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Estimation of carbon stock and emission of community forests in Eastern Amhara, Ethiopia

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Abstract. *Biadgligne A, Gobezie T, Mohammed A, Feleke E. 2022. Estimation of carbon stock and emission of community forests in Eastern Amhara, Ethiopia. Asian J For 6: 74-82.* Carbon emission resulting from deforestation and forest degradation contributes to climate change. Halting deforestation is, therefore, one strategy to mitigate the changing climate. As the global carbon market develops, an opportunity to halt deforestation can be contributed by community forests as a win-win solution for climate change mitigation and livelihood provision, yet knowing the carbon stock of the forest is important to enhance the bargaining power of the community to get carbon finance. Thus, a case study was conducted to quantify carbon stocks and emissions from three community forests (i.e., Asha-Guba, Jemely, and Beshilo) in Eastern Amhara, Ethiopia. Stratified systematic sample quadrate methods were used, and a total of 57 equally spaced nested square quadrats were laid for the measurement of carbon density. Carbon pools, including above-ground living biomass, dead wood, surface litter, belowground root biomass, soil organic carbon, and harvested wood product, were accounted for the estimation of site-level carbon density (t ha^{-1}) and carbon dioxide equivalent (CO_2e) emission. There was high variability in the estimated mean carbon density and CO_2e emission across the three community forests. The highest carbon density was recorded in the Asha-Guba community forest with 124.27 ± 8.29 t ha^{-1}, followed by Jemely and Beshilo forests with 91.24 ± 3.18 t ha^{-1} and 73.55 ± 3.13 t ha^{-1}, respectively. The largest proportion (59-63%) of carbon was stored in the soil pool, followed by the above-ground biomass (27-32%), while that in dead organic matter was insignificant. The community forests currently stored total carbon stocks of 57,612.14 ± 13.81ton (210,860.43 CO_2e). To ensure the sustainable management of the forests, long-term finance and investment must be introduced urgently.

Keywords: Biomass, carbon emission, carbon pools, community forest, deforestation

INTRODUCTION

Forest is one of the inherent and critical components of the earth's surface. It covers 31 percent of the earth's land surface and contains most of the terrestrial biodiversity (FAO 2022). Forests also play an important role in regulating the global climate, preventing land degradation, and contributing to environmental stability (De Groot et al. 2010; Nugroho et al. 2022). In addition, it is a home for half of all life on earth and a source of livelihood for more than 1.4 billion of the world's poor (Kendie et al. 2021). Nonetheless, many forests around the world are threatened by deforestation and forest degradation due to anthropogenic factors. As a result, the world's forests declined by 3%, from 4128 million hectares in 1990 to 3999 million hectares in 2015 (Keenan et al. 2015). Forest Resources Assessment (FRA) 2020 estimated that between 1990 and 2020, around 420 million ha of forest has been deforested and converted to other land uses. Although the rate declined over the period, deforestation was still estimated at 10 million ha per year in 2015-2020 (approximately 0.25 percent per year) (FAO 2020).

Forest carbon stocks in the world's forest biomass decreased by an estimated 0.5 Giga tons annually from 2005-2010 (Poulter et al. 2010). Globally, deforestation contributes to 20% of anthropogenic GHGs emissions (Stern 2006; Le Quéré et al. 2009). In Africa, about 70% of GHGs emission is caused by deforestation (Gibbs et al. 2007). Despite causing carbon emissions due to deforestation and forest degradation, forests have the potential to contribute to 50% GHGs mitigation (Eggelston et al. 2006). For instance, forest ecosystems in the conterminous United States store 52.0 Pg C across all pools, and carbon storage increased by 2.4 Pg C at an annualized rate of 126 Tg C year^{-1} (Sleeter et al. 2022). Considering the importance of the forest in balancing CO_2 in the earth's atmosphere (Thompson et al. 2013), there is a pressing need to quantify the sources and sinks of carbon contained in the forest. In this regard, forest management becomes the key factor in whether a forest acts as a source or sink of carbon.

Sustainable forest management positively contributes to regulating climate change by sequestering CO_2 from the atmosphere while helping to meet future demand for materials and ecosystem services and support greener and circular economies, particularly at the local level (Vignola et al. 2009; Kumar et al. 2016; FAO 2022). Despite the potential for climate change mitigation, managing forests sustainably is an enormous challenge. This is because a quarter of forests in developing countries are under community control (World Bank 2008). There are variations in terminologies, although they have similarities in concepts, for instance, social forestry (Danks and Fortmann 2004); Joint Forest Management (Poffenberger and McGean 1998); Community-Based Forest Management (Mbuvi and Kungu 2021); Community-Based Forestry (Gauld 2000), and so on. In Ethiopia, a community forest is a forest that is conserved, developed, utilized, and administered by the community (FDRE 2018). In this context, the quality of local-level institutions is one of the determinants of forest carbon sequestration (Beyene et al. 2013).

