https://doi.org/10.5194/egusphere-2024-1179
Preprint. Discussion started: 29 May 2024

Reviews and syntheses: One forest carbon model to rule them all? Utilizing ensembles of forest cover and biomass datasets to determine carbon budgets of the world's forest ecosystems

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Abstract. Understanding global forest carbon stocks is necessary to assess the world's global carbon budget, with land cover change being estimated to contribute roughly 20% of the emissions of greenhouse gases to the atmosphere. In the last decade or so, remote sensing has contributed estimates of above ground stocks of biomass - a key part of forest carbon stocks - with over twenty biomass maps available at pan-tropical and global scales. To further the understanding of forest carbon stocks, this research seeks to synthesize the findings of disparate data sources on: (i) forest cover, (ii) forest cover change, (iii) above ground biomass (AGB) / above ground carbon (AGC) stocks in forests. Satellite-derived forest cover and AGB estimates have substantial variability. In 2020, forests were estimated to cover between 22.6 million and 49.7 million km^2 of the Earth's land surface, thus ranging from 17.1% to 37.6% of total land cover. Likewise, examining forest cover change from available datasets, the estimated change in global forest cover between 2000 and 2020 was loss of approximately 88,734 to 124,184 km^2 per year, combined with regrowth of forest cover of approximately 58,628 to 169,912 km^2 per year. Combining that forest cover data with remotely sensed AGB estimates, total stocks of AGB for the year 2000 were estimated to be 325 - 697 Gt, while for the year 2020, the range was 401 - 580 Gt. The equivalent quantity of CO_2 (i.e., CO_2e) of that stock of forest biomass was therefore estimated to be 560 to 1,200 Gt for the year 2000, and 692 - 999 Gt for the year 2020. Our analysis found that the forest cover loss in tropics was the largest, at the rate of 1.4% to 3.5% net reduction between 2000 and 2020, whereas for the same period, the temperate and boreal zones showed substantially lower forest cover loss (-2.5% to 0.5% and 1% to 5.3% respectively). ***This synthesis paper demonstrates that there is a wide range of variability in estimates related to forest cover, forest cover change, and above ground biomass stocks, which are the main inputs for estimating forest carbon stocks and greenhouse gas emissions from land cover change.***

I. Introduction

What do we truly know about the state of the world's forests and their contribution to the global balance of carbon? Based on inter-linked methodologies established by the Intergovernmental Panel on Climate Change (IPCC), countries utilize data on forest cover and land cover change - referred to as one of various "activity data" - along with "emission factors" such as biomass stocks to determine budgets of standing forest carbon, and emissions related to land use change (IPCC et al., 2019b). Intrinsically tied to data on forest cover, land cover change, and biomass are key questions of import to the scientific community, related to the status of the world's forests, their rates of change (e.g. from deforestation and degradation), and the quantities of carbon sequestered in the world's forests. While it is possible to address such questions by essentially summing up the outputs of respective countries' reports to the United Nations Framework on Climate Change (UNFCCC) and other multilateral environmental agreements, global scale datasets also offer complementary vantage points.

For that purpose, over the past fifteen years or so, at least a dozen sources of global and near-global biomass map datasets have been developed, mainly using methods combining [wall-to-wall] remotely sensed data[1] with sparser coverage data from field plots. While there are methods for more accurately measuring the biomass stored in forest plots, such methods involve destructive sampling techniques, are cost restrictive, are impractical and undesirable to implement at large scales, and findings are seldom widely accessible. Other non-destructive methods involve measuring tree diameters and heights and using allometric equations to estimate biomass stocks at the plot level, but such methods are not considered to be as accurate as destructive sampling.

Part of the challenge is that there is no single authoritative source for global forest cover data, nor a single authoritative source for above ground biomass (AGB) data, with each new study essentially advocating for use of its version of AGB data. Multiple studies have provided estimates of AGB stocks or alternatively, above ground carbon (AGC) stocks, at the global or pan-tropical scale, but because their geographical frames of reference differ - including whether they also include estimates of non-forest (AGB) - it becomes difficult to make "apples to apples" comparisons, necessitating the type of analysis this study pursues.

While "apples to apples" comparisons are therefore not immediately possible just using summary statistics from the various studies, spatial analysis does allow for homing in on such details, including limiting analyses to frames of reference including specific climate zones (e.g., boreal, temperate, or tropical), or specific ecosystems (e.g., forests). Forests are used as a frame of reference, specifically because it is a common denominator in the various global biomass map datasets, with a handful of the mapping efforts not considering non-forest biomass. Furthermore, Trumper et al. (2009) indicates that over 60% of the world's carbon stocks are found within forest ecosystems, with tropical forests storing a disproportionately large percentage of global forest biomass compared to boreal and temperate forests. Therefore, it would be useful to understand the potential range of values associated with forest cover and AGB within forests, especially in tropical climes.

This study's approach differs from previous studies which have characterized forest carbon stocks based on single sources. This study thus constitutes both a synthesis of the existing datasets and applied research which digs deeper into those datasets to explore their implications for tropical forest carbon monitoring and management.

[1] Some of the remotely sensed data used (e.g. vegetation index data derived from spectral reflectance data or radar backscatter) are acquired wall-to-wall, while other remotely sensed data (e.g. spaceborne profiles of vegetation height, from ICESat, ICESat-2, or GEDI) are obtained at sparser sampling.

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II. Methods

This study's principal objective was to characterize global forest carbon stocks based on an analysis of an ensemble of available AGB datasets. Sub-objectives included the characterization of the following:

- 1: forest cover
- 2: forest cover change
- 3: forest AGB / AGB stocks

This study's research questions were therefore framed as follows:

- What are the ranges and variabilities of estimates of the area of the world's forests?
- What are the ranges and variabilities of estimates of AGB / carbon in the world's tropical forests?
  - How do the different sources of forest cover impact the resulting standing forest carbon stock estimates?
- How do the findings of this study compare with the findings of earlier studies?

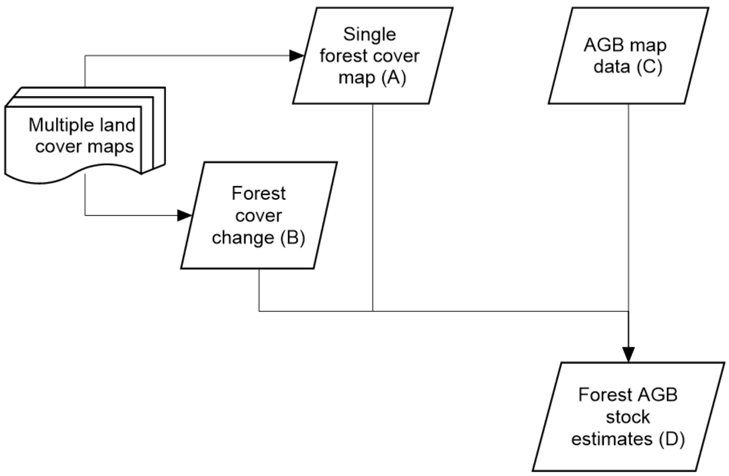

Figure 1: Simplified relationship between the study's input datasets and outputs

It is important to note that in determining forest carbon stocks [D], one must first estimate the extent of forests [A], one also needs data on the stocks contained within those forests [C], and the rates of change of such forests [B] (**Fig. 1**). It should be noted that, unlike many of the studies this paper follows, this investigation does not seek to derive new

https://doi.org/10.5194/egusphere-2024-1179
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data on forest cover or AGB / AGC stocks. This study merely seeks to synthesize the outcomes of a growing body of remote sensing research on forests and their carbon stocks.

Geographical domain

Based on the 2019 refinement to the 2006 IPCC's Guidelines for National Greenhouse Gas Inventories, and using the WorldClim 2.1 database's 1km spatial resolution precipitation and temperature datasets as the input data sources, global land areas were stratified into three main climatic categories: boreal, temperate, and tropical zones (Hijmans et al., 2005; IPCC et al., 2019b) (**Fig. 2**). For instance, tropical areas were identified based on having a mean annual temperature at or exceeding 20 degrees C, in line with the IPCC's climate typology, instead of merely representing areas between the Tropics of Cancer and Capricorn (IPCC et al., 2019a). Antarctica was excluded from the analysis given its lack of forest.

