed to the high stand density within AG-SSB, which restricts the growing space available for trees and consequently impacts tree diameters. According to Morin (2015), heightened density intensifies interactions among vegetation due to the increased resource demands (e.g., light, water, nutrients). This elevates competition for these resources among vegetation. Vegetation that receives insufficient resources tends to exhibit smaller diameters or heights. Furthermore, AG-SSB is notably characterized by newly planted vegetation, particularly palm oil, leading to considerably smaller diameters for palm oil vegetation in AG-SSB than POP and AG-SS. Larger vegetation diameters correspond to greater stored biomass, and vice versa (Shirima et al. 2015; Gogoi and Sahoo 2018; Mildrexler et al. 2020).

**Potential carbon storage**

The total potential carbon storage represents the accumulation of soil organic carbon (SOC) and aboveground carbon (AGC) stores, including standing understorey and litter carbon. As displayed in Table 4, the standing carbon stocks in POP, AG-SS, and AG-SSB exhibited significant differences (P=0.00). AG-SS had the highest standing carbon stock (65.75 ton.ha$^{-1}$), followed by AG-SSB (59.49 ton.ha$^{-1}$), with POP having the most minor standing carbon stock (47.68 ton ha$^{-1}$). The size of carbon storage within the stand is directly proportional to the stand's biomass (Lutz et al. 2018), with AG-SS showing the highest standing biomass, thus yielding greater carbon stocks than POP and AG-SSB.

Conversely, understorey carbon stocks in POP and AG-SS demonstrated no significant difference (P=0.90), while understorey carbon stocks in AG-SSB differed significantly from both POP (P= 0.03) and AG-SS (P=0.00). The most extensive understorey carbon storage was observed in AG-SSB (0.19 ton.ha$^{-1}$). This notable carbon storage can be attributed to the less palm oil-centric land management practices in AG-SSB than POP and AG-SS. In contrast, POP and AG-SS prioritize palm oil management, leading to more routine weeding practices to curb the interference of understorey vegetation, which can hinder palm oil growth and production. Saragih et al. (2018) elucidate how weeds can compete with palm oil for vital resources like water, sunlight, and space. In addition, weeds can host pests and diseases that threaten palm oil.

Litter carbon storage across the three land uses showcased significant variation. The largest litter carbon storage was found in AG-SSB (0.47 ton.ha$^{-1}$), while POP had the smallest (0.31 ton.ha$^{-1}$). The Mann-Whitney test established that litter carbon storage in POP and AG-SSB was significantly different (P=0.00), as was the case between AG-SS and AG-SSB (P=0.01). However, no significant difference was found in litter carbon storage POP and AG-SS (P=0.16). Differences in litter carbon storage can be attributed to altitudinal differences in soil fertility, climate, stand structure, and composition (Parsons et al. 2014; Becker et al. 2015). Based on stand structure and composition, land with mixed commodities tends to possess more litter than monoculture land (Giweta 2020).

**Table 2.** Land biophysical conditions

| Land use type | Stand density (ind.ha$^{-1}$) | Topography | | Soil fertility | | | |
|---|---|---|---|---|---|---|---|
| | | Altitude (masl) | Slope (%) | C-organic (%) | N total (%) | Soil pH | Bulk Density (g.cm$^{-3}$) |
| POP | 274$^{a}$ | 56.60$^{a}$ | 3.67$^{a}$ | 4.02$^{a}$ | 1.58$^{a}$ | 5.06$^{a}$ | 1.06$^{a}$ |
| AG-SS | 445$^{b}$ | 64.40$^{b}$ | 12.13$^{b}$ | 3.71$^{a}$ | 0.23$^{a}$ | 5.17$^{a}$ | 1.04$^{a}$ |
| AG-SSB | 433$^{b}$ | 56.83$^{a}$ | 7.90$^{b}$ | 3.98$^{a}$ | 0.23$^{a}$ | 5.06$^{a}$ | 1.14$^{a}$ |

Note: Number followed by different letters in the same column indicates a significant difference according to Mann-Whitney (P=0.05)