An increasing interest in carbon trading and offsetting provides an opportunity for better forest management, a win-win solution for climate change mitigation and livelihood provision for forest-based communities. This can manifest by establishing carbon reserves in the forest ecosystem through afforestation and reforestation in a degraded landscape. Such efforts could be implemented with carbon trading mechanisms in a community forest. Nonetheless, the magnitude of carbon stock should be quantified to enact a benefit-sharing mechanism under a carbon trading scheme in a community forest (Pandey 2002). In Ethiopia, there is a great prospect of reducing 50% GHG emission between 2010 and 2030 from forest-based activities. However, the baseline information on the forest carbon stock is lacking. Specifically, no studies have been conducted to assess carbon stocks in community forests. Therefore, reliable and up-to-date quantification of the sources, sinks, and carbon changes is essential to assess the potential of community forests in reducing carbon emissions (Schelhas et al. 2010). Knowing the carbon stock of the forest enhances the community's bargaining power in the global carbon market. Thus, it is expected to provide meaningful information for local management decisions and planning.

This study is designed to estimate the organic carbon stocks of the community forests in Eastern Amhara, Ethiopia, and to set a baseline carbon dioxide emission level for future monitoring and evaluation activities. In this study, stratified systematic sample quadrate methods were used. A total of 57 equally spaced nested square quadrates were laid for the measurement of carbon density. Carbon pools, including above-ground living biomass, dead wood, surface litter, belowground root biomass, soil organic carbon, and harvested wood product, were considered to estimate site level carbon density (t Cha^{-1}) and CO_2e emission.

MATERIALS AND METHODS

Study area description

The study was conducted in Eastern Amhara, Ethiopia, extends between 11°7'30" to 11°26'20" N and from 39°18'50" to 39°37'00" E (Figure 1).

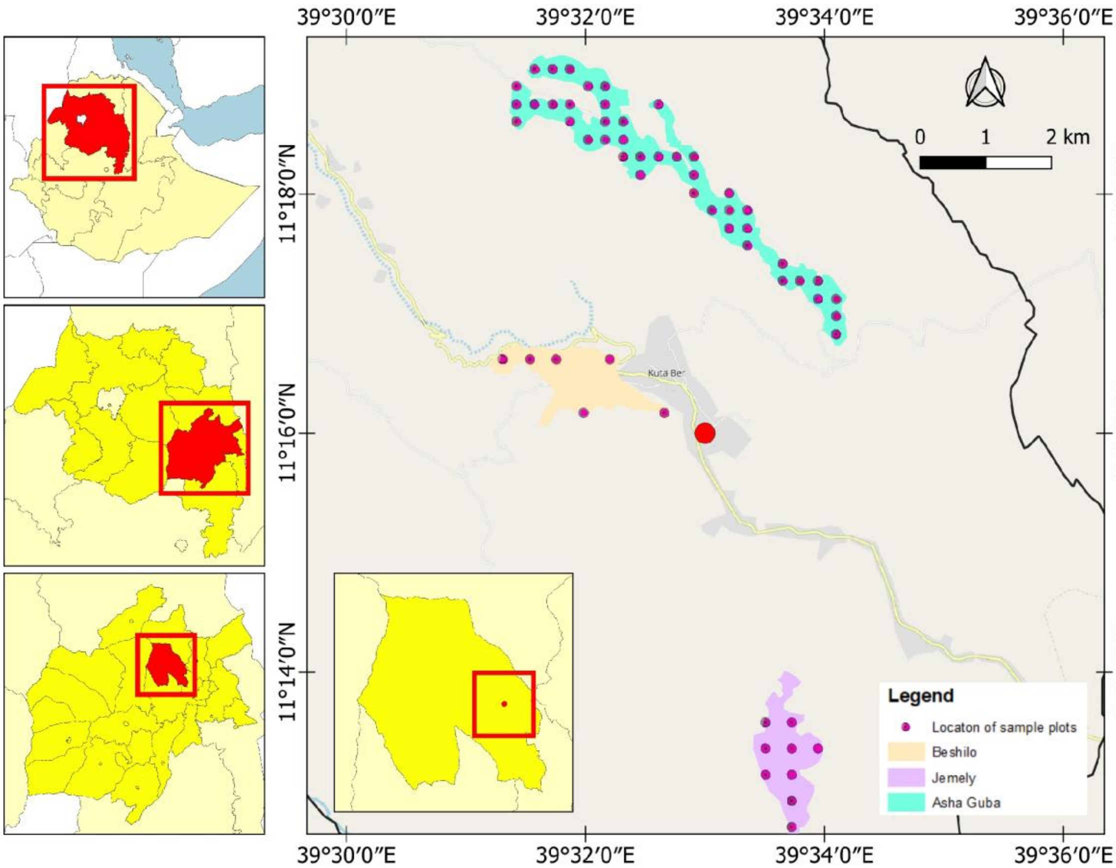

Figure 1. Map of study area and sample sites in Eastern Amhara, Ethiopia

Table 1. Determination and allocation of sample size in the studied area

Statistical parameters	Community forest			Total
	Asha-Guba CF	Beshilo CF	Jemely CF	
Forest area (ha)	322	78	130	530
Quadrat size (ha)	0.25	0.25	0.25	
Mean biomass carbon density (t ha^{-1})	85	61.5	67	
(SD) Standard deviation	22.7	5.5	3.4	
Ni (total no. of quadrat)	1288	312	520	2120
Desired precision (90%)				0.9
Permissible error (100-90= ±10%)	±8.5	±6.1	±6.7	
t value at 95% confidence level (~ 1.96)	1.96	1.96	1.96	
Coefficient of variation in % (CV)	26.71	8.94	5.07	
n (sample size)	38	5	8	51
10% contingency	4	1	1	6
Sampling units allocated to stratum	42	6	9	57

