



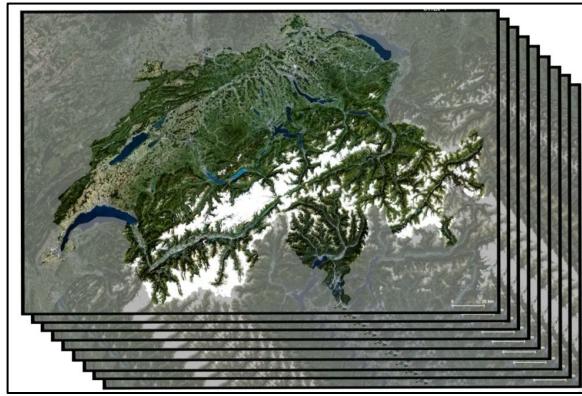
SITS: Satellite Image Time Series Analysis for Big Earth Observation Data

Equipe SITS
INPE (National Institute for Space Research, Brazil)

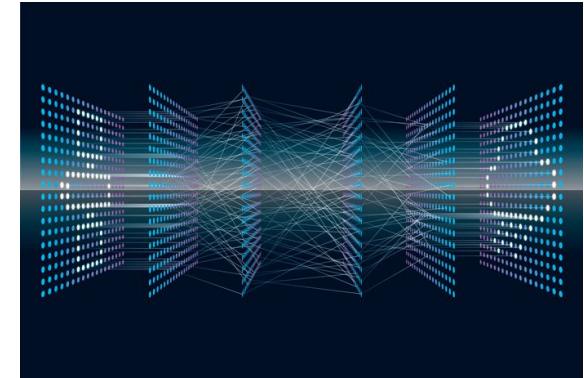
Grandes dados de observação da Terra



Dados de
satélite



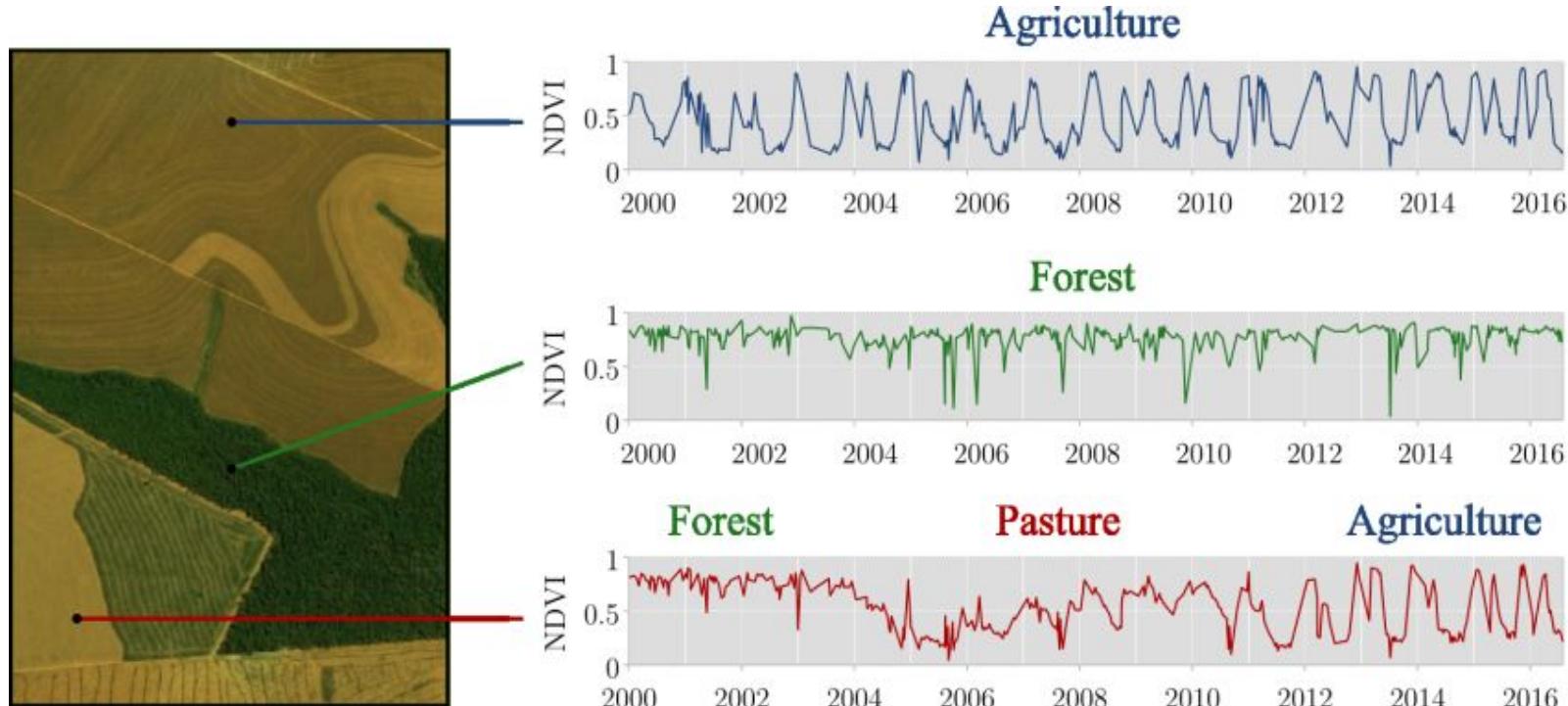
Cubo de
dados



Machine
learning

images: NASA, Swiss Data Cube, ECMWF

Séries Temporais de Imagem de Satélite

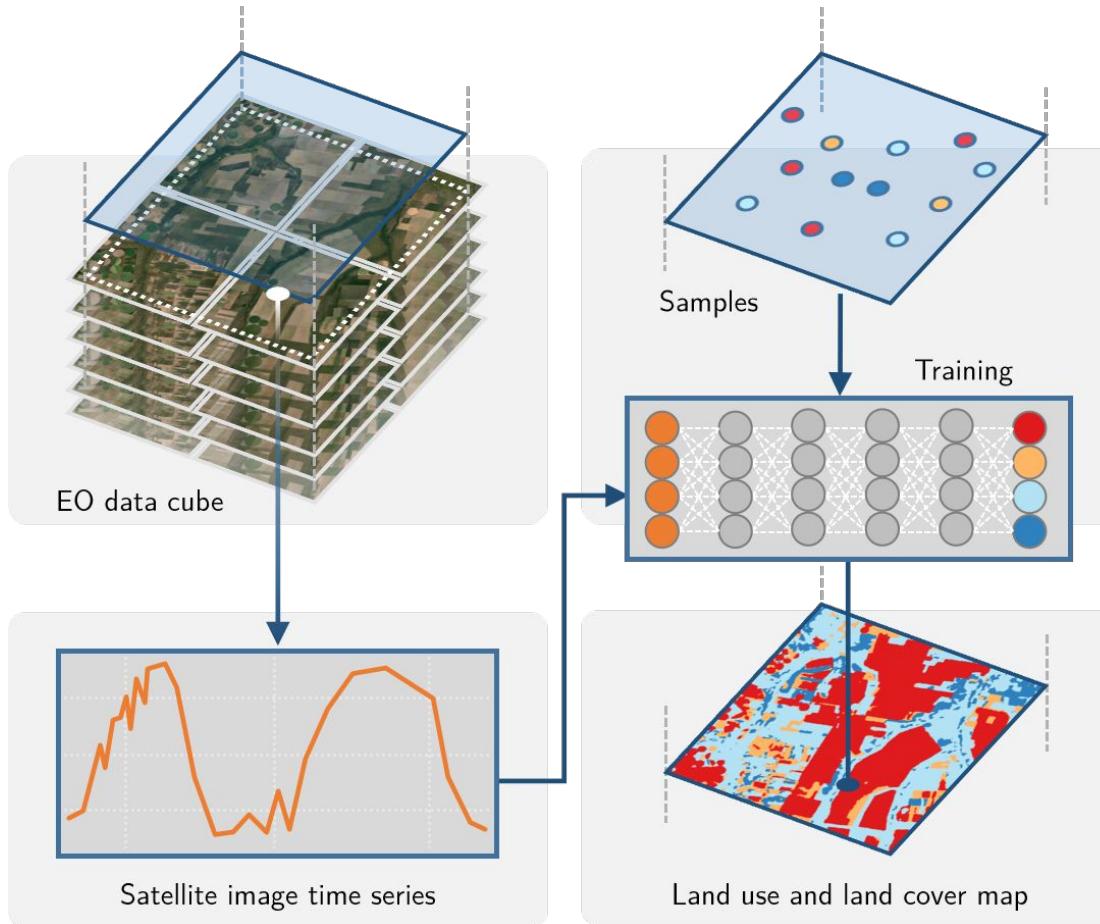


Como classificar a cobertura e o uso da terra usando séries temporais?

graphics: Maus, Victor



Classificação de cubo de dados usando sits



```
graph LR; samples([samples]) --- cube1[cube]; samples --- model1[model]; cube1 --- probsCube[probs cube];
```

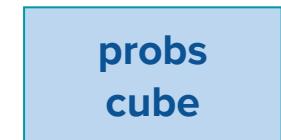
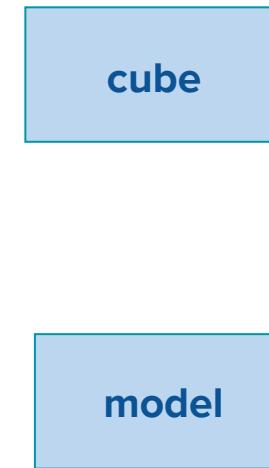
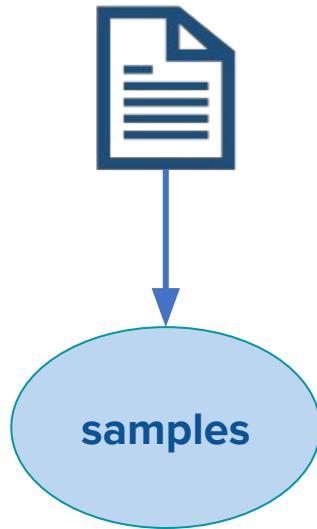
samples

