Estimating soil moisture and vegetation at multiple scales using satellite data assimilation over Europe

Gabriëlle De Lannoy, Michel Bechtold, Zdenko Heyvaert, Samuel Scherrer, Hans Lievens, Louise Busschaert, Shannon de Roos

KU Leuven, Dept of Earth and Environmental Sciences, Belgium

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Outline

- Land surface
- Coarse-scale satellite data assimilation
  - Soil moisture (~25 km)
  - Vegetation (~25 km)
  - Operational SMAP Level 4 product (9 km)
- Sentinel-1 data assimilation (1 km)
  - Hydrological modeling
  - Crop modeling

Finer scale

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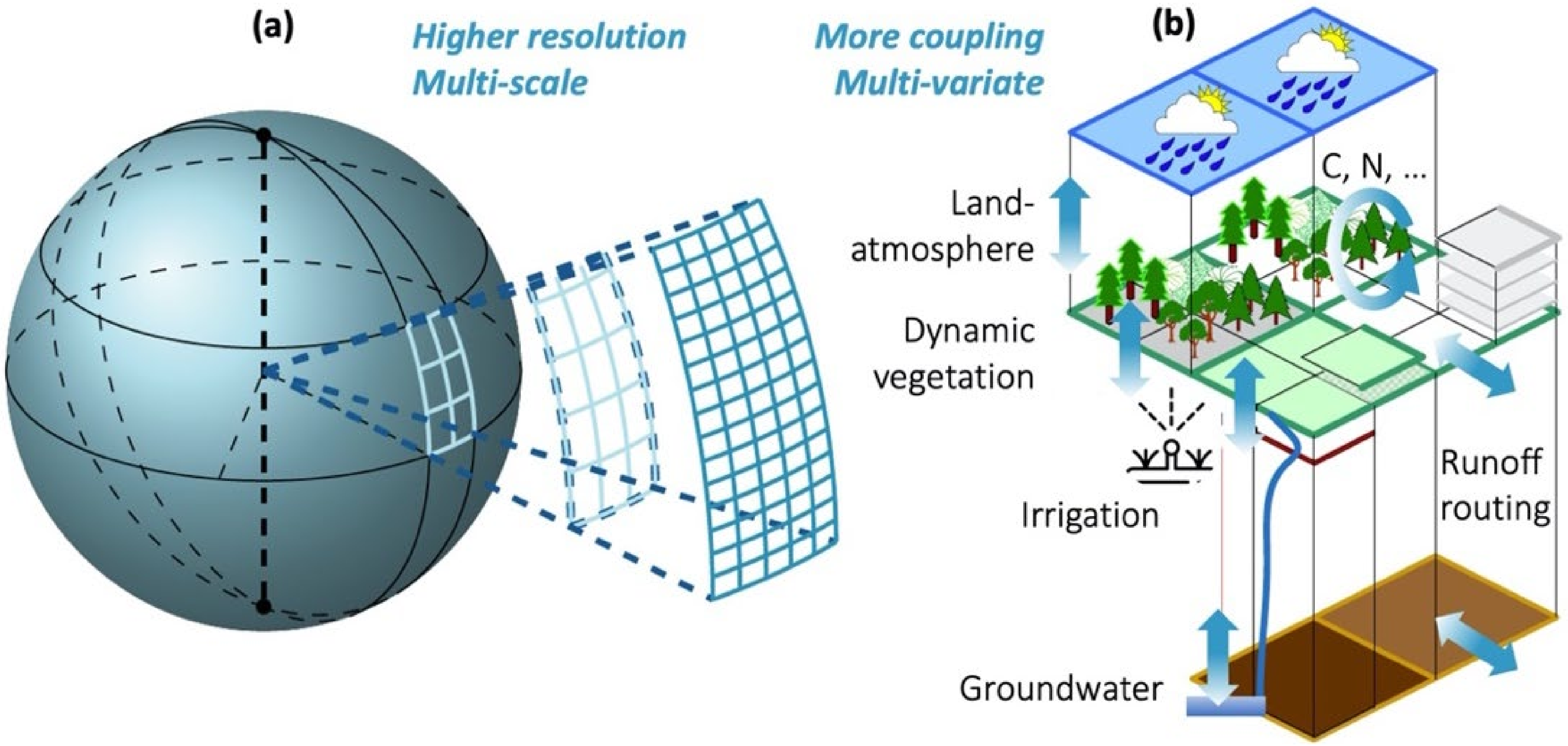
Land surface model sophistication



De Lannoy et al., 2022, Frontiers in Water

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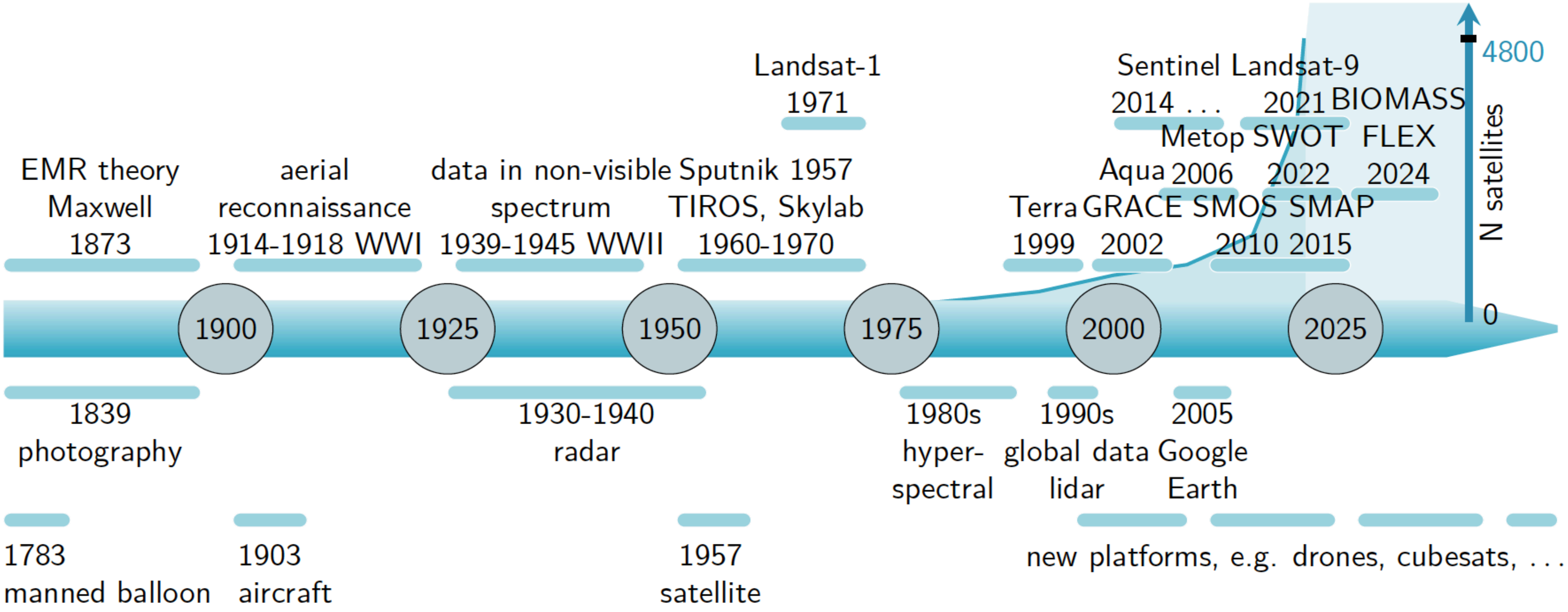
Land surface data availability



Higher resolutions
More variables

De Lannoy et al., 2022, Frontiers in Water

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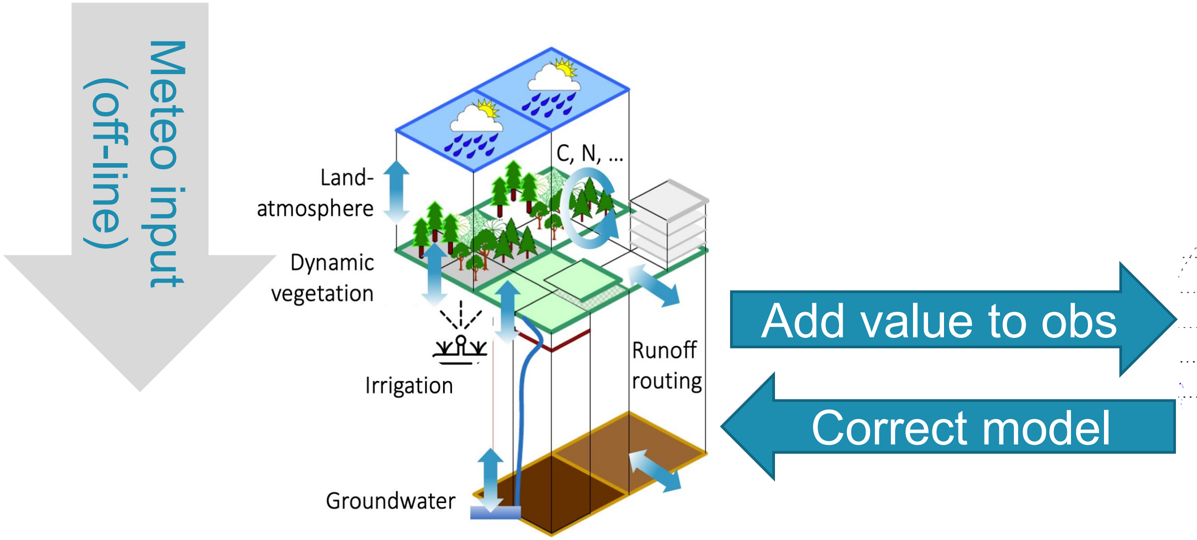
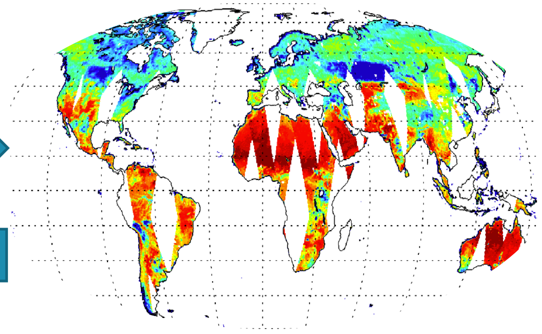
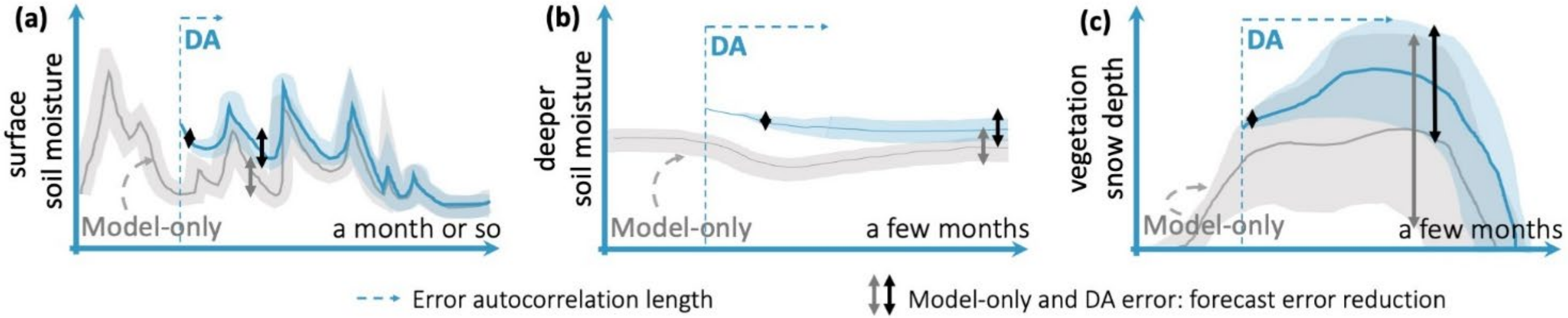
Land surface data assimilation



- Soil moisture or LAI retrievals
- Radiometer brightness temperature, radar backscatter



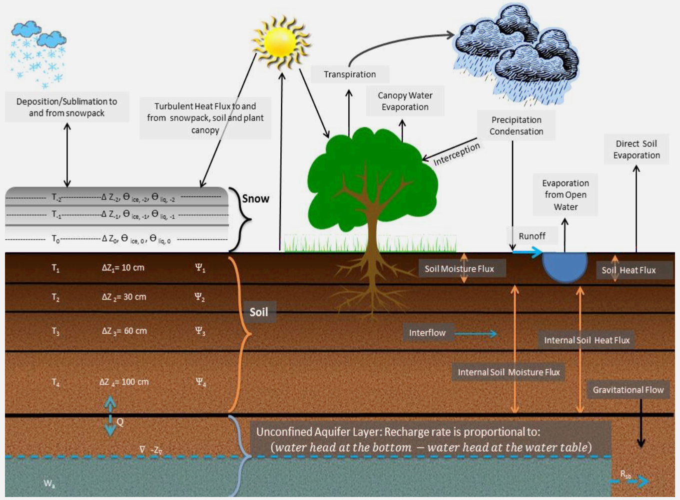


Coarse-scale soil moisture data assimilation (~25 km)

