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High-resolution forest canopy height estimation in an African blue carbon ecosystem

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Introduction

Blue carbon ecosystems are environments at the transition between the land and sea. Mangrove forests, in particular, are some of the most productive and economical blue carbon ecosystems (Pendleton et al. 2012). As of late, mangrove forests have been of great interest to the carbon and biomass communities because of their large carbon storage pools (Donato et al. 2011), and the high rates of carbon sequestration that are two to four times higher than in mature tropical forests (Mcleod et al. 2011). Measuring current conditions and monitoring how these ecosystems

Abstract

Mangrove forests are one of the most productive and carbon dense ecosystems that are only found at tidally inundated coastal areas. Forest canopy height is an important measure for modeling carbon and biomass dynamics, as well as land cover change. By taking advantage of the flat terrain and dense canopy cover, the present study derived digital surface models (DSMs) using stereophotogrammetric techniques on high-resolution spaceborne imagery (HRSI) for southern Mozambique. A mean-weighted ground surface elevation factor was subtracted from the HRSI DSM to accurately estimate the canopy height in mangrove forests in southern Mozambique. The mean and H100 tree height measured in both the field and with the digital canopy model provided the most accurate results with a vertical error of 1.18-1.84 m, respectively. Distinct patterns were identified in the HRSI canopy height map that could not be discerned from coarse shuttle radar topography mission canopy maps even though the mode and distribution of canopy heights were similar over the same area. Through further investigation, HRSI DSMs have the potential of providing a new type of three-dimensional dataset that could serve as calibration/validation data for other DSMs generated from spaceborne datasets with much larger global coverage. HSRI DSMs could be used in lieu of Lidar acquisitions for canopy height and forest biomass estimation, and be combined with passive optical data to improve land cover classifications.

> change over time is instrumental for modeling future ecosystem responses to disturbances from natural and artificial factors, particularly in coastal communities that are undergoing rapid urbanization and expansion.

> Despite the surge in our scientific understanding of the carbon storage and sequestration dynamics in mangrove ecosystems, there is still uncertainty regarding the global above-ground carbon stocks and structure of mangroves (Bouillon et al. 2008; Donato et al. 2011; Hutchison et al. 2014). This is mainly a result of the rapid global mangrove forest degradation, limited accessibility, generalized global allometries, harsh field conditions and logis-

tics of visiting and revisiting field sites. In addition, African mangroves studies have been largely absent from global carbon studies (Valiela et al. 2001; Alongi 2002; Bouillon et al. 2008) even though there is a significant global fraction of mangroves on the continent (Giri et al. 2011; Fatoyinbo and Simard 2013).

Earth observing satellites have pioneered the way in estimating vegetation cover, forest canopy heights and carbon stocks across the globe. Canopy height estimates can provide invaluable information regarding structure, function and health of the ecosystems at various spatial scales. Different types of sensors can provide information on various forest parameters to measure and monitor carbon stocks, sequestration and land cover change, but primarily at relatively coarse spatial scales (Heumann 2011). Early stereophotogrammetric techniques have been applied to paired aerial photos and have estimated regional- and local-scale tree height measurements at relatively high accuracy (Lucas et al. 2002). As different sets of satellite data became available, the stereographic technique was then respectably applied to datasets from platforms such as ASTER, IKONOS and QuickBird (Hirano et al. 2003; Heumann 2011; Neigh et al. 2014). Commercial and open-sourced stereoanalyses of high-resolution spaceborne imagery (HRSI) from WorldView1 have been used to create digital surface elevation models (DSMs) in temperate and taiga forests (Hobi and Ginzler 2012; Montesano et al. 2014).

The open-sourced NASA Ames stereo pipeline (ASP) was developed to provide high-quality DSMs and quick processing of HRSI stereopairs from remotely sensed planetary imagery, in particular for the High-Resolution Imaging Science Experiment (HiRISE) aboard the Mars Reconnaissance Orbiter (MRO) (Moratto et al. 2010). Originally, the opensource program was tuned for Mars surface reconstructions, though it has more recently been updated to process images from Earth observing missions (Beyer et al. 2013). By incorporating a fast image correlation algorithm, the ASP can quickly calculate geographic disparities between corresponding points on the left and right images of each stereopair (Moratto et al. 2010). The disparities between positions are then used in conjunction with the known sensor geometry to create a three-dimensional triangle mesh of the overlapping geographic area (Moratto et al. 2010).

