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Irrigation estimation through backscatter data assimilation with a buddy check approach

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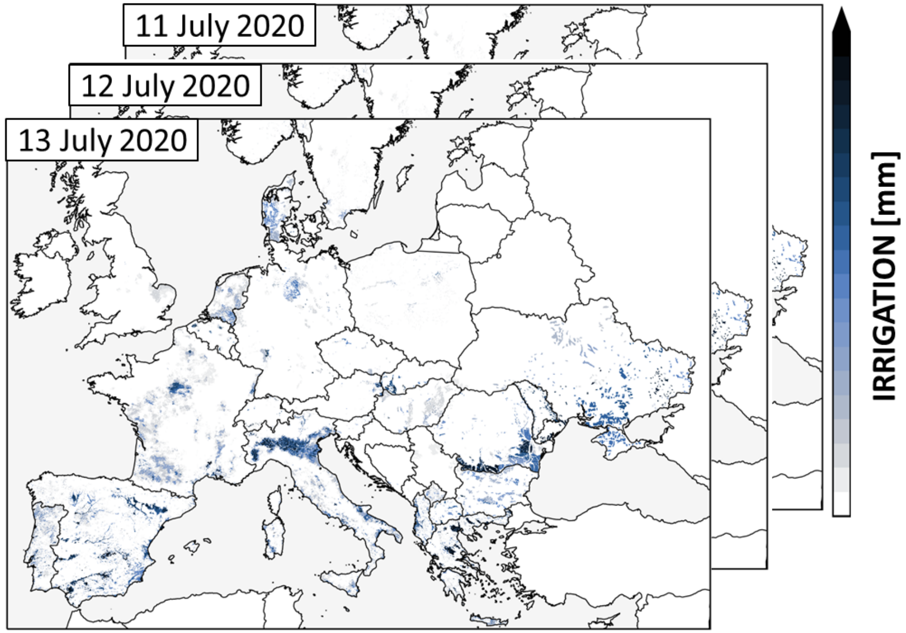
Opening new horizons

esa

Irrigation estimation

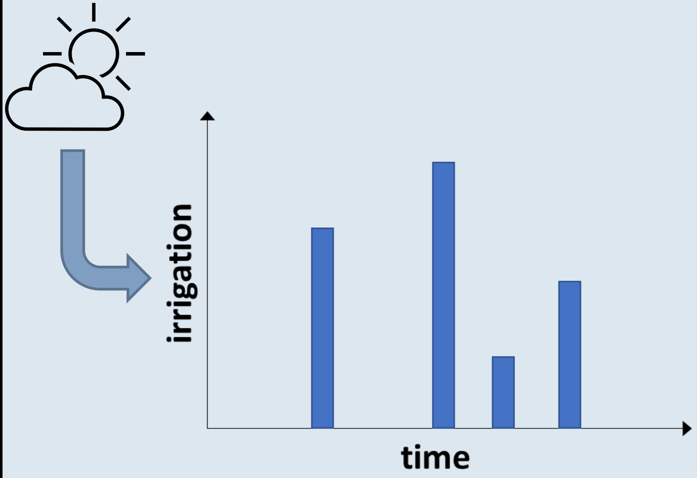
- Why?
  - Monitoring irrigation water use
  - Climate research: improved coupled land-atmosphere systems
- How?
  - Modeling
  - Remote sensing

→« the ideal dataset » (high spatial and temporal resolution)



Data assimilation

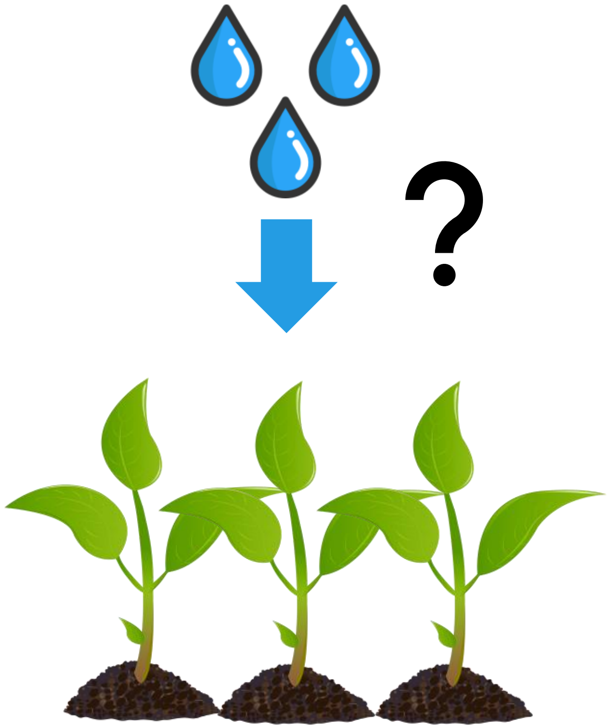
Modeling
land surface models
(Noah-MP)



