

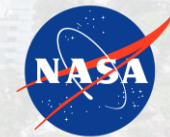
# A Comparison of Sentinel-1 Approaches to Map the May-June 2022 Floods in Sylhet, Bangladesh

**Alex Saunders**<sup>1</sup>, Jonathan Giezendanner<sup>1</sup>, Beth Tellman<sup>1</sup>, Ariful Islam<sup>1</sup>,  
Arifuzzaman Bhuiyan<sup>2</sup>, A.K.M. Islam<sup>3</sup>

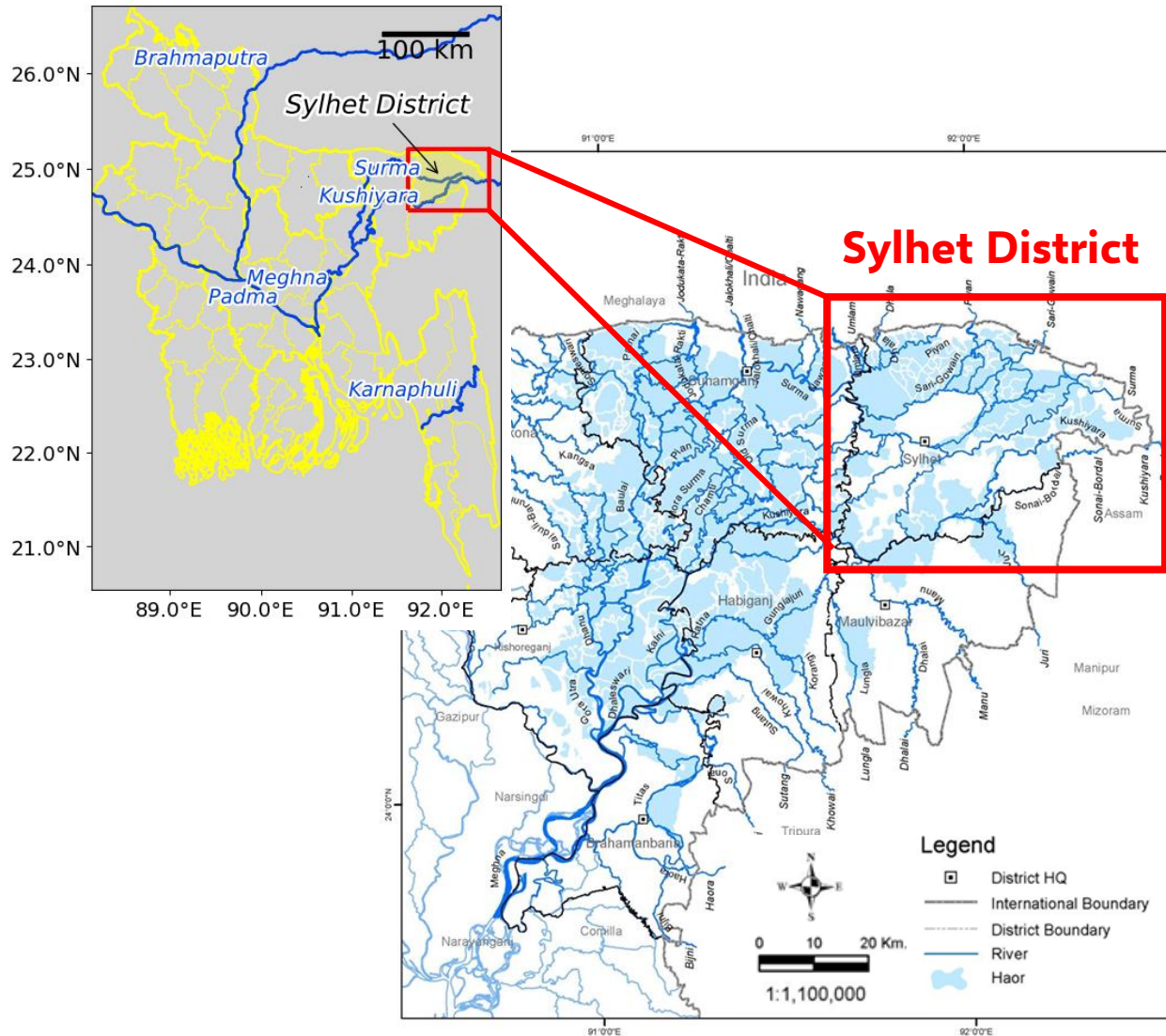
<sup>1</sup>University of Arizona

<sup>2</sup>Flood Forecasting and Warning Centre, Bangladesh

<sup>3</sup>Bangladesh Institute of Water and Flood Management



# Sylhet experienced extreme flooding in May-June 2022



2022 floods



Getty images via NY Times

# Sylhet experienced extreme flooding in May-June 2022



Gowainghat, Sylhet Division

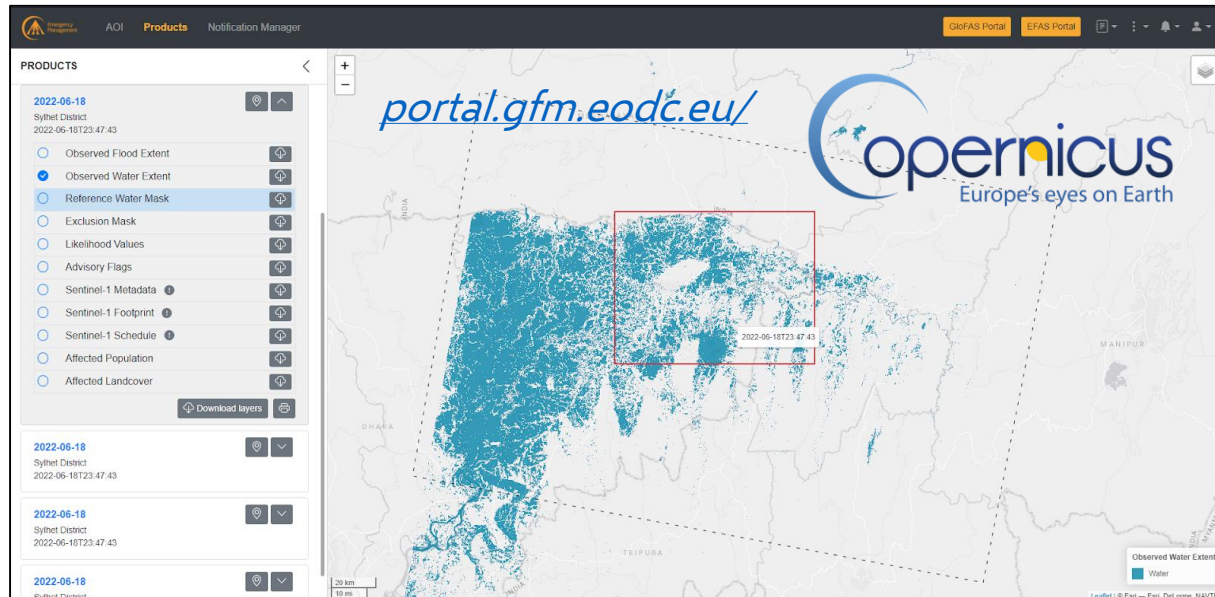


Companiganj, Sylhet Division

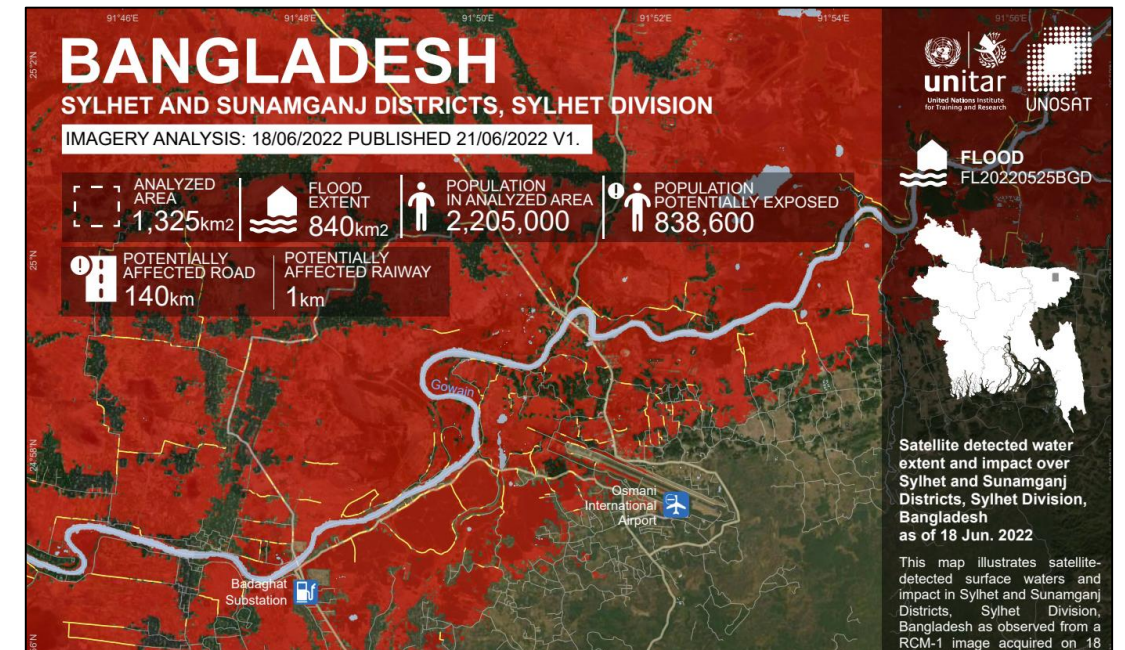
# Why create remotely sensed maps after the floods?

- Assess accuracy of commonly used mapping methods and products
