ENHANCING SHORT- AND MEDIUM-RANGE INUNDATION PREDICTIONS VIA THE INTEGRATION OF GLOFAS AND GFM PRODUCTS

A case study of the Alzette River, Luxembourg

Luxembourg Institute of Science and Technology

April 2025

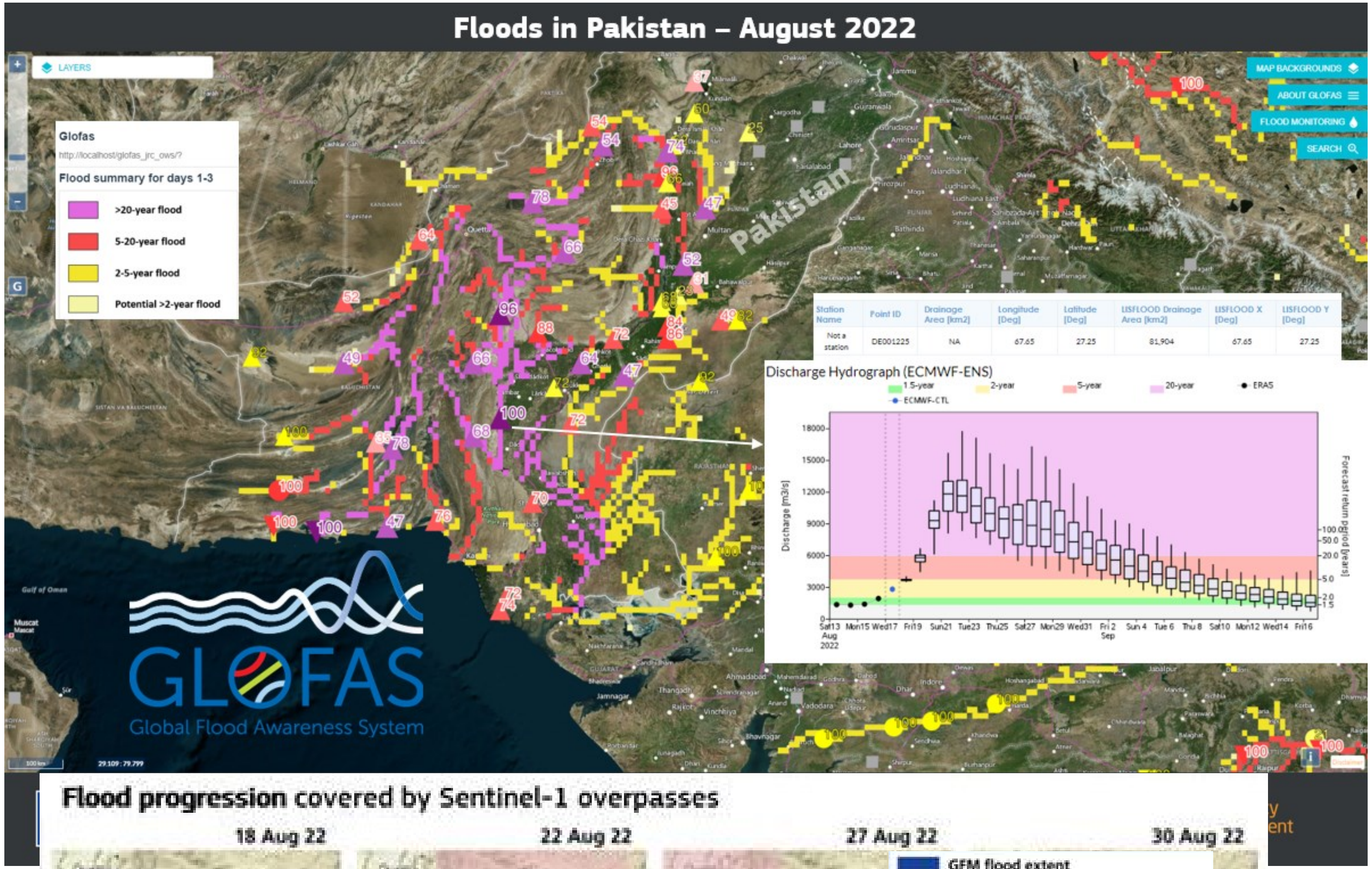
SETTING THE SCENE

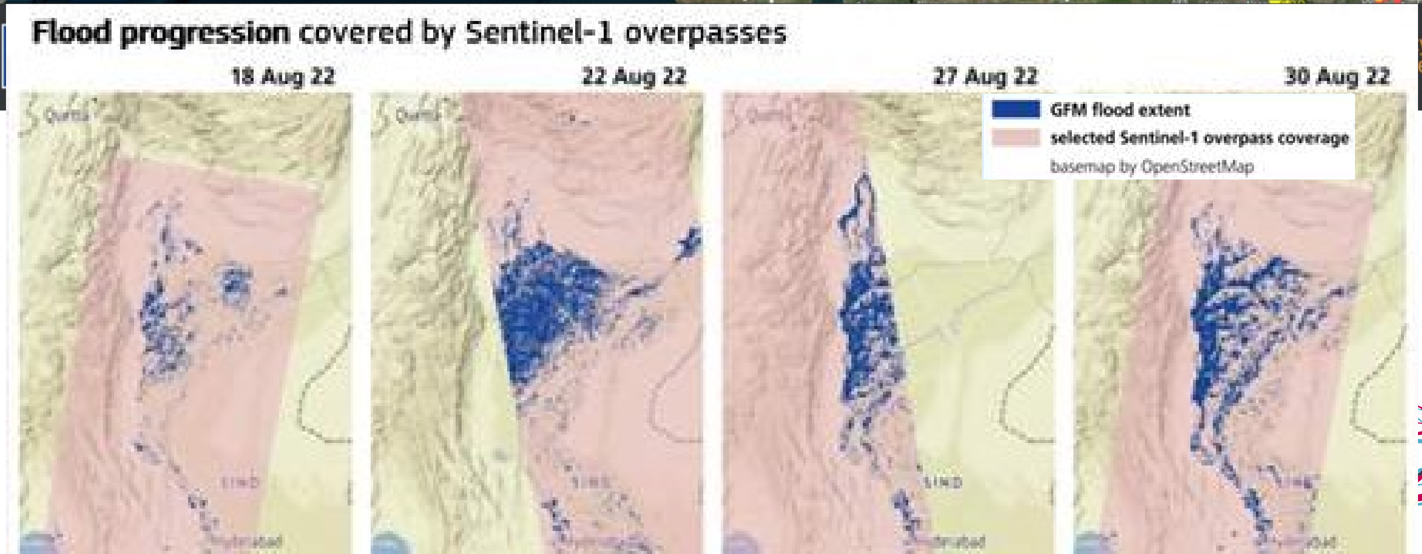
GloFAS:

- Extent predictions using pre-computed map catalogue
- Approximation to nearest flood return period map
- Coarse resolution for comprehensive impact assessment

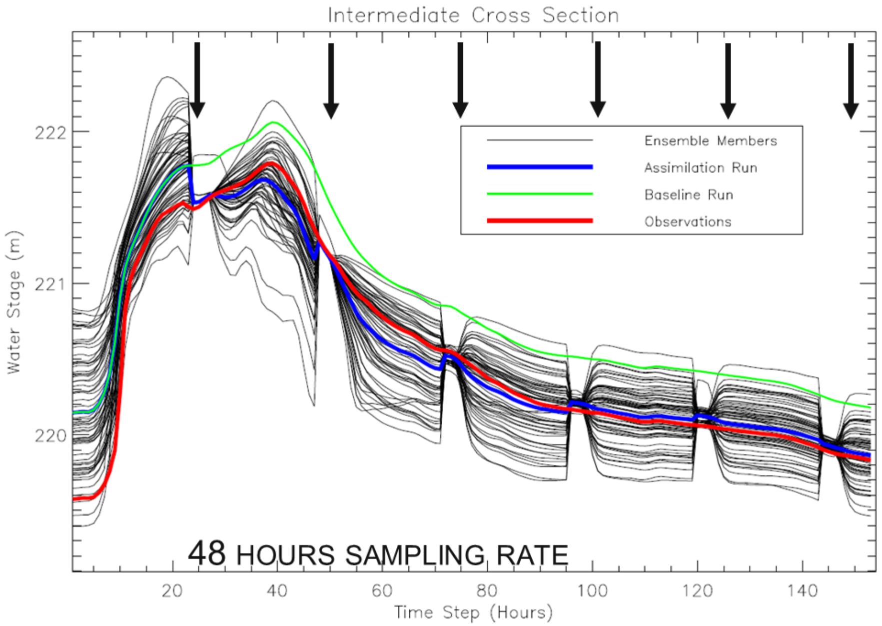
GFMS:

- Dependent on S1 overpass frequency
- Does not provide urban/forest flooding
- No forecasting capabilities

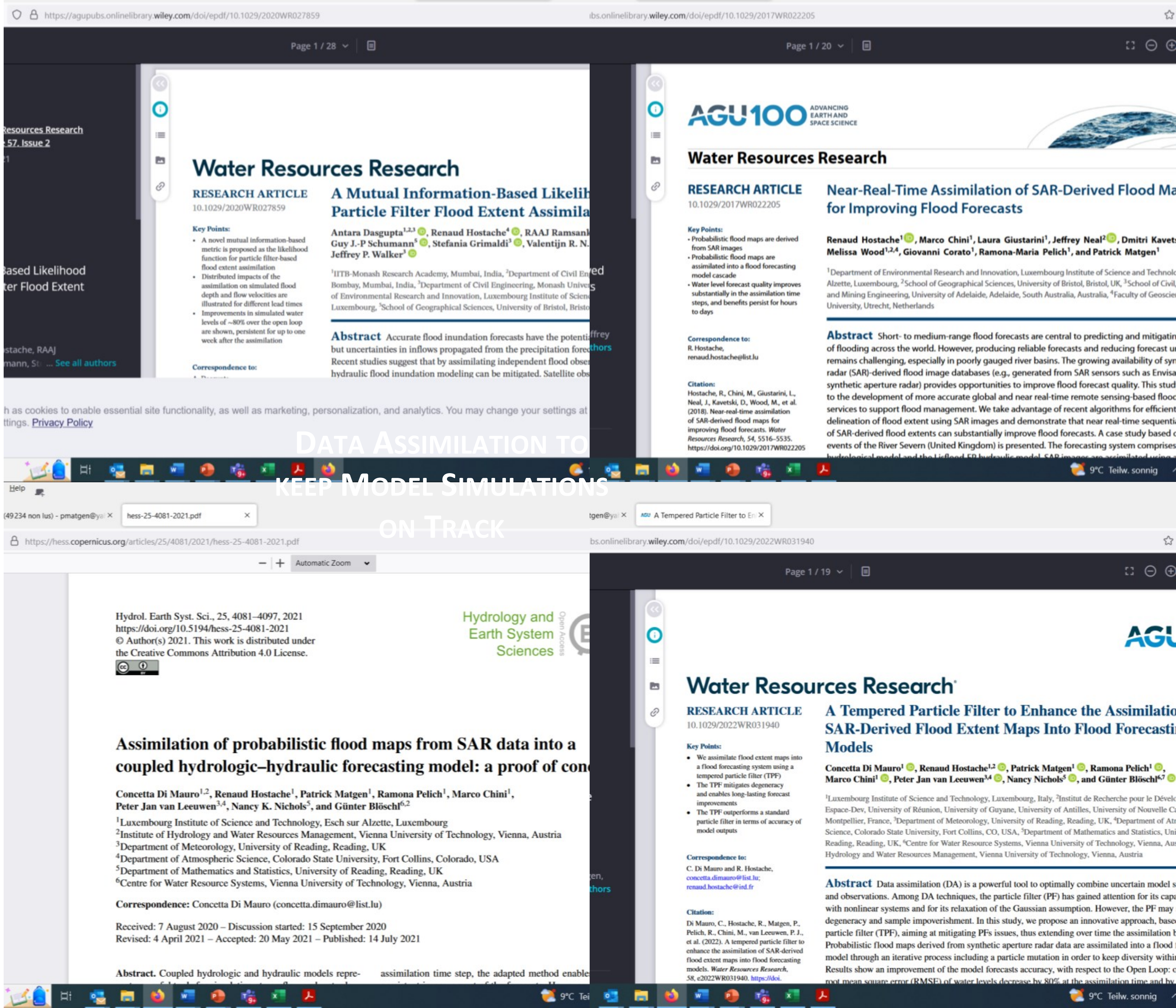




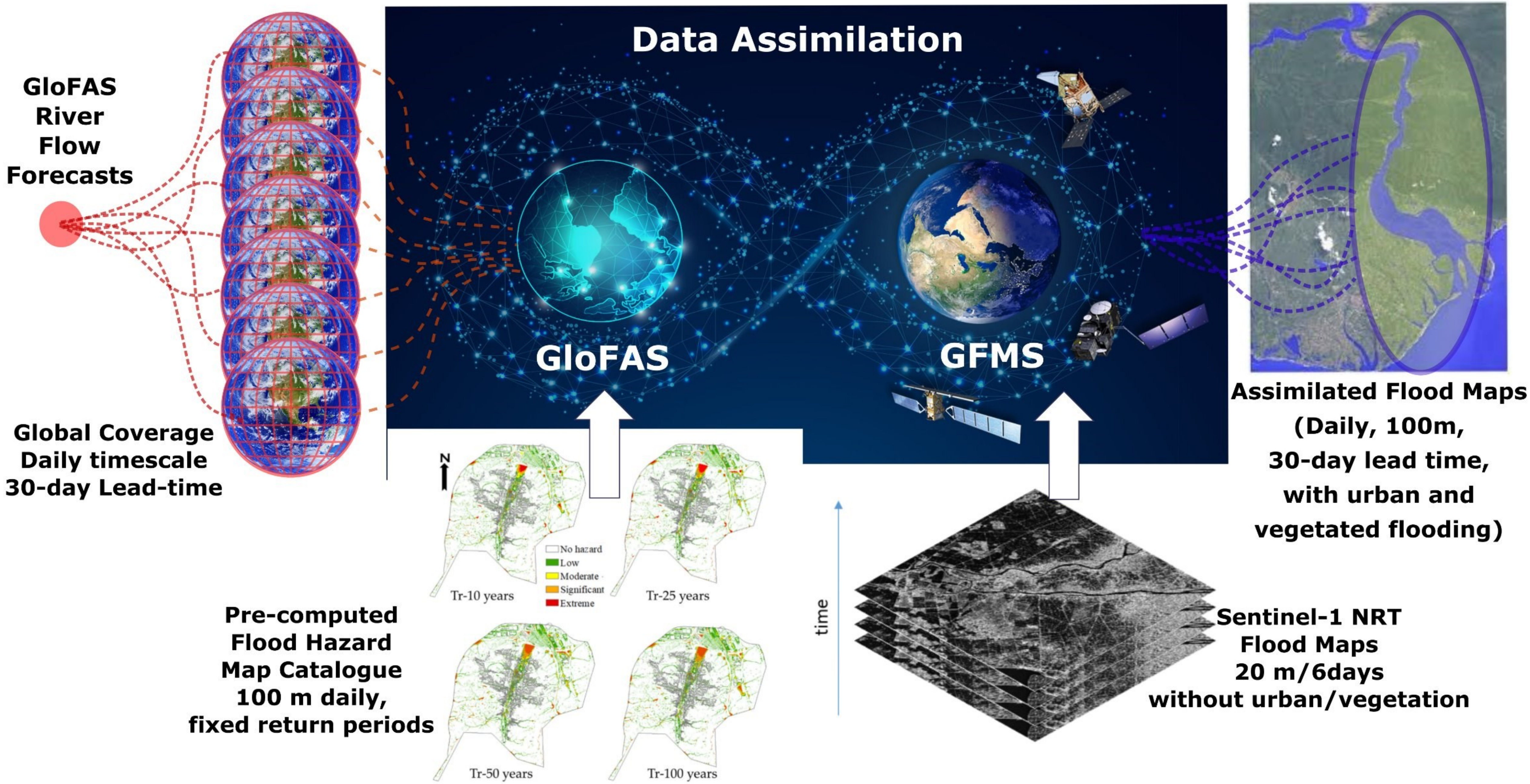
ASSIMILATION OF SYNTHETIC APERTURE RADAR-DERIVED FLOOD EXTENT INTO HYDRODYNAMIC MODELS



Feasibility study (Matgen et al., 2010)

