ARTICLE

Deforestation in Latin America in the 2000s predominantly occurred outside of typical mature forests

Zhiyu Zhang,[1] Wenjian Ni,[1,2,*] Shaun Quegan,[3] Jingming Chen,[4] Peng Gong,[5] Luiz Carlos Estraviz Rodriguez,[6] Huadong Guo,[1,2] Jiancheng Shi,[7] Liangyun Liu,[1,2] Zengyuan Li,[8] Yating He,[9] Qinhuo Liu,[1,2] Yosio Shimabukuro,[10] and Guoqing Sun[11]

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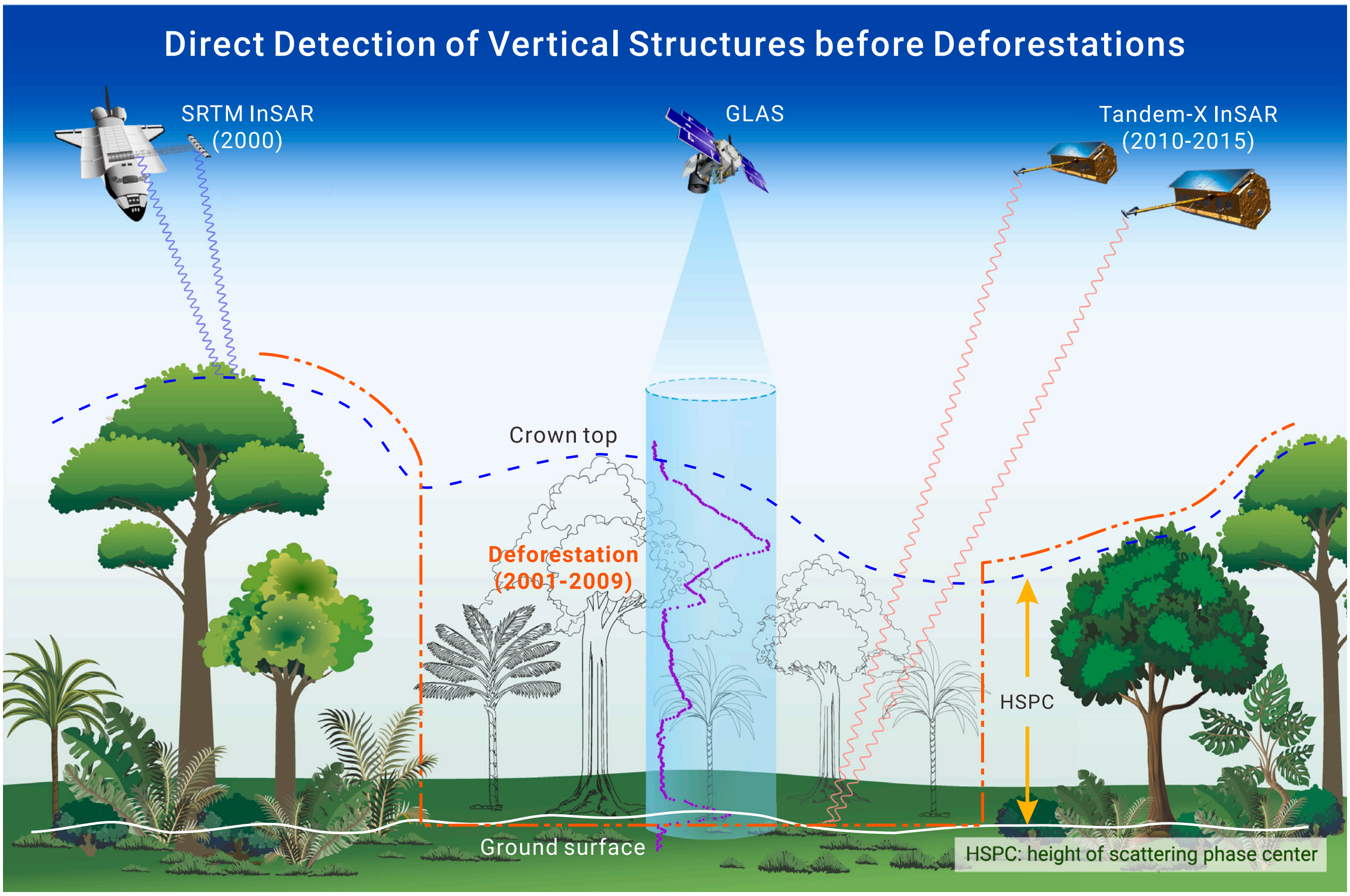
Received: July 25, 2023; Accepted: March 8, 2024; Published Online: March 12, 2024; https://doi.org/10.1016/j.xinn.2024.100610

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- The accuracy of existing carbon density maps is limited owing to the lack of direct measures of vertical forest structures.
- The synergy of interferometric synthetic aperture radar (InSAR) data acquired before and after deforestation has been proposed as a direct measure of vertical forest structures.
- An accurate map of carbon density in the deforested areas was produced using light detection and ranging (lidar) data, forest-loss maps, and vertical forest structures.
- New results have revealed that carbon loss caused by deforestation in the 2000s in Latin America was severely overestimated.
- Knowledge of the role of Latin American forests in the 2000s in global carbon budgets has been challenged by this new result.

Deforestation in Latin America in the 2000s predominantly occurred outside of typical mature forests

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Received: July 25, 2023; Accepted: March 8, 2024; Published Online: March 12, 2024; https://doi.org/10.1016/j.xinn.2024.100610

Citation: Zhang Z., Ni W., Quegan S., et al., (2024). Deforestation in Latin America in the 2000s predominantly occurred outside of typical mature forests. The Innovation **5(3)**, 100610.

The role of tropical forests in the global carbon budget remains controversial, as carbon emissions from deforestation are highly uncertain. This high uncertainty arises from the use of either fixed forest carbon stock density or maps generated from satellite-based optical reflectance with limited sensitivity to biomass to generate accurate estimates of emissions from deforestation. New space missions aiming to accurately map the carbon stock density rely on direct measurements of the spatial structures of forests using lidar and radar. We found that lost forests are special cases, and their spatial structures can be directly measured by combining archived data acquired before and after deforestation by space missions principally aimed at measuring topography. Thus, using biomass mapping, we obtained new estimates of carbon loss from deforestation ahead of forthcoming space missions. Here, using a high-resolution map of forest loss and the synergy of radar and lidar to estimate the aboveground biomass density of forests, we found that deforestation in the 2000s in Latin America, one of the severely deforested regions, mainly occurred in forests with a significantly lower carbon stock density than typical mature forests. Deforestation areas with carbon stock densities lower than 20.0, 50.0, and 100.0 Mg C/ha accounted for 42.1%, 62.0%, and 83.3% of the entire deforested area, respectively. The average carbon stock density of lost forests was only 49.13 Mg C/ha, which challenges the current knowledge on the carbon stock density of lost forests (with a default value 100 Mg C/ha according to the Intergovernmental Panel on Climate Change Tier 1 estimates, or approximately 112 Mg C/ha used in other studies). This is demonstrated over both the entire region and the footprints of the spaceborne lidar. Consequently, our estimate of carbon loss from deforestation in Latin America in the 2000s was 253.0 ± 21.5 Tg C/year, which was considerably less than existing remote-sensing-based estimates, namely 400–600 Tg C/year. This indicates that forests in Latin America were most likely not a net carbon source in the 2000s compared to established carbon sinks. In previous studies, considerable effort has been devoted to rectify the underestimation of carbon sinks; thus, the overestimation of carbon emissions should be given sufficient consideration in global carbon budgets. Our results also provide solid evidence for the necessity of renewing knowledge on the role of tropical forests in the global carbon budget in the future using observations from new space missions.

