Title: Quantifying Terrestrial Drivers of Uncertainty in Earth System Model Predictions Using Machine Learning

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Project Abstract: Climate scientists strive to improve predictive understanding of Earth system variability and change using models of ever-increasing mechanistic complexity and resolution. Continuing to improve such Earth system models (ESMs) will require increasing integration across several disciplines to determine key mechanisms and model parameters, where and when to place observations, the nature of impacts to human systems, and how to deal efficiently with large model output datasets. Uncertainty quantification (UQ) algorithms that use machine learning and artificial intelligence link observations and models together to produce credible simulations of Earth system behavior with uncertainty estimates. Deep neural networks (DNNs) combined with dimension-reduction techniques can be used to build fast-to-evaluate surrogate models of spatiotemporally varying model output fields using a smaller number of ESM ensemble members and higher accuracy than other methods. These surrogate models can then be used for uncertainty quantification techniques such as global sensitivity analysis, data assimilation or model calibration, leading to more rapid advances in model development, prediction of climate processes, and the design of new observation systems that are optimally suited to reducing model output uncertainties. Here we focus on uncertainty quantification of historical multi-site and global-scale predictions from the Energy Exascale Earth System land model (ELM) considering uncertainty in 12 key model parameters related to photosynthesis and water cycling. We constrain these model parameters using FLUXNET observations and present a new framework using surrogate models to calibrate using globally gridded remote sensing observations, including sun-induced fluorescence (SIF).