Soil moisture data assimilation system

Land surface model

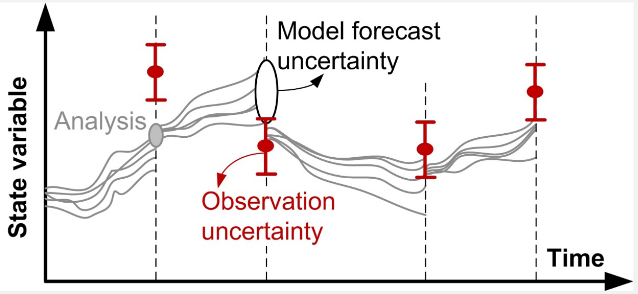
- Noah-MP (0.25°)
- 4 soil layers
- **dynamic vegetation**



Niu et al. (2011)

Data assimilation

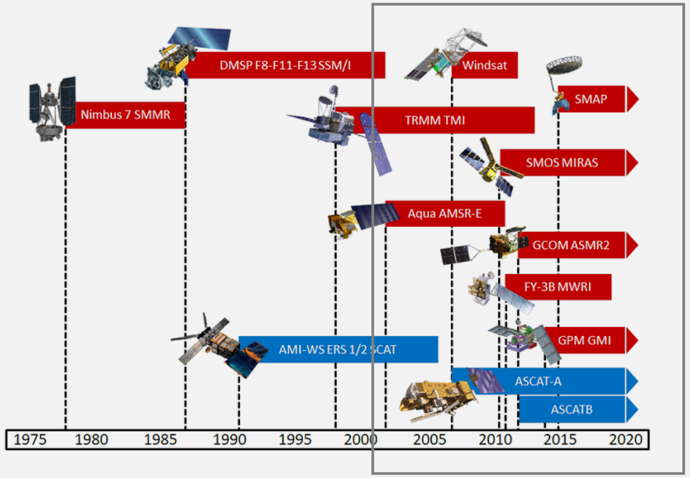
- 1D EnKF w/ CDF matching
- NASA-LIS



Reichle et al., (2002)
Kumar et al. (2008)

Satellite observations

- surface soil moisture retrievals (0.25°)
- combined ESA CCI SM



Dorigo et al. (2017)

Heyvaert et al. 2022, JHM, in review

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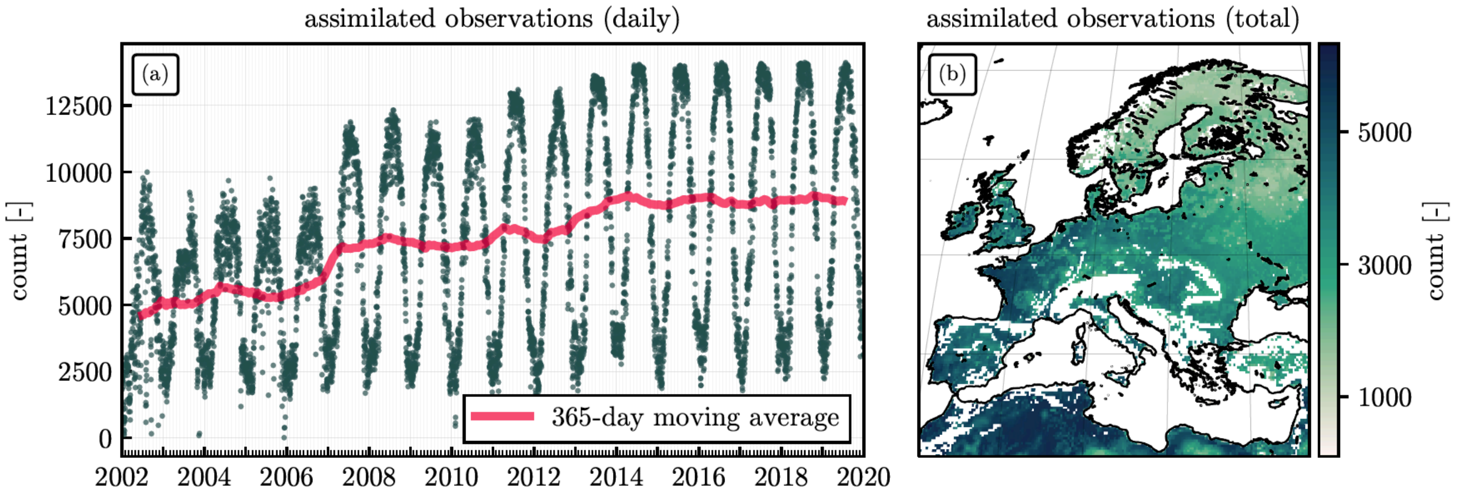
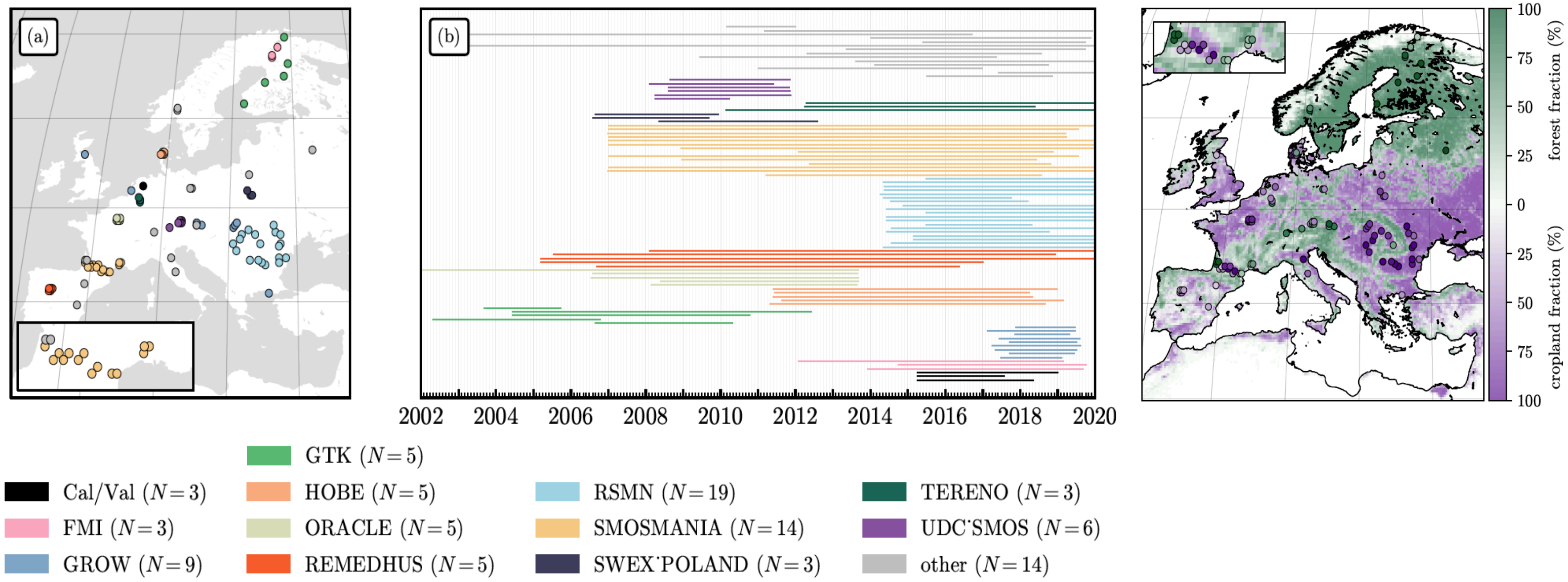
Validation

- **Independent point measurements**
- Regional DA diagnostics



Assimilation



Validation

Heyvaert et al. 2022, JHM, in review

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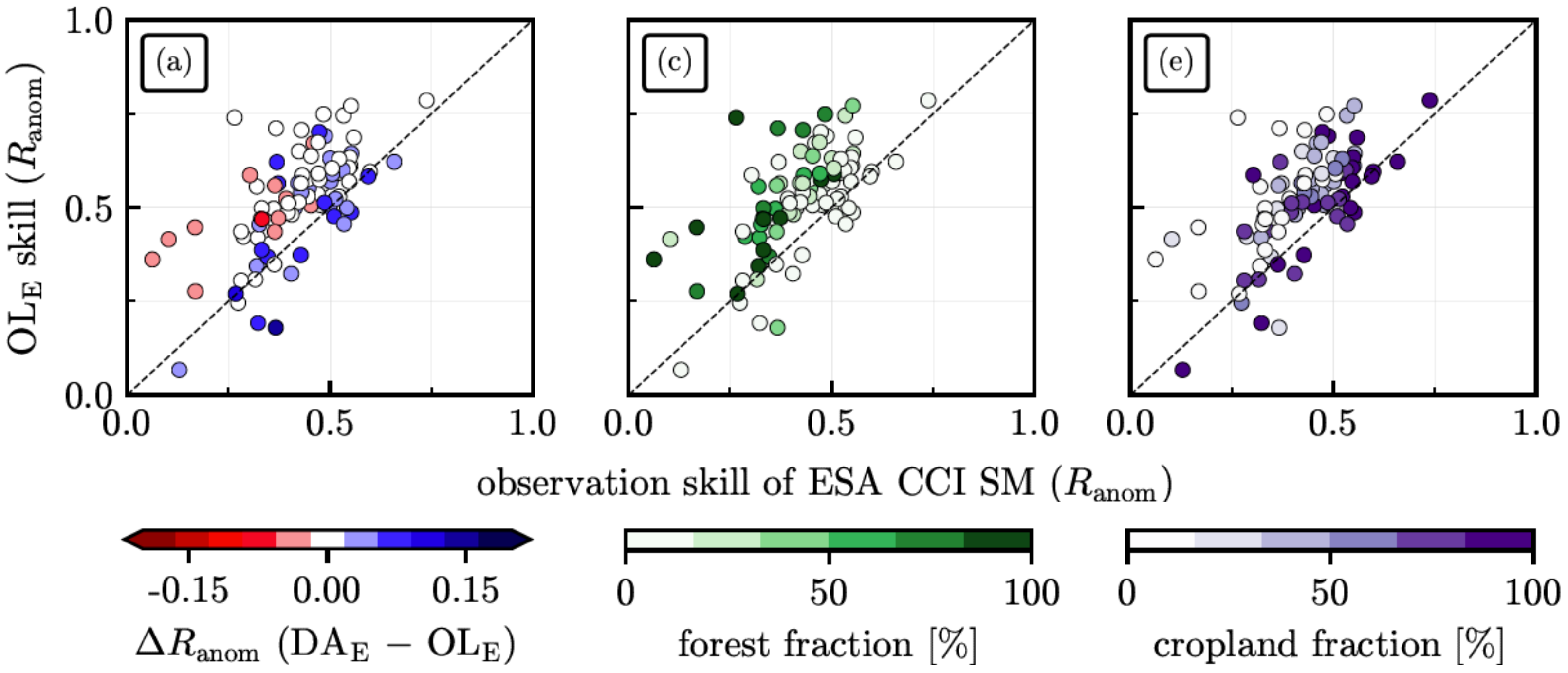
In situ validation

Impact of observation quality



- Forest: ESA CCI SM obs < model skill
- Crops: ESA CCI SM obs ~ model skill
- DA improvements when obs ~ model skill

