Mangrove canopy height globally related to precipitation, temperature and cyclone frequency

Marc Simard1*, Lola Fatoyinbo2*, Charlotte Smetanka1,3, Victor H. Rivera-Monroy4, Edward Castañeda-Moya4,5, Nathan Thomas2,6 and Tom Van der Stocken1

Mangrove wetlands are among the most productive and carbon-dense ecosystems in the world. Their structural attributes vary considerably across spatial scales, yielding large uncertainties in regional and global estimates of carbon stocks. Here, we present a global analysis of mangrove canopy height gradients and aboveground carbon stocks based on remotely sensed measurements and field data. Our study highlights that precipitation, temperature and cyclone frequency explain 74% of the global trends in maximum canopy height, with other geophysical factors influencing the observed variability at local and regional scales. We find the tallest mangrove forests in Gabon, equatorial Africa, where stands attain 62.8 m. The total global mangrove carbon stock (above- and belowground biomass, and soil) is estimated at 5.03 Pg, with a quarter of this value stored in Indonesia. Our analysis implies sensitivity of mangrove structure to climate change, and offers a baseline to monitor national and regional trends in mangrove carbon stocks.

Global distribution of mangrove canopy height

We used the global mangrove extent map26, the Shuttle Radar Topography Mission (SRTM) 30 m resolution global digital elevation model (DEM), and Geoscience Laser Altimeter System (GLAS) global Lidar altimetry products to produce two baseline canopy height maps for the year 2000: a map of maximum canopy height (that is, height of the tallest tree; Fig. 1) and a map of basal area weighted height (that is, individual tree heights weighted in proportion to their basal area). The latter map was used to generate the aboveground mangrove biomass map (see Methods). Our analysis of mangrove canopy height distribution is based on the maximum canopy height map. Both maps were validated using in situ field measurements of tree height from 331 plots (Supplementary Table 1), resulting in overall root-mean-square errors of 3.6 m and 6.3 m, respectively (Supplementary Fig. 1). The maximum canopy height map shows that half of the world’s maximum mangrove canopy height is shorter than 13.2 m (Fig. 2). The maximum canopy height exceeds 62 ± 6.8 m (Fig. 2), rivaling maximum tree heights found in upland tropical forests27. Equatorial regions of the West African and South American coasts stand out as hotspots with the tallest mangroves (Table 1a and Supplementary Tables 2–6). The top five countries (Table 1a) with the tallest mangroves are Gabon (62.8 m, Fig. 3), Equatorial Guinea (57.7 m), Colombia (54.3 m), Venezuela (52.6 m) and Panama (50.9 m). These productive forests are significantly taller than previously reported values6,18,28 and are located in estuarine environments of the world’s most remote, cloudiest, wettest (precipitation >500 cm yr−1) and hottest (mean air temperature 25.6°C, ref. 29) regions. In addition, these wetlands grow in river-dominated coastal settings with low human population densities,
potentially high nutrient availability, reduced soil salinity values and significant protection from cyclone-induced high-energy winds and waves\(^{17,30}\).

