Journal of Tropical Forest Science 36(1): 117–131 (2024)
https://doi.org/10.26525/jtfs2024.36.1.117
ISSN: 0128-1283, eISSN: 2521-9847

DEVELOPMENT OF A CARBON IN ABOVEGROUND BIOMASS FORECAST MODEL FOR UNDERUTILISED SPECIES IN QUIRINO FOREST LANDSCAPE PROJECT, PHILIPPINES

Orpiano GB[1], Manuel RP[2], Carig ET[1, *] & Carig JG[1]

[1]*College of Agriculture Forestry and Engineering, Quirino State University, Diffun, 3401, Philippines*
[2]*Nueva Vizcaya State University, Bayombong, Nueva Vizcaya, 3700, Philippines*

**elizabeth.carig@qsu.edu.ph*

Submitted May 2023; accepted August 2023

Sustaining forest carbon sinks is a priority in climate change mitigation and forest management strategies. However, several issues confront the role of Philippine forests in climate change mitigation. These include the loss of old-growth cover, unsustainable forest landuse practices, and lack of site-specific modelling. These are the realities in the Quirino Forest Landscape Project (QFLP), a semi-contiguous collection of secondary forests in four municipalities of Quirino Province. This study was undertaken to develop a forecast model for carbon in aboveground of underutilised trees in QFLP. Data were collected through field inventory, the National Mapping and Resource Information Authority Land Cover Databases, and secondary sources. Multiple linear regression, principal components analysis, and biodiversity indices were used to analyse the data collected from different sampling areas to develop a forecast model. Findings suggest that the QFLP forest was secondary, as evidenced by the fact that > 60% of the trees were underutilised. With the ongoing decline in forest cover due to resource use and lack of forestry policy enforcement, it is worth noting that the carbon sequestration potential of underutilised species is not dependent on ecological dominance; that is, species that are more vulnerable to local extinction have higher potential to gain carbon. Given all the variables and their high forecasting power, the study demonstrated that the developed model was precise enough to provide future carbon capture values for QFLP.

Keywords: Allometric equation, carbon sequestration, climate change mitigation

INTRODUCTION

Predicting the impacts of climate change on the environment and biodiversity has drawn a great deal of scientific attention. One of the most important anthropogenic contributors to climate change is the emission of greenhouse gases, especially carbon dioxide. Carbon storage is regarded as one of the most important forest ecosystem services (Bello et al. 2015), and the role of trees and forests in carbon sequestration has also earned immense research recognition. Forests can help reduce carbon in the air, not only when people increase it, but also when people prevent losing it. Most of the studies, however, concentrated only on a particular group of tree species and specific landscapes. Often, researchers only focus on the carbon sequestration ability of very large or high-priority species and pay little attention to the lesser-known groups or species of forest trees.

In a real-world forest, functional and species diversity are not only the qualities of dominant trees, but also of the obscure ones. According to Yeom (1984), 93% of the tropical forest volume consists of species that are lesser known and/or lesser used. These species that make up the majority of forest diversity end up being destroyed or wasted. Given that diversity of these underutilised species is a substantial part of a forest, removal of lesser-known and/or lesser-used species also removes from the forests their capacity to store carbon. Worse, wasting (e.g. burning) these trees will revert carbon dioxide to the atmosphere. As Lasco et al. (2006) found, after logging operations, about 40% of the woody aboveground biomass carbon is converted to lumber and veneer/plywood or sold as logs. The remaining 60% of carbon is emitted to the atmosphere as carbon dioxide through burning as fuel and decay. This 60% of woody aboveground biomass carbon, which comprises mostly of underutilised tree species, is not used and is left in the forest.

The province of Quirino in Northeastern Philippines has diverse forest resources. Situated in the Sierra Madre Mountains, 77% (235,460 ha) of its total land area (305,718 ha) are categorised as forestlands (http://www.rdc2.gov.ph/invest/quirino/index.php). The Philippine Forestry Statistics 2010–2017 (https://forestry.denr.gov.ph/index.php/statistics/philippines-forestry-statistics) published by the Forest Management Bureau, Department of Environment and Natural Resources (DENR) showed that the Province of Quirino has a natural broadleaf forest cover of approximately 126,515 ha, and 73% are listed as closed forest. It is also generally known that the forests of Quirino are some of most anthropogenically impacted forests and continually face undocumented logging, land conversion, burning, squatting and many other poor and unsustainable uses.

Several conservation projects have been led by various organisations to help protect the natural resources of the province, one of which is the Quirino Forest Landscape Project (QFLP). The QFLP covers the semi-contiguous open (secondary) and closed (old growth) forests that run along four out of six Quirino towns: Aglipay, Cabarroguis, Diffun and Maddela. QFLP was intended to resolve the underlying problems that cause the decline in forest cover (SERD 2018).

SERD (2018) estimated that around 40% of the forest cover is made up of underutilised species. Following the insights from the Yeom (1984) paper, if the utilisation and ecological values of underutilised species are not defined, it is likely that the ecosystem services that these resources provide will be wasted. In the context of carbon sequestration and climate change mitigation, it is important to assess the capacity of these underutilised community of species to store carbon in their biomass. Thus, the main objective of this study was to develop a carbon in aboveground biomass (C-AGB) forecast model for underutilised trees in QFLP, hereinafter referred to as $QFLUS_{Carbon}$. To accomplish this, we (1) described the tree diversity and importance values (IVs) of underutilised tree species sampled in QFLP, (2) calculated C-AGB of all inventoried underutilised species in QFLP, (3) determined the rate of forest cover change in QFLP, (4) determined the interrelationships of the carbon sequestration variables, (5) developed a regression model that could forecast C-AGB accumulation of underutilised tree species in QFLP, and (6) forecasted a 30-year C-AGB value.

