Wetlands Ecol Manage
DOI 10.1007/s11273-015-9474-7

ORIGINAL PAPER

The assessment of mangrove biomass and carbon in West Africa: a spatially explicit analytical framework

Wenwu Tang · Wenpeng Feng · Meijuan Jia · Jiyang Shi · Huifang Zuo · Carl C. Trettin

Received: 12 March 2015 / Accepted: 7 December 2015
© Springer Science+Business Media Dordrecht 2015

Abstract Mangrove forests are highly productive and have large carbon sinks while also providing numerous goods and ecosystem services. However, effective management and conservation of the mangrove forests are often dependent on spatially explicit assessments of the resource. Given the remote and highly dispersed nature of mangroves, estimation of biomass and carbon in mangroves through routine field-based inventories represents a challenging task which is impractical for large-scale planning and assessment. Alternative approaches based on geospatial technologies are needed to support this estimation in large areas. However, spatial data processing and analysis approaches used in this estimation of mangrove biomass and carbon have not been adequately investigated. In this study, we present a spatially explicit analytical framework that integrate remotely sensed data and spatial analyses approaches to support the estimation of mangrove biomass and carbon stock and their spatial patterns in West Africa. Forest canopy height derived from SRTM and ICESat/GLAS data was used to estimate mangrove biomass and carbon in nine West African countries. We developed a geospatial software toolkit that implemented the proposed framework. The spatial analysis framework and software toolkit provide solid support for the estimation and relative comparisons of mangrove-related metrics. While the mean canopy height of mangroves in our study area is 10.2 m, the total biomass and carbon were estimated as 272.56 and 136.28 Tg. Nigeria has the highest total mangrove biomass and carbon in the nine countries, but Cameroon is the country with the largest mean biomass and carbon density. The resulting spatially explicit distributions of mangrove biomass and carbon hold great potential in guiding the strategic planning of large-scale field-based assessment of mangrove forests. This study demonstrates the utility of online geospatial data and spatial analysis as a feasible solution for estimating the distribution of mangrove biomass and carbon at larger or smaller scales.

W. Tang (✉) · W. Feng · M. Jia · J. Shi · H. Zuo
Center for Applied Geographic Information Science, University of North Carolina at Charlotte, Charlotte, NC 28223, USA
e-mail: WenwuTang@uncc.edu

W. Tang · W. Feng · M. Jia · J. Shi · H. Zuo
Department of Geography and Earth Sciences, University of North Carolina at Charlotte, Charlotte, NC 28223, USA

C. C. Trettin
Center for Forested Wetlands Research, U.S. Forest Service, Cordesville, SC 29434, USA

Keywords Mangrove biomass · Canopy height · Forest inventory · West Africa

Introduction

Mangrove forests are recognized as highly productive ecosystems that store large amounts of carbon (Alongi

Published online: 11 December 2015

2014; Gilman et al. 2008; Jennerjahn and Ittekkot 2002; Kristensen et al. 2008). However, quantifying carbon stocks in mangrove forests at a large scale (e.g., national, regional, continental) has been precluded by the lack of national-level forest inventory data. Recent advances in geospatial technologies including remote sensing and geographic information systems (GIS; see Goodchild 1992; Longley 2005), suggest that they may be used to provide a first approximation of carbon pools, and serve as a useful basis for designing field-based inventories to quantify carbon stocks for REDD+ projects (Angelsen 2009) and carbon-based markets. Accordingly, our objective was to present a spatially explicit analytical framework for estimating the distribution of biomass and carbon stocks of mangroves using available geographically referenced data and GIS-based spatial analyses in West Africa, specifically along the Atlantic coast from Guinea to Cameroon.

Large scale assessment of mangrove biomass and carbon stocks requires information about the distribution of the mangroves on the landscape and structural characteristics of the forest. However, mangroves are usually located in inaccessible and difficult working environments, posing a distinct challenge for conducting field-based assessments (Dittmar et al. 2006; Fatoyinbo and Simard 2013). Remote sensing, primarily using Landsat, has been used since the late 1990's to assess the global mangrove area with estimates ranging from 110,000 to 240,000 km^2 (Dahdouh-Guebas et al. 2000, 2002; FAO 2007; Kovacs et al. 2001; Wilkie and Fortuna 2003). More recently, Giri et al. (2011) utilized the Global Land Survey data from the US Geological Survey (USGS) and a hybrid approach that combined supervised and unsupervised classification of Landsat data to map the distribution of mangrove forests, concluding with a global mangrove area of 137,760 km^2. This data is readily available from the USGS (see http://marine-portal.unepwcmc-001.vm.brightbox.net/datasets/21), and serves as the current bench mark for large scale assessments of mangroves.

The structural assessment of mangroves needs support from sensors that can penetrate the forest canopy and return information about canopy relative to the land surface (e.g., Lidar, radar). Simard et al. (2006) used Shuttle Radar Topography Mission (SRTM; see SRTM 2015; http://www2.jpl.nasa.gov/srtm/) and the Ice, Cloud, and land Elevation Satellite/Geoscience Laser Altimeter System (ICESat/GLAS; see ICESAT 2015) data to estimate canopy height of mangroves in the Everglades National Park in south Florida and Columbia, which was in turn processed using relationships derived from Day et al. (1987), Fromard et al. (1998), and Smith and Whelan (2006). Subsequently, three dimensional structure and biomass of mangrove forests were assessed and mapped using SRTM and ICESat/GLAS data (Fatoyinbo and Simard 2013; Fatoyinbo et al. 2008; Lucas et al. 2007; Simard et al. 2006, 2008). At the global scale, the SRTM (see SRTM 2015; http://www2.jpl.nasa.gov/srtm/) is the only data source available for estimating mangrove structure (e.g., canopy height). The SRTM dataset consists of global-scale elevation data with a spatial resolution of 90 m $\times$ 90 m, which was collected in February, 2000. Vegetation canopy height information is included in SRTM data, which allows estimation of mangrove canopy height with the assumption that mangroves are observed at sea level (Fatoyinbo et al. 2008).

The application of SRTM data to estimate mangrove biomass and carbon was conducted in Africa, originally in Mozambique (Fatoyinbo et al. 2008) and more recently at a continental scale (Fatoyinbo and Simard 2013). The SRTM data has also been used effectively in Mozambique for designing an inventory of mangrove carbon stocks for REDD+ (Stringer et al. 2015). The utility of the large-scale SRTM database will be further realized (in particular, for those regions that are relatively less studied) if a systematic analytical framework to guide the derivation of the spatial distribution of canopy height, biomass, and carbon at regional or higher scales is available. Thus, in this study, we present a spatially explicit analytical framework and software toolkit developed for West Africa, which may serve as an example for general applicability for the assessment of mangrove biomass and carbon in other regions.

Materials and methods

Study area

Our study area includes nine countries on the Atlantic coast of West Africa, including Guinea, Sierra Leone, Liberia, Cote d'Ivoire, Ghana, Togo, Benin, Nigeria, and Cameroon (Fig. 1). The annual average

temperature of the region is approximately in the range of 23–31 °C (along the coast; obtained from World Bank's Climate Change Knowledge Portal; see www.worldbank.org/climateportal/). West Africa has distinct wet and dry seasons due to the interplay between continental and maritime air masses and the ocean currents. The annual precipitation ranges from 1000 to 2000 mm (Saenger and Bellan 1995). There are seven species of mangroves in the region: *Acrostichum aureum*, *Avicennia germinans*, *Conocarpus erectus*, *Conocarpus erectus*, *Rhizophora harrisonii*, *R. mangle*, and *R. racemosa*. In addition, an introduced species, *Nypa fruticans*, has been observed in West Africa (Beentje and Bandeira 2007).

