Forest biomass estimates in the Amazon

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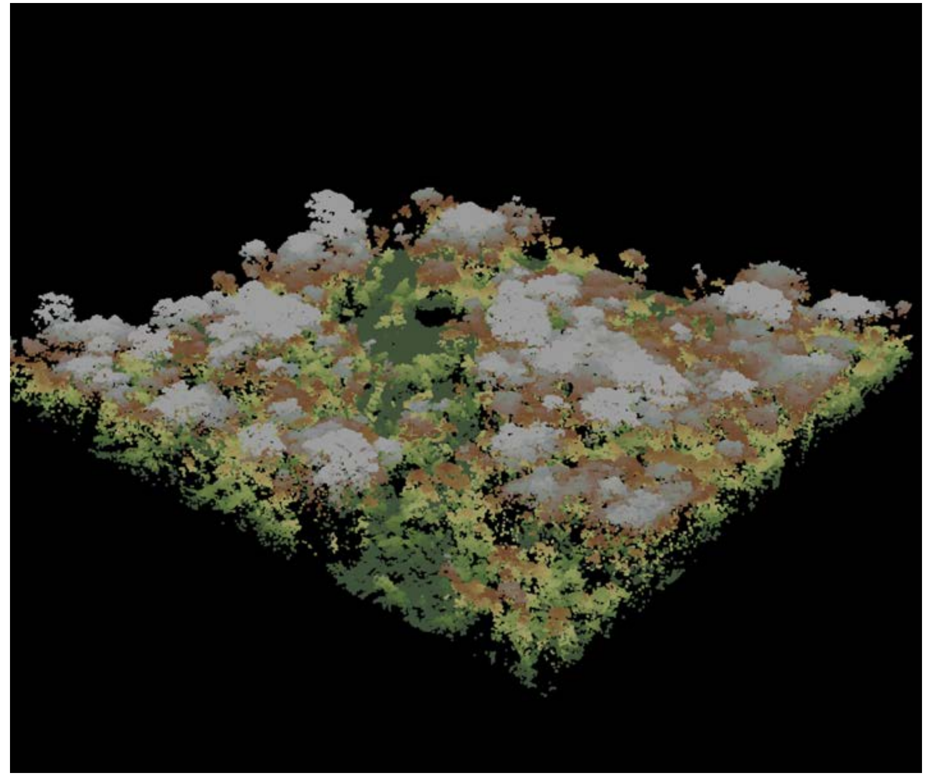
Outline

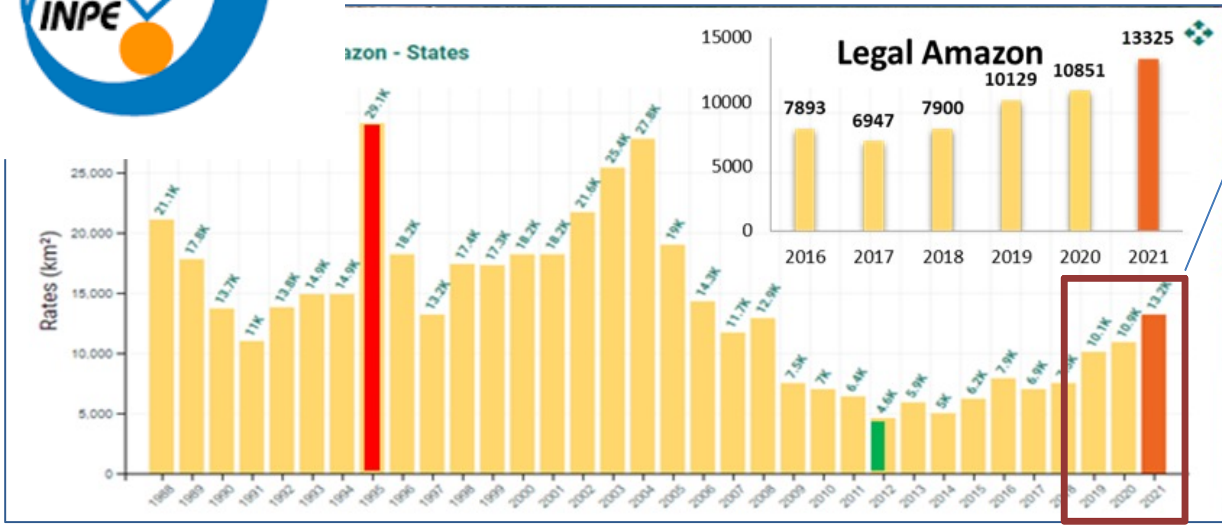
- Tropical Forest and Carbon balance;
- ALS (LiDAR Data);
- Biomass maps and data bases;
- National GHG emissions inventory and Forest Reference Level

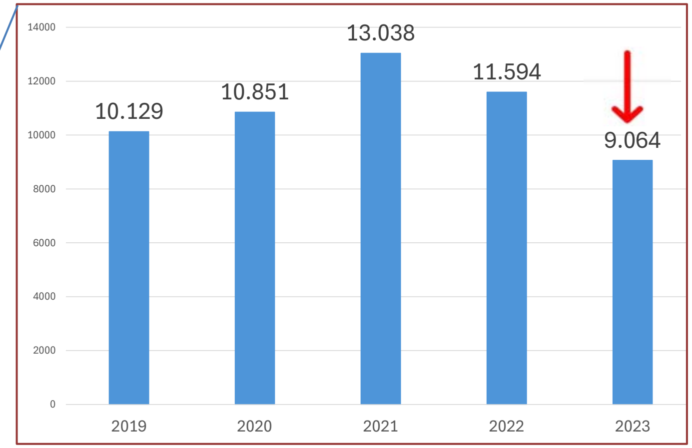


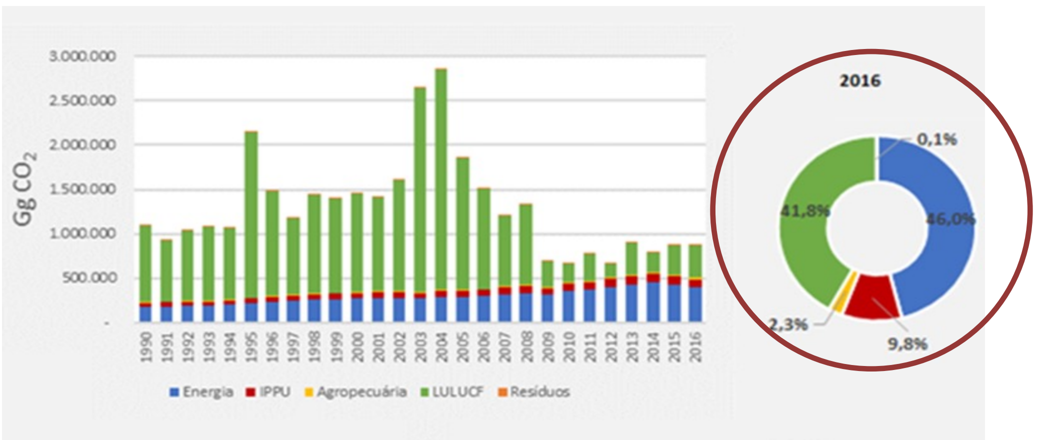
FUNDO AMAZÔNIA BNDES FUNCATE Fundação de Ciência Aplicações e Tecnologia Espaciais

CCST Science for Sustainability

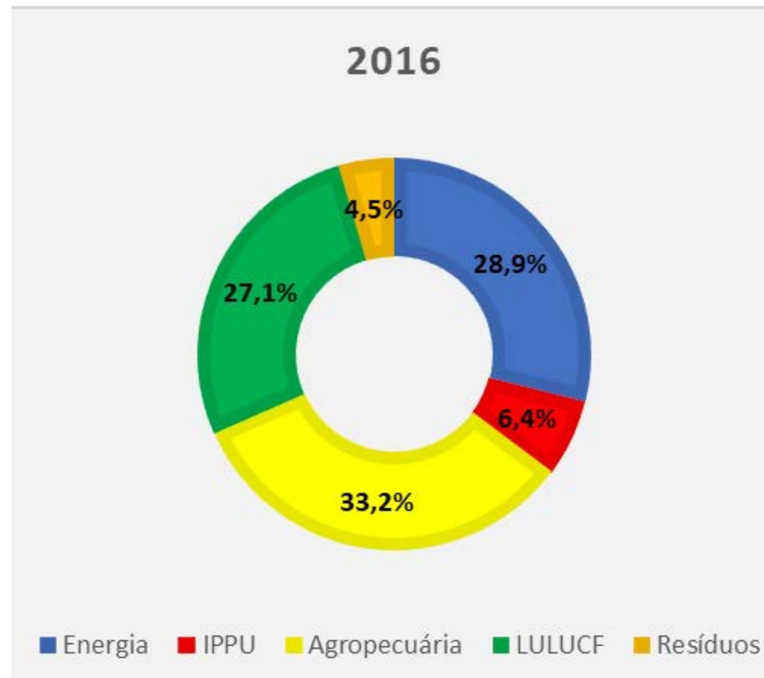
PRODES – Official System to monitor deforestation in Brazil