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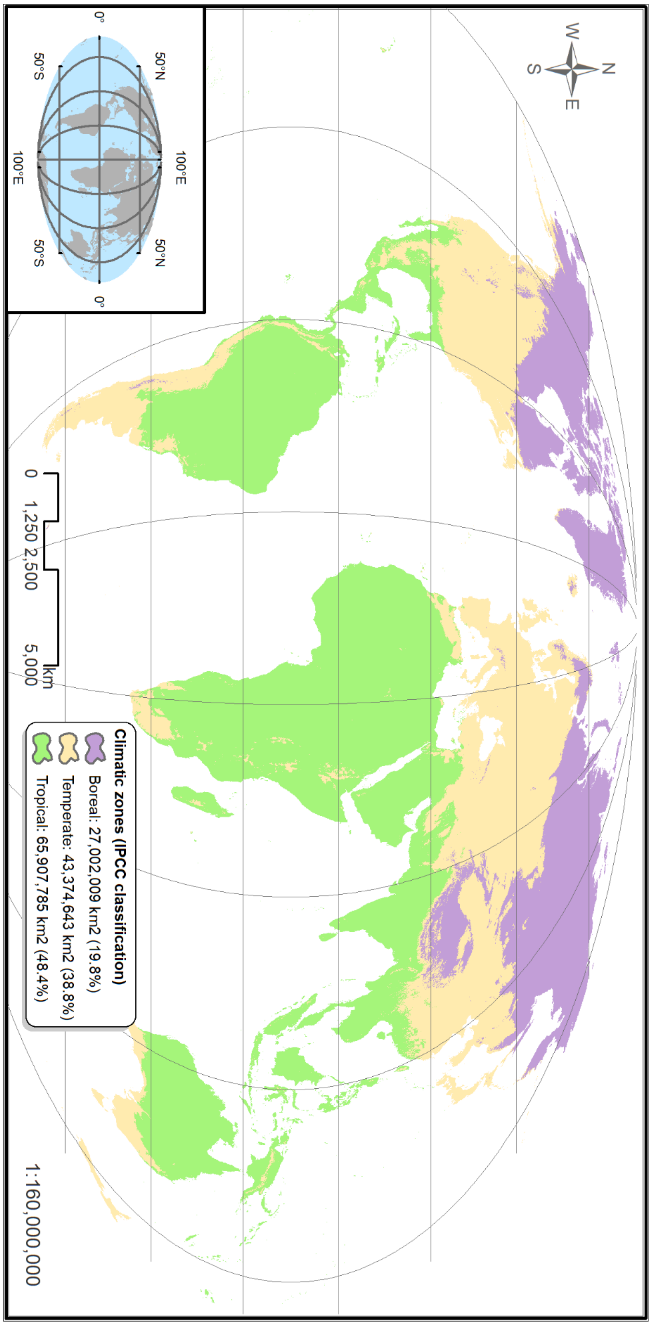

Figure 2: Global terrestrial climate zones, based on the IPCC's classification methodology (IPCC et al., 2019a).

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From the various global land cover datasets available, data on forest cover were extracted. It should, however, be noted that for some datasets, in place of a "forest cover" class, a "tree cover" class had to suffice. To consider forest carbon stocks in the year 2000, the following land cover datasets were also acquired, from which forest cover was extracted:

- CCI-Land Cover (300 m) (Lamarche et al., 2017)
- Global Land Cover 2000 (1 km) (Bartholomé and Belward, 2005)
- Hansen et al. / Global Forest Watch (30 m) (Hansen et al., 2013)
- MODIS MCD12Q1 [*for 2001*] (500 m) (Friedl et al., 2010)

To consider forest carbon stocks in the year 2020, the following global land cover datasets- all pertaining to calendar year 2020 - were utilized:

- CCI-Land Cover (300 m) (Lamarche et al., 2017)
- Dynamic World (10 m) (Brown et al., 2022)
- Esri / Impact Observatory (10 m) (Karra et al., 2021)
- Hansen et al. / Global Forest Watch (30 m) (Hansen et al., 2013)
- JAXA Forest / Non-Forest Cover (25 m) (Shimada et al., 2014)
- MODIS MCD12Q1 (500 m) (Friedl et al., 2010)
- World Cover (10 m) (Zanaga et al., 2021)

For the most part, the 2020 land cover datasets possessed a relatively high spatial resolution, with only the CCI-Land Cover and MCD12Q1 products not being available at 30 m spatial resolution or finer. For biomass, for a first level of analysis, twenty-two global and pan-tropical datasets were compiled, from the sixteen sources outlined in **Table 1**. Three of the data sources listed possess biomass maps for multiple years, allowing for a selection of fifty-one datasets spanning the period 2000 to 2020. Twenty-nine maps from two sources (Liu et al., 2015; Xu et al., 2021) were not considered, to avoid skewing the statistical analysis in favor of those sources. The data were also considered in terms of how they might contribute to an understanding of forest AGB stocks for specific time periods (i.e., circa 2000, circa 2010, and circa 2020).

Spatial resolutions of the 16 datasets varied. To facilitate comparisons, the land cover datasets were resampled to the 1km spatial resolution of the AGB datasets, and the eight AGB datasets which were not 1 km spatial resolution were resampled to 1 km using nearest neighbor resampling. To facilitate equal area comparisons among the datasets, all data were also reprojected to the Mollweide projection shown in **Fig. 1**.

For the estimation of carbon stocks in the tropics, using zonal statistical analysis, weighted sums of AGB were derived by spatially subsetting the biomass datasets to the derived tropical forest extents. The data were therefore resampled

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to be able to analyze them across a common frame of reference, focusing on pan-tropical zones. While the twenty-two AGB datasets were utilized for the first level of analysis, these were further down-selected to nineteen AGB datasets to ensure that multiple maps from the same source (in this case, CCI-Biomass maps for 2017, 2018, and 2019) did not skew the analyses. Consequently, that translated to having 11 AGB datasets for the circa 2000 period, 6 AGB datasets for circa 2010, and 3 datasets for circa 2020.

Table 1: Characteristics of the AGB datasets used.[2]

No.	Source	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Scale	Includes non-forest AGB?	Pixel size (km)
1	Ruesch and Gibbs, 2008	x																						global	yes	1
2	**Liu et al., 2015**	*	*	*	*	*	*	*	*	*	*	*	*	*										global	yes	25
3	**Xu et al., 2021**	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*			global	yes	10
4	Baccini et al., 2021	x																						global	yes	0.03
5	Saatchi et al., 2011	x	-	-																				tropics	yes	1
6	Hu et al., 2016					x																		global	no	1
7	Kindermann et al., 2008						x																	global	no	50
8	Avitabile et al., 2016	-	-	-	-	-	x	-	-	-	-													tropics	yes	1
9	GeoCarbon, 2016	-	-	-	-	-	x	-	-	-	-													global	no	1
10	Yang et al., 2020						x																	global	no	1
11	Zhang and Liang, 2020		-	-	-	-	x	-	-	-	-	-												global	yes	1
12	Baccini et al., 2012								-	x														tropics	yes	0.5
13	Spawn et al., 2020											x												global	yes	0.3
14	Santoro et al., 2021											x												global	yes	0.1
15	Dubayah et al., 2023																				-	x	-	tropics	yes	1
16	**Santoro et al., 2023**											*							*	*	*	*		global	yes	0.1

[2] For AGB data which are not available for multiple years, an x denotes the mean year the dataset is interpreted to represent, and - symbols indicate the input years for the product. Bold text for source studies indicates multi-year data, and the individual years of available data are also indicated by * symbols.

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Characterizing forest cover and forest cover change

The four land cover datasets for c.2000 and the seven land cover datasets for 2020 were in turn used to generate estimates of forest cover, with their respective classification schemes being referenced to translate from land cover classes to a ternary forest / non-forest / water scheme. All the land cover datasets were reclassified into forest / non-forest data based on widely accepted methods.

Characterizing forest AGB

For characterizing forest AGB through common frames of reference from the standpoint of forest masks, for circa 2000, combining the 11 AGB datasets with the 4 available derived forest cover masks allowed for 44 permutations of forest AGB. For circa 2020, combining the 3 AGB datasets with the 7 available derived forest cover masks translated to 21 permutations of forest AGB. Those data were in turn combined with the climate type masks (i.e., boreal, temperate, and tropical zones). This allowed for tuning into nuances in the data, especially for those datasets which were ostensibly pan-tropical in their geographic scope, but which often covered some part of temperate or boreal zones (e.g. boreal areas in Asia and in South America). Using the IPCC default carbon fraction value of 0.47, AGB could in turn be translated to estimates of AGC (IPCC et al., 2006). Nevertheless, because of the simplicity of that AGB to AGC conversion, from this point forward, we will be focusing principally on AGB.

