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GEDI Launches a New Era of Biomass Inference from Space

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Abstract

Accurate estimation of aboveground forest biomass stocks is required to assess the impacts of land use changes such as deforestation and subsequent regrowth on concentrations of atmospheric CO₂. The Global Ecosystem Dynamics Investigation (GEDI) is a lidar mission launched by NASA to the International Space Station in 2018. GEDI was specifically designed to retrieve vegetation structure within a novel, theoretical sampling design that explicitly quantifies biomass and its uncertainty across a variety of spatial scales. In this paper we provide the estimates of pan-tropical and temperate biomass derived from two years of GEDI observations. We present estimates of mean biomass densities at 1 km resolution, as well as estimates aggregated to the national level for every country GEDI observes, and at the sub-national level for the United States. For all estimates we provide the standard error of the mean biomass. These data serve as a baseline for current biomass stocks and their future changes, and the mission's integrated use of formal statistical inference points the way towards the possibility of a new generation of powerful monitoring tools from space.

Introduction

The place of formalized inference has long been recognized in applications such as opinion polling and product quality control, where measurement of every individual is impossible and there must be a means of understanding the likelihood that one's sample is representative.

Ground-based forest inventories have been organized around probabilistic sampling for well over 100 years (1). While the use of satellite remote sensing for forest inventory has grown considerably, methods have been slow to embrace formal estimation using remote sensing, in part because values predicted for variables such as biomass using wall-to-wall imagery may simply be summed or averaged over large areas without appealing to sampling theory. However, remote sensing scientists have begun to realize that a theoretical framework is needed to address the potential impact of modeling error in these maps when they are used to describe ecosystem properties, particularly when the remote sensing data themselves are samples, that is, are not spatially continuous (2, 3).

Forest biomass stocks are one of the major uncertainties in the global carbon cycle and their local-scale estimation is a prime challenge using remote sensing. Our ability to infer the impact of land use changes such as deforestation and reforestation on concentrations of atmospheric CO₂ rests upon accurate and spatially resolved estimates of aboveground biomass (AGB) and density (AGBD) (4, 5). Maps of localized biomass estimates, when combined with spatial records of recent land use change (6, 7), support policy-critical decisions about the role of ecosystem dynamics in the climate system. Additionally, having an accurate representation of biomass is essential for the initialization of prognostic ecosystem models used to explore carbon sequestration potential of forests under changing land use and climate change scenarios (8).

Aircraft-mounted laser-based lidar instruments have collected high-quality forest biomass measurements in local- to national-scale projects around the world (9, 10), and space-based lidar

data from ICESat GLAS (the Geoscience Laser Altimeter System) have figured centrally in many of the most prominent existing global-scale biomass maps (11–13). However, GLAS was not engineered for forest monitoring, and coverage of forests conformed to no identifiable sample design – often covering the same orbital paths dozens of times and leaving large areas unmeasured. Efforts to use GLAS have fallen into three general categories, each limited in a specific way. Some efforts have knowingly treated GLAS overpasses as if they were randomly allocated, allowing use of analytically grounded hybrid model-based methods of variance estimation but potentially underestimating variance due to the discrepancy between the hypothetical and actual sample designs (14, 15). One study alternatively subset available GLAS data to what could be presumed to be a spatially balanced random sample, but suffered a substantial drop in statistical power because of the large quantity of data that was eliminated (16). Lastly, some efforts have treated biomass predictions at GLAS footprints as pseudo-plots used to train a second level of model based upon passive optical reflectance data. Lack of an analytical framework linking uncertainties from multiple models and GLAS’ sampling process generally necessitated *ad hoc* error propagation in these efforts, which sometimes produced significantly different estimates over the same areas (17).

In response to the continuing need for accurate observation of canopy structure within an inferential sampling framework designed for biomass estimation across scales, the Global Ecosystem Dynamics Investigation (GEDI) was developed by NASA (18). GEDI uses a multi-beam lidar (Fig. S1) to provide 8 transects of canopy vertical structure at 25 m footprint resolution. Launched to the International Space Station in late 2018, GEDI is specifically optimized to estimate biomass through direct measurement of canopy structure. GEDI’s design supports analytical, closed-form estimation of AGBD in several ways. First, the spatial dimensions of the footprints over which GEDI measures canopy height distribution approximately match both the areas of conventional field plots and the pixel size of medium-

resolution sensors that may be used to model GEDI height metrics across continuous surfaces. Models linking lidar observables to both field measurements and biomass map units can suffer from dilution of precision when there are discrepancies in the amount of ground area covered or if there are significant geolocation errors between lidar metrics and plots (19). GEDI avoids the latter by using a pre-launch calibration strategy based on simulated lidar metrics from precisely located airborne lidar data. Secondly, GEDI predictions of biomass for every footprint are calibrated with the most extensive global set of coincident field and aircraft data yet compiled. Closed-form model-based statistical estimators conventionally accommodate only linear parametric models (3) (though see Esteban et al. (20)) and GEDI's footprint biomass estimation process was created to use such models. The consequence of these first two design strategies is that they enable closed-form estimators for AGBD. GEDI's 25 m footprint biomass predictions are used with hybrid model-based estimators (21) to infer biomass within each 1 km grid cell across the mission's range of observation. The parametric models mentioned above are used to predict biomass for all footprints within a given grid cell, and the hybrid estimates of variance of the mean account for both modeling uncertainty and uncertainty related to how the cell is sampled by GEDI's observations (18). Furthermore, hybrid inference directly enables robust estimates at any aggregation scale coarser than 1 km (e.g., a country) without resorting to the *ad hoc* and approximate methods used in other remote sensing biomass products.

Here, we report the 1 km estimates of biomass from this integrated mission. Current estimates use more than 5 billion footprint-level biomass predictions collected by GEDI across 2.5 years of observations beginning in April 2019. GEDI's frame of inference can also be focused upon broader scales, and we present additional estimates at: (1) the scale of individual countries observed by GEDI, and (2) at the scale of $\sim 12,000$, 640 km² hexagons covering the conterminous United States. We compare these estimates to available reference data by way of validation. We further describe the unplanned orbital resonance that affected the ISS after GEDI's first year on

orbit and detail how the mission's sample design accommodated this development. These new GEDI data provide a much-needed baseline for biomass stocks of tropical and temperate regions for the current epoch and serve as a foundational data set for higher resolution mapping using remote sensing fusion methods.

Methods

GEDI-based biomass estimation at the 1 km, hexagon, and country levels

Aboveground biomass density was estimated for every footprint that measured valid height metrics along each of GEDI's 8 tracks (see Supplementary Materials: Footprint-Level Biomass Estimation). All estimates presented here were produced through the same inferential process: (1) high-quality GEDI waveforms falling within an area of interest were treated as a randomly allocated cluster sample oriented around laser ground tracks; (2) aboveground biomass density was predicted for the footprint of each waveform using a parametric model derived from a global set of calibration data; (3) mean AGBD and uncertainty of that mean for the area of interest were estimated using hybrid model-based estimators (21).

Waveforms comprising the sample were collected from 18th April 2019 to 4th August 2021 and the following criteria were used to identify high-quality shots.

1. Shots flagged as quality by the GEDI L2A Footprint Height and Elevation (22) metric product which identifies surface waveforms with high fidelity.
2. Only shots with a beam sensitivity >0.98 for tropical Evergreen Broadleaf Tree prediction strata, and beam sensitivity >0.95 elsewhere, were included. Beam sensitivity was calculated using a 3-sigma signal threshold and thresholds were selected to provide a sufficiently high signal-to-noise ratio to penetrate the highest canopy cover expected in these regions (23).

3. Shots with high degradation of geolocation performance were excluded from the sample since these may fall outside the geographic extent of a 1 km cell.
4. Orbit granules affected by low cloud/fog, which were identified using an iterative local outlier detection algorithm.

All surface waveforms were used to generate footprint biomass AGBD estimates and standard errors within a 1 km cell and these footprint estimates are provided in the GEDI L4A Footprint Biomass Product (24). Shots that were not land surface or that were designated as urban were assigned a zero mean / zero covariance model. Additionally, leaf-off shots in deciduous forests where the L4A predictor variables included RH metrics below the top-of-canopy were excluded from the sample, as GEDI's L4A models are not applicable to these conditions. See the L4B Gridded Biomass product (25) and its associated algorithm theoretical basis (ATBD) document (GEDI_ATBD_L4B) for more details on the aforementioned data product flags and algorithms used for quality filtering and model assignment.

Not every 1 km cell has a biomass estimate currently due to incomplete spatial coverage as the result of persistent clouds in some areas and the orbital dynamics of the ISS. During the 1st year of GEDI's mission, the ISS was in a randomly precessing orbit and had relatively uniform spatial coverage as a function of longitude. The ISS was subsequently raised to an orbit approximately 16 km higher in early 2020 which resulted in a 4-day repeat cycle. This caused both a clustering of its observations along its orbital track and left unexpected gaps across track (Fig. S2). One requirement of hybrid estimation is that there be at least two tracks per cell for variance calculation. Consequently, biomass was not estimated for cells with only one track because the associated standard error could not be calculated. While GEDI's sampling to date leaves substantial areas without estimates at the 1 km scale, 6 km estimates may be made almost everywhere. For estimates presented here beyond the 1 km scale, we applied straightforward

aggregation, with attention to sampling and model dependencies to 6 km hybrid mean estimates and uncertainties.

The AGBD predictions for each waveform come from the GEDI L4A product which applies linear models to each *plant functional type x world region* combination within the latitudes covered by the ISS. Parametric models are currently required for hybrid model-based inference (26). Specifically, the variance estimators described combine sampling uncertainty—representing how well GEDI covers the area of interest—with modeling uncertainty, which is quantified by the parameter covariance matrix produced through the footprint-level modeling process. GEDI’s L4B Gridded Biomass product is the application of hybrid estimators to the shots within 1 km grid cells across Earth’s tropical and temperate terrestrial ecosystems.

As with any formal mode of inference, it is important to list assumptions associated with hybrid inference. First, the footprint-level AGBD model and its parameter covariance matrix are assumed to apply to the areas where they are used. Training data should ideally represent the range of conditions found in the modeled population (27). Practically, this assumption will be violated to some degree in parts of the world’s ecosystems, resulting in a bias for which the estimator does not account. Secondly, our hybrid variance estimator does not account for model residual error on the assumption that it is negligible when the area of interest is large enough. The residual error of a large number of predictions from a well-fit model should sum to near zero; simulations suggest that a 1 km area is typically large enough to support the assumption of negligible residual variance. (28) A third assumption is that GEDI’s sample conforms to the properties of a randomly allocated cluster sample. Flight lines are conventionally treated as cluster samples with airborne lidar samples (29) and we assume that missing waveforms (most frequently due to clouds) are the result of a random process.

GEDI's estimators do not account for varying probabilities of inclusion in the sample measured by the instrument. Thus, if an estimate is required for an area large enough to exhibit different sampling probabilities, estimates must be aggregated from smaller areas where sampling probability is uniform. For example, differential cloud cover makes GEDI's sample of the rainforests of Brazil sparser than the sample of the savannas in the country's Cerrado region. ISS orbital crossings are also at their sparsest at the equator. The mission's orbital resonance problem created an additional source of irregularity in sampling probability. These factors (uneven cloud cover, ISS orbital track density) are assumed here to be invariant at the scale of 1 km cells. For estimates of larger areas such as countries, we require an intermediate, aggregable estimation scale for which sampling probability may be assumed to be approximately uniform. Since the swath width of GEDI's 8 beams is 4.8 km, we concluded that intermediate estimates for 6 km grid cells ("tiles") would adequately mitigate varying sample intensity caused both by orbital resonance and broader latitude- and cloud-based factors, while minimizing the number of tiles with fewer than two tracks. Supplemental Methods section Aggregating Tile-level Estimates to Larger Areas details our methods of aggregating estimates from 6 km tiles under the hybrid inference paradigm. These methods account for the possibility of using multiple L4A models within a single tile and elaborate methods to consider dependencies when multiple tiles are combined to create mean and variance estimates over large areas, such as countries or the U.S. FIA hex estimates presented here.

USFS FIA estimates

We obtained FIA estimates of AGBD, AGB and the proportion of forest using a fine-scale equal-area hexagonal tessellation covering the conterminous US. The FIA hexagon estimates were published as a comprehensive biomass dataset (30) for validation of remotely sensed biomass estimation at the finest spatial resolution available from the FIA database. Included in the dataset are the FIA's estimate of AGBD across the entire land area within each hexagon, along

with the standard error of the estimate, the proportion of forested area, and the number of FIA plots used to make the estimate. The standard errors were then used to create confidence intervals for each hexagon and to assess the difference of means between GEDI and FIA. We used the values of aboveground live biomass based on the Jenkins et al. (31) allometries to ensure a similar comparison to GEDI's AGBD estimates, which use these same allometries.

On average there were 28 FIA plots per hexagon, with the vast majority having between 20 and 30 plots. The total number of plots across all hexagons was 338,451. GEDI footprint-level observations varied by latitude, with more coverage away from the equator, and by longitude as a function of the ISS orbital ground track with an average of ~20,000 footprints per hexagon, though some hexagons could exceed 100,000 footprints.

GEDI mean AGBD value for a hexagon was compared with the FIA estimate using a test statistic (see McRoberts et al. (32), Eq. 3c) for a difference of means:

$$t = \frac{\hat{\mu}_{FIA} - \hat{\mu}_{GEDI}}{\sqrt{M\hat{S}E(\hat{\mu}_{FIA}) + M\hat{S}E(\hat{\mu}_{GEDI})}} \quad (1)$$

where $\hat{\mu}_{FIA}$ and $M\hat{S}E(\hat{\mu}_{FIA})$ are the estimated mean AGBD and mean square error from the FIA design-based plots within a hexagon, and $\hat{\mu}_{GEDI}$ and $M\hat{S}E(\hat{\mu}_{GEDI})$ are the corresponding values from hybrid estimation using the GEDI AGBD values within the same hexagon. While formal hypothesis tests based on a specific confidence level could be performed, the value of such tests has been questioned (33) and in our case may be overly constraining where the goal is to use observed departures from the validation data as a guide towards discovering potential biases. Hence, we chose to report only the value of the test statistic (shown in Fig. 9) rather than whether the test statistic exceeded some value based on a set confidence level.

Country estimates

National-scale GEDI estimates of land surface mean AGBD and the associated standard error were calculated within country boundaries delineated by a 10-meter resolution vector dataset (34). National-scale NFI estimates of AGBD were taken from the 2020 Global Forest Resources Assessment (35) (FRA) published by the Food and Agriculture Organization (FAO) of the United Nations. This report is a global evaluation of forests, focusing on the state of forest resources and emerging trends from the past 30 years. FAO estimates are only for forested lands, whereas GEDI estimates are for all lands. Therefore, to ensure a similar comparison to GEDI-based estimates we retrieved estimates of AGBD of forested land, the area of forested land, and total land area for every available country in the FRA online database. We used these values to calculate each country's total land AGBD and total AGB, as follows: total AGB was determined by multiplying the forested AGBD by the area of forested land, and the country mean AGBD was calculated by dividing total AGB by the total country land area. For example, a country with an area of 150,000 km² that is 40% forested with a forested AGBD of 260 Mg/ha has a country-level mean AGBD of 104 Mg/ha, and a total AGB of 1.56 Pg. Note that in deriving the total land AGBD and AGB using FAO data we assume there is no biomass on non-forest land, which is the same assumption made in the U.S. FIA estimates.

The country-level comparisons include all countries located entirely within the ISS orbital extent (51.6 °N & °S) that the FRA included in its 2020 report. Large countries with a vast majority of land area within the ISS extent were also included, even if not entirely within the extent; specifically, China, Argentina, and Chile. The United States was also included but is a special case because of Alaska. The US estimate in the FRA report includes data from Alaska, but because the GEDI instrument does not sample any part of Alaska, we used the most recent FIA estimates for the US and its territories in place of the values presented in the FRA report. We did this by summing the hexagon-level total biomass (30) (AGB) to get a total biomass for the

coterminous U.S. as reported above, and for the non-conterminous U.S we used AGB values reported by the FIA. We then divided the total AGB by the total U.S. land area (excluding Alaska) to arrive at a total AGBD that is comparable to the GEDI estimate. We used FIA estimates to calculate the proportion forest value for the U.S. For country level estimates, only shots with a beam sensitivity >0.98 across all prediction strata were used to avoid systematic differences between prediction strata in the fraction of 6 km cells with fewer than two tracks.

Results

Pantropical and Temperate Biomass Estimates at 1 km Resolution

Mean aboveground biomass density estimates and their standard errors (SE) were created from the GEDI footprint level biomass estimates over a 1 km grid (Fig. 1). Biomass density had a mean of 108.9 Mg/ha for 1 km cells whose predominant plant functional type (PFT) class was forest. Values of AGBD varied considerably by PFT with evergreen broadleaf forests (EBT) showing the largest mean value (126.7 Mg/ha) and grassland/savanna/woodland (GSW) the lowest with a mean of 9.5 Mg/ha (Fig. 2 and Table S1). When considered by PFT and world region, EBT forests of North Asia had the largest AGBD with a value of 167.6 Mg/ha.

