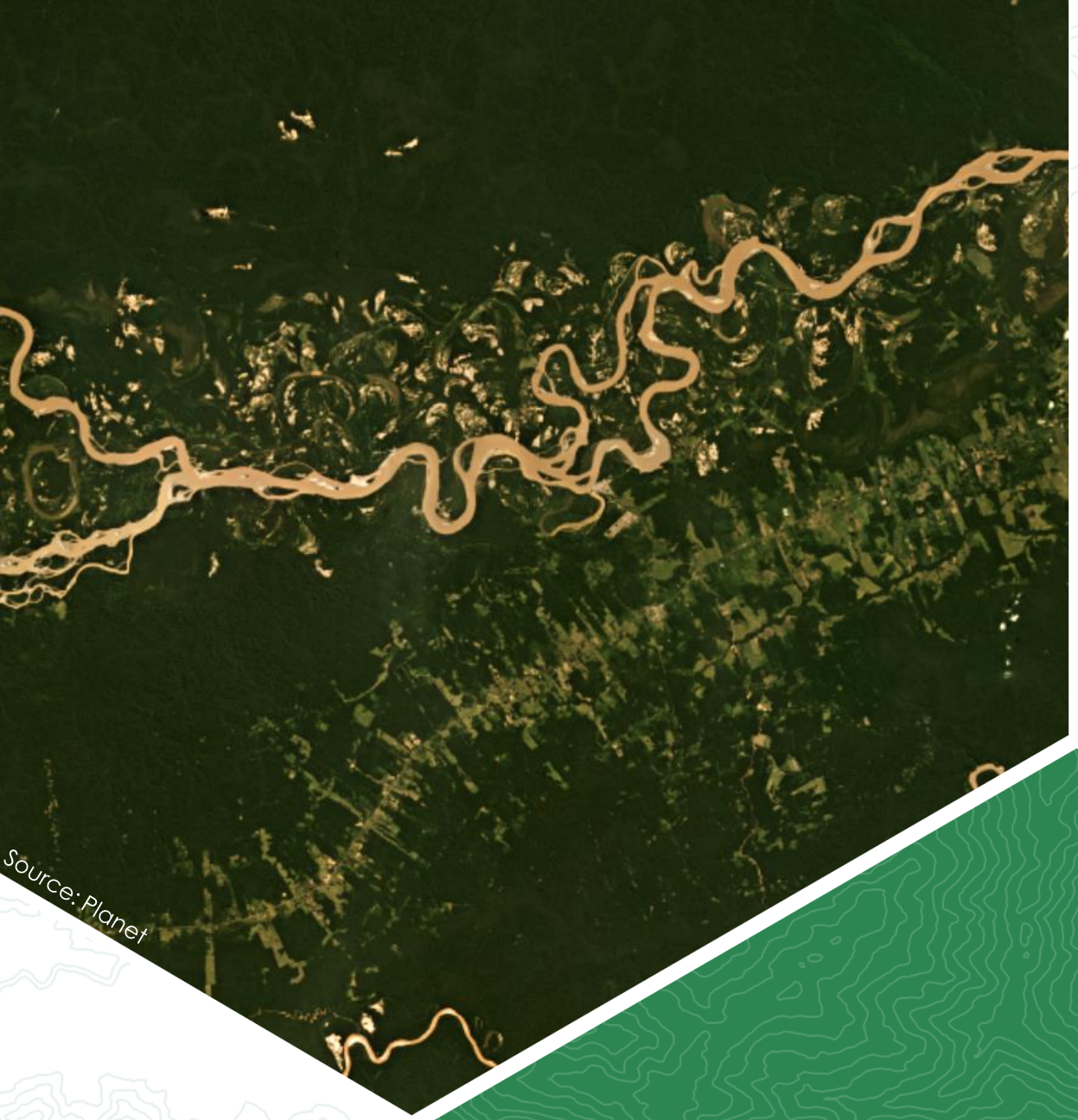


THE UNIVERSITY OF ALABAMA IN HUNTSVILLE

SERVIR

NASA

Applicability of SAR Sentinel-1 data to distinguish drivers of deforestation in the Amazon