Heyvaert et al. 2022, JHM, in review

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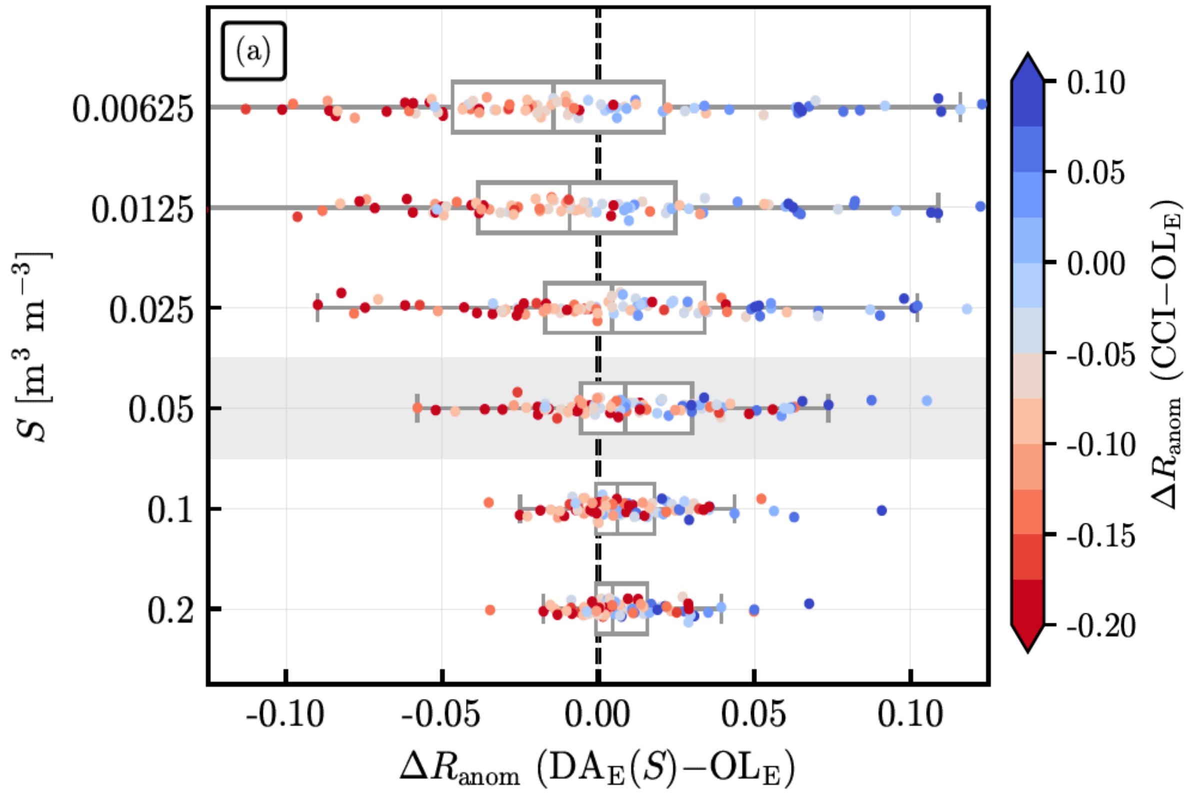
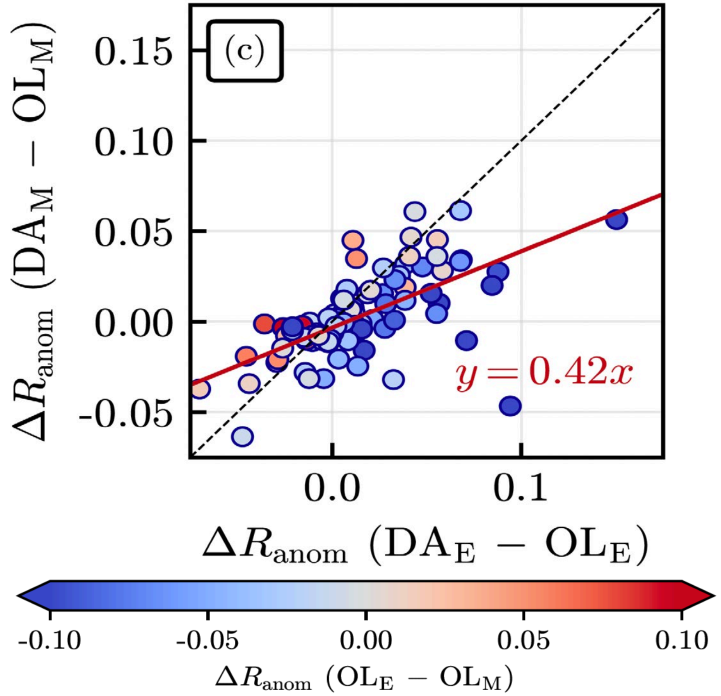
In situ validation

Impact of obs error choice



Obs error → trade-off in skill improvement

Impact of forcing choice



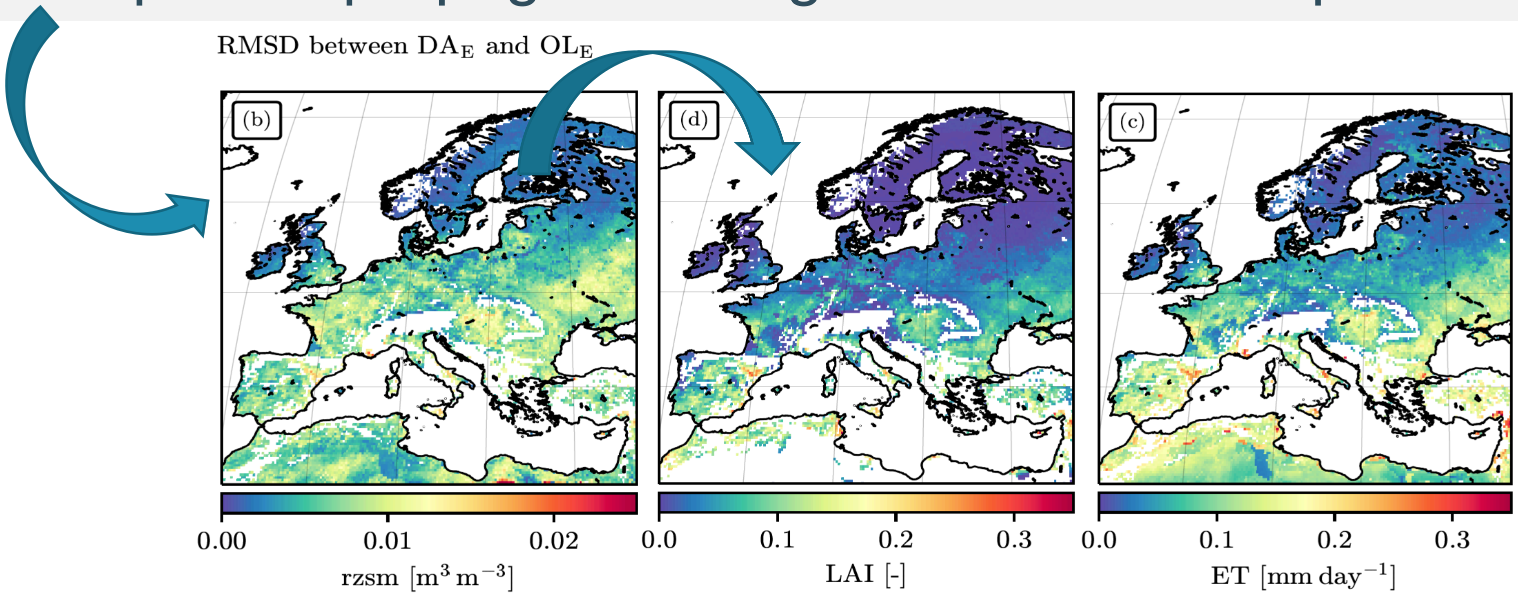
- Model (OL) skill w/ MERRA2 > ERA5
- DA improvement w/ ERA5 > MERRA2

Heyvaert et al. 2022, JHM, in review

State of the art, but…

Soil moisture (surface & root-zone) skill depends on
- quality of assimilated observations
- DA design factors (obs error, rescaling, model setup/forcings, …)

Soil moisture updates propagate to vegetation and flux updates:



Heyvaert et al. 2022, JHM, in review

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Coarse-scale vegetation data assimilation (~25 km)

Vegetation data assimilation

Observations

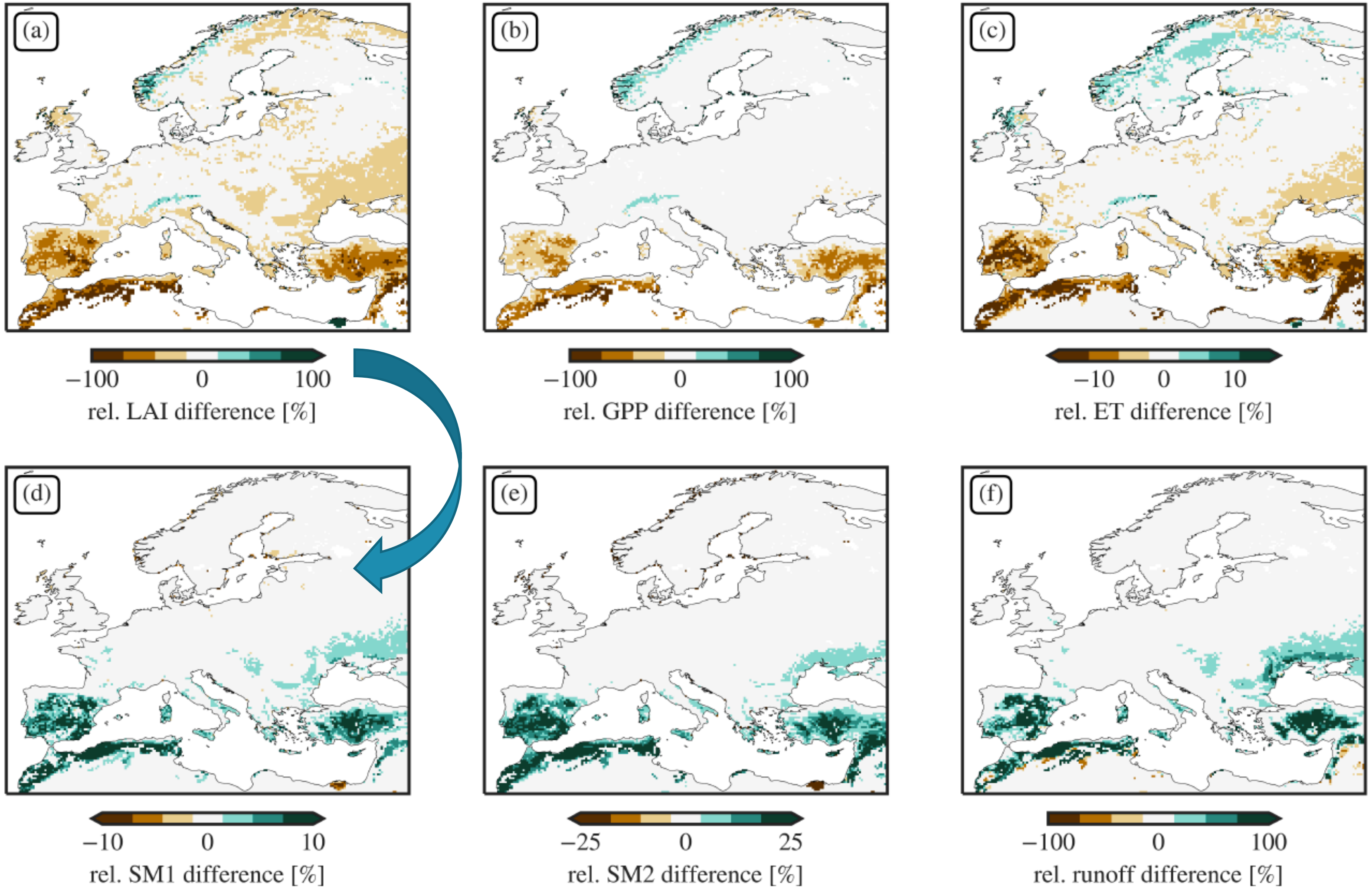
- CGLS LAI (0.25°) aggregated
- 10-daily DA, 2002-2019

Smets et al. (2019)

Data assimilation

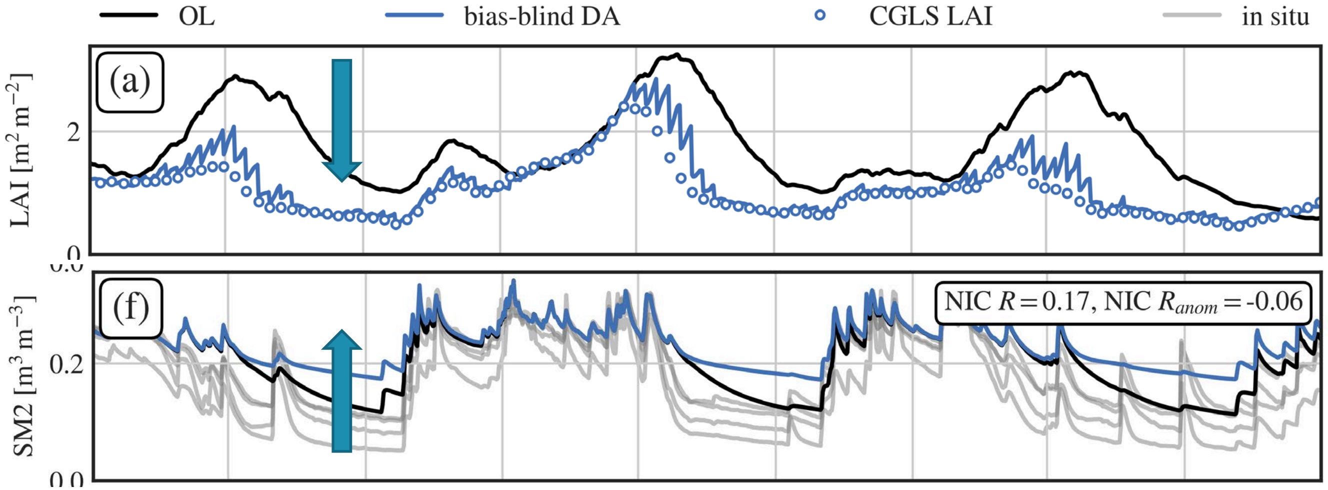
- Bias-blind 1D EnKF
- Bias-aware 1D EnKF