INTRODUCTION

Approximately 200–300 Pg carbon is stored in living tropical trees, which is approximately one-third of that present in the atmosphere.[1,2,8] Roughly 60% of the world's photosynthesis is realized by tropical trees capturing approximately 72 Pg C/year from the atmosphere. Tropical ecosystems also release a slightly smaller amount of carbon back to the atmosphere through respiration, leading to a net carbon uptake of more than 2 Pg C/year.[8] In addition to these natural fluxes, gross carbon emissions occur owing to land-use change.[9] This mainly occurs in tropical regions and is the second largest anthropogenic source of carbon dioxide in the atmosphere but has the largest relative uncertainty, namely in the order of 50%, among the components of the global carbon balance.[1,10-12] Current estimates of gross carbon emissions from deforestation in tropical forests range from 0.81 to 2.9 Pg C/year[13-21] in the 1990s and 2000s, and uncertainty exists regarding whether tropical forests are a net carbon sink or source. Some studies have shown that the amount of CO_2 released into the atmosphere from tropical deforestation is similar to that absorbed by growing forests,[17,22] whereas others have reported that tropical forests are a net carbon source.[7]

One important source of uncertainty in estimating carbon emissions from deforestation is the methods and data used to estimate the areas of forest loss and carbon stock density before deforestation. In early studies, the forest areas reported to the United Nations Food and Agriculture Organization by country and forest inventory plot data were used to obtain the statistics of global forest changes and carbon emissions from deforestation.[6,12,13,15-17] The advent of global coverage by high-resolution optical satellite imagery led to the widespread use of satellite data to map forest loss.[3,14,21-23] However, the estimation of forest carbon stock density requires different techniques. Several pan-tropical maps of forest aboveground biomass (AGB; in Mg dry biomass/ha) and carbon stock density (AGCD; in Mg C/ha)[18,24,25] have been derived from satellite images and substituted for forest inventory data in methods of carbon loss accounting.[6,7,18-21,25] These maps were mainly produced using 1.0-km or 500-m optical reflectance data[7,18,24] assisted by the point sampling of AGCD using the Geoscience Laser Altimeter System (GLAS) onboard ice, cloud, and land elevation satellite. Several studies have indicated that these pan-tropical maps created during the year 2000 overestimate AGB, leading to an overestimation of the carbon loss from deforestation.[26,27]

In the past three decades, considerable effort has been devoted to estimating the carbon stock density of forests using satellite-based optical reflectance, radar backscattering intensity, and passive microwave signatures.[28-30] However, none of these technologies can directly measure forest carbon stock or its decisive variables. Additionally, the spatial resolution of spaceborne passive microwave data is too coarse, whereas optical reflectance data have little sensitivity to AGCD outside low biomass areas,[31] as they are sensitive to the biochemical properties and not to the volumetric properties of forests related to AGB.[32] Radar backscattering is sensitive to AGB but is affected by environmental factors and tends to become saturated with increasing carbon stock density wherein the saturation level increases with decreasing frequency.[33] Hence, new space missions aiming to estimate forest carbon stocks rely on direct measurements of the forest spatial structure using lidar (NASA's Global Ecosystem Dynamics Investigation [GEDI])[34] or long-wavelength radar (the European Space Agency P-band BIOMASS[33] and the NASA-ISRO NISAR missions[35]). Until these new space missions are in complete operation, the estimation of forest AGB from space data must rely on the imaginative use of sensors designed for purposes other than measuring forest structure. We found that vegetation carbon loss

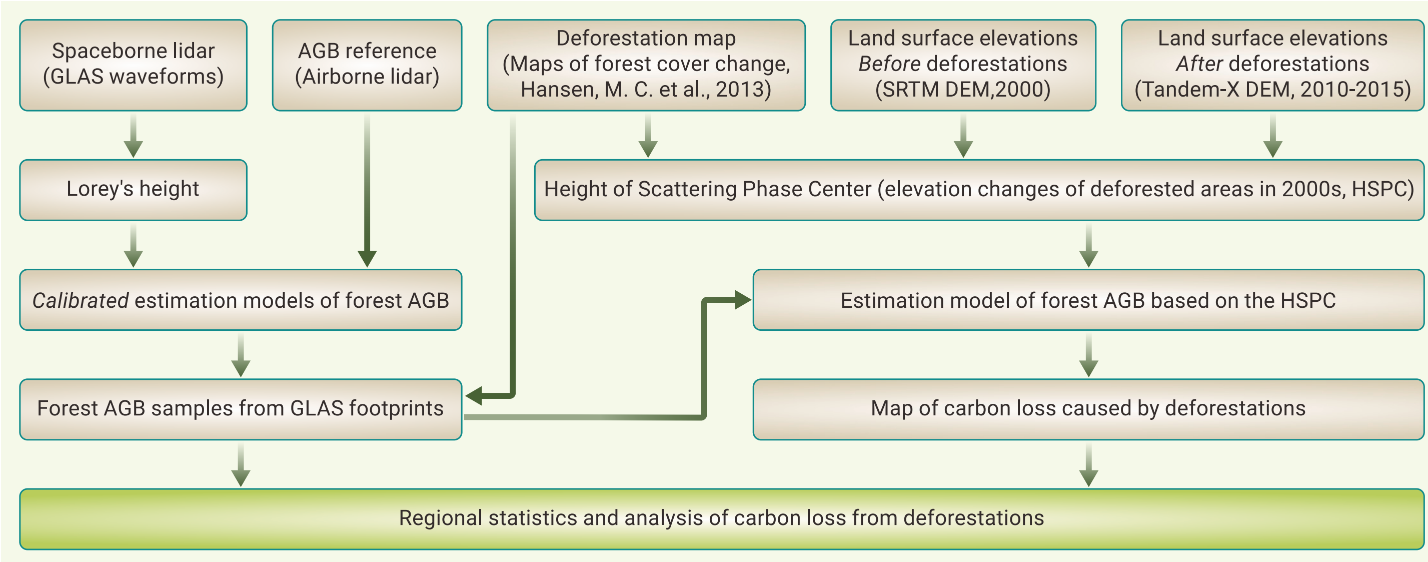

Figure 1. Workflow for mapping the carbon loss in deforested areas

from deforestation can be estimated based on the direct measurement of forest spatial structures by changes in land surface elevation before and after deforestation. This study reports new estimates based on this idea.

MATERIALS AND METHODS

The workflow for this study for mapping carbon loss from deforestation in Latin America between 2001 and 2009 is shown in Figure 1. The map of deforestation areas was obtained from high-resolution global maps of forest cover change in the 21st century,[3] as shown in Figure S1. Land surface elevations before and after deforestation were obtained from two global digital elevation models (DEMs): the Shuttle Radar Topography Mission (SRTM) and TanDEM-X DEMs. The SRTM-DEM was produced using interferometric synthetic aperture radar (InSAR) images acquired in February 2000,[36,37] whereas the TanDEM-X DEM was generated using InSAR images acquired between 2010 and 2015.[38] Therefore, the changes in elevation between the SRTM and TanDEM-X DEMs after precise co-registration[39] could help determine the height of the scattering phase center (HSPC) relative to the ground surface for forest loss between 2001 and 2009 (with possible uncertainty owing to regrowth). This idea was demonstrated by comparing samples of deforested areas with elevational changes, as shown in Figures 2A and 2B, respectively. These images comprised spatial patterns, although they were derived from independent remote-sensing datasets. Notably, non-zero HSPC values were observed in deforested areas.

HSPC has been demonstrated to be strongly related to forest AGB.[40-44] The estimation model of forest AGB based on HSPC was developed using AGB samples from the waveforms of the geoscience laser altimeter system (GLAS) acquired before deforestation. We located 9,132 GLAS footprints acquired between 2003 and 2005 in forest areas that were subsequently deforested. Their spatial distributions are shown in Figure 3A. A typical GLAS waveform before forest loss is shown in Figure 3B, along with elevations from the SRTM and TanDEM-X DEMs (more cases are shown in Figure S2). Notably, the ground peak of the GLAS waveform is located close to the elevation provided by TanDEM-X (the error in the ground surface elevation obtained from TanDEM-X is less than 2.0 m[45]), whereas HSPC is the difference between the elevations of the SRTM and TanDEM-X DEMs.