Mangrove forests provide a unique and beneficial ecosystem to evaluate canopy height because these forests only exist along tropical and subtropical coastal areas where the ground elevation is at or near sea level. Surface elevations where mangroves exists have been shown to range globally from a low of ~0.4 m below mean sea level to a high of ~1.6 m above mean sea level at the most landward locations (Ellison 2006). Microtidal environments show less spread around mean sea level than in macrotidal areas. The flat and low topography allow for a presumptuously homogenous soil surface elevation within the mangrove zone that can easily be subtracted from DSMs to get forest canopy heights. In addition, the adaption and resilience of mangrove species allow them grow in a wide range of harsh hydrogeomorphic conditions that can create low woody species diversity and structure zonations of different forests stands; from stunted forests that are less than two meters in height to tall forests that can reach 40 m (citation?). By taking advantage of the flat terrain, the present study used HRSI to create spatially explicit canopy height maps for southern coastal regions of Mozambique. The main objectives of the present study were to: (1) compare high-resolution canopy height estimates with field surveys and coarse-resolution remote sensing; (2) evaluate the adaptability of the ASP to accurately estimate bare ground and canopy forest canopy surfaces; and (3) discuss the potential for using HRSI canopy height maps as a technique to validate other spaceborne imagery products.

Materials and Methods

Study sites and field data

Mozambique has one of the 15 largest mangrove areas globally and the second largest within Africa, covering ~2909 km² in the year 2000 (Giri et al. 2011; Fatoyinbo and Simard 2013), over a quarter less than the 3600 km^2 that was previously estimated in 1990 (Saket and Matusse 1994). Three study areas, two on Inhaca Island and one in the Maputo Elephant Reserve, were located in the southern province of Maputo. Mangrove forests cover approximately 8 ha within the study area (Fig. 1). The mangrove communities were comprised of five species; Avicennia marina, Rhizophora mucronata, Bruguieria gymnorrhiza, Ceriops tagal and Lumnitzera racemosa. As reported in Fatoyinbo et al. (2008), the near-shore and landward species zonations qualitatively resemble other mangrove forest across Mozambique. A low species diversity and similar forest structures are typical of mangrove communities worldwide. These common forest characteristics across all mangrove communities provide for relatively easier cross-site applications and comparisons despite their global distributions (Lugo and Snedaker 1974).

Field surveys were conducted in 2005 on Inhaca Island and in 2008 on the Maputo Elephant Reserve. A total of 61 plots were surveyed with 51 plots on Inhaca Island and 10 in the Elephant Reserve (Fig. 1). All trees with a diameter greater than 2.5 cm were measured within a 15 m diameter circular plot at each of the 51 plots on Inhaca Island. In the Maputo Elephant Reserve, a variable plot method was used for each of the 10 locations to esti-



Figure 1. Location of study sites on Inhaca Island (A and B) and Maputo Elephant Reserve (C) in southern Mozambique.

mate forest structure (Shiver and Borders 1996; Simard et al. 2010). The size of each plot was dependent on the size of the respective trees in the area. Larger trees that were further away from the plot center could then be included, improving the estimates for dominate trees while preserving smaller trees (Simard et al. 2010). All the surveyed trees were measured for diameter at breast height (DBH) and tree height.

World view stereopairs

Three sets of orthorectified pairs of HRSI from World-View1 (DigitalGlobe, Longmont, CO) were collected over southeastern Maputo Province in Mozambique in September of 2012. These panchromatic images were acquired via an agreement with the National Geospatial-Intelligence Agency (NGA) (Neigh et al. 2013). Each image pair was acquired along-track to help alleviate the confounding issues of stereo viewing associated with date and time of collection, and roll and incident angles. This means that the two images for each set of stereopairs were collected in the same orbit and use optimal viewing angles for better image accuracy and corrections. Each stereopair set was comprised of a left and right panchromatic image with an overlapped portion of geographic area. The duplicated region was then used to derive a DSM using a series of open-sourced stereo-photogrammetric algorithms in the NASA ASP 2.4 software, developed by NASA Ames Research Center in Mountain View, CA (Moratto et al. 2010). User guides and program software are available at http://ti.arc.nasa.gov/tech/asr/intelligent-robotics/ngt/stereo/.

