

## TECHNICAL RESPONSE

## CARBON CYCLE

# Response to Comment on “Tropical forests are a net carbon source based on aboveground measurements of gain and loss”

A. Baccini<sup>1\*</sup>, W. Walker<sup>1</sup>, L. Carvalho<sup>2</sup>, M. Farina<sup>1</sup>, R. A. Houghton<sup>1</sup>

The Hansen *et al.* critique centers on the lack of spatial agreement between two very different datasets. Nonetheless, properly constructed comparisons designed to reconcile the two datasets yield up to 90% agreement (e.g., in South America).

The Comment by Hansen *et al.* (1) provides the opportunity to distinguish our research, which quantifies dynamics in carbon density, from studies focused on the binary classification of changes in forest area (2). We use a multisensor (ICESat/MODIS), multi-stage approach combined with field measurements to map net change (i.e., losses and gains) in carbon density for the period 2003–2014 for each 463 m × 463 m (21.4 ha) pixel in our dataset. Within each pixel, dynamic processes occurring at both the tree and stand level are necessarily considered in aggregate, meaning that losses and gains are happening always and concurrently wherever woody biomass is present. A loss is registered when losses are greater than gains, and vice versa. In this way, we estimate the above-ground contribution to what the atmosphere “sees” at the scale of individual pixel-level units of measurement.

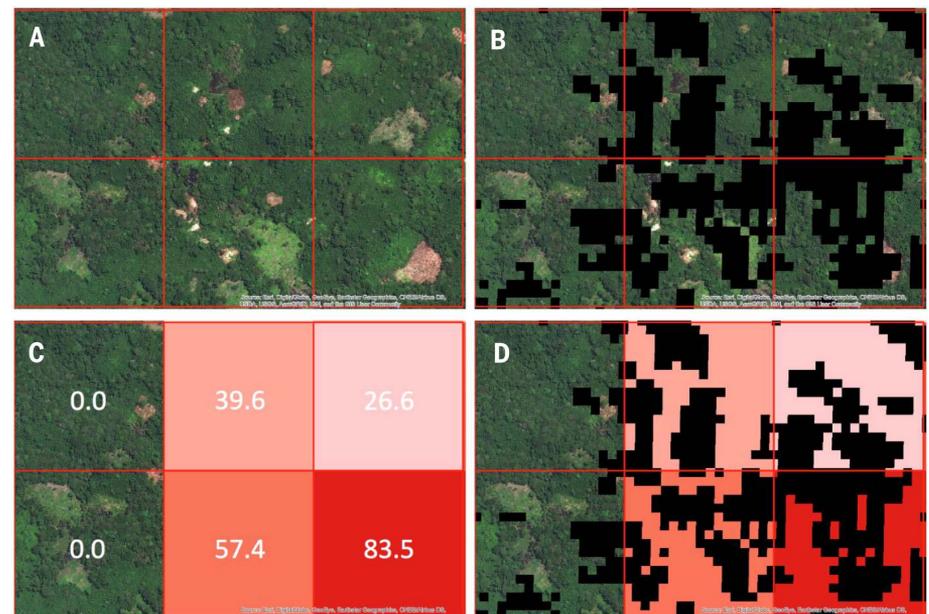
Hansen *et al.* (2) provided pixel-level (30 m) estimates of forest cover loss and gain from 2000 to 2012. Forest cover loss is defined as “stand-replacement disturbance”—that is, any instance where forest cover decreases from >50% to 0% (e.g., deforestation). Trees must be taller than 5 m and forest degradation is not estimated. Gain is the inverse of loss and is defined as any instance of a forest cover increase from 0% to 50%. Whereas loss is reported annually, gain is reported as a 12-year total. The data of (2) are, strictly speaking, binary insofar as a given pixel in a given year is either forest (>50% cover) or nonforest (<50% cover). Moreover, the data are effectively gross binary estimates, meaning that once a loss is recorded in a pixel, a second loss event cannot be recorded even if (i) a second loss event in fact occurs following (ii) a gain being recorded for the same pixel in the gain layer. In

short, the forest cover gross loss and gain layers have no influence on the present or future states of one another.

With these inherent differences in mind, the data products can be compared in regions such as central Africa, where slash-and-burn agriculture is a dominant land-use practice. In the Democratic Republic of Congo (DRC), Barbosa *et al.* (3) report that 92.2% of forest cover loss is linked to

small-scale shifting agriculture. In these systems, the data of (2) record successive loss pixels annually as forest (i.e., >50% cover) is converted to small-scale agriculture (i.e., 0% cover). Despite the cyclical on-the-ground pattern of forest loss and gain observed in any one location, (2) captures only gross losses, recording a loss only once per pixel during the period of study. Similarly, the gain layer captures only gross gains, recording a gain only once per pixel but without reporting the timing of the gain.

