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Monitoring Forest Change in the Amazon Using Multi-Temporal Remote Sensing Data and Machine Learning Classification on Google Earth Engine

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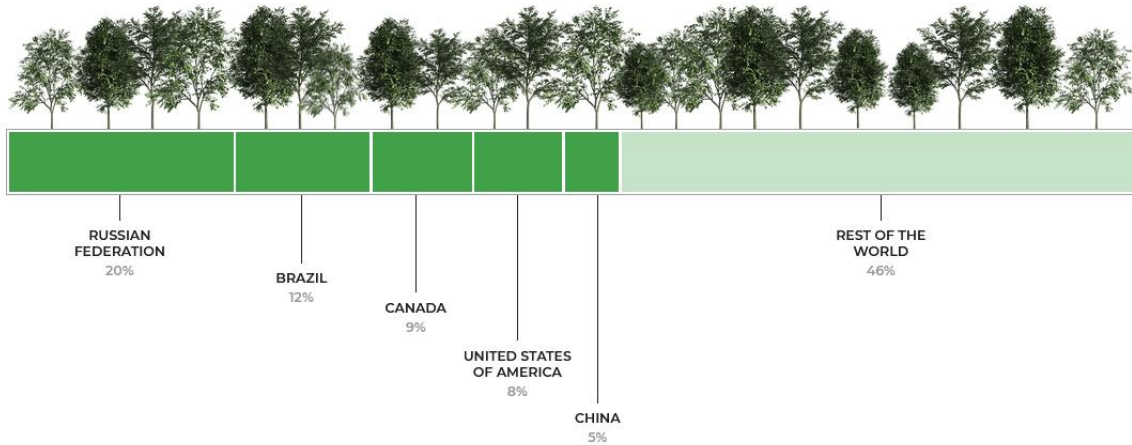
Politecnico di Milano – DICA | GEOlab

FOSS4G Korea 2020 13/11/2020

1. Research problem
2. Introduction to the Amazon case study
3. Methods and tools
4. Results
5. Discussion and conclusion

Deforestation

- Forest area covers around 31% of the total land area
- Forest has important ecological roles:
 - It is a home for different species
 - It provides food and livelihood for people
 - It helps to mitigate climate change



Top five countries for forest area (FAO, 2020)

According to FAO **deforestation** is the conversion of forest to other land uses, regardless of whether it is human-induced.

Consequences of deforestation:

- Soil erosion
- Biodiversity loss
- Water cycles
- Greenhouse gas emissions

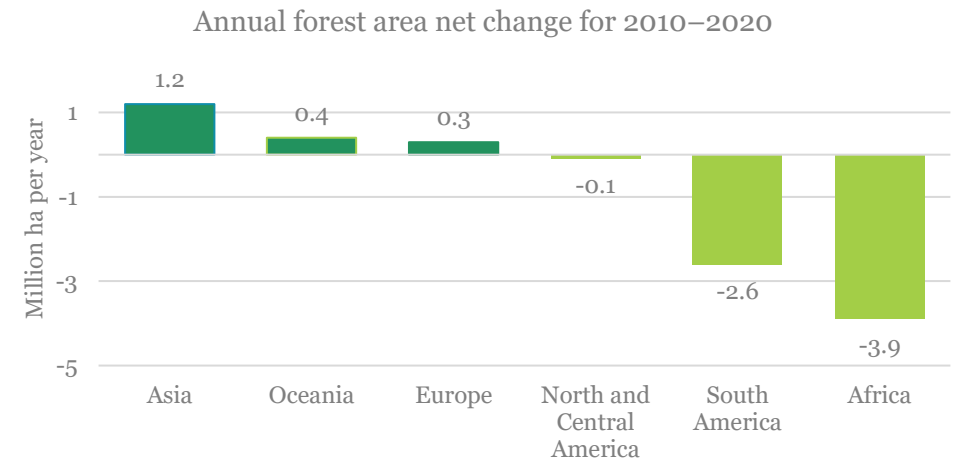
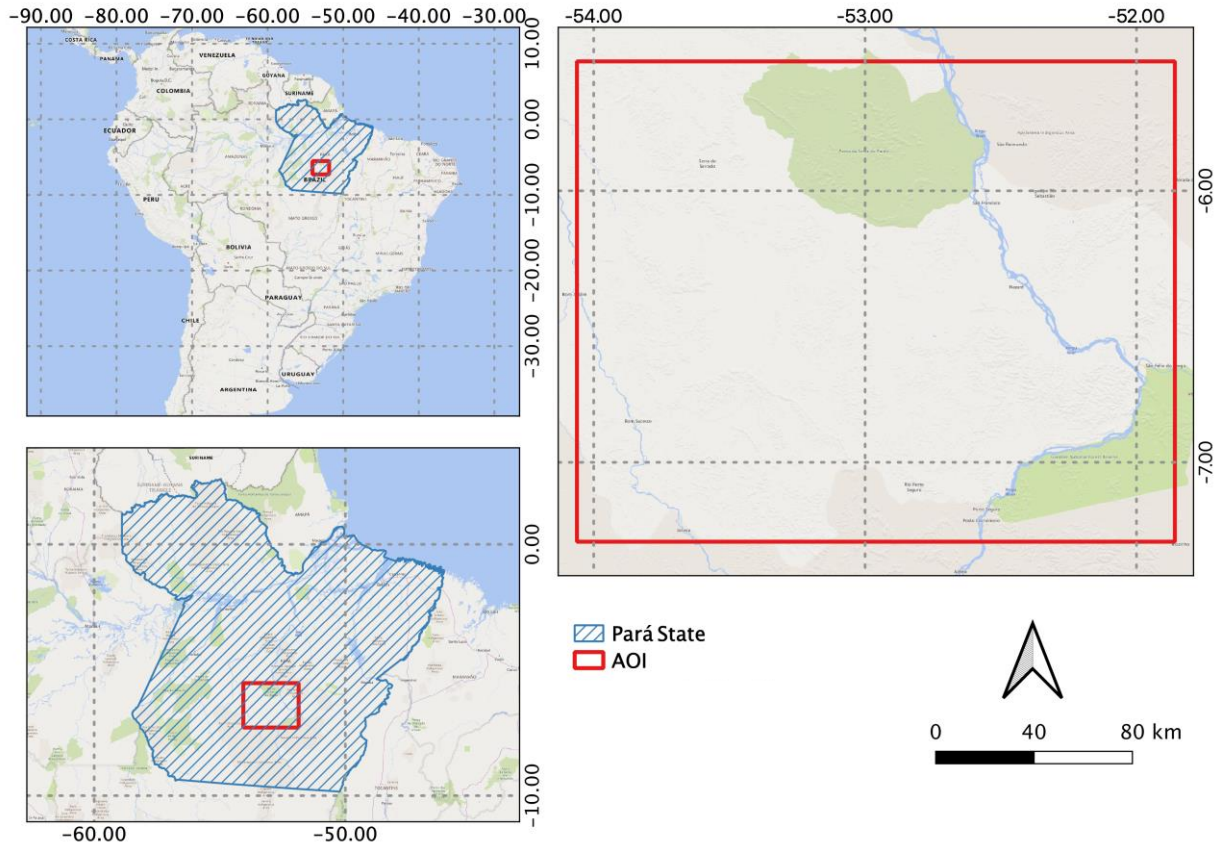
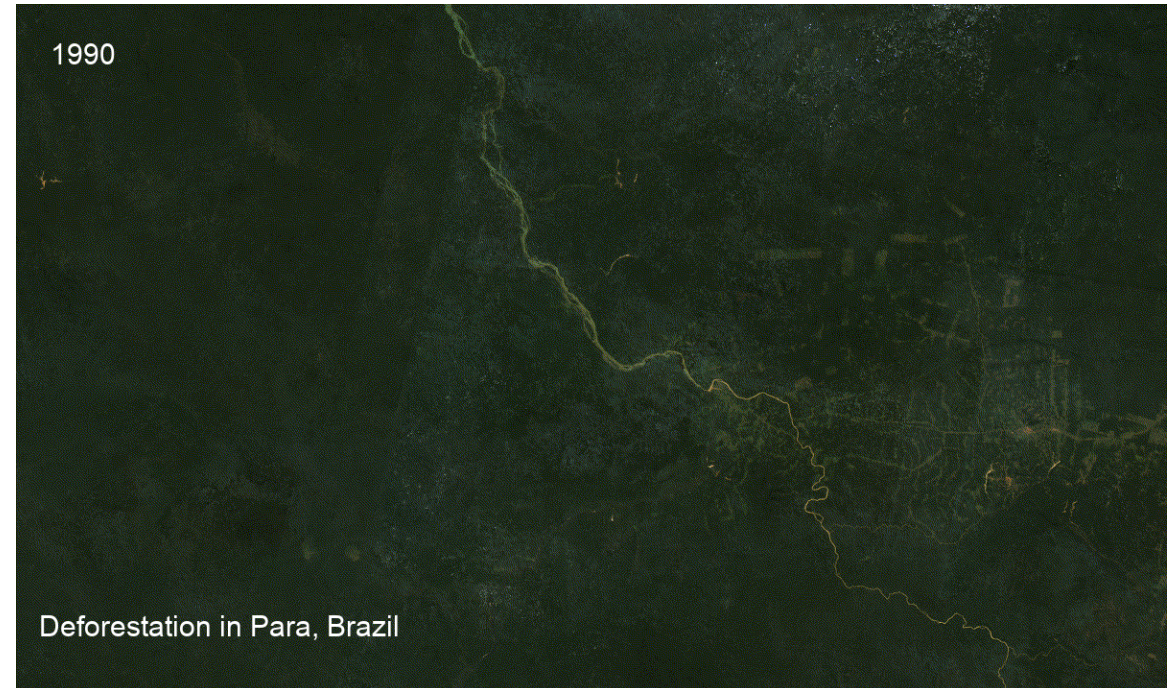