- Compare “local” vs “global” approaches
- Compare machine learning (ML) vs “traditional” non-ML approaches

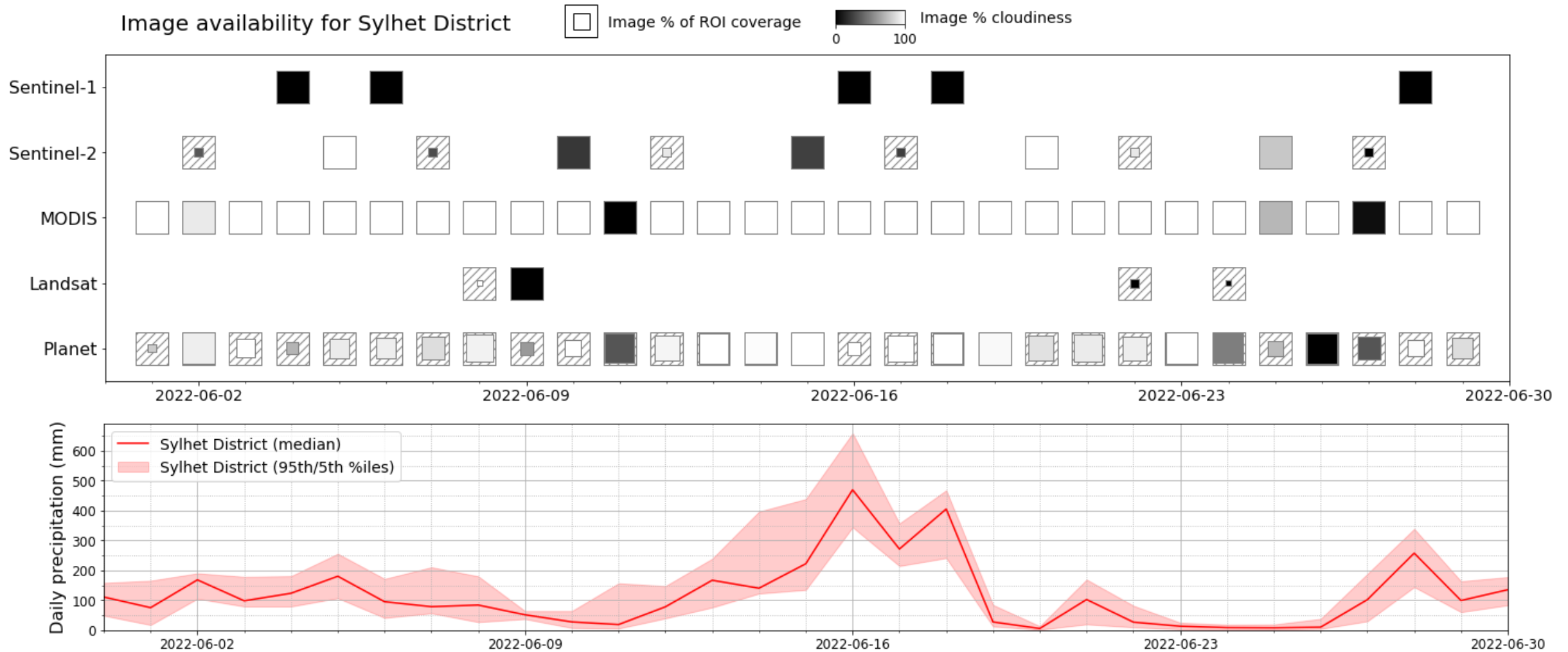
## Copernicus Global Flood Monitoring



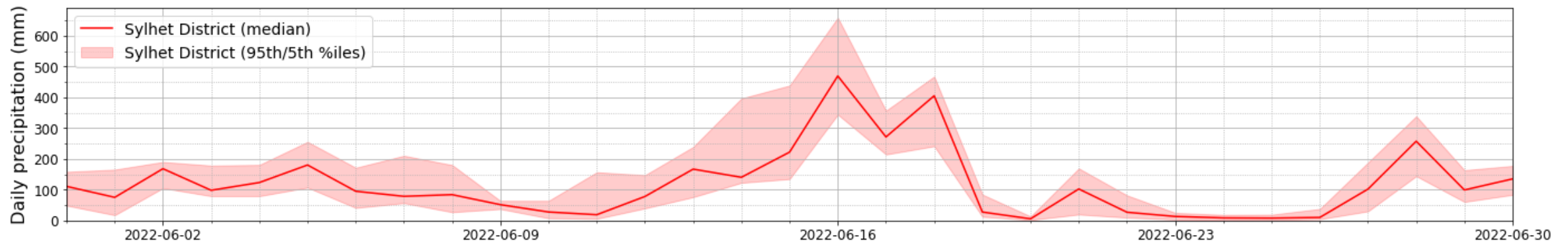
## UNOSAT Analysis



# Synthetic Aperture Radar gives us the chance to map the May-June 2022 floods



# Synthetic Aperture Radar gives us the chance to map the May-June 2022 floods



# We compared three Sentinel-1 algorithms / datasets

Method / dataset	Description	Sensor	Resolution
Thomas et al., 2023	<b>“Local”</b> change detection, developed for Bangladesh	Sentinel-1	2-10 days, 10 m
Paul & Ganju, 2021	Pre-trained <b>“global” machine learning</b> (CNN)	Sentinel-1	2-10 days, 10 m
Copernicus Global Flood Monitoring <b>“GFM”</b>	<b>Automated “global”</b> emergency mapping product	Sentinel-1	2-10 days, 10 m