MATERIALS AND METHODS

Area selection and sampling design

The study was performed in 12 barangays (communities) across the four municipalities of Quirino Province under the QFLP, namely, Aglipay, Cabarroguis, Diffun and Maddela. Sampling was done using transects and paired quadrats, following the method by Manuel et al. (2019). Given the time constraints and safety precautions, the inventory team used pacing (undulating distance) and established a transect of 150 m. At each end of the transect, one pair of 20 m × 20 m quadrats was established; quadrats were perpendicular and adjacent to the transect. Total sampling area was 1.92 ha.

The inventory team identified, measured, and counted all canopy trees (diameter at breast height (DBH) ≥ 10 cm) within each quadrat. Tree identification was facilitated by resident dendrologist and local guides. For dubious species, minimal leaf samples were gathered and dry-pressed for verification in the laboratory. For species known to locals only by vernacular names, identities were checked using literatures and resources including *Revised Lexicon of Philippine Trees* by Rojo and Salvosa (2011), and *PhytoImages* (http://www.phytoimages.siu.edu). DBH was measured for each tree using diameter tape. Individual counts were made in the field then sorted by species and plots.

C-AGB of underutilised species in QFLP

Estimating C-AGB was a two-stage process. Since destructive sampling of large trees was not feasible, the AGB was approximated using the allometric equation for tropical trees developed by Brown (1997). This allometric equation was based on the premise that DBH was positively correlated with biomass. Rasmussen et al. (2012) established that moist zone equations developed by Brown (1997) provide the same biomass estimates as polynomial and quadratic equations. Brown's (1997) equation applies to trees having DBH of 5–148 cm, which was about the same range of DBH of trees measured in the QFLP.

The second stage was the derivation of C-AGB using known proportions of carbon in wood. While there are many conservative estimates for C-AGB, we used the C-AGB multiplier of 0.50 as carbon content of each living tree is estimated to be 50% of the AGB (Barrett & Christensen 2011, Barrett 2014, Tashi et al. 2016, Vijayakumar et al. 2016). AGB to carbon content conversion was based on the guidelines established in the *IPCC Good Practice Guidance for Land Use, Land-Use Change and Forestry* (Aalde et al. 2006).

Forest cover change

The forecast model would require spatiotemporal information on forest cover increase or decrease. For this, we obtained the Philippine Land Cover Database for years 2000, 2005, 2010, 2015 and 2018 from the National Mapping and Resource Information Authority (NAMRIA) to evaluate the forest cover (open and closed types) in the QFLP. The vector data for each period were classified separately, and from these, a change matrix was developed. The rate of annual forest cover change was computed using the formula by Puyravaud (2003). The formula was derived from the Compound Interest Law, making it more intuitive than any other formula.

Estimation of C-AGB of underutilised tree species in QFLP using regression model

Multiple linear regression was used to model C-AGB of underutilised tree species in QFLP. Variables such as DBH, abundance, density and rate of annual AGB accumulation of species were used as the final set of variables, on the premise that these were not interinfluenced by each other (multicollinear). The annual accumulation rate of AGB (3.40 t ha^{-1} $year^{-1}$) was taken from the IPCC data on aboveground net biomass growth in tropical rainforests in Asia (Aalde et al. 2006). This multiplier is essential to capturing the landscape-level capacity of underutilised trees to fix carbon dioxide. This value was factored to obtain an estimated yearly aboveground biomass accumulation of each species. Forecasting power of the resulting model was based on the r^2 value.

To avoid multicollinearity, a diagnostic test (Pivac 2010, Shrestha 2020) was performed among forecast variables. Modern statistical software has built-in decision protocol whether variables with multicollinearity or multicollinearity tendencies should be excluded from the final form of the model (i.e. coefficients). Using IBM-SPSS v.23, multicollinearity diagnostics were used to avoid problems with fitting and interpreting the regression model.

Using forest cover change in the model to forecast carbon

At this stage, the developed regression still lacked key spatiotemporal variables for full use of the forecast model. The main conundrum for the use of the forecast is that forest cover and year progression data have to be projected, then incorporated. We were not able to find any literature or studies where change in forest cover was incorporated without data on plant growth curves. Using the plant growth curve and other related variables as forecast variables was one of the limitations of this study, as data vary in species level.

In order to integrate the change in forest cover and the yearly progression to the developed model, assuming that all forecast variables were equal, the annual rate of change in forest cover was factored into the minimum and maximum values of the regression model to determine the possible decrease or increase in forest area for a given year. Using forest cover data for 2020, and with the corresponding rate of forest cover change, we forecasted C-AGB of underutilised tree species in QFLP for 2020 to 2050.

RESULTS AND DISCUSSION

Tree diversity

Quadrat sampling in QFLP yielded 125 species in 491 individuals. Overall community diversity was very high (H' = 3.90) and highly heterogeneous (Shannon evenness (E) = 0.81).

Dominance was found to be shared by about 20 species (Simpson's diversity reciprocal index = 1/D = 20.11). Highest possible diversity, H'_{max} was computed using the natural logarithm (ln) of total observed species (S), i.e. ln/S = 4.83 (Table 1).

Forest formation in the QFLP is akin to tropical lowland evergreen rainforest (Manuel et al. 2019). The most prominent climax species and species associations conform to the descriptions by Fernando (2008). Specifically, the QFLP forest is a mix of the lowland "Lauan-oak type" and lower montane "Tanguile-oak type" of dipterocarp forest. These *Shorea–Lithocarpus* associations are the most prominent climax species in the area. The Philippines DENR still classifies this forest formation as "dipterocarp forest", a forest typical of elevations < 600 m asl.

