

SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

Day 2: Quantifying secondary forest regrowth rates: a synthesis

São José dos Campos, 30 Oct 2025



Session 2.1 (Part 1): Biomass Datasets and Missions

SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

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Biomass maps used in inventory

Jean Ometto

Session 2.1 (Part 1): Biomass datasets and missions

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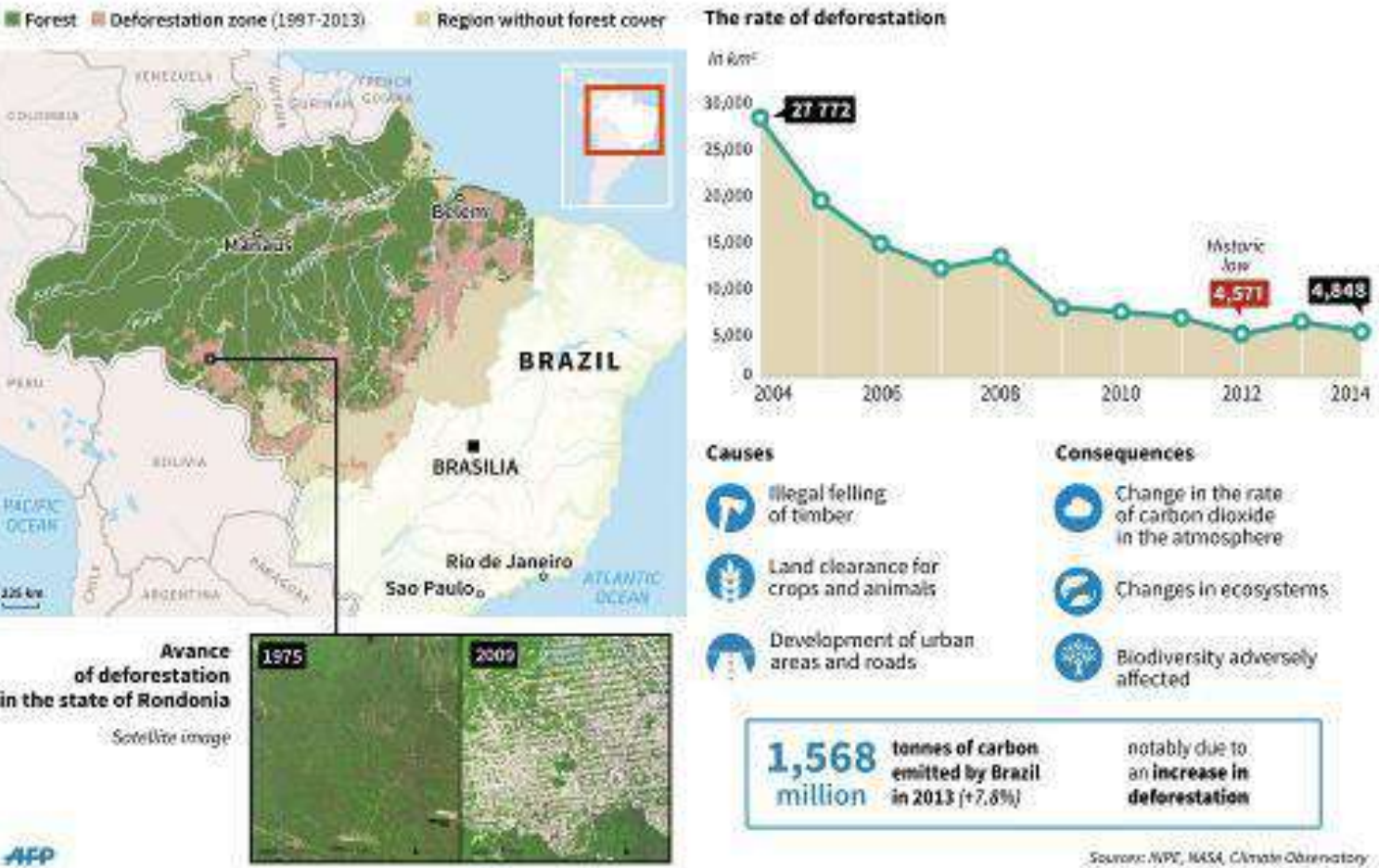
Biomass estimation in the Amazon basin and GHG emissions inventories

Jean Ometto
jean.Ometto@inpe.br

Some of the Carbon world in 2014

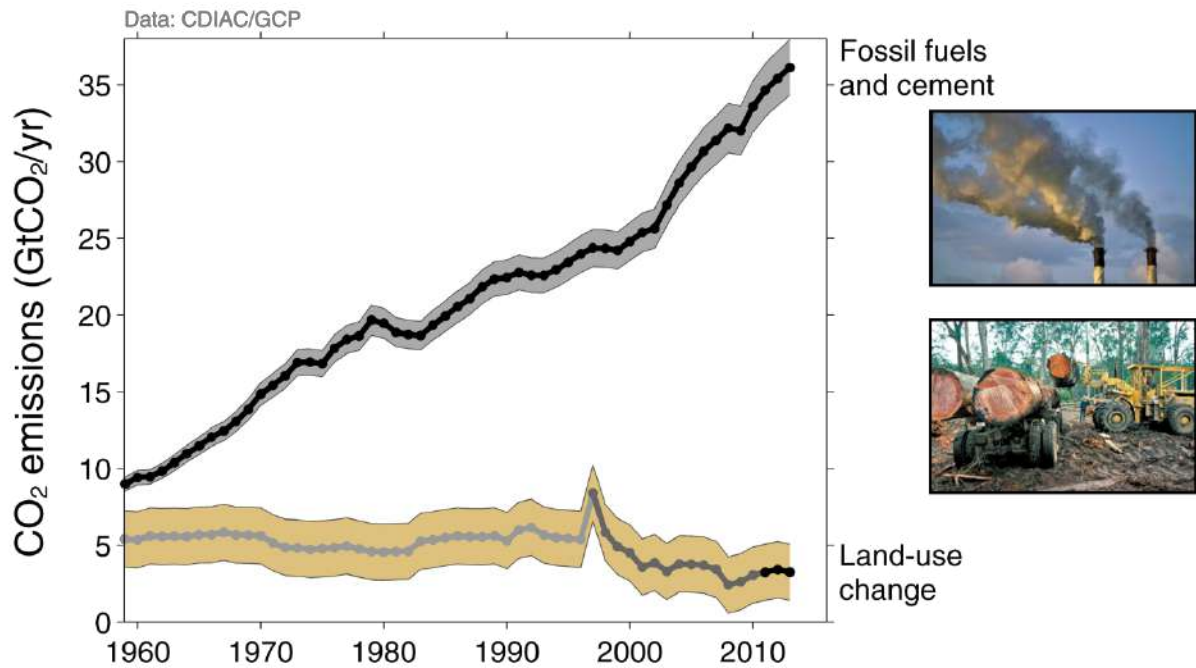
Brazil: deforestation in the Amazon forest

Scientists are concerned by the rate at which it is disappearing



Total Global Emissions

Total global emissions: 39.4 ± 3.4 GtCO₂ in 2013, 42% over 1990
Percentage land-use change: 36% in 1960, 19% in 1990, 8% in 2013



Three different methods have been used to estimate land-use change emissions, indicated here by different shades of grey

Source: [CDIAC](#); [Houghton et al 2012](#); [Giglio et al 2013](#); [Le Quéré et al 2014](#); [Global Carbon Budget 2014](#)

2014 set to be world's hottest year ever

Record average temperatures highlight the urgent need to agree a deal on emissions at the UN climate change talks in Lima

The hottest year on record - in pictures



Vehicles drive by a 134ft-high thermometer in Baker, California. Average land and sea surface temperatures have reached record levels in 2014. Photograph: Ethan Miller/Getty Images

The world is on course for the hottest year ever in 2014, the United Nations weather agency said on Wednesday, heightening the sense of urgency around climate change negotiations underway in Lima.



NEWS ARTICLE | 14 April 2014 | Directorate-General for Climate Action | 4 min read

IPCC report highlights need for collective and significant action to keep warming below 2°C

WMO: Global Climate in 2014 marked by extreme heat and flooding

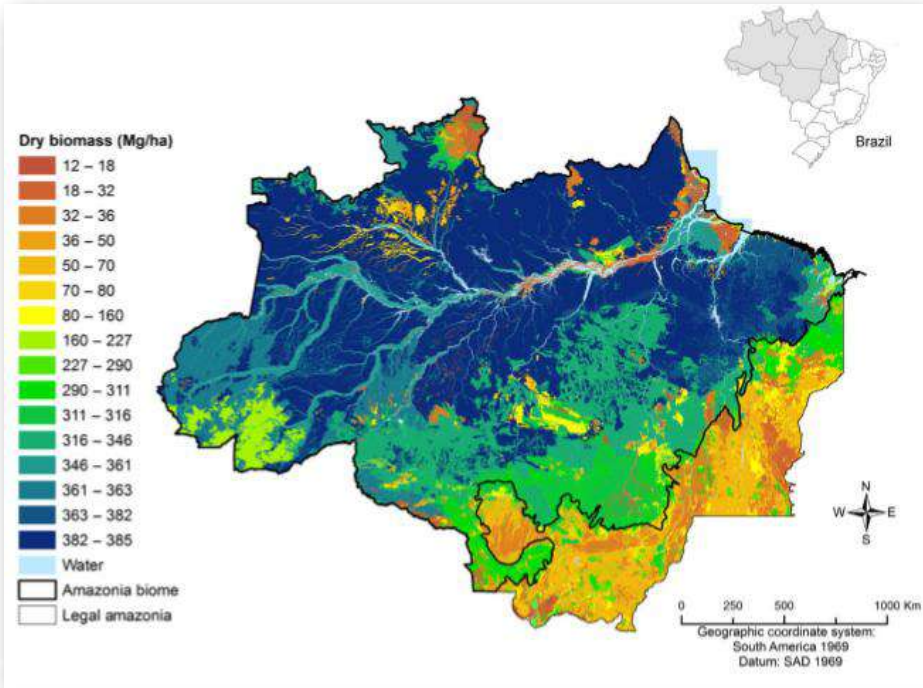
NEWS

23 March 2015

Report Released for World Meteorological Day: Climate Knowledge for Climate Action
Record ocean heat, high land-surface temperatures and devastating flooding were some of the defining characteristics of the global climate in 2014, which was...

Forest Biomass Maps

MCTI, TCN, 2016.

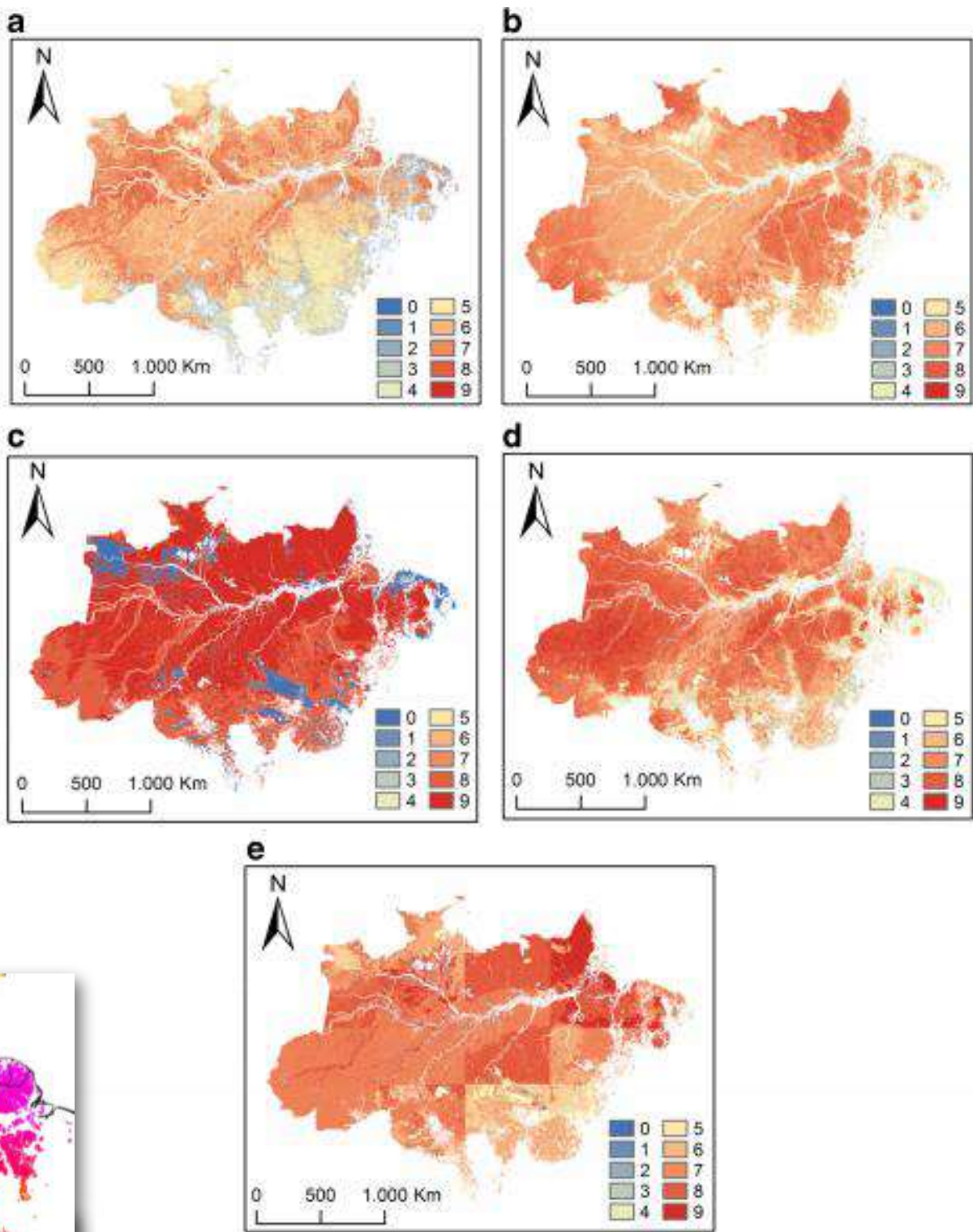


Global Change Biology (2015) 21, 1271–1292, doi: 10.1111/gcb.12798

Carbon stock loss from deforestation through 2013 in Brazilian Amazonia

EULER MELO NOGUEIRA, AURORA M YANAI, FREDERICO O R FONSECA and PHILIP MARTIN FEARNSIDE

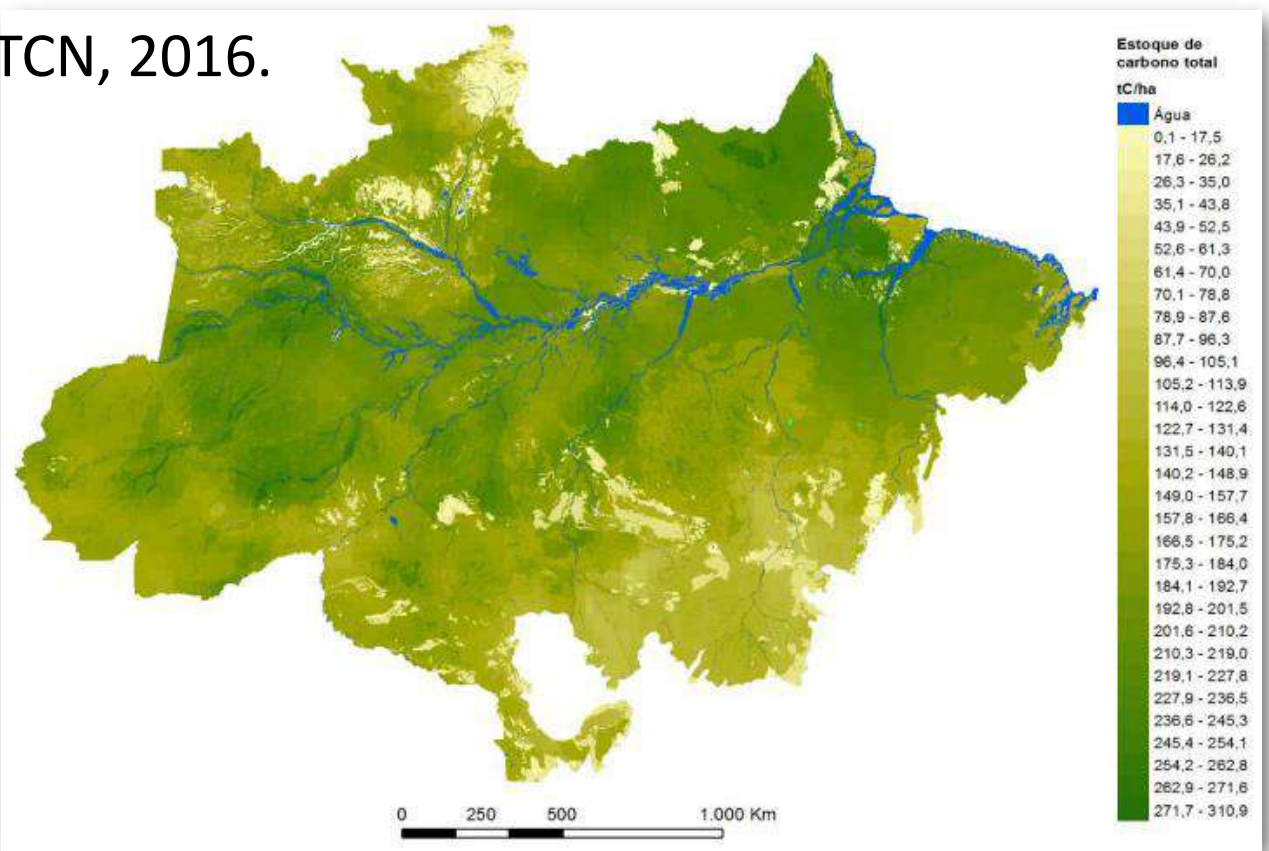
Department of Environmental Dynamics, National Institute for Research in Amazonia (INPA), Av. André Araújo no 2936, Manaus, Amazonas, CEP 69 067-375, Brazil



Ometto et al., 2014

Climatic Change

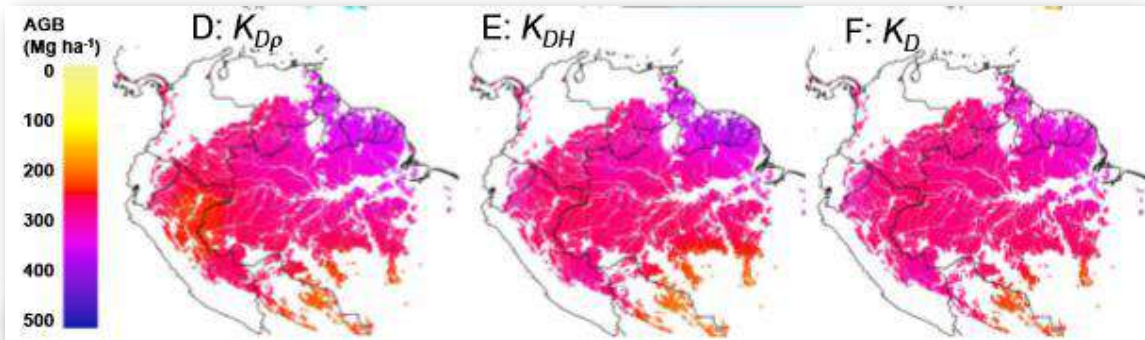
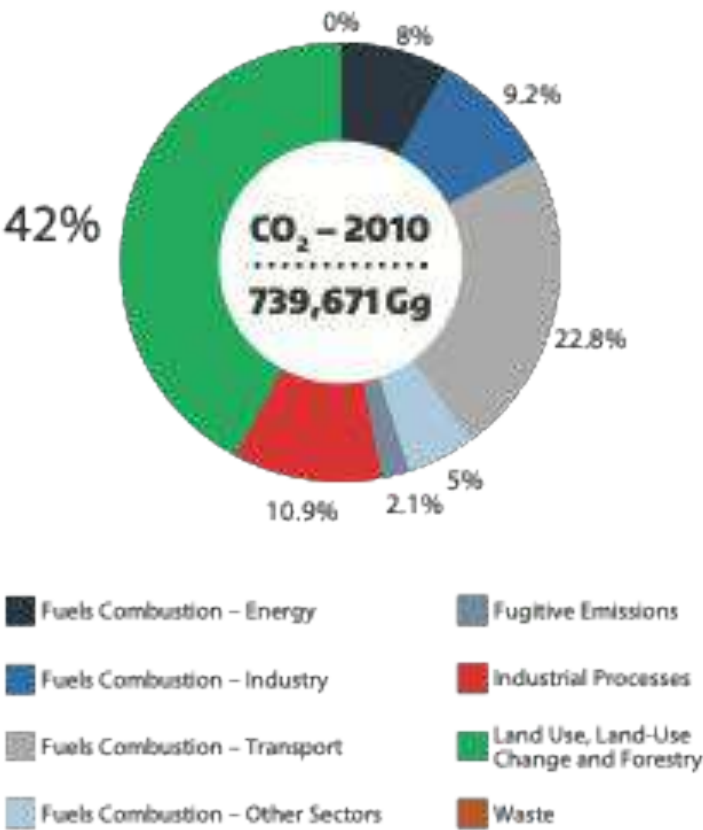
DOI 10.1007/s10584-014-1058-7



EMISSIONS OF THE MAIN GREENHOUSE GASES

FIGURE II

Sectors and sub-sectors shares of net CO₂ emissions in 2010



RESEARCH PAPER

Markedly divergent estimates of Amazon forest carbon density from ground plots and satellites

Edward T. A. Mitchard^{1*}, Ted R. Feldpausch^{2,3}, Roel J. W. Brienen², Gabriela Lopez-Gonzalez², Abel Monteagudo⁴, Timothy R. Baker², Simon L. Lewis^{2,5}, Jon Lloyd⁶, Carlos A. Quesada⁷, Manuel Gloor⁸, Hans ter Steege^{4,9}, Patrick Meir^{1,10}, Esteban Alvarez¹¹, Alejandro Araujo-Murakami¹², Luiz E. O. C. Aragão^{3,13}, Luzmila Arroyo¹², Gerardo Aymard¹⁴

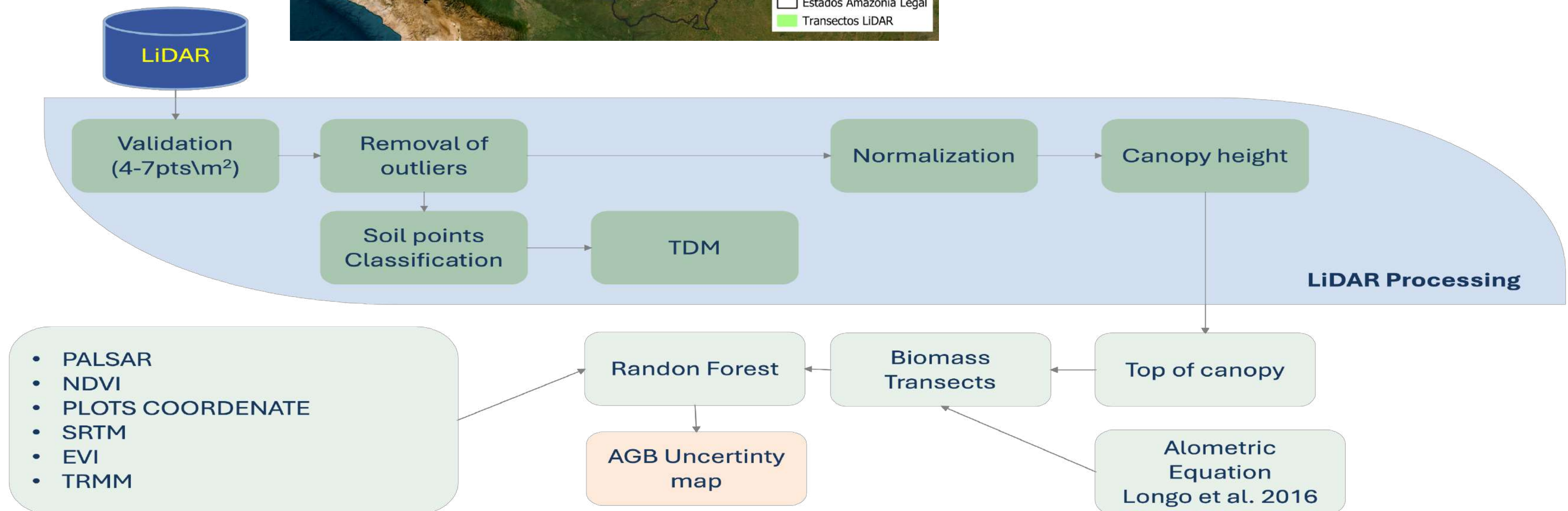


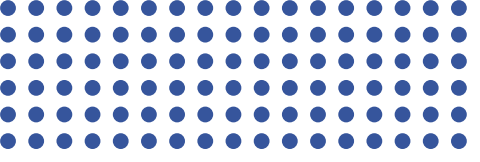
Transect: 3,75 km²

Total area: 3.750 km²

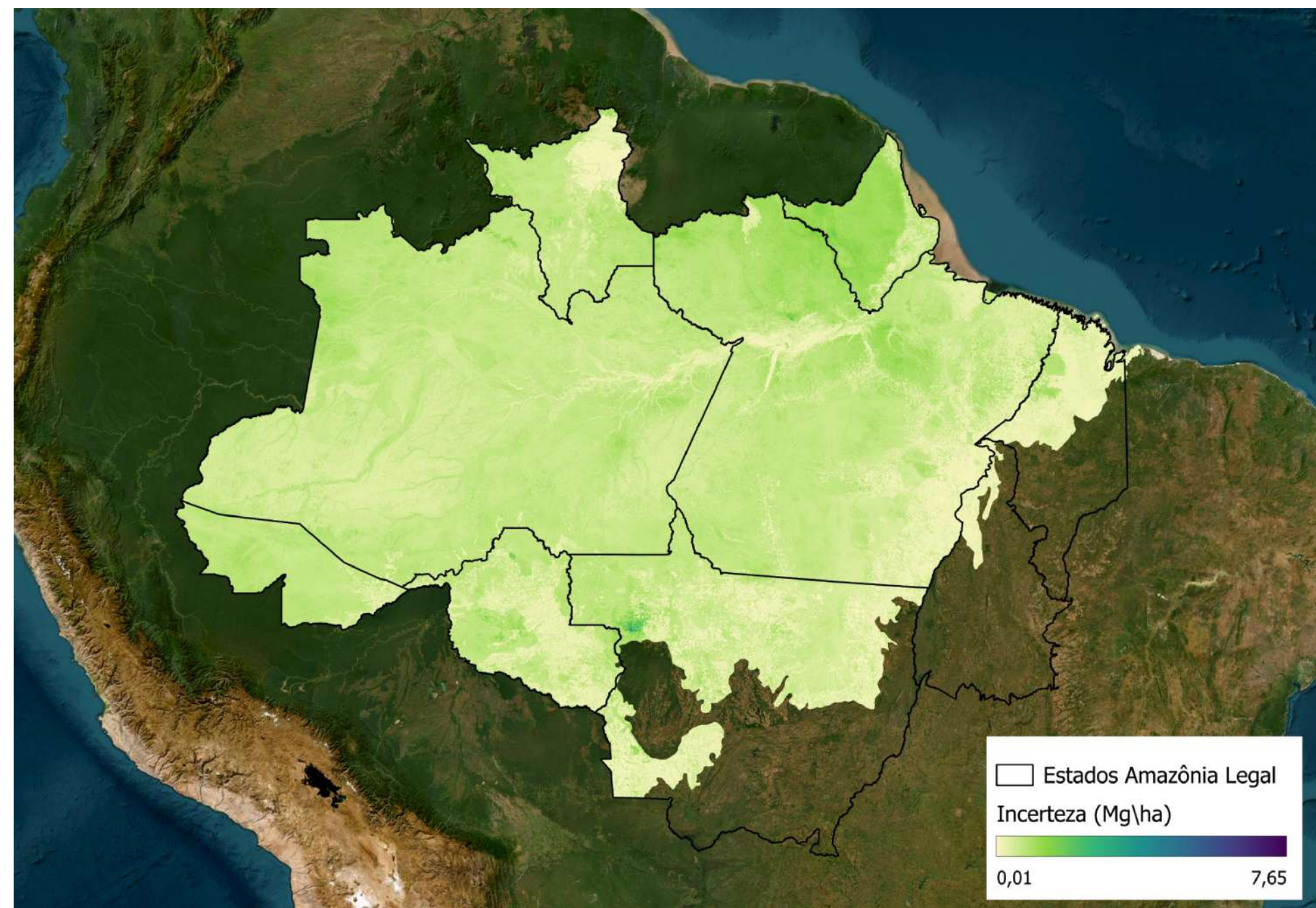
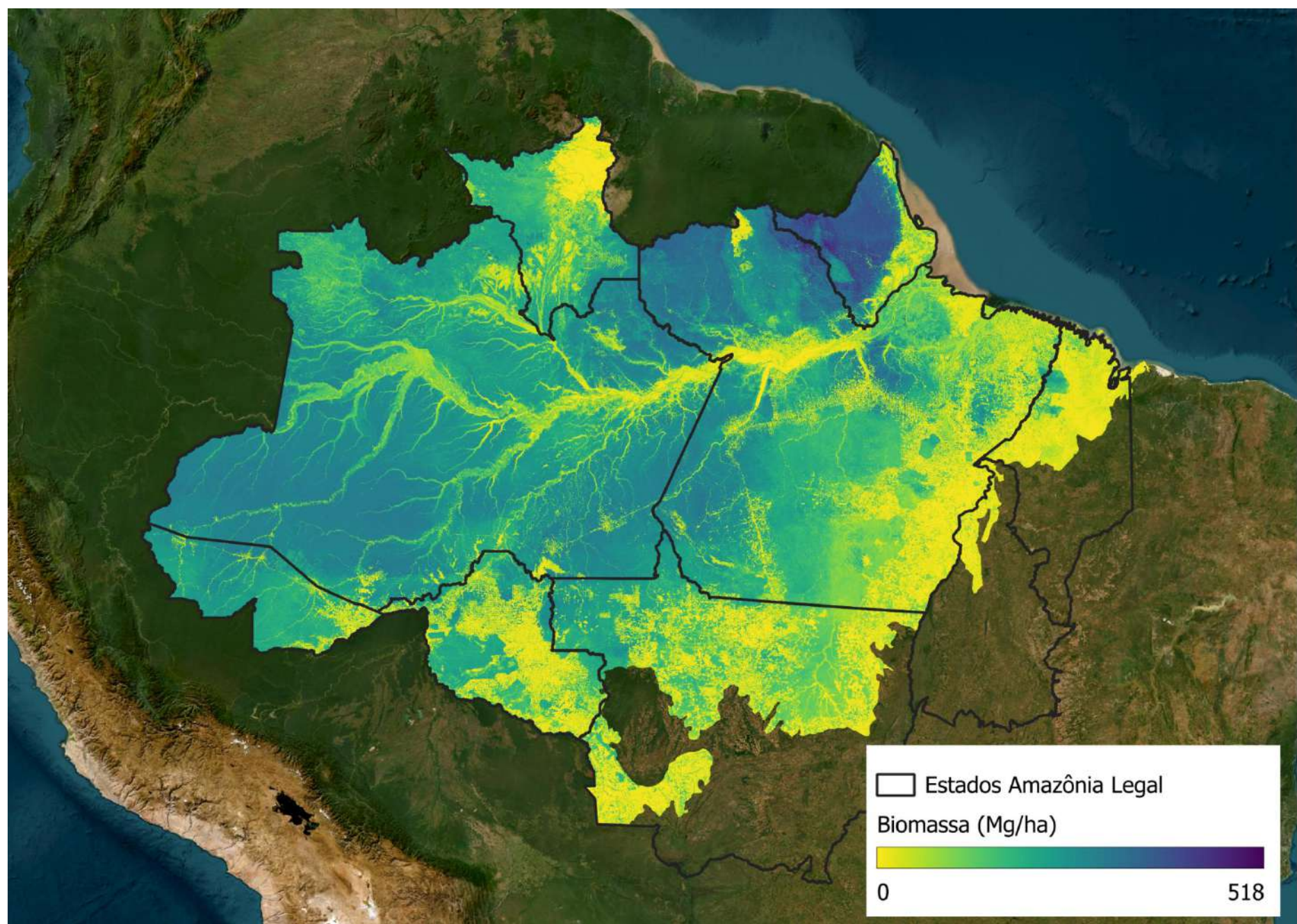
Randomly distributed considering :

- PRODES mask
- TerraClass
- Flooded areas





AGB (Mg/ha)



Uncertainty Map (Mg/ha)

Mapa de Incertezas

Nível 1

Nível 2

Nível 3

Parcelas de Campo

- Calcula a AGB das parcelas de campo – equações alométricas
- Extrai do LiDAR as métricas de altura do Topo da Vegetação – das mesmas áreas das parcelas

LiDAR 50 m

- Ajusta um modelo:

LiDAR x Campo

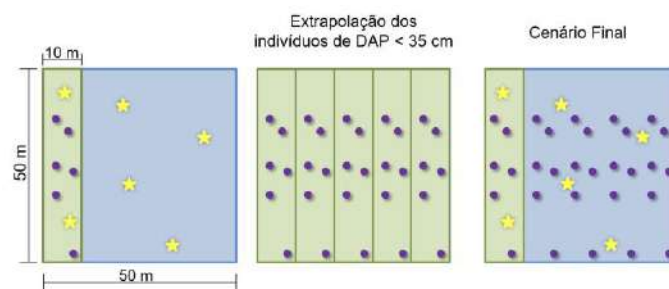
Longo et al. 2016

LiDAR 250 m

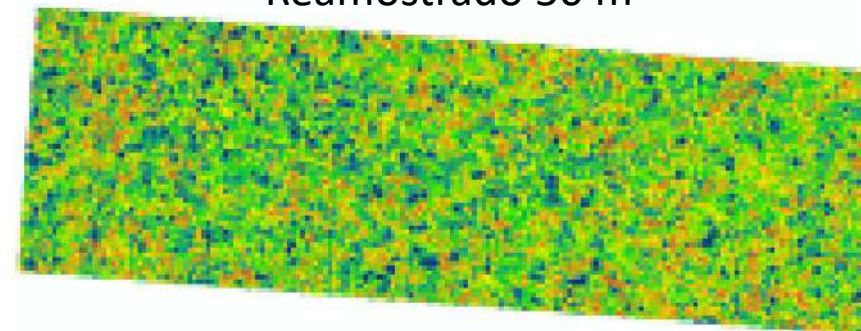
- AGB e incerteza de 50 m são reamostradas para 250 m (compatível com os dados de satélite).
- Resultado: AGB e incerteza de 250 m para todos os pixels de dados LiDAR

AGB\Incerteza 250 m

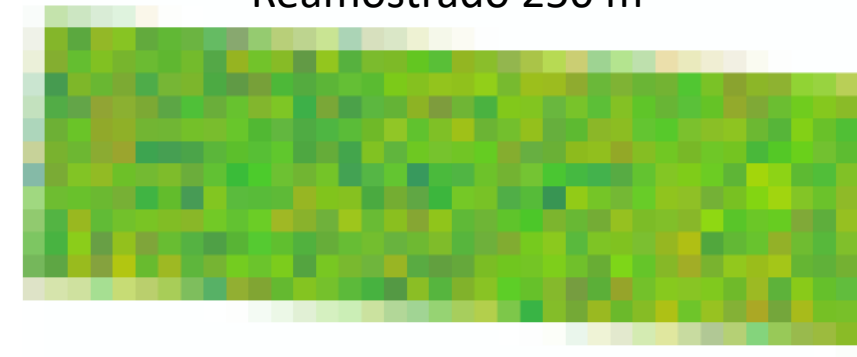
- Para a Amazônia: modelo Random Forest prever AGB a partir de camadas de satélite (índices de veg., terreno, precipitação)
- O modelo gera AGB para todos os pixels (inclusive onde não temos LiDAR)



Reamostrado 50 m



Reamostrado 250 m



AGB\Incerteza 250 m



Outras Análises

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

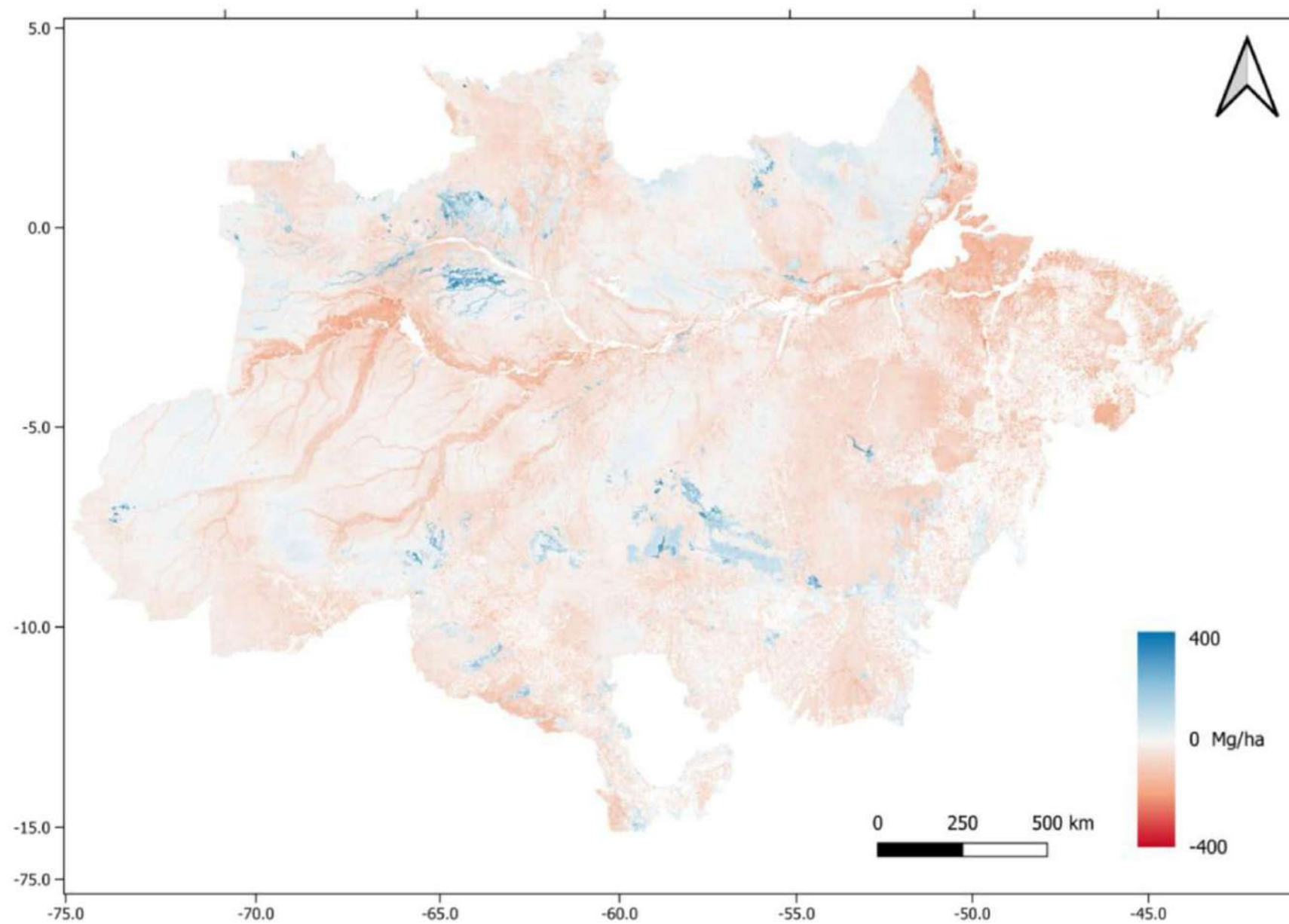
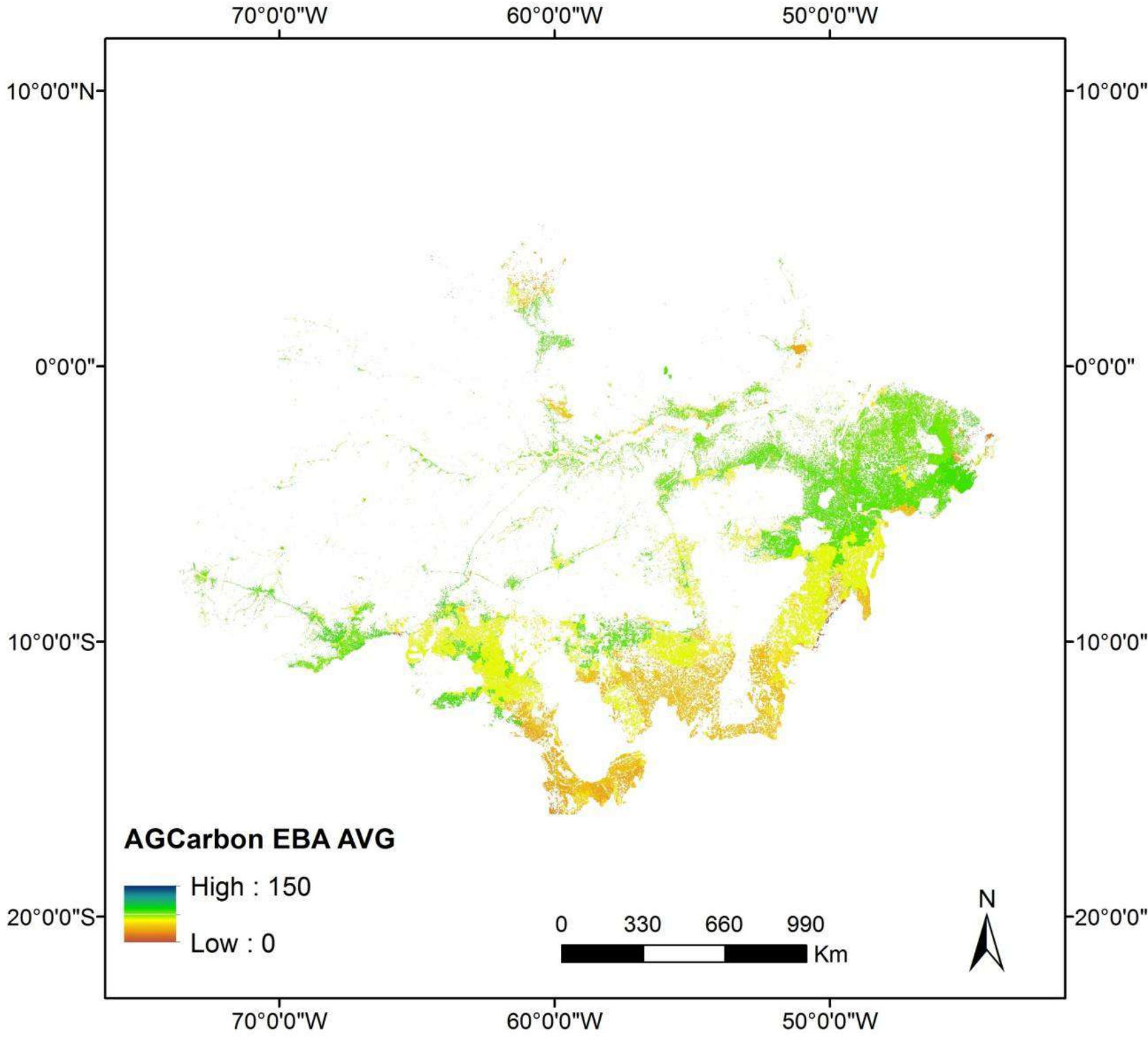


Fig. 6 Comparison with the 3rd Brazilian National Communication. Negative values (red) indicate lower values to 3rd National Communication. Positive values (blue) indicate higher values to the new estimations.

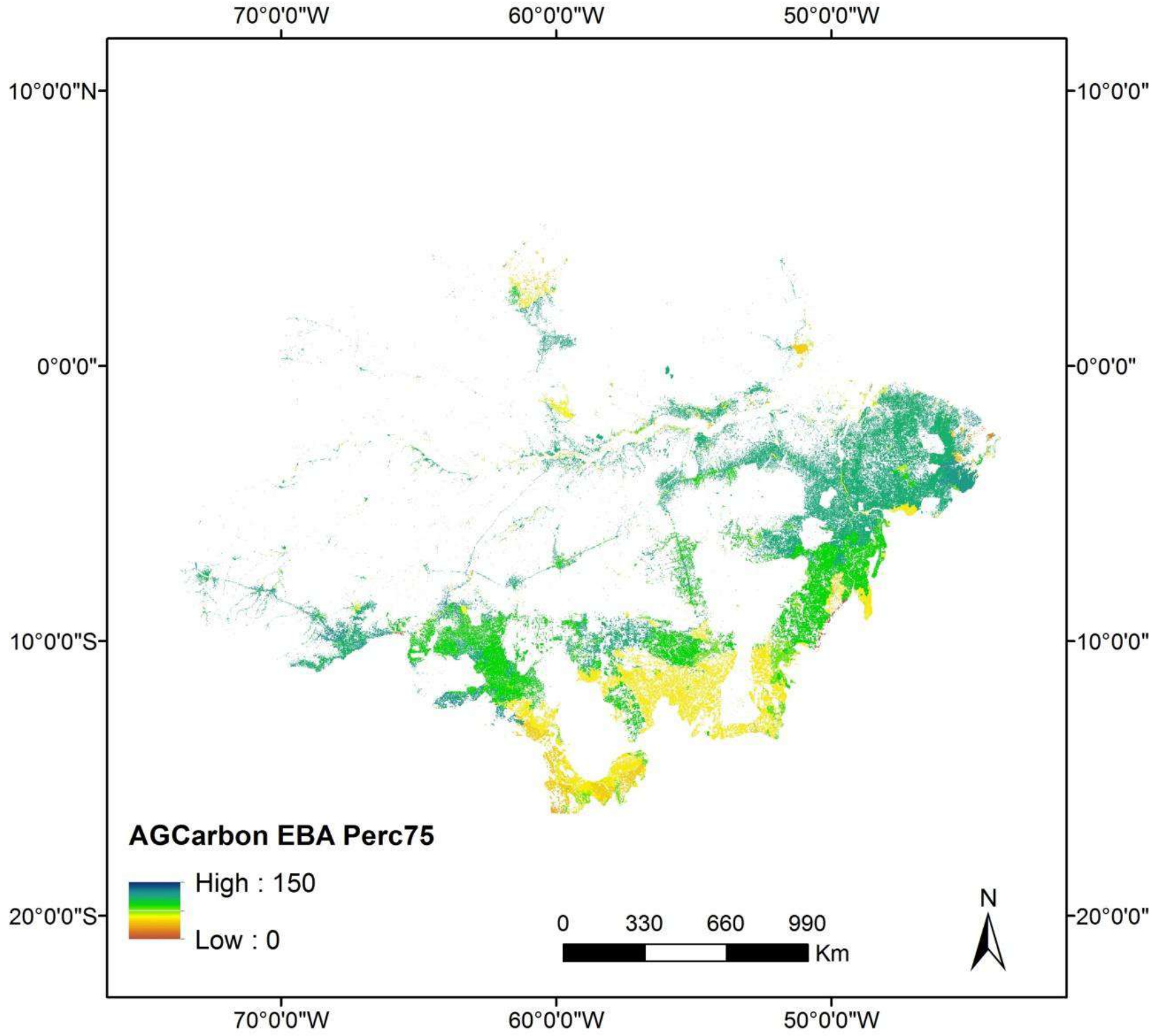


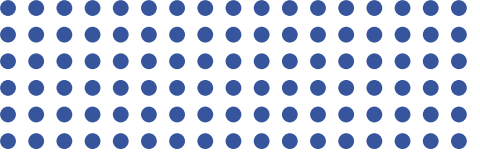
Áreas antropizadas até 2016

AGCarbon EBA considering the average content from vegetation classes



AGCarbon EBA considering the Percentil 75 content from vegetation classes





A few other contributions

scientific reports

OPEN

Large-scale variations in the dynamics of Amazon forest canopy gaps from airborne lidar data and opportunities for tree mortality estimates

Ricardo Dalagnol^{1,2}, Fabien H. Wagner^{1,2}, Lênio S. Galvão¹, Annia S. Streher¹, Oliver L. Phillips³, Emanuel Gloor³, Thomas A. M. Pugh^{4,5}, Jean P. H. B. Ometto⁶ & Luiz E. O. C. Aragão^{1,7}

remote sensing



Article

Characterizing Canopy Structure Variability in Amazonian Secondary Successions with Full-Waveform Airborne LiDAR

Aline D. Jacon¹, Lênio Soares Galvão¹, Rorai Pereira Martins-Neto², Pablo Crespo-Peremarch^{3,4}, Luiz E. O. C. Aragão¹, Jean P. Ometto⁵, Liana O. Anderson⁶, Laura Barbosa Vedovato⁷, Celso H. L. Silva-Junior⁸, Aline Pontes Lopes¹, Vinícius Peripato¹, Mauro Assis¹, Francisca R. S. Pereira¹, Isadora Haddad¹, Catherine Torres de Almeida⁹, Henrique L. G. Cassol^{1,10} and Ricardo Dalagnol^{11,12,*}

Science of Remote Sensing 6 (2022) 100067



Contents lists available at ScienceDirect

Science of Remote Sensing

journal homepage: www.sciencedirect.com/journal/science-of-remote-sensing

Assessment of terrain elevation estimates from ICESat-2 and GEDI spaceborne LiDAR missions across different land cover and forest types

Mikhail Urbazaev^{a,*}, Laura L. Hess^b, Steven Hancock^c, Luciane Yumie Sato^d, Jean Pierre Ometto^d, Christian Thiel^e, Clémence Dubois^a, Kai Heckel^a, Marcel Urban^a, Markus Adam^a, Christiane Schmullius^a

PNAS

RESEARCH ARTICLE

ECOLOGY
SUSTAINABILITY SCIENCE

OPEN ACCESS



A large net carbon loss attributed to anthropogenic and natural disturbances in the Amazon Arc of Deforestation

Ovidiu Csillik^{1,2}, Michael Keller^{3,4}, Marcos Longo⁵, Antonio Ferraz⁶, Ekena Rangel Pinagé⁷, Eric Bastos Görgens⁸, Jean P. Ometto¹, Vinícius Silgueiro⁹, David Brown¹⁰, Paul Duffy¹¹, K. C. Cushman¹², and Sassan Saatchi¹³

nature communications



Article

<https://doi.org/10.1038/s41467-025-61856-1>

Human influence on Amazon's aboveground carbon dynamics intensified over the last decade

Received: 23 August 2024

Accepted: 3 July 2025

Published online: 21 July 2025

Arthur Fendrich^{1,2}, Yu Feng^{1,3}, Jean-Pierre Wigneron⁴, Jérôme Chave⁵, Arnan Araza⁶, Zheyuan Li⁷, Martin Herold^{8,9}, Jean Ometto¹⁰, Luiz E. O. C. Aragão^{11,12}, Isabel Martinez Cano¹, Lei Zhu^{1,13}, Yidi Xu¹ & Philippe Ciais¹

Environ. Res. Lett. 20 (2025) 054024

<https://doi.org/10.1088/1748-9326/adc58c>

ENVIRONMENTAL RESEARCH
LETTERS

LETTER

Degradation and deforestation increase the sensitivity of the Amazon Forest to climate extremes

Marcos Longo^{1,2,*}, Michael Keller^{3,4}, Lara M Kueppers^{1,4}, Kevin W Bowman⁵, Ovidiu Csillik^{2,5}, António Ferraz⁶, Paul R Moorcroft⁴, Jean Pierre Ometto⁷, Britaldo S Soares-Filho⁸, Xiangtao Xu⁹, Mauro L R de Assis⁷, Eric B Görgens¹⁰, Erik J L Larson⁶, Jessica F Needham¹, Elsa M Ordway^{11,12}, Francisca R S Pereira⁷, Ekena Rangel Pinagé¹³, Luciane Sato⁷, Liang Xu^{2,14} and Sassan Saatchi^{2,11}

More than 10,000 pre-Columbian earthworks are still hidden throughout Amazonia

VINICIUS PERIPATO, CAROLINA LEVIS, GUIDO A. MOREIRA, DANI GAMERMAN, HANS TER STEEGE, NIGEL C. A. PITMAN, JONAS G. DE SOUZA, JOSÉ IRIARTE, MARK ROBINSON, [...] AND LUIZ E. O. C. ARAGÃO

+220 authors

[Authors Info & Affiliations](#)

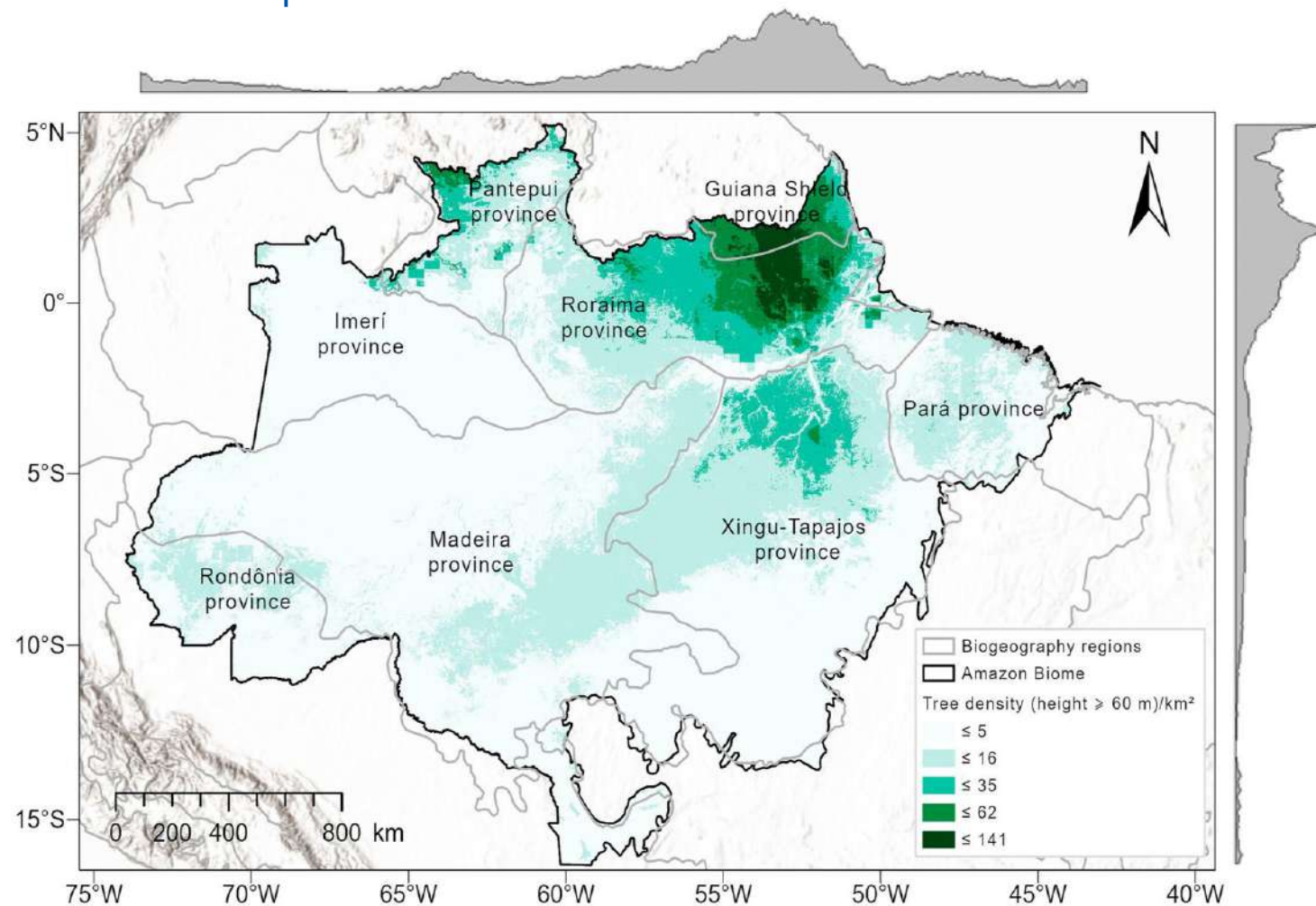
Science 382, 103–109 (2023)

[...]

Mapping the density of giant trees in the Amazon

Robson Borges de Lima¹, Diego Armando Silva da Silva², Matheus Henrique Nunes³, Paulo R. de Lima Bittencourt⁴, Peter Groenendyk⁵, Cinthia Pereira de Oliveira¹, Daniela Granato-Souza⁶, Rinaldo L. Caraciolo Ferreira⁷, José A. Aleixo da Silva⁷, Jesús Aguirre-Gutiérrez⁸, Toby Jackson⁹, João R. de Matos Filho¹⁰, Perseu da Silva Aparício¹, Joselane P. Gomes da Silva¹, José Julio de Toledo¹¹, Marcelino Carneiro Guedes¹², Danilo R. Alves de Almeida¹³, Niro Higuchi¹⁴, Fabien H. Wagner¹⁵, Jean Pierre Ometto¹⁶ and Eric Bastos Görgens¹⁷

DOI: [10.1111/nph.70634](https://doi.org/10.1111/nph.70634)



Potential map generated by the random forest spatial model to define ideal zones for the occurrence of high density of giant trees in the Amazon.

Resolution Tree Height Mapping of the Amazon forest using Planet NICFI and LiDAR-Informed U-Net Model

Wagner et al (Remote Sensing in Ecology and Conservation)

model successfully estimated canopy heights up to 40–50 m without much saturation, outperforming existing canopy height products from global models in this region. We determined that the Amazon forest has an average canopy height of ~22 m. Events such as logging or deforestation could be detected from changes in tree height, and encouraging results were obtained to monitor the height of regenerating forests.

Very high resolution map of the Amazon canopy height

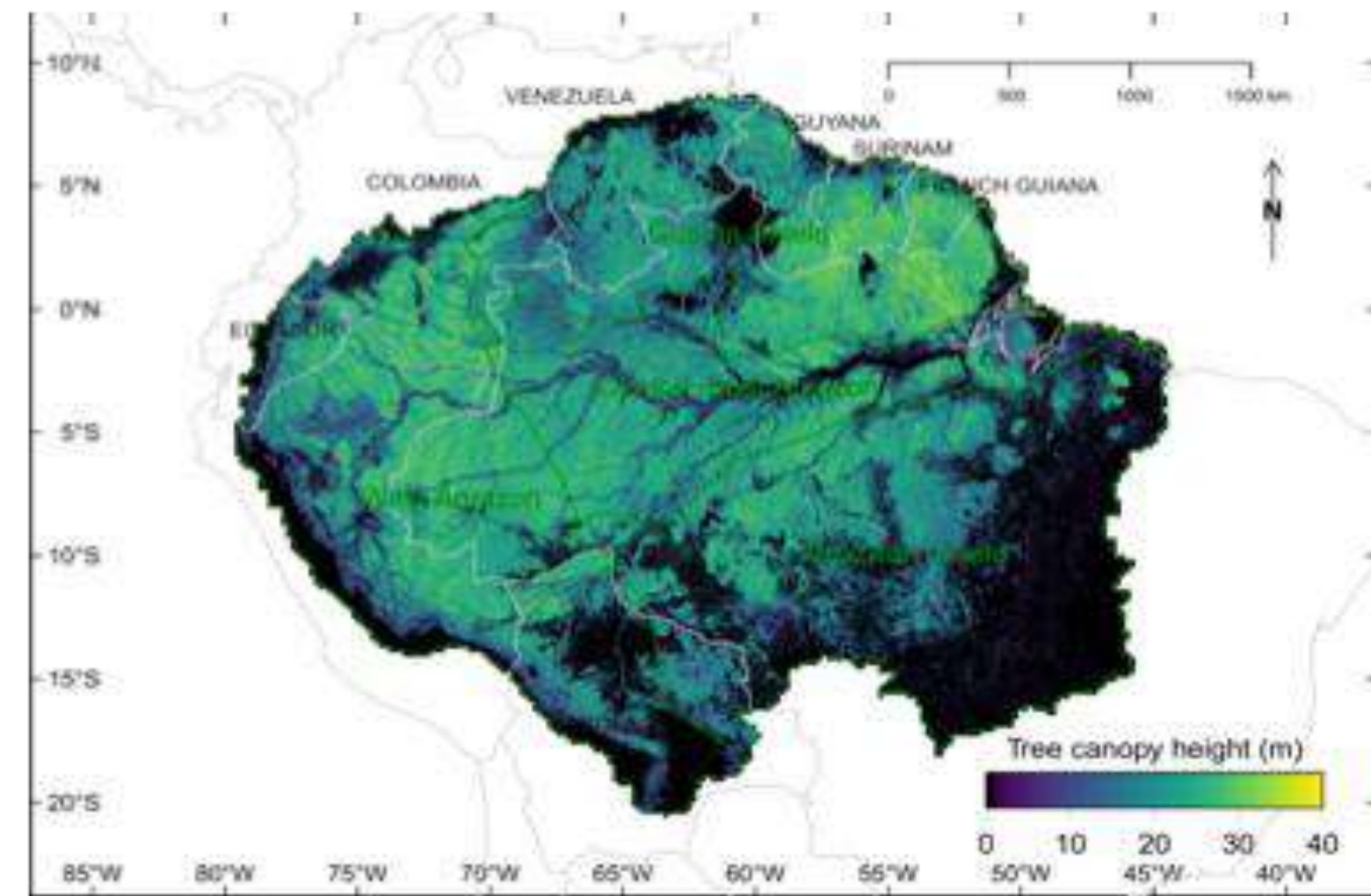
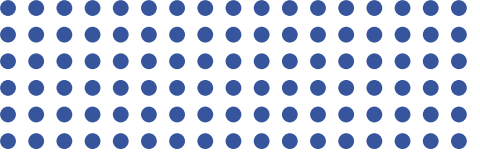


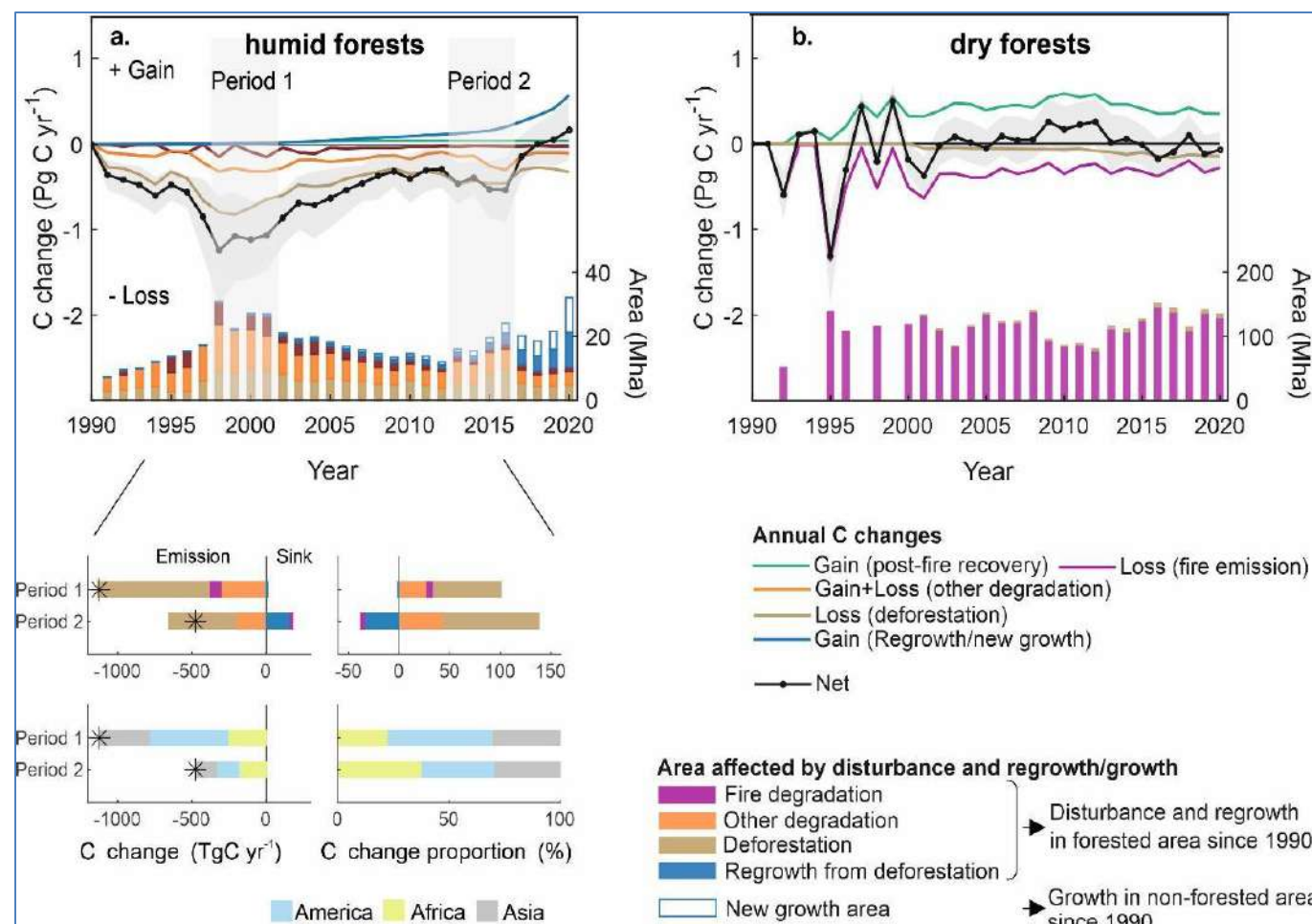
Figure 14. Canopy height of the Amazon forest (m). To facilitate visualization at very high resolution, the colors represent the estimates from our model, aggregated to an 80 m spatial resolution using the median.



A few other contributions (in review)

Small persistent humid forest clearings drive tropical forest biomass losses

Xu et al (in review)



Beyond forest height and biomass: characterizing the vertical structure of forests in the Brazilian Amazon

Valle et al (in review)

[...] secondary forests fully recover or even exceed reference areas at the 1-10 m height stratum after 5 to 10 years but that full recovery for the 20-30 m height stratum has not been achieved even after 35 years

The Global Canopy Atlas: analysis-ready maps of 3D structure for the world's woody ecosystems

Fischer et al (in review)

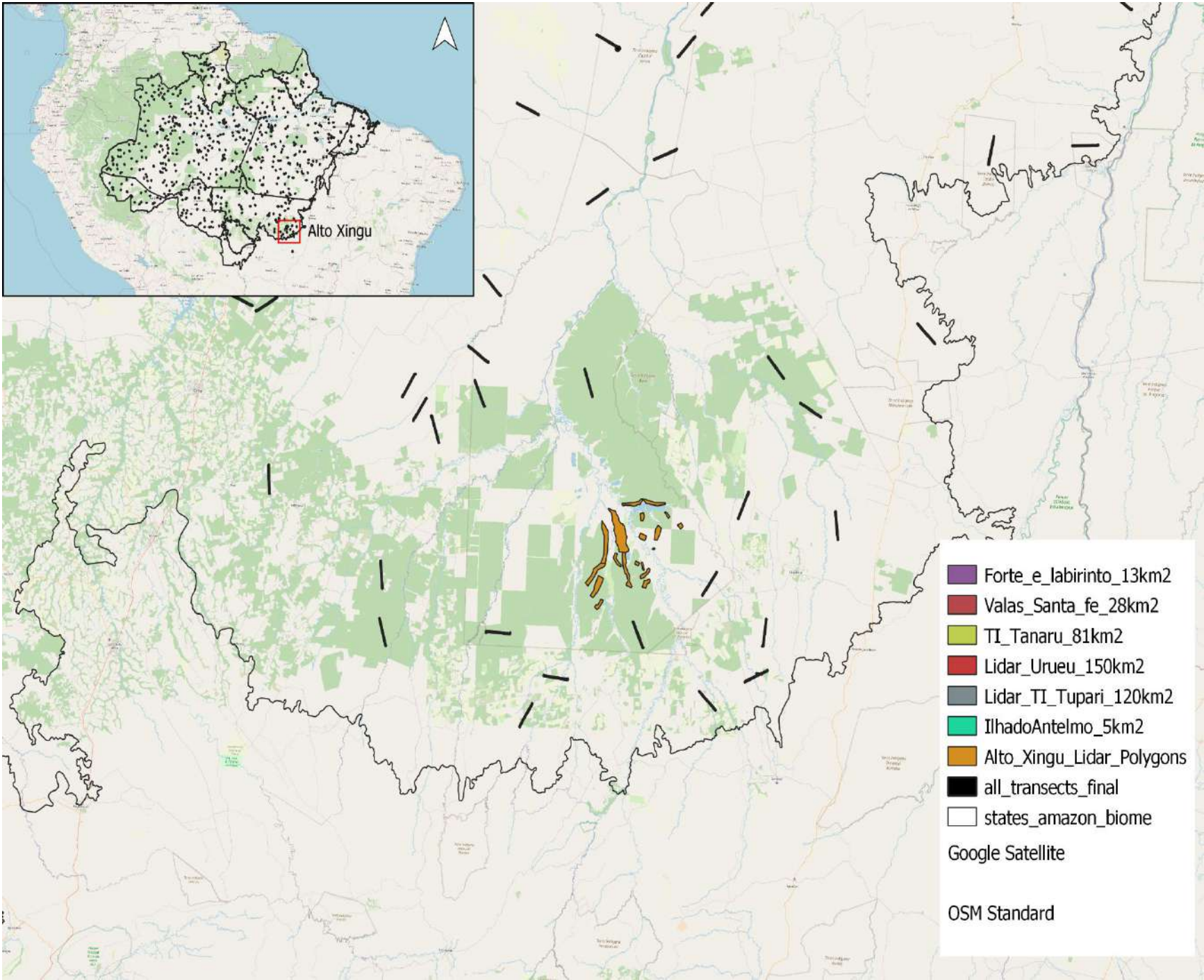
[...] Global Canopy Atlas (GCA): 3,458 ALS acquisitions transformed into standardized and analysis-ready maps of canopy height and elevation at 1 m² resolution. The GCA covers 56,554 km² across all major biomes.

Fire in a Central Amazon forest: Lingering top canopy loss and initial understory regrowth revealed by repeated LiDAR

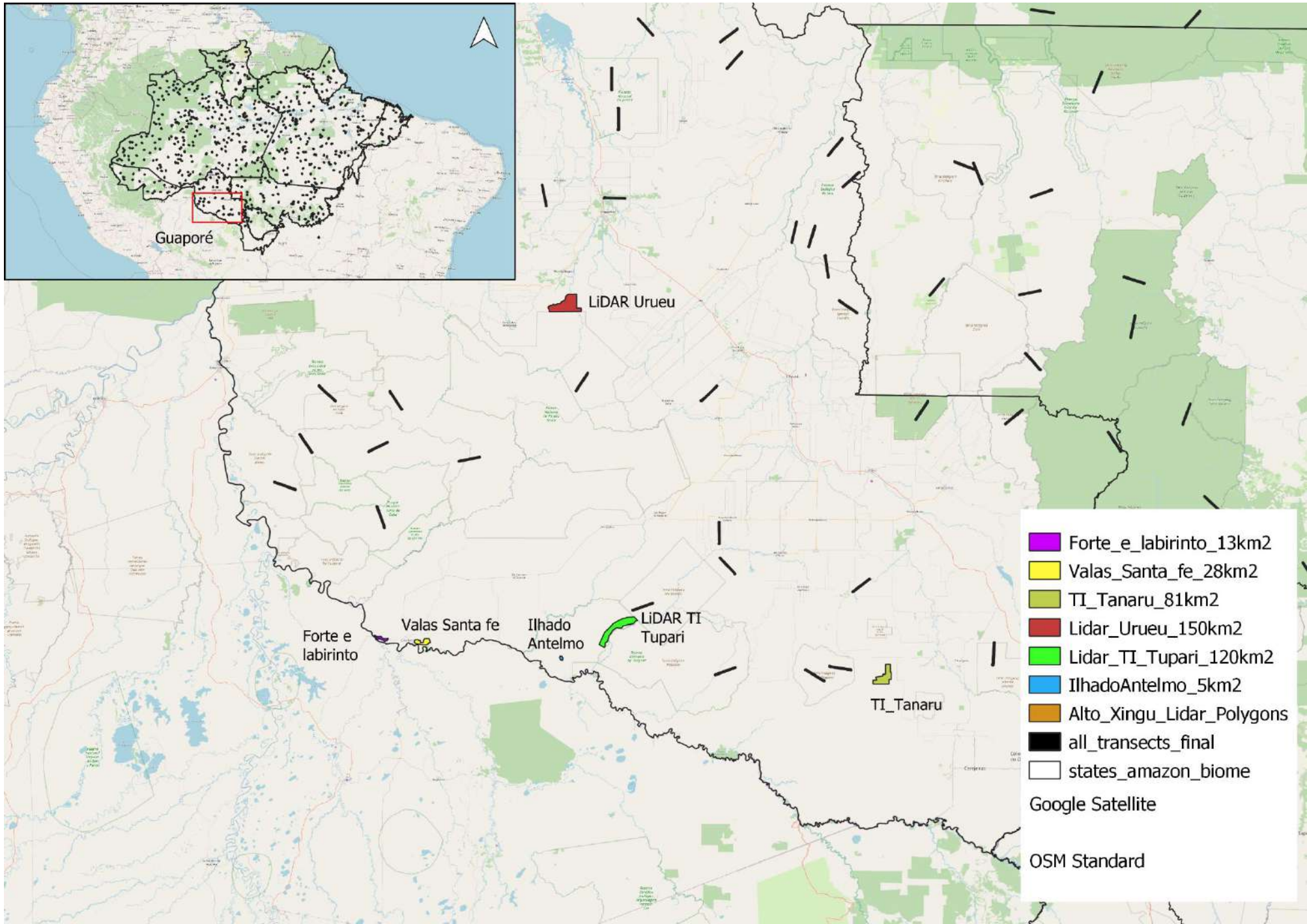
Pontes-Lopes et al (in review)

[... results revealed initial incipient recovery occurring simultaneously to delayed large tree mortality—where a prior field study did not because of sample scale dependent detection—highlighting pervasive impacts of fire that may contribute to a greater sensitivity of rainforests to climate change.”

[...]



Alto Xingu



Guaporé

Obrigado

Estimation of Aboveground Biomass in Old-Growth Forests and Classification of Forests Across Successional Stages

Polyanna Bispo

Session 2.1 (Part 1): Biomass datasets and missions

São José dos Campos, 30 Oct 2025



Estimation of Aboveground Biomass in Old-Growth Forests and Classification of Forests Across Successional Stages

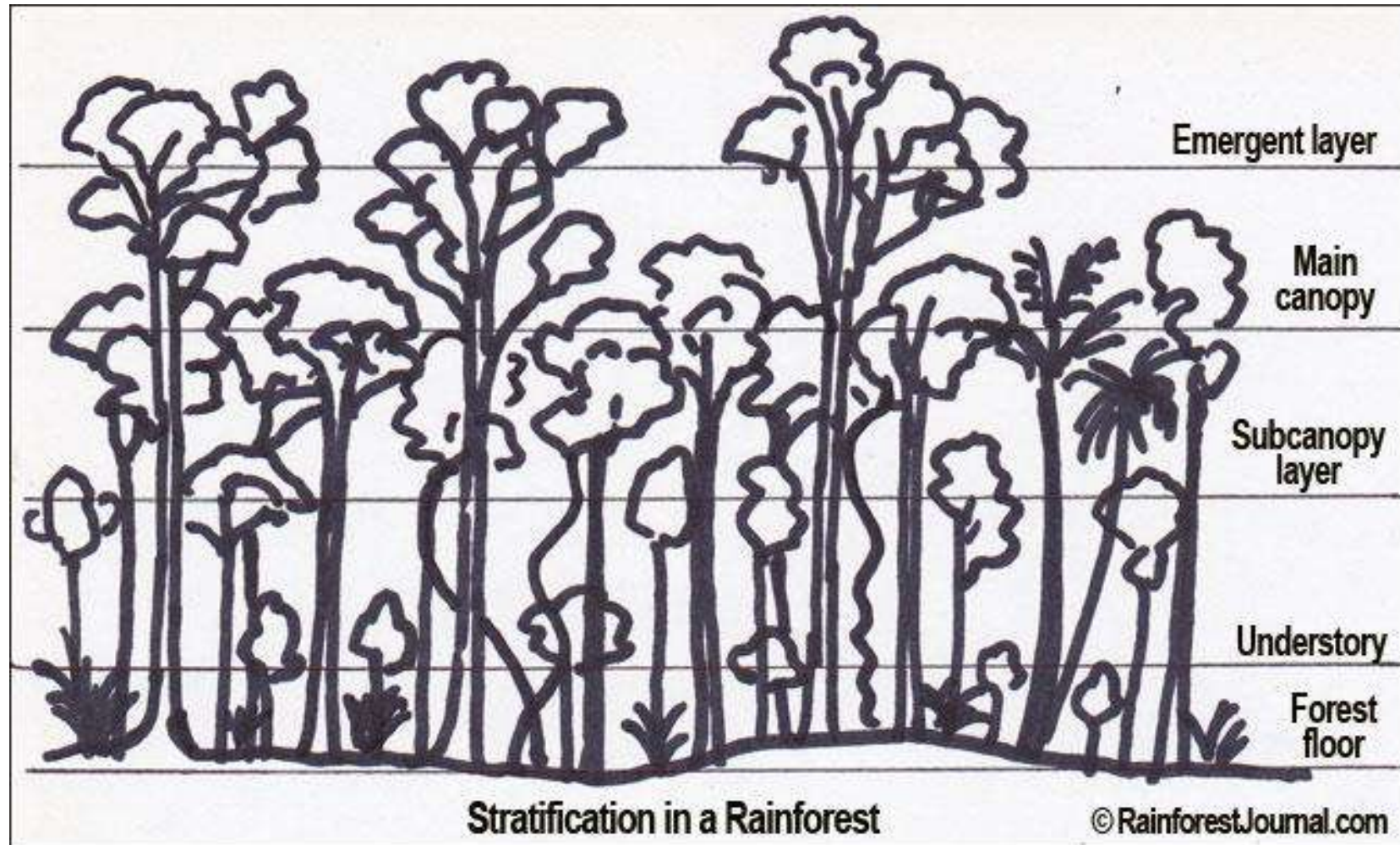
Dr. Polyanna da Conceição Bispo

Senior Lecturer (Associate Professor) in Physical Geography
Department of Geography, University of Manchester (UK)

Co-Lead of Land and Resources research theme of MERI (Manchester Environmental Institute)

Internal Reviewer Editor of IPBES (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services)

Email: polyanna.bispo@manchester.ac.uk
Linkedin: Polyanna Bispo



Estimation: 1,053 species account for half of the planet's 800 billion tropical forest trees. The other half are comprised of 46,000 tree species. The number of rare species is extreme, with the rarest 39,500 species accounting for just 10% of trees (Slik et al 2015).

Deforestation/ Clear Cut



A degraded forest is the result of a process of degradation which negatively affects the structural and functional characteristics of that forest

What happens to make a forest 'degraded'?

INTACT ZONE

Tree canopy creates an enclosed cover

More species of animals



Less wind at ground level

Soil and air are more humid, making it more difficult for fire to spread

DEGRADED ZONE

Canopy is more open because of tree loss

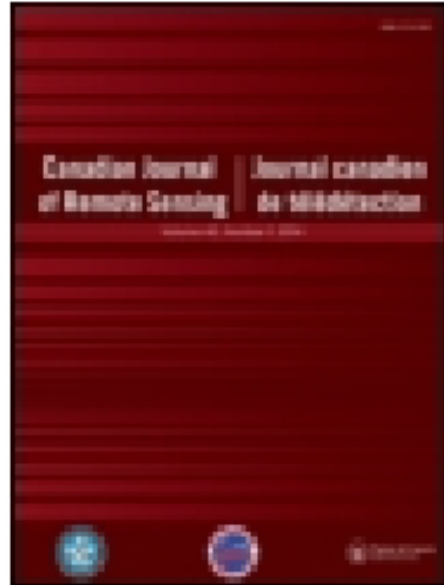
Fewer species of animals



More wind at ground level

Soil is drier and there are more dead trees, making it easier for fire to spread

Above Ground Biomass



Canadian Journal of Remote Sensing
Journal Canadien de Télédétection



ISSN: 0703-8992 (Print) 1712-7971 (Online) Journal homepage: www.tandfonline.com/journals/ujrs20

Integration of Polarimetric PALSAR Attributes and Local Geomorphometric Variables Derived from SRTM for Forest Biomass Modeling in Central Amazonia

P. C. Bispo, J. R. Santos, M. M. Valeriano, R. Touzi & F. M. Seifert

To cite this article: P. C. Bispo, J. R. Santos, M. M. Valeriano, R. Touzi & F. M. Seifert (2014) Integration of Polarimetric PALSAR Attributes and Local Geomorphometric Variables Derived from SRTM for Forest Biomass Modeling in Central Amazonia, Canadian Journal of Remote Sensing, 40:1, 26-42, DOI: [10.1080/07038992.2014.913477](https://doi.org/10.1080/07038992.2014.913477)

To link to this article: <https://doi.org/10.1080/07038992.2014.913477>

Modeling of forest biomass

Estimated biomass from polarimetric variables (SAR):

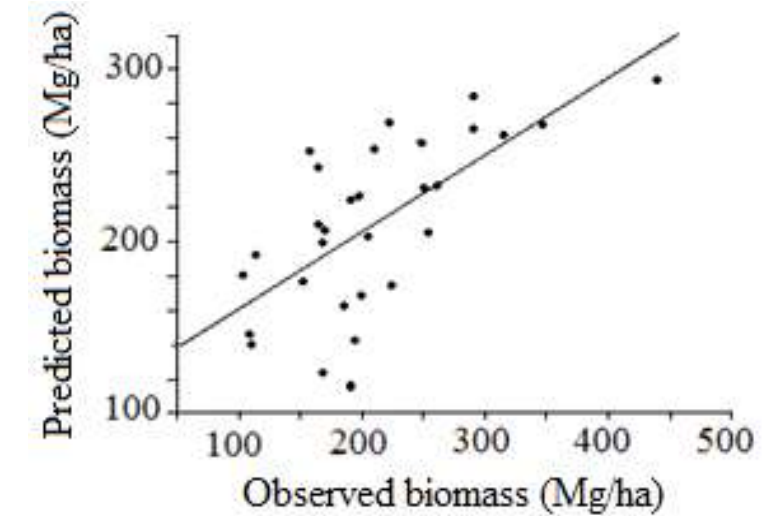
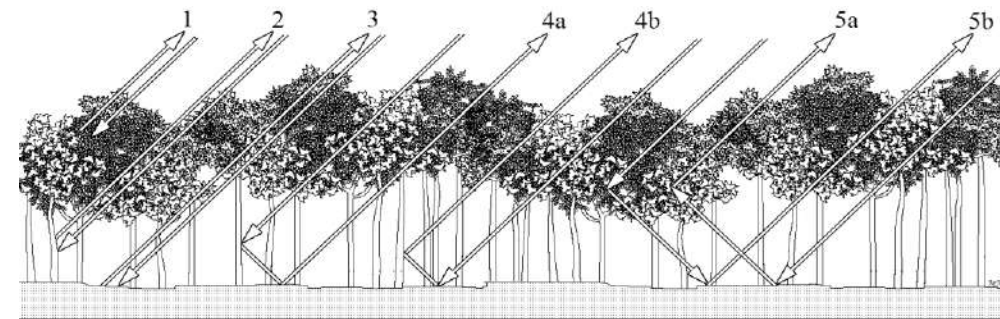
$$BM = -191,8 - 10,595 \tau_{m1} - 11,562 \alpha_{s1} + 634,6 H - 463,9 An$$

$$r^2=0,35, p=0,004$$

$$error=54,32 \text{ Mg/ha}$$

(26% from biomass mean)

τ_{m1} : first component of the Touzi helicity; α_{s1} : first component of the Touzi magnitude; H : entropy; An : anisotropy;



Estimated biomass from geomorphometric variables:

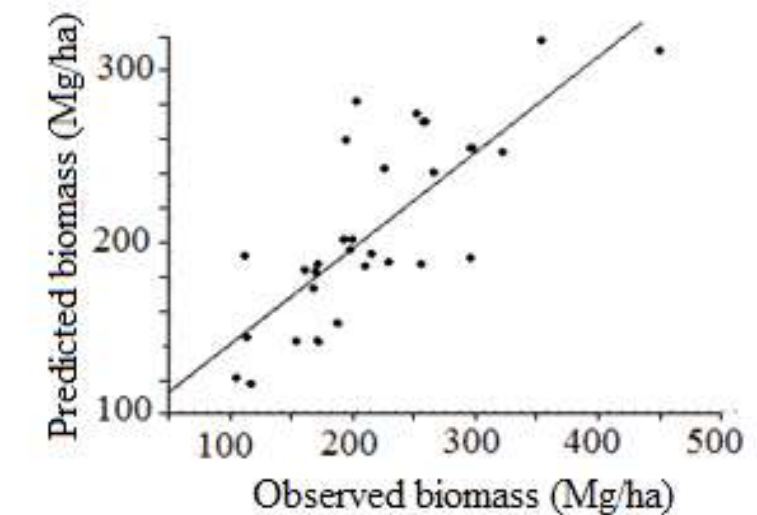
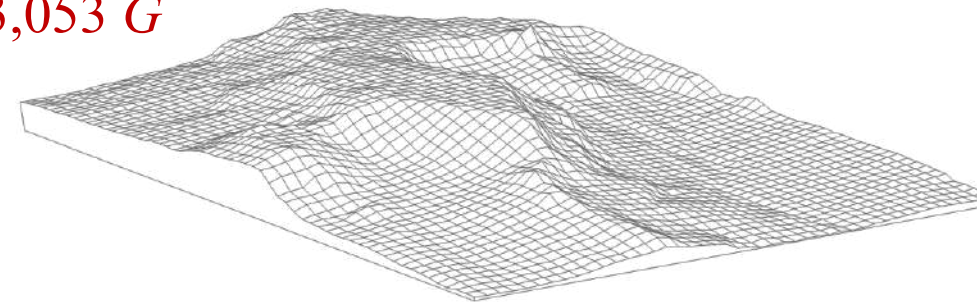
$$BM = -19,67 + 1,3467 h + 3,053 G$$

$$r^2=0,58, p=0,000$$

$$error=45,80 \text{ Mg/ha}$$

(22% from biomass mean)

h : elevation; G : slope



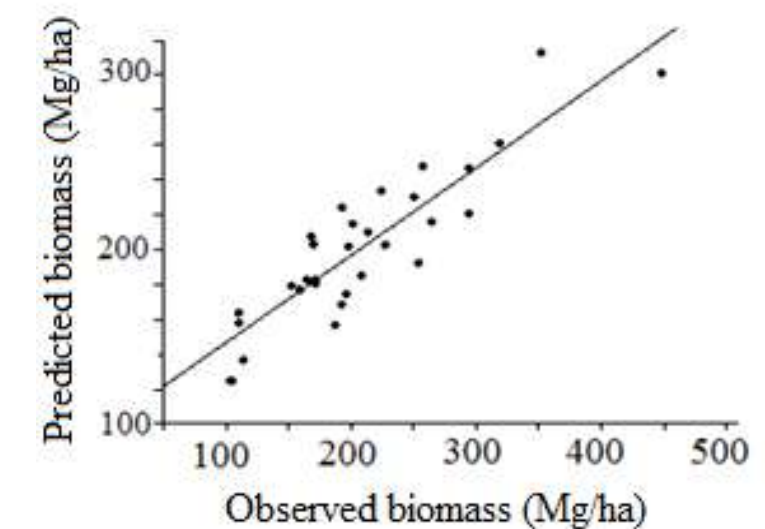
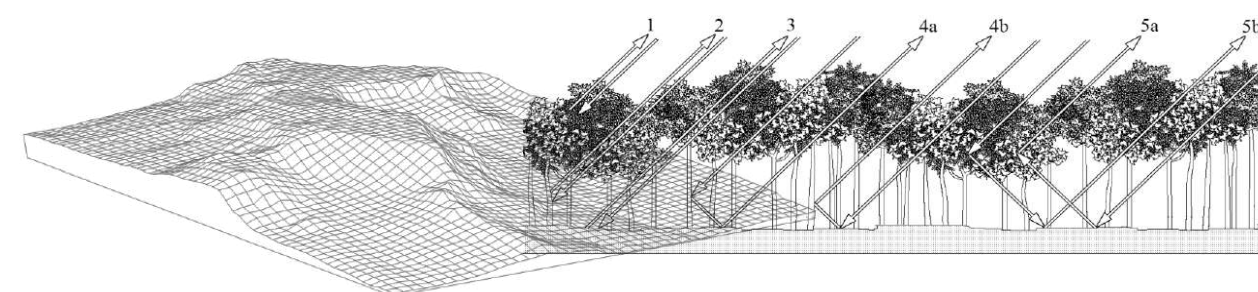
Estimated biomass from composite model:

$$BM = 31,11 + 142,01 Pv - 598,3 An + 1,465 h + 3,35 G + 0,4288 \tau_{m3} - 9,478 \tau_{m1}$$

$$r^2=0,74, p=0,000$$

$$erro=33,15 \text{ Mg/ha}$$

(15% from biomass mean)



Estimated biomass from composite model:

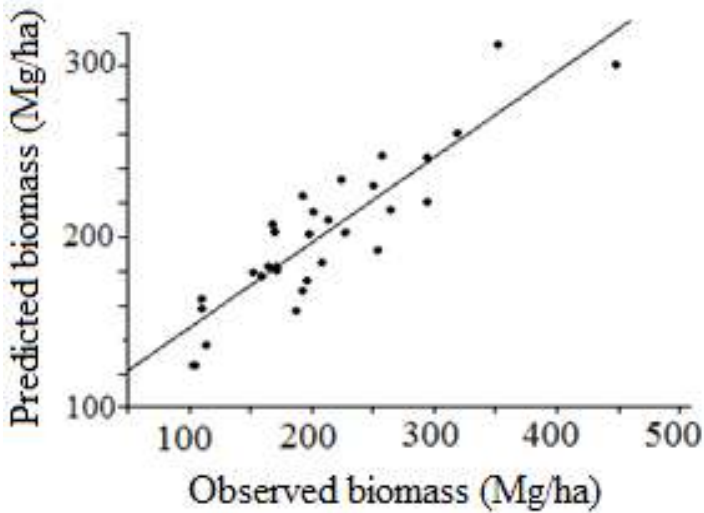
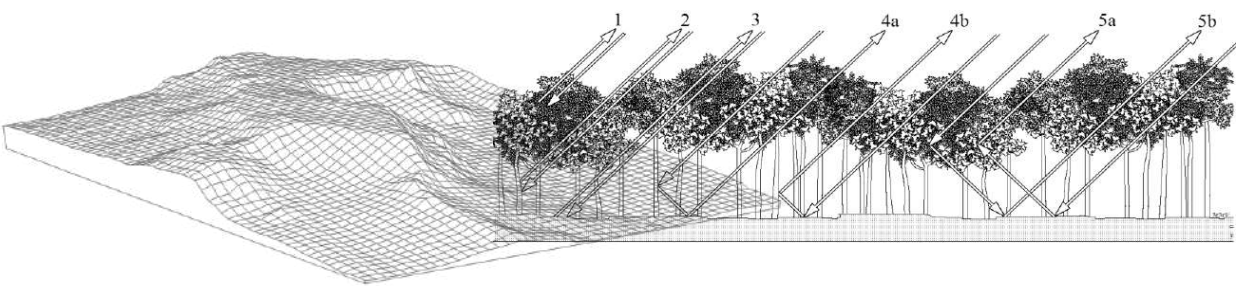
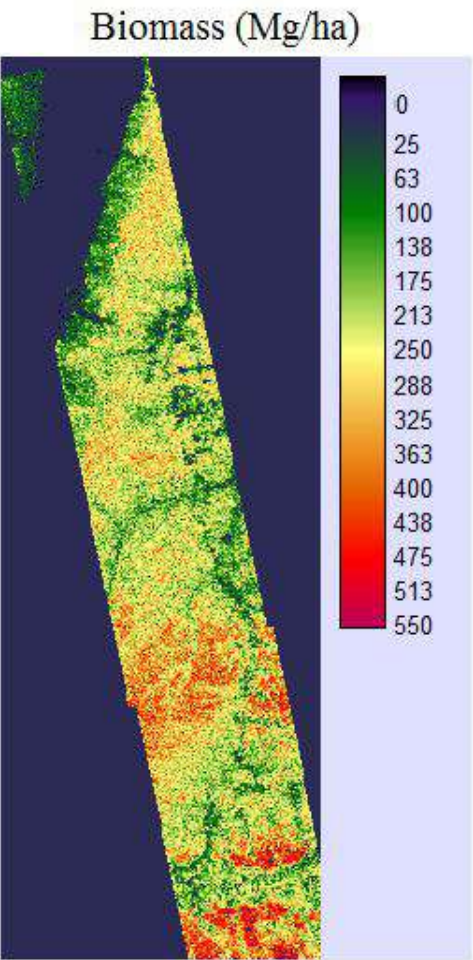
$$BM = 31,11 + 142,01 Pv - 598,3 An + 1,465 h + 3,35 G + 0,4288 \tau_{m3} - 9,478 \tau_{m1}$$

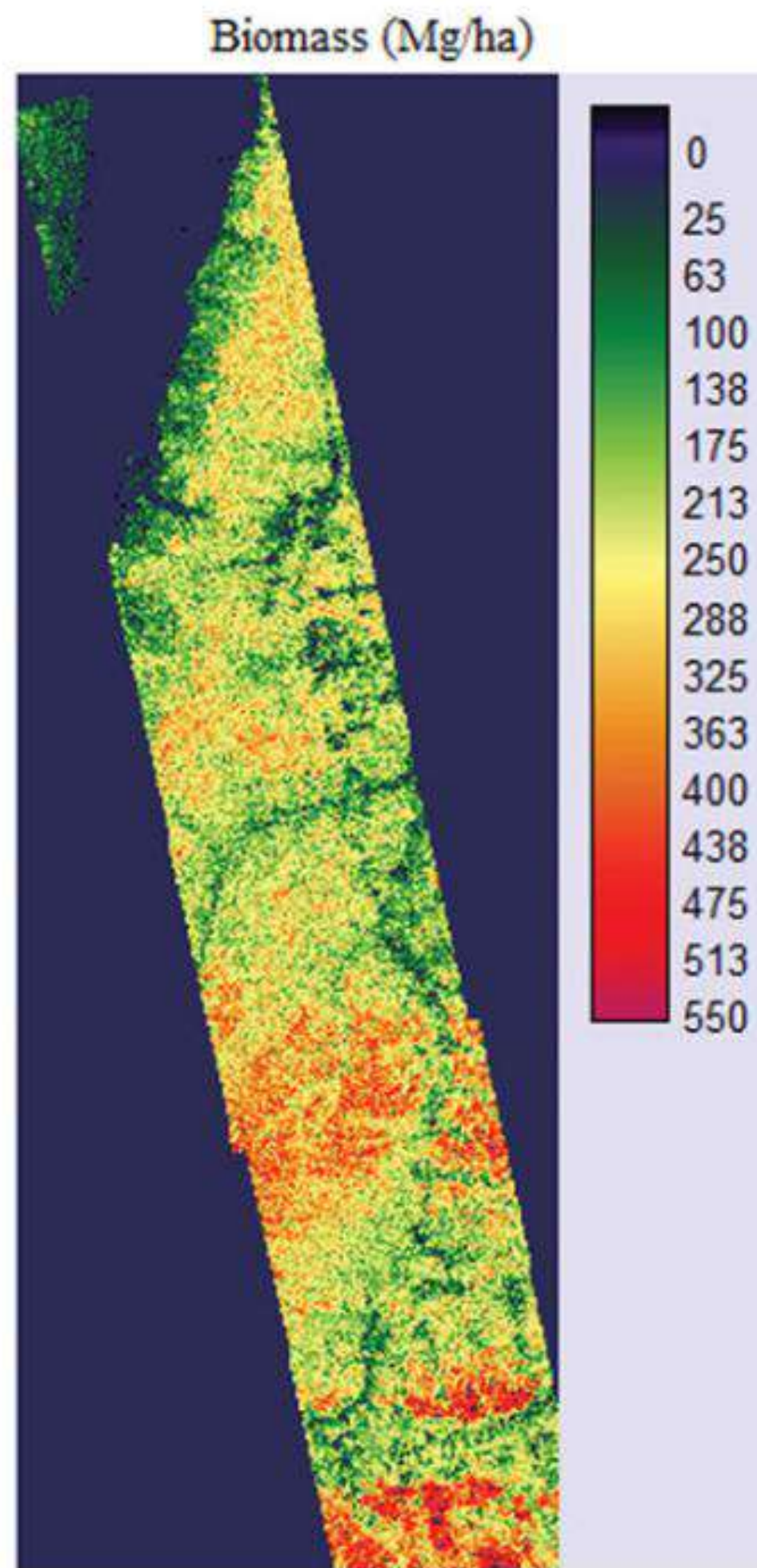
$$r^2=0,74, p=0,000$$

$$erro = 33.15 \text{ Mg/ha}$$

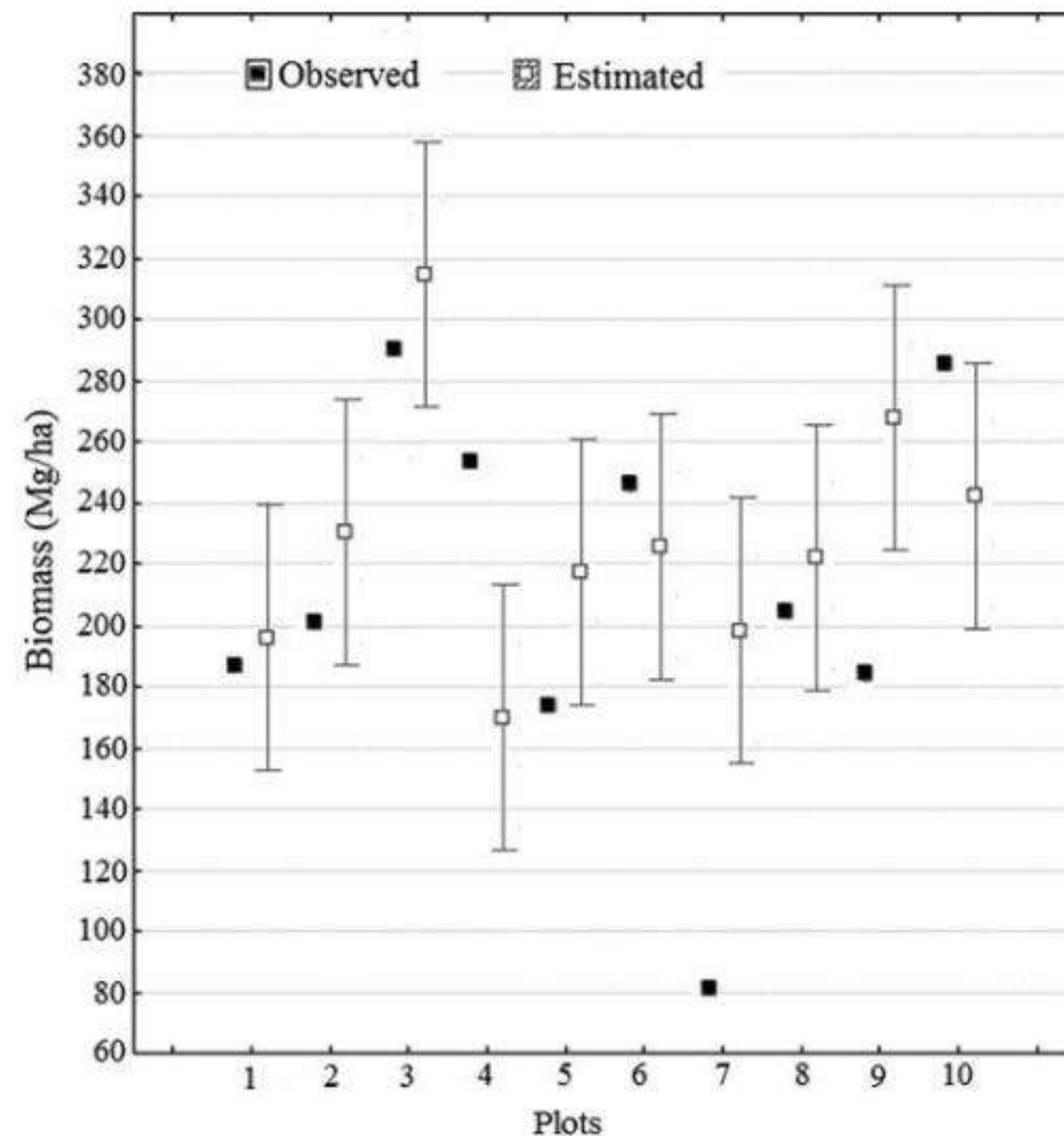
(15% from biomass mean)

BM: Biomass; *Pv*: Volumetric Scaterring Freeman; *An*: Anisotropy; *h*: Altitude; *G*: Slope; τ_{m3} : Third Component of Touzi Helicity; τ_{m1} : First Component of Touzi Helicity





Biomass model image.



Observed and estimated values of biomass data for the 10 sample parcels of the forest inventory. The vertical bars correspond to prediction intervals computed with a 95% confidence level.

The validation of was conducted utilizing the biomass values of 10 independent samples from the 56. The mean biomass value of these 10 parcels was 210.68 ± 40.09 Mg/ha. The RMSE was approximately 42.96 Mg/ha. Comparing the values derived from the model and those measured in the field (graph on the left), there is a mean error of 20.31%, a value considered adequate for biomass inventory estimation conducted by traditional methods that employ allometric equations.

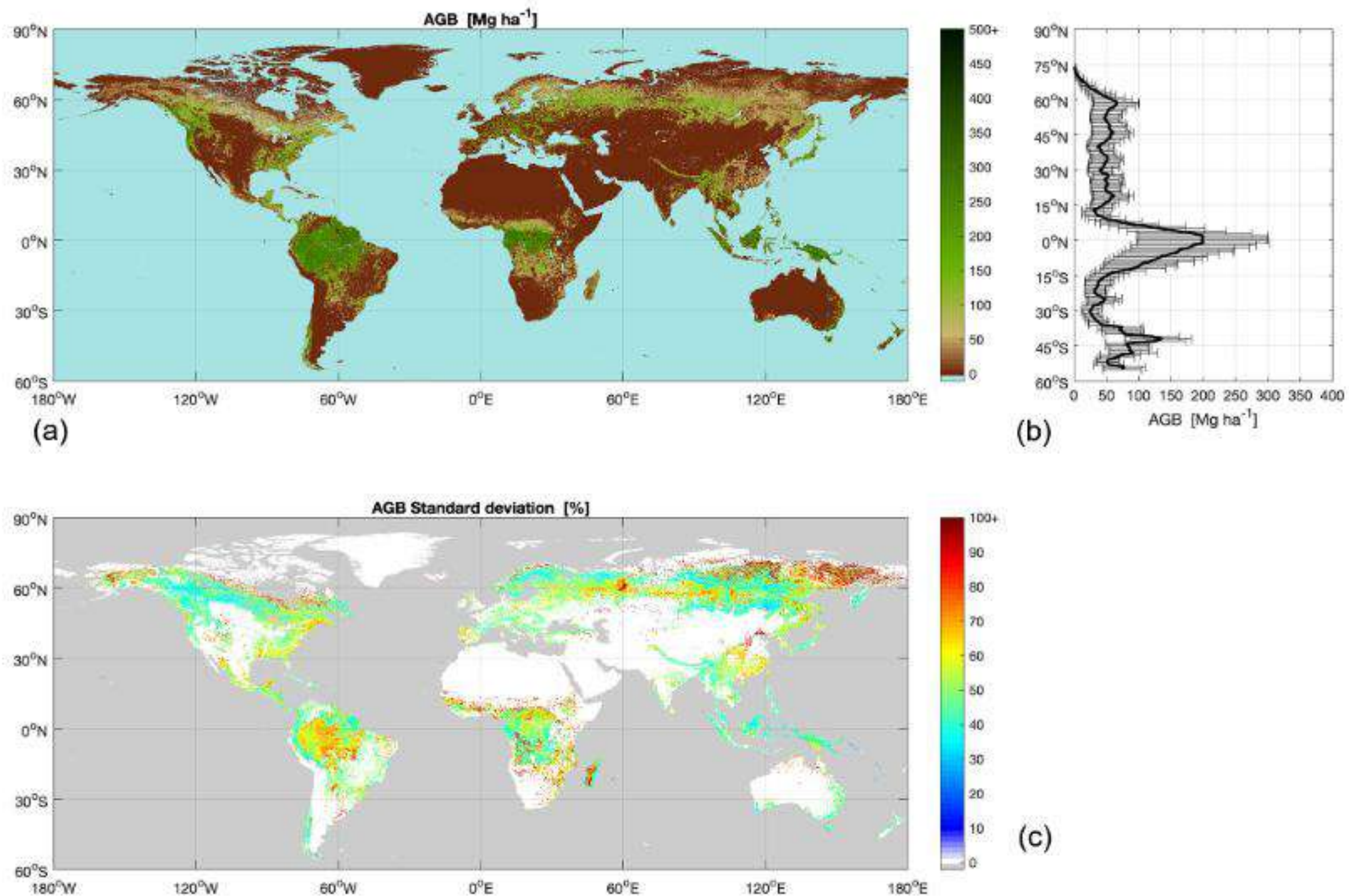


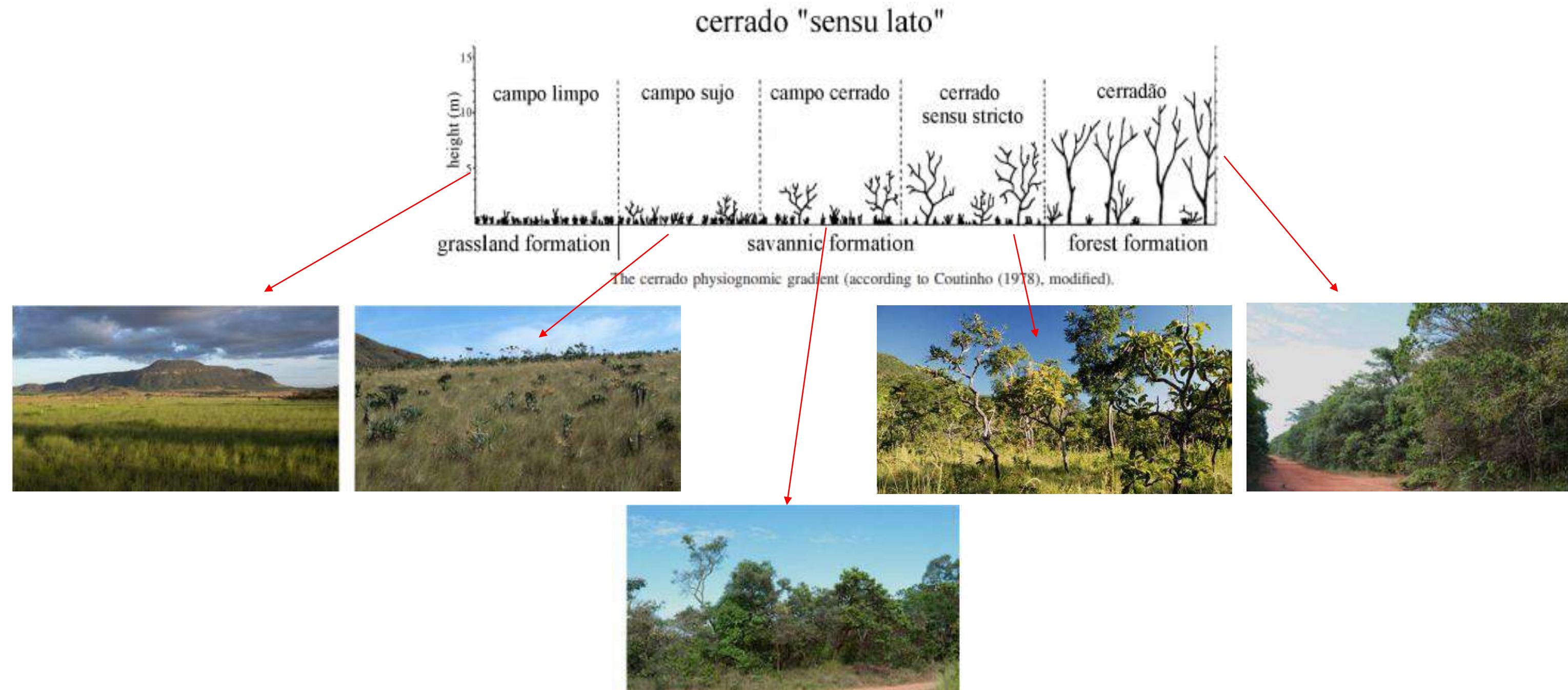
Figure 2. Map estimates of AGB (a) and AGB standard deviation expressed relative to the AGB (b). The colour bar of the AGB map has been truncated at 500 Mg ha^{-1} to increase contrast. Similarly, the colour bar of the AGB relative standard deviation has been truncated at 100 %. The right-hand panel shows the profile of average AGB along latitude (thick solid line) and the two-sided average standard deviation of AGB at a given latitude (horizontal bars).

Woody aboveground biomass mapping of the Brazilian savanna (Cerrado) with a multi-sensor and machine learning approach

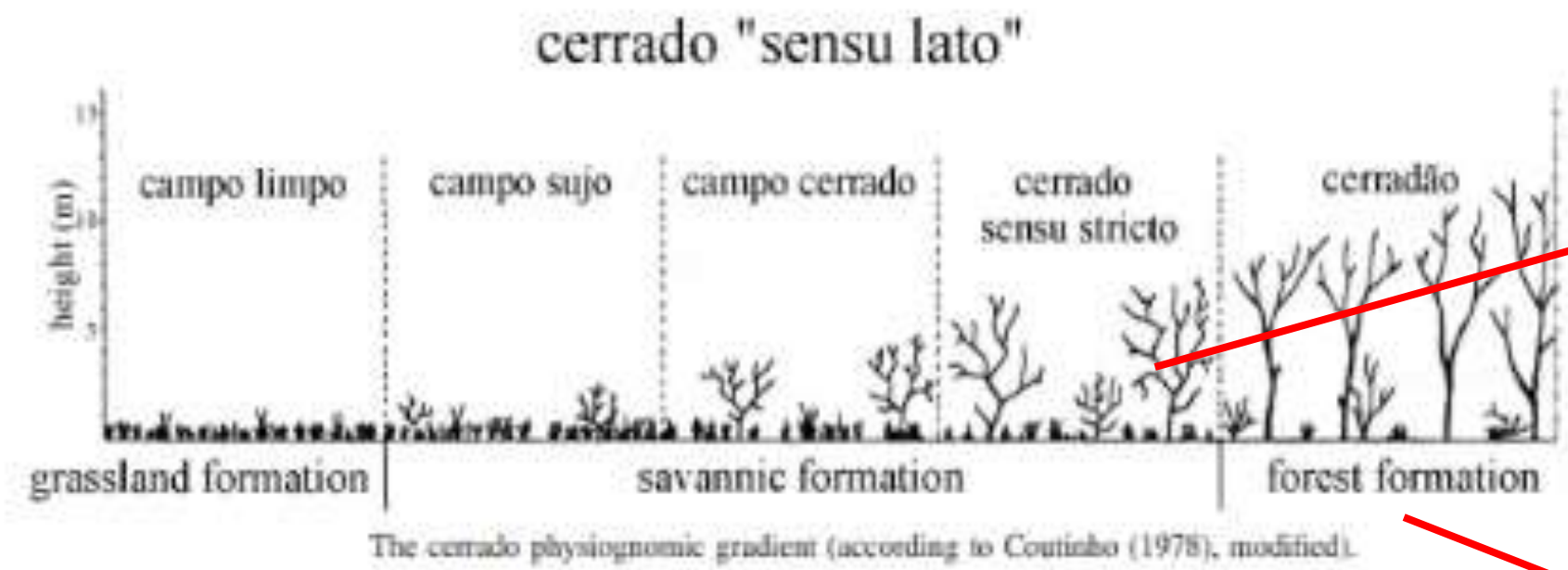
The Brazilian Savanna, known as Cerrado (*Cerrado sensu lato* (s.l.)), is the second largest biome in South America.