We analysed global trends in mangrove canopy height with latitude, cyclone landfall frequency, precipitation, temperature, sea surface salinity (SSS) and tidal range. Globally, the distribution of maximum mangrove canopy height follows a Gaussian latitudinal trend (\(R^2 = 0.91\)), peaking at 1.13° N (Fig. 4a), similar to trends of precipitation and temperature. The global distribution of canopy height suggests that cyclone landfall frequency may limit the growth of mangrove forests (Fig. 4a). Cyclone disturbance has been shown to be important at more regional scales\(^{31}\). However, the impact may be confounded by other environmental factors (Fig. 4b). Our results indicate that coastline-specific trends in maximum canopy height reflect the important role of precipitation (Fig. 4b) in controlling mangrove structure and distribution, as shown recently by Osland and colleagues\(^{32}\). For example, the trends reflect similar differences between the east and west coasts of the Americas and Africa. While large-scale SSS appears to align with mangrove canopy height (Fig. 4b), the explanatory role of this factor remains unclear as it varies strongly over short distances in estuarine environments, and is regulated by precipitation, evapotranspiration, riverine input and ocean circulation\(^{17}\). We did not find a significant relationship of canopy height variability with local tidal range (see Methods and
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Sequestration rates are estimated by using wood production and biomass allocation patterns, regardless of latitude. However, quantifying the relative contributions of these factors to the global variability observed in our canopy height map is beyond the scope of this study, particularly because they currently cannot be resolved by remote sensing measurements. Instead, our maps can help define the spatial variability in canopy height also reflects the role of local-scale geophysical factors driving environmental gradients within distinct ecogeomorphic settings (for example, nutrient availability and soil pore water salinity). For instance, where we located the tallest mangrove canopy height in the upper Gabon estuary (Africa, Fig. 3), we also detected low stature mangrove wetlands near the mouth of the same estuary (see also ref. 35). The relative influence of regional and local factors within a given latitude hosting a diversity of ecogeomorphic settings determines not only the species-specific mangrove spatial distribution in a given coastal region, but also the spatial distribution of above- and belowground biomass allocation patterns, regardless of latitude. However, quantifying the relative contributions of these factors to the global variability observed in our canopy height map is beyond the scope of this study, particularly because they currently cannot be resolved by remote sensing measurements. Instead, our maps can help define research agendas and field campaigns to quantify the relative contribution of local drivers such as hydroperiod, a critical factor controlling nutrient availability and soil salinity in mangrove wetlands.

Global trends of mangrove biomass and carbon stocks

Much attention is directed at mangrove forests because of their significant allocation of carbon belowground. However, carbon sequestration rates are estimated by using wood production and litterfall rates, which are positively correlated with tree height and AGB. We developed and validated regional and global AGB models (Supplementary Table 8) from 313 field plots distributed across three continents (Fig. 1), spanning 51° in latitude and 168° in longitude (see Methods).

Our maps indicate that mangroves can store substantial aboveground carbon stocks (maximum AGB of 910.5 ± 84.2 Mg ha−1, Table 1a), and show considerable spatial variability. Similar to canopy height, the global distribution of AGB maxima in mangrove forests follows a Gaussian latitudinal trend with a peak near 0.47° S (Supplementary Fig. 3). The top five countries in terms of total AGB are (Table 1b): Indonesia (574.3 Tg, 2.7 Mha), Papua New Guinea (452.5 Tg, 1.5 Mha), Australia (372.6 Tg, 1.2 Mha), Brazil (364.3 Tg, 1.1 Mha), and Malaysia (357.8 Tg, 1.0 Mha). These countries are characterized by vast expanses of mangrove forests and a high proportion of tall stands. The top ten list (Table 1b) differs from previously reported rankings that include Indonesia and Papua New Guinea, but not Bangladesh, Myanmar, Venezuela, and Cameroon. Furthermore, our field data set underscores major regional differences in allometric relationships between canopy height and AGB (Supplementary Fig. 4 and Supplementary Table 8). For example, our allometric model for East African coastal regions derived from in situ data shows that, for the same forest canopy height, AGB in East Africa is significantly higher than in the Americas. This difference in values highlights the relative importance of tree density when calculating AGB in sites within the same latitude, and the need to develop regional allometry covering a wide range of environmental settings.

