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FY 2019 First Quarter Performance Metric: Evaluate the Effects of Uncertainty in Biogeochemistry Methodology in the Land Model

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1.0 Product Definition

Soils contain the largest terrestrial pool of organic carbon (C), storing at least twice as much C as earth's atmosphere (Köchy et al., 2015; Scharlemann et al., 2014). Uncertainties surrounding the response of soils to climatic and other changes contribute substantial uncertainty to C cycle and climate projections in the Earth system (Arora et al., 2013; Friedlingstein et al., 2014; Todd-Brown et al., 2013): the magnitude of their uncertainty is comparable to that of cloud feedbacks, traditionally regarded as the most significant unknown in climate modeling (Gregory et al., 2009). For example, Jones and Falloon (2009) reported a strong relationship between changes in soil organic C (SOC) and the strength of simulated C-climate feedbacks within ESMs, while Riley et al. (2018) and Gaudio et al. (2015) found that model representation of nitrogen biogeochemistry and uptake patterns had significant climatic effects at larger spatial scales. At the same time, models' structural uncertainty (the uncertainty deriving from how various models represent particular processes differently) is an unknown factor (Tebaldi and Knutti, 2007); there have been few attempts to examine how structural uncertainty within a single model—as opposed to model-to-model variability in, e.g., CMIP5 (Friedlingstein et al., 2014; Knutti and Sedláček, 2012)—affects model behavior and performance (Ricciuto et al., 2008). The investigation here indicates that the structural uncertainty deriving from models' biogeochemical process representation is significant, although not as large as other sources such as parametric uncertainty (uncertainty deriving from the model inputs such as field-based data).

2.0 Product Documentation

The U.S. Department of Energy's Energy Exascale Earth System Model (E3SM) is unusual among ESMs in that it has two approaches to terrestrial biogeochemistry in its land model, the E3SM Land Model (ELM): the primary approach ELMv1-CTC-CNP (led by a team at Oak Ridge National Laboratory) and the alternative ELMv1-ECA-CNP (led by Lawrence Berkeley National Laboratory group). These differ in three key aspects of biogeochemistry—stoichiometry, allocation, and nutrient competition—and represent distinct approaches to the overall problem, as described below. To evaluate the effects of uncertainty in biogeochemistry methodology, we performed a series of site- and global-scale uncoupled simulations using both CTC and ECA. The models' outputs were compared against a variety of observational reference data sets. This work will allow the model structural uncertainty in this area to be assessed, for the first time, against other sources of uncertainty, e.g., parametric and ensemble sources.

3.0 Detailed Results

Structural and Conceptual Differences between the Approaches

The CTC approach is grounded in the v1 E3SM coupled biogeochemistry science questions, as the team argues that models must be designed to address specific research problems. This aims for the simplest and most tractable set of model changes that can still represent dominant ecosystem-level processes hypothesized to exert control over climate system feedbacks in the face of coupled C-nutrient interactions and multiple nutrient limitations. A specific CTC feature is phosphorus cycle dynamics (Yang et al., 2014) in the soil and vegetation components of the E3SM Land Model (ELM), using newly developed global-scale data sets describing the spatial distribution of different soil phosphorus pools (Yang et al., 2013). Rather than proceed to second- and third-order process representations that could not be parameterized effectively from existing observations, the team first addressed the emergent problems in related processes. This approach prioritizes the spatial distribution of different nutrient pools, and integrates ecosystem-level nutrient cycle to study CO2-climate system feedback interactions. The modeling approach is flexible and simple, but able to capture process-level understanding at global scales.

In contrast, the ECA approach embraces and implements many of the complexities of the biogeochemical processes that explain observed nutrient constraints on the C cycle, with the team including in ECA what they consider to be the most important and relevant trait-based processes: (1) N and P competition between microbes, abiotic processes, and roots using the trait-based Equilibrium Chemistry Approximation (ECA) approach (Zhu et al., 2017); (2) dynamic plant CNP stoichiometry (Ghimire et al., 2016); (3) leaf CNP effects on photosynthesis (Riley et al., 2018); and (4) dynamic CNP allocation within the plant. The highly mechanistic ECA constitutes a novel approach to representing competition between plants and soil microbes for limiting nutrients; this process sophistication and flexibility means that ECA may be more likely to correctly represent perturbation responses to factors likely to change over coming decades (e.g., CO2, temperature, hydrology).