- The Cerrado Biome comprises different physiognomies due to variations of soil, topography and human impacts.
- The gradients of tree density, tree height, above ground biomass (AGB) and wood species cover vary according to the Cerrado formation, ranging from different grassland formations (*Campo limpo*), savannah intermediary formations (*Campo sujo*, *Campo cerrado*, and *Cerrado sensu stricto* - s.s) and forest formations (*Cerradão*).

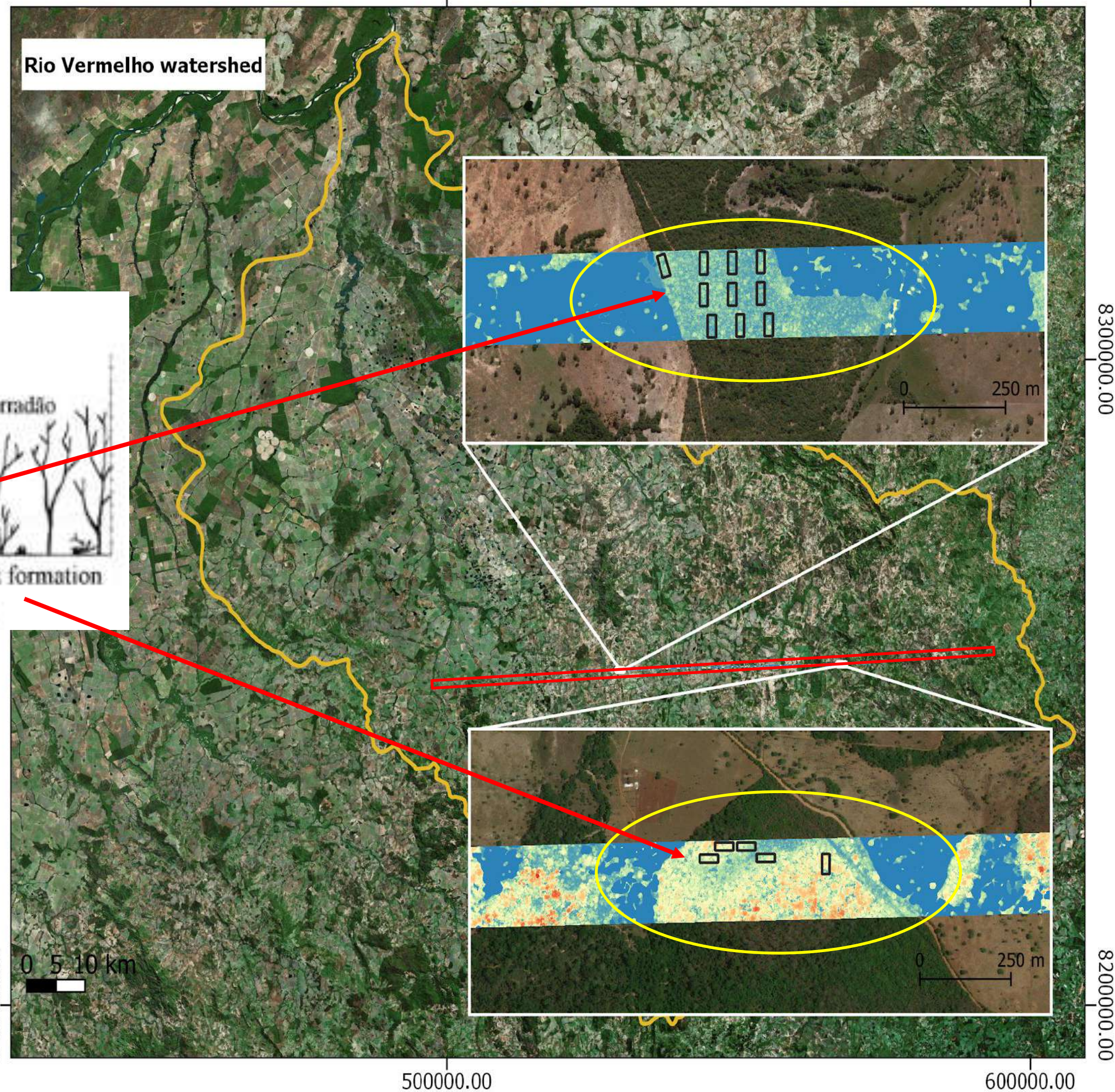
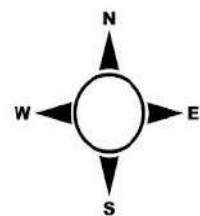


Study site



- Study area
- Cerrado biome
- Administrative boundaries

Canopy Height Model [m]



30 Floristic and structural characterisation of the plots located in fragments of native Cerrado vegetation in the Rio Vermelho watershed, Goiás State, Brazil. **WS-FS** = savanna-cerradão transition zone, **TFS** = cerradão, **FS-SF** = cerradão-seasonal forest transition zone; S = species richness, DBH =diameter at breast height.

Plot ID	Vegetation Type	S (Species)	TD (Ind. ha ⁻¹)	DBH Range (cm) (Mean/CV%)	H (m) (Mean/CV%)	TBA (m ² /ha)	AGB (Mg ha ⁻¹)
Itapirapuã 1	WS-FS	38	990	5.0–36.7 (9.1/56.9)	1.7–11.2 (5.8/26.9)	13.5	19.3
Itapirapuã 2	WS-FS	32	920	5.0–45.5 (9.5/54.7)	1.6–13.4 (5.6/35.5)	10.8	21.2
Itapirapuã 3	WS-FS	45	1030	5.0–29.4 (10.4/54.5)	2.1–14.0 (5.8/35.9)	15.0	24.5
Itapirapuã 4	WS-FS	41	1040	5.3–52.0 (9.8/58.4)	1.3–12.6 (5.5/33.4)	14.4	28.2
Itapirapuã 5	TFS	36	1140	5.0–41.4 (10.3/60.4)	2.0–12.8 (6.0/31.9)	16.4	32.2
Itapirapuã 6	TFS	45	1570	5.0–34.7 (10.5/47.0)	1.5–12.9 (6.5/31.6)	22.6	35.3
Itapirapuã 7	TFS	50	1990	5.0–43.7 (9.1/52.9)	1.8–13.2 (6.5/33.6)	21.9	36.8
Itapirapuã 8	TFS	60	1440	5.0–48.0 (10.4/61.2)	2.6–13.2 (6.1/31.8)	20.1	40.2
Itapirapuã 9	TFS	35	1210	5.0–53.3 (10.1/62.9)	1.8–13.1 (6.5/30.8)	17.0	40.9
Goiás 10	TFS	41	1260	5.0–35.3 (10.9/57.3)	3.6–19.6 (8.7/38.6)	20.5	52.8
Itapirapuã 11	TFS	39	1260	5.0–42.3 (11.2/65.9)	1.7–14.9 (6.3/36.3)	24.3	54.3
Goiás 12	FS-SF	38	1310	5.0–49.3 (11.3/61.5)	2.5–19.3 (9.3/33.3)	24.6	70.4
Goiás 13	FS-SF	26	690	5.0–49.0 (13.0/73.6)	3.4–22.0 (10.2/43.5)	18.3	77.0
Goiás 14	FS-SF	27	820	5.0–44.2 (13.2/63.5)	3.0–38.0 (12.5/48.7)	22.0	98.3
Goiás 15	FS-SF	24	760	5.0–41.7 (14.0/67.3)	2.5–26 (10.9/52.5)	24.4	103.9

WS-FS

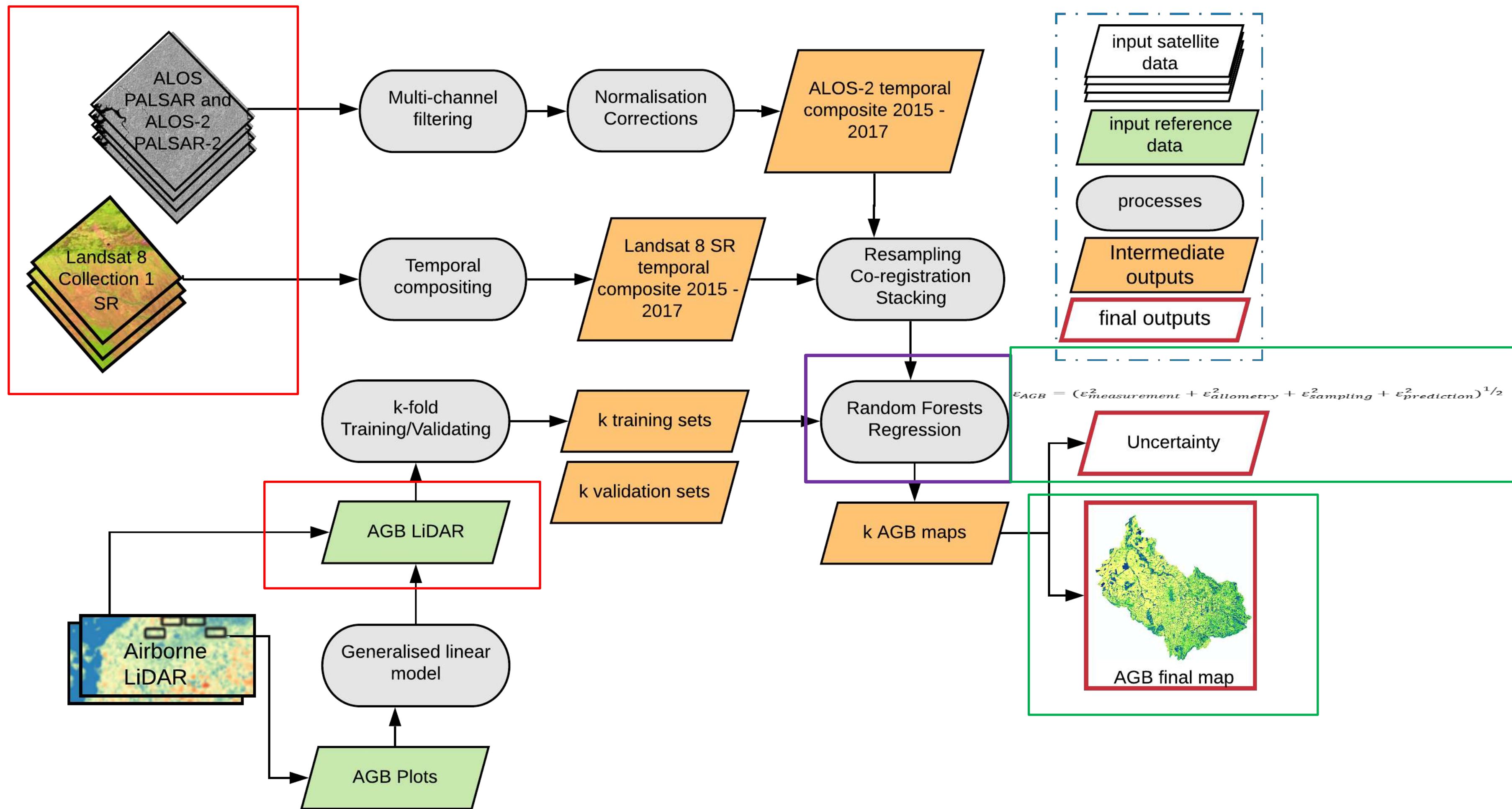


TFS

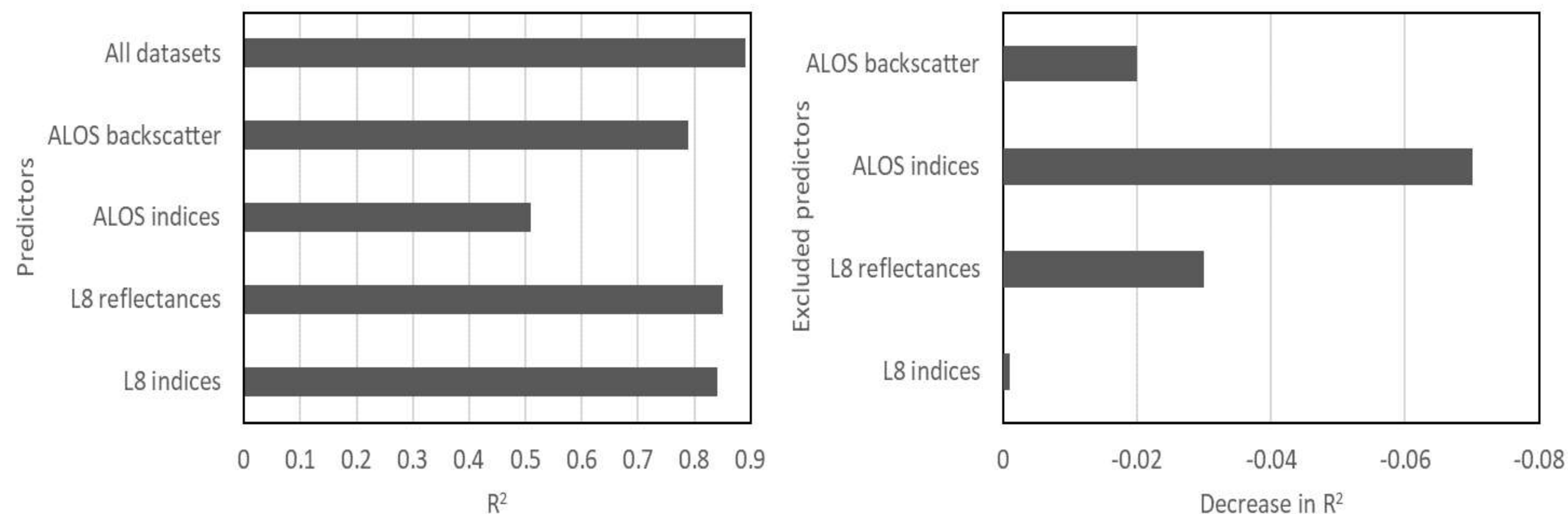


FS-SF



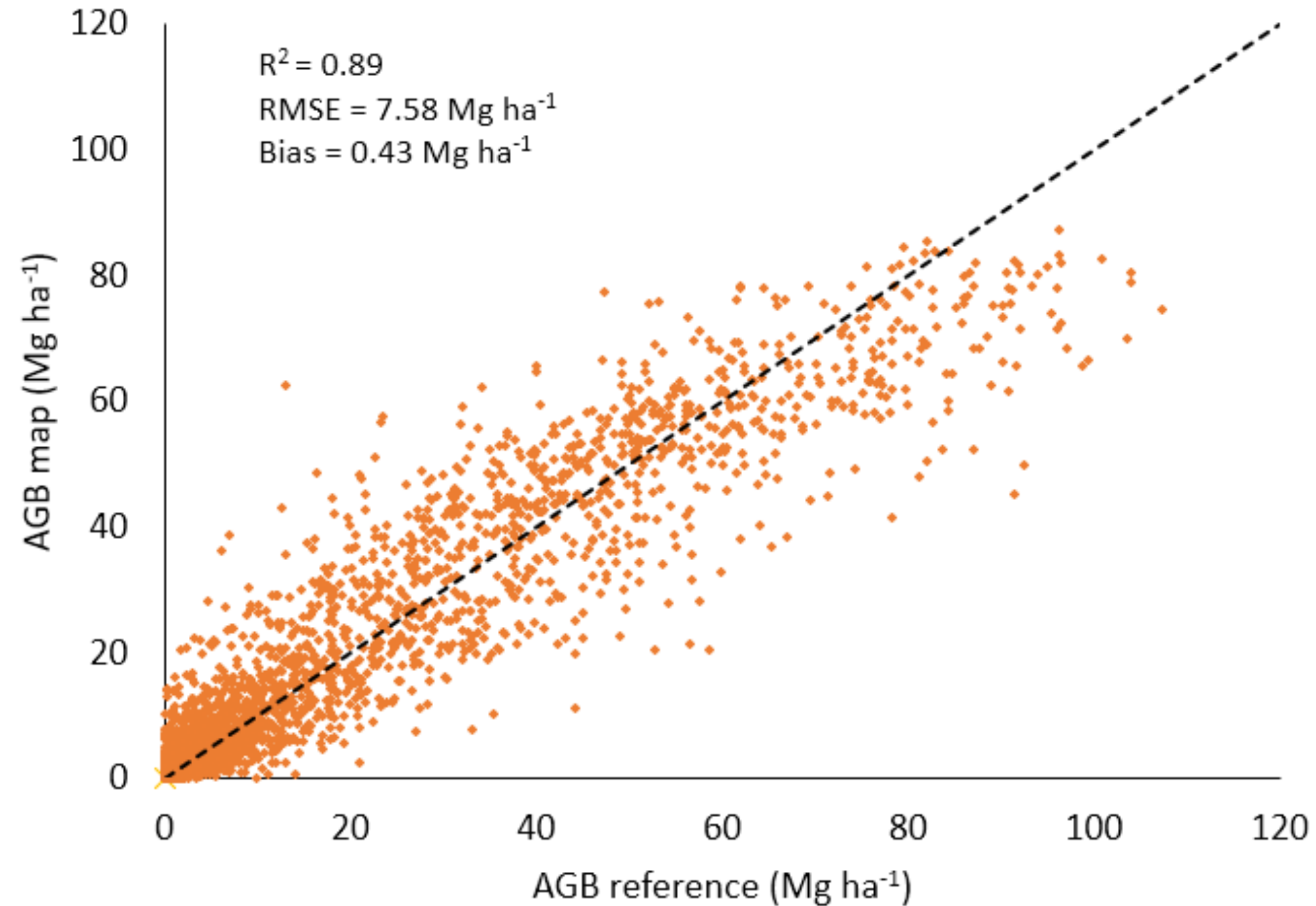


Variable importance analysis



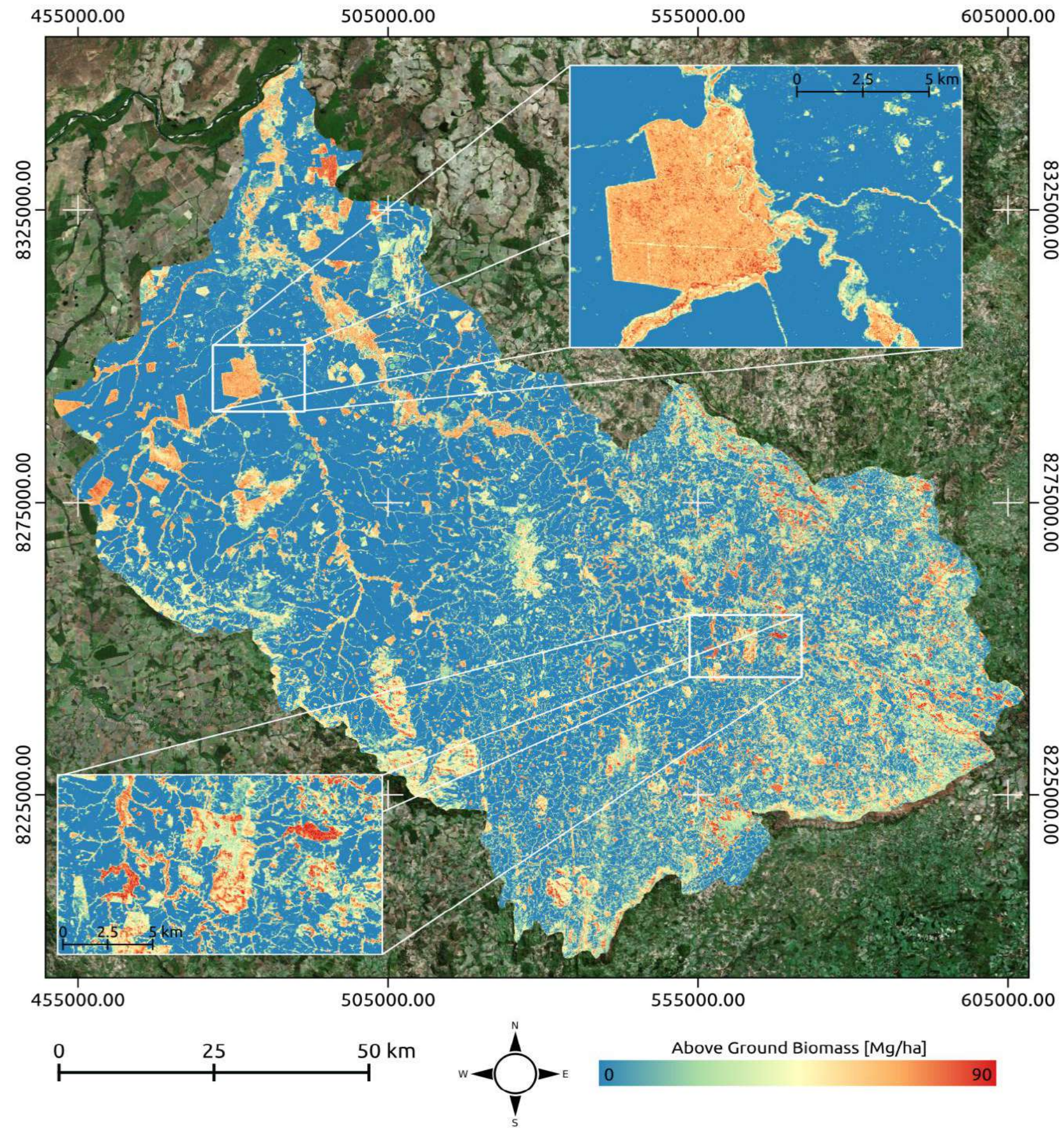
Averaged variable importance analysis across the k-fold procedure for each set of variables derived from Landsat 8 (L8) and ALOS-2/PALSAR-2 (ALOS) included in the RF model. The R^2 for each single set of variables and all variables together (left), and decrease in R^2 for models excluding a single set of variables (right). ALOS backscatter: γ_{HV}^0 , γ_{HH}^0 . ALOS indices: RFDI, CpR. L8 reflectances: blue, green, red, near infrared, shortwave infrared-1, shortwave infrared-2. L8 indices: NDVI, NBR, NBR2, NDMI, and SAVI.

Cross-validation

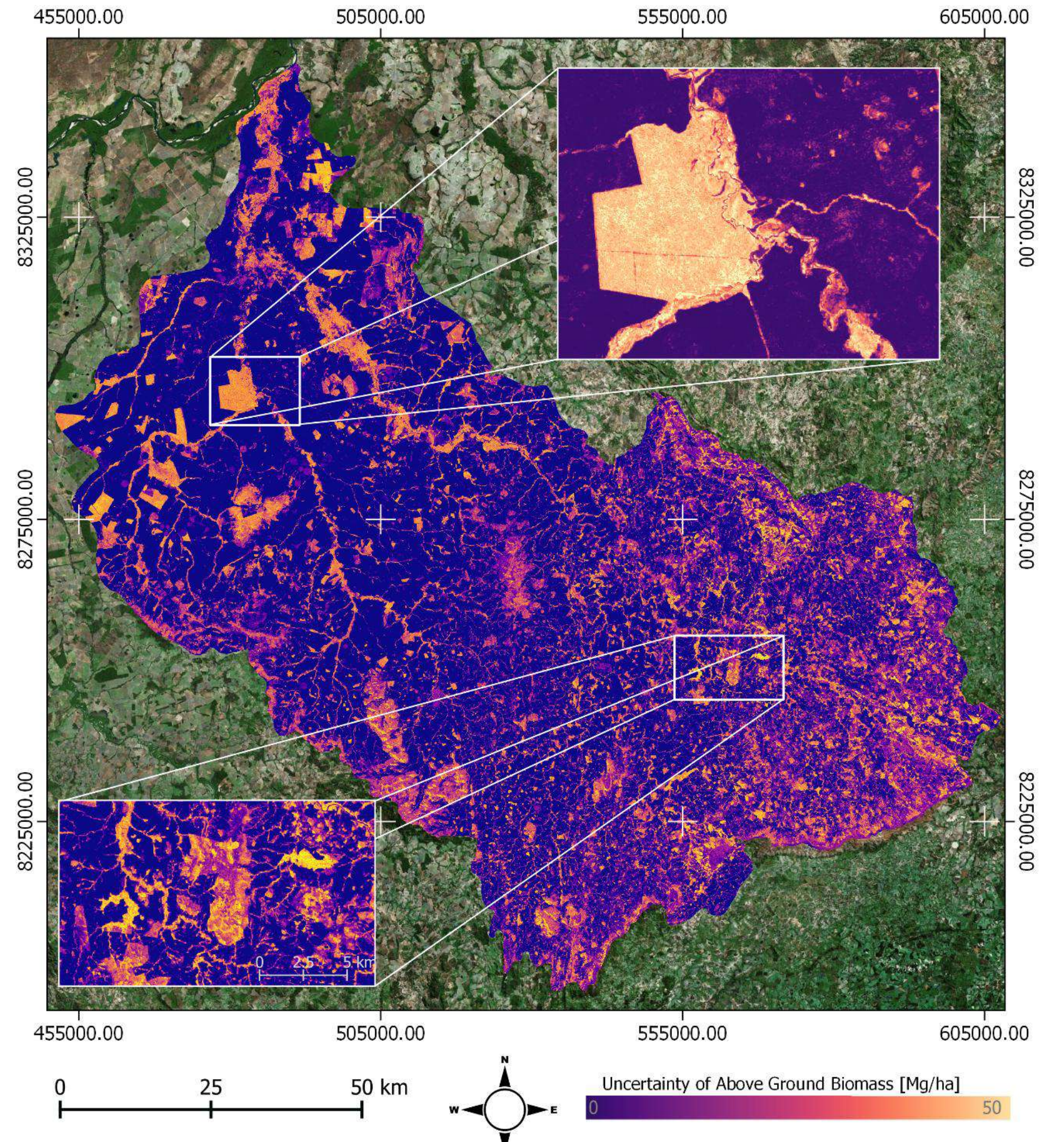


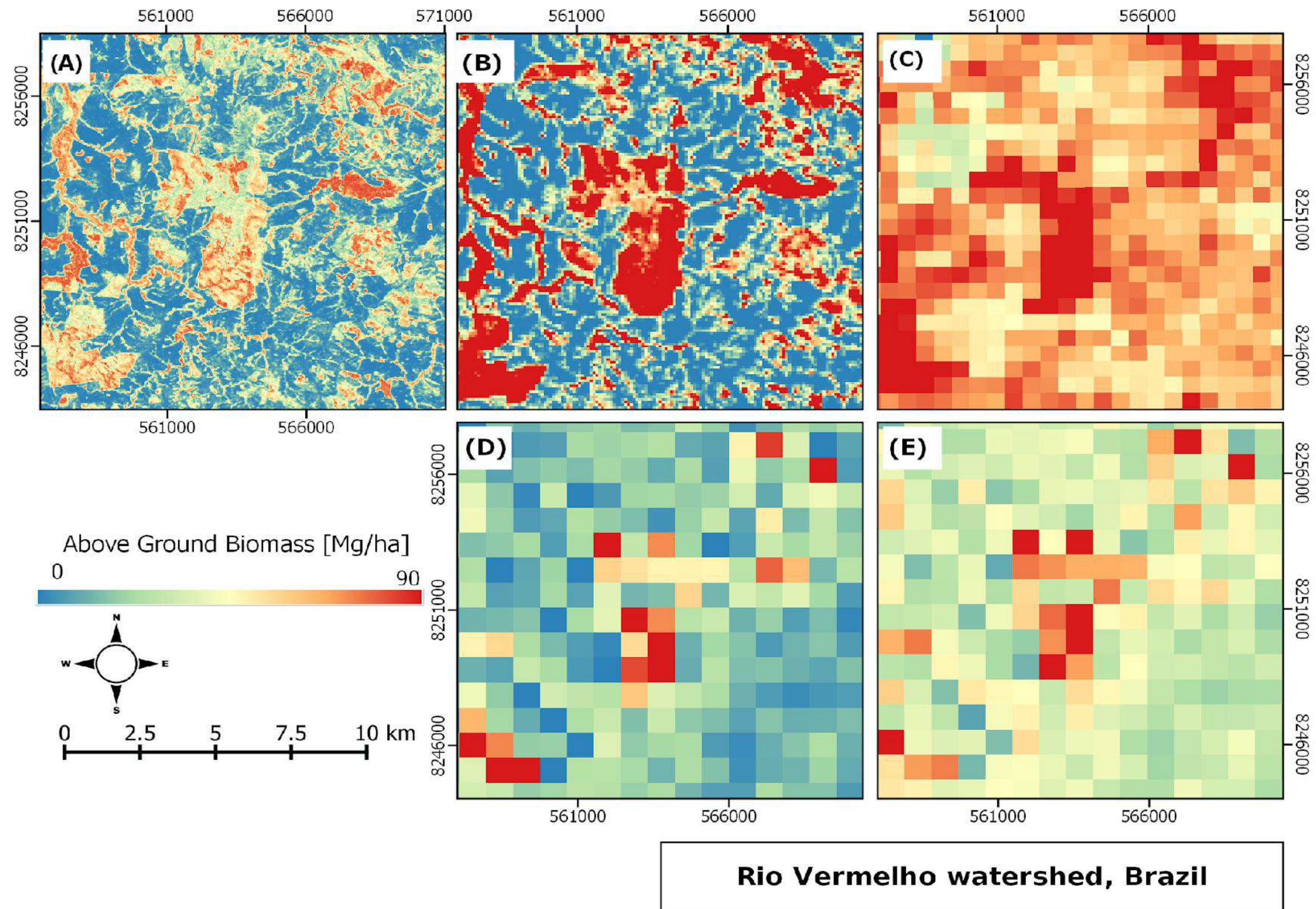
Cross-validation between the AGB map predictions and AGB reference data derived from the LiDAR point clouds. The black dash line corresponds to the $y = x$ line.

AGB



Uncertainty



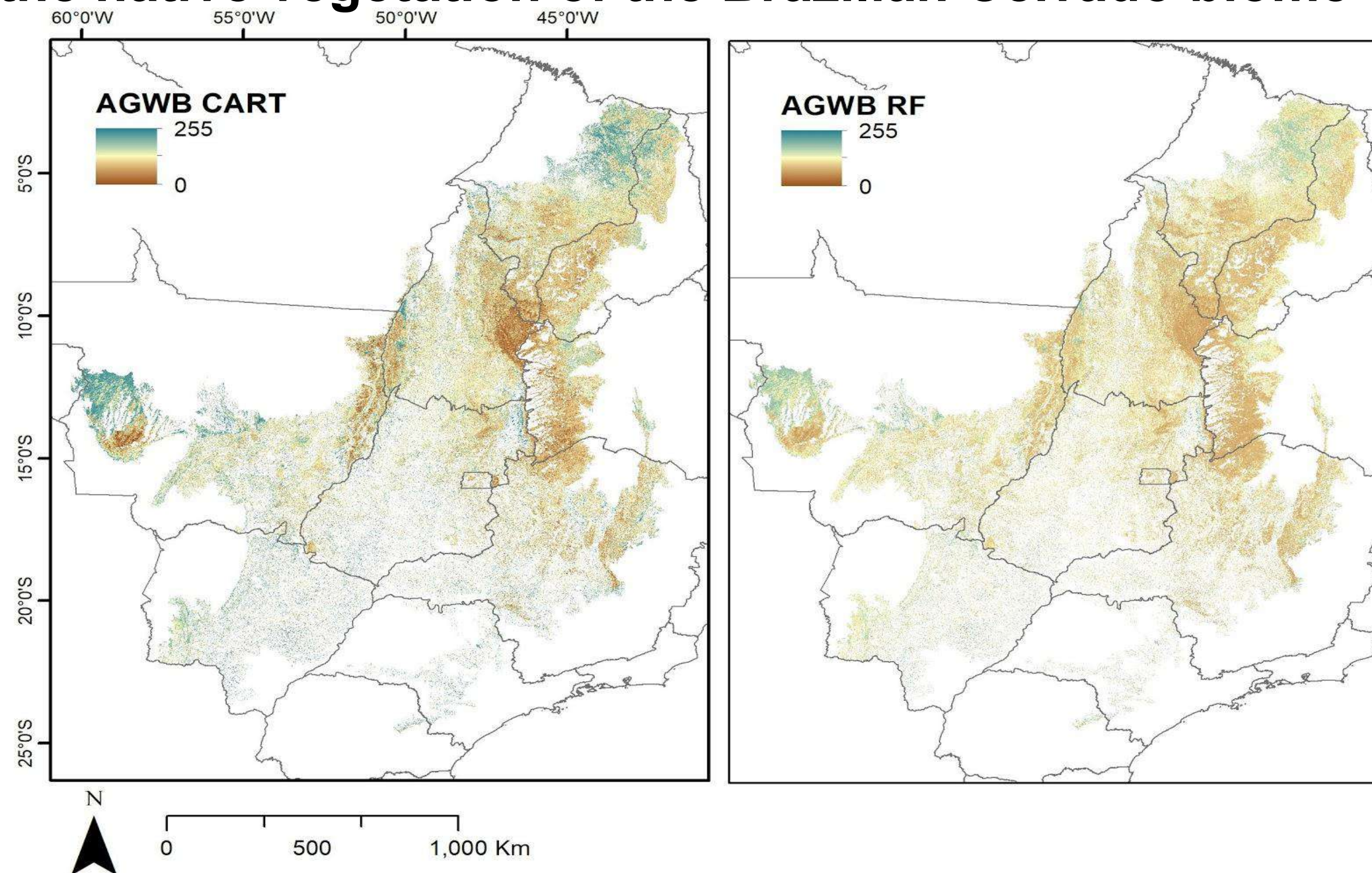


AGB maps over part of the Rio Vermelho watershed, Goiás State, Brazil, produced by this study (30 m) (A) and by Santoro *et al.* 2018 (100 m) (B); Baccini *et al.* 2012 (500m) (C); Avitabile *et al.* 2016 (1 km) (D); and Saatchi *et al.* 2011(1 km) (E).

Conclusion

- One of is the most accurate AGB map ($R^2 = 0.89\%$, RMSE = 7.58 Mg/ha) over the Brazilian Savannah
- The AGB map showed similar performance for the different vegetation types in Rio Vermelho watershed
- Our methodology characterises the spatial distribution of aboveground biomass over Brazilian Cerrado using **two stage estimates**: from the field to LiDAR, and LiDAR to EO data in order to upscale the AGB estimations
- The method was applied later on over the whole Brazilian Cerrado biome
- Our results represent an important contribution as a method to monitoring the carbon emissions in Brazilian Cerrado within the framework of REDD+ under the United Nations Framework Convention on Climate Change

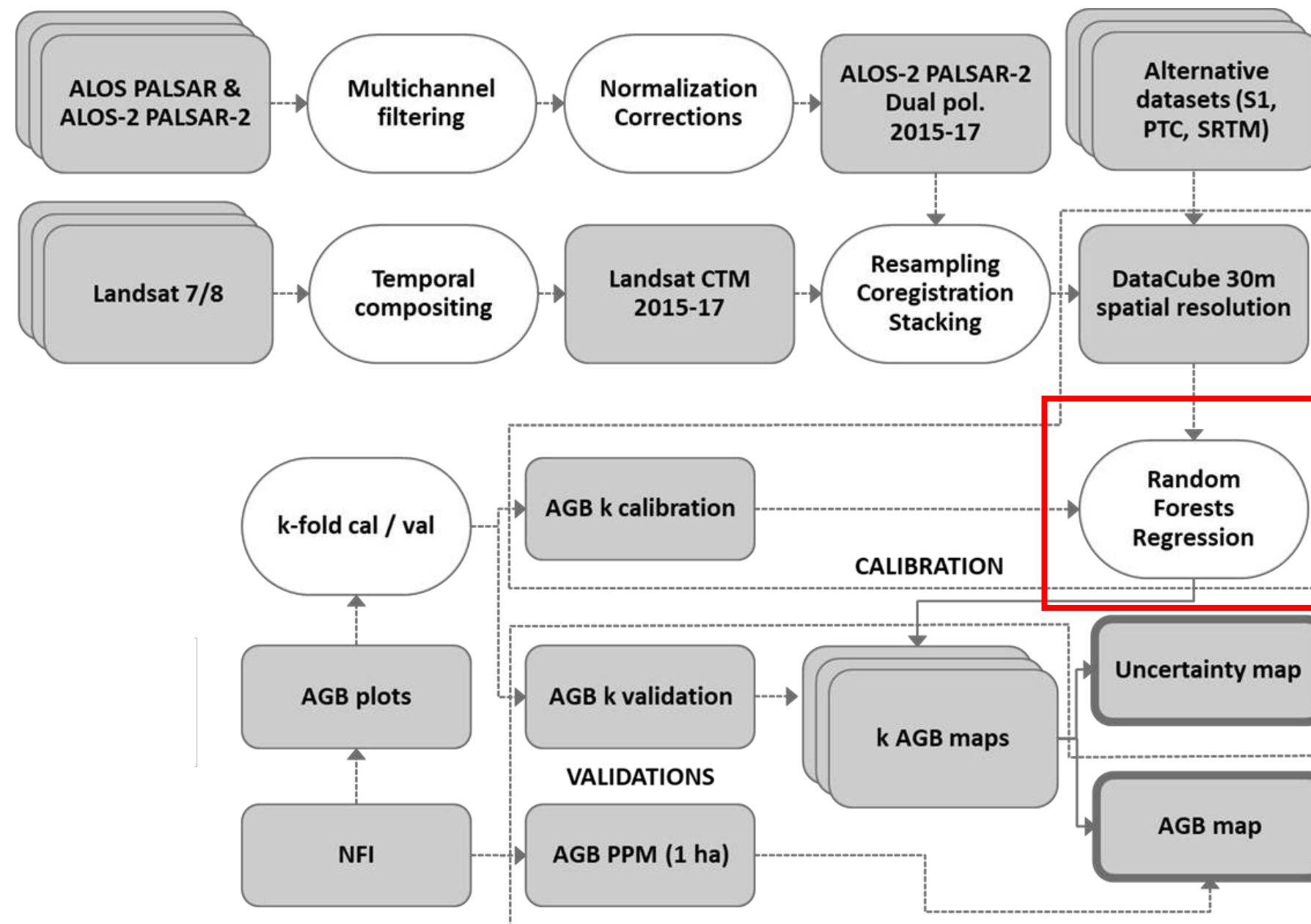
Mapping the stock and spatial distribution of aboveground woody biomass in the native vegetation of the Brazilian Cerrado biome



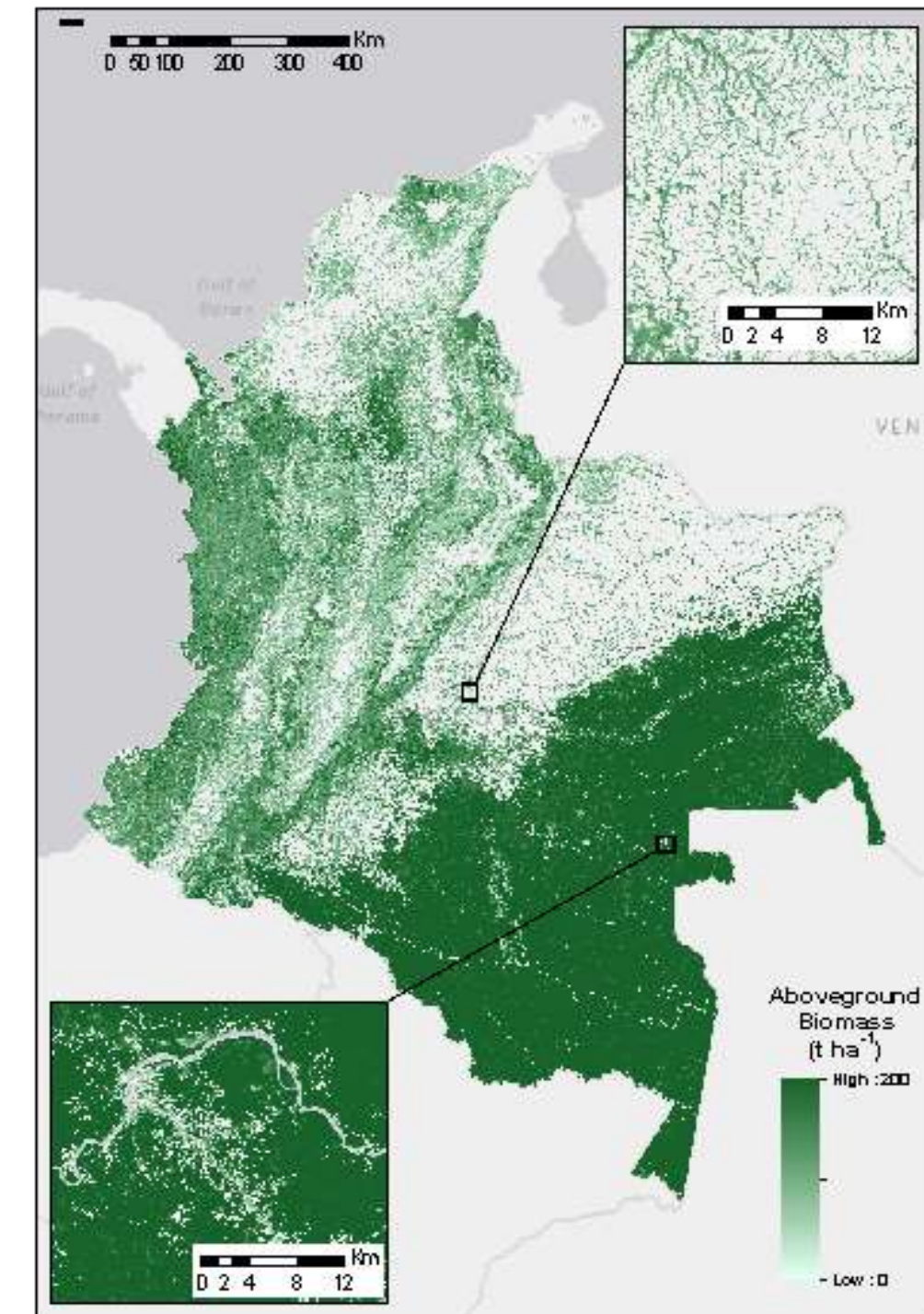
Aboveground woody biomass (AGWB, in $\text{t} \cdot \text{ha}^{-1}$) maps at 30-m resolution for the Cerrado biome, based on two machine learning algorithms tested (CART, left panel, and RFRandom Forest, right panel). Predictions are mapped over the native vegetation pixels, classified by the MapBiomass Project Collection 5.0 (forest, savanna, and grasslands).

Zimbres, *et al.* 2021, Forest Ecology and Management, <https://doi.org/10.1016/j.foreco.2021.119615>

Aboveground biomass and multisensory approach



AGB Colombian Amazon



Forest in different successional stages

Remote Sensing of Environment 232 (2019) 111194



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journal homepage: www.elsevier.com/locate/rse



Mapping forest successional stages in the Brazilian Amazon using forest heights derived from TanDEM-X SAR interferometry



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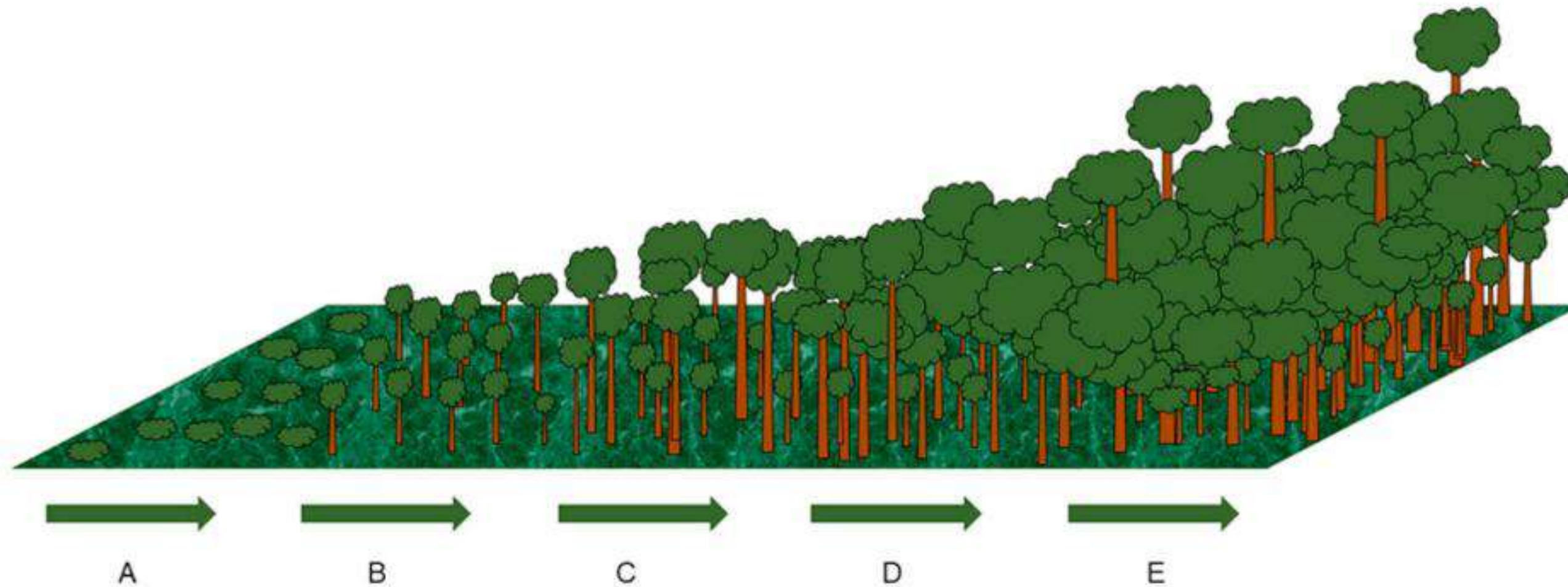
^h Embrapa Agricultural Informatics, Brazilian Agricultural Research Corporation (Embrapa), Campinas, SP, Brazil

ⁱ Embrapa Environment, Brazilian Agricultural Research Corporation (Embrapa), Jaguariúna, SP, Brazil

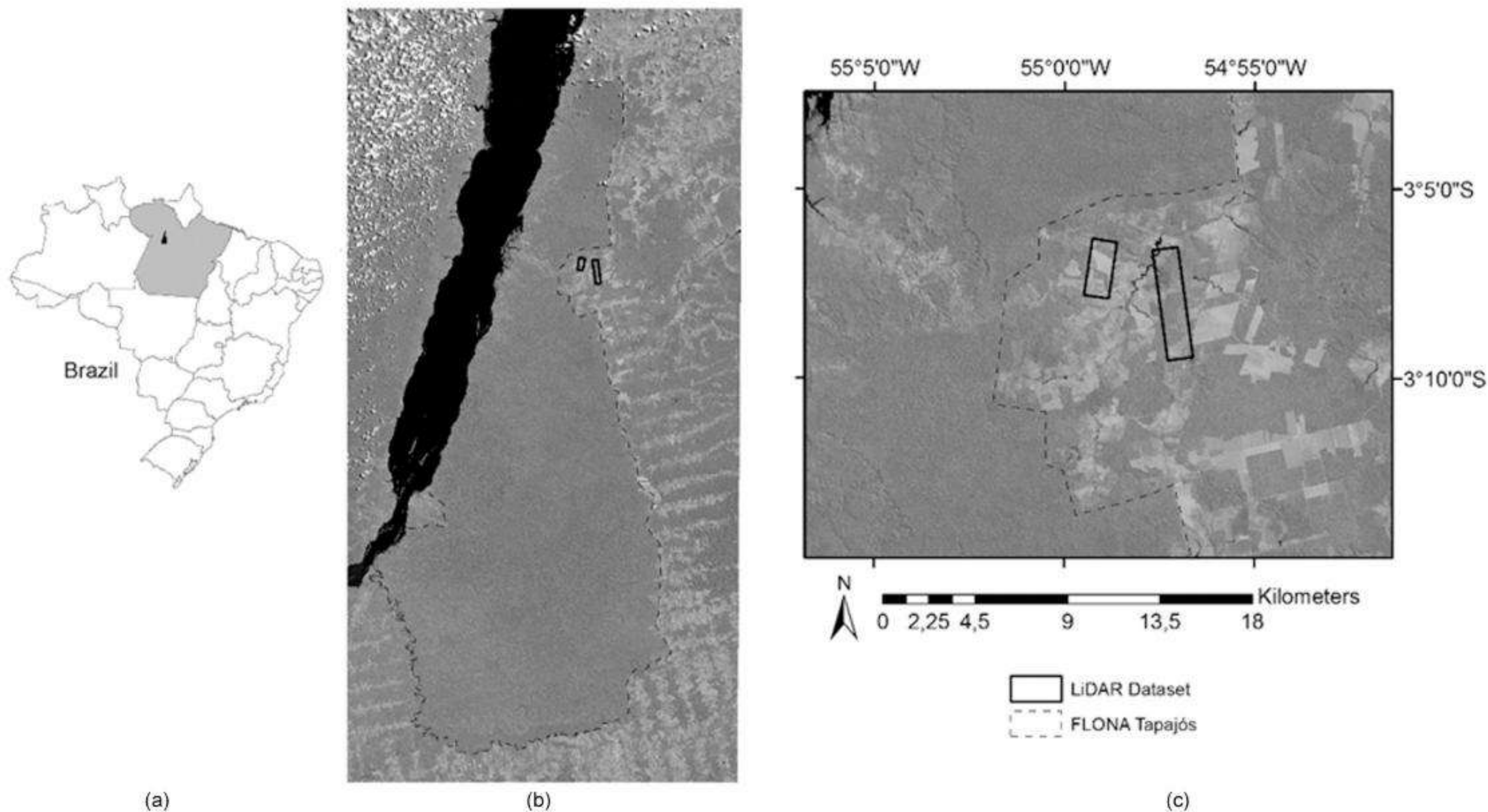
Forest in different successional stages

P.C. Bispo, et al.

Remote Sensing of Environment 232 (2019) 111194



Schematic representation of a tropical forest with different successional stages: A (non-forest); B (secondary forest in initial stage - SFIni); C (secondary forest in intermediated stage - SFInt); D (secondary forest in advanced stage - SFAdv); E (old growth forest or primary forest - OF).



(a) Location of the TNF in the Brazilian territory. (b) Zoom on the TNF, enclosed by the dashed line (TNF limits from 2013). The two small rectangles delimit the area covered by the LiDAR acquisition. (c) Zoom on the LiDAR coverage. The whole area inside and outside of the two LiDAR rectangles is covered by each TanDEM-X acquisition used in this study (2012, 2013 and 2016). Background image: Landsat 8 (14/08/2015).

General characteristics of forests types representative for the area of the TNF (which is part of eastern Amazon region) collected by [Lu \(2005\)](#). DBH, H, AGB and Age represent the interval of the means of stand diameter (cm), stand height (m), aboveground biomass (kg/m²) and age (years) respectively.

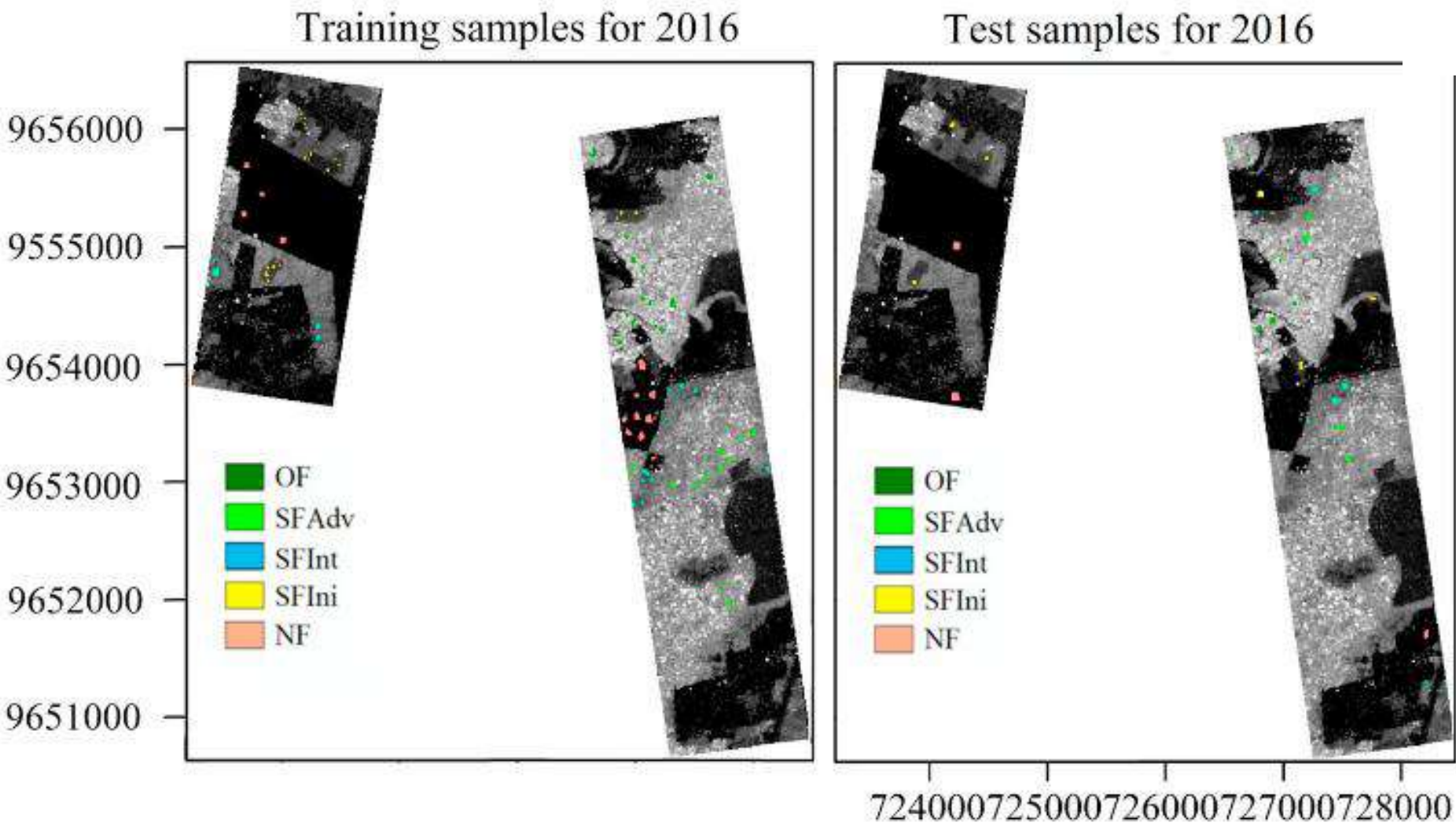
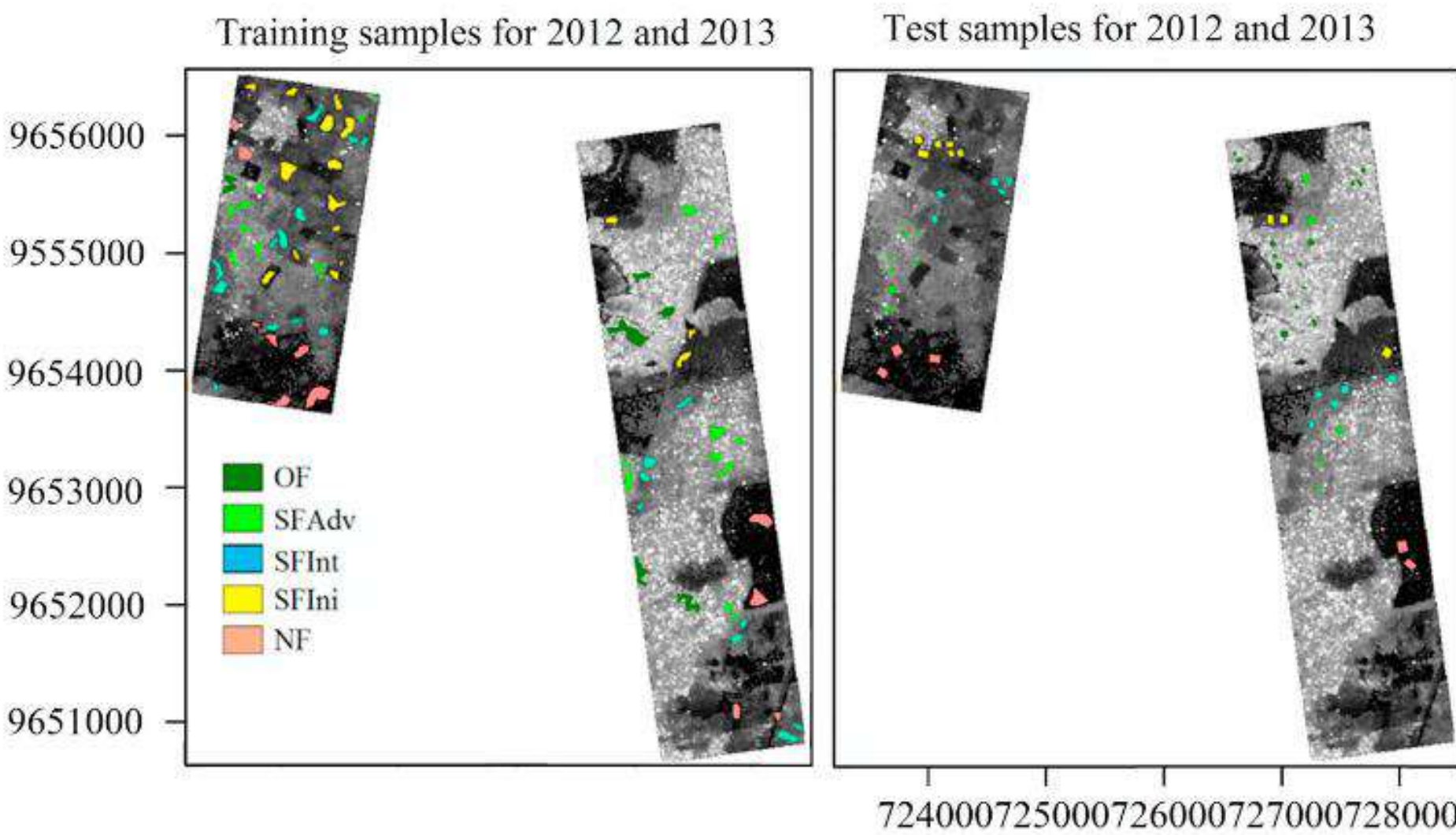
Forest types	Characteristics	DBH (cm)	H (m)	AGB (kg/m ²)	Age (years)
SFIni	Herbaceous plants, seedlings, and saplings together are responsible for > 90% of total biomass. The vertical structure is characterized by a full profile of saplings and herbaceous plants. Saplings are the main structure element and represent the majority of the aboveground biomass.	2–5	2–6	0.5–5	1–5
SFInt	Saplings still account for most of the biomass in SFInt. Vegetation structure provides a mix of dense ground cover of saplings and young trees with higher canopy than SFIni. There is very small internal difference between canopy and understory individuals. SFInt is characterized by a lack of stratification between canopy and understory.	5–15	6–12	4–10	4–15
SFAdv	Trees occupy the canopy and present obvious stratification of forest stand structure in SFAdv. In this stage, there is a major shift in structure that differentiates understory from canopy individuals; that is, the presence of saplings is less significant than that of trees. One can find differences between the canopy and understory in terms of height and density of individuals at both levels.	10–25	9–17	8–25	10–50
OF or PF	In the mature forest, aboveground biomass and vegetation density can be considerably different depending on soil conditions, species composition, and topography at the site. In a typical mature forest, trees account for the majority of aboveground biomass, reaching > 90%. Many tree individuals are taller than 17 m, and some are between 25 m and 30 m, followed by a few scattered individuals over 35 m tall or emergent.	13–30 or more	11–25 or more	12–50	–

Acquisition parameters of TanDEM-X. HoA indicates the InSAR height of ambiguity (see [Section 3.1](#)).

Date	Mode	Polarization	Orbit	Incidence Angle (°)	Effective Baseline (m)	HoA (m)
05/12/2012	Bistatic/StripMap	Dual (HH, VV)	Ascending	40.60	110.44	60.65
30/05/2013	Bistatic/StripMap	Dual (HH, VV)	Ascending	40.56	83.38	80.67
23/01/2016	Bistatic/StripMap	Dual (HH, VV)	Ascending	40.56	102.00	65.41

Field data from forest plots (0.25 ha) used as reference data. For H, DBH, Age and AGB the mean and the standard deviation (SD) is given with H being the stand height, DBH the diameter at breast height and AGB the aboveground biomass.

N. of Plots	Forest Types	H (m)		DBH (cm)		Age (years)		AGB (kg/m ²)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	SFIni	5	1.2	5	1.8	5	2	0.5	0.1
2	SFInt	9	0.8	10	3.0	15	1	4	0.8
3	SFAdv	14	2.1	19	2.0	30	1	17	1.2
1	OF	19	3.6	21	2.2	> 50	–	29	1.4



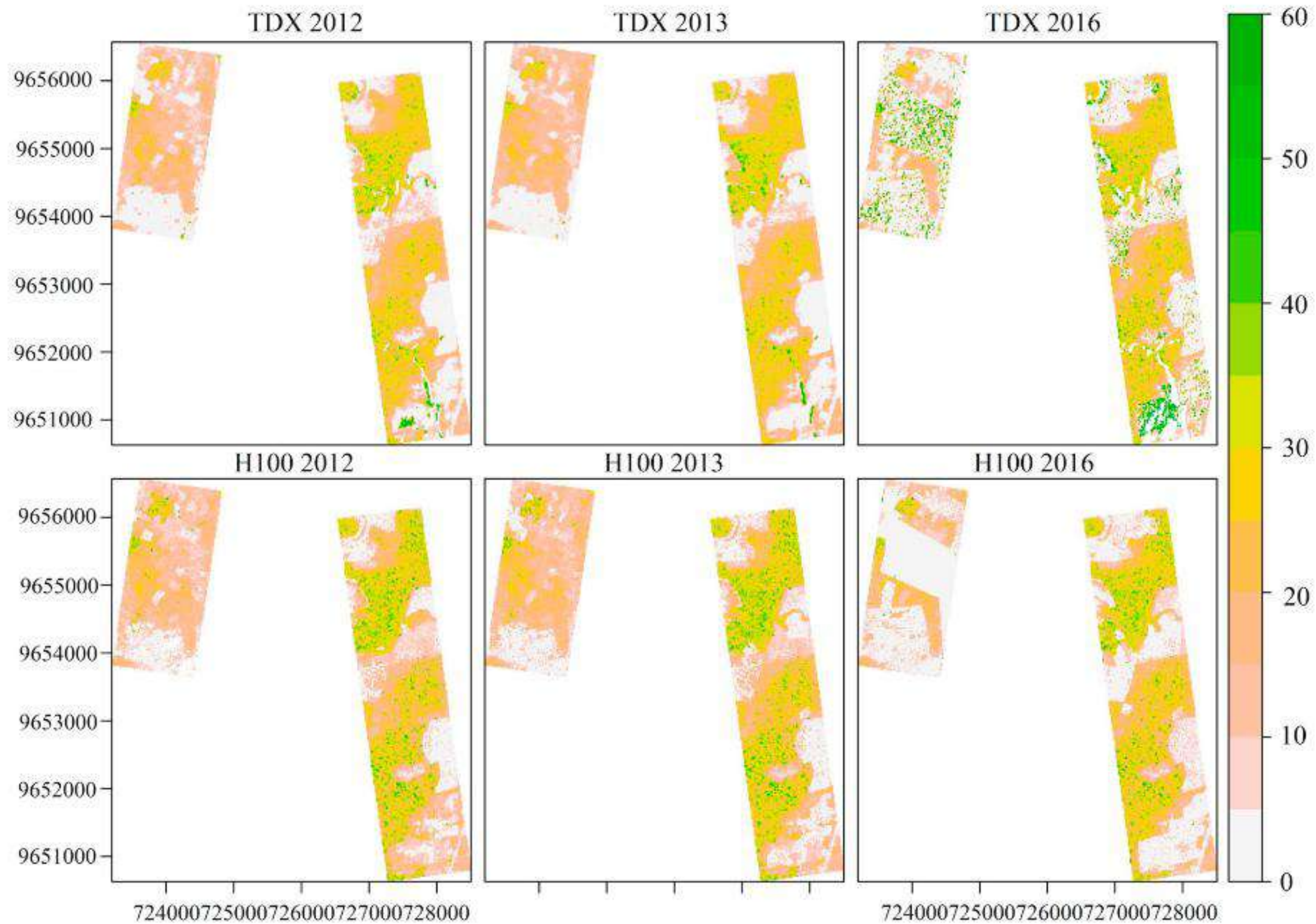


Fig. 6. Interferometric heights derived from TanDEM-X (top panel) and H100 (bottom panel) derived from LiDAR CHM, for 2012, 2013 and 2016. For each year and sensor, the two rectangles correspond to the LiDAR coverage.

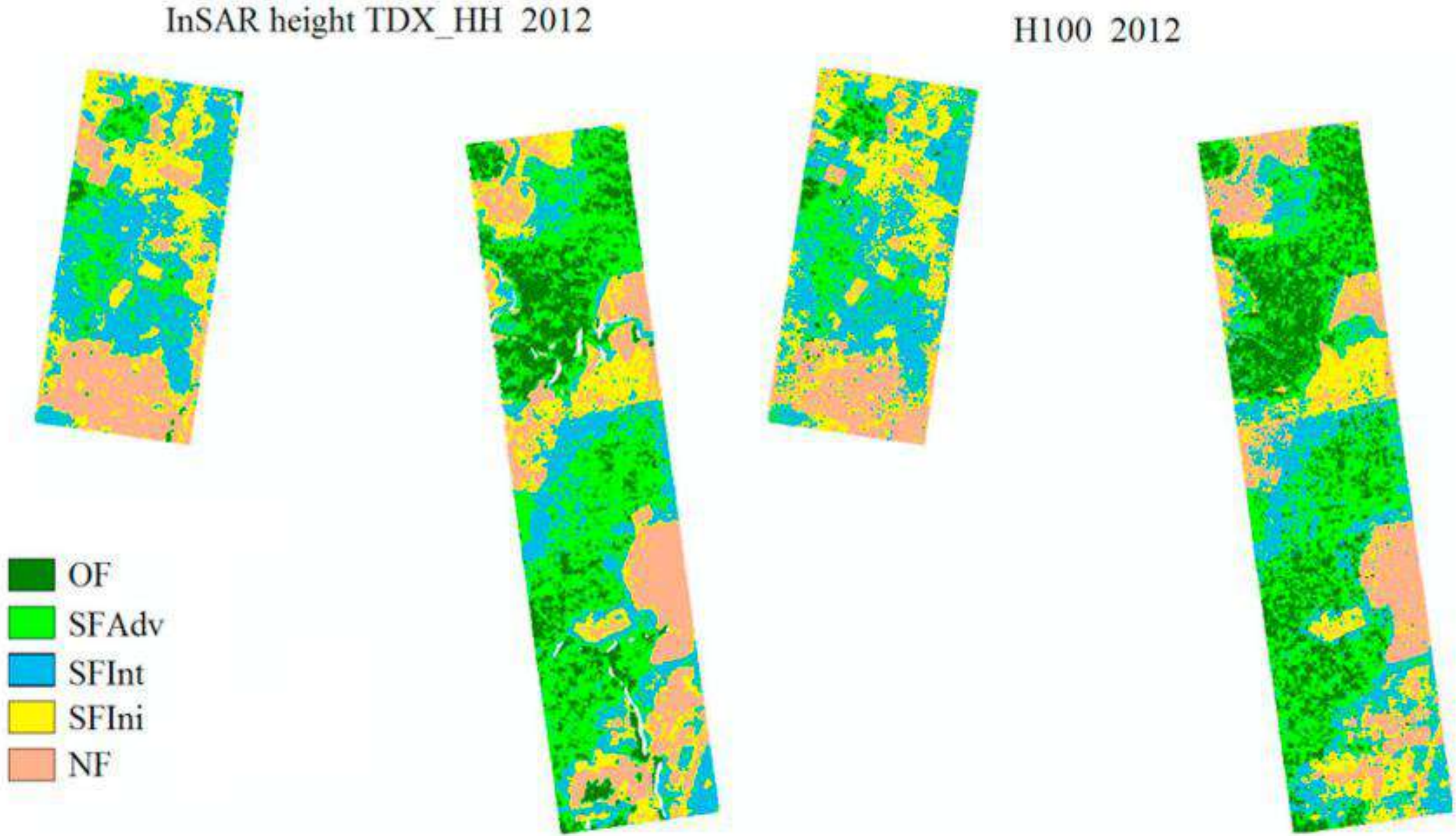


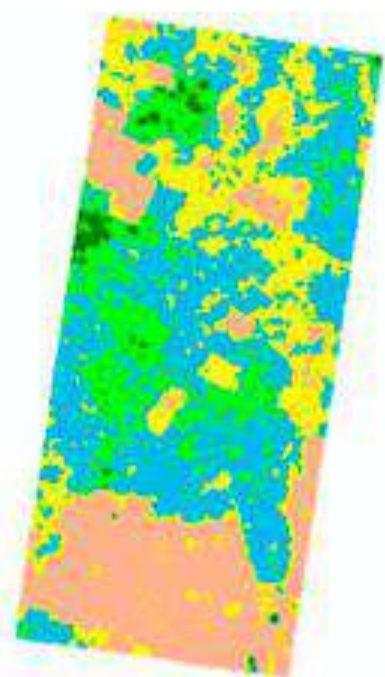
Fig. 9. Supervised classification of interferometric heights from TanDEM-X HH (05/12/2012) and LiDAR H100 (31/07/2012). The selected classes were old growth forest (OF), secondary forest in advanced stage (SFAdv), secondary forest in intermediary stage (SFInt), secondary forest in initial stage (SFIni) and non-forest (NF). The two rectangles correspond to the LiDAR coverage.

Table 12

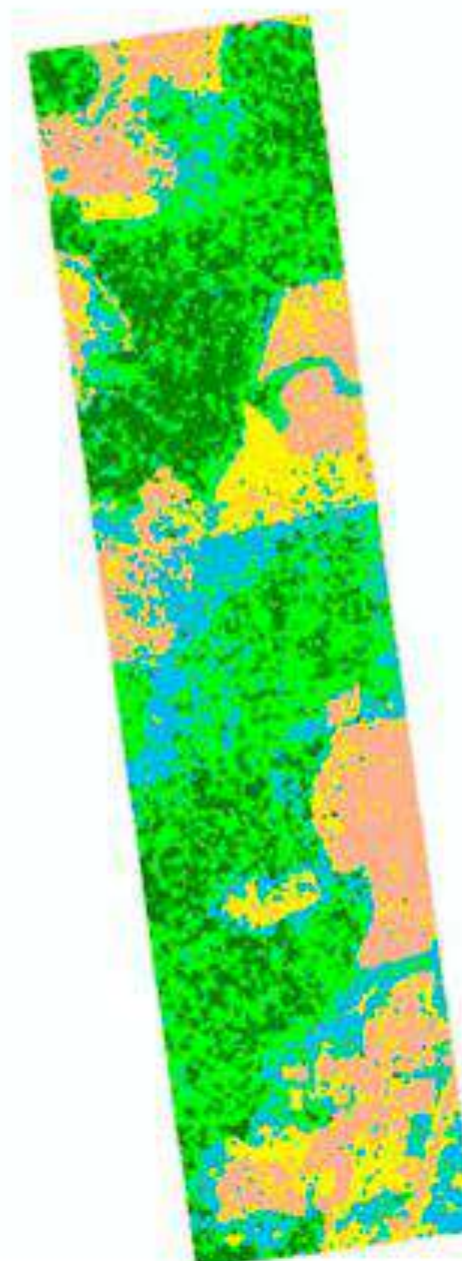
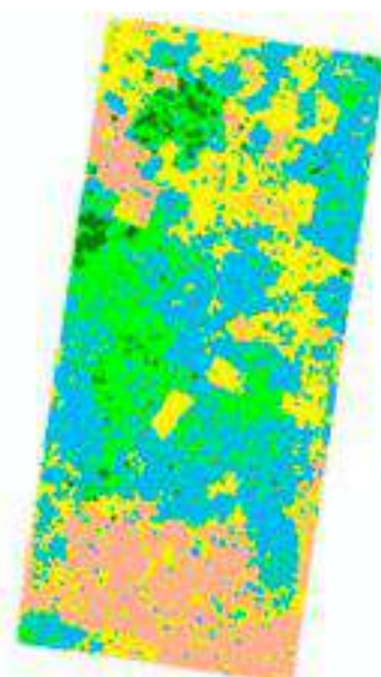
Confusion matrix and cross-validation of TanDEM-X and H100 for 2012.

Classes	Ref. OF	Ref. SFAdv	Ref. SFInt	Ref. SFIni	Ref. NF
H100%					
OF	96	3	0	0	0
SFAdv	4	87	8	0	1
SFInt	0	10	83	1	0
SFIni	0	0	9	98	4
NF	0	0	0	1	95
	100	100	100	100	100
Overall Accuracy = 0.92; Kappa = 0.90					
TDX HH%					
OF	93	2	0	0	0
SFAdv	7	84	9	0	0
SFInt	0	14	79	6	0
SFIni	0	0	12	85	1
NF	0	0	0	9	99
	100	100	100	100	100
Overall Accuracy = 0.87; Kappa = 0.84					

InSAR height TDX_HH 2013



H100 2013



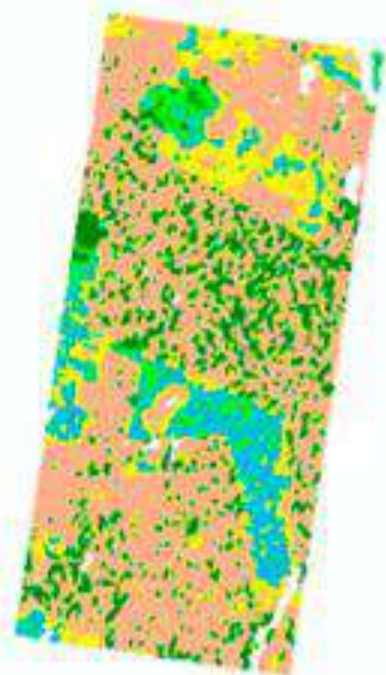
Supervised classification of interferometric height from TanDEM-X HH (30/05/2013) and H100 (10/09/2013). The selected classes were old growth forest (OF), secondary forest in advanced stage (SFAdv), secondary forest in intermediary stage (SFInt), secondary forest in initial stage (SFIni) and non-forest (NF). The two rectangles correspond to the LiDAR coverage.

Table 13

Confusion matrix and cross-validation of TanDEM-X and H100 for 2013.

Classes	Ref. OF	Ref. SFAdv	Ref. SFInt	Ref. SFIni	Ref NF
H100%					
OF	95	4	0	0	0
SFAdv	5	88	8	0	0
SFInt	0	8	84	1	0
SFIni	0	0	8	99	0
NF	0	0	0	0	100
100	100	100	100	100	100
Overall Accuracy = 0.93; Kappa = 0.91					
TDX HH%					
OF	93	5	0	0	0
SFAdv	7	82	8	0	0
SFInt	0	13	80	13	0
SFIni	0	0	12	80	0
NF	0	0	0	7	100
	100	100	100	100	100
Overall Accuracy = 0.87; Kappa = 0.84					

InSAR height TDX_HH 2016



H100 2016



Supervised classification of interferometric height from TanDEM-X HH (23/01/2016) and H100 (23/03/2016). The selected classes were old growth forest (OF), secondary forest in advanced stage (SFAdv), secondary forest in intermediary stage (SFInt), secondary forest in initial stage (SFIni) and non-forest (NF). The two rectangles correspond to the LiDAR coverage.

Confusion matrix and cross-validation of TanDEM-X and H100 for 2016.

Classes	Ref. OF	Ref. SFAdv	Ref. SFInt	Ref. SFIni	Ref. NF
H100%					
OF	84	16	0	0	0
SFAdv	8	74	23	0	0
SFInt	7	10	64	3	0
SFIni	1	0	13	70	0
NF	0	0	0	27	100
	100	100	100	100	100
Overall Accuracy = 0.80; Kappa = 0.75					
TDX HH %					
OF	82	15	0	21	0
SFAdv	15	79	28	11	0
SFInt	3	6	46	11	0
SFIni	0	0	25	18	50
NF	0	0	1	39	50
	100	100	100	100	100
Overall Accuracy = 0.55; Kappa = 0.43					

Conclusions

- Our results suggest that the approach described here allows to monitor the successional forest stages
- More investigations are needed to confirm these capabilities in different tropical forest test sites, and to further assess the robustness of the methodology.
- The availability of an external (LiDAR) DTM, which often is not the case in other tropical regions, limits the use of this approach with TanDEM-X data and the coverage of the resulting classification maps.

SCIENTIFIC EXPEDITIONS NEW CALL FOR PROPOSALS

AMAZON+10 Initiative

<https://www.amazoniamaisdez.org.br/en/iniciativa>

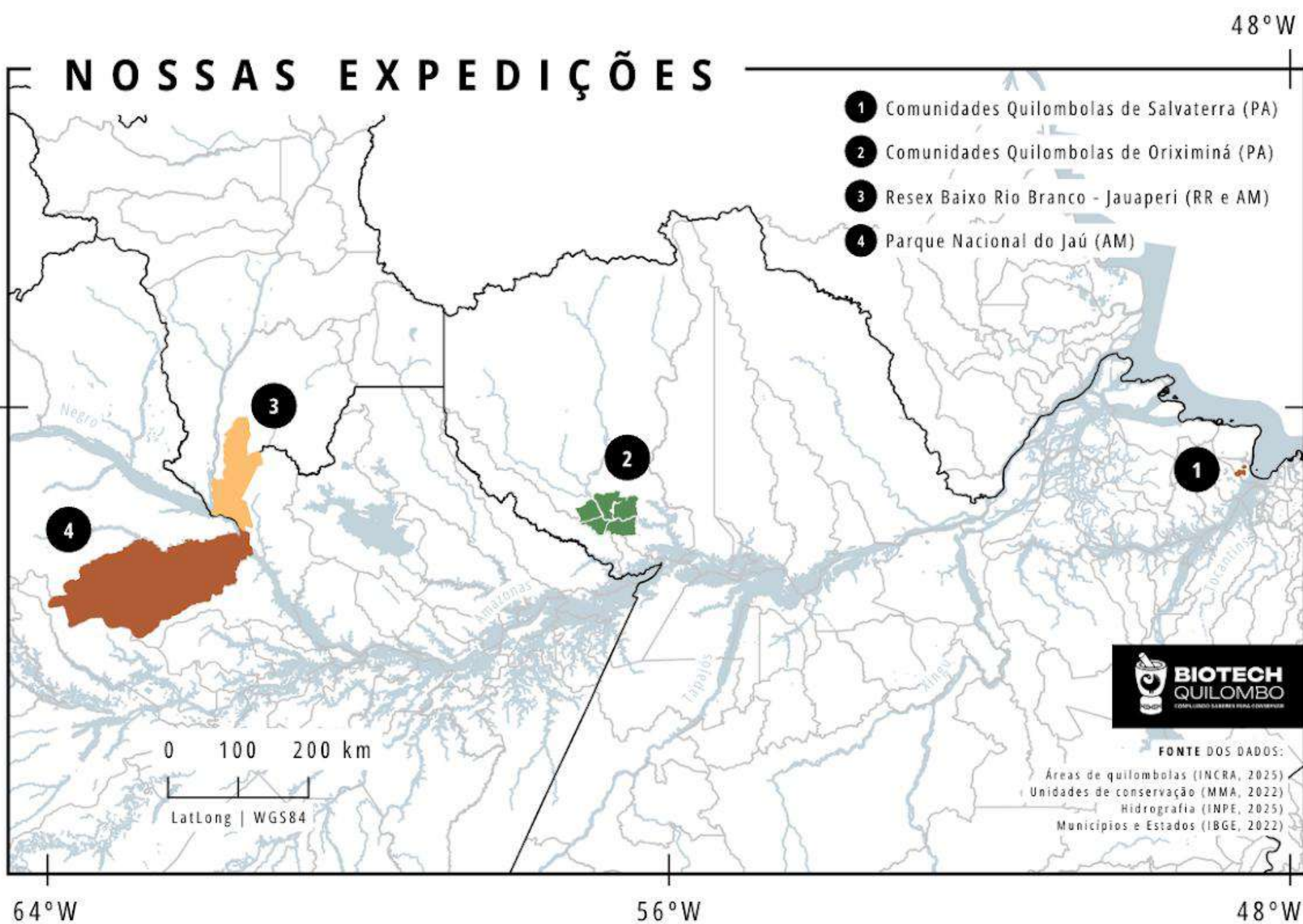
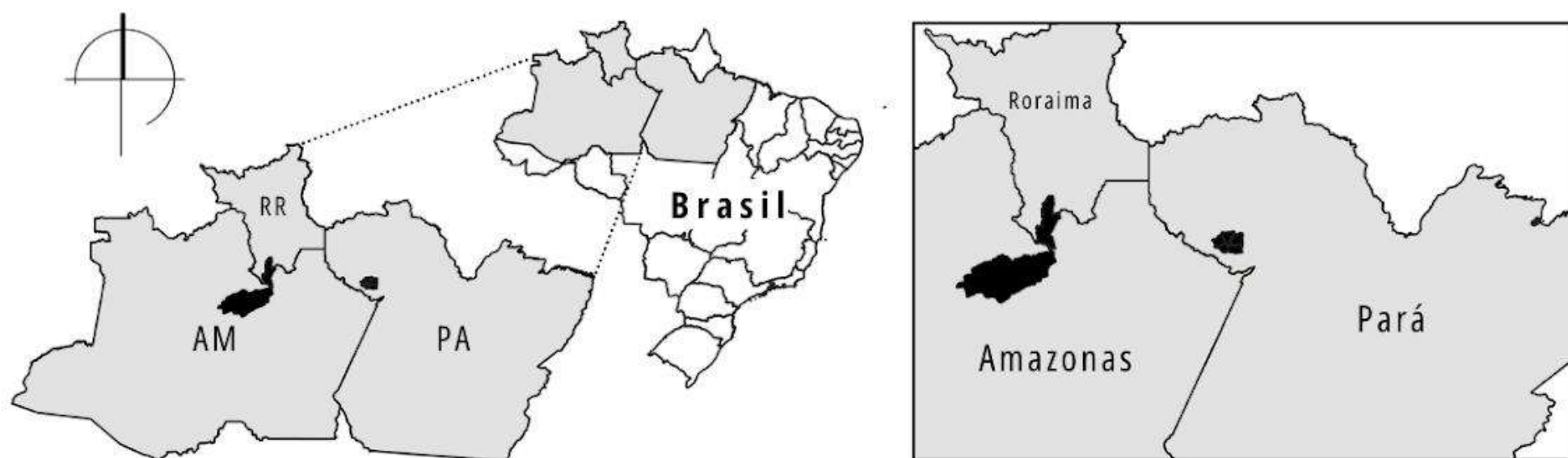


Amazonian BioTechQuilombo - Amazonian Biodiversity, Technology Assessment, and Knowledge Exchange with Quilombos



“Amazon +10 Initiative: Research Expeditions to the Amazon” The project involves the funding agencies UKRI (UK), SNSF (Switzerland), FAPESP (Brazil), FAPESPA (Brazil), FAPEAM (Brazil), FAPERR (Brazil), and CNPq (Brazil). **More than 40 scientists and 10 Quilombola leaders (Project started in Feb 2025)**

Total funding: £1,972,651.43 ~ €2,320,503.31 ~ R\$14,862,722.69



O mapa apresenta as áreas previstas para expedições de campo. As coletas de dados serão realizadas em comunidades quilombolas da Amazônia, entre os anos de 2026 e 2028. *Fonte: BiotechQuilombo/ TERAQ-G projects.*

PP0106231 - BioMassQuilombo-Amazon: Participatory Calibration and Validation of ESA **BIOMASS SAR**

Links

- **BioTechQuilombo: Pioneering Community-Led Biodiversity Monitoring in the Amazon**
<https://www.manchester.ac.uk/about/news/biotech-quilombo-pioneering-community-led-biodiversity-monitoring-in-the-amazon/>
- **Initiative brings together quilombola knowledge and technology for the benefit of biodiversity**
<https://ipam.org.br/initiative-brings-together-quilombola-knowledge-and-technology-for-the-benefit-of-biodiversity/>
- **Amazonia +10 Initiative**
<https://www.amazoniamaisdez.org.br/en/iniciativa>



BIOTECH
QUILOMBO
MERGING KNOWLEDGE FOR CONSERVATION

<https://www.instagram.com/projetobiotechquilombo/>

Some challenges

- Persistent uncertainties in biomass estimation and in detecting biomass changes over time.
- Inconsistent classification of secondary forests.
- Limited understanding of vegetation recovery dynamics under different disturbance regimes—both anthropogenic and natural—and how these affect forest regrowth and resilience.
- The need to standardize and harmonize datasets—including field measurements, LiDAR, and satellite imagery—to ensure long-term comparability, consistency, and interoperability across spatial and temporal scales.
- Lack of field plots specifically designed to validate remote sensing data and capture the complexity of tropical forest regeneration processes.

Future investigations

- Integrate other variables such as: microclimate, geomorphometric variables (e.g., slope, elevation, curvature, topographic position index) to capture terrain-driven variations influencing vegetation patterns
- Incorporate structural metrics such as canopy height, canopy density, and vertical complexity derived from LiDAR or radar data.
- Use contextual variables (e.g., proximity to mature forest, land-use history, disturbance type and frequency, trends) to better characterize regeneration environments.
- Analyse temporal trends in spectral and structural indicators to distinguish stages of forest recovery and succession dynamics.
- Combine field data (forest inventory) multisource remote sensing data (optical, radar, LiDAR) to enhance separability between successional stages.
- Apply machine learning or deep learning approaches to integrate diverse features and improve classification accuracy.
- Validate classifications using well-designed field plots representing different successional stages and disturbance histories.

A satellite image of Earth showing a coastline. The land is green and brown, with a blue ocean to the right. The text is overlaid on the image.

Thank you!

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Synthesis of regrowth rates in secondary forests

Mikhail Urbazaev, Viola Heinrich, Maurizio Santoro, Martin Herold

Session 2.1: Biomass datasets + missions

São José dos Campos, 30 Oct 2025



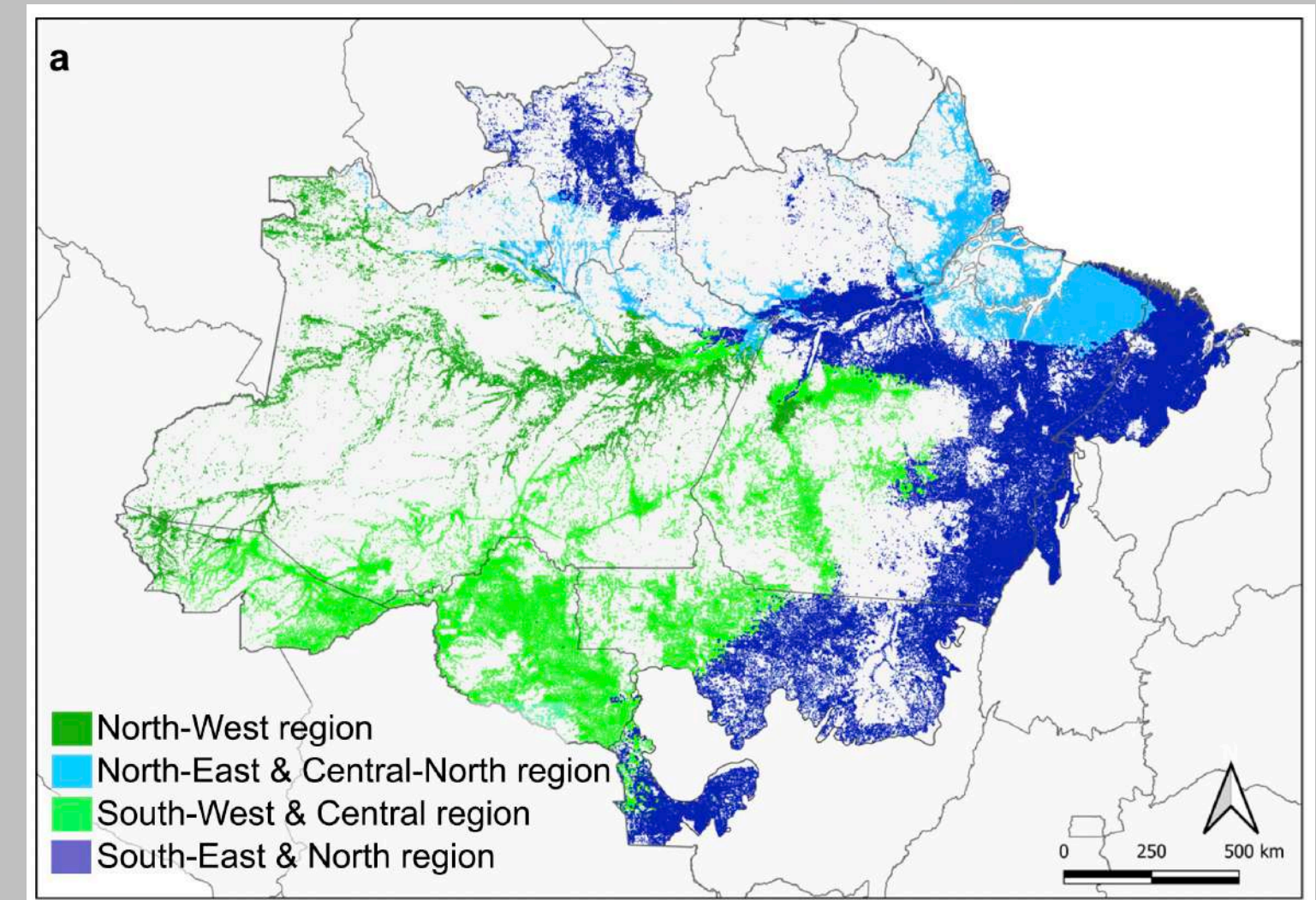
Regrowth rates from different sources

- ESA CCI Biomass regrowth rates
 - slope from time series maps
 - overlaid with MapBiomas Age
- INPE-ALS space-for-time approach

Literature

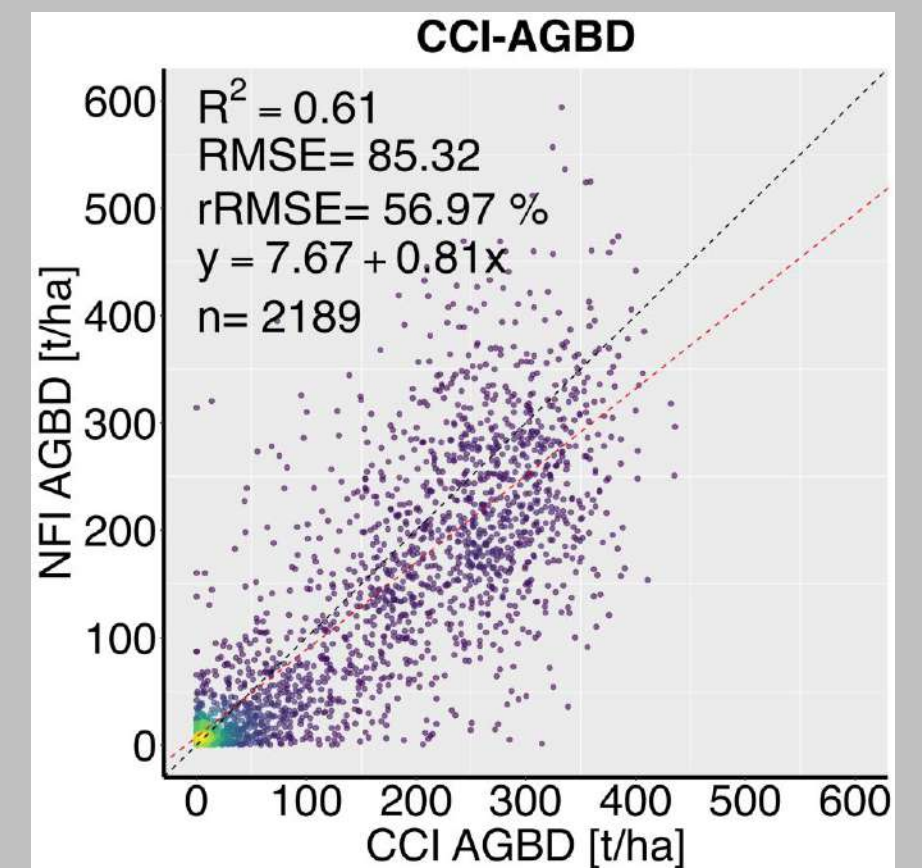
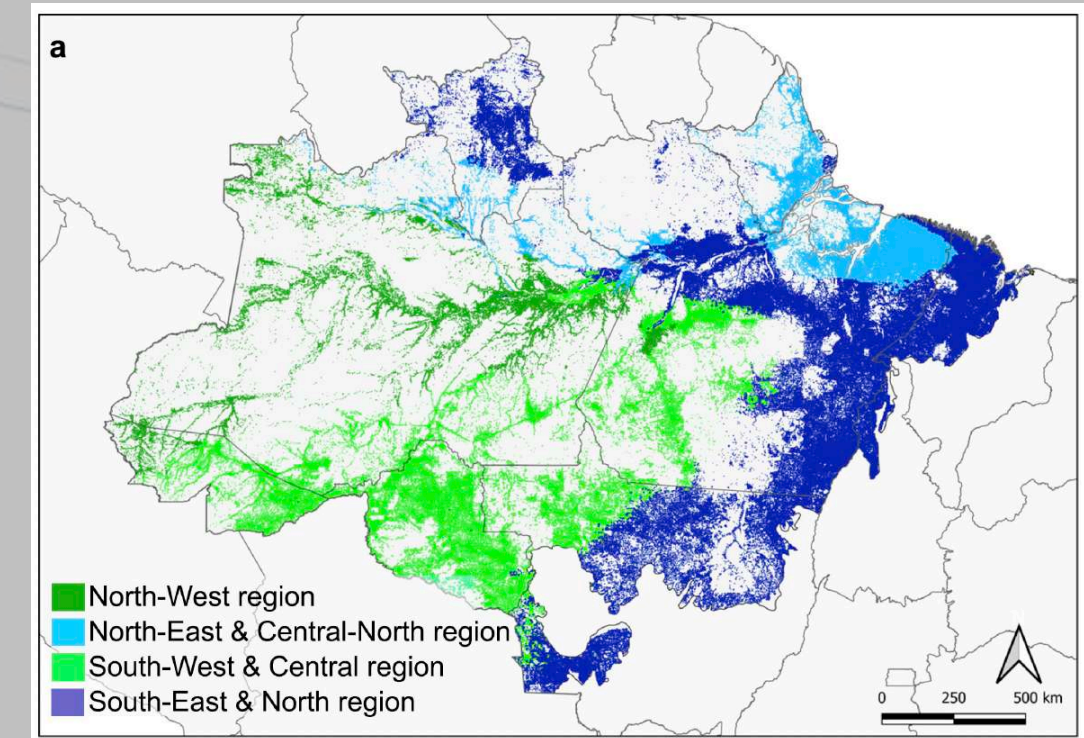
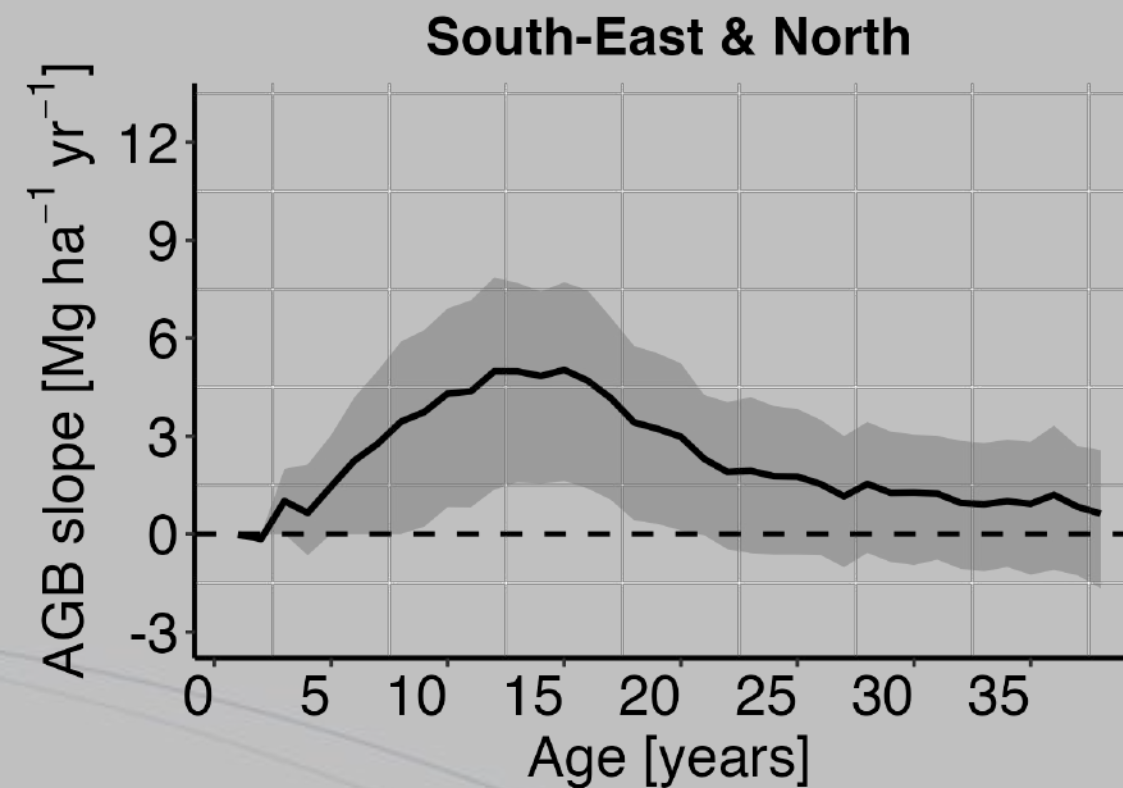
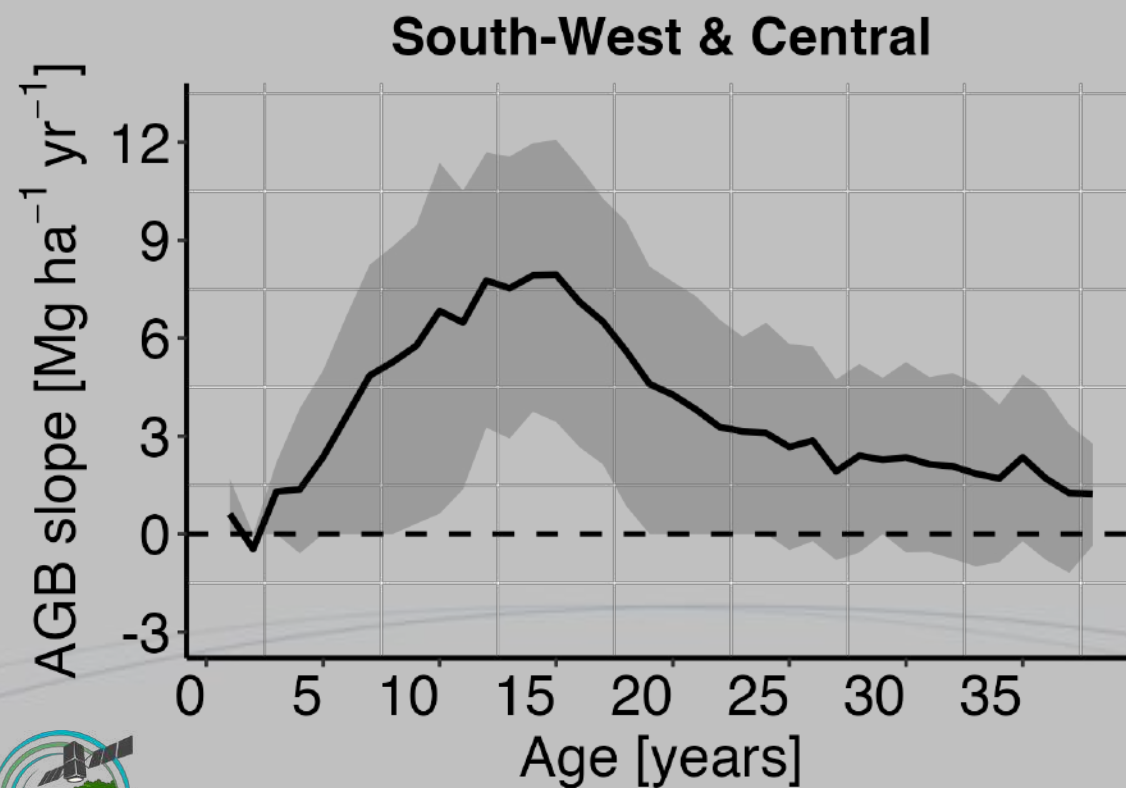
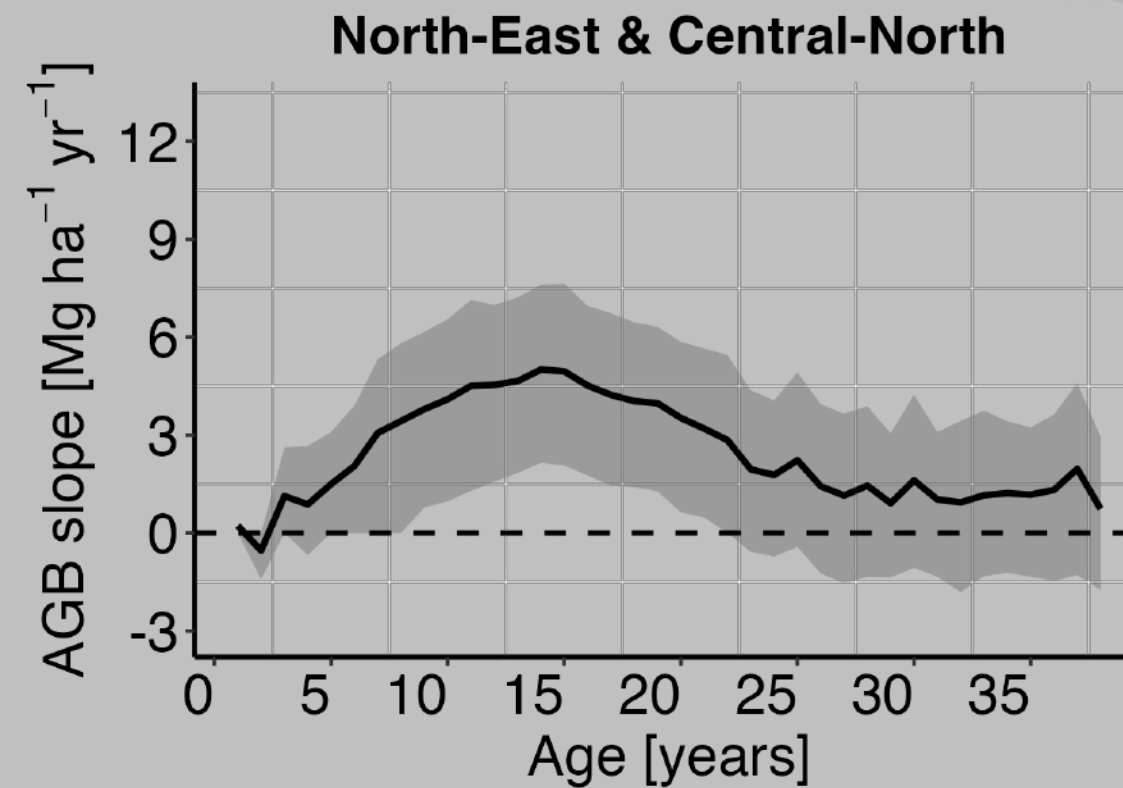
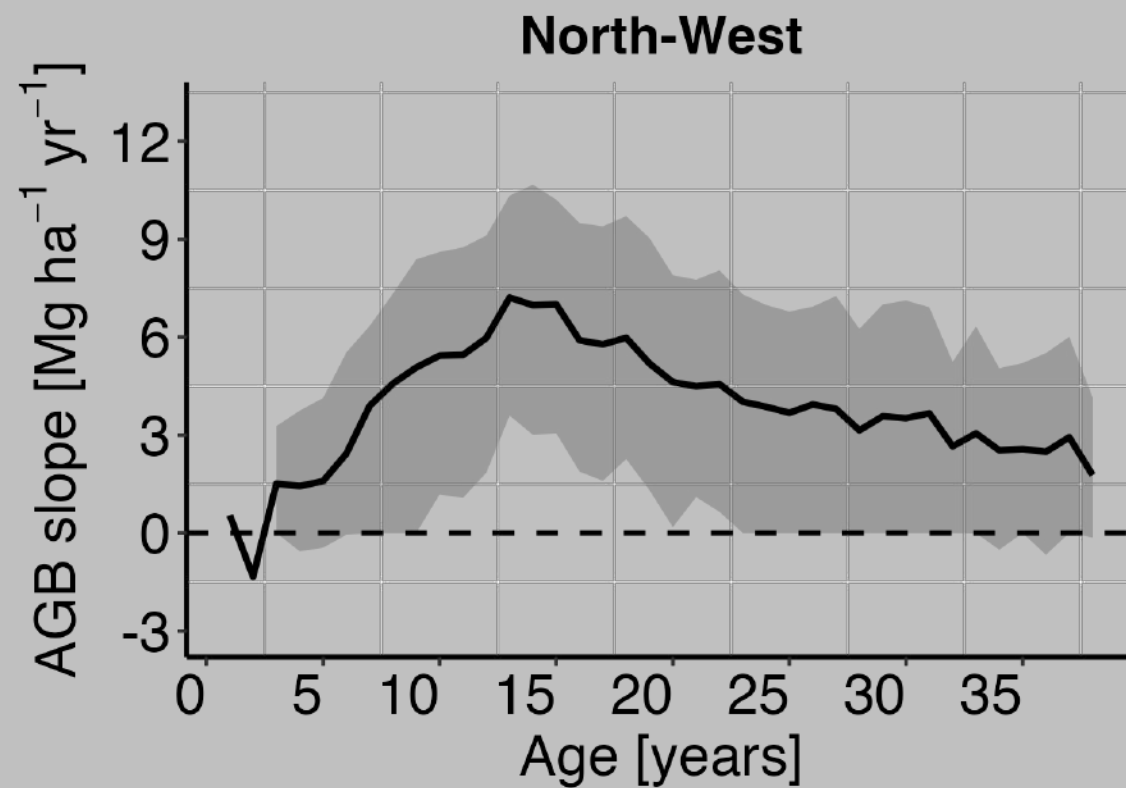
- Heinrich et al. 2021
 - CCI Biomass v3 space-for-time
- Holcomb et al. 2023*
 - GEDI space-for-time

*different forest age map
- Robinson et al. 2025
 - based on field estimates and modeling



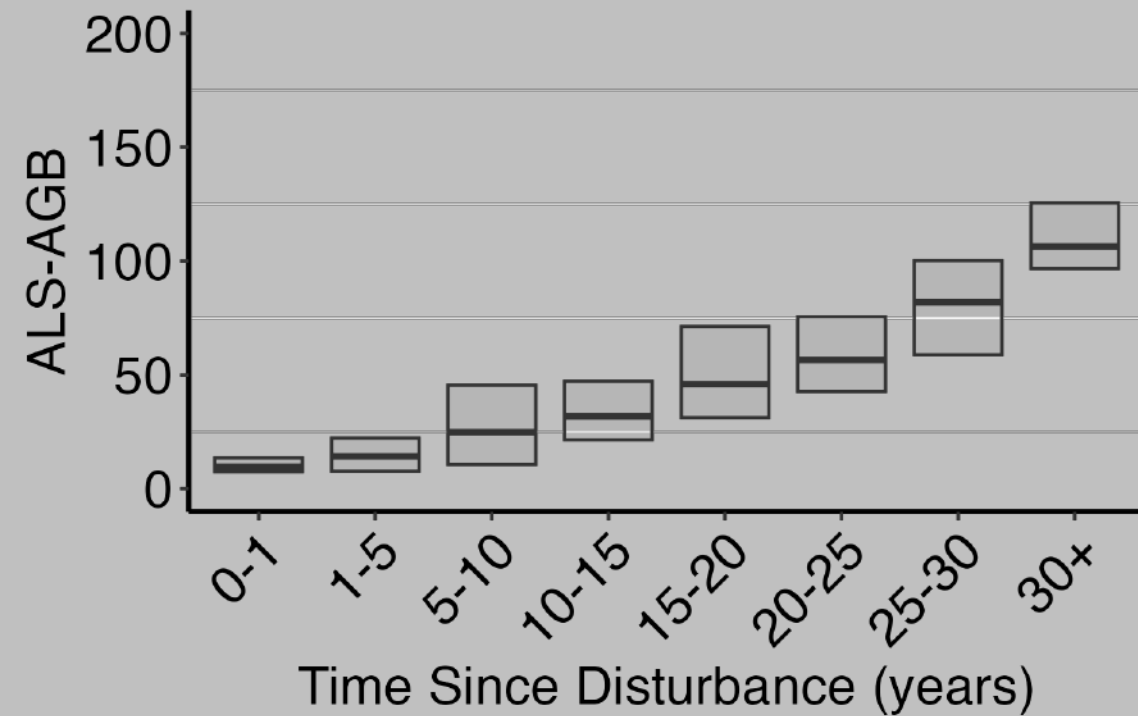
Regions for estimating regrowth rates
(Heinrich et al. 2021)