**Table 3.** Aboveground biomass

| Land use type | Biomass (ton.ha$^{-1}$) | | | AGB (ton.ha$^{-1}$) |
|---|---|---|---|---|
| | Stands | Understorey | Litters | |
| POP | 96.43$^{a}$ | 0.33$^{a}$ | 0.66$^{a}$ | 97.42$^{a}$ |
| AG-SS | 139,90$^{b}$ | 0.31$^{a}$ | 0.72$^{a}$ | 140,93$^{b}$ |
| AG-SSB | 126.58$^{b}$ | 0.41$^{b}$ | 0.99$^{b}$ | 127.98$^{c}$ |

Note: Numbers followed by different letters in the same column indicate significant differences according to Mann-Whitney (P=0.05)

**Table 4.** Estimation of carbon storage in each land use

| Land use type | Carbon storage (ton.ha$^{-1}$) | | | | |
|---|---|---|---|---|---|
| | AGC | | | SOC | Total |
| | Stands | Understorey | Litters | | |
| POP | 47.68 ± 19.40$^{a}$ | 0.16 ± 0.12$^{a}$ | 0.31 ± 0.21$^{a}$ | 1922.12 ± 1252.97$^{a}$ | 1970.27 ± 1250.61$^{a}$ |
| AG-SS | 65.75 ± 29.27$^{b}$ | 0.15 ± 0.10$^{a}$ | 0.34 ± 0.19$^{a}$ | 1846.72 ± 738.54$^{a}$ | 1912.96 ± 747.16$^{a}$ |
| AG-SSB | 59.49 ± 19.07$^{b}$ | 0.19 ± 0.08$^{b}$ | 0.47 ± 0.21$^{b}$ | 2163.21 ± 812.08$^{b}$ | 2223.36 ± 817.56$^{b}$ |

Note: Numbers followed by different letters in the same column indicate significant differences according to Mann-Whitney (P=0.05)

The largest total AGC was observed in AG-SS (66.24 ton.ha$^{-1}$), while the smallest total AGC was found in POP (48.15 ton.ha$^{-1}$). This pattern aligns with the findings of Karuru et al. (2021), which assert that total AGC in agroforestry surpasses that of POP. Compared with this study, the total AGC in agroforestry (131.31 ton.ha$^{-1}$) and POP (100.89 ton.ha$^{-1}$) in East Luwu was greater than in Gunung Mas. Notably, this study's total AGC of agroforestry was lower than that Nur et al. (2022) reported from Trenggalek, East Java (168.18 ton.ha$^{-1}$). Meanwhile, the total AGC of POP in this study was greater than the report of Khasanah et al. (2015) from mineral soils in various regions of Indonesia (35.28 ton.ha$^{-1}$).

Besides AGC, carbon is stored in soil organic carbon (SOC) form. According to Buraka et al. (2022), SOC is one of the Earth's largest carbon repositories and is pivotal in the global carbon cycle. In addition, carbon stored within soil is estimated to be three times greater than that stored in plants. In line with these insights, this study demonstrated higher SOC values than AGC. AG-SSB exhibited the highest SOC value (2163.21 ton.ha$^{-1}$), followed by POP (1922.12 ton.ha$^{-1}$) and AG-SS (1846.72 ton.ha$^{-1}$). SOC values for POP and AG-SS were not significantly different (P=0.55), whereas the SOC values for AG-SSB significantly differed from both POP (P=0.01) and AG-SS (P=0.04). Variations in SOC values can be attributed to land use types, soil types, climate, topography, hydrology, geology, land management systems, and farming practices (Lal et al. 2015; Mondal et al. 2016). Table 4 illustrates that SOC substantially influences the total carbon storage across the three land uses. The magnitude of SOC directly correlates with the overall carbon accumulation; higher SOC corresponds to greater total carbon storage.

**Effect of land biophysical conditions on carbon storage**

SEM-PLS analysis was used to determine the effect of biophysical conditions on carbon storage within each land use. Before assessing the effect's magnitude, it is necessary to evaluate the outer model to test the validity and reliability of each variable or indicator. This evaluation includes tests for convergent and discriminant validity. Convergent validity assesses the relationship between reflective indicators and their corresponding latent variables based on the Loading Factor (LF) value. An indicator is considered valid when its loading factor ranges from 0.5-0.6 (Chin 1998) or exceeds 0.6 (Shi and Maydeu-Olivares 2020; Dash and Paul 2021).

