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1 **Assessment of Forest Carbon Stocks for REDD+ Implementation in the Muyong Forest**

2 **System of Ifugao, Philippines**

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9 **Abstract**

10   Forests hold significant potential for carbon sequestration and climate change mitigation.
11 Forest biomass estimation is vital for sustainable forest management, providing critical input
12 data for implementing the United Nations Reducing Emissions from Deforestation and forest
13 Degradation-plus (REDD+) mechanism. This study investigates the total carbon pools—
14 aboveground biomass (AGB), belowground biomass (BGB), forest floor biomass, and soil
15 carbon—using field-based information in the muyong forest management system, which is
16 native to Ifugao in the Philippines. This study reveals that a difference may be observed between
17 the total carbon stock of the private woodlots (muyong) and that of the communal forest (bilid).
18 The results indicate that the bilid forest has trees with small diameter at breast height (DBH) and
19 high tree density in contrast to the muyong, which has trees with high DBH and low tree density.
20 The average carbon stock per unit area is higher in muyong (150.8 tC/ha) than in bilid (126.1
21 tC/ha). These findings are valuable in determining whether Ifugao's muyong forest system
22 should be included under the REDD+ framework. Human mediation and management helps
23 forests to sequester a greater amount of carbon than they would without human intervention.
24 Implementation of REDD+ should promote Ifugao's ecosystem and biodiversity conservation
25 and agroforestry practices in addition to protecting traditional agricultural practices and
26 livelihoods in relation to rice terraces.

27 **Keywords:** Forest carbon stocks, REDD+, muyong, climate change mitigation

28 **1. Introduction**

Tropical forests are important carbon reservoirs, storing large quantities of biomass over long periods compared to agriculture and other systems (Ravindranath and Ostwald 2008; Avtar, et al., 2013a). They also fulfill an important role in the global carbon cycle because they act as reservoirs during succession and sources when deforested or degraded by natural or human disturbances (Marin-Spiotta and Sharma, 2013). Continued deforestation and forest degradation pose the threat of releasing large amounts of carbon, which may exacerbate the effects of climate change. The Philippines is one of the world's seventeen countries recognized as megadiverse and is particularly vulnerable to climate change (World Bank, 2010). The total area of forest cover in the Philippines is 8.4 million hectares with 1,160 million tons of aboveground biomass (AGB) in forests and other woodlands (FAO-FRA, 2015). The promotion of restoration initiatives has the potential to increase the country's carbon sink.

Deep in the heart of the Philippine Cordilleras mountain range lies the Ifugao province, which is famous for its rice terraces (UNESCO, 2019). The Ifugao agricultural system is an "agro-cultural complex system," characterized by the interlocking of nature with agricultural practices, social systems, and historical, political, and cultural changes (O'Connor, 1995). The muyong system plays a major role in the survival of the Ifugao rice terraces, providing water and preventing soil erosion (Avtar et al., 2019; Soriano et al., 2019). In the local dialect of the Tuwali tribe, "muyong" translates literally to "forest," although the precise definition may vary depending on the locality. Local people specifically use this term to denote privately-owned and managed woodlots located above rice terraces (*payoh*). Muyong forests differ from other systems with respect to their management and protection (Herath et al., 2015). The Ifugao land classification system designates land categories according to the location, function, and type of agronomic activity that takes place (Butic and Ngidlo, 2003). The muyong system is Ifugao's native forest management system and is vital to the rice terracing system due to its watershed function (Durst et al., 2001). Globally, it has been acclaimed as a comprehensive ecosystem that provides a host of various ecosystem services.

During the last decade, various efforts have been made to accurately quantify forest carbon stock with the aim of understanding global and regional carbon budgets (Lindsell et al., 2013; Ma et al., 2018). Maps of the spatial distribution of biomass can assist in decreasing uncertainty in relation to the global carbon cycle (Duncanson, 2019). The quantification of

global forest biomass relies on AGB estimation. Therefore, most recent studies have focused on the estimation of AGB using ground-based and remote sensing-based methods to improve accuracy. AGB can be estimated from ground-based forest inventory parameters using allometric equations (Brown, 1997; Chave et al., 2014). Geospatial data can also be used to improve AGB estimation using various satellite sensor data. Accuracy in biomass estimation is vital for the implementation of climate change mitigation mechanisms such as Reducing Emissions from Deforestation and forest Degradation-plus (REDD+) as well as for forest management in Asian countries (Andoh and Lee, 2018; Borah et al., 2018).

The Ifugao rice terrace system was first recorded as a World Heritage site in 1995 by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (Department of Environment and Natural Resources, 2008). However, the maintenance and conservation of World Heritage sites require financing (Timothy and Nyaupane, 2009). Toorn (2013) found that funding availability is the main issue in the conservation of these cultural landscapes. This study focuses on the assessment of forest biomass stock in the Ifugao system, which will be useful in creating funding opportunities under the existing REDD+ mechanism. Earlier studies have shown that population growth has led to increased demand for firewood and timber products, thereby contributing to deforestation and also affecting ecosystem services (Ravindranath and Ostwald 2008; Avtar et al., 2019). This study explores how REDD+ initiatives can mitigate climate change and value forests to help the traditional cultures of Ifugao communities and livelihoods (UN-REDD 2016). In the Philippines, the Department of Environment and Natural Resources (DENR) is pushing for the nationwide implementation of REDD+ initiatives to reduce the impact of climate change. Lasco et al. (2013) reviewed REDD+ projects in the Philippines and discussed the critical factors for their successful implementation. This study aims to assess the total forest carbon stock of the muyong and bilid forests in Ifugao and its role in climate change mitigation strategies under the REDD+ framework. The REDD+ intervention can also support the area's indigenous people in adopting inventive mechanisms aimed at managing the transformation of the Ifugao economy.

2. Study Area

The Nagacadan barangay is one of the fourteen barangays of the Kiangan municipality of the Ifugao province of the Philippines. It is located about 320km from Metro Manila. The total

population of Nagacadan was 831 as per the 2015 census data. Agriculture and tourism are the main sources of income in the study area. Ifugao is a landlocked mountain province in the epicenter of the Philippine Cordilleras region. The topography of the area is marked by rugged terrain with mountainous forests. The Kiangan is situated in an upland area with an elevation ranges from 500 to 1,300 meters above the mean sea level. The highest point in Ifugao is Mt. Pulag, a popular hiking destination. The Ifugao rice terraces, with an estimated area of 10,323 ha, are listed in the UNESCO World Heritage site as part of the agricultural system used by the Ifugao (Calderon et al., 2009). Figure 1 shows the Ifugao rice terrace system with mountainous areas covered with the muyong and bilid forests. This shows how forest management and rice terraces are complementary to each other.

Figure 1. Ifugao rice terraces with mountains covered with muyong and bilid forests

The forests in the region are classified as the amalgamation of moss, pine, and dipterocarp forests, respectively (Daniel, 2014). Figure 2 shows the location of Nagacadan and variations of topographic conditions. Shuttle Radar Topographic Mission (SRTM) digital elevation (DEM) data shows the change in the topography in the study area.
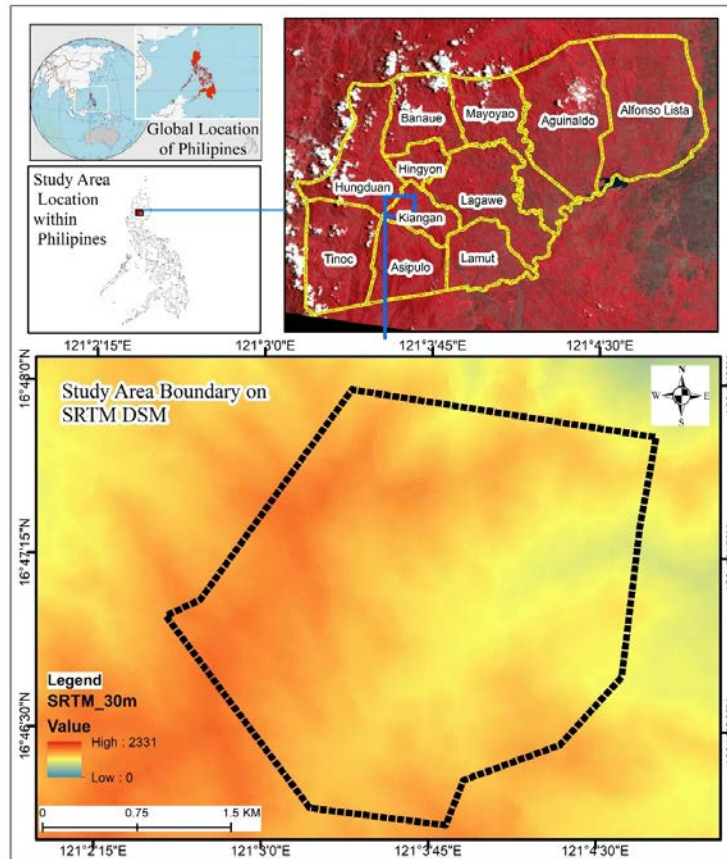
105

Figure 2. Representation of the study area

There are five land use classes in the study area namely: (1) *muyong*, (2) rice terrace (*payoh)*, (3) *bilid*, (4) *habal*, and (5) fallow/open agricultural land. Table 1 shows the land use types in the study site and their description.