Lorey's height (LoreyH), a basal area-weighted mean tree height,[46] can be estimated from GLAS waveforms and is linearly correlated with the HSPC (correlation coefficient r = 0.86), as demonstrated by the scatterplot of HSPC against LoreyH for the full set of GLAS footprints in Figure 3C. LoreyH is known to be well correlated with AGB, enabling the estimation of forest AGB in the GLAS footprints acquired before deforestation using the model described in Saatchi et al.[24] We did not possess concurrent field measurements of AGB at GLAS footprints but utilized the advantage of an airborne laser scanner (ALS) dataset collected in 2012 at sites shown in Figure S4A, which has previously been used to estimate AGB in Brazil.[47] A total of 112 GLAS footprints in forests undisturbed after the acquisition of GLAS data were located within the coverage of the ALS. As shown in Figure S4B, the GLAS-based AGB was clearly underestimated, which was corrected by a calibration factor of 1.96, as shown in Figure S4C. Finally, the calibration factor was applied to the AGB for all 9,132 GLAS samples.

The strong correlation between the HSPC and LoreyH enabled the direct estimation of the AGB lost from all areas of forest loss in Latin America between 2001 and 2009 without

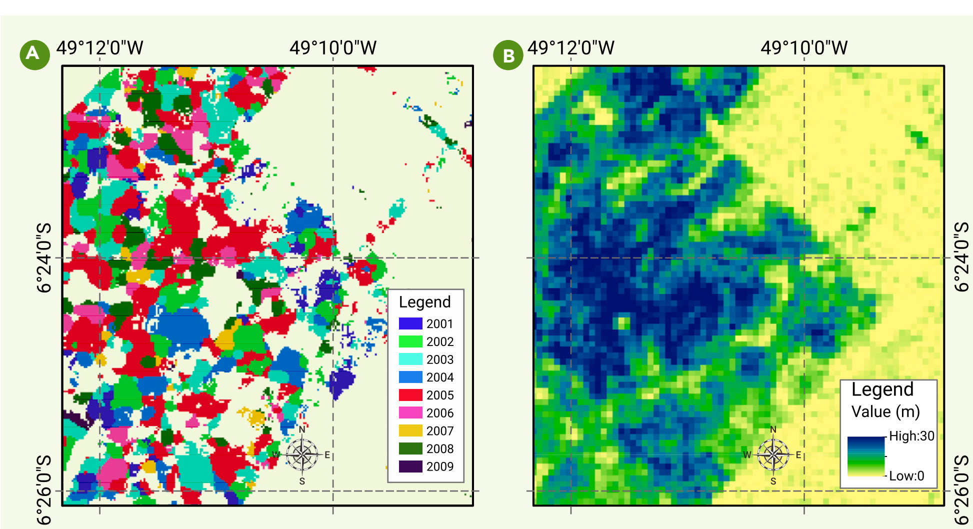

Figure 2. Height of the scattering phase center of SRTM-DEM extracted in deforested areas (A) Samples of deforestation areas provided by the maps of forest cover change. (B) Samples of elevation changes between SRTM-DEM and TanDEM-X DEM corresponding to (A).

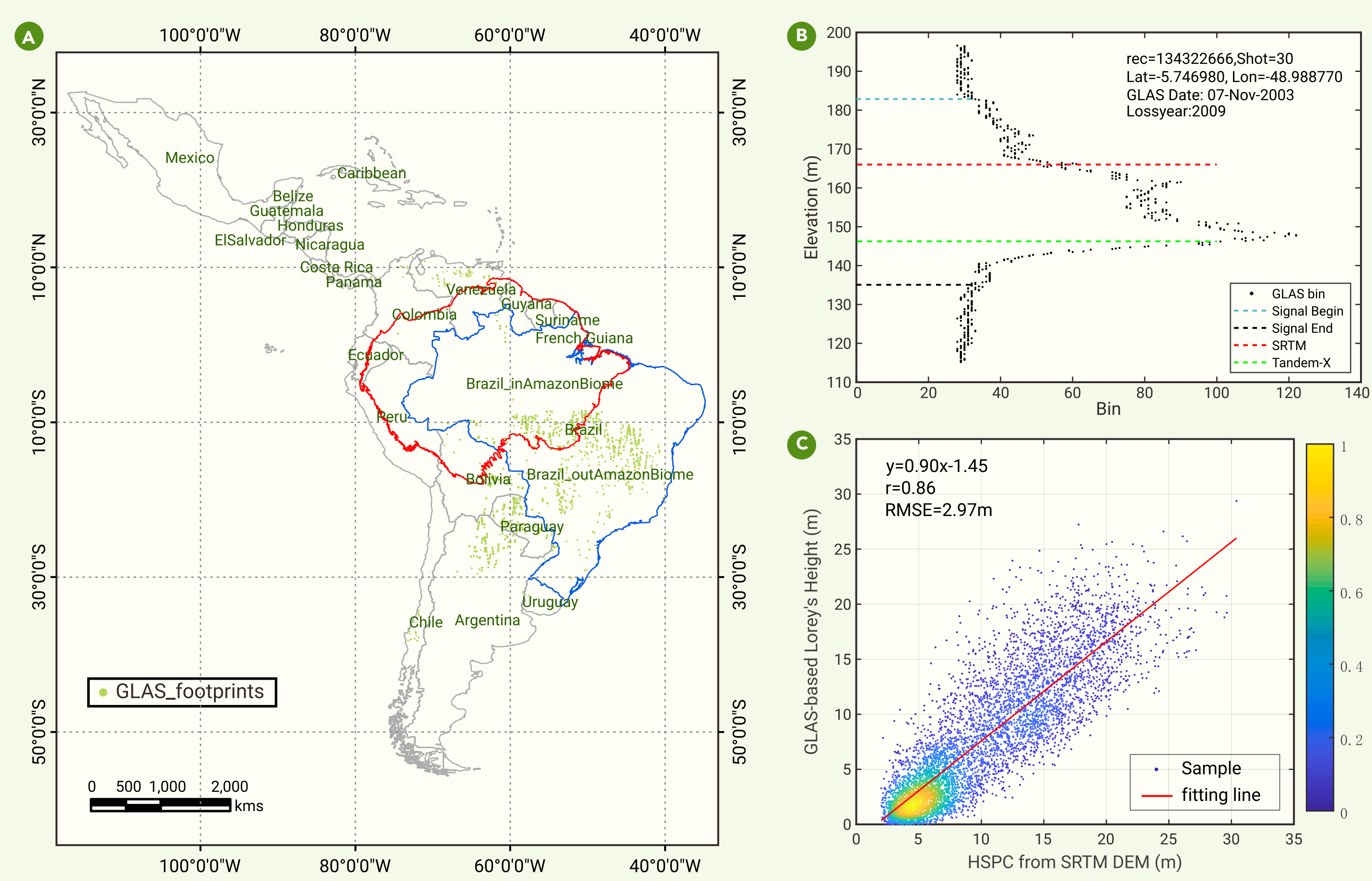

Figure 3. Relationship between HSPC and LoreyH (A) The spatial distribution of GLAS footprints. (B) Elevations from SRTM and TanDEM-X data superimposed on a typical GLAS waveform acquired in November 2003 at a forest site cleared in 2009. (C) Scatterplot of LoreyH against HSPCs for all 9,132 GLAS waveforms.

extrapolation using any other data. Belowground biomass (BGB) was then estimated using the equations from Mokany et al.[48] In accordance with the Intergovernmental Panel on Climate Change Report (IPCC, 2014),[12] a factor of 0.5 was used to convert AGB and BGB to estimate the carbon stock density.