Figure source FAO, 2020 – Key Findings

Area of Interest



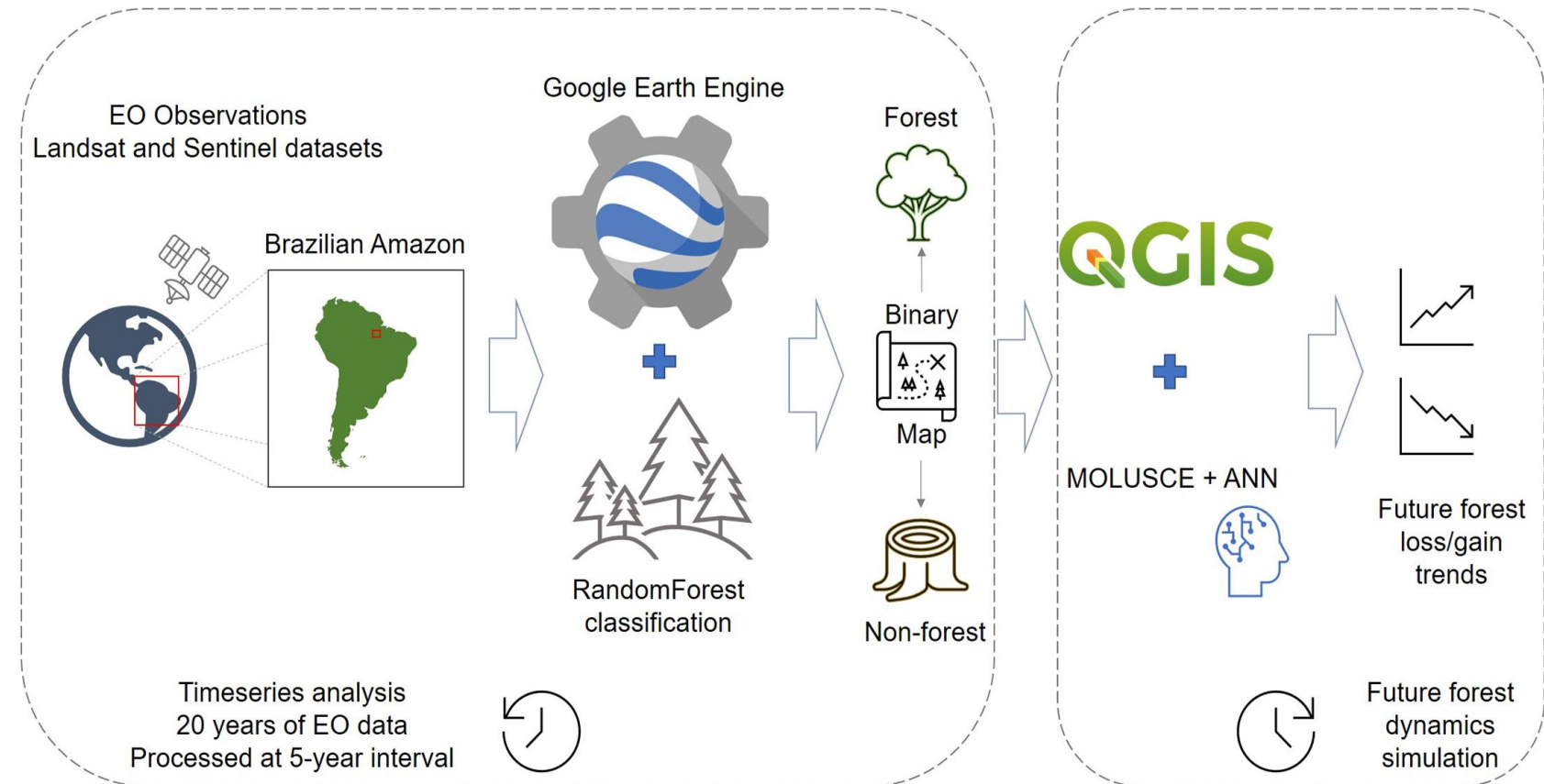
- In the state of Pará, Brazil
- About 50,000 km²



Timely and continuous monitoring of forest dynamics is important

Main aims

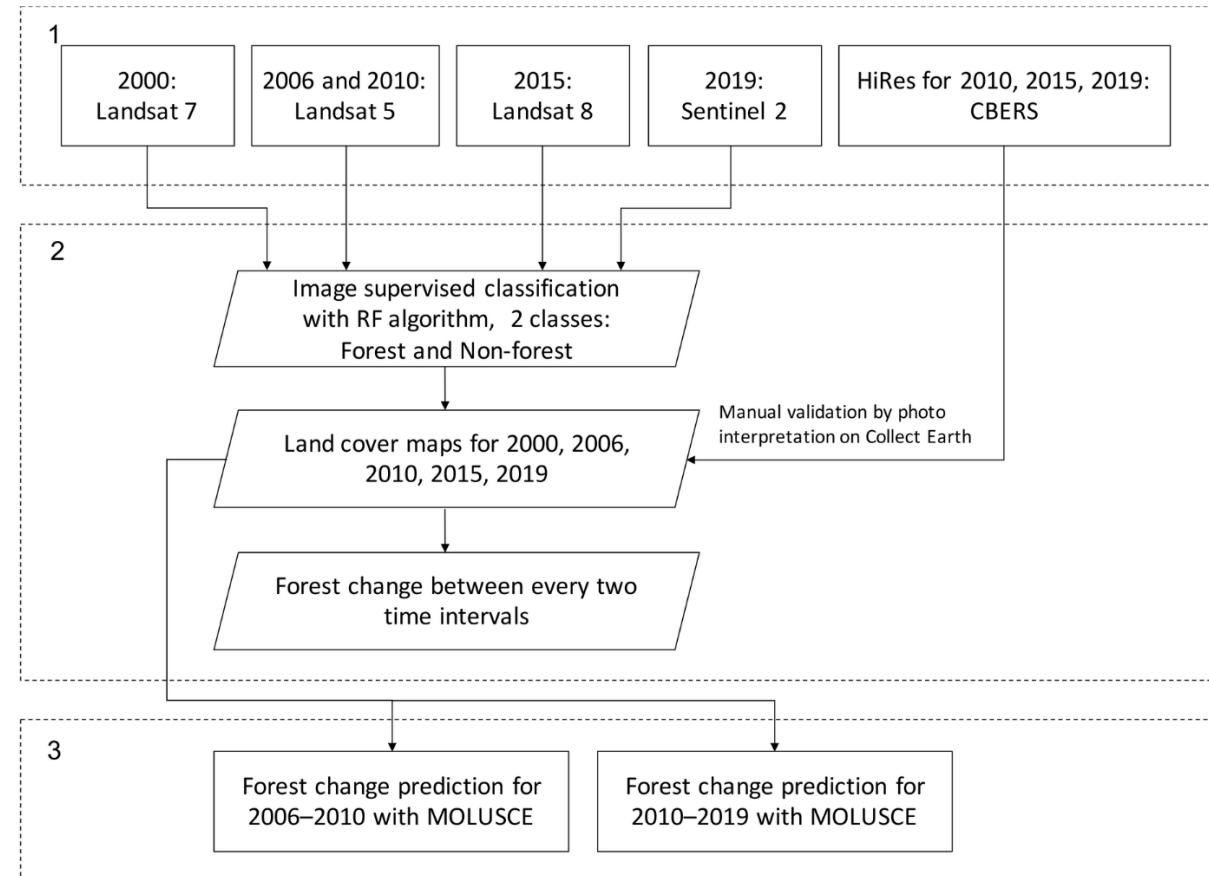
- Timeseries analysis of forest cover for the last 20 years using EO data (Landsat, Sentinel-2) using Google Earth Engine and ML
- Assess the image classification through photointerpretation using CollectEarth and high-resolution imagery (CBERS)
- Simulate future forest dynamics based on the previously derived historic trends (QGIS and MOLUSCE)



