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Non-linear Tree Height (h-d) Model Development and Forest Resource Productivity Assessment of Diguyo Limestone Forest within Northern Sierra Madre Natural Park

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Forest resource monitoring of different forest types is of great importance in sustainable forest management and climate change mitigation. Monitoring the productivity of forest resources could be achieved by modeling the basic tree parameters necessary for forest growth and yield. This study was conducted to develop a height-diameter at breast height (h-d) model necessary for tree height (h) estimation since h measurement is difficult in the field, especially in dense forests, and to estimate the forest productivity of the Diguyo limestone forest within the Northern Sierra Madre Natural Park (NSMNP). The diameter at breast height (d) and h of 124 trees were measured in seven 400-m^2 plots as the basis for the model development. The h-d model was developed using different non-linear models such as the Chapman-Richards (CR), exponential (EX), Korf/Lundqvist (KL), modified logistic (ML), Schnute (SC), and Weibull (WE) models. The models were evaluated using the adjusted coefficient of determination (R^2 adjusted), Akaike information criterion (AIC), Bayesian information criterion (BIC), mean absolute error (MAE), root mean square error (RMSE), percentage root mean squared error (PRMSE), and root mean squared percentage error (RMSPE). The performance of the species-specific allometric models and the generic models were compared for the biomass productivity of the limestone forest. Results showed that the CR h-d model performed best with MAE, RMSE, PRMSE, RMSPE, R^2 adjusted, AIC, and BIC values of 1.47 m, 1.74 m, 19.31%, 28.71%, 0.79, 32.46, and 36.00, respectively. The highest average predicted tree biomass and carbon stock of the Diguyo limestone forest was 112.52 ± 97.65 t/ha and 50.64 ± 43.94 tC/ha, respectively, which is lower than other karst forests in Asia. The low forest resource productivity is due to the physical condition of the forest aggravated by natural and anthropogenic disturbances, thereby needing immediate attention to achieve forest sustainability.

Keywords: h-d model, forest productivity, Diguyo limestone forest, NSMNP

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INTRODUCTION

Forest resource monitoring of different forest types is of great importance in sustainable forest management to understand and respond to the effects of natural and anthropogenic forest disturbances. In recent years, reliably calculating forest productivity, biomass, and carbon stocks have become important bases to estimate the effects of deforestation and, conversely, forest conservation in relation to greenhouse gas emissions as a driver of global climate change (Vashum and Jayakumar 2012). Lasco *et al*. (2004) recommended the periodic inventory of the carbon storage of different Philippine forest types to mitigate the greenhouse gas emission in the country. However, an easy and cost-efficient monitoring procedure is wanting in a developing country like the Philippines.

Species-specific and site-specific allometric equations that produce carbon storage estimates more closely reflecting the characteristics of species and conditions in the Philippines are not readily available. Developing allometric models requires the destructive method of cutting the trees to measure their volume. The use of species-specific allometric models for carbon estimation using Philippine species through destructive sampling is demonstrated in the works of Tandug (1987), Banaticla *et al.* (2007), Santos *et al.* (2010), and Tandug *et al.* (2010). However, the cutting of trees has been prohibited in the Philippines to conserve the country's forest cover. As a result, very few local species- or site-specific allometric equations are available for other researchers to use. Generic equations have become an alternative method to sufficiently estimate the volume and carbon storage of forest ecosystems in the Philippines (Lasco *et al*. 2004, 2005, 2006; Patricio and Tulod 2010). An advanced method such as remote sensing combined with ground data information also enabled carbon storage reporting of large-scale areas with high efficiency (Magcale-Macandog *et al.* 2006; Lumbres and Lee 2014; Pillodar *et al.* 2016; Castillo *et al*. 2017; Doyog *et al.* 2018; Makinano-Santillan *et al.* 2019). However, ground features might be covered by clouds depending on the site's location, and high spatial resolution images are costly.

An alternative non-destructive and cost-effective way to calculate forest biomass and carbon storage is to make use of allometric equations based on data gathered in forest inventories (Brown *et al.* 1989; Brown 1997). The tree diameter at breast height (d) and height (h) information are the basic tree parameters in forest inventories. Forest growth and yield models of forest resources use h and d, and they can be used to calculate standing biomass and carbon stocks. The allometric relationship of tree d and h is also often used to describe the growth stages of tree species. During ground inventories, the d of trees can be measured readily with high accuracy. However, it is often difficult to measure the h of trees accurately in the field, either because it is impractical and dangerous to climb tall trees to measure them, or as a result of human or technical errors if instruments are used. Furthermore, stratified forest formations often pose problems in measuring the h with the use of instruments, especially in uneven-aged and dense forests where the neighboring trees are covering the top of each tree. h-d models can be used to predict missing tree h information using the d as the independent variable.

However, h-d models are specific for different forest types and, thus, need to be developed for the various forest types found in the Philippines, such as mangrove, beach, molave, dipterocarp, pine, mossy, and limestone forest. Limestone forest is a distinct forest type characterized by calcium-rich soil with irregular geomorphology referred to as karsts (Tolentino *et al.* 2020). Because of their unique landscape, limestone forests often harbor endemic species and have a specific forest structure (Clements *et al.* 2006).

Despite the emerging research on carbon accounting and reporting for the different types of forests in the Philippines, data on limestone forests are still limited. Even the neighboring Southeast Asian countries with large formations of limestone landscapes are underexplored, including Malaysia and Indonesia.