Regrowth rates from ESA CCI Biomass

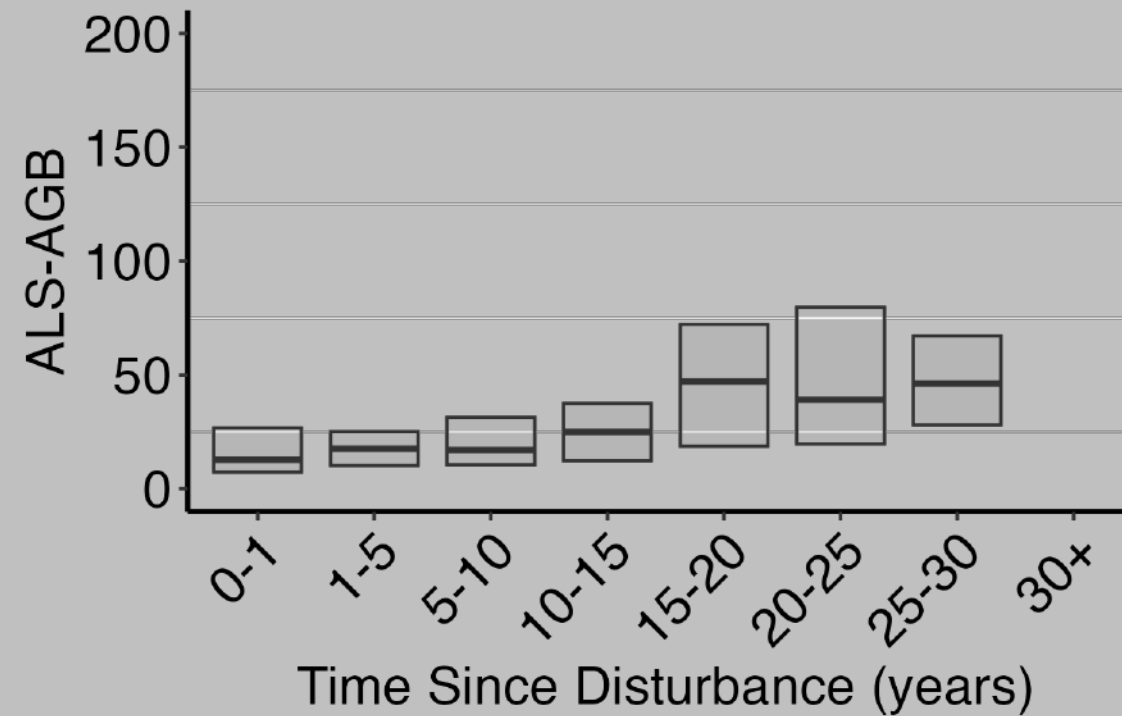


Regrowth rates from INPE-ALS

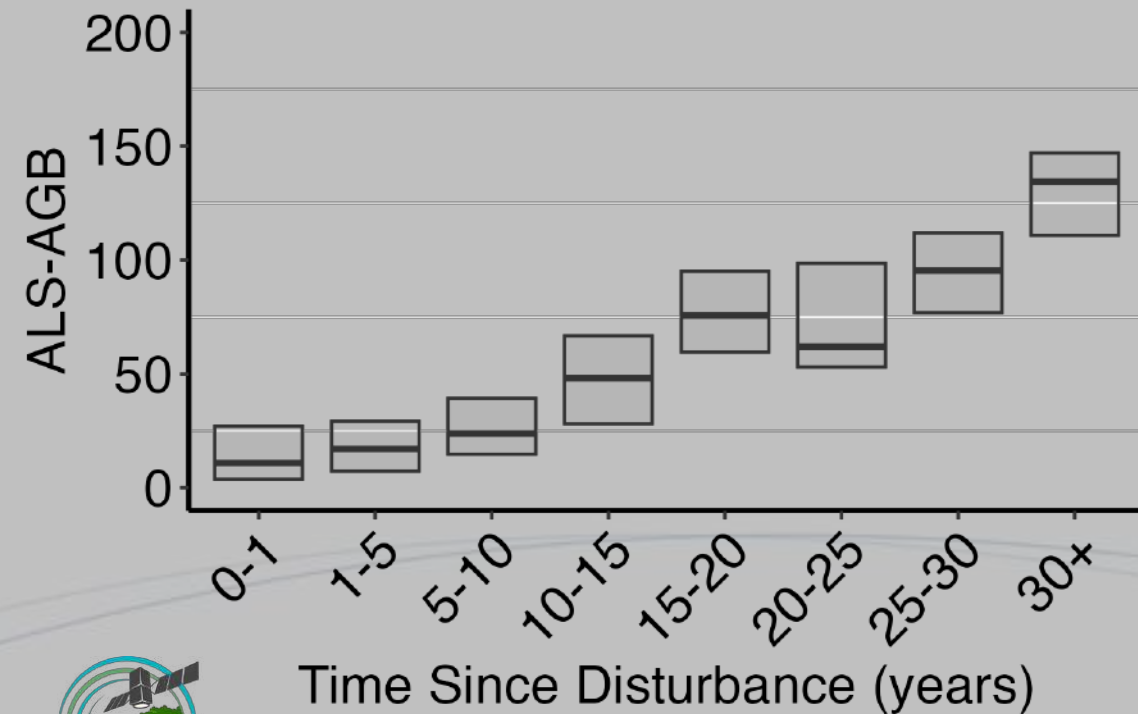
North-West



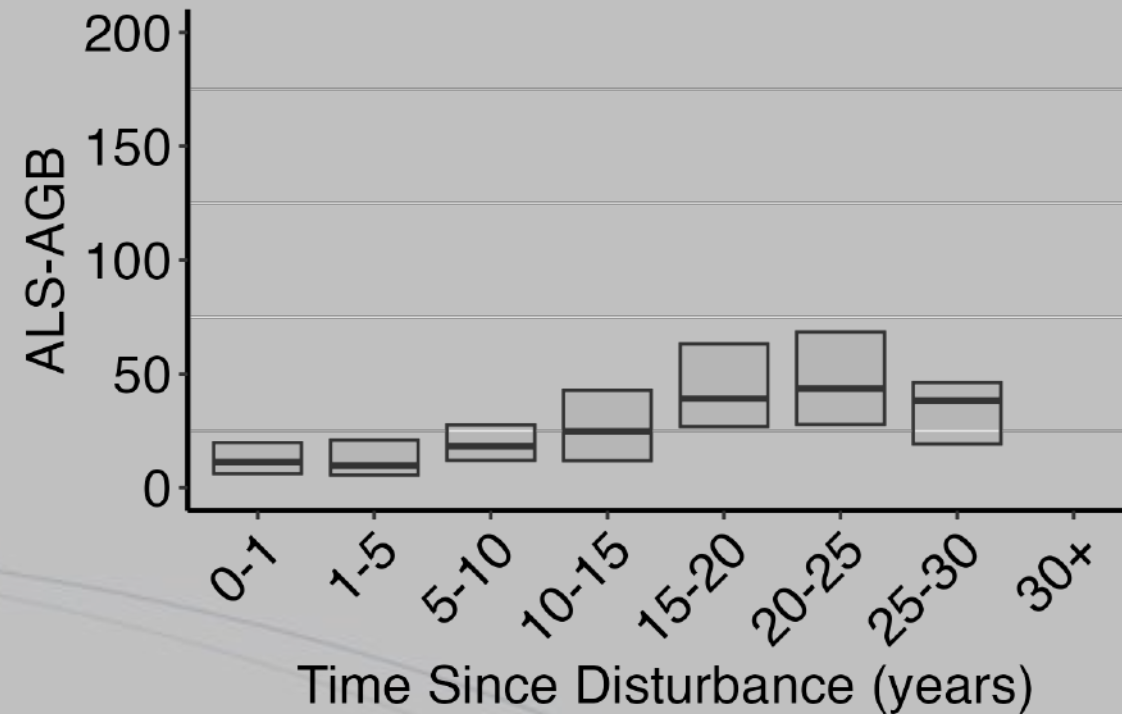
North-East & Central-North



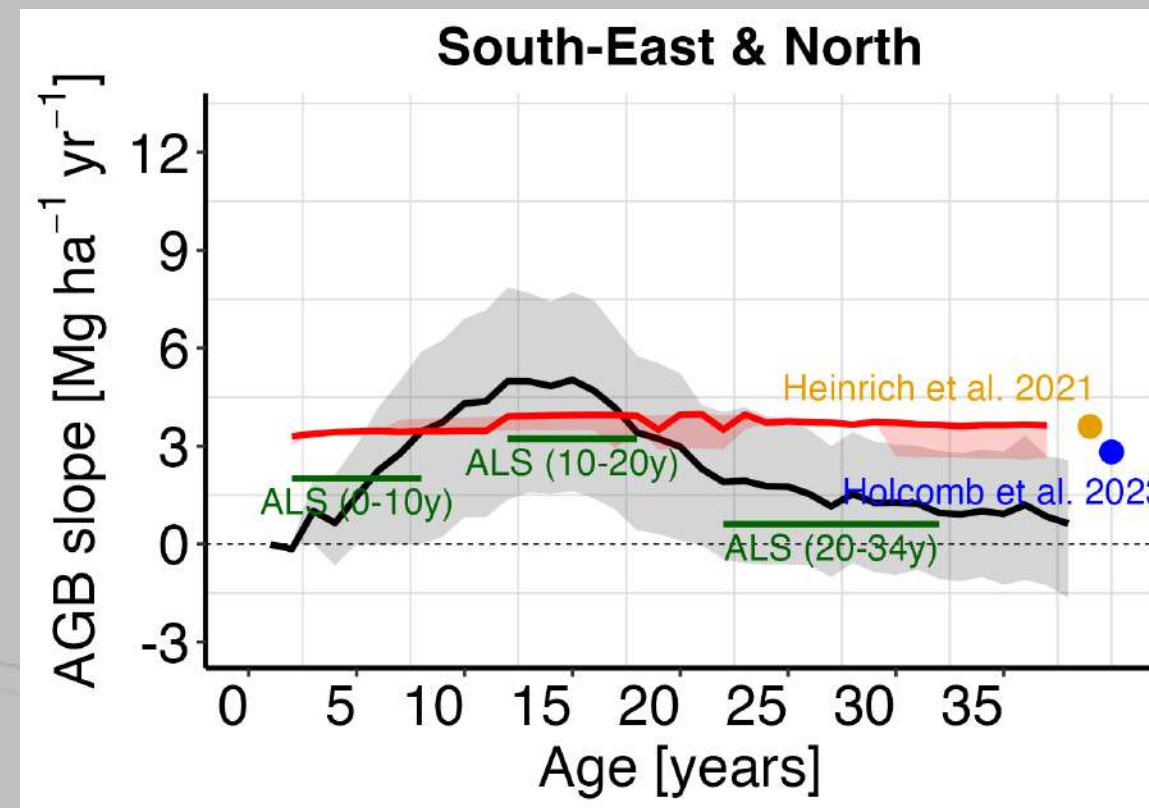
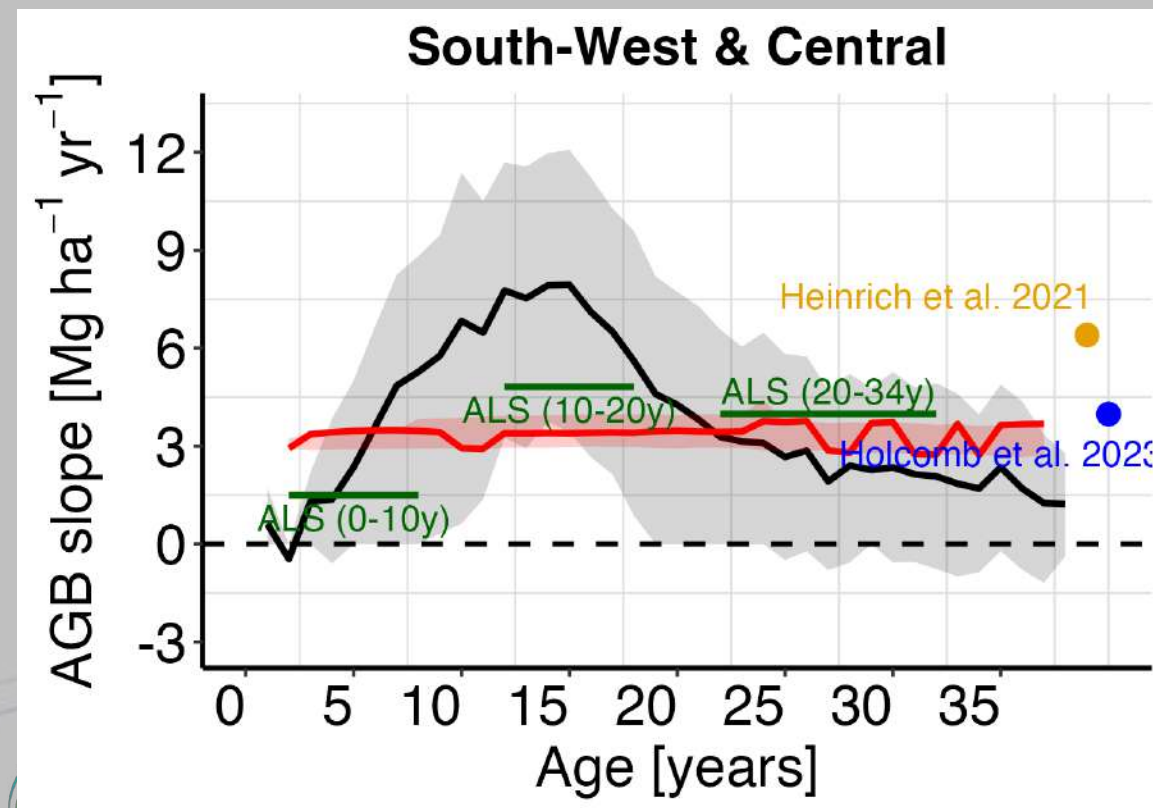
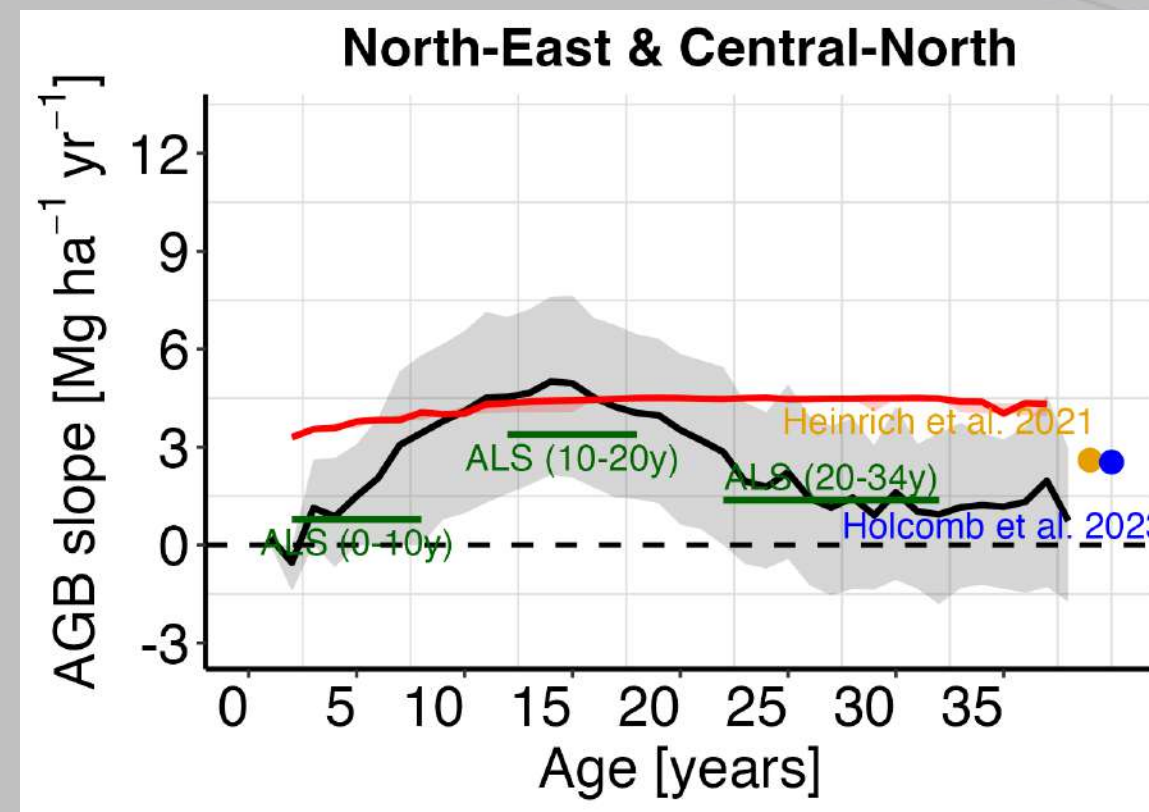
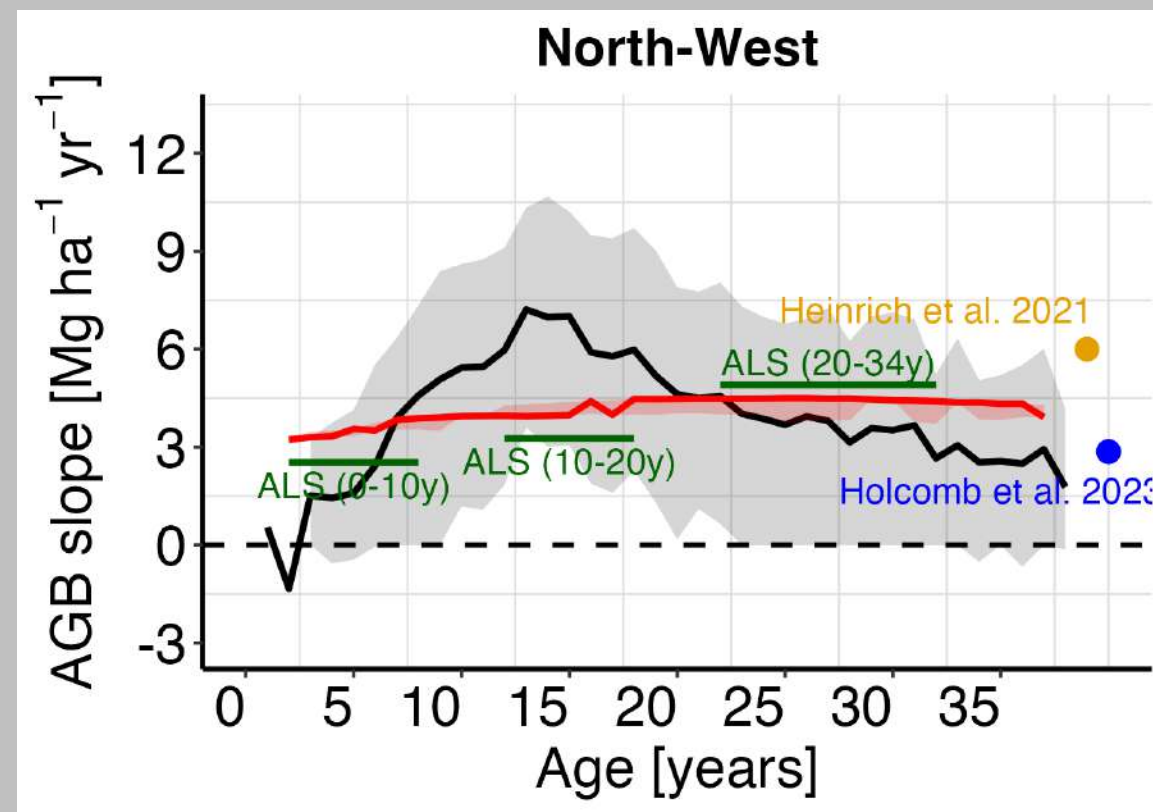
South-West & Central



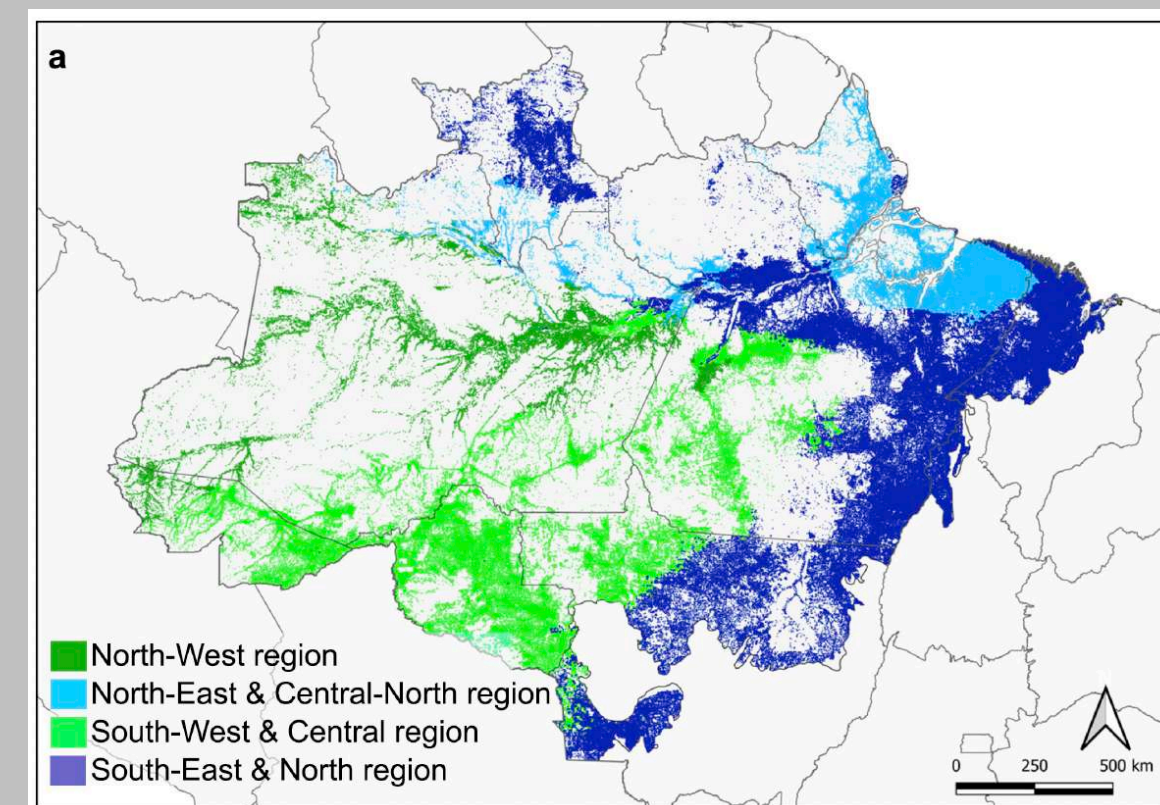
South-East & North



Regrowth rates from different sources



ESA CCI Biomass (10 annual maps)
 INPE ALS-AGB (2016)
 Heinrich et al. 2021
 Holcomb et al. 2023
 Robinson et al. 2025



Regions for estimating regrowth rates
 (Heinrich et al. 2021)

Summary

- ESA CCI Biomass time-series products allow the estimation of regrowth rates for individual secondary forest age classes
- Regrowth rates from INPE-ALS show a similar pattern to the CCI in the Eastern Brazilian Amazon, with the highest rates at around 10-20 years
- Since INPE-ALS represents sampled AGB, its estimated regrowth rates are influenced by the MapBiomas product and its definition of secondary forest
- Robinson et al. 2025 report relatively little variation in regrowth rates across the age classes

First results from the ESA BIOMASS Mission in Brazilian Forests

Mikhail Urbazaev, Viola Heinrich, Martin Herold

Session 2.1: Biomass datasets + missions

São José dos Campos, 30 Oct 2025

work conducted under ESA BIOMASS DISC
as part of the BIOMASS In-Orbit Commissioning Programme



The BIOMASS mission: ESA's forest mission

Key facts

- ESA's 7th Earth Explorer
- Designed to observe forest height and biomass
- Launch date: April 29, 2025
- First civilian full polarimetric P-band SAR (Synthetic Aperture Radar)
- Two mission phases:
 - TomoSAR (18 months: one global coverage at the beginning of the mission)
 - PolInSAR (3.5 years: five repeated global coverages)
- 5 years lifetime
- Swath width is 51.1 km
- Spatial resolution (SLC):
~59 m (range) x 8 m (azimuth)



Primary science objectives

Forest biomass	Forest height	Disturbances
Above-ground biomass (tons/hectare)	Upper canopy height (meter)	Areas of forest clearing (hectare)
<ul style="list-style-type: none">• 200 m resolution• accuracy of 20%, or 10 t ha⁻¹ for biomass < 50 t ha⁻¹	<ul style="list-style-type: none">• 200 m resolution• accuracy of 20-30%	<ul style="list-style-type: none">• 50 m resolution• 90% classification accuracy
• 1 map every 9 months of all forested areas (excl. SOTR region)		

Signature analysis of BIOMASS L1B amplitude (commissioning data) across secondary forests and their ages

Summary

- First comparison of BIOMASS L1B IOC products with reference data (Brazilian NFI and INPE-ALS)
- The data are not yet radiometrically or polarimetrically calibrated, nor terrain normalized
- BIOMASS amplitude correlates with NFI-AGBD and ALS canopy height at cross-pol
- BIOMASS amplitude shows a stronger correlation with forest age as ALOS-2 PALSAR-2
- Further improvements (geolocation, calibration, terrain normalization) are expected to improve the correlation with the reference data
- Ground notched data (i.e., excluding the signal from ground) are expected to provide a significant improvement

work conducted under ESA BIOMASS DISC
as part of the BIOMASS In-Orbit Commissioning Programme

Acknowledgments



SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

(10:35-11:00) Break

São José dos Campos, 30 Oct 2025



Temporal trajectories of biomass in Brazil from the ESA CCI Biomass dataset

Maurizio Santoro (Online)

Session 2.1 (Part 1): Biomass datasets and missions

São José dos Campos, 30 Oct 2025



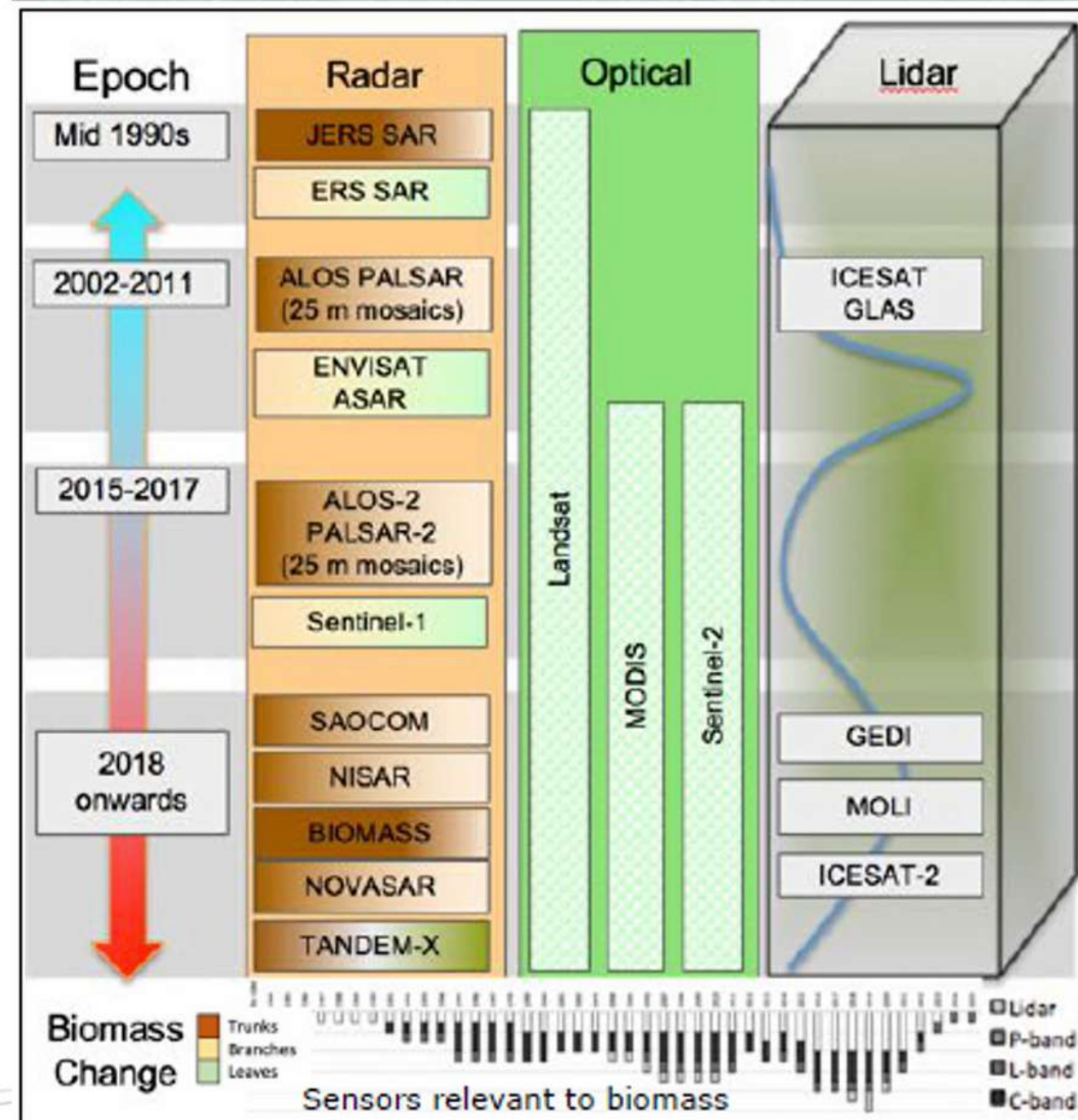
GFZ Helmholtz Centre
for Geosciences



The CCI Biomass project - background

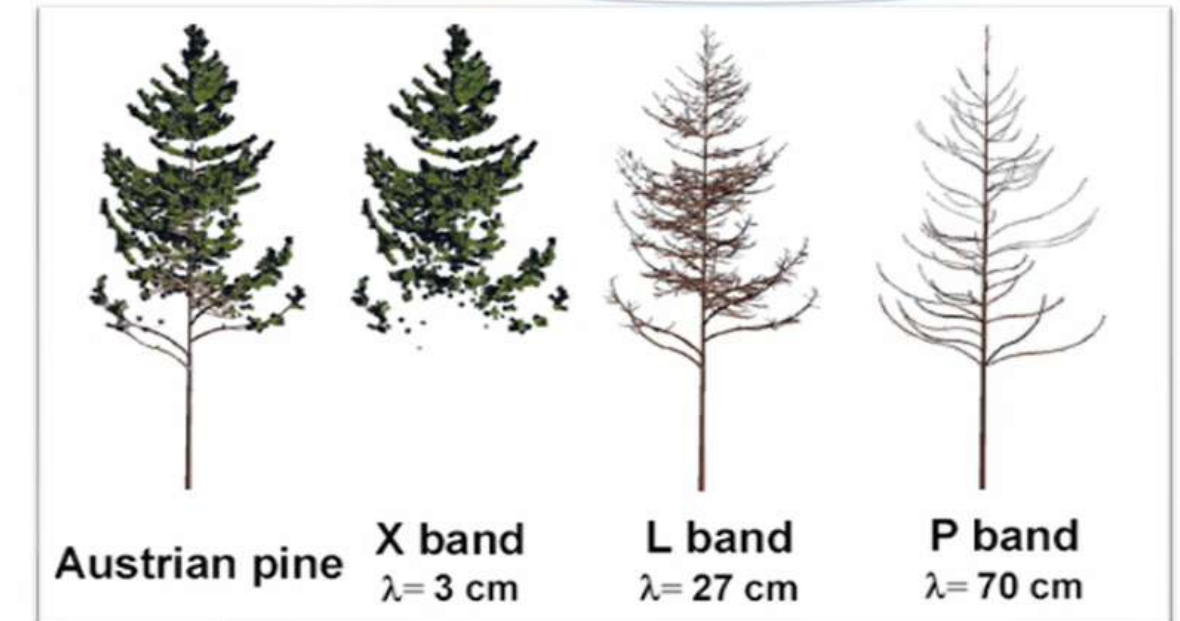
- Above-ground biomass (AGB) is an Essential Climate Variable (ECV) within the Global Climate Observing System (GCOS).
- One of the objectives of the CCI Biomass project is to generate global maps of AGB using a variety of Earth Observation (EO) datasets and state-of-the-art models for several epochs spanning two decades and assess biomass changes
- Specs of the data products were shaped by requirements from the climate and carbon modelling community (GCOS) as well as from other communities including climate policy

Satellite observations of forests



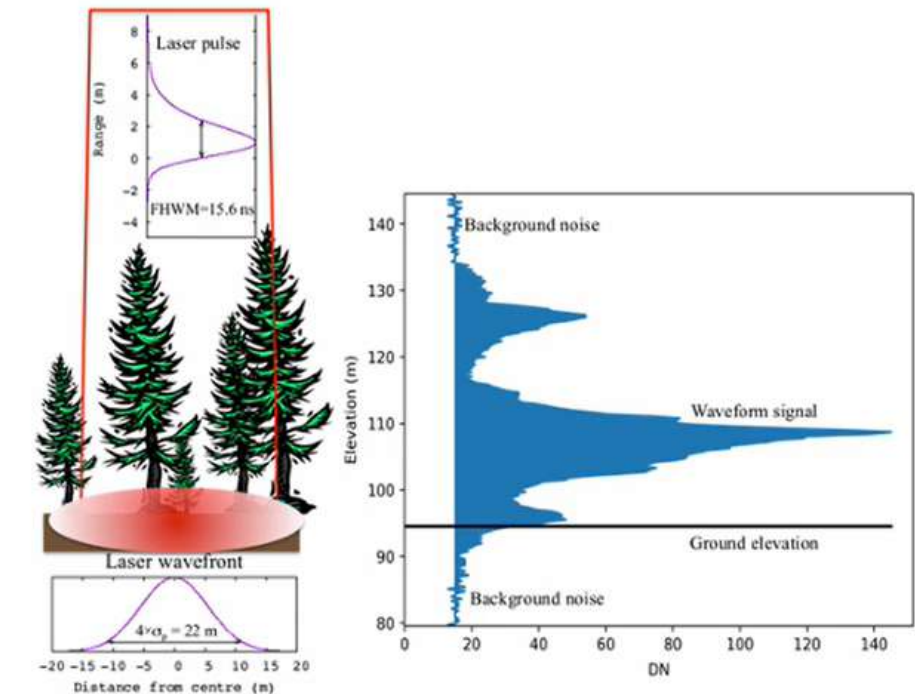
Radar

(Courtesy T. Le Toan)



LiDAR

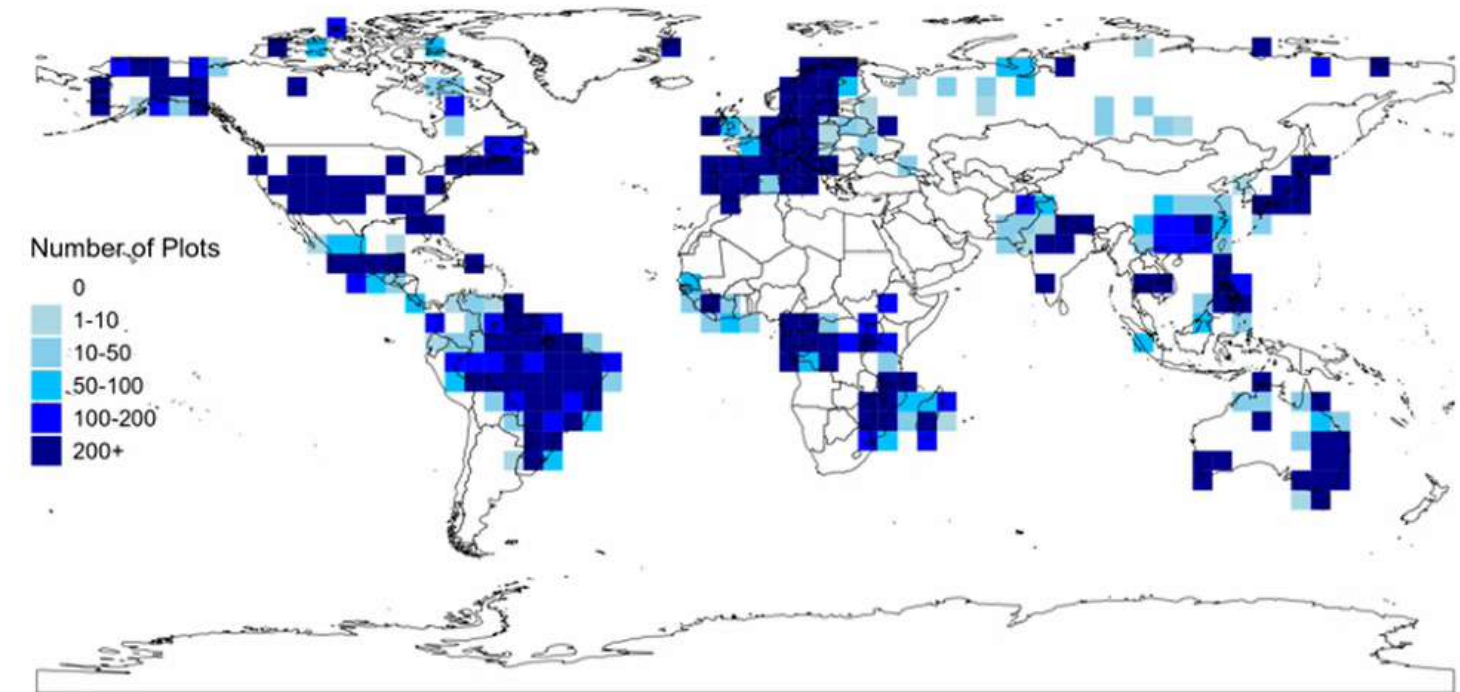
(Hancock et al., RSE, 2019)



Field measurements of biomass

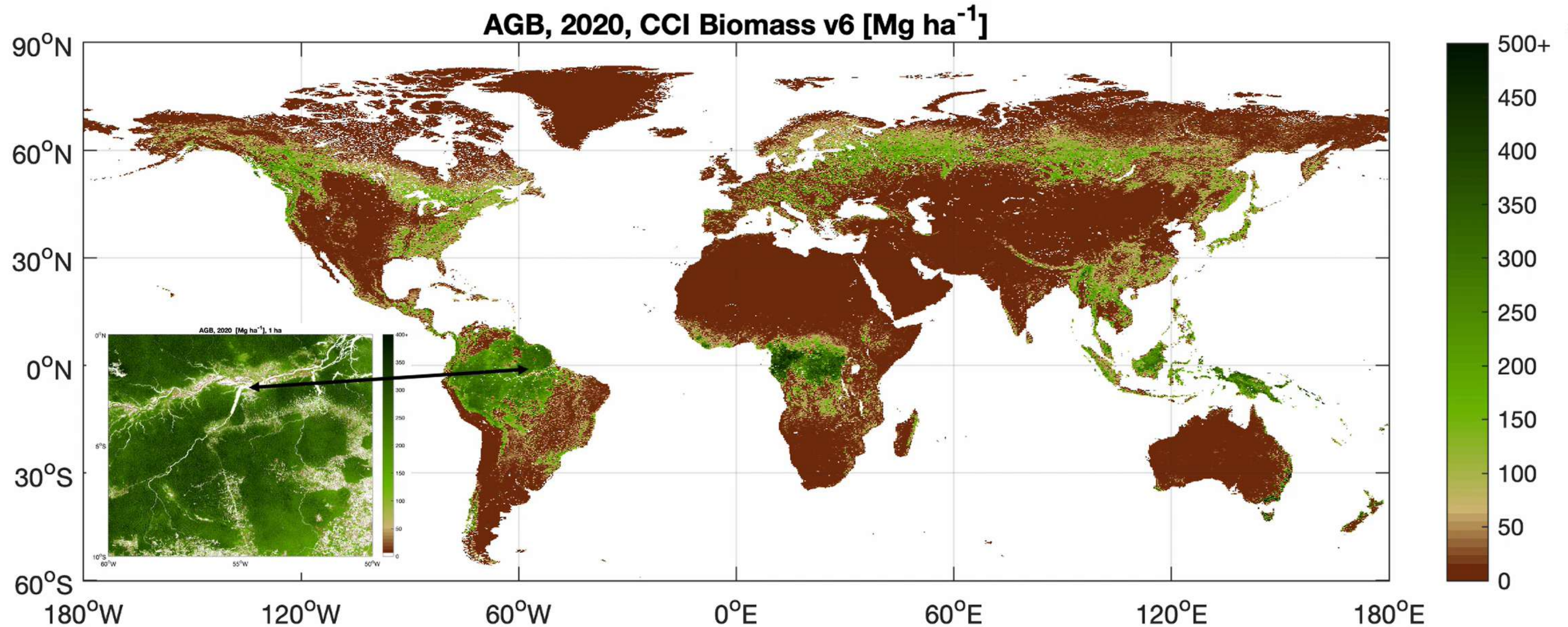
- Measurements from on ground surveys typically form the backbone of a biomass retrieval algorithm
- In practice, access to such data is cumbersome resulting in an uneven geographic distribution
- This constraint also decimates the amount of retrieval models relating space data to biomass

Gridded Heatmap of Plot Count (0.5 deg. Grid)



- In CCI Biomass, biomass is estimated without reference plot measurements

The CCI Biomass AGB product

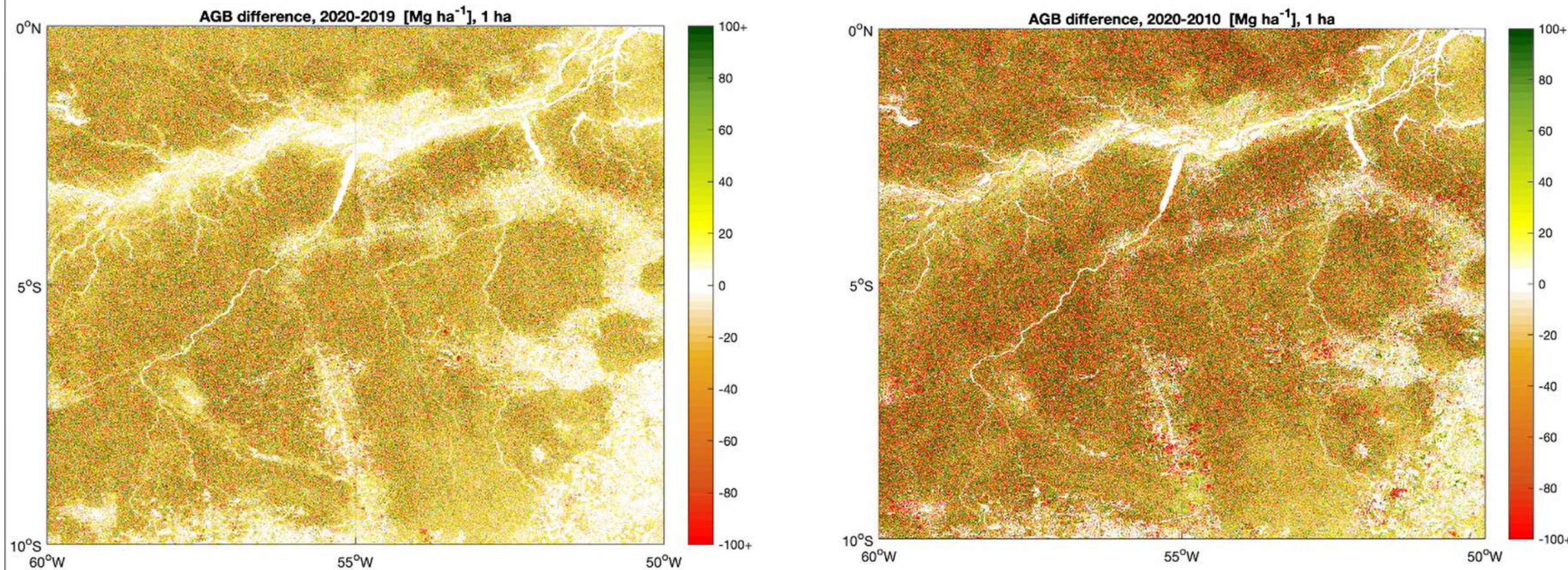


The CCI Biomass AGB change product

- AGB change = AGB difference between two years
- AGB change is accompanied by the AGB change SD & quality flag layer

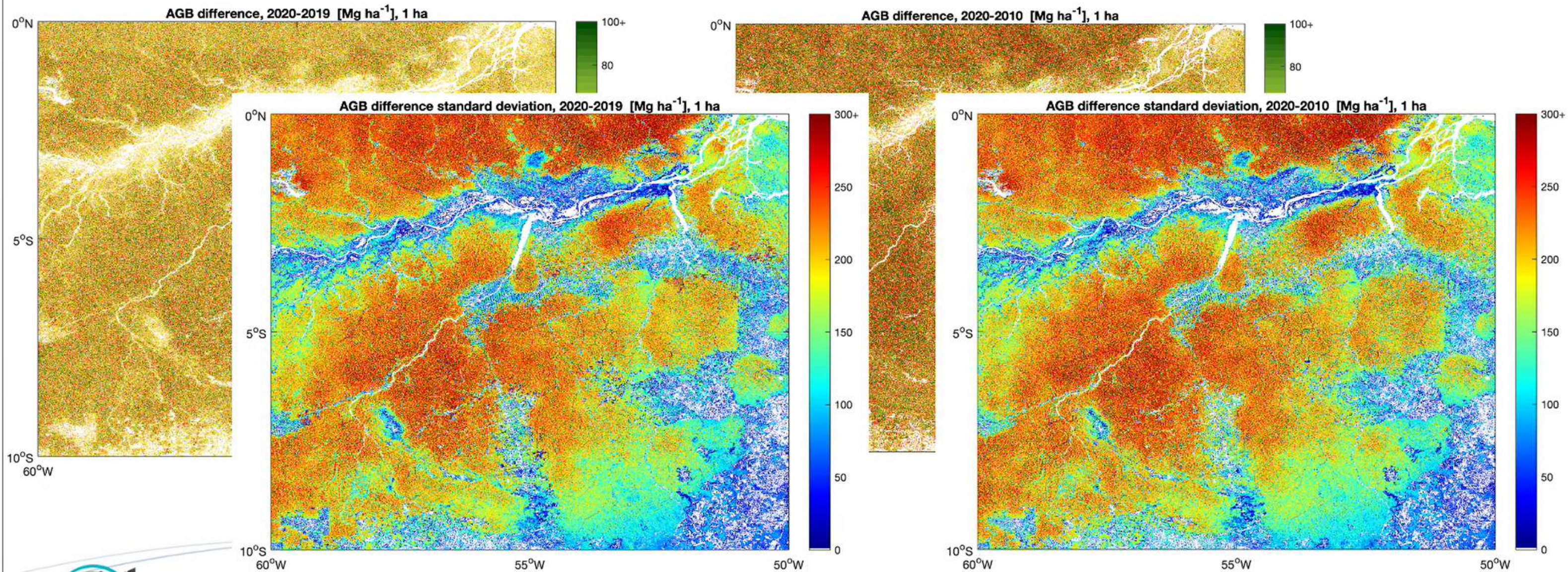
The CCI Biomass AGB change product

- AGB change = AGB difference between two years
- AGB change is accompanied by the AGB change SD & quality flag layer



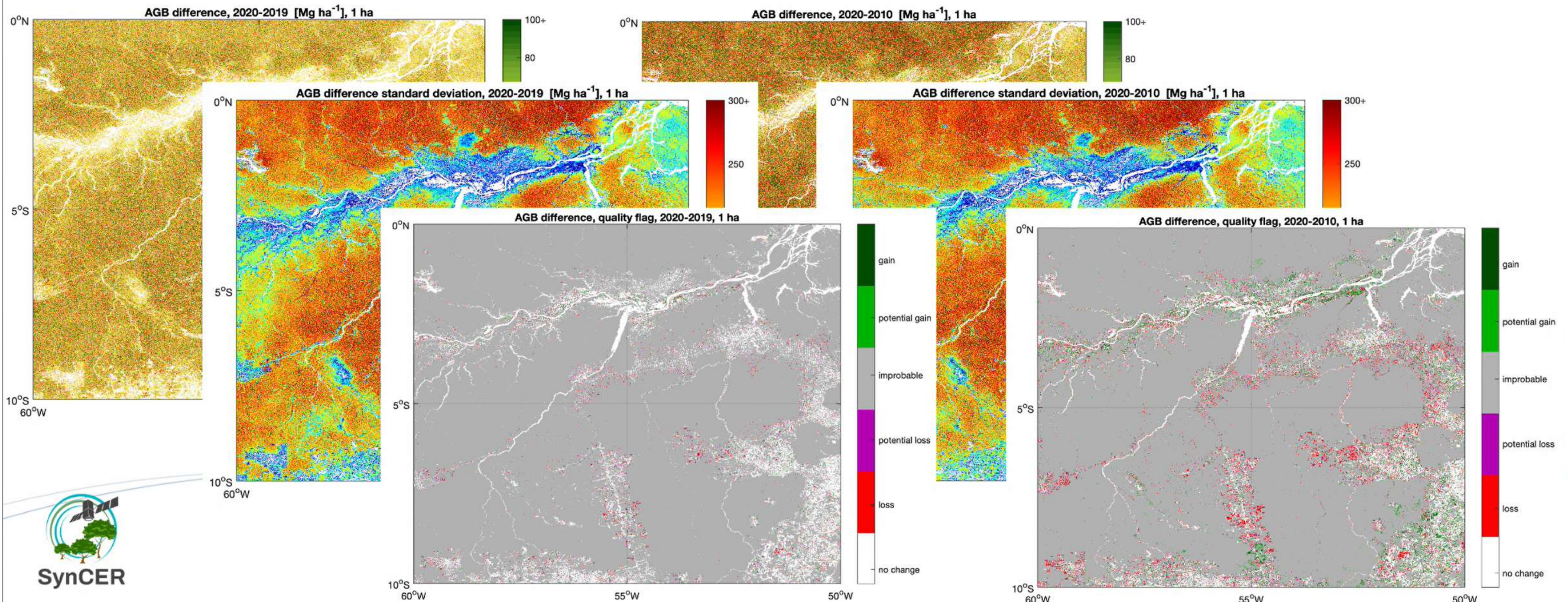
The CCI Biomass AGB change product

- AGB change = AGB difference between two years
- AGB change is accompanied by the AGB change SD & quality flag layer

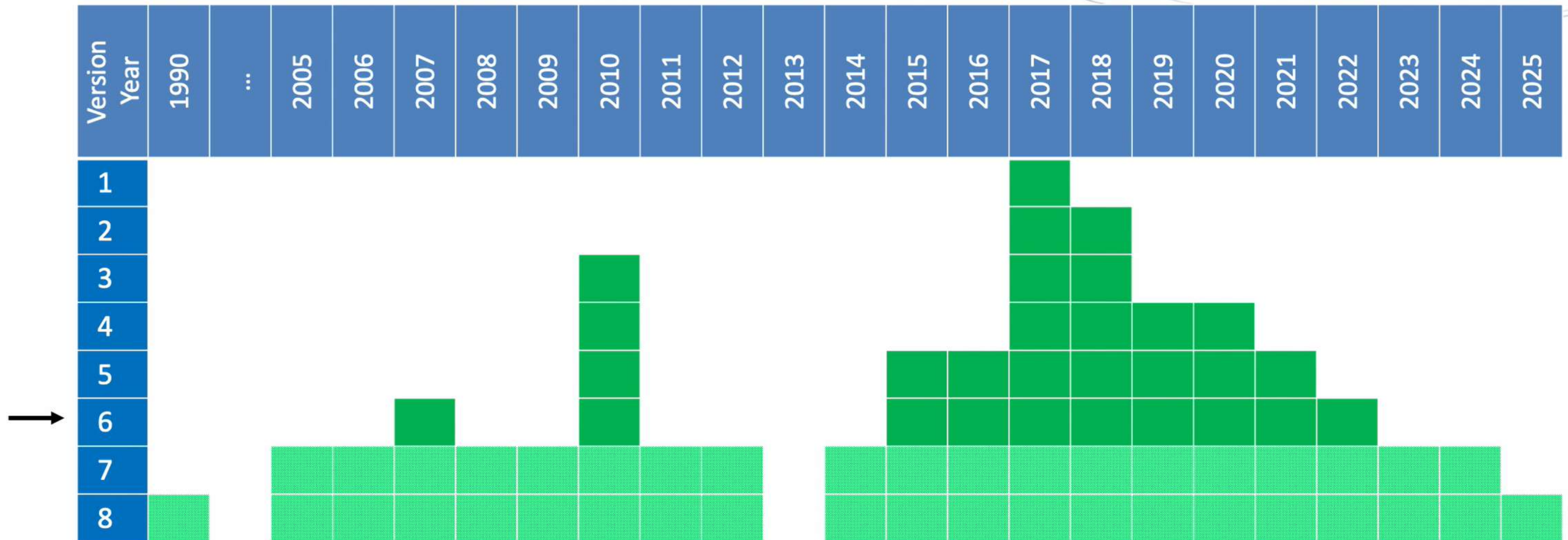


The CCI Biomass AGB change product

- AGB change = AGB difference between two years
- AGB change is accompanied by the AGB change SD & quality flag layer



Timeline of the CCI Biomass dataset



→ v6 is the current release (May 2025)

v7: Release in spring 2026

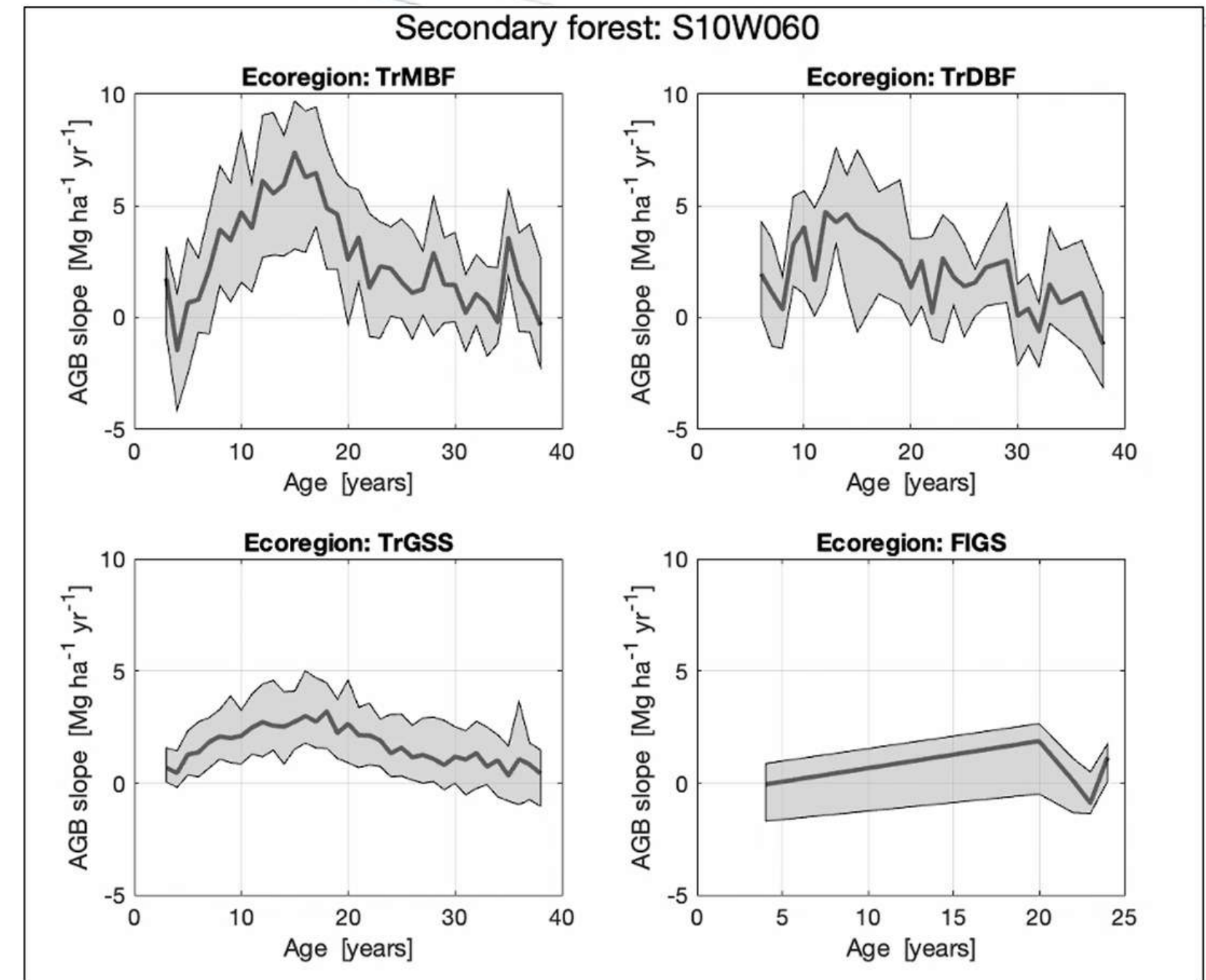
v8: Release in spring 2027

Biomass accumulation from CCI Biomass

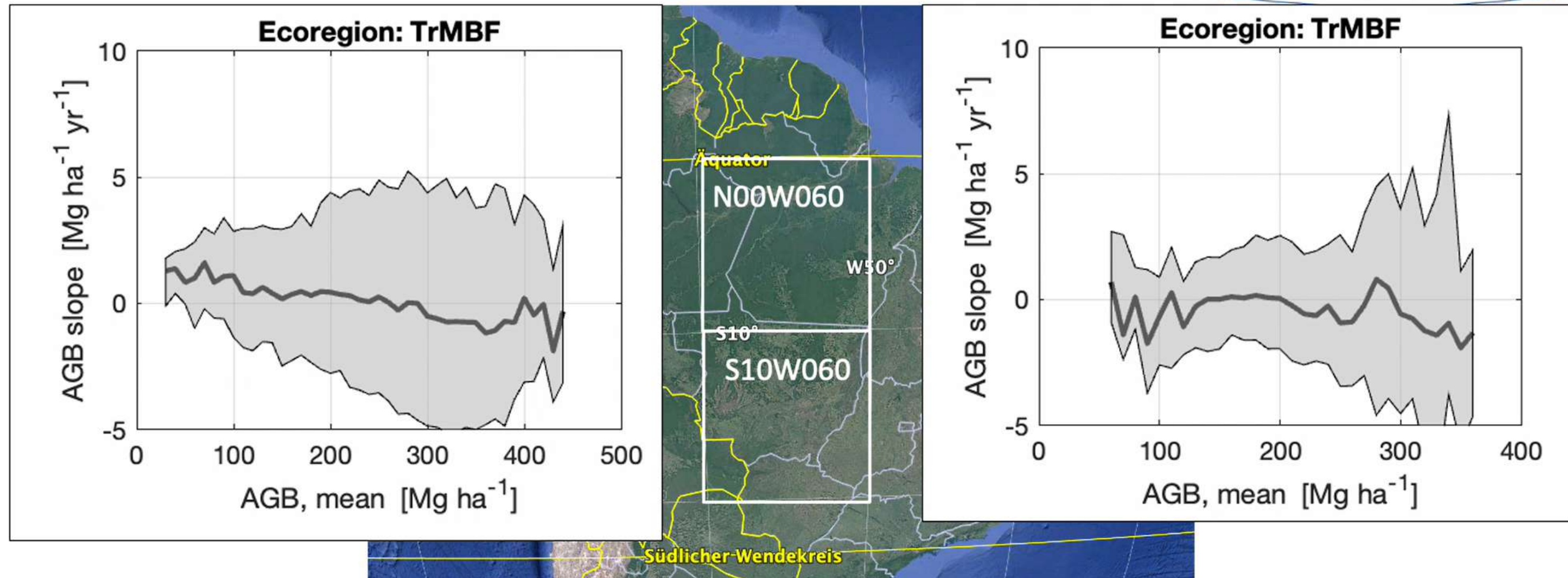
1. For each CCI pixels, we computed the slope coefficient of a linear regression between year of the CCI AGB maps and the AGB values
2. Stratification of slope values (based on MapBiomas datasets)
 - Primary forest / Secondary forest / Plantation / Agroforestry (reference: MapBiomas)
 - Undisturbed forest (once detected as such) (reference: MapBiomas)
 - 10x10 deg latitude/longitude blocks
 - Ecoregion (reference Dinerstein et al., 2017)
3. For each secondary forest pixel (based on MapBiomas) we extracted the age
4. For each primary forest pixel (based on MapBiomas), we computed the average map-based AGB

Regrowth rates from CCI Biomass

- Displaying mean and interquartile range of slope values per age of secondary forest
- The parabolic shape is consistent across Brazil but the peak differs, being higher in the NW than in the SE.



What happens in primary forests?

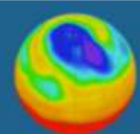


Is this real or is it an artefact of the CCI Biomass maps?

Conclusions

1. The CCI Biomass dataset is valuable to identify spatial and temporal patterns
2. The dataset should not be used at the pixel level!!
3. The AGB changes between two years make sense only for fast losses or fast growth (young forest, plantation)
4. The regrowth rates in secondary forests appear to be realistic (see also talk by M. Urbazaev)
5. The trends detected in primary forests need to be taken with care!!
6. Future versions of CCI Biomass will reinforce our initial interpretation of the biomass trajectories

Access to the CCI Biomass datasets



CEDA
Archive

[About](#) [News](#) [Search Catalogue](#) [Get Data](#) [Deposit](#) [Tools](#)



ESA Biomass Climate Change Initiative
(Biomass_cci): Global datasets of forest above-ground biomass for the years 2007, 2010, 2015, 2016, 2017, 2018, 2019, 2020, 2021 and 2022, v6.0

Permitted Use: Any



Open Access



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Abstract

This dataset comprises estimates of forest above-ground biomass (AGB) for the years 2007, 2010, 2015, 2016, 2017, 2018, 2019, 2020, 2021 and 2022. They are derived from a combination of Earth observation data, depending on the year, from the Copernicus Sentinel-1 mission, Envisat's ASAR (Advanced Synthetic Aperture Radar) instrument and JAXA's (Japan Aerospace Exploration Agency) Advanced Land Observing Satellite (ALOS-1 and ALOS-2), along with additional information from Earth observation sources. The data has been produced as part of the European Space Agency's (ESA's) Climate Change Initiative (CCI) programme by the Biomass CCI team.

This release of the data is version 6. Compared to version 5, version 6 consists of an update of the maps of AGB for the years 2010, 2015, 2016, 2017, 2018, 2019, 2020, 2021 and new AGB maps for 2007 and 2022. AGB change maps have been created for consecutive years (e.g., 2020-2019), for a decadal interval (2020-2010) as well as for the interval 2010-2007. The pool of remote sensing data includes multi-temporal observations at L-band for all biomes and for all years and extended ICESat-2 observations to calibrate retrieval models. A cost function that preserves the temporal features as expressed in the remote sensing data.

Citable as: Santoro, M.; Cartus, O. (2025): ESA Biomass Climate Change Initiative (Biomass_cci): Global datasets of forest above-ground biomass for the years 2007, 2010, 2015, 2016, 2017, 2018, 2019, 2020, 2021 and 2022, v6.0. NERC EDS Centre for Environmental Data Analysis, 17 April 2025. doi:10.5285/95913ffb6467447ca72c4e9d8cf30501.

<https://dx.doi.org/10.5285/95913ffb6467447ca72c4e9d8cf30501>



EO-based forest carbon removals and emissions in Amazon

Yidi Xu (Online)

Session 2.2: Other metrics for identifying secondary forest success

São José dos Campos, 30 Oct 2025





EO-based forest carbon removals and emissions in Amazon

Yidi Xu, Liang Wan, Philippe Ciais

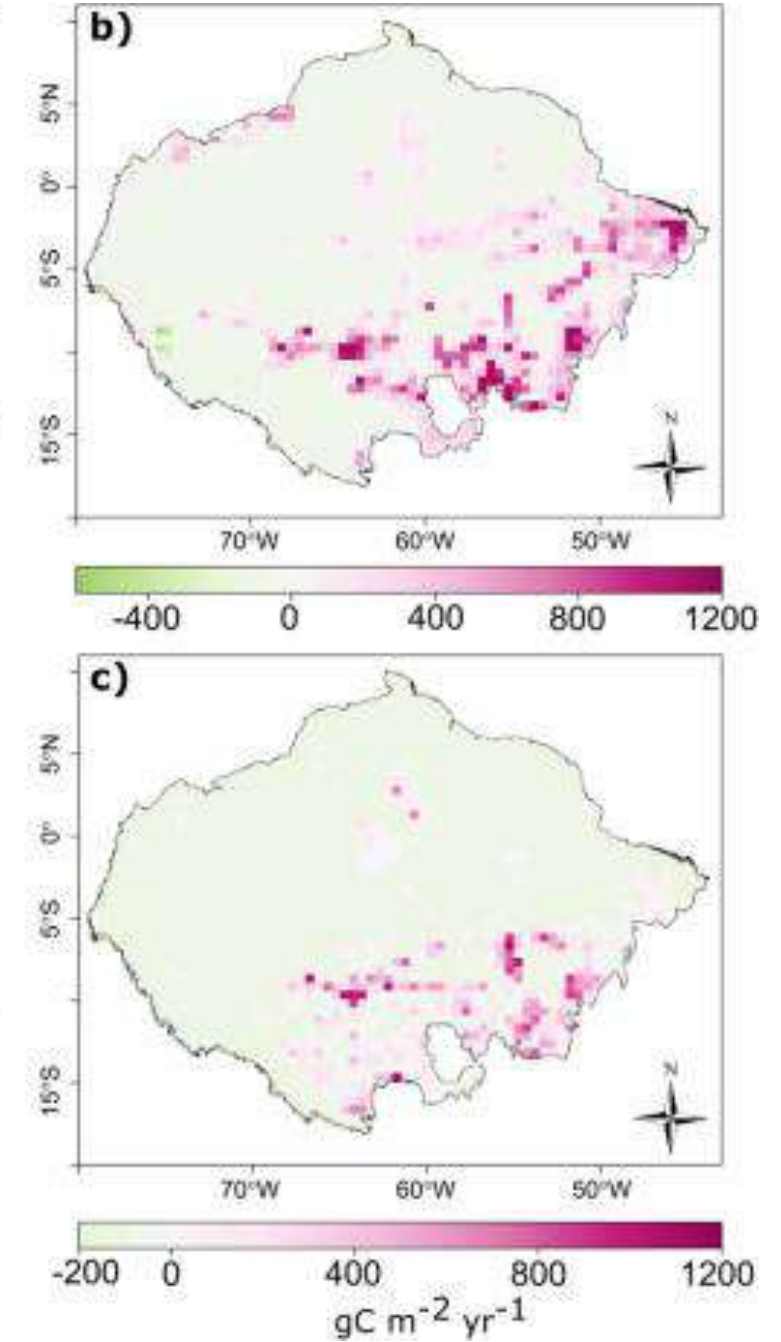
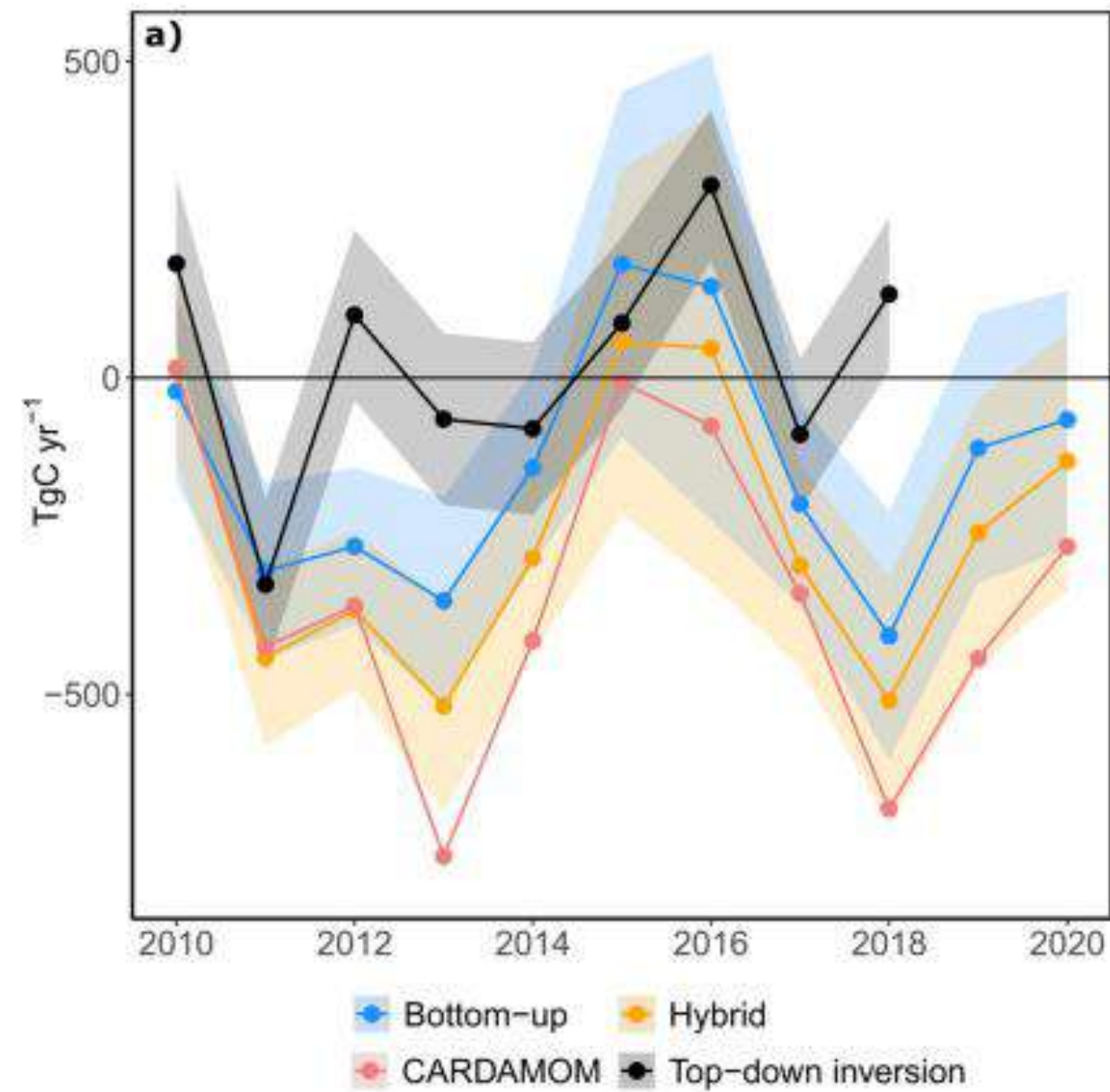
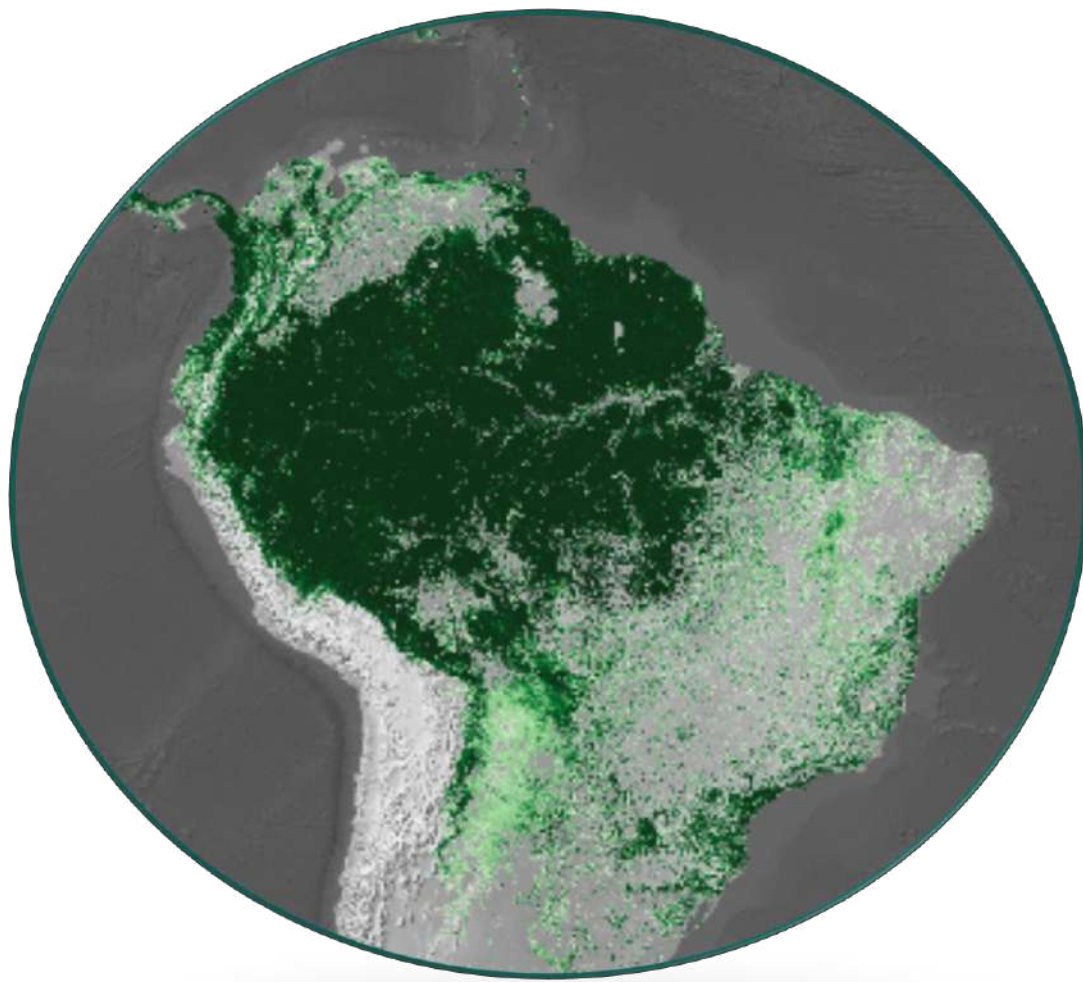
Laboratory for Climate and Environmental Sciences, France

2025.10.29

Background

Amazon: globally important carbon stocks

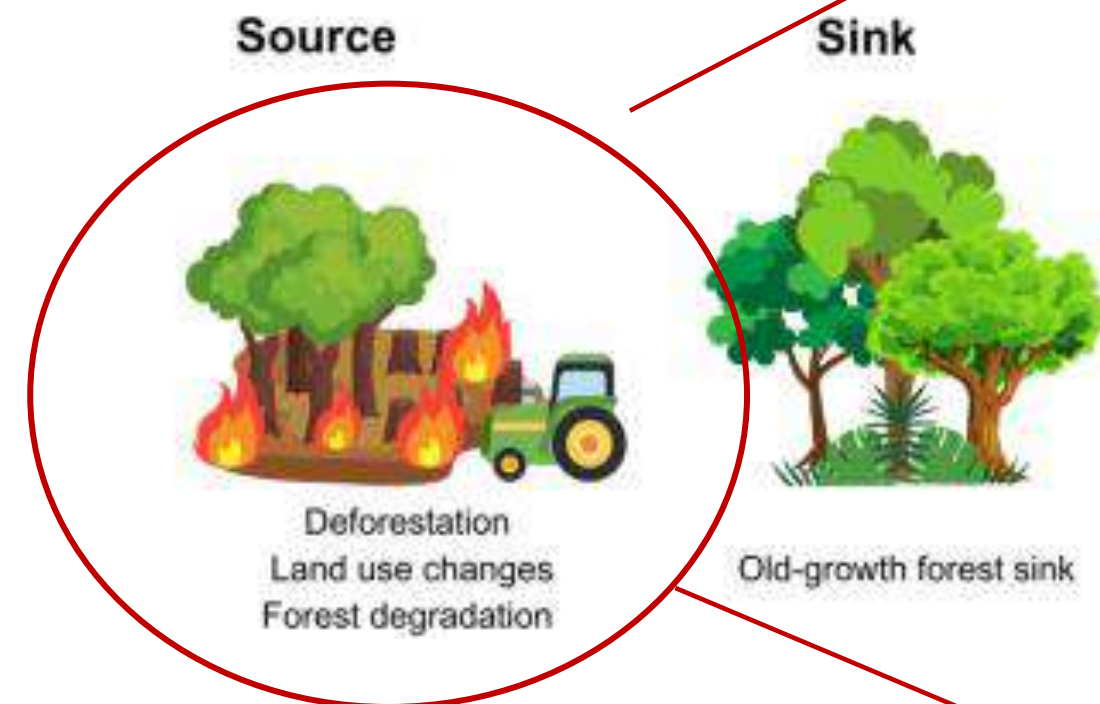
C sink? C sources ?



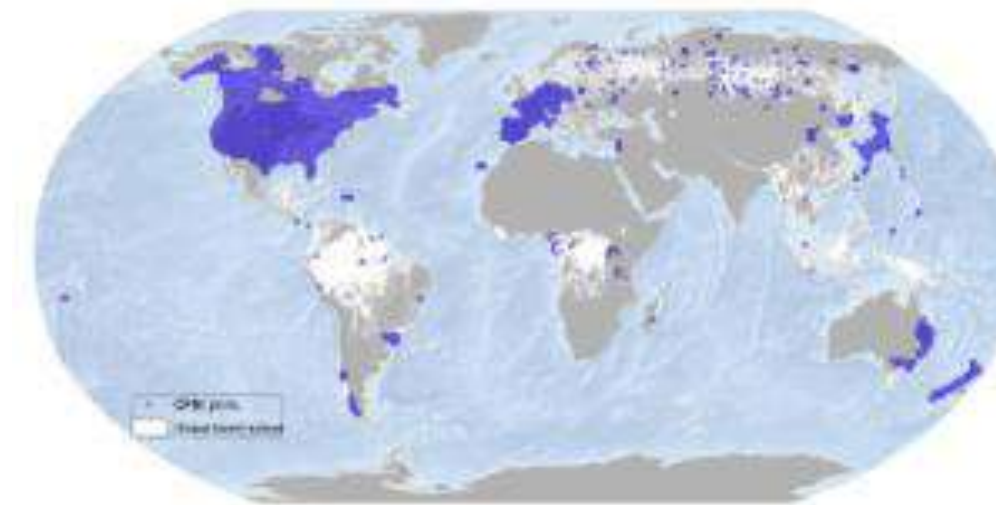
Rosan et al., 2024

Background

Bottom-up BK model DGVM simulation

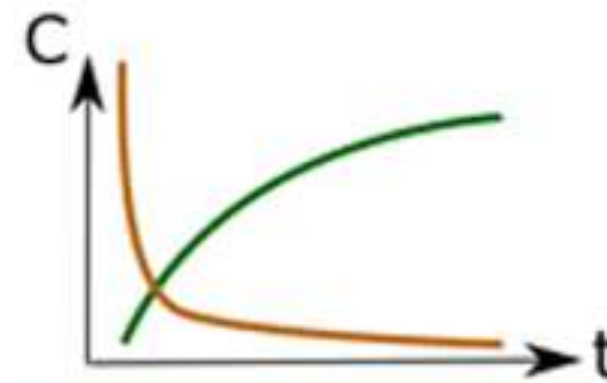


Rosan et al., 2024

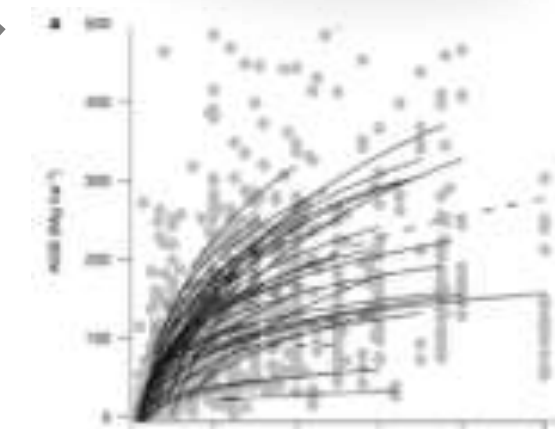
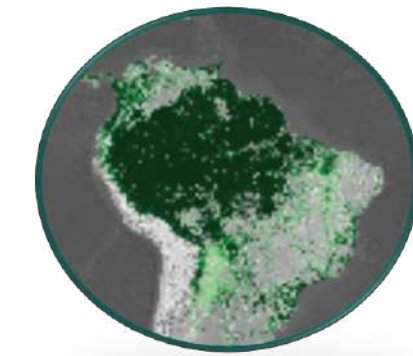


Sparse Inventory plot in tropics

Response curves



Regional response curves
used in BK models



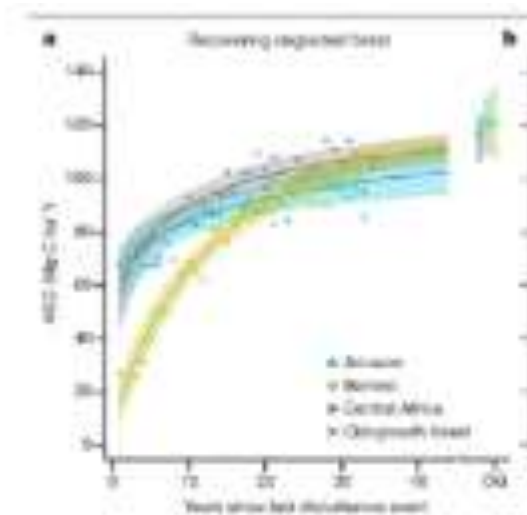
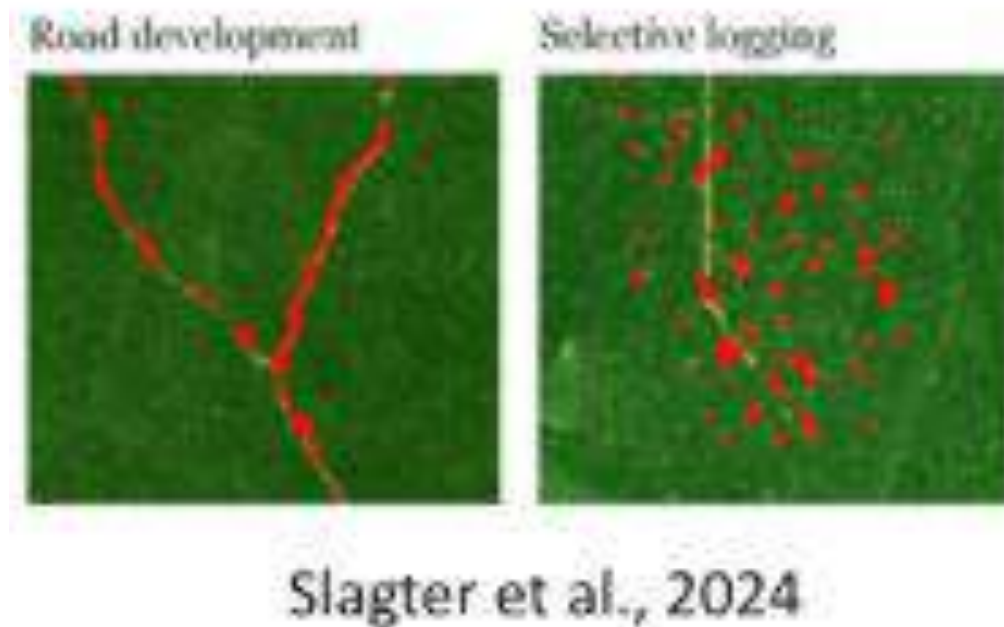
(Poorter et al., 2016)

Background

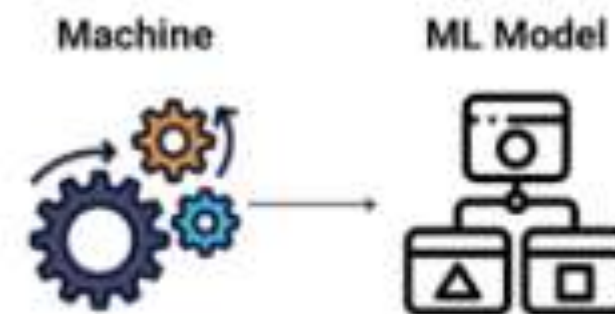
Satellite approach



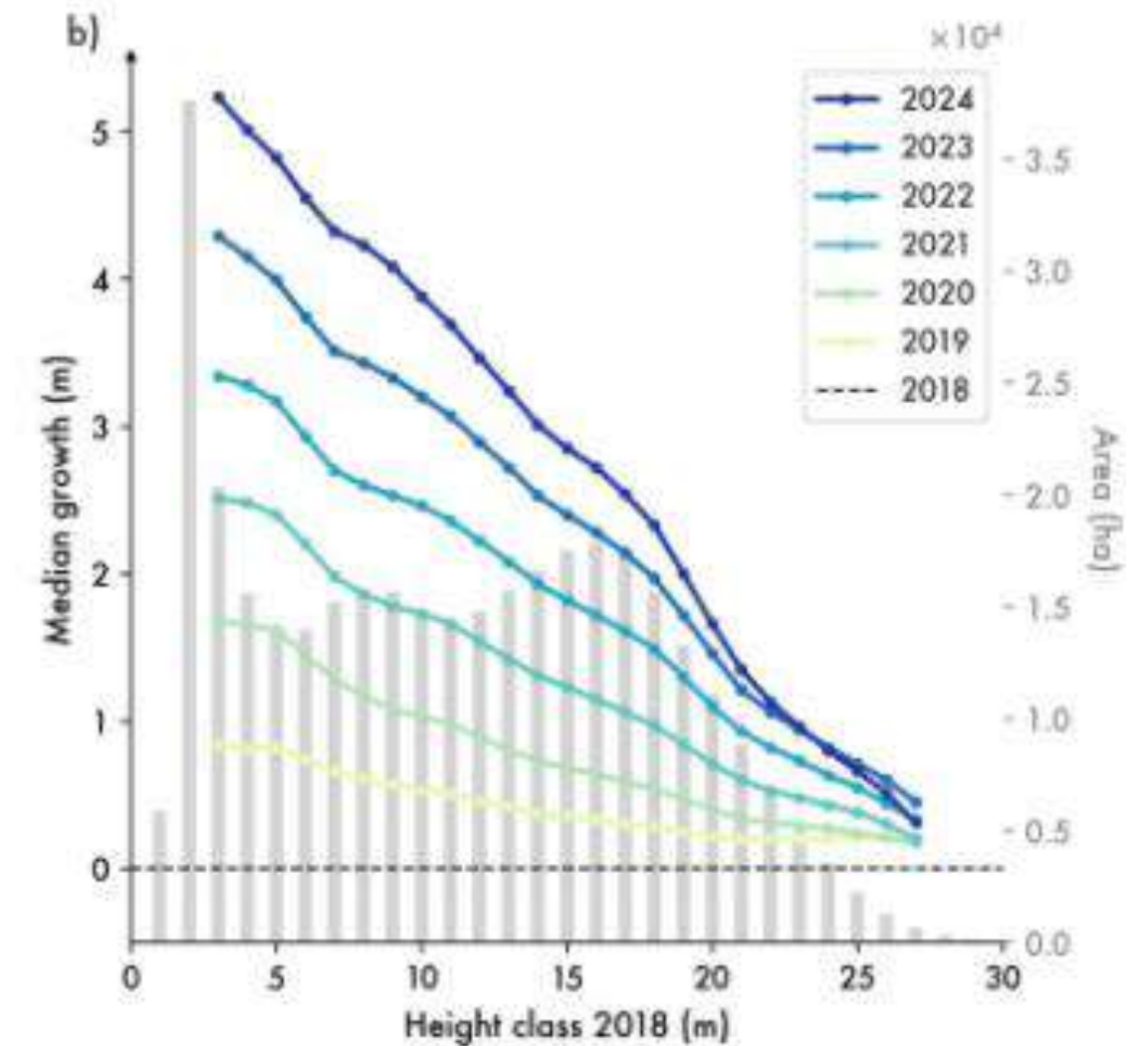
- 1) Improve the BK model with spatially-explicit regrowth curves
- 2) Annual canopy height and biomass mapping



(Heinrich et al., 2023;
Holcomb et al., 2024)



(Cook-patton, 2020; Nathinial et al., 2025)



(Schwarz et al., 2025)

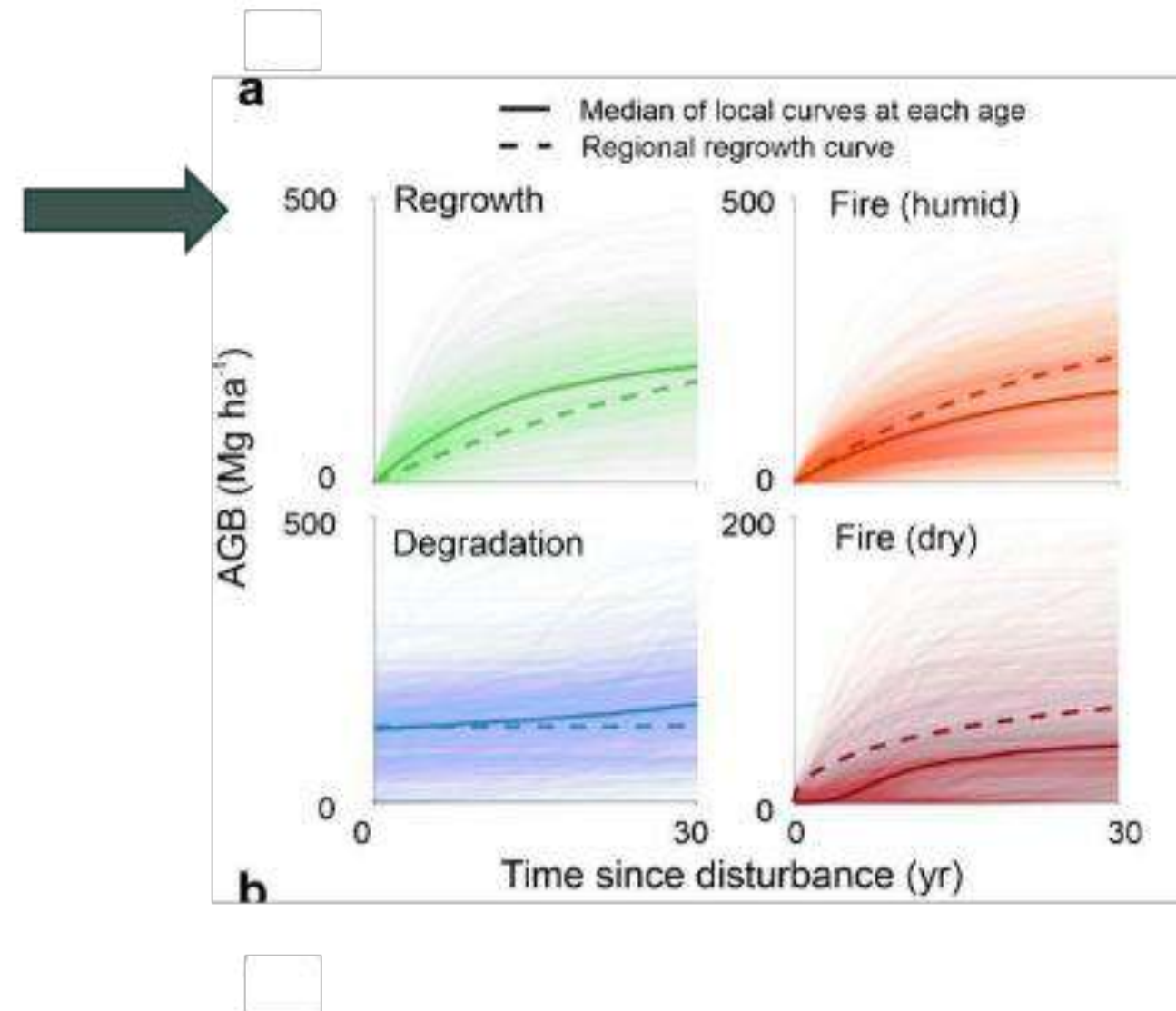
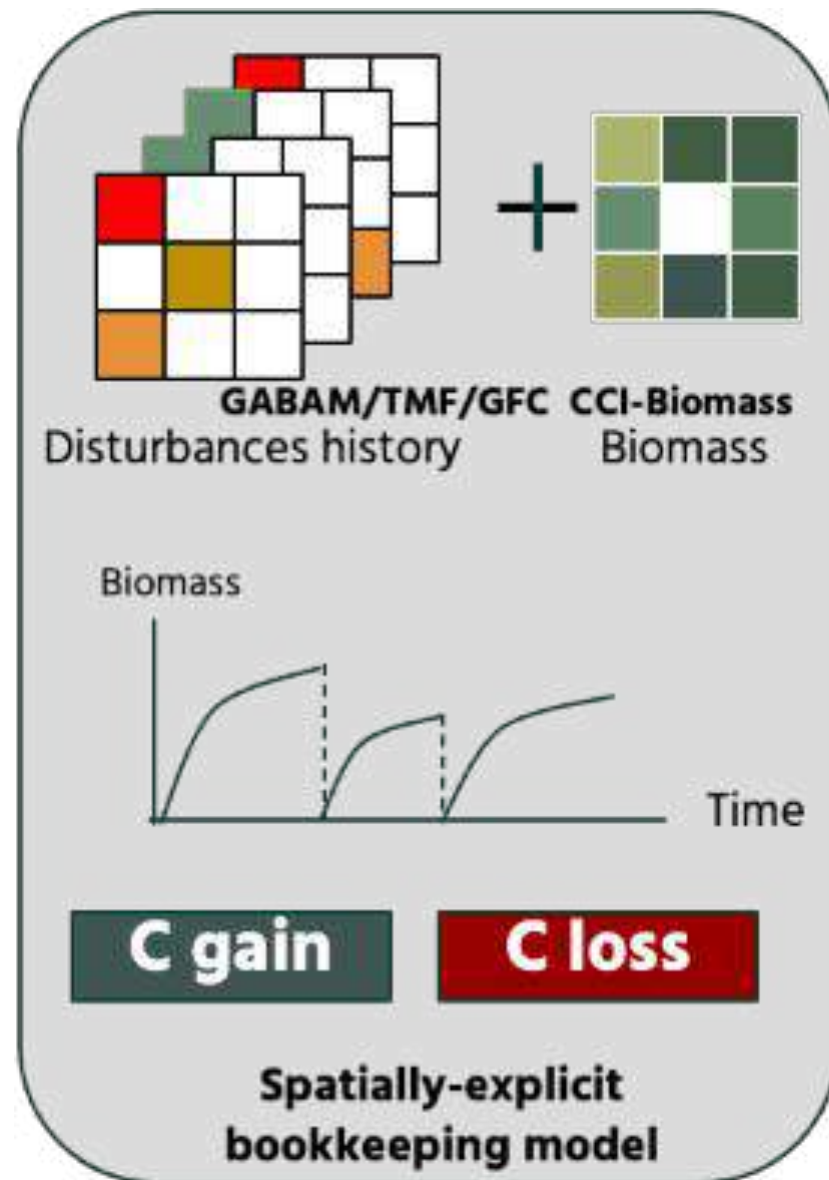
Small size disturbance

Satellite-based regrowth curve

Yearly CH growth of French forest

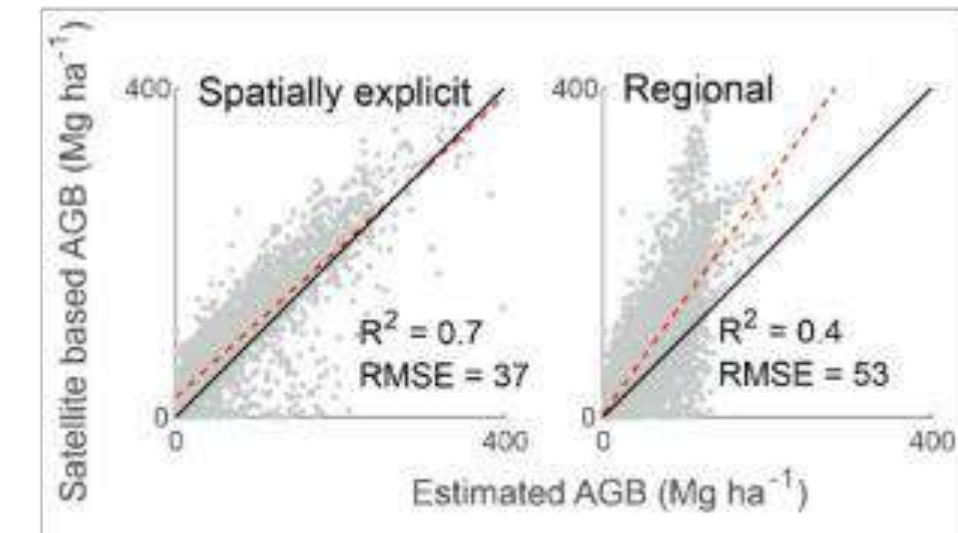
1. Gain-loss method: A spatially-explicit BK model

- Tropical disturbances + ESA CCI Biomass + space-for-time (1990-2020)
- Spatially-explicit BK model performs better than the model based on a continental-average curve



Performance

$$AGB_{2020} = \sum_{t=1990}^{2020} \left(\sum_{ti=0}^p \left[GR_{ti+1} - GR_{ti} \right] - \Delta AGB(t) \right)$$

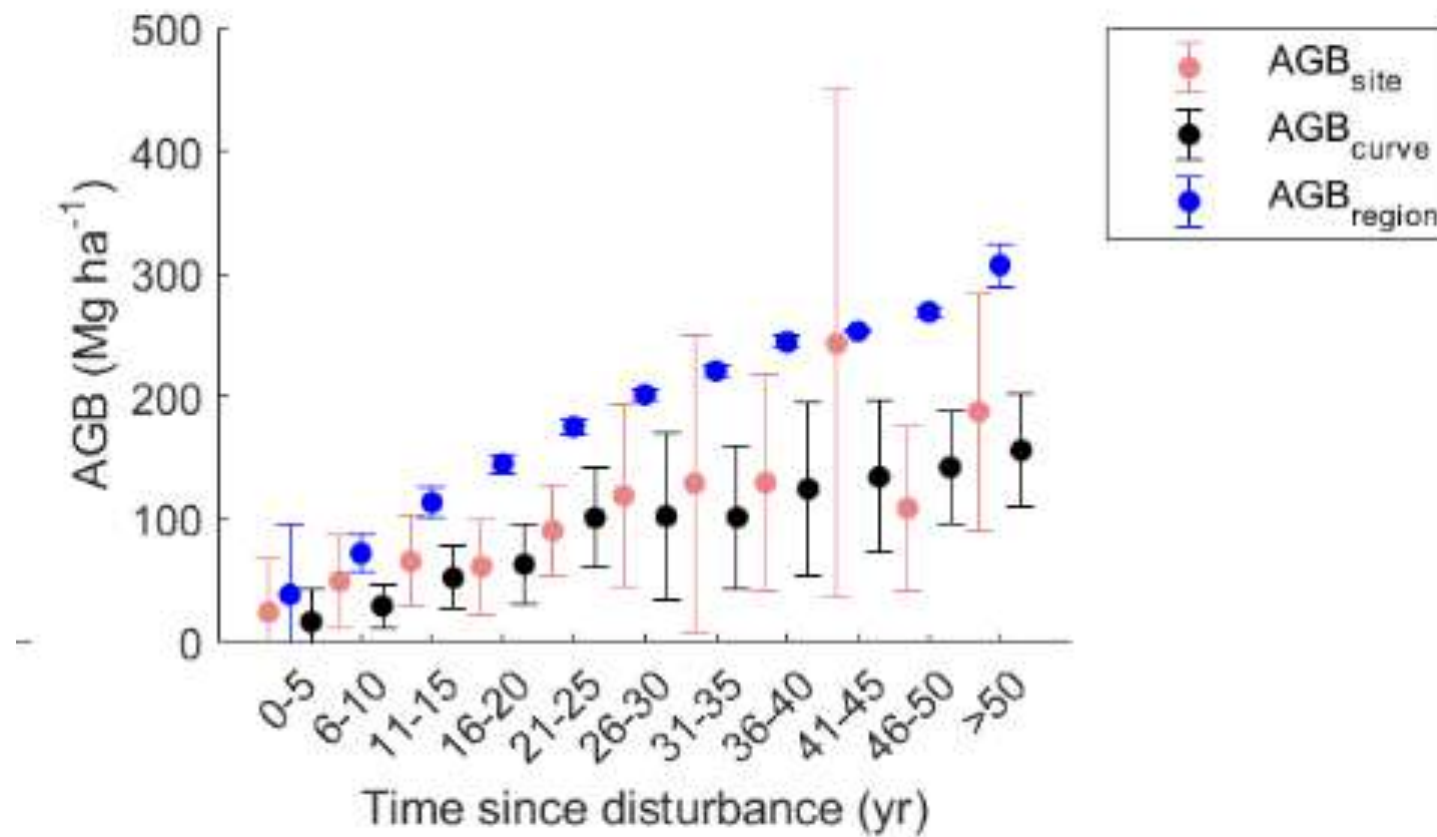


1. Gain-loss method: A spatially-explicit BK model

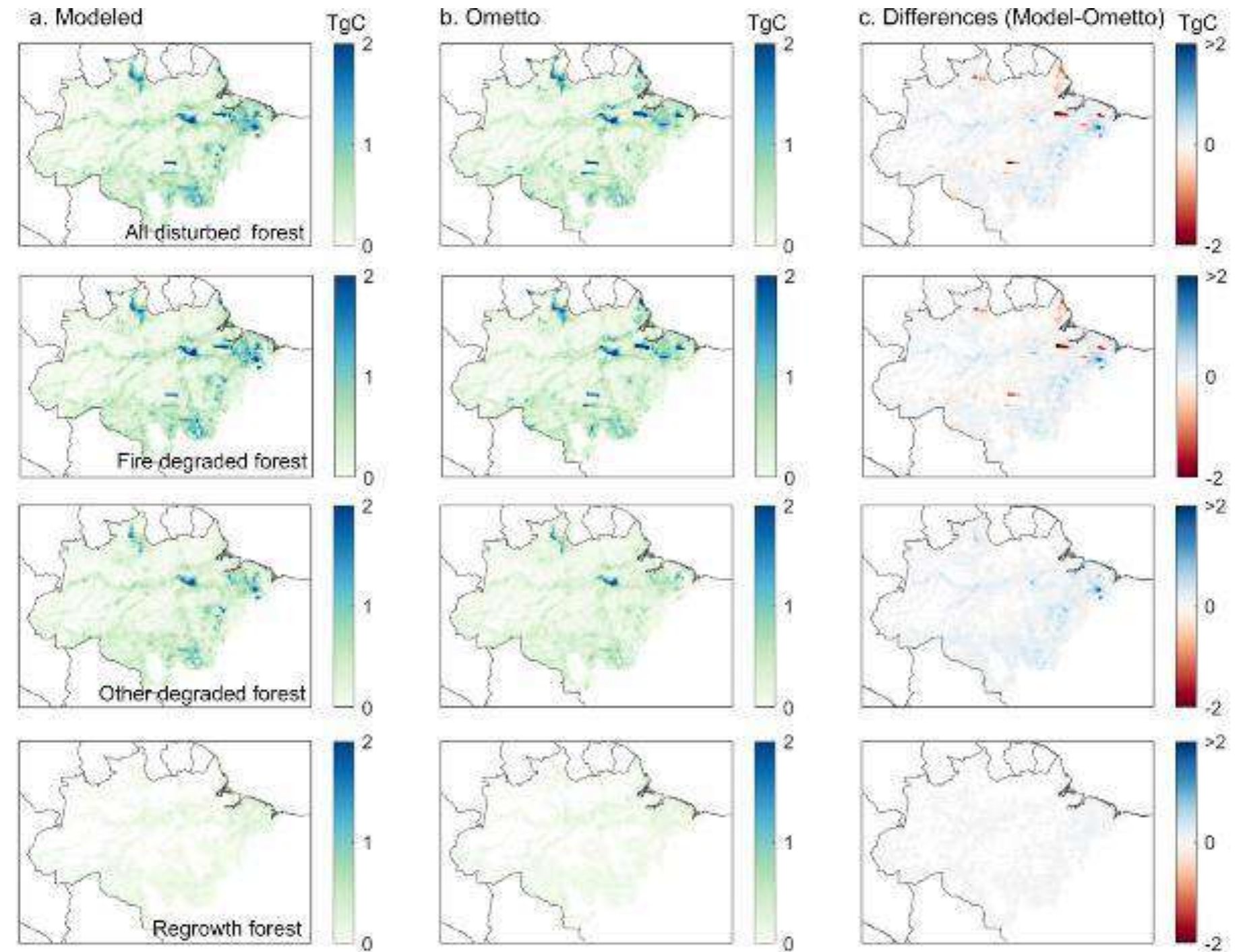
Ours modeled AGC for disturbed pixels

Independent Lidar based Biomass (Ometto et al)

Outperforms the continental curves



The Spatially-explicit BK model can reproduce the biomass for disturbed forests following different disturbances

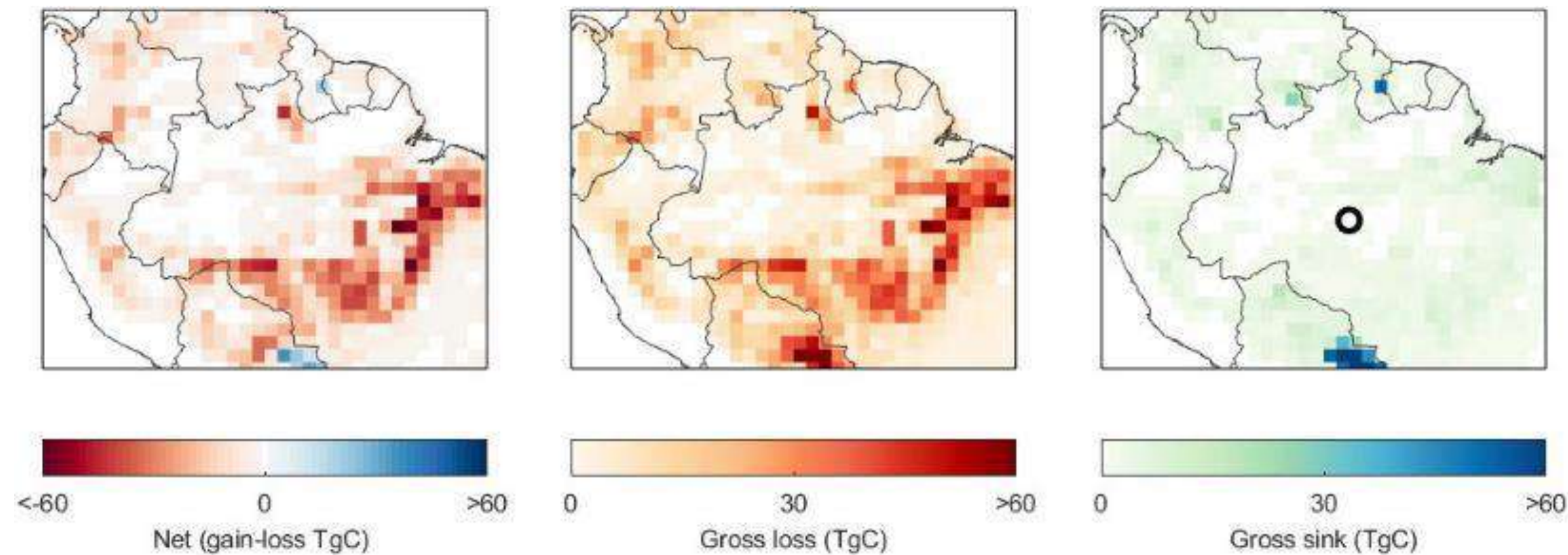


1. Gain-loss method: A spatially-explicit BK model

Carbon budgets from 1990-2020:

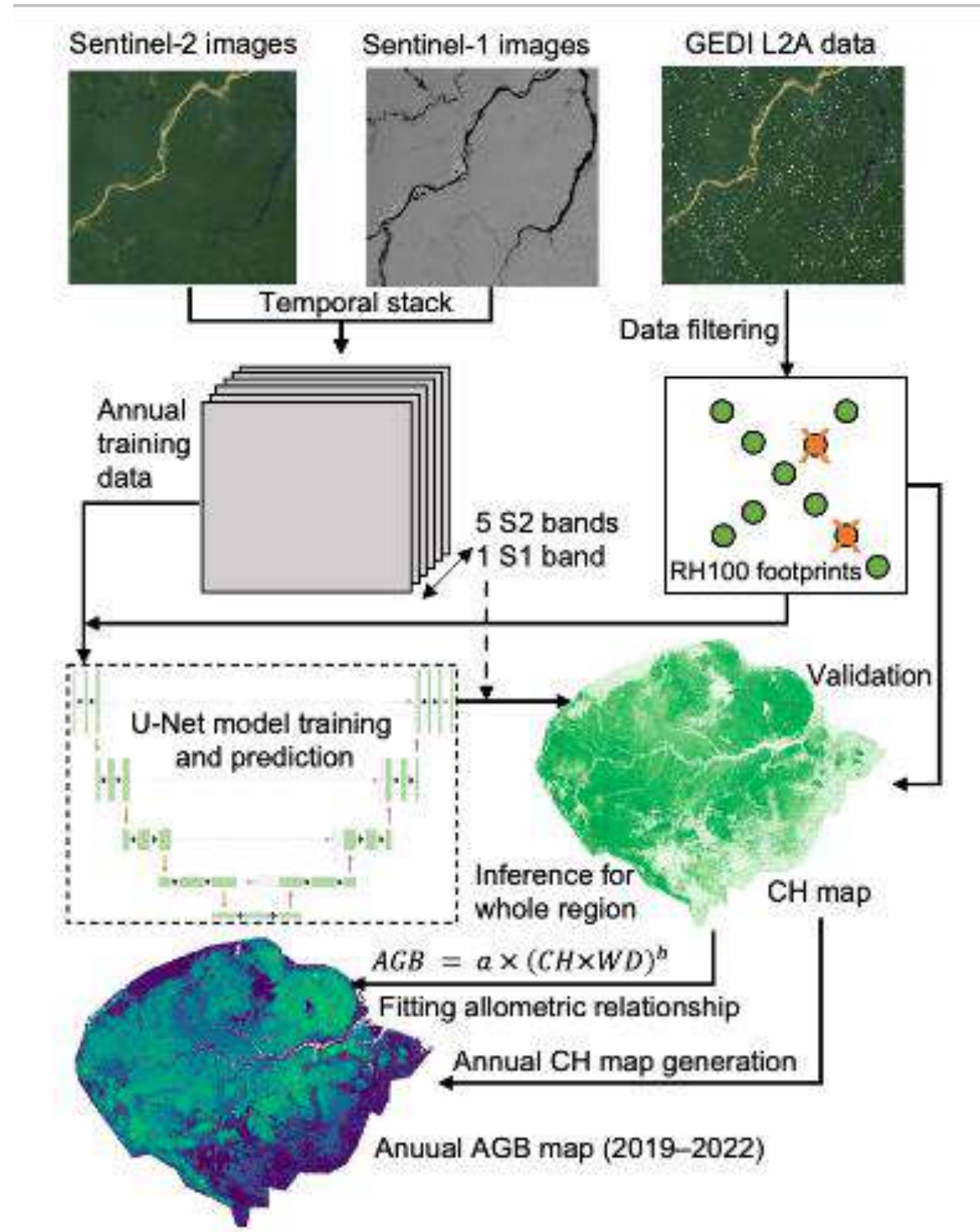
Biogeographical Amazon

Gross gain: 1.4 Pg C ; Gross loss: -6.2 Pg C ; Net: -4.9 Pg C (161.8 TgC/yr)

