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ABoVE: Annual Aboveground Biomass for Boreal Forests of ABoVE Core Domain, 1984-2014

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Summary

This dataset provides estimated annual aboveground biomass (AGB) density for live woody (tree and shrub) species and corresponding standard errors at a 30 m spatial resolution for the boreal forest biome portion of the Core Study Domain of NASA's Arctic-Boreal Vulnerability Experiment (ABoVE) Project (Alaska and Canada) over the time period 1984-2014. The data were derived from a time series of Landsat-5 and Landsat-7 surface reflectance imagery and full-waveform lidar returns from the Geoscience Laser Altimeter System (GLAS) flown onboard IceSAT from 2004 to 2008. The Change Detection and Classification (CCDC) model-fitting algorithm was used to estimate the seasonal variability in surface reflectance, and AGB density data were produced by applying allometric equations to the GLAS lidar data. A Gradient Boosted Machines machine learning algorithm was used to predict annual AGB density across the study domain given the seasonal variability in surface reflectance and other predictors. The data received statistical smoothing to reduce noise and uncertainty was estimated at the pixel level. These data contribute to the characterization of how biomass stocks are responding to climate and disturbance in boreal forests.

Data are provided in the ABoVE standard Albers equal area conic projection (30 m spatial resolution) and are gridded into 180x180 km ABoVE standard "B" grid tiles (Loboda et al., 2019). For this study, there are a total of 106 grid tiles over the ABoVE Core Study Domain.

There are 212 files in geoTIFF (*.tif) format included in this dataset; 106 files of estimated AGB for each tile and 106 files of corresponding standard errors for estimated AGB.