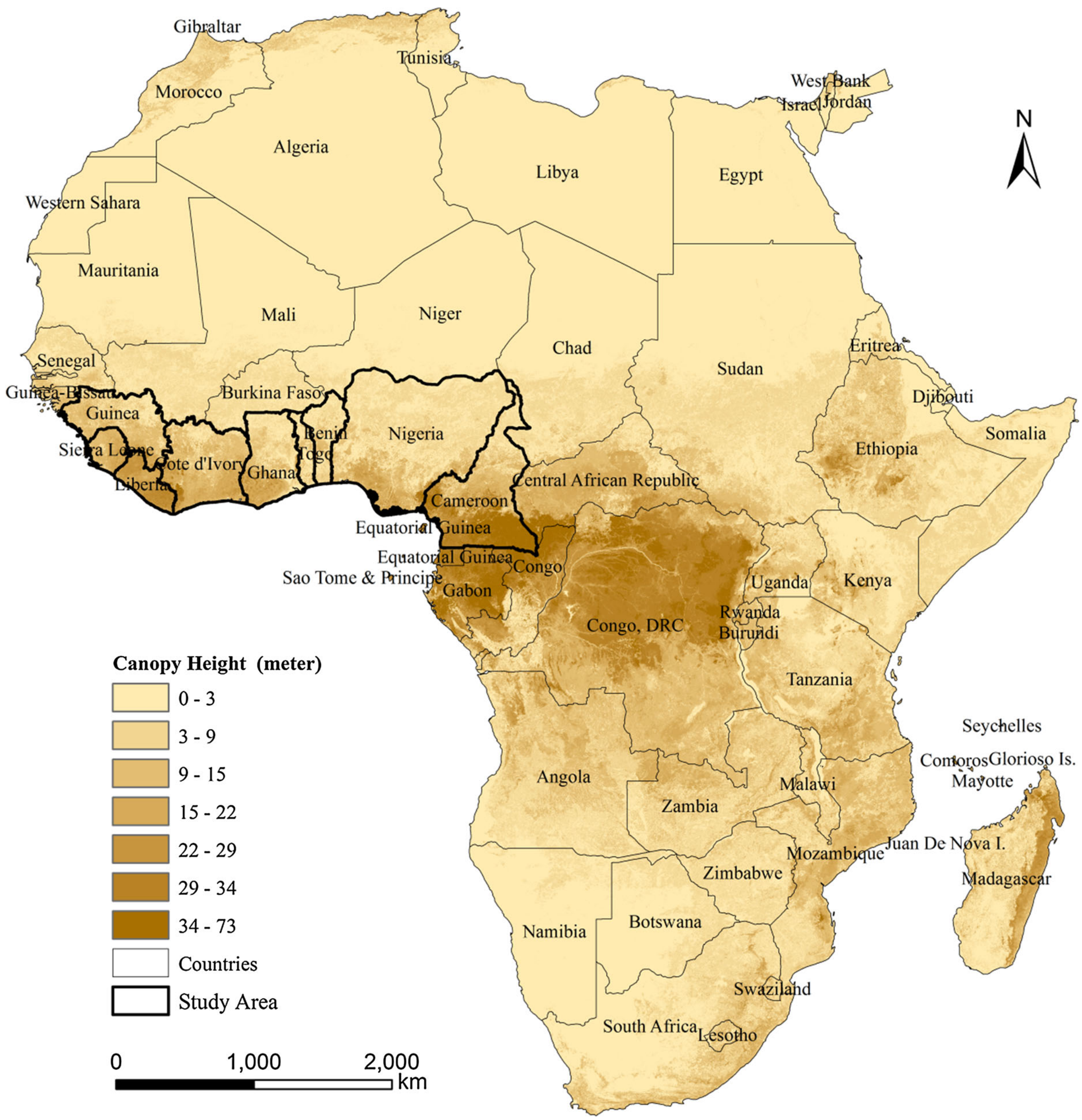

Fig. 1 Map of canopy heights in Africa (*data source*: NASA; spatial resolution: 1 km × 1 km; our study area covers countries from Guinea to Cameroon)

Spatially explicit analytical framework

Our estimation of mangrove biomass and carbon in West Africa is based on a collection of datasets, including SRTM data, mangrove coverage, and country boundary (see Table 1). A series of GIS processing and spatial analysis approaches are needed to estimate mangrove biomass and carbon based on these datasets. Thus, we developed this spatially explicit analytical framework that integrates these data and analytical approaches to facilitate the estimation of mangrove biomass and carbon (see Fig. 2). The spatially explicit analytical framework consists of three modules: extraction of mangrove canopy heights and area, refinement of mangrove canopy heights and stratification, and estimation of mangrove extent, biomass, and carbon.

Extraction of mangrove canopy heights and area

The SRTM dataset was obtained from NASA, and the mangrove coverage datasets from USGS. The SRTM dataset from NASA includes a collection of GeoTIFF (GeoTIFF 2015) files covering the nine countries in our study area. After converting SRTM data to a GIS-based raster format, these datasets were merged into a single raster dataset. Then, mangrove canopy heights can be extracted through overlay analysis of SRTM and mangrove coverage data (extraction of raster data using vector-based polygons). The boundary data of each country were from the Global Administrative Area (GADM) database (see GADM 2015). The boundary of our study area was merged from boundaries of countries of interest.

The assessment of mangrove area in the nine countries in our study area is based on the USGS data of mangrove coverages and country boundaries (see Fig. 3). Two datasets were available: global mangrove coverage for the year of 2000 (Giri et al. 2011), and unpublished USGS data (Personal Communication, G. Tappin, USGS) for Guinea, Sierra Leone, Liberia, Ghana, and Benin. The areas were calculated via GIS-based overlay analysis. Table 2 reports the results of mangrove area in the nine countries. Once we extracted mangrove canopy heights from NASA's SRTM data through overlay analysis, another version of mangrove area at the regional level and for each country can be derived (see NASA2 in Table 2).

Refinement of mangrove canopy heights and stratification

The value of canopy height ranged from 0 to 255 m in the extracted mangrove canopy height data; the exceedingly high values are attributed to an inherent error rate of approximately 10 % in the calculated data (M. Simard, personal communication). Thus, refinement needs to be applied on the extracted mangrove canopy height data to handle those raster cells with exceedingly high values, while these cells were ignored in previous studies by Fatoyinbo and Simard (2013). Figure 4 shows the histogram of mangrove canopy heights for the entire study area. Accordingly, we applied a cut-off threshold (corresponding to 32 m) to further process the canopy height data: cells with height values less than or equal to 32 m remain unchanged, while for these cells with height values above 32 m their heights were replaced with values estimated using spatial interpolation. Our spatial

Table 1 Summary of original datasets used for the estimation of mangrove biomass and carbon in West Africa

Theme	Format	Year	Scale	Source
Canopy height (90 m × 90 m)	Raster TIF	2000	Country	SRTM dataset from NASA (http://www2.jpl.nasa.gov/srtm/)
Canopy height (1000 m × 1000 m)	Raster TIF	2005	Global	NASA (see http://lidarradar.jpl.nasa.gov/)
Mangrove coverage	Shapefile	2000	Global	USGS data released in 2011 for the year of 2000 (Giri et al. 2011)
Mangrove coverage	Shapefile	2014[a]	Country	Unpublished USGS data by G. Tappin
Country boundary	Shapefile	2012	Country	Global Administrative Area (GADM) database (see http://www.gadm.org)

[a] Unpublished data 2014 for Guinea, Sierra Leone, Liberia, Ghana, Togo, Benin

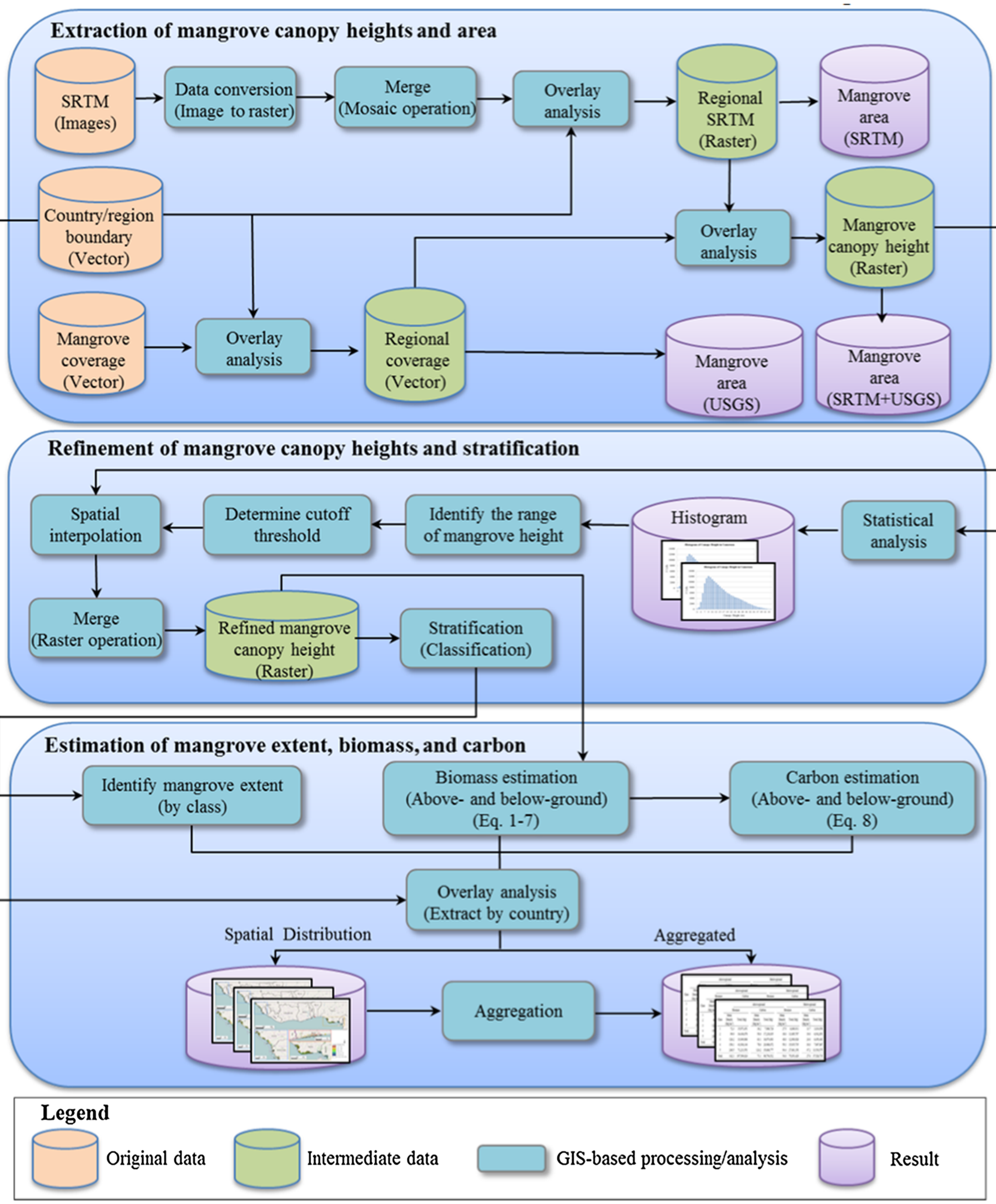

Fig. 2 Spatially explicit analysis framework for the estimation of mangrove biomass and carbon

interpolation procedures include the following steps. First, we selected those cells with height values less than or equal to 32 m, and use them as sample points for spatial interpolation, with an inverse distance weighting (IDW) approach (see Burrough and McDonnell 1998). For the area without sample points

