Satellite soil moisture assimilation in a hydrological model
- Bias-aware L-ETKF & downscaling

Marc-Etienne Ridler *(DHI, Denmark)*

Henrik Madsen *(DHI, Denmark)*
Simon Stisen *(GEUS, Denmark)*
Simone Bircher *(CESBIO, France)*
Rasmus Fensholt *(Copenhagen University)*

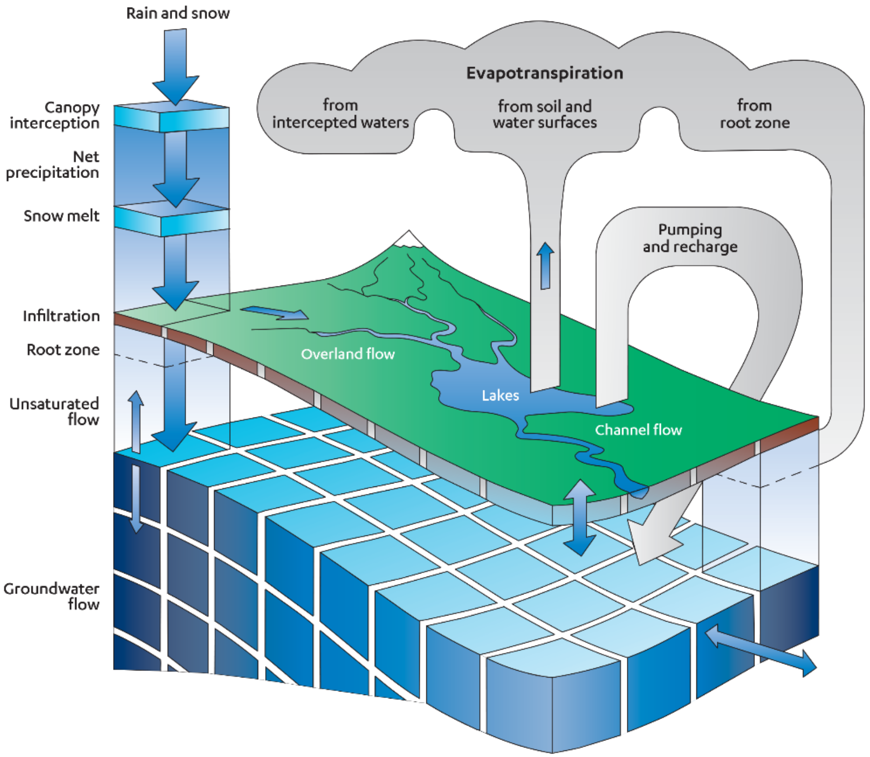
Hydrological modelling: Applications

Flood forecasting and infrastructure planning

Agriculture and irrigation

Water resource management

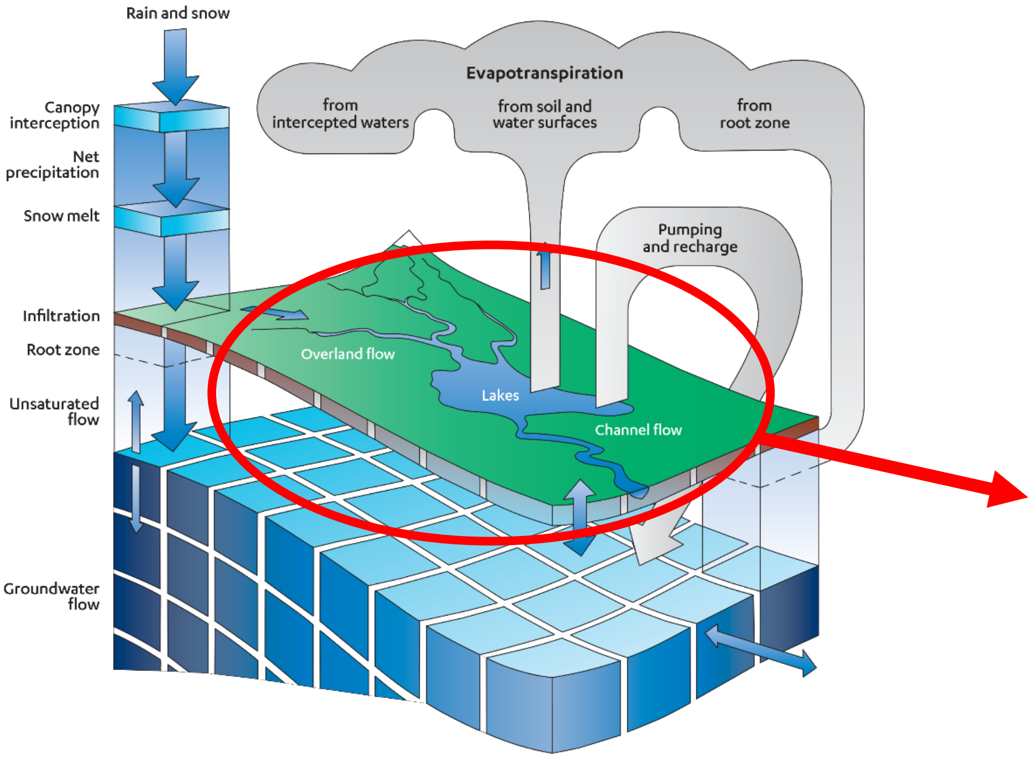
MIKE SHE Hydrological model: Components



Distributed & Coupled

- Rainfall
- Evapotranspiration
- Overland flow
- River model (MIKE 11)
- Infiltration