The topography is dominated by a chain of a mountain, mountain ridges, and valley bottom (Kasssaw 2010). The total population of Kutaber district was 126,805 (male = 62,918; female = 63,887) of which only 5.18% live in the urban area and 94.82% live in the rural area (CSA 2007). Mixed agriculture remains the main livelihood activity (Mekuria et al. 2020). An agricultural landscape dominated the study area, while only a small portion of the area was covered by forest (Kasssaw 2010). The local community depends on the forest for energy and construction materials (KOA 2021).

Research design and sample size determination and allocation

The study object includes all community forests in eastern Amhara. Among them, purposively selected Asha-Guba, Beshilo, and Jemely community forests. Systematic and purposive sampling with stratification methods were employed to obtain representative samples from the targeted studied area (Pandey 2002). First, the forest area was stratified based on dominant tree species composition, forest origin, and geographic location to draw a sample from non-overlapping sub-populations. Second, a precision level of ± 10% of the mean with a 95% confidence interval was implemented to get a reliable estimate. Third, the variance and standard deviation between the means of biomass carbon (t ha^{-1}) were computed from subjectively selected nine plots of an equal area (Pearson and Brown 2005). Thus, based on the data obtained in the preliminary survey, the sample size and sampling procedure used in this study are shown in Table 1.

Vegetation and soil data were collected during the dry season of the year 2020. A nested square sample quadrat was chosen for a simultaneous inventory of different carbon pools. In this design, the main quadrat (50 m x 50 m), the mid-sized quadrat (10 m x 10 m), and the small quadrats (1 m x 1 m) were established for the measurement of the tree, shrubs, and litter plus herbaceous vegetation, respectively. The sampling units were automated using the ArcGIS fishnet tool. Quadrats were laid starting from the northwest corner to the south, then proceeding to the southeast and towards the north. GPS was used to locate quadrats and meter tape was used to set quadrat dimensions, and nylon rope was used to demarcate the boundary.

In the main quadrat, the diameter of all trees (DBH ≥ 2 cm) was measured using a caliper, and tree height was estimated using a hypsometer, while in the mid-size quadrat (10 m x 10 m), shrubs having a collar diameter of 30 cm above the ground were measured its diameter and the values were recorded on a data collection sheet. Furthermore, in the small quadrat, soil parameters were collected from five circular pits (30 cm in depth and 30 cm in diameter) lying at the four corners and the center of the main quadrat. The 30 cm soil thickness was further classified into 3 layers to treat SOC in the top 0-10 cm, 10-20 cm, and the bottom 20-30 cm separately.

Data analysis

The ground data were coded and properly arranged before applying descriptive statistics such as mean, standard error of the mean, range, and ratio, and inferential analysis such as Pearson product-moment correlation using Statistical Package for Social Science version 20.1. Finally, the findings were presented using statistical tools like tables and figures to facilitate interpretation.

Forest carbon stock analysis

General and species-specific allometric equations (AE) can be used to estimate carbon in the forest ecosystem. General AE estimates of biomass are common equations applied over a large area (Houghton 2005) and were derived from many trees with a wide range of DBH (Brown 2002). However, generalized AE does not accurately predict above-ground biomass (Litton et al. 2006), leading to a bias in estimating biomass for a particular species. Therefore, species-specific AEs are used to predict tree and stand biomass based on easily measured tree variables such as height, diameter, and crown (Kangas and Maltamo 2006). Such equations are specific to species, sites, tree age, and management (Kairo et al. 2009), resulting in higher accuracy levels for biomass estimation and quantifying carbon. Studies in temperate and tropical regions have proven the advantages of species-specific biomass and volume allometry (Basuki et al. 2009). In addition, species-specific AE is preferred because tree species may differ greatly in tree architecture and wood gravity (Ketterings et al. 2001). The allometric equations used to estimate above-ground biomass in this study are shown in Table 2.

