# Modeling of a forested study site with the Community Land Model version 5 using climate projections for the 21st century.

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## The objective

i) Using model-data fusion to improve ecosystem modeling of forested sites over Europe to create ecosystem reanalysis products. ii) Improving models for the use with climate projections to better understand the impacts of climate change on water resources and vegetation.

## Study site - Wüstebach

- Small (38.5 ha) forested catchment.
- Mean annual precipitation and temperature of 1100mm and 7°C. (Bogena et al., 2015)
- Located in the Eifel National Park near the German-Belgian border.
- Part of the terrestrial environmental observatories (**TERENO**) network. *(www.tereno.net)*
- SoilNet sensors provide soil water content and soil temperature measurements since 2009. (Bogena et al., 2010)
- 150 measurements stations, measurements at 5 cm, 20 cm, and 50 cm depth.
- Data from 2009 to 2018 pre-processed using quality criteria, thresholds, removing frozen soil measurements, and removing local spikes.
- Measurements from a nearby German weather service station are used as atmospheric forcing.
- In this study, measurements are spatially averaged since the catchment is represented in the model as a single grid cell.
- Modeling the catchment as single grid cell allows the use of a large ensemble for data assimilation, in this study an ensemble of 96 simulations is used.
- The ensemble is generated from perturbed atmospheric forcings according to the correlation matrix in Reichle et al. (2007) and perturbed sand and clay fractions.

## Newly coupled Community Land Model version 5 and the Parallel Data Assimilation Framework

- Current version of the Community Land Model (CLM) part of the Community Earth System Model (CESM). (Lawrence et al. 2018)
- Models a broad collection of important land-surface processes, including hydrology, carbon and nitrogen cycle, and prognostic vegetation states, e.g. leaf area index.
- In this study, newly coupled to the Parallel Data Assimilation Framework (PDAF) (Nerger et al. 2005)
- Data assimilation in this study is done via the Ensemble Kalman Filter. (Evensen 1994)
- The Ensemble Kalman Filter is used to assimilate state variables (soil water content), and update state variables as well as soil parameters.
- The included parameters are updated based on the assimilation of the state variables. The updated soil parameters can be used further even when observational data are no longer available.
- Currently, the included parameters are sand and clay fraction.