Among the identified species, 65.6% are either classified as lesser-known species, lesser-used species, and/or species not listed under any of the commercial groups in the DENR Administrative Order 19 (1995). The list of underutilised tree species found in the QFLP is shown in Appendix 1.

Community diversity of underutilised tree species was found higher than the whole QFLP tree assemblage (H' = 4.01). Further, the dominance was distributed to 46 species (Simpson 1/D = 46.27) (Table 1). Computed Shannon's evenness also implied that the community was highly heterogeneous (0.91) (Table 1). Using *t*-test formula specifically designed for comparing diversities (H'), it was found that there was significant difference between underutilised species and timber-producing tree assemblage (Table 2). This affirms that the underutilised trees were indeed more dominant than the supposedly dominant commercial trees.

In the sampling and surrounding areas, the underutilised and inferior timber species such as Balobo (*Diplodiscus paniculatus*), Magabuyo (*Celtis luzonica*), Binuang (*Octomeles sumatrana*) and Banato (*Mallotus philippinensis*) were the bigger dominant trees. This shows that (1) the forest is in fact secondary, i.e. it has been subjected to timber extraction, and (2) the

Table 1 Diversity summary of tree assemblages found in Qurino Forest Landscape Project (QFLP)

Measure/index	Tree assemblage		
	Overall	Commercial	Underutilised
Abundance (N)	491	278	213
Number of species (S)	125	43	82
Shannon-Weiner index (H')	3.90	2.61	4.01
Simpson's reciprocal index (1/D)	20.11	n/a*	46.27
Shannon evenness (E)	0.81	0.69	0.91

Simpson's reciprocal index (1/D) was not computed because model distribution of individuals in the sample was 1 per species, making the notion of dominance misleading

Table 2 Hutcheson's *t*-test results between the Shannon-Weiner indices of commercial and underutilised trees sampled in QFLP

	Underutilised	Commercial
t-value	13.7978	452.11
df	4.01	2.61
Variance	0.003	0.0074
Abundance	213	278

p-value (2-tailed) = 0.0000, df = degree of freedom secondary ecological succession of the QFLP forest is well underway since the underutilised trees are still colonising the forest landscape.

C-AGB of underutilised tree species in QFLP

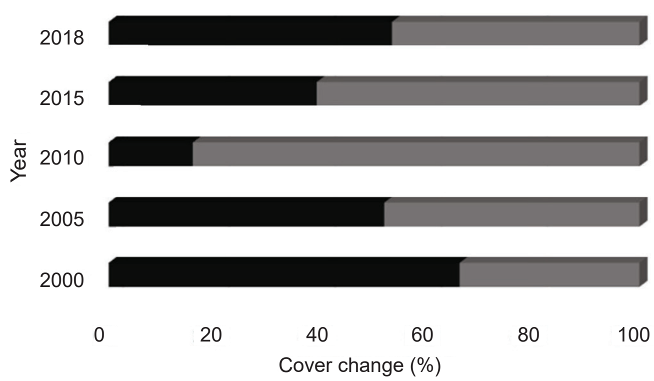
Total C-AGB of underutilised species in QFLP was 1.502 t ha^{-1}(Appendix 2), or approximately 16 kg per standing tree. On per-species basis, the average C-AGB was 0.018 t (standard deviation (SD) = 0.0025). The combined C-AGB of the high-IV species was 0.059 t ha^{-1}, almost 4.0% of the total carbon sequestered by all sampled trees in the QFLP. Surprisingly, the underutilised trees with the lowest IVs comprised 6.9% of C-AGB (0.104 t ha^{-1}) in QFLP study sites (Appendix 1). From these computations, we conclude that the more threatened species have more carbon-storing capacity than the ecologically dominant underutilised trees. The high C-AGB of low-IV underutilised species compared with high-IV counterparts affirm the management importance of lesser-known and/or lesser-used species in the QFLP. These species, having higher potential to sequester carbon, warrant protection, conservation and population enhancement.

Scanning of AGB and carbon sequestration studies yielded no comparative findings for the underutilised tree species. The estimated C-AGB of forests in Eden and Dibibi in Cabarroguis (also with commercial trees) are 263.67 and 359.85 t ha^{-1} respectively (Manuel et al. 2019), while in Palali-Mamparang Range, the value is 45.12 t ha^{-1} (Oceana Gold Philippines 2016, unpublished report).

Forest cover change

Forest cover (open and closed types) in the QFLP for years 2000 to 2018 are presented in Figure 1. As per NAMRIA Land Cover Database, the closed forests in QFLP peaked at 67% in year 2000 but dropped to just above 15% in 2010. The sudden loss of forest cover over this period could have been caused by widespread logging since the log export ban was temporarily lifted at the end of the 1990s. Nonetheless, forest cover began increasing until 2018. Unfortunately, this was the only available forest cover data from the NAMRIA provided by DENR at the time of study. The rise in forest cover may be attributed to logging moratorium and forestation projects that had been implemented by the provincial local government unit. The National Greening Program organised by DENR also conributed to the improvement of forest cover.

