Towards Robust Parameterizations in Ecosystem-level Photosynthesis Models

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Photosynthesis model parameters represent vegetation properties or sensitivities of photosynthesis processes. As one of the model uncertainty sources, parameters affect the accuracy and generalizability of the model. Ideally, parameters of ecosystem-level photosynthesis models, i.e., gross primary productivity (GPP) models, can be measured or inversed from observations at the local scale. To extrapolate parameters to a larger spatial scale, current photosynthesis models typically adopted fixed values or plant-functional-type(PFT)-specific values. However, the fixed and PFT-based parameterization approaches cannot capture sufficiently the spatial variability of parameters and lead to significant estimation errors. Here, we propose a Simultaneous Parameter Inversion and Extrapolation approach (SPIE) to overcome these issues[1].

SPIE refers to predicting model parameters using an artificial neural network (NN) constrained by both model loss and ecosystem features including PFT, climate types, bioclimatic variables, vegetation features, atmospheric nitrogen and phosphorus deposition and soil properties. Taking a light use efficiency (LUE) model[2] as an example, we evaluated SPIE at 196 FLUXNET eddy covariance flux sites. The LUE model accounts for the effects of air temperature, vapor pressure deficit, soil water availability (SW), light saturation, diffuse radiation fraction and CO_2 on GPP using five independent sensitivity functions. The SW was represented using the water availability index[3] and can be optimized based on evapotranspiration. Thus, we optimized the NN by minimizing the model loss which consists of GPP errors, evapotranspiration errors, and constraints on sensitivity functions[2]. Furthermore, we compared SPIE with 11 typical parameter extrapolating approaches, including PFT- and climate-specific parameterizations, global and PFT-based parameter optimization, site-similarity[4], and regression methods using Nash-Sutcliffe model efficiency (NSE), determination coefficient (R^2) and normalized root mean squared error (NRMSE).

The results in ten-fold cross-validation showed that SPIE had the best performance across various temporal and spatial scales and across assessing metrics. None of the parameter extrapolating approaches reached the same performance as the on-site calibrated parameters (NSE=0.95), but SPIE was the only approach showing positive NSE (=0.68) in cross-validation across sites. Moreover, the site-level NSE, R^2, and NRMSE of SPIE all significantly outperformed per biome and per climate type. Ranges of parameters were more constrained by SPIE than site calibrations.

Overall, SPIE is a robust parameter extrapolation approach that overcomes strong limitations observed in many of the standard model parameterization approaches. Our approach suggests that model parameterizations can be determined from observations of vegetation, climate and soil properties, and expands from customary clustering methods (e.g., PFT-specific parameterization). We argue that expanding SPIE to other models overcomes current limits in parameterization and serves as an entry point to investigate the robustness and generalization of different models.

References:

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