MIKE SHE Hydrological model: Components



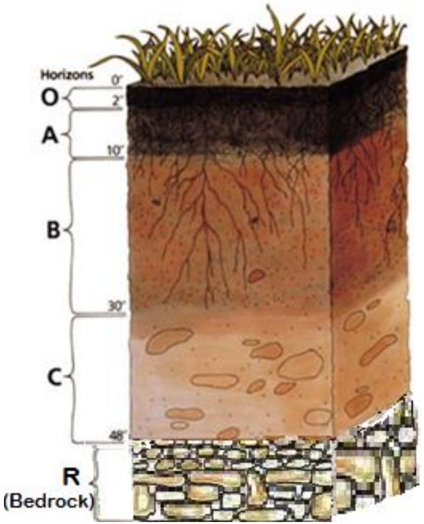
Distributed & Coupled

- Rainfall
- Evapotranspiration
- Overland flow
- River model (MIKE 11)
- Infiltration

Soil Moisture

- **Partitioning of rainfall**
  (runoff / infiltration)
- **Evapotranspiration**

Soil Moisture: Measured from space



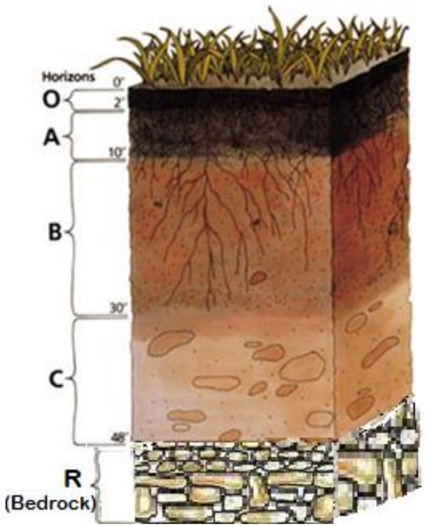
Variable in:

- 3D space
- Time

Dependent on:

- Type of soil
- Type of vegetation
- Weather

Soil Moisture: Measured from space



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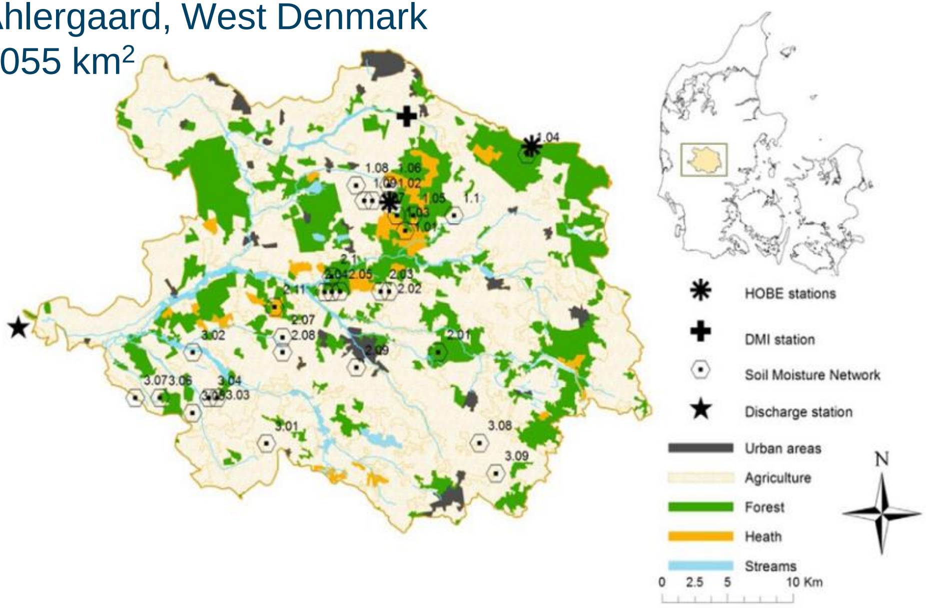
Soil Moisture and Ocean Salinity (SMOS)