Modeling Runs and Comparison Benchmarks

The following series of simulations was performed using both the CTC and ECA biogeochemistry models:

- Four global 2° runs with vertically resolved soil BGC using the observed atmospheric CRUNCEP versus GSWP3 driving data sets, and no land use change versus land use change. These each had varying CO2 concentrations and standard data sets for changing N deposition over the historical time period.
- A series of site-level runs co-located with FLUXNET observations (Baldocchi, 2008) using site-specific driving data but global parameterizations of, e.g., Plant Functional Types (PFTs).
- A series of site-level runs at nitrogen (N) and phosphorus (P) fertilization sites.

We performed three primary groups of evaluations based on these runs, model-data comparisons that aimed to test the models' relative performance in biogeochemical cycling, energy, and water exchange:

- ILAMB: the primary E3SM diagnostic tool, with multifaceted global coverage (Hoffman et al., 2017; Luo et al., 2016); https://www.ilamb.org.
- FLUXNET: single sites (not global) but high-quality and widely accepted measurements of land-atmosphere CO_2 and energy exchange (Baldocchi, 2008); http://fluxnet.fluxdata.org.
- GOLUM: model-data product, not observational; global coverage, integrated carbon, nitrogen, and phosphorus stocks and fluxes (Wang et al., 2018).

Results: ILAMB

Carbon stocks and fluxes were generally better simulated using GSWP3 than CRUNCEP; with land use than without; and slightly better, overall, by CTC than by ECA (although there were exceptions such as burned area, see below; net ecosystem exchange (NEE); and soil C). There was no obvious difference when examining relationships between biotic and abiotic variables, except perhaps for GPP versus air temperature and LAI versus precipitation, where the CTC model seemed significantly better (Figure 1). The GSWP3 driving data almost always produced higher scores than did the CRUNCEP data. The CTC runs did not exhibit burned area commensurate with the GFED benchmark data, scoring 0.44 compared to ECA's 0.53 score. Neither model fully captured the annual fire cycle, but ECA came closer.