Using the formula by Puyravaud (2003), the grand moving average annual rate of forest cover change in QFLP was -0.033 ha year^{-1} (SD = 0.06) (Appendix 3). This implies that despite restoration efforts over the recent years, QFLP forests still tend to decline. This may be



Year	2000	2005	2010	2015	2018
■ Closed forest (ha)	15,468	12,150	2327	4099	6114
■ Open forest (ha)	7920	11,249	12,344	6358	5337
Total area (ha)	23,388	23,399	14,671	10,457	11,451

Figure 1 Summary of vegetation cover changes in the Quirino Forest Landscape Project (QFLP) from years 2000 to 2018

attributable to growing resource demands by the locals. This includes, among others, timber harvesting (for domestic purposes), land conversion, i.e. forest clearing to establish farms, and expansion of household areas. During field work, it was observed that livelihood of the community members was either adjacent to or within the forested sites. We also came across felled logs in the forest and wood being transported out. As local populations rise, demands for forest resources (including lands for farming and domiciles) are seen to increase correspondingly.

Interrelationships between carbon sequestration variables

The correlations among the forecast variables were analysed using Principal Components Analysis. (Figure 2, Tables 3a and b). Variance percentages showed that Principal Component 1 (PC1) explained 99.86% of the interrelationships across the four forecast variables. All variables could be condensed into one dimension, i.e. PC1 and this alone could explain most of the values in all the forecast variables.

PC1 was correlated with total DBH. However, correlations of DBH to the rest of the variables under PC1 were very weak. Interestingly, tree girth was revealed to be negatively (albeit very weakly) correlated to C-AGB. This counter-intuitive relationship can be explained by the concept of trade-offs. Trees in resource-constrained environments must choose between allocating resources to growth (diameter) and biomass accumulation (carbon). A tree cannot maximise both at the same time. The pool of resources available for trees to allocate appears to be limited. A tree can choose to increase its diameter and become thick and strong at the expense of storing less carbon. A tree, on the other hand, can concentrate on accumulating carbon and biomass, resulting in a slenderer but potentially taller structure.

Forest lands do not necessarily expand with growing trees. Therefore, competition for space and nutrients affects the tree girth, abundance, density and, ultimately, the capacity to store carbon. In PC1, it was illustrated that DBHs of trees increased but other variables were stagnant (Table 3b). As mature trees occupy more basal area, less regeneration could be accommodated within existing forest areas. There may come a point where trees become so clumped that trees eventually fail to store carbon in their biomass. It further implies that density should always be at the optimum level to achieve the ideal carbon accumulation of the area.

Interpreting PC2 is somewhat disputable since the variances lodged in this dimension were only remainders (0.14%) of all variances

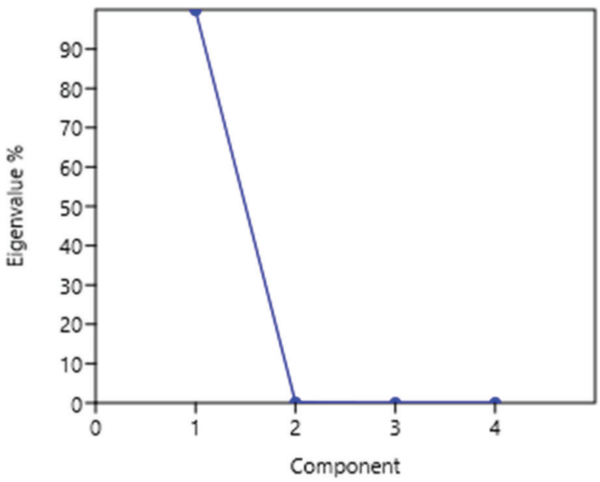


Figure 2 Scree plot of Principal Components Analysis of total DBH, abundance, density and rate of AGB accumulation measurements for underutilised species in QFLP

across all forecast variables. Nonetheless, applying the concept of trade-offs, as abundance of trees increases, density remains at standstill, but girth and carbon storage correspond inversely.

Logical forestry sense dictates that the best way to ensure continual absorption of carbon into growing forest biomass is to expand the forest cover. By planting more trees at the fringes, juvenile trees are ensured proper spacing, and resource/nutrient allocation to facilitate growth, recruitment of more species, and carbon sequestration.

Development of $QFLUS_{Carbon}$ regression model

We propose that there are determinants of annual carbon stored in the biomass of underutilised species per unit area in the QFLP. Abundance, density, total DBH and rate of AGB accumulation affected by density are non-interdependent variables that can be used to develop the carbon accumulation model. For purposes of brevity, the model name $QFLUS_{Carbon}$ was designated for "annual carbon stored in the biomass of underutilised species per unit area in the QFLP".

$QFLUS_{Carbon}$ variables fitted well into the model with a r^2 value of 0.986. This implies that the regression model, as a function of above variables, offers very precise forecasting power. Variance inflation factor (Table 4) above 10 may indicate multicollinearity issues across variables values, and values above 30 may indicate very strong problems with multicollinearity. Hair et al. (2013) suggests that variables having variance proportion values above 0.90 in the dimension with a high condition index are most likely to have collinearity. Collinearity diagnostics on the abovementioned variables suggest that rate of AGB correspond to abundance. This makes sense because density of trees in QFLP, after all, was derived from abundance data. Density of trees was in turn used to determine the annual rate of accumulation of AGB per species. Results of the regression modelling nonetheless accepted all the above variables due to strong forecasting power of the regression model. Essentially, apparent collinearity among forecast variables is well within acceptable limits.

Expression of the $QFLUS_{Carbon}$ model now assumes the syntax:

0.021 – (0.005) TDBH – (0.00005202) abd + (.037) Rate.AGB + (.264) Density

where, TDBH = total DBH (cm), abd = abundance, or number of individuals per species, Rate.AGB = the rate of AGB accumulation as a function of tree density, and Density = tree density or number of trees ha^{-1} (Table 5).

