

Global and boreal estimates of woody aboveground biomass for 2020: Filling GEDI's northern data gap with ICESat-2 and Harmonized Landsat Sentinel-2

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ABSTRACT

Forest aboveground biomass Density (AGBD) maps provide important constraints on climate and carbon cycle models and enable the long-term monitoring of carbon stocks. NASA's latest spaceborne lidar instruments provide unprecedented observations of forest structure that are used to compile spatially continuous, locally trained maps of circa 2020 AGB density and stock. To address a geographical limitation of the International Space Station deployed GEDI instrument, herein we map high northern latitude forests with a fusion of NASA's ICESat-2 mission, Harmonized Landsat Sentinel-2 (HLS), and Copernicus GLO-30 topographic data. We report a domain-wide estimate for boreal forests of 72.96 $\pm$ 0.61 Pg AGB. Combining these maps with those of tropical and temperate forests from GEDI products provides a global estimate of 2020 biomass stocks of 593.49 $\pm$ 11.47 Pg AGB. We analyze biomass means and totals across the boreal domain in different land cover types, slope classes, and ecoregions. We compare these products to national estimates of AGB stocks for high latitude countries,

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finding good general agreement between national reports and EO-based estimates, particularly for countries with robust National Forest Inventories (NFIs) and boreal forests, while underestimation of high AGBD in tall, dense forests remains a challenge for AGBD mapping. Satellite products can be used to support wide area estimation of aboveground biomass, and the maps described here provide insights into carbon stocks, patterns, and dynamics at scales relevant to forest management. These open access data products serve as a baseline to assess future changes associated with drought, fire, insects, deforestation, and degradation.

1. Introduction

Since 1990, forests have been found to sequester approximately 31% of global fossil fuel emissions, storing carbon in long-term pools including soils and trees (Friedlingstein et al., 2024). Accurate estimation and monitoring of forest carbon stocks is critical to improving forest management towards climate change mitigation, as well as to constrain climate models, and potentially contribute to accurate and robust carbon credits for forest conservation and restoration (Griscom et al., 2017). Historically, wide-area biomass maps were generated using various combinations of passive optical data (e.g. MODIS, Landsat), regional zones, sparse spaceborne lidar (ICESat-1 GLAS), and/or airborne lidar transects (Avitabile et al., 2016; Matasci et al., 2018; Neigh et al., 2013; Santoro et al., 2021). Reflecting the nature of the data available at the time, implementations using ICESat-1 GLAS data were limited by having spatially sparse and temporally restricted spaceborne lidar, leading to multistage and statistically informed approaches. The use of optical imagery from earth observation satellites has demonstrated capability for spatially extensive (Matasci et al., 2018; Puliti et al., 2020) and temporally dense mapping of a variety of forest attributes (Matasci et al., 2018). Combining Landsat with spatial predictors such as topographic variables, and informed by response variables (e.g. biomass, basal area) derived from the combination of airborne lidar and ground sample measurements, has been demonstrated to generate robust biomass estimates over large spatial extents (as reviewed in Coops et al. (2021)).

The launch of two NASA lidar missions in 2018, the Global Ecosystem Dynamics Investigation (GEDI; Dubayah et al., 2020) and the ICESat-2 ATLAS laser altimeter (Neuenschwander and Pitts, 2019), offered novel and informative spatial predictors with both the required spatial coverage and the fine, sub-hectare, spatial detail necessary to inform modeling and mapping efforts at management-relevant scales over large areas. GEDI has produced a suite of tropical and temperate products including biomass maps (Dubayah et al., 2020), but GEDI does not collect data north of ~51.6 degrees latitude, thus missing much of the boreal forest. ICESat-2 collects global data but was not originally designed for forest applications. While ICESat-2 has been found to have increased uncertainties in height measurements in tall, dense canopies relative to GEDI (Neuenschwander et al., 2020), ICESat-2 data has been used to predict canopy height accurately in boreal systems (Feng et al., 2023). As such, GEDI may be preferred where available, but ICESat-2 is well suited to fill GEDI's boreal data gap for global biomass mapping.

To align with GEDI-based temperate-tropical AGB products (Dubayah et al., 2022, Duncanson et al., 2022, Kellner et al., 2023), the boreal biomass product described herein not only fills a spatial gap for GEDI but also provides wall-to-wall estimates on a 30 by 30 m spatial grid. Until recently, high spatial resolution, locally calibrated biomass maps have been largely unavailable across the entire boreal system due to a lack of active remote sensing data sensitive to forest structure at the spatial scales of boreal forest processes (~30 m - 1 ha). Wide area estimates were drawn from much coarser passive instrument datasets (1 km - 0.1 degrees), and/or used sparse lidar samples to estimate strata-level AGBD means and stratify and multiply approaches. The circumpolar boreal forest, spanning North America and Eurasia, occupies approximately one third of global forest area, coincides with amplified climate warming observed across high northern latitudes (Price et al., 2013), and is associated with an ongoing shift in forest structure (Bernier and

Goetz, 2022; Feng et al., 2025; Montesano et al., 2024). Additionally, the boreal forest is subject to complex natural and anthropogenic disturbance regimes, impacting aboveground biomass (Wulder et al., 2020). Aboveground biomass stocks for the circumpolar boreal have been estimated by previous studies as ~75–80 Pg (Neigh et al., 2013; Thurner et al., 2014). Typical approaches for producing spatially contiguous northern forest biomass maps using lidar either generate coarse spatial resolution products by aggregating satellite lidar samples to larger pixels (e.g., Dubayah et al., 2022), or use lidar primarily for model calibration and validation, drawing on either satellite lidar (e.g., Margolis et al., 2015; Neigh et al., 2013,) or airborne lidar samples (e.g., Wulder et al., 2020; Matasci et al., 2018). The spatial coverage of ICESat-2 and GEDI is substantially greater than that of earlier satellite lidar missions (e.g., ICESat/GLAS) and most airborne lidar campaigns, enabling new strategies for training spatial prediction models. For example, (Healey et al., 2020) used a moving-window framework to relate GEDI observations to Landsat predictors, demonstrating improved performance through the use of locally trained models for wide-area mapping. We employ a similar strategy here for northern forests using ICESat-2, leveraging its extensive spatial sampling to train tile-based models that enable wall-to-wall biomass estimation at 30 m resolution.

The global coverage of ICESat-2 ATLAS data affords the opportunity to reconcile and incorporate aboveground forest biomass estimates for the boreal domain with those generated by the GEDI mission, thereby enabling a complete global accounting of aboveground forest biomass density circa 2020. Our goals in this study were two-fold: 1) to fill GEDI's northern data gap through a fusion of ICESat-2 and HLS for spatially contiguous biomass mapping at 30 m, and 2) to combine ICESat-2 and GEDI-based products to produce a cohesive estimate of global biomass for 2020.

2. Methods

This paper focuses primarily on the methods to produce the high northern latitude ICESat-2 based biomass product. Details on the production of GEDI's tropical and temperate biomass products have been previously reported (Dubayah et al., 2022, Duncanson et al., 2022, Kellner et al., 2023). Herein we describe the rationale, data, methods, and accuracy of the high northern latitude circumpolar boreal biomass AGB density map produced at a 30 m spatial resolution representing circa 2020 conditions (Fig. 1). AGB is defined as the aboveground oven-dry woody biomass (Duncanson et al., 2019), and thus does not include foliage or belowground components, expressed either as a total (AGB) or density (AGBD), the latter in units of Mg/ha.

2.1. Coincident field-based AGBD, airborne lidar, and simulated ICESat-2

We acquired coincident field-based AGBD ($AGBD_{field}$) estimates at ground plots with corresponding airborne laser scanning (ALS) data used to simulate coincident ICESat-2. These data were acquired for a variety of plant functional types (PFTs) in and near the boreal domain (Fig. 2). Field estimates of AGBD are for woody aboveground biomass and derived from individual tree data. Shrubs and non woody AGB are not included in our models.

The $AGBD_{field}$ estimates were used in the first set of models (Table SI1), which related $AGBD_{field}$ to vegetation height, following the GEDI

approach as outlined by Duncanson et al. (2022). The AGBD_{field} data were acquired from 30 different projects. These projects were not collected specifically for the purpose of boreal AGBD modeling with ICESat-2, and thus are not uniformly distributed across this study domain. They feature a variety of plot sizes, shapes, densities, and airborne lidar instruments. See (Neuenschwander et al., 2024) for details on the field data and developed ordinary least squares (OLS) regression models.

The AGBD_{field} estimates are based on the best available individual tree-based generalized allometric models (in the contiguous United States, (Jenkins et al., 2003), in Canada and Alaska, (Ung et al., 2008), in Europe, (Forrester et al., 2017). Individual tree AGB was calculated from diameter-at-breast height measurements, then aggregated to the plot-level. In some cases these (plot-level) AGBD_{field} estimates were provided directly by data collaborators. Plots ranged in size from 10 × 10 m to 30 × 30 m. Additional information about each field data site can be found in Table S1 of (Neuenschwander et al., 2024). We simulated vegetation height estimates for ICESat-2 footprints (ICESat-2_{sim}; ~30 m × 11 m) from ALS data over each field plot. ALS data was collected within five years of AGBD_{field}. Paired AGBD_{field} and ICESat-2_{sim} were then used as training data to calibrate ICESat-2 AGBD models, described below.

2.2. Simulating ICESat-2 from airborne lidar links field and spaceborne data

The simulation of ICESat-2_{sim}, a key step in the modeling process, provided a method to link AGBD_{field} to spaceborne ICESat-2-derived AGBD. The ICESat-2 AGBD model calibration followed the method developed for the GEDI biomass product, described in (Duncanson et al., 2022; Kellner et al., 2023). This model calibration used a lidar simulator (Hancock et al., 2019) to generate ICESat-2_{sim}, which is ICESat-2-like data derived from ALS data over the ground plots. This simulation overcomes limitations of matching field plots to satellite lidar, both in terms of spatial resolution (ICESat-2 segments vs. plots) and spatial collocation. The simulator used ALS point-cloud data to produce pseudo-waveforms over ground plots and then extracted the relative height (RH) metrics as they would appear if ICESat-2 had passed over that plot. Note that real ICESat-2 measurements will include photon-sampling noise, with around 80 signal photons per segment. This noise is unbiased

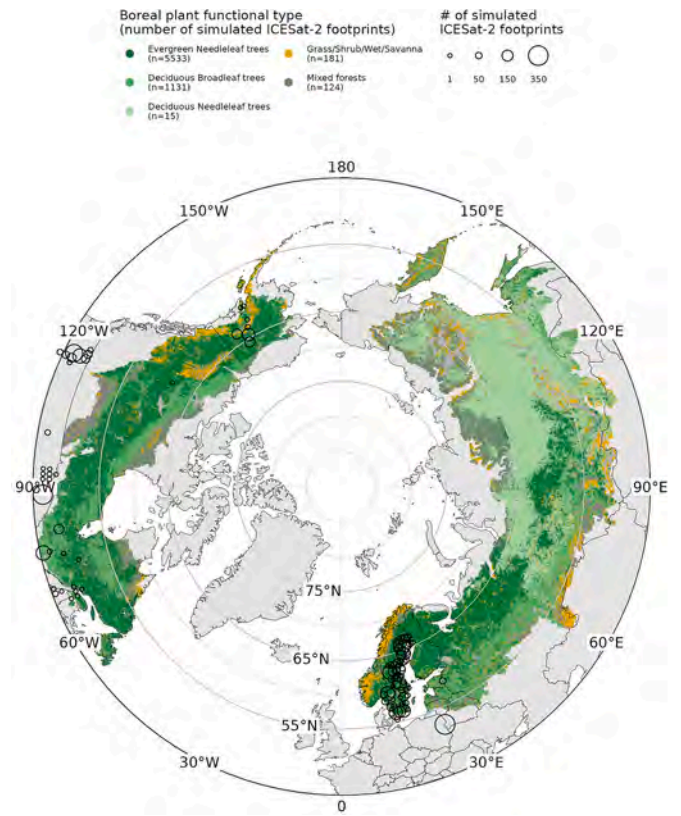


Fig. 2. The circumpolar boreal domain, defined from a collection of WWF ecoregion polygons (Olson et al., 2001), its PFTs, and training sites with corresponding AGBD_{field}, ALS, and ICESat-2_{sim}. Training sites used in this study are in and near the boreal domain and were used for AGBD model development. The PFTs mapped here were spatially clipped by the boreal domain from MODIS MCD12Q1 v006 LC_Type1 (Friedl and Sulla-Menashe, 2019). N is the number of each training samples per PFT.

and, for ≥ 40 signal photons, has a sub-1 m RMSE. The simulated pseudo-waveforms are representative of what ICESat-2 would see without photon-counting noise. The simulator has been validated and

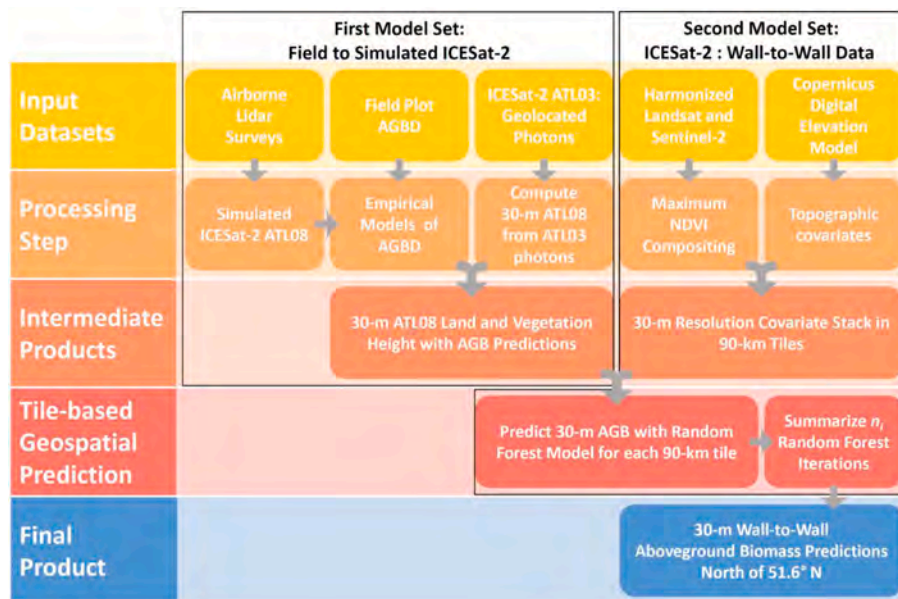


Fig. 1. Methodological workflow for predicting 30-m spatial resolution wall-to-wall aboveground biomass density (AGBD) from the ICESat-2 ATL03 geolocated photons and ATL08 Land and Vegetation Height data product.

found to have negligible bias and approximately 2.5 m RMSE for RH metrics, as long as the canopy-ground reflectance ratio is correctly specified (Purslow et al., 2023). An error in the canopy-ground reflectance ratio would lead to a bias in the simulated RH metrics. In the absence of a boreal wide map of canopy-ground reflectance ratio at ICESat-2's wavelength, a fixed value of 1.21 was assumed, taken from data at the Wind River reserve NEON site (Purslow et al., 2023). Simulations were run to test the sensitivity of RH metrics on this reflectance ratio selection, with an extreme envelope of 0.5 to 2 yielding an RMSE on RH50 and RH98 of 10% and 0.9%, respectively. Propagating this extreme range through the ICESat-2 AGBD models yielded RMSE on AGBD of up to 2.3% for DBT, 3.7% on ENT and 4.5% on the panboreal model. Realistically we expect the majority of the boreal to be close to the 1.2 value selected, thus we expect uncertainty in AGBD from uncertainty in the reflectance ratio to be far less than 5%. For full details on the ICESat-2 data and simulations refer to (Neuenschwander et al., 2024).