Table 2. Species specific allometric equations used in this study to calculate above-ground biomass (in kg)

Tree and shrubs species	Allometric equations	Reference
Eucalyptus globules	ABG = 0.0673* (WD*DBH2*Ht)0.976	Chave et al. (2014)
Cupressus lusitanica	AGB= Exp[-2.187 + (0.916 *ln(WD*DBH2*Ht))]	Chave et al. (2005)
Juniperous procera	AGB= 0.348 * DBH 0.57* Ht 0.032	Gereslassie et al. (2019)
Maytenus arbutifolia	AGB= 0.288 * WD 1.1864 * DBH 2.0649 * Ht 0.6096	Debela (2017)
Rosa abyssinica	AGB= 1.215 * WD 0.9726 * DBH 1.0817 * Ht -0.2603	Debela (2017)
Olea africana	AGB= (0.6806*DSH) + (0.0422*(DSH*exp2.7))	WBSPP (2005)
Acacia abyssinica	AGB= Exp[-2.409+ (0.9522 * ln (WD * DBH2 * Ht))]	Brown et al. (1989)
Psychoteria orophila	ln(AGB)= 2.160*ln(DSH)+0.796*ln(Ht)+ε	Dibaba (2018)
Allophylus abyssinicus	AGB= Exp[-2.557+ (0.94 * ln (WD2 * Ht)]	Dibaba (2018)
Tropical shrubs	AGB= Exp[-2.557+ (0.091 * DBH2.472)]	Kuyah et al. (2013)

Note: WD: Wood Density (kg/m^3), DBH: Diameter at breast height (cm), Ht: Total height of tree (meter), Exp: "e to the power of ", ln: Natural logarithm to the base 'e' (i.e., the value of 'e' ≡ 2.718) and DSH: diameter at stump height (cm)

The biomass of aboveground woody vegetation (DBH ≥ 2 cm) was estimated by combining forest inventory data with a species-specific allometric biomass regression model (Brown 2002; Houghton 2005; Chave et al. 2005, 2014; Gereslassie et al. 2019). Then, the biomass stock density of a sampling quadrat was converted to carbon stock densities after multiplication with the default carbon fraction of 0.47.

Below-ground root biomass carbon stocks were estimated based on a series of root-to-shoot ratios set for major forest types (Eggelston et al. 2006) as provided by (Cairns et al. 1997) below.

$$BGRB(kg) = Exp\left[1.0587 + \left(0.8836 * ln(ABGB)\right)\right]$$

The total biomass of dead wood (DW) was estimated by summing up the standing and felled dead wood (Pearson and Brown 2005). Then, the biomass of above-ground non-woody vegetation (< 2 cm DBH) and surface litter per 1 m^2 area was computed using the equation proposed by Pearson and Brown (2005), as shown below.

$$Dry\ Mass\ (Kg) = \frac{Sub\ Sample\ Dry\ Mass\ (kg)}{Sub\ Sample\ Fresh\ Mass\ (kg)} * Field\ Mass\ (kg)$$

Soil organic carbon analysis was carried out at Dessie Soil Testing and Fertility Management Center. In this laboratory, the Walkley-Black method was applied to estimate the concentrations of organic carbon in the soil. The soil organic carbon (t ha^{-1}) was thus computed from soil bulk density (BD), soil depth (D), and carbon concentration (C) following Pearson and Brown (2005) as below.

$$tC/ha = \left[\left(BD\ \left(\frac{g}{cm3}\right) x\ D\ (cm) x\ C\%\right] x\ 100$$

The total carbon stock (TCS) was estimated by summing all carbon stored in each forest's carbon pools (i.e., above ground living tree biomass (ABGLTB) + above ground living non-tree biomass (ABGNTB) + below-ground root biomass (BGRB) + dead wood biomass (DW) + litter biomass (SL) + soil organic carbon (SOC)).

Setting baseline emission in community forests

Baseline emission refers to the carbon stocks or CO_2 equivalent GHG emission expected for a given time period. This is the sum of emission per year during the projection period under the baseline scenario. This involves a simple multiplication of the average tons of CO_2e emissions per hectare obtained from field inventory (i.e., Emission Factor) by the area deforested per year as shown in equation below.

$$Baseline\ Emission = \sum_{n=1}^{t}(AD * EF)$$

Where;
AD: Deforested area (ha/year) under baseline scenario
EF : Carbon stocks (tCO_2e/ha) in the forest
T : Projection life span (i.e., 2020 to 2030)

Reference Emission Level (REL) analysis

Setting REL or baseline emission involves a simple multiplication of the average tons of CO_2e carbon per hectare obtained from field inventory (Emission Factor) by the rate of deforestation, as shown below.

$$Overall\ Uncertainty\ (U\ \%) = \sqrt{(U\_Carbon)^2 + (U\_area)^2}$$

$$= \sqrt{\left(\frac{t*SEM}{\mu} * 100\right)^2 + (1 - \check{k})^2}$$

Where;
U-carbon %: Percentage uncertainty in the estimate of mean carbon density (t ha^{-1}), which is ½ (95% CI) *100/μ
95% CI = C density ± t*SEM
μ : The mean carbon density of the forests (t ha^{-1})
U-area (%): Percentage uncertainty in land cover change analysis

RESULTS AND DISCUSSION

Structure and basal area of community forests

In the study area, the total number of tree species observed were nine species of which three species (25%) were found in Asha-Guba, two species (16.7%) in Beshilo, and seven species (58%) were found in Jemely community forests. The DBH and height structure showed a pattern with relatively high frequency in the lower DBH class and gradually declining towards the higher DBH classes (Figure 2).