cube

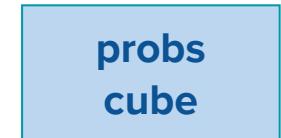
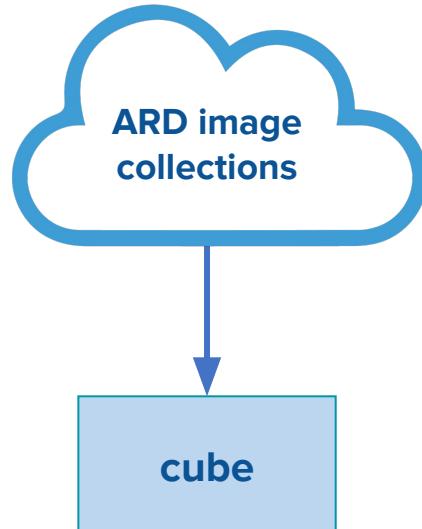
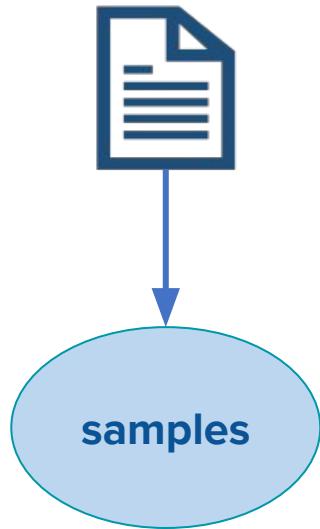
**probs
cube**

model

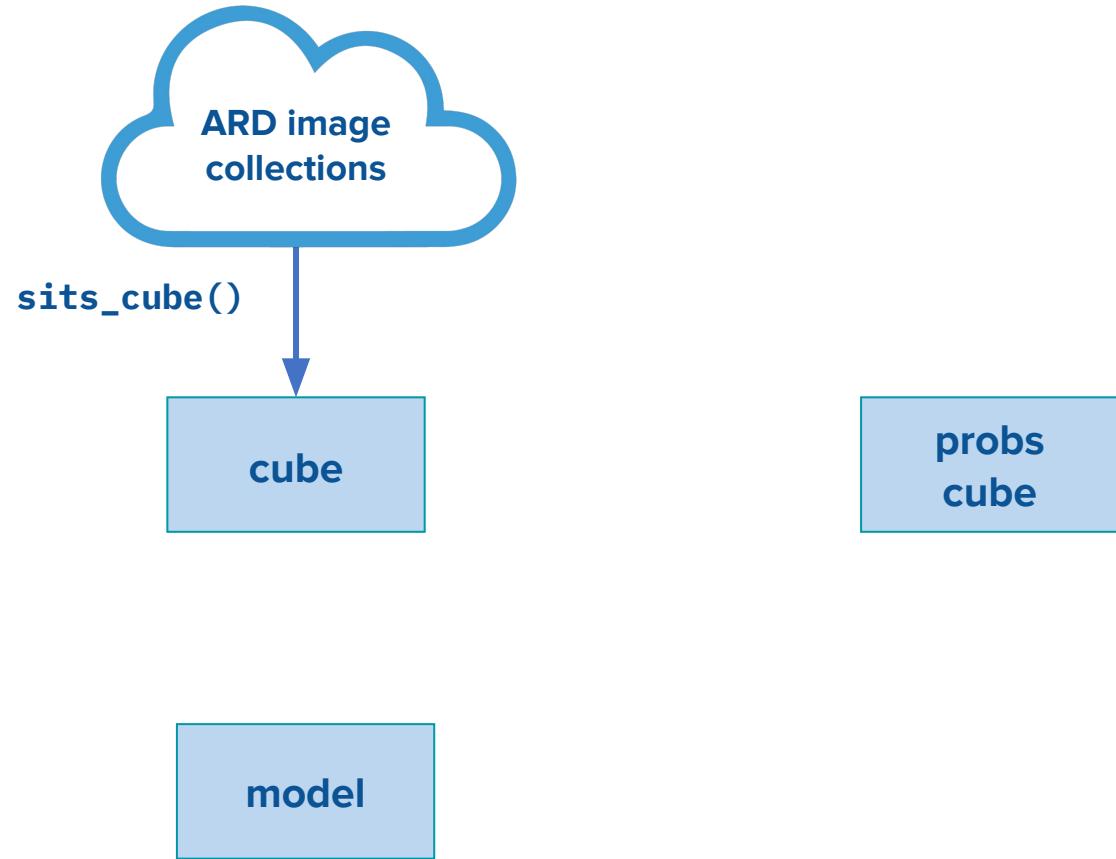
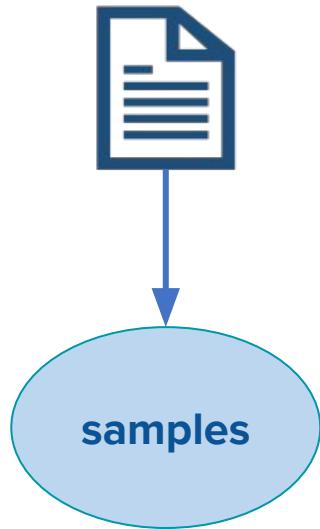
Ground truth



