The BGC Feedbacks Project

Quantifying Feedbacks and Uncertainties of Biogeochemical Processes in Earth System Models

Laboratory Research Manager:
Forrest M. Hoffman (ORNL)

Senior Science Co-Lead:
William J. Riley (LBNL)

Chief Scientist:
James T. Randerson (University of California Irvine)

Technical Co-Managers, University Co-PIs, and Science Co-Leads:
Forrest M. Hoffman (ORNL), William J. Riley (LBNL), James T. Randerson (UCI), Scott M. Elliott (LANL), Gretchen Keppel-Aleks (UM), Charles D. Koven (LBNL), Umakant Mishra (ANL), J. Keith Moore (UCI), and Peter E. Thornton (ORNL).

Biological and Environmental Research (BER) Regional & Global Climate Modeling (RGCM) Program

Scientific Focus Area (SFA) Annual Progress Report

Tuesday, June 30, 2015

The BGC Feedbacks Project will identify and quantify the feedbacks between biogeochemical cycles and the climate system, and quantify and reduce the uncertainties in Earth System Models (ESMs) associated with those feedbacks. The BGC Feedbacks Project will contribute to the integration of the experimental and modeling science communities, providing researchers with new tools to compare measurements and models, thereby enabling DOE to contribute more effectively to future climate assessments by the U.S. Global Change Research Program (USGCRP) and the Intergovernmental Panel on Climate Change (IPCC).

Contents

1 Program Overview

As Earth system models (ESMs) become increasingly complex, there is a growing need for comprehensive and multi-faceted evaluation, analysis, and diagnosis of model results. The relevance of model predictions to DOE's energy-related mission hinges in part on the assessment and reduction of uncertainty in predicted biogeochemical cycles, requiring repeatable, automated analysis methods and new observational and experimental data to constrain model results and inform model development. Over the past nine months in this Scientific Focus Area (SFA) (October–June) and the prior four years of the preceding project, our team has pioneered the development and application of new diagnostic approaches, resulting in 68 published papers, 6 manuscripts in review or revision, and additional papers in preparation. 35 of those papers have been published in the last 18 months (since January 1, 2014; see Appendix A). To advance our understanding of biogeochemical processes and their interactions with climate under conditions of increasing atmospheric CO_2 levels, we will continue to expand these analyses and diagnostics capabilities for assessing biogeochemistry–climate feedbacks, including assessment of ocean biogeochemical cycles and more effective use of integrated constraints provided by atmospheric trace gas measurements. We have undertaken a broader effort through this SFA activity that will advance the field through systematic evaluation of predicted biogeochemical processes and feedbacks in ESMs, with a focus on DOE's Accelerated Climate Modeling for Energy (ACME) Model, the DOE-NSF Community Earth System Model (CESM), and simulations from model intercomparison projects (e.g., CMIP5 and CMIP6). Our SFA also engages experimentalists in identifying model weaknesses and needed measurements and field experiments.

The overarching goals of this activity are to identify and quantify the feedbacks between biogeochemical cycles and the climate system, and to quantify and reduce the uncertainties in ESMs associated with those feedbacks. Through a comprehensive program of hypothesis-driven research, we are pursuing these goals by performing multi-model sensitivity analyses and comparison with best-available observations and derived metrics. We are focusing on biogeochemistry–climate feedbacks associated with changes on interannual to decadal timescales (including ecological impacts of changes in disturbance regimes and climate extremes) and longer-term trends (including potential tipping points). Important classes of observations that we use in our analysis include DOE Ameriflux observations of energy and carbon exchange, NASA remote sensing observations of land and ocean ecosystem characteristics, NOAA and NSF atmospheric trace gas observations from aircraft and surface sites, aboveground and belowground carbon inventories, atlases of three-dimensional ocean carbon and nutrient distributions compiled from shipboard observations, and syntheses of terrestrial ecosystem manipulations of carbon dioxide, warming, nutrients, soil moisture, and vegetation cover.