2.3. Developing a tiling system for sampling, gridding, and modeling

We developed a tiling system to guide sampling with ICESat-2, gridding of covariates, and modeling of AGBD. This system was based on a set of geo-referenced tiles spanning the North American and Eurasian continents in and near the circumpolar boreal domain. Each tile was $90 \text{ km} \times 90 \text{ km}$ (tile_{90}) to accommodate a 3000×3000 array of 30 m pixels. Tiles were projected to a custom conical Albers equal-area projection with standard parallels at 50 N and 70 N.

These tiles defined the spatial units for sampling ICESat-2 observations, compiling gridded covariates, and performing tile-specific model calibration and prediction. For each tile, ICESat-2 observations from the focal tile and adjacent tiles were used to train local models in equal-area projection. Our study domain of 3902 tiles included all tiles associated with the boreal domain as well as tiles that included most continental land above 51.6 N (Fig. 3a).

2.4. Modified spaceborne measurements of vegetation height from ICESat-2

In 2018, NASA launched the space-based laser altimetry mission

ICESat-2 (Ice, Cloud, and Land Elevation Satellite-2) (Neumann et al., 2019). The primary science objective of ICESat-2 is to collect critical surface height measurements needed to understand changes to the Earth's surface by providing an accurate 3D representation of Earth's surface from 88° S to 88° N latitude. Since ICESat-2 is in a nearly polar orbit, it is the only space-based laser altimeter that can collect measurements over northern latitudes, including boreal forests. Over non-polar surfaces (roughly 70° and below), the satellite is intentionally pointed away from the reference ground track every 91 days to decrease the distance between adjacent ground tracks and increase the spatial sampling. The data collected by ICESat-2 was designed to resolve new spatial detail over a variety of surfaces, including vegetated land (Glenn et al., 2016), and forest ecosystems (Neuenschwander and Pitts, 2019).

The ICESat-2 mission produces two key datasets used in the production of the ICESat-2 AGBD training data described in this paper, ATL03 and ATL08. First, ATL03 is produced by an algorithm developed specifically for land and vegetation data collected from the ATLAS instrument on ICESat-2 to extract terrain and canopy heights produces a dataset (ATL03 v6). This ATL03 dataset is then used to produce the ATL08 geophysical data product that aggregates photons to a specific segment length (step size) in the along-track direction, with segment widths of $\sim 13 \text{ m}$. Based on the distribution of signal photons, this algorithm estimates the ground surface and top of the canopy surface and then subsequently labels the individual photons as either noise, ground, canopy, or top of canopy photons (Neuenschwander and Pitts, 2019). Statistics calculated based on the labeled photons include terrain heights, canopy heights, and canopy Relative Height (RH) metrics (e.g. RH50, RH100) as well as radiometric estimates for both terrain and canopy. The ATL08 canopy height is calculated as RH98 instead of using RH100 with the motivation to not include a stray errant noise photon in the height calculations. For ICESat-2, these RH metrics are calculated as percentile height metrics of canopy classified photons, relative to the fitted ground elevation. Note that this differs from how the GEDI mission calculates RH metrics, see Neuenschwander et al., 2024 for details.

While the published ATL08 data product aggregates photons to along-track segments of 100 m, in this study we modified this aggregation to return a version of the product at 30 m segment lengths (ATL08 30 m). Details on the generation of this dataset, and data filtering, are provided in the Supplementary Information. Our adopted filters resulted

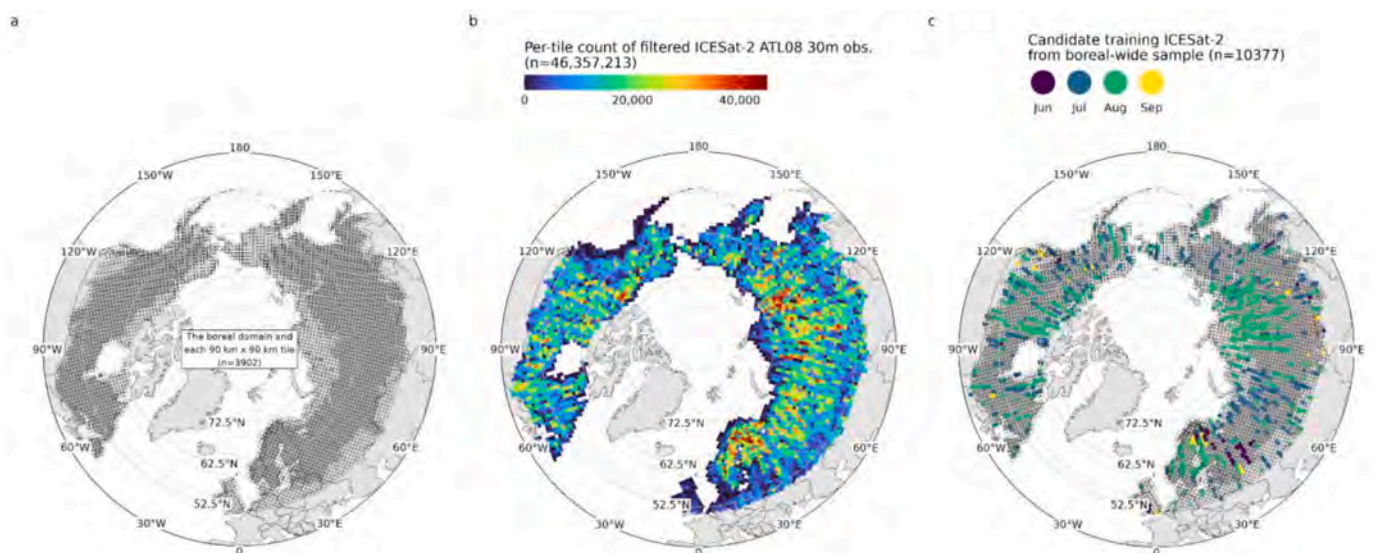


Fig. 3. (a) The set of $90 \text{ km} \times 90 \text{ km}$ processing tiles (tile_{90}) atop the circumpolar boreal domain (dark grey) used to identify and aggregate a set of (b) per-tile filtered samples of ICESat-2 ATL08 30 m observations in SlideRule. A final filtering step reduced the initial filtered set of >46 million by >50% to produce a set of per-tile candidate training. From all the per-tile candidate training observations, a boreal-wide training dataset was extracted that was used as a complementary domain-wide set of model training for each tile-specific local model (c). The tiling system covers the entire boreal domain, as well as land south of the boreal down to 51.6 N, and a large portion of the continental tundra domain.

in a set of local (tile-specific) “candidate training” observations that reduced the initial set of >46 million year 2020 ATL08 30 m observations by >50% (Fig. 3). This reduced set of observations were those to which the first AGBD model was applied, yielding ATL08 30 m point estimates of AGBD. Five years of quality-filtered canopy heights from ICESat-2 Release 005 were compared against airborne lidar data collected over Finland. ICESat-2 RH98 had a mean underestimation of 1.71 m and a RMSE of 3.85 m.

2.5. Gridding data sources: compiling topographic and multi-spectral covariates

Using our tiling system (Fig. 3a), we compiled a set of gridded covariates to serve as the independent variables for modeling and mapping of AGBD. For each tile, we identified the corresponding Copernicus GLO-30 digital elevation model 30 m (DEM_{GLO30}) and multispectral Harmonized Landsat Sentinel V 2.0 ($L30_{HLS}$, $S30_{HLS}$) (Ju et al., 2025) data and produced a gridded stack of topography (TOP_{GLO30}) and multispectral covariates, respectively.

The $TOPO_{GLO30}$ stack featured five gridded layers that included elevation, slope, topographic solar radiation index (TSRI), topographic position index (TPI), and a binary mask based on slope = 0. The first four layers were included amongst the biomass predictors and the last was used to identify some water bodies post-prediction. TPI is a terrain-derived metric that describes the relative elevation of a pixel compared to its surrounding neighborhood (Weiss, 2001). Each of these layers was derived from DEM_{GLO30} using the GDALDEM processing module within Python (Ceri, 1993). The TSRI layer is an estimate of directionally-varying exposure to solar radiation, and was computed as a cosine-based adjustment of the aspect of DEM_{GLO30} (Matasci et al., 2018).

The source of our pan-boreal spaceborne multispectral data was the $L30_{HLS}$ and $S30_{HLS}$ products from the Harmonized Landsat and Sentinel-2 V 2.0 dataset (Ju et al., 2025). This ‘harmonized’ collection of 30 m data from HLS ($H30_{HLS}$) is a surface reflectance data product generated, for our map year of 2020, from a virtual constellation of Landsat-8 OLI and Sentinel-2a/b MSI imagery. The $H30_{HLS}$ data provides surface reflectance estimates, corrected for spatial coregistration, bandpass differences, view and illumination angles, that are resampled to 30 m into the Sentinel-2 tiling system. This yields a version of Landsat-8 that is prepared for merging with Sentinel-2 multi-spectral observations in future gridded versions. The primary advantage of using the HLS product over Sentinel-2 or Landsat-8 alone in this study is the availability of many more scenes throughout the growing season to increase the accuracy of composites at the desired spatial mapping resolution or 30-m. This data is available via the LPDAAC Earth Data Cloud S3 bucket (Masek et al., 2021).

For each $tile_{90}$, eligible $L30_{HLS}$ and $S30_{HLS}$ scenes were identified with a query via the s3fs python API. Spatial and temporal search parameters, including $tile_{90}$ boundary, seasonal date range, and year, were used with cloud cover thresholds to guide the per- $tile_{90}$ data query to return a list of $L30_{HLS}$ and $S30_{HLS}$ images that intersected the particular $tile_{90}$. This list of images was used to build a seasonal multi-spectral ‘greenest pixel’ composite map across our study domain. Because the quality of a seasonal ‘greenest-pixel’ compositing depends on the ability to fill each pixel with a robust estimate derived from the peak growing season (Meng et al., 2023), we had to balance the number of observations available for each pixel-level estimate with the acquisition time of those estimates. As such, these $H30_{HLS}$ seasonal composites built for this study drew primarily from acquisitions within the seasonal window from July1–August 31 of year 2020. However, some tiles in areas of frequent cloud cover were composited with scenes drawn from an extended seasonal window of June 15 - Sept. 15, 2020, mostly in southern regions of the domain. The vast majority of scenes used for compositing had less than 25% scene-level cloud cover. In persistently cloudy areas, this threshold was relaxed to ensure robust cloud-free

composites (Fig. SI7).

We adopted an interactive approach to assuring that per-tile composite results featured spatially continuous observations that minimized no-data gaps. This resulted in a variety combinations of search parameters that combined to form this study’s multispectral data acquisition strategy classes. These classes featured a combination of the maximum cloud cover threshold per scene and the seasonal search window for valid scenes. These were adapted, and applied to sets of tiles to return more scenes if previous compositing runs were returning tiles with large swaths of no-data gaps. Fig. SI4[a, c] maps and summarizes per-tile arrangement of these acquisition strategy classes, which reflect patterns of tile-level search strategies based on the presence of validation data, ad-hoc region-based batch processing, as well as frequently cloud-covered regions. Fig. SI4[b, d] maps and summarizes the resulting per-tile number of scenes used in building each tile’s composite.

After filtering, ‘greenest pixel’ Best Available Pixel (BAP) seasonal compositing strategy was used to combine all HLS data from search queries (Hermosilla et al., 2017). For each tile, all pixels from $L30_{HLS}$ and $S30_{HLS}$ bands 3 (red) and 4 (NIR) within the tile bounds were read for all scenes returned from searches, and the Normalized Difference Vegetation Index (NDVI) was calculated for each scene and indexed into a 3-dimensional array stack. From this stack, an image index location (look up table) of the pixel with the highest NDVI value was recorded. This index was then used to compile a per-tile stack of all $L30_{HLS}$ and $S30_{HLS}$ bands, returning the per-band value from the specific scene from which the ‘greenest pixel’ was identified. This resulted in a single $tile_{90}$ $H30_{HLS}$ composite based upon the maximum corresponding NDVI value, outlined in Fig. SI6. This approach created cloud free composites and maximized the use of photosynthetic cover in the growing season. Once composites were created, several additional spectral indices were computed from the 6 original multispectral bands and a final suite of 21 bands were returned for each tile’s 2020 $H30_{HLS}$ composite (Table 1). The first 16 bands were used for modeling while the ValidMask and the remaining 5 bands were used for metadata analyses. The ValidMask used a red band threshold to remove any cloud, cloud shadow or water pixels that were not removed by previous filters prior to computation of the NDVI values. This effect was commonly observed with clouds over water where clouds have a higher NDVI value than water, thus producing non-zero biomass predictions.

2.6. First model set: Field to simulated ICESat-2

The simulated ICESat-2 RH metrics were used as predictors in a suite

Table 1

Description of the set of bands of the 21-band stack for the $L30_{HLS}$ composite. These bands include Landsat Spectral Indices Products courtesy of the US Geological Survey Earth Resources Observation and Science Center (<https://www.usgs.gov/landsat-missions/landsat-surface-reflectance-derived-spectral-indices>).

Composite Band Names	Description
Green, Red, NIR, SWIR, SWIR2	6 original $L30_{HLS}$ and corresponding $S30_{HLS}$ bands
NDVI (Rouse, 1973)	Normalized difference vegetation index
SAVI (Huete, 1988)	Soil adjusted vegetation index
MSAVI (Qi et al., 1994)	Modified soil adjusted vegetation index
NDMI (Gao, 1996)	Normalized Difference Moisture Index
EVI (Huete et al., 2002)	Enhanced Vegetation Index
NBR (Key and Benson, 2005)	Normalized Burn Ratio
NBR2 (Key and Benson, 2005)	Normalized Burn Ratio
TCB (Crist and Cicone, 1984; Kauth and Thomas, 1976)	Tasseled Cap Brightness
TCG (Crist and Cicone, 1984; Kauth and Thomas, 1976)	Tasseled Cap Greenness
TCW (Crist and Cicone, 1984; Kauth and Thomas, 1976)	Tasseled Cap Wetness
ValidMask	Binary mask separating land (valid) from water (invalid) based on a red band threshold.

of stratum-based OLS models, where plot-based estimates of AGBD served as reference data. Following GEDI's approach (Duncanson et al., 2022; Kellner et al., 2023), the domain was spatially divided by Plant Functional Type (PFT) (in this case Deciduous Broadleaf Trees, DBT, and Evergreen Needleleaf Trees, ENT, Fig. 2). Where sufficient training data were available, OLS models were fit to each PFT, while a pan-boreal model was fit for application to PFTs without training data. An exhaustive set of models were fit, and the models that performed best based on geographic transferability were selected (Duncanson et al., 2022; Kellner et al., 2023). These models (Neuenschwander et al., 2024, Table S11) were applied to on-orbit 30-m ATL08 data. Models were selected based on the segment_landcover value in the ATL08 product, which was derived from the Copernicus 2019 landcover product (Table S12). For each on-orbit prediction, the variance-covariance matrix from the associated OLS model was iteratively resampled to produce a suite of per-segment AGBD predictions that were sampled from to produce the second model set. For clarity, hereafter the ICESat-2 based transect AGBD estimates from model 1 will be referred to as ICESat-2 AGBD, and the outputs of the second model described below will be referred to as ICESat-2/HLS AGBD.

