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ASSESSING NATURE-BASED CARBON IN SENTOSA

FINAL REPORT

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Assessing Nature-based Carbon in Sentosa

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EXECUTIVE SUMMARY

This report presents the first comprehensive assessment of nature-based carbon for the island of Sentosa. The findings from this project pave the way for more efficient and robust estimating and monitoring of nature-based carbon in tropical forests, increasing the quality of carbon projects and their role in climate change mitigation.

Here, we estimated the aboveground carbon density (ACD) and total carbon stock of Sentosa's forest areas in two ways: (1) Using past inventory data and (2) using new inventory and remote sensing data to predict and map carbon stocks.

Key findings:

- Past inventory data suggested that Sentosa's native-dominated secondary forest had the highest ACD (58.52 Mg C ha^{-1}) and a total island carbon content of 6,263.17 Mg. [Section 4.1]
- The predicted ACD from new inventory plots and remote sensing was highest for the coastal forest habitat (97.3 Mg C ha^{-1}) and lowest for the coastal forest with sandy shore habitat (37.5 Mg C ha^{-1}). [Section 4.2.1]
- The total carbon stock predicted for Sentosa's forest was 6,140.34 Mg with around two thirds being contributed by non-managed forests (4,116.95 Mg) and one third by managed forests (2,023.39 Mg), despite their similar predicted ACDs (66.3 and 58.0 Mg C ha^{-1} respectively). [Section 4.2.1]
- Our model partially explains the variation in ACD (R^2 = 0.52, RSE = 38.1). [Section 4.2.1]

1.INTRODUCTION

In response to rising emissions and urgent mitigation needs, public institutions and private organisations are increasingly looking to leverage nature-based solutions as critical pathways toward achieving global climate goals (Rogelj et al., 2016; Friedlingstein et al., 2022; IPCC, 2022). Nature-based climate Solutions (NbS) correspond to conservation, restoration and management efforts aiming to aid in climate change mitigation through improved carbon sequestration potential and a reduction in greenhouse gas emissions (Griscom et al., 2017; Novick et al.,2022). Aside from climate change mitigation, NbS can entail a variety of co-benefits such as pollination, water quality regulation and biodiversity conservation (Sarira et al., 2022). Consequently, NbS have become a major focus with 60% of the Paris Accord signatories including NbS in their mitigation plans (Seddon et al., 2020).

Despite the high potential of NbS, there are concerns including the credibility and integrity of NbS projects (Swinfield & Scott, 2025). Some examples include concerns of additionality in tropical areas (West et al., 2023) and infrastructure integration in areas of high development (Nelson et al., 2020). Consequently, we focus on improving the accuracy and credibility of urban forest carbon stock estimations whilst also ensuring time-efficient methods to enable trustworthy NbS projects.

To date, the most accurate ways of estimating the volume of carbon stored in trees involved destructive methods and extensive forest inventory surveys (Gibbs et al., 2007), but these methods rely on accessibility, available time and manpower (Vashum & Jayakumar, 2012). Since the 1990s, novel remote sensing methods such as Light Detection And Ranging (LiDAR) allow efficient, high-resolution collection of forest structure data over large areas (Naesset, 1997; Means et al., 1999). These remote sensing technologies can be used to model and predict aboveground carbon density across large spatial areas with calibration through field plots (Asner et al., 2012; Csillik et al., 2019).

In this study, we focus on Singapore. Singapore has put a strong emphasis on integrating nature into its urban environment since its independence, with the first tree-planting campaign occurring in 1963 (National Parks Board, n.d.). Since then, the city-state has launched multiple campaigns such as the “Garden City” campaign in 1967 and the “City in Nature” campaign since 2020 to prioritise the inclusion of green areas and reforestation in the country (Marin et al., 2025). Throughout recent years, there has been a strong focus on carbon estimation for nature parks and neighbourhoods (Velasco et al., 2013; Velasco et al., 2016) through fieldwork (Ngo et al., 2013) and the use of remote sensing technologies (Velasco et al., 2019).

Here, we develop an Aboveground Carbon Density (ACD) map for forested areas in Sentosa, an island off the southern coast of Singapore. We combine field measurements, remote sensing technologies and predictive modelling to estimate and predict ACD. The results of the project will provide high-quality, accurate estimates that can be used to guide the land use and sustainability teams in project development and land management, ensuring a sustainable future for Sentosa.

The aims of this project are to:

1. Estimate tree carbon from existing forest inventories;
2. Develop carbon estimation models using field measurements, allometric models, and remote sensing technologies such as LiDAR scans; and,
3. Generate aboveground carbon density maps for forested areas in Sentosa.

2. STUDY AREA

The study area is on Sentosa, a 500 ha resort island located off the South coast of Singapore in the Southern islands region (Sentosa Development Corporation, n.d.). The island has gone through many changes over the past years; originally inhabited by Malay, Bugis and Chinese communities in the 1800s, subsequently turned into a British military base in the second half of the 19th century and finally developed as a tourism hotspot since the 1970s under the management of the Sentosa Development Corporation (SDC) (Connolly and Muzaini, 2021).

In an endeavour to beautify the island for tourism, SDC planted coconut trees along the coast throughout the 1970s (Connolly and Muzaini, 2021) and a range of ornamental trees and shrubs have been planted along trails. Native species of trees and shrubs are also widely present on the island (National Parks Board, n.d.). Over the years, over 100 species of trees have been observed across Sentosa (Public Service Division, n.d.).

Currently, SDC considers 148 ha of the island's publicly accessible areas as vegetated. These can be broadly separated into managed vegetation and non-managed vegetation (Figure 1).