Setor	1990	1995	2000	2005	2010	2016	Variação 2010-2016
	------------------	------------------	Gg CO2	------------------	------------------		---- % ----
Energia	177.046	216.613	272.173	292.351	352.903	401.690	13,8
IPPU	45.192	53.139	64.506	67.660	82.049	85.943	4,7
Agropecuária	9.771	6.765	10.645	9.975	13.698	19.732	44,1
LULUCF	860.893	1.875.495	1.110.480	1.479.731	220.461	365.404	65,7
Resíduos	533	585	926	1.108	1.154	504	-56,4
TOTAL	1.093.435	2.152.596	1.458.729	1.850.825	670.265	873.272	30,3



IPCC, 2006

Amazon biomass maps and data base

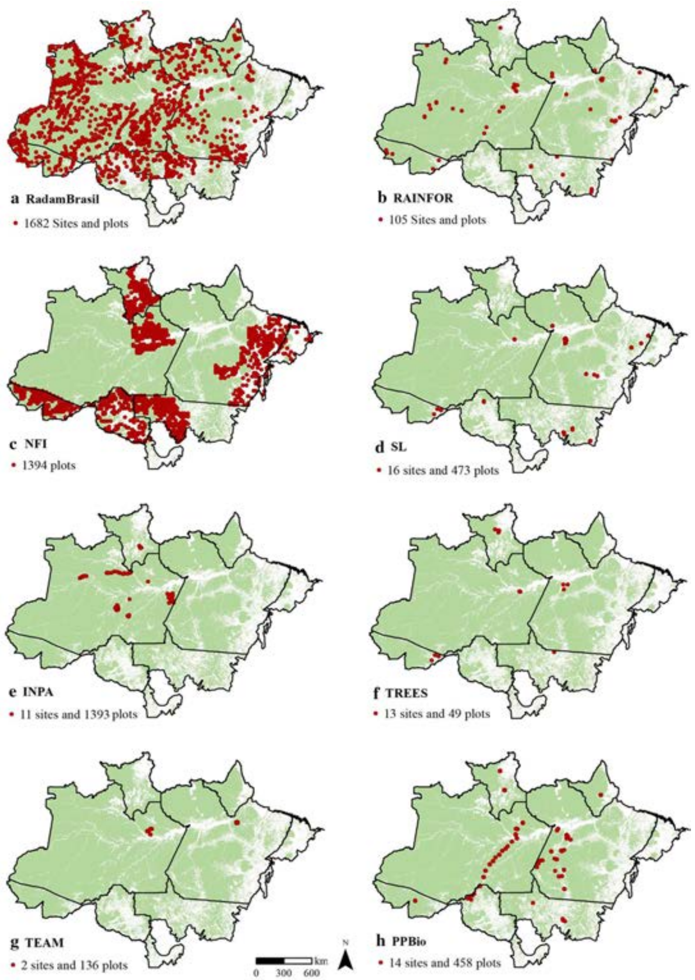
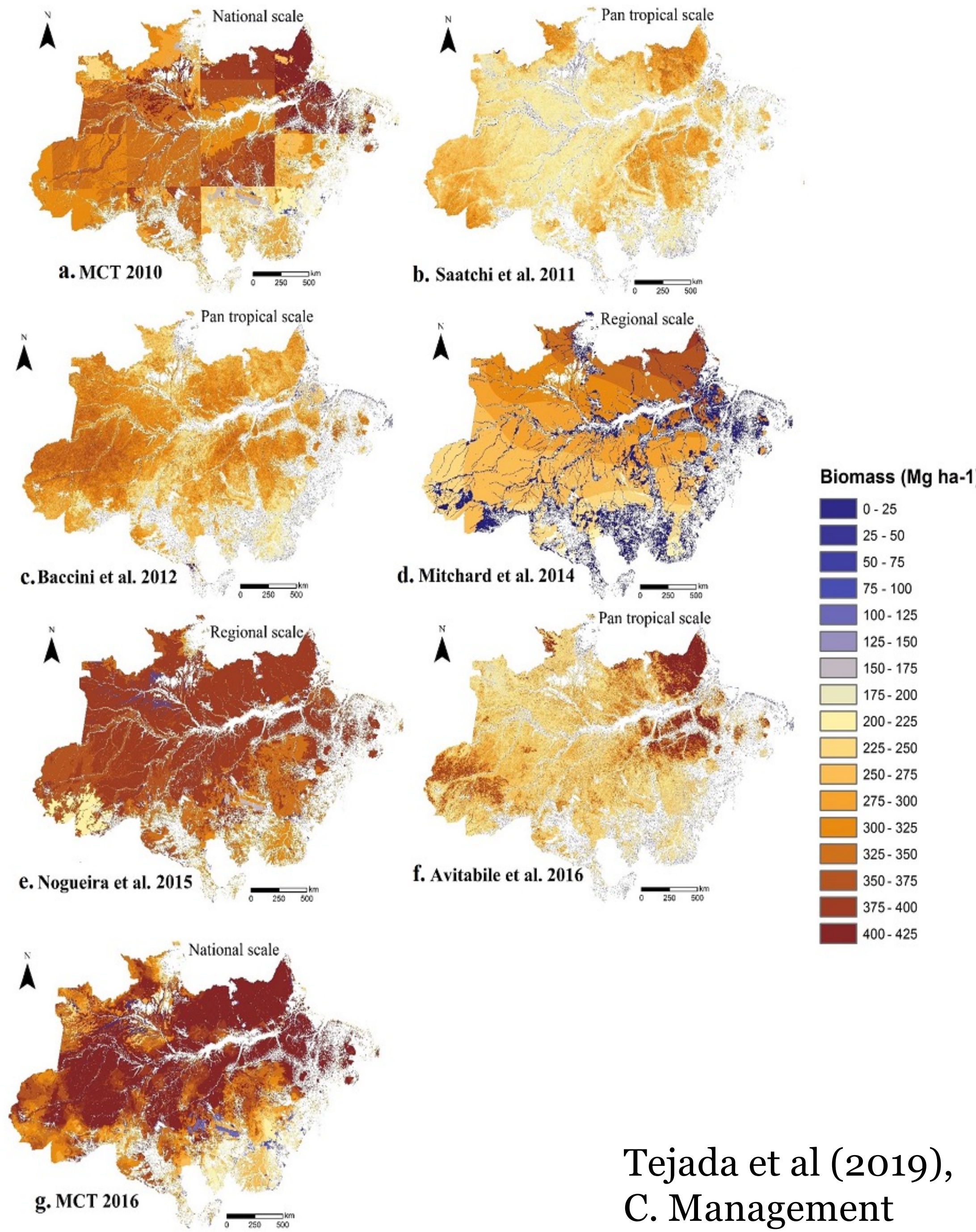
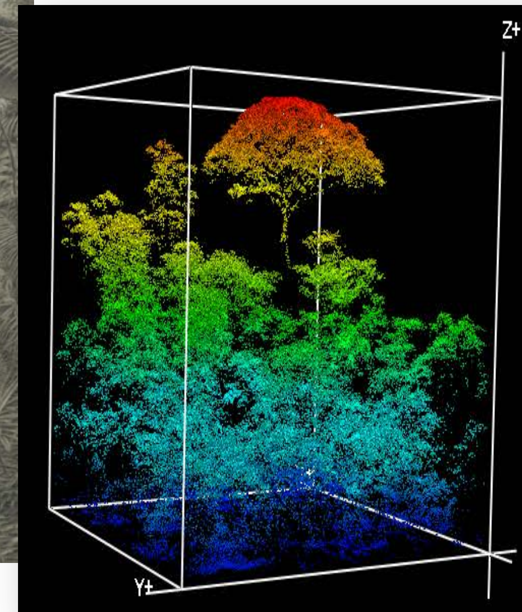


