Climate Change AI

Climate Change AI Virtual Summer School 2026





Climate Change AI

INPE

MINISTRY OF
SCIENCE, TECHNOLOGY
AND INNOVATION

AI for Forestry

AI Contributions to Vegetation Monitoring

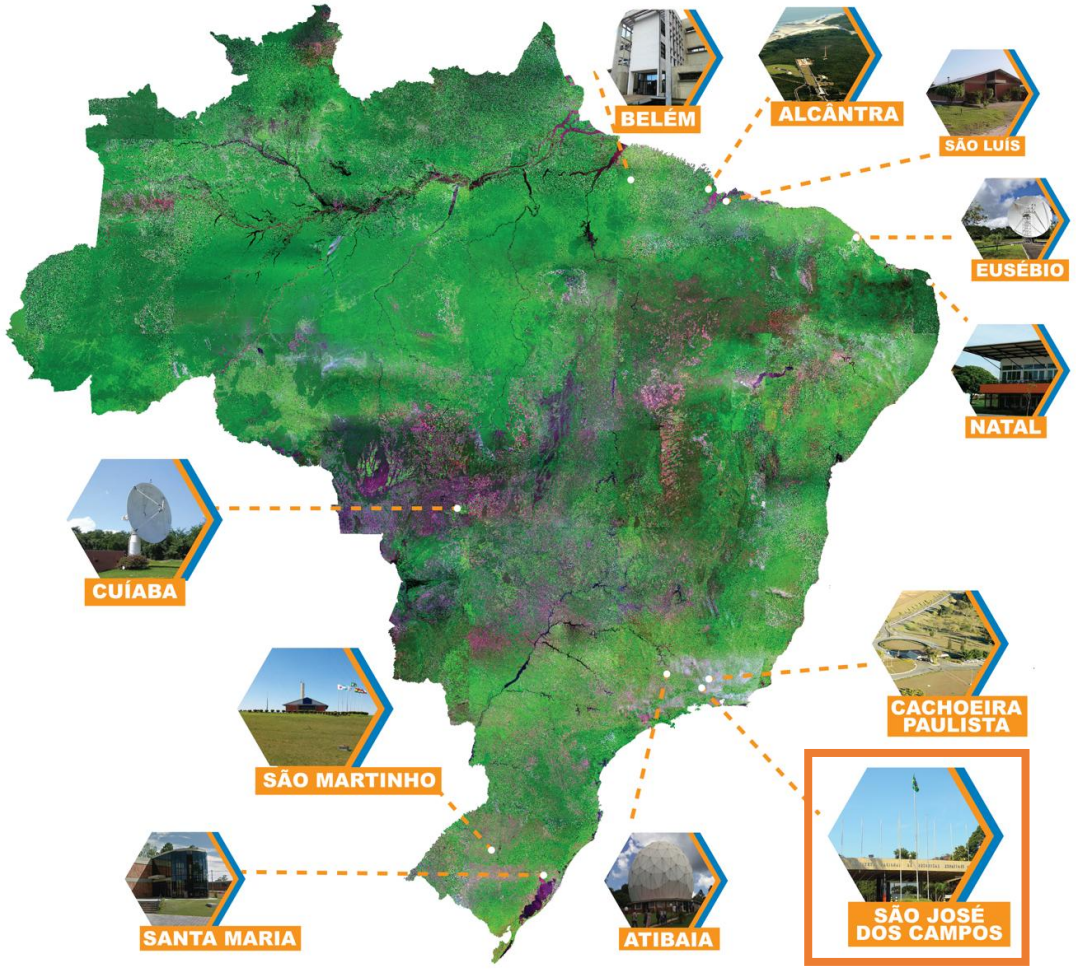


Silvana Amaral

Deputy Coordinator of the Strategic Project Division 1 – DIPE 1
Earth Observation and Geoinformatics Division - DIOTG
National Institute for Space Research - INPE

São José dos Campos, SP, August, 4th, 2026

Where I am from...



627 civil servants, ~360 students, ~460 contractors

Space & Atmospheric Science



Weather & Climate



Space Technology



Earth System Sciences



Satellite Tracking & Control



Earth Observation



Associated Laboratories



Integration & Testing Lab.



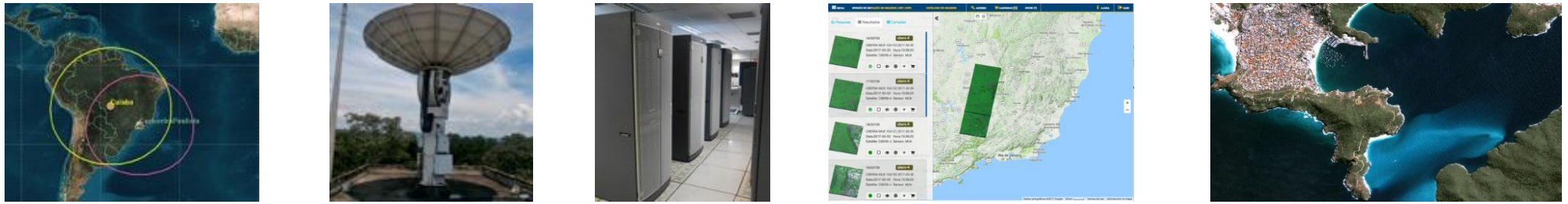
Slide: Kampel (2025)

MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E INOVAÇÃO

GOVERNO FEDERAL BRASIL UNIÃO E RECONSTRUÇÃO

What we do





SPRING TerraLib TerraView TerraME GeoDMA TerraHidro TerraAmazon TerraMA²



SBSR
XXI SIMPÓSIO BRASILEIRO DE SENSORIAMENTO REMOTO

GEOINFO
May 19 to 21, 2025
INPE, São José dos Campos, SP, Brazil

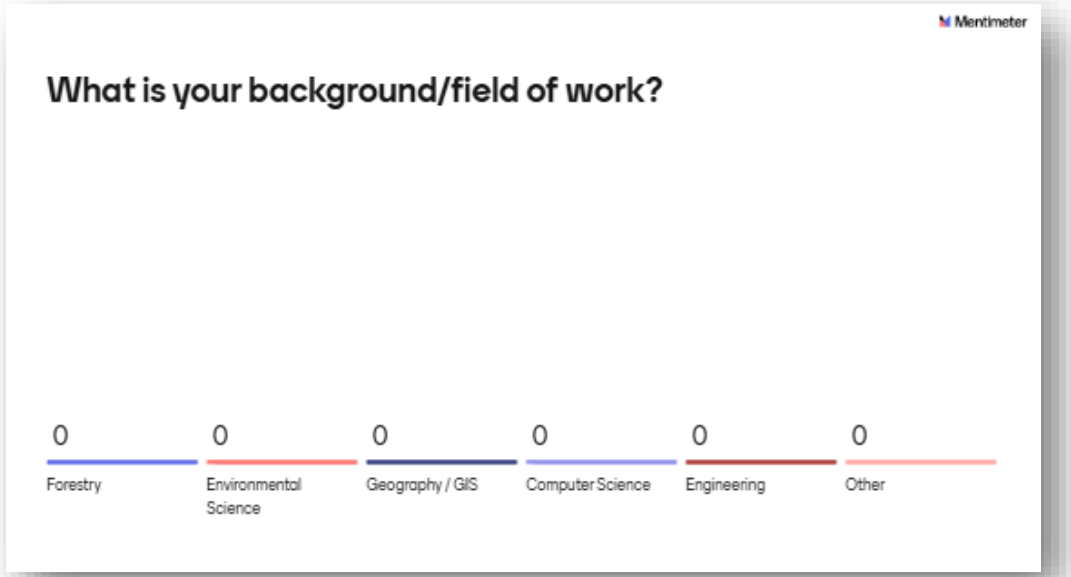
8º Simpósio de Geotecnologias no Pantanal

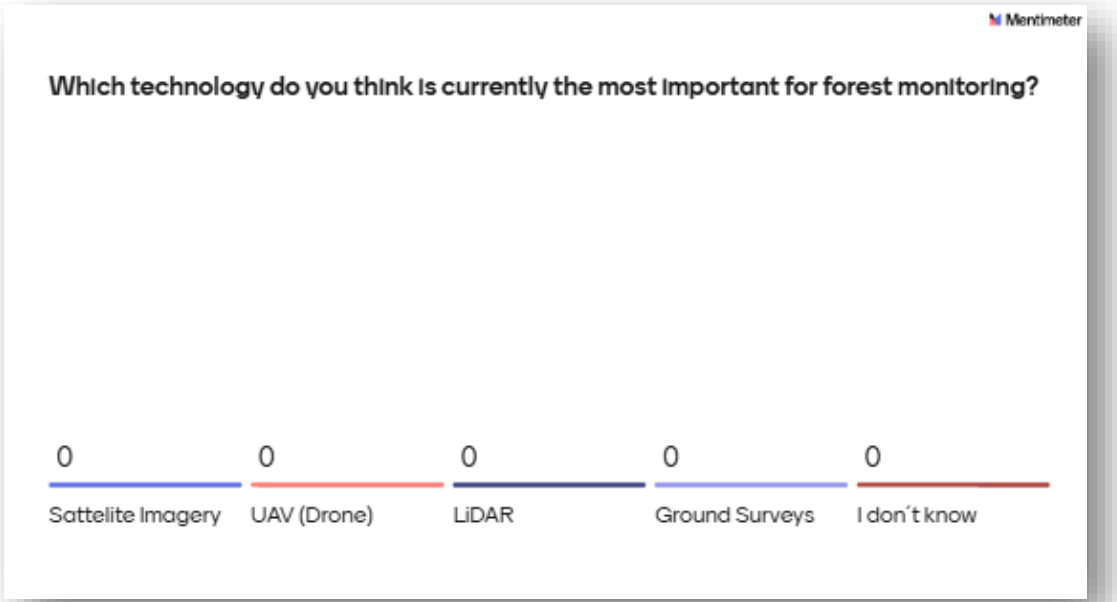
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E INOVAÇÃO

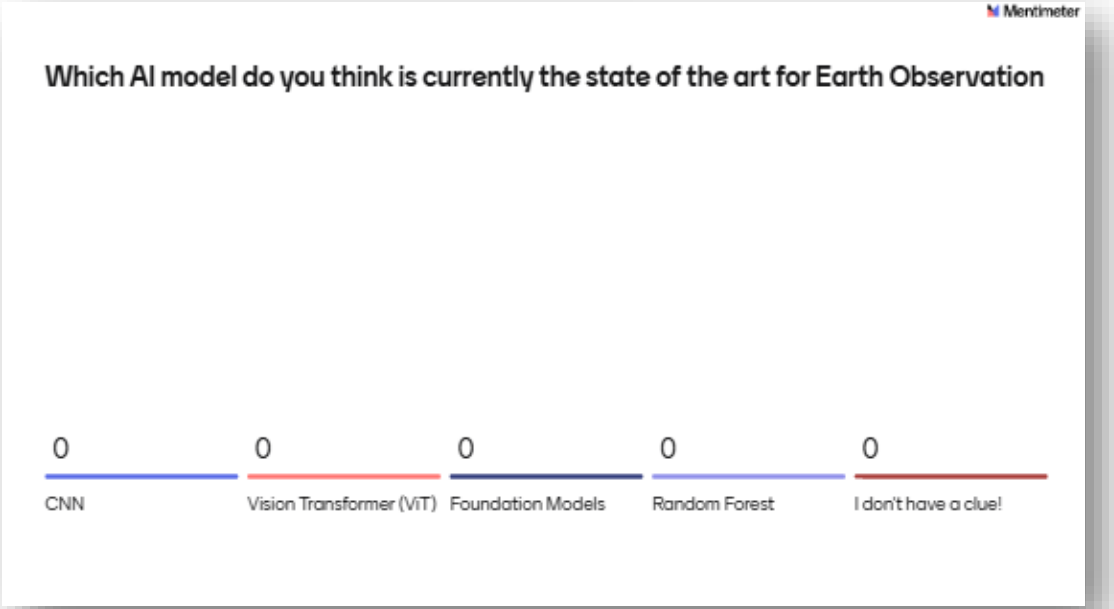
GOVERNO FEDERAL BRASIL UNIÃO E RECONSTRUÇÃO

Slide: Kampel (2025)

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Why is forest monitoring important?

How has AI been used in forest applications?

Evolution of AI for forest monitoring

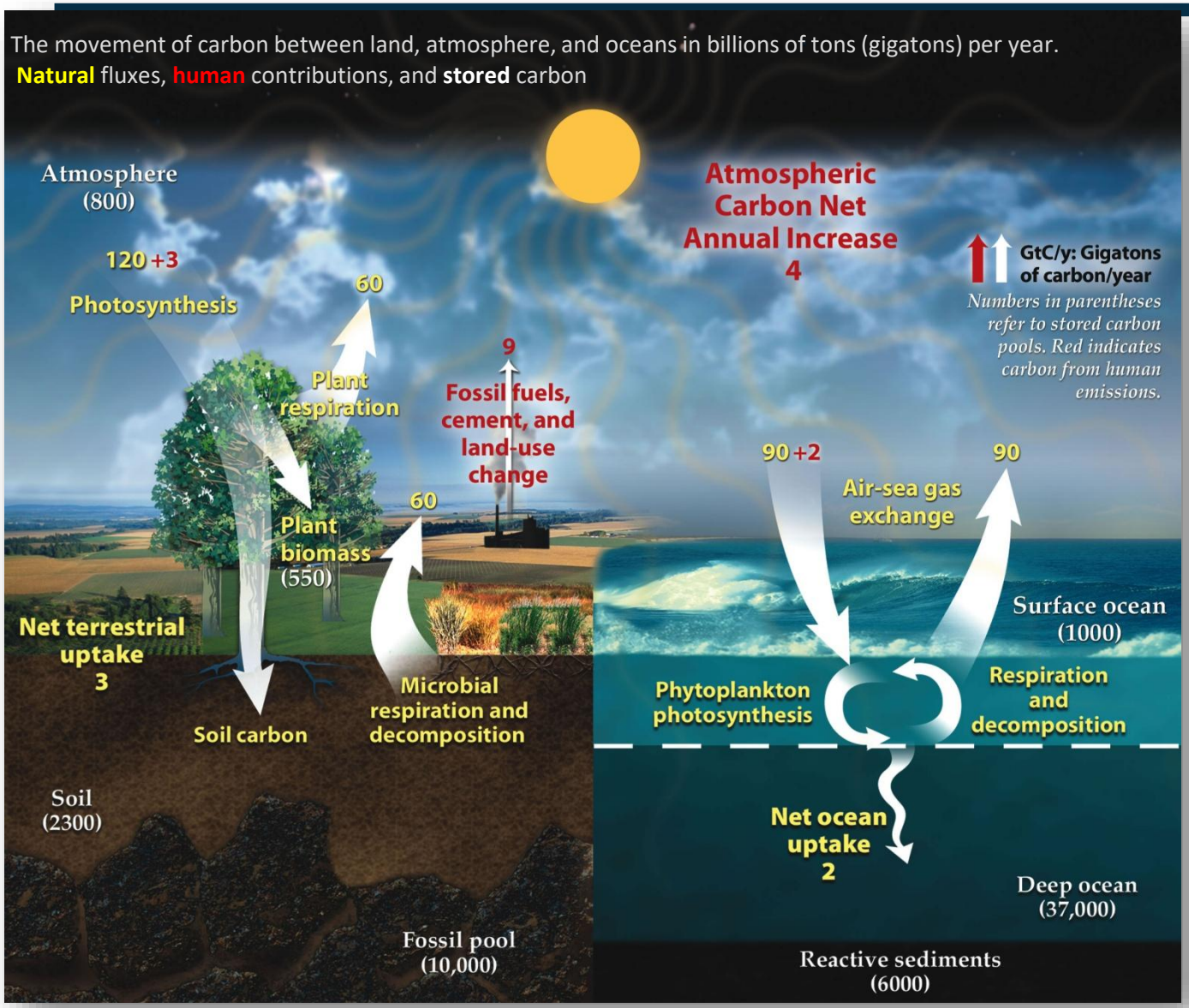
The basics (concepts) related to the most used AI models from

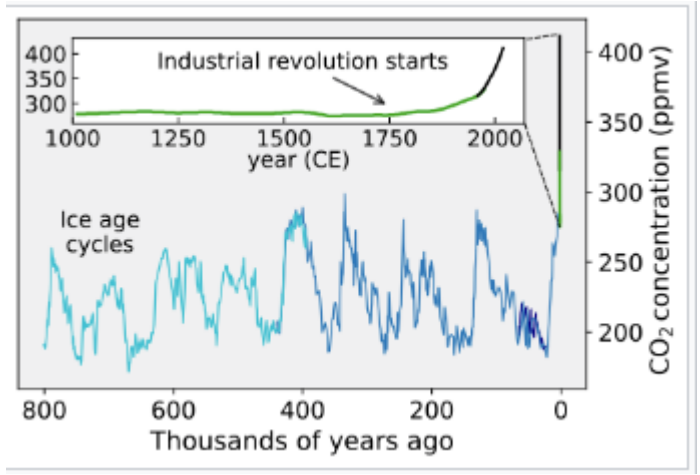
Examples – tree species classifications, forest fire assessment, biomass and carbon estimation

The Evolution of AI Use for Monitoring Vegetation in Brazilian Biomes

"The Carbon Cycle"

https://earthobservatory.nasa.gov/features/CarbonCycle

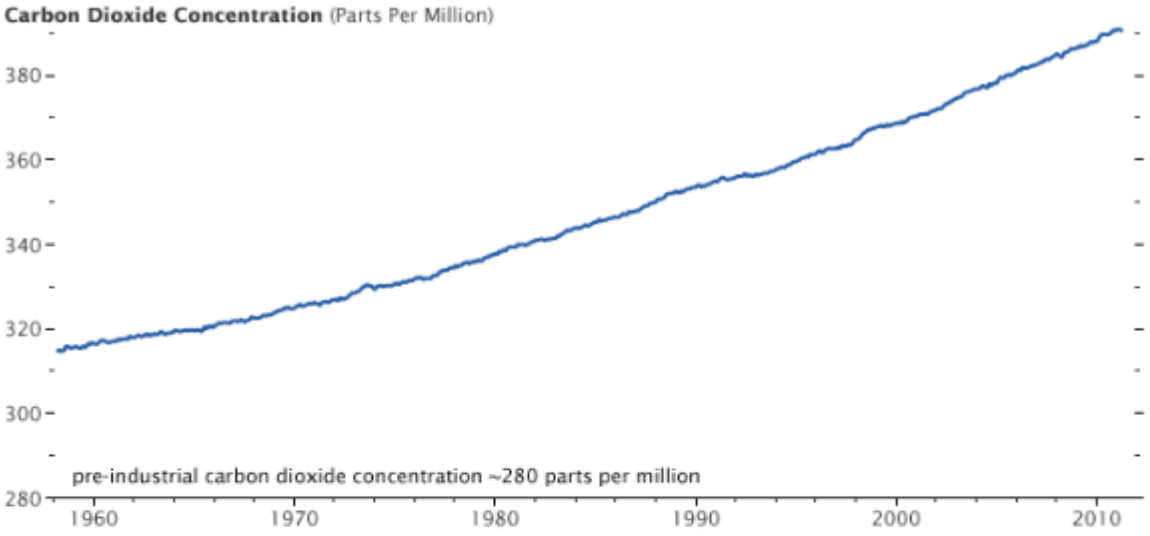


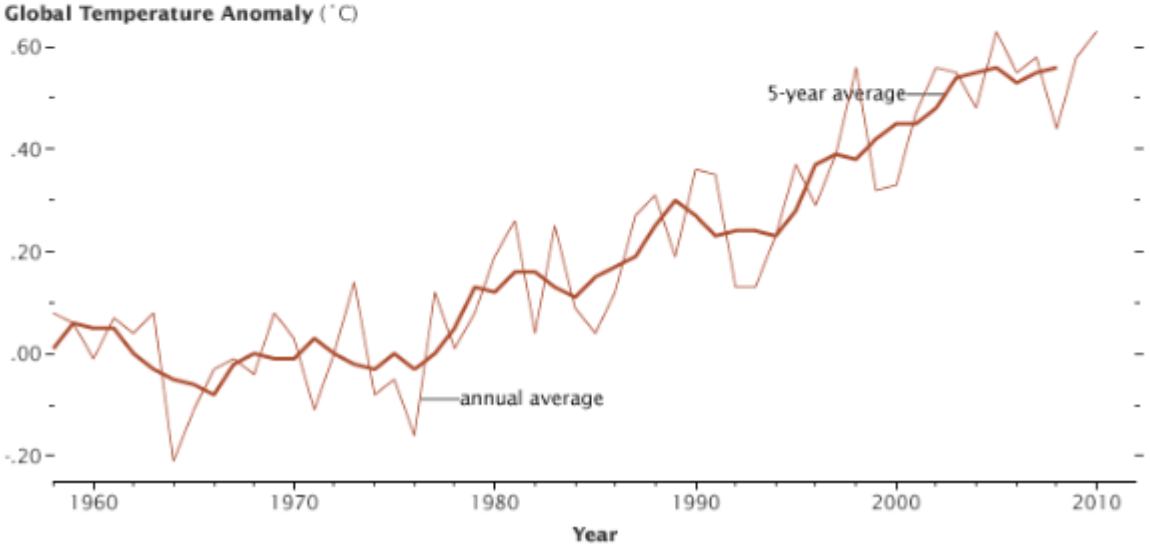


CO_2 concentrations over the last 800,000 years measured from ice cores (blue/green) and directly (black)

"The Carbon Cycle"

https://earthobservatory.nasa.gov/features/CarbonCycle



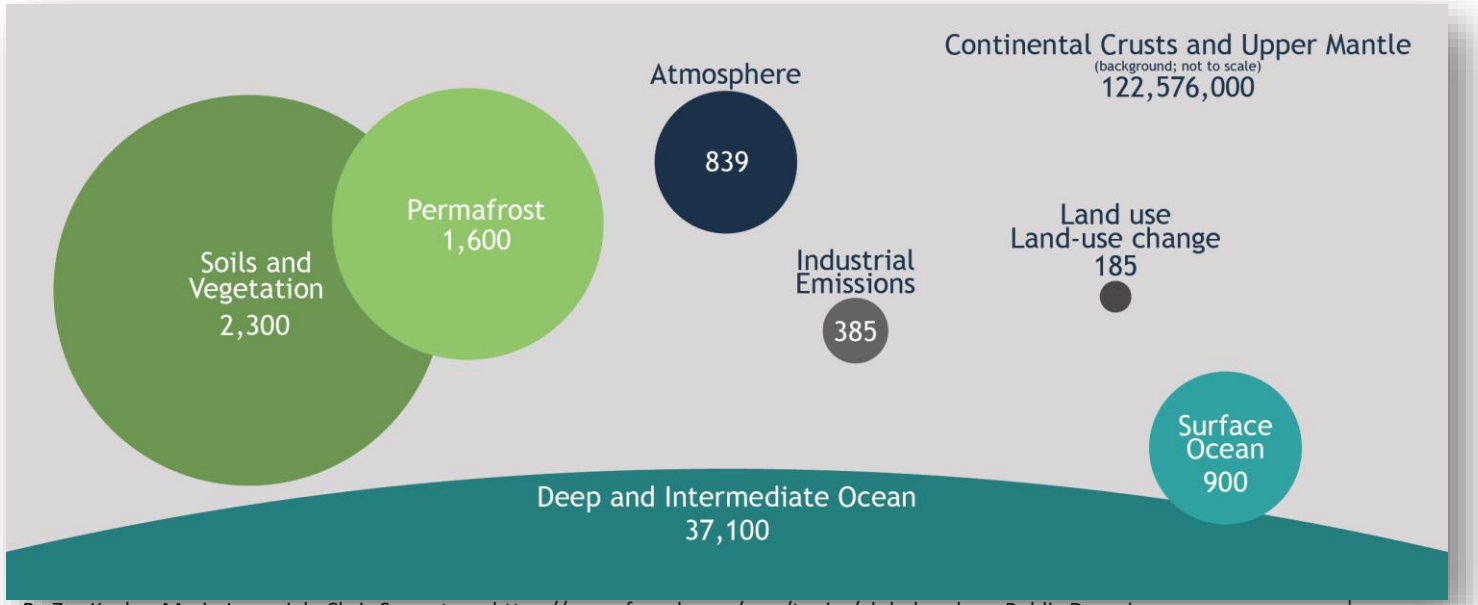


Carbon dioxide is the gas that sets the temperature.

Carbon dioxide controls the amount of water vapor in the atmosphere and thus the size of the greenhouse effect.

We are made of carbon (and need it)!
But…
that need is also entwined with one of the most serious problems facing us today:
global climate change.

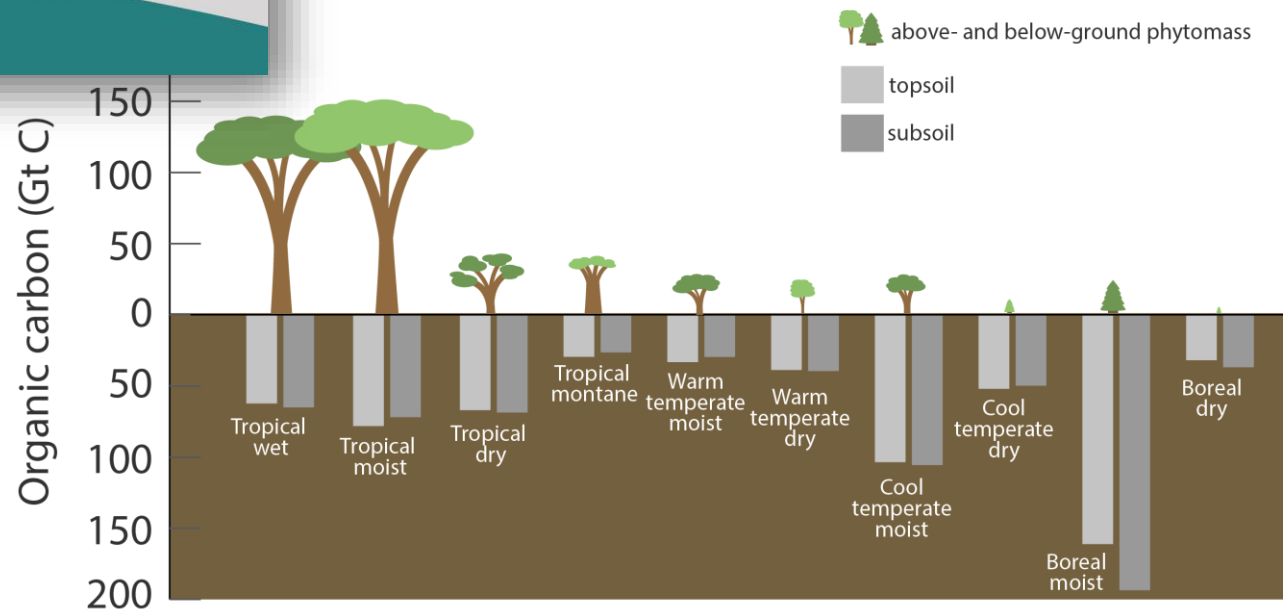
The Carbon Stock



By Zac Kayler, Maria Janowiak, Chris Swanston - https://www.fs.usda.gov/ccrc/topics/global-carbon, Public Domain, https://commons.wikimedia.org/w/index.php?curid=95324208

Relative sizes (in gigatonnes)
of the main storage pools of carbon on Earth.

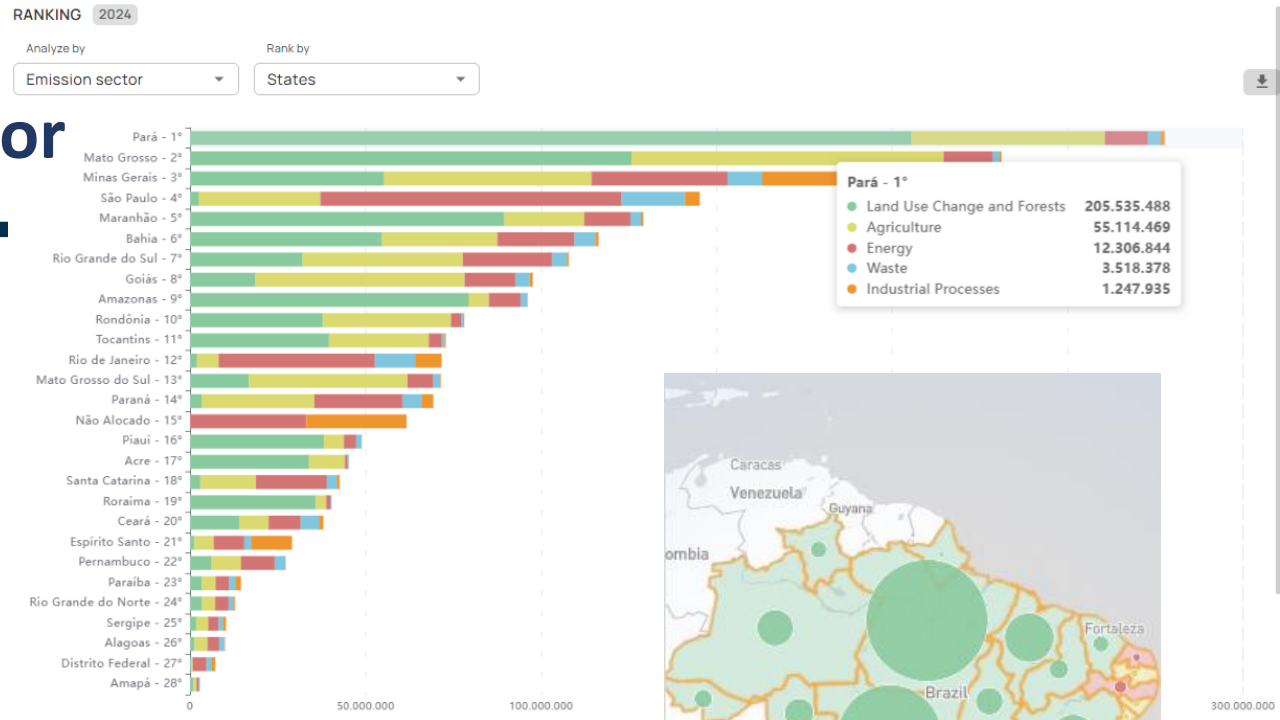
Amount of carbon stored in Earth's various terrestrial ecosystems (in gigatonnes).

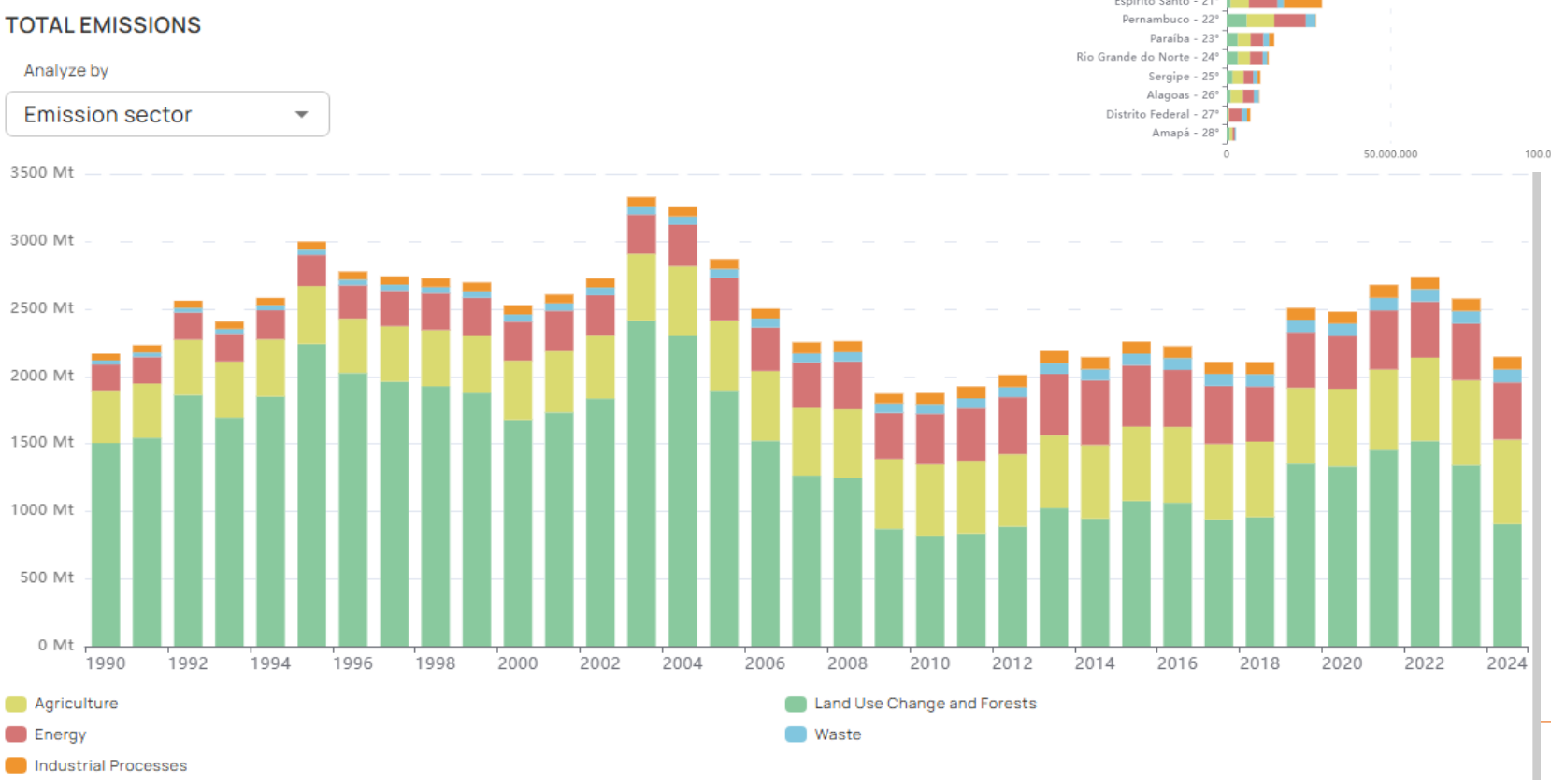


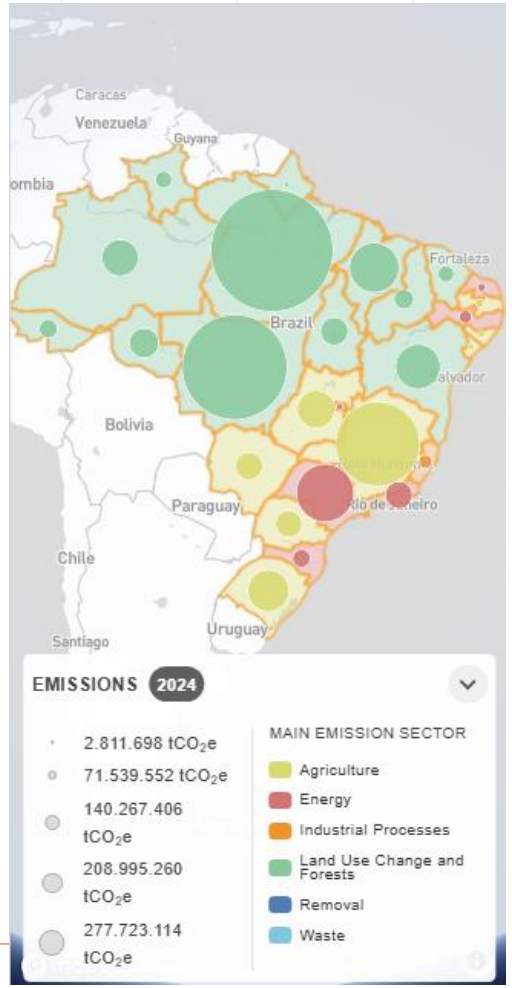
By Zac Kayler, Maria Janowiak, Chris Swanston - https://www.fs.usda.gov/ccrc/topics/global-carbon, Public Domain, https://commons.wikimedia.org/w/index.php?curid=95677627

BR Gross Emissions by Sector

https://plataforma.seeg.eco.br/

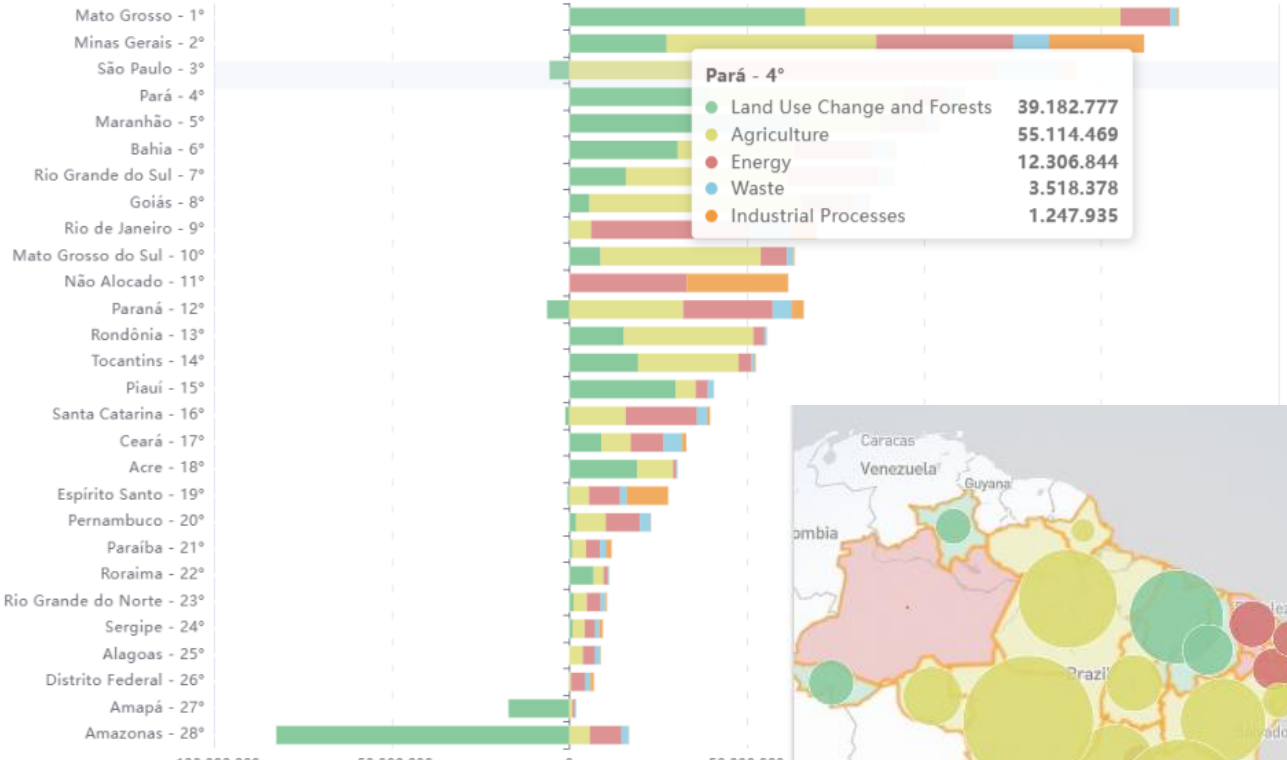


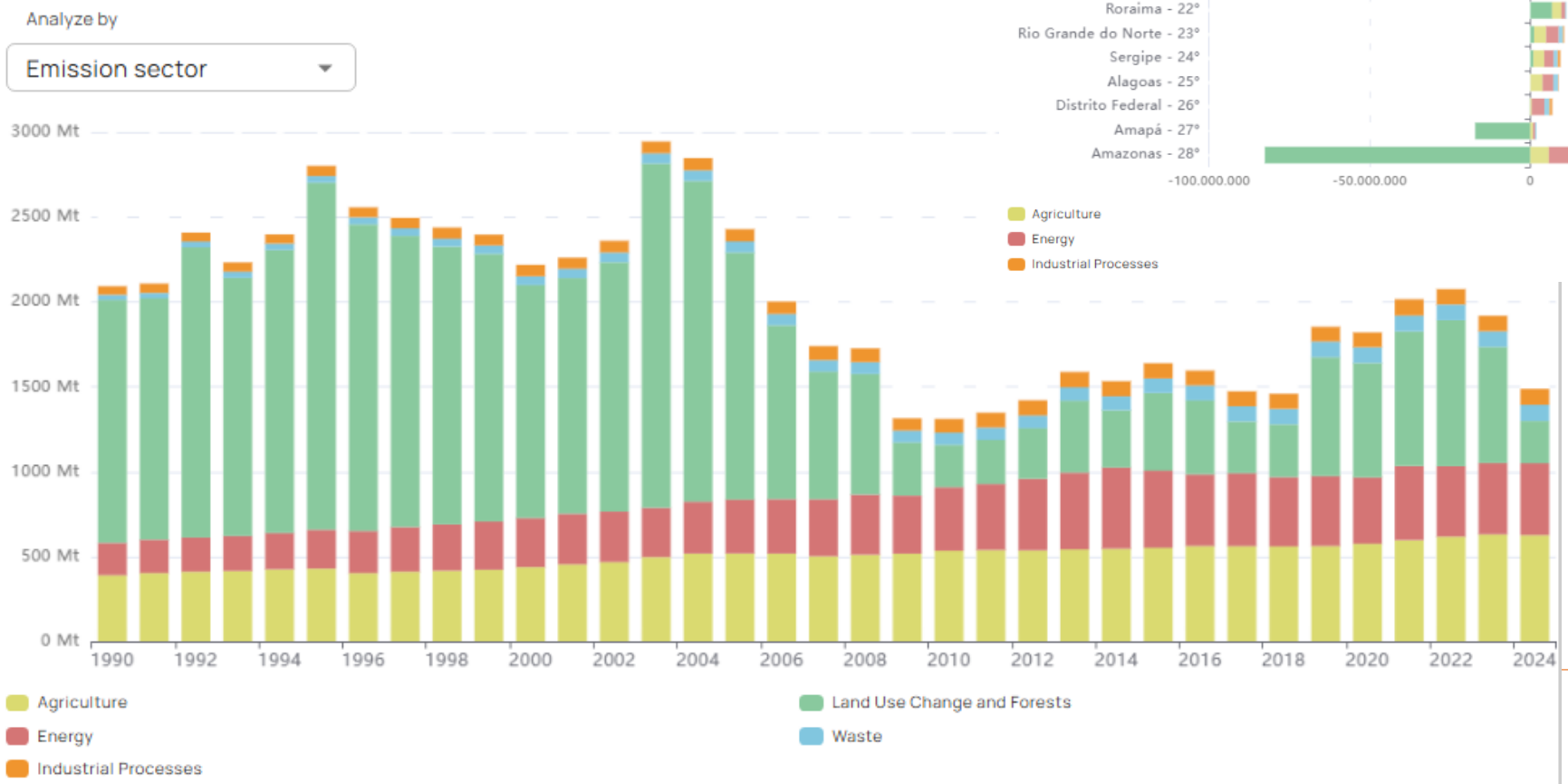


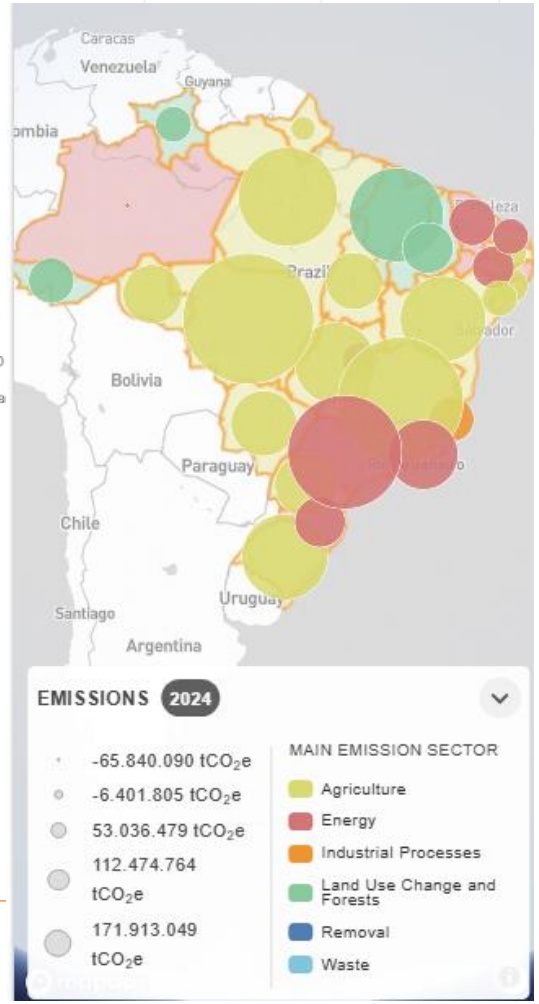


Brazilian Net Emissions

https://plataforma.seeg.eco.br/







Climate Change 2022: Impacts, Adaptation and Vulnerability

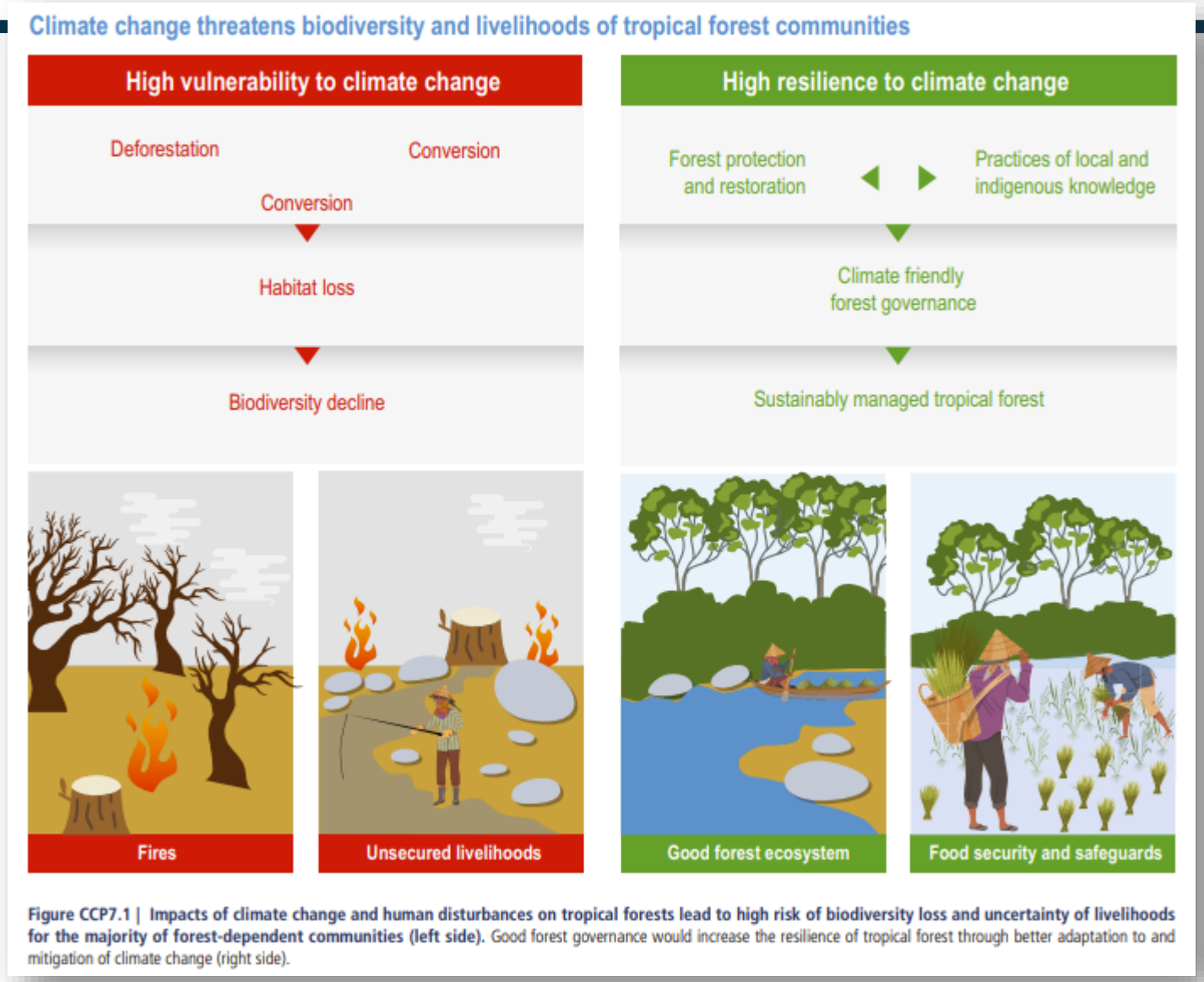


Figure CCP7.1 | Impacts of climate change and human disturbances on tropical forests lead to high risk of biodiversity loss and uncertainty of livelihoods for the majority of forest-dependent communities (left side). Good forest governance would increase the resilience of tropical forest through better adaptation to and mitigation of climate change (right side).

Over 420 million ha of forest were lost to deforestation from 1990 to 2020;

more than 90% of that loss took place in tropical areas,

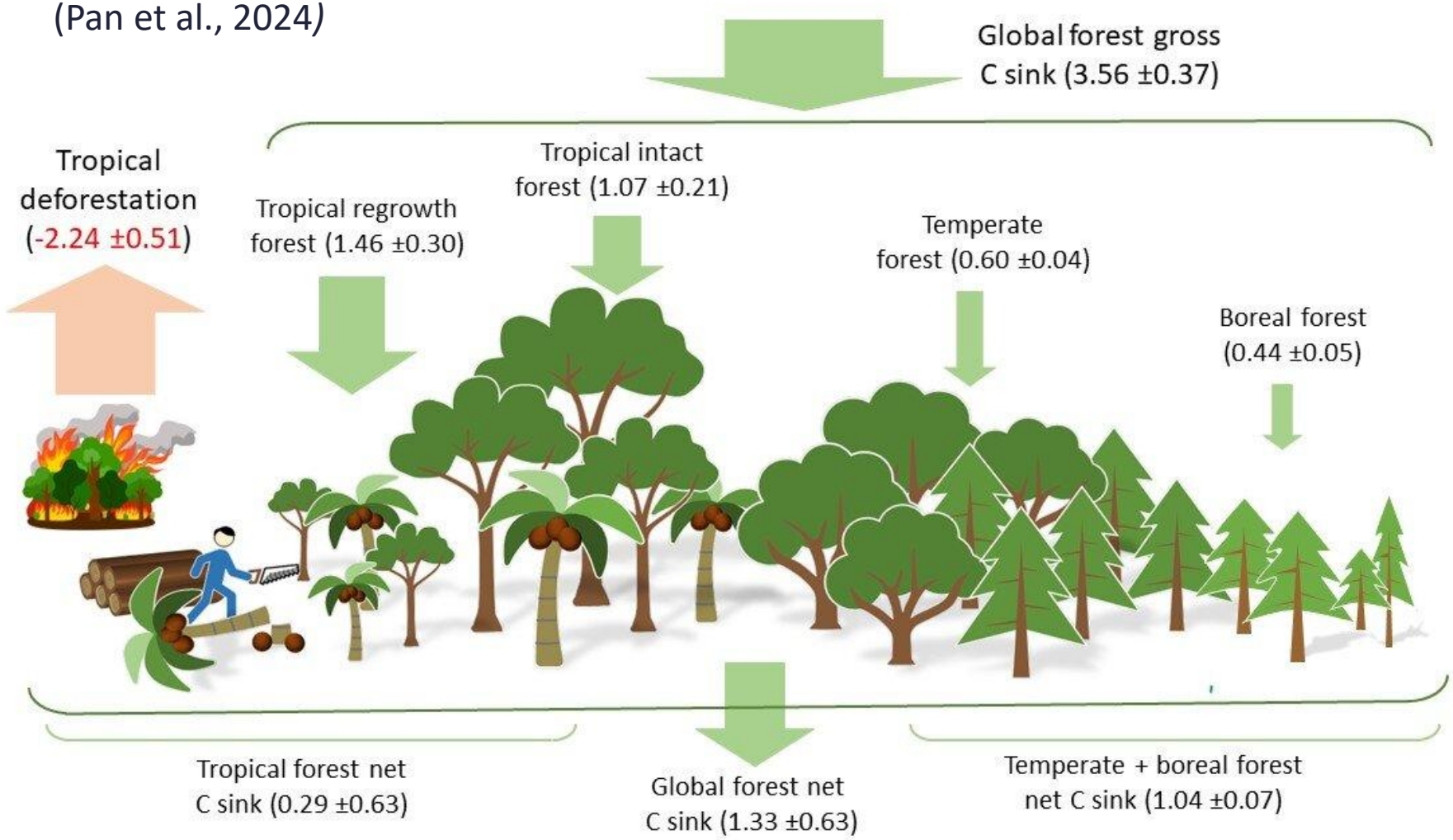
threatening biodiversity, environmental services, livelihoods of forest communities and resilience to climate shocks

(Ometto et al., 2022)
IPCC AR6 CCP7 on Tropical Forests

https://www.ipcc.ch/report/ar6/wg2/downloads/report/IPCC_AR6_WGII_CCP7.pdf

Why is deforestation/vegetation monitoring important?

The enduring world forest carbon sink
(Pan et al., 2024*)*



To protect the carbon sink**, land management policies are needed to limit deforestation,** promote forest restoration, and improve timber-harvesting practices

Carbon sinks and sources in global forests (Pg C year^{-1}) mean annual rate across 1990 to 2019.

Why is deforestation/vegetation monitoring important?

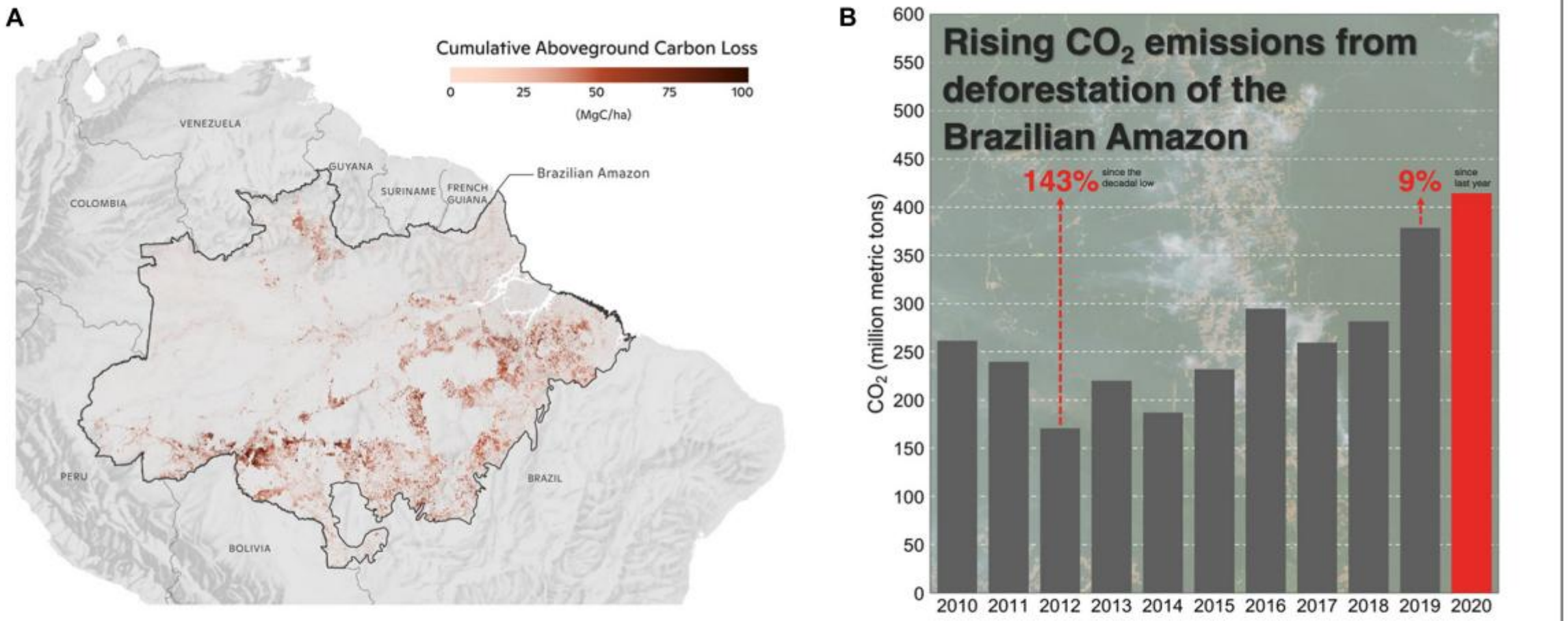


FIGURE 1 | Carbon dynamics in the Brazilian Amazon forest biome. **(A)** Cumulative aboveground carbon losses (MgC/ha) from 2003 to 2019. **(B)** Annual carbon dioxide emissions (million metric tons of CO_2) from deforestation over the last decade. Deforestation data is from the Brazilian National Space Agency [INPE, 2021] and biomass change data is from Walker et al. (2020). Background image depicts smoke from fires following deforestation near Novo Progress, PA, Brazil (MODIS/Terra images from August 19, 2019; NASA Earth Observatory).

Why is deforestation/vegetation monitoring important?