### Table 1 | Distribution of mangrove canopy height and total AGB

<table>
<thead>
<tr>
<th>Country</th>
<th>Max height (m)</th>
<th>Mean height (m)</th>
<th>Max AGB (Mg ha⁻¹)</th>
<th>Mean AGB (Mg ha⁻¹)</th>
<th>Total AGB (Mg)</th>
<th>Total carbon (Mg)</th>
<th>Percent of global AGB (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gabon</td>
<td>62.8</td>
<td>23.5</td>
<td>910.5</td>
<td>244.0</td>
<td>33,578,276</td>
<td>61,504,323</td>
<td>137,597</td>
</tr>
<tr>
<td>Equatorial Guinea</td>
<td>57.7</td>
<td>21.6</td>
<td>800.0</td>
<td>208.6</td>
<td>2,630,892</td>
<td>5,337,399</td>
<td>12,613</td>
</tr>
<tr>
<td>Colombia</td>
<td>54.3</td>
<td>24.0</td>
<td>413.3</td>
<td>129.5</td>
<td>26,648,548</td>
<td>75,973,344</td>
<td>205,179</td>
</tr>
<tr>
<td>Venezuela</td>
<td>52.6</td>
<td>30.7</td>
<td>392.8</td>
<td>184.0</td>
<td>45,505,364</td>
<td>100,551,457</td>
<td>247,252</td>
</tr>
<tr>
<td>Panama</td>
<td>50.9</td>
<td>27.7</td>
<td>372.6</td>
<td>156.6</td>
<td>23,676,218</td>
<td>58,979,743</td>
<td>152,189</td>
</tr>
<tr>
<td>French Guyana</td>
<td>49.2</td>
<td>23.2</td>
<td>352.9</td>
<td>129.2</td>
<td>10,290,431</td>
<td>29,453,310</td>
<td>79,640</td>
</tr>
<tr>
<td>Cameroon</td>
<td>47.5</td>
<td>22.6</td>
<td>594.5</td>
<td>208.7</td>
<td>41,603,704</td>
<td>84,360,030</td>
<td>199,303</td>
</tr>
<tr>
<td>Angola</td>
<td>45.8</td>
<td>16.6</td>
<td>562.3</td>
<td>139.7</td>
<td>3,738,534</td>
<td>10,090,736</td>
<td>26,779</td>
</tr>
<tr>
<td>Costa Rica</td>
<td>45.8</td>
<td>23.4</td>
<td>314.7</td>
<td>116.4</td>
<td>4,512,007</td>
<td>13,998,836</td>
<td>38,752</td>
</tr>
<tr>
<td>Papua New Guinea</td>
<td>45.8</td>
<td>27.7</td>
<td>432.5</td>
<td>242.4</td>
<td>113,948,576</td>
<td>209,577,515</td>
<td>469,983</td>
</tr>
</tbody>
</table>

### Table 1b | The largest total AGB pools

<table>
<thead>
<tr>
<th>Country</th>
<th>Max height (m)</th>
<th>Mean height (m)</th>
<th>Max AGB (Mg ha⁻¹)</th>
<th>Mean AGB (Mg ha⁻¹)</th>
<th>Total AGB (Mg)</th>
<th>Total carbon (Mg)</th>
<th>Percent of global AGB (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indonesia</td>
<td>44.1</td>
<td>24.3</td>
<td>409.5</td>
<td>215.3</td>
<td>574,318,208</td>
<td>1,140,797,712</td>
<td>32.7</td>
</tr>
<tr>
<td>Papua New Guinea</td>
<td>45.8</td>
<td>27.7</td>
<td>432.5</td>
<td>242.4</td>
<td>113,948,576</td>
<td>209,577,515</td>
<td>6.5</td>
</tr>
<tr>
<td>Australia</td>
<td>25.5</td>
<td>11.9</td>
<td>212.6</td>
<td>119.4</td>
<td>112,797,816</td>
<td>342,085,251</td>
<td>6.4</td>
</tr>
<tr>
<td>Brazil</td>
<td>40.7</td>
<td>19.9</td>
<td>260.5</td>
<td>92.5</td>
<td>97,833,808</td>
<td>363,245,344</td>
<td>5.6</td>
</tr>
<tr>
<td>Malaysia</td>
<td>33.9</td>
<td>19.9</td>
<td>290.6</td>
<td>172.9</td>
<td>95,561,040</td>
<td>220,641,786</td>
<td>5.4</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>25.5</td>
<td>15.4</td>
<td>421.2</td>
<td>171.7</td>
<td>73,916,552</td>
<td>171,532,878</td>
<td>4.2</td>
</tr>
<tr>
<td>Nigeria</td>
<td>33.9</td>
<td>13.4</td>
<td>355.3</td>
<td>96.5</td>
<td>66,791,716</td>
<td>240,715,439</td>
<td>3.8</td>
</tr>
<tr>
<td>Myanmar</td>
<td>30.5</td>
<td>13.7</td>
<td>257.3</td>
<td>130.7</td>
<td>61,974,552</td>
<td>175,266,415</td>
<td>3.5</td>
</tr>
<tr>
<td>Venezuela</td>
<td>52.6</td>
<td>30.7</td>
<td>392.8</td>
<td>184.0</td>
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<td>208.7</td>
<td>41,603,704</td>
<td>84,360,030</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Total top 10 AGB: 1,284,251,336, 3,048,773,825, 73.2
When adding our global aboveground carbon stock value to recently published values for average organic soil carbon stock (283 Mg ha\(^{-1}\); ref. \(^{15}\)) and root biomass (from allometric models, see ref. \(^{41}\)), we obtain a total global carbon stock estimate of 5.03 Pg, of which nearly a quarter (22.7\%) is stored in Indonesia (see Supplementary Tables 2–6 for the per country and per continent overview). Our estimate is in line with recently published total carbon stock estimates (Supplementary Table 9), in part due to the significant contribution of belowground carbon to the total global carbon estimate.