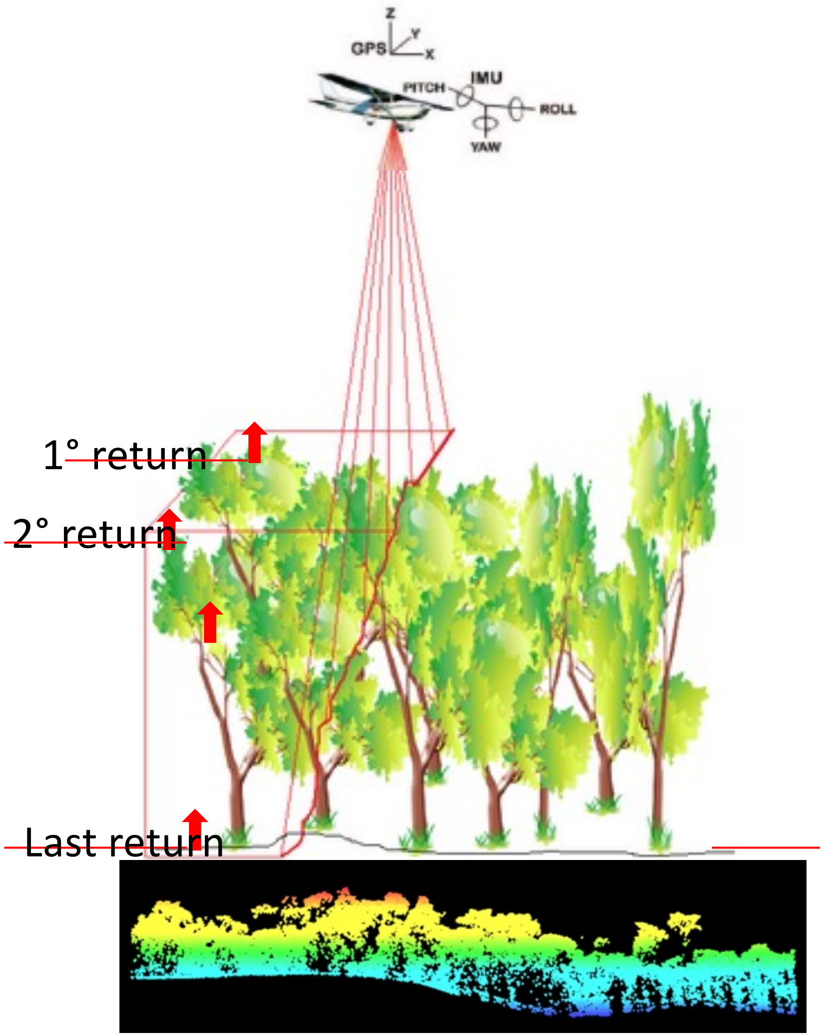
Fig. 2 Distribution of forest inventory plots in the Brazilian Amazon. **a** RadamBrasil [41]; **b** Amazon Forest Inventory Network (RAINFOR) [75]; **c** National Forest Inventory [26]; **d** sustainable landscapes project [27]; **e** National Institute of Amazon Research (INPA) (personal communication); **f** Tropical Ecosystems and Environmental Sciences Laboratory (TREES) [30]; **g** Tropical Ecology, Assessment and Monitoring Network (TEAM) [42]; and **h** Research Program for Biodiversity (PPBio) [45]

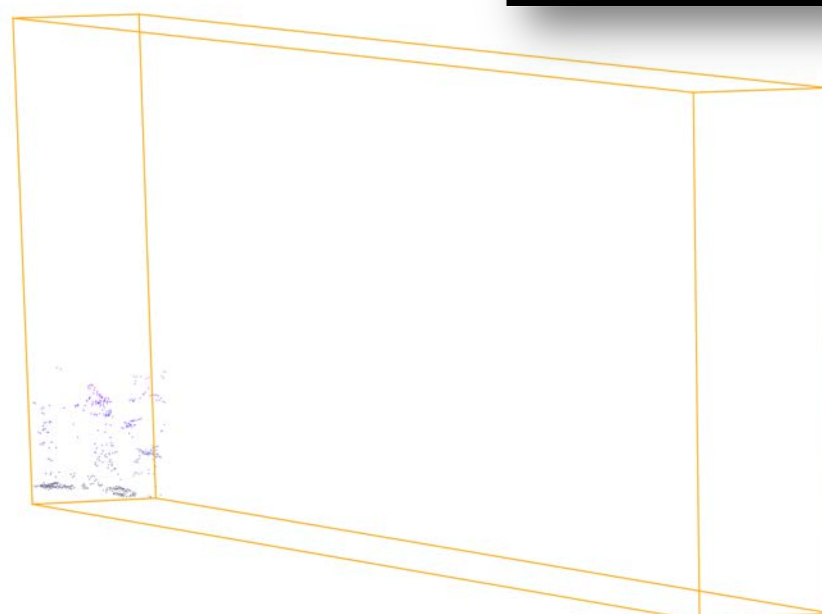
The quantification of carbon stored in forests at large scale still carries high uncertainty