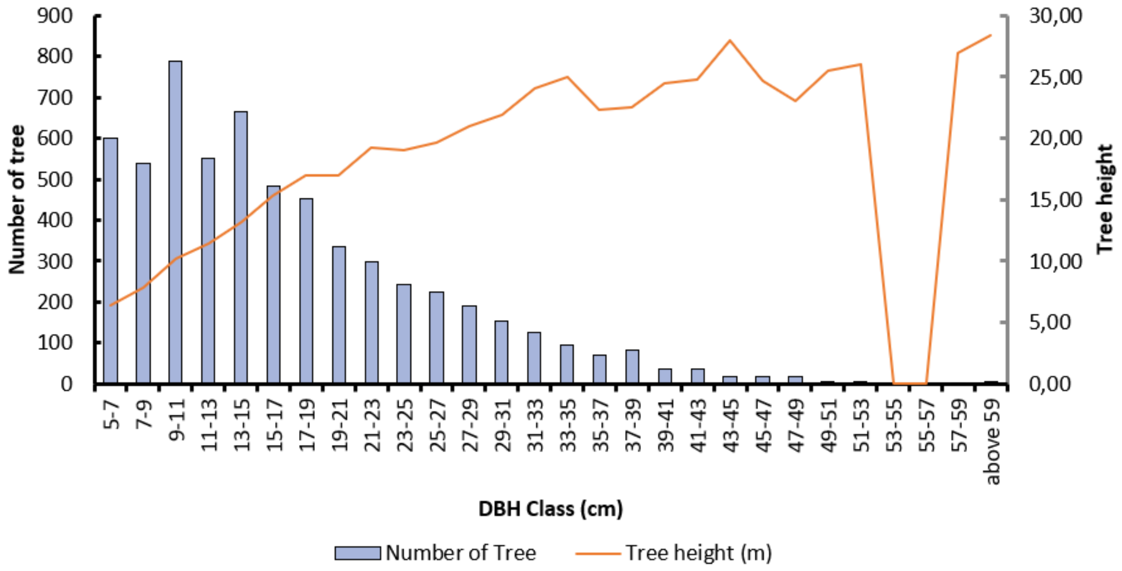

Figure 2. Tree species structure in across varying DBH class in the community forests in the studied area

Table 3. Total carbon stocks from various pools and its CO_2 equivalent in three community forests in Amhara, Ethiopia

Carbon pool		ABG		H	BGRB	DOM		Soil C	Total	CO_2e
		LT (t ha^{-1})	LS (t ha^{-1})	H (t ha^{-1})	LDR (t ha^{-1})	DW (t ha^{-1})	SL (t ha^{-1})	SOC (t ha^{-1})	(t ha^{-1})	
CF	Stat									
Asha-Guba	M	43.01	0.71	0.2	10.5	1.04	0.06	68.75	124.27	485.46
	SE	3.62	0.17	0.04	0.67	0.31	0.01	0.39	4.23	16.25
Jemely	M	13.37	1.47	0.01	3.56	0	0.12	72.71	91.24	336.94
	SE	0.83	0.44	0	0.14	0	0.03	0.77	1.22	3.89
Beshilo	M	3.31	0.18	0.03	1.34	0.11	0.1	68.47	73.55	275.32
	SE	0.56	0.1	0.01	0.14	0.06	0.02	0.77	1.17	3.45
Total	M	34.15	0.78	0.15	8.44	0.78	0.07	69.34	113.71	439.89
	SE	3.33	0.15	0.03	0.68	0.23	0.01	0.37	3.95	15.85

Notes: M: Mean; SE: Std. Error; ABG: Above ground biomass (LT: Living tree and LS: Living shrubs); BGRB: Below-ground root biomass (LDR: Live + Dead roots); H: herbaceous; DOM: Dead organic matter (SL: Surface litter; DW: Dead wood); CO_2e: carbon dioxide equivalent emissions

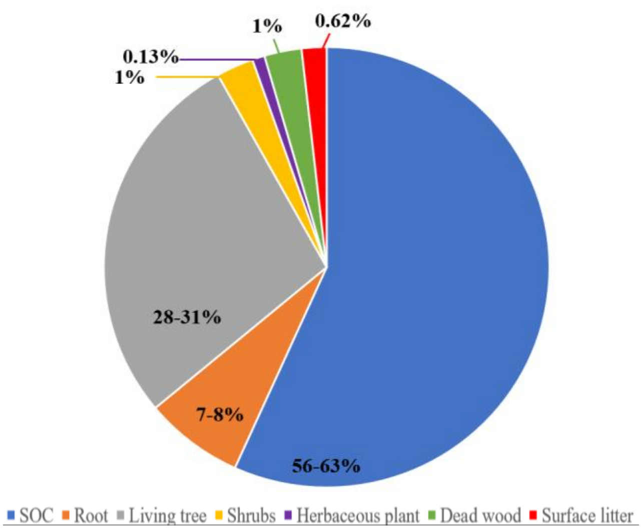

Figure 3. Proportion of estimated carbon stocks in various carbon pools in community forests in Amhara, Ethiopia

In line with the carbon stock of community forests

An estimated carbon stock in a unit area (t ha^{-1}) of the community forests is shown in Table 3. The mean carbon stock was estimated to be 124.27 ± 4.23 t ha^{-1} in Asha-Guba, 91.24 ± 1.22 t ha^{-1} in Jemely, and 73.55 ± 1.17 t ha^{-1} in the Beshilo community forest.