## Time-series of Soil Water Content

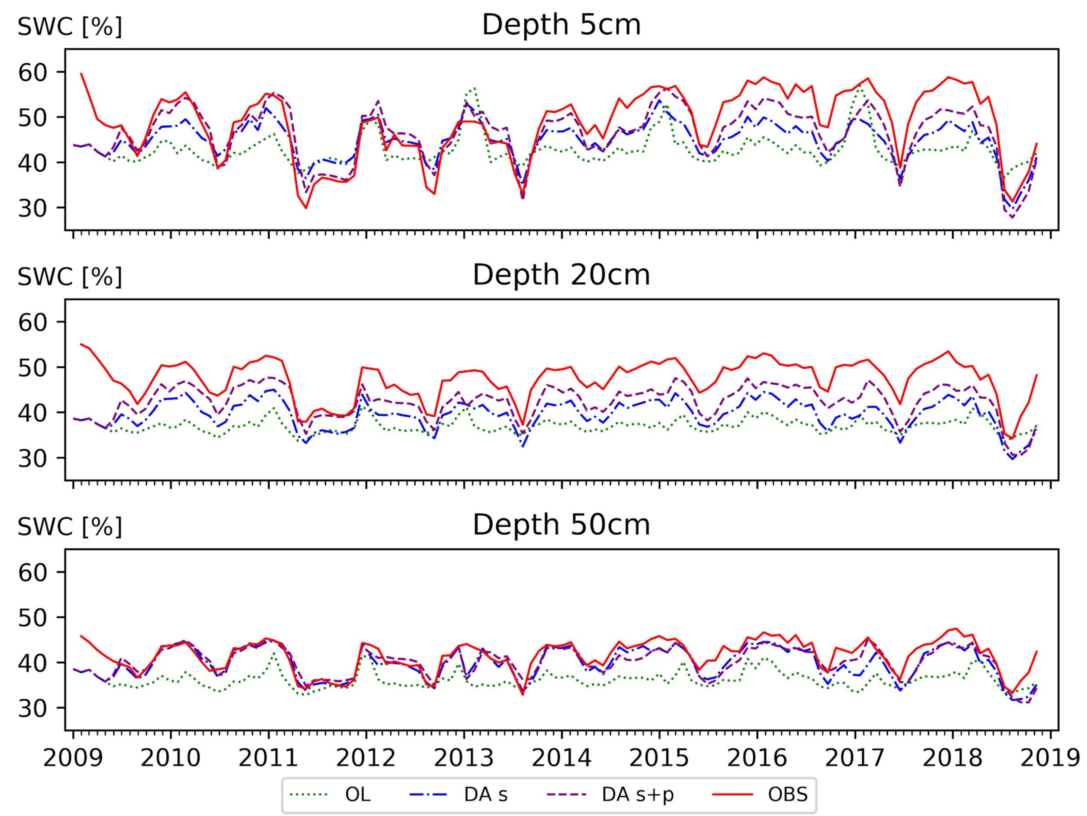


Fig. 1) Time series of the monthly average soil water content (SWC) from 2009 to 2018 at the three measurement depths. Monthly averages are used for visual clarity, model output is in daily averaged SWC as shown for 2018 below.
The green, dotted line shows open loop (OL), i.e. model output without data assimilation. The blue, dot-dashed line shows the output from data assimilation of the state variable (DA s). The purple, dashed line shows the output from data assimilation of both state and parameter variables (DA s+p). The red, solid line shows the observational data (OBS).

- In 5 cm and even more in 20 cm depth the higher soil water content in the observational data is visible.
- As expected, data assimilation of the state variable reduces the difference and including parameters improves model performance further.
- The large difference in 20 cm depth is a target of further analysis.