XXV IUFRO World Congress

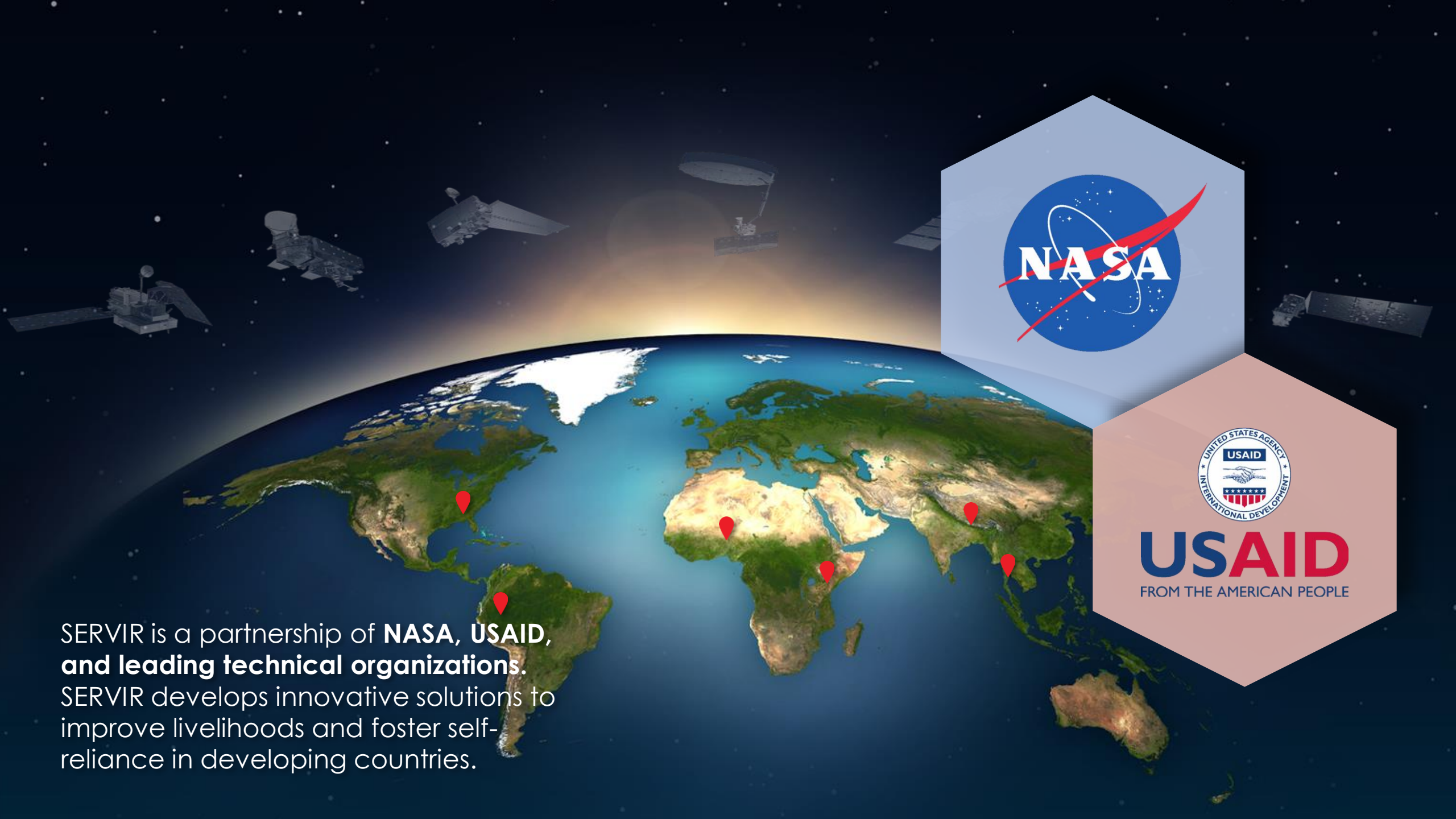
Saturday, October 5, 2019

Andrea Puzzi Nicolau

Africa Flores-Anderson

Dr. Robert Griffin

Kelsey Herndon



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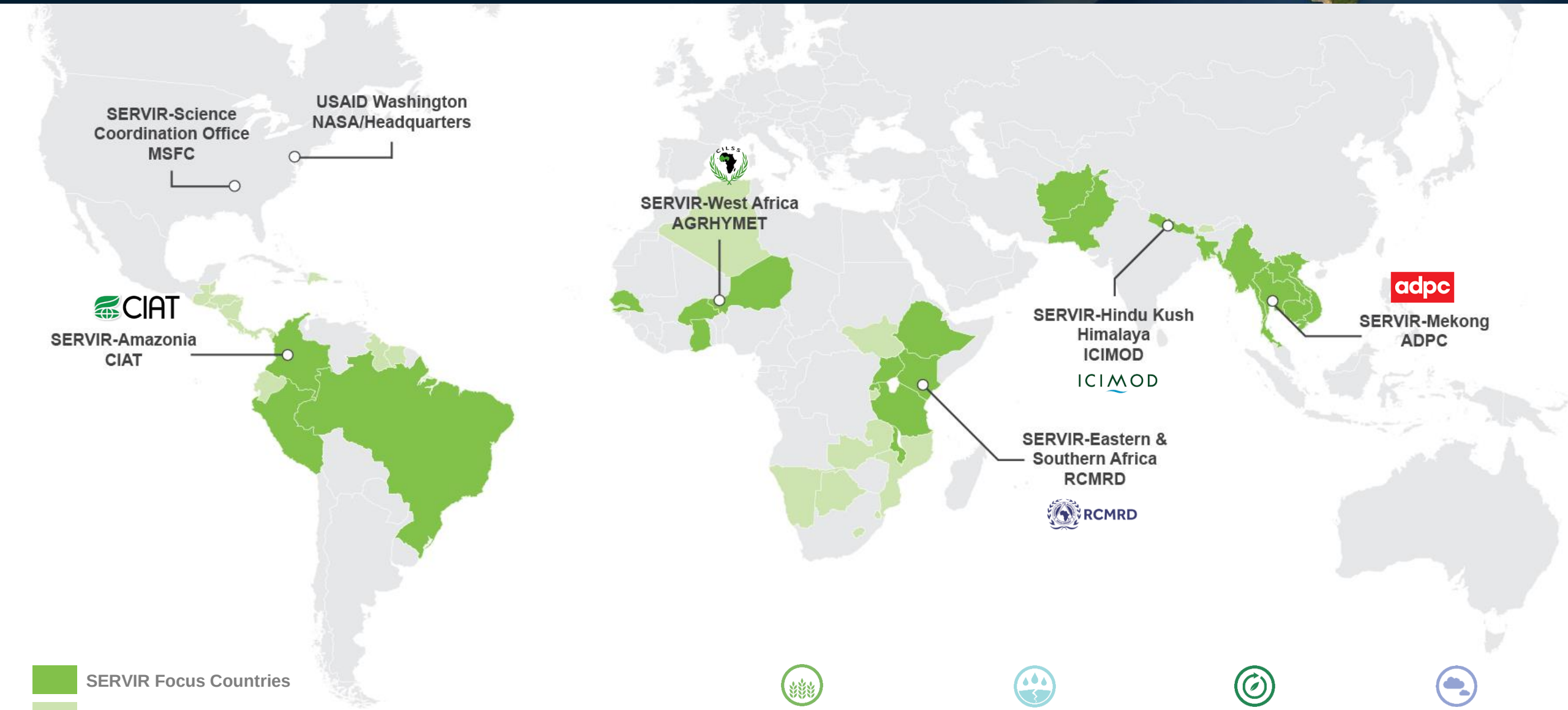

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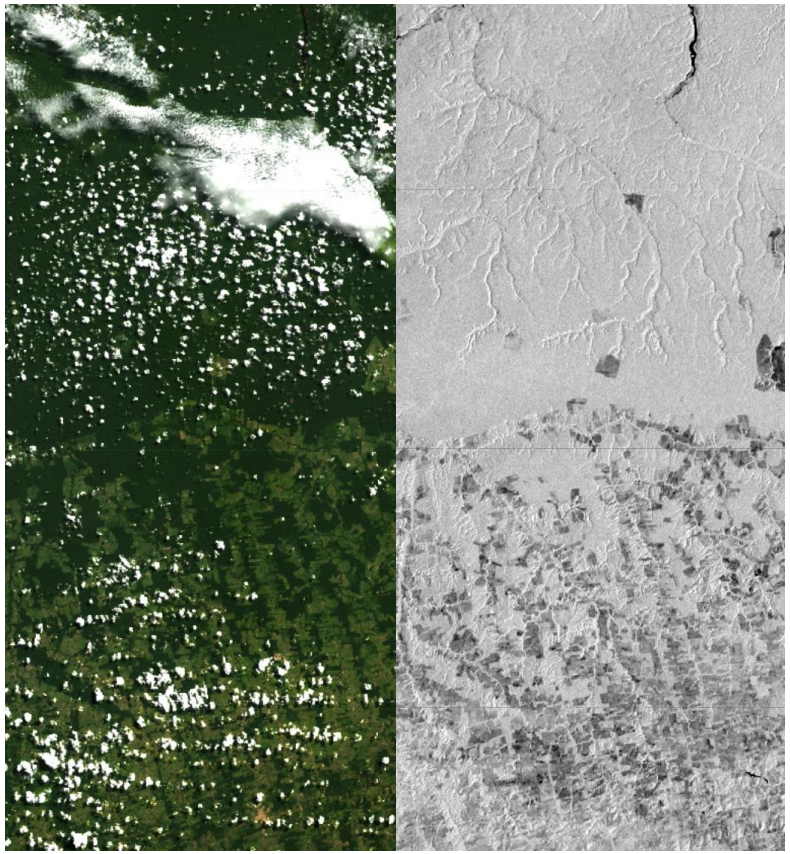
imaflora

Motivation

- Is it possible to use Sentinel-1 data to distinguish drivers of deforestation?
  - Why is it important to distinguish drivers of deforestation?



Landsat 8 RGB and Sentinel-1 VV median composites January-July 2019 (Altamira, Brazil)

- We know where and when deforestation is happening, but in order to have an impact in how to prevent deforestation, we need to know what is causing it
- Optical systems:
  - Cloud cover
  - Hard to distinguish different land uses with similar land cover (Joshi et al., 2016; Hagensieker et al., 2017)
- The identification of drivers of deforestation is a need for early warning deforestation monitoring systems (International Forum of Early Warning Systems, Lima, July 2018)
- Important towards more sustainable land management and to aid global initiatives such as REDD+ (UNFCCC, 2013)
- The use of SAR data is a priority by GFOI (GFOI, 2013)

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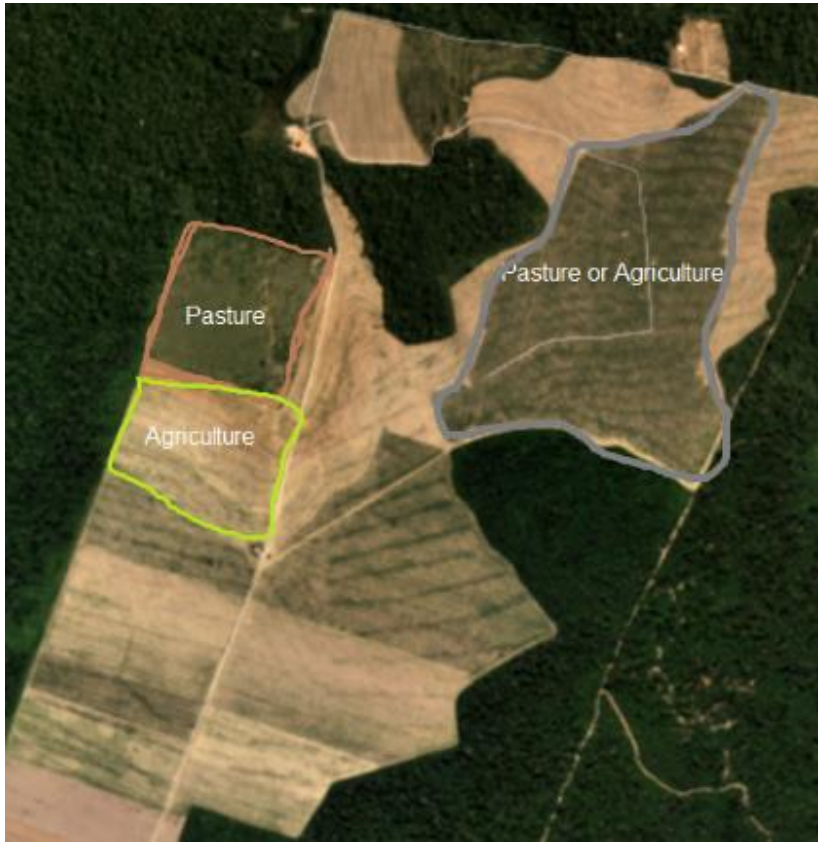

MapBiomas/TerraClass Classification (Brazil)

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Research Questions and Study Area