(bias-blind DA – OL) / OL

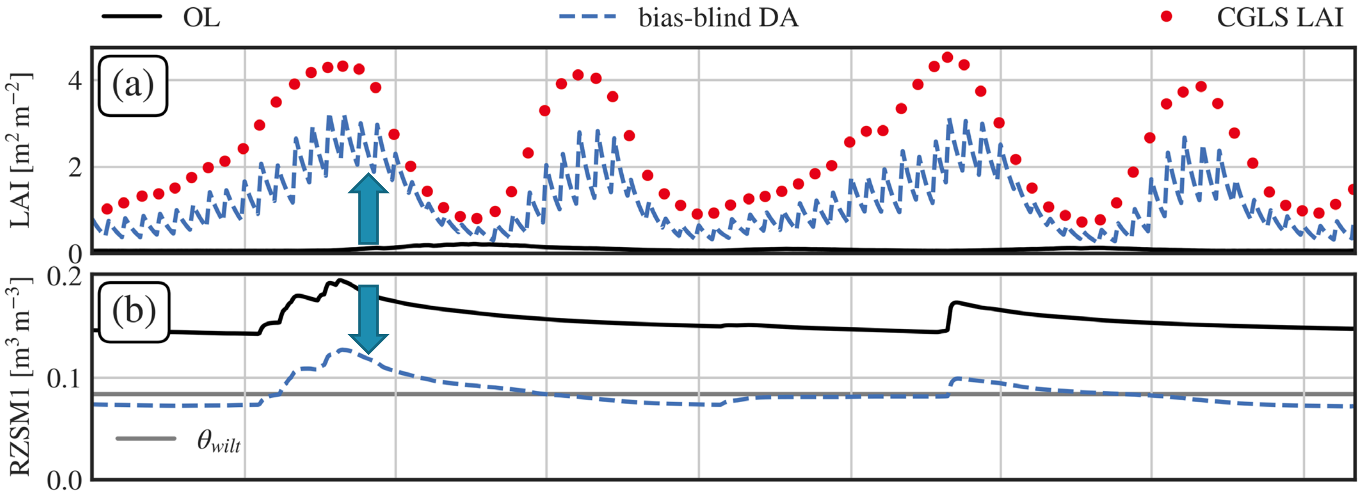


Scherrer et al. 2022, in prep

Evaluation



- **Spain**: obs LAI < model LAI
- DA: sawtooth pattern <-> model equilibrium



- **Nile**: obs LAI > model LAI due to unmodeled irrigation
- DA: deteriorates

Scherrer et al. 2022, *in prep*

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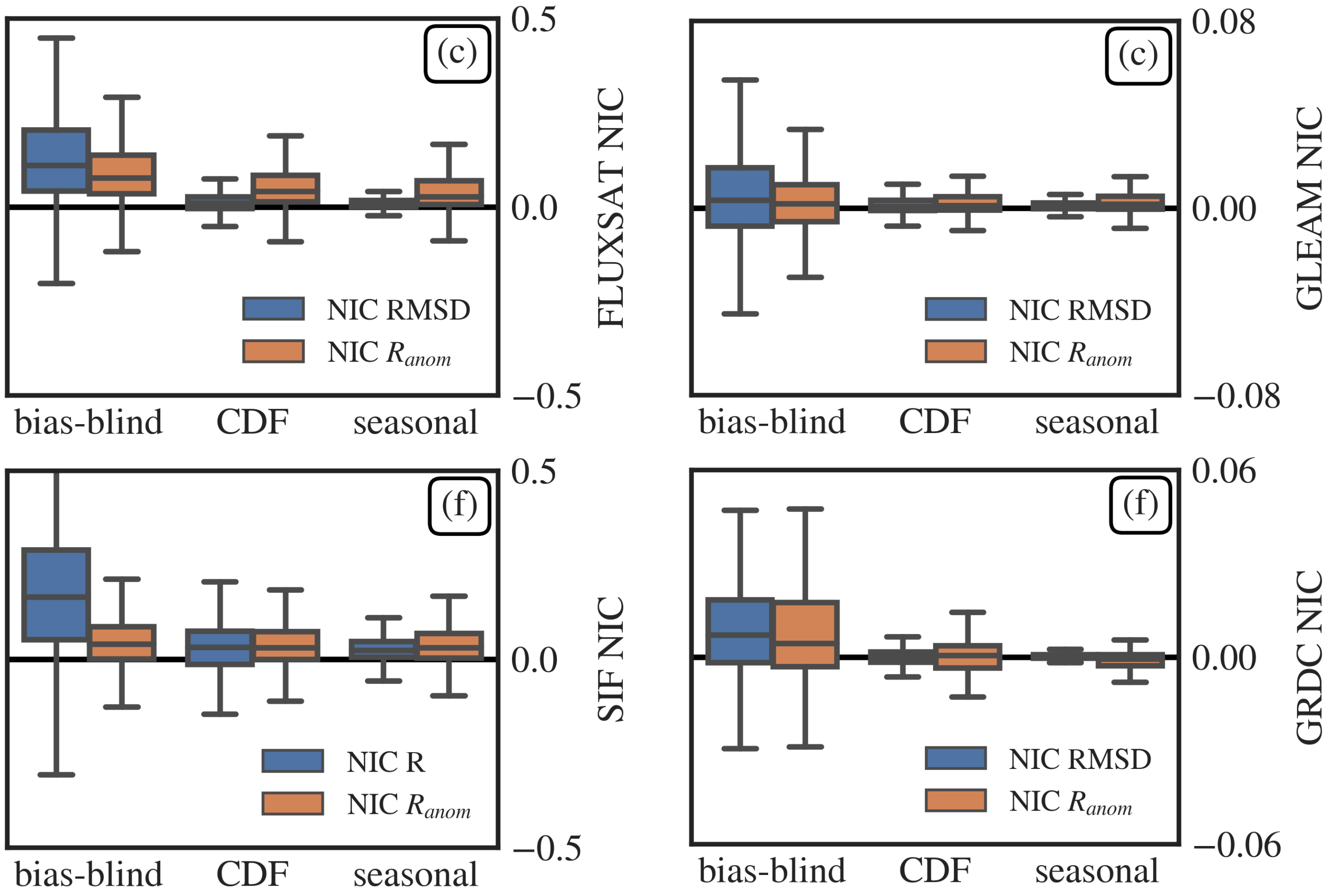
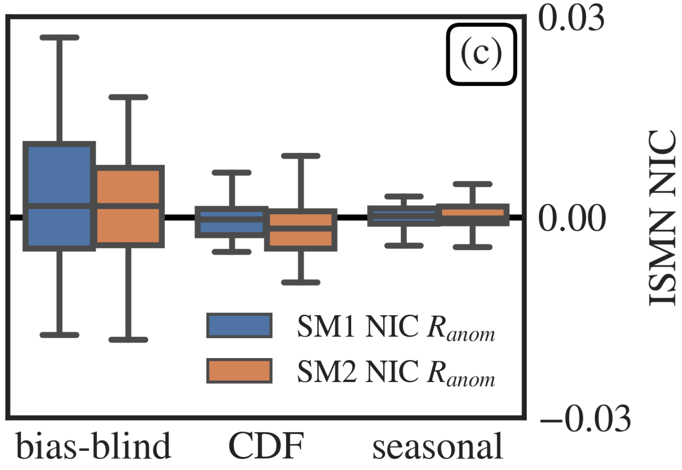
Evaluation

$$NIC\ RMSD = \frac{RMSD_{OL} - RMSD_{DA}}{RMSD_{OL}}$$

$$NIC\ R = \frac{R_{DA} - R_{OL}}{1 - R_{OL}}$$





- **Bias-aware DA:** reduced impact, but better DA diagnostics
- Parameter updating needed?

Scherrer et al. 2022, in prep

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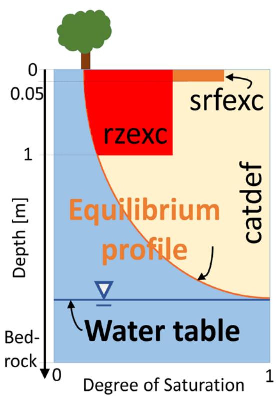
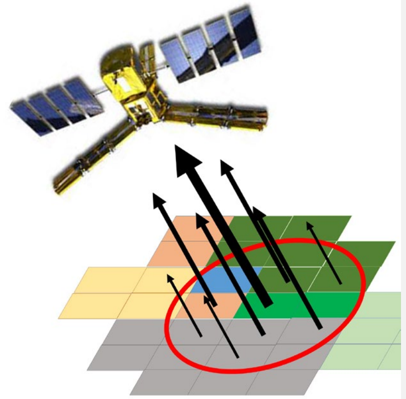
Operational SMAP L4_SM product (9 km)

SMAP L4_SM

Land model

- Catchment LSM (**9 km**)
- soil compartments
- climatological vegetation
- L-band RTM

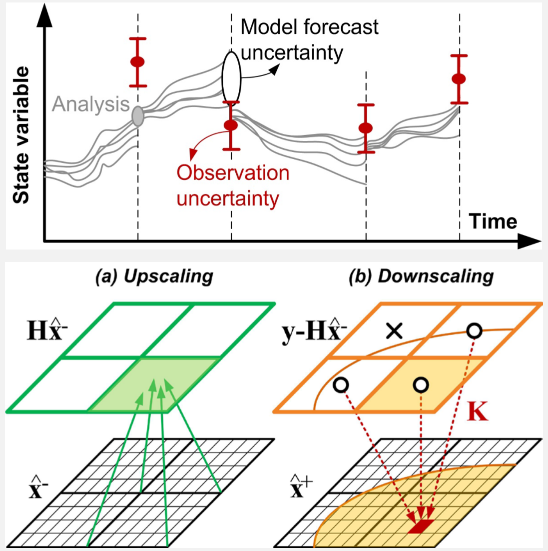




Koster et al. (2010); De Lannoy et al. (2013)

Data assimilation

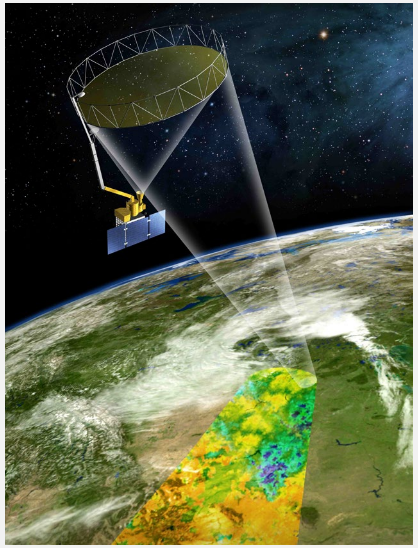
- **3D EnKF**
- GEOSldas



De Lannoy and Reichle (2016a, b)

Satellite observations

- SMAP brightness temperature (**36 km**)



Reichle et al., 2019, JAMES

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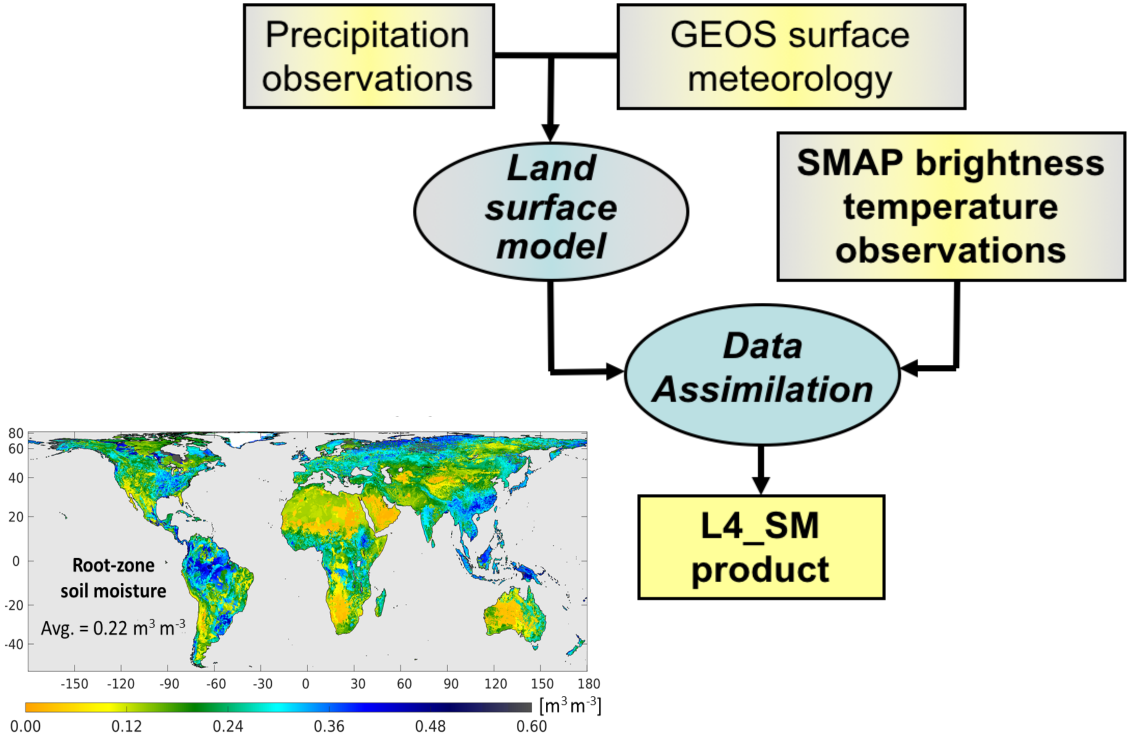
SMAP L4_SM version 6