The dataset of (4) produces a fundamentally different result in a shifting agriculture system (Fig. 1). Assuming a case where an entire 21.4-ha pixel is dominated by a slash-and-burn mosaic where the ratio of forest to nonforest is approximately 50/50 at any one time, the Baccini *et al.* product would record no change in carbon density in that pixel over the 12-year period of study because, from a net carbon accounting perspective (Fig. 1), the amount of biomass measured aboveground remains constant even though its spatial distribution “shifts.” In other words, the atmosphere registers neither a loss nor a gain in carbon. If the ratio of forest to nonforest is instead 45/55, a small net loss would be recorded. Conversely, if the ratio of forest to nonforest is 55/45, a small net gain would be recorded. That is, a net gain in carbon density would be recorded in the same location where (2) record a gross loss in forest area. On the basis of this example alone, it is not at all surprising—indeed, it is expected—

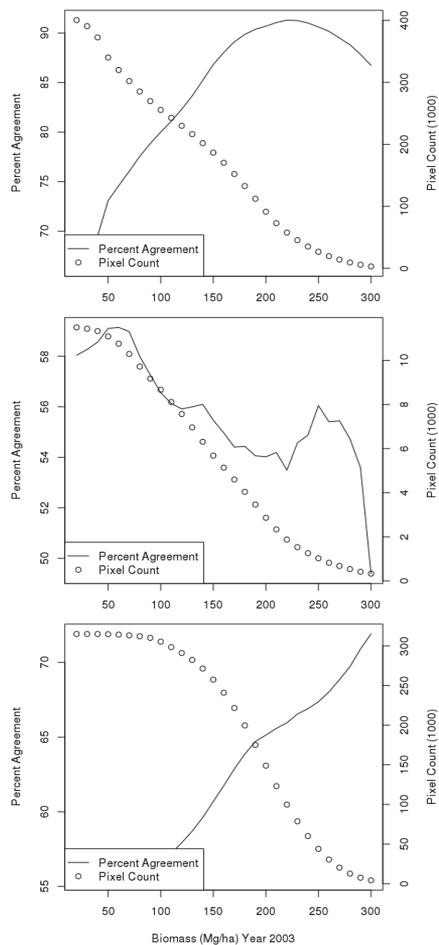


**Fig. 1. Comparison of spatial patterns in Hansen *et al.* and Baccini *et al.* datasets.** (A) Digital Globe image (2013) of shifting cultivation in South Kivu province, Democratic Republic of Congo, with Baccini *et al.* 21.4-ha pixel boundaries shown in red. (B) Hansen *et al.* 30-m forest area loss pixels (2003–2014) shown in black. (C) Baccini *et al.* carbon density change (2003–2014) pixels with loss values in Mg ha<sup>-1</sup> shown in white. (D) Combination of (B) and (C). Hansen *et al.* losses (black) inside Baccini *et al.* pixels (red) can and do agree in terms of overall trend (four eastern pixels); however, depending on the underlying pattern of land use, below some threshold of loss, carbon density change tends toward zero (net neutral; two western pixels) because gains are observed to be equivalent to losses over time. Hence, Hansen *et al.* records gross forest area loss, whereas Baccini *et al.* records no net carbon density change.

<sup>1</sup>Woods Hole Research Center, Falmouth, MA 04523, USA.

<sup>2</sup>Department of Mathematics and Statistics, Boston University, Boston, MA, USA.

\*Corresponding author. Email: abaccini@whrc.org



**Fig. 2. Agreement between Hansen *et al.* and Baccini *et al.* data products.** Tropical America, Africa, and Asia (top to bottom), expressed as a percentage for Baccini *et al.* loss pixels having  $\geq 90\%$  of forest area loss as determined by Hansen *et al.*

that (2) find a lack of spatial agreement between the two datasets.

A comprehensive diagnosis of the lack of agreement between the two datasets is additionally dependent on their inherent error and

uncertainty. At the pixel level, Baccini *et al.* (4) record a net change only if the change is statistically significant at the 95% level ( $P \leq 0.05$ ). For each significant change pixel, the standard error can then be used to compute the 95% confidence interval (CI; uncertainty envelope) for each change value [figure S6 of (4)]. We maintain that our estimates are unbiased, meaning not skewed by magnitude (large versus small) or type (loss versus gain) of change; however, we do not claim that they are without error.