## Highlighting 2018

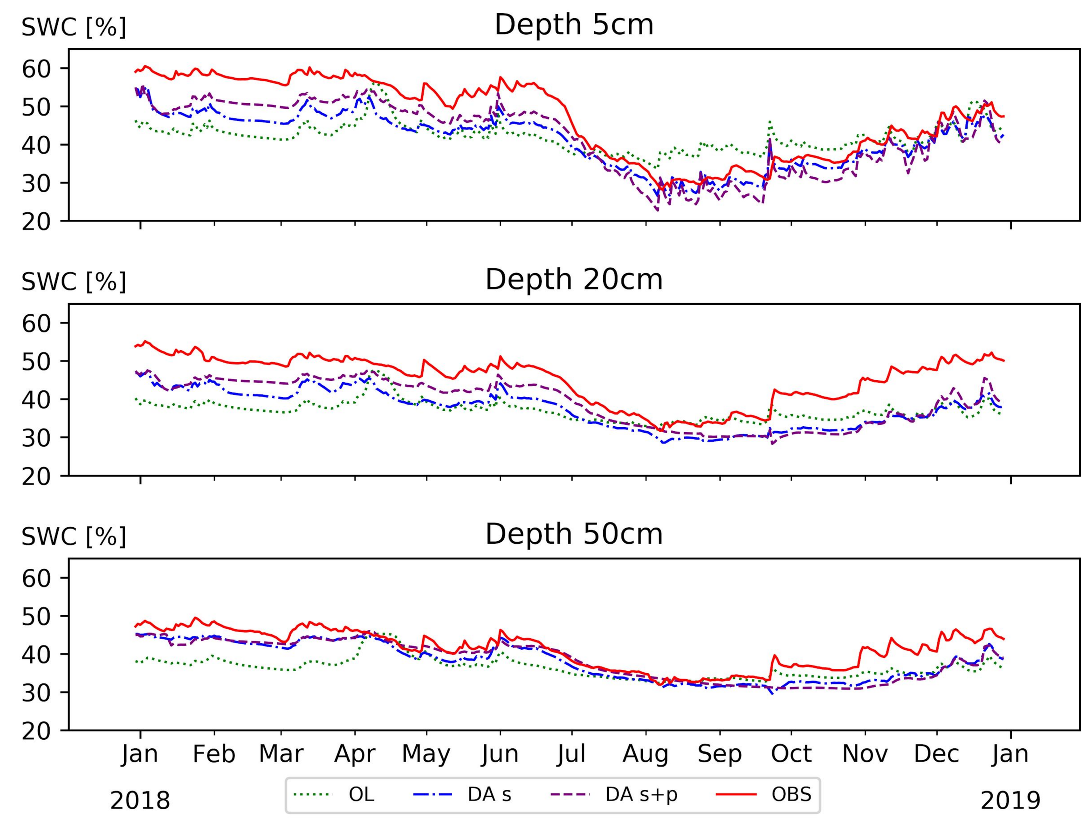


Fig. 2) Time series of the daily average soil water content (SWC) for 2018 at the three measurement depths.
The green, dotted line shows open loop (OL), i.e. model output without data assimilation. The blue, dot-dashed line shows the output from data assimilation of the state variable (DA s). The purple, dashed line shows the output from data assimilation of both state and parameter variables (DA s+p). The red, solid line shows the observational data (OBS).

- Dry summer of 2018 visible in soil water content decline starting in June.
- The model without data assimilation does not show the same decline as the observations.
- After the dry summer the model does not show the same increase in soil water content in 20 cm and 50 cm depth even with data assimilation.

## Correlation comparison

Both figure 1 and 2 have shown that there are still differences between all model variants and observation. Nevertheless, the figure below show the improvements with data assimilation (with and without parameter updating)..

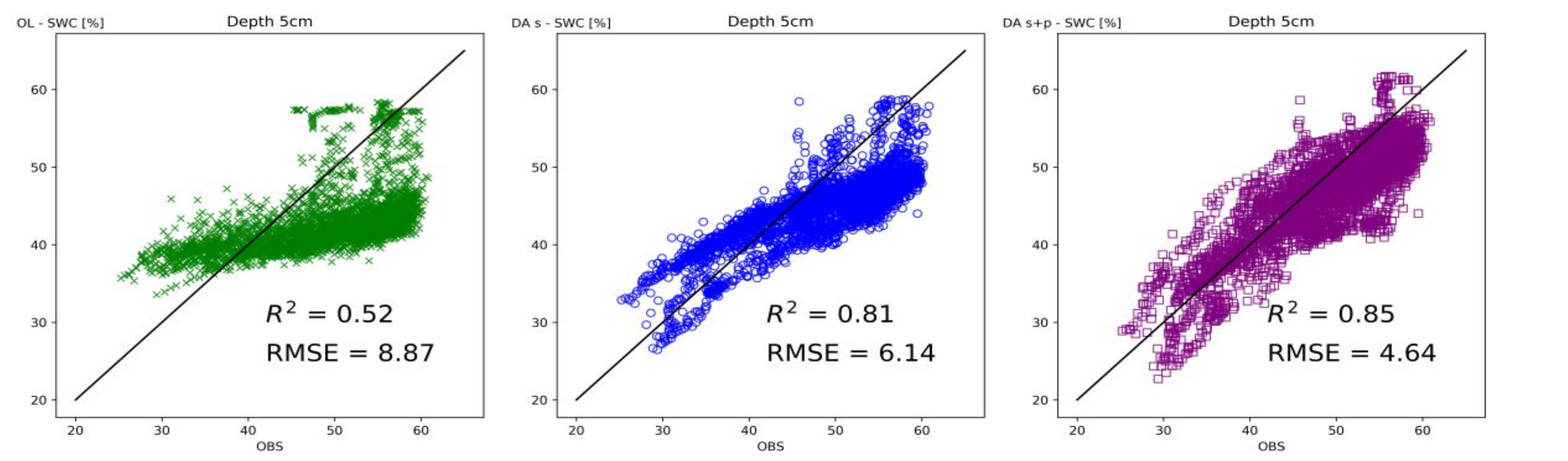


Fig. 3) Correlation plots of the three model variants compared to observational data. Each point represents one daily average soil water content in the 10-year simulation period. On the left the open loop (OL), in the middle the data assimilation of the state variable (DA s) and on the right the data assimilation of the state and parameter variables is shown.