2.7. Second model set: modeling 30 m ICESat-2 AGBD with gridded covariate data

The second set of models produced predictions of ICESat-2 + HLS AGBD as a function of 30 m gridded covariate data from H30_{HLS} and DEM_{GL030} (Table 1). The random forests (Breiman, 2001) approach was used to model and predict per-pixel AGBD from the covariate stack. One RF model was fit per tile₉₀ for each iteration (see uncertainty section below). The combination of all quality-filtered ICESat-2 AGBD predictions within a center tile₉₀, as well as its immediate neighbor tiles

(typically 8, i.e. a 3×3 tile grid, except for tiles at the edge of the domain) were used to build a per-tile₉₀ database of 'local' candidate training observations (ICESat-2_{cand_train_local}).

Additionally, we compiled a set of complementary boreal-wide candidate training observations that provided broad domain-wide context to tile-specific local models that did not have a sufficient ($n > 10,000$) number of local observations (ICESat-2_{cand_train_boreal}; Fig. 3c). To do this we high-graded each tile₉₀ set of ICESat-2_{cand_train_local} to only include correspondences of ATL08 30 m and H30_{HLS} whose observation dates ($\Delta t_{\text{spaceborne}}$) matched ($\Delta t_{\text{spaceborne}} = 0$). This precise matching of the spatially coincident spaceborne lidar and multispectral observations was a unique luxury of the data volume considered in this study. A maximum of 10 samples from each tile₉₀ were provided to this set of ICESat-2_{cand_train_boreal}, yielding a final set of $n = 10,377$ high-graded boreal-wide candidate training observations.

To finalize each tile₉₀ set of training observations, this set of ICESat-2_{cand_train_local} was then combined with a random sample of boreal-wide candidate training observations (ICESat-2_{cand_train_boreal}). Here, one single observation was randomly sampled per-tile from each of tile₉₀ in the full domain. If sufficient ($n > 10,000$) ICESat-2_{cand_train_local} were not available, a random sample of ICESat-2_{cand_train_boreal} were used to increase the size of the training sample to at least 10,000. Typically, this was the case for the highest latitude and domain edge tiles, where fewer ICESat-2_{cand_train_local} were the result of reductions from filtering for those collected on land during the limited night and low sun elevation angle periods during the growing season in and near the Arctic.

Each tile₉₀ had 250 RF model fits, each iteratively sampling from the type 1 model coefficients and a random sample of at least 10,000 training points from the 'local' database. The exact same 'global' training dataset was included in each model to reduce tile edge effects. These RF models were then used to produce a suite of 30-m maps per tile

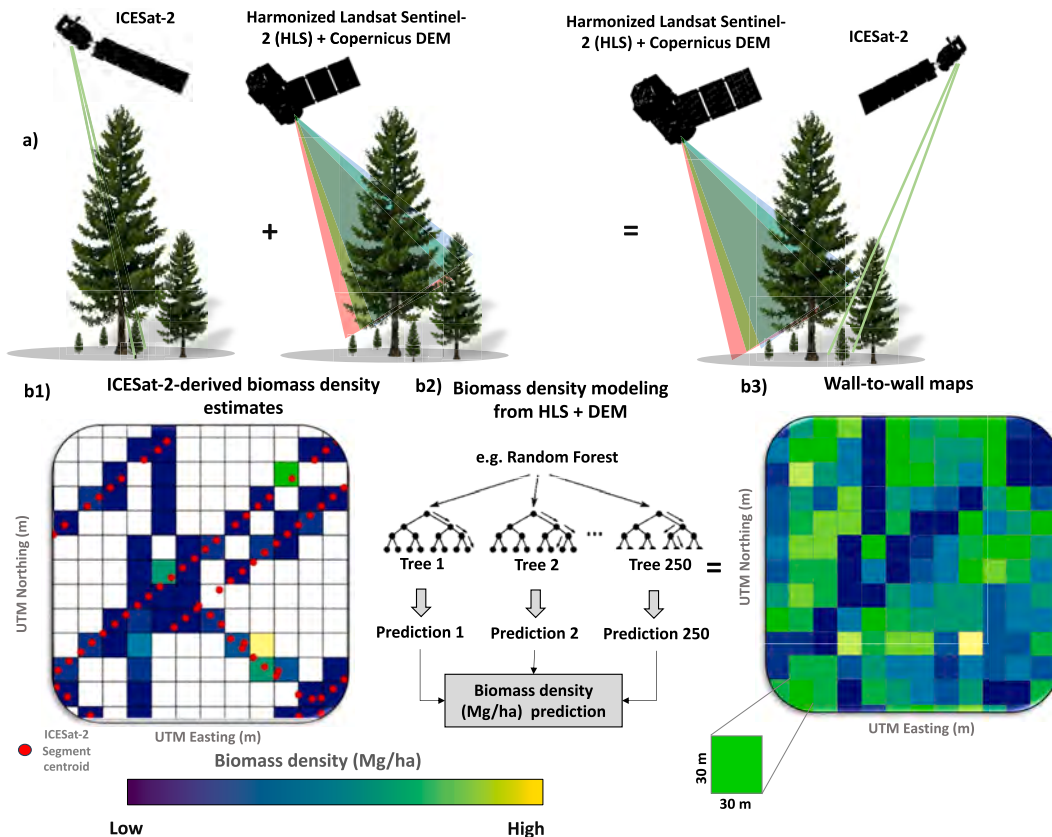


Fig. 4. Conceptual illustration of ICESat-2 and Harmonized Landsat Sentinel-2 (HLS) data used for wall-to-wall AGBD mapping. ICESat-2 and HLS missions a); ICESat-2-derived AGB density estimates at the segment level and gridded at the 30 m resolution b1); random forest modeling for AGB density upscaling based on HLS-derived metrics b2); and wall-to-wall AGB density mapping b3). Fig. 4 shows the general approach for combining the two sets of AGBD models.

(Fig. 4). The mean, total, and associated standard deviations from these ICESat-2/HLS AGBD maps were used for pan-boreal, domain-wide, world cover, slope class, and national estimates.

2.8. Estimating uncertainty for pixels and landscape domains

We estimated uncertainty in AGBD (Mg/ha) at the pixel-level and in total AGB (Pg) across various landscape domains using a parametric Bootstrap approach. We first resampled the parameters of the field: ICESat-2 OLS models and then refitted the ICESat-2: gridded covariates RF models $B = 250$ times to estimate per-pixel and domain-wide uncertainties. For the first set of models, we kept the same AGBD predictors and stratum-dependent combination of RH60, RH70 and RH98, but resampled the associated OLS parameters. For each iteration, we sampled a new coefficient for each parameter by randomly sampling from the variance-covariance matrix of the associated OLS model, assuming multivariate-normally distributed coefficients. For the second set of models (*tile₉₀*-based random forest models prediction of ICESat-2 AGBD as a function of a gridded covariate stack), we then re-fit B random forest models and examined the relative change in the standard deviation (SD) of model predictions of *tile₉₀* total AGB to ensure the uncertainty is captured. Specifically, we used a variant of a measure of stability of the bootstrapped estimates (McRoberts et al., 2023) defined by

$$m_t(n) = \frac{\text{abs}(\text{sd}(\text{AGB}_t[1:n] - \text{sd}(\text{AGB}_t[1:n-25])))}{\text{sd}(\text{AGB}_t[1:n])} * 100\% \quad (1)$$

Here t is the *tile₉₀* index, n is the bootstrap iteration index, and m_t measures the relative change in SD of tile total AGB with addition of 25 iterations. Experimentally, we observed that although m_t fluctuates as a function of n , the magnitude of fluctuations decreases as n increases. For example, $m_t(n)$ remained below 5% as early as $n=125$ for over 75% of the tiles and this proportion increased to 98% of tiles at $n=225$. For each iteration, a new suite of ICESat-2 AGBD predictions were included based on the coefficient resampling from the field:ICESat-2 models. Thus, for each of the B iterations we use a different set of OLS model coefficients, resulting in a different set of ICESat-2 predictions, which were applied to produce a different set of training data for B random forest models that produced B maps per tile. The standard deviation of each suite of models was calculated at the pixel level.

The uncertainty reported for total AGB (in Pg) in each geographic domain was calculated from the B bootstrapped estimates of total AGB for that domain. Specifically, tiles were partitioned by geographic domain (e.g., circumpolar boreal boundary, ecoregions, countries, slope classes and landcover classes). For each bootstrap iteration, total AGB (Pg) per unit was calculated as a sum of the pixel level AGBD values (Mg/ha) multiplied by their corresponding pixel areas (0.09 ha) then converted from Mg to Pg. This produced B predictions of AGB in Pg per geographical domain. When a domain intersected multiple tiles, predictions were aggregated accordingly. Finally, the B predictions were used to calculate the mean and standard deviation for each geographical domain.

2.9. Wide area biomass stock estimation

The total biomass stock for the boreal was estimated from the mean AGBD of the B iterations of models per pixel. First, we converted per pixel AGBD (Mg/ha) to AGB (Pg) as described above, and summed this per-pixel AGB for all pixels that fell within our circumpolar boreal domain (Fig. 2, SI10) which is defined from a collection of WWF ecoregions (Olson et al., 2001) associated with the circumpolar boreal forest with the addition of several transitional ecoregions that also include boreal conditions, using the same definitions and boreal extent adopted by (Neigh et al., 2013). The uncertainty associated with that total AGB was estimated as twice the standard deviation of the total, which was

calculated as the standard error of the 250 bootstrapped estimates across the boreal domain. The same method was used to produce total biomass estimates for other geographic domains, north of 51.6 degrees latitude for fusion with GEDI, and the northern portion of each country spanning 51.6 degrees latitude.

2.10. Estimating national total AGB stocks

We estimated country-level total AGB for countries predominantly located at high northern latitudes and not included in GEDI-based national estimates as reported in (Dubayah et al., 2022). For countries entirely north of 51.6 latitude, national total AGB were simply the sum of all pixels in the ICESat-2/HLS AGBD product (after conversion from AGBD to AGB). For countries that extend south of 51.6 latitude, the GEDI total for the southern part of countries was taken by following the approaches presented in (Dubayah et al., 2022) using the GEDI AGBD mean and area, with uncertainties propagated to the wide area estimates including model and sampling uncertainties. The southern total from GEDI and the northern total from ICESat-2 were then combined for country-wide estimation, and the associated confidence intervals calculated using the sum of squares approach. Our totals represent all national AGB, not just forested AGB. We compared these estimated totals to estimates from national reports included for 2020 in the 2025 FAO FRA report (FAO, 2025) for the 14 northern countries that had more than 50% of their estimated national AGB north of 51.6 degrees latitude, thus mostly from the ICESat-2 derived product outlined in this study and not from GEDI.

2.11. Assessing systematic discrepancies between AGBD estimates from ICESat-2 and GEDI

To assess potential systematic discrepancies between GEDI and ICESat-2 AGB predictions, we compared an aggregated 1 km map of the ICESat-2/HLS AGBD predictions to those from GEDI's 1 km L4B product for an overlap area between 50- and 52-degrees latitude. All 30-m ICESat-2/HLS all pixels in each GEDI 1 km cell were averaged, with differences being the GEDI AGBD prediction minus the ICESat-2 prediction. We repeated this comparing ICESat-2/HLS height predictions to GEDI's L3 gridded 1 km product in order to discern where discrepancies in AGBD did not match discrepancies in height between the two product sets.

2.12. Validation of AGBD in year 2020

The uncertainties reported at the pixel, boreal-wide, and national levels account for precision in our estimates, and assume no systematic error in our models. In reality, biomass maps typically exhibit systematic error, particularly by underestimation of high biomass densities (Stahl et al., 2024). Exhaustive reference data to estimate systematic errors was not available for this study and indeed are only available from countries with robust NFI programs. While several of the high northern latitude countries in this study do, indeed, have robust NFIs (Nesha et al., 2021), those data were not readily available for this study. However, a set of independent reference maps were available, as were national totals (Food and Agriculture Organization, 2025), and these two datasets became our independent reference data for map comparison.

We used a suite of locally trained airborne lidar AGBD maps to independently validate our product and address the degree to which systematic error is exhibited, following recommendations from the Committee on Earth Observing Satellites (CEOS) biomass protocol (Duncanson et al., 2020). Nine sites were used for validation, three in Alaska, and six in Norway (Fig. 5). Note that while the Norway sites are entirely independent reference data, field data and coincident lidar from the Alaskan site were used as training data for the models and are thus not fully independent, although still provide useful reference data as the field data only cover a very small portion of the airborne collection used

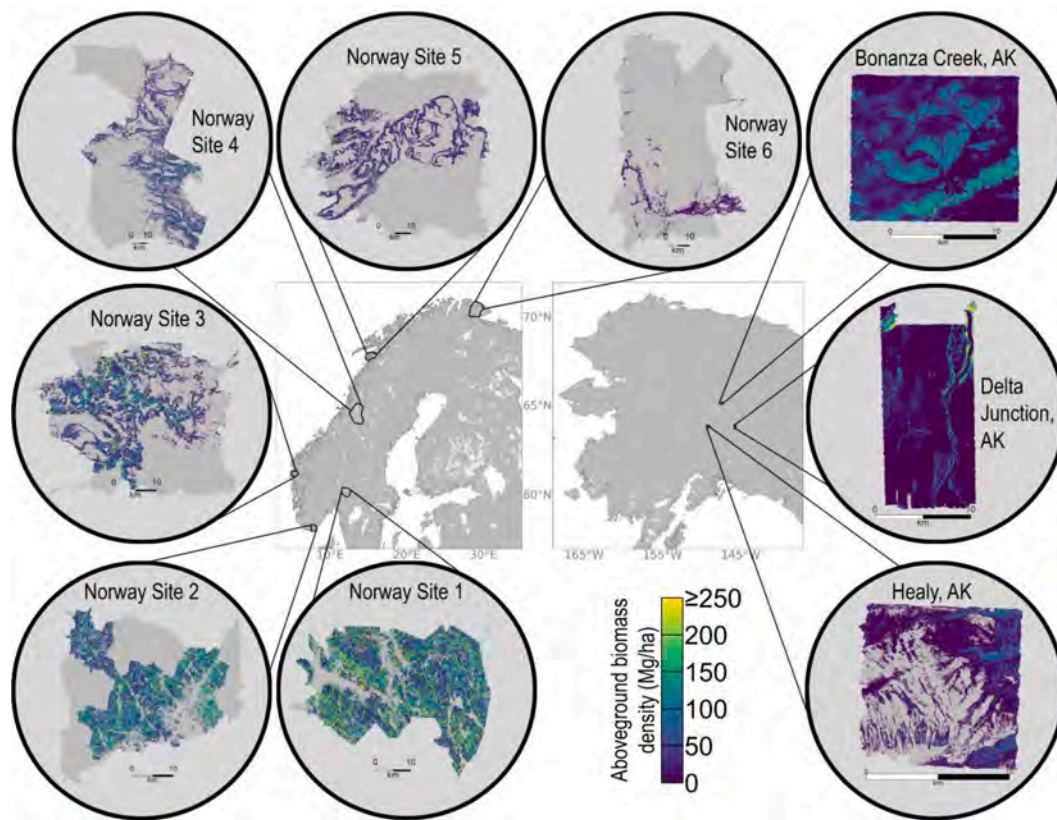


Fig. 5. Airborne lidar validation sites for study area, with AGBD representing the local mapped estimates of AGBD trained with local field plots.

for validation. Additionally, country-level total AGB was compared to total country-level NFI AGBD estimates from [Dubayah et al. \(2022\)](#), which are derived from the reported mean AGBD values and forest areas reported for 2020 in the United Nations Food and Agriculture Organization (FAO)'s Forest Resources Assessment ([Food and Agriculture Organization, 2025](#)).