Simulate irrigation

Uncertainty

Data assimilation

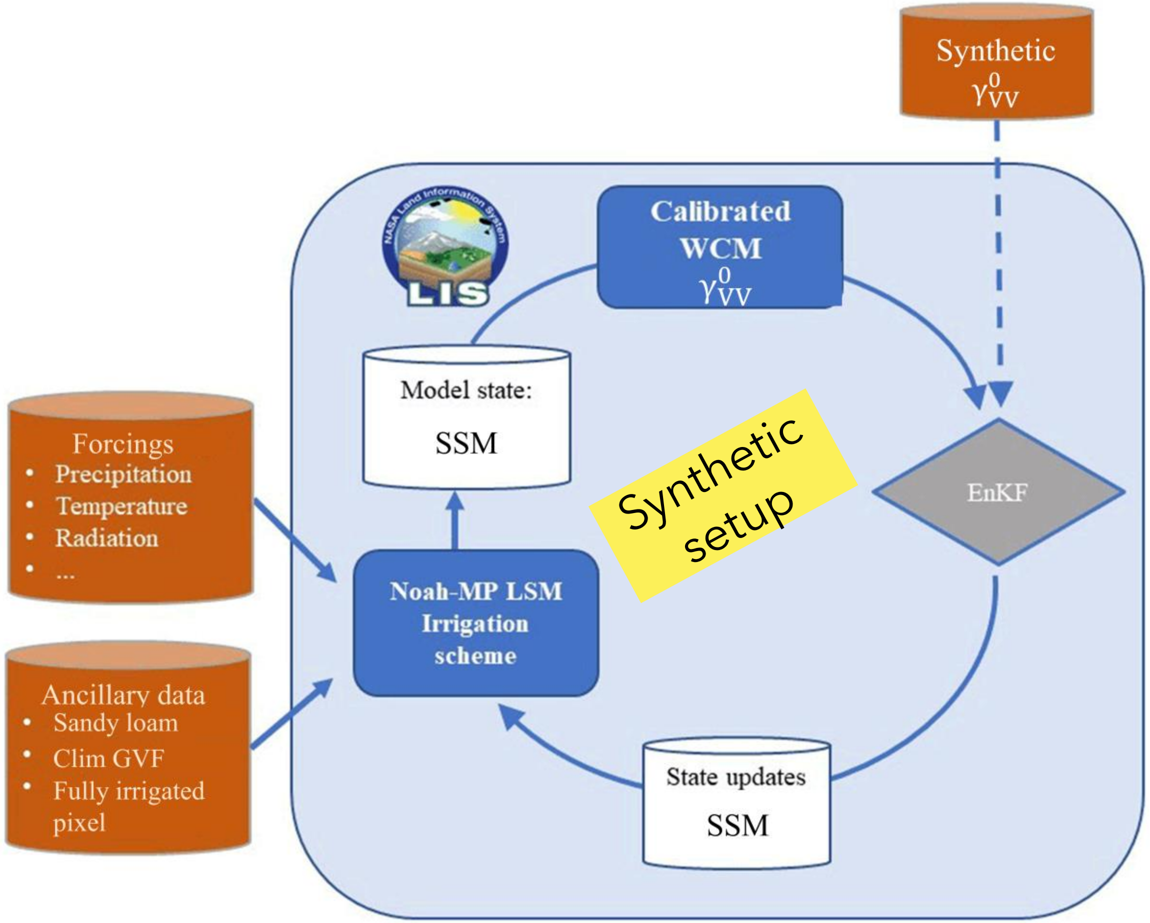


Remote sensing
Sentinel-1

'See' irrigation

Gaps in time & space
Only surface soil moisture

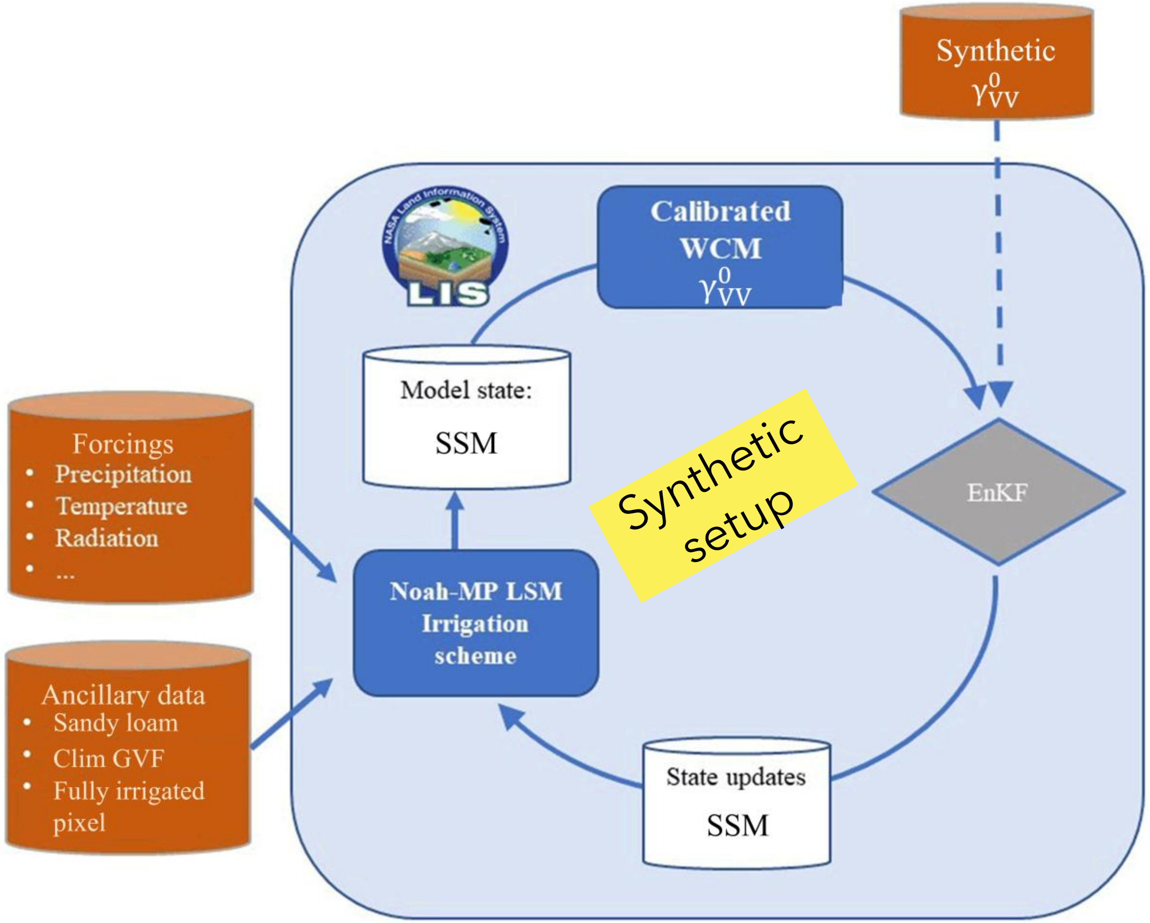
Synthetic setup



Adapted from Modanesi et al. (2022, HESS)

Assimilate **synthetic backscatter $\gamma°_{VV}$** into the **Noah-MP LSM** coupled to an irrigation scheme to update SSM and improve initial conditions for irrigation estimation

Synthetic setup



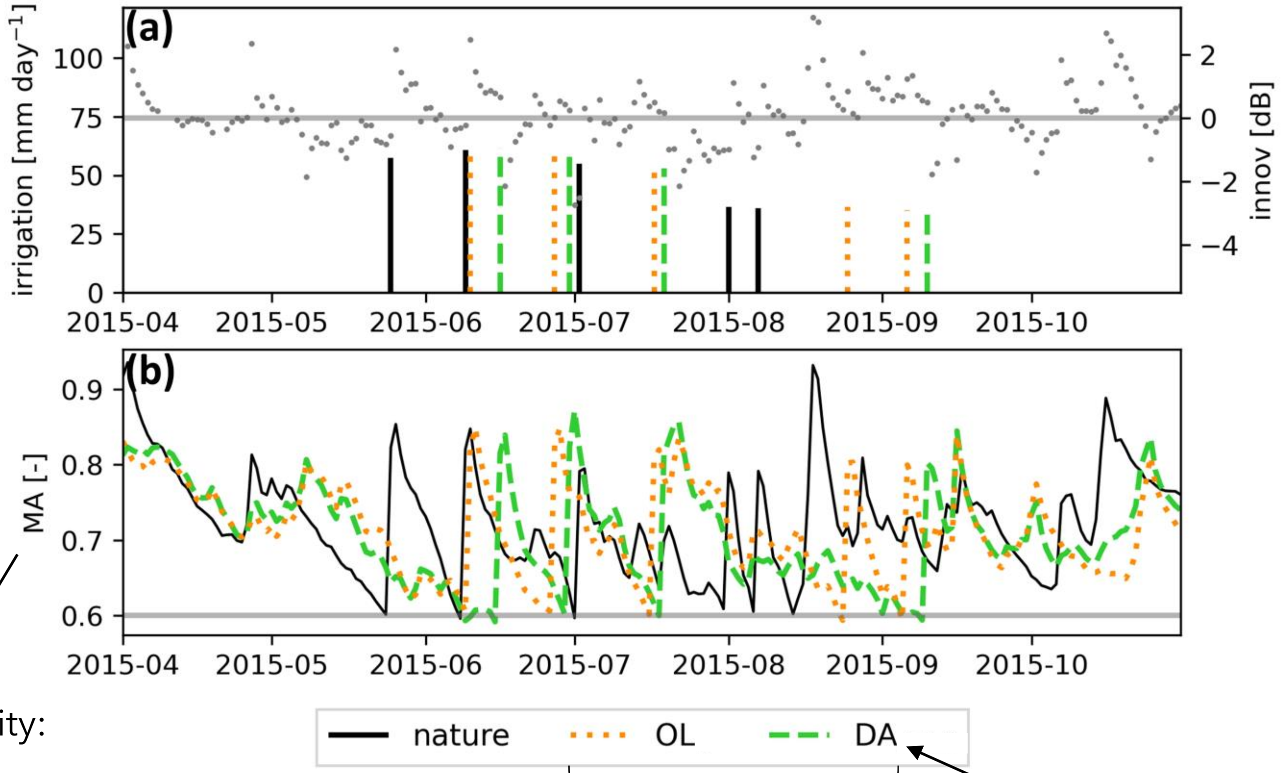
Adapted from Modanesi et al. (2022, HESS)

Assimilate **synthetic backscatter $\gamma°_{VV}$** into the **Noah-MP LSM** coupled to an irrigation scheme to update SSM and improve initial conditions for irrigation estimation

Objectives

- Better understand the system in a synthetic setup
  → default DA
- Improve the DA for irrigation
  → buddy check approach

EnKF DA for irrigation quantification



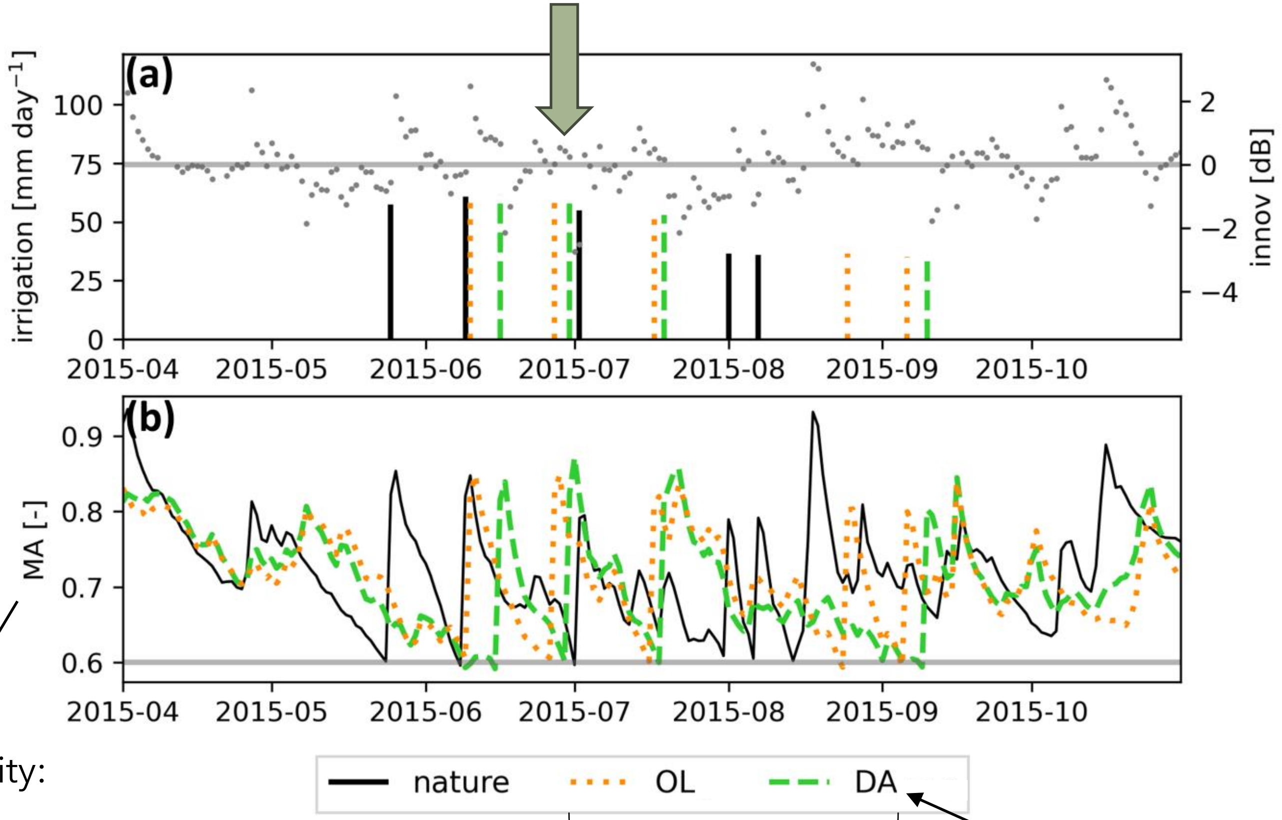
Moisture availability:

$$MA = \frac{\theta - \theta_{WP}}{\theta_{FC} - \theta_{WP}}$$

Precipitation error

perfect (no noise) daily $\gamma°_{VV}$

EnKF DA for irrigation quantification



Precipitation error

perfect (no noise) daily $\gamma°_{VV}$

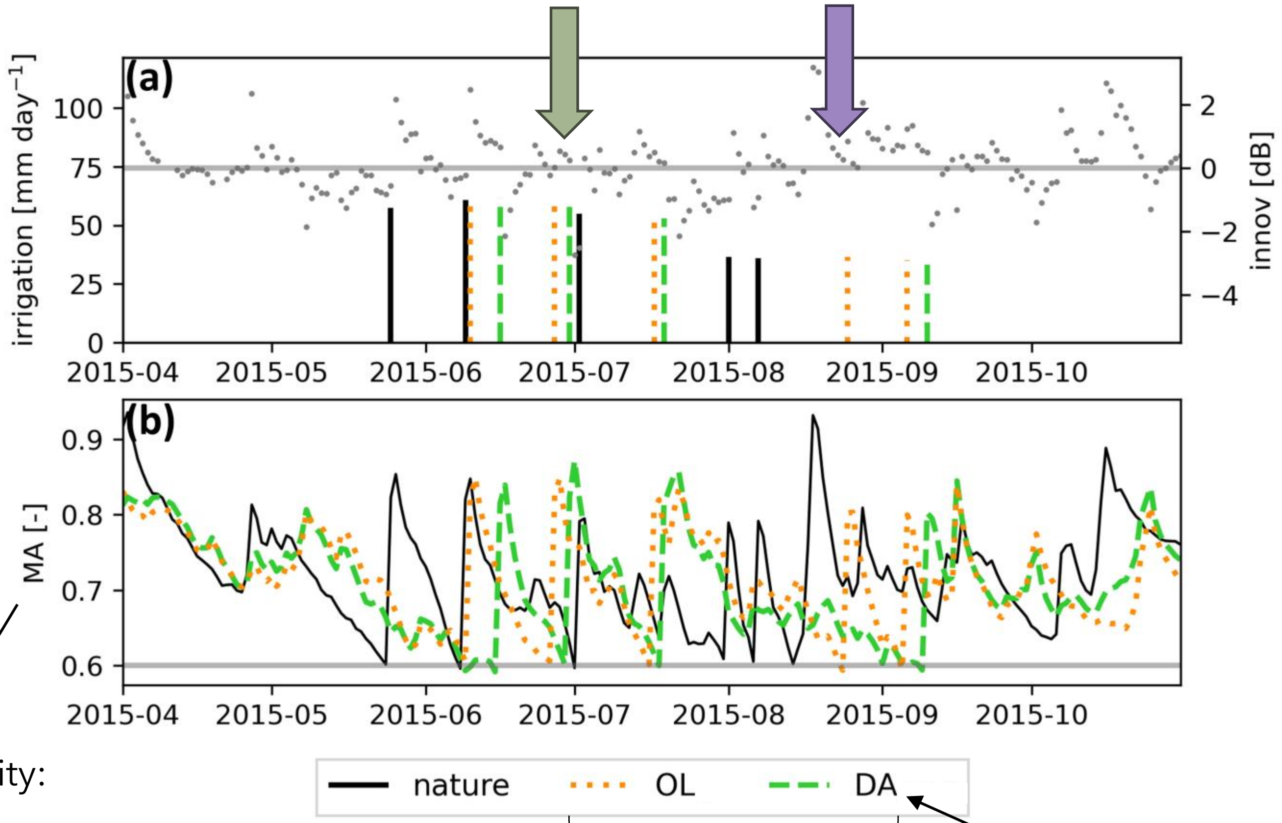
Moisture availability:

$$MA = \frac{\theta - \theta_{WP}}{\theta_{FC} - \theta_{WP}}$$

Benefits

MA closer to the nature correcting the timing of irrigation events

EnKF DA for irrigation quantification



Benefits
MA closer to the nature correcting the timing of irrigation events

Limitations
Updates to wetter soil moisture delays/inhibits irrigation

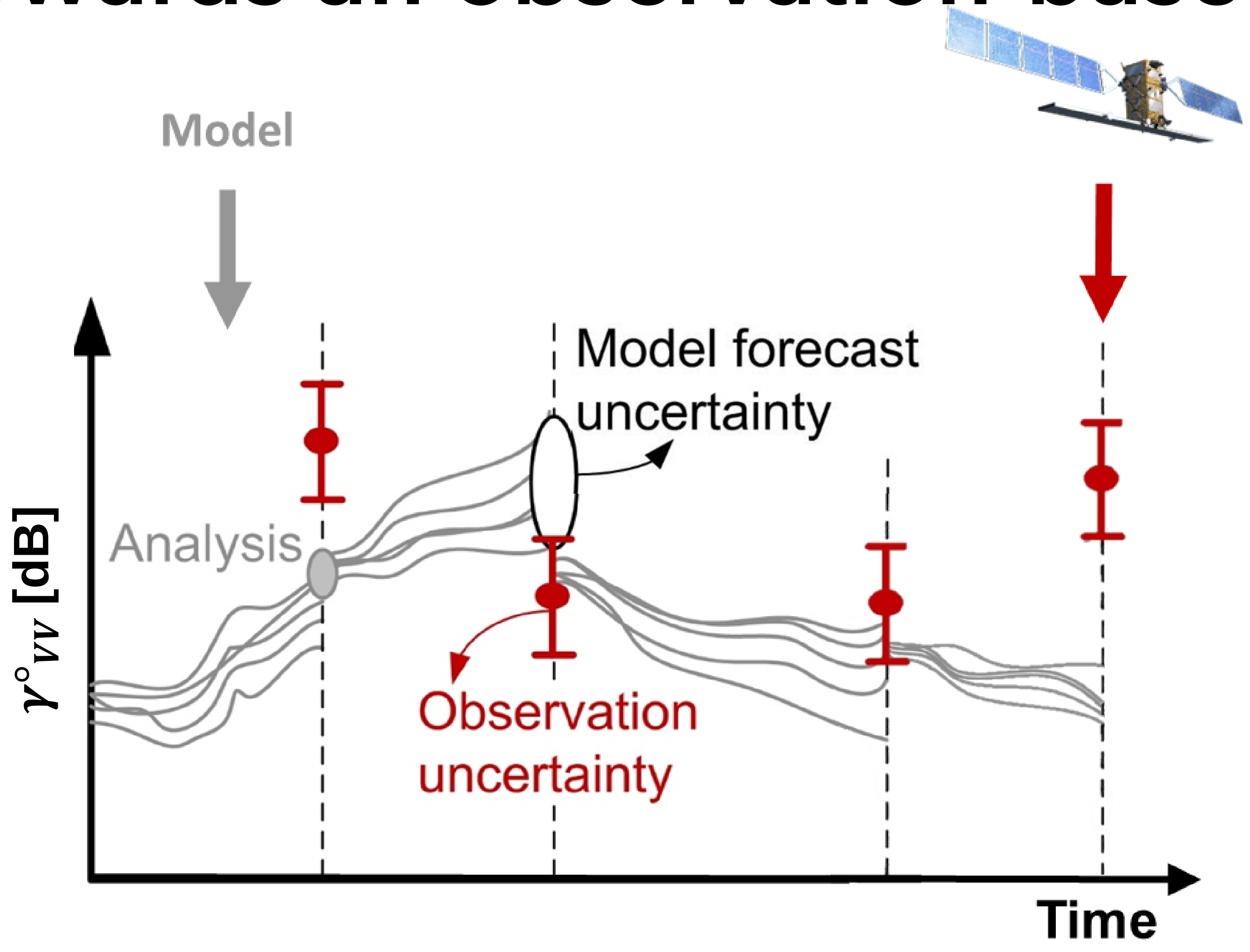
Moisture availability:

$$MA = \frac{\theta - \theta_{WP}}{\theta_{FC} - \theta_{WP}}$$

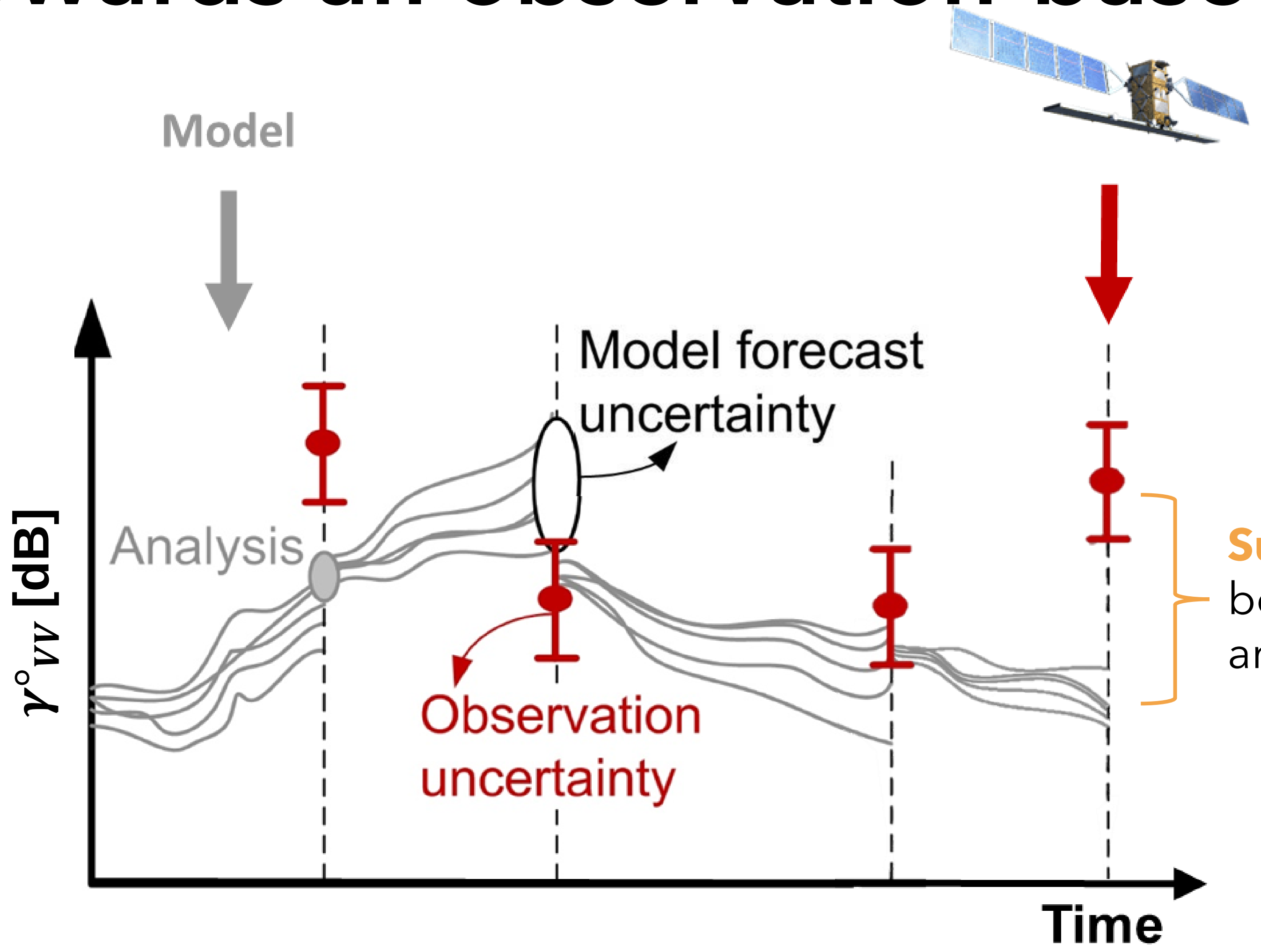
Precipitation error

perfect (no noise) daily $\gamma°_{VV}$

Towards an observation-based irrigation trigger

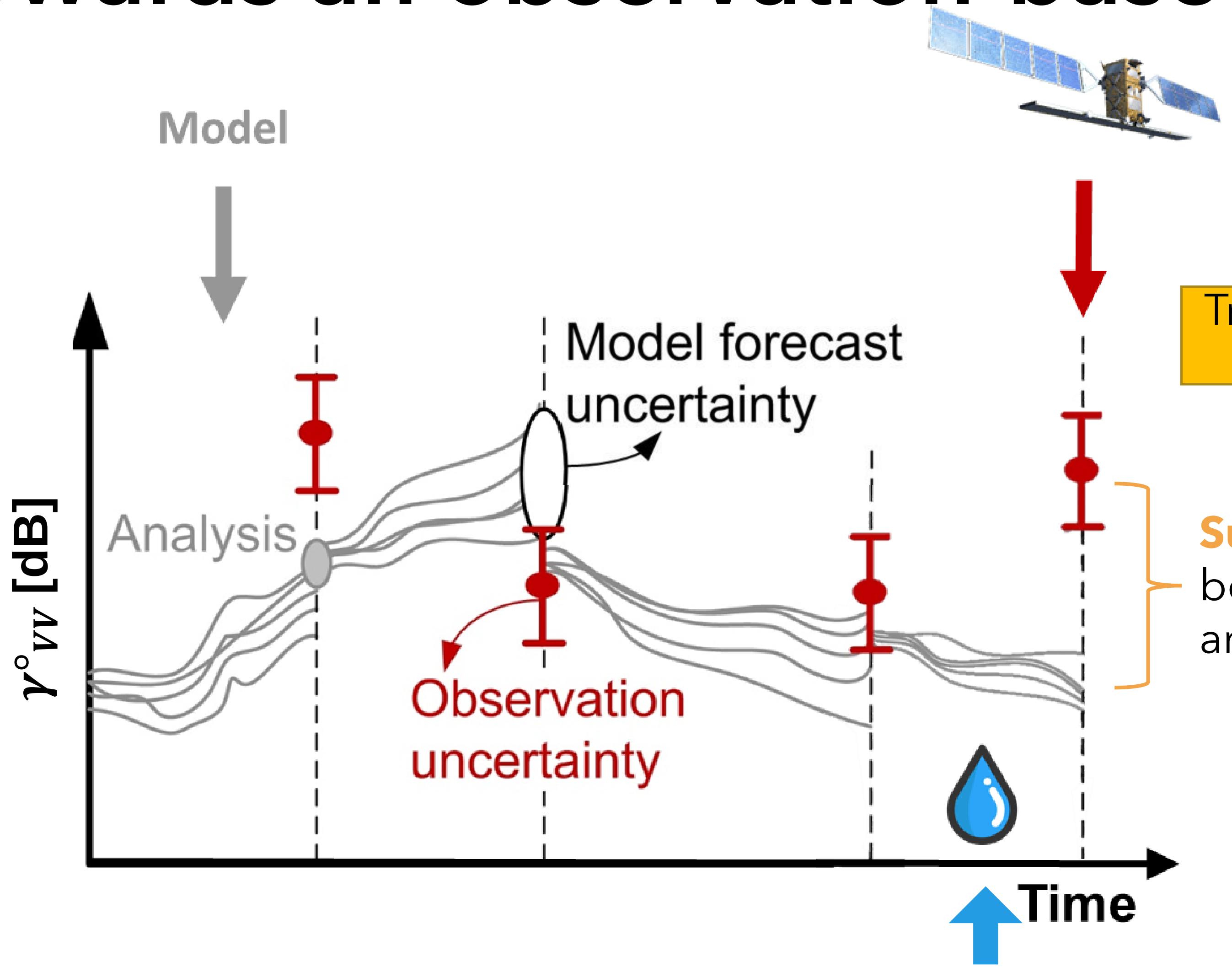


Towards an observation-based irrigation trigger



Sudden large difference between the forecast (model) and the observation

Towards an observation-based irrigation trigger

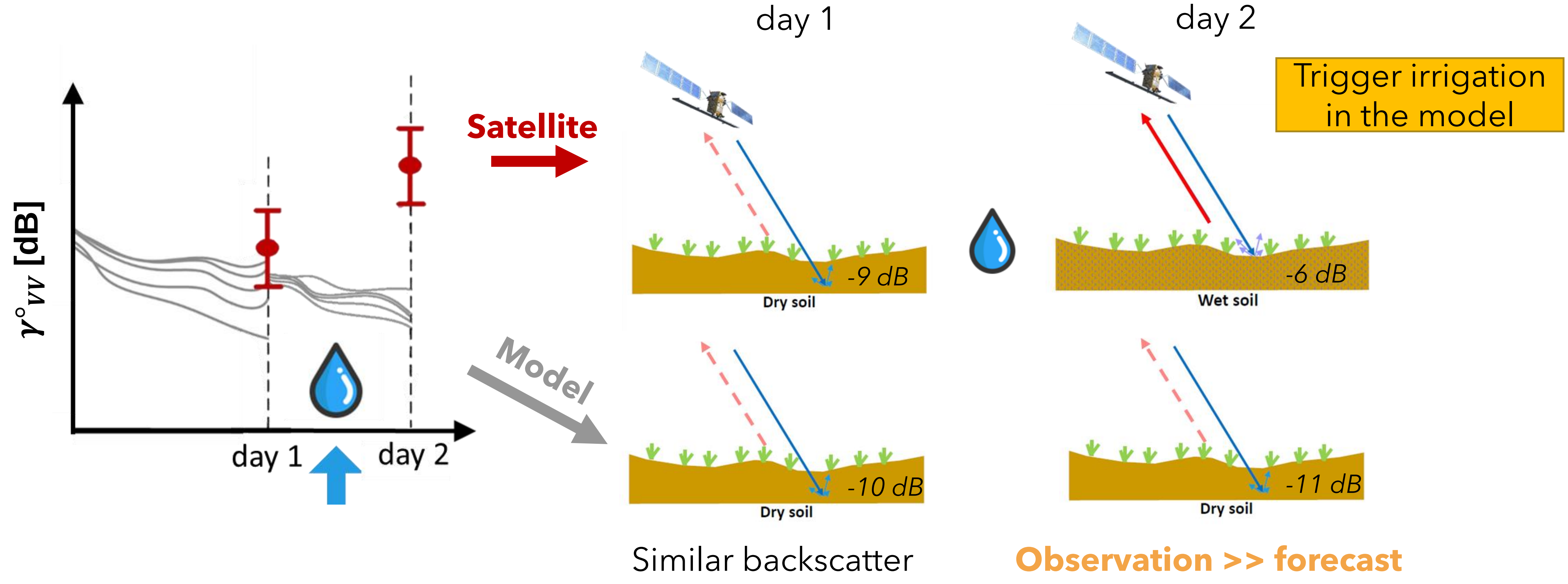


Trigger irrigation in the model

Sudden large difference between the forecast (model) and the observation

Hints towards an unmodeled process
=
IRRIGATION

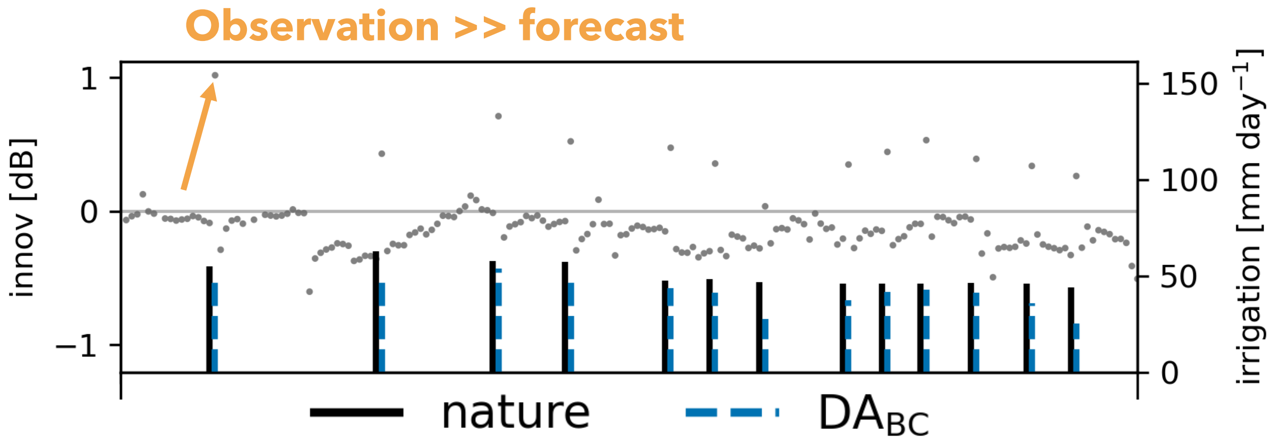
Towards an observation-based irrigation trigger



