A Deep Learning Framework for Regularly Monitoring the Amazon Forest with Sentinel-1 InSAR data: Seasonal Challenges and Insights

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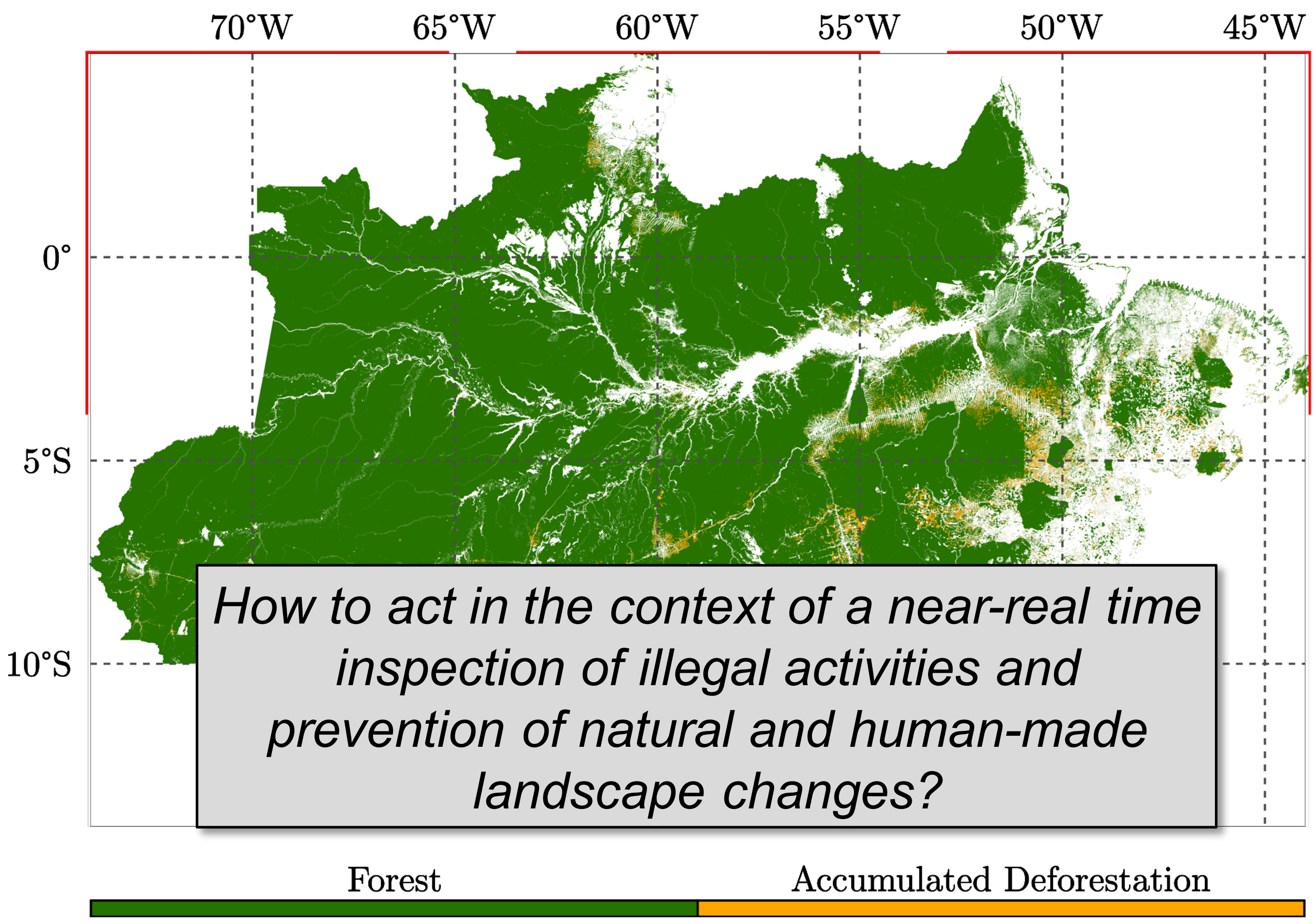
Problem Overview and Motivation

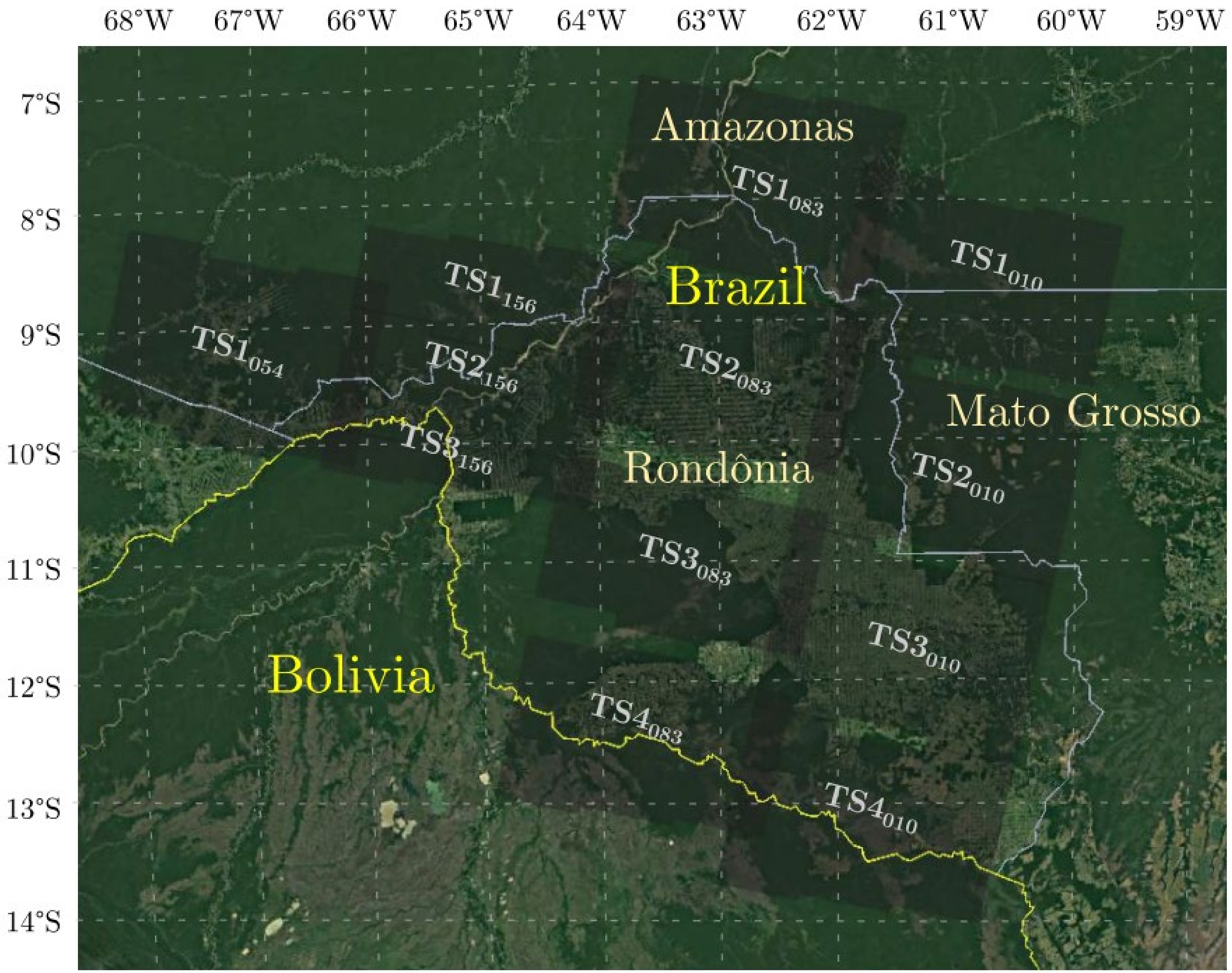
- Investigating land cover change patterns in forest ecosystems is of utmost importance in the context of environmental policy-making
- Monitoring systems rely on optical remote sensing data in areas whose mean annual cloud cover ≥ 70%
- Some maps might only be updated with reliability once a year, during the dry season
- We investigate the potential of Sentinel-1 IW to regularly monitor these environments

