Multi-source monitoring of forest loss using SAR and multispectral time series

by

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isae Institut Supérieur de l'Aéronautique et de l'Espace SUPAERO cnes

FOREST LOSS

100 Mha

2000 - 2020

France ~55 Mha

~50% illegal

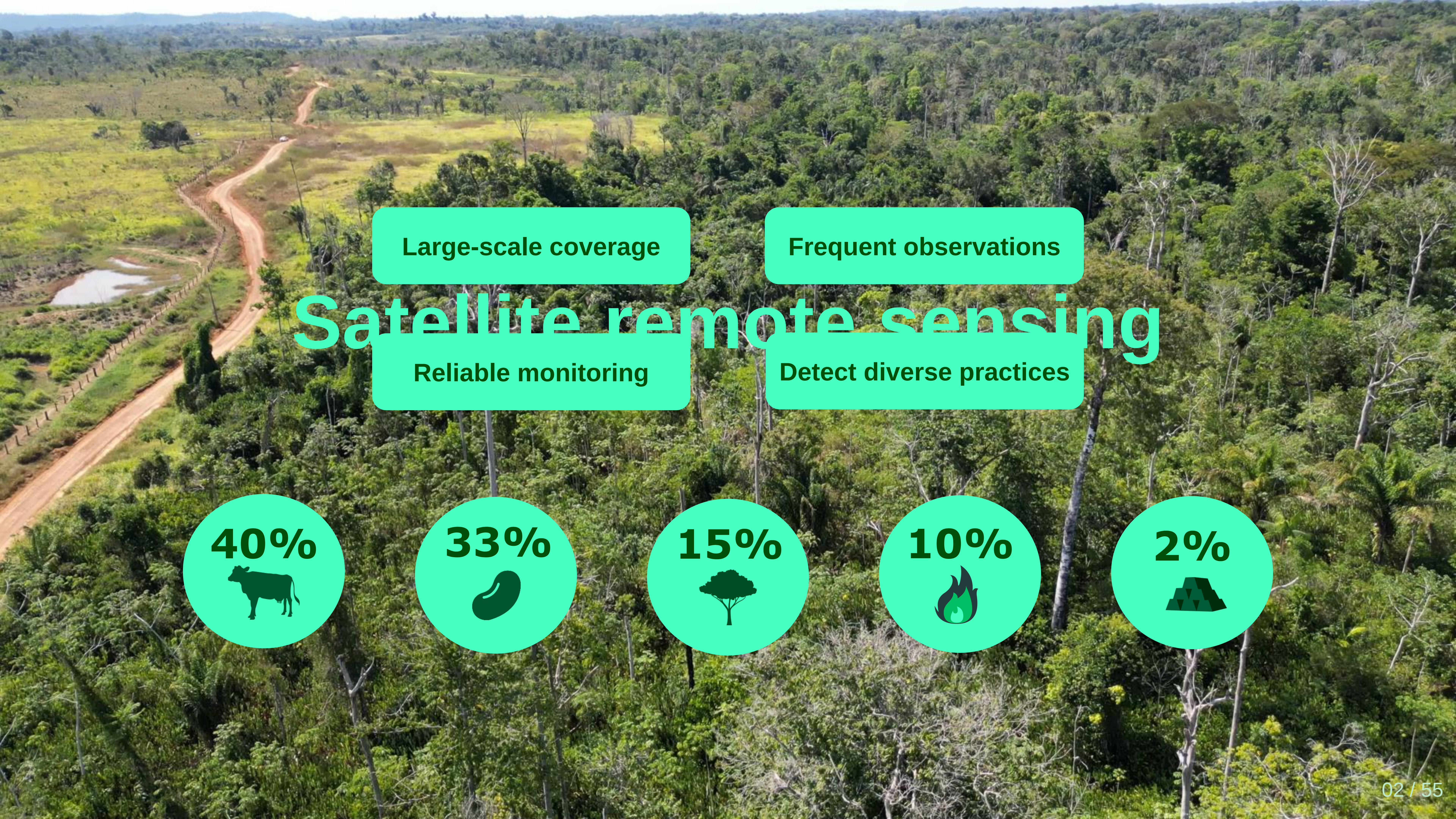
↓

1.5 Gt

CO_2 per year

[Harris et al. 2021]


We need forest loss monitoring to
support conservation actions

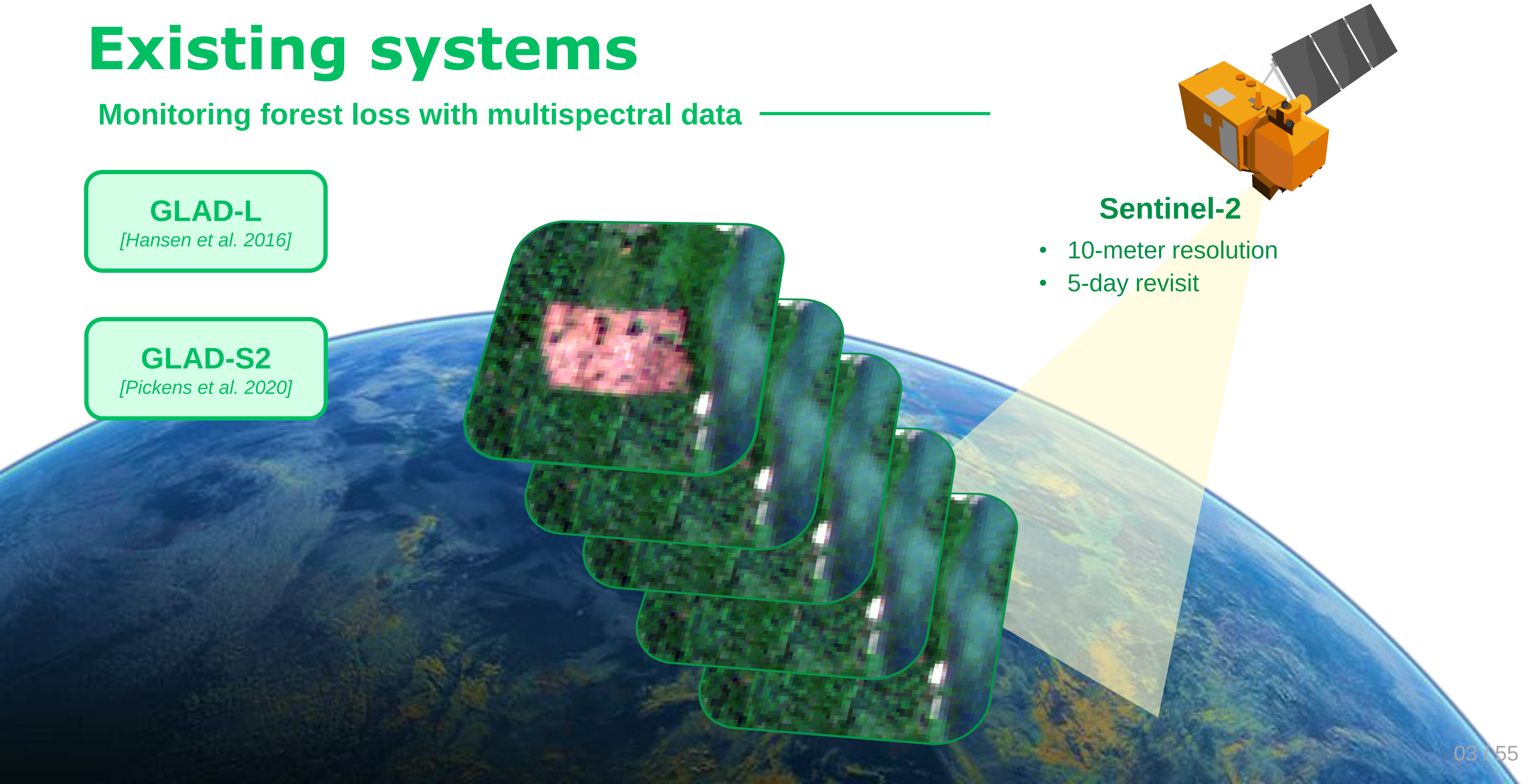

Satellite remote sensing
Large-scale coverage
Frequent observations
Reliable monitoring
Detect diverse practices
40%
33%
15%
10%
2%

Existing systems

Monitoring forest loss with multispectral data

GLAD-L
[Hansen et al. 2016]

GLAD-S2
[Pickens et al. 2020]



Sentinel-2

- 10-meter resolution
- 5-day revisit

Existing systems

Monitoring forest loss with multispectral data

GLAD-L
[Hansen et al. 2016]

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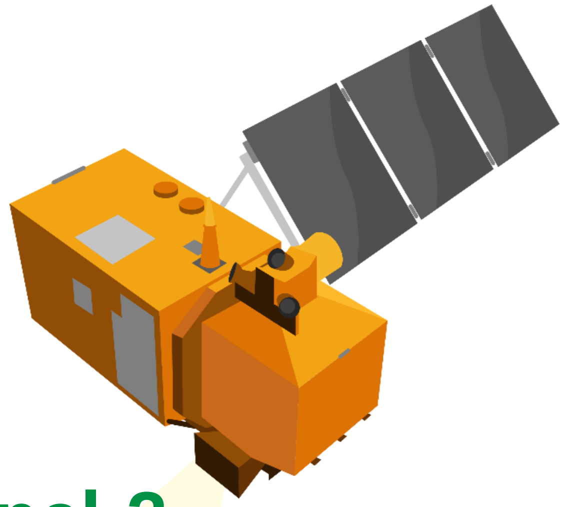
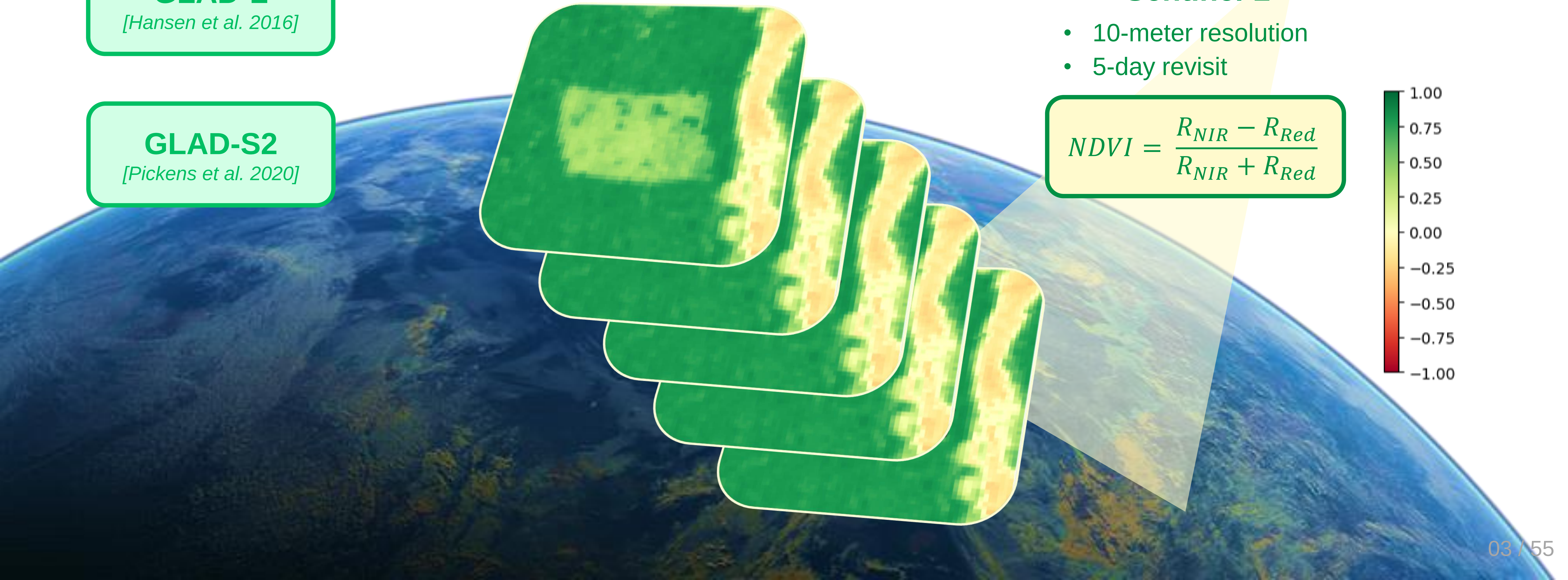


Sentinel-2

- 10-meter resolution
- 5-day revisit

$$NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}$$



Existing systems

Monitoring forest loss with multispectral data

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[Hansen et al. 2016]

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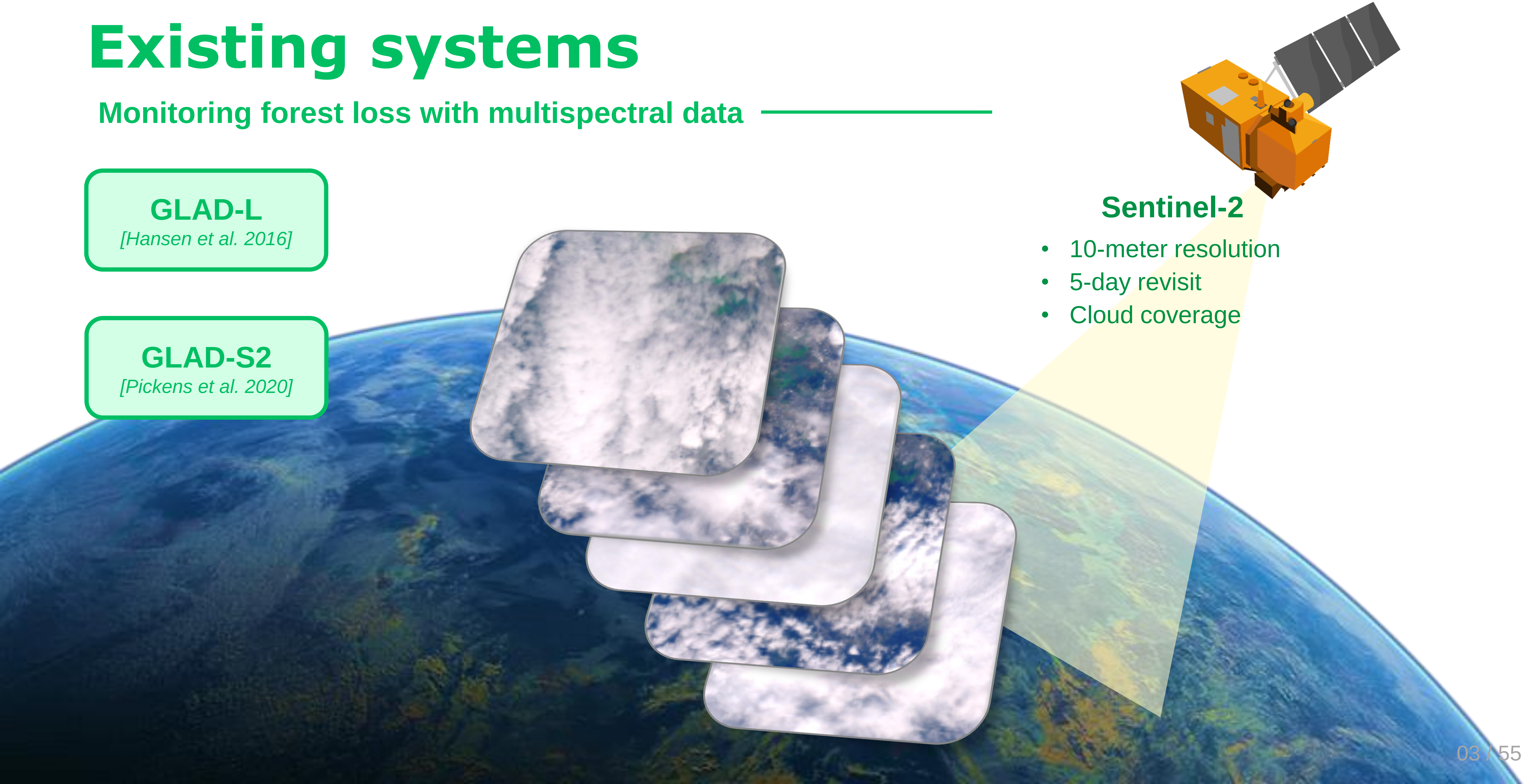


Sentinel-2

- 10-meter resolution
- 5-day revisit
- Cloud coverage

Existing systems

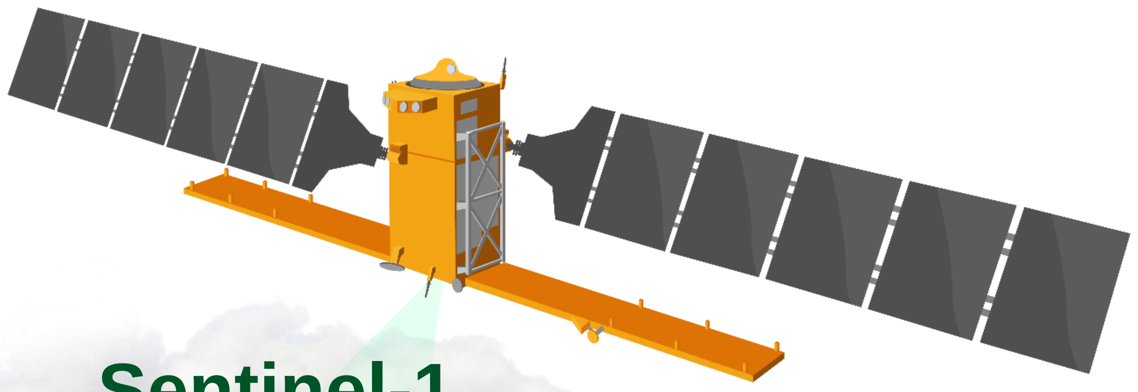
Monitoring forest loss with SAR data

TropiSCO
[Mermoz et al. 2021]

DETER-R
[Doblas et al. 2022]

RADD
[Reiche et al. 2021]

LUCA
[Mulissa et al. 2023]



Sentinel-1

- C-band (f_c=5.405 GHz)
- ~20-meter resolution
- 6-day revisit
- All-weather capability

Existing systems

Monitoring forest loss with SAR data

TropiSCO
[Mermoz et al. 2021]

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[Doblas et al. 2022]

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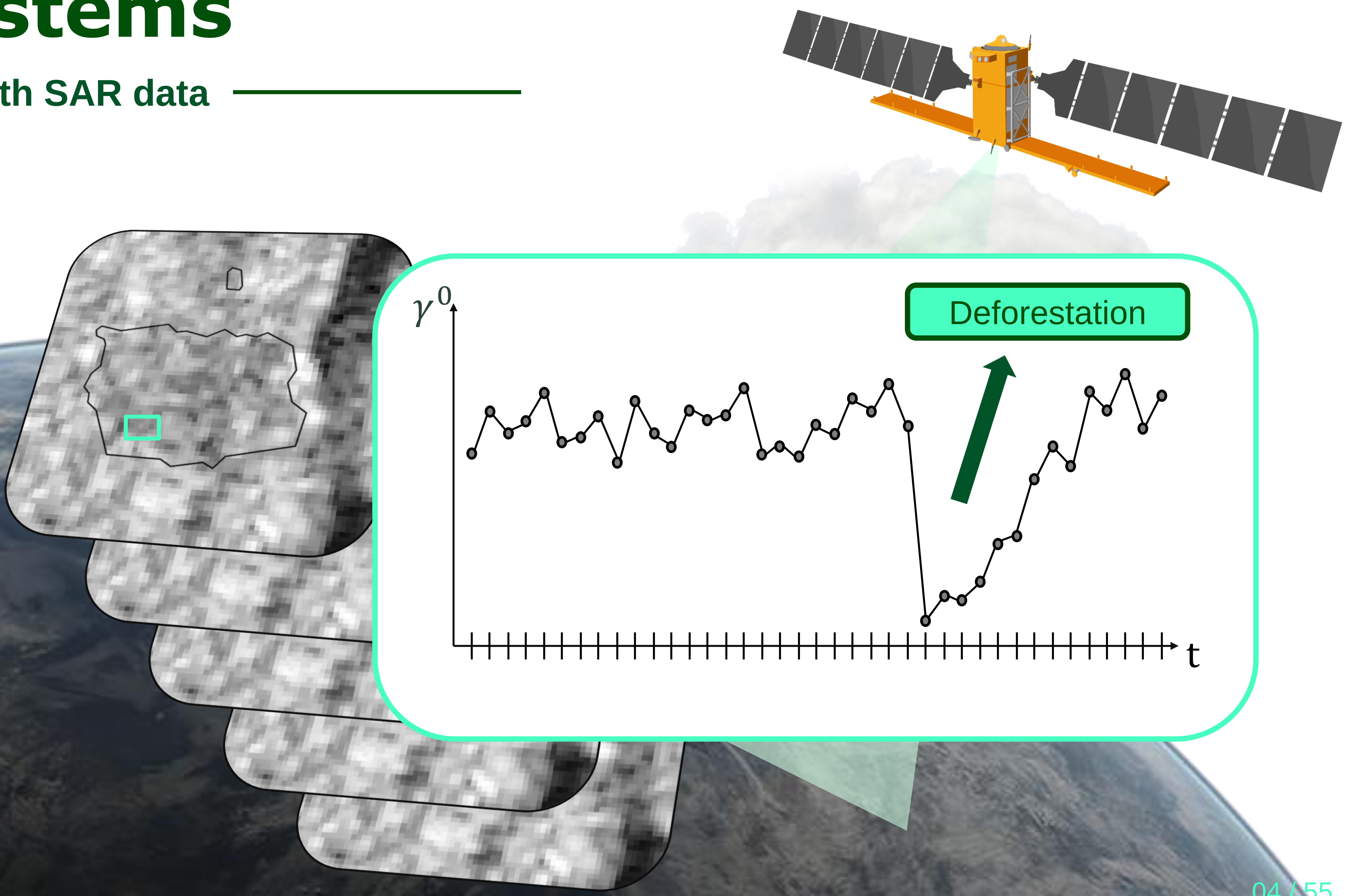

Existing systems

Monitoring forest loss with SAR data

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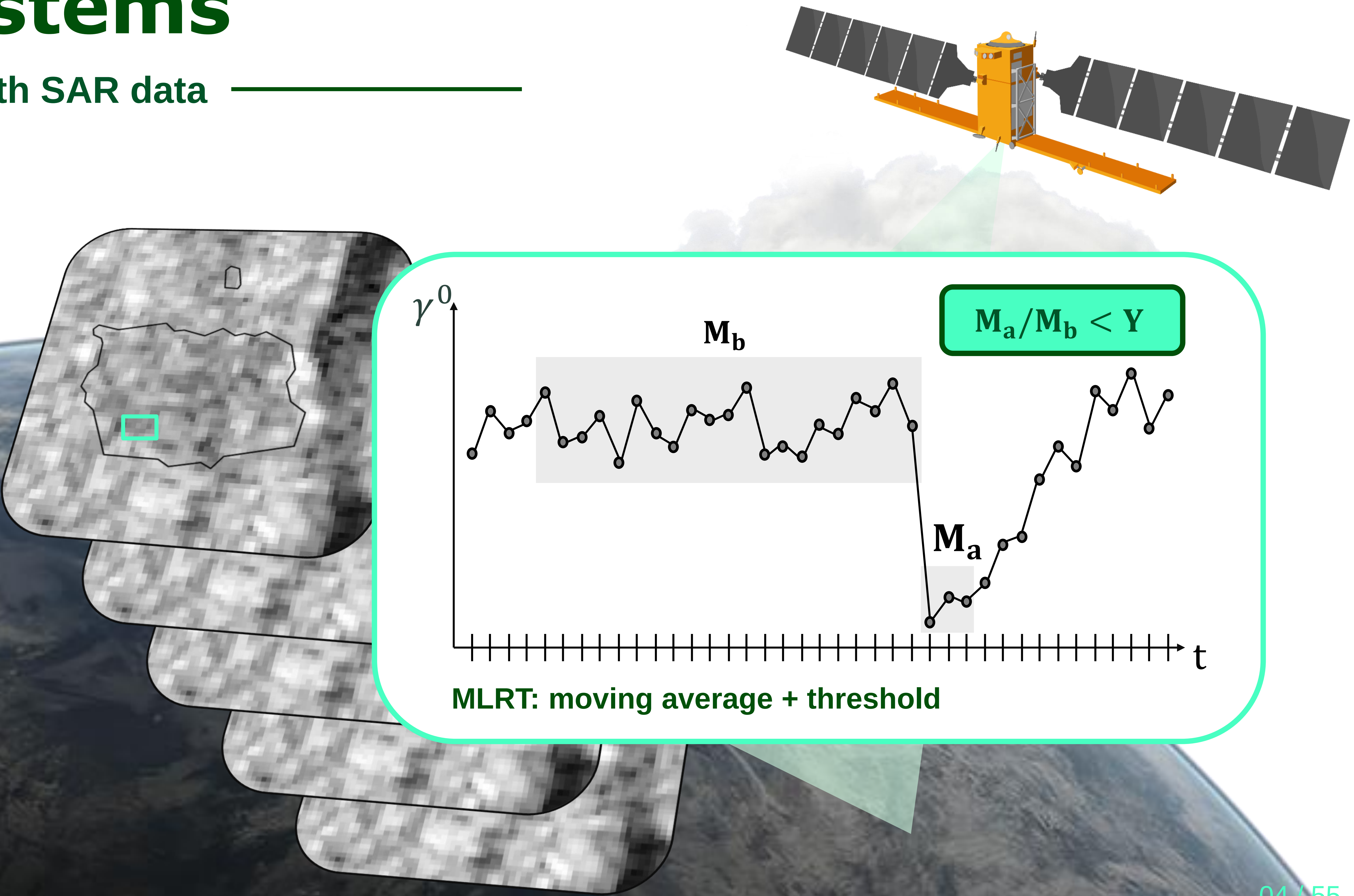
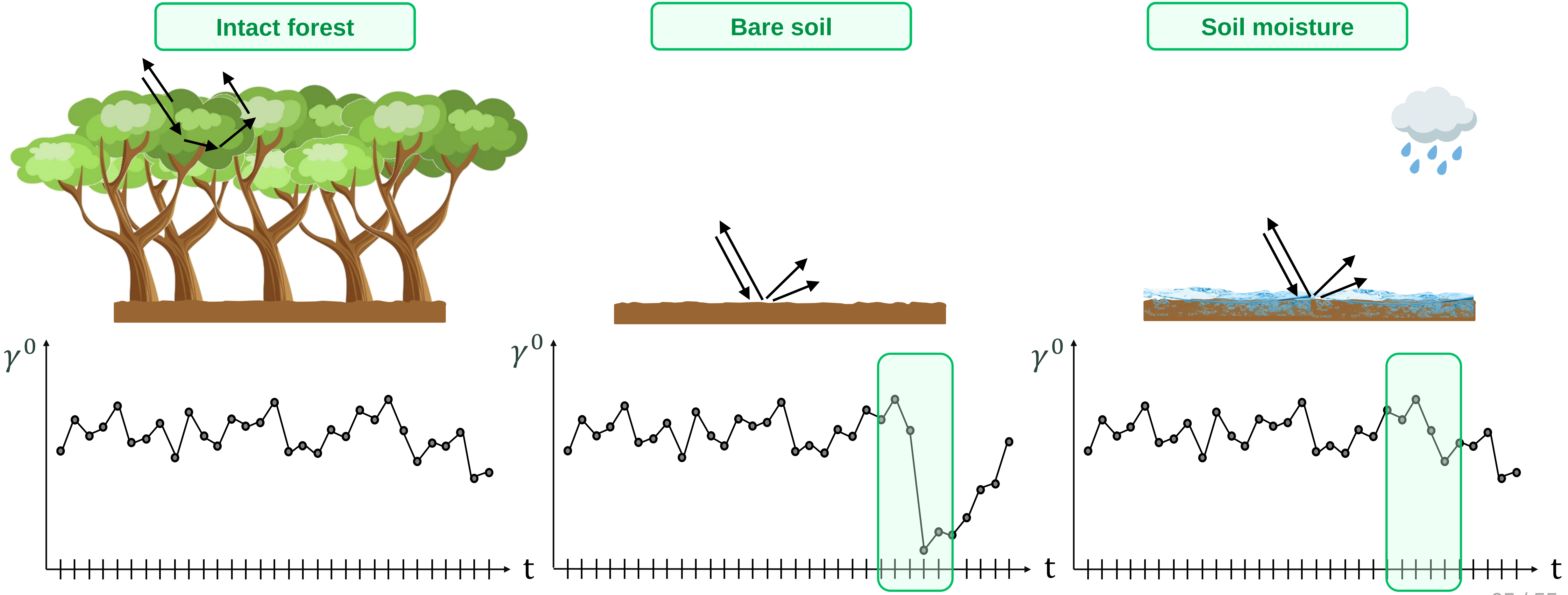


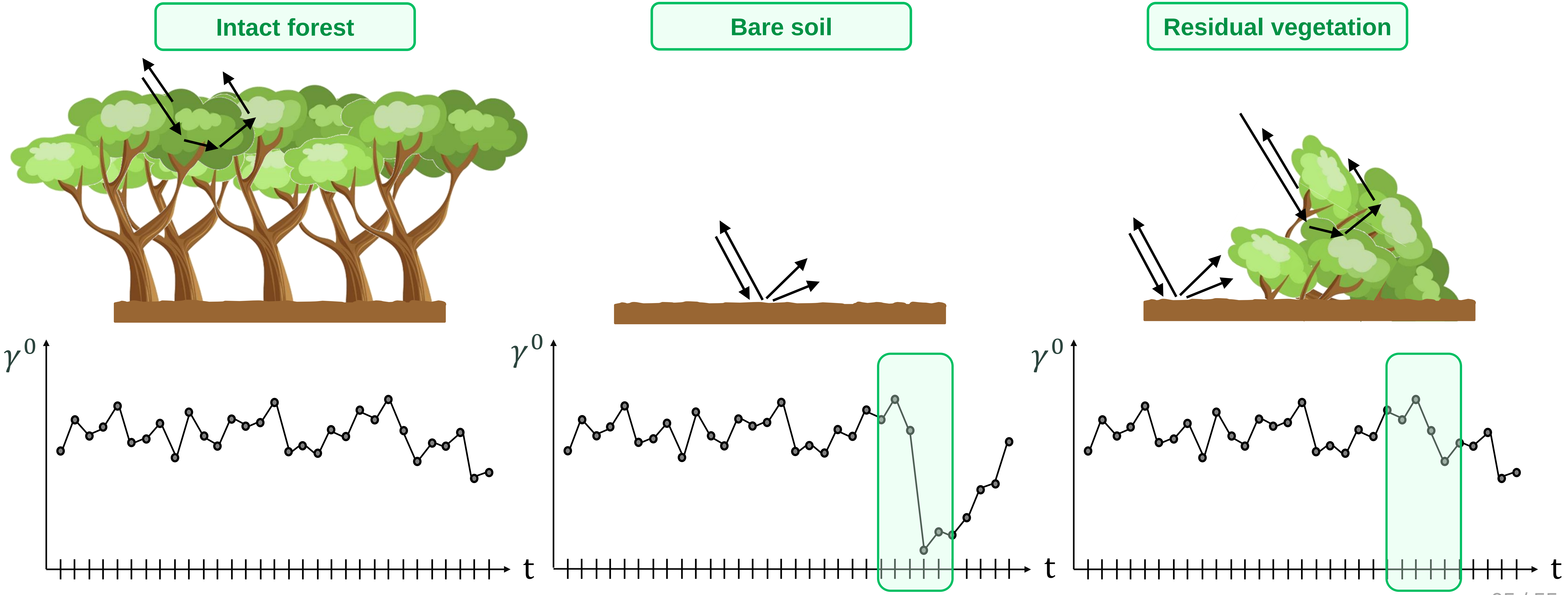
Challenges for SAR systems

1. Signal variability at C band due to soil conditions



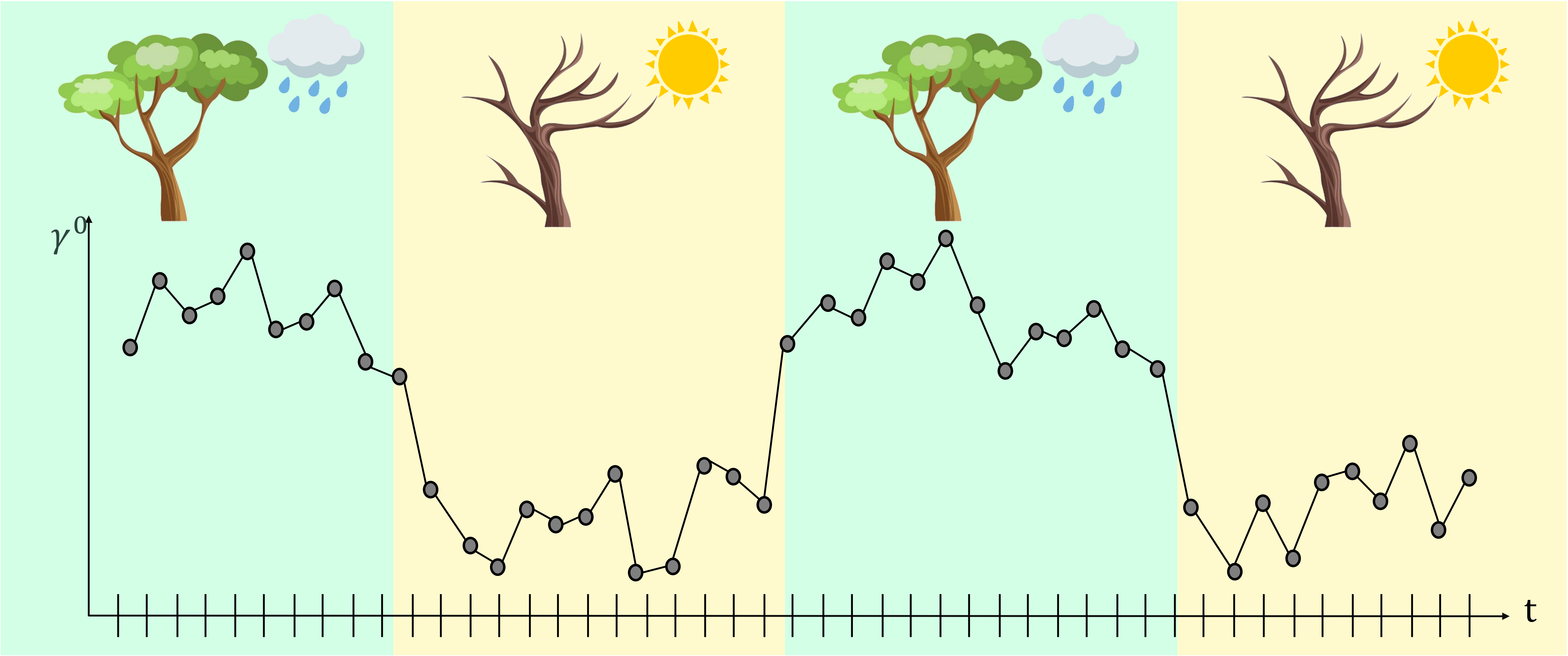
Challenges for SAR systems

1. Signal variability at C band due to soil conditions



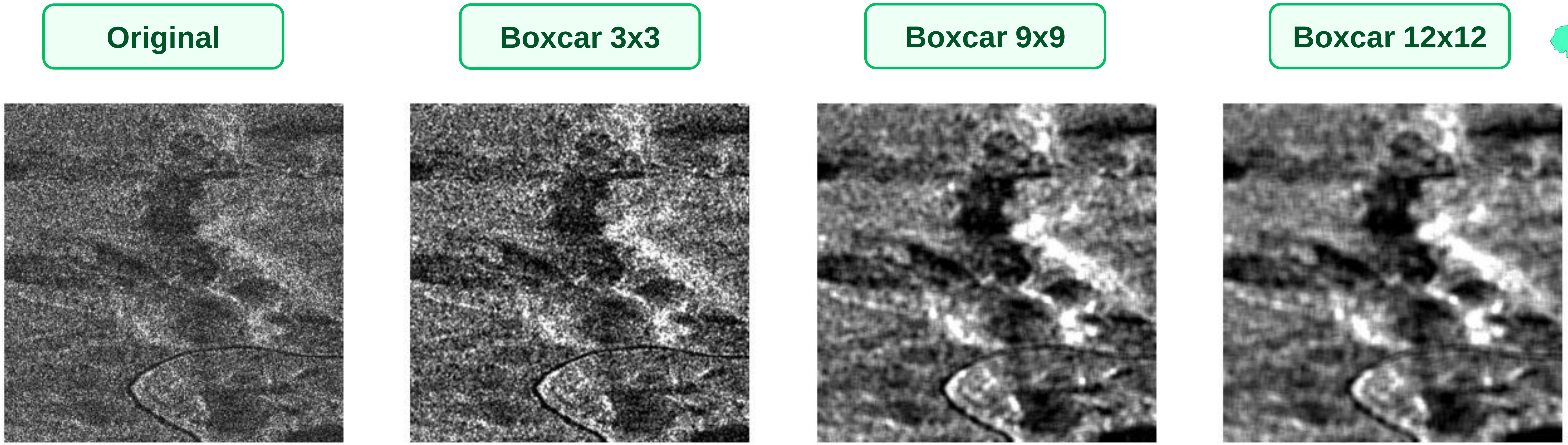
Challenges for SAR systems

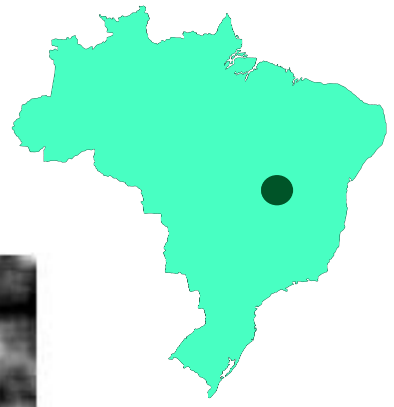
2. Seasonality



Challenges for SAR systems

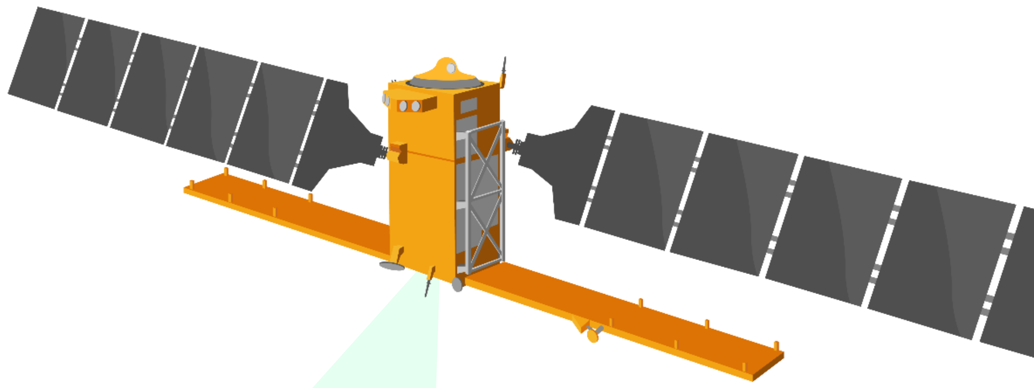
3. Detection of small details due to filtering