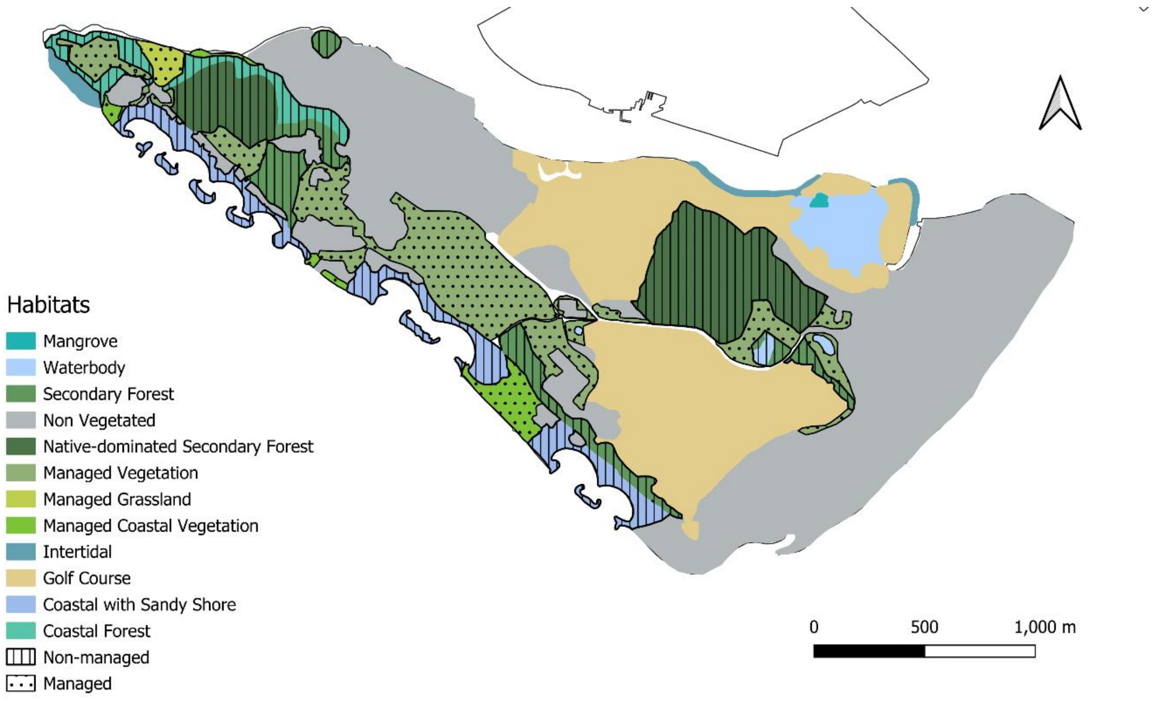

Figure 1.Map of Sentosa island and its 12 habitats as described and delineated by Sentosa Development Corporation. The forest habitats have been classified as Managed (dots) or Non-Managed (lines) by NUS CNCS.

2.1. Managed vegetation

Sentosa's managed forests correspond to areas that frequently undergo management such as tree crown trimming and species curation SDC. They are located mostly in the Centre and West of the island in areas such as the Coastal Trail and Palawan area (Figure 1) and comprised of:

- Managed grassland (2.6 ha)
- Managed vegetation (53.2 ha)
- Managed coastal vegetation (7.4 ha)

2.2. Non-managed vegetation

Sentosa's non-managed forests are considered areas with natural growth and limited management or curation. These can be found in Serapong and Imbiah areas as well as along the South Coast (Figure 1). Non-managed areas contain:

- Coastal Forest (10.7 ha)
- Coastal Forest with Sandy Shore (16.6 ha)
- Secondary Forest (19.6 ha)
- Native-dominated Secondary Forest (44.2 ha)

3. RESEARCH METHODOLOGY

3.1 Summary

Two main analyses were performed for this collaboration: A) estimating Sentosa's stored carbon from existing tree inventory data, and B) developing carbon estimation models from plot inventory data and Airborne Laser Scans (ALS).

Firstly, the AGB and ACD of Sentosa were estimated from previous field inventory data provided by SDC. We then used shapefiles of Sentosa's different habitat extents shared by SDC to estimate the ACD by habitat. This enabled a preliminary estimation of Carbon stored across the island and an initial look at the importance of different habitats for carbon storage.

Following these first estimations, a new set of inventory plots was established and surveyed. We estimated the corresponding AGB and ACD for each plot and then proceeded with modelling to predict ACD from remote sensing data. The remote sensing data corresponds to ALS obtained from the Singapore Land Authority (SLA). The model was used to predict and map ACD across Sentosa's vegetated areas at 10-meter resolution.

3.2 Existing Field Inventory

The existing tree inventory data verified and shared by SDC was collected by a secondary contractor between 2016 and 2023. Trees were surveyed opportunistically across the island. The GPS location of each tree was collected using mobile devices (phones, tablets) with tripods as support for accuracy. The girth was taken at 1.2m above ground and the height of each tree was estimated visually. Finally, each tree was identified to the species level. For AGB and ACD estimation, we converted the girth measurements into diameter at breast height (DBH) using the following equation:

(1) $D = \frac{100*G}{\pi}$

Where D= Diameter at Breast Height (cm), G= Girth (m)

Before proceeding with analyses, we performed a selection on the full dataset and kept trees measured on the island, with both species and girth information, and a corresponding DBH above 5 cm. Palms (Arecaceae) were excluded from our analysis due to their distinct allometry and anatomy (Chave et al., 2014; Goodman, Phillips and Baker, 2013).

3.3 Establishing and surveying new plots

New survey plots were established for this project to verify the existing tree inventory data and calibrate the carbon estimation models. 20x20 m square plots (0.04 ha) were established in the managed and non-managed vegetation areas. This design followed previous CISG and Singapore National Parks Board methods for a more standardised operation and smooth incorporation of new data into model training and testing.

The number of plots required per area (managed vs non-managed) was determined through the Winrock calculator (CGIAR, n.d.). The Winrock methodology uses the area and expected AGB variance of each stratum to allocate an appropriate number of plots to ensure statistical representation (Winrock International, 2018). Once the number of plots was quantified, we determined the location of the plots in conjunction with the SDC Environmental Management team. When establishing the plots, the teams tried to avoid roads and trails, and to distribute plots in areas with low, medium and high biomass. When surveying the plots, we marked the plot corners and centre with PVC pipes and recorded the corresponding coordinates with a GPS.

For each plot, the diameter at breast height (DBH) of all live trees above 5 cm was measured at 1.3 m with DBH tape and recorded. The height of each tree was measured three times using a Nikon Forestry Pro rangefinder, and the average was taken as the final height. Finally, the scientific name of each tree was recorded to match the corresponding species' wood density from the Global Wood Density Database (Chave et al., 2009).

3.4 From field measurements to aboveground biomass and carbon estimates

Chave's general pantropical allometric model was used to calculate the AGB of the measured trees (Chave et al., 2014):

$$(2)\ AGB = 0.0673 * (D^2 H\rho)^{0.976}$$

Where, D= DBH (cm), H= height of the tree (m) and ρ = species-specific wood density (g cm^{-3})

The species-specific wood density values were obtained from the Global Wood Density database (Chave et al., 2009); if the species was not identified, we used the genus-averaged wood density value.

AGB values were multiplied by an emission factor of 0.475 to obtain aboveground carbon content (IPCC, 2006).

a) Existing tree inventory data

As the heights in the shared past inventory data had been measured through a combination of methods, we estimated height using height-DBH models in the BIOMASS package (Réjou-Méchain et al., 2017). We compared the modelled heights from four built-in models – Weibull, Michaelis, log1 and log2 – to the species or genus tree heights in the global Tallo database (Jucker et al., 2022). The Weibull estimates were closest to the dataset heights and were thus used in Equation (2).