Data used

Satellite	Operational (as for 2020)	Year	Spatial Resolution	Bands
Landsat 5	1984–2012	2000		1(Blue), 2(Green), 3(Red), 4(NIR)
Landsat 7	1999–Present	2006 and 2010	30 m	2(Blue), 3(Green), 4(Red), 5(NIR)
Landsat 8	2013–Present	2015		2(Blue), 3(Green), 4(Red), 8(NIR)
Sentinel-2	2015–Present	2019	10 m	2(Blue), 3(Green), 4(Red), 8(NIR)
CBERS 2B	2007–2010	2010	2.7 m	Panchromatic
CBERS 4	2014–Present	2015 & 2019	5 m	Panchromatic

Processing flow



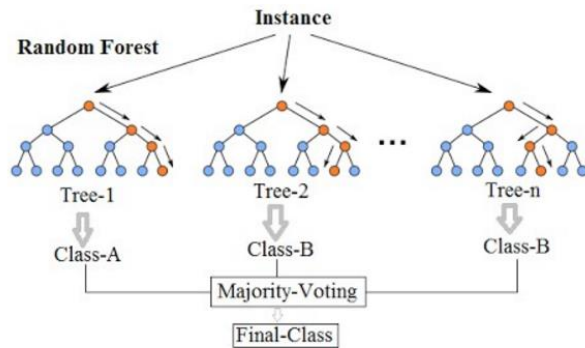
Google Earth Engine

Labels in the screenshot:

- Script manager
- API documentation
- Asset manager
- Search for datasets or places
- Get a link (URL) to the script
- Save the script
- Run the script
- Help button
- Feedback button
- Code Editor
- Task manager
- Console output
- Inspect locations, pixel values, objects on the map
- Layer manager
- Map
- Geometry Tools
- Zoom