Observation-based trigger

Buddy check approach

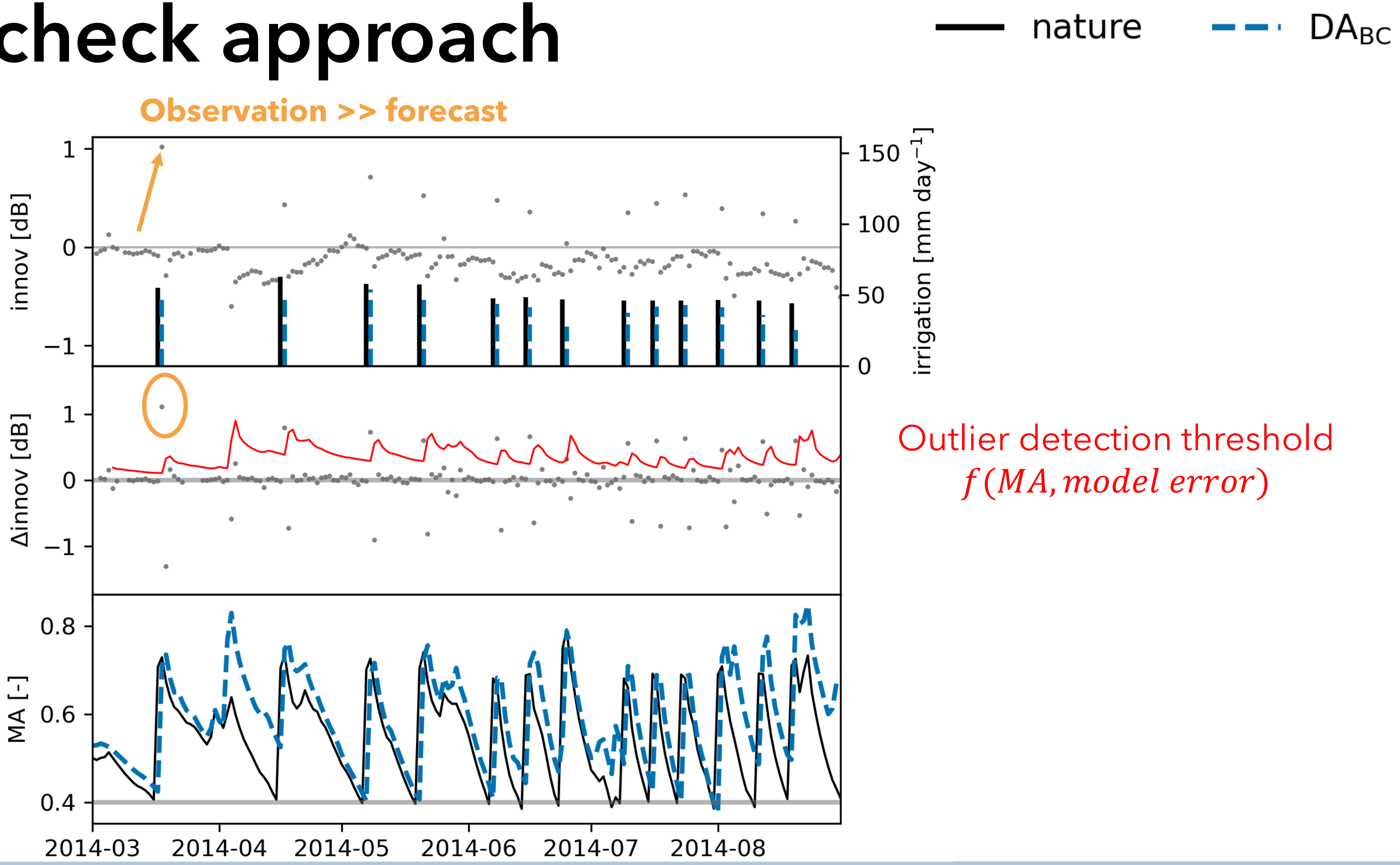
Innovation = observation – forecast



Buddy check approach

Innovation = observation – forecast

Δinnov = $\mathrm{innov}_t - \mathrm{innov}_{t-1}$

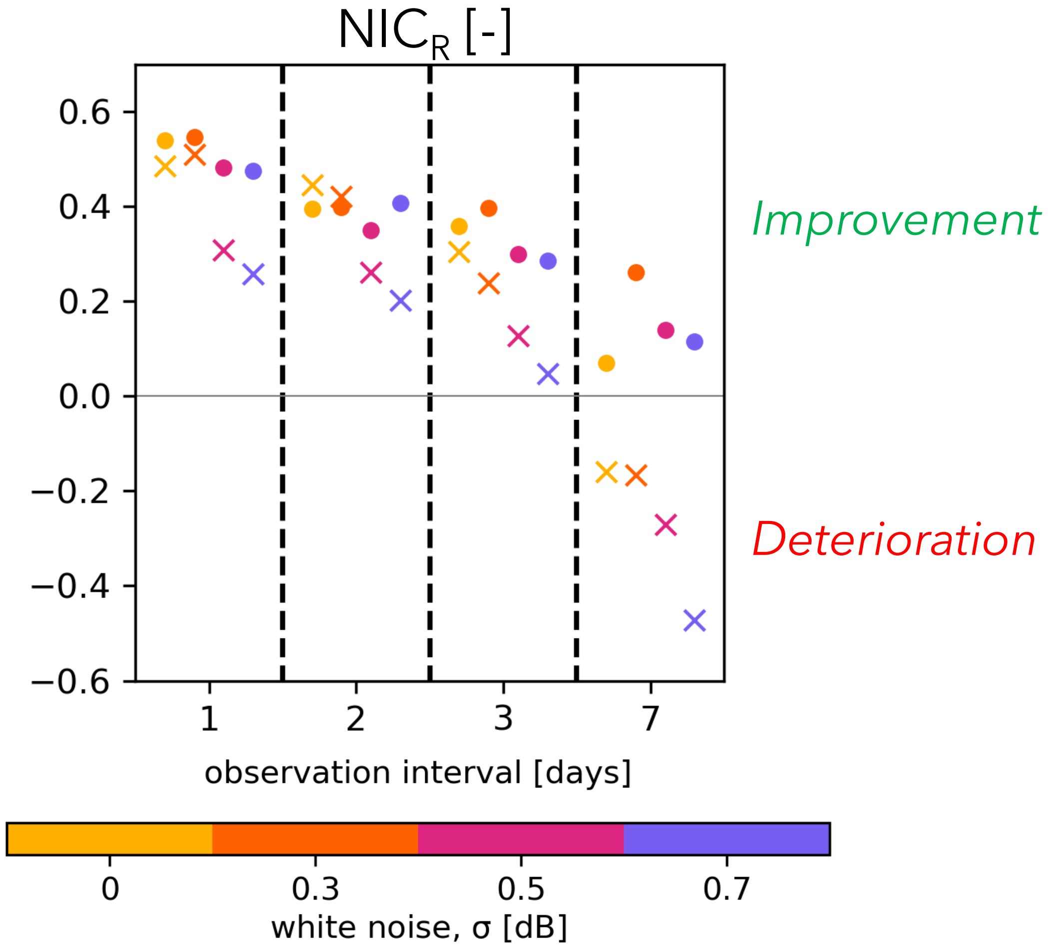


Outlier detection threshold
$f(MA, model\ error)$

Performance in a synthetic setup

- NIC_R: change in Pearson correlation compared to a model only run (soil moisture-based threshold)

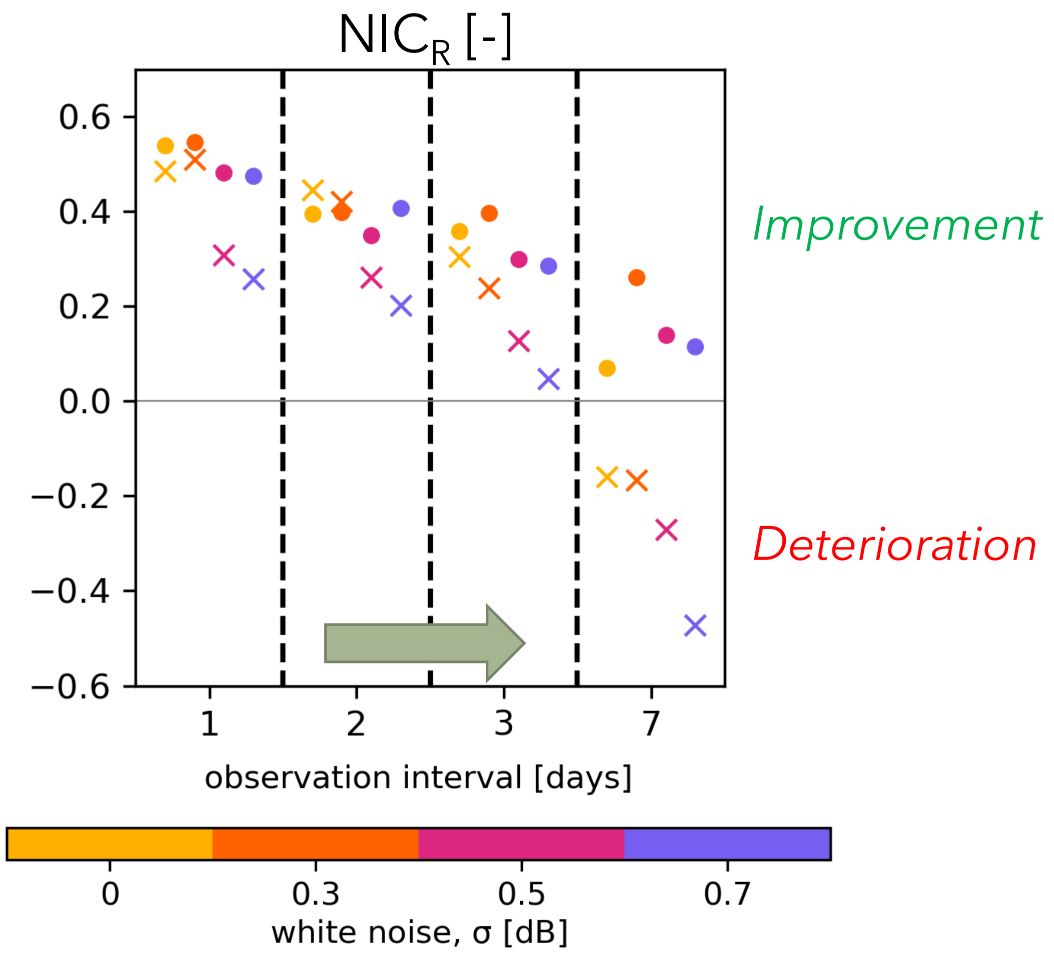
