Soil moisture assimilation into TerrSysMP at different scales

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Introduction

- Soil moisture is a key driver for water and energy exchange at the land surface and plays an essential role for water management, food production, flood forecasting, or climate projections.
- Soil moisture can be measured at different spatial and temporal scales: point scale with in-situ sensor networks (e.g., TDR, FDR); intermediate-scale with for example cosmic-ray probes; large-scale with remote sensing (e.g., SMOS, SMAP).
- Data assimilation techniques (e.g. ensemble Kalman filter by Evensen, 1994) can be used to merge soil moisture observations with simulations by the Earth system model TerrSysMP (Shrestha et al., 2014) at different scales, using the Parallel Data Assimilation Framework PDAF (Nerger & Hiller, 2013, Kurtz et al., 2016).

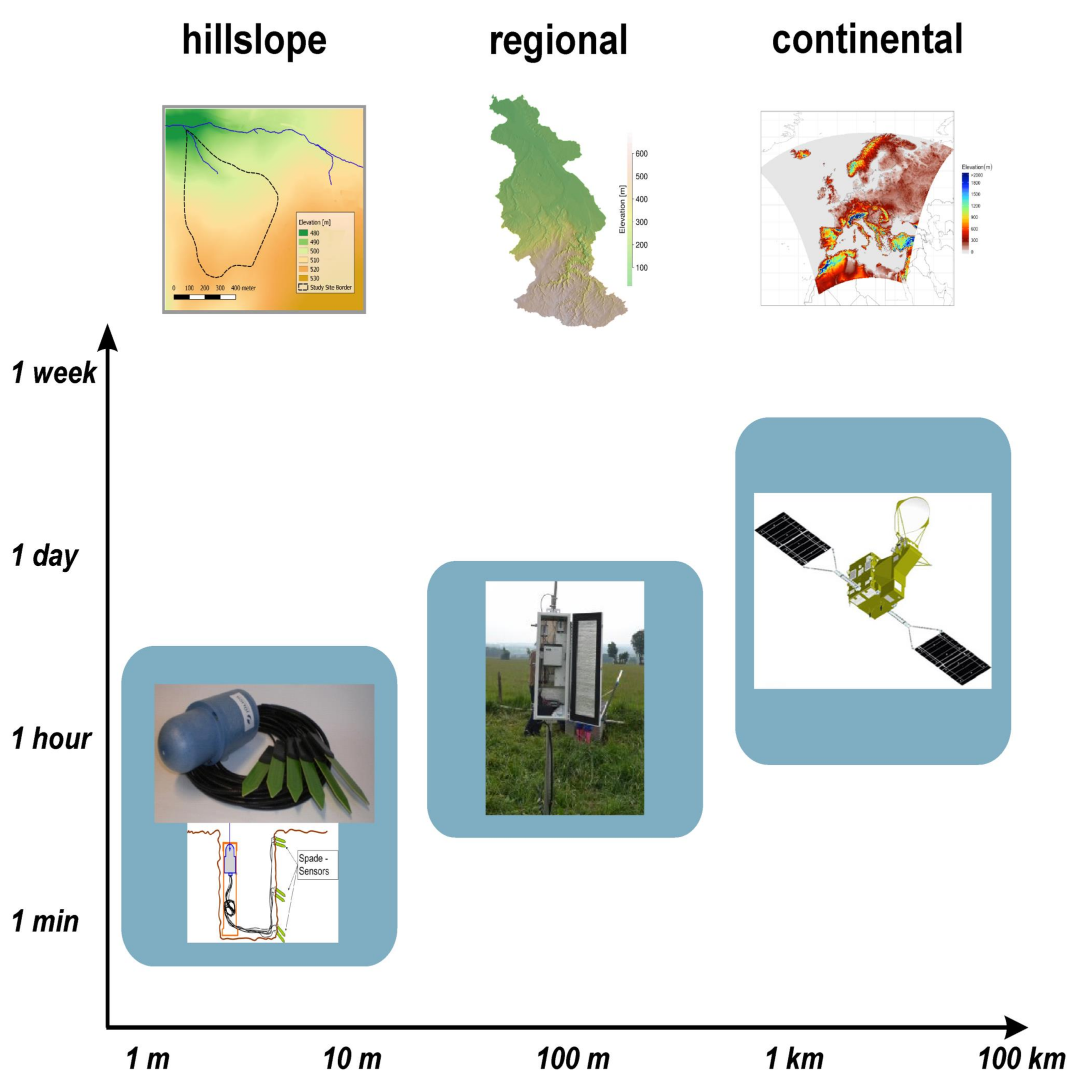

Fig. 1: Soil moisture observations and modelling projects at different scales. The blue boxes indicate typical spatial and temporal ranges of the assimilated observation data .