Limestone forest is found in some areas of the NSMNP in the Sierra Madre Mountain Range in Northeast Luzon. The objective of this study is to develop an h-d model and to estimate tree biomass and carbon stock of the Diguyo limestone forest in Palanan, Isabela, within the NSMNP. We developed, tested, and evaluated several non-linear growth models to predict h from d. We also compared biomass and carbon stock calculations using a variety of allometric equations to see if the results were significantly different. The hypothesis (Ho) of this study is that the various estimates of the biomass equations tested are not significantly different and the alternative hypothesis (Ha) is that the estimates of the biomass equations tested are significantly different at a 0.05 significance level. The results of this study contribute to the limited data we have on tree growth parameters, biomass, and carbon stock for Philippine limestone forests.

MATERIALS AND METHODS

Study Site

The limestone forest of this study is located in Diguyo, Palanan, Isabela within the boundaries of the NSMNP (Appendix Figure I). This area, along the eastern seaboard of Northeast Luzon, has a type IV climate characterized by evenly distributed rainfall throughout the year. Although long-term weather data are not available for Palanan, the PAGASA (Philippine Atmospheric, Geophysical, and Astronomical Services Administration) weather station along the eastern seaboard in Casiguran 80 km to the south has an average annual temperature of 26.1 °C, with a daily minimum of 18.7 °C in January and a maximum of 33.6 °C in June. Mean annual rainfall is 3,379 mm/yr in Casiguran but is estimated to be even higher in Palanan with 5,000 mm/yr (Co *et al.* 2004). The elevation of the study area ranged from 12–146 masl. The NSMNP is one of the Philippines' largest protected areas by virtue of Proclamation No. 978 s. 1997 and NSMNP Act s. 2001, covering 287,861 ha of land and 71,652 ha of coastal waters, totaling 359,486 ha. The NSMNP provides various ecosystem services such as freshwater for irrigation and domestic uses, food, and flood control. It is the home of several rare and threatened species of flora (*e.g.* Narra, Almaciga, Kamagong) and fauna (*e.g.* Philippine Eagle, Isabela Oriole, Hawksbill and Green Sea Turtles, Philippine Crocodile, and Northern Sierra Madre Forest Monitor Lizard) (van Weerd and Udo de Haes 2010). However, forest and habitat degradation are estimated at 1,400 ha/yr as a result of illegal logging, fuelwood collection, slash and burn cultivation, and residential expansion (DENR 2015), and fauna species are also threatened by illegal hunting.

Ground Data Inventory

The sample sufficiency was calculated through statistical equation presented in Equation 1:

$$n \geq \left(\frac{4AC^2}{e^2 A + 4aC^2} \right) \quad (1)$$

where A is the area (ha) of the study site, C is the coefficient of variation, e is the error, and a is the sampling size.

It was determined from the equation that seven plots, measuring an area of 400 m^2 each, are sufficient in sampling 25 ha of forest, with an error allowance of 15% and coefficient of variation of 20. The 15% error takes into consideration other possible sources of errors during data collection such as instrument inaccuracies.

The seven plots of 20 m x 20 m each were established in the study site along a transect line – from the Magsinarao cave (16.94187 ºN, 122.45015 ºE) to the coastline. An approximate distance of 200 m between each plot was observed depending on the terrain. A 100% inventory of trees per plot was conducted resulting in a total of 124 trees.

All the 124 trees, regardless of species, were measured in the plots using standard diameter tape for the d and a laser instrument for the h. A GPS receiver was used to record the geographical location and elevation of each plot ranging from 12–146 masl with an accuracy of 3–9 m. The highest accuracy was recorded near the coastline because it was a relatively open area, while the lowest was recorded at Magsinarao cave due to closed forest canopy.

The tree species identified in the sampling plots belong to the families Myrtaceae, Meliaceae, Lauraceae, Urticaceae, and Rubiaceae. There were also *Mangifera* sp., *Garcinia* sp., *Ficus* sp., *Syzygium* sp., and several other unidentified species.

The descriptive statistics of the measured trees (Appendix Table I) and the histogram of the observed data for d and h show that the data are suited for model development as varying d and h classes are well represented (Appendix Figures IIa and b). All ground survey data were inspected for possible outliers, as well as the non-linear relationship of the tree d and h through scatter plots (Appendix Figures IIIa and b). The ground survey data were divided into 80% for model selection and development and 20% for model verification.

Development of Growth Models for Tree Species in Limestone Forest

In growth and yield modeling, the correlation between the dependent and independent variables is established through regression analysis. In this study, the different non-linear curves – namely, CR (Richards 1959; Chapman 1961), EX (Ratkowsky 1990), KL (Stage 1963; Zeide 1989), ML (Ratkowsky and Reedy 1986; Huang *et al.* 1992), SC (Schnute 1981), and WE (Yang *et al.* 1978) – were analyzed to develop the h-d model. The chosen candidate models are very popular in the field and have shown satisfactory performance for Philippine tree species (Lumbres *et al.* 2013; Anacioco *et al.* 2018; Doyog *et al.* 2021).

The h was treated as a function of d as shown by the mathematical equation of the different non-linear models (Appendix Table II). The dataset was randomly divided into 80% (100 trees) and 20% (24 trees). The 80% was used for the model selection and fitting, and the 20% was solely for model validation. The model development consisted of two major steps. First, 80% of the data were fitted to the six non-linear h-d models to select the three models with the best performance. The performance of the h-d models was evaluated using the adjusted coefficient of determination (R^2 adjusted), AIC, and Schwartz's BIC as evaluation criteria and was ranked following the ranking of models by Poudel and Cao (2013). A higher R^2 adjusted (Equation 2) and a lower AIC (Equation 3) and BIC (Equation 4) value indicate a better model. Second, the models were validated using 20% of the data. The mathematical equations of the evaluation criteria used in the model selection and fitting, as well as the ranking of models, are presented in Equations 2–5.

$$R^2 adjusted = 1 - \left[\frac{(1-R^2)*(n-1)}{n-p-1}\right] \quad (2)$$

$$\text{if} \quad R^2 = 1 - \left[\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}\right]$$

$$AIC = n * \ln\left(\frac{RSS}{n}\right) + 2k \quad (3)$$

$$BIC = n * \ln\left(\frac{RSS}{n}\right) + logn * k \quad (4)$$

$$R_x = 1 + \left[\frac{(m-1)*(S_x - S_{min})}{S_{max} - S_{min}}\right] \quad (5)$$

where n is the number of observations, p is the number of independent variables, y_i is the observed h for the $_i$th tree, $\hat{y}_i$ is the predicted h of $_i$th tree, $\bar{y}$ is the mean of the observed h, k is the number of model parameters, RSS is the residual sum of squares, R_x is the relative rank of model x (x = 1, 2,…m), m is the total number of models being compared, S_x is the value of the evaluation criteria produced by model x, and S_{min} and S_{max} are the minimum or the best value and maximum values or the worst value of the evaluation criteria, respectively.