Tejada et al (2019), C. Management


Z+
Y+


Z
Y
GPS
X
IMU
PITCH
ROLL
YAW
1° return
2° return
Last return

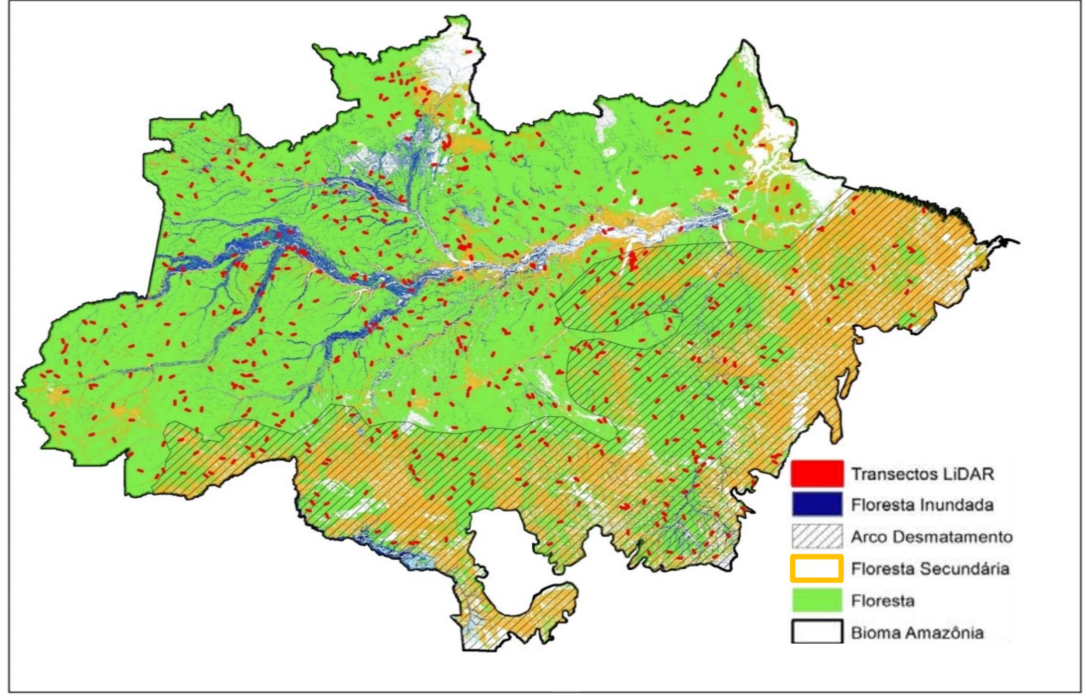


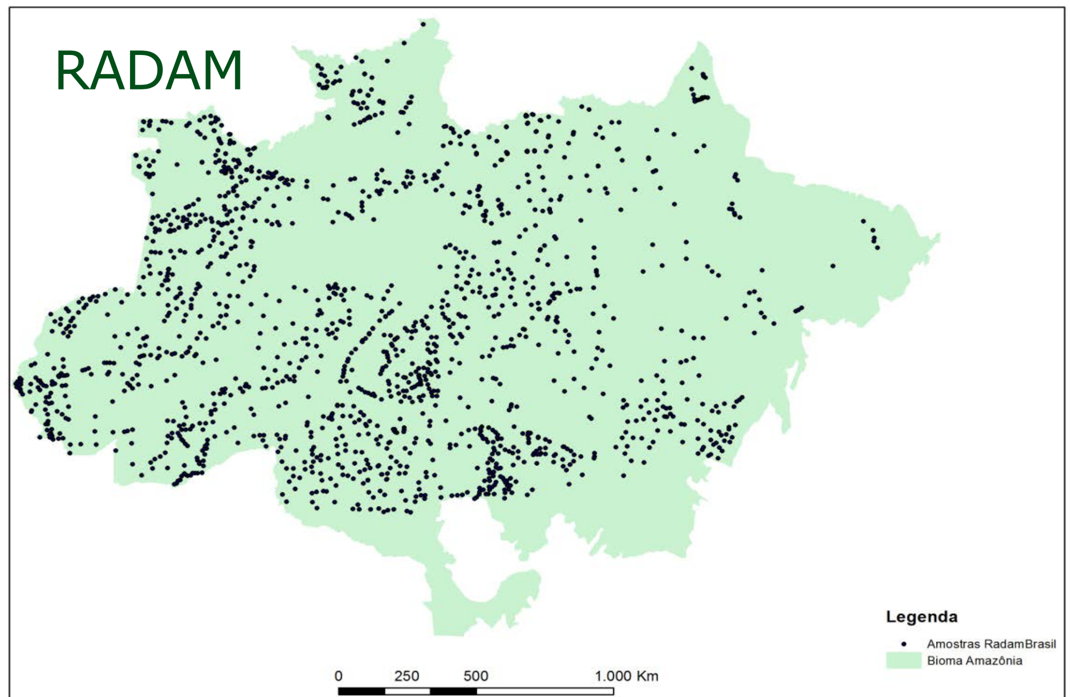
LiDAR

975 LiDAR transects
Width: **300m**
Length: **12,5Km**
Area: **375**ha

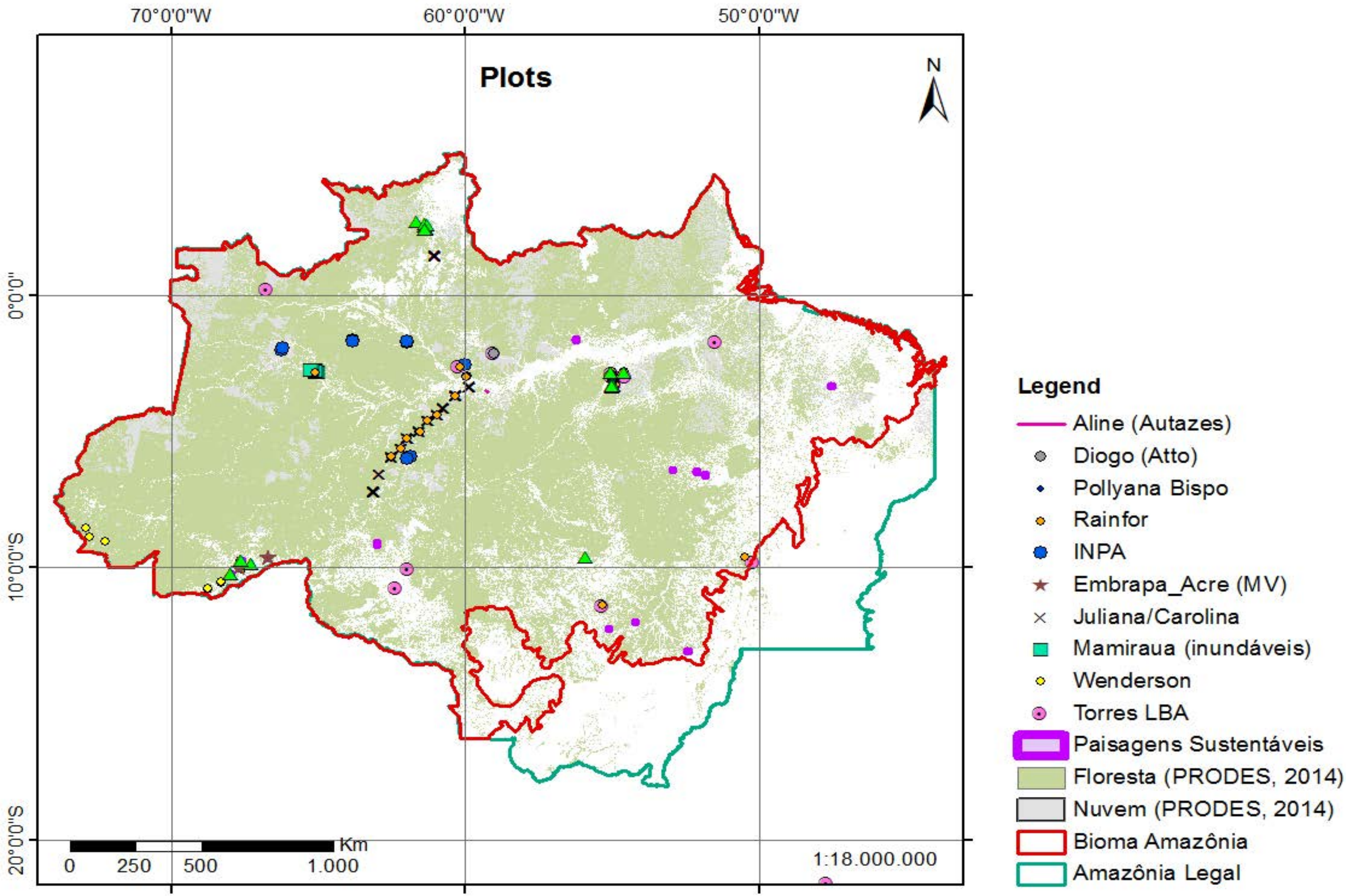
192 flown twice (Arc/Degradation)
91 directed to field plots
405 field plots

Randomly distributed:
- PRODES forest (INPE)
- TERRACLASS Secondary vegetation (INPE) and
- Wetlands – (*Hess et al. 2015*)



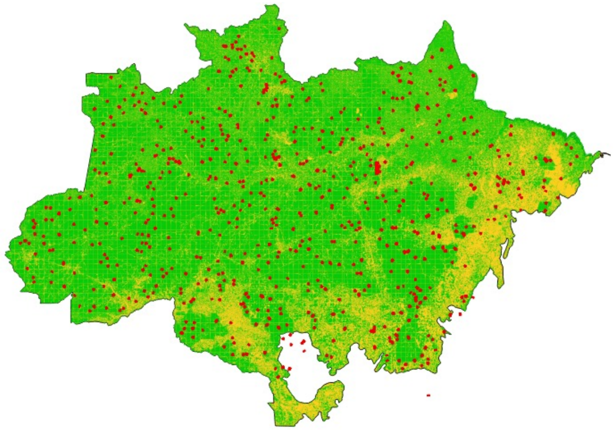


Field data



Plots
70°0'0"W
60°0'0"W
50°0'0"W
0°0'0"
10°0'0"S
20°0'0"S
N
Km
0
250
500
1.000
1:18.000.000
Legend
Aline (Autazes)
Diogo (Atto)
Pollyana Bispo
Rainfor
INPA
Embrapa_Acre (MV)
Juliana/Carolina
Mamiraua (inundáveis)
Wenderson
Torres LBA
Paisagens Sustentáveis
Floresta (PRODES, 2014)
Nuvem (PRODES, 2014)
Bioma Amazônia
Amazônia Legal

AGB Map Project EBA/MSA



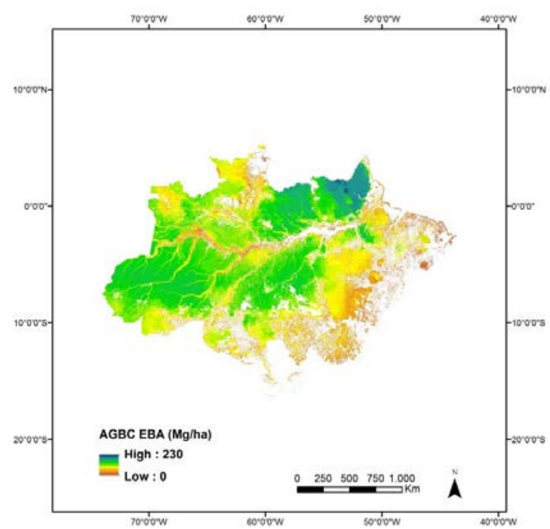
Lidar Transects
AGB Lidar
(Longo et al. 2016)

Remote Sensing data 250m

EVI, NDVI – Modis; SRTM; TRMM; X, Y; PALSAR – HH, HV

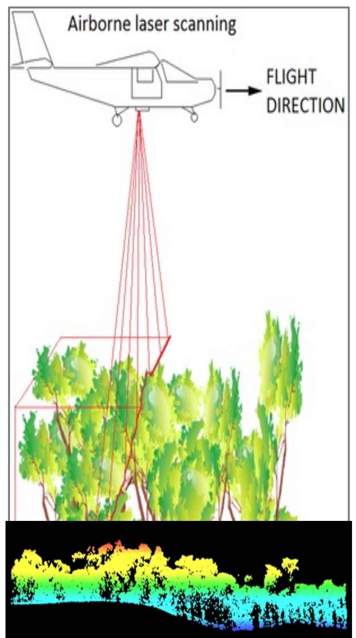
Random forest Regression Model (148.013 cell)
R2=0.7485
RMSE = 54.36 Mg/ha

Extrapolation



The model was fitting using approximately 148013 cells with 250 meter of spatial resolution representing the mean value of AGB and remote sensing variable.