Conversely, discriminant validity evaluates the distinctness of variables. A variable is deemed valid if its Average Variance Extracted (AVE) value exceeds 0.5 (Yang and Liu 2023). Composite Reliability (CR) is used to test the reliability of a variable. An indicator is considered reliable if its composite reliability value exceeds 0.7 (Aghili and Amirkhani 2021).

Table 5 shows several indicators that do not meet the established validity and reliability criteria. Specifically, in the case of POP, indicators failing the validity and reliability test include slope (TO1), total N-content (KT2), bulk density (KT3), and C-organic content (KT4). For AG-SS, the indicators failing tests were height (TO2), soil pH (KT1), and bulk density (KT3). Similarly, in AG-SSB, the non-compliant indicators comprised slope (TO1), soil pH (KT1), and bulk density (KT3). According to Goenawan and Subandriyo (2023), indicators failing these tests should be excluded as they deviate from the research criteria. Consequently, a re-evaluation yielded the final validity and reliability test outcomes, summarized in Table 6.

Upon completion of the validity and reliability tests, the SEM-PLS analyses revealed the discernible impact of the three factors as indicated by the R-square values (Table 7). This analysis underscores that within POP, the biophysical factors consisting of topography, soil fertility, and stand density exert influence over AGC (25.90%), SOC (62.90%), and total carbon storage (59.20%). Similarly, in AG-SS, the biophysical conditions contribute to the variance in AGC (38.80%), SOC (80.20%), and total carbon storage (81.10%). Likewise, AG-SSB experiences comparable effects with biophysical conditions influencing AGC, SOC, and total carbon storage at 53.80%, 50.50%, and 51.10%, respectively. These findings align harmoniously with previous research, which stated that the potential for carbon storage is influenced by several factors, such as topography consisting of height and slope, stand density, stand age, soil fertility, compositional and structural attributes of vegetation (Oliver and Morecroft 2014; van der Sande et al. 2018; Bayat et al. 2021; Shiferaw et al. 2022; Sukartono et al. 2023).

**Table 5.** Results of validity and reliability tests before elimination

| Variable | Indicator | LF | | | AVE | | | CR | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | POP | AG-SS | AG-SSB | POP | AG-SS | AG-SSB | POP | AG-SS | AG-SSB |
| AGC | KA1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| SOC | KA2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| TCS | KA3 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| SD | KG1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| TO | TO1 | -0.654 | 0.915 | -0.438 | 0.490 | 0.465 | 0.582 | 0.008 | 0.258 | 0.264 |
| | TO2 | 0.744 | -0.306 | 0.986 | | | | | | |
| SF | KT1 | 0.879 | -0.090 | 0.228 | 0.505 | 0.501 | 0.495 | 0.357 | 0.342 | 0.553 |
| | KT2 | -0.690 | 0.912 | 0.957 | | | | | | |
| | KT3 | -0.582 | -0.658 | -0.484 | | | | | | |
| | KT4 | -0.657 | 0.855 | 0.882 | | | | | | |

Note: AGC: Aboveground Carbon; SOC: Soil Organic Carbon; TCS: Total Carbon Storage; TO: Topography; SF: Soil Fertility; SD: Stand Density; KA1: AGC; KA2: SOC; KA3: TCS; KG1: SD; TO1: Slope; TO2: Altitude; KT1: Soil pH; KT2: Total N-content; KT3: Bulk Density; KT4: C-organic

**Table 6.** Results of validity and reliability tests after elimination

| Variable | Indicator | LF | | | AVE | | | CR | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **POP** | **AG-SS** | **AG-SSB** | **POP** | **AG-SS** | **AG-SSB** | **POP** | **AG-SS** | **AG-SSB** |
| AGC | KA1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| SOC | KA2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| TCS | KA3 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| SD | KG1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| TO | TO1 | - | 1.000 | - | 1.000 | 1.000 | 0.582 | 1.000 | 1.000 | 1.000 |
| | TO2 | 1.000 | - | 1.000 | | | | | | |
| SF | KT1 | 1.000 | - | - | 1.000 | 0.803 | 0.852 | 1.000 | 0.890 | 0.852 |
| | KT2 | - | 0.906 | 0.950 | | | | | | |
| | KT3 | - | - | - | | | | | | |
| | KT4 | - | 0.886 | 0896 | | | | | | |