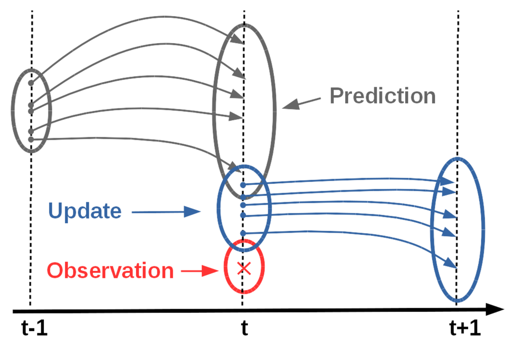

Fig. 2: Basic concept of the ensemble Kalman filter. Arrows represent model state trajectories and circles represent uncertainty.

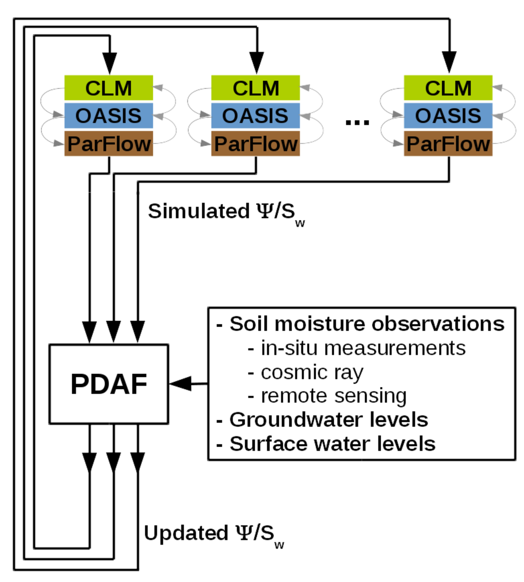

Fig. 3: Data flow for the data assimilation with TerrSysMP and PDAF.

Regional scale: Rur catchment

Model: PDAF-CLM-ParFlow

Domain extent and resolution:

100 × 162 horizontal grid cells with 500m x 500 m resolution, 20 layers, variable vertical resolution (0.02 – 1.0 m)

Observations:

Daily averaged soil moisture data from 8 cosmic-ray stations

Ensemble generation:

128 realizations with perturbed atmospheric forcings (precipitation, short wave/ long wave radiation, 2-m temperature) and perturbed hydraulic conductivity fields (geostatistical simulation)

Simulation period: 1 April 2013 – 31 August 2013 (5 months)

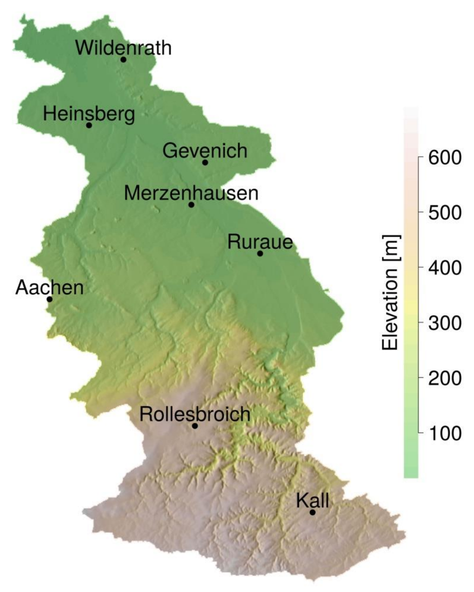

Fig. 7: Cosmic-ray sensor network within the Rur catchment.