Source: Google Earth Engine

Random Forest



Source: Wikimedia Commons

Validation

Collect Earth



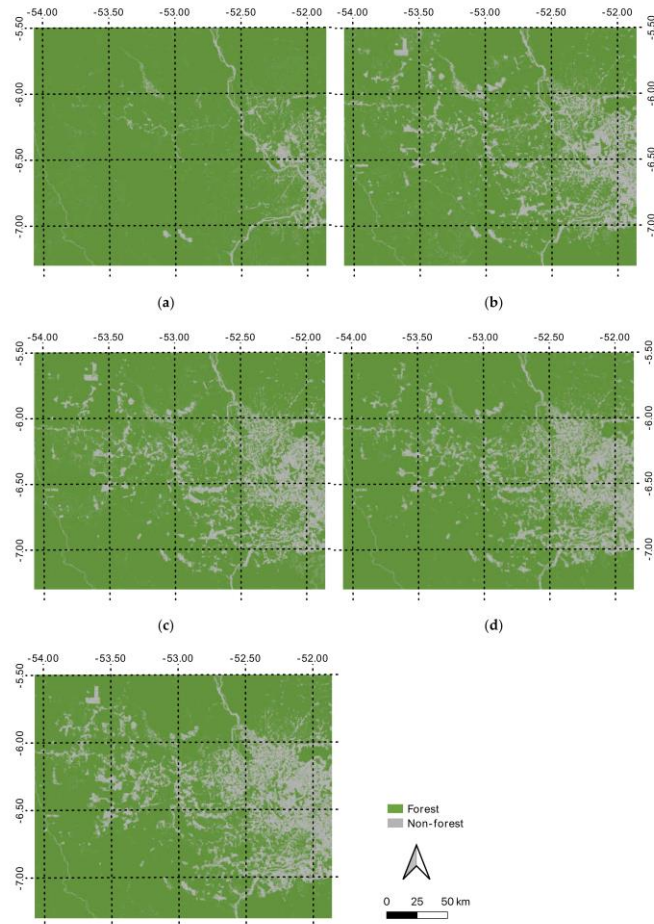
openforis
COLLECT EARTH

Source: OpenForis

Future forest dynamic simulation

QGIS + **MOLUSCE**
(Modules for Land Use Change Simulations) by NextGIS

Results – image classification

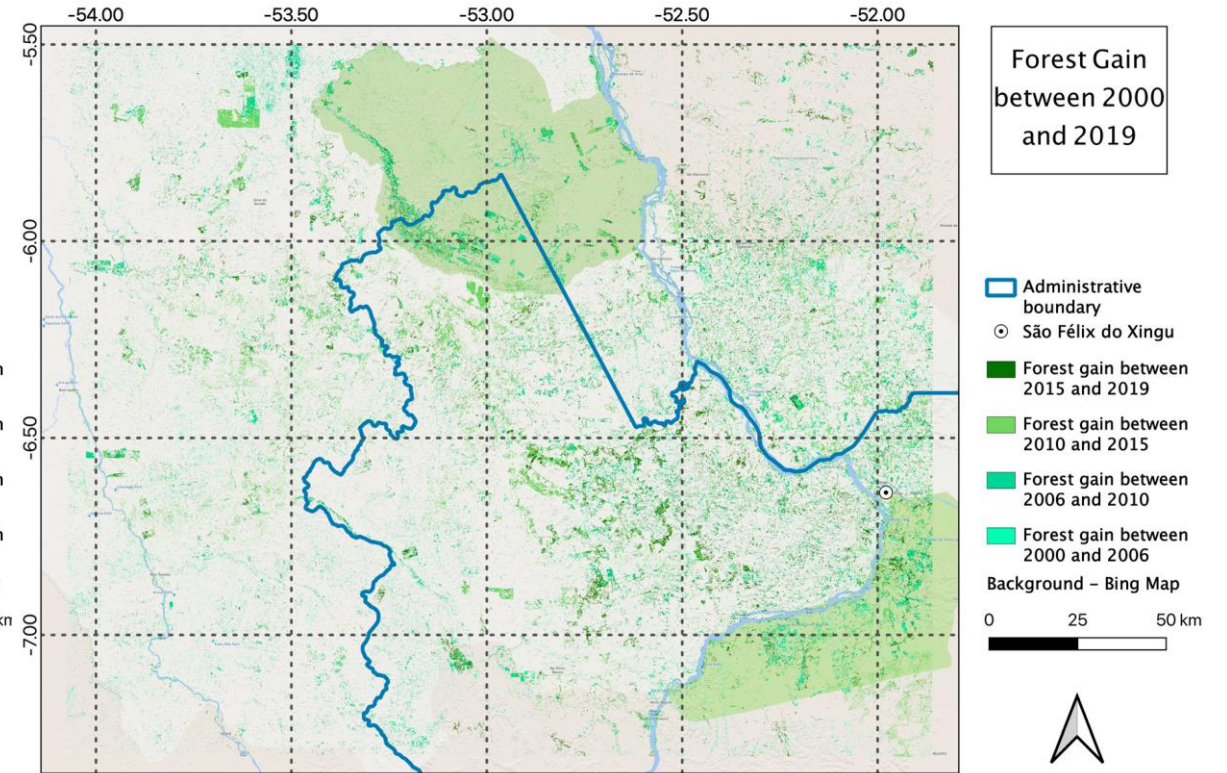
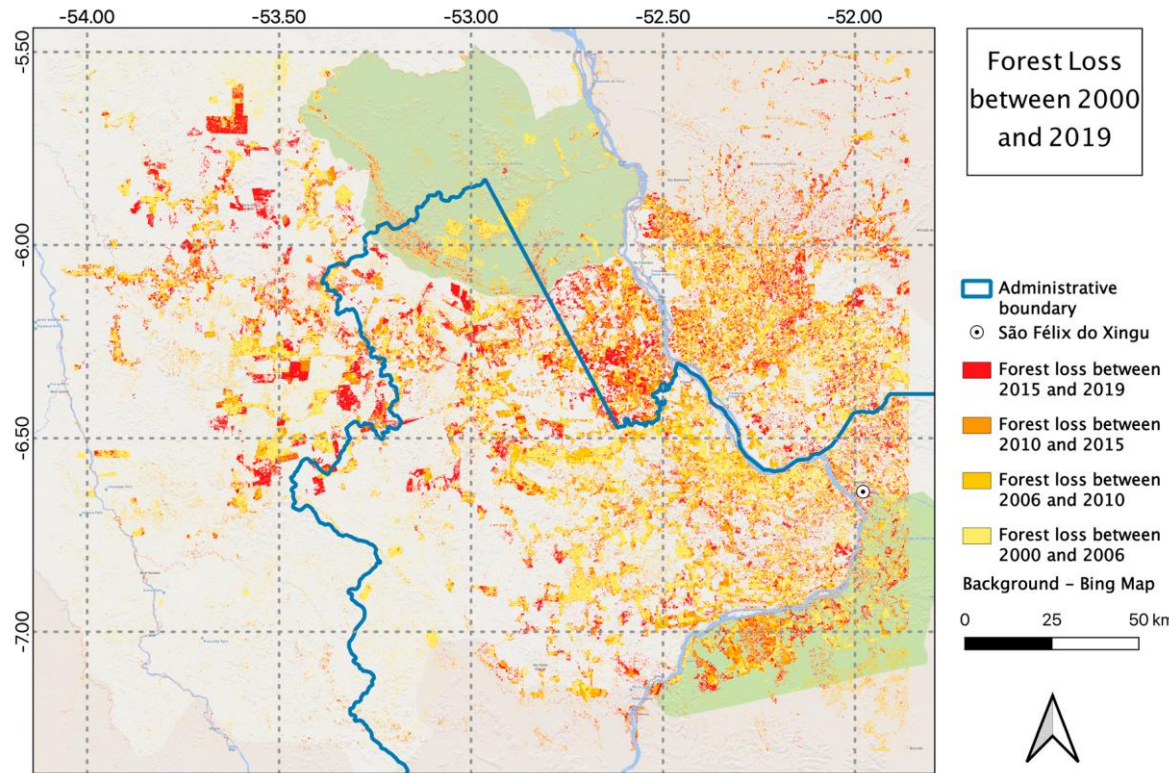