Table 1. Various land-use types in the study area

Land-use type	Ownership	Description
Muyong	Private	Forest woodlot
Payoh	Private	Rice terrace
Bilid	Communal	Forest area around the mountain
Habal	Private	Swidden farms designated for food production located on a steep incline
Fallow	Private	Drained rice terraces

2.1. Forest Woodlots (Muyong)

The muyong is a privately managed woodlot with diverse plant species, constituting an important part of the agricultural and social system. Within the context of the local culture, the muyong system is a highly functional and efficient mosaic of forest resources and is the product of thousands of years of experimental learning. The local people have observed a link between forest management and food security. Therefore, the protection of muyong is a vital component for the survival of rice terraces (Dugan et al., 2003). As muyong are located at higher elevations relative to the rice terraces, they are considered to regulate the supply of water, which is essential for rice production. Furthermore, the vegetation helps to reduce surface water runoff and erosion, thus also preventing the sediment accumulation in the underlying paddy fields (Matsushima and Tojo, 2010).

2.2. Mountain Forest (Bilid)

The bilid is defined as the forested area around the mountain ridge, which operates under a regime of communal management. Not all of the area on the mountain ridge consists of bilid, as the mountain top is also inhabited by large swaths of tall cane grass and occasional swidden farms (Jang and Salcedo, 2013). The bilid is free for anyone to harvest. Therefore, many farmers take advantage of this when they feel that they have harvested too much from their muyong. The bilid can appear physically similar to a muyong, but it has different management and tenure system.

2.3. Swidden Fields (Habal)

Also known as the *kaingin* in Nagacadan, the habal refers to an area that is explicitly designated for food production. It is one of the most important lands uses in the area and is created through slash-and-burn agriculture. Habal is often established on slopes that are too steep for rice terrace cultivation. As they do not require much maintenance, they are generally located far from the homestead. The habal is a necessary component of the muyong system because local communities rely on it to supplement their diet and it also offers insurance against years with low rice yields (Conklin, 1980).

3. Methodology

This study's methodology was designed to assess forest carbon stocks with the aim of implementing the REDD+ mechanism in Nagacadan, Ifugao. It consists of field- and remote sensing-based biomass estimation. To understand the benefits of the REDD+ mechanism and achieve the objective of this study, forest biomass in the Ifugao system was estimated. Fieldwork was conducted to collect biomass data from February 8–14 2015. We adopted methodologies from Ravindranath and Ostwald (2008) for ground-based biomass calculation using forest inventory data. Avtar et al.'s (2013b) methodologies were used for Phased Array L-band type Synthetic Aperture Radar (PALSAR)-based forest biomass estimation. Figure 3 shows the outline of the methodology for biomass estimation using field-based observation for direct measurement and satellite-based observation for indirect measurement.
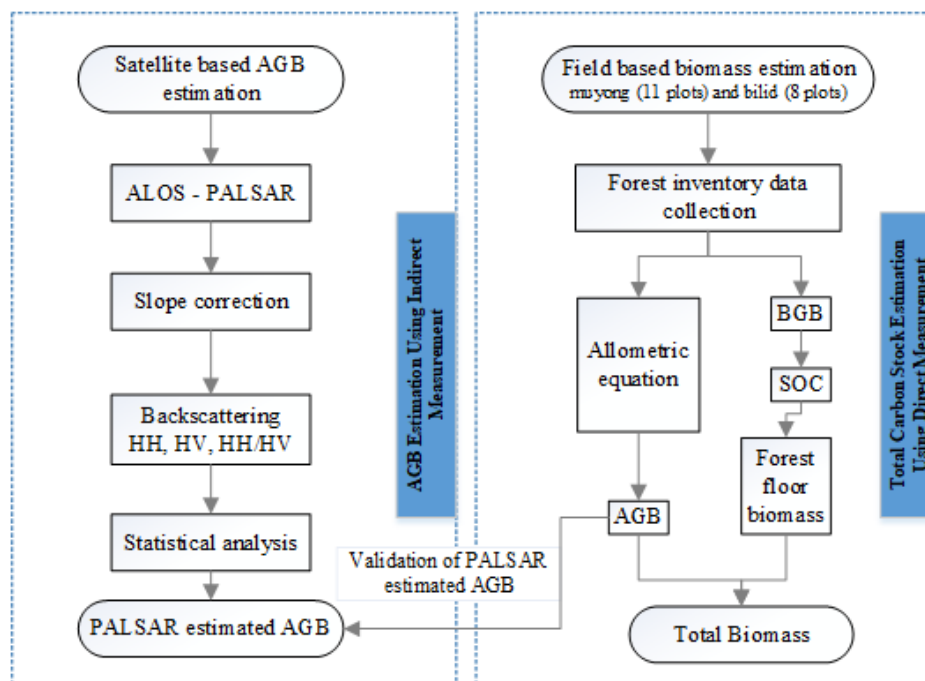

Figure 3. Flow chart of forest biomass estimation using satellite-based and ground-based measurement

Measurement and analysis of different carbon pools were performed to estimate total carbon stock in the forest. In most forest biomass studies, forest biomass and soil organic carbon (SOC) are the two major carbon pools. Forest biomass pools can be further divided into living AGB and belowground biomass (BGB), which includes litter, roots, litterfall, detritus, dead

7

organic material, and woody debris (Houghton, 2003). AGB is the major and most evident carbon pool in the terrestrial ecosystem (Ravindranath and Ostwald, 2008). BGB includes live roots that support the carbon cycle by transferring and storing carbon in the soil (Eggleston et al., 2006). Biomass from litter, litterfall, detritus, dead organic material, and woody debris constitutes a small fraction of forest carbon stocks (Ravindranath and Ostwald, 2008). Soil organic matter is also a major contributor to forest carbon stocks and releases CO_2 as a consequence of deforestation (Lal, 2005). Table 2 shows the various methods available for measuring different biomass pools and their suitability for carbon measurement. In this study, the plot-based method was used to estimate AGB.

Non-destructive biomass measurement methods are popular in protected areas because AGB estimation can be achieved without destruction of trees. Data collected from sample plots can be used to estimate the mean carbon stock per unit area of each land-use type, which can then be extrapolated using remote sensing techniques (Avtar, Suzuki, et al., 2013b). This method of AGB estimation was considered the most suitable for the study area. However, the presence of steeply sloping mountainous terrain can cause errors and limit the use of synthetic aperture radar (SAR) data. Furthermore, the region's tropical climate is associated with high amounts of cloud cover, which limits the availability of cloud-free multispectral remote sensing data (Minh et al., 2019). Therefore, the use of field-based measurements (*in-situ*) implementing non-destructive sampling techniques can minimize the uncertainties in AGB estimation.

Table 2. Methods to measure carbon pools (Ravindranath and Ostwald, 2008)

Pools	Methods	Suitability for carbon measurement
AGB	Plot method	Commonly used and familiar method Cost-effective and suitable
	Harvest method	Not appropriate all the time Time-consuming, labor-intensive and expensive
	Plot-less or transect method	This method is good but it is not suitable in dense forest as well as for periodical monitoring
	Modelling	Need basic input data for building the models It is suitable for projections

		Requires basic input parameters
	Satellite/remote sensing	These methods are suitable for regional and national level monitoring but expensive for small projects.
	Carbon flux measurements	This is an expensive method and requires skilled people.
BGB	Root extraction and weight measurement	Time-consuming, labor-intensive and expensive
	Root to shoot ratio method	This method is commonly used based on AGB data
	Biomass equations	Need data e.g. DBH, tree height, girth etc.
Dead organic matter	Litter	This method needs huge efforts
	Stock measurement	This method is commonly adopted and feasible
Soil carbon	Diffuse reflectance spectroscopy method	This method is expensive and requires skilled human resources
	Modelling	Need basic input data from other methods and suitable for projection
	Laboratory estimation	This is the most suitable method and commonly adopted