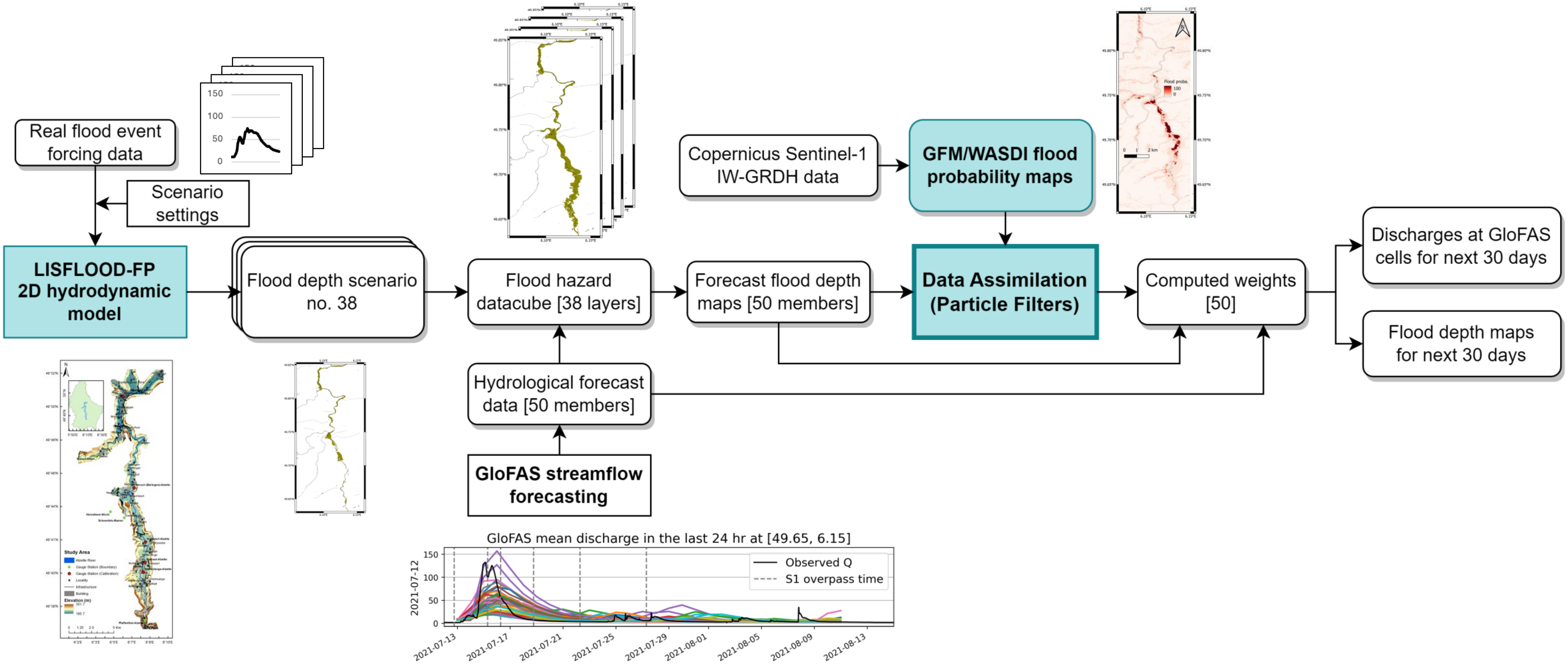


Data Assimilation to keep Model Simulations on Track

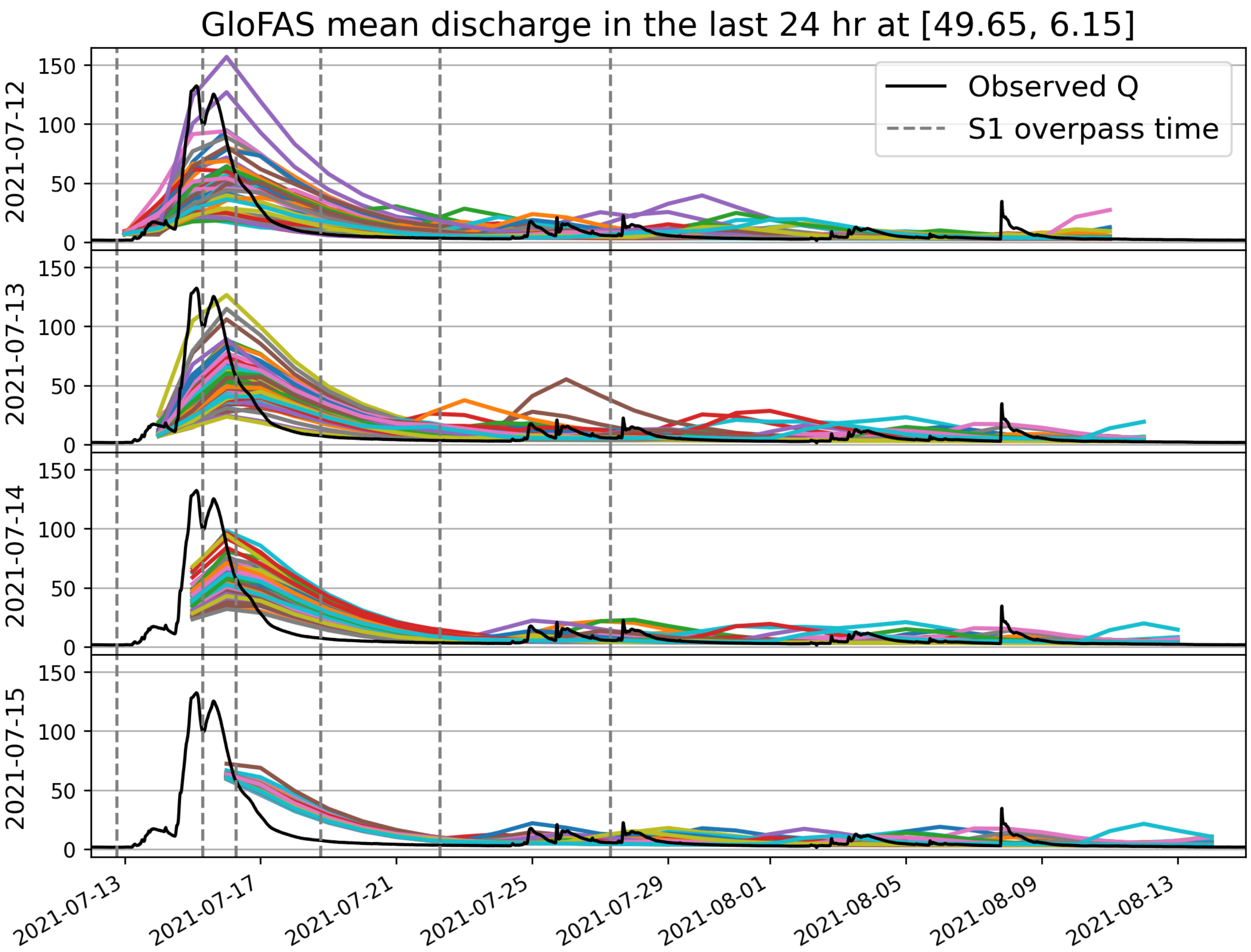


Best of different approaches?

EXPERIMENT DESCRITPTION



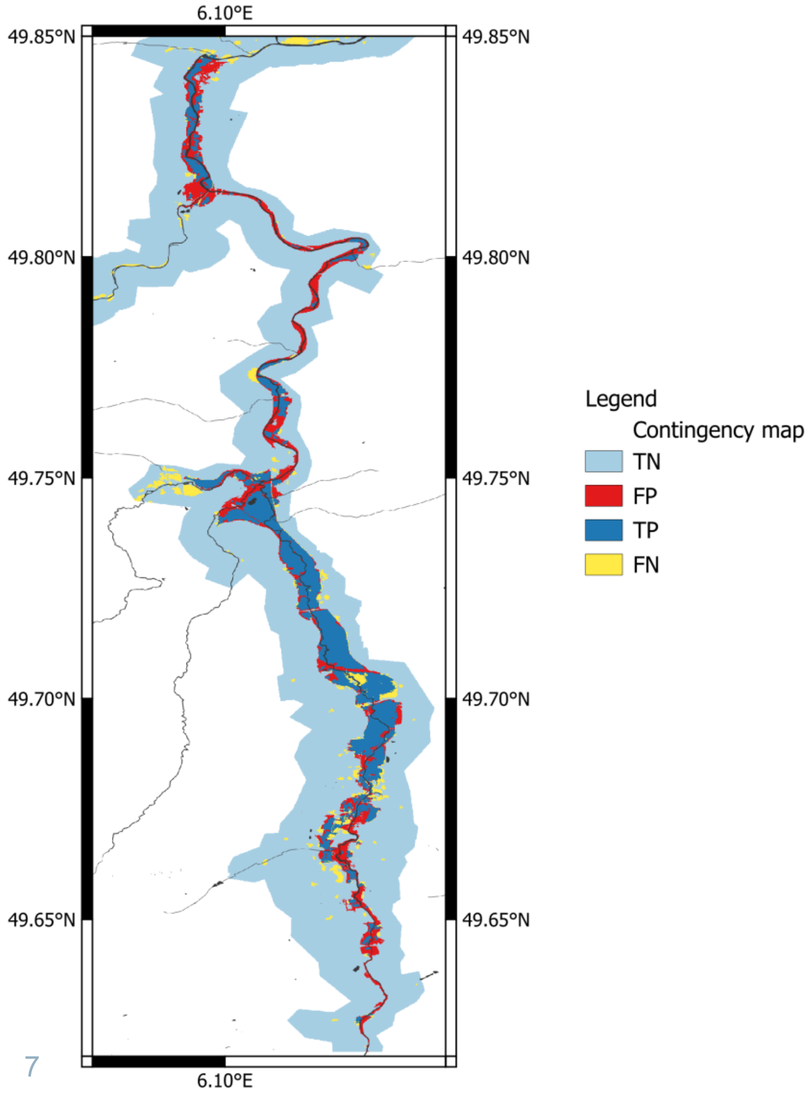
INPUT DATA – GLOFAS STREAMFLOW FORECASTS