Comparison of Existing Allometric Models for the Tree Biomass Prediction

Two species-specific and three existing generic aboveground biomass (AGB) equations were analyzed in this study. The species-specific model for limestone species in the Philippines is not yet developed. Hence, we adopted the generic allometric equations for AGB developed by Brown *et al.* in 1989 (coded as Brown-89) and Brown in 1997 (coded as Brown-97), and the Intergovernmental Panel on Climate Change in 2003 (coded as IPCC). For the species-specific models, we followed the models developed by Stas *et al.* (2017), with d as the predictor (coded as Stas-d) and with d and h as predictors (coded as Stas-d-h). The equation developed by Cairns *et al.* in 1997 for the below-ground biomass (BGB) was used. The AGB estimates of the allometric models were summed up with the BGB estimates for the determination of the total tree biomass (totB). Equations 6–10 represent the models Brown-89, Brown-97, IPCC, Stas-d, and Stas-d-h, respectively, and Equation 11 for the BGB.

$$AGB = exp\,(-3.1141 + 0.9719 * ln(d^2 * h) \quad (6)$$

$$AGB = exp\,(-2.134 + 2.53 * LN(d)) \quad (7)$$

$$AGB = \left(\left(\frac{d}{200}\right)^2 * 3.1416 * h * f\right) * BEF * p \quad (8)$$

$$AGB = exp(-0.245 + 2.082 * LN(d) + LN(p)) \quad (9)$$

$$AGB = exp\,(-1.927 + 1.837 * LN(d) + 0.905 * LN(h) + d * LN(p)) + \varepsilon \quad (10)$$

$$BGB = exp\,(-1.0587 + 0.8836 * LN(AGB) \quad (11)$$

where *p* (wood density) value is 0.574g/cm^3 (Chave *et al.* 2014). In the absence of local equations, the form factor equivalent to 0.42 and biomass expansion factor (BEF) of 3.4 that are specific for tropical tree species can be used (FAO 2005). The ε is the bioclimatic stress variable.

The carbon stock was computed using the carbon fraction (CF) of 45%, as recommended by Lasco and Pulhin (2003) for Philippine forest tree species.

Performance Evaluation for the Developed Growth Models

The obtained ground survey data were randomly split into 80% for model selection and development and 20% for validating the performance of the h-d models. The h estimates of the top three performing h-d models were validated using MAE, RMSE, PRMSE, RMSPE, R^2 adjusted, AIC, and BIC. The MAE (Equation 12) and RMSE (Equation 13) are usually used to assess the estimation accuracy of the model. The PRMSE (Equation 14) is a scale-independent measure that can evaluate the precision of a model's estimation performance. The RMSPE presented in Equation 15 is a measure of the average deviation from the true value and is frequently used to compare the estimation performance of models across different data sets.

$$MAE = \frac{1}{n}\left[\sum_{i=1}^{n} abs(\hat{y}_i - y_i)\right] \quad (12$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (13$$

$$PRMSE = \left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)\,/\,\bar{y}}\right) * 100\% \quad (14$$

$$RMSPE = \left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\hat{y}_i - y_i}{y_i}\right)^2}\right) * 100\% \quad (15$$

After the evaluation, the best h-d model was used to predict the h of the observed ground data. The linear model (predicted h = b_0 + b_1 * observed h) was used to determine the correlation of the observed and predicted h. If the respective model correctly estimated the tree parameter, which is the h, then the intercept (b_0) would not be significantly different from zero and the slope (b_1) would not be significantly different from one. A simultaneous F-test was also conducted to evaluate the hypothesis: Ho: $(b_0, b_1) = (0, 1)$, Ha: $(b_0, b_1) \neq (0, 1)$.

To compare the performance of the different allometric models in predicting the biomass of the limestone forest, Duncan's test was conducted to evaluate the null hypothesis (Ho) (Eq. 1 = Eq. 2 = Eq. 3 = Eq. 4 = Eq. 5) and the alternative hypothesis (Ha) (Eq. 1 ≠ Eq. 2 ≠ Eq. 3 ≠ Eq. 4 ≠ Eq. 5) at 0.05 significance level.

RESULTS

Performance of the Developed Non-linear h-d Model for Limestone Forest

The data collected to develop the h-d model indicate that the trees found in the area are not that tall, ranging from 3.75–17.13 m with an average of 8.54 m (Appendix Table I). The standard deviation (SD) of 3.39 m infers an uneven-aged forest. The d of the trees ranged from 6.36–63.39 cm, with an average of 14.76 cm. On the other hand, the stand density suggests that the study area is a low-density forest with an average of 453 trees per ha (TPH), with a range of 350–525 TPH.