The local AGBD maps in Alaska are from the National Ecological Observatory Network (NEON, [Krause and Goulden, 2015](#)), where field plots and spatially contiguous airborne lidar are available. The wall-to-wall AGBD maps in three NEON field sites (Delta Junction, Bonanza Creek, Healy) spanning across southern and central Alaska were incorporated in this independent validation. The annually repeated ground and lidar survey within three NEON sites facilitates our direct assessment of ICESat-2 biomass products using spatially and temporally coincident local biomass maps (Fig. 5). To create these maps, field-based AGBD measurements from 20 m square plots were matched with ALS observations after a series of pre-processing procedures (e.g., noise filtering, normalization). Plot-level lidar height and structure metrics were generated and correlated with field-based AGBD (~15 plots per site) through a random forest regression for site-specific biomass model development. Finally, we applied the model to lidar-derived structure attribute layers and generated spatially explicit local biomass maps.

The Norway reference data were extracted from the Norwegian forest resource map (SR16; [Astrup et al., 2019](#); [Hauglin et al., 2021](#)), which is produced using a combination of national forest inventory field plot data, Sentinel-2 mosaics, and countrywide ALS data. The latter is available as part of a national program aimed at the production of a high-resolution digital terrain model. The AGB map has 2020 as the reference year and a spatial resolution of 16x16m. Amongst the many available ALS projects, we selected a sample of six areas covering a range of latitudes (58°N – 69°N), longitudes (5°E–18°E), and the corresponding diversity in landscapes and forest types in Norway. The selected areas, described by ([Becker et al., 2023](#)), are divided into three main

forest types. The first is actively managed boreal forest in southeastern Norway used to produce timber products. In these areas the terrain is generally characterized by mild slopes and continental climate. The second is deciduous-dominated areas in the north with a large portion of low-productivity birch forests. These forests represent the transition from subpolar oceanic vegetation towards the tundra and subarctic climates. The third forest type is deciduous dominated forest alternating with patches of productive coniferous forests in the western coastal areas. These areas are characterized by a milder oceanic climate that, due to the steep slopes (i.e., fjords), can transition to tundra and alpine vegetation within short distances.

Accuracy statistics were computed for each of these 9 reference sites as follows. AGBD residuals are calculated as $\Delta AGBD = AGB_{predicted} - AGBD_{reference}$. The following absolute and relative metrics were calculated over various subsets of the reference data and summarized in table SI4. N denotes the number of pixel pairs where both the reference and predicted AGBD maps contain valid data. An unbiased RMSE metric was also calculated as the sum of the square root of the summed AGBD residuals and mean deviations.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \Delta AGBD_i^2}$$

$$RMSE\% = \frac{RMSE}{\frac{1}{N} \sum_{i=0}^N AGBD_{reference_i}} \times 100$$

$$MAE = \frac{\sum_{i=1}^N |\Delta AGBD_i|}{N}$$

$$MAE\% = \frac{MAE}{\frac{1}{N} \sum_{i=0}^N AGBD_{reference_i}} \times 100$$

$$Mean\ Deviation = \frac{1}{N} \sum_{i=1}^N \Delta AGBD_i$$

$$\text{ubRMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \Delta \text{AGBD}_i^2} + \text{Mean Deviation}^2.$$

All data processing was conducted on the ESA-NASA Multi-mission Algorithm and Analysis Platform (Albinet et al., 2019). This open science system allowed efficient parallel cloud-based computation. All associated code can be accessed in a public git repository https://github.com/lauraduncanson/icesat2_boreal.

3. Results

3.1. AGB stock totals and distributions

The estimated 2020 total pan-boreal AGB total was 72.96 $\pm$ 0.61 Pg, while the total north of 51.6 latitude was 75.09 $\pm$ 0.63 Pg. The previously reported total from GEDI for countries entirely south of 51.6 latitude (Dubayah et al., 2022) was 492.3 Pg $\pm$ 11.3, and for the southern portion of higher latitude countries was 26.1 $\pm$ 1.9 Pg. The GEDI-domain total was therefore 518.4 $\pm$ 11.45 Pg, resulting in a global 2020 AGB total from GEDI and ICESat-2 products of 593.49 Pg $\pm$ 11.47 Pg (Fig. 6). Note these estimates use different boreal extents, with this paper, Neigh et al. (2013), and CCI Biomass (2020) using the same definition of the boreal extent (i.e., based on boreal WWF ecoregions plus additional non-boreal “transition” ecoregions), while Thurner et al. (2014) used a combination of boreal classified ecoregions from Olson et al. (2001) and a forest landcover map to define their boreal extent, and Santoro et al. (2021) uses a latitudinal definition. The spatial extents used to describe the boreal domain for these products is available in Fig. SI10, with associated metadata in Table SI7. Thus, discrepancies in total AGB shown in Fig. 6b are related both to how the boreal extent was defined and the mapped biomass densities. Our total AGB estimate using only those WWF ecoregions classified as boreal by Olson et al. (2001) yields an estimate of 52.6 $\pm$ 0.45 Pg total AGB, compared to 72.96 $\pm$ 0.61 Pg total AGB for the broader boreal zone shown in Fig. 6b. The boreal estimates from the other studies shown in Fig. 6 would likely also be lower by a comparable amount for a more constrained definition of the boreal domain.

Comparisons between country-level totals of AGB for 14 northern nations, and national reported values from the FRA 2020 report (Fig. 8) show that the combined national estimates from GEDI and ICESat-2/HLS products predict national totals within 1 Pg of AGB with the exception of

Canada (Fig. 8a). FAO-reported statistics for Canada indicate significantly larger biomass stocks (9.25 Pg) than the GEDI/ICESat-2/HLS based estimate reported herein, while Russia reports lower total stocks by 0.98 Pg. All of these countries use completely independent data sources in their reporting, with the exception of Sweden as Swedish NFI sites were used to train the ICESat-2 models.

3.2. Analysis of biomass density and stock by environmental gradient

High-resolution AGBD mapping (Fig. 7) enabled an analysis of the relationships between AGBD and environmental gradients, such as latitude, topography and biogeography. The 30-m spatial scale of the ICESat-2/HLS product enabled mapping distributions of AGBD across high-resolution slope products. The flattest areas (0–5 degrees) exhibited the lowest mean AGBD (~28 Mg/ha) compared to moderate (5–30 degrees) and steep (>30 degrees) slopes, with AGBD decreasing as a function of slope when slopes are >5 degrees. It is important to note however that the vast majority of AGBD in the boreal domain occurs in relatively flat (<10 degree) areas (Fig. 9a,c).

Similar to the slope analysis, a high-resolution accounting of boreal AGB by ESA WorldCover classes (Zanaga et al., 2022) and ecoregions indicated that the majority of boreal AGB is stored in areas classified as trees (Fig. 9b). We found ~10% of total woody AGB are stored outside of tree classes, with the majority of this coming from ESA Worldcover ‘grassland’ class (~5.7% of this total), with the remainder (~4% of total) falling in other classes such as ‘shrublands’ (Fig. 9b). AGBD densities were also higher in treed landscapes, with the average boreal density of 57.2 $\pm$ 0.8 Mg/ha, compared to other land cover classes spanning 4–11 Mg/ha (Fig. 9d).

Further analyzing results by continent (Fig. 10), we found similar general patterns to the pan-boreal results, but with more biomass found in Eurasia than North America. Treed areas hosted more than three times the total aboveground biomass in Eurasia than North America but also occupied approximately twice as much land area. However, biomass densities in Eurasia were also higher, with almost double the average biomass density compared to that of North America (Fig. 10).

An analysis of mean AGBD by ecoregion highlighted that denser AGBD forests were found in Eurasia than North America (Fig. 11). The highest densities in Eurasia found in mountainous areas (Ural montane

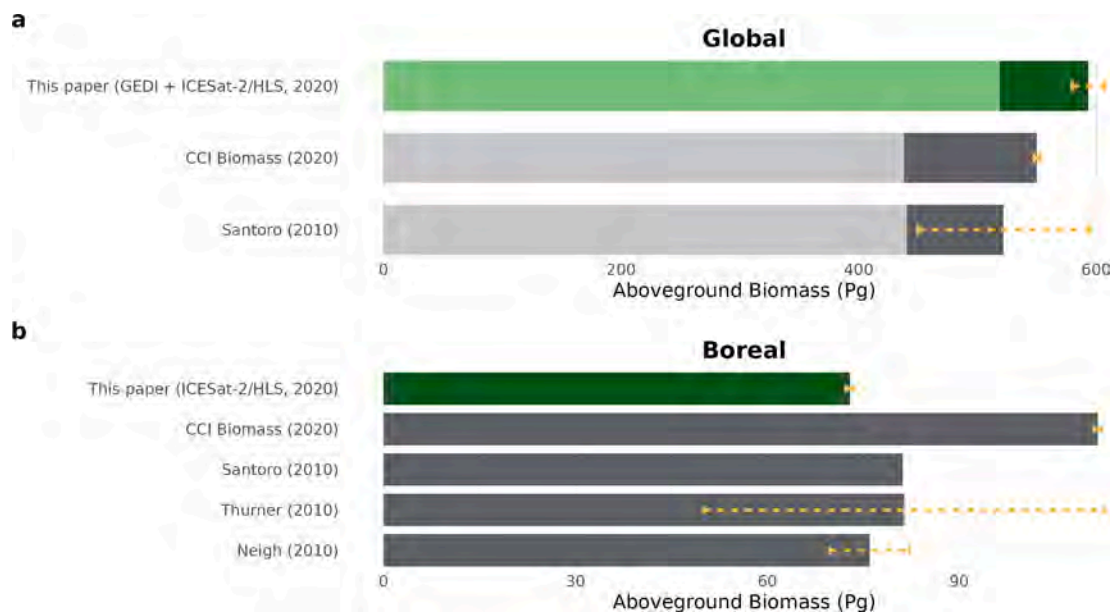


Fig. 6. A comparison of this paper's total AGB estimates to other published estimates for the globe (a) and boreal ecozone (b). For the global estimates the light green is the contribution from GEDI south of 51.6 degrees latitude, the dark green is the northern boreal estimate from the ICESat-2/HLS product. The light grey is from other papers, with their boreal proportion in dark grey.

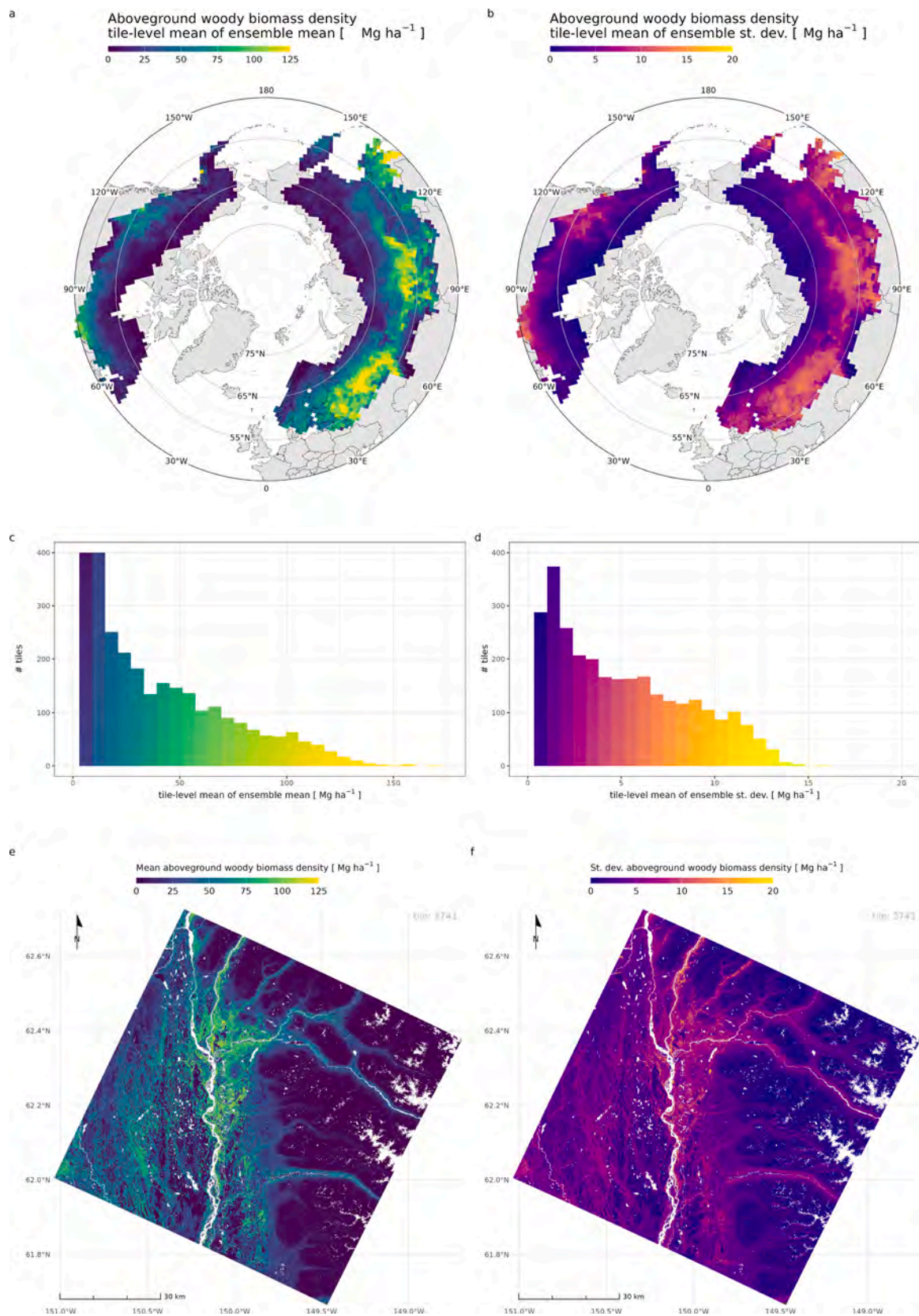


Fig. 7. Map of 2020 aboveground biomass density (a: mean) and its uncertainty (b: standard deviation) for the boreal domain using the ensemble aggregations at the tile-level from 250 bootstrapped predictions for the circumpolar boreal domain. Histograms (c, d) correspond to these aggregations. The 30 m data was aggregated to means for each $tile_{90}$ for display. Examples of a pixel-level map for a single 90 km $\times$ 90 km processing tile of 2020 AGBD mean (e) and standard deviation (f). At this scale, detailed forest structure patterns associated with hydrology and disturbance history, and the results of landcover masking, are apparent.

forests and tundra, 89.7 Mg/ha), and in southeast Siberia (Okhotsk-Manchurian taiga and Sakhalin Island taiga). The highest stocks are from lower biomass density but larger area ecoregions of East Siberian Taiga (16.37 Pg, mean 42.6 Mg/ha), Scandinavian and Russian Taiga (12.3 Pg, 60.1 Mg/ha), West Siberian Taiga (7.7 Pg AGB, mean 48.4 Mg/ha).