LiDAR



Ground data

AGB MAP

AGB estimate - CHM

Aboveground biomass variability across intact and degraded forests in the Brazilian Amazon

Marcos Longo[1], Michael Keller[1,2,3], Maiza N. dos-Santos[1], Veronika Leitold[4], Ekena R. Pinagé[1,5], Alessandro Baccini[6], Sassan Saatchi[3], Euler M. Nogueira[7], Mateus Batistella[8], and Douglas C. Morton[4]

GBC
doi:10.1002/2016GB005465.

Aboveground Carbon - total

ADC = Abovegorund carbon density
TCH = Top canopy height

$$\begin{aligned}\mathrm{ACD_{TCH}} &= 0.054(0.012)\,\mathrm{TCH}^{1.76(0.07)} \\ &+E_N\left[\mu = 0, \sigma = 0.17(0.05)\,\mathrm{TCH}^{1.04(0.10)}\right], \qquad \text{(S1)}\end{aligned}$$

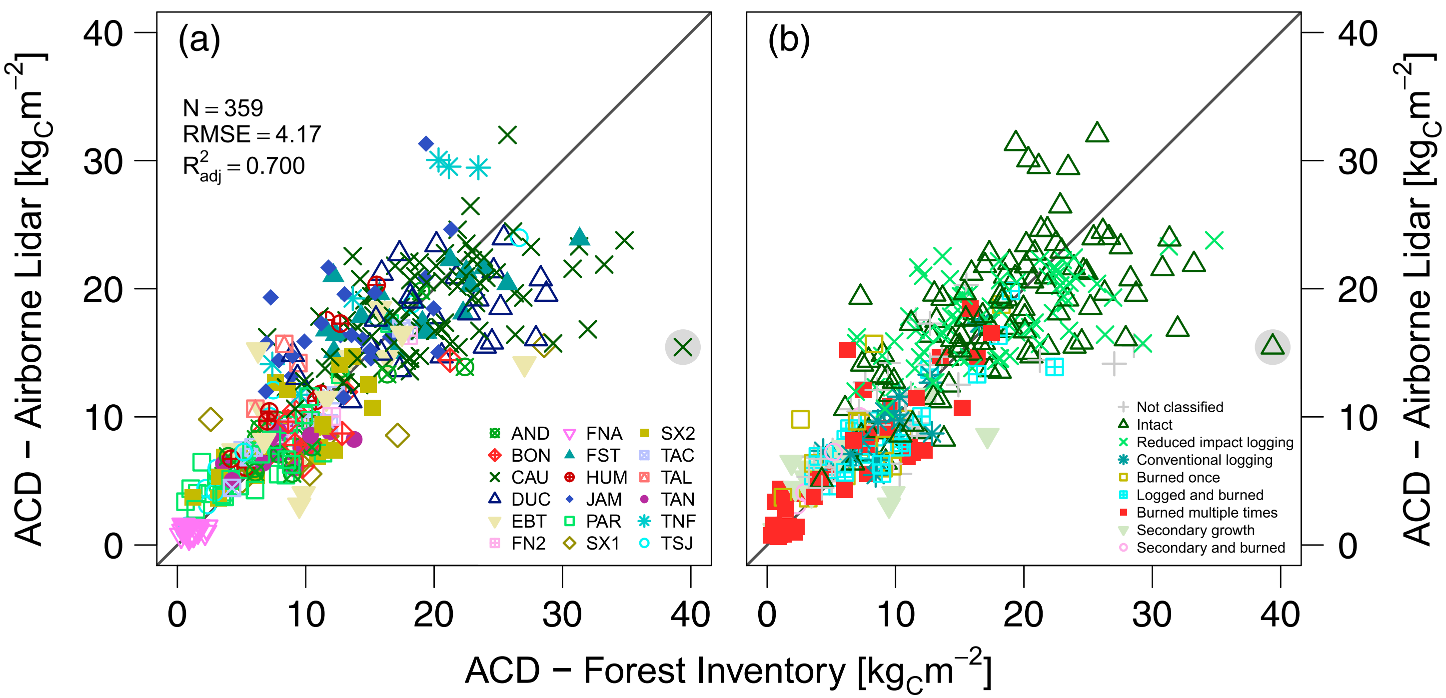


Figure 3. Scatterplots of estimated aboveground carbon density based on airborne lidar metrics using the subset selection of regression (ACDALS) as a function of forest inventory ACD (ACDFI). Color and shapes correspond to (a) different study sites and (b) different disturbance histories

Geodatabase

- **Construction of a Geodatabase: PostgreSQL**

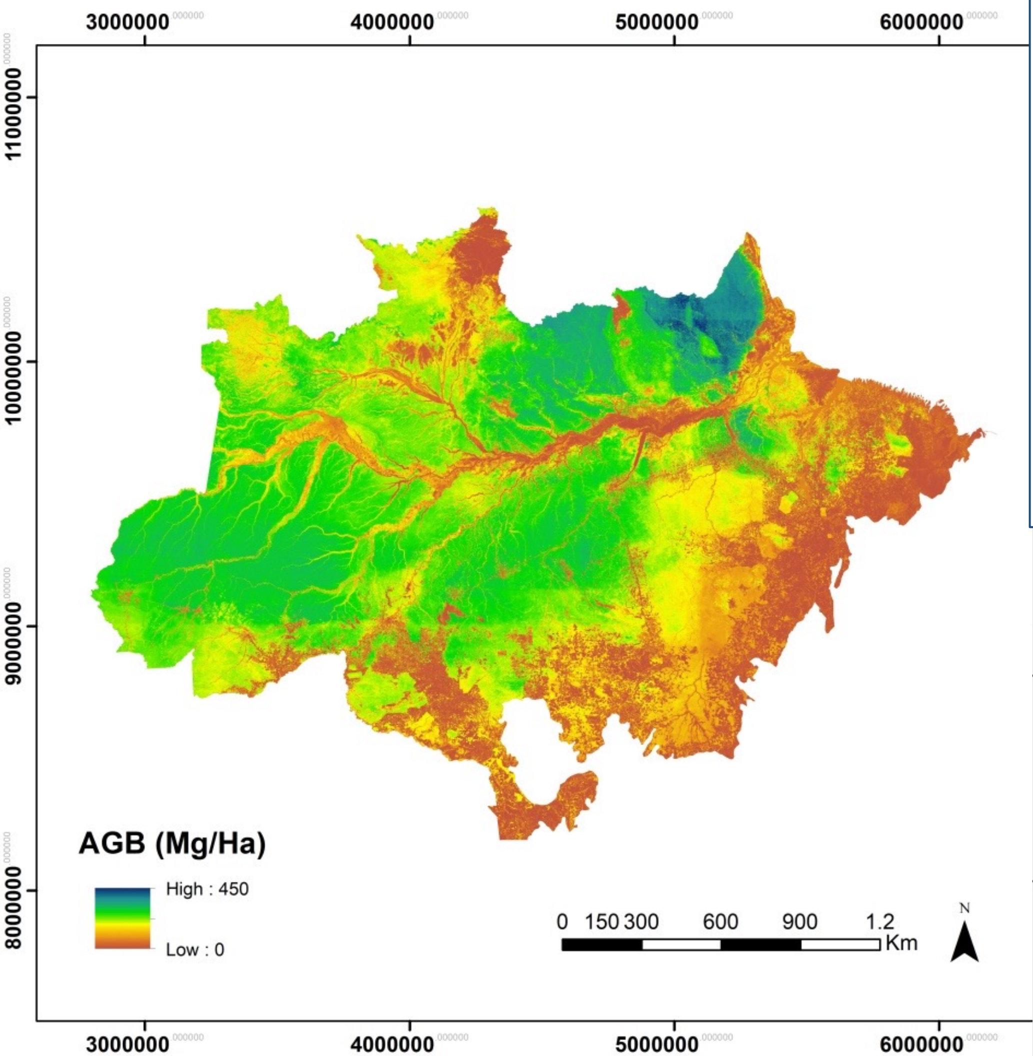
→ Automate the biomass calculation and the generation of the biomass map