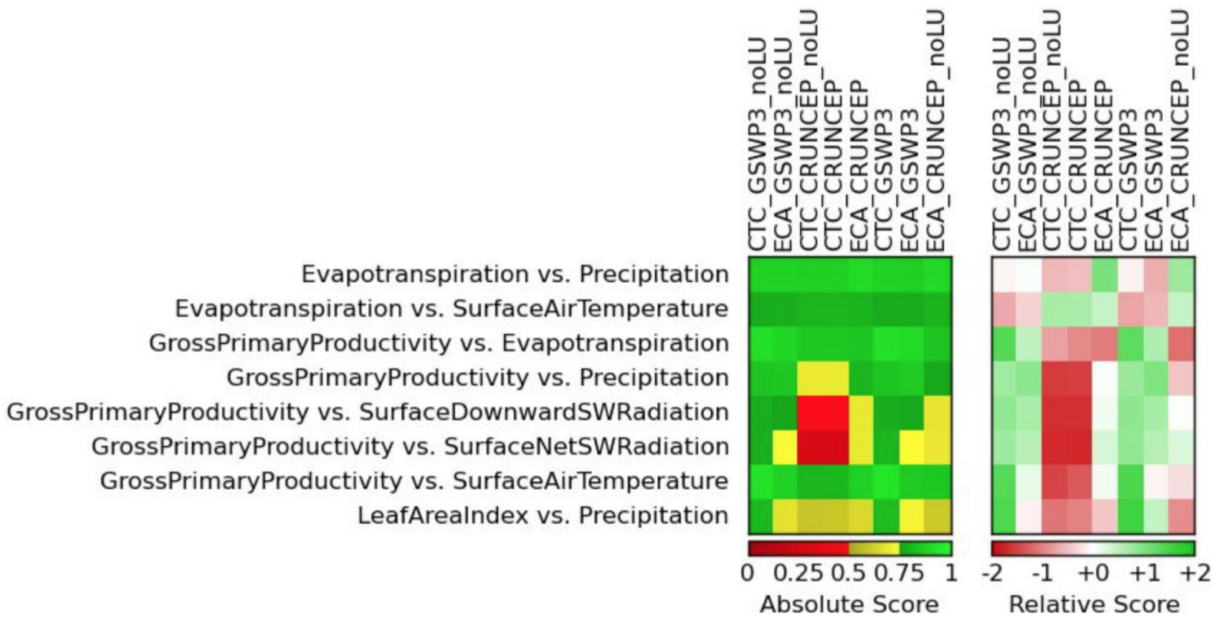

Figure 1. Summary graphic from the ILAMB system showing model performance in a variety of two-variable relationships; green is better in both the absolute (left) and relative (right) panels.

Results: FLUXNET

The FLUXNET2015 Tier1 data release (http://fluxnet.fluxdata.org/data/fluxnet2015-dataset/) includes data collected at sites from multiple regional flux networks, and features several improvements to the data quality control protocols and the data processing pipeline. Many studies have compared model and remote-sensing results to its data, and/or used these data for upscaling to global gridded products. Model performance was assessed at both monthly and annual timescales.

Both models tend to under-predict annual GPP at medium to high values. The ECA model outperformed CTC for monthly and annual GPP, but this difference was driven by a single evergreen broadleaf forest site (AU-Tum). The models' predictive ability varied wildly by IGBP code (i.e., ecosystem type, Figure 2). They exhibited particular problems with deciduous broadleaf forests, open shrublands, and wetlands, and particular strengths in evergreen broadleaf forests, grasslands, savannas, and woody savannas. Significant divergences between the models were seen for mixed forests, open shrublands, and wetlands.