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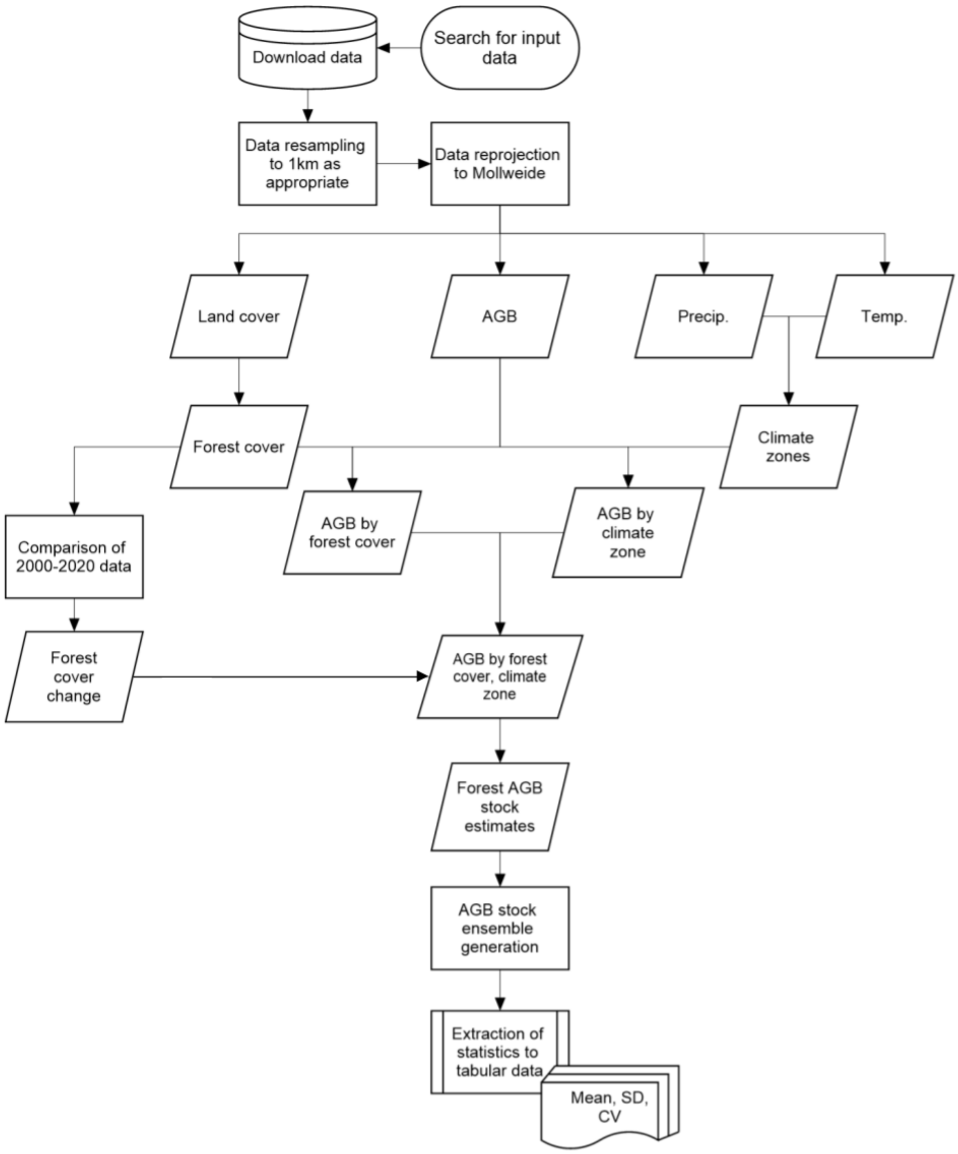

180 **Figure 3:** Data processing workflow

Statistical analysis

In addition to extracting the various datasets outlined above, such as AGB, basic statistical analyses were performed
185 on a per-pixel basis, at a 1 km spatial resolution. The approach of extracting per-pixel statistics (e.g., mean, standard deviation, range, coefficient of variation) is a novel approach compared to direct dataset-to-dataset comparisons employed in other studies, many of which have looked at latitudinal trends in AGB or AGC. Zonal statistical analysis

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was also performed on the datasets to produce summary tables. This process also served as a quality check on the data, illustrating for instance when certain data might have been overlooked as representing AGB when in fact the data represented AGC.

III. Results

To estimate standing global stocks of forest biomass, we need estimates of (i) current forest area, and (ii) AGB stocks. These can also be reframed in terms of activity data (i.e. estimates of forest area).

i. Forest Cover Estimates

Fig. 5 illustrates the diverging estimates of global forest cover in 2020, based on seven global scale land cover datasets. The MODIS-based MCD12Q1 data for 2020 indicate a global forest cover of only 22.3 million km^2, compared to the six over estimates, all of which each exceed 39 million km^2, with JAXA estimating the highest forest cover of the datasets at 49.7 million km^2. Translating those data into proportions of land covered by trees or forest, the MCD12Q1 data indicate that just under a fifth of the global land surface excluding Antarctica is covered by forest, while estimates range from 30.4% for the CCI-LC dataset to 37.6% for the JAXA dataset. Excluding the two outliers, the loss estimates were closer in agreement, ranging from 39.9 to 44.5 million km^2.

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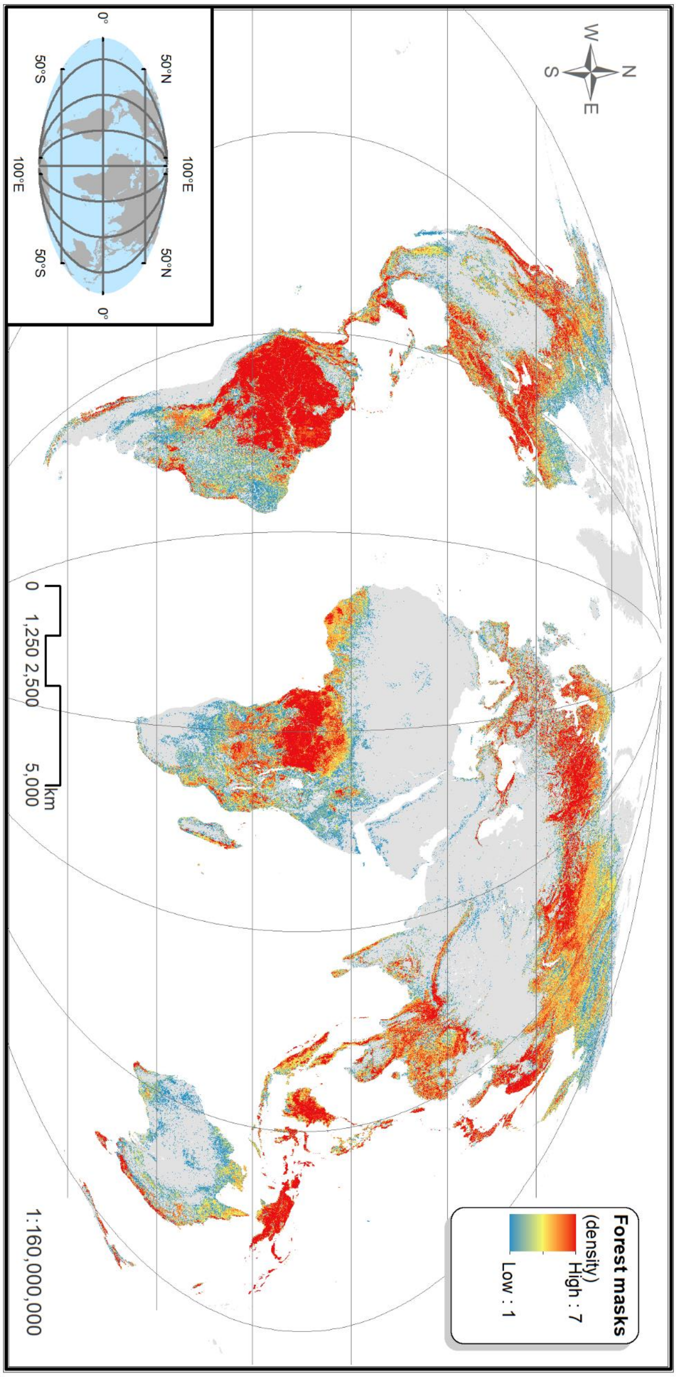

205 **Figure 4:** Combination of the various 2020 forest cover maps, with 1 indicating where only one forest cover map indicates the presence of forest cover, and 7 indicating where all seven maps coincide.

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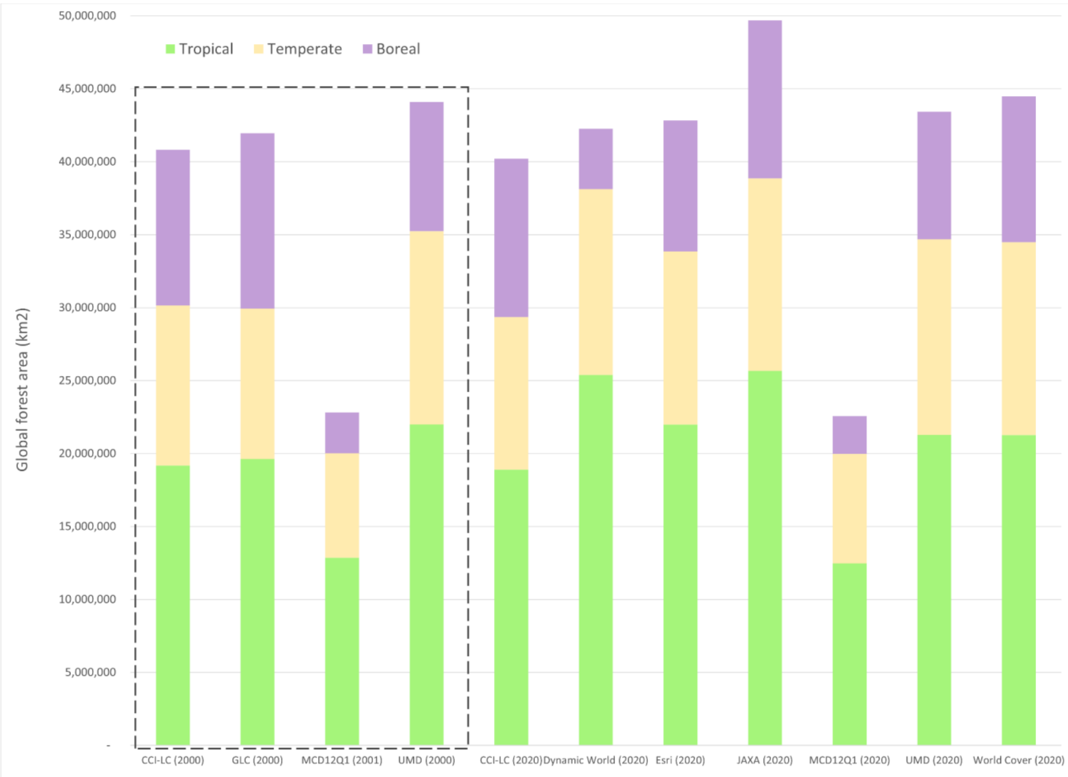