Once we obtained the aboveground carbon estimations for individual trees, we summed up the aboveground carbon for all trees to get the total island aboveground carbon. We then also summed up the aboveground carbon in each habitat following the shapefiles shared by SDC to get total carbon per habitat. Finally, we divided the total carbon of each habitat by the habitat area in hectares to get the corresponding Aboveground Carbon Density (ACD) per habitat.

b) Newly established plots

As all the tree heights for the new plots were measured by the team in a standardised way, we directly used the estimated height and DBH in Equation (2). Once the AGB and aboveground carbon of each tree were obtained, we summed up the values for each plot and divided them by the plot area in hectares – 0.04 ha – to get ACD values per plot.

3.5 Remote Sensing data – Airborne Laser Scans (ALS)

LiDAR data covering the entire Singapore was obtained from the Singapore Land Authority (SLA). The LiDAR point cloud was collected in between March and April 2024 using a Cessna F406 Caravan II aircraft equipped with a Leica CityMapper-2 with Hyperion2 LiDAR scanning system and an integrated Global Positioning System-Inertial Measurement Unit. A point density of at least 10 points per square metre was attained for the entire country. The point cloud was processed and classified using LAStools (Isenburg, 2014) to obtain 10 m resolution rasters of 22 different height and density metrics (Table 1). Following this, the mean of each metric was extracted for each plot using QGIS (version 3.34.0-Prizren).

Table 1. The 22 LiDAR metrics extracted for each inventory plot from the Airborne Laser Scan (ALS) data provided by the Singapore Land Authority (SLA).

Metric code	Metric name	Definition
avg	Average	Mean height of returns
cov	Canopy cover	Proportion of returns above height threshold
d2_10	Relative density 2-10 m	Fraction of returns between 2 and 10 m
d10_20	Relative density 10-20 m	Fraction of returns between 10 and 20 m
d20_30	Relative density 20-30 m	Fraction of returns between 20 and 30 m
d30_40	Relative density 30-40 m	Fraction of returns between 30 and 40 m
dns	Canopy density	Vertical density of returns
kur	Kurtosis	Measure of tailedness of height distribution
max	Maximum	Maximum recorded height
min	Minimum	Minimum recorded height
p01	Height percentile 1%	Height below which 1% of points occur
p05	Height percentile 5%	Height below which 5% of points occur
p10	Height percentile 10%	Height below which 10% of points occur
p25	Height percentile 25%	Height below which 25% of points occur
p50	Height percentile 50%	Height below which 50% of points occur
p75	Height percentile 75%	Height below which 75% of points occur
p90	Height percentile 90%	Height below which 90% of points occur
p95	Height percentile 95%	Height below which 95% of points occur
p99	Height percentile99%	Height below which 99% of points occur
qav	Average square height	Mean of squared return heights
ske	Skewness	Measure of asymmetry in canopy height distribution
std	Standard deviation	Spread of return heights

3.6 Carbon Estimation models

Data manipulation and modelling were performed in R (version 4.3.3) using the *dplyr* and *tidyr* packages (Wickham et al., 2023; Wickham, Vaughan and Girlich, 2024). ACD was taken as the response variable and the 22 extracted metrics as response variables. We used a correlation analysis to quantify the relationship between each response variable and ACD. Pearson correlation coefficients were calculated, and a correlation matrix was generated. We then extracted and ranked the absolute correlation values to identify the metric most correlated to ACD.

A simple linear model between ACD and the number one metric was run and used to predict ACD across Sentosa's forest areas. An intercept term was retained in the model to allow for non-proportional scaling of ACD at low tree heights. Model assumptions were evaluated using standard residual diagnostics, including Q–Q plots and residuals-versus-fitted plots.

We predicted the final model onto the vegetated areas in the managed and non-managed polygons. To do so, we clipped the polygons to the vegetated areas defined by Gaw et al. 2019. We retained land classes 4, 5 and 6 corresponding to limited management with tree canopy, limited management without canopy and managed with tree canopy respectively.

From this, we could also estimate the total aboveground carbon stock for Sentosa's forested areas as follows:

$$(3)\ Total\ Carbon\ Stock\ = \sum_{i=1}^{n}\left(ACD_i \times\ A_{pixel}\right)$$

With the total carbon stock in Mg, ACD_i = Aboveground Carbon Density of pixel i, A_{pixel}= Area of one pixel (in hectares) and n= Total number of pixels.

3.7 Model performance analysis

We compared the predicted to the observed ACD for our inventory plots to judge the model's predictive accuracy. A simple t-test was performed to see if the predicted and observed values of the inventory plots were significantly different.

4. RESULTS

4.1. Carbon Estimations from Existing Tree Inventory Data

There was a total of 25,597 trees in the shared raw tree inventory file. After the selection process, 15,879 trees were considered for the analysis (Annex Table 1), with the highest proportion (43.2%) being in the “native dominated secondary forest” habitat (Figure 2). A total of 164 species was reported across the island, across 116 genus and 47 families (Annex Table 3). The observed DBH for the trees measured ranged from 6.4 cm to 254.6 cm with a mean of 30.0 cm and a median of 25.5 cm.