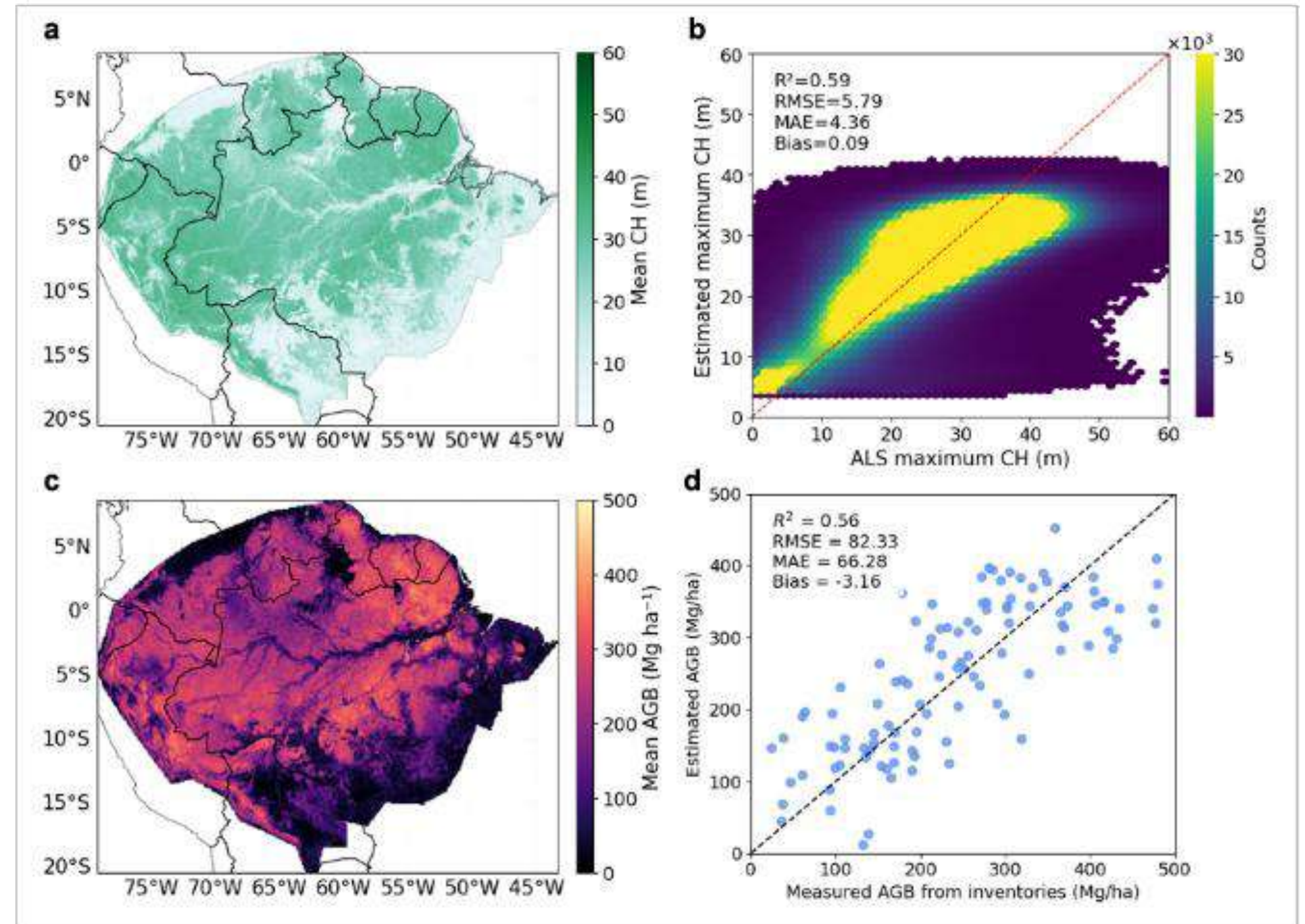


2. High-resolution mapping of forest height and biomass

Mapping framework for forest height and biomass mapping from 2019-2022



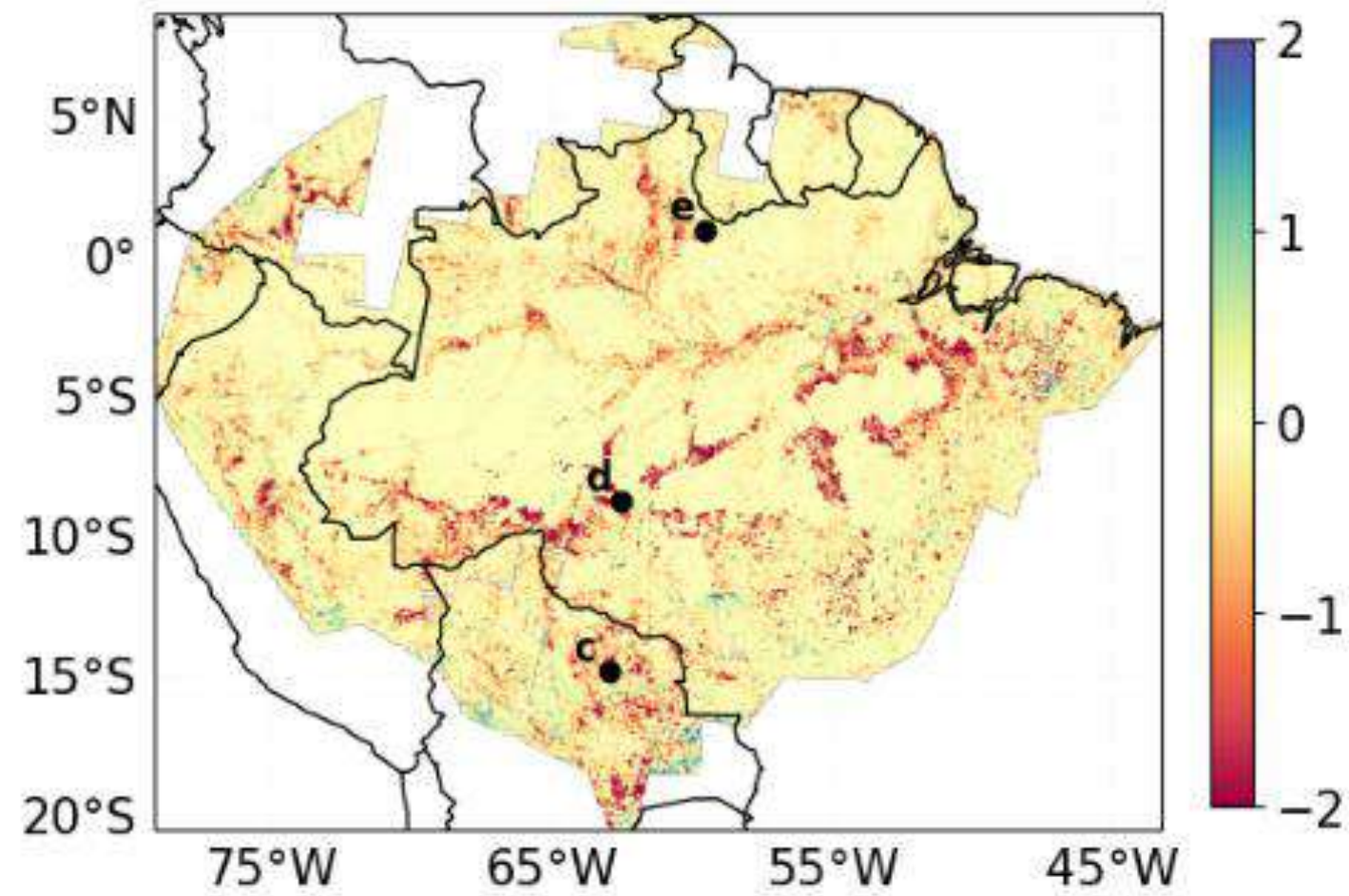
Mapping framework



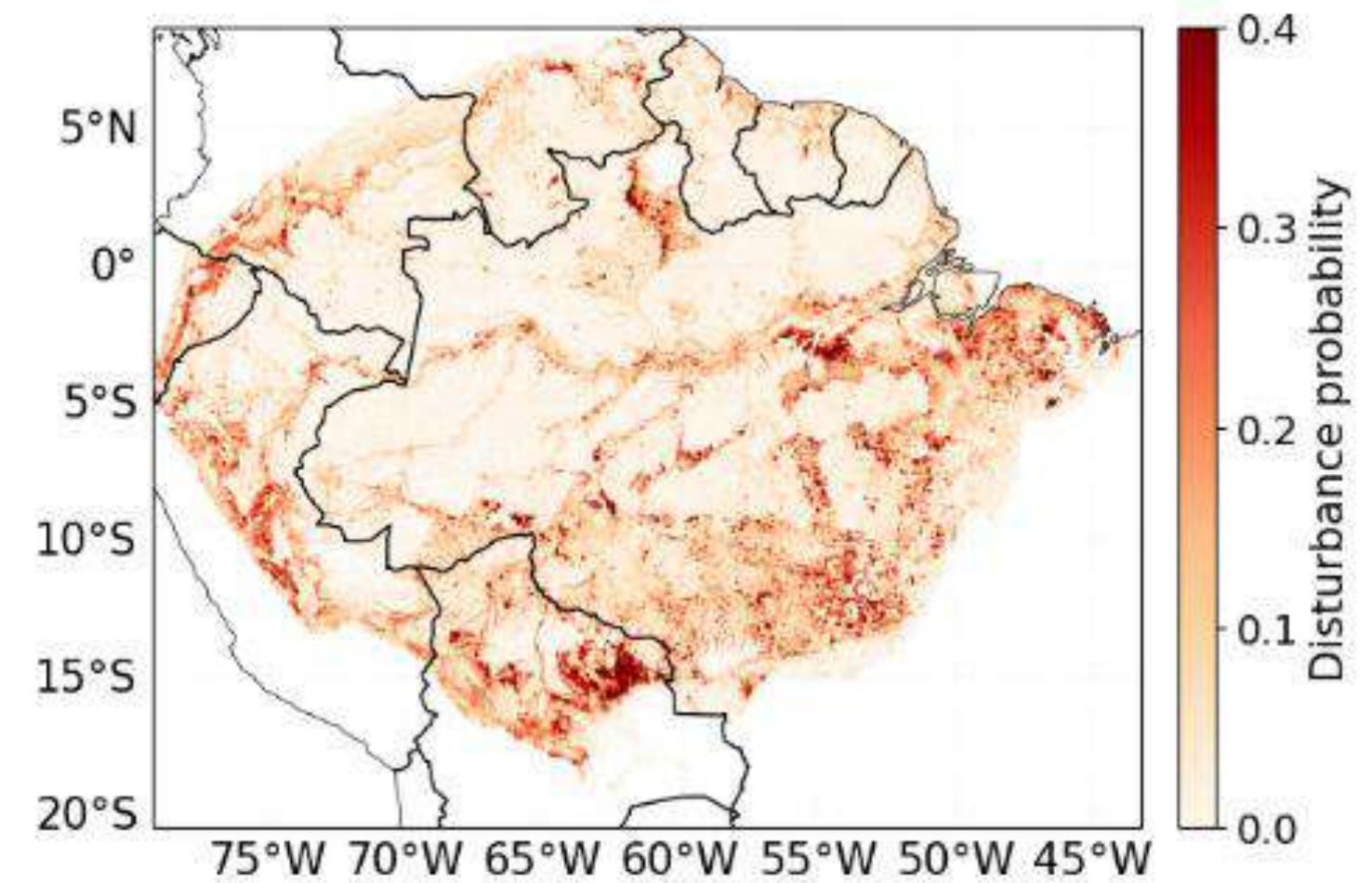
Validation of canopy height (10 m) and biomass (30 m) maps

Height changes mapping and the comparison with other products

New height change map (10 m) from 2019 to 2022



Our Height change maps (10m)



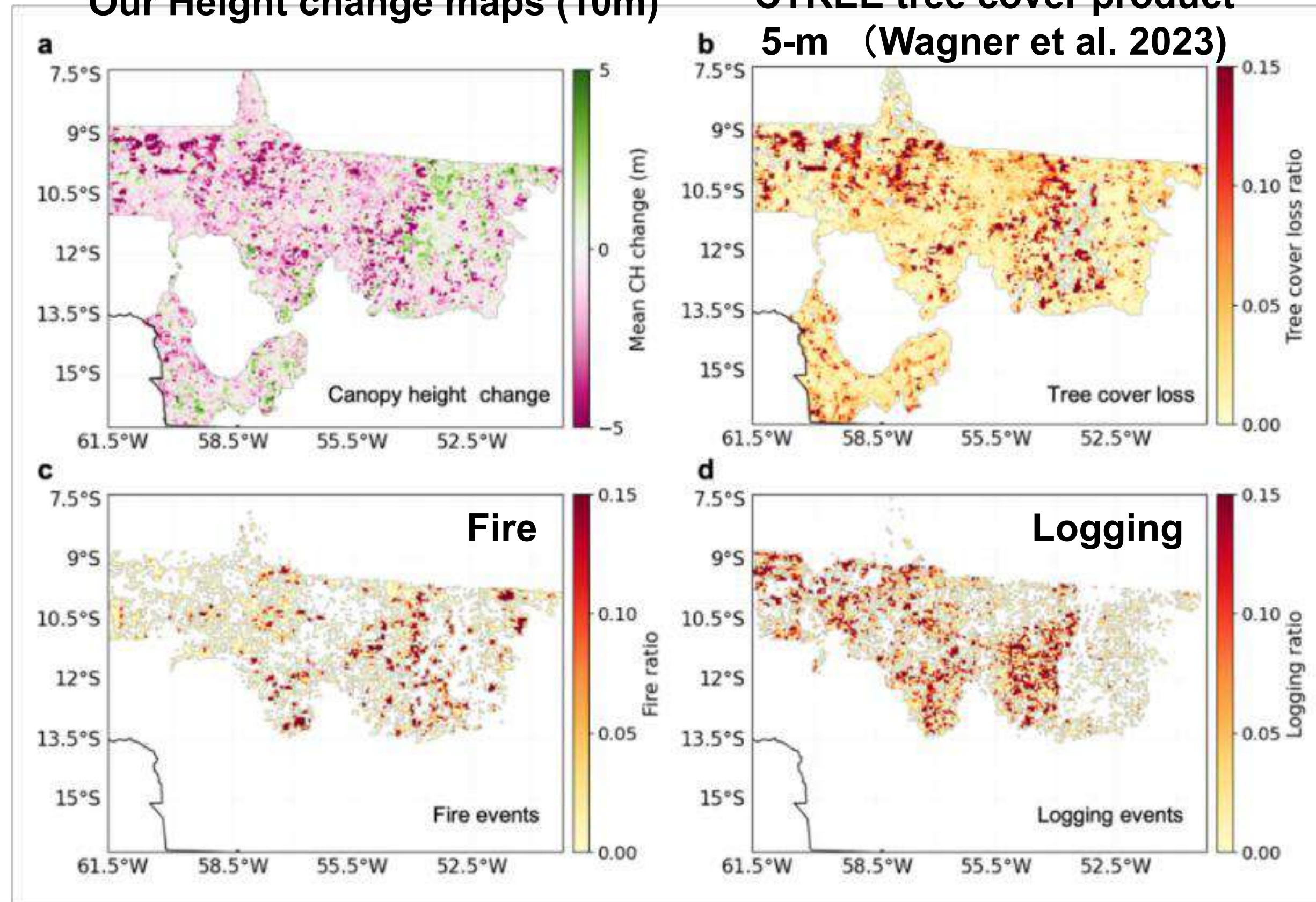
TMF disturbance

Height changes mapping and the comparison with other products

Mato Grosso

Our Height change maps (10m)

CTREE tree cover product
5-m (Wagner et al. 2023)



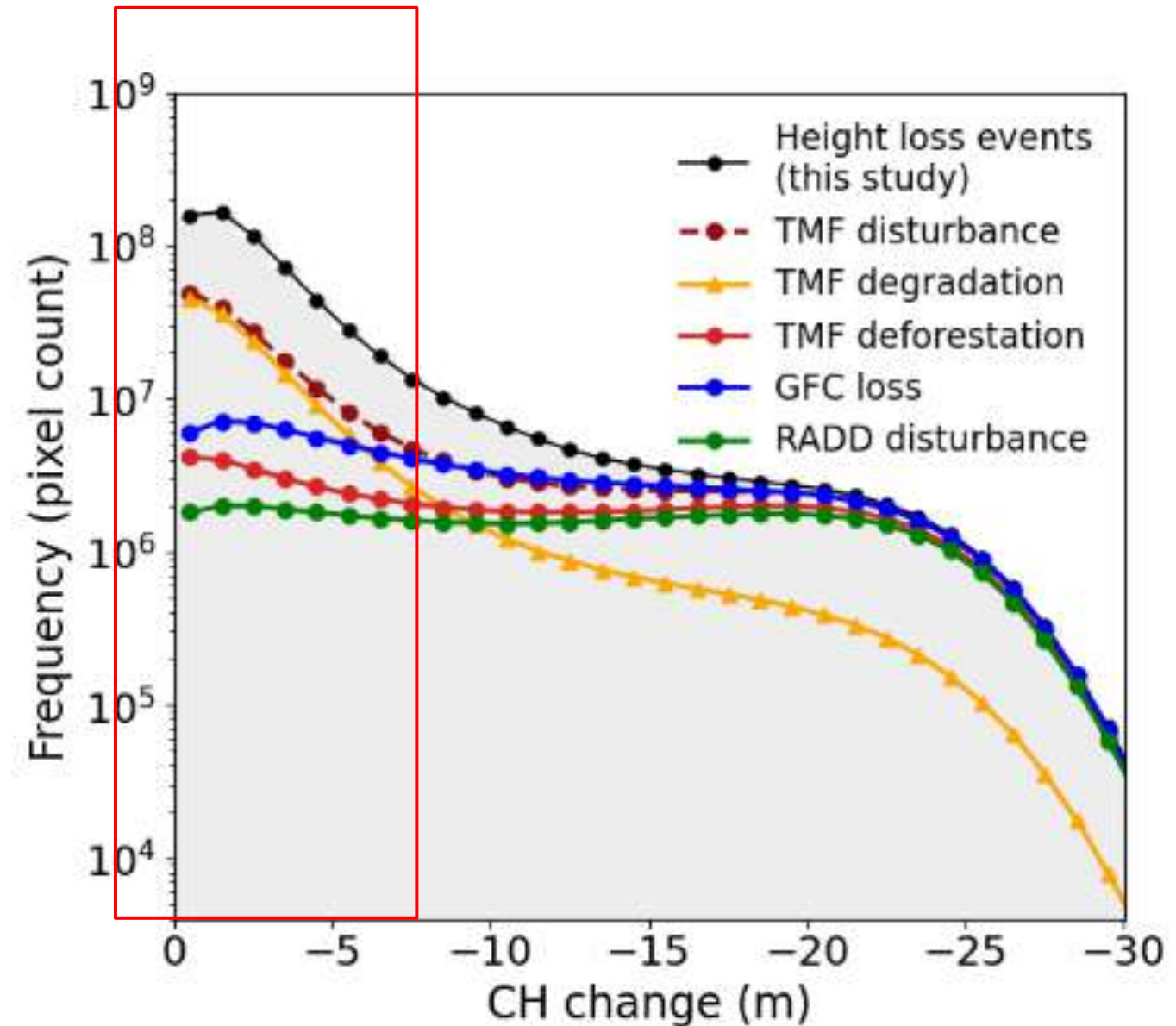
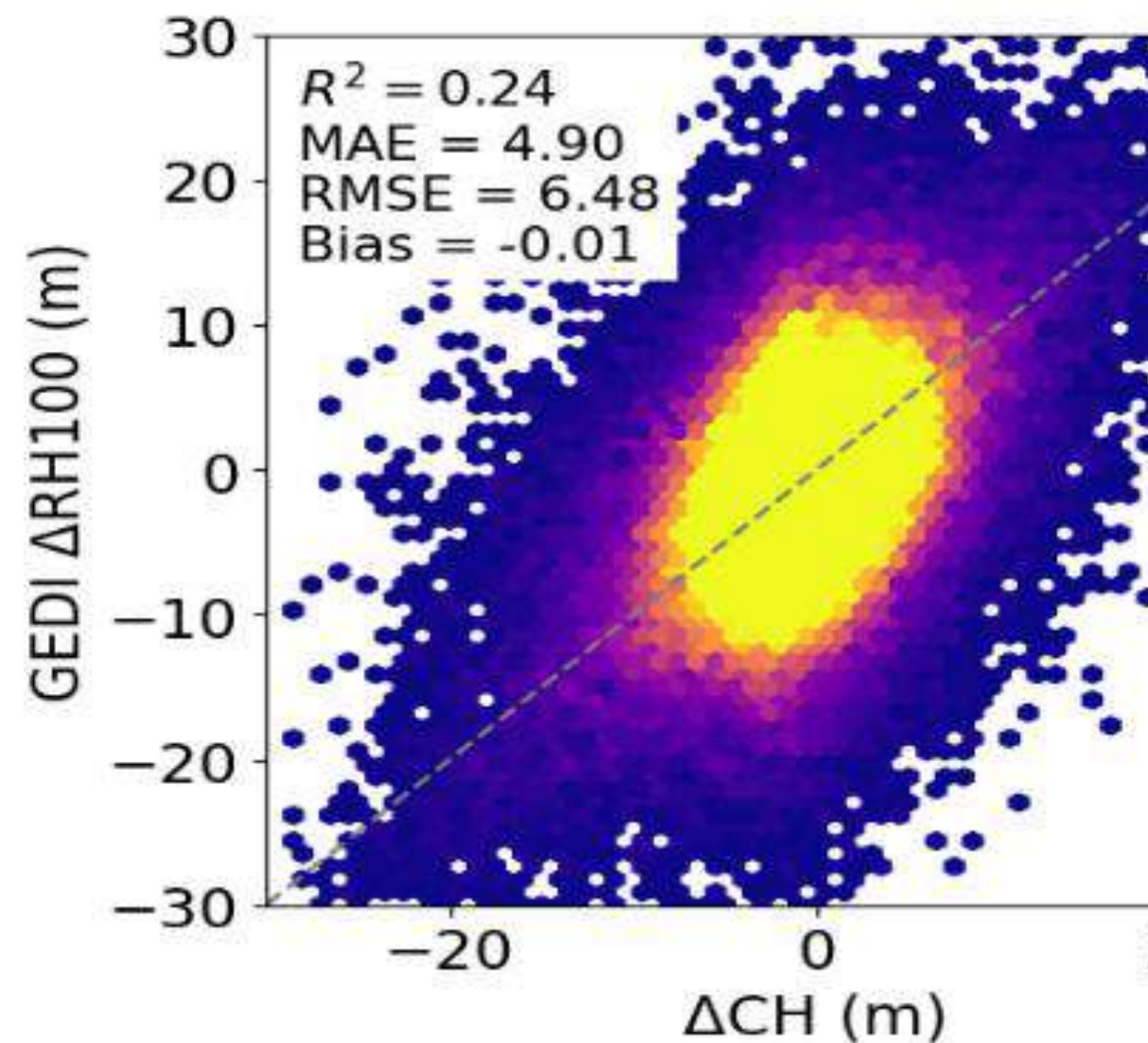
CTREE planet-based disturbance (Dalagnol et al., 2023)

Wan et al., in preparation

Evaluation of the canopy height change maps

Evaluation: GEDI RH100, Landsat TMF disturbance, GFC tree cover loss, and radar alter

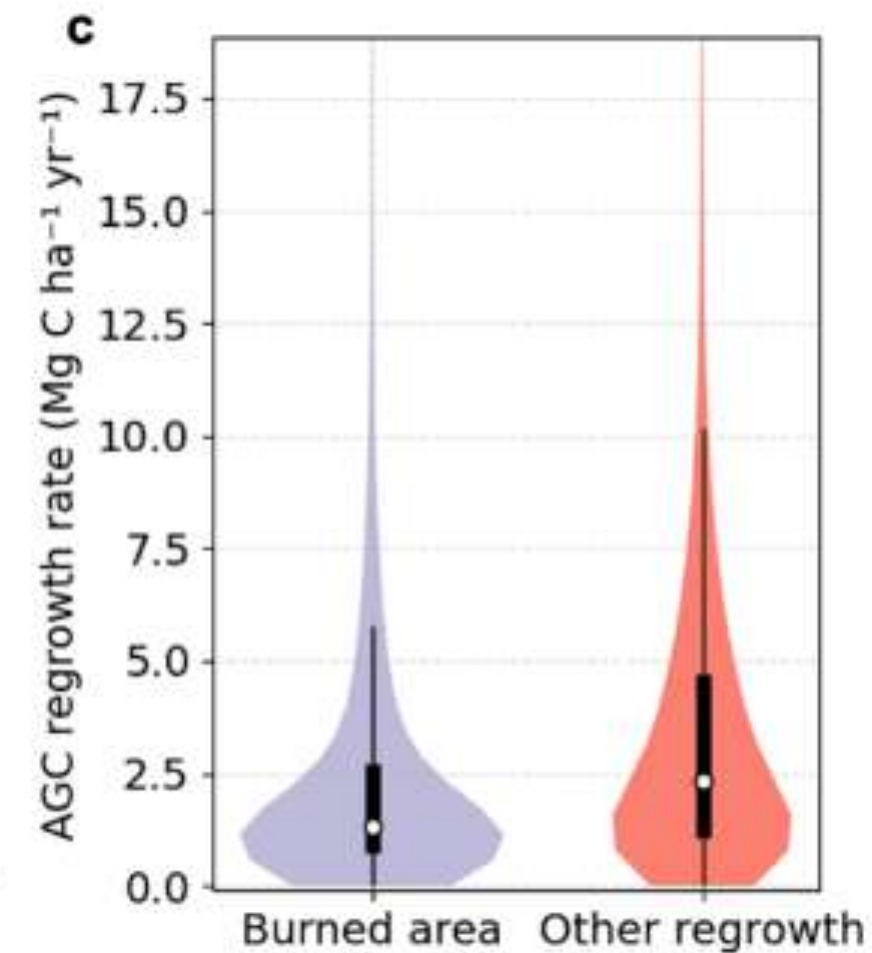
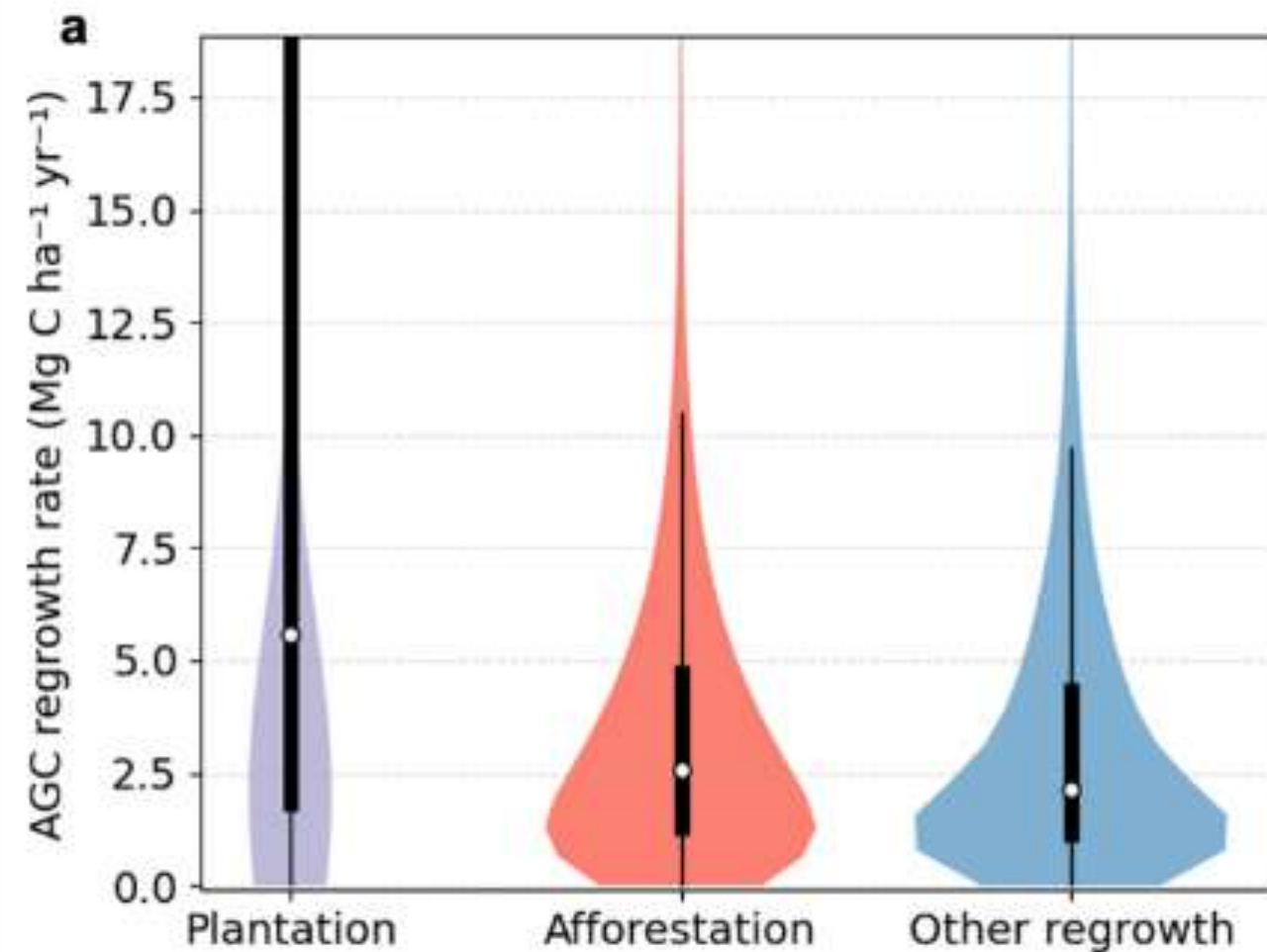
Our CH change is consistent with GEDI RH100 change but can detect more small disturbances than Landsat disturbance data



Regrowth rates based on the annual AGC estimation

Method:

- Overlap TMF plantation/Afforestation(new growth) /regrowth from deforestation (other regrowth)
- AGC rate: CH change and the allometry function.



Growth rate from plantation is higher than the natural regenerated forest
AGC Recovery rate from fire is lower than the regrowth from deforestation

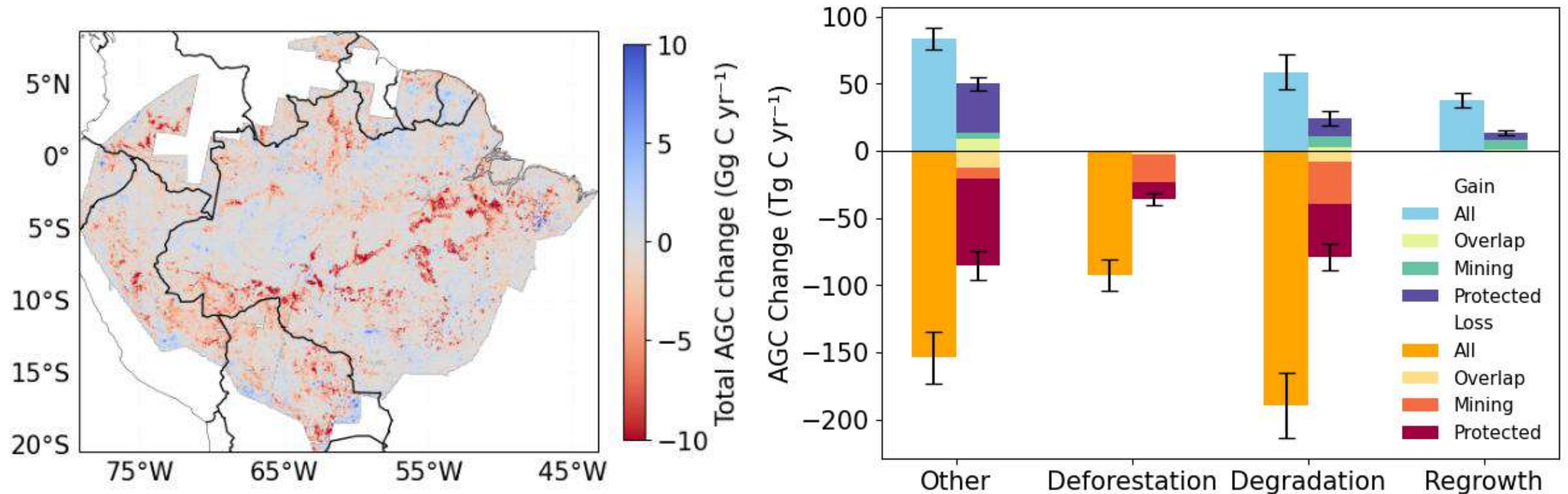
Direct estimation of AGB change

Method:

- Combine height change and Landsat data to classify C loss and gain from degradation, deforestation, Regrowth, Other (undisturbed forests).
- AGC map and change maps : CH map + allometry function.

Carbon budgets from 2019 to 2022:

Gross gain: 179.8 ± 16.4 Tg C/y ; **Gross loss:** -436.6 ± 33.3 Tg C/y ; **Net:** -256.7 ± 37.1 Tg C/y



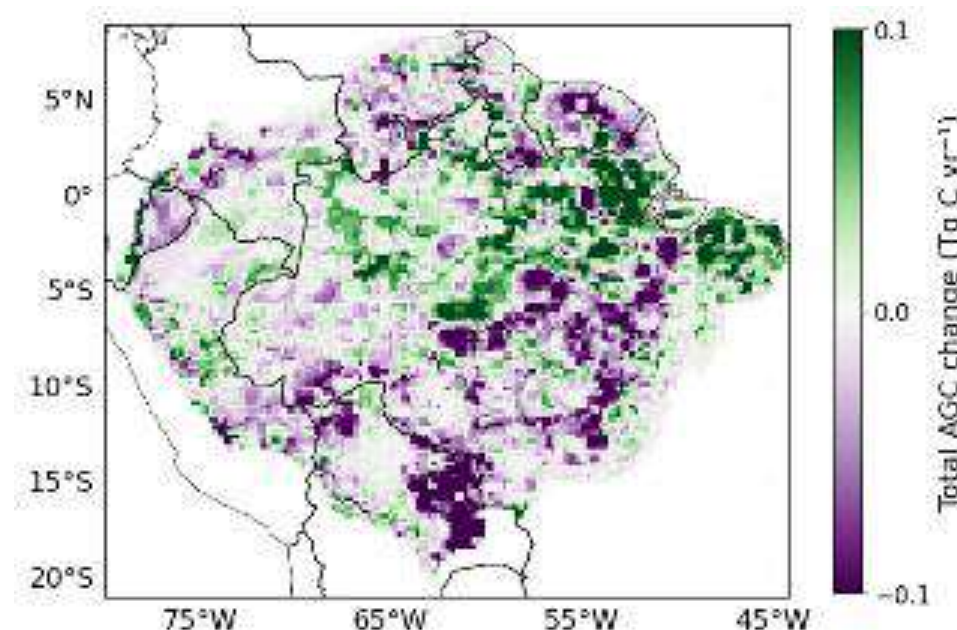
Summary

- Our EO-based approach
 - Provide the spatially-explicit bk model with outperforms the previous BK model by integrating regional response curves
 - Offering new insights into **fine-scale (10m)** carbon dynamics **overlooked** by moderate 30m satellite products

Next step: Synthesis of the different satellite approach

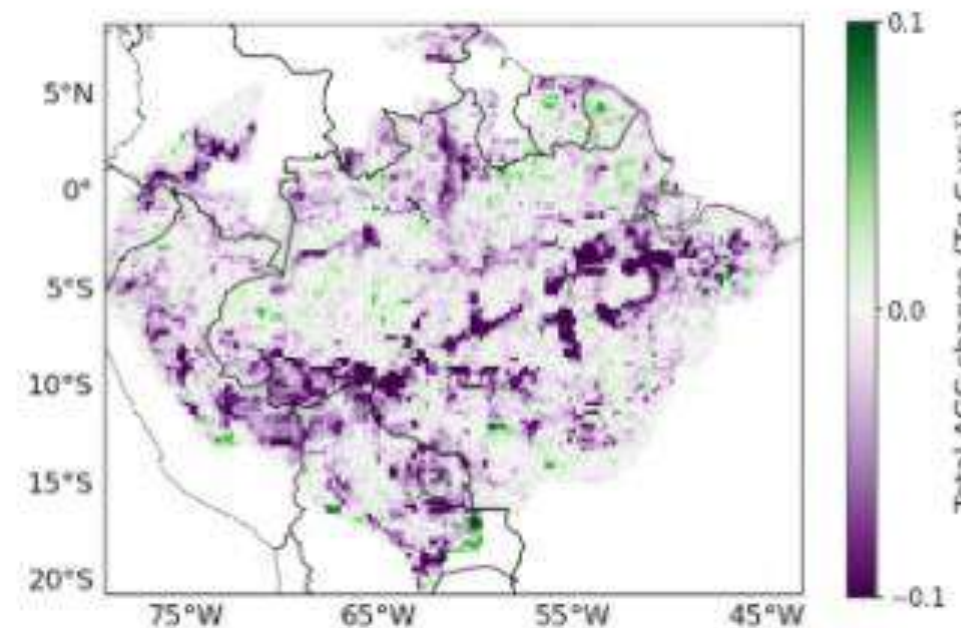
Very preliminary!!!!

All forest



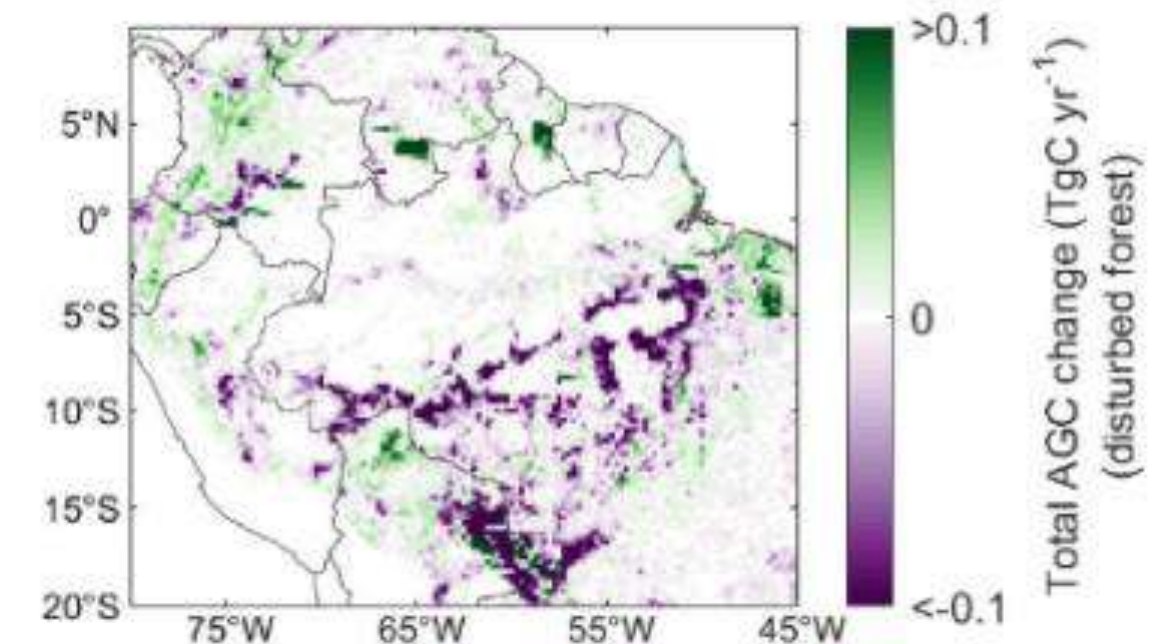
**L-VOD AGC
Fendrich 2025**

All forest



**Direct AGC mapping
2019-2022**

TMF Disturbed forest only



**BK model
(2011-2020)**

An aerial photograph of a dense, lush green forest. The trees are tightly packed, creating a vibrant green canopy. The lighting suggests a sunny day, with some areas appearing brighter than others.

Thanks!

Yidi.xu@lsce.ipsl.fr

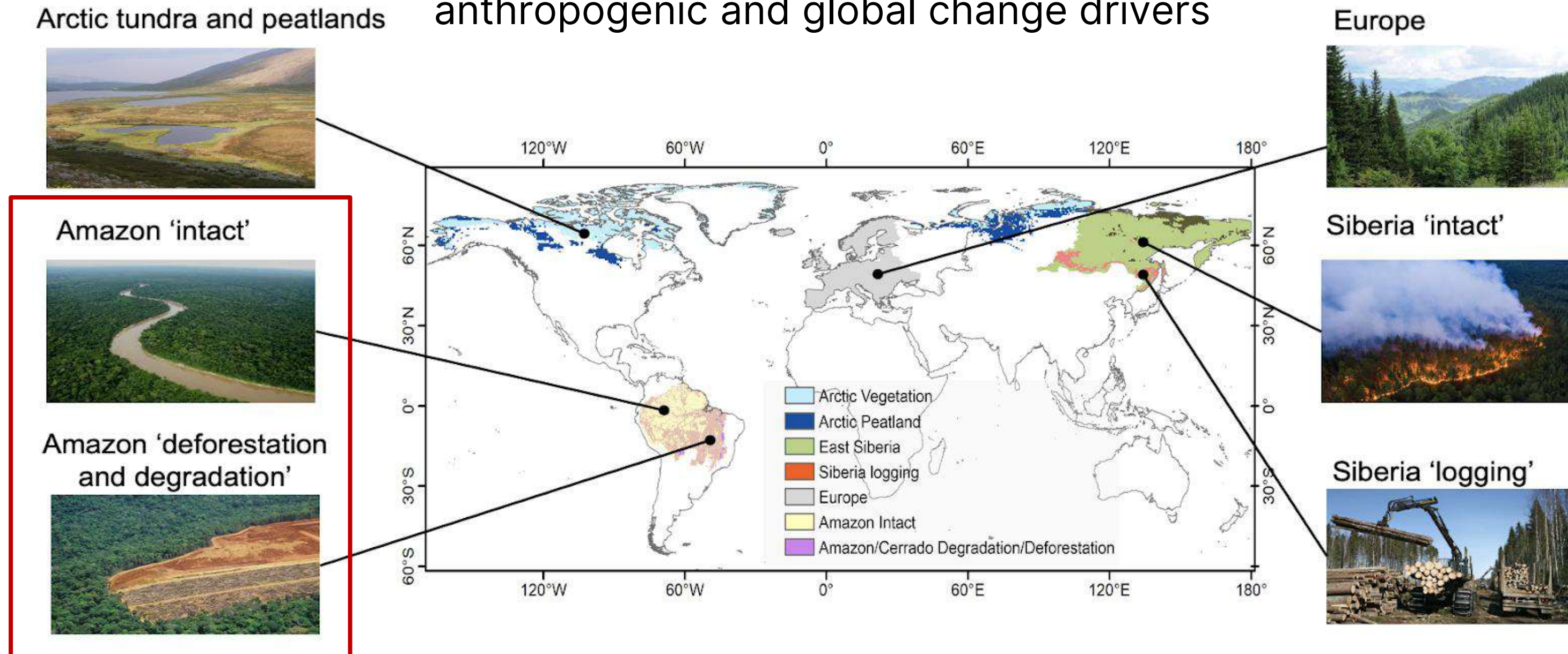
Mapping *Cecropia* distribution to adjust biomass estimates in the Amazon [RECCAP2-CS]

Scott Barningham, UNEXE

Session 2.1: Estimates of carbon accumulation from various approaches

São José dos Campos, 30th Oct 2025

Harness satellite based ECV to make a giant leap for
reducing the uncertainty on the emissions and sinks of CO₂,
and CH₄ over key land regions, and attributing them to
anthropogenic and global change drivers



Mapping key species to improve wood density and biomass mapping

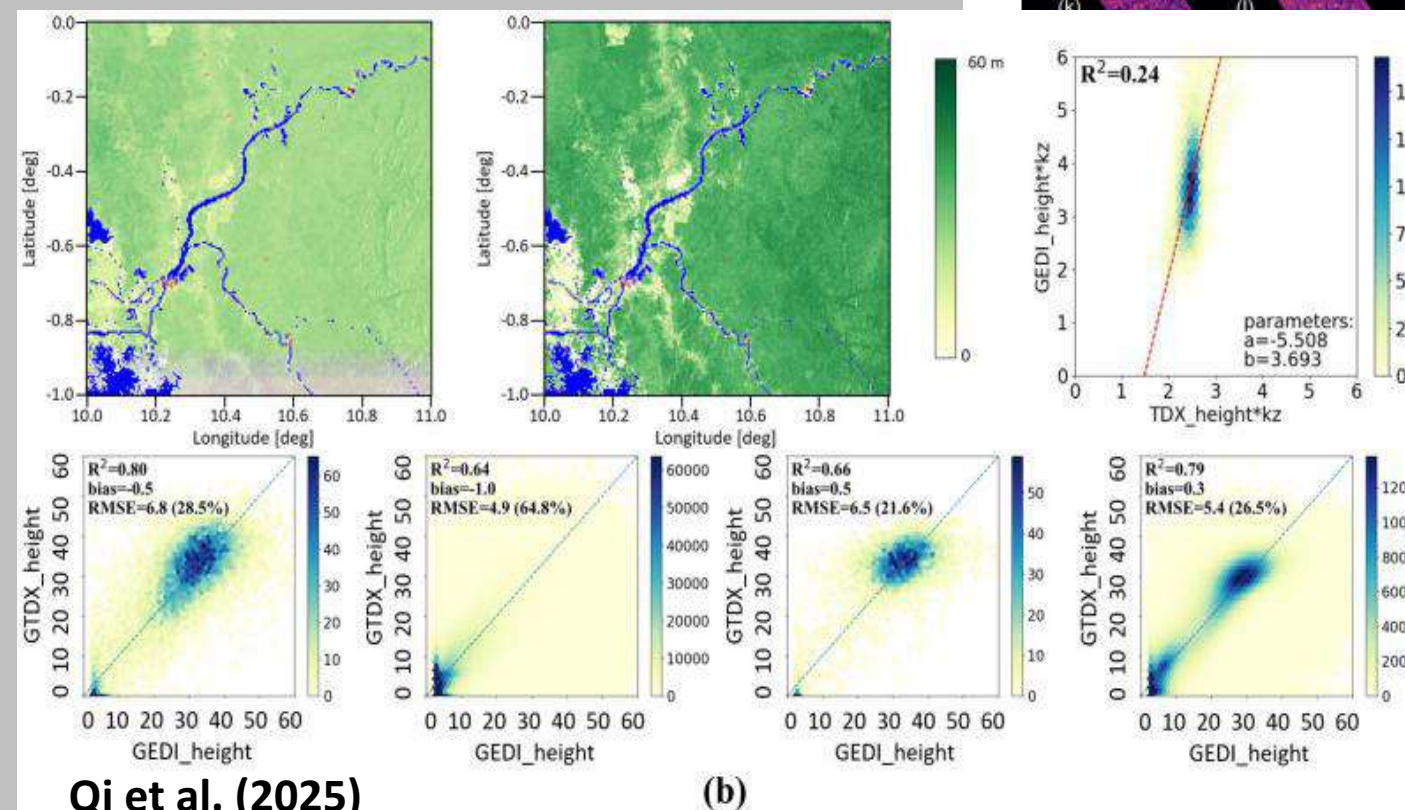
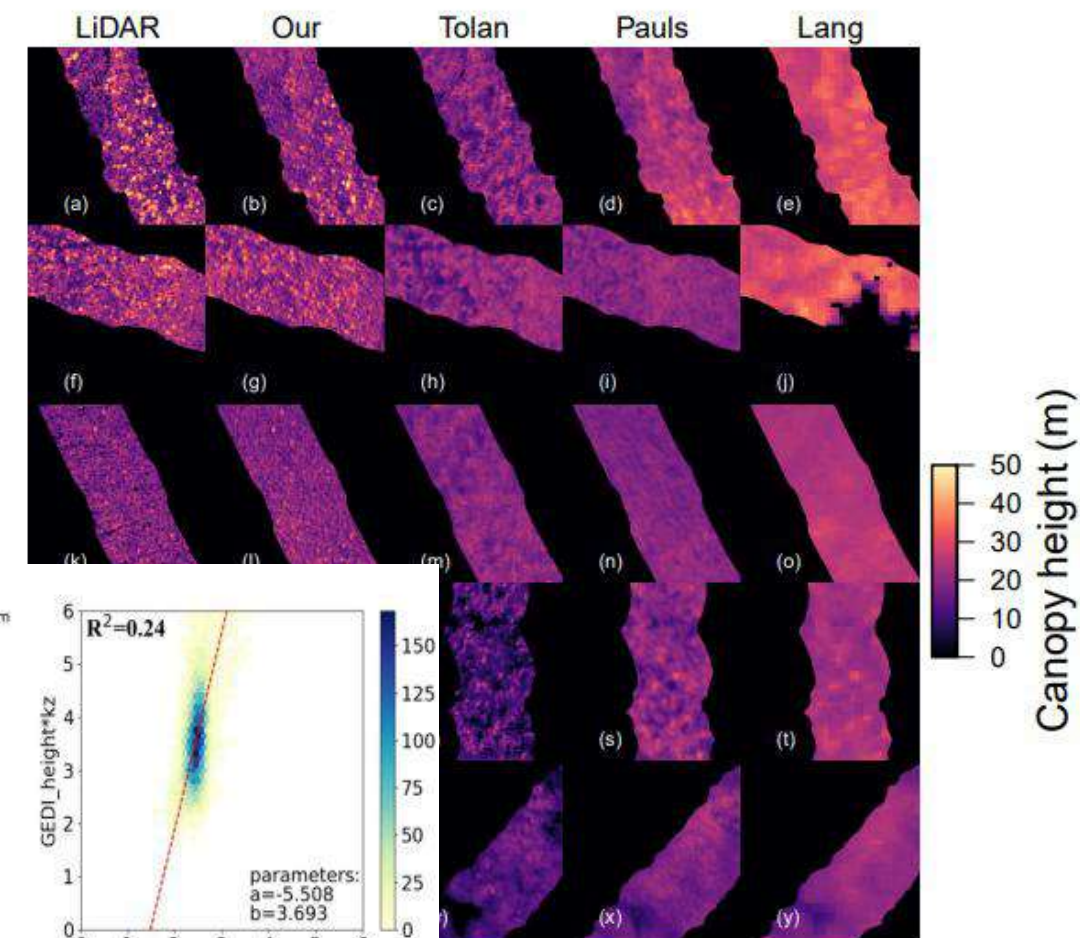
Existing AGB/ CH estimates

Recent advancements

- Trained on LiDAR using optical/ SAR through deep learning
- Canopy height spatial resolutions 1-30 m
- Small disturbances captured

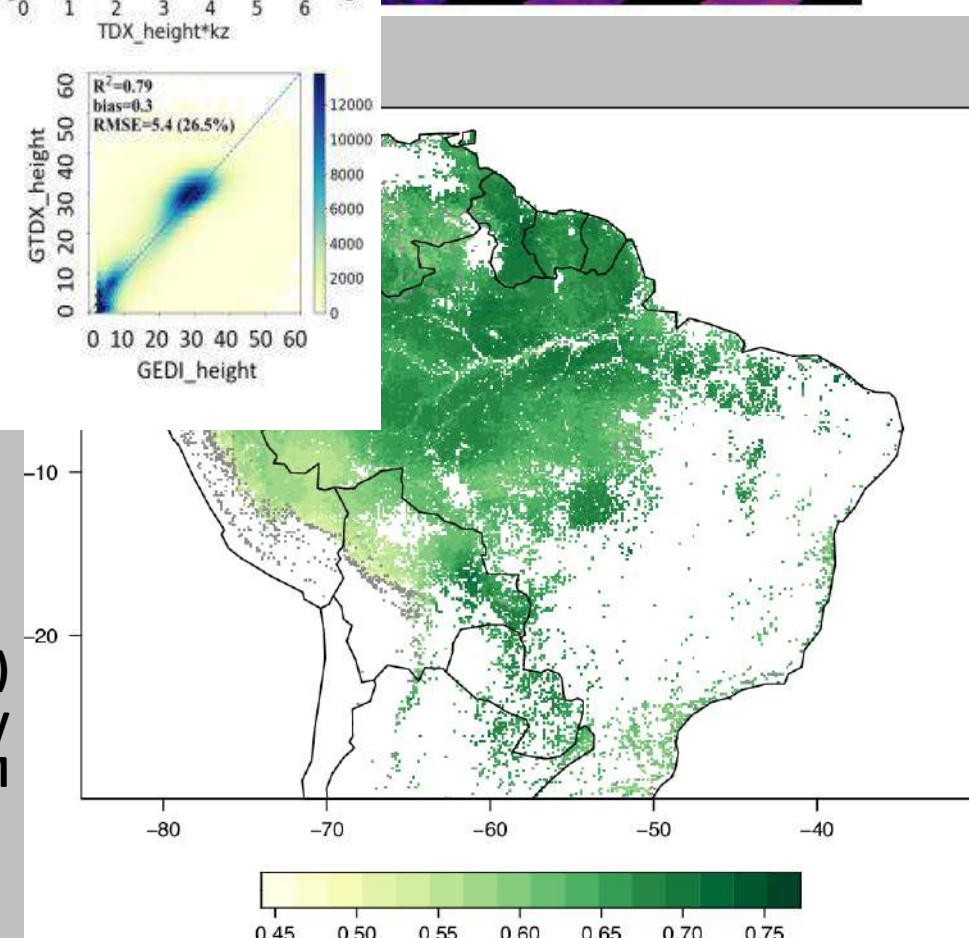
$$AGB = f(CH \cdot WD)$$

Wagner et al. (2025)
5m Canopy Height
U-Net
Planet + airborne LiDAR



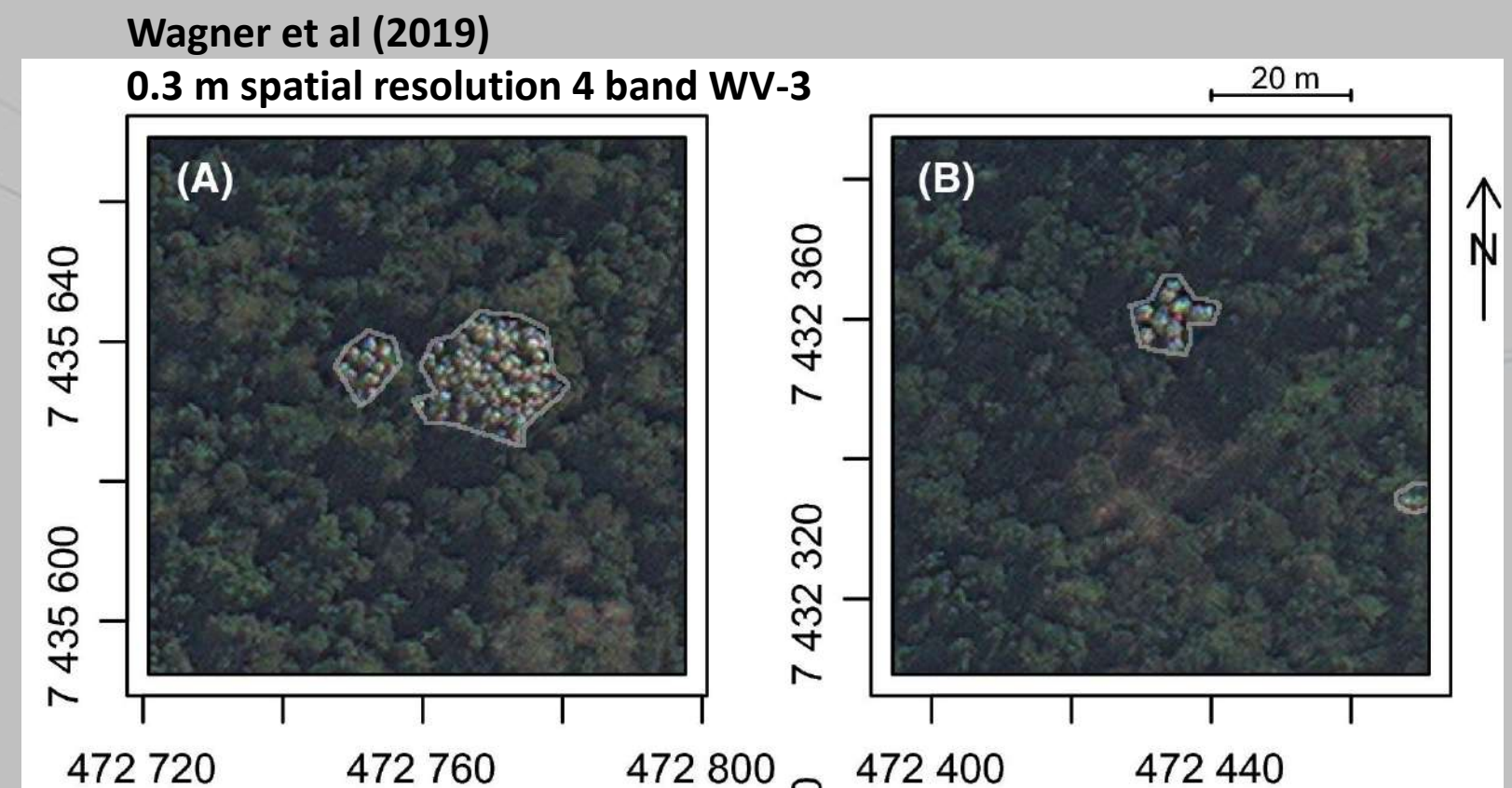
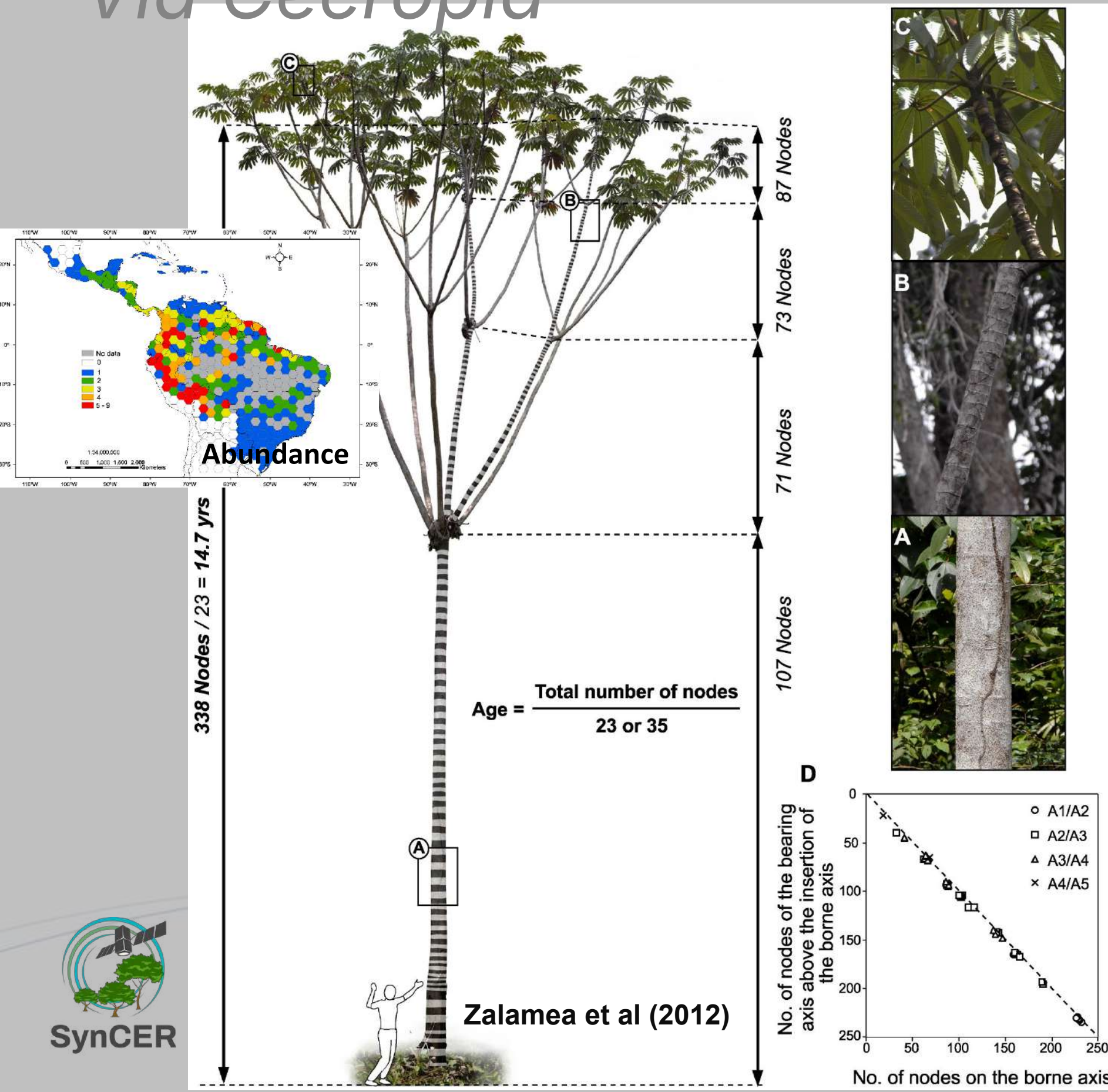
Qi et al. (2025)
25 m Canopy Height
TanDEM-X + GEDI

Sullivan et al. (2025)
1 km wood density
GAM



Estimating wood density

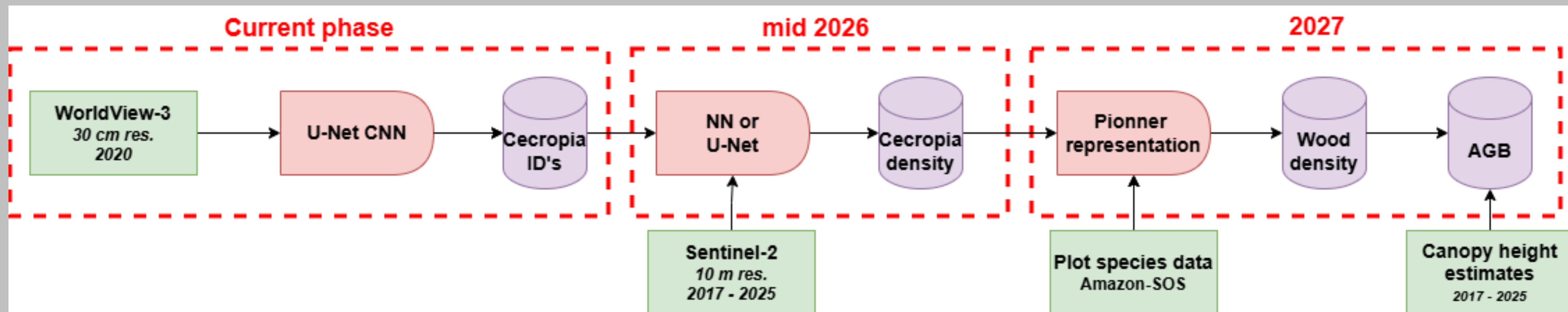
Via Cecropia



- Pioneer genus
- Low wood density
- Indicator of disturbance
- +ve AGB bias in disturbed regions

Estimating wood density and AGB

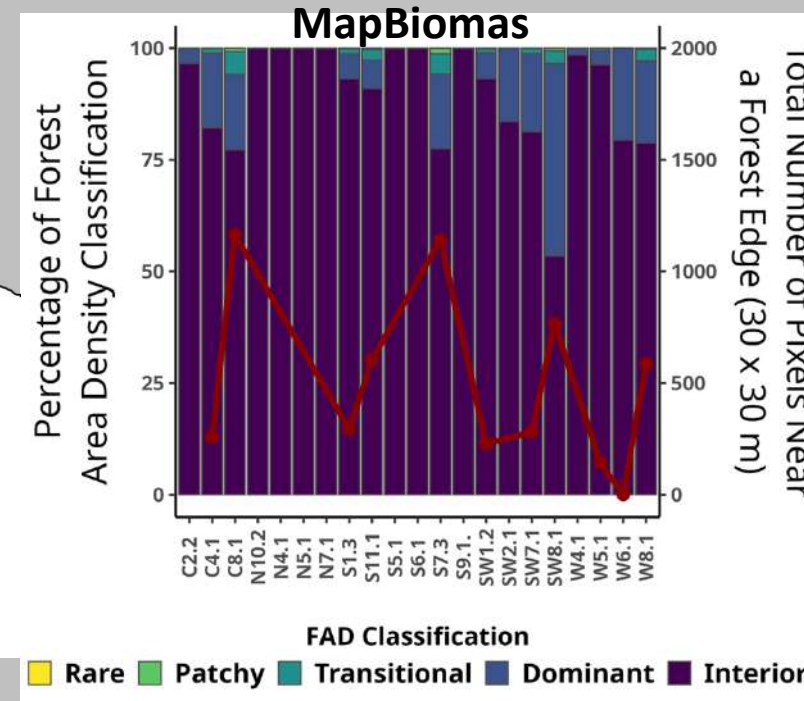
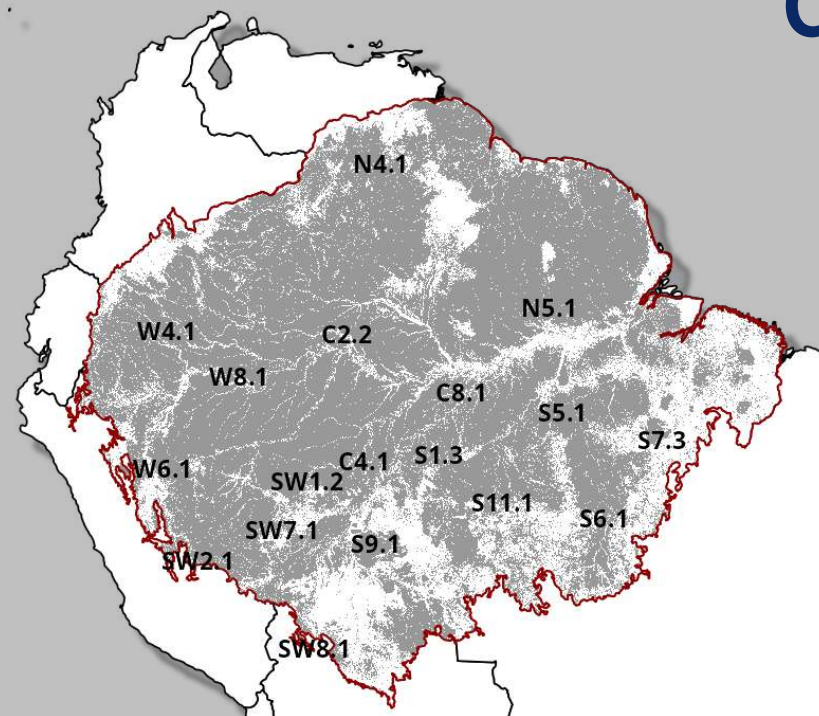
Simplified workflow



Cecropia Identification

WorldView-3 data (ESA 3rd Part Mission)

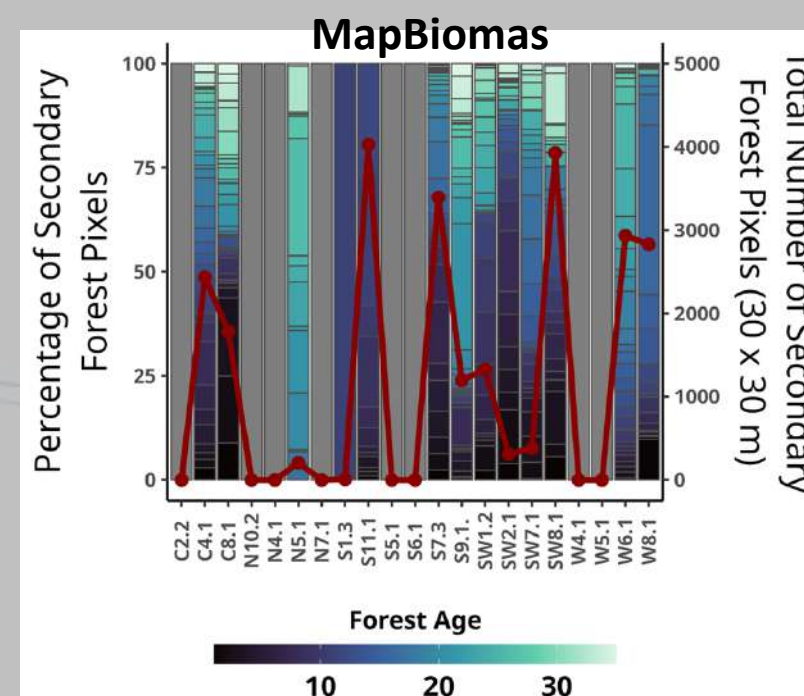
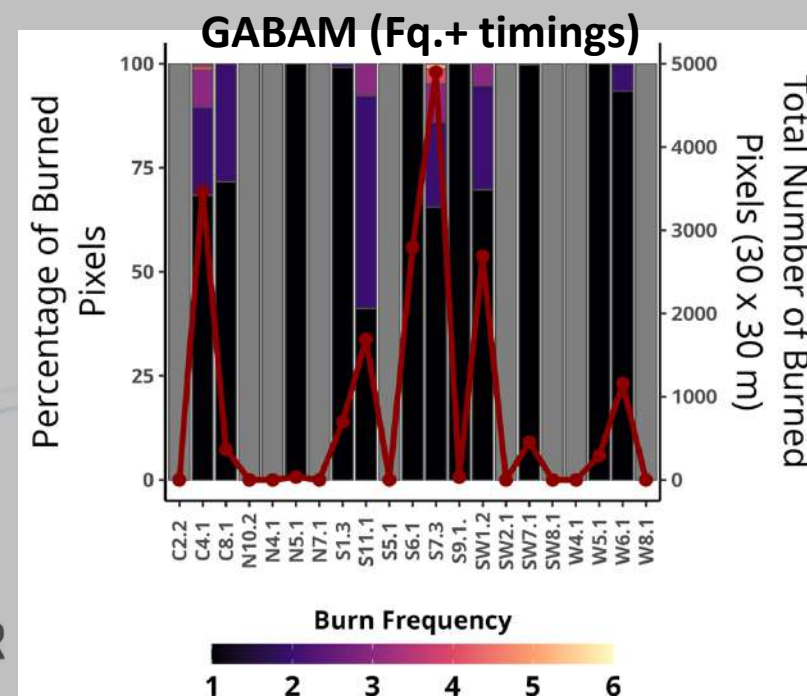
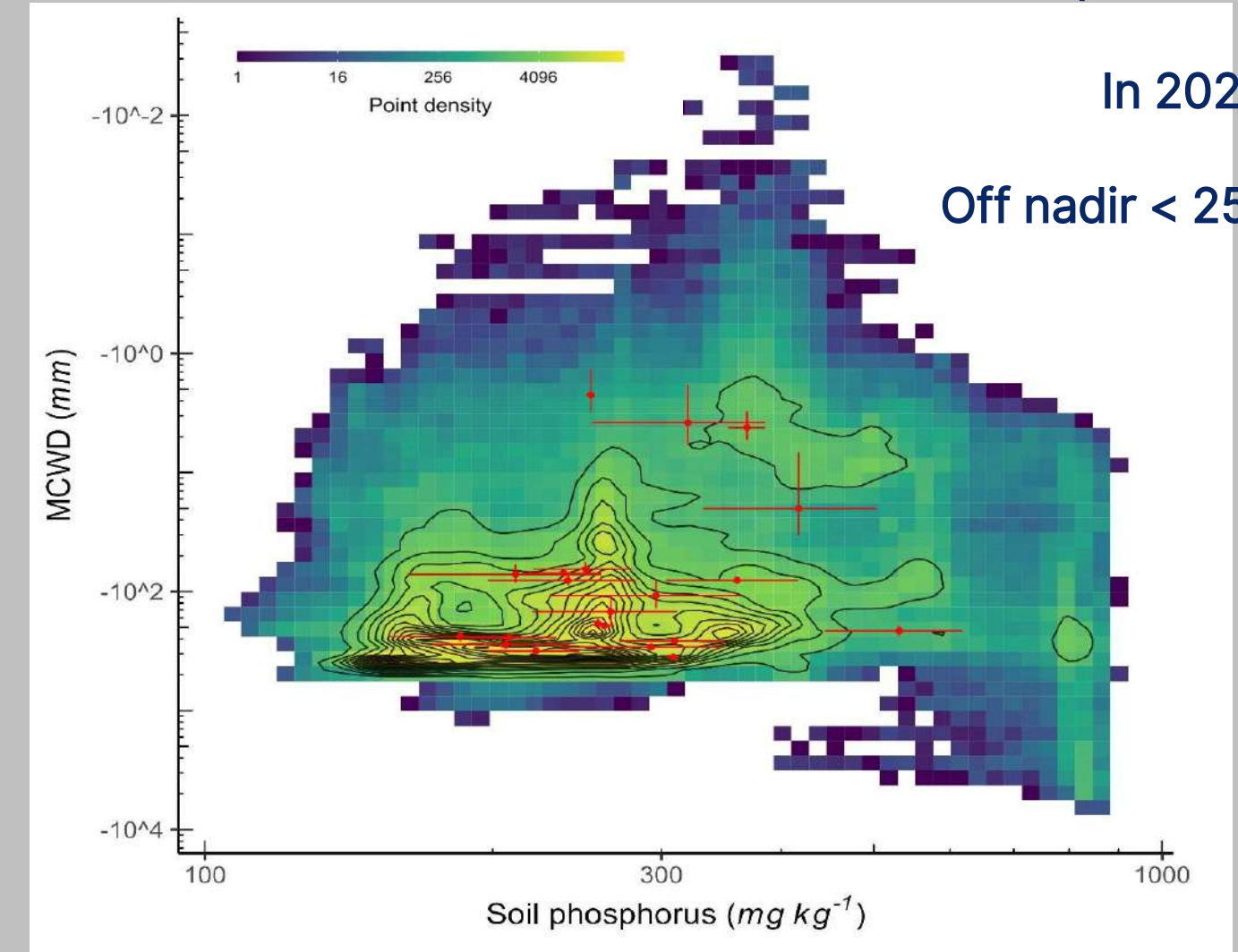
Objective: Cover environmental gradients across Amazonia
disturbance, climatic + edaphic



Total area = 450 km² (18 sites)

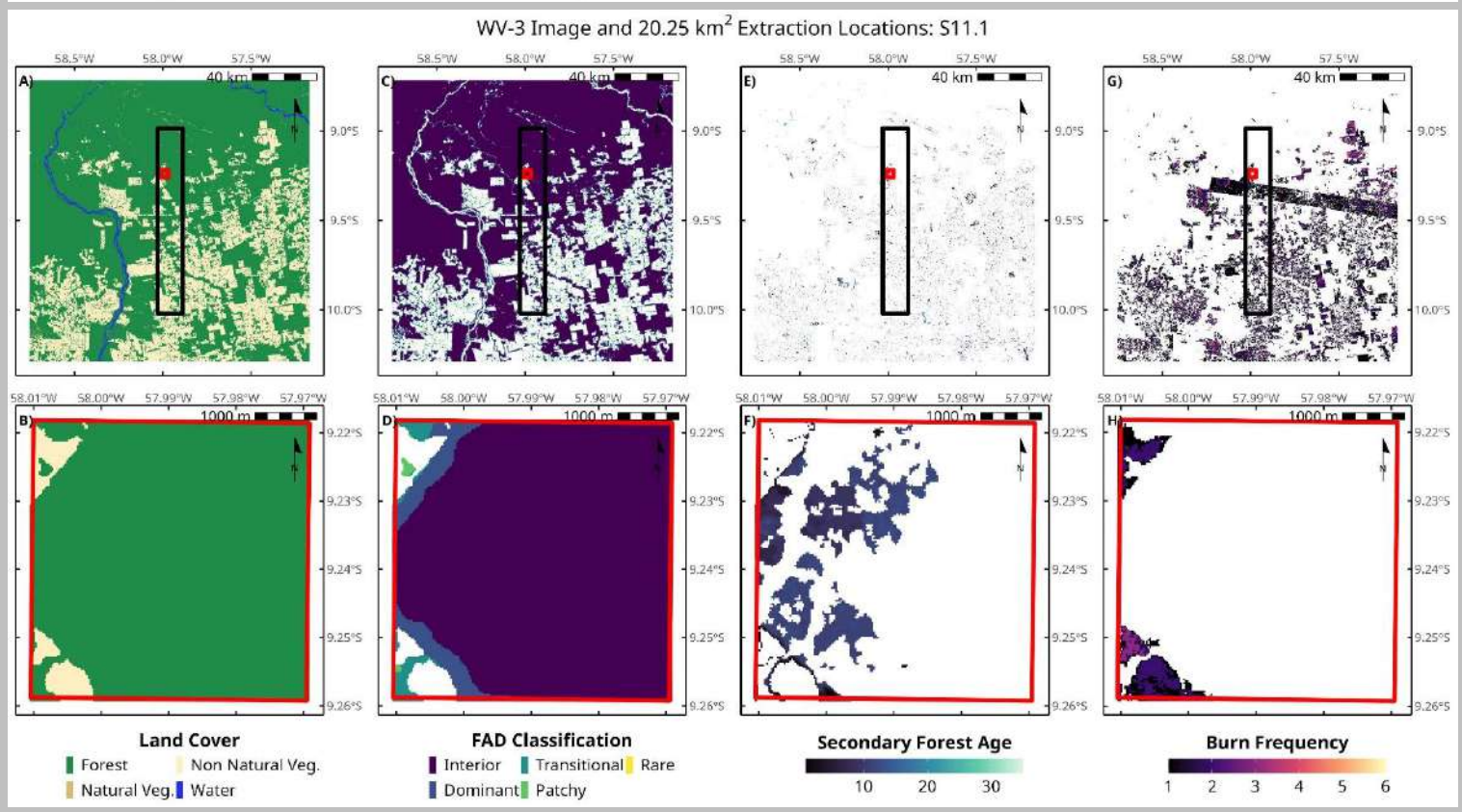
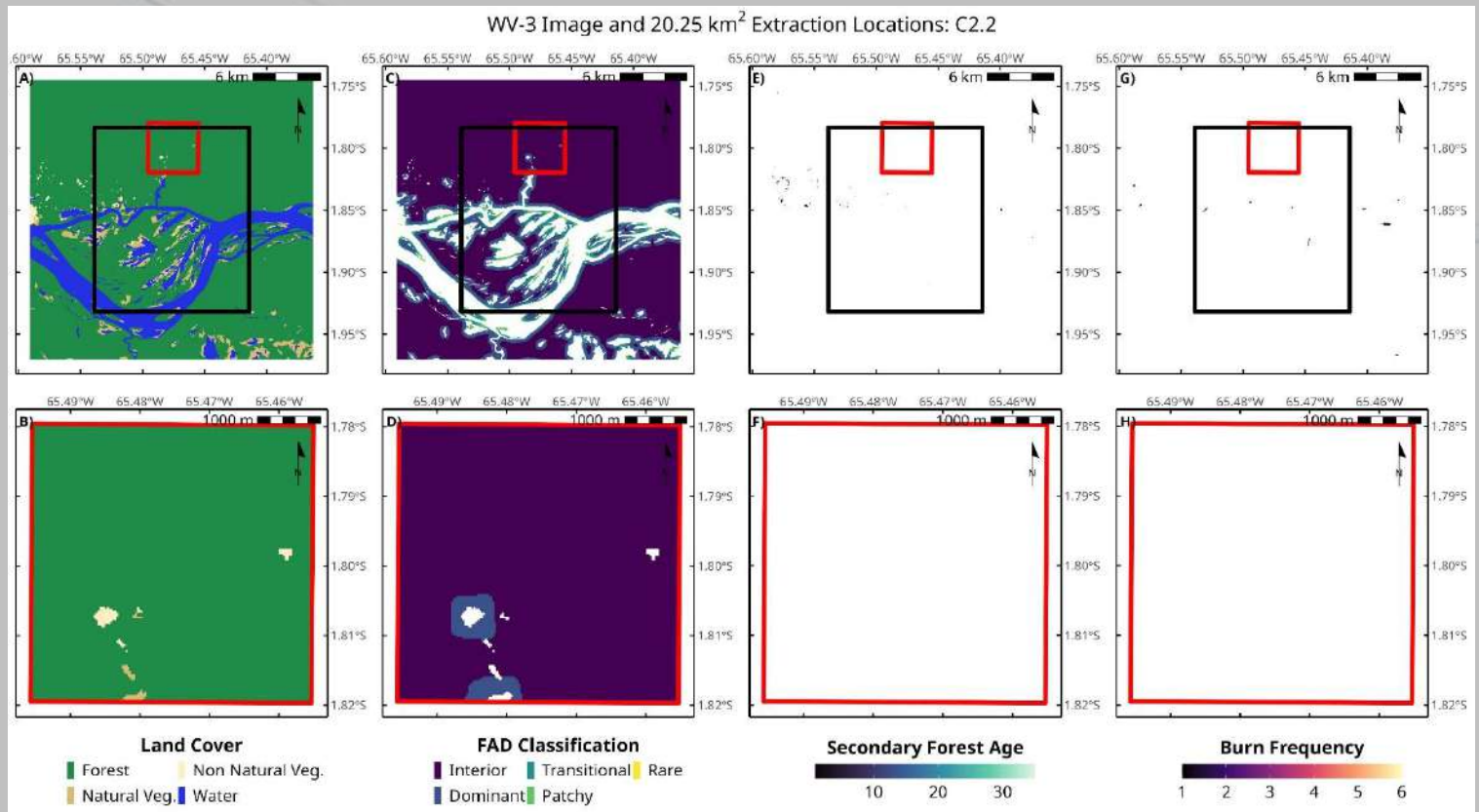
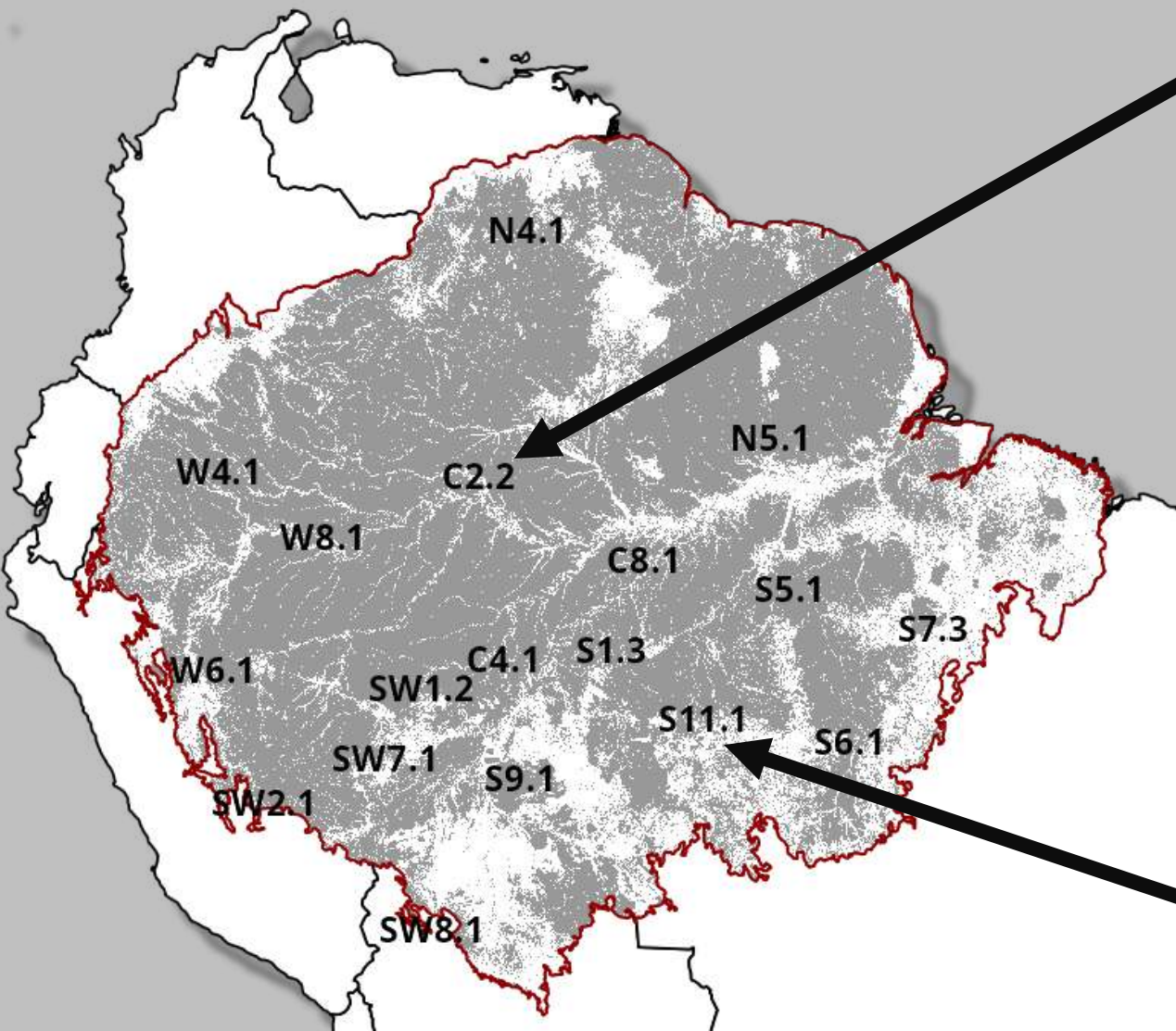
In 2020

Off nadir < 25°



Cecropia Identification

WorldView-3 data
(ESA 3rd Part Mission)

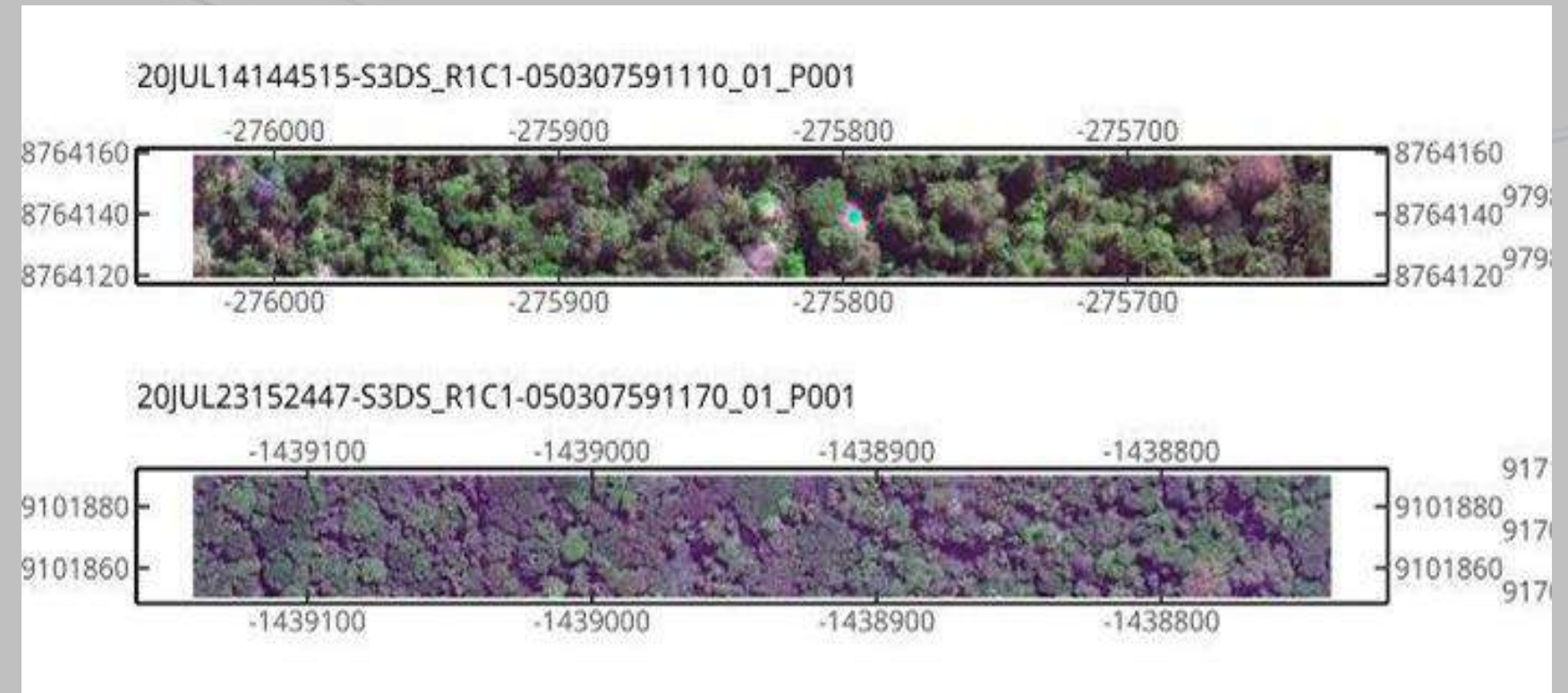
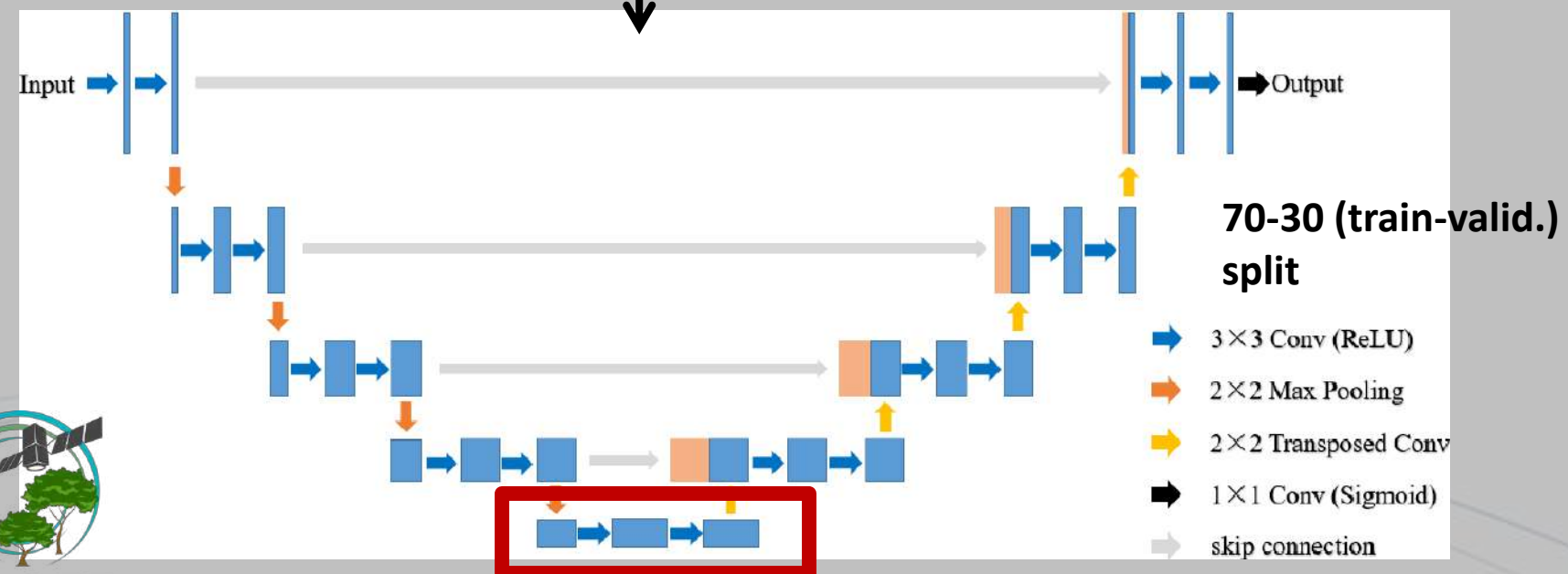
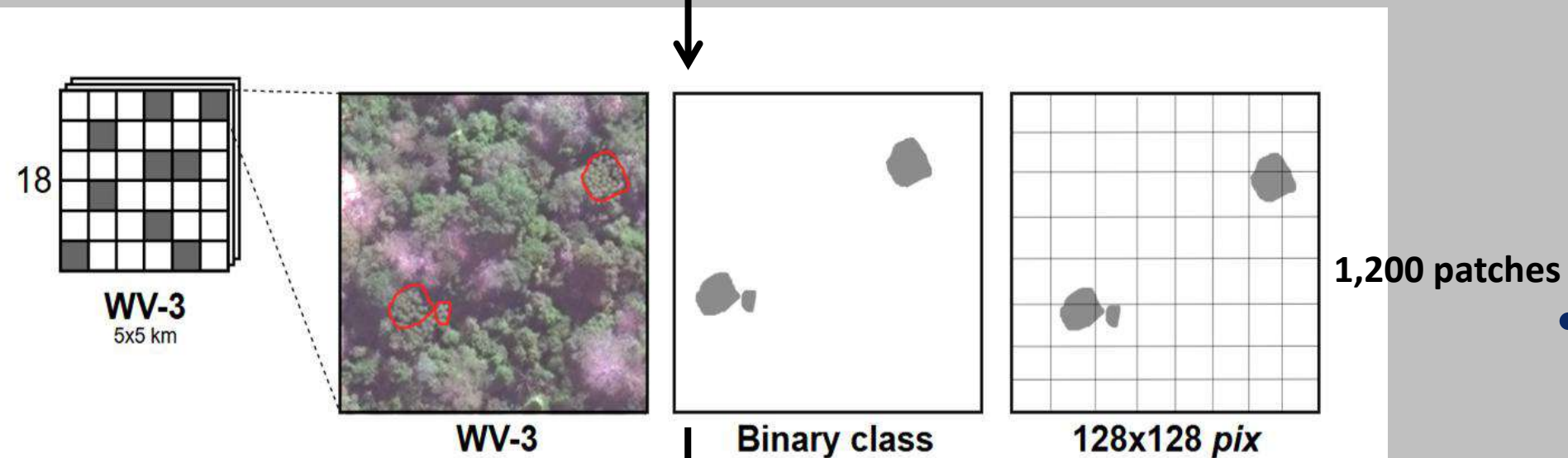


Cecropia Identification

U-Net modelling

Manual delineation of
Cecropia

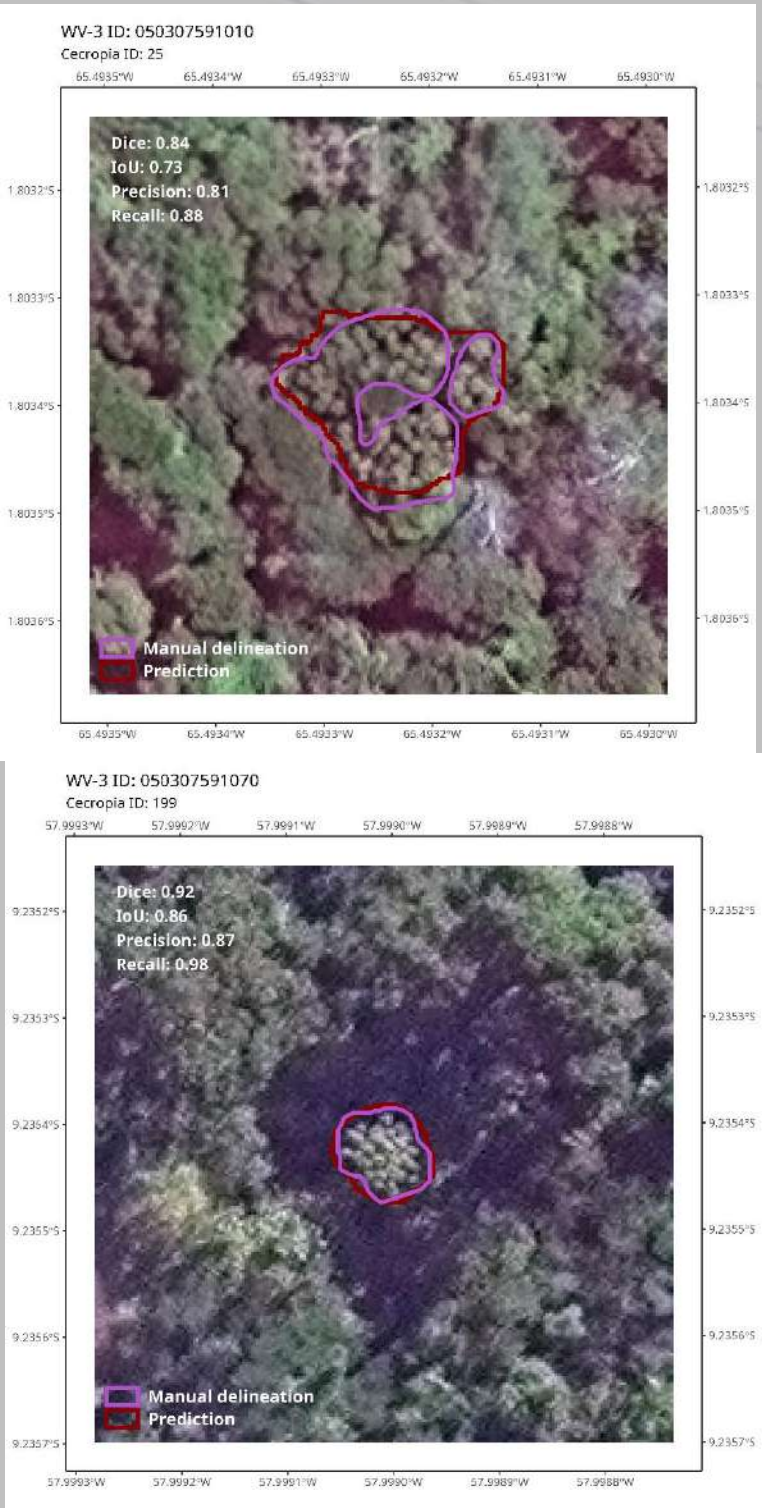
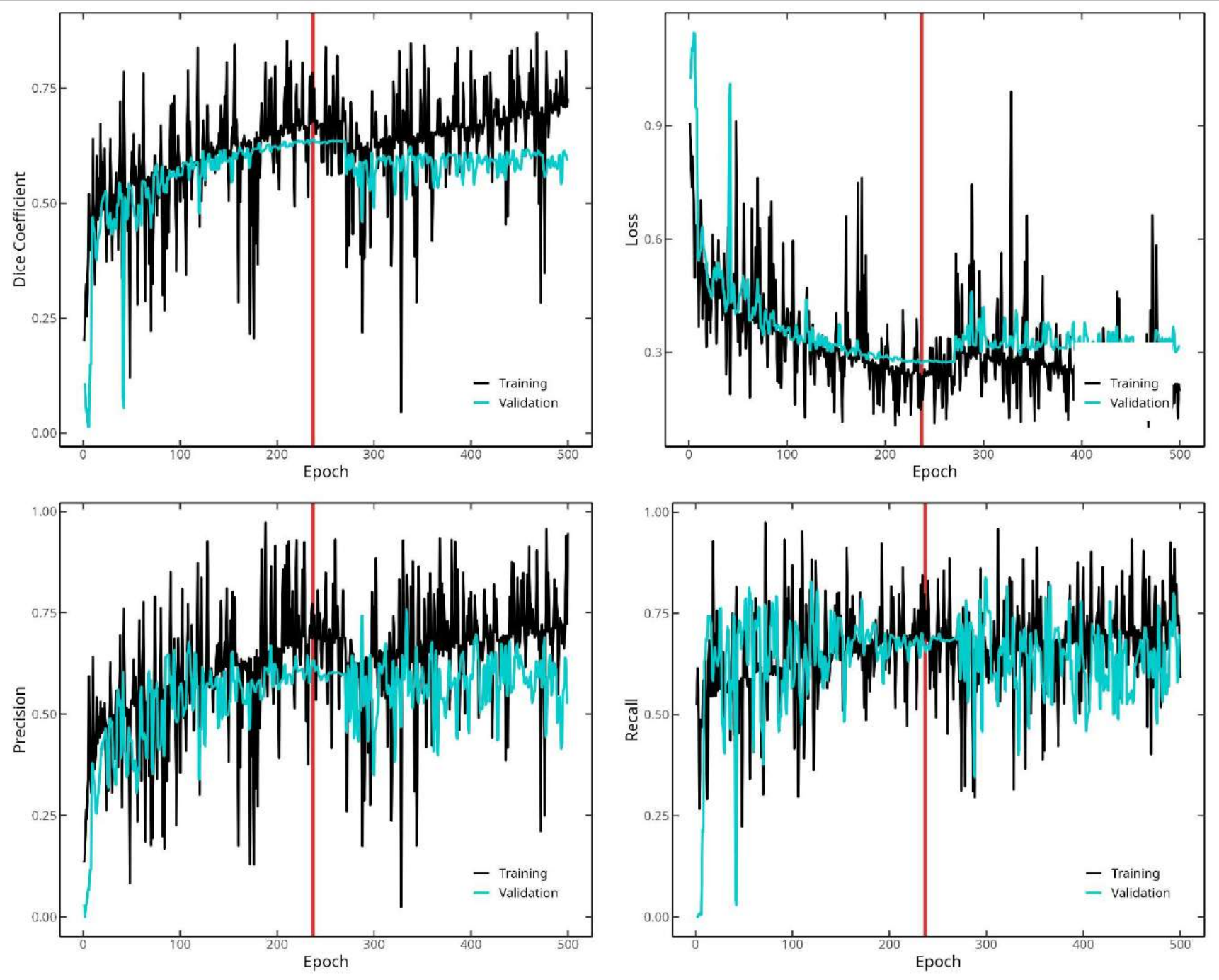
700 crown delineated



- Changing domains hinders performance i.e., shadowing and $p()$
- Heavy training augmentation applied
- Down sampled scene (5x5 km) **subnetwork embedded at bottleneck describing global variability (automatic correction)**

Cecropia Identification

U-Net modelling

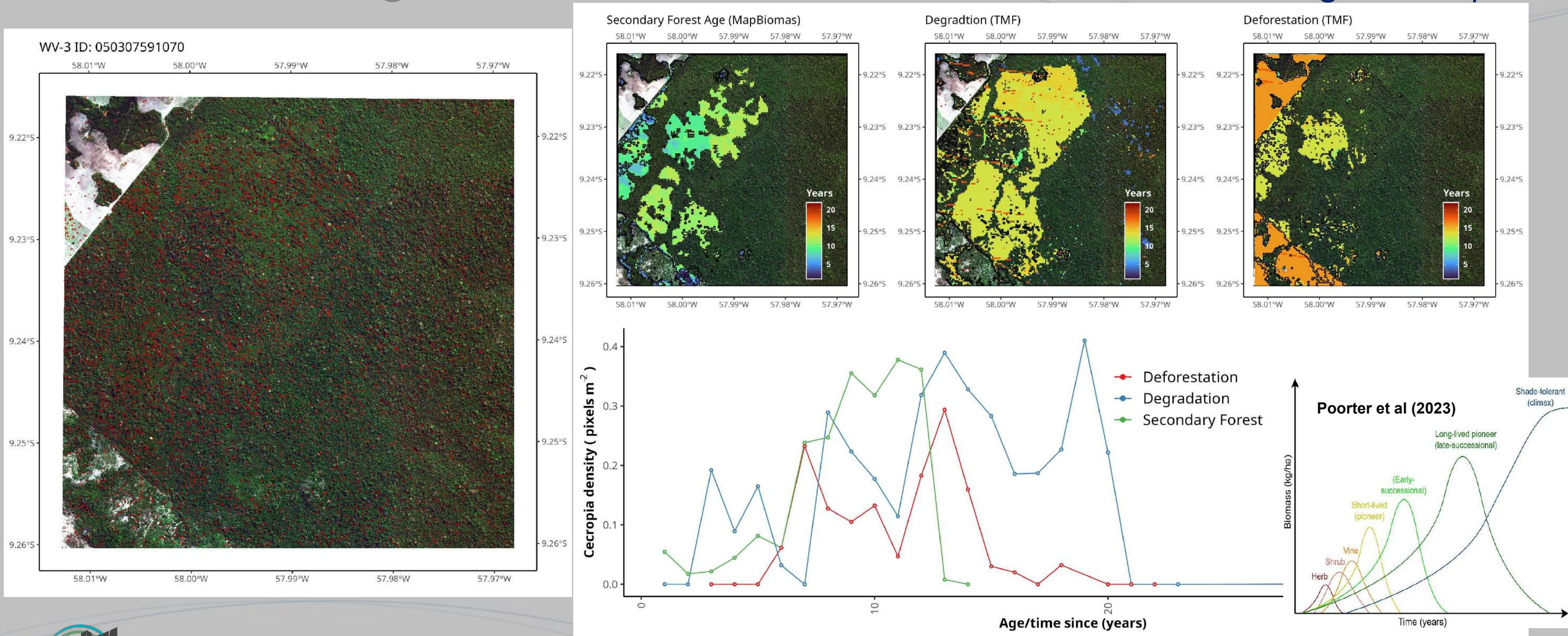


**Validation dice coefficient = 0.638
(epoch 237)**
Good but still unsatisfactory...

Cecropia Predictions

Disturbance gradients (30m)

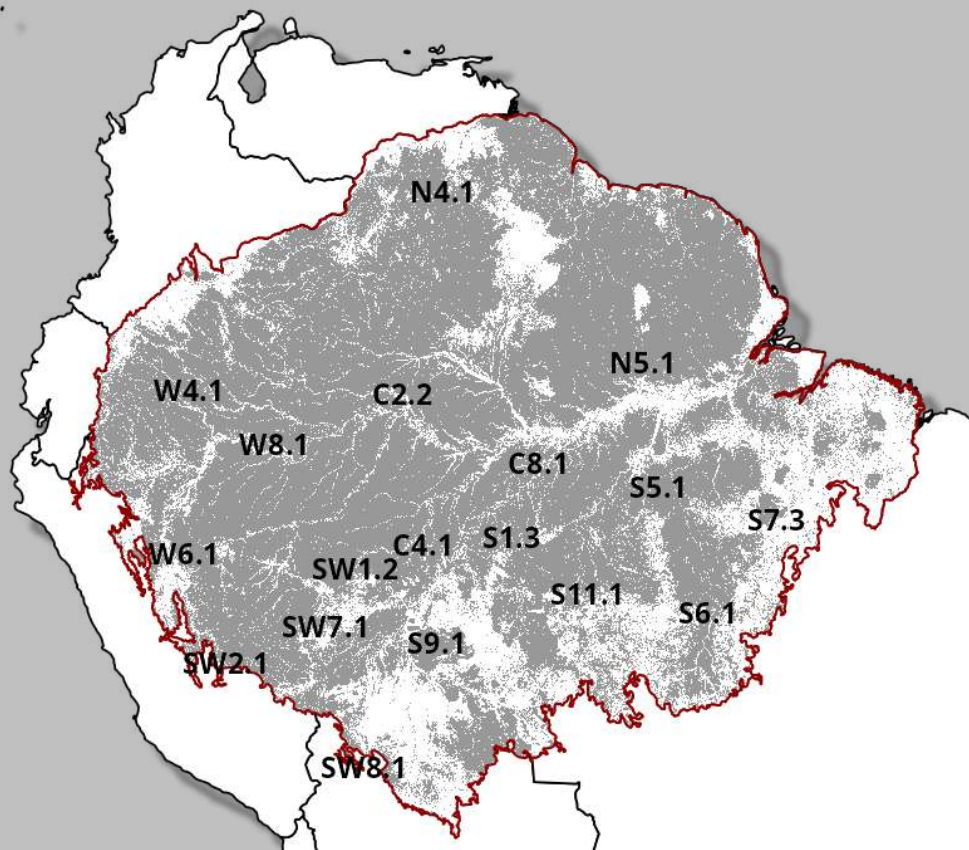
Successional dynamics of pioneer functional species observed through Cecropia...