PRODES - Native vegetation supression between 2008 and 2021



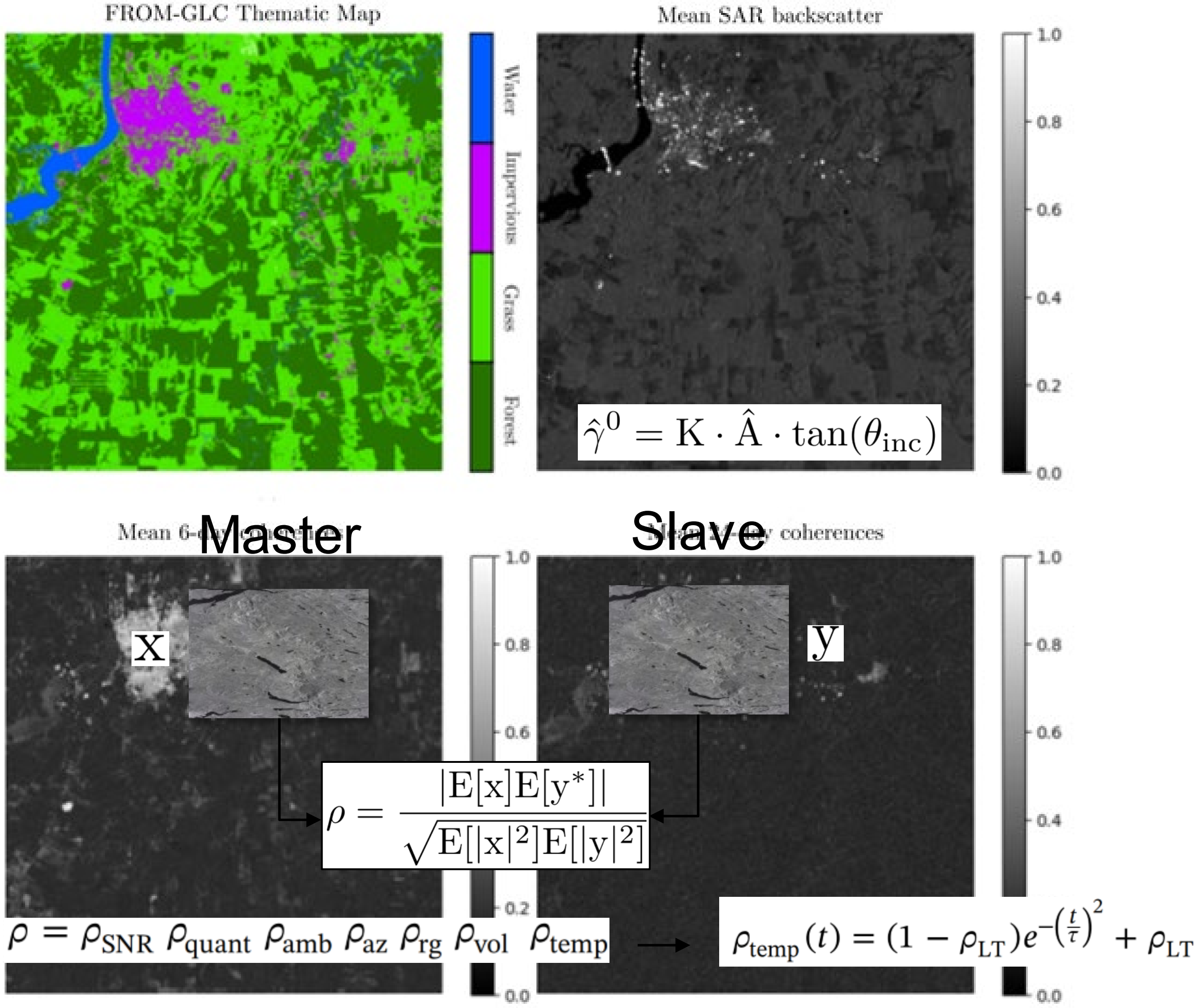
Problem Overview and Motivation

- We initially define our region of interest over the Brazilian state of Rondonia (ca. 238,000 km^2)
- This area is one of the most deforested and studied places in the Amazon basin, and during 2019 was focus of a special campaign with a 6 days repeat-pass coverage
- Thus, we selected 12 scenes, each composed of time series covering only 24 days to regularly map land cover classes of interest at 50 m resolution with single VV polarization



Problem Overview and Motivation

- As external reference, we chose the FROM-GLC 2017, a thematic map containing 10 land cover classes with a resolution of 10 m
- First feature of interest is the SAR backscatter, here denoted by the gamma naught coefficient
- Next, the interferometric coherence is defined as the amplitude of the complex correlation between a pair of images
- The idea is also to exploit how different land cover classes decorrelate over time