For biweekly irrigation estimates



Performance in a synthetic setup

- NIC_R: change in Pearson correlation compared to a model only run (soil moisture-based threshold)
- Observations sparse in time (x-axis) ↓

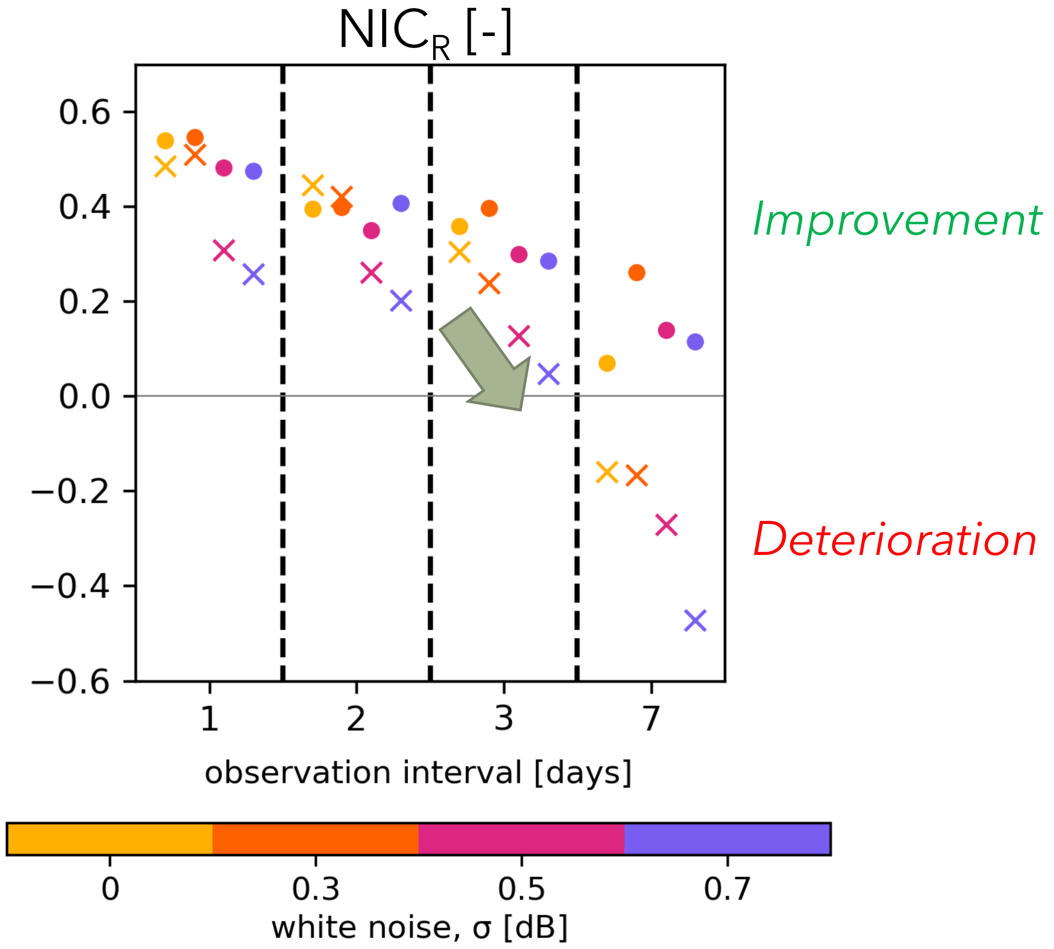
For biweekly irrigation estimates



Performance in a synthetic setup

- NIC_R: change in Pearson correlation compared to a model only run (soil moisture-based threshold)
- Observations sparse in time (x-axis) ↓
- White noise in the signal (colors) ↓

