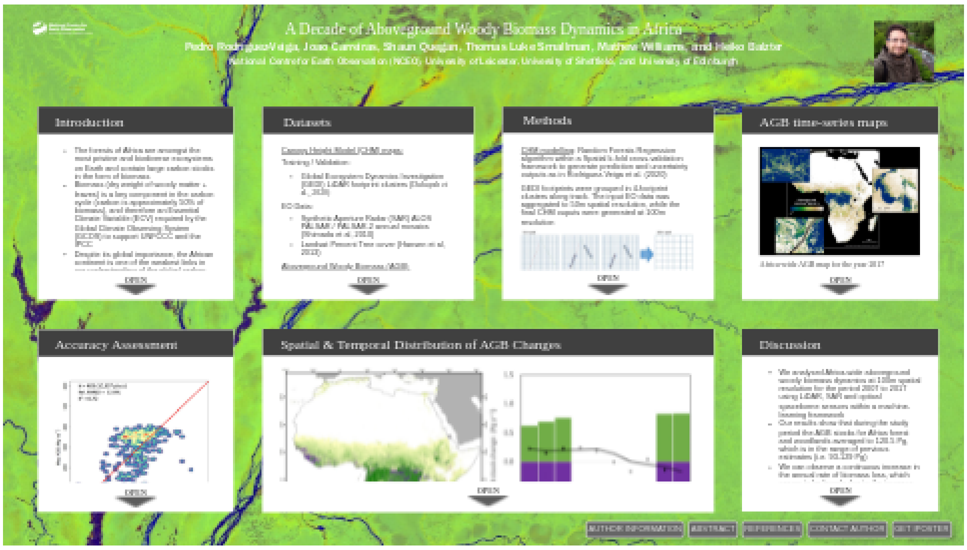
A DECADE OF ABOVEGROUND WOODY BIOMASS DYNAMICS IN AFRICA



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PRESENTED AT:

INTRODUCTION

- The forests of Africa are amongst the most pristine and biodiverse ecosystems on Earth and contain large carbon stocks in the form of biomass
- Biomass (dry weight of woody matter + leaves) is a key component in the carbon cycle (carbon is approximately 50% of biomass), and therefore an Essential Climate Variable (ECV) required by the Global Climate Observing System (GCOS) to support UNFCCC and the IPCC
- Despite its global importance, the African continent is one of the weakest links in our understanding of the global carbon cycle due to its sparse observation network.
- Africa stores 13% of live plant carbon, and contributes to 17% of the world’s deforestation carbon emissions (Williams et al. 2007)
- Previous studies suggested that the forests and savannas in Africa act as a sink of biomass carbon (net gains), while others indicate that this sink is declining or it is already turning into a source (net losses)
- Better estimates of aboveground woody biomass (AGB) stocks across Africa and their inter-annual changes (losses and gains) are needed to improve the quantitative knowledge of the African carbon cycle

DATASETS

Canopy Height Model (CHM) maps:

Training / Validation:

- Global Ecosystem Dynamics Investigation (GEDI) LiDAR footprint clusters (Dubayah et al., 2020)

EO Data:

- Synthetic Aperture Radar (SAR) ALOS PALSAR / PALSAR-2 annual mosaics (Shimada et al, 2010)
- Landsat Percent Tree cover (Hansen et al, 2013)

Aboveground Woody Biomass (AGB):

Training / Validation:

- Airborne Laser Scanner (ALS)-based AGB pixels (see ALS references)

Validation:

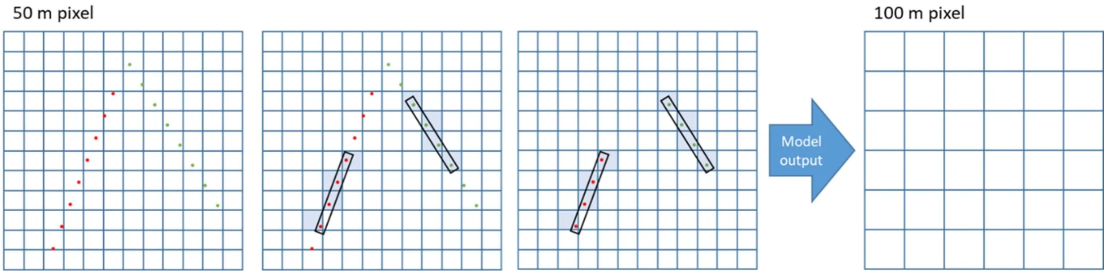
- Large dataset of circa 11,000 field plots