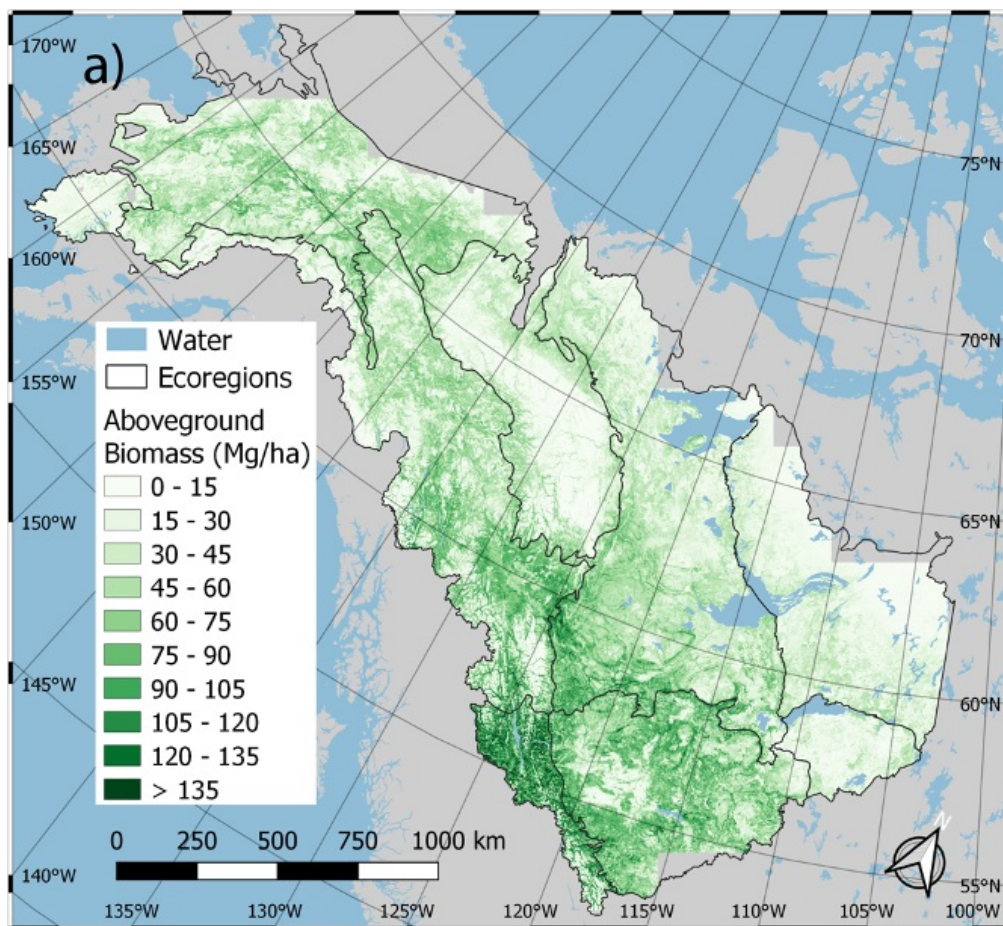


Figure 1. Spatial distribution of predicted aboveground biomass (AGB) density averaged over 1984-2014 for the ABoVE Core Study Domain. Solid black lines indicate the EPA Level 2 Ecoregion boundaries. Source: Wang et al. (2021)

Citation

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1. Dataset Overview

This dataset provides estimated annual aboveground biomass (AGB) density for live woody (tree and shrub) species and corresponding standard errors at a 30 m spatial resolution for the boreal forest biome portion of the Core Study Domain of NASA's Arctic-Boreal Vulnerability Experiment (ABoVE) Project (Alaska and Canada) over the time period 1984-2014. The data were derived from a time series of Landsat-5 and Landsat-7 surface reflectance imagery and full-waveform lidar returns from the Geoscience Laser Altimeter System (GLAS) flown onboard IceSAT from 2004 to 2008. The Change Detection and Classification (CCDC) model-fitting algorithm was used to estimate the seasonal variability in surface reflectance, and AGB density data were produced by applying allometric equations to the GLAS lidar data. A Gradient Boosted Machines machine learning algorithm was used to predict annual AGB density across the study domain given the seasonal variability in surface reflectance and other predictors. The data received statistical smoothing to reduce noise and uncertainty was estimated at the pixel level. These data contribute to the characterization of how biomass stocks are responding to climate and disturbance in boreal forests.

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Project: [Arctic-Boreal Vulnerability Experiment](#)

The Arctic-Boreal Vulnerability Experiment (ABoVE) is a NASA Terrestrial Ecology Program field campaign being conducted in Alaska and western Canada, for 8 to 10 years, starting in 2015. Research for ABoVE links field-based, process-level studies with geospatial data products derived from airborne and satellite sensors, providing a foundation for improving the analysis, and modeling capabilities needed to understand and predict ecosystem responses to, and societal implications of, climate change in the Arctic and Boreal regions.

Related Publication

Wang, J.A., A. Baccini, M.K. Farina, J.T. Randerson, and M.A. Friedl. 2021. Disturbance suppresses the aboveground biomass carbon sink in North American boreal forests. In revision at Nature Climate Change.

Related Dataset

Wang, J.A., D. Sulla-Menashe, C.E. Woodcock, O. Sonnentag, R.F. Keeling, and M.A. Friedl. 2019. ABoVE: Landsat-derived Annual Dominant Land Cover Across ABoVE Core Domain, 1984-2014. ORNL DAAC, Oak Ridge, Tennessee, USA. <https://doi.org/10.3334/ORNLDAAC/1691>

Acknowledgments

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2. Data Characteristics

Spatial Coverage: Boreal forest areas of Alaska and Canada

ABoVE Reference Locations

Domain: Core ABoVE

Data are provided in the ABoVE standard Albers equal area conic projection

State/Territory: Alaska

Grid Cells (106): Bh01v04, Bh01v05, Bh02v03, Bh02v04, Bh02v05, Bh03v03, Bh03v04, Bh03v05, Bh04v03, Bh04v04, Bh04v05, Bh05v03, Bh05v04, Bh05v05, Bh05v06, Bh06v03, Bh06v04, Bh06v05, Bh06v06, Bh06v07, Bh06v08, Bh06v09, Bh07v04, Bh07v05, Bh07v06, Bh07v07, Bh07v08, Bh07v09, Bh07v10, Bh08v04, Bh08v05, Bh08v06, Bh08v07, Bh08v08, Bh08v09, Bh08v10, Bh08v11, Bh08v12, Bh08v13, Bh08v14, Bh09v05, Bh09v06, Bh09v07, Bh09v08, Bh09v09, Bh09v10, Bh09v11, Bh09v12, Bh09v13, Bh09v14, Bh09v15, Bh10v05, Bh10v06, Bh10v07, Bh10v08, Bh10v09, Bh10v10, Bh10v11, Bh10v12, Bh10v13, Bh10v14, Bh10v15, Bh10v16, Bh11v06, Bh11v07, Bh11v08, Bh11v09, Bh11v10, Bh11v11, Bh11v12, Bh11v13, Bh11v14, Bh11v15, Bh11v16, Bh12v08, Bh12v09, Bh12v10, Bh12v11, Bh12v12, Bh12v13, Bh12v14, Bh12v15, Bh13v08, Bh13v09, Bh13v10, Bh13v11, Bh13v12, Bh13v13, Bh13v14, Bh13v15, Bh14v09, Bh14v10, Bh14v11, Bh14v12, Bh14v13, Bh14v14, Bh14v15, Bh15v11, Bh15v12, Bh15v13, Bh15v14, Bh15v15, Bh16v11, Bh16v12, Bh16v13, Bh16v14