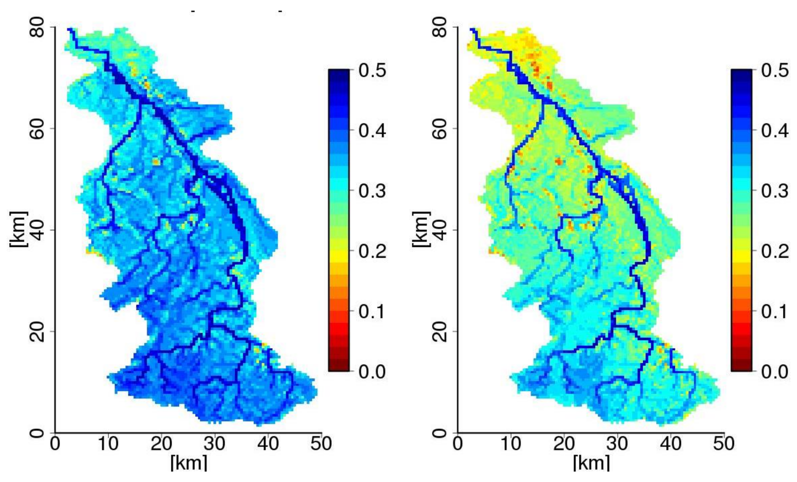

Fig. 8: Average soil moisture pattern of the uppermost model layer for open-loop simulation (left) and state update (right).

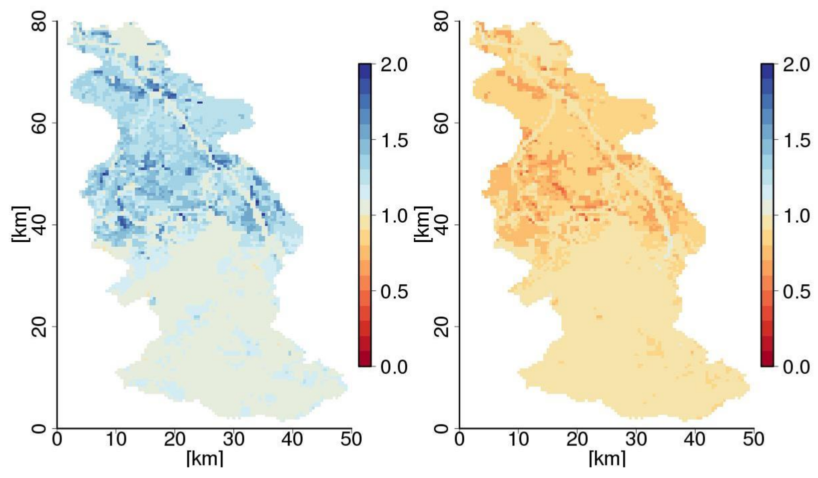

Fig. 9: Relative change of land surface fluxes (left: sensible heat flux; right: latent heat flux) through soil moisture assimilation. Blue colours indicate a relative increase of the corresponding flux.