Digital surface models

The ASP algorithm was used to estimate a DSM that included the mangrove canopy around Inhaca Island, the Machangulo Peninsula and the Maputo Elephant Reserve. An image correlation routine within the ASP is used to match similar pixels on each stereo pair and calculate the distance between the image focal plane and the Earth's surface using epipolar geometry (Ni et al. 2014). The affine adaptive window mode option (subpixel mode = 2) was used to estimate the most accurate surface elevation relative to the WGS84 ellipsoid. The geoid reference for the study area is approximately ~17.5 m. The gridded spatial resolution for each DSM was approximately $\sim 0.8 \times 0.8$ m which was a function of the sensor viewing geometry of the original HRSI. The absence of accurate ground control points in the study area limited the accuracy of DSM. Ground control points are scarce in mangroves environments, and particularly in the regions of Africa and Asia. A horizontal accuracy of 5.5 m or less was expected for each DSM without the use of ground control points (Hobi and Ginzler 2012).

The HRSI DSM was compared to coarse radar altimetry data collected from the shuttle radar topography mission (SRTM) in 2000. In 2014, the global 30 m resolution SRTM was released to the public by the NGA. The SRTM measurements did not record the top of forest canopy, but the interferometric scattering phase center of the canopy (Kellndorfer et al. 2004; Simard et al. 2006). Canopy heights over the study area were estimated from both the finer 30 m (SRTM30) resolution SRTM data, using a height correction equation (Simard et al. 2006).

Mangrove canopy heights

Nonmangrove areas were masked from the DSM analyses using a combination of an unsupervised classification and manual interpretations from the HRSI data. The unsupervised classification was performed using ENVI 5.1 using 10 classes (Exelis Visual Information Solutions; Boulder, CO) and applied to a Landsat 8 OLI image that was acquired on August 23, 2014 (row 78 path 167). A quality control comparison was made between the unsupervised classification, a recent global mangrove cover map by Giri et al. (2011) and from visual interpretations of high-resolution imagery.

In order to correct the DSM and estimate mangrove canopy height, bare ground surfaces (e.g., lighting gaps, mud flats) within the mangrove zone were identified manually using the HRSI (Fig. 2). The manual interpretations of the ground surfaces were surrounded by a small buffer to help limit overlap of forested and ground areas caused by georegistration errors. Individual layers were created from each of the bare ground surfaces (*ground*) and overlaid on the DSM. Elevation data were extracted from the DSM over each masked *ground* layer. The minimum, maximum, mean and standard deviation were all calculated from the extracted elevation data for each layer.



Figure 2. Single panchromatic image (WorldView1) with examples of manual interpretations of bare ground surfaces delineated in black.

The product of the *ground* layer area and mean elevation was summed for all delineated *ground* surfaces and then divided by the total area of all *ground* surfaces. The resulting mean-weighted ground elevation was subtracted from the original DSM resulted in mangrove canopy height surface. The forest canopy height estimates are based on the assumption that the ground surface within the mangrove zone is relatively flat and thereby, the ground creates a spatially extensive, flat surface to easily subtract from the DSM (Fig. 2).

Analysis

Canopy height estimates using the HRSI stereopair methodology were compared with local field surveys and SRTM estimates (Fatoyinbo et al. 2008) to identify the bias and error associated with the technique. Field measurements were collected in 2005 (Inhaca Island) and 2009 (Maputo Elephant Reserve) and SRTM data were acquired in 2000. See Fatoyinbo et al. (2008) for detailed information of plot structures, and field and SRTM data on Inhaca Island. Mean tree height (F_{mean}) and H100 (F_{H100}) were calculated for each of the plots based on the field data. H100, or the average of the 100 tallest trees ha⁻¹, was determined from the average of the two tallest trees for each field plot:

$$0.0176 \text{ ha} \times \frac{100 \text{ trees}}{1 \text{ ha}} = 1.76 \text{ trees}$$

Mean tree height (HRSI_{mean}) and H100 (HRSI_{H100}) were also calculated from the HRSI forest canopy map using an area similar in size to the field plots (0.0200 ha). The HRSI_{mean} was determined by the sum and number of

good pixels within each 0.0200 ha buffer. To determine $HRSI_{H100}$, a top of canopy height map was created by determining the maximum pixel value in a 10×10 m moving window before calculating the mean height (Aulinger et al. 2005). The H100 parameter has been shown to correspond well with canopy heights estimates derived from radar and lidar datasets because it removes the pixels that measure ground or understory which can bias mean canopy height (Mette et al. 2004; Aulinger et al. 2005). Canopy height estimates from HRSI_{mean} and HRSI_{H100} were also compared to the SRTM top canopy heights over each field plot.