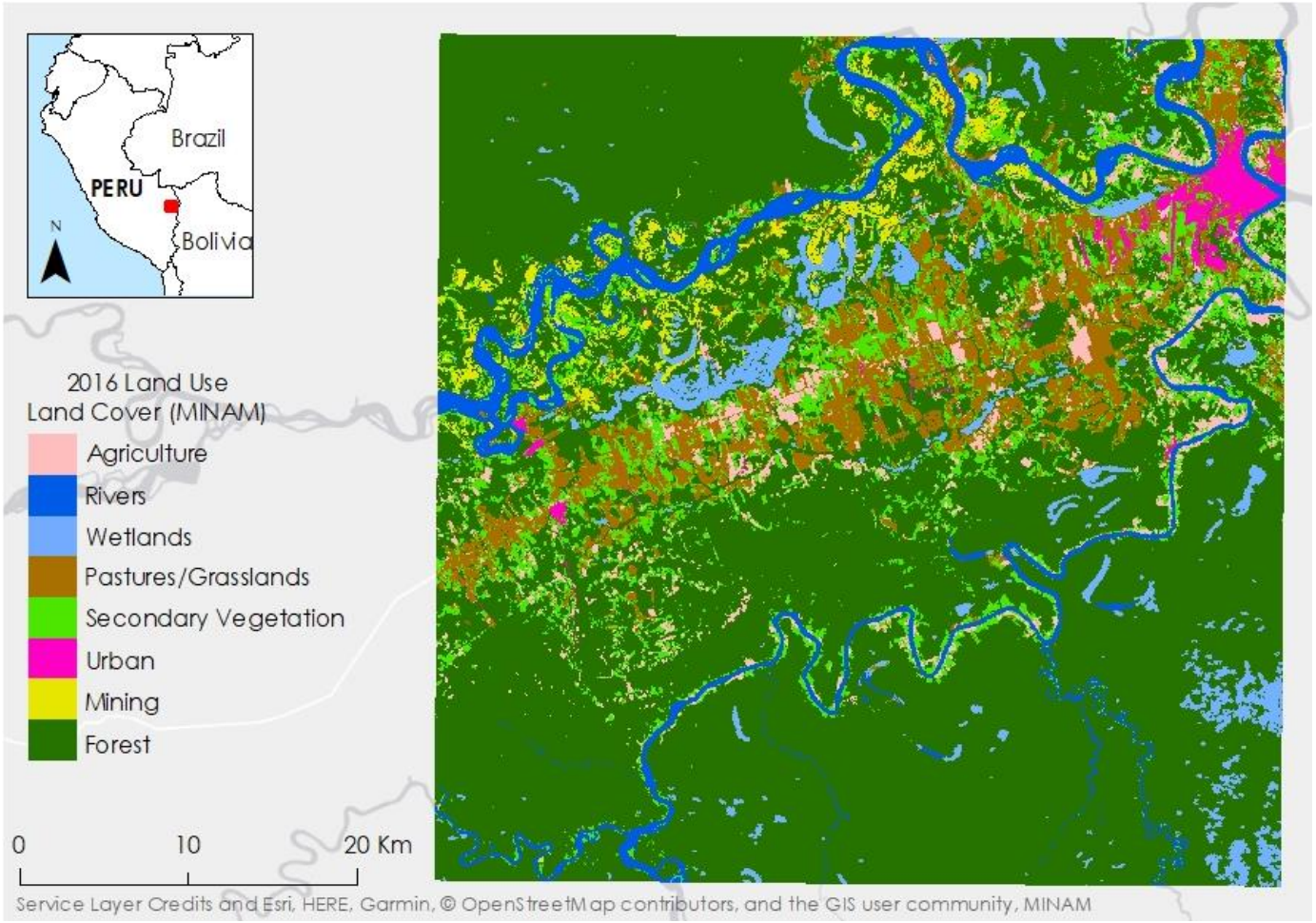
Can we use Sentinel-1 data to distinguish land uses/covers?

Can we observe signature trends on Sentinel-1 time series data for different LULC?

Which metrics are the best to distinguish LULC?

Can LULC maps be produced with high accuracy?

Madre de Dios



Total area: ~2,500 km^2

Research Questions and Study Area

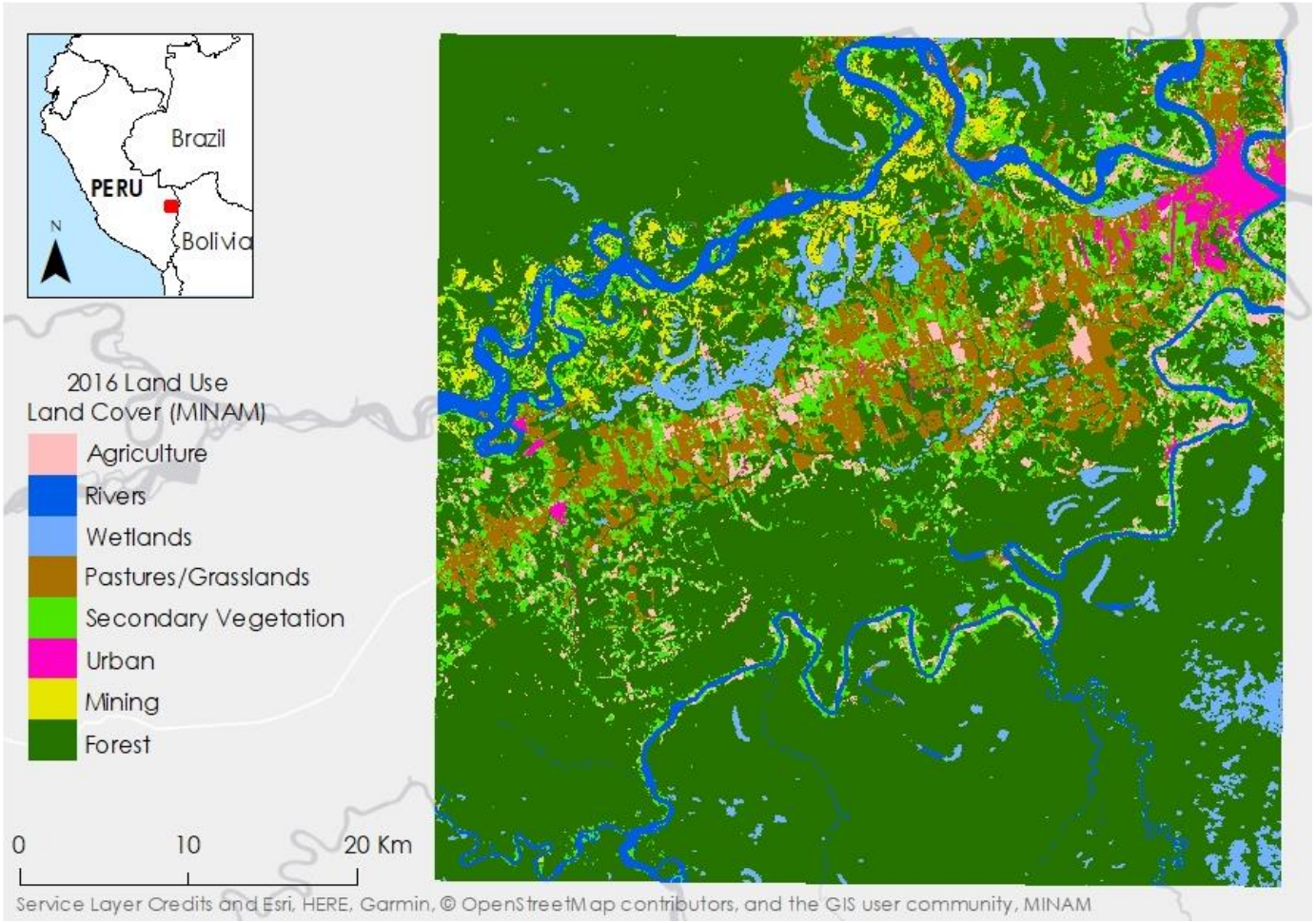
Madre de Dios

Capital of Biodiversity (Peruvian Law N° 26311; Myers et al., 2000)

Deforestation rates have been increasing since 2001 (MINAM, 2017)

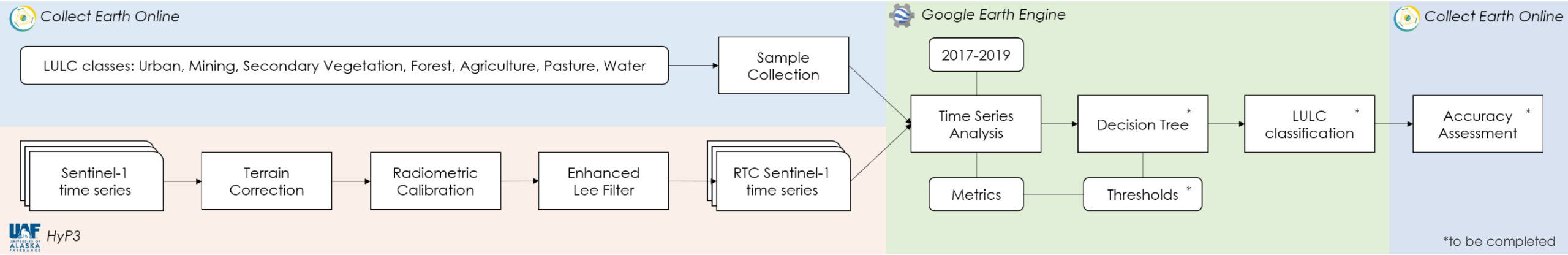
Presents a mosaic of land uses and covers

Madre de Dios



Total area: ~2,500 km^2

Methodology



- Quarterly Composites
- VV, VH, VV/VH, Radar Forest Degradation Index (RFDI; Sassan, 2019) modified
- Metrics: Mean, Min, Max, Max-Min ratio, Standard Deviation, Coefficient of Variation

$$RFDI = \frac{\gamma^o_{HH} - \gamma^o_{HV}}{\gamma^o_{HH} + \gamma^o_{HV}}$$

$$RFDI\ mod. = \frac{\gamma^o_{\boldsymbol{VV}} - \gamma^o_{HV}}{\gamma^o_{\boldsymbol{VV}} + \gamma^o_{HV}}$$