177

3.1. Carbon Stock Estimation using Direct Measurement

179   Field-based biomass estimation methods were used to collect forest inventory parameters
180 with the assistance of local people in the study area. The random sampling method was used to
181 collect forest inventory parameters to measure forest carbon stock. Figure 4 shows the
182 distribution of sampling plots in the Nagacadan area. In this study, temporary sampling plots
183 were used in light of the limited budget. Moreover, we did not intend to conduct long-term
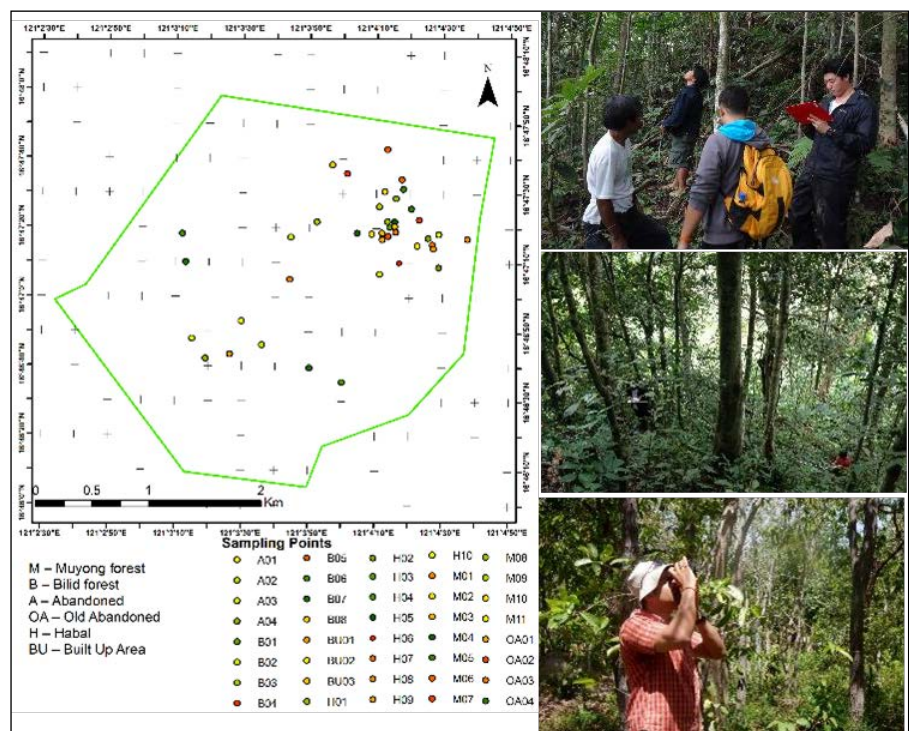184 monitoring of the biomass pattern.

Figure 4. Field data collection and location of sampling plots

Square plots of 10×10 m were laid out with measuring tape for AGB estimation. The corners of the plots were located with the help of the Global Positioning System (GPS). The shape and size of the sampling plots constitutes a trade-off between time, accuracy, and cost of measurement. Wondo (2013) suggested that square plots tend to include more heterogeneity and favor more representation than circular plots in the same study area (Wondo, 2013). As suggested by Pearson et al. (2005), based on the consideration of medium-size diameter at breast height (DBH) at the study site, we adopted 10×10-m plots to minimize the heterogeneity. This was also due to the steep slope conditions in the mountainous forest. Moreover, the plots were the same size as the pixels of the Advanced Visible and Near-Infrared Radiometer type-2 (AVNIR-2) data.

Data were collected from four carbon pools: AGB, BGB, forest floor biomass, and soil carbon. To estimate forest carbon stock, forest inventory parameters, including tree height, DBH, tree species, tree density, and forest types were collected. Tree height refers to the total height of trees instead of the height of the merchantable stem, which is used in some allometric equations. DBH of each tree was measured at 130 cm height from the ground by using DBH tapes and markers. All the trees with DBH ≥ 5 cm were measured with a DBH tape. To measure the DBH

10

212 in the steep slope, the measurement was conducted on the uphill side of the tree (Ravindranath
213 and Ostwald, 2008).

214 The following allometric equation was used for the AGB calculation (Brown, 1997). It was
215 developed specifically for forest biomass estimation in moist tropical forests and covered most of
216 the species of tropical forests.

217 $$AGB = \exp (-2.289 + 2.649 \times \ln(dbh)-0.021 \times \ln(dbh^2)) \qquad (1)$$

218 Where, ln = natural log, exp = "e to the power of"

219 To estimate BGB (root biomass) from the AGB, an allometric equation was used as follows
220 (Ravindranath and Ostwald, 2008):

221 $$BGB = \exp [-1.0587 + 0.8836 * \ln (AGB)] \qquad (2)$$

222 Where, ln = natural log, exp = "e to the power of"

223 The biomass value obtained from the above equations is converted to carbon stock using a
224 carbon conversion factor of 0.47 (McGroddy et al., 2004).

225 $$\text{Carbon stock (tC/ha)} = \text{biomass (t/ha)} \times 0.47 \qquad (3)$$

226 Within the sample plot, a smaller plot of 1×1 m was established to measure the forest
227 floor layer and soil carbon. The measurement design is presented in Figure 5. A 1×1-m plot was
228 used to collect litter, herbaceous (live above ground non-woody with DBH < 2 cm), and soil
229 samples. Deadwood, litter, and dead roots were also collected from the forest floor and separated
230 into fresh and litter types before being dried in the oven. In the same plot, soil samples were
231 randomly collected at a depth of 10 cm and then oven-dried at 70°C for 2 days. Walkley and
232 Black's (1934) methods were used to calculate organic carbon (%). The soil carbon (t/ha) was
233 calculated using the method developed by Nelson and Sommers (1996). Earlier studies have
234 found that the highest percentage of soil carbon is present in the upper soil layer (Racelis et al.,
235 2008 in the Philippines, Ullah et al., 2012 in Bangladesh; Hobley et al., 2016 in Australia).

236 $\text{Soil carbon} = [\text{soil bulk density (gm}^{-3}) \times \text{soil depth (cm)} \times \text{soil organic carbon (\%)}] \times 100$ (4)

237 The total number of square plots for the collection of forest inventory data for muyong
238 and bilid were 11 and 8, respectively. In contrast to the forest carbon stock and forest floor areas,

239 the total number of samples for soil carbon was five (three in muyong, two in bilid). Total carbon
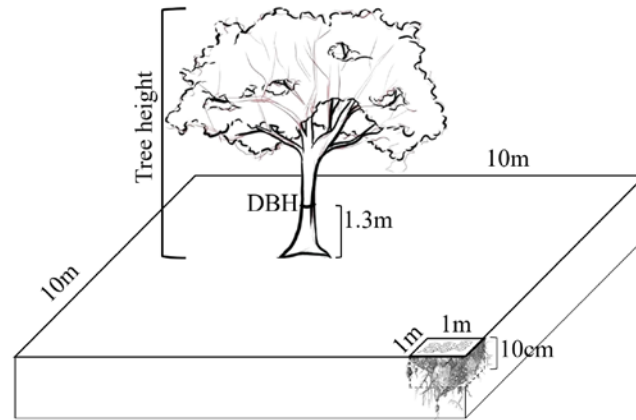240 stock is the summation of carbon stock from AGB, BGB, forest floor, and soil carbon.

242 **Figure 5. The design of plot samples and carbon measurement in the field**

243 **3.2. Carbon Stock Estimation using Indirect Measurement**

244   Conventional allometric-based biomass estimation is one of the most accurate methods
245 used in carbon stock estimation. However, it is expensive, time-consuming, and labor-intensive
246 (Avtar et al., 2012; Avtar et al., 2013c; Avtar et al., 2016). Moreover, it is only applicable in
247 small areas for which forest inventory data are available. Remote sensing can overcome the
248 above-mentioned limitations.

249   Several studies have modeled forest biomass using various satellite sensors (Anaya et al.,
250 2009; Baccini et al., 2004; Drake et al., 2003; Vashum and Jayakumar, 2012). Avtar et al.
251 (2013b) reported that SAR data are more effective than optical data in measuring AGB in
252 tropical regions due to the limitation of clouds. Other studies have shown that light detection and
253 ranging (LiDAR)-based biomass estimation offers greater accuracy than other remote sensing-
254 based observation methods (Nelson et al., 1988; Vashum and Jayakumar, 2012). However, the
255 use of LiDAR data in developing countries is particularly limited owing to acquisition and
256 processing costs. Therefore, PALSAR data were used to estimate AGB in this study. SAR data
257 with cross-polarization (horizontal and vertical: HV) can detect tree volume and are useful in
258 estimating forest biomass (Avtar et al. 2013b). SAR-based backscattering information is useful
259 for estimating forest biomass and has been used extensively by other researchers (Englhart et al.,
260 2011). Furthermore, due to its penetrative capacity, SAR has the advantage of being insensitive

261   to weather conditions, such as clouds and rain, which is useful in tropical regions. SAR

262   backscatter information is affected by the topography with steep slopes due to layover and

263   foreshortening effects of SAR data (Avtar et al., 2013b).

264   The satellite data were acquired from the Advanced Land Observation Satellite (ALOS)

265   mission of the Japan Aerospace Exploration Agency (JAXA) in 2010. AVNIR-2 and PALSAR

266   were used to estimate biomass in the study area. AVNIR-2 is a multispectral image with four

267   bands consisting of blue, green, red, and near-infrared (NIR) bands with a 10-m pixel size.