210 **Figure 5:** Global forest / tree cover estimates for c.2000 and 2020, stratified by climate zones

When such data are stratified by climate zones, the majority of the seven datasets generally converge in indicating that the tropical zone possesses roughly half or more of the world's forest cover, with estimates ranging from 47% for CCI-LC to 60.1% for Dynamic World. The proportion of forest in the boreal zone nearly converges for four of the datasets (i.e., Esri, JAXA, UMD, World Cover), which all indicate that the zone possesses roughly a fifth of the world's forests. This contrasts the Dynamic World and MCD12Q1 datasets that indicate that the boreal zone contains only roughly a tenth of the world's forest cover, and the CCI-LC dataset which had 27% of forest in the boreal zone. The seven datasets, however, practically converge in indicating that the temperate zone possess roughly a third of the world's forests, with estimates ranging from 26% (CCI-LC) to 33.2% (MCD12Q1). The differences in what the various datasets thus indicate for forest cover consequently have implications for estimating global forest biomass stocks.

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ii. Forest Cover Change

Table 2: Global forest cover / tree cover change estimates for c.2000-2020

Data source	Period	Climate zone	Stable	Deforestation	Regrowth
			Area (km^2)		
CCI-LC	2000-2020	boreal	10,598,948	305,582	194,235
		temperate	10,913,617	251,352	195,042
		tropical	18,625,855	698,176	423,373
MCD12Q1	2001-2020	boreal	2,173,844	569,837	425,607
		temperate	6,678,253	521,920	699,515
		tropical	11,486,422	1,255,652	840,006
UMD	2000-2020	boreal	7,644,754	443,399	229,979
		temperate	11,430,503	263,820	210,687
		tropical	20,209,408	922,431	182,545
			Change / year (km^2)		
CCI-LC	2000-2020	boreal	-	15,279	9,712
		temperate	-	12,568	9,752
		tropical	-	34,909	21,169
MCD12Q1	2001-2020	boreal	-	29,991	22,400
		temperate	-	27,469	36,817
		tropical	-	66,087	44,211
UMD	2000-2020	boreal	-	22,170	11,499
		temperate	-	13,191	10,534
		tropical	-	46,122	9,127

Table 2 provides summaries of forest cover change based on the three forest cover datasets for which time series are available (i.e., CCI-Land Cover, MCD12Q1, and UMD / Global Forest Watch). Since there is a slight mismatch in terms of the periods covered, the annual rates of change are the most useful to examine, especially in terms of forest cover loss (i.e., deforestation) and forest cover gain (i.e., forest regrowth). The CCI-LC product indicates that globally, forest cover loss was on the order of only 81,000 km^2 / year, compared to the MCD12Q1's estimates of a loss of 124,000 km^2 / year. Similarly, it was also possible to extract data on forest cover gain, whose estimates ranged from

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~31,000 km^2 / year for the CCI-LC dataset to ~103,000 km^2 / year for the MCD12Q dataset. At the global scale, the data indicate slight relative declines in forest cover. The CCI-LC data indicate that forest cover only declined by 1.1% over 20 years, compared to a 1.7% decline over 19 years estimated from the MCD12Q1 data, and a 2.5% decline over 20 years for the UMD data.

The forest cover loss for the tropical zone ranged from ~35,000 to 66,000 km^2 / year in the three data sources, compared to the boreal zone, where forest loss was estimated to be in the range of ~15,000 to 30,000 km^2 / year, and ~13,000 to 27,000 km^2 / year for the temperate zone. All three datasets indicated net forest cover loss for the periods indicated, ranging from a net loss of ~20,000 km^2 / year for the MCD12Q1 to ~50,000 km^2 / year for the UMD dataset. Those data likewise translate to overall declines of 1.4% (CCI-LC) to 3.5% (UMD) for the tropics. For the temperate zone, the data ranged from an estimate of a net gain of 2.5% forest cover based on the MCD12Q1 data to net losses of 0.5% forest cover for the CCI-LC ad UMD datasets. For the boreal zone, estimates of net loss ranged from 1% (CCI-LC) to 5.3% (MCD12Q1). Combined with AGB data, the forest cover change data in turn became inputs for estimating CO_2 emissions from forest cover loss.

iii. AGB Stocks in Forests

Globally, the distribution of forest AGB by latitude is displayed in **Fig. 6**, utilizing a forest mask generated from the individual datasets displayed in **Fig. 4**. An interactive version of the **Fig. 6** is available online (https://servirbz.users.earthengine.app/view/scap-agb-lat-01). The mean of all the datasets is also displayed as a thick black line.

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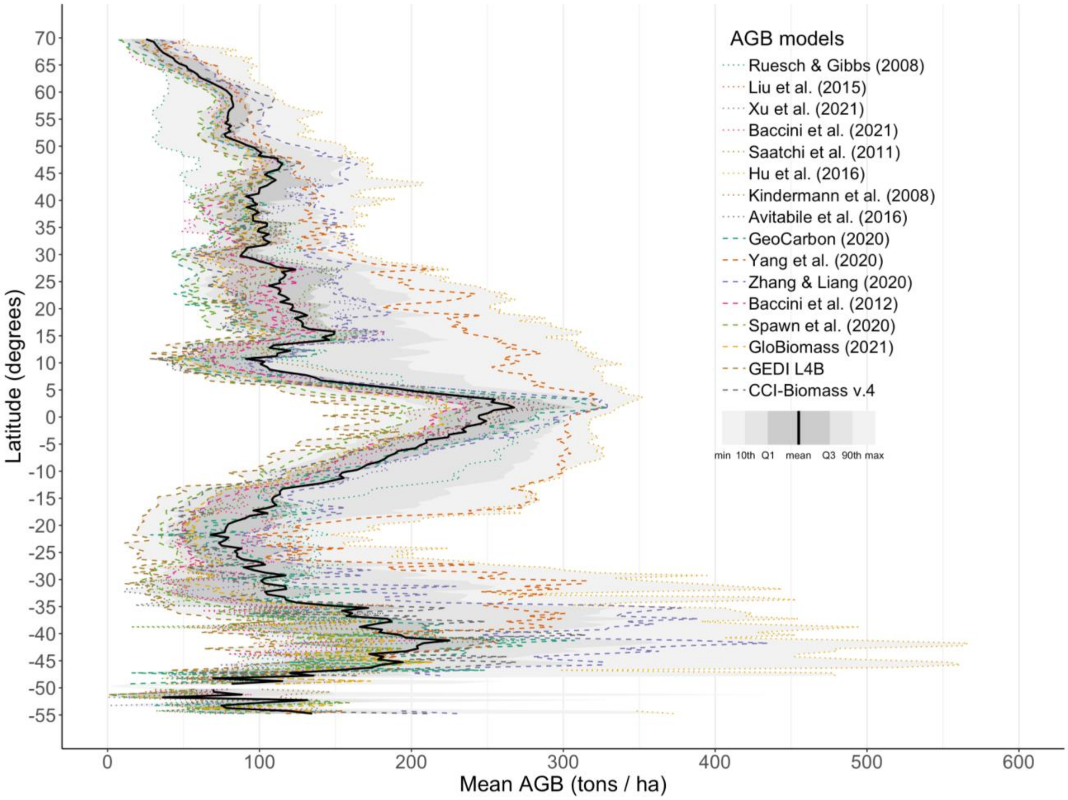

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Figure 6: Latitudinal averages of forest AGB (based on Santoro et al., 2023).