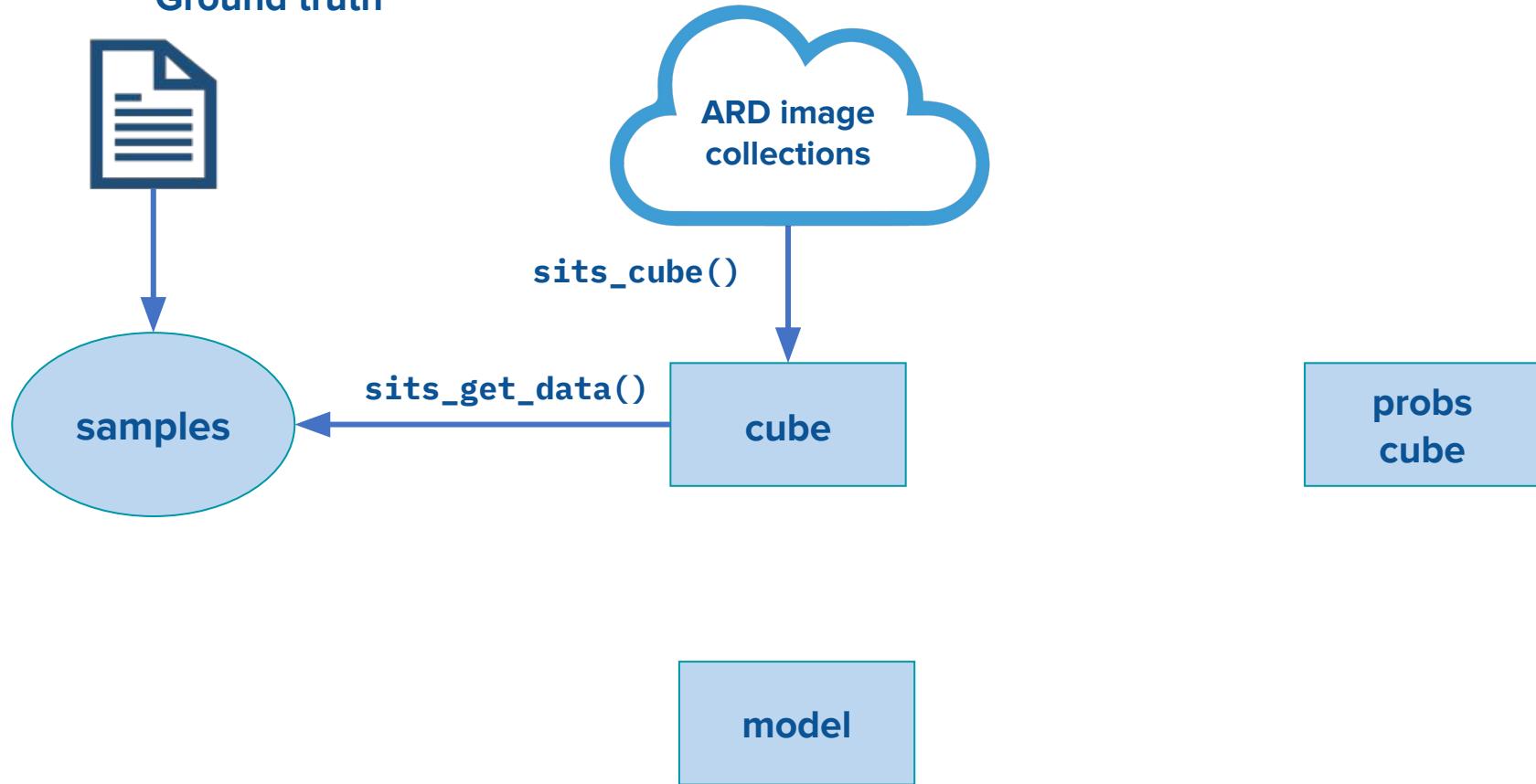
Ground truth



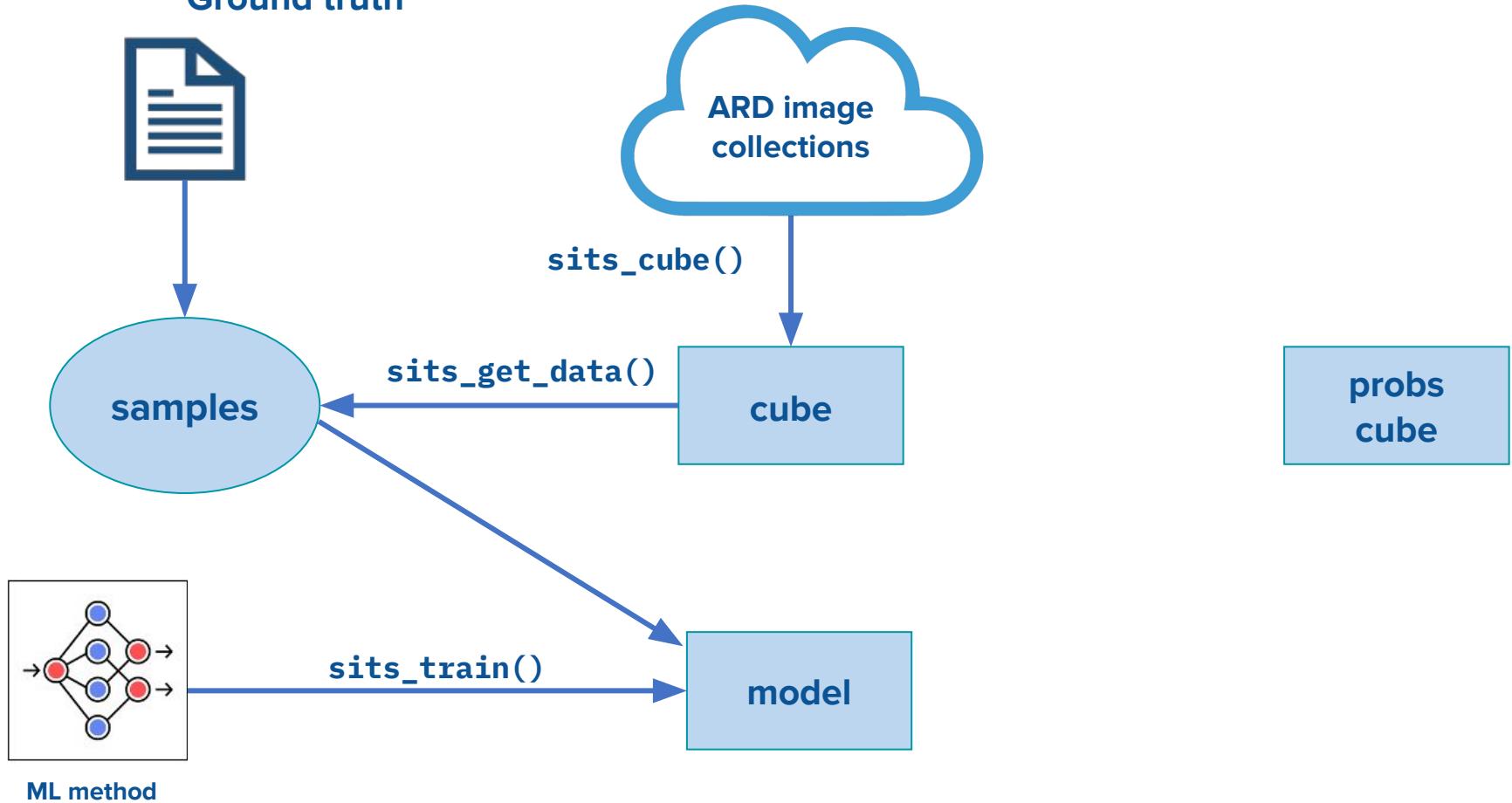
Ground truth



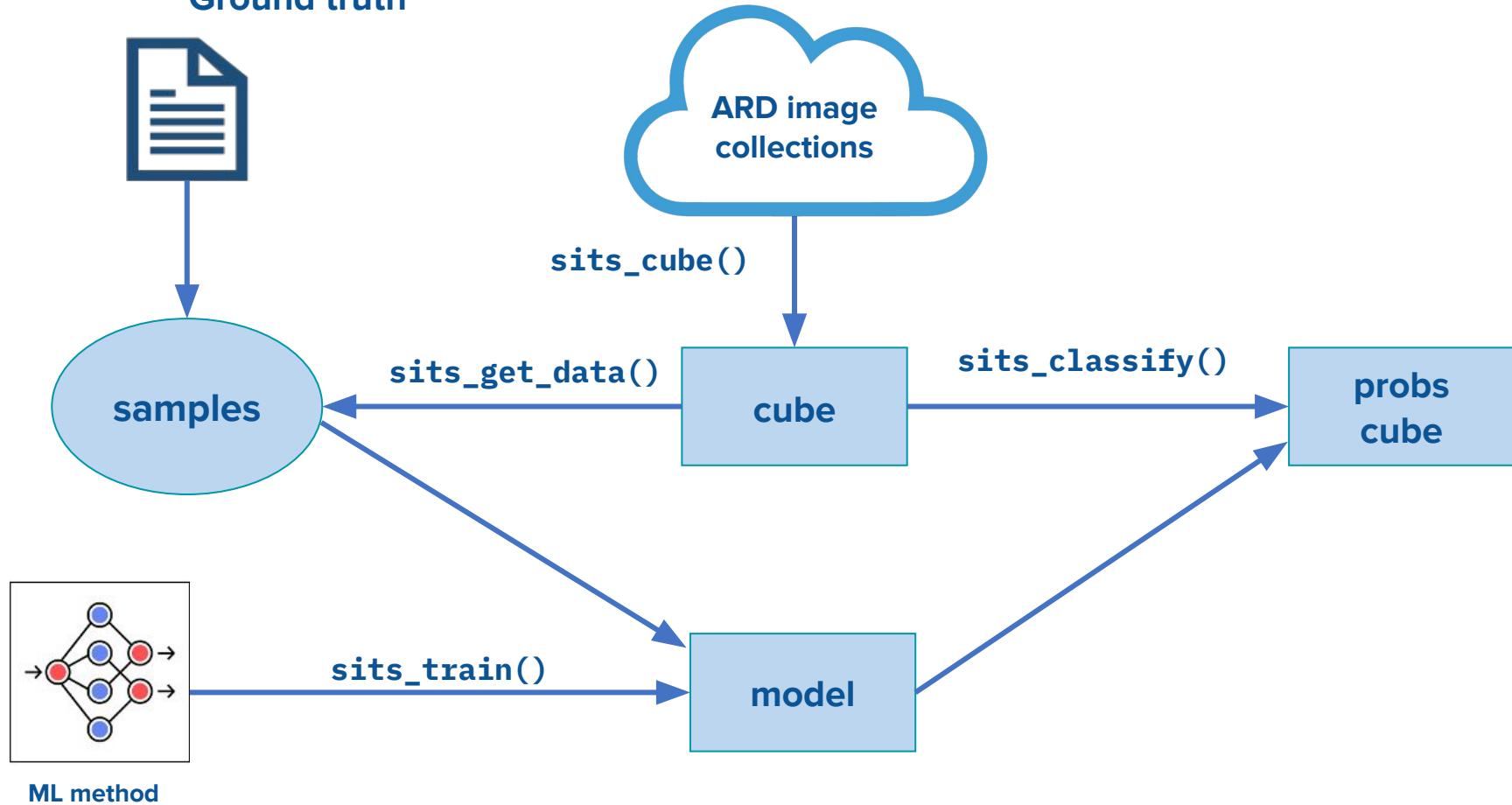
Ground truth



Ground truth

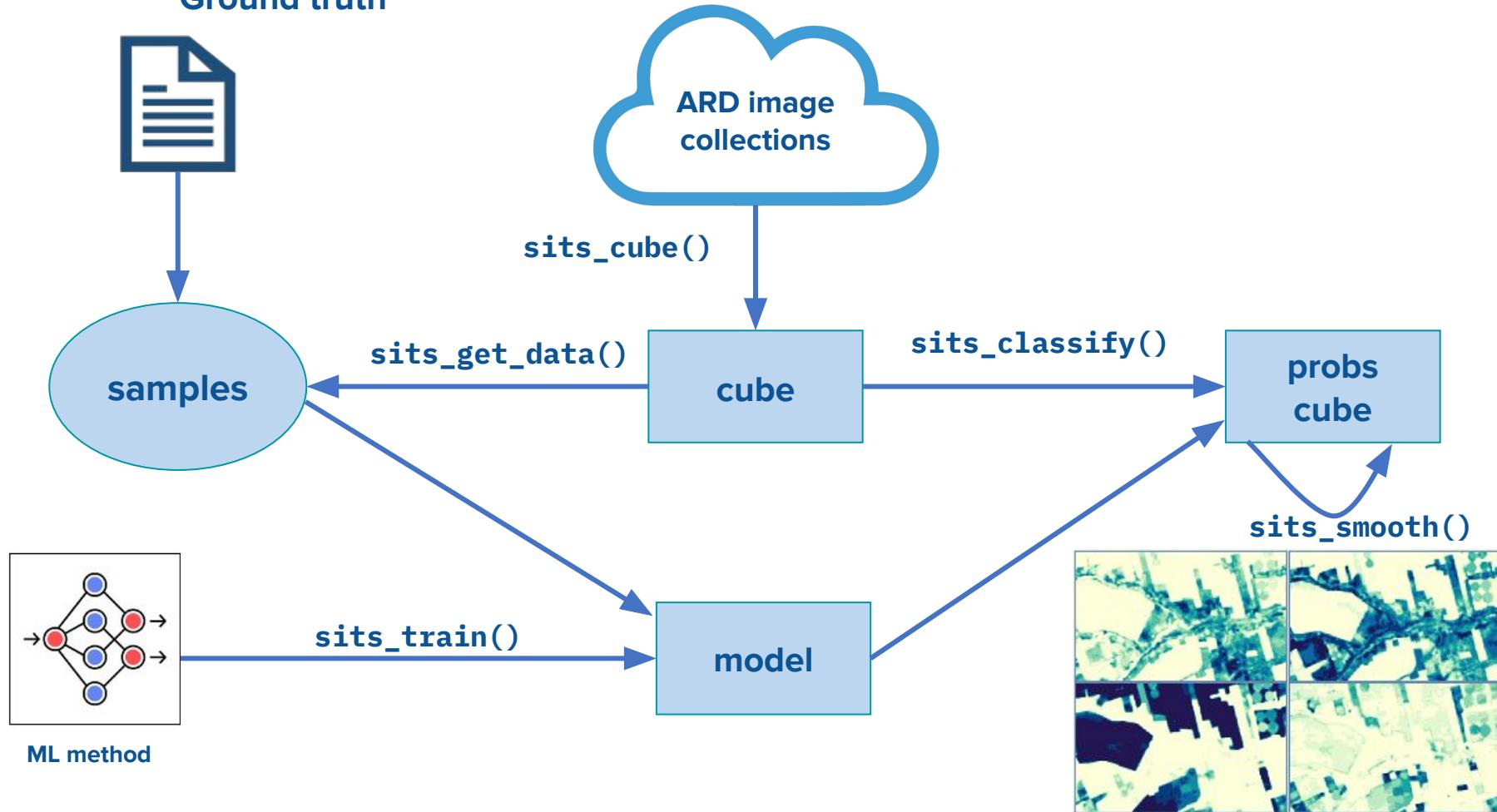


Ground truth

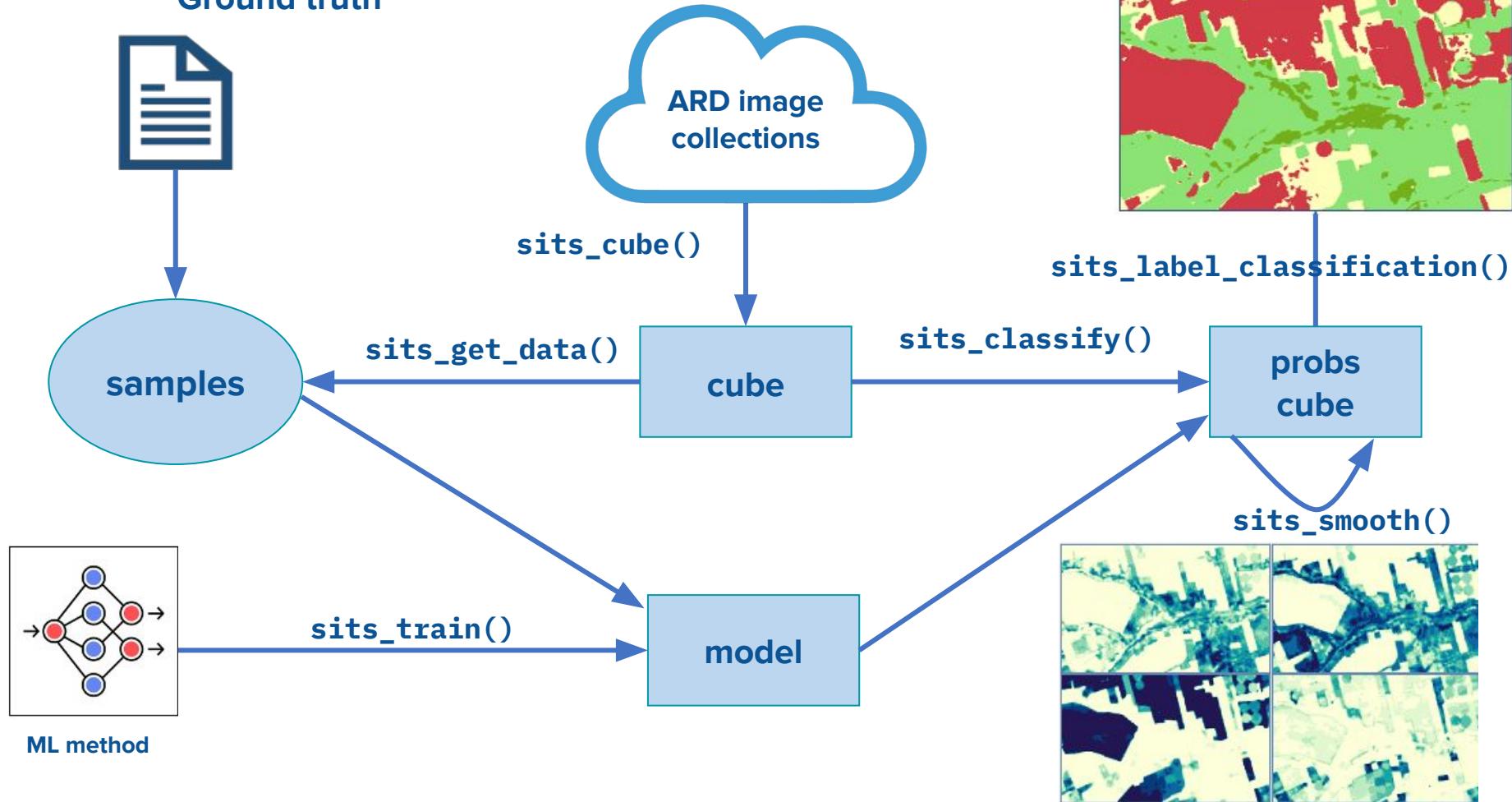