268   Similarly, PALSAR images have a spatial resolution of approximately 16 m with dual

269   polarization (Tadono et al., 2009). Land use/land cover (LULC) classification of AVNIR-2 data

270   was performed to distinguish various LULC classes in the study area, including bilid, muyong,

271   rice terraces, built-up areas, grassy mountain terrain, open mountain, and water bodies. The

272   maximum likelihood classification algorithm was used to classify AVNIR-2 data (Lillesand and

273   Kiefer, 1999). Forest cover information can be a useful parameter for calculating total carbon

274   stocks in the study area. Samreth et al. (2012) used remote sensing and a ground-based forest

275   inventory approach to estimate carbon stocks in Cambodian forests. The use of forest area and

276   average carbon stock in a particular forest can provide total carbon stock information. We

277   explored similar methodological approaches to calculate average carbon stock in muyong and

278   bilid forests using the following equation.

279   Total carbon stock = Σ (forest area$_i$ × averaged carbon stock$_i$)   (5)

280   Where, $_i$ = forest types (muyong or bilid)

281   We also used backscattering information from dual-polarization PALSAR data to

282   estimate AGB using the methodology described in Avtar et al. (2013b). Field-calculated AGB

283   was used to validate the PALSAR-estimated biomass.

284   **4. Results and Discussion**

285   This study aimed to assess the forest carbon stocks in the Ifugao system using direct and

286   indirect measurement methods to obtain information from four carbon pools: (1) AGB, (2) BGB,

287   (3) forest floor layer, and (4) SOC. We also attempted to generate a land-use map of the area

288   using AVNIR-2 data and biomass estimation using equation 5. PALSAR-based methods were

289   also used to estimate forest biomass.

4.1. Carbon Stock Estimation using Direct Measurement

4.1.1. Forest Carbon Stock (AGB + BGB)

To quantify forest carbon stocks, we collected forest inventory parameters (tree height, DBH, species, tree density, and forest types) in muyong and bilid forests. This study evaluated total forest biomass in the Ifugao forest management system. Appendices A1 and A2 show the forest inventory parameters and calculation of forest biomass stocks in the muyong and bilid forests, respectively. Statistical analysis was conducted to compare the various forest inventory parameters. Figure 6 shows the linear regression between tree density and average DBH of the sampling plots. A moderate relationship was observed between tree density and average DBH in muyong with a correlation value of 0.56 (R^2 = 0.31), while a strong relationship was observed in bilid with a correlation value of 0.7 (R^2 = 0.49). As tree density increases, the trees' DBH values tend to be smaller. The relationship between average DBH and tree density demonstrates that in dense forests, tree growth rate can be restricted due to the limited space and greater competition among trees for growth determinants such as nutrients, space, and access to sunlight. Similarly, Takahashi et al. (2018) also noticed a large DBH and a low tree density for evergreen conifers in the Shizumo forest reserve. Comparison of average DBH between the muyong and bilid revealed that the muyong features trees with a high average DBH and low tree density in contrast to the bilid forest. Furthermore, the findings show that tree density per hectare is higher in the bilid, which supports the theory that lack of maintenance allows the natural regrowth of plants in the bilid.

(a)

(b)
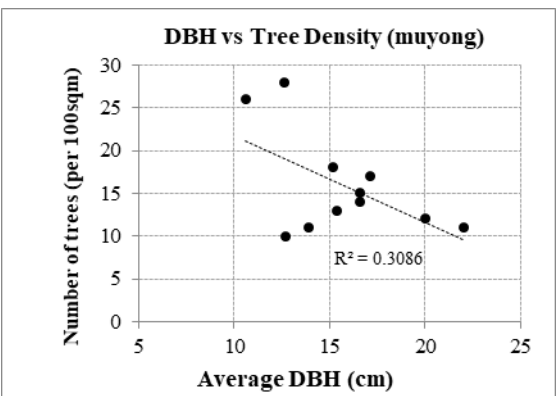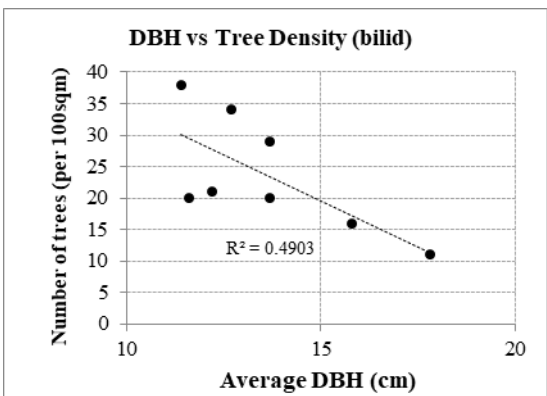
310 **Figure 6. Linear regression between DBH and tree density in (a) muyong and (b) bilid**

311 **forests**

312   Figure 7 shows a histogram of the DBH frequency distribution with respect to tree

313 density. The histogram shows the normal distribution of DBH in the muyong and bilid. The

314 average and standard deviation of DBH were 15.79 cm and 11.63 cm in muyong, while the

315 values were 13.14 cm and 6.29 cm in bilid. The muyong showed a greater difference in DBH

316 than bilid. Despite the uneven number of sample plots, the data support the view that the muyong

317 management system enables the growth of larger trees. This is evidenced by the measurement of

318 the largest tree in the bilid at 36 cm DBH while 10 trees larger than 36 cm and one larger than 70

319 cm (accounting for 0.6%) were observed in the muyong. The histogram illustrates the muyong's

320 association with the growth of larger trees owing to the maintenance and protection activities

321 implemented by private forest holders.

322
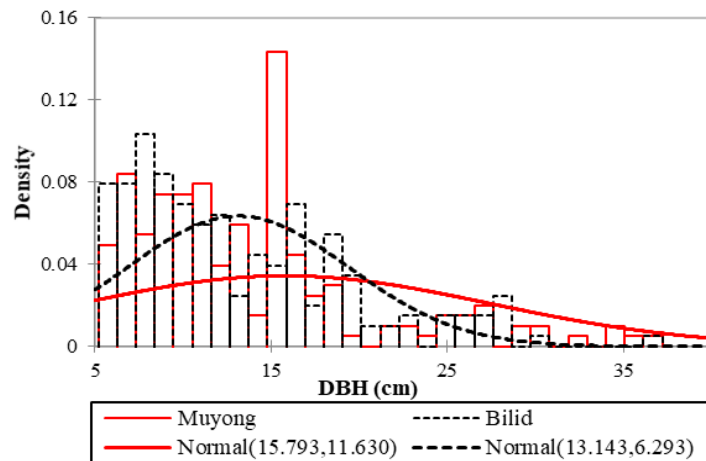
323   **Figure 7. Histogram of tree density and DBH in muyong and bilid forests**

324   In this study, Brown's (1997) allometric equation was used to determine the AGB based

325 on DBH information. In tropical forests, the biomass of trees with DBH greater than 70 cm can

326 account for 40% of the total forest biomass density, and these trees represent less than 5% of all

327 trees (Brown and Lugo, 1992). Appendices A1 and A2 show the mean AGB (215 t/ha), BGB

328 (38.9 t/ha) and total biomass (254.7 t/ha) recorded in the muyong forest, and the mean AGB

329 (166.3 t/ha), BGB (33.5 t/ha) and total biomass (199.7 t/ha) recorded for bilid forest. The

330 muyong forest had high average carbon stocks with 119.7 ± 76 tons of carbon per hectare (tC/ha)

compared to the bilid which had 93.9 ± 27.6 tC/ha. Although the plots in the bilid showed high tree density compared to the muyong, the muyong showed higher total forest carbon stock values.

4.1.2. Forest Floor Biomass

Table 3 shows the amount of fresh and litter samples in the 1-m^2 sampling plots within the 10-m^2 plots. The bilid forest showed higher coverage of fresh and litter samples than the muyong forest. After the fresh samples were collected, they were oven-dried to determine the dry mass.

Table 3. Amounts of fresh and litter samples collected per square meter

Forest types	Fresh (herbaceous) (g)	Litter (g)	Total Sample (g)
Muyong	419±188	1,075±446	1,494±481
Bilid	673±447	1,776±412	2,449±608

Table 4 shows the average dry mass and carbon content in the fresh and litter samples of the forest floor. The bilid showed higher average levels of dry mass in both fresh and litter samples than the muyong. The presence of high fresh and litter carbon in the bilid is due to the natural growth of herbaceous vegetation on the forest floor.

Table 4. Average dry mass and carbon content in the fresh and litter samples of the forest floor

Forest types	Average Dry Mass			Average Carbon		
	Fresh	Litter	Total	Fresh	Litter	Total
	(t/ha)	(t/ha)	(t/ha)	(tC/ha)	(tC/ha)	(tC/ha)
Muyong	2.99	7.93	10.92	1.41	3.73	5.13
Bilid	4.86	13.15	18.01	2.28	6.18	8.46

4.1.3. Soil Carbon

Soil carbon is the main contributor to forest carbon stocks next to AGB (Lal, 2005). Soil samples were collected from the 10-cm topsoil layer to estimate SOC. The soil samples were oven-dried

at 70°C for 48 h in the laboratory. They were then subjected to carbon content analysis under laboratory conditions. Table 5 shows the average soil organic carbon stock in muyong and bilid forests. The average SOC was 26.02 and 23.78 tC/ha in the muyong and bilid forests, respectively, to a soil depth of 10 cm. The 0–10-cm level of the soil is expected to be rich in carbon owing to the presence of humus or organic matter accumulated from the decomposed litter (Ullah et al., 2012; Hobley et al., 2016). The soil carbon results revealed a higher SOC value in muyong than in bilid. This may be attributed to the bilid's greater exposure to sunlight and its greater susceptibility to soil erosion. Furthermore, the practices of weeding, regular thinning, and treatment can play a beneficial role in carbon sequestration in muyong. Finkral and Evas (2008) also reported that thinning treatments can re-establish ecological processes and help in ecosystem restoration and function.