Note: AGC: Aboveground Carbon; SOC: Soil Organic Carbon; TCS: Total Carbon Storage; TO: Topography; SF: Soil Fertility; SD: Stand Density; KA1: AGC; KA2: SOC; KA3: TCS; KG1: SD; TO1: Slope; TO2: Altitude; KT1: Soil pH; KT2: Total N-content; KT3: Bulk Density; KT4= C-organic

**Table 7.** The resulting R-squares value

| Variable | R-square value on each land use | | |
|---|---|---|---|
| | **POP** | **AG-SS** | **AG-SSB** |
| AGC | 0.259 | 0.388 | 0.538 |
| SOC | 0.629 | 0.802 | 0.505 |
| TCS | 0.633 | 0.811 | 0.511 |

**Table 8.** The influence of each biophysical condition factor on carbon storage

| Variable | P-values | | | Influence path coefficient (path coefficient) | | |
|---|---|---|---|---|---|---|
| | **POP** | **AG-SS** | **AG-SSB** | **POP** | **AG-SS** | **AG-SSB** |
| TO → AGC | 0.031* | 0.001* | 0.045* | -0.322 | -0.306 | -0.324 |
| TO → SOC | 0.358 | 0.883 | 0.615 | 0.227 | 0.013 | 0.067 |
| TO → TCS | 0.370 | 0.996 | 0.654 | 0.220 | 0.000 | 0.059 |
| SF → AGC | 0.906 | 0.346 | 0.060 | 0.014 | 0.143 | 0.220 |
| SF → SOC | 0.004* | 0.000* | 0.000* | 0.752 | 0.863 | 0.671 |
| SF → TCS | 0.003* | 0.000* | 0.000* | 0.754 | 0.858 | 0.672 |
| SD → AGC | 0.025* | 0.035* | 0.001* | 0.372 | 0.486 | 0.475 |
| SD → SOC | 0.290 | 0.607 | 0.299 | -0.137 | 0.053 | 0.121 |
| SD → TCS | 0.277 | 0.485 | 0.262 | -0.140 | 0.072 | 0.131 |

Note: * has a significant effect (p-value <0.05)

A variable's significant effect on carbon storage is established when the p-value is less than 0.05 (Nangin et al. 2020). The extent of influence exerted by each variable can be quantified through the path coefficient of influence (Table 8). The outcomes of the SEM-PLS analysis divulge the influence of topographical factors, soil fertility, and stand density on carbon storage within each land use. The altitude estimated the topographical factor in POP and AG-SSB, while in AG-SS, it was estimated by the slope. Notably, the impact of topographical factors within AGC on POP and AG-SS was 32.30%, 32,40%, and 30.60%, respectively. This effect is demonstrated to be negative or inversely proportional, implying that higher altitudes and steeper slopes correlate with reduced AGC. This follows the study of Chimdessa (2023), which asserts that the highest AGC values are realized at lower altitudes. Temperature decreases with higher elevation, which consequently impacts photosynthesis rates.

The soil fertility factor, assessed by soil pH in POP and by C-organic and N-content in AG-SS and AG-SSB, constitutes another pivotal determinant of carbon storage in the three land uses. This aspect of soil fertility directly impacts SOC and total carbon storage. The extent of the effect of soil fertility on SOC within POP, AG-SS, and AG-SSB was determined to be 75.20%, 86.30%, and 67.10%, respectively. In contrast to SOC, the influence of soil fertility on total carbon storage in these three land uses was calculated at 75.40%, 85.80%, and 67.20%, respectively. The relationship between soil fertility and SOC and total carbon storage is positive, which means that the higher the soil fertility level, the greater the amount of carbon that can be stored. According to Javed et al. (2022), high soil fertility will accelerate vegetation growth, facilitating greater carbon storage.