2 Scientific Objectives

The overarching goals of the proposed SFA are to identify and quantify the feedbacks between biogeochemical cycles and the climate system, and to quantify and reduce the uncertainties in ESMs associated with those feedbacks. These goals will be accomplished through hypothesis-driven multi-model sensitivity analyses and comparisons with observational data. In recognition of DOE science priorities for understanding the structure and function of ecosystems that may be impacted by a changing climate, the project will focus on biogeochemistryclimate feedbacks associated with changes on interannual to decadal timescales (including ecological impacts of changes in disturbance regimes and climate extremes) and longer-term trends (including potential tipping points). Our hypothesis-driven approach will be focused on model evaluation and reduction in the spread of model predictions. In particular, our SFA will have the following five overarching objectives:

1. Develop new hypothesis-driven approaches for evaluating ESM biogeochemical representations at site, regional, and global scales. Resulting derived data products will be used to evaluate the predicted mean state, seasonal cycle, interannual variability, and long term trends of ESMs, using observations from DOE field experiments, data centers, and other sources. These analyses will span land, ocean, and atmosphere domains, and will include biogeochemical and physical processes.

2. Investigate the degree to which contemporary observations can be used to reduce uncertainties in future scenarios, using an "emergent constraint" approach that draws upon the full ensemble of CMIP5 models.

3. Build an open-source benchmarking software system that leverages the growing collection of laboratory, field, and remote sensing data sets for systematic evaluation of ESM biogeochemical processes. This software will have well-developed land and ocean components and will be made freely available to the international community for the Coupled Model Intercomparison Project phase 6 (CMIP6) model development and evaluation.

4. Evaluate the performance of biogeochemical processes and feedbacks in different ESMs using the benchmarking system described in Objective 3. This will include comparisons of different versions of the Community Earth System Model (CESM) and DOE's Accelerated Climate Modeling for Energy (ACME) Model with the CMIP5 set of ESMs.

5. Provide international leadership for biogeochemistry model evaluation and benchmarking. Improve model experiment and model output archiving design to enable more effective model evaluation.

3 Management and Scientific Personnel

Effective management and integration of research activities across institutions into a cohesive and focused research effort requires active and involved leadership at multiple levels. Management of this project is shared among the team listed in Table 1, consisting of a Laboratory Research Manager (Principal Investigator), an Executive Council, a Chief Scientist, a Technical Co-Manager at each Laboratory, and Science Co-Leads. The Laboratory Research Manager is responsible, along with the Executive Council, for overall project coordination, including organization of meetings and conference calls, tracking of progress, and reporting to DOE Program Managers. The Executive Council—composed of the Laboratory Research Manager, the Chief Scientist, and the Senior Science Co-Lead—are responsible for the overall direction and conduct of scientific research, appointing Science Co-Leads, negotiating budget priorities, co-organizing community workshops, and coordinating research activities across institutions. Technical Co-Managers, one at each DOE Laboratory plus a single representative for university partnerships, are responsible for allocating resources and personnel and coordinating budget and progress reports for their institution(s). University Co-PIs, one at each university, are responsible for allocating resources and personnel and coordinating budget and progress reports for their respective institutions, and report to the Technical Co-Manager for University Partnerships. The Chief Scientist is selected by a majority of the Science Co-Leads and the Laboratory Research Manager, and establishes the scientific direction and evolutionary path of the project, in concert with the Executive Council and the Science Co-Leads. The Senior Science Co-Lead is selected by a majority of the Science Co-Leads, the Chief Scientist, and the Laboratory Research Manager. The Senior Science Co-Lead assists the Laboratory Research Manager in coordinating the overall project and must be from a DOE Laboratory. Science Co-Leads direct individual research efforts and coordinate research activities with the Executive Council.

Personnel who contributed to research, development, and management of the SFA and the preceding project in 2014 and 2015 are listed, along with their roles, in Table 2. Personnel include laboratory staff, university faculty and researchers, postdocs, and graduate students.

Table 1: The project management team consists of both Laboratory and university personnel.