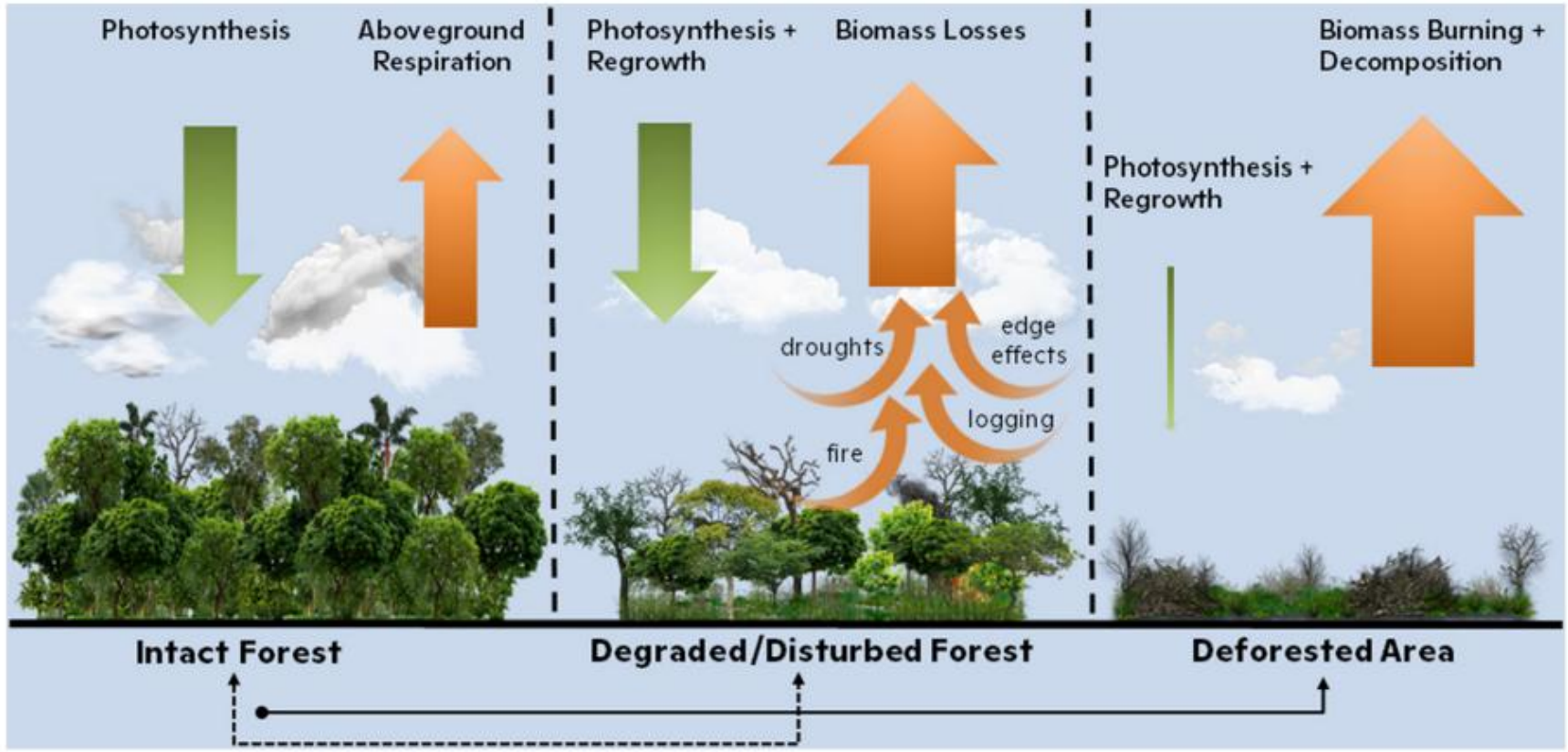


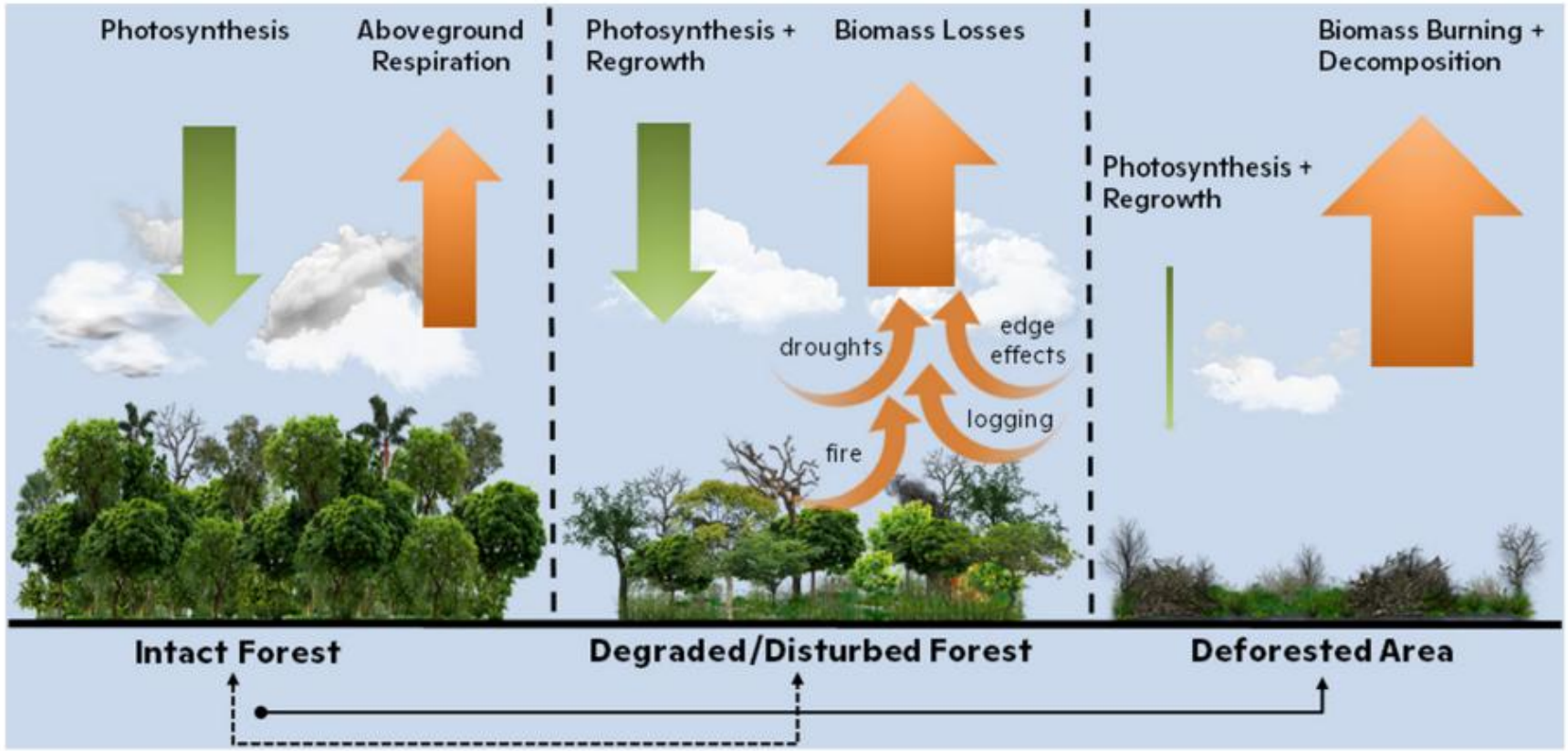
FIGURE 2 | Conceptual diagram showing above-ground carbon fluxes typical of healthy forests (left), degraded/disturbed forests (middle), and newly deforested areas (right) in the Amazon. In each panel, carbon stocks are represented by the standing vegetation, losses by the orange upward arrows, and gains by the green downward arrows. Sources contributing to degradation and disturbance include direct (logging, fire) and indirect (droughts, edge effects) anthropogenic drivers. The one-way, solid black arrow represents forest clearing (deforestation) and conversion to another land use/cover— once deforested, these areas are unlikely to regenerate to an intact forest. The two-way, dashed line reflects degradation/disturbance of intact forests. Depending on the intensity and frequency of disturbances, degraded/disturbed forests may regenerate into intact forests.

Understanding the **drivers and patterns of forest carbon losses**

First step for designing **effective climate mitigation strategies**

key for Brazil/ tropical countries commitments under the **Paris Agreement**.

Why is deforestation/vegetation monitoring important?



Conserving Amazon forests is a prerequisite for any global **solution to the climate crisis.**

FIGURE 2 | Conceptual diagram showing above-ground carbon fluxes typical of healthy forests (left), degraded/disturbed forests (middle), and newly deforested areas (right) in the Amazon. In each panel, carbon stocks are represented by the standing vegetation, losses by the orange upward arrows, and gains by the green downward arrows. Sources contributing to degradation and disturbance include direct (logging, fire) and indirect (droughts, edge effects) anthropogenic drivers. The one-way, solid black arrow represents forest clearing (deforestation) and conversion to another land use/cover— once deforested, these areas are unlikely to regenerate to an intact forest. The two-way, dashed line reflects degradation/disturbance of intact forests. Depending on the intensity and frequency of disturbances, degraded/disturbed forests may regenerate into intact forests.



IA – *friendly reminder….*

Artificial Intelligence (AI) is a field of computer science that develops computational systems capable of simulating human cognitive processes such as learning, reasoning, and decision-making (Russell & Norvig, 2010).

IA methods?

- Machine Learning
  (with **supervised**, **unsupervised**, and reinforcement learning);
- Deep Learning and Neural Networks;
- Natural Language Processing (NLP);
- Computer Vision;
- Symbolic AI (including expert systems and rule-based modeling);
- Evolutionary Computation;
- Fuzzy Logic



Current Trends in AI for Forest Monitoring

From Machine Learning to Deep Learning

Period	Predominant AI methods
~2010–2017	Random Forest, Support Vector Machines (SVM)
~2017–2022	Convolutional Neural Networks (CNNs) and U-Net architectures
~2022–2024	Vision Transformers and temporal deep learning models
~2024–present	Foundation Models, multimodal AI, and self-supervised learning

Land-cover classification and biomass estimation

Robustness and low demand for training data



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Forest mapping, deforestation detection, and canopy characterization.

Ability to capture complex spatial patterns.



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Extraction of long-range **spatial dependencies** and

Exploitation of dense satellite **image time series** for monitoring forest dynamics.



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Massive unlabeled EO data

Integrate sources (optical, SAR, LiDAR, climate, topographic)

Transferability across regions and sensors

Reduce dependence on labeled datasets,

Support multiple downstream tasks with minimal fine-tuning.



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LUC, biomass, and applications with limited labeled data

Forest degradation, disturbance mapping, continuous monitoring, and large-scale analyses



AI for Forest Monitoring Using Remote Sensing

Task	Representative applications	Key references
Forest mapping and land-cover classification	Forest/non-forest mapping, forest type classification, tropical forest inventories	Belgiu & Drăguț (2016); Mountrakis et al. (2011); Ma et al. (2019)
Deforestation detection	Clear-cut detection, illegal logging, near-real-time monitoring	Zhu et al. (2017); Chen et al. (2021); Bandara & Patel (2022)
Forest degradation monitoring	Selective logging, understory disturbance, canopy degradation	Rußwurm & Körner (2018); Pelletier et al. (2019)
Forest recovery and regeneration	Secondary forest succession, restoration monitoring, vegetation recovery	Pelletier et al. (2019); Ma et al. (2019)
Biomass and carbon estimation	Aboveground biomass, carbon stocks, REDD+ monitoring	Belgiu & Drăguț (2016); Maxwell et al. (2018)
Individual tree detection and canopy characterization	Tree crown delineation, species recognition, canopy gaps	Ma et al. (2019); Zhu et al. (2017)
Forest disturbance and change detection	Fire scars, storms, insect outbreaks, land-use conversion	Chen et al. (2021); Bandara & Patel (2022)
Forest fire assessment	Burned area mapping, fire severity, post-fire recovery	Ma et al. (2019); Zhu et al. (2017)
Near-real-time forest monitoring	Operational alert systems, continuous forest surveillance	Ayush et al. (2021); Jakubik et al. (2024)
General-purpose geospatial analysis	Multi-task learning, transfer learning, continental and global forest monitoring	Robinson et al. (2024); Jakubik et al. (2024)



AI for Forest Monitoring Using Remote Sensing

Task	Main AI methods
Forest mapping and land-cover classification	Random Forest, SVM, CNNs, Vision Transformers
Deforestation detection	CNNs, U-Net, Siamese Networks, Transformers
Forest degradation monitoring	CNNs, Temporal CNNs, LSTM, Vision Transformers
Forest recovery and regeneration	LSTM, GRU, Temporal Transformers
Biomass and carbon estimation	Random Forest, Gradient Boosting, Deep Neural Networks
Individual tree detection and canopy characterization	CNNs, Mask R-CNN, U-Net, YOLO
Forest disturbance and change detection	Siamese CNNs, BIT, ChangeStar, Vision Transformers
Forest fire assessment	CNNs, DeepLab, Transformers
Near-real-time forest monitoring	Temporal Transformers, Self-supervised Learning, Foundation Models
General-purpose geospatial analysis	Foundation Models, Multimodal AI



AI for Forest Monitoring Tasks

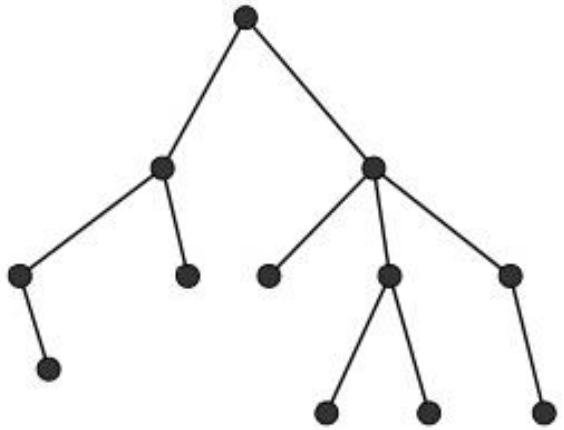
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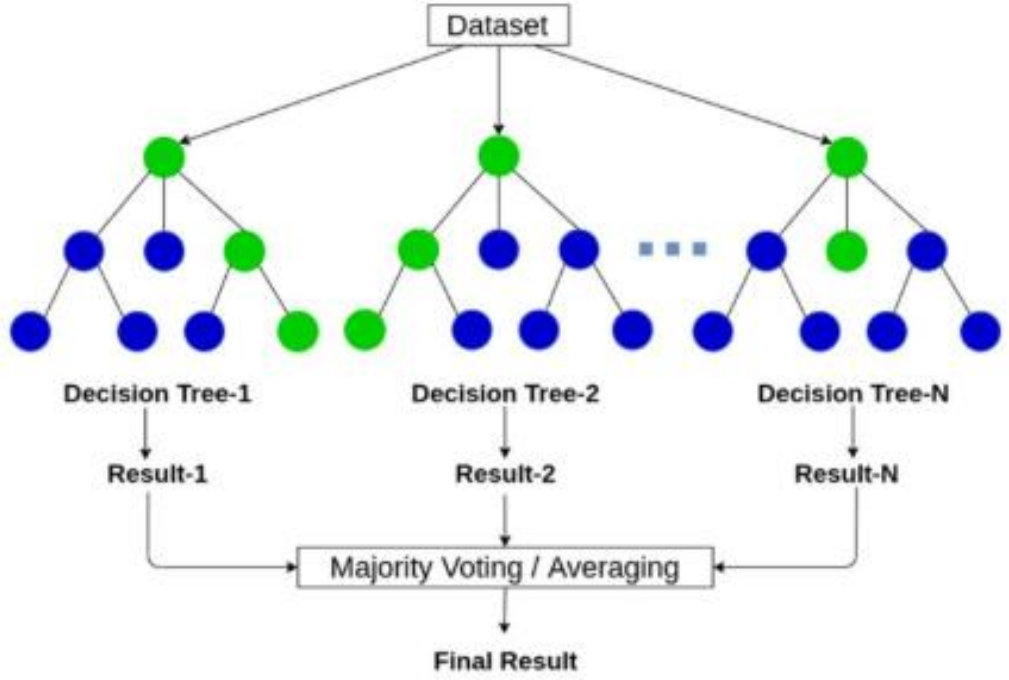
Random Forest

Decision Trees – **Machine Learning** algorithms

Decision point = “nodes” of the tree, deciding to follow one or another path
Path = “branches”
The variable with the highest information gain will be at the first node of the tree.







Random Forest - an ensemble of decision trees - for classification and regression

Entropy / Gini index – to define variable influence

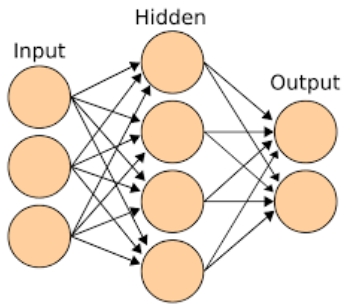
https://pt.stackoverflow.com/questions/216885/o-que-seria-uma-%C3%A1rvore-e-uma-floresta

https://www.linkedin.com/pulse/entendendo-o-algoritmo-random-forest-e-suas-aplica%C3%A7%C3%B5es-julio-rena-aa1yc/

CNN Convolutional Neural Network

Deep learning models use three-dimensional data for *image* classification and object recognition (**processing grid-like data topologies)**

Mathematical convolutions - to **preserve spatial structure and automatically extract features** such as edges, textures, and shapes



Artificial Neural Network (ANN)

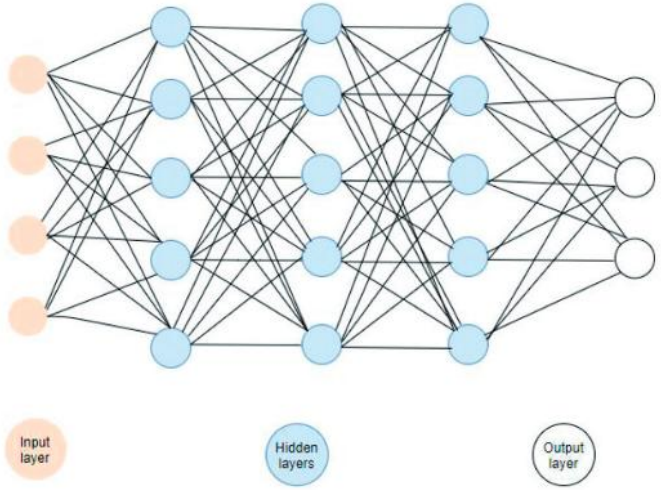
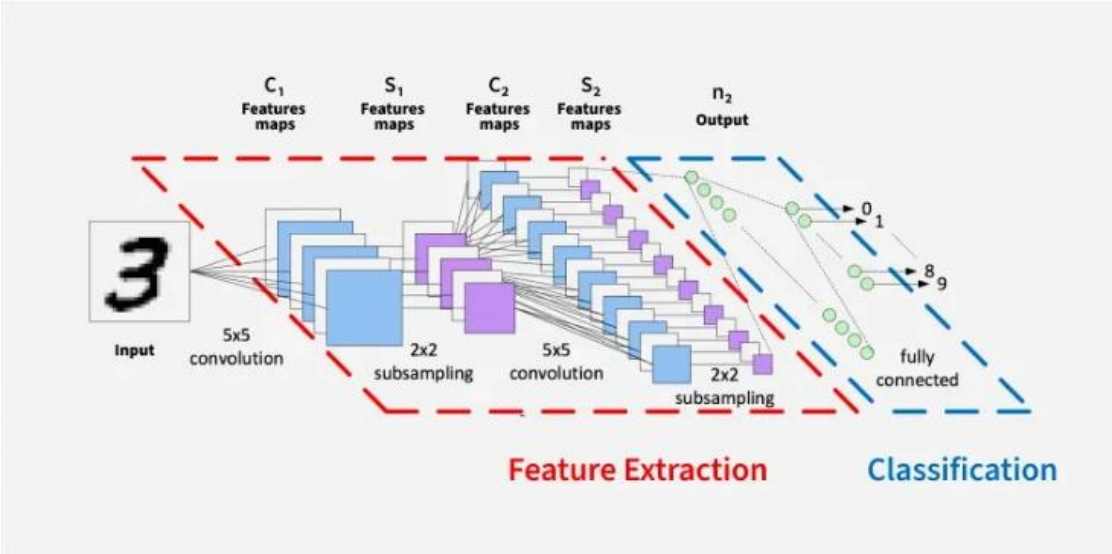


Figure 2.
Deep neural network.

Advancements in Deep Learning Theory and Applications: Perspective in 2020 and beyond
DOI: http://dx.doi.org/10.5772/intechopen.92271



Convolutional Neural Network

A neural network with many hidden layers is called deep learning

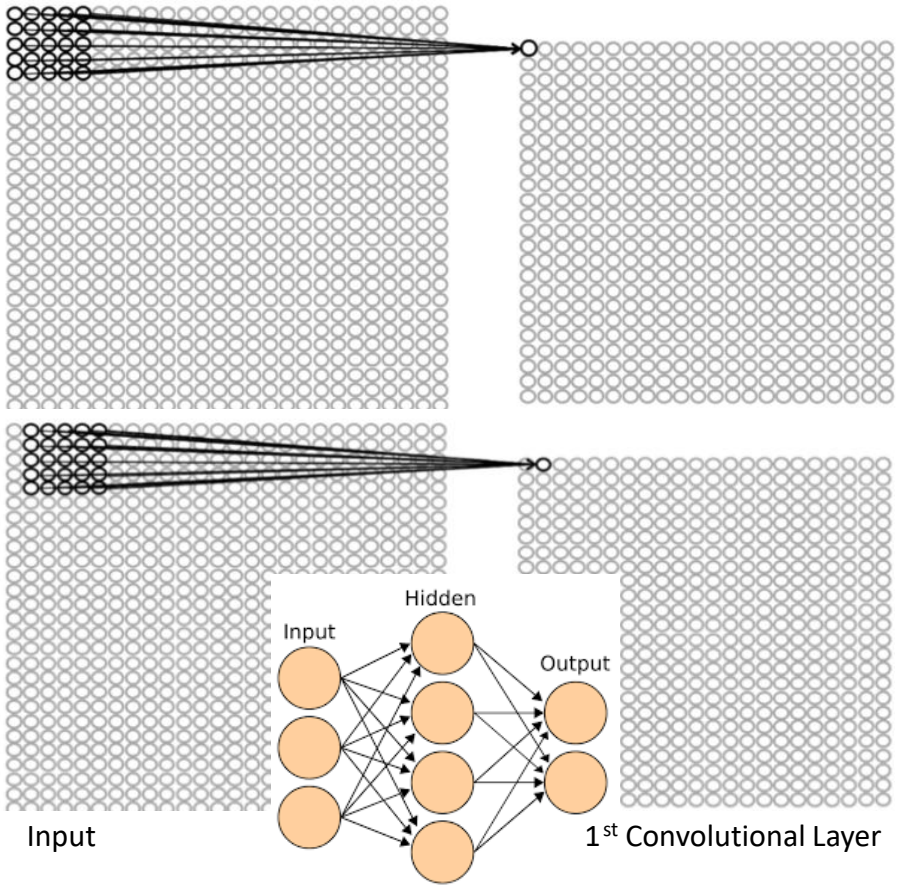
https://www.geeksforgeeks.org/deep-learning/convolutional-neural-network-cnn-in-machine-learning/

CNN Convolutional Neural Network

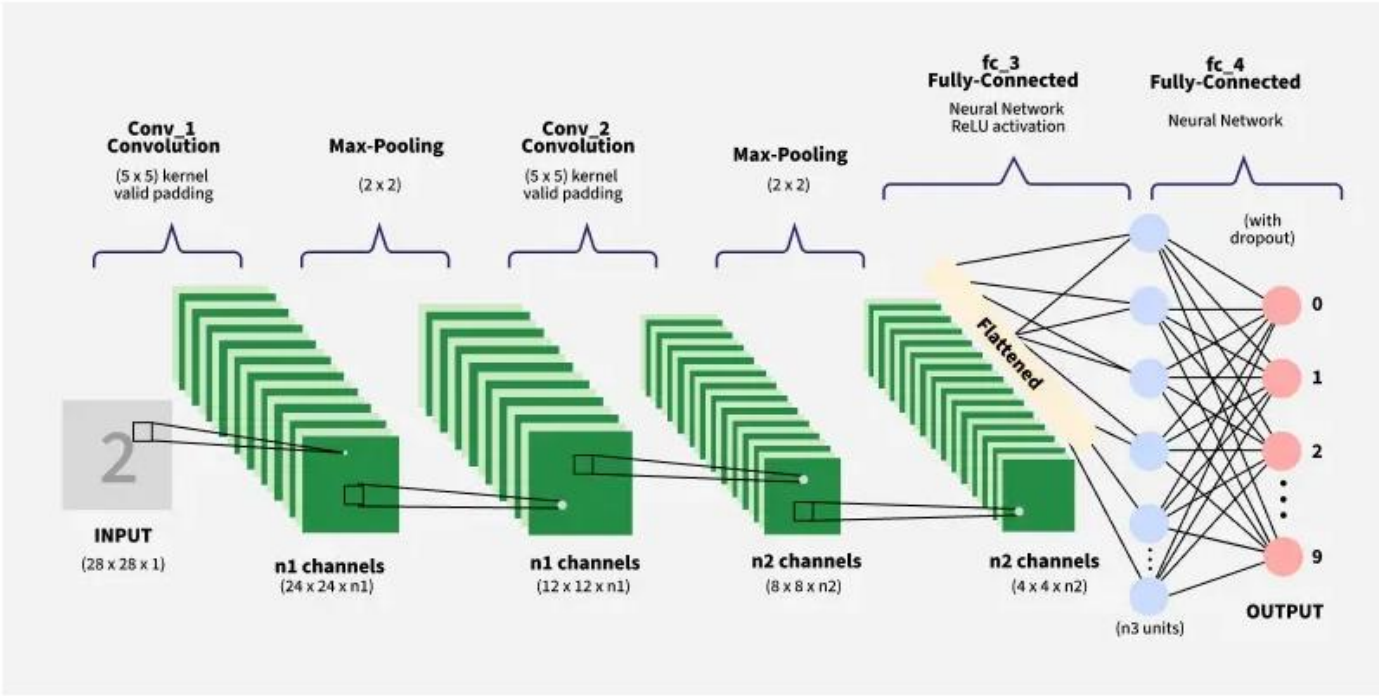




(Not fully-connected as dense NN)



Convolution and sampling before fully-connected



Convolutional Layers: Filters to extract features (edges, textures, shapes).
Pooling Layers: Downsample the feature maps from the convolutional layers → reduce dimensionality.
Fully Connected Layers: The downsampled feature maps are passed through fully connected layers to produce the output → classification label.
Output: prediction → class of the image.

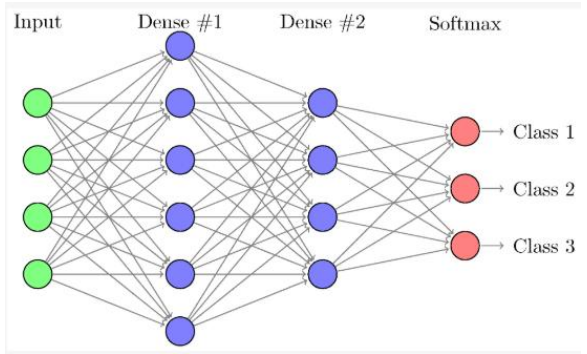
https://www.geeksforgeeks.org/deep-learning/convolutional-neural-network-cnn-in-machine-learning/

TempCNN

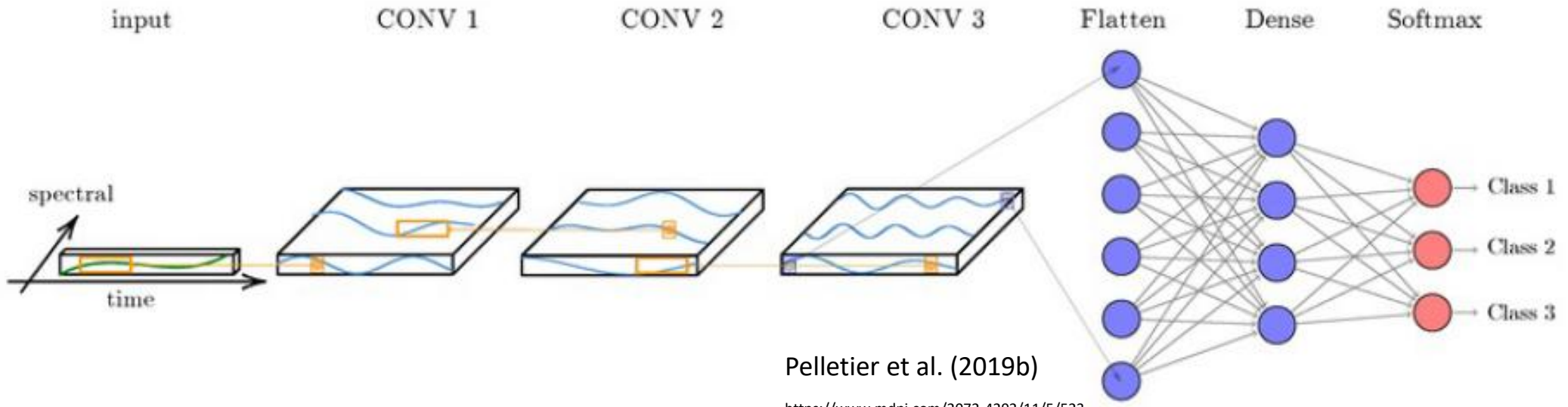
Temporal Convolutional Neural Network

The network input is a multivariate time series.
Three convolutional filters are consecutively applied, then one dense layer, and finally the Softmax layer, which provides the predicted class distribution.

Fully connected neural network



TempCNN architecture for a classification task.



Pelletier et al. (2019b)

https://www.mdpi.com/2072-4292/11/5/523



Transformers

Attention Is All You Need

Vaswani et al. (2017)

Based solely on attention mechanisms, dispensing with recurrence and convolutions entirely

From NLP (natural language processing)
– automatic translation instead of words and phrases
– the whole book with attention (markers)
– retrieve easily one paragraph (like people chatting – what is interesting?)

Self-Attention - modeling relationships among all elements in the input;
Multi-Head Attention - simultaneous learning of different types of relationships;
Elimination of recurrent networks;
Parallel processing;
Transformer architecture.

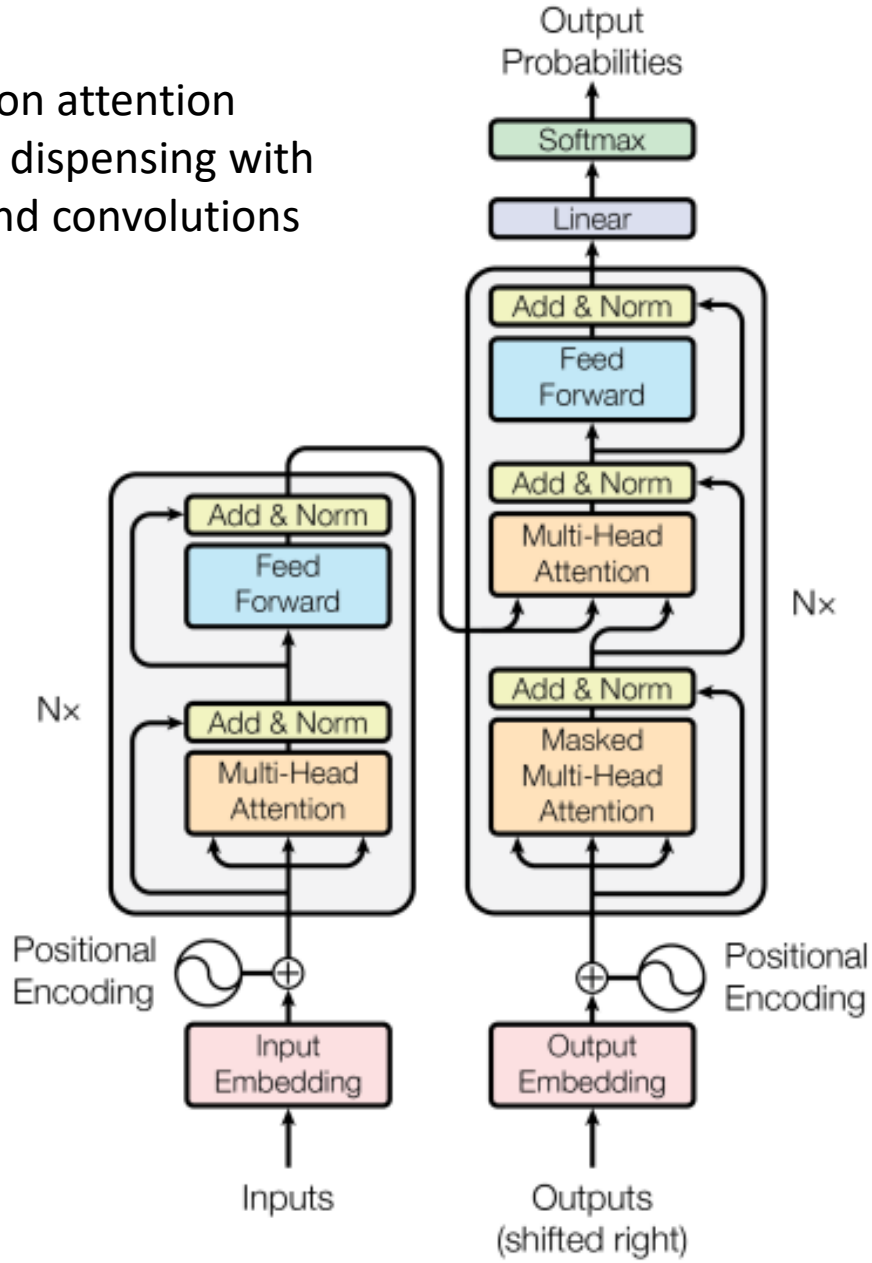


Figure 1: The Transformer - model architecture.



Transformers

Attention Is All You Need

Vaswani et al. (2017)

Vision Transformer (ViT)
Masked Autoencoder (MAE)
SatMAE
Prithvi
Clay
DOFA

Self-attention mechanisms to model both spatial relationships and temporal trajectories across vast landscapes

A fragment can be identified as **secondary vegetation**
not only by its spectral signature,
but also because
it is located within a previously deforested area,
near other regenerating fragments, and
because it shows consistent evolution over a time series of images.

It is this integration of spatial and temporal context that makes Transformers particularly promising for remote sensing applications.

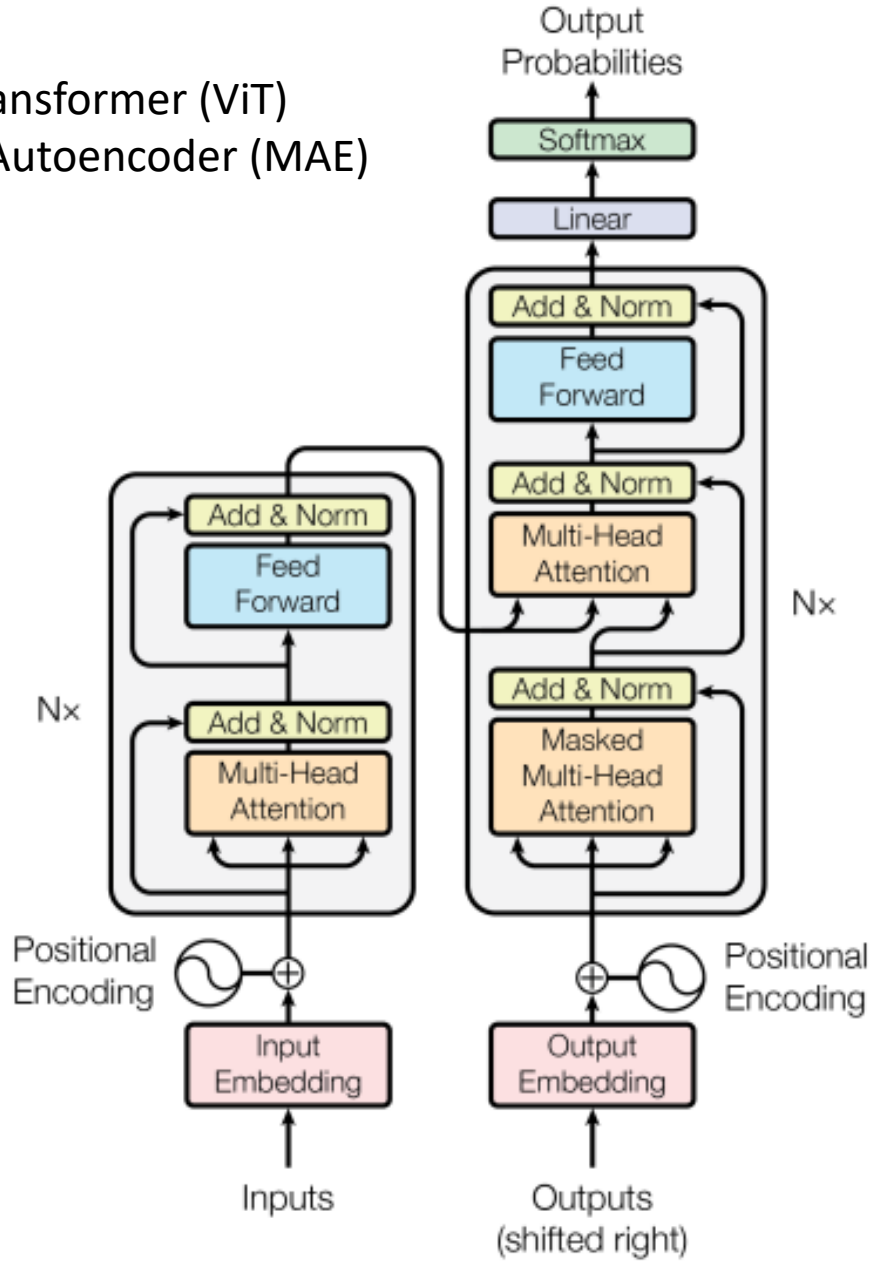
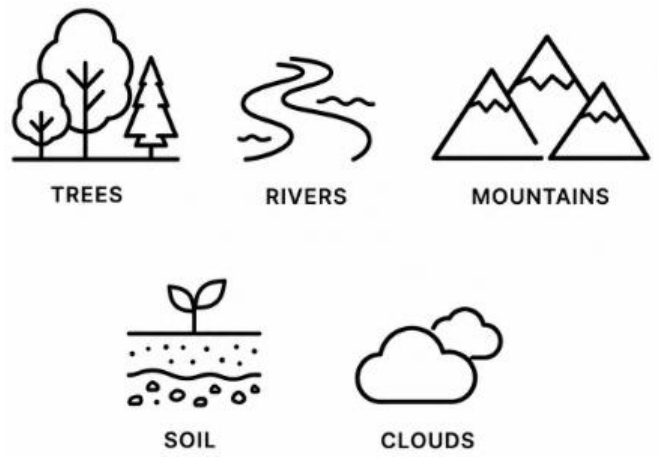


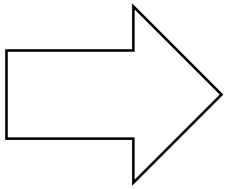
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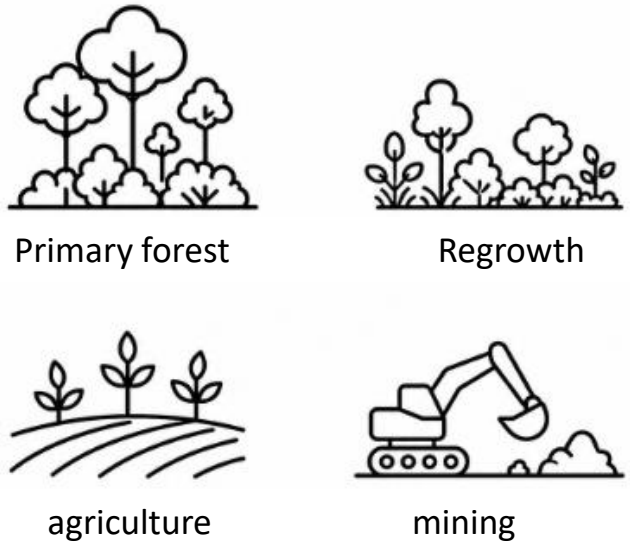


Foundation Models

A **Transformer** is a neural network **architecture** (the "engine").
A Foundation Model (FM) is a **training paradigm** (a way of building general-purpose models that can be adapted to many downstream tasks)



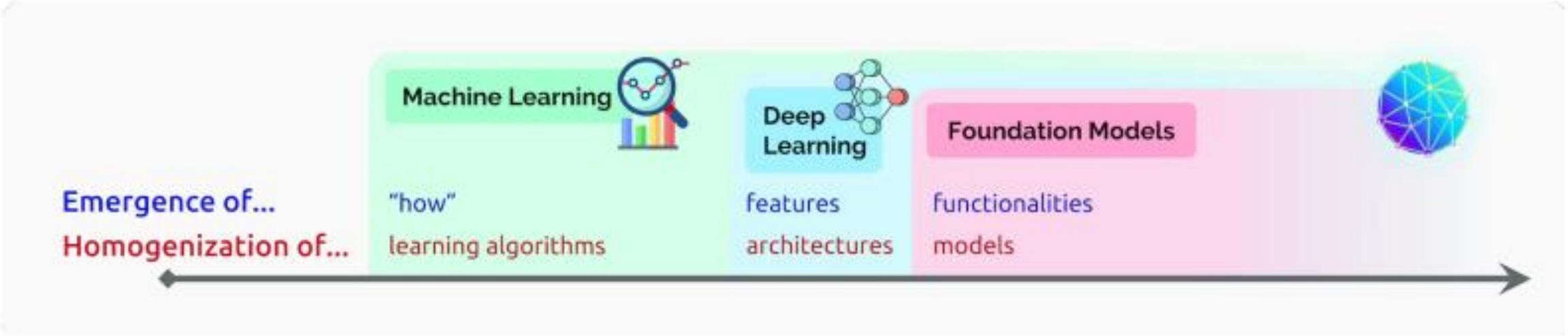




Pretraining
Instead of directly teaching the model that "**this is a forest**",
the model first learns more **fundamental concepts** such as textures, spatial patterns, spectral relationships, temporal dynamics, object shapes, and contextual information.
Afterward, the model can be specialized for a particular application.

Foundation Models

Stanford University:
On the Opportunities and Risks of Foundation Models
(Bommasani et al., 2021).



"How can we build a better model for this task?"

"How can we adapt a general-purpose model to solve this task as effectively as possible?"

A paradigm shift in the way AI systems are developed

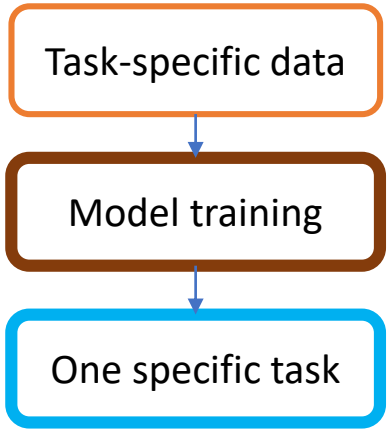


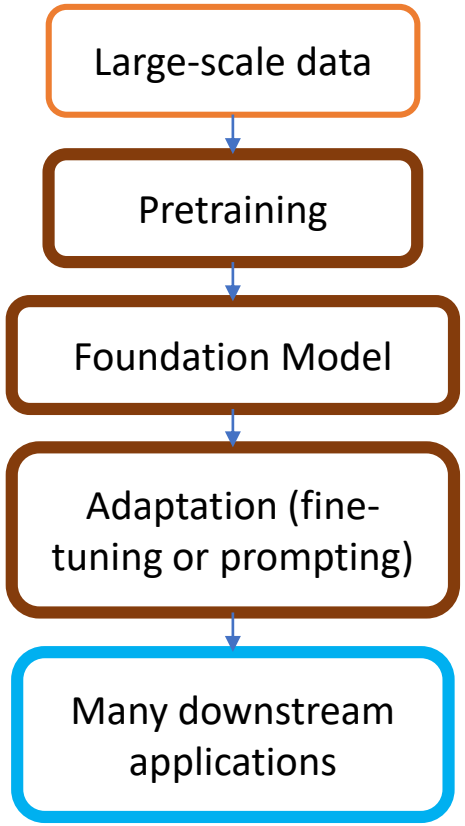
Foundation Models

Stanford University:
On the Opportunities and Risks of Foundation Models
(Bommasani et al., 2021).

A model trained on large and diverse datasets, typically through large-scale, self-supervised learning, that can be adapted for a wide variety of downstream tasks.

Self-supervised learning





Advantages:

- Knowledge reuse: a single model for different applications.
- Reduced dependence on labeled data, learning large-scale self-supervised pretraining.
- Improved performance compared with models trained on task-specific datasets.
- Knowledge transfer across domains and applications.

- Accelerated innovation: researchers can focus on adapting pretrained models instead of developing new models from scratch.

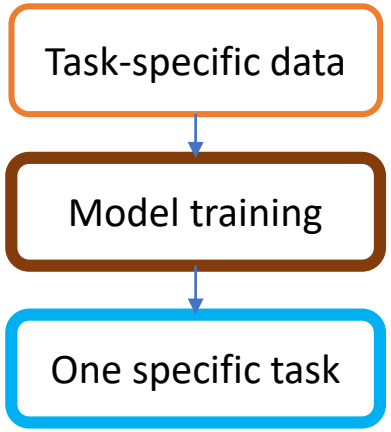


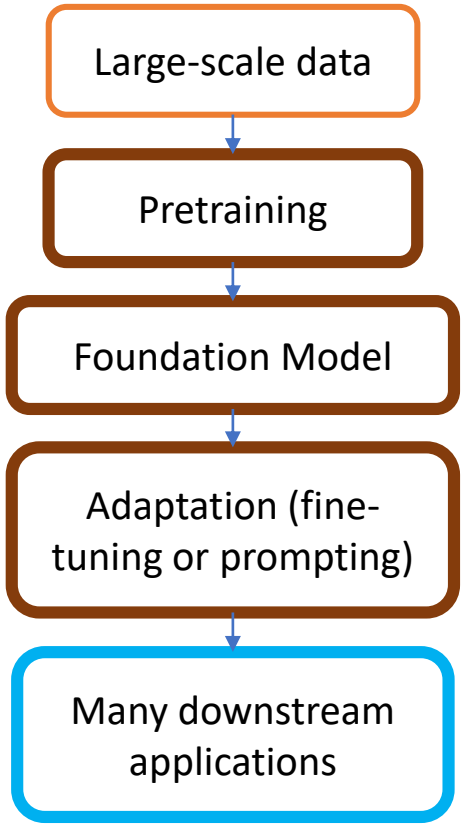
Foundation Models

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A model trained on large and diverse datasets, typically through large-scale, self-supervised learning, that can be adapted for a wide variety of downstream tasks.

Self-supervised learning





- Emergent Capabilities - exhibit behaviors that **were neither explicitly programmed nor observed in smaller models**.
- Technical Challenges: computational cost of training, need for very large datasets, limited interpretability of model behavior
- Social and Ethical Risks: **biases** inherited from training data, **lack of transparency**, **malicious use**, environmental impacts, **concentration of technological power.**

Foundation Models

Challenges

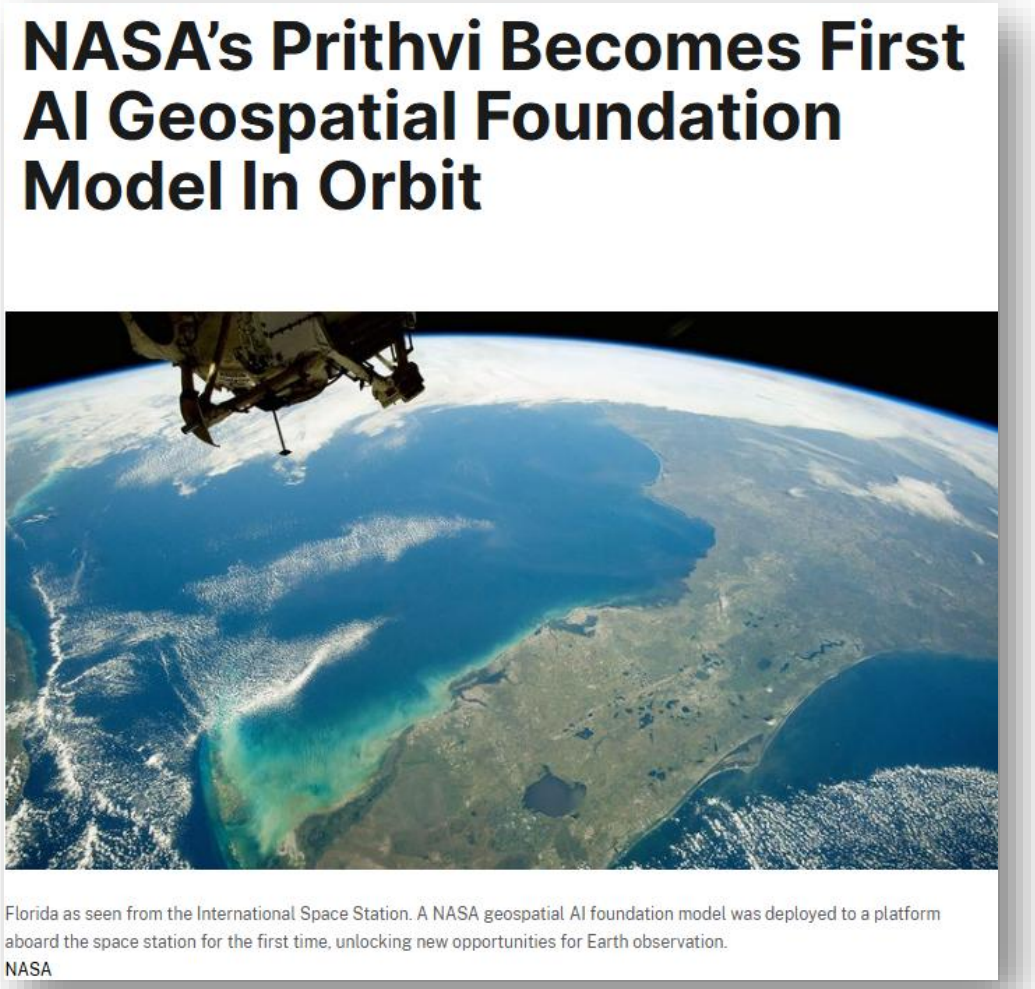
1. **High Data and Computational Requirements**

   Training

   Millions to billions of images
   Hundreds of millions (or even billions) of parameters
   Thousands of GPUs running for weeks or months

   Few research institutions can afford to train a foundation model from scratch
   Most users rely on publicly available pre-trained models and perform fine-tuning for their own applications.

Prithvi (NASA/IBM)
Clay Foundation Model
SatMAE
CROMA
DOFA
AnySat



https://science.nasa.gov/science-research/ai-foundation-model-in-orbit/

Foundation Models

Challenges

2. Limited Generalization - They do not generalize perfectly



A model pre-trained on
- U.S. agricultural landscapes,
- European cities,
- Boreal forests,



May perform poorly when applied to
the Amazon,
the African Savannah,
the New Zealand´s forests

The ecosystems differ in:
species composition,
climate,
sensor characteristics,
phenology,
vegetation structure.

Therefore, high performance often still requires
- fine-tuning,
- domain adaptation,
- locally collected training data.



Foundation Models

Challenges

3. Dependence on Pre-training Data - depends on the diversity of the pre-training dataset.

Currently, publicly available datasets contain relatively limited information on:

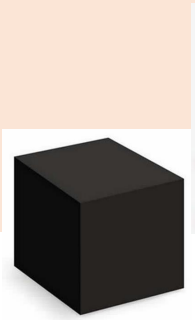
tropical forests,
secondary forests,
forest degradation,
forest management,
wildfire damage across multiple recovery stages.

4. Limited Interpretability – "black boxes."

Can not answer questions about the contribution or importance of variables

This lack of transparency complicates

- scientific validation,
- model explainability,
- operational trust.







Foundation Models

Challenges

5. High Computational Cost During Inference - computationally demanding, even after training.

Limitations:

Large GPU memory requirements,
slow inference,
high cloud-computing costs,
limited scalability for operational systems.

Some current models contain hundreds of millions of parameters, making nationwide operational deployment computationally expensive.

6. Sensor Generalization – basic pre-training

Many foundation models pre-trained
- Sentinel-2,
- Landsat,
- RGB imagery.

Forest monitoring relies on
- Sentinel-1 SAR,
- LiDAR,
- GEDI,
- Planet imagery,
- CBERS,
- hyperspectral imagery.

6. Time-Series Modeling Remains Challenging

A few foundation models currently exploit long-term satellite image time series effectively (AnySat, Prithvi)

It needs active development.

Research frontiers in AI-based forest monitoring



AI for Forest Monitoring Tasks

Task	Main AI methods
Forest mapping and land-cover classification	Random Forest, SVM, CNNs, Vision Transformers
Deforestation detection	CNNs, U-Net, Siamese Networks, Transformers
Forest degradation monitoring	CNNs, Temporal CNNs, LSTM, Vision Transformers
Forest recovery and regeneration	LSTM, GRU, Temporal Transformers
Biomass and carbon estimation	Random Forest, Gradient Boosting, Deep Neural Networks
Individual tree detection and canopy characterization	CNNs, Mask R-CNN, U-Net, YOLO
Forest disturbance and change detection	Siamese CNNs, BIT, ChangeStar, Vision Transformers
Forest fire assessment	CNNs, DeepLab, Transformers
Near-real-time forest monitoring	Temporal Transformers, Self-supervised Learning, Foundation Models
General-purpose geospatial analysis	Foundation Models, Multimodal AI

Tree species classification

Taher et al. (2026)

ISPRS Journal of Photogrammetry and Remote Sensing 233 (2026) 278–309

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ISPRS Journal of Photogrammetry and Remote Sensing

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

Multispectral airborne laser scanning for tree species classification: A benchmark of machine learning and deep learning algorithms



Fig. 1. (a) The Espoonlahti study area is located in southern Finland. (b) Orthophoto of the Espoonlahti study area together with collected tree segments colored by the species in the reference dataset. The coverage of the HeliALS data is shown with the light blue line. Areas A and B are separated by the orange line. (c) A close-up of the orthophoto shown in (b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Tree species classification

Develop the **largest benchmark** for multispectral **Airborne Laser Scanning (ALS) tree species classification** and evaluate the performance of state-of-the-art **ML** and **DL** algorithms.

Dataset

- 6,326 individually labeled trees
- 9 tree species
- Two multispectral ALS datasets with different point densities

Algorithms Compared

- **Machine Learning:** Random Forest, XGBoost, LightGBM, MLP
- **Deep Learning:** PointNet++, PointMLP, **Point Transformer**, DetailView

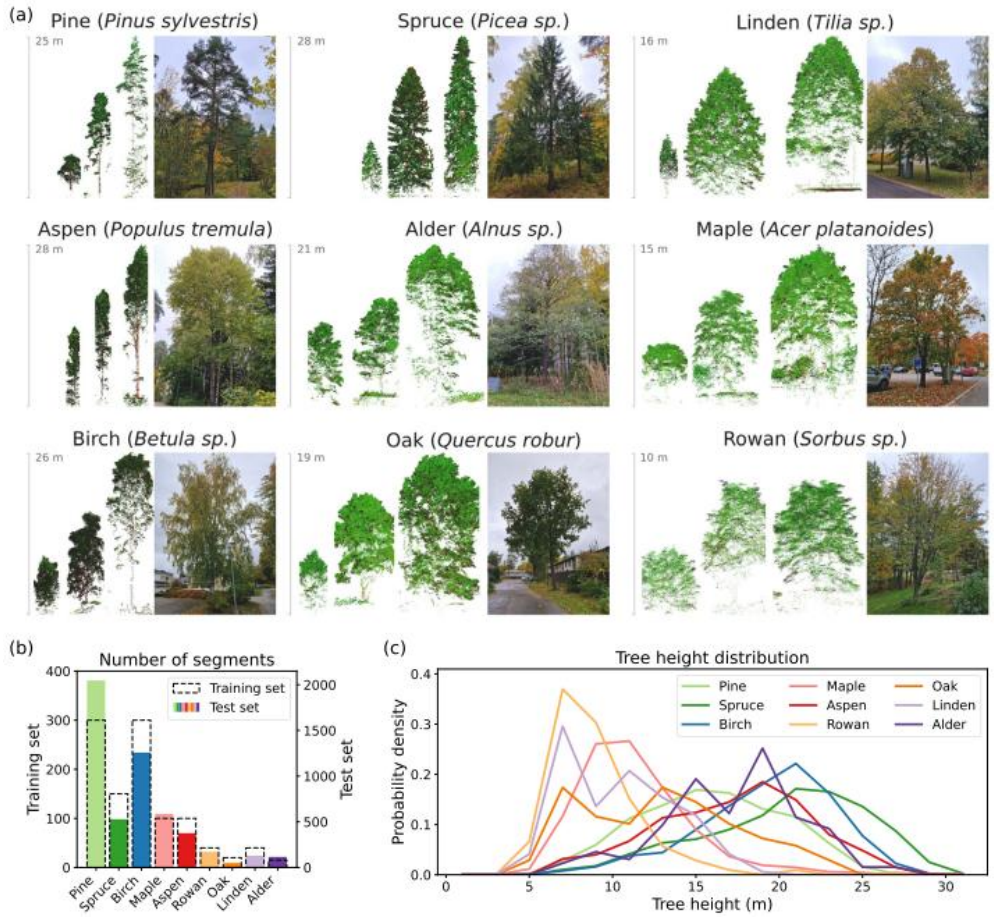
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Tree species classification

Performance Comparison

- **Point Transformer** achieved the highest classification accuracy (**~92% Overall Accuracy**).
- Deep Learning consistently outperformed traditional Machine Learning.
- Multispectral information significantly improved classification accuracy compared with geometry alone.
- Performance gains were especially evident for:
  - Sparse point clouds
  - Larger training datasets
  - Difficult-to-distinguish species

Taher et al. (2026)

ISPRS Journal of Photogrammetry and Remote Sensing 233 (2026) 278–309

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

Multispectral airborne laser scanning for tree species classification: A benchmark of machine learning and deep learning algorithms

Main Contributions

- First comprehensive benchmark comparing ML and DL for multispectral ALS tree species classification.
- Demonstrated the superiority of **Transformer-based models** over traditional approaches.
- Confirmed the importance of combining **3D structural** and **spectral** information.
- Provides an **open benchmark dataset**, supporting reproducible research and the development of next-generation AI methods for forest monitoring.

Tree species classification

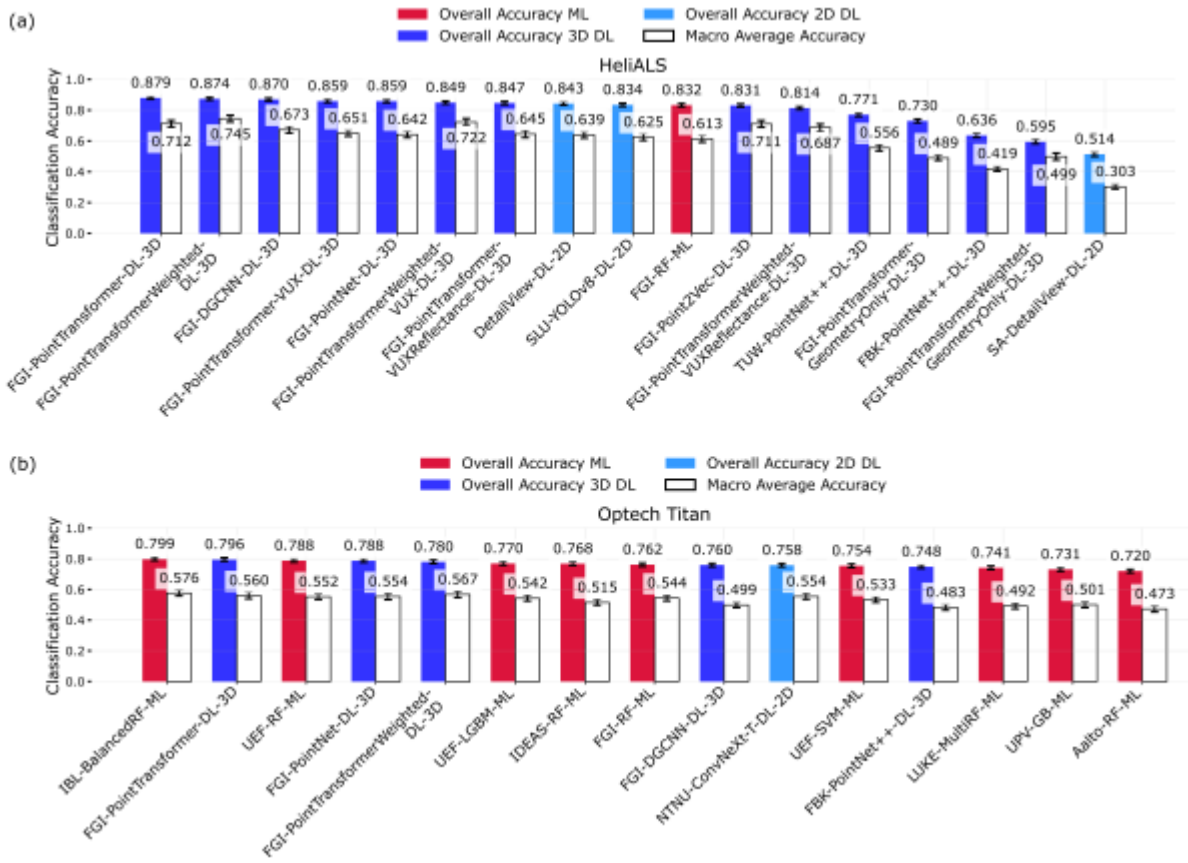


Fig. 6. (a) Comparison of overall (filled bar) and macro-average (outline) accuracy for methods using HeliALS data, with point-based DL methods shown with dark blue color, image-based DL methods shown with light blue color, and machine learning methods shown with red color. The error bars represent 95% confidence intervals based on a bootstrapping approach, see Section 3.3. SA-DetailView-DL-2D was not retrained on the training set of the current study, and the model parameters were directly transferred from Puliti et al. (2025). When neglecting aspens, rowans and alders not present in the FOR-species20K dataset (Puliti et al., 2025), SA-Detailview-DL-2D reached an overall accuracy of 58.8% and a macro-average accuracy of 45.4%. (b) Same as (a) but for the methods using the Optech Titan dataset. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Forest fire assessment

fire

MDPI

Forest fire assessment

Article

Explainable AI-Driven Wildfire Prediction in Australia: SHAP and Feature Importance to Identify Environmental Drivers in the Age of Climate Change

Zina Abohaia [1,*], Abeer Elkhouly [2,*], May El Barachi [1] and Obada Al-Khatib [2]

Objective

- Develop an **interpretable machine learning framework** to predict wildfire characteristics across Australia's diverse climate regions.
- Identify the **environmental drivers** of wildfire behavior using **Explainable AI (XAI)**.

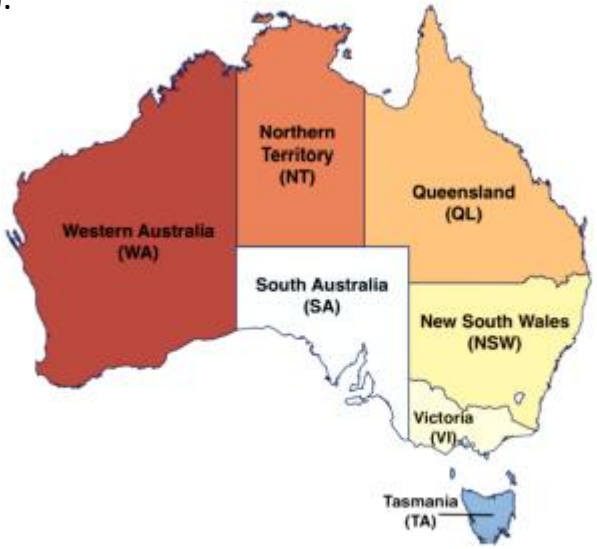


Figure 1. Study area: the seven Australian regions.

Methodology

Study area: Seven Australian regions (2005–2021).

Input data:

- ERA5 climate variables (temperature, precipitation, humidity, wind speed, soil moisture, solar radiation)
- MODIS active fire products

Predicted wildfire variables:

- Fire Area (FA)
- Fire Brightness Temperature (FBT)
- Fire Radiative Power (FRP)

Machine Learning models:

- Lasso Regression
- Random Forest
- LightGBM
- XGBoost

Explainability:

- SHAP (SHapley Additive exPlanations)
- Feature importance analysis to quantify each variable's contribution.