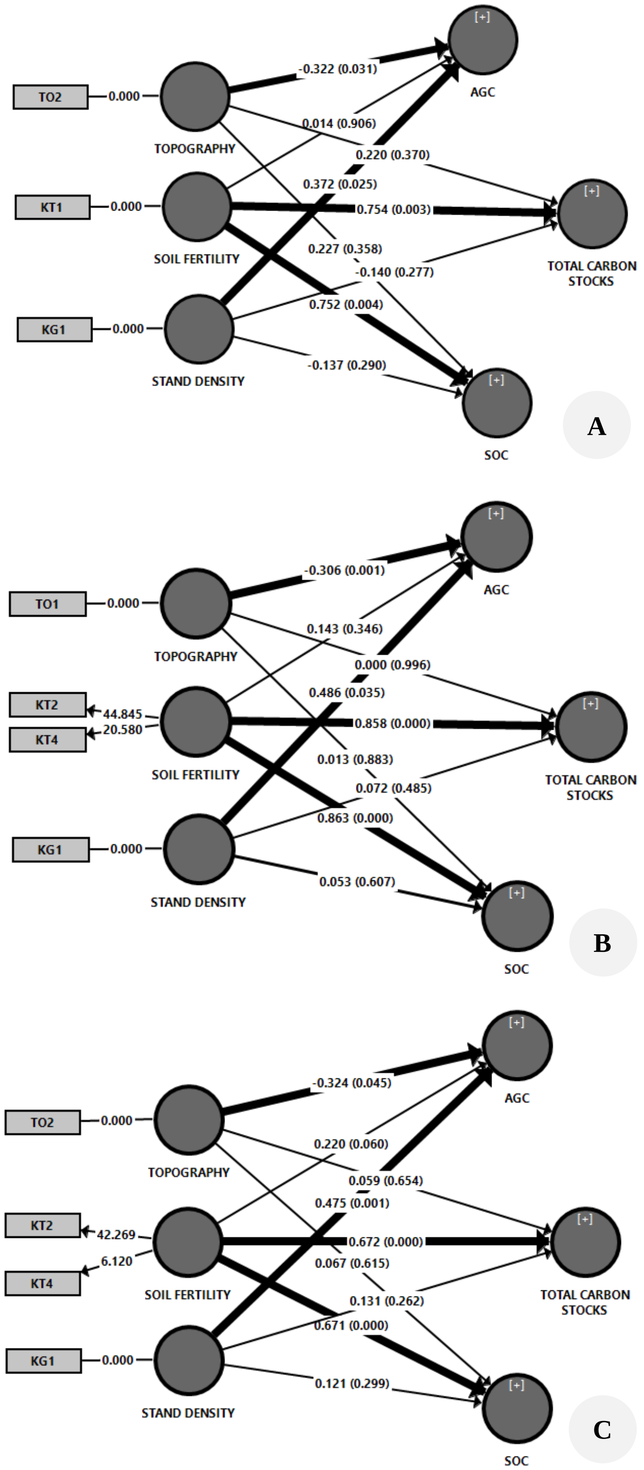


**Figure 2.** Model of SEM-PLS on A. POP, B. AG-SS, and C. AG-SSB

Moreover, stand density emerged as a significant determinant of AGC within the three land uses (Figure 2). The effect of stand density on POP, AG-SS, and AG-SSB was quantified at 75.40%, 85.80%, and 67.20% respectively. This positive relationship between stand density and AGC underscores that the denser stands yield greater AGC. Notably, the findings align with the study of Darmawan et al. (2022), who employed the SEM-PLS model to elucidate the effect of stand density and age class on carbon storage. A study by Darmawan et al. (2022) also highlights the effect of tree density on carbon storage to be 10%. Furthermore, the observation of Na et al. (2021) lends credence to this assertion by stating that higher stand density corresponds to increased carbon storage. It is pertinent to acknowledge that excessively high stand density may hinder carbon storage if vegetation spacing is not adequately considered, as the proliferation of density could impede optimal vegetation growth.

In conclusion, there were significant differences between AGC, SOC, and total carbon storage in POP, AG-SS, and AG-SSB. The largest total AGC was observed in AG-SS (66.24 ton.ha$^{-1}$), whereas POP (48.15 ton.ha-1) had the smallest total AGC. Additionally, the largest SOC value was present in AG- SSB (2163.21 ton.ha$^{-1}$), followed by POP (1922.12 ton.ha$^{-1}$) and AG-SS (1846.72 ton.ha$^{-1}$). Likewise, the largest total carbon storage was noted in AG-SSB (2223,36 ton.ha$^{-1}$), then POP (1970.27 ton.ha$^{-1}$), and the smallest was in AG-SS (1912.96 ton. ha$^{-1}$). Carbon storage in each land use was profoundly shaped by biophysical factors consisting of topography, soil fertility, and stand density. Topography and stand density factors significantly influenced AGC, while soil fertility factors significantly affected SOC and total carbon storage in these three land uses.

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