SFA Team Member	**Institution**	**Laboratory Research Manager**	**Chief Scientist**	**Executive Council Member**	**Technical Co-Manager**	**University Co-PI**	**Science Co-Lead**
Hoffman, Forrest M.	ORNL	✓		✓	✓		✓
Riley, William J.	LBNL			✓	✓		✓†
Randerson, James T.	UCI		✓	✓	✓	✓‡	✓
Elliott, Scott M.	LANL				✓		✓
Keppel-Aleks, Gretchen	UM					✓	✓
Koven, Charles D.	LBNL						✓
Mishra, Umakant	ANL				✓		
Moore, J. Keith	UCI						✓
Thornton, Peter E.	ORNL						✓

†Senior Science Co-Lead
‡Lead University Co-PI

Table 2: Project personnel include laboratory and university staff, postdocs, and graduate students.

	SFA Team Member	Institution	Researcher	Developer	Manager	Title/Position
1.	Basile, Samantha[2]	UM	✓			Atmosphere Researcher
2.	Bisht, Gautam	LBNL	✓	✓		Scientific Developer for ILAMB
3.	Bouskill, Nicholas J.[1]	LBNL	✓			Land Researcher
4.	Collier, Nathan	ORNL	✓	✓		Scientific Developer for ILAMB
5.	Elliott, Scott M.	LANL	✓		✓	Ocean Co-Lead
6.	Fu, Weiwei[2]	UCI	✓			Ocean Researcher
7.	He, Yujie[1]	UCI	✓			Land Researcher
8.	Hoffman, Forrest M.	ORNL	✓		✓	Science Co-Lead, Land Co-Lead
9.	Keppel-Aleks, Gretchen	UM	✓		✓	Atmosphere Lead
10.	Koven, Charles D.	LBNL	✓		✓	Land Researcher
11.	Kumar, Jitendra	ORNL	✓			Land Researcher
12.	Levine, Paul[2]	UCI	✓			Land Researcher
13.	Maddalena, Damian[1]	ORNL	✓			Land Researcher
14.	Mao, Jiafu	ORNL	✓			Land Researcher
15.	Mishra, Umakant	ANL	✓		✓	Land Researcher
16.	Moore, J. Keith	UCI	✓		✓	Ocean Co-Lead
17.	Mu, Mingquan	UCI	✓	✓		Scientific Developer for ILAMB
18.	Negrón Juárez, Robinson I.	LBNL	✓			Land Researcher
19.	Randerson, James T.	UCI	✓		✓	Science Director, University Lead
20.	Riley, William J.	LBNL	✓		✓	Sr. Science Co-Lead, Land Co-Lead
21.	Shi, Xiaojing	ORNL	✓			Land Researcher
22.	Song, Xia[1]	ORNL	✓			Land Researcher
23.	Tang, Jinyun	LBNL	✓			Land Researcher
24.	Thornton, Peter E.	ORNL	✓		✓	Land Researcher
25.	Wang, Gangsheng	ORNL	✓			Land Researcher
26.	Wang, Shanlin[1]	LANL	✓			Ocean Researcher
27.	Xu, Min	ORNL	✓			Land Researcher
28.	Xu, Xiyan[1]	LBNL	✓			Land Researcher
29.	Yang, Cheng-En[2]	ORNL/UTK	✓			Land Researcher
30.	Yang, Xiaojuan	ORNL	✓			Land Researcher
31.	Zhu, Qing[1]	LBNL	✓			Land Researcher

[1]Postdoc

[2]Graduate Student

4 Performance Milestones and Metrics

Over the past year, the BGC Feedbacks SFA team has made substantial progress on many of the tasks associated with benchmarking development and on many of the science questions for marine and terrestrial carbon–climate analyses. In this section, we report on this progress and present results from manuscripts that are published or in press. Due to the requested page limit for this report, only a representative subset of our research papers are presented. Reported progress on development tasks and science questions is later summarized in Table 3.