The curve fitting analysis was conducted to establish the correlation between d and h in the developed model. During the model selection, the six candidate h-d models were ranked according to their performances as indicated by the three evaluation criteria (Appendix Table II). All the candidate h-d models had a good performance, indicated by the R^2 adjusted value ranging from 0.65–0.76. The CR had the highest R^2 adjusted value with 0.76, followed by EX, WE, ML, KL, and SC with 0.75, 0.72, 0.71, 0.70, and 0.65, respectively. The BIC values of the candidate models ranged from 103.00–338.12, while the AIC values ranged from 95.18–330.30. The CR still had the best performance for both the BIC and AIC. The CR was followed by EX, SC, WE, KL, and ML, respectively, still for both the BIC and AIC. Based on the overall relative rank, the three models that best performed were CR, EX, and SC. The parameter estimates of the three best-performing models are presented in Table 1.

For the model evaluation, the three non-linear h-d models were fitted to the remaining 20% of the dataset. The accuracy of the performance of the top three performing h-d models was assessed and ranked (Appendix Table III). When the deviation of the predicted h from the observed h was tested, the CR model had the best performance with MAE, RMSE, PRMSE, RMSPE, R^2 adjusted, AIC, and BIC values of 1.47 m, 1.74 m, 19.31%, 28.71%, 0.79, 32.46, and 36.00 respectively. Next was the EX model with MAE, RMSE, PRMSE, RMSPE, R^2 adjusted, AIC, and BIC values of 1.52 m, 1.83 m, 20.34%, 26.89%, 0.78, 34.96, and 38.49, respectively. The SC model was the third best-performing with MAE, RMSE, PRMSE, RMSPE, R^2 adjusted, AIC, and BIC values of 3.35 m, 4.24 m, 47.18%, and 36.03%, 0.56, 75.34, and 78.87, respectively. The plot with the relative rank of the models is shown in Figure 1. Models CR and EX perform similarly, with almost the same rank, while the SC model performs less.

The relationship between the observed and predicted data was plotted using simple linear regression. The correlation of the predicted and observed h is shown by the linear model, which is predicted h = 0.7701 * observed h + 1.9724 with an R^2 value of 0.77 (Appendix Figure IV). There was no significant difference between the observed and estimated h (t-test, p = 0.95).

Table 1. The parameter estimates of the chosen top three best performing h-d models.

Model	Code	Mathematical equation	Parameter estimates		
			a	b	c
Chapman-Richards	CR	$h = 1.3 + a * \left(1 - e^{-b*d}\right)^c$	13.6022	0.0887	1.5629
Exponential	EX	$h = 1.3 + a * e^{\frac{b}{(d+c)}}$	16.1783	–9.1714	–1.4805
Schnute	SC	$h = 1.3^b + \left\{\left(c^b - 1.3^b\right) * \left[\frac{1 - e^{-a*(d-d_{min})}}{1 - e^{-a(d_{max}-d_{min})}}\right]\right\}^{\frac{1}{b}}$	0.1817	1.7652	7.6263

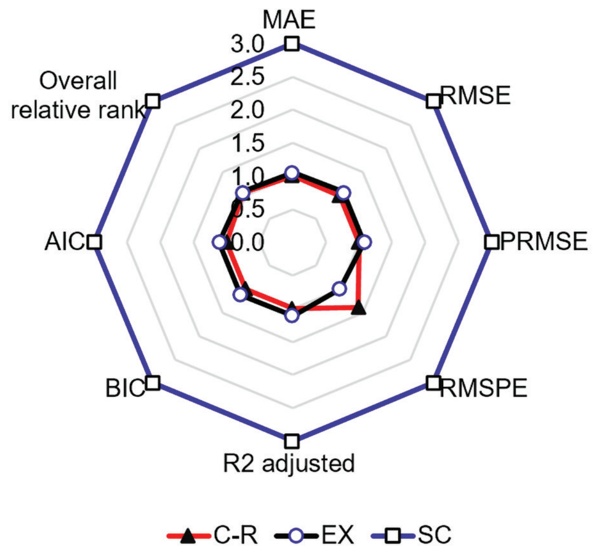

Figure 1. The relative ranks of the performance of h-d models developed for limestone forest species. The model with the smallest area is the best.

Tree Biomass and Carbon Stock of the Limestone Forest within the NSMNP

The totB in the study site is predicted using the sum of the adopted generic and species-specific AGB and BGB allometric models. The totB estimates are presented in terms of totB/ha and totB/individual tree (Table 2). The totB estimated using Brown-89 ranged from 13.33–139.84 t/ha with an average of 59.66 t/ha. The individual totB ranged from 6.75–2236.44 kg with an average of 138.39 kg. The totB per hectare computed with Brown-97 ranged from 20.57–230.87 t/ha with an average of 97.72 t/ha, while the individual totB ranged from 12.77–4289.98 kg with an average of 227.11 kg. The IPCC-based model provided totB per hectare and individual totB estimates ranging from 23.74–266.90 t/ha with an average of 112.52 t/ha and 11.31–4432.57 kg with an average of 261.30 kg, respectively.

The Stas-d-h model provided an average totB estimate of 89.30 t/ha from the range of 18.84–211.82 t/ha. The totB of individual trees ranged from 8.98–3517.75 kg with an average of 207.37 kg. The Stas-d model estimates ranged from 25.52–178.17 t/ha with an average of 82.13 t/ha. The individual totB estimates ranged from 21.16–2537.77 kg with an average of 189.38 kg. The IPCC-based allometric model provided the highest estimates followed by Brown-97, Stas-d-h, Stas-d, then Brown-89.