Recalling the broad boreal domain used (but which excludes high productivity forests in coastal and central British Columbia) the highest boreal AGBD in the North American boreal is found in the mid continental Canadian Forests (1.29 Pg, mean 37.8 Mg/ha), Northern Cordillera forests (0.77 Pg, 33.2 Mg/ha), Central Canadian Shield forests (1.27 Pg, mean 31.4 Mg/ha), and Eastern Canadian Forests (1.1 Pg, mean 25.4 Mg/ha). A full accounting of boreal and boreal transitional ecoregions is provided in Table SI5.

3.3. Product uncertainties

The mapped standard error of estimated AGBD is shown in Fig. 7b and encompasses propagated uncertainties between the two types of models. For uncertainties in the first model please refer to Neuenschwander et al. (2024). The second type of model (tile-based random forests models) generates 250 training sets from the first model and fits 250 random forest models each with different training data. The associated model uncertainties from these random forest models therefore include uncertainties in the first model, and the random forest mean RMSE and r^2 for the 250 model sets per tile are shown in Fig. 12a and b, respectively. This highlights that model fit between ICESat-2 AGB predictions and the gridded covariates (HLS and topography) varied considerably in terms of accuracy, with a correlation typically seen between r^2 and RMSE, where higher predictive power (r^2) typically occurred at lower latitudes where AGB densities are higher and more variable. Conversely, RMSE decreased with increasing latitude, likely due to smaller AGB values in higher latitude, colder environments approaching the tree line. It is well documented that RMSE will increase with increasing AGB (Zolkos et al., 2013; Duncanson et al., 2020), and the patterns seen in Fig. 12 likely reflect the relationships between AGB and latitude. This is attributed to a combination of a) less variance in allometries between height and AGB for younger and/or shorter trees (Lambert et al., 2005; Vorster et al., 2020), b) AGBD well below saturation limits of optical sensors such as HLS (Urbazaev et al., 2018), and c) ICESat-2 height uncertainties increase in taller forests (Neuenschwander et al., 2020). Thus it is expected that AGBD uncertainties are greatest in the higher AGBD areas of the boreal, as seen in Fig. 12.

3.4. Comparison of GEDI and ICESat-2

Fig. 13 compares 1 km means from the ICESat-2/HLS product to GEDI's 1 km L4B AGBD product between 50- and 52-degrees latitude, where the products overlap. The distribution of predicted AGBD between GEDI and ICESat-2 at GEDI's northern limit shows that while areas of relatively low AGBD (0–50 Mg/ha) are fairly consistent between the two products, areas of higher AGBD exhibit larger discrepancies, with GEDI predicting higher AGBD relative to the ICESat-2/HLS product in most high AGBD areas. Estimates between the two product sets differ in three primary ways: 1) they are based on different height measurements (GEDI vs. ICESat-2 relative height metrics), 2) they use models trained from different geographic domains (the ICESat-2 models include data from the northern latitudes while GEDI does not, while GEDI's PFT-wide models include data from both tropical and temperate areas), and 3) the ICESat-2 HLS product is a wall-to-wall 30 m products while GEDI's product is based on spatial samples of GEDI aggregated to 1 km. This last point is largely negligible in the latitudinal band use for comparison, as this has the greatest data sampling for GEDI with near wall-to-wall coverage due to the turning of the ISS. Therefore, we focus our analysis on a comparison of the AGBD models and ICESat-2 vs GEDI height metrics. Figs. SI3, SI4 and SI5 show comparisons of gridded height products, and discrepancies between the patterns of Fig. 13 and Fig. SI3 are attributed to differences in AGBD models rather than height measurements. The portion of 50–52 N latitude that falls within the boreal forest domain has higher consistency than non-boreal forested areas (e. g. southwest Canada which includes tall, mature, temperate rainforests), or non-forest GSW pixels.

3.5. ICESat-2/HLS product local validation

An additional set of validation results were gleaned from comparison to ALS reference products (Fig. 14). This allows validation at the pixel level; however, these sites are not representative of the full range of forests in the boreal and therefore should be interpreted in combination with the reported product uncertainties (Figs. 7, 12) as well as the national totals presented in Fig. 8. The AGBD residuals ΔAGBD relative to reference AGBD gradients were further assessed and demonstrated in Fig. SI9, with relationships between satellite predictions and local reference maps seen in Fig. 15 and Table SI6. Most sites exhibit an underestimation of AGBD except within the smaller reference bin of [0, 50] Mg/ha, and the magnitude of the residual is a function of AGBD reference bins. The worst performance was seen at Norway Site 6 which is a very high latitude mountain birch forest with short trees and complex topography, where ICESat-2 may have had limited sensitivity to low short sparse vegetation. This highlights challenges for the ICESat-2/HLS product in lower AGBD areas.

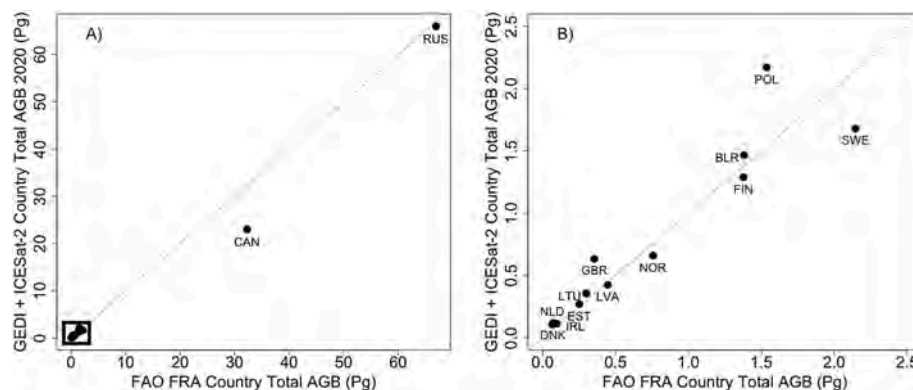


Fig. 8. Total national AGB compared to FAO 2020 FRA tables, for all majority high latitude countries with FRA reports (A) and a zoom in to the lower left box (B). Where CAN=Canada, RUS = Russian Federation, DNK = Denmark, NLD = the Netherlands, IRL = Ireland, EST = Estonia, LTU = Lithuania, GBR = Great Britain, LVA = Latvia, NOR = Norway, FIN = Finland, BLR = Belarus, POL = Poland, SWE = Sweden.

4. Discussion

4.1. Considerations for wide area mapping

To guide this work, we implemented a set of principles identified for defining and operationalizing satellite-derived products following (Radeloff et al., 2024). These include the need for systematic generation using community-endorsed algorithms, robust quality assurance and validation protocols, and institutional support for long-term continuity. Additionally, products should be policy-informative, meet diverse user needs, and be openly accessible. These criteria provide a valuable framework for evaluating the maturity and utility of emerging remote sensing products. In Radeloff et al. (2024), forest biomass is identified as a critical but currently underdeveloped component of medium-resolution satellite product suites at the global scale. It is identified as an aspirational product, with importance related to the global carbon cycle, carbon emissions from biomass burning, and sequestration by forests. Biomass mapping is identified as feasible, although requiring further algorithm development and validation before it can be considered operational beyond regional examples. The work presented here is a required and vital step towards making routine, operational, fine-grain, production of biomass at the global level possible. Below we discuss project-specific findings and share insights regarding how the global-scale AGB mapping presented here can inform and illustrate concrete steps towards specification and routine generation of global forest biomass.

4.2. Wide area biomass estimates

By integrating data from two active spaceborne lidar instruments, we produced a comprehensive estimate of aboveground forest biomass circa 2020, complete with associated uncertainties. The total estimated AGB north of 51.6 degrees latitude (derived from ICESat-2/HLS) was 75.09 $\pm$ 0.63 Pg, and south of 51.6 degrees latitude was 518.4 $\pm$ 11.45 Pg, for a combined, global total AGB circa 2020 of 593.49 Pg $\pm$ 11.47 Pg. By combining ICESat-2, HLS, airborne lidar, and ground plot data, we were able to generate an AGB product using a multi-phase approach that complements the GEDI AGB product.

We found that our pan-boreal total 2020 AGB estimate (72.96 $\pm$ 0.61 Pg) is similar to boreal-wide estimates from the past decade, suggesting relative stability in net AGB boreal stocks between 2010 and 2020. A regional-based estimate using ICESat-GLAS lidar linked to ground and airborne lidar (Neigh et al., 2013) estimated a boreal biome total of 38 Pg Carbon, or 76 Pg AGB for the year 2010. Similarly, (Santoro et al., 2021) estimated a boreal total of 81.2 Pg AGB, 15.5% of their global estimate of 522 Pg AGB. Our higher global AGB estimate of 593.49 Pg relative to those of Santoro et al. (2021), is driven primarily by higher tropical and temperate estimates from GEDI in comparison to previous estimates of AGB (Dubayah et al., 2020). Past products for tropical and temperate forests have been demonstrated to underestimate biomass densities in tall, dense forests, primarily due to signal saturation (Mermoz et al., 2015; Yu and Saatchi, 2016). As GEDI's lasers can penetrate the densest canopies found on Earth (Dubayah et al., 2020), the signal saturation is likely overcome. Given accurate capture of absolute height, it is likely that error can be traced to the biomass models used. It has been shown that GEDI's biomass models have highest uncertainties in these carbon-rich forests (Duncanson et al., 2022), and while they are likely less susceptible to underestimation of biomass than past models, it is likely that future improvements from data fusion (e.g. GEDI and SAR) will yield higher total AGB estimates.

Comparing GEDI and ICESat-2/HLS predictions in the 50–52 degree latitudinal suggests that ICESat-2's application within boreal forests is generally consistent with GEDI's estimates in the southern boreal, but that caution should be exercised when aggregating these products outside the boreal, particularly in tall, high biomass forests. The comparison of height products shows that ICESat-2 predicts lower heights in

tall forests than GEDI, but <30 m forests heights generally match well (Fig. SI3). Where both products are available, we recommend the uptake of GEDI's products in North America as GEDI does not exhibit the same magnitude of underestimation of biomass stocks in tall, dense, high biomass forests found in parts of North America, and the ICESat-2/HLS product under-predicts AGB in comparison to Canadian National Inventory data, both within and outside the boreal (Liang et al., 2026). The application of PFT-wide models trained with data primarily in the northern US in North America and in Western Europe is attributed for the under predictions of AGBD in North America. GEDI used models in North America trained with only data for North America, while ICESat-2/HLS used boreal-wide DBT and ENT models. However, GEDI still likely underestimates in high biomass regions such as southwestern British Columbia, which hosts similar forests to the US Pacific Northwest where GEDI has been documented to underestimate biomass with respect to forest inventory data (Dubayah et al., 2022).

For Eurasia, the ICESat-2/HLS product matches closely with National Reporting even in Siberia. Both the GEDI and ICESat-2/HLS products lack training data for Eastern Eurasia. Fig. SI3 shows that there is no clear and consistent discrepancy between heights from the two product suites in Eastern Eurasia, but Fig. 13 shows GEDI's AGBD products predicting higher, particularly in Northern China and Southeast Russian Federation. This area is dominated by Deciduous Needleleaf Forests and Deciduous Broadleaf Forests, and in both products have PFT-wide ENT and DBT models applied. For GEDI, these models include DBT and ENT data from tropical and temperate systems (Duncanson et al., 2022), while for ICESat-2/HLS only data from relatively high latitude temperate forests and boreal forests are included (Fig. 2). While GEDI predicts higher AGBD overall in Eurasia, given the close match to NFI data for the ICESat-2/HLS product and the models trained primarily with northern forests data there, for areas in the southern boreal where both products are available, we recommend the use of the ICESat-2/HLS AGBD product.

Our boreal products exhibit more refined (higher resolution, more spatially representative satellite AGB training data from ICESat-2) than past boreal-focused products. The reasonable match with national reports on biomass stocks for 2020, especially for Eurasia, lends confidence in the general methodologies and datasets used in the production of this map. However, independent reference data show that for any given local area, the map is likely to overestimate low biomass and underestimate high biomass (Fig. 14), and the magnitudes of these over and underestimations vary considerably across sites. Use of this product for local applications may benefit from local calibration with available field or airborne lidar data, particularly if the application is for decision support. The provided AGBD standard deviation layer can help inform the uptake of products but is not akin to systematic error. Typically, higher standard deviations at the pixel level will correlate to higher variability in AGBD, but this does not necessarily account for systematic over or under estimations in AGBD estimates at a local scale (Ståhl et al., 2024). As seen in comparison to local reference maps from Norway and Alaska, our product can exhibit minimal systematic error in some locations but have substantial systematic error in others (e.g. the mean underestimation of AGBD in our map relative to the reference lidar maps is $\sim$ 18 Mg/ha). That said, the high spatial resolution of this product enables analysis of drivers of biomass stocks.