Results

The HRSI stereopairs cover approximately 9 km of shoreline along the western end of Inhaca Island and the Machangulo Peninsula, and the northern end of the Maputo Elephant Reserve (Fig. 1). Nine flat and bare ground surfaces were identified and delineated across the study area and ranged in size between 0.08 and 5.1 ha with a total area of 7.9 ha (Table 1). A mean-weighted ground surface elevation of 21.78 m (RMSE = 0.69 m) for the entire study area was derived using the total area of each ground surface measured (Table 1). The 21.78 m ground surface was referenced to the WGS84 ellipsoid with a geoid height of ~17.5 m. Since mangroves occur at elevation near mean sea level, the difference between the ellipsoid elevation for the ground surfaces and the geoid approximates mean sea level relative to the geoid. The meanweighted ground surface of 21.78 m was then subtracted from the HRSI DSM. By subtracting the mean-weighted ground surface from the entire DSM, the resulting calculation represents canopy height, that is, the relative difference between the top of the canopy and the ground.

The canopy heights across the Inhaca and Machangulo mangrove ecosystem were derived from the field, SRTM

and HRSI datasets (Table 2). The highest mean canopy heights centered on each of the field plots, 7.93 and 7.11 m, were estimated from the SRTM30 and HRSI, respectively. Mean canopy heights were ~1.5–1.8 m lower from the field surveys and SRTM30. H100 averages were only calculated for field surveys and HRSI data because of the spatial scale of the SRTM30 was much larger than that of the field surveys and HRSI data. Mean H100 canopy heights measured in the field surveys were just 0.6 m higher than the 8.35 m HRSI_{H100} (Table 2).

The majority of mangroves taller than 10 m were located in the Maputo Elephant Reserve, while shorter trees less than 10 m were located on Inhaca Island and the Machangulo Peninsula (Fig. 3).

Field measurements of tree heights were collected in 2005 and 2008 while the HRSI was acquired in 2013. Despite the eight years separating the two datasets, the F_{mean} , F_{H100} , HRSI_{mean} and HRSI_{H100} canopy heights were highly correlated (Table 3 and Fig. 3A).

Comparing the mean tree heights of the field plots with the HRSI mean height, determined from averaging all pixels within a 200 m² circle centered on the field plot, yielded an R-squared of 0.81 and RMSE of 1.41 m. The slope was less than a 1:1 ratio and an offset of -0.77 m (Table 2). F₁₀₀ and HRSI_{H100} heights had a higher R^2 and

 Table 2. Canopy height values from field, shuttle radar topography

 mission (SRTM) and high-resolution spaceborne imagery (HRSI) datasets.

	Canopy height					
Data sources	Mean	SD	H100	SD		
Field surveys HSRI	5.46 7.11	3.73 3.90	8.95 8.35	5.11 4.05		
SRTM 30 m	5.28	2.98	-	-		

 Table 1. General characteristics of each manually interpreted ground surface layer.

Layer	Area (m ²)	Minimim	Maximum	Mean	SD	Mean × area
Ground 1	8,353.14	20.81	25.47	21.51	1.83	179,688.17
Ground 2	13,854.36	21.23	28.39	21.66	3.15	300,034.66
Ground 3	484.05	20.78	26.67	22.37	2.16	10,826.74
Ground 4	847.92	23.06	26.25	23.10	1.87	19,585.33
Ground 5	1,703.17	20.24	24.84	20.92	4.02	35,629.24
Ground 6	51,304.98	20.98	23.53	21.83	0.47	1,120,210.22
Ground 7	1,243.30	21.01	25.29	21.54	1.68	26,779.46
Ground 8	779.03	20.85	23.39	22.36	0.40	17,418.07
Ground 9	905.08	21.75	25.02	22.77	0.67	20,611.70
Total area	79,475.02					21.78
				Weighted mean	RMSE	0.69

The weighted mean is a function of the size of each ground surface layer divided by the total area.