Table 5. Average soil organic carbon stock

Forest types	Average Soil Bulk Density	Mean Soil Organic Carbon (%)	Avg. Soil Organic Carbon Stock (tC/ha)
Muyong	0.72+0.19	3.88±0.09	26.02±4.81
Bilid	0.73±0.03	3.26±0.90	23.78±0.98

4.1.4. Total Carbon Stock

Table 6 shows the total carbon stocks in the muyong and bilid. The results show that the carbon stock in the muyong was higher than that in the bilid. The average carbon stock in the muyong was estimated to be 150.86 tC/ha compared to the 126.14 tC/ha found in the bilid. The presence of large DBH trees in muyong forests can contribute to the majority of forest biomass, as has been confirmed by other studies (Brown & Lugo, 1992; Brown et al., 1995; Culmsee, et al., 2010). Among the all-carbon pools, most of the carbon stock was in the AGB pool. Forest carbon stock information is important for planning, management, and carbon sequestration in the Ifugao system. Information of this nature is essential to understanding carbon stock potential in the forest system at a micro-level. Climate, soil type, topographic factors, and biotic factors are the main determinants of forest biomass and its spatial distribution (Xu et al., 2015). Biomass

374 accumulation in forests also varies according to microclimate and anthropogenic disturbances
375 (Brown and Lugo, 1990).

376 **Table 6. Total carbon stocks based on field data**

Forest types	AGB (tC/ha)	BGB (tC/ha)	Forest Floor		Soil carbon (0-10cm)	Total Carbon Stock
			Fresh	Litter	(tC/ha)	(tC/ha)
Muyong	101.4	18.3	1.41	3.73	26.02	150.86
Bilid	78.2	15.7	2.28	6.18	23.78	126.14

377

378 **4.2. Carbon Stock Estimation using Indirect Measurement (remote sensing-based analysis)**

379   Geospatial data can be used to study forest biomass, which is fortunate, as conventional
380 field-based methods are expensive and time-consuming. Moreover, conventional field-based
381 methods are only applicable to small-scale analysis. Therefore, remote sensing-based methods
382 can be applied to a larger area (Vashum et al., 2012). In this study, the maximum likelihood
383 classification algorithm was used to classify AVNIR-2 data with the help of field data. Figure 8
384 shows the LULC map of the study area. The area was classified into seven classes: muyong, bilid,
385 rice terraces, built-up areas, grassy mountain area, open mountain, and water bodies. The
386 classified image attempts to distinguish muyong (sea-green) forests from the bilid (green). Some
387 misclassification with respect to bilid or muyong occurred owing to the presence of steep
388 topography in the area. Most of the area is covered by bilid (32.5%), followed by rice terraces
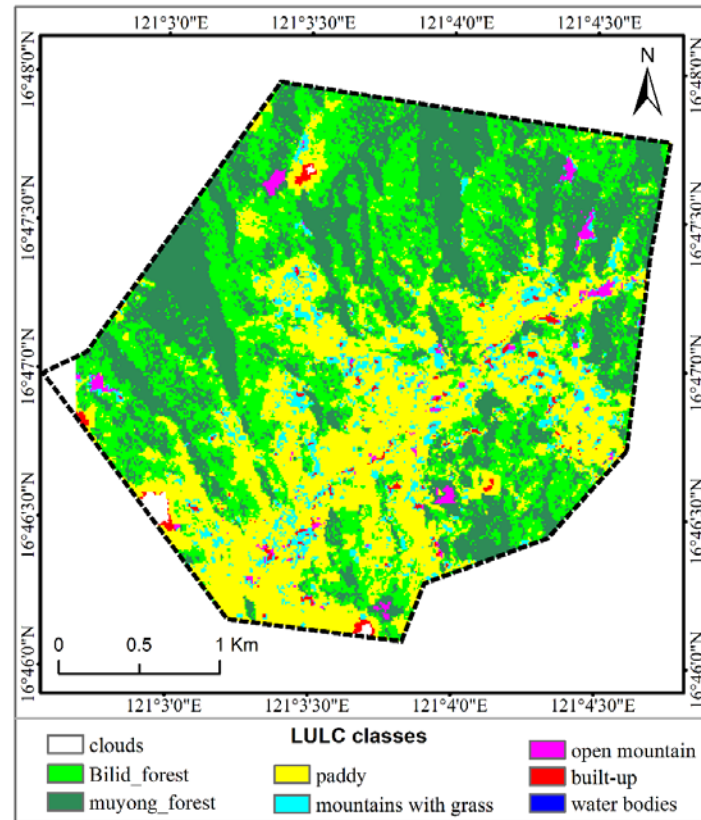389 (30.4%) and muyong (29.5%).

390

391

392

Figure 8. Land use/land cover map of the study area

AVNIR-2-based forest area information and average carbon stocks in bilid and muyong forests were used to estimate total carbon stocks. Table 7 shows the estimated average carbon stocks in the muyong and bilid forests using field-based and remote sensing-based information. The total carbon stocks were 401,061.3 and 369,804.6 tC in muyong and bilid forests, respectively. This information will be useful for policy-makers in designing REDD+ policies for the study area. Some uncertainties in the biomass estimation may potentially arise because soil carbon up to soil depth of 10 cm is considered in this study.

Table 7. Total carbon stocks in muyong and bilid based on remote sensing and field data

Forest Types	Forest area (ha) (2010)	Average carbon stock (tC/ha)	Total carbon stock (tC)
Muyong	2658.5	150.86	401061.3
Bilid	2931.7	126.14	369804.6

414   Avtar et al.'s (2013b) methodology was used to estimate AGB using PALSAR data.
415 Figures 9a and 9b show the biomass map using PALSAR data and the slope map using SRTM-
416 DEM data from the study area. The slope map of the study area (Fig. 10b) clearly shows that
417 most of the area had a slope greater than 20 degrees with the exception of the paddy fields.
418 Therefore, the biomass estimation using PALSAR data may have low accuracy due to the
419 topographic effects on SAR data. Attarchi and Gloaguen (2014) also noticed the effect of
420 topography on PALSAR-based biomass estimation in a mountain forest in Iran and proposed the
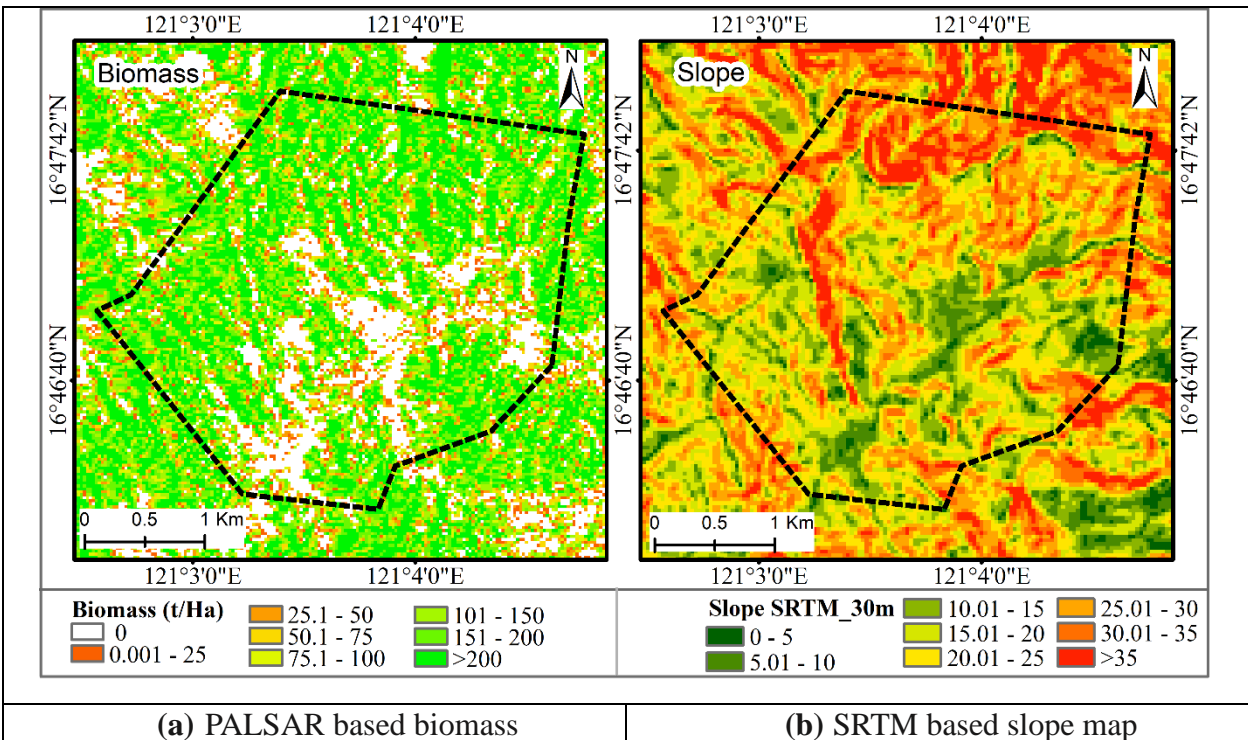421 use of multi-satellite data to overcome topographic effects.