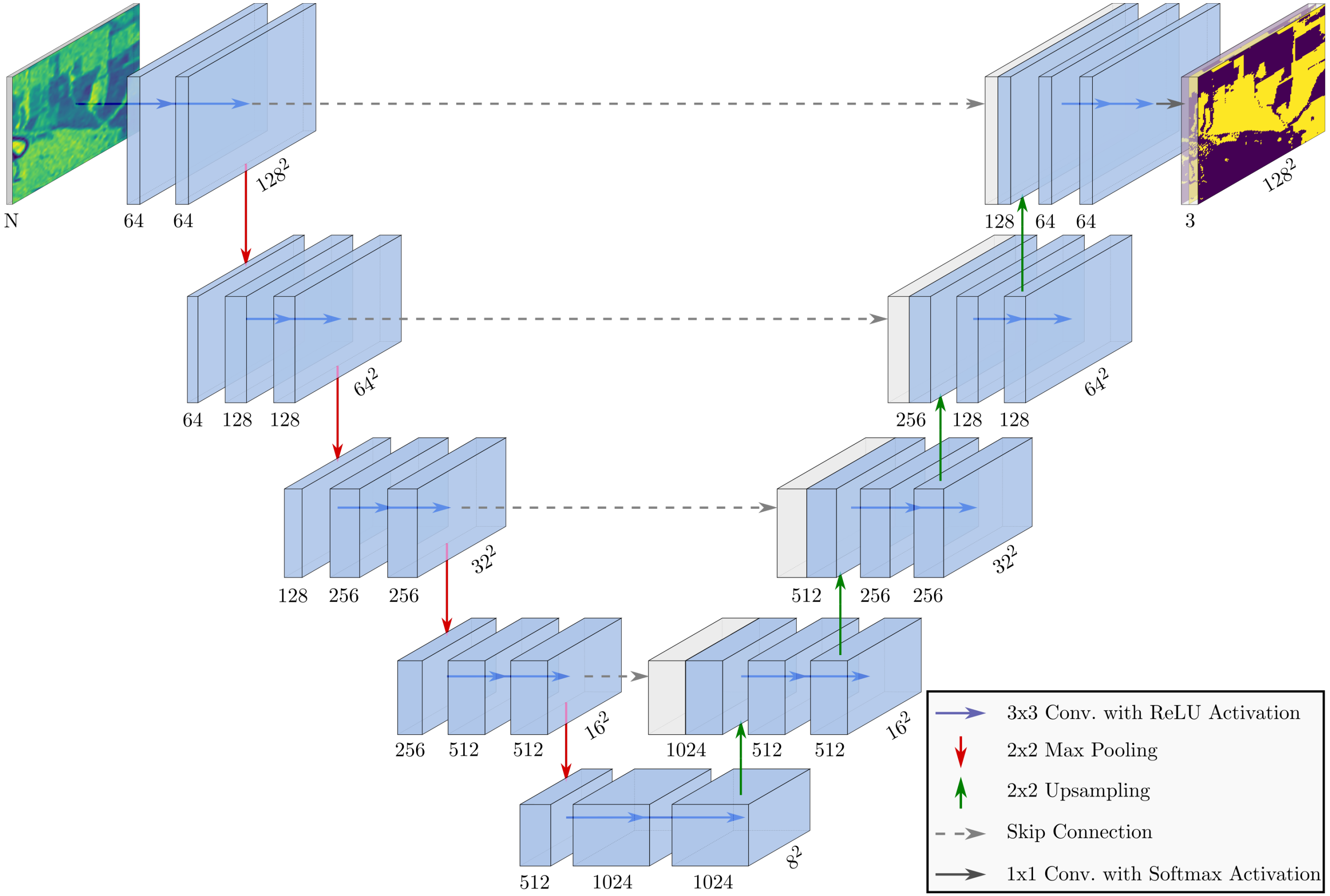


Proposed Approach and Proof of Concept

- <u>U-Net</u>: CNN originally proposed for biomedical binary segmentation problems with a nearly symmetric encoder-decoder nature → we build our own model adapted to land cover

- Advantages:
  - few input features → lots of learnable parameters
  - convolutional kernels account for spatial context
  - full resolution of the image is preserved

- Limitations:
  - requires a considerable amount of training data
  - patch-based nature → difficult class balancing
  - optimal fine-tuning of the network might be challenging