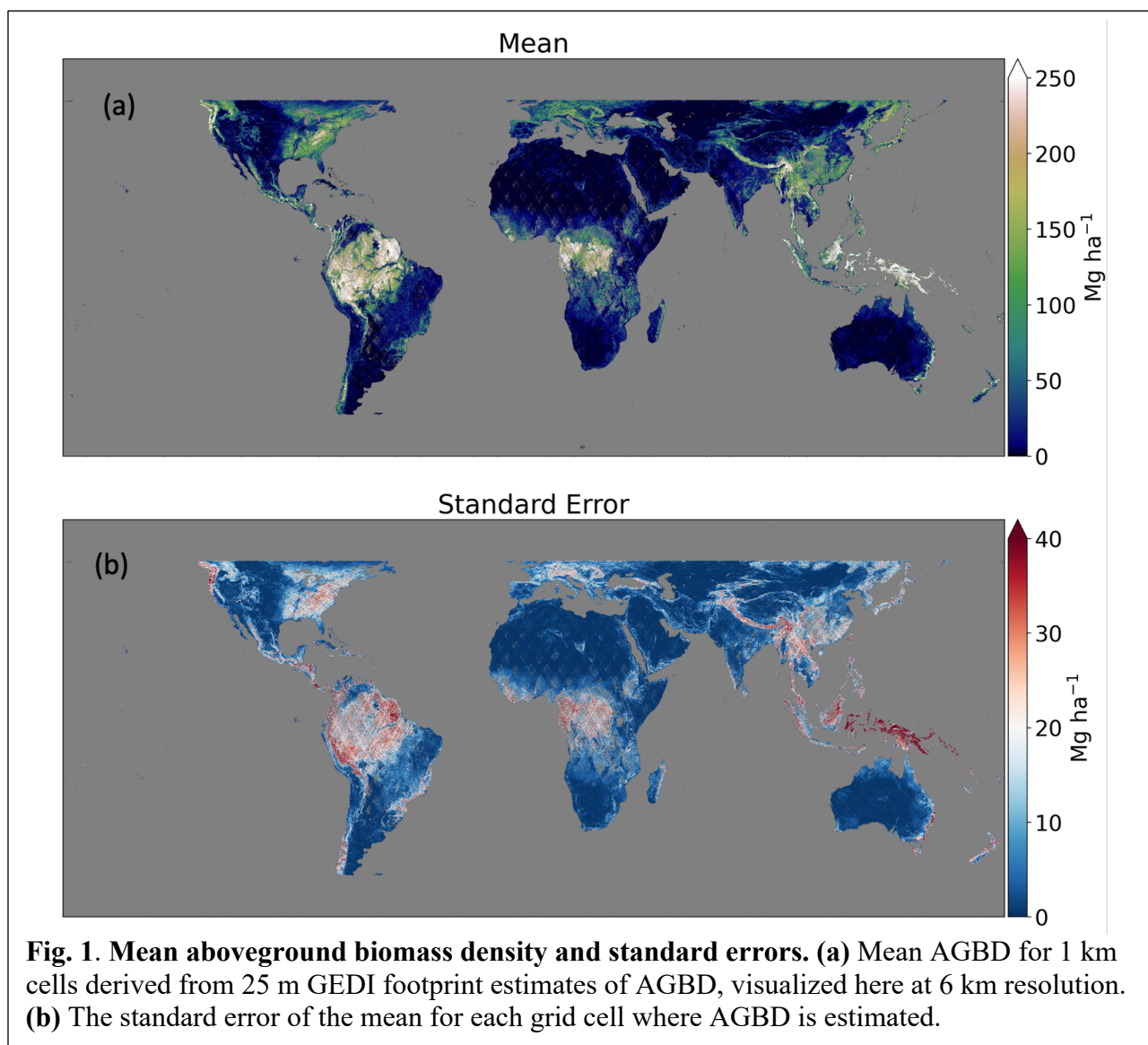
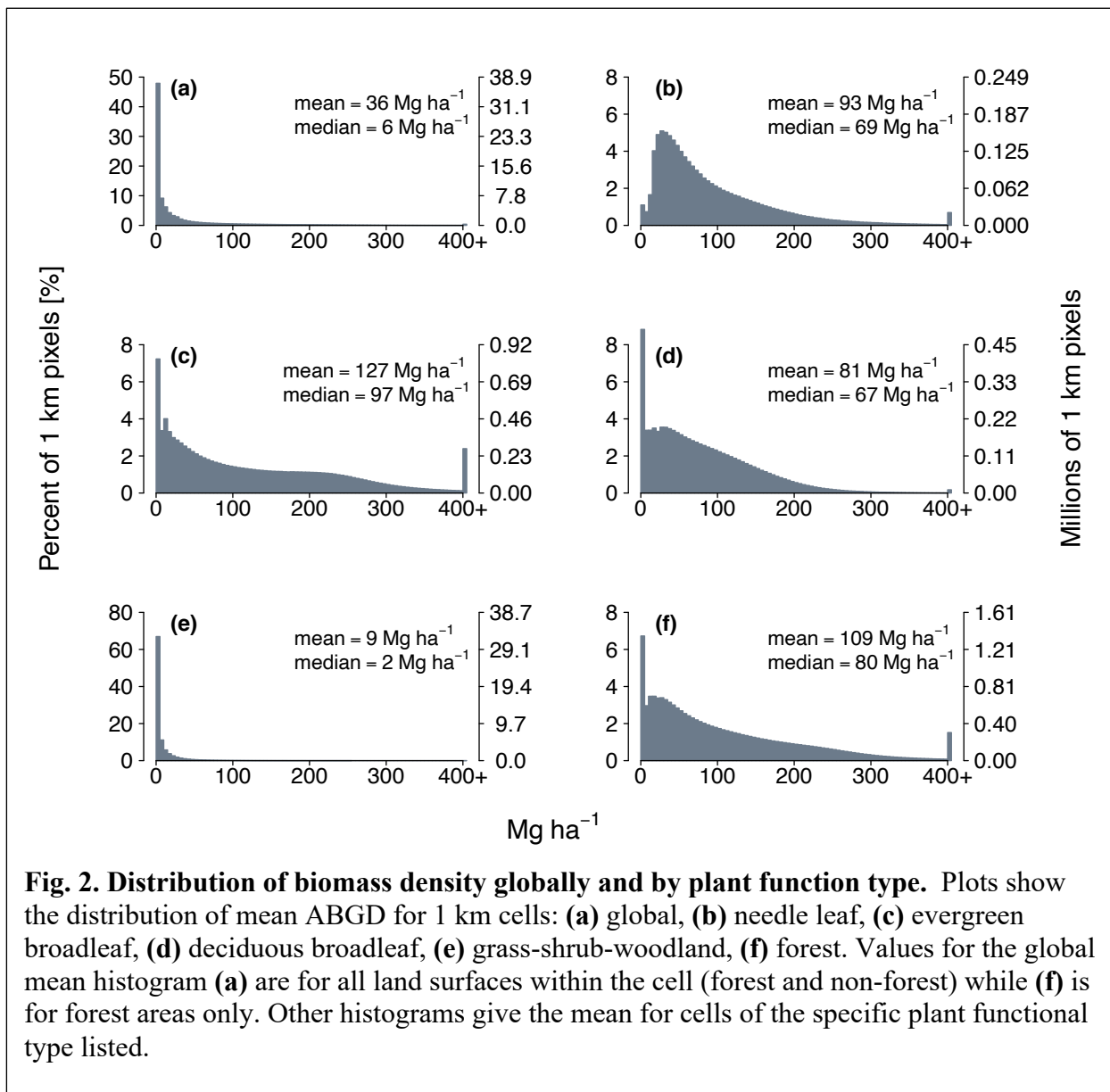


Fig. 1. Mean aboveground biomass density and standard errors. (a) Mean AGBD for 1 km cells derived from 25 m GEDI footprint estimates of AGBD, visualized here at 6 km resolution. (b) The standard error of the mean for each grid cell where AGBD is estimated.

GEDI was designed to meet stated precision requirements; specifically, that 80% of the 1 km land surface cells on the land surface between 51.6° N&S must have a standard error of the mean of $\leq 20\%$ for cells where AGBD > 100 Mg/ha and < 20 Mg/ha for cells where AGBD ≤ 100 Mg/ha (18). As described above, there must be at least two tracks through a cell for variance estimation. It is therefore useful to describe error statistics with respect to (a) the percentage of those cells that have met the observational requirements and (b) all cells in total (the latter on which the GEDI formal requirements are based). For the land surface as a whole (between 51.6° N&S) GEDI had sufficient observations (two or more tracks) in 74.2% of the 1 km cells (Fig.



S2) and 70.4% of all land surface cells meet the GEDI biomass requirements for standard error of the mean. Considering only those cells with sufficient observations, 77.3% of the high biomass cells meet requirements, and 97.2% of the low biomass cells meet requirements, and for both ranges collectively 94.8% met requirements (Fig. 3). Standard errors of mean AGBD for high biomass cells were generally below 20% with an average of 15.2% but with some relatively small variations by PFT (Fig. S3) and region (Fig. S4). The one exception was the GSW PFT

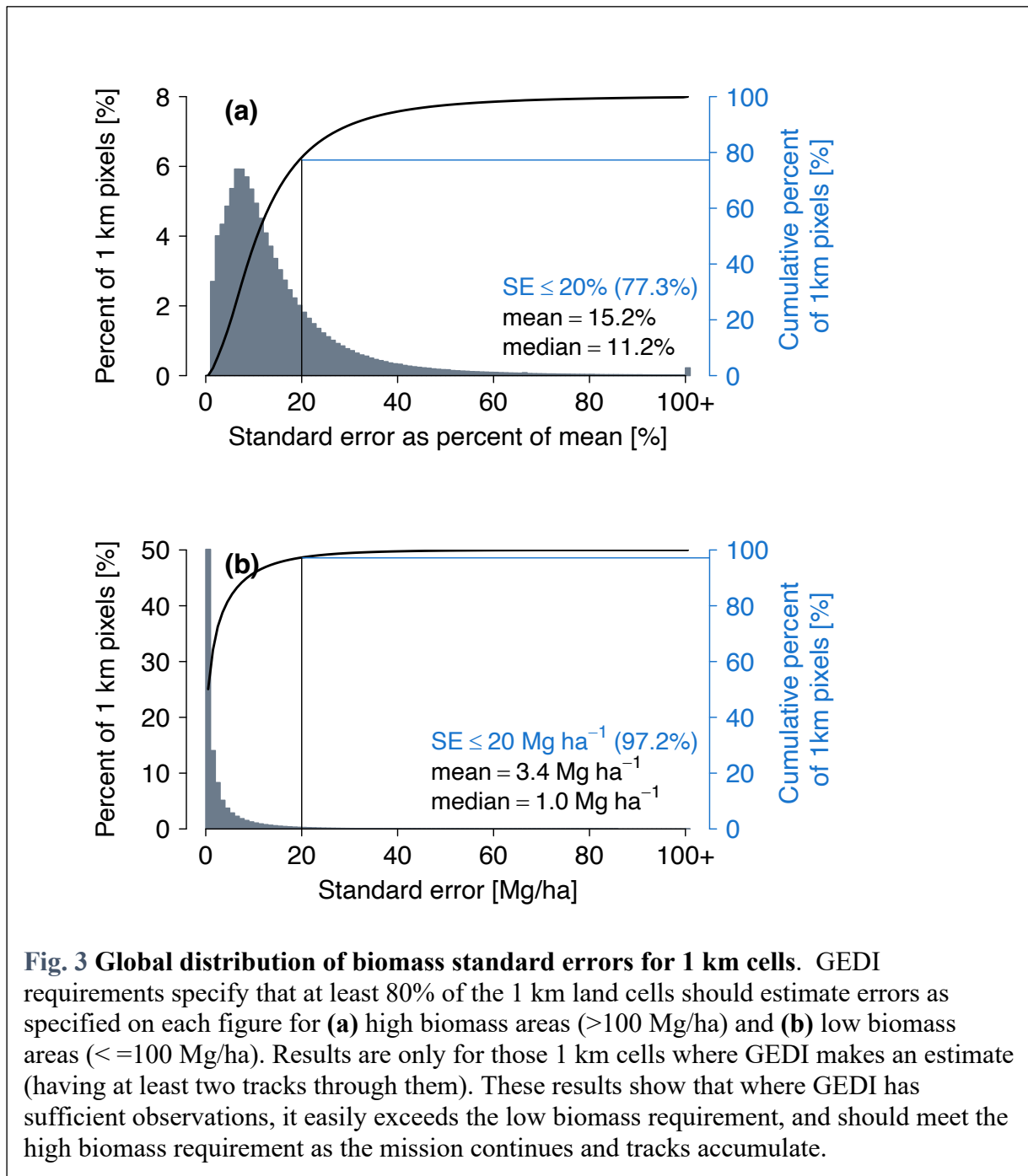


Fig. 3 Global distribution of biomass standard errors for 1 km cells. GEDI requirements specify that at least 80% of the 1 km land cells should estimate errors as specified on each figure for **(a)** high biomass areas (>100 Mg/ha) and **(b)** low biomass areas (\leq 100 Mg/ha). Results are only for those 1 km cells where GEDI makes an estimate (having at least two tracks through them). These results show that where GEDI has sufficient observations, it easily exceeds the low biomass requirement, and should meet the high biomass requirement as the mission continues and tracks accumulate.

which showed a mean error of 30.8% but noting that the values of AGBD are also much lower for this PFT. For the lower biomass range, the average standard error was 3.4 Mg/ha.

Country-Level Estimates

We next found AGB for countries whose borders were within the latitudinal limits of ISS observation (Fig. 4a), with minor exceptions for China, Chile, and Argentina where only a small part of the country is beyond 51.6° N or S and excluding Alaska for the United States. Total biomass stocks were then compared with those from the FAO (Fig. 4b). While GEDI estimates of AGB were strongly correlated with FAO estimates ($r^2 = 0.86$, RMSD = 3.2 Pg; Fig. 5), GEDI's biomass totals trended slightly higher with an average difference (FAO – GEDI) of -0.63 Pg. For two countries, China, and Indonesia, GEDI's total AGB were considerably larger at 27.7 Pg and 23.3 Pg respectively. Relative standard errors for AGBD at the country level had a mean of 7.7% and a median of 3.9%. GEDI and FAO estimates of AGB, AGBD and their standard errors for observed countries are given in Table S2.

GEDI does not observe the entire global land surface, so it is not possible to estimate total AGB for the Earth. Additionally, due to data availability issues, FAO does not provide an estimate for every country where there is a GEDI estimate. For those 169 countries with both a GEDI and FAO estimate, the GEDI estimated total biomass was 480.2 Pg. FAO estimates for these same countries totalled 373.1 Pg, a total difference of 107.1 Pg. Thus, GEDI estimates about 29% more AGB for the tropical and temperate land surface compared to FAO estimates. This difference is related, in part, to the fact that GEDI measures the biomass of both forest and non-forest areas, whereas FAO estimates are only for those areas denoted as forest (>10% canopy

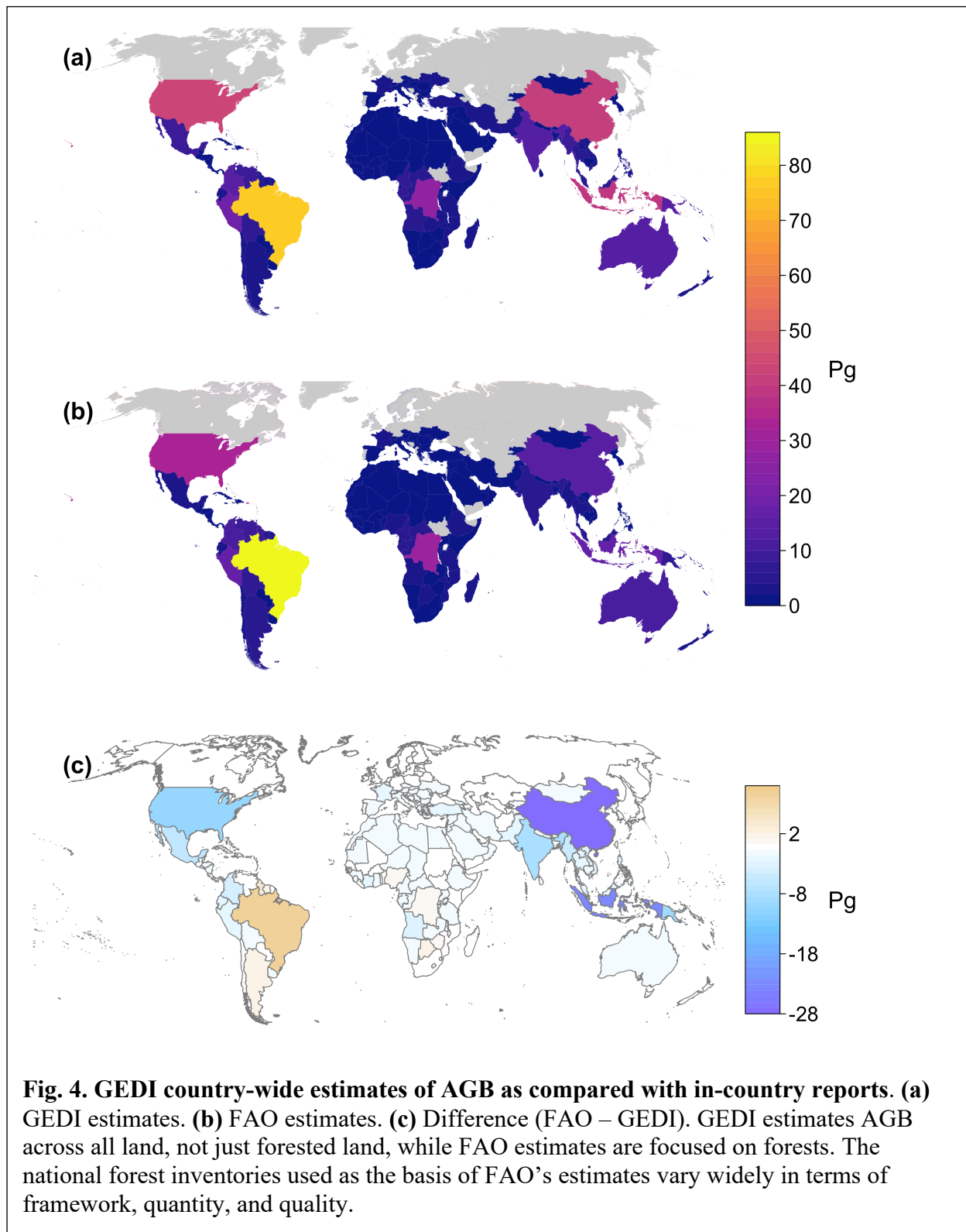


Fig. 4. GEDI country-wide estimates of AGB as compared with in-country reports. (a) GEDI estimates. **(b)** FAO estimates. **(c)** Difference (FAO – GEDI). GEDI estimates AGB across all land, not just forested land, while FAO estimates are focused on forests. The national forest inventories used as the basis of FAO’s estimates vary widely in terms of framework, quantity, and quality.

cover of minimum 5 m height over 0.5 ha area). Incomplete filtering of anomalous waveform data, topographic artefacts, and model misspecification can also result in estimates of AGB that

are too large from GEDI. These issues are addressed in GEDI data processing and are further considered in the Discussion section.