Lower spatial resolution → Omissions | Over-estimation

Objective



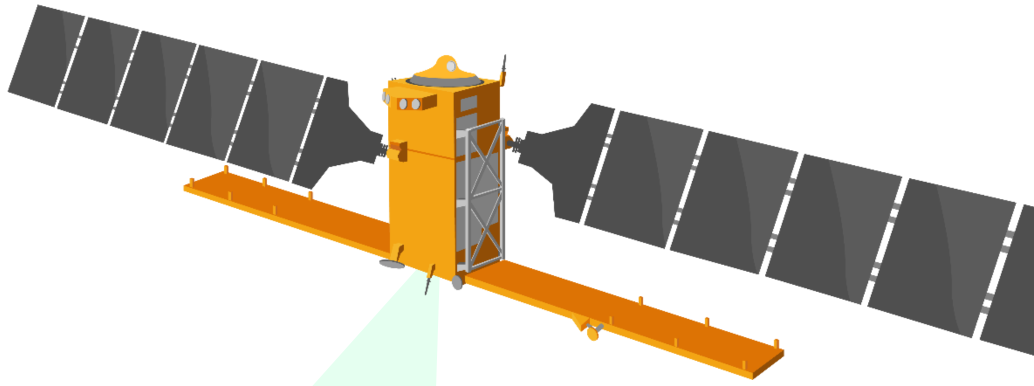
New forest loss monitoring method

- Unsupervised
- Near real-time
- Large scale
- Adaptive

↓

Sequential processing through Bayesian formalism

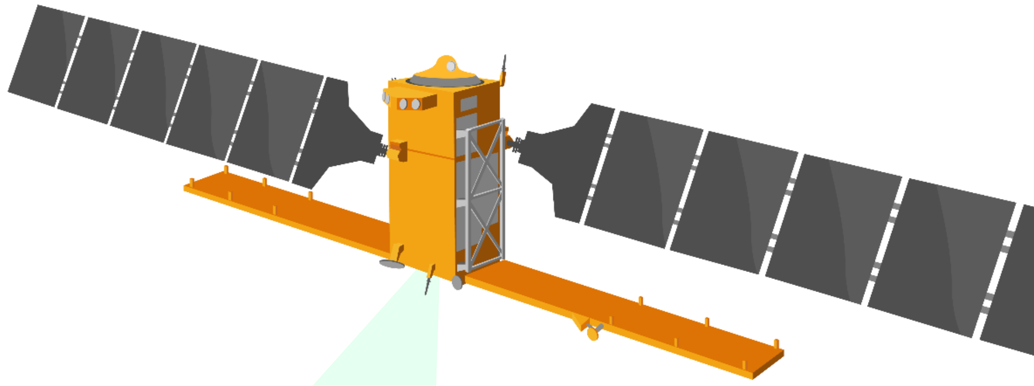
Contributions



New forest loss monitoring method

- **Method for single-polarization Sentinel-1 data**
- **Extension to dual-polarization Sentinel-1 data**
- **Generalization to Sentinel-1 and Sentinel-2 fusion**
- **Study case: fire-induced forest loss detection**

Contributions



New forest loss monitoring method

BOCD

***pol*-BOCD**

***ms*-BOCD**

***F*-BOCD**

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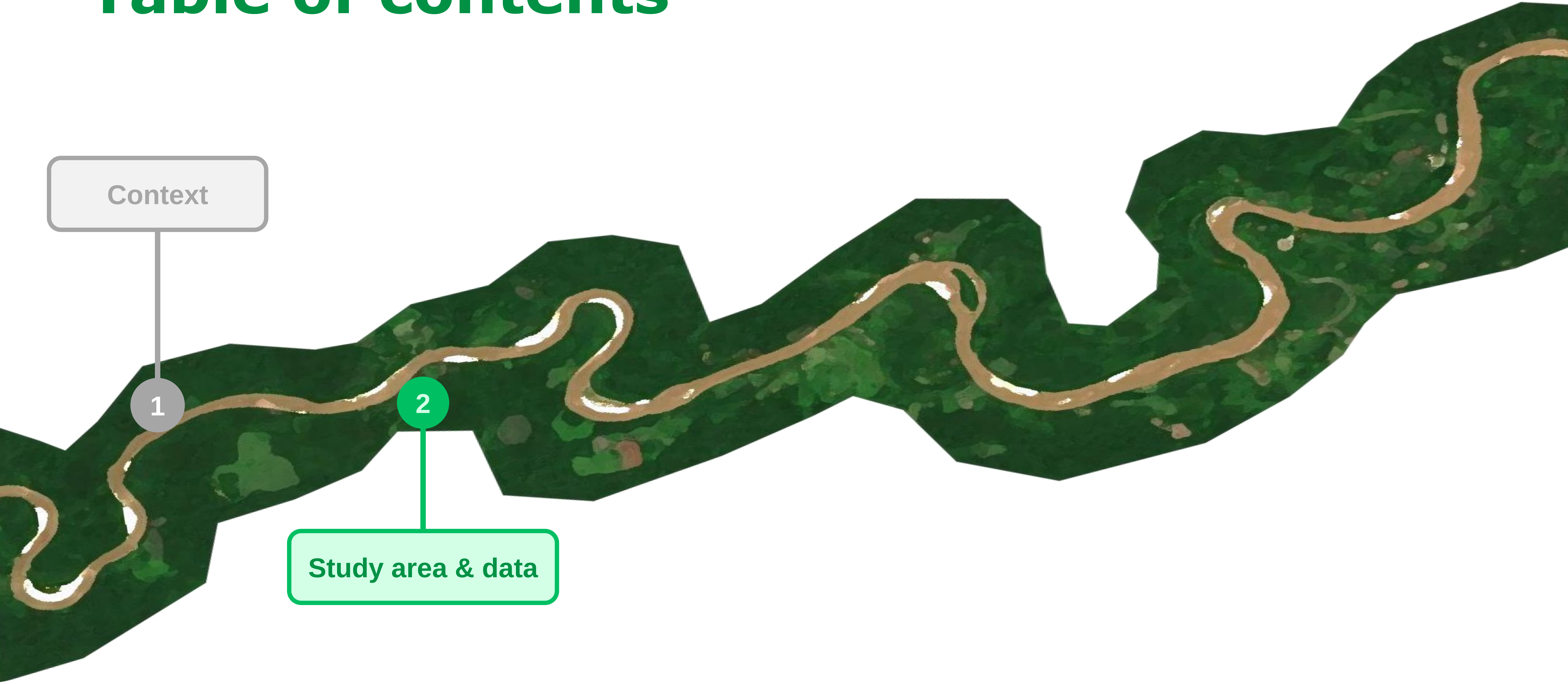
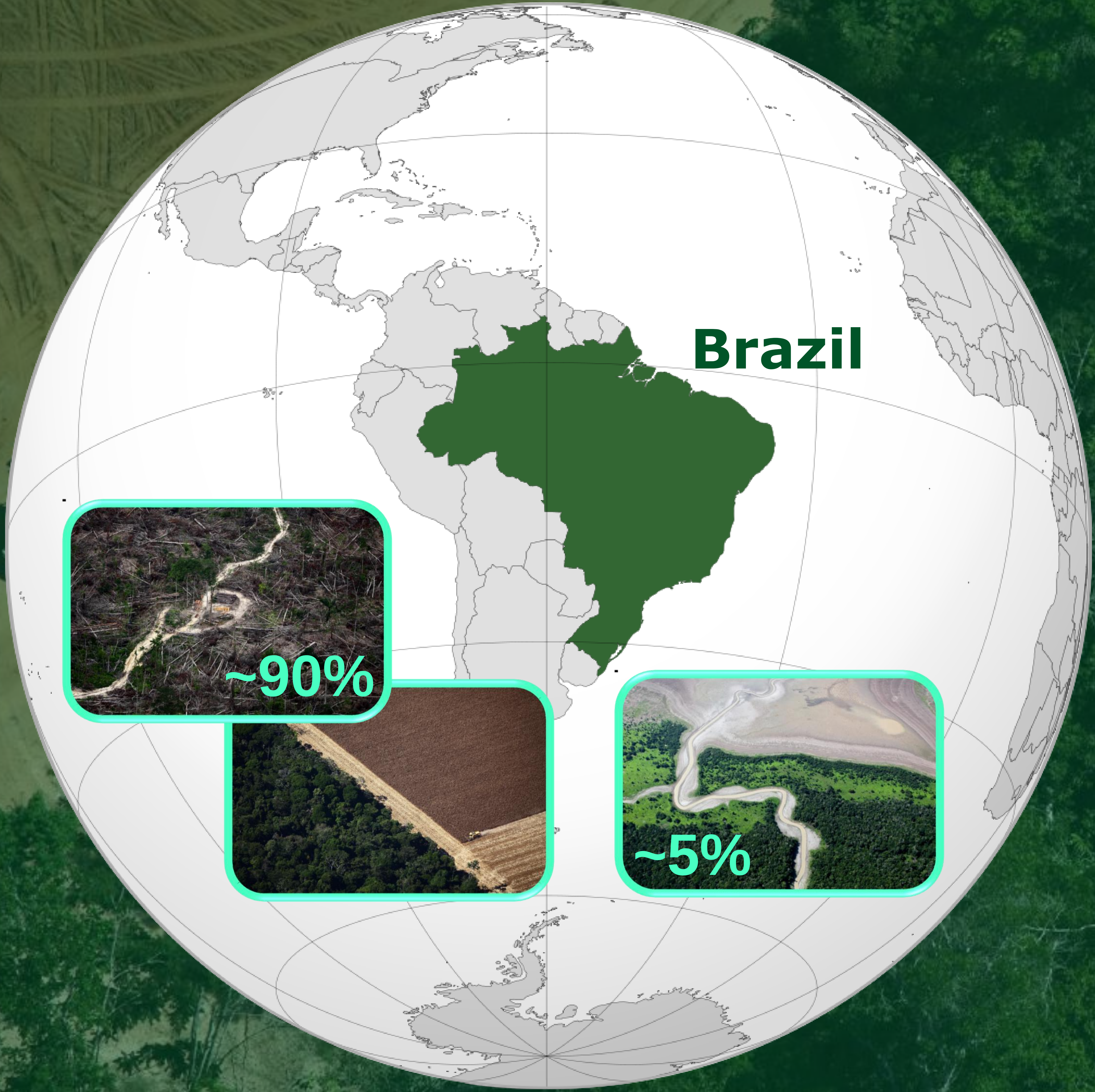




Study area

2019 - 2022

6.5M ha → **12%**

90% → **2** Brazilian Biomes

21 trees per second

[RAD 2023]

Study area

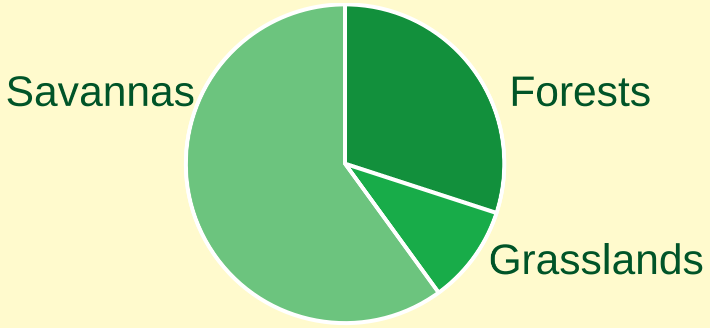
Two biomes

Amazonia

- Rainforest
- 40% of Brazil
- **Well monitored** in NRT
- Small-scale / fragmented deforestation

Cerrado

- Savanna
- 20% of Brazil
- Mixed land cover :

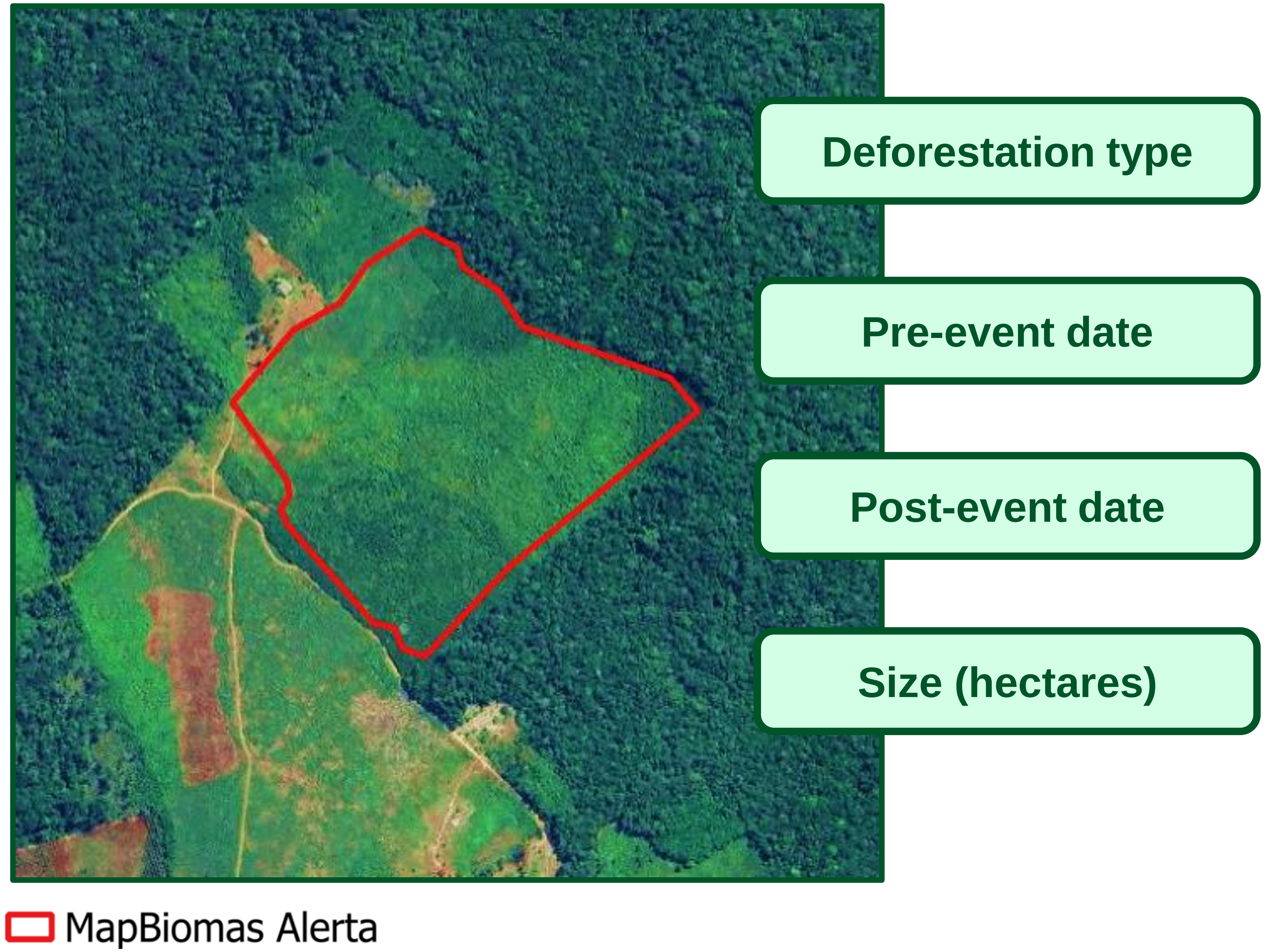


- **Strong seasonality**
- **Under-monitored** in NRT
- Industrial agriculture

Reference data

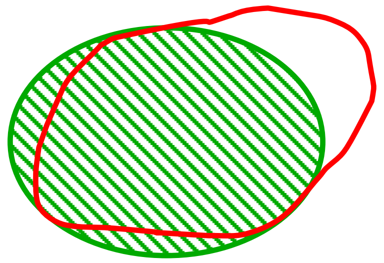
- **MapBiomas Alerta**

  Visual inspection of high-resolution optical imagery



Reference data

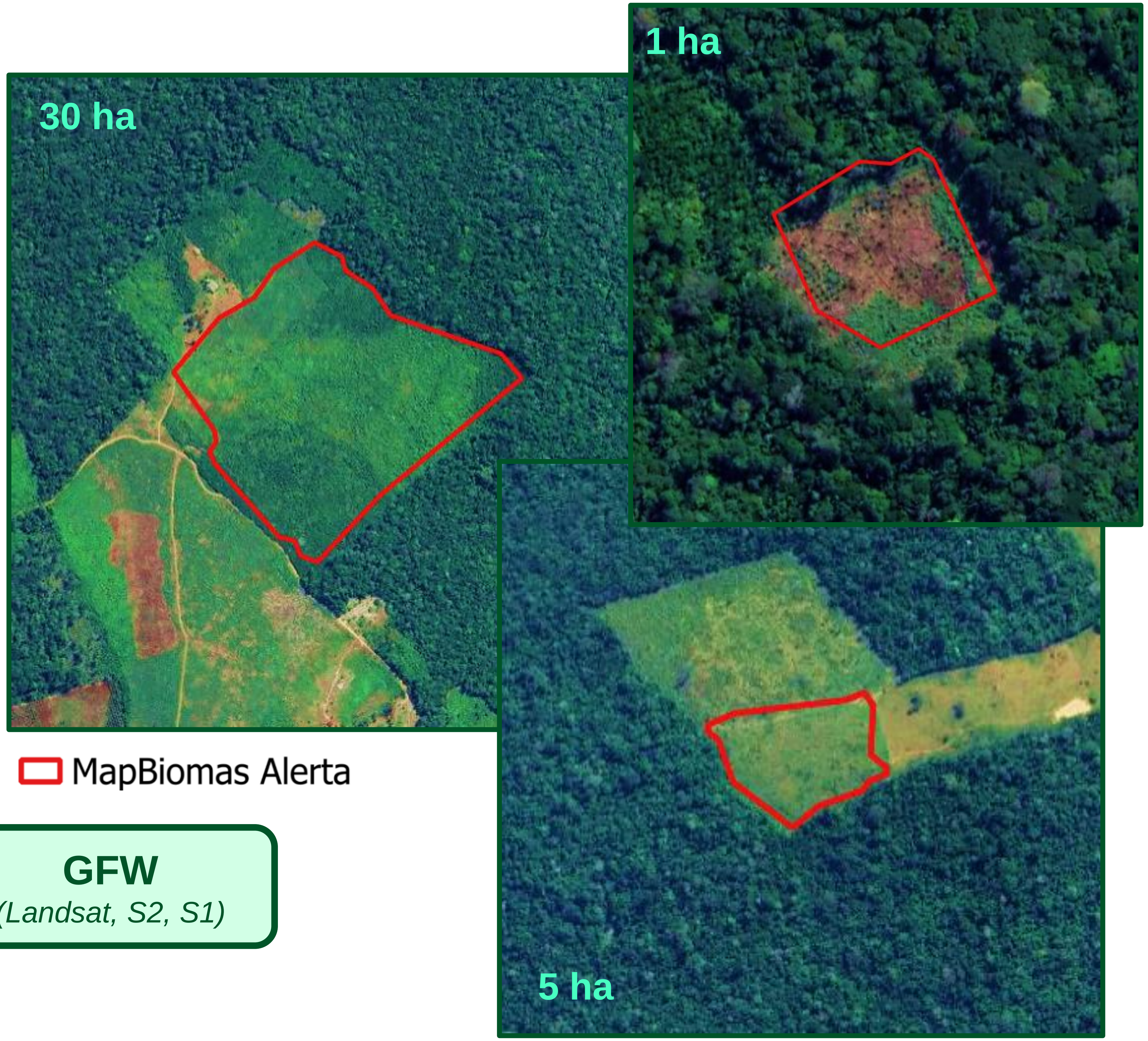
- **MapBiomas Alerta**
- **Monitoring year 2020**
- **Principle of detection**



$$\frac{A_{\text{detected}}}{A_{\text{polygon}}} \geq T_{\text{poly}}$$

- **Comparison**

RADD	GLAD-L	GFW
(Sentinel-1)	*(Landsat)*	*(Landsat, S2, S1)*



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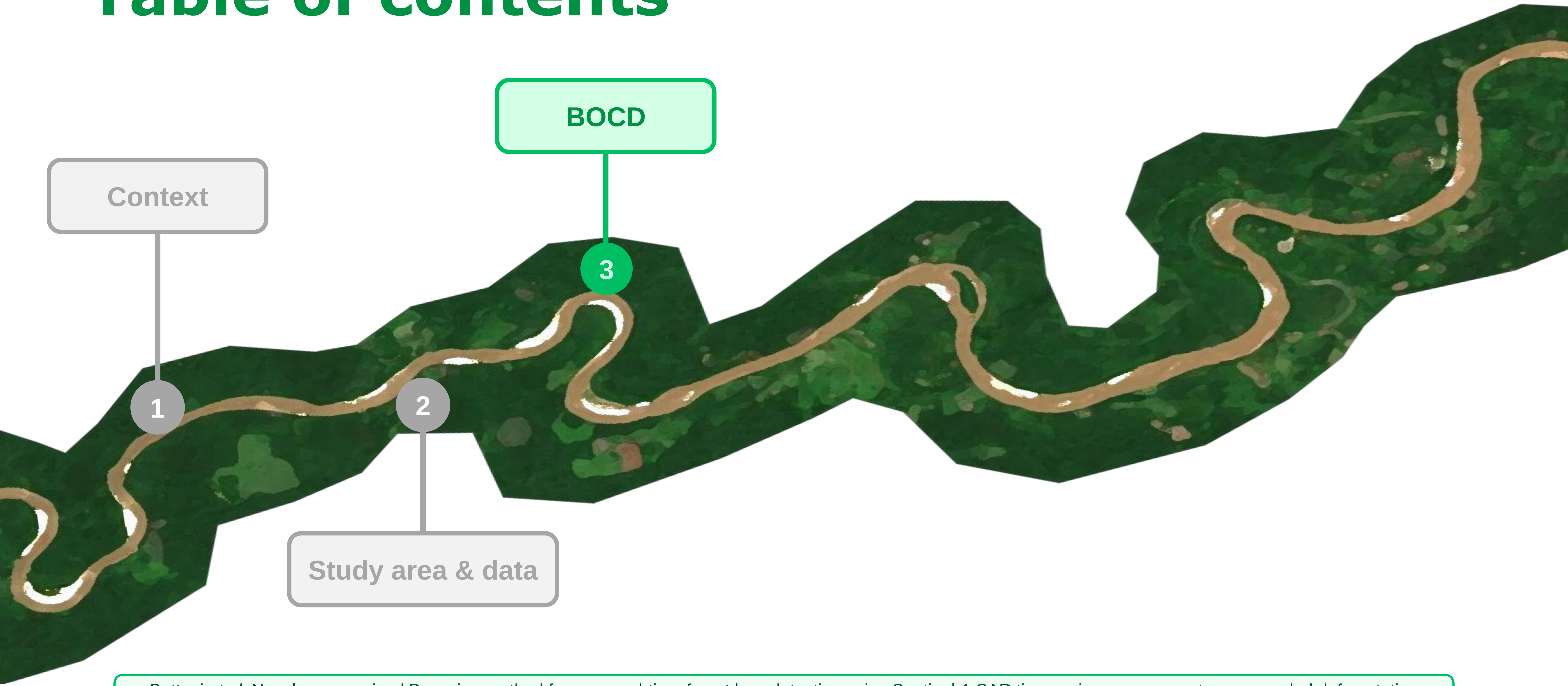


Bottani *et al*. Novel unsupervised Bayesian method for near real-time forest loss detection using Sentinel-1 SAR time series: assessment over sampled deforestation events in Amazonia and the Cerrado. *Remote Sensing of Environment*, 2025.

Bayesian method

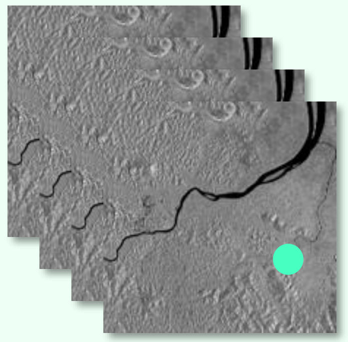
BOCD: recursive online MAP estimation

“Bayesian Online Change Point Detection”

[Adams and Mackay 2007]

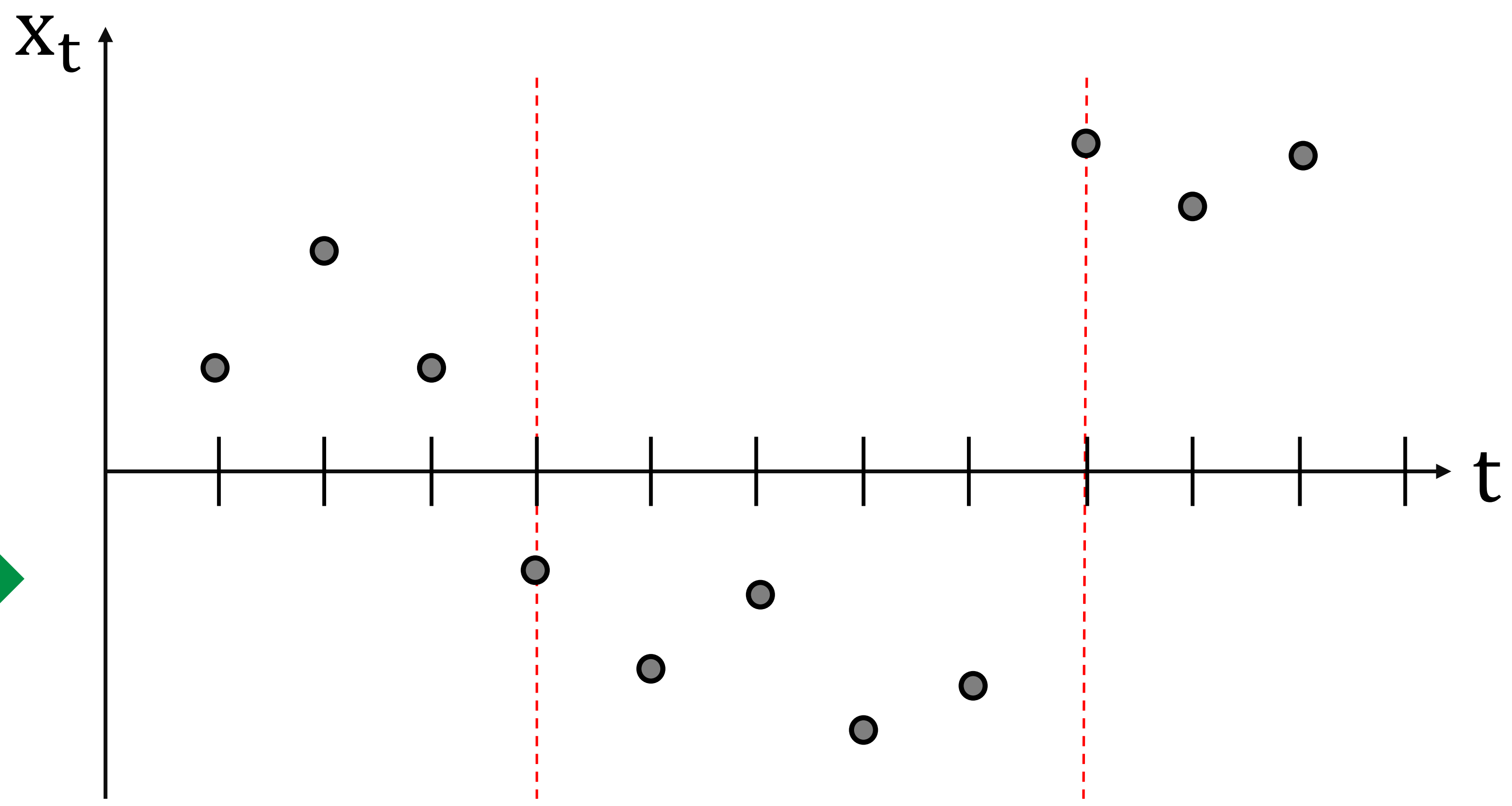
Bayesian method

BOCD: recursive online MAP estimation

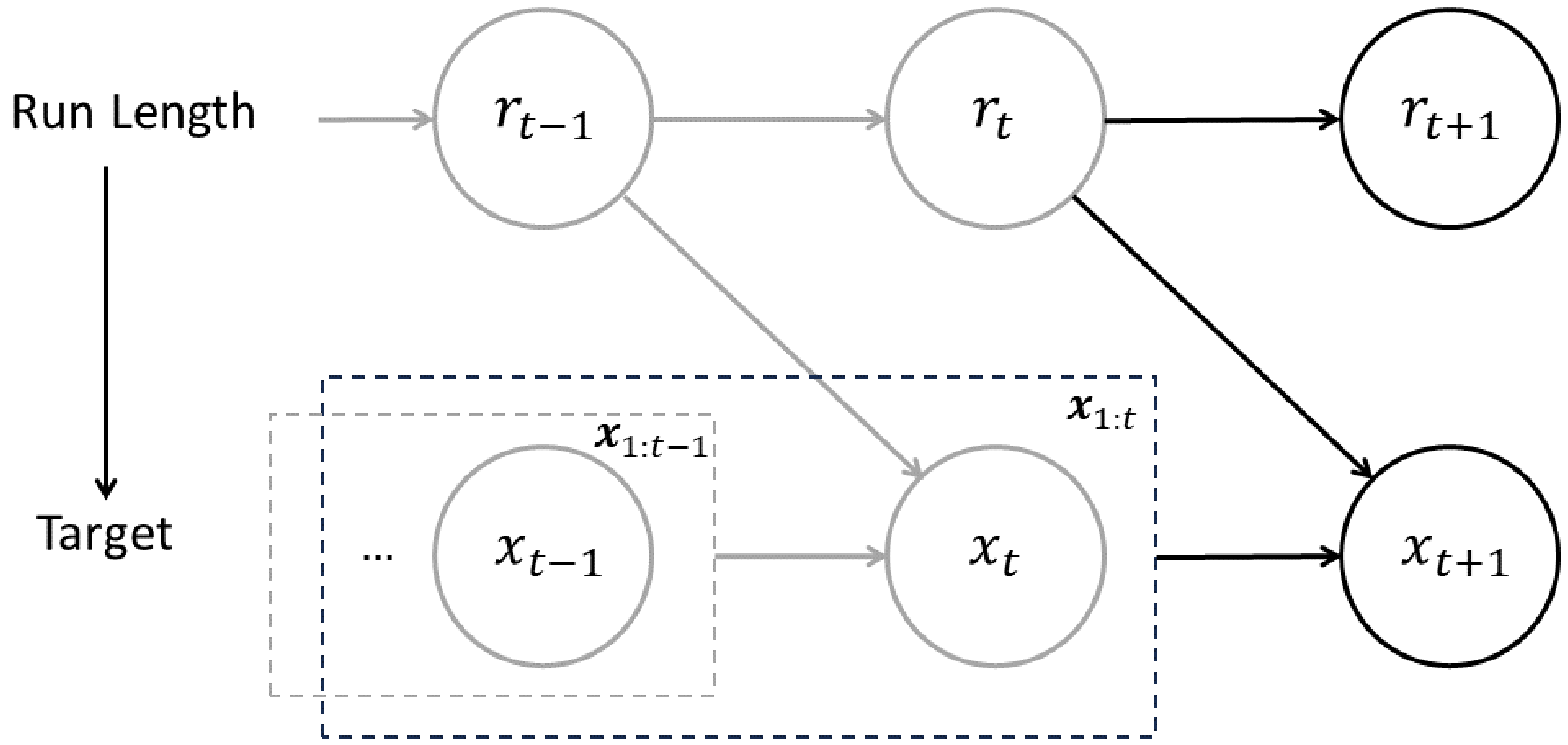


Sentinel-1 data

$\boldsymbol{x}_{1:t} = (x_1, \ldots, x_t)^T \in \mathbb{R}^t,\ x_i = \gamma^0_{VH}$ [dB]