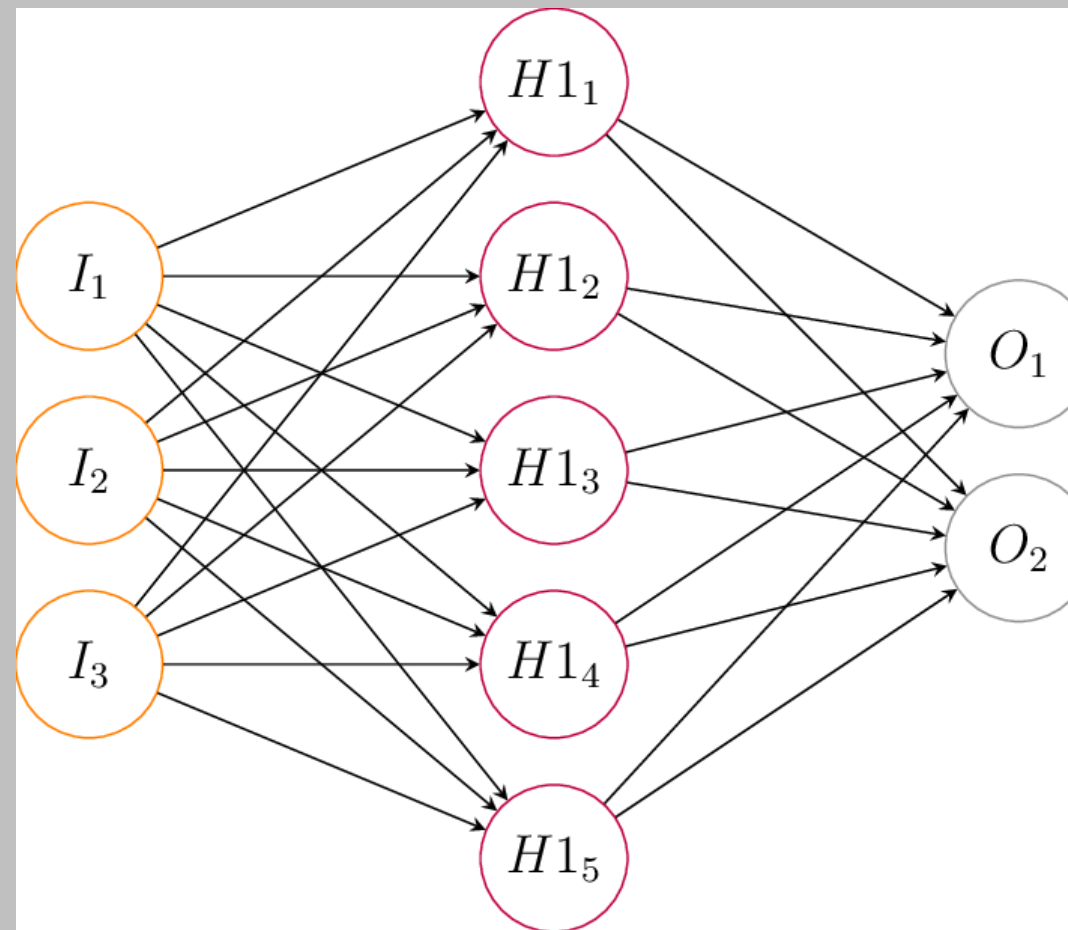
Expanding Cecropia predictions

Cecropia density (Amazon)

10 m *Cecropia* density
(aggregated U-Net output)
18 scenes of 25 km²



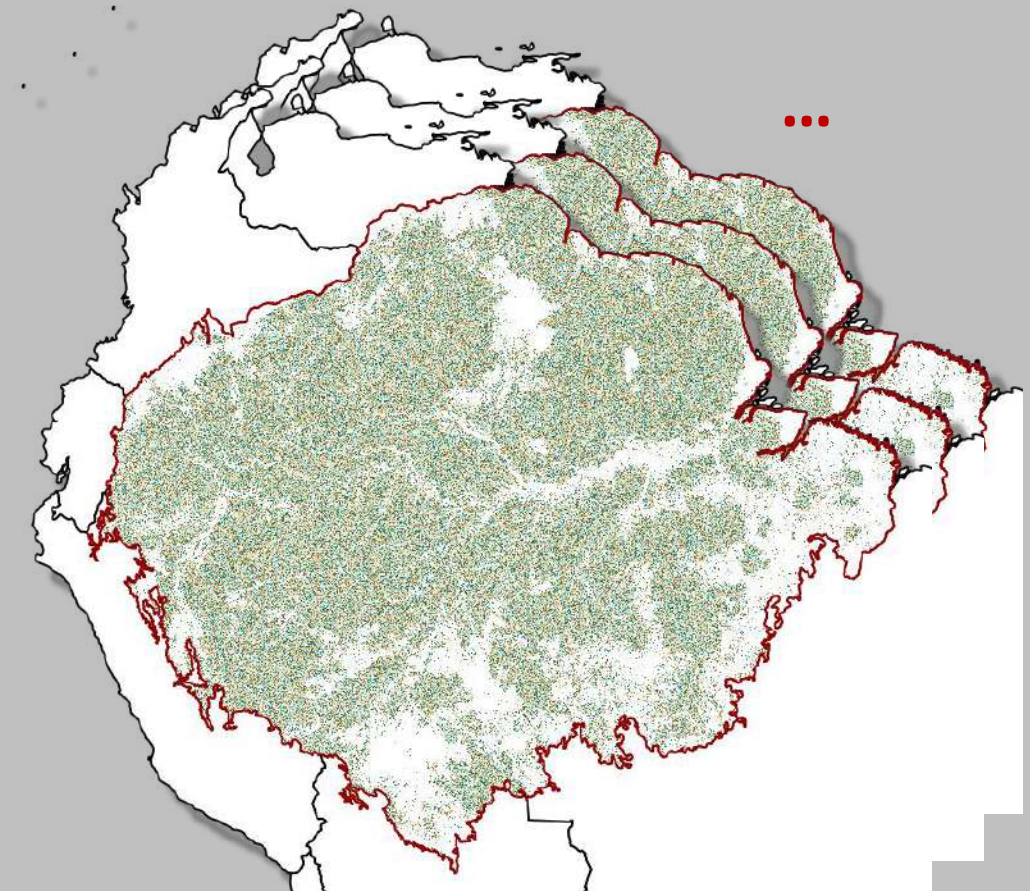
Train + validate NN/DL model
18 scenes of 25 km²



WV-3
predictions

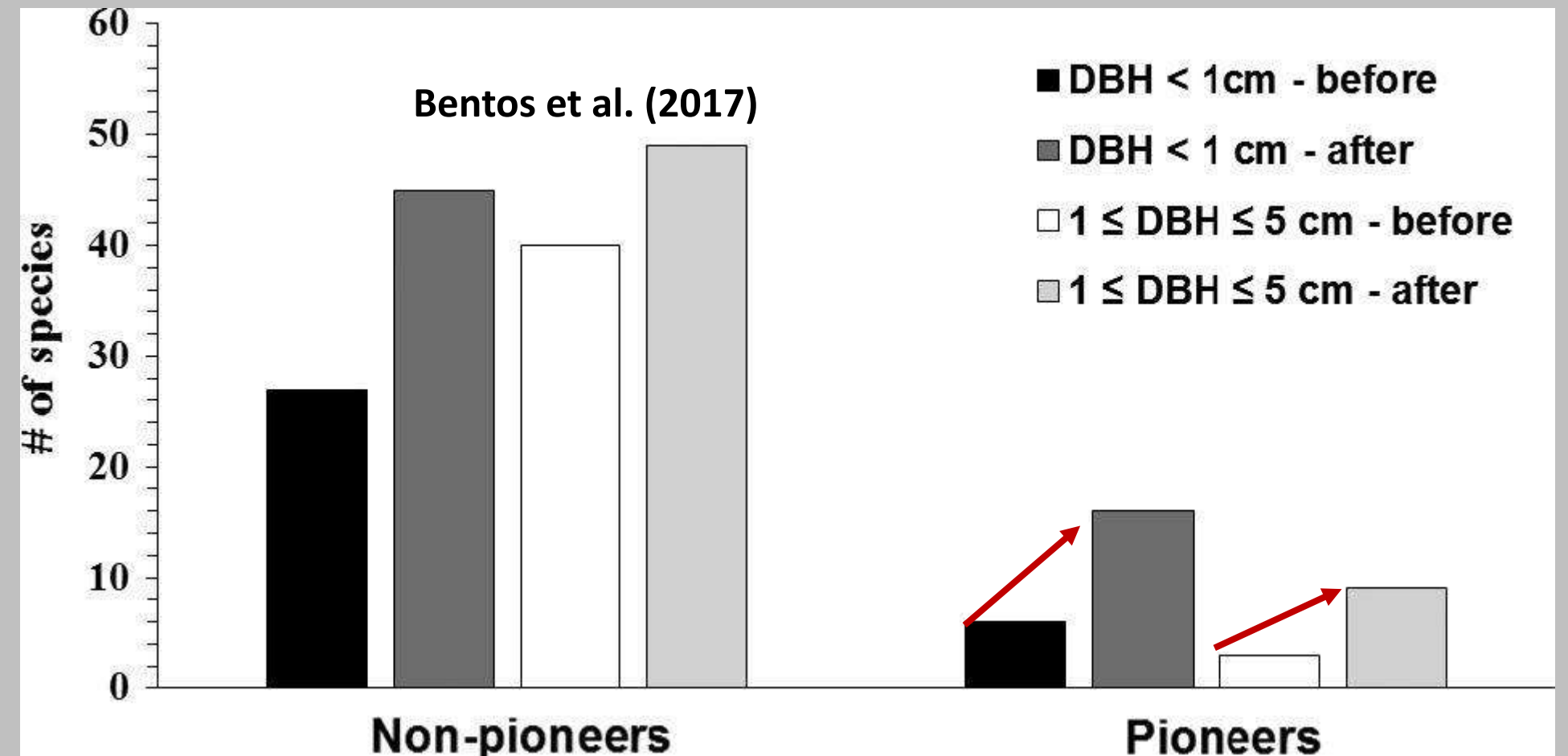
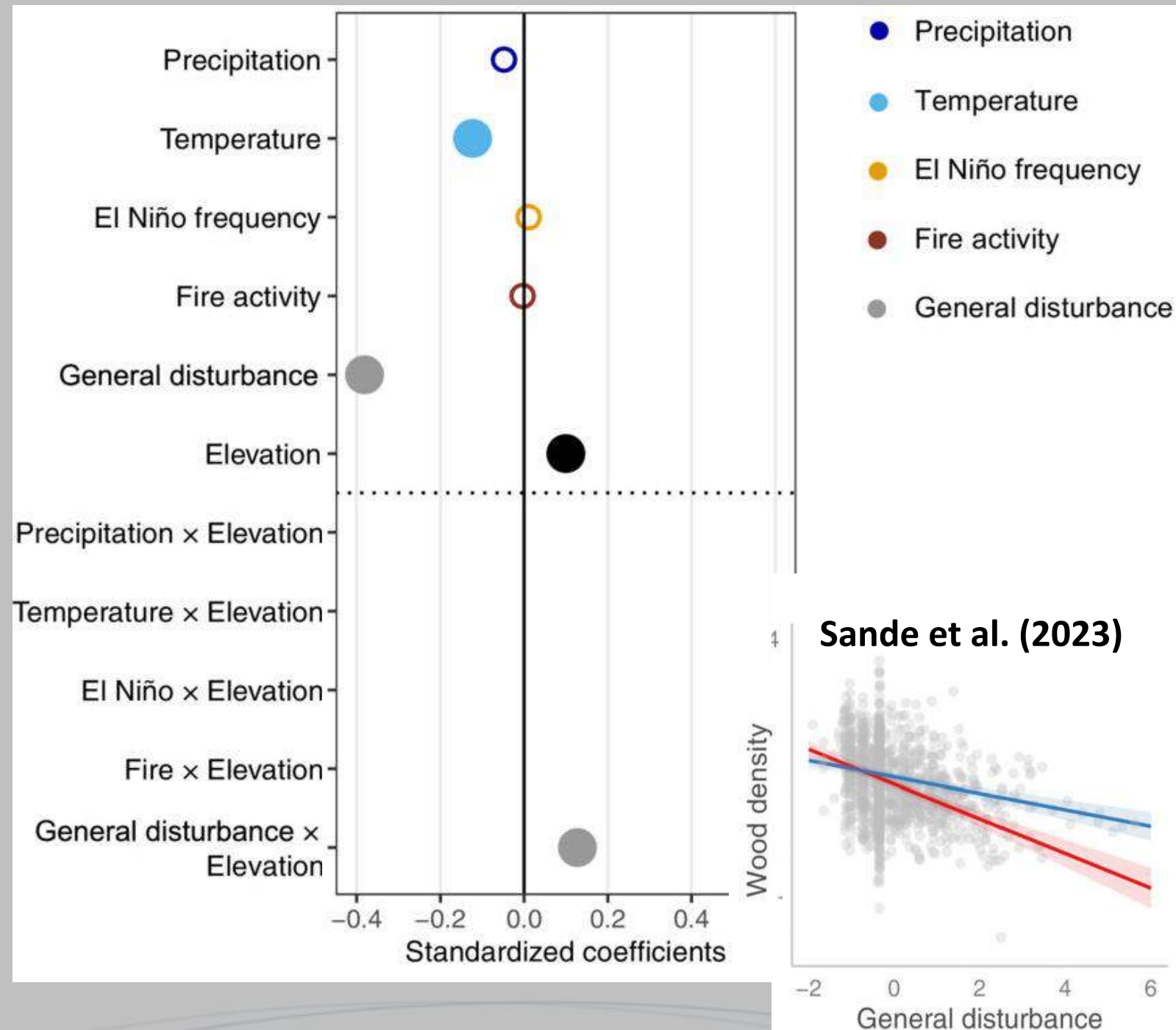
Sentinel-1/2
predictions

Application across the Amazon
10 m annual maps 2017 – 2025
6.7 Mkm²



Estimating wood density

Community composition



“Vismia, Bellucia, Miconia and Cecropia, comprised 90% of the emerging seedlings that established”

Estimating AGB

Final product specification and utility

- New annual 10 m wood density and AGB maps between 2017-2025
- Insight into community composition at ecosystem scale
- Successional dynamics from disturbance explicitly incorporated into earth observation C stocks

$$AGB = f(CH \cdot WD)$$

**Consistent
specificity**



Thank you for listening!

Scott Barningham
sdb221@exeter.ac.uk



Special thanks to:
Stephen Sitch
Lina Mercado
Luiz Aragão

Fire triples the recovery time of carbon stocks in eastern Amazonian secondary forests

Isadora Haddad

Session 2.1 (Part 2): Estimates of carbon accumulation from various approaches

São José dos Campos, 30 Oct 2025

Landscape Analysis of Brazilian Forest Regeneration: A Novel National Database of Secondary Vegetation

Débora Giancola

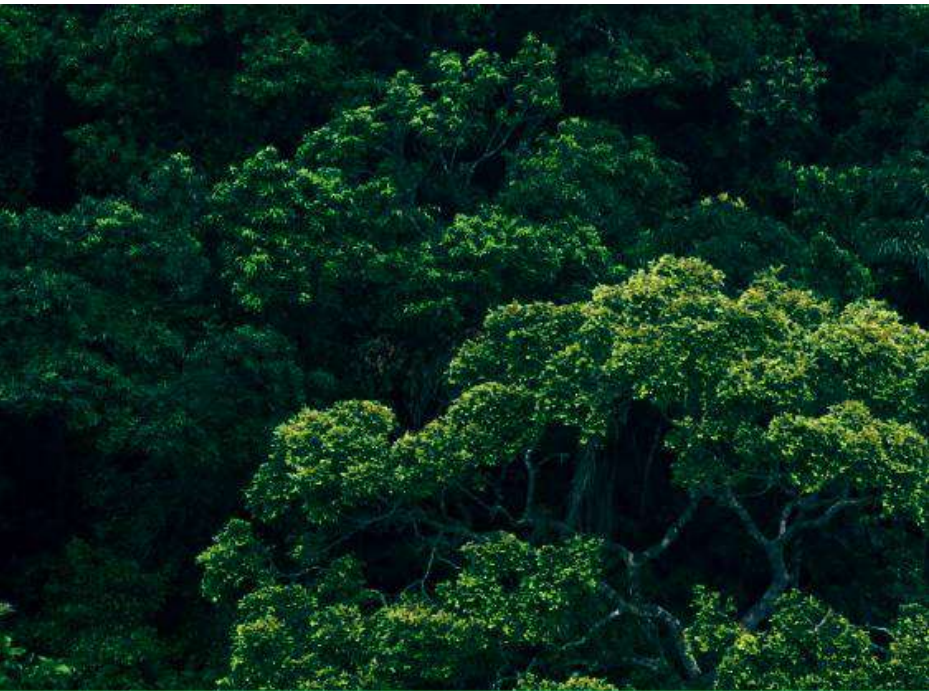
Session 2.2: Other metrics for identifying secondary forest success.

São José dos Campos, 30 Oct 2025



GFZ Helmholtz Centre
for Geosciences





Objectives

National Vegetation Recovery Plan

Recover of 12 million hectares of native vegetation by 2030

Kunming-Montreal Global Biodiversity Framework

Commitment at COP15 to restore at least 30% of degraded areas of terrestrial, inland, coastal and marine ecosystems



2020 UN BIODIVERSITY CONFERENCE
COP 15 - CP/MOP10-NP/MOP4
Ecological Civilization-Building a Shared Future for All Life on Earth
KUNMING – MONTREAL

Objectives

National Vegetation Recovery Plan



STRATEGIES

RECOVERY
PRODUCTION
CHAIN

SPATIAL
INTELLIGENCE
AND MONITORING

RECOVERY
FINANCING

RESEARCH,
DEVELOPMENT
AND INNOVATION

Guidelines:

(III) ...consolidation of spatial intelligence and a monitoring system that qualifies decision-making processes and publicizes progress in achieving the goal and the final impacts resulting from monitoring these goals.

Objectives

National Vegetation Recovery Plan



STRATEGIES

RECOVERY
PRODUCTION
CHAIN

SPATIAL
INTELLIGENCE
AND MONITORING

RECOVERY
FINANCING

RESEARCH,
DEVELOPMENT
AND INNOVATION

Guidelines:

(III) ...consolidation of spatial intelligence and a monitoring system that qualifies decision-making processes and publicizes progress in achieving the goal and the final impacts resulting from monitoring these goals.

Objectives

National Vegetation Recovery Plan



STRATEGIES

RECOVERY
PRODUCTION
CHAIN

SPATIAL
INTELLIGENCE
AND MONITORING

RECOVERY
FINANCING

RESEARCH,
DEVELOPMENT
AND INNOVATION

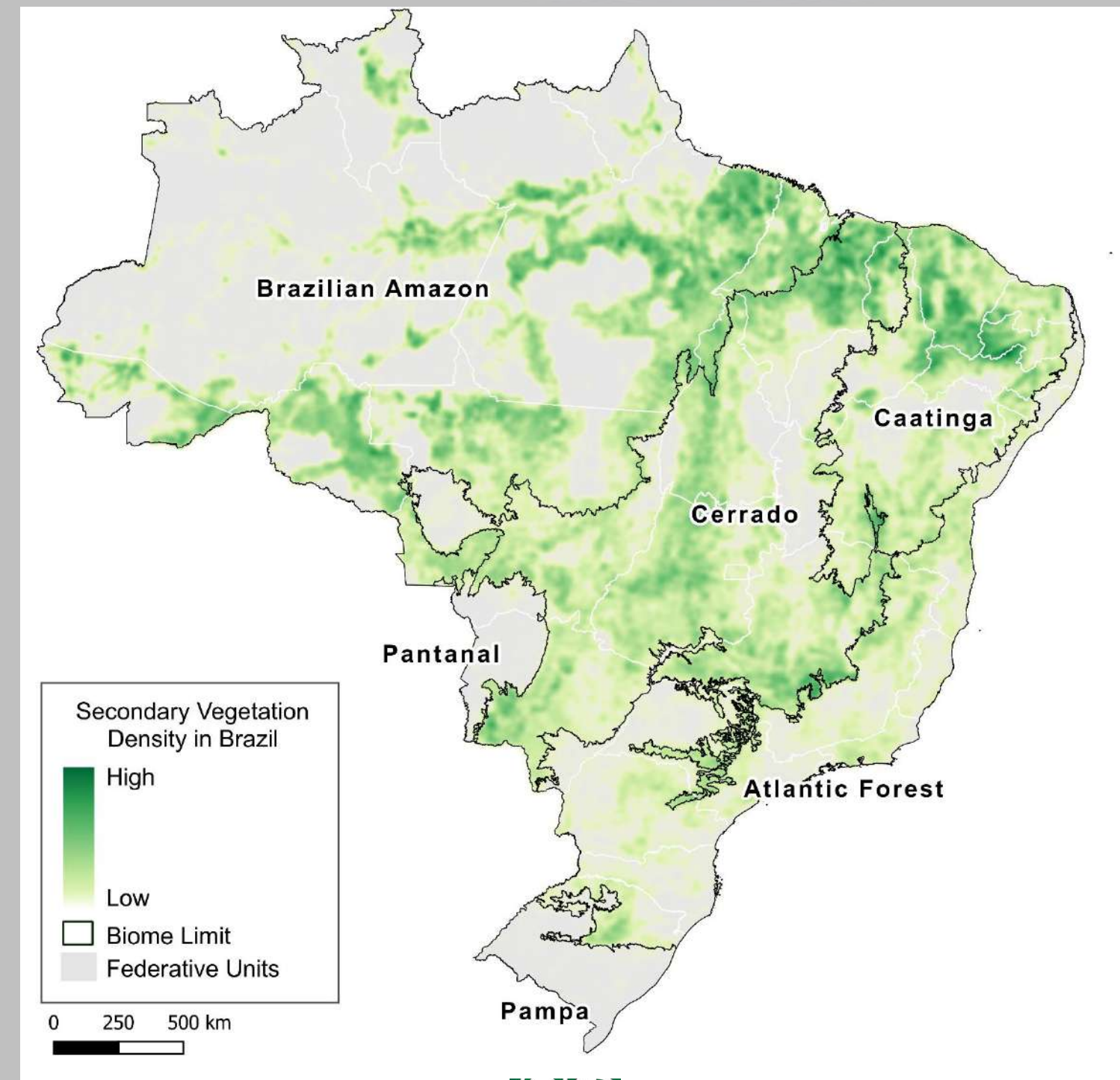
To improve the understanding of the **dynamics** of SV areas in Brazil

- Persistence
- Connectivity
- Land tenure category

Secondary Vegetation

Definitions

“Areas that have been deforested and are in an advanced stage of regeneration, with the presence of trees and shrubs.”



Data Source

Data base for qualification

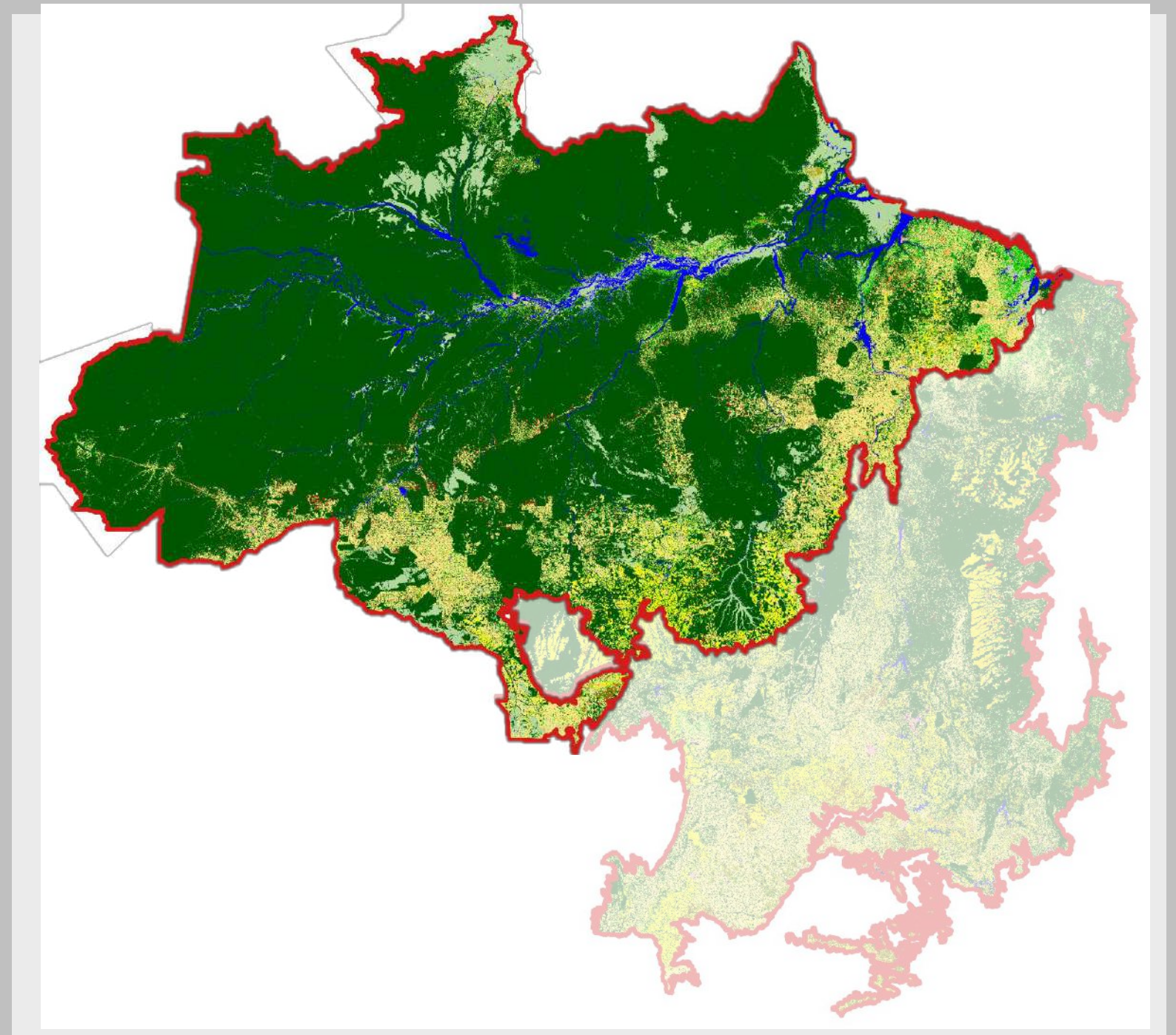


2008

Amazon

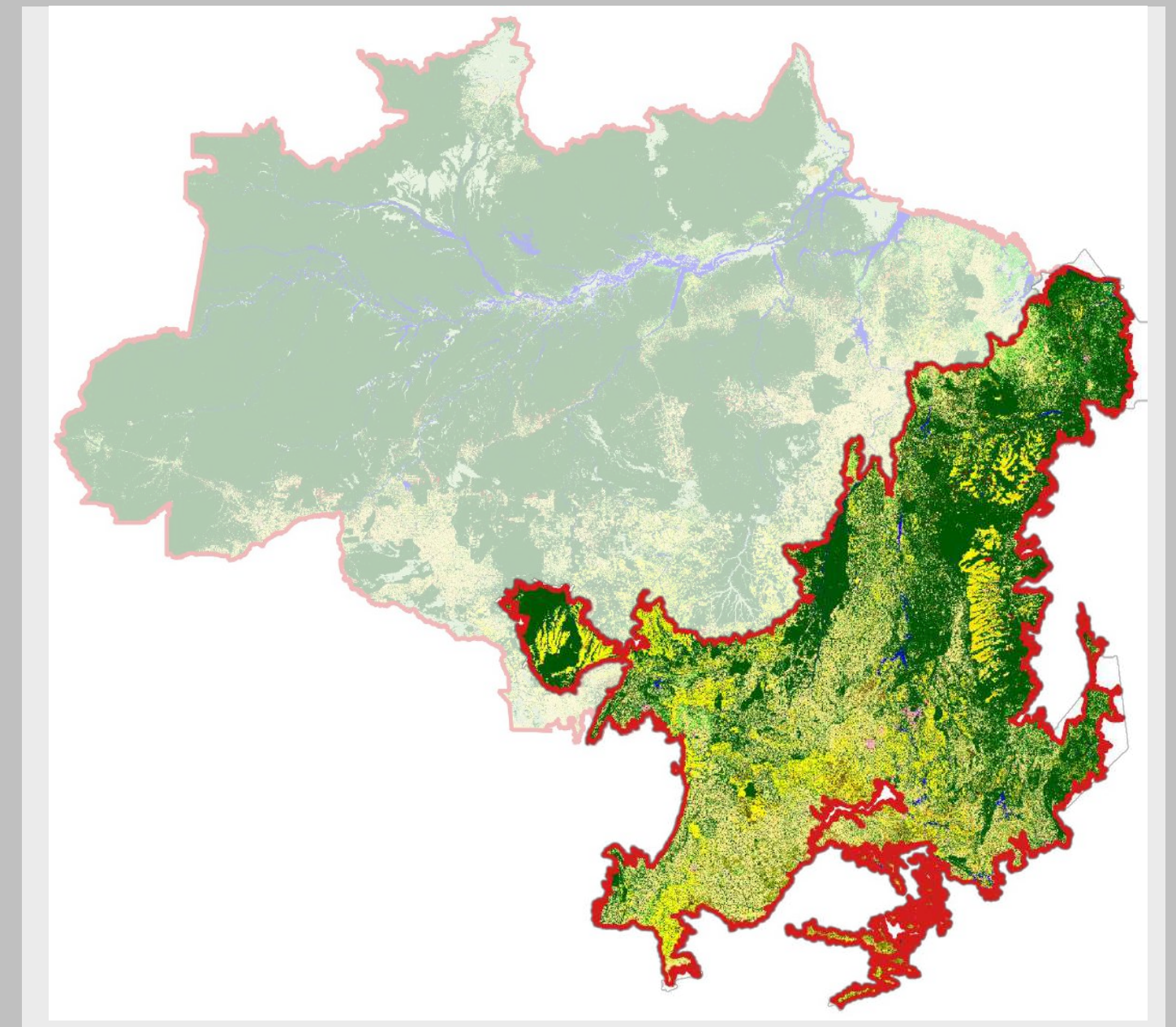
2022

- Mapped each 2 years



Data Source

Data base for qualification



Data Source

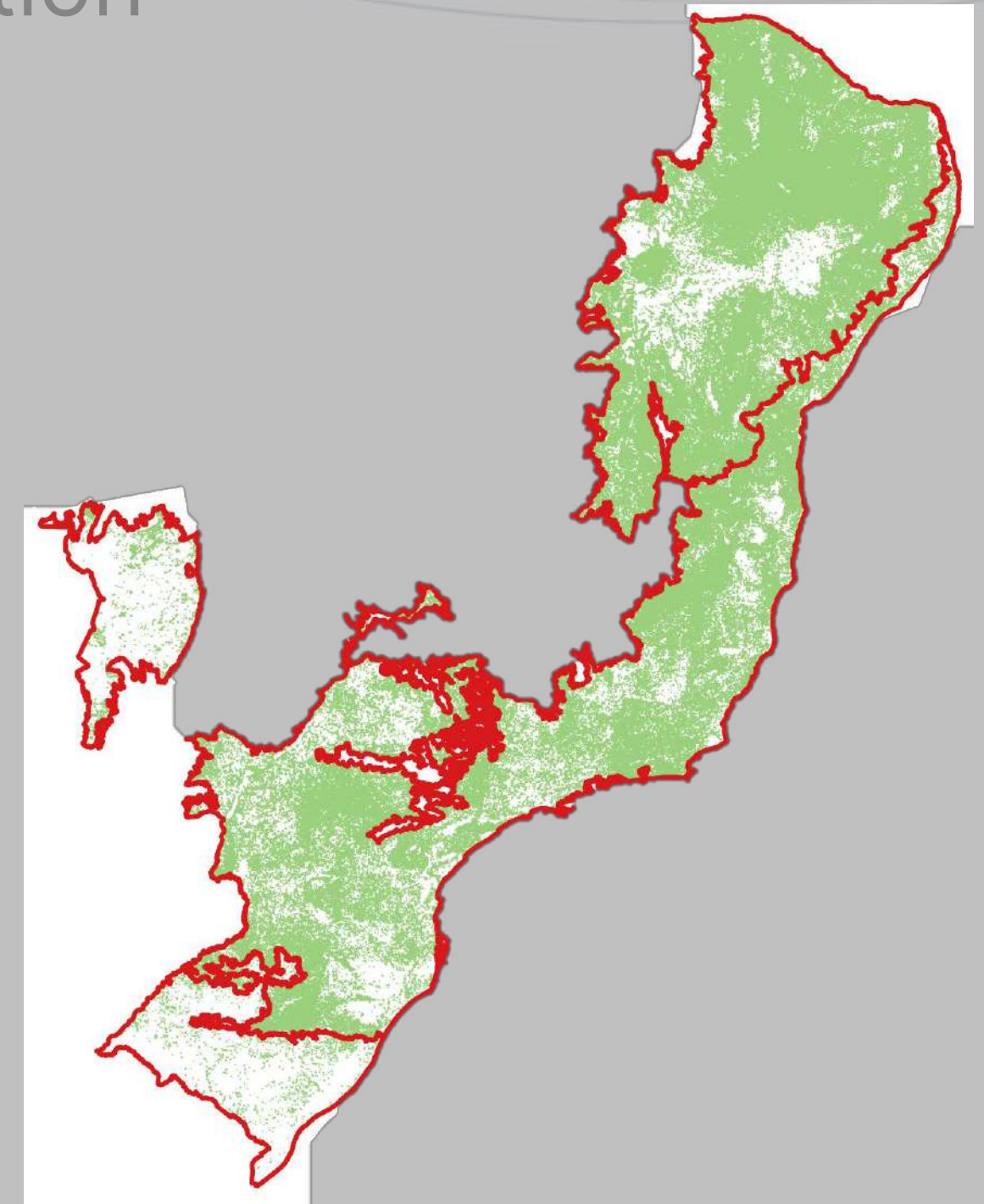
Data base for qualification



Atlantic Forest, Caatinga, Pantanal
and Pampa

2018

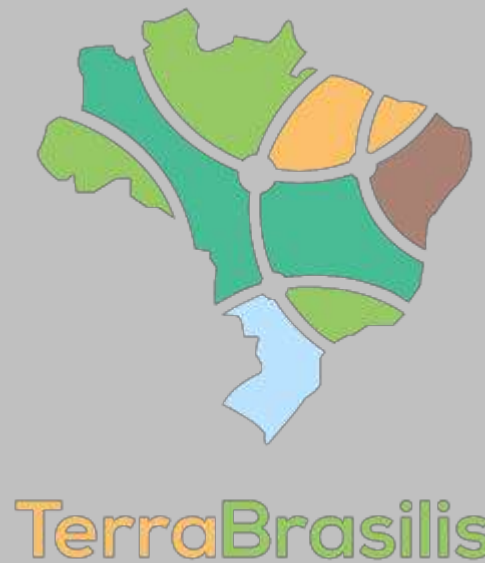
2022



Data Source

Land Tenure

- Indigenous Land
- Integral Protection Conservation Units
- Sustainable Use Conservation Units (excluding APA);
- Quilombola Territories
- Rural Settlements
- Environmental Protection Areas (APA)
- Private Properties
- Undesignated Public Forests
- Areas without Land Registration



FUNAI, ICMBio and INCRA

Landscape Ecology

Methodology

Landscape Metrics:

- Area (ha)
- Core area (ha) – 30, 60, 90 e 120 m
- Fractal dimension index
- Euclidean distance to the nearest neighbor (m)
- Type of nearest neighboring vegetation

Landscape Ecology

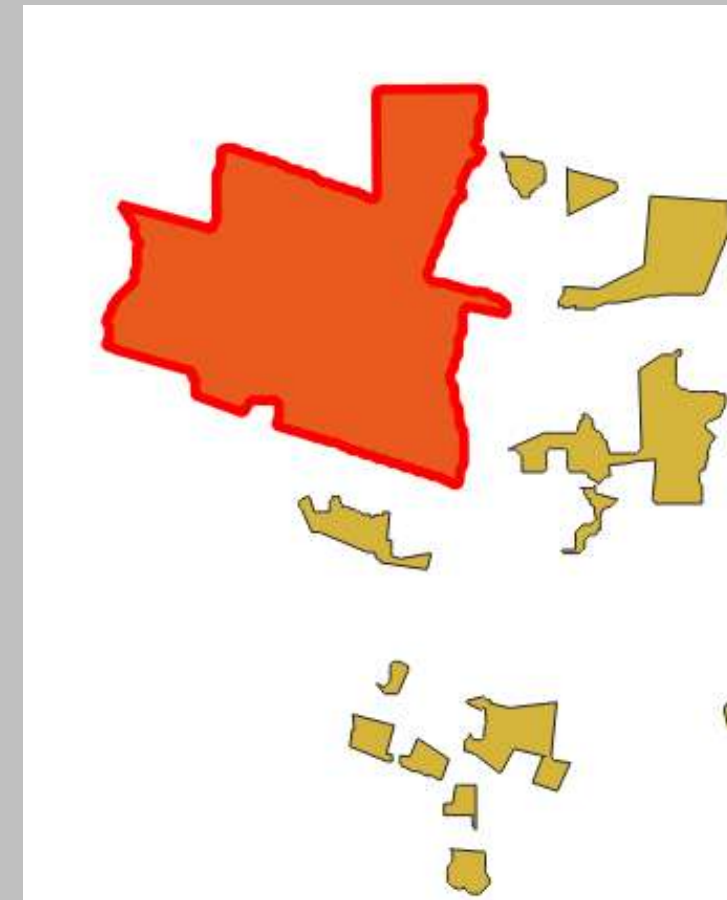
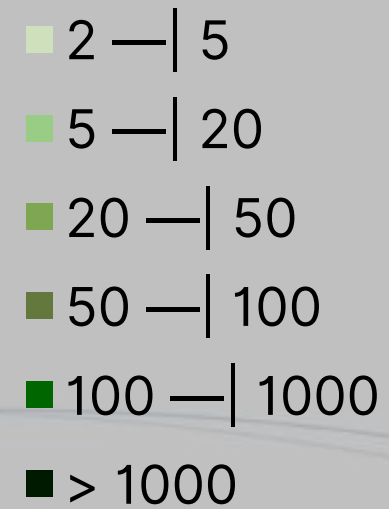
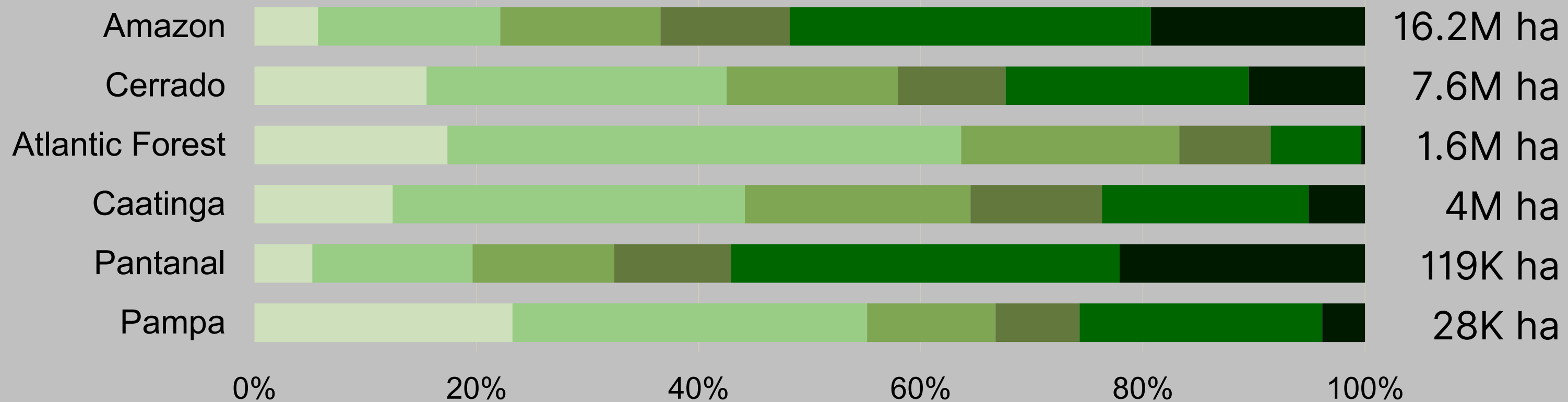
Methodology

Landscape Metrics:

- Area (ha)
- Core area (ha) – 30, 60, 90 e 120 m
- Fractal dimension index
- Euclidean distance to the nearest neighbor (m)
- Type of nearest neighboring vegetation
- Weighted age (years)
- Area (ha) of the fragment according to land tenure parcels in the region

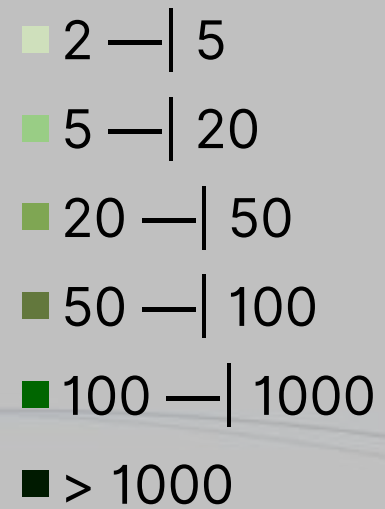
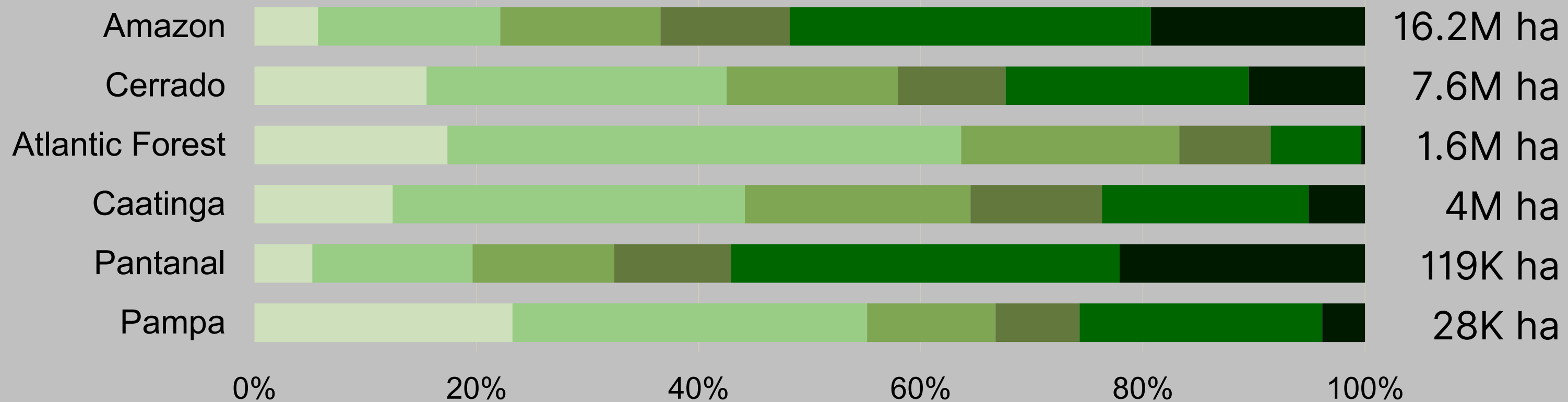
Area (ha)

Total area

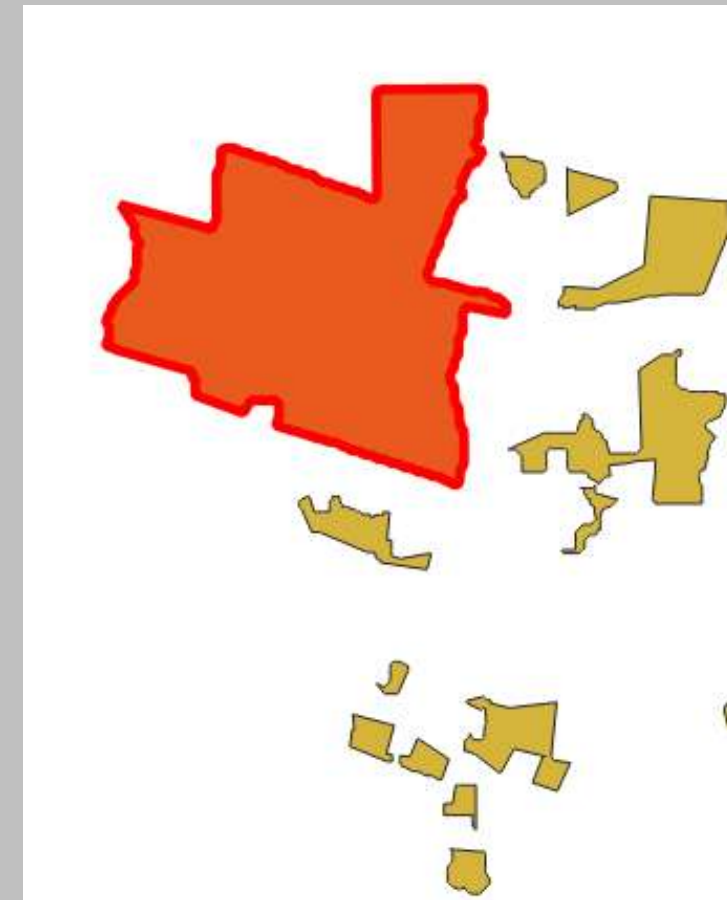


Area (ha)

Total area

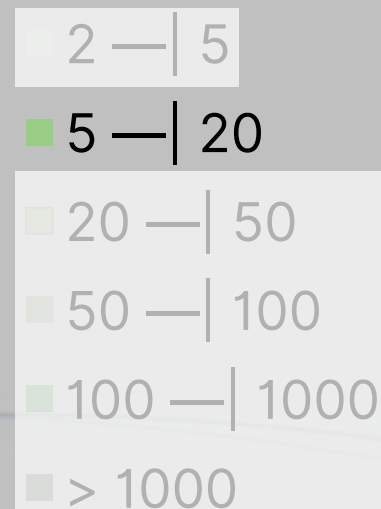
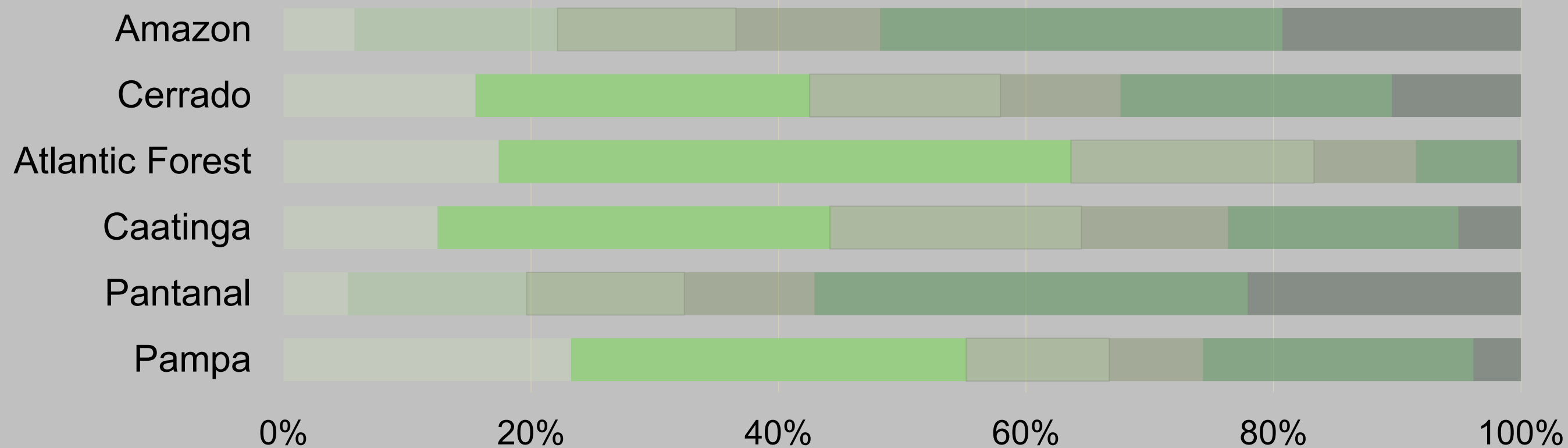


29,5M ha of SV Brazil

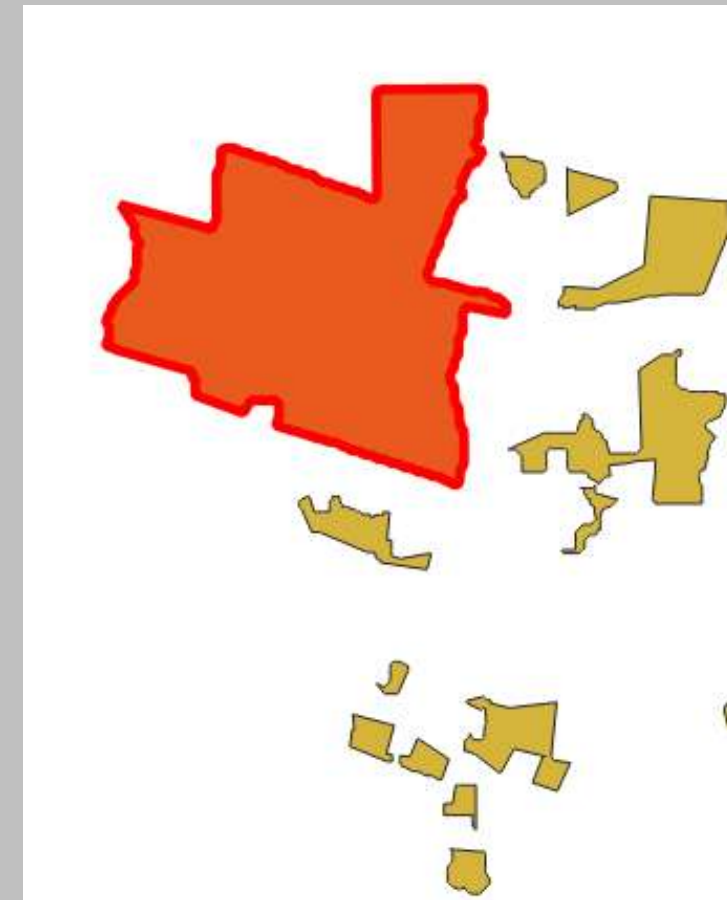


Area (ha)

Total area

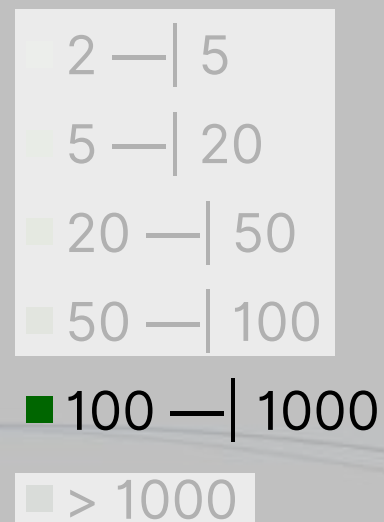
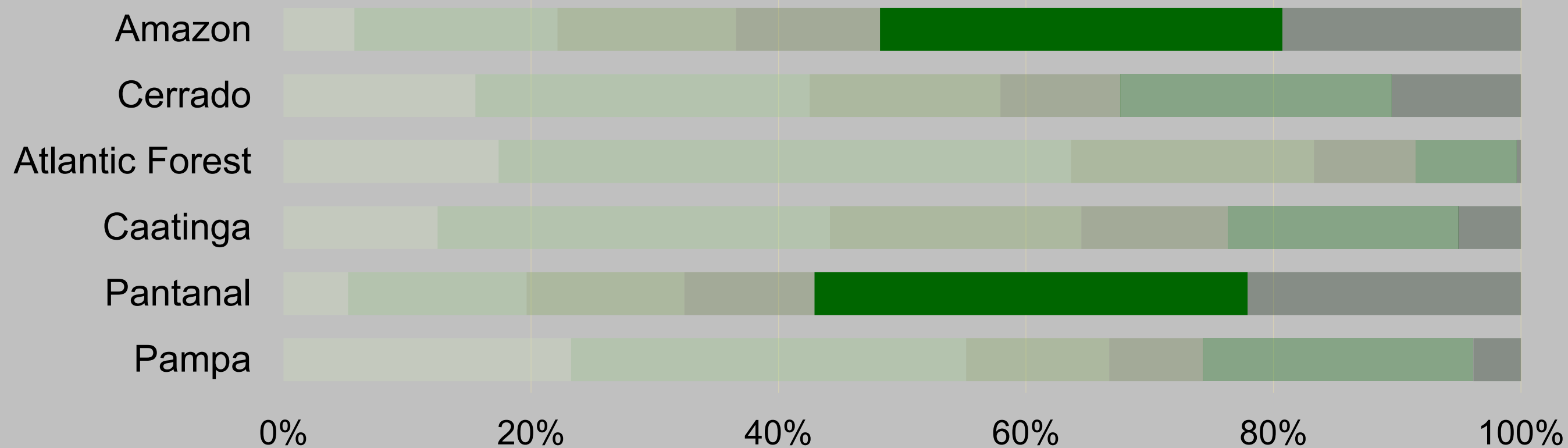


5 —| 20 → ~ 30 - 40%

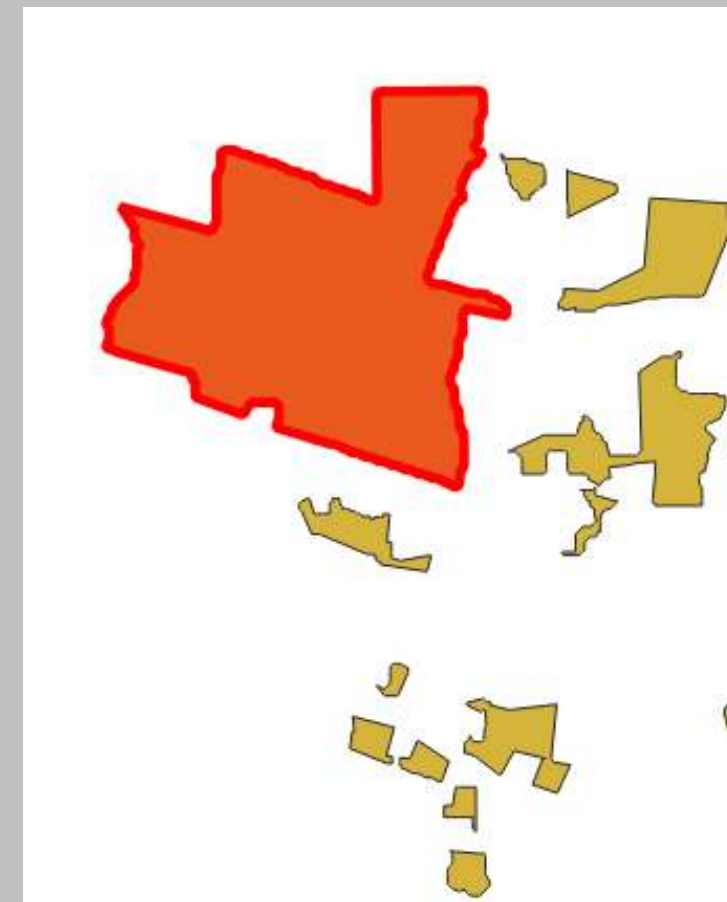


Area (ha)

Total area



100 —| 1000 → ~ 30 - 40%



Core area (ha)

Results by edge distance

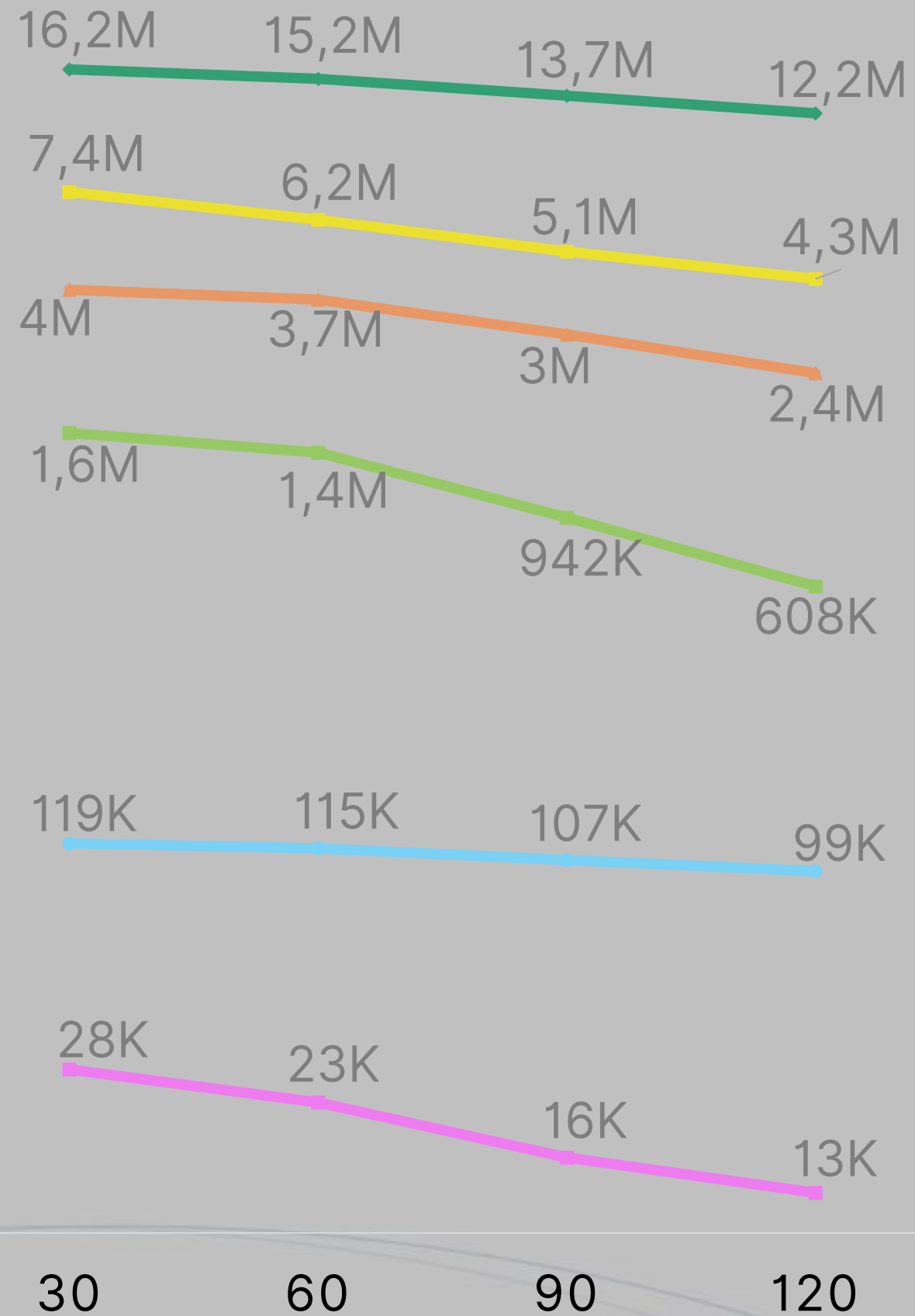
Core area (ha)

10,000,000

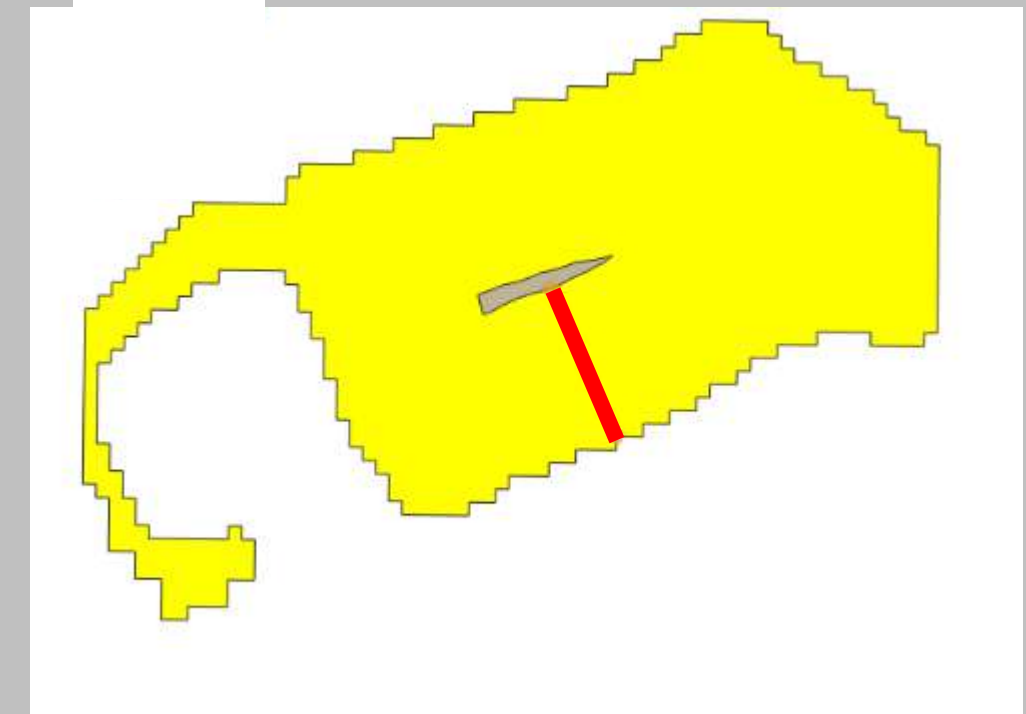
1,000,000

100,000

10,000



- Amazon
- Cerrado
- Caatinga
- Atlantic Forest
- Pampa
- Pantanal



Core area (ha)

Loss along edge
distance

Core area (ha)

10,000,000

1,000,000

100,000

10,000

16,2M 15,2M 13,7M 12,2M -25%

7,4M 6,2M 5,1M 4,3M -42%

4M 3,7M 3M 2,4M -40%

1,6M 1,4M 942K 608K -62%

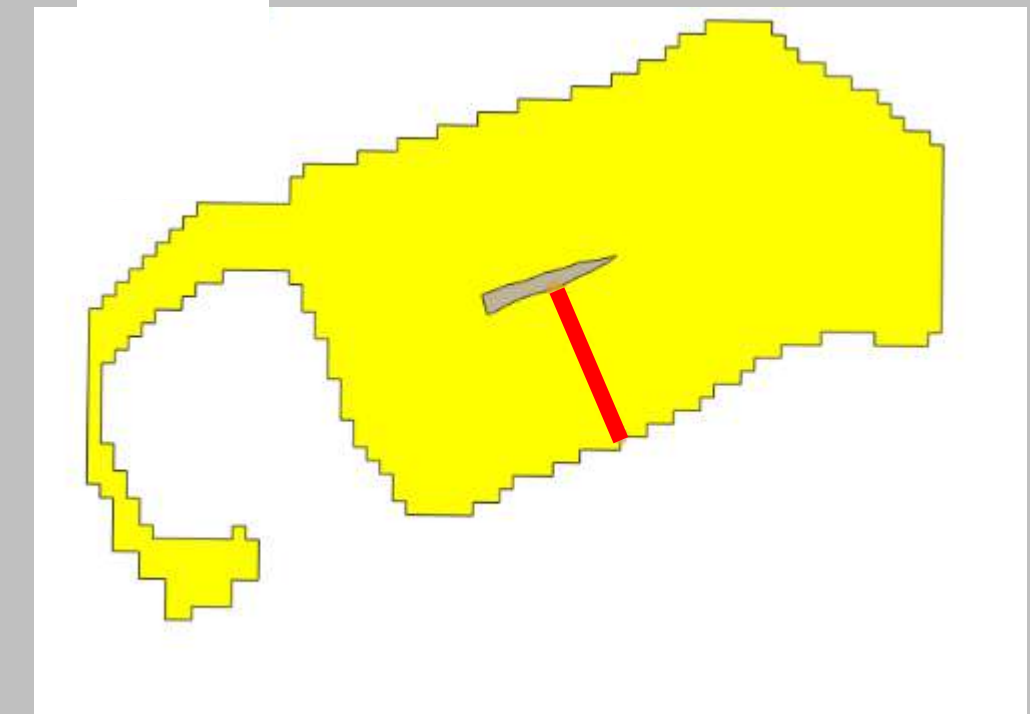
119K 115K 107K 99K -17%

28K 23K 16K 13K -54%

30 60 90 120

Edge distance (m)

- Amazon
- Cerrado
- Caatinga
- Atlantic Forest
- Pampa
- Pantanal



Core area (ha)

Loss along edge
distance

Core area (ha)

10,000,000

1,000,000

100,000

10,000

16,2M 15,2M 13,7M 12,2M **-25%**

7,4M 6,2M 5,1M 4,3M **-42%**

4M 3,7M 3M 2,4M **-40%**

1,6M 1,4M 942K 608K **-62%**

119K 115K 107K 99K **-17%**

28K 23K 16K 13K **-54%**

30 60 90 120

Edge distance (m)

Amazon

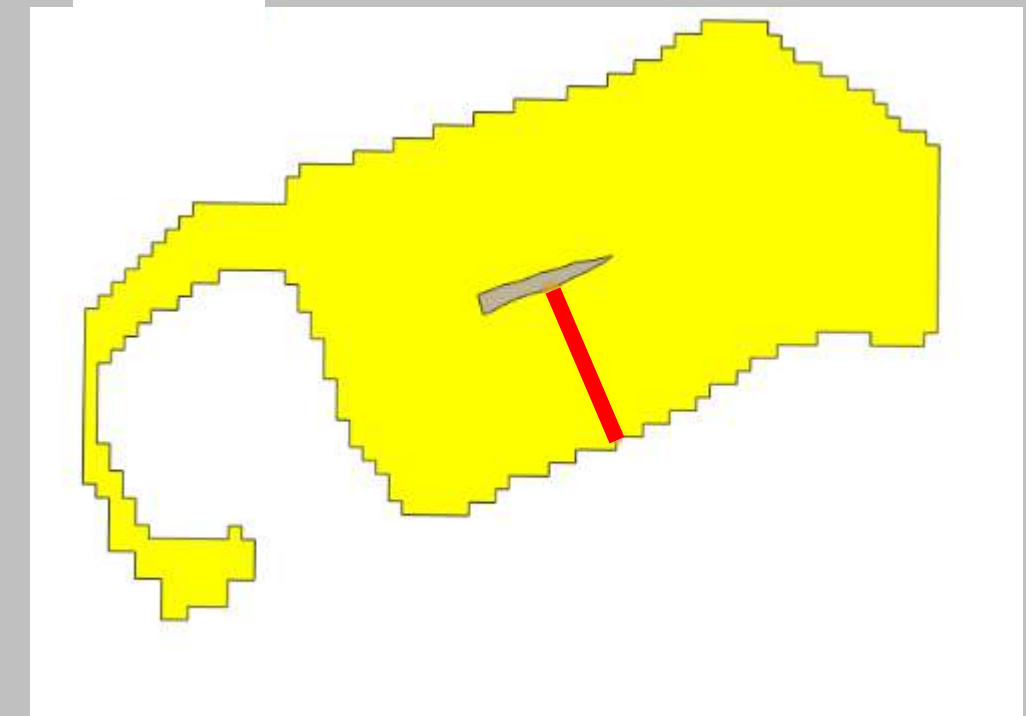
Cerrado

Caatinga

Atlantic
Forest

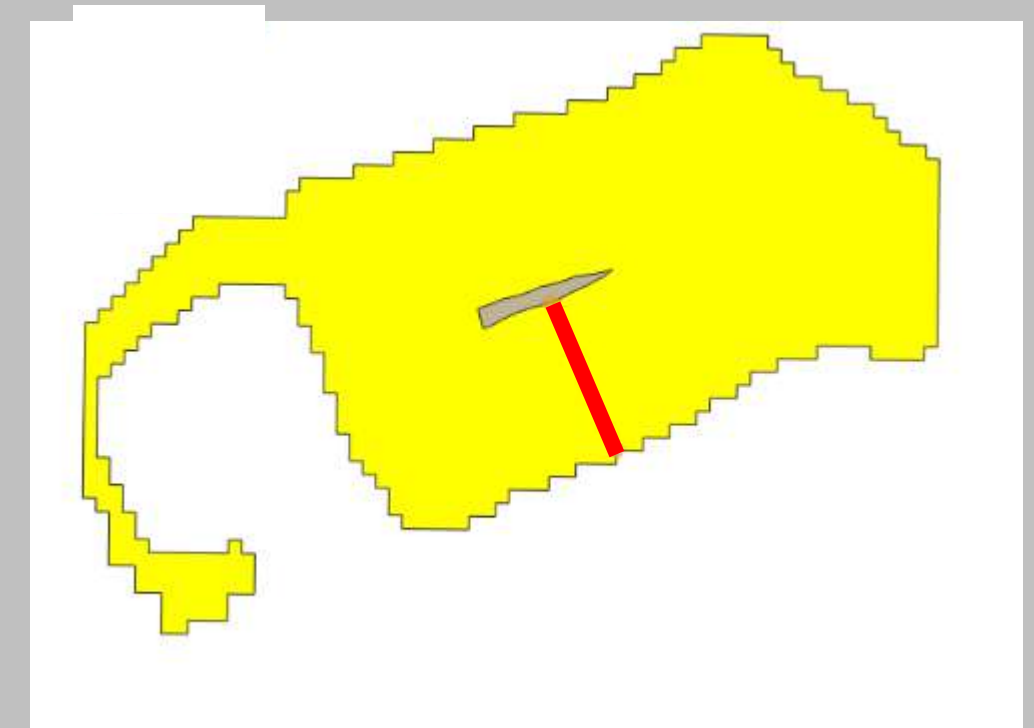
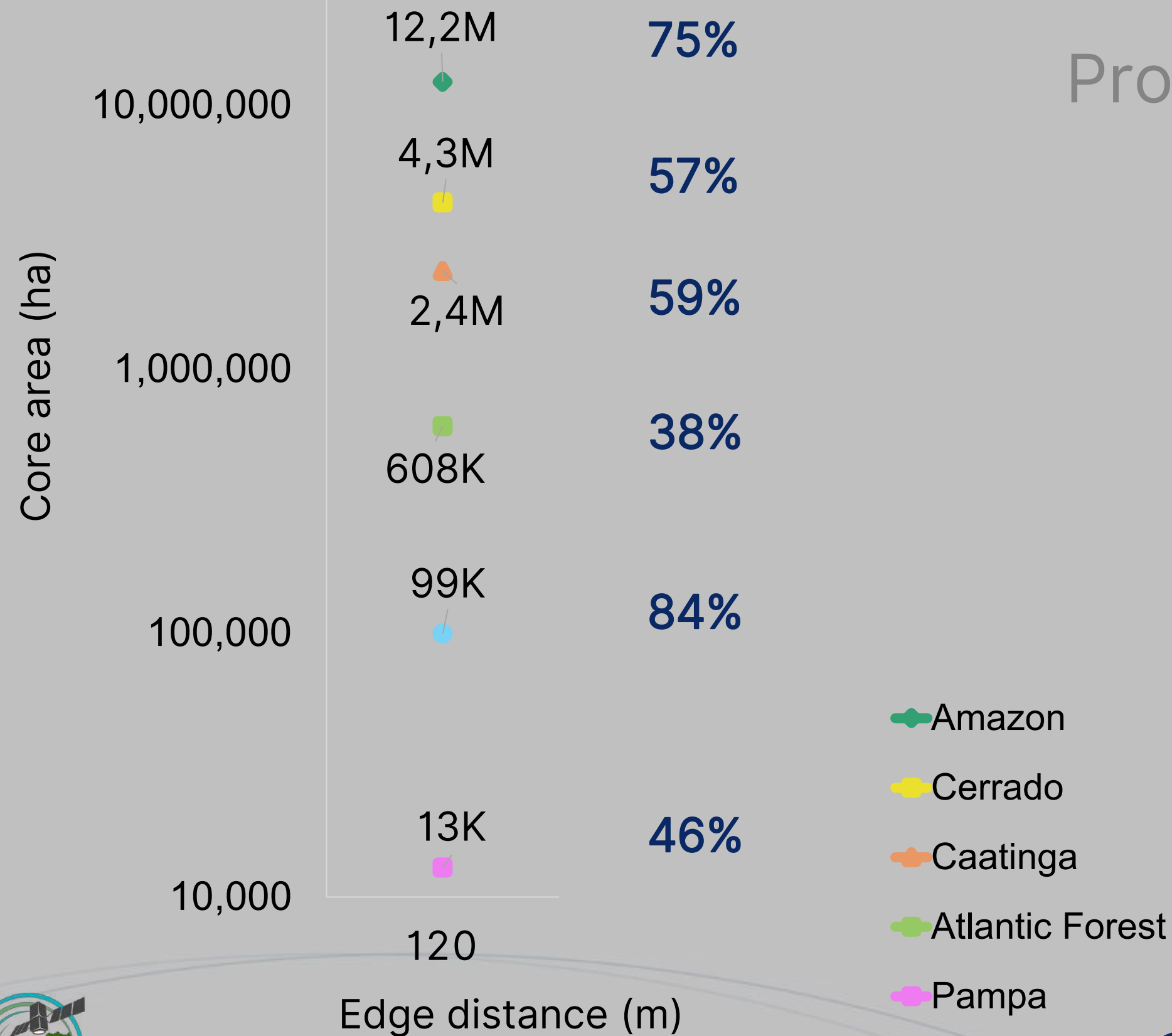
Pampa

Pantanal



Core area (ha)

Proportion by biome



Core area (ha)

Proportion by biome

Core area (ha)

10,000,000

1,000,000

100,000

10,000

12,2M

75%

4,3M

57%

2,4M

59%

608K

38%

99K

84%

13K

46%

120
Edge distance (m)

Amazon

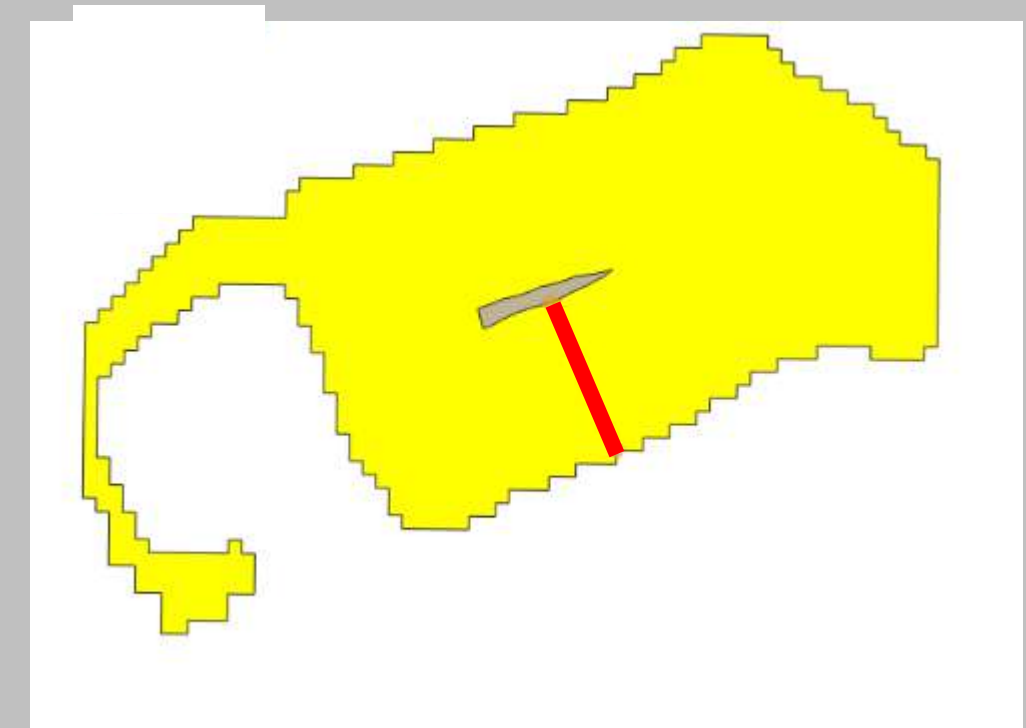
Cerrado

Caatinga

Atlantic Forest

Pampa

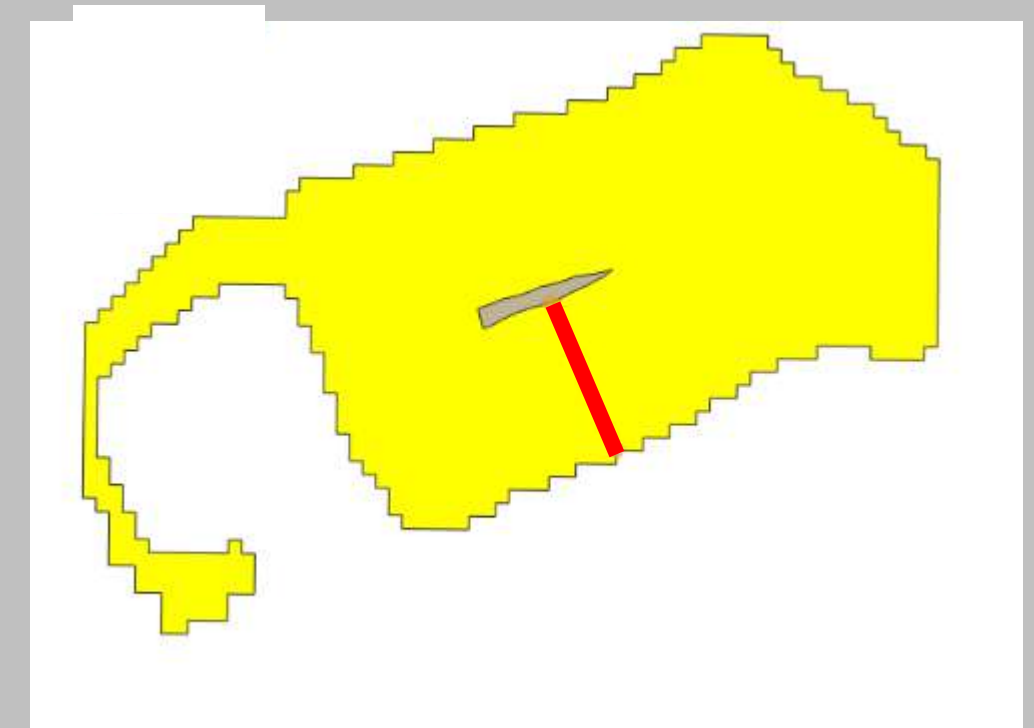
Pantanal



Core area (ha)

Proportion by biome

Smaller proportions
=
Smaller fragments
=
Greater edge effect*



Core area (ha)

10,000,000

1,000,000

100,000

10,000

12,2M

75%

4,3M

57%

2,4M

59%

608K

38%

99K

84%

13K

46%

120

Edge distance (m)

Amazon

Cerrado

Caatinga

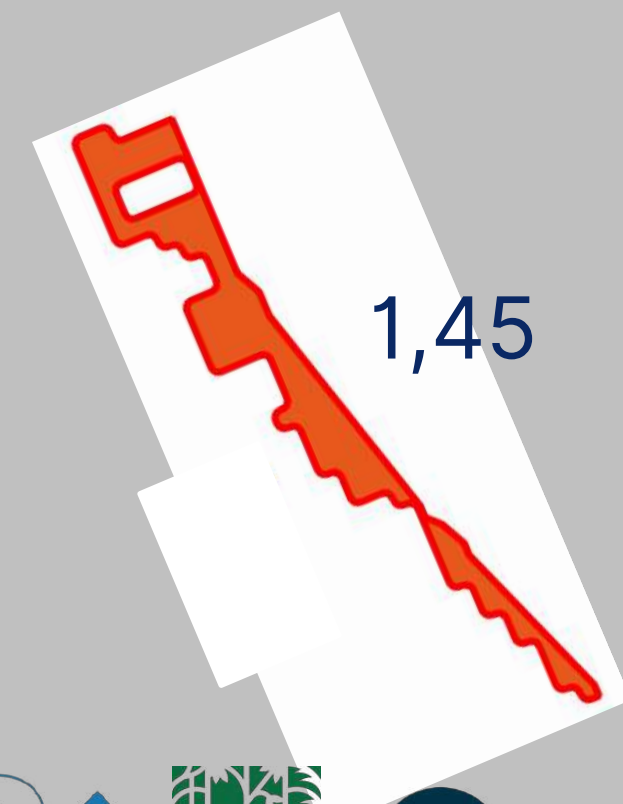
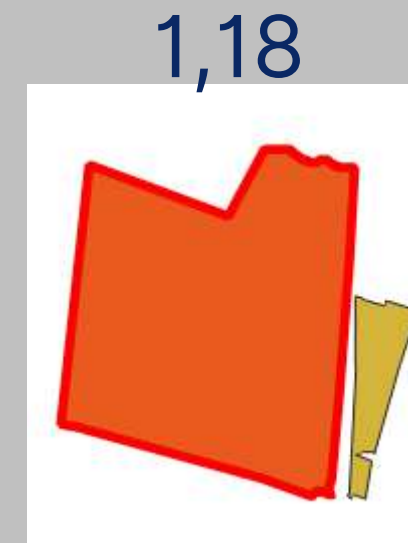
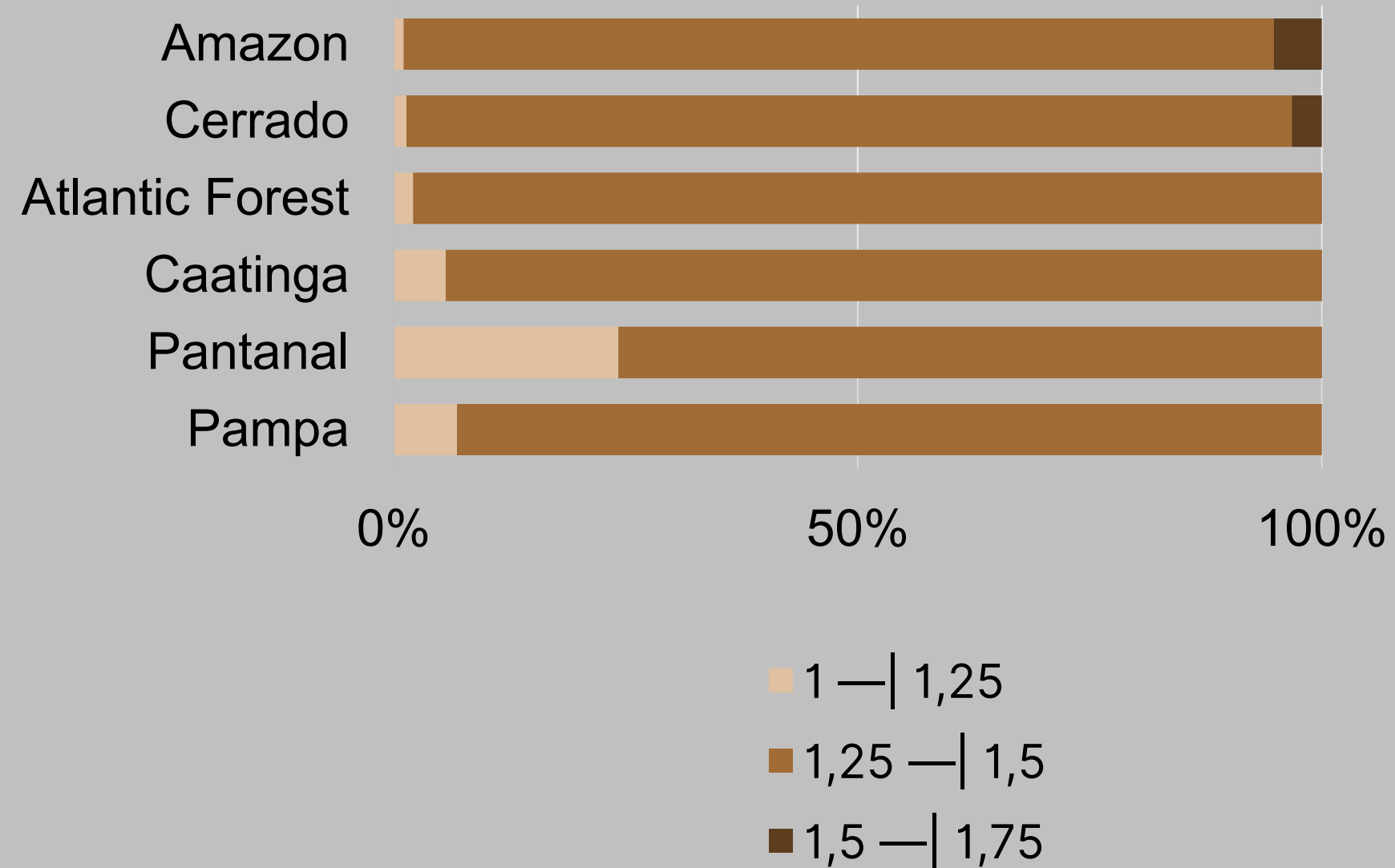
Atlantic Forest

Pampa

Pantanal

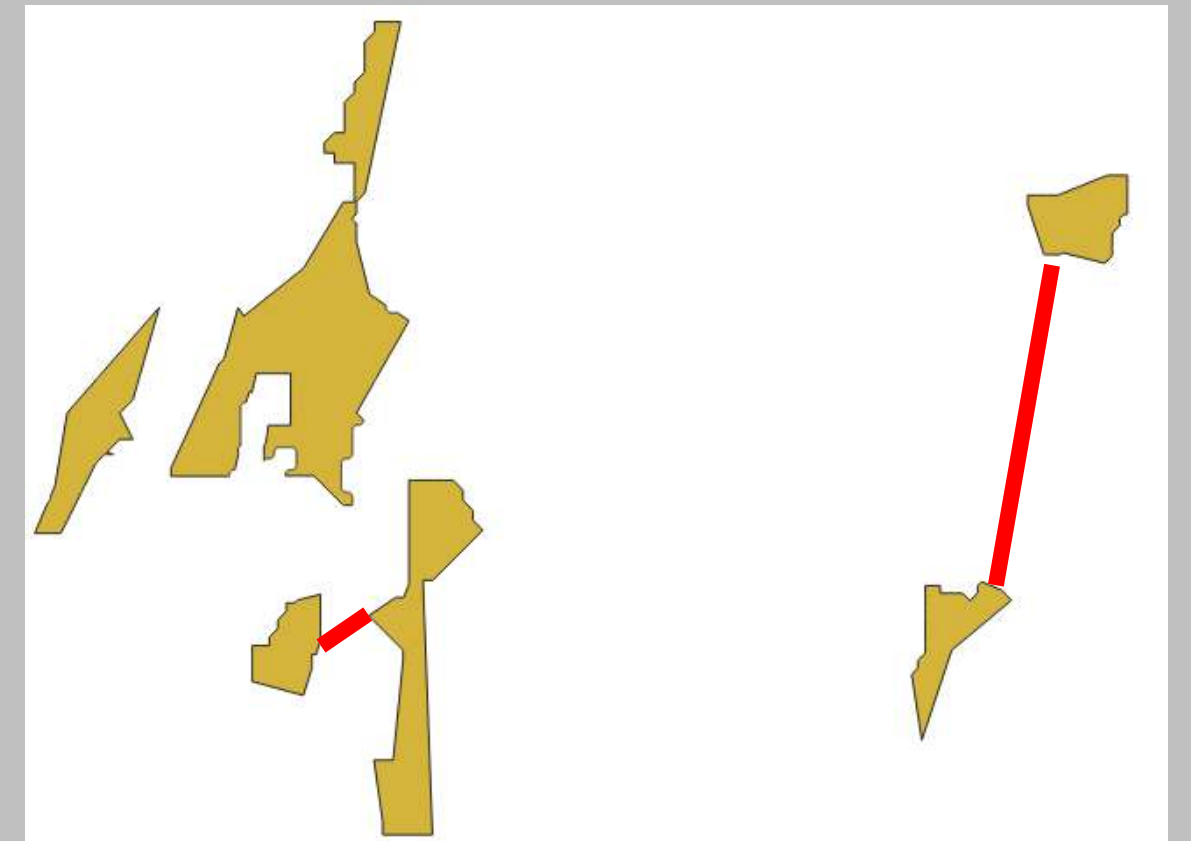
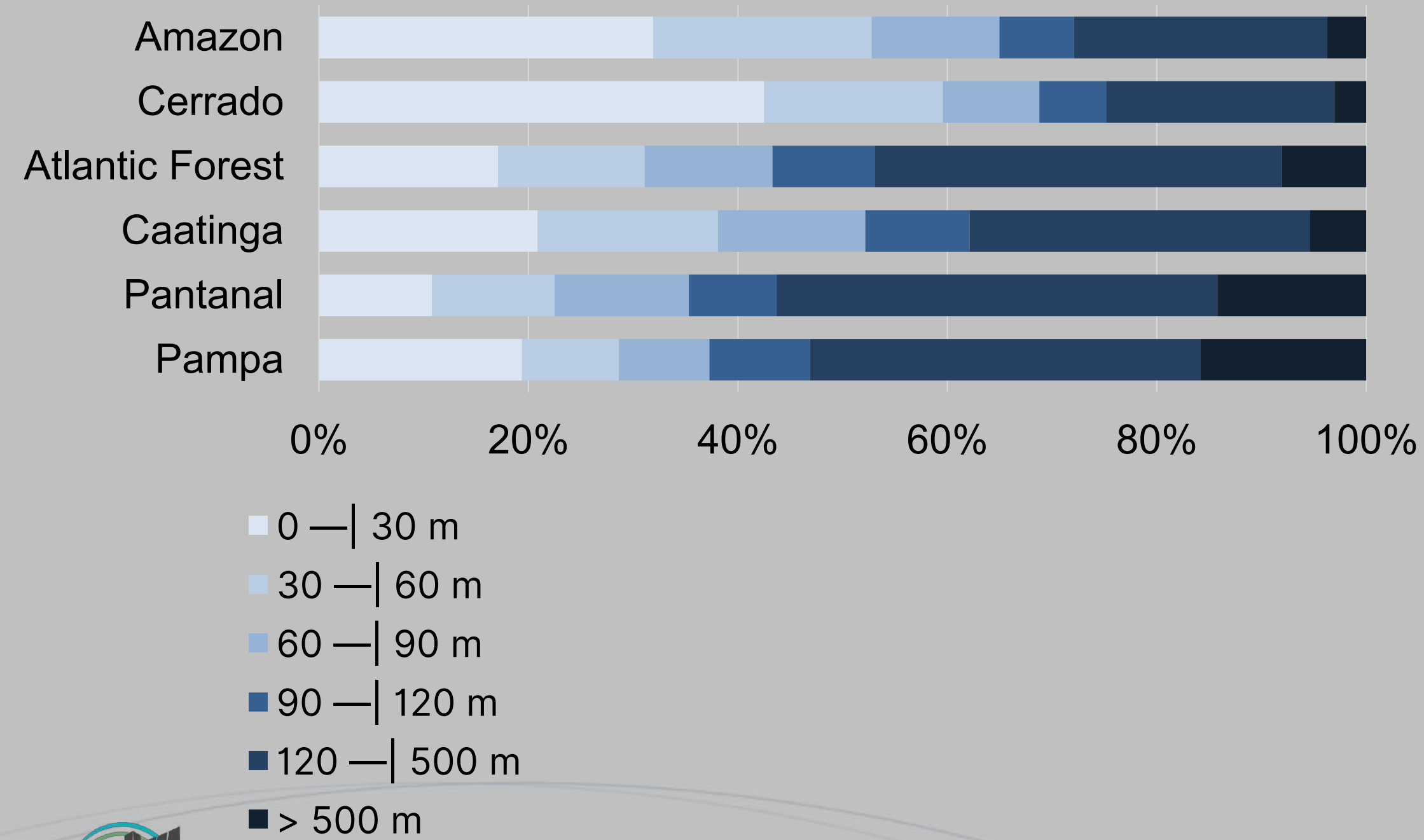
Fractal dimension index

Results



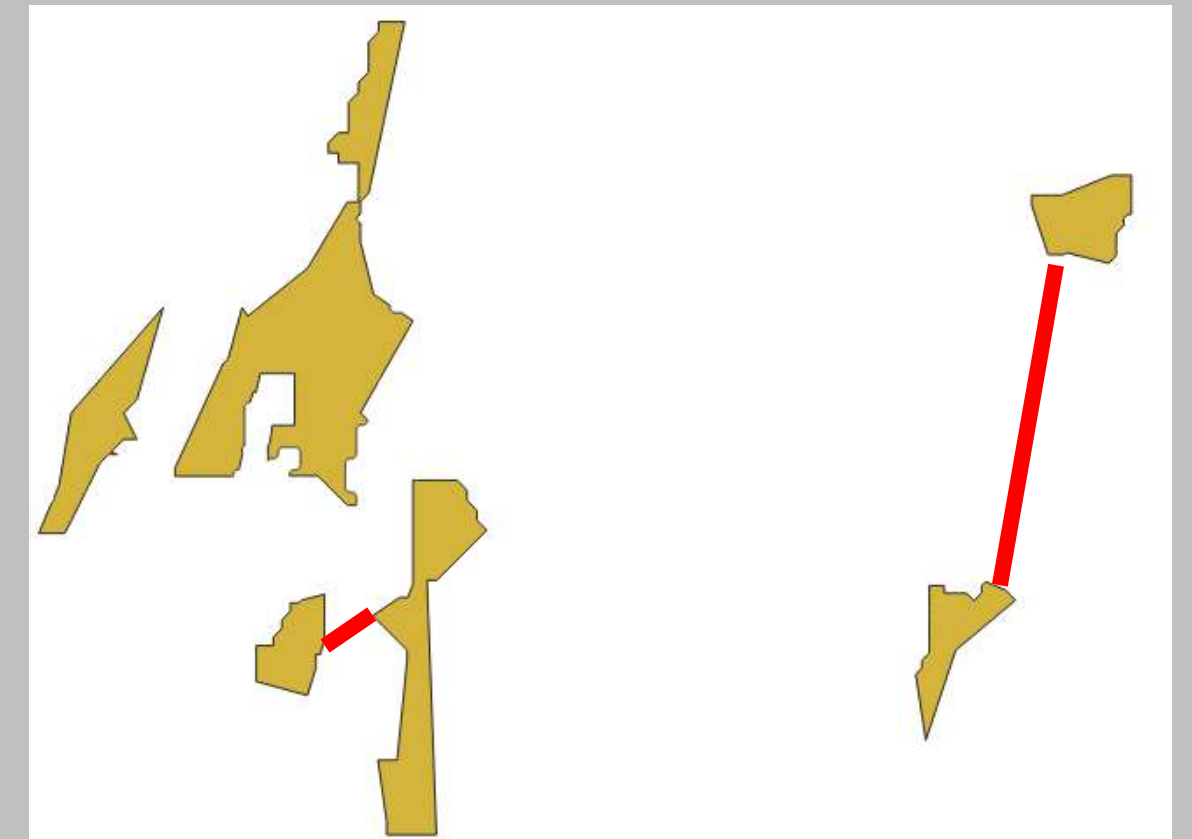
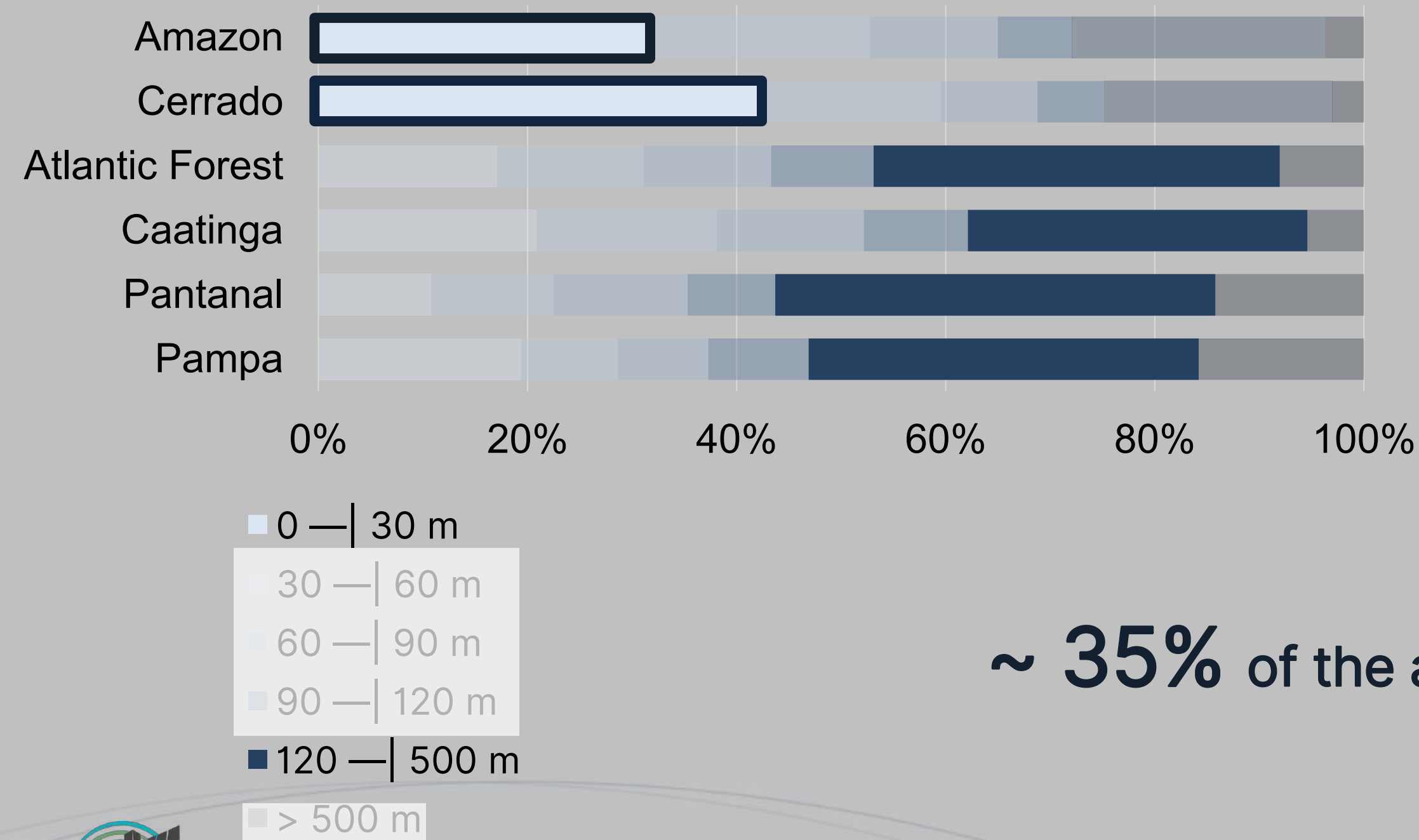
Distance to the nearest neighbor (m)

Results



Distance to the nearest neighbor (m)

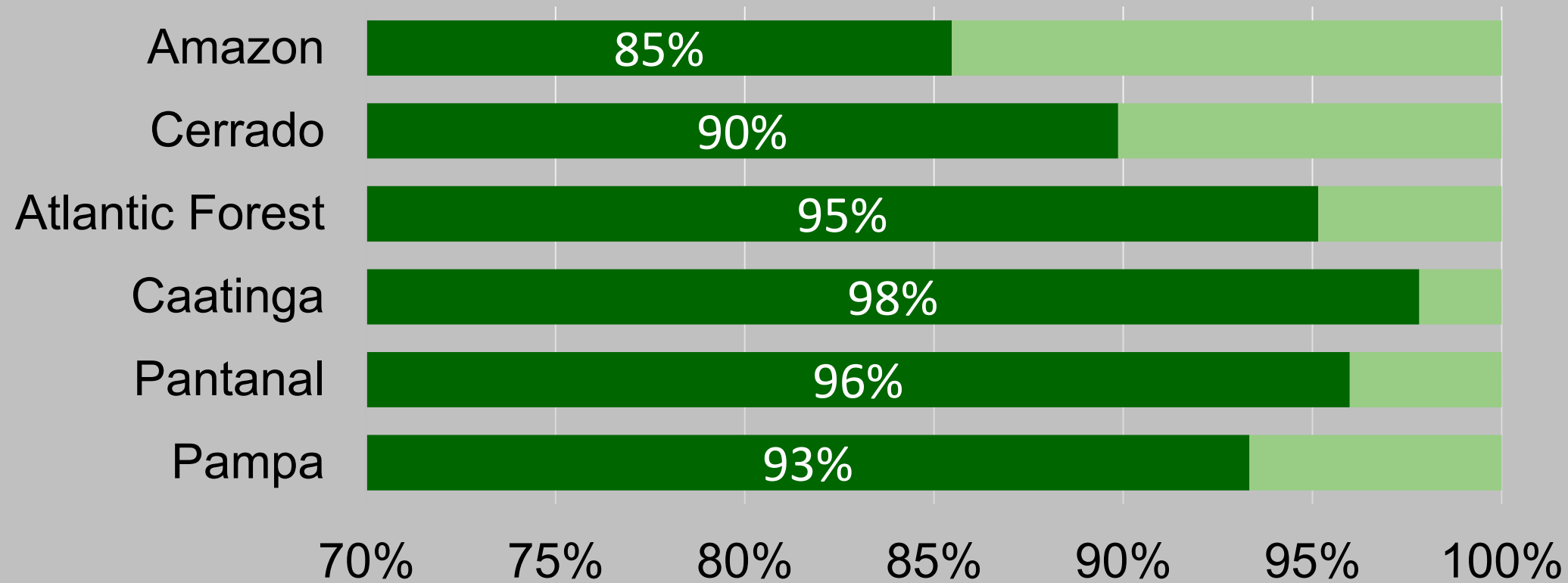
Results



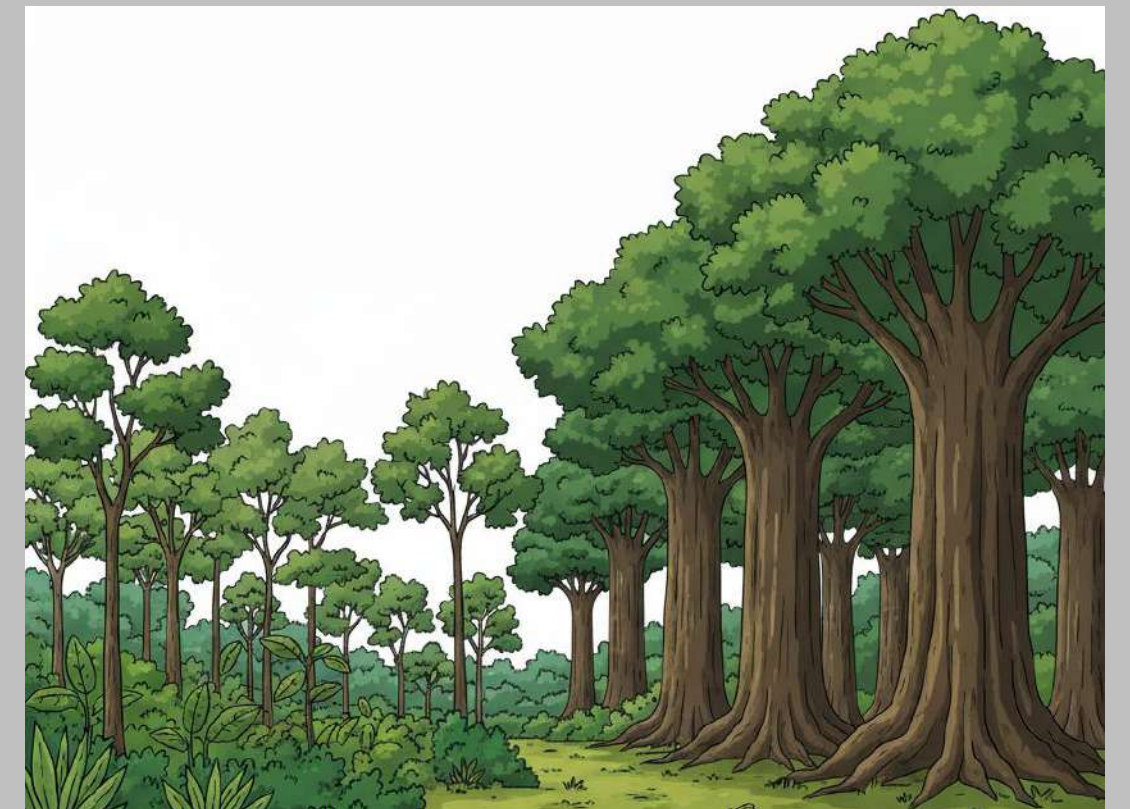
~ 35% of the area

Type of nearest neighboring vegetation

Results

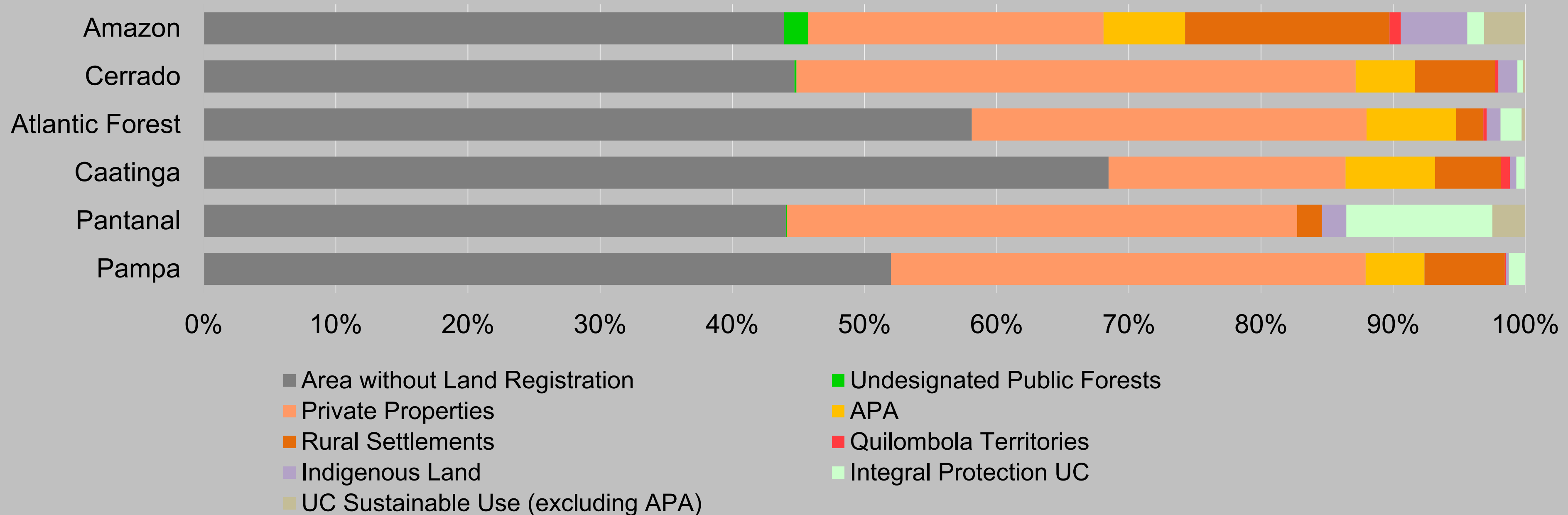


■ Primary Vegetation
■ Secondary Vegetation



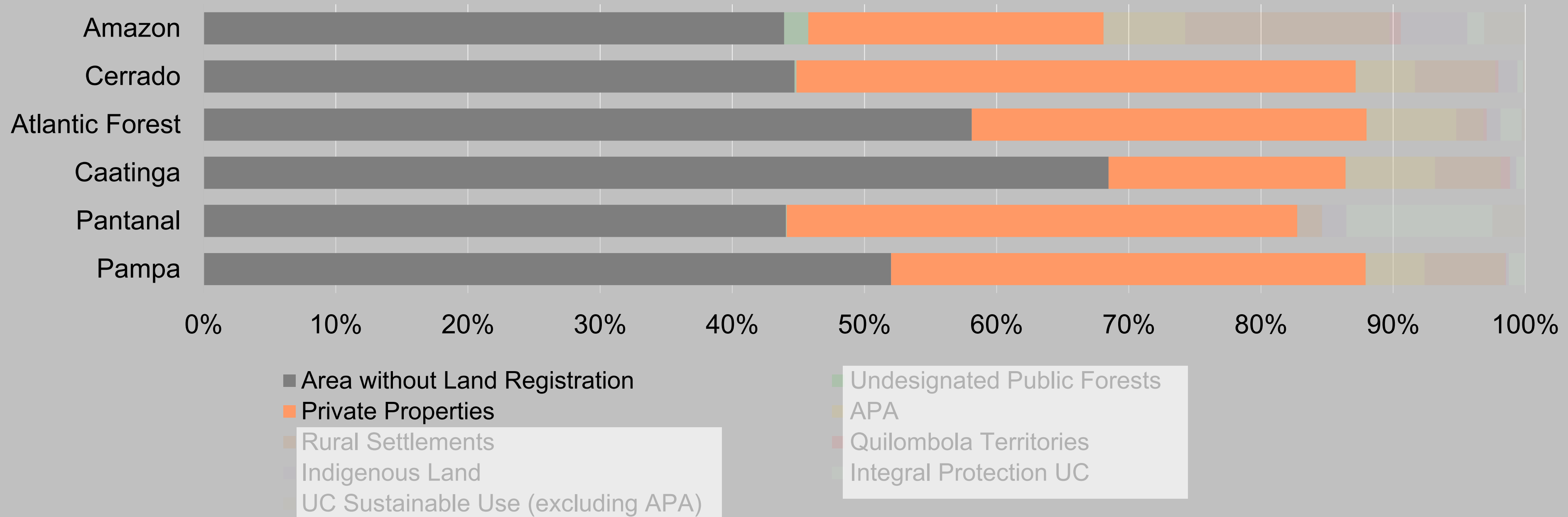
Land Tenure

Results



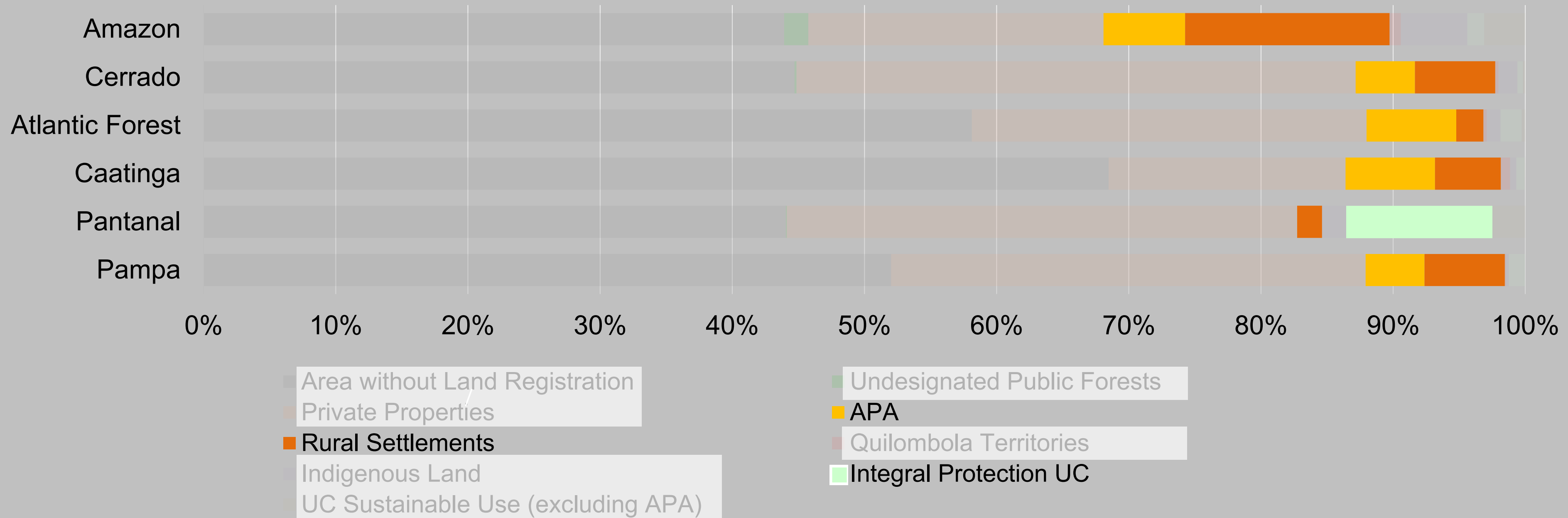
Land Tenure

Results



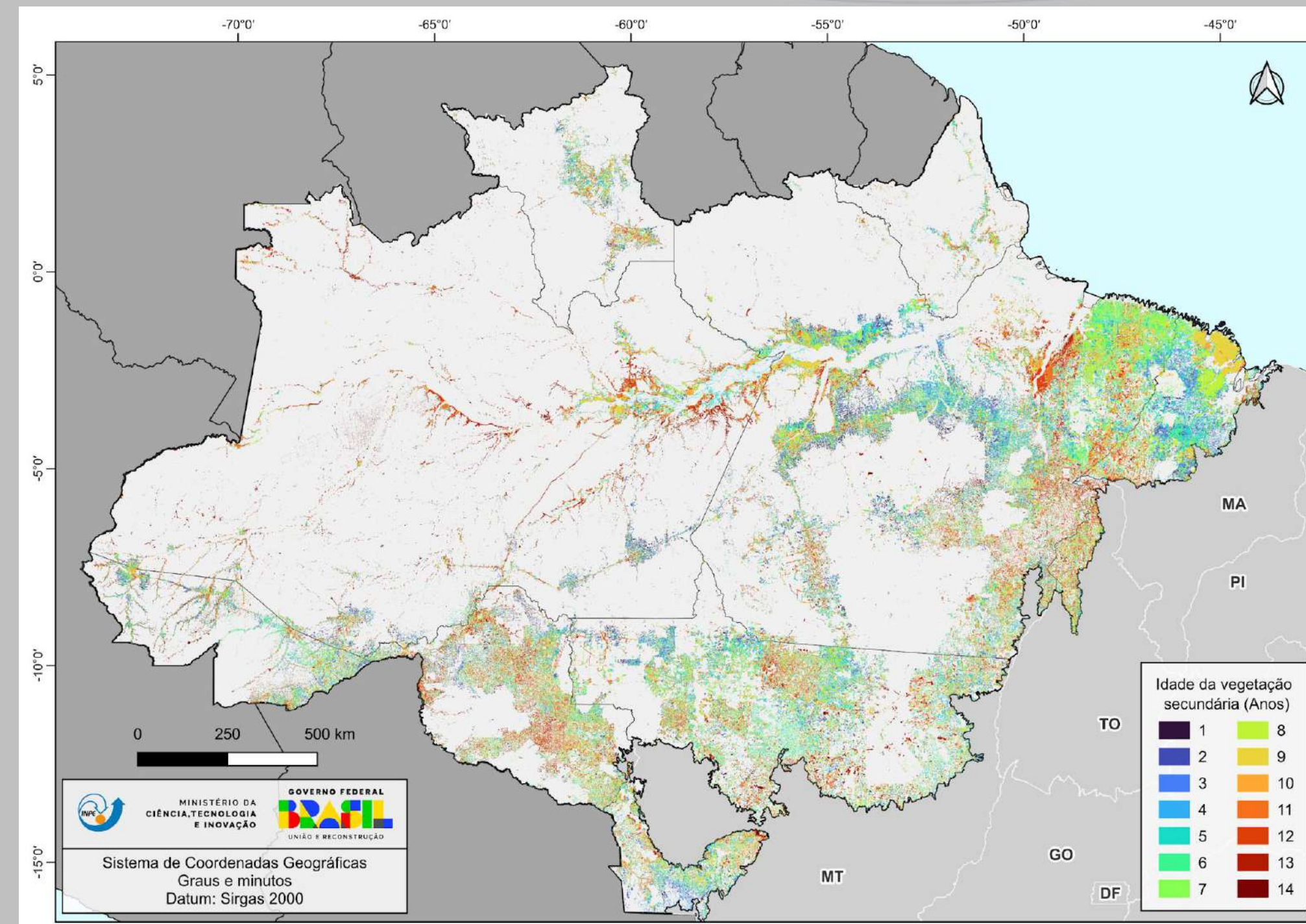
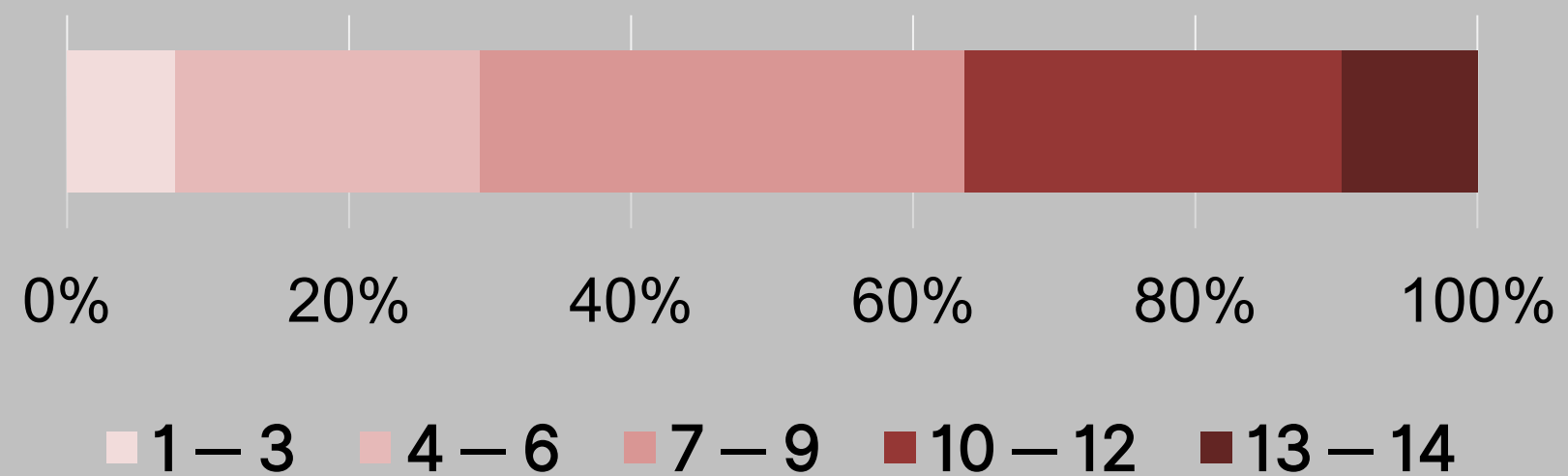
Land Tenure