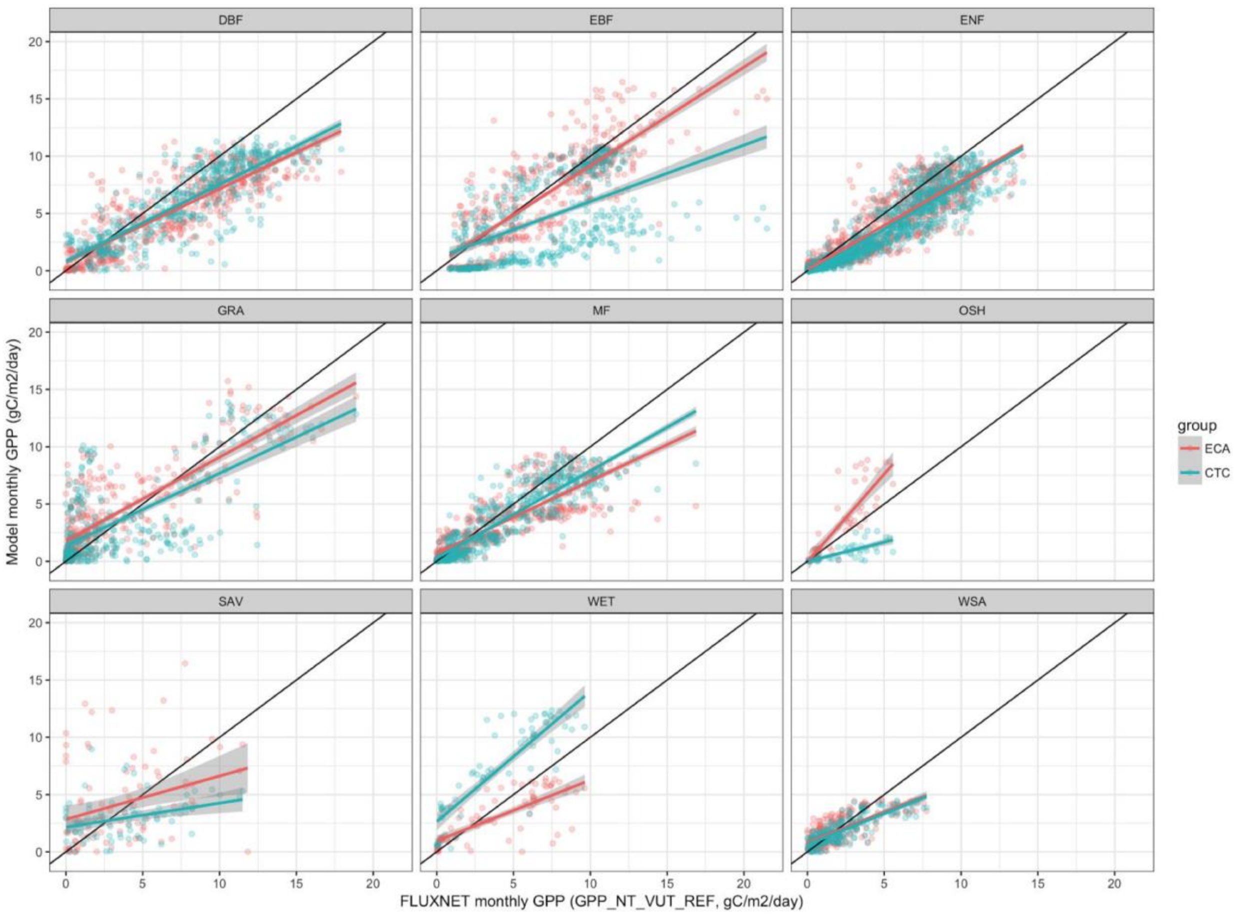

Figure 2. Monthly FLUXNET GPP versus simulated GPP, by ecosystem type: deciduous broadleaf forests (DBF), evergreen broadleaf forests (EBF), evergreen needleleaf forests (ENF), grasslands (GRA), mixed forests (MF), open shrublands (OSH), savannas (SAV), wetlands (WET), and woody savannas (WSA). Solid black lines are 1:1.

Both models had trouble with NEE, particularly at sites with strong annual carbon sinks. FLUXNET annual NEE is known to be quite problematic, however, because of CO2 advection and storage-term uncertainties. The models generally did a good job with latent heat flux at the FLUXNET sites.

Results: GOLUM

This analysis compared the area-weighted latitudinal variations of mean annual pools and fluxes from 2001 to 2010 as simulated by the models with those from the GOLUM data set, a new (Wang et al., 2018) gridded product that combines the CARDAMOM (Pinnington et al., 2016) data-constrained C-cycle analysis with spatially explicit data-driven estimates of N and P inputs and losses and with observed stoichiometric ratios. The variables compared included a wide variety of root, wood, vegetation, and soil pools of C, N, and P; NPP; and plant N and P uptake. For each variable, an agreement index, the Pearson correlation coefficient, and RMSE were computed.

In general, CTC outperformed ECA when comparing against GOLUM (Figure 3). ECA simulated higher P in vegetation biomass than in soil; much higher litter C and N than both CTC and GOLUM data; and highly variable litter P.