The computed mean and SD of the total tree carbon stock (totC) of the limestone forest with 45% CF were 26.85±22.75 tC/ha, 43.97±38.49 tC/ha, 50.64±43.94 tC/ha, 40.19±34.87 tC/ha, and 36.96±26.99 tC/ha based on the Brown-89, Brown-97, IPCC, Stas-d-h, and Stas-d models, respectively

Assessment of the Allometric Models for the Prediction of totB of Limestone Forest

A *post hoc* test (one-way analysis of variance) was conducted to evaluate the Ho (Eq. 1 = Eq. 2 = Eq. 3 = Eq. 4 = Eq. 5) and the Ha (Eq. 1 ≠ Eq. 2 ≠ Eq. 3 ≠ Eq. 4 ≠ Eq. 5) at 0.05 significance level. The result of Duncan's test shows that the mean difference of the estimates for the Brown-89 and Brown-97 models were significantly different with a p-value of 0.001; Brown-89 and IPCC with a p-value of < 0.001; Brown-89 and Stas-d-h with 0.02; and Stas-d and IPCC were significantly different at p-0.018 (Appendix Table IV). Further, the Stas-d and Brown-97, Stas-d and Stas-d-h, Stas-d-h and Brown-97, and Brown-97 and IPCC models were not significantly different at p-1.00 as well as Brown-89 and Stas-d (p = 0.21) and Stas-d-h and IPCC models (p = 0.17).

DISCUSSION

Limitations and Applications

The d and h are the basic tree parameters that are used as independent variables for a tree growth model development. Based on the validation criteria applied in this study, the CR model qualifies as the best. This newly developed model offers an easier method for h estimation for limestone forests when the tree h is difficult to measure

Table 2. Total biomass estimates of the allometric models for the Diguyo limestone forest.

Allometric equations	totB density (t/ha)		totB of individual trees (kg)	
	Range	Mean ± SD	Range	Mean ± SD
Brown-89	13.33–139.84	59.66 ± 50.56	6.75–2236.44	138.39 ± 290.12
Brown-97	20.57–230.87	97.72 ± 85.53	12.77–4289.98	227.11 ± 524.77
IPCC	23.74–266.90	112.52 ± 97.65	11.31–4432.57	261.30 ± 567.67
Stas-d-h	18.84–211.82	89.30 ± 77.49	8.98–3517.75	207.37 ± 450.51
Stas-d	25.52–178.17	82.13 ± 59.99	21.16–2537.77	189.38 ± 337.98

in the field, especially in dense forests. However, the use of this model is limited to limestone forest, and, thus, non-optimized tree growths. In addition, the maximum h that was used in the model development is around 17 m; thus, higher errors could be generated when estimating trees taller than 20 m.

When the predicted h of the CR model was used instead of the observed h in calculating the totB using the sum of the IPCC model and the BGB allometric equation, the predicted totB ranged from 14.32–3838.86 kg/tree with a mean of 255.34 kg/tree. The predicted totB of the IPCC model (Table 2) using the observed h ranged from 11.31–4432.57 with a mean of 261.30 kg/tree. When the two sets of predictions were compared through a paired T-test, a *p*-value of 0.99 indicated no significant differences, thereby inferring that the predicted h of the CR model is reliable.

Effects of the Number of Predictors of Allometric Models to the Tree Biomass Prediction

To assess the effect of the number of predictors in predicting the tree biomass, all the computed estimates using the four allometric models were grouped based on the number of predictor/s used. Biomass Group 1 are those estimates that were predicted by the allometric models with d as a predictor (Stas-d and Brown). The Biomass Group 2 are those estimated by the allometric models that have both the d and h as predictors such as the Stas-d-h and IPCC. The result of the *t*-test concluded that the means of the two sets of biomass predictions were significantly different, indicated by the *p*-value of < 0.001. The mean tree biomass densities of 89.92 and 100.91 t/ha were computed for Biomass Groups 1 and 2, respectively.

In this study, we did not evaluate the accuracy of the allometric models used. However, previous studies show that the combination of d and h as predictors has higher accuracy compared to models with only d (Lumbres and Lee 2013; Seo *et al.* 2015; Lee *et al.* 2017; Doyog *et al.* 2019). Nevertheless, the researchers still recommended the use of models with only d as a predictor because h is often difficult to measure in the field.

totB and totC of the Limestone Forest

This study presumed that the mean totB of the limestone forest could be as low as 59.66 t/ha and could be as high as 112.52 t/ha, which is related to the non-optimized growth of trees in the area due to the karst and disturbed environment.

Generally, the role of forests in the carbon cycle could not be quantified directly if the biomass is not measured. Carbon is quantified from the biomass using CF. According to the recommendation of the IPCC, 50% of biomass is carbon. In this study, we adopted the 45% CF.

The computed mean totC of 26.85–50.64 tC/ha in the Diguyo limestone forest is lower compared to reports from other Asian countries. Nevertheless, these values fall within the 25–300 tC/ha range of the reported aboveground carbon for the tropical forest in Asia (Iverson *et al.* 1994; Lasco 2002). The reported total living tree carbon stocks in China range from 163–258tC/ha (Lú *et al.* 2010). The mean carbon stock of the tree layer in the tropical forest over limestone in Xishuangbanna, China was 155 ± 24 tC/ha (Tang *et al.* 2012). The carbon stock in the tropical limestone forest in Sarawak, Malaysia was about 170 tC/ha (Proctor *et al.* 1983). The total AGB of an old secondary forest on limestone in the Moluccas, Indonesia through destructive sampling was estimated to be 177 t/ha (Stas *et al.* 2017), which is equivalent to 79.65 tC/ha using a CF of 45%.

The low totC of the Diguyo limestone forest could be explained by the physical condition of the area. The limited soil volume in the limestone forest results in limited water retention capacity and nutrient absorption. These factors prevent the optimal growth of the trees in the area, thereby affecting the total carbon stock.

In addition, the presence of large trees has a strong influence on the biomass and carbon stock of a forest. In the study site, no large trees were observed, and this probably contributed to the recorded low totB of the limestone forest.

