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Machine Learning and Deforestation in Amazonia

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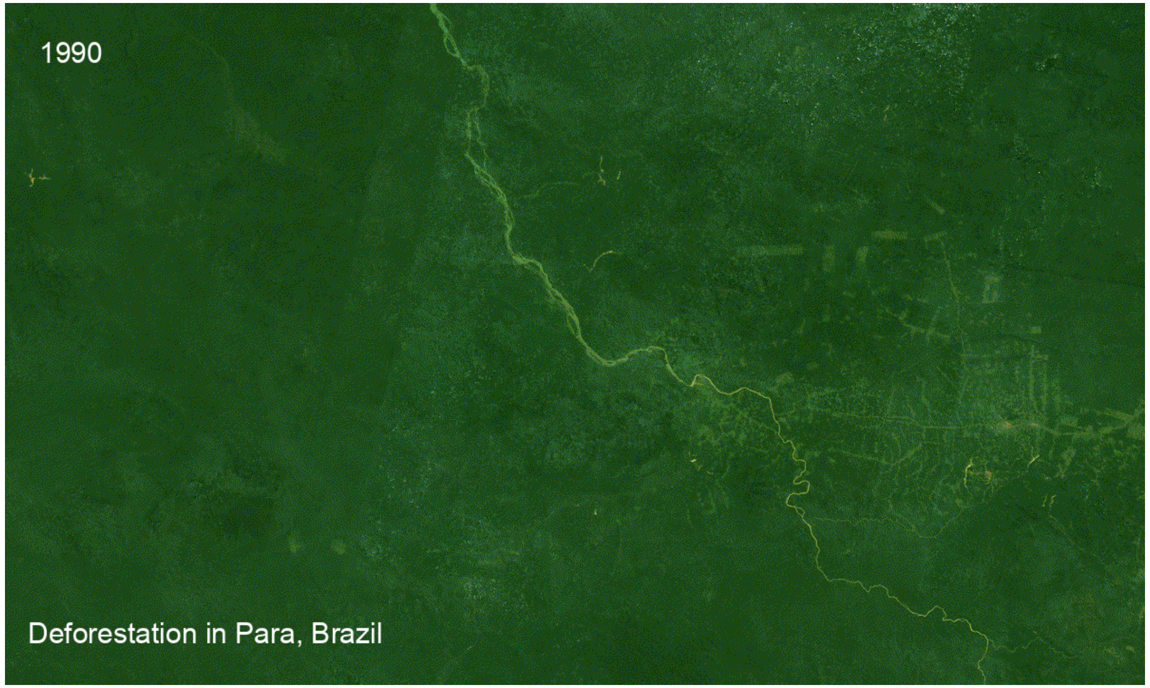
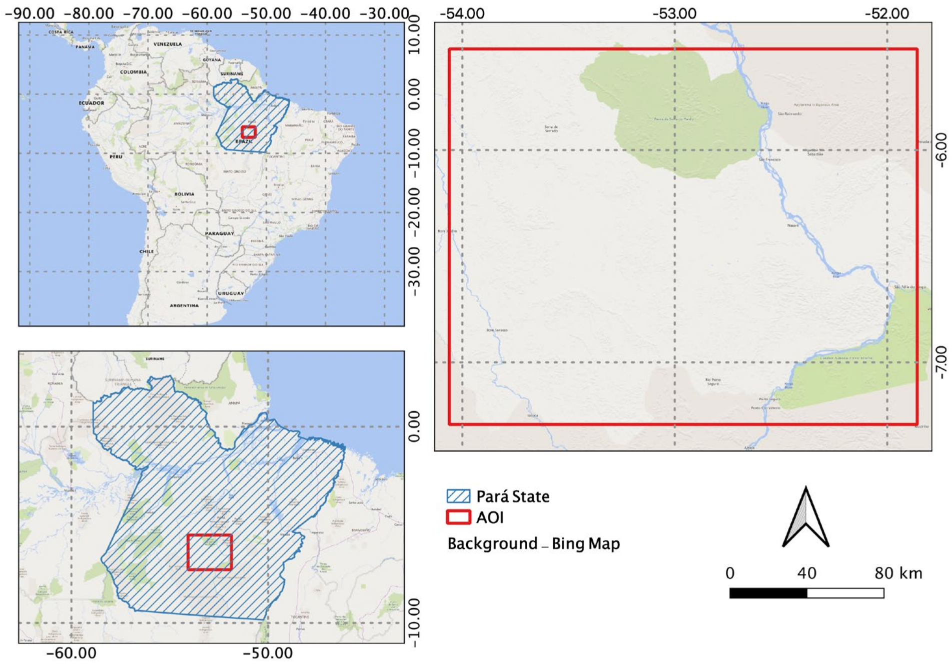
Main goal and area of Interest

- Deforestation is a global problem, not only in Amazonia (Earth's green lung).
- Re-forestation is also very important. Continuous monitoring of the forest dynamics can help re-forestation policies and initiatives.



Deforestation in Para, Brazil



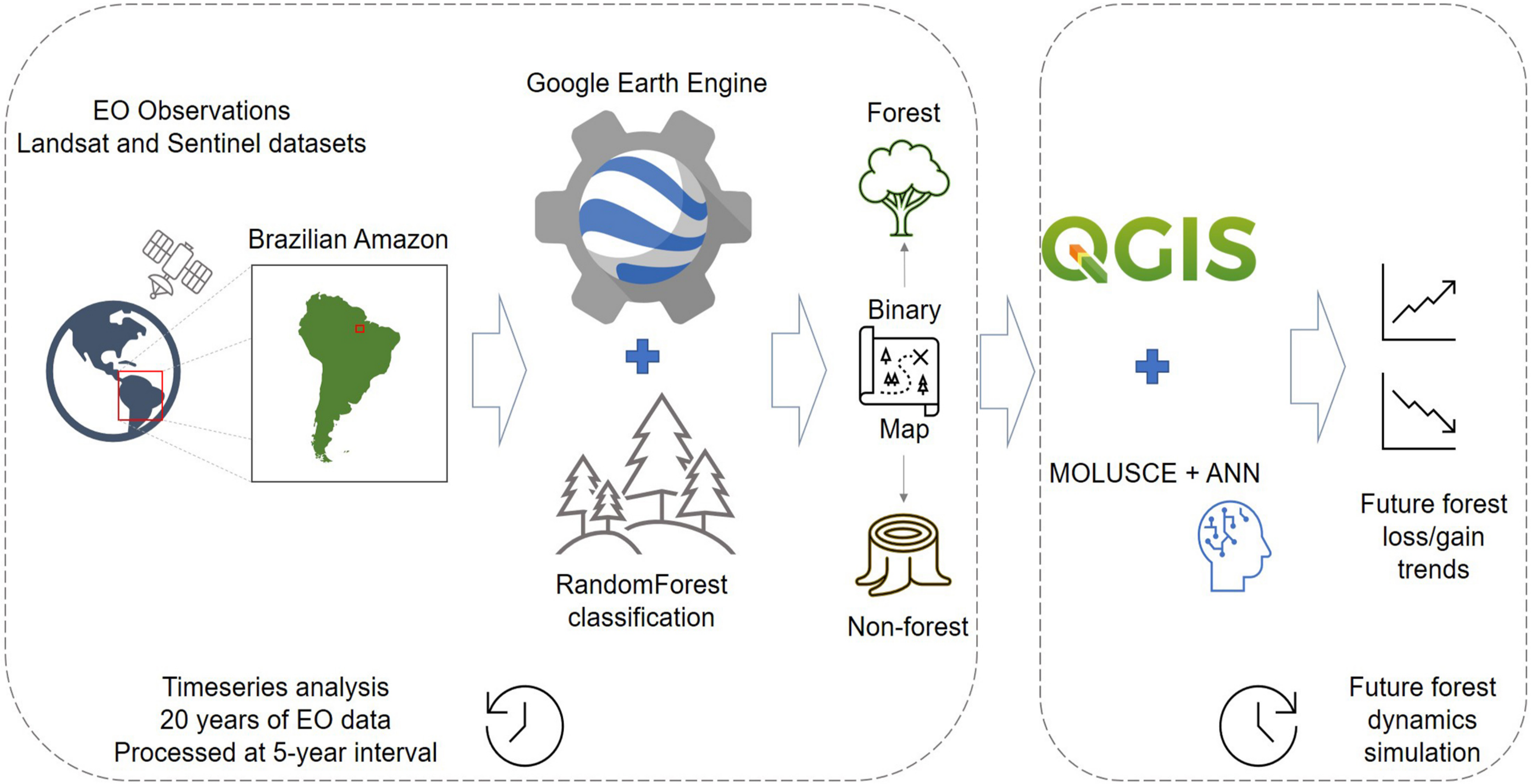
- In the state of Pará, Brazil.
- About 50,000 km^2.
- Monitoring period from 2000 to 2019 at 5-year intervals.