4.1 ILAMB prototype software package

A prototype version of the International Land Model Benchmarking (ILAMB) software package was developed ahead of schedule and was demonstrated to DOE Program Managers on September 8, 2014, in Germantown, Maryland. Over the last nine months, additional metrics and capabilities have been added to this ILAMB prototype. The most recent prototype, version 0.7.7, is in use at NCAR for testing the Community Land Model (CLM) as new process representations are being introduced, leading to CLM5. In addition, version 0.7.7 is presently being introduced into the Accelerated Climate Model for Energy (ACME) workflow system for routine evaluation of ACME model simulation results. The ILAMB prototype will be the subject of a manuscript, currently in preparation, that describes its use in assessing CMIP5 results. We further expect that ILAMB diagnostics from this prototype will be integral to a paper describing the released CLM5 model.

This effort contributes directly to performance on Tasks D1 and D2.

4.2 Next generation benchmarking software package

We have begun developing a next generation python package for performing model-data benchmarking activities. The package is implemented in python and schematically represented in Figure 1. First we have built a small library (`ilamblib`, shown in green) for many commonly performed operations in analysis code. This is an important layer as it gives developers an efficient and unified way of writing new analysis code. On top of this library we build two main abstract objects. The `ModelResults` object makes querying a set of results associated with a model more simple, circumventing the need for the user to directly work with the output files. This interface to models also allows us to write code which executes the model, opening a door for models to more actively interact with the python package. The Confrontation object is a single place where a developer can add all the analysis code needed for a particular benchmark. This allows for great modularity as well as parallelism as the work over a model-confrontation pair is local.

In addition to analysis code, we have developed more dynamic methods for presenting the results of the analysis using HTML and javascript. The screenshot depicted in Figure 2 represents a webpage which our python package generates. As a model is clicked in the table or a region selected from the pulldown menu, the graphics and information update to reflect the changes. Furthermore, we have saved the results of the analysis into datafiles which can be downloaded from the table. This gives scientists the ability to dig into and scrutinize the results.

This effort contributes directly to performance on Tasks D1 and D3.