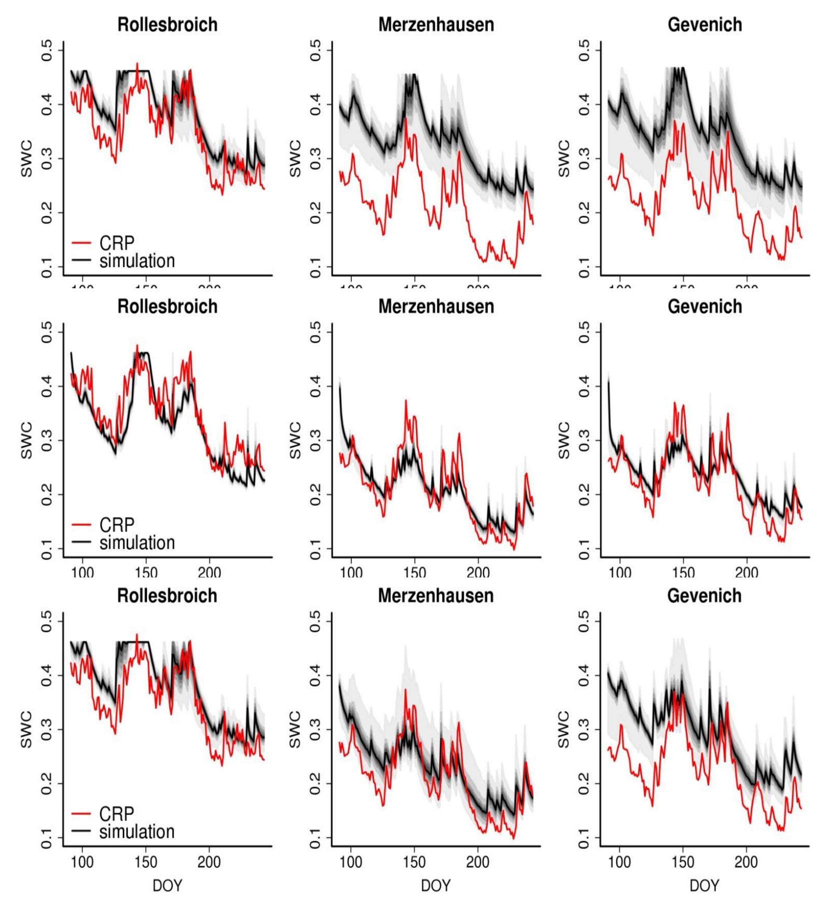

Fig. 10: Predicted (black) and measured (red) soil moisture time series at three cosmic-ray stations for open-loop simulation (upper), state update (middle) and open-loop with updated hydraulic conductivity (lower).

Hillslope scale: Rollesbroich site

Model: PDAF-CLM-ParFlow

Domain extent and resolution:

128 × 112 horizontal grid cells with 10 x 10 m resolution; 20 layers with variable (0.025 – 0.58 m) vertical resolution

Observations:

Hourly averaged soil moisture data from 61 SoilNet locations in 5, 20, and 50 cm depth.

Ensemble generation:

128 realizations with stochastic precipitation and fully heterogeneous 3D fields of van Genuchten soil hydraulic properties.

Simulation period:

1 May 2011 – 31 December 2011 (assimilation)

1 January 2012 – 31 December 2012 (verification)

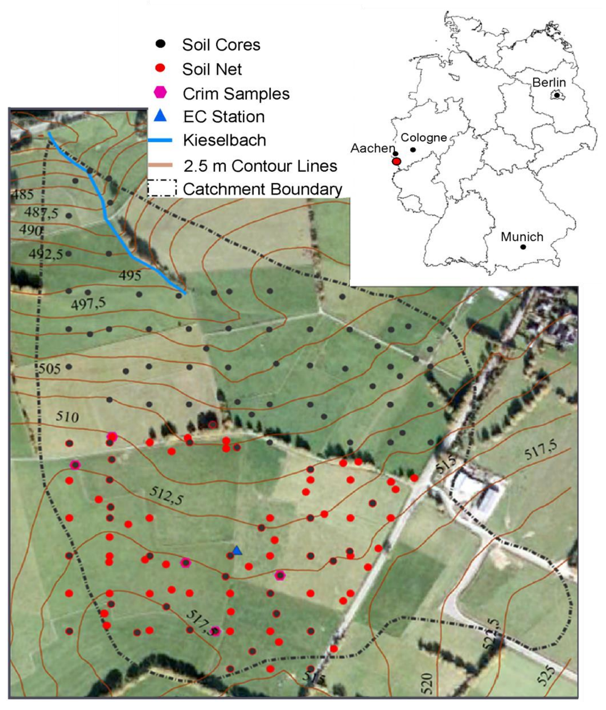

Fig. 4: Overview of the Rollesbroich study site (mod. from Qu et al. 2016).