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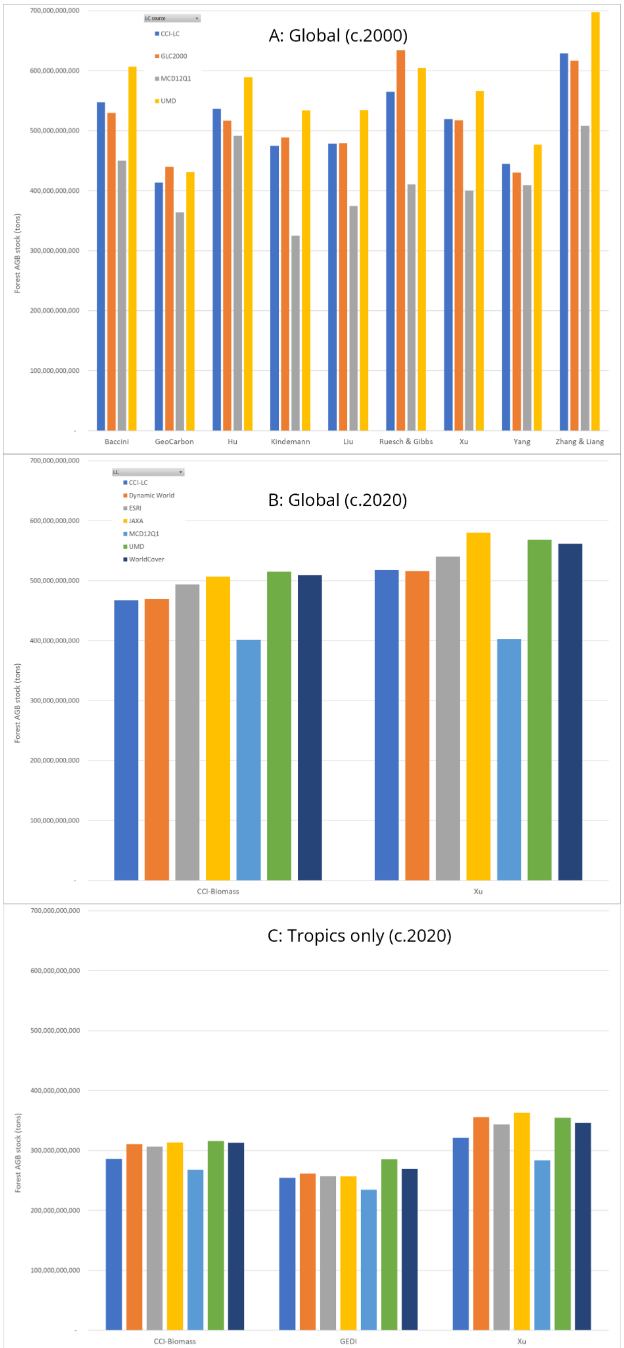

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Figure 7: Global forest AGB stocks for c. 2000 (A), and c. 2020 (B), and tropical forest AGB stocks for 2020 (C). GEDI data were not included in B as its geographic coverage is mainly tropical.

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While there is variance among the datasets and consequently variance from the mean across latitudes, in general, north of -20 degrees latitude, there is a fair amount of convergence, although a few datasets (e.g., Hu et al., 2016; Yang et al., 2020; Zhang and Liang, 2020) display higher values overall than the other datasets. The Ruesch and Gibbs (2008) data - based on nationally reported data from the IPCC's Emission Factor Database - and the spaceborne LiDAR-derived GEDI L4B data generally had lower forest AGB averages. For instance, near the equator, the GEDI L4B data had the lowest forest AGB estimates, while the Ruesch and Gibbs (2008) data had the overall lowest forest AGB estimates at higher latitudes. As is to be expected, the highest overall forest AGB estimates can be seen near the equator. While the mean forest AGB is lower south of the equator, a number of datasets, notably Hu et al. (2016), Zhang and Liang (2020), Yang et al. (2020)and also the CCI-Biomass v.4 (Santoro et al., 2023) data, had high forest AGB estimates between approximately -27 and -47 degrees latitude.

With four global land cover datasets from which forest cover could be extracted for 2000, and eleven pan-tropical and global AGB datasets for that period, the result was forty-four combinations of forest cover and AGB for c.2000, while for c. 2020, there were twenty-one such combinations, stemming from the combination of seven land cover datasets and three AGB datasets. The sums of forest AGB resulting from those combinations are displayed in **Fig. 7**. Both sets of combinations could further be stratified into the three broad IPCC climate zones (boreal, temperate, and tropical).

For c. 2000, the range of forest AGB stocks was wide, from 325.1 to 697.3 Gt. Irrespective of land cover data sources, the forest AGB stock estimates based on Zhang and Liang (2020) were the highest overall estimates, with 3 of the 4 AGB / LC combinations exceeding 600 Gt of AGB. In contrast, the GeoCarbon data had the lowest overall forest carbon stock estimates, with the AGB / LC combinations generally resulting in total forest AGB stock estimates between 363.6 and 439.6 Gt. Focusing on the tropics, forest AGB stock estimates ranged from 221.9 to 495.2 Gt in c. 2000. For c. 2020, the spread of combinations shown in **Fig. 7** is lower at the global scale since the GEDI data are largely pan-tropical. Hence, forest AGB stocks ranged from 401.3 to 580 Gt. However, when zooming into the tropics for c.2020, and adjusting GEDI-based data to generate wall-to-wall estimates, the range of estimates was from 234.4 to 362.6 Gt of forest AGB.

Complementing **Fig. 7**, **Fig. 8-11** show the spatial distribution of forest AGB for c.2000 and c. 2020. **Fig. 8** and **10** respectively show the derived mean forest AGB for c.2000 and c.2020 (based on the forest mask derived from the data shown in **Fig. 4**, while **Fig. 9** and **11** respectively show the scaled coefficients of variation, CV (i.e., standard deviation divided by the mean) for c.2000 and c.2020. The mean forest AGB maps for both periods show that overall, areas in the tropics such as the Amazon, Congo Basin, and Southeast Asian islands of Borneo and New Guinea have the highest estimated AGB stocks. The CV maps for both periods show that while there is divergence among the various AGB datasets, in areas with high estimated AGB stocks in the tropics in particular, the estimates converge. Low convergence (shown as bright red colors) mainly occurs in areas with lower forest AGB stocks, indicating that the various models did not agree.

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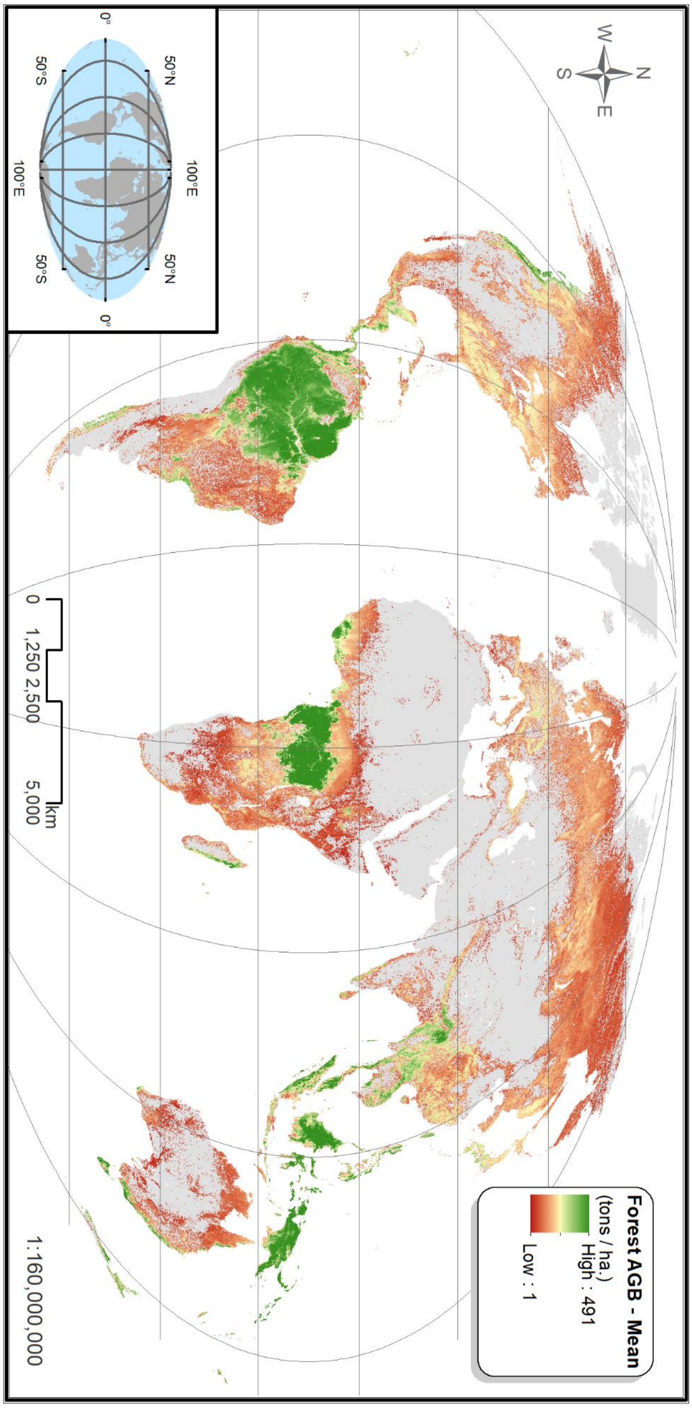