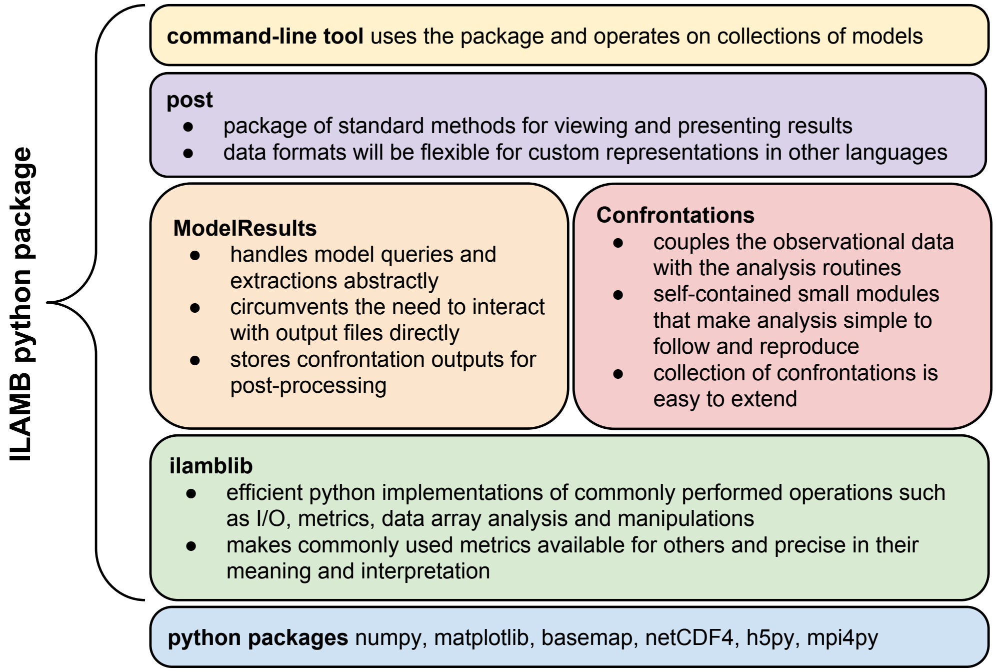
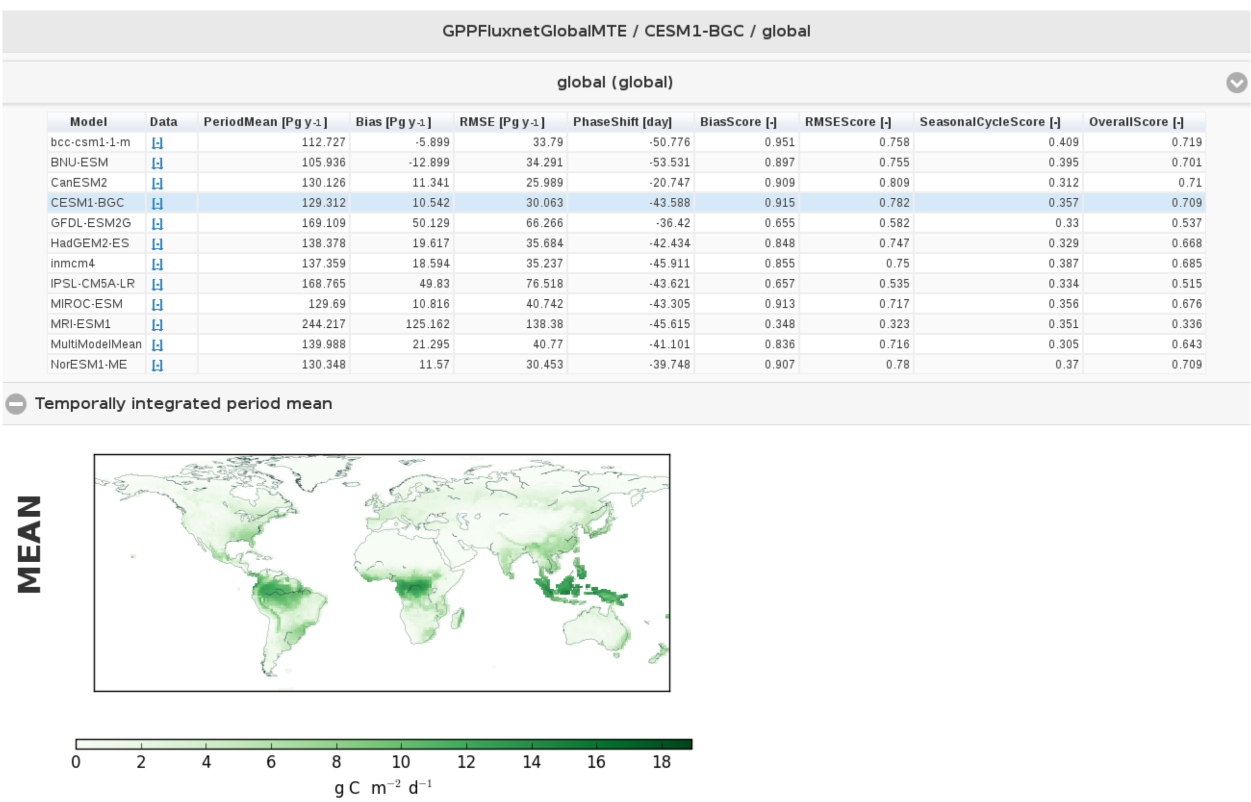


Figure 1: Schematic depiction of the next generation ILAMB python package.