(a) PALSAR based biomass	(b) SRTM based slope map

422   **Figure (9a) PALSAR-based biomass of the study area (9b) SRTM-based slope map**

423   Figure 10 shows a weak correlation ($R^2 = 0.029$) between PALSAR-estimated biomass
424 and field-measured biomass. No significant relationship was observed with PALSAR-estimated
425 biomass because most of the plots were on a steep slope and SAR data are not effective in steep
426 areas owing to the topographic effects. Lone et al. (2017) also used PALSAR data to study the
427 influence of slope and aspect in AGB estimation in India and found that topography influences
428 the saturation of backscattering. The high slope areas have a high saturation limit of
429 backscattering with 50–60 t/ha uncertainty. The key limitation to the PALSAR-based biomass
430 estimation was the topographic effect of SAR data in the study area, which limits the

431 applications of remote sensing techniques. To overcome the topographic limitations, LiDAR data
432 can be useful for more precise biomass estimation in mountainous areas. Further studies on
433 forests in other areas of Ifugao would be useful in addressing the lack of information available
434 for remote sensing analysis. However, the potential for remote sensing opportunities in the area
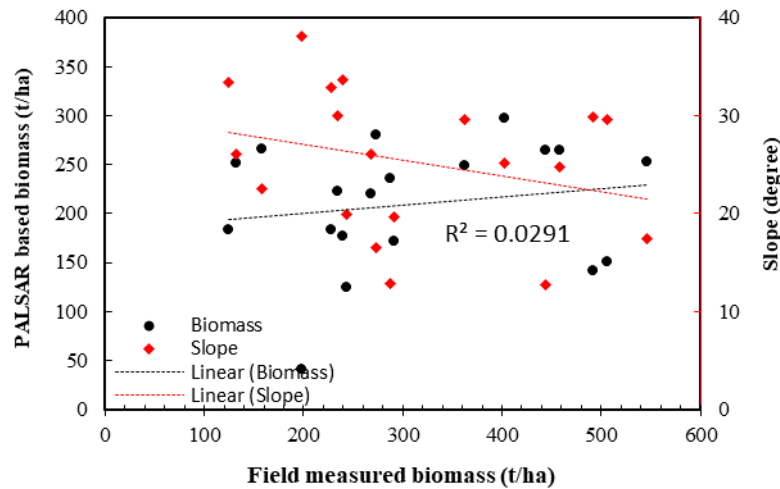435 remains limited due to the cloud cover and topography.

436

437 **Figure 10. Correlation between PALSAR-estimated biomass and field-measured biomass**

438   The estimation of total carbon stock is an important input for several current and future
439 initiatives. The results can improve our understanding of how the muyong forest contributes
440 potential carbon stock and the role of a landscape. The muyong forest showed higher total
441 biomass than the bilid forest, and a greater difference in DBH was found in the muyong than in
442 the bilid. Tree density is higher in the bilid forest than in the muyong, and this supports the
443 hypothesis that the selective cutting and facilitated growth practices in the muyong are beneficial
444 for carbon sequestration. Interestingly, the maintenance of muyong forests not only promotes
445 carbon sequestration but also provides water for the rice fields during the dry season.

446   Implementation of the REDD+ mechanism can provide opportunities for the local people
447 to conserve and manage the muyong system more sustainably in addition to reaping the financial
448 benefits associated with carbon sequestration in the muyong system. Furthermore, the
449 implementation of REDD+ can help protect the environment and biodiversity. It can conserve
450 carbon stocks and provide a better adaptation mechanism to climate change in the Philippines,
451 which is one of the climate change mitigation policies (Center et al., n.d.; Roe, 2012).

452   Climate change and other anthropogenic factors are affecting the rice terraces, and local

453   people are struggling to sustain their livelihoods. Consequently, people have begun to leave the

454   muyong area in search of employment elsewhere (Avtar et al., 2019). As part of the effort to

455   reduce the outward migration of local people, REDD+ can make a positive impact with respect

456   to long-term maintenance of the muyong forest. As a means of generating more income, REDD+

457   supports coffee tree growth in the muyong forest and taps into the organic food market rather

458   than wood collection. Thus, REDD+ is still considered a promising means of creating incentives

459   and other livelihood options to reduce deforestation and sustain the economic transformations of

460   the Ifugao economy.

461   This preliminary study had several limitations, including the limited number of sampling

462   plots and the relative spacing of sampling plots due to steep topography. Systematic sampling

463   with a sufficient number of plots may be the optimal approach to accurately estimate total carbon

464   stocks. The use of species-specific allometric equations may be more effective than generic

465   allometric equations in reducing uncertainties (Kiyono et al., 2010; Samreth et al., 2012). We

466   measured soil carbon only at a soil depth of 10 cm, although earlier studies used soil carbon data

467   from a soil depth of 1 m. The number of sampling plots was also limited and should be increased

468   to improve measurement accuracy. The use of permanent sampling plots (PSPs) may help to

469   enhance the accuracy of carbon estimation (Samreth et al., 2012). Continuous monitoring is

470   required to determine the rate of sequestration with the establishment of PSPs.

471   The use of remote sensing techniques for biomass estimation in this study was limited by

472   cloud cover and topographic conditions (i.e., slope). However, this could be improved through

473   the application of advanced topographic correction techniques (Umarhadi and Danoedoro, 2019)

474   as well as the use of high-resolution satellite data with object-based classification methods, such

475   as GEOBIA (Weih Jr. and Riggan Jr., 2010) and the use of advanced modeling methods to

476   estimate biomass, such as random forest (RF), stepwise regression (SR), and support vector

477   regression (SVR) (Liu et al., 2017). The use of multi-sensor remote sensing data can improve the

478   accuracy of image classification and biomass estimation. Improvement of biomass estimation is

479   essential for an effective measurement, reporting, and verification (MRV) system. The incentives

480   from REDD+ can help muyong forests with high carbon stock. The biomass products will also

481 be useful for Sustainable Development Goals (SDG) Goal 15, which includes the improvement
482 of carbon management.

483 **5. Conclusions**

484   This study has demonstrated the effective use of direct and indirect methods to assess
485 forest carbon stocks. The results reveal that carbon stock differs among muyong and bilid forests
486 of the Ifugao system, and most of the carbon stock is found in AGB. Field-based methods are
487 useful for calculating average carbon stocks in muyong (150.86 tC/ha) and bilid (126.14 tC/ha)
488 forests. Owing to the positive role of human interventions, muyong forests happen to sequester a
489 larger amount of carbon (than the natural capacity). This makes the muyong an appropriate forest
490 management system for the implementation of the REDD+ framework. These data can play an
491 important role in filling the gaps in the existing national forest biomass estimation. It is essential
492 that high-quality carbon stock data be generated to facilitate the monitoring of forest carbon and
493 understanding resilience under the REDD+ mechanism. Remote sensing data have limited
494 applications in the study area due to cloud cover and topographic effects. Accurate and reliable
495 biomass estimation models are necessary for the non-destructive estimation of carbon stocks.
496 Furthermore, carbon sequestration safeguards against deforestation and also helps to develop
497 symbiotic linkages between agroforestry and biodiversity conservation. REDD+ mediation is
498 expected to support the Ifugao economy by providing additional incentives and opportunities that
499 will assist local communities in maintaining their traditional rice terraces system.

506

507 **References**

508   Anaya, J. A., Chuvieco, E., & Palacios-Orueta, A. (2009). Aboveground biomass assessment in

509   Colombia: A remote sensing approach. *Forest Ecology and Management*, *257*(4), 1237–

510   1246.

511   Andoh, J., & Lee, Y. (2018). National REDD+ Strategy for Climate Change Mitigation: A

512   Review and Comparison of Developing Countries. *Sustainability*, *10*(12).

513   https://doi.org/10.3390/su10124781

514   Attarchi, S., & Gloaguen, R. (2014). Improving the estimation of above ground biomass using

515   dual polarimetric PALSAR and ETM+ data in the Hyrcanian mountain forest (Iran).