- Launched in 2009
- Resolution
  ~ 44 km, 2-3 days
- Microwave L-band (1.4 GHz)

HOBE Center for Hydrology
Hydrological Observatory

Catchment, Data & Model

Ahlergaard, West Denmark
1055 km^2



<u>Data</u> (HOBE)

- Soil moisture network
  30 locations (5, 25, and 50 cm depths)
- River discharge
- 2 flux towers (forest, agriculture)

<u>Model</u>

- 1 hour time step
- Requires meteorological data
- 500 x 500 meter grid (4525)
- Soil (122 vertical layers)

<u>State Vector</u> → 4525 x 122 = 552,050

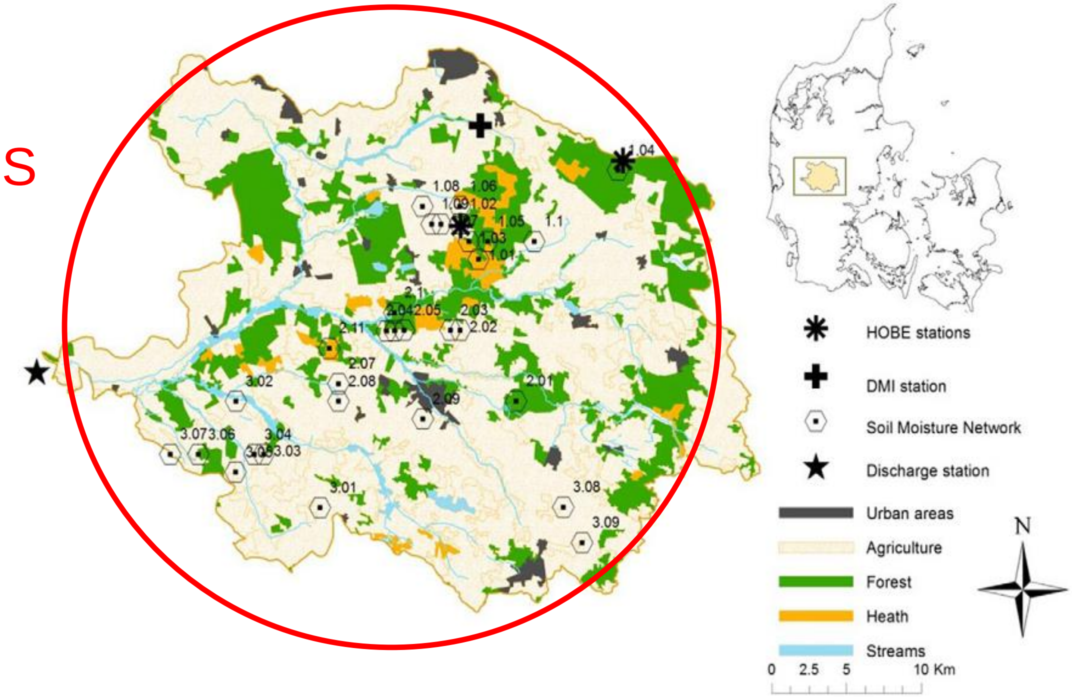
Figure: Andreasen et al., “Estimation of regional groundwater recharge using data from a distributed soil moisture network”, (2013)

→ *Can we use SMOS soil moisture to improve a hydrological model ?*

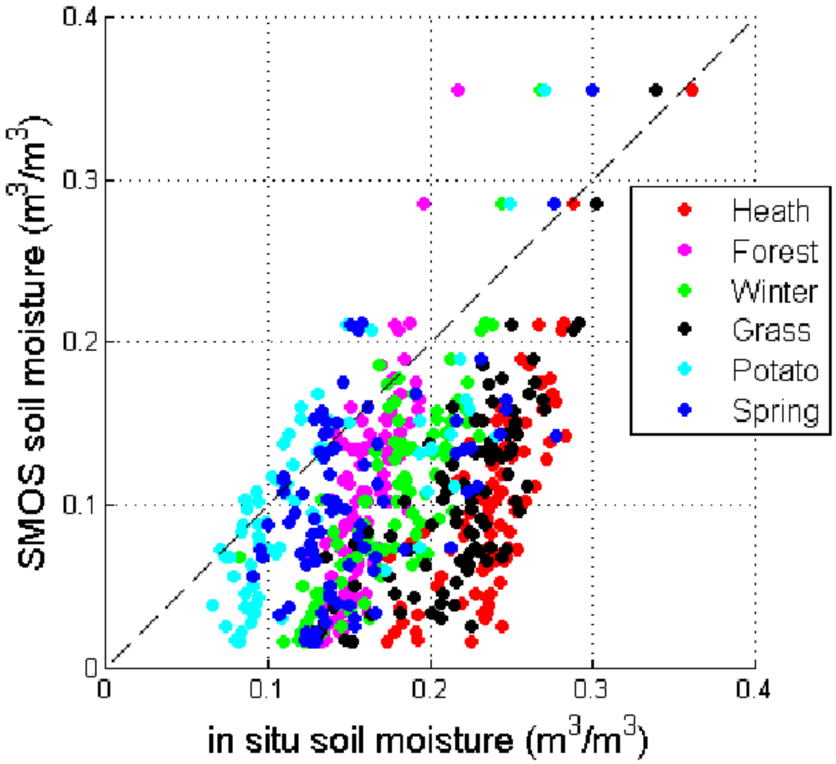
…. Challenges (3)