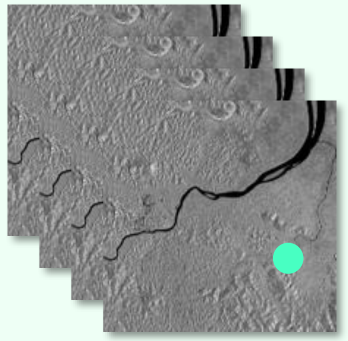


Hidden Markov Model



Bayesian method

BOCD: recursive online MAP estimation



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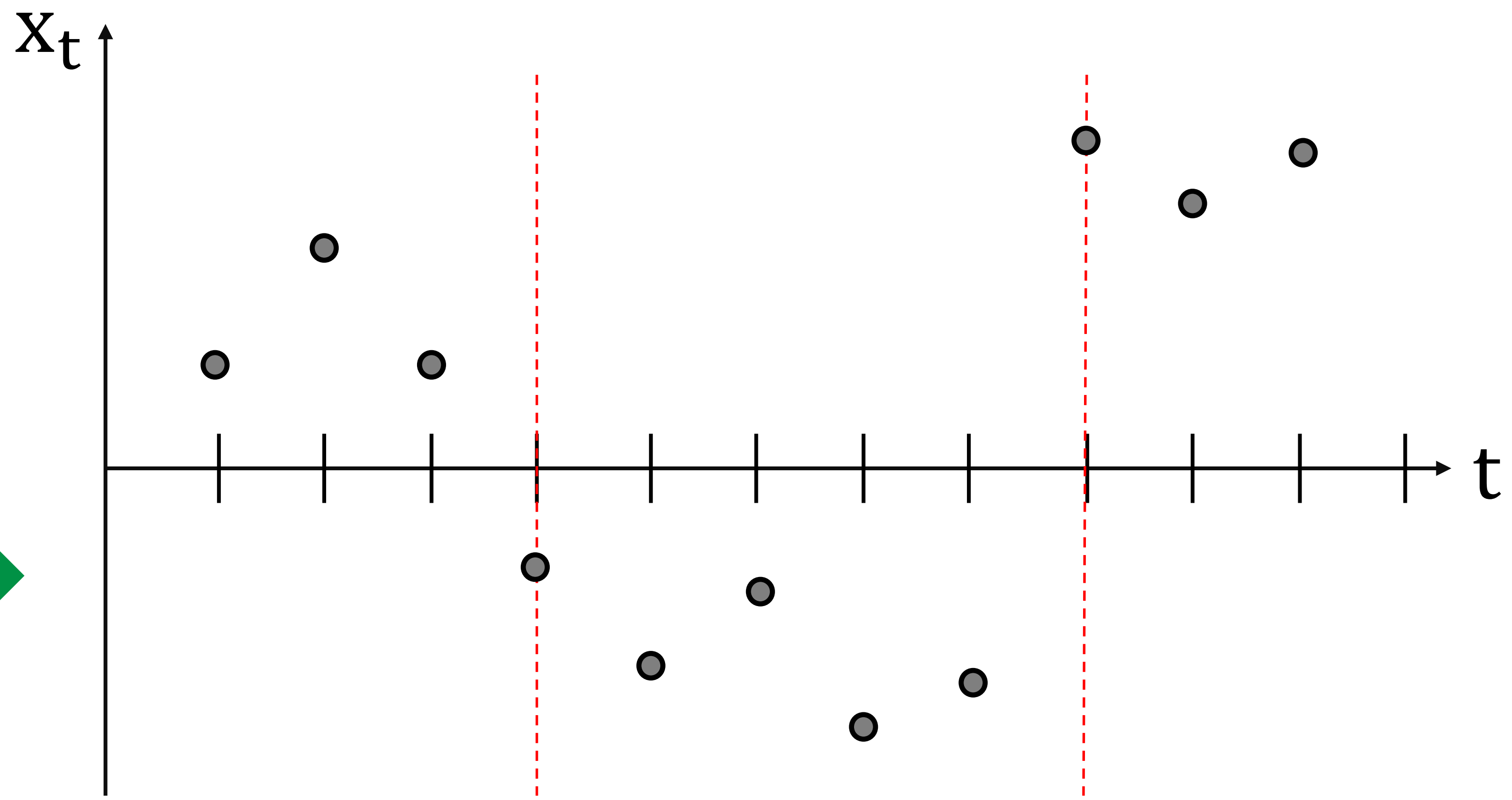
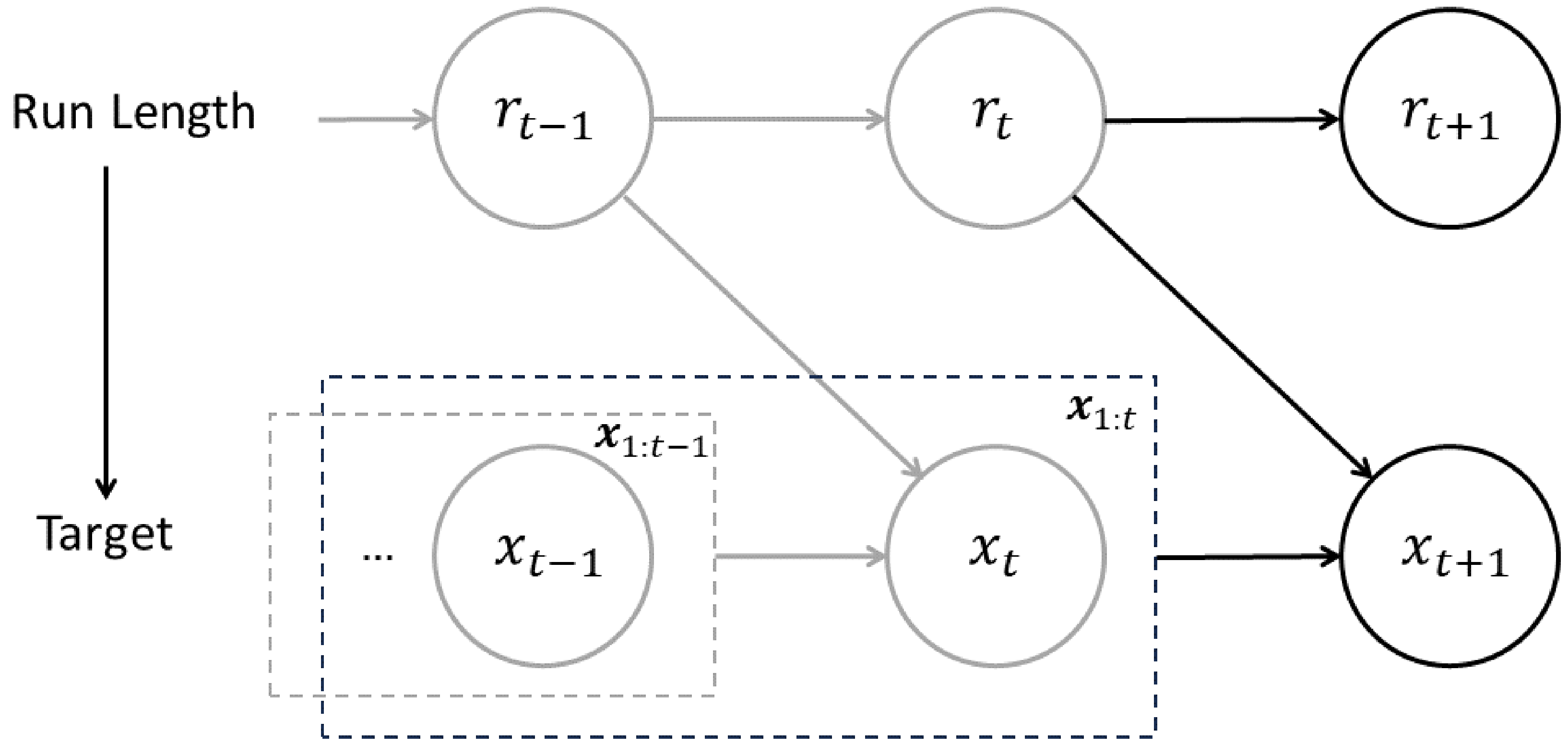
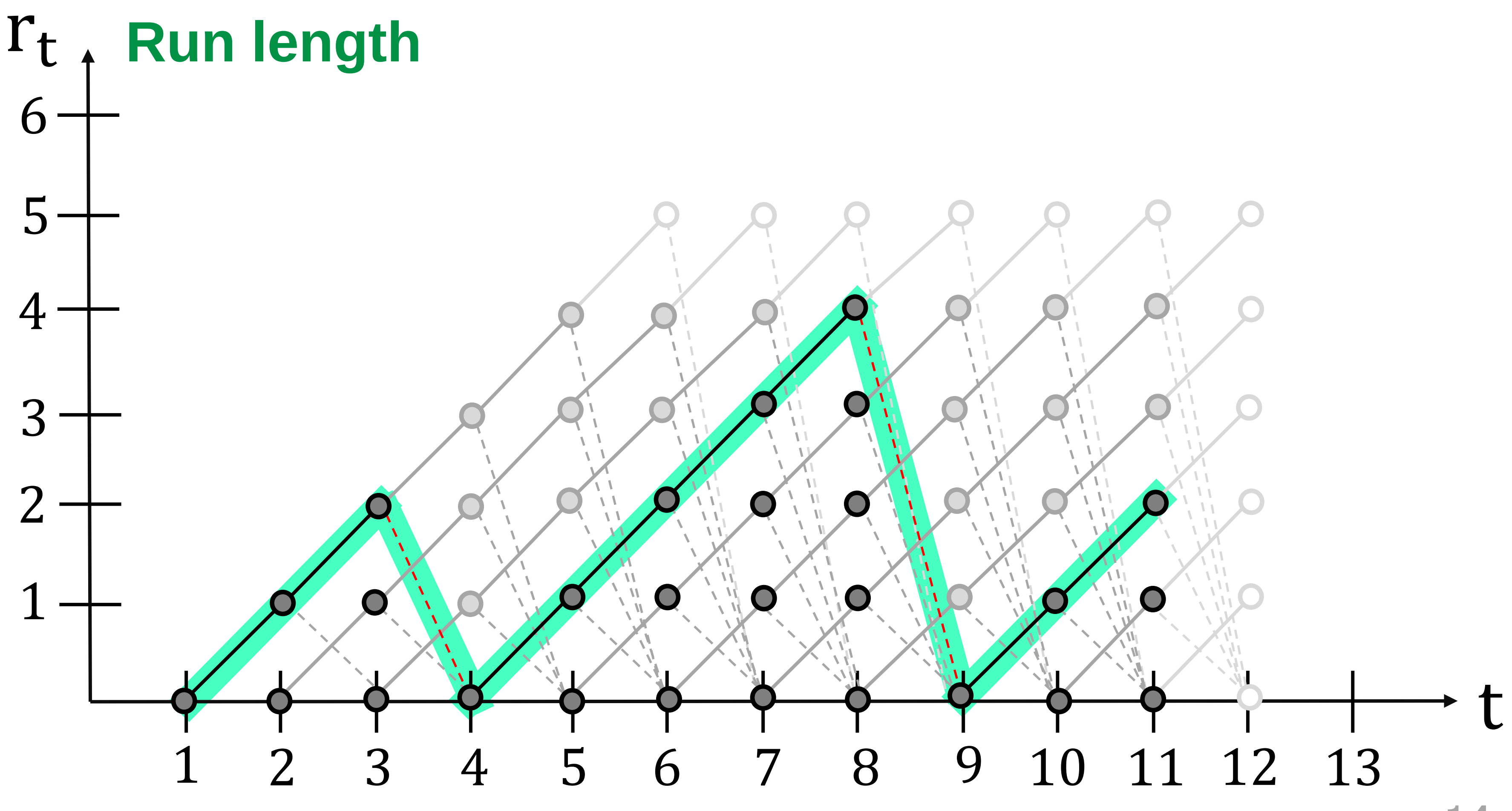


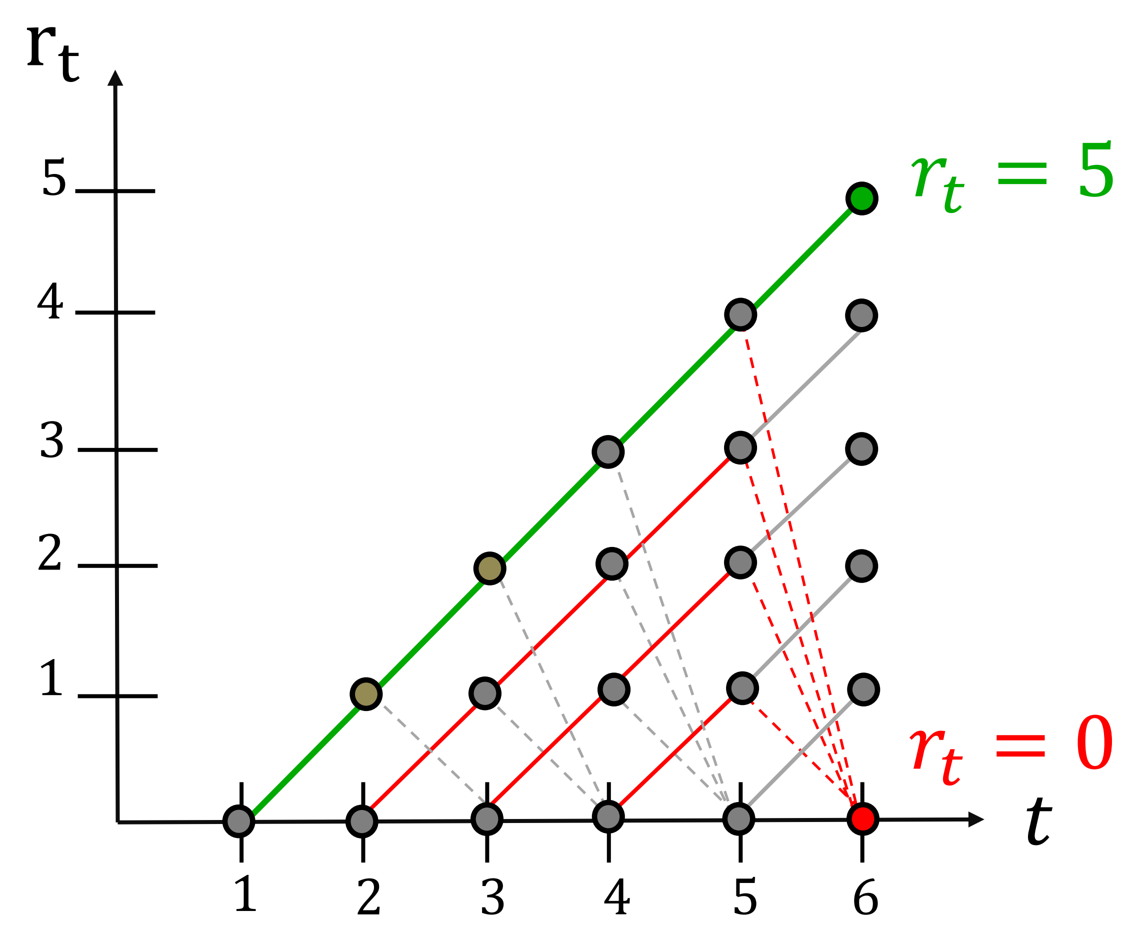
Hidden Markov Model





Bayesian method

Sequential processing through message-passing



$$p(r_t|\boldsymbol{x}_{1:t}) = \frac{p(r_t, \boldsymbol{x}_{1:t})}{\sum_{r_t=0}^{t} p(r_t, \boldsymbol{x}_{1:t})}$$

Joint distribution
[Adams and Mackay 2007]

$$p(r_t, \boldsymbol{x}_{1:t}) = \sum_{r_{t-1}=0}^{t-1} p(x_t|\boldsymbol{r}_{t-1:t}, \boldsymbol{x}_{1:t-1}) p(r_t|r_{t-1}) p(r_{t-1}, \boldsymbol{x}_{1:t-1})$$

Posterior predictive distribution

Prior probability of a transition

Message from previous iteration

Bayesian method

Posterior predictive distribution

- Data likelihood between changepoints $\sim p_{\boldsymbol{\theta}}\left(\boldsymbol{x}_t\right)$
- Parameter prior distribution $\boldsymbol{\theta} \sim \pi_{\boldsymbol{\eta}_0}(\boldsymbol{\theta})$

High computational complexity

$$p\left(x_t \middle| \boldsymbol{x}_{t-1}^{(r_{t-1})}\right) = \int p(x_t|\boldsymbol{\theta})\pi_{\boldsymbol{\eta}_0}\left(\boldsymbol{\theta}\middle|\boldsymbol{x}_{t-1}^{(r_{t-1})}\right) d\boldsymbol{\theta}$$

$$\pi_{\boldsymbol{\eta}_0}\left(\boldsymbol{\theta}\middle|\boldsymbol{x}_{t-1}^{(r_{t-1})}\right) = \frac{p\left(\boldsymbol{x}_{t-1}^{(r_{t-1})}\middle|\boldsymbol{\theta}\right)\pi_{\boldsymbol{\eta}_0}(\boldsymbol{\theta})}{\int p\left(\boldsymbol{x}_{t-1}^{(r_{t-1})}\middle|\boldsymbol{\theta}\right)\pi_{\boldsymbol{\eta}_0}(\boldsymbol{\theta})d\boldsymbol{\theta}}$$

A solution:

Conjugate priors:

$$\pi_{\boldsymbol{\eta}_0}\left(\boldsymbol{\theta}\middle|\boldsymbol{x}_{t-1}^{(r_{t-1})}\right) = \pi_{\boldsymbol{\eta}(r_t-1)}(\boldsymbol{\theta}) \quad \Rightarrow \quad p\left(x_t\middle|\boldsymbol{x}_{t-1}^{(r_{t-1})}\right) = f\left(x_t; \boldsymbol{\eta}(r_{t-1})\right)$$

Simple parameter update

Bayesian method

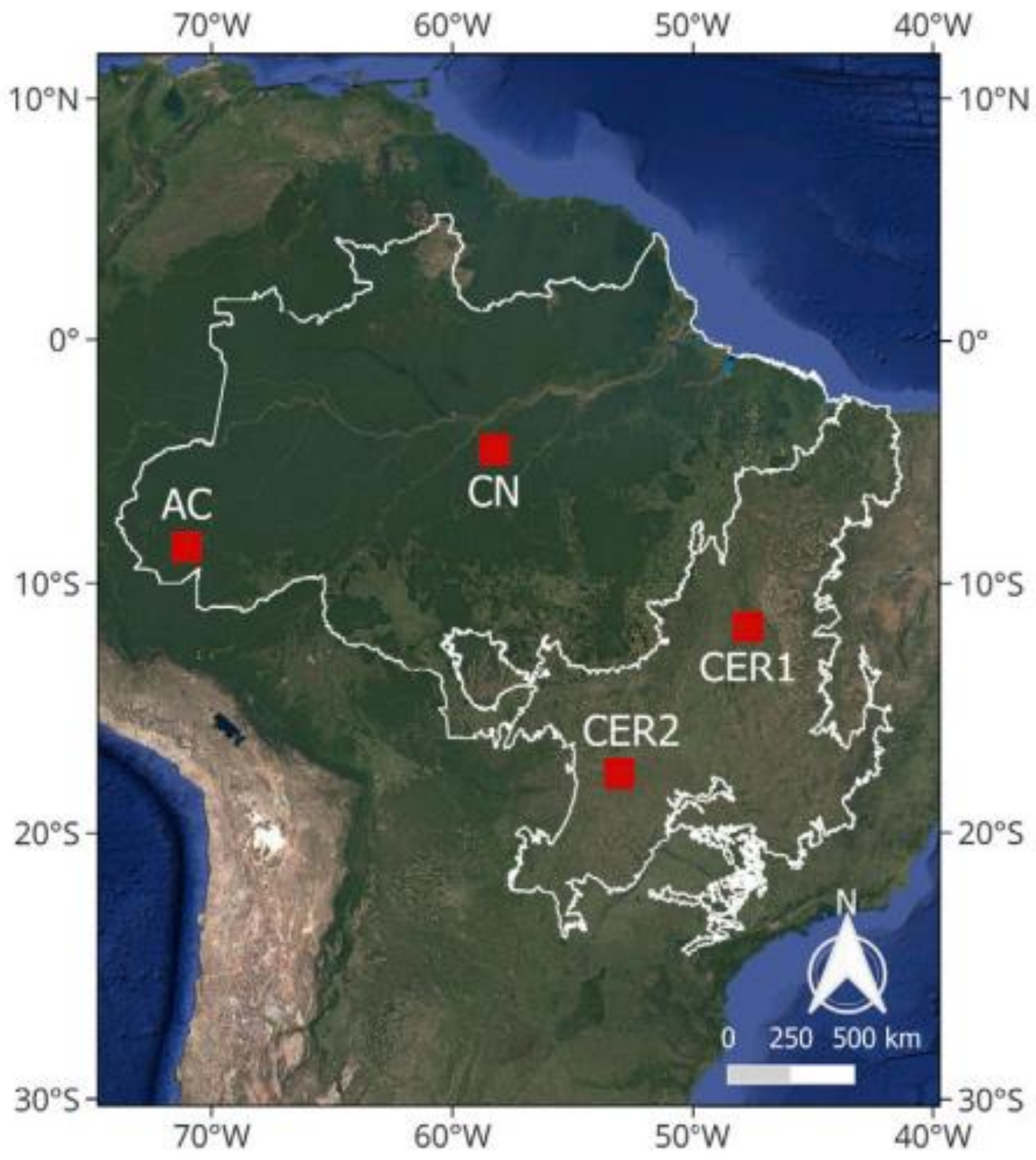
In practice

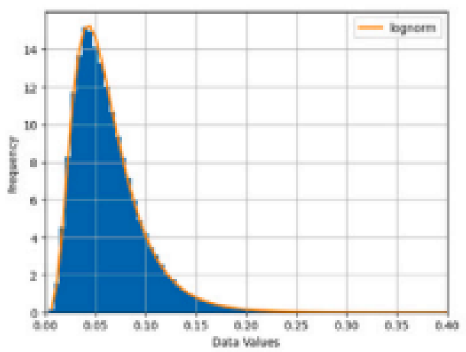
- S1 RTC log-intensity → **Normal likelihood**
- Parameter prior → **Normal Inverse-Gamma**

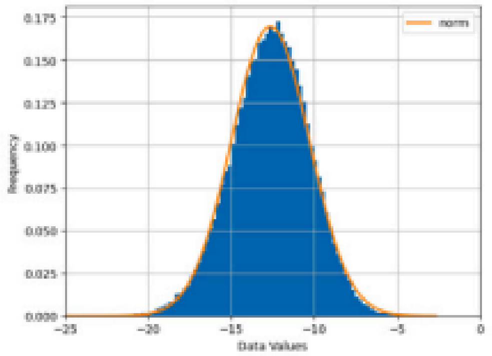
Closed-form posterior predictive:

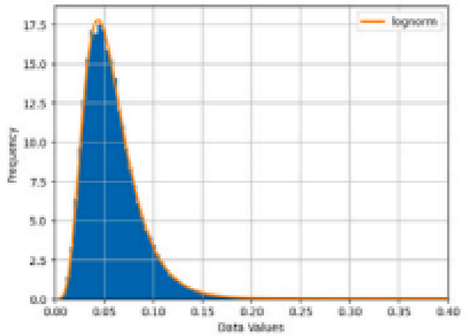
$$p(x|\,\boldsymbol{x}_m)=t_{2\alpha_m}\left(x;\mu_m,\frac{\beta(\kappa_m+1)}{\alpha_m\kappa_m}\right)$$
$$\boldsymbol{\eta}(m)=(\mu_m,\alpha_m,\kappa_m,\beta_m)$$

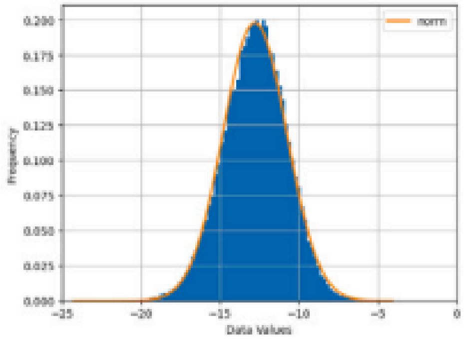
***t*-distribution**

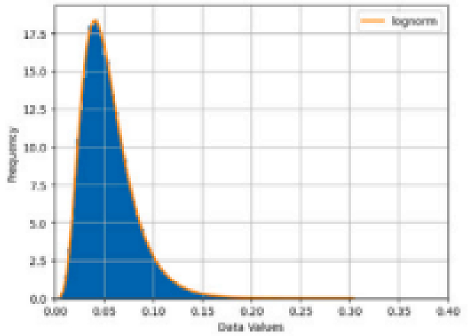


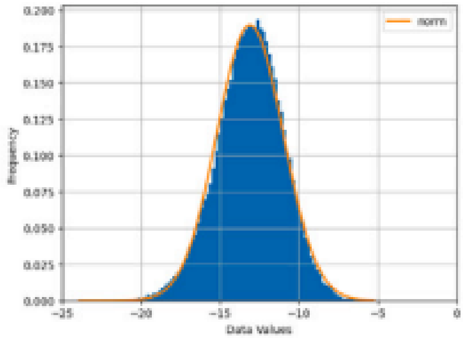

(b) AC, I, p=0.45

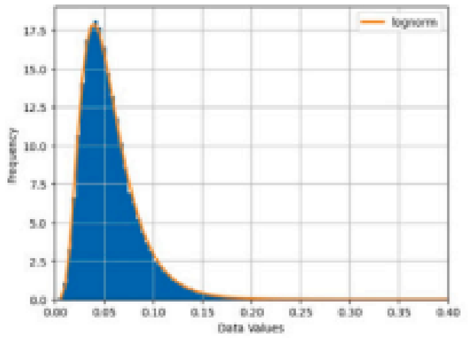

(f) AC, I_{dB}, p=0.16

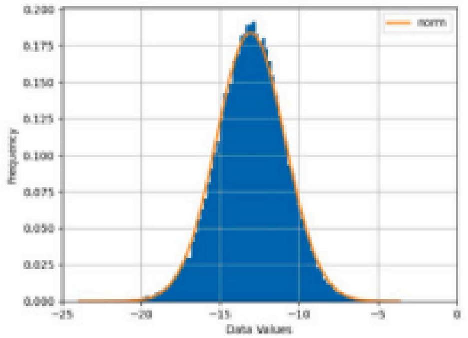

(c) CN, I, p=0.20


(g) CN, I_{dB}, p=0.08


(d) CER1, I, p=0.36


(h) CER1, I_{dB}, p=0.06


(e) CER2, I, p=0.44


(i) CER2, I_{dB}, p=0.09

Bayesian method

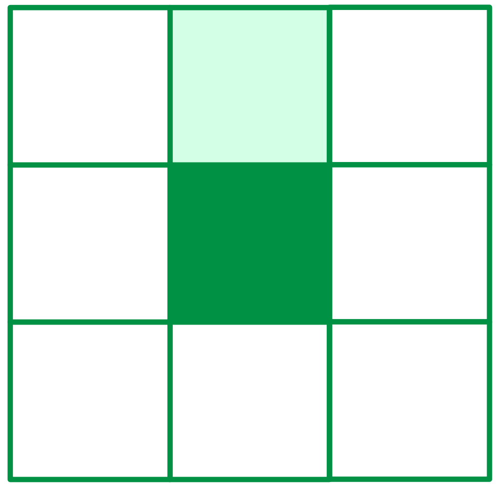
Transition probability and spatial context adaptation

$$p(r_t = 0 | r_{t-1}) = 1 - e^{-\int_{t-1}^{t} h(u)du}$$

$$h(t) = c + N_l a e^{b(t-t_l)}$$

Gompertz-Makeham model
[Stevenson 2007]

$N_l = 1$



Bayesian method

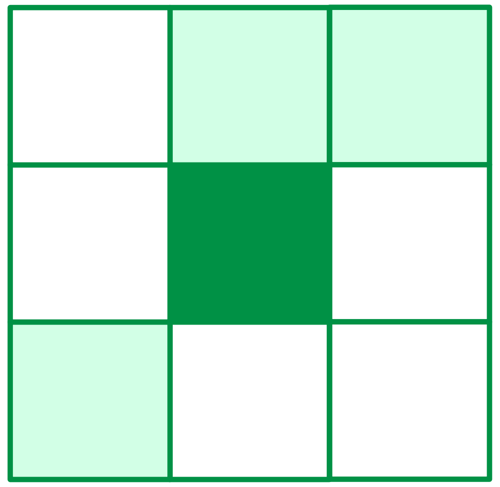
Transition probability and spatial context adaptation

$$p(r_t = 0|r_{t-1}) = 1 - e^{-\int_{t-1}^{t} h(u)du}$$

$$h(t) = c + N_l a e^{b(t-t_l)}$$

Gompertz-Makeham model
[Stevenson 2007]

$N_l = 3$



Bayesian method

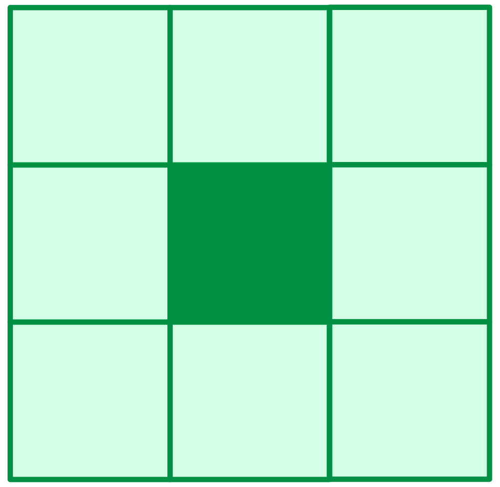
Transition probability and spatial context adaptation

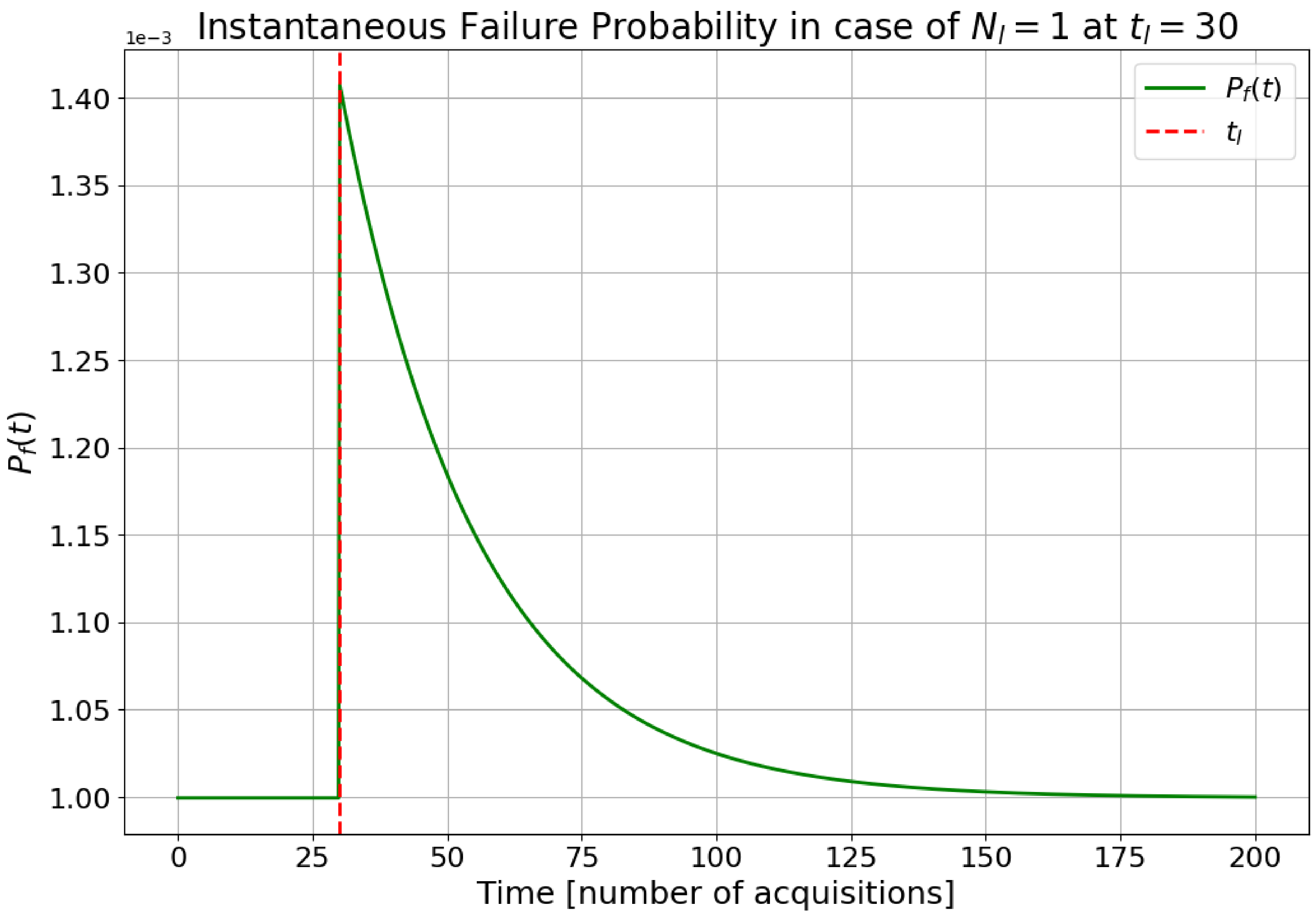
$$p(r_t = 0|r_{t-1}) = 1 - e^{-\int_{t-1}^{t} h(u)du}$$

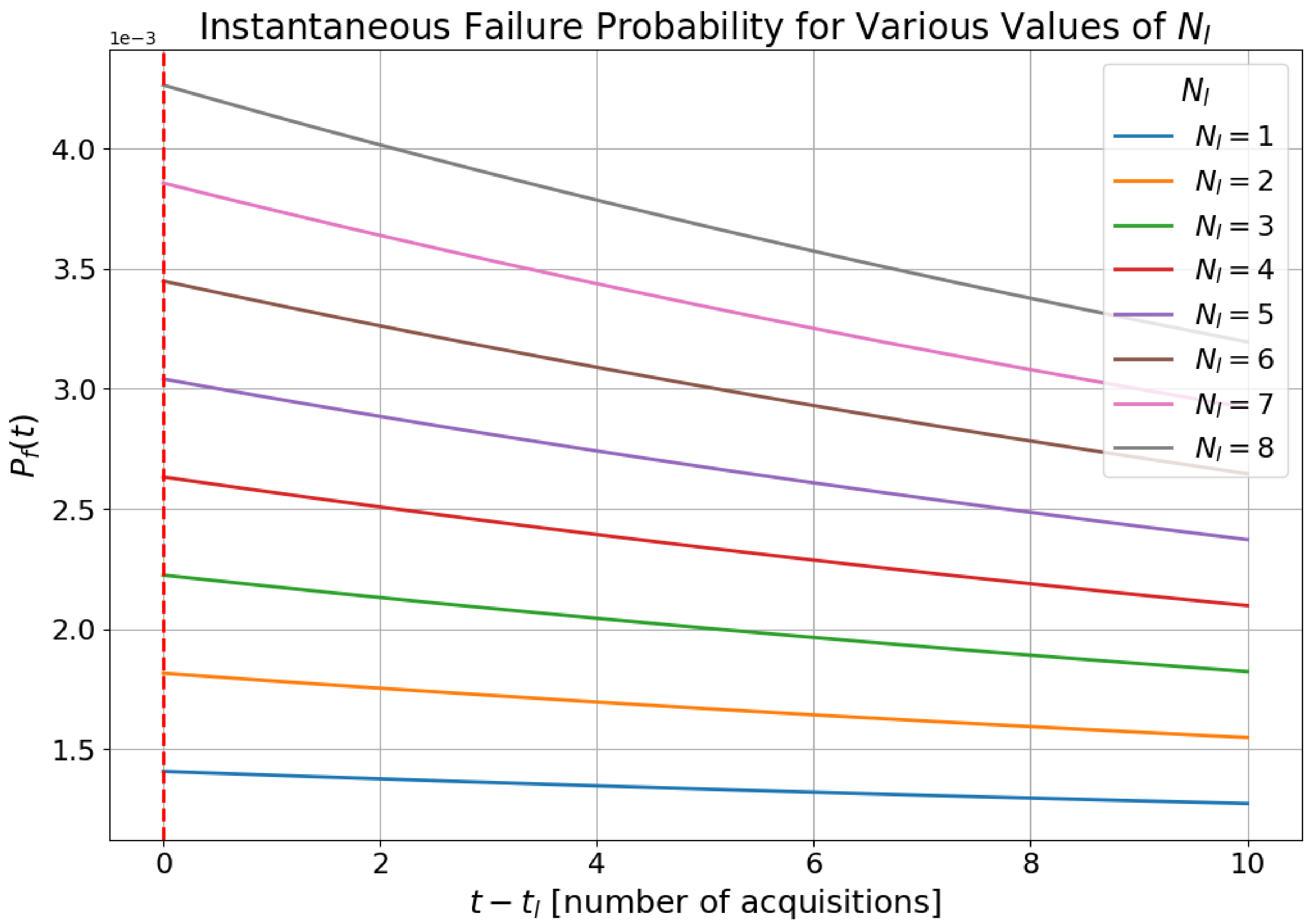
$$h(t) = c + N_l a e^{b(t-t_l)}$$

Gompertz-Makeham model
[Stevenson 2007]

$N_l = 8$







Detection strategy

Maximum *a posteriori* (MAP)

$$M_t = \arg\max_{r_t} p(r_t | \boldsymbol{x}_{1:t})$$

If:

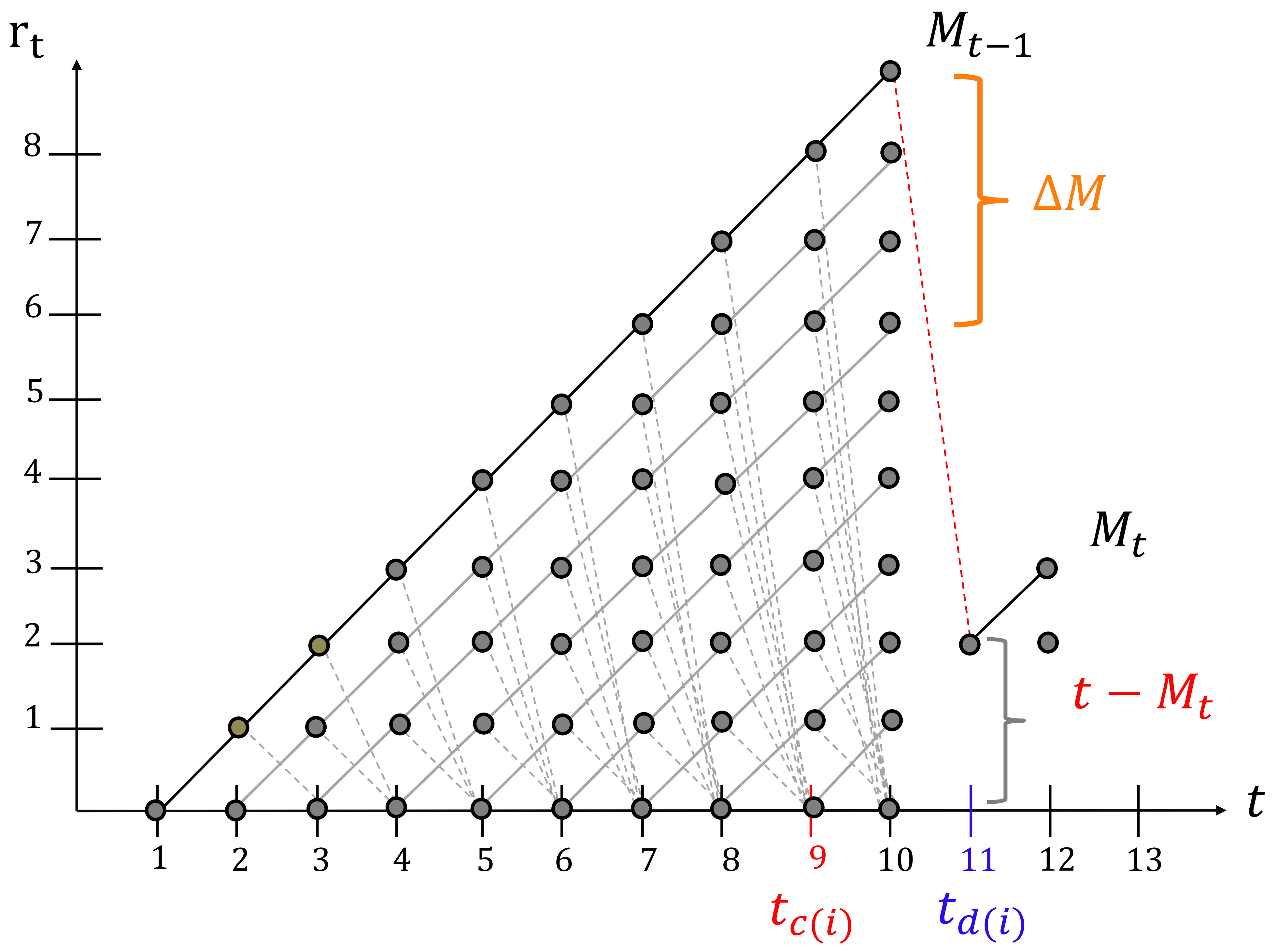
$M_t < M_{t-1} + 1$ → change

In practice:

$M_t \leq M_{t-1} - \Delta M$

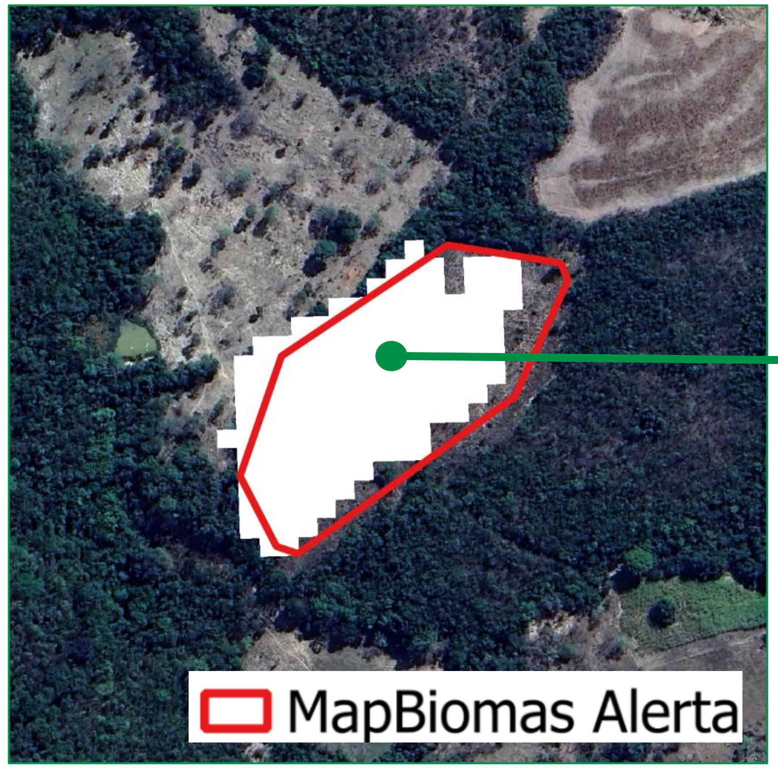
Detection delay:

$$M_t$$

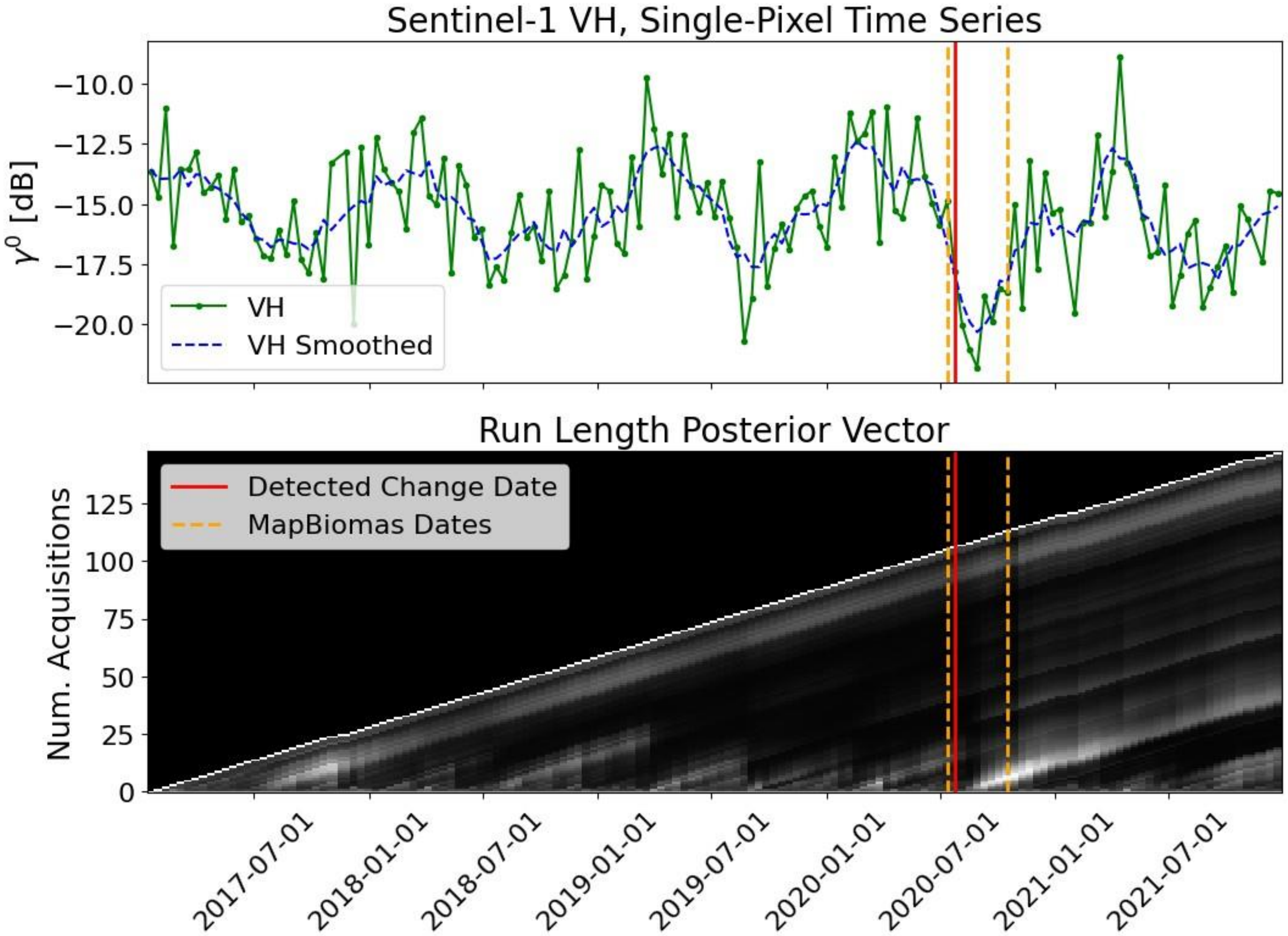


Example of detection

BOCD on a single-pixel time series



- (45.40°W,19.96°S)
- 1.5 hectares
- Deforestation: 15/07/2020



Reference data

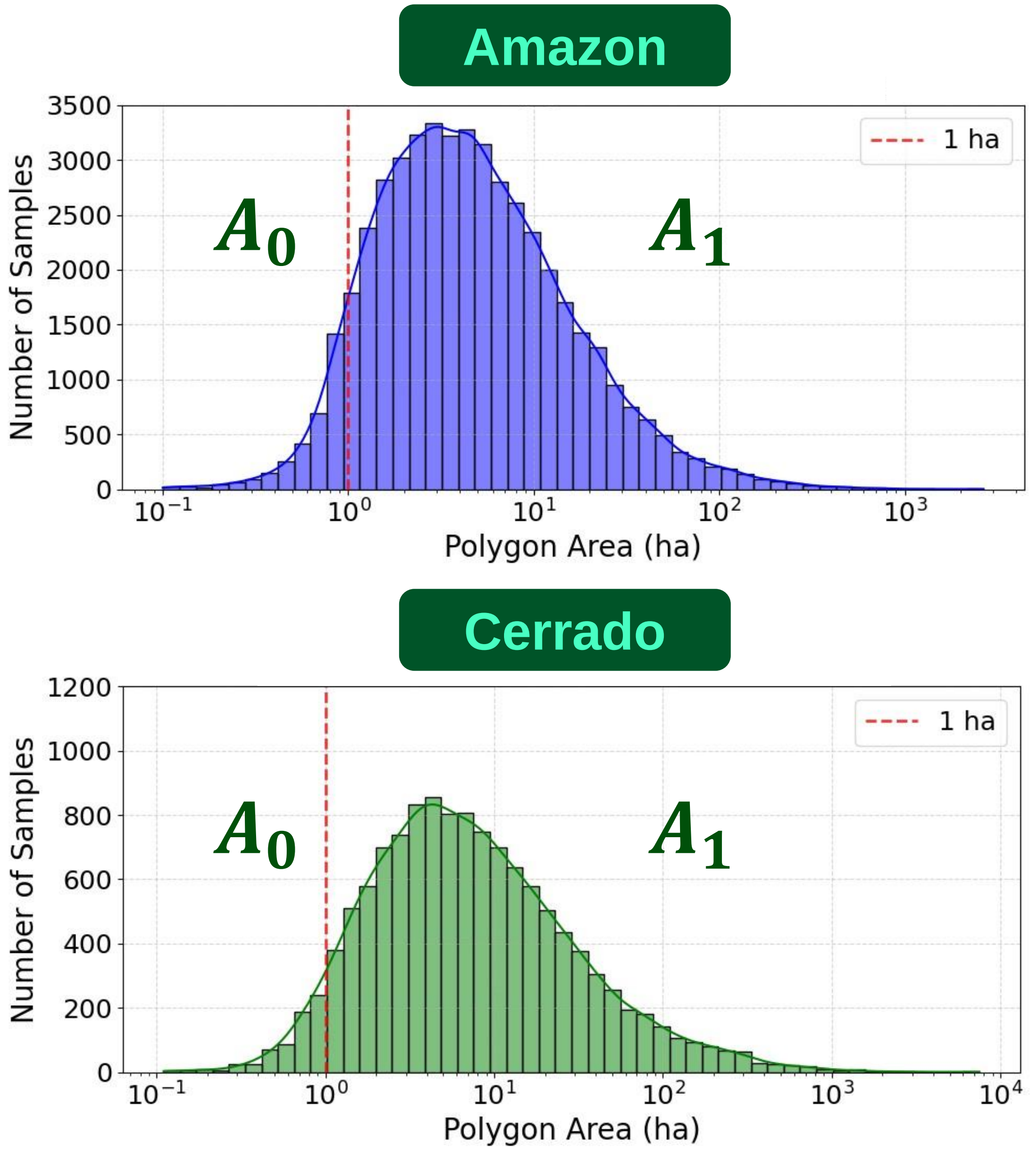
MapBiomas Alerta

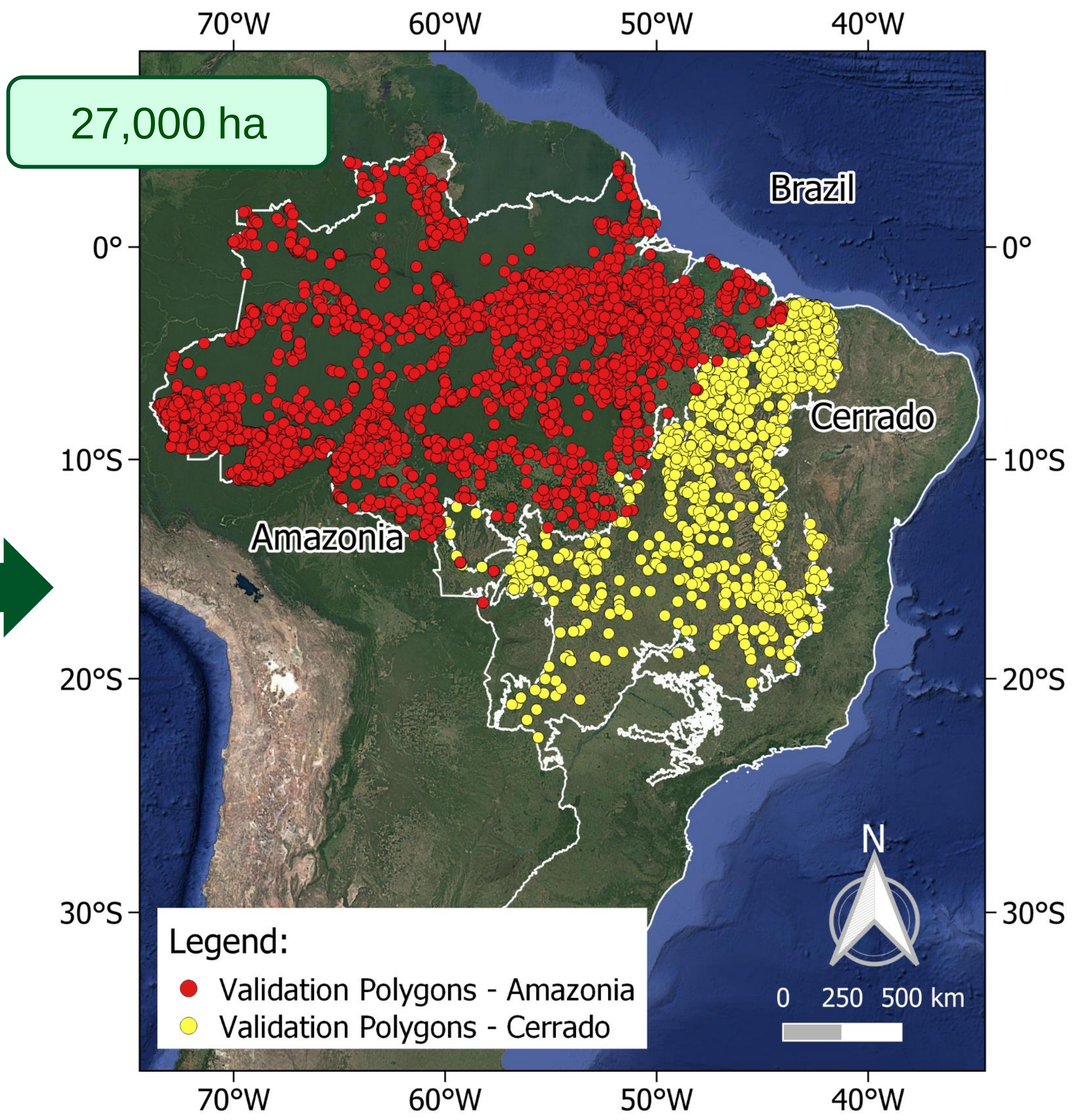
- **Small** polygons dataset

$0.1 \leq A_0 < 1$ ha

- **Large** polygons dataset

$1 \leq A_1 \leq 50$ ha

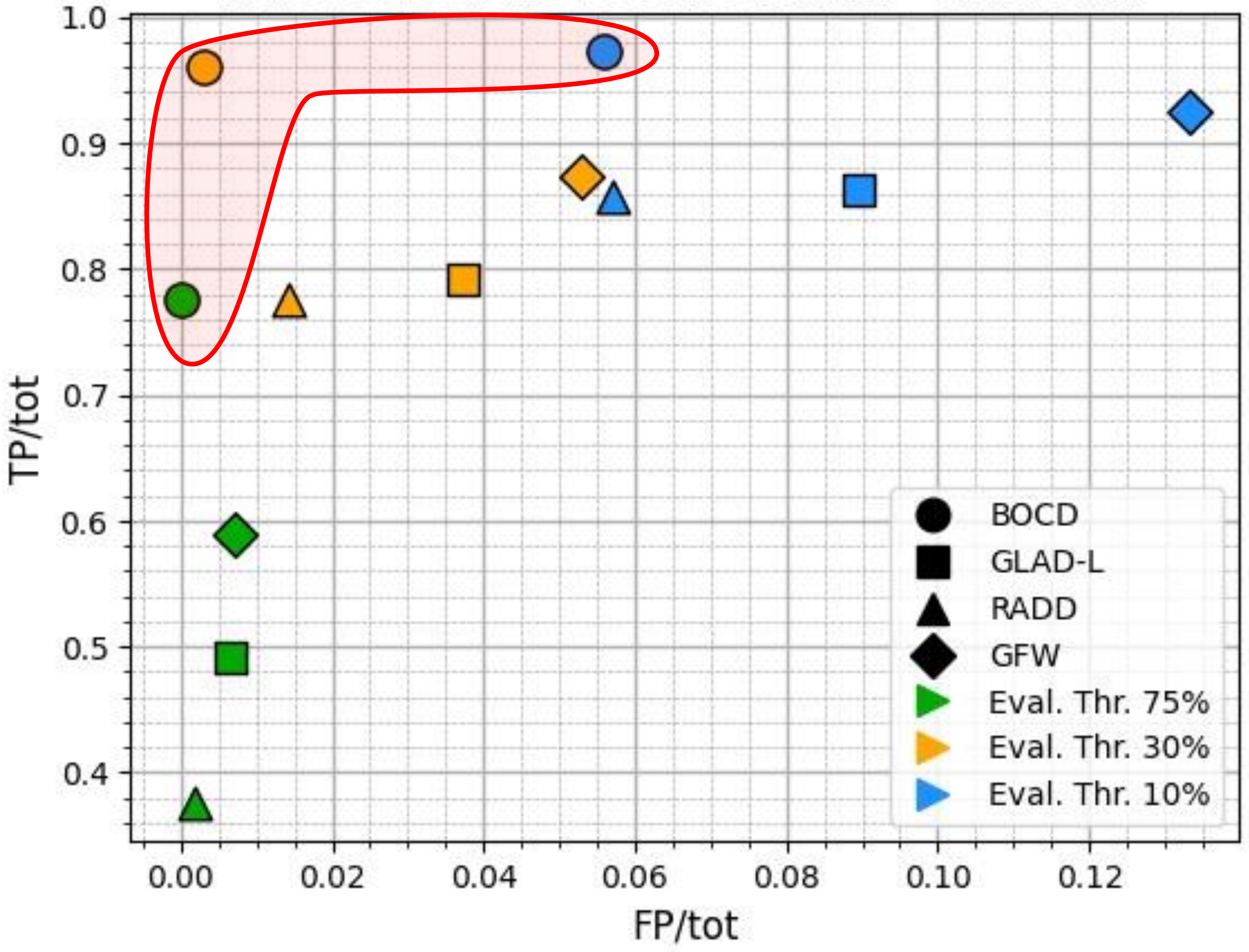


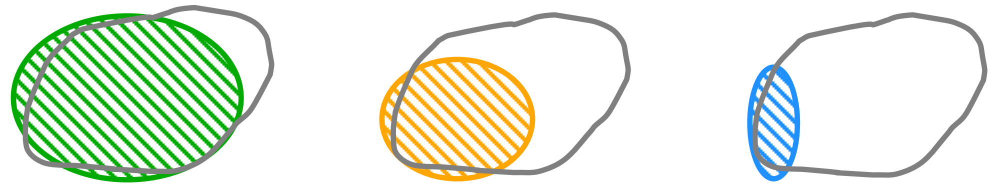


Spatial results: the Amazon

Small-scale forest loss in 2020

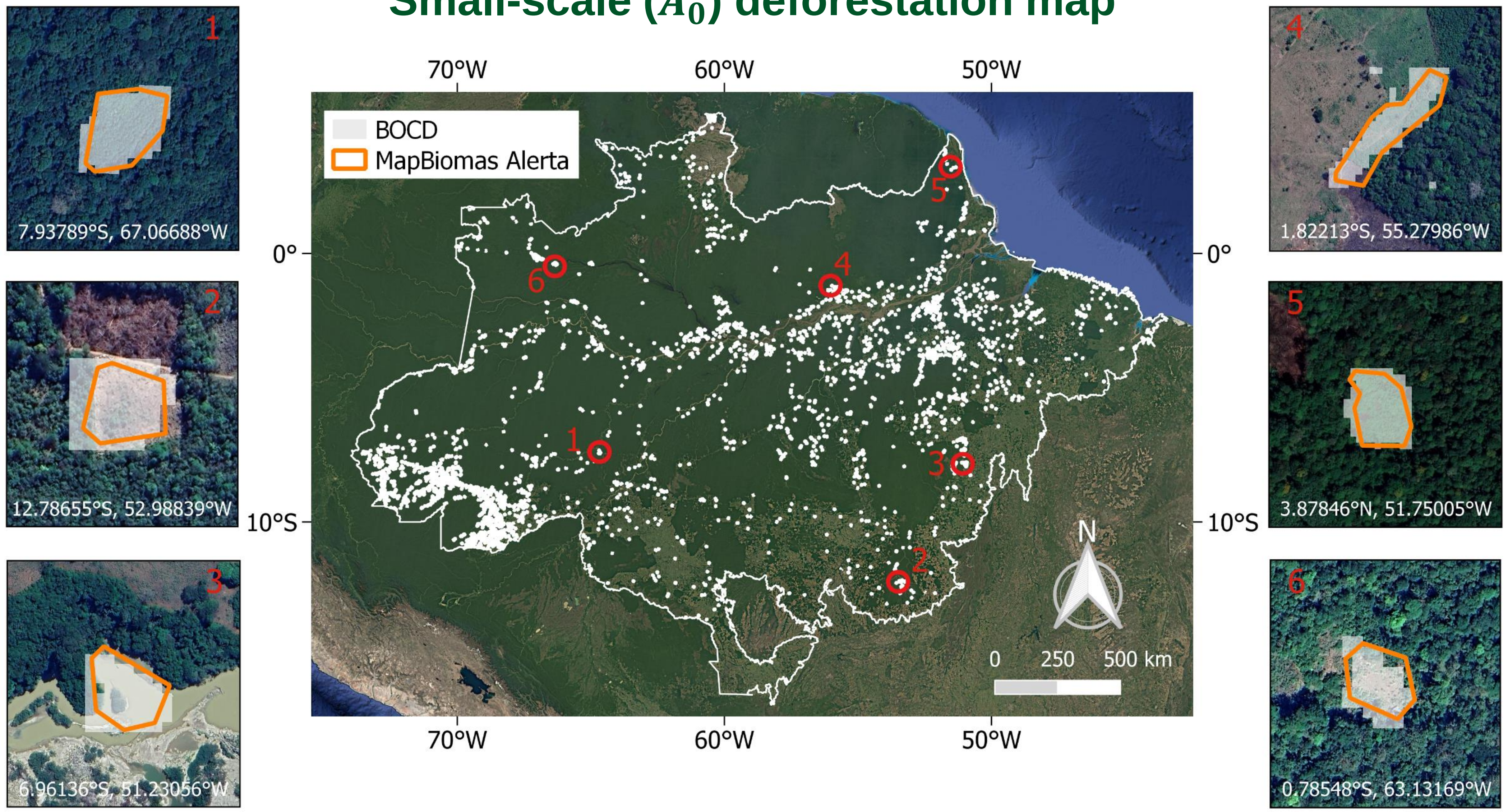
True detections vs false alarms





75% 30% 10%

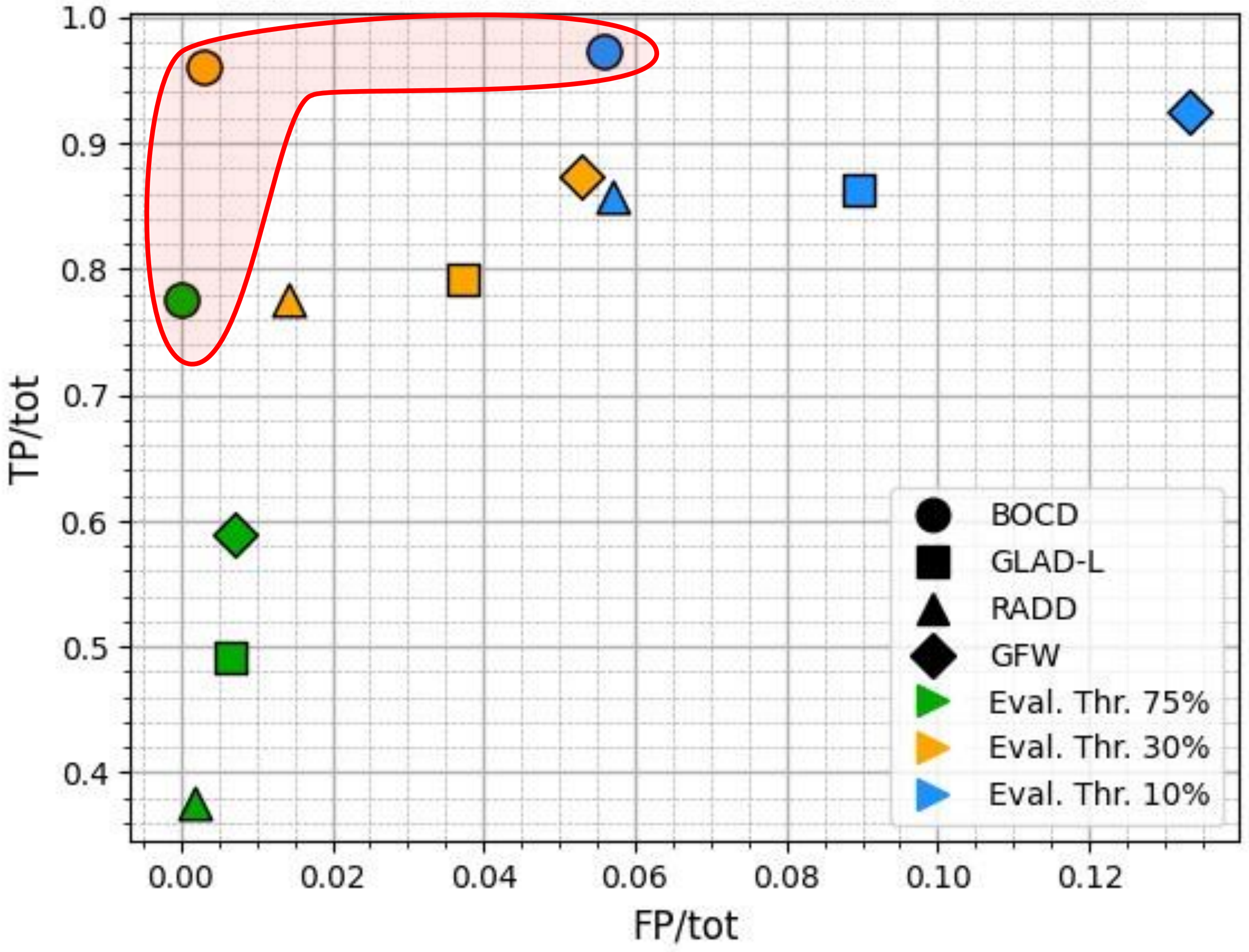
Small-scale (A_0) deforestation map

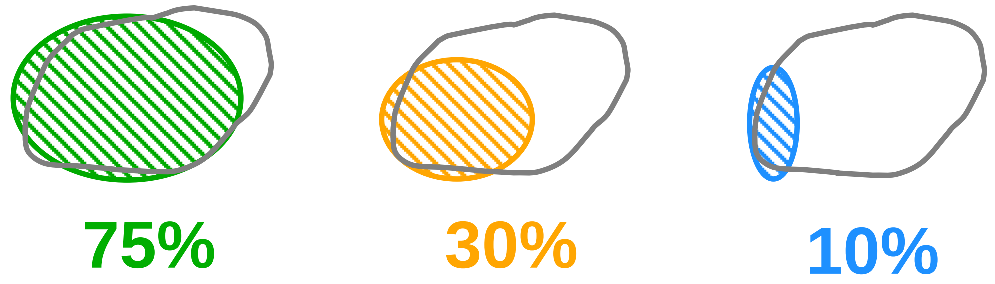


Spatial results: the Amazon

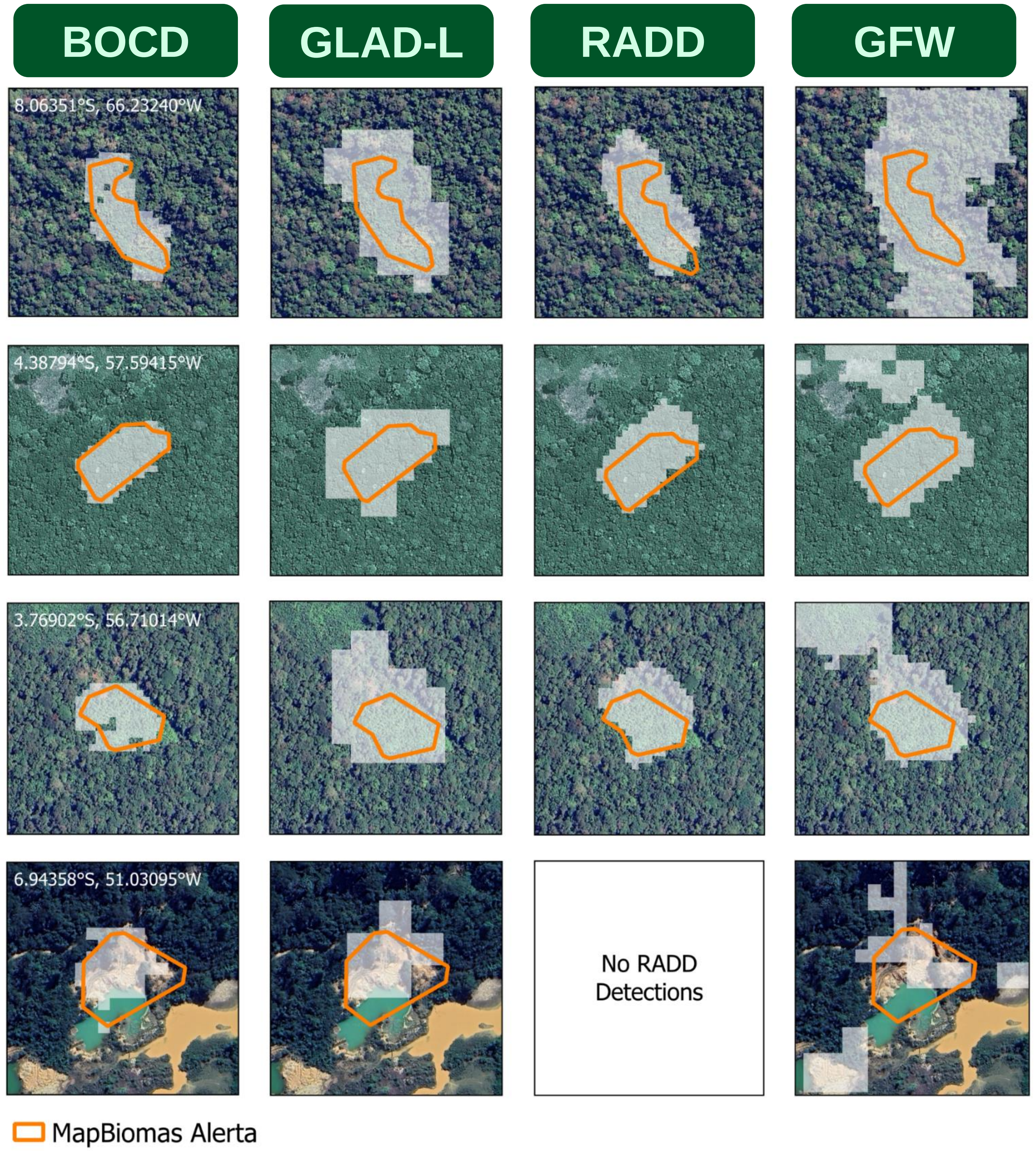
Small-scale forest loss in 2020

True detections vs false alarms





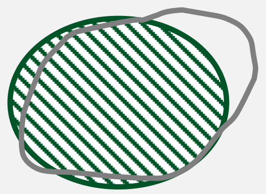
Illustrations of spatial accuracy



Spatial results: the Amazon

Small- vs large-scale forest loss in 2020

F1-score [%]
compromise between detections and false alarms



75%

Small (A_0)			Large (A_1)		
BOCD	**GFW**	**RADD**	**BOCD**	**GFW**	**RADD**
87	74	55	49	81	50

+ 13%

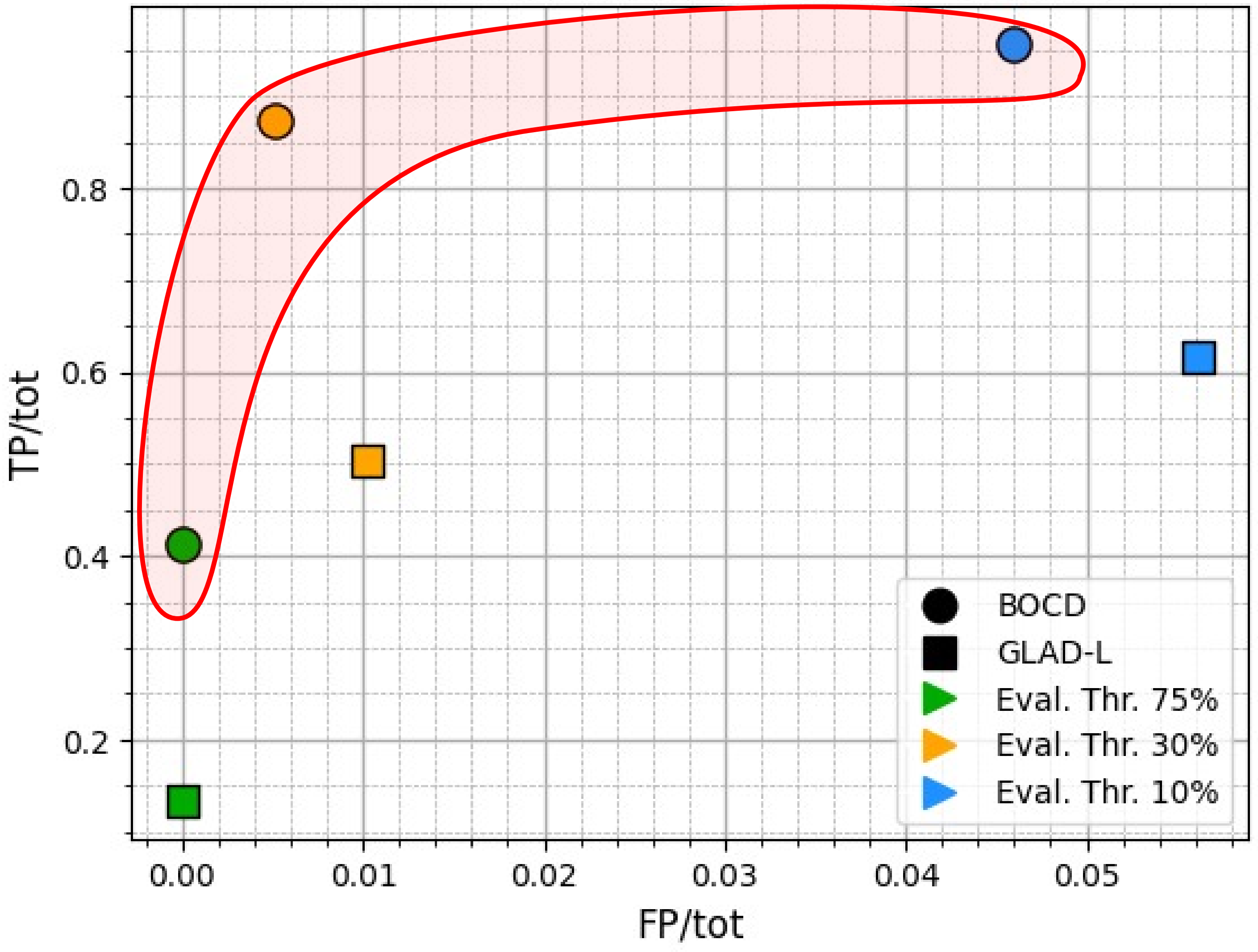
+ 32%

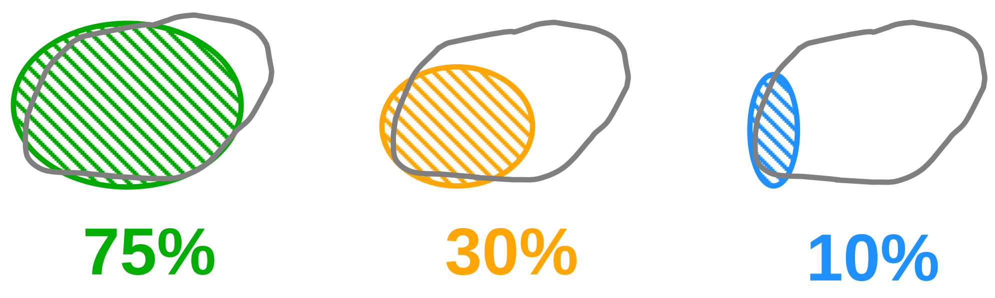
GFW largely affected by false alarms

Spatial results: the Cerrado

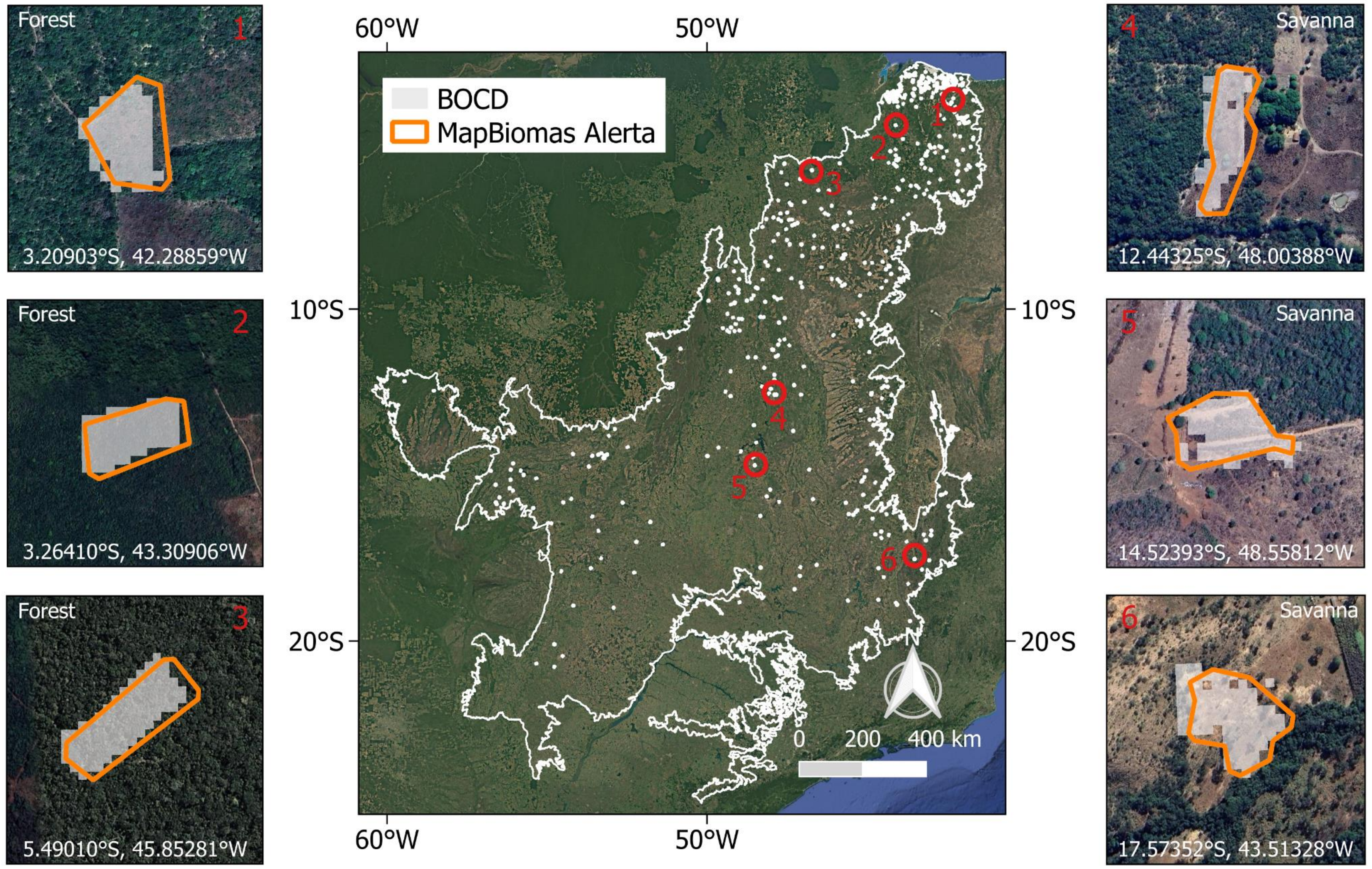
Small-scale forest loss in 2020

True detections vs false alarms





Small-scale (A_0) deforestation map

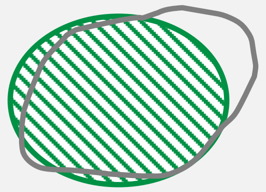


Robust to **seasonality**, improvements vs GLAD-L

Spatial results: the Cerrado

Small- vs large-scale forest loss in 2020

F1-score [%]
compromise between detections and false alarms



75%

Small (A_0)		Large (A_1)	
BOCD	GLAD-L	BOCD	GLAD-L
57	3	78	4

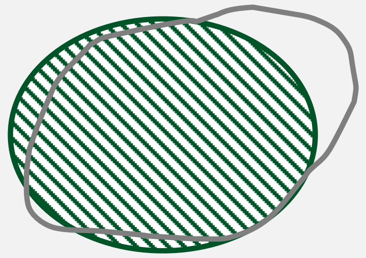
+ 54%

+74%

Spatial results: comparison

BOCD performance between biomes

F1-score [%]
compromise between detections and false alarms



75%

	Small (A_0)		**Large (A_1)**	
	Amazon 	**Cerrado** 	**Amazon** 	**Cerrado** 
	87	57	49	**78**