(a) Classification result derived from Landsat 7 for 2000; (b) Classification result derived from Landsat 5 for 2006; (c) Classification result derived from Landsat 5 for 2010; (d) Classification result derived from Landsat 8 for 2015; (e) Classification result derived from Sentinel-2 for 2019.

Validation

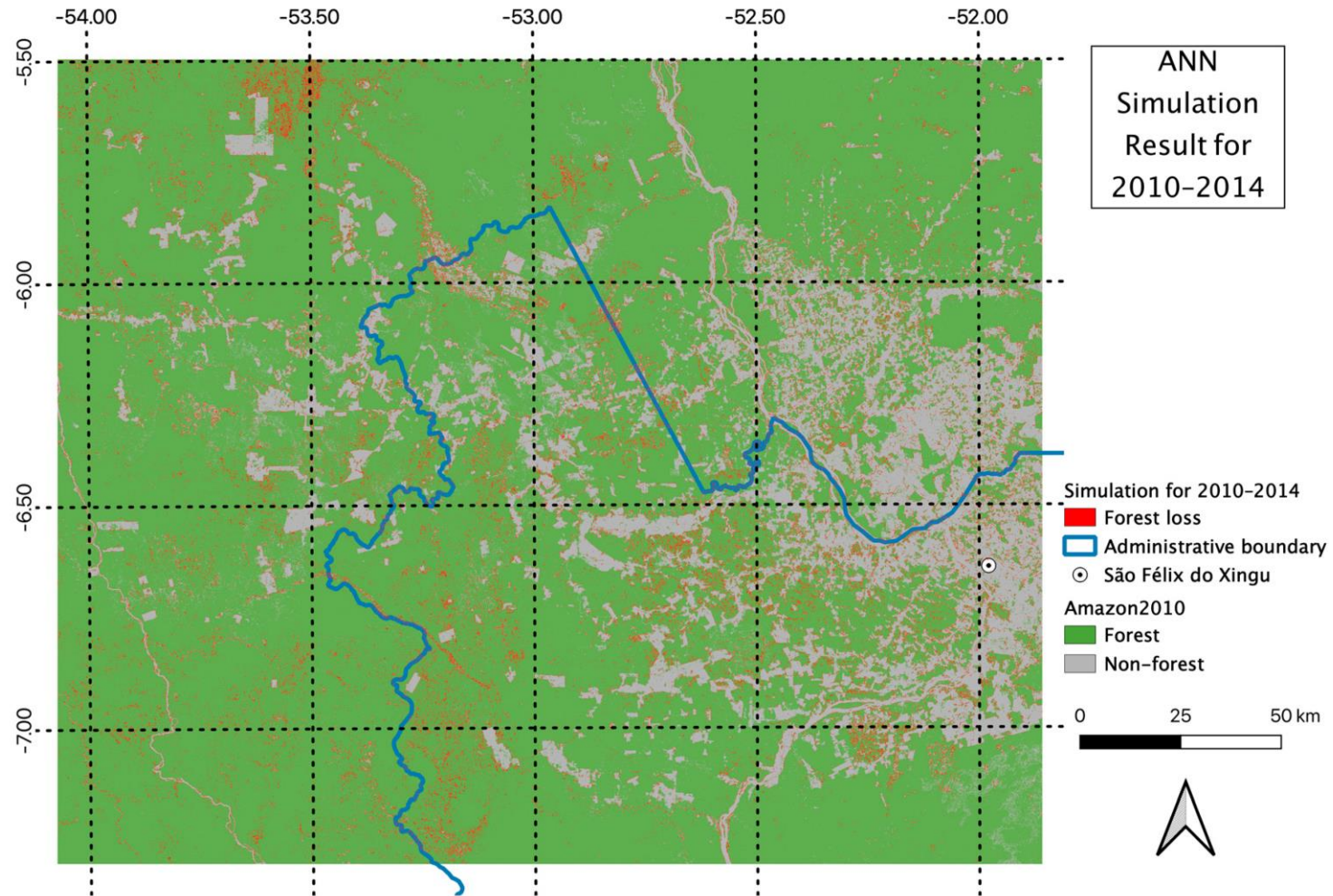
	Classified (Landsat)	Reference (HiRe)		User Accuracy
		Forest	Non-forest	
2010	Forest	521	13	0.98
	Non-Forest	37	496	0.93
	Producer accuracy	0.93	0.97	
	Overall accuracy		0.95	
	Kappa		0.91	
	Precision		0.98	
	Recall		0.93	
AUCPRC		0.95		
2015	Forest	526	8	0.99
	Non-forest	36	497	0.93
	Producer accuracy	0.94	0.98	
	Overall accuracy		0.97	
	Kappa		0.94	
	Precision		0.99	
	Recall		0.94	
AUCPRC		0.96		
2019	Forest	523	11	0.98
	Non-forest	32	501	0.94
	Producer accuracy	0.94	0.98	
	Overall accuracy		0.97	
	Kappa		0.94	
	Precision		0.98	
	Recall		0.94	
AUCPRC		0.96		