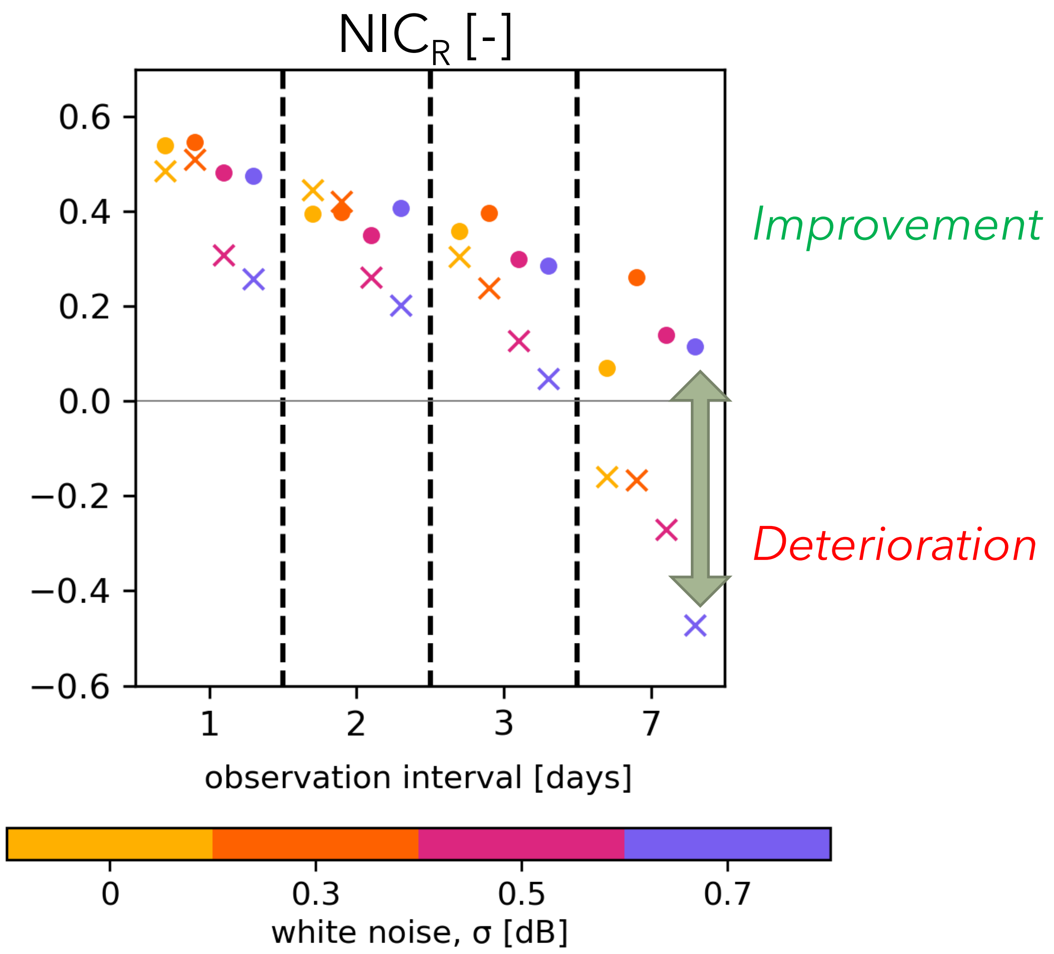
For biweekly irrigation estimates



Performance in a synthetic setup

- NIC_R: change in Pearson correlation compared to a model only run (soil moisture-based threshold)
- Observations sparse in time (x-axis) ↓
- White noise in the signal (colors) ↓
- Larger improvements when the model error is large (• vs **x**) ↑

For biweekly irrigation estimates



Performance in a synthetic setup

	Factor	Performance of buddy check approach (compared to OL)
Satellite observations	Observation interval	↓
	Observation error	↓
Model	Model error (e.g. precipitation)	↑
Location (soil type and climate)	Irrigation application depth [mm/event]	↑
	Irrigation frequency	↓

Take home messages

- The default EnKF DA shows potential but also limitations for irrigation estimation
- Novel method based on an **innovation outlier detection (buddy check) approach**
  → Double effect of the DA:
    - ✓ sets better initial conditions to trigger irrigation
    - ✓ observation-based irrigation trigger
- Tested in a synthetic setup to understand the limitations
- Ready to be tested in the real world, but will need further research/developments

Thank you!

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Busschaert L., Bechtold M., Modanesi S., Massari C., Brocca L., De Lannoy G. J. M. Irrigation quantification through backscatter data assimilation with a buddy check approach. Accepted by the Journal of Advances in Modeling Earth System (JAMES).