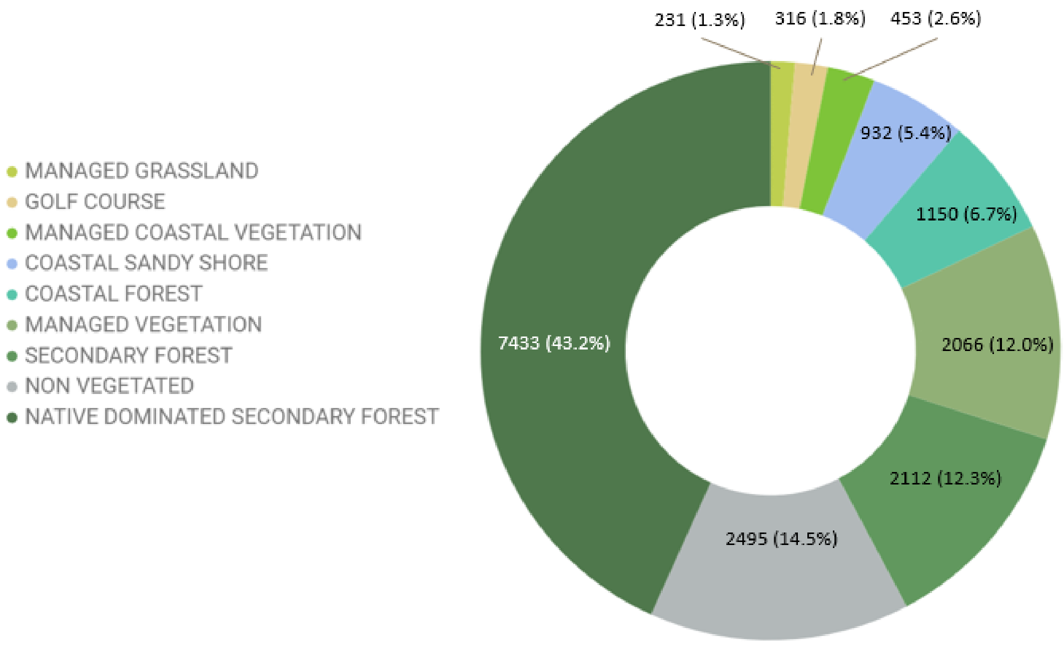

Figure 2. Number of trees measured in each habitat and the respective percentage of total trees measured for the original Sentosa tree inventory survey.

The calculated Aboveground Carbon Density (ACD) of the habitats ranged between 1.85 Mg C ha^{-1} and 58.53 Mg C ha^{-1} (Figure 3), the lowest being the golf course area and the highest being the native dominated secondary forest. Overall, the habitats considered as non-managed had an ACD superior to the managed and built habitats (Figure 3).

The total sum of carbon across the island based on the tree inventory was 6,263.17 Mg (Annex Table 2).

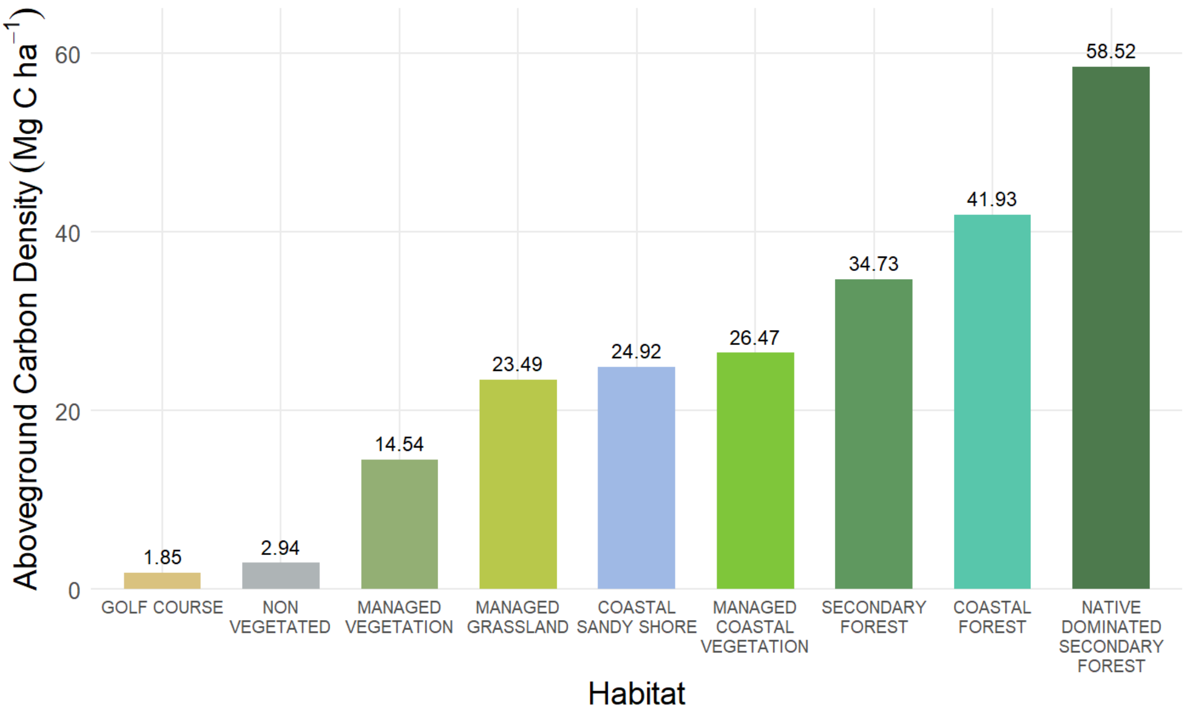

Figure 3. Estimated ACD (Mg C ha^{-1}) of all habitats for which trees were measured in the original Sentosa tree inventory survey.

4.2. Carbon Estimations from New Plots and Remote Sensing

Winrock analyses suggested 15 plots with 5 plots in managed areas and 10 plots in non-managed areas. Plots were established to have no overlapping roads or trails and across different vegetation densities to have sufficient representation (Annex Figure 1).

A total of 318 trees were measured, with plots having between 7 and 47 trees. Across the 15 plots, 68 species were observed with a single plot containing up to 15 species. The top five most common species recorded were all native to Singapore (Table 2). The top five species contributing to biomass, however, included mostly roadside or ornamental species, including the non-native species *Delonix regia* and *Pterocarpus indicus* (Table 3). The mean DBH was 21.8 cm (min 5.0, max 165.0 cm) and the mean height was 10.4 m (min 3.6, max 32.8 m).

Table 2. Most common tree species and the respective percentage of total trees measured in the 15 surveyed plots

Species	Number of Trees	Proportion of Total Trees (%)
Sloetia elongata	51	16.0
Terminalia catappa	38	12.0
Syzygium grande	36	11.3
Syzygium lineatum	23	7.2
Alstonia angustiloba	12	3.8

Table 3. Top 5 species contributing to biomass and carbon storage in the 15 surveyed plots with Aboveground Biomass (AGB) in Mg.

Species	Total AGB (Mg)	Proportion of total AGB (%)
Syzygium grande	41.8	32.5
Delonix regia	13.5	10.5
Sloetia elongata	10.7	8.3
Terminalia catappa	8.1	6.3
Pterocarpus indicus	6.8	5.3

The ACD observed in the plots ranged from 6.31 Mg C ha^{-1} to 404.12 Mg C ha^{-1}, with a mean of 101.67 Mg C ha^{-1} and a median of 84.77 Mg C ha^{-1}. Non-managed areas had a median ACD of 93.8 Mg C ha^{-1} and managed areas had a median of 69.5 Mg C ha^{-1} (Figure 4). There was an outlier in the Managed areas with a plot ACD value above 400 Mg C ha^{-1} (Figure 4).