To adopt precise and efficient monitoring method which is applicable on larger areas and a shorter time-step.

Approach 1: Optical MSI pixel-based approach

Main aims

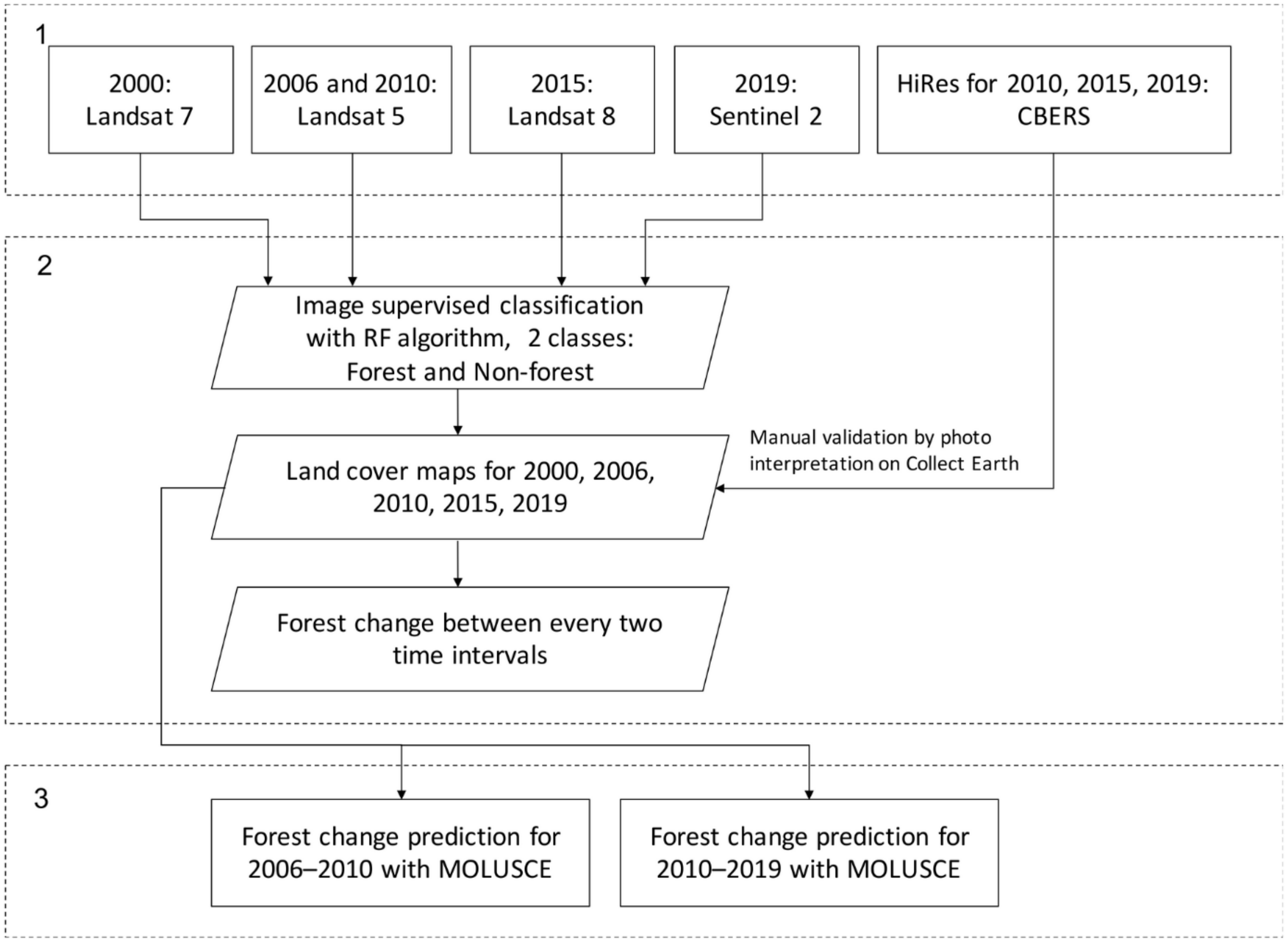
- Timeseries analysis of forest cover for the last 20 years using EO data (Landsat, Sentinel-2) using Google Earth Engine and ML
- Assess the image classification through photointerpretation using CollectEarth and high-resolution imagery (CBERS)
- Simulate future forest dynamics based on the previously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



Data used

Satellite	Operational (as for 2020)	Year	Spatial Resolution	Bands
Landsat 5	1984–2012	2000	30 m	1(Blue), 2(Green), 3(Red), 4(NIR)
Landsat 7	1999–Present	2006 and 2010		
Landsat 8	2013–Present	2015		2(Blue), 3(Green), 4(Red), 5(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	

Processing flow

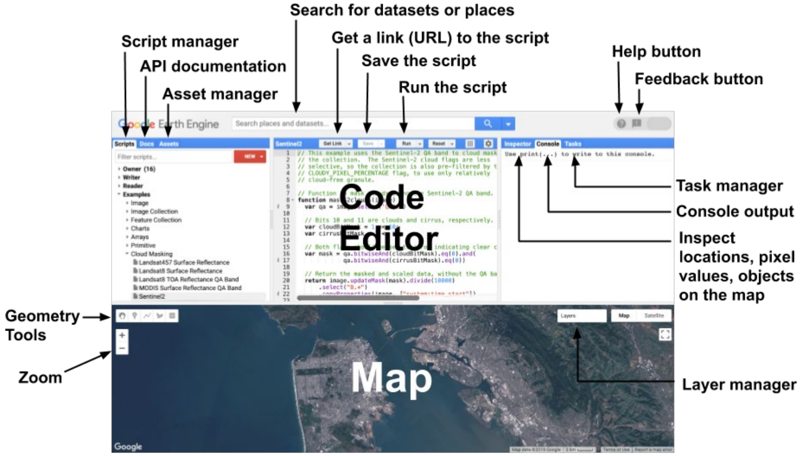


- Simple to apply method.
- Fast to deploy model.
- Needs pixel value as training information for both classes (60 polygons photo-interpreted – around 260000 pixels)
- Forest change prediction is based on the derived historical trends.