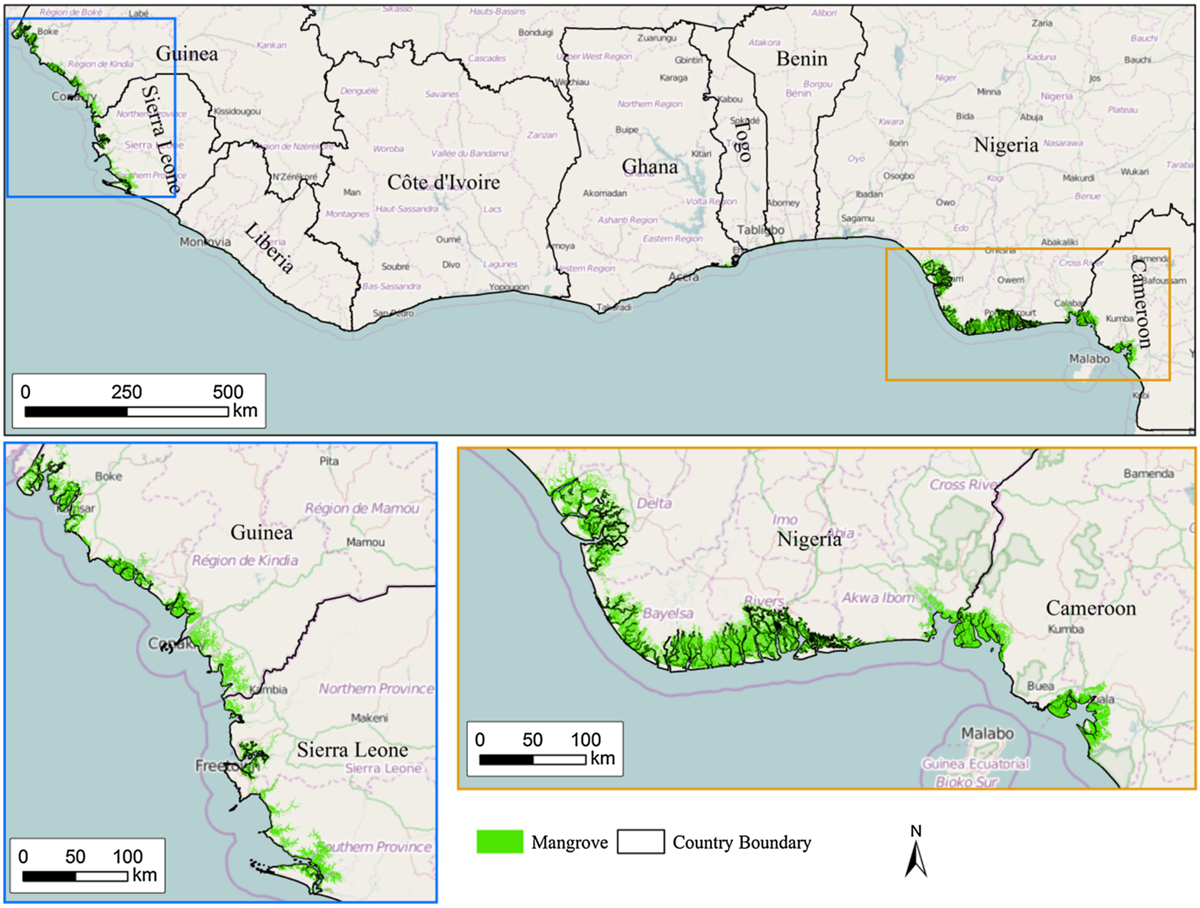

Fig. 3 Map of mangrove coverage in West Africa (*data source*: USGS; base map: OpenStreetMap)

Table 2 Summary of area of mangroves in each country for USGS and NASA datasets

Country	Mangrove area (km²)				Difference (km²)	
	USGS 1	USGS 2	NASA 1	NASA 2	USGS	NASA
Benin	39.4	0.2	18	19.2	−39.2	1.2
Cameroon	2124.8	NA	1483	1578.9	NA	95.9
Cote d'Ivoire	42.3	NA	32	35.3	NA	3.3
Ghana	113.0	211.7	76	80.6	98.7	4.6
Guinea	2344.0	2191.1	1889	1804.6	−152.9	−84.4
Liberia	99.8	399.9	189	202.6	300.0	13.6
Nigeria	6179.9	NA	8573	9109.3	NA	536.3
Sierra Leone	1401.0	1899.6	955	1024.6	498.5	69.6
Togo	6.4	26.6	2	2.3	20.2	0.3
Total	11,710.1	NA	13,217	13,897.8	NA	680.8

USGS 1: USGS data released in 2011 for the year of 2000 (see Giri et al. 2011); USGS 2: G. Tappin unpublished data 2014; NASA 1: Fatoyinbo and Simard (2013); NASA 2: estimates from this study

in our study region, we used nearest neighboring sample points to predict height values of these cells. We applied jackknife-based cross-validation approach (Tomczak 1998) to find the optimal parameter set for the spatial interpolation (number of nearest points: 12; power coefficient on distance: 14.209; minimized root

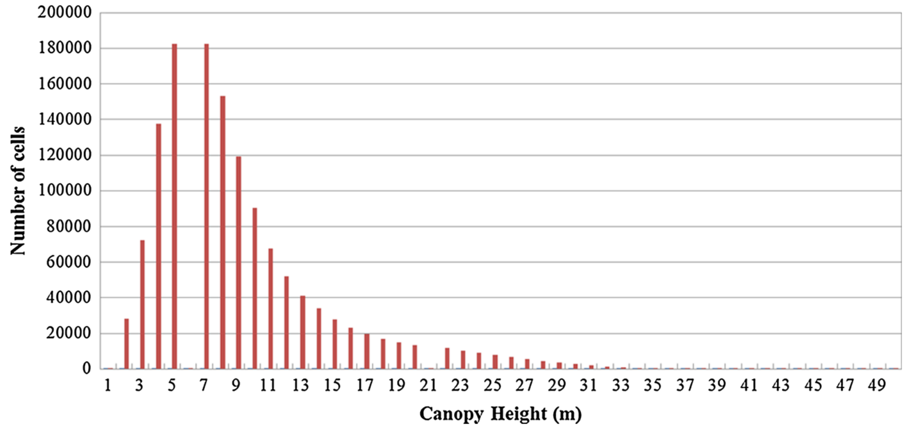

Fig. 4 Histogram of canopy heights for the entire study area (maximal height was set to 50 m; cell size: 90 m × 90 m; height values of 6 and 22 m are missing in original data)

mean square error: 2.217). Then, the height value of cells higher than 32 m in the original dataset was extracted based on the interpolated surface of canopy height. Third, the raster grid data of canopy height were generated by merging cells with correct height values from the original dataset and those with interpolated height values. The proportion of those cells with height values higher than the cut-off is about 0.8 % (13,770 cells out of 1,605,836 total cells with mangrove coverage) in our canopy height data. To facilitate the GIS-based data processing, we merged these raster datasets together into a single one to represent the canopy height of the entire study area.

Stratification is often suggested or used in mangrove studies to better explore the composition and structure of mangrove forests (see Kauffman and Donato 2012; Kovacs et al. 2010). For example, Kovacs et al. (2010) conducted a study to map mangroves in Mabala and Yelitono, islands in Guinea. The work of Kovacs et al. (2010) was based on defining four classes (tall, medium, dwarf red, and black mangrove) within 10,442 ha mangrove forests. Our spatial analysis framework supports the stratification of mangroves based on canopy heights. According to the statistical distribution of canopy heights in the entire study area, we classified canopy heights into five classes using a Jenks natural break method (see Slocum et al. 2009): Class 1: 1–4 m (15.9 % of the entire study area); Class 2: 5–7 m (24.8 %); Class 3: 8–9 m (19.4 %); Class 4: 10–13 m (19.3 %); and Class 5: 14–32 m (20.6 %).

Estimation of mangrove extent, biomass, and carbon

Based on the mangrove area extracted for the entire study region, the area of mangrove extent can be further derived by canopy height class and country. Biomass was estimated based on canopy height using the allometric equation from Fatoyinbo and Simard (2013). The allometric equation is a linear regression model that establishes the relationship between relative canopy height of GLAS point (rh_{75}; unit: m) and SRTM DEM height (H_{SRTM}; unit: m):

$$rh_{75} = a \times H_{SRTM} + b \tag{1}$$

where a and b are the slope and intercept correspondingly. To calculate aboveground biomass, Fatoyinbo and Simard (2013) used a global allometric equation developed by Saenger and Snedaker (1993) (same notation used as in Fatoyinbo and Simard (2013)), which is a function of canopy height:

$$B_H = 10.8 \times H + 35 \tag{2}$$

where B_H is mean aboveground biomass (unit: Mg ha^{-1}); H is canopy height (unit: m).

The mean aboveground biomass of a canopy height class in the entire study area was calculated by:

$$B^{ClassID} = \frac{1}{\sum_{H \in ClassID} N_H} \sum_{H \in ClassID} (N_H \times B_H) \tag{3}$$

where $B^{ClassID}$ is the mean aboveground biomass for a specific canopy height class (unit: Mg ha^{-1}); N_H is the number of cells with the canopy height H; B_H is the mean aboveground biomass for canopy height H