Natural and anthropogenic disturbances could have influenced the low recorded carbon stock. According to Toma *et al.* (2005), the AGB of the forest that has a fire history in East Kalimantan, Indonesia was reported to have lowered from > 400 t/ha to 117, 280, and 315 t/ha in heavily, moderately, and lightly disturbed stands, respectively. In addition, Hashimotio *et al.* (2000) reported that the AGB of a fallow forest varies from 45–56 t/ha after 10–12 yr of disturbance caused by fire, logging, and shifting cultivation in East Kalimantan.

The NSMNP experiences both natural and anthropogenic disturbances. The Philippines is visited by at least 20 tropical cyclones every year and northern Luzon is in the regular pathway of these cyclones. Also, despite the fact that the NSMNP is officially protected, illegal logging is prevalent in the area. In 2011, there were 11 illegal logging hotspots in the NSMNP resulting in 20,000–35,000 m^3 of wood extraction every year (van der Ploeg *et al.* 2011). Agricultural encroachment is an additional threat since several people have settled and are cultivating areas through slash-and-burn farming within the Diguyo forest area.

CONCLUSION

The non-linear CR h-d model with RMSPE of 28.71% was developed in this study to aid in inventories of limestone forests within the NSMNP with the use of d measurements.

In addition, this study reveals that the limestone forest within the NSMNP can store up to an average of 112.52 ± 97.65 t/ha and 50.64 ± 43.94 tC/ha of totB and totC, respectively. The low productivity of the forest in terms of totB and totC is attributed to the physical condition of the area and the natural (*e.g.* typhoons) and anthropogenic forest disturbances such as over-extraction of fuelwood, illegal logging, shifting cultivation, and residential expansion. It is recommended that more effective protection of forest and stricter implementation of the existing rules and regulations within the NSMNP be imposed to protect this area.

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NOTE ON APPENDICES

The appendices section of the study is accessible at https://philjournsci.dost.gov.ph

STATEMENT ON CONFLICT OF INTEREST

There is no conflict of interest that the authors need to declare.

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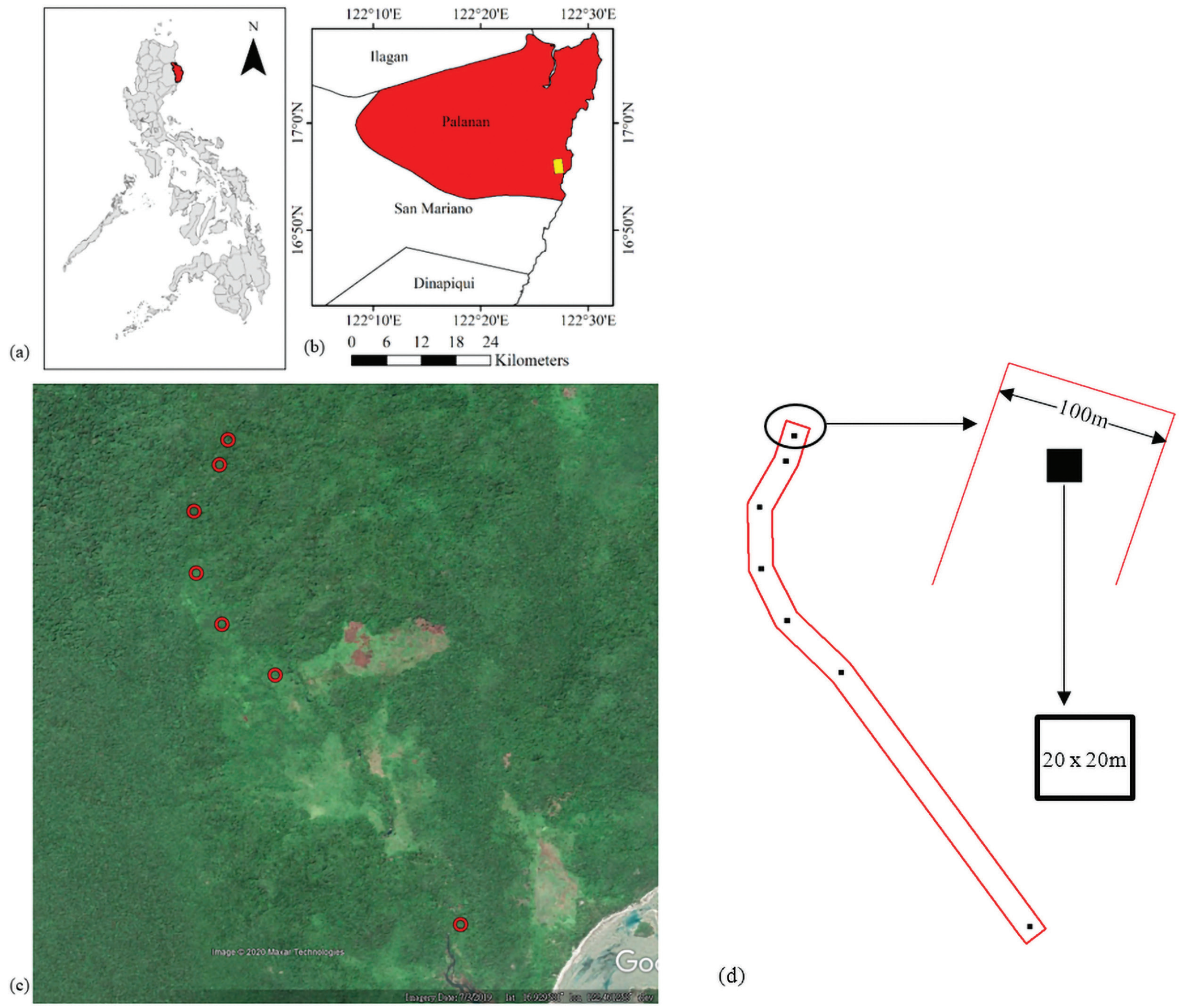

Figure I. The geographical location of the study site: [a] the location of the NSMNP (red) in the Philippines; [b] the location of the research area (yellow) in Palanan (red) and the administrative boundaries of its neighboring municipalities; [c] the aerial view of the established plots (red) retrieved from the Google Earth Pro desktop application at an eye altitude of 3.60 km; the imagery date is 03 Jul 2019; and [d] layout of the sample plot.