Tools

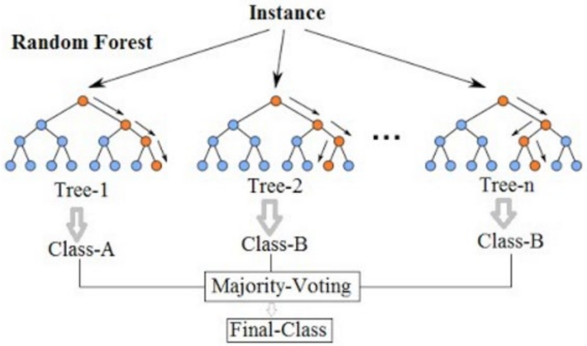
Image Classification

Google Earth Engine



Source: Google Earth Engine

Random Forest



Source: Wikimedia Commons

Validation

Collect Earth

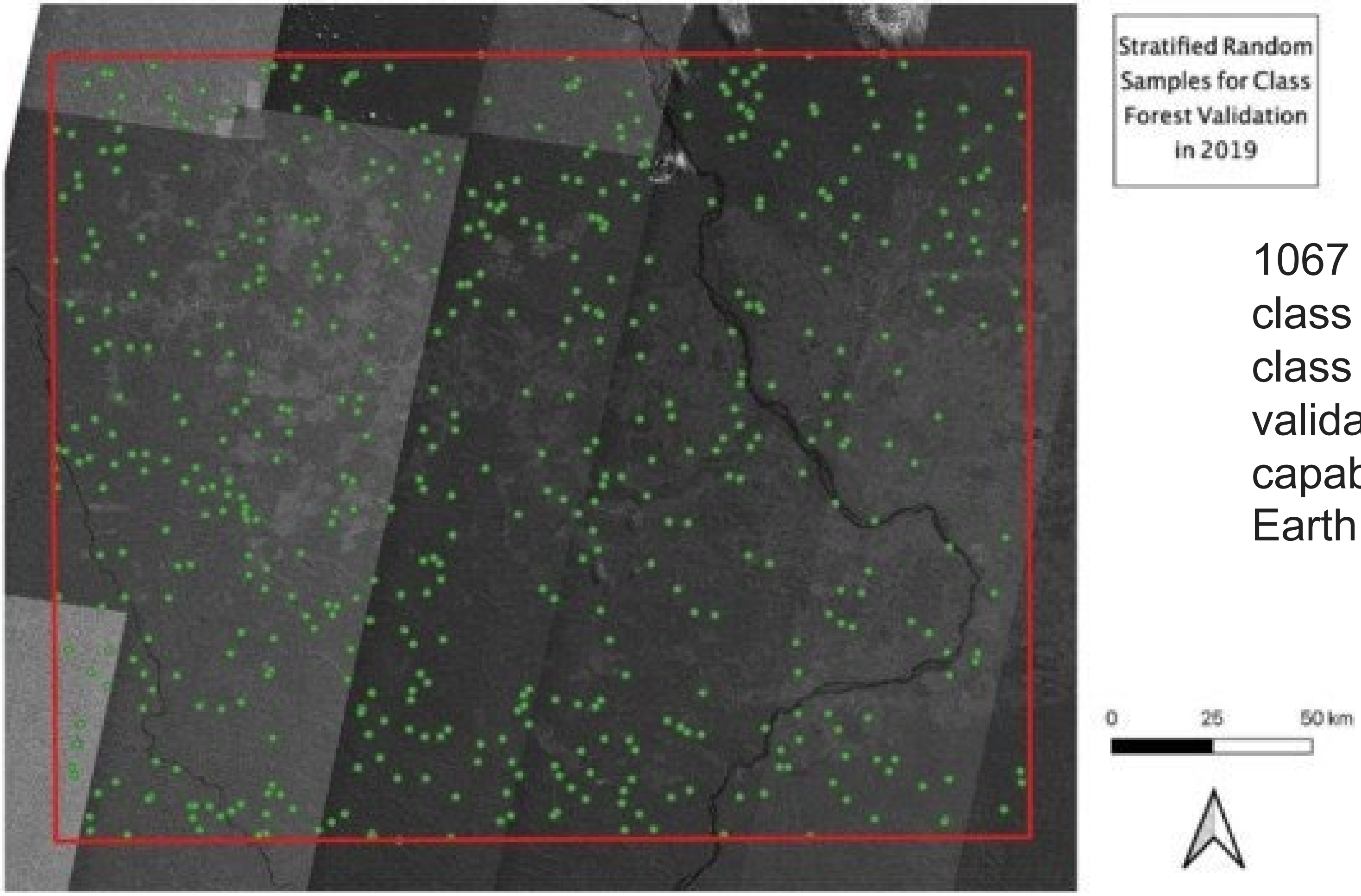
openforis COLLECT EARTH

Source: OpenForis

Future forest dynamic simulation

QGIS + MOLUSCE

(Modules for Land Use Change Simulations) by NextGIS



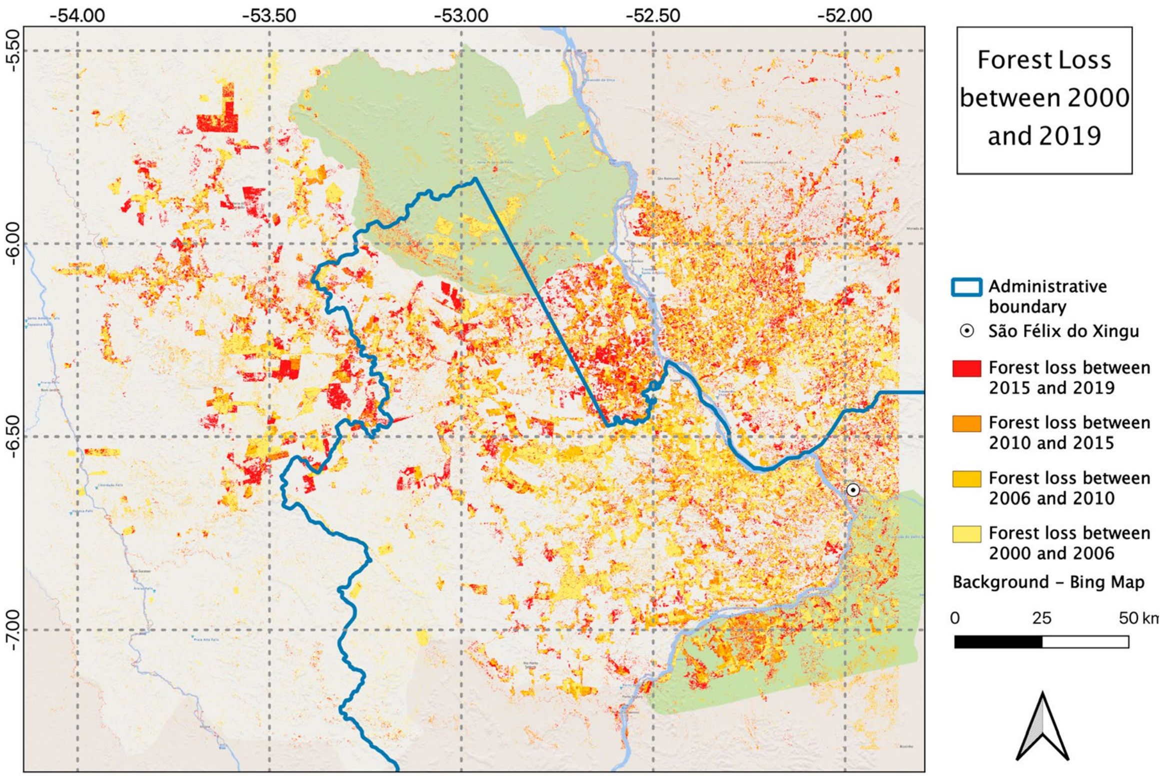
1067 points (534 for the class forest, 533 for the class non-forest) were validated with the survey capabilities of Collect Earth.

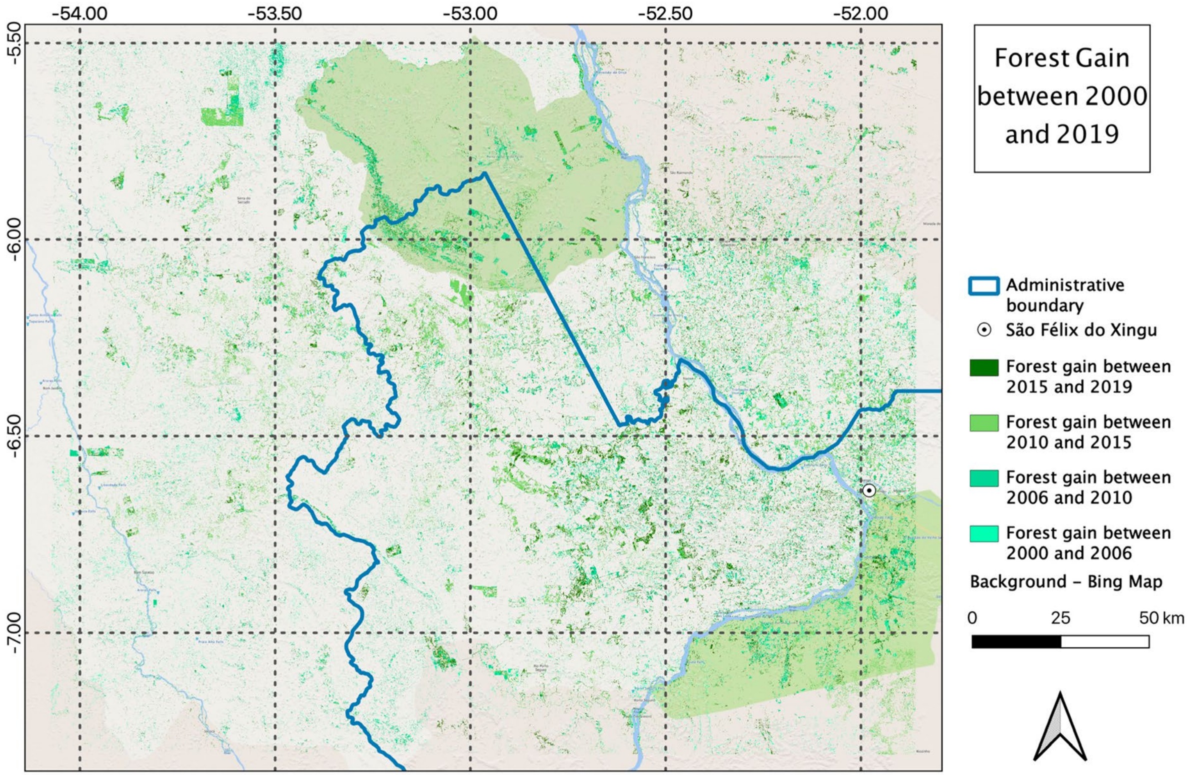
Results – Validation

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

			Reference (HiRe)		User Accuracy
			Forest	Non-forest	
	Classified (Sentinel)	Forest	523	11	0.98
		Non-forest	32	501	0.94
	Producer accuracy		0.94	0.98	
2019	Overall accuracy				0.97
	Kappa			0.94	
	Precision			0.98	
	Recall			0.94	
	AUCPRC			0.96	