Results – forest loss



Year	Loss (km ²)/Gain (km ²)	Percentage (Loss/Gain)	Relative Percentage (Loss/Gain)	Cumulative Loss/Gain (km ²)
2000–2006	5081.90/570.28	10.28%/1.15%		
2006–2010	1942.71/1615.15	3.93%/3.27%	−61.77%/183.22%	7024.61/2185.43
2010–2015	1779.41/1731.78	3.60%/3.50%	−5.41%/7.22%	8804.02/3917.21
2015–2019	2569.81/1115.86	5.20%/2.26%	44.42%/−35.57%	11,373.83/4462.79

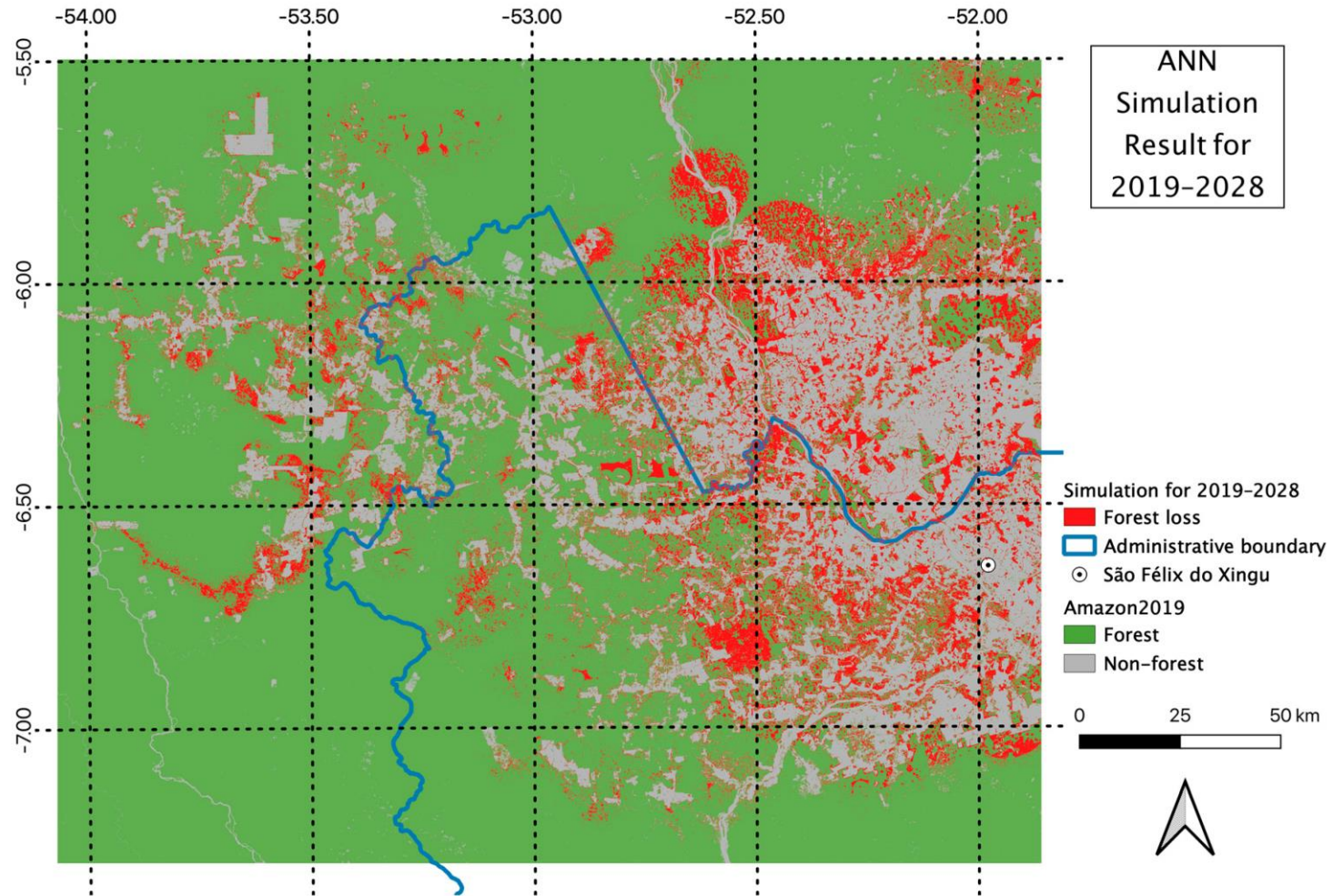
Results – MOLUSCE ANN test simulation for the period 2010-2014