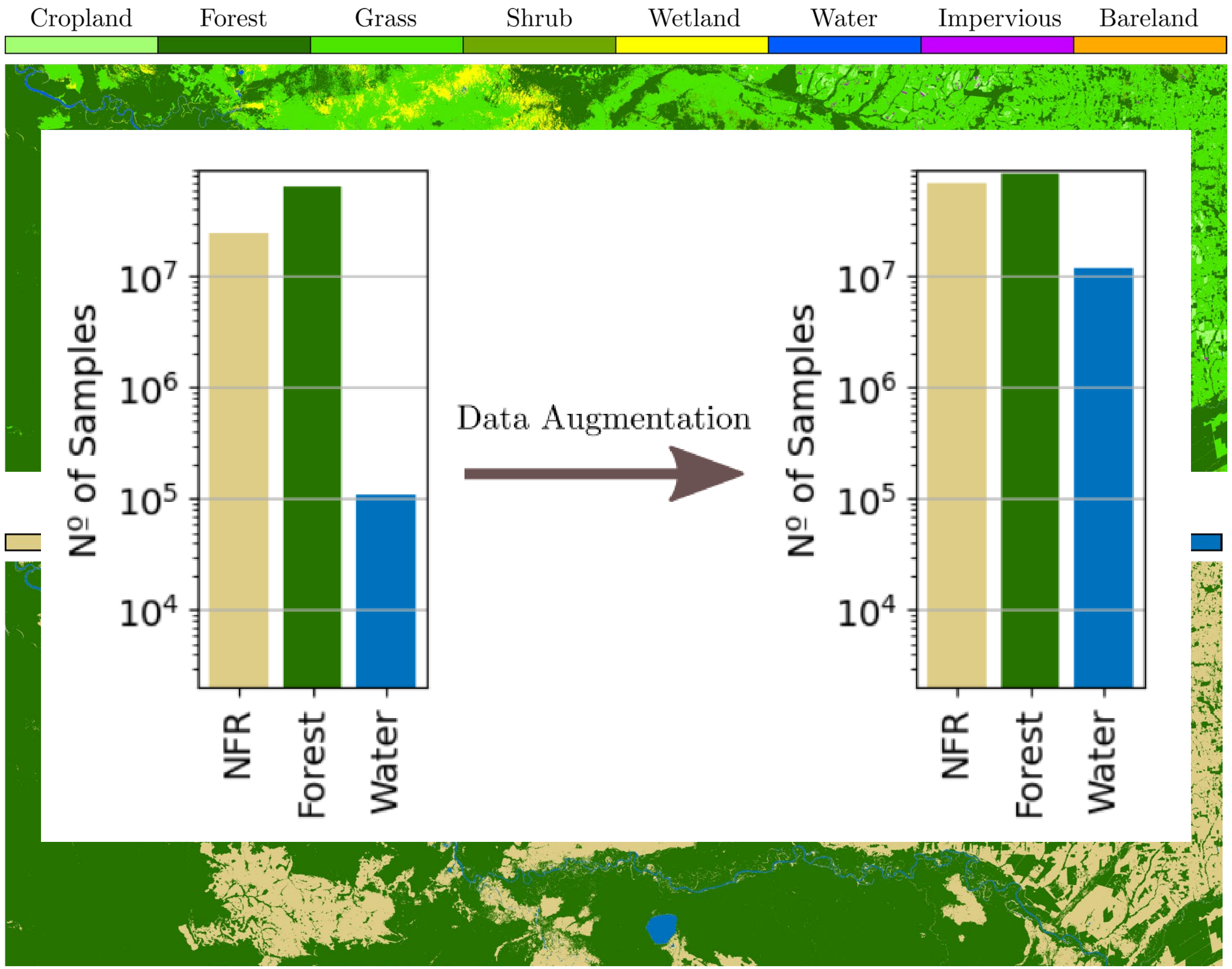
Proposed Approach and Proof of Concept

- When looking at a landscape in the Amazon region, it becomes clear that there is a high class imbalance

- Due to this constraint, we simplify our classification problem to 3 classes of environmental interest

- Even so, the problem persists in a way that could bias the predictions towards the majority classes

- To this end, we virtually augment patches containing mostly water with flipping and rotation operations



Proposed Approach and Proof of Concept

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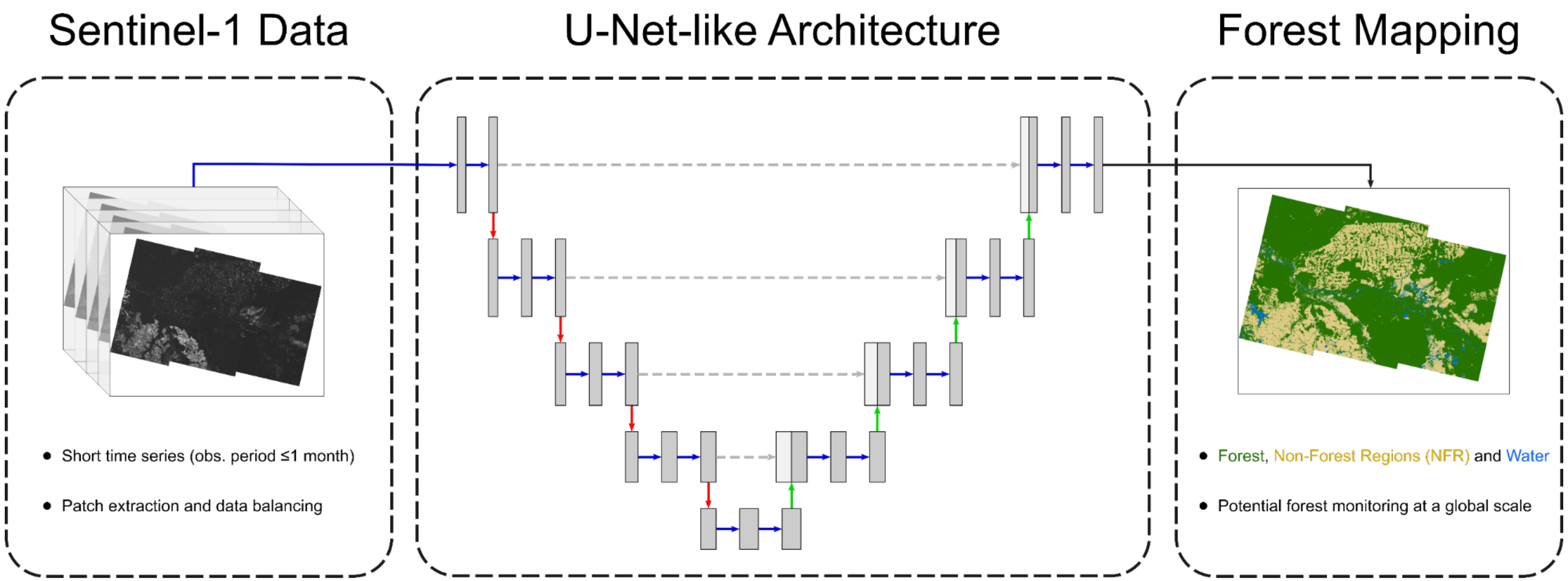
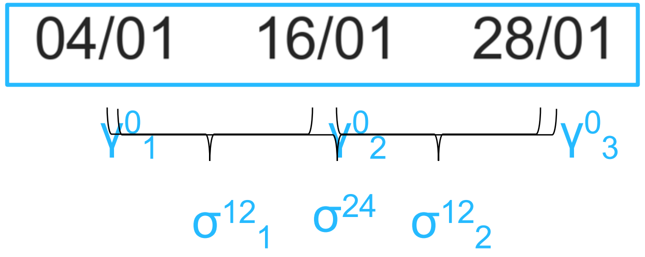
- By considering time series of only 24 days:
  - 5 acquisitions with revisit of 6 days, which provides more information
  - 3 acquisitions every 12 days, with potential to be applied on a global scale



In this case, an example of backscatter and interferometric coherence input features would be:

- Mean of the 3 backscatter γ^0 images
- Mean between the pair of 12-day coherences
- The 24-day long-term coherence



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- Experimental setup with different sets of input features to evaluate the following:

1. Can the network learn local spatial information and outperform state-of-the-art shallow learners?
2. Is the CNN able to learn the temporal decorrelation trend by itself by simply relying on stacks of interferometric coherences?
3. Is it viable to consider a minimum revisit time of 12 days (global cover)?

Approach	#	Backscatter		Coh. Stacks$_{[days]}$				Exp. Model		Geom.
		γ^0_{avg}	Textures	ρ_6	ρ_{12}	ρ_{18}	ρ_{24}	τ	ρ_{LT}	θ_{inc}
RF [1]	I	●	-	*	*	*	*	●	●	●
RF [2]	II	●	●	*	*	*	*	●	●	●
CNN	III	●	-	*	*	*	*	●	●	●
CNN	IV	●	-	●	●	●	●	-	-	●
CNN	V	●	-	-	●	-	●	-	-	●