EO Data:

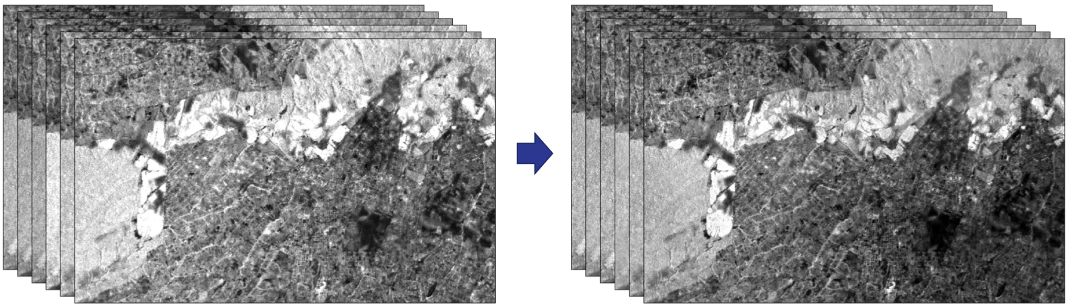
- CHM maps

METHODS

CHM modelling: Random Forests Regression algorithm within a Spatial k-fold cross-validation framework to generate prediction and uncertainty outputs as in Rodriguez-Veiga et al. (2020)



GEDI footprints were grouped in 4-footprint clusters along track and used as reference units to train the algorithm. The input EO data was aggregated to 50m spatial resolution, while the final CHM ouputs were generated at 100m resolution



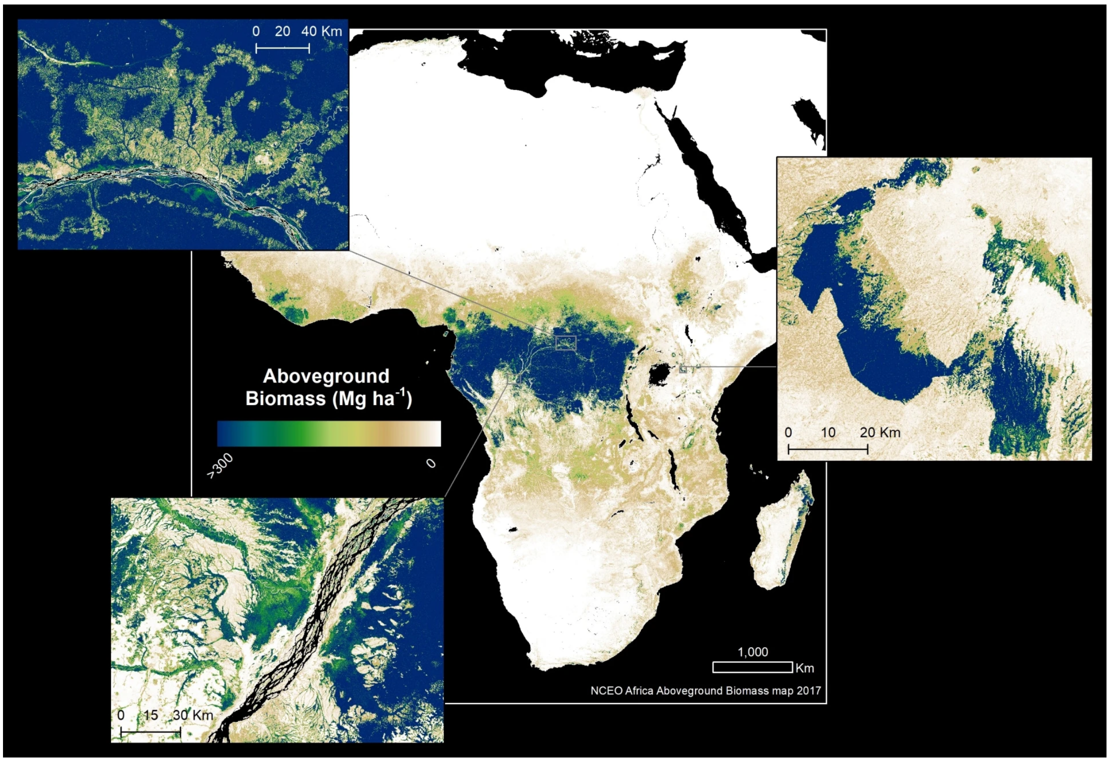
PALSAR/PALSAR-2 mosaics were cross-calibrated to a PALSAR baseline using a 2,000 ha moving window, similar to Marshak et al. (2019) to ensure temporal consistency