4.3. Biomass stocks by land cover and ecoregion

The vast majority of boreal AGB in 2020 was stored in pixels classified as trees, with 10% found in pixels categorized as non-tree, which emphasizes the importance of non-forest classes to biomass stocks. European taiga collectively store more than one third of boreal AGB stocks between East Siberian taiga, Scandinavian and Russian taiga and West Siberia taiga (Fig. SI1), reflecting the higher mean AGB densities and larger extents in the Eurasian boreal compared to North America. Indeed, the top five boreal ecoregions by total AGB are all found in

Eurasia, with the sixth highest AGB found in the Mid-Continental Canadian forests in Northern Alberta and Saskatchewan. The top eight highest mean AGBD boreal ecoregions are all found in Eurasia, followed again by the Mid-Continental Canadian forests. Ecoregions that contain boreal conditions but are not classified by Olson et al. (2001) are typically higher in AGBD but not in total AGB as they are typically smaller in area. The availability of higher spatial resolution forest structure and landcover data could enable a reconsideration of the classification of boreal forests to include the portion of boreal adjacent ecoregions that exhibit boreal conditions in terms of tree species and environment. Our inclusion of boreal adjacent, transitional ecoregions was adopted both to compare our boreal totals to other papers using the same broader boreal extent, but also to be inclusive of all ecoregions that likely overlap with the boreal regardless of definition. We provide ecoregion means and AGB summaries to easy recalculation of biomass totals over different combinations of northern ecoregions, but our open dataset and code also enables the regeneration of any statistic reported in this paper over an updated boreal polygon, or other geographic domain desired by a user.

4.4. Topographic influences on biomass

The vast majority of AGB in the boreal is stored in flat (<10 degree) areas (Fig. 9a), however topography influences the distribution of AGBD, and we found that mean AGBD decreased with increasing slope (Fig. 9c) in the relatively rare, steeper areas of the boreal. However, we found an increase in mapped mean AGBD between 0 and 10 degrees and > 10 degrees (Fig. 9c) which is counterintuitive given limitations to tree growth over steeper slopes. Uncertainties in AGBD models are higher in

areas with complex topography, largely due to difficulties in resolving sloped terrain from ICESat-2 (Feng et al., 2023). Heights from ICESat-2 are typically underestimated near peaks in topography and overestimated in valleys, which may result in systematic over- or underestimations in areas of complex topography. Previous studies focused on boreal biomass mapping often masked steep slopes from training data (e.g. Margolis et al., Simard et al.) due to issues with extracting accurate forest structure information from GLAS data over steep slopes (Duncanson et al., 2010). Monitoring how forests over steep slopes (>20 degrees) change over time in the face of climate change will inform on their fate in driving carbon balances of northern forests. Moderate and steep slopes (>10 degrees) account for only ~13% of AGB in the boreal domain in this study, but they may be more or less susceptible to changing temperature and hydrology compared to their flatter counterparts. Mapping high-resolution AGBD therefore enables monitoring changes in these topographically complex areas, and while uncertainties are higher, we anticipate future improvements in lidar and algorithms will enable more accurate carbon accounting over slopes in the future. This analysis therefore provides a baseline against which to analyze future changes in AGB and AGBD over slopes (e.g. decadal trends by slope class).

4.5. Country comparisons

Given the importance of Russia and Canada representing 90% of boreal forest area (FAO 2020), we compare the numbers we derive herein to independently reported statistics for those nations. Russia and Canada have their own processes for generating forest statistics (Wulder

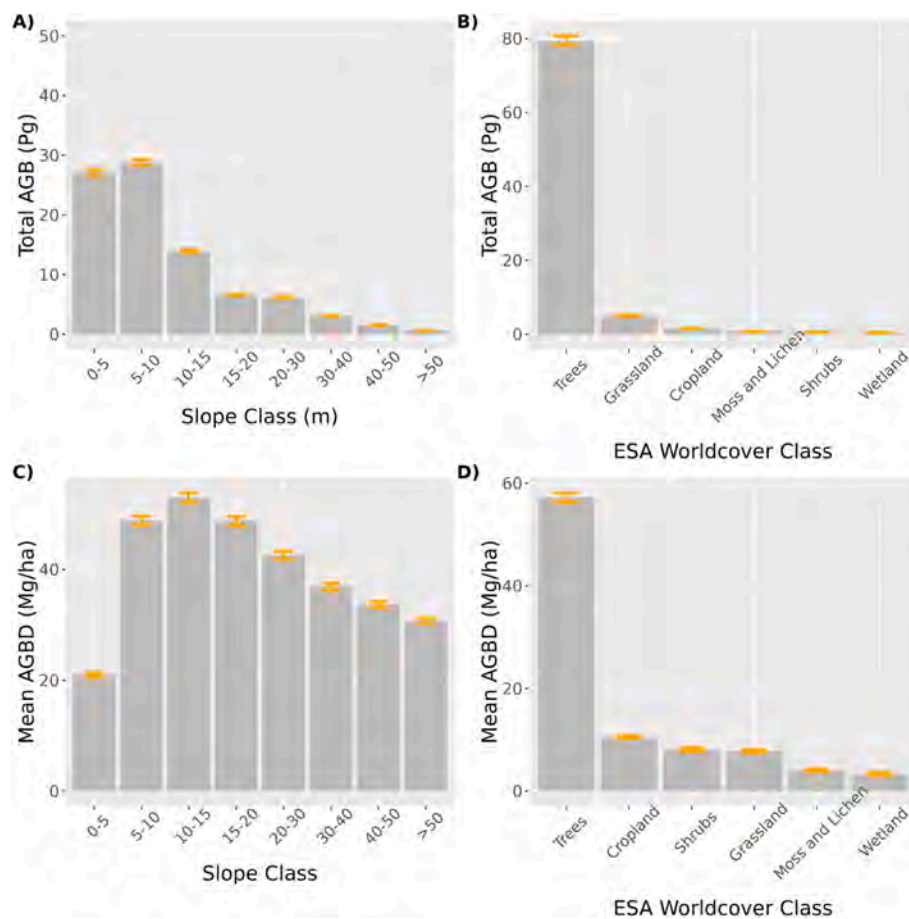


Fig. 9. Distribution of total woody AGB and AGBD by slope and landcover class. Total AGB in Copernicus GLO-30 derived slope classes (A) and land cover classes (B) across the pan-boreal domain. The vast majority of boreal AGB is stored in forested (tree class) flat areas. The mean AGBD per slope class (C) shows that lowest densities of AGBD are found in flat areas (where most boreal biomass is found). Error bars represent the standard errors on the total (A, B) and means (C, D) per class.

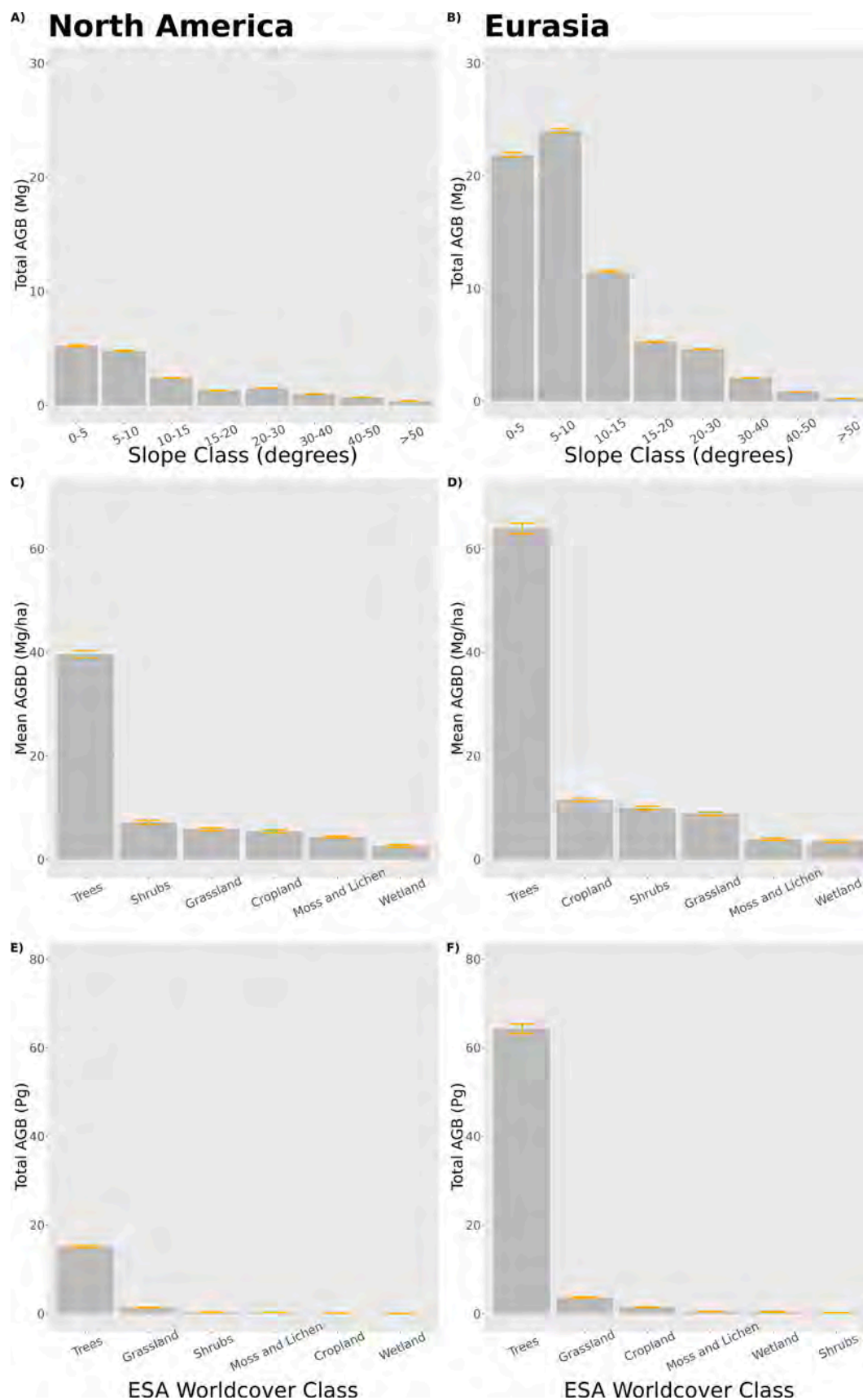


Fig. 10. The total woody biomass density (Pg) divided by slope class for A) North America and B) Eurasia, mean AGBD (Mg/ha) by landcover class for C) North America and D) Eurasia, and total AGB (Pg) by landcover class for E) North America and F) Eurasia.

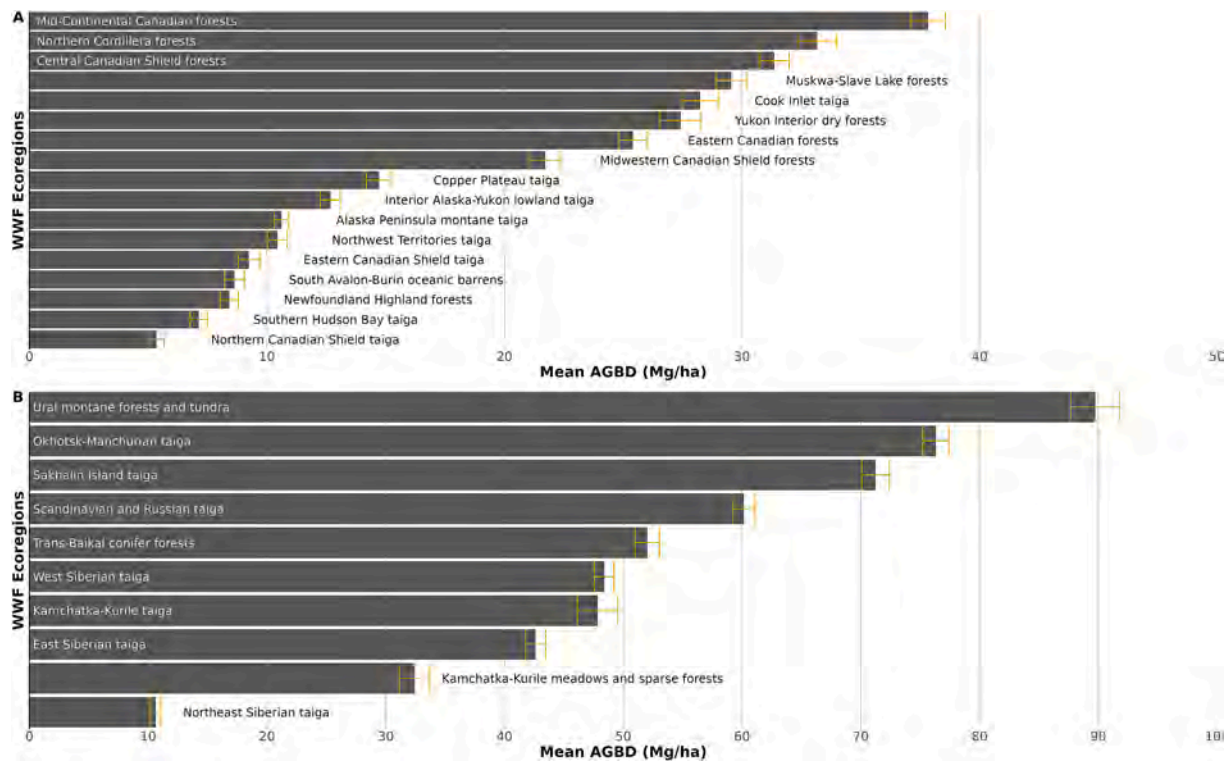


Fig. 11. Mean woody AGBD (Mg/ha) per ecoregion in A) North America and B) Eurasia. All ecoregions classified as boreal biome by Olson et al., 2001 with >10 Mg/ha mean AGBD are included.

et al., 2020), with standardized values also reported via the FAO. Of note, the forests of the Russian Federation are almost exclusively boreal, while Canada's forests are not, with about 25% of national forest area found outside of the boreal (NRCan 2025).

4.5.1. Canada

Our estimate of total AGB for Canada (23.02 Pg) has the largest departure from the FAO-based estimate (31.37 Pg; Fig. 8). Similar to the FAO, Canada's NFI reports 30.4 Pg of biomass, with an estimate of 19.39 Pg for Canadian boreal forests (Canada's National Forest Inventory NFI, 2026). Other national estimates for Canadian total AGB have included 27.32 Pg treed AGB for 2016 (Matasci et al., 2018; Wulder et al., 2020), and 26.66 Pg treed AGB for 2019 (Pelletier et al., 2024). The estimates in Wulder et al. (2020) are compared to several other estimates applicable to Canada's forests, including those reported by the Canadian NFI. While there are differences in spatial extents and remote sensing approaches applied between those of Wulder et al. (2020) and herein, the independent outcomes generally show an underestimation by the satellite lidar-based approach for Canada. In our national totals, forests south of 51.6 degrees latitude biomass totals were estimated from GEDI's L4A product, which is shown to predict higher AGBD in southern British Columbia than the ICESat-2 product, but still likely underestimates based on assessments done in comparable forests in the Pacific Northwest of the United States (Dubayah et al., 2022). Outside the boreal, but north of 51.6, the ICESat-2/HLS fusion product was used for estimation, which underestimates AGBD more than GEDI (Fig. 13) and represents one of the most challenging regions for ICESat-2 based AGBD mapping given the topographic complexity and high AGBD of forests in this region.