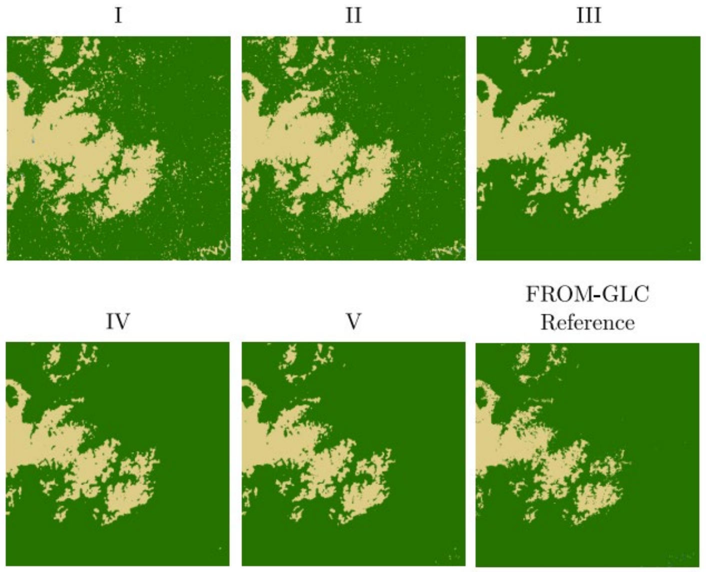
[1] Sica, F.; Pulella, A.; Nannini, M.; Pinheiro, M.; Rizzoli, P. Repeat-pass SAR interferometry for land cover classification: A methodology using Sentinel-1 Short-Time-Series. Remote Sens. Environ. 2019, 232.

[2] Pulella, A.; Aragão Santos, R.; Sica, F.; Posovszky, P.; Rizzoli, P. Multi-Temporal Sentinel-1 Backscatter and Coherence for Rainforest Mapping. Remote Sens. 2020, 12, 847.

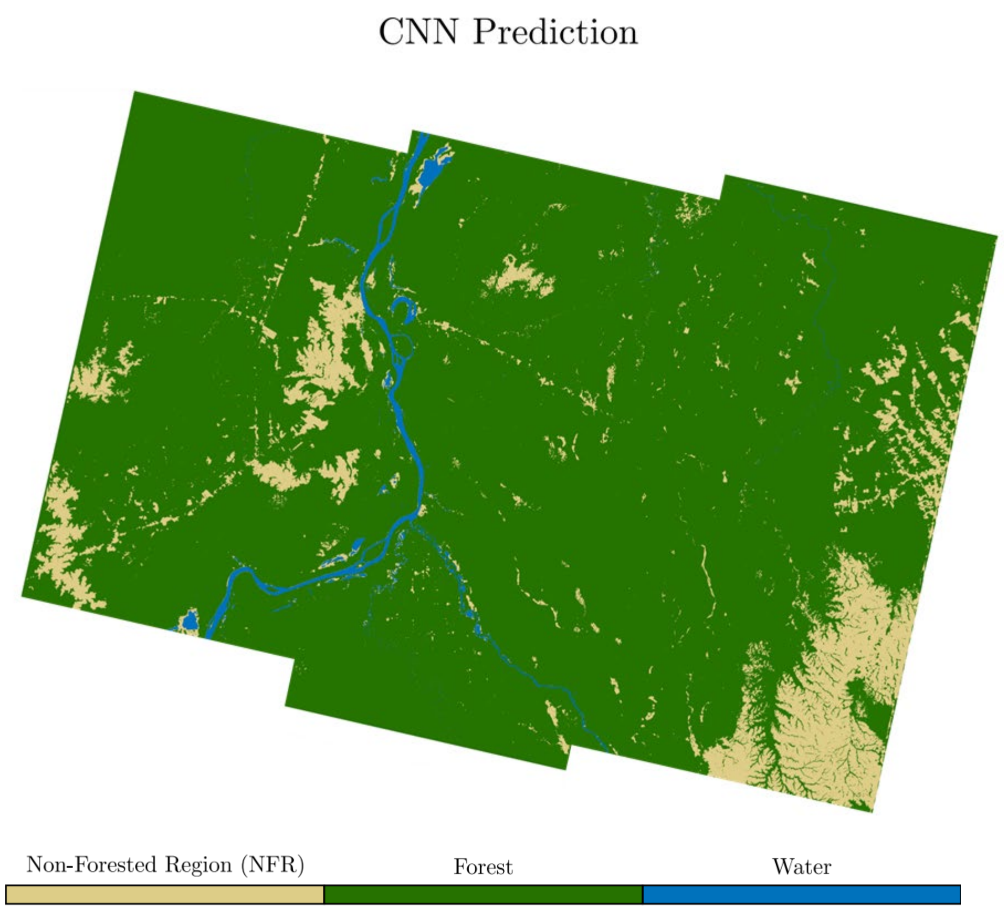
Proposed Approach and Proof of Concept

- Best results by using solely the coherence stacks to describe the temporal decorrelation trends
- With a min. revisit time of 12 days → global potential