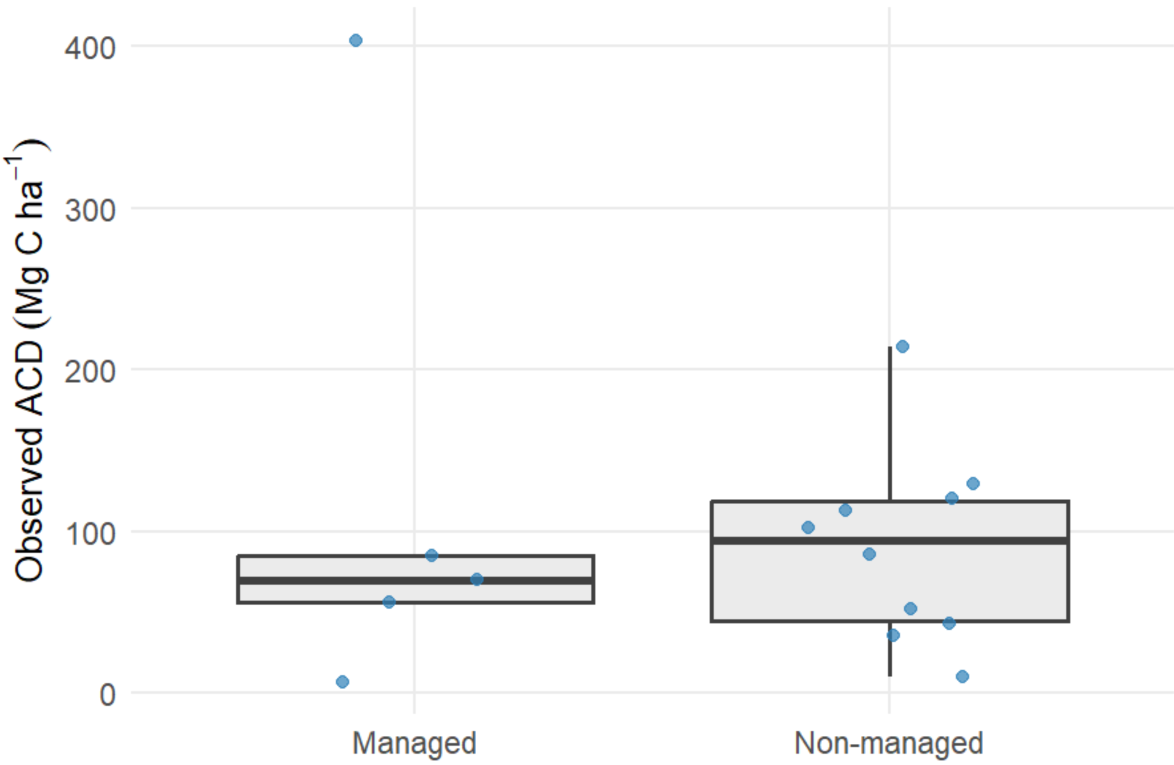

Figure 4. Distribution of the ACD across the plots for the Managed and Non-Managed forest areas. Each point represents a 20x20m plot.

As no statistically significant difference was observed between the medians of the managed and non-managed plots (Wilcoxon test: W=22; p-value= 0>0.7), all plots were grouped for the modelling process. Additionally, a Dixon's Q test identified the highest ACD value (plot MA02 with and ACD of 404.12 Mg C ha^{-1}) as a significant outlier ($Q = 0.744$, $p < 0.001$) and we thus removed MA02 from the modelling process.

4.2.1. Model results and predictions

Several predictor variables were strongly intercorrelated ($|r| > 0.75$), indicating potential multicollinearity (Annex Figure 2). To avoid collinearity effects, only the variable most strongly correlated with ACD ($r = 0.74$) corresponding to p75, or the 75th height percentile, was retained for modelling. A simple linear model was made with the formula ACD ~ p75. P75 was found to be a significant positive predictor of ACD ($\beta = 9.51 \pm 2.46$ SE, t(12), $R^2 = 0.518$), with a residual standard error of 38.07. Visual inspection of residual plots indicated no strong deviations from linearity or homoscedasticity.

A predicted carbon map was generated (Figure 5). Overall, the mean predicted ACD was 69.06 Mg C ha^{-1} and the median predicted ACD was 63.57 Mg C ha^{-1}, with a minimum ACD of 0.04 Mg C ha^{-1} and a maximum of 286.32 Mg C ha^{-1} (Figure 5). The habitat with the highest average ACD was coastal forest and the lowest coastal forest with sandy shore (Table 4).

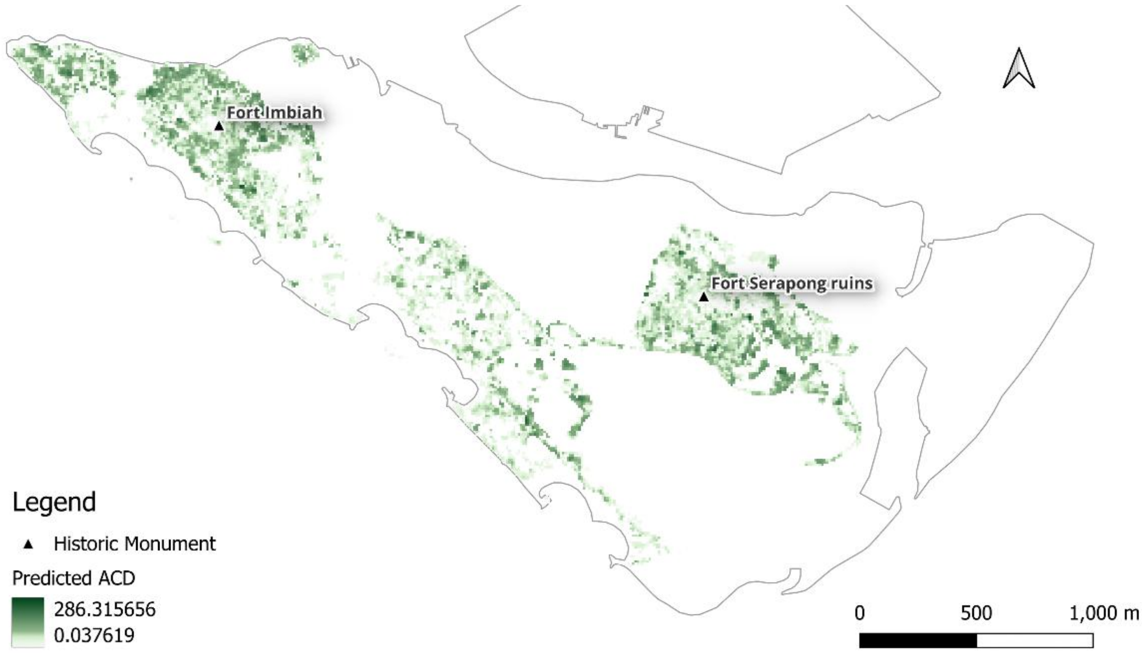

Figure 5. Predicted Aboveground Carbon Density (ACD) in Mg C ha-1 from the 2024 Airborne Laser Scan (ALS) data. Key historic monuments are marked by triangles.