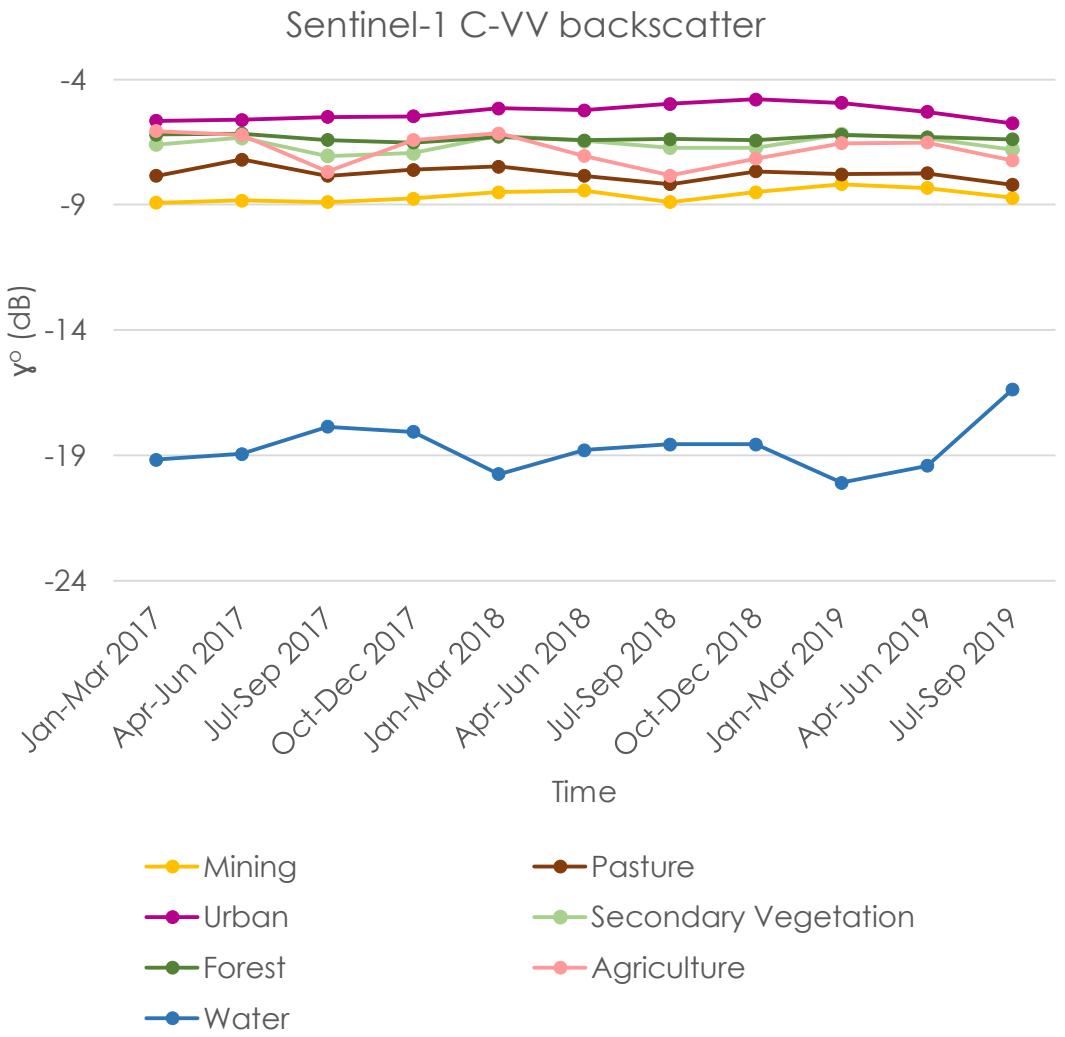
Sample Collection (CEO)

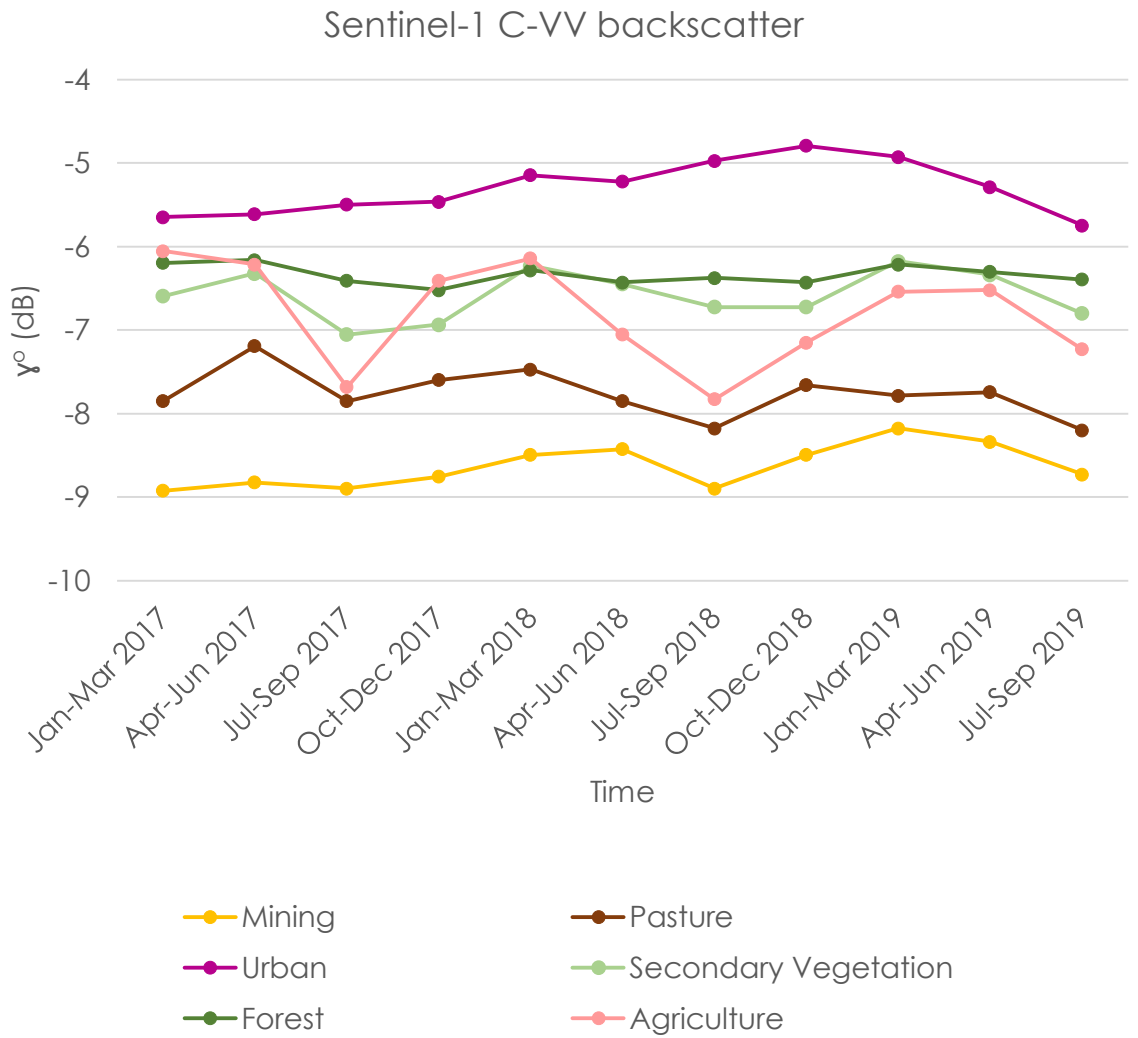
http://collect.earth

- Land Use Land Cover Map (2016) from Geobosques (MINAM)
- Sample Design: Stratified Random Sampling (Olofsson et al., 2014)
  - 900 points for all classes
  - 88 random plots (5 ha) with 25 gridded points each
  - Minimum of 25 reference points each class
  - Addition of 4 and 6 extra for Agriculture and Mining classes, respectively (10 plots; 250 points)