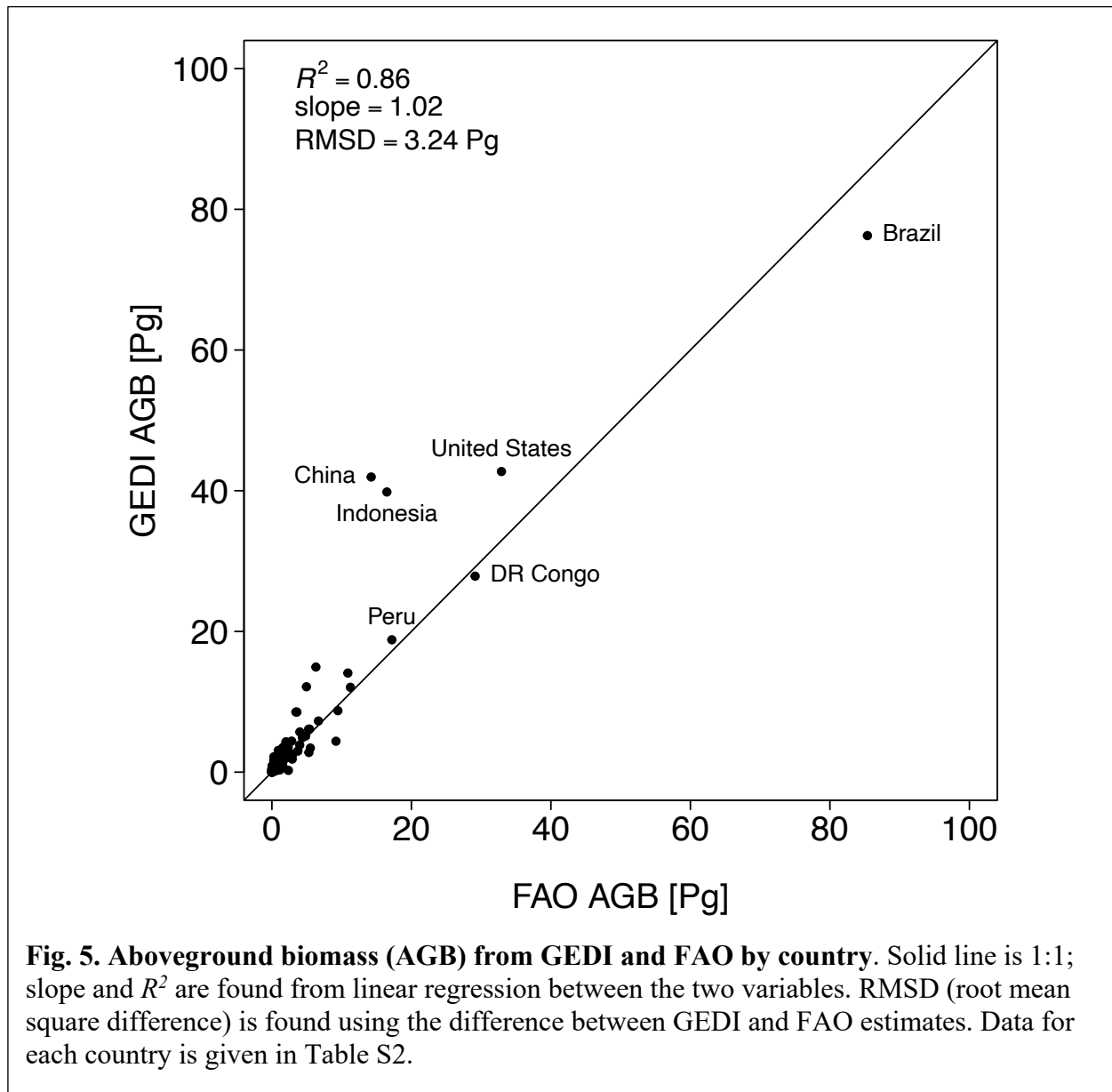
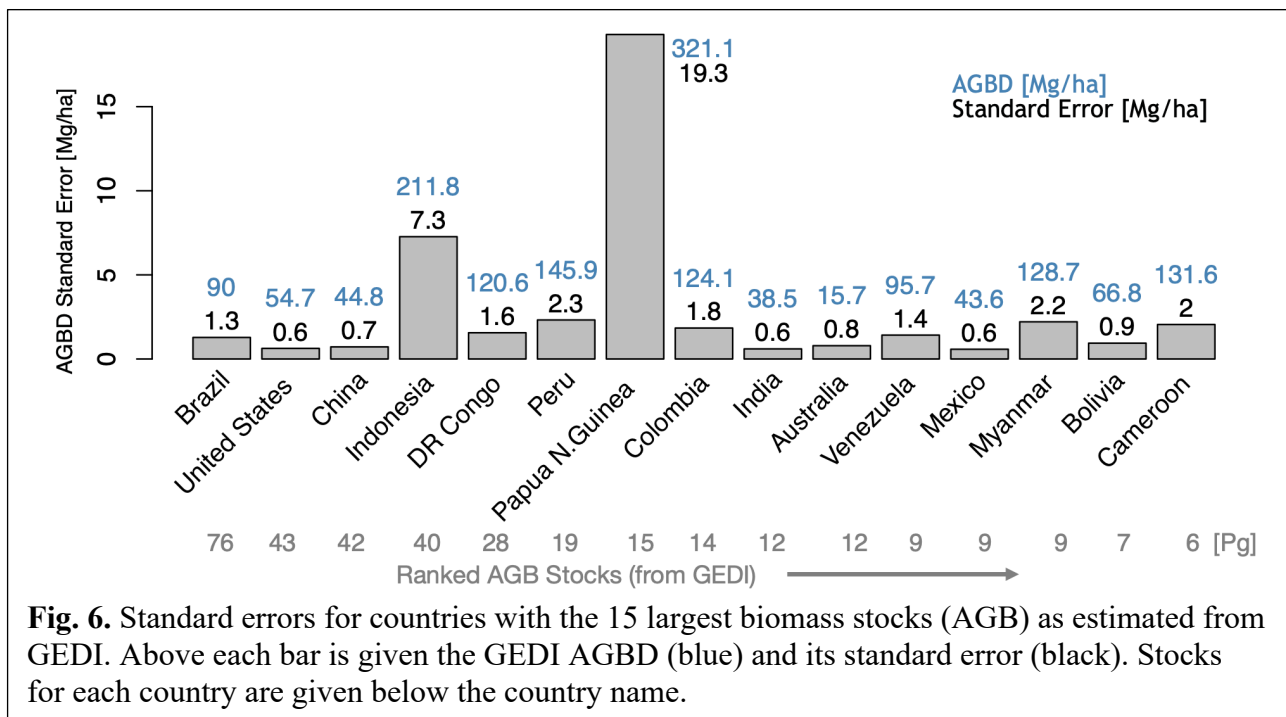
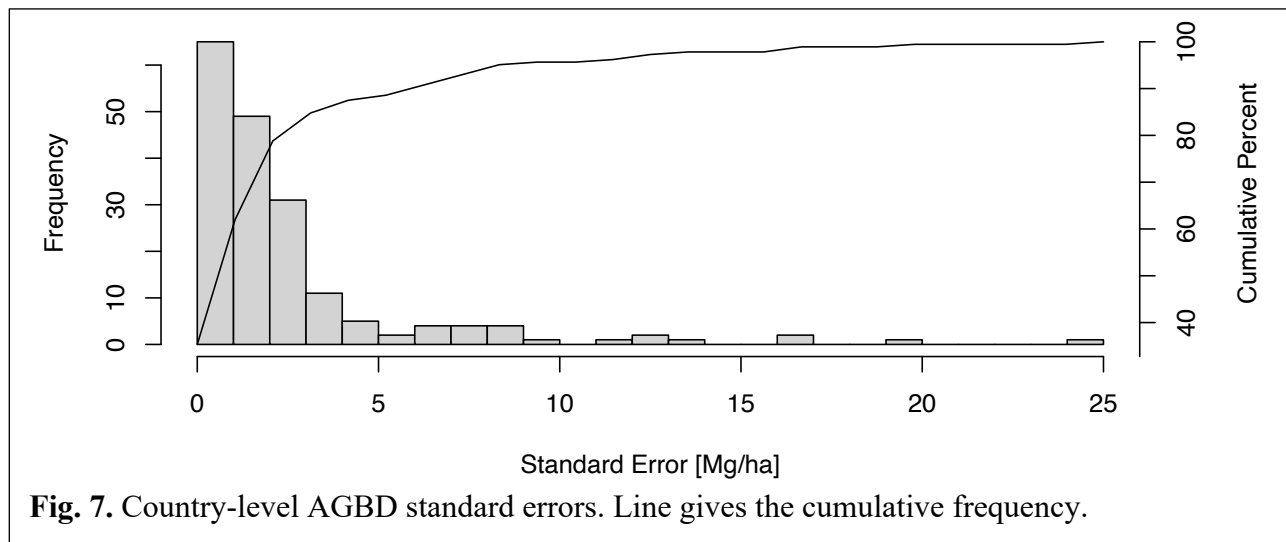


Fig. 5. Aboveground biomass (AGB) from GEDI and FAO by country. Solid line is 1:1; slope and R^2 are found from linear regression between the two variables. RMSD (root mean square difference) is found using the difference between GEDI and FAO estimates. Data for each country is given in Table S2.

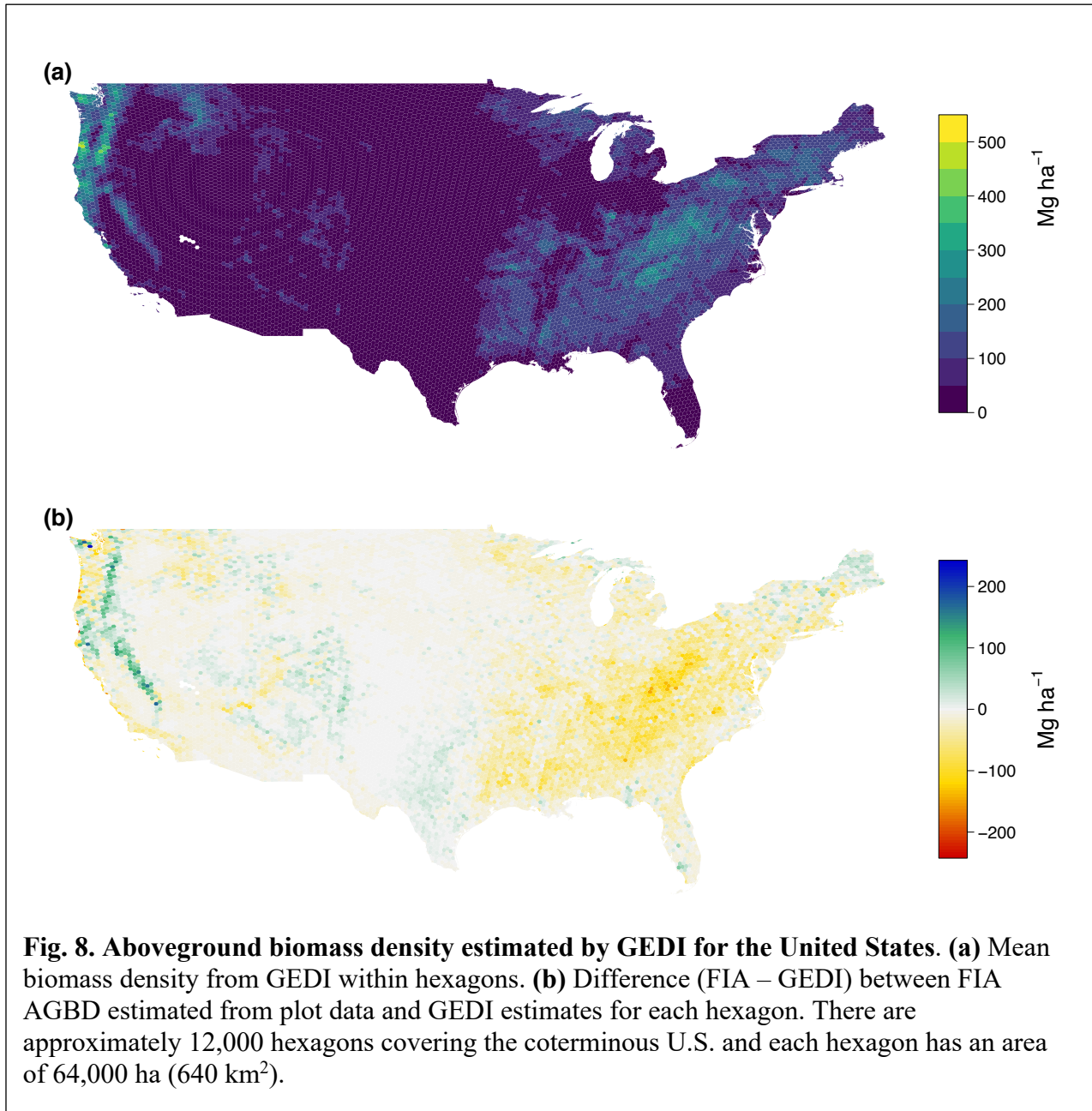
Biomass density showed more variability than total biomass in comparisons with FAO ($R^2 = 0.57$, RMSD = 47.7 Mg/ha) but the relationship was influenced by a few outliers from smaller countries (Fig. S5). GEDI estimates were mostly higher than FAO, with 126 of the 169 countries assessed having higher AGBD from GEDI. This is again related to the factors listed above as well as the differences in how the densities are calculated. GEDI estimates are the average density over all lands, whereas FAO densities are the total biomass of lands supporting biomass,

as reported by FAO, divided by the total area of the country (not just forested lands), which necessarily must lead to lower estimates of AGBD from FAO. Standard errors of mean AGBD were small with a mean of 3.4 Mg/ha (Fig. 6). Errors exceeding 5 Mg/ha occurred almost exclusively over small island nations having incomplete sampling and low biomass stocks. Two notable exceptions were Indonesia and Papua New Guinea which had AGBD errors of 7.3 Mg/ha and 19.3 Mg/ha, respectively (Fig. 7).



Comparison with U.S. National Forest Inventory Data

We applied hybrid inference with GEDI data to 64,000-ha hexagons covering the United States and compared our estimates to those derived from the USFS FIA plots (Fig. 8). There are some systematic differences apparent between the two: GEDI estimates of AGBD were low relative to FIA data in the conifer dominated PFT of the Pacific Northwest and northern East Coast regions while the mixed broadleaf forests of the Eastern U.S mountainous areas showed consistently higher AGBD in comparison to FIA. For the U.S. hexagons, GEDI data compare well to FIA estimates, with $r^2 = 0.81$, $\text{RMSD} = 28.3 \text{ Mg/ha}$, and the slope of the relationship equal to 0.99 (Fig. 9a). GEDI estimated an average AGBD of 52.6 Mg/ha and AGB of 3.2 Tg per hexagon. The equivalent FIA estimates were AGBD of 41.9 Mg/ha and AGB 2.6 Tg, bearing in mind that FIA only measures biomass on lands meeting its definition of forest but density here was calculated as a function of the entire land surface area of the hexagon. The mean AGB difference (FIA – GEDI) was -0.64 Tg; GEDI thus estimates about 24.3% more biomass stock in the U.S. relative to the FIA total. This histogram of differences is negatively skewed reflecting the larger GEDI values in Eastern U.S. (Fig. 9b) and a direct comparison of quantiles shows both that GEDI estimates tend larger than FIA for values of AGBD below around 250 Mg/ha and smaller for values above that. Note that in contrast to country comparisons, there is little difference in the patterns and relationships using AGB or AGBD relative to FIA because the land area of every hexagon is the same, aside from a few on the coasts or the borders with Canada and Mexico.



The standard errors of the mean from GEDI for hexagons as derived from hybrid estimation, along with the standard errors derived from the designed-based FIA network may be used to assess the likelihood that observed hexagon-level differences are meaningful (Fig. 9c) and to compare the precision of their mean estimates through their individual confidence intervals (Fig. 10).