Spatial Resolution: 30 m

Temporal Coverage: 1984-01-01 to 2014-12-31 (31 years)

Temporal Resolution: Annual

Study Area: Latitude and longitude are given in decimal degrees.

Site	Northernmost Latitude	Southernmost Latitude	Easternmost Longitude	Westernmost Longitude
Alaska and Canada	69.7323361	51.7769389	-101.736394	-165.4101389

Data File Information

There are 212 files in geoTIFF (*.tif) format included in this dataset; 106 files of estimated AGB for each tile and 106 files of corresponding standard errors for estimated AGB. Each file has 31 bands, one for each year of data (from 1984 to 2014, inclusive). The first band is the year 1984, the second band is the year 1985, and so on through to the 31st band being the year 2014.

File Naming Convention

This dataset uses the ABoVE standard Albers equal area conic projection (30 m spatial resolution) and is gridded into 180x180 km ABoVE standard "B"

grid tiles. There are a total of 106 B grid tiles over the ABoVE core domain in this dataset. Each of the resulting data filenames includes the respective ABoVE Standard B grid tile coordinates (BHHV VV). The respective ABoVE standard "B" grid tiles can be identified based on location by using the shapefiles provided in the related dataset (Loboda et al., 2019; <https://doi.org/10.3334/ORNLDAAC/1527>).

The files are named **ABoVE_variable_BhHHVV.tif** (e.g., ABoVE_AGB_Bh01v04.tif, ABoVE_AGB_SE_Bh01v04.tif), where

- variable = AGB or AGB_SE
- HH = 01-16, the horizontal ABoVE B grid tile location
- VV = 03-16, the vertical ABoVE B grid tile location

Table 1. File names and descriptions.

File Names	Units	Description
ABoVE_AGB_BhHHVV.tif	Mg ha ⁻¹	Estimated live aboveground woody (tree and shrub) biomass (AGB) in megagrams of carbon per hectare. There is a scale factor of 0.01.
ABoVE_AGB_SE_BhHHVV.tif	Mg ha ⁻¹	The standard error of estimated live AGB in megagrams of carbon per hectare. There is a scale factor of 0.01.

Data File Details

For each file,

- There are 31 bands that correspond to the time period 1984-2014, where band 1 is the year 1984, band 31 is 2014, etc.
- Missing values are represented by "65535."
- The spatial reference system is "Canada_Albers_Equal_Area_Conic" (EPSG:102001), PROJ4: +proj=aea +lat_1=50 +lat_2=70 +lat_0=40 +lon_0=-96 +x_0=0 +y_0=0 +datum=NAD83 +units=m +no_defs.
- There are 6000 rows and 6000 columns (180 km x 180 km) in a "B" grid tile.
- The data have a scale factor of 0.01. Provided values should be multiplied by the scale factor to obtain true values.

3. Application and Derivation

Boreal forests are a critical component of the global carbon cycle due to their vast extent, climate sensitivity, and the immense amount of carbon they store in biomass and organic soils. Accurate characterization of how biomass stocks are responding to climate and disturbance is essential to understanding recent and future changes in the northern high-latitude terrestrial carbon sink. Prior to this study, however, remote sensing-based maps of AGB in boreal forests typically cover a single period, precluding analysis of temporal dynamics arising from climate change or disturbance. These data were used to quantify how disturbances influence boreal AGB trends, how this influence is changing over time, and how estimates of AGB stocks and changes compare to estimates from earth system models used to forecast climate change.