Challenge 1. Coarse ~44 km

- 1 SMOS Pixel



Challenge 2. Bias (Underestimates actual Soil Moisture)

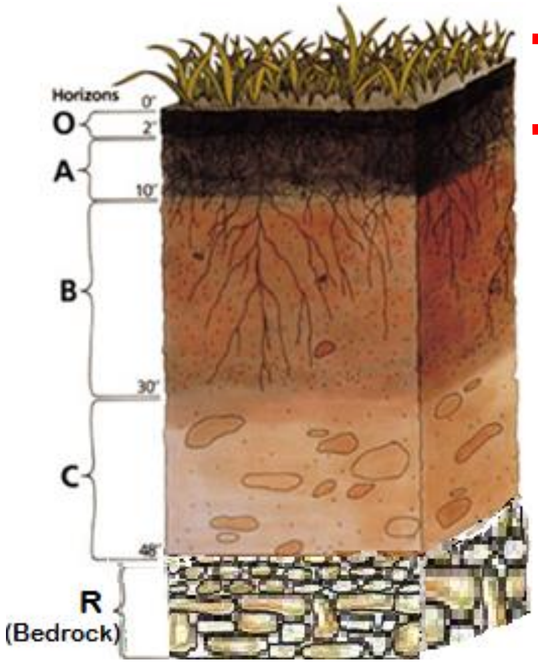


Dry Bias
0.02 – 0.23 m^3/m^3

Consistent with previous studies

Australia (*Rudiger et al 2011*)
Upper Danube (*Schlenz et al. 2012*)
USA (Al Bitar et al 2012,
Jackson et al. 2012)

Challenge 3. Surface (Upper 1-5 cm)



Only upper few cm are estimated

But

- Plants extract soil water through the roots (~ top 1m of soil)
- There are often significant vertical gradients in the soil moisture

Objective

Previous studies

- Assimilate SMOS in continental scale model
- Downscale SMOS (surface temperature)
- Assimilate Synthetic SMOS in catchment model

Objective of study:

- Assimilate real SMOS soil moisture in a catchment scale model
- Can land cover classification be used for downscaling
- Develop an online downscaling assimilation technique

Bias aware filtering (using land cover for initial bias guess)

- Assign a land cover class to every surface model grid & initial bias (β_0)