RESULTS

Carbon loss statistics by country

A carbon stock density map of the forest lost before deforestation is shown in Figure 4. The statistics of the yearly and average carbon losses from deforestation for Latin America and its constituent countries are presented in Table S1. Histograms and cumulative frequencies of the associated carbon losses for Latin America and the selected countries are shown in Figure 5 (note the different scales on the axes for different regions). Notably, deforestation in most countries predominantly occurred in forested areas with lower carbon stock densities. In Latin America, pixels with carbon stock densities less than 20, 50, and 100 Mg C/ha accounted for 42.1%, 62.0%, and 83.3% of the total deforested area, respectively (Figure 5A). Those in Brazil were similar to the overall region with percentages of 35.5%, 54.4%, and 79.3%, respectively (Figure 5B). The situation within and outside the Amazon biome was considerably different, as shown in Figure 4, wherein the percentages of deforested areas with a carbon stock density of >50 Mg C/ha were 63.56% and 14.75%, respectively. Different countries exhibited slightly different patterns. The percentages of deforested pixels in Argentina and Mexico were 54.8% and 53.0%, respectively, with carbon stock densities below 10 Mg C/ha (Figures 5C and 5D). In French Guiana, 10.2%, 32.3%, and 52.9% of the deforested pixels had carbon stock densities of less than 10, 50, and 100 Mg C/ha, respectively (Figure 5E). In Chile, approximately 40.1% of the deforested pixels had a carbon stock density below 50 Mg C/ha (Figure 5F).

The relative contributions of countries in terms of the forest area and carbon loss, along with their mean carbon stock densities, are shown in Figures 4A–4C. The total area of forest loss from Latin America in the 2000s was 46,348 kha and predominantly occurred in Brazil (28,573 kha, 61.65%) (Table S1 [4]). Other countries contributing more than 2% to the total area of forest loss are Argentina (7.37%), Paraguay (5.53%), Bolivia (4.27%), Colombia (4.17%), Mexico (4.06%), Peru (2.20%), and Venezuela (2.19%) (Figure 4C). The cumulative forest loss for these eight countries was 42,378 kha accounting for 91.4% of the total forest loss. The carbon loss in Brazil was also significant. The total carbon loss owing to deforestation in Latin America was 2,277.1 Tg C in the 2000s, approximately 70.9% of which occurred in Brazil. Five other countries produced carbon losses greater than 2% of the total: Bolivia (5.98%), Colombia (4.21%), Chile (2.84%), Peru (2.55%), and Argentina (2.09%) (Figure 4A). The carbon loss from these six countries was 2,017.9 Tg C accounting for 88.6% of the total carbon loss.

The countries have different relative importance in terms of forested areas and carbon losses. Paraguay, Mexico, and Venezuela contribute to less than 2% of the carbon loss but more than 2% of the forest area loss owing to their lower carbon stock densities before deforestation, namely 15.16, 19.35, and 36.46 Mg C/ha, respectively (Figure 4B). Hence, the map of forest area loss does not represent carbon loss. Although Brazil contributed to 61.65% of the total loss of forested area, its contribution to carbon loss was 70.9%. French Guiana, Chile, and Suriname are three countries with the highest carbon stock densities of lost forests before deforestations (101.98, 75.15, and 74.4 Mg C/ha, respectively) (Figure 4B) but are relatively unimportant in terms of both forest area loss and carbon loss from deforestation.

Figures 4D–4F and 6 show the trends of deforestation in the 2000s for all Latin American and selected countries, respectively. In Latin America (Figures 4D–4F), the maximum forest area loss occurred in 2004, whereas the maximum carbon loss occurred in 2005 owing to the increase in the carbon stock density of deforestation. Slight increases in forest area loss were observed in 2007 and 2008, but we did not observe carbon loss owing to

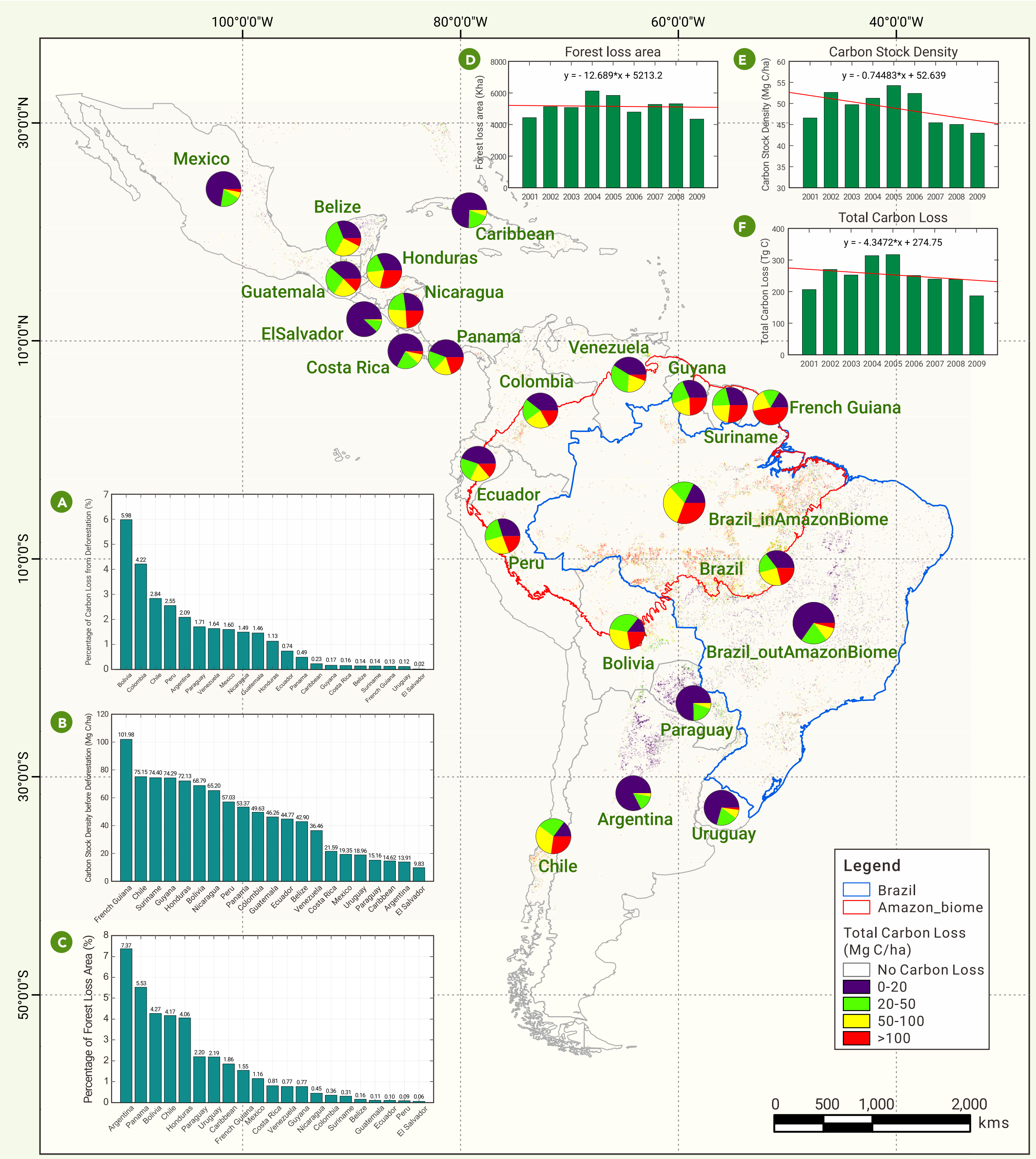

Figure 4. Carbon stock density map of lost forests before deforestations and statistical analysis The background image is the carbon stock density map. (A–C) Relative importance of different countries in terms of total carbon loss, carbon stock density and deforestation areas. (D–F) Trends of deforestations in the 2000s in terms of areas, carbon stock density and total carbon loss.