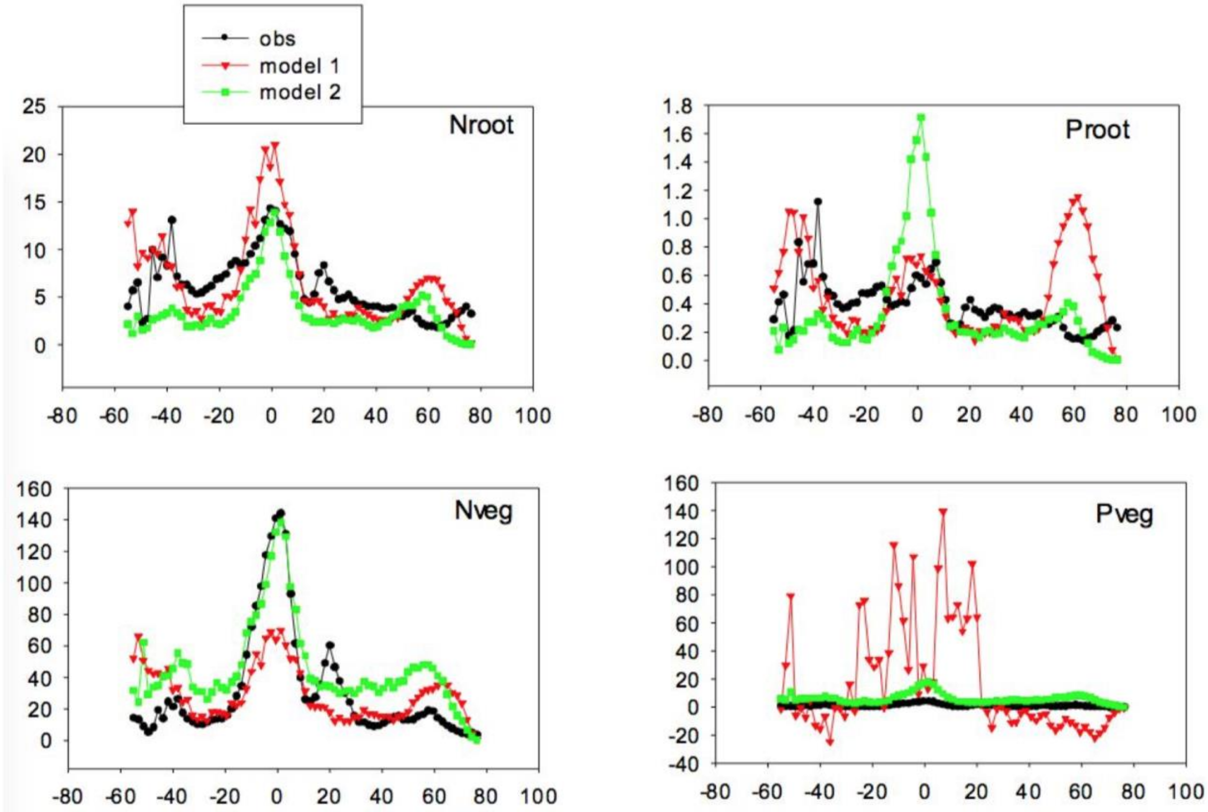

Figure 3. Zonal latitudinal values for root and vegetation N and P for ECA (“Model 1”), CTC (“Model 2”), and GOLUM data.

4.0 Summary

Typical model-to-model comparisons, e.g., using CMIP5 (Taylor et al., 2012) outputs, typically confound at least two separate aspects: the structural uncertainty of different process representations, and the model uncertainty derived from different approaches to modeling the earth system. This effort afforded a rare look at structural uncertainty within a single model framework, allowing for a direct comparison with model variability. For example, the CTC and ECA approaches within ELM differ in their estimation of global heterotrophic respiration (RH), a major terrestrial C flux, by 16-20%, with a standard deviation of ~5 Pg C. This can then be directly compared to the CMIP5 RH spread of 41-72 Pg C with a standard deviation of ~9 Pg C (Shao et al., 2013). Input scenarios—the emissions projections used to drive ESMs during the 21st century—and internal variability (Kay et al., 2015) constitute even larger sources of uncertainty.

Looking specifically at ELM, we conclude that both the CTC and ECA approaches have made progress in improving aspects of the performance of the model's terrestrial biogeochemistry: the former prioritizing longer timescales and ecosystem- to global-level questions, and the latter shorter timescales and soil biogeochemical process fidelity. This raises interesting questions about the degree of model process realism and parametric complexity appropriate for a global ESM, versus short- and medium-term risk in terms of model performance and work required. It may be, for example, that the most 'realistic' approach at the site scale does not provide adequate global performance because of scaling or driving data issues. Finally, this analysis provides the basis for a subsequent, quantitative assessment of structural factors relative to other sources of model variability.

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