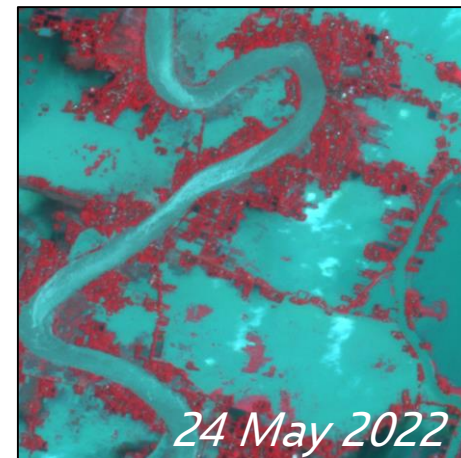
## We hand labeled Planet images for validation

- 1024x1024 pixels @ 3 m resolution
- 36 labels across three cloud-free dates

*True color (RGB)*



*False color (NIR-B-G)*



*Hand label*



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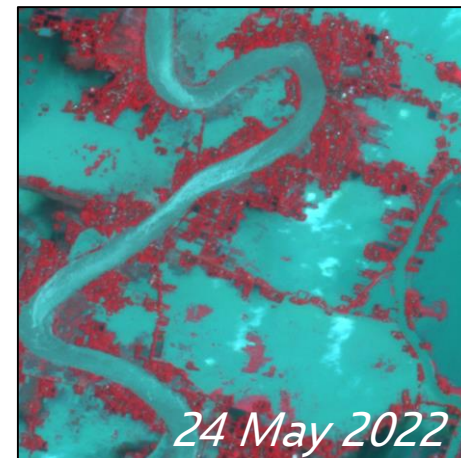
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# Local non-ML and global ML algorithms give higher accuracy than GFM

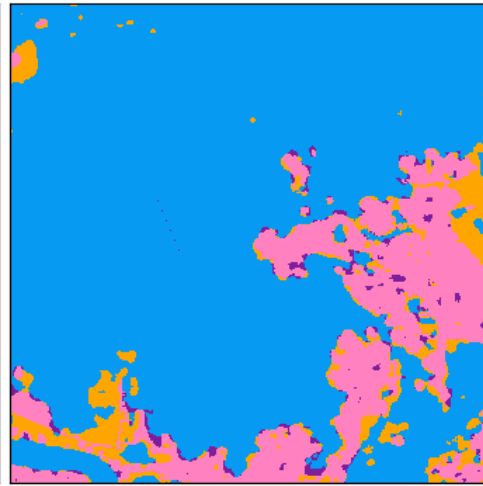
False-color



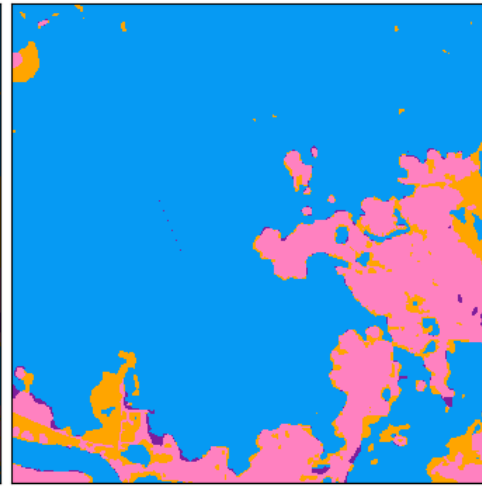
Label 2022-05-24



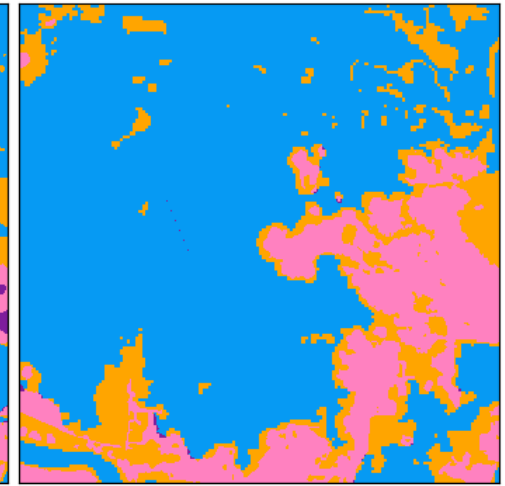
Thomas et al. 2022-05-25  
IOU: 0.907



Paul & Ganju 2022-05-25  
IOU: 0.914



GFM 2022-05-25  
IOU: 0.806



# Local non-ML and global ML algorithms give higher accuracy than GFM

*\*IoU = intersection over union*

Global automated,  
non-ML

Local, non-ML

Global, ML

non-ML

False-color

Label 2022-05-24

Thomas et al. 2022-05-25

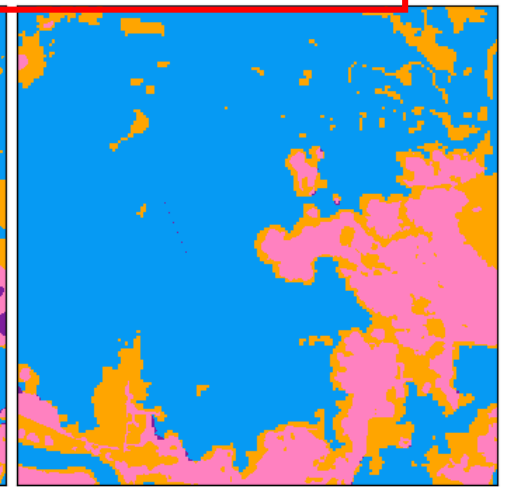
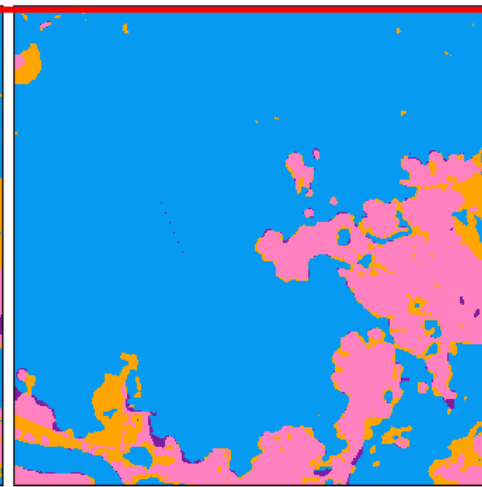
Paul & Ganju 2022-05-25