Innovation

High predictive performance with **model interpretability** → identification of the physical processes controlling wildfire occurrence and intensity.

fire

MDPI

Forest fire assessment

Article

Explainable AI-Driven Wildfire Prediction in Australia: SHAP and Feature Importance to Identify Environmental Drivers in the Age of Climate Change

Main Results

Soil moisture, solar radiation, precipitation, and relative humidity are the dominant wildfire predictors.

Climate variability and extreme conditions (variance, minimums and maximums) are **more informative than long-term averages**.

The importance of predictors varies among Australian climate zones:

- **Arid regions:** Lasso effectively captures linear relationships.
- **Tropical regions:** Tree-based ensemble models (LightGBM, Random Forest, XGBoost) better represent complex non-linear interactions.

Best predictive performance:

- **Fire Area:** Tasmania (LightGBM)
- **Fire Radiative Power:** Queensland (Lasso)

Fire radiate power

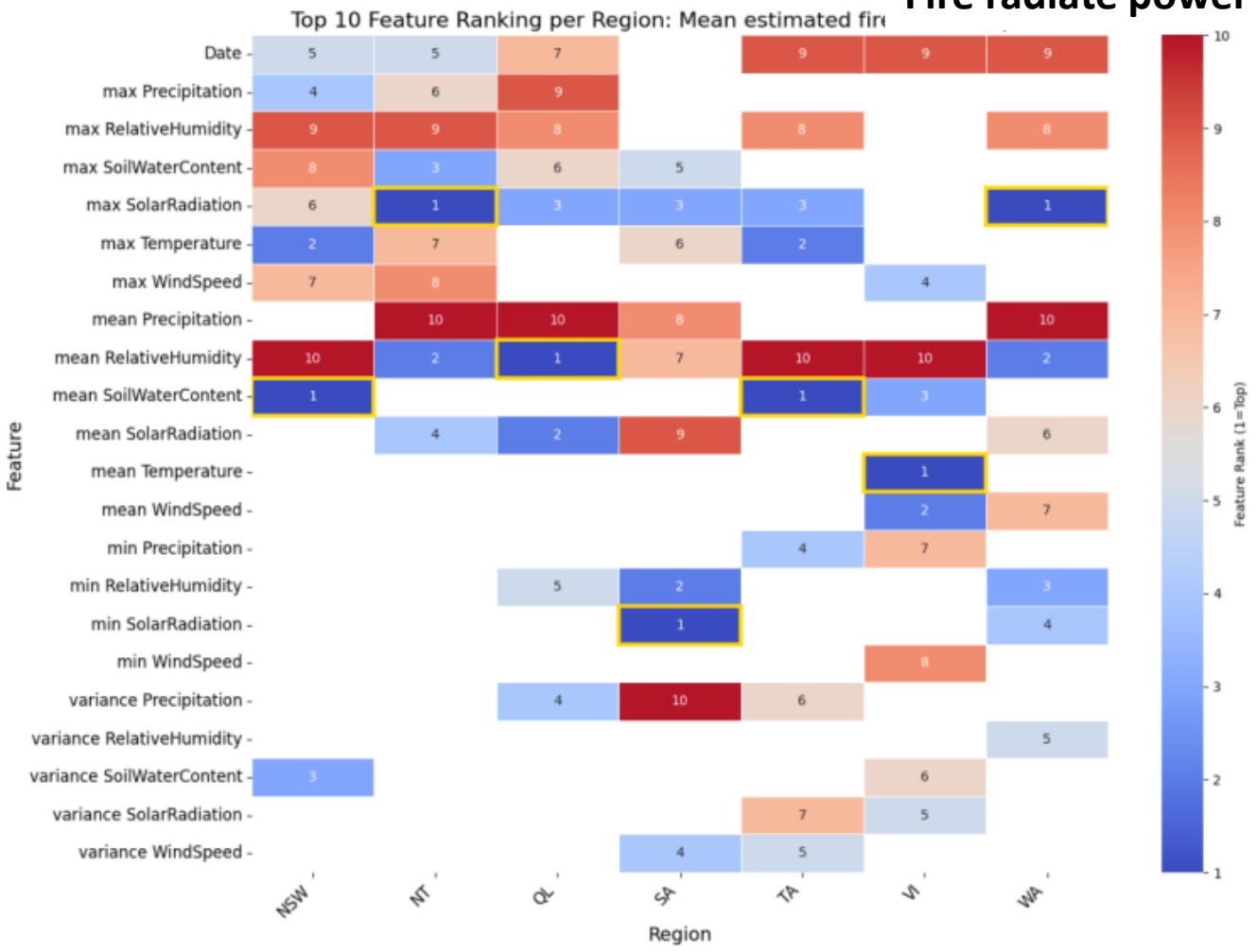


Figure 5. Top 10 features for each region's best model in predicting FRP, with 1 = Most Important to 10 = Least Important, and the yellow outline highlighting the top feature for that region.

fire

MDPI

Article

Explainable AI-Driven Wildfire Prediction in Australia: SHAP and Feature Importance to Identify Environmental Drivers in the Age of Climate Change



Key Conclusions

Wildfire behavior follows a hierarchical process:

- **Long-term environmental stress** (soil moisture depletion + solar radiation) determines fire potential.

- **Short-term weather variability** (humidity, temperature, wind) controls ignition and fire spread.

Explainable AI provides transparent information for **region-specific wildfire management**, supporting climate adaptation and operational decision-making.

Future work should integrate **foundation models, transformers, generative AI, and multi-source data fusion** for real-time wildfire forecasting.

forests Shahid et al. (2023) MDPI

Article

Forest Fire Segmentation via Temporal Transformer from Aerial Images

Mohammad Shahid [1], Shang-Fu Chen [1], Yu-Ling Hsu [2], Yung-Yao Chen [3], Yi-Ling Chen [1] and Kai-Lung Hua [1,*]

Objective

Develop an efficient **real-time wildfire segmentation model** for UAV video monitoring.

Overcome limitations of CNN-based methods, which often fail to capture temporal information and accurately localize fire boundaries.

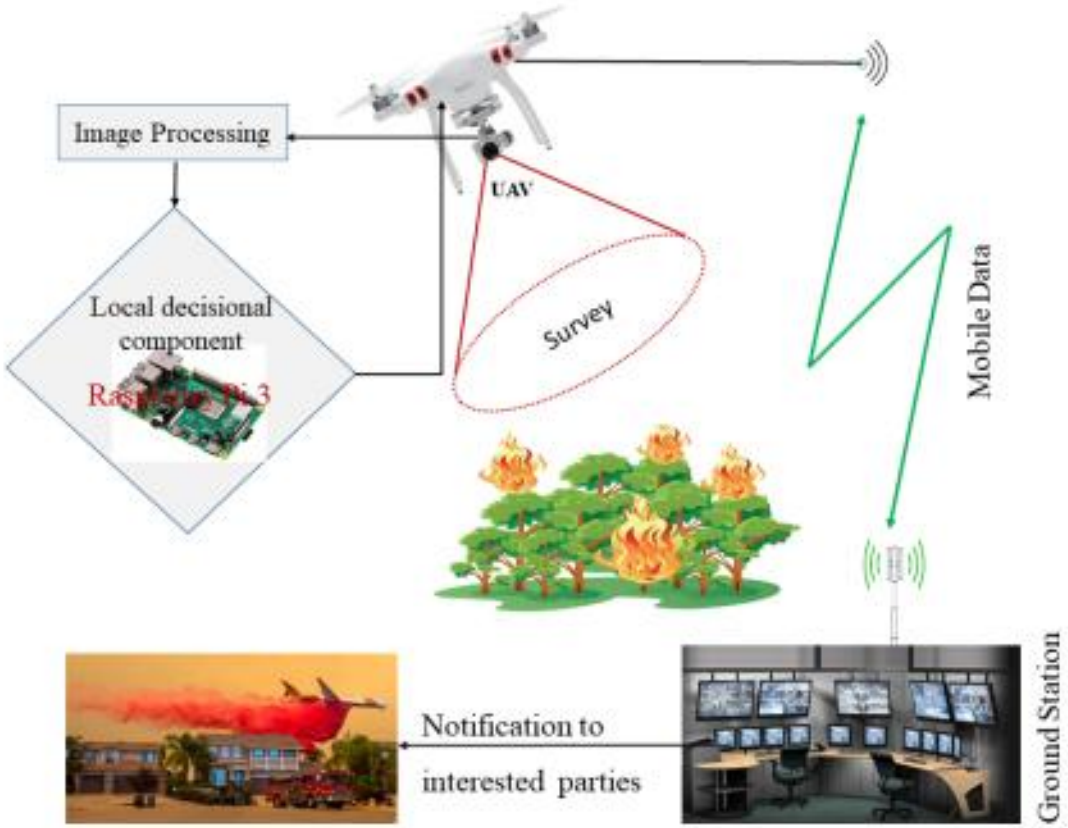


Figure 1. A conceptual model for early forest fire detection.

forests Shahid et al. (2023) MDPI

Article

Forest Fire Segmentation via Temporal Transformer from Aerial Images

Mohammad Shahid [1], Shang-Fu Chen [1], Yu-Ling Hsu [2], Yung-Yao Chen [3], Yi-Ling Chen [1] and Kai-Lung Hua [1,*]

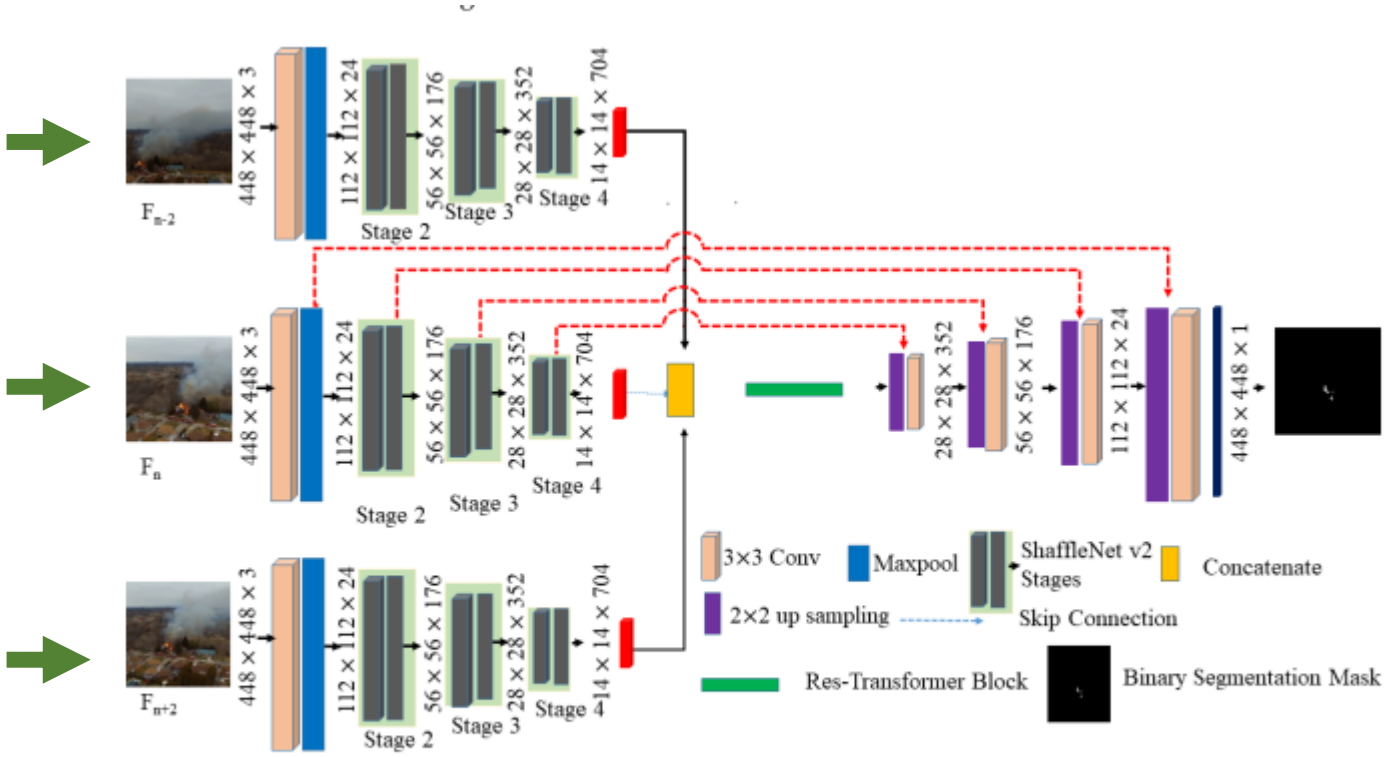


Figure 2. The architecture of our proposed FFS-UNet network. It comprised two paths: the encoder path was accountable for extracting spatiotemporal features for understanding view transformation. At the same time, the decoder path was used to retrieve progressively more refined attributes by combining information from the peer-encoder path.

Proposed Method: FFS-UNet

Novel **UNet + Vision Transformer(ViT)** architecture for semantic fire segmentation.

Three parallel encoder branches process three consecutive UAV frames (Fn−2, Fn, Fn+2) to learn both **spatial and temporal information**.

Transformer module models **long-range temporal dependencies**, improving discrimination between fire and visually similar objects.

Lightweight **ShuffleNetV2** backbone reduces computational cost, making the model suitable for **edge devices and UAV applications**.

Combined **Dice + Binary Cross-Entropy loss** improves segmentation under class imbalance.

forests Shahid et al. (2023) MDPI

Article

Forest Fire Segmentation via Temporal Transformer from Aerial Images

Mohammad Shahid [1], Shang-Fu Chen [1], Yu-Ling Hsu [2], Yung-Yao Chen [3],



Main Results and Contributions

Performance

Achieved **state-of-the-art performance** on UAV wildfire datasets:
(**IoU:** 86.8%; **Precision:** 96.3% , **Recall:** 94.0%, **F1-score:** 95.1%, **Accuracy:** 97.9%)

Advantages

Outperformed **UNet, DeepLabV3+, TransUNet, Swin-UNet, SegFormer, and STNet+DenseFire**.

More accurate fire localization with fewer false positives, especially in challenging scenes (smoke, shadows, cluttered backgrounds).

Demonstrated strong **generalization** on the independent Corsican Fire dataset.

Robust against image degradation (fog, Gaussian noise, and motion blur).

Lightweight implementation (**14.2 million parameters**) with **66 FPS**, enabling **real-time deployment on UAV platforms**.

Temporal information is crucial for wildfire detection.

Integrating **Vision Transformers** with **UNet** enables more reliable fire segmentation than single-image CNN approaches, providing a practical solution for **real-time wildfire monitoring and early warning systems**.

An early example of combining **Vision Transformers** with **semantic segmentation** for **wildfire detection**

Innovation: The use of **temporal context from UAV videos**, instead of single-frame image classification or segmentation.

INPE Programa Queimadas

INPE's **QUEIMADAS PROGRAM** researches, develops, operates, and disseminates data and information systems for monitoring vegetation fires via satellite.

ACTIVE FIRE FOCI

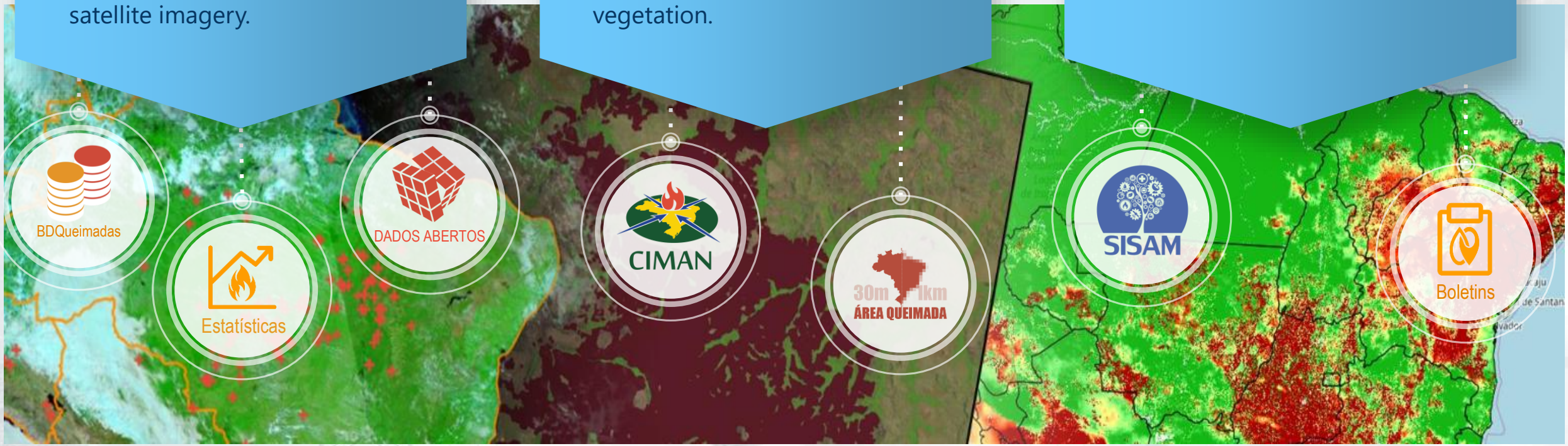
Shows **where** active fires are located in near real time using satellite imagery.

BURNED AREA

Determine the **extent** of the area affected by the fire in the vegetation.

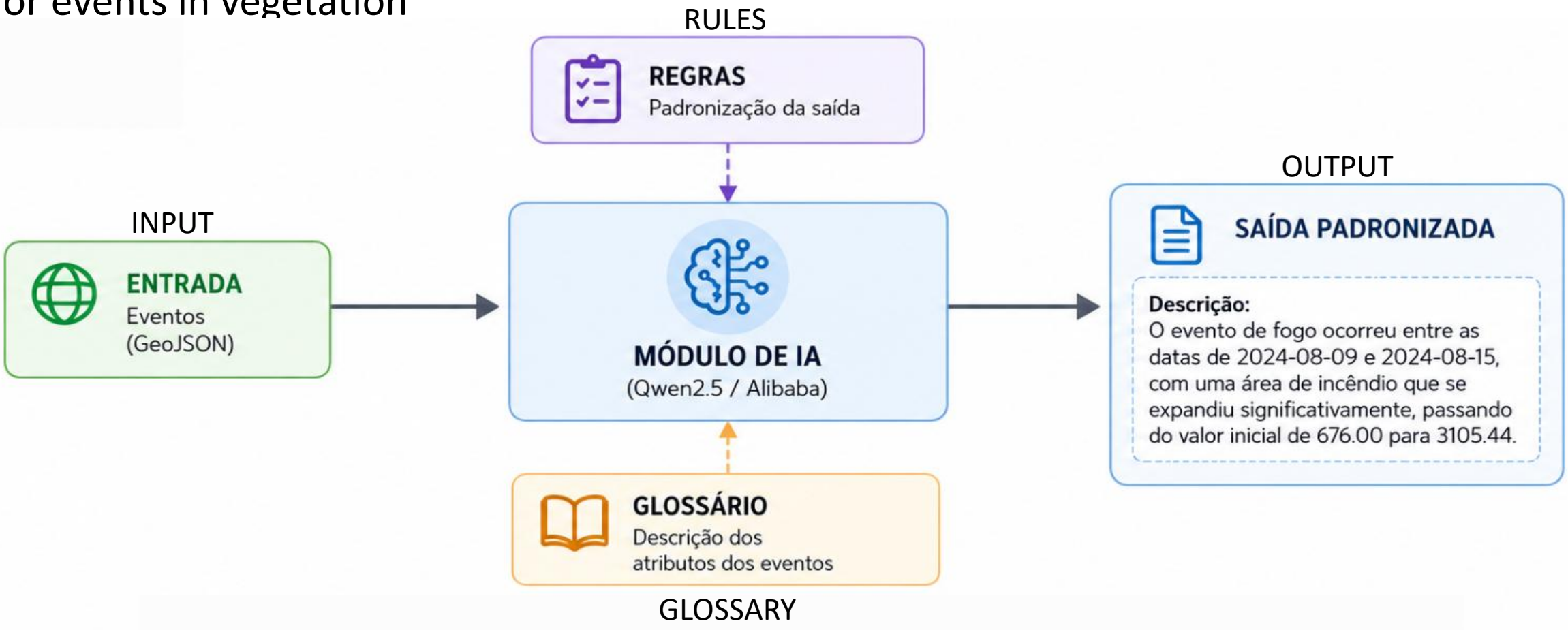
FIRE RISK

Forecasting vegetation fire risk based on meteorological data.



Use of AI for Fire Characteristics: **Descreve Fogo**

Generation of a consolidated, data-integrated text to describe fire regions or events in vegetation



Use of AI for Fire Characteristics: **Descreve Fogo**

Examples of information generated by **DescrEVE**

Descrição situação atual do município de CAXIAS-MA

Na data de **15/10/2025**, o município de Caxias obteve **7 eventos** de fogo, sendo o **1º maior registrado** para o histórico do período, representando **1,4%** dos eventos do Maranhão, que teve **503 eventos**. A média FRP foi de **51,71 MW**. O maior evento em área de Caxias teve um acumulado de **12.427,93 hectares**.

Descrição do evento mais significativo do município

Local:	Classificação:	Período:	Área acumulada afetada:
Assentamento Pa Engenho Dgua	**Incêndio**	**17/08/2025 a 15/10/2025 (60 dias)**	**12.427,93 ha**

- É registrada uma sequência de **19 dias** sem precipitação, contribuindo para a senescência/envelhecimento da vegetação e aumentando a probabilidade de continuidade do evento.
- O evento apresenta **91 frentes** de fogo ativas ao longo do período monitorado.
- A análise da progressão do evento demonstra que a área afetada apresenta um acréscimo de **1.791,35 hectares** desde a última atualização.
- Comparando-se com a amplitude histórica de expansão da área para este evento, observa-se que a variação permanece dentro da faixa de **99,97 a 12.427,93 hectares**.
- O evento é o maior evento em quantidade de frente, maior evento em duração e maior evento em área acumulada para a data de **17/08/2025** no Assentamento Pa Engenho Dgua.

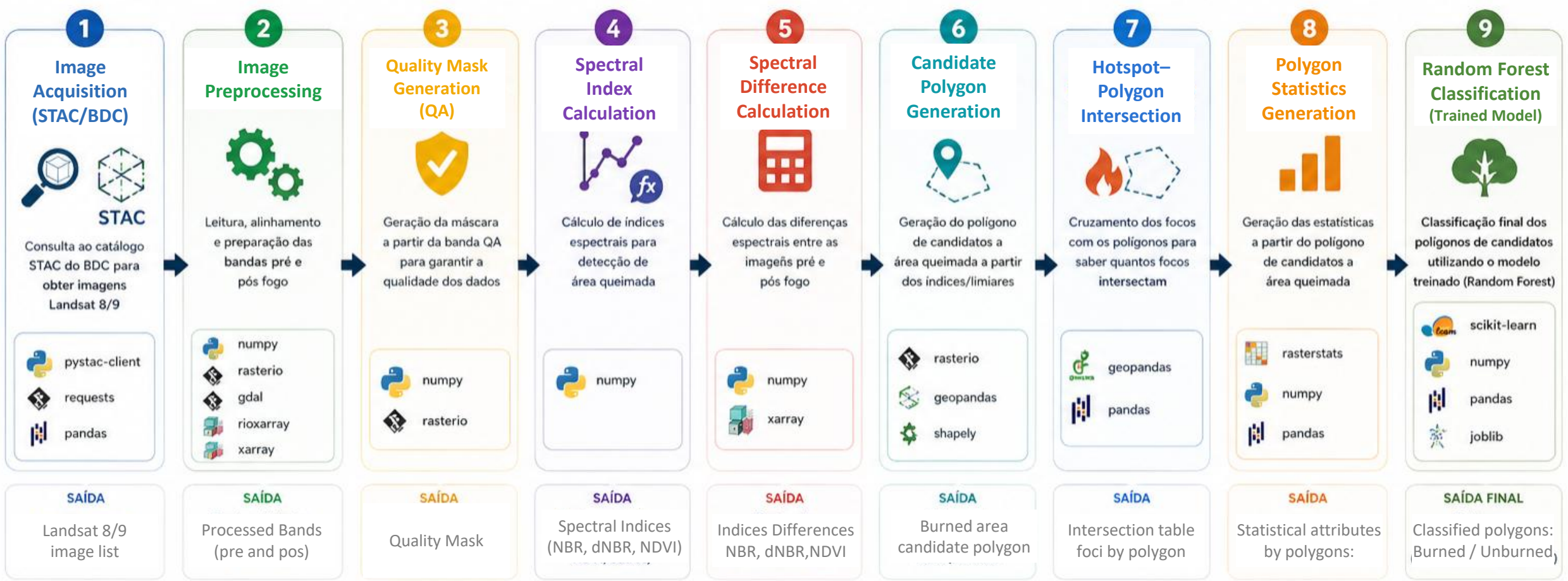
Quantidade de frentes
91 frentes
Média na região: **48** frentes
Posicionado entre os **100%** maiores

Duração do evento
60 dias
Média na região: **32** dias
Posicionado entre os **100%** que duram mais tempo

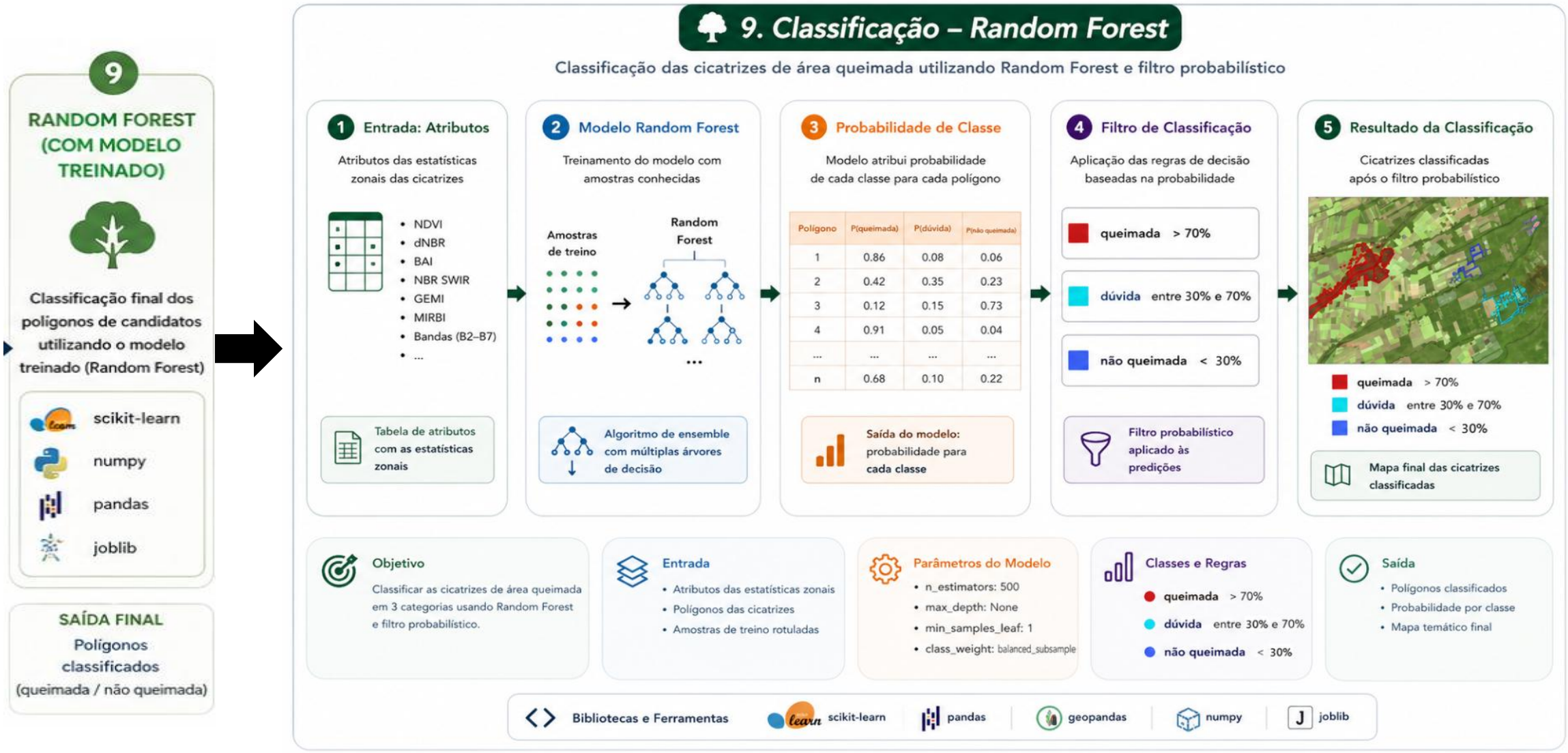
Área afetada
12.427,93 ha
Média na região: **7.177,11** ha
Posicionado entre os **100,0%** que afetam as maiores áreas

Resumo geral
Este evento apresenta atividade acima do normal para a região em todos os aspectos analisados, destacando-se como um evento extremo em frentes de fogo, duração e área afetada.

MAPIA30M - Mapping of Burned Areas in the BDC



Methodology for quality control of the data made available to users.





IA-FogoBio

Instituto Federal do Amazonas (IFAM)



Foto: CARL DE SOUZA/AFP

LSTM (Long Short-Term Memory) neural networks, convolutional networks, and Random Forest

Information on fire history over the past 20 years, vegetation, soil type, and environmental conditions → areas at higher risk of fire.

Risk areas (7-14 days) and alerts (6 hours)

Ibama /ICMBio → Time to plan strategies for deploying firefighters, equipment, and routes for preventive action

Monitors 100% of Indigenous Land, Conservation Units and Quilombola Territories in the Amazon biome

Funded by Google.org with R$ 1.9 million

IFAM Innovation Hub/ Management and Operations Center of the Amazon Protection System (Censipam)

https://18horas.com.br/noticias/ia-desenvolvida-no-instituto-federal-do-amazonas-promete-prever-queimadas-na-amazonia-com-ate-14-dias-de-antecedencia/

Biomass and carbon estimation

Biomass and Carbon Estimation - evolution

Aboveground Biomass (AGB) as an Essential Climate Variable

Forest biomass estimation has evolved from local empirical models to global AI-driven approaches integrating remote sensing and field observations.

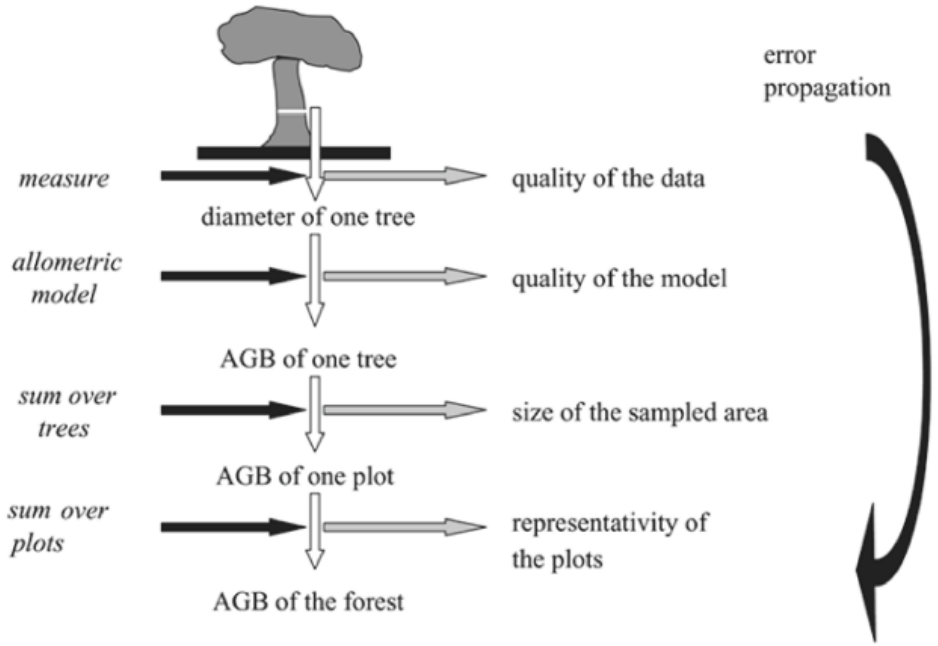


Fig. 1. Procedure for biomass estimation in plots and its error propagation (Rodríguez et al., 2017).

Trees, Forests and People 22 (2025) 101057

Contents lists available at ScienceDirect

Trees, Forests and People

journal homepage: www.sciencedirect.com/journal/trees-forests-and-people

Quantifying forest above ground biomass: a critical review of methods, challenges, and opportunities

Fortunate Kemigyisha [a,*], Evet Naturinda [b], Emmanuel Omia [a], Jackline Aboth [a], Denis Mutiibwa [c], Isa Kabenge [a], Anthony Gidudu [b], Nicholas Kiggundu [a]

[a] Department of Agricultural and Biosystems Engineering, Makerere University, P.O. Box 7062, Kampala, Uganda
[b] Department of Geomatics and Land Management, Makerere University, P.O. Box 7062, Kampala, Uganda
[c] 1410 Montello Ave NE #2 Washington DC, 20002, USA

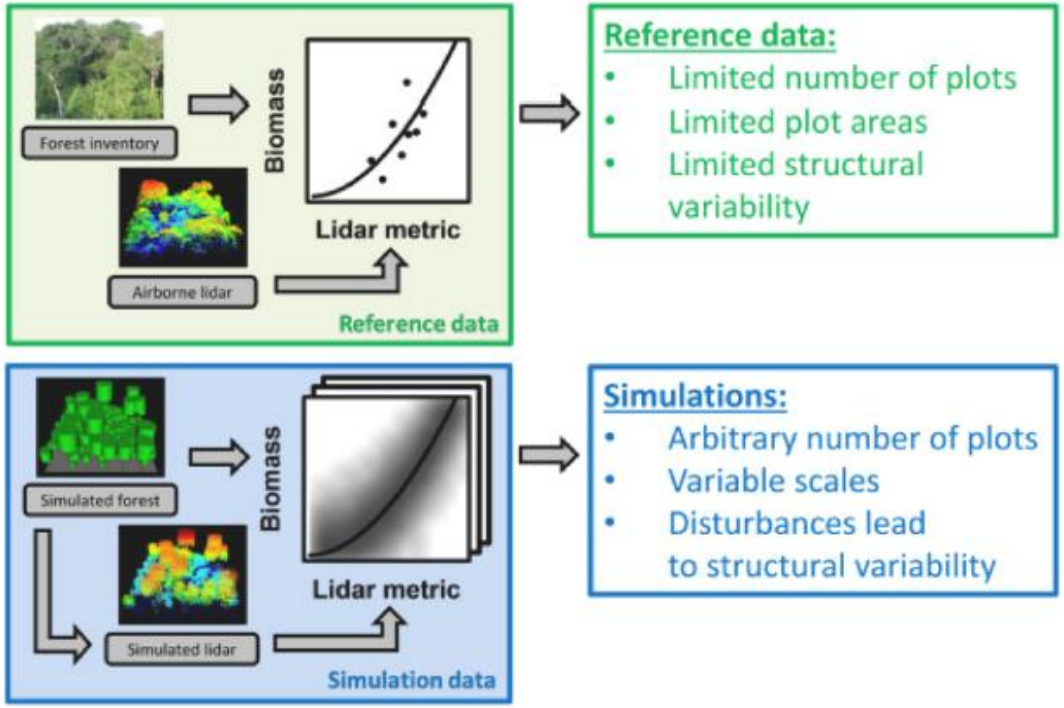


Fig. 2. Use of LiDAR data for biomass estimation (Knapp et al., 2018).

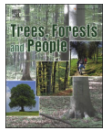
Biomass and Carbon Estimation - evolution

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[c] 1410 Montello Ave NE #2 Washington DC, 20002, USA

Forest inventories → Remote sensing → Artificial Intelligence

Environmental variables and biomass:
ML (Random Forest, SVM, Artificial Neural Networks) and DL
→ outperforming conventional statistical methods.

Statistical Models → Random Forest / XGBoost → Deep Learning (CNN) → Vision Transformers → Foundation Models → Global-scale Models

AI is transforming forest biomass and carbon estimation **from site-specific models into scalable, globally applicable prediction systems.**

Multi-sensor data fusion, Explainable AI (XAI), spaceborne LiDAR, and cloud computing

Data Integration

Optical + SAR + LiDAR → improves AGB estimation

Multi-Source Remote Sensing is More Important than Any Single Algorithm

forests

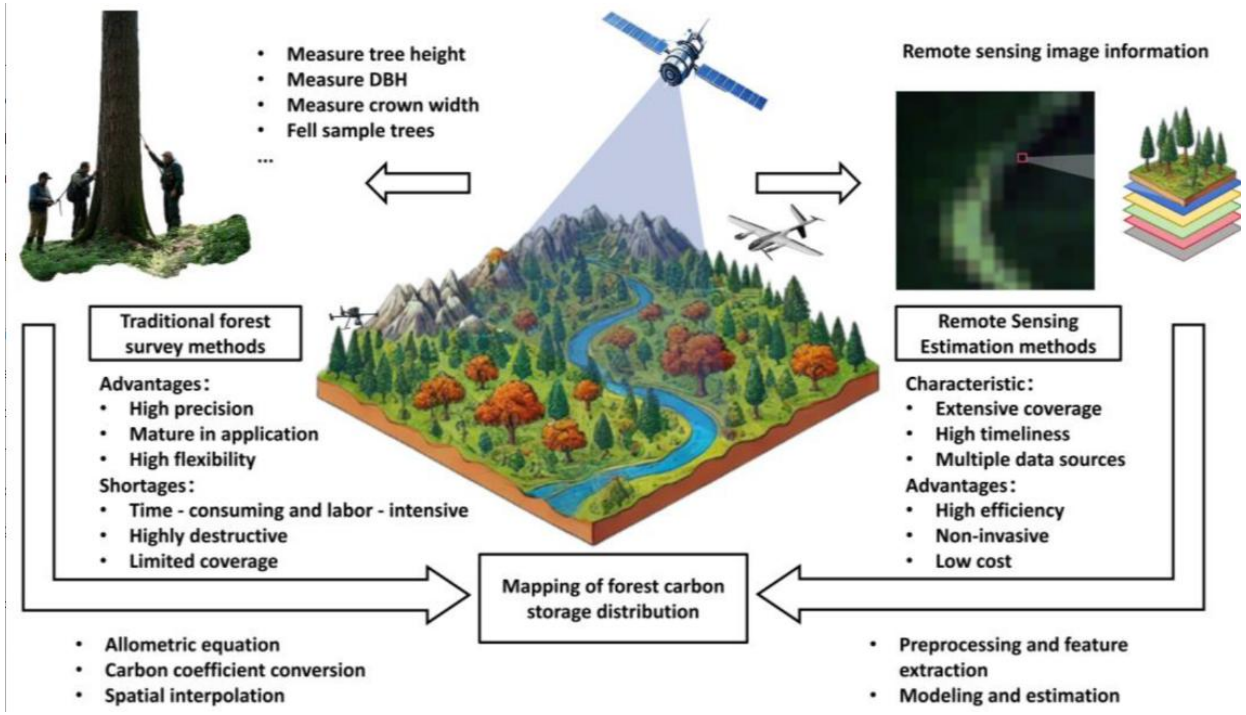
MDPI

Review

Progress and Limitations in Forest Carbon Stock Estimation Using Remote Sensing Technologies: A Comprehensive Review

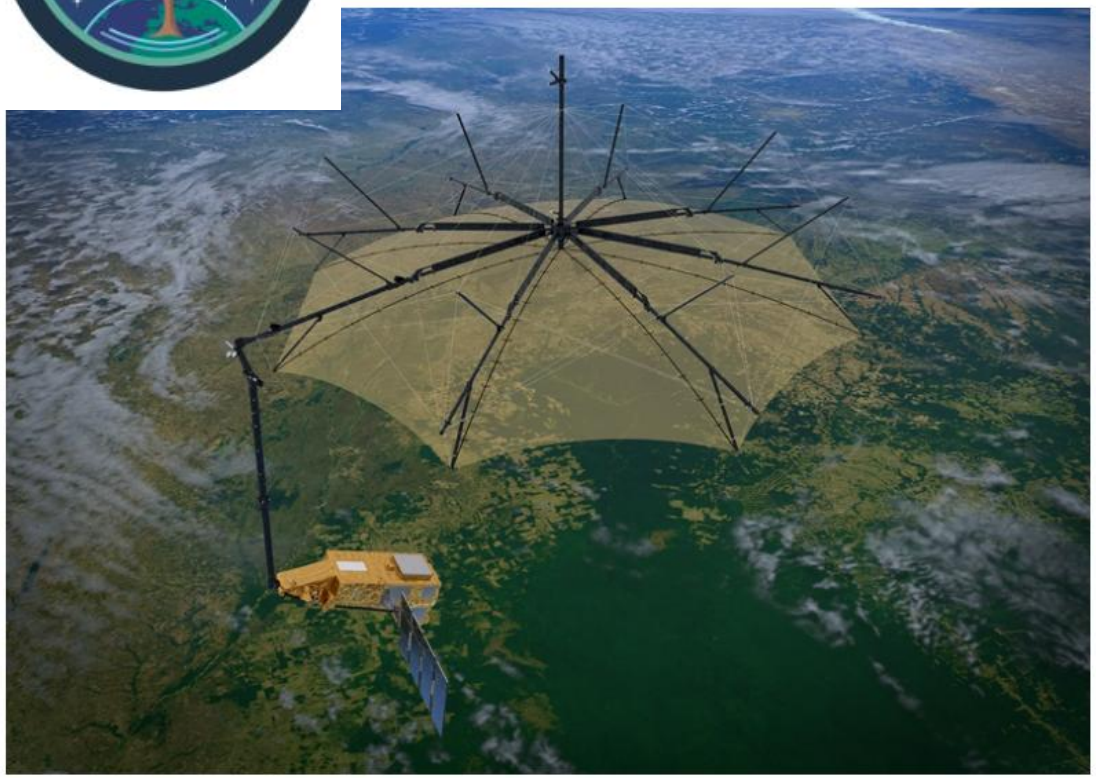
Weifeng Xu [1,†], Yaofei Cheng [2,†], Mengyuan Luo [3], Xuzhi Mai [4], Wenhuan Wang [3,4], Wei Zhang [4,*] and Yinghui Wang [3,4,*]

(2025)

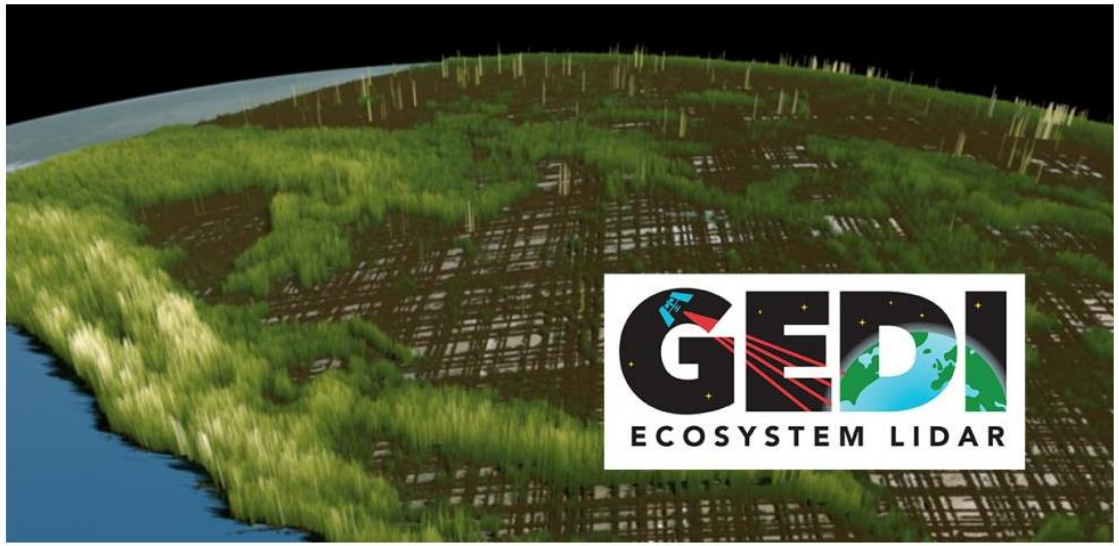


Perspectives

- Greater integration of **spaceborne LiDAR missions** (GEDI, ICESat-2).
- Increased use of **Artificial Intelligence** and hybrid modeling approaches.
- Development of **global, transferable models** capable of generalizing across ecosystems.
- Improved **uncertainty assessment** and **standardized validation protocols**.
- Emerging **Foundation Models** and self-supervised learning are expected to improve carbon estimation by leveraging large-scale multimodal Earth Observation datasets.



BIOMASS - ESA's forest mission



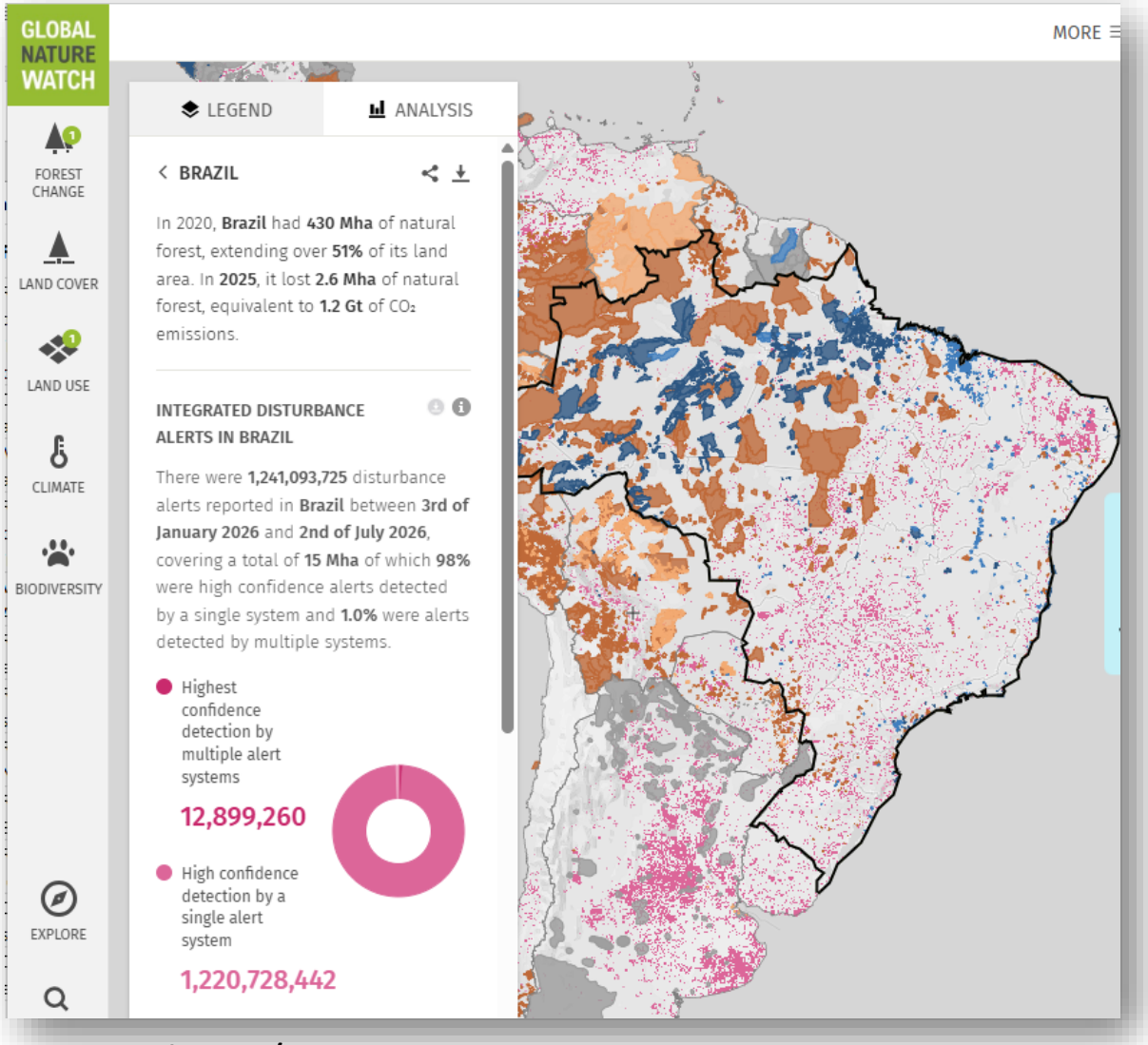
Global Ecosystem Dynamics Investigation Lidar (GEDI Lidar)

AI for forestry in….
AFRICA?

Initiative	Geographic Scope	Main Application	AI Use	Data Sources
FAO AIM4Forests	Pan-African (e.g., DRC, Ghana, Kenya, Uganda)	National Forest **Monitoring** Systems (NFMS), **REDD+**, **carbon** accounting	**Machine learning** for forest mapping, biomass estimation, change detection, and decision support	Sentinel-1, Sentinel-2, Landsat, GEDI, field inventories
Open Foris / SEPAL (FAO)	Pan-African	Operational forest **monitoring**, land-cover mapping, deforestation assessment	**Machine learning** classification, cloud-based **AI workflows**, deforestation risk modeling	Landsat, Sentinel, Planet (where available), field data
SERVIR Africa (NASA–USAID)	Multiple African countries	Forest **monitoring**, fire detection, **restoration**, **biomass** assessment	**Machine learning** for land-cover classification, forest degradation detection, predictive environmental models	Optical, SAR, climate, and geospatial datasets
Global Forest Watch Africa (WRI)	Pan-African	Near-real-time deforestation alerts and forest change **monitoring**	**AI-assisted change detection**, predictive deforestation models, risk assessment	Landsat, Sentinel, radar, ancillary spatial datasets
Congo Basin Forest Monitoring Programs	Central Africa	Forest cover, **biomass, carbon stock,** illegal **logging** monitoring	**Machine learning** for biomass estimation, land-cover classification, change detection	Sentinel-1, Sentinel-2, Landsat, LiDAR, field plots
AI for Cocoa Landscape Monitoring	Ghana, Côte d'Ivoire	**Cocoa-driven deforestation monitoring and EUDR compliance**	**Deep learning** image segmentation, land-use classification, change detection	Sentinel-1, Sentinel-2, high-resolution imagery
Regreening Africa (CIFOR-ICRAF)	East and West Africa	Forest landscape **restoration** and **agroforestry** planning	**AI-assisted** restoration planning, species suitability modeling, restoration monitoring	Satellite imagery, climate, soils, field observations
M-Situ	Kenya	Illegal **logging** and wildfire detection	**Embedded AI** for acoustic event detection (chainsaws, gunshots, fires) with automated alerts	Acoustic sensors (IoT), edge AI
Miti360 Research Initiative	Kenya	**Reforestation** monitoring and tree inventory	**Deep learning** for tree detection, crown delineation, growth monitoring	UAV imagery, field data, weather observations

AI at Forest Monitoring Systems - GFW

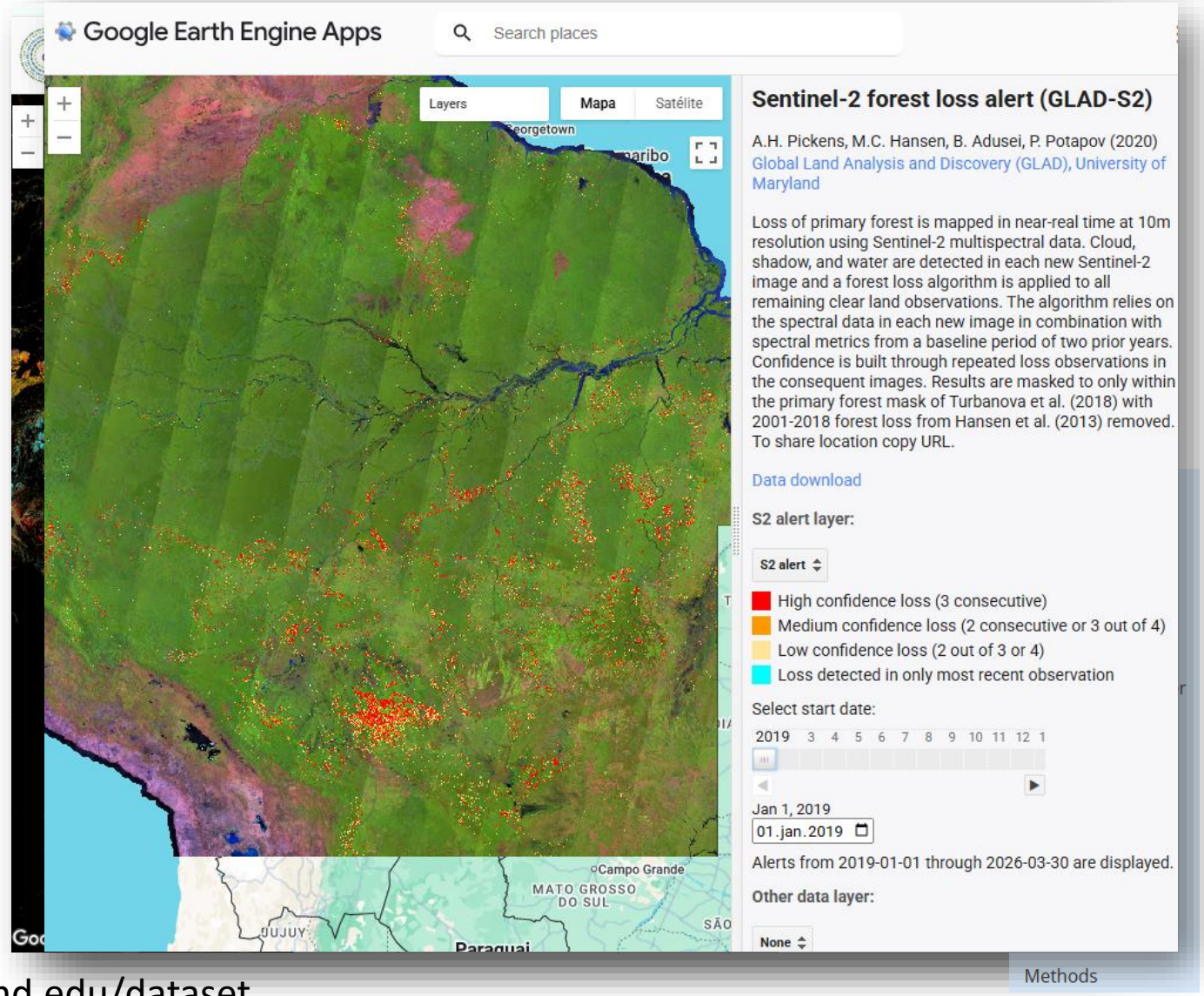
Monitoring system	Global Forest Watch (GFW)
Region	Global
Primary AI / analytical methods	Random Forest, temporal change detection, machine learning, increasingly integrating deep learning products from partner institutions
Main applications	Forest loss alerts, forest extent, forest change monitoring
Remote sensing data	Landsat, Sentinel-1/2, Planet



https://www.globalforestwatch.org/

AI at Forest Monitoring Systems - GLAD

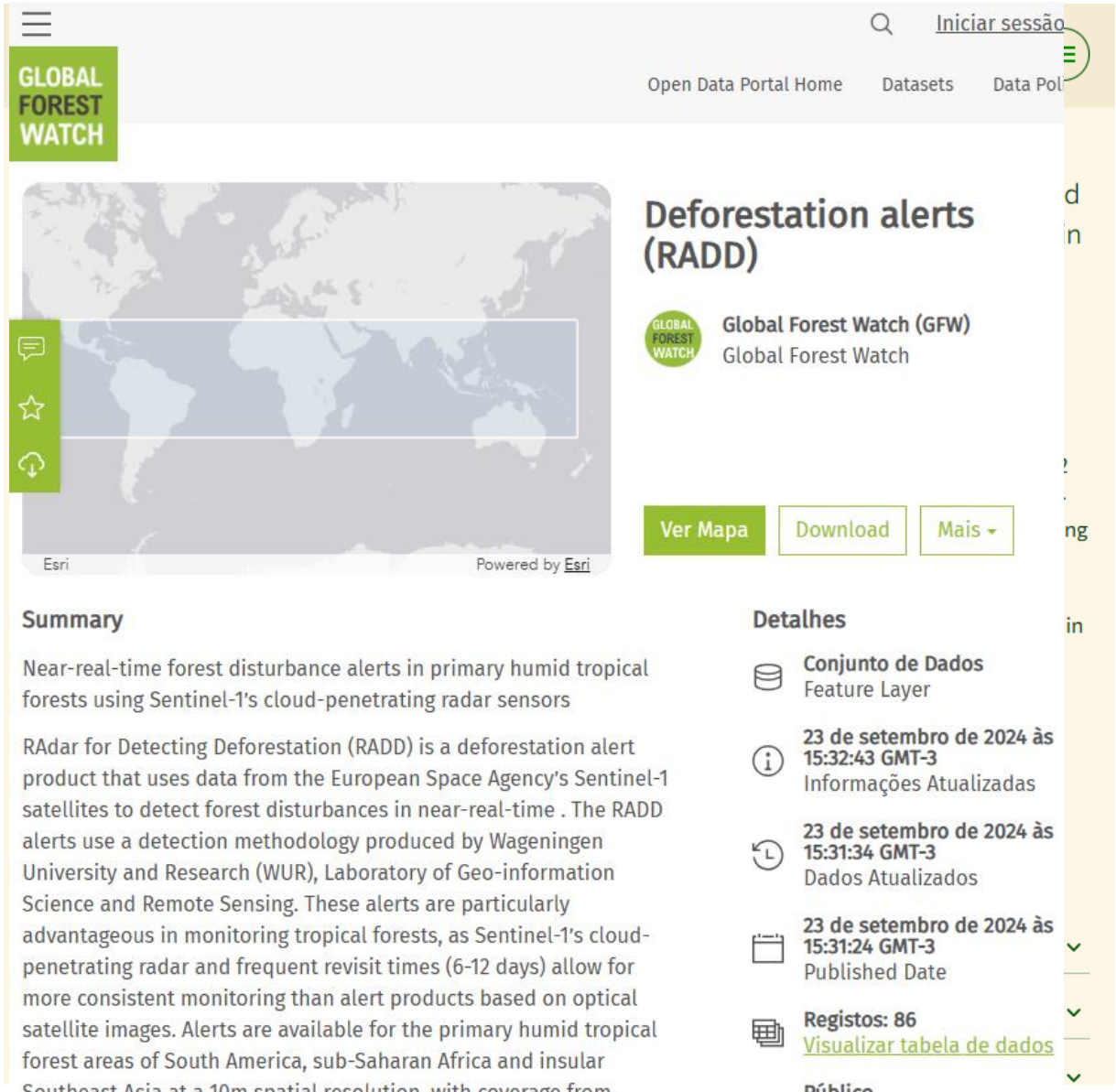
Monitoring system	GLAD Alerts (University of Maryland)
Region	Global Tropics
Primary AI / analytical methods	Decision-tree algorithms, time-series analysis, statistical change detection, machine learning
Main applications	Near-real-time forest disturbance detection
Remote sensing data	Landsat (GLAD-L) Sentinel (GLAD-S2)



https://glad.umd.edu/dataset

AI at Forest Monitoring Systems - RADD

Monitoring system	RADD Alerts (Wageningen University & WRI)
Region	Tropical Forest
Primary AI / analytical methods	Machine learning, SAR time-series analysis, Bayesian change detection
Main applications	Near-real-time deforestation under cloud cover
Remote sensing data	Sentinel 1 SAR



https://www.wur.nl/en/research/products-services/radd-forest-disturbance-alert

AI at Forest Monitoring Systems - GEDI

Monitoring system	NASA GEDI Biomass Products
Region	Global
Primary AI / analytical methods	Random Forest, Gradient Boosting , Deep Neural Networks, (CNNs, Transformer Encoder-based models), Transfer Learning
Main applications	Aboveground biomass estimation, forest structure
Remote sensing data	GEDI LiDAR, Landsat, Sentinel

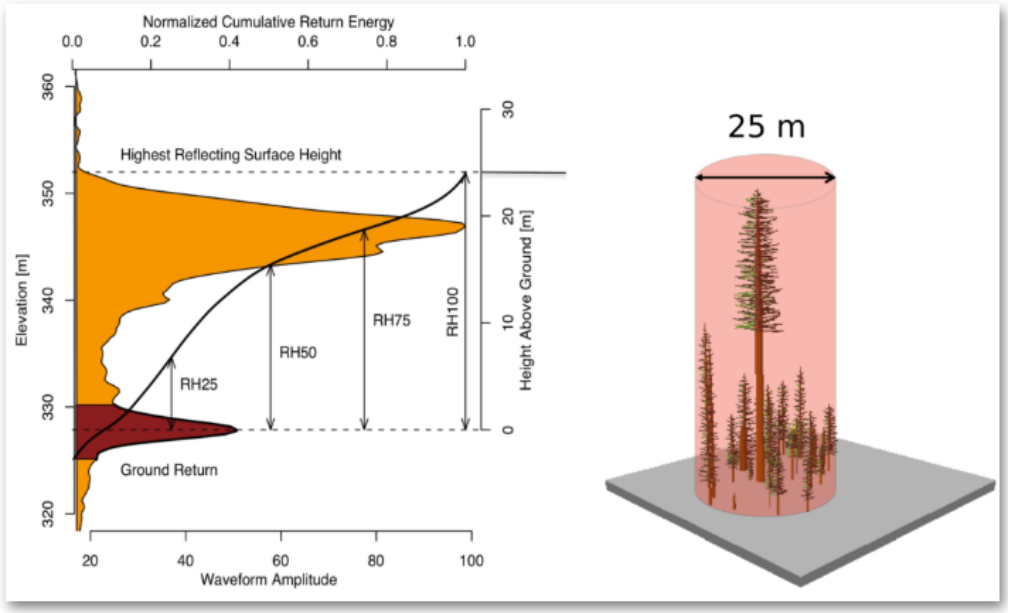
https://gedi.umd.edu/dataproducts/products/

LEVEL 1 - GEOLOCATED WAVEFORMS

The raw GEDI waveforms as collected by the GEDI system are geolocated by our science team.