decreases in the carbon stock density during deforestation. Latin American countries exhibited different temporal trends. In Brazil, the patterns of forested area loss and carbon loss were similar, both of which increased from 2001 to 2004 and subsequently decreased thereafter (Figures 6A–6C). In Paraguay, an abrupt increase in carbon loss occurred in 2007 owing to forest area loss, although the carbon stock density continuously decreased (Figures 6D–6F). In Guyana, an abrupt increase in carbon loss occurred in 2008 owing to an increase in both the forest area loss and carbon stock density (Figures 6G–6I). Uruguay, Mexico, and Guyana exhibited statistically significant increases in forest area loss (Figure S7), whereas Mexico, Venezuela, and Guyana showed

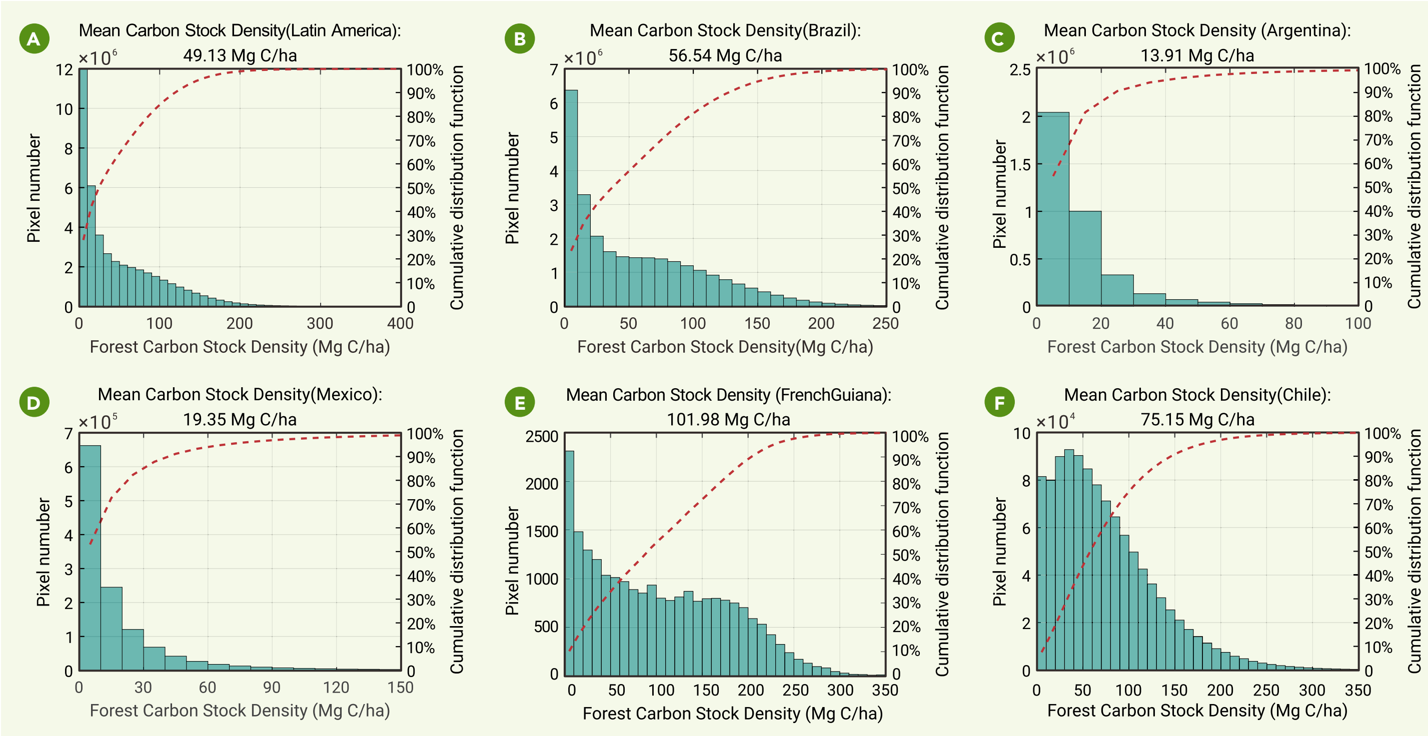

Figure 5. Carbon densities and relative loss contribution of countries (A) Histogram and cumulative frequency of carbon stock density of deforested pixels in Latin America between 2001 and 2009. (B–F) Histograms and cumulative frequencies of pixels for selected countries.

statistically significant increases in carbon loss (Figure S8). Guyana, Peru, and French Guiana exhibited an increasing trend in the carbon stock density before deforestation, indicating that deforestation shifted to areas with a higher carbon stock density, whereas Paraguay showed a decreasing trend in the carbon stock density (Figure S9).

Comparisons with existing results

Table 1 presents the comparison of our results with those of other studies based on remote-sensing data. The areas of annual forest loss based on Hansen et al.[3] for 2001–2012 and Harris et al.[6] for 2000–2005 were 5,052 and 4,873 kha/year, respectively, whereas the value obtained in our study was 5,150 kha/year. The small difference (approximately 1.9%) between our estimate and that of Hansen et al.[3] was attributed to the different time periods of the investigations. However, our estimate of carbon loss from deforestation was 253.0 Tg C/year, which is only approximately half those of Baccini et al. (2017)[7] and Harris et al.[6] (519.8 and 438 Tg C/year, respectively). Brazil was the major contributor to the total carbon loss: our estimate was 179.5 Tg C/year, whereas those of Baccini et al. and Harris et al.[6] were 332.5 and 340 Tg C/year, respectively. Although the estimates of Baccini et al. and Harris et al.[6] were similar for Brazil, their estimates outside Brazil were considerably different. The estimate of Baccini et al. for the rest of Latin America was 187.3 Tg C/year, which is nearly double that of Harris et al.[6] (98 Tg C/year), whereas our estimate is 73.5 Tg C/year. The estimates of Baccini et al. were considerably higher than those of our study and Harris et al.[6] in Bolivia, Colombia, Peru, and Venezuela (Figure 7A).

Our estimates of carbon loss were significantly lower than those of other studies, both inside and outside Brazil, mainly owing to different estimation methods of carbon stock density before deforestation. To examine this further, we investigated the estimates of GLAS footprints. We could not directly use the carbon stock density dataset of Baccini et al. (2012),[18] as it was not publicly available. However, the 30-m carbon stock density map from the NASA Carbon Monitoring System (CMS) was generated by the same group using the same methods but with LANDSAT data instead of MODIS reflectance data.[49] Hence, the CMS dataset, referred to as Baccini et al. (2016), was considered representative of the map of Baccini et al. (2012).

The GLAS-based forest carbon stock density can be used as reference data, as it is located on flat terrain with slopes less than 5° and has been calibrated using ALS data. In the scatterplots of carbon stock density against GLAS-based estimates (Figures 7B and 7C) in Baccini et al. (2016) and Harris et al.[6], most points lie above the 1:1 diagonal line, indicating that the carbon stock densities were severely overestimated by Harris et al.[6] and Baccini et al. (2016). Figure 7D shows the histogram and cumulative distribution function of different carbon densities for all GLAS footprints. Notably, 51.1% and 43.4% of GLAS footprints show carbon stock densities lower than 20 Mg C/ha in the GLAS-based data and our estimations, respectively. In contrast, in Harris et al.[6] and Baccini et al. (2016), only 22.4% and 6.1% of the GLAS footprints were within this interval of low carbon stock density. This translates into an overestimation of the total carbon loss in these GLAS footprints. The carbon loss estimates of Harris et al.[6] and Baccini et al. (2016) were 0.218 and 0.252 Tg C, respectively, assuming the radius of a GLAS footprint is 32.5 m, whereas the GLAS-based results and our estimates were 0.140 and 0.147 Tg C, respectively.