Table I. Descriptive statistics of the trees in the Diguyo limestone forest within NSMNP.

Parameters	n	100%		n	80% (model development)		n	20% (model validation)	
		Range	Mean ± SD		Range	Mean ± SD		Range	Mean ± SD
d (cm)	124	6.36–63.39	14.76 ± 10.19	100	6.36–44.24	14.14 ± 8.74	24	6.52–63.39	17.35 ± 14.49
h (m)	124	3.75–17.13	8.54 ± 3.39	100	4.00–15.79	8.43 ± 3.23	24	3.75–17.13	8.99 ± 3.93
TPH		350–525	453 ± 66		350–525	453 ± 67		350–525	456 ± 61

TPH – trees per hectare; SD – standard deviation; n – number of observations

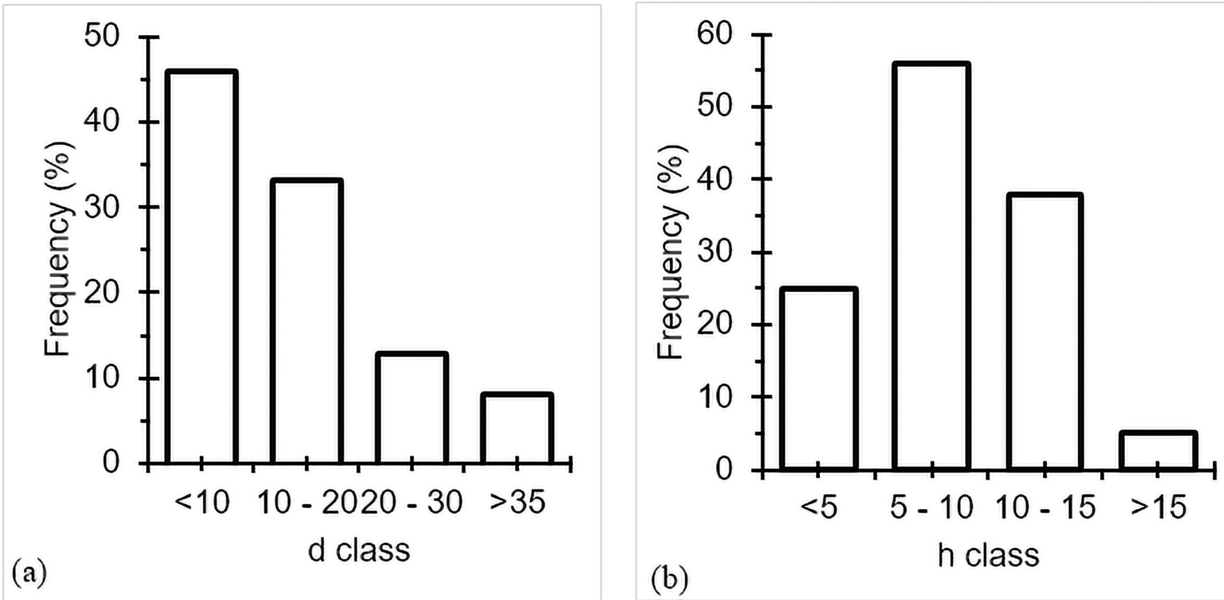

Figure II. Histogram of the observed d (a) and h (b).

Table II. Relative rank of the candidate h-d models for the model selection based on the evaluation criteria.

Model	**Code**	**Mathematical equation**	**Evaluation criteria**			**Overall relative rank**
			R^2 adjusted	BIC	AIC	
Chapman-Richards	CR	$h = 1.3 + a * (1 - e^{-b*d})^c$	0.76	103	95.18	1
			(1.0)	(1.0)	(1.0)	
Exponential	EX	$h = 1.3 + a * e^{\frac{b}{(d+c)}}$	0.75	117.67	109.85	1.29
			(1.26)	(1.31)	(1.31)	
Korf	KL	$h = 1.3 + a * e^{(-b*d^{-c})}$	0.7	322.82	315.01	4.94
/Lundqvist			(3.46)	(5.67)	(5.67)	
Modified logistic	ML	$h = 1.3 + \frac{a}{(1 + b^{-1*d^{-c}})}$	0.71	338.12	330.3	5.1
			(3.29)	(6.00)	(6.00)	
Schnute	SC	$h = 1.3^b + \left\{(c^b - 1.3^b) * \left[\frac{1 - e^{-a*(d-d_{min})}}{1 - e^{-a(d_{max}-d_{min})}}\right]\right\}^{\frac{1}{b}}$	0.65	157.31	149.49	3.47
			(6.0)	(2.21)	(2.21)	
Weibull	WE	$h = 1.3^b + a * \left(1 - e^{-b*d^c}\right)$	0.72	309.22	301.4	4.44
			(2.54)	(5.39)	(5.39)	

Numbers in parenthesis are the model's relative rank based on the specific criteria.