LEVEL 2 - FOOTPRINT LEVEL CANOPY HEIGHT AND PROFILE METRICS

The waveforms are processed to provide canopy height and profile metrics. These are values calculated directly from the waveform return for each footprint such as terrain elevation, canopy height, RH metrics and Leaf Area Index (LAI). These metrics provide easy-to-use and interpret information about the vertical distribution of the canopy material.



LEVEL 3 - GRIDDED CANOPY HEIGHT METRICS AND VARIABILITY

AI at Forest Monitoring Systems

Dynamic World

Monitoring system	Google Dynamic World
Region	Global
Primary AI / analytical methods	Deep neural networks (CNN-based semantic segmentation)
Main applications	Near-real-time land-cover classification
Remote sensing data	Sentinel-2



https://dynamicworld.app/

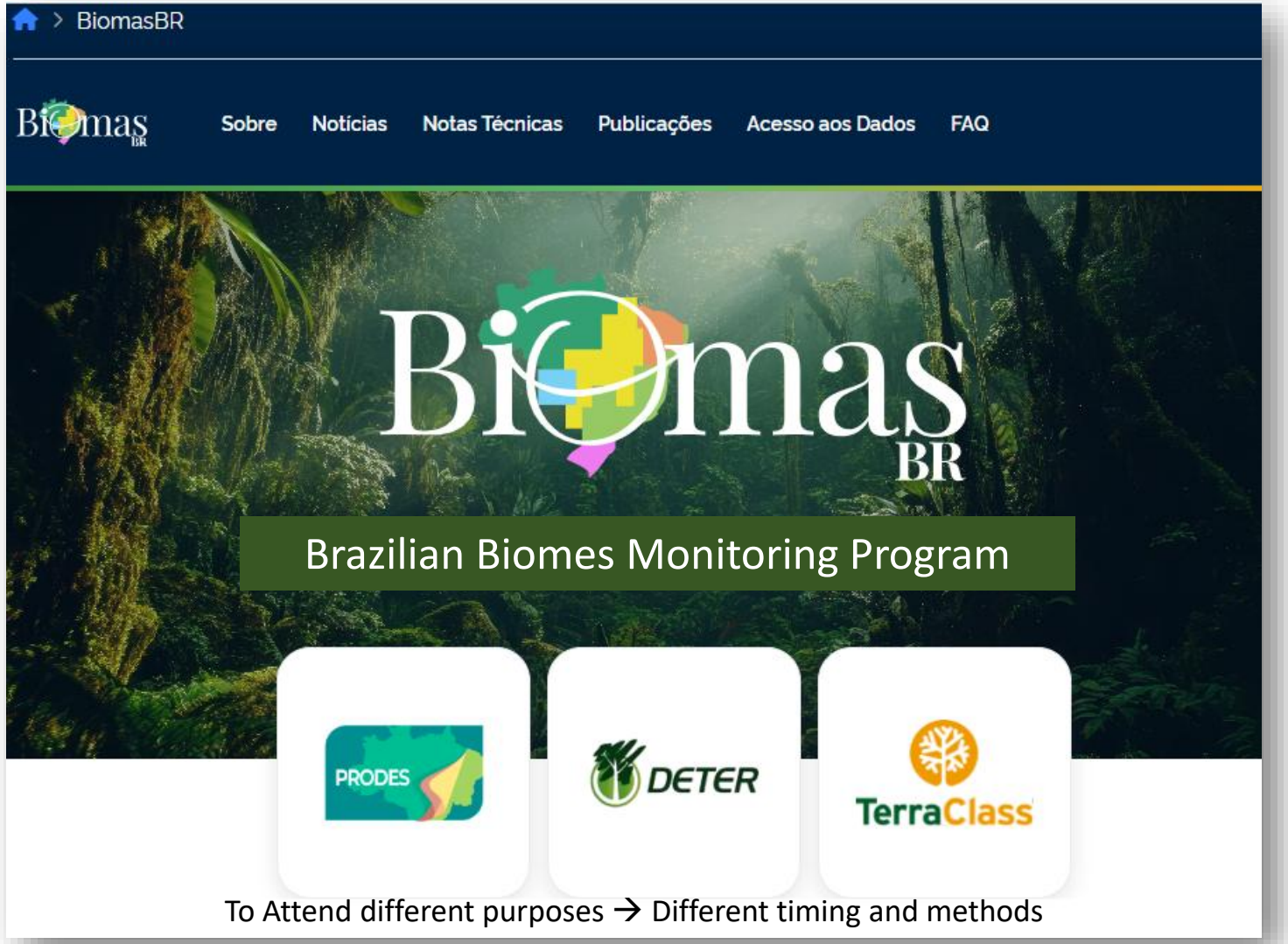
BiomasBR - INPE

INPE´s vegetation monitoring program by satellite image

Systematic information on native vegetation, **deforestation** (suppression) and **degradation** activities for all Brazilian biomes

Official Brazilian deforestation data for public policies

Conservation and sustainable development

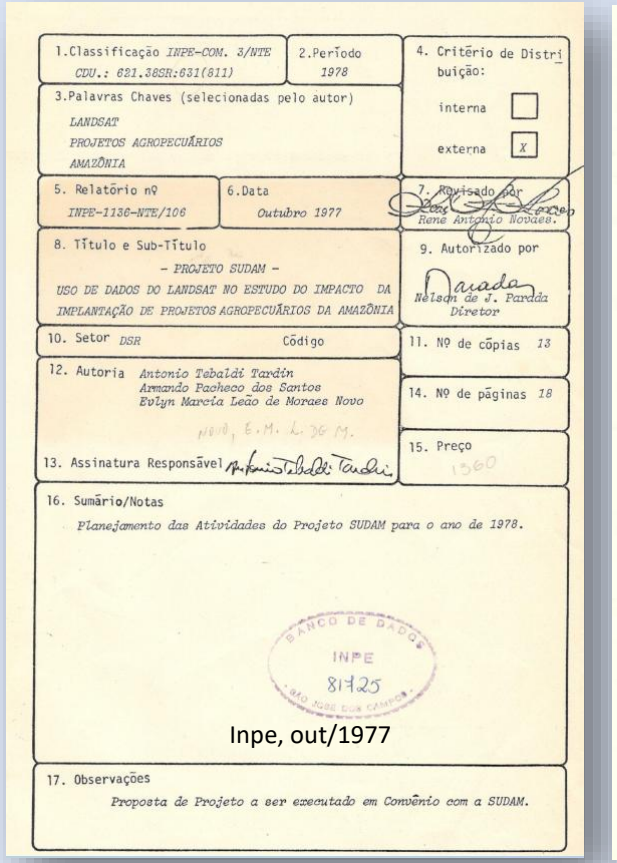


https://data.inpe.br/big/web/biomasbr/

Historical Context – RS data and Research at INPE



INPE – Cuiabá 1973
Reception and Processing of Landsat Images



1.Classificação INPE-COM. 3/NTE
CDU.: 621.38SR:631(811)

2.Período
1978

4. Critério de Distribuição:
interna
externa X

3.Palavras Chaves (selecionadas pelo autor)
LANDSAT
PROJETOS AGROPECUÁRIOS
AMAZÔNIA

5. Relatório nº
INPE-1136-NTE/106

6.Data
Outubro 1977

7. Revisado por
René Antonio Novaes.

8. Título e Sub-Título
- PROJETO SUDAM -
USO DE DADOS DO LANDSAT NO ESTUDO DO IMPACTO DA IMPLANTAÇÃO DE PROJETOS AGROPECUÁRIOS DA AMAZÔNIA

9. Autorizado por
Nelson de J. Parada
Diretor

10. Setor DSR
Código

11. Nº de cópias 13

12. Autoria
Antonio Tebaldi Tardin
Armando Pacheco dos Santos
Evlyn Marcia Leão de Moraes Novo

14. Nº de páginas 18

13. Assinatura Responsável

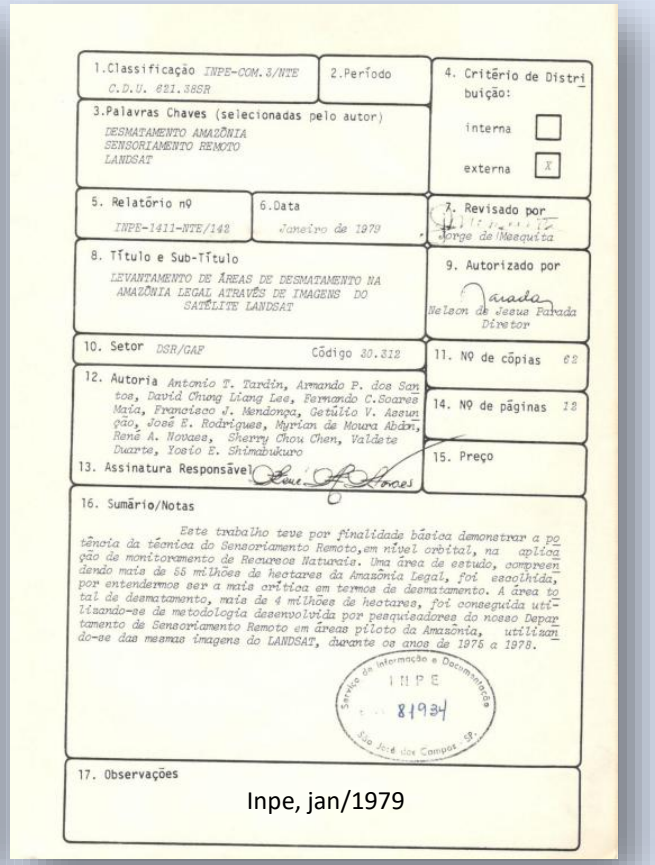
15. Preço
1360

16. Sumário/Notas
Planejamento das Atividades do Projeto SUDAM para o ano de 1978.

BANCO DE DADOS INPE 81725 SÃO JOSÉ DOS CAMPOS

17. Observações
Proposta de Projeto a ser executado em Convênio com a SUDAM.

Inpe, out/1977



1.Classificação INPE-COM.3/NTE
C.D.U. 621.38SR

2.Período

4. Critério de Distribuição:
interna
externa X

3.Palavras Chaves (selecionadas pelo autor)
DESMATAMENTO AMAZÔNIA
SENSORIAMENTO REMOTO
LANDSAT

5. Relatório nº
INPE-1411-NTE/142

6.Data
Janeiro de 1979

7. Revisado por
Jorge de Mesquita

8. Título e Sub-Título
LEVANTAMENTO DE ÁREAS DE DESMATAMENTO NA AMAZÔNIA LEGAL ATRAVÉS DE IMAGENS DO SATÉLITE LANDSAT

9. Autorizado por
Nelson de Jesus Parada
Diretor

10. Setor DSR/GAF
Código 30.312

11. Nº de cópias 62

12. Autoria
Antonio T. Tardin, Armando P. dos Santos, David Chung Liang Lee, Fernando C.Soares Maia, Francisco J. Mendonça, Getúlio V. Assunção, José E. Rodrigues, Myrian de Moura Abdon, René A. Novaes, Sherry Chou Chen, Valdete Duarte, Yosio E. Shimabukuro

14. Nº de páginas 18

13. Assinatura Responsável

15. Preço

16. Sumário/Notas
Este trabalho teve por finalidade básica demonstrar a potência da técnica do Sensoriamento Remoto, em nível orbital, na aplicação de monitoramento de Recursos Naturais. Uma área de estudo, compreendendo mais de 55 milhões de hectares da Amazônia Legal, foi escolhida, por entendermos ser a mais crítica em termos de desmatamento. A área total de desmatamento, mais de 4 milhões de hectares, foi conseguida utilizando-se de metodologia desenvolvida por pesquisadores do nosso Departamento de Sensoriamento Remoto em áreas piloto da Amazônia, utilizando-se das mesmas imagens do LANDSAT, durante os anos de 1975 a 1978.

Serviço de Informação e Documentação INPE 81934 São José dos Campos SP

17. Observações

Inpe, jan/1979

1970s: Start of research into satellite monitoring

In the Amazon

- 32 Landsat images
- 55 million ha Deforested

(~1 France)

- 10% of the Amazon



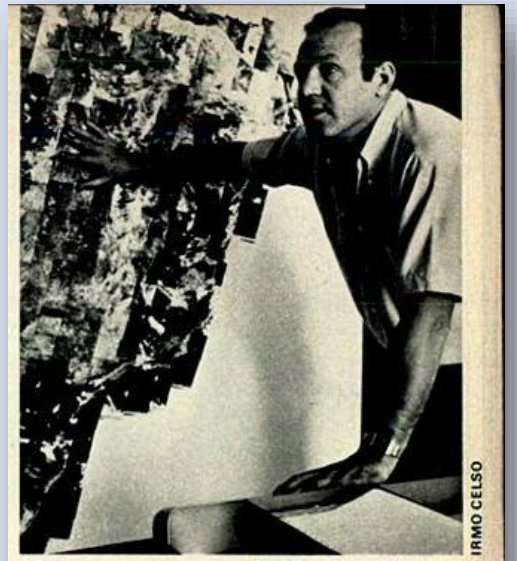
Ambiente

A devastação

Um satélite mostra o que acontece na Amazônia

Pela primeira vez, depois de mais de dez anos de denúncias não fundamentadas, provas concretas do desmatamento que atinge os 5 milhões de quilômetros quadrados da Amazônia. Na semana passada, durante o I Simpósio Brasileiro de Sensoramento Remoto, realizado na cidade paulista de São José dos Campos, 32 fotos demonstraram a um seleto auditório de mais de oitenta cientistas do Brasil e exterior o grau de devastação da área amazônica. O engenheiro René Novaes, chefe da Divisão de Desenvolvimento e Pesquisas do Instituto Nacional de Pesquisas Espaciais (Inpe), ligado ao Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), divulgou os resultados de uma pesquisa efetuada por técnicos da sua divisão, que escolheram para seu trabalho uma região de 55 milhões de hectares (superfície equivalente ao território da França).

Novaes exibiu dados assustadores — apenas nessa área, 4 milhões de hectares já estão totalmente devastados. *(Nas duas fotos ao lado, as áreas mais claras correspondem a zonas desmatadas.)* Desde que o governo federal voltou-se para a ocupação da região, confiando-a tanto a modestas agrovilas quanto a gigantescas empresas agropecuárias, ecologistas, botânicos e zoólogos têm chamado a atenção para a ameaça a que estaria submetida sua exuberante flora e variadíssima fauna. Alguns deles



IRMO CELSO

Novaes: as provas da devastação

se baseou o professor Novaes. Graças às imagens retransmitidas pelo Landsat e analisadas no INPE, o resultado da investigação autoriza a constatação de que 10% de toda a floresta amazônica estão destruídos. E, fundamentalmente, levantam sérias questões a serem resolvidas na elaboração de uma política de desenvolvimento para toda a Amazônia.

Revista Veja, 06/dez/1978

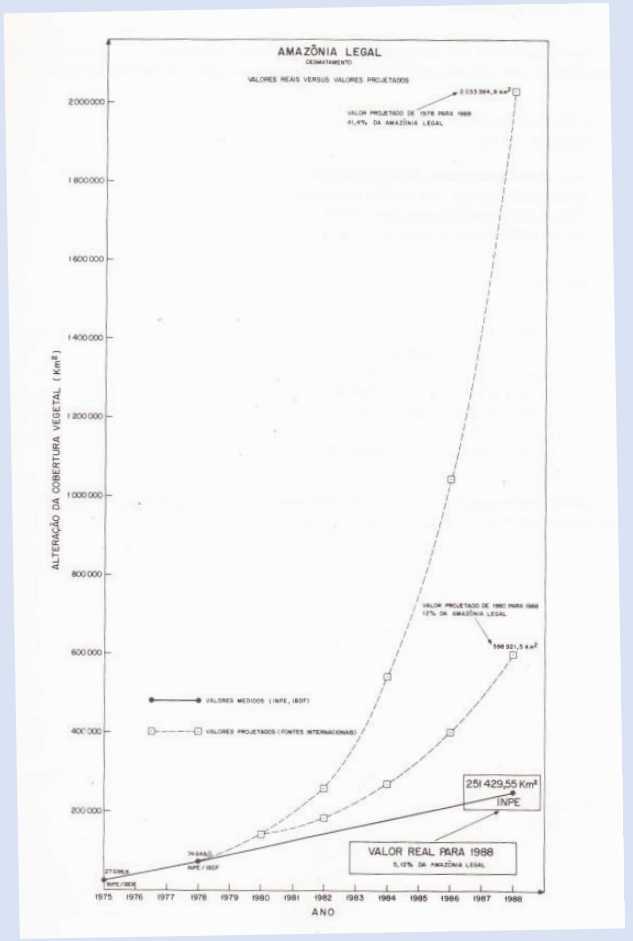
72

1980s: beginning of satellite monitoring - PRODES

Deforestation Projected > 2.000.000 km²



1989 - First complete mapping of the Brazilian Legal Amazon Region



MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E INOVAÇÃO

GOVERNO FEDERAL BRASIL UNIÃO E RECONSTRUÇÃO

73

Brazilian Biomes















8.515.767,049 km²

https://data.inpe.br/big/web/biomas/

Biomas Br

PRODES



https://data.inpe.br/big/web/biomasbr/prodes-monitoramento-anual-da-supressao-de-vegetacao-nativa/

Prodes - Annual Monitoring of Native Vegetation Suppression

Prodes – Methodology

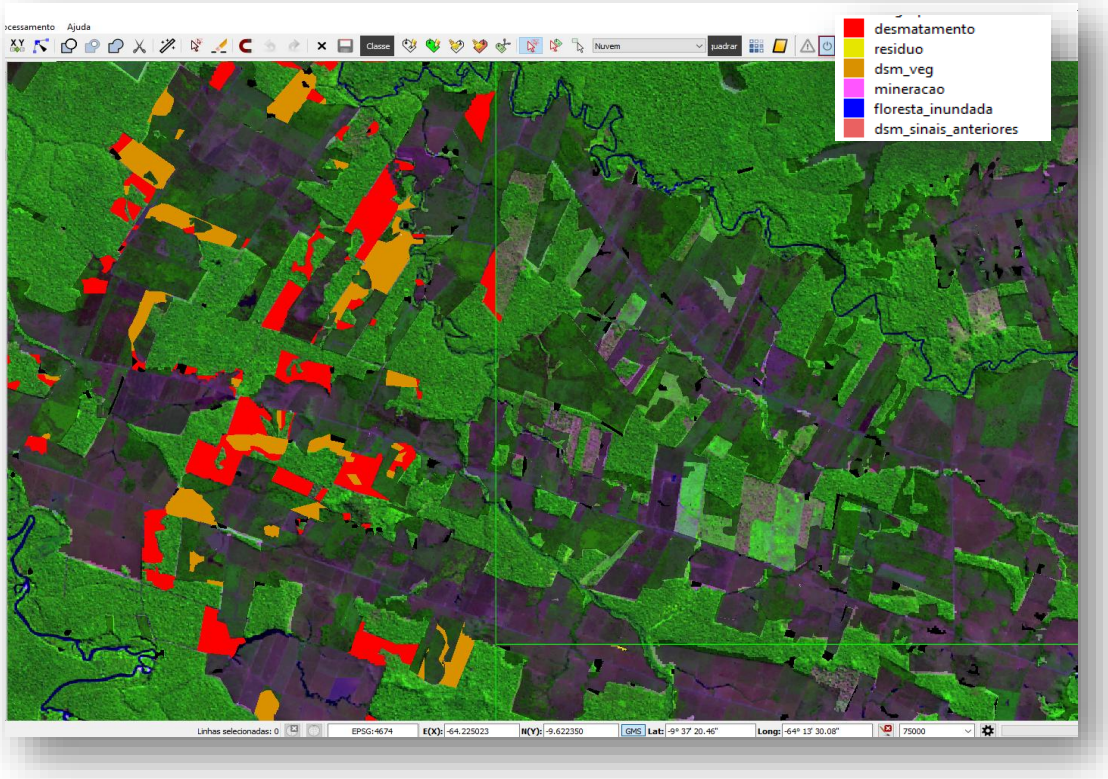
Incremental system - Annual increase of **deforestation**
→ Suppression of native vegetation

Medium spatial resolution (**10**-30 m) – Sentinel-2
Minimum Mapping Unit = **1 ha** (6,25 ha - longest historic series)
Wall-to-wall coverage (only Amazon = 516 Sentinel tiles)

Up to 2023 - Visual identification by **interpreters**, review by **auditors** and **independent validation** by external experts from each biome

Accuracy > 93% (*Maurano et al. 2019, Parente et al. 2021*)

Open data – Terrabrasilis (https://terrabrasilis.dpi.inpe.br/)



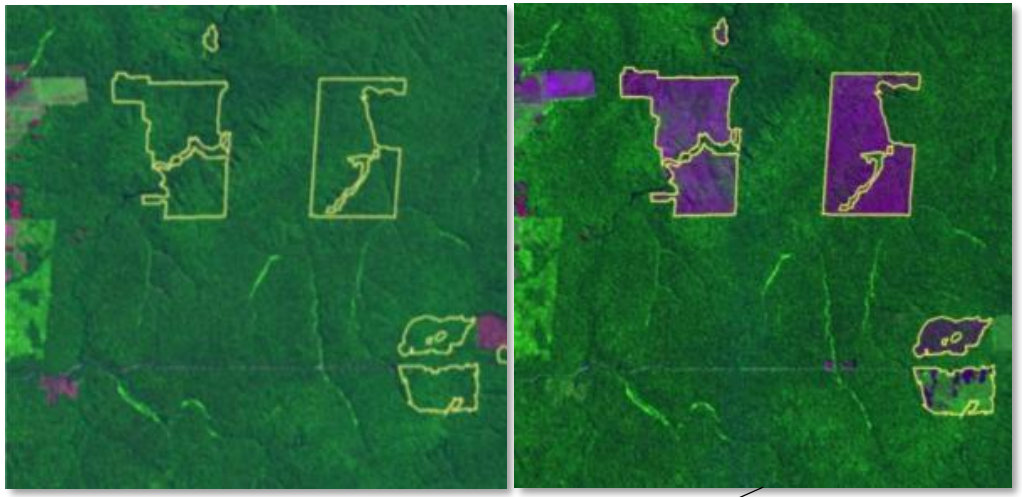
Almeida *et al*. Methodology for Forest Monitoring used in PRODES and DETER projects. 2022 . http://urlib.net/ibi/8JMKD3MGP3W34R/443H3RE

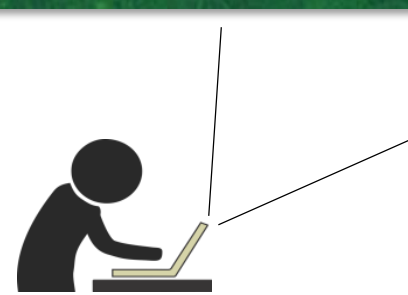
Prodes - Methodological Evolution

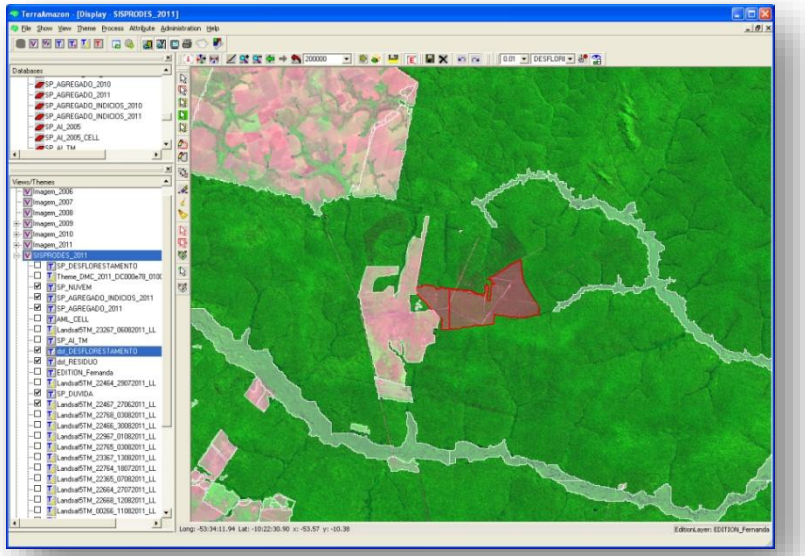
Prodes Amazon – previous methodology

Previous Year

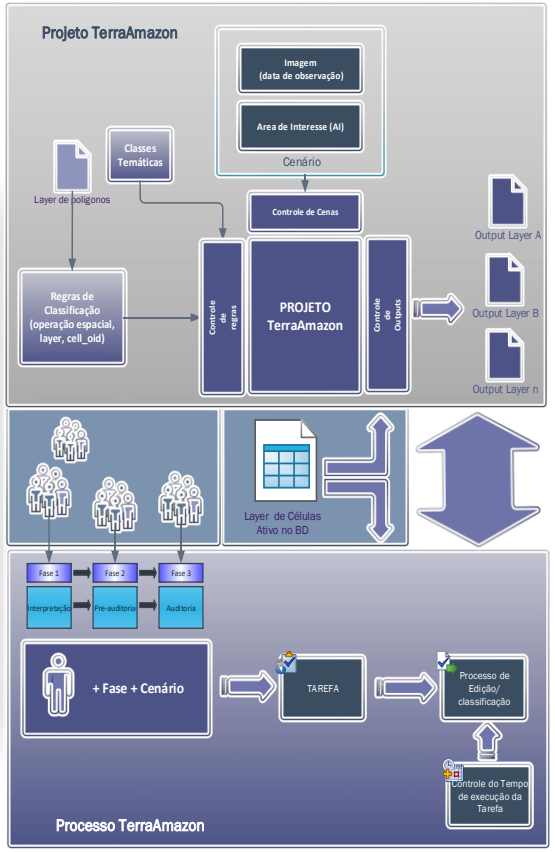
Mapping Year







TerraAmazon



Prodes - Methodological Evolution

Prodes – From single annual Landsat images to Sentinel time series Data Cube

Big data from remote sensing images modeled as multidimensional data cubes

Motivation: Technological innovation for INPE's environmental monitoring projects (**BiomasBR**)

Land use and land cover mapping



BRAZIL DATA CUBE

Time series analysis

Big data machine learning technology

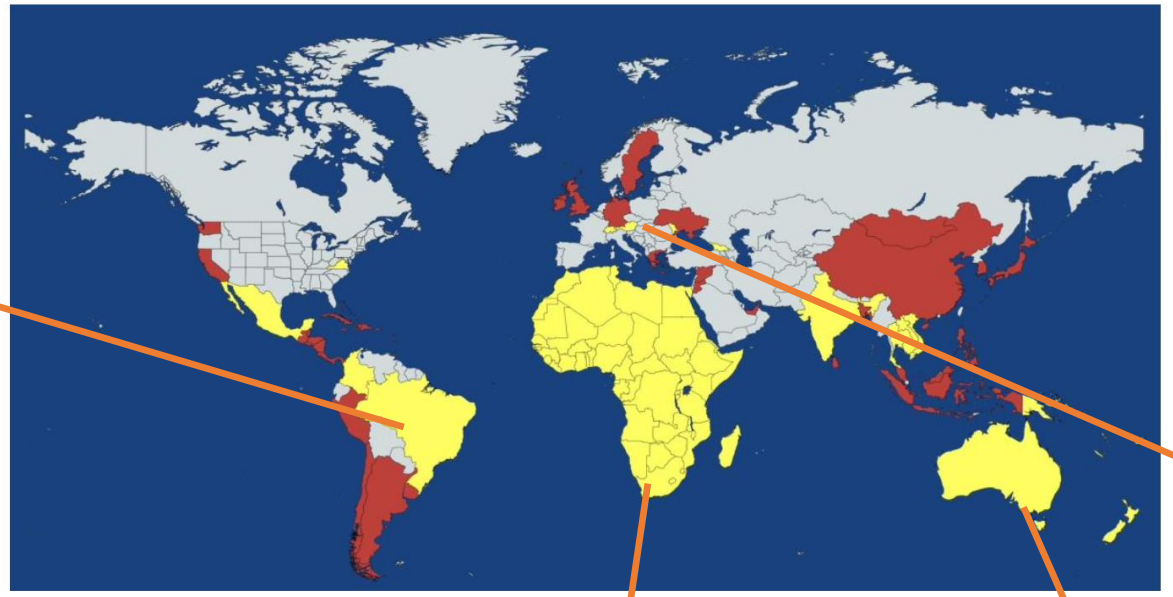
Source: Ferreira and Queiroz (2025)

Partnership with international and similar initiatives

BRAZIL DATA CUBE

Source: [Sudmanns et al, 2022]

Yellow: operational
Red: under development



BRAZIL DATA CUBE

http://brazildatacube.org

data — MDPI

Article

Paving the Way towards an Armenian Data Cube

Swiss Data Cube

https://www.swissdatacube.org/

Naciones Unidas CEPAL — NASA — INEGI

Digital Earth Americas

A vision for a solution that provides relevant Earth observation data for the benefit of the Americas

Digital Earth AFRICA

https://digitalearthafrica.org/

Digital Earth AUSTRALIA

https://www.dea.ga.gov.au/

Source: Ferreira and Queiroz (2025)

Source: Ferreira and Queiroz (2025)

Brazil Data Cube - BDC

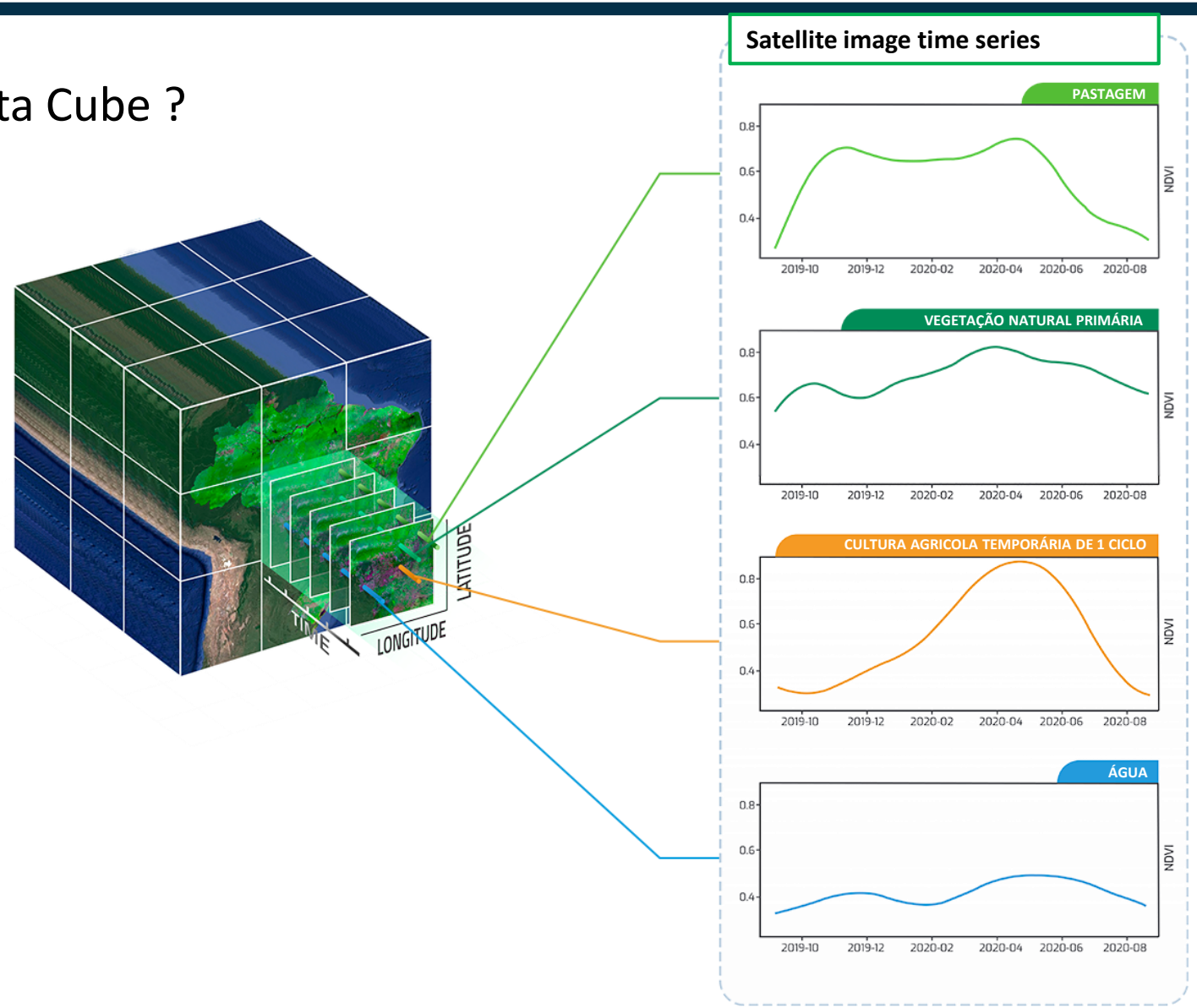
Why an Earth Observation Data Cube ?

Multidimensional array of satellite images with

4 dimensions
latitude, longitude, date, and attributes

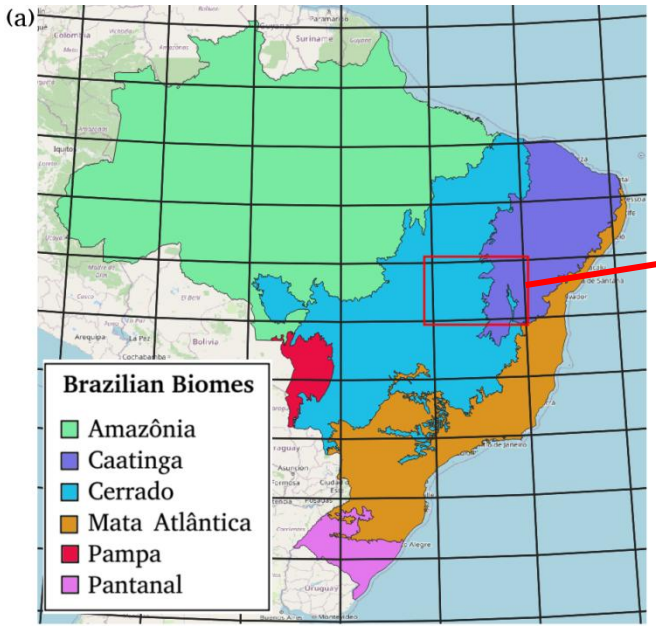
to support time series analysis.

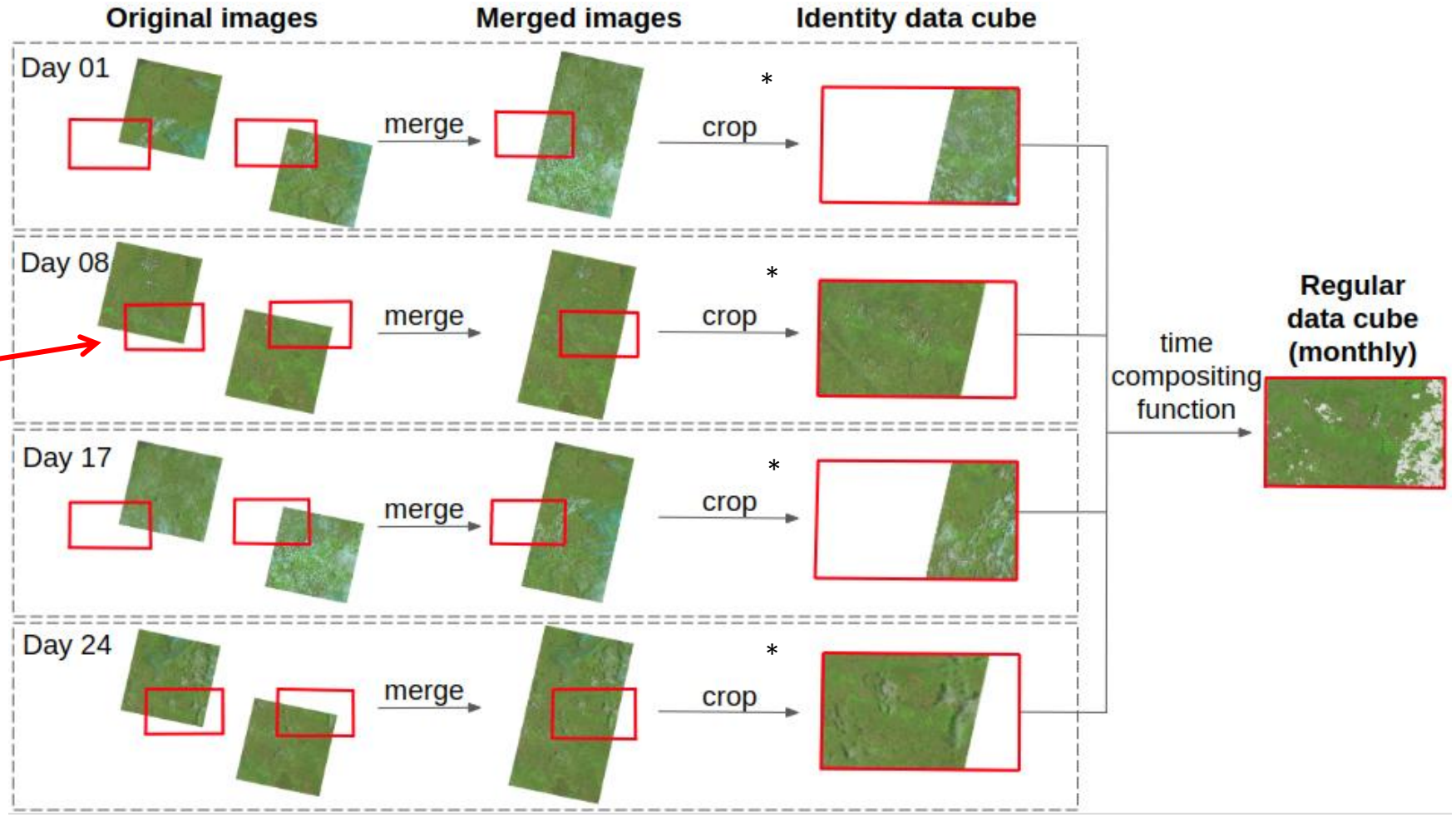
(Appel et al., 2019)



Source: Ferreira and Queiroz (2025)

Building data cubes



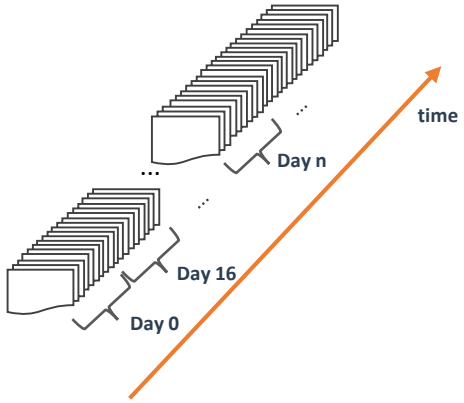


*bilinear resampling for better spatial resolution band

Source: Ferreira and Queiroz (2025)

Brazil Data Cube - BDC





For each tile in time and space, there is a set of COG (Cloud Optimized GeoTIFF) files:

(1) Original bands; (2) Vegetation indices (EVI/NDVI); (3) Cloud mask; (4) Number of valid observations (excluding clouds and debris); (5) Data source; ...

brazildatacube.dpi.inpe.br/portal/explore



BDC – Small
Each tile: 105600m x 105600m

Sentinel-2/MSI – 10 meters
Each file (band/tile): 400 MB
Each tile: ~ 5.4 GB

Source: Ferreira and Queiroz (2025)

Prodes - Annual Monitoring of Native Vegetation Suppression

Prodes Amazon – new technologies - BIG DATA ANALYSIS

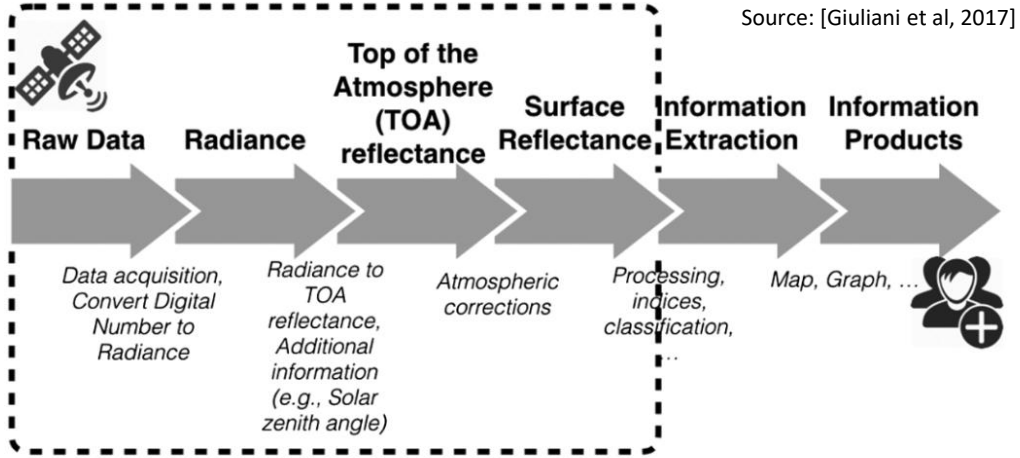
Brazil Data Cube

(1) Analysis-Ready Data (ARD) of medium-resolution satellite images for Brazil: CBERS-4 Landsat 8 Sentinel 2.

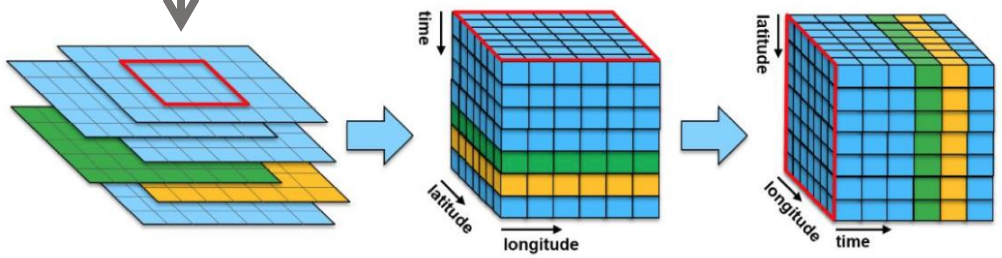
(2) Multidimensional data cubes.

CEOS Analysis Ready Data for Land:
https://ceos.org/ard/index.html

Source: [Giuliani et al, 2017]



Source: [Kopp et al, 2019]



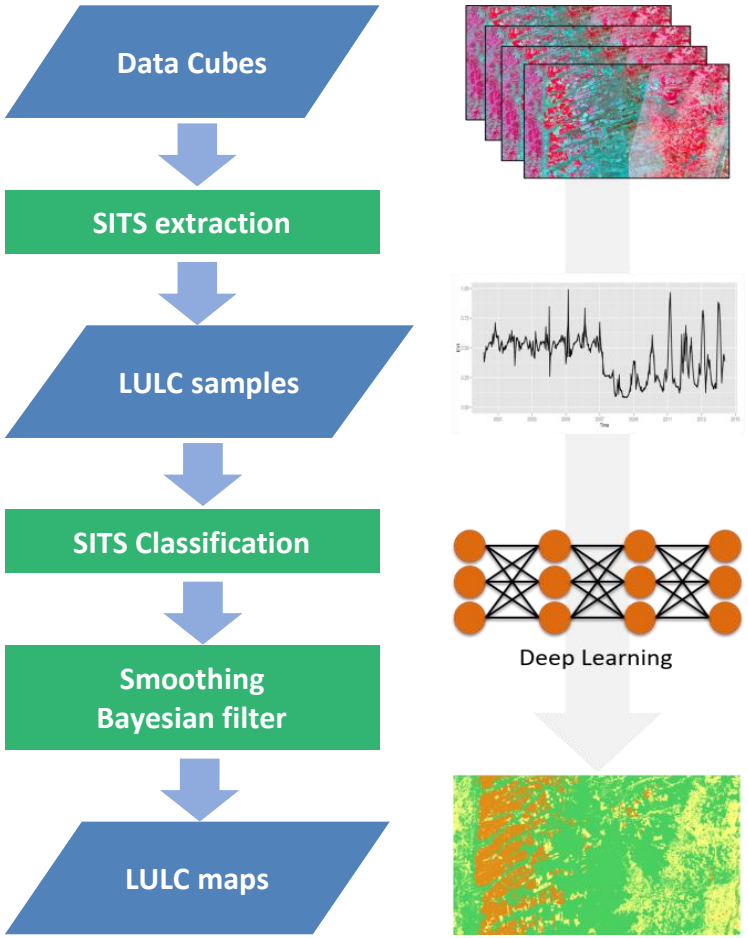
Collections of Earth observation satellite imagens – ARD

Data cubes – four-dimensional array.

Source: Ferreira and Queiroz (2025)

Brazil Data Cube - BDC

Land use and Land Cover Mapping (LULC)



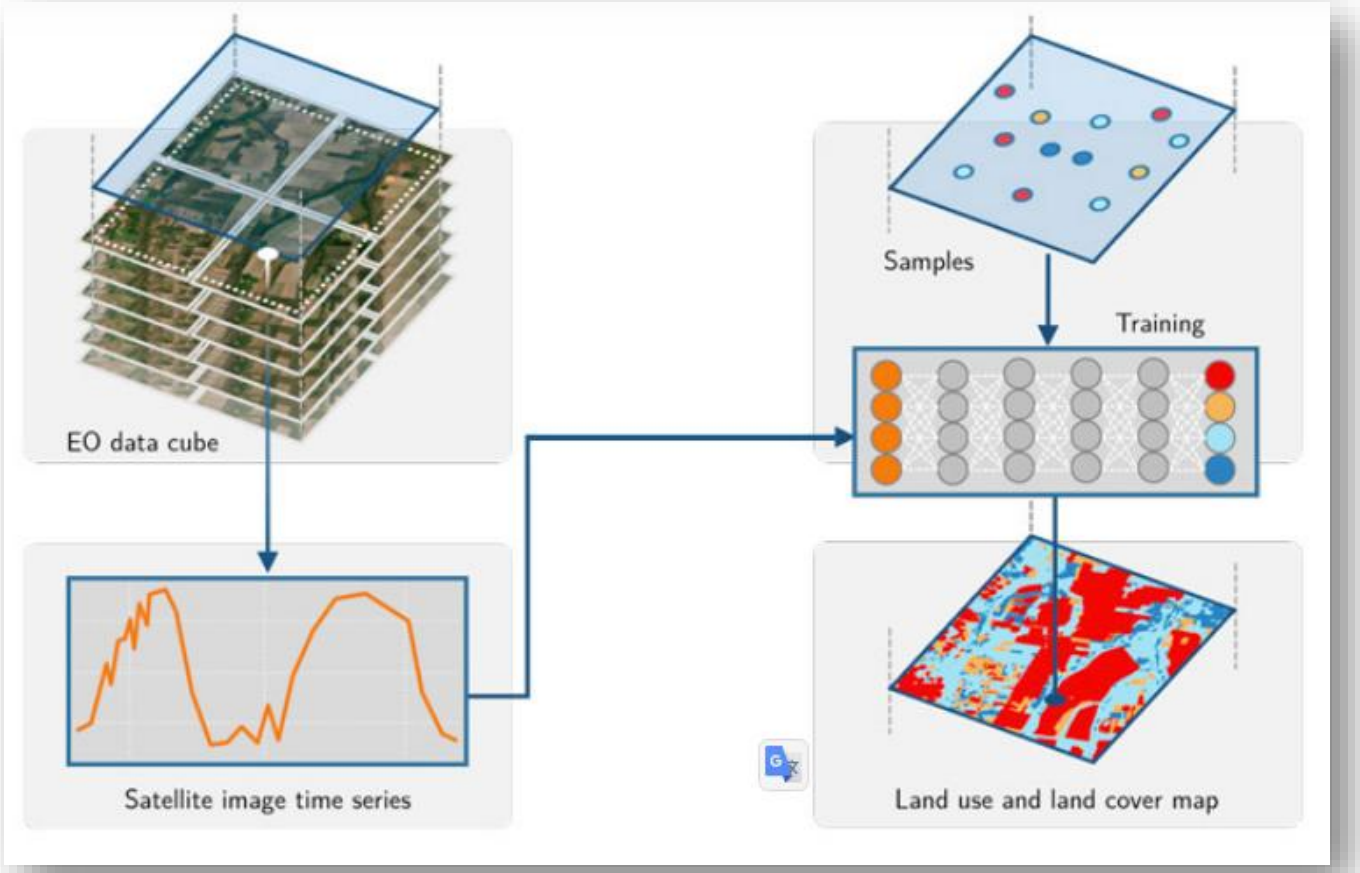
Source: [Ferreira et al, 2020]

EO data cube,
Satellite image time series analysis (SITS),
and
machine learning to produce LULC maps extracted from large EO databases.

SITS enable complex processing that would be difficult using bi-temporal or even annual approaches to change detection.

(Pasquarella et al., 2016)

SITS – Satellite Image Time Series



Simoes et al, (2021]

SITS - tools for analysis and classification of time series: self-organized maps, clustering, filtering, and data visualization.

Advanced machine learning algorithms for land use and land cover mapping from satellite image time series.

ML algorithms:

- Support Vector Machine (SVM),
- Random Forests (RF),
- Extreme Gradient Boosting,
- 1D fully connected Multi-layer Perceptrons,
- 1D Convolutional Neural Networks,
- 1D version of ResNet method.

https://data.inpe.br/bdc/sits-satellite-image-time-series/

Brazil Data Cube - BDC

Image time series analysis and **Machine Learning**
to produce
land use and land cover maps from large Earth Observation databases

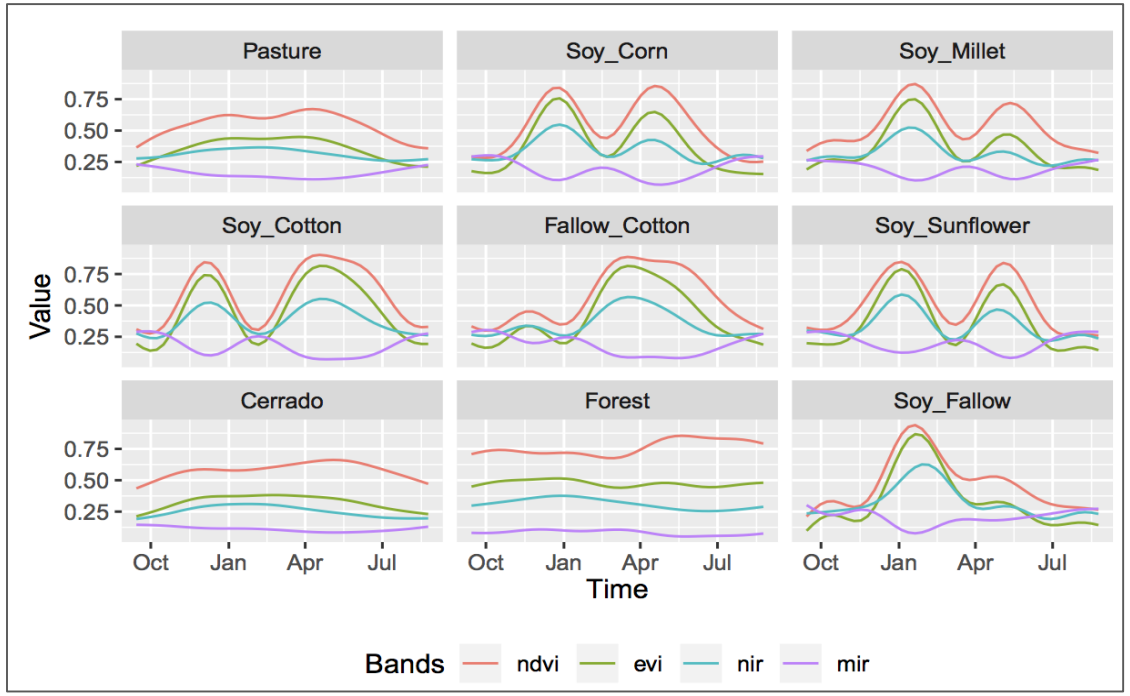
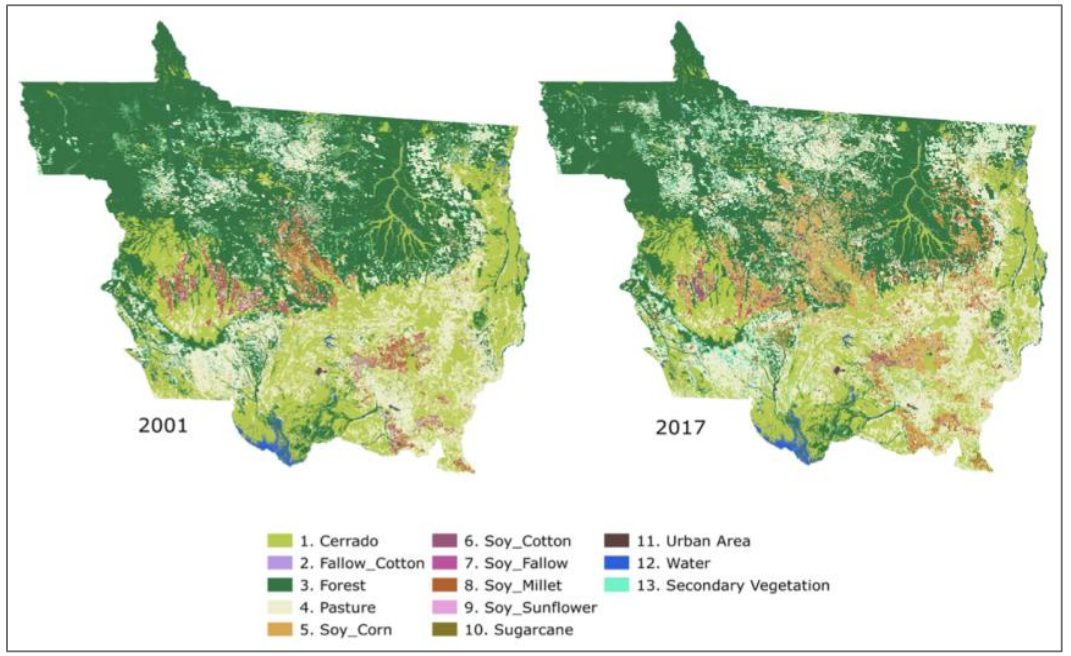


Image time series NDVI, EVI, NIR, MIR - agriculture year
MODIS – MOD13Q1 Product / Method – SVM (Support Vector Machine)



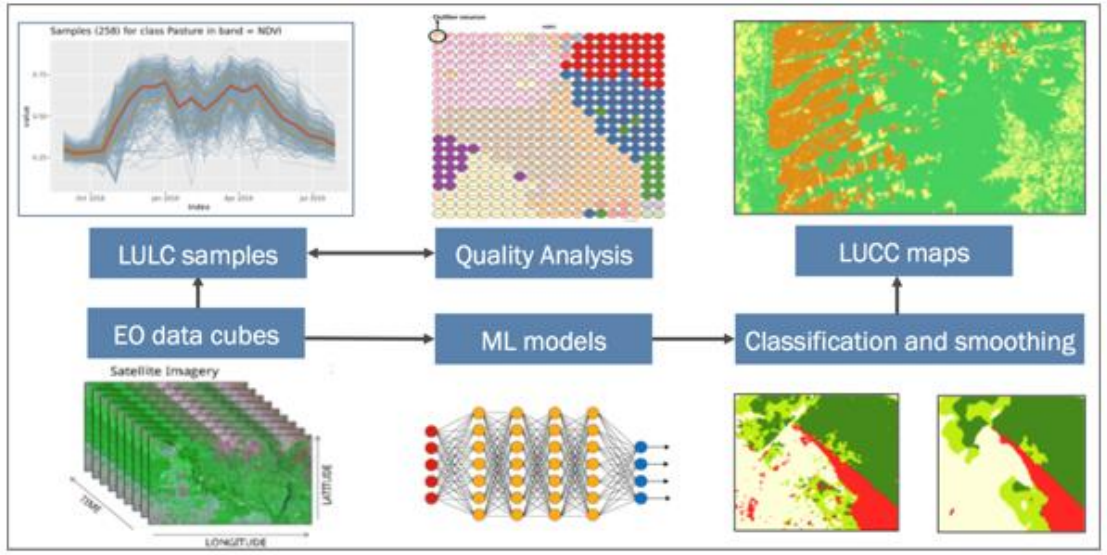
Land use and cover maps for Mato Grosso State in Brazil from 2001 to 2017, Scientific Data, 2020 (Simões et al., 2020)

Prodes - Annual Monitoring of Native Vegetation Suppression

Prodes – new technologies - AI Analysis

SITS (Satellite Image Time Series)
R package

https://github.com/e-sensing




```
cube <- sits_cube(source = "BDC",
                  collection = "S2_10_16D",
                  name = "s2_cube",
                  bands = c("NDVI", "EVI"),
                  tiles = "022024", start_date = "2018-09-01", end_date = "2019-08-28")

samples <- readRDS(url("https://bdc.dpi.inpe.br/rds/S2_10_16D.rds"))

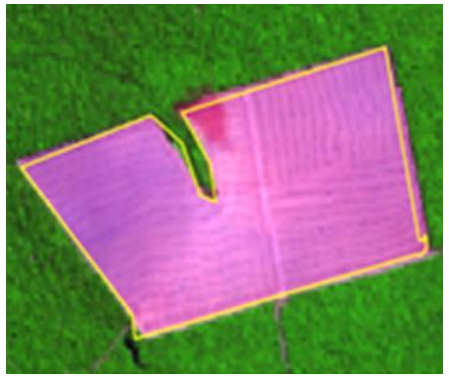
mlp_model <- sits_deeplearning(layers = c(512, 512, 512, 512, 512), activation = "relu")

dl_model <- sits_train(samples, mlp_model)

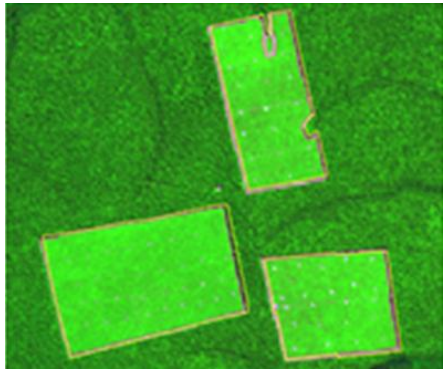
result <- sits_classify(data = cube, ml_model = dl_model, output_dir = tempdir())
```

Prodes Amazon – Class

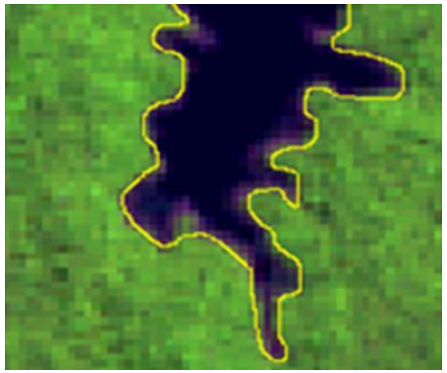
Clear-cut deforestation bare soil



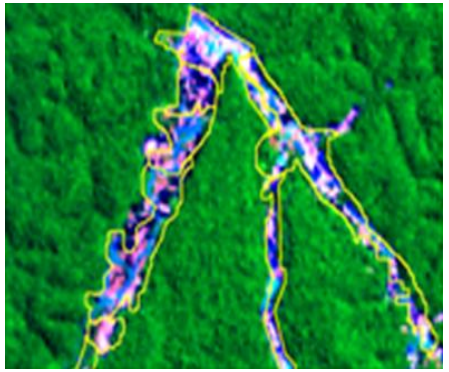
Clear-cut deforestation herbaceous vegetation



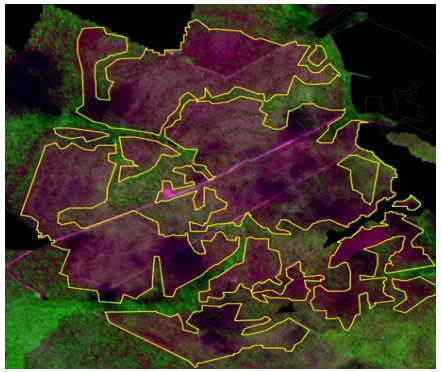
Clear-cut deforestation flooded forest



Clear-cut deforestation mining



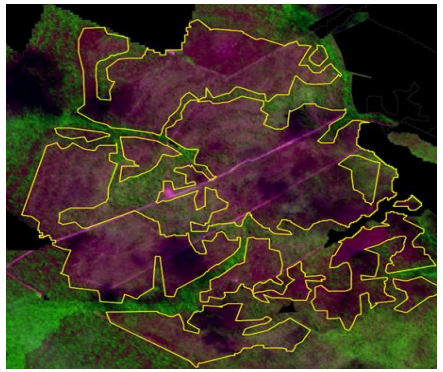
Deforestation by progressive degradation



Prodes - Annual Monitoring of Native Vegetation Suppression

Prodes Amazon – Degradation Classes - from 2022

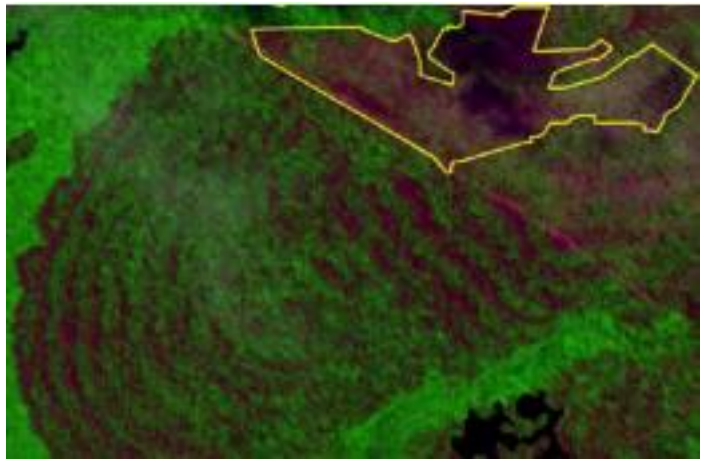
Deforestation by Progressive degradation



Selective logging



Forest fire recurrence



Prodes - Annual monitoring of native vegetation suppression

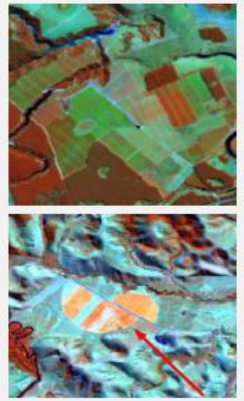
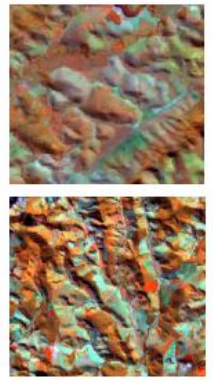
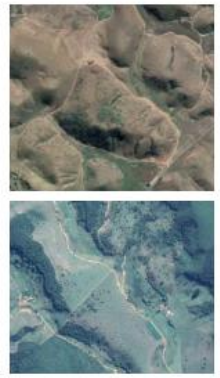
Other biomes

"DEFORESTATION"
Native Vegetation Suppression

Interpretation keys
Interpretive classes:

- Agriculture
- Pasture
- Mining
- Urban
- Forestry
- Water
- etc.