Owing to the even scattering of GLAS footprints across the entire region, as shown in Figure 3A, the statistics based on GLAS footprints reveal approximately the same facts as those based on HSPC, namely, the carbon stock density was significantly overestimated in existing maps produced using satellite-based optical reflectance. Samples of GLAS footprints confirmed that the forest loss in Latin America in the 2000s predominantly occurred in forest stands with lower carbon densities, rather than in typical mature forests, as indicated by the existing maps of the pre-deforestation carbon stock density.

DISCUSSION

Uncertainties

The critical difference between our study and previous ones is the estimation of carbon stock density in deforested areas. Instead of using a low-resolution (0.5–1 km) carbon stock density map based mainly on optical reflectance data, in our study, the carbon stock density in the deforested areas was estimated from HSPC at a much finer spatial resolution (90 m) after training with GLAS waveform measurements. The mismatch of scales between the coarse image resolution and GLAS footprint size in other studies may be an important source of uncertainty. Although the reported accuracies of the estimation models of existing coarse-resolution maps have not been questioned, their limited accuracies have been demonstrated in existing studies through comparison with ALS data[26,47] (as shown in Figures S10 and S11 for the convenience of readers). Additionally, coarser-resolution biomass maps may overestimate the biomass

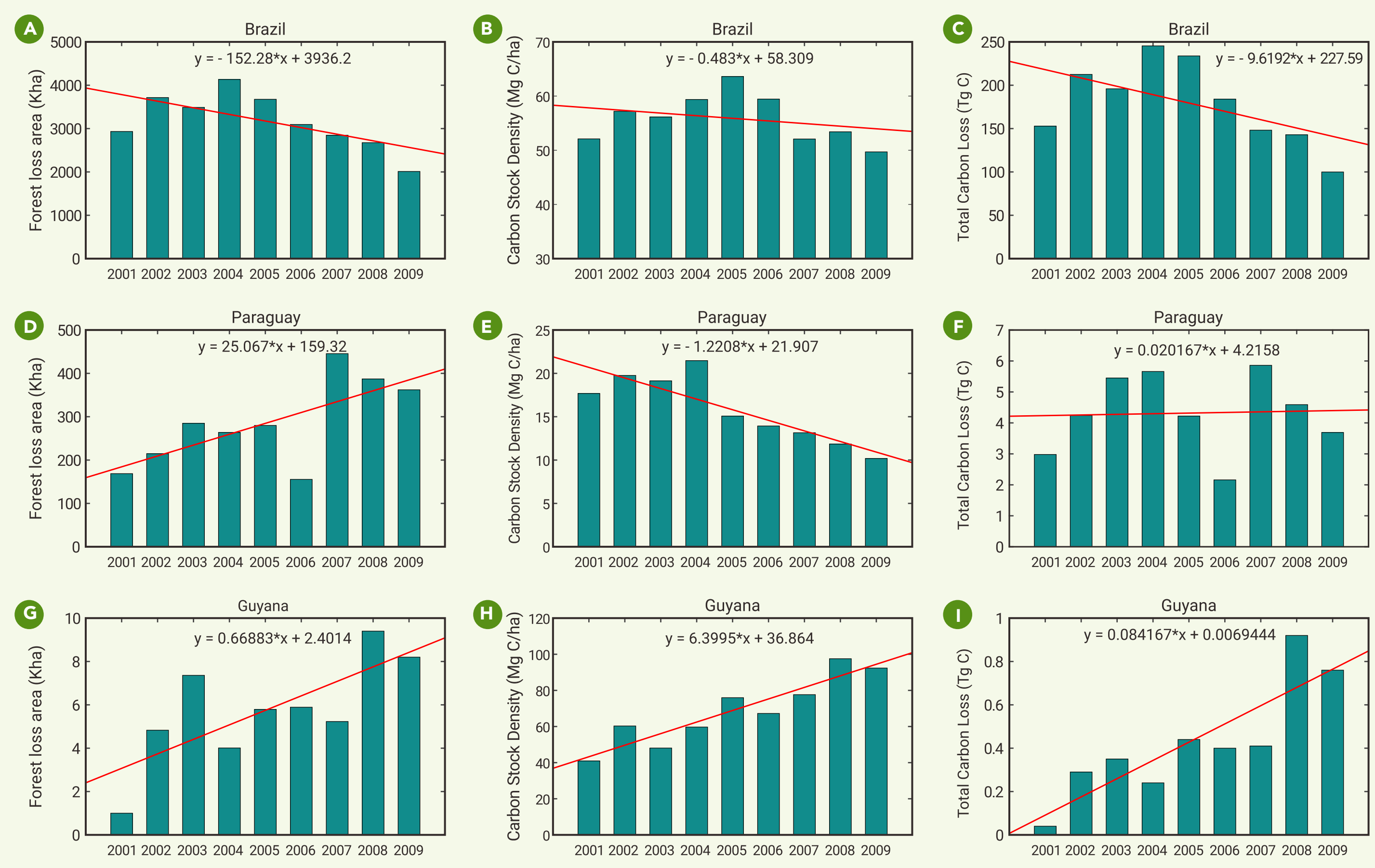

Figure 6. Trends of deforestations of selected countries in the 2000s The three rows represent Brazil (A–C), Paraguay (D–F), and Guyana (G–I), respectively; the three columns from left to right represent the deforestation areas (A, D, G), carbon stock density (B, E, H), and carbon loss (C, F, I).

carbon in heterogeneous pixels, as the data employed to calibrate the mapping algorithms often use sample plots that are much smaller than the image pixels. We avoided this mismatch by employing the same finer-spatial resolution data used in developing the model; thus, our method can yield more accurate results. The uncertainty in model development and its propagation were mathematically analyzed as described in the supplemental information. Considering GLAS-based estimations as references, the estimation uncertainty based on HSPC of all GLAS footprints was as follows: (0.147 − 0.14 Tg C)/0.14 Tg C = 5%.

Additionally, a bootstrap method was also used to quantify the uncertainty of the estimations of carbon emissions for all GLAS footprints. The maximum uncertainty was 8.3%. Correspondingly, the uncertainty of carbon loss estimation of the entire region was 253.0*0.083 = 20.9 Tg C/year, and the final estimation was 253 ± 20.9 Tg C/year.

Forest regeneration between the time of forest loss and TanDEM-X acquisition could reduce the estimate of overall carbon emissions, as the height estimated from TanDEM-X would lie above the true ground level. The forest gain map (from non-forest to forest) produced by Hansen et al. was used to assess the effects of forest regeneration in our estimates. The LANDSAT data used for the map were acquired approximately in 2010, during which approximately 7.2% of the forest-based pixels lost between 2001 and 2009 were converted back to forest. Using an annual growth rate[50] of 3.05 Mg C ha^{-1} $year^{-1}$ and the number of years between forest loss and 2010, the total carbon accumulated from regrowth was estimated as 8.06 Tg C/year; this value is only approximately 3.2% of our current estimate of carbon emissions of 253.0 Tg C/year.

Another source of uncertainty is terrain-related issues, such as aspects or slopes. Notably, terrain features exist on the direct difference maps of SRTM and TanDEM-X, which could cause uncertainties in the estimation of the forest carbon stock density. We previously found that errors related to aspects or slopes in the difference image of the two DEMs were caused by their mismatch in terms of the geolocation, which is obvious even if the mismatch is only approximately one pixel, especially over mountainous areas. We developed an automatic algorithm for the accurate co-registration of any two DEMs,[39] which can match the DEMs with sub-pixel accuracy. The terrain-related features on the direct difference maps of SRTM and TanDEM-X disappeared once they were accurately matched using the proposed algorithm.