305 **Figure 8:** Mean forest AGB for c. 2000, based on data from 11 sources

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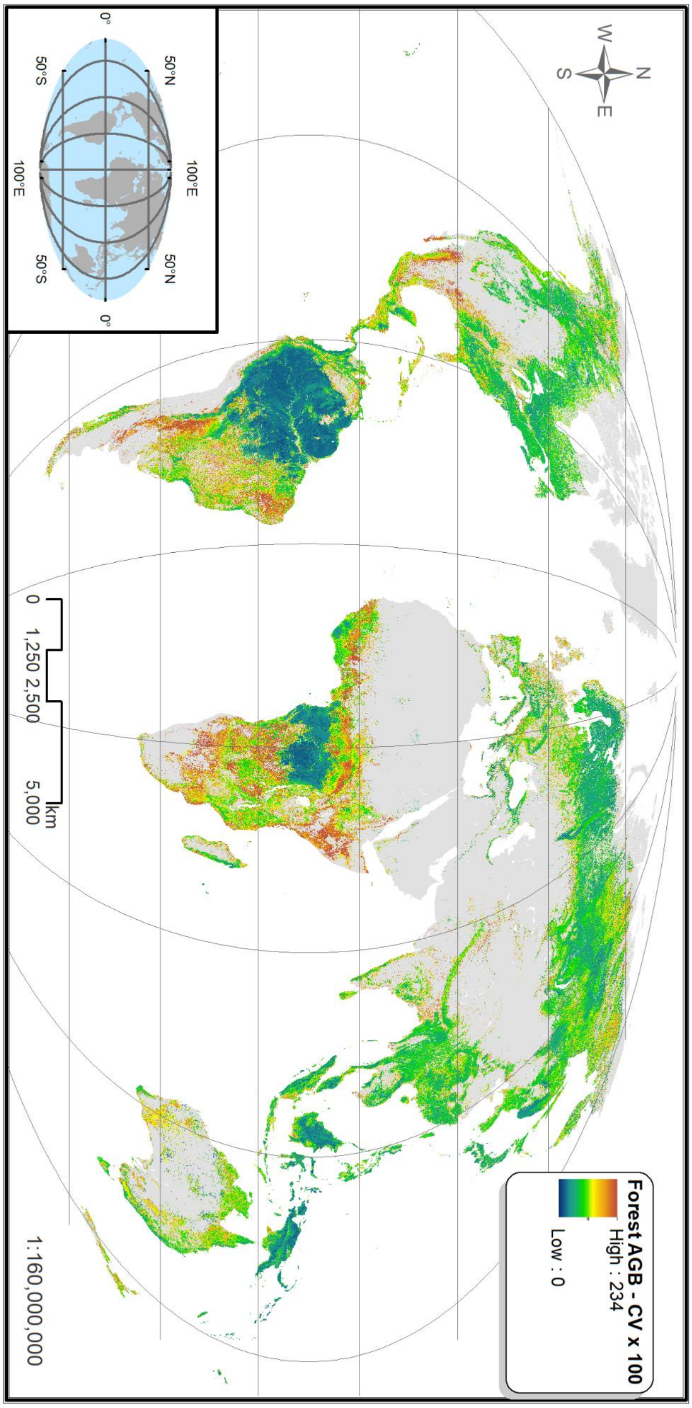

Figure 9: Coefficient of Variation (CV) of the forest AGB, for c. 2000, based on data from 11 sources

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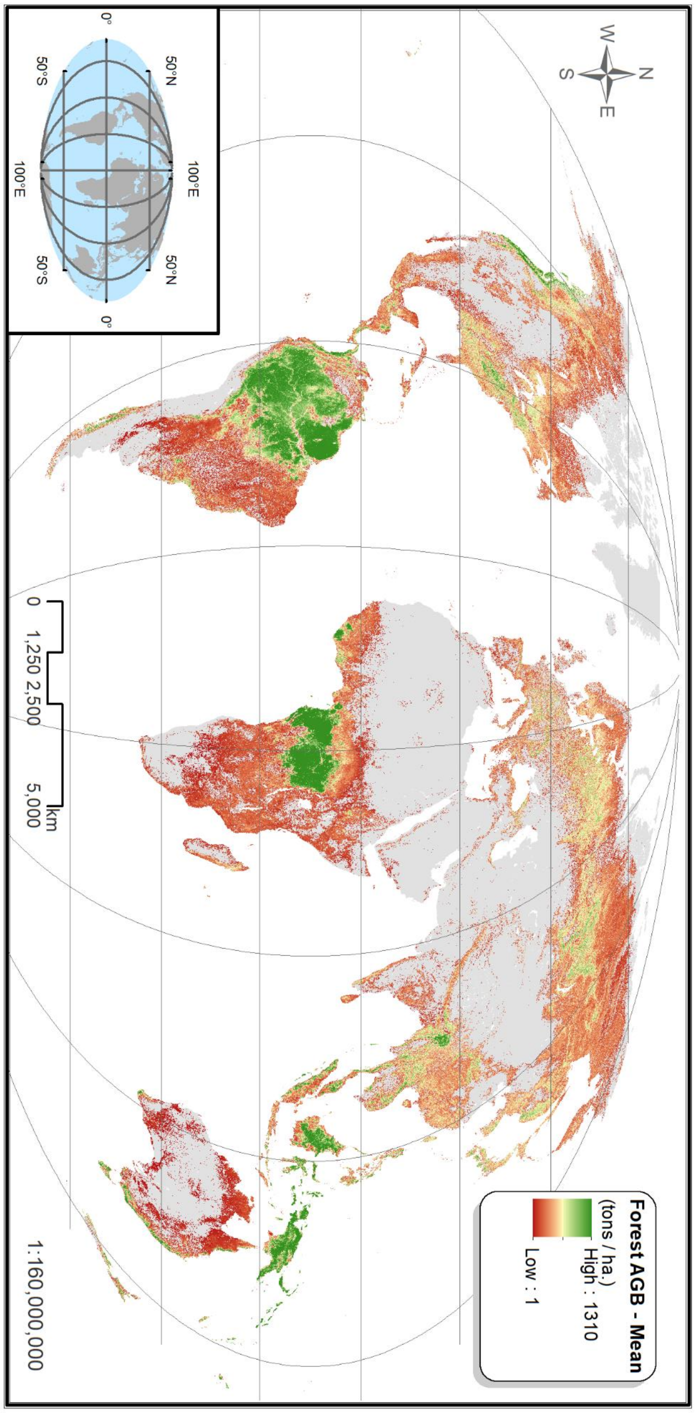

310 **Figure 10:** Mean forest AGB for c. 2020, based on data from 3 sources

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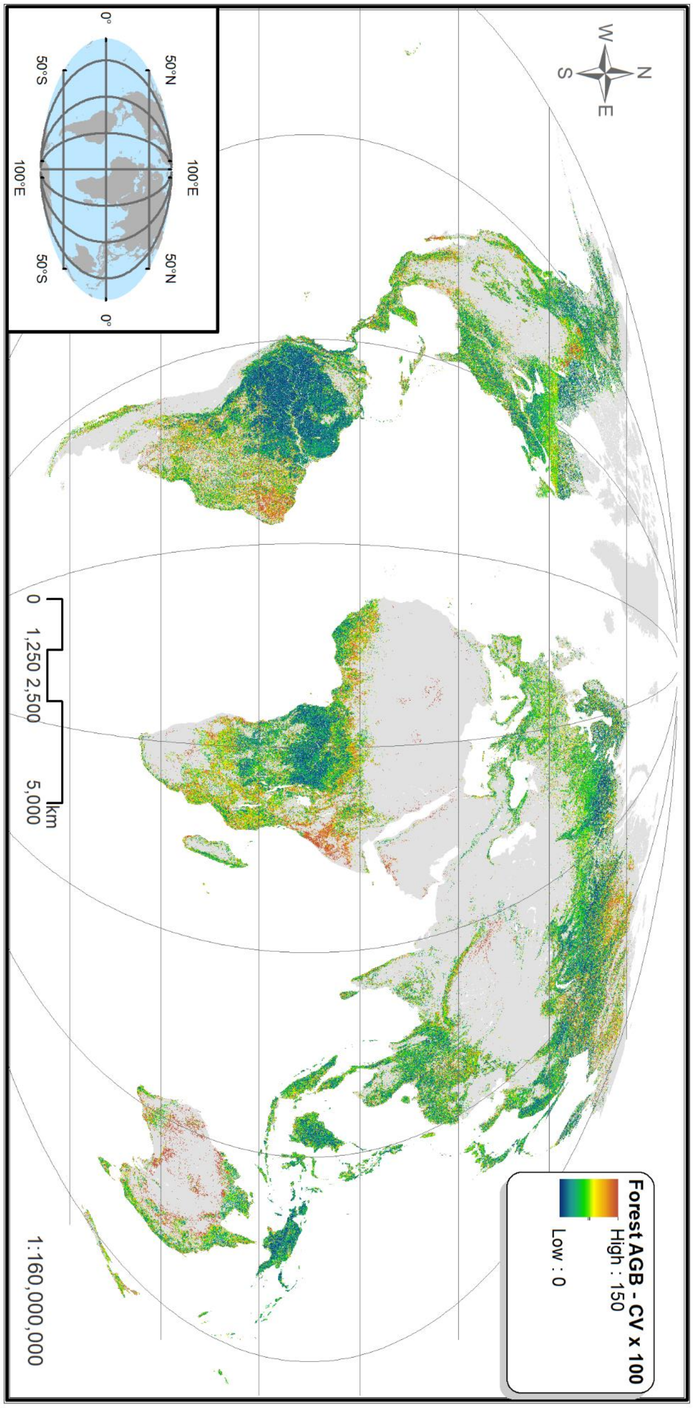