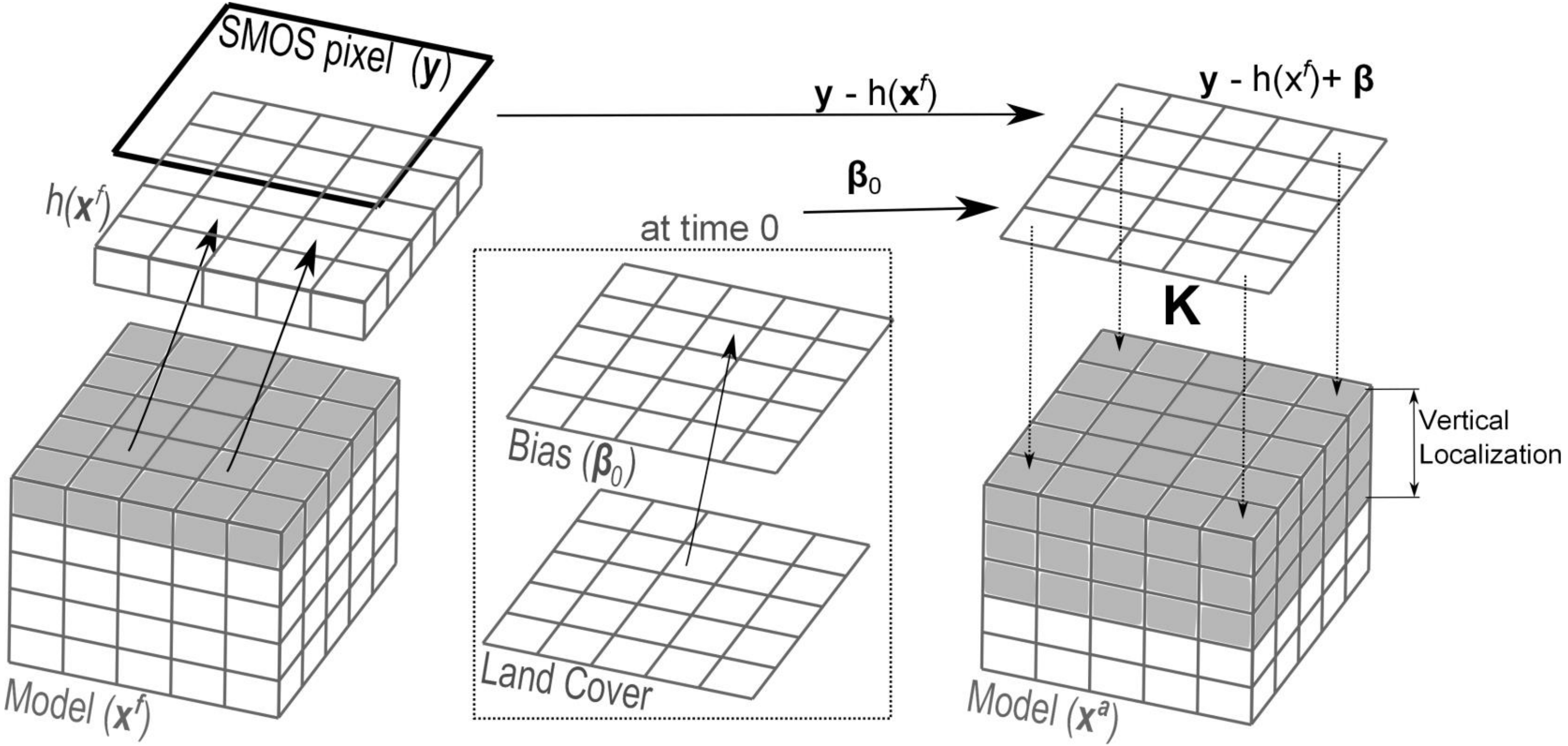
- Allow the Local Ensemble Transform Kalman Filter[1,2] (LETKF) to update bias estimates

$$\mathbf{z} = \begin{bmatrix} \mathbf{x} \\ \boldsymbol{\beta} \end{bmatrix} \qquad \boldsymbol{\beta}_t^b = \boldsymbol{\beta}_{t-1}^a \qquad \tilde{\mathbf{h}}(\mathbf{x}, \boldsymbol{\beta}) = \tilde{\mathbf{h}}(\mathbf{z}) = \boldsymbol{h}(\mathbf{x}) + \boldsymbol{\beta}$$

- Localization (Local Analysis)
  - Vertical (fixed number of layers is considered)
  - Horizontal Gaussian Distance $\boldsymbol{f}(\boldsymbol{d}) = \boldsymbol{e}^{\frac{-1}{2}\left(\frac{\boldsymbol{d}}{\boldsymbol{radius}}\right)^2}$

1. Hunt, B. R., Kostelich, E. J., & Szunyogh, I. (2007). Efficient data assimilation for spatiotemporal chaos: a local ensemble transform Kalman filter. *Physica D: Nonlinear Phenomena*, *230*(1-2), 112–126.
2. Fertig, E. E. J., Baek, S.-J. S., Hunt, B. R., Ott, E., Szunyogh, I., Aravéquia, J. a., … Liu, J. (2009). Observation bias correction with an ensemble Kalman filter. *Tellus A*, *61*(2), 210–226

Bias aware filtering (using land cover for initial bias guess)