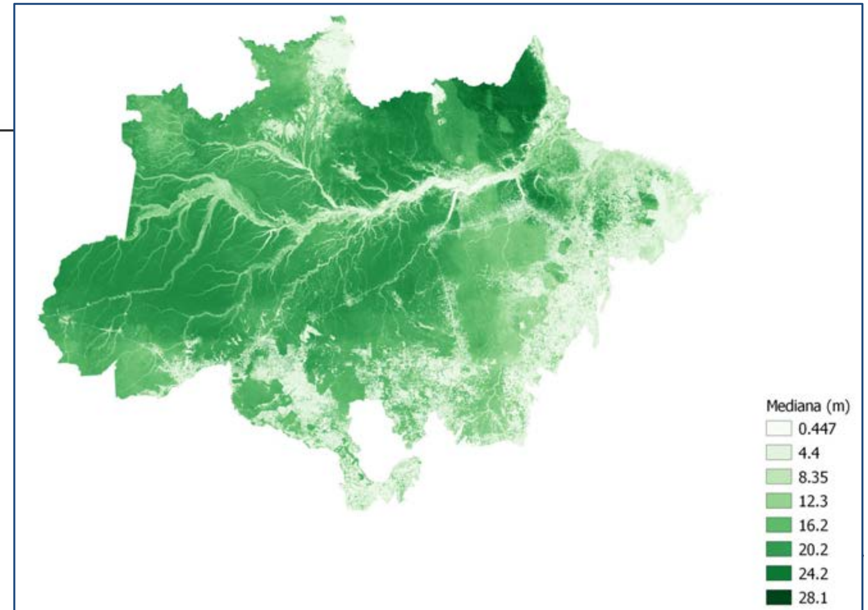
LiDAR data process

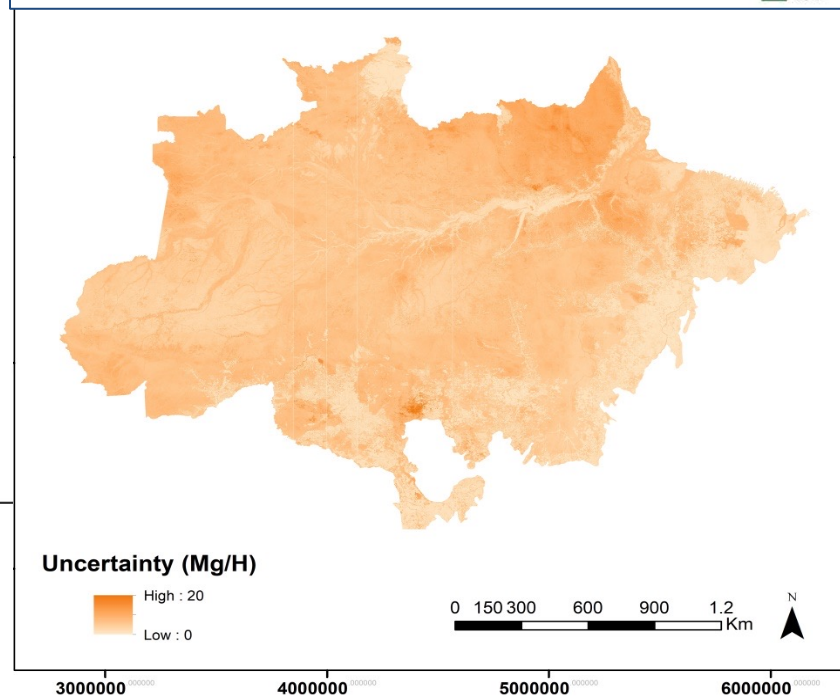
--> LiDAR metrics are automatically generated for each new transect delivered by the ALS flight company