Results

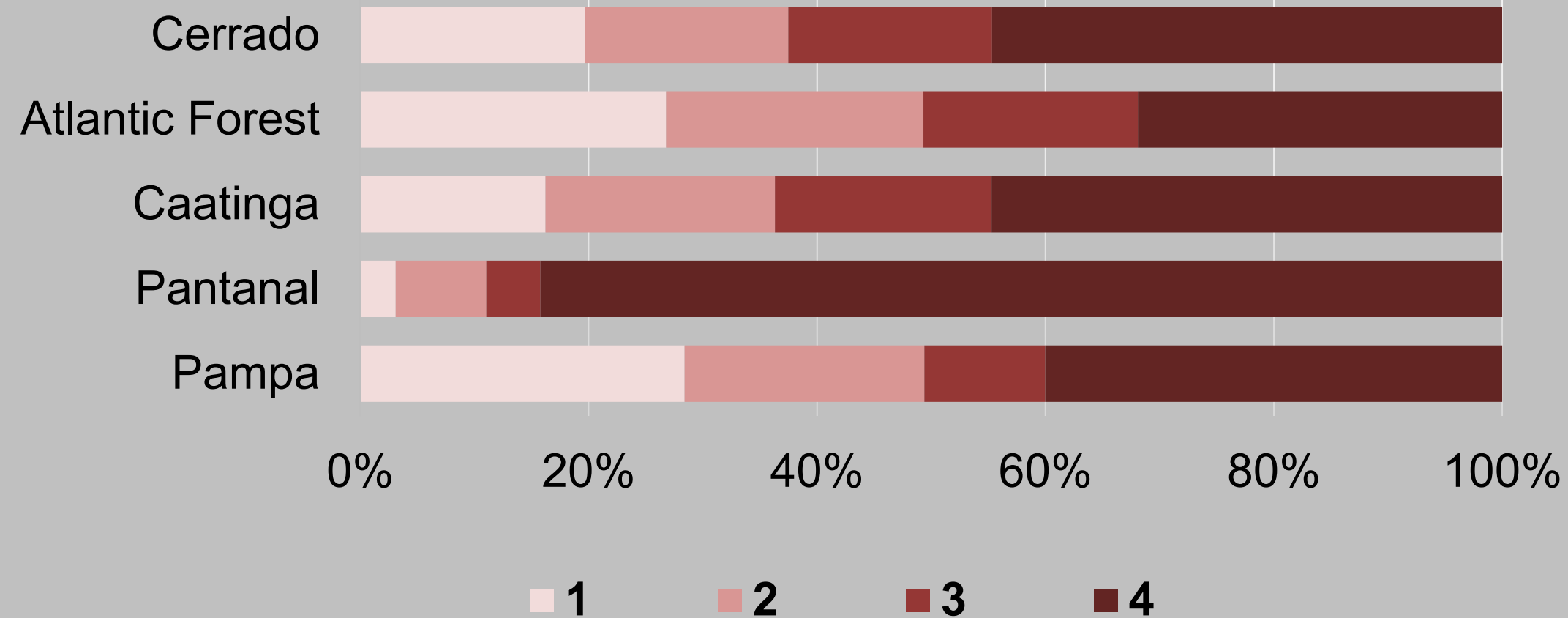


Age Results

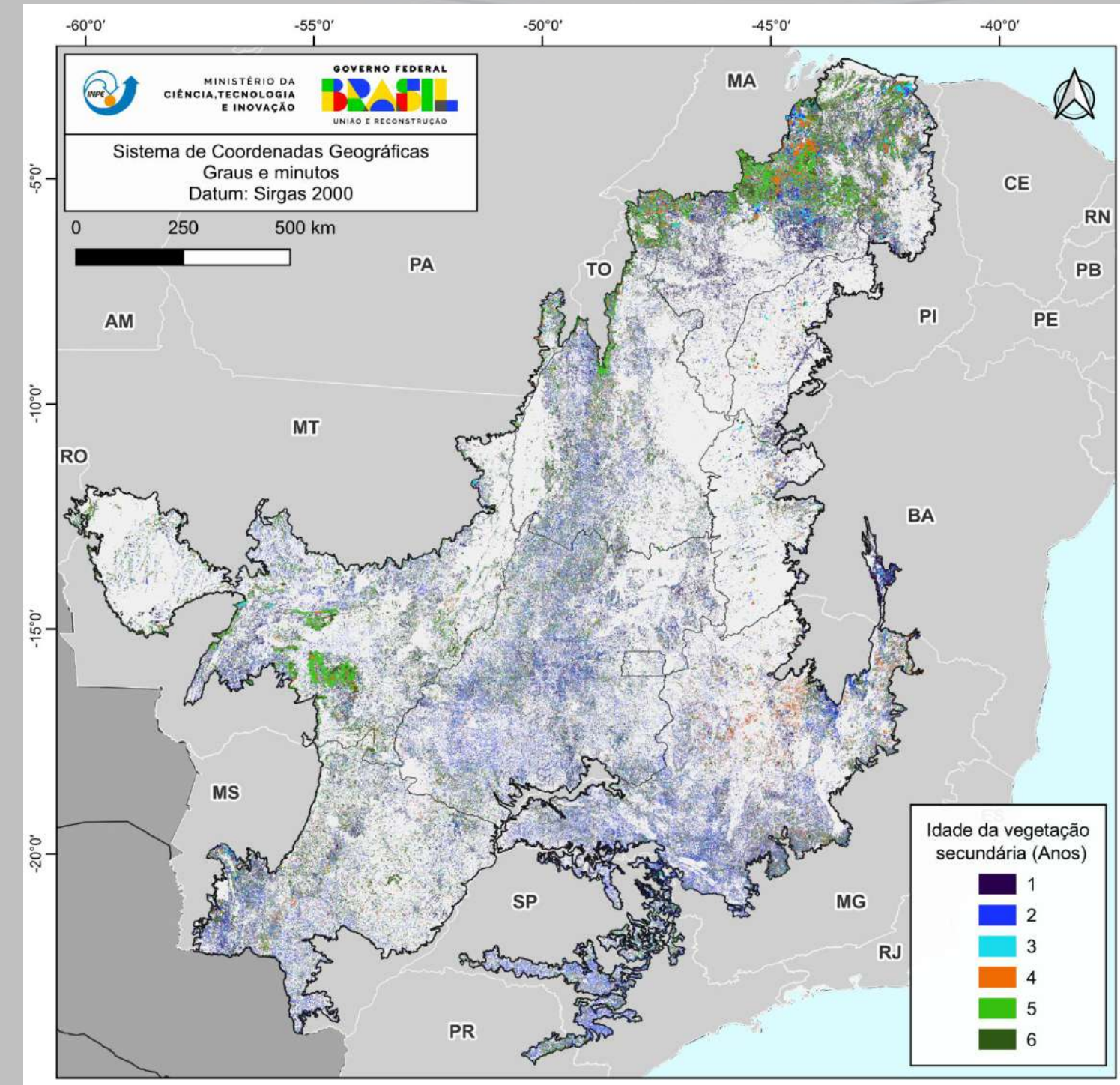
Amazon



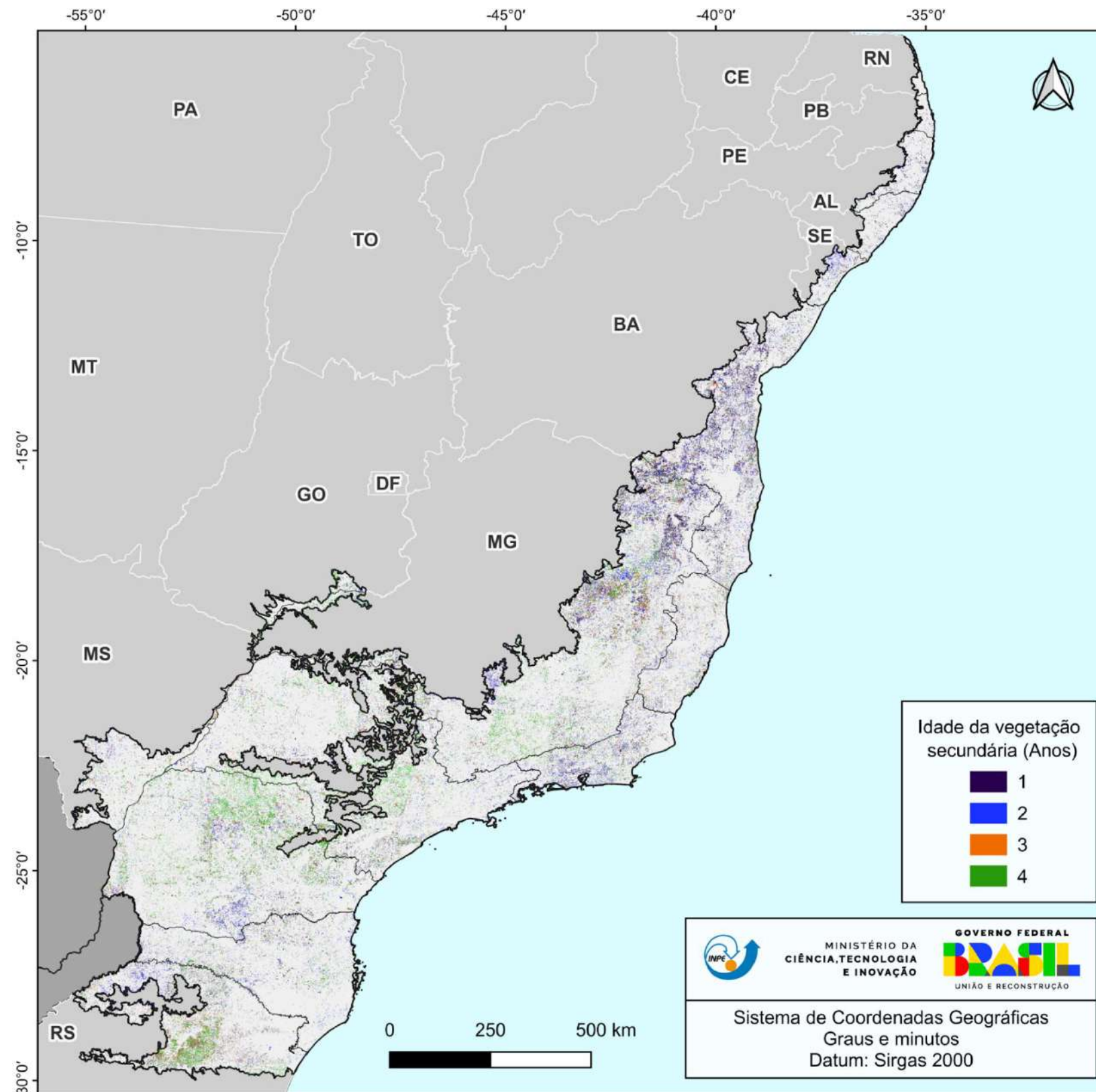
Age Results



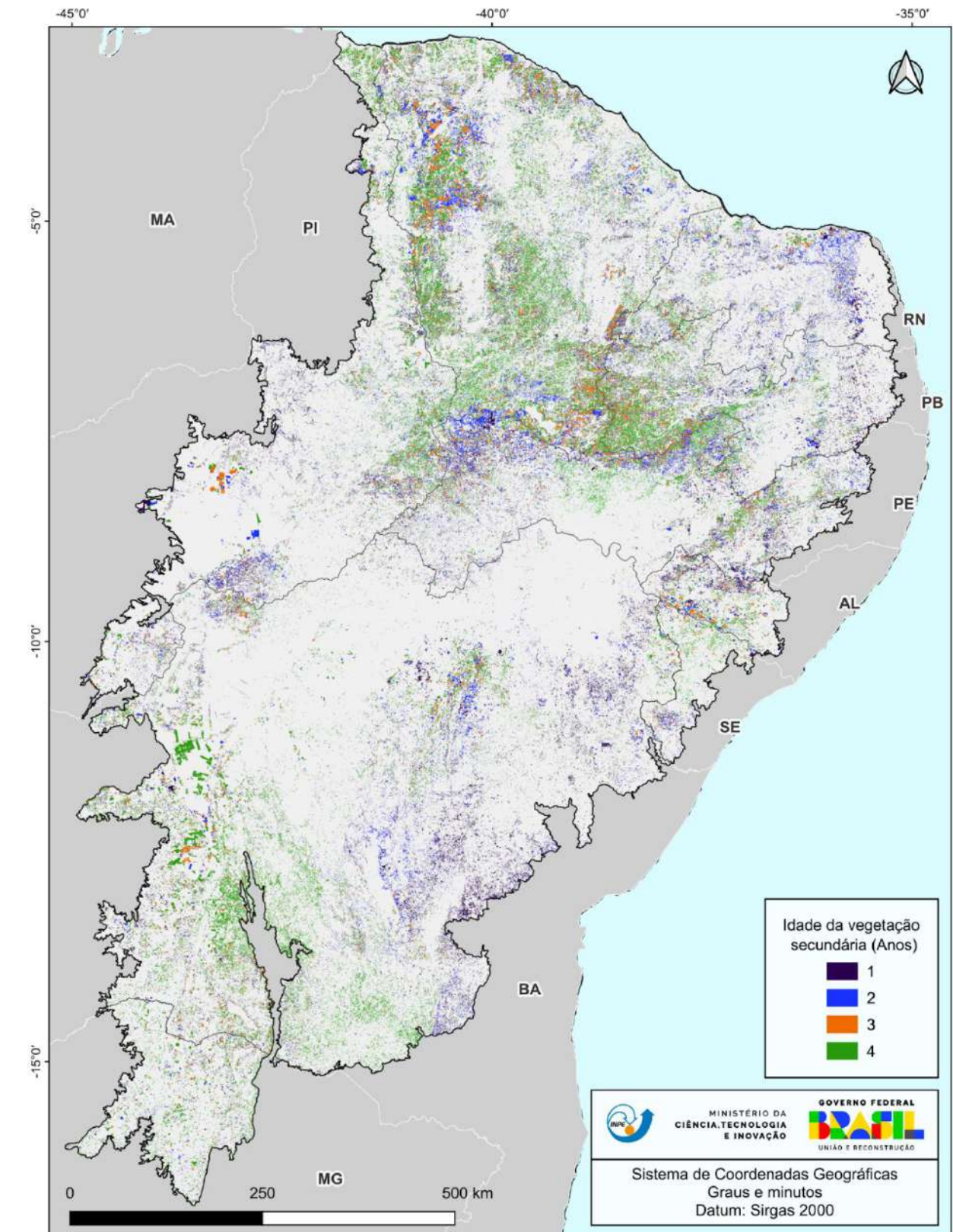
Cerrado



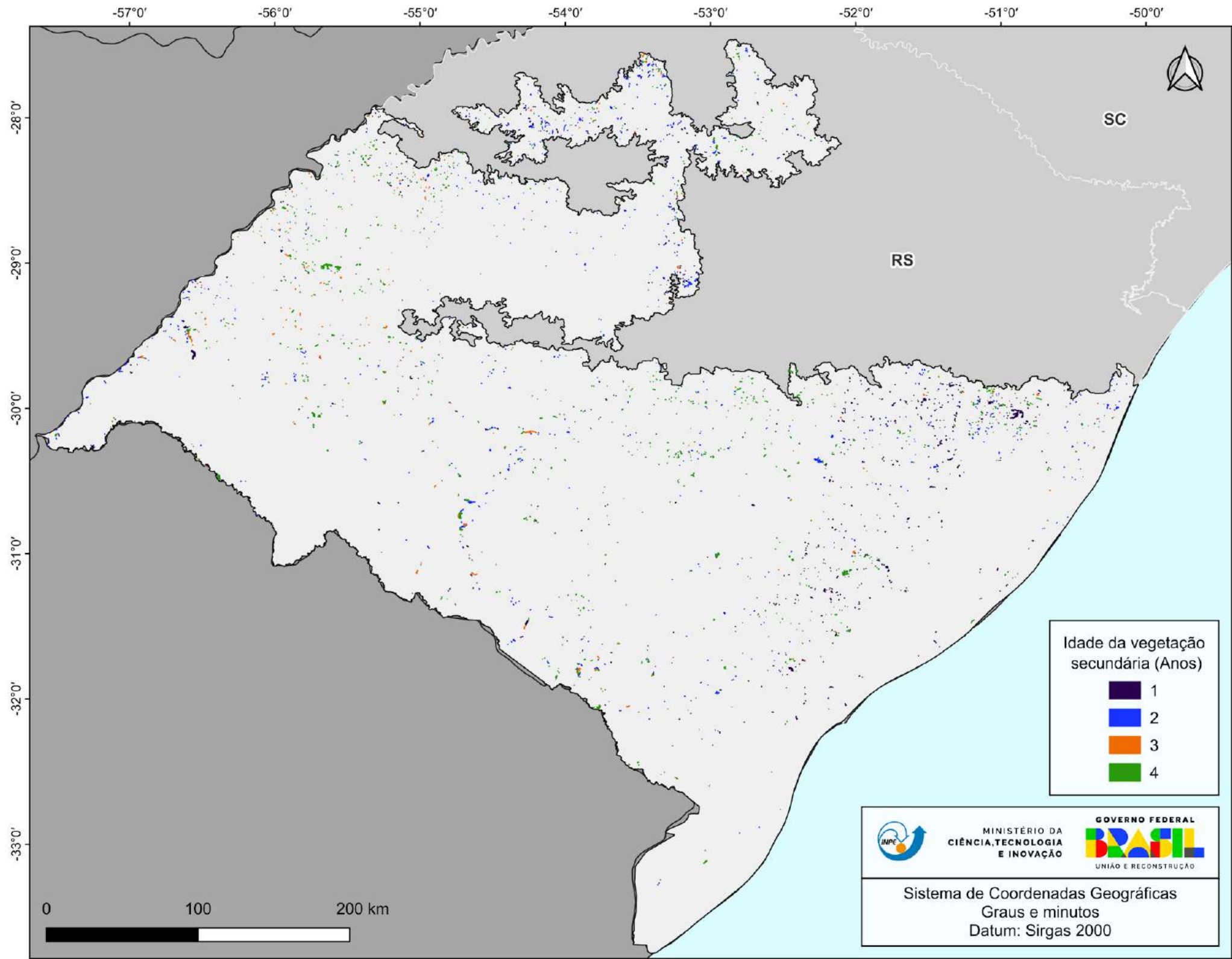
Atlantic Forest



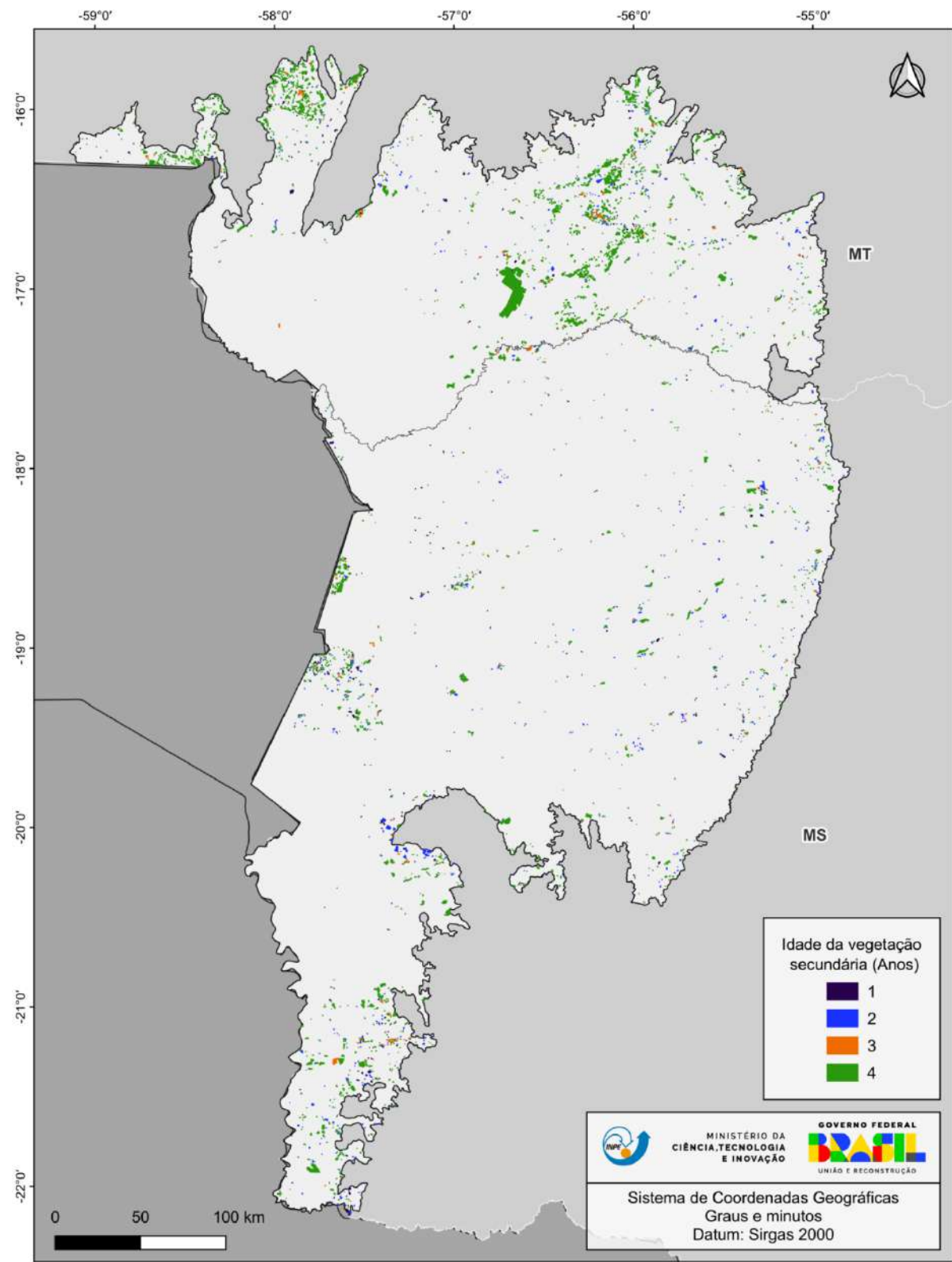
Caatinga



Pampa



Pantanal





Thank you!

Obrigada!

MINISTÉRIO DO
MEIO AMBIENTE E
MUDANÇA DO CLIMA



MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E INOVAÇÕES
INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS



Forest regeneration and the climate regulation ecosystem service in the Amazon

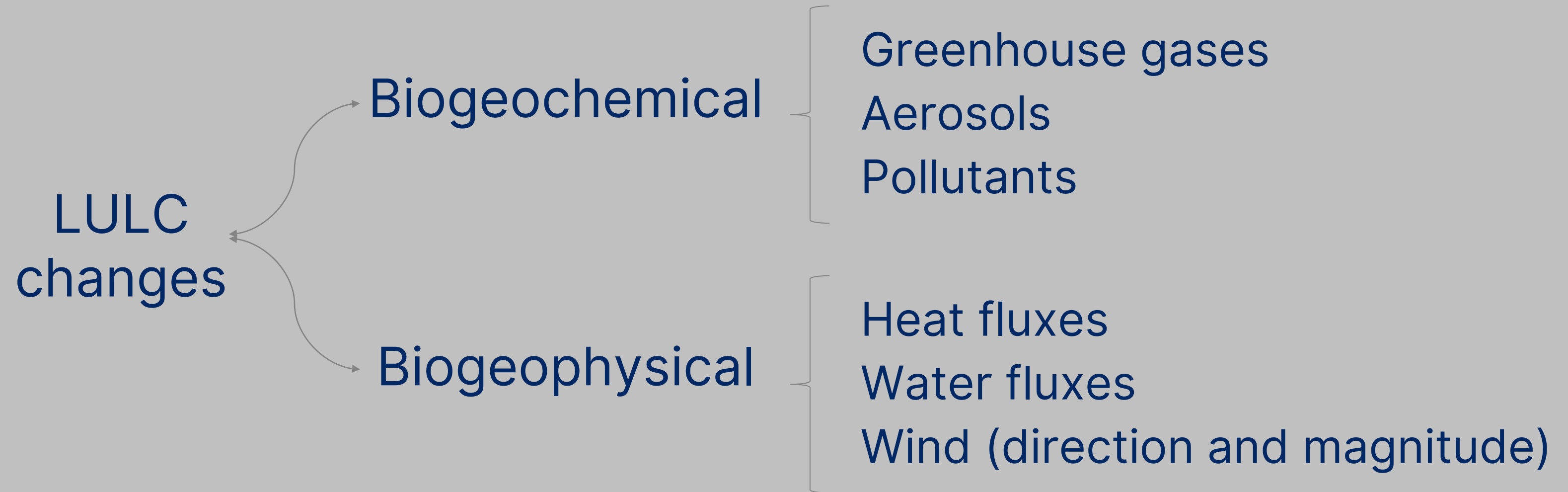
Lais Oliveira

Session 2.2: Other metrics for identifying secondary forest success

São José dos Campos, 30 Oct 2025

Contextualization

Biogeochemical and biogeophysical process



LULC
changes



Process



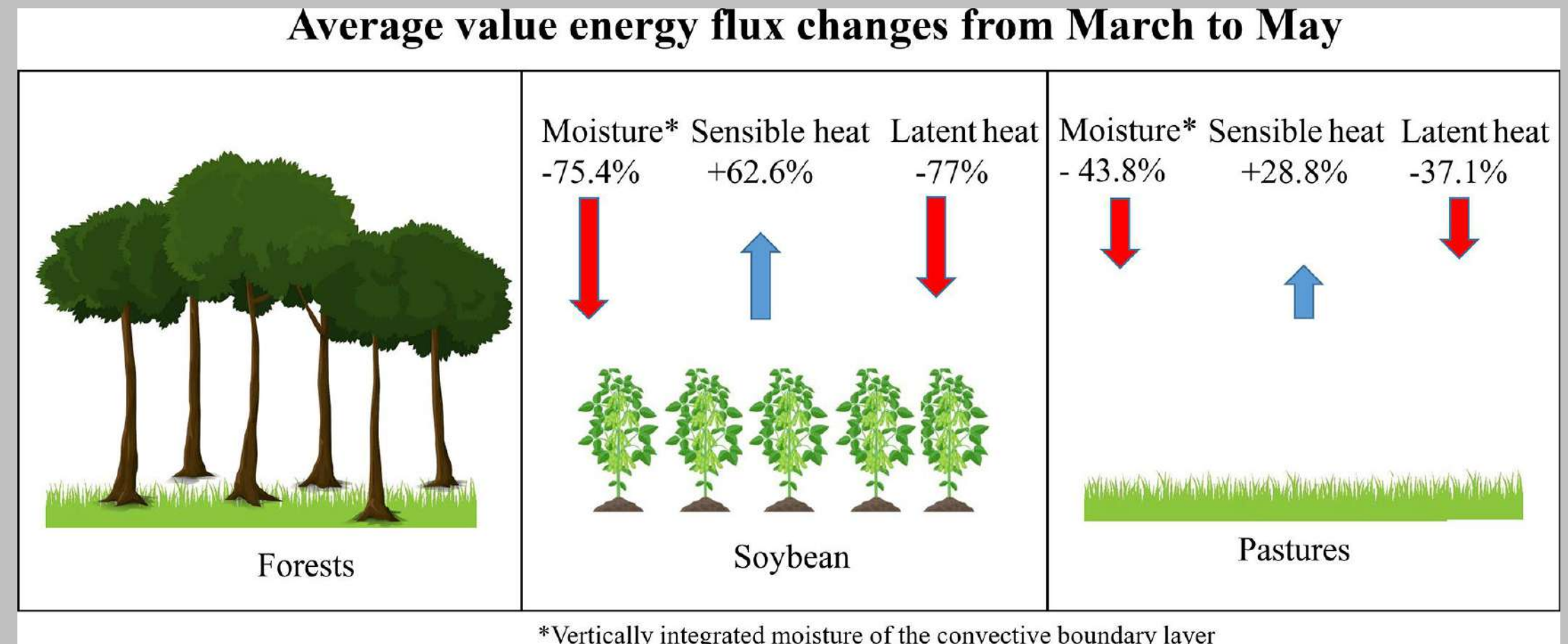
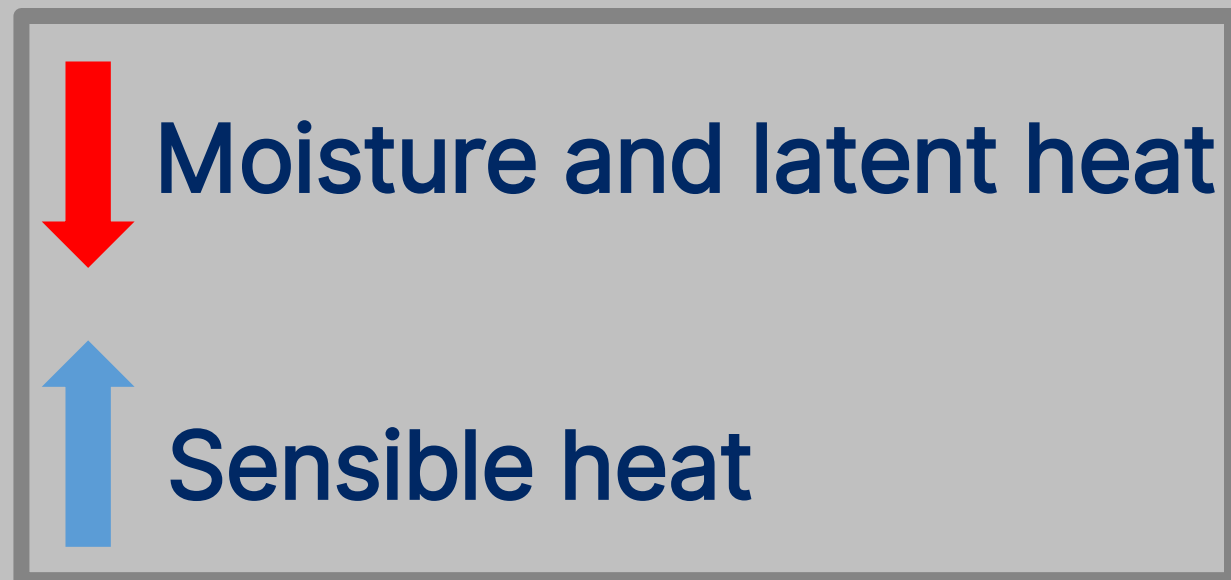
Climate stability

Ability of forests to regulate climate

Contextualization

Climate regulation → Energy and water balance

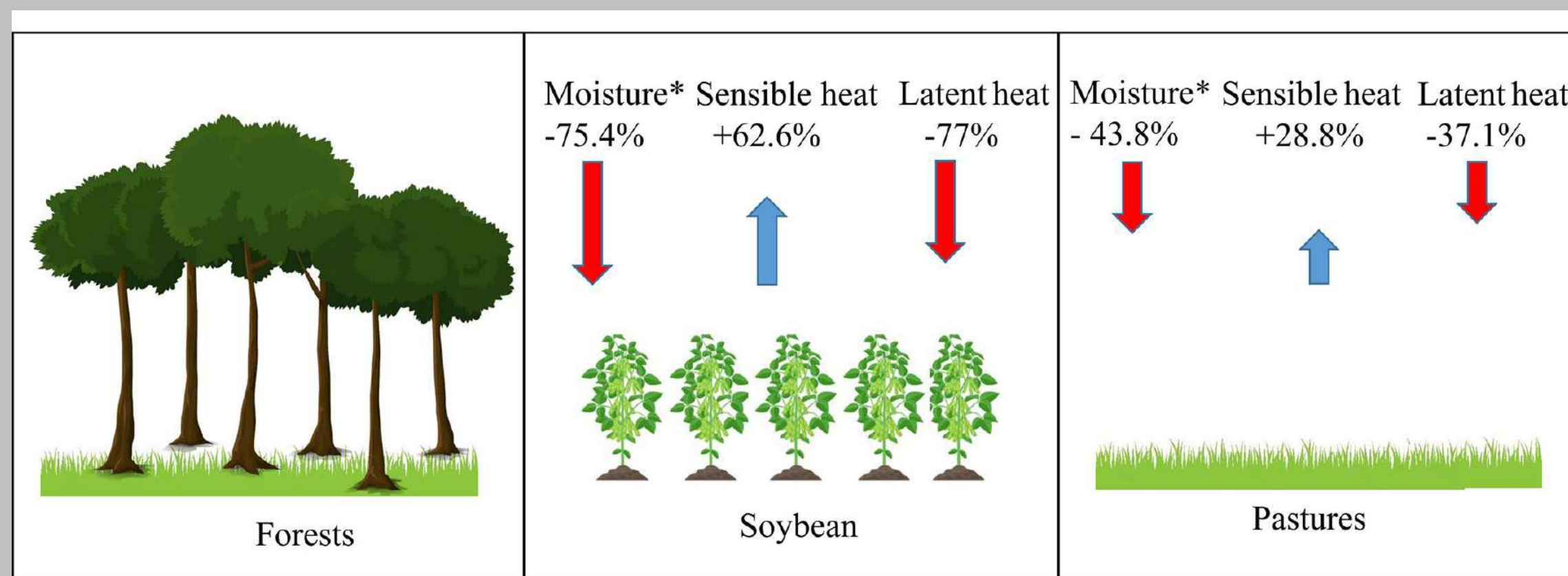
- Different Land covers → different fluxes
- Soybean and Pastures:



Zhang *et al.*, (2023)

Main question

Can secondary forests (SF) regulate local climate with the same potential as primary forests (PF)?



?

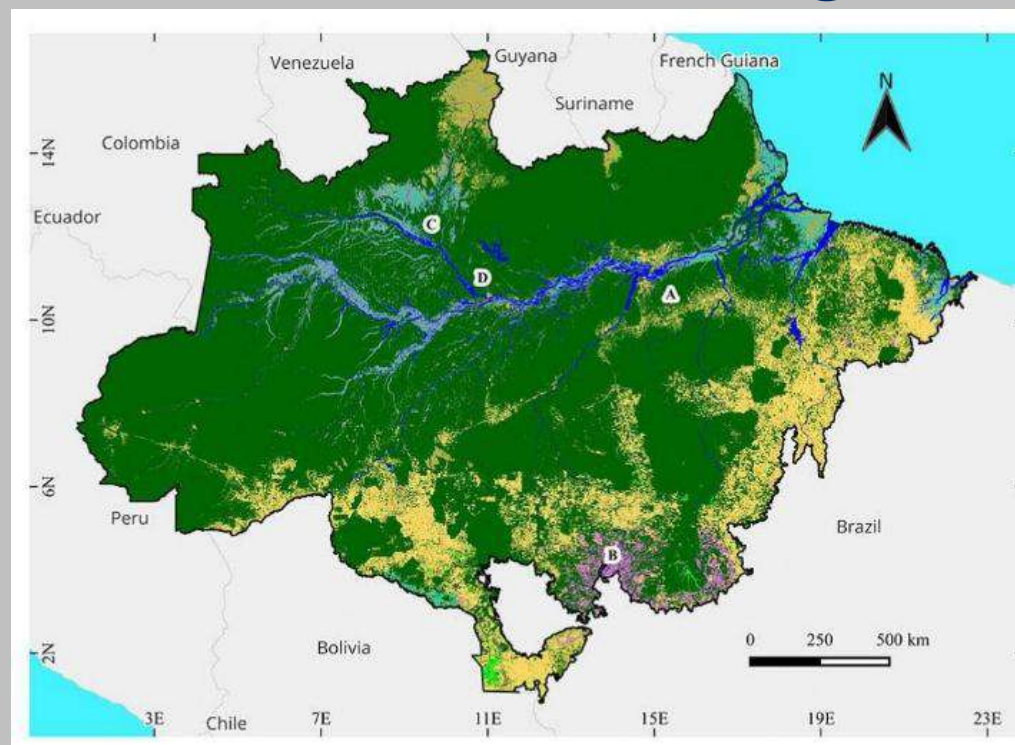


Zhang *et al.*, (2023)

Study area

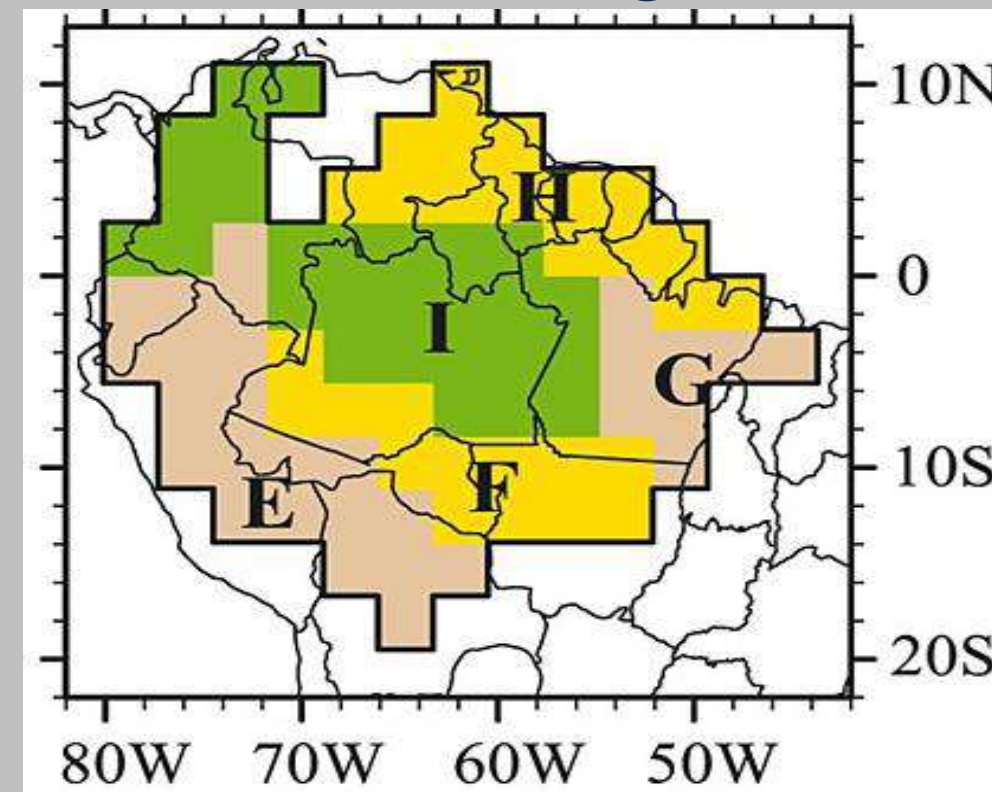
Different patterns

Land use change



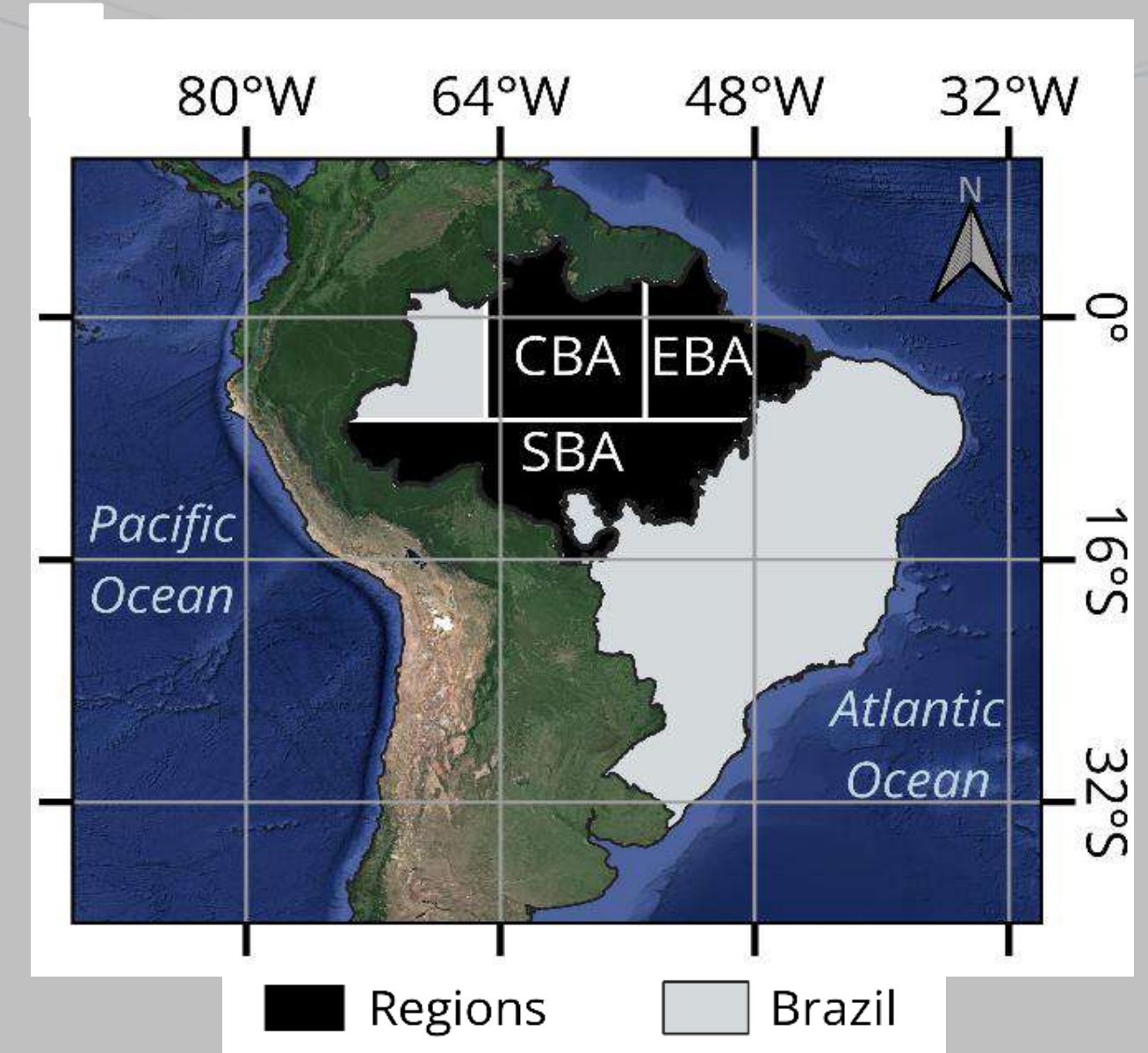
Adapted of Souza Jr. *et al.*, (2023)

Bioclimatic regions



Pires & Costa (2013)

- Remains in forest bioclimatic equilibrium
- Tendency to bioclimatic seasonalization
- Bioclimatic savannization



Central Brazilian Amazon (CBA)
Eastern Brazilian Amazon (EBA)
Southern Brazilian Amazon (SBA)

What we are developing

Analysis

Descriptive



Understand
the *behavior*
of *observed*
data

Inferencial



Test the
consistency and
significance of
empirically
observed
relationships

Variables

Precipitation

Evapotranspiration

Land surface temperature

X

Fracional forest cover

Primary

Secondary

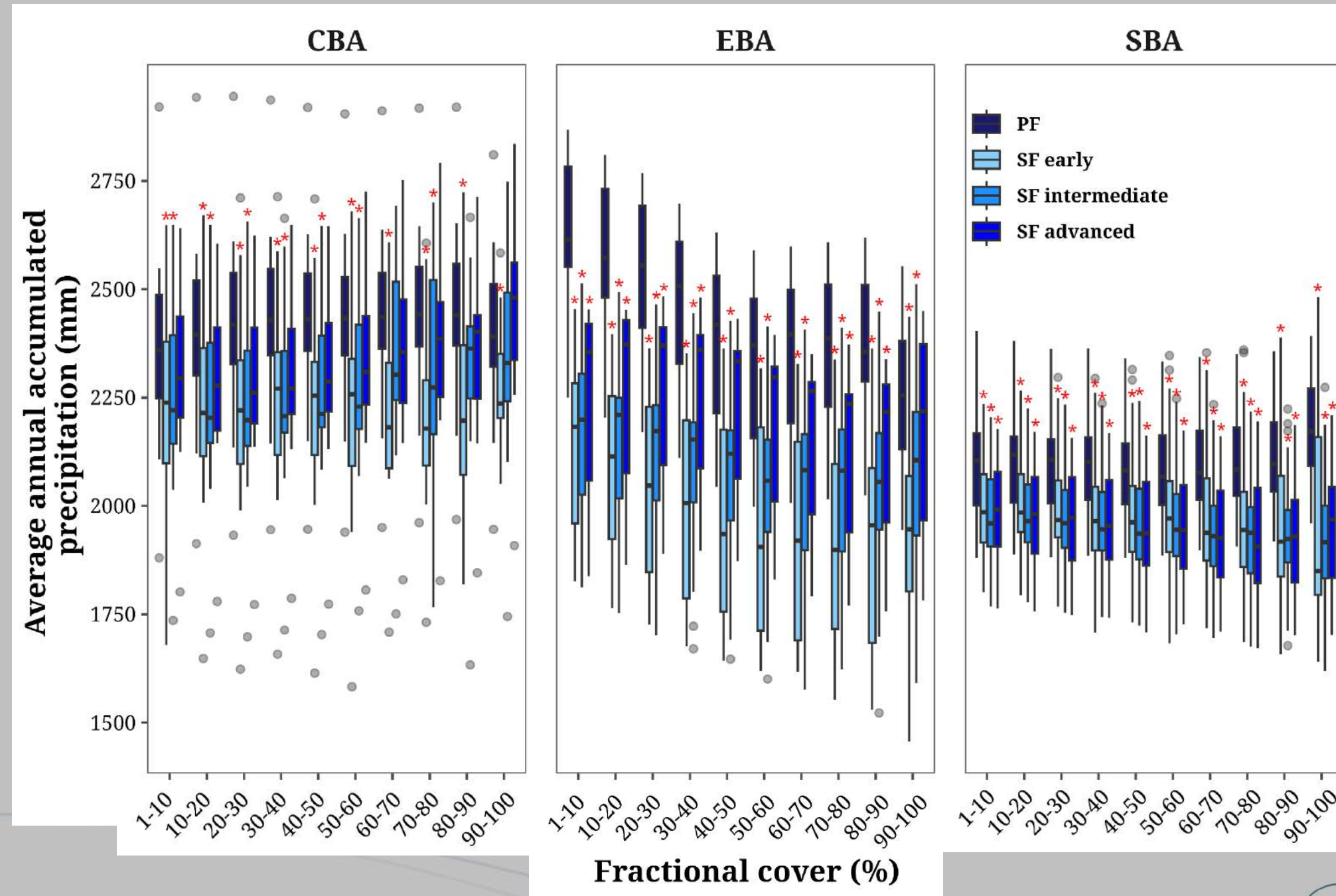
Early

Intermediary

Advanced

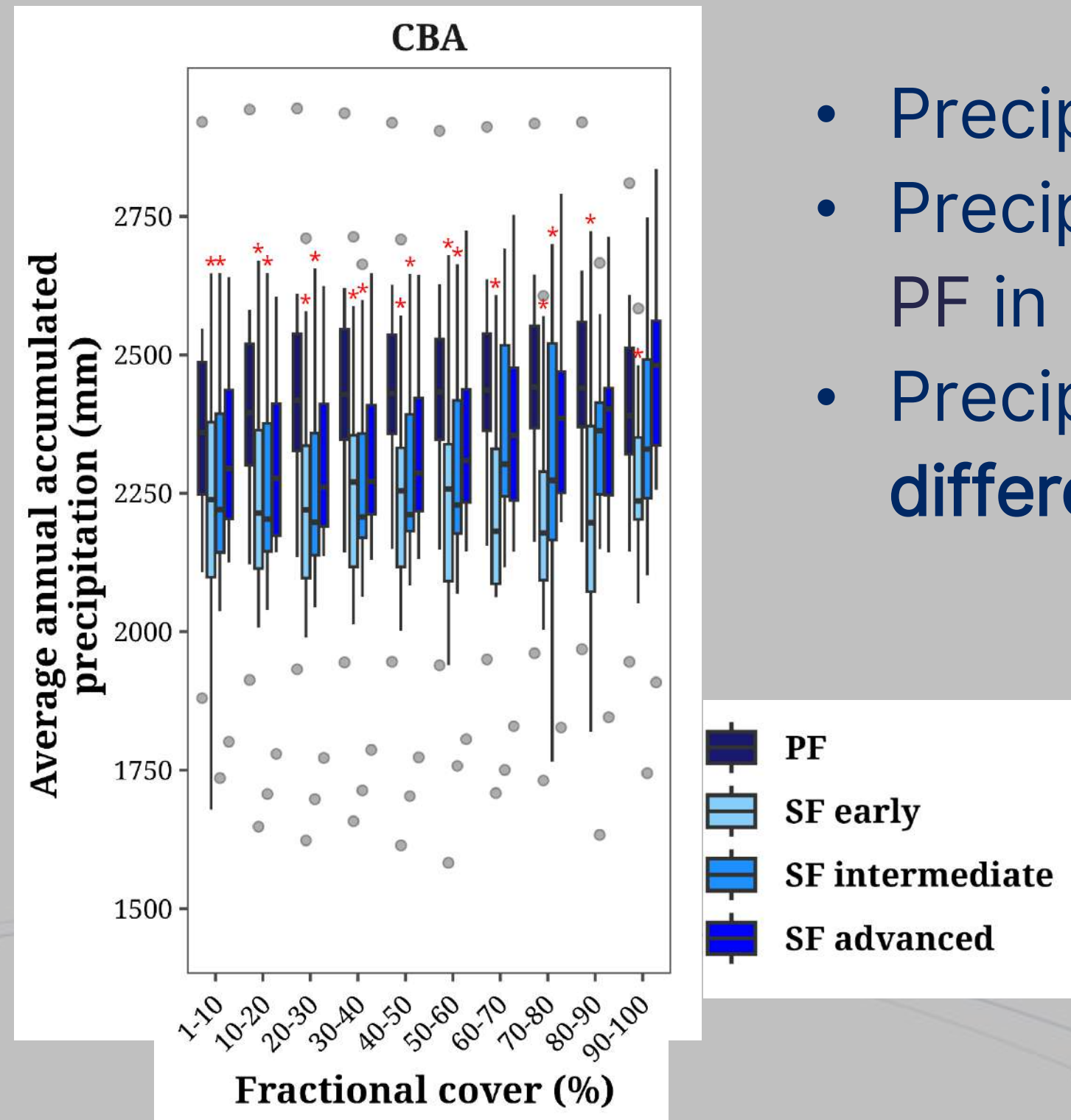
Our discovers

Observed data - Precipitation



Our discovers

Observed data - Precipitation

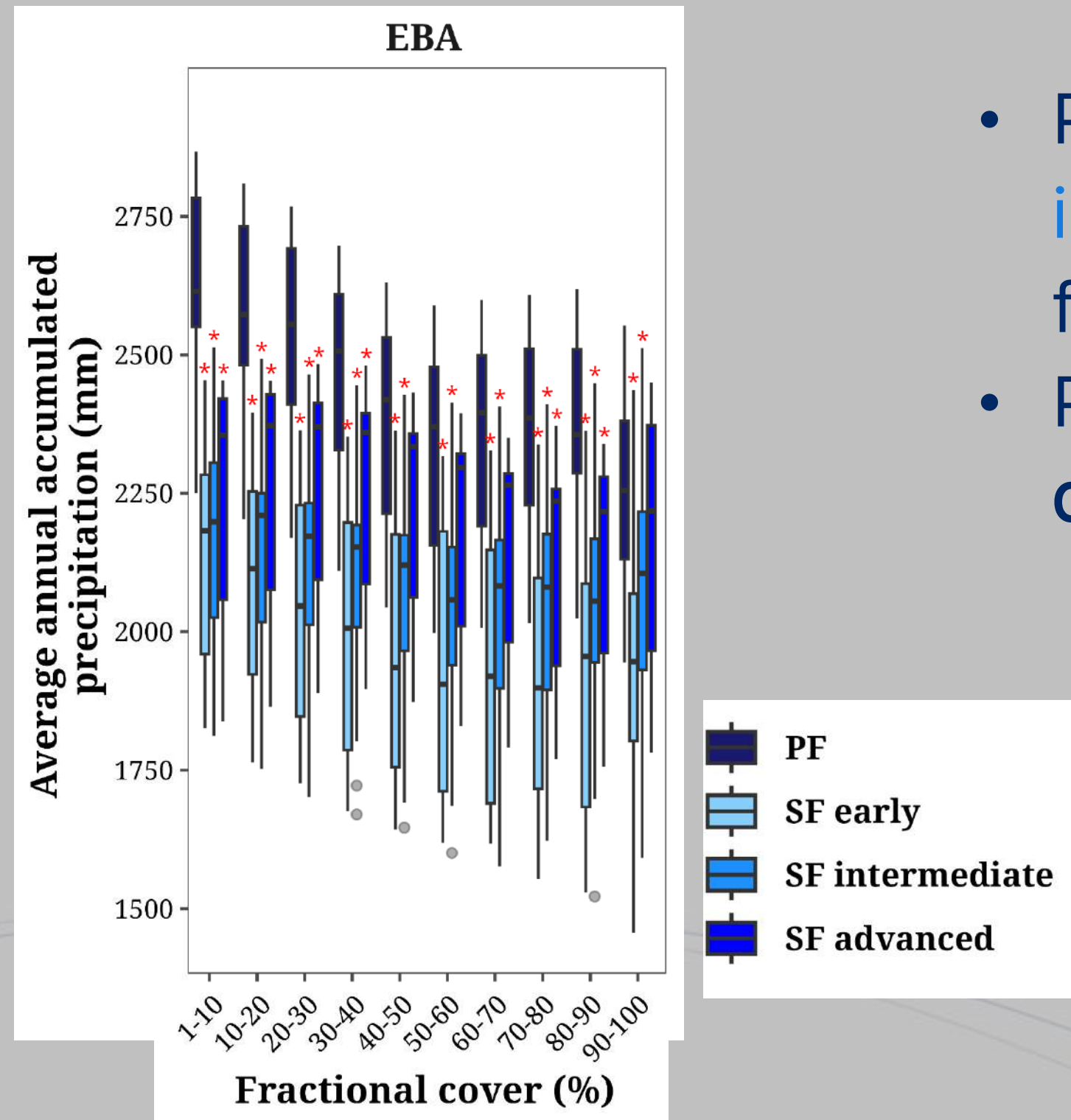


- Precipitation in **SF early** is lower than in PF
- Precipitation in **SF intermediary** is lower than in PF in some forest fractional cover ranges
- Precipitation in **SF advanced** not statistically different of PF

The ability of SF to regulate climate like PF increases with both fractional cover and successional stage advancement

Our discovers

Observed data - Precipitation

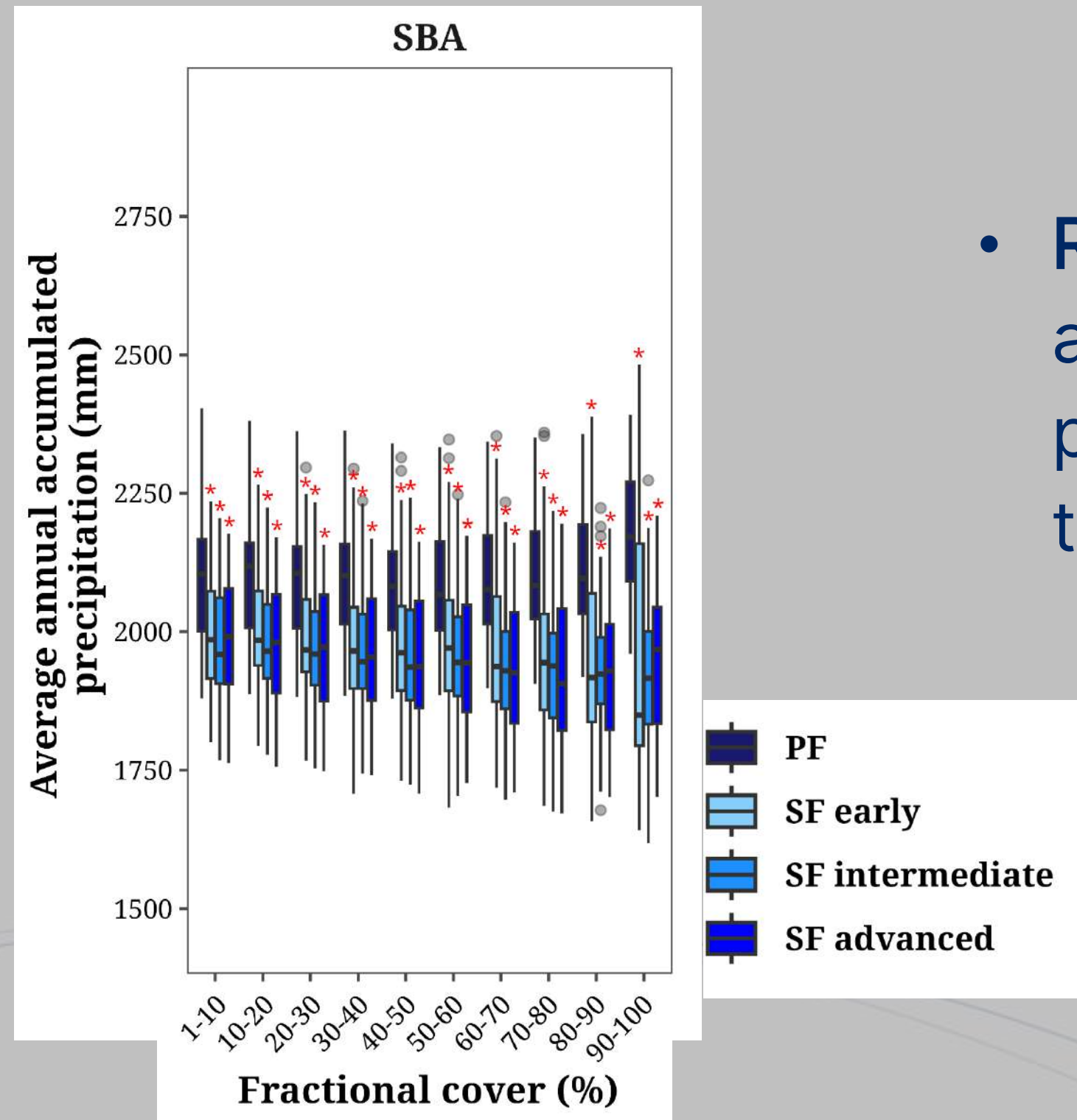


- Precipitation in **SF early** and **SF intermediary** is **lower** than in PF in all forest fractional cover ranges
- Precipitation in **SF advanced** not statistically different of PF in same ranges

Even in the intermediary stage, SF **still cannot reach the climate regulation potential of PF**

Our discovers

Observed data - Precipitation



- Regardless of the successional stage of SF and fractional forest cover range, precipitation in the SF is statistically lower than in the PF.

SF still cannot reach the climate regulation potential of PF

Concluding remarks

- We adopted **simple approaches** to explore how climate responds to **forest cover** and **successional stage**.
- These methods are a **first step** toward understand processes that are **still not well known** in the Amazon.
- Results show that **secondary forests help regulate climate**, but their **potential is not yet fully recovered**.
- There is **still much to learn** about how forest regeneration affects **local and regional climate**.
- **Future studies** should improve and expand these approaches to better capture the **complexity of climate–forest interactions**.

For reflection

There has never been a more urgent need to revive damaged ecosystems than now.



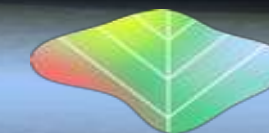
Thank you for your attention!

lais.rosa@ufv.br

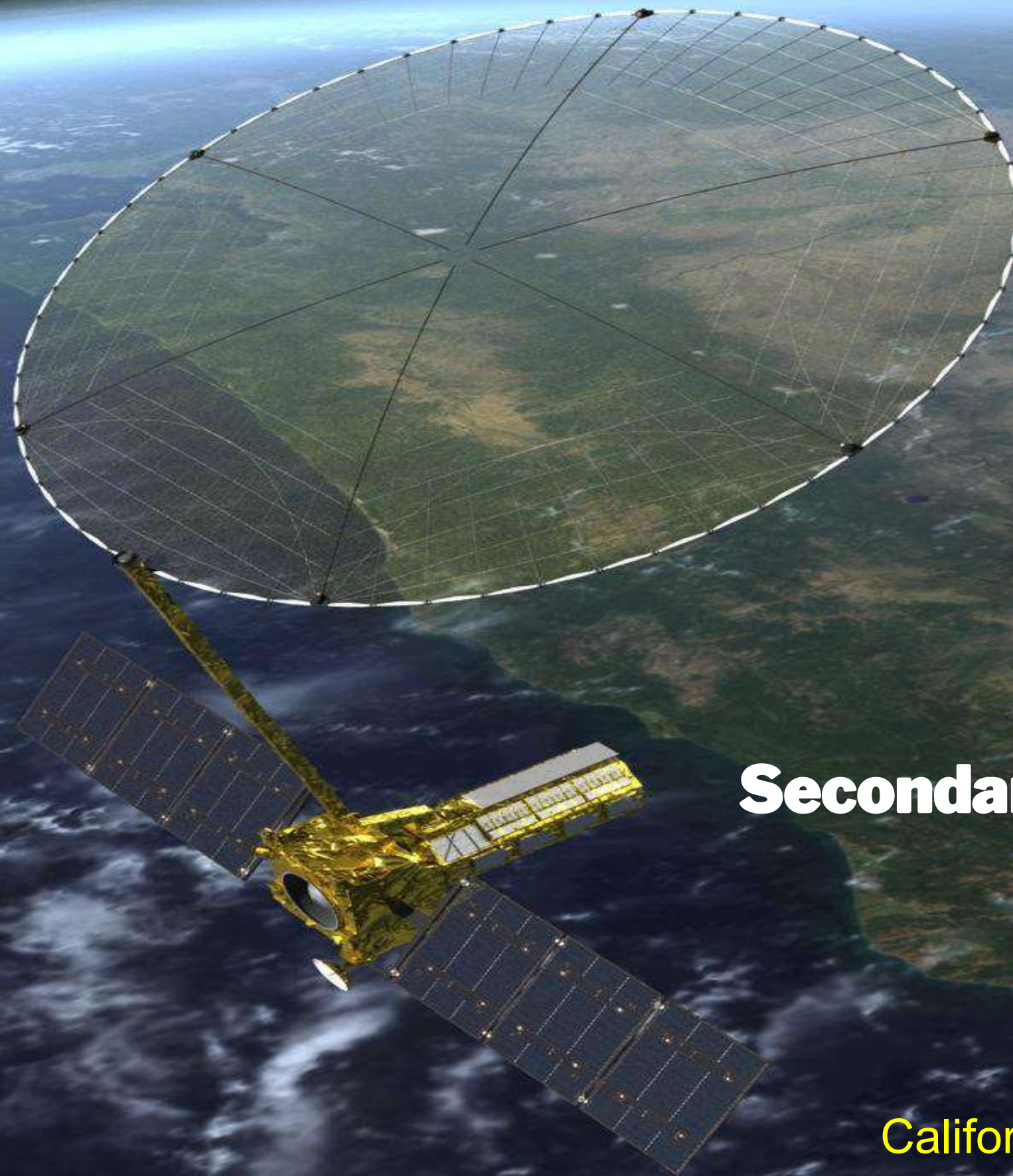


JPL

Jet Propulsion Laboratory
California Institute of Technology



CTrees



Secondary Forests growth with NISAR

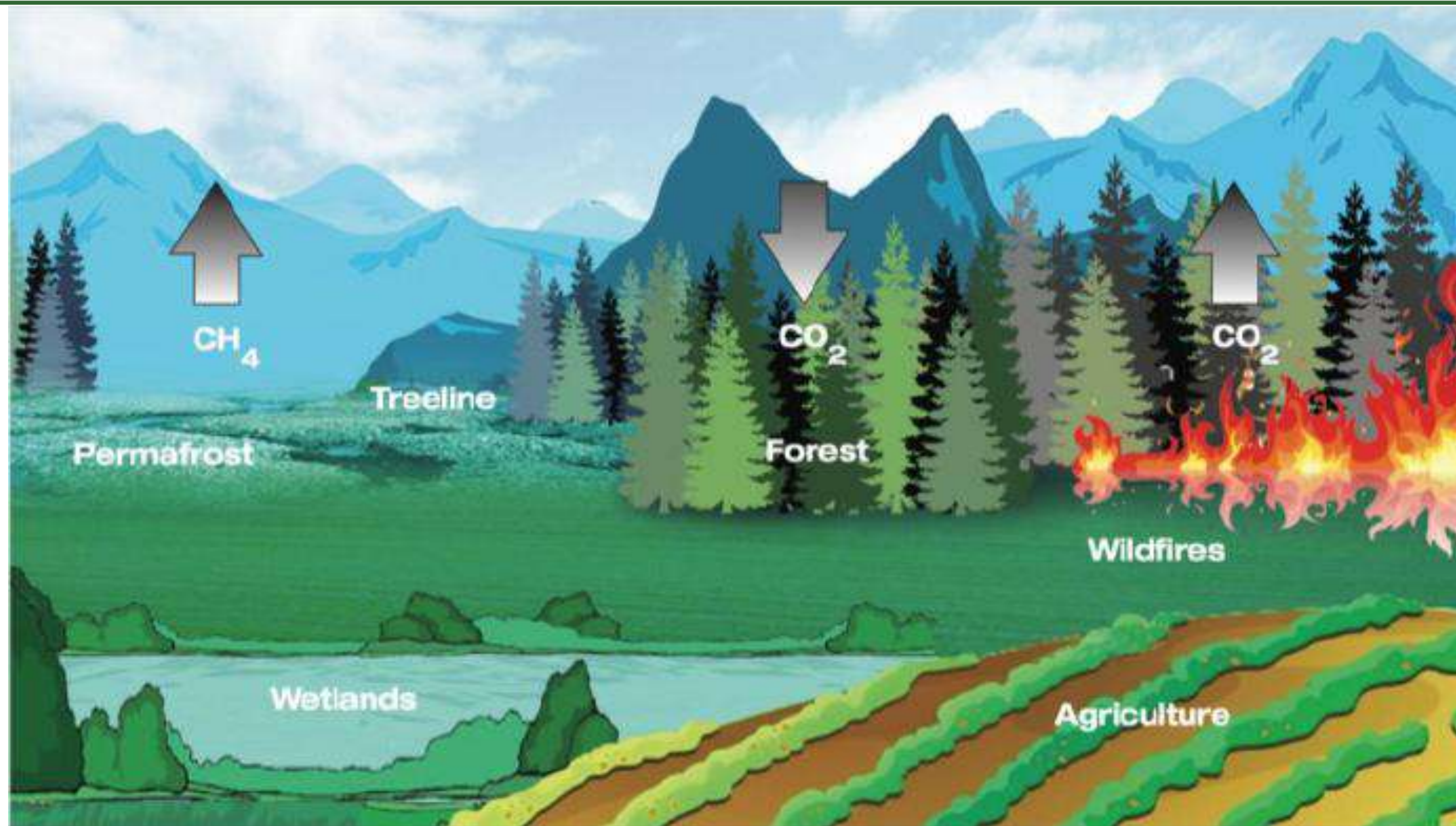
Sassan Saatchi

Science Team Member

Jet Propulsion Laboratory

California Institute of Technology

CEO, CTREES



Biomass: Annually map aboveground woody vegetation biomass at the hectare scale. Accuracy shall be within 20 Mg/ha for 80% of areas of biomass less than 100 Mg/ha.

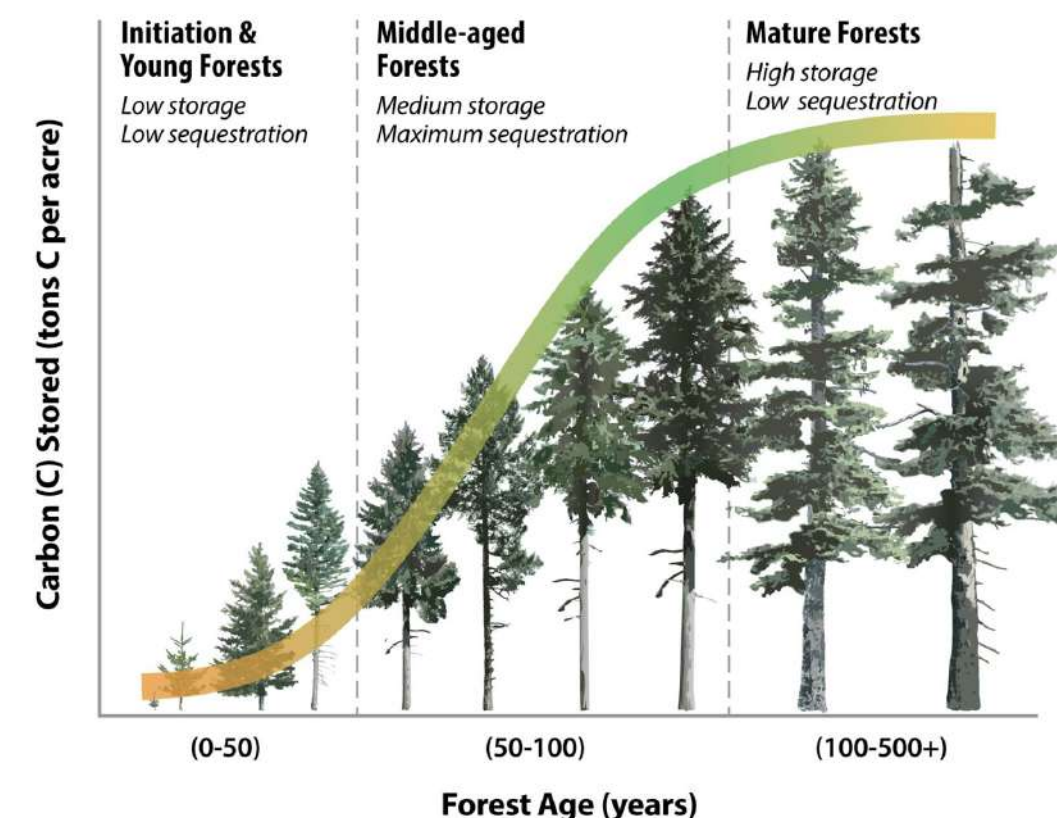
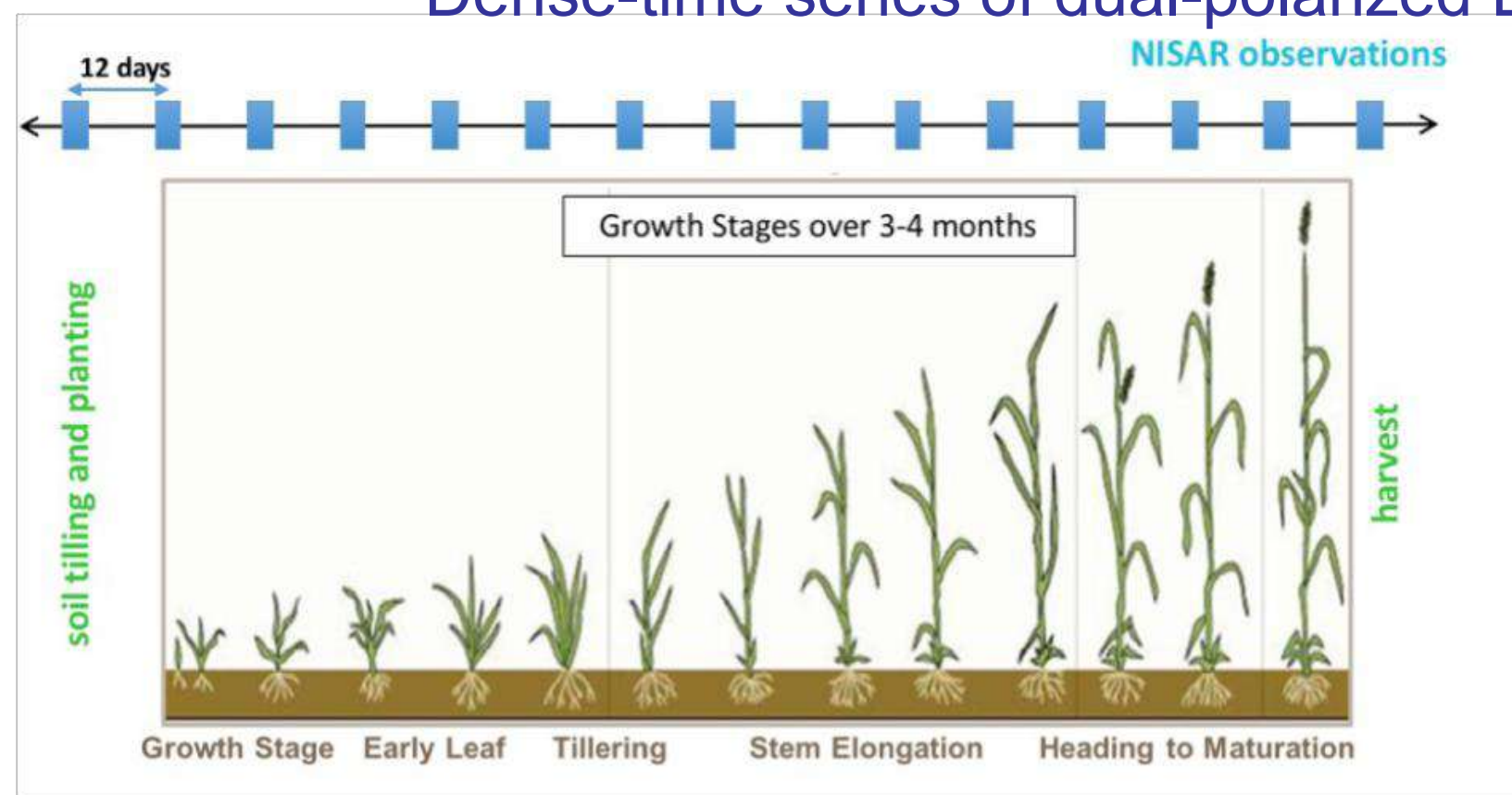
Disturbance: Map global areas of vegetation disturbance at 1 ha resolution annually for areas losing at least 50% canopy cover with a classification accuracy of 80%

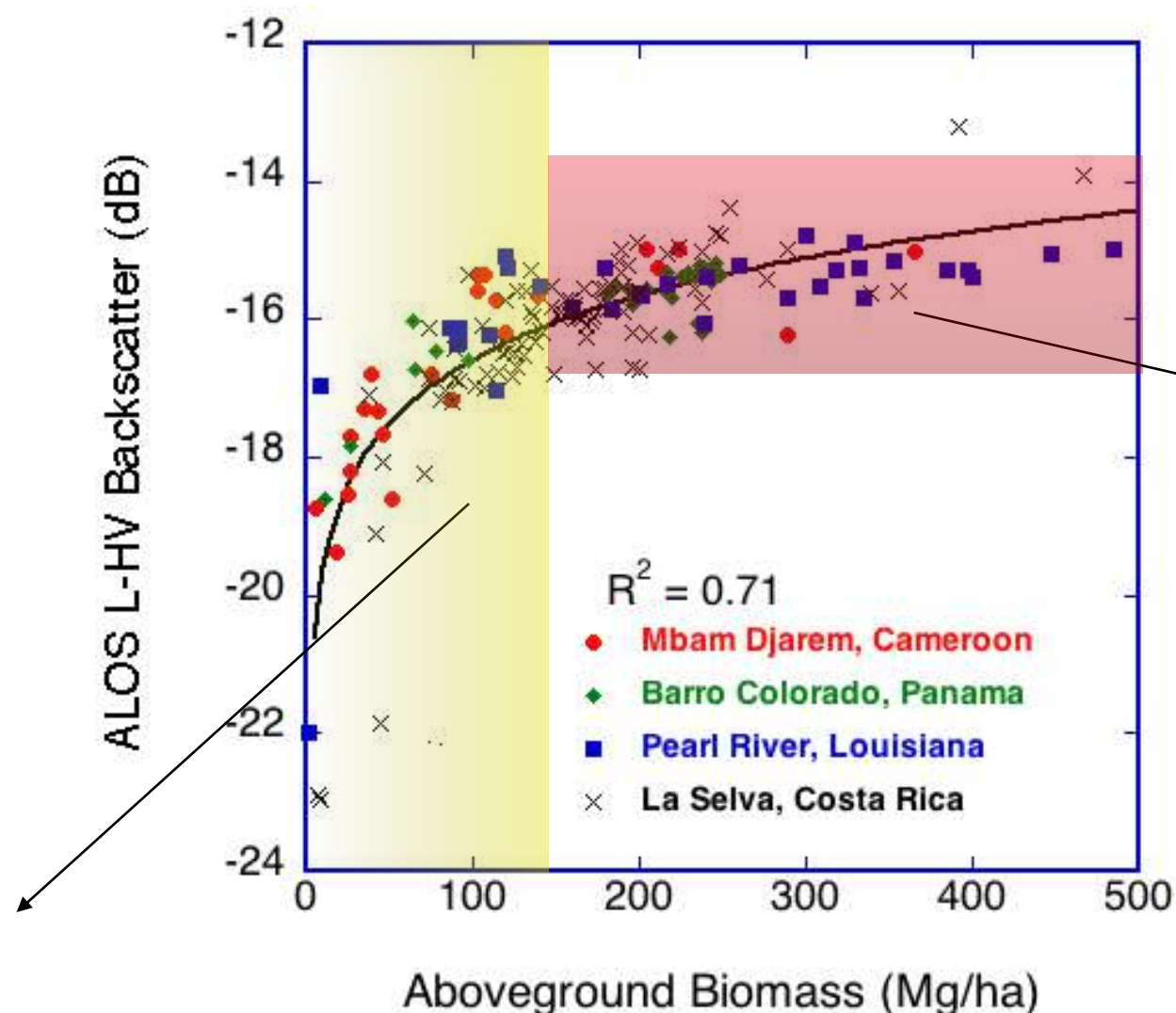
Map crop area at 1 ha resolution every 3 months with a classification accuracy of 80%.

Agriculture:

Inundation: Map inundation extent within inland and coastal wetlands areas at a resolution of 1 hectare every 12 days with a classification accuracy of 80%.

Dense-time series of dual-polarized L-band & S-band data





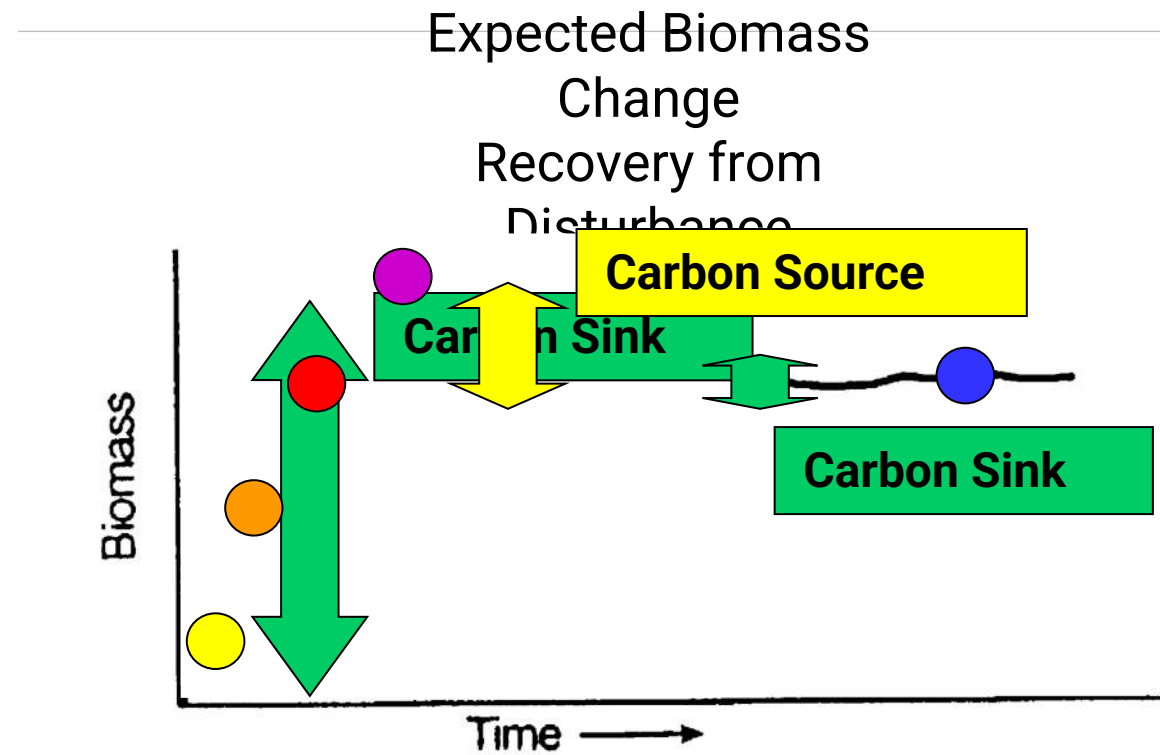
High Priority Fusion Region
Lower to no sensitivity of
radar
Domain of data fusion and
synergism with GEDI and
BIOMASS

Biomass < 150 Mg/ha
Low Priority Fusion Region
Higher sensitivity of radar
Domain of NISAR Performance

Global Biomass Product must be derived from Fusion Approach

For low biomass density (150 Mg/ha) radar sensitivity is high but impacted by structure & environment
For high biomass density (>150 Mg/ha) data fusion with GEDI and/or BIOMASS required

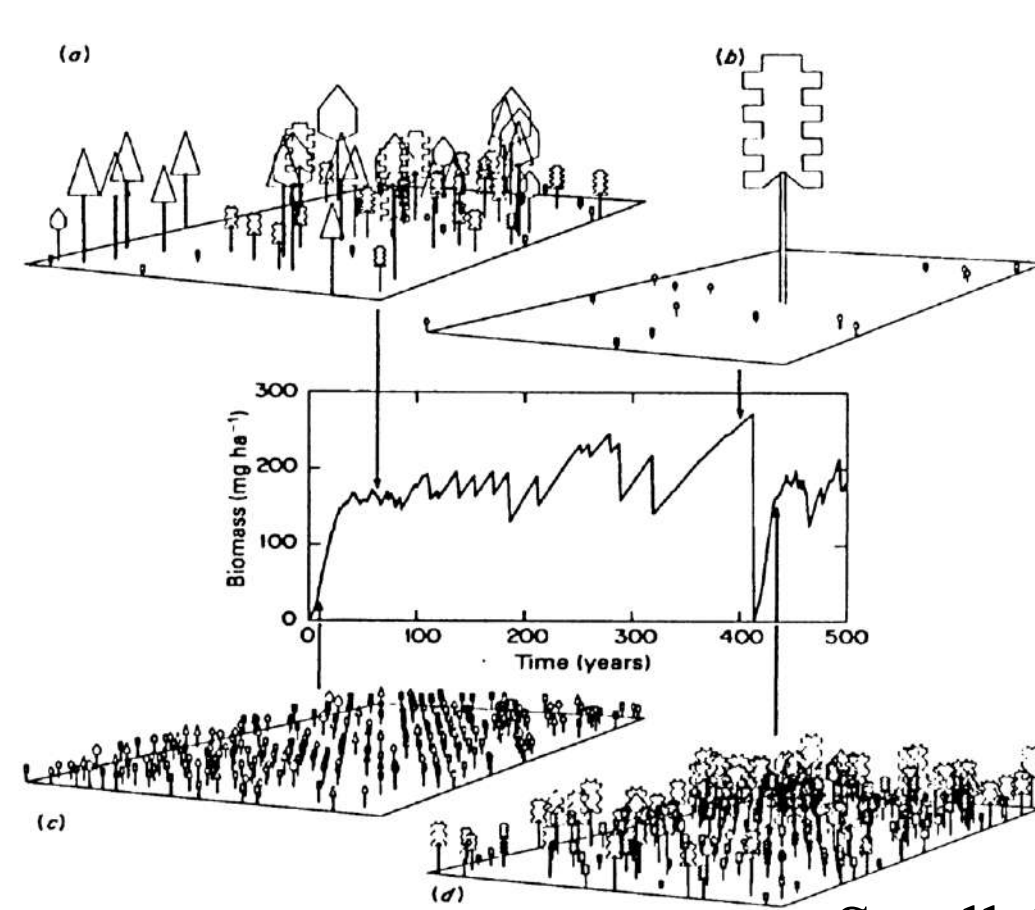
Trees, Forests, Time, Space, Scale



Carbon disturbance recovery dynamics are non-linear as the all-aged successional patches become desynchronized to produce the mixed-aged mature-forest mosaic.

Mature forest is a mosaic.



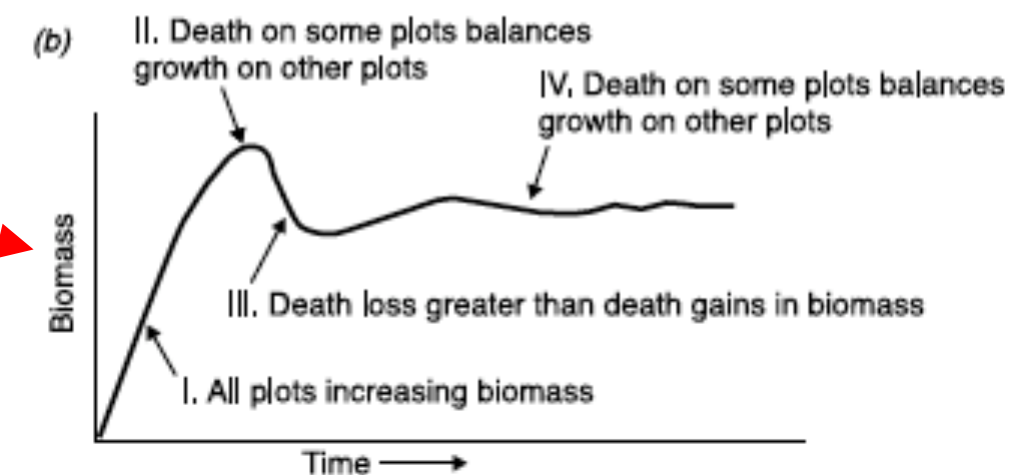
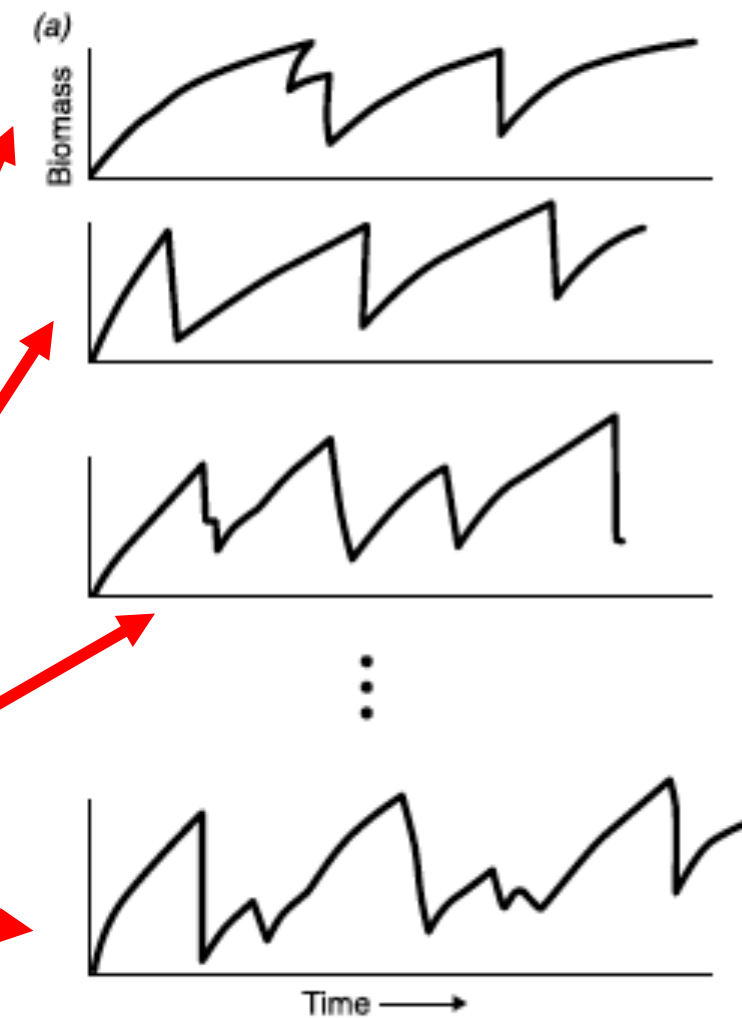


Small-Scale Dynamics

≠

Large-Scale Dynamics

The non-equilibrium dynamics cause forest behave differently at small area from expected landscape scale. (Shugart & Saatchi, 2011)



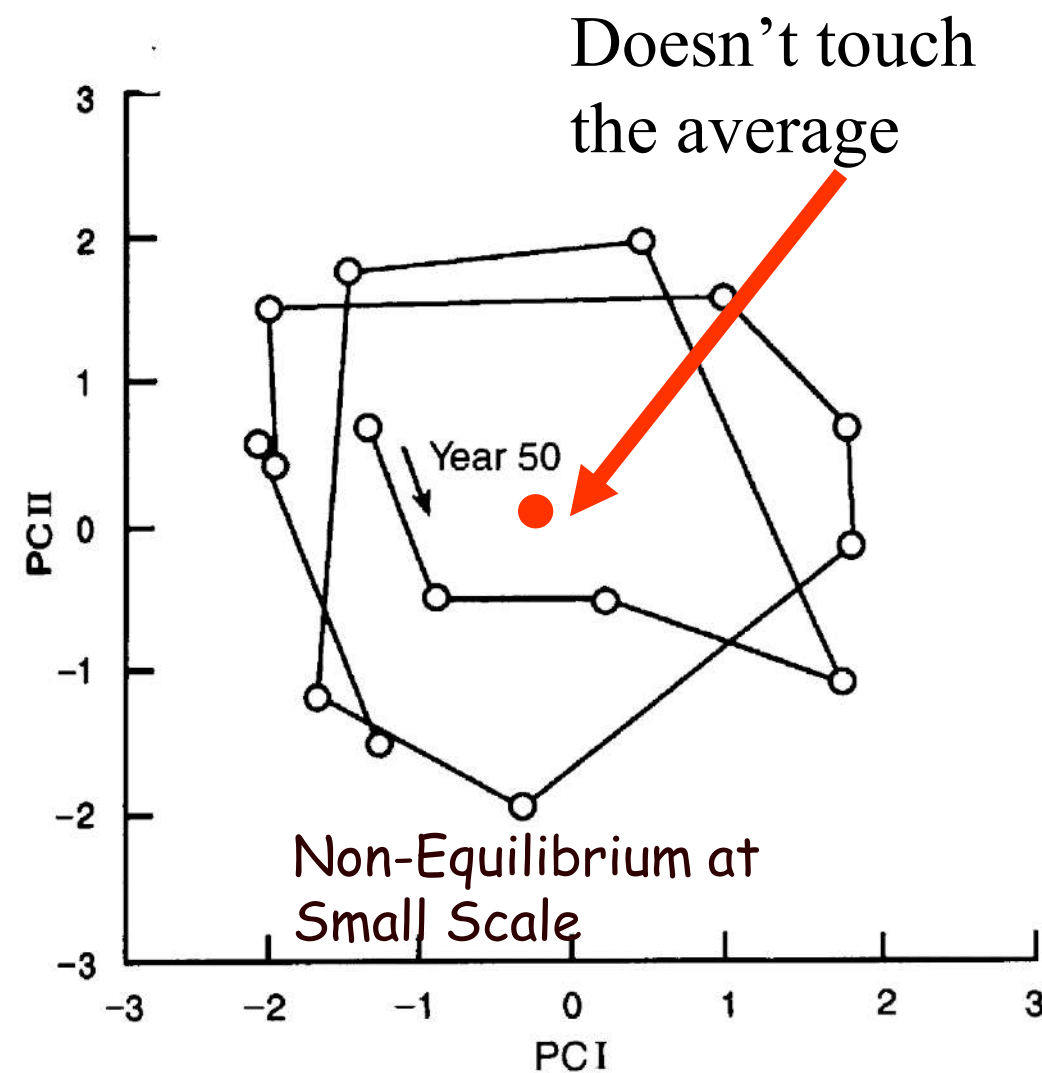
Scale of Disturbance & Recovery

Shugart, Saatchi, Hall, 2010

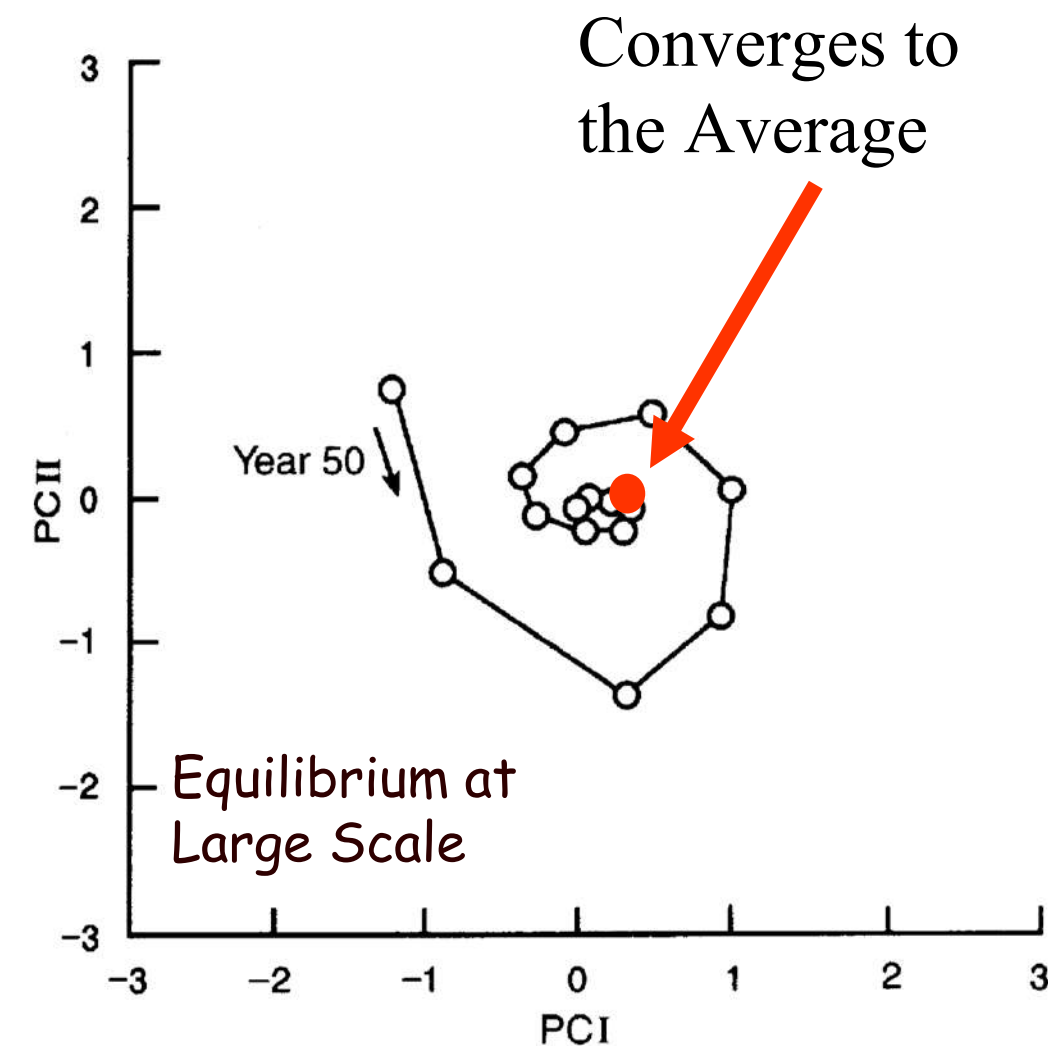
Forest Biomass Dynamics Can be Studied at two scale:

At a large scale: a forest stand seeks an equilibrium state with a particular mean configuration. This state once attained remains the same, thereafter.

At a small scale (the so-called the gap scale): the forest ecosystem never reaches an equilibrium state and is continuously undergoing changes driven by the presence of large trees.



\neq

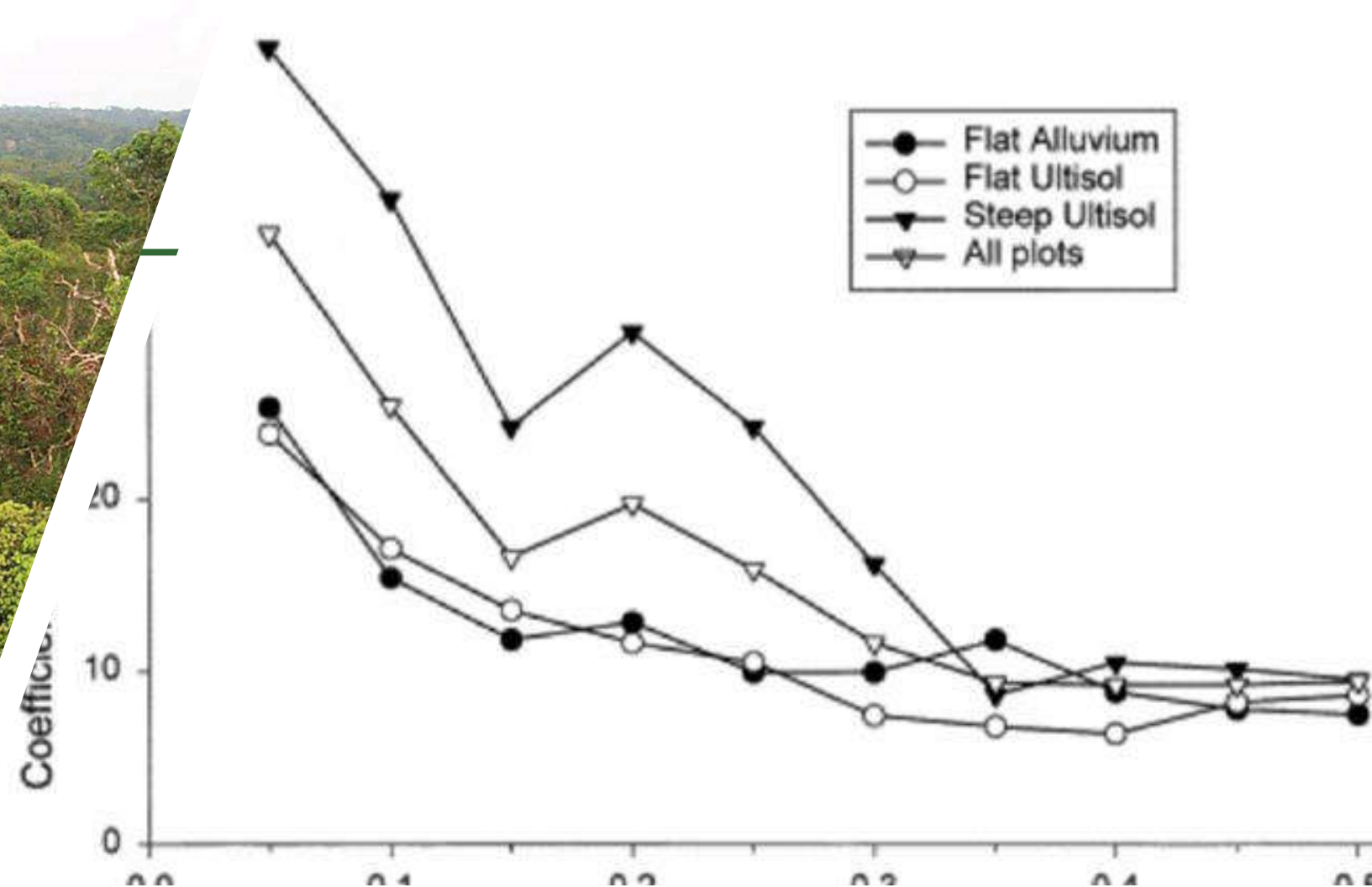




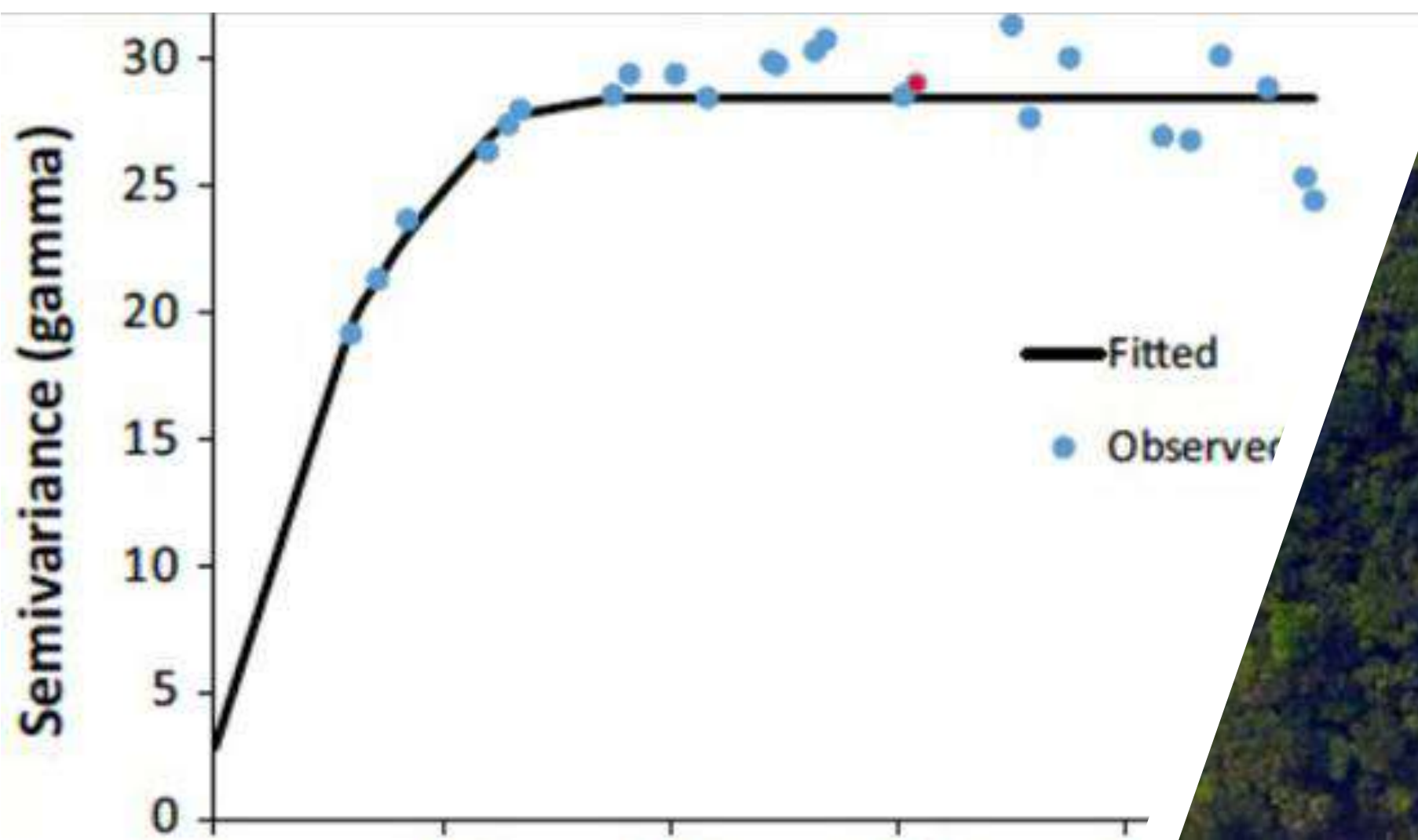
Jet Pro
Californ



Matu

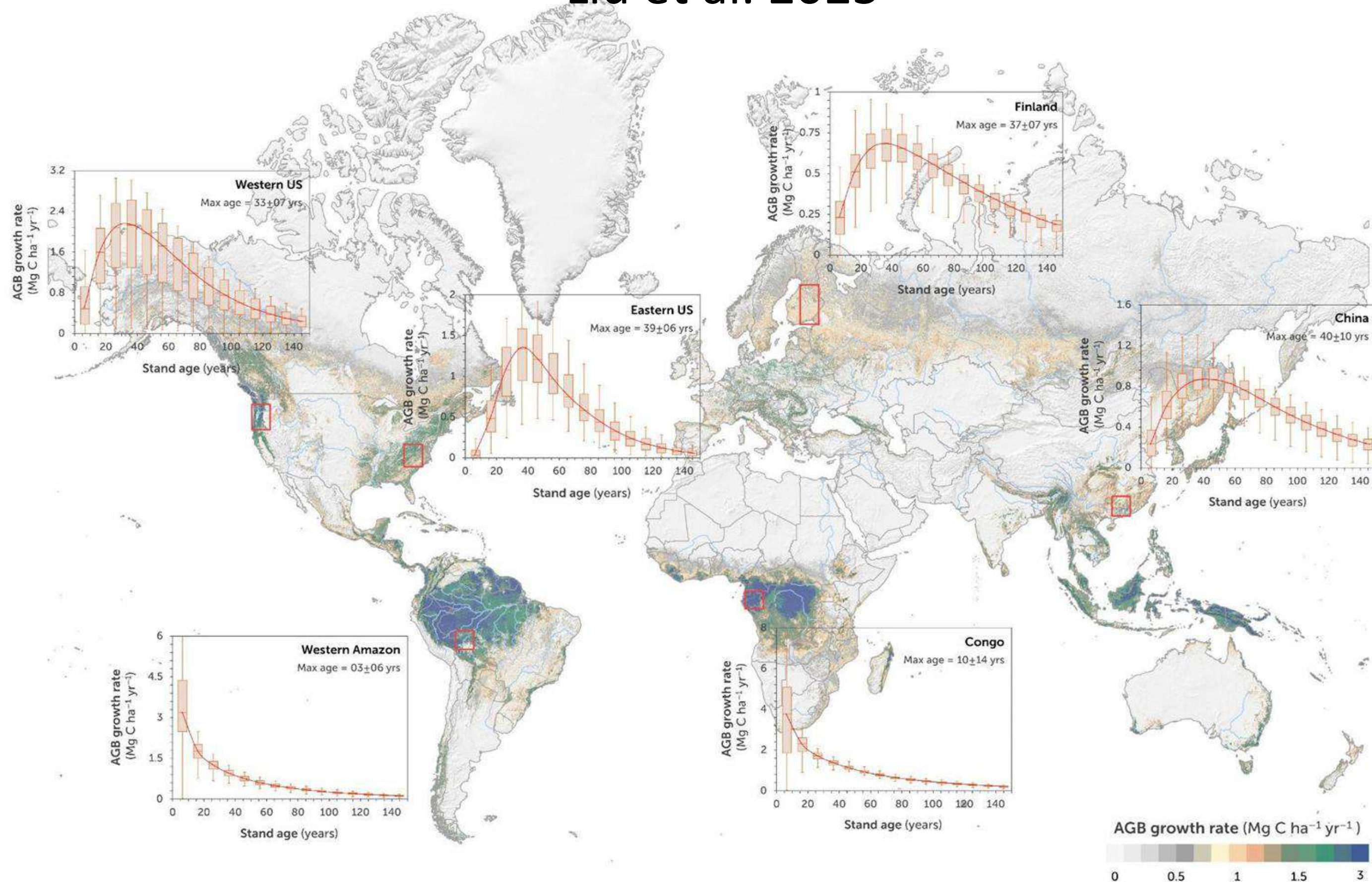


CTrees



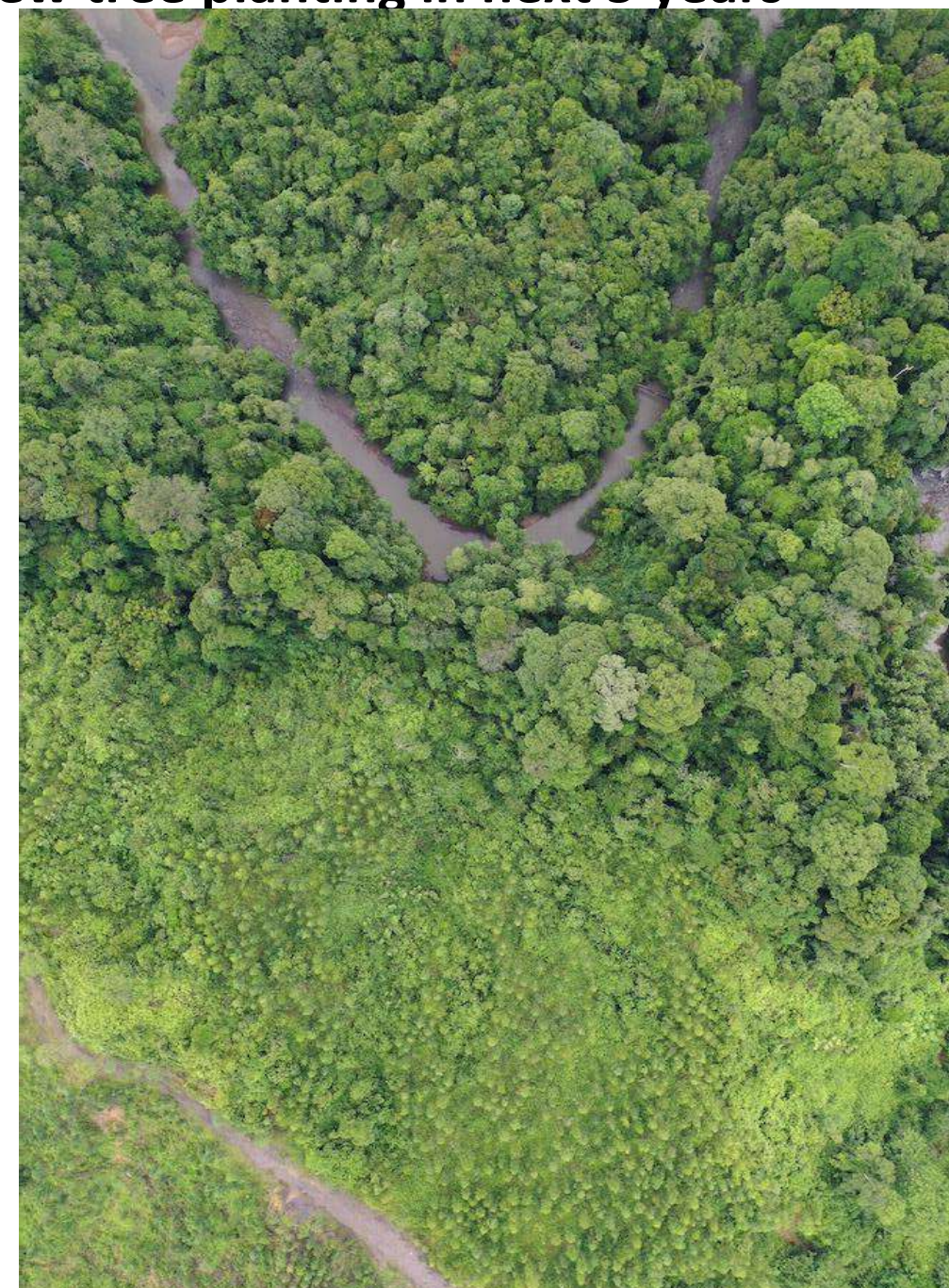
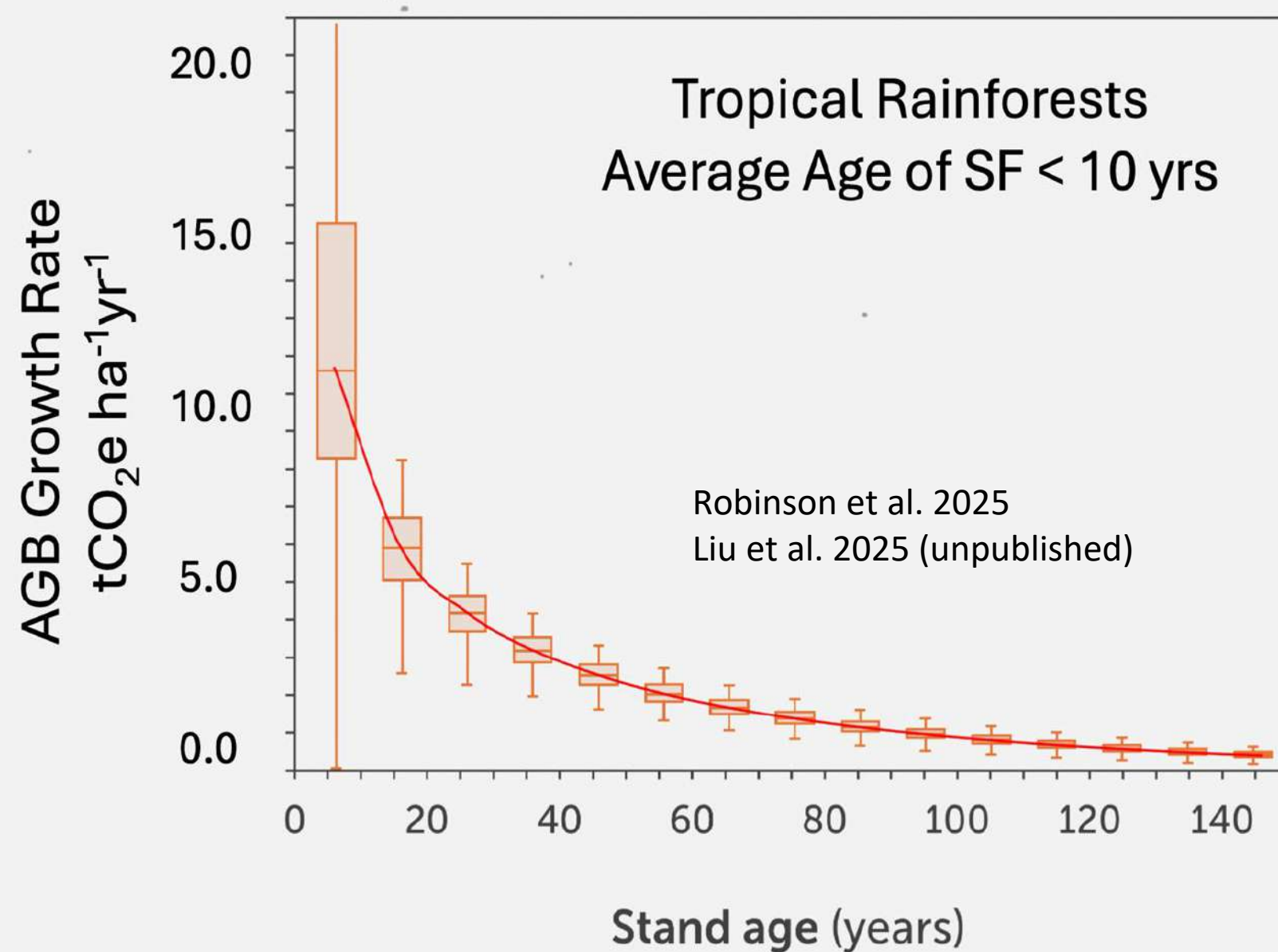
Global Forest Growth Rate 1-ha spatial resolution

Liu et al. 2025



Importance of Secondary Forests

- Tropical secondary forests (SF) in 2020
- Areas of SF < 100 years: 240 Mha
- Areas of SF < 20 years: 155 Mha
- Average Carbon Gain (2010-2020): $\sim 400 \text{ MtCO}_2\text{e yr}^{-1}$
- Allowing SF grow by 2050: $1.5 \text{ GtCO}_2\text{e yr}^{-1}$
- The same amount of carbon from ARR requires: **$\sim 340 \text{ M ha}$ of new tree planting in next 5 years**



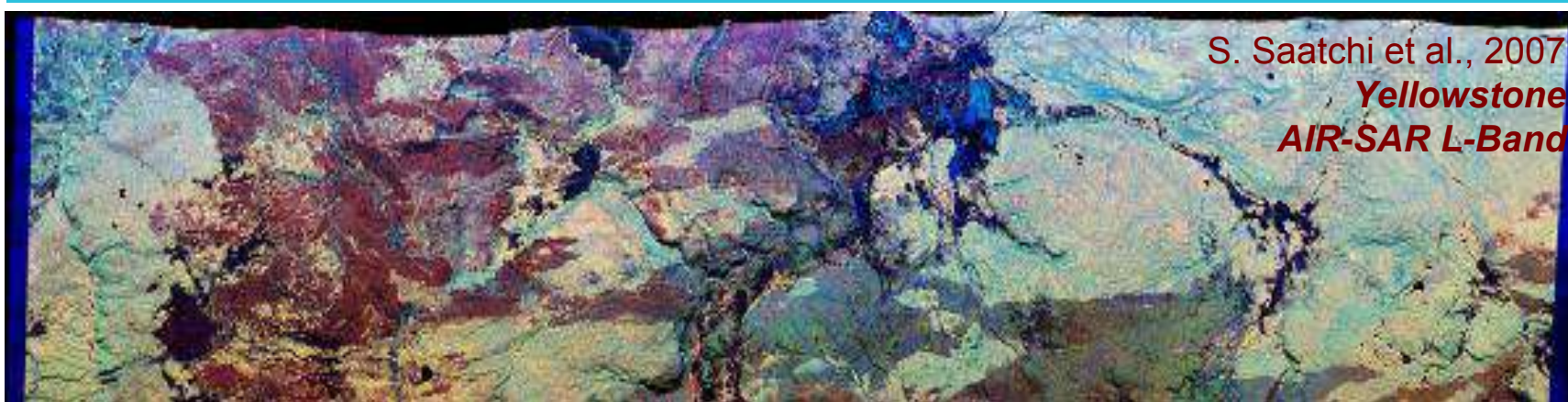
Drivers of Secondary Forests: Culture, Market, Policy

Secondary forests (SF) are part of the global land use activities. SF short-term and long-term carbon sequestration capacity depend strongly on local, national and international policy and market forces



Global Monitoring of Vegetation Disturbance and Recovery

NISAR would provide annual vegetation disturbance and deforestation maps globally at spatial scale of ~1 ha



Cross-pol measurement is key to detecting structural differences in vegetation, driving requirement for multi-pol baseline and cross-pol threshold radar capability.