Areas with a high predicted ACD (above 100 Mg C ha^{-1}) were found in Serapong and Imbiah. Areas with a low predicted ACD (below 100 Mg C ha^{-1}) were mainly concentrated in southern managed vegetation area near Palawan beach (Figure 5).

Overall, the estimated total aboveground carbon stored around Sentosa's forest areas was 6,140.34 Mg (Table 4). The habitats contributing the most were Native-dominated Secondary Forest followed by Managed Vegetation (Table 4).

Table 4. Aboveground Carbon Density (ACD) for the managed forest areas and non-managed forest areas as well as the individual habitats composing each of these areas.

Habitat	Mean ACD (Mg C ha^{-1})	Median ACD (Mg C ha^{-1})	Total Aboveground Carbon (Mg)
Non-managed Areas	71.5	66.3	4,116.95
Coastal Forest	92.1	97.3	801.00
Coastal Forest Sandy Shore	35.9	37.5	145.31
Native-dominated Secondary Forest	69.5	65.0	2,327.77
Secondary Forest	76.1	66.8	842.87
Managed Areas	64.5	58.0	2,023.39
Managed Coastal Vegetation	58.2	46.8	206.10
Managed Grassland	64.4	56.8	27.68
Managed Vegetation	68.3	60.3	1,789.61
TOTAL			**6,140.34**

4.2.2. Predicted versus Observed values

The predicted ACD was quite close to the observed ACD with a few exceptions (Figure 6). Notably, there was an underestimation of ACD for high values, with the only observed value above 200 Mg C ha^{-1} having a corresponding predicted ACD of 131.18 Mg C ha^{-1} (Figure 6).

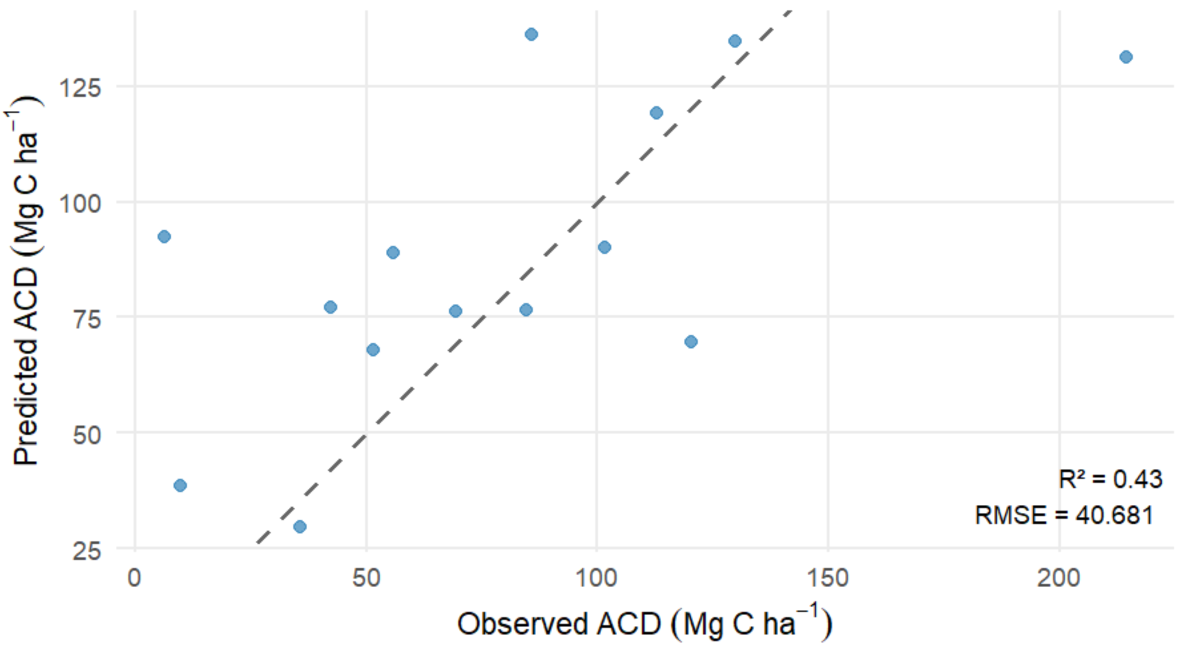

Figure 6. Scatterplot of the field-measured and predicted Aboveground Carbon Density (ACD) in Mg C ha^{-1} for the 14 plots used in the modelling process. Each circle represents the value of a 20x20 m inventory plot. The dashed line represents the identity.

5. DISCUSSION & RECOMMENDATIONS

Both analyses revealed a similar total carbon stock of about 6,000 Mg of carbon across the island. As the estimate from the model prediction is only for the forested areas, we can expect a slightly higher number for the whole island if we include the trees lining the streets and the ornamental trees in the built-up areas.

When looking at the newly established plots and their respective values, a large range of ACDs was observed. The overall mean ACD of 101 Mg C ha^{-1}and median of 85 Mg C ha^{-1} are a bit lower than the 104 Mg C ha^{-1} observed in the Bukit Timah Nature Reserve secondary forest (Ngo et al., 2013).

The predicted ACD values across the forested areas are closer to 60-70 Mg C ha^{-1} which is on the lower side of a previously logged forest in Borneo (Asner et al., 2018), with the exception of the coastal forest having values closer to 100 Mg C ha^{-1} which can be compared to values of a selectively logged lowland dipterocarp forest in Sabah (Saner et al., 2012). For comparison, the primary forest in Bukit Timah Nature Reserve had an estimated ACD of 169 Mg C ha^{-1} (Ngo et al., 2013) and pristine forests in the region can average 200 Mg C ha^{-1} with peaks up to 500 Mg C ha^{-1} (Asner et al., 2018).

A potential explanation of the values being on the lower end of the spectrum would be the disposition of the forest areas across the island as well as the soil quality. Indeed, as the forest areas across Sentosa are composed of small patches linked by roads and trails, with many areas of development, we can expect edge effects impacting canopy height and leaf light capture into the first 100 m from the edge and thus lower ACD values (Ordway and Asner, 2020). Additionally, the geological nature of Sentosa as a small offshore island is paired with shallower, less fertile soils that are more likely impacted by erosion (Chua and Ikhsan, 2020) and have furthermore been impacted by high amounts of human disturbance (Connolly and Muzaini, 2021). Consequently, the carbon sequestration potential is highly constrained by the soil quality in Sentosa and is lower than the potential of the forests in mainland Singapore.