+ 30%

+ 29%

Results interpretation

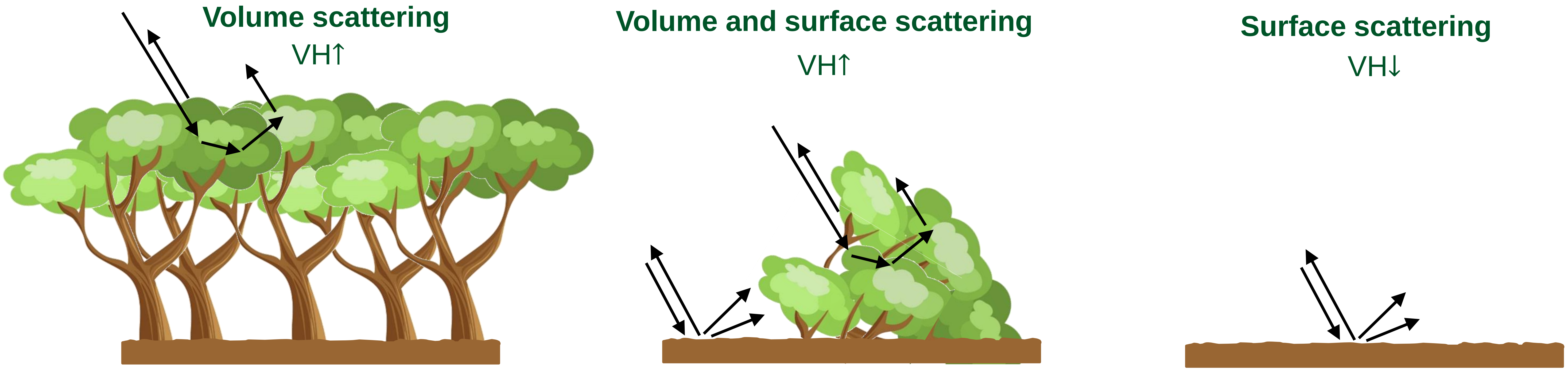
Different deforestation practices

Amazon

Big parcels → slash and burn
Small parcels → immediately cleaned

Cerrado

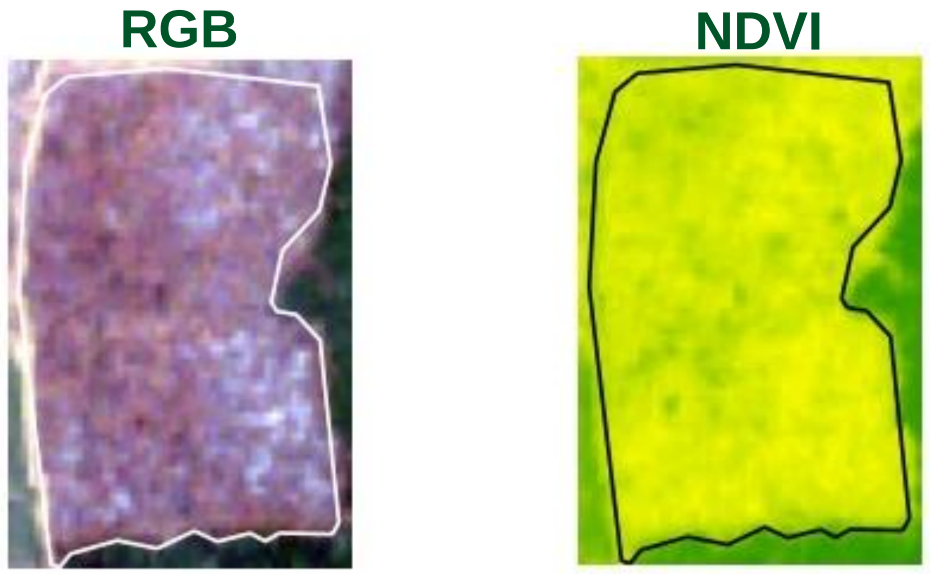
Big parcels → soja
Small parcels → subsistence farming

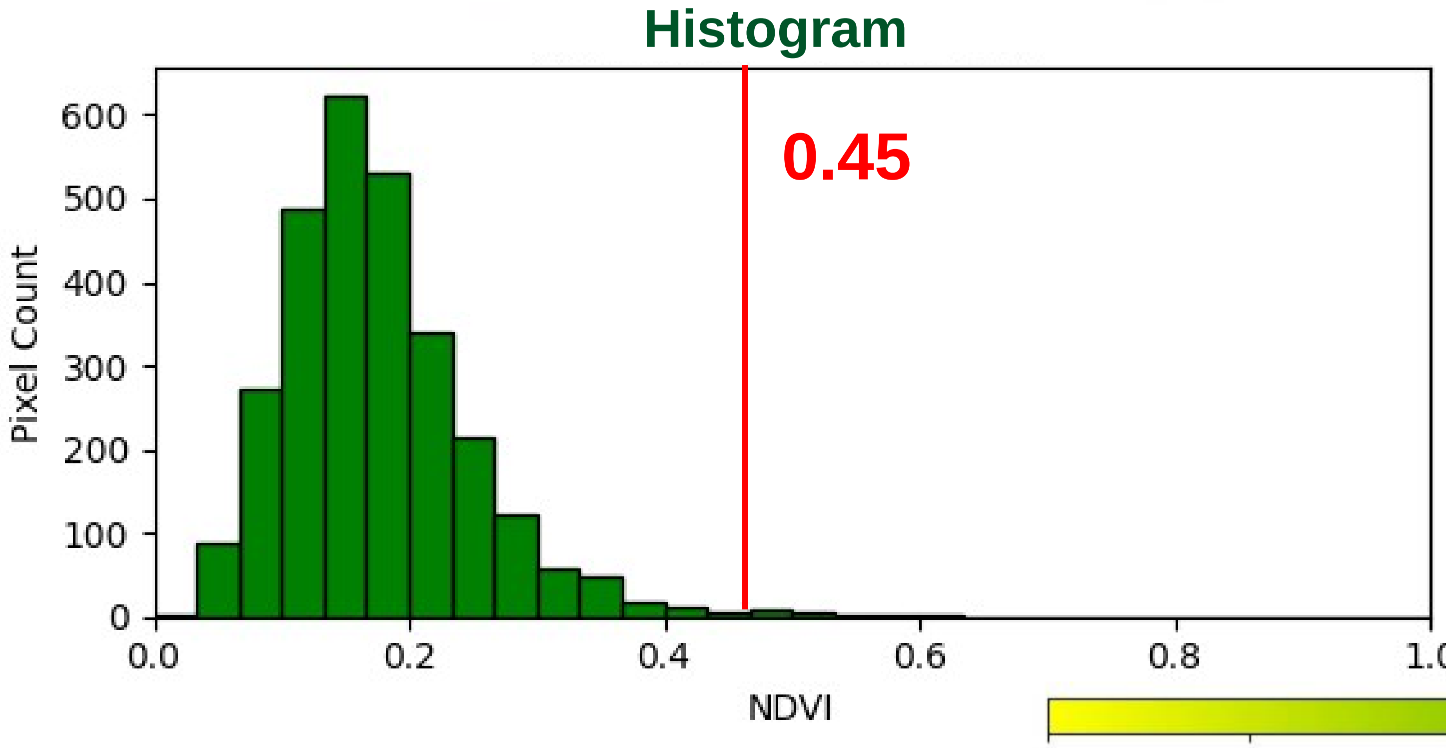


Results interpretation

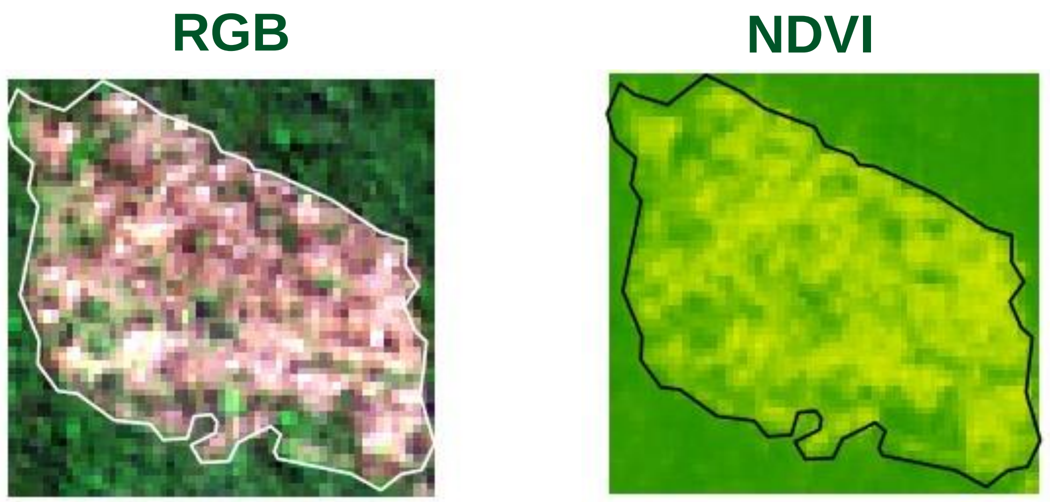
NDVI Examples

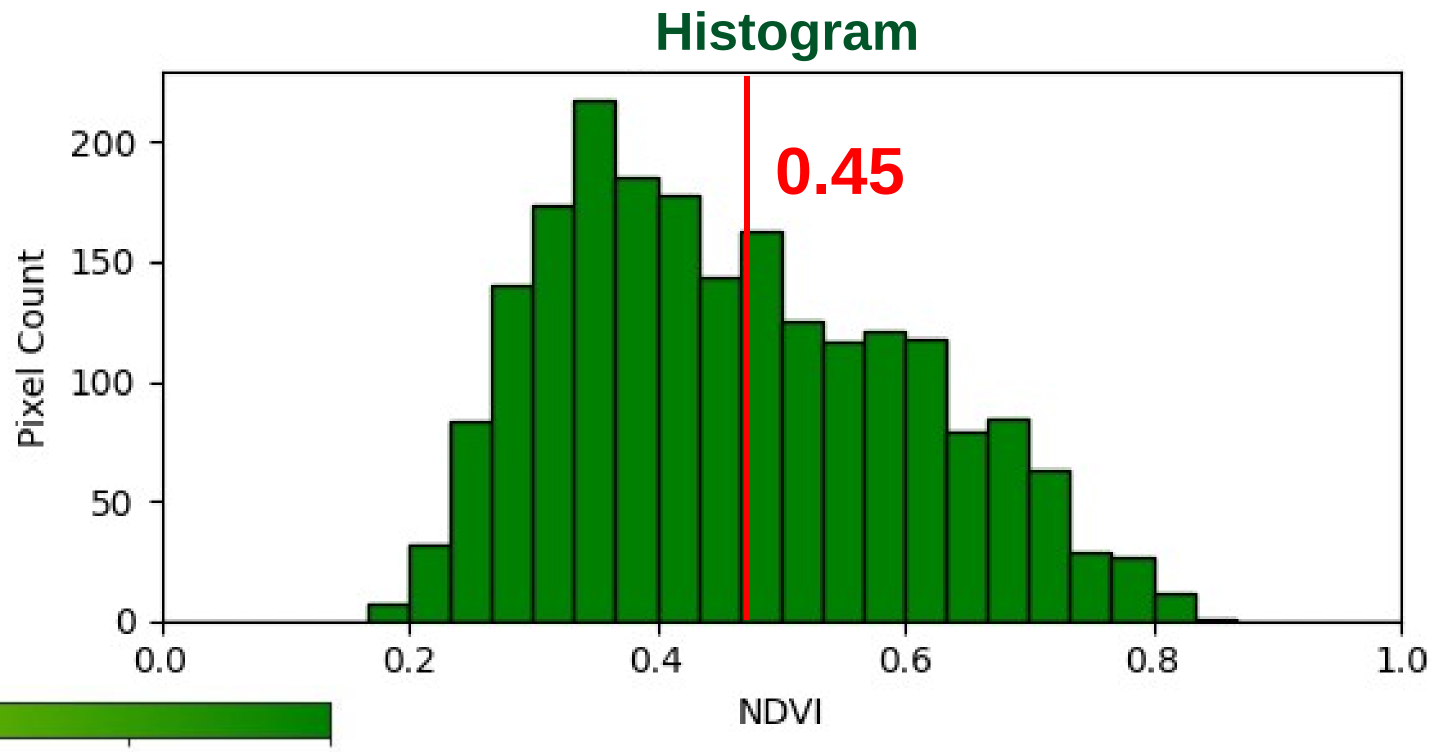
No residual vegetation

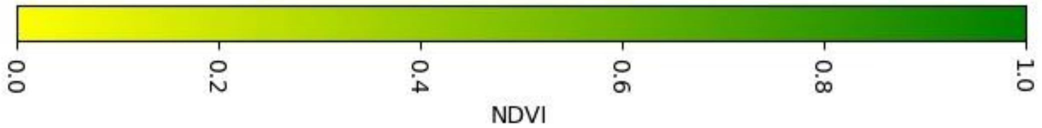




Residual vegetation





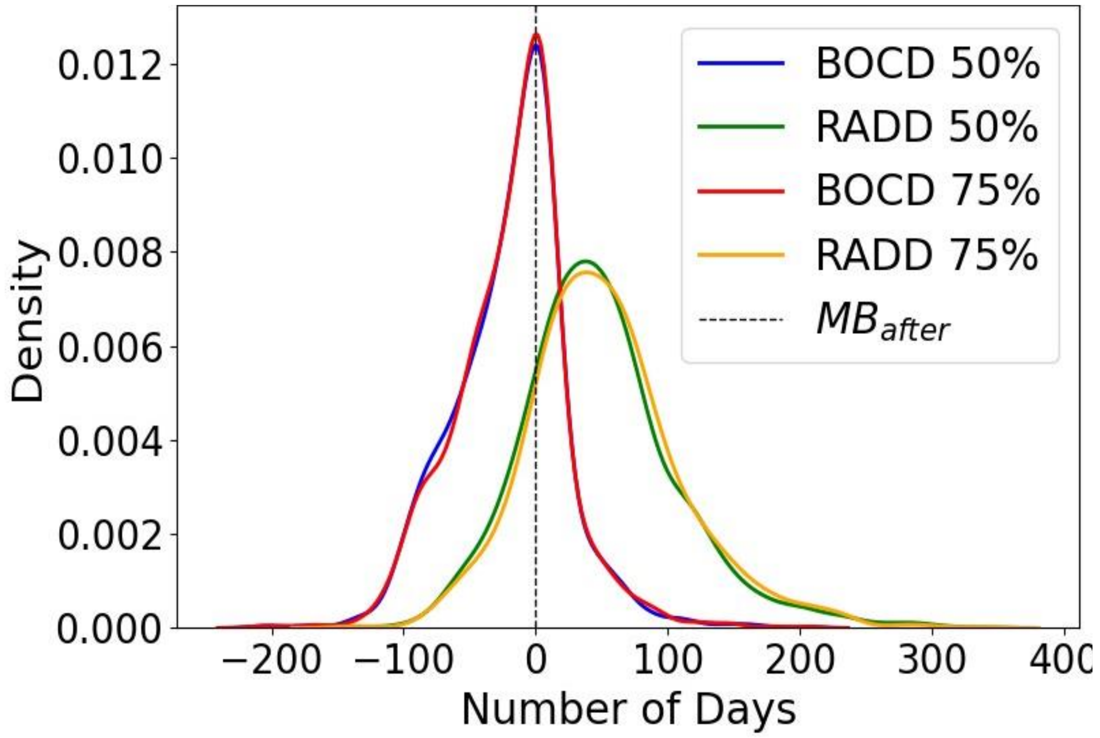


Temporal results

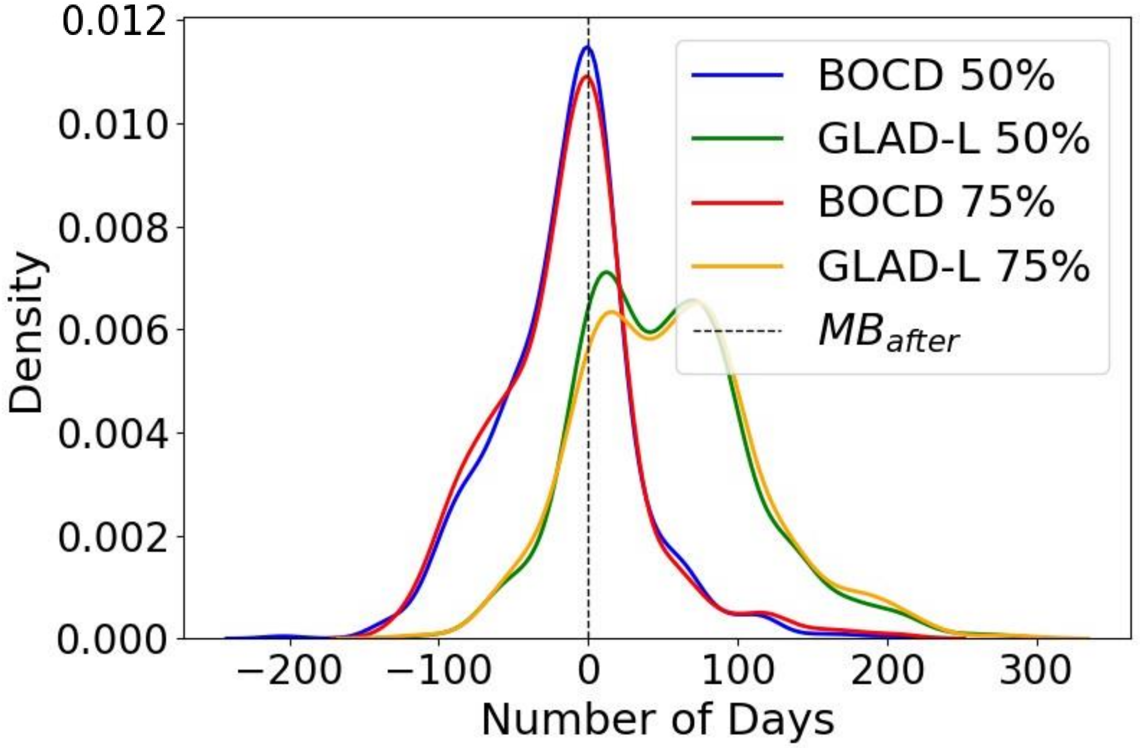
BOCD vs operational methods

Relative detection dates

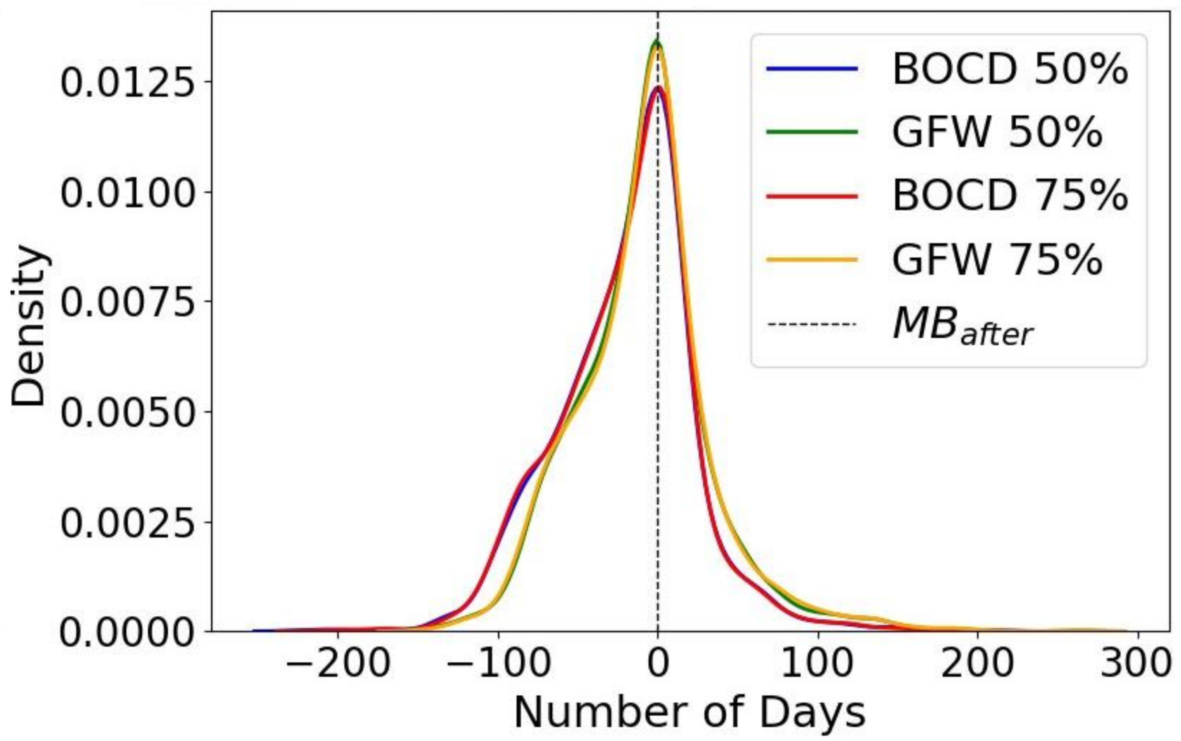
vs RADD



vs GLAD-L



vs GFW



2 months earlier

3 days earlier

MB_{after} : MapBiomas Alerta post-clearing date

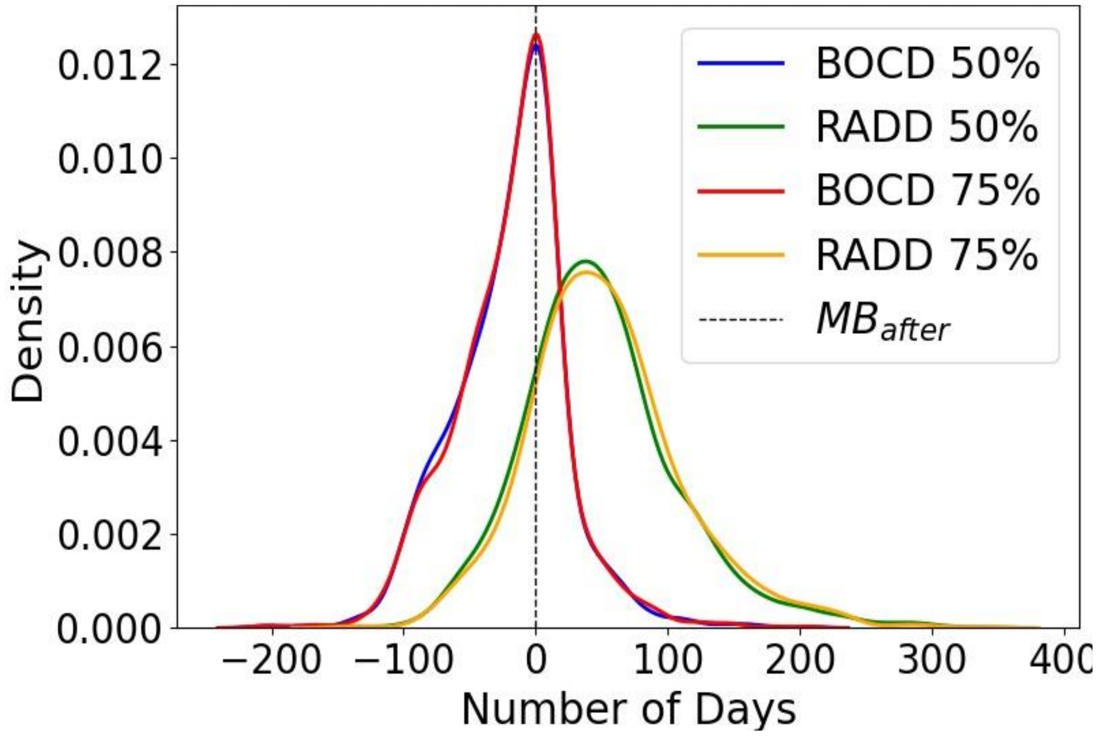
Temporal results

BOCD vs operational methods

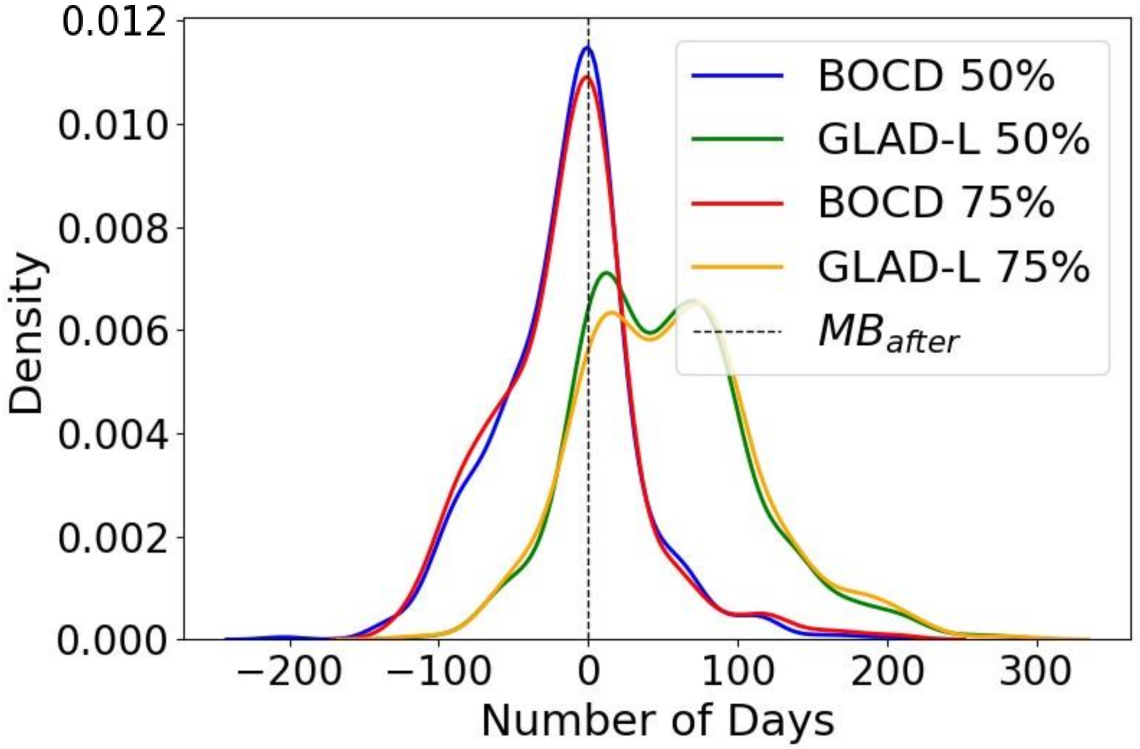
BOCD non affected by seasons

Relative detection dates

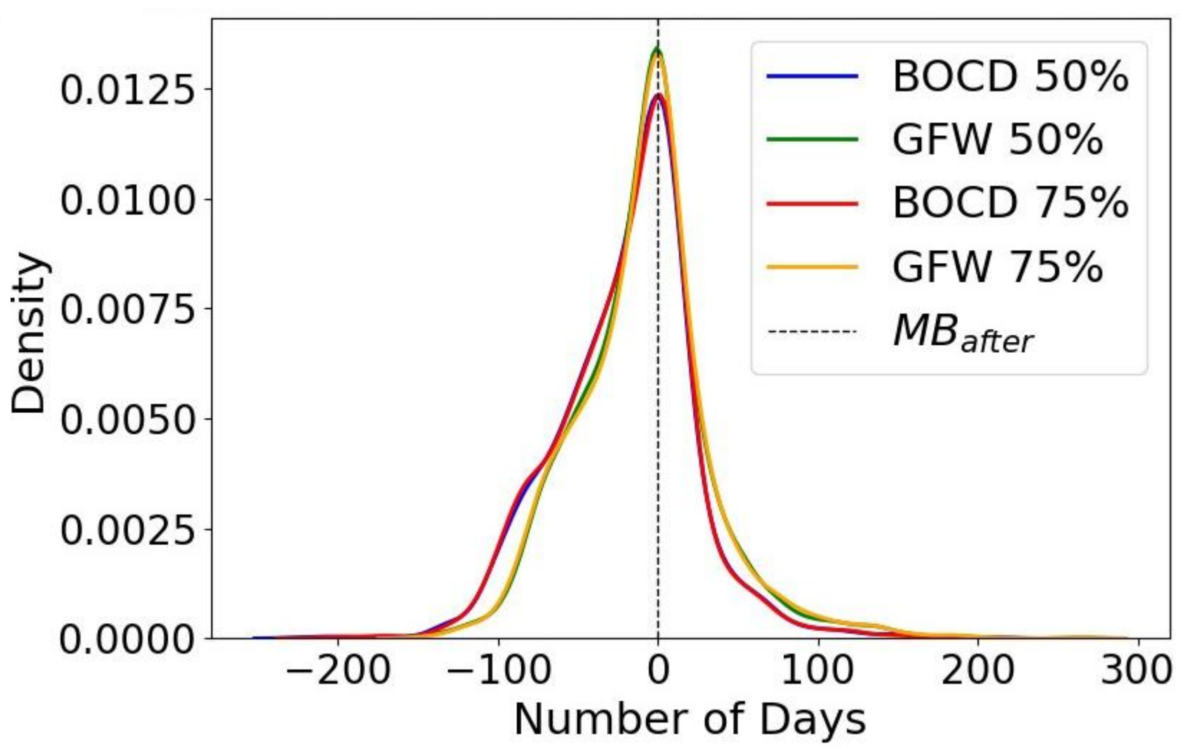
vs RADD



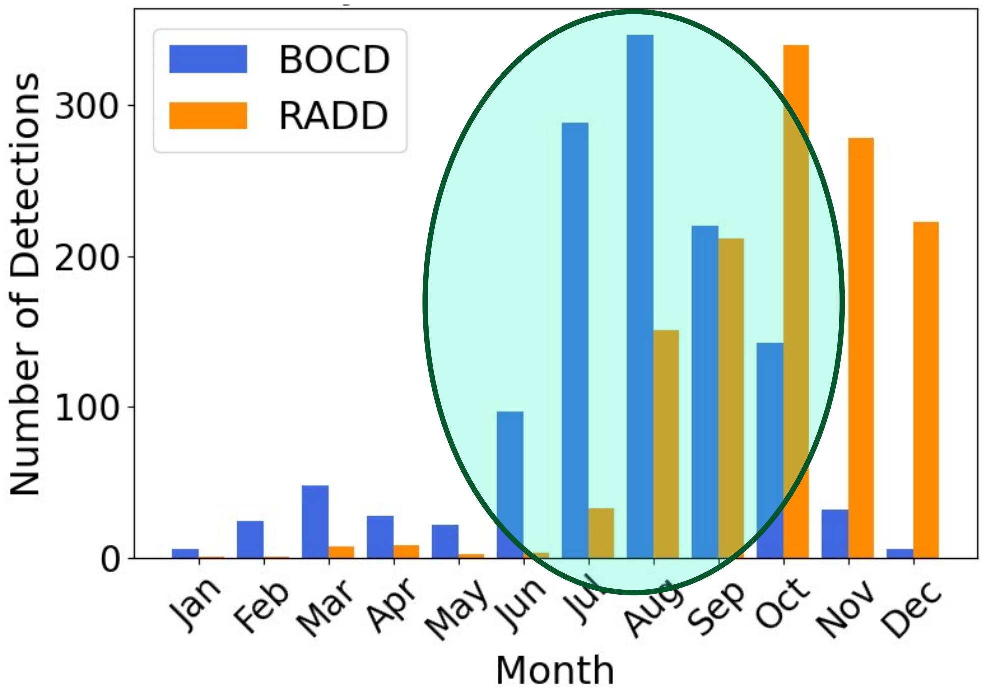
vs GLAD-L

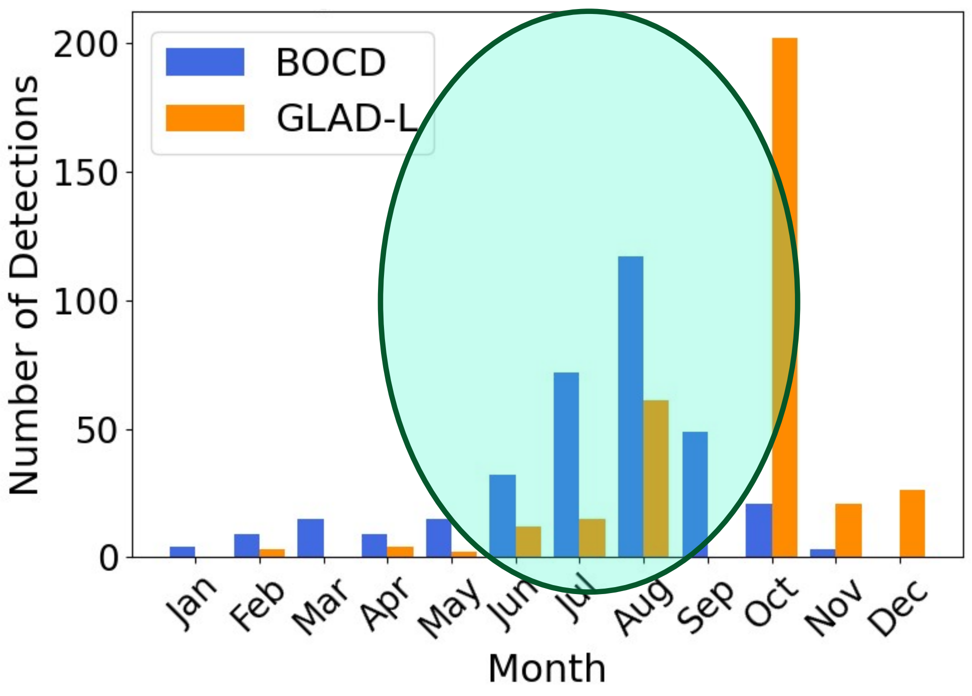


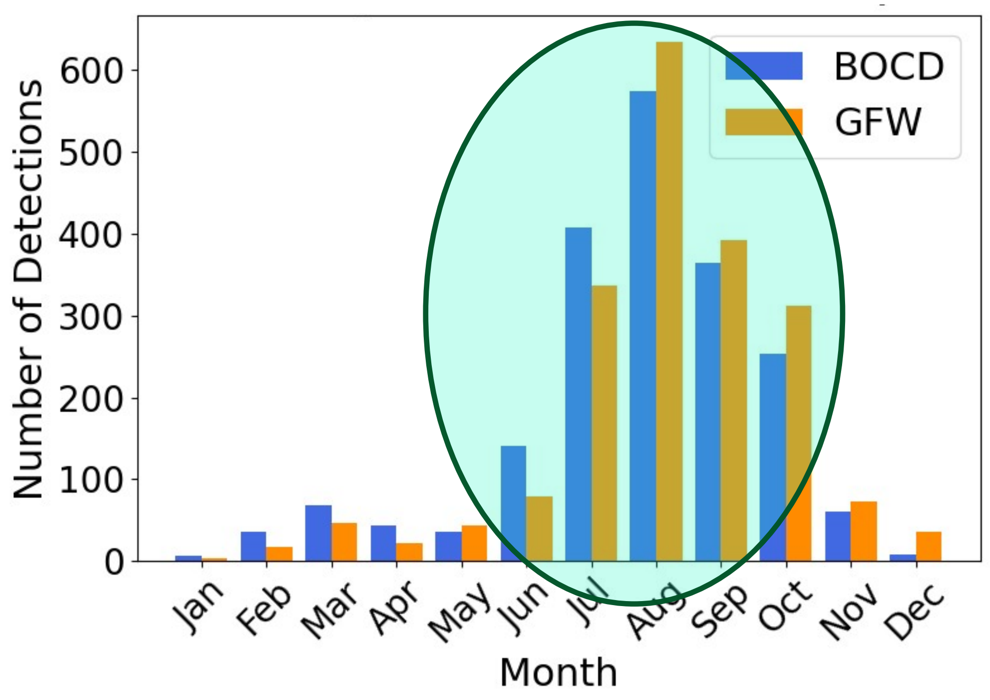
vs GFW



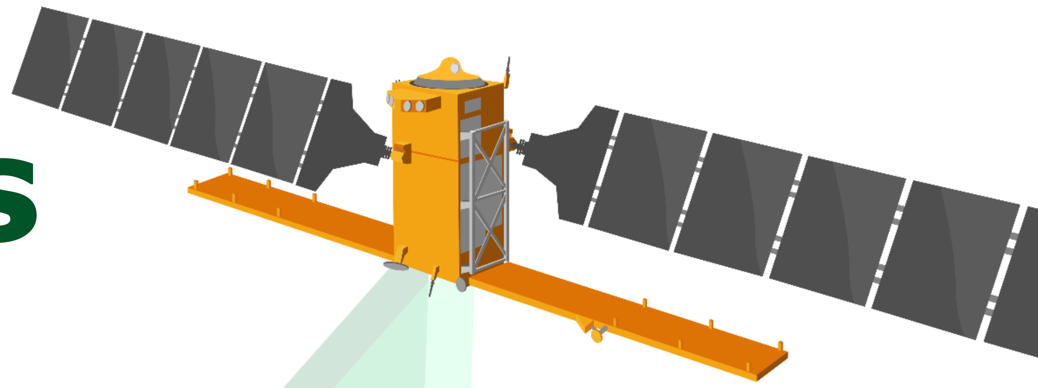
Monthly detections







Summary & objectives

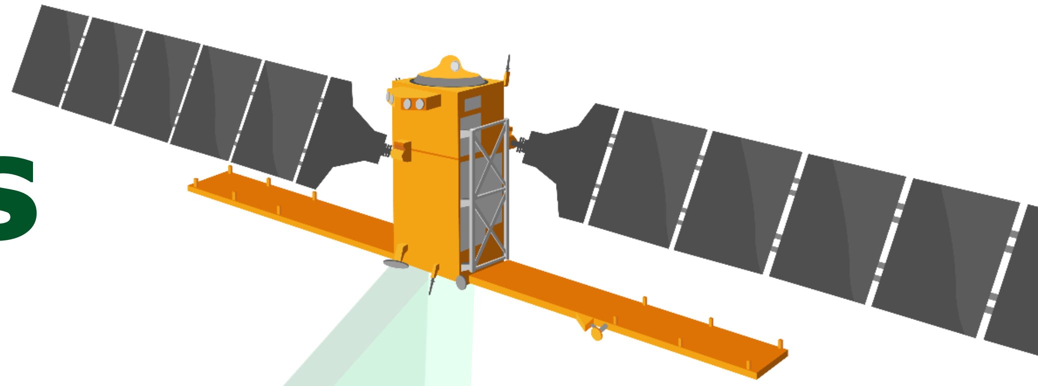


BOCD improves small-scale forest loss detection

Residual vegetation reduces BOCD performance

BOCD: lower detections vs GFW on large clearings

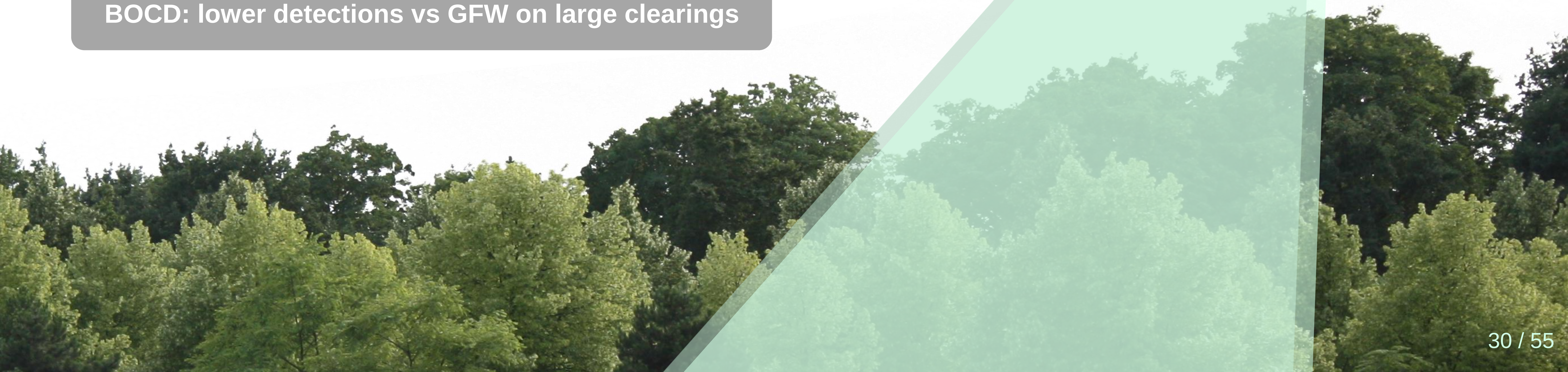
Summary & objectives



BOCD improves small-scale forest loss detection

Residual vegetation reduces BOCD performance → Dual-polarization BOCD

BOCD: lower detections vs GFW on large clearings



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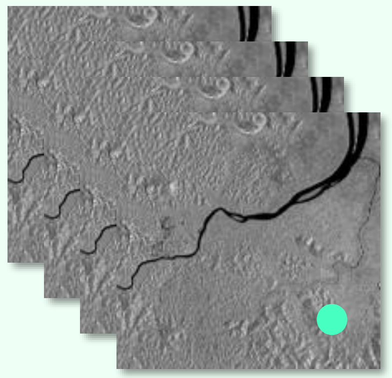
Bottani *et al*. Bayesian polarimetric detector for improved forest loss monitoring using dual-polarization Sentinel-1 data.
ISPRS Journal of Photogrammery and Remote Sensing (2025), Under Review.