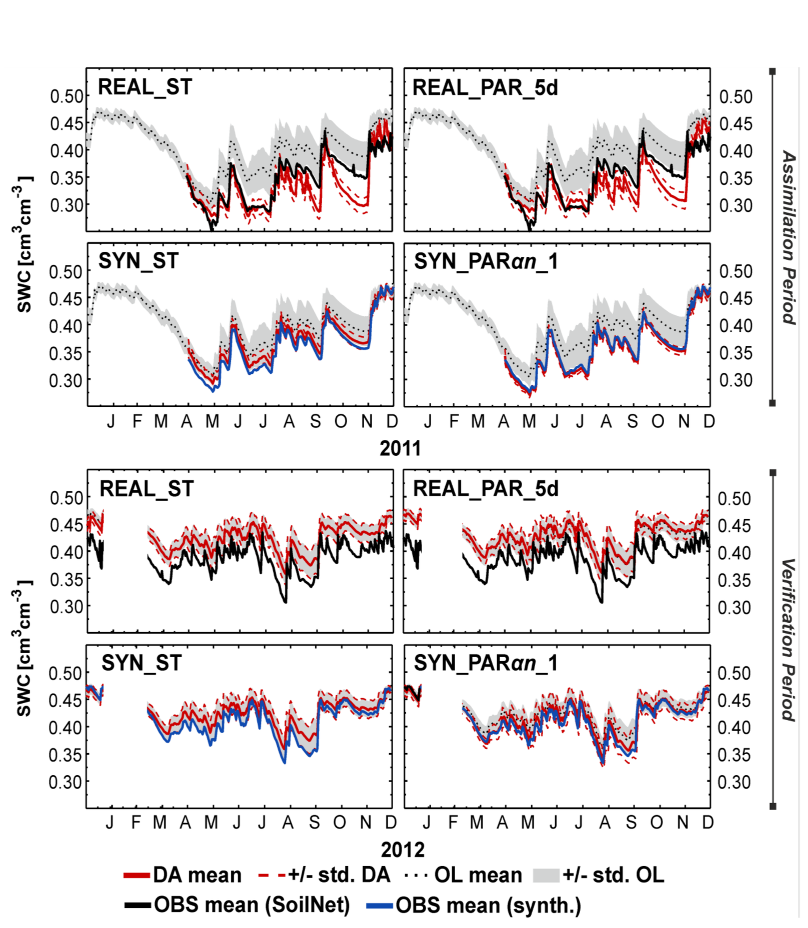

Fig. 5: Mean soil water content and standard deviation of soil water content at 20 cm depth.

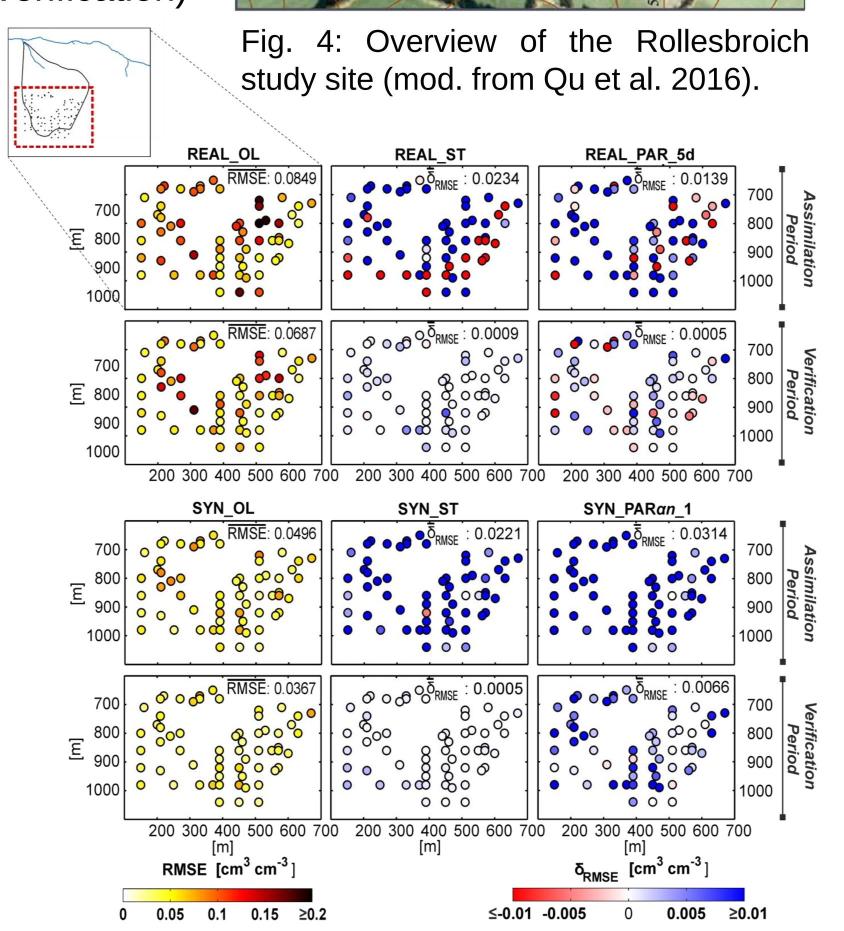

Fig. 6: RMSE of soil water content at individual locations for the open loop (left column) and changes in RMSE (increase implies improvement) at 20 cm depth .