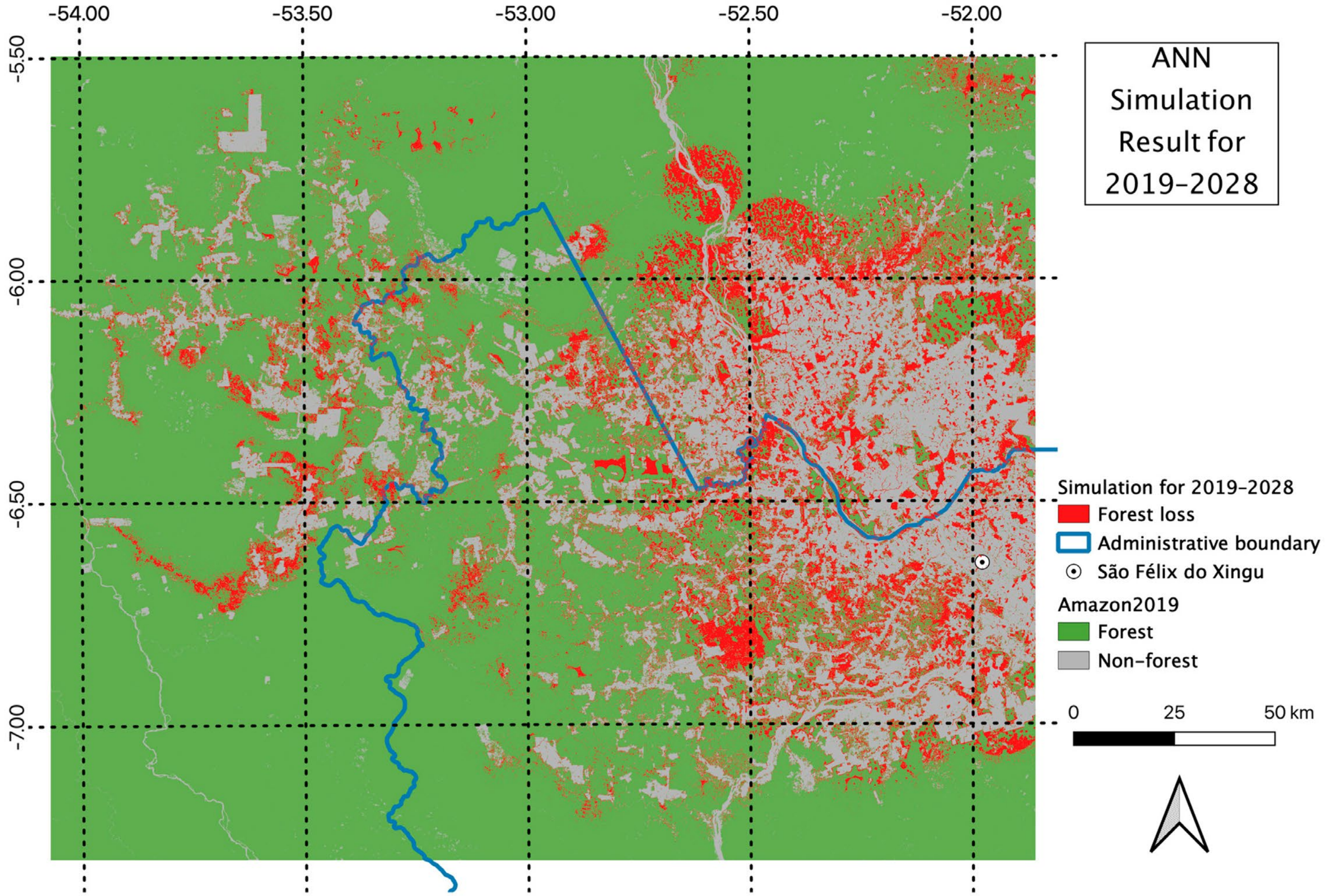
Results – forest loss





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 simulation for the period 2019-2028

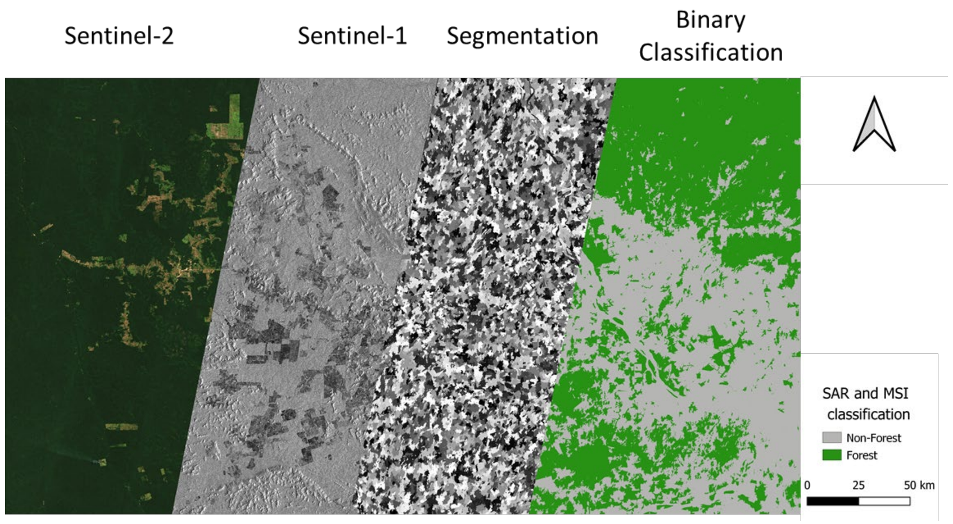


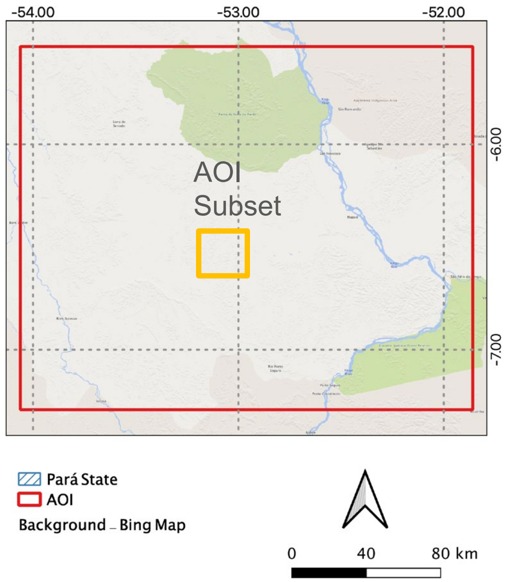
Estimated loss for 2019-2028: 3,057 km^2

Approach 2: SAR and MSI object-based approach

Main aims

- Apply object-based image classification, to reduce misclassification noise.
- Use of SAR datasets to overcome cloud cover related issues – Sentinel-1 GRD.
- Fusion with optical multispectral images.