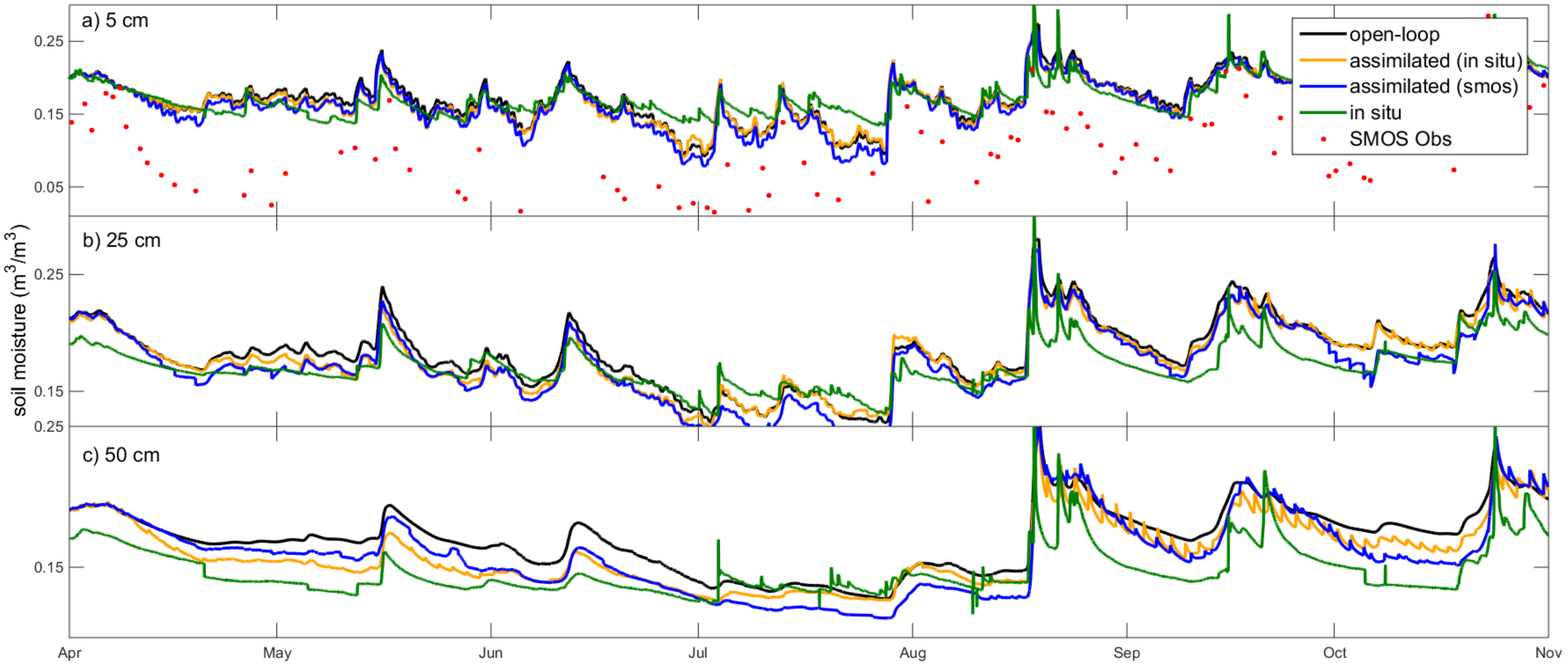


Assimilation setup

- Model Uncertainty
  - Perturb parameters (hydraulic conductivities & van Genuchten)
  - Perturb forcing (rainfall & Leaf Area Index)
- Ensemble size: 80
- Localization
  - Horizontally 900 meters & Vertically 30 cm (top 6 layers)

- 1 year (excluding winter) in 2010
- Validation → Network of 30 soil moisture probes (x 3 depths)

Result 1: Average soil moisture over the catchment



Result 2: Soil moisture by land cover class

	Land cover	5 cm RMSE	5 cm Bias	5 cm R^2	25 cm RMSE	25 cm Bias	25 cm R^2	50 cm RMSE	50 cm Bias	50 cm R^2
Open-loop	Heath	0.060	-0.056	0.714	0.031	0.025	0.746	0.025	0.012	0.615
	Forest	0.038	0.010	0.651	0.038	0.016	0.688	0.051	0.039	0.737
	Winter cereal	0.040	0.034	0.784	0.031	0.021	0.774	0.046	0.040	0.472
	Grass	0.049	-0.041	0.690	0.072	-0.070	0.765	0.112	-0.110	0.701
	Potato	0.067	0.051	0.398	0.029	0.014	0.660	0.036	-0.019	0.376
	Spring cereal	0.060	0.033	0.196	0.033	0.014	0.472	0.023	0.000	0.671
	Average	**0.022**	**0.002**	**0.718**	**0.018**	**0.001**	**0.798**	**0.020**	**-0.006**	**0.731**
Assimilation (SMOS)	Heath	0.059	-0.056	0.736	0.031	0.023	0.728	0.026	0.009	0.525
	Forest	0.038	0.007	0.654	0.038	0.012	0.655	0.048	0.033	0.722
	Winter cereal	0.041	0.036	0.793	0.033	0.026	0.790	0.045	0.039	0.411
	Grass	0.044	-0.037	0.749	0.072	-0.070	0.806	0.115	-0.113	0.645
	Potato	0.073	0.068	0.672	0.029	0.012	0.703	0.039	-0.022	0.351
	Spring cereal	0.060	0.045	0.171	0.035	0.017	0.533	0.022	-0.004	0.680
	Average	**0.020**	**0.006**	**0.807**	**0.020**	**0.001**	**0.826**	**0.024**	**-0.010**	**0.720**