Notably, TanDEM-X data acquired after deforestation were used to determine the elevation of the ground surface. Our estimation was based on the HSPC of SRTM, namely, the difference between the SPC of the C-band of InSAR and ground surface but not the different penetration capabilities of the C- and X-bands used by SRTM and TanDEM-X, respectively. The new findings of this study are not only based on the HSPC data of the entire region but also on the samples of the GLAS waveforms. Although some uncertainties in the estimation based on HSPC are inevitable, the estimations based on GLAS waveforms are more reliable from three aspects: (1) they are evenly distributed across the entire region, and their spatial representation is therefore guaranteed; (2) they are all located on terrain with slopes smaller than 5° and are therefore less affected by terrain conditions; and (3) they are calibrated by a scale factor by considering the estimations of ALS data as references, which eliminates systematic bias.

Implications on the regional and global carbon budgets

The estimation of carbon loss in this study is a great challenge owing to the current knowledge of the role of tropical forests in the global carbon budget. Table S4 presents a list of published estimates of carbon loss and gain in regional and global tropical forests.[7,17] Baccini et al.[7] reported that the yearly gain of aboveground carbon between 2003 and 2014 was 191.2 ± 18.2 Tg C/year in American tropical forests and 436.5 ± 31.0 Tg C/year in global tropical forests. The yearly losses of aboveground carbon were 516 ± 69.5 and 861.7 ± 80.2 Tg C/year in American and global tropical forests, respectively. Therefore, they concluded that tropical forests are a net source of carbon. However, their conclusion may be inaccurate based on our estimates of carbon loss. According to the gain of aboveground carbon in Baccini et al.[7] and that of belowground carbon

Table 1. Country-based statistics of the yearly deforestation from different studies

Country/ region	Gross forest cover loss (kha/year)			Forest carbon stock density (Mg C/ha)		Carbon loss from deforestation (Tg C year^{-1})		
	Hansen et al.,[a] 2001–2012	Harris et al.,[b] 2000–2005	This study, 2001–2009	Harris et al., 2000–2005	This study, 2001–2009	Baccini et al.,[c] 2003–2010	Harris et al.,[b] 2000–2005	This study, 2001–2009
Argentina	391.31	437	379.53	24	13.91	3.89 ± 0.34	10	5.28
Belize	10.04	9	8.42	105	42.90	0.60 ± 0.06	1	0.36
Bolivia	248.89	129	220.05	90	68.79	50.99 ± 4.11	11	15.14
Brazil	3,002.31	3,292	3,174.82	116	56.54	332.49 ± 26.9	340 (270,481)	179.49
Chile	98.99	67	95.55	52	75.15	0.04 ± 0.0	6	7.18
Colombia	209.93	137	214.87	138	49.63	34.75 ± 2.72	14	10.66
Costa Rica	13.77	12	18.38	105	21.59	0.94 ± 0.07	1	0.40
Ecuador	43.72	37	41.63	149	44.77	4.99 ± 0.31	4	1.86
El Salvador	4.73	2	5.40	49	9.83	0.18 ± 0.01	0	0.05
French Guiana	3.68	2	3.22	160	101.98	1.98 ± 0.16	0	0.329
Guatemala	74.02	50	79.73	92	46.26	3.87 ± 0.32	5	3.69
Guyana	7.62	13	5.75	161	74.29	6.69 ± 0.44	1	0.43
Honduras	40.50	17	39.66	77	72.13	2.04 ± 0.18	1	2.86
Mexico	198.84	140	208.85	48	19.35	10.88 ± 0.95	8	4.04
Nicaragua	68.54	50	59.50	113	65.20	2.39 ± 0.19	6	3.88
Panama	22.28	12	23.24	115	53.37	1.51 ± 0.09	1	1.24
Paraguay	316.32	242	284.65	27	15.16	10.89 ± 0.90	9	4.32
Peru	127.41	57	113.25	158	57.03	24.26 ± 1.92	7	6.46
Suriname	6.03	6	4.71	161	74.40	4.17 ± 0.38	1	0.35
Uruguay	16.89	19	16.01	28	18.96	–	1	0.30
Venezuela	107.98	115	112.69	134	36.46	20.83 ± 1.76	9	4.11
Caribbean	37.89	28	39.82	46	14.62	1.40 ± 0.12	2	0.58
Latin America	5,051.68	4,873	5,149.73	112	49.13	519.78 ± 42.49	438 (309,674)	253.01 ± 20.9

[a][h)+i)+j)+k)]*100/1,000/12 or *100/1,000/12, where h), i), j), and k) represent the column IDs presented in Table S3 in Hansen et al.[6]
[b]Median in Harris et al.[6] (low, high).
[c]Average of the first seven columns presented in Table S1 in Baccini et al. (2017).

estimated by the equations from Mokany et al.,[48] the gains of total carbon were 243.6 ± 18.7 and 545.8 ± 31.8 Tg C/year in American and global tropical forests, respectively. In American tropical forests, the carbon loss estimated in this study, namely 253 ± 20.9 Tg C/year, approximates the gain of total carbon estimated by Baccini et al.[7] These results do not support their conclusion that American tropical forests are a carbon source. Considering that the ratio of carbon loss between American and global tropical forests reported in Baccini et al.[7] is acceptable, based on our estimates, we deduced that carbon loss of global tropical forests was approximately 417.9 ± 34.5 Tg C/year. Considering a carbon gain value of 545.8 ± 31.8 Tg C/year, the global tropical forest is most likely not a carbon source.

In contrast to Baccini et al.,[7] Mitchard[8] concluded that the contributions of tropical forests to the global carbon budgets are approximately neutral based on literature reviews. The estimates of Pan et al.[17] provide important evidence. As listed in Table S4, their estimates of carbon gain and loss of global tropical forests were 2.74 ± 0.72 and 2.82 ± 0.45 Pg C/year, respectively, indicating the almost neutral role of the tropical forests in the global carbon budget. Our estimate of carbon loss of global tropical forests, namely 417.9 ± 34.5 Tg C/year, was only 15% of that of Pan et al.[17] The global tropical forest is definitely a carbon sink if the carbon loss is updated based on our estimate while also including the carbon gain of Pan et al. Considering American tropical forests, the carbon gain was approximately 1.22 ± 0.32 Pg C/year, which was determined based on the ratio of carbon gain of American to global tropical forests in Pan et al.[17] The deduced carbon gain was approximately 4.8-fold of our estimate of carbon loss, namely, 253 ± 20.9 Tg C/year. Therefore, according to the results of this study, both the American and global tropical forests are carbon sinks.

Our results indicate that the widely accepted typical carbon stock density of tropical old-growth forests, namely 100 Mg C/ha used in IPCC Tier 1[5] and 112 Mg C/ha proposed in existing satellite-based estimates,[5] does not represent that of many of the forests being cleared and should not be used to estimate carbon loss from deforestation in Latin America in the 2000s except for in French Guiana. The forest loss in Latin America in the 2000s did not mainly occur in old-growth tropical forests but predominantly in forests with an average carbon stock density of only 49.13 Mg C/ha (Table 1).