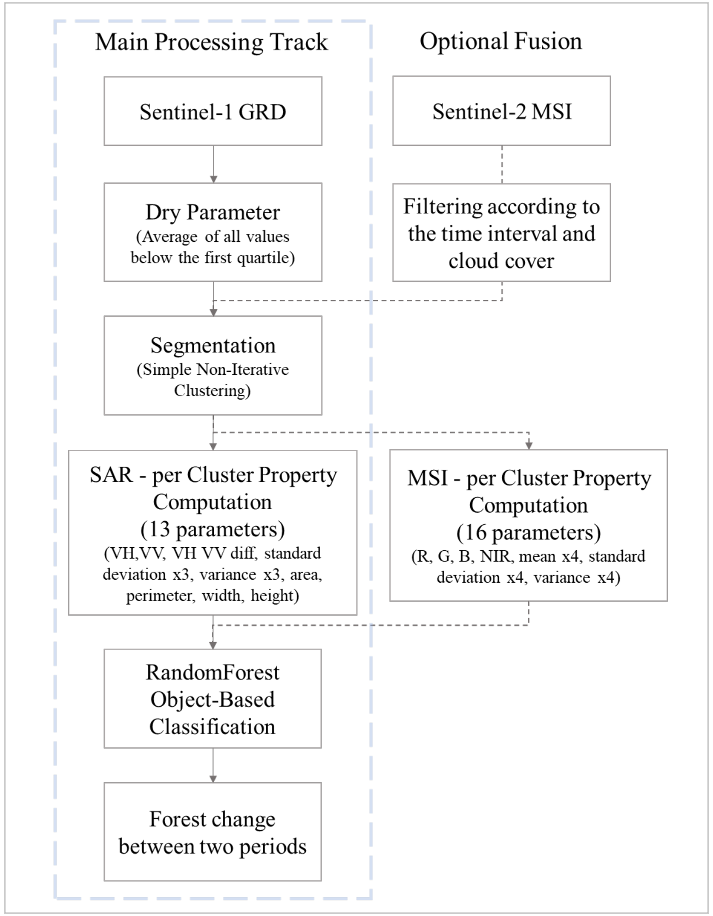




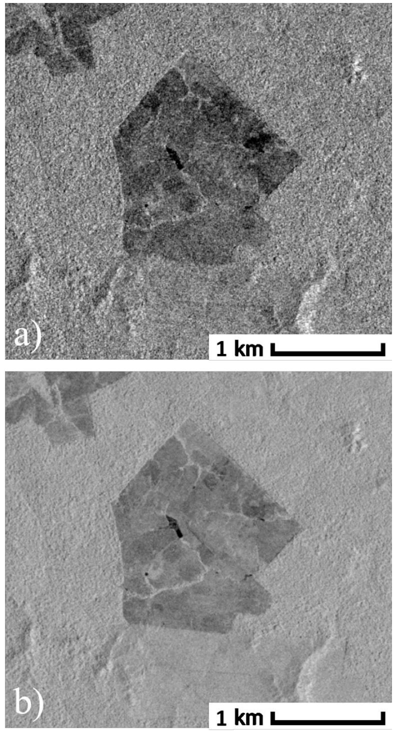
- Timeframe 1 – to verify the use of SAR-OBIA through GEE for deforestation monitoring. (AOI; May-August 2015 and 2019)
- Timeframe 2 – apply SAR-OBIA on a shorter time-step for timely monitoring of forest dynamics. (AOI Subset; 2020 on a monthly basis)

Data and processing

Processing flow

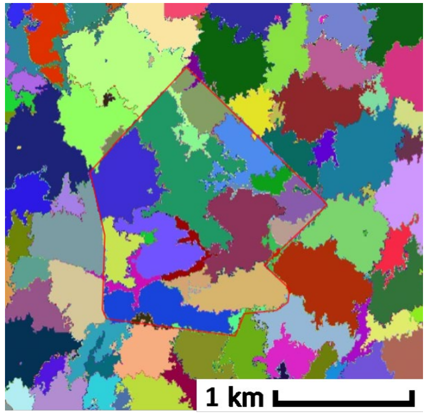


Dry Coefficient



Dry coefficient example, proposed by Dostálová et al. (2016)
a) VV polarization one scene
b) b) VV *dry coefficient* from 10 scenes.

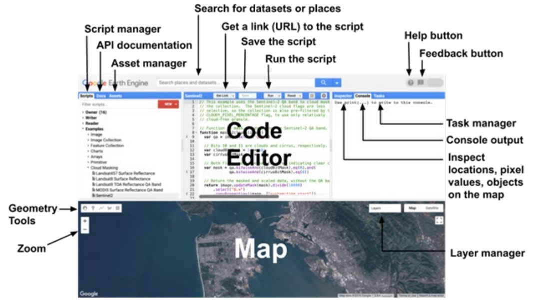
Segmentation



An example of SNIC clustering. The red contour represents the shape of the deforested area

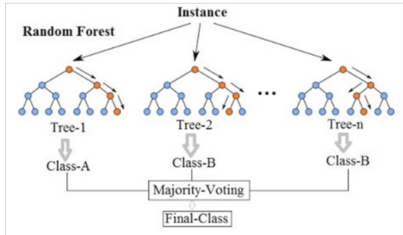
Image Classification

Google Earth Engine



Source: Google Earth Engine

Random Forest

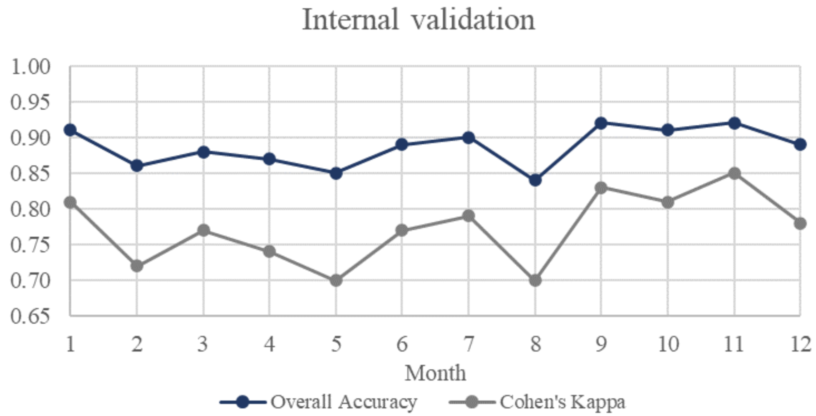


Source: Wikimedia Commons

Validation

NICFI
Norway's International Climate and Forest Initiative
planet.
AcATaMa

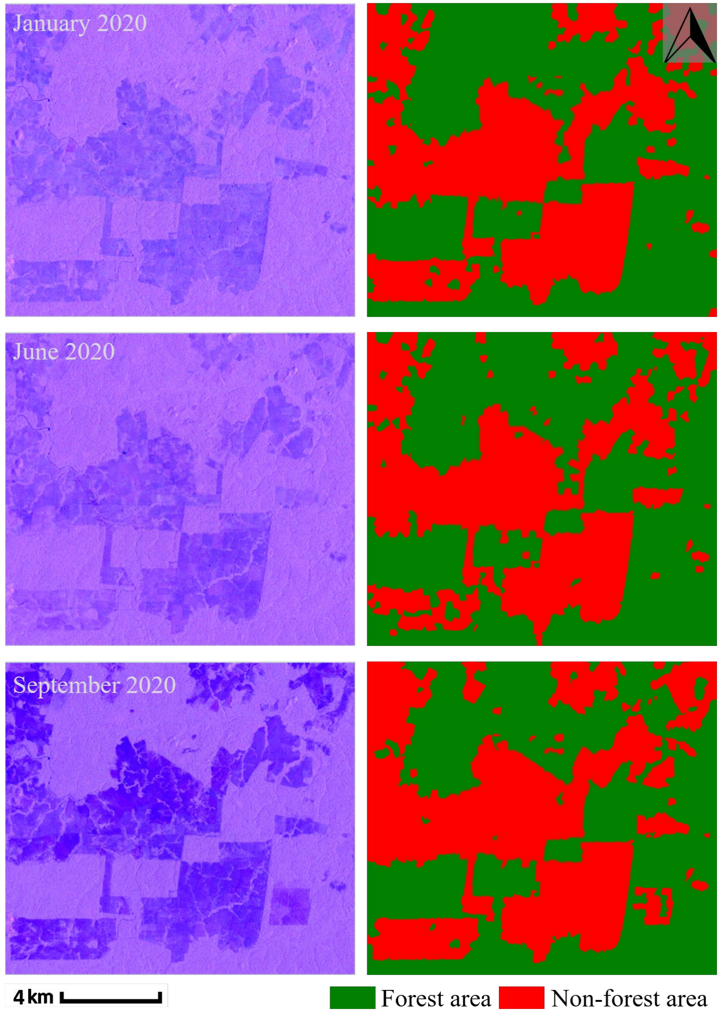
Results



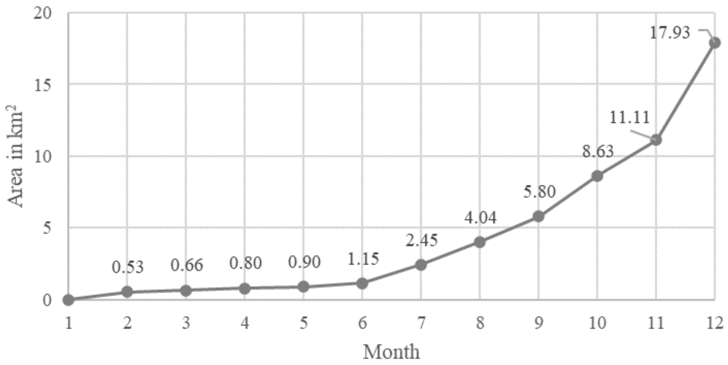
Overall accuracy and Cohen's Kappa from the internal validation for each month under consideration.