Tabela 3.2 – Chave de interpretação para as classes mapeadas e interpretadas pelo Prodes Mata Atlântica.

Classe	Subclasse interpretativa	Elementos da fotointerpretação	Exemplo composição Sentinel R8G11B4	Exemplo Google Earth
Desmatamento	Área Agrícola	**Cor:** Vermelho, Verde ou Azul **Tonalidade:** Clara (maioria), varia com o vigor da pastagem e tempo de colheita; **Textura:** Lisa (maioria), rugosidade leve a depender do estágio de crescimento da cultura; **Forma:** Regular, retangulares e cilíndricas; **Padrão:** Costuma ser regular a depender da região; **Tamanho:** Grande, porém pode variar de médio a pequeno conforme tipo de propriedade; **Contexto:** São geralmente cercadas por algum elemento físico; a matiz muda a depender do tipo de cultura e fase de desenvolvimento. Pode ser evidenciado periodicamente feições de solo exposto.		
Desmatamento	Área de pastagem	**Cor:** Verde ao Magenta; Tonalidade: Clara, varia com o vigor da pastagem; **Textura:** Lisa, pode variar conforme o manejo; **Forma:** Costuma ser regular a depender da região; **Padrão:** Costuma se regular a depender da região; **Tamanho:** Costuma ser grande a depender da região; **Contexto:** O vigor das herbáceas varia ao longo do ano, conforme a distribuição pluviométrica da região. Ocorre em toda a extensão do bioma; costuma acontecer em regiões de relevo acidentado montanhoso intercalados de fragmentos de florestas.		

METODOLOGIA DO SISTEMA PRODES MATA ATLÂNTICA – Edição 2023, INPE (2025)

Prodes - Annual Monitoring of Native Vegetation Suppression

Prodes BRASIL

Since 1988- Brazilian Legal Amazon

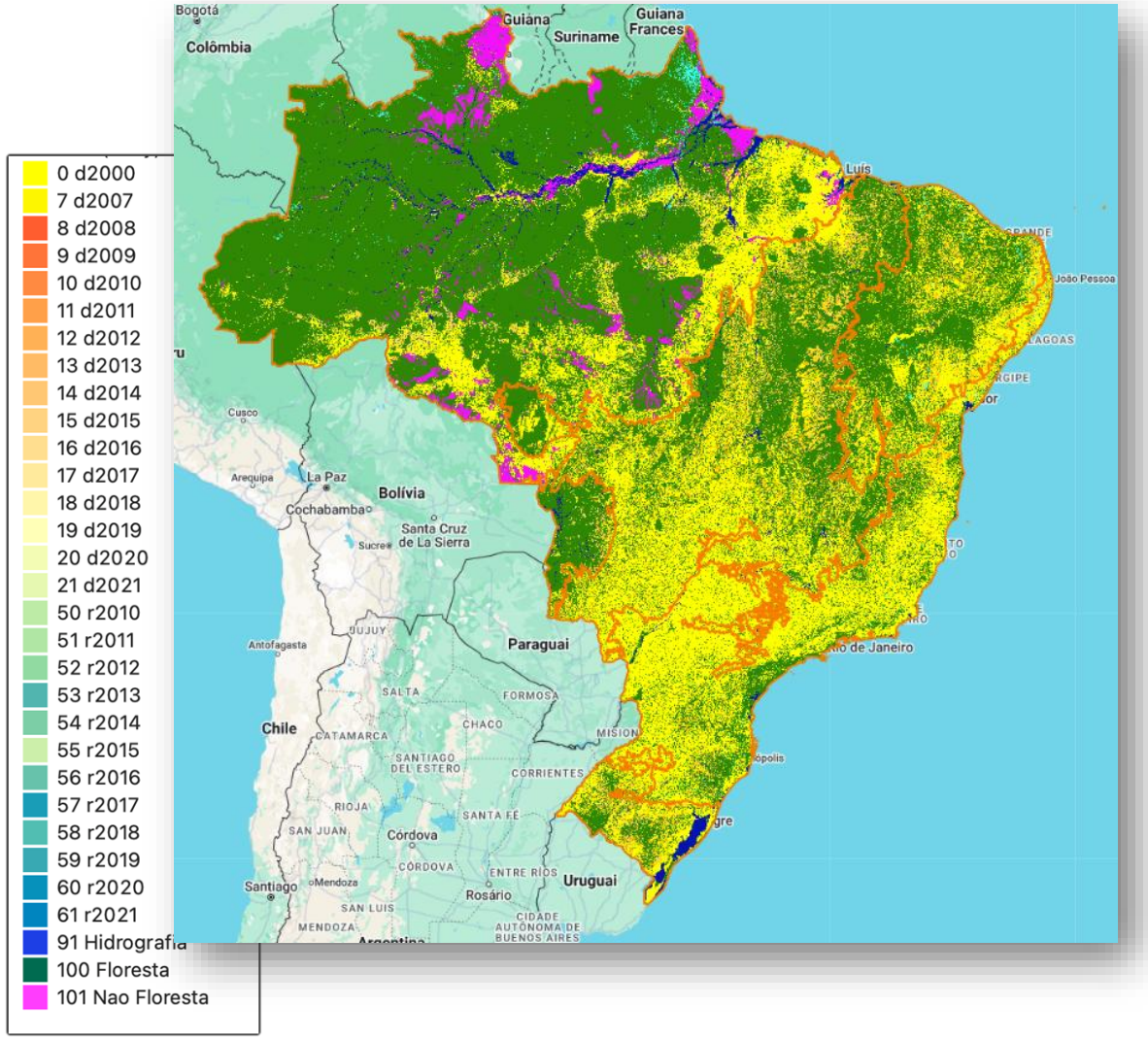
All Biomes from 2001 to **2025** (1ha)

Amazon, Non-Forest Amazon*
Cerrado, Caatinga, Atlantic Forest, Pantanal, and Pampa

Sentinel-2 - Brazil Data Cube, Process automation

Official deforestation data from the Brazilian government

Input for public policies and other initiatives: PPCDAm/PPCerrado, Amazon Fund, Soy Moratorium, Meat TAC, etc., as well as countless scientific productions.

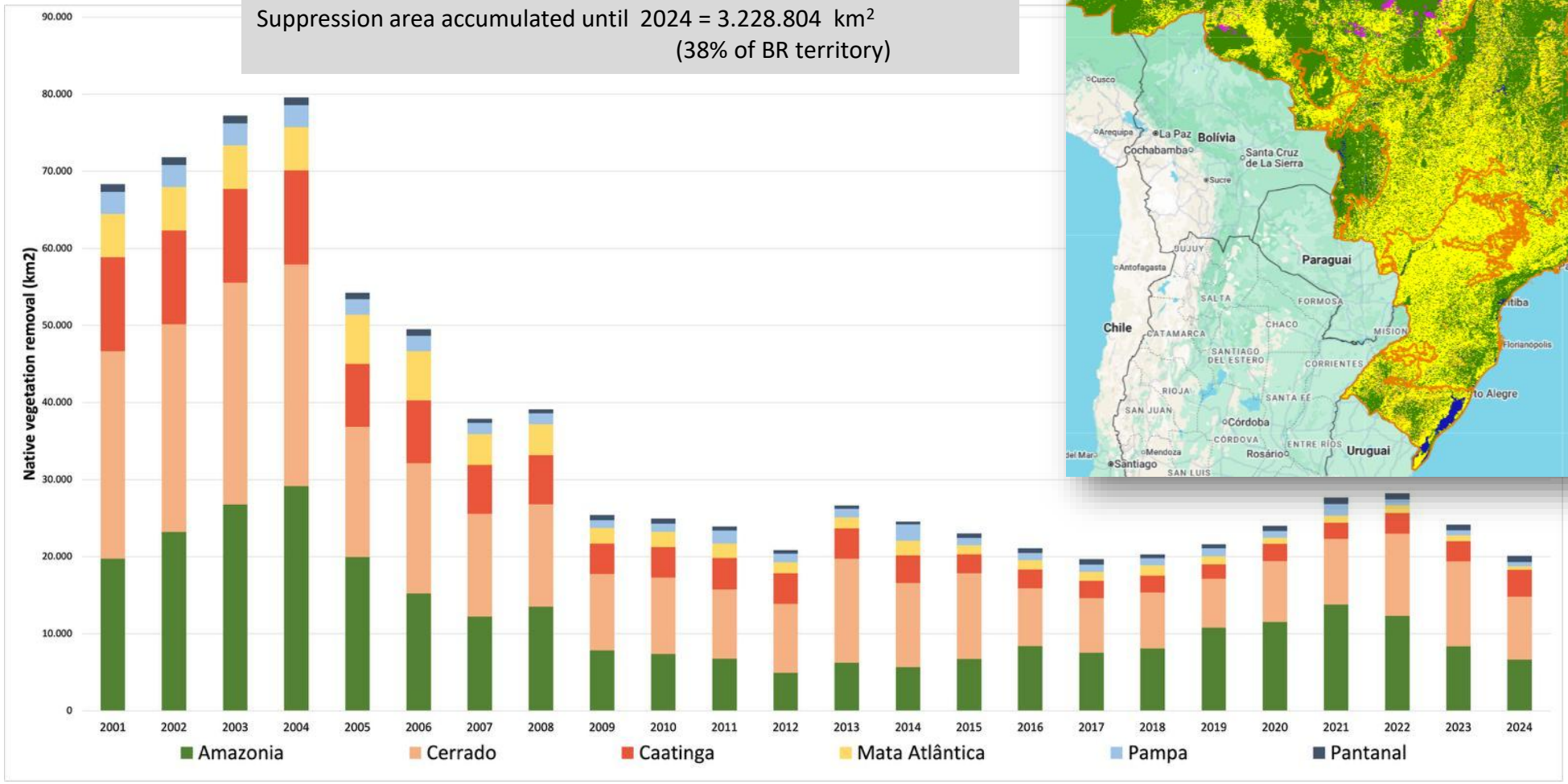


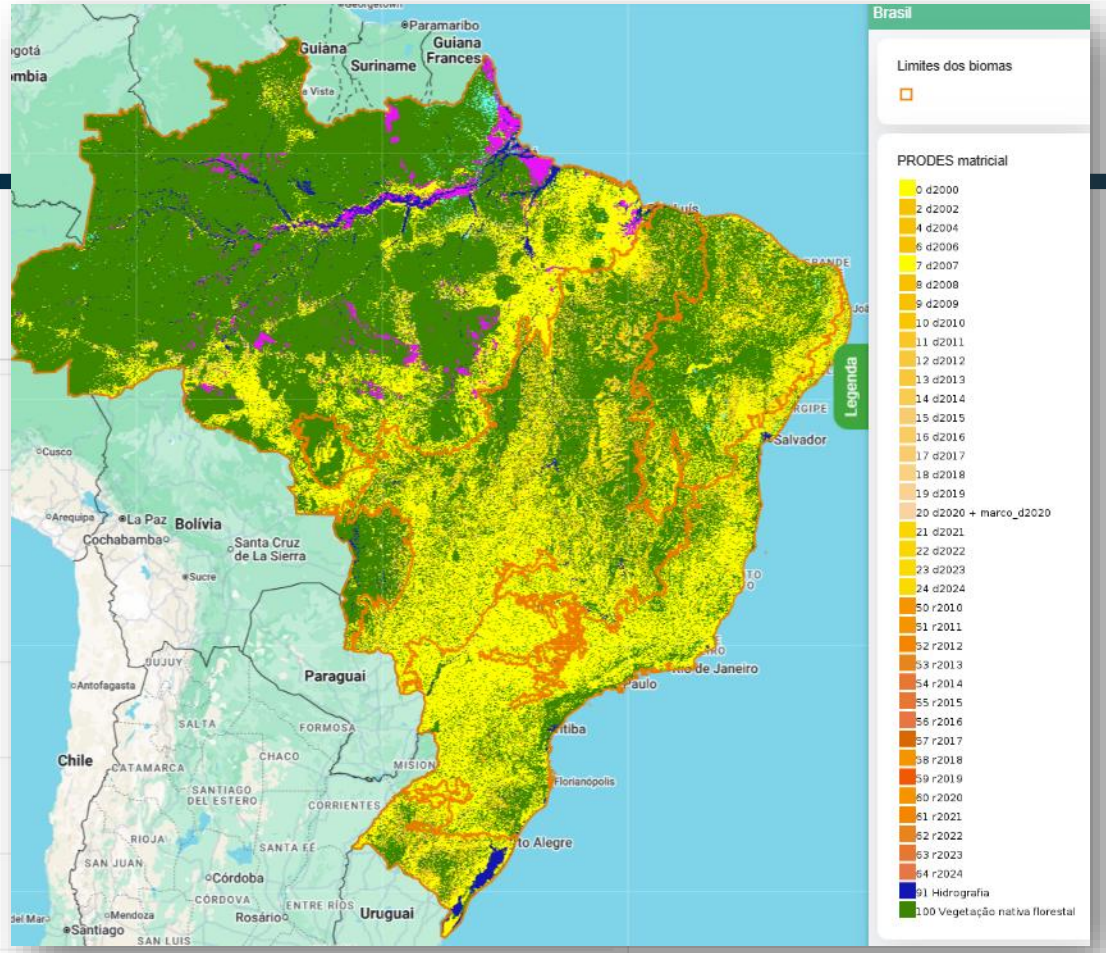
Prodes - Brasil

TerraBrasilis

Native vegetation suppression 2024

Suppression area accumulated until 2024 = 3.228.804 km^2
(38% of BR territory)



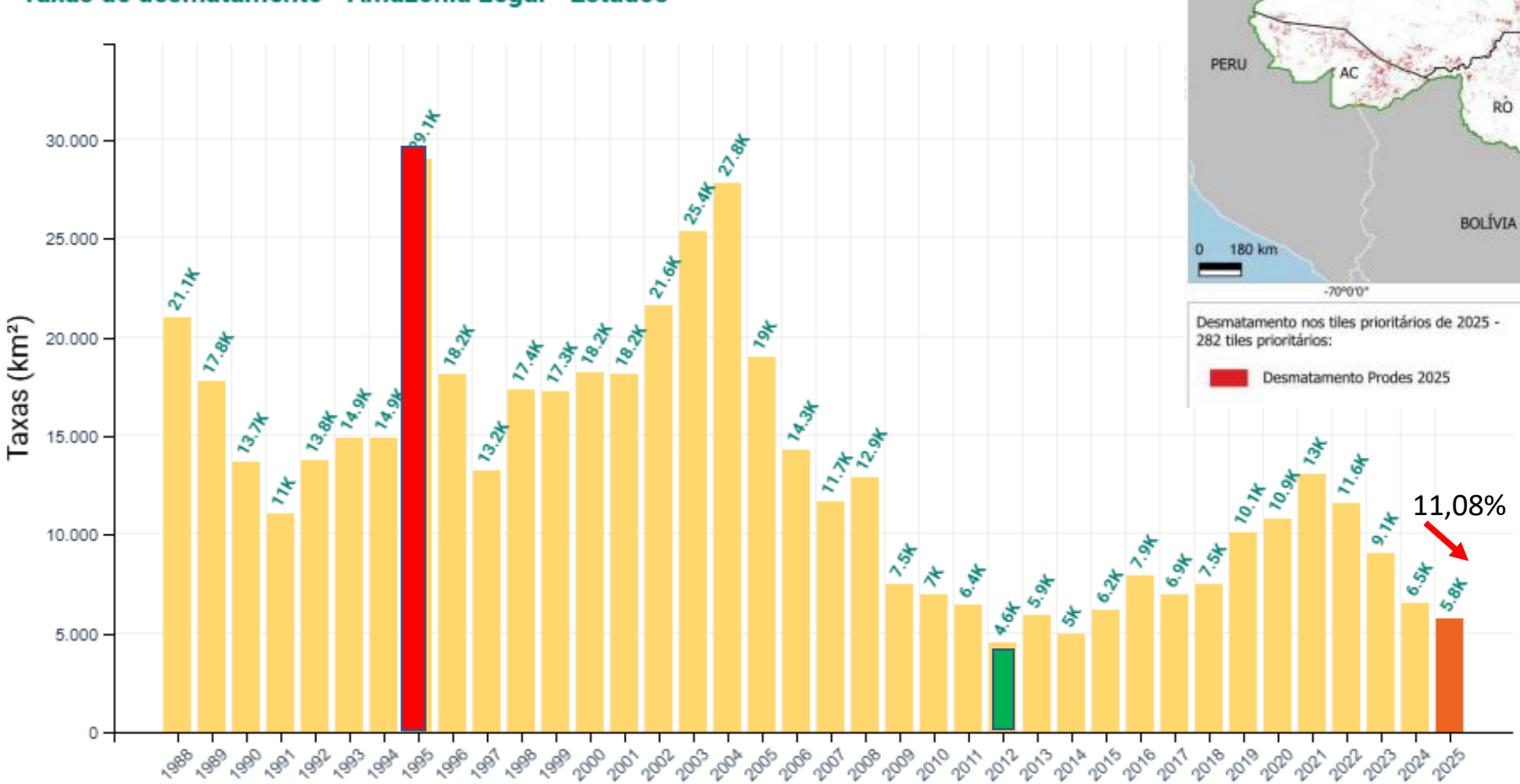


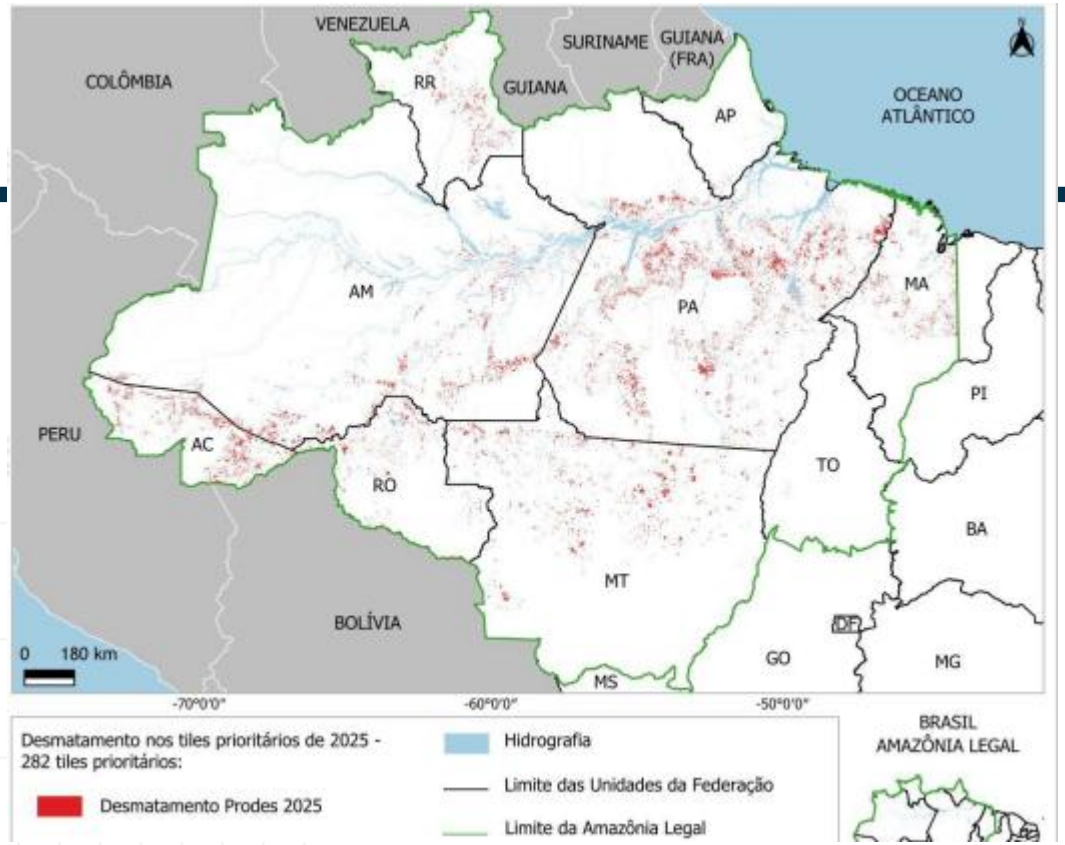
Poligons> 1ha
Sentinel Image (10m)
Native vegetation supression

https://terrabrasilis.dpi.inpe.br/app/map/deforestation?hl=pt-br

Prodes - Brazilian Legal Amazon

Cumulative deforestation by 2024 > 857.301,71 km^2
> 21% of the original forest of the Amazon region





5.731 km²
Deforestation rate 2025
(consolidated)

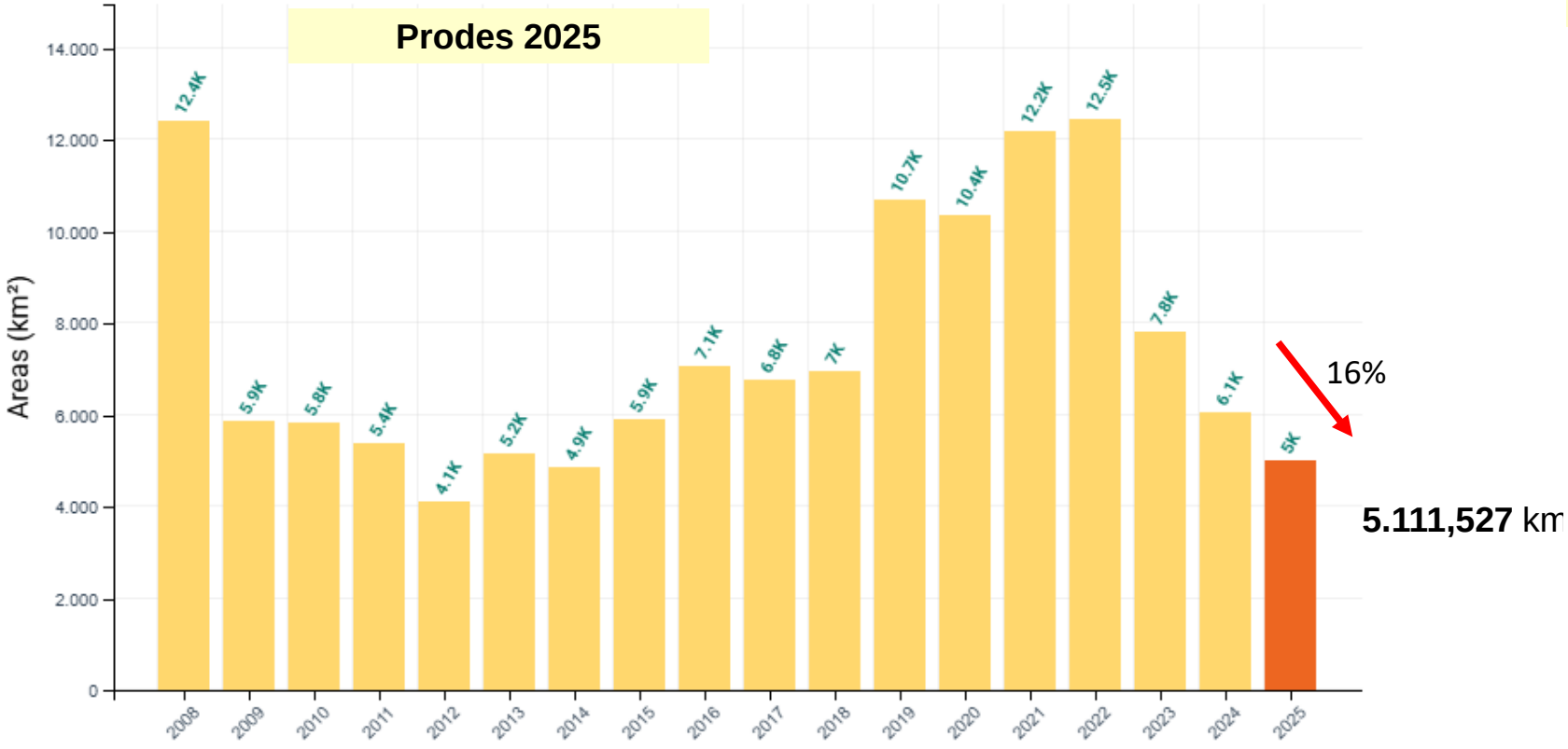
https://terrabrasilis.dpi.inpe.br

93

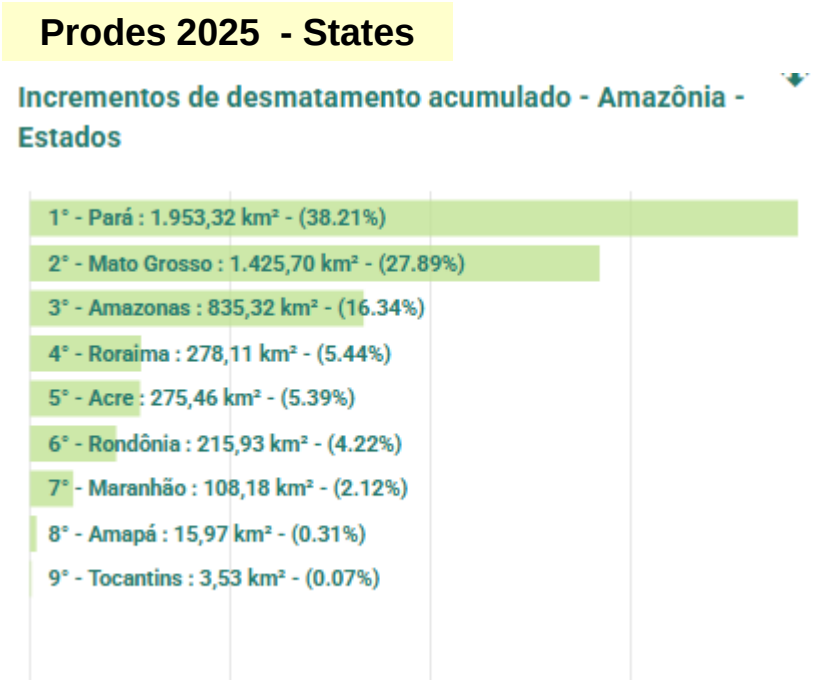
Prodes - Amazon Biome

Suppression of native vegetation

Deforestation 2025 = **5.111,52** km$^{2;}$ Deforestation 2024 = **6.075,86** km^2 (or 15,87% lower)



Polygons > 1ha, Sentinel Images (10-20m)



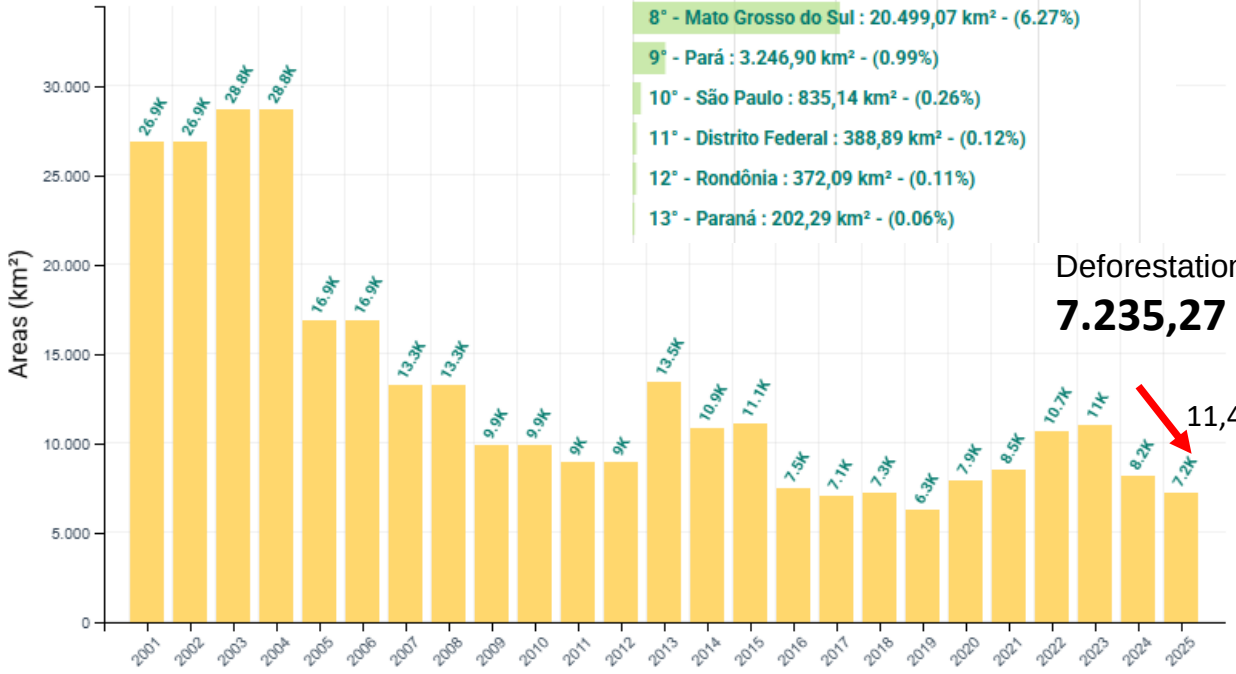
Prodes - Cerrado

Biomas Br

Incrementos de desmatamento acumulado - Cerrado - Estados

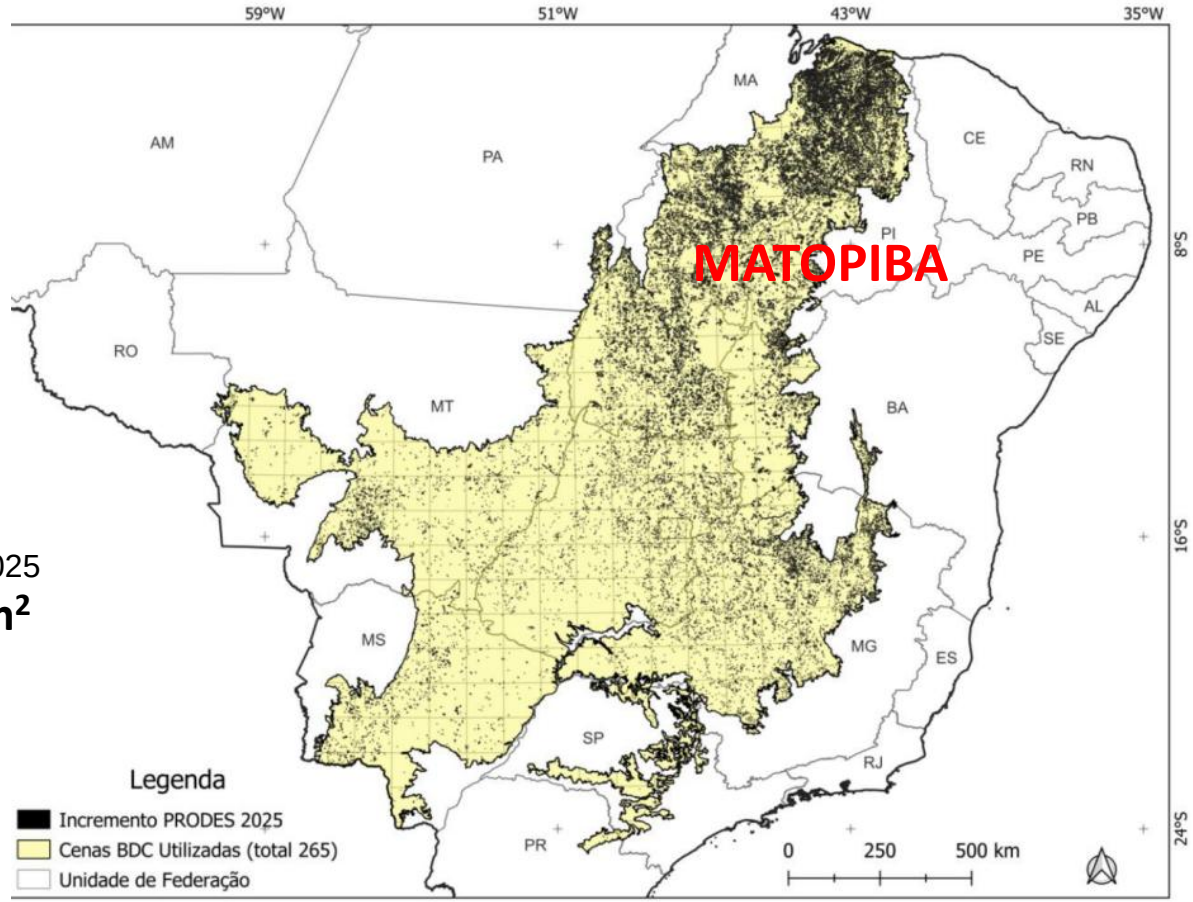
1° - Tocantins : 54.036,69 km² - (16.53%)
2° - Maranhão : 53.015,71 km² - (16.22%)
3° - Goiás : 49.676,22 km² - (15.20%)
4° - Mato Grosso : 46.667,56 km² - (14.28%)
5° - Minas Gerais : 43.137,03 km² - (13.20%)
6° - Bahia : 28.469,56 km² - (8.71%)
7° - Piauí : 26.265,48 km² - (8.04%)
8° - Mato Grosso do Sul : 20.499,07 km² - (6.27%)
9° - Pará : 3.246,90 km² - (0.99%)
10° - São Paulo : 835,14 km² - (0.26%)
11° - Distrito Federal : 388,89 km² - (0.12%)
12° - Rondônia : 372,09 km² - (0.11%)
13° - Paraná : 202,29 km² - (0.06%)

Incrementos de desmatamento - Cerrado - Estados



Deforestation 2025
7.235,27 km²

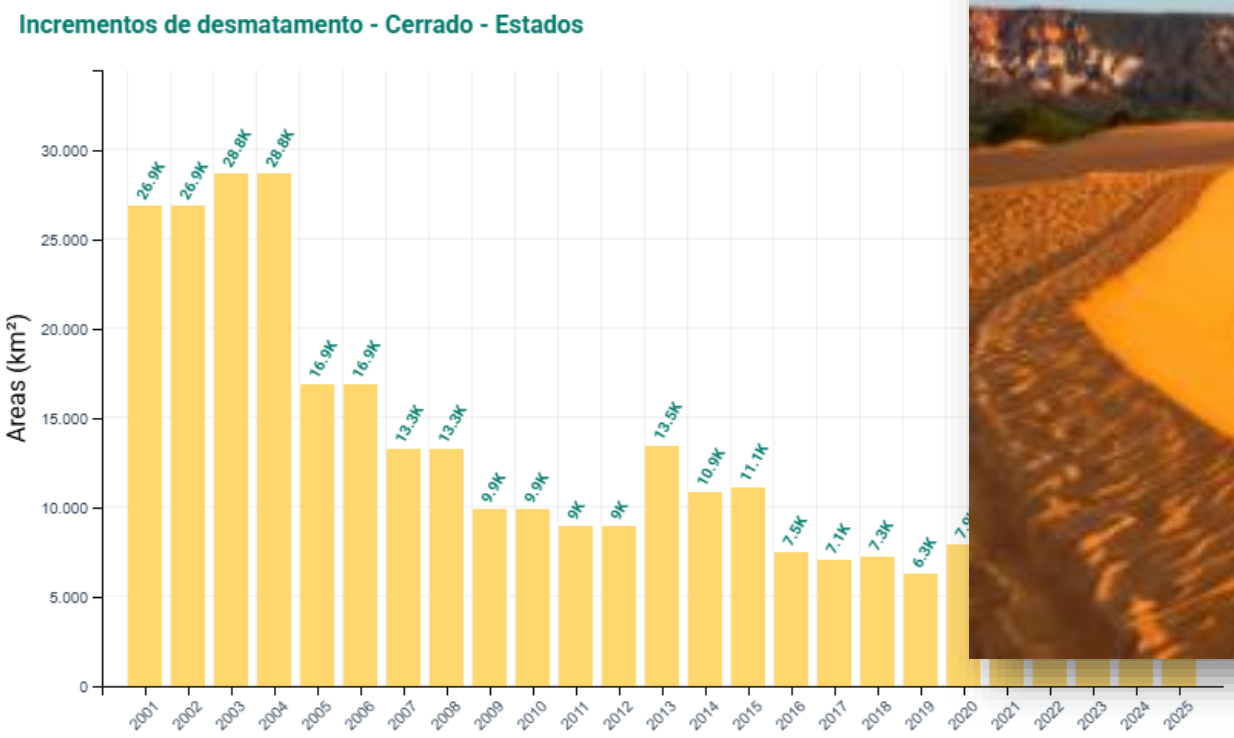
11,49%



https://terrabrasilis.dpi.inpe.br

95
95

Prodes - Cerrado





https://terrabrasilis.dpi.inpe.br

96
96

Prodes - 4 Biomes

Prodes 4 Biomes + NF

Caatinga, Atlantic Forest, Pantanal and Pampa

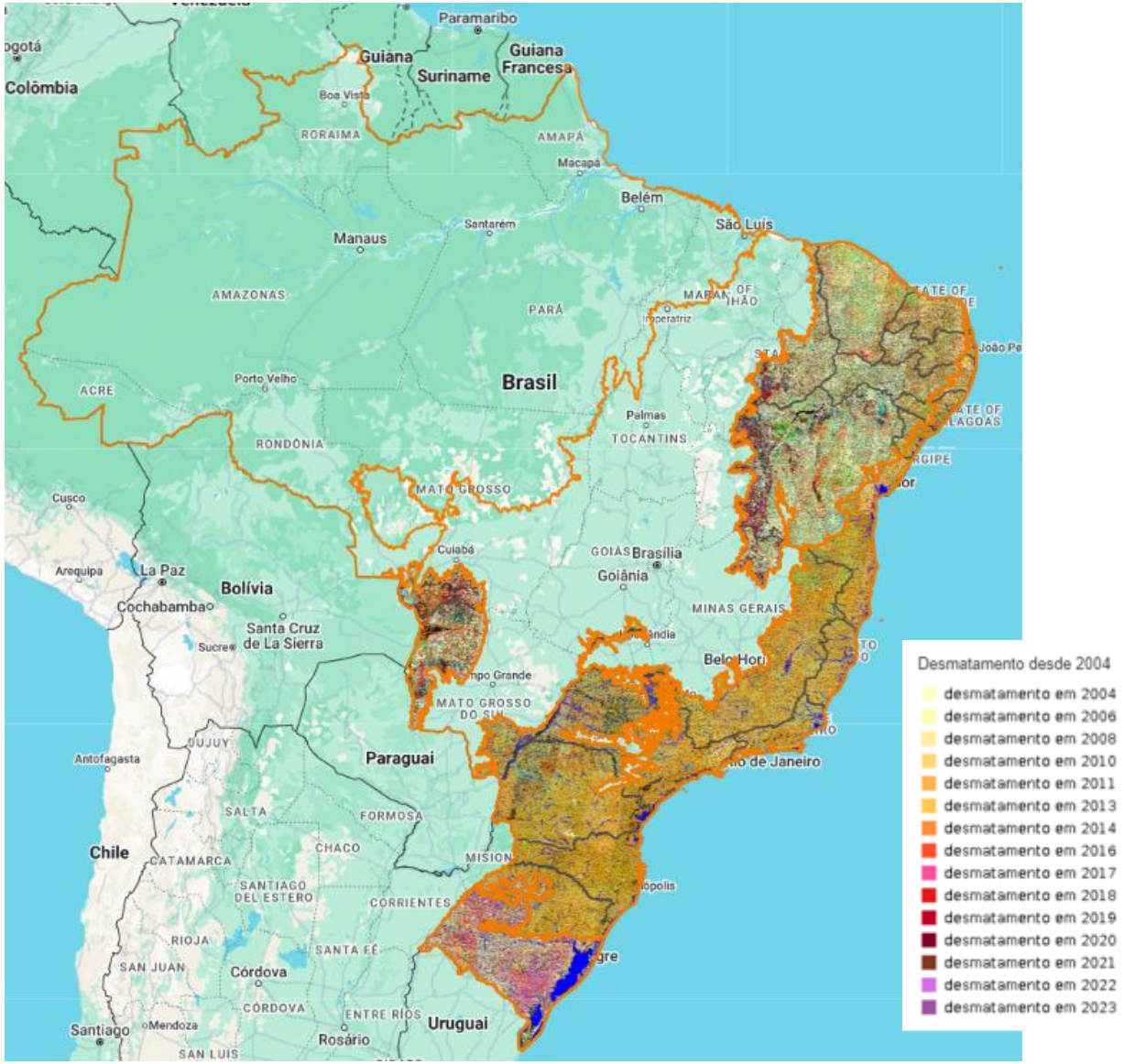
2024 available at TerraBrasilis

2025 – to be published in August

TerraBrasilis
(https://terrabrasilis.dpi.inpe.br/)

and

Technical Notes
(https://data.inpe.br/big/web/biomasbr/notas-tecnicas/)



Prodes - Non-Forest*



Figura 2: Exemplos de paisagens não florestais naturais observadas no trabalho de campo em Roraima, 2023 A) Savana Florestada; B) Savana Parque; C) Savana Gramíneo-Lenhosa; D) Vereda; E) Campinarana. Fonte: Messias et al. (2024b)

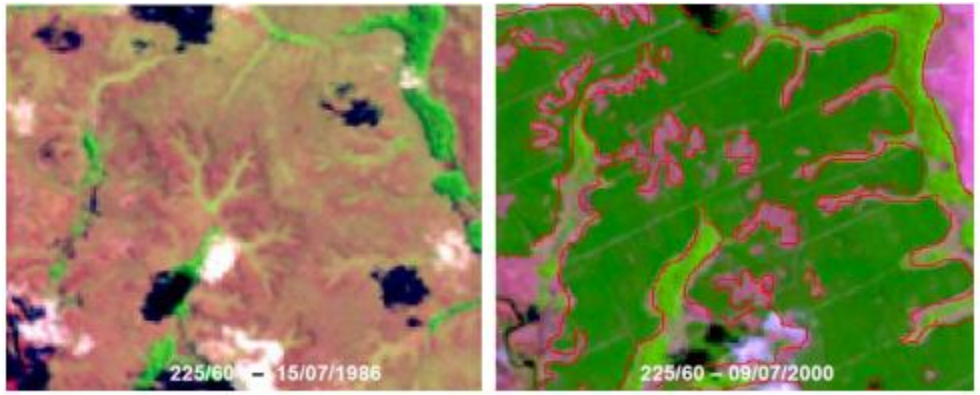


Figura 7: Delimitação de supressão (polígono vermelho) de vegetação não florestal mapeada no ano 2000, convertida em silvicultura

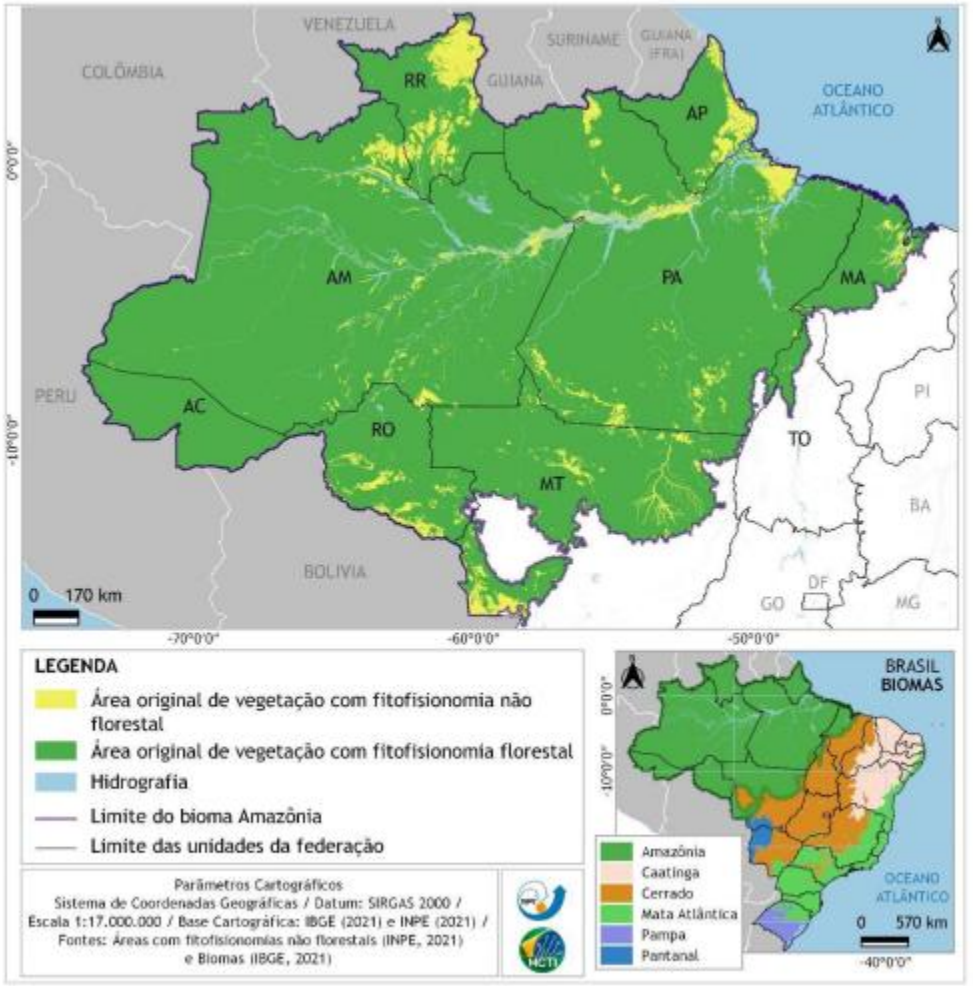
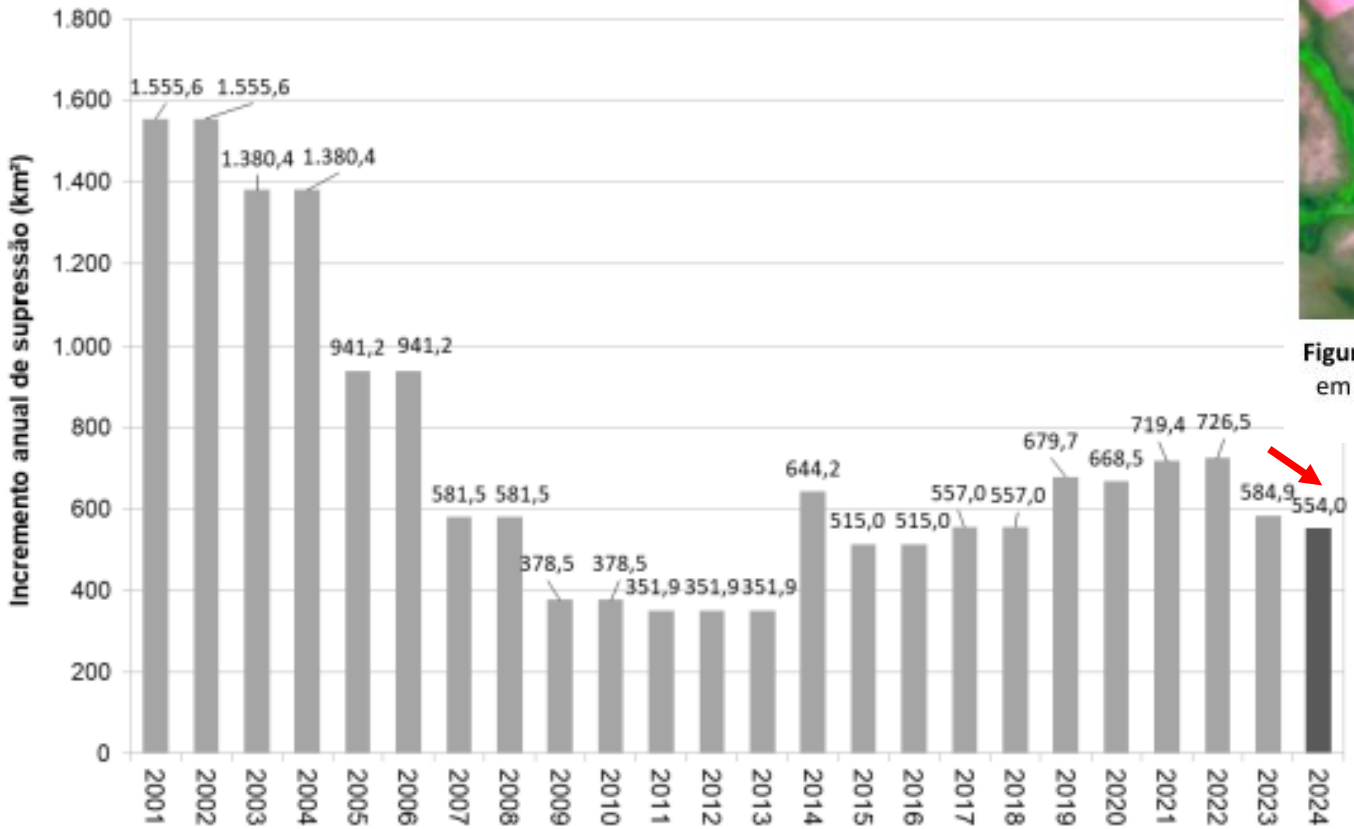


Figura 1: Localização das fitofisionomias não florestais e florestais e da hidrografia no bioma Amazônia considerados no sistema Prodes.

98

Prodes - Non-Forest

Native Vegetation Suppression by 2024 = 554.04 km^2 (~10.6% of Non-fores Amz area)
(2023= 584.63 km^2)



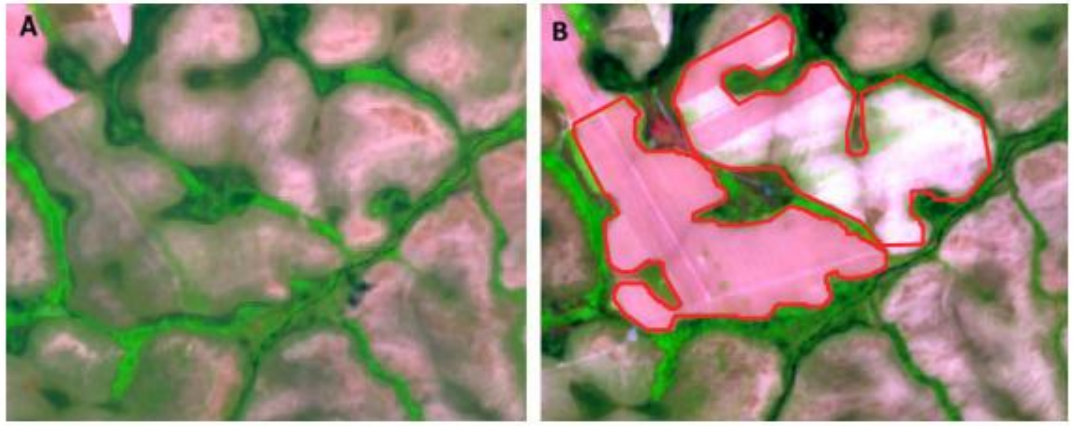


Figura 4 – Exemplo de detecção de supressão de vegetação não florestal na região do Lavrado, em Roraima. A) Vegetação não florestal natural; B) As áreas delimitadas em vermelho foram detectadas como supressão de vegetação não florestal.

5.27%

2024
554.04 km^2

99

Prodes - Caatinga

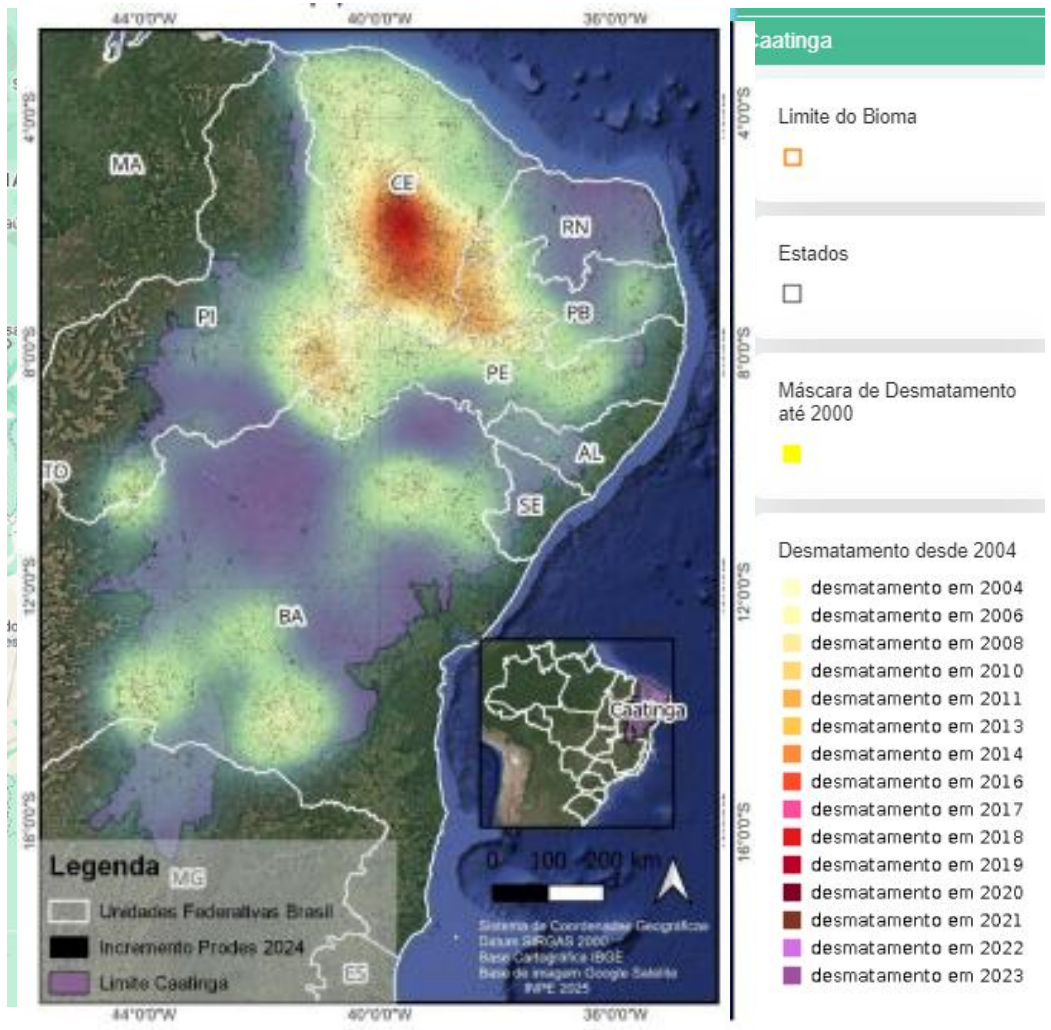


Suppression of native vegetation by 2024 = 374.248,40 km^2 (43,38% of the Biome)

Suppression 2024 = 3.484.37 km^2



9,93%



Prodes - Atlantic Forest

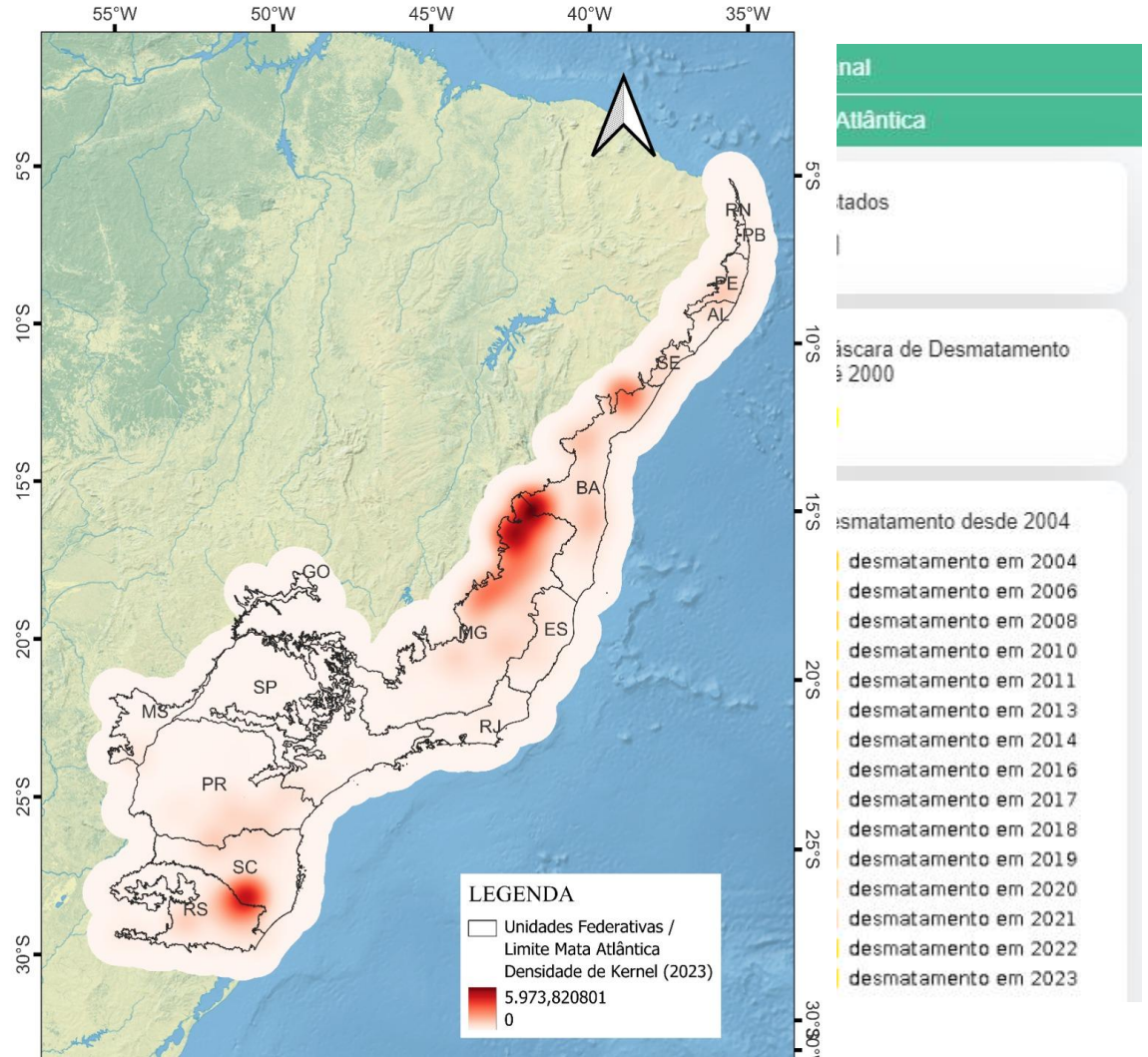


Suppression of native vegetation by 2024 = 790,364.17 km^2 (71,70% of the Biome)

Suppression 2024 = 475.18 km^2







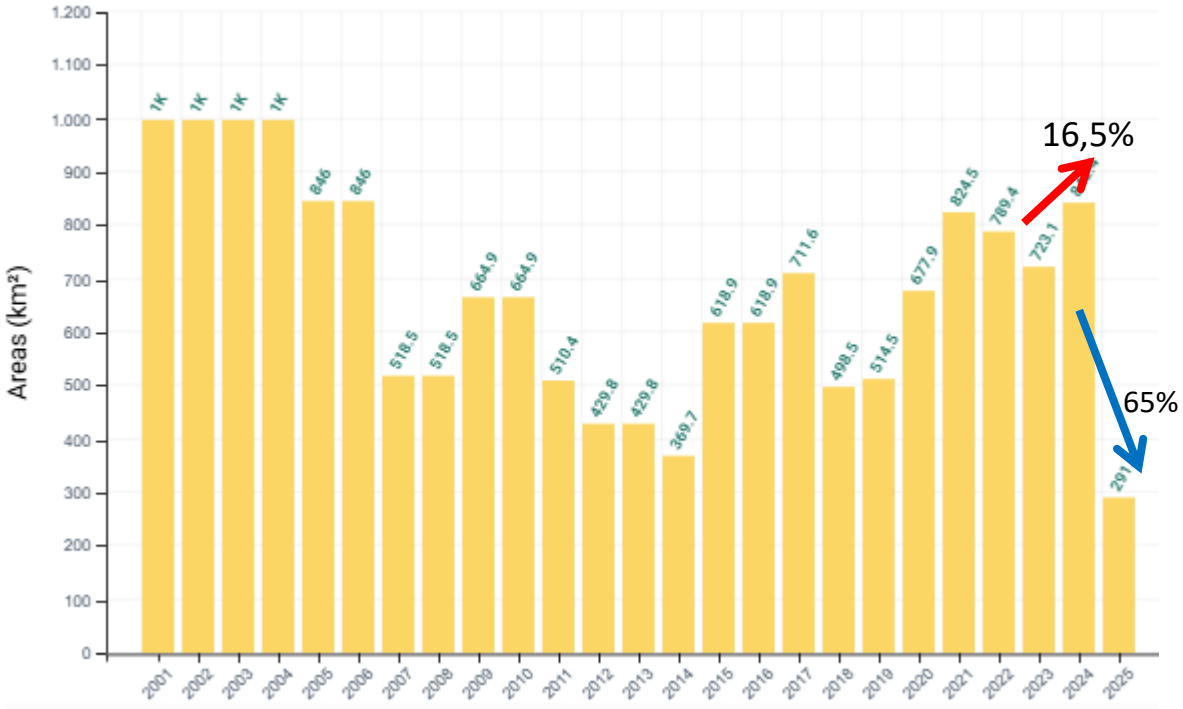
Prodes - Pantanal



Suppression of native vegetation by 2024 = 31.276,15 km^2 (20.71% do Bioma)

Suppression 2024 = 842,44 km^2





Suppression 2025 = 291,21 km^2

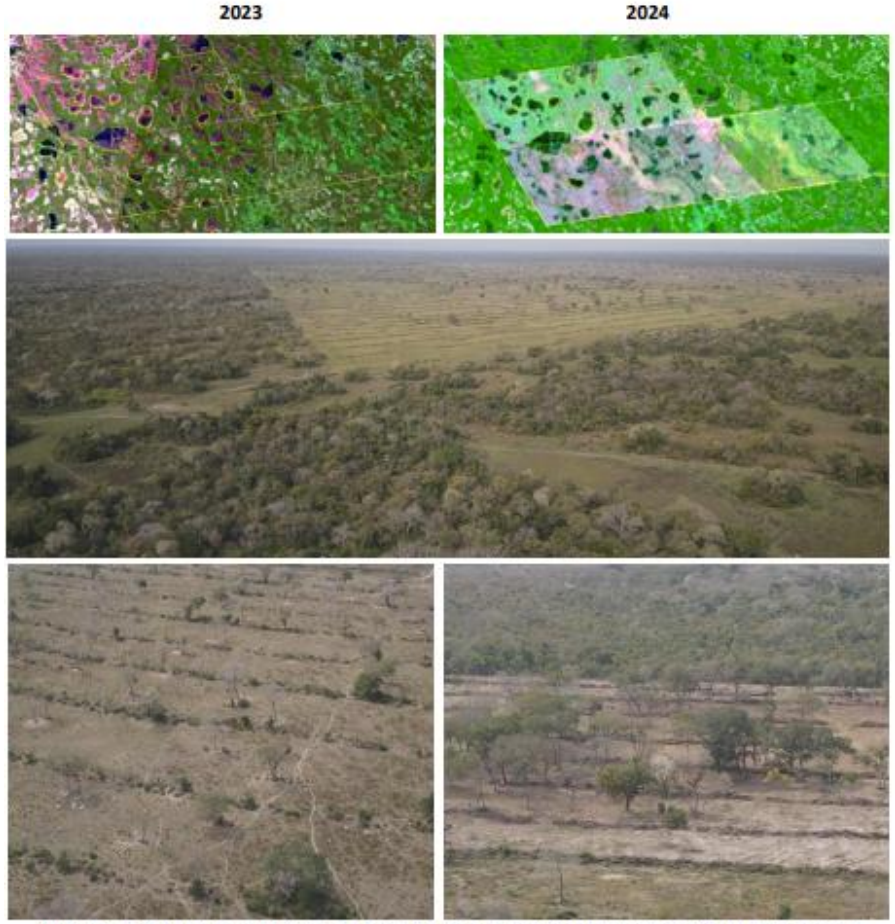


Figura 4 – Exemplo de detecção de supressão com pasto exótico na sub-região de Aquidauana, Aquidauana - MS (-55,80381; -19,83334).