While our estimates of total global AGB (1.75 Pg) and mean AGB density (129.1 ± 87.2 Mg ha\(^{-1}\)) are significantly lower than previously reported by Hutchison and colleagues\(^{16}\) (2.83 Pg and 184.8 Mg ha\(^{-1}\), respectively), our total is close to the mean (1.88 Tg) of a range of published values (Supplementary Table 9). The difference in estimates is primarily due to methodological approaches such as the use of different mangrove extent maps. Additionally, a few previous AGB estimates, such as the one of Hutchison and colleagues\(^{16}\), represent the potential AGB obtained by modelling biomass based on latitude\(^{43,44}\) and bioclimatic variables\(^{16}\). In contrast, our estimate is based on direct measurements of canopy height from spaceborne radar and lidar instruments, coupled with extensive in situ forest structure and composition measurements. As such, the differences between our estimates and those reported in previous studies reflect local-scale variability within mangrove forests and areas where mangroves are stressed or impacted by environmental and geophysical factors, and anthropogenic activity. For example, the differences in mean AGB between studies (shown as ‘satellite-based’ from this study versus ‘environmental model’ from ref. \(^{16}\)) in West Africa are as follows: Benin (10.0 Mg ha\(^{-1}\) versus 160.6 Mg ha\(^{-1}\)), Ghana (59.8 Mg ha\(^{-1}\) versus 166.9 Mg ha\(^{-1}\)), Nigeria (96.5 Mg ha\(^{-1}\) versus 195.1 Mg ha\(^{-1}\)), Sierra Leone (74.7 Mg ha\(^{-1}\) versus 180.2 Mg ha\(^{-1}\)) and The Gambia (42.0 Mg ha\(^{-1}\) versus 144.9 Mg ha\(^{-1}\)), suggesting that model-based estimates may have overestimated AGB by 100 Mg ha\(^{-1}\) or more. Mangrove wetlands in these regions are heavily impacted by anthropogenic pressures such as wood harvesting, bio-fuel plantations, development projects and industrial pollution\(^{15}\), and may explain discrepancies. Industrial pollution, for example, is a common cause of mangrove degradation in the Niger Delta region (Nigeria)\(^{39}\). Similarly, our total carbon estimate for Indonesia (1,141 Tg C) is less than half of that reported by Murdiyarso and colleagues\(^{7}\) (3,140 Tg C). This discrepancy is due to differences in the soil depth (1 m in this study; 2–3 m in ref. \(^{16}\)) that is being considered for estimating the soil carbon component and our use of a smaller total mangrove area (2.7 Mha versus 4.2 Mha). These findings also suggest that regions with deep carbon-rich soils can potentially yield higher values than those reported in this study. While we report on the top 1 m of soil as a first-order conservative estimate, we foresee the continued development of more spatially explicit maps of soil carbon in blue carbon ecosystems\(^{16,37,47}\) that can be coupled with our AGB and carbon data sets.