4. Quality Assessment

The accuracy of the AGB model was primarily assessed from a 20% hold-out independent validation dataset used in the Gradient Boosted Machines assessment. The model predicted AGB with $R^2 = 0.8001$ and $RMSE = 20.77 \text{ Mg ha}^{-1}$. The estimates of the stocks and uncertainties of AGB were compared to the equivalent domain and similar time periods from four other remote sensing-based AGB datasets, including those developed by the North American Carbon Program (Margolis et al., 2015), the European Space Agency (Santoro and Cartus, 2019), the Canadian Forest Service (Matasci et al., 2018), and Spawn et al. (2020). The model estimates for both the AGB density and the AGB stocks matched fairly well within the range of those comparable datasets.

There tended to be a slight low bias at high values of AGB density; that is the data are slightly underestimated within dense forests. Several instances where CCDC was unable to fit a model, likely because of lack of clear observations, resulted in missing values, primarily at mountain tops and in very cold areas with a limited growing season length.

5. Data Acquisition, Materials, and Methods

Study Area

The study is focused on the ABoVE Core Study Domain, a vast region of Alaska and western Canada that comprises $4.7 \times 10^6 \text{ km}^2$. Excluded areas included regions considered tundra according to the EPA's Level 2 Ecoregions for North America, and ecoregions with limited overlap with the ABoVE Core Study Domain and limited to observed aboveground live woody biomass (AGB) stocks (e.g., Marine West Coast Forest, Temperate Prairies). The resulting area was $2,821,806 \text{ km}^2$. Only AGB in trees and shrubs were considered and not other carbon stocks (e.g., dead wood, coarse woody debris, litter, and soil organic matter).

Data Processing

The data processing workflow consisted of five main parts: (1) preprocessing of Landsat surface reflectance data, (2) estimation of Landsat seasonal-spectral data using the Change Detection and Classification (CCDC) model-fitting algorithm; (3) production of AGB density data by applying allometric equations to spaceborne lidar data from the Geoscience Laser Altimeter System (GLAS); (4) fitting and applying the Gradient Boosted Machines machine learning algorithm to predict annual AGB density across the study domain; and (5) a statistical smoothing technique to reduce noise and estimate uncertainty at the pixel level (Figure 2).

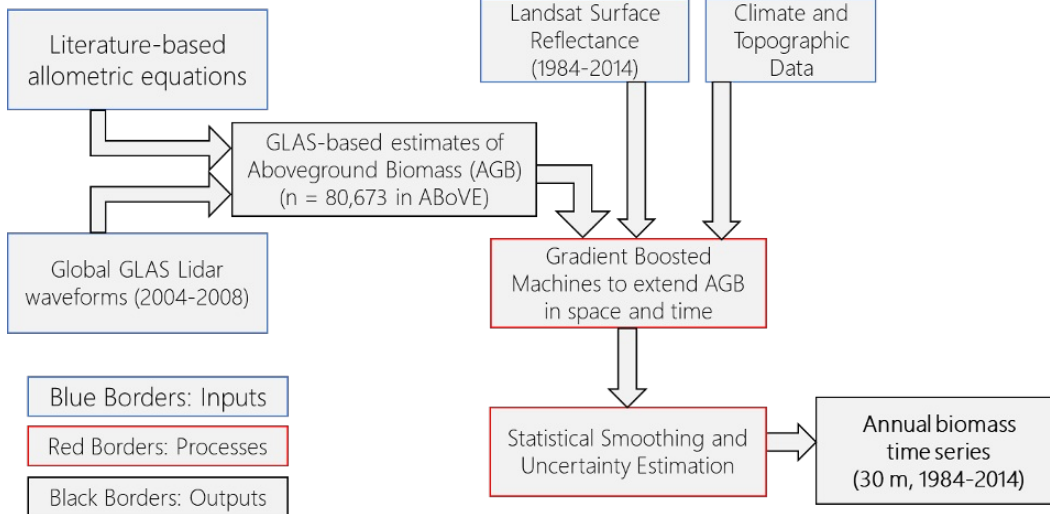


Figure 2. Flowchart detailing the inputs, computational processes, and outputs involved in the creation of this dataset. Source: Wang et al. (2021)