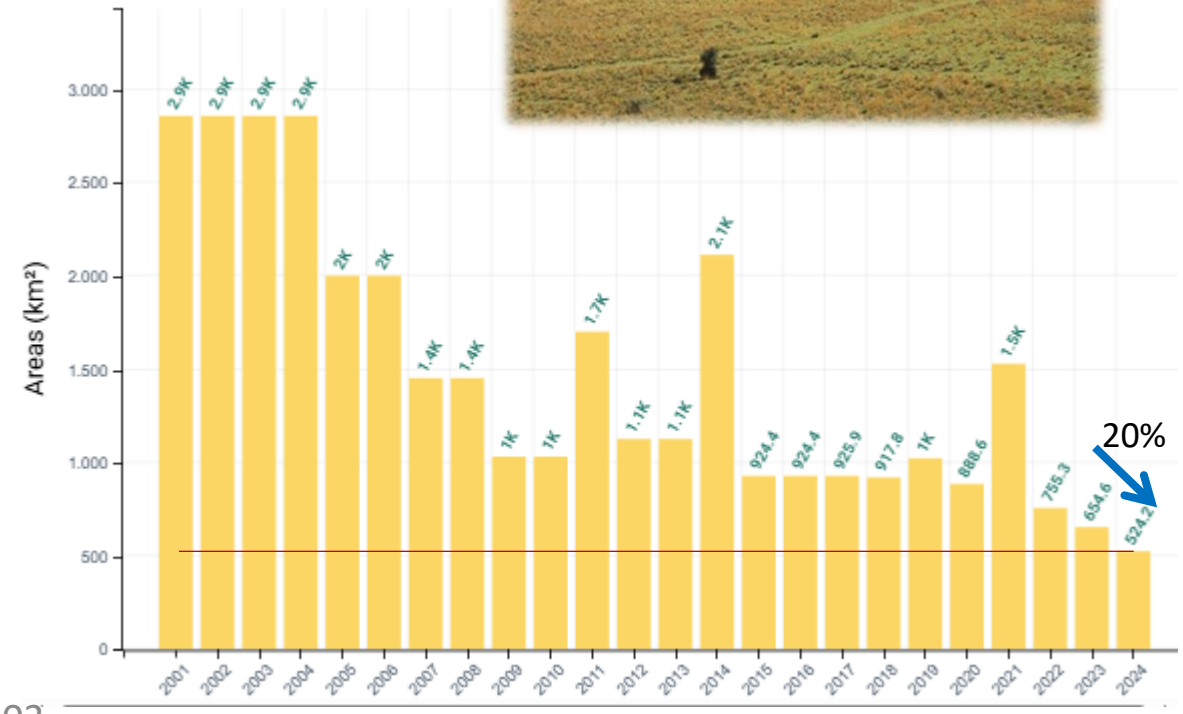
Prodes - Pampa

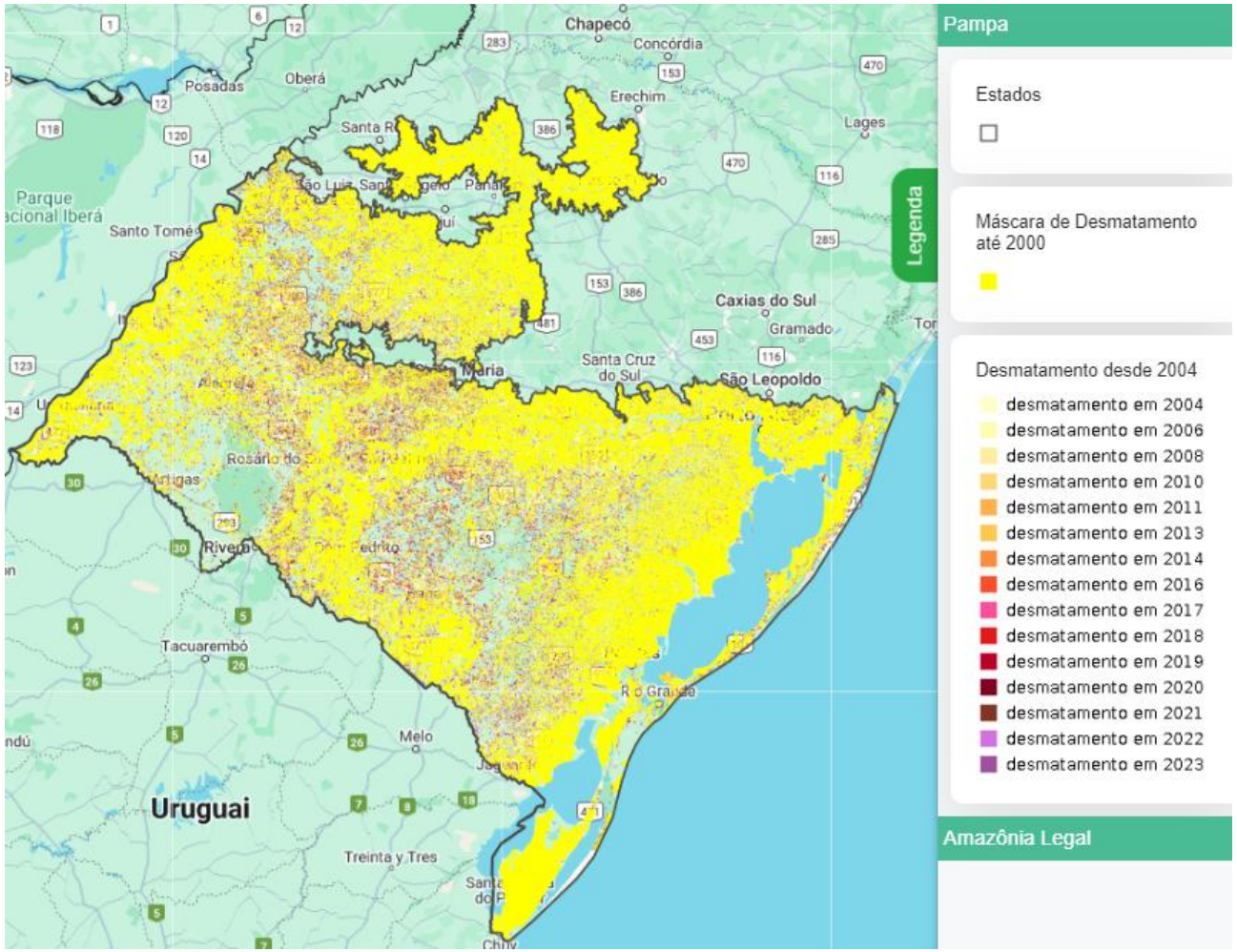


Suppression of native vegetation by 2023 = 114,164.65 km^2 (~65% of the Bioma)

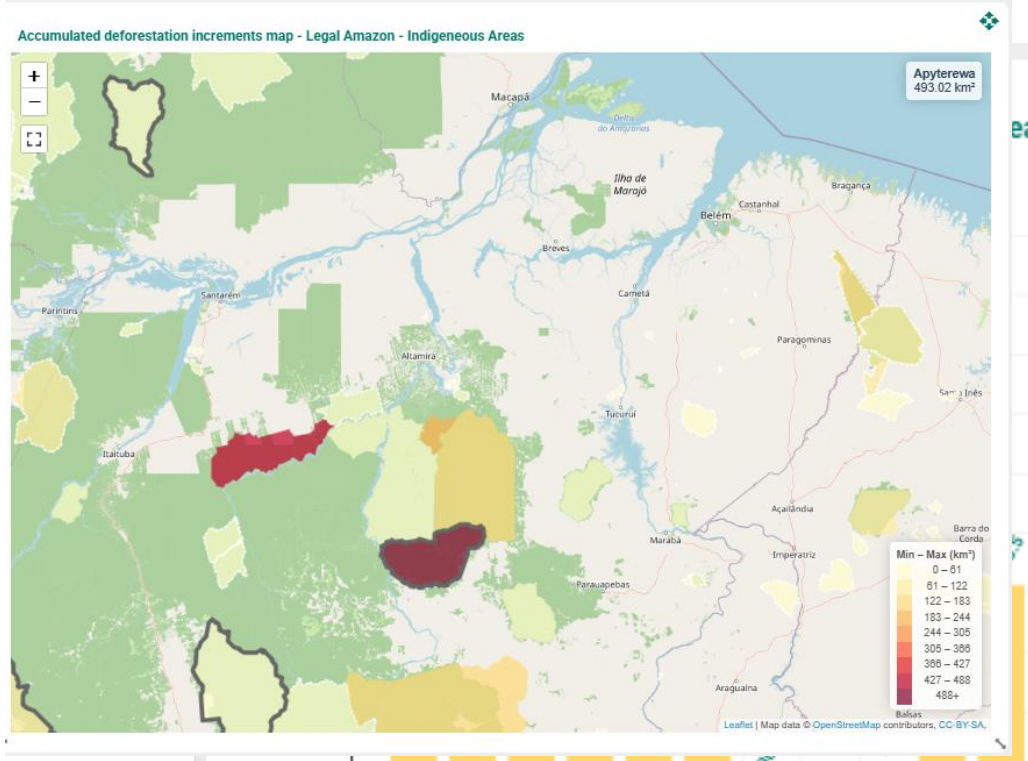
Suppression **2024 = 523,14 km^2**







Prodes - Indigenous Territory

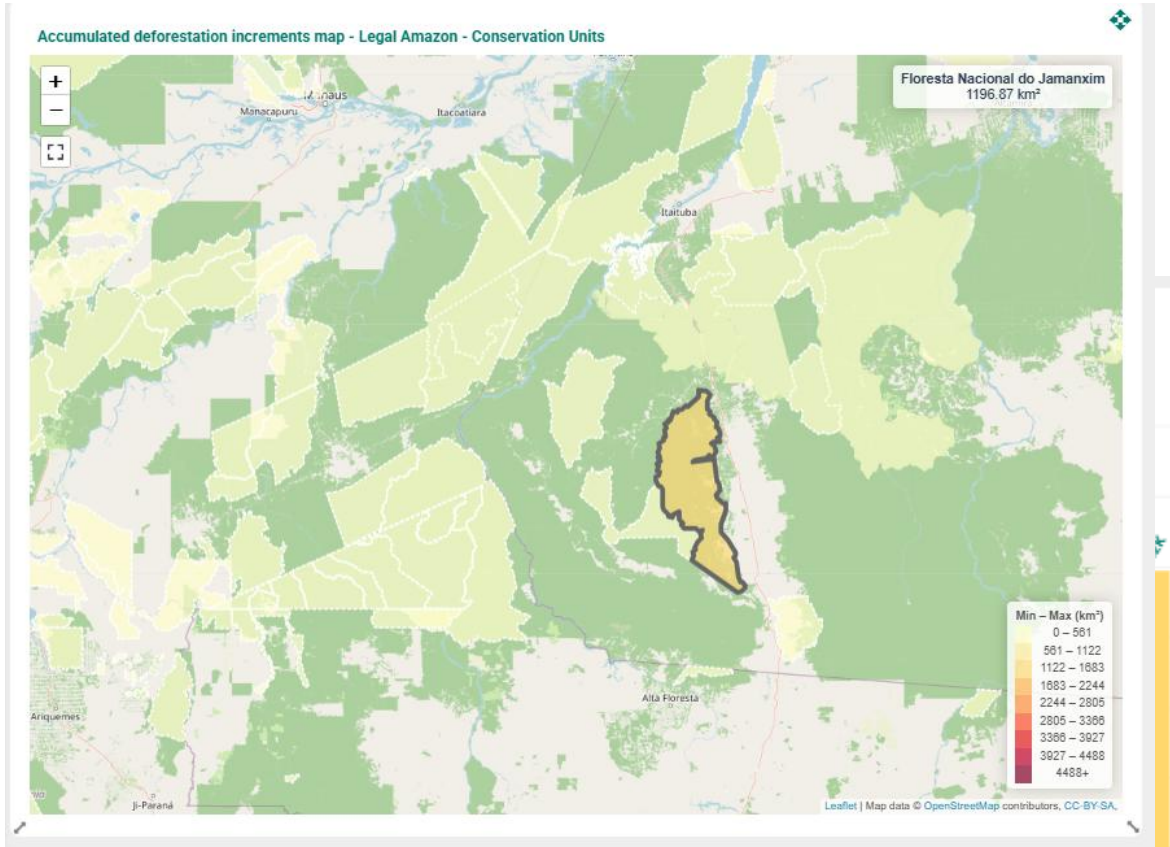


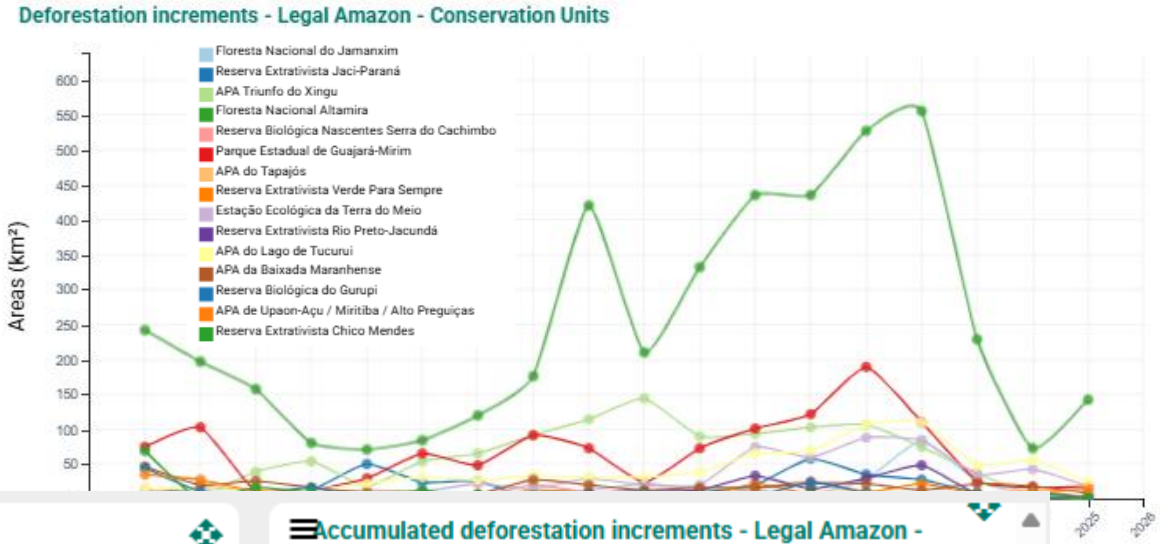
Deforestation 2025
489.11 km²



https://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/legal_amazon/increments

Conservation Units





Deforestation 2025
364.59 km²



https://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/amazon/increments

Biomas Br

Prodes

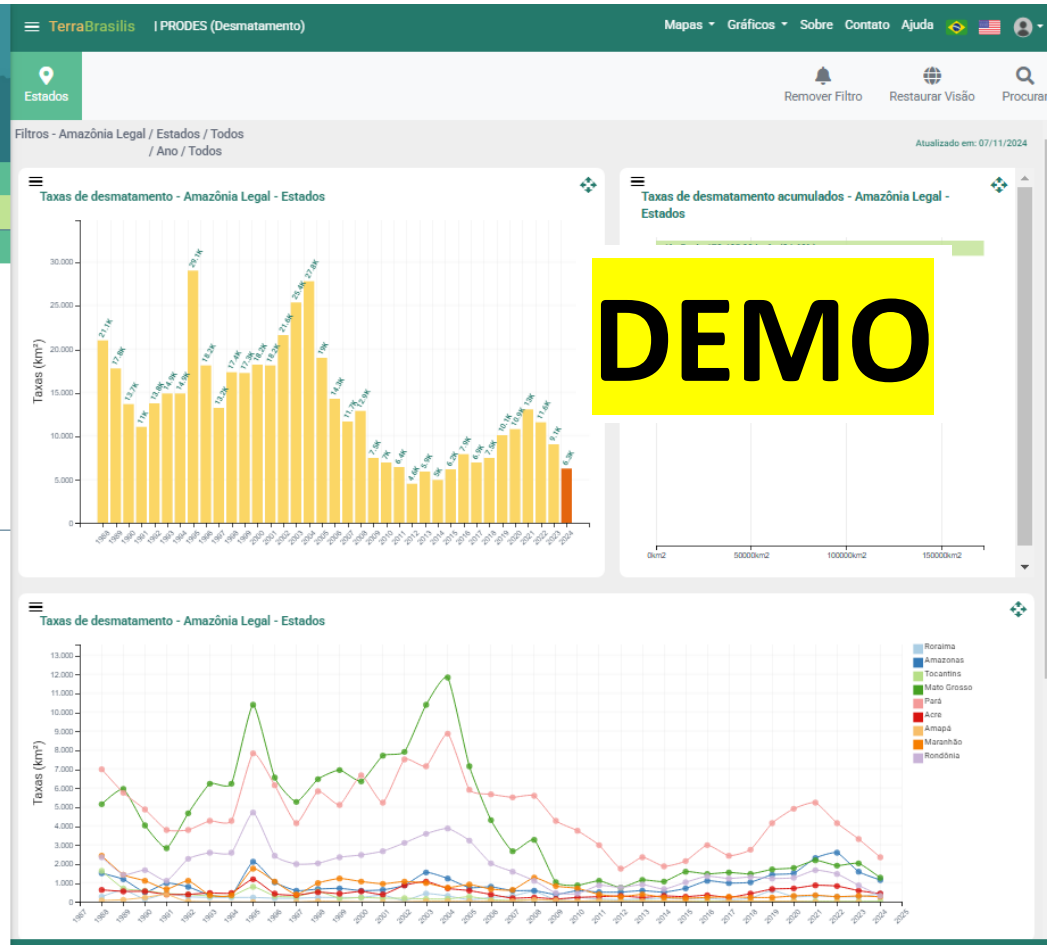
TerraBrasilis

TerraBrasilis - Platform developed by INPE for **organization, access and use** of geographic data from the environmental monitoring systems.

Maps



Dashboard - Graphics / Queries



DEMO

AND Download

https://terrabrasilis.dpi.inpe.br/

Prodes – Environmental compliance

Brazilian Institutions that assess compliance (CONAB / SERPRO) using Prodes Data

A) EUDR - European Union Deforestation Regulation

Commodities produced on land deforested after **31 December 2020** will not be traded

B) **Agricultural credit** (CMN Resolution No. 5,193/2024)

Credit restrictions for areas deforested after **31 July 2019**

C) **"Consolidated rural area"*** (Decree No. 6,514/2008),

Forest Code – Illegal deforestation before **22 July 2008** is considered consolidated and amnestied.



https://agriconline.com.br/portal/artigo/car-cadastro-ambiental-rural-guia-para-produtores-rurais/

* These are areas that were already occupied by agriculture, livestock farming, or infrastructure before 22 July 2008 (the date defined by the Forest Code).

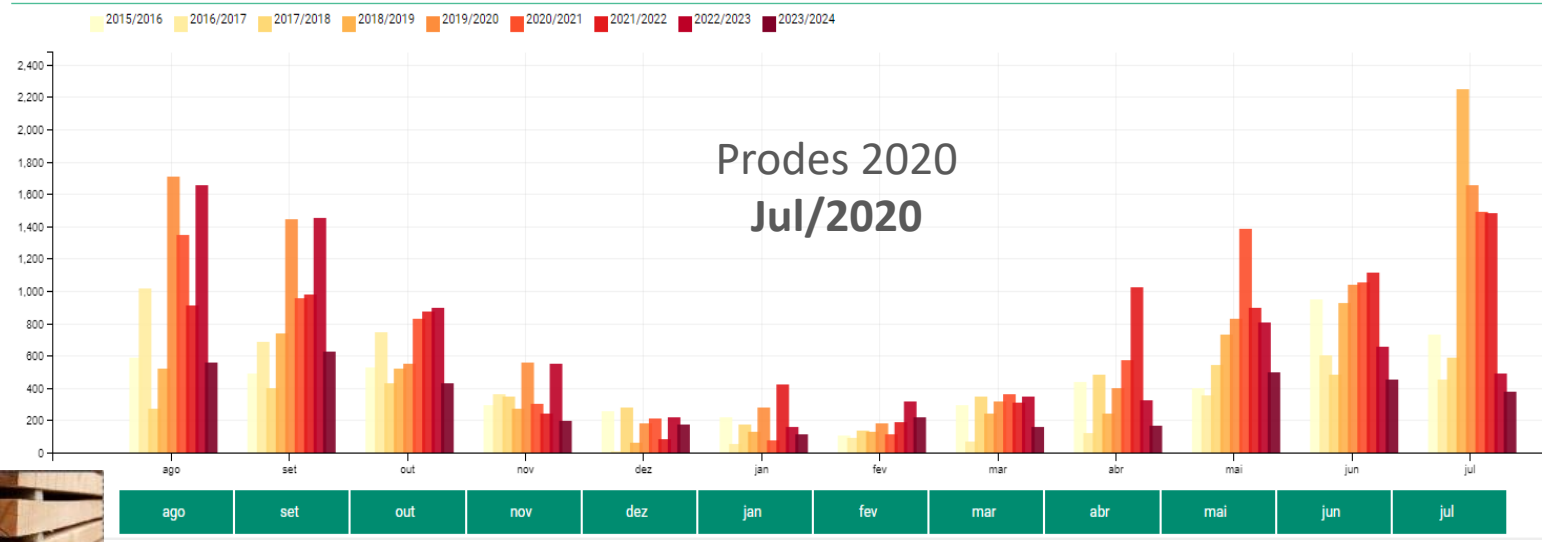
Prodes – December/2020 EUDR

European Union Deforestation Regulation (EUDR)*
(EUDR 2023/1115)

Reference – **31/Dez/2020**

Minimum area = **0,5ha**

Prodes – Calendar





** The EUDR2023/1115 aims to prevent deforestation and forest degradation linked to products placed on the EU market or exported from it, requiring companies to ensure the products do not originate from land deforested after December 31, 2020.*

Prodes – December/2020 EUDR

European Union Deforestation Regulation (EUDR)
(EUDR 2023/1115)

Methodology

Sentinel-2/MSI data – time series
Brazil Data Cube (BDC)

Spectral attributes:
B04, B8A, B11, NDVI, NBR, NDWI, AWEINSH, texture B8A (average).

Unsupervised clustering algorithms
SOM - Self-Organizing Map (SOM)
AHC - Agglomerative hierarchical clustering

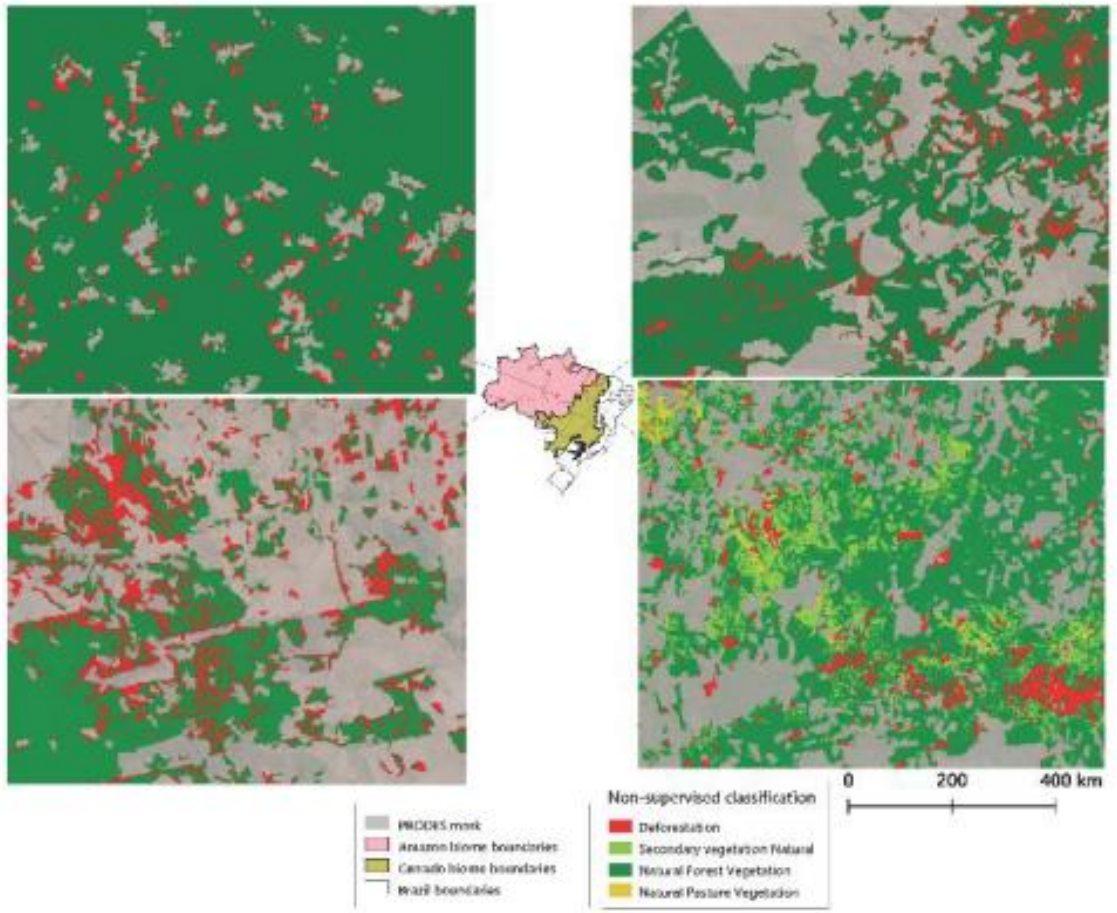
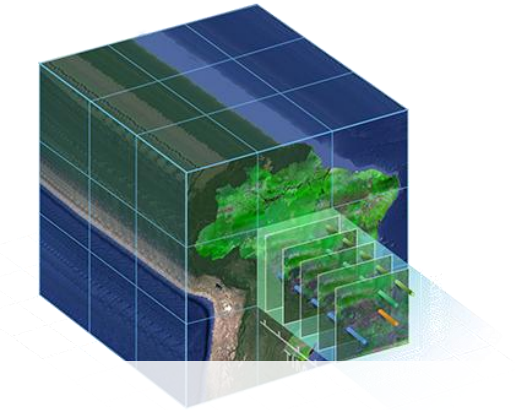


Figure 2. Tiles classified in the Brazilian Amazon and Cerrado biomes using the non-supervised approach.

Soler et al. (2025)

Prodes – dez/2020 EUDR

European Union Deforestation Regulation (EUDR)
(EUDR 2023/1115)



Brazil Data Cube

Ago-dez/2020

Self-Organizing Map (SOM)

Unsupervised algorithm based on AI
(Deep Learning)

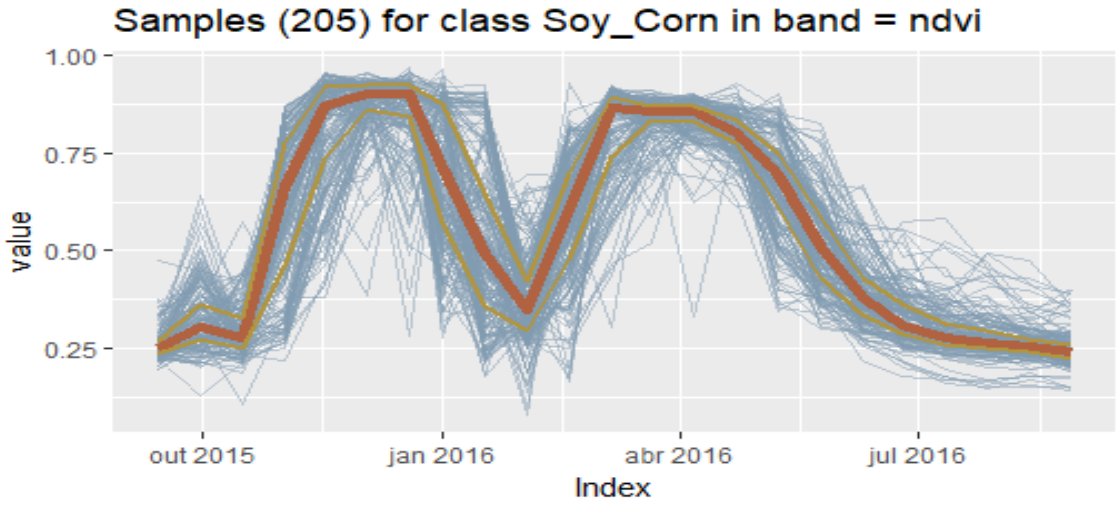
Dendograms - Number of neurons

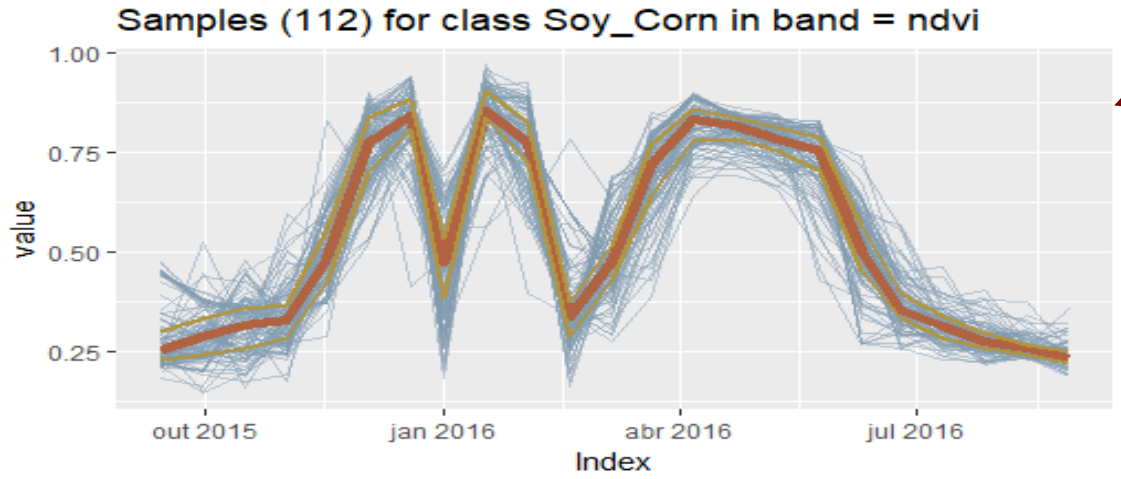
AHC - Agglomerative Hierarchical Clustering

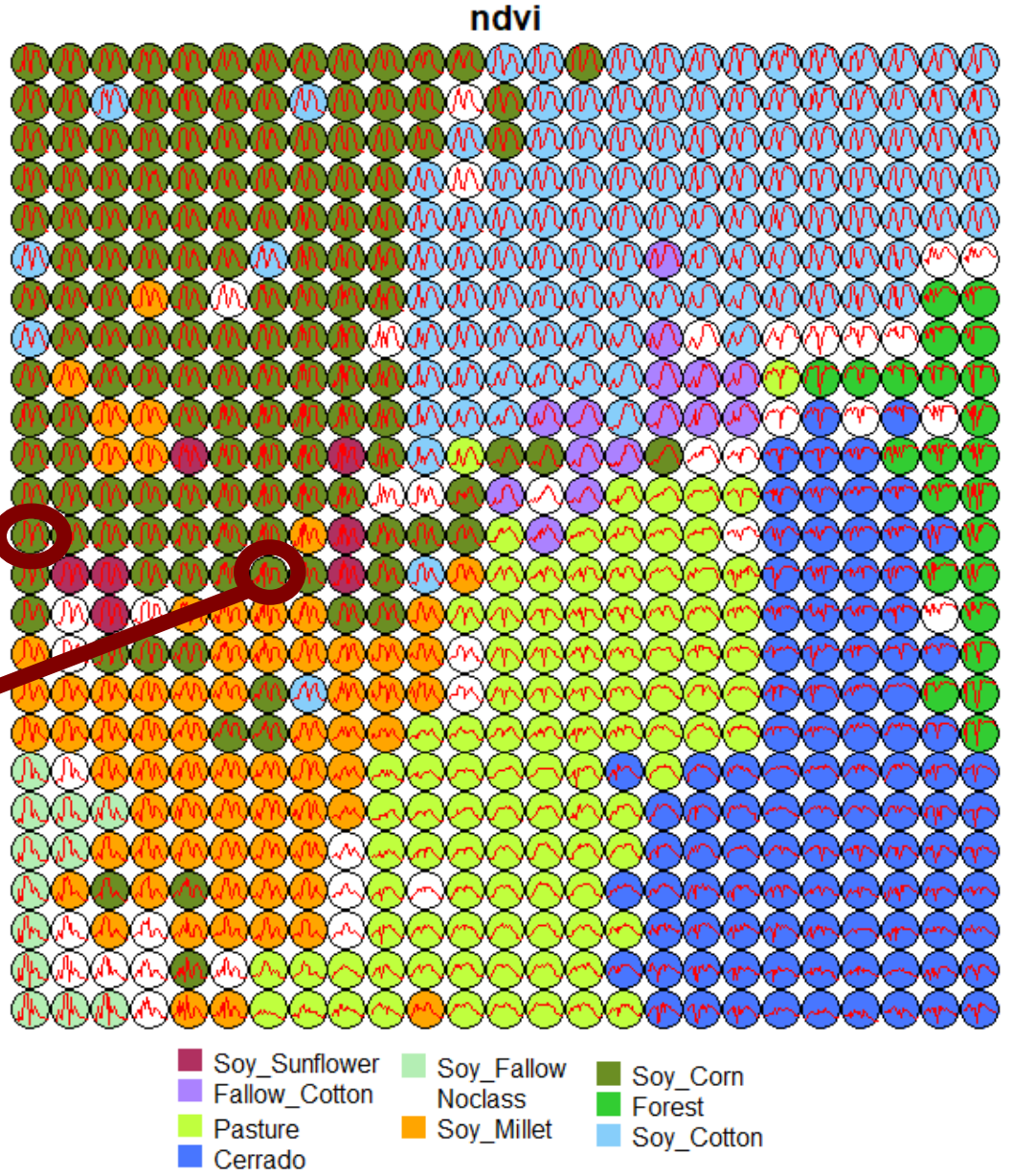
Segment labelling – Visual inspection

SOM to identify different SITS patterns

Self-Organizing Maps (SOM) neural network for SITS clustering

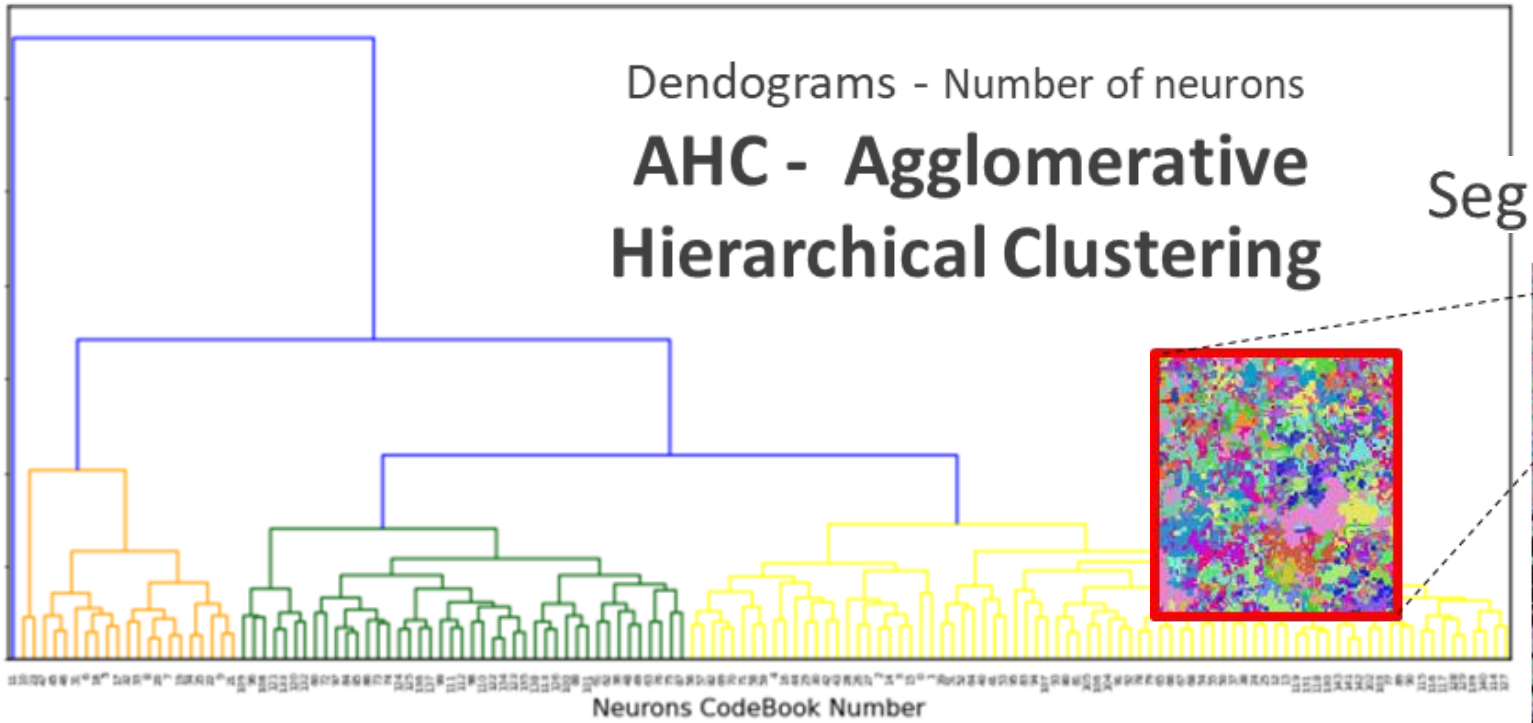




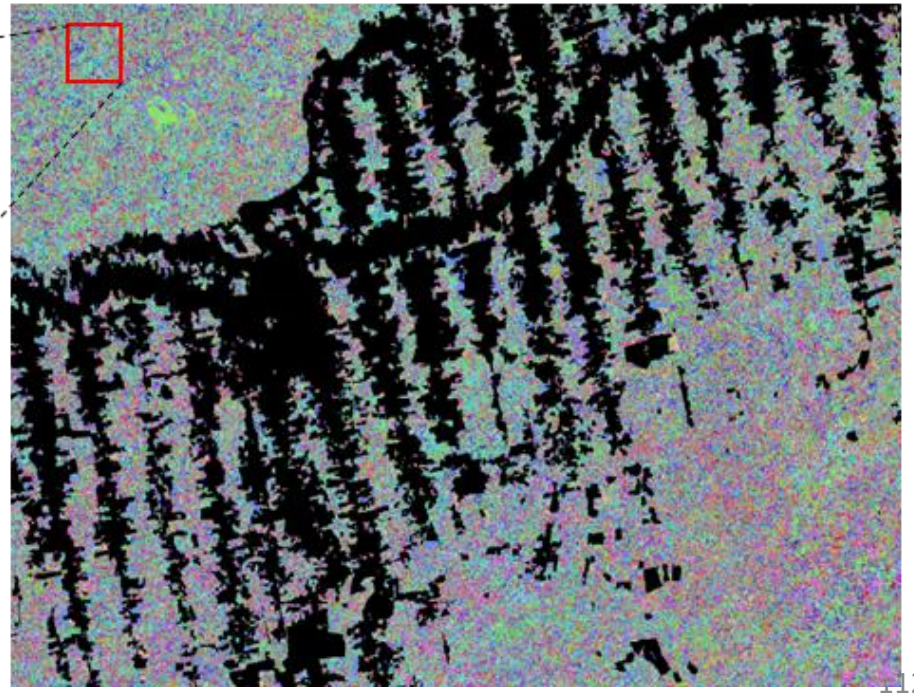


Prodes – dez/2020 EUDR

European Union Deforestation Regulation



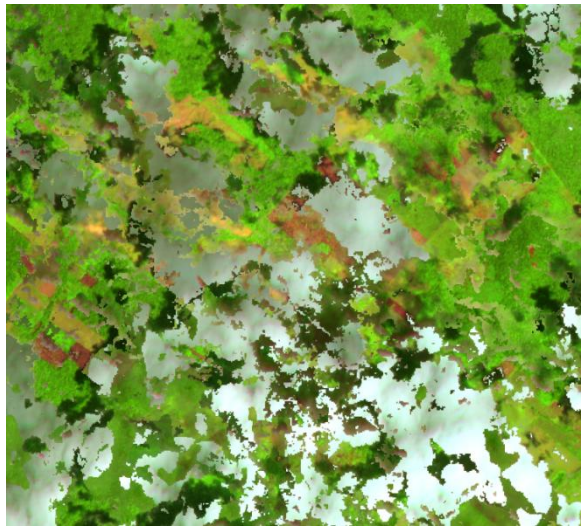
Segment labelling – Visual inspection



Prodes – December/2020 EUDR

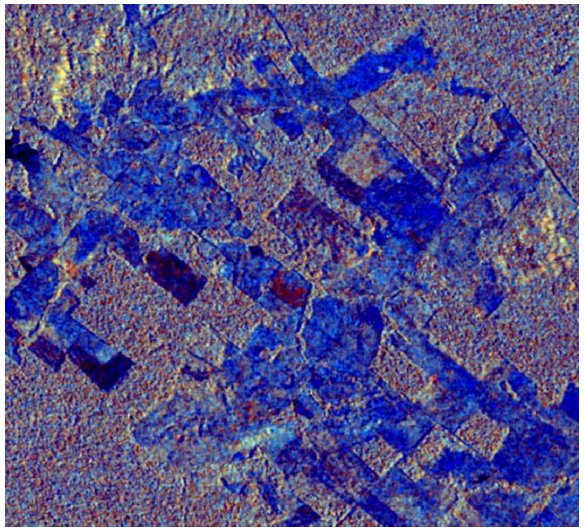
Radar – auxiliary data

Sentinel-2 Mosaic image
BDC dez/2020



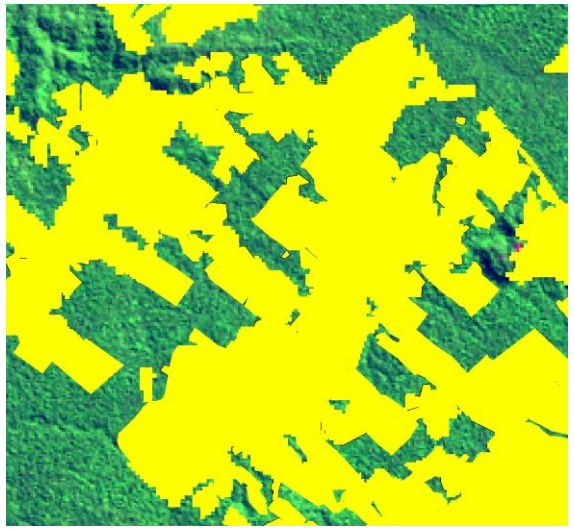
Sentinel - 2 (MSS)

Radar image 12/28/2020
(cloud free)



Sentinel - 1 (SAR)

Delimitation of deforested areas (yellow)



Prodes – Accuracy Validation

PRODES processes: implications on data quality

Aspects of **PRODES quality**:

I - Mapping processes requirements

II - External validation

III - Transparency

Image selection and processing	Best detection period Reduced cloud coverage
Visual inspection	Multi-disciplinary and experienced team Legend and protocol standardization Ancillary data Information about regional or local specificity
Auditing	Systematic process (100% of territory) Visual inspection
Post-processing	Consistency and processing rules checking
Map validation	Stratified and random sampling External staff
Data Dissemination	Transparency (http://terrabrasilis.dpi.inpe.br/) Technical reports Scientific publications

Independent auditor
Experts for each Biome

Validator

High resolution satellite images as reference

Planet monthly mosaic (5m)

WPM/CBERS4 – PCA (2m)

Prodes – Command and Control

Plano de Ação para Prevenção e Controle do Desmatamento na Amazônia Legal (PPCDAm)

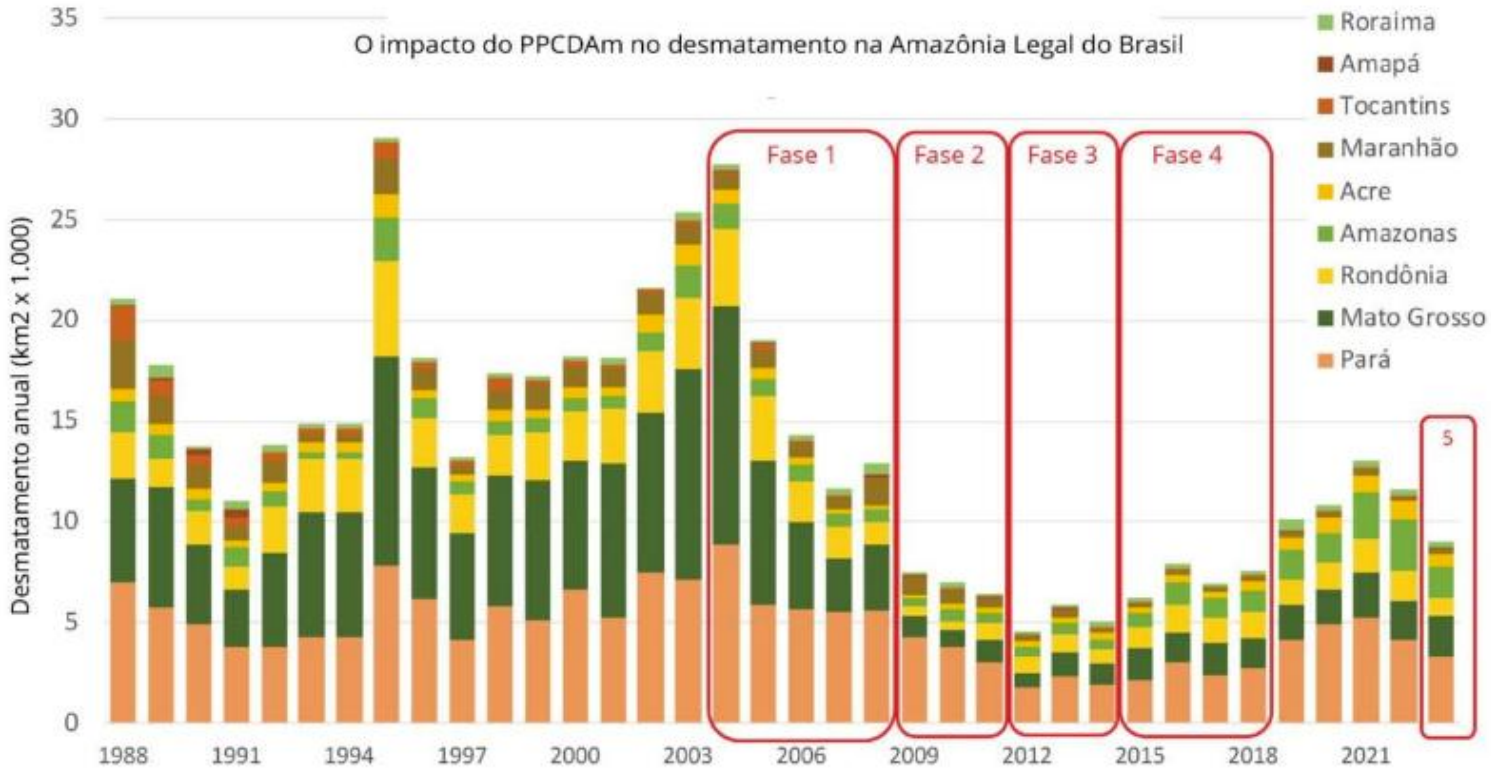
Launched in 2003 – a decline in deforestation between 2004 and 2012.

In 2009,
The United Nations Framework Convention on Climate Change (UNFCCC)
80% reduction in deforestation by 2020.

2012 – exceeded the target.
Annual rate = 20% of its historical twenty-year average.

2018- Gov Bolsonaro – dismantled the program

2023 - Phase 5 – NGOs, containment of deforestation and regularization of land ownershi for forest communities, agrarian settlements, and family farmers;- Sustainable production, REDD+, restoration

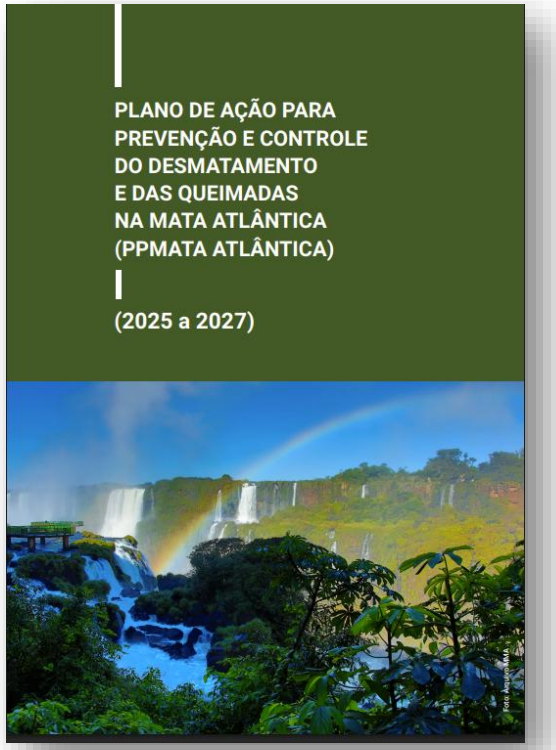


https://brasil.mongabay.com/2025/09/a-formula-que-reduziu-o-desmatamento-no-brasil-no-seculo-21/

Prodes – Command and Control

Plano de Ação para Prevenção e Controle do Desmatamento (PPCD)
All biomes

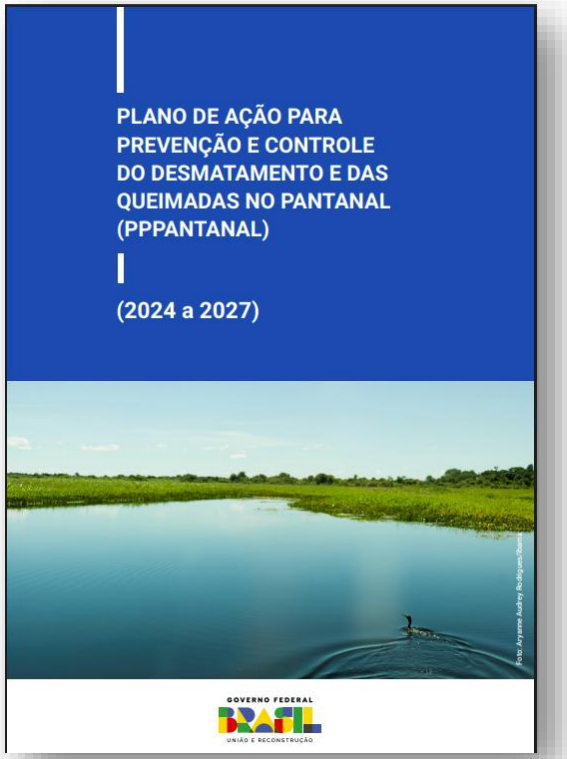
(2023 Decreet – besides PPCDAM and PPCerrado)



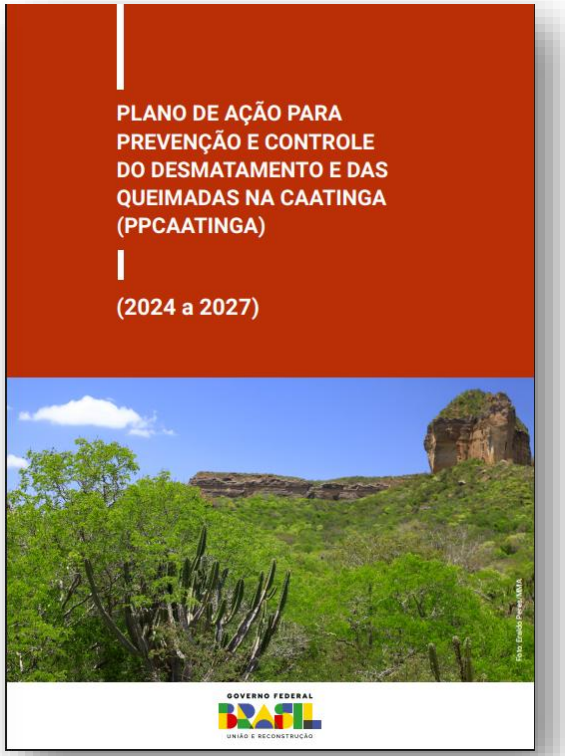
https://www.gov.br/mma/pt-br/assuntos/controle-ao-desmatamento-queimadas-e-ordenamento-ambiental-territorial/controle-do-desmatamento-1/ppmata-atlantica/PPMata_Atlantica_2025_internet_final.pdf



https://www.gov.br/mma/pt-br/assuntos/controle-ao-desmatamento-queimadas-e-ordenamento-ambiental-territorial/controle-do-desmatamento-1/pppampa/PPPampa_2025_internet.pdf



https://www.gov.br/mma/pt-br/assuntos/controle-ao-desmatamento-queimadas-e-ordenamento-ambiental-territorial/controle-do-desmatamento-1/pppantanal/pppantanal_2024.pdf

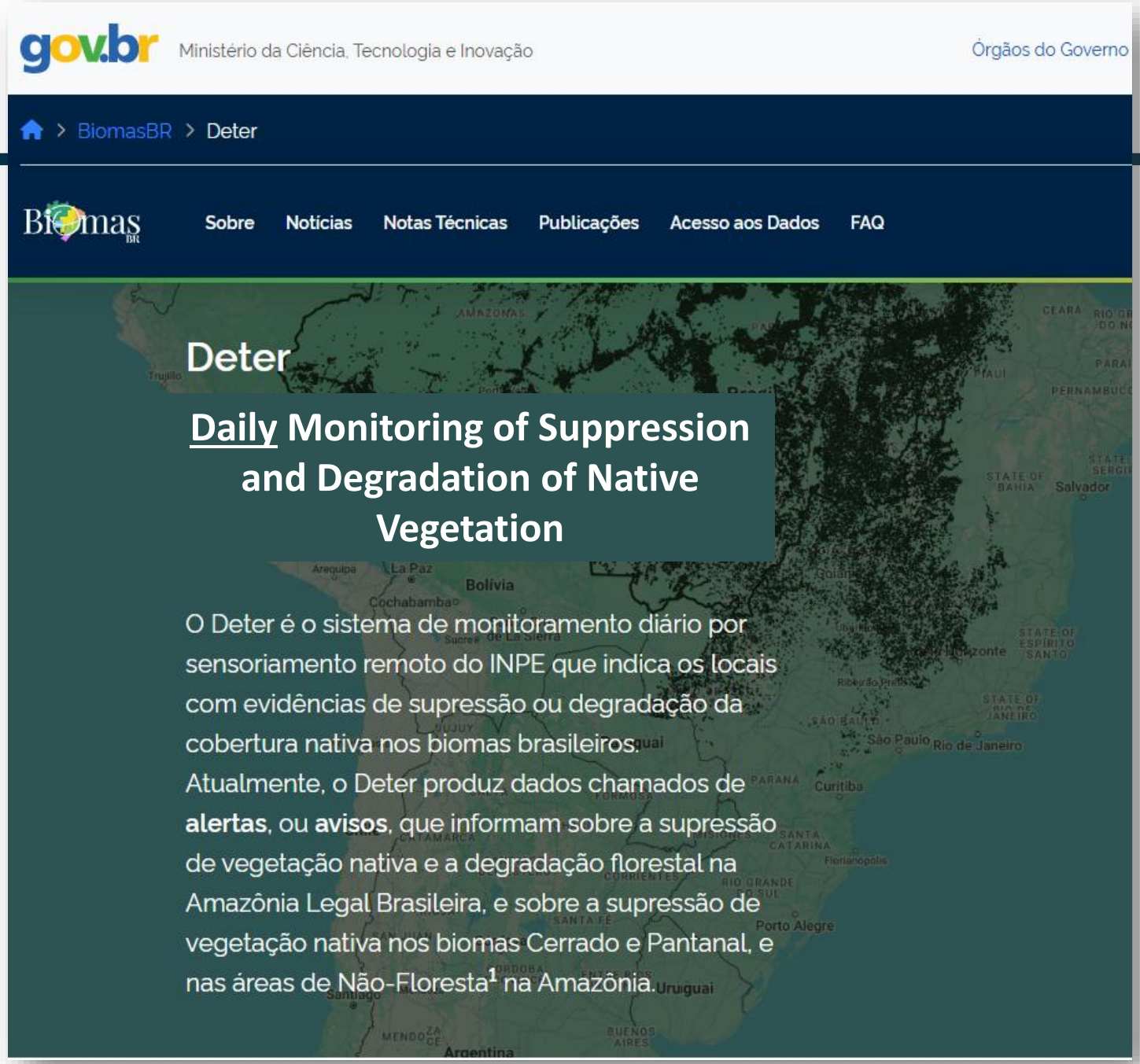


https://www.gov.br/mma/pt-br/assuntos/controle-ao-desmatamento-queimadas-e-ordenamento-ambiental-territorial/controle-do-desmatamento-1/ppcaatinga/ppcaatinga_2024_20_12.pdf

Biomas Br

DETER

Daily Monitoring of Suppression and Degradation of Native Vegetation



https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

Suppression and Degradation Alerts

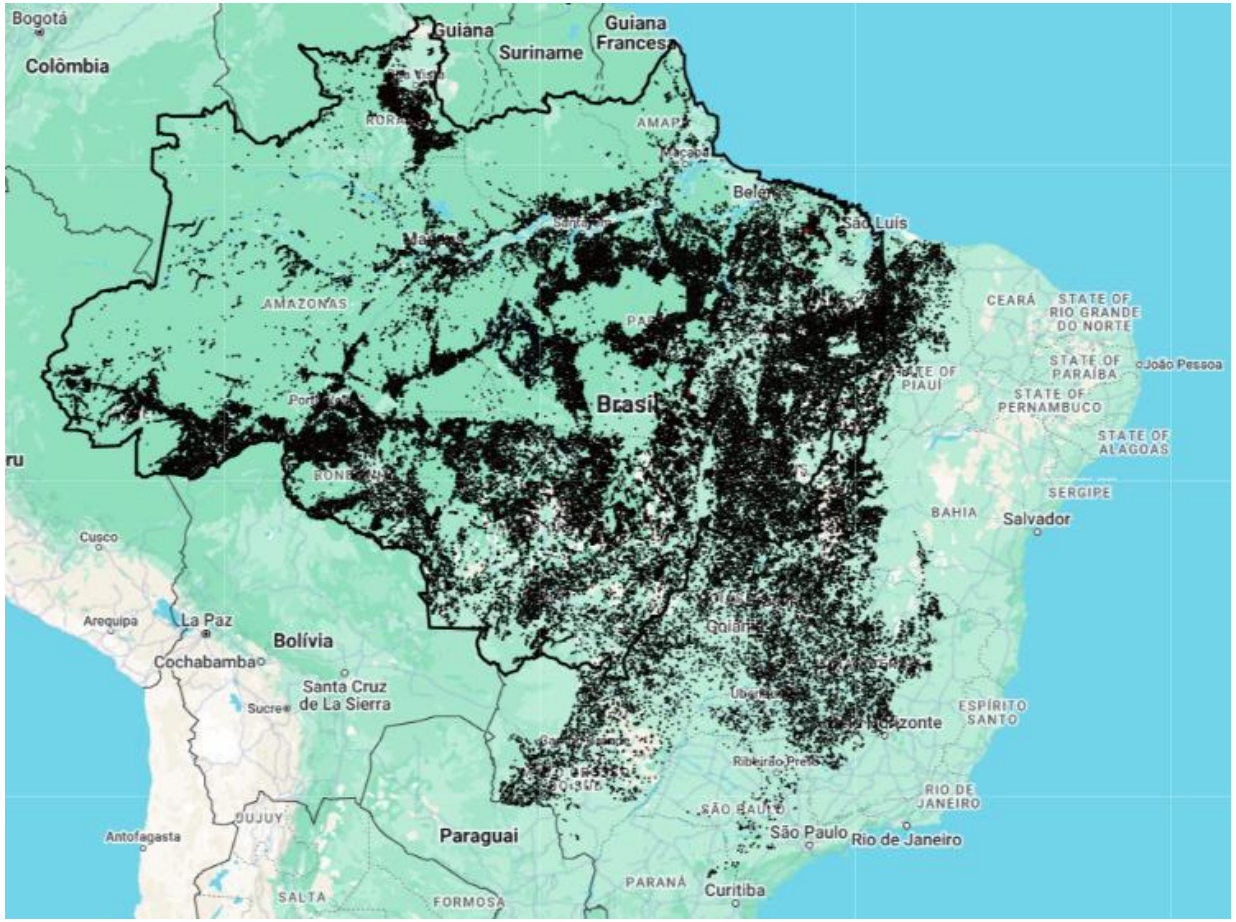
Deter

Amazon, Cerrado,
Pantanal and Non Forest Amz

Daily alerts are produced
Monthly aggregates - also released

Alerts are sent to control institutions
IBAMA, state and municipal environmental secretariats, etc.