Baseline for monitoring regional and global carbon trends

In this study we have shown that mangroves can store substantial aboveground carbon stocks and that continental to global patterns of mangrove canopy height and AGB follow precipitation, temperature and cyclone landfall frequency trends. Moreover, our spatially explicit maps indicate that local-scale geophysical and environmental conditions also regulate forest structure, and therefore carbon stocks and sequestration rates. Our mangrove canopy height map revealed a vast range of canopy heights, including maximum realized values (>62 m) that surpass maximum heights of other forest types worldwide\(^{25}\), and the discovery of the tallest stands of mangrove forests in the world, on the Atlantic coast of equatorial Africa and the Pacific coast of South America. Our AGB map can serve as a baseline input for estimating the contribution of mangroves to carbon sequestration by wetlands in general and the potential contribution of CO\(_2\) emissions resulting from mangrove degradation and loss\(^{13,39,44}\).

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of data availability and associated accession codes are available at https://doi.org/10.1038/s41561-018-0279-1.
Fig. 4 | Latitudinal variation of maximum canopy height (m) and global environmental variables. a, Relationship (black line) between latitude and maximum canopy height (green circles) calculated on the 95th percentile of maximum canopy height (red plus symbols) (right y axis) at every 5° of latitude between about 30° S and 30° N (that is, where most mangroves occur). Tropical cyclone frequency (left y axis) is shown in grey. b, Latitudinal trends in maximum canopy height (green bars), precipitation (blue line), SSS (red line) and cyclone relative frequency distribution (grey bins) along the major continental coastlines. p.s.u., practical salinity unit (grams of salt per 1,000 grams of water).

Received: 3 April 2018; Accepted: 20 November 2018; Published online: 20 December 2018

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Methods

Mangrove canopy height estimation with SRTM and ICESat/GLAS. The global maps of canopy height were generated using SRTM DEM data\(^7\) collected in February 2000 and lidar heights from the ICESat/GLAS Spaceborne Laser mission following the methodology that was successfully implemented on regional scales in Florida, Colombia and across Africa, with root-mean-square error (r.m.s.e.) values of 3 m or lower across the 1–30 m mean height range\(^7\)-\(^9\). The SRTM DEM values report elevations located at the InSAR scattering phase height centre, which corresponds to a height located between the ground elevation and the top of the canopy in vegetated areas. This is due to radar microwaves penetrating and interacting within the forest canopy, rather than with the top of the canopy or ground alone. To identify mangrove areas and mask non-mangrove regions in the SRTM elevation data set, we used the global mangrove extent map from ref. \(^7\). We only included areas with SRTM elevation values ranging from 0 to 55 m above mean sea level to remove areas falsely identified as mangroves in the ref. \(^7\) map. This threshold value preserved the tallest mangrove features (Fig. 3). This map was prefered over the more recent map developed by Hamilton and Casey\(^1\) as it is coincidental with the SRTM data set (that is, they are both from 2000) and, so far, it is the only one that specifically maps mangroves from Landsat data, as opposed to using global canopy cover from the Global Forest Change product\(^2\).

GLAS lidar altimetry data were collected globally from 2003 to 2009, providing the only global lidar canopy and height measurement, with sparse samples distributed across the globe. We used GLAS data to remove the elevation bias introduced by the limited penetration of the SRTM C-band microwave signal within the forest canopy, which allows for spatially comprehensive and accurate mapping of canopy height\(^10\). The GLAS-lidar-derived maximum canopy height is defined as the height of the lidar pulse containing all its energy between the ground and the top of the tallest tree (referred to as the relative height of the 100th percentile, RH100). We found a total of 37,369 lidar waveforms in mangrove areas using the entire GLAS archive spanning 2003–2009, filtering out the low-quality measurements\(^11\) and intersecting the GLAS estimates of maximum canopy height with the SRTM mangrove extent subset. Supplementary Fig. 5 presents a scatterplot of RH100 and SRTM elevation in mangrove areas. We applied regression model (1) relating GLAS RH100 to SRTM elevation measurements (Supplementary Fig. 5) to obtain a global map of maximum canopy height:

\[
\text{SRTM}_{\text{Hmax}} = 1.697 \times H_{\text{GRS}}
\]

where \(H_{\text{GRS}}\) represents the original SRTM DEM, and \(\text{SRTM}_{\text{Hmax}}\) is the new maximum canopy height data set. Regions with an SRTM elevation of 0 m but mapped as mangroves in the ref. \(^7\) map were assigned a default value of 0.5 m (based on field observations) as these are most probably scrub or low-density mangrove areas. This is due to radar microwaves penetrating and interacting within the forest canopy, rather than with the top of the canopy or ground alone. To identify mangrove areas and mask non-mangrove regions in the SRTM elevation data set, we used the global mangrove extent map from ref. \(^7\). We only included areas with SRTM elevation values ranging from 0 to 55 m above mean sea level to remove areas falsely identified as mangroves in the ref. \(^7\) map. This threshold value preserved the tallest mangrove features (Fig. 3). This map was prefered over the more recent map developed by Hamilton and Casey\(^1\) as it is coincidental with the SRTM data set (that is, they are both from 2000) and, so far, it is the only one that specifically maps mangroves from Landsat data, as opposed to using global canopy cover from the Global Forest Change product\(^2\).

In situ forest height and biomass estimation. Our selected field sites (331 plots in total) included a wide variety of forest structure and mangrove ecotypes (for example, scrub, fringe, riverine and basin) with measured in situ tree height ranges from 1 to 65 m (Supplementary Table 1). The SRTM data were distributed along a latitudinal range from 26°S (Maputo Reserve, Mozambique) to 25°N (Everglades, USA), encompassing the equatorial region (for example, Chocó, Colombia). Field data were used to estimate forest structure attributes (that is, \(H_{\text{ba}}, H_{\text{Hmax}}\) and AGB). Most of the data were collected in field plots throughout the Americas and Africa, using fixed or variable plots (Supplementary Fig. 4 and Supplementary Table 1). Within variable plots, trees were selected using a fixed-angle gauge. For each selected tree, we identified the species and measured the diameter at breast height (DBH) and height using a laser rangefinder or clinometer. Tree density (that is, the no. of stems) was estimated for each plot and expressed per unit area (in ha). Generally, the plot size depended on the largest tree size at each forest site. For instance, in Chocó (Colombia), where trees were very tall and tree density was low, we used a 25 m fixed-radius plot, while on Inhaca Island (Mozambique), where trees were small and tree density was high, plots had a 7.5 m radius. In the Zambezi River Delta (Mozambique), 40 plots of 0.52 ha were sampled with subplots\(^1\) each with a radius between 3 m and 5 m. On Inhaca Island (Mozambique), we sampled 51 plots with a radius of 7.5 m (0.0176 ha\(^2\)). For all sites, we computed field basal area weighted height \(H_{\text{ba}}\) as

\[
H_{\text{ba}} = \frac{\sum (\pi r^2 \times H)}{\sum (\pi r^2)}
\]

where \(H\) and \(r\) are the height and radius (that is, DBH/2) of tree i, respectively, in metres. \(H_{\text{ba}}\) accounts for tree size, which means larger trees have a stronger impact on the forest height estimate. \(H_{\text{Hmax}}\) was defined as the height of the tallest tree within a plot. In situ data were collected within the 15-year period after the SRTM data were obtained.