ML method

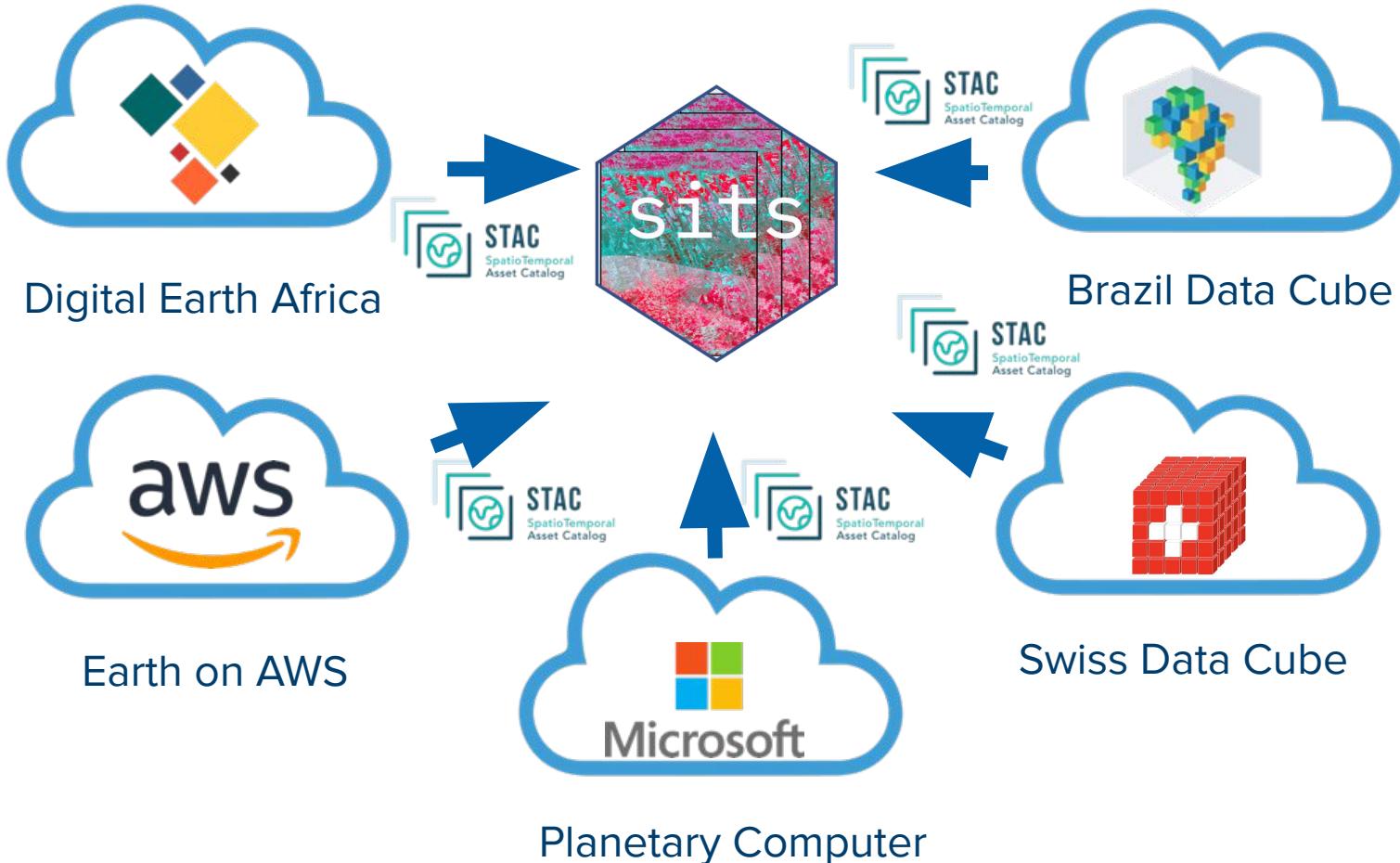
Ground truth



Ground truth

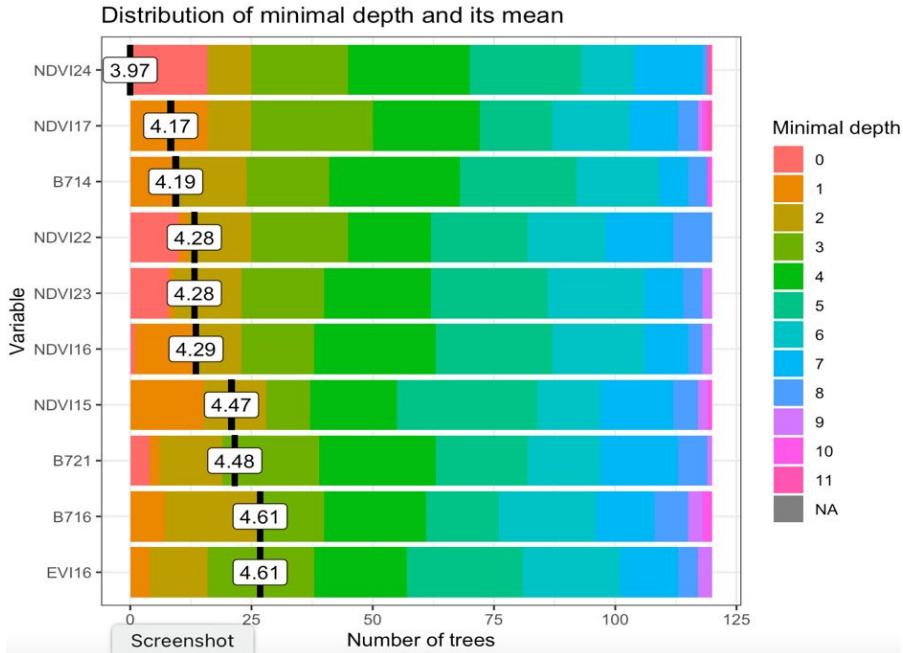


Acesso a cubos de dados com STAC

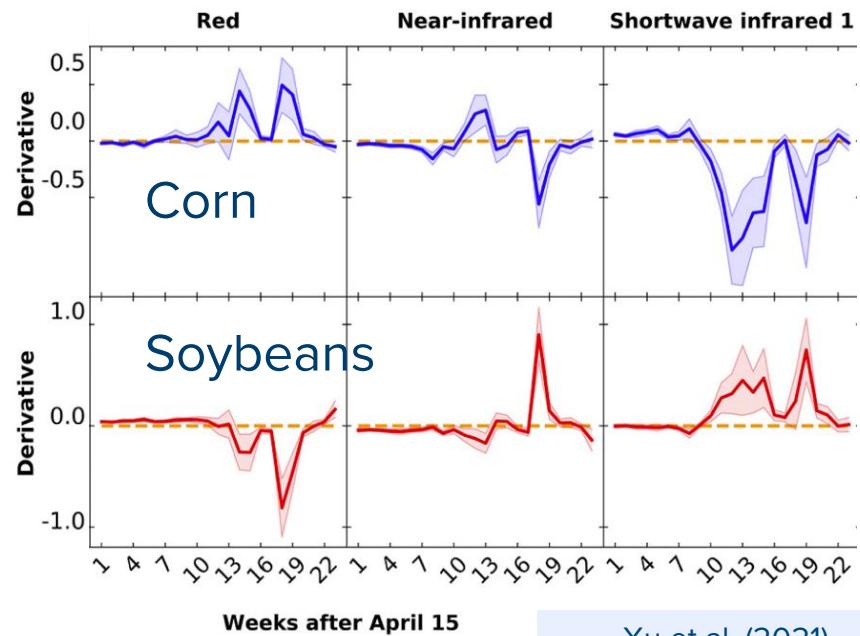


Dos métodos clássicos aos contemporâneos

Random forests (hierarchical model)