Polarimetric BOCD



Sentinel-1 dual-pol data

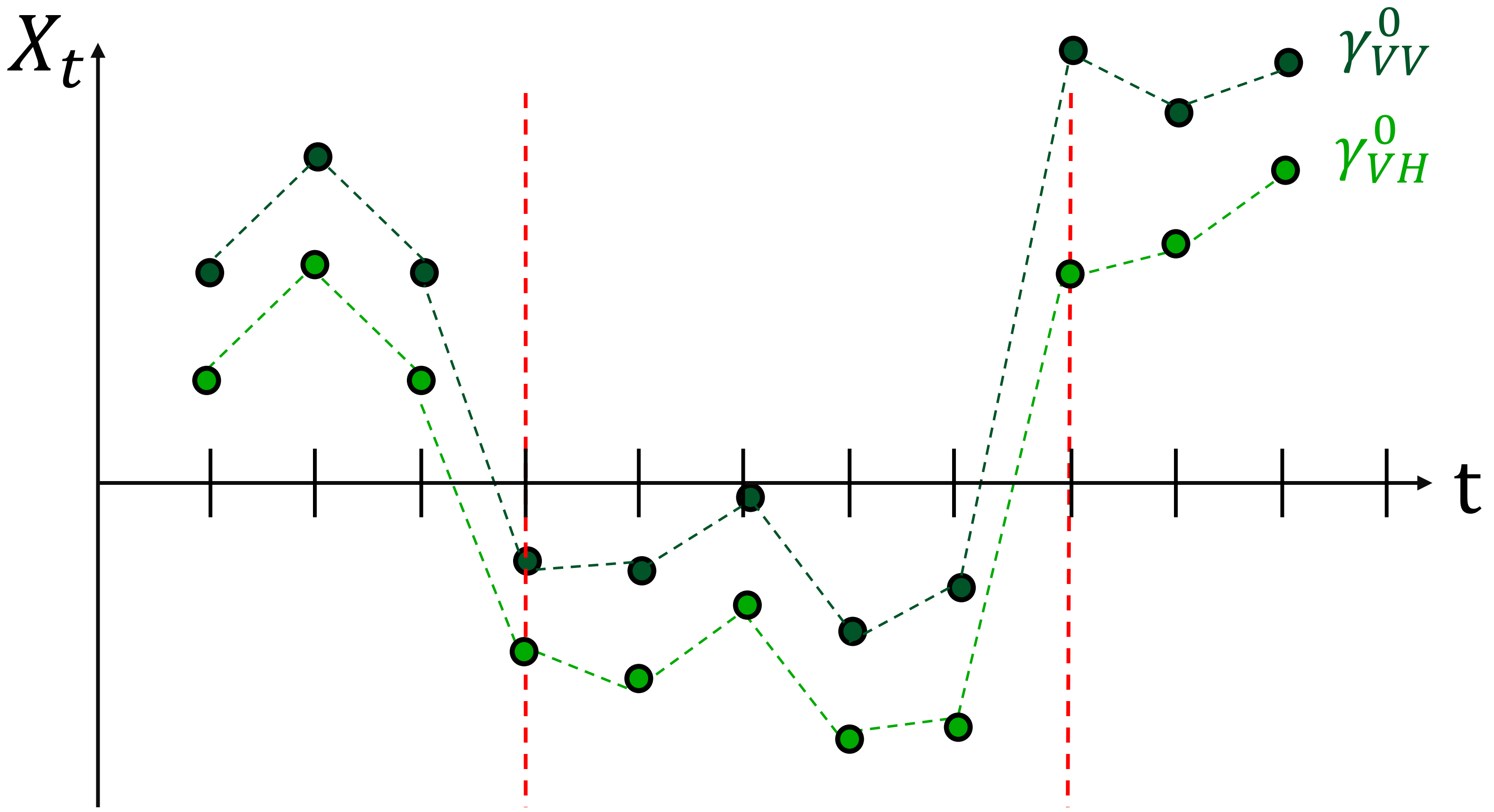
$\boldsymbol{X}_{1:t} = (\boldsymbol{x}_1, \dots, \boldsymbol{x}_t) \in \mathbb{R}^{2\times t}$

$\boldsymbol{x}_i = (x_1, x_2)^T = (\gamma^0_{VH}, \gamma^0_{VV})^T \in \mathbb{R}^2$ [dB]

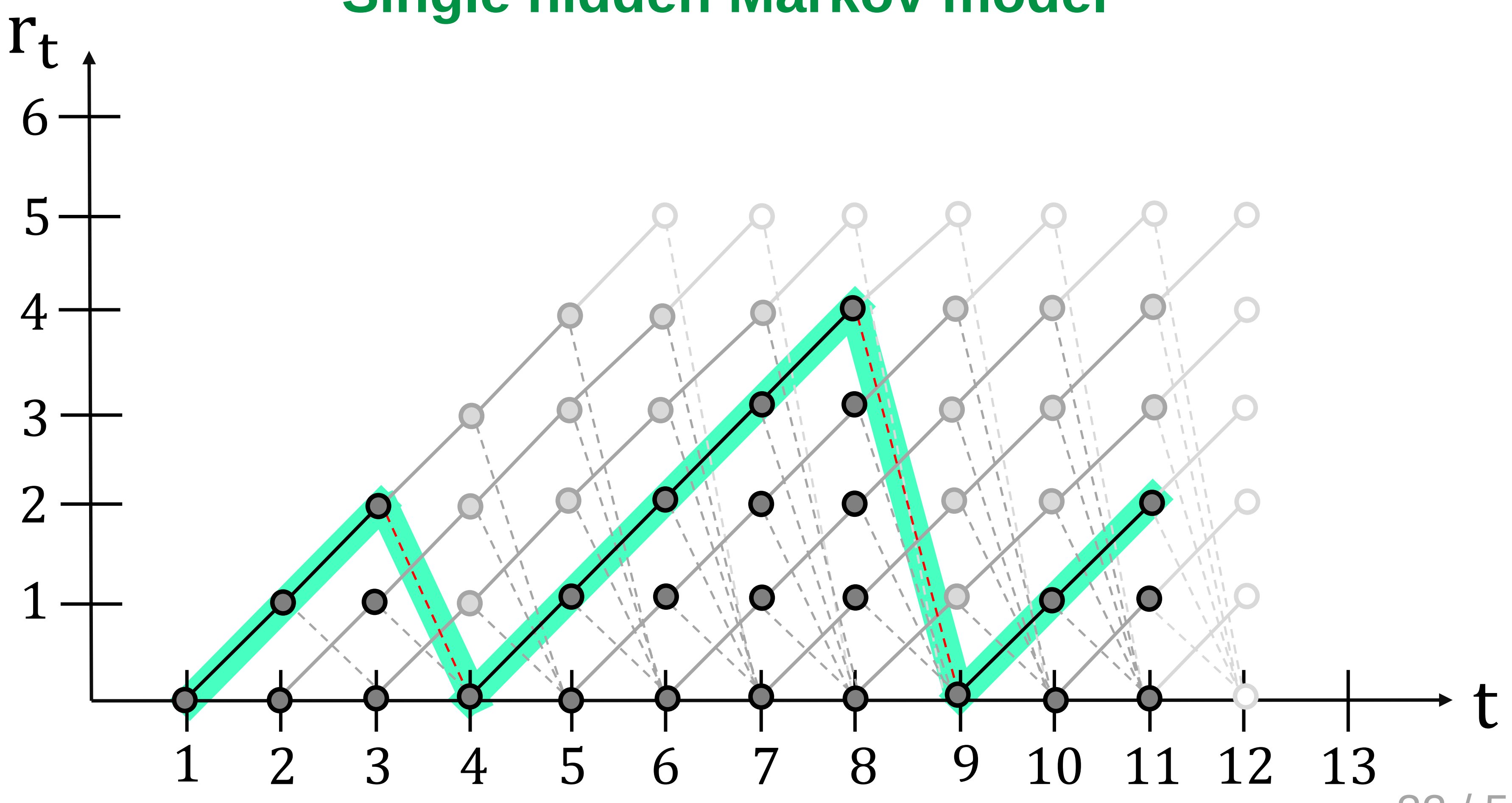
$$p(r_t|\boldsymbol{X}_{1:t}) = \frac{p(r_t, \boldsymbol{X}_{1:t})}{\sum_{r_t=0}^{t} p(r_t, \boldsymbol{X}_{1:t})}$$

$$p(r_t, \boldsymbol{X}_{1:t}) = \sum_{r_{t-1}=0}^{t-1} \boxed{p\left(\boldsymbol{x}_t \middle| \boldsymbol{X}_{t-1}^{(r_{t-1})}\right)} p(r_t|r_{t-1}) p(r_{t-1}, \boldsymbol{X}_{1:t-1})$$

Synchronous time series



Single hidden Markov model



Polarimetric correlation properties

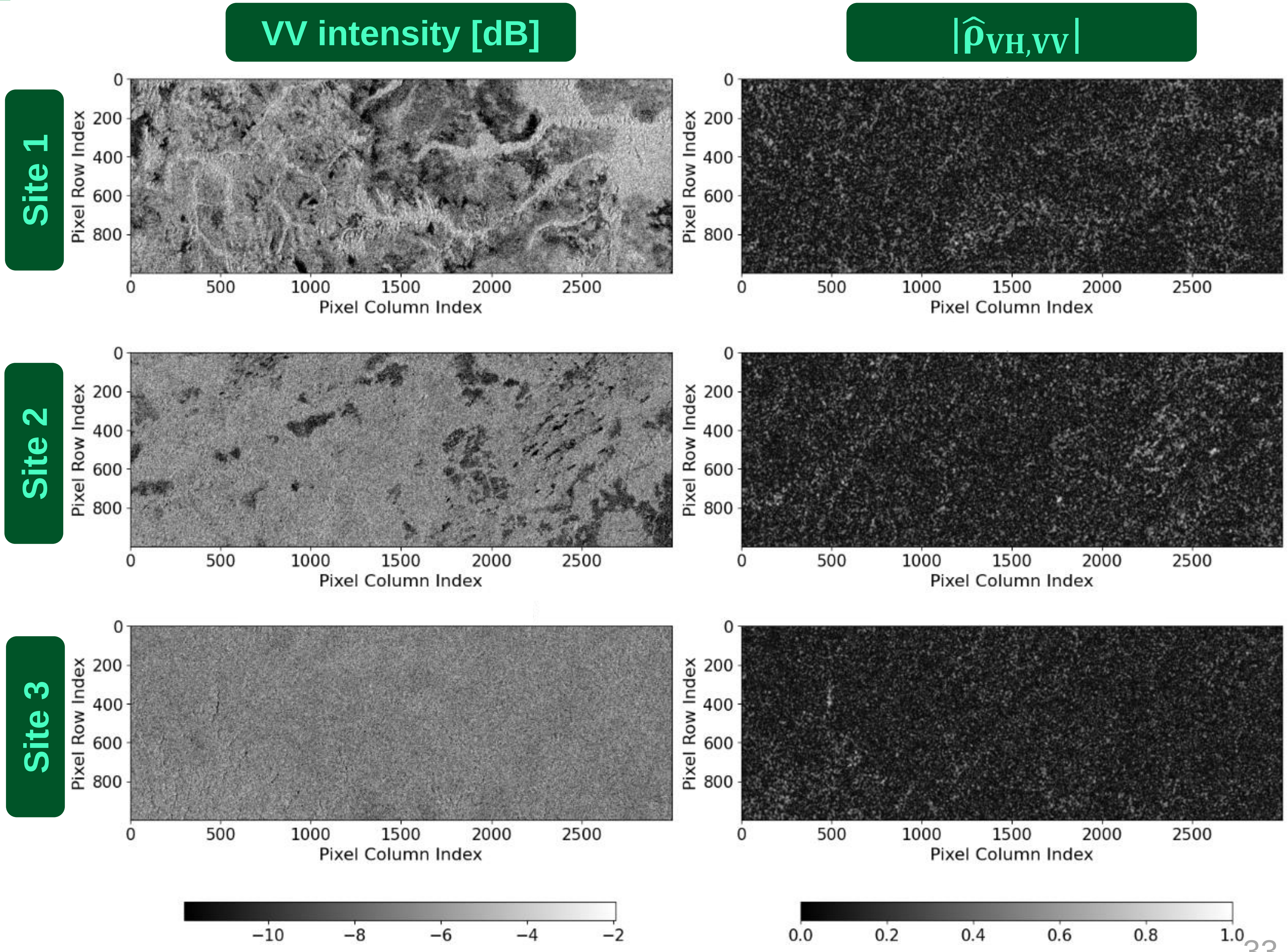
Over forested areas

$$|\hat{\rho}|_{VH,VV} = \frac{|\langle x_{1_c} x_{2_c} \rangle|}{\sqrt{\langle x_{1_c} x_{1_c} \rangle \langle x_{2_c} x_{2_c} \rangle}}$$

- $\langle \cdot \rangle$ boxcar filter $N \times N$
- Decorrelation of polarimetric channels
- Diagonal covariance matrix

Reflection symmetry

[Nghiem et al. 1992]



Polarimetric BOCD

Incorporating reflection symmetry

Likelihood:

$$p(\boldsymbol{x}_t|\boldsymbol{\Theta}) = \prod_{i=1}^{2} p_{\boldsymbol{\theta}_i}(x_{i,t})$$

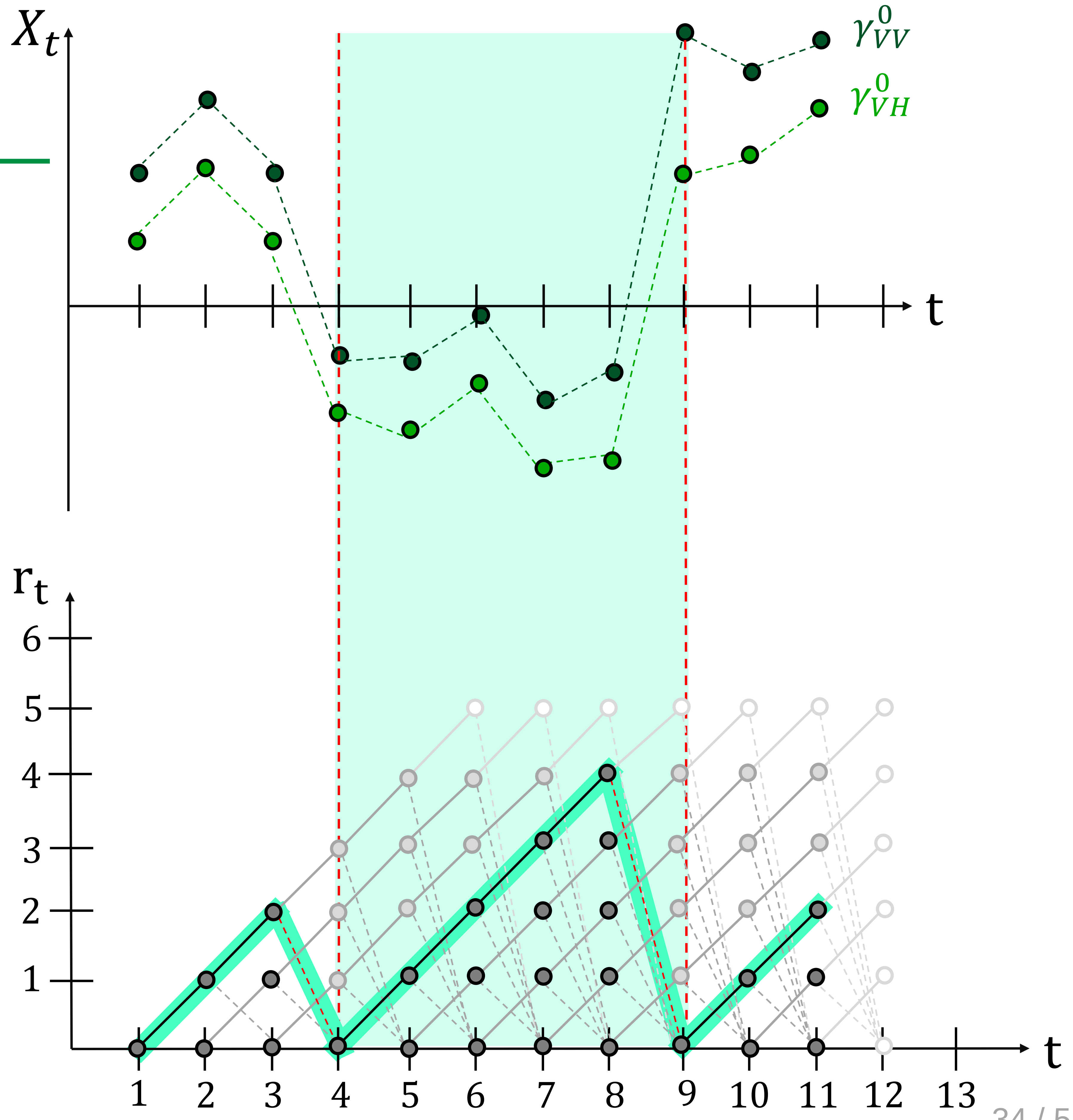
$$\boldsymbol{\Theta} = \{\boldsymbol{\theta}_i\}_{i=1}^{2}$$

Posterior predictive distribution:

$$p\left(\boldsymbol{x}_t \middle| \boldsymbol{X}_{t-1}^{(r_{t-1})}\right) = \prod_{i=1}^{2} f_i(\boldsymbol{x}_i;\boldsymbol{\eta}_i(m))$$

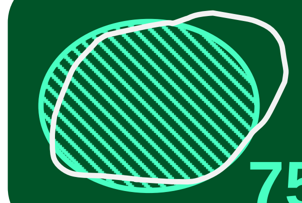
$$f_i(\boldsymbol{x}_{i,t};\boldsymbol{\eta}_i(m)) = t_{2\alpha_{i,m}}\left(x_{i,t};\mu_{i,m},\frac{\beta_{i,m}(\kappa_{i,m}+1)}{\alpha_{i,m}\kappa_{i,m}}\right)$$

Two univariate *t*-distributions



Spatial results: the Amazon

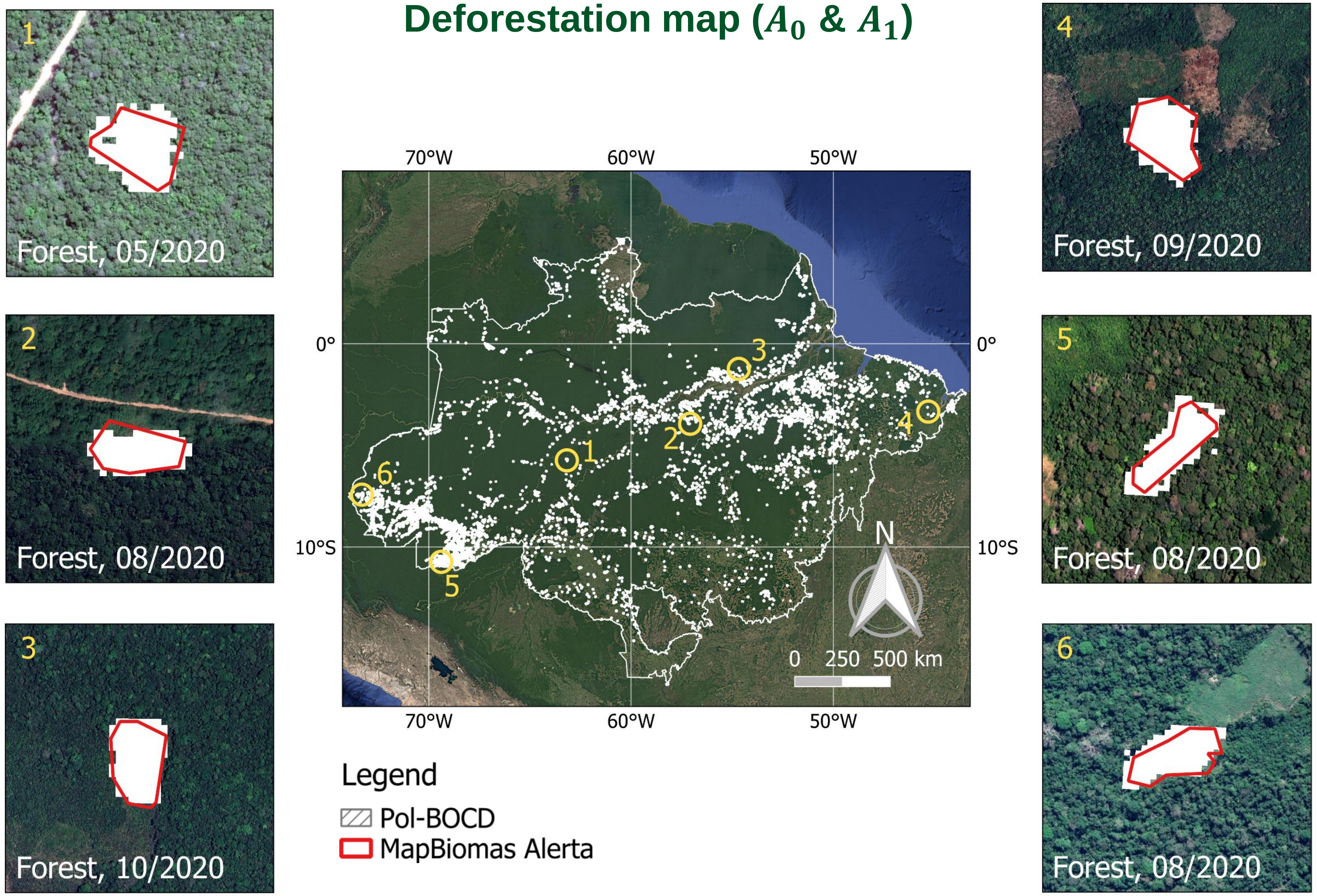
Small- vs large-scale forest loss in 2020



75%	F_1 [%]	
	A_0	A_1
pol-BOCD	83	56
VH-BOCD	81	44

+ 12%

Deforestation map (A_0 & A_1)



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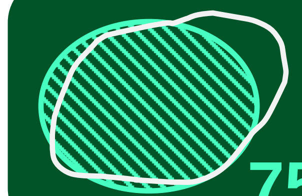
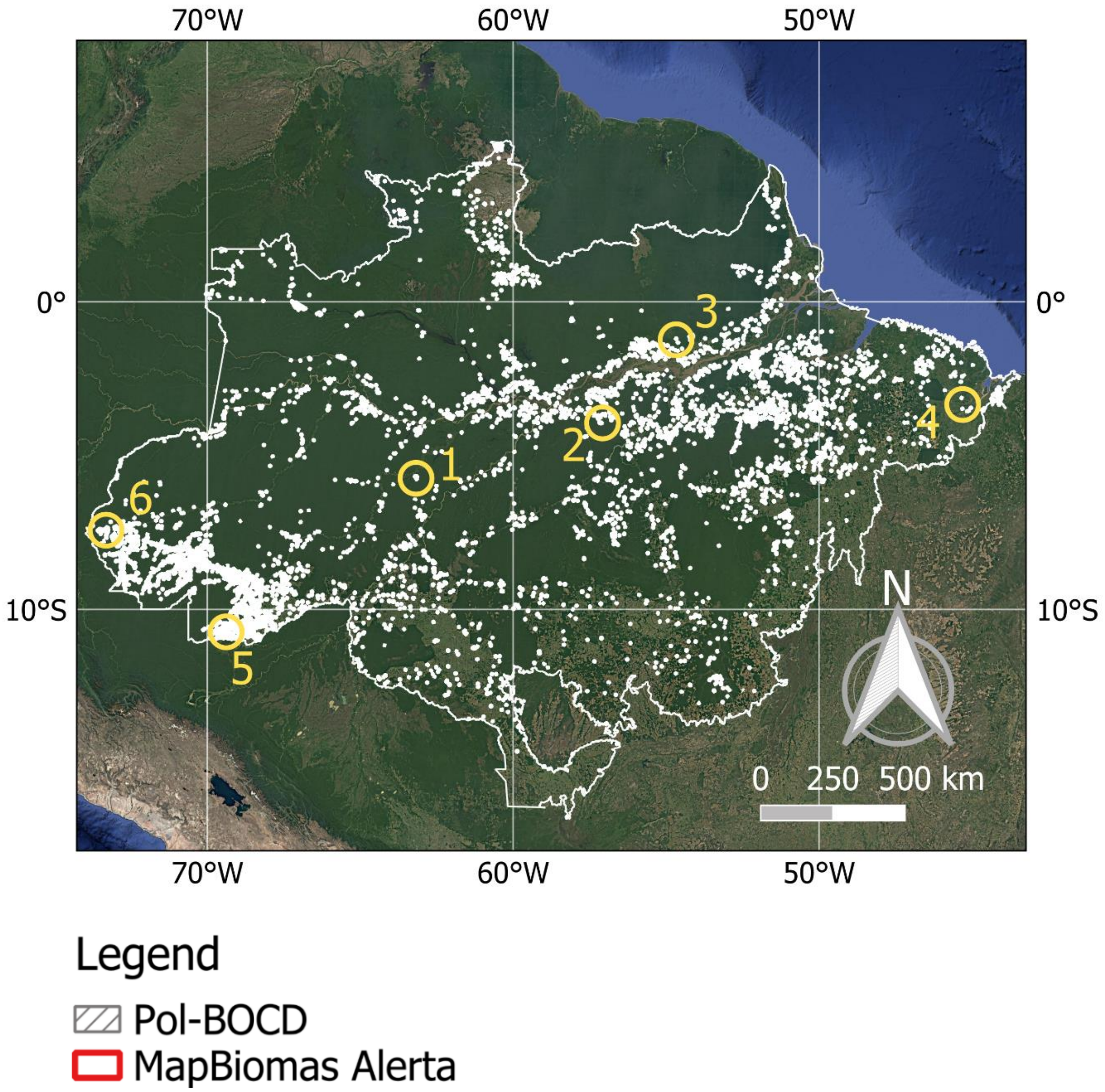
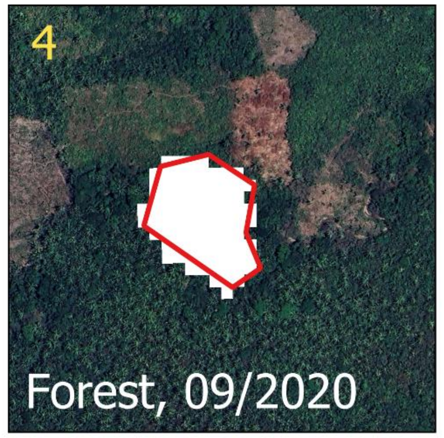
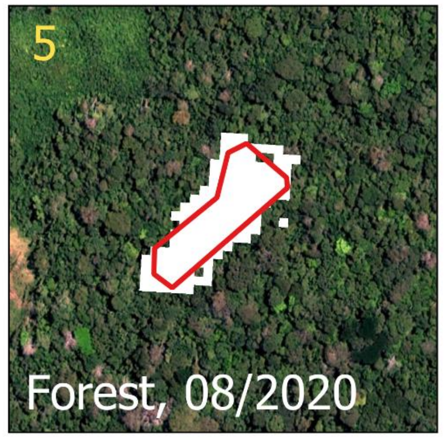


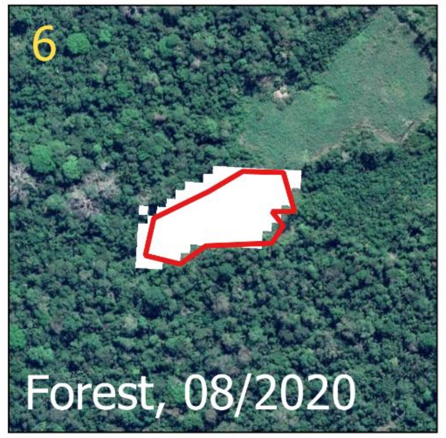
75%	F_1 [%]	
	A_0	A_1
pol-BOCD	83	56
VH-BOCD	81	44
		+ 12%
RADD	54	52
	+ 29%	

Deforestation map (A_0 & A_1)









Spatial results: the Amazon

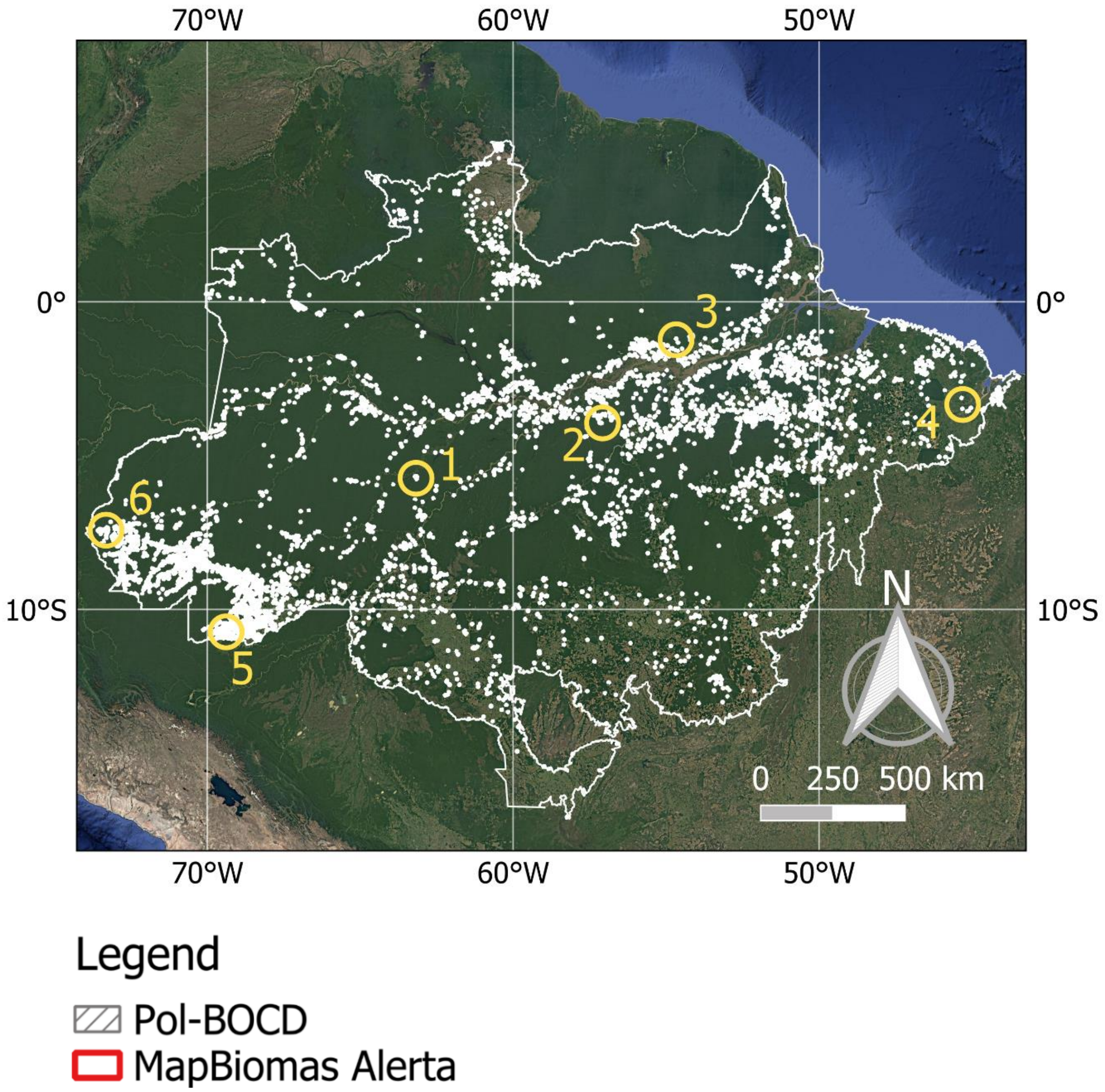
Small- vs large-scale forest loss in 2020

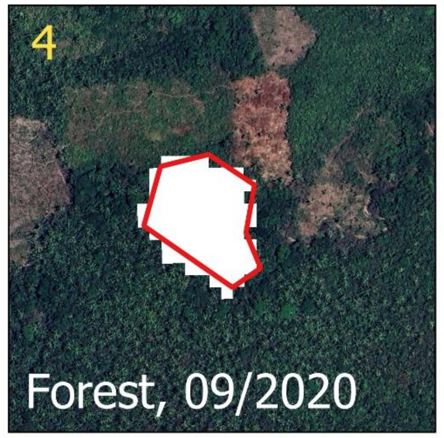
75%

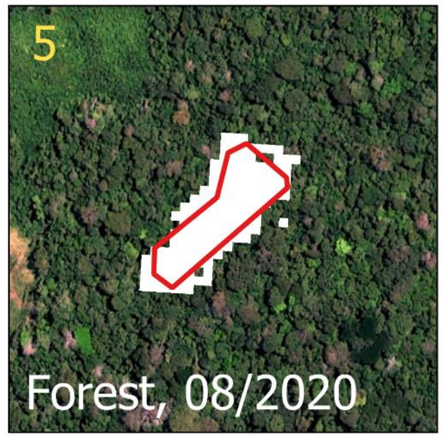
	F_1 [%] A_0	F_1 [%] A_1
pol-BOCD	83	56
VH-BOCD	81	44
		+ 12%
RADD	54	52
	+ 29%	

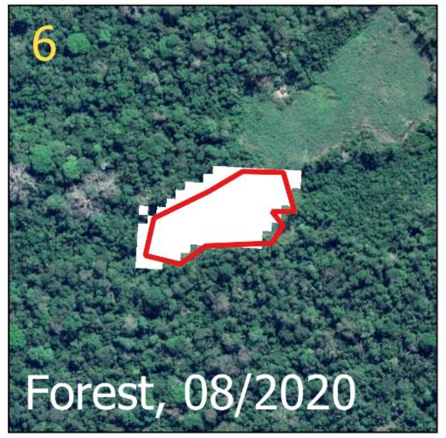
Slash and burn → residual vegetation

Deforestation map (A_0 & A_1)