The impact of human disturbance is visible on the predictions map in areas such as Imbiah and Serapong, where the lower ACD areas line up with past human activities such as Serapong fort (Figure 5). On the contrary, the areas with highest ACD being the coastal forest area agrees with the presence of mature coastal forest in Sentosa and more broadly the Southern islands (Tan et al., 2025).

Based on these findings, we recommend some actions to increase Sentosa's carbon storage capacity and support SDC's 2030 sustainability goals:

1. **Protect existing forests from clearing and fragmentation**

   We first recommend maintaining current forests and avoid further fragmentation or deforestation. By allowing Sentosa's forest to mature, SDC will enable efficient carbon sequestration by larger trees and complex forest structure. Indeed, older intact forests have higher carbon densities relative to degraded forests (Bryan et al. 2013). The biomass in these older patches is highly driven by large trees (Slik et al. 2013), and more complex canopies (Sun et al., 2023). Finally, larger, unfragmented forest patches are more stable in terms of structure and composition, making them more resilient to disturbances (Turner et al. 2001; Laurance and Bierregaard 1997).

2. **Prioritise strategic and informed planting with high-carbon, native and diverse species**

   As Sentosa is known to have high tree biodiversity and continued planting efforts especially in the managed areas, we recommend focusing on native species with high carbon-storage potential in future planting efforts. Compared to palms and low-biomass ornamental species, many native tropical trees can develop large AGB and complex structures which, in turn, guarantee improved carbon sequestration potential (Slik et al. 2013, Poorter et al., 2016).

In addition, a high-diversity, native species composition enhances ecosystem functioning and biodiversity which are key co-benefits of NbS and linked to stable carbon storage over time (Isbell et al., 2015; Mori et al., 2018). Biodiversity-rich forests are also more resilient to pests, diseases and climate disasters (Keesing and Ostfeld, 2024), leading to healthier ecological networks (Li et al., 2024).

3. **Regularly update carbon stock assessments to reflect the changing landscape**

   As this report is based on ALS data from 2024 and Sentosa's land use and forest conditions are rapidly evolving, periodic reassessment is essential. Updated remote sensing and field data will help ensure that carbon estimates accurately reflect on-the-ground conditions and that management decisions remain evidence-based.

6. SYNTHESIS

To summarise, this report assessed the aboveground carbon density (ACD) of Sentosa's forested areas in two ways: first through past inventory data covering the entire island and, secondly, through a predictive modelling approach involving the survey of 15 new plots across managed and non-managed forest areas as well as airborne laser scan (ALS) data.

Our key findings are:

- Past inventory data suggested that Sentosa's native-dominated secondary forest had the highest ACD (58.52 Mg C ha^{-1}) and a total island carbon content of 6,263.17 Mg. [Section 4.1]
- The predicted ACD from new inventory plots and remote sensing was highest for the coastal forest habitat (97.3 Mg C ha^{-1}) and lowest for the coastal forest with sandy shore habitat (37.5 Mg C ha^{-1}). [Section 4.2.1.]
- The total carbon stock predicted for Sentosa's forest was 6,140.34 Mg with around two thirds being contributed by non-managed forests (4,116.95 Mg) and one third by managed forests (2,023.39 Mg), despite their similar predicted ACDs (66.3 and 58.0 Mg C ha^{-1}respectively). [Section 4.2.1]
- Our model partially explains the variation in ACD (R^2 = 0.52, RSE = 38.1). [Section 4.2.1.]

Moving forward, we recommend that SDC continue maintaining the existing forest, prioritise planting high-carbon, native species, and regularly update the carbon stock assessment to reflect any change in land-use.

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ANNEX

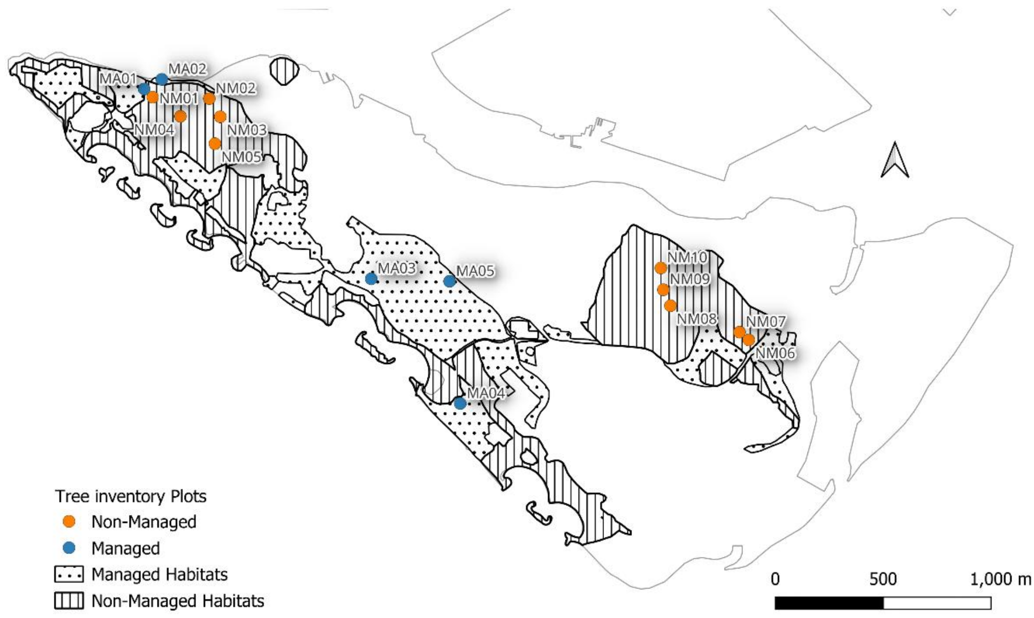
Annex Table 1. Tree selection process for the original Sentosa tree inventory data shared by SDC.