## Climate projections as forcings

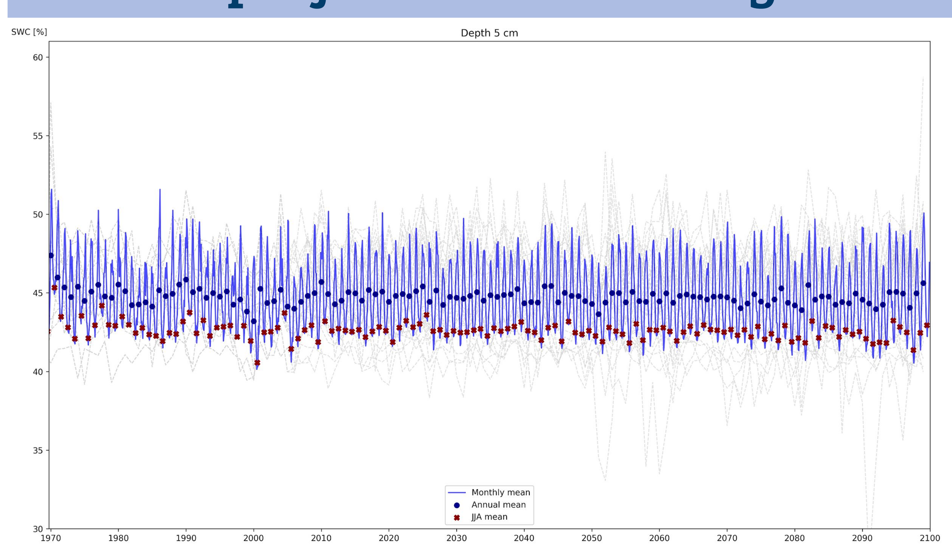

Fig 4.) Time-series from 1970 to 2100 of soil water content at 5 cm depth. CLM 5 simulations driven by daily atmospheric forcings from climate simulations. Blue, solid line shows monthly ensemble mean, dark blue points highlight annual ensemble means, dark red X-markers highlight the mean of the summer months, and light grey, dashed lines illustrate the various ensemble member's annual mean.

- The climate projections are combinations of regional (RCM) and global climate models (GCM) compiled for the H2020 eLTER project *(https://data.lter-europe.net/)*
- Ensemble of 28 combinations of different RCM, GCM and representative concentration pathways (RCP) consisting of daily atmospheric forcing variables.
- CLM works better with sub-daily atmospheric forcings, therefore partitioning into sub-daily forcings could improve simulation results.
- Preliminary results for Wüstebach site show no clear upward or downward trend of the ensemble mean for soil water content.

## Conclusion & Outlook

- The coupled CLM5 + PDAF improves soil water content simulations of the Wüstebach study site.
- Including parameter updates into the EnKF further improves simulation results.
- Large differences between model and observations still exist, especially in 20 cm depth. Therefore, in further studies the organic matter fraction will be updated as well..
- The impact of data assimilation on other modeled ecosystem variables, like leaf area index and evapotranspiration, as well as additional assimilation of soil temperature measurements are also subject of future studies.
- The analysis will be extended to other forested sites over Europe from the Resilient Forest project and the LTER network.

## Acknowledgments

The authors gratefully acknowledge the support by the the project LIFE RESILIENT FORESTS – Coupling water, fire and climate resilience with biomass production from forestry to adapt watersheds to climate change is co-funded by the LIFE Programme of the European Union under contract number LIFE 17 CCA/ES/000063.
Additionally, the authors gratefully acknowledge the computing time granted through JARA on the supercomputer JURECA at Forschungszentrum Jülich.

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