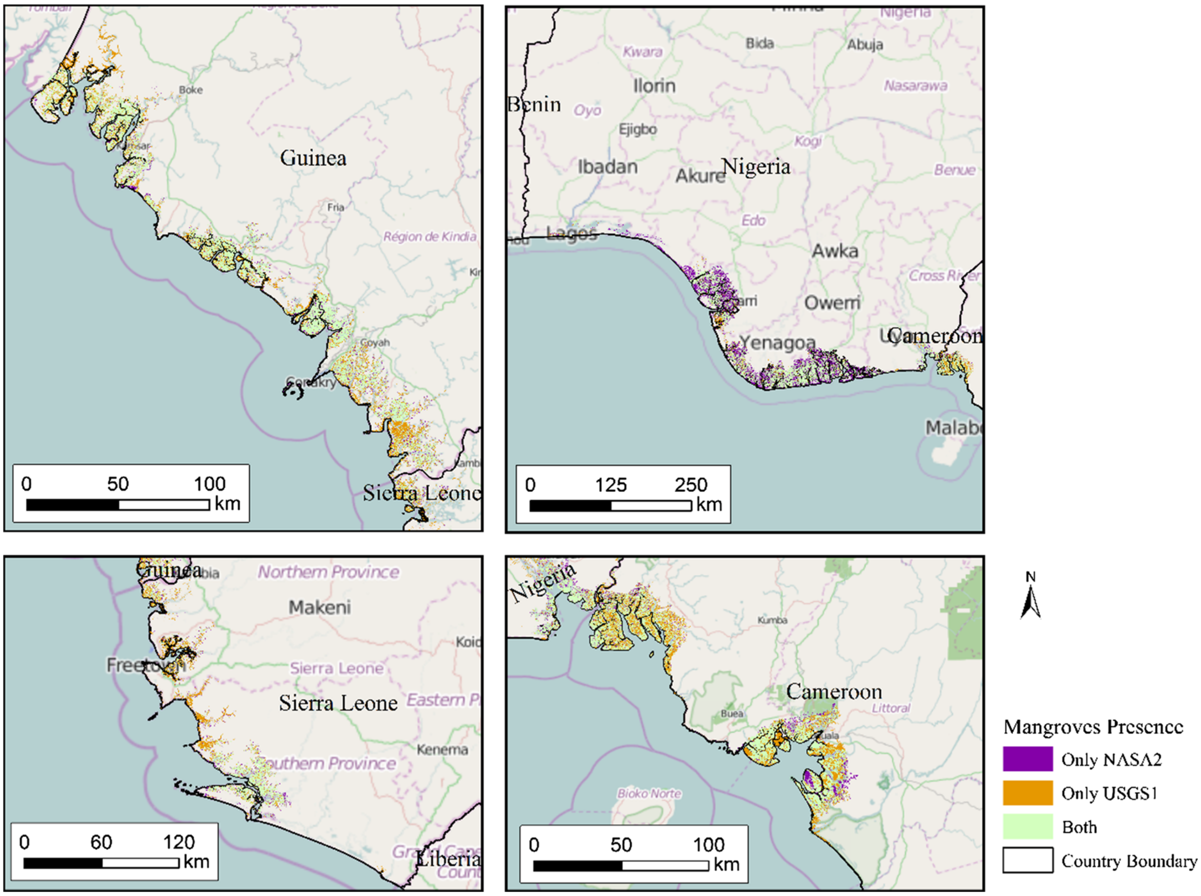

Fig. 5 Map of discrepancy of mangrove area in West Africa for different data sources (USGS1: USGS data released in 2011 for the year of 2000; NASA2: estimates from this study)

calculated by Eq. 2. Likewise, we calculated mean aboveground biomass for each country using the following formula:

$$B_{CountryID} = \frac{1}{\sum_{H \in CountryID} N'_H} \sum_{H \in CountryID} \left(N'_H \times B_H\right) \quad (4)$$

where $B_{CountryID}$ is the mean aboveground biomass of a country (unit: Mg ha^{-1}); N'_H is the number of cells in the country with canopy height H; B_H is the mean aboveground biomass for canopy height H calculated by Eq. 2.

The mean aboveground biomass of each class in each country was calculated by the following formula:

$$B_{CountryID}^{ClassID} = \frac{1}{\sum_{\substack{H \in CountryID \\ and\ H \in ClassID}} N''_H} \sum_{\substack{H \in CountryID \\ and\ H \in ClassID}} \left(N''_H \times B_H\right) \quad (5)$$

where $B_{CountryID}^{ClassID}$ is the mean aboveground biomass of a specific canopy class (class ID: *ClassID)* in a specific country (unit: Mg ha^{-1}); N_H'' is the number of cells in the country with canopy height H; B_H is the mean aboveground biomass for canopy height H (see Eq. 2).

The total aboveground biomass (unit: Mg) was calculated by the corresponding mean aboveground biomass (unit: Mg ha^{-1}) multiplied by the area (unit: ha). Since we used km^2 as the unit for the area, we need to convert the area to hectare (1 km^2 = 100 ha). The formula for calculating total aboveground biomass is:

$$TB = c \times B \times A \tag{6}$$

where TB is total aboveground biomass (unit: Mg). B is the corresponding mean aboveground biomass calculated by Eq. 3–5. A is area (unit: km^2). c is a scaling factor for unit conversion (c = 100.0 ha/km^2). Given aboveground biomass, we estimated belowground biomass using the following equation:

$$B_{bg} = r_{ba} \times B_{ag} \tag{7}$$

where r_{ba} is the ratio of belowground biomass compared to aboveground biomass [38 % in this study, based on Komiyama et al. (2008)]. B_{bg} and B_{ag} are the belowground and aboveground biomass.

Based on the relationship between carbon and biomass, we estimated the carbon (both below- and aboveground) using Eq. 8.

$$C = r_{cb} \times B \tag{8}$$

where r_{cb} is the ratio of above/below ground carbon compared to above/below ground biomass [50 % in this study based on Kauffman and Donato (2012)]. C and B are carbon and biomass (unit: Mg).

Implementation

We developed this analysis framework into a GIS-based toolkit, MangroveCarbon (see https://gis.uncc.edu/mangrove for its web portal). MangroveCarbon (current version: 1.0), with support from GIS-based scientific workflows (Taylor et al. 2014), provides spatial analysis functionality for the automated estimation of mangrove-related metrics of interest. MangroveCarbon 1.0 was developed as a toolbox in ESRI ArcGIS, a worldwide flagship GIS software platform (see http://www.esri.com). Users can download the MangroveCarbon tool (free for noncommercial use) and apply it into their study regions of interest. Because procedures for estimation of mangrove biomass and carbon were automated in MangroveCarbon, users can focus on their mangrove studies instead of manually assembling the set of GIS or spatial analysis approaches. Further, input and output data associated with our study region in West Africa are available through the web portal of MangroveCarbon to facilitate the verification and re-use of these data.

Assessing the effect of scale on biomass and carbon stocks

The spatially explicit analysis framework discussed above provides substantial guidance for estimating the spatial distribution of mangrove-related metrics, including canopy heights, biomass, and carbon. In this study, we applied this framework to evaluate the influence of scale on the estimation of mangrove-related metrics. Besides using canopy height data with a spatial resolution of 90 m × 90 m, we applied a coarser-resolution canopy height data (available at global scale; see JPL 2015) to estimate the mangrove biomass and carbon in our study area. The global canopy height has a spatial resolution of 1 km × 1 km, reported by Simard et al. (2011), based on the spaceborne LiDAR data collected from ICESat in 2005. To identify mangroves in our study region, global mangrove coverage data from Giri et al. (2011) were used. While the spatial resolution of canopy height data is coarse (1 km × 1 km), the combination of global canopy height data (from NASA) and mangrove coverage (from USGS) provides a mean of estimating mangrove biomass and carbon at a global scale, which may offer insight into regional- or continental-level mangrove studies.

Results and discussion

Mangrove area in West Africa

The total area of mangrove forests in the nine West African countries ranges from 11,710 to 13,897 km^2, depending on the source data (Table 2). The largest area of mangrove forests is located in Nigeria with an area of 9109 km^2 (65.5 % of the total area of mangrove forests in the study area), followed by

Table 3 Average canopy height of mangroves for each country and the total mangrove area

Country	Canopy Height	
	Average (m)	Standard deviation (m)
Benin	4.5	2.3
Cameroon	16.1	8.2
Cote d'Ivoire	10.7	8.5
Ghana	7.4	6.4
Guinea	7.8	4.2
Liberia	8.6	6.2
Nigeria	9.9	8.7
Sierra Leone	8.4	5.2
Togo	4.7	2.9
Total	10.2	8.2

Data source: NASA

Guinea (13 %), Cameroon (11.4 %), Sierra Leone (7.4 %), Liberia (1.5 %), Ghana (0.6 %), Cote d'Ivoire (0.3 %) and Benin (0.1 %). The smallest area of mangroves at the country level is found in Togo, where there are only 2 km^2 mangrove forests occupying 0.02 % of the total area of mangroves among the nine countries.

The mangrove area for the entire study region estimated from the USGS dataset (see Giri et al. 2011) is 11,710 km^2, 15.7 % smaller than our estimate which used the NASA dataset. Mangrove area reported in Fatoyinbo and Simard (2013) is close to our estimation, showing only a 4.9 % of difference for the entire study area. Among the 9 countries, Nigeria had the largest discrepancy (2929 km^2) in mangrove area between our estimate and Giri's. The country with the second largest difference of mangrove area is Cameroon, with a difference of 546 km^2 (25.7 % less in our estimate than that from the USGS dataset of Giri et al. (2011); much smaller than that in Nigeria). While the area difference in Togo is the smallest (about 4 km^2), it is the second largest percentage difference (64.5 % of decrease from the dataset of Giri et al. (2011) to our estimate based on NASA dataset). Nigeria and Liberia are the two countries in which the area of mangroves estimated from the USGS dataset is smaller than our estimate. The mangrove coverage for Liberia is 100 km^2 from the USGS dataset, but it is