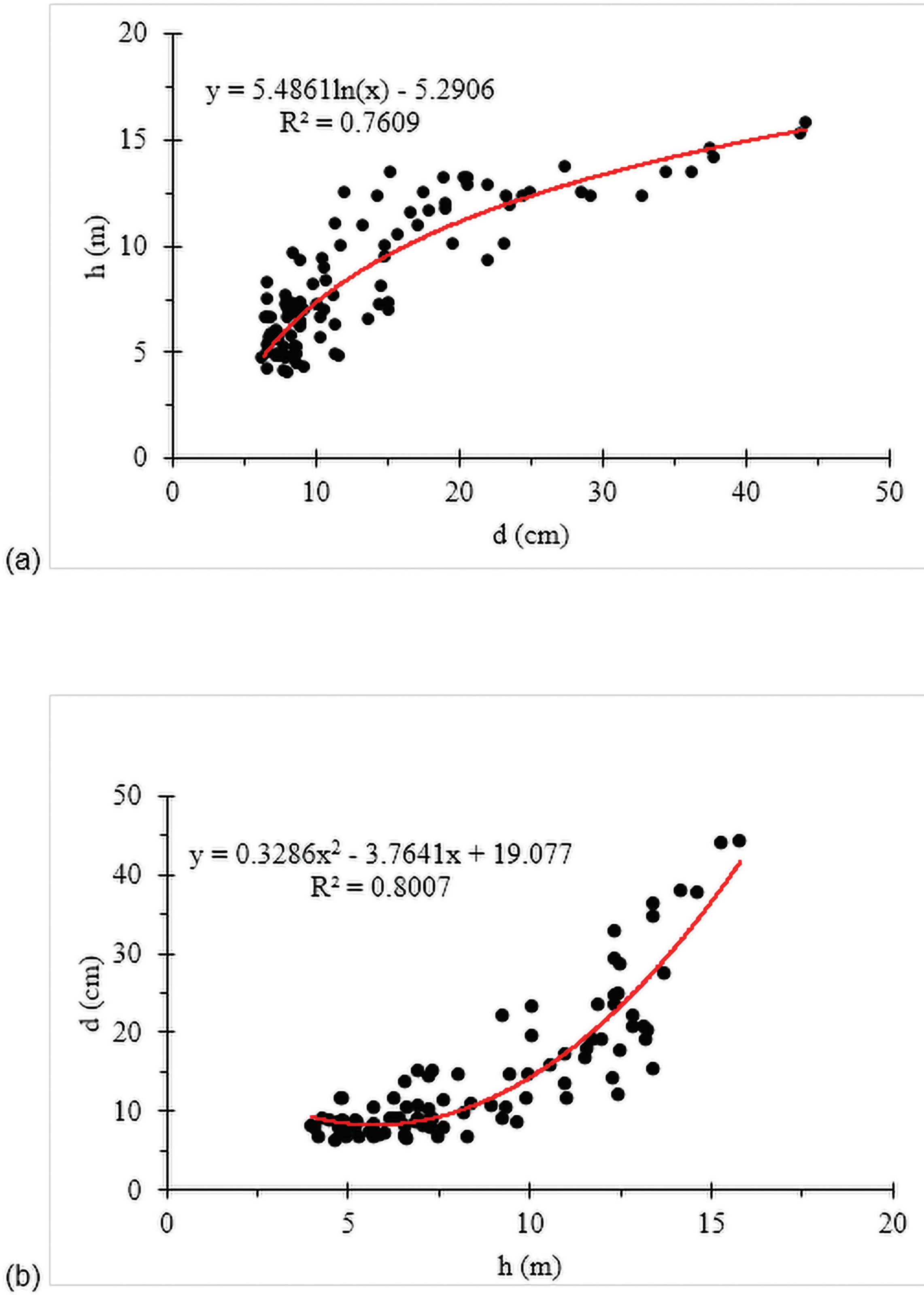

Figure III. Scatter plots of the 100% ground surveyed data for ocular inspection of outliers and non-linear relationships of d and h (a) and h and d (b).

Table III. Accuracy assessment of the performance of the top three performing h-d models.

Code	MAE (m)	RMSE (m)	PRMSE (%)	RMSPE (%)	R^2 adjusted	AIC	BIC	Overall relative rank
CR	1.47 (1.00)	1.74 (1.00)	19.31 (1.00)	28.71 (1.40)	0.79 (1.00)	32.46 (1.00)	36.00 (1.00)	1.06
EX	1.52 (1.05)	1.83 (1.07)	20.34 (1.00)	26.89 (1.00)	0.78 (1.10)	34.96 (1.12)	38.49 (1.12)	1.08
SC	3.35 (3.00)	4.24 (3.00)	47.18 (3.00)	36.03 (3.00)	0.56 (3.00)	75.34 (3.00)	78.87 (3.00)	3.00

Numbers in parenthesis are the model's relative rank based on the specific evaluation criteria.

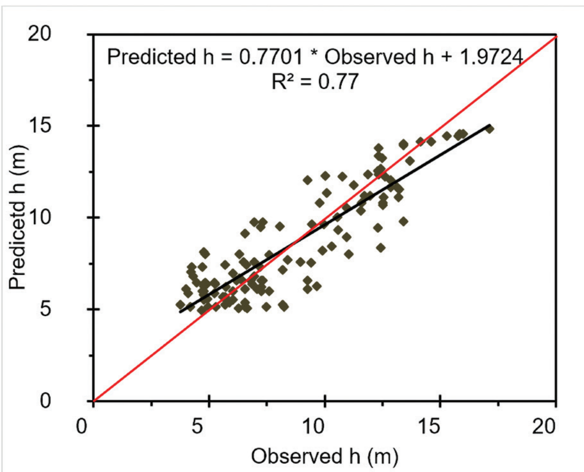

Figure IV. Correlation of the observed and predicted h using the best h-d model.

Table IV. Result of the Duncan test for the difference between the total biomass (t/ha) of the allometric equations.

Allometric equation	Brown-89	Brown-97	IPCC	Stas-d	Stas-d-h
totB (t/ha)	59.66[a]	97.72[ba]	112.52[ca]	82.13[c]	89.30[da]

The alphabetical codes are the grouping of the mean value of the totB, as determined by Duncan's test at a 0.05 level of significance. The same letter indicates that the mean difference is significant at the 0.05 level.