516   Remote Sensing, 6(5), 3693–3715.

517   Avtar, R., Sawada, H., Takeuchi, W., & Singh, G. (2012). Characterization of forests and

518   deforestation   in   Cambodia   using   ALOS/PALSAR   observation. Geocarto

519   International, 27(2), 119-137.

520   Avtar, R., Sawada, H., & Kumar, P. (2013a). Role of remote sensing and community forestry to

521   manage forests for the effective implementation of REDD+ mechanism: a case study on

522   Cambodia. *Environment,   Development   and   Sustainability*,   *15*(6),   1593–1603.

523   https://doi.org/10.1007/s10668-013-9448-y

524   Avtar, R., Suzuki, R., Takeuchi, W., & Sawada, H. (2013b). PALSAR 50 m Mosaic Data Based

525   National Level Biomass Estimation in Cambodia for Implementation of REDD+

526   Mechanism. PLOS ONE, 8(10), e74807. https://doi.org/10.1371/journal.pone.0074807

527   Avtar, R., Takeuchi, W., & Sawada, H. (2013c). Monitoring of biophysical parameters of cashew

528   plants   in   Cambodia   using   ALOS/PALSAR   data. Environmental   monitoring   and

529   assessment, 185(2), 2023-2037.

530   Avtar, R., Kumar, P., Oono, A., Saraswat, C., Dorji, S., & Hlaing, Z. (2016). *Potential*

531   *application of remote sensing in monitoring ecosystem services of forests, mangroves and*

532   *urban areas* (Vol. 32). https://doi.org/10.1080/10106049.2016.1206974

533   Avtar, R., Tsusaka, K., & Herath, S. (2019). REDD+ Implementation in Community-Based

534   Muyong Forest Management in Ifugao, Philippines. Land, 8(11), 164.

535   doi:10.3390/land8110164

536   Baccini, A., Friedl, M., Woodcock, C., & Warbington, R. (2004). Forest biomass estimation over

537   regional scales using multisource data. *Geophysical research letters*, *31*(10).

538   Borah, J. R., Evans, K. L., & Edwards, D. P. (2018). Quantifying carbon stocks in shifting

539   cultivation landscapes under divergent management scenarios relevant to REDD.

540   *Ecological applications : a publication of the Ecological Society of America*, *28*(6),

541   1581–1593. https://doi.org/10.1002/eap.1764

542   Brown, Sandra. (1997). *Estimating biomass and biomass change of tropical forests: a primer*

543   (Vol. 134). Food & Agriculture Org.

544   Brown, SANDRA, & Lugo, A. E. (1992). Aboveground biomass estimates for tropical moist

545   forests of the Brazilian Amazon. Interciencia. Caracas, 17(1), 8–18.

546   Brown, I. F., Martinelli, L. A., Thomas, W. W., Moreira, M. Z., Ferreira, C. C., & Victoria, R. A.

547   (1995). Uncertainty in the biomass of Amazonian forests: An example from Rondonia,

548   Brazil. Forest Ecology and Management, 75(1–3), 175–189.

549   Butic, M., & Ngidlo, R. (2003). Muyong forest of Ifugao: assisted natural regeneration in

550   traditional forest management. *Advancing assisted natural regeneration (ANR) in Asia*

551   *and the Pacific. Regional Office for Asia and the Pacific, Food and Agriculture*

552   *Organization of the United Nations, Bangkok, Thailand*, 23–27.

553   Calderon, M., Dizon, J., Sajise, A., Andrada II, R., Bantayan, N., & Salvador, M. (2009).

554   *Towards the Development of a Sustainable Financing Mechanism for the Conservation of*

555   *the Ifugao Rice Terraces in the Philippines*.

556   Center, E. L. A., GOM, G. O. M., Asia, G. S., NGOs, K. I., Areas, D.-P., & Bureau-DENR, W.

557   (n.d.). The Philippine National REDD-plus Strategy.

558   Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B., ... &

559   Henry, M. (2014). Improved allometric models to estimate the aboveground biomass of

560   tropical trees. Global change biology, 20(10), 3177-3190.

561   Conklin, H. C. (1980). Ethnographic atlas of Ifugao; a study of environment, culture, and society

562   in northern Luzon.

563   Culmsee, H., Leuschner, C., Moser, G., & Pitopang, R. (2010). Forest aboveground biomass

564   along an elevational transect in Sulawesi, Indonesia, and the role of Fagaceae in tropical

565   montane rain forests. Journal of Biogeography, 37(5), 960–974.

566   Daniel, C. (2014). Government confirms Ifugao 'muyong' system.

567   https://www.sunstar.com.ph/article/335314

568   Department of Environment and Natural Resources 2008. The Ifugao rice terraces Philippines
569   project framework, GIAHS. http://www.fao.org/3/a-bp814e.pdf

570   Drake, J. B., Knox, R. G., Dubayah, R. O., Clark, D. B., Condit, R., Blair, J. B., & Hofton, M.

571   (2003). Above-ground biomass estimation in closed canopy neotropical forests using

572   lidar remote sensing: Factors affecting the generality of relationships. *Global ecology and*

573   *biogeography*, *12*(2), 147–159.

574   Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N., Calders, K., ... & Falkowski,

575   M. (2019). The importance of consistent global forest aboveground biomass product

576   validation. *Surveys in geophysics*, *40*(4), 979-999.

577   Dugan, P., Durst, P. B., Ganz, D. J., & McKenzie, P. J. (2003). Advancing assisted natural

578   regeneration (ANR) in Asia and the Pacific. *RAP PUBLICATION*, *19*.

579   Durst, P. B., Waggener, T., Enters, T., & Laycheng, T. (2001). *Forests out of bounds: impacts*

580   *and effectiveness of logging bans in natural forests in Asia-Pacific*. FAO.

581   Eggleston, S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). *2006 IPCC guidelines for*

582   *national greenhouse gas inventories* (Vol. 5). Institute for Global Environmental

583   Strategies Hayama, Japan.

584   Englhart, S., Keuck, V., & Siegert, F. (2011). Aboveground biomass retrieval in tropical

585   forests—The potential of combined X-and L-band SAR data use. *Remote sensing of*

586   *environment*, *115*(5), 1260–1271.

587   FAO. (2015). In Global Forest Resources Assessment 2015 Country Report Philippines. *Forestry*

588   Department Food and Agriculture Organization of the United Nations, 164, 5.

589   Finkral, A. J., & Evans, A. M. (2008). The effects of a thinning treatment on carbon stocks in a

590   northern Arizona ponderosa pine forest. Forest Ecology and Management, 255(7), 2743-

591   2750.

592   Hobley, E. U., & Wilson, B. (2016). The depth distribution of organic carbon in the soils of

593   eastern Australia. Ecosphere, 7(1), e01214.

594   Houghton, R. A. (2003). Why are estimates of the terrestrial carbon balance so different? *Global*

595   *Change Biology*, *9*(4), 500–509. https://doi.org/10.1046/j.1365-2486.2003.00620.x

596   Herath, S., Tsusaka, K., & Diwa, J. (2015). Assessment on the feasibility of REDD+ in

597   Nagacadan Rice Terraces of Ifugao and its muyong forest. United Nations University

598   Institute for the Advanced Study of Sustainability: Tokyo, Japan.

599

600 Jang, J. W., & Salcedo, S. (2013). The socio-political structure that regulates the Ifugao Forest
601   Maintenance (Vol. 58, pp. 85–94). Presented at the 2013 4th international conference on
602   biology, environment and chemistry, IPCBEE.

603 Kiyono, Y., Furuya, N., Sum, T., Umemiya, C., Itoh, E., Araki, M., & Matsumoto, M. (2010).
604   Carbon stock estimation by forest measurement contributing to sustainable forest
605   management in Cambodia. Japan Agricultural Research Quarterly: JARQ, 44(1), 81-92.

606 Lal, R. (2005). Forest soils and carbon sequestration. *Forest Soils Research: Theory, Reality and*
607   *its Role in TechnologY*, *220*(1), 242–258. https://doi.org/10.1016/j.foreco.2005.08.015

608 Lasco, R. D., Mallari, N. A. D., Pulhin, F. B., Florece, A. M., Rico, E. L. B., Baliton, R. S., &
609   Urquiola, J. P. (2013). Lessons from early REDD. *International Journal of Forestry*
610   *Research*, *2013*.

611 Lindsell, J. A., & Klop, E. (2013). Spatial and temporal variation of carbon stocks in a lowland
612   tropical forest in West Africa. *Forest Ecology and Management*, *289*, 10-17.

613 Liu, K., Wang, J., Zeng, W., & Song, J. (2017). Comparison and evaluation of three methods for
614   estimating forest above ground biomass using TM and GLAS data. Remote Sensing, 9(4),
615   341.

616 Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). Remote sensing and image interpretation.
617   John Wiley & Sons.

618 Lone, J., Sivasankar, T., Sarma, K. K., Qadir, A., & L N Raju, P. (2017). *Influence of Slope*
619   *Aspect on above Ground Biomass Estimation using ALOS-2 Data* (Vol. 6).
620   https://doi.org/10.21275/ART20174506

621 Matsushima, N., & Tojo, Y. (2010). Satoyama Initiative: Use and Management of "Muyong" in
622   Ifugao Province, Northern Luzon Island in the Philippines.