Figure 11: Coefficient of Variation (CV) of the forest AGB, for c. 2020, based on data from 3 sources

IV. Discussion

There are many avenues of inquiry inspired by the results presented. Nevertheless, we will focus on a comparative analysis of the datasets, the implications of the findings, assumptions made which could have influenced those findings, caveats regarding the underlying data, and perspectives on the directions of future research.

Comparative analysis

In terms of a comparative analysis of the existing AGB datasets, it is acknowledged that Zhang et al. (2019) laid the groundwork in outlining the various products then existing at regional and global scales. They offer comparisons of the inputs and methods used to generate those datasets, and that analysis contributed to the development of their own global AGB dataset, Zhang and Liang (2020). To the extent that Zhang et al. (2019) have already provided a level of comparison of datasets, this study will not delve into similar comparisons, although just over half of the sources we utilized for the current study were generated since Zhang et al.'s study. Nevertheless, while Zhang et al. (2019) provides an overview of the datasets, they did not go as far as to compare the datasets to one another, which was the purview of this study.

The basic zonal statistical analysis we performed, both globally and by climate zone, allowed for understanding how overall estimates differ or converge. Segmenting the data by decade also assisted in understanding the differences as potentially a function of differences in time. Where most of the datasets have an implicit focus on forest biomass (as compared to the stocks in other types of 'natural' vegetation or in agricultural systems), we nonetheless found it useful to further analyze the data in terms of forest masks we were able to derive from existing global land cover sources, both for the year 2000, and for 2020. An interest contrast that should also be highlighted, however, is that while there are fewer land cover inputs available for 2000, the bulk of the AGB datasets are for the c. 2000 period, in contrast to there being more land cover datasets available for 2000 and fewer AGB datasets available for 2020. We mention this because the differences in the numbers of available datasets likely have some impact on the findings.

The forest cover change analysis shows that while at the global level, forest area decreased by between 1.1% and 2.5%, overall, losses were greatest in the tropics, with the estimated loss ranging from 1.4% to 3.5%. For the temperate zone, the datasets did not agree, with the MODIS-based data showing an increase in forest cover, relative to the other two datasets which had indicated a slight decline. For future research, it would be useful to drill deeper into the data to examine how deforestation differs across geographic regions (e.g. in the tropical parts of the Americas vs. tropical parts of Asia or Africa).

We should provide a caveat. From the data presented, while it may be useful to look at mean AGB values per data source, because the spatial distribution of areas with no data values varies significantly by dataset, the use of the sums

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of total AGB is much more illustrative. That said, as already indicated, there were different spreads of the estimated quantities of total AGB across the various decades, before controlling for factors such as climate zone and land cover type. Still, there were more AGB datasets available for c. 2000, which may likely have contributed to the greater spread (452 to 1,019 Gt of AGB) than for c. 2010 (562 to 737 Gt of AGB) and for c. 2020 (558 to 744 Gt of AGB).

Drilling down further, based on analysis of the tropics only, since there is more data for those areas due to the existence of maps covering only the pan-tropical zone, we see the spread decrease even further. For instance, for c. 2000, the spread is from 314 to 617 Gt of ABG, compared to 335 to 445 Gt for c.2010 and 336 to 435 Gt for c.2020. Nevertheless, while those numbers represent the total AGB mapped, do not control for internal data masks used by the various studies, which likely in turn influenced the extracted statistics. Thus, if we try to restrict the data to the same climate zones and the same land cover sources for 2020, we see a much smaller spread in terms of the AGB values when we make an additional area-based extrapolation for the GEDI data, which are not wall-to-wall unlike the other datasets. For instance, based on the MCD12Q1-derived forest cover and limited to the tropics, the spread between the three AGB datasets for 2020 is 234 to 283 Gt of AGB, while based on the JAXA forest cover data, that spread is from 257 to 362 Gt of AGB. Nevertheless, these spreads are only based on three AGB sources (i.e., Dubayah et al., 2023; Santoro et al., 2023; Xu et al., 2021), compared to the c. 2000 data which is based on eleven sources of AGB data.

Focusing solely on the global level for the year 2000, and considering only the four 2000 forest cover masks but not climate types, the spread is between 325 and 697 Gt of AGB. In terms of understanding the discrepancies among the various datasets, it is obvious that independent of the forest cover masks, the Zhang and Liang (2020) dataset had the highest overall AGB stock, with the various forest masks indicating AGB stocks between 507 and 697 Gt. In contrast, the GeoCarbon dataset had the lowest level of estimated total AGB stocks, ranging from 364 to 439 Gt. Why would one see such a difference in ranges? It is known that the Zhang and Liang data are based on a bootstrapping method involving existing datasets, compared to GeoCarbon, which is itself based on Avitabile et al. (2016) and Santoro et al. (2015), noting that the Avitable et al. data are themselves adjusted estimates based on the tropical AGB maps from Saatchi et al. (2011) and Baccini et al. (2012). In other words, Zhang and Liang's bootstrapping method may have inflated numbers, while the Avitable et al. method underlying GeoCarbon may have adjusted down the biomass estimates.

Part of the challenge to interpreting the findings is having an almost overwhelming array of estimates based on combinations of AGB and forest cover inputs. One way to sift the data would involve merely averaging the various datasets, or selecting only a single forest mask to use, because of the intricacies of the data. That is to say, the geographic domains differ, as do the focus vegetation types, and the timeframes, hence our seeking to put the data into common frames of reference to avoid having to discard useful data from the analysis. We are therefore of the perspective that an ensemble approach must be used to understand the full spread of the data. Instead of thinking that there is "one true" AGB dataset, it might be useful to consider that, given the uncertainties involved with each dataset, the most useful way forward is to use an ensemble approach. That approach is also employed in a related area of

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geoscience where it is likewise difficult to ascertain "true" values, namely numerical weather forecasting, where instead of focusing on the exact quantity of rain that will fall, the idea is to look at the spread and of various forecasts to determine a general idea of the likely range of rainfall quantity.

Making decisions under uncertainty is a main motivator for this review. When presented with a range of possible scenarios, decision makers may be better equipped to take appropriate actions and mitigate risk. An analogous case is the upstream weather and climate models that feed downstream flood and drought impact forecasts. Both upstream and downstream models can be produced in ensemble modes, allowing decision-makers to see how upstream uncertainties propagate downstream. Similarly, the global forest sector knows there is uncertainty in each specific model, but just how wide that uncertainty ranges has been difficult to capture. This review contextualizes individual AGB estimates on a more complete spread of all globally available AGB estimates.

Assumptions

Where we have used forest cover as a mask for understanding forest AGB stocks, it is therefore worth noting that there are discrepancies among how various datasets denominate forests or similar ecosystems. The JAXA and the MCD12Q1 products explicitly cite "forest cover," while the remaining products such as the CCI-Land Cover, Dynamic World, Esri land cover, GLC 2000, original UMD / Global Forest Watch, and WorldCover products all have a single "tree cover" class which they indicate may include not only forest cover but also certain tree crops or tree plantations. By assuming that the majority of "tree cover" is forest cover, in some cases, in the estimates of AGB stocks we may unwittingly be including potentially lower biomass areas. Nonetheless, we see this principally as a classification scheme translation challenge and consider it beyond the scope of this study to determine how to separate out "true" forest cover from forest-like tree formations.

Regarding forest cover and forest cover change specifically, another question concerns the extent to which spatial resolution is a [mediating] factor in determining how classes are mapped. For instance, of the various input land cover datasets used, the MODIS-based MCD12Q1 dataset was the most coarse, at 500 m spatial resolution, compared to the other datasets whose resolutions ranged from 10m (3 datasets) to 25m (the JAXA FNF dataset) to the 300m composite ESA CCI-LC dataset.