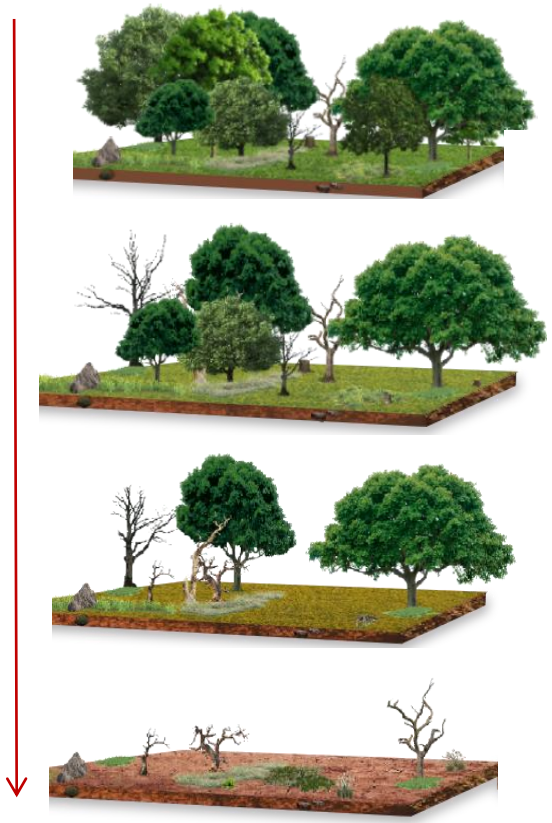
Data: polygons, tables, vectors;
Available on the TerraBrasilis platform

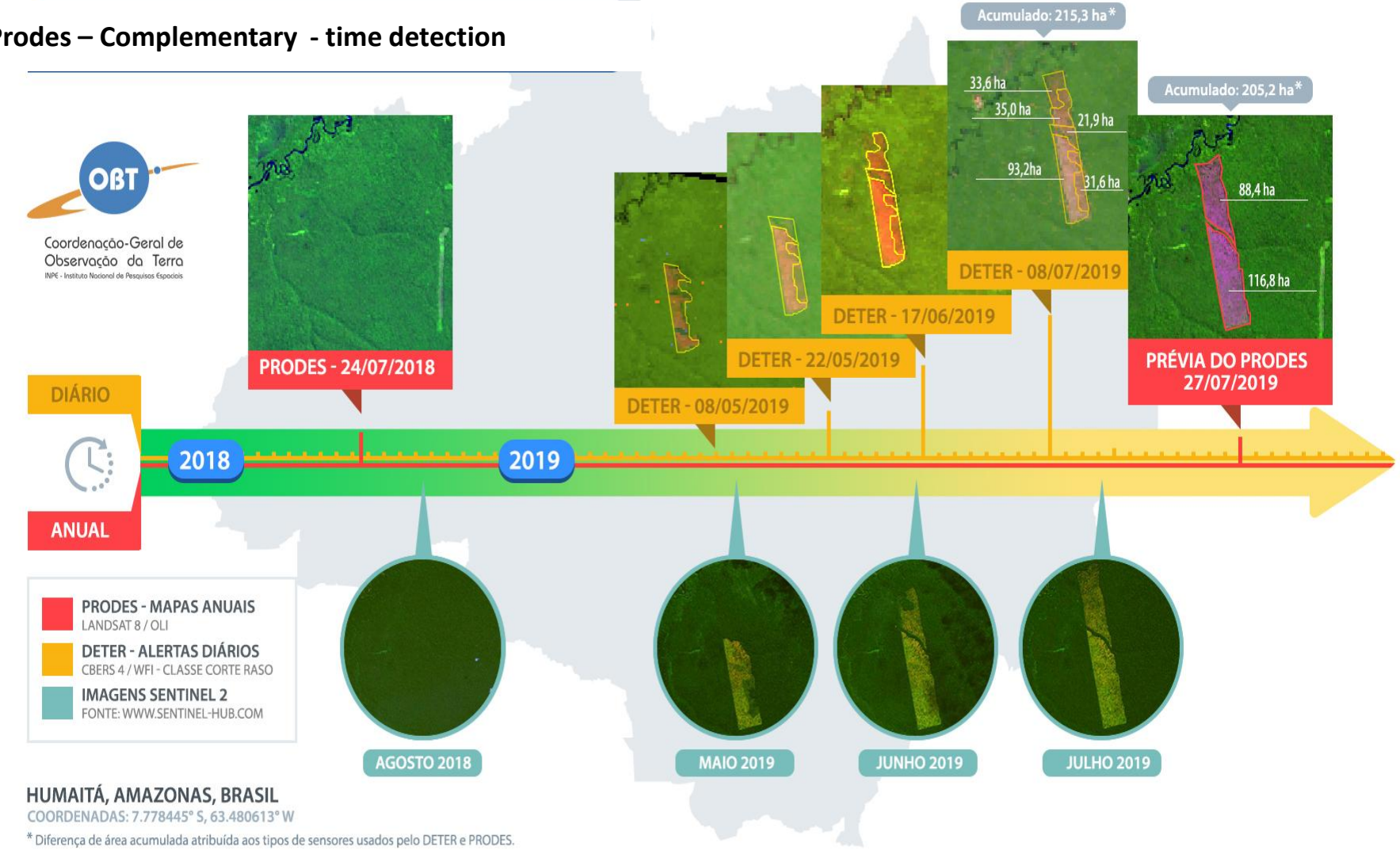


https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

Suppression and Degradation Alerts

Deter Daily Alerts x Prodes – Complementary - time detection





https://doi.org/10.1109/JSTARS.2015.2437075

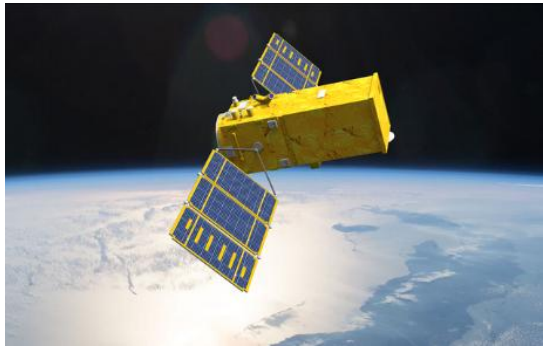
https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

Suppression and Degradation Alerts

Deter

Amazon, Cerrado,
Pantanal, and Non-Forest Amazon

Deforestation, suppression, and forest degradation



2004 – 2014 MODIS 250m (>25ha)
2015 – atual WFI 64 m (>3ha)

Brazilian Satellites
Amazonia 1, CBERS 4 and CBERS 4A
Sensor Wide Field Imaging – WFI



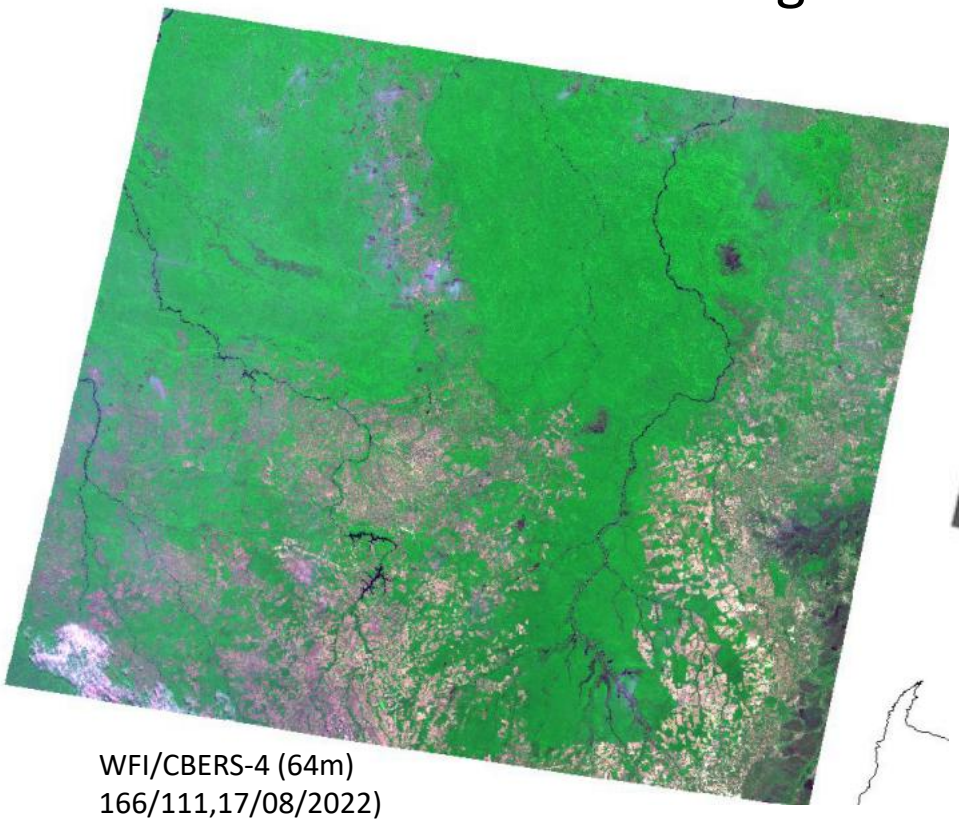
Alerts
Minimum area of **3 hectares**
Visual Image Interpretation

Prodes Mask
Incremental Mapping
May have 'repetition'

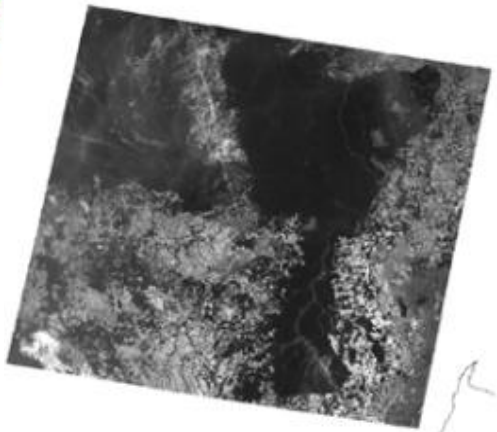
https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

Suppression and Degradation Alerts

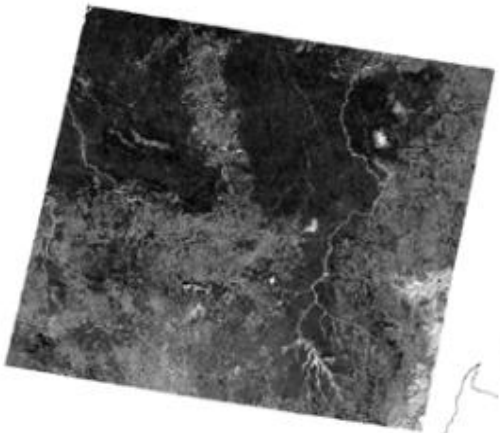
WFI images → Linear spectral mixing model - MLME



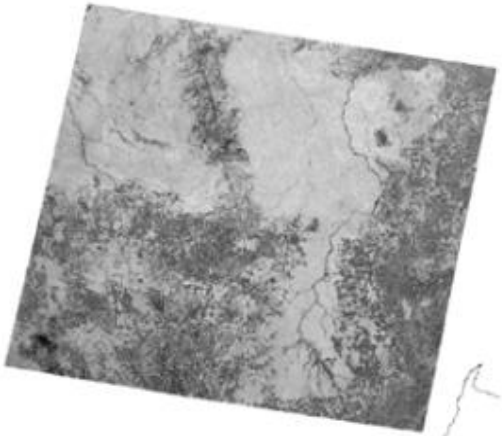
WFI/CBERS-4 (64m)
166/111,17/08/2022)
R(R)/IRp(G)/G (B)



Soil fraction



Shadow fraction



Vegetation fraction

***Prodes mask for detecting alerts**

Suppression and Degradation Alerts

Deter

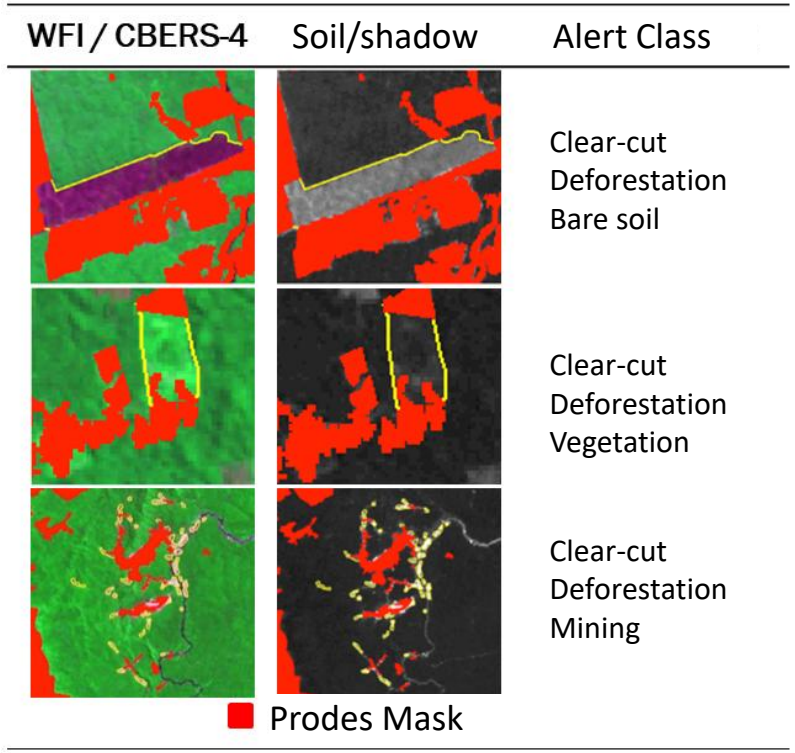
Daily alerts

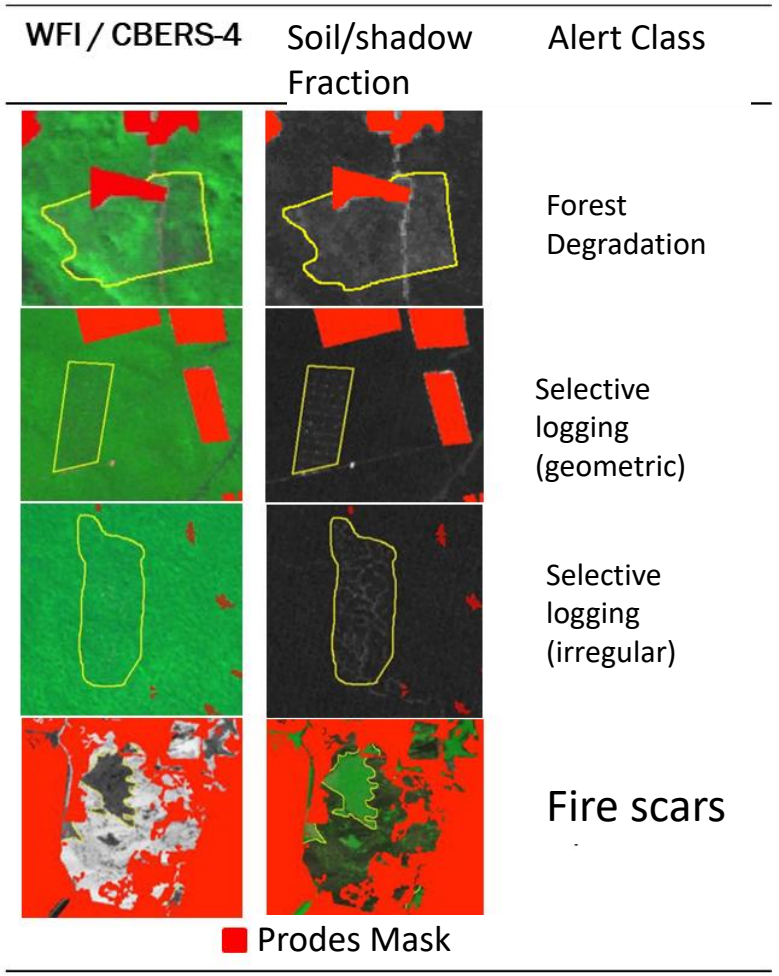
Class:
Deforestation/
Suppression,

and

Fire scars,
Forest Degradation, and
Selective logging
(Proxies of forest ***degradation****)*

DETER Class - Amazon





https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

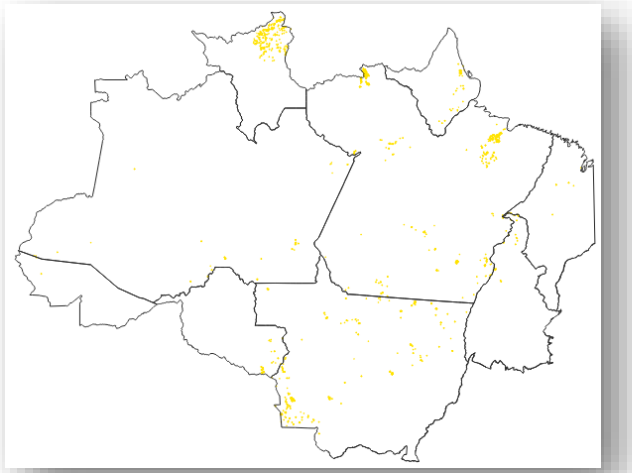
Suppression and Degradation Alerts

Deter

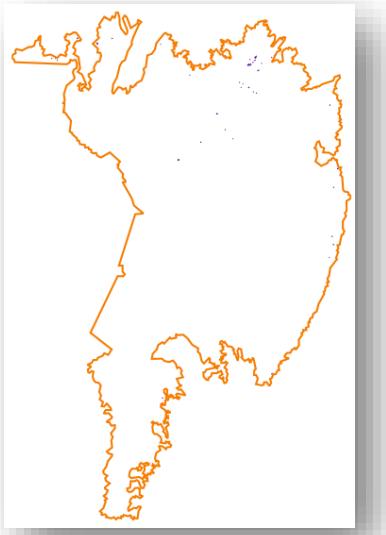
Daily alerts

Classes

Non-Forest Amz



Pantanal



Native Vegetation Suppression:

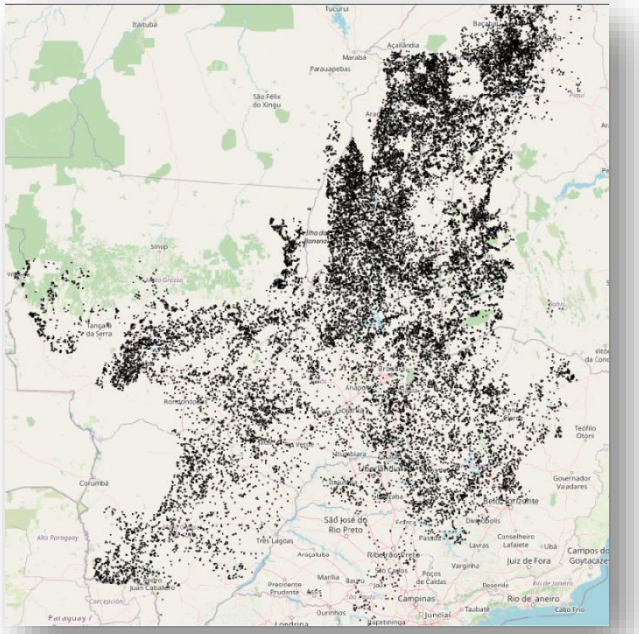
-With bare soil

-With vegetation

Mining

Fire scars ***(Proxies of forest degradation)***

DETER Class - Cerrado



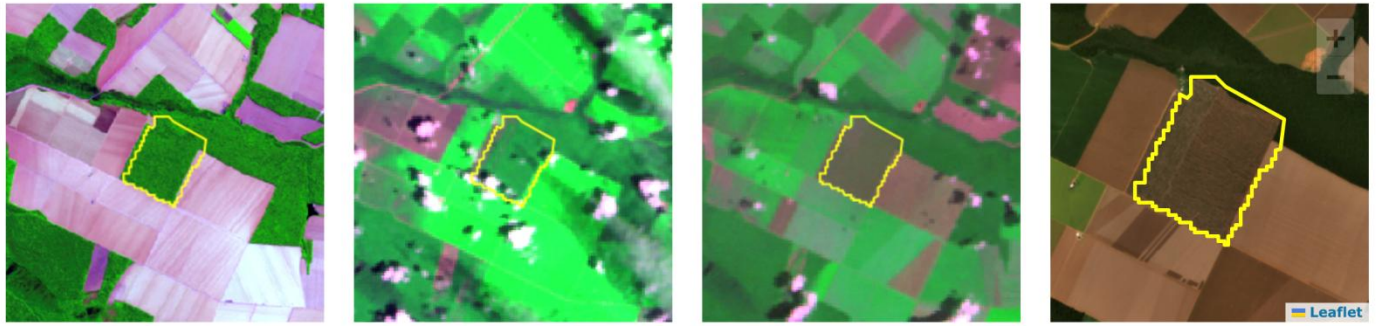
Native Vegetation Suppression

https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

Suppression and Degradation Alerts

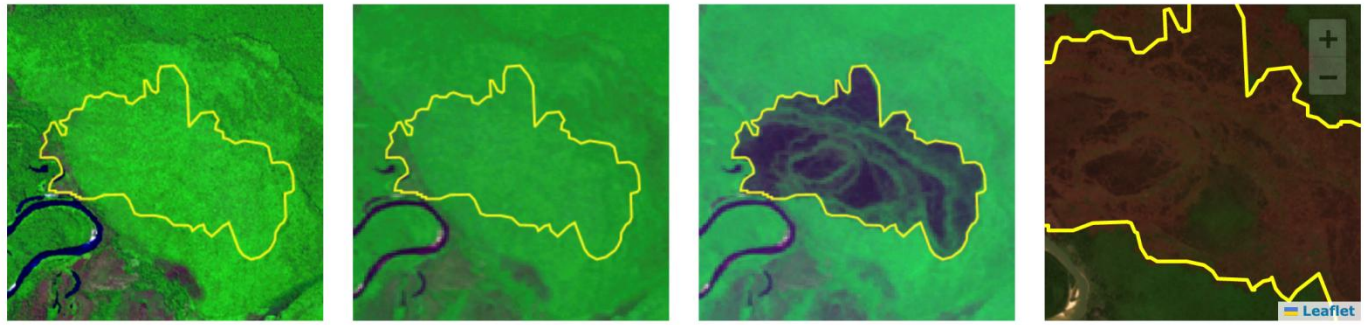
DETER - before and after

(4)
Id: 88234
Classe Deter: DESMATAMENTO_CR
Area Deter: 3.27 km2
Data imagem anterior deteccao: 2022-12-11 (CBERS-4/AWFI)
Data deteccao alerta Deter: 2023-02-01 (CBERS-4/AWFI)
Intervalo entre datas: 52 dias
Orbita/Ponto: 162/111
Ano da imagem Prodes: 2022
Ano mes mosaico Planet: 2023-02
UF: MT
Lat: -12.6941 Lon: -52.2662



L8 2022-08 | CB4 2022-12-11 | CB4 2023-02-01 | Planet 2023-02

(15)
Id: 77415
Classe Deter: CICATRIZ_DE_QUEIMADA
Area Deter: 19.30 km2
Data imagem anterior deteccao: 2022-08-29 (CBERS-4/AWFI)
Data deteccao alerta Deter: 2022-10-20 (CBERS-4/AWFI)
Intervalo entre datas: 52 dias
Orbita/Ponto: 162/117
Ano da imagem Prodes: 2022
Ano mes mosaico Planet: 2022-10
UF: MT
Lat: -12.7185 Lon: -52.8705



L8 2022-08 | CB4 2022-08-29 | CB4 2022-10-20 | Planet 2022-10

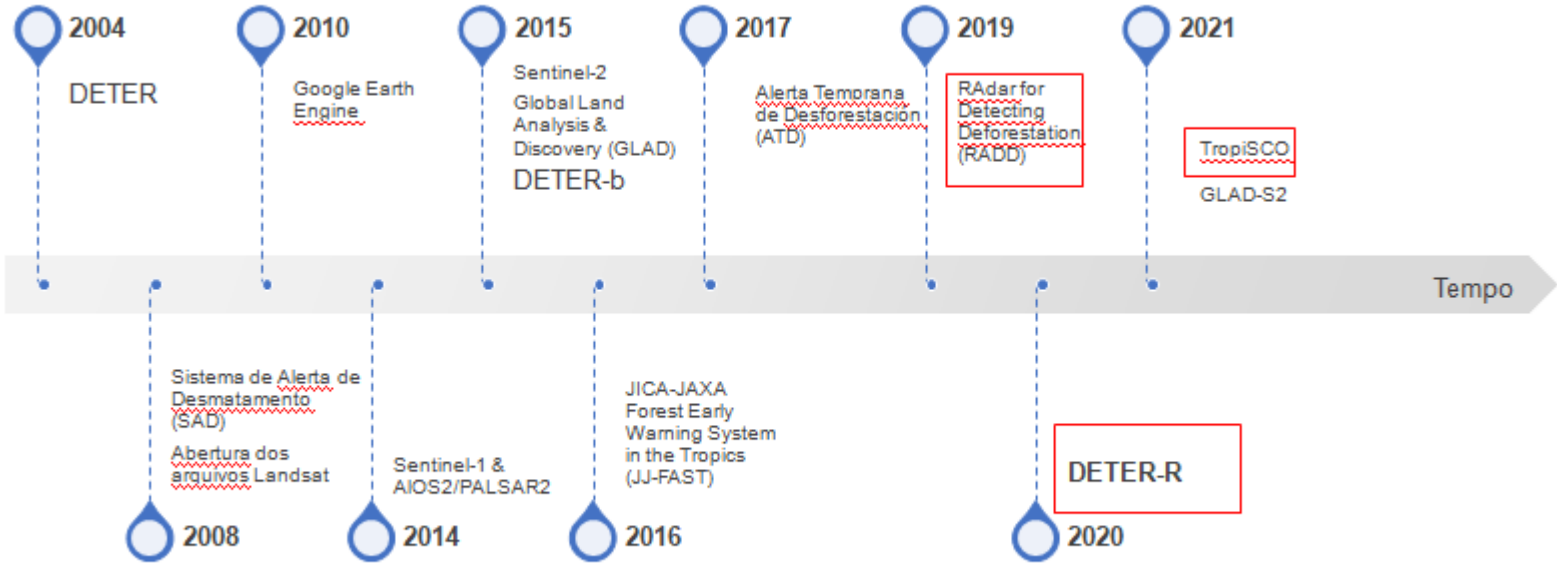
Suppression and Degradation Alerts

Deter-R

Automatic system for detecting forest disturbances in near real time based on C-band SAR images.

Operated from Nov 2020 until Aug 2024

The data generated is not public.



Sistemas baseados em banda C

Deter-RT

The new INPE-TropiSCO deforestation monitoring system in the Amazon biome.

https://data.inpe.br/big/web/biomasbr/deter-monitoramento-diario-da-supressao-e-degradacao-de-vegetacao-nativa/

125

Suppression and Degradation Alerts

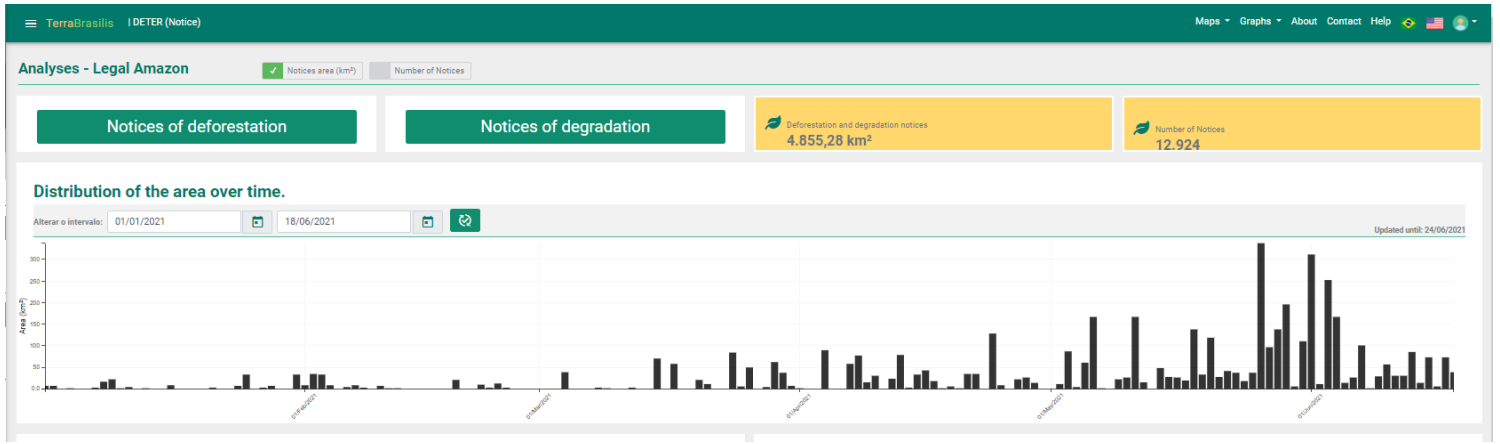
DETER

Maps, polygons and statistics

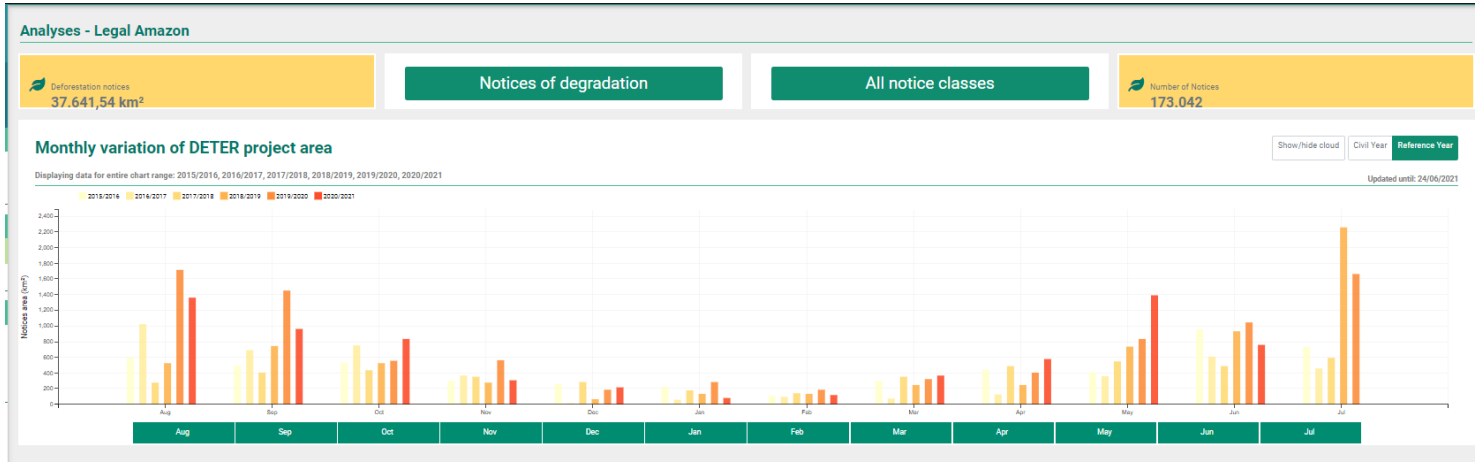
Visualization, queries and download

at TerraBrasilis Platform

Analyzes by user-defined period



Monthly aggregated analysis



https://terrabrasilis.dpi.inpe.br/app/dashboard/alerts/biomes/amazonia-nb/aggregated/

Suppression and Degradation Alerts

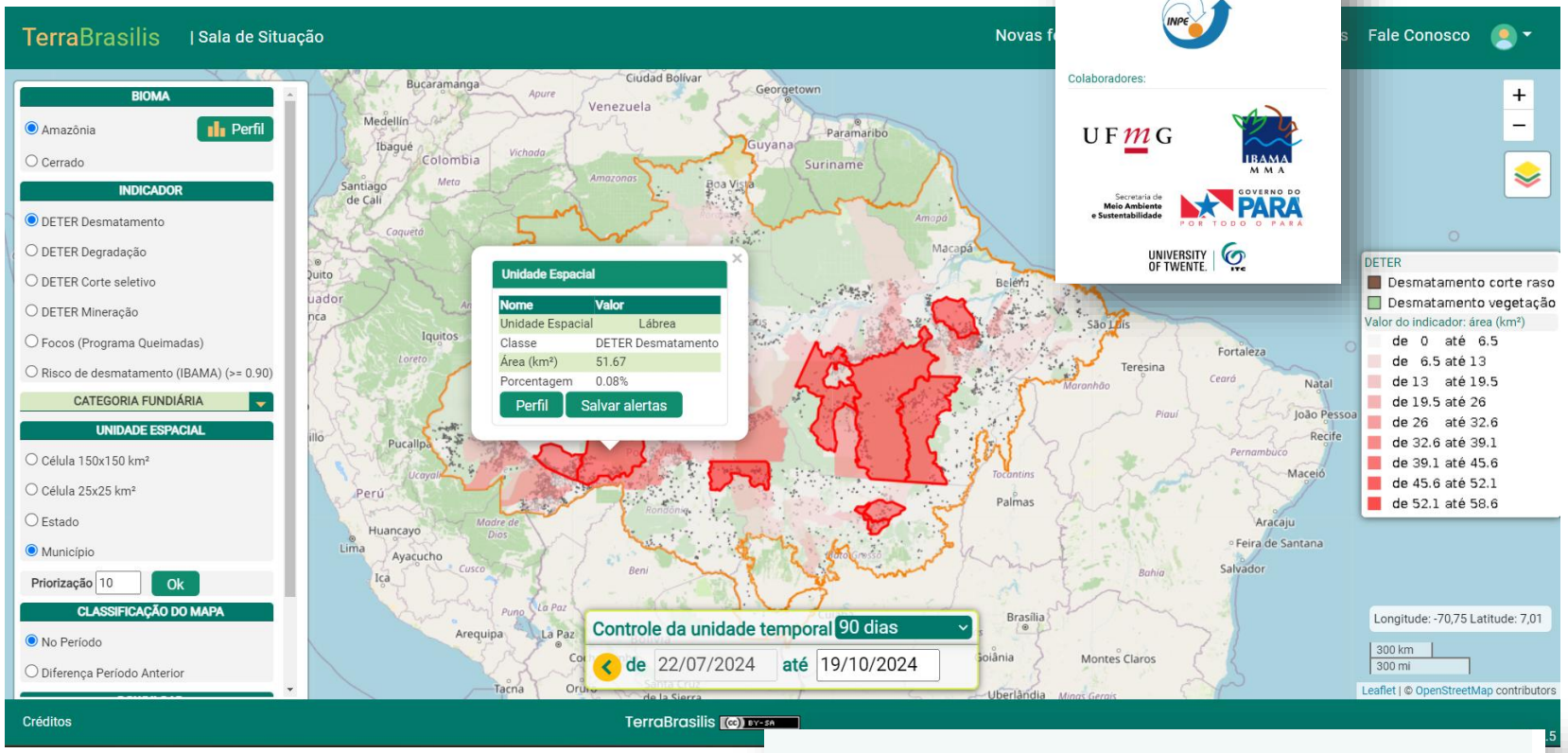
Situation Room

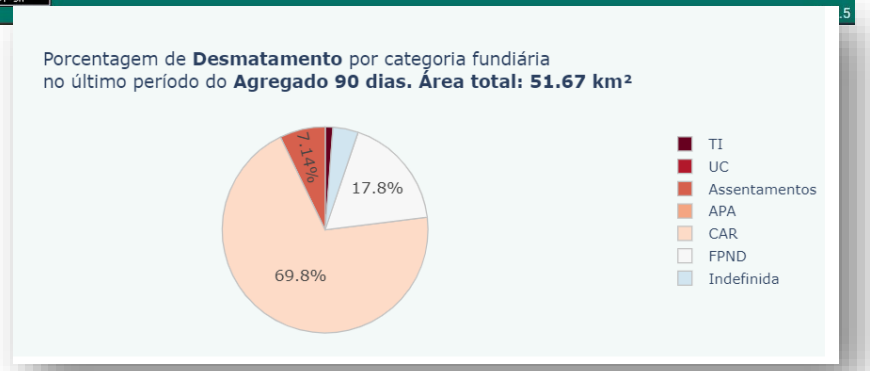
DETER and Forest Fires (Queimadas Program)

Deforestation Risk IBAMA Model

Decision makers' tool

MUNICIPALITIES





https://terrabrasilis.dpi.inpe.br/app/dashboard/alerts/biomes/amazonia-nb/aggregated/

Suppression and Degradation Alerts

Deter Evolution

Testing Deter Amazon Class

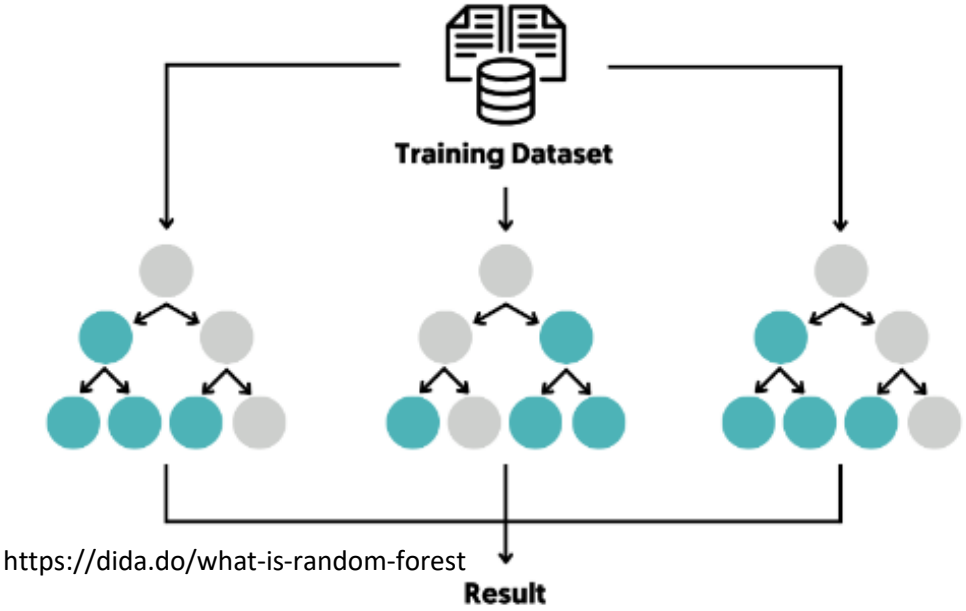


COEAM (2025)



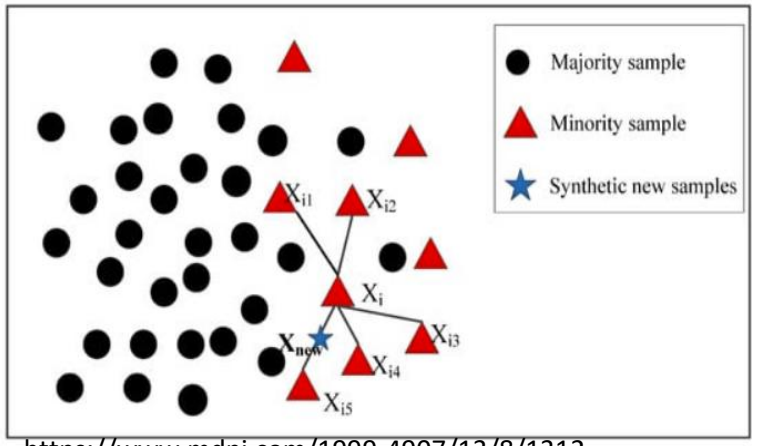
Deforestation

Randon Forest with synthetic samples



https://dida.do/what-is-random-forest

The SMOTE algorithm principle based on k proximity.



https://www.mdpi.com/1999-4907/13/8/1312

Suppression and Degradation Alerts

Deter Evolution

Testing Deter Amazon Class

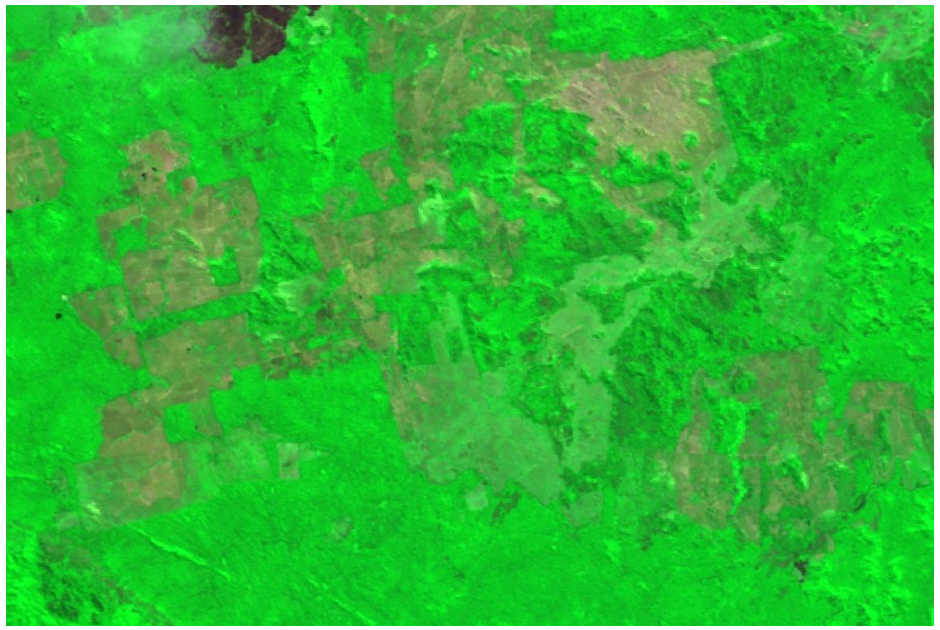


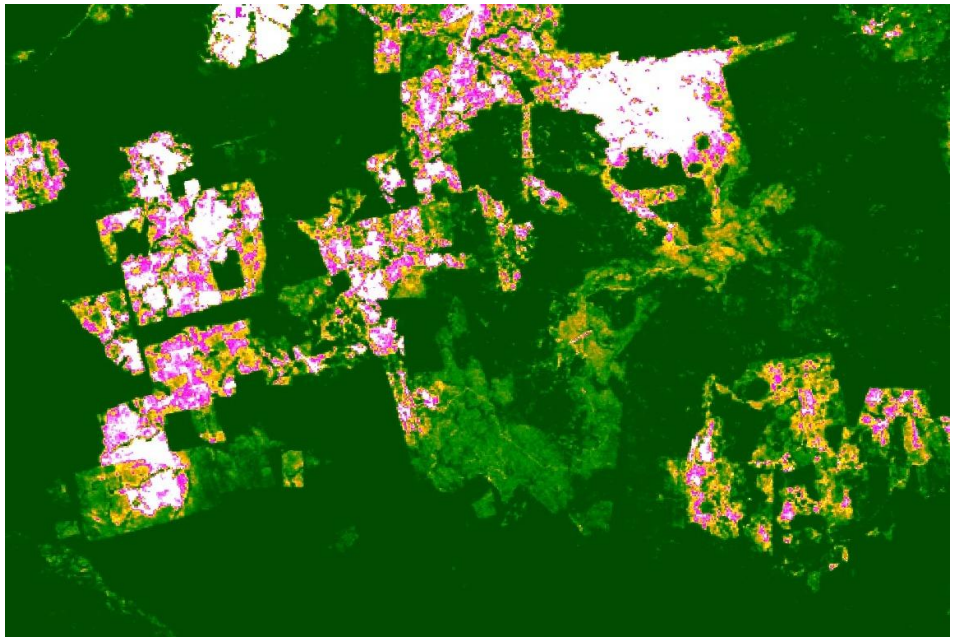
COEAM (2025)

Indices derived from the linear model NDFI (Normalized Difference Fraction Index) type



Degradation





Different forest Degradation Levels

Suppression and Degradation Alerts

Deter Evolution



COEAM (2025)

Testing Deter Amazon Class

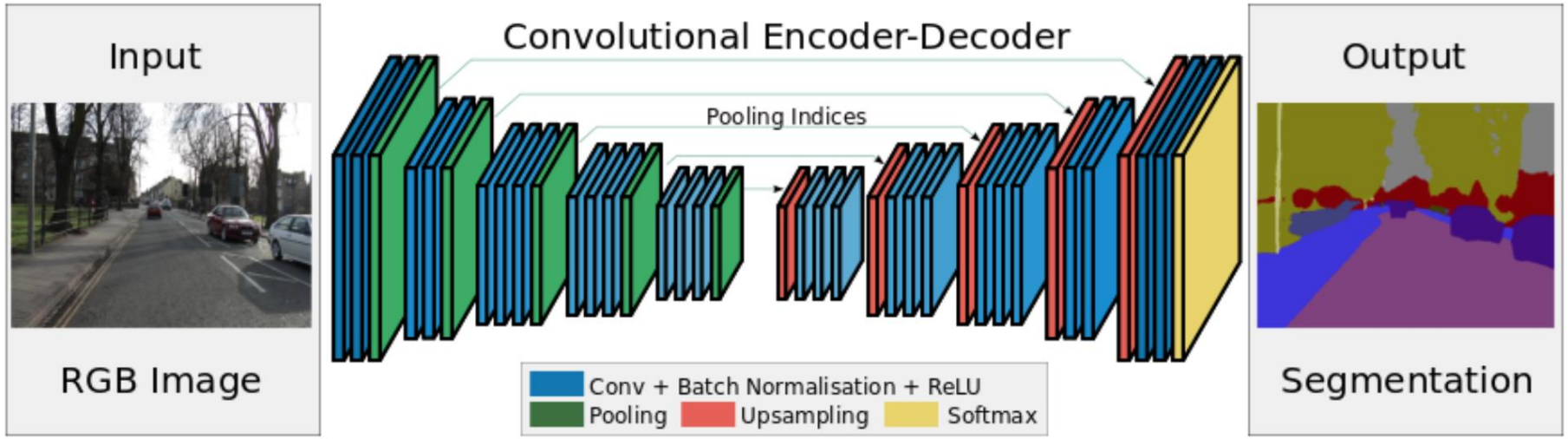


Forest Degradation by Fire



Mining

Segmentation identify context



Deep Learning with U-net architecture

Suppression and Degradation Alerts



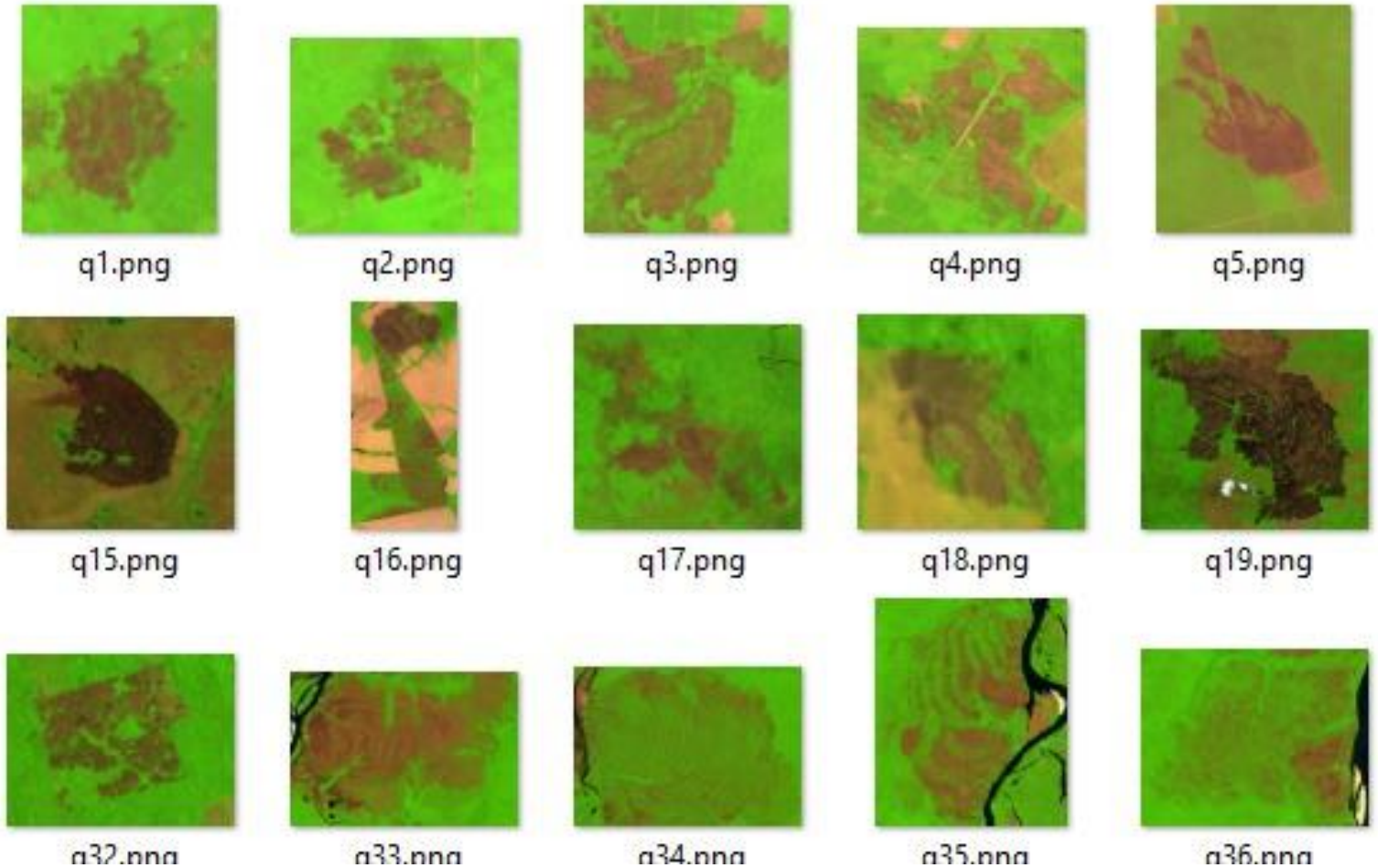
COEAM (2025)



Fire

Deter Evolution

Training



Deep Learning with U-net architecture

Suppression and Degradation Alerts



COEAM (2025)

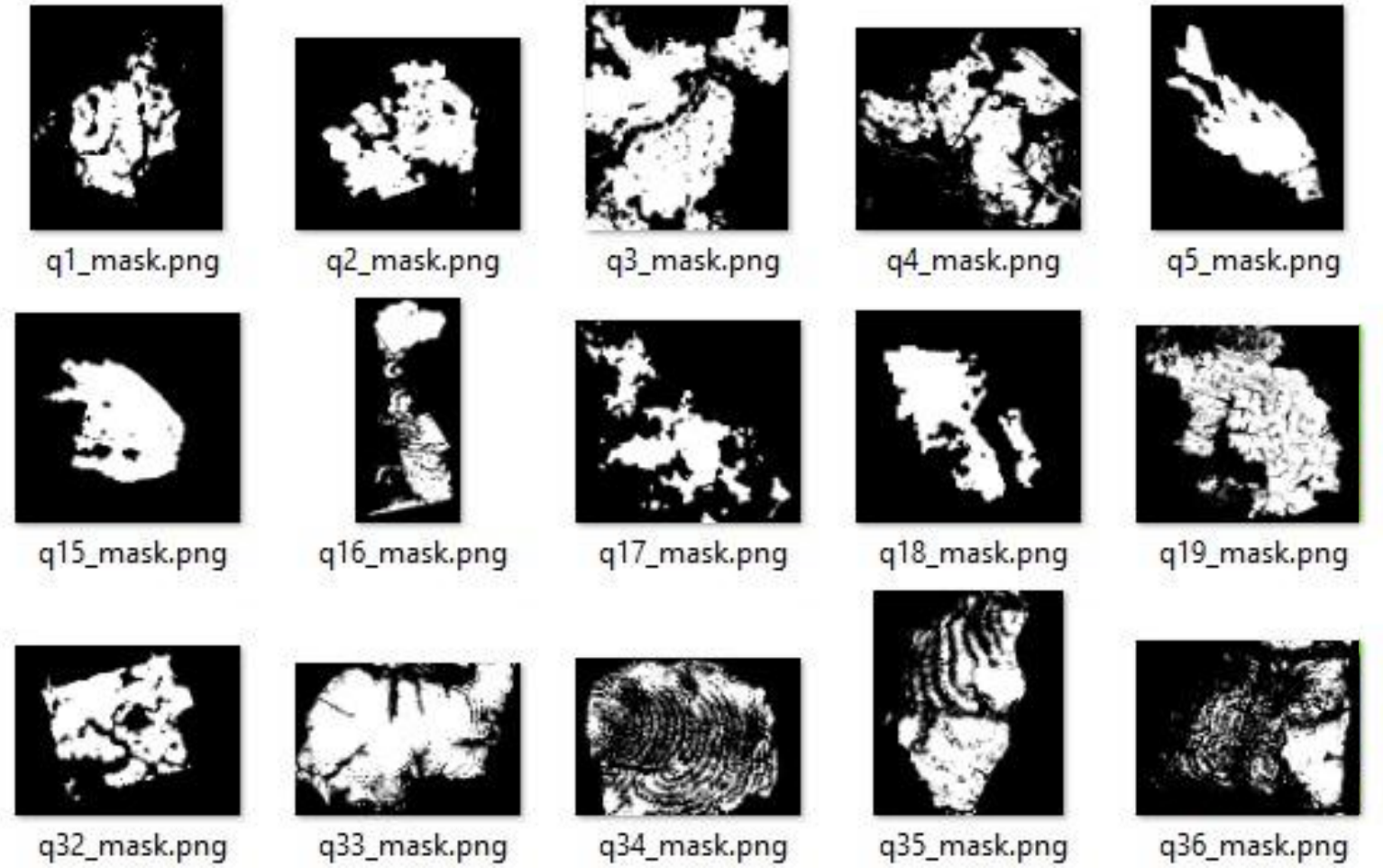
Mask to train the network to "see" a burn, and identify it.

As if it were training the eyes of the segmentation algorithm.