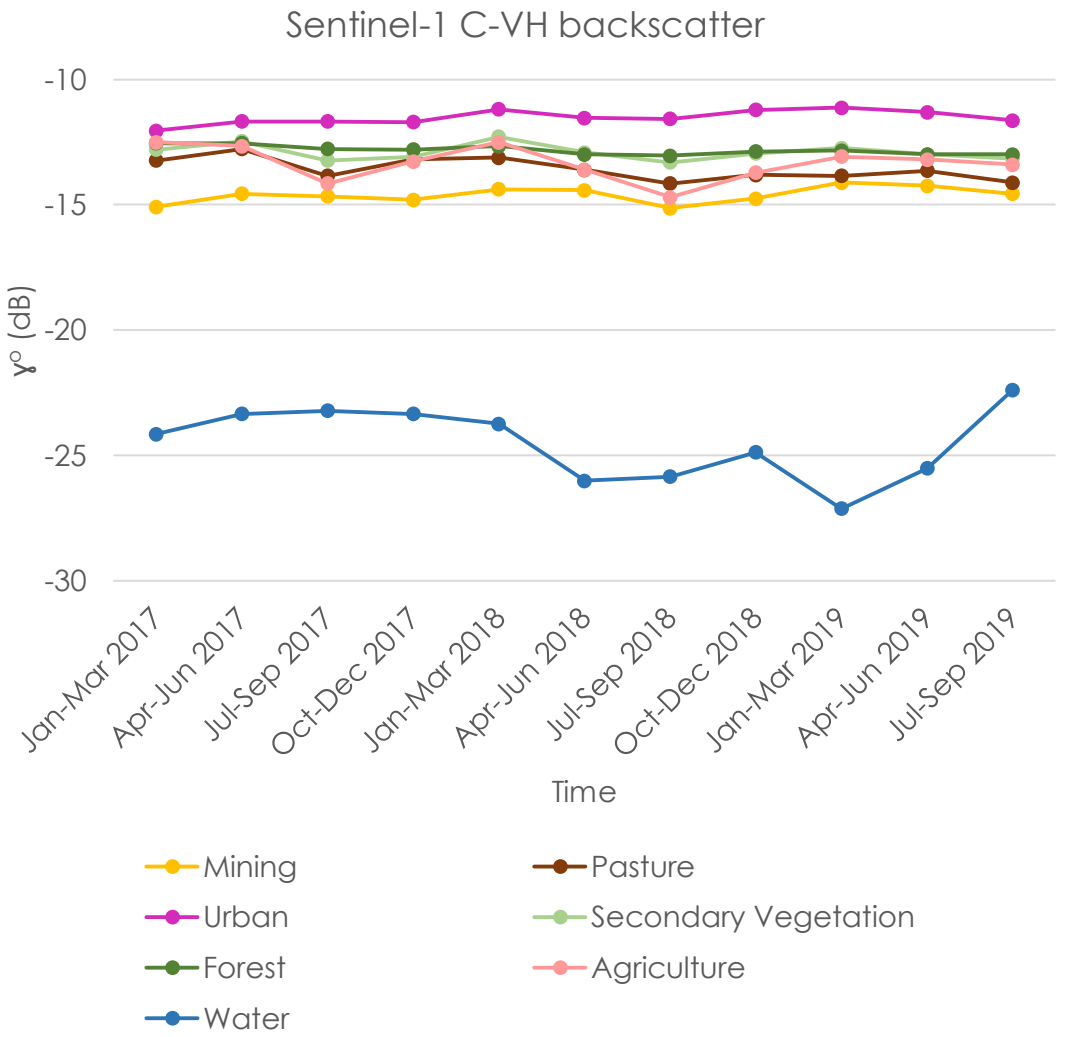
	Forest	Sec Veg	Agri-culture	Pasture	Mining	Urban	Water	Total
Plots	62	8	7	8	7	1	5	98
Pts	1550	200	175	200	175	25	125	2450
Total Pts	1718	163	75	53	73	25	66	2173

