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GLEAM4: Improving global terrestrial evaporation estimates with hybrid modelling

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Terrestrial evaporation (*E*) is a keystone flux linking water, energy and carbon cycles. Consequently, monitoring of *E* at high temporal and spatial resolution over an extended period is crucial to diagnose climate change and its influence on the acceleration of the global hydrological cycle. As *E* cannot be directly observed from space, a modelling approach is required to derive *E* from global, observational remote sensing and meteorological datasets[1]. The array of available approaches ranges from purely data-driven *E* retrievals[2] to physically-based estimates from traditional land surface models.

In this presentation, we introduce the fourth version of the Global Land Evaporation Amsterdam Model (GLEAM), a hybrid evaporation model that harnesses the synergy between process-based modelling and machine learning. The conceptual backbone of the model, a soil–vegetation water balance module, is updated from earlier GLEAM versions with new representations of interception loss[3], plant access to groundwater[4] and potential evaporation. Additionally, earlier empirical evaporative stress functions are replaced by deep neural networks trained on eddy-covariance and sapflow data to better represent the complex physiological response of vegetation to multiple environmental stressors[5]. Future research directions include the increase in temporal resolution to sub-daily and the training of the stress functions in an end-to-end differentiable modelling framework[6].

GLEAM4 continuous, daily datasets at 0.1° spatial resolution covering the period 1980–2023 — including evaporation and its components, soil moisture, potential evaporation and evaporative stress estimates — will be openly available via www.gleam.eu upon publication.

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