Figure 3. (A) Relationship between *high-resolution spaceborne imagery* (HRSI) canopy heights and field surveyed canopy heights. (B) Relationship between the HRSI canopy height (H100 and mean) with SRTM30 heights. Field measurements from Fatoyinbo et al. (2008). Black line represents 1:1.

 Table 3. Linear model characteristics and RMSE of canopy height comparisons.

		n	Slope (tan⊖)	Intercept (m)	R ²	RMSE (m)
Field	Mean	52	0.80	-0.77	0.80	1.18
plots	H100	52	1.00	-0.56	0.87	1.84
SRTM30	H100	43	1.23	-1.87	0.65	3.23

RMSE values, 0.87 and 1.84 respectively and were better able to estimate canopy heights of taller trees (Table 2 and Fig. 3B).

Canopy height estimates from the HRSI and SRTM datasets measured similar heights at each of the field plot locations (Fig. 4). Although the SRTM30 integrates tree heights over a larger area when compared to the finer scale resolution of HRSI data the two canopy height models, SRTM and HRSI_{H100}, show corresponding results. The comparison between the HRSI and SRTM height models reveals that the taller trees (>10 m) tend to be underestimated using SRTM data (Fig. 3B). The underestimation of the canopy heights results in a negative offset of -1.87 m, a lower R^2 value of 0.65, a higher RMSE of 3.23 m when compared to the field and HRSI canopy heights (Table 3).

A frequency distribution showing the number of pixels within a given canopy height for HRSI and SRTM data indicate a similar modal height value of 5 m and a positive skewness toward a taller canopy (Fig. 5). Five meter tall trees represent ~16% and ~22% of the total mangrove area within the study area for HRSI and SRTM, respectively. Nearly 6% of the canopy heights exceeded 14 m as estimated by HRSI while less than 0.2% of the SRTM mangrove canopy was greater than 14 m.

Discussion

The present study compared a HRSI canopy height model using open-sourced routines (ASP) with field measurements, derived ground measurements and updated SRTM canopy heights measurements from the same region (Fatoyinbo et al. 2008). Despite the lag in time between the field measurements in 2005, 2009 and the SRTM data acquired in 2000, canopy height estimates using the ASP and HRSI from WorldView1 resulted in a strong correlation between the mean and H100 canopy heights (Table 2). The lack of temporal decorrelation between the various datasets is consistent with forest ecological theory where tree height saturates and remains relatively consistent in mature and intact forests. A combination of low tropical cyclone frequency in East Africa, the location of the study sites in the conserved areas, like the Elephant Reserve, and the wave protection by Maputo Bay may help to limit mangrove mortality and create steady-state canopy height conditions. The H100 metric provides a more robust temporal measurement because of the lower mortality, less than 12% per year, associated with trees with a DBH greater than 10 cm (Jimenez et al. 1985). In a long term, six decade mangrove study conducted in Malaysia, Putz and Chan (1986) reported mean mortality rates to be less than 3% per year for mangroves with DBHs greater than 10 cm. The lower mortality rates in Malaysia were expected to be a result of protected equatorial waters and a moratorium on felling of mangroves for 80 years. Mangroves are protected by law in Mozambique, which could contribute to the steady-state canopy heights observed over the previous decade as measured from different methods.

The H100 canopy height exhibited the highest R^2 (0.87) and the higher RMSE (1.95 m) when compared with the field data. The spatial resolution of the HRSI



Figure 4. Canopy height map comparisons for Inhaca Island (A and B) and Maputo Elephant Reserve (C) between high-resolution spaceborne imagery digital surface models (DSM) (left) and SRTM30 DSM (right). See Figure 1 for site location reference.

allows for the integration of hundreds of pixels over a similar field plot-sized areas. Some of the uncertainty in canopy height can be attributed to forest change during the time between the forest surveys and the HRSI acquisitions as well as the georegistration between the two datasets. Forest growth or decline may have occurred at the field plots and could be the reason for the variability between canopy height measurements. The low offset determined from the linear regression of field and HRSI canopy suggest that there was a near negligible vertical bias in canopy height using the ASP routines (Table 2). Even though, resurveying the field sites may produce a better model, the uncertainties reported in the present study are within estimates using similar techniques (Hobi and Ginzler 2012; Montesano et al. 2014). From that end, spatially explicit mangrove canopy heights can be mapped across the coastal regions

of southeastern Maputo with a vertical error of 1.18–1.84 m (Fig. 4).