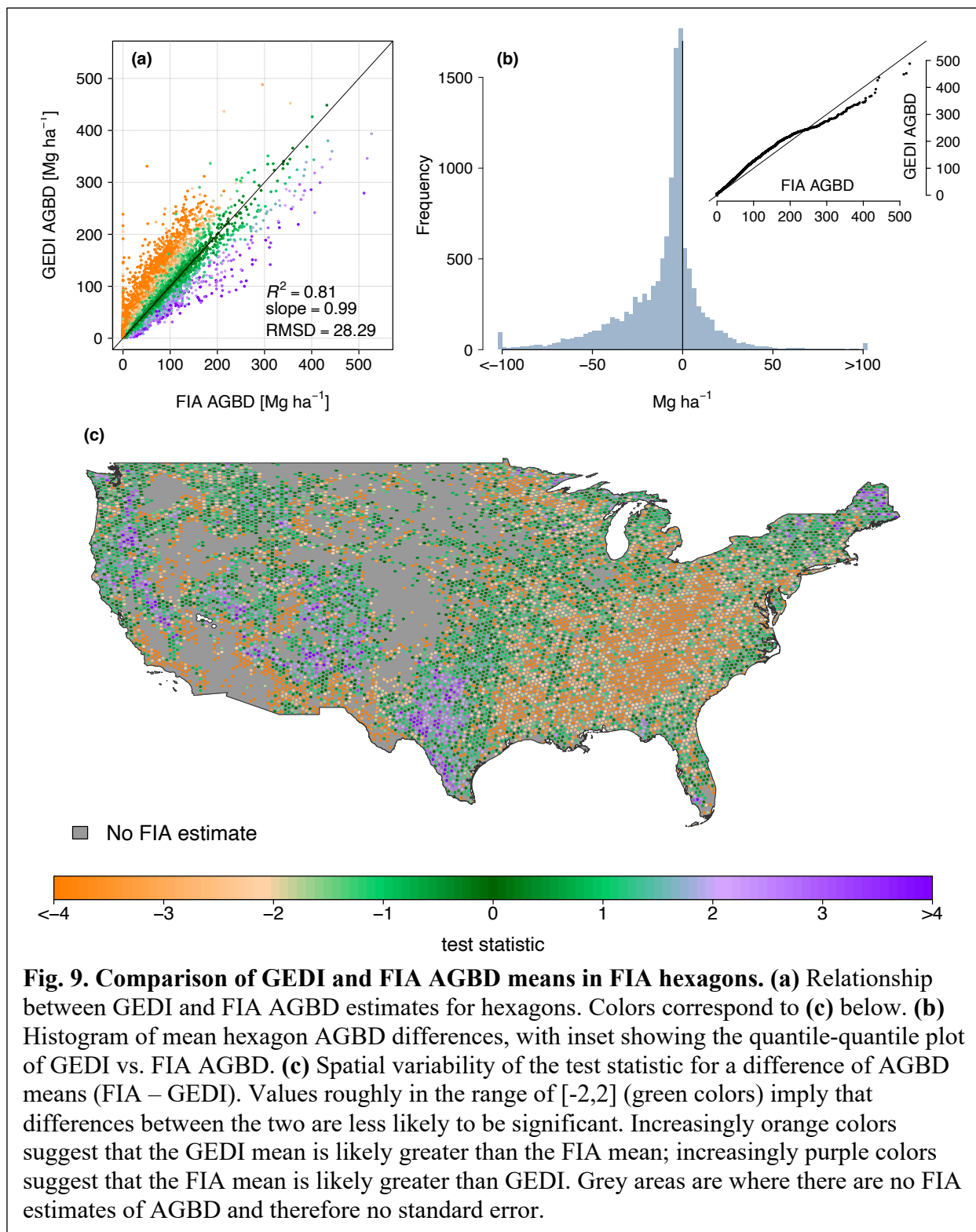
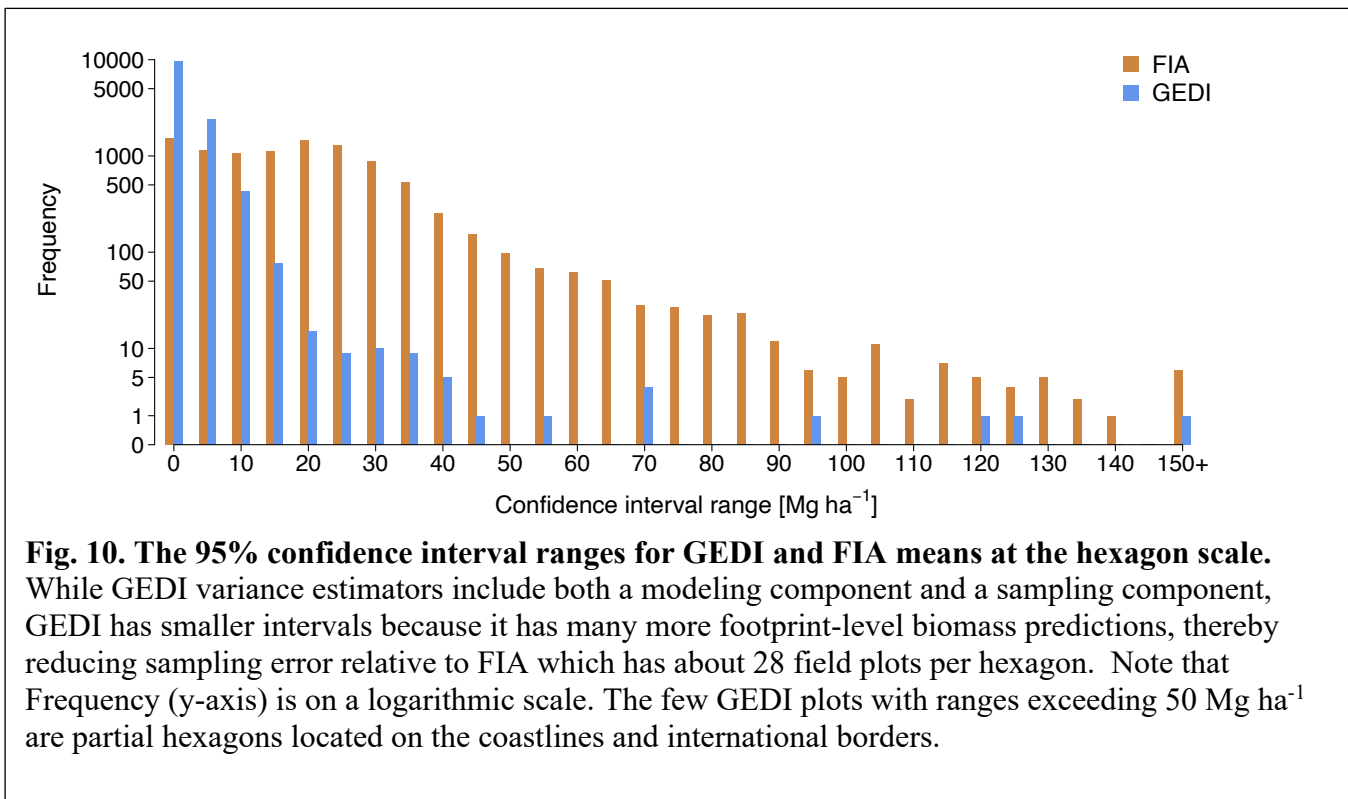


Fig. 9. Comparison of GEDI and FIA AGBD means in FIA hexagons. (a) Relationship between GEDI and FIA AGBD estimates for hexagons. Colors correspond to (c) below. (b) Histogram of mean hexagon AGBD differences, with inset showing the quantile-quantile plot of GEDI vs. FIA AGBD. (c) Spatial variability of the test statistic for a difference of AGBD means (FIA - GEDI). Values roughly in the range of [-2,2] (green colors) imply that differences between the two are less likely to be significant. Increasingly orange colors suggest that the GEDI mean is likely greater than the FIA mean; increasingly purple colors suggest that the FIA mean is likely greater than GEDI. Grey areas are where there are no FIA estimates of AGBD and therefore no standard error.

Approximately 21% of the hexagons did not have a confidence interval from FIA because the FIA AGBD estimate was zero. While the FIA assumes zero biomass for non-forest lands, GEDI estimates biomass for cells across all lands, and so has a non-zero biomass estimate for these.

The spatial distribution of a test statistic for the difference of means showed regional, systematic differences in estimated AGBD, most notably the Pacific Northwest and the Appalachian region of the Eastern U.S. GEDI generally has smaller confidence intervals about its means relative to FIA because it has many more observations within a hexagon as compared to FIA data. GEDI uncertainties also include a modelling error term from the calibration equations which is not present in FIA estimates. These modelling errors are not large and despite some dependence on the number of samples per tile and the number of models applied, remain relatively constant across scales, from 1 km cells to the areas of hexagons to entire countries. Note, however, that GEDI estimates of uncertainty do not account for any violations of the assumptions of hybrid inference, which may lead to biases and mean precisions and confidence ranges that are overly optimistic, discussed next.



Discussion

GEDI was conceived to provide the data on ecosystem structure required to address important questions about the Earth's forests, including quantifying the net impact of deforestation and subsequent regrowth on atmospheric CO₂ concentrations, among others. Key to these efforts is the creation of accurate maps of baseline carbon stocks of sufficient spatial resolution and with well-understand uncertainties that may be used to monitor changes through time and provide accurate initialization for prognostic studies of the impacts of land use and climate change.

Several aspects unique to GEDI set the mission and its resulting biomass maps apart from others that have been produced before. First, GEDI's biomass maps are based on GEDI data alone, and are not the product of fusion or spatial extrapolation with data from other sensors. Secondly, the models that relate waveform measurements, such as height to biomass, were created using the most extensive set of field and aircraft data yet compiled. Third, GEDI has provided vastly more observations of ecosystem structure than previously available; our study used over 5 billion of these estimates to make its products. Past studies using GLAS at country to global scales were based on one to two orders of magnitude less data (12–14). However, GEDI most fundamentally represents a turning point because of its focus on formalized inference. Specifically, while biomass products from previous satellites have assessed residual error uncertainty at the pixel level, GEDI recognizes the need to assess uncertainty when individual observations (pixels, for example) are combined to estimate biomass over a larger area. Residual error in that context has little relative impact compared to the uncertainty that arises due to estimating the parameters of the models linking field observations with GEDI metrics.

The model parameters themselves are a more relevant source of uncertainty under the model-based paradigm, as they affect all predictions in a systematic way. GEDI's hybrid model-based estimator explicitly accounts for uncertainty in the model-fitting process through the use of the

model's parameter covariance matrix (21). There are alternative methods for explicitly addressing the effects of model covariance upon population estimates for large areas; for example approaches involving bootstrapping have been proposed (20). The key is that GEDI is the first forest observation mission to embrace inference over large areas, employing an integrated design process to account for the instrument's sampling pattern, the fitting of biomass models, and the reporting of grid cell mean biomass estimates and their uncertainties. Previous remote sensing efforts that have ignored covariance among observations over large areas have had to rely upon ad hoc, and sometimes ambiguous, methods of uncertainty assessment (26, 36).

The precision requirement of the GEDI mission that 80% of 1 km cells not exceed a standard error of 20 Mg/ha or 20% of the mean AGBD (for low and high biomass levels, respectively) has not yet been met, due to changes in the ISS altitude, but as noted above, of those cells with the requisite two overpasses 95% meet the GEDI requirements. Substantial progress with respect to meeting the 80% mission goal is expected within the next year because: 1) the precision of GEDI's estimators is expected to increase rapidly as cells accumulate more than two overpasses (21); and, 2) recent changes to the ISS altitude are expected to substantially improve coverage of 1 km cells with no existing observations.

GEDI's variance estimates, accompanying the estimate of the mean for every 1 km cell, are crucial to monitoring progress toward the mission's precision goal. This cannot be achieved solely by validation using independent data. Validation using field data is not feasible globally and there are almost no 1 km field plots in any ecosystem, forested or otherwise. Comparison against 1 km estimates derived from airborne lidar is possible, however this process involves airborne estimates subject to some of the same model-related uncertainties affecting GEDI and would cover only a small fraction of the nearly 105 million grid cells over land in the study area. Direct comparisons with existing biomass maps are also difficult because they often have

differing resolutions and, as noted above, unclear statistical procedures to estimate uncertainty from pixels to some larger area - for example, comparing a 30 m biomass product to GEDI via aggregation of the 30 m pixels to 1 km – although progress continues to be made in this area (32).

Nevertheless, comparison against independent estimates of mean AGBD provide an opportunity to highlight potential problems with GEDI's current estimation process. Some degree of spread is to be expected in the hexagon- and country-level comparisons; field estimates have their own uncertainties, and important differences in definitions and allometric models can introduce large discrepancies among estimates that would otherwise be in agreement (30). Systematic differences between GEDI and reported estimates, though, suggest several issues worth exploring during GEDI's continued operations.

First, comparison with FAO data showed GEDI estimated more AGB for most countries. The UN FAO defines trees outside of forests and other wooded lands as those growing on lands with a combined cover of shrubs and trees of less than 10%, or tree cover less than 5%, or any trees growing in patches smaller than 0.5 ha or in urban or agricultural land. Such trees and patches are widespread in some areas (37–39) and represent biomass that is measured by GEDI but not by forest inventories. Application of standardized definitions of forest resulting in explicit and agreed upon forest/non-forest maps would enable refined comparisons. GEDI's footprint estimates of biomass could then be averaged only for forested areas for comparison to FAO estimates within countries.

Secondly, the footprint biomass calibration models linking field biomass to the GEDI waveforms are assumed under model-based estimation to be both properly specified and fitted with data representative of the areas to which the models will be applied (27). Estimated standard errors

may reflect a lack of fit with respect to available training data (for example somewhat lower R^2) but will not reflect biases in the selection of that data, and therefore potential biases in the calibration equations as applied. Comparisons with validation data can help reveal possible violations of the assumptions underlying model-based inference that are not revealed in the calibration model building process. For example, GEDI currently estimates far more AGB (a combined 51 Pg) in China and Indonesia than the countries themselves report (35). While these positive differences may be associated with the issue of non-forest biomass discussed above, we note that GEDI's AGBD calibration dataset is particularly sparse in Asia and therefore represents a potential source of bias. This lack of data in Asia may also help explain the relatively high standard errors for mean AGBD in Indonesia and Papua New Guinea; however, note that there is also a tendency for errors to increase as the magnitude of AGBD increases.

Similarly, comparison with FIA data in the western U.S. at the hexagon level reveals discrepancies that are, according to the respective confidence intervals, unlikely to be a result of sampling error on the part of GEDI or the field inventory. Some of these conifer systems may have biomass densities that exceed 2000 Mg/ha at the scale of GEDI footprints, and the calibration data set and derived calibration models (40) may not adequately represent the range of biomass present in this PFT as it occurs in these western montane regions. These examples indicate the need for additional data collection and a re-examination of the footprint biomass calibration models fitted for the region to refine GEDI's estimates of biomass for these areas. While improved model training in data sparse areas will help us better meet our assumptions, this may come at the cost of an increase in standard errors as potentially overly optimistic estimates are corrected.

Third, there is an assumption that the height metrics, as derived from the return waveform by GEDI algorithms, are unbiased and have errors that match pre-launch calibration analyses, e.g.,

1-2 m for canopy top height accuracy. The process of outlier detection, that is filtering of GEDI measurements to remove invalid data, while improving, is imperfect and errors in estimated biomass may remain. One example is misidentification of low-lying clouds that produce lidar waveforms that appear as tall canopy, an effect we noted in comparisons with FIA data in the ridge and valley complex of the Appalachians in the eastern United States. Steep topography also may lead to incorrect data interpretation. Over mostly bare-earth terrain with high slopes (generally exceeding about 15° to 20°), waveforms have vertical extents that may appear similar to canopies in GEDI algorithms yet provide spurious relative height metrics that are unrelated to real canopy height. This can lead to biomass estimates that are too large, say for very sparse woodlands, or estimates for areas that cannot support vegetation, such as deserts. For forested terrain, steep slopes may increase or decrease perceived canopy height based on canopy cover and tree distributions in the footprint (41). As GEDI outlier detection methods and waveform processing improve, such artifacts will decrease. For example, we have applied machine learning methods as an alternative to conventional waveform processing. Such methods have the potential to both increase accuracy but also provide improved error and outlier detection (42).

Comparisons such as these presented above are useful for highlighting potential modifications to biomass estimates as the mission progresses, and they also demonstrate the value of reliance upon an inferential framework where assumptions are clear and there are straightforward mechanisms through which violation of those assumptions may bias the estimates. In other words, because the framework allows for a direct estimate of the precision of its estimates, these may be used to flag deviations from validation data that are probabilistically unlikely and thus provide the means for detecting biases. As the mission works through these potential issues it may be that some new estimates of biomass are produced that are outside existing confidence intervals, reflecting a correction of bias in the process, as mentioned above. This is not a cause for concern; rather, it reflects the power of the GEDI approach.

Note that although many of the reported standard errors at the country level are small, for example 1.1% for the United States, these are in line with those reported by other studies (14, 15) that used methods related to our own. However, our approach, as with these other studies and almost all national forest inventories, does not consider model uncertainty from the allometric tree-level biomass models. Such uncertainty may be substantial, especially in tropical areas (43) where the data underpinning the models tend to be limited. Thus, a formally reported standard error, whether from a plot-based national inventory or one based on remote sensing, may be too optimistic considering these potentially larger allometric errors. Work is ongoing towards improving these allometric models, most recently using terrestrial lidar scanning (44).

Future Directions and Conclusions

It may seem that building a remote sensing mission upon a formal mode of inference is limiting; that is, that the necessary design considerations may limit the flexibility of future applications using its data. However, the experience of GEDI thus far has illustrated just the opposite. The orbital resonance resulting from the ISS altitude in 2020 and beyond challenged the application of hybrid inference across large areas, e.g., areas of differential probability of inclusion within the sample are not addressed by the estimators described by Patterson et al. (21). The orbital problem accentuated variable sample intensity that developed due to both the differential presence of clouds and the latitudinal differences in overpass density. This disruption was accommodated relatively simply by applying the estimators at the broadest scales for which probabilities of selection could be presumed equal (6 km tiles) and using a weighted aggregation process while accounting for dependencies due to non-independent sampling and modeling errors. This is similar to weighted averaging of smaller-domain estimates practiced by field inventories when sample intensities vary over larger domains (45).

The parametric models and sample design used by GEDI also support a type of contingency approach applicable when a 1 km cell has not been intersected by at least two ground tracks, meaning that hybrid inference (which treats ground tracks as cluster samples) is not an option. Even by the end of the mission we expect some cells to still have incomplete coverage. Our contingency approach, Generalized Hierarchical Model-Based inference (GHMB) (46, 47), uses two levels of models: one linking ground data and footprint scale lidar metrics (i.e. the footprint biomass calibration models) and one linking those footprint biomass predictions to wall-to-wall ancillary data. The GHMB framework uses probability theory under the model-based paradigm to appropriately combine uncertainty from the two models, as wall-to-wall predictions form the basis of a large-area estimate of biomass (47–49). Thus, the theory upon which GEDI’s estimation of uncertainty is built can be extended to sensor fusion. For example, GHMB has been used with GEDI and wall-to-wall imagery from TanDEM-X (50), which provides interferometric synthetic aperture radar (SAR) from two orbiting satellites, to produce both height and biomass estimates for areas where no GEDI data exist, and at finer spatial resolutions than 1 km (47). One strong feature of GHMB is that models relating GEDI data to the wall-to-wall data may be locally calibrated. The GEDI team intends to use GHMB to provide gap-free biomass maps in subsequent data product releases. This framework further provides a pathway for fusion with the next generation of SAR missions with science goals related to biomass and disturbance dynamics, including the NASA ISRO Synthetic Aperture Radar mission (NISAR) (51) to be launched in 2024 and the ESA BIOMASS mission (52), scheduled for launch in 2023.

In conclusion, GEDI has demonstrated the value of an instrument dedicated to and optimized for the retrieval of ecosystem structure in general, and for biomass estimation in particular. The sheer volume of GEDI estimates of biomass is unprecedented, vastly outstripping the existing spaceborne lidar archive. GEDI’s estimates continue to evolve as the instrument collects more data beyond its prime mission, and as footprint-level biomass models and their underlying

assumptions are refined in light of ongoing validation activities. The results reported here represent a watershed product of the first space mission longitudinally coordinated, from engineering to estimation, to generate biomass products in a transparent way with errors that are well-characterized using established probability theory. The GEDI investigation highlights the intrinsic value of an approach that explicitly address uncertainty as integral part of mission design. As GEDI and future missions invest in formal modes of inference, they bring statistical rigor long employed by field surveys to a new generation of powerful, globally consistent monitoring tools.

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Data and materials availability: The GEDI footprint biomass data used to create the GEDI 1 km data product are available at the Land Processes Distributed Archive and Analysis Center (LPDAAC) as follows: GEDI L4A Footprint Level Aboveground Biomass Density, Version 2. (2021) doi: 10.3334/ORNLDAAC/1986. The GEDI L4B 1 km gridded data set is available at the Land Processes DAAC: <https://doi.org/10.3334/ORNLDAAC/2017>. The GEDI country-level data are included in the Supplements. The GEDI results for mean and standard error of U.S. hexagons can be obtained by request from Ralph Dubayah.

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Supplementary Materials

Introduction

In these supplementary materials we present more details about the GEDI mission, describe how footprint-level biomass estimates are created that form the basis of gridded biomass estimates, and present the technical details of our statistical procedure that allows biomass estimates at the level of countries based on an efficient algorithm based on 6 km x 6 km tiles. These materials also include figures referenced in the main manuscript that provide additional insight into our results and two data tables that collect biomass results estimated globally by plant functional type and by country.