Conversely, (2) report no measures of error or uncertainty at the pixel level but rather cite accuracy assessments derived from probability-based samples [table S5 of (2)], which are relevant only at the biome scale. Although they are useful for applying corrections to biome-level summary statistics on forest area change, they allow for no inferences to be made about pixel-level uncertainty or about the geographic distribution of errors across the landscape. Subsequent to the publication of (2), an error assessment was reported by Tyukavina *et al.* (5), which indicates area-based errors in the forest cover loss map of 21% for the Pan-Amazon, 92% for humid tropical Africa, and 6% for South/Southeast Asia. The pantropical total was estimated to be 24%. Hansen *et al.* do not refer to nor account for these errors in their Comment, further undermining their comparison.

Above, we summarize the two main reasons why the datasets in question should differ: (i) inherent differences in what is being measured and (ii) inherent error and uncertainty characteristics. As a result, the comparisons made by Hansen *et al.* lack merit; however, an example of a proper comparison based on independent carbon density data can be found in figure S10 of (4). That said, Fig. 2 presents what we think is a fair method of comparing the datasets, all things (above) considered. Given the characteristics of (4), agreement with (2) is expected to increase with increasing “loss purity” at the pixel level, defined here as 21.4-ha pixels in (4) where (i) the majority of the area ( $\geq 90\%$  or  $\geq 19.3$  ha) is subject to forest conversion during the study period and (ii) biomass density at the beginning of the study period (2003) is relatively high. Focusing the analysis on “pure loss” pixels minimizes the net signal effect [i.e., concurrent losses/gains within a pixel of (4)], which

necessarily differs from the gross signal that the data in (2) are designed to detect. The results indicate that as loss purity increases, the agreement with the forest area loss data of (2) also increases, reaching more than 90% agreement in tropical America where the prevalence of large-scale deforestation is a dominant contributing factor. In tropical Africa, the agreement is much lower (averaging  $\sim 54\%$ ), given the dominance of mixed pixels across the mosaic of shifting agriculture.

In conclusion, we would like to address the claim in (1) that our data “overstate current monitoring capabilities and may serve to confuse ... practitioners working to establish robust ... carbon monitoring systems.” This statement fails to acknowledge the substantial shortcomings of current monitoring capabilities, which discount degradation and disturbance as noncontributors to emissions. The statement also fails to acknowledge that the status quo often relies upon carbon density data very similar to those being criticized here (6). The intent of our research is to reduce the uncertainty in current emissions estimates. This has meant, among other things, rendering data on forest area change unnecessary to the calculation. Although some may find this departure from standard practice confusing and even concerning, practitioners and policy makers should have every confidence that this new approach can be leveraged to provide estimates of forest carbon dynamics—including contributions from forest cover loss, losses from forest degradation and disturbance, and gains from forest growth—that are overall more comprehensive, more consistent, and less uncertain than before.

## REFERENCES

1. M. C. Hansen, P. Potapov, A. Tyukavina, *Science* **363**, eaar3629 (2019).
2. M. C. Hansen *et al.*, *Science* **342**, 850–853 (2013).
3. C. Barbosa *et al.*, “New map helps distinguish between cyclical farming and deforestation in the Congo Basin” (2018); <https://blog.globalforestwatch.org/data/new-map-helps-distinguish-between-cyclical-farming-and-deforestation-in-the-congo-basin>.
4. A. Baccini *et al.*, *Science* **358**, 230–234 (2017).
5. A. Tyukavina *et al.*, *Environ. Res. Lett.* **10**, 074002 (2015).
6. D. Zarin *et al.*, *Glob. Change Biol.* **22**, 1336–1347 (2016).

9 March 2018; accepted 8 November 2018  
10.1126/science.aat1205

## Response to Comment on "Tropical forests are a net carbon source based on aboveground measurements of gain and loss"

A. Baccini, W. Walker, L. Carvalho, M. Farina and R. A. Houghton

*Science* **363** (6423), eaat1205.  
DOI: 10.1126/science.aat1205

### ARTICLE TOOLS

<http://science.sciencemag.org/content/363/6423/eaat1205>

### RELATED CONTENT

<http://science.sciencemag.org/content/sci/358/6360/230.full>  
<http://science.sciencemag.org/content/sci/363/6423/eaar3629.full>

### REFERENCES

This article cites 5 articles, 3 of which you can access for free  
<http://science.sciencemag.org/content/363/6423/eaat1205#BIBL>

### PERMISSIONS

<http://www.sciencemag.org/help/reprints-and-permissions>

Use of this article is subject to the [Terms of Service](#)