External validation	September	October
Overall Accuracy	0.94	0.90
Kappa	0.87	0.79
Precision	0.93	0.88
Recall	0.94	0.91
F1 score	0.93	0.89

Results from external validation for the months of September and October 2020.

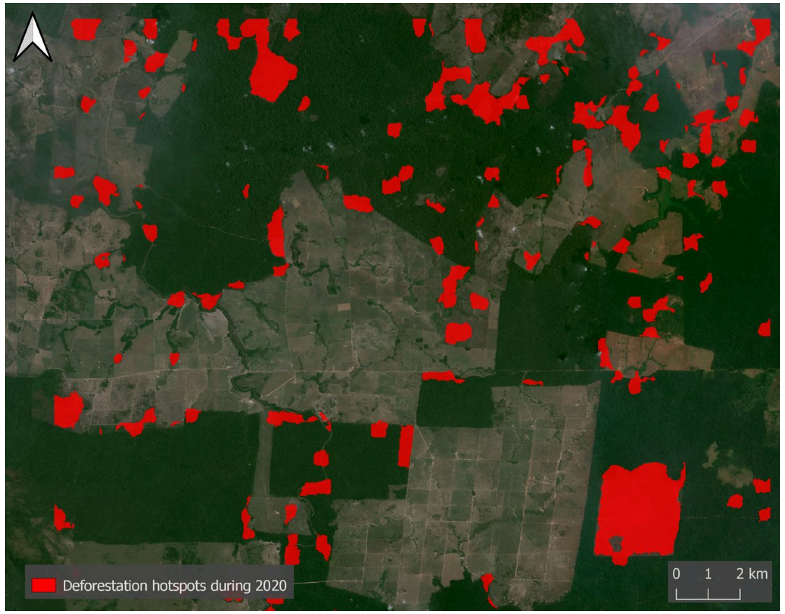


Some examples from the Timeframe 2 classification results. On the left: aggregated dry images for the months of January, June and September 2020. On the right: their relevant binary classifications.

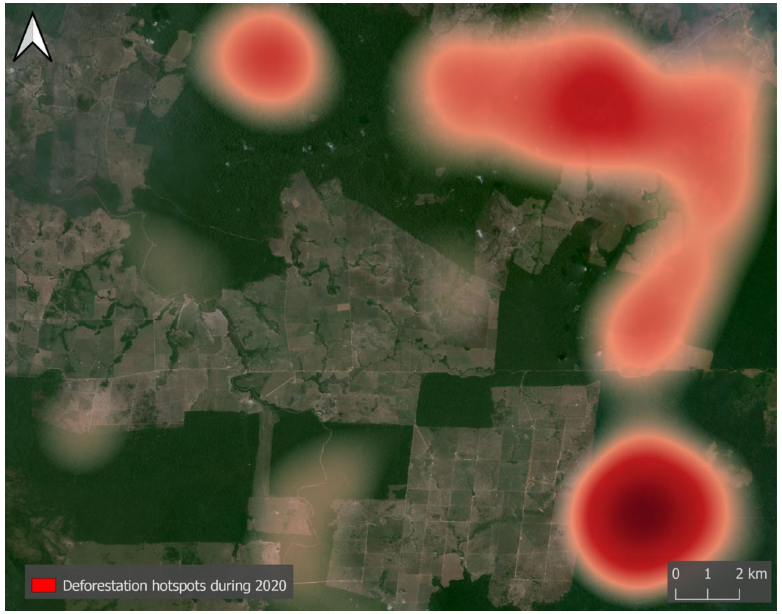


Cumulative forest loss per month in 2020.

Focused monitoring



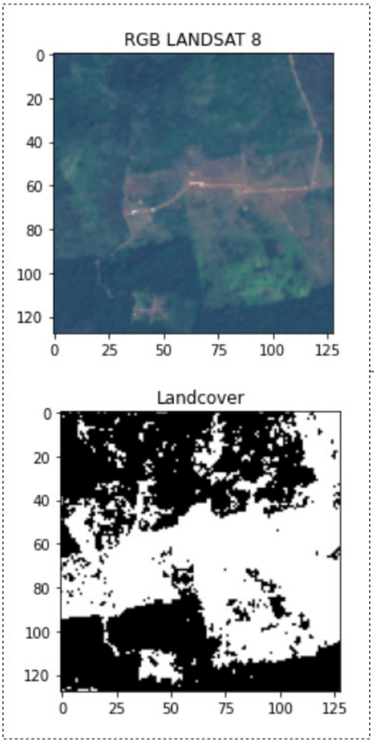
Forest loss in 2020. *(Basemap - September 2020 (monthly NICFI dataset, distributed by Planet Labs.)*



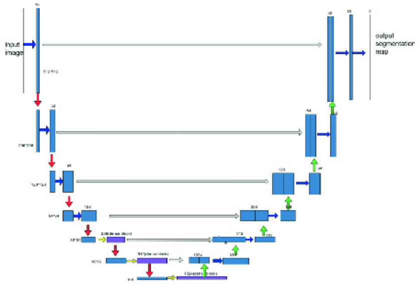
Deforestation hotspots. *(Basemap - September 2020 monthly NICFI dataset, distributed by Planet Labs.)*

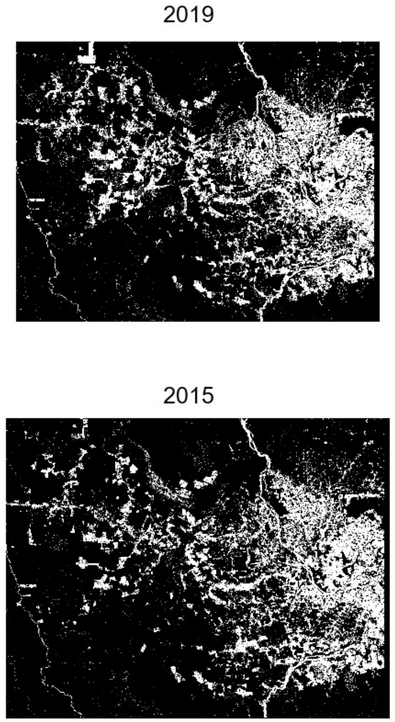
Snippet of ongoing deforestation processes. January 2021 image is not included due to a significant cloud coverage *(Imagery- monthly NICFI dataset, distributed by Planet Labs.).*