Aboveground and belowground biomass varied significantly among the community forests. Living tree biomass generally ranged from 3.86 t ha^{-1} in Beshilo to 210.1 t ha^{-1} in Asha-Guba, with the highest overall biomass of 72.65 ± 7.09 t ha$^{-1.}$ The highest proportion of ABG biomass (71%) was found in the living tree alone. Below-ground root biomass was thus computed from ABG biomass using the allometric equation as explained in the Methods. This resulted in below-ground root biomass of 17.94 t ha^{-1}, or 24% of the ABG biomass.

The largest proportion of carbon (Figure 3) was stored in the soil pool followed by AGB pool. The contribution of herbaceous, litter and non-tree woody vegetation carbon pools (together accounts 1.75% of the TCS).

Table 4. Reference emission level of three community forests in Amhara, Ethiopia under BAU scenario

Year	Forest area (ha)	Deforested area (AD) = Area*0.0193	Average emission factor (tCO_2e/ha) (a)	Anthropic Vegetation in Equilibrium (AVE) (tCO_2e/ha) (b)	Net emission (tCO_2e/ha) (a-b)	Baseline emission Ex-ante post-deforestation class tCO_2e Emission
Historic time	**530**					
2020	411.0	8.22	154	18	136	1117.92
2021	402.8	8.05	154	18	136	1094.80
2022	394.7	7.89	154	18	136	1073.04
2023	386.8	7.74	154	18	136	1052.64
2024	379.1	7.58	154	18	136	1030.88
2025	371.5	7.43	154	18	136	1010.48
2026	364.2	7.28	154	18	136	990.08
2027	356.8	7.13	154	18	136	969.68
2028	349.7	6.99	154	18	136	950.64
2029	342.7	6.85	154	18	136	931.60
2030	335.8	6.72	154	18	136	913.92
	329.20	81.8				11135.7

Estimated baseline emission of the community forests

Baseline emission refers to the carbon stocks or CO_2 equivalent GHG emission expected for a given time period. This is the sum of emission per year during the projection period under the baseline scenario. This involves a simple multiplication of the average tons of CO_2e emissions per hectare obtained from field inventory (Emission Factor) by the area deforested per year. Thus, to compute Emission Factor (tCO_2e ha^{-1}) in the pre-deforestation period, the amount of carbon estimated from harvested wood (HW), extracted through clear cutting and selective logging has been added to ABG biomass carbon which was 42.078 t ha^{-1}. The assumption is that all carbon in HW is oxidized in the removal year. Below-ground root carbon and SOC are disregarded in the computation because they were not easily subjected to deforestation as ABG pools. The average EF (tCO_2e/ha) was calculated for all forest sites together by considering the aggregate mean carbon stock density (Table 4).

concept of IPCC Good Practice Guidance (IPCC 2003), estimates of CO_2 emissions and carbon sequestrations have uncertainties associated with area and other activity data. In this study, uncertainty can arise both from land cover classifications and carbon stock estimation. Thus, the over-all uncertainty has been estimated by combining the two sources of uncertainties with simple error propagation as explained in the Methods. The calculation of oveall uncertainty resulted in a value of 13.5%, meaning that the annual rate of reference CO_2e GHG emissions extrapolated during the period 2020 to 2030 was 86.5% accurate.

Discussion

Structure and basal area of the forests

The analysis on forest structure revealed that the DBH class of 9-15 cm had higher frequency than that in the lower DBH 5-9 cm class. The DBH and height structure showed a pattern with relatively high frequency in the lower DBH class and gradually declining towards the higher DBH classes and vice versa for height (Figure 2). *Juniperus procera*, which was common across all forest sites, was observed in Jemely natural forest with importance value of 138. It was the basal area (8.21 m^2 ha^{-1}) that makes *Cupressus lusitanica* more dominant in Asha-Guba plantation than *Eucalyptus globulus* with a basal area of 5.54 m^2 ha^{-1}, having higher records of relative frequency and relative density than *C. lusitanica*. This was due to the inclusion of more *E. globules* coppice which had a lower relative dominancy value (33%) than *C. lusitanica* (non-coppicing species) having 49% dominancy.

The highest mean tree height (21.9 m) was observed in the Asha-Guba plantation and the lowest mean tree height (9.5 m) was in the Jemely natural forest. For the 55-57 cm DBH class, there was no record of the tree at all, while there were few old-growth trees above 59 cm. The graph in Figure 2 shows an almost positive relationship between DBH and height except for frequency. Medium-sized trees account for the largest share (66%) of stand structure at the study site, while very small trees (DBH = 0-30 cm) and very large trees (DBH >60 cm) contribute to less than 8.3% and 25.5% of the structure, respectively (Holtmann et al. 2021).