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Legend: Background (grey), Water (blue), True Positive (light blue), True Negative (pink), False Positive (purple), False Negative (yellow)

# Local non-ML and global ML algorithms give higher accuracy than GFM

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Label 2022-05-24

Local, non-ML

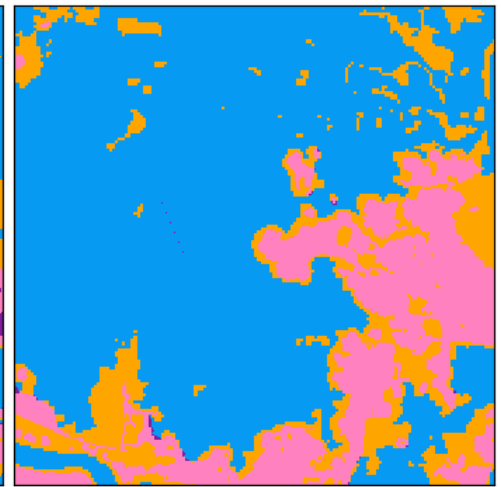
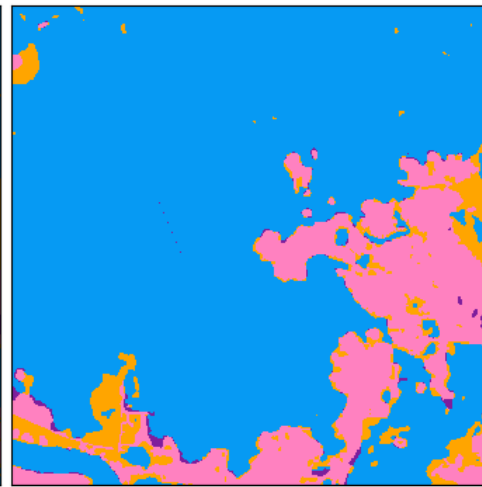
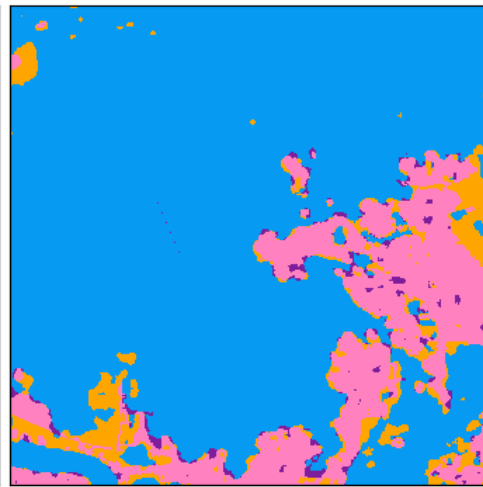
Global, ML

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Background  
  Water  
  True Positive  
  True Negative  
  False Positive  
  False Negative

Accuracy over 36 tiles  
over 3 dates

Model	Precision	Recall	Accuracy	IoU
Thomas et al.	85.2%	75.4%	82.0%	67.9%
Paul & Ganju	93.4%	70.0%	82.4%	66.6%
Copernicus GFM	93.1%	52.7%	73.4%	51.7%

# Local non-ML and global ML algorithms give higher accuracy than GFM

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False-color

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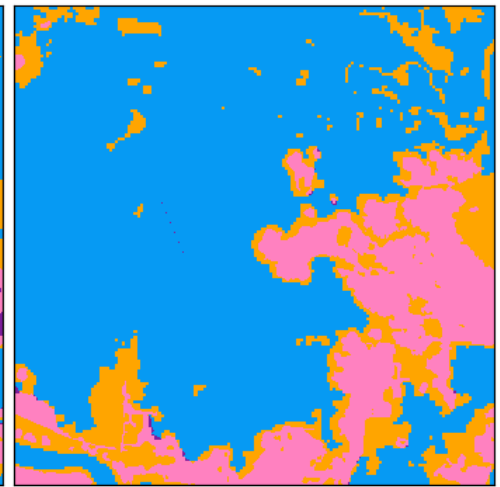
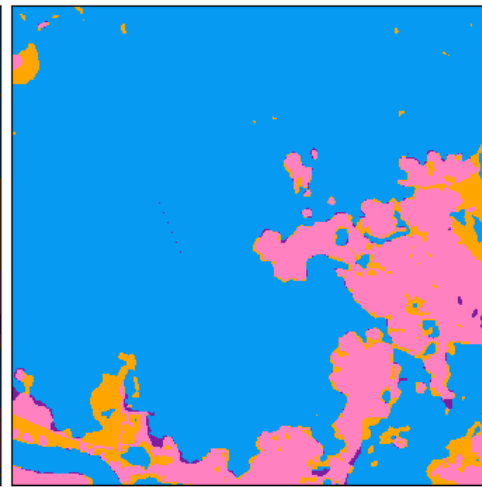
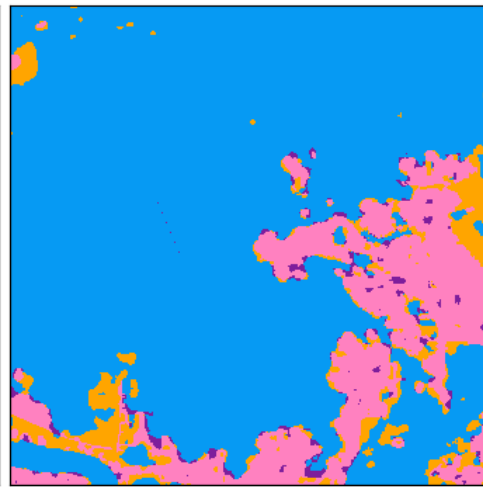
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Background   
  Water   
  True Positive   
  True Negative   
  False Positive   
  False Negative