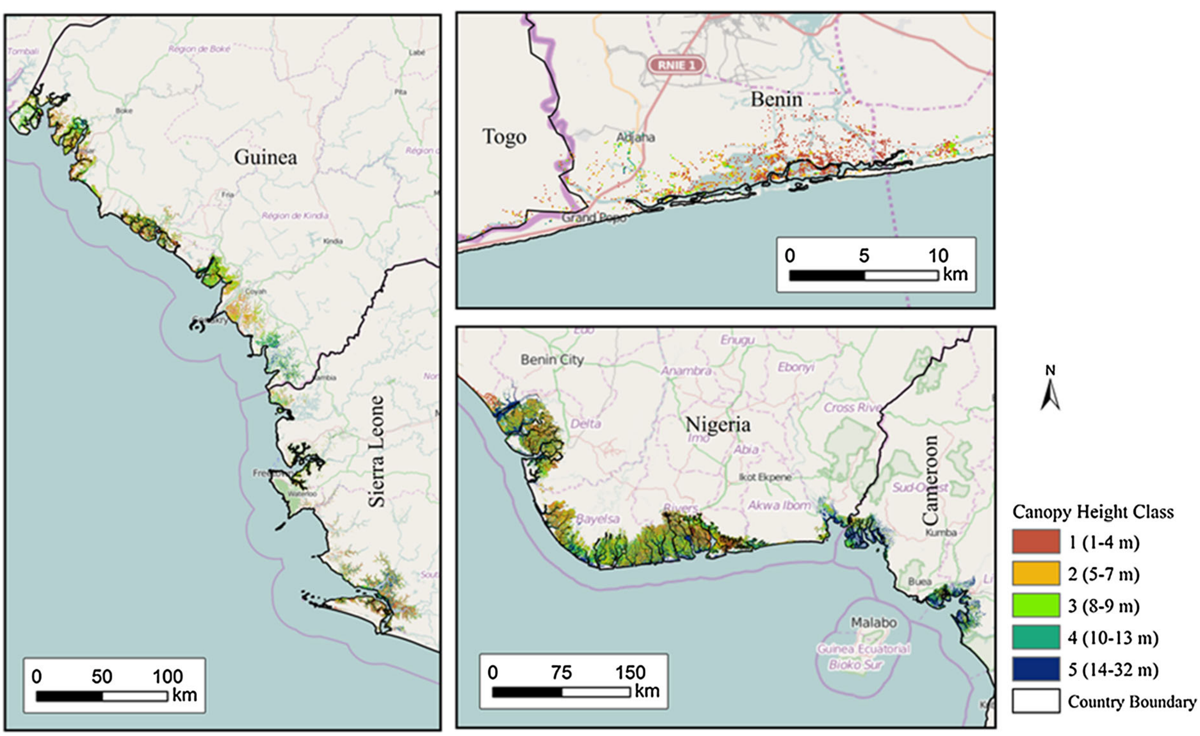

Fig. 6 Map of mangrove height class in West Africa (*data source*: USGS; base map: OpenStreetMap)

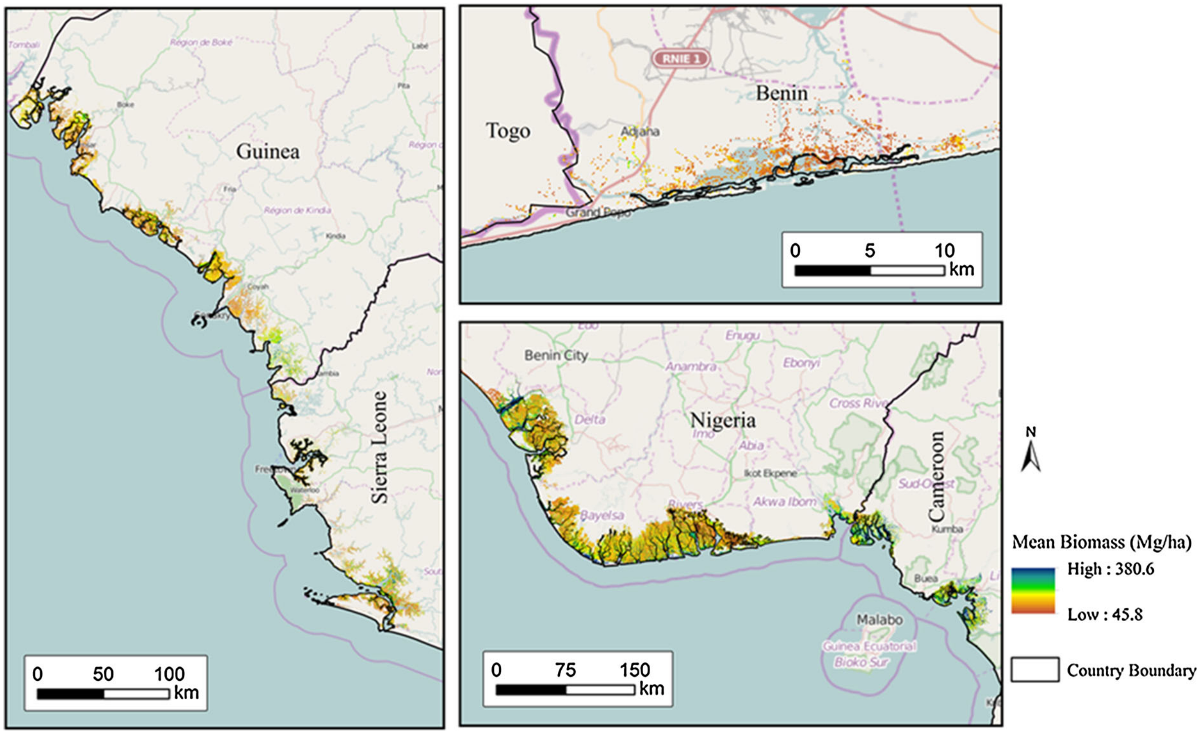

Fig. 7 Map of the mean aboveground biomass of mangroves for the study area in West Africa (spatial resolution: 90 m × 90 m; base map: OpenStreetMap)

202 km^2 for the NASA dataset from our estimation (103 % higher).

The occurrence of discrepancy between USGS and NASA datasets with respect to the presence of mangroves can be attributed to the use of different classification algorithms. The classification for estimating mangrove coverage for USGS and NASA datasets is based on Landsat images (about one thousand scenes in 2000 in the former and 117 scenes from 1999 to 2002 used by the latter). Hybrid supervised and unsupervised classification was used for the USGS data, and no classification accuracy information was reported due to their use of qualitative validation (see Giri et al. 2011). For the NASA dataset, unsupervised classification was applied and classification accuracy was reported as 83 % (see Fatoyinbo and Simard 2013). The spatial distribution of the estimation discrepancy regarding the presence of mangroves is of more interest (see Fig. 5). For example, the main difference of spatial distributions of mangroves is located in the southern part of coastline in Guinea, dominated by USGS data that show mangroves are present in those regions where estimation differences exist. For Cameroon, cell-level estimation differences in mangrove presence (dominated by the presence of mangroves from USGS data) tend to cluster in the northern and southern parts of the Cameroon coastline. In Sierra Leone, USGS data allow for the identification of mangroves in the middle of its coastline, which is not captured by NASA data. While Nigeria has the largest estimation difference of mangrove area, this difference is dominated by the presence of mangroves in the NASA data. The mapping of the estimation difference of the mangrove coverage provides support for identifying the locations where these differences occur, which facilitates the analysis and interpretation of estimates of mangrove coverage.

Canopy height, biomass, and carbon of mangroves in West Africa

The average canopy height of the entire study area is 10.2 m (Table 3). Cameroon ranks the highest (16.1 m) and Benin the lowest (4.5 m) in terms of average canopy height. Maps of spatial distribution of

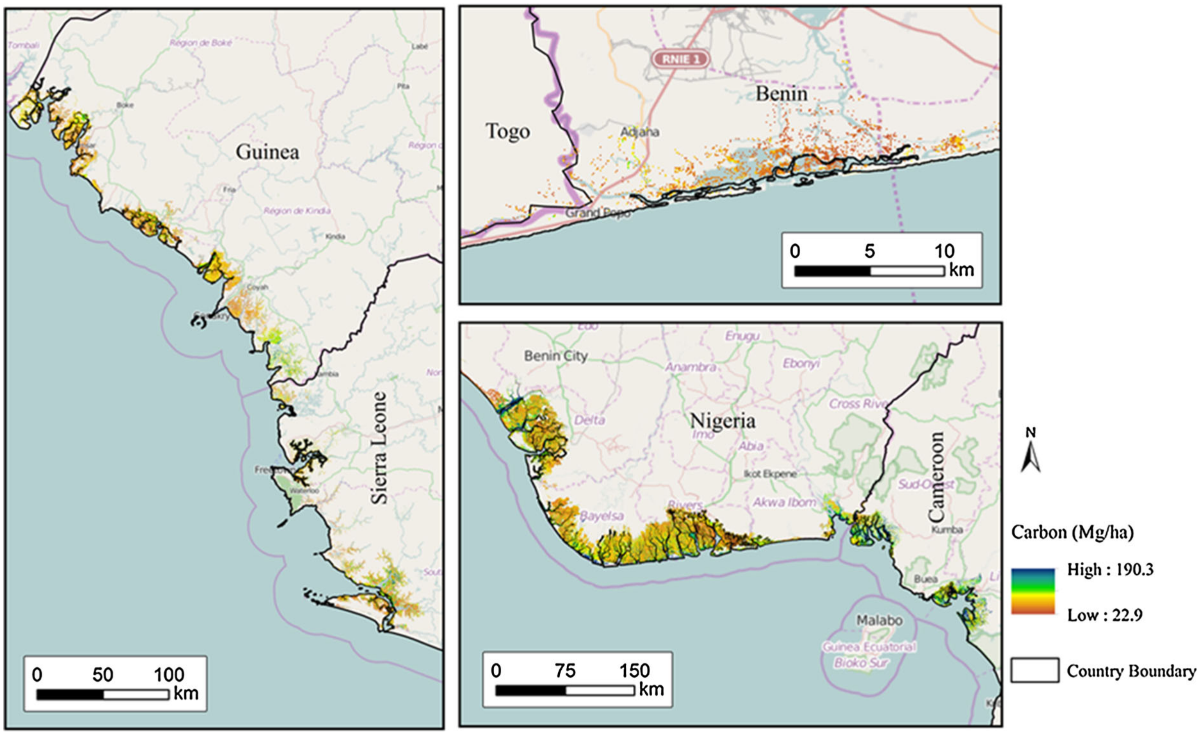

Fig. 8 Map of the carbon of mangroves for the study area in West Africa (spatial resolution: 90 m × 90 m; base map: OpenStreetMap)

Table 4 Above- and below-ground biomass and carbon for canopy height classes in the study region

Class	Above-ground				Below-ground			
	Biomass		Carbon		Biomass		Carbon	
	Mean density (Mg ha^{-1})	Total (Tg)	Mean density (Mg ha^{-1})	Total (Tg)	Mean density (Mg ha^{-1})	Total (Tg)	Mean density (Mg ha^{-1})	Total (Tg)
1	72.3	15.9	36.2	8.0	27.5	6.1	13.7	3.0
2	99.9	34.4	50.0	17.2	38.0	13.1	19.0	6.5
3	126.2	33.9	63.1	17.0	48.0	12.9	24.0	6.5
4	156.1	41.9	78.0	21.0	59.3	15.9	30.0	8.0
5	248.5	71.2	124.2	35.6	94.4	27.1	47.2	13.5
Total	142.1	197.5	71.1	98.8	54.0	75.1	27.0	37.5

canopy heights are of particular help for evaluating the spatial structure of mangroves (see Fig. 6). For example, in Cameroon and Nigeria (especially the former), mangrove forests are dominated by tall trees while in Benin short trees are dispersed along the coast of the country. Correspondingly, biomass and carbon density in our study area exhibited spatially heterogeneous characteristics within and across countries (see Figs. 7, 8). With support from the spatial analysis framework, we derived the mean biomass for each class in the entire study area, for each country, and for each class in each country (see Tables 4, 5, and 6).