The GEDI Mission

GEDI is led by the University of Maryland and NASA Goddard Spaceflight Center, in collaboration with the US Forest Service, Northern Arizona University and Brown University. GEDI began science collection on-board the ISS in April 2019. GEDI uses a laser altimeter comprised of 3 lasers to provide 8 transects of canopy structure observations along the Earth's surface. Each track is comprised of 25 m diameter footprints, with 60 m along track between footprints, and 600 m across track separating each of the transects. The ISS has orbital limit of 51.6° N&S and GEDI's observations are therefore constrained to fall within these latitudes. The ISS can be placed in either a repeating orbit or in a pseudo-random, precessing, and non-repeating orbit, dependent on altitude. In the first year of GEDI's mission, the ISS was in a precessing mode and GEDI's grouping of 8 ground tracks were randomly distributed across the Earth. During 2020 and 2021, the ISS was in an approximate 4-day, repeating orbit, which led to clustering of tracks on the surface, and the effects of which are visible in derived data products. As of 2022, changes in the ISS altitude have transitioned the platform away from 4-day repeats allowing GEDI to again achieve more uniform coverage.

The sole observable from GEDI is a return waveform which gives the vertical distribution of reflecting surfaces (e.g., leaves and branches) within the canopy, along with the underlying topographic elevation. Two of GEDI's three lasers are used in full-power mode with an approximate laser output of about 15 mJ, and the third laser is optically split into two beams. At any one instant four laser footprints illuminate the ground. The four tracks are then optoelectrically dithered across track every other shot, providing the 8 transects of data. Various metrics are derived from the waveform, including canopy height and canopy cover. These metrics are developed at the footprint (25 m) level.

Footprint-Level Biomass Estimation

Modeling AGBD from waveform lidar metrics at the scale of GEDI footprints is well-established from studies of airborne laser scanning. These studies link field estimates of AGBD from plot data to waveform lidar metrics to develop predictive models that can be applied within regions. Because no globally comprehensive data set of paired lidar and AGBD existed prior to GEDI, footprint models were developed using simulated waveforms paired with ground-based field estimates of AGBD that are used to create the GEDI04_A product. Each simulated waveform was generated using discrete-return airborne lidar and the GEDI waveform simulator (53). There are two advantages to using simulated waveforms to develop GEDI04_A models. One is that simulated waveforms reduce the impact of geolocation uncertainty (54). A second advantage is that few locations are associated with field estimates of AGBD that could be used to train GEDI models. Because GEDI is a sampling mission and most field plots are small, GEDI data will not intersect most of these locations during the mission life.

The comprehensive training data set currently contains 31,414 simulated GEDI waveforms. Quality control filters were used to exclude some measurements from the version-1 GEDI04_A calibration data set. A detailed description of data filtering and quality control is in the GEDI04_A ATBD (55). After filtering and quality control, the database used to develop the version-1 GEDI04_A models contained 8,587 simulated GEDI waveforms in 21 countries.

Building globally representative GEDI04_A models requires stratification. The models are stratified by world region and an error-corrected and infilled version of MODIS Type 5 plant functional type (PFT) classification MCD12Q1 version 6 (56, 57). PFT classes are deciduous broadleaf trees (DBT; class 4), deciduous needleleaf trees (DNT; class 3), evergreen broadleaf trees (EBT, class 2), evergreen needleleaf trees (ENT, class 1), and grasses, shrubs, and woodlands (GSW, classes 5, 6, and 11). Two world regions are the geologically defined continents of Africa and Europe. The South America world region contains the Caribbean Islands, Central America and southern Mexico and the continent of South America. Australia, Papua New Guinea, and the islands on the east side of the Wallace line comprise the Australia and Oceania world region. The North America world region includes geological North America north of southern Mexico. The continent of Asia is divided into north and south regions that approximately correspond to temperate and tropical forests. Taken together, combinations of world region and PFT constitute 35 unique prediction strata within the GEDI domain (58).

GEDI04_A models must be transferable to new regions outside the limited extent of training data. To quantify geographic transferability during model development, candidate models were evaluated within sets of 5-degree grid cells that contain simulated GEDI waveforms with coincident field data. Data from one grid cell were held out, and models were trained on the remaining grid cells. Candidate models were used to predict AGBD within the held-out grid cell and the process was repeated for all grid cells in each prediction stratum and for all models under consideration (58). The performance of all candidate models was evaluated by ranking every model in order of smallest mean residual error, smallest percentage root mean squared error, the maximum RH metric in the model, the number of coefficients in the model, and the number of RH metrics in the model (55).

Aggregating Tile-level Estimates to Larger Areas

The basic building blocks used in the procedure to estimate aboveground biomass at the level of countries, or larger areas, are 6×6 km tiles. Within these tiles models are applied to predict biomass for each of the GEDI footprints, following the hybrid inference methods described in Patterson et al. (21). As a result, the aboveground biomass density (AGBD) and the corresponding variance are estimated for each tile.

The tile level AGBD estimator under an unequal-size cluster (tracks with GEDI footprints) design, assuming the GEDI tracks to be randomly located, can be written as

$$\hat{\mu}_Y = \frac{\sum_{i=1}^m \sum_{k=1}^{P_i} \sum_{t=1}^{T_{ik}} g_k(x_{ikt}, \hat{\beta}_k)}{\sum_{i=1}^m T_i}, \quad (1)$$

where m is the number of sampled GEDI clusters, P_i is the number of models involved in the i^{th} cluster, T_{ik} is the number of GEDI footprints applying the k^{th} model in cluster i , x_{ikt} is the vector of GEDI variables, $g_k(x_{ikt}, \hat{\beta}_k)$ is predicted AGBD for the t^{th} GEDI footprint in the i^{th} cluster applying the k^{th} model, and T_i is the number of footprints in the i^{th} cluster.

Formula (1) may be rewritten as (see Ståhl et al. (59) Eq. 11 and Patterson et al. (21), Eq. 3),

$$\hat{\mu}_Y = \frac{\sum_{i=1}^m \sum_{k=1}^{P_i} \sum_{t=1}^{T_{ik}} g_k(x_{ikt}, \hat{\beta}_k)}{\sum_{i=1}^m T_i} = \frac{\sum_{i=1}^m \hat{G}_i}{\sum_{i=1}^m T_i}, \quad (2)$$

where, \hat{G}_i is the predicted AGBD total for the i^{th} cluster.

Patterson et al. (21) applied the estimator from Ståhl et al. (59) (Eq. 11) for 1×1 km units where it is straightforward to assume that a single AGBD prediction model has been applied to all GEDI footprints. For larger building blocks, such as 6x6 km tiles, different models may have been applied to different footprints, since a tile may be divided between two or more ecoregions. In developing a variance estimator for the estimator in Eq. 2, in case one or more models have been applied in a tile, we use the law of total variance, i.e.

$$V(\hat{\mu}_Y) = E_M[V_D(\hat{\mu}_Y)] + V_M(E_D[\hat{\mu}_Y]), \quad (3)$$

where $E_M[\cdot]$ and $E_D[\cdot]$ are expectations due to the model and design, respectively; and $V_M(\cdot)$ and $V_D(\cdot)$ are variances due to the model and design, respectively. First, we focus on the first term on the right-hand side of the expression. It is the model expectation of the design-based variance, i.e.,

$$E_M[V_D(\hat{\mu}_Y)] = V_D\left(\frac{\sum_{i=1}^m G_i}{\sum_{i=1}^m T_i}\right), \quad (4)$$

where, G_i is the expected i^{th} cluster total AGBD, according to the models. The estimator of $E_M[V_D(\hat{\mu}_Y)]$ follows Ståhl et al. (59) (Eq. 15, first term on the right-hand side),

$$\frac{1}{\bar{T}^2} \frac{\sum_{i=1}^m (\hat{G}_i - \hat{\mu}_Y T_i)^2}{m(m-1)}, \quad (5)$$

where \bar{T} is a cluster average number of GEDI footprints. That is, this part remains unchanged, also if several models are applied when the cluster totals are computed.

The second term in (3) can be rewritten by rearranging the order of summation and excluding specific account for clusters since they are not important in the model-based part of the variance. We thus express it as

$$V_M(E_D[\hat{\mu}_Y]) = V_M\left(\frac{\sum_{k=1}^P \sum_{q=1}^{Q_k} g_k(x_{kq}, \hat{\beta}_k)}{N}\right), \quad (6)$$

where P is the number of models employed in the tile, Q_k is the number of units in the tile where the k^{th} model should be applied and N is the total number of units in the tile. The expression can be developed further into

$$\begin{aligned} V_M\left(\frac{\sum_{k=1}^P \sum_{q=1}^{Q_k} g_k(x_{kq}, \hat{\beta}_k)}{N}\right) &= \frac{1}{N^2} \sum_{k=1}^P \left(\mathbf{1}_k^* \tilde{\mathbf{X}}_k^* Cov_k(\hat{\beta}_k) \tilde{\mathbf{X}}_k^{*T} \mathbf{1}_k^* \right) + \\ &\frac{1}{N^2} \sum_{k=1}^P \sum_{l=1, k \neq l}^P \left(\mathbf{1}_k^* \tilde{\mathbf{X}}_k^* Cov_{kl}(\hat{\beta}_k, \hat{\beta}_l) \tilde{\mathbf{X}}_l^{*T} \mathbf{1}_l^* \right), \end{aligned} \quad (7)$$

where $\mathbf{1}_k^*$ is a Q_k -sized vector of units, $\tilde{\mathbf{X}}_k^*$ is a matrix of partial derivatives with respect to the model parameters of the k^{th} model; the size of the matrix is $Q_k \times$ number of model parameters in the k^{th} model, and $Cov_k(\hat{\beta}_k)$ is the variance-covariance matrix of the estimated model parameters for the k^{th} model. Since the different models were developed independently all cross-covariances between parameters from different models are zero, i.e., the covariance $Cov_{kl}(\hat{\beta}_k, \hat{\beta}_l) = 0$. Thus,

$$V_M \left(\frac{\sum_{k=1}^P \sum_{q=1}^{Q_k} g_k(\mathbf{x}_{kq}, \hat{\boldsymbol{\beta}}_k)}{N} \right) = \frac{1}{N^2} \sum_{k=1}^P \left(\mathbf{1}_k^*{}^T \tilde{\mathbf{X}}_k^* \text{Cov}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_k^{*T} \mathbf{1}_k^* \right) \quad (8)$$

For the variance estimator, $\text{Cov}_k(\hat{\boldsymbol{\beta}}_k)$ is replaced by its estimator, and $\frac{Q_k}{N}$ is replaced by the corresponding sampling fraction. The variance estimator due to the modelling is then

$$\frac{1}{n^2} \sum_{k=1}^P \left(\mathbf{1}_k^T \tilde{\mathbf{X}}_k \widehat{\text{Cov}}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_k^T \mathbf{1}_k \right), \quad (9)$$

where n is the number of sampled GEDI footprints and $\mathbf{1}_k$ and $\tilde{\mathbf{X}}_k$ are taken over sampled GEDI footprints.

Thus, the variance estimator is

$$\hat{V}(\hat{\mu}_Y) = \frac{1}{T^2} \frac{\sum_{i=1}^m (\hat{G}_i - \hat{\mu}_Y T_i)^2}{m(m-1)} + \frac{1}{n^2} \sum_{k=1}^P \left(\mathbf{1}_k^T \tilde{\mathbf{X}}_k \widehat{\text{Cov}}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_k^T \mathbf{1}_k \right). \quad (10)$$

In estimating AGBD across larger areas, such as countries, the tile-level AGBD estimates need to be aggregated and averaged. The AGBD estimate for a larger area of interest thus is

$$\hat{\mu}_{AOI} = \sum_{h=1}^H W_h \hat{\mu}_{Y_h}, \quad (11)$$

where H is the number of tiles involved, $W_h = \frac{N_h}{\sum_{h=1}^H N_h}$ is the tile weight of the h^{th} tile (in case the tiles are not equally large), N_h is the number of units in the tile, and $\hat{\mu}_{Y_h}$ is the estimated AGBD in the tile.

In developing a variance estimator, it should be observed that the tile-level estimators typically are dependent since (i) the same models have been applied in several tiles and (ii) the GEDI tracks extend across several tiles and thus potentially cause correlated sampling errors.

A generic variance estimator for this case is given in Stahl et al. (59) (Eq. 14). Employing our notation, the variance estimator can be rewritten as

$$\begin{aligned} \hat{V}(\hat{\mu}_{AOI}) = & \sum_{h=1}^H W_h^2 \hat{V}_h(\hat{\mu}_{Y_h}) + \sum_{h=1}^H \sum_{r=1, h \neq r}^H \frac{W_h W_r \sum_{i=1}^{m_{hr}^*} (\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})(\hat{G}_{i_r} - \hat{\mu}_{Y_r} T_{i_r})}{\bar{T}_h \bar{T}_r m_{hr}^*(m_{hr}^* - 1)} + \\ & \sum_{h=1}^H \sum_{r=1, h \neq r}^H \frac{W_h W_r}{n_h n_r} \sum_{k=1}^{P_{hr}^*} \left(\mathbf{1}_{k_h}^T \tilde{\mathbf{X}}_{k_h} \widehat{\text{Cov}}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_{k_r}^T \mathbf{1}_{k_r} \right). \end{aligned} \quad (12)$$

The variance estimator (Eq. 12) has three terms on the right-hand side. The first term is just a weighted sum of estimated tile-level variances, i.e.

$$\begin{aligned} \sum_{h=1}^H W_h^2 \hat{V}_h(\hat{\mu}_{Y_h}) = & \sum_{h=1}^H W_h^2 \left(\frac{1}{\bar{T}_h^2} \frac{\sum_{i=1}^{m_h} (\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})^2}{m_h(m_h - 1)} \right) + \\ & \sum_{h=1}^H W_h^2 \left(\frac{1}{n_h^2} \sum_{k=1}^{P_h} \left(\mathbf{1}_{k_h}^T \tilde{\mathbf{X}}_{k_h} \widehat{\text{Cov}}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_{k_h}^T \mathbf{1}_{k_h} \right) \right). \end{aligned} \quad (13)$$

The second term in (12) is the sum of covariances because a GEDI track can cross several tiles, and hence, there is a dependency between clusters across tiles:

$$\sum_{h=1}^H \sum_{r=1, h \neq r}^H \frac{W_h W_r \sum_{i=1}^{m_{hr}^*} (\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})(\hat{G}_{i_r} - \hat{\mu}_{Y_r} T_{i_r})}{\bar{T}_h \bar{T}_r m_{hr}^*(m_{hr}^* - 1)}. \quad (14)$$

Here, m_{hr}^* is the number of union clusters of tiles h and r e.g., $m_{hr}^* = 5 + 10 - 3 = 12$, if the h^{th} tile has 5 clusters and the r^{th} tile has 10, and 3 clusters cross each of tiles h and r . However, numerically, the sum $\sum_{i=1}^{m_{hr}^*} (\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})(\hat{G}_{i_r} - \hat{\mu}_{Y_r} T_{i_r})$ should only be computed over those clusters, which cross both tile h and r , because for the other pairs the product $(\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})(\hat{G}_{i_r} - \hat{\mu}_{Y_r} T_{i_r})$ should be zero due to independency between clusters. In our example, the numerator is a sum over 3 common clusters and the denominator is $12 \times (12 - 1)$.

The third term in (12) is the sum of covariances because a given model can be applied across several tiles. Hence, there is a dependency due to the modelling between tiles:

$$\sum_{h=1}^H \sum_{r=1, h \neq r}^H \frac{W_h W_r}{n_h n_r} \sum_{k=1}^{P_{hr}^*} (\mathbf{1}_{k_h}^T \tilde{\mathbf{X}}_{k_h} \widehat{Cov}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_{k_r}^T \mathbf{1}_{k_r}). \quad (15)$$

Here, P_{hr}^* is the intersection of models used in tiles h and r . For example, if 3 models are employed to predict AGBD in tile h and 2 models in tile r , but only 1 model is common to both tiles, then $P_{hr}^* = 1$.

Thus, Eq. (12) provides a AGBD variance estimator when tiles are aggregated to obtain AGBD estimators for larger areas; the details of the components are explained in Eqs. 13-15. However, the computational burden related to computing the variance components presented in Eqs. 14-15 may be challenging when aggregation is made across a large number of tiles. Thus, for computational reasons further simplification is motivated.

First, it should be observed that sampling covariance according to Eq. (14) would only occur for units that are located close to each other geographically. For units separated by great distances, the covariance should be approximately zero. In practice this means that this component only needs to be computed for pairs of units that are located relatively close to each other and be assigned to zero for other pairs. In this paper, we ignore sampling dependencies beyond the scale of 72 km tiles.

For the model covariances in Eq. (15) another approach to simplification must be adopted since covariances exist also across great geographical distances if the same models have been applied. To address this, we merge Eq. (15) with the second term on the right-hand side of Eq. (13) to

$$\sum_{h=1}^H \sum_{r=1}^H \frac{W_h W_r}{n_h n_r} \sum_{k=1}^{P_{hr}^*} (\mathbf{1}_{k_h}^T \tilde{\mathbf{X}}_{k_h} \widehat{Cov}_k(\hat{\boldsymbol{\beta}}_k) \tilde{\mathbf{X}}_{k_r}^T \mathbf{1}_{k_r}), \quad (16)$$

i.e., the double sum now also includes diagonal elements. The expression can be further developed into

$$\sum_{h=1}^H \sum_{r=1}^H \frac{W_h W_r}{n_h n_r} \sum_{k=1}^{P_{hr}^*} \sum_{i=1}^{q_k} \sum_{j=1}^{q_k} (t_{h_{k_i}} \widehat{Cov}_k(\hat{\boldsymbol{\beta}}_{k_i}, \hat{\boldsymbol{\beta}}_{k_j}) t_{r_{k_j}}), \quad (17)$$

where q_k is the number of model parameters in the k^{th} model, $t_{h_{k_i}}$ is the sum of partial derivatives for the i^{th} model parameter in the k^{th} model for the h^{th} tile, $t_{r_{k_j}}$ is the sum of partial derivatives for the j^{th} model parameter in the k^{th} model for the r^{th} tile, and $\widehat{Cov}_k(\hat{\boldsymbol{\beta}}_{k_i}, \hat{\boldsymbol{\beta}}_{k_j})$ is the estimated covariance between the i^{th} and j^{th} model parameters in model k .