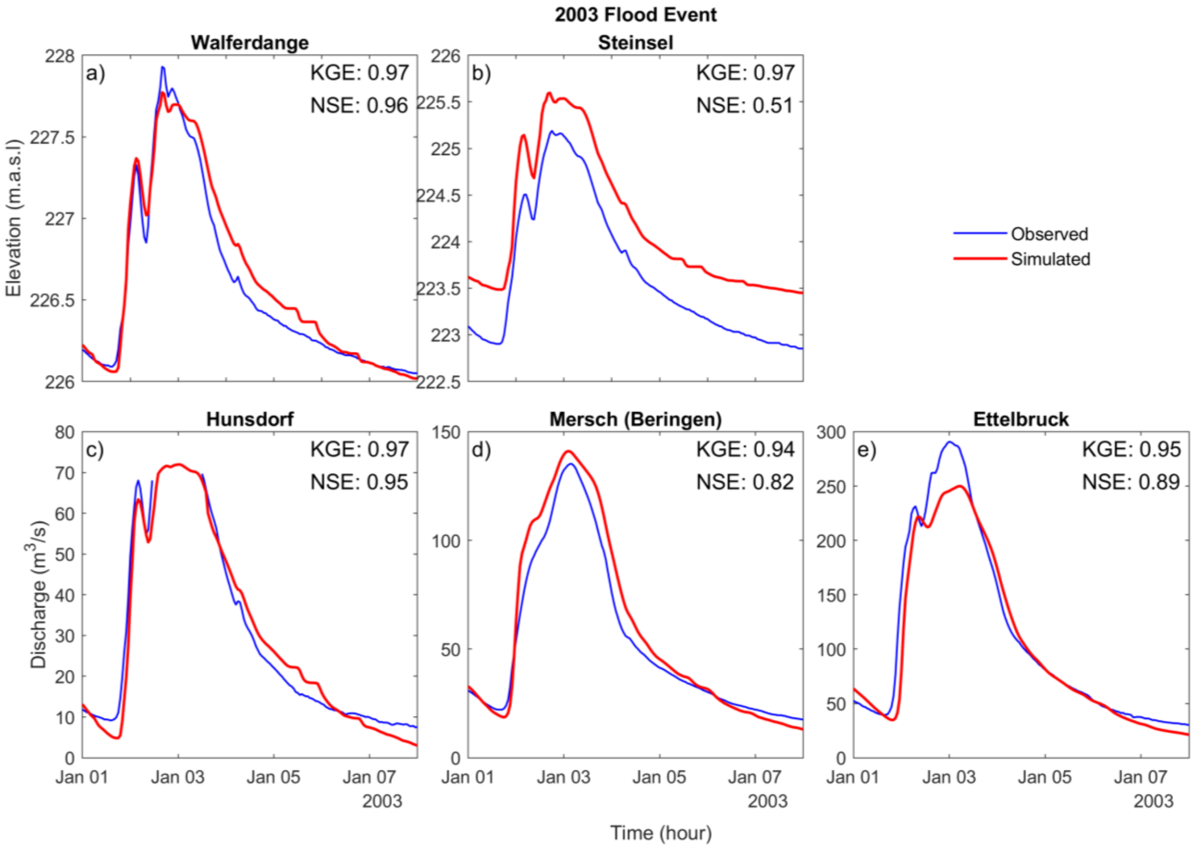


LIST

HYDRODYNAMIC MODEL – LISFLOOD-FP

- **Results (Model run @ 5m)**



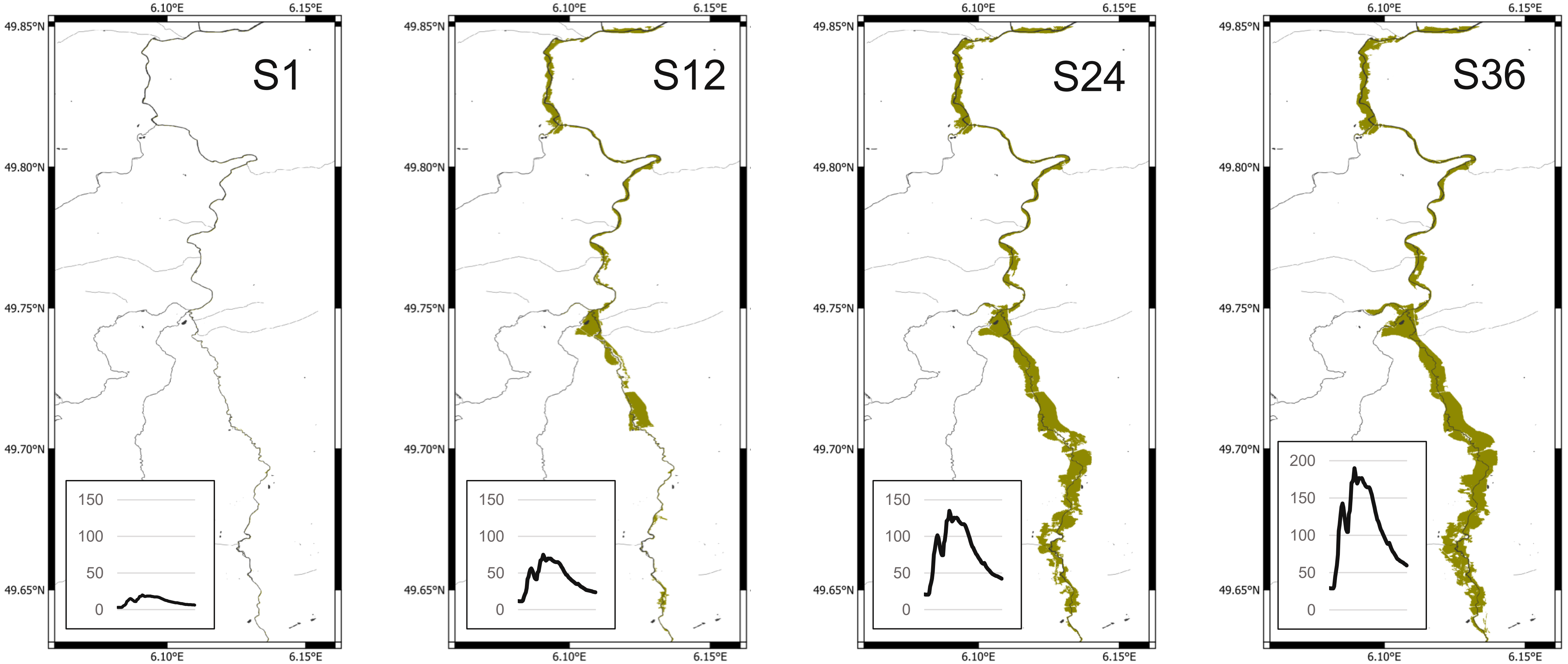


Comparison with measured water height/discharge and satellite-derived water extent:

- rising and falling limbs well reproduced
- tendency to sightly underestimate the peaks
- model performance rather good over entire model domain