Carbon stock density of the forests

Tree species composition influences patterns of maximum forest biomass accumulation in the study area. Mixed tree species increase the storage of SOC and biomass accumulation in the forest (Augusto and Boča 2022). Of the total shrubs biomass, Jemely natural forest contributed higher mean biomass estimates of 3.12 ± 0.32 t/ha, compared to Asha-Guba (1.51) and Beshilo (0.39). The biomass with ranges of 0 to 9.75 t/ha shows that there are quadrats devoid of shrubs biomass in Beshilo and Asha-Guba plantation sites. These forests accumulated a lower amount of dead wood than Alpine and Atlantic forests, which were 6.09 and 3.53 Mg ha^{-1}, respectively (Alberdi et al. 2020). Hence, standing adult-tree account for more proportion of the total volume.

The results of this study support the findings of Beaulne et al. (2021), who reported that peat layers, with an average of 22.6-66.0 kg m^{-2}, store much more C than AGB and BGB of boreal forests in Canada (2.8-5.7 kg m^{-2}). Forest soil has the potential to store carbon and contribute to mitigate GHGs. In total, soil contains about 3 times more carbon than the atmosphere and 4.5 times more carbon than living things. Hence, a relatively small increase in the proportion of soil carbon could make a significant contribution to reducing atmospheric carbon (Walcott et al. 2009).

Aboveground and belowground carbon biomass of the forests

The biomass of the study area was 94.38 ± 8.52 t ha^{-1}, with the minimum and maximum biomass estimates of 7.15 and 268.38 t ha^{-1}, respectively. The aboveground carbon biomass reported in the Asha-Guba forest (210 t C ha^{-1}) is higher than that in the Chilimo natural forest of Ethiopia (200 t C ha^{-1}) (Tesfaye et al. 2019), similarly, the belowground carbon biomass is higher than that that in the Muktar forest eastern Ethiopia (Wodajo et al. 2020).

Soil organic carbon (SOC) of the forests

Forests can store significant quantities of carbon in the biomass and the soil (Mukul et al. 2020). Soil depth, soil bulk density, and concentrations of SOC are the three major variables considered for the estimation of SOC. The mean SOC in the 0-10 cm, 10-20 cm and 20-30 cm soil depths was 24.09 ± 0.14 t C ha^{-1}, 22.77 ± 0.119 t C ha^{-1} and 22.49 ± 0.12 t C ha^{-1}, respectively. Thus, the highest SOC was stored in the upper soil surface of 0-10 cm depth, due to higher amount of organic matter accumulation in this layer. In this regard, similar studies conducted so far confirmed that SOC decreased with increasing depth in forest soils (Abere et al. 2017). The higher proportion of carbon stocks is stored in the organic layer (Wellbrock et al. 2017). Similarly, in this study, the highest percentage of carbon was stored in the form of soil organic carbon (61%) followed by the ABGL biomass carbon pool (30%). The results agree with other results reporting an important portion of total carbon stock was in the forest soils (Tolunay 2011). Hence, forest soil carbon management intervention is indispensable to safeguarding the leaching of soil organic carbon. Moreover, there is a need to adapt the carbon management approach to forest management (Tolunay 2011).

Carbon stock in dead organic matter (DOM) of the forests

Reliable estimates of the total forest carbon pool are lacking due to insufficient information on dead organic matter (Zhu et al. 2017). Here, we estimated the DOM in community forest of Ethiopia. Dead wood carbon accounts for standing and laying dead wood as well as dead stumps of logged trees. Carbon stocks generally ranged from 0.00-7.95 t ha^{-1}, with the highest mean dead wood carbon in Asha-Guba community forest (i.e., 1.04 ± 0.31 t ha^{-1}). While, the mean dead wood carbon stock in Beshilo plantation forest were 0.11 ± 0.06 t ha^{-1}, while there was no dead wood in Jemely natural forest. This might be due to the longer life span and lower timber quality of dominant tree species in Jemely natural forest. Regarding carbon stock in surface litter, the opposite was true, i.e. surface litter carbon is higher in natural forest than in plantation. The laboratory (field level) analysis of litter carbon provides a mean record of 0.12 ± 0.03 t ha^{-1} in Jemely natural forest. In terms of carbon accounting, the variation between natural and plantation forest was insignificant, but it has more meaning in the analysis of disturbance in the forest ecosystem (Figure 3).

Meanwhile, the amount of carbon harvested from the forest included the parameters of sound, coppiced and dead stump. Stumps height, diameter at the top of stumps and number of stumps were considered to compute the equivalent basal area at 1.3 m height of a given species. Accordingly, the regression equation developed from a sample height curve relationship (Murdiyarso et al. 2008) was considered for the estimation of missing tree DBH and height in the case of the stump. The result revealed that the highest value of HW carbon (i.e., 22.52 t ha^{-1}) was estimated from the Asha-Guba plantation and the list observation (i.e., 0) was from the Jemely natural forest. The mean HW carbon of 8.01 ± 0.81 t ha^{-1}, 0.57 ± 0.26 t ha^{-1}, and 1.47 ± 0.47 t ha^{-1}, respectively were estimated from Asha-Guba, Jemely, and Beshilo forest sites. This shows that the Asha-Guba plantation forest was at high risk of deforestation than the Beshilo and Jemely forests. This is due to selective harvesting of tree species (Zhu et al. 2017).