By rearranging the order of summation, summing over all models, but only for those tiles where a given model is applied, the expression can be rewritten as

$$\sum_{k=1}^P \sum_{i=1}^{q_k} \sum_{j=1}^{q_k} \sum_{h=1}^{H_k} \sum_{r=1}^{H_k} \left(\frac{W_h}{n_h} t_{h_{k_i}} \widehat{Cov}_k \left(\hat{\beta}_{k_i}, \hat{\beta}_{k_j} \right) t_{r_{k_j}} \frac{W_r}{n_r} \right), \quad (18)$$

where P is the total number of models used in the area of interest and H_k is the number of tiles where the k^{th} model is applied. Since the estimated model parameter covariances do not depend on tiles, they can be moved outside the tile-related double summation, i.e.

$$\sum_{k=1}^P \sum_{i=1}^{q_k} \sum_{j=1}^{q_k} \widehat{Cov}_k \left(\hat{\beta}_{k_i}, \hat{\beta}_{k_j} \right) \sum_{h=1}^{H_k} \sum_{r=1}^{H_k} \left(\frac{W_h}{n_h} t_{h_{k_i}} \frac{W_r}{n_r} t_{r_{k_j}} \right). \quad (19)$$

This expression can be further developed as

$$\sum_{k=1}^P \sum_{k=1}^{q_k} \sum_{j=1}^{q_k} \widehat{Cov}_k \left(\hat{\beta}_{k_i}, \hat{\beta}_{k_j} \right) \sum_{h=1}^{H_k} \frac{W_h}{n_h} t_{h_{k_i}} \sum_{r=1}^{H_k} \frac{W_r}{n_r} t_{r_{k_j}}. \quad (20)$$

and finally simplified to

$$\sum_{k=1}^P \sum_{k=1}^{q_k} \sum_{j=1}^{q_k} \widehat{Cov}_k \left(\hat{\beta}_{k_i}, \hat{\beta}_{k_j} \right) T_{k_i} T_{k_j}, \quad (21)$$

where T_{k_i} is a weighted sum of partial derivatives for the i^{th} model parameter in the k^{th} model across the H_k tiles (i.e., the tiles where the k^{th} model is applied), and T_{k_j} is the corresponding weighted sum for the j^{th} model parameter.

Although Eq. (21) involves a triple sum, its dimension typically is very small and thus the computational burden involved in estimating it is limited compared to applying Eq. 16 (or Eq. 15). Thus, the computationally more efficient version of the variance estimator for aggregated tile-based AGBD estimates is

$$\widehat{V}(\hat{\mu}_{AOI}) = \sum_{h=1}^H W_h^2 \left(\frac{1}{\bar{T}_h^2} \frac{\sum_{i=1}^{m_h} (\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})^2}{m_h(m_h-1)} \right) + \sum_{h=1}^H \sum_{r=1, h \neq r}^H \frac{W_h W_r}{\bar{T}_h \bar{T}_r} \frac{\sum_{i=1}^{m_{hr}^*} (\hat{G}_{i_h} - \hat{\mu}_{Y_h} T_{i_h})(\hat{G}_{i_r} - \hat{\mu}_{Y_r} T_{i_r})}{m_{hr}^*(m_{hr}^*-1)} + \sum_{k=1}^P \sum_{k=1}^{q_k} \sum_{j=1}^{q_k} \widehat{Cov}_k \left(\hat{\beta}_{k_i}, \hat{\beta}_{k_j} \right) T_{k_i} T_{k_j} \quad (22)$$

The estimators in Eq. (12) and Eq. (22) result in identical estimates, but Eq. (22) eases the computational burden.

References

References in the Supplemental Materials appear in the reference list of the main text.

Supplementary Figures

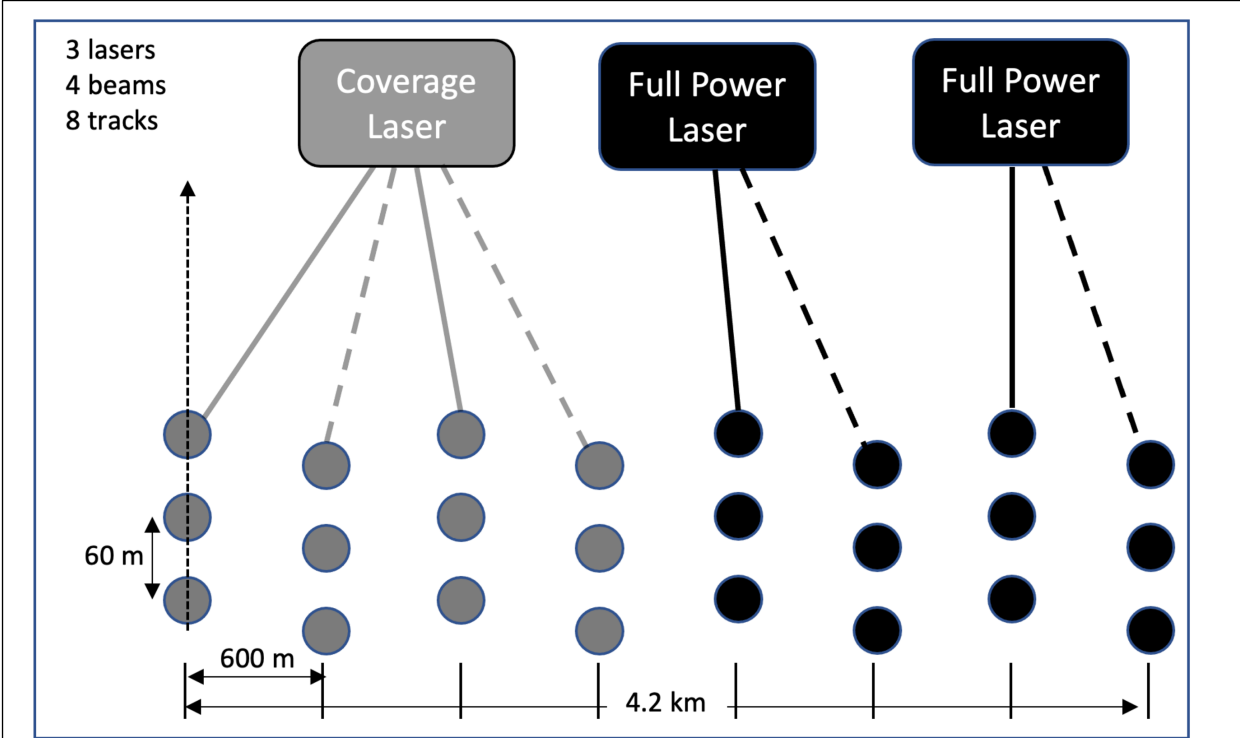
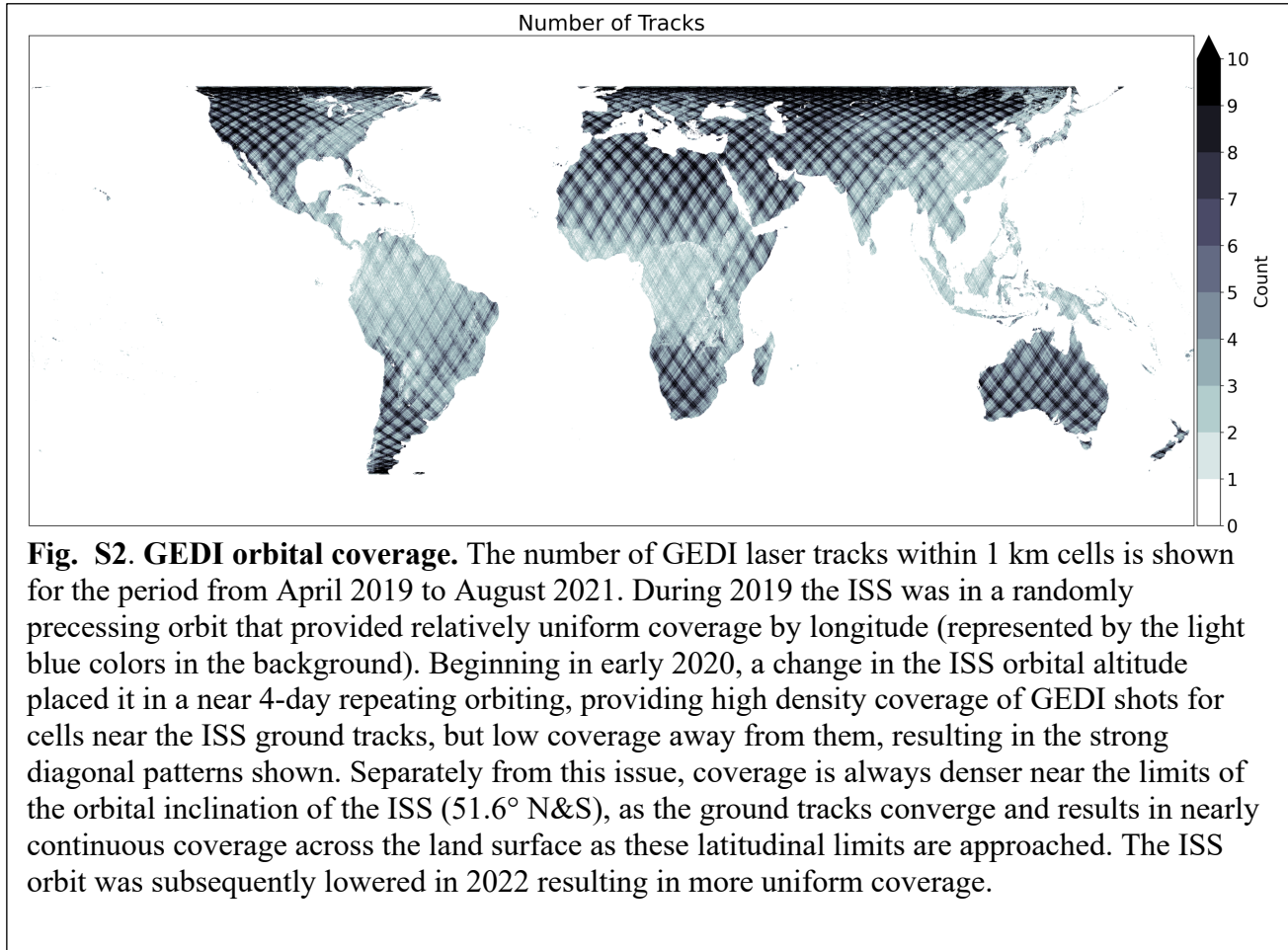


Fig. S1. The GEDI beam pattern. GEDI uses three lasers to produce 4 beams of 25 m diameter. The Coverage Laser output is split into two beams. Each of these beams are dithered across the ISS orbital track to produce 8 transects or tracks of data, where each footprint is separated by 60 m along-track and 600 m across track. Returned waveforms from each footprint are used to derive vertical canopy structure, such as height, as inputs to calibration equations that then predict aboveground biomass density for that footprint.



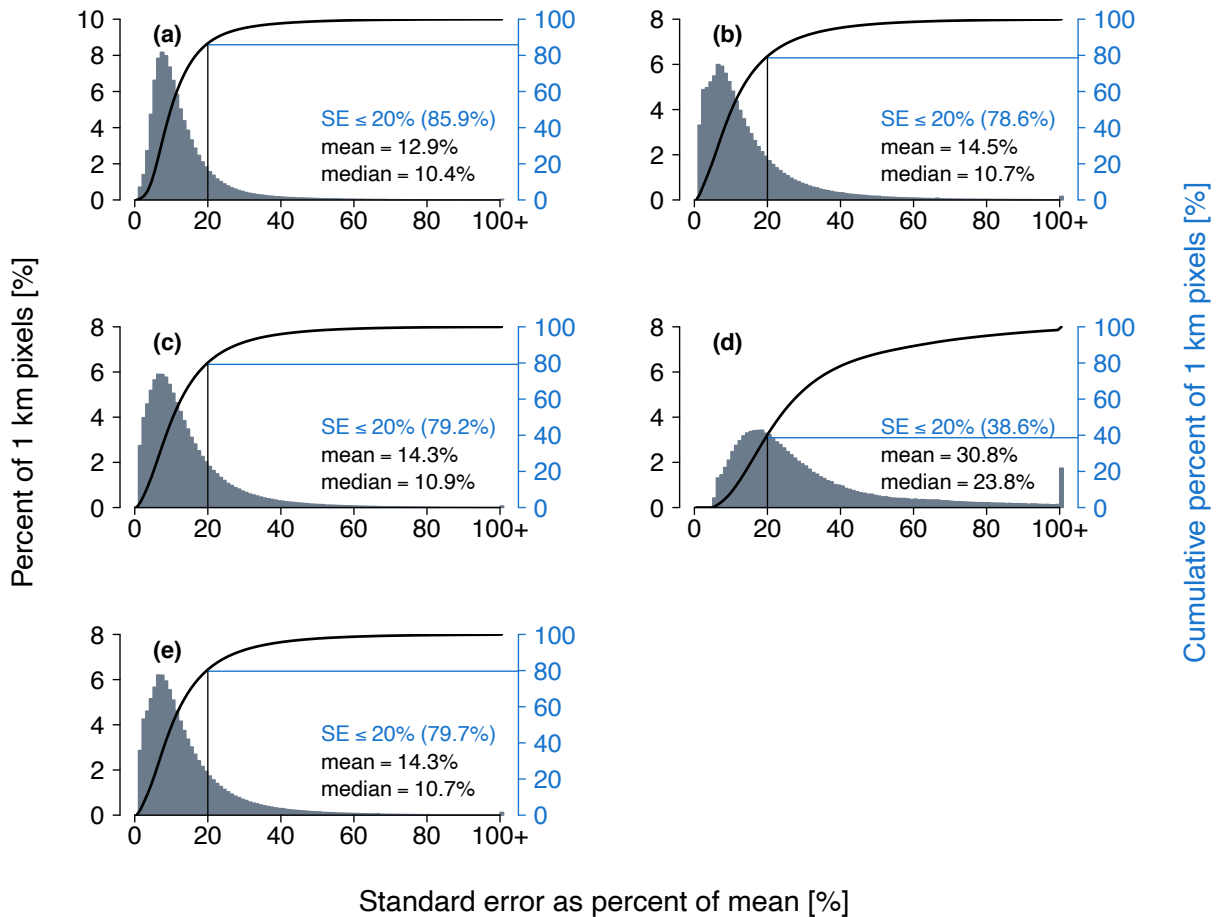


Fig. S3. Biomass standard errors for high biomass cells by PFT. Plots show errors for 1 km cells whose mean biomass is > 100 Mg/ha. Black line gives cumulative percentages. Blue horizontal lines give the cumulative percent of cells with standard errors $\leq 20\%$. **(a)** Needleleaf **(b)** Evergreen broadleaf **(c)** Deciduous broadleaf **(d)** Grass-shrub-woodland **(e)** Forested (all PFTs except Grass-shrub-woodland).

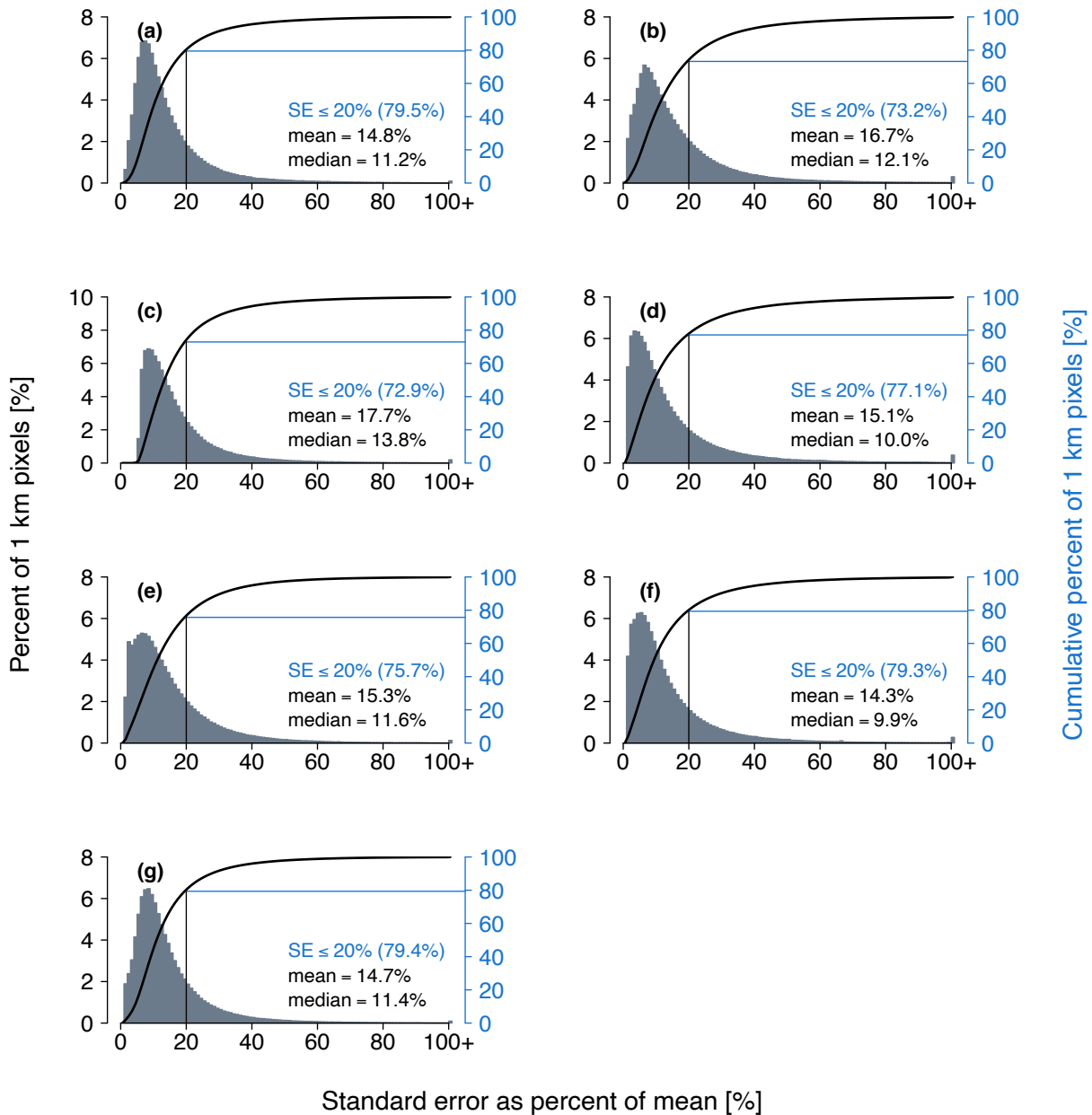
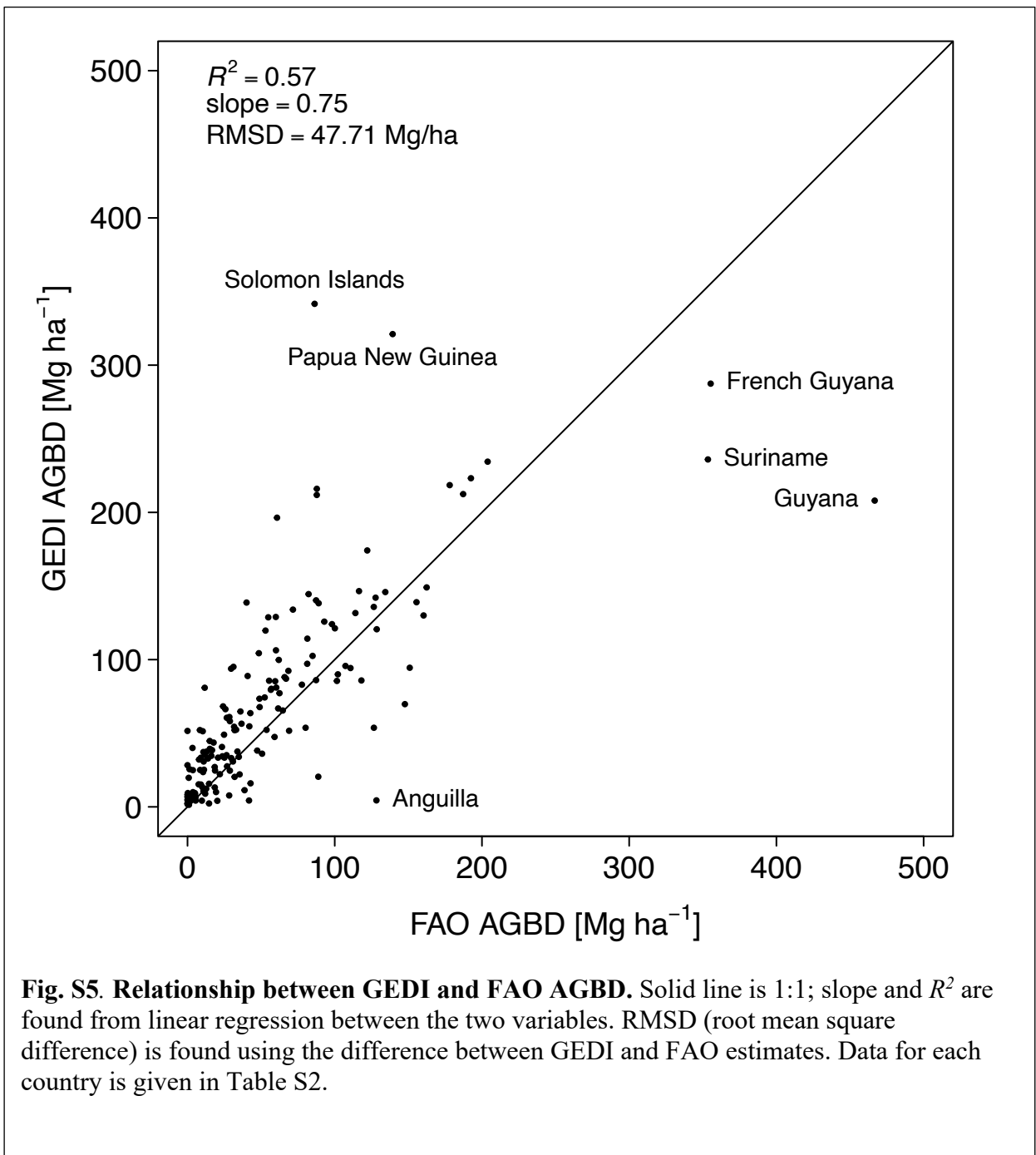