Height uncertainty. The combination of multiple data sets and the global approach of our study inevitably introduces some degree of uncertainty into our results. In the case of mangrove height, the SRTM\(_{\text{Hmax}}\) data had an r.m.s.e. of 5.6 m when compared to in situ \(H_{\text{Hmax}}\) measurements (shown in Supplementary Fig. 1). This means that in any particular pixel, if our SRTM\(_{\text{Hmax}}\) map indicates a 4 m mangrove forest, the in situ \(H_{\text{Hmax}}\) is likely to be between 0.4 m and 7.6 m. However, the SRTM\(_{\text{Hmax}}\) uncertainty is larger, as indicated by the regression with GLAS RH100 (r.m.s.e. of 5.7 m) (Supplementary Fig. 5) and in situ \(H_{\text{Hmax}}\) (r.m.s.e. of 6.3 m). Nonetheless, both height estimates are more accurate and provide a more reliable global map of mangrove canopy height. To construct this map, we followed the approach of our study inevitably introduces some degree of uncertainty into our results. In the case of mangrove height, the SRTM\(_{\text{Hmax}}\) data had an r.m.s.e. of 5.6 m when compared to in situ \(H_{\text{Hmax}}\) measurements (shown in Supplementary Fig. 1). This means that in any particular pixel, if our SRTM\(_{\text{Hmax}}\) map indicates a 4 m mangrove forest, the in situ \(H_{\text{Hmax}}\) is likely to be between 0.4 m and 7.6 m. However, the SRTM\(_{\text{Hmax}}\) uncertainty is larger, as indicated by the regression with GLAS RH100 (r.m.s.e. of 5.7 m) (Supplementary Fig. 5) and in situ \(H_{\text{Hmax}}\) (r.m.s.e. of 6.3 m). Nonetheless, both height estimates are more accurate and provide a more reliable global map of mangrove canopy height.
The mean SSS as a function of latitude for each continental region (Fig. 4b) was generated using 44 monthly mean maps (from 2011 and 2015) from version 4 of the Aquarius CAP Level 3 product. The sampled environmental variables were averaged per 1° of latitude, ranging from 34° S to 30° N. The occurrence of cyclones was counted per 1° interval. A multivariate regression analysis demonstrated the significant relationships between some environmental variables and mangrove structure (that is, maximum height) (Supplementary Table 7). Initially, all aforementioned variables were included in the analysis with insignificant (that is, p > 0.1) and highly correlated variables (for example, minimum temperature and mean temperature) gradually eliminated. Only temperature, precipitation and cyclone landfall frequency remained, explaining 74% of observed global trends in mangrove maximum canopy height (Supplementary Table 7). Further analysis also showed that precipitation alone explained 57% of global canopy height trends while temperature alone explained 33%. Together, precipitation and temperature explained 71% of global canopy height trends. The multivariate regression and variance inflation factor calculation were performed using the python statsmodels module. All of the remote sensing data processing and analysis were carried out using the Python scripting language, Quantum Geographical Information System (QGIS), the Geospatial Abstraction Library (GDAL), the Remote Sensing and GIS python library (RSGLiB) and GNU Parallel.

Global mangrove biomass allometry development. We used the in situ field data sets to derive stand-level allometry between AGB, basal area weighted height \( H_a \) and maximum canopy height \( H_{max} \). AGB was estimated for each individual tree tagged inside the plot, using regional or site-specific allometric equations as described by previous studies. We used the generalized pantropical tree allometric model with species-specific wood density from the global wood density database to calculate the above- and belowground (root) biomass of individual trees (Supplementary Table 1). The sum of individual trees within the plot was then computed and normalized, using plot sizes, to represent total forest stand AGB density in Mg ha\(^{-1}\). We then generated regional and global models between plot-level canopy height and plot-level AGB density, where height and AGB relationships were fitted to the regression model:

\[
AGB = a \times H_a^b
\]

(4)

where \( H_a \) can represent either \( H_a \) or \( H_{max} \). The allometric parameters \( a \) and \( b \) are fitted. The global model was generated using all of the plot data (n = 331) and \( H_a \) of the field data, while the regional models were generated for the Americas (using data from Colombia, USA, Venezuela, Brazil, Costa Rica, Ecuador, Mexico, n = 81), East Africa (using data from Mozambique, n = 101) and South Asia (using data from Bangladesh, n = 149). The analysis of the field data and the allometric regression models between field height and AGB confirmed that while canopy height alone explains most of the variability in AGB, adding stem density or basal area to the model, as in the case of \( H_{max} \) and developing region-specific regressions, improved the relationship (Supplementary Fig. 4). In addition, \( H_a \) is computed from multiple tree measurements, which reduces systematic random height measurement error at the stand level, as opposed to \( H_{max} \), which is reported from a single tree measurement. Supplementary Fig. 4 shows the relationship of AGB with \( H_a \) on a global scale as well as region-specific scales.