AGB modelling: An empirical model was developed to estimate AGB as a function of CHM using ALS-based AGB maps across Africa as reference. A root-squared tranformed regression model was used:

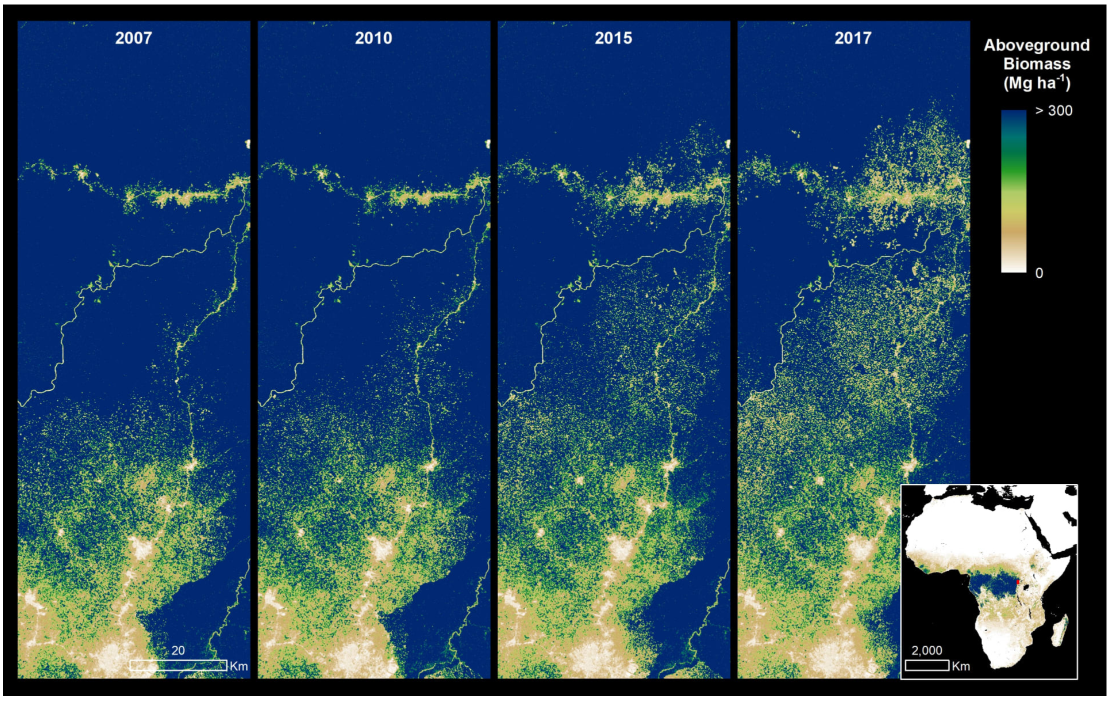
$$AGB = (\beta_0 + \beta_1 \cdot CHM)^2 \cdot \text{ratio estimator}$$