- Script

AGB, Uncertainty, Median height Maps

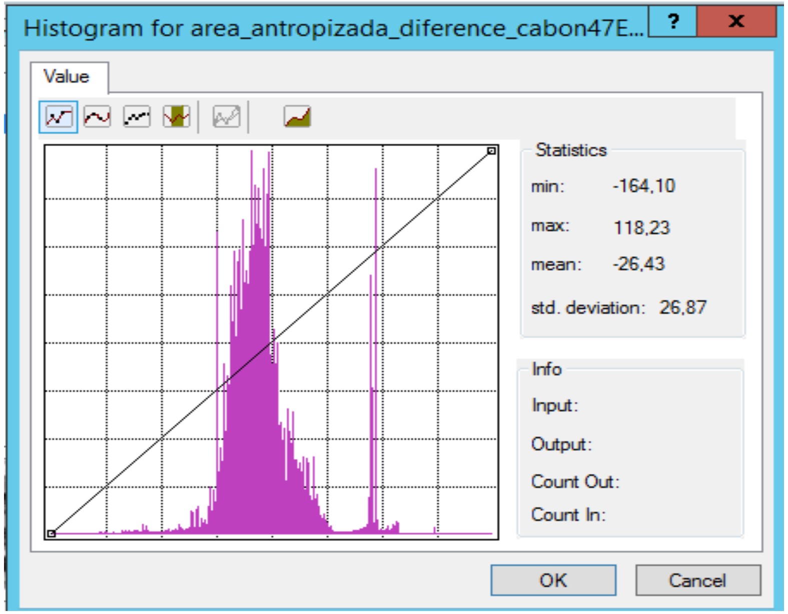


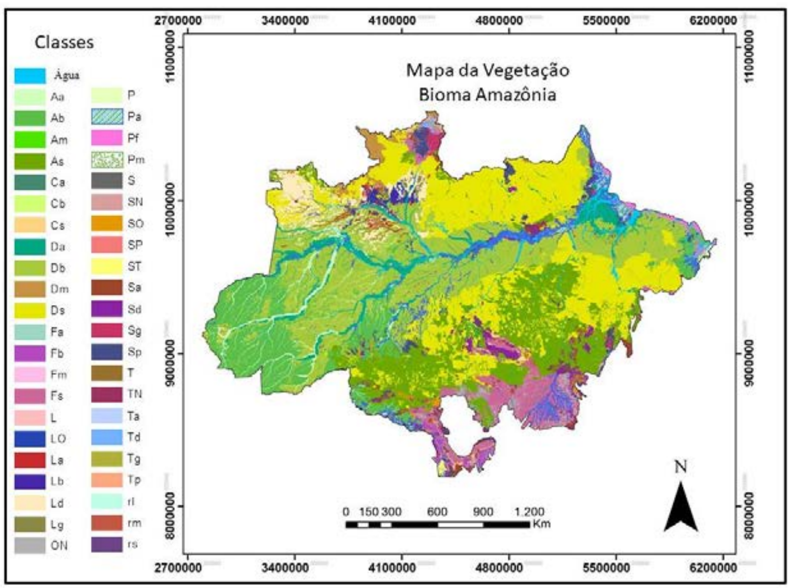


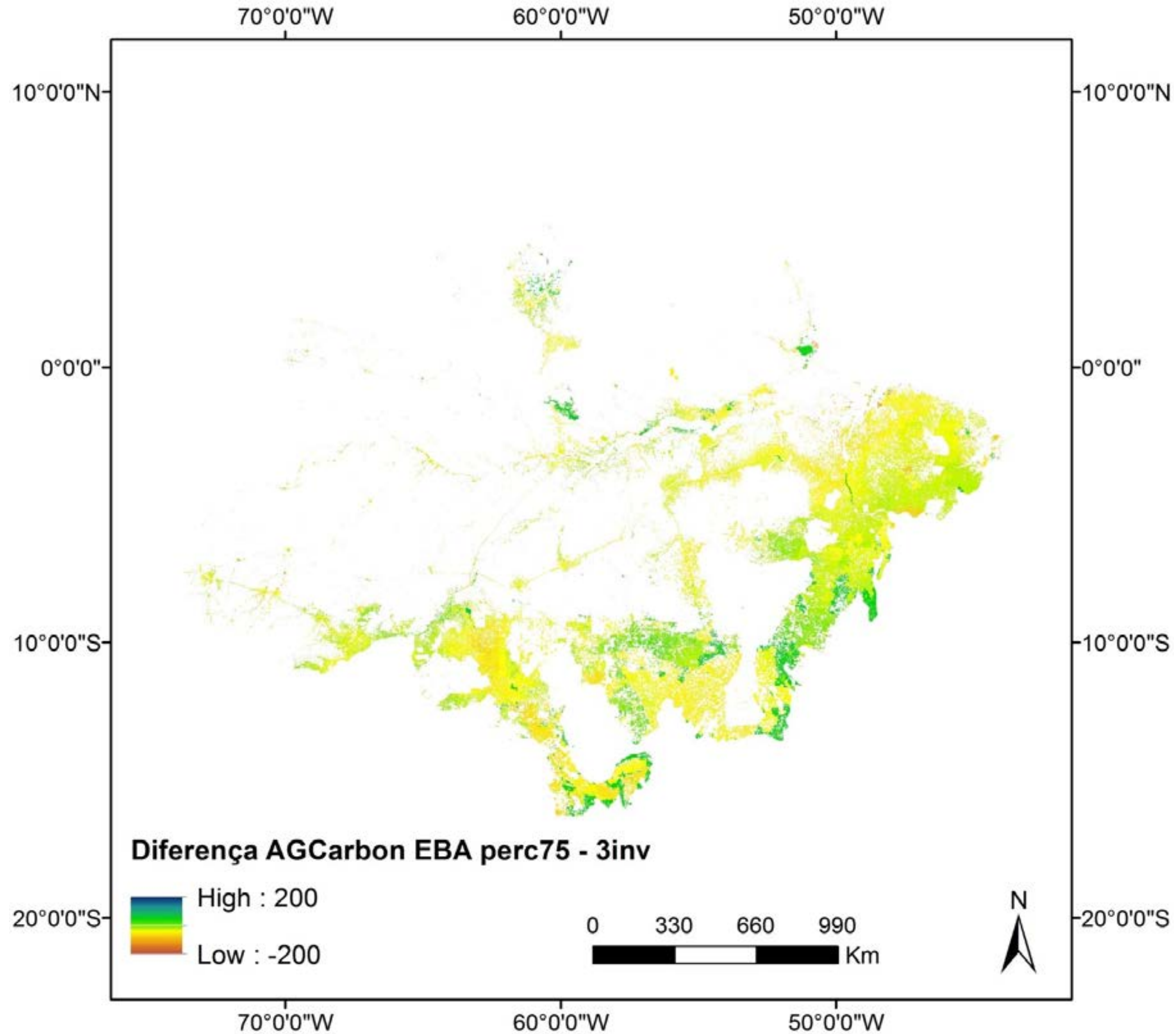


Biomass estimatioin on preterit vegetation

➔ 75 percentil of the natural, non distubance classes, based on a vegetation map







Positive values ➔ EBA > RADAM_3inv

Negative values --> EBA < RADAM_3inv

National Communication to the Climate Convention and as support for the Forest Reference Level (FREL)

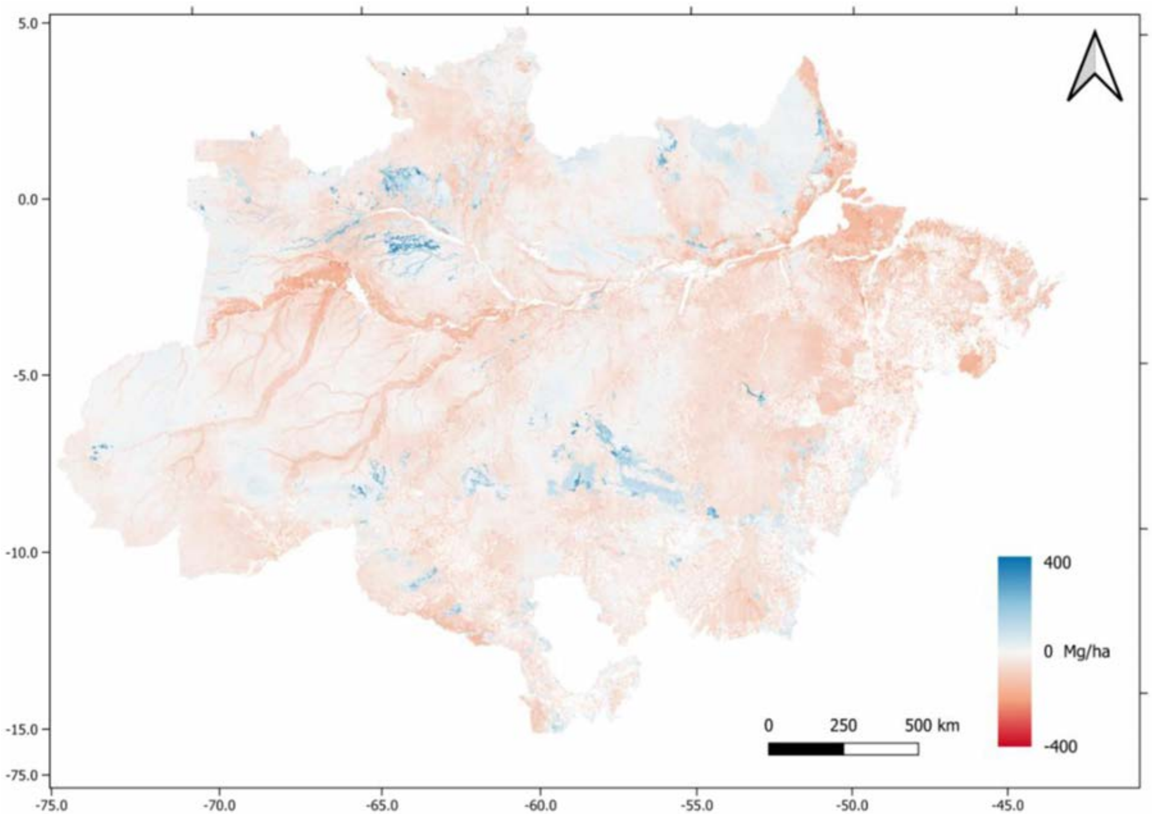
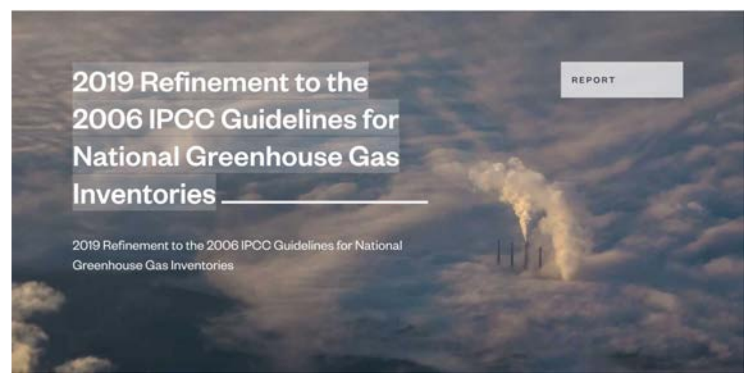


Fig. 6 Comparison with the 3rd Brazilian National Communication. Negative values (red) indicate lower values to 3rd National Communication. Positive values (blue) indicate higher values to the new estimations.

BOX 2.0E (NEW)
USING A BIOMASS MAP FOR GHG ESTIMATION: AN EXAMPLE FROM THE BRAZILIAN AMAZON

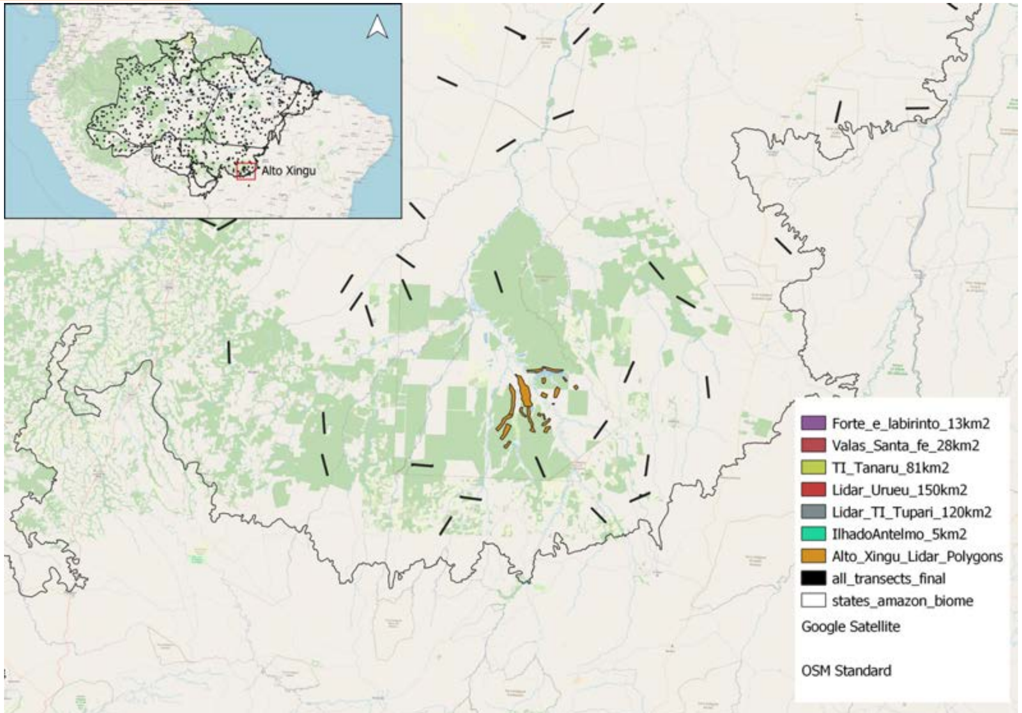
Brazil is applying a methodology for estimating forest biomass combining data from airborne LiDAR, satellite remote sensing and forest inventories. The aim for using the biomass map for the NGHGI is to provide coverage over the whole Amazon where the availability and quality of ground data varies. Deforestation and associated land use change in the Amazon are heterogeneous and patchy. Related estimates of carbon emissions carry some level of uncertainty unless this spatial variability in both types of change and biomass variability is captured.