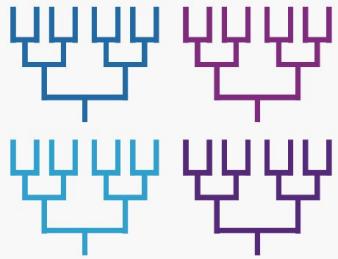


Transformers (relational model)

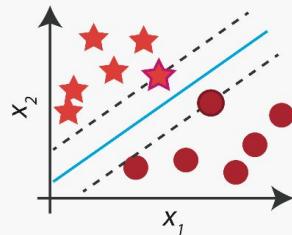


Métodos de Aprendizagem de Máquina suportados pelo SITS

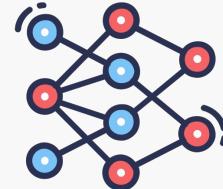
Random forests



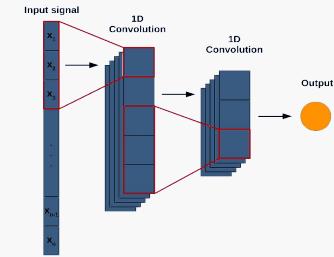
Support vector machines



Multilayer perceptrons



1D convolutional neural networks



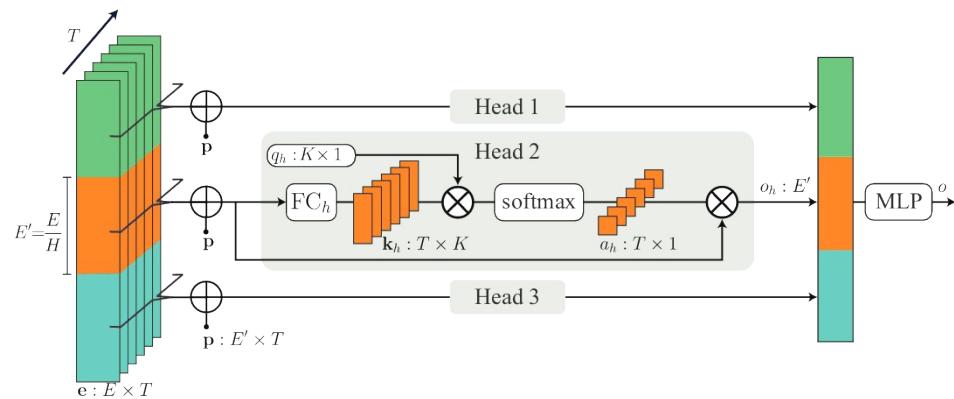
- Extreme gradient boosting
- Deep Residual Networks

- Temporal attention encoders
- Lightweight temporal attention encoders

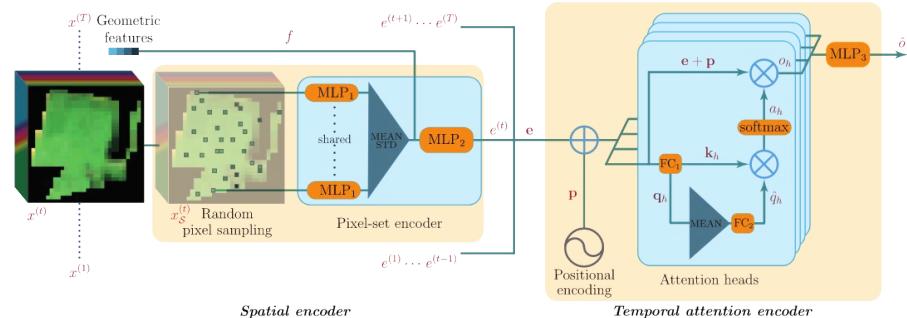
graphics: Cambridge Coding Academy and Alex Shenfield

State-of-the-art time series classification

Lightweight Temporal Self-Attention Encoder



Temporal Self-Attention Encoder



Garnot & Landrieu (2020)

Garnot et al. (2020)

Estimativa de acurácia



Remote Sensing of Environment 148 (2014) 42–57

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Review

Good practices for estimating area and assessing accuracy of land change

Pontus Olofsson ^{a,*}, Giles M. Foody ^b, Martin Herold ^c, Stephen V. Stehman ^d,
Curtis E. Woodcock ^a, Michael A. Wulder ^e

^a Department of Earth and Environment, Boston University, 685 Commonwealth Avenue, Boston, MA 02215, USA

^b School of Geography, University of Nottingham, University Park, Nottingham NG7 2RD, UK

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^e Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, Victoria, BC V8Z 1MS, Canada



Food and Agriculture
Organization of the
United Nations

Map Accuracy Assessment and Area Estimation

A Practical Guide



Mato Grosso classification from 2001 to 2017

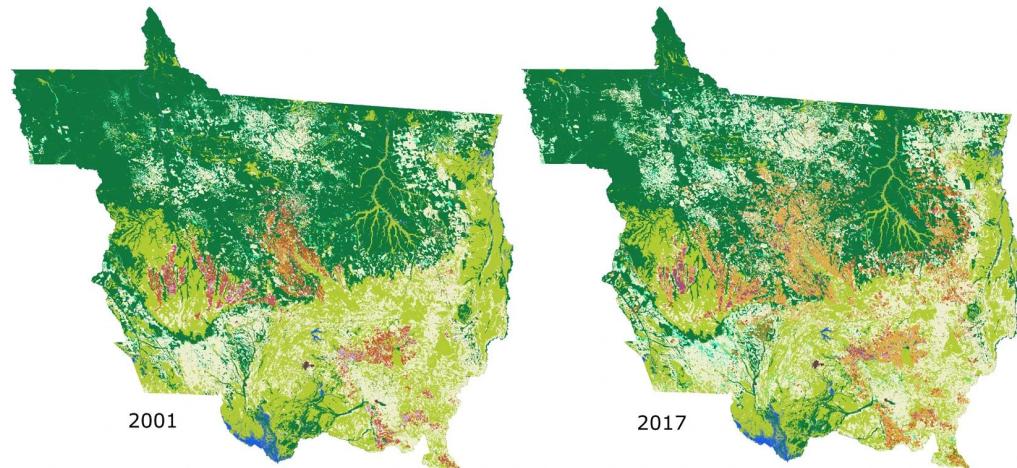


Data Descriptor | Open Access | Published: 27 January 2020

Land use and cover maps for Mato Grosso State in Brazil from 2001 to 2017

Rolf Simoes, Michelle C. A. Picoli, Gilberto Camara, Adeline Maciel, Lorena Santos, Pedro R. Andrade, Alber Sánchez, Karine Ferreira & Alexandre Carvalho

Scientific Data 7, Article number: 34 (2020) | [Cite this article](#)



1. Cerrado	6. Soy_Cotton	11. Urban Area
2. Fallow_Cotton	7. Soy_Fallow	12. Water
3. Forest	8. Soy_Millet	13. Secondary Vegetation
4. Pasture	9. Soy_Sunflower	
5. Soy_Corn	10. Sugarcane	

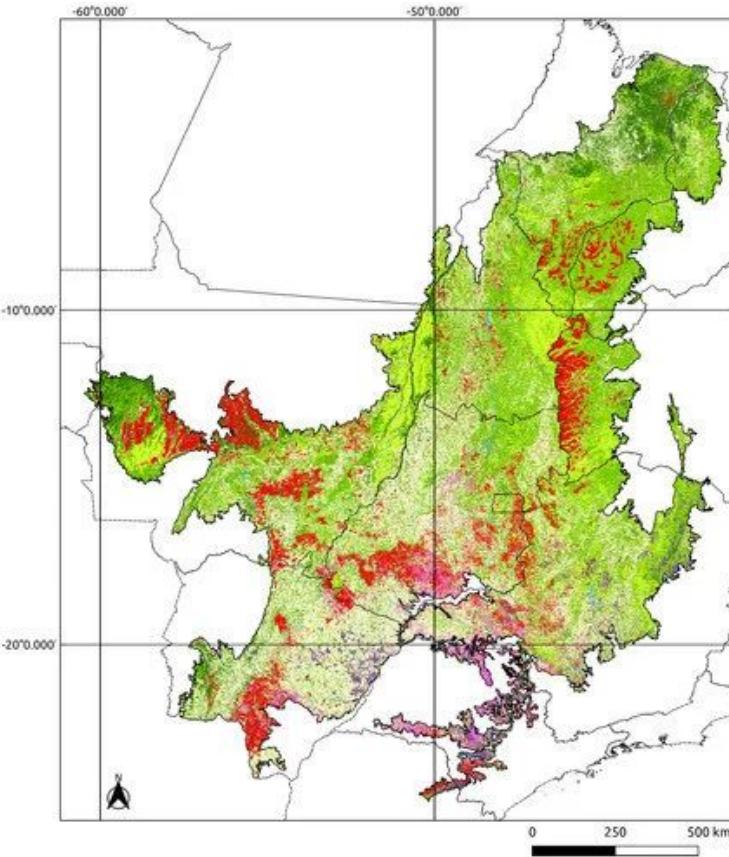
Cerrado biome classification



Article

Satellite Image Time Series Analysis for Big Earth Observation Data

Rolf Simoes ^{1,*}, Gilberto Camara ¹, Gilberto Queiroz ¹, Felipe Souza ¹, Pedro R. Andrade ¹, Lorena Santos ¹, Alexandre Carvalho ² and Karine Ferreira ¹