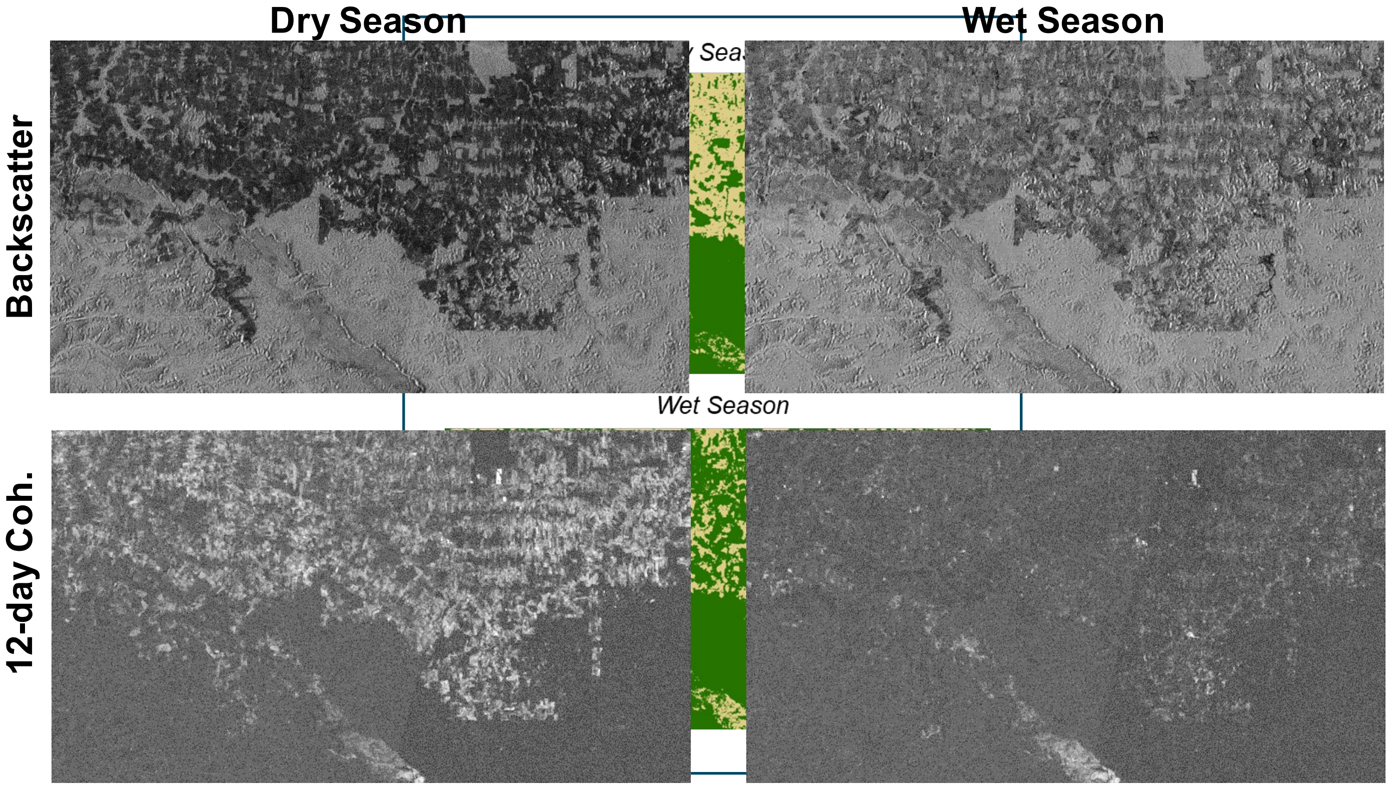
#	Metrics	Classes: NFR	Classes: Forest	Classes: Water	Mean	Overall	
I	F_1-Score	78.41%	91.26%	61.85%	77.17%	87.20%	RF [1]
	Accuracy	87.44%	87.85%	98.93%	91.41%	87.11%	
II	F_1-Score	80.81%	92.17%	69.56%	80.85%	88.62%	RF [2]
	Accuracy	88.86%	89.10%	99.18%	92.38%	88.57%	
III	F_1-Score	87.15%	94.92%	79.99%	87.35%	92.50%	CNN - Baseline Settings
	Accuracy	92.64%	92.87%	99.55%	95.02%	92.53%	
IV	F_1-Score	87.73%	95.18%	80.91%	**87.94%**	**92.85%**	CNN - Coherences 6, 12, 18, 24 days
	Accuracy	92.99%	93.21%	99.58%	**95.26%**	**92.89%**	
V	F_1-Score	83.21%	93.97%	80.52%	85.90%	90.69%	CNN - Coherences 12, 24 days ← *Global cover*
	Accuracy	91.07%	91.28%	99.57%	93.97%	90.96%	
N° of samples		16,157,783	38,624,552	579,201	55,361,536		



Proposed Approach and Proof of Concept



- Accurate classification @50m when compared with the ground truth in the Brazilian state of Rondonia, with the goal of moving towards operational large-scale forest monitoring
- Challenge of dealing with seasonal effects, for instance:

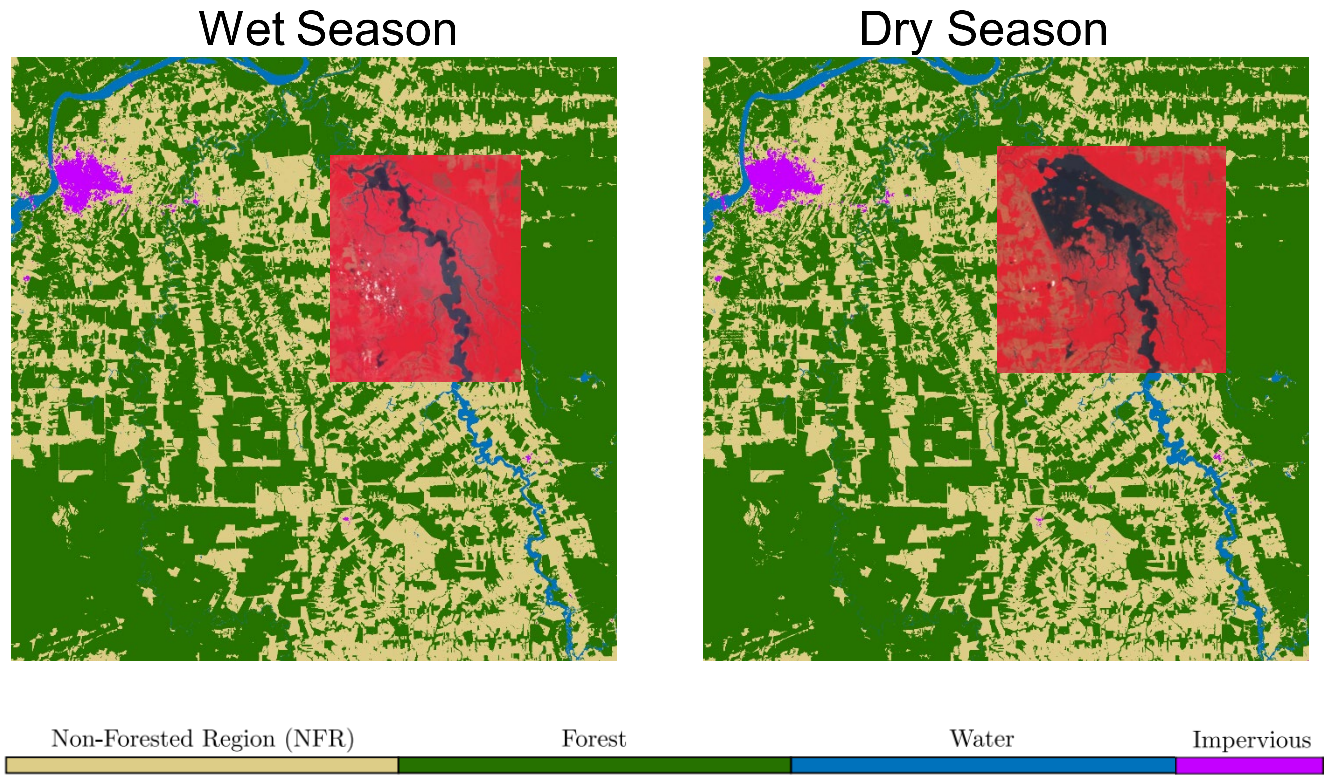


Overview of Seasonal and Geographical Effects on Forest Mapping

- We are currently pushing the resolution of the Sentinel-1 data to a res. @20m, also with dual VV + VH polarization, to further improve the description of LCC

- Challenge of usually having a single ground truth per year, typically acquired during the dry season, so we must determine what comes from actual changes on ground

- How to better validate our results, giving the lack of reliability or frequency in which the ground truths are available in this region