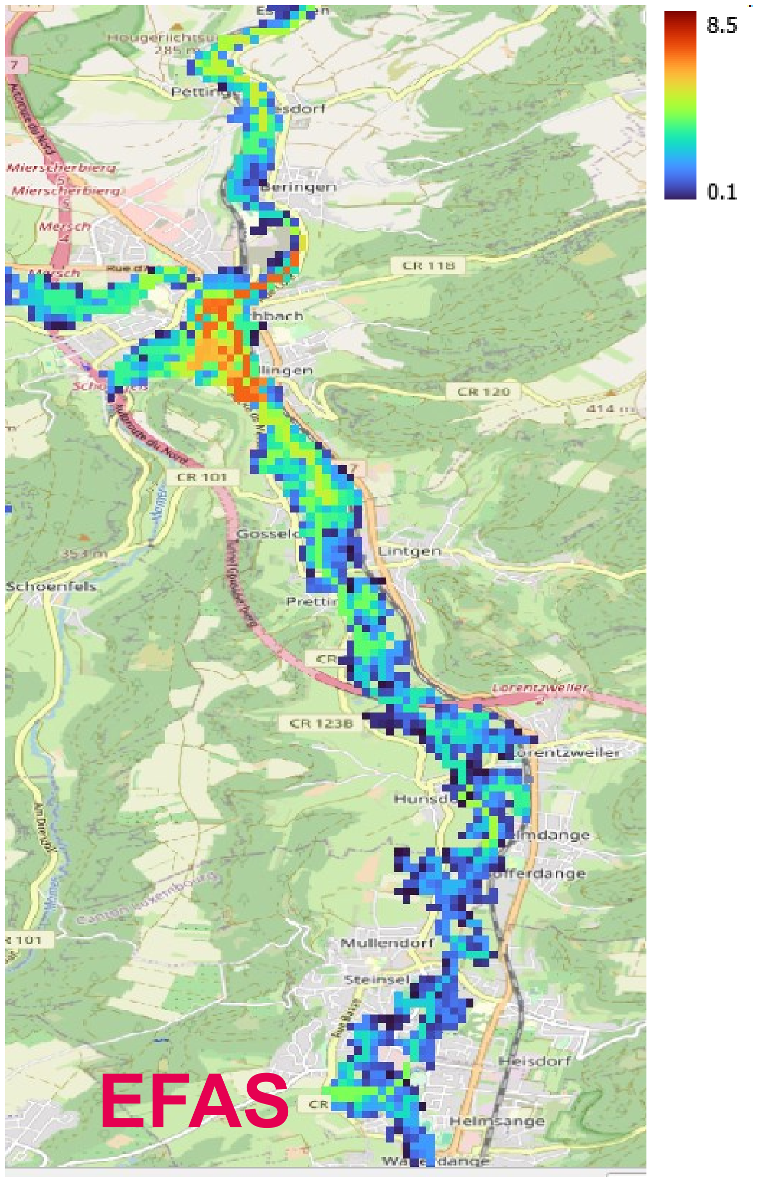
INPUT DATA - PRE-COMPUTATION OF SCENARIOS

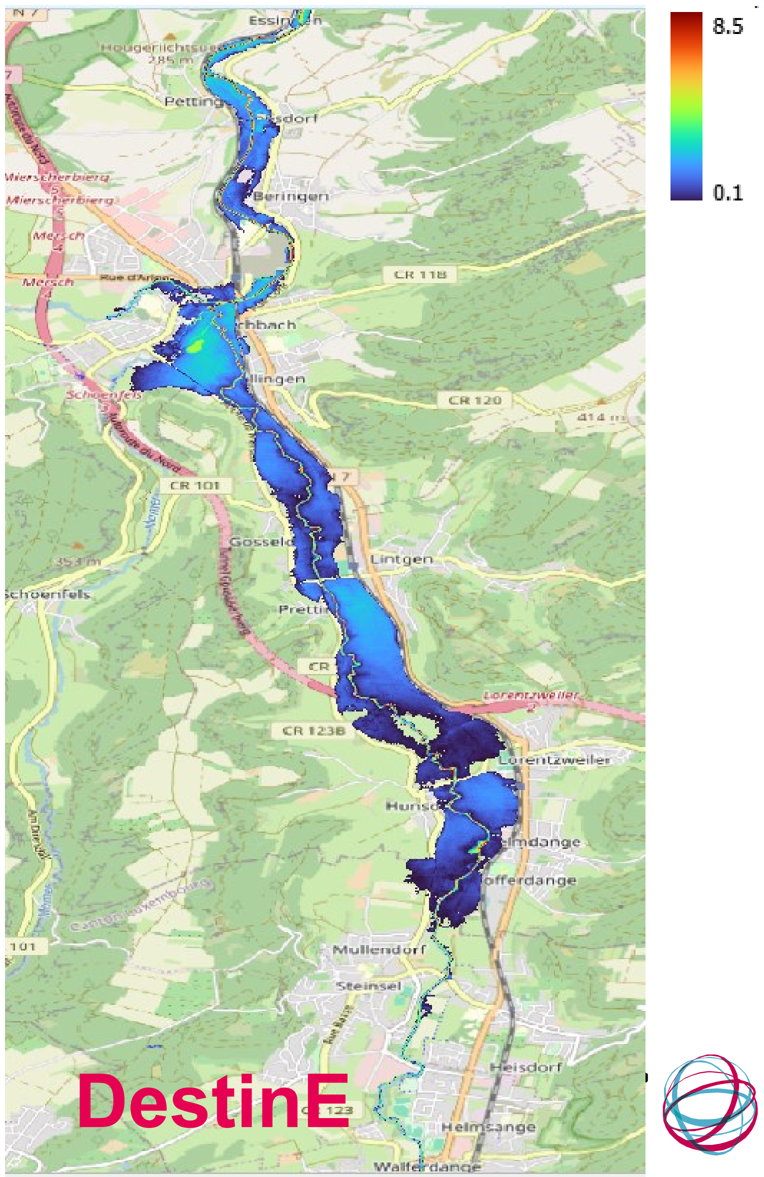
- **38 scenarios: Q=5 to 190 m³/s, interval = 5 m³/s**
- **Spatial resolution: 5 m**