(m^3 / m^3)

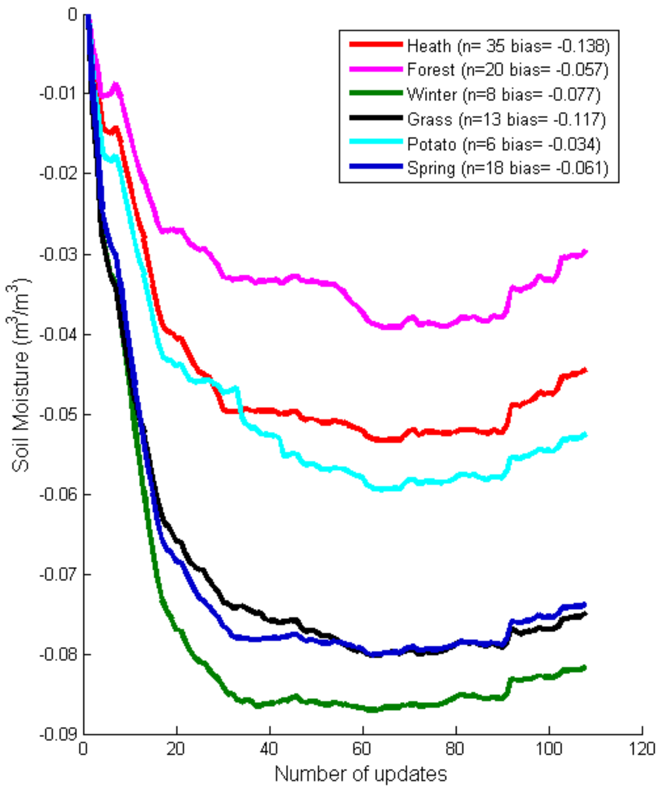
Improved statistics

Deteriorated statistics

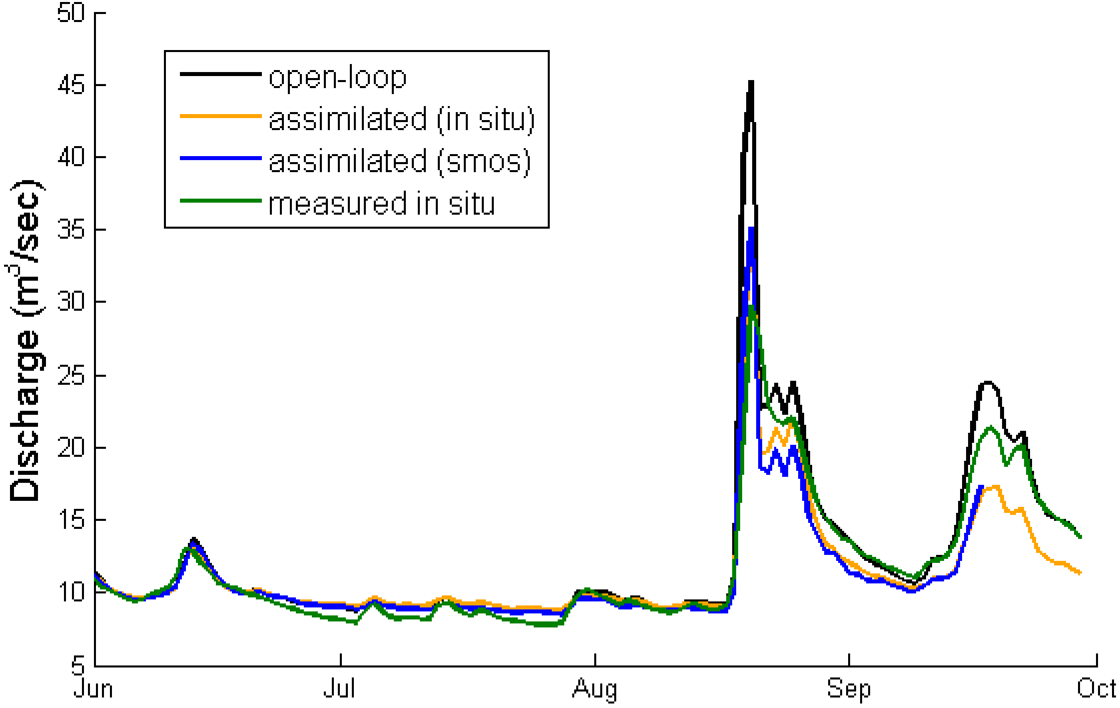
Result 3: Test → Can the filter estimate the bias?