2003 Burn

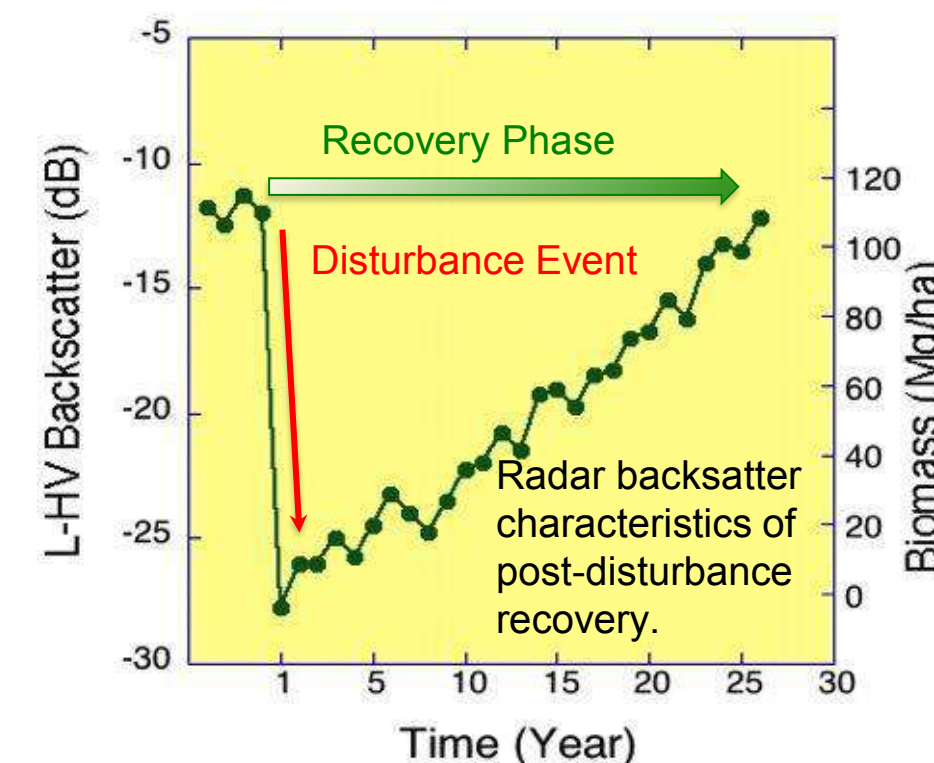


Recovery after 1988 Burn



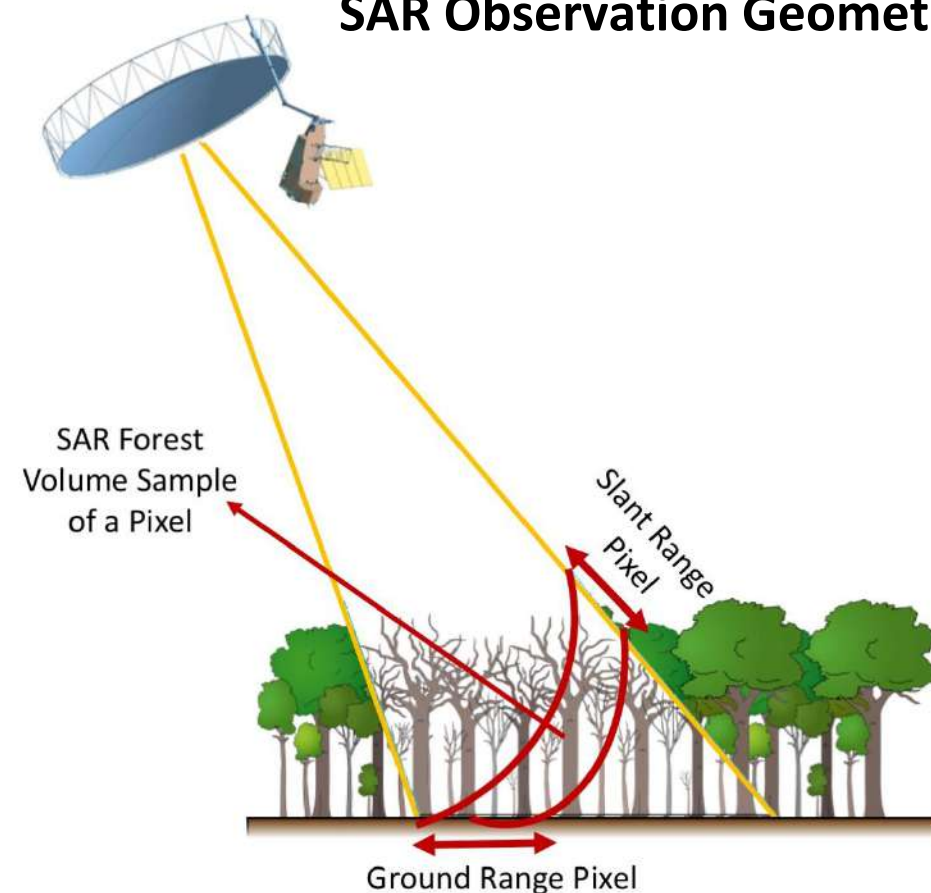
Pine Beetle Disease

NISAR would provide acquisitions with both polarization and incident angle variations; both critical for effective disturbance monitoring.

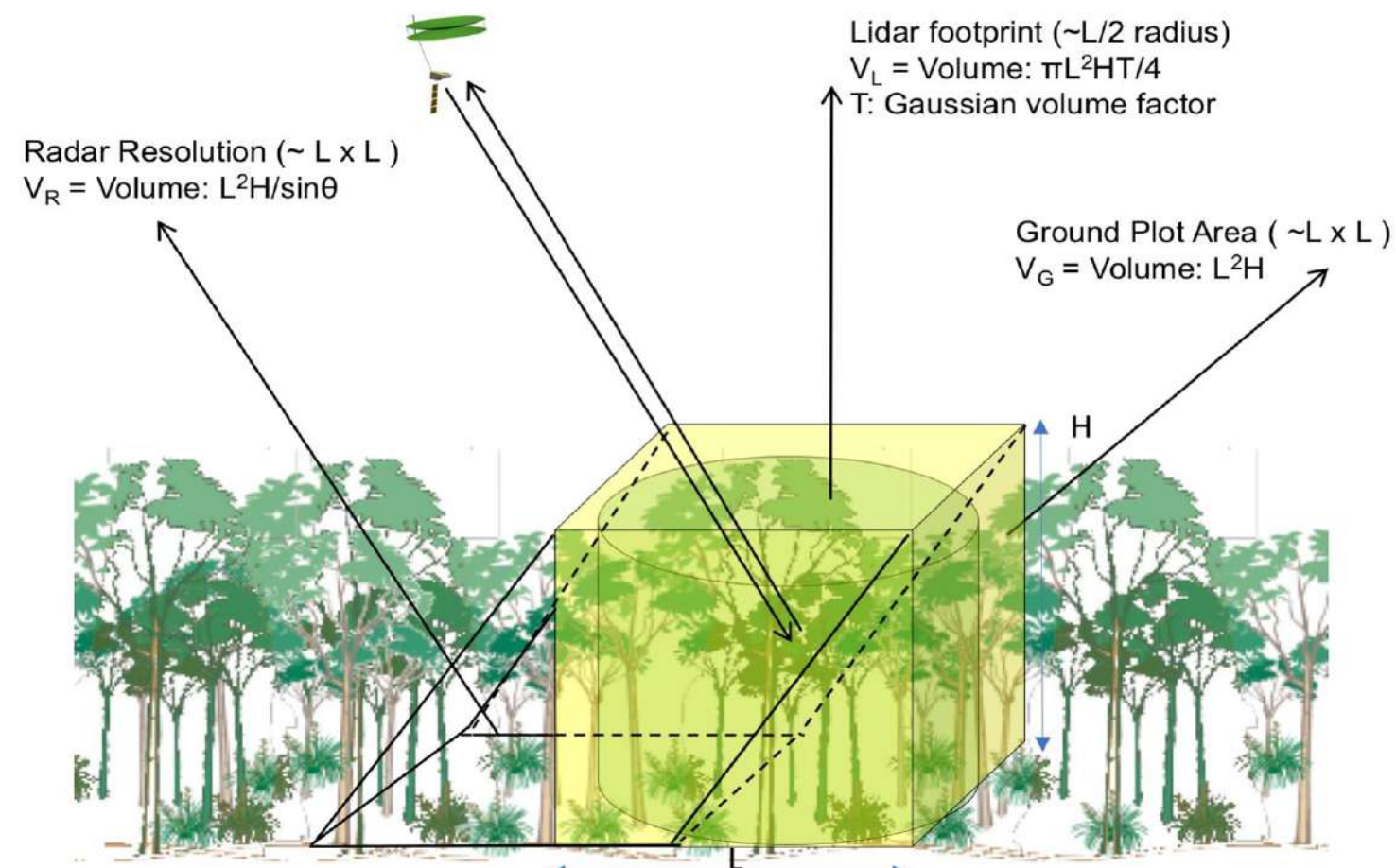


NISAR would quantify fluxes in terrestrial sources and sinks of carbon resulting from disturbance

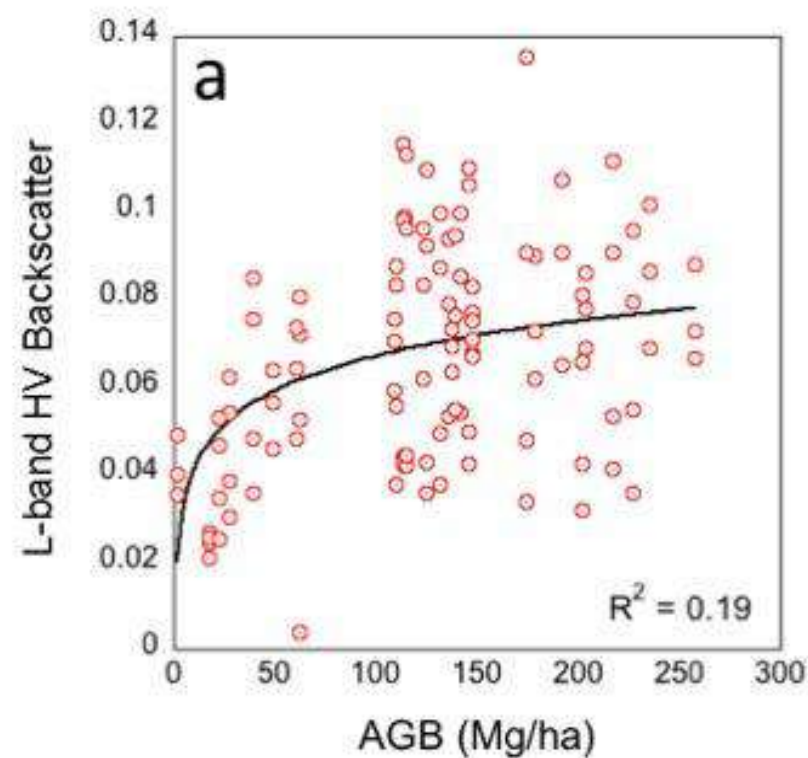
SAR Observation Geometry



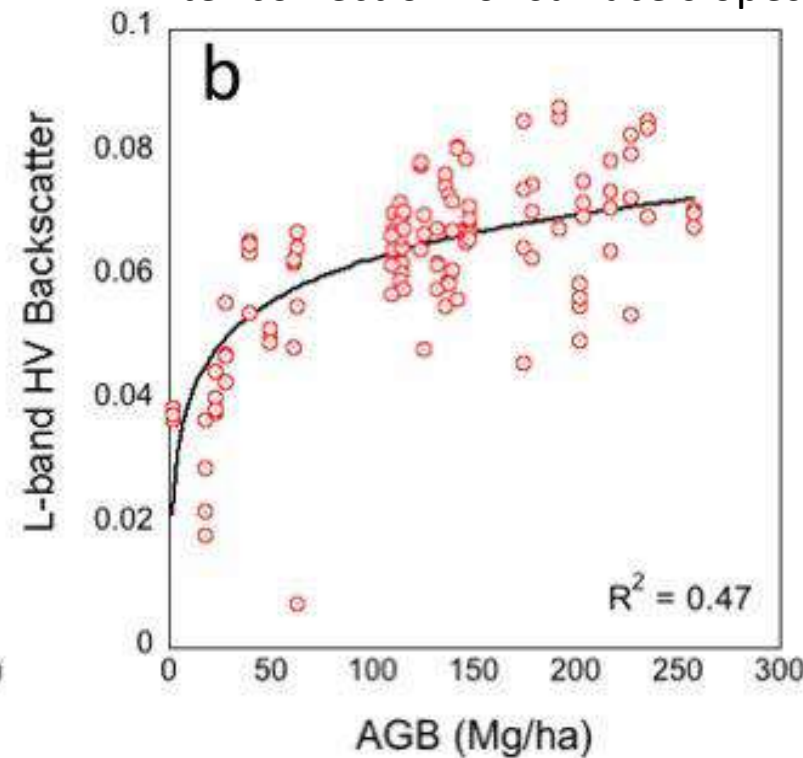
SAR Pixel vs Lidar and Ground Pixel



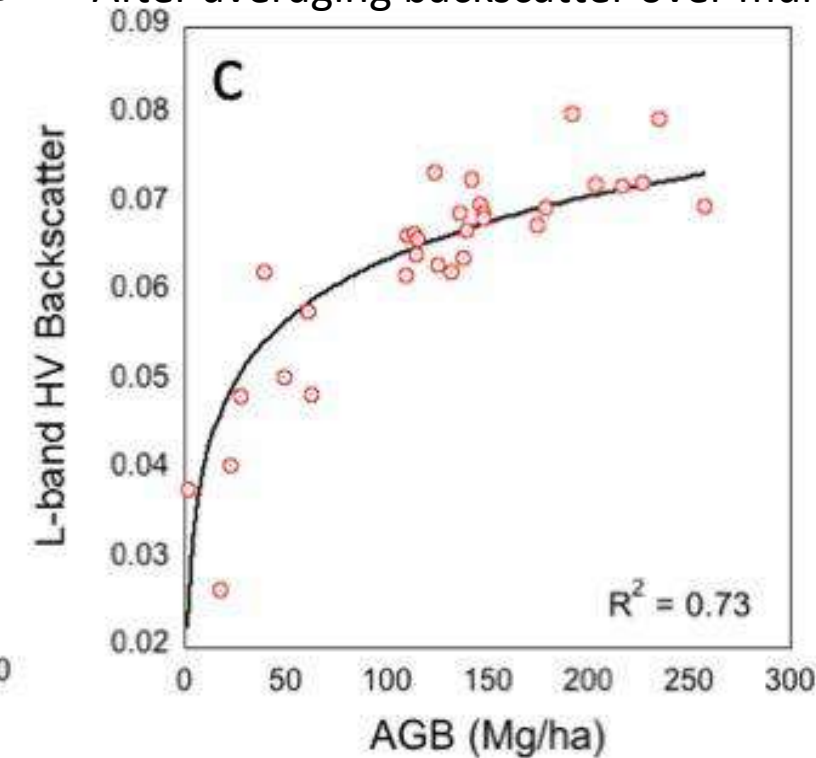
Multiple dates & multiple surface slope

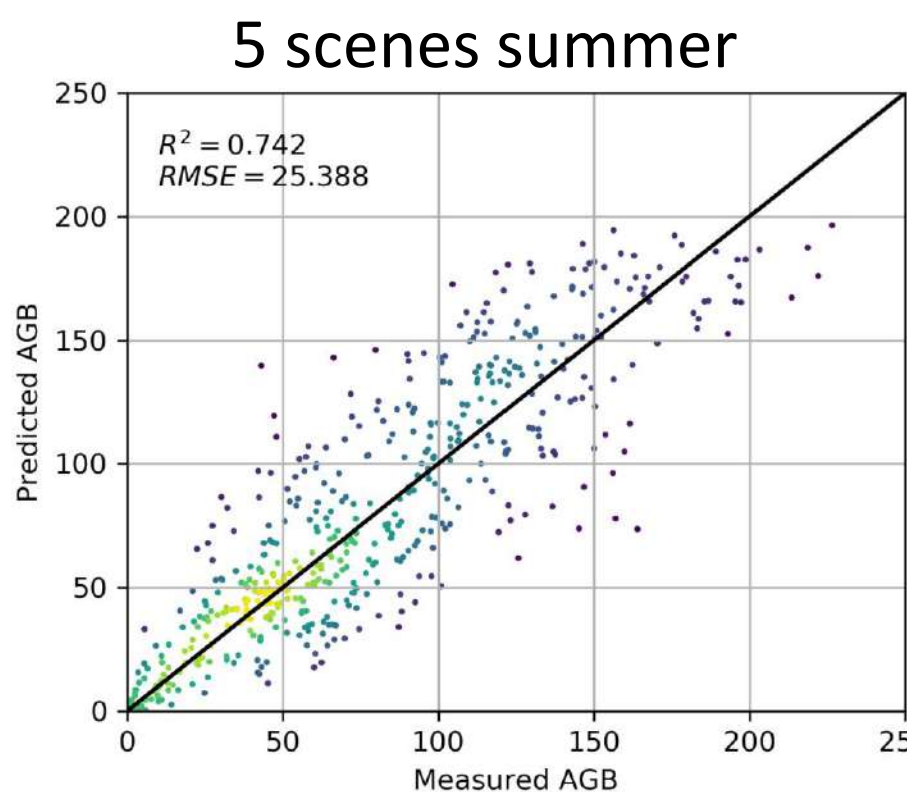


After correction for surface slopes

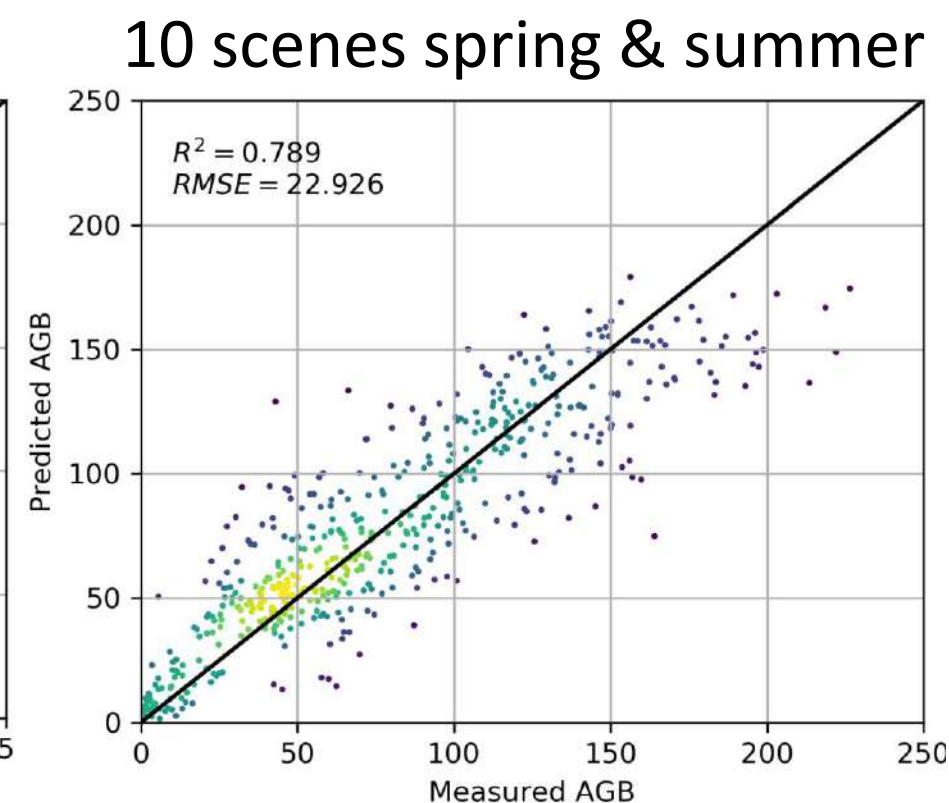


After averaging backscatter over multiple dates

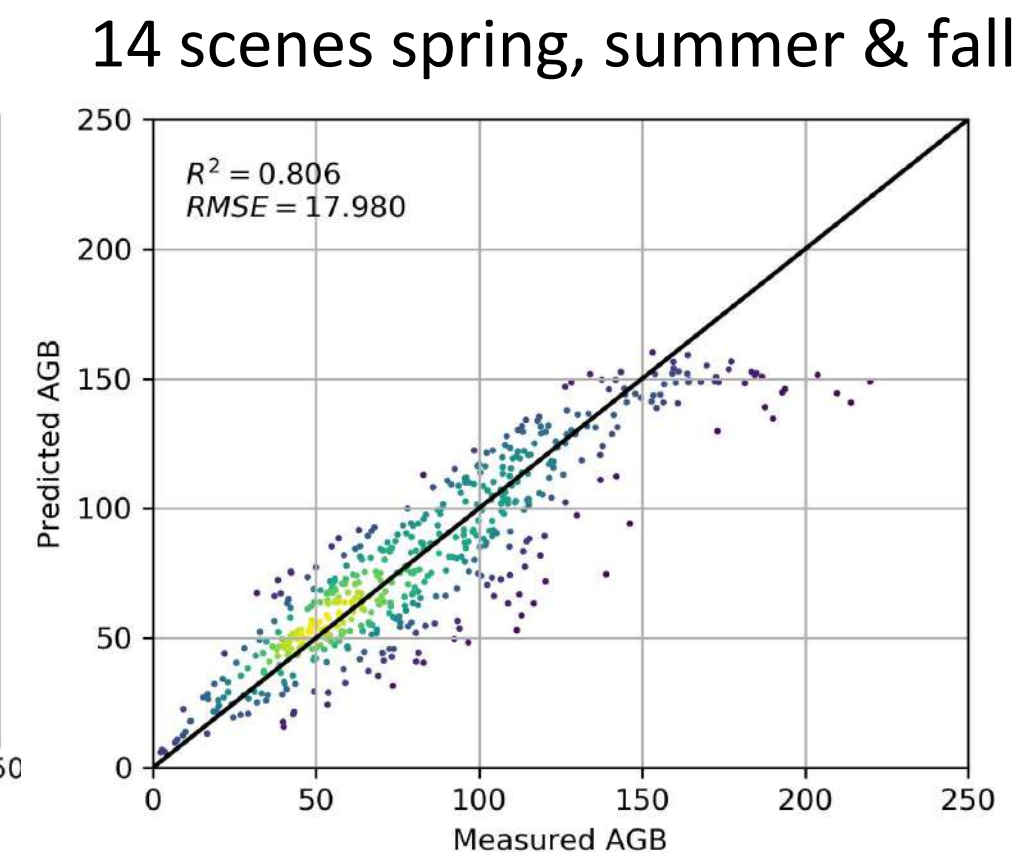




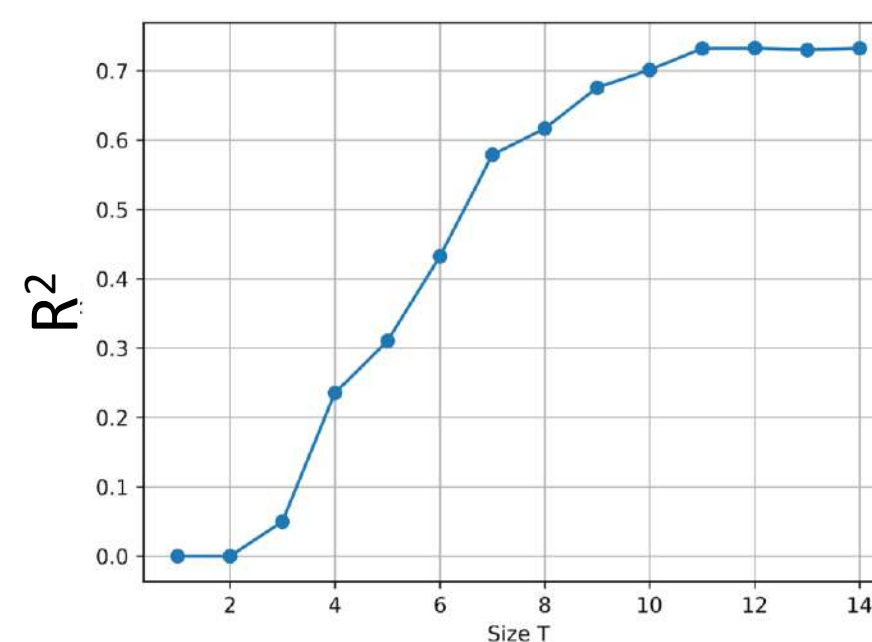
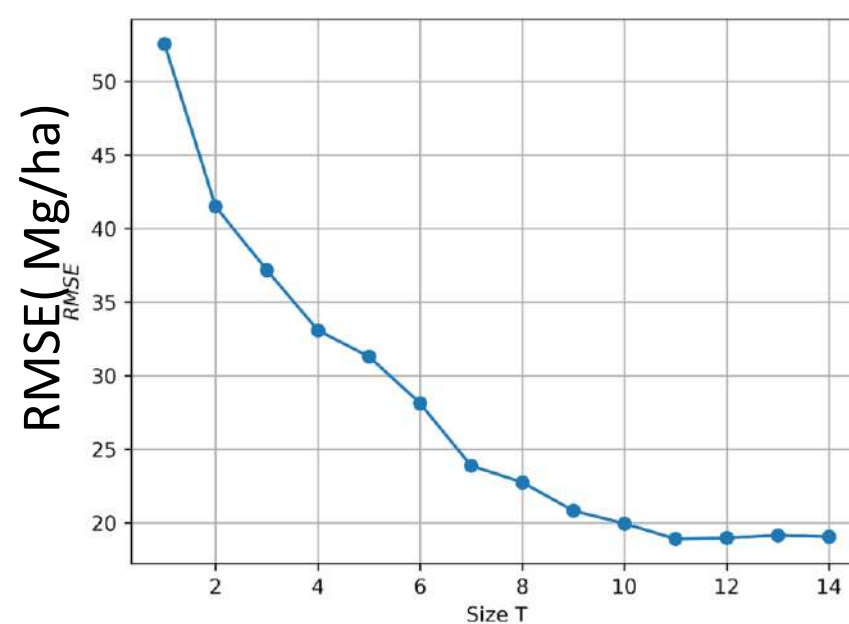
67.0% within 20 Mg/ha.
45.4% within 10 Mg/ha.



74% within ± 20 Mg/ha.
46% within ± 10 Mg/ha.



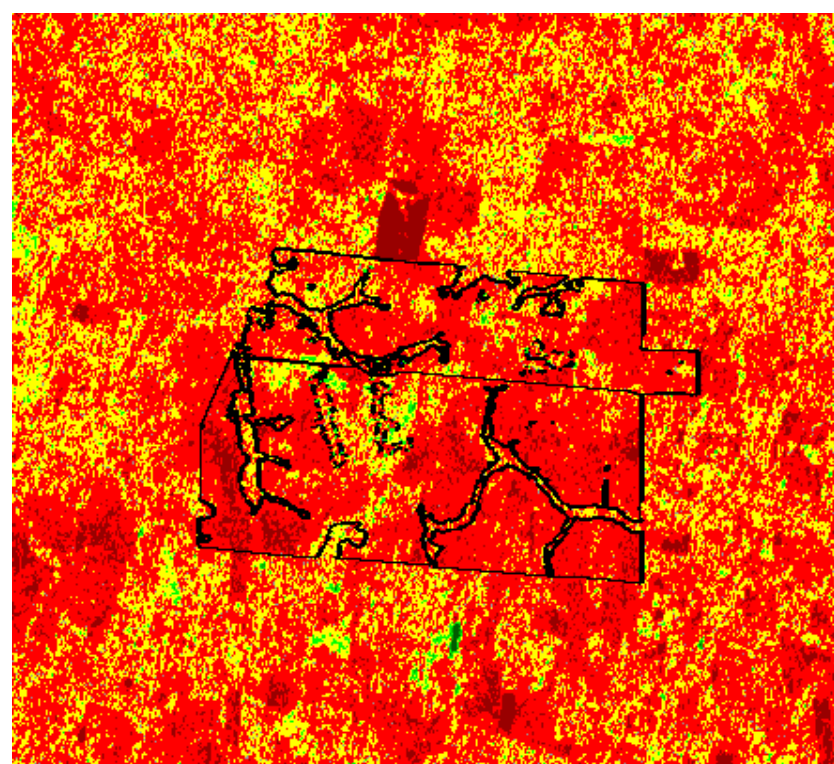
82% within ± 20 Mg/ha.
51% within ± 10 Mg/ha.



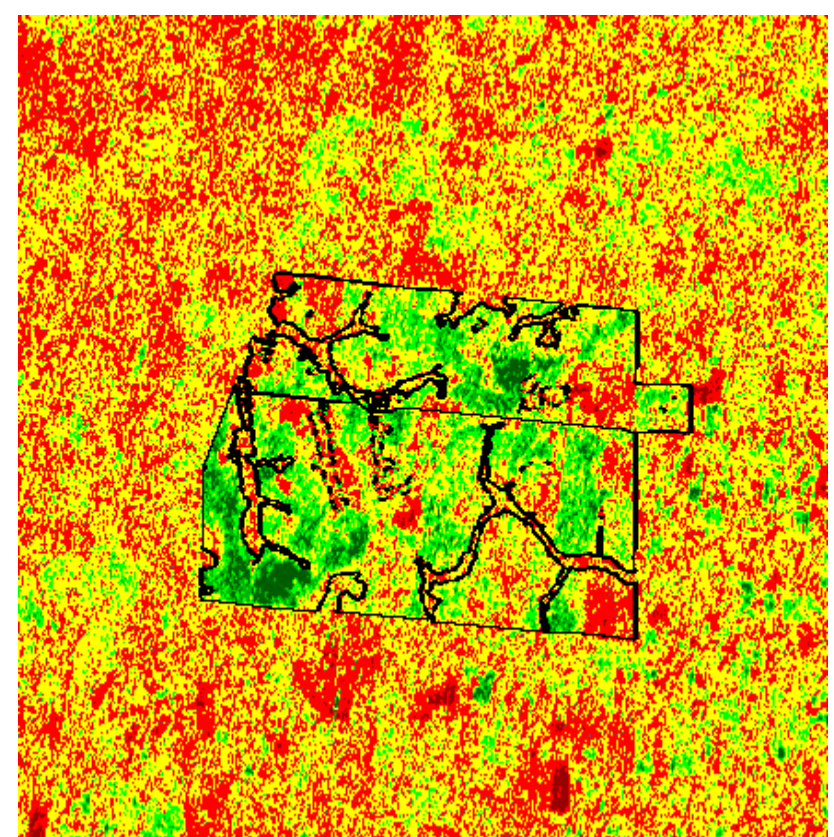
530 lidar derived biomass
used in model validation

Winter scenes with snow
cover require model
improvement

Radar Stocking Index Captures Growth of Tree Plantation



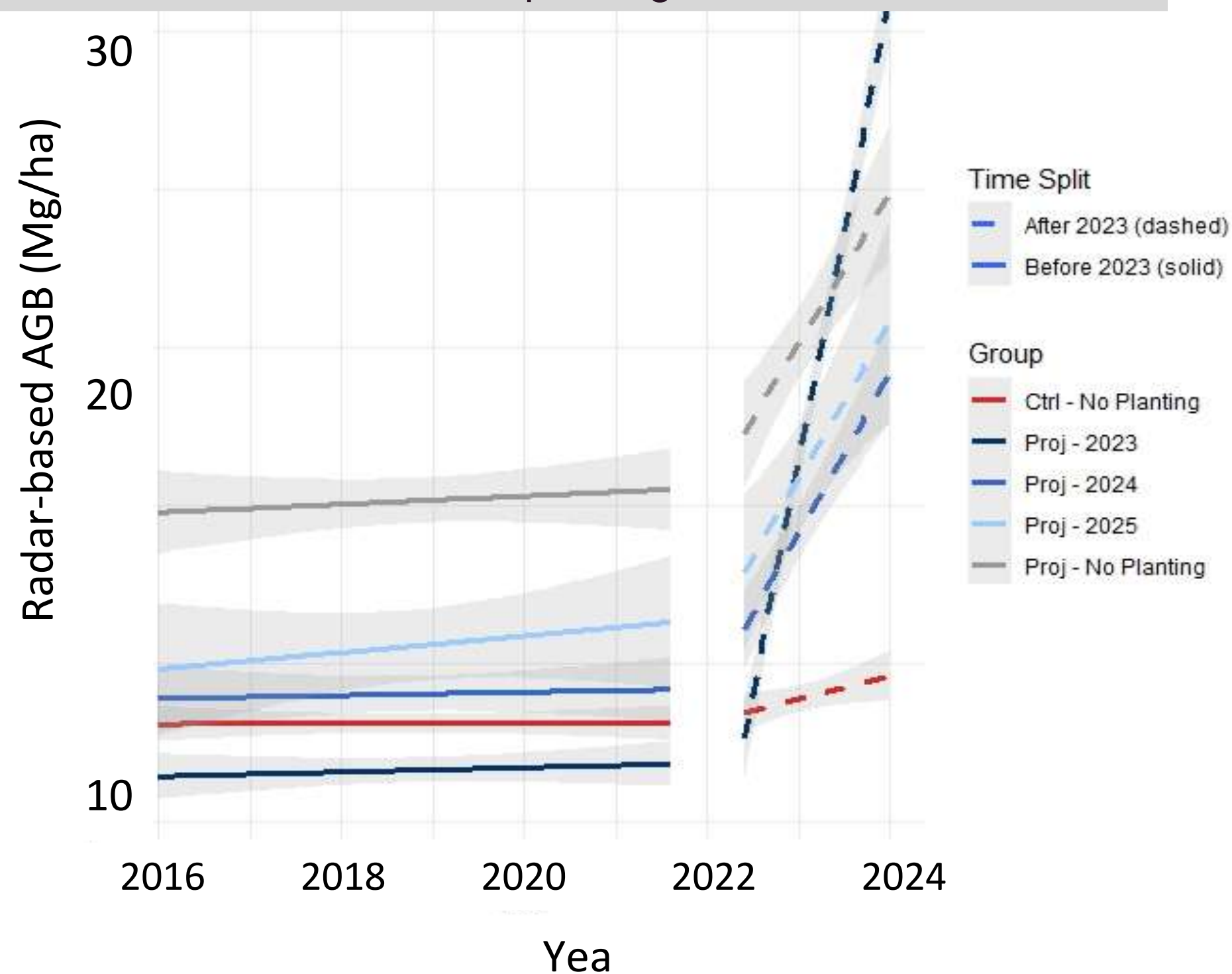
RSI: December 2022



RSI: March 2024

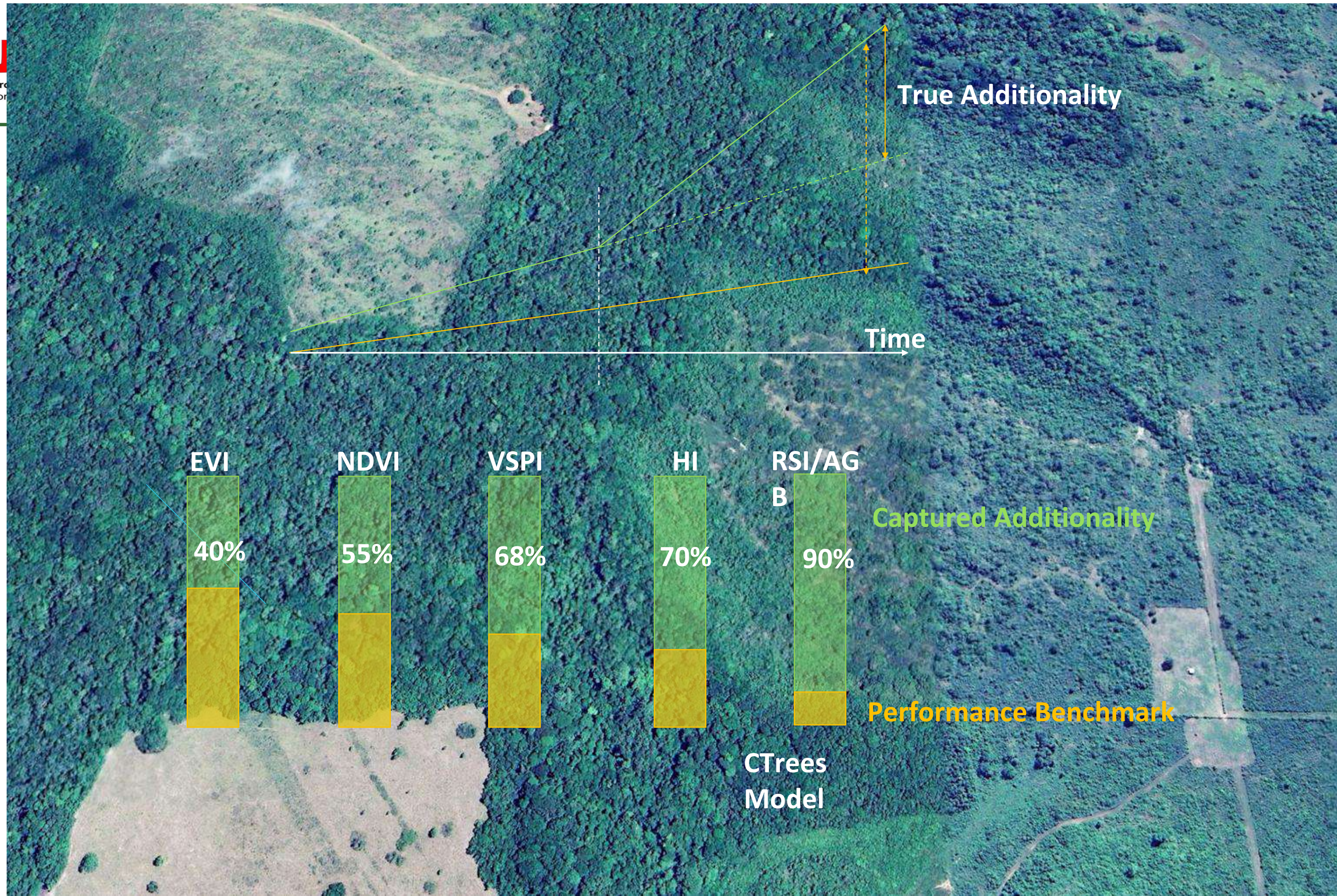


- ✓ Direct biomass and Radar-based Stocking Index can be used for dynamic baselining
- ✓ Estimate of additionality & tracking carbon credit available at 6-12 months after tree planting

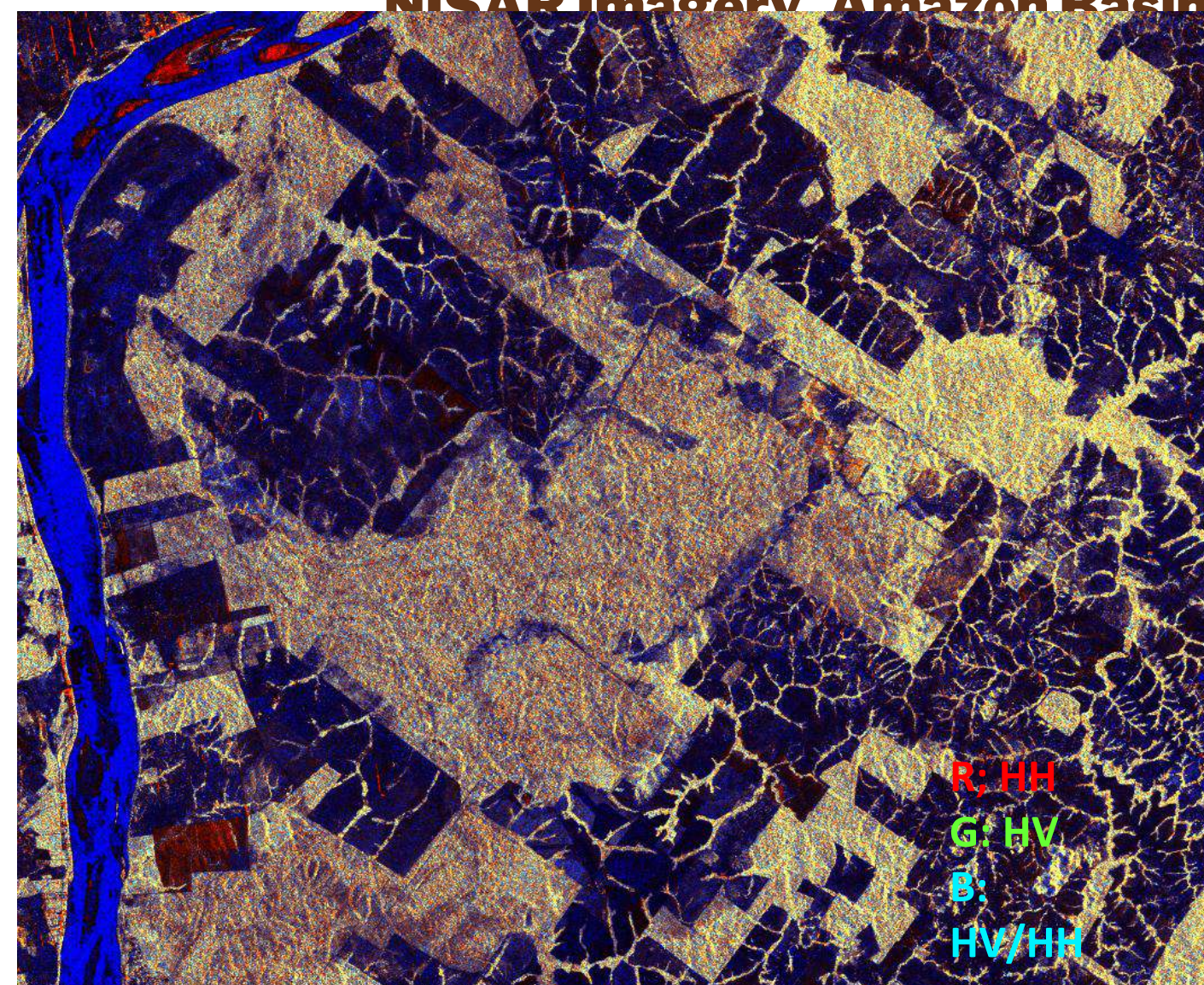




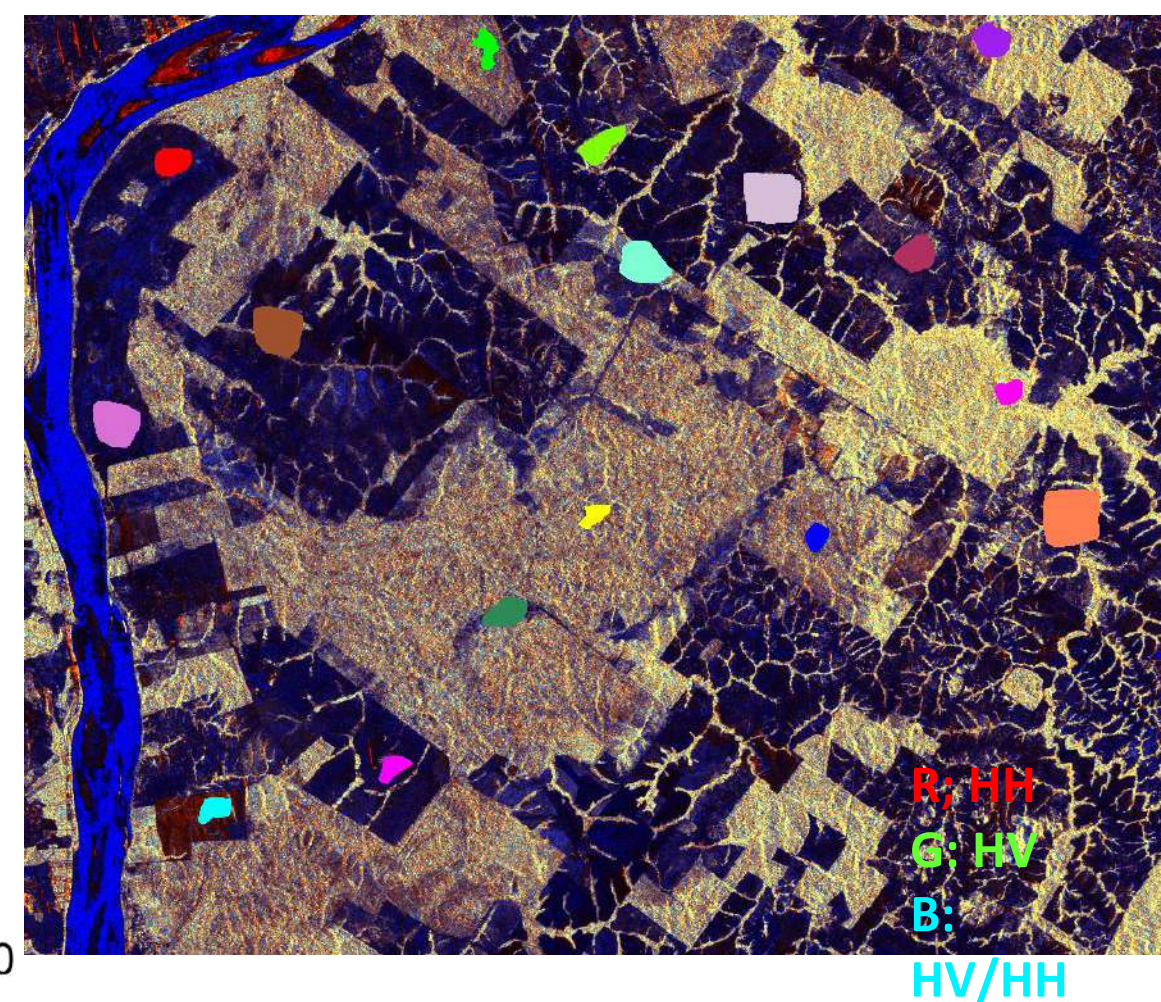
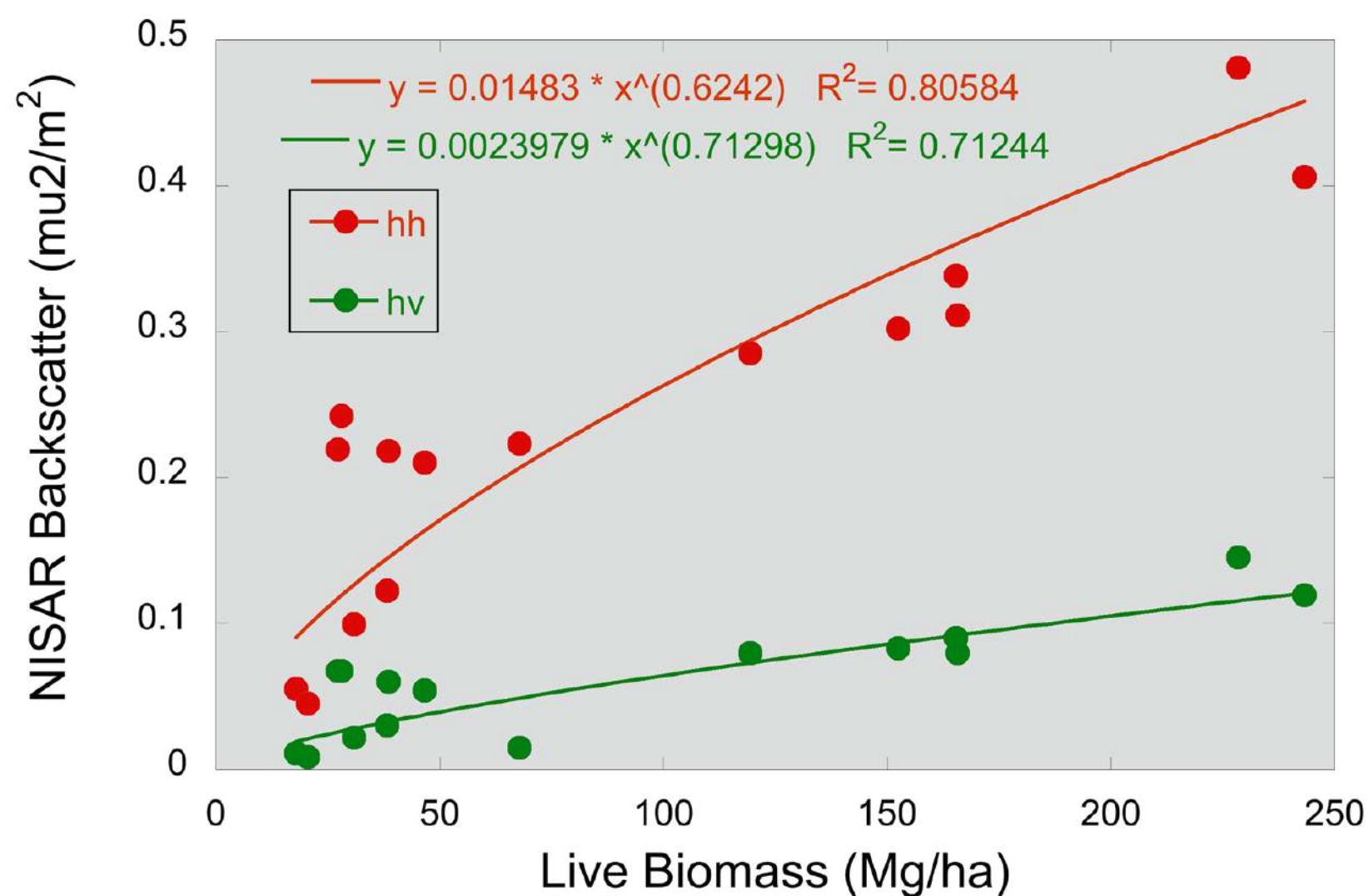
Jet Pro
Californ

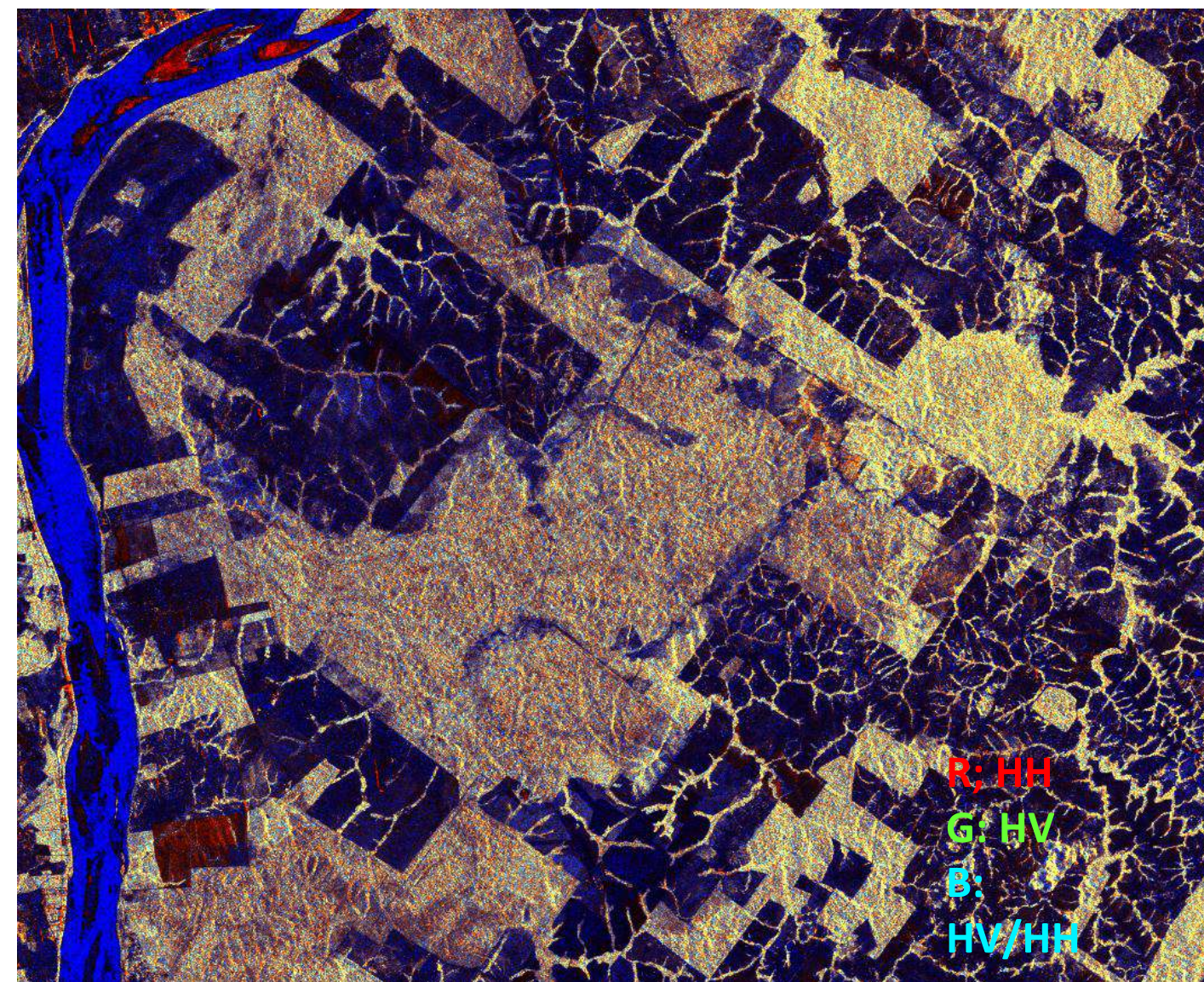
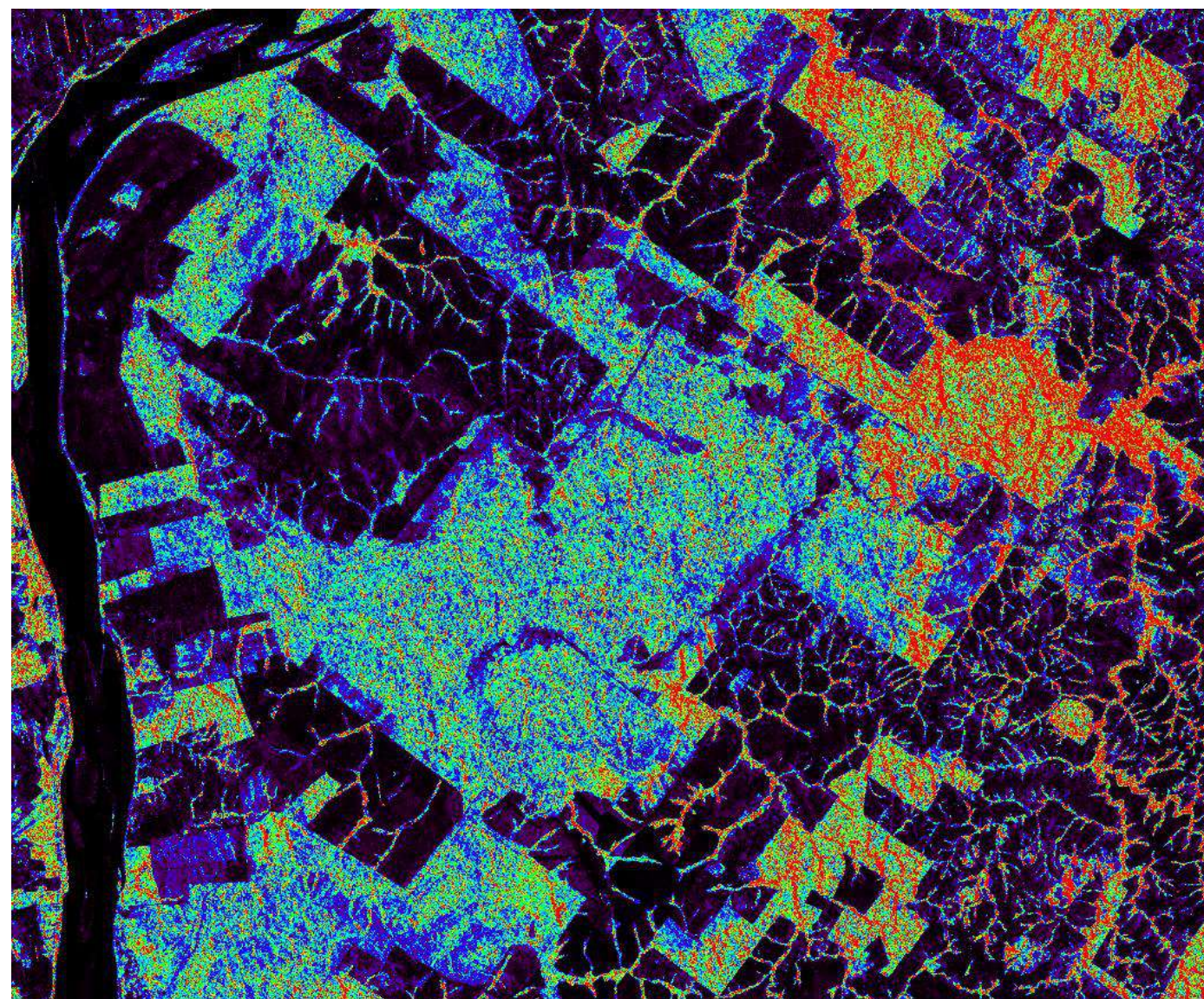


Agriculture Frontier in the State of Tocantins, Brazil (7.019 S, 49.072 W)



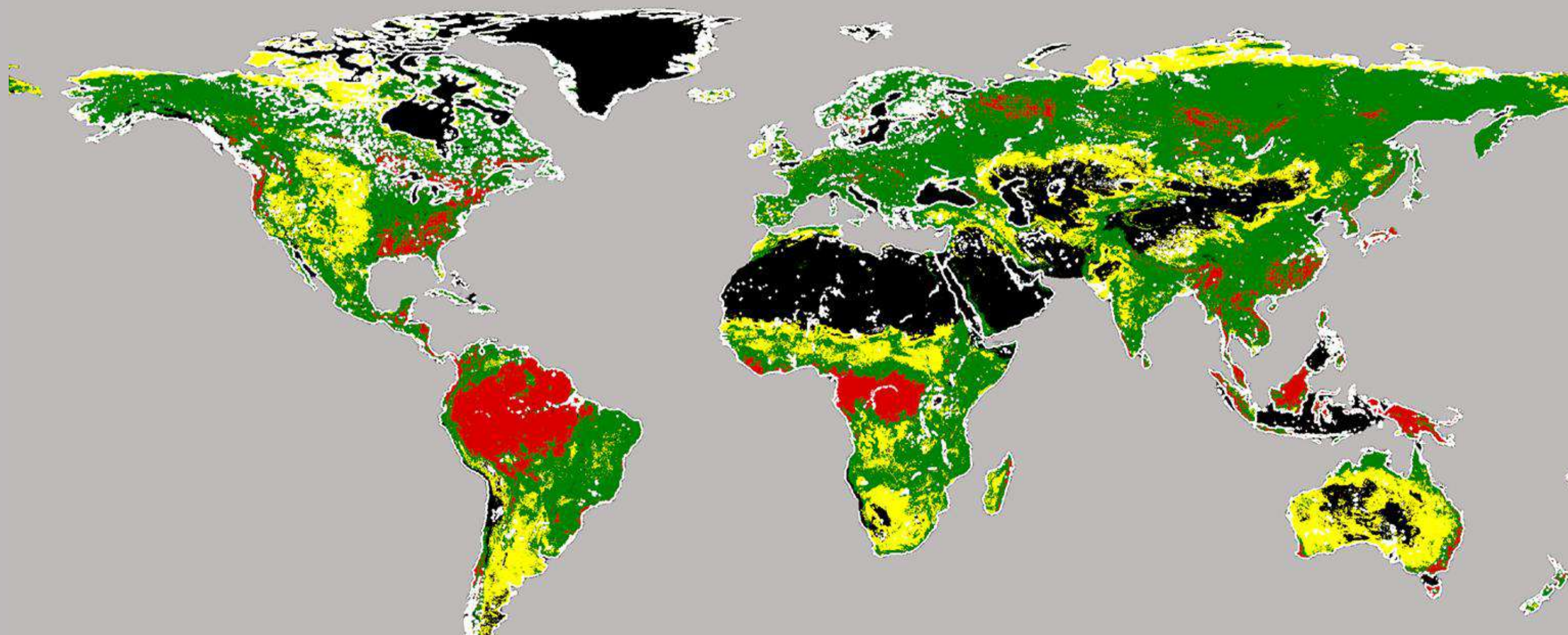
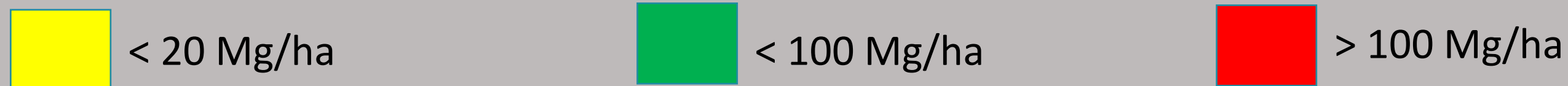
Comparison of NISAR data and Global GEDI-based Biomass Map



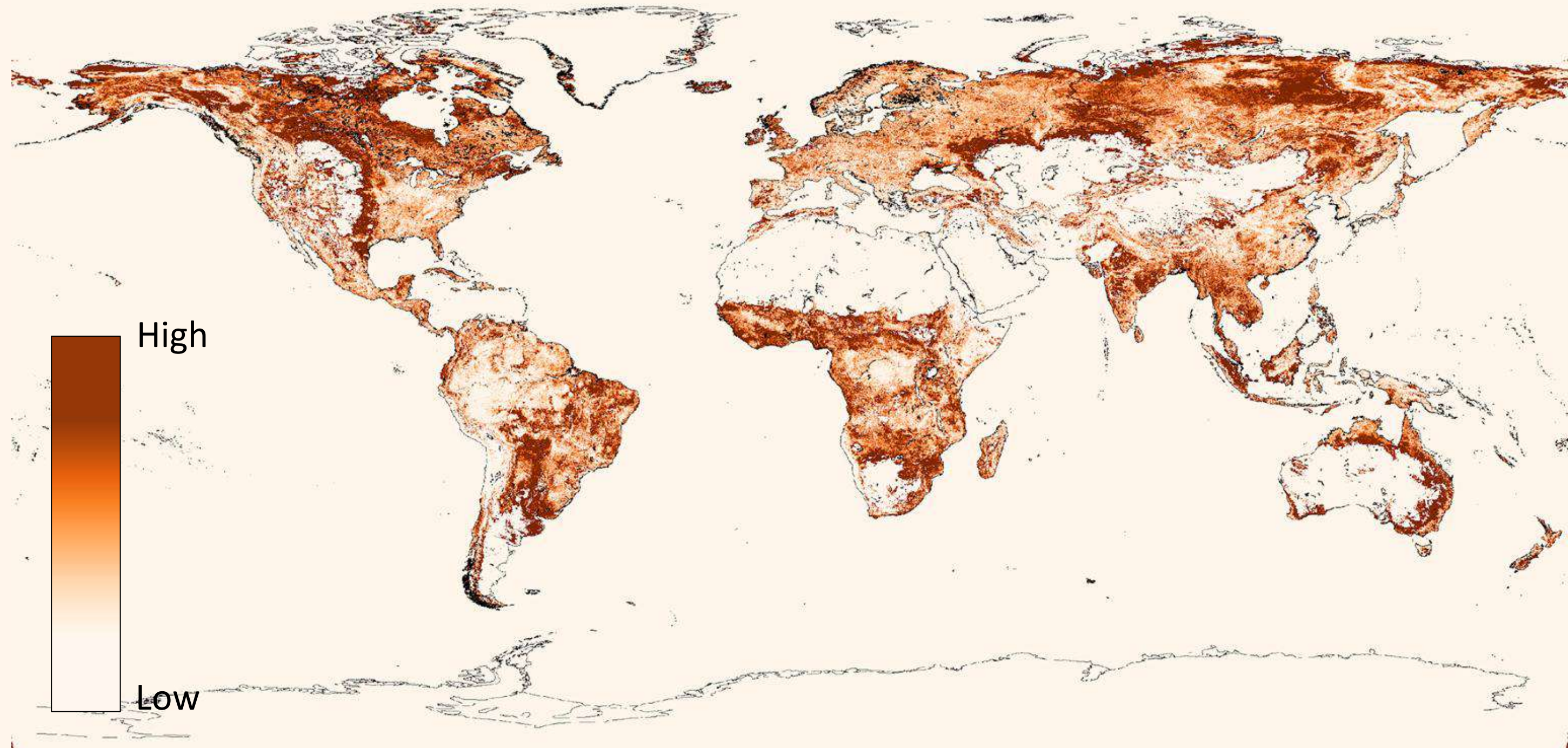




Global Vegetation Aboveground Biomass



STD of Biomass (2000-2024) 10 km Grid Cell



Yu and Saatchi et al., 2025



Summary

Trees

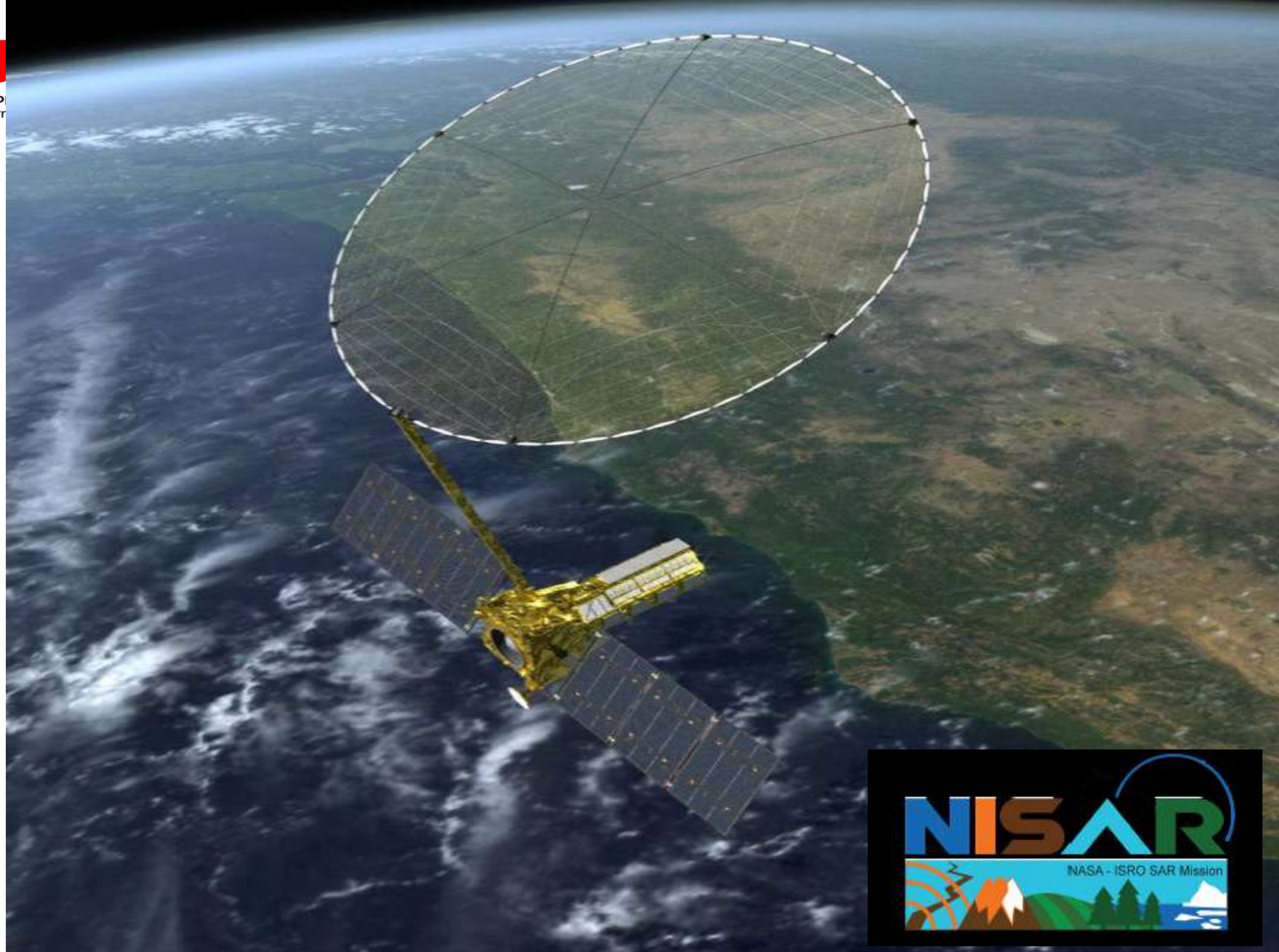
NISAR will provide the first forestry dedicated global observations

- NISAR focuses on the most dynamic components of global forests (A TRUE GEDI Satellite: Global Ecosystem Dynamic Investigation)
- Monitoring changes of forest cover from disturbance (fire, hurricane, insects, droughts)
- Monitoring recovery of forest after disturbance and land use
- Monitoring forest health and productivity by providing habitat structure, changes of canopy water content, monitoring soil moisture changes and drought stress



Jet Propulsion
California

CTrees



Session 2.1 (Part 2): Estimates of carbon accumulation from various approaches

SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

São José dos Campos, 30 Oct 2025



GFZ Helmholtz Centre
for Geosciences



Session 2.2: Other metrics for identifying secondary forest success

(eg. biodiversity, landscape metrics, permanence)

São José dos Campos, 30 Oct 2025



Catarina Jakovac

Patterns and Drivers of Vegetation Structure in Amazonian Secondary Forests

20th June 2025

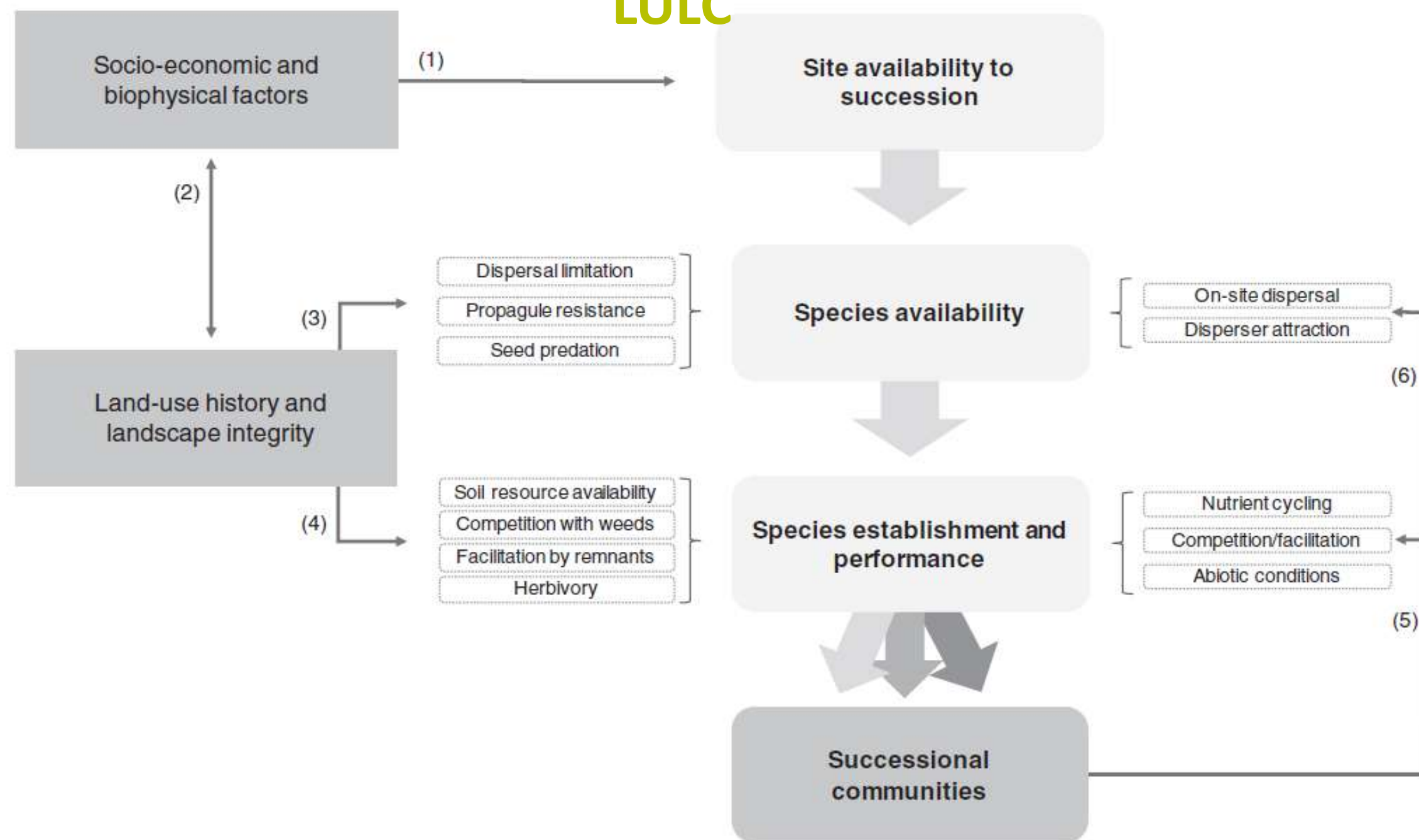


LAB
REFLOR
Laboratório de
Restauração e
Ecologia Florestal

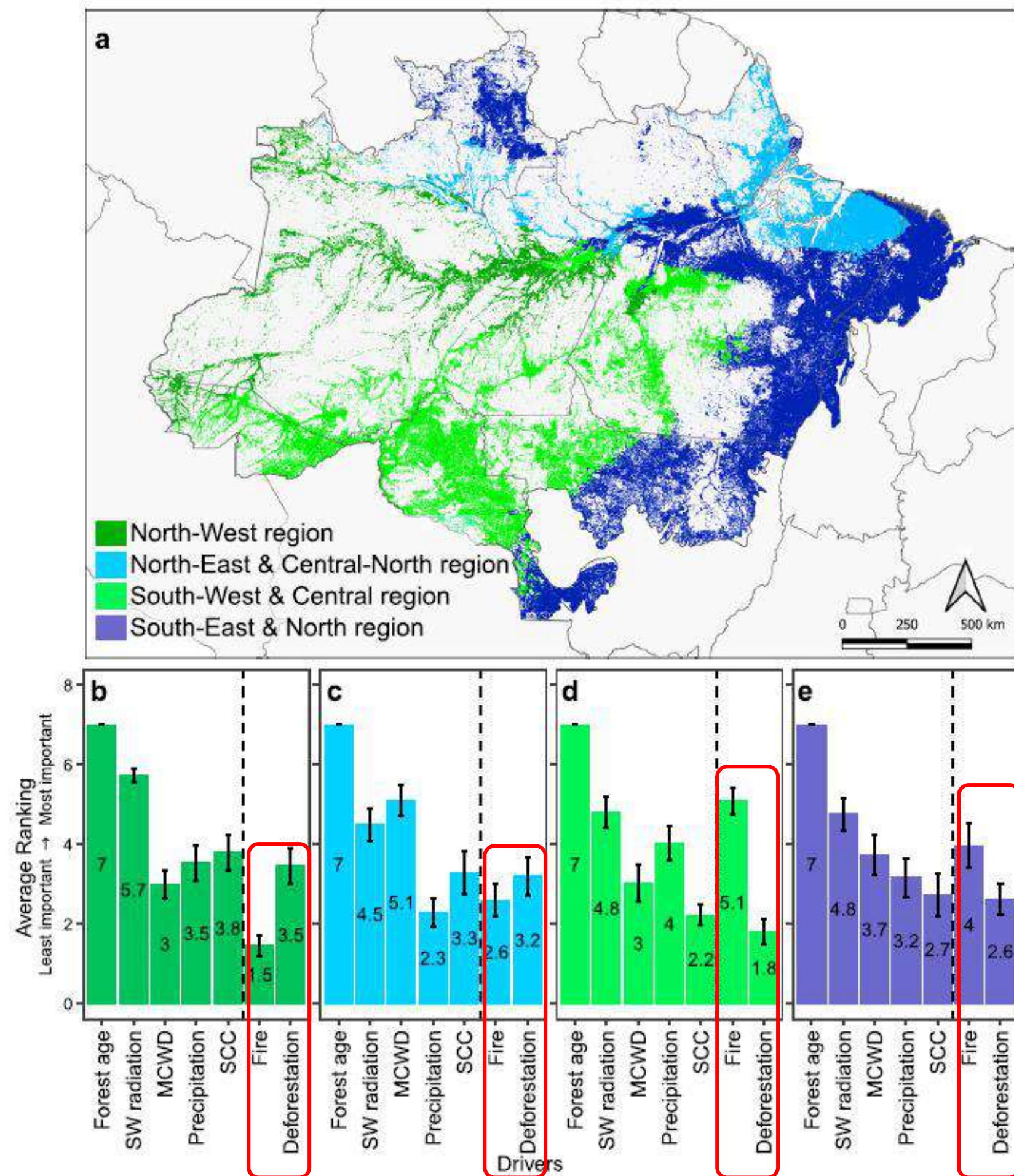


Continental scale = Environmental conditions

Regional scale = Environ + LULC



Environmental conditions and anthropogenic factors vary across space



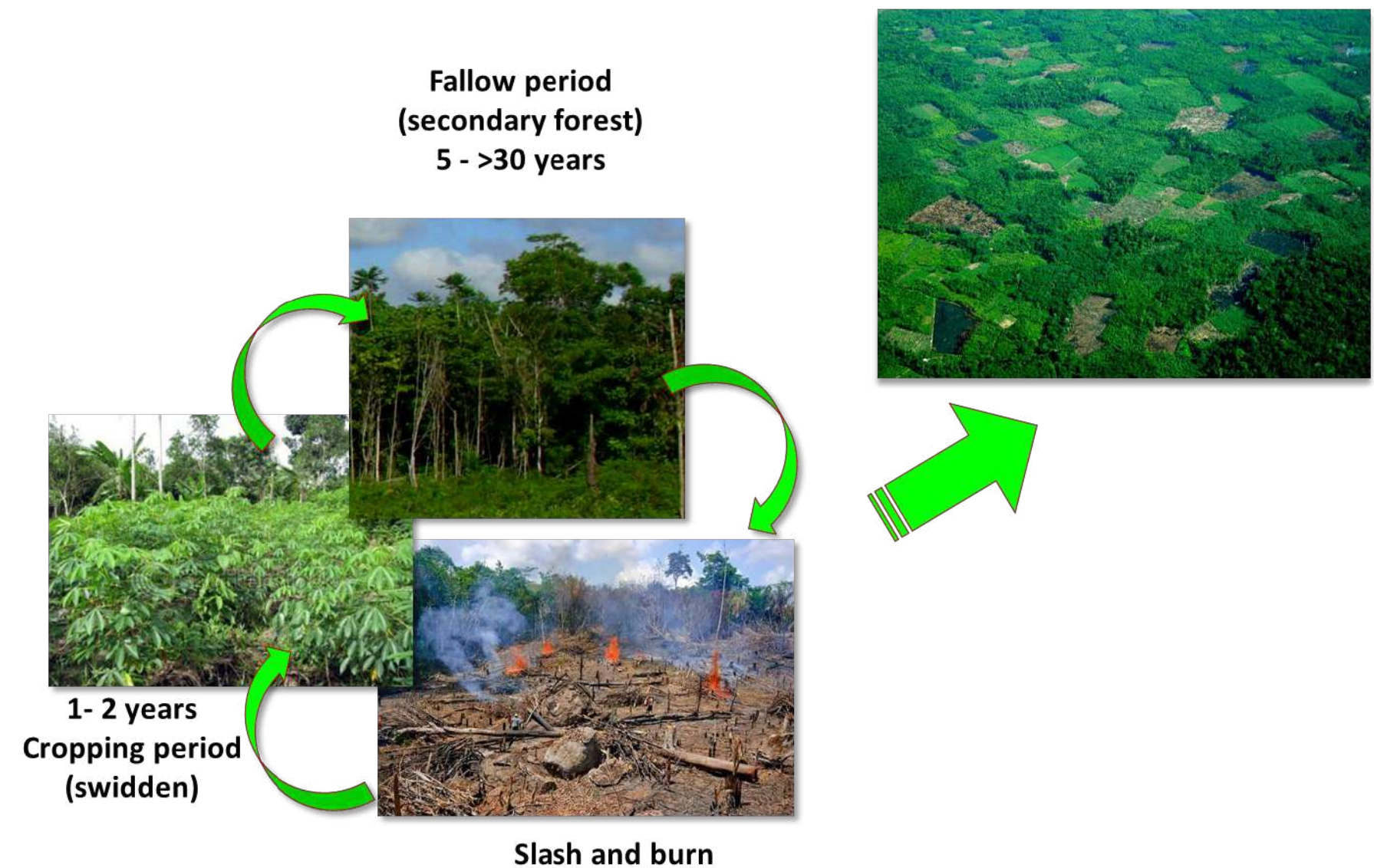
of disturbances: fire and deforestation (Fig. 3). Our analysis shows distinct regrowth regimes emerging in these four heterogeneous climate regions (Fig. 3), with regrowth in some regions conditioned largely by natural, environmental drivers, and others by anthropogenic disturbance drivers (Fig. 2b-e). In the North-

Drier (more seasonal) regions were more affected by anthropogenic drivers. Why?

- ❖ ? less resilient to anthropogenic impacts
- ❖ ? higher fire and deforestation frequency (broader gradient = stronger effect)
- ❖ ? lower forest cover in the landscape due to longer LU lead to lower regrowth rates

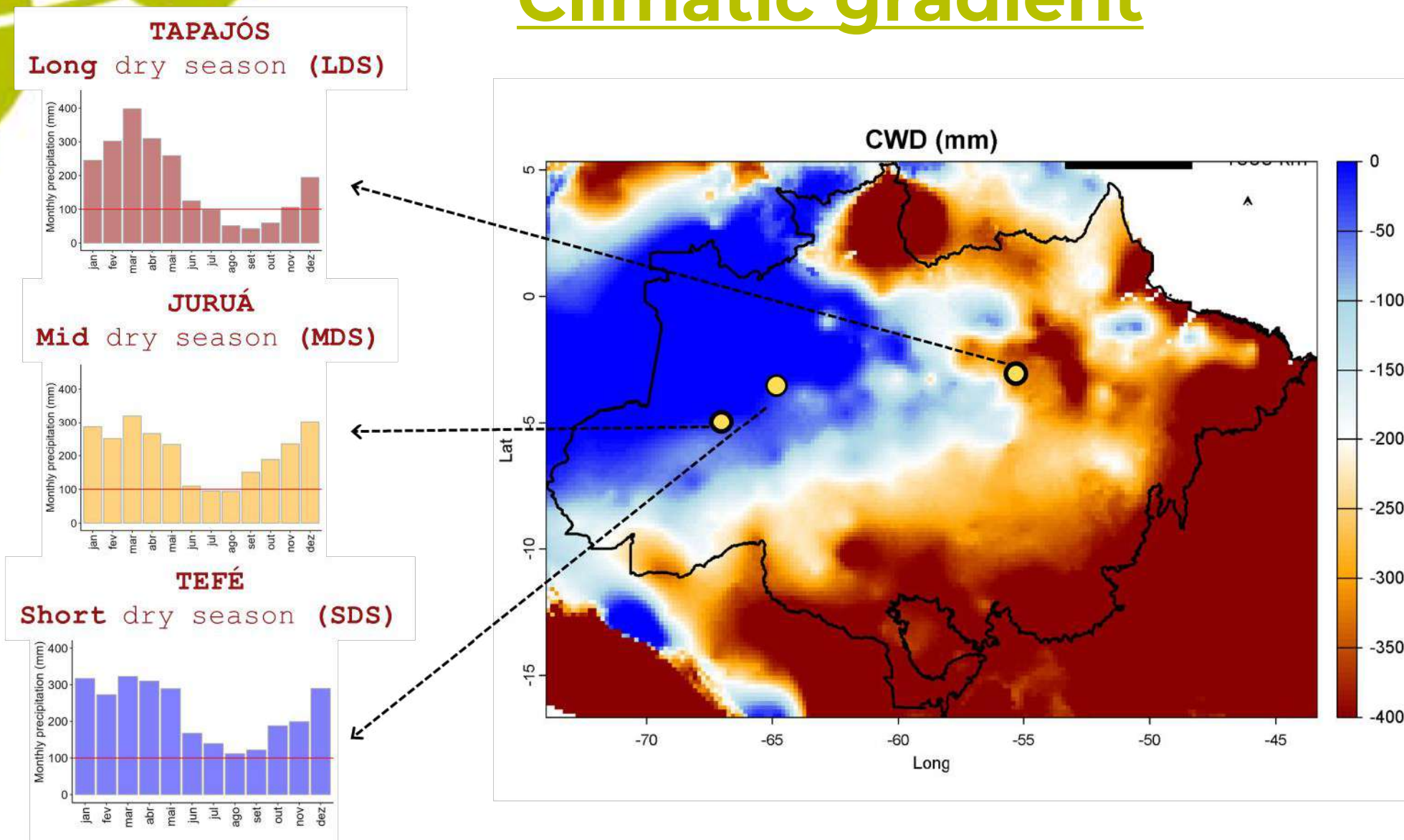
How environmental and land use drivers interact?

Hypothesis: Wetter regions are more strongly affected by anthropogenic impacts than drier regions, because species did not evolve with fire.



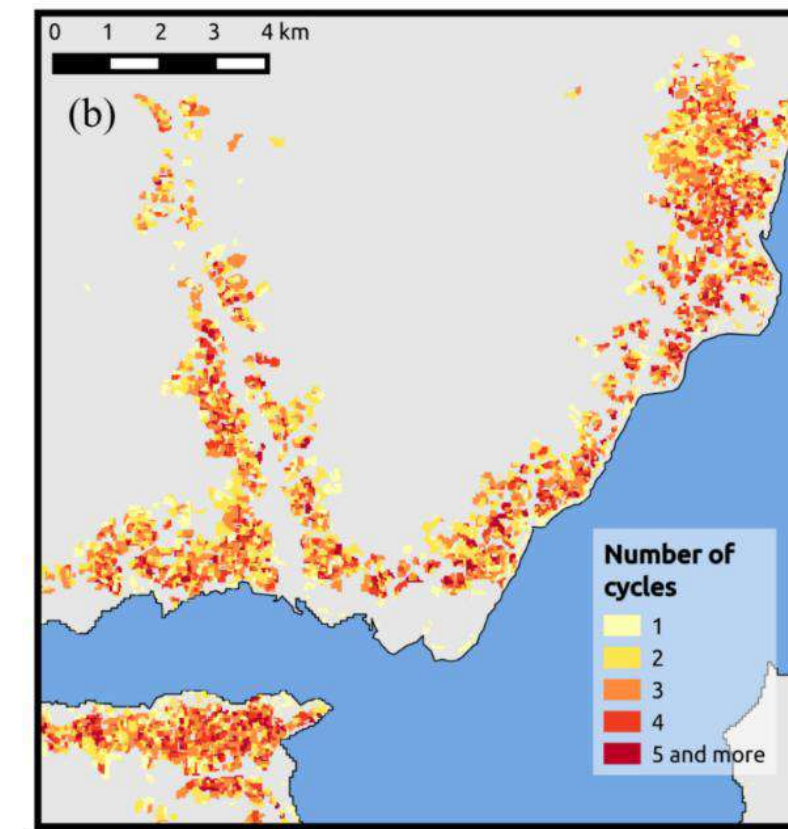
How environmental and land use drivers interact?

Climatic gradient



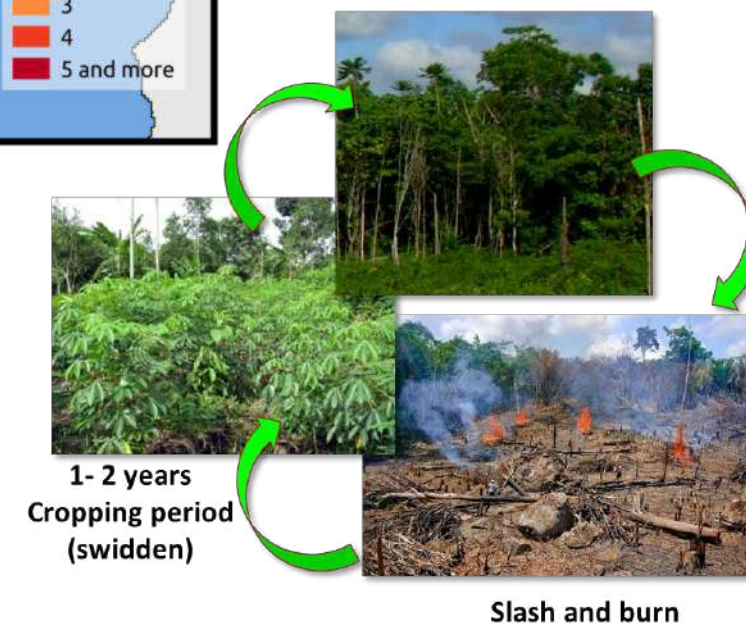
Same-aged Young SF: 4-8 yrs old
n= 88 forest inventory plots

Land use gradients



FARMER INTERVIEWS

- # slash and burn events
- Date OGF was cut
- Age of SF

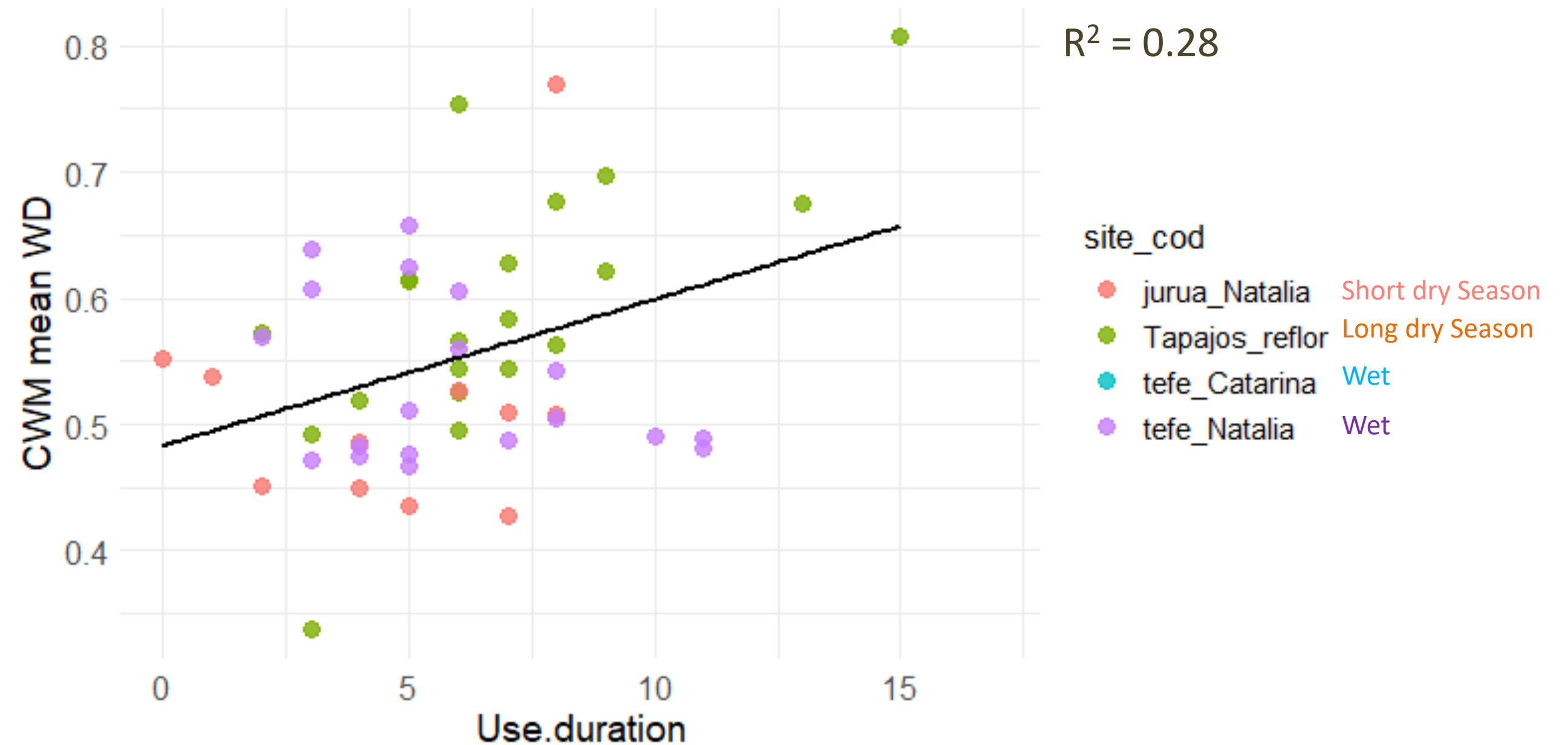


Vegetation structure

- Increase wood density
- No interaction effects of site * LU
 - ❖ Change in species composition to more conservative species and reduced dominance by “classic pioneer species”



n= 55 plots

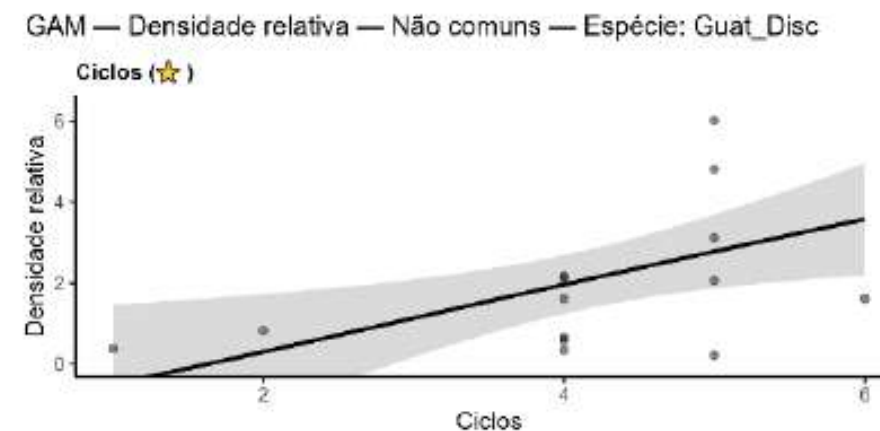
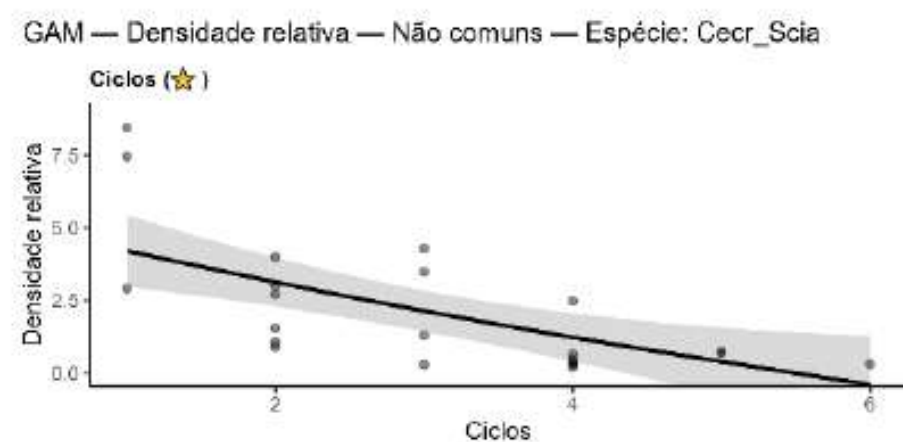


Vegetation structure

- Change in wood density is related to changes in species composition

Wood density

Shift species composition

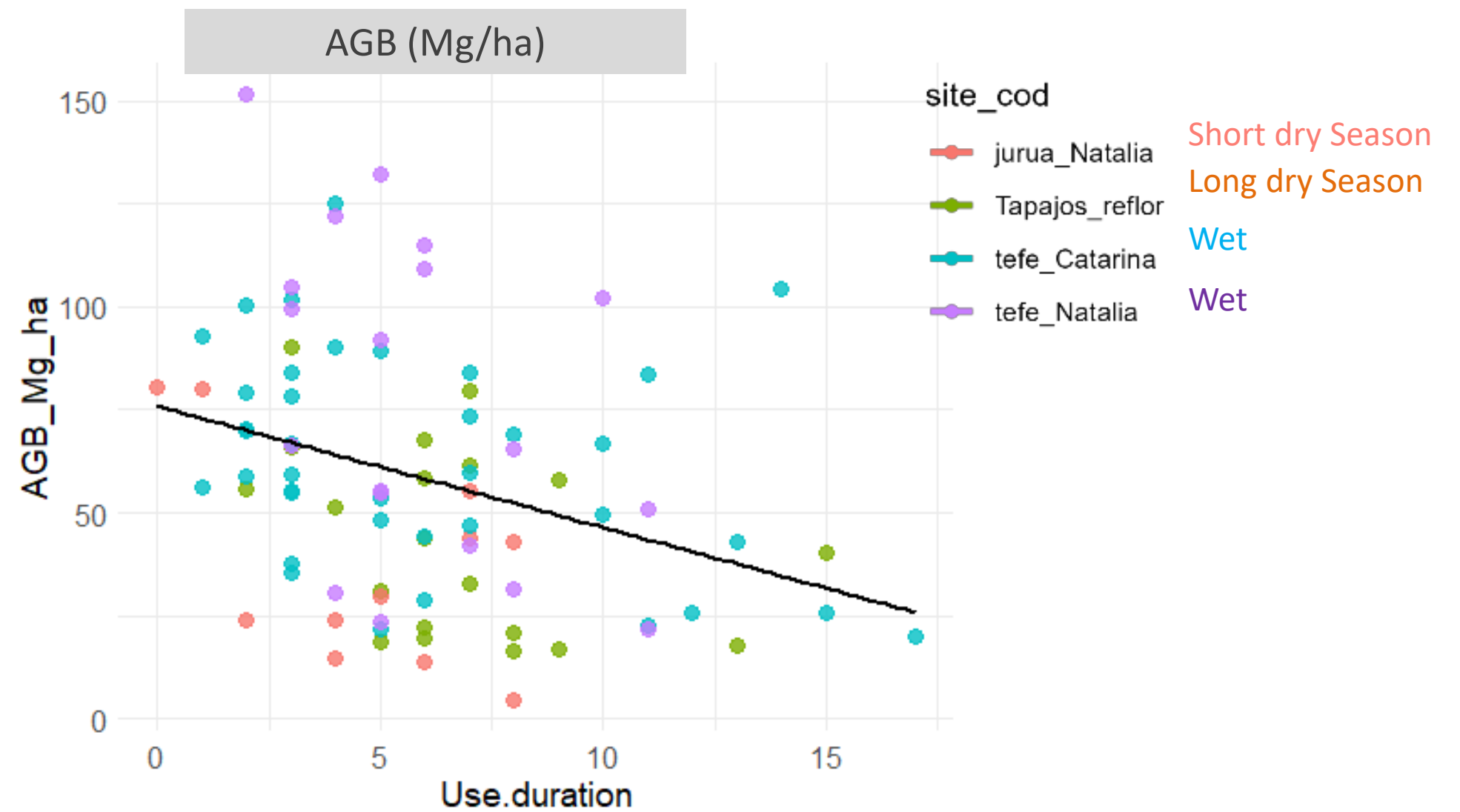
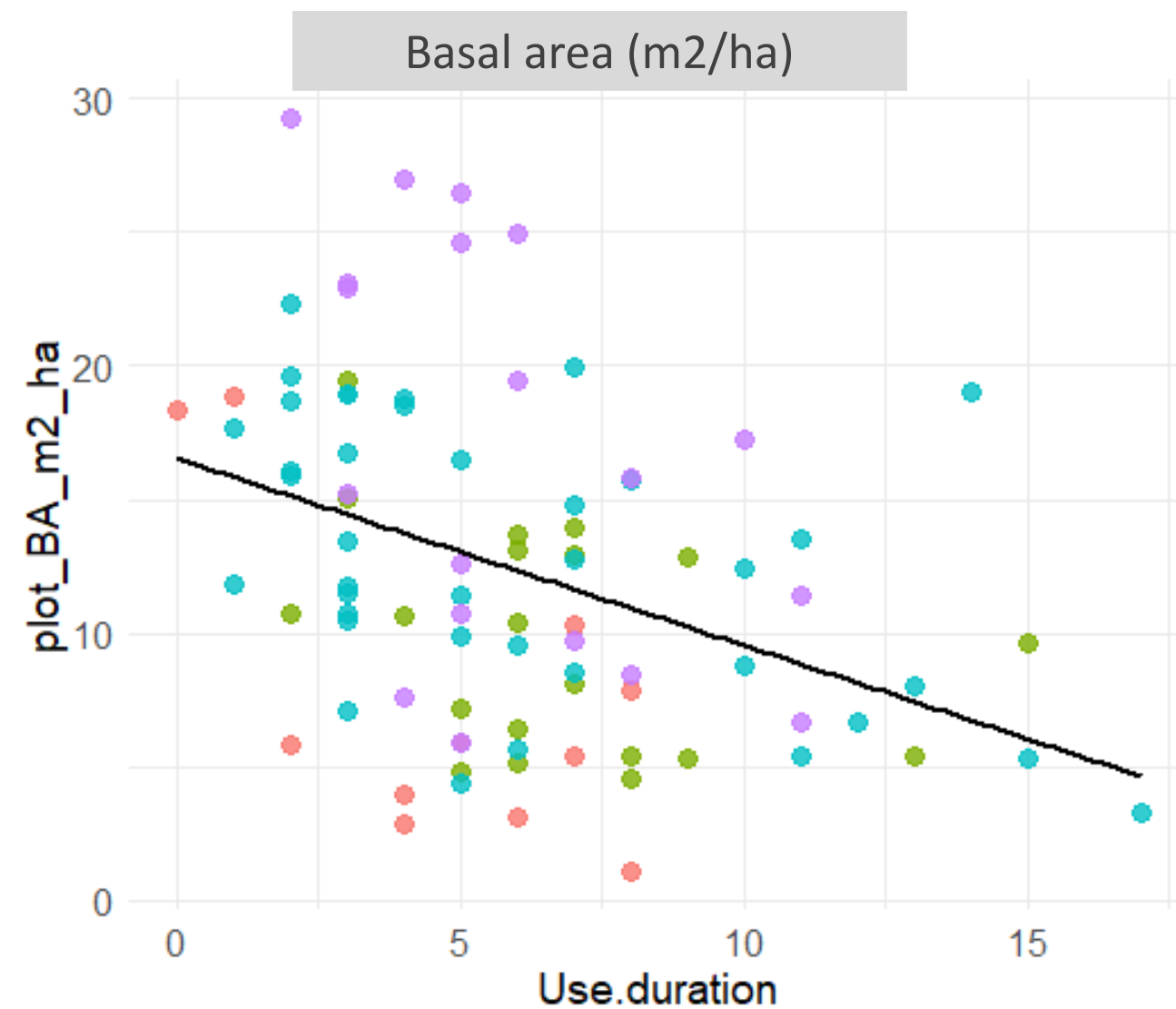


Regrowth rate

Duration/frequency of previous land use

Vegetation structure

- Decrease basal area
- Decrease AGB
- No interaction effect of site * LU



n = 88 plots

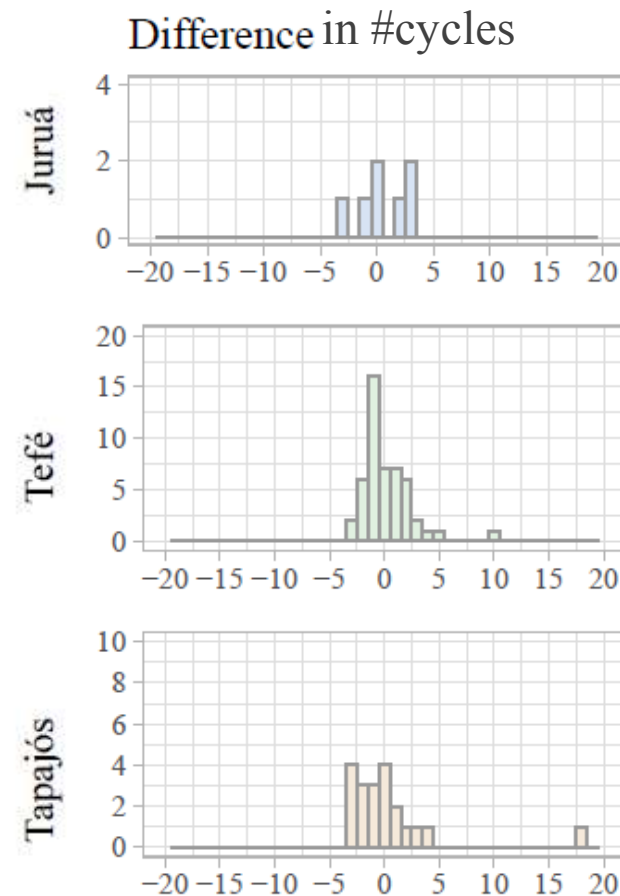
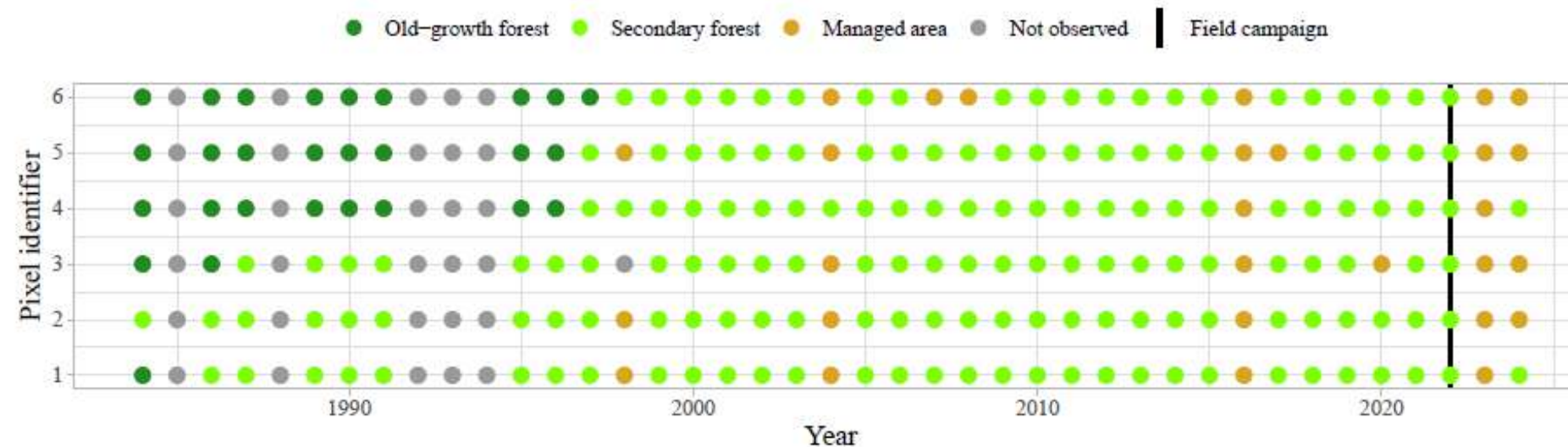


How environmental and land use drivers interact?