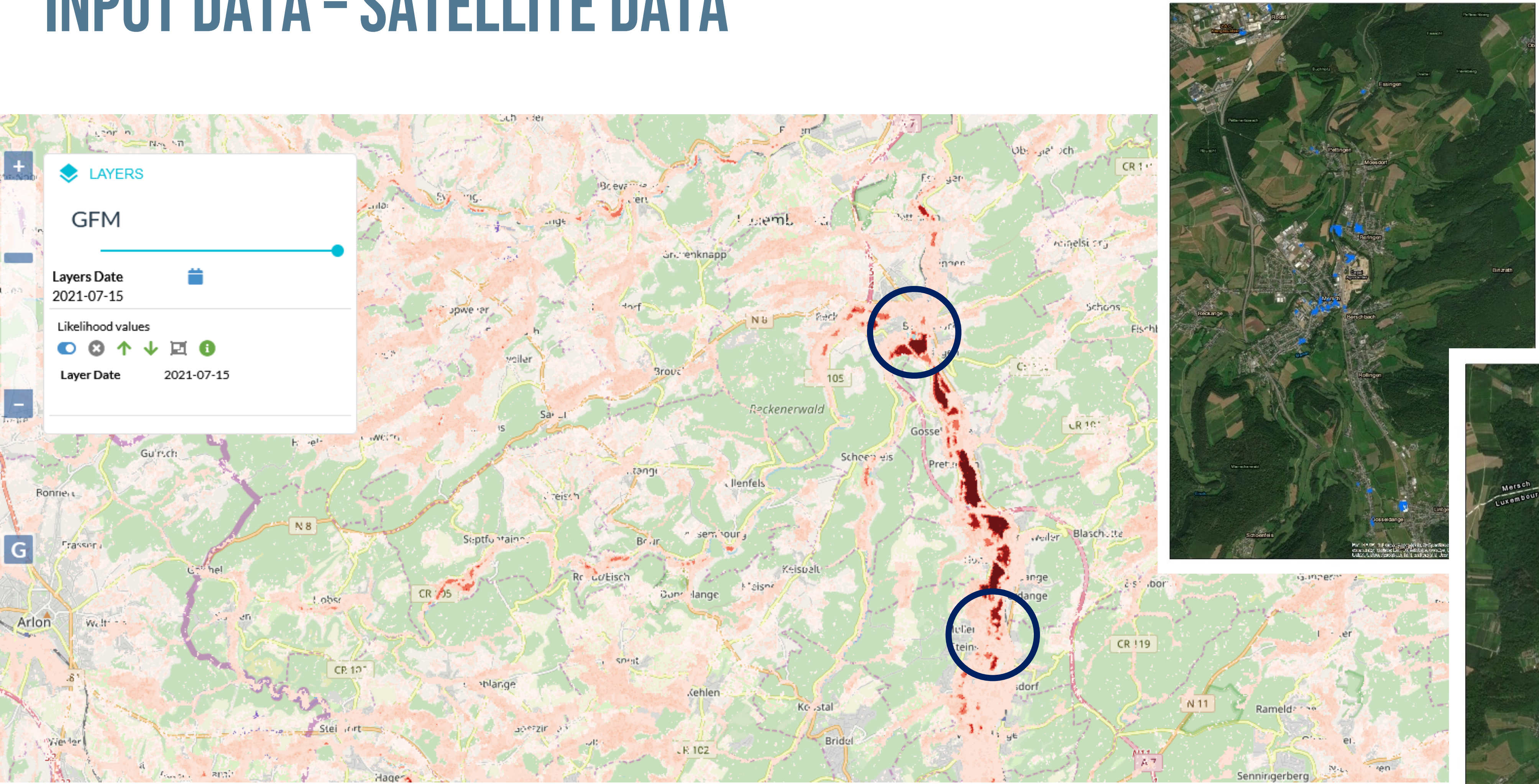
COMPARISON WITH EFAS FLOOD HAZARD MAP

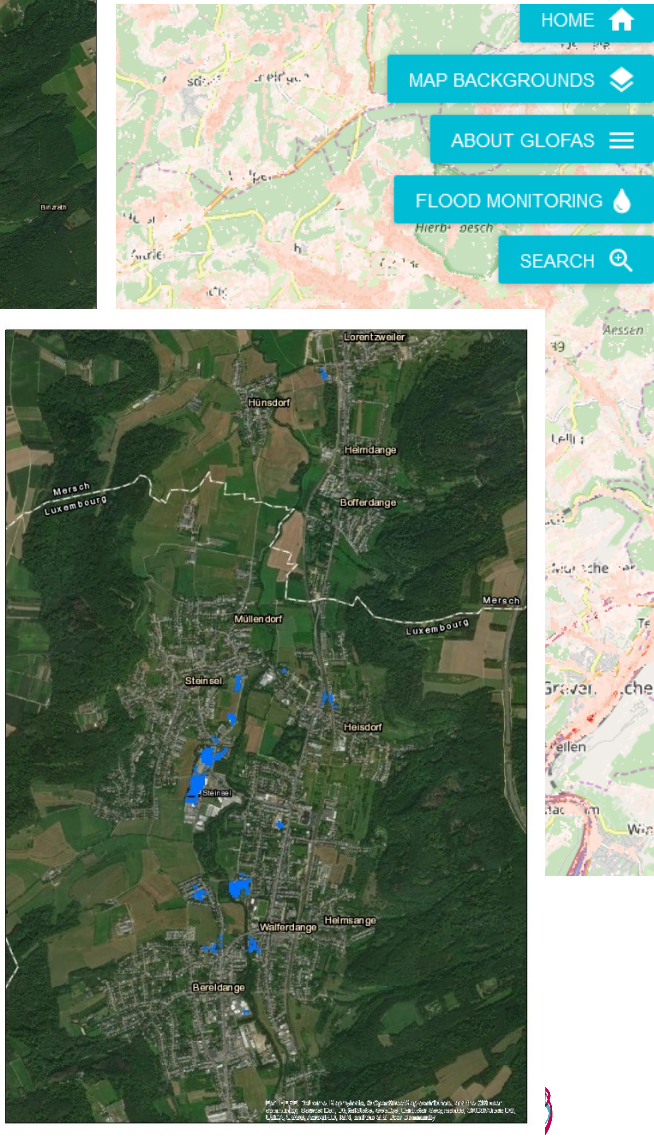
1-in-100 years flood event





INPUT DATA – SATELLITE DATA





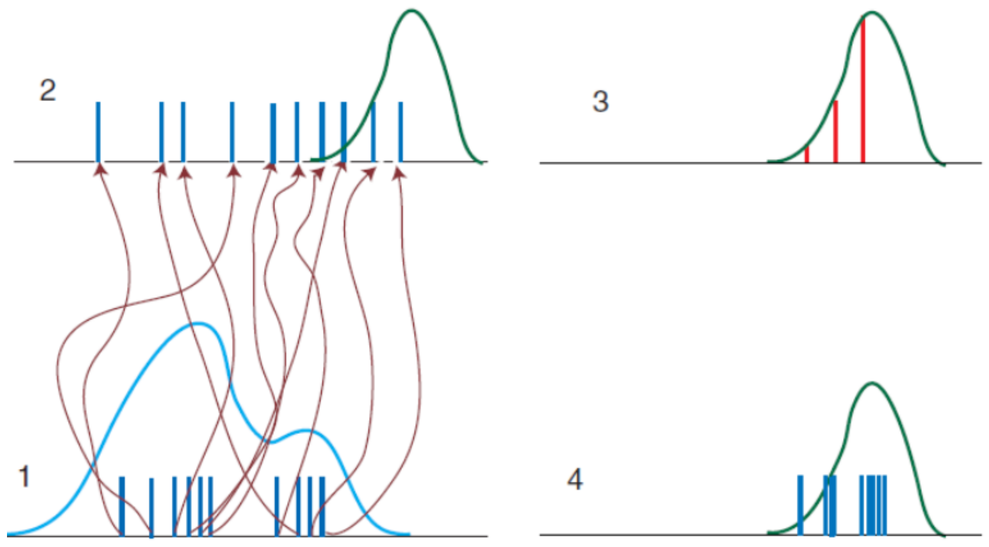
Flood probabilities published by the Global Flood Monitoring System (15 July 2021)
→ PF1 experiment

Floodwater in built up areas through WASDI (added to GFM-based flood extent in 'open' areas)
→ PF2 experiment

DATA ASSIMILATION FRAMEWORK

Bayes' Theorem: $$p(\boldsymbol{\theta}|\boldsymbol{o}) = \frac{p(\boldsymbol{o}|\boldsymbol{\theta})}{p(\boldsymbol{o})} p(\boldsymbol{\theta})$$

- Prior and posterior probability is approximated by a set of particles.
- Posterior probability is computed using weights.



STAGE 2: Propagation

STAGE 3: Analysis

STAGE 1: Discretization

STAGE 4: Resampling step

DATA ASSIMILATION – PARTICLE WEIGHT COMPUTATION

$$p(\boldsymbol{\theta}|\boldsymbol{o}) = \frac{p(\boldsymbol{o}|\boldsymbol{\theta})}{p(\boldsymbol{o})}p(\boldsymbol{\theta})$$

Model^{t,n}

1	0	1
0	1	1
1	0	0

$$w_{1,1}^{t,n} = \theta_{1,1}$$

Simulated wet pixel

$$w_{3,3}^{t,n} = 1 - \theta_{3,3}$$

Simulated dry pixel

Satellite observation

$\theta_{1,1}$	$\theta_{1,2}$	$\theta_{1,3}$
$\theta_{2,1}$	$\theta_{2,2}$	$\theta_{2,3}$
$\theta_{3,1}$	$\theta_{3,2}$	$\theta_{3,3}$

Prob (Obs | Model)

$w_{1,1}^{t,n}$	$w_{1,2}^{t,n}$	$w_{1,3}^{t,n}$
$w_{2,1}^{t,n}$	$w_{2,2}^{t,n}$	$w_{2,3}^{t,n}$
$w_{3,1}^{t,n}$	$w_{3,2}^{t,n}$	$w_{3,3}^{t,n}$