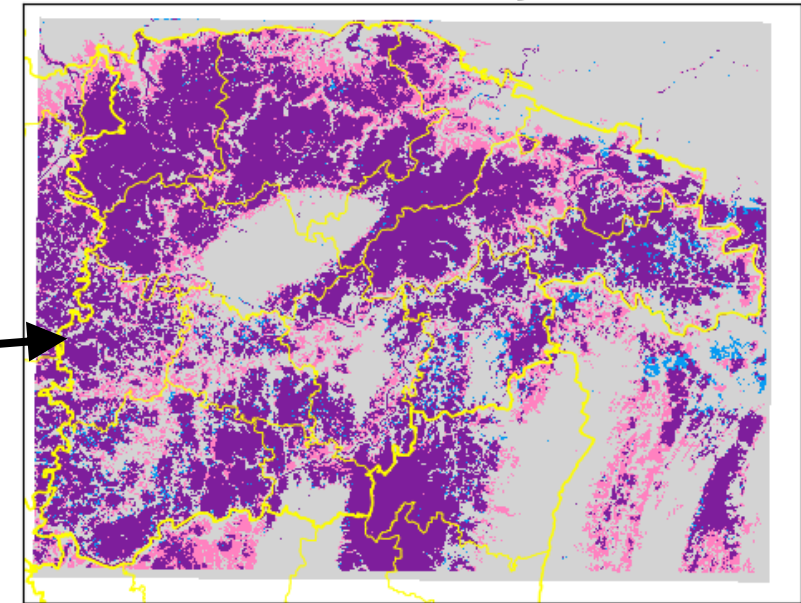
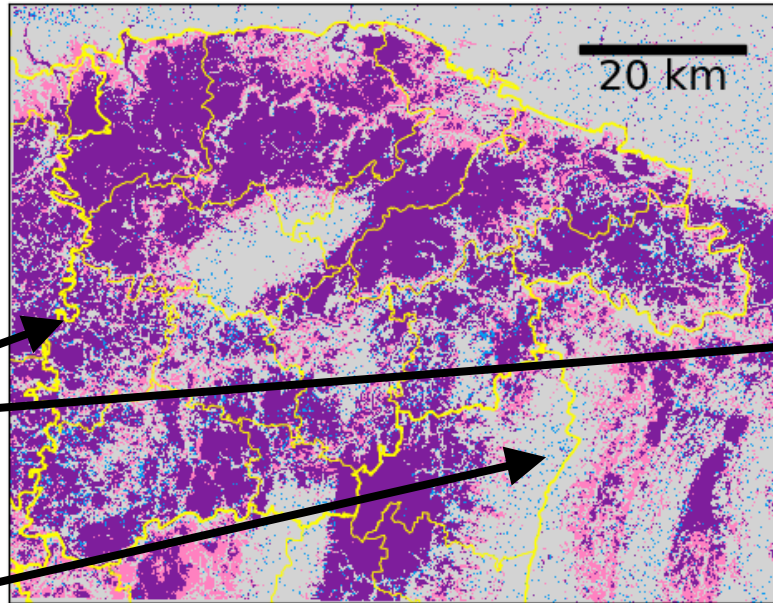
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# Spatial comparison of inundation extent

Thomas et al.

Paul & Ganju

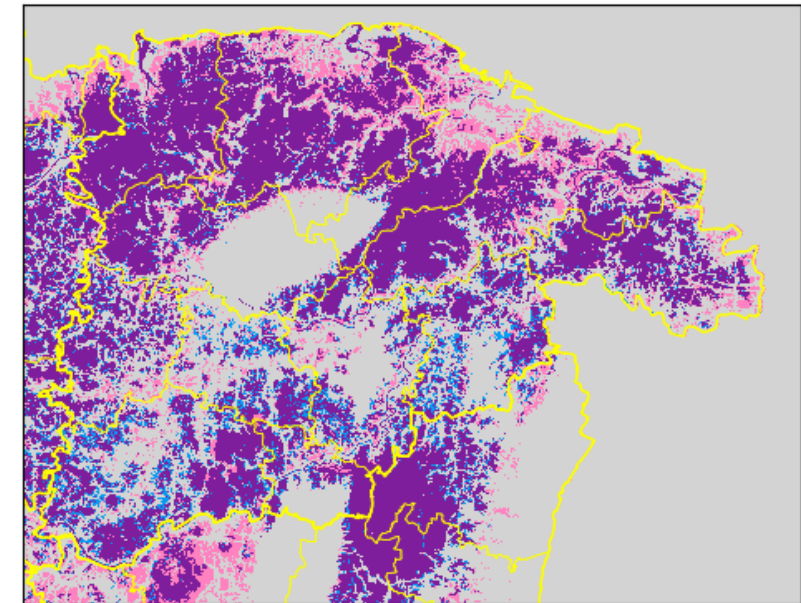
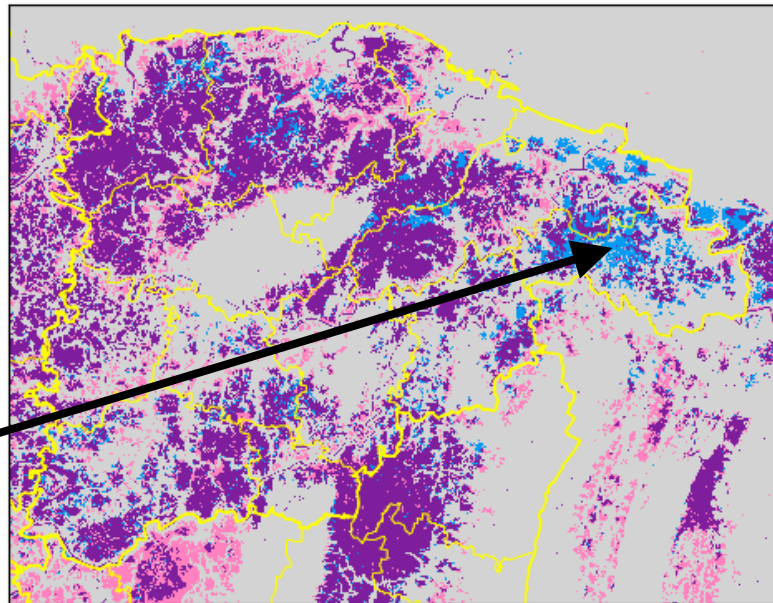


Largely in agreement

Speckle due to thresholding approach?