This study provides strong evidence of the overestimation of carbon sources in the global carbon budget. Earth system science data show that global carbon budgets were not balanced between 2001 and 2009.[1,51] For convenience, the updated data are listed in Table S3. The carbon emissions from fossil fuels and land-use change were 84.18 Pg C, and the carbon uptake in the atmosphere, ocean, and land was 82.90 Pg C. The carbon emission was larger than the carbon uptake by an amount of 1.28 Pg C; however, based on mass conservation, they should be equal. This imbalance is caused by either an overestimation of carbon sources or an underestimation of carbon sinks. Considerable effort has been devoted to the possible underestimation of carbon sinks, particularly land sinks, whereas possible errors in the source terms have been ignored. In this study, we

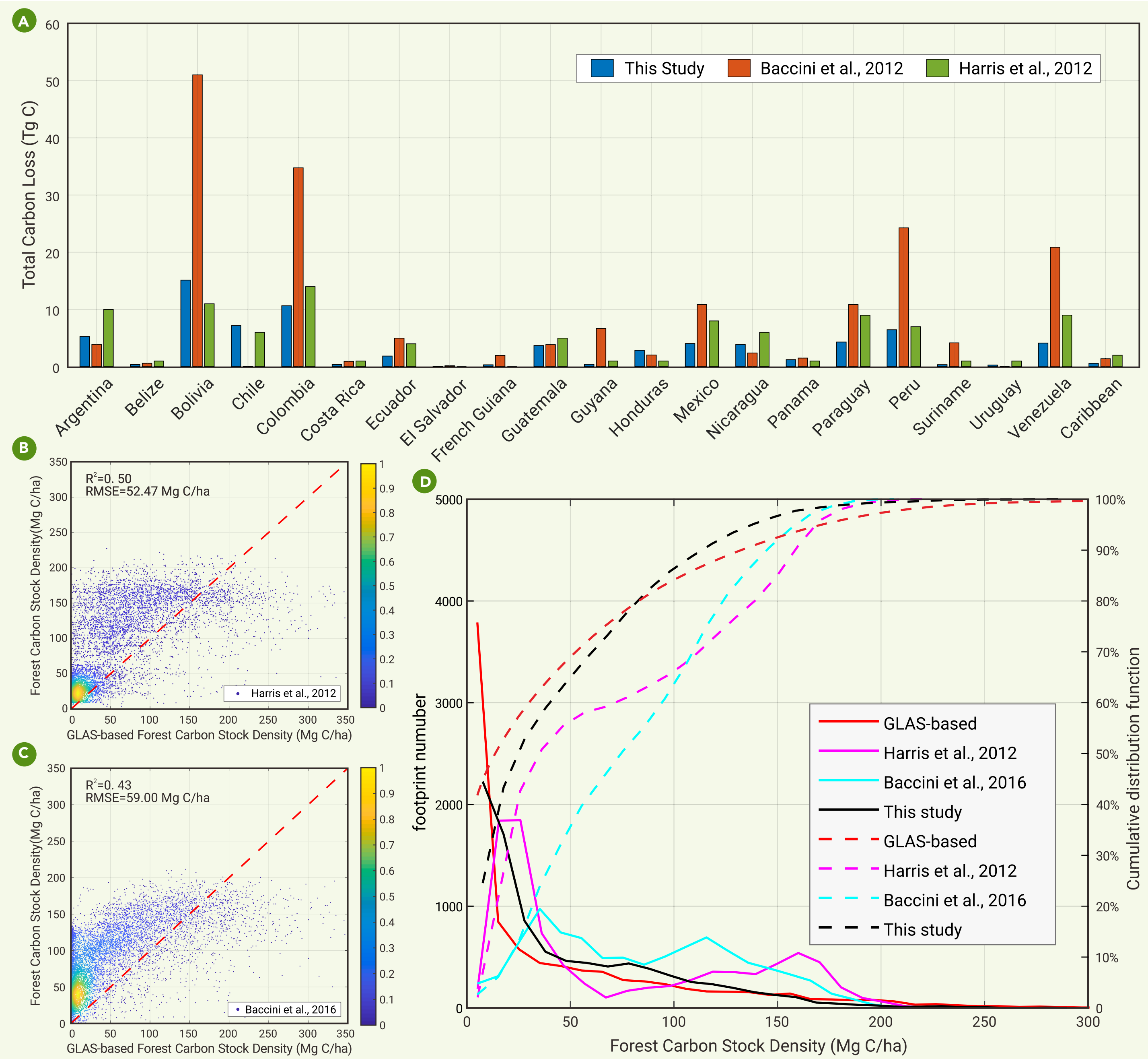

Figure 7. Comparison of our results with those of existing studies (A) The estimated carbon loss (Tg C/year) of this study and those of Harris et al.[6] and Baccini et al. (2012) for all Latin American countries except Brazil. (B) The carbon stock density of Harris et al.[6] against GLAS-based estimates. (C) The carbon stock density in Baccini et al. (2016) against GLAS-based estimates. (D) Histograms (solid lines) and cumulative distribution functions (dashed lines) of different carbon densities of all GLAS footprints.

found that the carbon stock density was previously overestimated in deforested areas between 2001 and 2009, which is the correct method to rectify the aforementioned imbalance.

This imbalance has been an important issue in global carbon budgets since 1990s, namely, carbon sources are larger than carbon sinks. This sustained imbalance suggests an overestimation of emissions and/or underestimation of sinks. However, considerable effort has been devoted to rectify the underestimation of sinks,[22,52] whereas rectifying the overestimation of emissions has been ignored. The consistency between statistics based on limited field samples of typical tropical forests and regional estimations based on existing remote-sensing maps has limited the exploration of the issue of overestimation. Notably, existing coarse-resolution maps have better performance in capturing the spatial heterogeneity of tropical forests than field sampling measurements; therefore, they are anticipated to provide reliable estimations. However, two aspects indicate that the consistency between field measurements and statistics of existing maps may not be reliable: (1) although the aforementioned maps are developed based on GLAS samples, the scale mismatch between the image resolution and GLAS footprint size cannot be ignored, as discussed in the previous section, and could be an explanation for the limited accuracy when compared to ALS data; and (2) as highlighted by Hansen et al.,[32] both MODIS and LANDSAT are only sensitive to surface properties and types of vegetation and not to the volumetric properties of forests. Consistency was anticipated, as these maps were produced based on training using typical tropical forest samples. Moreover, according to the results of global carbon budgets, the relative uncertainty of the estimations of carbon emissions from land-use change was the largest among all items with a value of 43.7%. Therefore, we demonstrated the importance of the accurate quantification of emissions to solve the issue of imbalance, which has been neglected thus far.

Although measurements of the spatial structure of forests are not direct measurements of carbon stocks, they are determined by the number of trees and tree size, which are decisive variables of carbon stocks. Therefore, new space missions of carbon stocks mostly rely on direct measurements of the forest spatial structure using lidar or radar.[33-35] These new missions may ultimately resolve the apparent disparity between our results and existing estimates and renew our knowledge of the role of tropical forests in the global carbon budget.

Our study provides a new perspective on the role of tropical forests in the global carbon balance. Mitchard[8] reported that the carbon budget in tropical areas is approximately balanced. If this estimate of carbon uptake owing to forest growth was correct, then our new estimate of emissions would indicate that the Latin American tropical forests would have been a net carbon sink in the 2000s. This weakens the case made by Zarin et al.,[25] who stated that halving carbon emissions from tropical deforestation is important to limit the increase in the global average temperature to below 2°C from the pre-industrial level. Although the lack of data prevents the extension of the methods used in this study beyond the 2000s, we provided a more accurate baseline to evaluate the terms and changes in the global carbon cycle. In the future, the data acquired by GEDI, NISAR, BIOMASS, and forthcoming satellite missions may help update our results using the approaches adopted in this study.[53]

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ACKNOWLEDGMENTS

This work was mainly supported by the National Natural Science Foundation of China (42022009), the National Key Research and Development Program of China (2017YFA0603002), and the National Natural Science Foundation of China (41471311), as well as by partial support from the National Key Research and Development Program of China (2020YFE0200800) and the National Natural Science Foundation of China (42090013).

AUTHOR CONTRIBUTIONS

Z.Z., W.N., and G.S. contributed equally to this work. W.N. designed the research; Z.Z. performed the research; G.S. analyzed the data; Z.Z., W.N. and G.S. participated in drafting the paper; S.Q. and J.C. helped to revise the draft; and P.G., H.G., J.S., L.L., Z.L., Y.H., Q.L., L.C.E.R., and Y.S. gave advice on drafting the paper.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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