Table 3a Ordination summary (Principal Components Analysis) of total DBH, abundance, density and rate of AGB accumulation measurements for underutilised species in QFLP

PC	Eigenvalue	% variance
1	2311.75	99.858
2	3.29625	0.14238
3	6.03052E-08	2.6049E-09
4	3.39023E-08	1.4644E-09

PCA performed using PAST 3.2 software

Table 3b Eigenvectors for all five principal components

	PC1	PC2	PC3	PC4	PC5
Total DBH	0.99901	-0.04441	5.03E-05	-4.47E-06	-8.74E-06
Abundance	0.044407	0.99901	-2.35E-05	-0.00035	-0.00014
Density	5.95E-06	0.000115	0.14705	-0.08723	0.98527
Rate of AGB accumultion	1.90E-05	0.000358	0.041146	0.99578	0.082022
Carbon-AGB	-5.14E-05	-5.98E-06	0.98827	-0.02848	-0.15002

Use of model and forest cover change to forecast C-AGB in QFLP

At this point, the $QFLUS_{Carbon}$ model, expressed as tonnes of carbon ha^{-1} $year^{-1}$, is still regarded as "semi-final form" of the actual forecast model. This is because the spatiotemporal variables (i.e. forest area change and year progression) still need to be inserted into the equation. The final value should be expressed in tonnes of carbon. However, inserting spatiotemporal factors tend to compel the forecast model to incorporate even more complex and real-world factors such as tree growth curves, edaphic qualities and climate influences. Tree growth curves, which is generally considered sigmoidal, will vary across species and that by itself will complicate the model. Additional forest area, especially during initial years of planting, may not immediately provide carbon gain since trees would still be at their juvenile stage, and would be affected by many environmental factors. At present there is no single AGB or carbon model that completely incorporates these variables. This is the most pressing limitation of $QFLUS_{Carbon}$.

To curb this conundrum, we devised an oversimplified, but plausible approach to integrating forest cover change and time progression (expressed in years) to $QFLUS_{Carbon}$. Assuming that all variables, i.e. computed abundance, total DBH, density and rate of AGB accumulation values are equal, the rate of annual forest cover change was factored in as min–max values to $QFLUS_{Carbon}$, to obtain a $QFLUS_{Carbon}$ value for a particular year (e.g. 2018). This by default integrates forest area increase/decrease. Since the forest cover data for 2020 was not yet available at the time of writing, the data for 2018 and the corresponding rate of forest cover change were used to forecast the 2020 $QFLUS_{Carbon}$ value, as well as $QFLUS_{Carbon}$ forest area requirements for the next 30 years (2050).

The forecasting was achieved by compounding the resulting possible change in forest cover ($QFLUS_{Carbon}$* ± 0.033) of a particular year to succeeding years (2019, 2020, 2021, 2022 and henceforth) using annual forest cover change. To minimise bias, the computed min–max multiplier of ± 0.033 was randomised every year (which was easy to implement in MS Excel using the function RANDBETWEEN) to forecast future values up to year 2050. This procedure was reiterated 100 times, then averaged to achieve a refined forecasted $QFLUS_{Carbon}$ value, now expressed in tonnes of carbon. Resulting values are presented in Figure 3.

The 30-year forecast data (2020 to 2050) showed that the average carbon sequestration in AGB of underutilised species of all forested areas in QFLP amounted to 228.88 kt C (SD = 3.70). The lowest forecasted $QFLUS_{Carbon}$ was 221.522 kt C; highest was 239.11 kt C. The resulting time series, despite the limitations discussed elsewhere in this paper, use strong set of forecasted $QFLUS_{Carbon}$ values.

The seasonality of values implies that the forest cover multiplier of ± 0.033 can impart strong fluxes in $QFLUS_{Carbon}$ gain/loss. In a study by Johnston et al. (2019) it was forecasted that global forest net carbon capture would be 1.5 and 6.8 Gt C $year^{-1}$ by 2030 and 2065 respectively. The authors also identified various factors

Table 4 Collinearity diagnostics[a] among $QFLUS_{Carbon}$ variables

Model	Dimension	Eigenvalue	Condition index	Variance proportion				
				(Constant)	TDBH (cm)	Abundance	Annual rate of AGB accumulation	Density
1	1	4.040	1.000	0.01	0.01	0.00	0.00	0.01
	2	0.695	2.410	0.18	0.01	0.00	0.00	0.07
	3	0.141	5.347	0.25	0.71	0.00	0.00	0.22
	4	0.110	6.073	0.03	0.20	0.04	0.09	0.61
	5	0.014	17.227	0.54	0.08	0.96	0.90	0.09

[a]Dependent variable: carbon in AGB; TDBH = total DBH regression analysis performed using SPSS v23 software

causing uncertainty in the projected changes in forest areas, such as the impact of socio-economic drivers and climate policy objectives, as well as the interaction between forests and climate. Also, Singh et al. (2012) estimated net carbon accumulation in Madhya Pradesh forests up to 2025 and found that carbon accumulation would fall from 3465.232 Mt in 1991 to 3406.429 Mt in 2025. The authors explained that the decline in carbon accumulation was significantly affected by changes in the forest cover area, structural change in the geographical area, changes in landuse and disproportionate variations in dense and open forests. Our results show that it is imperative for QFLP managers and stakeholders to maintain an annual increase in forest cover if the QFLP carbon capture service is to be prioritised, especially since the scenarios presented in Johnston et al. (2019) and Singh et al. (2012) papers are similar to QFLP forests. Hence, there is a likelihood that carbon sequestration potentials of the area may be hampered, unless proper utilisation, production and conservation strategies are implemented to increase forest cover.