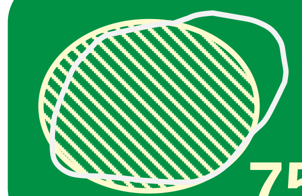






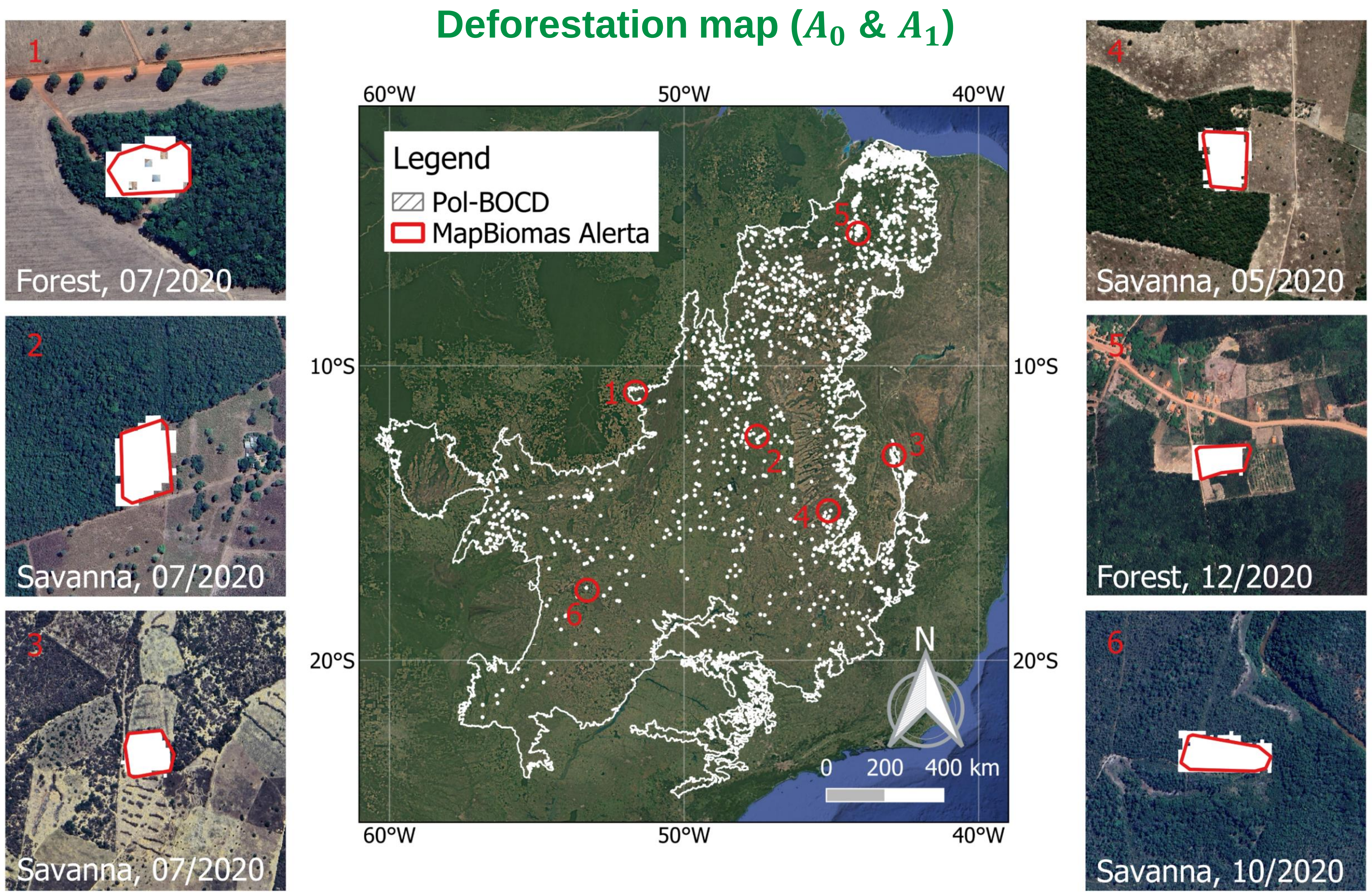
Spatial results: the Cerrado

Small- vs large-scale forest loss in 2020



75%	F_1 [%]	
	A_0	A_1
pol-BOCD	66	76
VH-BOCD	57	73

+ 9%



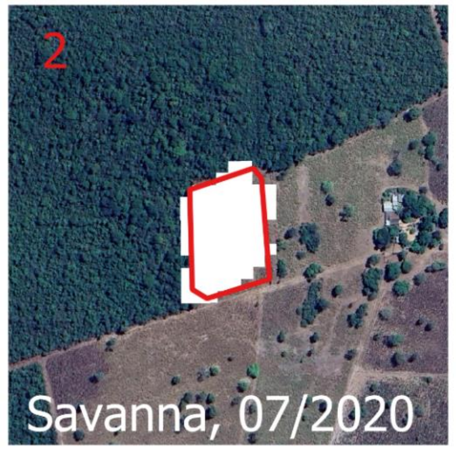
Spatial results: the Cerrado

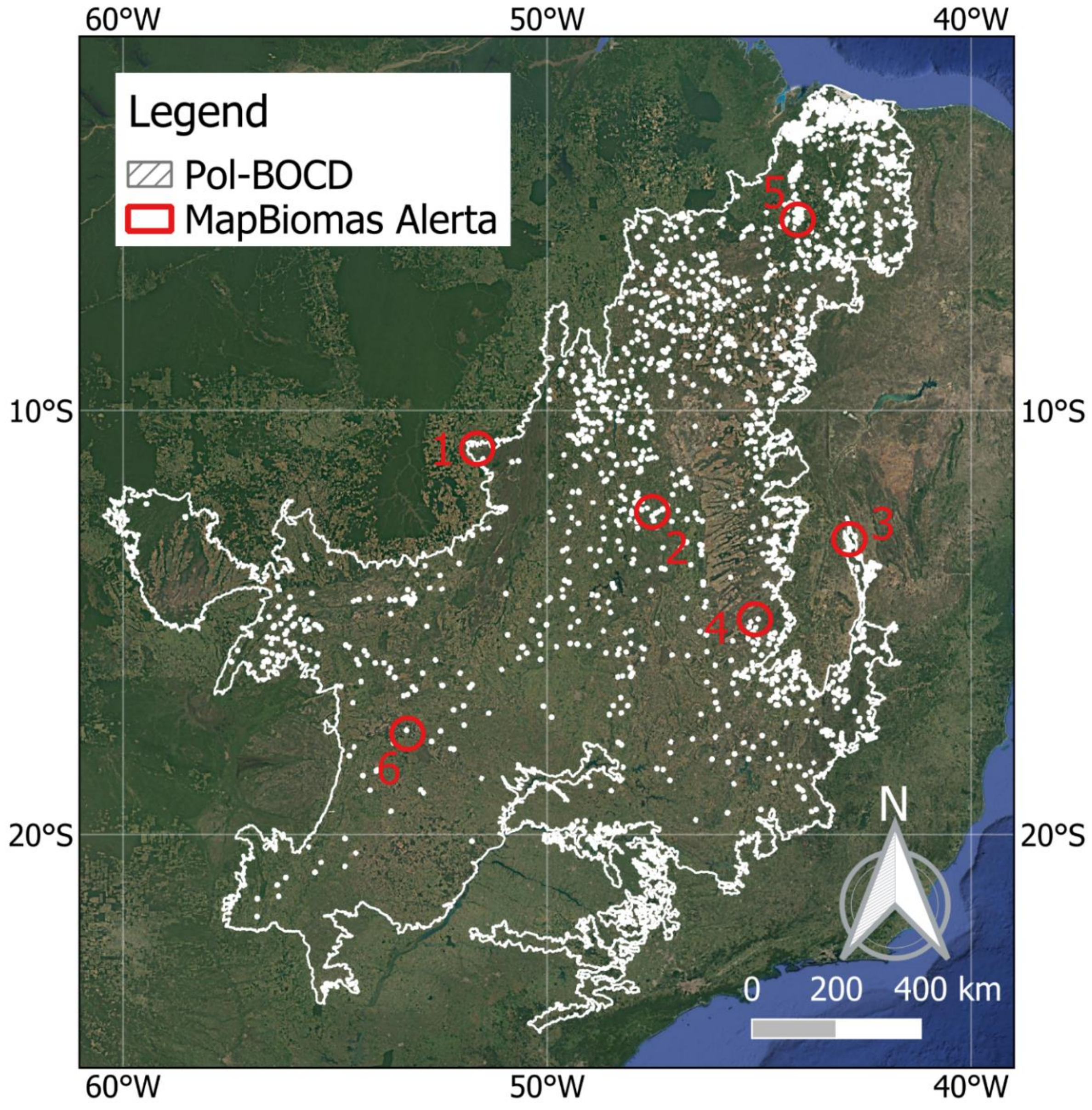
Small- vs large-scale forest loss in 2020

od 75%	F_1 [%]	
	A_0	A_1
pol-BOCD	66	76
VH-BOCD	57	73
	+ 9%	
GLAD-L	32	45

+ 32%

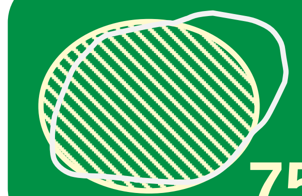
Deforestation map (A_0 & A_1)





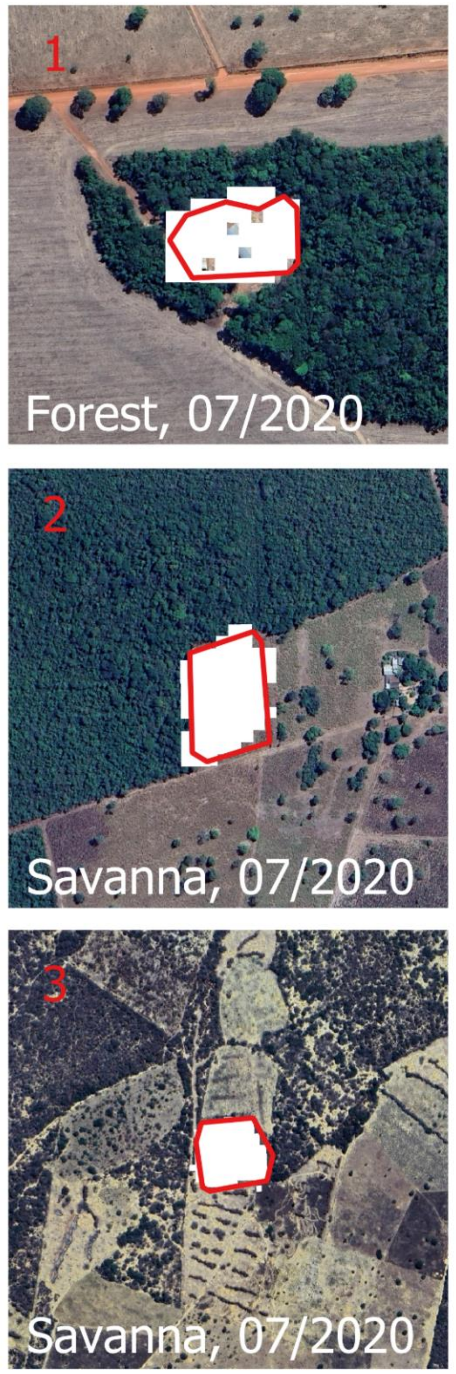
Spatial results: the Cerrado

Small- vs large-scale forest loss in 2020

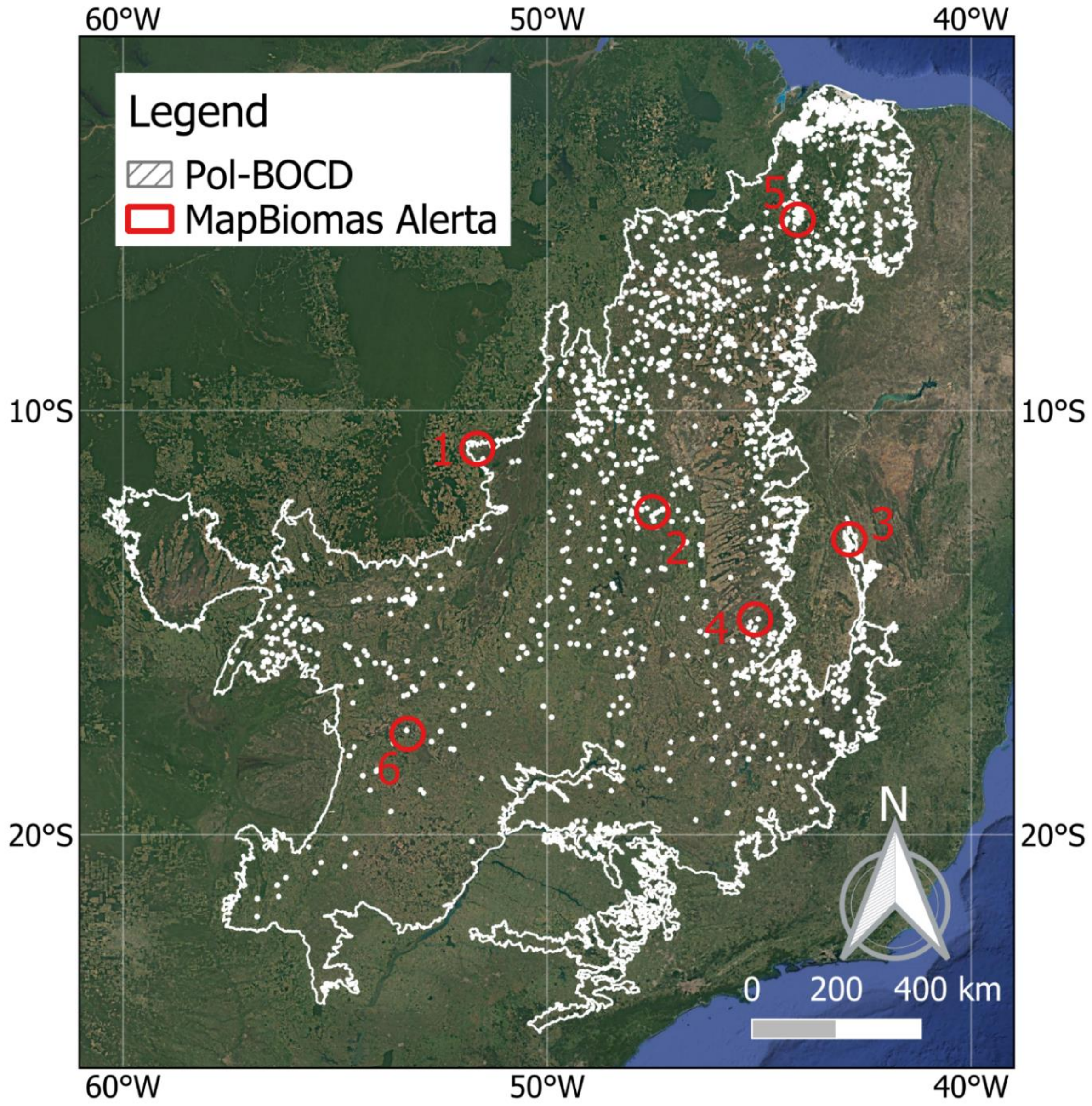


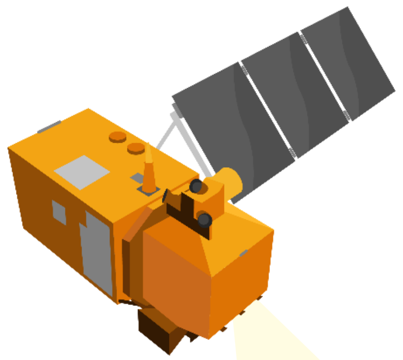
	F_1 [%] A_0	F_1 [%] A_1
pol-BOCD	66	76
VH-BOCD	57	73
	+ 9%	
GLAD-L	32	45
	+ 32%	

Artisanal clearing → residual vegetation

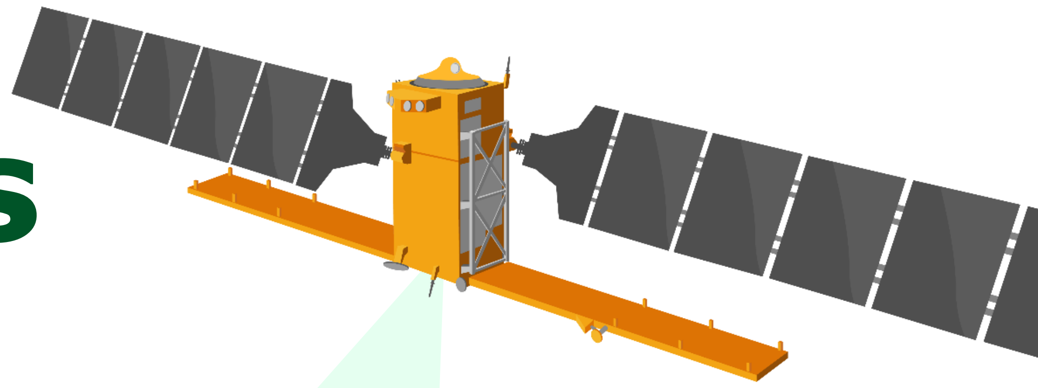


Deforestation map (A_0 & A_1)



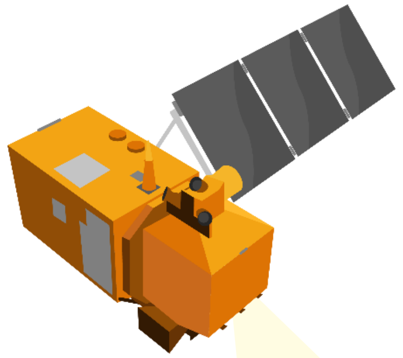


Summary & objectives

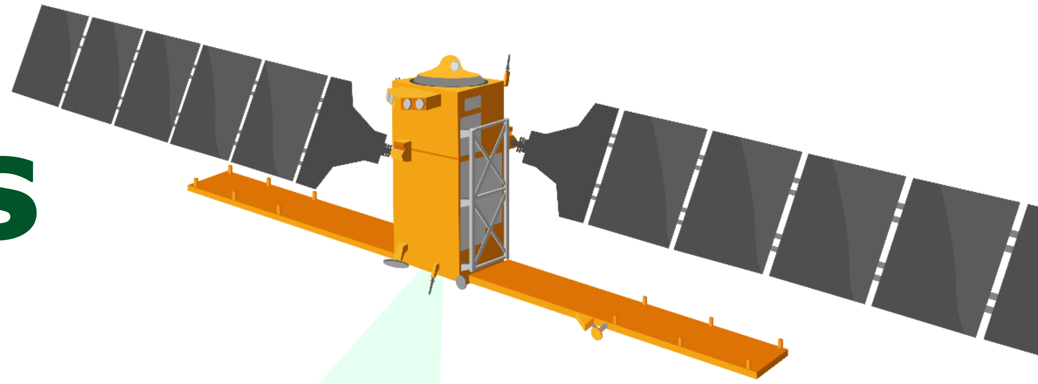


pol-BOCD: +10% over areas with post-clearing debris

BOCD: lower detections vs GFW on large clearings



Summary & objectives



pol-BOCD: +10% over areas with post-clearing debris

BOCD: lower detections vs GFW on large clearings → Multi-source BOCD

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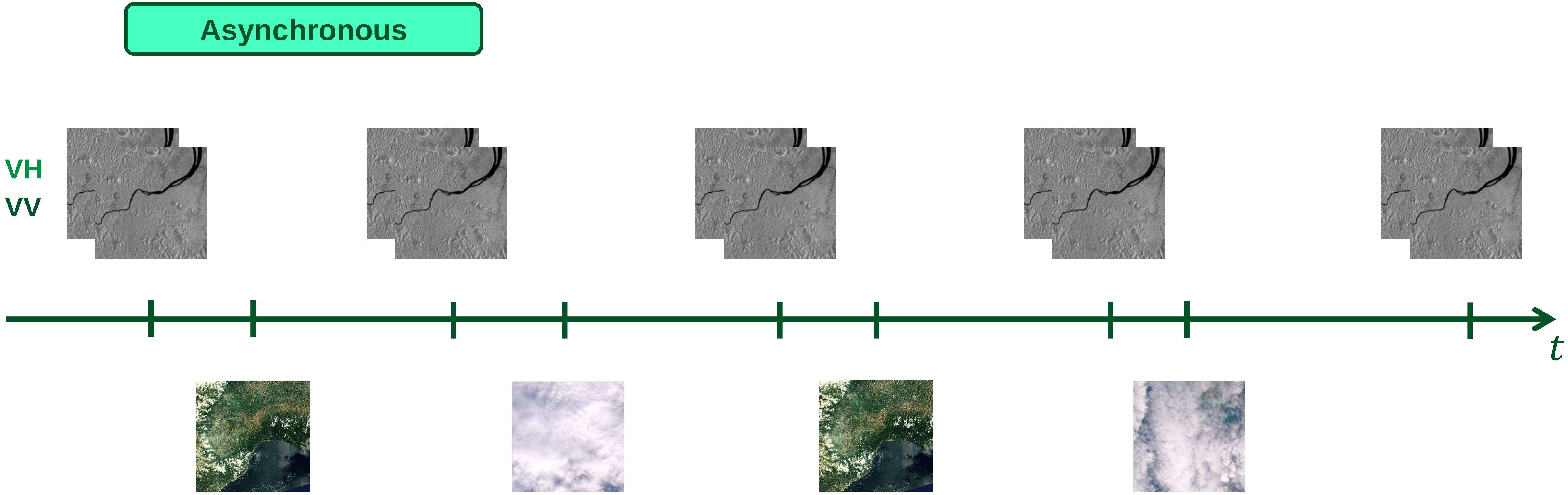
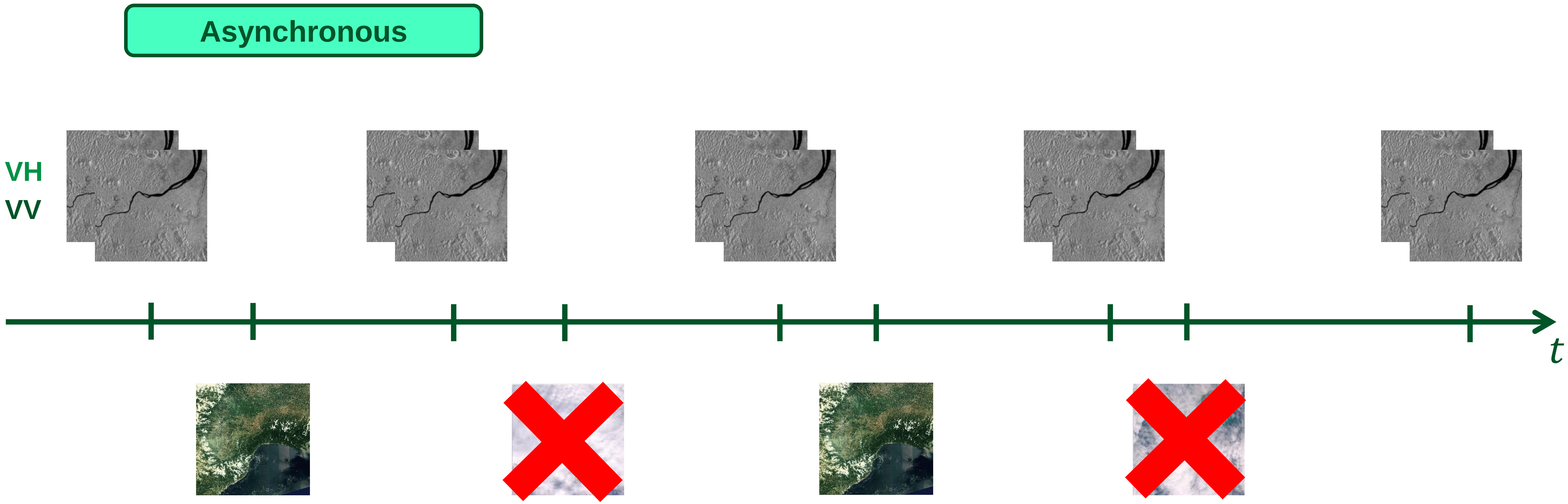
Bottani *et al*. Multi-source fusion using Bayesian online change detection: application to deforestation monitoring using SAR-optical time series. *In proceedings IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, 2025.

Insights on SAR-multispectral fusion

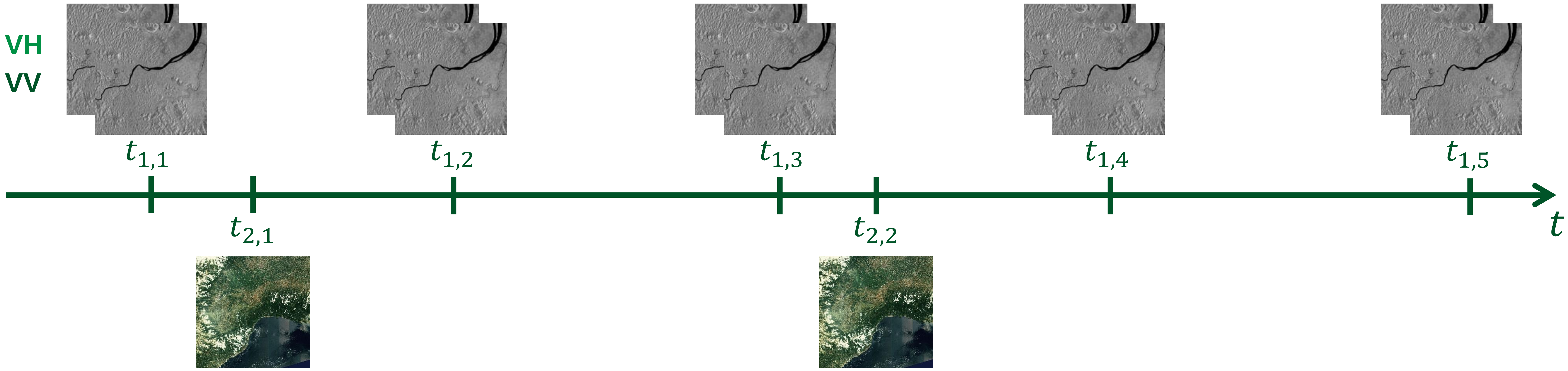


Insights on SAR-multispectral fusion



Insights on SAR-multispectral fusion

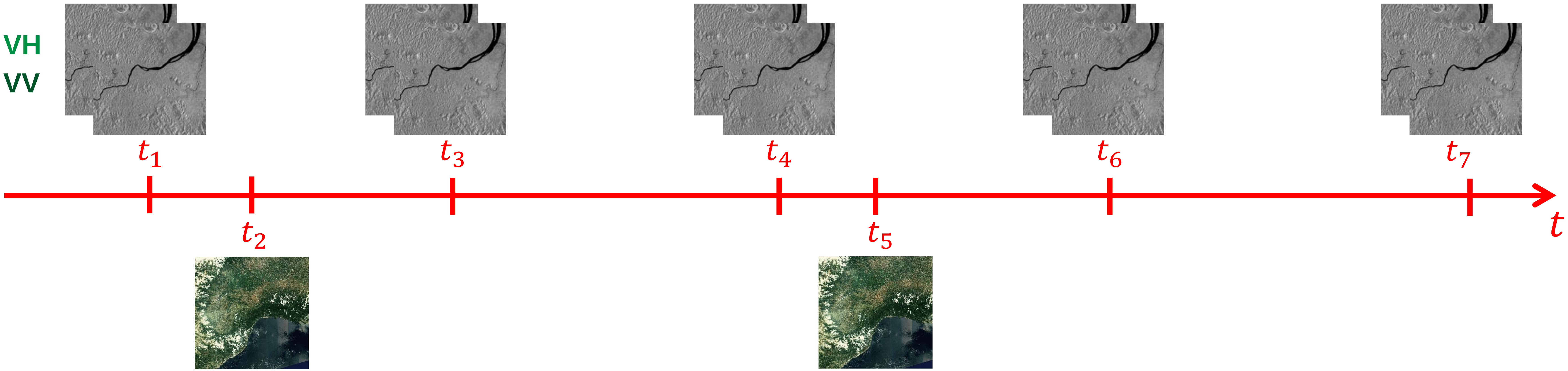
Asynchronous **Irregularly sampled**



Insights on SAR-multispectral fusion

Asynchronous

Irregularly sampled



$$\boldsymbol{t} = \{t_{i,n}, i = 1, \dots, N_s, n = 1, \dots, n_i\}$$

n: acquisition index
t: acquisition date

Fusion of asynchronous data

Single Markov chain

How to write the posterior predictive of r_n ?

- Individual posterior predictives:

$$f_i\left(x_{i,n_i};\boldsymbol{\eta}_i(t_n)\right) = p\left(x_{i,n_i}\middle|\boldsymbol{x}_{i,n_i-1}^{(r_n-1)}\right)$$

- Global posterior predictive:

$$p\left(\boldsymbol{x}_n\middle|\boldsymbol{X}_{n-1}^{(r_n-1)}\right)=\mathcal{G}\{f_i(\boldsymbol{x}_{i,n_i};\boldsymbol{\eta}_i(t_n))\}_{i=1,2}$$

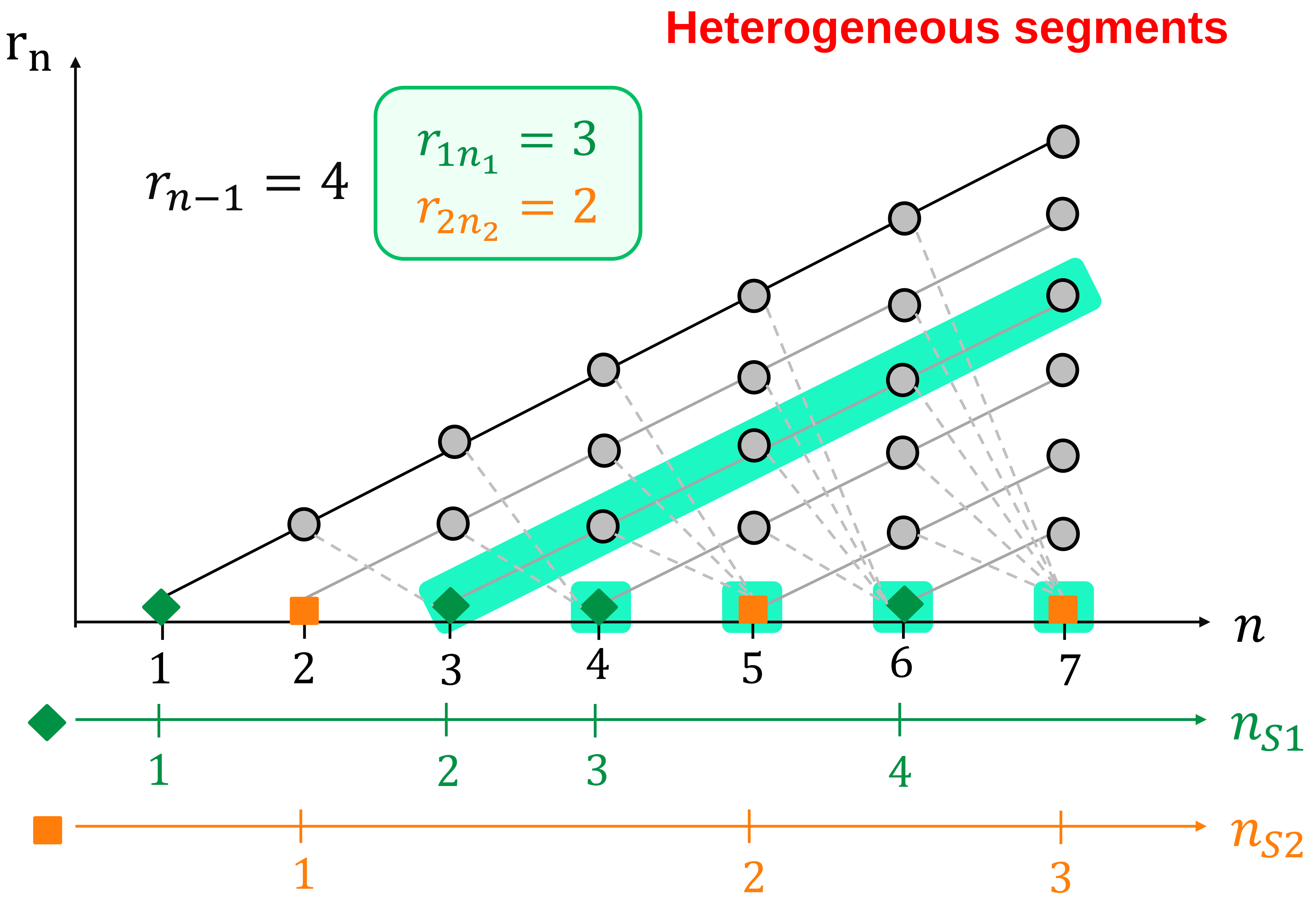
Full memory

$$\prod_{i=1}^{N_s} f_i\left(\boldsymbol{x}_{i,n_i};\boldsymbol{\eta}_i(t_n)\right)$$

No memory

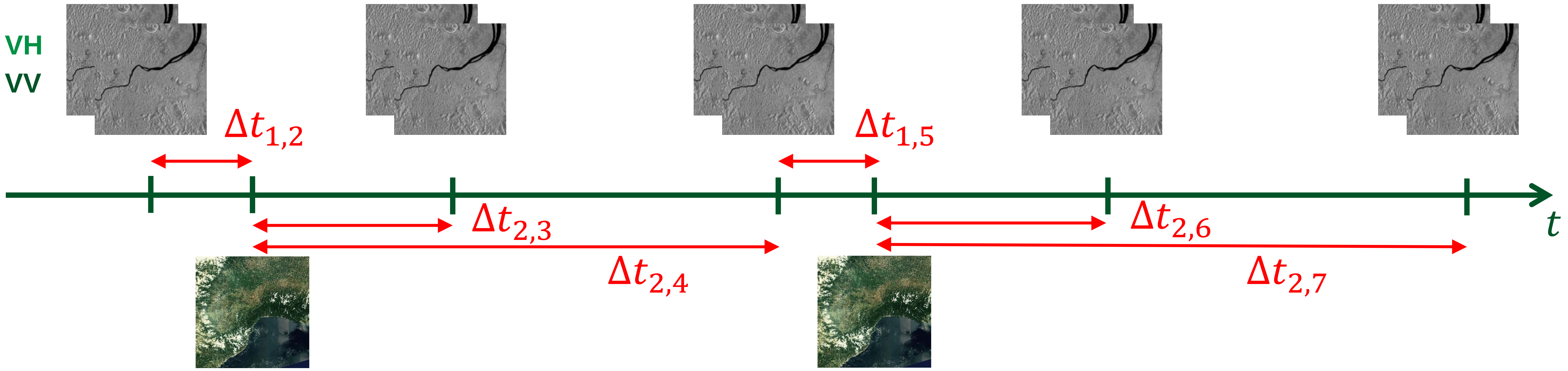
$$f_m\left(\boldsymbol{x}_{m,n_m};\boldsymbol{\eta}_m(t_n)\right)$$

m: measured source



Fusion of asynchronous data

Adaptive power weighting



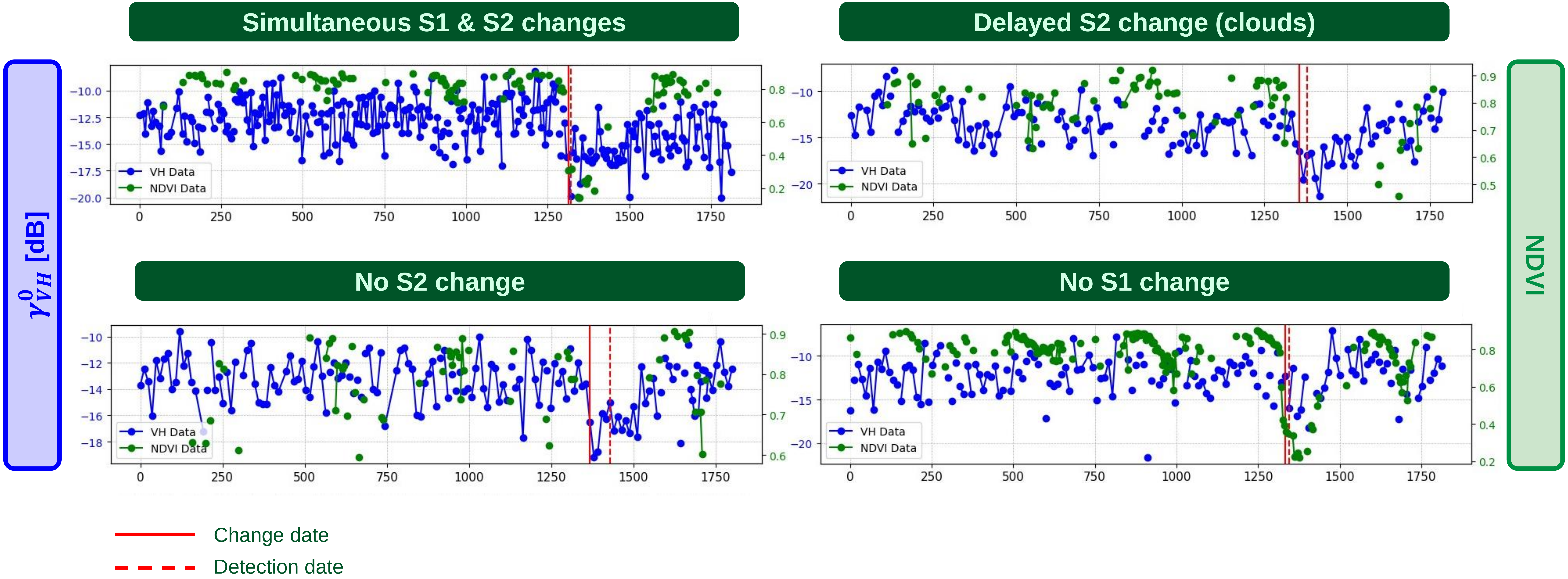
Down-weight old acquisitions

$$p_{\boldsymbol{w}(r_n-1)}\left(\boldsymbol{x}_n \middle| \boldsymbol{X}_{n-1}^{(r_n-1)}\right)=\prod_{i=1}^{N_s} f_i^{w_i(r_n-1)}\left(\boldsymbol{x}_{i,n_i};\boldsymbol{\eta}_i(t_n)\right)$$

- Deterministic: $w_i(r_n-1)=e^{-\lambda\Delta t_{i,n}}$ $\quad 0\leq\lambda\leq+\infty$
- Bayesian: $w_i\sim\mathrm{Beta}(\alpha_i,\beta_i)$ or $w_i\sim\mathrm{Dirichlet}(\alpha_i)$

Examples of detections

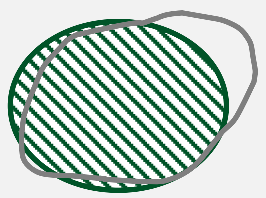
ms-BOCD on single-pixel time series



Spatial result: the Amazon

Small- vs large-scale forest loss in 2020

F1-score [%]
compromise between detections and false alarms

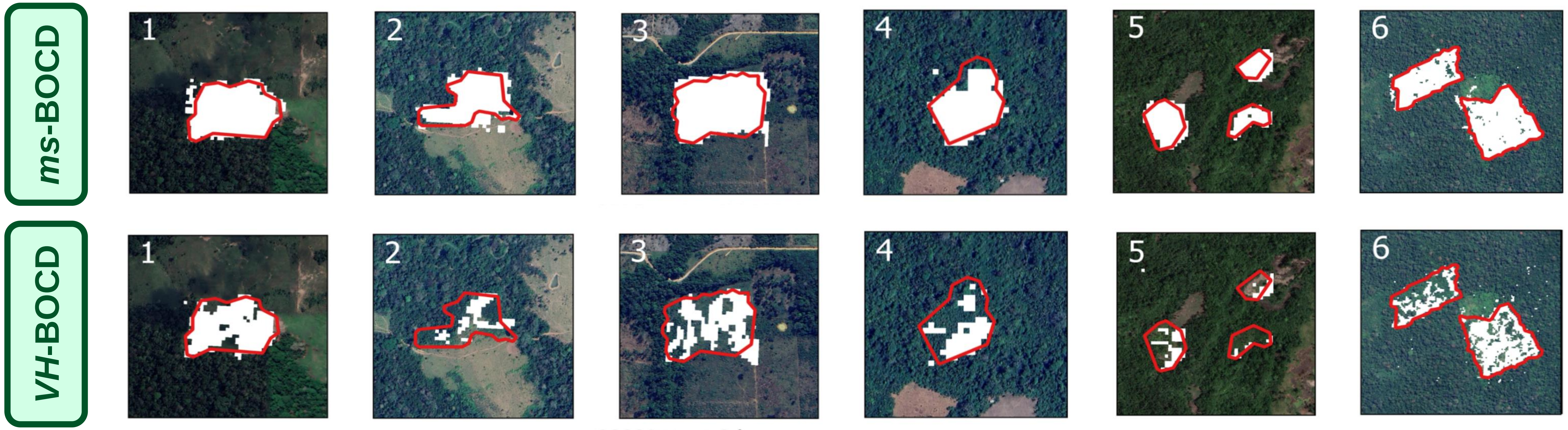


75%

Small (A_0)				Large (A_1)			
ms-BOCD	*VH*-BOCD	RADD	GFW	*ms*-BOCD	*VH*-BOCD	RADD	GFW
89	85	56	85	75	45	48	74