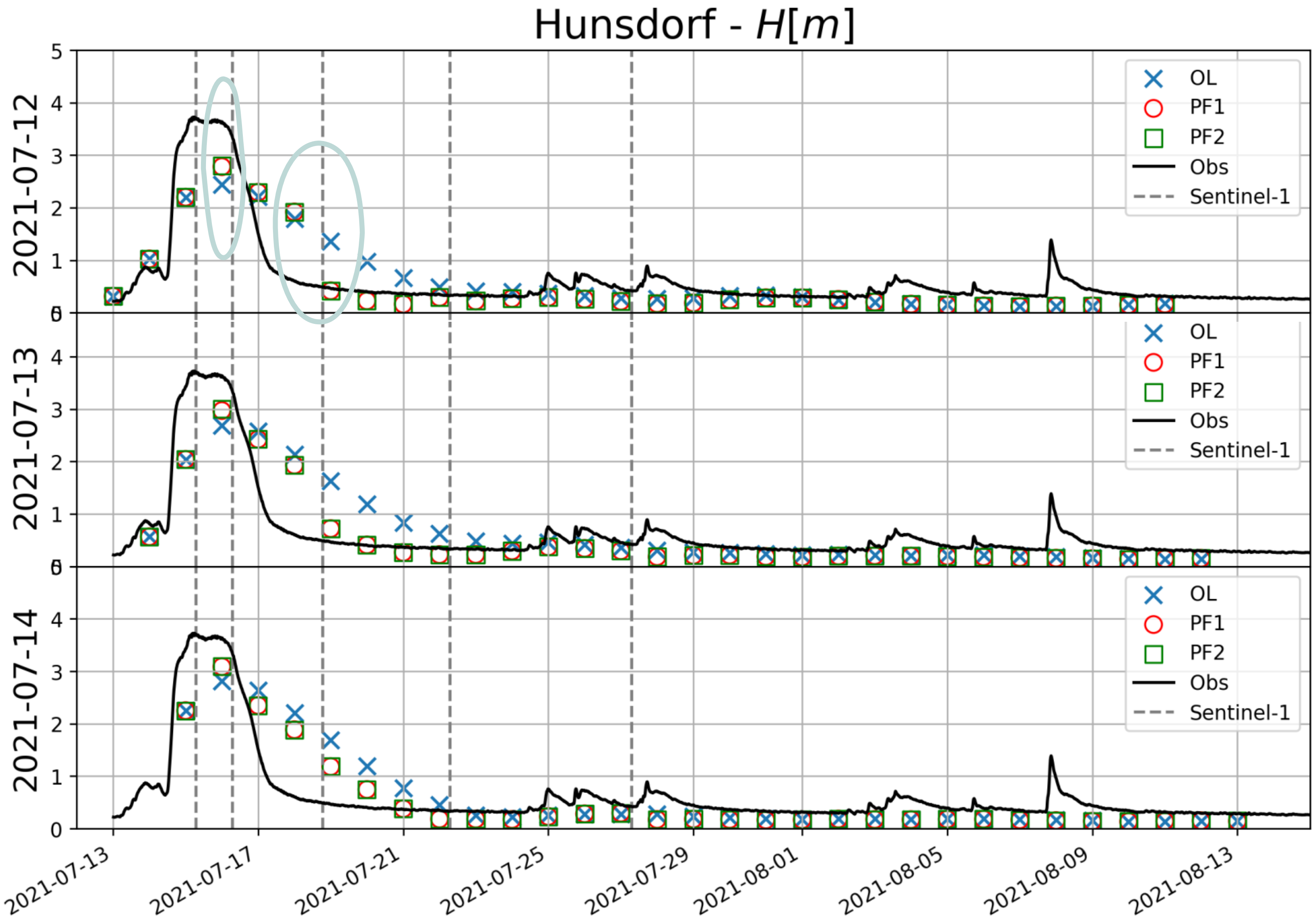
Spatial aggregation of local weights

$$W^{t,n} = \frac{\prod_{j,k}\left(w_{j,k}^{t,n}\right)^{\varphi}}{\sum_i\left(\prod_{j,k}\left(w_{j,k}^{t,n}\right)^{\varphi}\right)}$$

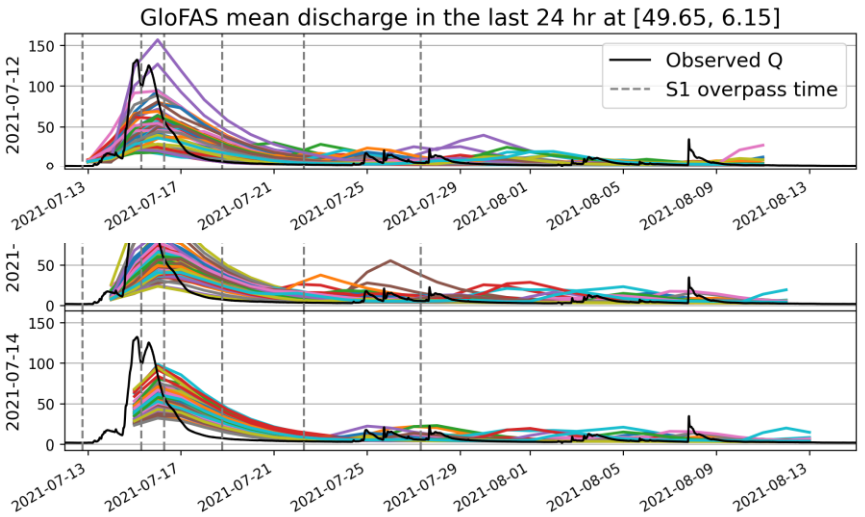
- Hostache, R., Chini, M., Giustarini, L., Neal, J., Kavetski, D., Wood, M., Corato, G., Pelich, R., & Matgen, P. (2018). Near-Real-Time Assimilation of SAR-Derived Flood Maps for Improving Flood Forecasts. *Water Resources Research*, *54*(8), 5516–5535. https://doi.org/10.1029/2017WR022205
- Di Mauro, C., Hostache, R., Matgen, P., Pelich, R., Chini, M., van Leeuwen, P. J., Nichols, N., & Blöschl, G. (2022). A Tempered Particle Filter to Enhance the Assimilation of SAR-Derived Flood Extent Maps Into Flood Forecasting Models. *Water Resources Research*, *58*(8), 1–19. https://doi.org/10.1029/2022WR031940

RESULT - FLOOD FORECASTING

Forecast waterdepth at gauging station



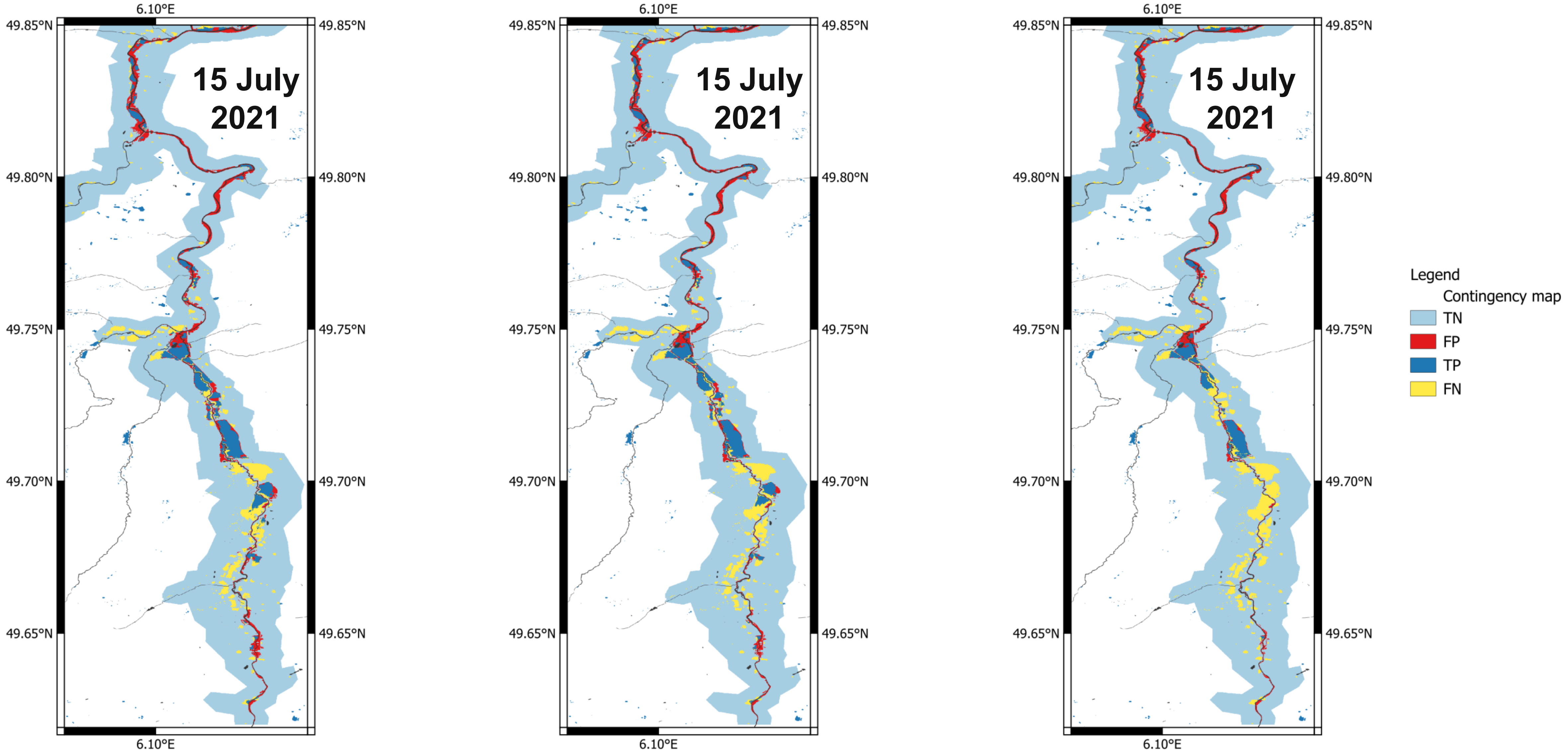
Upstream boundary conditions



RMSE [m] over 30 days

	GloFAS forecast issue date								
	July 12			July 13			July 14		
Exp.	OL	PF1	PF2	OL	PF1	PF2	OL	PF1	PF2
Hunsdorf	0.179	**0.151**	0.151	0.191	**0.127**	0.127	0.206	**0.143**	0.144
Steinsel	0.181	0.141	**0.139**	0.145	0.106	**0.104**	0.130	0.103	**0.102**