CONCLUSION AND RECOMMENDATIONS

The QFLP is a secondary forest dominated by underutilised tree species. The carbon in AGB of these underutilised species was not dependent on their ecological dominance. This means that overdensity and overabundance of trees can actually have a negative impact on landscape-level carbon sequestration. However,

Figure 3 Forecasted carbon in AGB accumulation in QFLP (2020–2050); the figure shows projected carbon in aboveground biomass accumulation in QFLP for the next 30 years; the pathway shows the possible decrease and increase in carbon accumulation were greatly affected by the change in forest cover for the next years to come; average $QFLUS_{Carbon}$ = 228.88 kt

Table 5 Coefficients of the multiple linear regression model

Model	Unstandardised coefficient		Standardised coefficient	t	Sig	95.0% Confidence interval for B		Collinearity	
	B	SE	Beta			Lower bound	Upper bound	Tolerance	VIF
1 (Constant)	0.021	0	-0.992	274.313	0	0.021	0.021		
TDBH (cm)	-0.005	0	-0.992	-43.255	0	-0.005	-0.005	0.357	2.805
Abundance	-5.20 E-05	0	-0.058	-0.893	0.374	0	0	0.044	22.86
Rate of annual AGB accumulation	0.037	0.139	0.017	0.266	0.791	-0.24	0.314	0.046	21.925
Density	0.264	0.185	0.042	1.428	0.157	-0.104	0.633	0.213	4.699

Dependent variable: carbon in AGB; TDBH = total DBH, B = unstandardised regression coefficient, SE = standard error, Sig = significance level, VIF = variance inflation factor those species that are more susceptible to local extirpation are also those that have a higher capacity to gain carbon.

Forest cover in QFLP is decreasing, likely due to expanding resource use by QFLP residents and a lack of enforcement of forestry policies to protect and manage forest cover. Regression analysis has shown that variables such as abundance, DBH, density and rate of AGB accumulation can be used to forecast future values of QFLP-level carbon capture. This model is precise enough to provide valuable insights into how to manage QFLP for optimal carbon sequestration.

To improve the predictive accuracy of the model and to ensure that the forest is managed in a way that maximises carbon sequestration and benefits local communities, the following recommendations are made: conduct extensive simulations, develop a predictive model that incorporates other variables, develop allometric equations for underutilised species, and use the research findings as a basis for forest management strategies and for developing policy options for underutilised species.

REFERENCES

Aalde H, Gonzales P, Gytarsky M et al. 2006. Forest land. Chapter 4 in Eggelston S et al. (eds) *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Institute for Global Environmental Strategies, Hayama.

Barrett TM. 2014. *Storage and Flux of Carbon in Live Trees, Snags, and Logs in the Chugach and Tongass National Forests*. General Technical Report PNW-GTR-889. USDA Forest Service, Portland.

Barrett TM & Christensen GA. 2011. *Forests of Southeast and South-Central Alaska, 2004–2008: Five-Year Forest Inventory and Analysis Report*. General Technical Report PNW-GTR-835. USDA Forest Service, Portland.

Bello C, Galetti M, Pizo MA et al. 2015. Defaunation affects carbon storage in tropical forests. *Science Advances* 1: e1501105. https://doi.org/10.1126/sciadv.1501105

Brown S. 1997. *Estimating Biomass and Biomass Change of Tropical Forests, a Primer*. FAO Forestry Paper 134. FAO, Rome.

Fernando ES. 2008. *Forest Formations of the Philippines*. ASEAN–Korea Environmental Cooperation Unit, Seoul.

Hair JF, Ringle CM & Sarstedt M. 2013. Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance. *Long Range Planning: International Journal of Strategic Management* 46: 1–12. https://doi.org/10.1016/j.lrp.2013.01.001

Johnston C, Buongiorno J, Nepal P & Prestemon JP. 2019. From source to sink: past changes and model projections of carbon sequestration in the global forest sector. *Journal of Forest Economics* 34: 47–72. http://dx.doi.org/10.1561/112.00000442

Lasco RD, Macdicken G, Pulhin F, Guillermo IQ, Sales RF & Cruz RVO. 2006. Carbon stocks assessment of a selectively logged dipterocarp forest and wood processing mill in the Philippines. *Journal of Tropical Forest Science* 18: 212–221.

Manuel RP, Pascual RL, Carig JG & Carig ET. 2019. Biodiversity assessment and functions of secondary forest ecosystems in Eden and Dibibi, Quirino, Philippines. *Asian Journal of Biodiversity* 9: 66–90. http://dx.doi.org/10.7828/ajob.v9i1.1235

Pivac S. 2010. Detection and solving of regression modeling problems in SPSS. Pp 914–919 in *Proceedings of the 33rd International Convention MIPRO*. 24–28 May 2010, Opatija.

Puyravaud JP. 2003. Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management* 177: 593–596. https://doi.org/10.1016/S0378-1127(02)00335-3

Rasmussen K, Bruun TB, Birch-Thomsen T et al. 2012. *Analysis of the Potential for Sustainable, Cassava-Based Bio-Ethanol Production in Mali*. Technical University of Denmark, Kongens Lyngby.

Rojo JC & Salvosa FM. 2011. *Revised Lexicon of Philippine Trees*. Department of Science and Technology, Laguna.

SERD (Sustainable Environment For Rural Development Foundation Incorporated). 2018. *Quirino Forest Landscape Project 2018: Participatory Forest Assessment Technical Report*. Forest Foundation Philippines, Makati.

Singh AK, Jha RK & Gupta VB. 2012. Land use pattern and forecasting of carbon sequestration in Madhya Pradesh forests. *International Journal of Multidisciplinary Research* 2: 29–39.