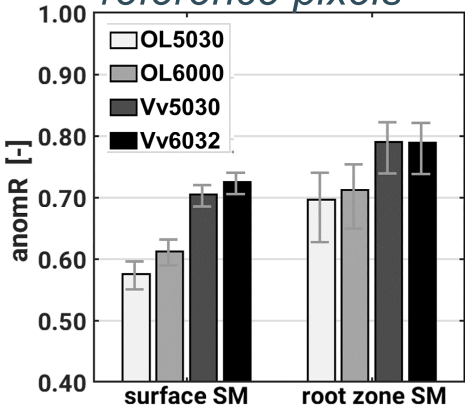
- Add value to SMAP Tb data
- Global 3-hourly **9 km** EASEv2 grid
- https://nsidc.org/data/SPL4SMGP/versions/6



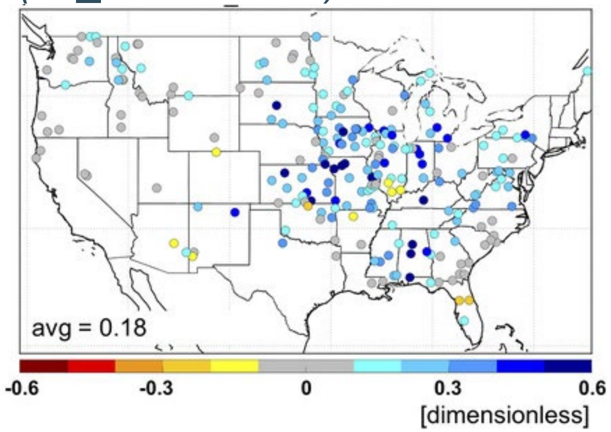
In situ validation:

- soil moisture in mineral soils, limited reference sites
- runoff

9-km reference pixels



Streamflow ΔR (L4_SM – CTRL)



Reichle et al. 2021, NASA/TM-2021-104606/Vol.58
Reichle et al., 2019, JAMES, Reichle et al., 2021, JHM

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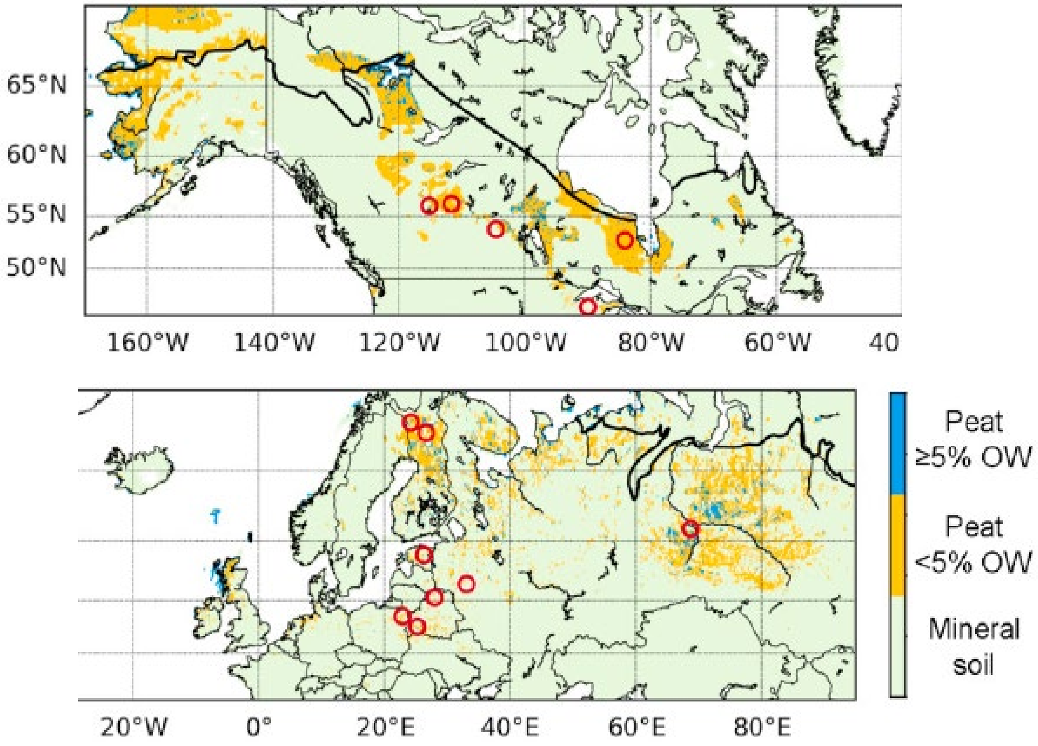
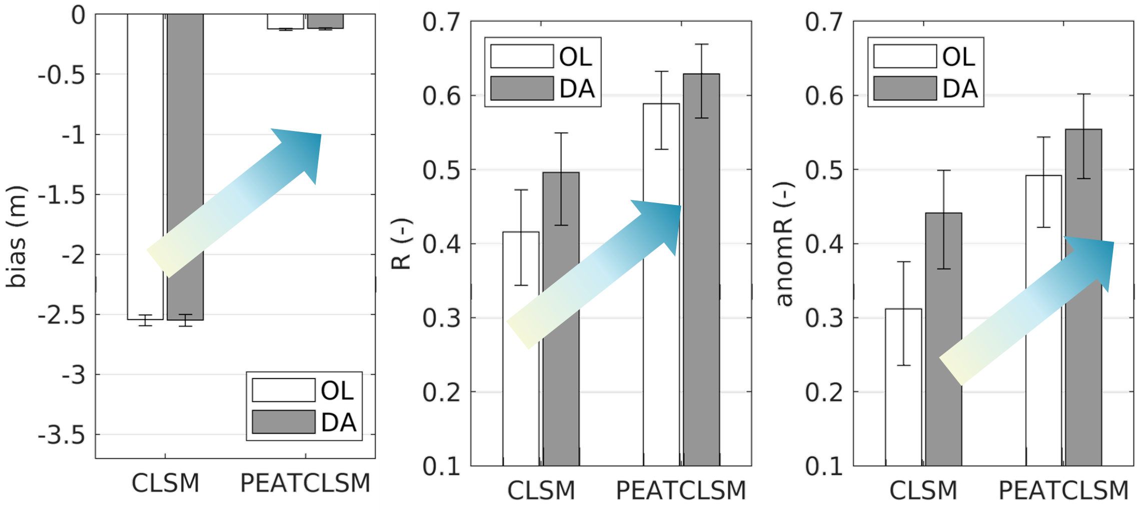
SMAP L4_SM version 7

- Various updates – release soon
- Including peatland physics



In situ validation:

- water table depths in <u>peatlands</u>
- drastic model-only improvement
- added value Tb DA



(example SMOS Tb DA)

Bechtold et al., 2020, RSE

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Hydrological modeling and Sentinel-1 γ^0 data assimilation (1 km)

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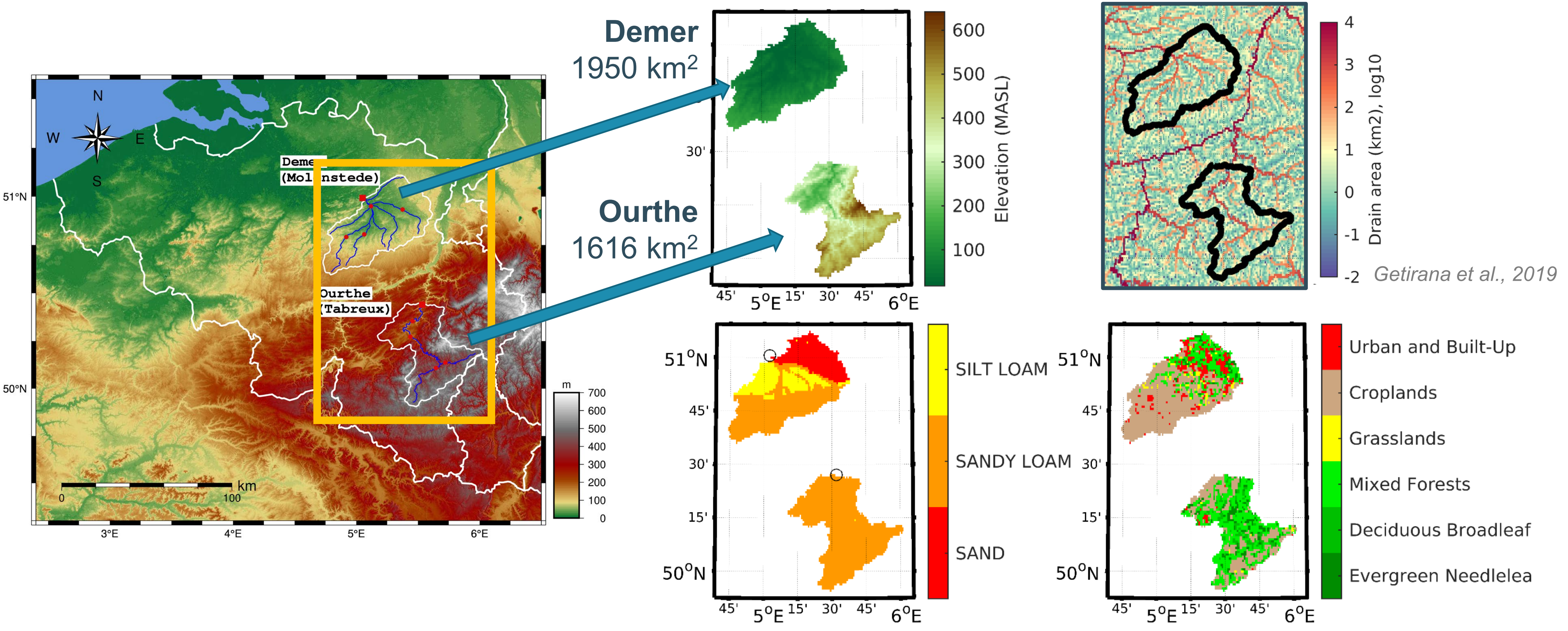
Study area



Bechtold et al. 2022, in prep.

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Sentinel-1 data assimilation system

Land model

- Noah-MP (1 km)
- 4 soil layers
- **dynamic vegetation**

- **HYMAP2 routing**

Getirana et al., 2019

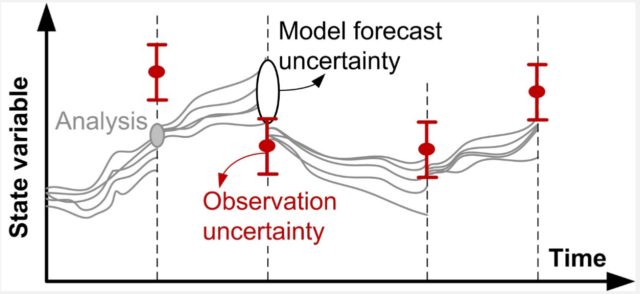
- **Water Cloud Model**

  $\gamma^0 = f(SFSM, LAI)$

Attema and Ulaby (1978)

Data assimilation

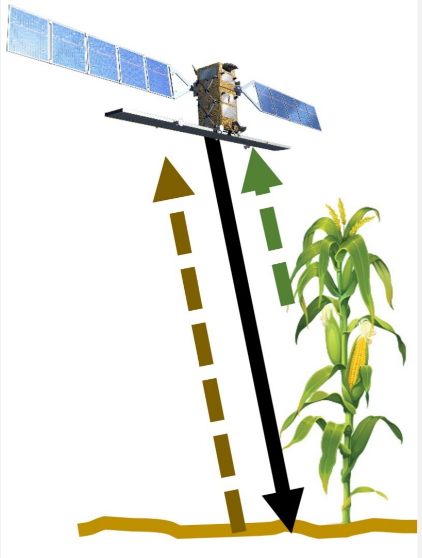
- 1D EnKF
- NASA-LIS



Reichle et al., (2002)
Kumar et al. (2008)

Satellite observations

- C-band γ^0 VV (& VH)
- Sentinel-1a & b
- Oct 2014 - 2021



Bechtold et al. 2022, in prep.