Mangrove canopy height information derived from NASA SRTM data, as reported in Fatoyinbo and Simard (2013), is very accurate (with a root mean square error of 3.55 m) and recommended for mangrove biomass and carbon studies. Our estimation on biomass and carbon for the entire study region is about

Table 5 Mean biomass and carbon density for each country in the study region (unit: Mg ha^{-1})

Country	Above-ground				Below-ground			
	Mean biomass density		Mean carbon density		Mean biomass density		Mean carbon density	
	NASA 1	NASA 2	NASA 1	NASA 2	NASA 1	NASA 2	NASA 1	NASA 2
Benin	76	83.2	38.0	41.6	28.9	31.6	14.4	15.8
Cameroon	171	204.4	85.5	102.2	65.0	77.7	32.5	38.8
Cote d'Ivoire	124	143.2	62.0	71.6	47.1	54.4	23.6	27.2
Ghana	97	113.1	48.5	56.6	36.9	43	18.4	21.5
Guinea	108	119.2	54.0	59.6	41.0	45.3	20.5	22.7
Liberia	113	125.8	56.5	62.9	42.9	47.8	21.5	23.9
Nigeria	111	138.4	55.5	69.2	42.2	52.6	21.1	26.3
Sierra Leone	112	125.5	56.0	62.7	42.6	47.7	21.3	23.8
Togo	78	85.9	39.0	42.9	29.6	32.6	14.8	16.3

NASA 1: Fatoyinbo and Simard (2013); NASA 2: estimates from this study

15.02 % higher than that reported in Fatoyinbo and Simard (2013). This disparity in biomass and carbon can be attributed to the way that those cells with exceedingly high canopy height values are handled and the use of different country boundaries for mangrove coverage estimation. In Fatoyinbo and Simard (2013), these cells are excluded from their analysis but we applied spatial interpolation to estimate canopy height values of these cells (about 0.8 % in proportion). The contribution of these 0.8 % cells to our biomass estimation is about 1.36 % (with respect to NASA's estimation), which means about 13.64 % of difference in biomass (15.02 %-1.36 %) is from the estimation of mangrove coverage area. Our estimation on mangrove coverage for the entire study region is about 5.15 % higher than that reported by Fatoyinbo and Simard (2013) mainly due to the use of different country boundaries because the mangrove canopy height data is the same as in Fatoyinbo and Simard (2013). This 5.15 % difference in mangrove coverage area is propagated to about 13.64 % of difference in mangrove biomass estimation after the application of allometric model.

The total aboveground biomass and carbon of mangrove forests for the entire study area are 197.51 and 98.75 Tg (see Table 7). The total belowground biomass and carbon of mangroves in the study area are 75.05 and 37.53 Tg, respectively. Consistent with their total mangrove areas, Nigeria has the highest total aboveground biomass and carbon of mangroves (126.04 and 63.02 Tg) and Togo has the lowest total biomass and carbon of mangroves. The mean canopy height of mangroves in Cameroon is the largest (16.12 m), leading to the highest values of mean biomass and carbon density (204.47 and 102.24 Mg ha^{-1}) in West Africa. In general, the estimation of spatial patterns of mangrove canopy heights, biomass, and carbon using online available geospatial data from remote sensing and GIS is practically effective, and the spatial analysis framework presented in this article provides efficacious support for this estimation.

Comparison of coarse- and fine-resolution data for biomass and carbon estimation

To evaluate the influence of spatial resolution on biomass and carbon estimation, we derived results of mangrove area, biomass (mean and total), and carbon (mean and total) from data at two spatial resolutions (see Table 8). The fine-resolution provides more detail about the spatial distribution of mangroves than using the coarse-resolution data (Fig. 9), and the total mangrove area for West Africa is 20.16 % lower when using coarse-resolution data, compared to fine-resolution data. With respect to mangrove area estimated by fine-resolution data, the largest difference between two datasets is in Liberia: 57.06 %, followed by Nigeria (41.6 %) and Cote d'Ivoire (37.74 %). Unlike mangrove area, the mean biomass and carbon of mangroves estimated from the coarse-resolution data are lower than those from the fine-

Table 6 Mean biomass and carbon density of each canopy height class for each country in the study region (total: mean biomass/carbon density for all canopy heights; unit: Mg ha^{-1})

Country	Benin	Cameroon	Cote d'Ivoire	Ghana	Guinea	Liberia	Nigeria	Sierra Leone	Togo
Above-ground									
Mean biomass density									
Class 1	67.3	74.3	67.2	68.9	72.7	70.8	72.6	71.6	68.6
Class 2	97.5	102.3	99.9	97.2	100.2	98.4	99.8	99.1	96.6
Class 3	124.6	127.0	126.8	126.0	126.1	126.1	126.1	126.2	123.4
Class 4	150.4	158.4	157.0	158.1	153.9	157.1	156.0	156.1	155.2
Class 5	204.2	264.4	238.7	230.1	220.2	235.3	244.3	231.2	200.1
Total	83.2	204.5	143.1	113.1	119.2	125.8	138.4	125.5	85.9
Mean carbon density									
Class 1	33.6	37.1	33.6	34.4	36.33	35.4	36.3	35.8	34.3
Class 2	48.8	51.2	50.0	48.6	50.1	49.2	49.9	49.5	48.3
Class 3	62.3	63.5	63.4	63.0	63.1	63.1	63.0	63.1	61.7
Class 4	75.2	79.2	78.5	79.0	76.9	78.5	78.0	78.0	77.6
Class 5	102.1	132.2	119.4	115.0	110.1	117.6	122.2	115.6	100.0
Total	41.6	102.2	71.6	56.6	59.6	62.9	69.2	62.7	42.9
Below-ground									
Mean biomass density									
Class 1	25.6	28.2	25.5	26.2	27.6	26.9	27.6	27.2	26.1
Class 2	37.1	38.9	38.0	36.9	38.1	37.4	37.9	37.6	36.7
Class 3	47.4	48.2	48.2	47.9	47.9	47.9	47.9	48.0	46.9
Class 4	57.1	60.2	59.7	60.1	58.5	59.7	59.3	59.3	59.0
Class 5	77.6	100.5	90.7	87.4	83.7	89.4	92.8	87.9	76.0
Total	31.6	77.7	54.4	43.0	45.3	47.8	52.6	47.7	32.6
Mean carbon density									
Class 1	12.8	14.1	12.8	13.01	13.8	13.5	13.8	13.6	13.0
Class 2	18.5	19.4	19.0	18.5	19.0	18.7	19.0	18.8	18.4
Class 3	23.7	24.1	24.1	24.0	24.0	24.0	24.0	24.0	23.5
Class 4	28.6	30.1	29.8	30.0	29.2	29.8	29.6	29.7	29.5
Class 5	38.8	50.2	45.4	43.7	41.8	44.7	46.4	43.9	38.0
Total	15.8	38.8	27.2	21.5	22.7	23.9	26.3	23.8	16.3

resolution data in each country, especially in Liberia (63.6 %), Benin (60.18 %), and Cote d'Ivoire (52.69 %). The total biomass and carbon for the entire study area estimated from the two datasets are similar. At the country level, the total biomass and carbon of mangrove forests in Cote d'Ivoire, Liberia, and Nigeria obtained from coarse-resolution data are underestimated with respect to those from fine-resolution data, while they are overestimated in the other 6 countries.

Our analyses results suggest that, with comparison to the fine-resolution data (90 m $\times$ 90 m), using the coarse-resolution data (1 km $\times$ 1 km) tends to overestimate the biomass (mean and total) and carbon (mean and total) of mangrove forests in our study area. Yet, the combination of coarse-resolution canopy height data (from NASA) and mangrove area (from USGS) provides a feasible and convenient approach for estimating biomass and carbon of mangroves at regional or global levels.