Shrestha N. 2020. Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics* 8: 39–42. http://dx.doi.org/10.12691/ajams-8-2-1

Tashi S, Singh B, Keitel C & Adams M. 2016. Soil carbon and nitrogen stocks in forests along an altitudinal gradient in the eastern Himalayas and a meta-analysis of global data. *Global Change Biology* 22: 2255–2268. https://doi.org/10.1111/gcb.13234

Vijayakumar DBIP, Raulier F, Bernier P et al. 2016. Cover density recovery after fire disturbance controls landscape aboveground biomass carbon in the boreal forest of eastern Canada. *Forest Ecology and Management* 360: 170–180. https://doi.org/10.1016/j.foreco.2015.10.035

Yeom FBC. 1984. Lesser-known tropical wood species: how bright is their future. *Unasylva* 36: 3–16.

Appendix 1 List of underutilised tree species identified in QFLP with their corresponding importance values and conservation status as classified by IUCN

Common name	Scientific name	Importance value
Alim	*Melanolepis multiglandulosa* var. *multiglandulosa*	0.81
Ambalag	*Pedicellia fuscescens*	0.33
Anang	*Diospyros pyrrhocarpa*	1.10
Anitap[8]	*Macaranga cumingii*	0.32
Anongo	*Turpinia ovalifolia*	1.34
Apaas	*Opar sp.*	0.49
Apanang	*Mallotus cumingii*	0.35
Aplas	*Ficus irisana*	1.89
Babulo[1]	*Alseodaphne longipes*	0.33
Bagarilau	*Cryptocarya ampla*	0.71
Bagna[6]	*Glochidion* sp.	0.32
Balakat gubat[10]	*Balakata luzonica*	0.31 (V)
Balobo	*Diplodiscus paniculatus*	9.85 (V)
Banato	*Mallotus philippensis*	1.65
Bangkal	*Nauclea orientalis*	0.37
Batag ukay	*Neo-uvaria acuminatissima*	2.54
Bayok-bayokan	*Pterospermum niveum*	0.35
Binunga	*Macaranga tanarius*	1.70
Caimito	*Chrysophyllum cainito*	0.40
Dalingsi	*Terminalia pellucida*	1.84 (E; V)
Dangloi	*Pseuduvaria philippinensis*	1.97
Dangloi buntotan	*Pseuduvaria caudata*	0.93
Dapdap	*Erythrina orientalis*	0.39
Duguan	*Myristica philippensis*	0.44 (E; V)
Dungon	*Heritiera sylvatica*	0.85
Gangranada	*Punica granatum*	0.52
Gatasan	*Garcinia venulose*	1.16
Hagimit	*Ficus minahassae*	3.08
Hamindang	*Macaranga bicolor*	0.37 (E; V)
Hauili	*Ficus septica*	0.33
Igyo	*Dysoxylum decandrum*	0.48
Kaburo	*Phoebe sterculioides*	0.67
Kalimutain	*Dysoxylum arborescens*	1.15
Kalomata	*Clausena brevistyla*	1.04
Kalubkob	*Syzygium calubcob*	0.37
Kamulang	*Microcos stylocarpa*	1.70
Kangko	*Aphanamixis perrottetiana*	0.36
Kape	*Coffea arabica*	4.22
Kapulasan	*Nephelium mutabile*	0.34
Karaksan	*Linociera ramiflora*	2.57

Continued

Appendix 1 Continued

Common name	Scientific name	Importance value
Katap	*Trigonostemon philippinensis*	0.015
Katong Matsing	*Chisocheton pentandrus*	2.76
Kobi	*Artocarpus nitida*	0.34
Kulatingan	*Pterospermum obliquum*	0.34
Kuling Baboy	*Dysoxylum altissimum*	0.39
Laneteng gubat	*Kibatalia gitingensis*	0.89 (V)
Ligas	*Semecarpus cuneiformis*	0.35
Lukban	*Citrus grandis*	1.31
Lunas	*Lunasia amara*	0.34
Magabuyo[3]	*Celtis luzonica*	6.27 (E; V)
Magilik	*Premna cumingiana*	0.64
Makaasim[9]	*Syzygium nitidum*	0.32
Malabuho	*Sterculia oblongata*	0.65
Malaikmo	*Celtis philippensis*	0.74
Malugai liitan	*Pometia pinnata*	0.34
Manaring[5]	*Lithocarpus soleriana*	4.35
Mangga	*Mangifera indica*	1.24
Matang-hipon	*Breynia rhamnoides*	0.34
Ngarusangis	*Cryptocarya cagayanensis*	0.35
Pagsahing liitan[4]	*Discocalyx micrantha*	5.02
Pagsahingin	*Canarium asperum*	0.33
Pagsahingin bulog	*Canarium calophyllum*	1.06
Pakiling	*Ficus odorata*	0.36
Palindan	*Orania palindan*	0.41
Palonapoi	*Lithocarpus castellarnauiana*	1.27
Panan		0.41
Paronapin	*Mallotus tliifolius*	0.54
Piling liitan	*Canarium luzonicum*	2.53 (V)
Salaki	*Aglaia elliptica*	0.33
Tabgun	*Ficus ruficaiulis*	0.39
Takip asin	*Macaranga grandifolia*	0.69 (E; V)
Taklang anak[7]	*Garcinia dulcis*	0.32
Talot-ot	*Ficus variegata* var. *garciae*	1.05
Tambalau	*Knema glomerata*	0.33
Tangisang bayawak[2]	*Ficus variegate*	6.37
Tangisang lakihan	*Ficus latsoni*	0.63
Terminalia sp.	*Terminalia* sp.	0.41
Tiagkot	*Abarema clypearia*	0.44
Tibig	*Ficus nota*	1.88
Tinaang-pantay	*Drypetes maquilingensis*	0.36
Upling gubat	*Ficus ampelas*	0.43