GFM

UNOSAT

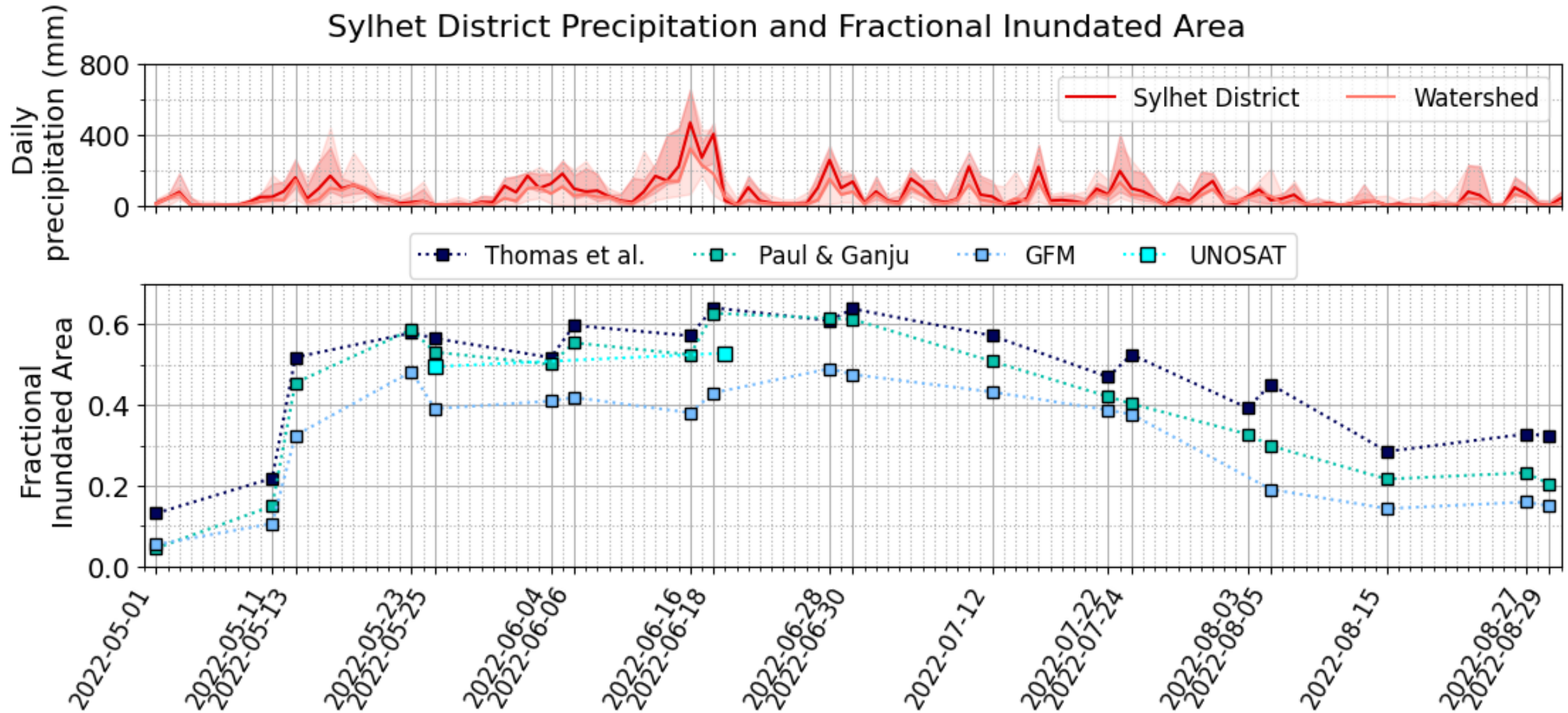


Areas where water receded between the two dates?

2022-05-25 only    2022-06-18 only    Both dates

# Temporal comparison of inundation extent

Sylhet District Precipitation and Fractional Inundated Area



# Takeaways

1. Local algorithm and global ML algorithm give equally high accuracy – *ML generalizes well, but had advantage of training on other Bangladesh data*
2. GFM shows lower accuracy – *tradeoff for global coverage and ready-to-use maps? Underprediction due to ensemble method?*

**Future work:** more studies to understand utility of emergency mapping products in different contexts

# References

Paul, S., Ganju, S., 2021. Flood Segmentation on Sentinel-1 SAR Imagery with Semi-Supervised Learning. <https://doi.org/10.48550/arXiv.2107.08369>

Thomas et al. 2023. A framework to assess remote sensing algorithms for satellite-based flood index insurance. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 1–17. <https://doi.org/10.1109/JSTARS.2023.3244098>



# Thank you for listening!

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[@aleksaunderstwt](#)

***Access the code and data →***



*Thanks to Ana Torres, Nicolas Lopez-de-Silanes and Zazoe van Lieshout who hand-labeled PlanetScope tiles.*

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# Appendices

# SAR surface water mapping algorithm recently developed for Bangladesh

- Sentinel-1 backscatter thresholding developed by Thomas et al. (2023)
  - Regional dry baseline from soil moisture
  - Additional VH condition
  - Additional smoothing
- Improved accuracy across four recent events

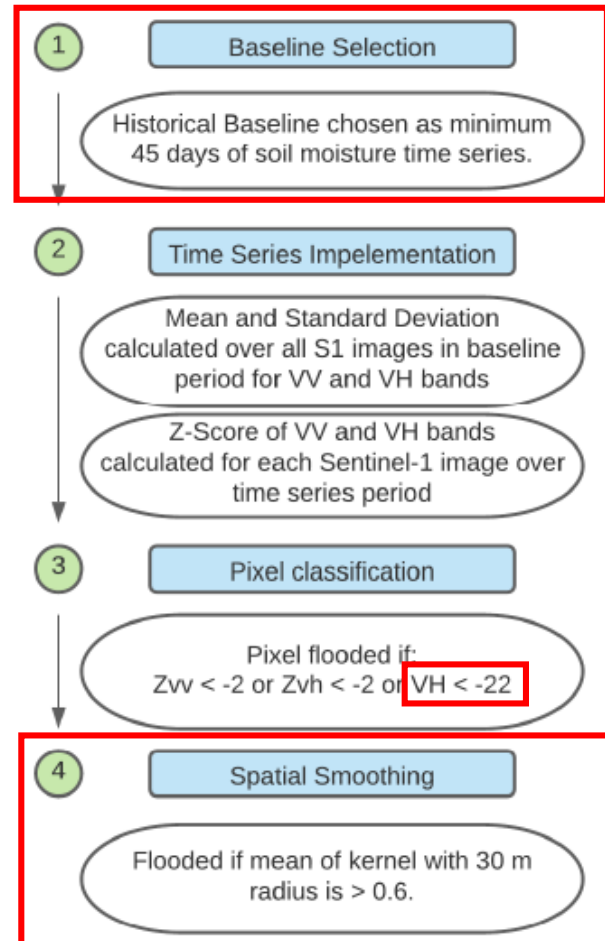
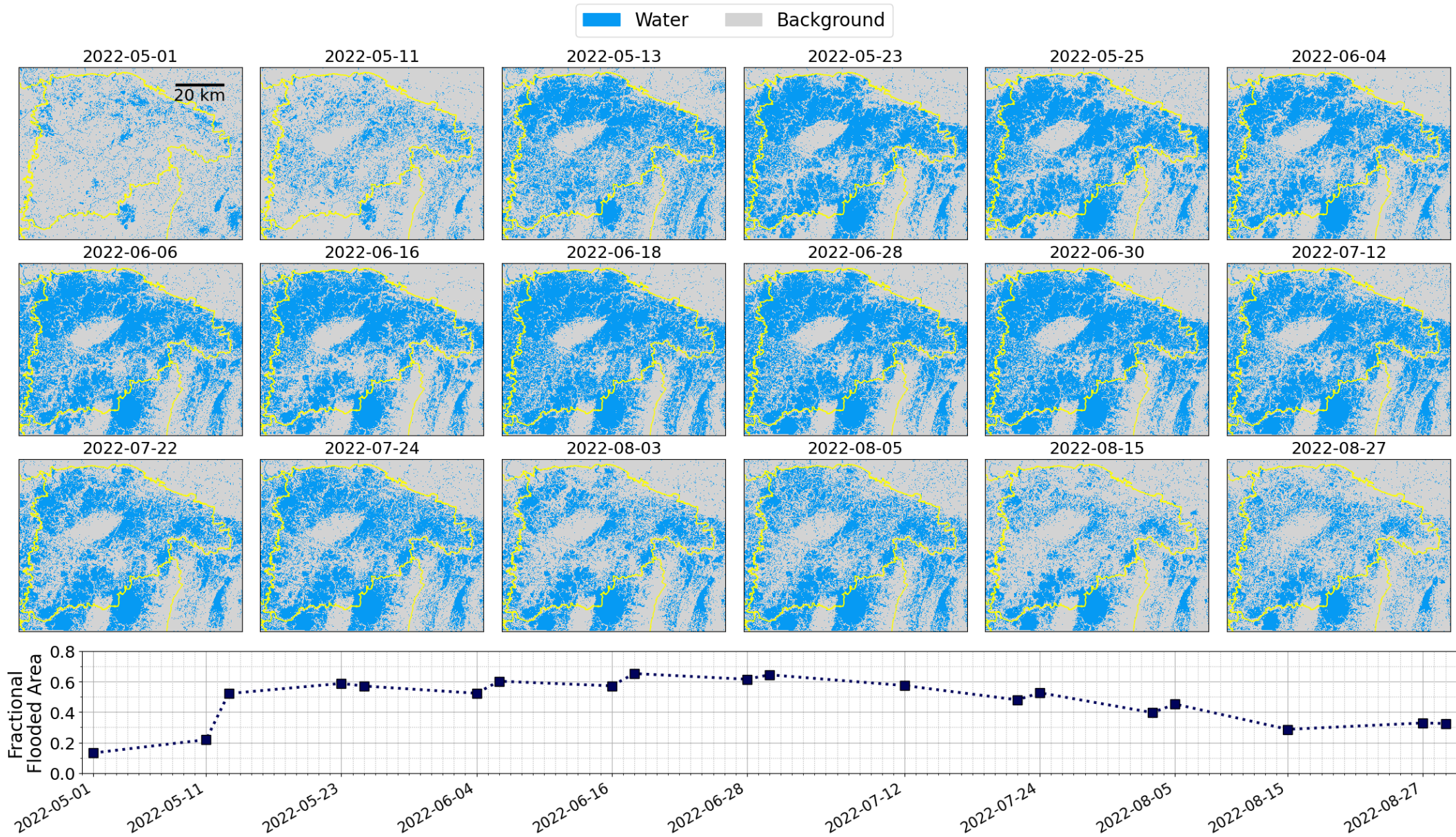