Classification using Fully Convolutional Neural Network *(Ongoing work)*

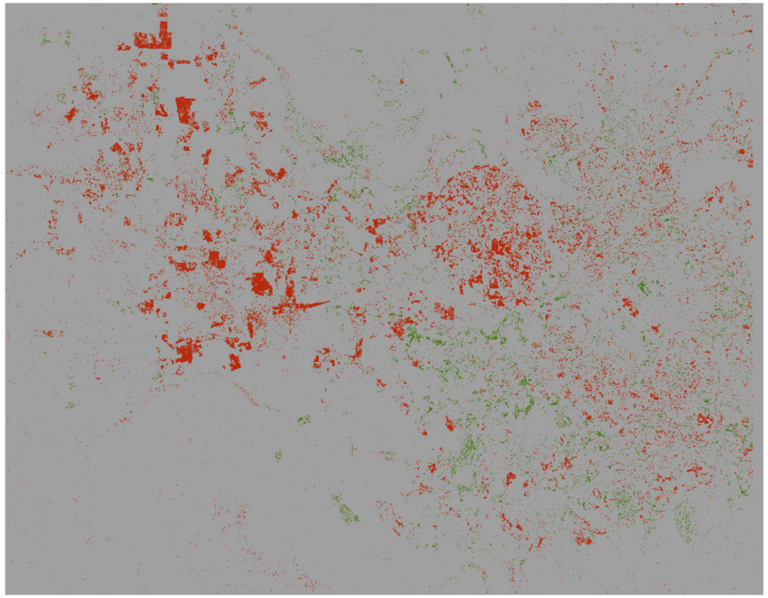


Train U-Net model and perform classifications

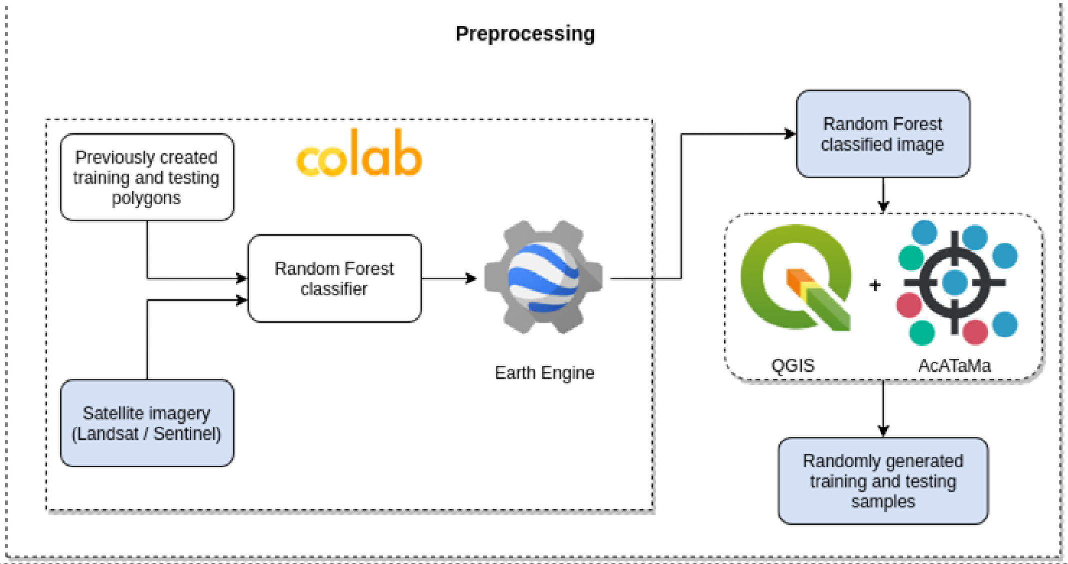


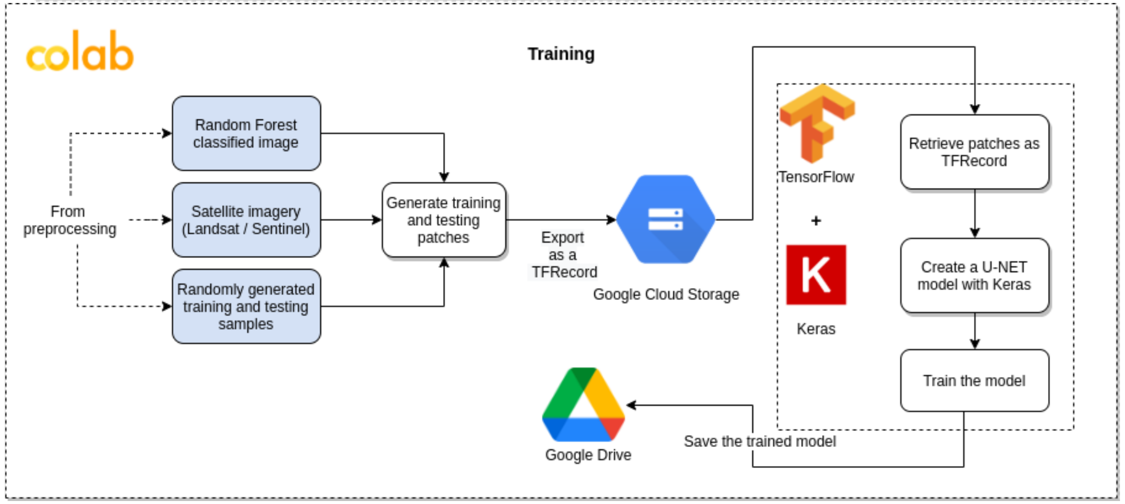


Forest change

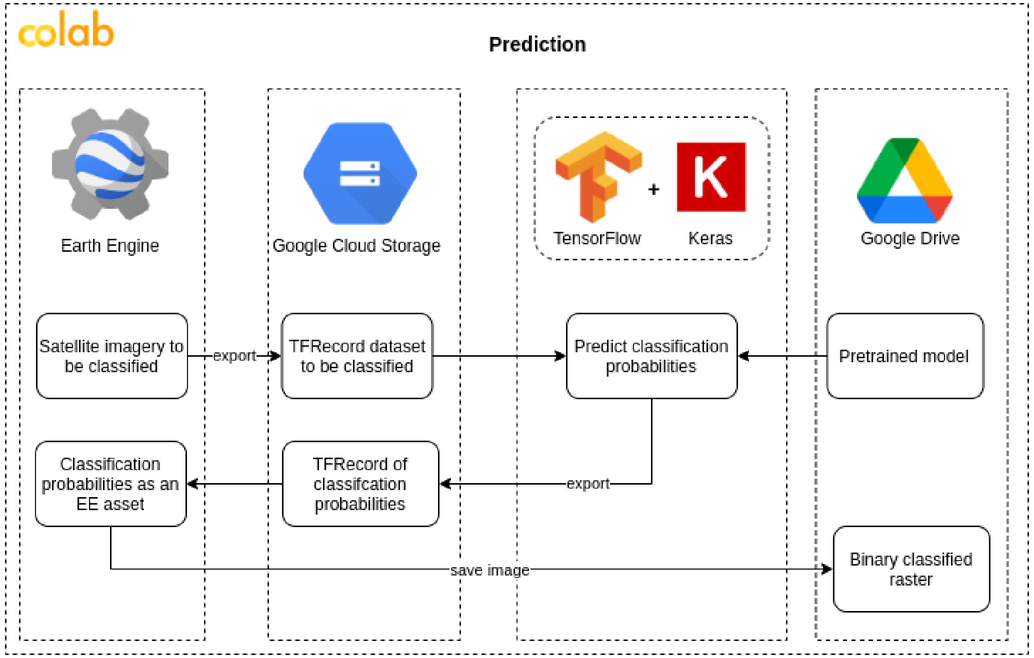


Approach 3: Classification using Fully Convolutional Neural Network



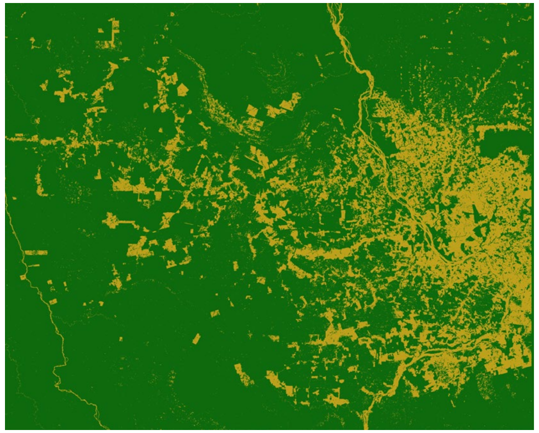


- Uses previously classified and validated machine learning products as input data.
- Input data is patch-based around point of interest.
- Kernel size and patch diversity are important for the final output.

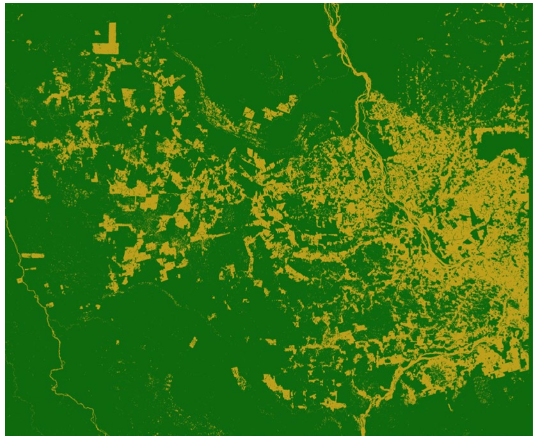


Choice of parameters

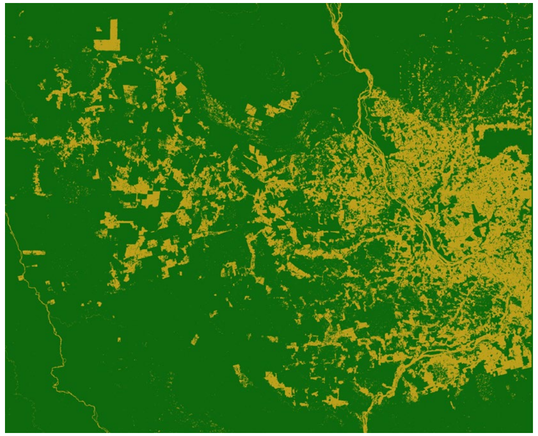
Kernel size	Training data size	Testing data size
64	1000	300
	500	150
	100	30
	50	15
32	1000	300
	500	150
	100	**30**
	50	15
16	1000	300
	500	150
	100	30
	50	15