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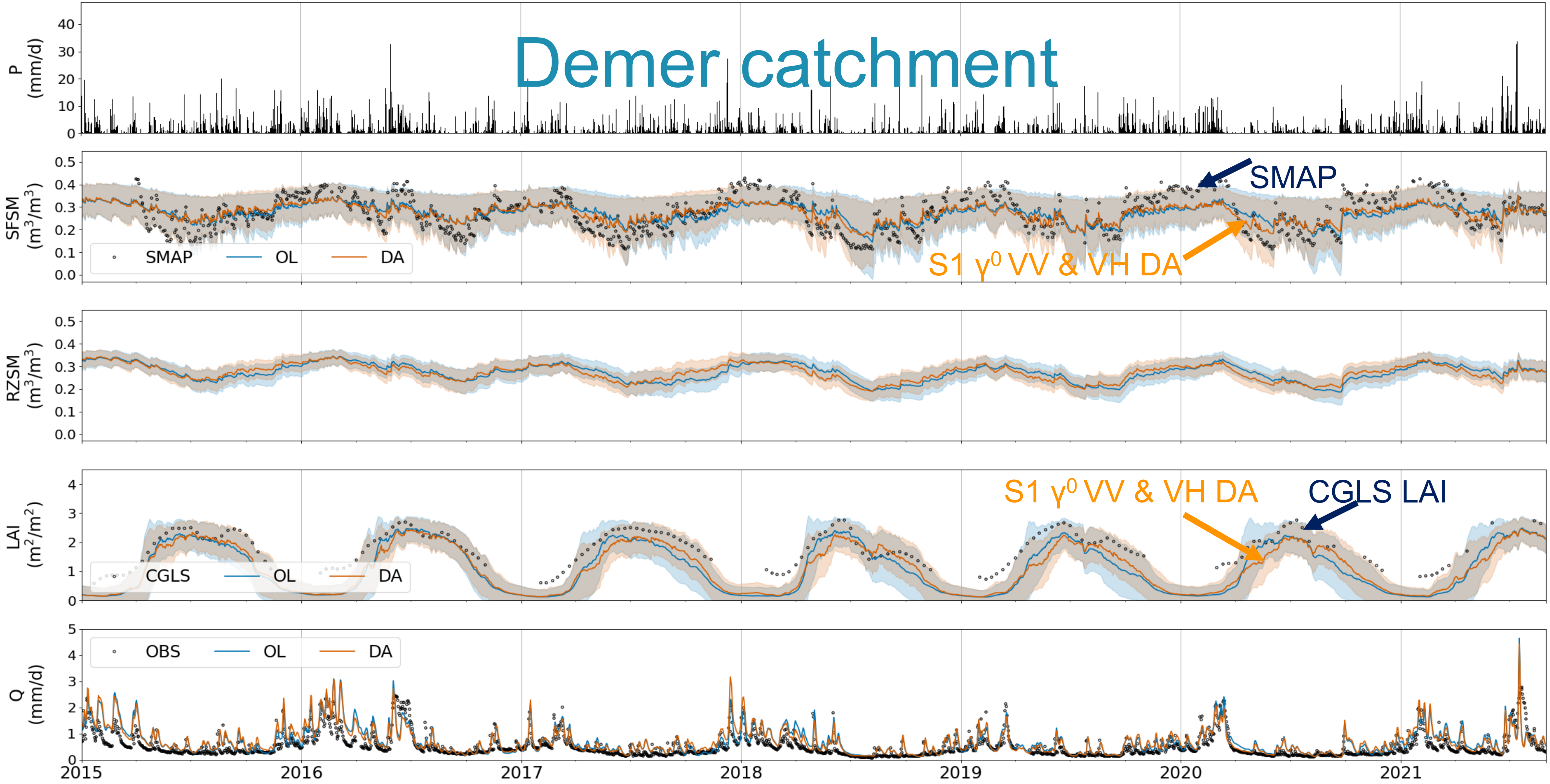

Bechtold et al. 2022, in prep.

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Streamflow evaluation (all days)

KGE

	OL No routing	OL	VV DA SM	VV & VH DA SM & LAI
Demer	0.23	0.60	0.60	0.58
Ourthe	0.55	0.59	0.62	0.62

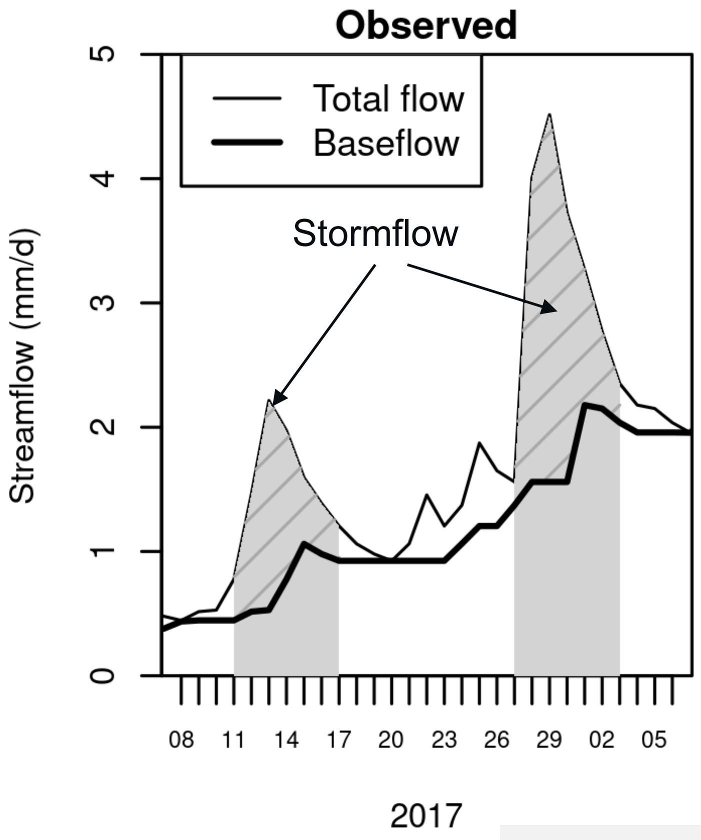
KGEsq (KGE w/ sqrt(Q) to reduce weight of peak flows)

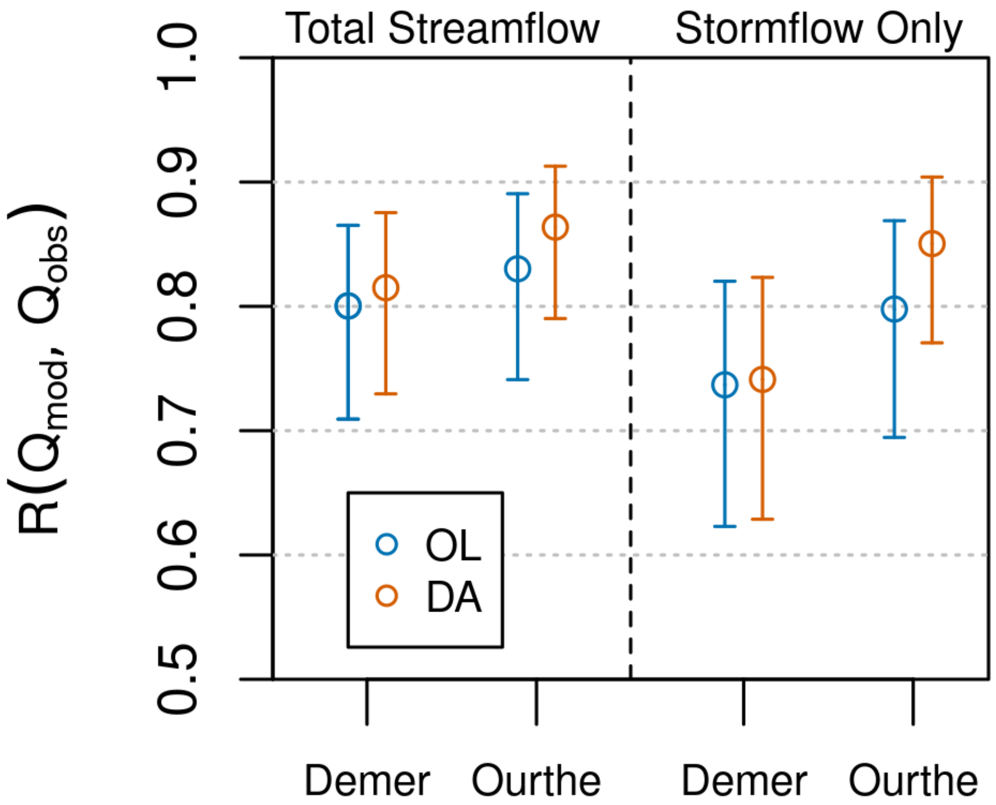
Demer	0.46	0.73	0.73	0.73
Ourthe	0.74	0.80	0.83	0.83

- Benefit of routing
- DA improvements for Ourthe, not for Demer
- LAI updating degrades KGE for Demer

Bechtold et al. 2022, in prep.

Streamflow evaluation (6-day events)





- Overall improvement for Ourthe
- No harm for Demer

Bechtold et al. 2022, in prep.

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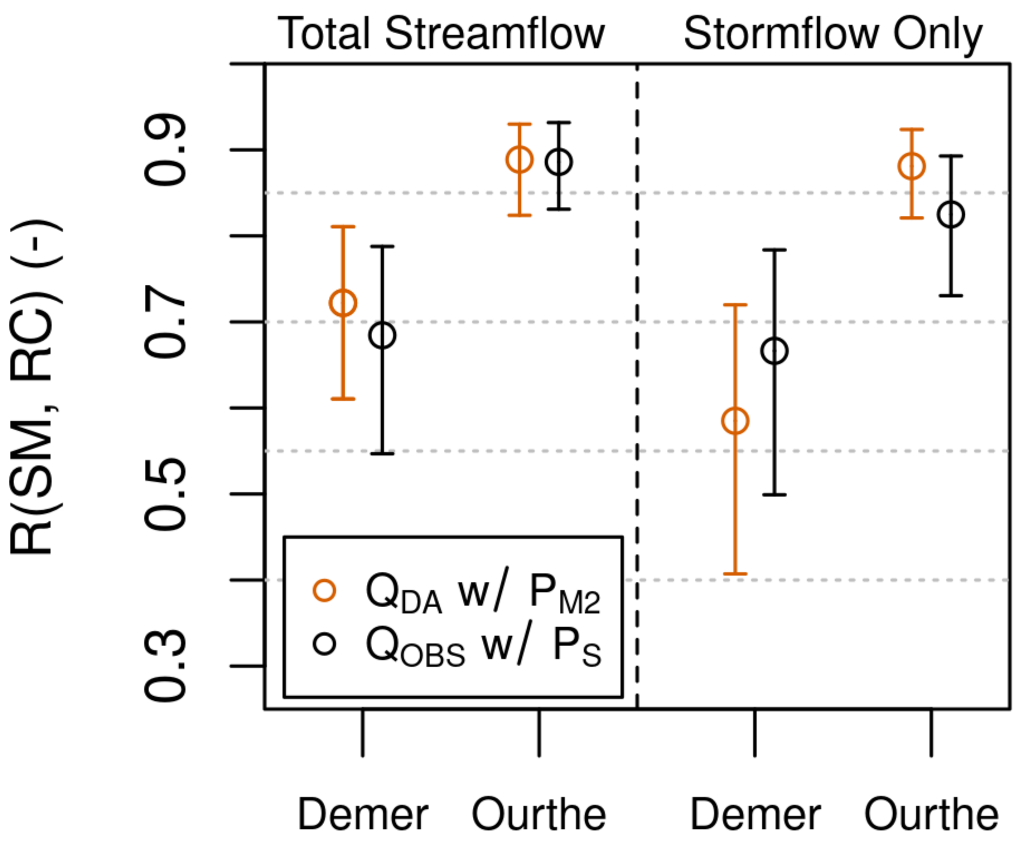
Difference between Ourthe and Demer?



- **Ourthe**: stronger SM-runoff coupling (both observed and modeled)
  → stronger impact from SM DA
- **Demer**: weaker SM-runoff coupling, due to agricultural management, built up area, …

- Demer: crop rotation may limit effectiveness of S1 γ^0 DA

Bechtold et al. 2022, in prep.

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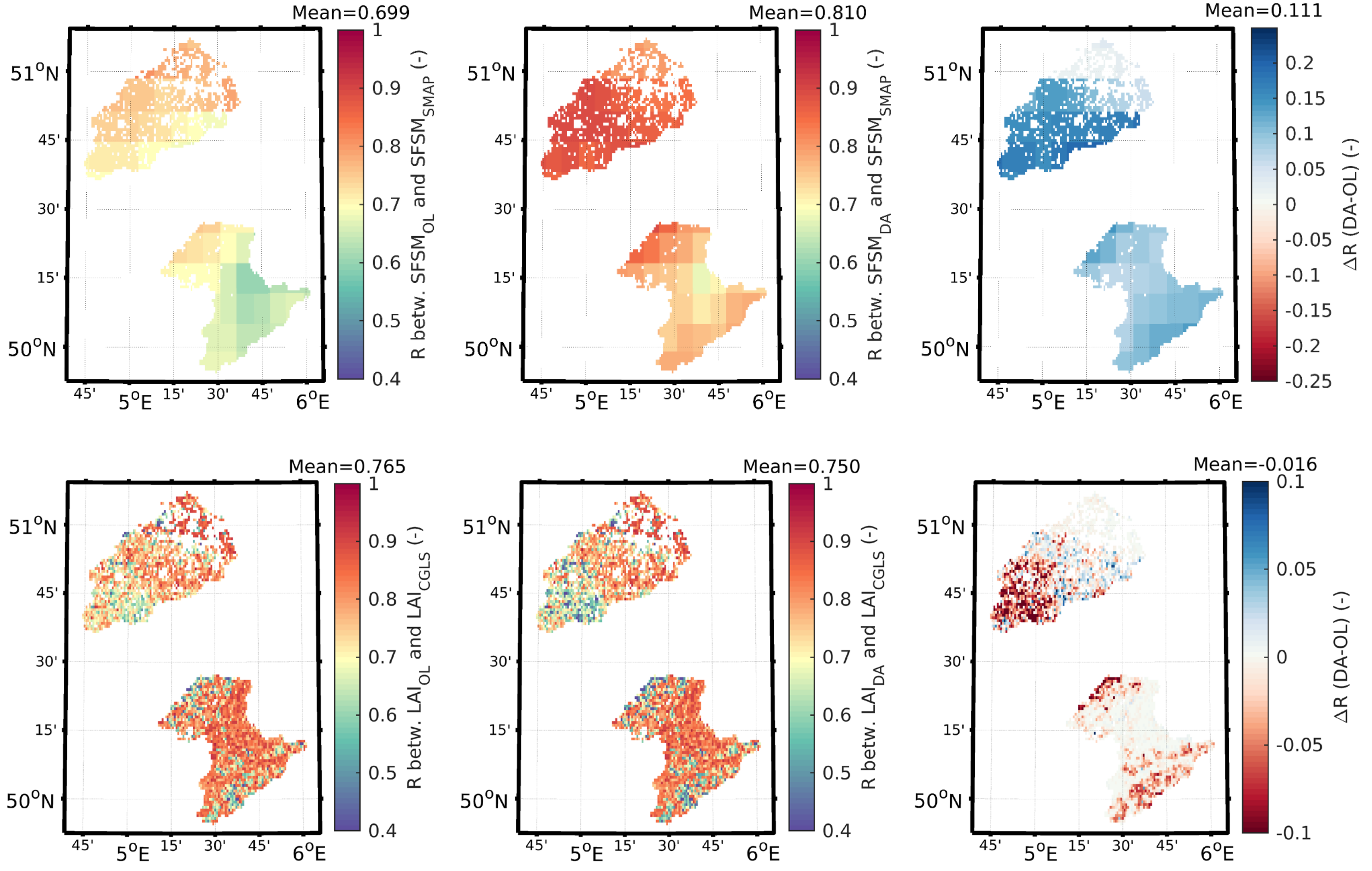
Soil moisture & vegetation evaluation



- SFSM improves relative to SMAP SFSM
- LAI slightly degrades relative to CGLS LAI

Similar for
γ^0 VV DA (SM only updating)
and
γ^0 VV & VH DA (SM and LAI updating)

Bechtold et al. 2022, in prep.