TABLE III  
ACCURACY METRICS FOR THE PROPOSED SENTINEL-1 ALGORITHM, THE PREVIOUS SENTINEL-1 ALGORITHM, AND THE MODIS ALGORITHM.

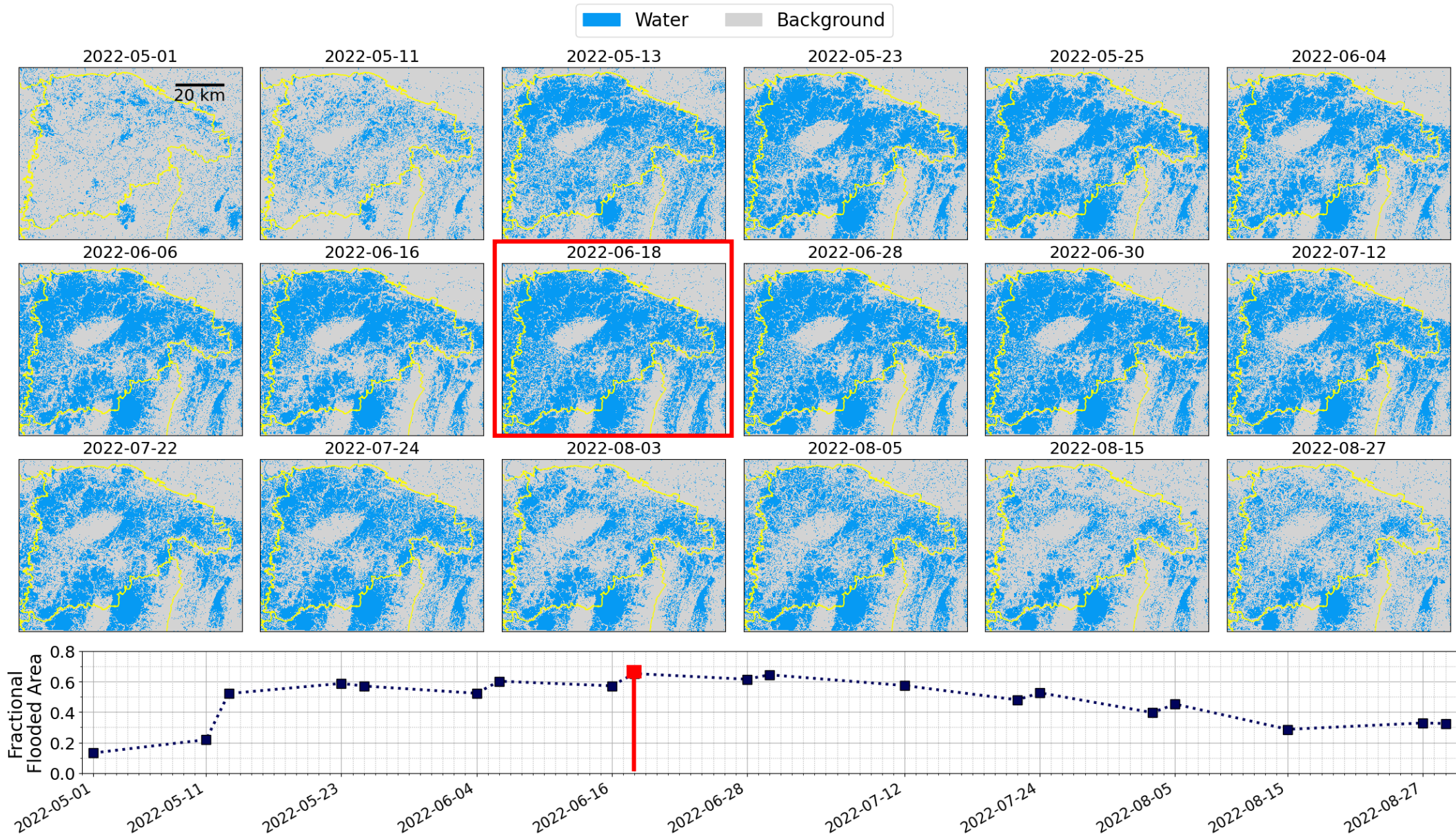
Event	Proposed Sentinel-1 Algorithm		Sentinel-1, DeVries <i>et al.</i> [31]		MODIS, Islam <i>et al.</i> [76]	
	F1	Bias	F1	Bias	F1	Bias
1. Sylhet	0.901	1.043	0.818	0.908	0.737	2.535
2. Natore/Naogoan	0.970	1.047	0.953	0.887	0.931	1.100
3. Sirajganj/Pabna	0.930	0.875	0.822	0.590	0.849	1.527
4. Jamalpur	0.897	1.293	0.873	0.727	0.835	1.871
Average	0.925	1.065	0.867	0.778	0.838	1.758
Standard Deviation	0.034	0.172	0.063	0.149	0.080	0.606

Thomas *et al.* (2023)