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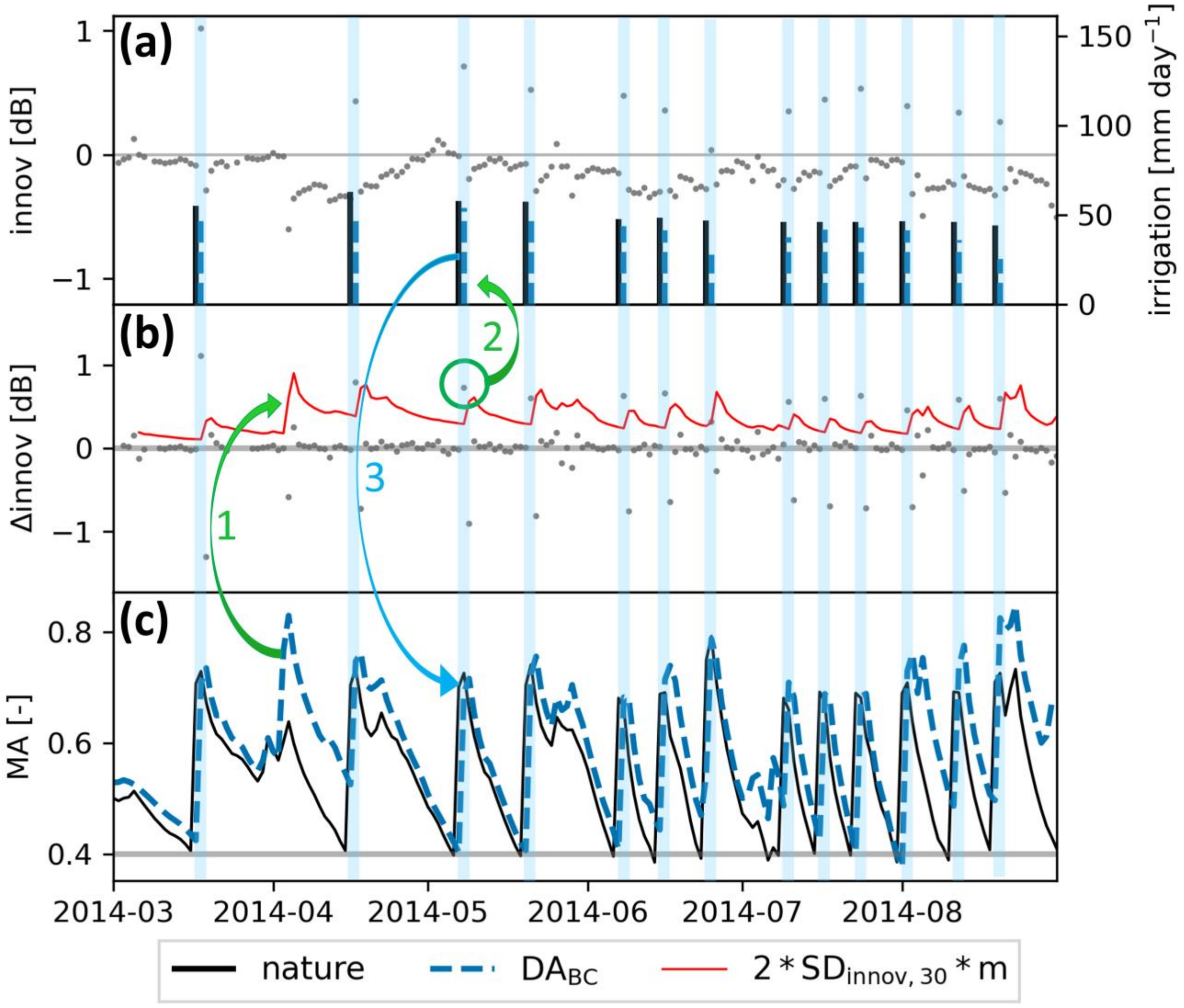
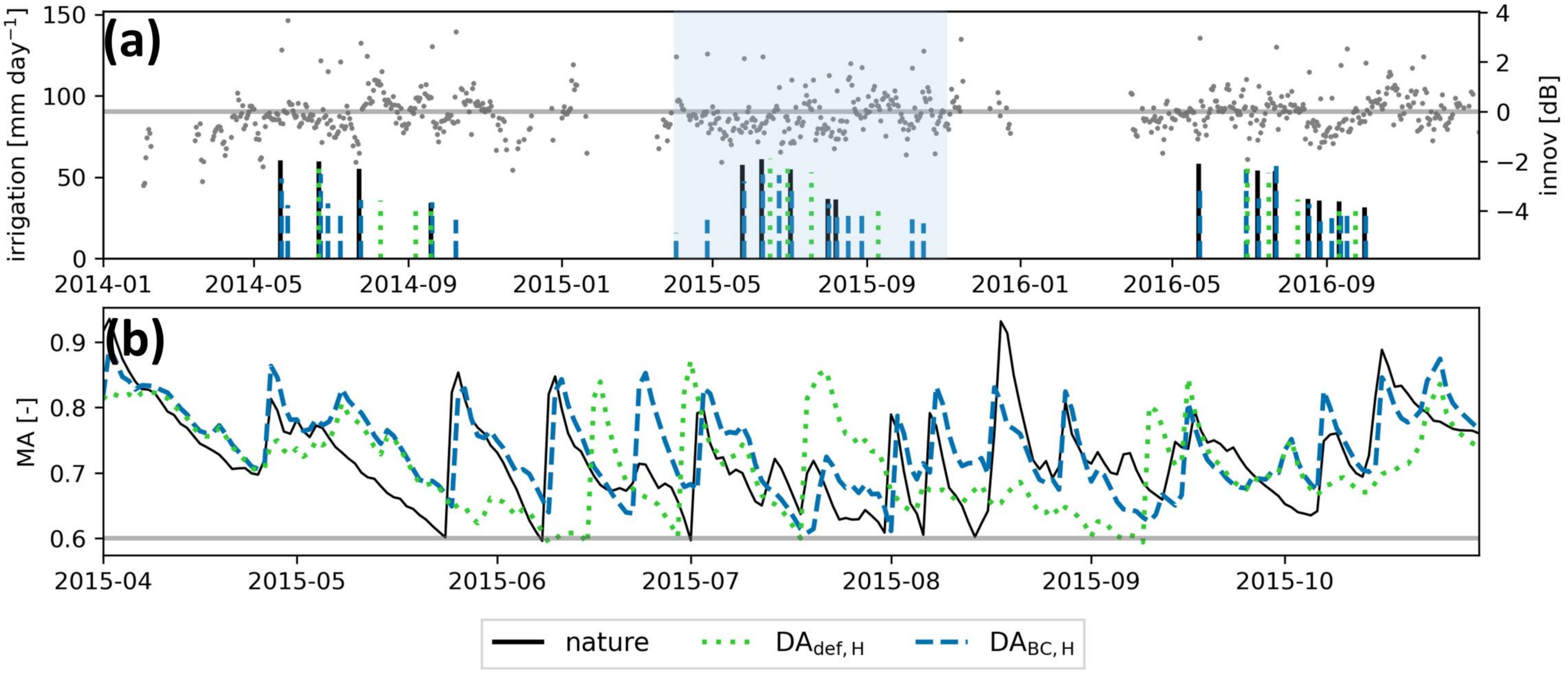
Detailed method

$$\Delta innov_i \geq 2 * SD_{innov,n} * m \text{ if MA<1}$$

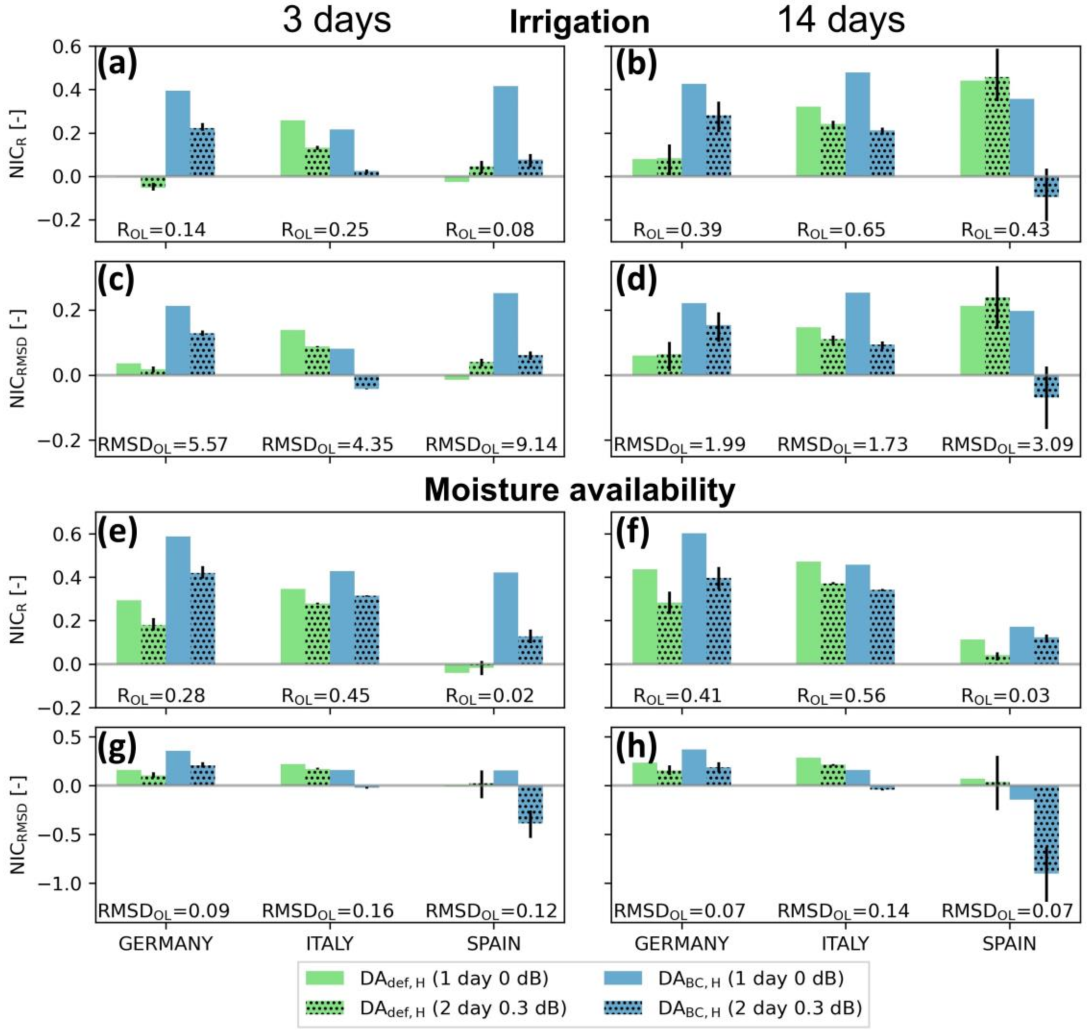
$$m = \frac{1-MA_{irr}}{1-MA} \text{ if MA<1}$$



Example in Germany (rainfall error)



For different locations



$$\mathrm{POD} = \frac{TP}{TP+FN}$$

$$\mathrm{FAR} = \frac{FP}{TP+FP}$$

For different locations

Table 2. POD and FAR for daily irrigation estimates ± 1 day for high model error (OL_H, $\mathrm{DA}_{def,H}$, $\mathrm{DA}_{BC,H}$) and mild model error (OL_M, $\mathrm{DA}_{def,M}$, $\mathrm{DA}_{BC,M}$) experiments. The DA experiments assimilated daily observations without noise. The total numbers of true irrigation events are presented between parentheses for each site.

	OL_H	$\mathrm{DA}_{def,H}$	$\mathrm{DA}_{BC,H}$	OL_M	$\mathrm{DA}_{def,M}$	$\mathrm{DA}_{BC,M}$
POD						
Germany (56)	0.23	0.20	0.91	0.21	0.29	0.98
Italy (180)	0.46	0.66	0.80	0.49	0.52	0.91
Spain (127)	0.29	0.21	0.94	0.26	0.34	1.00
FAR						
Germany (56)	0.73	0.74	0.42	0.64	0.50	0.40
Italy (180)	0.57	0.38	0.16	0.28	0.27	0.05
Spain (127)	0.72	0.79	0.15	0.69	0.59	0.13