E = Endangered, CE = Critically Endangered, V = Vulnerable; [1–5] and [6–10] = top five underutilised species in QFLP with high and low importance values respectively

Appendix 2 Carbon in in aboveground biomass (AGB) of underutilised trees in QFLP

Common name	Scientific name	Carbon in AGB (t)
Alim	*Melanolepis multiglandulosa* var. *multiglandulosa*	0.018
Ambalag	*Pedicellia fuscescens*	0.020
Anang	*Diospyros pyrrhocarpa*	0.019
Anitap	*Macaranga cumingii*	0.021
Anongo	*Turpinia ovalifolia*	0.016
Apaas	*Opar* sp.	0.018
Apanang	*Mallotus cumingii*	0.020
Aplas	*Ficus irisana*	0.016
Babulo	*Alseodaphne longipes*	0.020
Bagarilau	*Cryptocarya ampla*	0.019
Bagna	*Glochidion* sp.	0.021
Balakat gubat	*Balakata luzonica*	0.021
Balobo	*Diplodiscus paniculatus*	0.009
Banato	*Mallotus philippensis*	0.015
Bangkal	*Nauclea orientalis*	0.020
Batag ukay	*Neo-uvaria acuminatissima*	0.017
Batikuling	*Pterospermum niveum*	0.018
Bayok-bayokan	*Macaranga tanarius*	0.020
Binunga	*Chrysophyllum caimito*	0.015
Caimito	*Terminalia pellucida*	0.019
Dalingsi	*Pseuduvaria philippinensis*	0.016
Dangloi	*Pseuduvaria caudata*	0.019
Dangloi buntotan	*Erythrina orientalis*	0.018
Dapdap	*Myristica philippensis*	0.019
Duguan	*Heritiera sylvatica*	0.019
Dungon	*Punica granatum*	0.018
Gangranada	*Garcinia venulose*	0.018
Gatasan	*Ficus minahassae*	0.017
Hagimit	*Macaranga bicolor*	0.018
Hamindang	*Ficus septica*	0.020
Hauili	*Dysoxylum decandrum*	0.020
Igyo	*Phoebe sterculioides*	0.019
Kaburo	*Dysoxylum arborescens*	0.020
Kalimutain	*Clausena brevistyla*	0.017
Kalomata	*Syzygium calubcob*	0.019
Kalubkob	*Microcos stylocarpa*	0.020
Kamulang	*Microcos stylocarpa*	0.017
Kangko	*Aphanamixis perrottetiana*	0.020
Kape	*Coffea arabica*	0.012
Kapulasan	*Nephelium mutabile*	0.020
Karaksan	*Linociera ramiflora*	0.019
Katap	*Trigonostemon philippinensis*	0.015

Continued

Appendix 2 Continued

Species	Scientific name	Carbon in AGB (t)
Katong matsing	*Chisocheton pentandrus*	0.015
Kobi	*Artocarpus nitida*	0.020
Kulatingan	*Pterospermum obliquum*	0.020
Kuling baboy	*Dysoxylum altissimum*	0.019
Laneteng gubat	*Kibatalia gitingensis*	0.018
Ligas	*Semecarpus cuneiformis*	0.020
Lukban	*Citrus grandis*	0.020
Lunas	*Lunasia amara*	0.020
Magabuyo	*Celtis luzonica*	0.012
Magilik	*Premna cumingiana*	0.020
Makaasil	*Syzygium nitidum*	0.021
Malabuho	*Sterculia oblongata*	0.020
Malaikmo	*Celtis philippensis*	0.019
Malugai liitan	*Pometia pinnata*	0.020
Manaring	*Lithocarpus soleriana*	0.014
Mangga	*Mangifera indica*	0.018
Matang-hipon	*Breynia rhamnoides*	0.020
Ngarusangis	*Cryptocarya cagayanensis*	0.020
Pagsahing liitan	*Discocalyx micrantha*	0.013
Pagsahingin	*Canarium asperum*	0.021
Pagsahingin bulog	*Canarium calophyllum*	0.019
Pakiling	*Ficus odorata*	0.020
Palindan	*Orania palindan*	0.019
Palonapoi	*Lithocarpus castellarnauiana*	0.020
Panan		0.019
Paronapin	*Mallotus tliifolius*	0.018
Piling liitan	*Canarium luzonicum*	0.014
Salaki	*Aglaia elliptica*	0.020
Tabgun	*Ficus ruficaiulis*	0.019
Takip asin	*Macaranga grandifolia*	0.020
Taklang anak	*Garcinia dulcis*	0.021
Talot-ot	*Ficus variegata* var. *garciae*	0.016
Tambalau	*Knema glomerata*	0.020
Tangisang bayawak	*Ficus variegate*	0.010
Tangisang lakihan	*Ficus latsoni*	0.018
Terminalia sp.	*Terminalia* sp.	0.019
Tiagkot	*Abarema clypearia*	0.019
Tibig	*Ficus nota*	0.018
Tinaang-pantay	*Drypetes maquilingensis*	0.020
Upling gubat	*Ficus ampelas*	0.019

Appendix 3 Summary of vegetation cover changes in the QFLP from 2000 to 2018 and its computed annual rate of change using Puyravaud's (2003) formula

	Year	Closed forest	Open forest	Total	Annual rate of change
Effective Area (ha) per 5 years interval	2000	15,468	7920	23,388	
	2005	12,150	11,249	23,399	0.0000940432
	2010	2327	12,344	14,671	-0.0933641061
	2015	4099	6358	10,457	-0.0677202291
	2018	6114	5337	11,451	0.0302684839
				Average	-0.033
				SD	0.06

SD = standard deviation