Three region-specific allometric models were derived from field data for East Africa, the Americas and Middle East Asia. For Southeast Asia and Australia, a published allometric model was used. Finally, for West Africa, we applied the global allometric equation, as no field data were available to generate a regional allometry. The regional biomass allometric models developed in this study have r.m.s.e. values ranging from 54.3 Mg ha\(^{-1}\) to 103.4 Mg ha\(^{-1}\). All models generated for this study are shown in Supplementary Fig. 4, and all models used in the study can be found in Supplementary Table 8.

Large-scale AGB estimation with SRTM. The global mangrove forest AGB map was generated by linking the field-measured biomass–height allometry (described above) with SRTM estimates of \( H_a \) (that is, SRTMHA). This procedure implies a two-step process where SRTM is converted to SRTMHA, and then to AGB using appropriate field-derived \( H_a \) to AGB allometry (Supplementary Table 8). This approach is meant to facilitate potential updates by the user community as more region-specific height-to-biomass models are developed. Supplementary Fig. 1a shows the relationship between SRTM elevation and field-measured canopy height data, used to convert SRTM elevation to SRTMHA. Using this method, the predicted AGB was estimated with an accuracy of 84.2 Mg ha\(^{-1}\) at the plot level (Supplementary Fig. 1b).

Finally, total (above- and belowground) biomass and carbon stock estimates by country were generated by summing all corresponding pixels, while accounting for belowground biomass and soil carbon. We computed the total aboveground carbon stocks per country, assuming a stoichiometric factor of 0.451 as the AGB conversion factor, following the IPCC guidelines. We also accounted for belowground carbon and soil carbon biomass using published allometric models. It is important to note that all allometric equations are site-specific and extrapolation may result in a bias. For instance, in the Florida Everglades, root biomass in scrub forests can be three to four times higher compared to AGB. Furthermore, most allometric models do not account for scrub forests, thereby adding uncertainty to the AGB and total carbon estimates. Nevertheless, we believe we have used the most complete data sets and the most accurate values currently available, which can be updated as new global belowground data and new allometry become available. Country-wide belowground carbon stocks were estimated with a mean of 283 Mg C ha\(^{-1}\) within the top 1 m of soils. Total root biomass was estimated as 49% of the AGB following the IPCC guidelines. These generic values, uncertainties in the allometric models, as well as the uncertainty of 12% in the mangrove extent map, will propagate as a bias in country-wide totals.

Data availability

The data that support the findings of this study are available from the Oak Ridge National Data Archive (ORNL DAAC; https://doi.org/10.3334/ORNLDAAC/1665) as GEOTIFF files and as an online webmapping tool (https://mangrovescience.earthengine.app/view/mangroveheightandbiomass). The in situ field data that have been published previously are also available through the ORNL DAAC as .csv files listing individual tree measurements (https://doi.org/10.3334/ORNLDAAC/1665). The SRTM and ICESat/GLAS data sets used as input to generate the maps can be downloaded from https://lta.cr.usgs.gov/SRTM and https://nsidc.org/data/iccsat/data.html, respectively. The global mangrove map is freely available at http://data.unep-wcmc.org/datasets/4. The tropical cyclone and SSS data are available from NOAA archives https://data.nodc.noaa.gov/cgi-bin/iso?id=gov.noaa.ncco.c00834 (https://doi.org/10.7289/V5NK3BZP) and https://podac.jpl.nasa.gov/dataset/AQUIAURUS_L3_SSS_CAP_MONTHLY_V4?ids=Platform&values=AQUIAURUS_SAC-D (https://doi.org/10.5067/AQR04-TMCS). The WorldClim data are available at http://worldclim.org/version2.

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