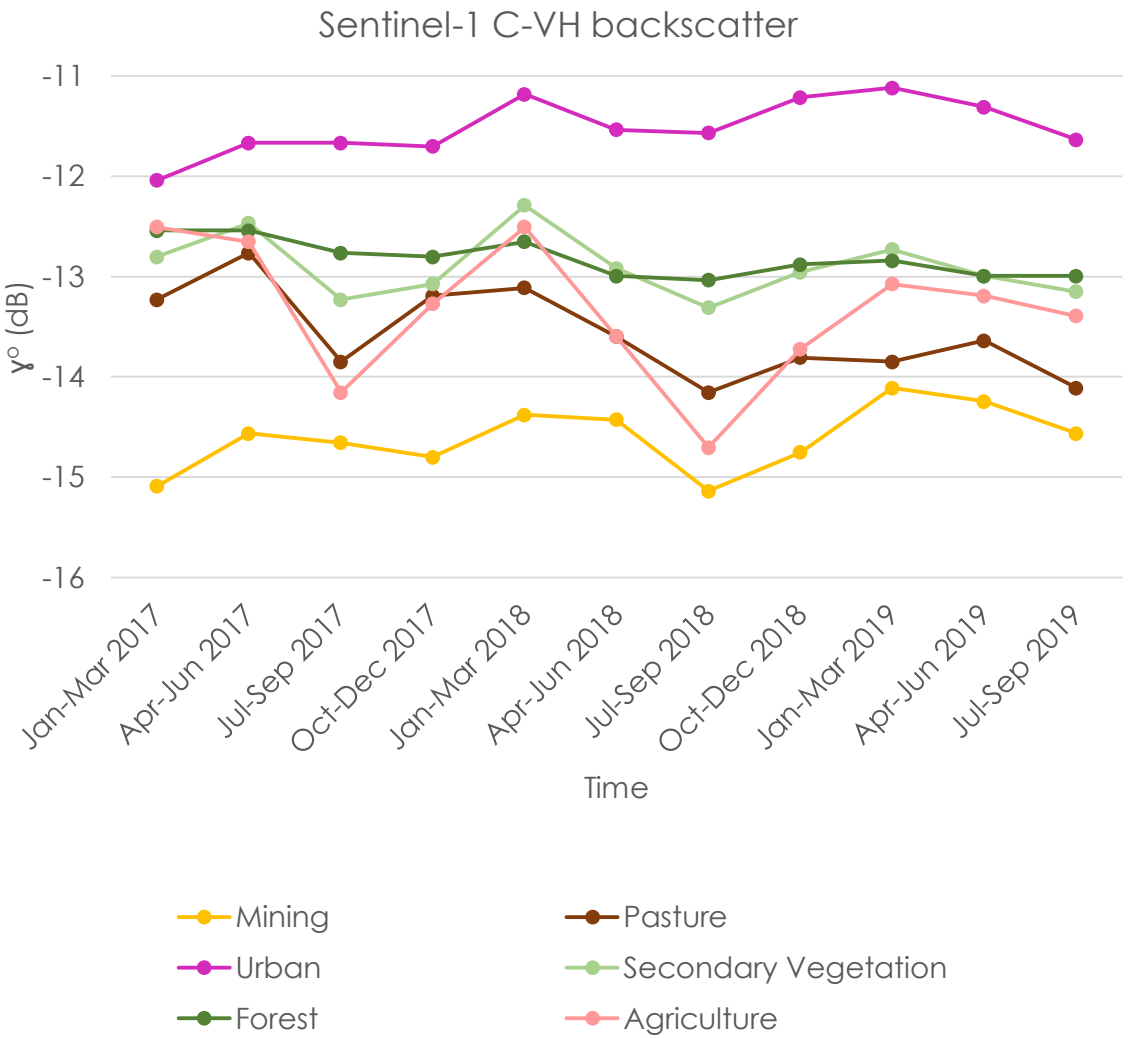
Time Series Analysis





Time Series Analysis





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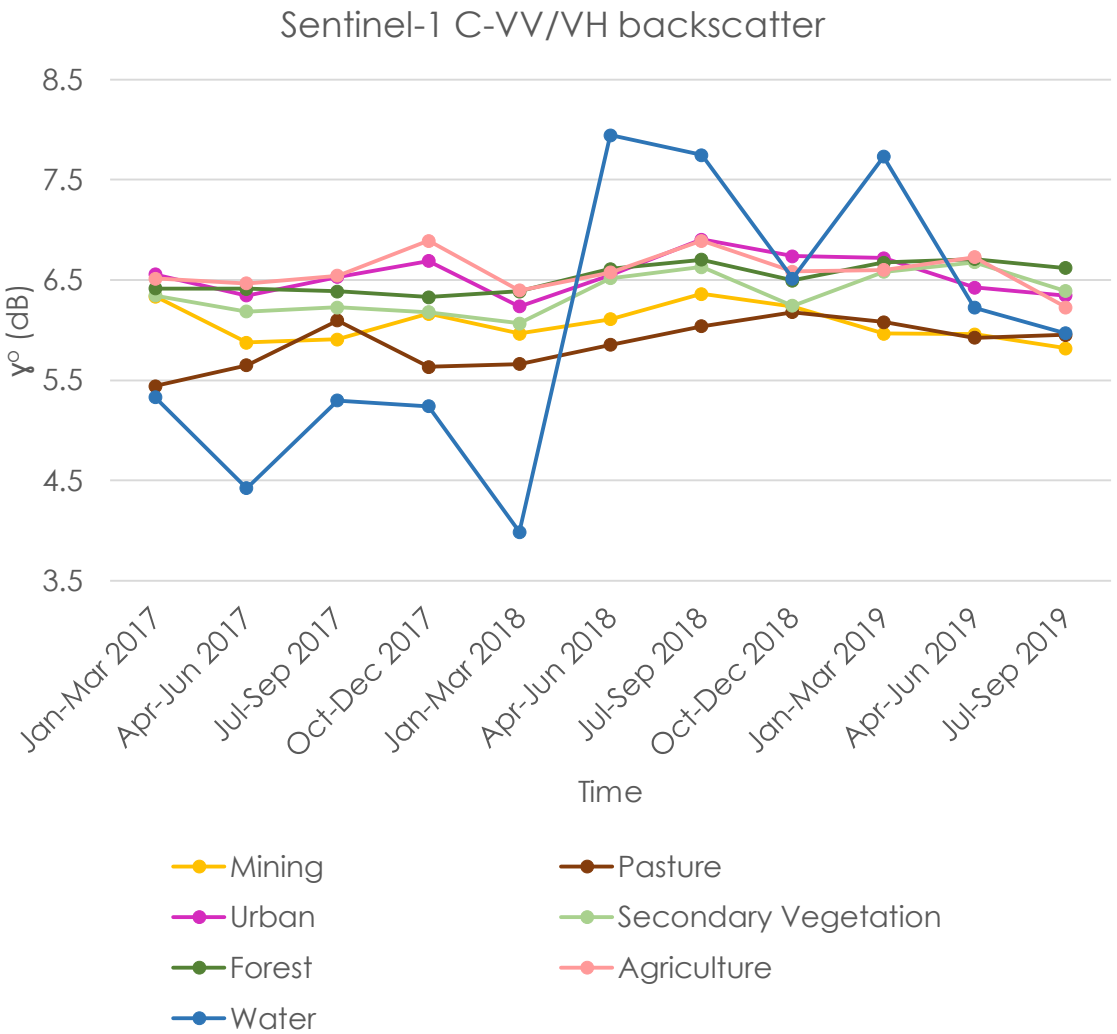
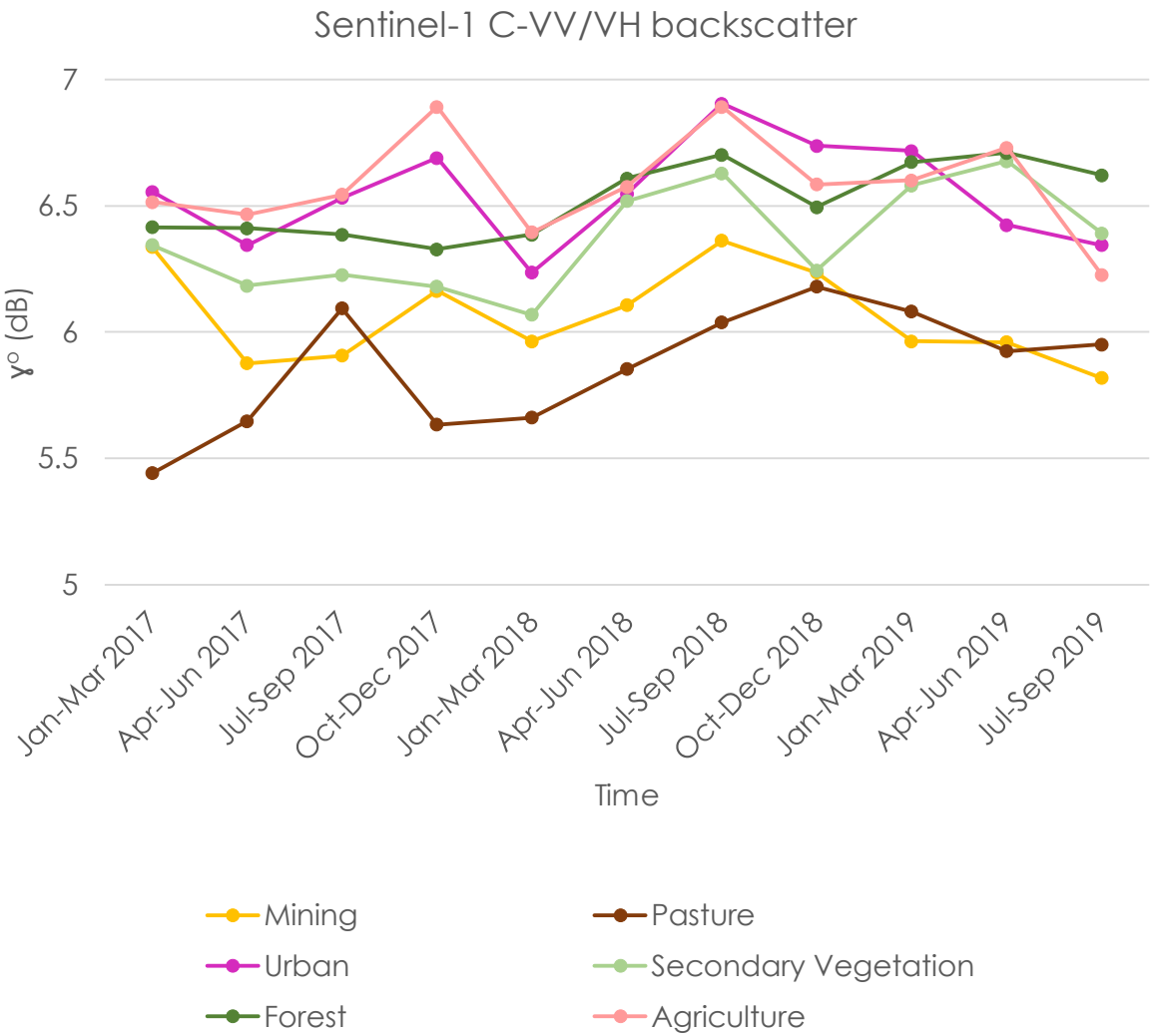
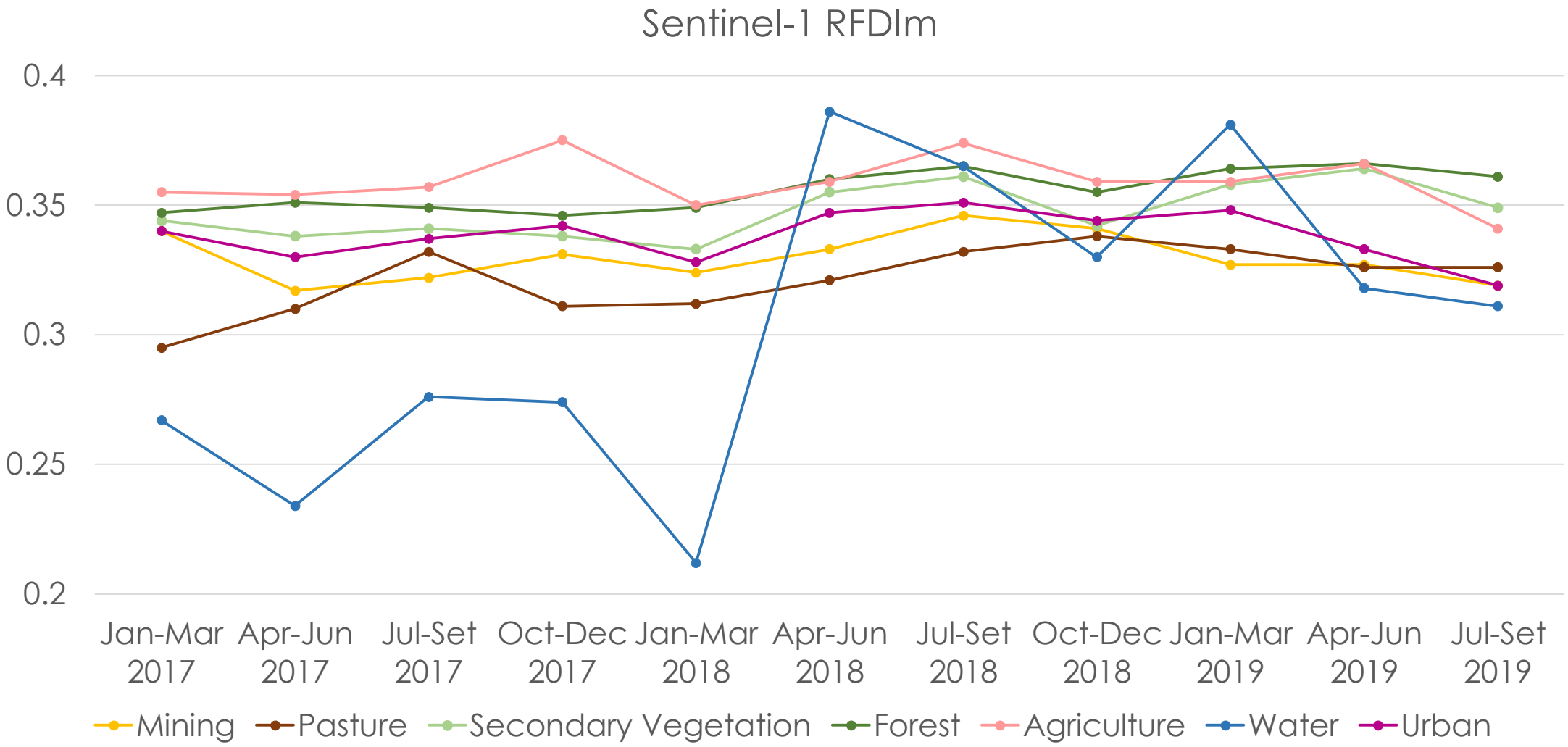
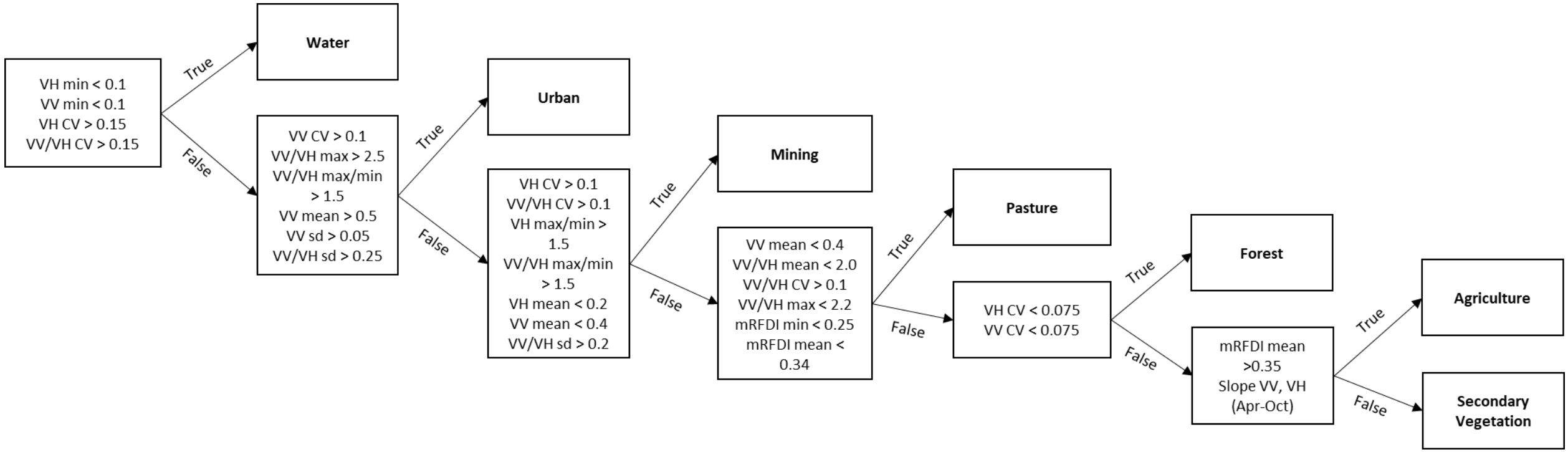