Steps:
- SMOS measurement
- $\beta_0 = 0$
- See how bias-aware filter estimates bias over time.
- Compare with in-situ data

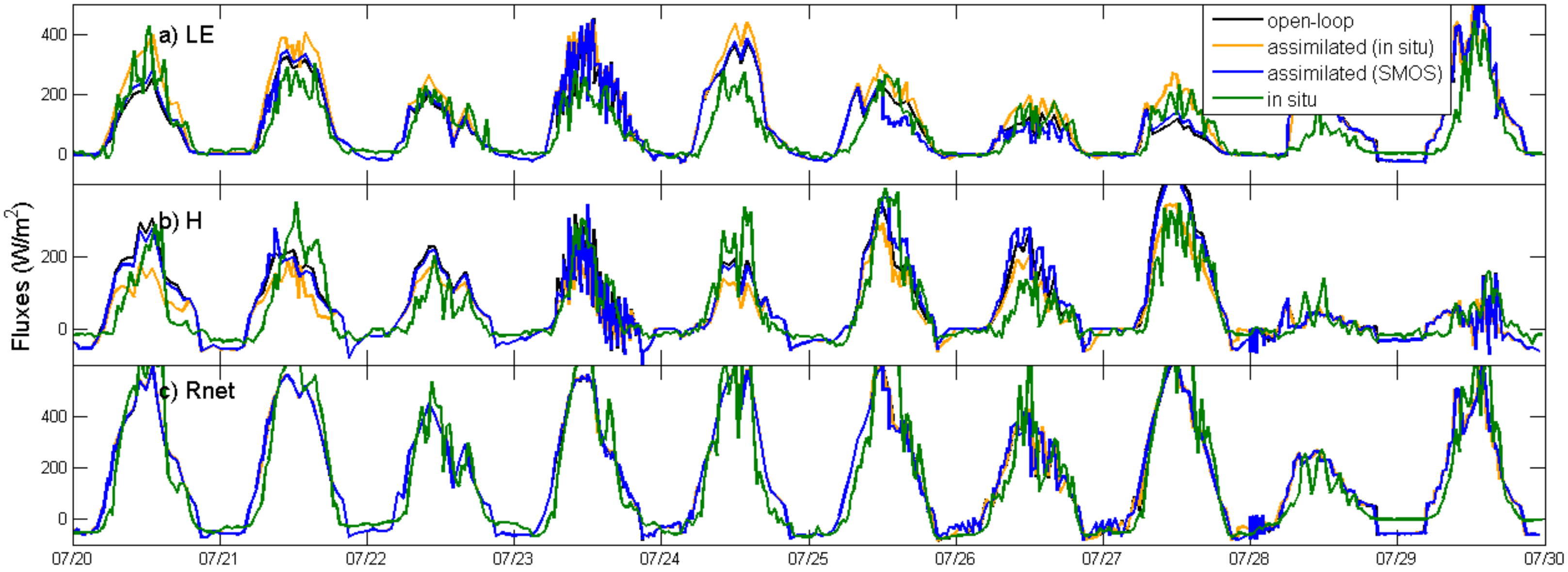
Result:
- Pretty good agreement.
- 'U-shape' → seasonality?



Result 4: River discharge



Result 5: Energy fluxes → little difference overall



Summary

- First study to assimilate real SMOS data in a catchment
- Bias aware LETKF (Biased observations)
- SMOS useful for correcting the dynamics in the model

AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2014WR015392

Key Points:
- SMOS is assimilated in a catchment scale model
- A new bias aware ensemble Kalman filter approach
- The method improves soil moisture in the model

Assimilation of SMOS-derived soil moisture in a fully integrated hydrological and soil-vegetation-atmosphere transfer model in Western Denmark

Marc-Etienne Ridler[1], Henrik Madsen[1], Simon Stisen[2], Simone Bircher[3], and Rasmus Fensholt[4]

[1]DHI, Hørsholm, Denmark, [2]Geological Survey of Denmark and Greenland, Copenhagen, Denmark, [3]Centre d'Etudes Spatiales de la Biosphère, Toulouse, France, [4]Department of Geosciences and Natural Resource Management, University of Copenhagen, Copenhagen, Denmark

Future work

- Multi-year
- Soil type for downscaling
- Multivariate assimilation
- New satellite

Contact: Marc-Etienne Ridler (mer@dhigroup.com)