Continental scale: EURO-CORDEX

Model: PDAF-CLM

Domain Extent and resolution:

EU-CORDEX at 0.0275° (~3km) x 0.0275°(~ 3km)

Observations:

ESACCI satellite soil moisture observation (2000 – 2006) at 0.25° resolution. For data assimilation 100 grid cells were randomly selected where daily data are available.

Ensemble generation:

12 realizations of perturbed precipitation and soil texture.

Simulation period:

1 January 2000 – 31 December 2006

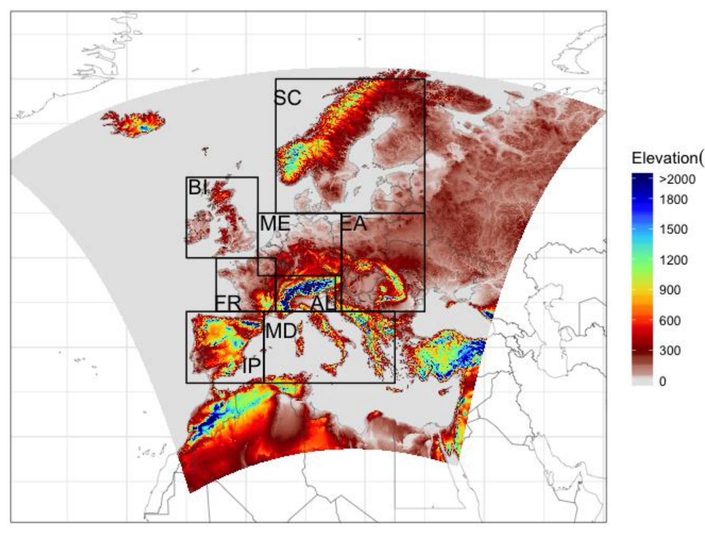

Fig. 11: Topography over the European CORDEX domain. The small inner boxes show the PRUDENCE regions.