Summary

Mangroves are generally recognized for the considerable values derived from ecosystem services, which

Table 7 Total biomass and carbon of each canopy height class for each country in the study region (total: total biomass/carbon for all canopy heights; unit: Mg)

Country	Benin	Cameroon	Cote d'Ivoire	Ghana	Guinea	Liberia	Nigeria	Sierra Leone	Togo
Above-ground									
Total biomass									
Class 1	79,777	239,031	58,206	257,432	2,343,312	409,530	10,650,097	1,900,679	10,302
Class 2	47,738	1,357,900	45,275	150,263	5,692,611	480,997	24,034,928	2,556,648	4474
Class 3	21,877	2,575,596	64,548	88,516	5,919,776	371,172	22,614,218	2,206,931	1693
Class 4	8970	5,844,246	132,804	135,811	5,179,836	555,632	27,108,108	2,801,289	1997
Class 5	1059	22,267,048	205,010	280,318	2,379,654	731,409	41,632,316	3,391,305	1201
Total	159,422	32,283,823	505,845	912,341	21,515,191	2,548,743	126,039,670	12,856,853	19,669
Total carbon									
Class 1	39,889	119,516	29,103	128,716	1,171,656	204,765	5,325,049	950,340	5151
Class 2	23,869	678,950	22,638	75,132	2,846,306	240,499	12,017,464	1,278,324	2237
Class 3	10,939	1,287,798	32,274	44,258	2,959,888	185,586	11,307,109	1,103,466	847
Class 4	4485	2,922,123	66,402	67,906	2,589,918	277,816	13,554,054	1,400,645	999
Class 5	530	11,133,524	102,505	140,159	1,189,827	365,705	20,816,158	1,695,653	601
Total	79,711	16,141,912	252,923	456,171	10,757,596	1,274,372	63,019,835	6,428,427	9835
Below-ground									
Total biomass									
Class 1	30,315	90,832	22,118	97,824	890,459	155,621	4,047,037	722,258	3915
Class 2	18,140	516,002	17,205	57,100	2,163,192	182,779	9,133,273	971,526	1700
Class 3	8313	978,726	24,528	33,636	2,249,515	141,045	8,593,403	838,634	643
Class 4	3409	2,220,813	50,466	51,608	1,968,338	211,140	10,301,081	1,064,490	759
Class 5	402	8,461,478	77,904	106,521	904,269	277,935	15,820,280	1,288,696	456
Total	60,580	12,267,853	192,221	346,690	8,175,773	968,522	47,895,075	4,885,604	7474
Total carbon									
Class 1	15,158	45,416	11,059	48,912	445,229	77,811	2,023,518	361,129	1957
Class 2	9070	258,001	8,602	28,550	1,081,596	91,389	4,566,636	485,763	850
Class 3	4157	489,363	12,264	16,818	1,124,757	70,523	4,296,701	419,317	322
Class 4	1704	1,110,407	25,233	25,804	984,169	105,570	5,150,541	532,245	379
Class 5	201	4,230,739	38,952	53,260	452,134	138,968	7,910,140	644,348	228
Total	30,290	6,133,926	96,111	173,345	4,087,886	484,261	23,947,537	2,442,802	3,737

are threatened by sea-level rise, deforestation and other changes in land use. Accordingly, there is considerable interest in conservation, restoration and sustainable use, and in particular capitalizing on the large carbon stocks that characterize many mangroves in REDD+ or other activities for ecosystem service projects. However, context is needed to develop provincial, national or regional projects. Until recently, only the distribution of mangroves was readily available globally. With the advent of the SRTM canopy height data, there exists a global database that provides structural information about forested areas, and can be integrated with mangrove area data to assess the spatial patterns of forest canopy height. Correspondingly, since forest canopy height is functionally related to above-ground biomass, the data can be processed to assess the spatial distribution of biomass and carbon, as we have shown for West Africa. The spatially explicit analytical framework and software toolkit presented in this study provides systematic support for the efficacious processing and analysis of these data for the mangrove biomass and carbon assessment.

This assessment approach provides an effective basis for relative comparisons of canopy height, biomass and carbon stocks within for West Africa.

Table 8 Comparison of biomass and carbon estimated from datasets at coarse and fine spatial resolutions

	Country	Benin	Cameroon	Cote d'Ivoire	Ghana	Guinea	Liberia	Nigeria	Sierra Leone	Togo
Area (km^2)	1 km × 1 km	20	1968	22	81	2217	87	5320	1346	3
	90 m × 90 m	19.2	1578.9	35.3	80.6	1804.6	202.6	9109.3	1024.6	2.3
Above-ground										
Mean biomass (Mg ha^{-1})	1 km × 1 km	133.3	240.5	218.6	117.8	137.9	205.8	186.4	180.5	107
	90 m × 90 m	83.2	204.5	143.2	113.1	119.2	125.8	138.4	125.5	85.9
Total biomass (Mg)	1 km × 1 km	266,560	47,326,440	480,920	954,180	30,566,940	1,790,580	99,141,560	24,295,720	32,100
	90 m × 90 m	159,422	32,283,823	505,845	912,341	21,515,191	2,548,743	126,039,670	12,856,853	19,669
Mean carbon (Mg ha^{-1})	1 km × 1 km	66.6	120.2	109.3	58.9	68.9	102.9	93.2	90.3	53.5
	90 m × 90 m	41.6	102.2	71.6	56.6	59.6	62.9	69.2	62.7	42.9
Total carbon (Mg)	1 km × 1 km	133,280	23,663,220	240,460	477,090	15,283,470	895,290	49,570,780	12,147,860	16,050
	90 m × 90 m	79,711	16,141,912	252,923	456,171	10,757,596	1,274,372	63,019,835	6,428,427	9835
Below-ground										
Mean biomass (Mg ha^{-1})	1 km × 1 km	50.6	91.4	83.1	44.8	52.4	78.2	70.8	68.6	40.7
	90 m × 90 m	31.6	77.7	54.4	43.0	45.3	47.8	52.6	47.7	32.6
Total biomass (Mg)	1 km × 1 km	101,293	17,984,047	182,750	362,588	11,615,437	680,420	37,673,793	9,232,374	12,198
	90 m × 90 m	60,580	12,267,853	192,221	346,690	8,175,773	968,522	47,895,075	4,885,604	7474
Mean carbon (Mg ha^{-1})	1 km × 1 km	25.3	45.7	41.5	22.4	26.2	39.1	35.4	34.3	20.3
	90 m × 90 m	15.8	38.8	27.2	21.5	22.7	23.9	26.3	23.8	16.3
Total carbon (Mg)	1 km × 1 km	50,646	8,992,024	91,375	181,294	5,807,719	340,210	18,836,896	4,616,187	6099
	90 m × 90 m	30,290	6,133,926	96,111	173,345	4,087,886	484,261	23,947,537	2,442,802	3737

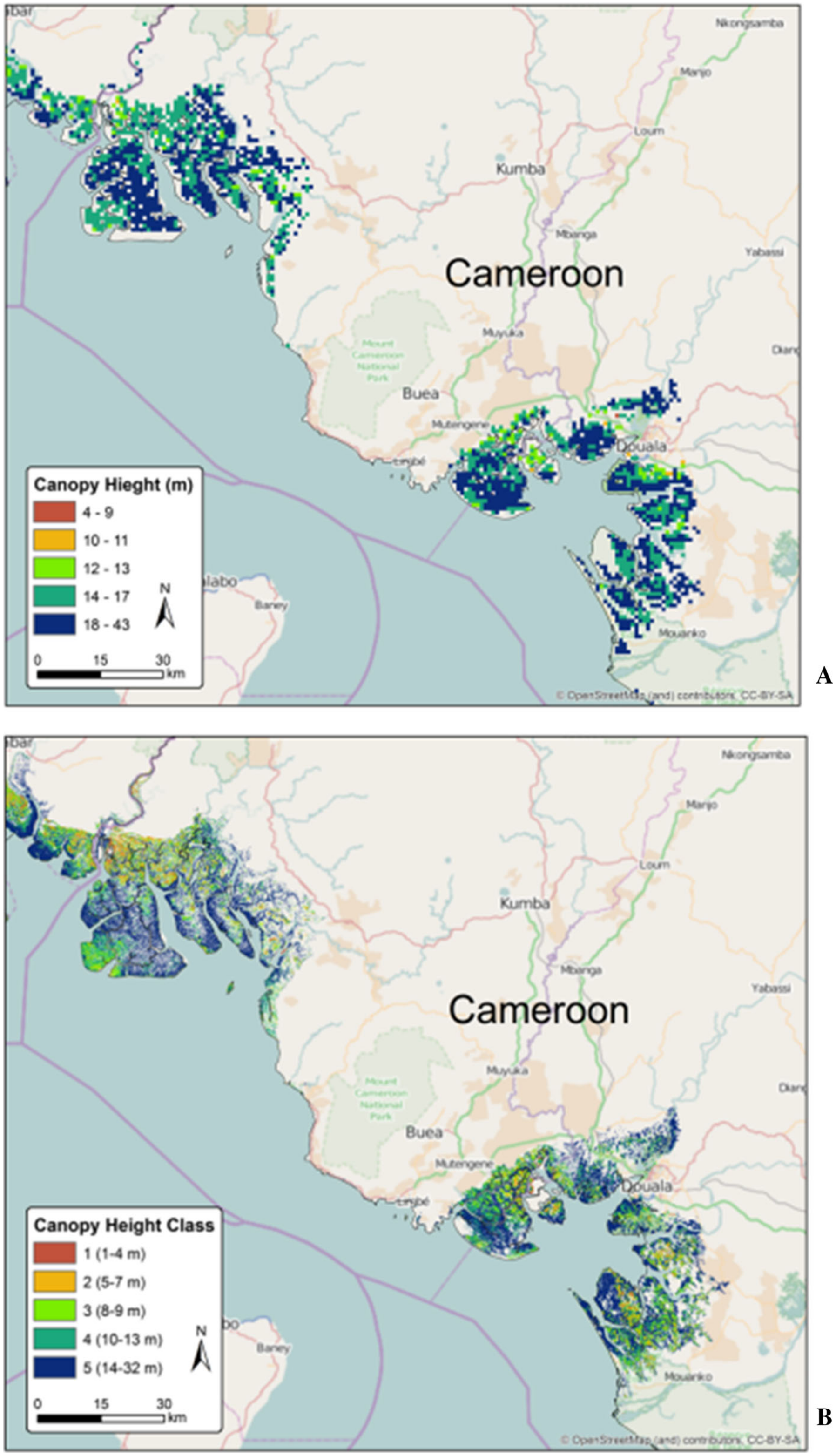

Fig. 9 Comparison of coarse- and fine-resolution canopy heights (using Cameroon as an example; **a** spatial resolution: 1 km × 1 km; **b** 90 m × 90 m; base map: OpenStreetMap)

In this manner, the accuracy of the estimated canopy height or calculated biomass is not a determining factor in the utility of the assessment. This type of analysis is particularly useful in program planning, strategic assessments, and in developing forest inventory plans, and the application can be at a very large scale as we have shown for West Africa or it can be used in designing specific projects. For example, the spatial distribution of mangrove canopy heights derived using our spatially explicit analytical framework and software toolkit provided support for developing a stratified random sampling design to inventory the carbon stocks in the Zambezi River delta with an accuracy that was well within IPCC standards (Stringer et al. 2015). That work suggests that the spatial patterns of mangrove canopy height can provide an effective basis for designing field-based inventories, and likely other applications as noted.

