EGU22-9890
https://doi.org/10.5194/egusphere-egu22-9890
EGU General Assembly 2022

Hybrid Modelling of Land-Atmosphere Fluxes: Estimating Evapotranspiration using Combined Physics-Based and Data-Driven Machine Learning

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Evapotranspiration (ET) is a central water flux in the global hydrological cycle, closely coupled to the energy balance and carbon cycle. It is primarily governed by non-linear energy processes controlled by meteorological conditions as well as different heterogeneous properties of the ecosystem. Various physical models of ET are widely used, such as the Penman-Monteith (PM) equation, which preserves physical laws and accounts for phenomenological behavior. However, these mechanistic models are often subject to large uncertainties, largely due to the limited understanding of the biological controls, particularly how plants control the land-to-atmosphere water flux by closing and opening their stomata.

Here, we propose a data-adaptive hybrid modeling approach for ET that combines the physics-based PM equation with machine learning (ML) by inferring the biological and aerodynamic regulator of the evaporative water flux from observations. Specifically, the framework comprises setting up a feed-forward neural network and integrating the physically-constraining PM equation in the loss function of the latent heat flux (LE). The stomatal resistance (r_s) and aerodynamic resistance (r_a) are modeled as intermediate latent variables, based on micro-meteorological observations collected and curated in the FLUXNET database. For baseline comparison, two conceptually different ML models have been set up, where the first model simulates LE directly without imposing any physical constraints and the second model is an alternative pseudo-hybrid model approach [1], where the main distinction lies in the formulation of the loss function.

Our hybrid model is capable of capturing the diurnal and seasonal variations between the mean values of predicted and observed LE. The obtained data-driven parameterizations of the latent variables r_s and r_a are evaluated against the micro-meteorological conditions to validate their physical plausibility. We show that our hybrid modeling approach not only improves the rigid ad-hoc formulations of mechanistic models using observations, but also that hybrid models provide interpretable results that obey the physical laws of energy and mass conservation, in contrast to

black-box ML models.

Our presented hybrid modeling approach can be extended to global generalizations of LE flux estimates and serve as observation-based parameterizations of r_s and r_a in complex land surface and Earth system models.

[1] W. L. Zhao *et al.*, “Physics‐Constrained Machine Learning of Evapotranspiration,” *Geophys. Res. Lett.*, vol. 46, no. 24, pp. 14496–14507, Dec. 2019, doi: 10.1029/2019GL085291.