Trees in Raw data file	**25,597**
Trees not geographically on Sentosa	731
Trees missing girth or species information	331
Trees with DBH<5cm	247
Palms/Trees of the Arecacea family	8,409
Trees considered for analysis	**15,879**

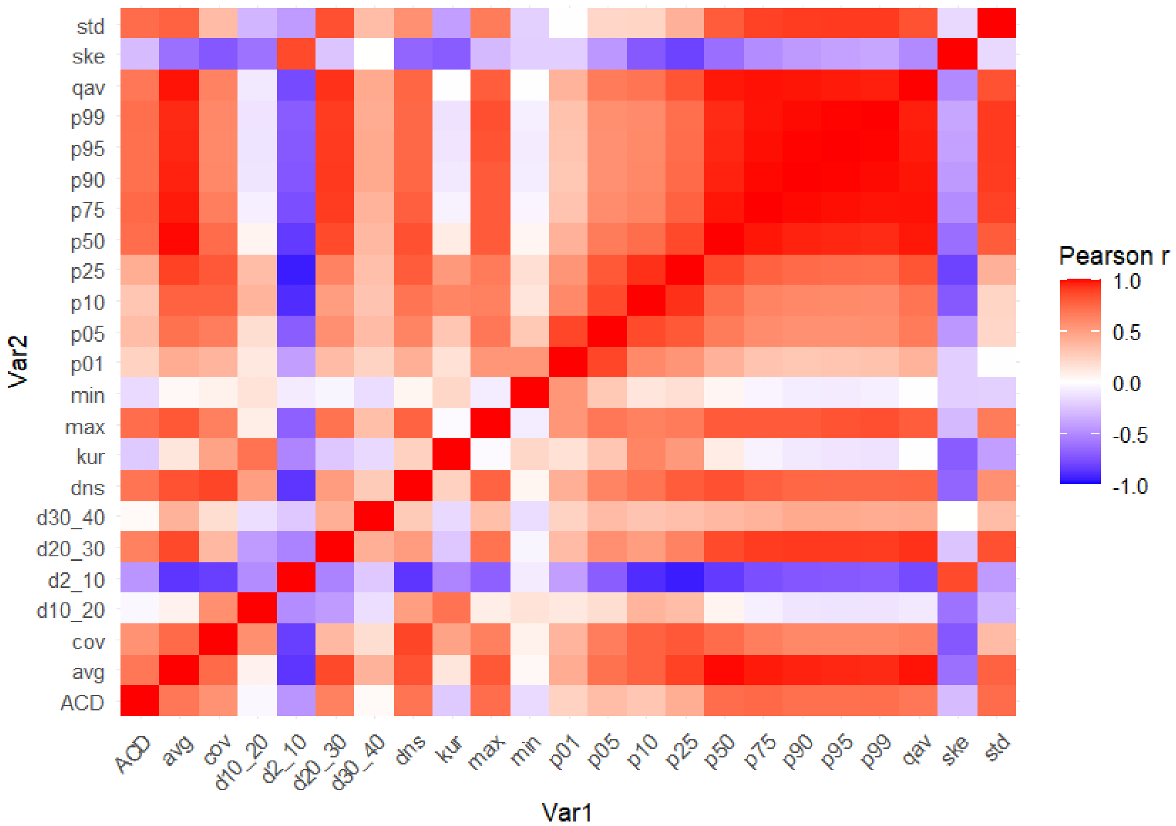
Annex Table 2. Summary estimated Aboveground Biomass (AGB) and Aboveground Carbon Density (ACD) for each of Sentosa's habitats according to the original inventory data shared by SDC.

Habitat	Area (ha)	Number of trees	AGB Sum (Mg)	ACD (Mg)	ACD per ha (Mg.C.ha^{-1})
Intertidal	4.38	0	NA	NA	NA
Mangrove	0.37	0	NA	NA	NA
Coastal Forest	10.65	1150	940.09	446.54	41.93
Coastal Forest Sandy Shore	16.60	932	870.93	413.69	24.92
Golf Course	111.99	316	435.18	206.71	1.85
Managed Coastal Vegetation	7.41	453	412.77	196.07	26.47
Managed Grassland	2.59	231	127.99	60.80	23.49
Managed Vegetation	53.23	2066	1629.65	774.08	14.54
Native-dominated Secondary Forest	44.23	7433	5449.58	2588.55	58.52
Non-vegetated	197.47	2495	1223.82	581.31	2.94
Secondary Forest	19.58	2112	1431.54	679.98	34.73
Trees under 5cm DBH	NA	207	0.316	0.150	NA
Trees in "Land_Use_Change" Polygon	NA	928	663.76	315.29	NA

** The estimations for the trees <5cm in the dataset and trees in the "Land_Use_Change" polygon shared by SDC are also included.*



Annex Figure 1. Map of the inventory plots established by SDC and CNCS in 2025. Total plot number per type of habitat was determined using the Winrock calculator. Each circle represents one 20x20 m plot.



Annex Figure 2. Pearson correlation matrix between aboveground carbon density (ACD; Mg C ha $^{-1}$) and airborne laser scanning (ALS)–derived structural metrics. Colour scale indicates the strength and direction of the correlation coefficient (r), ranging from −1 (blue, strong negative correlation) to +1 (red, strong positive correlation), with white indicating weak or no correlation. ALS metrics include height percentiles (p01–p99), minimum and maximum height (min, max), mean and standard deviation of height (avg, std), coefficient of variation (cov), skewness (ske), kurtosis (kur), canopy density (dns), quadratic mean canopy height (qav), and proportional returns within height strata (d2_10, d10_20, d20_30, d30_40).

Annex Table 3. Top 10 most abundant species recorded in the original Sentosa tree inventory along with the respective number of trees recorded and the minimum, mean and maximum Diameter at Breast Height (DBH) and tree height.

Species	Individuals	Family	Min DBH (cm)	Mean DBH (cm)	Max DBH (cm)	Min height (m)	Mean Height (m)	Max Height (m)
Syzygium grande	1144	Myrtaceae	6.4	34.2	108.2	7.1	18.9	33.7
Terminalia catappa	1143	Combretaceae	6.4	33.6	127.3	3.6	17.3	41.4
Alstonia angustiloba	1062	Apocynaceae	6.4	31.0	111.4	8.5	24.0	35.6
Cinnamomum aromaticum	975	Lauraceae	6.4	27.0	79.6	6.1	14.3	28.2
Cytrophyllum fragrans	726	Gentianaceae	9.5	32.0	79.6	8.8	16.9	27.8
Acacia auriculiformis	588	Fabaceae	9.5	27.9	95.5	6.7	16.2	35.4
Syzygium myrtifolium	541	Myrtaceae	6.4	19.0	82.8	7.1	13.6	30.2
Dillenia suffruticosa	525	Dilleniaceae	9.5	28.7	54.1	8.2	11.4	12.2
Hevea brasiliensis	486	Euphorbiaceae	9.5	33.9	89.1	8.5	21.3	44.1
Khaya senegalensis	479	Meliaceae	12.7	45.5	121.0	7.8	19.2	39.6