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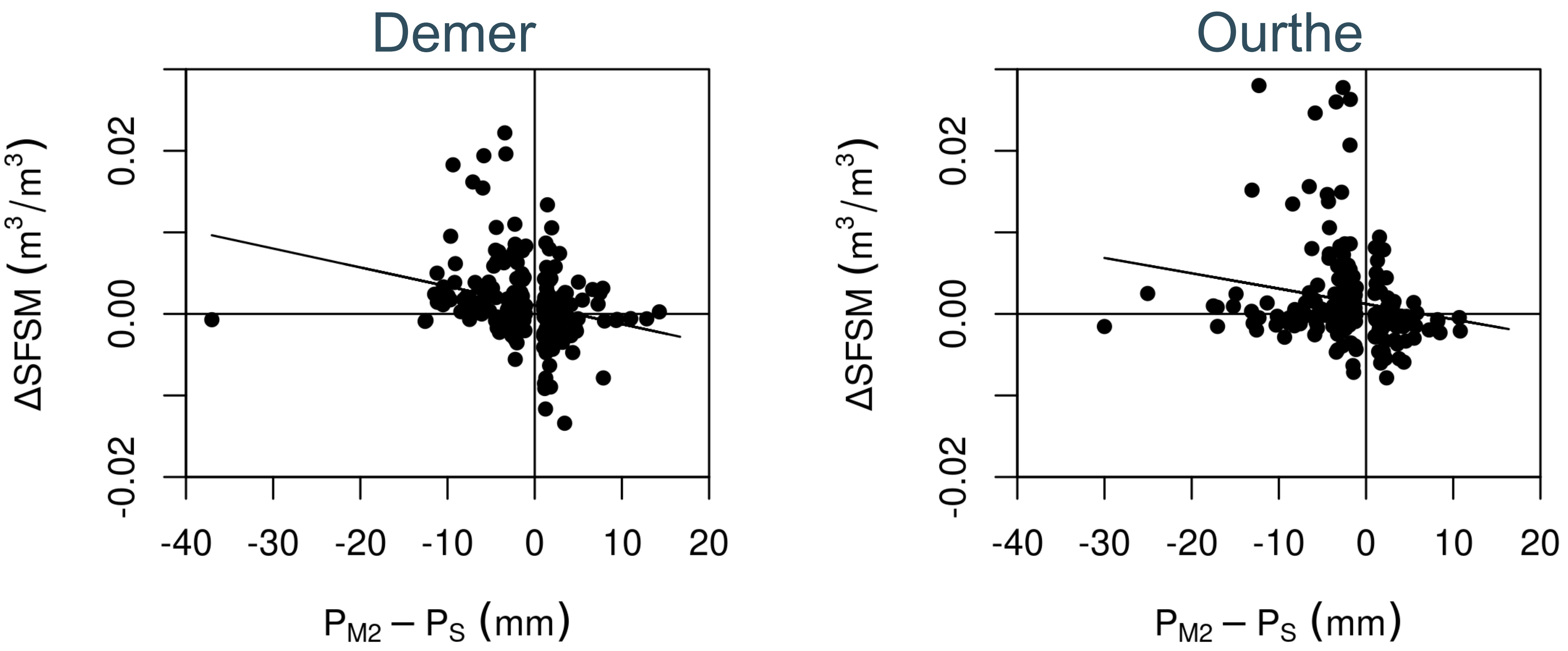
Soil moisture evaluation



SFSM increments correct for significant precipitation errors on the previous day

Bechtold et al. 2022, in prep.

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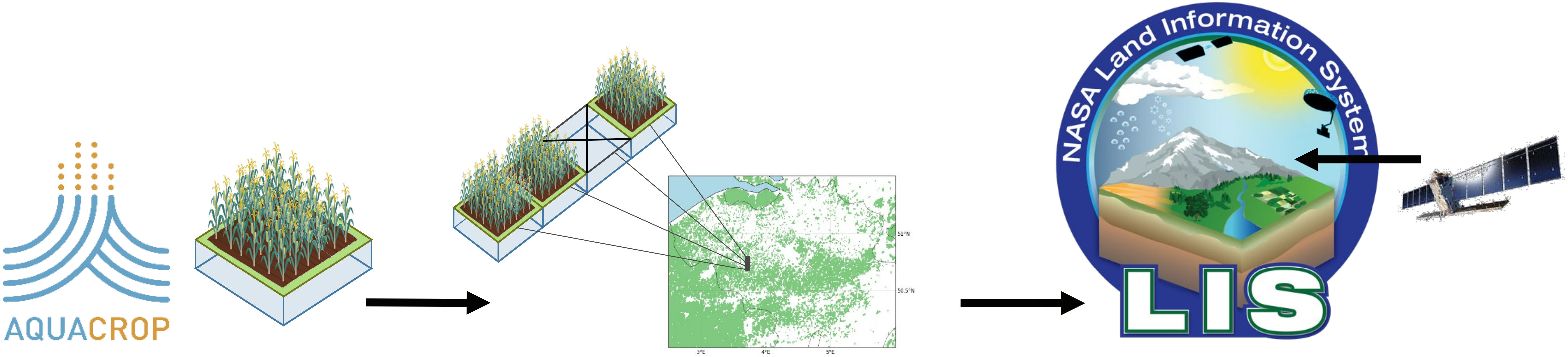
Crop modeling and Sentinel-1 γ^0 data assimilation (1 km)

Crop modeling and data assimilation



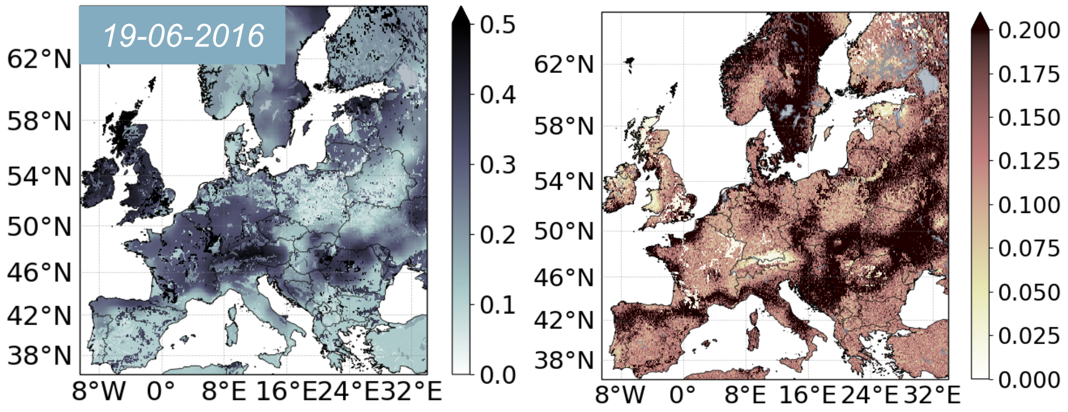
https://github.com/KUL-RSDA/AquaCrop

- AquaCrop v7, robust model
- Many crop varieties
- Management options (irrigation, fertilization, etc.)

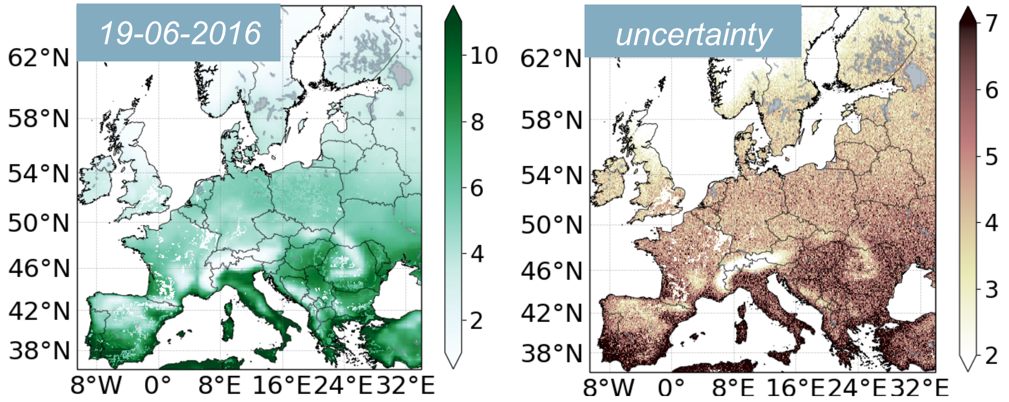
De Roos et al., 2021, Busschaert et al., 2022

Crop modeling and data assimilation

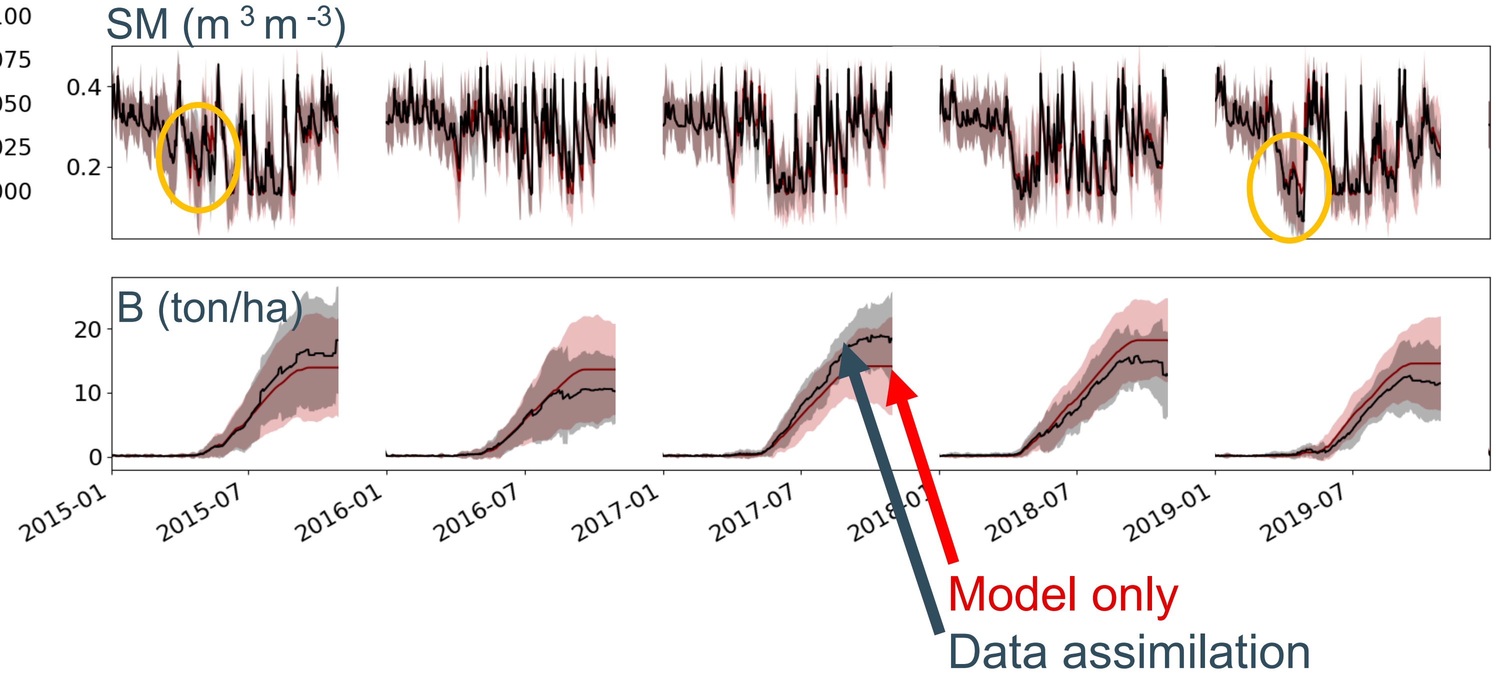
SSM 0-30 cm (m^3 m^{-3})