+ 33%

+ ~30%



Spatial result: the Amazon

Small- vs large-scale forest loss in 2020

F1-score [%]
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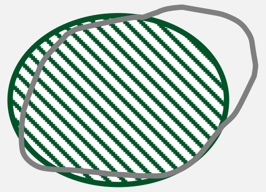
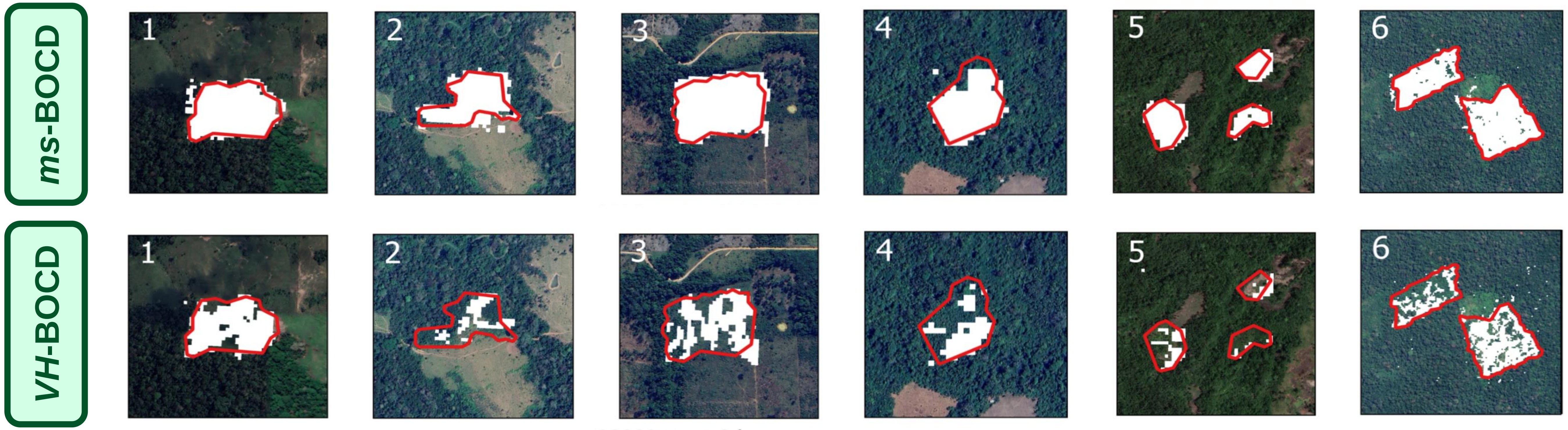
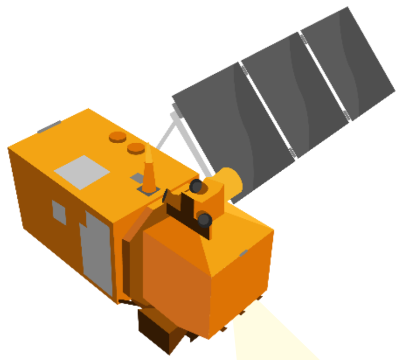


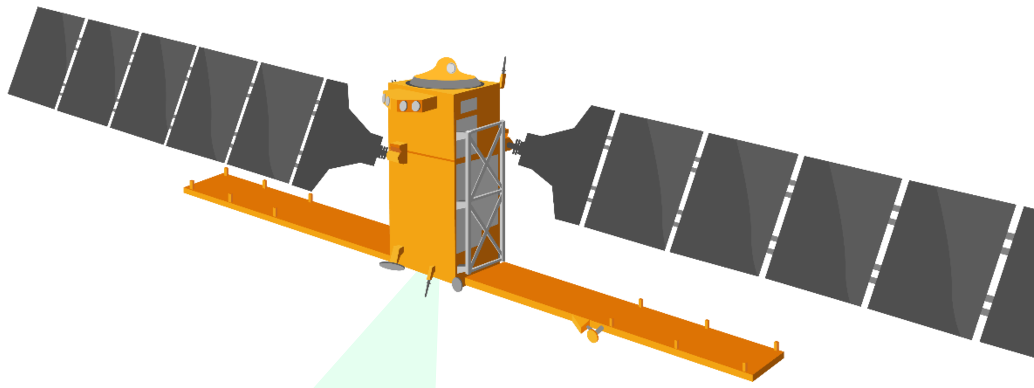
	Small (A_0)				Large (A_1)			
	ms-BOCD	*VH*-BOCD	RADD	GFW	*ms*-BOCD	*VH*-BOCD	RADD	GFW
75%	89	85	56	85	75	45	48	74

+ 13% FA





Summary



Sensor-agnostic change detection algorithm

Multi-source

Asynchronous

Unequally sampled

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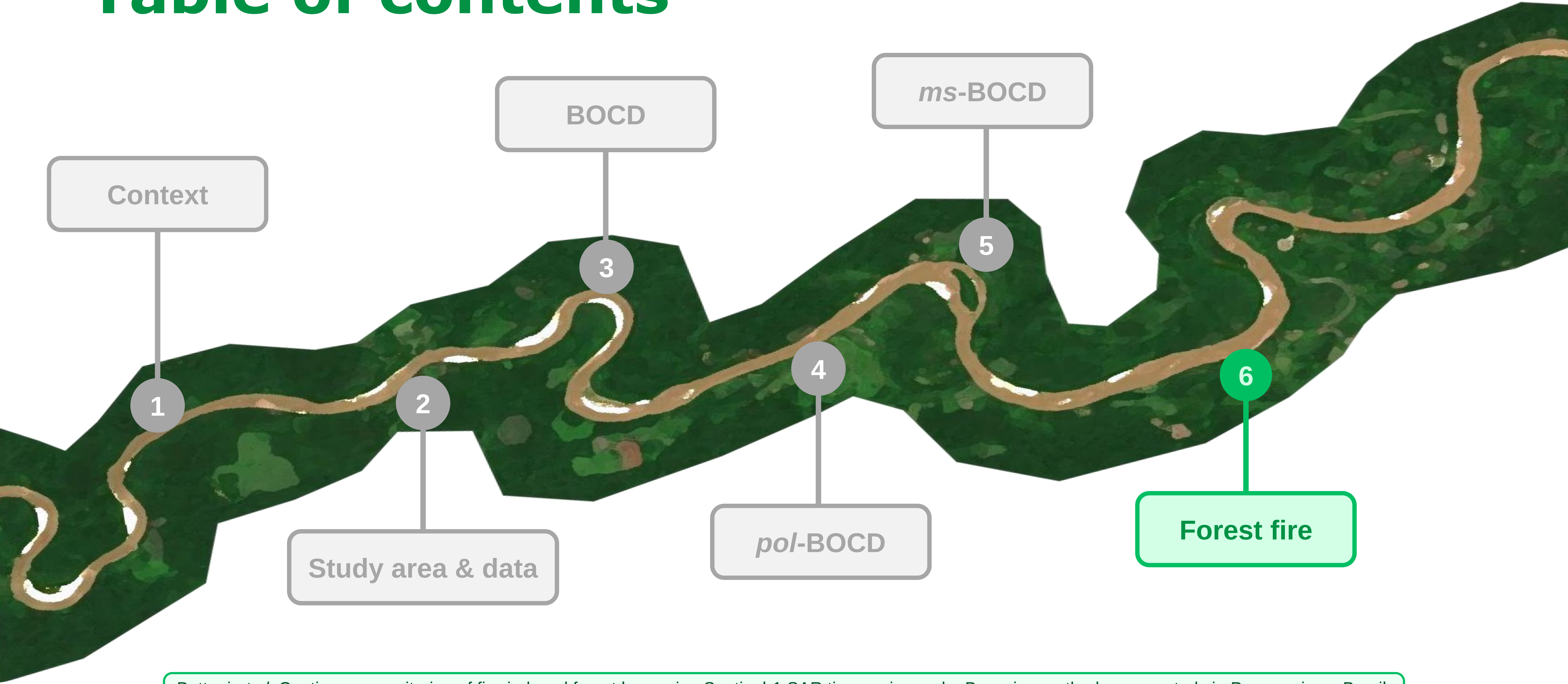


Bottani *et al*. Continuous monitoring of fire-induced forest loss using Sentinel-1 SAR time series and a Bayesian method: a case study in Paragominas, Brazil. *Remote Sensing*, 2025.

Motivation & objective

Paragominas, Pará

September-November 2024

Availability of field-validated reference data

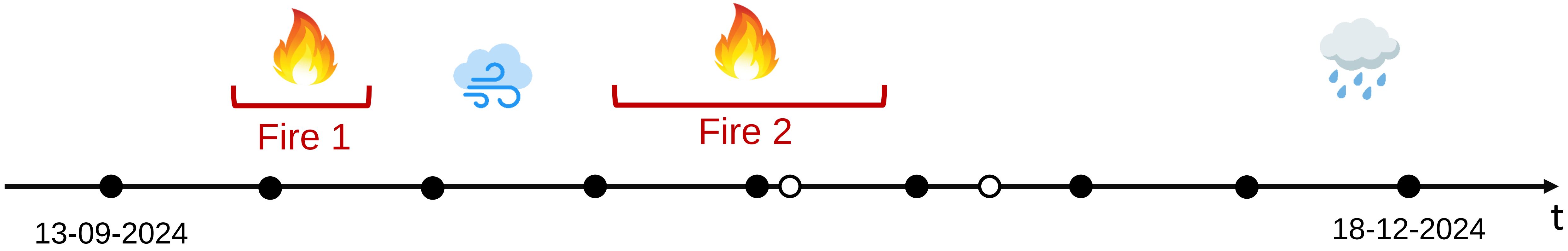
105 ha of primary forest

Test BOCD on fire-induced forest loss

Complementarity with multispectral imagery

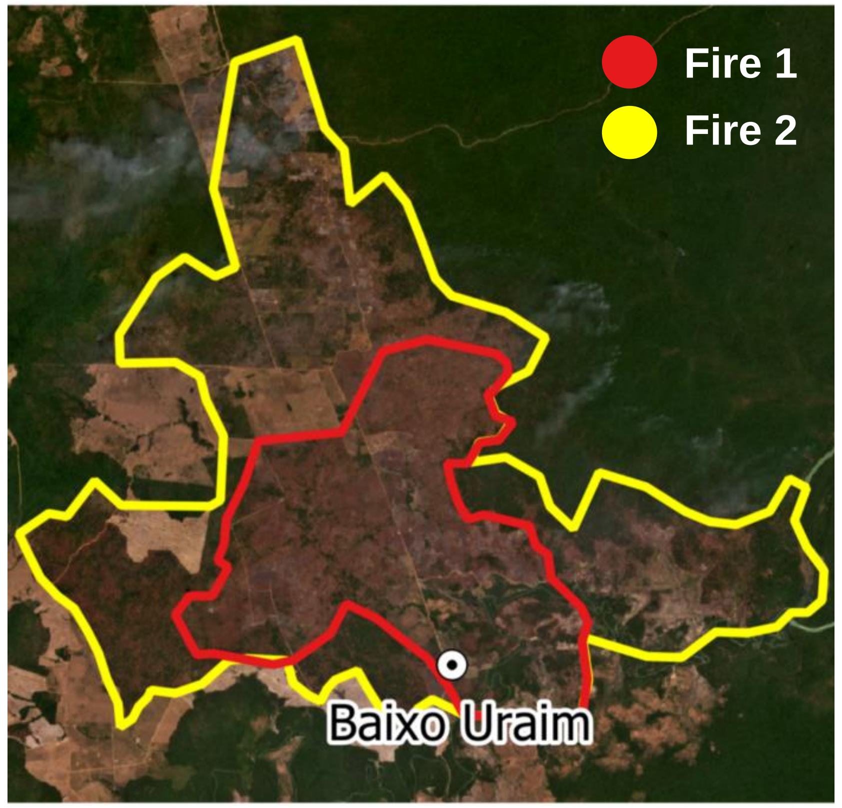
Data sources

Fire timeline

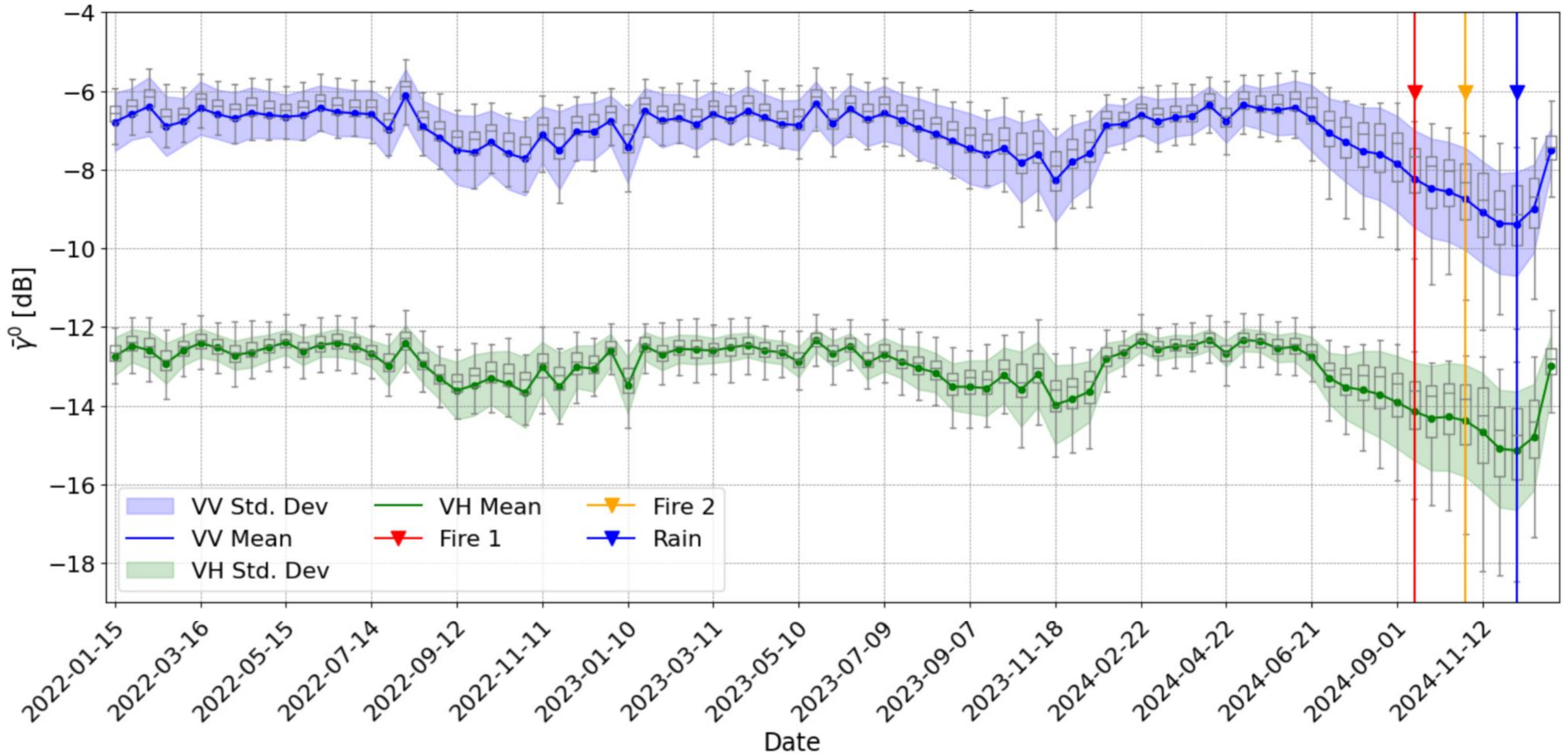


● Sentinel-1
○ Cloud-free Sentinel-2

PlanetScope – November 2024



Sentinel-1A reflectivity



Sentinel-2 dNBR

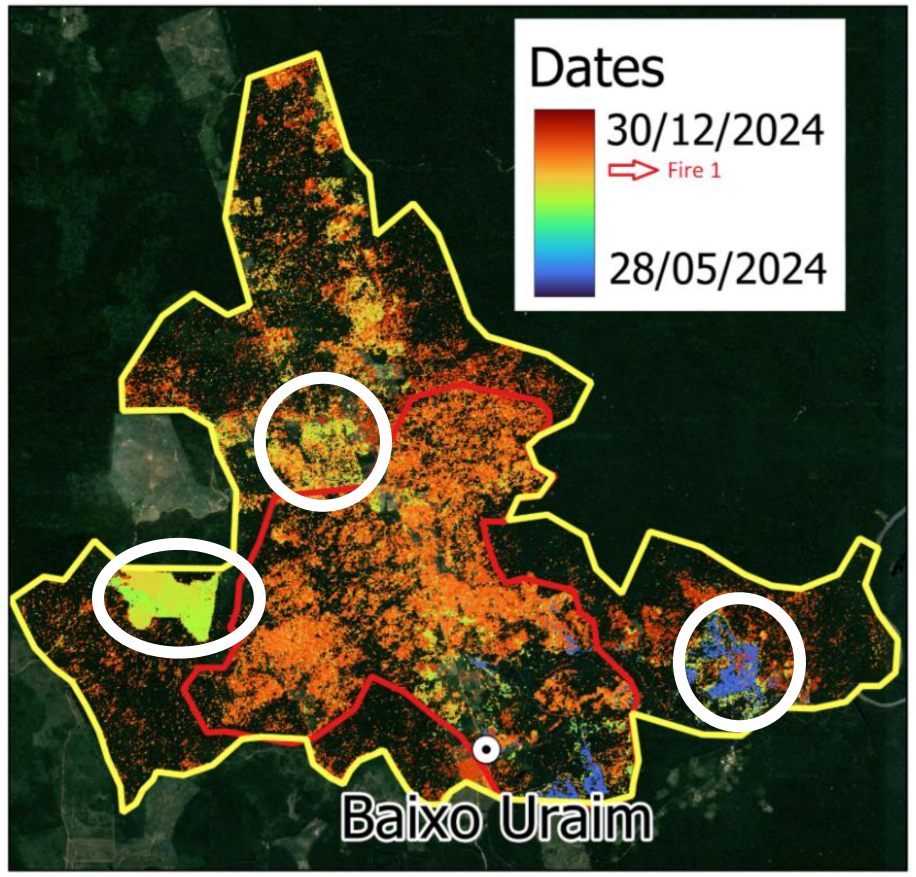
$$NBR = \frac{R_{NIR} - R_{SWIR}}{R_{NIR} + R_{SWIR}}$$

$$dNBR = NBR_{pre} - NBR_{post}$$

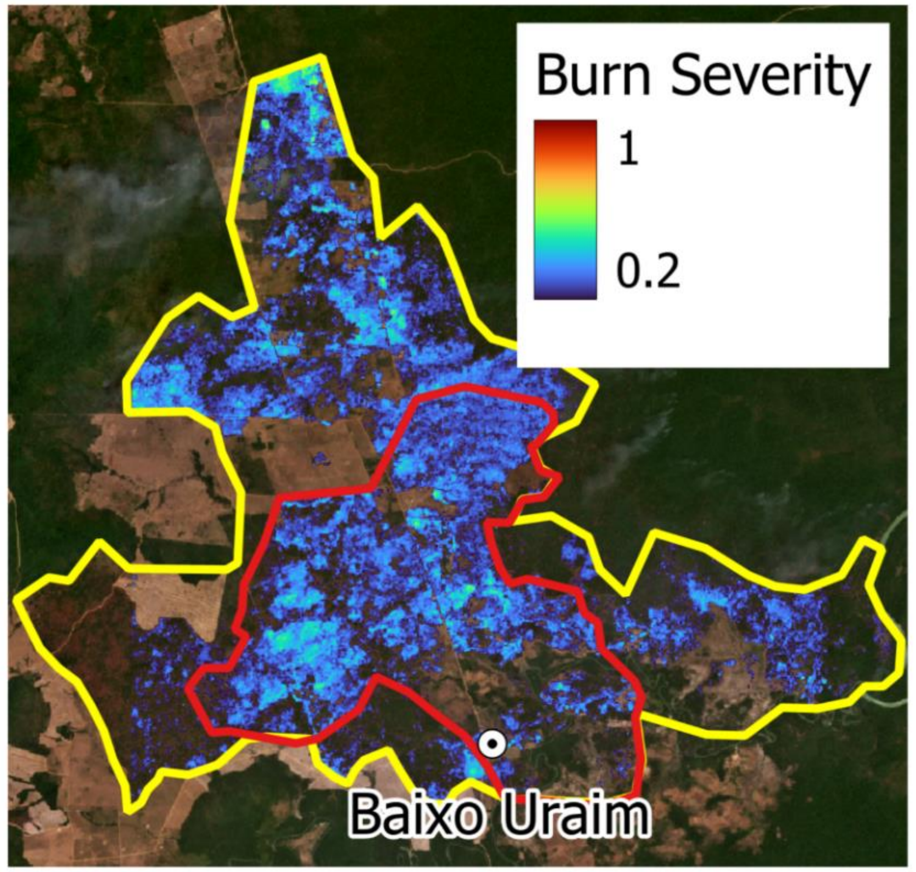
- 6 Sentinel-1A images
- 2 cloud-free Sentinel-2 images

Comparison of results

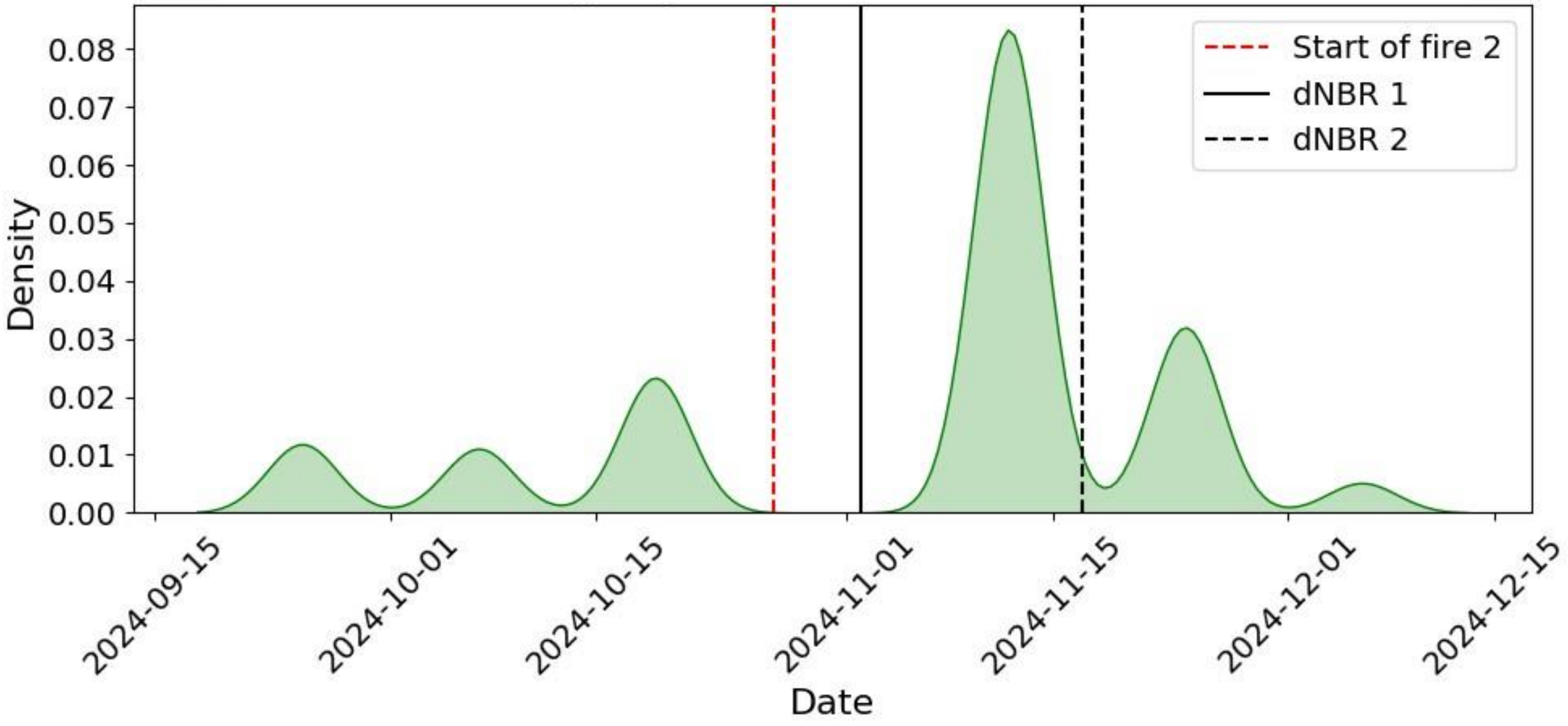
F-BOCD



S2 dNBR



Density of *F*-BOCD detection events



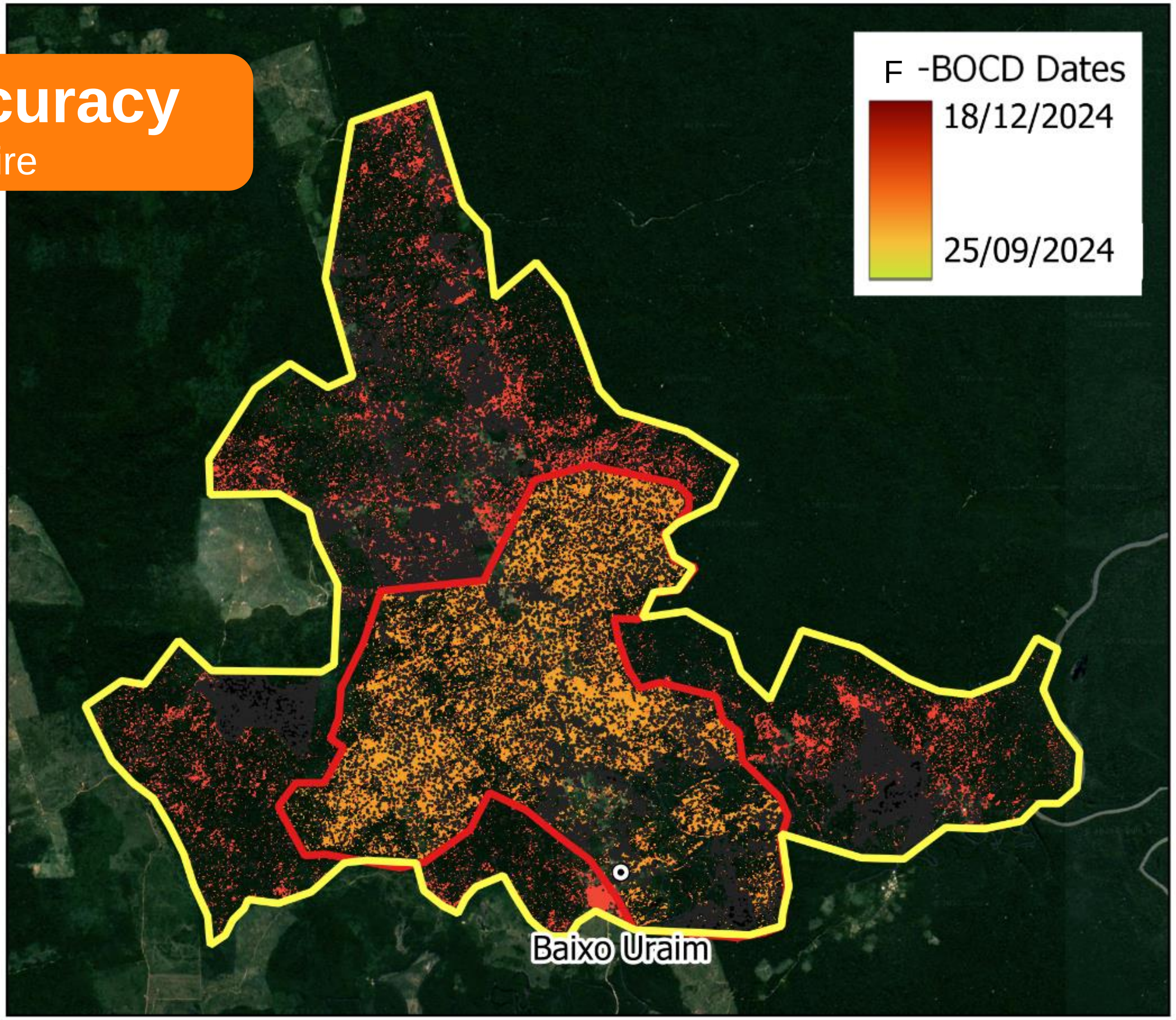
S1 → *F*-BOCD: continuous monitoring

S2 → *dNBR*: discrimination of change type

Complementarity of SAR-optical

F-BOCD refined by S2 dNBR

88% accuracy
first fire



Continuous map

Exclusion of non-fire related events

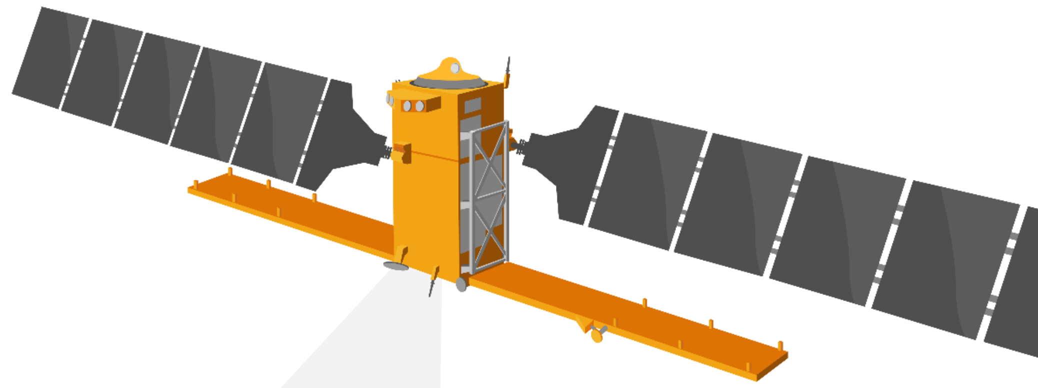
Second fire: beginning rainy season

Summary

Potential of BOCD for monitoring degradation

Multi-source

Complementarity SAR-multispectral



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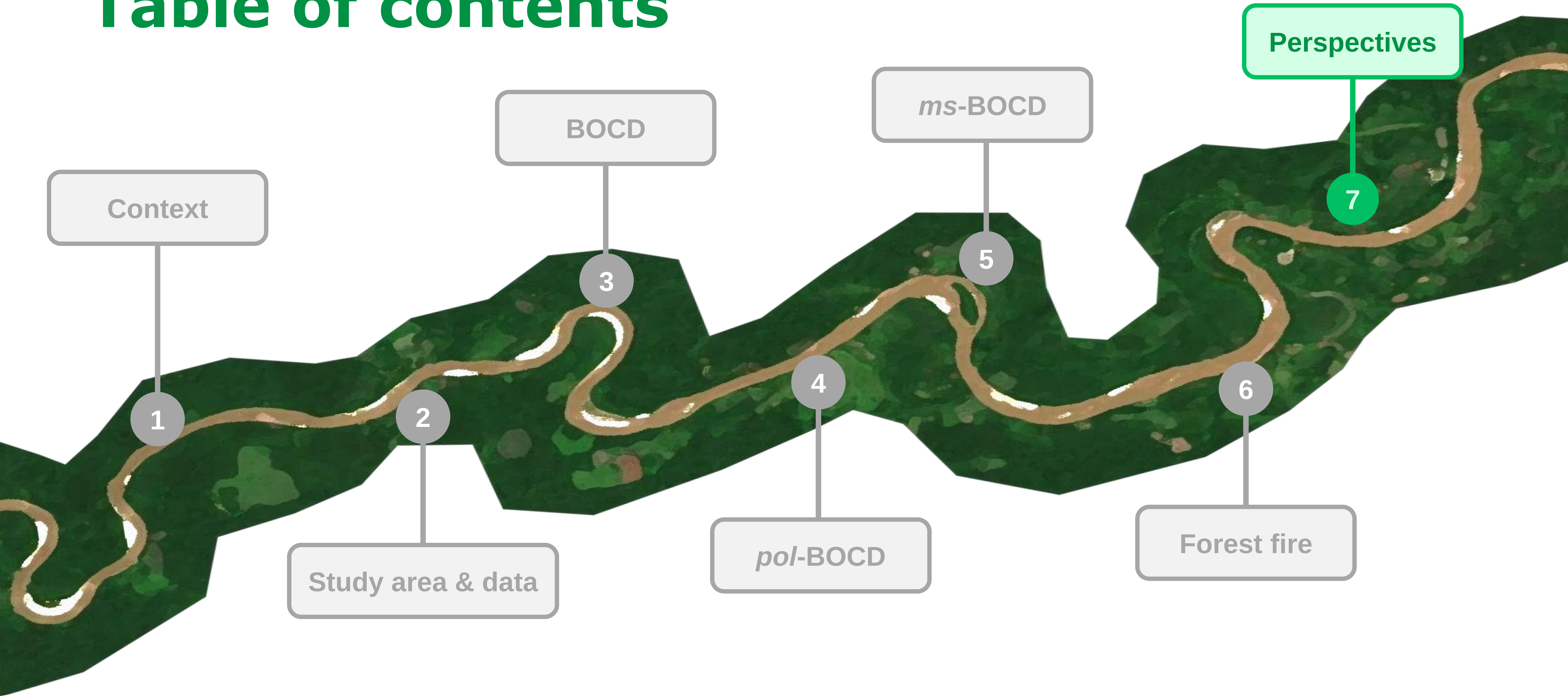
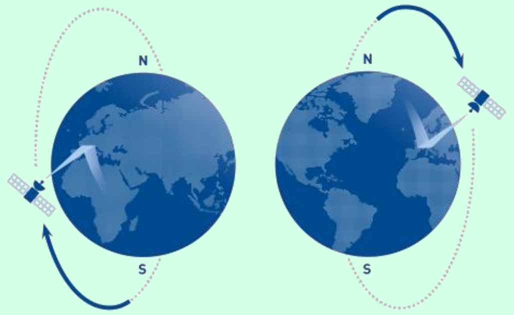


Perspectives

1 Advancing multi-source fusion

- Sentinel-1 ASC/DES
- Multi-frequency SAR



NASA - ISRO SAR Mission

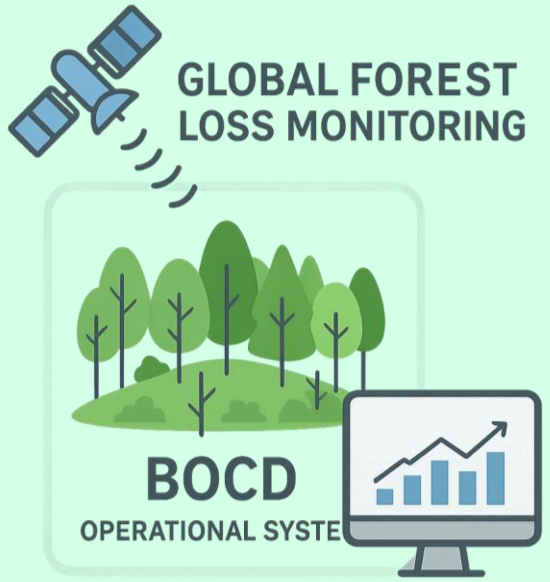
2 Monitoring selective logging

3 Synergies between BOCD and BIOMASS

- P-band
- Revisit: 9 months
- Products: FD, AGB

4 Operational system

- Computational scalability
- Wall-to-wall validation
  [Olofsson et al. 2014]



Conclusion

New method for NRT forest loss monitoring
unsupervised, scalable, multi-source fusion

Up to 30% improved detection vs existing systems
especially effective for small-scale deforestation

Robust to false alarms
outperforms current systems

Works in regions affected by seasonality
effective in the Cerrado

Faster detection
lower detection delays than existing methods

Conclusion

Peer-reviewed journal articles

Bottani *et al*. Novel unsupervised Bayesian method for near real-time forest loss detection using Sentinel-1 SAR time series: assessment over sampled deforestation events in Amazonia and the Cerrado. *Remote Sensing of Environment*, 2025.

Bottani *et al*. Continuous monitoring of fire-induced forest loss using Sentinel-1 SAR time series and a Bayesian method: a case study in Paragominas, Brazil. *Remote Sensing,* 2025.

Bottani *et al*. Bayesian polarimetric detector for improved forest loss monitoring using dual-polarization Sentinel-1 data. *ISPRS Journal of Photogrammery and Remote Sensing* (2025), Under Review.

Peer-reviewed conference proceedings

Bottani *et al*. Multi-source fusion using Bayesian online change detection: application to deforestation monitoring using SAR-optical time series. *IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP)*, December 2025.

Bottani *et al*. Approche bayésienne pour la detection de la deforestation à partir de series temporelles d'images SAR polarimétriques Sentinel-1. *XXXème Colloque Francophone de Traitement du Signal et des Images (GRETSI)*, August 2025.

Bottani *et al*. Advanced Bayesian method for timely small-scale forest loss detection in the Brazilian Amazon and Cerrado with Sentinel-1 time series. Archives of the *International Society for Photogrammery and Remote Sensing (ISPRS)*, November 2024.

Bottani *et al*. A statistical method for near real-time deforestation monitoring using time series of Sentinel-1 images. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, July 2024.

Awards

Mikio Takagi Student Price at IGARSS 2024

Best Poster at ESA Dragon Symposium 2024

Nominee for Best Student Paper at CAMSAP 2025

3 months of field-work in Brazil

Thank You!

Multi-source monitoring of forest loss using SAR and multispectral time series

PhD defense, 4 November 2025