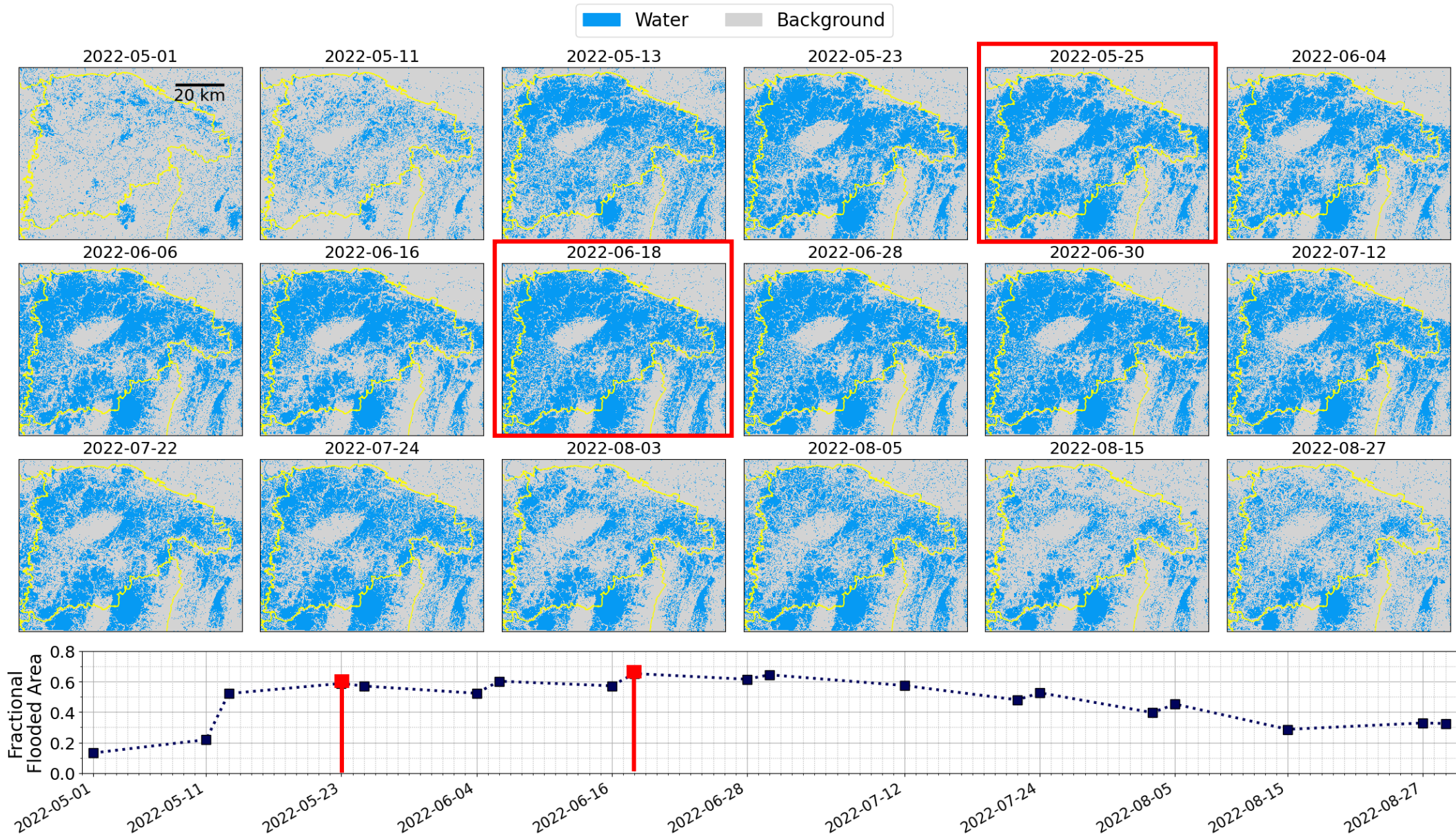
# Peak water extent occurred around 18 June



# Peak water extent occurred around 18 June

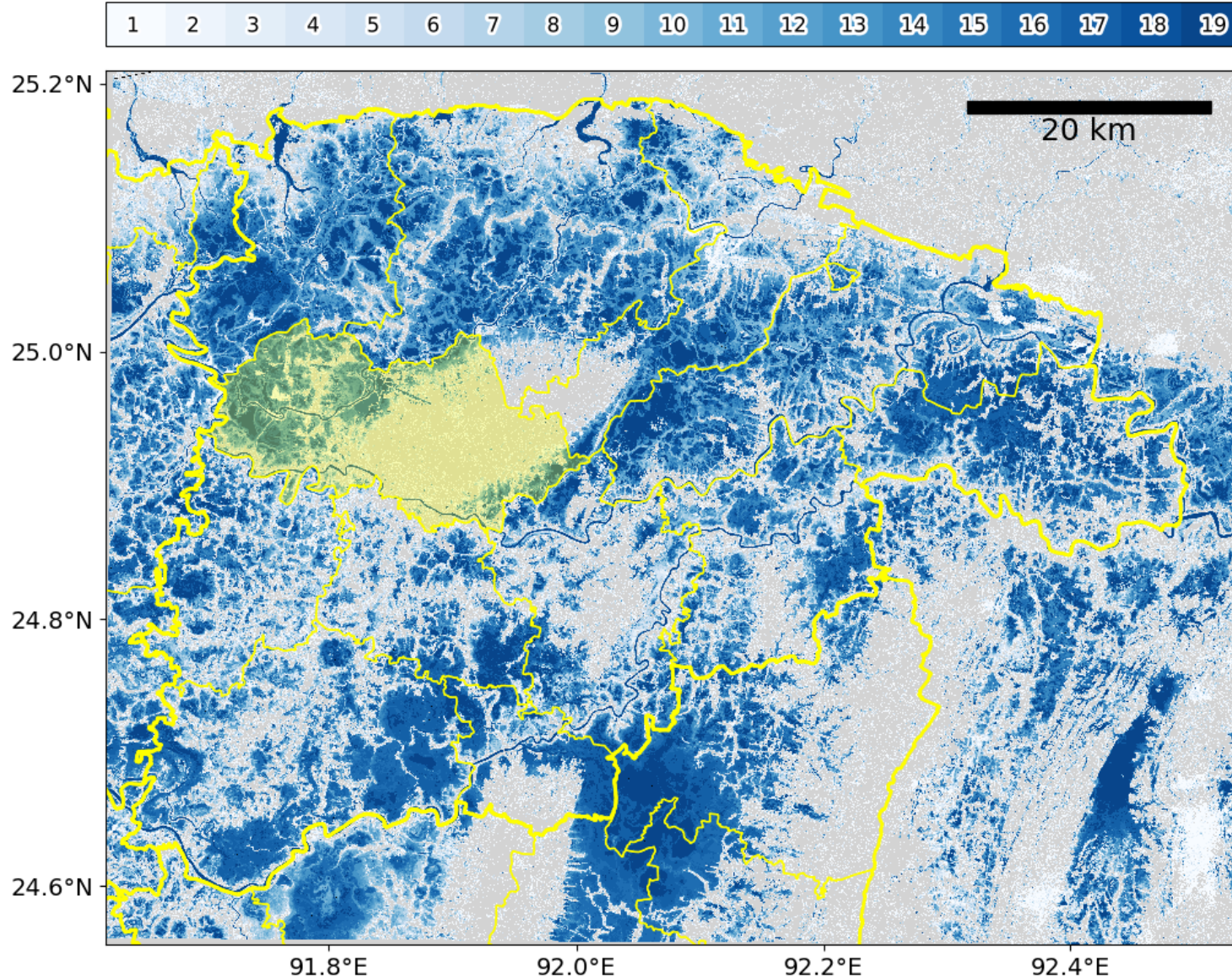


# But most water accumulated during May



# Large parts remained flooded for up to several months

Number of image dates with water, from 2022-05-01 to 2022-08-29



- Deepest depressions in the Haor Basin remained inundated throughout May-August
- *Was duration an important factor in the severity of impacts?*

Number of image dates with water, from 2022-05-01 to image date