- Higher duration of land use (and frequency of deforestation) reduces AGB recovery
- The effect size of land use is similar across climatic regions (preliminary)
- Reduction in AGB is driven by basal area and height more than by wood density
- Vegetation diversity...

Retrieving land-use history (interviews x RS)

LULC classification along landsat time series - CMAP



Comparison with local landowner interviews shows CMAP effectively estimates:

cycles: mean diff -0.8 ± 1.9 cycles (55% of samples within ± 1 cycle)

SF age: 0.4 ± 3.0 years (93% of samples within ± 3 years for age)

(n = 88 samples)

Breakpoint detection

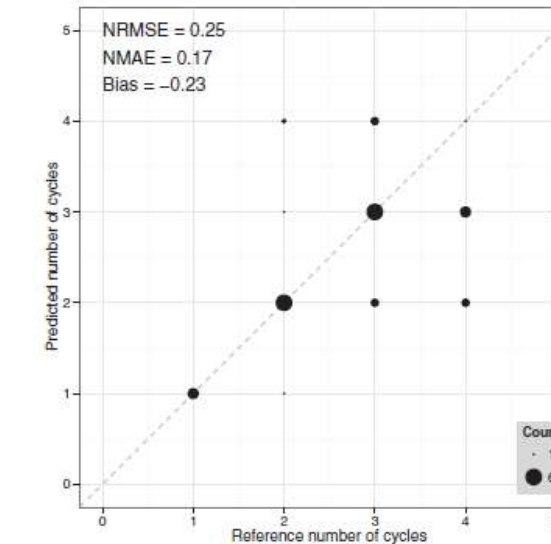
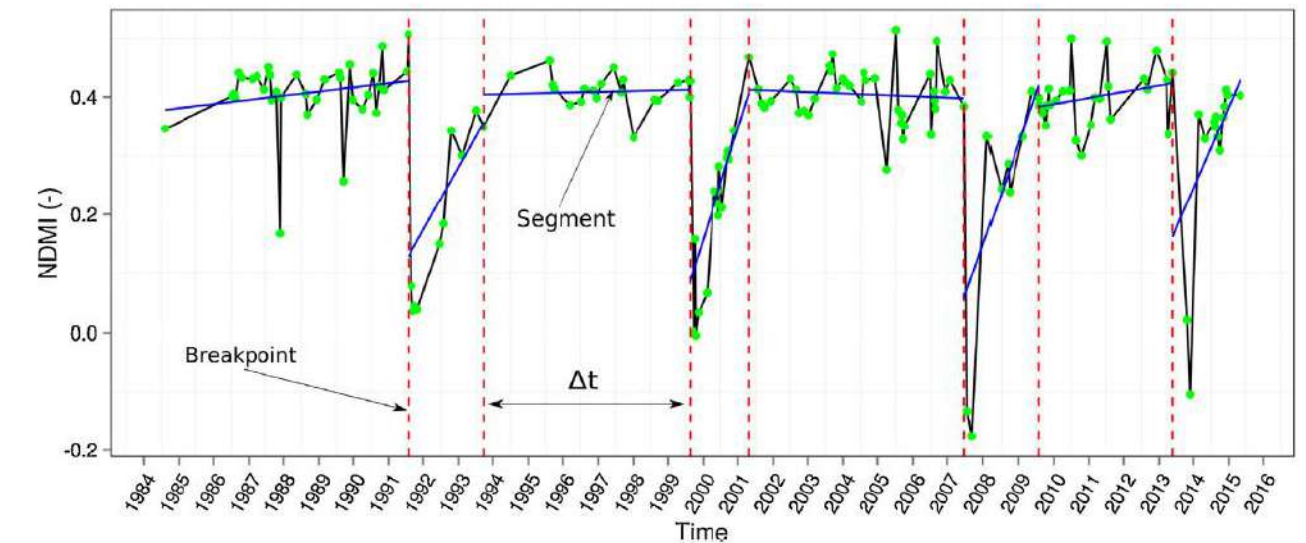


Fig. 6. Scatter plot of predicted number of cultivation cycles against information reported by farmers.

Mean diff of -0.23 cycles;

No strong systematic error of over-or underestimation

Proxies for Land-use history

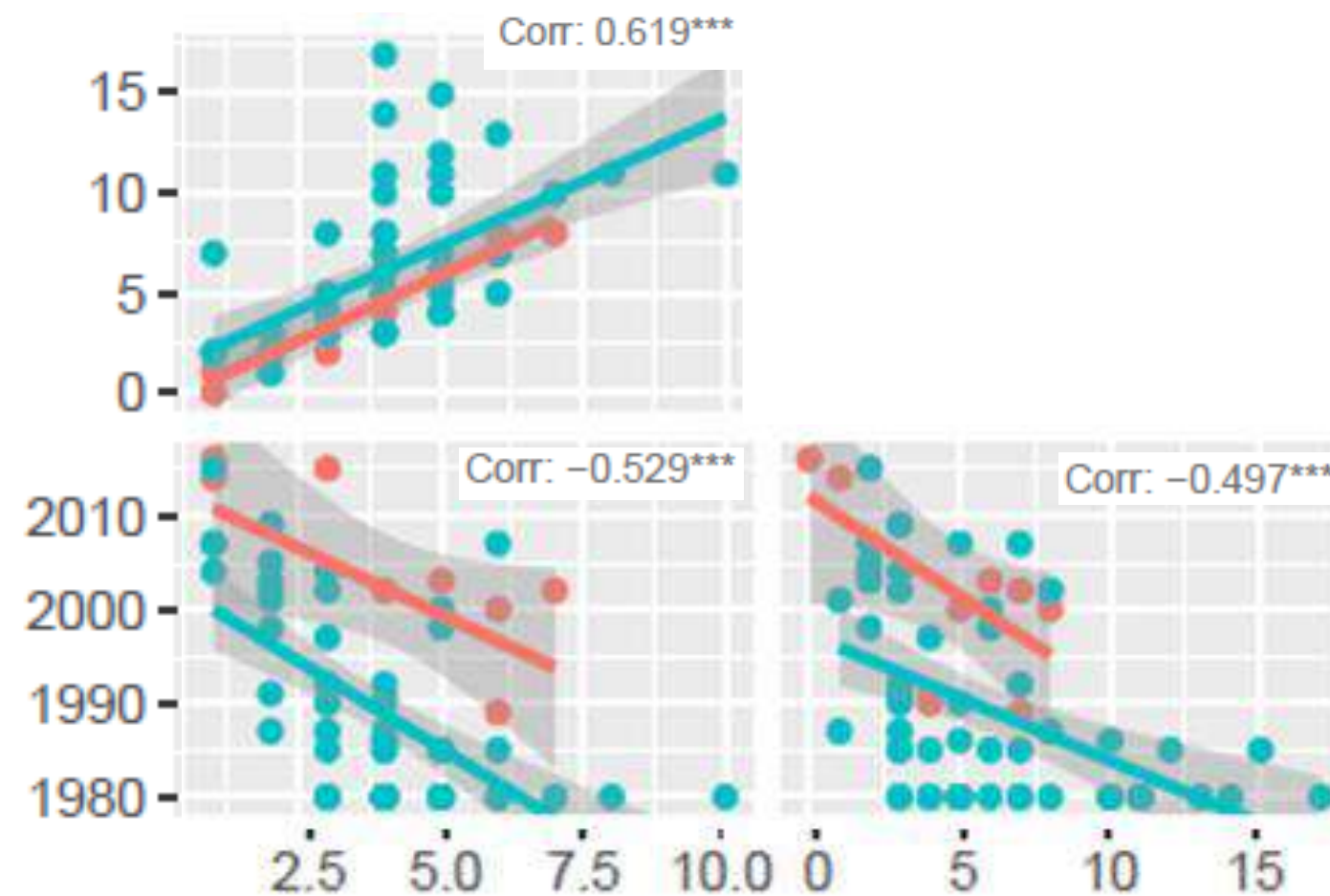
- #deforestation events since OGF deforestation
- Land use duration = total time in agric/pasture use since deforestation
- Year of OGF deforestation (e.g. PRODES)

LU duration (yrs)

Year of
deforestation of
OGF

#defor events

LU duration



Retrieving land-use history

Limitations

- Requires long time series (landsat, 30m res)
- Secondary forest patches are small (require high res)
- Rapid vegetation recovery = short time window to detect "deforestation" events may underestimate deforestation frequency and overestimate SF age
- Current SF patches are mosaics with different LU histories



6 months cassava field

Obrigada
catacj@gmail.com



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Restauração e
Ecologia Florestal



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Proxies for Land-use history

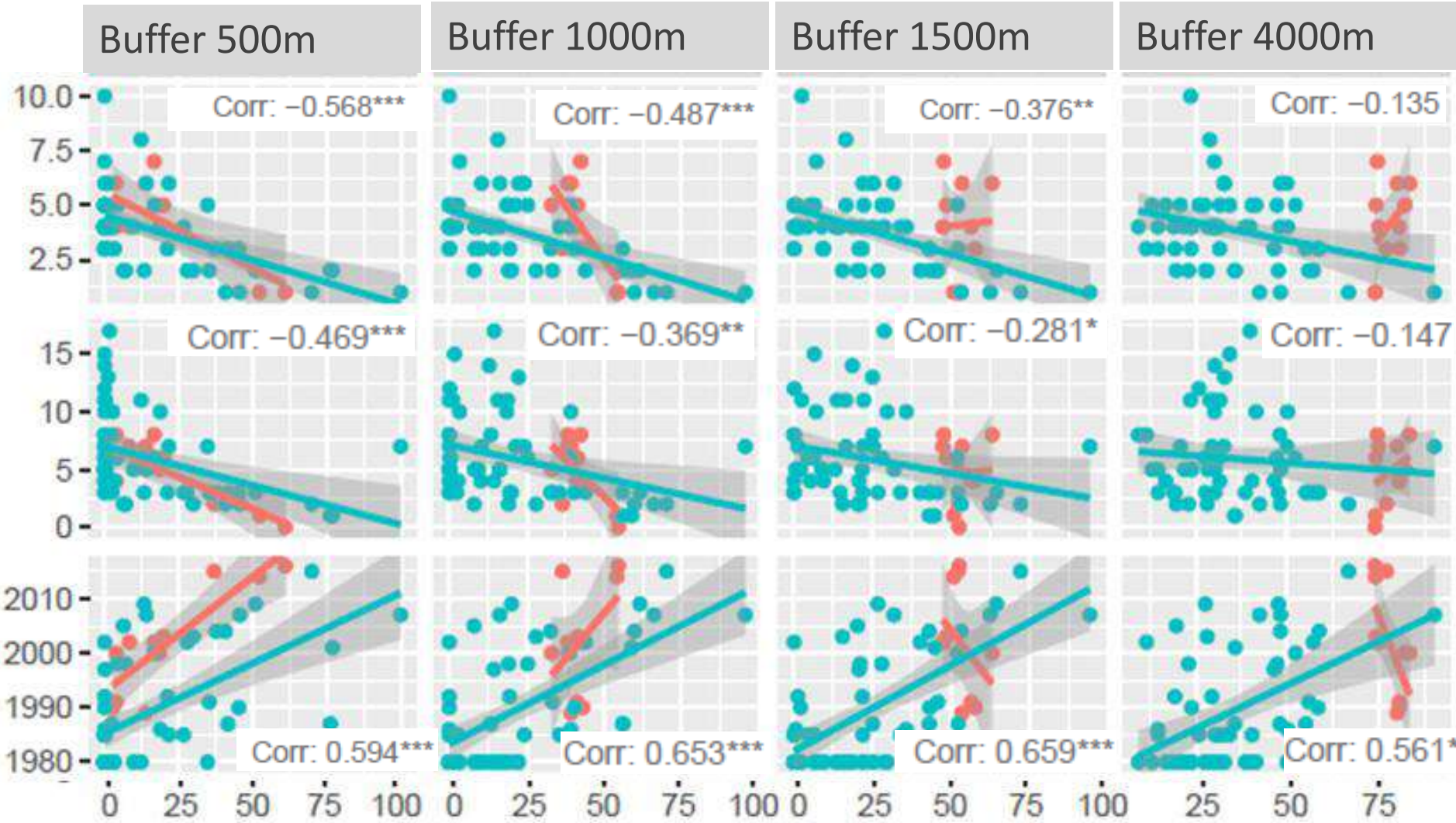
- Landscape forest cover



#deforestation events

LU duration (yrs)

Year of deforestation of OGF



Simple ecological indicators benchmark regeneration success of Amazonian forests

André Giles

Session 2.2: Other metrics for identifying secondary forest success

São José dos Campos, 30 Oct 2025



Regeneration Success

Ecological Integrity

Low limitation to successional trajectories

1. High landscape integrity
(Forest cover/Species availability)

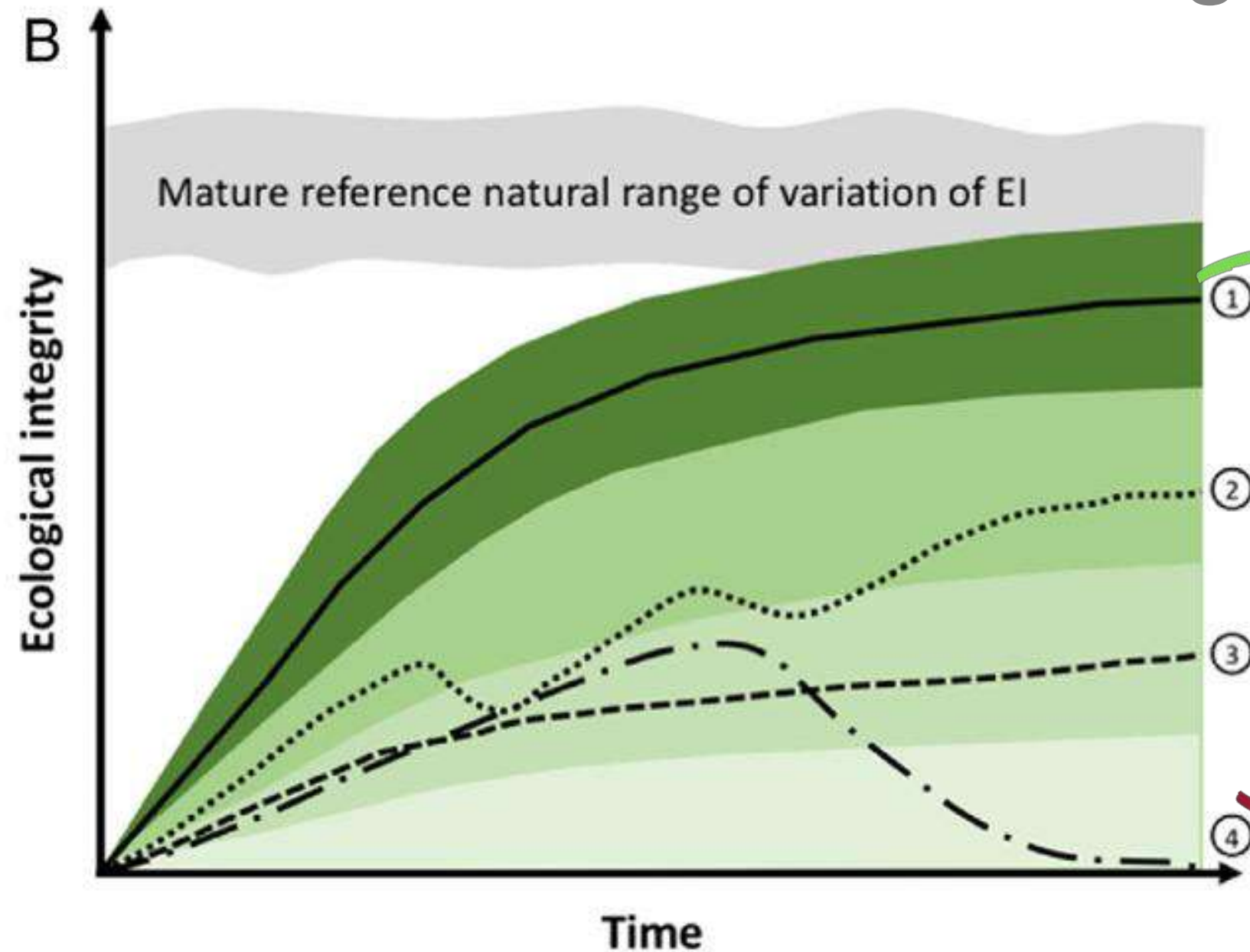
2. Low Intensity previous land-use

Sample illustration



Regeneration Success

Ecological Integrity

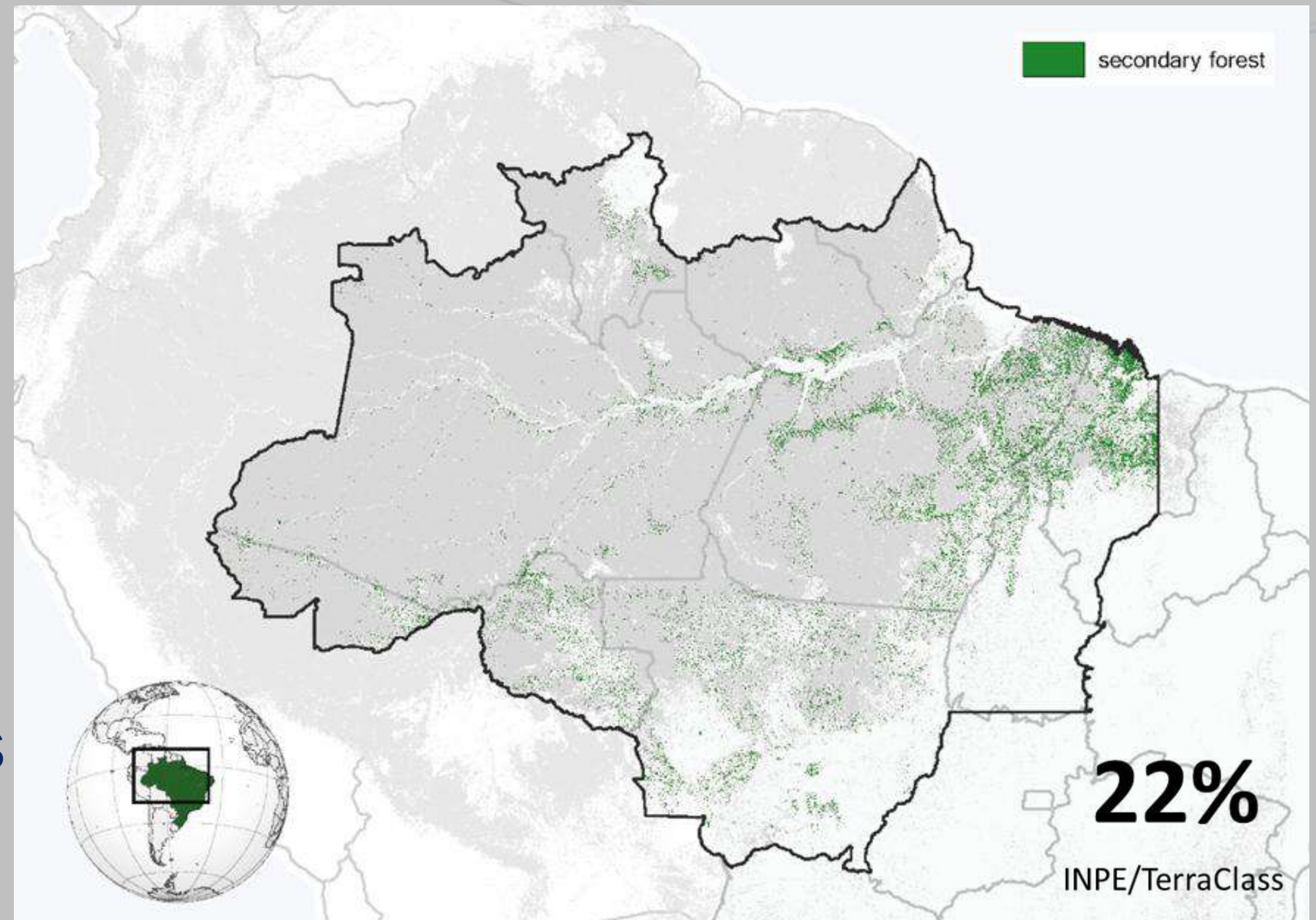


- Diversity
- Forest structure
- Functioning

Sample illustration

NR Amazônia

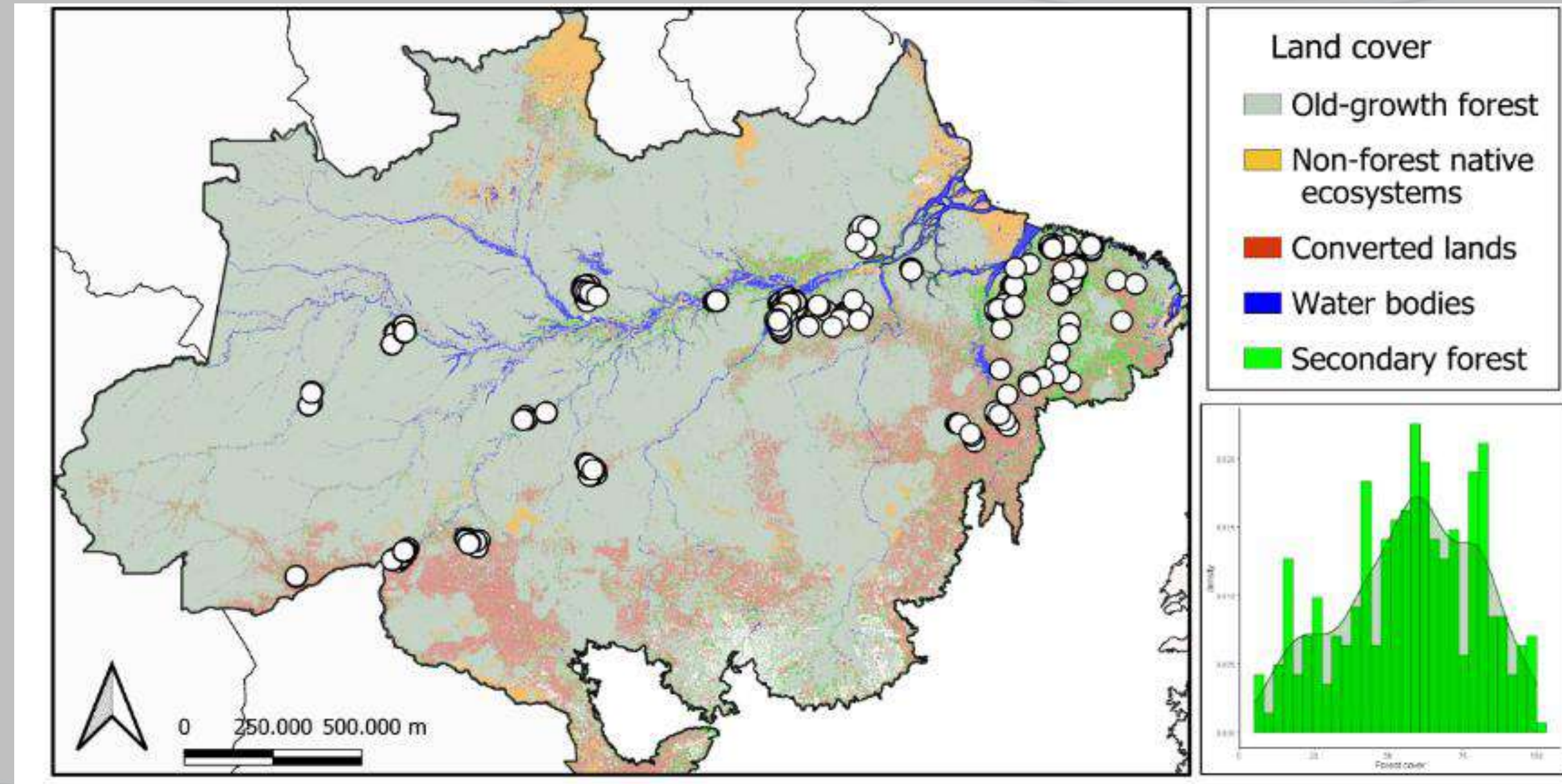
1. The drivers of forest regeneration in the Amazon
1. Set ecological indicators to evaluate regeneration success



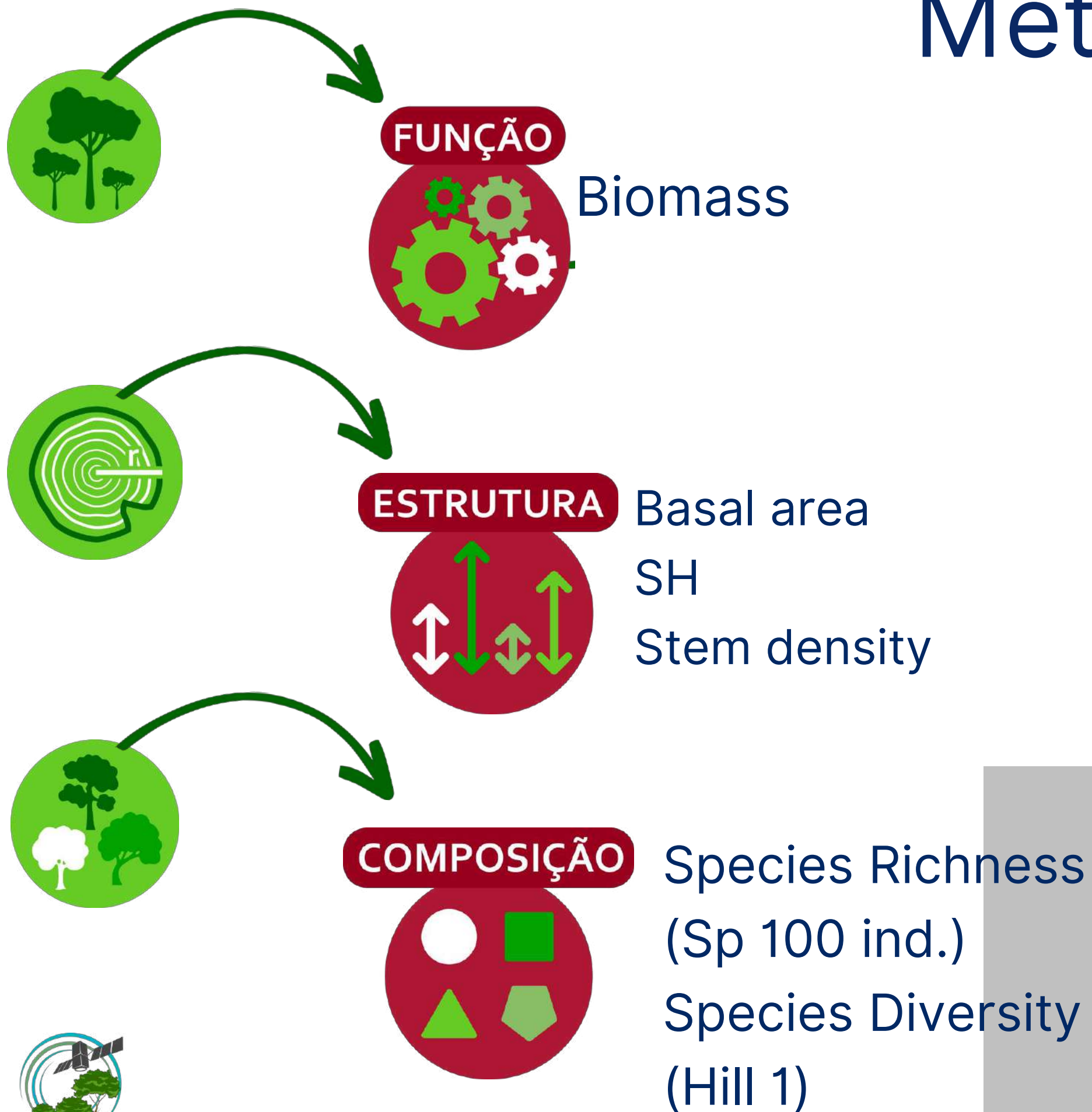
Methods

Data compilation

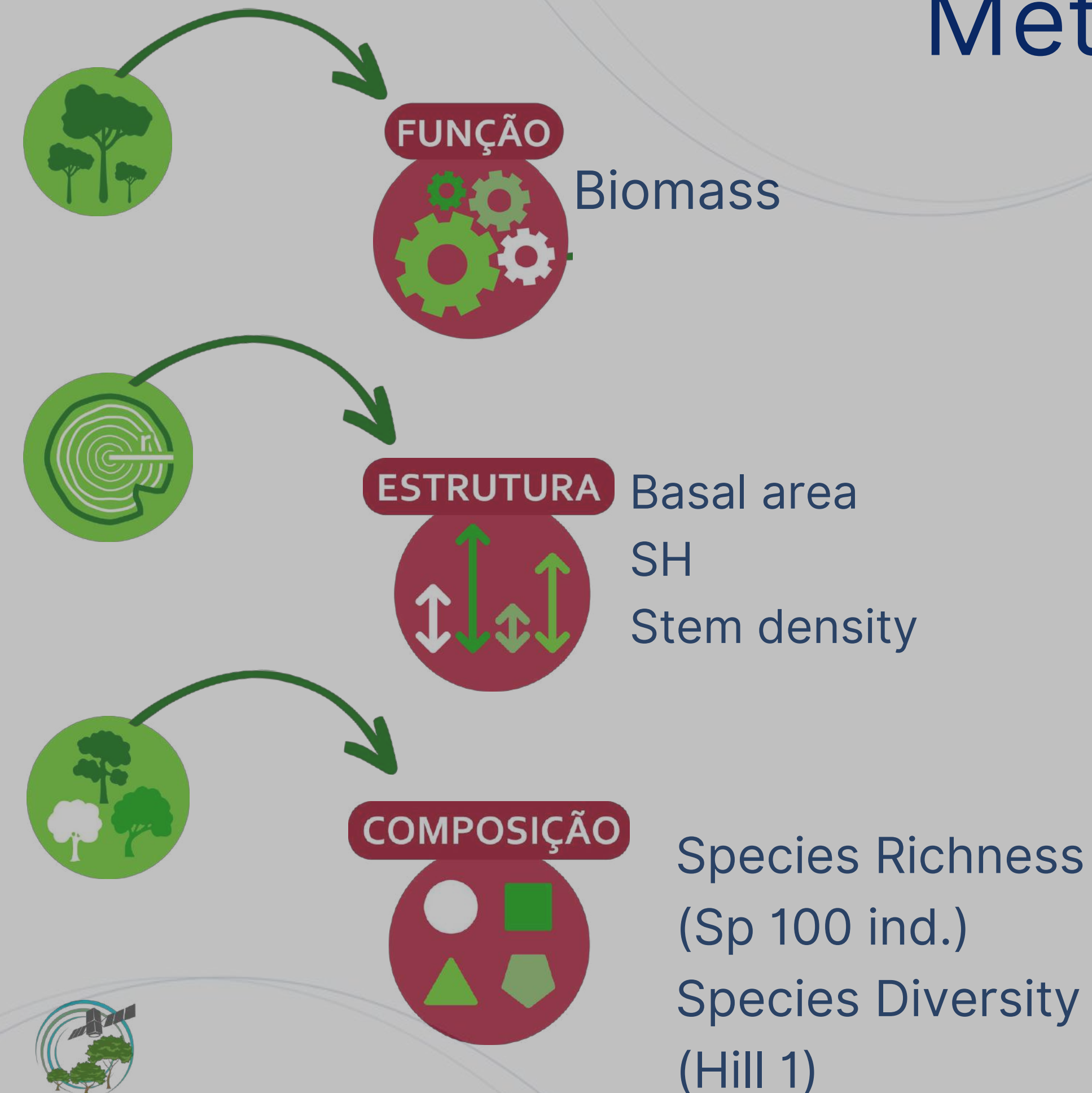
- 448 SFs plots
- 24 sites
- 150 000 trees
> 5 cm DAP
- 5 - 70 years
- 88% < 30 years
- 1.500 a
3.000 mm ano-1



Methods



Methods



Climate (CHELSA)

CWD, temperature, seasonality

Soils (SoilGrids & Zuquim et al. 2023)

pH, base saturation, CEC, and bulk density

Anthropogenic impacts (MapBiomas)

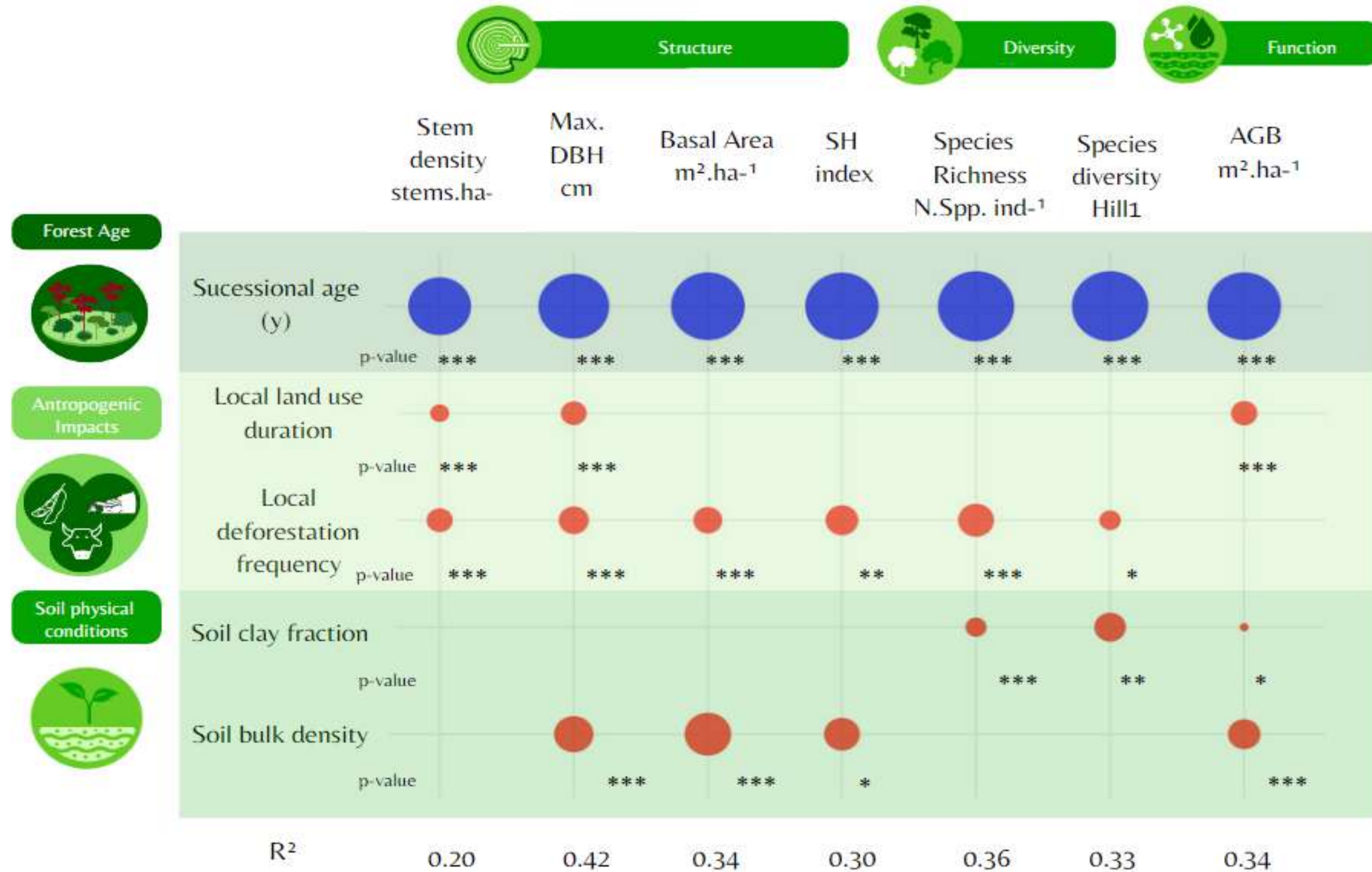
Land-use duration

Forest cover

Deforestation frequency

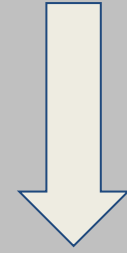
Fire frequency

Drivers of Forest Regeneration



Setting Reference Values

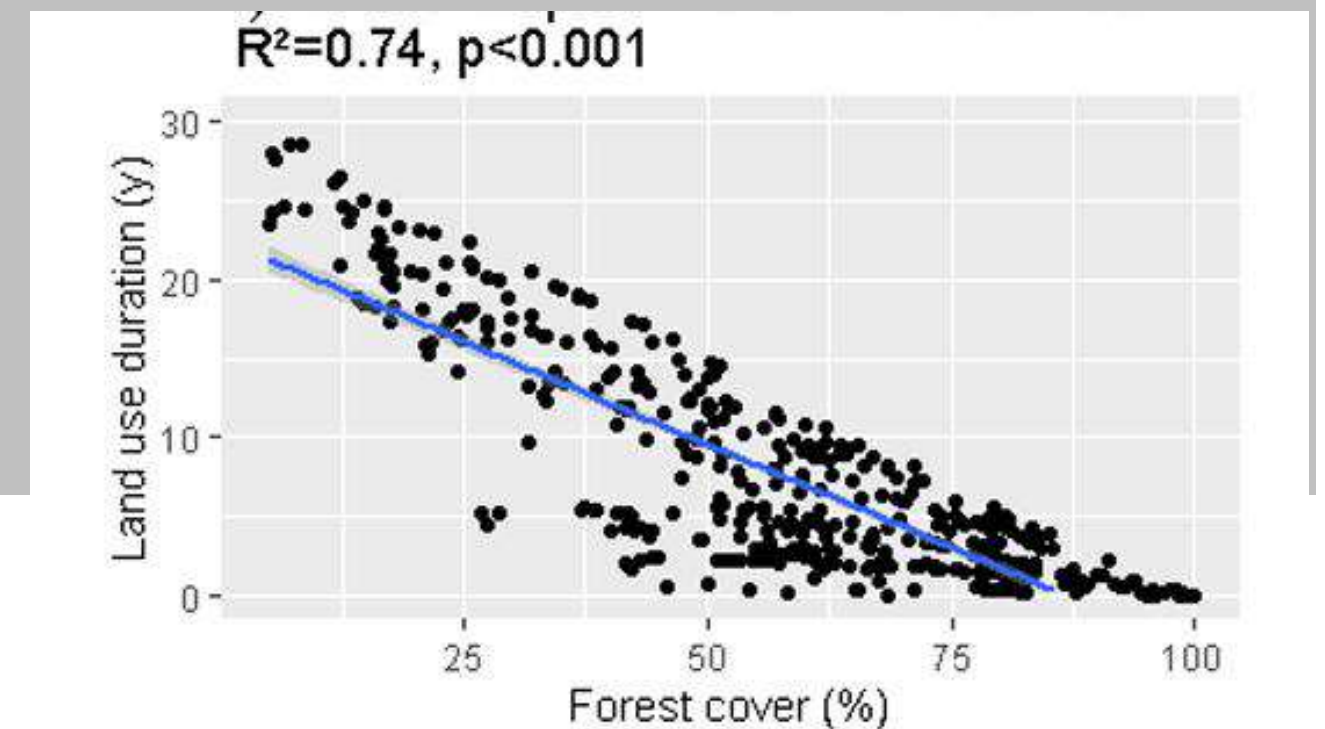
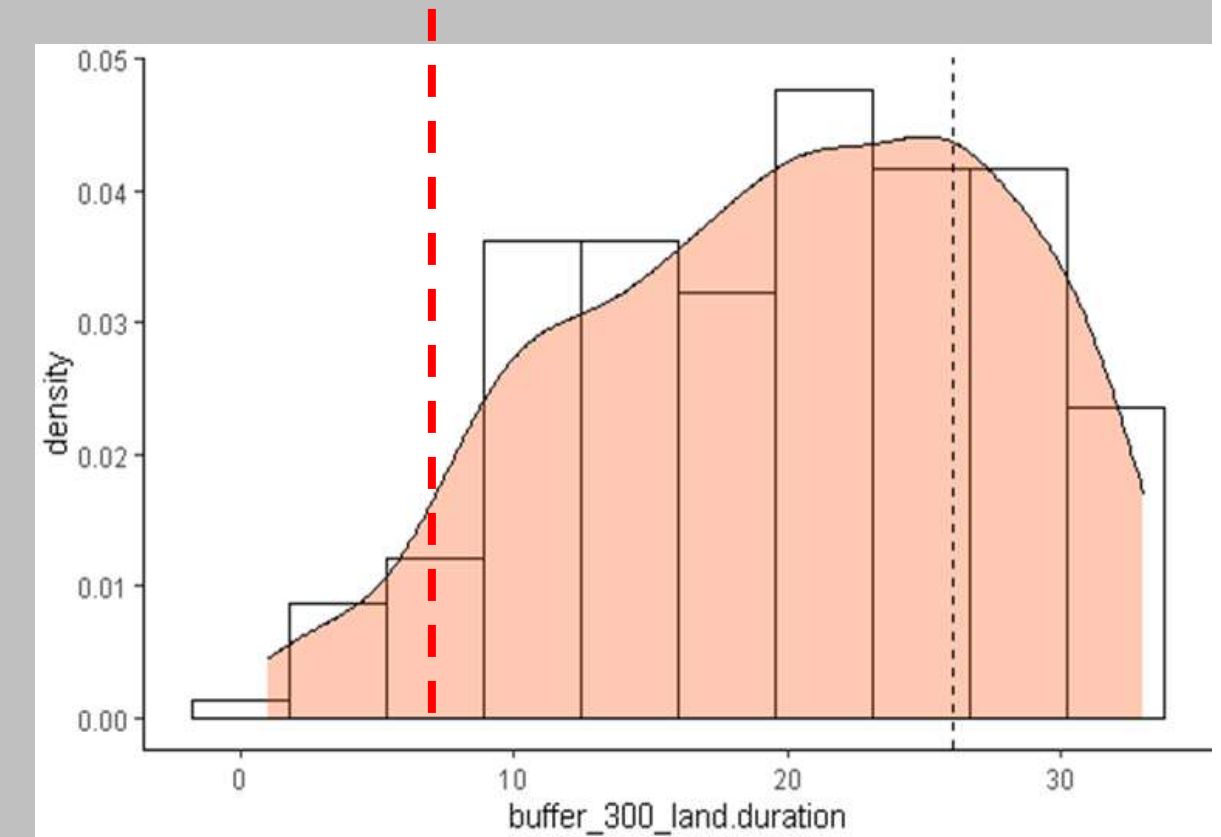
El= Age + Soil + Previous land-use + Error



Deforestation Frequency (<1
Deforest.)



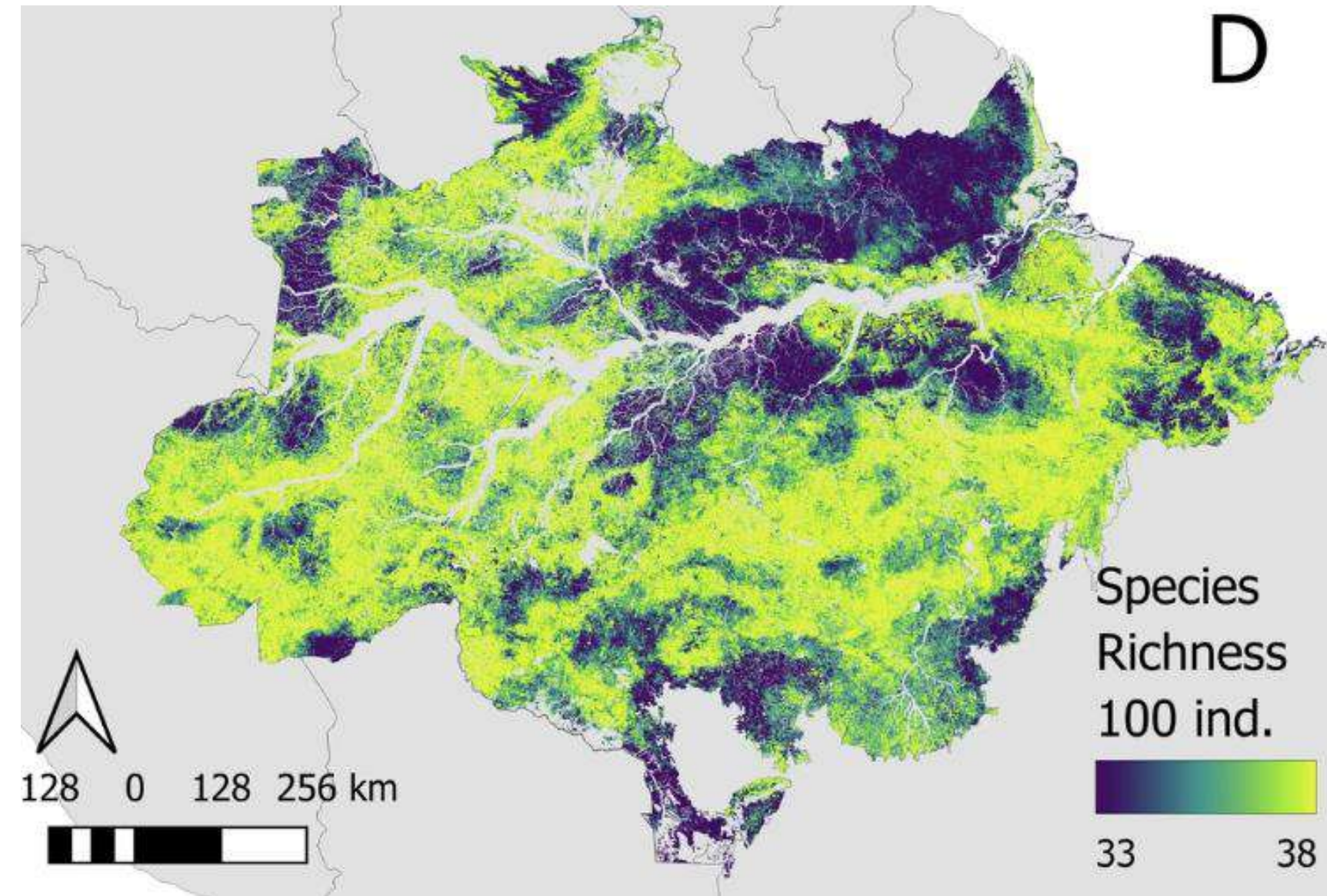
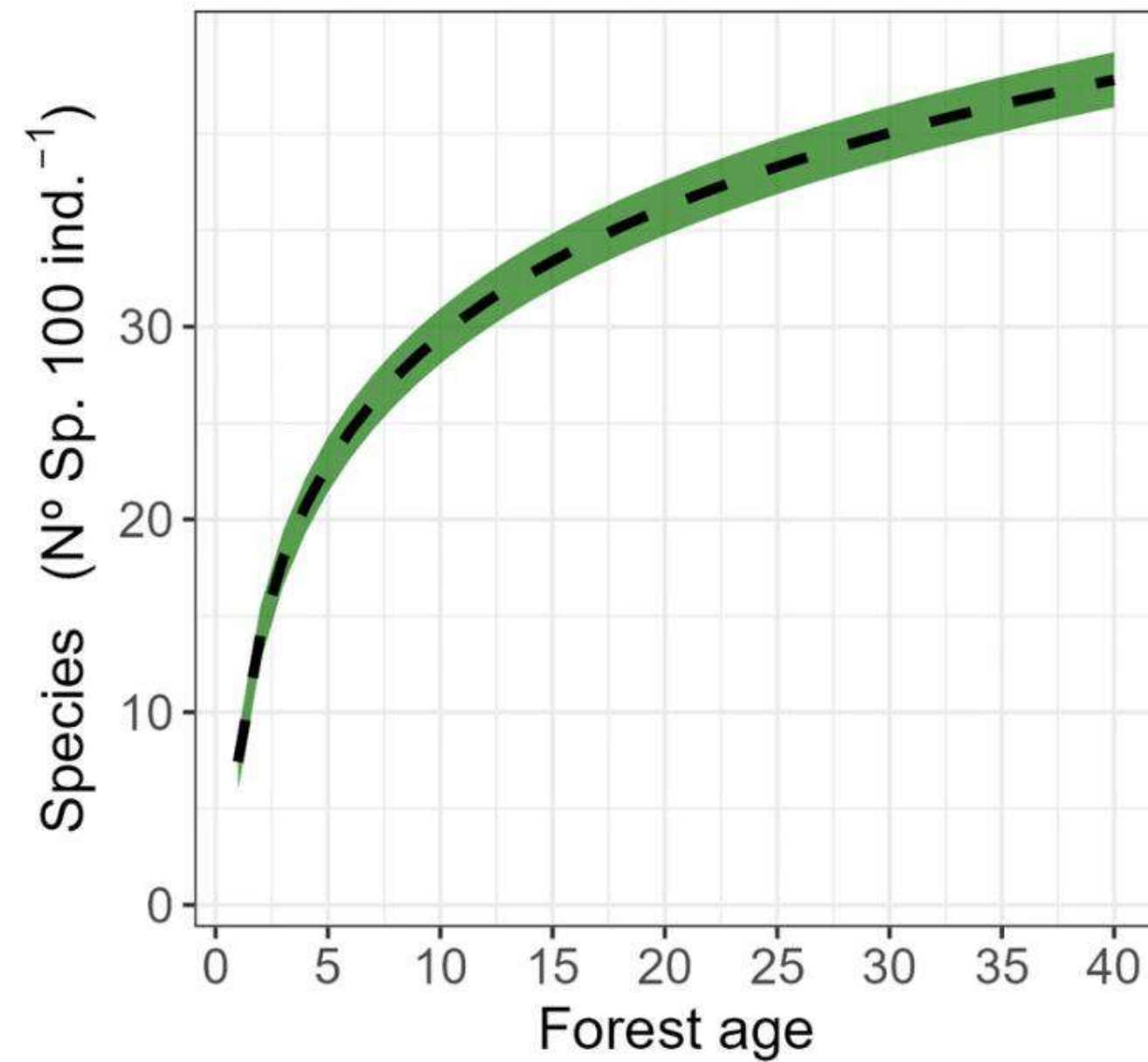
Land-use Duration (<8 years)



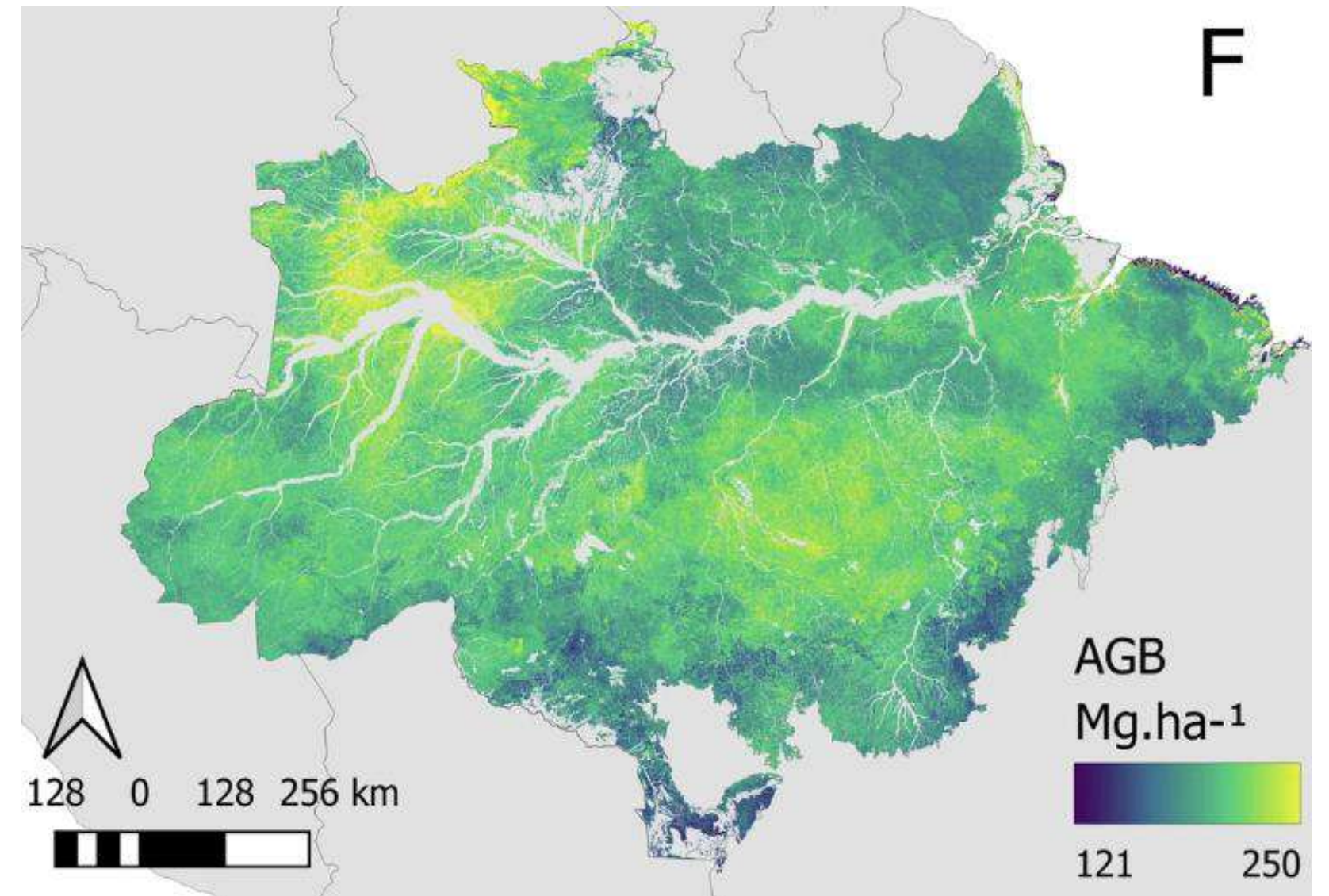
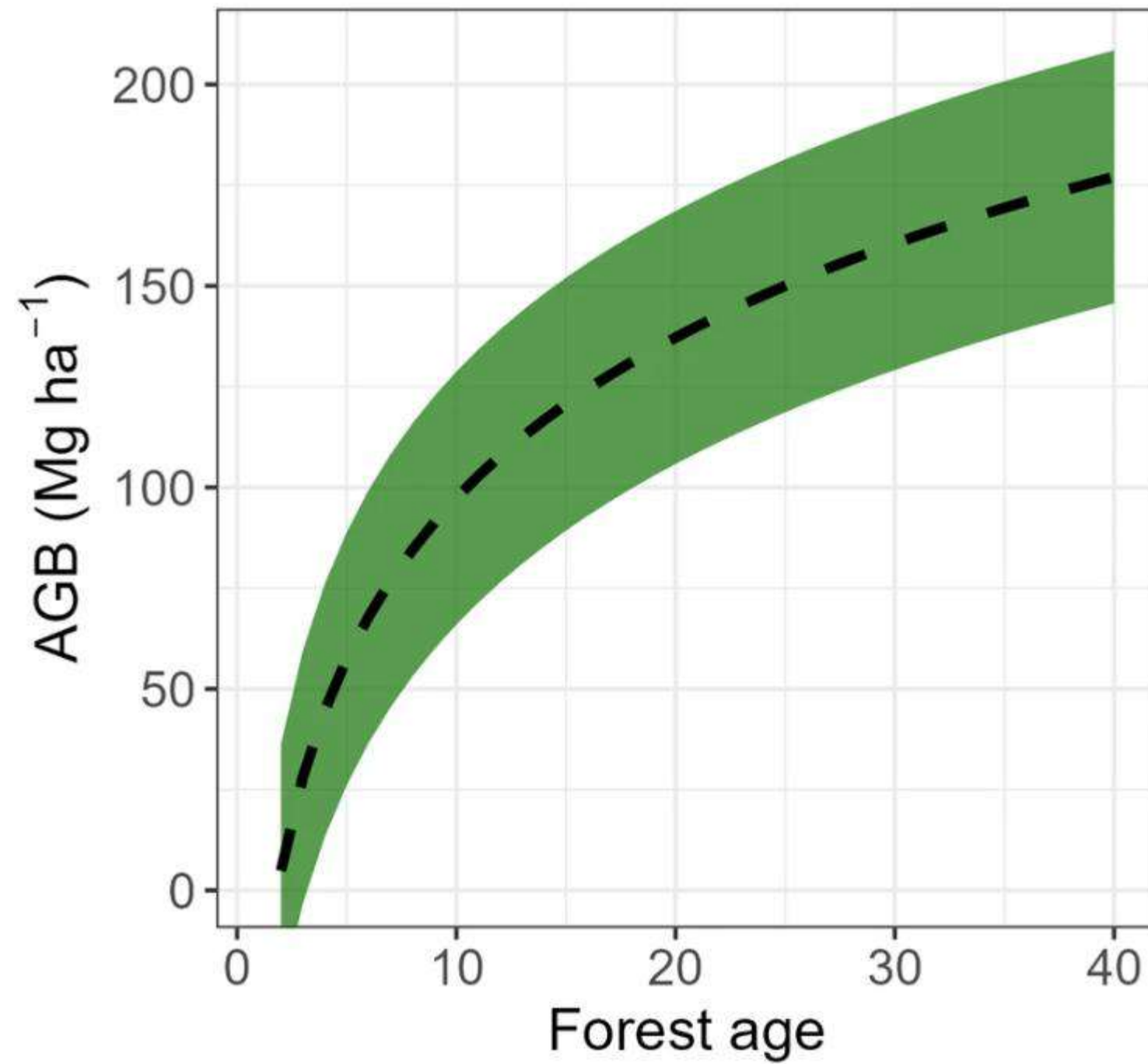
Setting reference values



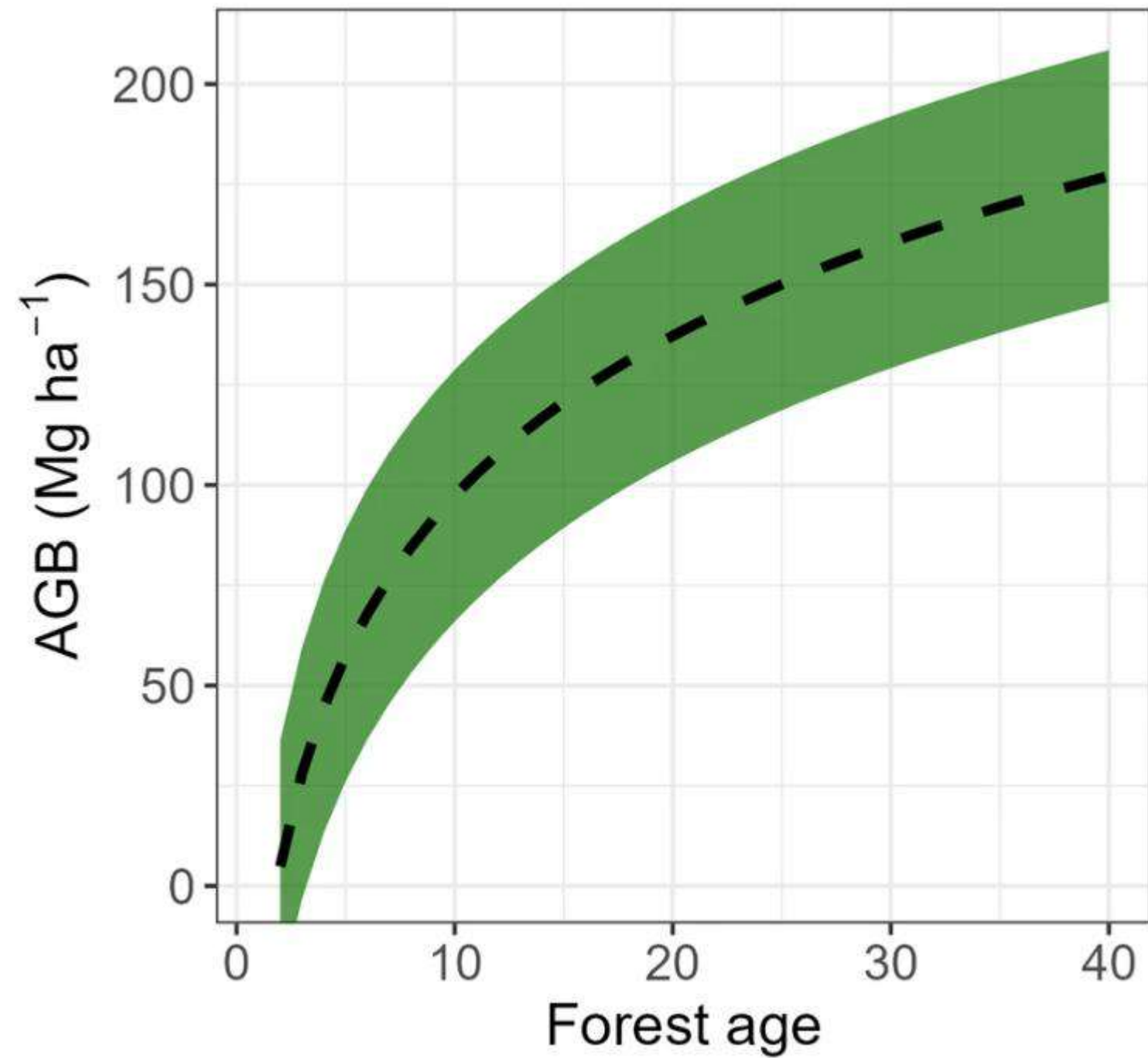
D) Species Richness



Setting reference values



Setting reference values



5 years	10 years	15 years	20 years
43 (Mg. ha ⁻¹)	83.4 (Mg. ha ⁻¹)	106.2 (Mg. ha ⁻¹)	123 (Mg. ha ⁻¹)

Implications

- We identify the main drivers of Amazon forest regeneration and provide reference values for ecological integrity across successional stages and regions.
- These reference values guide restoration outcomes, reduce policy uncertainties, and support the effective implementation of public policies

Next steps


- Identify these indicators and reference values using remote sensing tools (Ecological Integrity from remote sensing)
- Increase the predictive capacity from early-years and across successional trajectories (SF Permanence).
- Integrate field and remote sensing data

Furthermore Information



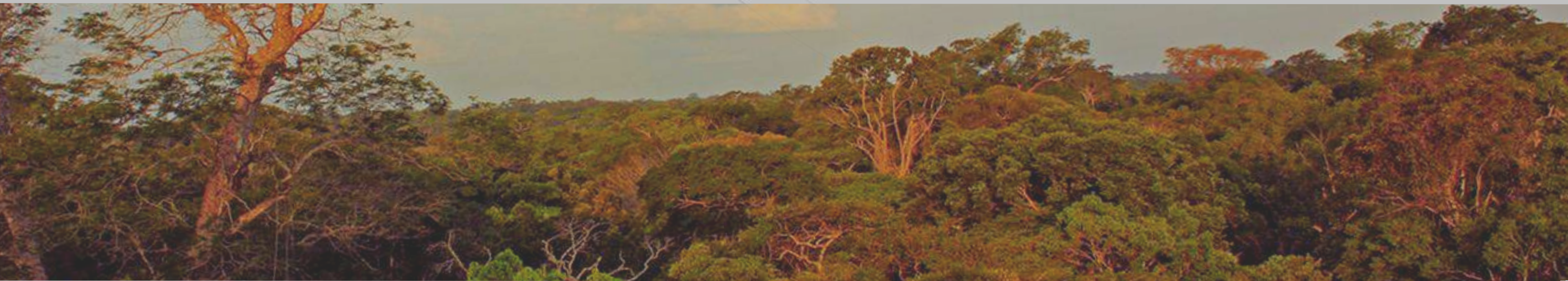
Article | [Open access](#) | Published: 20 December 2024

Simple ecological indicators benchmark regeneration success of Amazonian forests

[André L. Giles](#) , [Juliana Schietti](#), [Milena F. Rosenfield](#), [Rita C. Mesquita](#), [Daniel Luis Mascia Vieira](#), [Ima C. G. Vieira](#), [Lourens Poorter](#), [Pedro H. S. Brancalion](#), [Marielos Peña-Claros](#), [João Siqueira](#), [Luis Oliveira Junior](#), [Mário Marcos do Espírito-Santo](#), [Priscila Sanjuan de Medeiros Sarmiento](#), [Joice N. Ferreira](#), [Erika Berenguer](#), [Jos Barlow](#), [Fernando Elias](#), [Henrique Luis Godinho Cassol](#), [Richarlly C. Silva](#), [Sabina Cerruto Ribeiro](#), [Natália Medeiros](#), [André B. Junqueira](#), [Paulo Massoca](#), [Marciel Jose Ferreira](#), ... [Catarina C. Jakovac](#) [+ Show authors](#)



<https://www.regenera-amazonia.eco.br/>



Obrigado
Thank you
Gracias

andregiles.bio@gmail.com



Monitoring carbon and biodiversity during natural regeneration: contributions from Sustainable Amazon Network (RAS)

Rodrigo Nascimento

Session 2.2: Other metrics for identifying secondary forest success.

São José dos Campos, 30 Oct 2025



RAS

Aims, distribution, and contributions

- Multidisciplinary network founded in 2009
- >400 plots data
- Biodiversity groups
 - Trees, lianas and palms (small and large)
 - Birds
 - Dung beetles
- Soil conditions (macro, micronutrients, and texture) and microclimate
- Integration between ecological and social dimensions

Joice Ferreira Jos Barlow



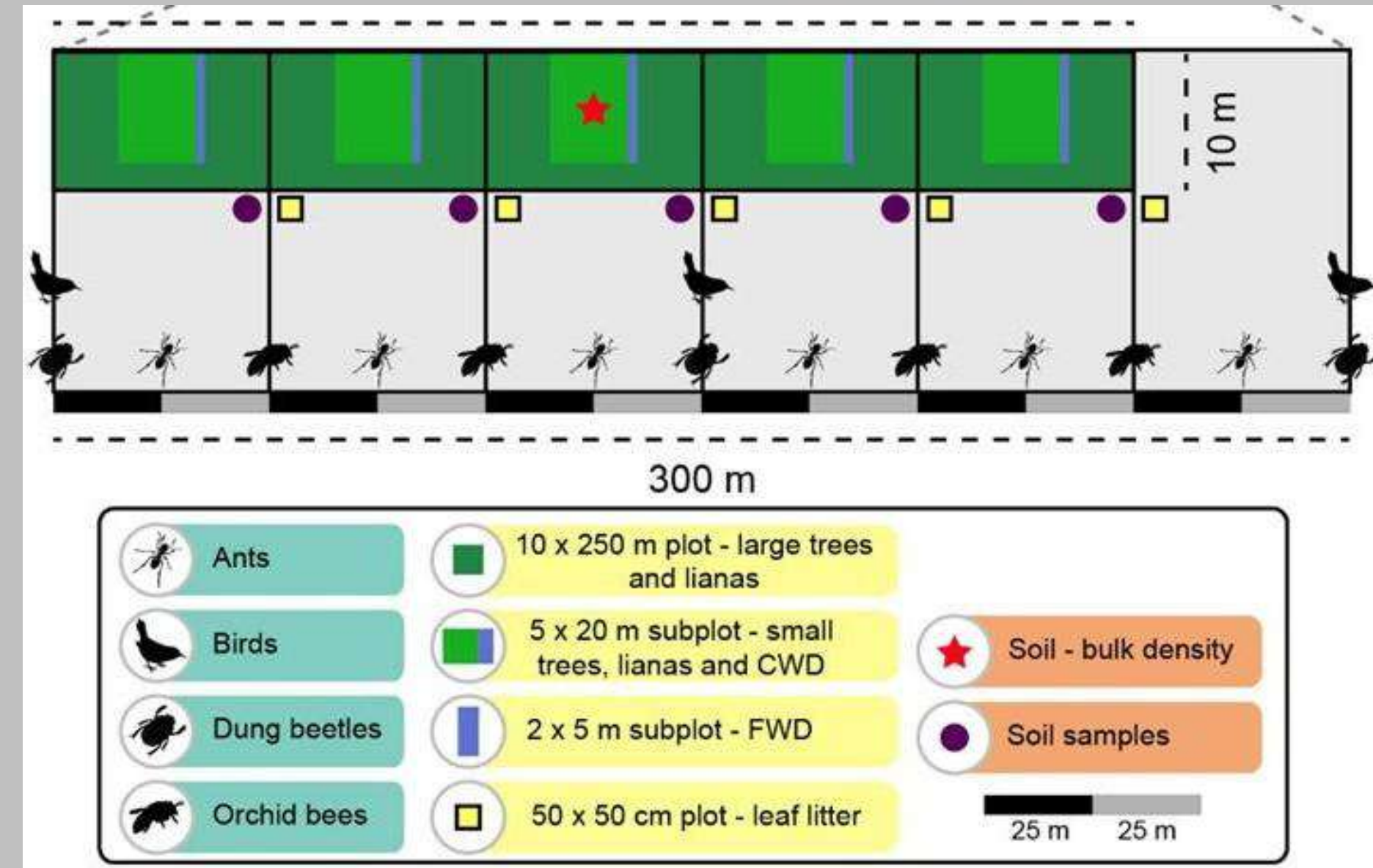
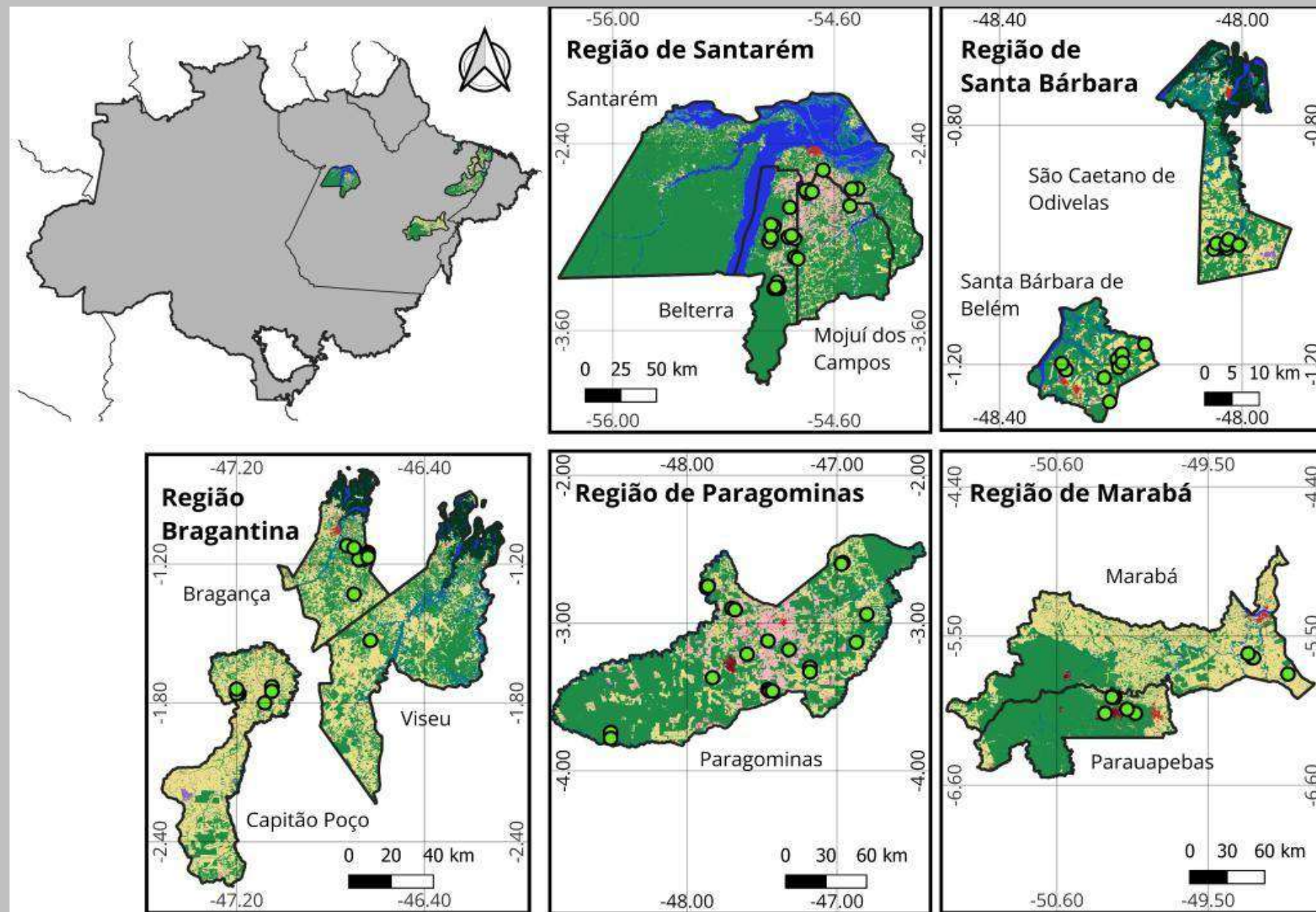
Co-founders



A social and ecological assessment of tropical land uses at multiple scales: the Sustainable Amazon Network

Toby A. Gardner^{1,2}, Joice Ferreira³, Jos Barlow², Alexander C. Lees⁴, Luke Parry², Ima Célia Guimarães Vieira⁴, Erika Berenguer², Ricardo Abramovay⁵

Sampling methods

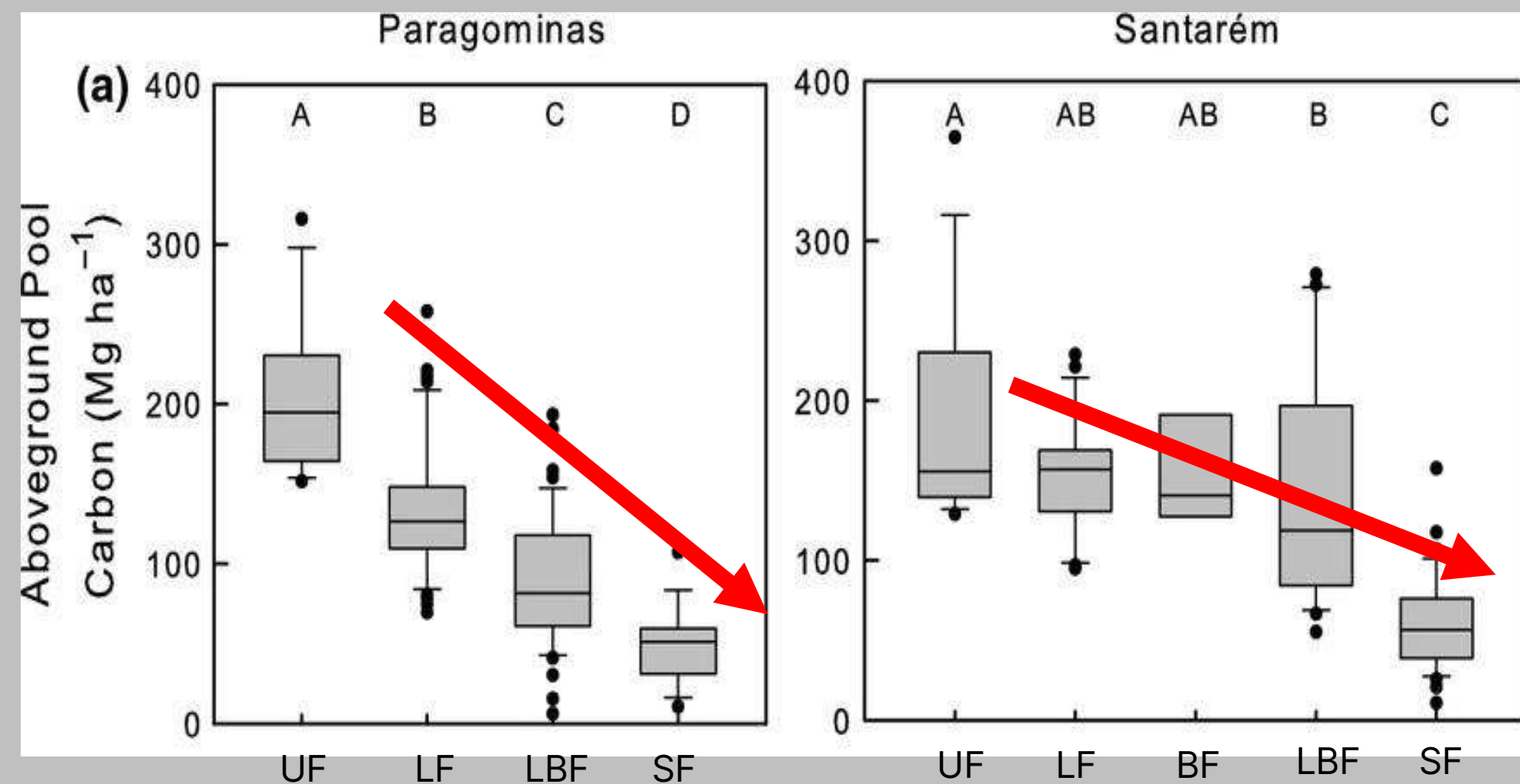


*Santarém Region – intensive RAS research sites

Nunes et al. 2022 PNAS

Some key messages about carbon estimates from field data

Disturbances significantly impact forest carbon stocks

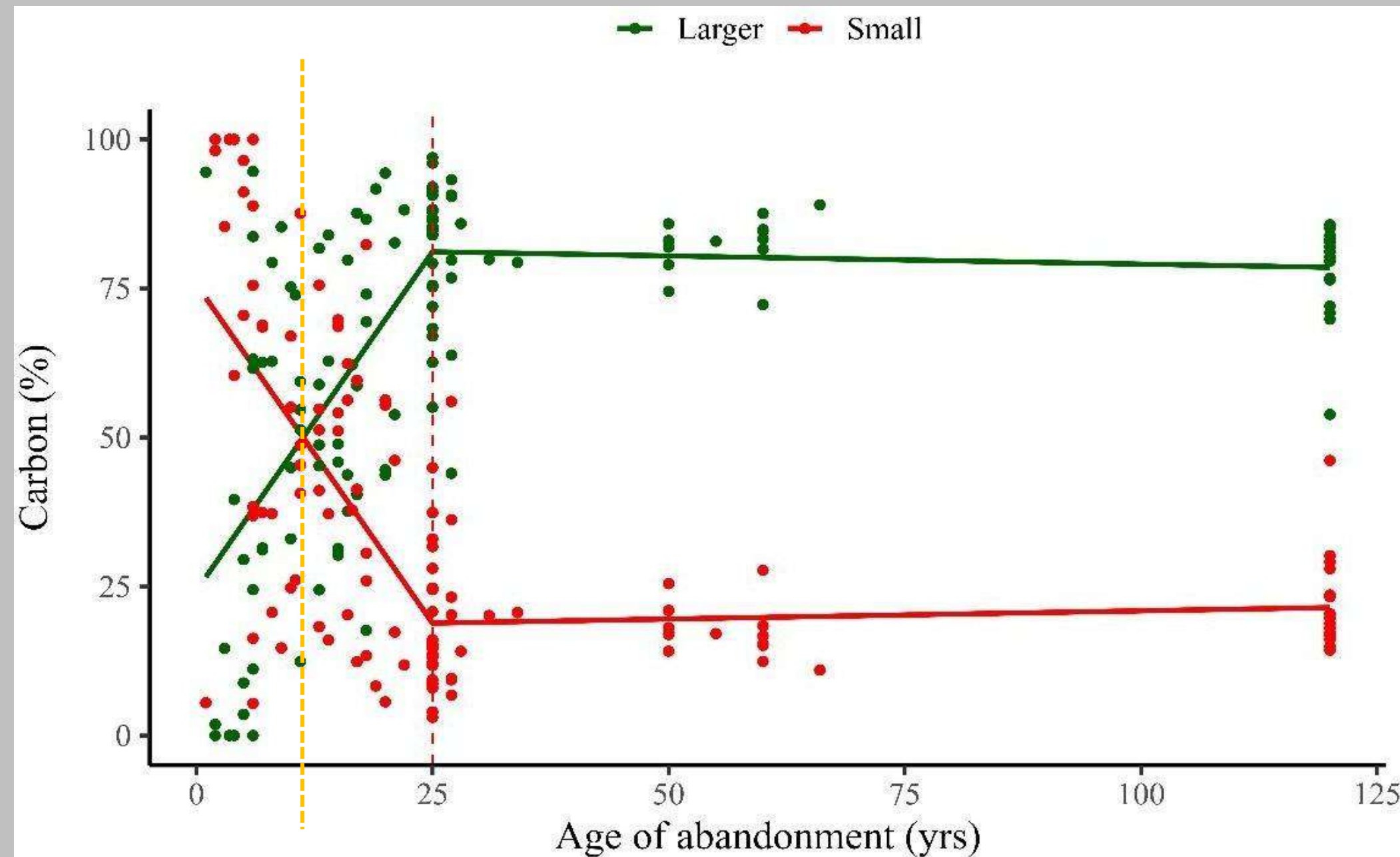


Berenguer et al., 2014 GCB

Even highly degraded primary forests store more carbon than secondary forests

Secondary forests stock ~ 75 and 67% less carbon respectively than primary forests.

Furthermore, small individuals are very important in the initial carbon stocks

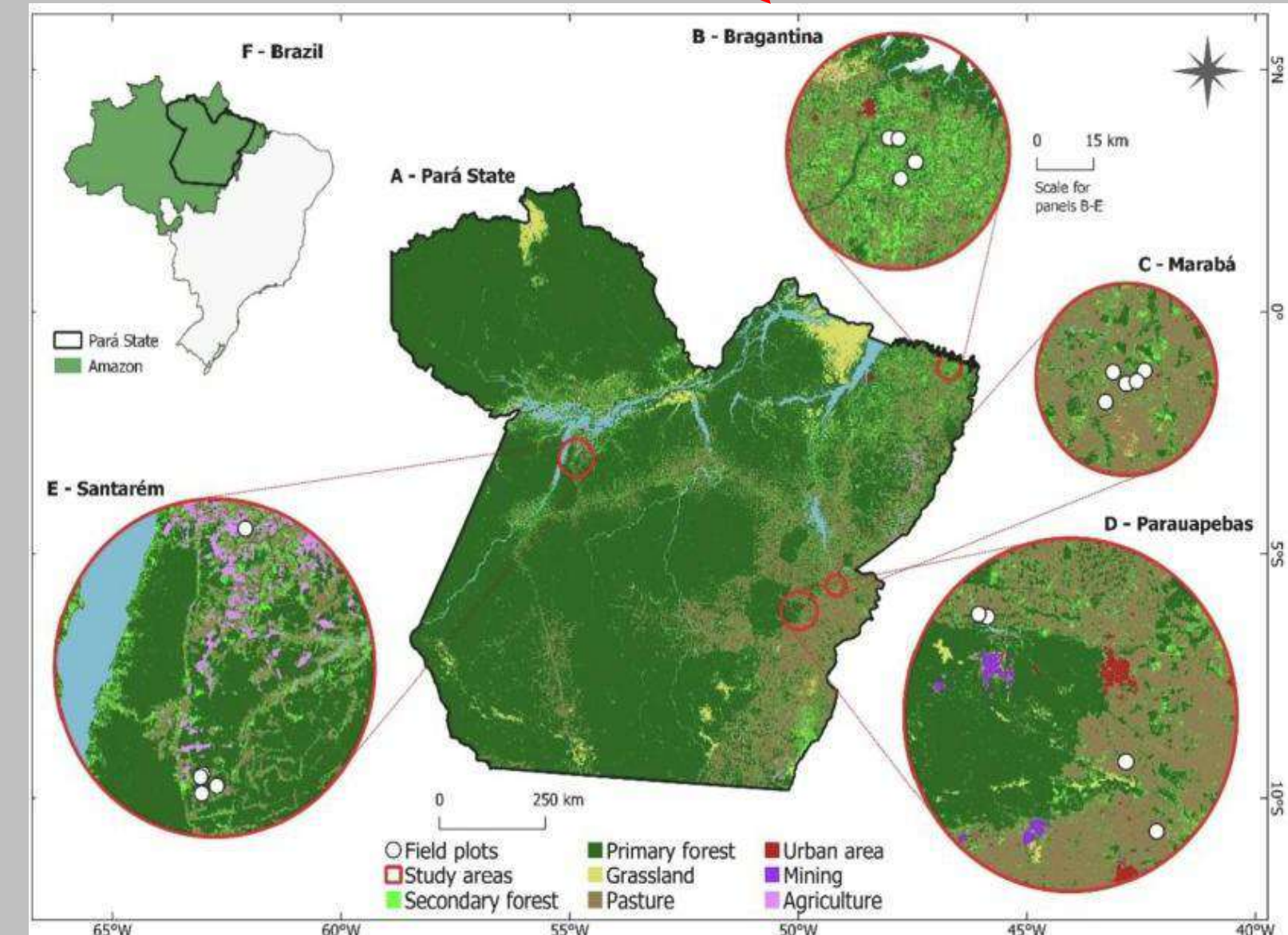
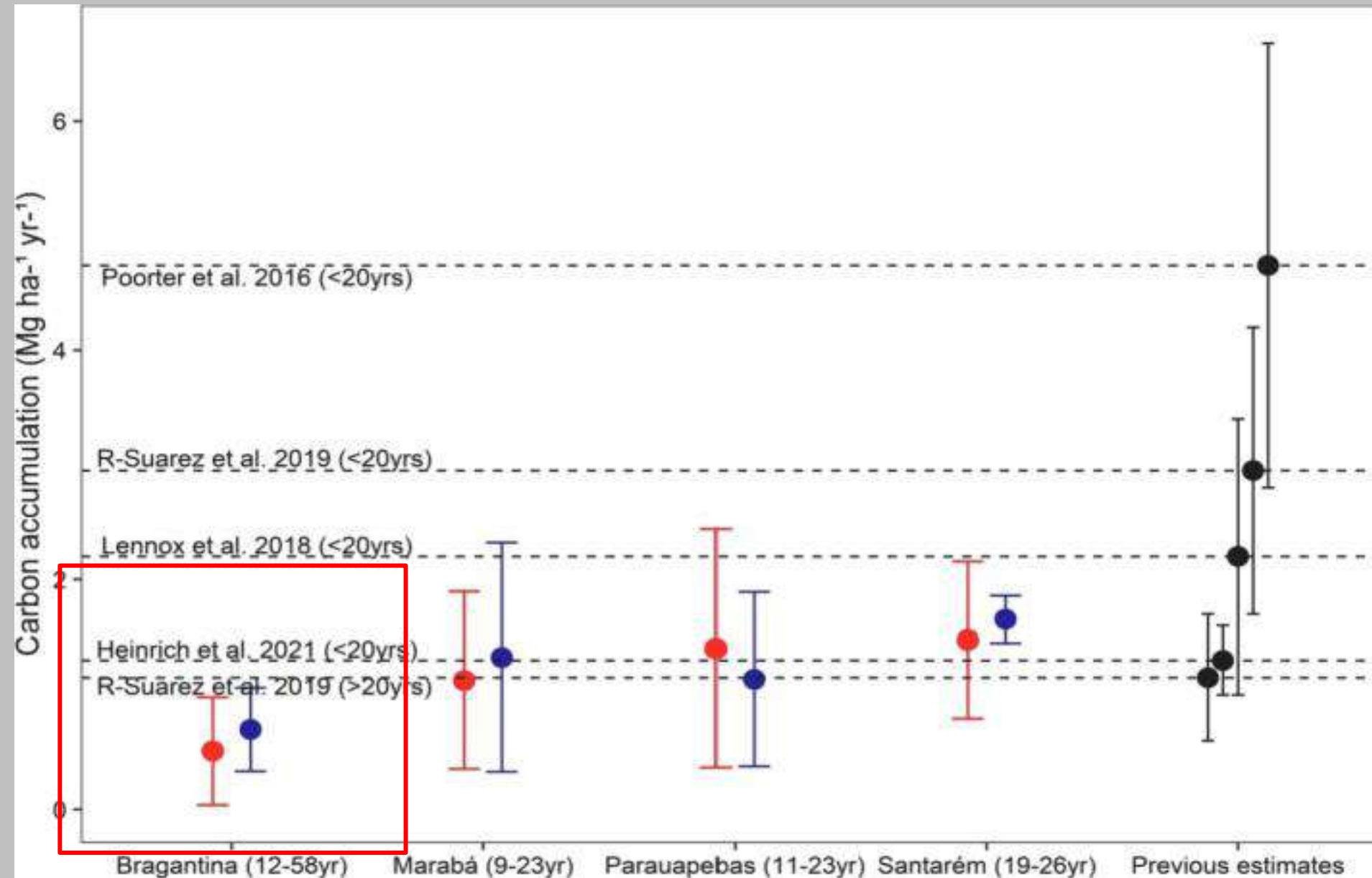


82%

18%

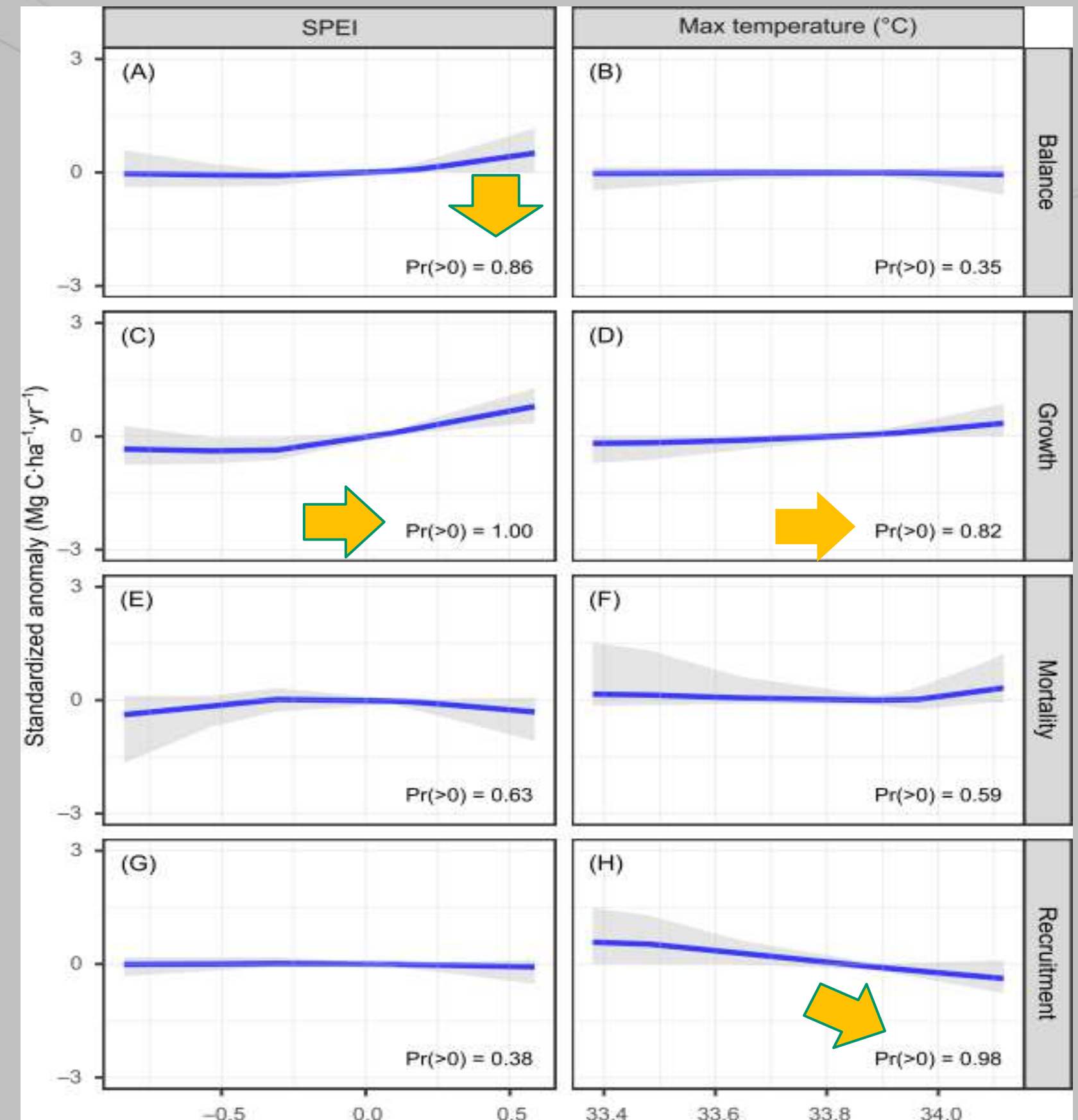
Cardoso et al. Submitted - Ecosphere

Carbon accumulation varies greatly between regions



Elias et al. (2022)-FORECO

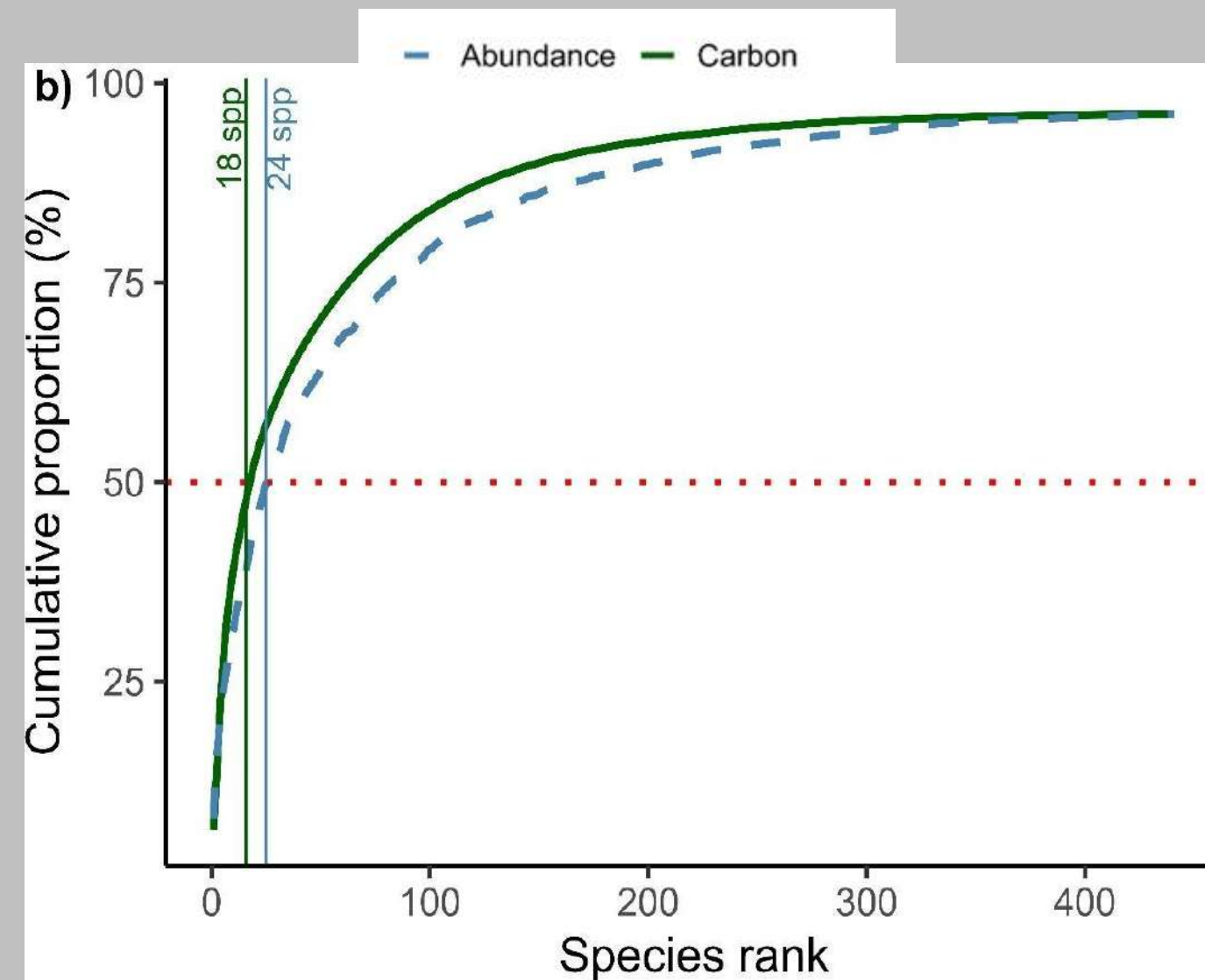
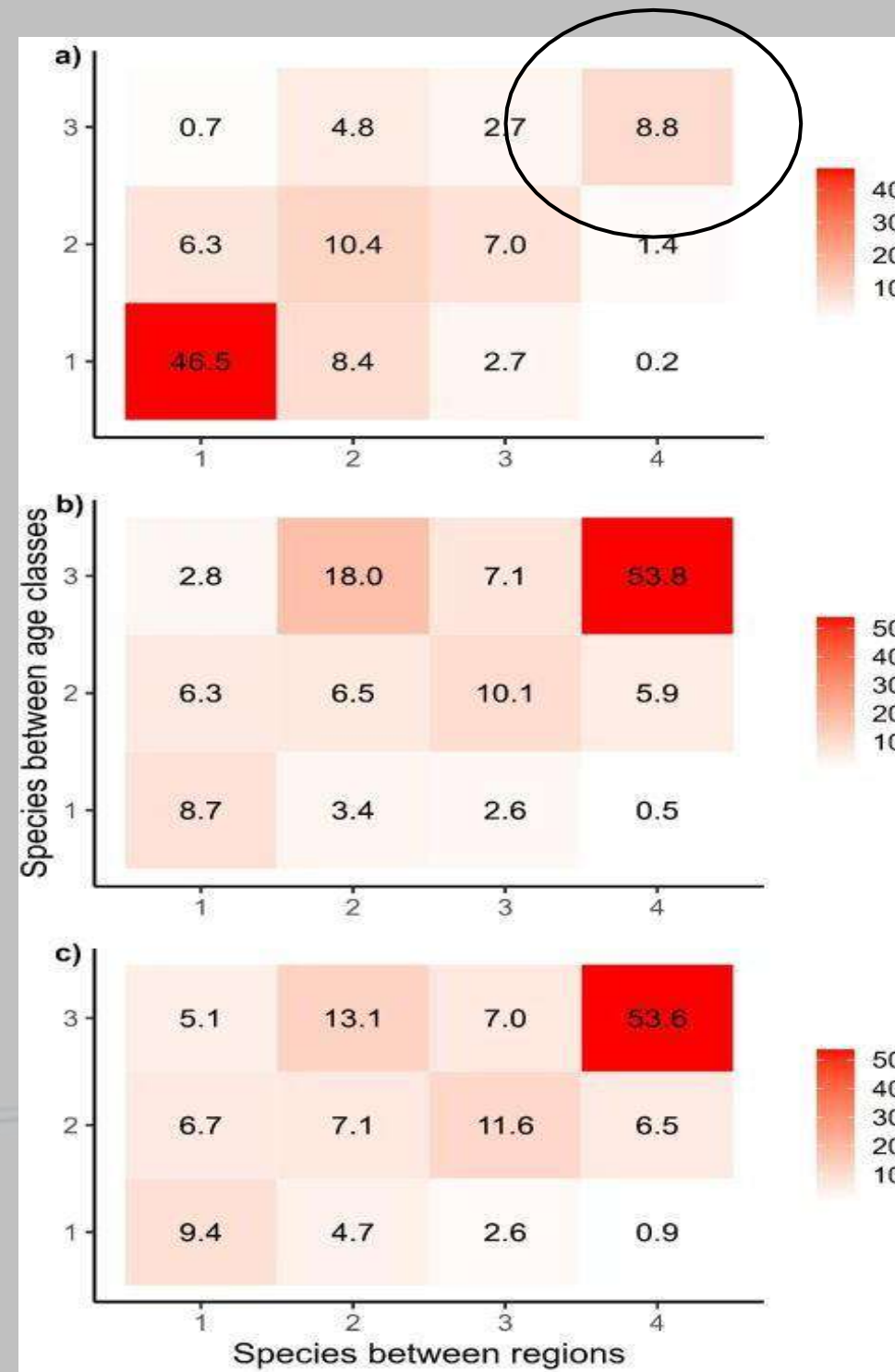
- The carbon balance of secondary forests is negatively affected by severe droughts
- Growth reduction



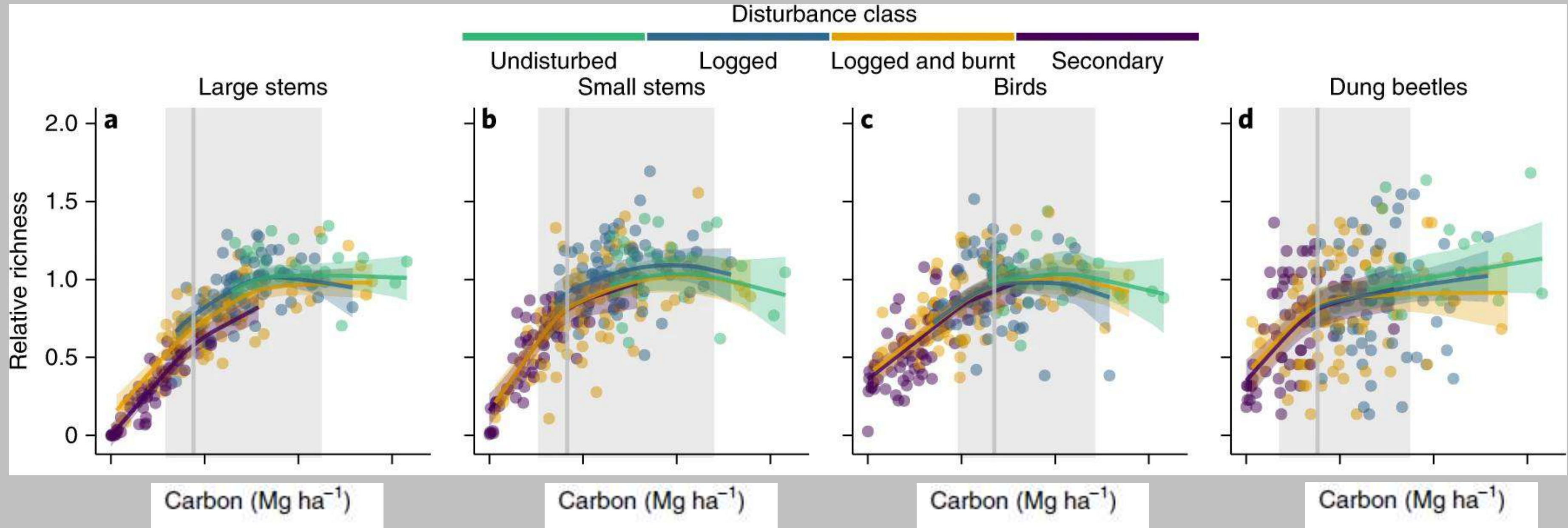
Elias et al. (2020)-Ecology

Hyperdominance of carbon and abundance in secondary forests - ~ 5% of spp.

~ 9% occur in all regions and successional stages

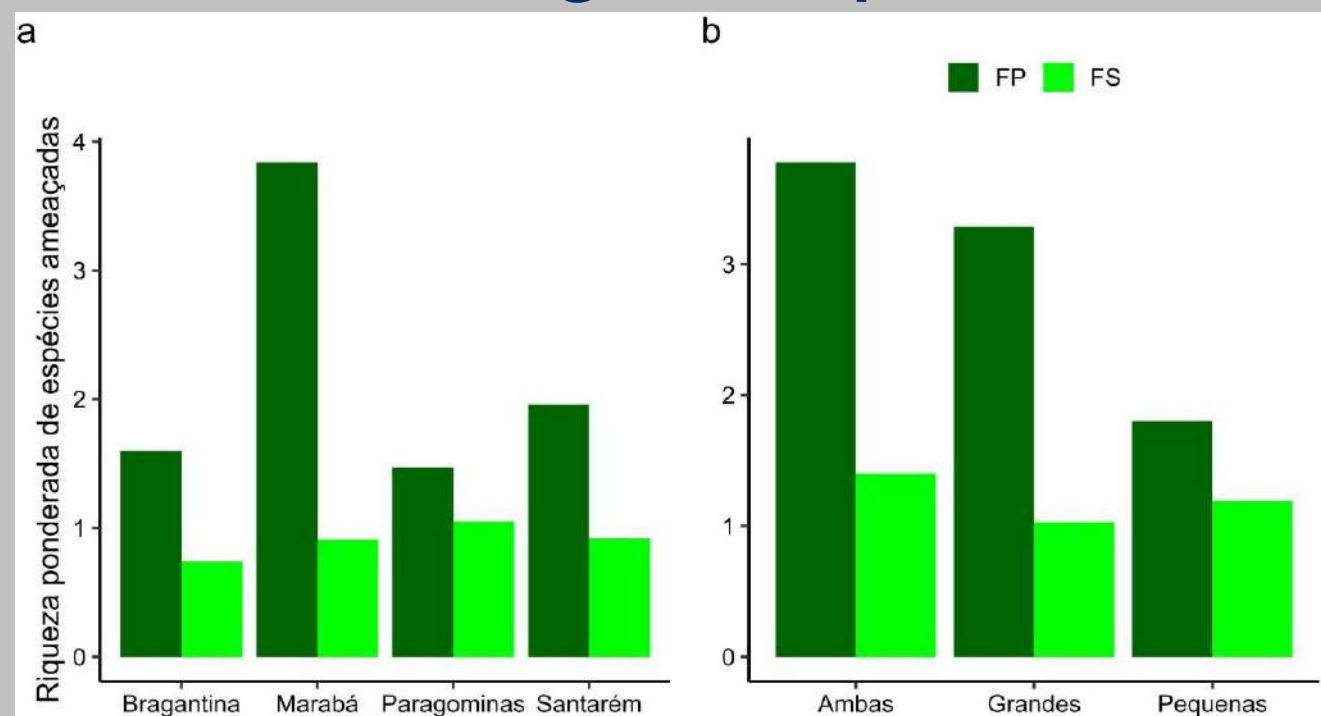


Biodiversity grows alongside carbon



Ongoing research and contributions to public policies

Endangered species



Lima et al. in prep.

Microclimate



Functional traits

Tree Physiology

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Abstract

JOURNAL ARTICLE ACCEPTED MANUSCRIPT

Unraveling intraspecific trait variation in Amazonian secondary forests: interactions among succession, soils, plant height, and species strategies

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Flora

Volume 326, May 2025, 152712

Exploring plant functional traits and their relationship to biomass dynamics in secondary forests in Eastern Amazonia

Luane Botelho^{a,d}, Fernando Elias^{b,1}, Beatriz V. Barbosa^d, Karoline C. Silva^c, Vanessa Negrão-Rodrigues^c, Euciney E.S. Barbosa^d, Jucelino S. Coutinho^c, Joice Ferreira^e, Jos Barlow^f, Grazielle Sales Teodoro^{d,1}

Public policies

GOVERNO DO ESTADO DO PARÁ
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INSTRUÇÃO NORMATIVA Nº 07 DE 05 OUTUBRO DE 2015
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DOE Nº 36.017, DE 04/11/2024

Institui o Plano Estadual Amazônia Agora (PEAA).

Thank you, and see you next time!



<https://ras-network.org/>
rodrigoliveira.nascimento@gmail.com



SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

(12:30-13:30) Lunch

São José dos Campos, 30 Oct 2025



SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

Workshop and breakout groups

São José dos Campos, 30 Oct 2025



SynCER: Synthesising post-disturbance Carbon Emissions and Removals across Brazil's forest biomes

Plenary: Feedback from discussions

São José dos Campos, 30 Oct 2025