2015 Landsat 8
Overall accuracy - **0.99**
Kappa - **0.98**



2019 Landsat 8
Overall accuracy - **0.96**
Kappa - **0.96**

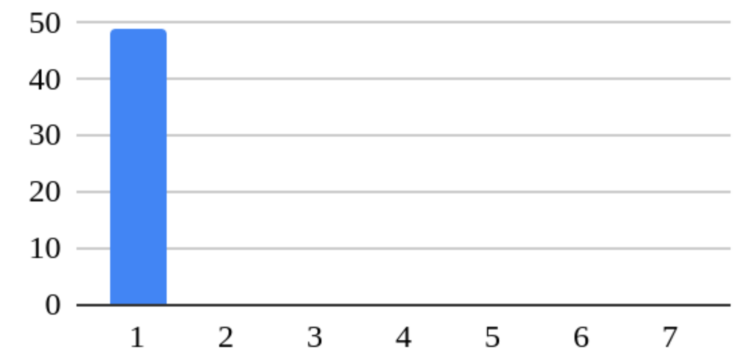


Sentinel-2 2019
Overall accuracy - **0.96**
Kappa - **0.96**

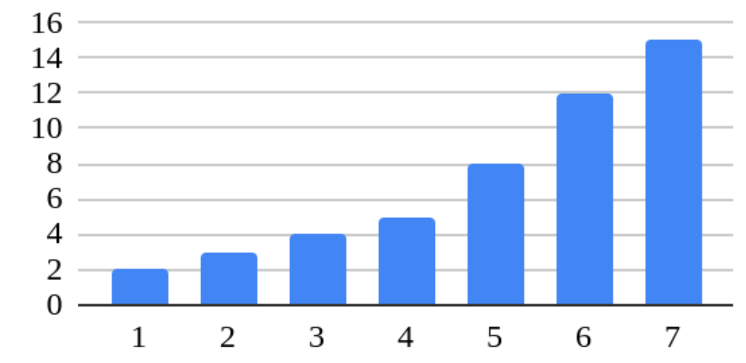
Forest
Non-forest

Preliminary consideration - Kernel size of 32 with 100 training patches is deriving very satisfactory results.

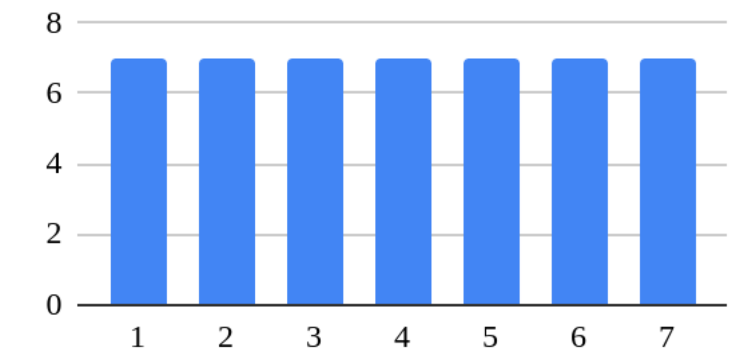
Results



Shannon index non-forest - Low diversity dataset



Shannon index forest - High diversity dataset



Shannon index forest - Sym. diverse dataset

Dataset comparison	***Landsat 8 2019***		***Landsat 8 2015***	
	Overall accuracy	***Kappa Index***	***Overall accuracy***	***Kappa Index***
Dataset with low diversity	0.7849	0.5686	0.7877	0.5754
Dataset with high diversity	0.9474	0.8946	0.9651	0.9302
Symmetrically diverse dataset	0.9474	0.8946	0.9587	0.9174

Approach I

Optical MSI classification

- Very accurate approach.
- Fast implementation.
- Restricted usage because of cloud cover.
- Generates misclassified noise.

Approach II

SAR Object-based classification

- Increased observation time-step (depending on the available data can be applied to weekly/bi-weekly step).
- Fusion of SAR and MSI leads to higher precision.
- Computationally demanding processing.

Approach III

FCNN – Deep Learning

- Highly precise approach.
- Once the model is trained is quickly applicable at larger scale.
- Attention should be paid at the training input.

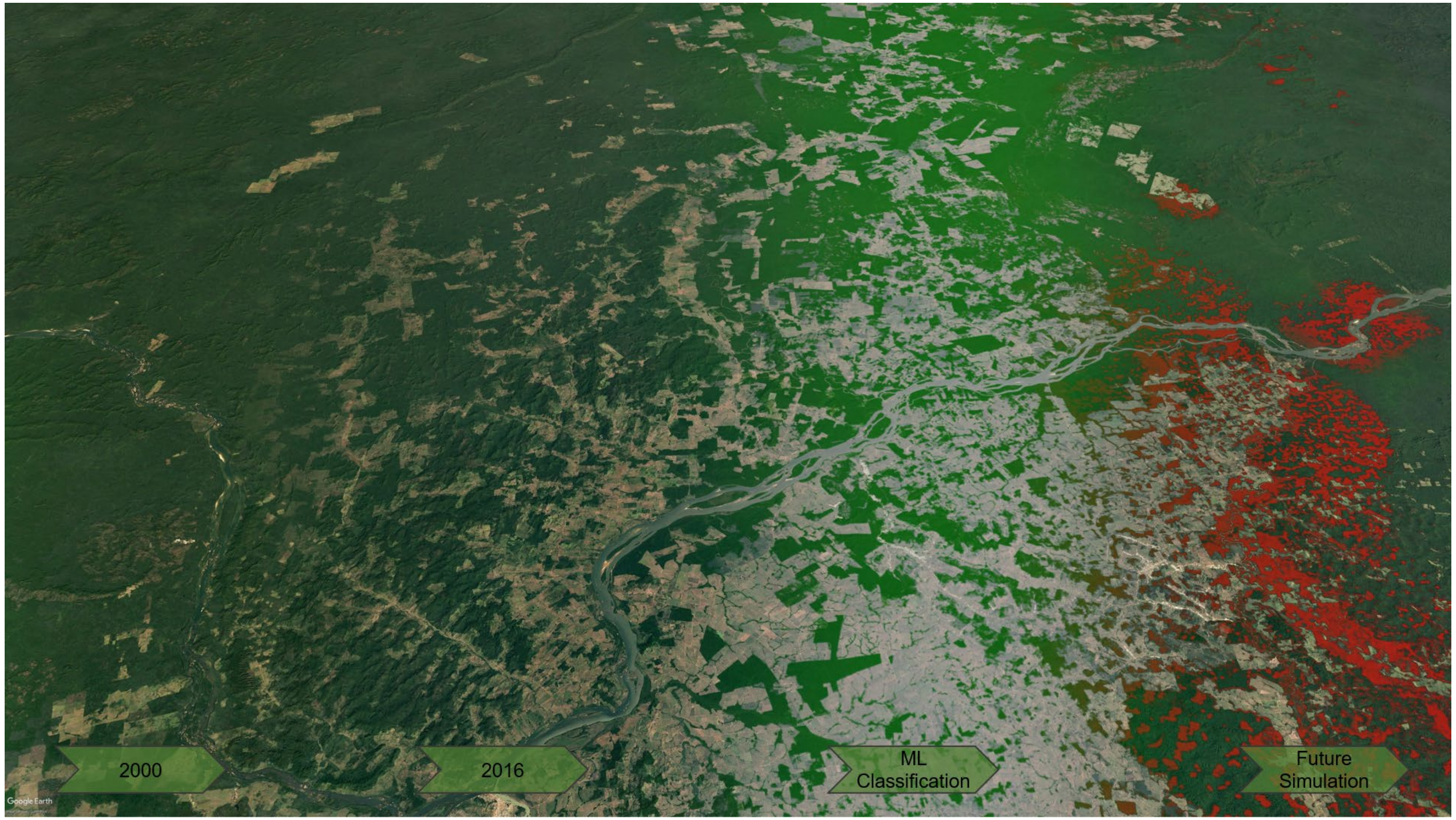
Publications

- 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

- Yordanov, V. and Brovelli, M. A.: Deforestation mapping using sentinel-1 and object-based random forest classification on google earth engine, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLIII-B3-2021, 865–872, https://doi.org/10.5194/isprs-archives-XLIII-B3-2021-865-2021 , 2021.

- Pugliese, A.; Yordanov, V.; Delipetrev, B.; Brovelli M. A.: Amazon forest monitoring using fully convolutional neural networks. AIT Series Trends in earth observation Volume 2 - Planet Care from Space, 99-103, https://doi.org/10.978.88944687/00 , 2021.

Thank you for the attention!



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