There are other limitations to working with data from multiple spatial resolutions. While most of the datasets analyzed have a spatial resolution of 1km, a few (e.g., from Baccini et al., 2021; Santoro et al., 2021, 2023; Spawn et al., 2020) had spatial resolutions finer than 1km, while a few other datasets (e.g., from Kindermann et al., 2008; Liu et al., 2015; Xu et al., 2021) had resolutions exceeding 1km. The solution we came to was to resample all datasets to 1 km spatial resolution. It is noted that recent studies have, likely to facilitate rapid calculations, have analyzed AGB data differences on a scale of $5 km^2$ and $10 km^2$, which represents 500 to 1,000 hectares (Araza et al., 2023; Labrière et al., 2023).

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Caveats

As an in-depth exploratory analysis, this study has sought to determine the implications of the various data outputs from a host of globally significant studies focused on forest carbon. Therefore, to the extent that this study has limited itself to analyzing that data in place of generating new data, there are certain research avenues that this study does not delve into, specifically topics such as below ground carbon and soil carbon stocks. This is so because most of the inputs analyzed did not themselves address such carbon pools. Nevertheless, in terms of those carbon pools, it is known that above ground biomass makes up a significant portion of carbon pools, with AGB estimated to make up almost three quarters of total forest biomass in tropical forests (Trumper et al., 2009). In lieu of evaluating accuracy, this study has allowed for an assessment of the precision of the various AGB datasets in showing how much they differ from each other.

Another important caveat to note is that most of the sources evaluated utilized similar approaches to estimating AGB using remote sensing, but as Santoro et al. (2023) notes, "AGB can only be inferred from observations since remote sensing instruments do not have the capability to measure the organic mass stored in vegetation." Studies such as Saatchi et al. (2011), Baccini et al. (2012), Hu et al. (2016), Spawn et al. (2020), Yang et al. (2020), and Xu et al. (2021) used similar methods and multispectral and spaceborne LiDAR data inputs, while Santoro et al. (2021) and Santoro et al. (2023) used modeling approaches using radar data inputs. The data generated by both sets of approaches - which depended heavily on wall-to-wall remotely sensed data seemed to be more similar than the products of the approaches taken by Kindermann et al. (2008) or Ruesch and Gibbs (2008), one of which interpolated field plot data, and the other which mapped biomass essentially based on ecoregional characteristics encoded in the IPCC's Emission Factor Database. From the datasets based on modeling using remotely sensed data, it is likely that the spatial variability inherent in the underlying multispectral or radar data influenced the AGB variability that was in turn mapped.

Where the analysis of a score's worth of AGB datasets and multiple land cover and land cover change data inputs could have gone in multiple, diverse directions, this paper has focused on AGB and carbon from an applications perspective. That is, rather than seeking to determine which dataset is the "best," we have sought to explore the implications of the various datasets, especially from the perspective of AGB stocks. Likewise, from an applications perspective, if one is looking to utilize any or all of the respective AGB, land cover, and land cover change datasets for regional or national applications, it is useful to understand how the datasets differ and how they converge. From an applications perspective, we would merely ask what the wide range of AGB datasets ultimately means for several questions that data users and policymakers are already asking.

One such application is the use of AGB data to quantify AGB stocks in protected areas. For instance, a recent study elaborated on AGB stocks in protected areas globally for the year 2020, using the GEDI biomass data (Duncanson et al., 2023). Had that study based its findings on any of the two other datasets available for that period, i.e. data from

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the CCI-Biomass product or from Xu et al. (2021), they would have come to different conclusions at least in terms of the magnitude of AGB stocks. In other words, the availability of multiple AGB datasets poses certain implications in terms of quantifying forest AGB / forest carbon stocks.

Implications

This study has significant ramifications for estimates of global carbon budgets, and further work could show implications for greenhouse gas emissions estimates (specifically CO_2) from land use change. Each new land cover and biomass dataset – whether global, regional, or national – presents yet another scenario for AGB estimates (and related GHG emissions). It also remains to be seen how a study like the current one might influence policy. For instance, could the acknowledgement that remotely sensed AGB datasets differ substantially in their assessments of forest carbon stocks and emissions potentially factor into countries' estimates of their own forest carbon stocks? Could this research potentially influence upcoming stock take activities like the recently concluded joint global stock take activity by the Committee on Earth Observation Satellites (CEOS) and the UNFCCC to evaluate how countries take more advantage of Earth observation data? And to what extent can decision-makers in national governments act on the available data, especially considering the slightly different pictures they paint?

Future research directions

A key question concerns how the use of validated regional land cover and land cover change datasets can further refine carbon budgets. For instance, the SERVIR program - an initiative of the U.S. Agency for International Development (USAID), NASA, and leading regional organizations - operates in five key regions where the regional 'hub' organizations have generated regional land cover datasets with high relative accuracies, and which are considered reference datasets (Herndon et al., 2019). While the use of those datasets could essentially make the ensemble of land cover datasets even larger, since the data are considered references in their respective regions, these might lead to refinements in understanding of forest carbon stocks by potentially thinning the ensemble down. This is also the subject of ongoing research by the authors of this paper (e.g. Evans et al., in prep. and https://s-cap.servirglobal.net).

In addition to the possibility of refining regional carbon budgets using higher accuracy regional land cover datasets, another future research direction could involve a variant on that topic by quantifying carbon budgets using the respective national forest reference emission level (FREL) reports submitted by various countries (Melo et al., 2023). Essentially similar to the approach taken by Kindermann et al. (2008), that route could involve comparing the various national estimates with remotely sensed ones, especially where FREL reports include information on carbon stocks, rates of forest cover change, and emissions estimates.

Where this study has largely focused on understanding the levels of precision, i.e. the agreement among various AGB datasets, another obvious area of interest is understanding the accuracy of the datasets in terms of comparisons with field data. While some of the datasets used such reference data for both calibration and validation purposes, it would be useful to perform a systematic analysis of accuracy across the range of available datasets. Another related future research direction would involve evaluating the biomass products' findings through direct comparisons with the findings of the national FREL reports, e.g. determining if the FREL reports' biomass ranges are on par with the remotely sensed AGB datasets.

Lastly, reviewing the traditional machine learning methods used in generating many of the AGB datasets, e.g., use of regression models to integrate plot-level AGB estimates, spaceborne LiDAR heights, multispectral reflectance, and radar backscatter among others, we would therefore anticipate that it is only a matter of time before newer studies come along with different methods. Such methods would likely involve the use of more sophisticated deep learning techniques for estimating AGB using the input datasets mentioned. It bears to be seen, however, whether such techniques would result in more accurate AGB estimates. It also remains to be seen the extent to which more regionally and nationally relevant AGB models are going to be derived, although Zhang et al. (2019) documented a number of these, for instance, for countries such as Brazil, Cambodia, China, Colombia, Madagascar, Mexico, Panama, Peru, and the United States of America. They also documented regional scale models for Africa and the Amazon. It is anticipated that the development of finer scale models would likely provide for higher accuracies than might be afforded by global models.

V. Conclusions

Stemming from the uncertainties associated with the different existing AGB and forest cover datasets, we propose an ensemble approach to evaluate the spread of the various data, and we have utilized that approach to evaluate the AGB data, toward refinement of the biomass component of global carbon budgets. We have quantified forest carbon stocks by crossing forest cover estimates from multiple sources with AGB estimates from multiple sources. By separating the existing biomass datasets into their corresponding applicable time periods, i.e., c. 2000, c. 2010, and c. 2020, we have demonstrated that based on the range of available AGB and forest cover datasets, forest AGB stocks potentially ranged from 325 to 697 Gt for c. 2000, and 401 to 580 Gt for c. 2020, based on the spread of forest cover estimates for 2000 and 2020. Future studies could combine the AGB data with the forest cover loss data to determine further implications on global CO_2 emissions from deforestation.

Acknowledgements

This study was done in the framework of the ongoing SERVIR-CArbon Pilot (S-CAP) activity which is funded by the NASA Earth Science Division's Applied Sciences Capacity Building Program. SERVIR is a joint NASA- and USAID-led program. We acknowledge and appreciate strong support from Nancy Searby and Lawrence Friedl from NASA Headquarters. This study was also conducted in the framework of the University of Alabama in Huntsville (UAH)'s Cooperative Agreement No. 80MSFC22M001 with NASA. Prof. Robert Griffin of the UAH Department of

Atmospheric and Earth Science and the Earth System Science Center is acknowledged for all his support. The Technical Assessment Group established for evaluating the S-CAP activity, composed of Steven Ogle (Colorado State University), Laura Duncanson (University of Maryland), and Pontus Olofsson (NASA Marshall Space Flight Center) are also acknowledged for having provided feedback to the precursor to this effort. Peter Epanchin, Evan Notman, and Janet Nackoney of USAID, and Sylvia Wilson of the U.S. Geological Survey and the SilvaCarbon initiative are also acknowledged for their feedback at different stages in the elaboration of this work.

Code/Data availability

The synthesized data and code for analysis will be made available in a public repository.

Author contribution

EAC, AIFA, and ASL designed the analyses, while EAC analyzed the data, and CAE did additional analyses for a supplementary study. EAC prepared the manuscript, with contributions from all the co-authors, including significant revisions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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