With respect to large-scale assessments, the GIS-based spatial analyses of SRTM canopy height data offer an effective approach to estimate the distribution of biomass and carbon in mangrove forests in nine West Africa countries from Guinea to Cameroon. The distribution of forest canopy height across the study region provided a basis for stratifying the mangrove area to reflect the spatial variation in forest structure (e.g., height). To illustrate the application, we used equal-area classification to segregate the SRTM data into five classes to support the analysis of spatial distributions of mangrove forests in West Africa. The country-level estimates are dependent on the delineation of mangrove area where differences in area among three data sets used in this study varied by 4.5–220 % due to alternative classification algorithms and GIS data for country boundaries. Accordingly, it is important that a common basis for determining the mangrove distribution be used in any large-scale assessment, and our study here (including the framework and software toolkit) provides such support.

Since carbon stock estimates of forest vegetation are driven by biomass, utilizing the SRTM data to estimate biomass is a convenient means to assessing the spatial distribution of mangrove biomass within a region, country or smaller project area. The general allometric equation to calculate biomass density based on canopy height of mangroves provides a relative basis of comparison across the assessment area. The comparison of data resolution demonstrated that scale affects the estimated biomass, but as long as the resolution is consistent for the specific assessments, it will be adequate for relative comparisons. Accordingly, the accessible NASA and USGS databases provide an accessible and cost effective basis for large-scale assessments of mangrove biomass and carbon stocks.

Acknowledgments This study was made possible with support from the U.S. Agency for International Development (USAID) West Africa Mission that was managed through the International Programs Office of the USDA Forest Service. The contents are the responsibility of the authors and do not necessarily reflect the opinion of USAID or the U.S. Government. We appreciate the help from Dr. Marc Simard and Dr. Lola Fatoyinbo, NASA, in the application of the SRTM data, and Mr. Gray G. Tappan and Mr. John Hutchinson from USGS for kindly sharing their datasets to support this study. We owe our gratitude to Dr. Eric Wolanski, Dr. Randy Kolka, Dr. Daniel Murdiyarso, and two anonymous reviewers for their constructive comments.

References

Alongi DM (2014) Carbon cycling and storage in mangrove forests. Ann Rev Mar Sci 6:195–219. doi:10.1146/annurev-marine-010213-135020

Angelsen A (2009) Realising REDD+: national strategy and policy options. CIFOR, Bogor

Beentje H, Bandeira S (2007) Field guide to the mangrove trees of Africa and Madagascar. Royal Botanical Garden, Kew

Burrough PA, McDonnell RA (1998) Principles of geographical information systems. Oxford University Press, Oxford

Dahdouh-Guebas F, Verheyden A, De Genst W, Hettiarachchi S, Koedam N (2000) Four decade vegetation dynamics in Sri Lankan mangroves as detected from sequential aerial photography: a case study in Galle. Bull Mar Sci 67:741–759

Dahdouh-Guebas F, Zetterström T, Rönnbäck P, Troell M, Wickramasinghe A, Koedam N (2002) Recent changes in land-use in the Pambala–Chilaw lagoon complex (Sri Lanka) investigated using remote sensing and GIS: conservation of mangroves vs. development of shrimp farming. Environ Dev Sustain 4:185–200

Day JW Jr, Conner WH, Ley-Lou F, Day RH, Navarro AM (1987) The productivity and composition of mangrove forests, Laguna de Terminos, Mexico. Aquat Bot 27:267–284

Dittmar T, Hertkorn N, Kattner G, Lara RJ (2006) Mangroves, a major source of dissolved organic carbon to the oceans. Global Biogeochem Cycles 20:GB1012. doi:10.1029/2005GB002570

FAO (2007) Mangroves of Africa 1980–2005: country reports. Forest Resources Assessment working paper no. 135. FAO, Rome

Fatoyinbo TE, Simard M (2013) Height and biomass of mangroves in Africa from ICESat/GLAS and SRTM. Int J Remote Sens 34:668–681. doi:10.1080/01431161.2012.712224

Fatoyinbo TE, Simard M, Washington-Allen RA, Shugart HH (2008) Landscape-scale extent, height, biomass, and carbon estimation of Mozambique's mangrove forests with Landsat ETM + and Shuttle Radar Topography Mission elevation data. J Geophys Res Biogeosci 113:6. doi:10.1029/2007JG000551

Fromard F, Puig H, Mougin E, Marty G, Betoulle J, Cadamuro L (1998) Structure, above-ground biomass and dynamics of mangrove ecosystems: new data from French Guiana. Oecologia 115:39–53

GADM (2015) Global administrative areas. http://www.gadm.org

GeoTIFF (2015) GeoTIFF. http://trac.osgeo.org/geotiff/

Gilman EL, Ellison J, Duke NC, Field C (2008) Threats to mangroves from climate change and adaptation options: a review. Aquat Bot 89:237–250

Giri C et al (2011) Status and distribution of mangrove forests of the world using earth observation satellite data. Glob Ecol Biogeogr 20:154–159. doi:10.1111/j.1466-8238.2010.00584.x

Goodchild MF (1992) Geographical information science. Int J Geogr Inf Syst 6:31–45

ICESAT (2015) Ice, cloud, and land elevation satellite/geoscience laser altimeter system. http://icesat.gsfc.nasa.gov/

Jennerjahn TC, Ittekkot V (2002) Relevance of mangroves for the production and deposition of organic matter along tropical continental margins. Naturwissenschaften 89:23–30

JPL (2015) NASA JPL Mangroves. http://www-radar.jpl.nasa.gov/coastal/

Kauffman JB, Donato D (2012) Protocols for the measurement, monitoring and reporting of structure, biomass and carbon stocks in mangrove forests. Center for International Forestry Research (CIFOR), Bogor

Komiyama A, Ong JE, Poungparn S (2008) Allometry, biomass, and productivity of mangrove forests: a review. Aquat Bot 89:128–137. doi:10.1016/j.aquabot.2007.12.006

Kovacs JM, Wang J, Blanco-Correa M (2001) Mapping disturbances in a mangrove forest using multi-date Landsat TM imagery. Environ Manage 27:763–776

Kovacs JM, de Santiago FF, Bastien J, Lafrance P (2010) An assessment of mangroves in Guinea, West Africa, using a field and remote sensing based approach. Wetlands 30:773–782

Kristensen E, Bouillon S, Dittmar T, Marchand C (2008) Organic carbon dynamics in mangrove ecosystems: a review. Aquat Bot 89:201–219. doi:10.1016/j.aquabot.2007.12.005

Longley P (2005) Geographic information systems and science. Wiley, West Sussex

Lucas RM, Mitchell AL, Rosenqvist A, Proisy C, Melius A, Ticehurst C (2007) The potential of L-band SAR for quantifying mangrove characteristics and change: case studies from the tropics. Aquat Conserv Mar Freshw Ecosyst 17:245–264. doi:10.1002/aqc.833

Saenger P, Bellan M (1995) The mangrove vegetation of the Atlantic coast of Africa: a review. Universite de Toulouse, Toulouse

Saenger P, Snedaker SC (1993) Pantropical trends in mangrove above-ground biomass and annual litterfall. Oecologia 96:293–299

Simard M et al (2006) Mapping height and biomass of mangrove forests in Everglades National Park with SRTM elevation data. Photogramm Eng Remote Sens 72:299–311

Simard M, Rivera-Monroy VH, Mancera-Pineda JE, Castañeda-Moya E, Twilley RR (2008) A systematic method for 3D mapping of mangrove forests based on Shuttle Radar Topography Mission elevation data, ICEsat/GLAS waveforms and field data: application to Ciénaga Grande de Santa Marta, Colombia. Remote Sens Environ 112:2131–2144. doi:10.1016/j.rse.2007.10.012

Simard M, Pinto N, Fisher JB, Baccini A (2011) Mapping forest canopy height globally with spaceborne lidar. J Geophys Res Biogeosci 116:G04021. doi:10.1029/2011JG001708

Slocum TA, McMaster RB, Kessler FC, Howard HH (2009) Thematic cartography and geovisualization, 3rd edn. Pearson Prentice Hall, Upper Saddle River

Smith TJ III, Whelan KR (2006) Development of allometric relations for three mangrove species in South Florida for use in the Greater Everglades Ecosystem restoration. Wetl Ecol Manage 14:409–419

SRTM (2015) Shuttle radar topography mission. http://www2.jpl.nasa.gov/srtm/

Stringer CE, Trettin CC, Zarnoch SJ, Tang W (2015) Carbon stocks of mangroves within the Zambezi River Delta, Mozambique. For Ecol Manag 354:139–148. doi:10.1016/j.foreco.2015.06.027

Taylor IJ, Deelman E, Gannon DB, Shields M (2014) Workflows for e-Science: scientific workflows for grids. Springer, New York

Tomczak M (1998) Spatial interpolation and its uncertainty using automated anisotropic inverse distance weighting (IDW)-cross-validation/jackknife approach. J Geogr Inf Dec Anal 2:18–30

Wilkie ML, Fortuna S (2003) Status and trends in mangrove area extent worldwide. In: Forest resources assessment programme working paper (FAO)