Deter Evolution

Masking





Deep Learning with U-net architecture

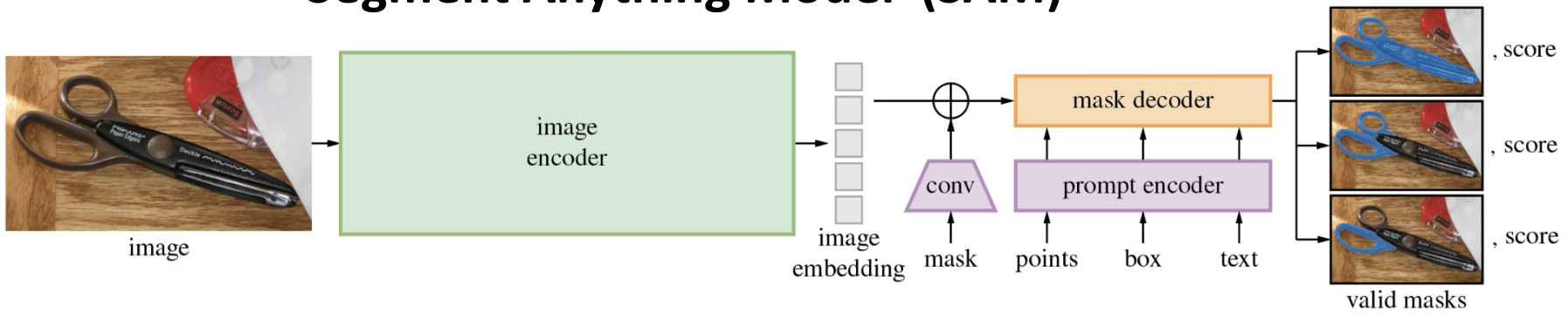
Suppression and Degradation Alerts

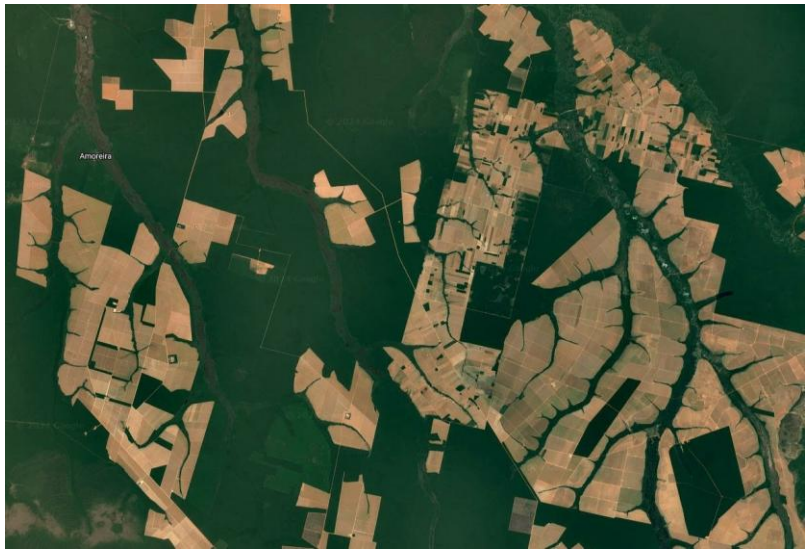
Deter Evolution – algorithms testing

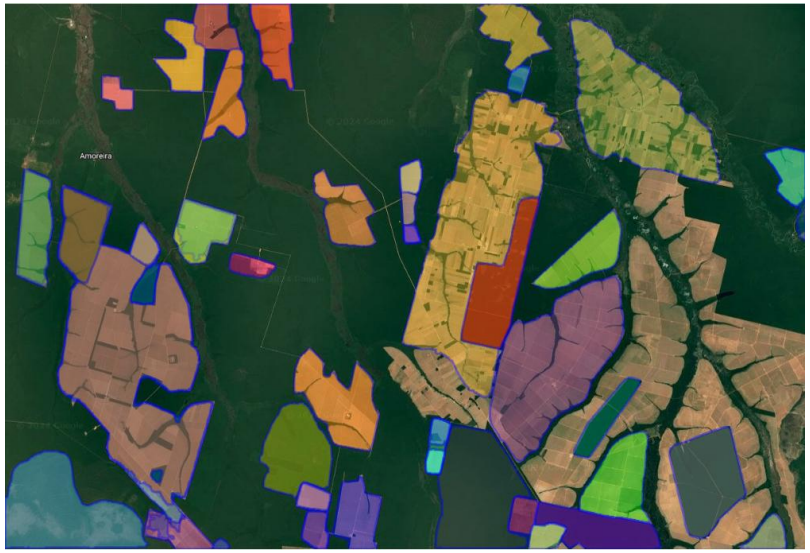


COEAM (2025)

Segment Anything Model (SAM)







YOLO
(You Only
Look Once)
CNN

Suppression and Degradation Alerts

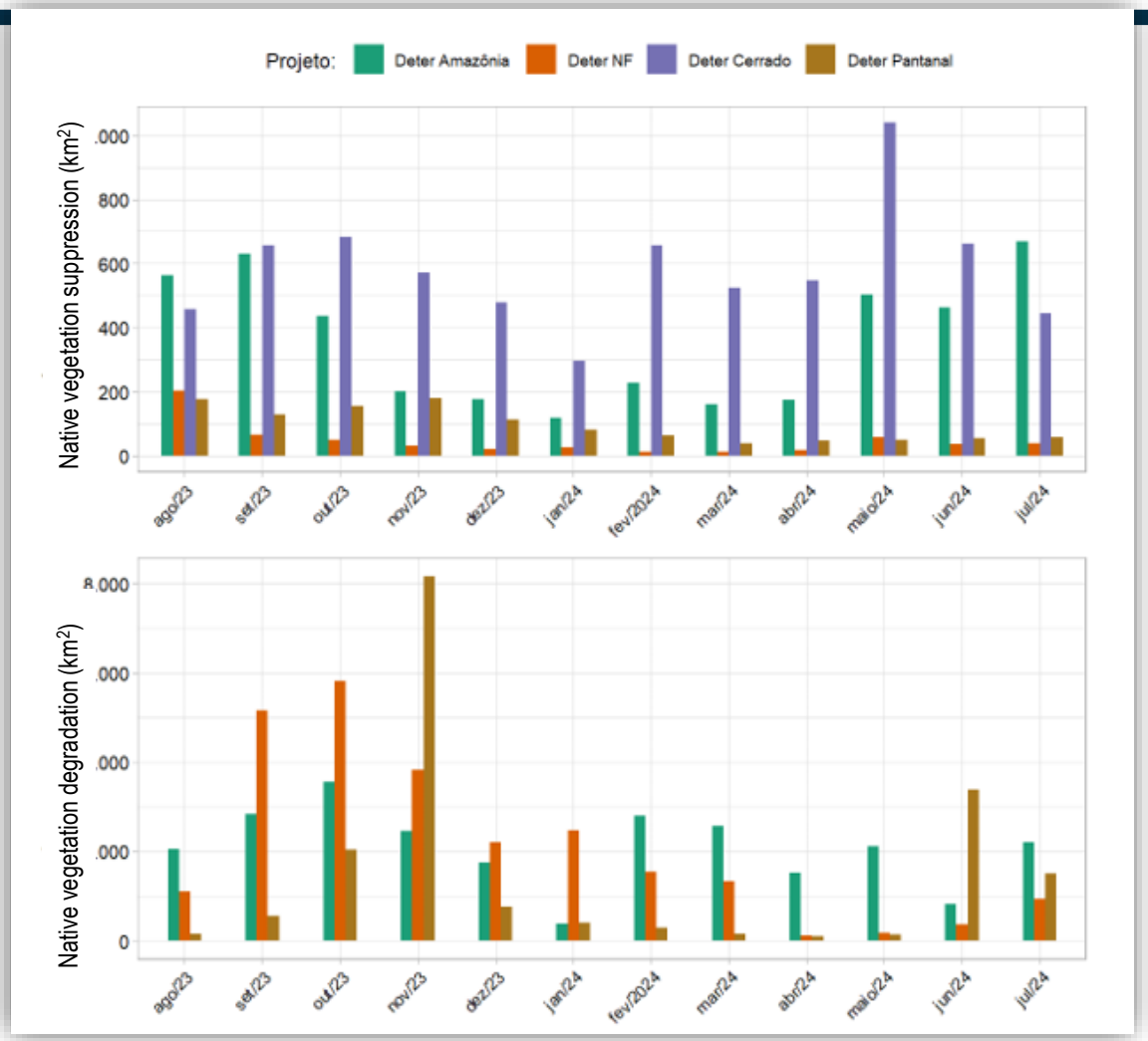
DETER maps, polygons and statistics available at TerraBrasilis Platform

Data valuable for:

- *planning and monitoring strategies*
- *analyse **deforestation trends** by comparing periods*

Deter degradation 2025 → Amazon 2025 deforestation forecast

**Evolution – Integrated system: Prodes from Deter*



Native vegetation suppression and forest degradation. DETER Aug 2023 – Jun 2024

https://terrabrasilis.dpi.inpe.br/app/dashboard/alerts/biomes/amazonia-nb/aggregated/

Alerts also for the society

Ministério do Meio Ambiente e Mudança do Clima

O que você procura?

CONTROLE DO DESMATAMENTO

Áreas sob alerta de desmatamento caem 37,5% na Amazônia e 8,2% no Cerrado de agosto de 2025 a maio de 2026

Divulgados pelo presidente Lula, dados do Deter/INPE indicam que Brasil segue no caminho para cumprir a meta de zerar o desmatamento até 2030

Publicado em 11/06/2026 15h56

Compartilhe:



G1

https://g1.globo.com › amazonas › noticia › 2026/06/15

Desmatamento no Amazonas cai 57% nos primeiros meses ...

há 19 horas — O desmatamento no Amazonas caiu 57% entre janeiro e maio de 2026, com redução de 45% nos alertas ambientais monitorados pelo Inpe e órgãos ...





Desmatamento na Amazônia aumenta na temporada 2024/2025 — Foto: Reprodução/TV Globo

Biomas Br

TerraClass

Systemic Monitoring of land use and land cover



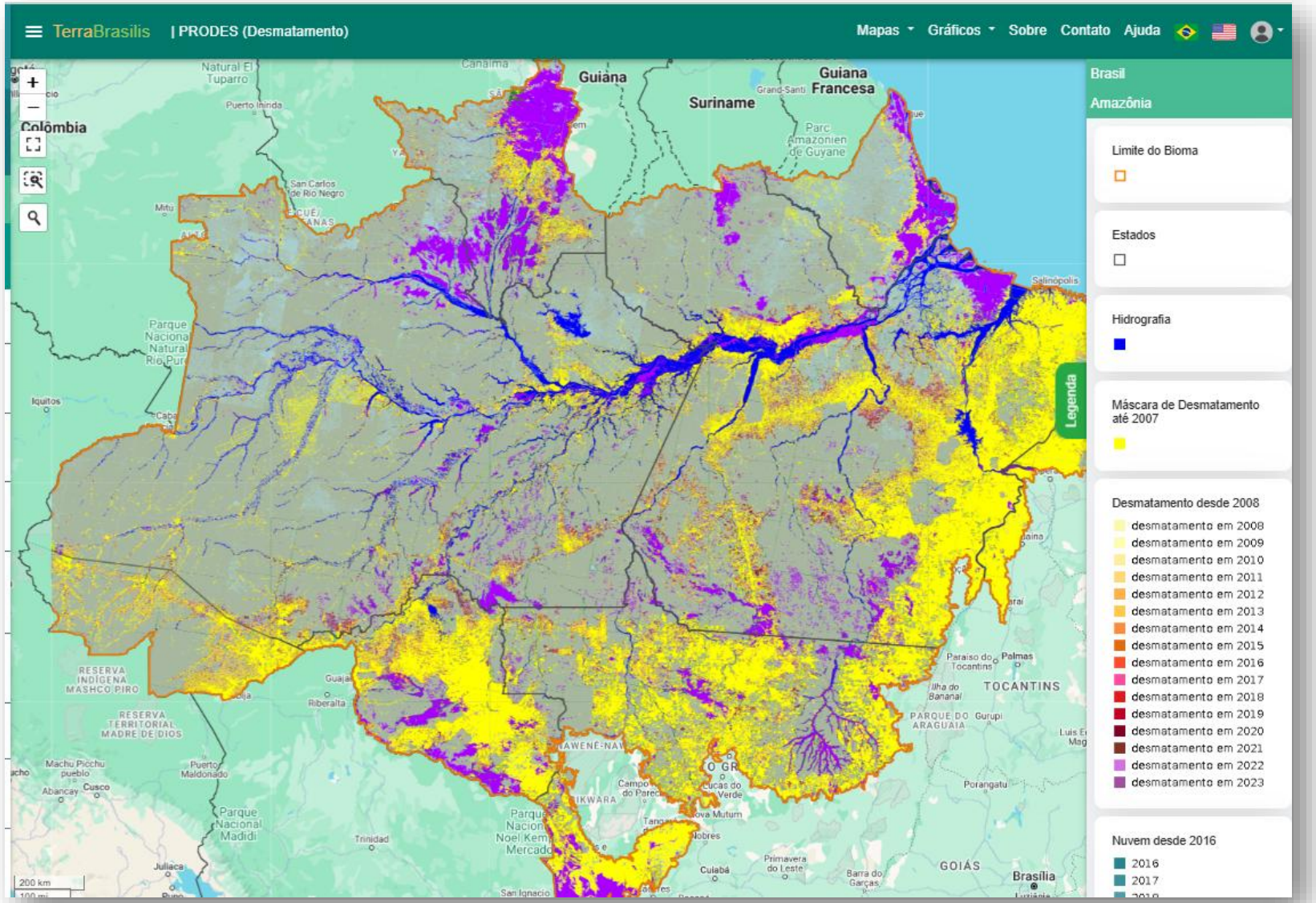
Embrapa

Brazilian Agricultural Research Corporation

INPE

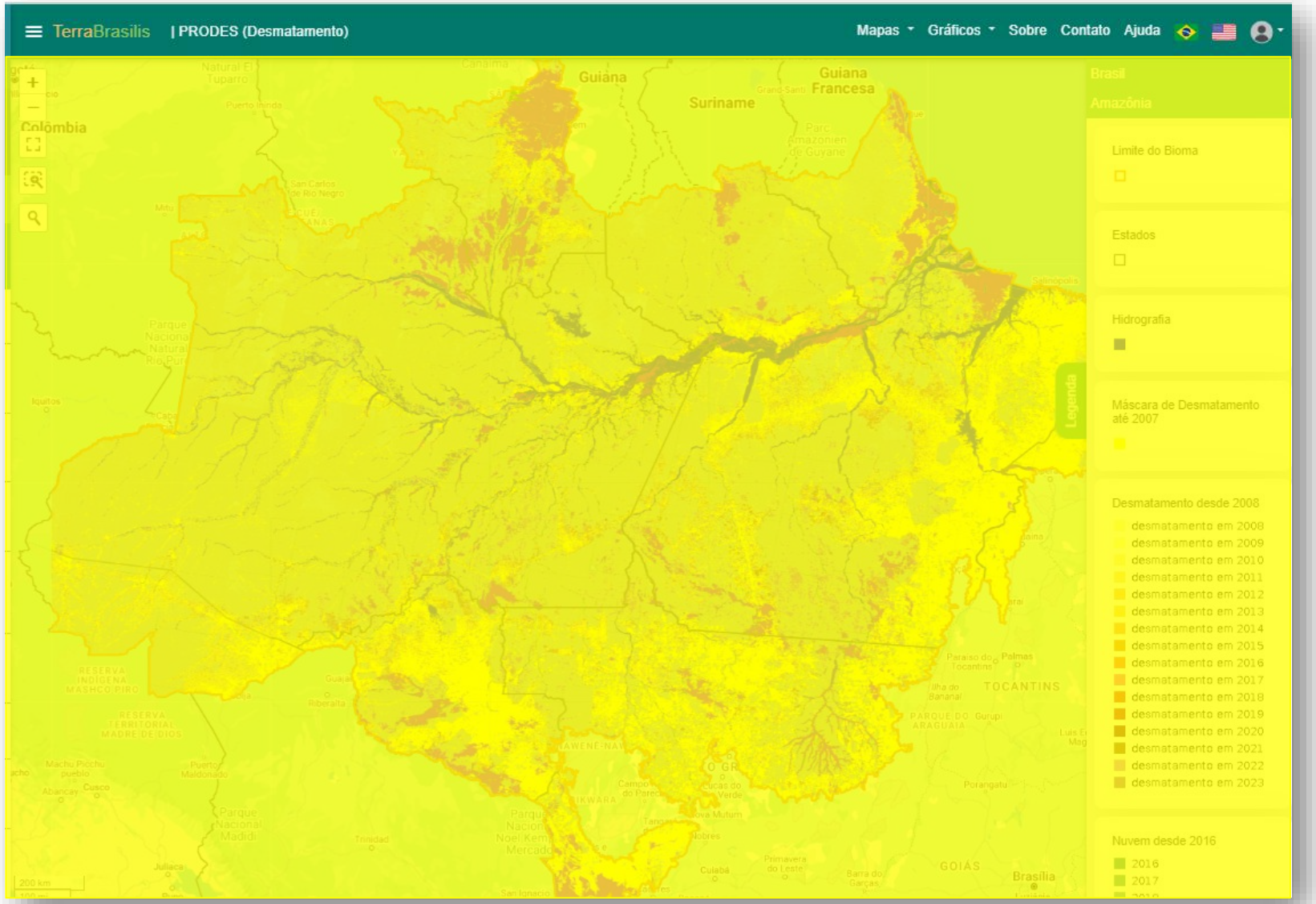
https://data.inpe.br/big/web/biomasbr/terraclass-monitoramento-sistemico-de-uso-e-cobertura-da-terra/

What land use and land cover has replaced native vegetation?



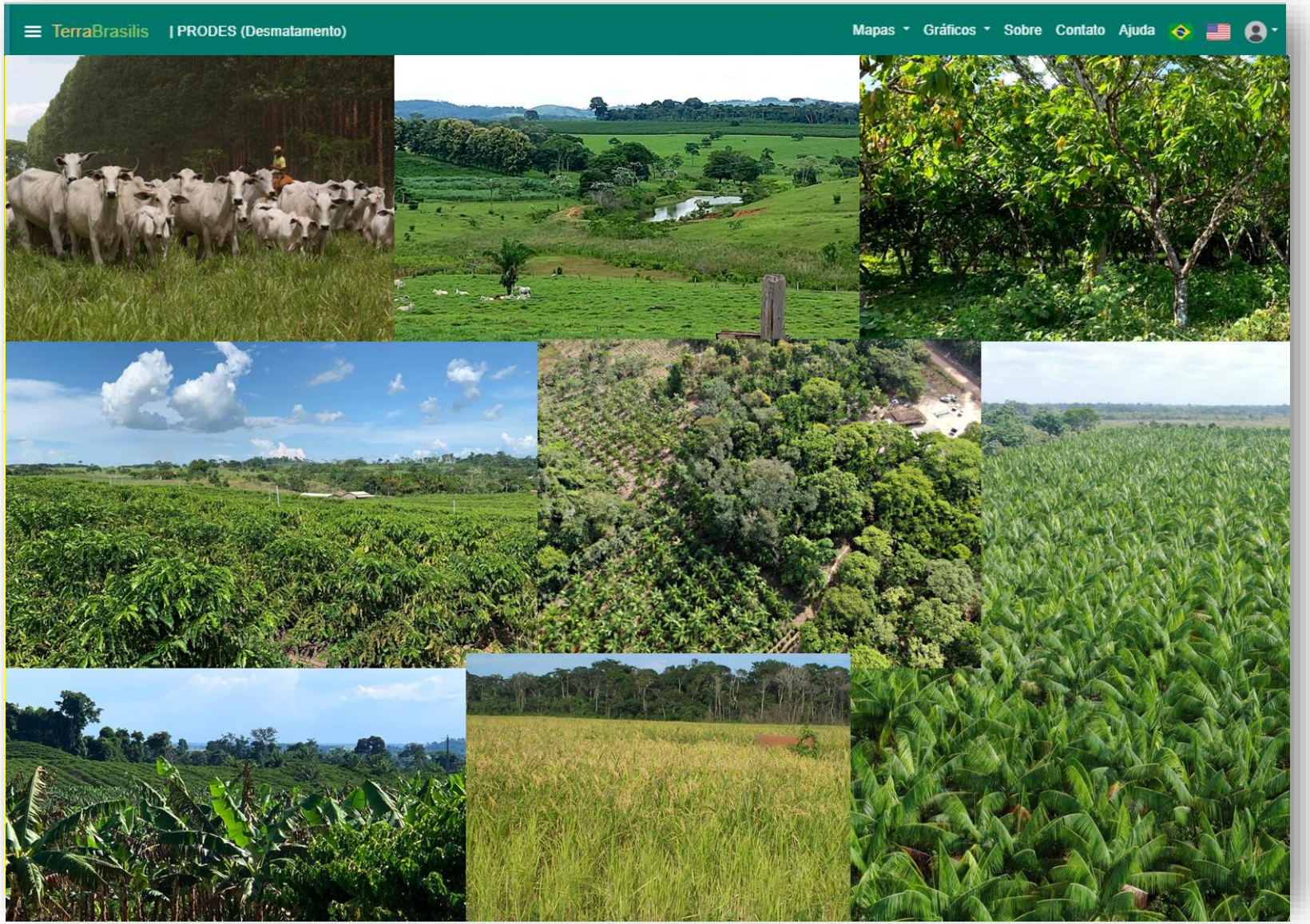
From deforestation (Prodes)

What land use and land cover has replaced native vegetation?



From deforestation (Prodes)

What land use and land cover has replaced native vegetation?



From deforestation (Prodes)
to
Land use and cover TerraClass

Ventirueri (2025)

TERRACLASS PROJECT

Partnership between INPE and EMBRAPA (since 2011)



METHODOLOGY



Sentinel-2 10 m Images

BRAZIL DATA CUBE

Brazil Data Cube



Machine Learning Algorithms

sits

SITS computing package

Coutinho (2023)

METHODOLOGY

Thematic Classes



Coutinho (2023)

METHODOLOGY

Thematic Classes



Agriculture

1. Perennial
2. Semi-perennial
3. Temporary 1 cycle
4. Temporary 2 or more cycles



Pasture

1. Herbaceous Predominance
2. Shrub/Tree Predominance

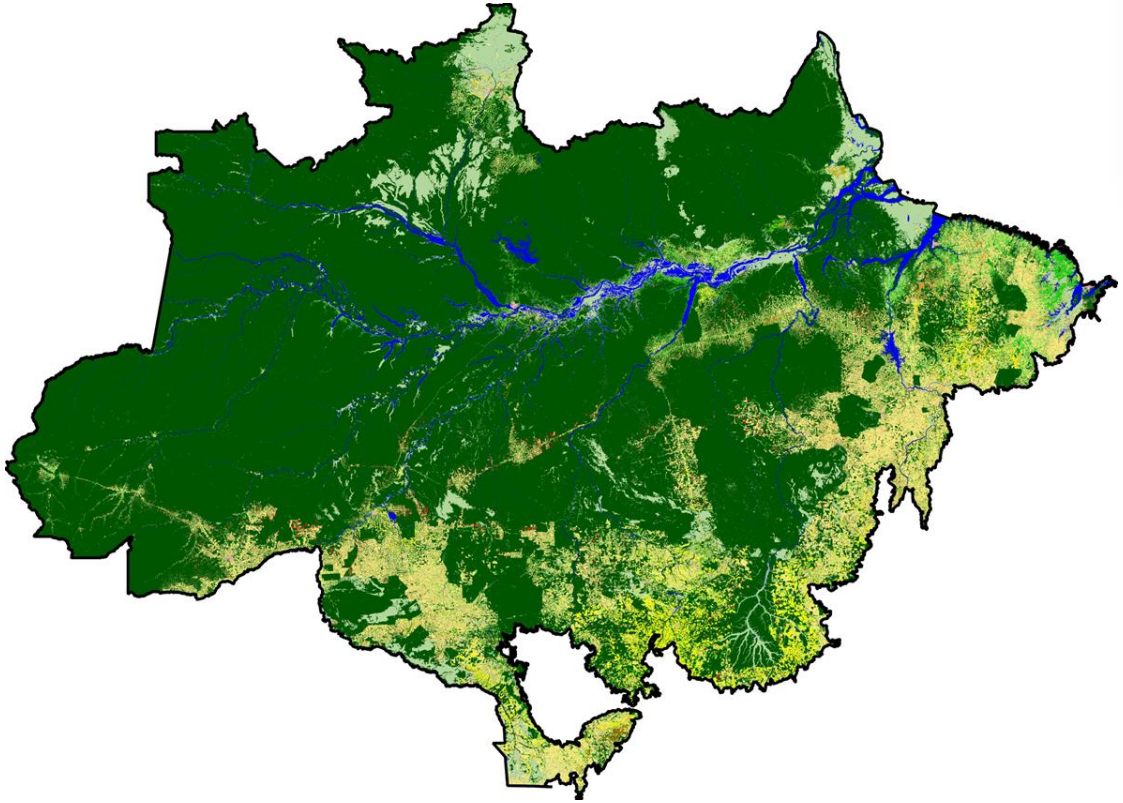


Secondary Vegetation

Coutinho (2023)

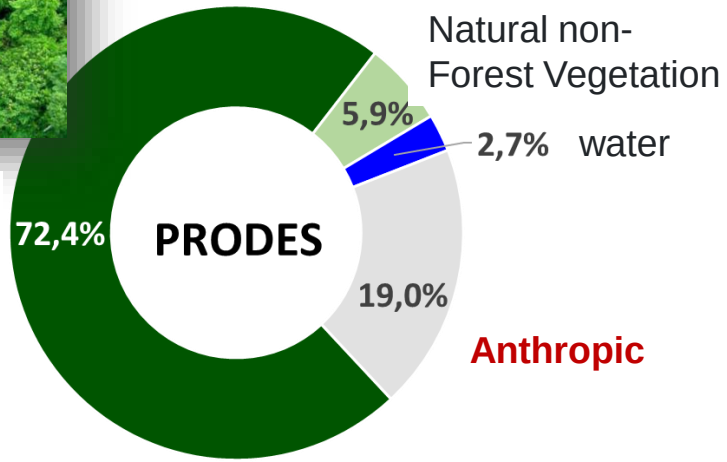
RESULTS

TerraClass 2022





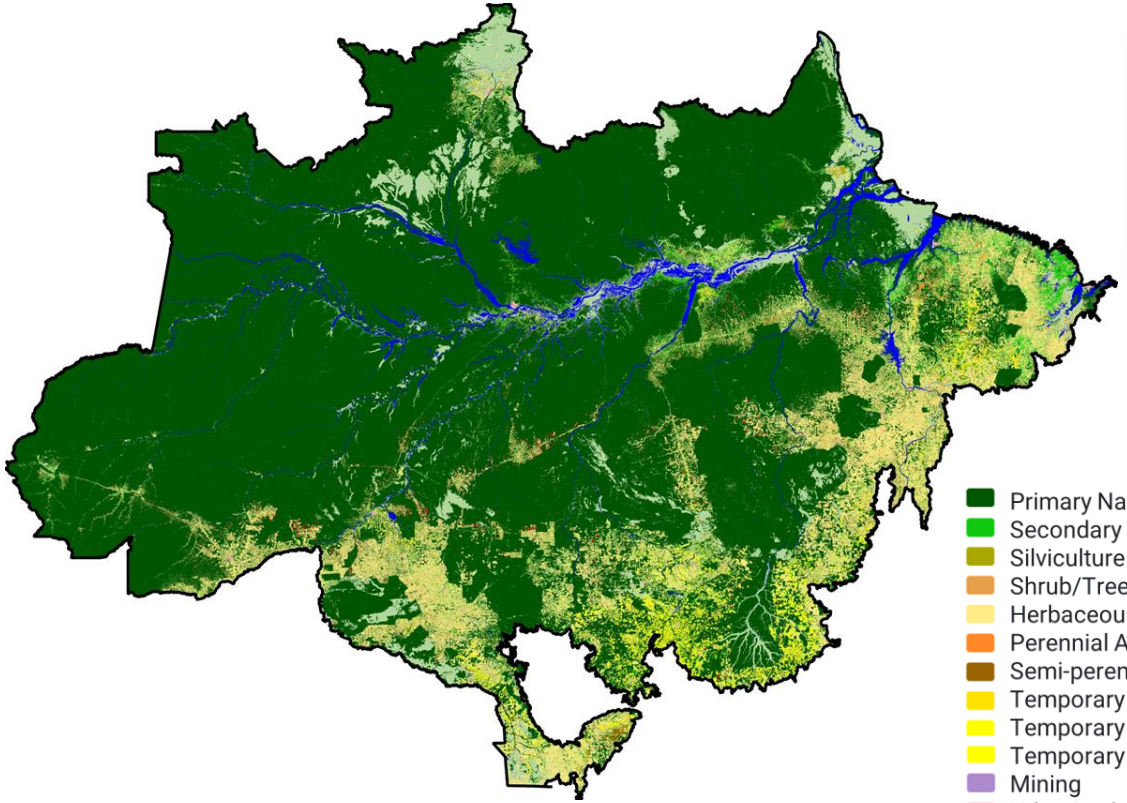
Primary Natural Forest Vegetation



PRODES (2022)

RESULTS

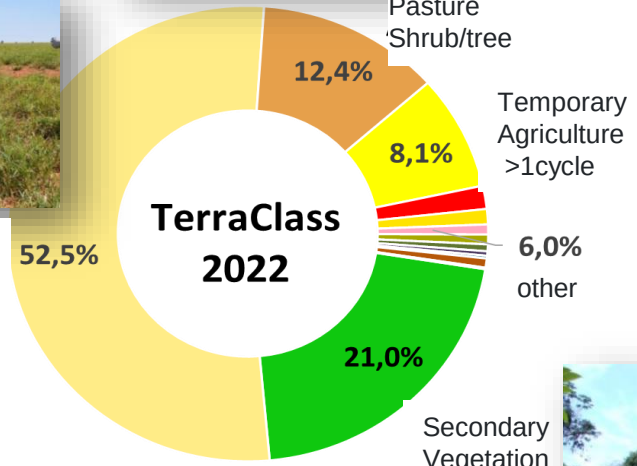
TerraClass 2022











TerraClass (2022)

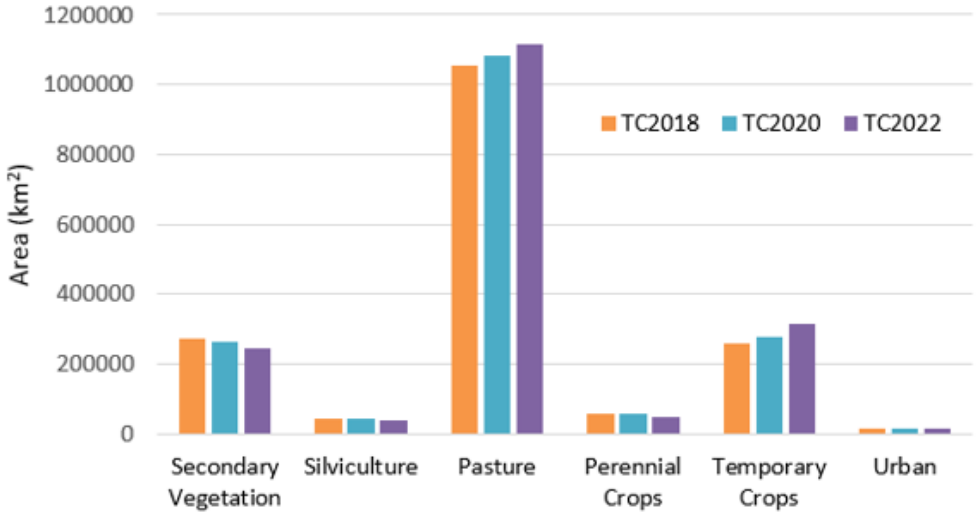


- Primary Natural Forest Vegetation
- Secondary Natural Forest Vegetation
- Silviculture
- Shrub/Tree Pasture
- Herbaceous Pasture
- Perennial Agricultural Crop
- Semi-perennial Agricultural Crop
- Temporary Agricultural Crop of 1 Cycle
- Temporary Agricultural Crop of More than 1 Cycle
- Temporary Agricultural Crop
- Mining
- Urbanized
- Other Uses
- Not Observed
- Deforestation in the Year
- No Forest
- Natural Non-Forest
- Water Body

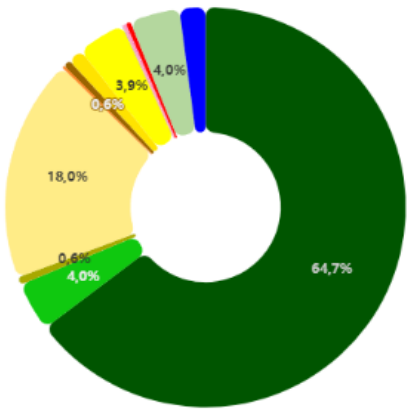
LAND USE / COVERAGE TRAJECTORIES

Amazon (2008 – 2022) and Cerrado – 2018, 2020 and 2022 (unified)

Biannual Mapping



2018
2020
2022







Amaral et al. 2025

https://www.terraclass.gov.br/webgis/

TerraClass

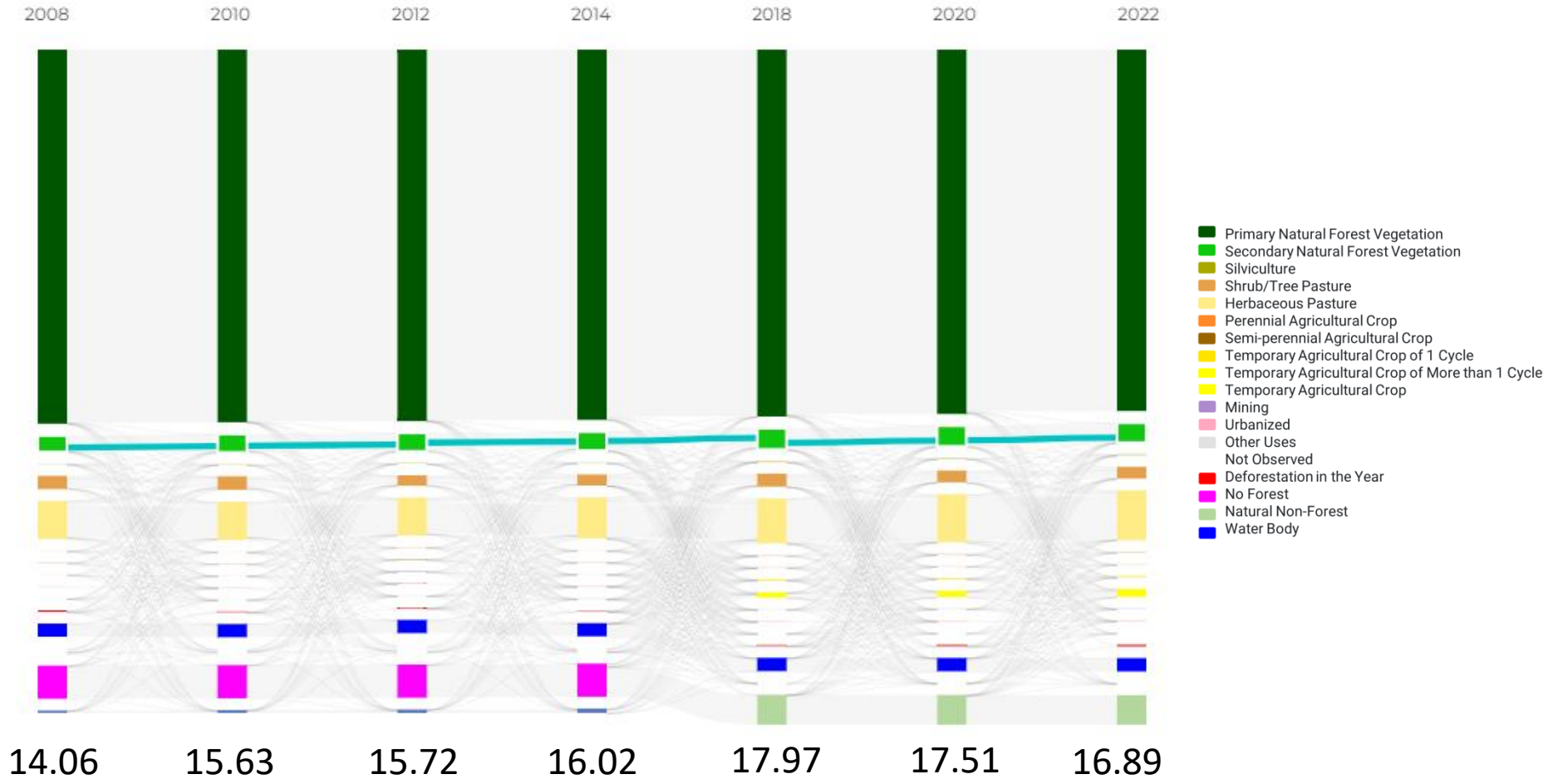
Secondary Vegetation (SV) for Amazon

Persistence

6,735,018.71 ha
2012 – 2022
(10 years)

6,027,202.24 ha
2010 – 2022
(12 years)

5,304,131.67 ha
2008 – 2022
(14 years)



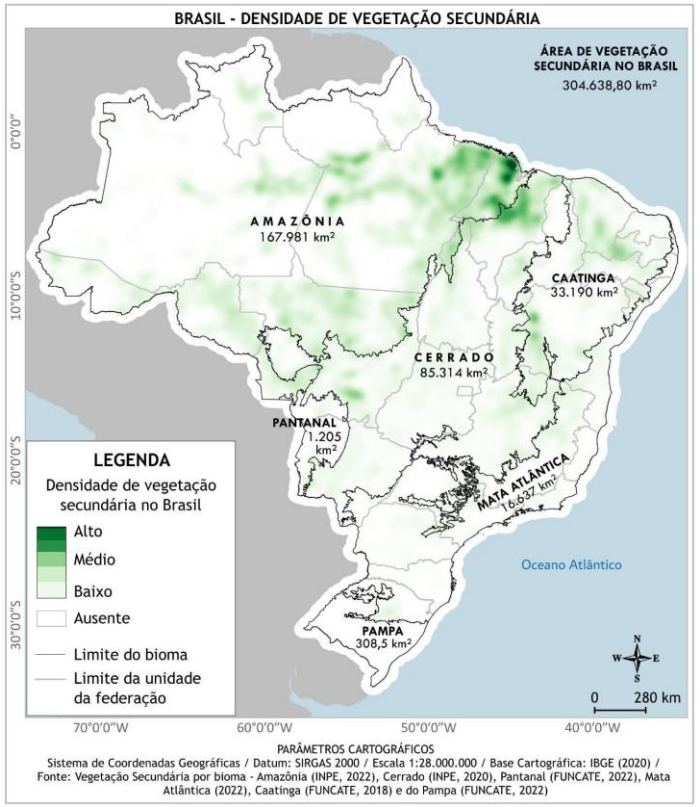
Thousand of ha	14.06	15.63	15.72	16.02	17.97	17.51	16.89

TerraClass - Landscape

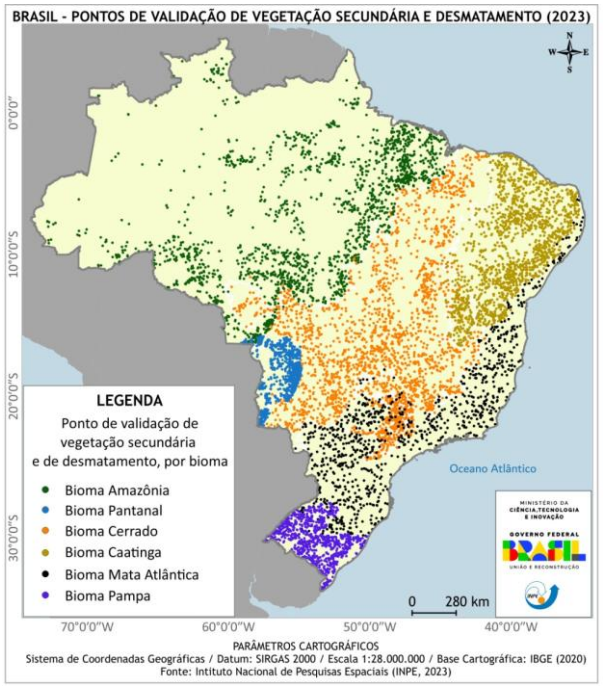
Secondary Vegetation (SV) Mapping

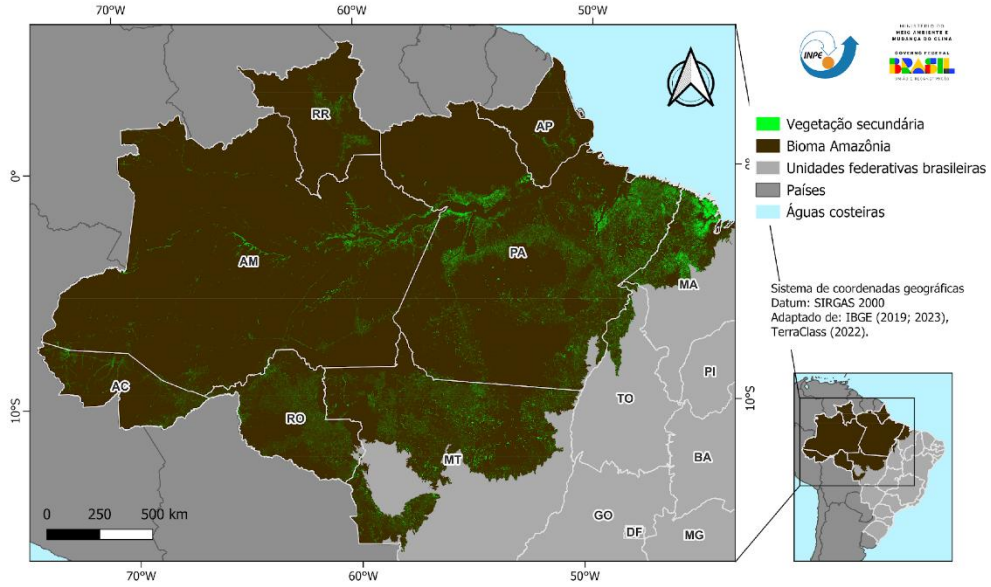
Secondary Vegetation areas for all Brazilian Biomes
2018, 2020 and 2022

To be integrated and made available in TerraBrasilis in 2025



VS 2022 - Bioma Validation





Amazon Biome
Secondary Vegetation

TerraClass - Landscape

Secondary Vegetation (SV) Landscape analysis – BRAZIL

Land Category	Area (%)
Quilombola territories	0.85
Integral Protection UC	1.28
Undesignated Public Forests	1.82
Sustainable Use UC (without APA)	3.11
Indigenous Lands	5.03
Environmental Protection Area (APA)	6.18
Rural settlement	**15.46**
Private properties (SIGEF)	**22.34**
Area without Land Registration	**43.92**

Total area (SV) = 16,247,366.72 ha (689,288 patches)

METRIC	Analysis		
	Area	Polygons	OBS
Weighted age (years)	(34.38%) 7–9 (07.66%) 1–3	(34.69%) 4 - 6 (09.36%) 13 - 14	young (4 – 9 years)
Area (ha)	(32.51%) 100 –| 1,000 (19.28%) > 1,000	(42.25%) 2 –| 5 (39.40%) 5 –| 20	Many small, relevant big ones
Core area	(41.40%) 10 –| 1,000	(87.04%) zero	relevant edge effect
Fractal Dimension	(99,33%) 1.25–1.5	(93.76%) 1.25–1.5	geometric shape - anthropogenic
Euclidean distance nearest neighbor	84.30% - 0 m	69.80% - 0m	adjacent to vegetation
Nearest neighboring vegetation	85.47% - primary vegetation	73.85% - primary vegetation	primary vegetation

TerraClass & PLANAVEG

Comissão de Recuperação da Vegetação Nativa (Conaveg)
The Native Vegetation Recovery Commission
common goal of restore 12 million hectares of native vegetation in our country.
This new pact and milestone are now reflected in Planaveg 2025-2028.

Planaveg
Plano Nacional de Recuperação da Vegetação Nativa
National Plan for the Recovery of Native Vegetation
(Article 5 of Decree No. 8,972, dated 23 January 2017,
Interministerial Ordinance No. 230, dated 14 November 2017)

"The secondary vegetation (SV) data generated by the TerraClass project will be consolidated as a structural layer of spatial intelligence and monitoring of native vegetation recovery in Brazil, appearing as one of the main layers of the national monitoring platform".

OBJETIVE
Restoration of native vegetation in degraded areas in Conservation Units (UC), Indigenous Lands (TI), and other collective territories.



Planaveg

PRODES DATA USERS

Public Policy

National Adaptation Plan to Climate Change

General Strategy

VOLUME I

Reducing Emissions from Deforestation and forest Degradation

conservation of forest carbon stocks

+ sustainable management of forests

enhancement of forest carbon stocks

United Nations Framework Convention on Climate Change

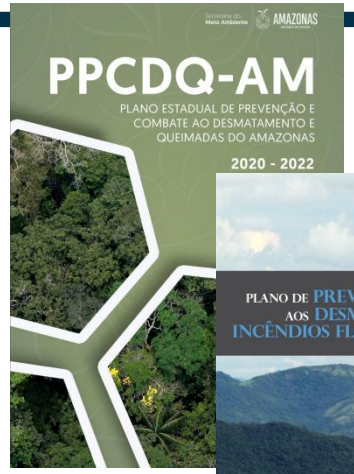


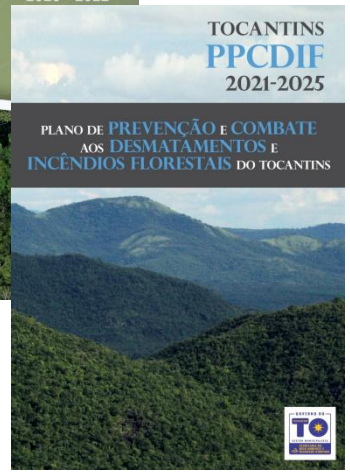
Plano de controle do desmatamento na Amazônia entra em consulta pública

Governo federal abre espaço para sugestões para o PPCDAm, que chega a sua quinta versão

João Gabriel

BRASÍLIA O governo federal abriu, na noite desta segunda-feira (10), a consulta pública para o Plano de Ação para Prevenção e Controle do Desmatamento na Amazônia Legal, o PPCDAm, diretriz que norteia as ações de proteção da floresta no bioma amazônico.





Science and Academic Studies

PRODES

01/09/2025:

1.726 articles in

555 journals

CLIMATE POLICY INITIATIVE
NÚCLEO DE AVALIAÇÃO DE POLÍTICAS CLIMÁTICAS PUC-Rio

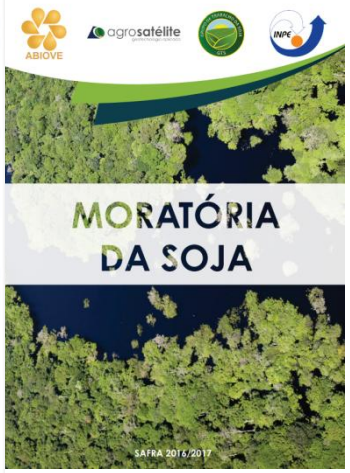
DETERring Deforestation in the Brazilian Amazon: Environmental Monitoring and Law Enforcement

Climate Policy Initiative



Economic trade control

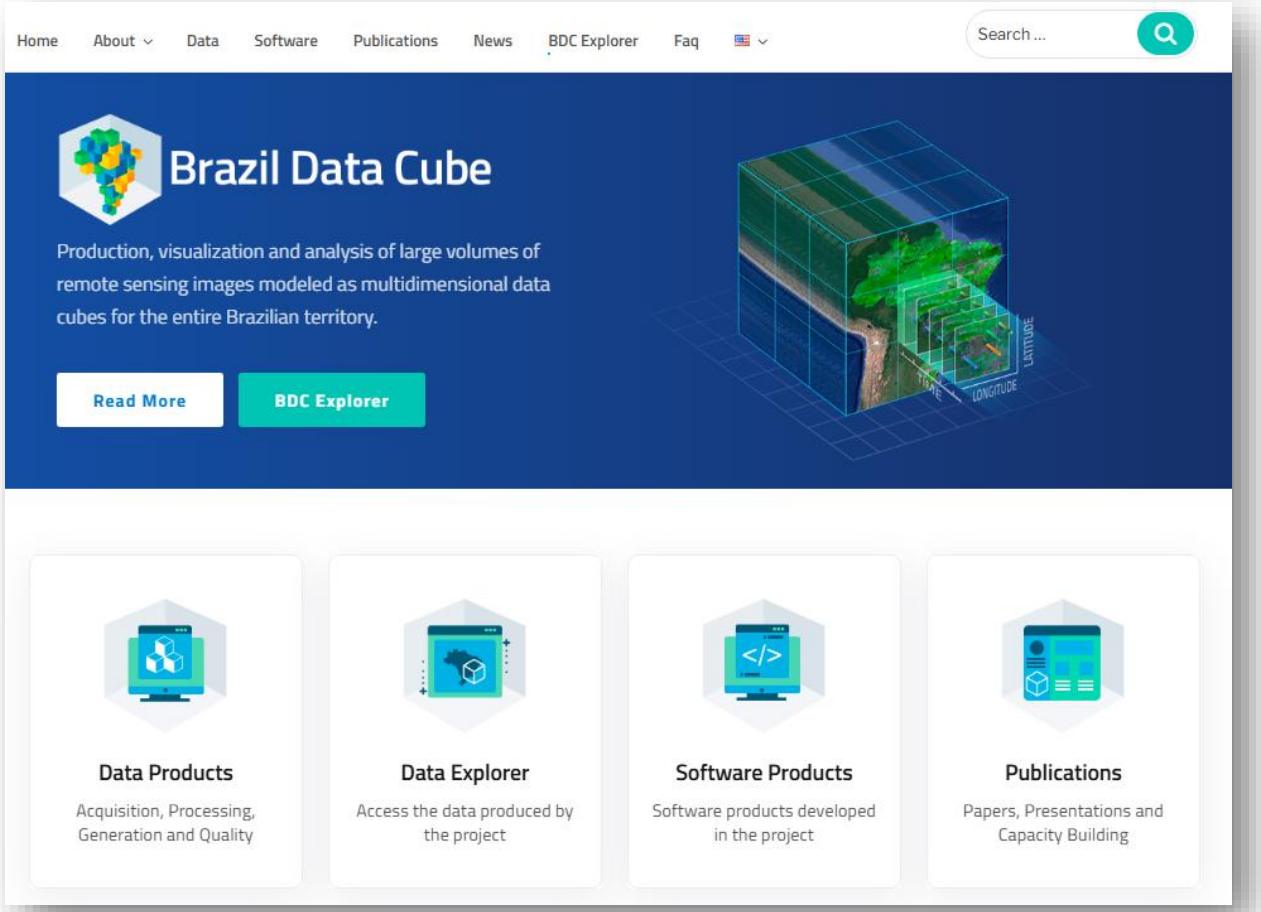




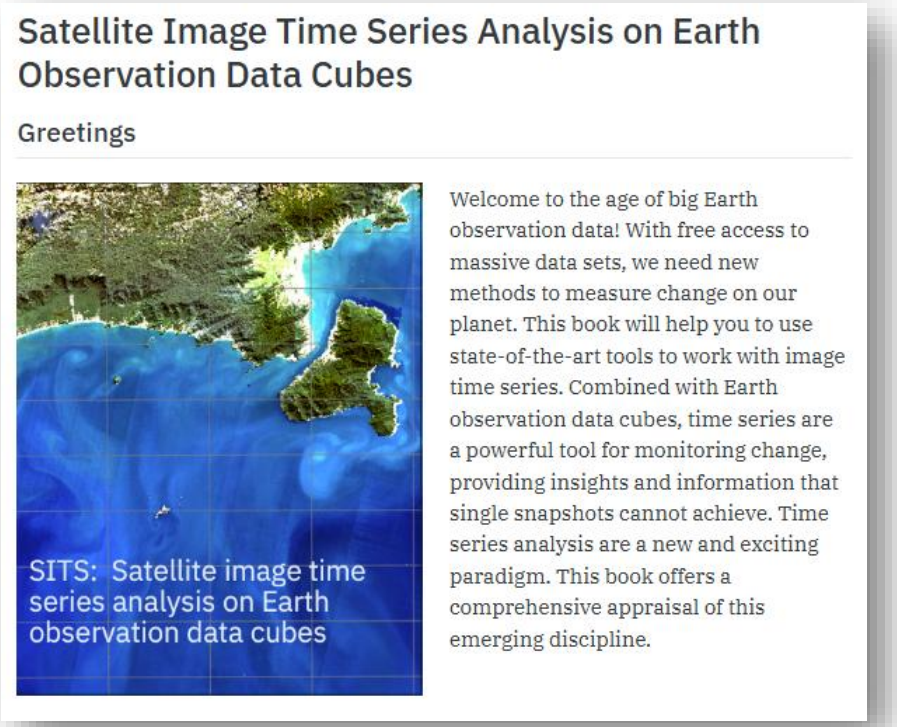
http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes/citacoes-ao-prodes

BDC - SITS

Prodes new INPE´s technologies - Open Access - AI Analysis for Remote Sensing -



https://data.inpe.br/bdc/



https://e-sensing.github.io/sitsbook/

BiomasBR

https://data.inpe.br/big/web/biomasbr/

An strategic INPE´s Program

Construction / history
Teams – Scientific Research
Collaborations Partnerships

Open Access
Wall to wall
Consistent data accuracy
Historical series
Continuous improvement
AI methods – Image classification
Contribution to Climate Change

Open data and
AI tools for the society



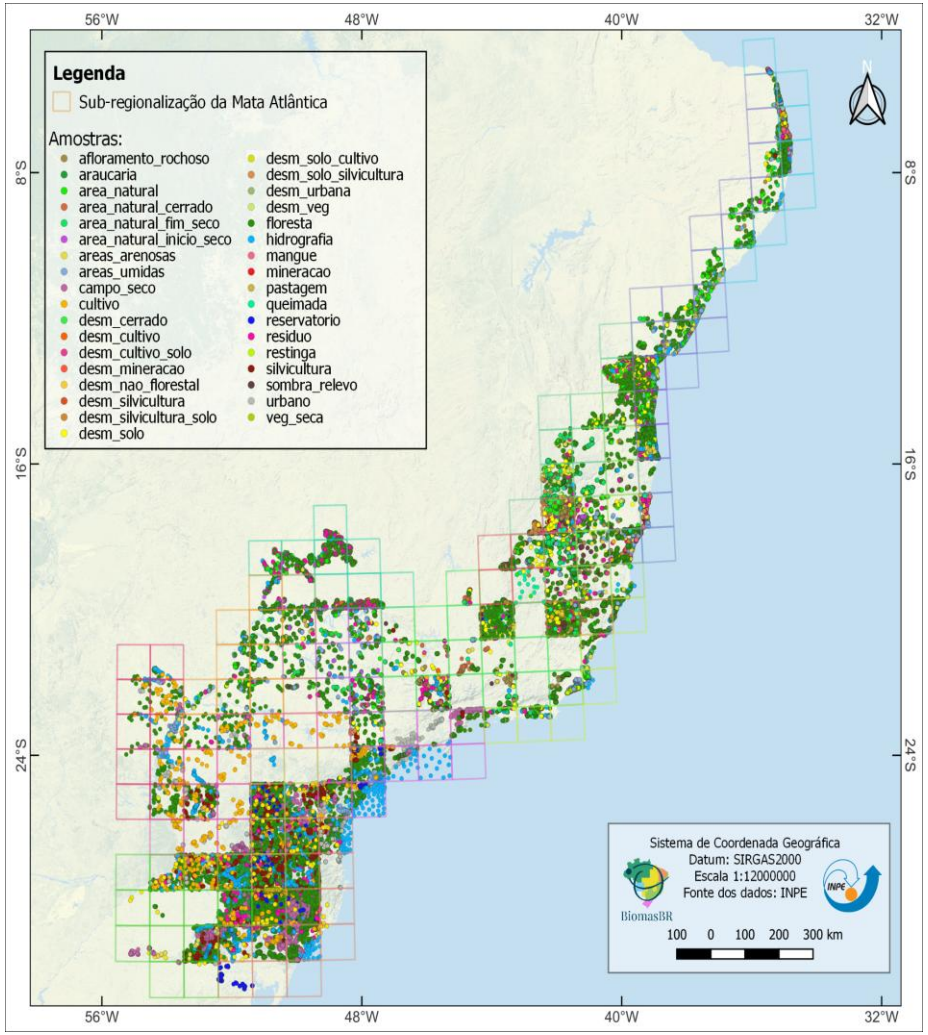


IA for Forestry monitoring – Major Challenges

Limited labeled datasets

High-quality reference data are expensive and time-consuming to produce.

Restricts supervised learning and model accuracy.



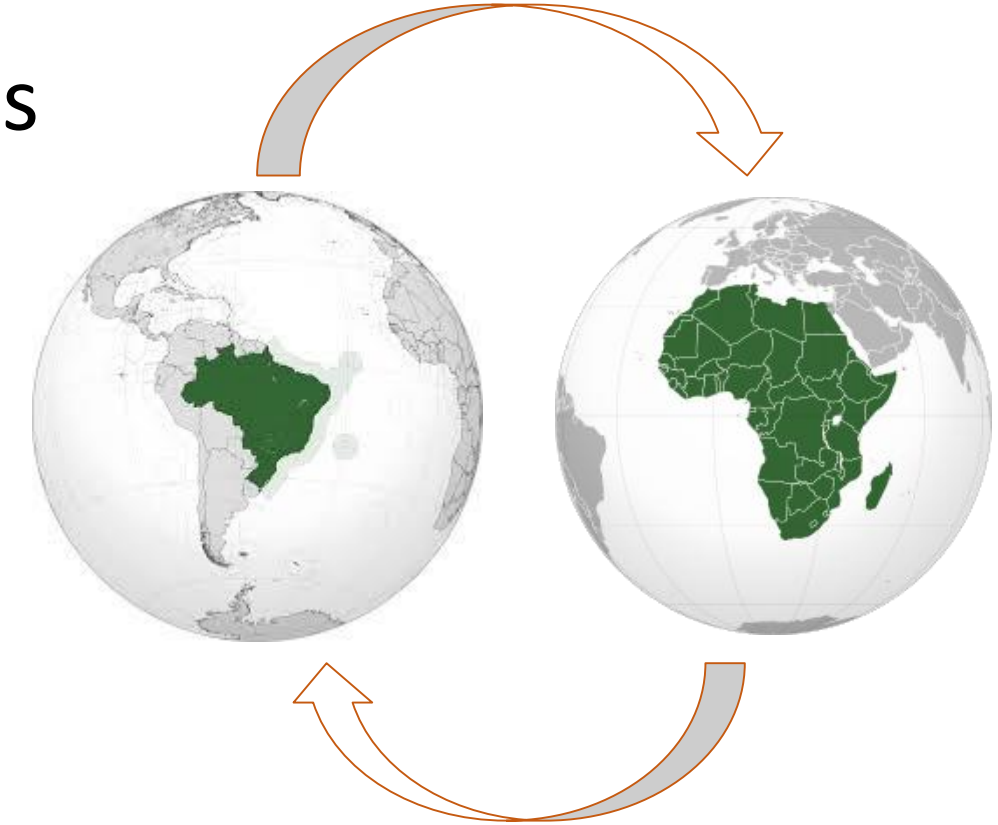


IA for Forestry monitoring – Major Challenges

Generalization across ecosystems

Models trained in one biome or country often perform poorly elsewhere

Reduces transferability to new ecosystems and climates.





IA for Forestry monitoring – Major Challenges

Temporal Variability
Cloud cover

Seasonality, phenology, disturbances
Degradation x deforestation

Tropical forest – cloud cover

AI misses selective logging, fire damage, and understory degradation

Incomplete time series





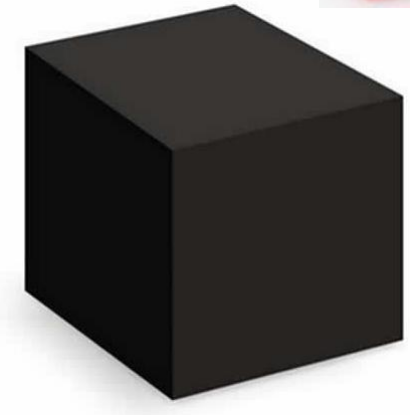
IA for Forestry monitoring – Major Challenges

Explainability and uncertainty estimation



Deep learning models are often "black boxes.“

Difficult for agencies and decision-makers to trust operational products.





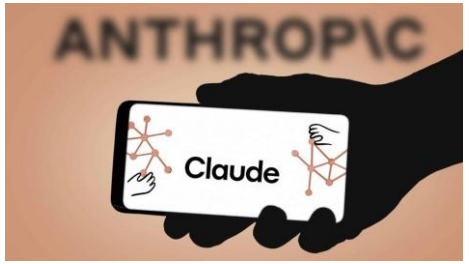
IA for Forestry monitoring – Major Challenges

Large computational requirements

Modern deep learning and foundation models require GPUs, large storage, and high-performance computing.

Currently, access is restricted to certain organizations





Google DeepMind

OpenAI



IA for Forestry monitoring – Major Challenges

- Integration into **operational monitoring systems**
- Long-term consistency for environmental reporting
- Scaling foundation models for global forest monitoring

Ethical and governance issues

menti.com

3825 2546

Do you believe Foundation Models will replace traditional machine learning methods in forest monitoring within the next 10 years?



What is the biggest challenge for applying AI to forest monitoring worldwilde?

What topics should be included in the next version of this presentation?



IA for Forestry

Forest monitoring for Carbon & Climate Change

Remote Sensing and AI – Evolution and challenges

Discussion – use of forestry data → another talk

Research & development – counting on you!

Thank you!

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