AGB changes: Significant changes were estimated using the uncertainty chatacterization for inter-annual losses (disturbances), and the long-term slope ($p<0.05$) for inter-annual gain of undisturbed pixels

AGB TIME-SERIES MAPS

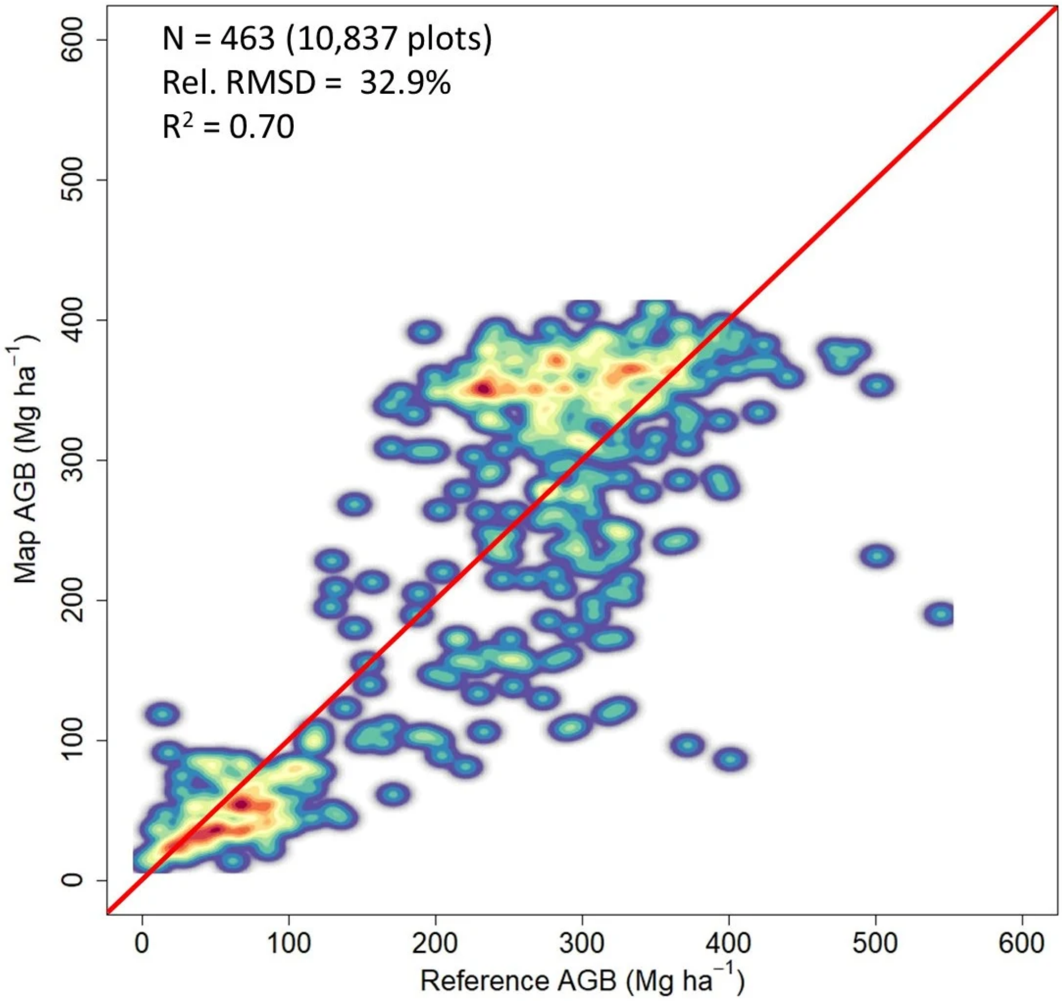


Africa-wide AGB map for the year 2017



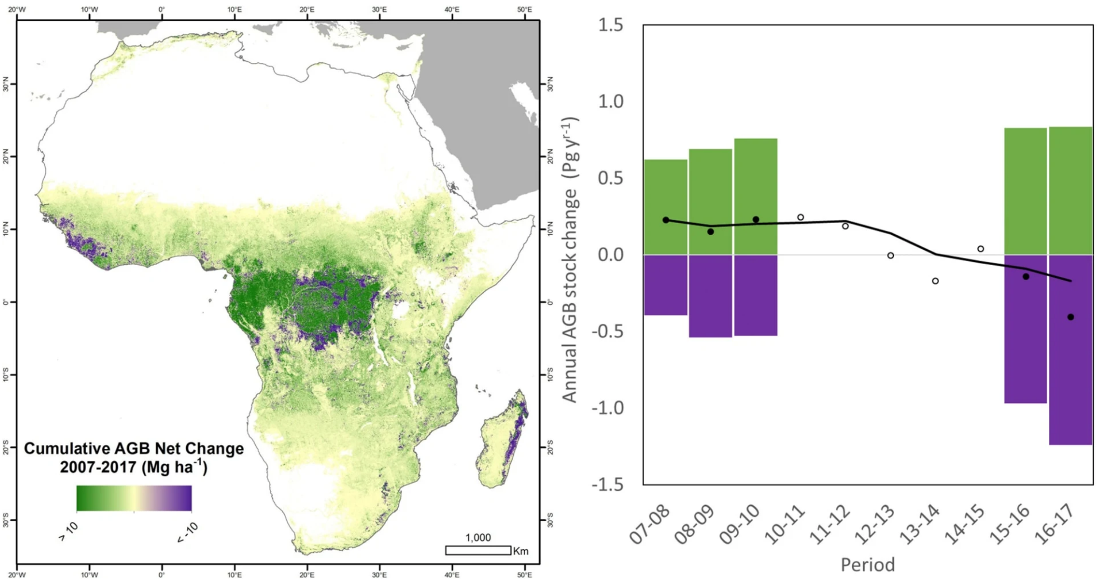
Detail AGB time-series maps for years 2007, 2010, 2015 and 2017

ACCURACY ASSESSMENT



Accuracy assessment of the AGB time series maps using a large independent field plot reference dataset within 0.1º grid cells accross Africa. Warmer colours indicate higher point density. The red solid line corresponds to the y = x line

SPATIAL & TEMPORAL DISTRIBUTION OF AGB STOCK CHANGES



Left panel: Spatial distribution of the cumulative AGB net change from 2007 to 2017 (at 1km spatial resolution for better display). Right panel: Annual AGB stock change for continental Africa. Green columns represents AGB gross gain, while purple columns are AGB gross loss. The black points represent the annual AGB net change for the study period (Pg yr^{-1}). Annual AGB net change for 2010 to 2015 is interpolated using the strong correlation between annual AGB change and annual forest loss rates derived by Hansen et al (2013) at continental level (hollow points). The trend line is a 3-year moving window.

DISCUSSION

- We analysed Africa-wide aboveground woody biomass dynamics at 100m spatial resolution for the period 2007 to 2017 using LiDAR, SAR and optical spaceborne sensors within a machine-learning framework
- Our results show that during the study period the AGB stocks for Africa forest and woodlands averaged to 120.5 Pg, which is in the range of previous estimates (i.e. 93-129 Pg)
- We can observe a continuous increase in the annual rate of biomass loss, which seems to be largely due to the increase of biomass loss in the Tropical Dry Broadleaf Forests of the Congo Basin

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ABSTRACT

The temporal dynamics of aboveground woody biomass across the landscape is one of the most uncertain aspects of the global carbon cycle. Previous studies suggest that the forests and savannas of Africa act as a sink of biomass carbon, while others indicate that it might already be turning into a source. In this study we analysed continental-wide biomass dynamics using a time-series of aboveground biomass maps for the 2007 to 2017 period. We developed these maps at a spatial resolution of 100m using LiDAR, SAR and multispectral spaceborne sensors within a machine-learning framework. Our results show that the aboveground biomass stocks in Africa were 120.5 Pg. At the same time, we can observe a continuous increase in the annual rate of biomass loss in the continent due to the increasing deforestation rates occurring in the Congo Basin.

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