Time Series Analysis

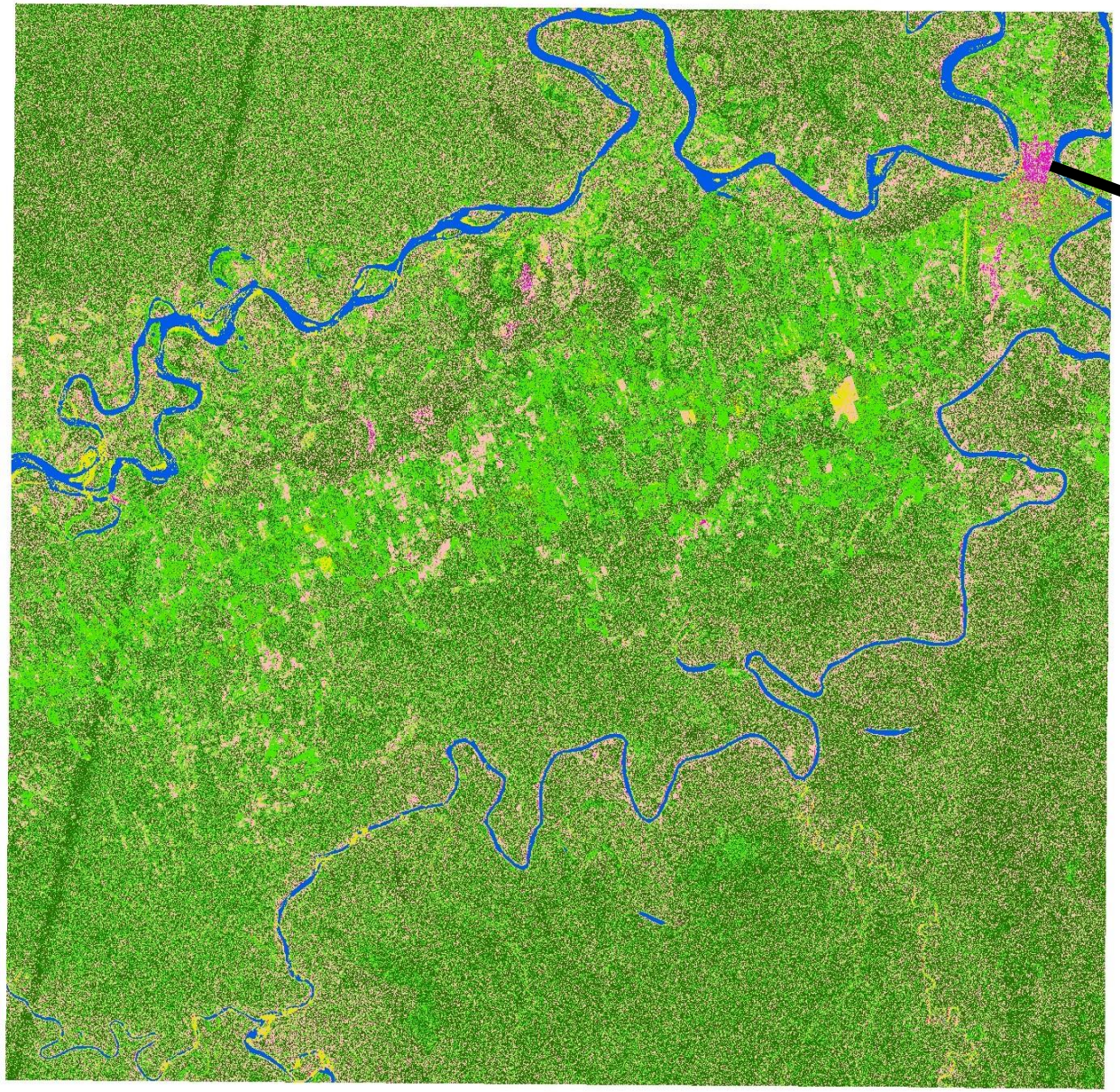


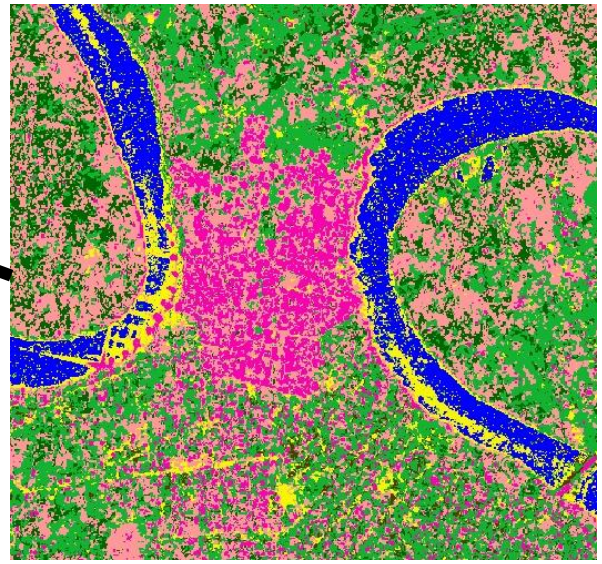
Decision Tree



315 new samples to attest thresholds (High rate of True Positives vs. Low rate of False Positives)