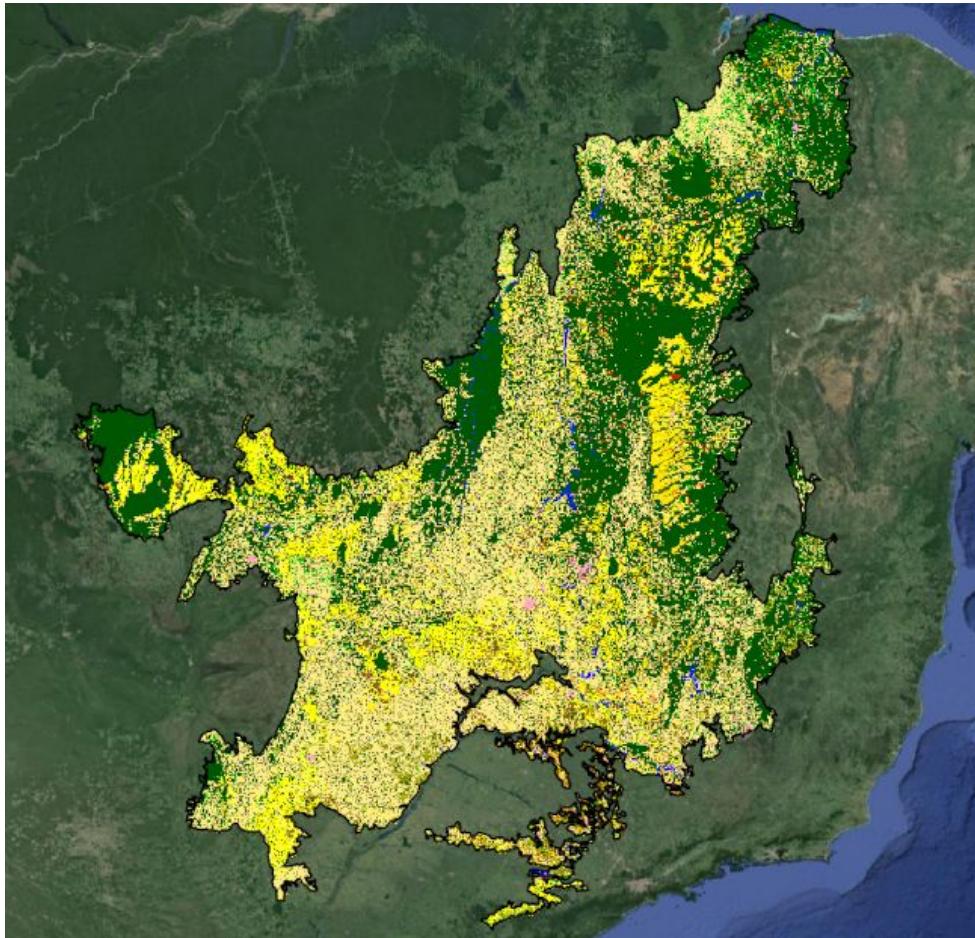


1 Annual_Crop	5 Open_Cerrado	9 Sugarcane
2 Cerradão	6 Pasture	10 Water
3 Cerrado	7 Perennial_Crop	Brazilian states
4 Nat_NonVeg	8 Silviculture	