A similar study using the ASP was conducted in taiga forests of northern Siberia which reported lower vertical uncertainty, 0.86–1.37 m but based on a moderate model fit for estimating maximum tree heights (Montesano et al. 2014). The differences between the taiga forest in Montesano et al. (2014) and the mangrove forests in the present study were related to the terrain elevation and the tree density measured at the respective field plots. Ground elevation in the taiga forests spanned over 200 m of topographic relief which added a layer of complexity and uncertainty to the overall canopy height measurements and could change the model offsets. Alternatively, the ground elevations estimated in the mangrove forests were relatively homogenous across the study region, only varying a few meters. Tree density was also different between



Figure 5. Frequency distributions of high-resolution spaceborne imagery (HRSI) and shuttle radar topography mission (SRTM)30-derived canopy height estimates. Canopy heights were binned into 1 m height intervals. N equals the number of pixels used in the distribution. Despite the different between the spatial scales and number of pixels of the HRSI and SRTM data, the frequency distribution of height classes is very similar in both datasets.

the two regions with the sparse deciduous forests in Siberia containing 500–2500 fewer trees ha^{-1} than the mangroves forests in Mozambique and elsewhere (Alongi 2002; Fatoyinbo et al. 2008; Montesano et al. 2014).

Distinct canopy height patterns can be seen in the HRSI canopy height map that cannot be discerned in the coarse SRTM map even though the spatial resolution did not necessarily change the mode and distribution of the canopy heights over the same area (Figs. 4 and 5). However, the evident spatial patterning could provide information about the forest structure regarding species zonation and composition, hydrogeomorphology, as well as other environmental indicators. Adding HRSI to the repertoire of remote sensing of mangrove forests can provide researchers with more detail and create another layer of data integration to improve land cover, species and height classification maps and ergo, develop more appropriate biomass and productivity models (Heumann 2011).

An accuracy assessment of HRSI stereo analyses was conducted by Hobi and Ginzler (2012) which examined vertical errors in DSMs generated over various land covers in Switzerland; grass, artificial and forest. DSMs over areas covered by forest were the most difficult to model with reported median errors of less than 1.9 m using HRSI from WorldView2. However, Hobi and Ginzler (2012) compared HRSI DSMs to one acquired from airborne lidar and recognized differences associated in the phenology during lidar and HRSI acquisitions. Another advantage of mangrove forests is the lack of leaf senescence phenology as a result of the evergrowing morphology (Gill and Tomlinson 1971). Therefore, aerial and spaceborne imagery, from lidar and radar acquisitions can be more readily comparable regardless of the time of year of collection. The results of this study suggest that stereo DSM from HRSI products can be used to validate other airborne and spaceborne datasets at local and regional scales.

Conclusions

Using HRSI to derive DSMs of mangrove forests in the present study highlight the unique characteristics in mangrove forests that may be more apt at successfully modeling canopy height. First, mangrove forests tend to have tree densities in excess of 1000 trees ha⁻¹ for most stand ages which may be captured more readily by the HRSI and the ASP routines. Secondly, the ground elevation in mangrove forests is relatively flat across the entire ecosystem because of its geographic limitation to coastally inundated regions. The latter is beneficial to HRSI DMSs as it reduces the errors associated with topography in order to accurately measure changes to canopy height and structure related to natural and anthropogenic disturbances. Lastly, in regions with minimal environmental disturbances, mangrove forests can reach steady-state canopy height conditions and remain stable over time.

Many mangrove forests have a dearth of ground-validated field surveys because of financial, logistical and environmental setbacks. The accuracy of HRSI DSMs in representing mangrove canopy height at the field scale could provide useful data for validating canopy height estimates from other more globally available spaceborne imagery, yet with a scarcity of ground validation points. For example, IceSAT/GLAS, SRTM and TanDEM-X data have global data coverage, yet the height accuracy of some DSMs in certain regions of the world is less constrained because of the lack of ground validation sites. Similarly, remote sensing estimates of aboveground biomass derived from tree height allometry would be improved by HRSI because of the higher accuracy at taller tree canopies. Through further investigations, HRSI DSMs could serve as supplementary independent comparisons to global surface models and enhance their accuracy as well as be combined with biomass models and species zonation to improve classification cover.

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Conflicts of Interest

The authors declare no conflict of interest.

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