1. Preprocessing of Landsat Surface Reflectance Data

A time series of 30 m surface reflectance data from the Thematic Mapper (TM) onboard Landsat-5 and the Enhanced Thematic Mapper Plus (ETM+) onboard Landsat-7 were collected for the time period 1984–2014. The Landsat surface reflectance data were masked for ephemeral contamination using the Fmask algorithm (Zhu and Woodcock, 2012). The area mapped was defined by an ocean-land mask that was adopted from a 10 m ocean mask from the Natural Earth data repository (Kelso and Patterson, 2010) and manually edited to closely fit the coastline of the study region. Data within the “tundra” areas (i.e., EPA NA CODE=2) of the EPA Level 1 North America ecoregions (Omernik and Griffith, 2014) were removed.

2. CCDC Model Fitting

Reflectance data from each Landsat standard WRS2 row/path scene was reprojected into the ABoVE defined Albers equal area conic projection, 30 m spatial resolution, and tiled into the ABoVE reference grid; a standard used by all ABoVE projects (Loboda et al. 2019). The CCDC algorithm (Zhu and Woodcock, 2014) was used to detect statistical breaks in the time series of the Landsat surface reflectance data and to model seasonal variability in surface reflectance. For each year at each pixel, the CCDC algorithm was used to fit piecewise harmonic models to the Landsat surface reflectance data at each 30 m pixel. Then the mean growing season and non-growing season values for each of the six spectral reflectance bands (e.g., normalized difference vegetation index) were calculated, resulting in estimated Landsat seasonal-spectral data. Because the CCDC models can be unstable when growing seasons are short (i.e., fewer than 100 days), the snow-free growing season was normalized to the 5th and 95th percentiles of the snow-free days of the year at each pixel. Areas classified as “herbaceous” throughout the entire period were not included in the analysis.

3. GLAS-Based Estimation of AGB

Allometric equations retrieved from existing literature (see Wang et al., 2020) were applied to forest height metrics derived from full-waveform lidar data from GLAS/ICESat L1A Global Altimetry Data (HDF5), Version 33 (Zwally et al. 2013), that flew onboard ICESat from 2003 through 2009. Data from the Canadian Earth Observation for Sustainable Development land cover dataset (Wulder et al., 2008), the Alaskan National Land Cover Database (Jin et al., 2017), the Ecoregions2017 ecoregion numbers (Dinerstein et al., 2017), and the MODIS global burned area product (MCD45; Roy et al., 2008) were used in the allometric equations to derive AGB density for each GLAS observation. For quality control, ASTER digital elevation models (Tachikawa et al. 2011) were used to exclude data on terrain that had slopes greater than 10 degrees, and annual land cover maps for the ABoVE Domain (Wang et al., 2019) were used to exclude data that fell within areas of heterogeneous land cover. This yielded 80,673 GLAS-based estimates of AGB.

4. Application of Gradient Boosted Machines Algorithm

The GLAS-derived estimates of AGB were used as a response variable and the estimated Landsat seasonal-spectral data were used as predictor variables in an ensemble machine learning model called Gradient Boosted Machines (Greenwell et al., 2019). Long-term mean annual temperature and precipitation from WorldClim (Fick and Hijmans, 2017) and annual land cover (Wang et al. 2019) were also used as predictors. The mlr package in R (Bischl et al. 2016) was used to tune hyperparameters for the model. The resulting model was applied across the ABoVE Core Study Domain.

5. Statistical Smoothing

The initial time series of GLAS-based AGB at each pixel showed non-negligible interannual variation, resulting in many instances of spurious changes in AGB. Following the methodology of Baccini et al. (2017), this issue was resolved using a temporal change-point algorithm that fits piecewise linear models to the pixel-wise time series of AGB. Pixel-level changes in AGB were evaluated on the basis of the temporal segmentation and linear model fits, rather than the Gradient Boosted Machine-predicted biomass values themselves.

6. Data Access

These data are available through the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC).

[ABoVE: Annual Aboveground Biomass for Boreal Forests of ABoVE Core Domain, 1984-2014](#)

Contact for Data Center Access Information:

- E-mail: uso@daac.ornl.gov
- Telephone: +1 (865) 241-3952

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