Classification

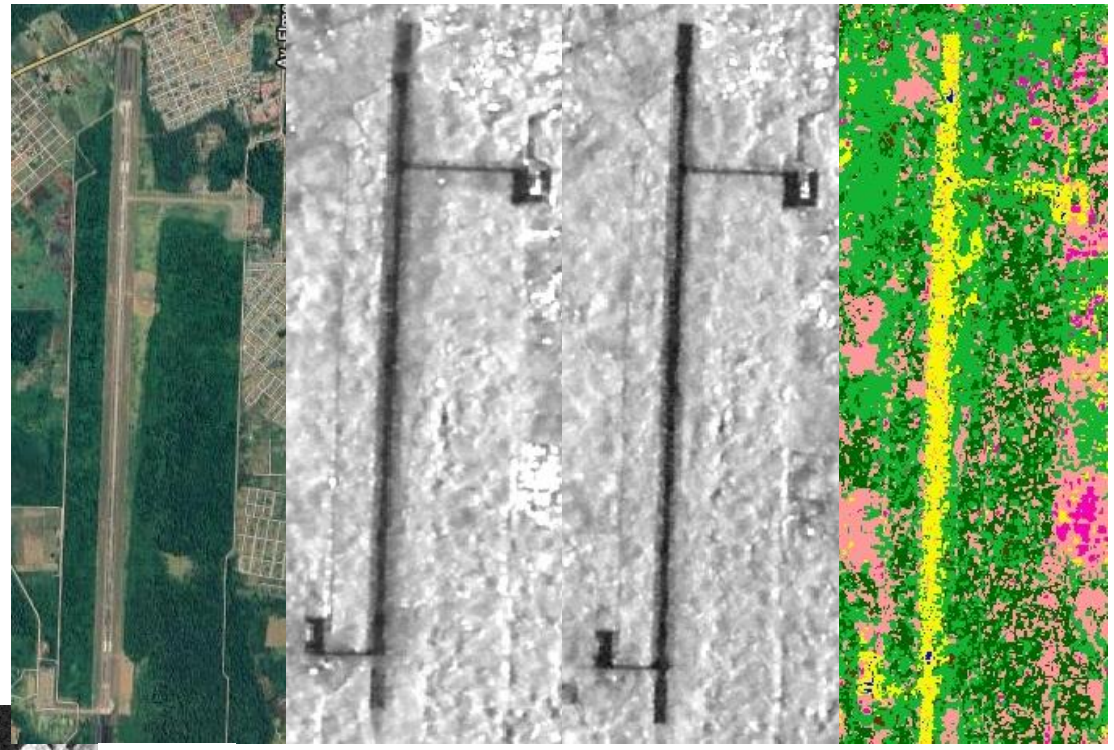




- Forest
- Sec. Veg.
- Mining
- Urban
- Agriculture
- Pasture
- Water

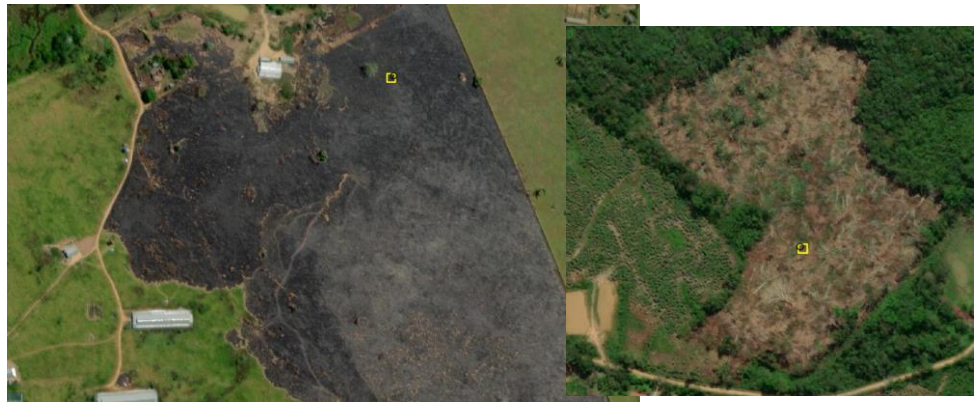
Challenges

- Dual pol → Issues with mapping Urban Areas (HH)
- Airport runway → Misclassification
- Limited to 7 classes
- "Forest Line" on classification



RGB VV VH Classified

RGB VV VH



Source: Maxar Technologies

Conclusions and Future Work

- Similar backscatter values when analyzing Forest, Secondary Vegetation, Agriculture, and Pasture
- Some seasonality trends are observed – info for classification – slope
- Limitations: only two polarizations; noise; airport runway, urban areas
- Finish application of decision tree and classification
- Accuracy assessment (Confusion matrix following Oloffson et al., 2014)
- Adapt the algorithm to be applied only on areas that were deforested
- SERVIR-Amazonia: expected that this project can contribute with the Amazon basin conservation

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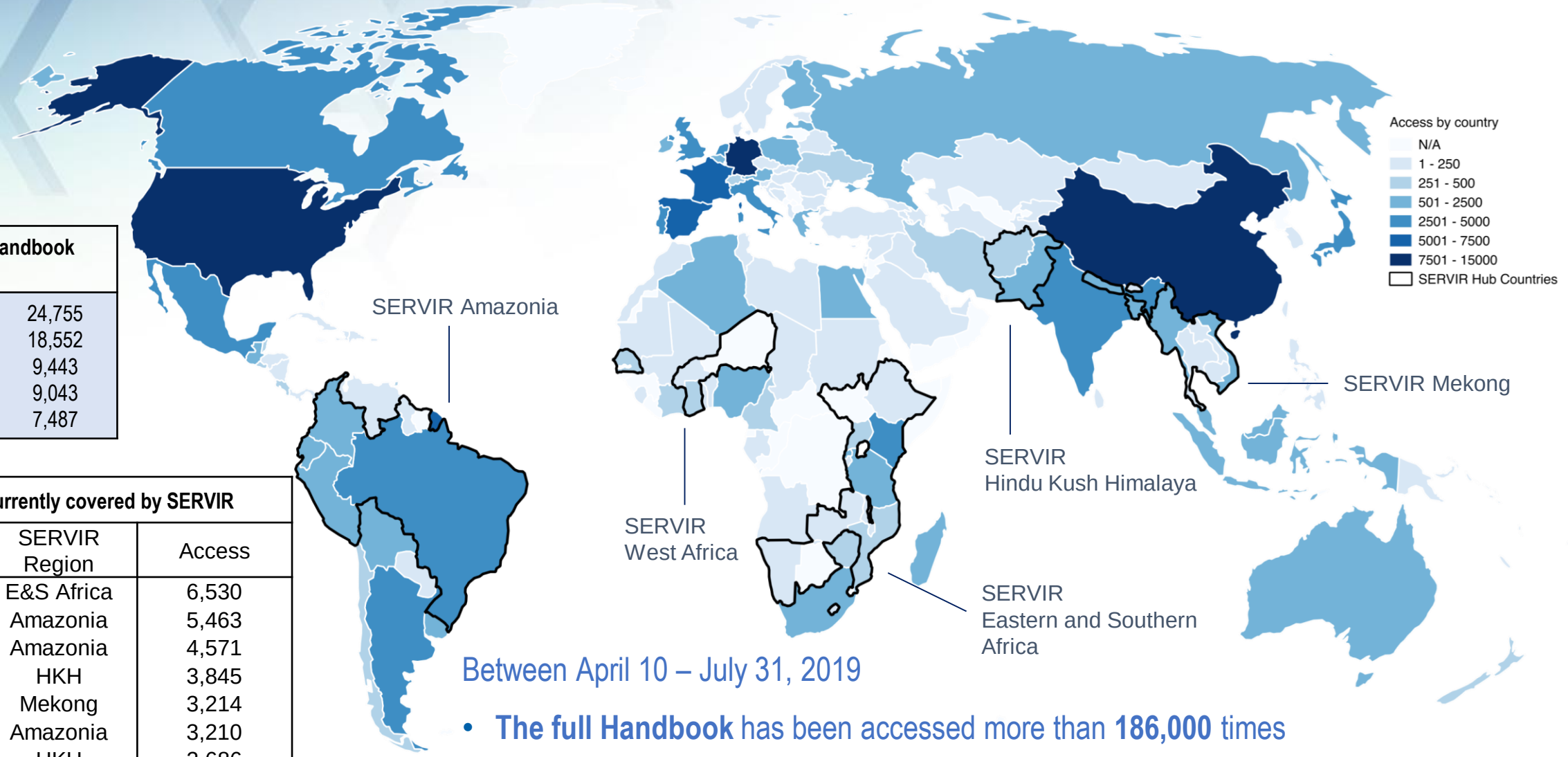

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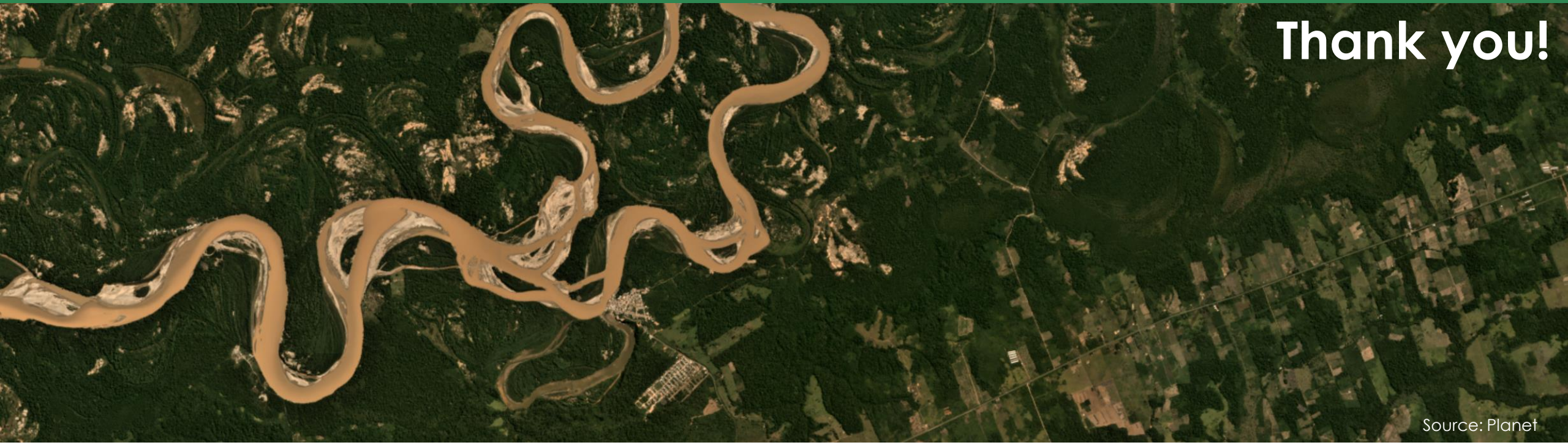

Questions?

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