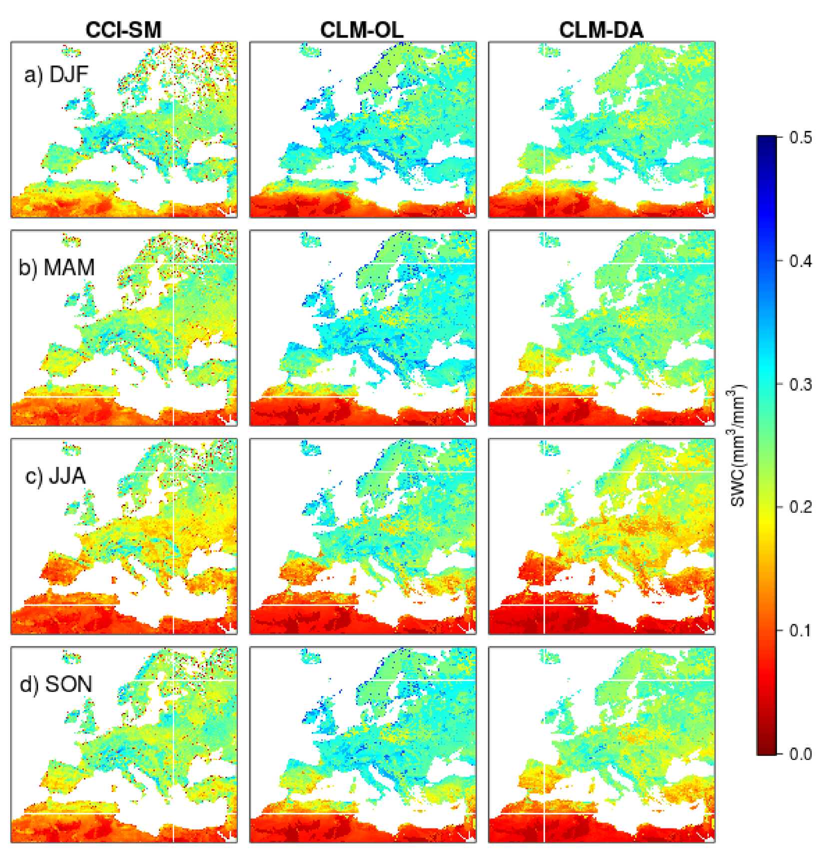

Fig. 12: Comparison of seasonal mean open loop soil moisture (CLM-OL) and data assimilation (CLM-DA) with CCI-SM satellite data, for a) DJF,(b) MAM, c) JJA and d) SON.

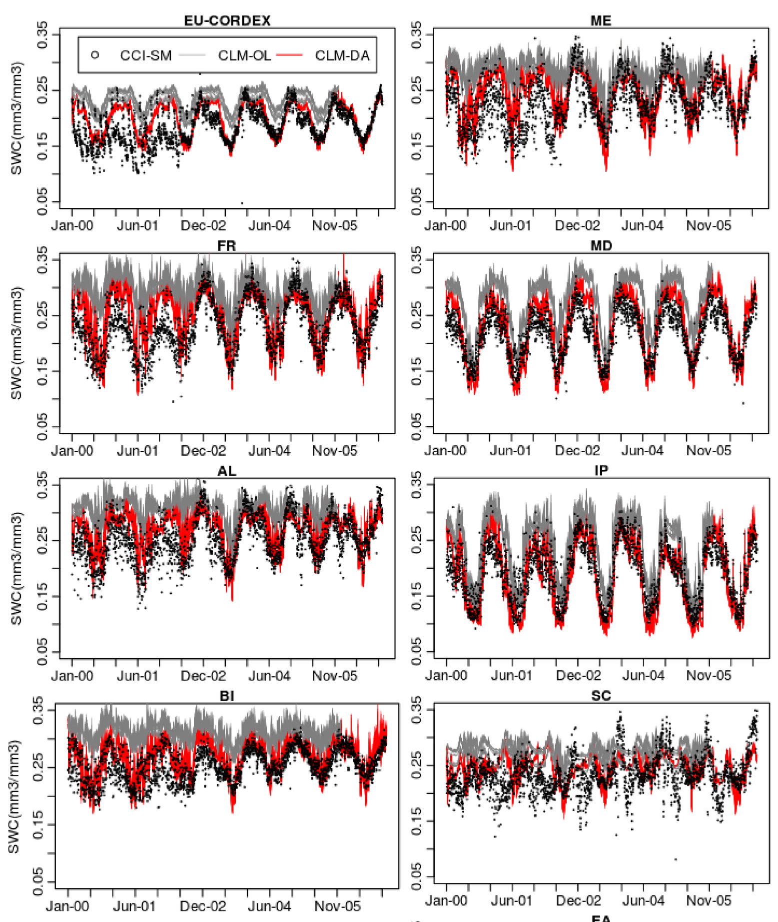
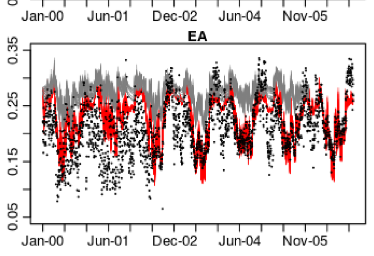

Fig. 13: Aggregated daily average soil moisture from CCI-SM, CLM-DA and CLM-OL in Prudence regions.

Conclusions

- The TerrSysMP-PDAF framework improves soil moisture predictions for hillslope to continental scale models using data from different soil moisture monitoring techniques.
- Soil moisture characterization at the hillslope scale was only slightly improved in spite of the high observation density. This is related to the small volume support of those measurements and small-scale variability which is difficult to characterize.
- Soil moisture data from cosmic-ray sensor network improved soil moisture characterization at the catchment scale even though observation density is low. Joint estimation on states and parameters has slight positive effects on soil moisture predictions.
- At the continental scale, the assimilation of CCI-SM data improves the soil moisture predictions over most part of the Europe by reducing systematic biases of CLM simulations. Improvements are sensitive to spatio-temporal data coverage.

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