Estimated loss for 2010-2014:
1,564 km²

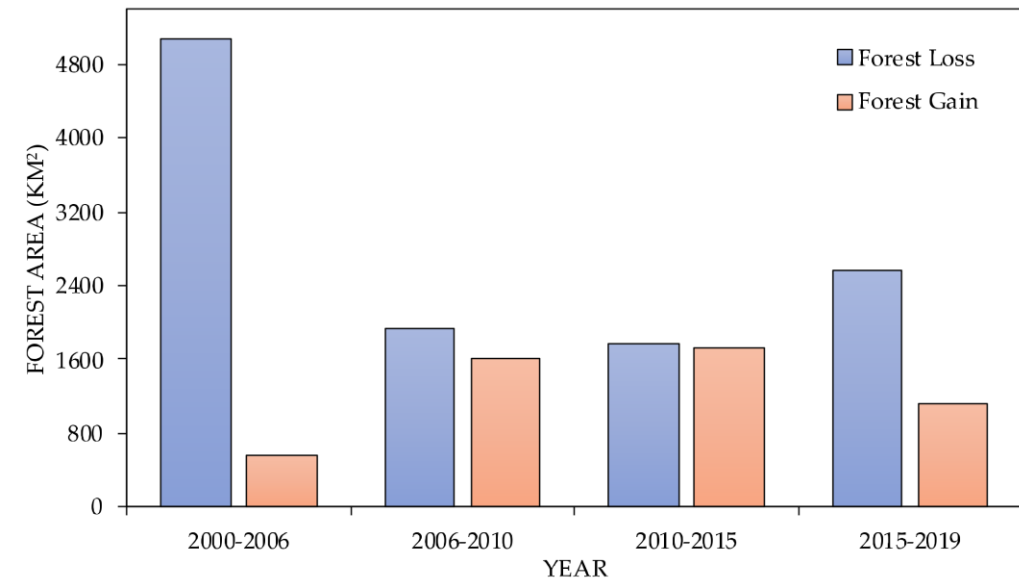
Computed loss for 2010-2015:
1,779 km²

Results – MOLUSCE ANN simulation for the period 2019-2028

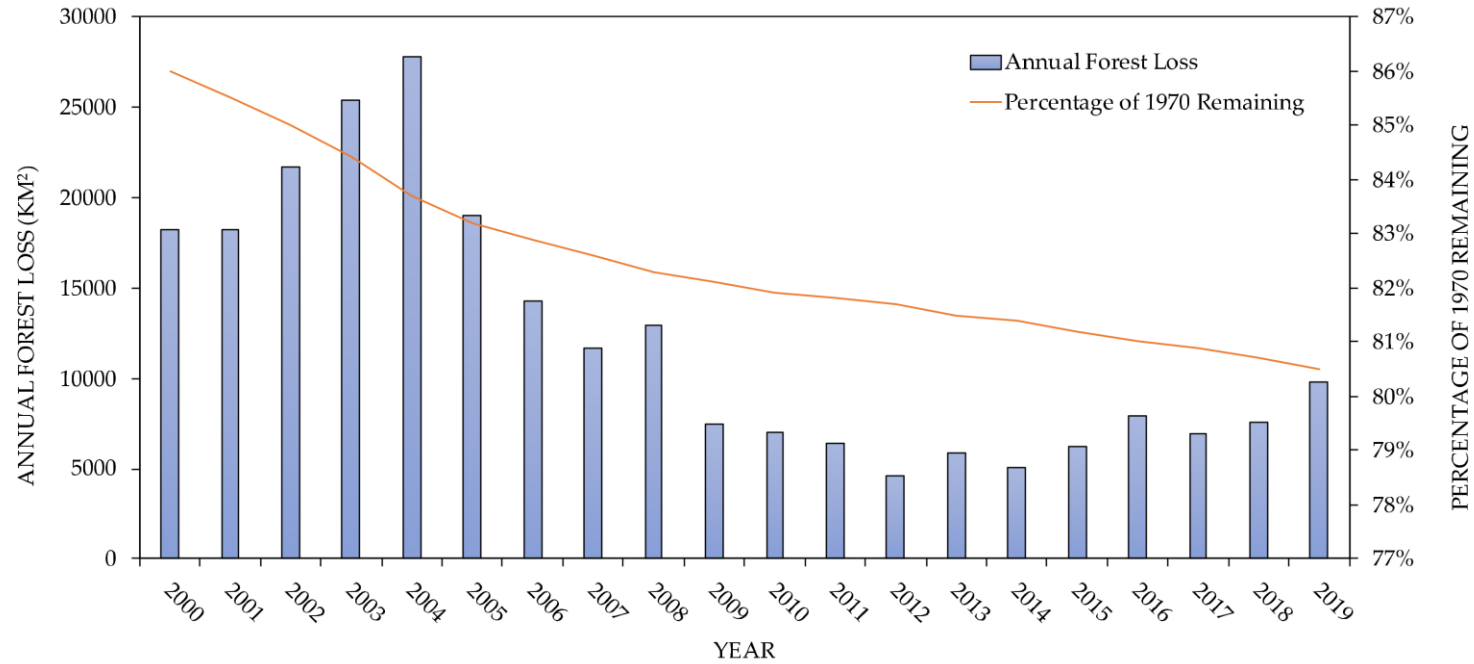


Estimated loss for 2019-2028:
3,057 km²

Results



Forest change from 2000 to 2019



Forest change from 2000 to 2009 Amazon forest change over time.
(Source: Instituto Nacional de Pesquisas Espaciais—INPE).

Conclusions

- Google Earth Engine with the vast EO data archive proved as invaluable tool for time-series machine learning image classification
- Satellite observations with high temporal resolution + Google Earth Engine + CollectEarth + MOLUSCE can produce very accurate and reliable results
- Such setups can help into implementing, tuning and monitoring appropriate sustainable policies and regulations.
- Few considerations:
 - Shorter time-step
 - Different data type
 - Not considering any external interferences

You can read more here:

Brovelli, M.A.; Sun, Y.; Yordanov, V. Monitoring Forest Change in the Amazon Using Multi-Temporal Remote Sensing Data and Machine Learning Classification on Google Earth Engine. ISPRS Int. J. Geo-Inf. 2020, 9, 580.

<https://doi.org/10.3390/ijgi9100580>

Thank you for the attention!

2000

2016

ML
Classification

Future
Simulation