623 Ma, L., Shen, C. Y., Fu, S. L., Lian, J. Y., & Ye, W. H. (2018). TEMPORAL AND SPATIAL
624   PATTERNS IN ABOVEGROUND BIOMASS WITHIN DIFFERENT HABITATS IN
625   A SUB-TROPICAL FOREST. *Journal of Tropical Forest Science*, *30*(2), 143-153.

626 McGroddy, M.E., Daufresne, T. and Hedin, L.O. (2004). Scaling of C:N:P stoichiometry in
627   forests worldwide: Implications of terrestrial Redfield-type ratios. Ecology 85: 2390-
628   2401.

629 Minh, H. V. T., Avtar, R., Mohan, G., Misra, P., & Kurasaki, M. (2019). Monitoring and
630   Mapping of Rice Cropping Pattern in Flooding Area in the Vietnamese Mekong Delta
631   Using Sentinel-1A Data: A Case of An Giang Province. *ISPRS International Journal of*
632   *Geo-Information*, *8*(5). https://doi.org/10.3390/ijgi8050211

633 Marín-Spiotta, E., & Sharma, S. (2013). Carbon storage in successional and plantation forest
634   soils: a tropical analysis. *Global Ecology and Biogeography*, *22*(1), 105-117.

635 Nelson, R., Krabill, W., & Tonelli, J. (1988). Estimating forest biomass and volume using
636   airborne   laser   data.   *Remote   Sensing   of   Environment*,   *24*(2),   247–267.
637   https://doi.org/10.1016/0034-4257(88)90028-4

638 Nelson DW, Sommers LE (1996) Total carbon, organic matter. In: Sparks DL et al (eds) Method
639   of soil analysis. Part 3. Chemical methods. Soil Science Society of America, Madison, pp
640   961–1010

641 O'Connor, R. A. (1995). Agricultural change and ethnic succession in Southeast Asian states: a
642   case for regional anthropology. *The Journal of Asian Studies*, *54*(4), 968–996.

643 Pearson, T., Walker, S., & Brown, S. (2013). Sourcebook for land use, land-use change and
644   forestry projects.

645 Ravindranath, N., & Ostwald, M. (2008). Methods for estimating above-ground biomass. *Carbon*
646   *inventory methods handbook for greenhouse gas inventory, carbon mitigation and*
647   *roundwood production projects*, 113–147.

648 Racelis, E. L., Carandang, W. M., Lasco, R. D., Racelis, D. A., Castillo, A. S., & Pulhin, J. M.
649   (2008). Assessing the carbon budgets of large leaf mahogany (Swietenia macrophylla
650   King) and Dipterocarp plantations in the Mt. Makiling Forest Reserve,
651   Philippines. Journal of Environmental Science and Management, 11(1).

652 Samreth, V., Chheng, K., Monda, Y., Kiyono, Y., Toriyama, J., Saito, S., ... & Ito, E. (2012).
653   Tree biomass carbon stock estimation using permanent sampling plot data in different
654   types of seasonal forests in Cambodia. Japan Agricultural Research Quarterly:
655   JARQ, 46(2), 187-192.

656 Soriano, M. A., & Herath, S. (2019). Climate change and traditional upland paddy farming: a
657   Philippine case study. Paddy and Water Environment, 1-14.

658 Tadono, T., Shimada, M., Murakami, H., & Takaku, J. (2009). Calibration of PRISM and
659   AVNIR-2 onboard ALOS "Daichi". IEEE Transactions on Geoscience and Remote
660   Sensing, 47(12), 4042-4050.

661 Takahashi, K., Ikeyama, Y., & Okuhara, I. (2018). Stand dynamics and competition in a mixed
662   forest at the northern distribution limit of evergreen hardwood species. *Ecology and*
663   *evolution*, *8*(22), 11199–11212.

664 Timothy, D. J., & Nyaupane, G. P. (2009). *Cultural heritage and tourism in the developing*
665   *world: A regional perspective*. Routledge.

666 Toorn, S. I. aan den. (2013, August 31). *Conserving the Ifugao Rice Terraces World Heritage*
667   *Site: Financing cultural landscapes in a less-developed country through an ecosystem*
668   *services framework* (Bachelor). Faculty of Archaeology, The Netherlands.

669 UNESCO. (2019, April 1). Rice Terraces of the Philippine Cordilleras.
670   http://whc.unesco.org/en/list/722

671 UN-REDD, P. (2016). Global & Regional Support. https://www.un-redd.org/. Accessed 1 April
672   2019

673 Umarhadi, D. A., & Danoedoro, P. (2019, November). Correcting topographic effect on Landsat-

674   8 images: an evaluation of using different DEMs in Indonesia. In Sixth Geoinformation

675   Science Symposium (Vol. 11311, p. 113110L). International Society for Optics and

676   Photonics.

677 Ullah, M. R., & Al-Amin, M. (2012). Above-and below-ground carbon stock estimation in a

678   natural forest of Bangladesh. Journal of forest science, 58(8), 372-379.

679 Vashum, K. T., & Jayakumar, S. (2012). Methods to estimate above-ground biomass and carbon

680   stock in natural forests-A review. *J. Ecosyst. Ecogr*, *2*(4), 1–7.

681 Walkley A, Black IA (1934) An examination of Degtjareff method for detemination soil organic

682   matter and a proposed modification of the chromic acid titration method. Soil Sci 37:29–

683   37

684 Weih, R. C., & Riggan, N. D. (2010). Object-based classification vs. pixel-based classification:

685   comparative importance of multi-resolution imagery. The International Archives of the

686   Photogrammetry, Remote Sensing and Spatial Information Sciences, 38(4), C7.

687 World bank. (2010). *A Strategic Approach to Climate Change in the Philippines*. Sustainable

688   Development Department East Asia & Pacific Region.

689 Wondo Genet, E. (2013). Training manual on: forest carbon pools and carbon stock assessment

690   in the context of SFM and REDD+.

691   https://pdfs.semanticscholar.org/4559/ca2a2516838d03103cec1a8ea07ddac51e8b.pdf

692   access on 9 July 2015

693 Xu, Y., Franklin, S. B., Wang, Q., Shi, Z., Luo, Y., Lu, Z., ... & Jiang, M. (2015). Topographic

694   and biotic factors determine forest biomass spatial distribution in a subtropical mountain

695   moist forest. *Forest ecology and management*, *357*, 95-103.

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Appendix

699 **Table A1. Muyong Forest Carbon Stock**

Muyong	AGB		BGB		AGB+BGB		C Stock	
	kg	tons/ha	kg	tons/ha	kg	tons/ha	kg	tons/ha
M01	666.22	70.1	133.30	14.0	799.52	84.1	375.8	39.5
M02	2345.49	246.6	417.87	43.9	2763.36	290.6	1298.8	136.6
M03	3167.92	333.1	535.70	56.3	3703.62	389.4	1740.7	183.0
M04	1066.22	112.1	209.00	22.0	1275.21	134.1	599.3	63.0
M05	2465.64	259.3	515.15	54.2	2980.79	313.4	1401.0	147.3
M06	1008.68	106.1	191.53	20.1	1200.21	126.2	564.1	59.3
M07	1500.47	157.8	291.27	30.6	1791.74	188.4	842.1	88.5
M08	1965.55	206.7	375.16	39.4	2340.72	246.1	1100.1	115.7
M09	5421.45	570.0	834.79	87.8	6256.24	657.8	2940.4	309.2
M10	1248.71	131.3	240.64	25.3	1489.35	156.6	700.0	73.6
M11	1723.20	181.2	322.56	33.9	2045.76	215.1	961.5	101.1
Average	**2052.7**	**215.8**	**369.7**	**38.9**	**2422.41**	**254.7**	**1138.5**	**119.7**
Std. Dev	**1338.0**	**140.7**	**201.5**	**21.2**	**1537.1**	**161.6**	**722.5**	**76.0**

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701 **Table A2. Bilid Forest Carbon Stock**

Bilid	AGB		BGB		AGB+BGB		C Stock	
	kg	tons/ha	kg	tons/ha	kg	tons/ha	kg	tons/ha
B01	1383.0	145.4	264.6	27.8	1647.6	173.2	774.4	81.4
B02	1243.6	130.8	252.9	26.6	1496.5	157.3	703.4	73.9
B03	1324.9	139.3	273.2	28.7	1598.1	168.0	751.1	79.0
B04	915.9	96.3	196.6	20.7	1112.5	117.0	522.9	55.0
B05	1542.0	162.1	303.1	31.9	1845.1	194.0	867.2	91.2
B06	2389.5	251.2	464.9	48.9	2854.4	300.1	1341.6	141.0

B07	1589.8	167.2	346.3	36.4	1936.2	203.6	910.0	95.7
B08	2262.8	237.9	443.6	46.6	2706.3	284.6	1272.0	133.8
Average	**1581.4**	**166.3**	**318.2**	**33.5**	**1899.6**	**199.7**	**892.8**	**93.9**
Std. Dev	**471.8**	**49.6**	**88.2**	**9.3**	**559.4**	**58.8**	**262.9**	**27.6**

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