Biomass (ton ha^{-1})



HOAL, Austria (48.15°, 15.15°)



Bechtold, Busschaert, de Roos, De Lannoy and many others

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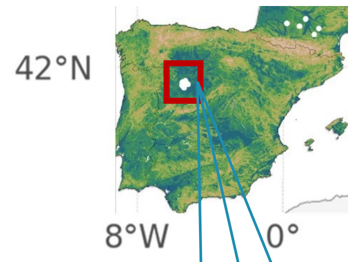
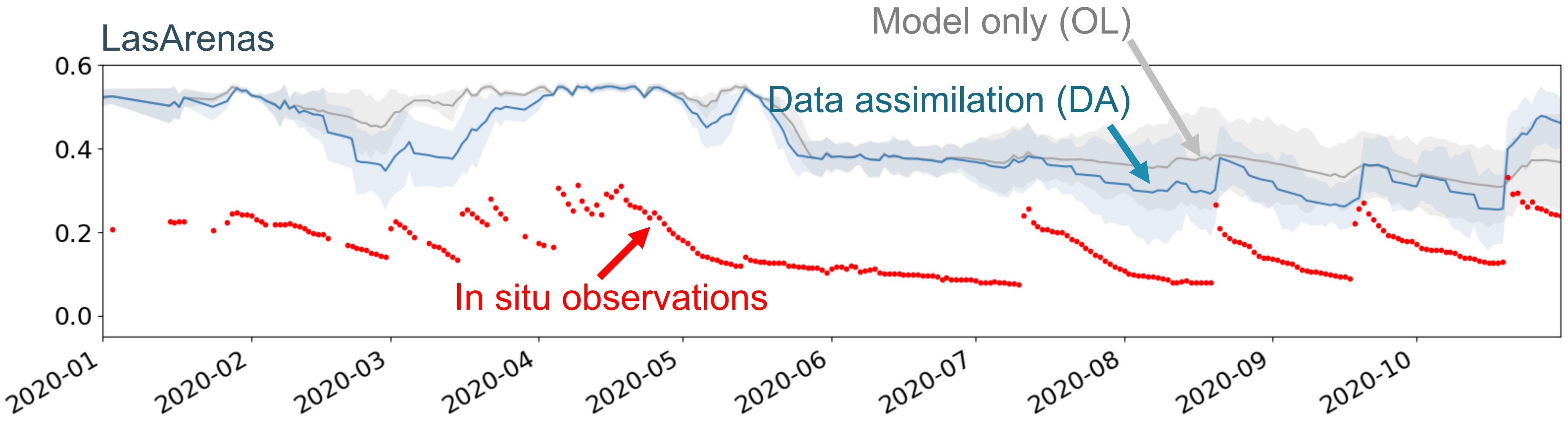
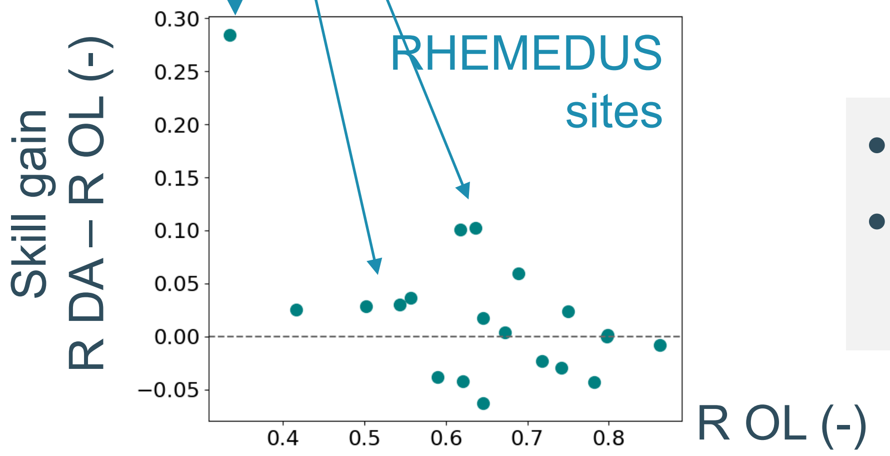
In situ validation

NW-Spain







- Assimilate S1 **γ^0 VV & VH** from 2015 onwards
- Improvement in 1-km **soil moisture** largest at sites where the model-only (OL) performs poorly

Preliminary results – not optimized yet

Conclusion

- Land surface model sophistication
- Coarse-scale satellite data assimilation:

  → state of the art vs. optimal design?
- Benefit of land DA on unobserved variables depends on ‘true’ and simulated **coupling** between SM, vegetation, runoff

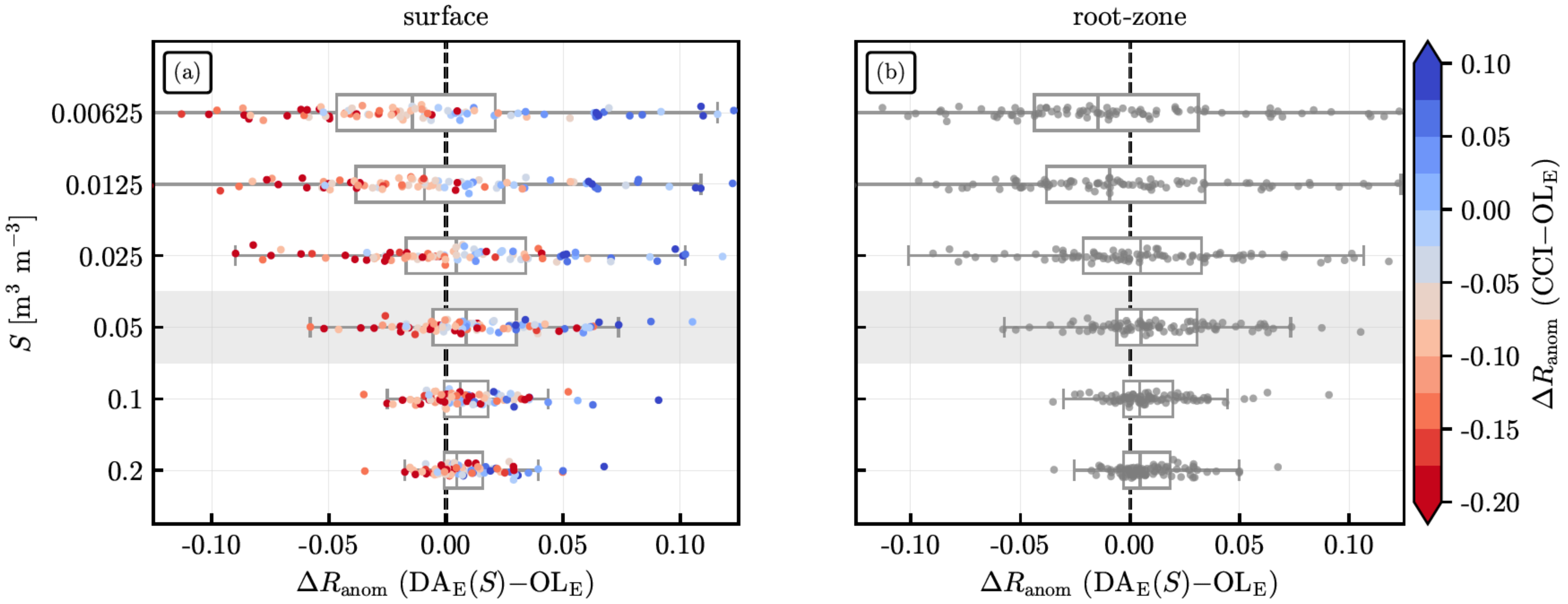
  → improvement in one catchment or variable, but not another
- **Higher spatial resolutions**: resolving more detail and complexity

  → LSM details and S1 γ^0 simulation more difficult under crop rotation, human influences…

  → needed for **regional** water and agricultural management

Backup

In situ validation



Heyvaert et al. 2022, JHM, in review

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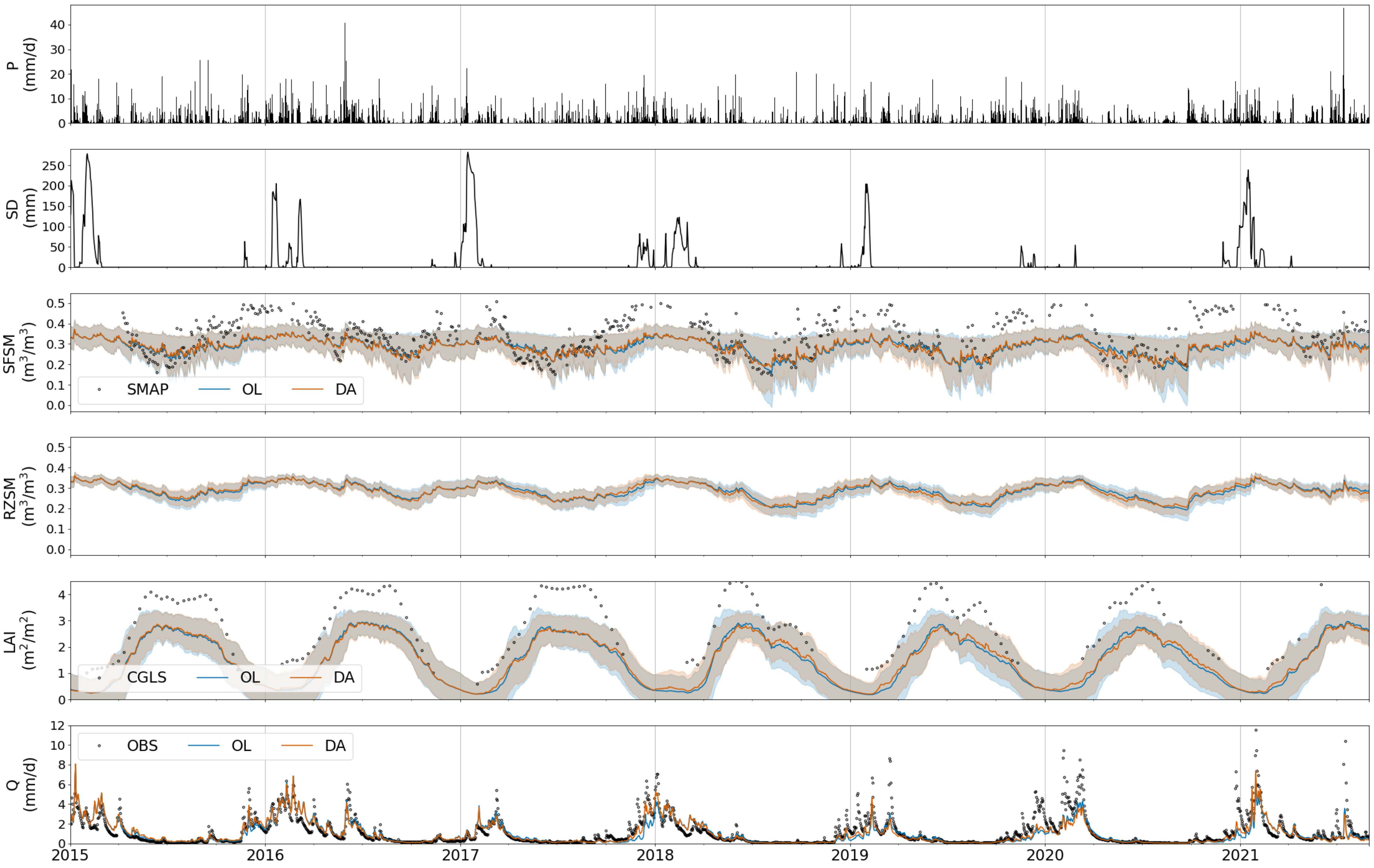
Ourthe (basin aggregated)

VVVH for SMLAI



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Streamflow evaluation

KGE

Catchment	NoR	OL	DASM	DASMLAI
Demer	0.226	0.602	0.600	0.581
Ourthe	0.547	0.587	0.622	0.621

KGEsq (KGE w/ sqrt(Q) to reduce weight of peak flows)

Catchment	NoR	OL	DASM	DASMLAI
Demer	0.461	0.730	0.732	0.726
Ourthe	0.741	0.795	0.828	0.827

$\beta = (\mu_s - \mu_o)/\sigma_o$ and $\alpha = \sigma_s/\sigma_o$. As in Equation 5, the algebraic dec
ause the variance and correlation terms cannot be separated cleanly.

he Kling-Gupta Efficiency (KGE)

GE metric differs from the NSE metric in that it is not derived fron
ean distance computed using the coordinates of bias, standard devi
009). The theoretical version of the KGE metric is

$$\text{KGE} = 1 - \sqrt{(\beta' - 1)^2 + (\alpha - 1)^2 + (\rho - 1)^2}$$

$\beta' = \mu_s/\mu_o$. Note that the definition of β' in Equation 9 is different frc