Total forest carbon stock (TCS) of the forests

The overall mean carbon stock density (t ha^{-1}) of the study area was computed from all major carbon pools and all forest sites, resulting in value of 113.71 ± 3.95 t ha^{-1}. The use of this value for total carbon stock estimation was misleading because the Analysis of Variance conducted showed a significant difference between and among carbon density in the forests at 95% CI. Thus, the total carbon stock of the study area was computed by summing up the product of carbon density per site with the respective areas in a hectare. Accordingly, TCS currently stored in Asha-Guba, Jemely, and Beshilo forests was 40,014.94 ± 8.29 tons; 11,861.2 ± 2.39 tons; and 5,736 ± 3.13 ton respectively. Therefore, the unknown true value of TCS currently estimated in community forests was within the interval of 57,598.33 to 57,625.95 tons.

The TCS density (t ha^{-1}) estimated for Jemely (91.24 t ha^{-1}) was 3 to 5 times lower compared to other natural forest such as 586.7 t ha^{-1} in Gerba Dima (Dibaba et al. 2019), 353.6 t ha^{-1} in Anbesa forest (Yohannes 2016) , and against the national average TCS density of natural high forest 128 t ha^{-1} (Yitebitu et al. 2010). On the other hand, the biomass carbon from Asha-Guba and Beshilo plantation forests was lower by 29 t ha^{-1} compared with the national average (147.6 t ha^{-1}) (Tadesse et al. 2020). Also, the total carbon biomass density of both plantation and natural forest (94.38 t ha^{-1}) was 50% of the tropical rain forest estimate of 200 t ha^{-1} (Eggelston et al. 2006).

Estimated the baseline emission of the community forests

The total forest area reduced from 530 ha (pre-deforestation) to 411 ha as a result of historic deforestation (Biadgligne 2021). The annual rate of deforestation in the period of 2010 to 2020 was 1.87% per year. However, after deforestation some amount of carbon stocks were deposited in the residual vegetation known as Anthropic Vegetation in Equilibrium (AVE). Thus, the Ex-ante post deforestation class tCO_2e emission was computed by subtracting the default value of AVE which is 18 tCO_2e ha^{-1}. Therefore, through BAU scenario 76.96 ha or 18.72% of the current forest area (411ha) will be converted to non-forested area by 2030. Even, this figure will be escalated due to the aggregate effect of severe forest degradation in the area. Likewise, with the average net emission factor of 136 tCO2e ha^{-1}, by 2030 a total of 10466.8 tCO_2e emission expected in the post deforestation class. Unless immediate remedial measures be taken to curve this scenario, it is impossible to receive result-based payment. Under the Business-As-Usual scenario, the next 20 years would lead to the emission of 90 million tCO_2 from the forest sector (FDRE 2018). It was stated in the USAID (2011) the annual emission of GHGs in Ethiopia is 150 Mt CO_2 equivalents. In Ethiopia, the forest sector is the second largest source of national GHG emission (55 million tCO_2e) after agriculture (75 million tCO_2e). Projections indicate that mean annual temperature across the country will increase with a range of 1.4 to 2.9°C by the 2050s (Conway and Schipper 2011). Compared to the global annual emission of the same year, the emission from Ethiopia is less than 0.3%, yet it is among the top 40 countries (of 185) that are considered most vulnerable to climate change (USAID 2011). Halting deforestation and maintaining forests using forests and building green value (FAO 2022) is a good opportunity to better understand the existing forest condition.

In conclusion this study estimated carbon stock and emission in community forests of Eastern Amhara, Ethiopia. The carbon stock density and emission factor (tCO_2e) were computed using data generated from 57 systematically aligned nested quadrats. The empirical analysis revealed that, currently on average 113.71±3.95 t ha^{-1} (416.18 tCO_2e ha^{-1}) of carbon is sequestered and stored in the various forest carbon pools with a significant difference between and among sites. The highest proportion of carbon (61%) was stored in the soil pool followed by ABGL biomass (30%). However, the contribution of shrubs, herbaceous vegetation, surface litter and dead wood was insignificant, with no statistically significant difference between ABGL shrubs and DW carbon (P=0.05). This result calls an adaptive community forest management practice in the area. Harvesting forest products may results carbon leaching so that attention should be given on construction of soil conservation structure before harvesting. The TCS estimated at 95% CI was within the range of 56,001.12 to 59,224.96 tons or 204,964.1 to 216,763.4 tons of CO_2e carbon. The next main question in this study sought to estimate the baseline CO_2e emission factor of the study area. Emission Factor (tCO_2e ha^{-1}) in the pre-deforestation period, the amount of carbon estimated from HW (extracted through clear-cutting and selective logging) has been added to ABG biomass carbon which was 42.078 t ha^{-1}. The average net emission factor of 136 tCO_2e ha^{-1}, by 2030 a total of 10466.8 tCO_2e emissions are estimated. Setting reference data is vital for the implementation of carbon credit systems and to undertake performance evaluation in community forest management.

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