RESULT - FLOOD FORECASTING



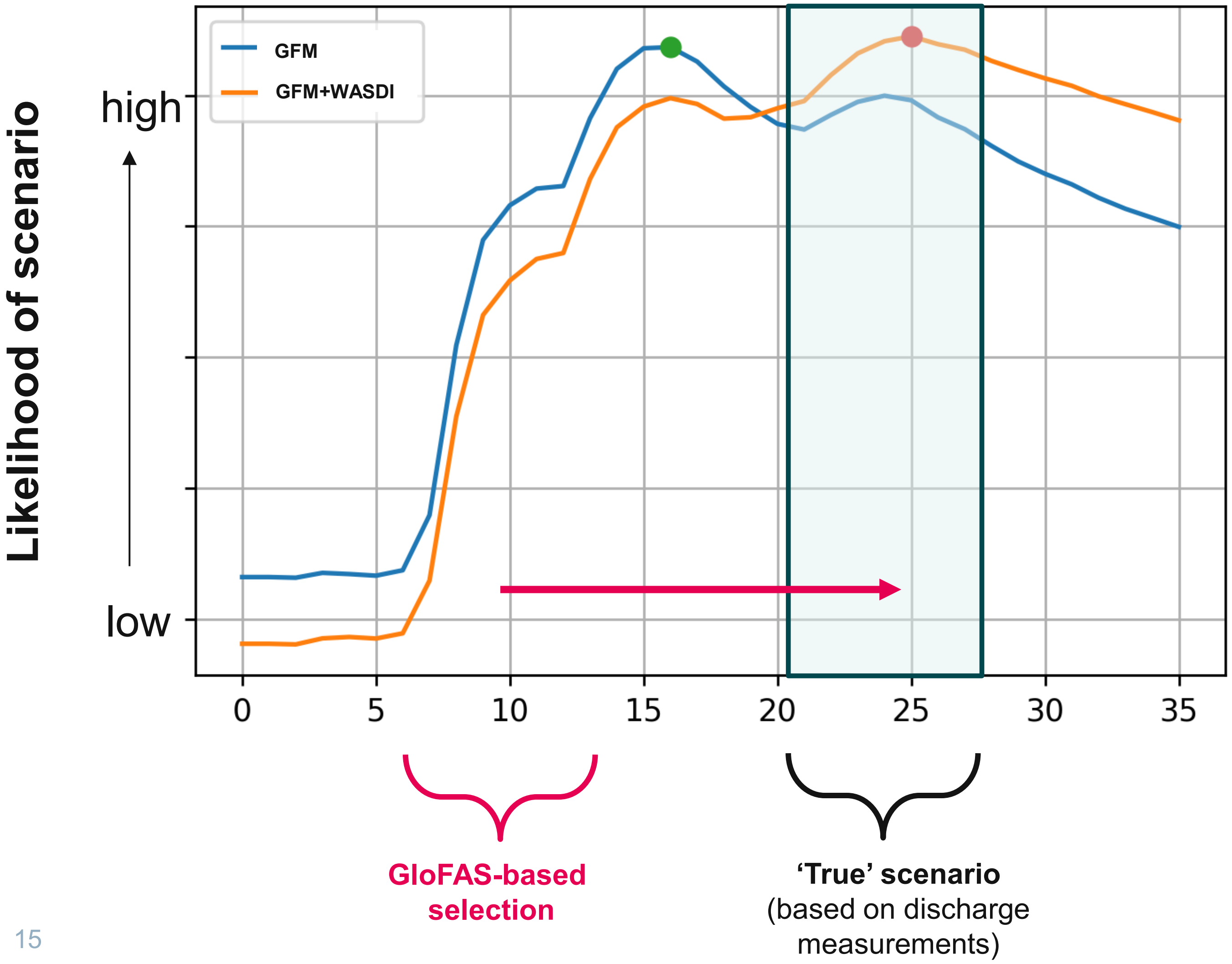
Model run 12 July

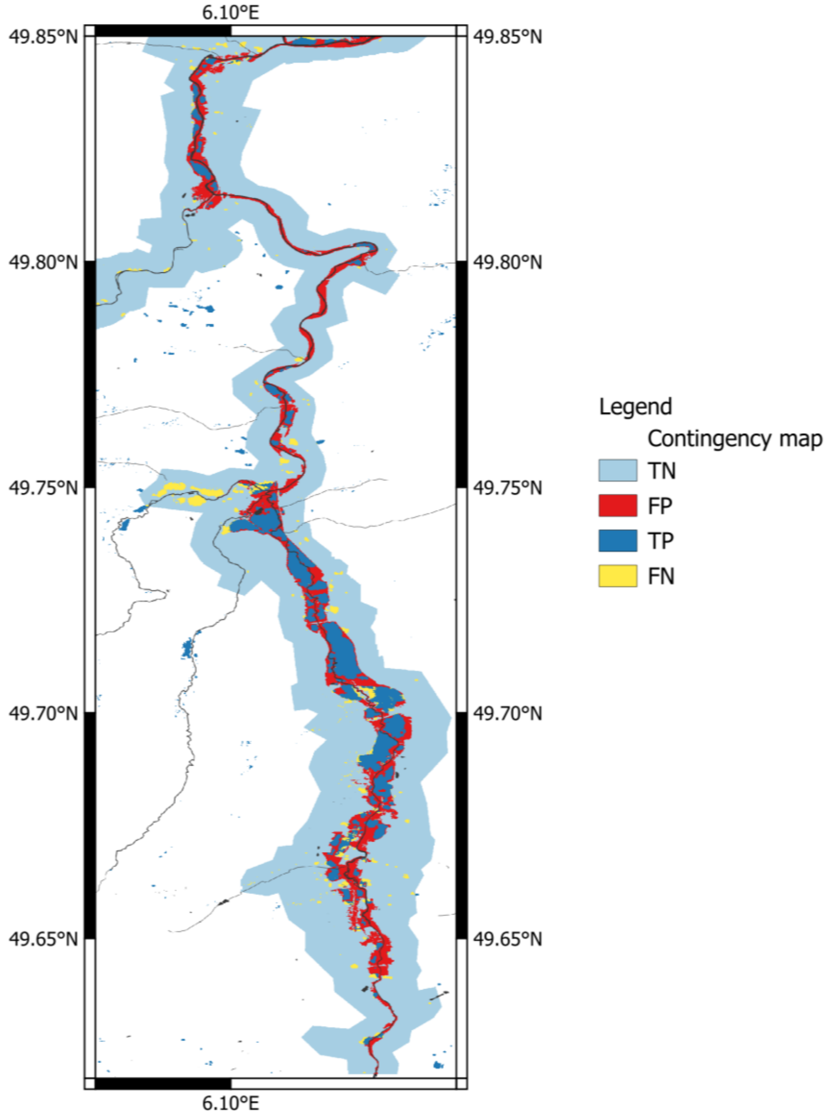
Model run 13 July

Model run 14 July

ADDED VALUE OF SATELLITE DATA ASSIMILATION

Comparison of model runs with and without GFM+WASDI data assimilation on 15 July





Scenario of the highest weight w.r.t. WASDI+GFM map

CONCLUSION

- Data assimilation framework enabling integration of GloFAS and GFM
- ‘à la carte’ modelling framework where GloFAS streamflow forceasts can be converted into inundation forecasts using regional hydrodynamic model (complementing GloFAS’ own inundation products)
- Results show that integration of satellite data enables selection of ‘true’ flood scenario, thereby reducing predictive uncertainty and confirming potential of GFM-GloFAS integration for enhanced inundation predictions

PERSPECTIVES

- Repeating experiment with GloFAS pre-computed hazard cube
- Connecting floodhazard datacube and discharge particles via return period
- Improving PF weight computation scheme (e.g. enabling refinements at sub-reach level)
- Upscaling requires localization of DA filters (i.e. to connect GloFAS-based streamflow predictions with relevant GFM observations

(+ improvements of GloFAS and GFM products)

THANK YOU FOR YOUR ATTENTION

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