TerraClass Cerrado



TerraClass

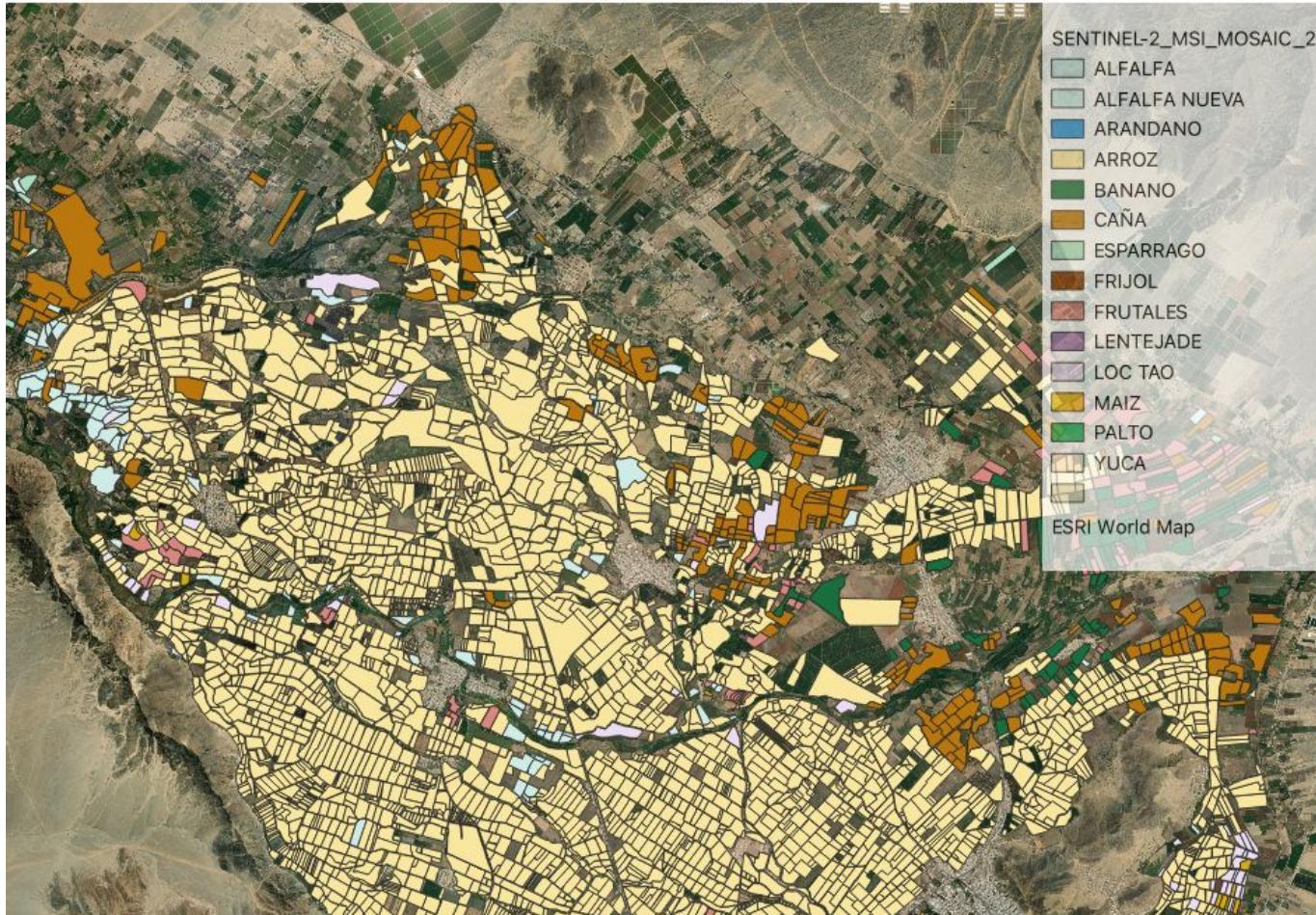


Mapeamento de LULC em Peru

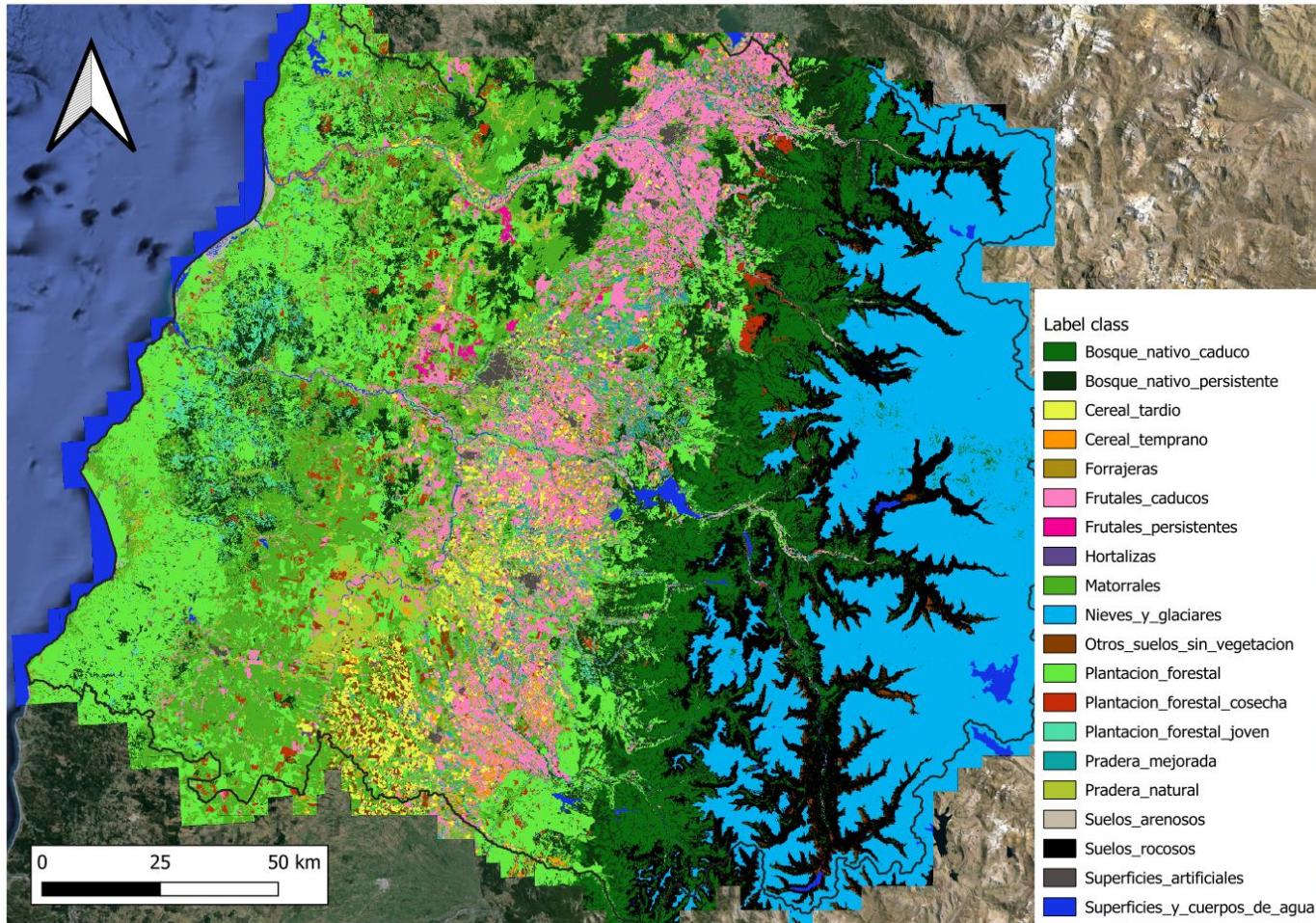


PERÚ

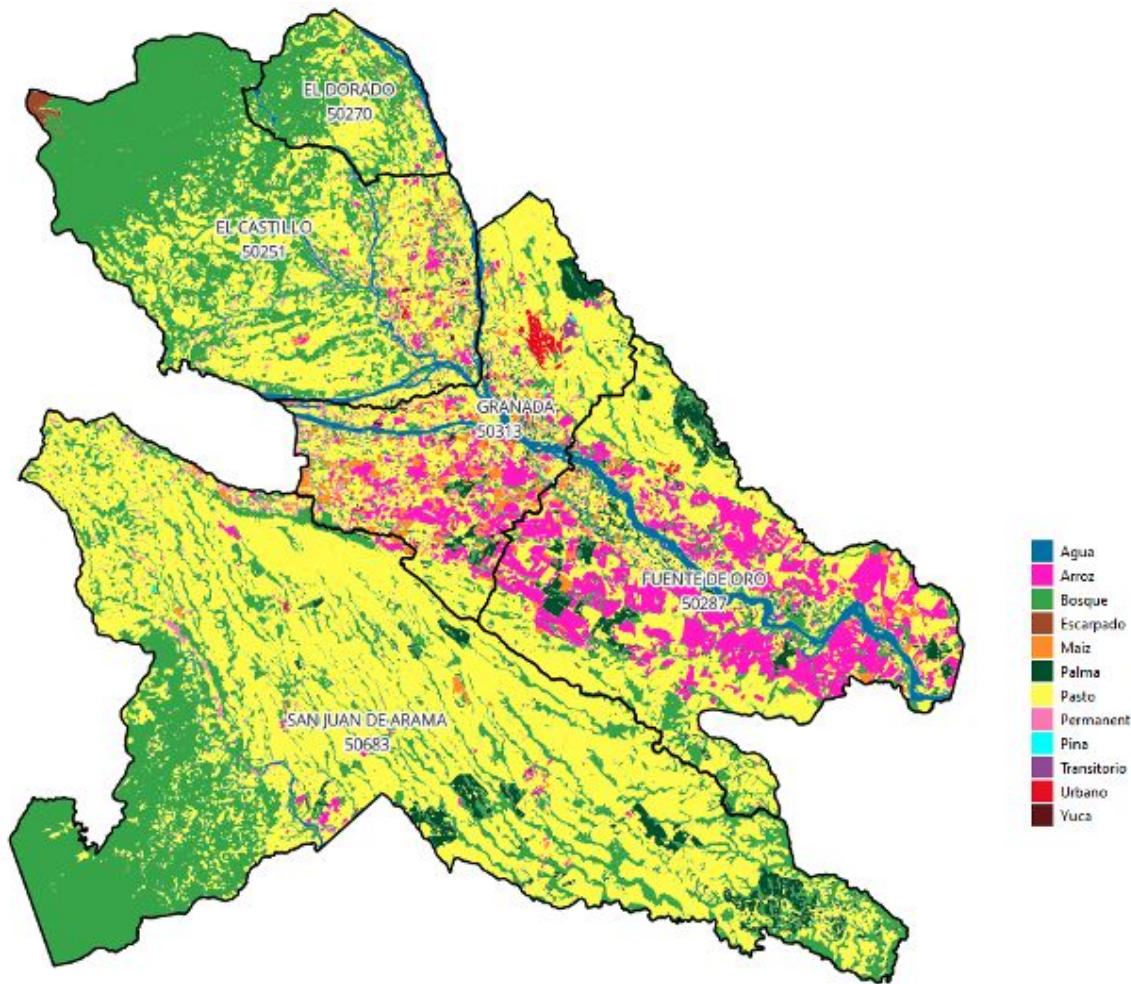
MIDAGRI



Mapeamento de LULC em Chile



Mapeamento de LULC em Colombia



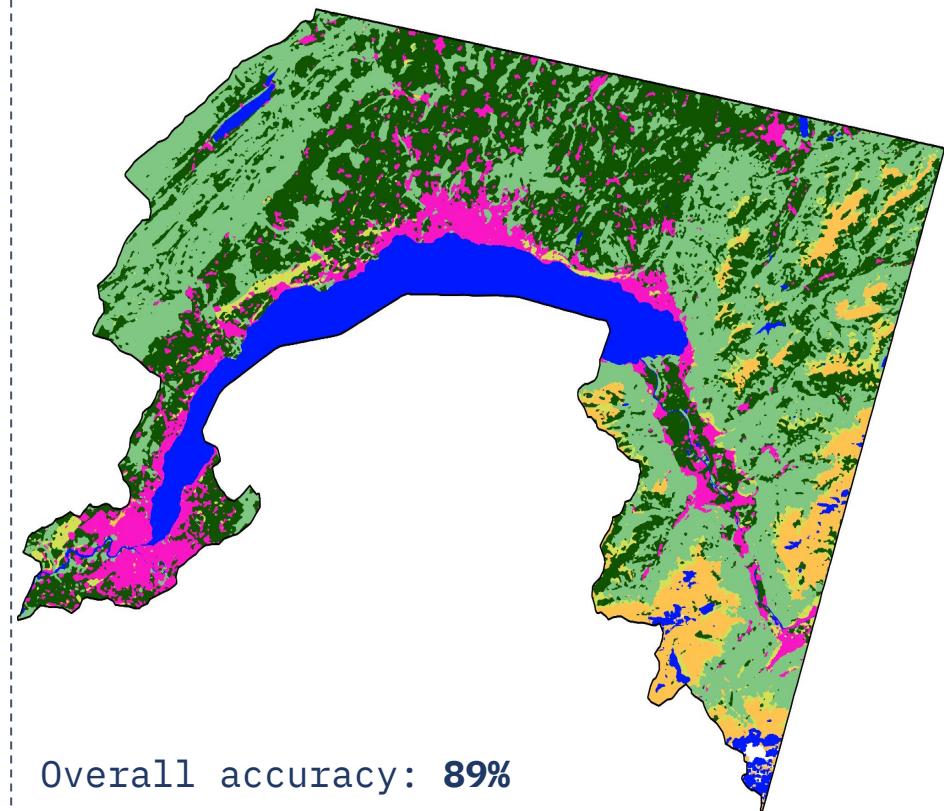
Mapeamento de LULC em Genebra



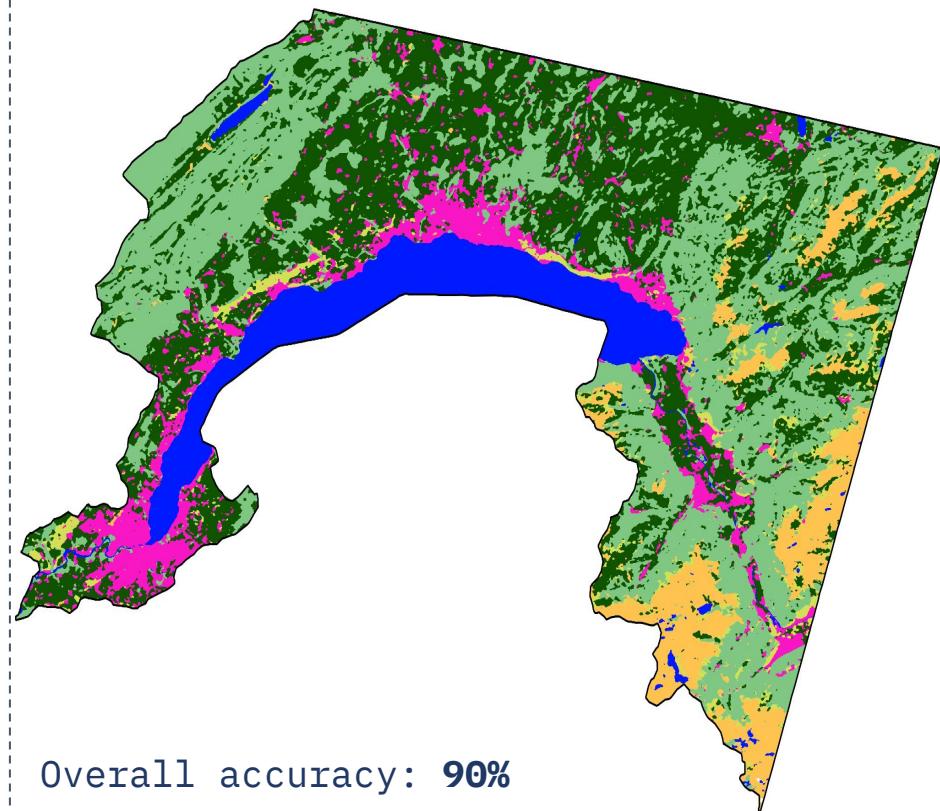
UNIVERSITÉ
DE GENÈVE

Reference: 2018

Target: 2009



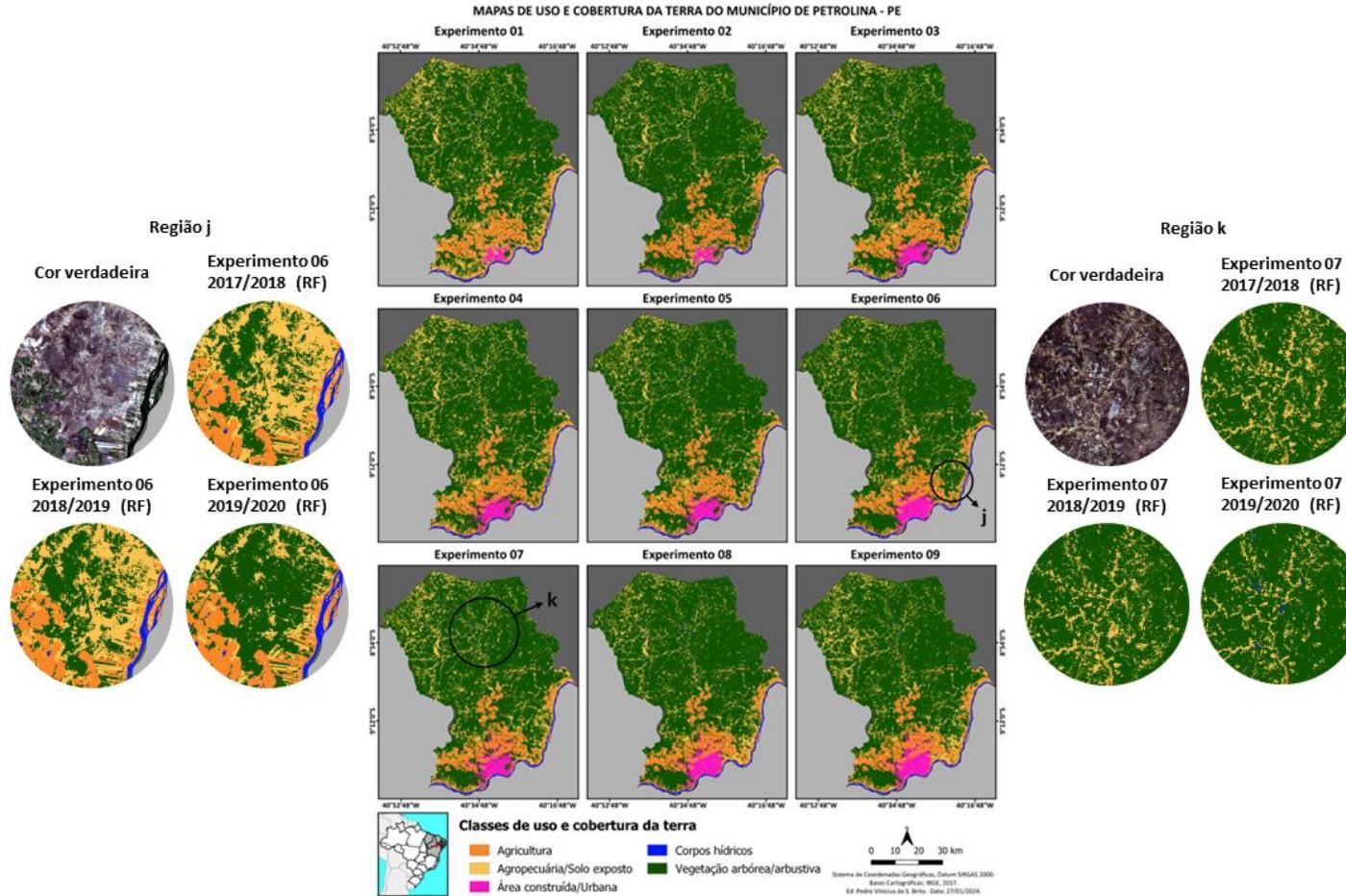
Overall accuracy: 89%



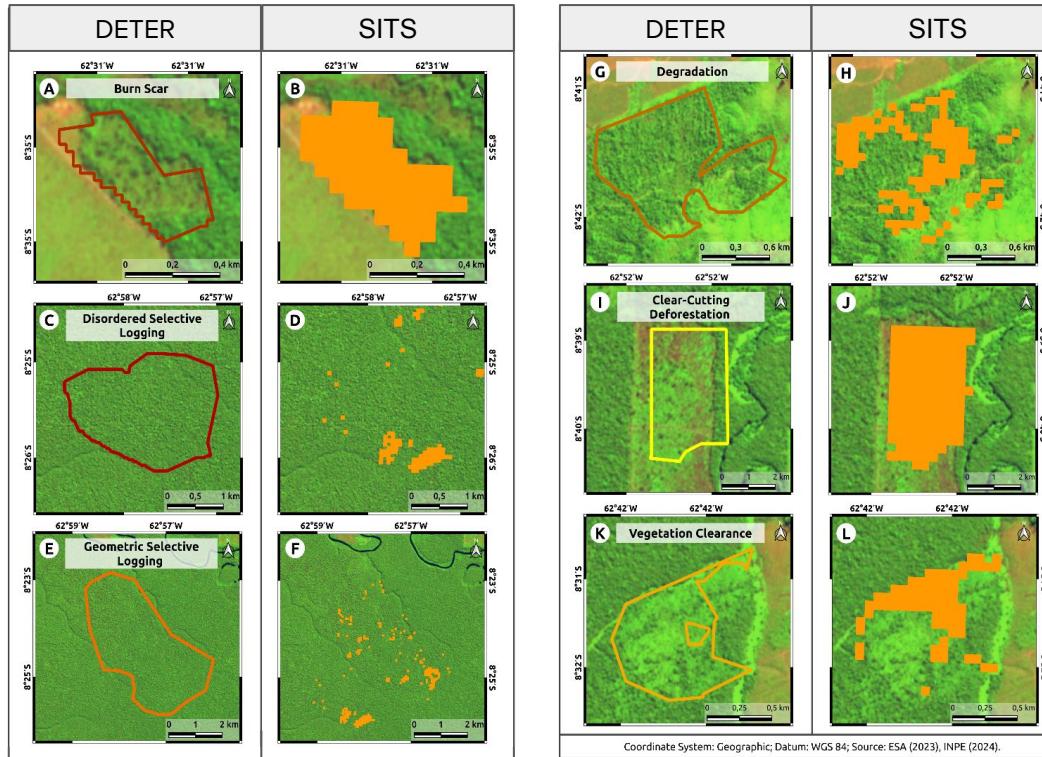
Overall accuracy: 90%

Artificial Areas	Brush Vegetation	Tree Vegetation
Bare Land	Grass Herb Vegetation	Watery Areas

Combinação de dados meteorológicos e dados ópticos na Caatinga



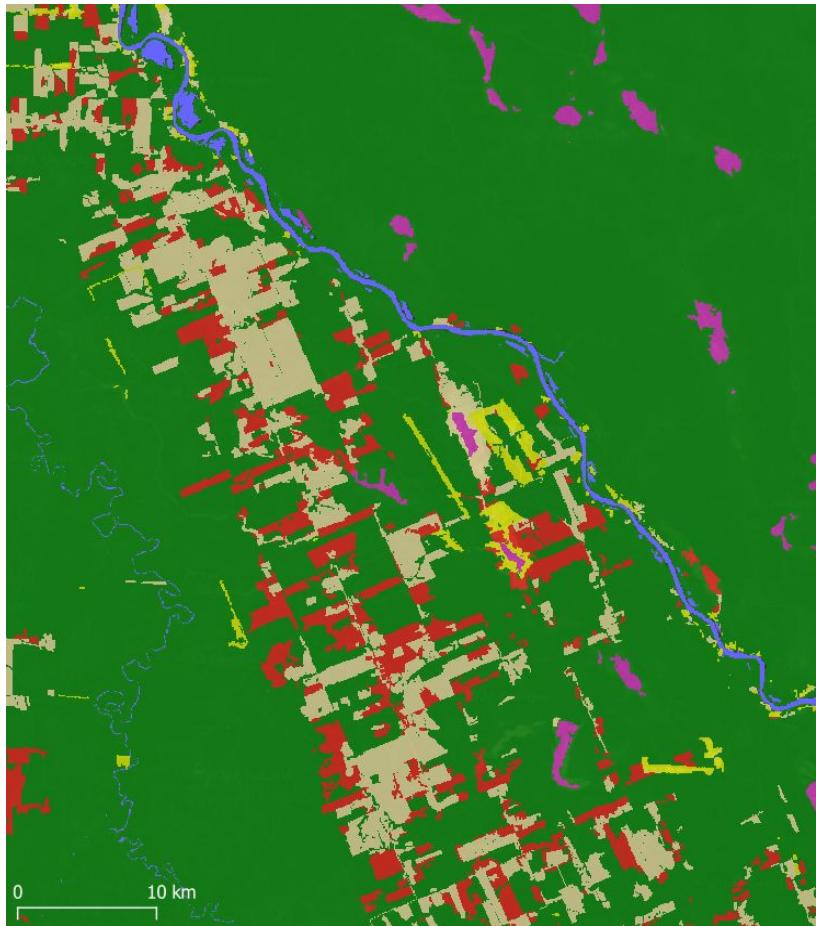
Combinação de dados SAR e ópticos para detecção de distúrbios florestais na Amazônia



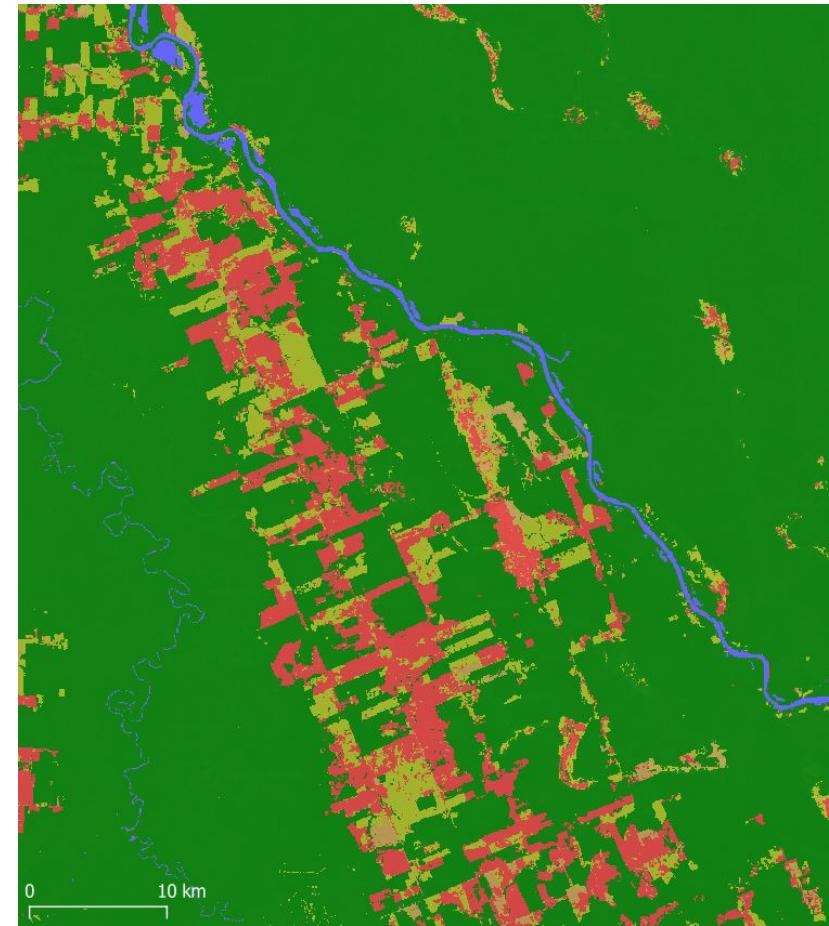
Combinação de dados SAR e ópticos para detecção de distúrbios florestais na Amazônia

DETER classification	Mean detection difference (in days ±)
Burn Scar	-87.8
Disordered Selective Logging	-183.
Geometric Selective Logging	-142.
Degradation	-89.4
Clear-Cutting Deforestation	-16.6
Vegetation Clearance	-61.1

Monitoramento de desmatamento em Rondônia



PRODES (reference)



400 samples, LTAE (97% agreement)

e-sensing.github.io/sitsbook/

Referências

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3. Gilberto Câmara, “On the semantics of big Earth observation data for land classification”, *Journal of Spatial Information Science*, 20, p. 21–34, 2020.
4. Michelle Picoli, Ana Rorato, et al., “Impacts of Public and Private Sector Policies on Soybean and Pasture Expansion in Mato Grosso—Brazil from 2001 to 2017”. *Land*, 9(1), 2020.
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3. Monarch, R., “Human-in-the-Loop Machine Learning: Active Learning and Annotation for Human-centered AI”. Manning Publications, 2021.
4. Garnot, Landrieu, et al., “Satellite Image Time Series Classification With Pixel-Set Encoders and Temporal Self-Attention”. *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020.
5. Garnot, Landrieu, et al., “Lightweight Temporal Self-attention for Classifying Satellite Images Time Series”. *Arxiv:2007.00586.*, 2021.
6. Ofori-Ampofo, Pelletier, and Lang, “Crop Type Mapping from Optical and Radar Time Series Using Attention-Based Deep Learning”. *Remote Sensing*, 2021.