The methodology to estimate the biomass was based on 1,000 LiDAR transects randomly distributed across 3.5 million km^2 of the Amazon forests. Aboveground biomass is estimated at three different levels. At field plot level (first level), the data are used to validate the biomass estimated by LiDAR (second level) by adopting and using the models and data provided by Chave et al 2014 and Longo et al 2016. A total of 407 field plots were used for this validation. At the third level the biomass was estimated by extrapolating the biomass to the Brazilian Amazon Biome by the use of MODIS vegetation index, Shuttle Radar Topography Mission data, precipitation data from the Tropical Rainfall Measuring Mission and Synthetic Aperture Radar data of the Phased Array type L-band Synthetic Aperture Radar, soil and vegetation maps. A nonparametric regression method (Random Forest) is used for correlating the above ground biomass within the LiDAR transects to a list of variables, and then used for the extrapolation of the biomass to the region. The coefficient of determination and the root mean squared error between the third level extrapolated biomass data and the LiDAR data were R2=0.7485 and RMSE=27.18 $MgC ha^{-1}$, respectively. In this process, the SRTM elevation data were the most important variable for the biomass extrapolation process, followed by the TRMM precipitation data and Enhanced Vegetation Index data. The estimated biomass map uncertainty is calculated by propagating the uncertainties through the different levels of biomass estimation, i.e., field plots, LiDAR and satellite (Longo et al 2016). This process allows us to obtain total uncertainty estimates for each pixel in the final biomass map.



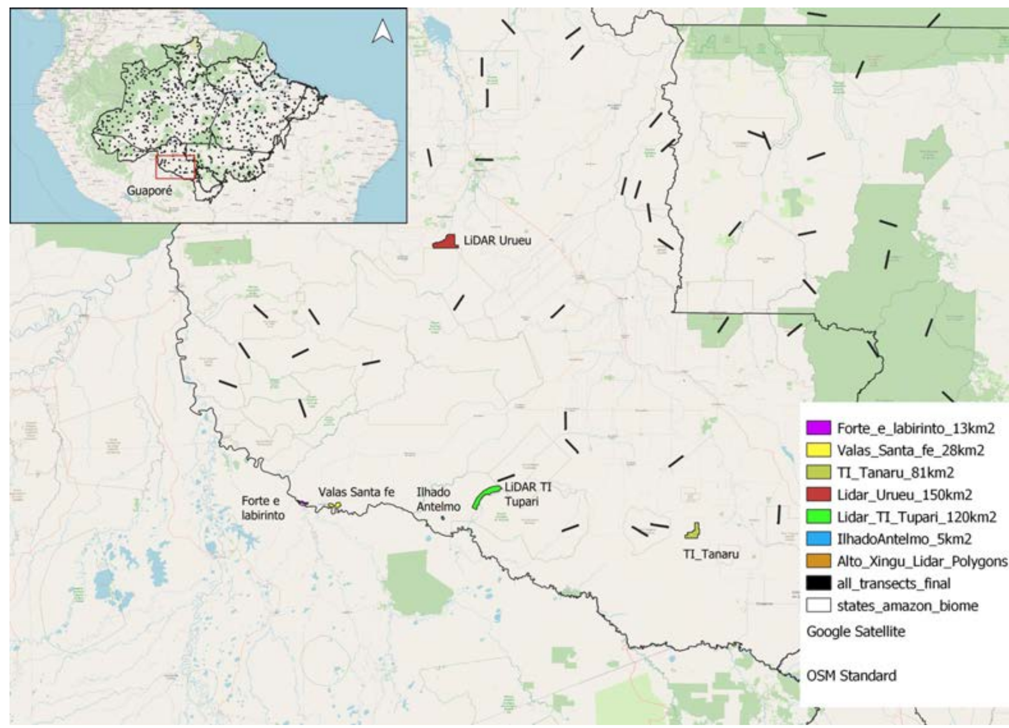
Amazonia Revelada (Neves et al)

Alto Xingu



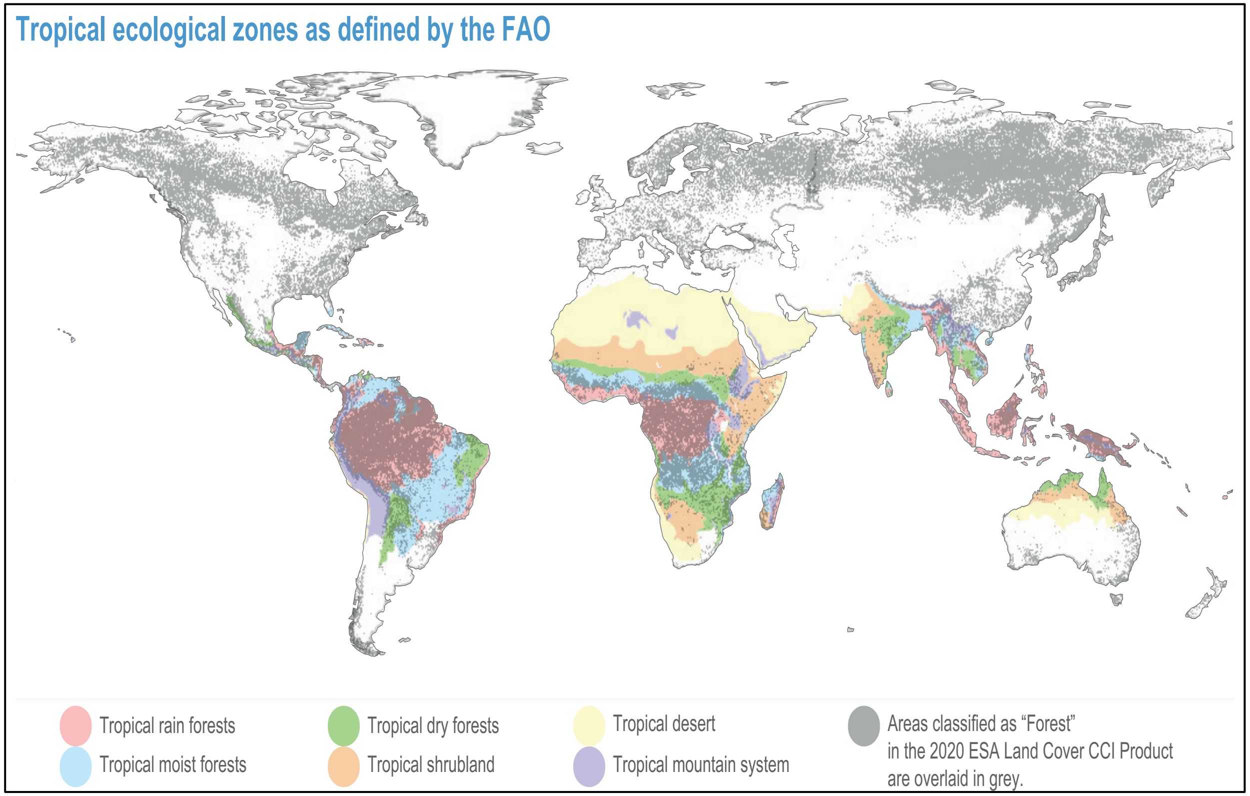
AMAZÔNIA REVELADA

Guapore



TROPICAL FORESTS

Climate change affects tropical forests through warming and increased occurrence of extreme events such as droughts and heatwaves, as well as more frequent fires, **which increase tree mortality and reduce tree growth**, limiting the ability of forests to regenerate and reducing their biodiversity.



- Over 420 million ha of forest were lost to deforestation from 1990 to 2020; more than **90% of that loss took place in tropical areas**, threatening biodiversity, environmental services, livelihoods of forest communities, and resilience to climate shocks (IPCC WG2, CCP7, 2022).