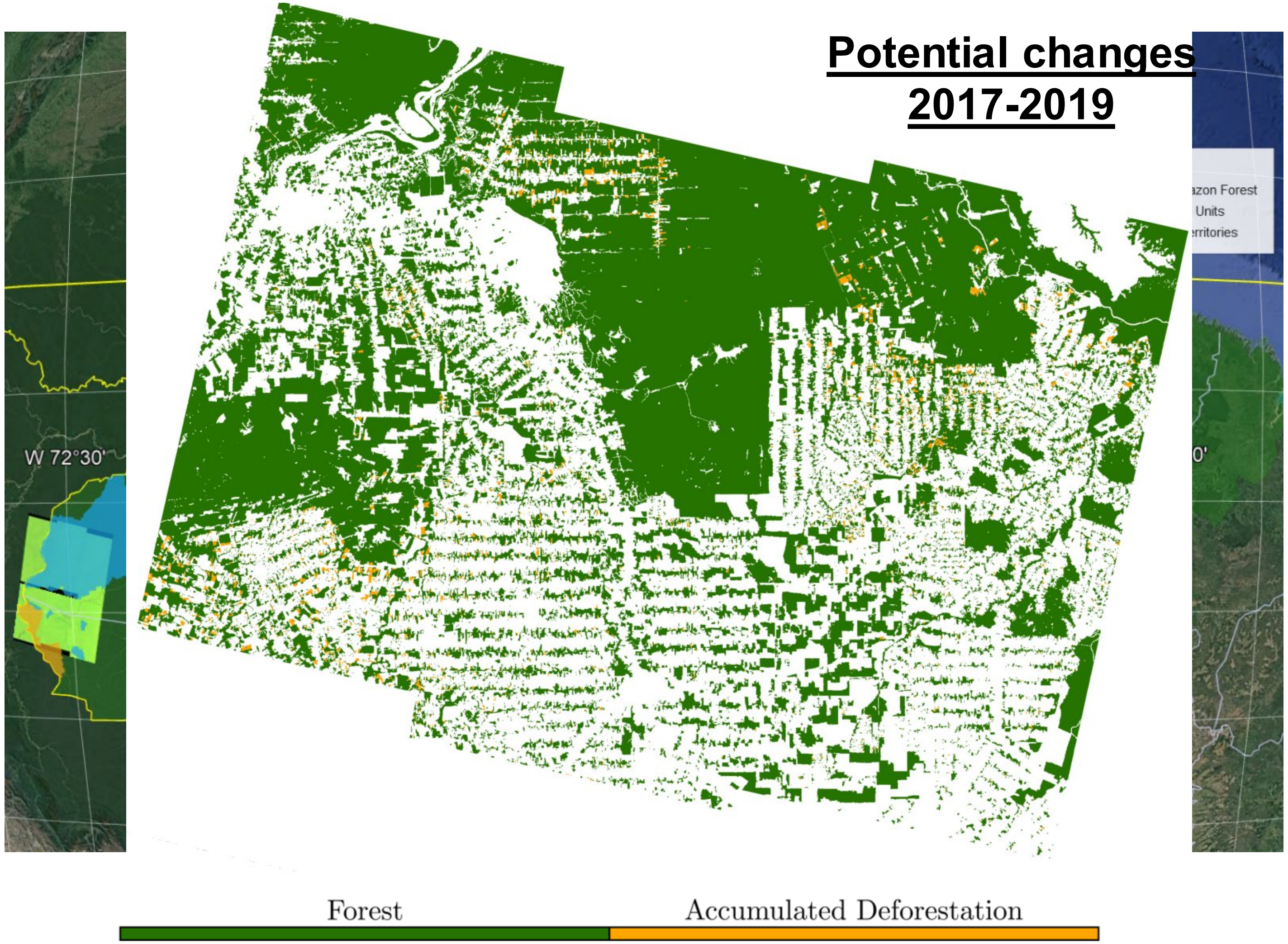


Overview of Seasonal and Geographical Effects on Forest Mapping

- We first mask out potential land cover changes by using annual data from Brazilian deforestation monitoring programs such as PRODES and DETER to focus on the seasonal components affecting each class

- Another challenge comes from the fact that the definition of dry and wet seasons may vary within the forest, just as landscape characteristics

- In order to be able to generate a robust database, we are now sampling data from different regions, prioritizing those expected to be stable over time