Differences in estimates between remote sensing products may also be related to how the different products are trained, for example the use of ground-to-airborne lidar multistage sampling as demonstrated by (Matasci et al., 2018), while noting a lack of even sampling over full latitudinal gradient of boreal forests in Canada. That being said, the NFI is independent from these lidar based products, and is based upon forest

inventory data. Additional lidar transect sampling is ongoing (Bater et al., 2025), with further opportunities for targeted extraction of point-cloud ground-plot combinations over much of Canada's managed forests (White et al., 2025). The models applied in this paper are pan-boreal, and considering the discrepancies in AGBD densities between North America and Eurasia observed in our results, generating refined AGBD models for North American forests specifically would likely improve our estimates. The underestimation of total AGB for Canada's forests is likely due to a combination of EO-based errors associated with signal saturation in higher AGBD and/or topographically complex regions of the country, and a lack of reference data to create accurate AGBD models relating field plots and simulated ICESat-2. These areas represent key targets for improved algorithm development.

4.5.2. Russian Federation

We predict slightly higher AGB values than those derived from the FAO FRA 2020. However, it is acknowledged that the FRA reference data are based on outdated forest inventories and therefore underestimate the current state of Russia Federations' AGB (Filipchuk et al., 2023; Schepaschenko et al., 2021). More recent NFI-based estimates suggest that AGB is 37% higher (Schepaschenko et al., 2021) or 35% higher (Filipchuk et al., 2023) than the figures reported to the FAO FRA. These recent estimates closely match the approach taken in Dubayah et al., 2022, who derived Russian Federation AGB estimates from FAO data on total forest area and UNFCCC data on mean AGBD. Thus, four relatively independent approaches to estimating total Russian AGB for 2020 are within ~4% of each other. As the vast majority of Russia Federations' AGBD is stored in boreal forests, the discrepancies seen between NFI-based and EO-based estimates in Canada resulting from areas of very high biomass and complex topography are not expected to occur to the same degree in boreal-dominated Russia Federation. It should also be noted that no field and simulated ICESat-2 training data were available from Siberia, and therefore our reported uncertainties in Siberian forests may be underestimated as they do not account for training data representativeness. However, the close match to independent NFI estimates

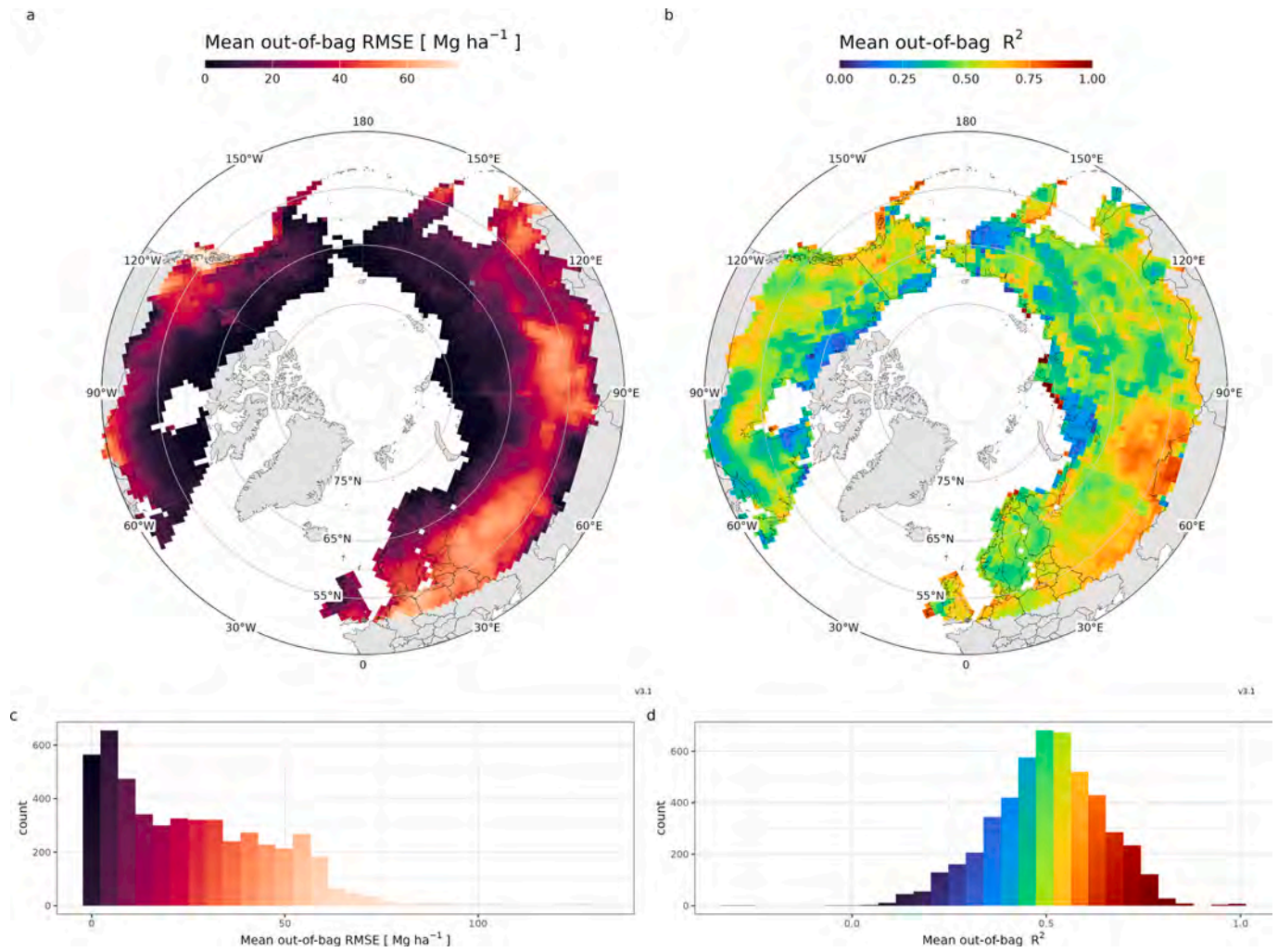


Fig. 12. Model fit statistics for the tile-based random forest models show variability in model performance.

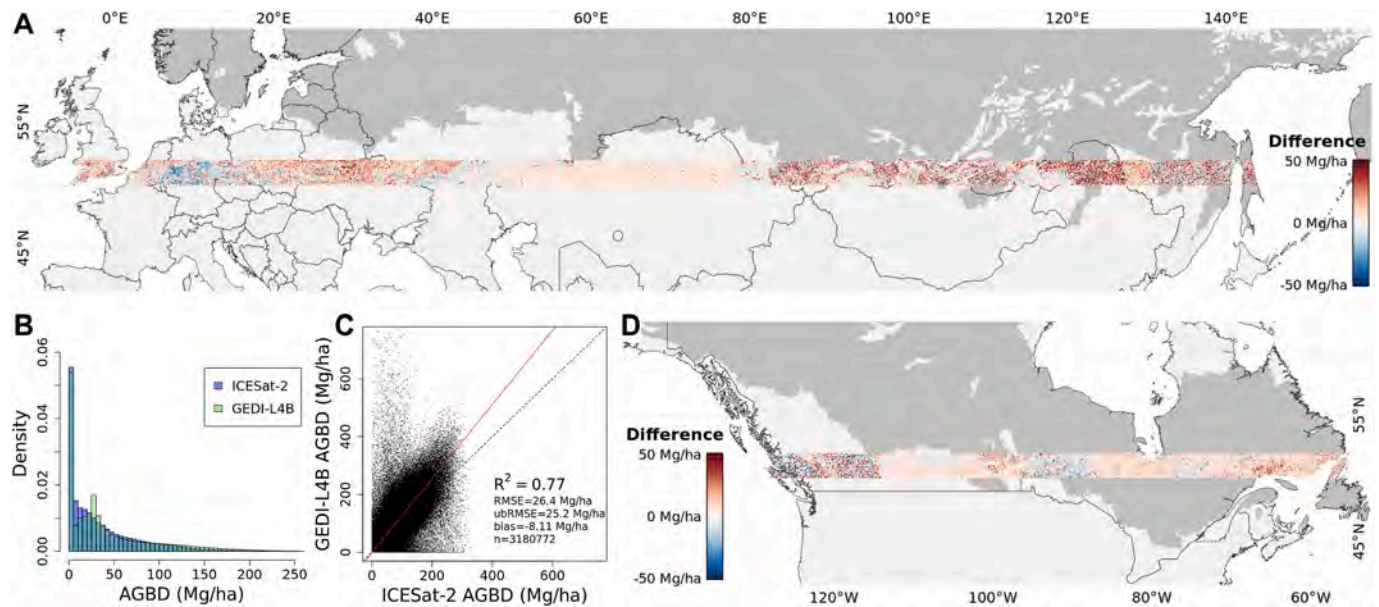


Fig. 13. Comparison of 1 km mean estimates of AGBD from the ICESat-2 boreal product compared to GEDI 1 km L4B between 50 and 52 degrees latitude. A) and D) show the mapped differences in AGBD with positive (red) values where GEDI is higher and negative (blue) values where ICESat-2 is higher. The distributions of AGBD of the two products (B) generally match well, with a slightly lower overall prediction of AGBD from ICESat-2, also seen in the scatterplot between the two products (C). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

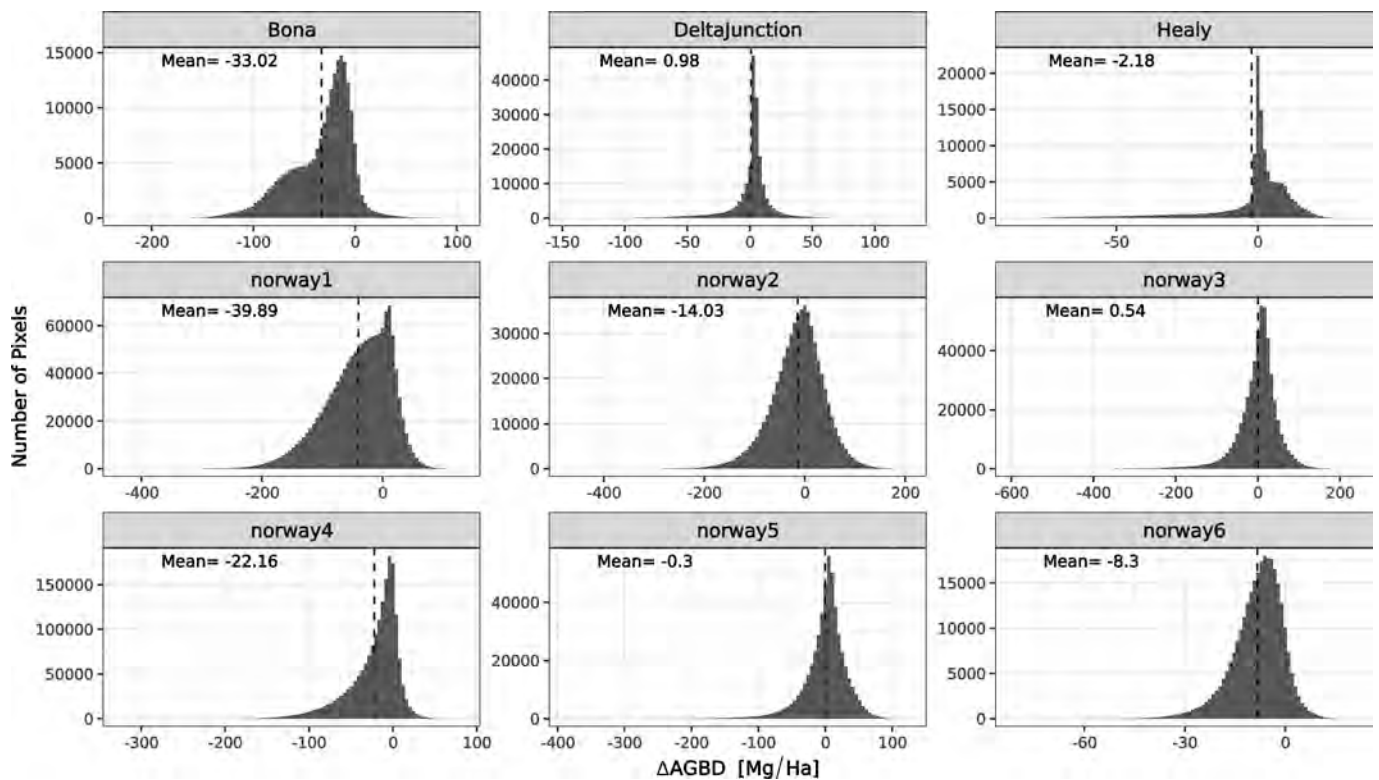


Fig. 14. Validation results from Norwegian and Alaskan reference sites, showing the distribution of AGBD residuals.

from the Russian Federation suggests that the training data extrapolated well to Siberia.

4.6. Precision, accuracy assessment, and limitations

The uncertainty layers available with the northern ICESat-2 AGBD product and the tropical and temperate GEDI products represent the precision of predictions (internal uncertainty), but not their accuracy relative to true AGBD values. Here, we refer to precision as the spread in predictions around our reported mean pixel value from the 250 iterations of model fits, and we report this as the standard deviation of estimates, or as a confidence interval around a reported mean or total for broader regions. Accuracy reflects the deviation from the true value. Systematic deviation (bias) is one component of inaccuracy (over or under estimation). We divide this section thus into a discussion of precision estimation and accuracy reporting. For clarity, precision is assessed using the training data for model calibration of both ICESat-2 AGBD and ICESat-2/HLS AGBD models, while accuracy is assessed through comparisons to independent reference data (ALS AGBD maps and national reporting). Both precision and accuracy assessments are dependent on the availability of suitable calibration and validation data for biomass, which is an ongoing challenge for all global-scale mapping activities. In this paper we were limited to accessible co-incident field and airborne lidar data for training which are not spatially representative of boreal conditions. We use some data from northern temperate forests south of the boreal, and have no training data in many important areas of the boreal, e.g. Siberia. We are unable to validate our maps locally in places without reference data. The nine ALS AGBD maps used to independent validation are not intended for boreal-scale product validation interpretation, but to assess the local drivers of product accuracy across available sites. We urge the continued funding and dedication to the collection of high-fidelity field and lidar data for biomass map calibration and validation, as the accuracy of all satellite biomass products are ultimately dependent on these crucial reference datasets. Initiatives such as GEO-TREES (<https://geo-trees.org/>, Labrière et al.,

2023) are encouraging in this space, and expansion into boreal systems is recommended.

4.6.1. Precision estimation

For mapping and estimation of precision relevant to forest carbon estimation, a wide range of approaches have been used, and there is often confusion related to comparability of products and uncertainties (Hunka et al., 2023). We adopted a heuristic framework for uncertainty (precision) estimation assembled by the NASA Carbon Monitoring System Uncertainties Working Group for reporting on uncertainty estimation (Kennedy et al., 2024) to facilitate communication about estimated uncertainties (Fig. SI8). Considerable effort was spent attempting to be thorough and transparent about the uncertainty (precision) mapping and wide area estimation.