Fig. S4. Biomass standard errors for high biomass cells by region. Plots show errors for 1 km cells whose mean biomass is > 100 Mg/ha. Black line gives cumulative percentages. Blue horizontal lines give the cumulative percent of cells with standard errors \leq 20%. **(a)** Europe **(b)** North Asia **(c)** Australasia **(d)** Africa **(e)** South Asia **(f)** South America **(g)** North America.



Supplementary Tables

Table S1. Aboveground biomass densities (AGBD). GEDI estimated AGBD by plant functional type (PFT) and by *PFT x region*.

Name	Global Area [%]	PFT Area [%]	Region Area [%]	AGBD mean [Mg ha ⁻¹]	AGBD standard deviation [Mg ha ⁻¹]	Among all land cells, percent that meet requirements	Among land cells where GEDI makes an estimate, percent that meet requirements
Global	100.000	100.000	100.000	35.890	69.763	70.451	94.841
NT	3.310	100.000	3.312	92.778	78.290	83.030	92.316
EBT	21.362	100.000	21.374	126.727	115.148	42.273	82.509
DBT	12.118	100.000	12.126	81.229	68.525	38.137	86.772
GSW	52.480	100.000	52.511	9.500	22.051	86.569	98.238
FORESTED	36.791	100.000	36.813	108.886	101.091	44.578	85.206
Europe	4.169	4.169	100.000	49.102	54.894	85.099	93.623
North Asia	20.190	20.190	100.000	21.984	46.625	83.359	96.309
Australia	8.970	8.970	100.000	37.915	97.235	81.887	95.795
Africa	28.348	28.348	100.000	17.363	44.010	68.615	97.844
South Asia	9.391	9.391	100.000	62.900	85.760	49.191	90.139
South America	17.606	17.606	100.000	65.025	95.025	56.594	90.173
North America	11.267	11.267	100.000	45.116	64.618	76.788	93.503
NT Europe	0.445	13.422	10.665	95.500	59.539	89.969	94.262
NT North Asia	0.703	21.236	3.484	123.569	78.585	68.671	87.745
NT Australia	0.087	2.639	0.974	100.812	52.038	76.952	86.292
NT Africa	0.024	0.729	0.085	48.137	34.139	83.132	95.035
NT South Asia	0.165	4.982	1.757	80.948	71.228	58.123	90.412
NT South America	0.150	4.542	0.854	102.684	88.990	71.039	83.854
NT North America	1.735	52.396	15.404	82.121	80.318	90.784	94.342
EBT Europe	0.164	0.770	3.945	55.896	32.954	88.758	94.468
EBT North Asia	0.186	0.869	0.919	167.649	101.561	57.644	84.974
EBT Australia	2.244	10.502	25.014	156.049	167.966	56.445	82.428
EBT Africa	4.416	20.668	15.577	112.012	93.063	33.081	84.592
EBT South Asia	4.376	20.480	46.594	130.687	99.813	35.264	78.474
EBT South America	9.563	44.760	54.317	124.142	108.856	44.055	82.540
EBT North America	0.413	1.935	3.670	101.173	83.613	71.129	88.993
DBT Europe	1.026	8.466	24.615	107.082	59.169	62.549	82.241
DBT North Asia	1.662	13.712	8.231	122.173	74.028	39.869	84.841
DBT Australia	0.001	0.004	0.006	17.712	35.354	32.982	93.532
DBT Africa	3.710	30.608	13.086	44.728	40.966	27.512	94.055
DBT South Asia	0.866	7.148	9.225	77.097	48.140	26.734	88.671

DBT South America	1.858	15.326	10.551	12.647	26.512	40.866	97.574
DBT North America	2.996	24.723	26.595	106.777	65.385	43.575	79.604
GSW Europe	0.822	1.564	19.714	18.315	34.855	89.593	94.749
GSW North Asia	15.779	30.038	78.152	12.088	26.928	88.641	97.241
GSW Australia	6.359	12.106	70.894	7.120	15.403	90.775	99.340
GSW Africa	18.945	36.065	66.828	5.742	13.340	84.636	99.466
GSW South Asia	1.101	2.097	11.729	13.028	25.467	77.900	97.302
GSW South America	5.201	9.900	29.538	13.311	27.650	81.013	96.727
GSW North America	4.273	8.135	37.928	12.212	24.984	89.640	97.788
FORESTED Europe	1.635	4.444	39.225	97.648	59.083	72.640	87.384
FORESTED North Asia	2.551	6.932	12.634	126.628	79.498	49.104	85.949
FORESTED Australia	2.332	6.337	25.995	153.366	164.683	57.208	82.616
FORESTED Africa	8.150	22.147	28.748	85.765	83.701	30.694	88.294
FORESTED South Asia	5.407	14.694	57.576	122.428	96.179	34.595	80.158
FORESTED South America	11.571	31.446	65.722	109.254	108.261	43.894	84.514
FORESTED North America	5.145	13.983	45.669	94.958	75.245	61.712	87.216

Table S2. Country-level biomass estimates. GEDI and FAO estimates of mean aboveground biomass (AGB), density (AGBD) and standard errors (SE) of the mean.

Country	Percent Forest [%]	FAO Forested AGBD [Mg ha ⁻²]	FAO Total AGBD [Mg ha ⁻²]	GEDI Total AGBD [Mg ha ⁻²]	GEDI AGBD SE [Mg ha ⁻¹]	GEDI AGBD SE [%]	FAO AGB [Pg]	GEDI AGB [Pg]	GEDI AGB SE [Pg]
Afghanistan	1.851	NA	NA	24.665	1.321	5.358	NA	1.584E+00	8.486E-02
Åland	NA	NA	NA	NA	NA	NA	NA	NA	NA
Albania	28.792	NA	NA	56.874	1.421	2.498	NA	1.612E-01	4.026E-03
Algeria	0.818	29.390	0.241	3.864	0.548	14.171	5.728E-02	8.921E-01	1.264E-01
Andorra	34.043	154.000	52.426	74.302	4.684	6.303	2.464E-03	3.360E-03	2.118E-04
Angola	53.427	30.300	16.188	34.647	0.645	1.862	2.018E+00	4.312E+00	8.028E-02
Anguilla	61.111	210.000	128.333	4.392	0.988	22.501	1.155E-03	3.544E-05	7.973E-06
Antigua and Barbuda	18.455	210.000	38.755	11.306	1.513	13.378	1.705E-03	5.105E-04	6.829E-05
Argentina	10.441	185.740	19.393	10.041	0.481	4.789	5.307E+00	2.796E+00	1.339E-01
Armenia	11.537	NA	NA	29.318	1.201	4.096	NA	8.675E-02	3.553E-03
Aruba	2.333	NA	NA	2.094	0.494	23.600	NA	3.554E-05	8.388E-06
Ashmore and Cartier Islands	NA	NA	NA	NA	NA	NA	NA	NA	NA
Australia	17.443	83.980	14.649	15.686	0.792	5.048	1.125E+01	1.206E+01	6.090E-01
Austria	47.251	172.300	81.413	114.239	2.179	1.907	6.718E-01	9.595E-01	1.830E-02
Azerbaijan	13.692	NA	NA	29.509	0.977	3.309	NA	2.545E-01	8.423E-03
Bahrain	0.909	NA	NA	2.955	0.478	16.162	NA	1.728E-04	2.793E-05
Bangladesh	14.469	62.820	9.089	33.378	0.925	2.770	1.183E-01	4.570E-01	1.266E-02
Barbados	14.651	NA	NA	14.043	1.148	8.174	NA	6.238E-04	5.099E-05
Belarus	43.195	156.100	67.427	NA	NA	NA	1.369E+00	NA	NA
Belgium	22.764	NA	NA	57.921	1.423	2.457	NA	1.776E-01	4.364E-03
Belize	55.986	211.000	118.131	85.845	1.469	1.712	2.695E-01	1.914E-01	3.277E-03
Benin	27.804	103.560	28.794	24.566	0.927	3.775	3.247E-01	2.852E-01	1.077E-02
Bermuda	20.000	NA	NA	20.308	1.468	7.226	NA	1.265E-04	9.143E-06
Bhutan	71.487	269.320	192.528	223.188	3.516	1.576	7.339E-01	9.009E-01	1.419E-02
Bolivia	46.925	131.260	61.594	66.840	0.945	1.414	6.672E+00	7.264E+00	1.027E-01
Bosnia and Herzegovina	42.733	NA	NA	97.419	1.826	1.874	NA	5.049E-01	9.462E-03
Botswana	26.917	155.250	41.789	4.301	0.688	15.988	2.368E+00	2.491E-01	3.982E-02
Brazil	59.417	171.920	102.151	90.008	1.283	1.426	8.538E+01	7.626E+01	1.087E+00
British Indian Ocean Territory	NA	NA	NA	44.928	10.494	23.357	NA	2.204E-04	5.148E-05
British Virgin Islands	24.133	210.000	50.680	36.103	3.368	9.330	7.602E-04	5.233E-04	4.882E-05
Brunei	72.106	247.000	178.102	218.515	6.617	3.028	9.386E-02	1.249E-01	3.783E-03
Bulgaria	35.860	180.500	64.728	65.432	1.444	2.208	7.027E-01	7.378E-01	1.629E-02
Burkina Faso	22.721	47.790	10.858	10.709	0.892	8.330	2.971E-01	2.921E-01	2.433E-02
Burundi	10.889	119.380	13.000	37.569	0.964	2.565	3.338E-02	9.375E-02	2.405E-03
Cabo Verde	11.345	95.000	10.778	37.244	2.419	6.494	4.343E-03	1.446E-02	9.392E-04
Cambodia	45.708	69.300	31.676	54.393	0.977	1.796	5.591E-01	9.848E-01	1.769E-02

Cameroon	43.030	265.050	114.050	131.622	2.050	1.558	5.391E+00	6.111E+00	9.519E-02
Canada	38.151	90.430	34.500	NA	NA	NA	3.137E+01	NA	NA
Cayman Islands	53.000	NA	NA	5.400	0.922	17.071	NA	1.670E-04	2.851E-05
Central African Republic	35.801	217.090	77.719	82.979	1.061	1.278	4.842E+00	5.128E+00	6.555E-02
Chad	3.425	91.230	3.125	8.729	0.618	7.075	3.935E-01	1.105E+00	7.821E-02
Chile	24.492	219.270	53.704	52.282	0.986	1.887	3.993E+00	3.851E+00	7.266E-02
China	23.341	64.720	15.106	44.748	0.721	1.611	1.424E+01	4.195E+01	6.756E-01
Clipperton Island	NA	NA	NA	NA	NA	NA	NA	NA	NA
Colombia	53.305	184.130	98.151	124.083	1.837	1.481	1.089E+01	1.408E+01	2.085E-01
Comoros	17.699	66.000	11.681	80.896	2.202	2.722	2.173E-03	1.353E-02	3.683E-04
Cook Islands	64.958	NA	NA	142.774	13.583	9.514	NA	2.729E-03	2.596E-04
Coral Sea Islands	NA	NA	NA	NA	NA	NA	NA	NA	NA
Costa Rica	59.437	196.000	116.497	146.522	2.771	1.891	5.948E-01	7.494E-01	1.417E-02
Croatia	34.652	174.010	60.297	81.014	1.707	2.107	3.374E-01	4.462E-01	9.400E-03
Cuba	31.167	113.590	35.403	22.044	0.359	1.627	3.683E-01	2.423E-01	3.942E-03
Curaçao	0.158	79.000	0.125	5.080	0.648	12.753	5.530E-06	2.353E-04	3.001E-05
Cyprus	18.672	41.930	7.829	32.138	1.140	3.548	7.234E-03	1.734E-02	6.152E-04
Czechia	34.673	163.230	56.596	79.508	1.586	1.994	4.370E-01	6.262E-01	1.249E-02
Democratic Republic of the Congo	55.647	231.000	128.545	120.614	1.557	1.291	2.914E+01	2.786E+01	3.595E-01
Denmark	14.966	113.100	16.927	NA	NA	NA	7.108E-02	NA	NA
Djibouti	0.250	86.510	0.216	9.370	0.835	8.908	5.018E-04	2.047E-02	1.824E-03
Dominica	63.827	NA	NA	162.851	7.532	4.625	NA	1.189E-02	5.501E-04
Dominican Republic	44.382	82.700	36.704	56.468	0.988	1.749	1.773E-01	2.735E-01	4.784E-03
East Timor	61.944	150.000	92.915	125.799	6.915	5.497	1.382E-01	1.897E-01	1.043E-02
Ecuador	50.321	177.020	89.079	138.284	2.440	1.764	2.212E+00	3.526E+00	6.222E-02
Egypt	0.045	120.000	0.054	4.698	0.534	11.374	5.398E-03	4.704E-01	5.350E-02
El Salvador	28.180	113.610	32.015	52.067	1.000	1.920	6.633E-02	1.069E-01	2.054E-03
Equatorial Guinea	87.288	214.500	187.232	212.412	3.865	1.820	5.252E-01	5.665E-01	1.031E-02
Eritrea	10.448	72.520	7.577	15.293	1.019	6.661	7.653E-02	1.874E-01	1.248E-02
Estonia	56.094	115.870	64.996	NA	NA	NA	2.825E-01	NA	NA
eSwatini	28.928	76.050	22.000	22.187	1.036	4.671	3.784E-02	3.797E-02	1.773E-03
Ethiopia	15.244	121.310	18.492	27.053	0.786	2.904	2.071E+00	3.050E+00	8.857E-02
Falkland Islands	0.000	0.000	0.000	6.855	0.508	7.415	0.000E+00	7.950E-03	5.895E-04
Faroe Islands	0.057	NA	NA	NA	NA	NA	NA	NA	NA
Federated States of Micronesia	92.029	NA	NA	197.577	16.591	8.397	NA	1.252E-02	1.052E-03
Fiji	62.398	202.790	126.538	135.785	8.082	5.952	2.312E-01	2.570E-01	1.530E-02
Finland	73.736	59.770	44.072	NA	NA	NA	1.339E+00	NA	NA
France	31.509	135.500	42.695	63.643	1.308	2.055	2.338E+00	3.487E+00	7.164E-02
French Guyana	97.358	365.000	355.358	287.437	4.943	1.720	2.921E+00	2.391E+00	4.112E-02
French Polynesia	40.836	148.920	60.813	196.387	16.181	8.240	2.226E-02	6.552E-02	5.399E-03
Gabon	91.321	223.250	203.873	234.448	3.896	1.662	5.253E+00	6.095E+00	1.013E-01
Gambia	23.979	41.800	10.023	13.472	1.132	8.402	1.014E-02	1.415E-02	1.189E-03