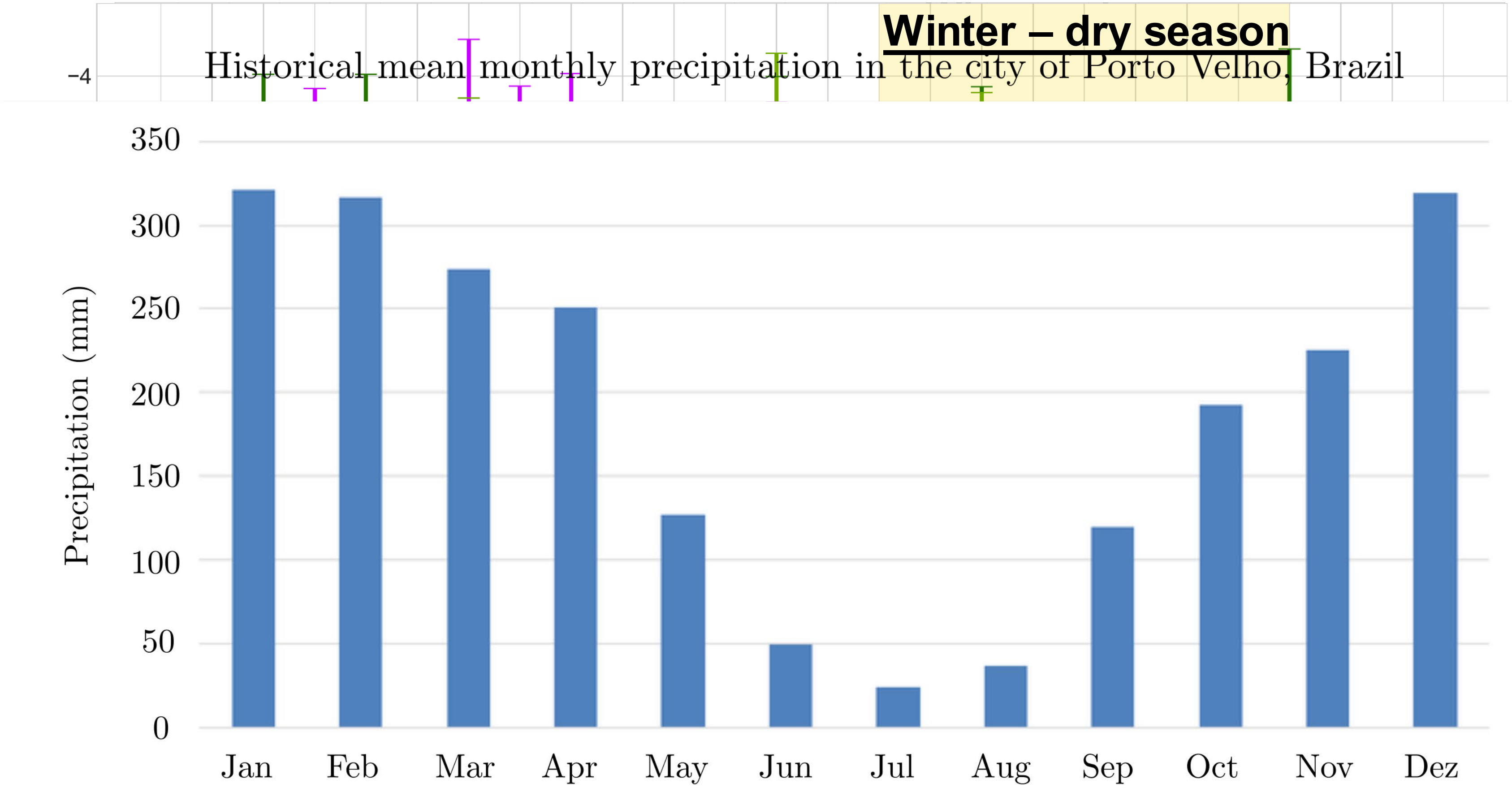
http://terrabrasilis.dpi.inpe.br

Overview of Seasonal and Geographical Effects on Forest Mapping

- The SAR backscatter values of different classes can be relatively similar during the wet season

- These effects are also pronounced for the coherences, in particular concerning croplands

- Ancillary data such as the local average monthly precipitation might help mitigating this problem



Overview of Seasonal and Geographical Effects on Forest Mapping

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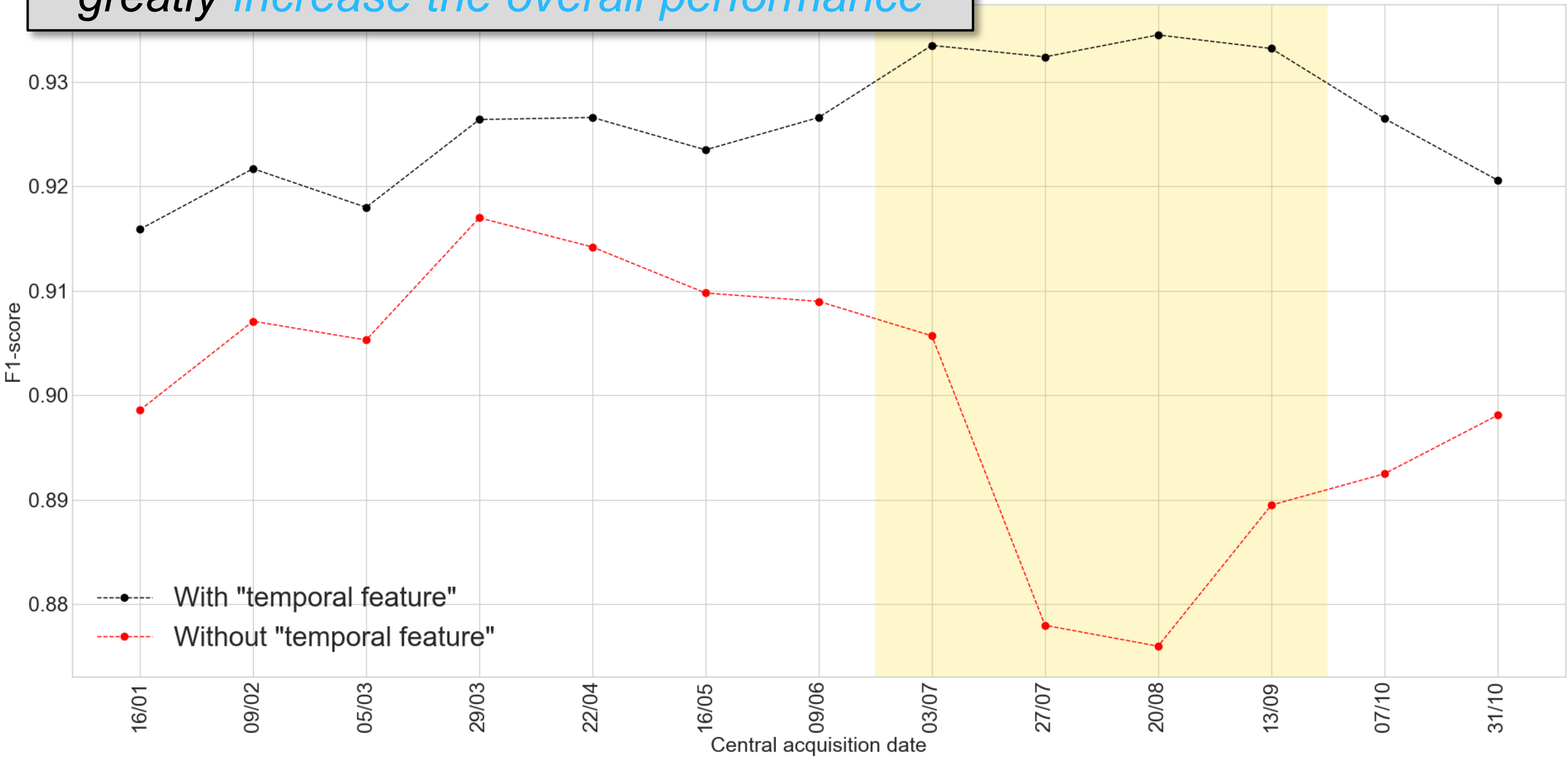
- We now apply our DL-model to the target area for the entire year, now also inputting the acquisition dates as "temporal" features

- Further investigation and a larger sampling is still needed for achieving a model which can be robust to seasonal and regional effects on a large scale

Preliminary results showed that by including a temporal feature we can greatly increase the overall performance



Final Remarks and Outlook

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- S-1 short time series showed a high potential for mapping the Amazon rainforest at ≤ 1 month with a spatial resolution as fine as 20m
- By exploiting the potential of a deep learning model, which can learn texture information and temporal decorrelation patterns by itself, we could achieve an overall acc. ≥ 90% even with only 3 acquisitions at 12 days revisit
- Validation with regular and reliable reference data is a challenge in the Amazon region, where e.g. semi-supervised methods might be attractive for monitoring an environment with high seasonal variability
- We are still investigating the performance and potential of the proposed approaches on a larger scale and over different years to keep track of regional and seasonal patterns

THANK YOU!

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