Our AGBD estimation does account for a number of key sources of remote sensing and modeling uncertainty. We account for sampling error in the ICESat-2 data through our bootstrapping approach. Second, we assume that 250 bootstrap resamples is sufficient to estimate tile-level precision, which we deem reasonable based on the stabilization of estimates of tile-level SD AGBD (Fig. SI6). However, a number of relevant uncertainties were not considered or quantified that would likely increase the tile-level SD estimate. In this work, we do not quantify uncertainty from the predictors ($H30_{HLS}$, DEM_{GLO30} , world cover). Additionally, the model form for the OLS model was adopted to be as transferable as possible outside the area of training data, following the GEDI approach (Duncanson et al., 2022; Kellner et al., 2023). We do estimate the uncertainties from model parameters on the OLS models and RF models through our iterative bootstrapping approach. With respect to observations, we do not propagate measurement or allometric uncertainty from field datasets and treat field estimates of AGBD as without error. This, of course, may lead to underestimates in both precision and accuracy as there are significant uncertainties from field AGBD estimates. Additionally, the OLS models in this study are built on simulated ICESat-2 heights from ALS data, and we do not propagate uncertainties due to the simulation of RH metrics to our final mapped

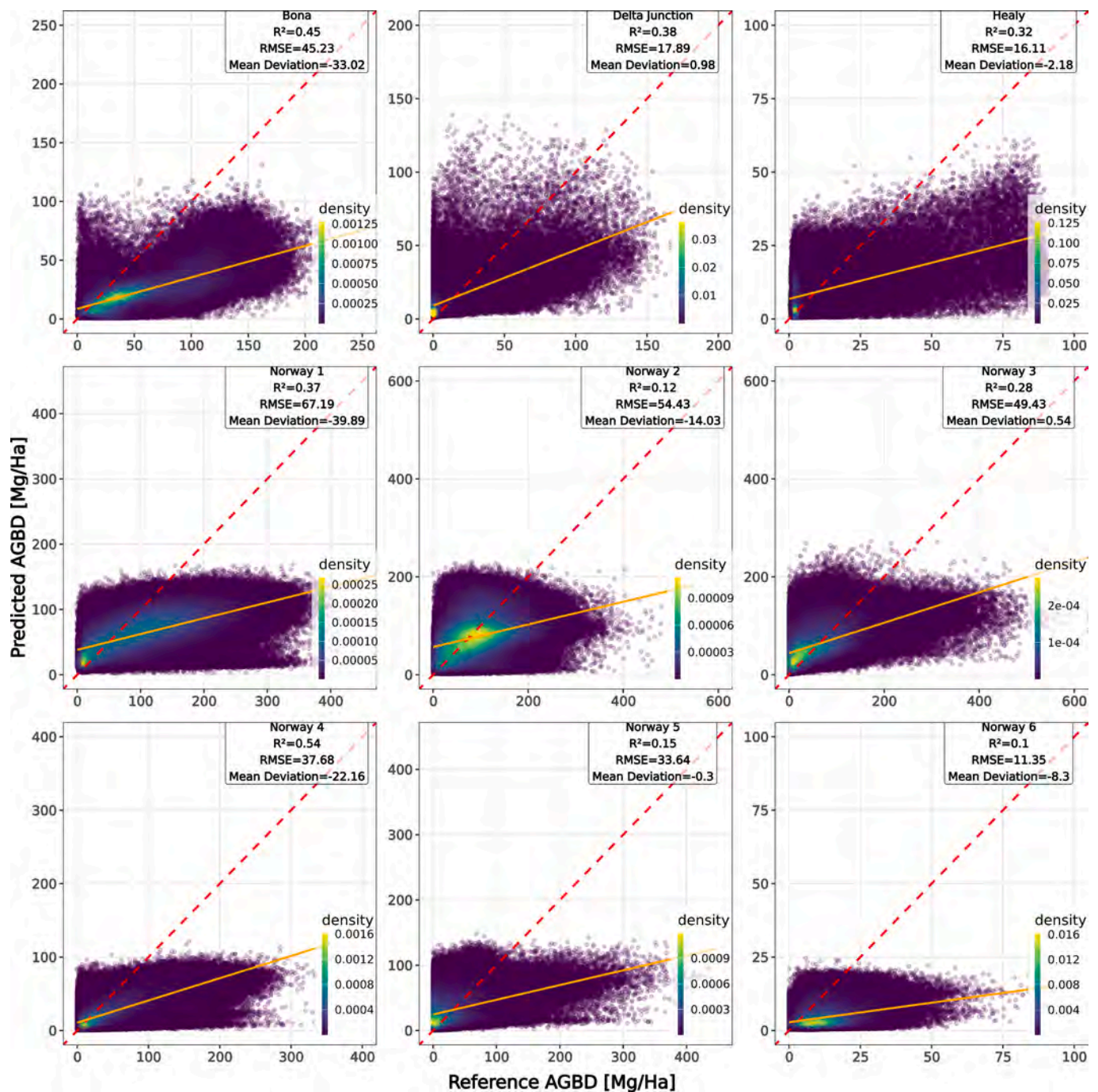


Fig. 15. Validation results from Norwegian and Alaskan reference sites, showing ICESat-2/HLS AGBD predictions compared to reference map pixel-level AGBD predictions.

results. Similarly, we do not explicitly account for height measurement errors in ICESat-2 which are estimated to be ~ 3 m RMSE and vary as a function of topography, height, and canopy cover in boreal forests (Feng et al., 2023; Neuenschwander et al., 2020).

In addition to the uncertainty considerations outlined in (Kennedy et al., 2024), it is relevant to note that the uncertainties in all AGBD products will almost always be underestimated due to uncertainties in AGBD reference data and associated allometries. International efforts to improve forest structure reference data are under way, e.g. through the GEO-TREES program (Labrière et al., 2023). Advancements will likely improve uncertainty estimation but not always decrease reported uncertainties. For example, there is an anticipation that uncertainties in AGBD maps will decrease over time due to improved algorithms, while

further research into more precise uncertainty estimation related to e.g. tree AGB allometries may also increase uncertainty estimates. As more types of uncertainties are considered, the largely underestimated uncertainties in biomass maps may converge to larger numbers.

4.6.2. Accuracy assessment

While the uncertainties (precision) in our product are accounted for and reported to the best of our ability, and we can follow a framework to communicate which uncertainties were included or omitted, estimation of the accuracy of our maps and associated AGB totals is more challenging and fundamentally limited by available independent reference data. We have provided accuracy assessments of our boreal product compared to national estimates from NFIs as well as over a limited

number of airborne reference maps. These independent accuracy assessments are provided to give users a sense of where the products generally agree or disagree with independent estimates and hopefully provide increased confidence in products. However, the independent data sources are themselves not without error, further limiting accuracy assessments. For example, while some countries have robust NFI programs to accurately estimate stocks and fluxes of AGB, other countries have incomplete or even non-existent NFIs or rely on less accurate methods for their national reporting e.g. to the FRA program. Our accuracy assessments here do not account for differences in the accuracies amongst country reporting programs.

The reference AGBD maps also include errors, which remains an ongoing challenge for AGBD product validation activities. Typically, local products will be more accurate than wide area products and thus are recommended as validation sources where available. At the time of writing there is no systematic set of reference AGBD maps to assess global-scale AGBD products, although programs such as GEO-TREES are attempting to fill this need. Local maps cannot be used for overall accuracy assessment of a product unless they are representative of the range of conditions the product covers, and the very limited sample of reference maps we use in this paper is not representative of many mapped geographies. However, high resolution AGBD reference maps enable a better understanding of the drivers of inaccuracies in maps; they enable an analysis of the relationships between systematic deviations and structural and environmental conditions, such as AGBD itself, slope, canopy cover, etc. Without the use of such maps, comparisons to national statistics would not help guide the community to focus on areas where data and algorithm improvements are most needed. For example, we see that slopes remain a large source of systematic errors in AGBD maps and can recommend further attention to this issue.

For biomass map producers, reporting general accuracy statistics is neither straightforward nor commonplace. To our knowledge, methodological limitations remain in estimating the accuracy (i.e., mean squared error) that not only consider the variance but also the bias of AGBD maps within a model-based inference framework. Whereas methods for precision estimation, that is, variance estimation, are well established (Saarela et al., 2023; Saarela et al., 2022), methods for estimating mean squared error (MSE), i.e., accuracy, without access to ground references are yet to be developed (Ståhl et al., 2026).

4.7. Scalability, reproducibility, transparency

The northern AGBD map presented in this paper is novel in its spatial resolution and geographic scope (> 19 billion 30 m pixels were mapped in the boreal envelope), but also as an example of an open science product following NASA's 'Transition to Open Science' initiative, where the product is fully reproducible and based on fully open code. The product was built on the Multi-Mission Algorithm and Analysis Platform (MAAP, scimaap.org) (Albinet et al., 2019) which supports science collaboration, algorithm development, and at-scale implementation. Bootstrapping the >5000 OLS and RF tile-level models at the 30 m pixel level was computationally intensive, but MAAP enabled the production of this product, as well as an associated height map for 2020 in the same domain. That said, in the production of the latest version of the boreal product outlined here, we re-generated the product for the full boreal domain ~10 times, with estimated costs of ~\$15 K USD. Without the availability of the MAAP platform and support teams the wide area iterations would have been challenging or impossible. Oftentimes mapping issues (e.g. from edge effects, areas with steep slopes, compositing issues, etc.) are not apparent in test datasets and are only illuminated when mapping over the full domain. Thus, multiple runs are likely needed for any wide area application of novel datasets and algorithms, and compute costs can be non-trivial. We found a cloud-based parallelized solution to mapping was key for product development at scale.

There are several advantages of developing such a workflow in addition to scalability. This enables rapid redeployment of algorithms

over new datasets, for example as new versions of ATL08 became available they could be integrated simply for an updated boreal map. Additionally, the same code and workflows have since been applied to mapping annual AGBD from 2019 to 2024 and can be applied for future years given available satellite data. Thus, this workflow is fully scalable and flexible to application in other geographic domains. The code has been openly available since the onset of this project (circa 2019), without embargo while waiting for publication of the product or paper. This level of transparency is relatively new for remote sensing science, as code is often not released until products are completed (if ever) and in a competitive science environment there are some tradeoffs between protection of individual and institutional intellectual property (Gentemann et al., 2022). However, the benefits in terms of rapid advancement of science, increased community engagement, and ultimately trust in products are significant. The northern biomass product, as well as the GEDI products, will continue to evolve and improve as the field advances. Full transparency in algorithms should enable these workflows to evolve with the field and be adopted by researchers in other countries and institutions.

5. Conclusion

This paper presents estimates for global forest aboveground biomass from NASA Lidar missions representing the year 2020, with the global total of 593.49 $\pm$ 11.47 Pg AGB representing a combination of tropical, temperate, and southern boreal (<51.6 degrees latitude) from GEDI while the northern portion of the planet was provided by a product developed using HLS and terrain information and trained with ICESat-2 AGBD estimates. Our boreal AGB estimate of 72.96 $\pm$ 0.61 Pg is in line with past (circa 2010) estimates, suggesting relative stability of the boreal forest stocks over the past decade. These estimates have very high precisions and assume no systematic under- or over-estimation in AGBD, which may be unrealistic given 1) the relatively small amount of field training data and 2) demonstrated overestimation of low AGBD areas, and underestimation of higher AGBD areas. While the algorithms developed by both the GEDI and ICESat-2 biomass products aim to minimize systematic error through selection based on geographic transferability (Kellner et al., 2023), future improvements in reference data availability will aim to further improve wide area estimation.

The high spatial resolution (30 m) of the boreal biomass product enabled analyses of biomass distributions across different land cover classes, slopes, and ecoregions. For example, the differences in biomass distributions across slope classes between North America and Eurasia illuminates the importance of mapping and monitoring biomass over steep slopes. Assessment of biomass stocks and densities by ecoregion provides an ecological lens for analyzing future changes in northern forest ecoregions. Future applications of these methods are anticipated to produce time series data that will enable carbon accounting associated with disturbance by tracking biomass changes in areas disturbed by fire, harvest, mining, etc. These processes often occur at high (<1 ha) spatial resolutions and thus this framework is geared towards assessing the trends associated with carbon losses from these disturbances over time. The values reported in this paper can thus serve as a baseline for future carbon assessments.

CRedit authorship contribution statement

L. Duncanson: Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **P.M. Montesano:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **A. Neuenschwander:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation. **A. Zarrinhalam:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **N. Thomas:**

Writing – review & editing, Methodology, Formal analysis, Data curation. **D.M. Minor:** Writing – review & editing, Validation, Project administration, Data curation. **M.A. Wulder:** Writing – review & editing, Writing – original draft. **J.C. White:** Writing – review & editing, Writing – original draft. **E. Guenther:** Writing – review & editing, Formal analysis, Data curation. **T. Feng:** Validation, Formal analysis, Data curation. **V. Leitold:** Writing – review & editing, Visualization, Formal analysis. **S. Hancock:** Writing – review & editing, Methodology, Formal analysis, Data curation. **J. Armston:** Writing – review & editing, Methodology, Formal analysis. **S. Puliti:** Writing – review & editing, Methodology, Formal analysis, Data curation. **A.I. Mandel:** Visualization, Software, Investigation, Data curation. **S. Shah:** Software, Methodology, Data curation. **C. Silva:** Writing – review & editing, Visualization, Formal analysis. **M. Purslow:** Methodology, Formal analysis. **J. Bruening:** Writing – review & editing, Formal analysis. **J. Breidenbach:** Writing – review & editing, Methodology. **E. Næsset:** Writing – review & editing, Methodology. **S. Saarela:** Writing – review & editing, Methodology, Investigation. **N. Hunka:** Writing – review & editing, Formal analysis. **J.R. Kellner:** Writing – review & editing, Methodology. **S.P. Healey:** Writing – review & editing, Methodology, Formal analysis. **D. Schepaschenko:** Writing – review & editing. **J. Wallerman:** Data curation. **C.S.R. Neigh:** Writing – review & editing. **N. Carvalhais:** Writing – review & editing. **R. Dubayah:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rse.2026.115406>.

Data availability

The boreal biomass product presented in this paper is a fully open science product following best practices of the NASA Transition to Open Data Program (TOPS). All code is fully public while product development is ongoing and can be accessed at https://github.com/lauraduncanson/icesat2_boreal. The product itself is housed at the NASA ORNL DAAC, <https://doi.org/10.3334/ORNLDAAAC/2437>. The GEDI biomass estimates are taken directly from the national totals from the Dubayah et al., 2022 paper, and northern country partial totals are derived from the fully open GEDI biomass L4B product, also available at ORNL DAAC: <https://doi.org/10.3334/ORNLDAAAC/2017>. The

field and airborne lidar data used to develop footprint and transect-level AGBD models are not fully available as many of these datasets are private and shared with the GEDI and/or ICESat-2 science teams under express data sharing agreements. However, the intermediary GEDI L4A data are fully open, including the derived models, and available here: <https://doi.org/10.3334/ORNLDAAAC/1986>. Similarly, the 30-m transect-level ALT08 height and biomass estimates are available here: <https://doi.org/10.5067/D2E2L5GK7ER3>. The ecoregions used in this paper are from Olson et al. (2001) and can be visualized online at <https://www.oneearth.org/navigator/> or <https://ecoregions.appspot.com>.

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