Geophysical Research Abstracts
Vol. 21, EGU2019-8325-1, 2019
EGU General Assembly 2019

Multi-model verification of evapotranspiration in the Iberian Peninsula

Johannes Brenner (1), Martin Schrön (2), Stephan Thober (1), Oldrich Rakovec (1), Rohini Kumar (1), Ming Pan (3), Niko Wanders (4), and Luis Samaniego (1)

(1) Department for Computational Hydrology, UFZ-Helmholtz Centre for Environmental Research, Leipzig, Germany (johannes.brenner@ufz.de), (2) Department of Monitoring and Exploration Technologies, UFZ-Helmholtz Centre for Environmental Research, Leipzig, Germany, (3) Department of Civil and Environmental Engineering, Princeton University, Princeton, New Jersey, USA, (4) Physical Geography, Utrecht University, Utrecht, Netherlands

In the Iberian Peninsula, state-of-the-art, large-domain, hydrological models show limitations in adequately capturing the dynamics of actual evapotranspiration fluxes (ET). Possible reasons for poor performance may be related to either the uncertainties evolving from a relatively coarse resolution of the forcing data, or the poor process parameterizations, or the simplicity in the model structure, among other factors.

The End-to-end Demonstrator for improved decision making in the water sector in Europe (EDgE) project, commissioned by the Copernicus Climate Change Service (ECMWF), provides a unique dataset of hydrological fluxes and states over Europe. The dataset includes historical simulations of a model ensemble of four hydrological/land-surface models (Noah-MP, mHM, PCR-GLOBWB and VIC) at spatial resolution of 5 km and daily temporal resolution. The same meteorological forcing data (based on E-OBS dataset) and geophysical/land-cover properties were used to drive all model ensemble simulations.

In this study, we scrutinize the ensemble of model-specific simulations against: 1) available observations at the FLUXNET eddy covariance stations, 2) gridded ET product (1), and 3) MODIS aET (MOD16) data (2).

This study applies innovative and multiple measures to inter-compare and contrast ET outputs among different models and reference observations, with an overall goal to enhance the process understanding of ET (and related) conceptualizations in different hydrological and land-surface models. These include: 1) model benchmarking approach following approach adapted in Best et al. (3); 2) analysis of empirical orthogonal functions (EOF), as an assessment for spatial performance metrics; and 3) processes linkage among storages and fluxes; specifically, evaporative fraction (EF) vs. soil moisture (SM) relationships.

Model benchmarking shows modest performance for all models at the FLUXNET eddy covariance stations. The model ensemble outcompetes the Penman-Monteith physical based model, assigned as lowest benchmark, but is outcompeted by simple linear models, which do predict ET by the ensemble's meteorological input. Therewith, model structure complexity could be enhanced to foster model performance in estimating ET dynamics. We assess the spatial similarity between the model-specific simulations and gridded ET products (FLUXNET, Modis MOD16) by calculating a similarity score based on the EOF of a joint dataset proposed by Koch et al. (4). The similarity score distinctly differs depending on the gridded ET product used; for MODIS MOD16 the most conceptualized model PCR-GLOBWB gains highest similarity during the vegetation period, whereas for FLUXNET grid similarity is highest for mHM followed by Noah-MP. For the models such as mHM, PCR-GLOBWB and VIC the meteorological input (air temperature and precipitation) and vegetation dynamics (leaf area index) determine ET spatial patterns according to the EOF analysis. Whereas for the most complex model tested in this study, Noah-MP, the similarity between the first EOF and model meteorological input and the LAI is less pronounced. We argue that Noah-MP defines the ET spatial pattern by a medium complex soil-vegetation-atmosphere transfer scheme, whereas in the other models the estimated ET spatial patterns are determined by the meteorological forcing data.

1 Jung, M. et al. 2011, https://doi.org/10.1029/2010JG001566

2 Mu, Q. et al. 2011, https://doi.org/10.1016/j.rse.2011.02.019

3 Best, M. J. et al. 2015, https://doi.org/10.1175/JHM-D-14-0158.1

4 Koch, J., et al. 2015, https://doi.org/10.1002/2014WR016607