Georgia	40.616	119.340	48.471	104.356	1.747	1.674	3.368E-01	7.260E-01	1.215E-02
Germany	32.732	185.140	60.601	NA	NA	NA	2.114E+00	NA	NA
Ghana	35.096	96.640	33.917	37.606	0.788	2.095	7.717E-01	8.975E-01	1.880E-02
Gibraltar	0.000	0.000	0.000	51.573	9.932	19.259	0.000E+00	1.904E-05	3.668E-06
Greece	30.270	34.240	10.364	51.351	1.263	2.460	1.336E-01	6.745E-01	1.659E-02
Greenland	0.001	NA	NA	NA	NA	NA	NA	NA	NA
Grenada	52.059	109.400	56.952	80.200	3.847	4.796	1.936E-03	2.785E-03	1.336E-04
Guadeloupe	42.556	347.000	147.670	69.759	2.336	3.348	2.496E-02	1.156E-02	3.871E-04
Guatemala	32.921	124.050	40.838	88.875	1.629	1.833	4.376E-01	9.671E-01	1.772E-02
Guernsey	5.250	NA	NA	38.197	6.862	17.965	NA	2.826E-04	5.077E-05
Guinea	25.187	131.190	33.043	52.373	0.847	1.616	8.119E-01	1.279E+00	2.068E-02
Guinea-Bissau	70.413	84.000	59.147	47.468	0.996	2.098	1.663E-01	1.558E-01	3.269E-03
Guyana	93.550	498.960	466.778	208.000	3.200	1.538	9.189E+00	4.393E+00	6.759E-02
Haiti	12.602	94.530	11.912	35.239	0.719	2.041	3.283E-02	9.476E-02	1.934E-03
Heard Island and McDonald Islands	NA	NA	NA	NA	NA	NA	NA	NA	NA
Honduras	56.835	105.720	60.086	106.327	1.909	1.795	6.723E-01	1.193E+00	2.142E-02
Hong Kong S.A.R.	NA	NA	NA	54.324	2.957	5.443	NA	5.629E-03	3.064E-04
Hungary	22.678	109.490	24.830	49.005	1.796	3.664	2.248E-01	4.567E-01	1.674E-02
Iceland	0.512	23.660	0.121	NA	NA	NA	1.215E-03	NA	NA
India	24.270	68.700	16.674	38.522	0.599	1.555	4.957E+00	1.214E+01	1.888E-01
Indian Ocean Territories	NA	NA	NA	172.175	8.879	5.157	NA	1.927E-03	9.938E-05
Indonesia	49.072	178.950	87.814	211.832	7.268	3.431	1.649E+01	3.982E+01	1.366E+00
Iran	6.601	137.670	9.088	15.166	0.798	5.261	1.480E+00	2.461E+00	1.295E-01
Iraq	1.900	51.110	0.971	3.700	0.518	13.996	4.217E-02	1.618E-01	2.265E-02
Ireland	11.352	111.640	12.673	NA	NA	NA	8.730E-02	NA	NA
Isle of Man	6.070	NA	NA	NA	NA	NA	NA	NA	NA
Israel	6.470	NA	NA	11.854	0.898	7.576	NA	2.596E-02	1.967E-03
Italy	32.522	110.600	35.970	64.779	1.247	1.925	1.058E+00	1.951E+00	3.756E-02
Ivory Coast	8.920	94.450	8.425	52.136	0.874	1.676	2.679E-01	1.672E+00	2.801E-02
Jamaica	55.114	158.500	87.356	86.060	1.539	1.789	9.461E-02	9.495E-02	1.698E-03
Japan	68.398	NA	NA	136.960	1.156	0.844	NA	5.116E+00	4.318E-02
Jersey	5.000	NA	NA	38.497	2.210	5.741	NA	4.583E-04	2.631E-05
Jordan	1.098	56.900	0.625	6.222	0.631	10.148	5.548E-03	5.529E-02	5.611E-03
Kazakhstan	1.280	82.470	1.055	NA	NA	NA	2.849E-01	NA	NA
Kenya	6.345	200.380	12.714	12.309	0.675	5.482	7.236E-01	7.159E-01	3.925E-02
Kiribati	1.457	NA	NA	20.593	2.918	14.171	NA	1.956E-03	2.772E-04
Kosovo	NA	NA	NA	54.639	2.040	3.734	NA	5.963E-02	2.226E-03
Kuwait	0.351	NA	NA	1.719	0.603	35.079	NA	3.004E-03	1.054E-03
Kyrgyzstan	6.858	49.660	3.406	40.009	2.316	5.789	6.532E-02	7.961E-01	4.608E-02
Laos	71.904	121.500	87.364	140.253	2.998	2.138	2.016E+00	3.199E+00	6.839E-02
Latvia	54.853	128.130	70.284	NA	NA	NA	4.370E-01	NA	NA
Lebanon	14.011	61.270	8.584	25.064	1.515	6.045	8.782E-03	2.506E-02	1.515E-03
Lesotho	1.137	73.720	0.838	19.730	1.315	6.667	2.545E-03	5.940E-02	3.960E-03

Liberia	79.085	205.400	162.440	149.037	2.353	1.579	1.565E+00	1.420E+00	2.242E-02
Libya	0.123	49.260	0.061	2.453	0.516	21.037	1.069E-02	3.984E-01	8.380E-02
Liechtenstein	41.875	242.410	101.509	85.524	11.487	13.432	1.624E-03	1.174E-03	1.577E-04
Lithuania	35.132	133.900	47.041	NA	NA	NA	2.947E-01	NA	NA
Luxembourg	36.502	180.700	65.959	88.124	2.384	2.706	1.603E-02	2.299E-02	6.220E-04
Macao S.A.R	NA	NA	NA	7.128	3.823	53.633	NA	2.144E-05	1.150E-05
Macedonia	39.710	71.640	28.448	61.028	1.461	2.393	7.175E-02	1.549E-01	3.708E-03
Madagascar	21.364	163.200	34.867	33.953	0.748	2.203	2.029E+00	2.013E+00	4.434E-02
Malawi	23.777	78.700	18.713	24.627	0.699	2.839	1.764E-01	2.405E-01	6.827E-03
Malaysia	58.177	209.870	122.096	174.140	3.370	1.935	4.011E+00	5.710E+00	1.105E-01
Maldives	2.733	135.000	3.690	9.979	6.600	66.139	1.107E-04	1.085E-04	7.177E-05
Mali	10.897	46.360	5.052	4.861	0.597	12.285	6.164E-01	6.089E-01	7.481E-02
Malta	1.438	NA	NA	26.903	2.805	10.428	NA	8.762E-04	9.137E-05
Marshall Islands	52.222	132.130	69.001	51.668	9.921	19.202	1.242E-03	8.516E-04	1.635E-04
Martinique	49.330	306.000	150.950	94.467	3.471	3.674	1.600E-02	1.037E-02	3.809E-04
Mauritania	0.303	53.110	0.161	1.734	0.520	29.965	1.661E-02	1.797E-01	5.386E-02
Mauritius	19.099	124.180	23.717	34.356	1.154	3.360	4.814E-03	6.921E-03	2.325E-04
Mayotte	37.541	NA	NA	70.923	2.571	3.626	NA	2.801E-03	1.015E-04
Mexico	33.793	52.440	17.721	43.643	0.578	1.323	3.445E+00	8.545E+00	1.131E-01
Moldova	11.755	93.360	10.974	30.794	2.026	6.578	3.608E-02	1.023E-01	6.726E-03
Monaco	NA	0.000	NA	70.127	8.049	11.478	NaN	1.321E-04	1.516E-05
Mongolia	9.123	54.900	5.008	9.351	0.604	6.463	7.781E-01	1.463E+00	9.457E-02
Montenegro	61.487	96.870	59.562	85.322	2.254	2.642	8.011E-02	1.171E-01	3.095E-03
Montserrat	25.000	NA	NA	50.760	9.031	17.791	NA	5.056E-04	8.994E-05
Morocco	12.867	39.890	5.133	8.757	0.624	7.131	2.291E-01	5.182E-01	3.695E-02
Mozambique	46.725	101.370	47.365	38.212	0.847	2.216	3.725E+00	2.986E+00	6.616E-02
Myanmar	43.707	125.540	54.869	128.739	2.213	1.719	3.583E+00	8.537E+00	1.468E-01
Namibia	8.064	67.400	5.435	6.383	0.671	10.511	4.475E-01	5.252E-01	5.520E-02
Nauru	0.000	0.000	0.000	28.300	6.009	21.233	0.000E+00	8.141E-05	1.729E-05
Nepal	41.591	172.230	71.632	133.964	2.540	1.896	1.027E+00	1.971E+00	3.736E-02
Netherlands	10.968	55.130	6.046	NA	NA	NA	2.037E-02	NA	NA
New Caledonia	45.844	146.000	66.932	87.037	5.975	6.865	1.224E-01	1.640E-01	1.126E-02
New Zealand	37.570	294.650	110.700	94.275	4.423	4.692	2.915E+00	2.531E+00	1.188E-01
Nicaragua	28.316	91.020	25.773	66.336	1.208	1.821	3.102E-01	8.537E-01	1.554E-02
Niger	0.852	38.200	0.326	2.156	0.538	24.942	4.124E-02	2.546E-01	6.352E-02
Nigeria	23.746	134.770	32.002	20.354	0.537	2.637	2.915E+00	1.847E+00	4.872E-02
Niue	72.577	112.050	81.322	97.162	12.186	12.542	2.114E-03	2.143E-03	2.688E-04
Norfolk Island	12.250	NA	NA	97.764	15.832	16.194	NA	4.023E-04	6.514E-05
North Korea	50.080	62.300	31.200	95.091	1.714	1.802	3.757E-01	1.164E+00	2.097E-02
Northern Cyprus	NA	NA	NA	9.742	0.839	8.612	NA	3.234E-03	2.785E-04
Norway	40.049	64.160	25.695	NA	NA	NA	7.815E-01	NA	NA
Oman	0.008	107.670	0.009	8.303	0.585	7.051	2.692E-04	2.584E-01	1.822E-02
Pakistan	4.833	75.300	3.639	24.932	1.190	4.772	2.806E-01	2.176E+00	1.039E-01

Palau	90.022	NA	NA	109.849	12.123	11.036	NA	5.404E-03	5.964E-04
Palestine	1.684	NA	NA	12.120	1.058	8.726	NA	7.610E-03	6.641E-04
Panama	56.683	145.100	82.248	144.485	3.196	2.212	6.114E-01	1.077E+00	2.382E-02
Papua New Guinea	79.176	176.000	139.350	321.084	19.293	6.009	6.311E+00	1.494E+01	8.974E-01
Paraguay	40.529	69.860	28.314	7.747	0.187	2.416	1.125E+00	3.098E-01	7.486E-03
Peru	56.508	237.790	134.371	145.882	2.322	1.591	1.720E+01	1.882E+01	2.995E-01
Philippines	24.109	219.770	52.984	119.728	2.173	1.815	1.580E+00	3.511E+00	6.372E-02
Pitcairn Islands	70.000	NA	NA	37.336	3.762	10.077	NA	1.589E-04	1.602E-05
Poland	30.971	166.000	51.412	NA	NA	NA	1.574E+00	NA	NA
Portugal	36.153	NA	NA	37.360	1.441	3.857	NA	3.414E-01	1.317E-02
Qatar	0.000	0.000	0.000	2.020	0.495	24.523	0.000E+00	2.252E-03	5.524E-04
Republic of Serbia	31.130	156.990	48.871	73.449	1.913	2.604	4.274E-01	5.698E-01	1.484E-02
Republic of the Congo	64.264	198.800	127.756	142.063	2.186	1.538	4.363E+00	4.900E+00	7.538E-02
Reunion	39.219	125.000	49.024	67.755	2.625	3.874	1.230E-02	1.750E-02	6.779E-04
Romania	30.116	207.500	62.490	77.204	1.384	1.793	1.438E+00	1.825E+00	3.272E-02
Russia	49.784	77.330	38.498	NA	NA	NA	6.305E+01	NA	NA
Rwanda	11.188	146.060	16.341	38.381	1.287	3.353	4.031E-02	9.712E-02	3.257E-03
São Tomé and Príncipe	54.063	162.500	87.852	216.015	6.190	2.866	8.434E-03	2.240E-02	6.420E-04
Saint Barthelemy	8.500	124.500	10.583	23.611	3.778	15.999	2.117E-05	5.766E-05	9.226E-06
Saint Helena	5.128	NA	NA	103.571	21.698	20.950	NA	3.797E-03	7.956E-04
Saint Kitts and Nevis	42.308	210.000	88.846	20.454	2.839	13.879	2.310E-03	5.402E-04	7.498E-05
Saint Lucia	34.049	294.020	100.111	121.243	6.501	5.362	6.107E-03	7.337E-03	3.934E-04
Saint Martin	24.800	124.500	30.876	30.793	4.463	14.493	1.544E-04	2.103E-04	3.047E-05
Saint Pierre and Miquelon	5.304	26.250	1.392	25.550	5.249	20.544	3.203E-05	6.203E-04	1.274E-04
Saint Vincent and the Grenadines	73.179	219.130	160.358	129.996	7.839	6.030	6.254E-03	4.780E-03	2.882E-04
Samoa	57.127	105.000	59.984	128.965	8.051	6.243	1.698E-02	3.586E-02	2.239E-03
San Marino	16.667	90.990	15.165	39.411	6.946	17.625	9.099E-05	2.377E-04	4.190E-05
Saudi Arabia	0.454	26.610	0.121	4.367	0.541	12.385	2.600E-02	8.391E-01	1.039E-01
Scarborough Reef	NA	NA	NA	NA	NA	NA	NA	NA	NA
Senegal	41.906	44.250	18.543	13.182	0.835	6.335	3.570E-01	2.587E-01	1.638E-02
Serranilla Bank	NA	NA	NA	NA	NA	NA	NA	NA	NA
Seychelles	73.261	172.810	126.602	53.716	3.410	6.349	5.824E-03	2.340E-03	1.486E-04
Siachen Glacier	NA	NA	NA	64.401	5.828	9.050	NA	1.345E-02	1.217E-03
Sierra Leone	35.119	82.000	28.797	58.199	1.075	1.846	2.079E-01	4.168E-01	7.696E-03
Singapore	21.930	135.710	29.761	33.098	2.566	7.753	2.113E-03	1.690E-03	1.310E-04
Sint Maarten	10.882	NA	NA	2.978	80.005	2686.430	NA	6.956E-06	1.869E-04
Slovakia	40.056	171.110	68.540	92.376	1.683	1.822	3.295E-01	4.476E-01	8.155E-03
Slovenia	61.461	253.100	155.558	138.997	2.470	1.777	3.133E-01	2.825E-01	5.020E-03
Solomon Islands	90.138	95.780	86.334	341.637	24.867	7.279	2.417E-01	9.292E-01	6.763E-02
Somalia	9.532	102.490	9.770	4.187	0.636	15.182	6.129E-01	1.976E-01	2.999E-02
Somaliland	NA	NA	NA	6.245	0.600	9.614	NA	1.045E-01	1.005E-02
South Africa	14.055	85.660	12.040	8.935	0.584	6.537	1.461E+00	1.090E+00	7.125E-02

South Georgia and the Islands	NA	NA	NA	NA	NA	NA	NA	NA	NA
South Korea	64.518	131.690	84.964	102.526	1.719	1.676	8.279E-01	1.010E+00	1.694E-02
South Sudan	11.329	NA	NA	25.612	0.681	2.657	NA	1.606E+00	4.266E-02
Spain	37.170	55.870	20.767	33.413	0.921	2.757	1.038E+00	1.694E+00	4.670E-02
Spratly Islands	NA	NA	NA	NA	NA	NA	NA	NA	NA
Sri Lanka	33.695	79.160	26.673	60.490	1.122	1.854	1.673E-01	4.010E-01	7.436E-03
Sudan	9.836	55.980	5.506	4.262	0.568	13.334	1.028E+00	7.918E-01	1.056E-01
Suriname	97.412	362.880	353.489	235.952	4.172	1.768	5.514E+00	3.424E+00	6.054E-02
Sweden	68.695	72.470	49.783	NA	NA	NA	2.028E+00	NA	NA
Switzerland	32.113	193.060	61.998	99.795	2.447	2.452	2.450E-01	4.135E-01	1.014E-02
Syria	2.843	49.980	1.421	3.341	0.536	16.054	2.609E-02	6.212E-02	9.974E-03
Tajikistan	3.054	NA	NA	47.861	2.904	6.068	NA	6.808E-01	4.131E-02
Tanzania	51.643	48.580	25.088	33.416	0.633	1.893	2.222E+00	2.981E+00	5.644E-02
Thailand	38.899	142.500	55.431	85.657	1.497	1.748	2.832E+00	4.407E+00	7.701E-02
The Bahamas	50.935	39.800	20.272	4.095	0.343	8.375	2.029E-02	5.156E-03	4.318E-04
Togo	22.233	120.950	26.891	27.539	0.722	2.623	1.463E-01	1.566E-01	4.108E-03
Tonga	12.431	194.440	24.170	68.249	7.022	10.289	1.740E-03	4.116E-03	4.235E-04
Trinidad and Tobago	44.481	90.170	40.109	138.748	2.795	2.014	2.058E-02	7.108E-02	1.432E-03
Tunisia	4.523	58.740	2.657	4.736	0.606	12.791	4.128E-02	7.418E-02	9.488E-03
Turkey	28.871	48.110	13.890	32.820	0.804	2.450	1.069E+00	2.560E+00	6.273E-02
Turkmenistan	8.782	NA	NA	3.715	0.575	15.480	NA	1.749E-01	2.708E-02
Turks and Caicos Islands	11.074	132.260	14.646	2.312	0.691	29.894	1.391E-03	1.029E-04	3.077E-05
Tuvalu	33.333	NA	NA	141.660	22.680	16.010	NA	3.261E-04	5.220E-05
Uganda	11.659	96.000	11.193	25.205	0.626	2.485	2.244E-01	5.290E-01	1.315E-02
Ukraine	16.727	140.000	23.418	40.680	1.039	2.554	1.357E+00	2.327E+00	5.943E-02
United Arab Emirates	4.468	74.430	3.325	4.974	0.642	12.910	2.362E-02	3.535E-02	4.564E-03
United Kingdom	13.186	115.000	15.163	NA	NA	NA	3.668E-01	NA	NA
United States	35.401	118.704	42.023	54.684	0.628	1.149	3.291E+01	4.273E+01	4.911E-01
United States Minor Outlying Islands	NA	NA	NA	5.933	2.094	35.290	NA	1.661E-05	5.863E-06
Uruguay	11.604	97.000	11.256	11.827	0.346	2.922	1.970E-01	2.097E-01	6.129E-03
Uzbekistan	8.673	NA	NA	5.700	0.589	10.332	NA	2.508E-01	2.591E-02
Vanuatu	36.284	NA	NA	147.054	9.525	6.478	NA	1.808E-01	1.171E-02
Vatican	NA	0.000	NA	NA	NA	NA	NaN	NA	NA
Venezuela	52.413	204.720	107.300	95.691	1.416	1.480	9.464E+00	8.734E+00	1.292E-01
Vietnam	47.225	62.710	29.615	93.824	1.794	1.912	9.183E-01	3.086E+00	5.900E-02
Wallis and Futuna	41.643	192.600	80.204	53.722	8.647	16.095	1.123E-03	7.485E-04	1.205E-04
Western Sahara	2.500	39.890	0.997	1.399	0.542	38.789	2.653E-02	1.266E-02	4.909E-03
Yemen	1.040	NA	NA	17.071	0.926	5.423	NA	7.734E-01	4.194E-02
Zambia	60.283	44.000	26.525	35.122	0.740	2.108	1.972E+00	2.634E+00	5.553E-02
Zimbabwe	45.094	94.980	42.830	15.974	0.957	5.994	1.657E+00	6.219E-01	3.728E-02