GPPFluxnetGlobalMTE / CESM1-BGC / global

global (global)

Model	Data	PeriodMean [Pg y-1]	Bias [Pg y-1]	RMSE [Pg y-1]	PhaseShift [day]	BiasScore [-]	RMSEScore [-]	SeasonalCycleScore [-]	OverallScore [-]
bcc-csm1-1-m	[-]	112.727	-5.899	33.79	-50.776	0.951	0.758	0.409	0.719
BNU-ESM	[-]	105.936	-12.899	34.291	-53.531	0.897	0.755	0.395	0.701
CanESM2	[-]	130.126	11.341	25.989	-20.747	0.909	0.809	0.312	0.71
CESM1-BGC	[-]	129.312	10.542	30.063	-43.588	0.915	0.782	0.357	0.709
GFDL-ESM2G	[-]	169.109	50.129	66.266	-36.42	0.655	0.582	0.33	0.537
HadGEM2-ES	[-]	138.378	19.617	35.684	-42.434	0.848	0.747	0.329	0.668
inmcm4	[-]	137.359	18.594	35.237	-45.911	0.855	0.75	0.387	0.685
IPSL-CM5A-LR	[-]	168.765	49.83	76.518	-43.621	0.657	0.535	0.334	0.515
MIROC-ESM	[-]	129.69	10.816	40.742	-43.305	0.913	0.717	0.356	0.676
MRI-ESM1	[-]	244.217	125.162	138.38	-45.615	0.348	0.323	0.351	0.336
MultiModelMean	[-]	139.988	21.295	40.77	-41.101	0.836	0.716	0.305	0.643
NorESM1-ME	[-]	130.348	11.57	30.453	-39.748	0.907	0.78	0.37	0.709

Temporally integrated period mean

Figure 2: Sample HTML output from the next-generation ILAMB python package.

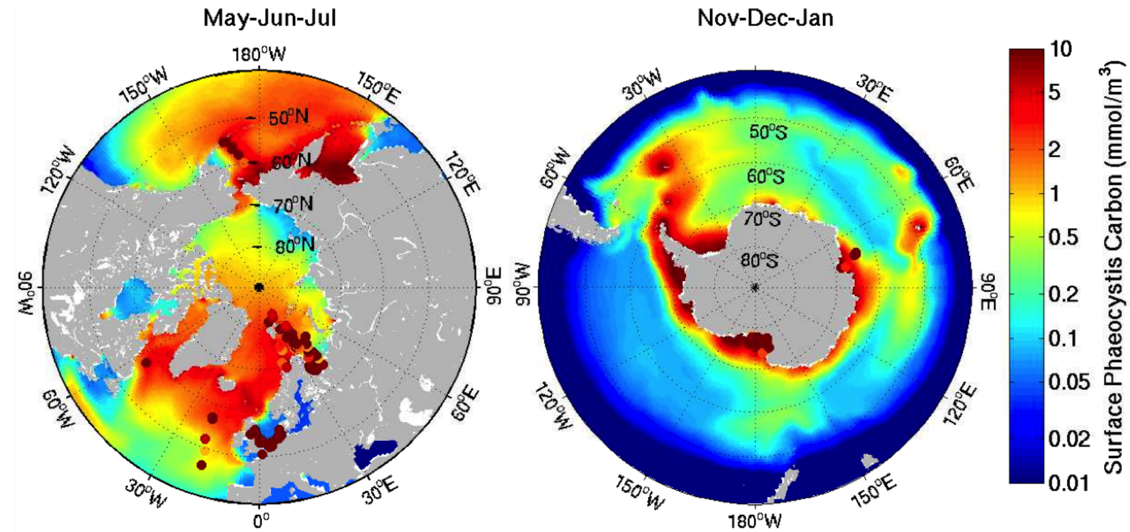


Figure 3: Benchmarking of specialized DOE marine geocycles: controls on surface ocean DMS. In review, Wang et al. (*J. Geophys. Res.*). Improved simulation for the polar ecodynamics and distributions of colonial *Phaeocystis*, a significant producer of marine organo(reduced)-sulfur. Computations conducted in CESM versions now utilized for ongoing HiLAT simulations. Measurement comparison points were taken from the PANGAEA data set. All progress on the DMS mechanism will transfer to ACME.

4.3 Marine biogeochemistry (organics and aerosols)

Surface ocean organosulfur mechanisms involving full phytoplanktonic and bacterial interactions now provide realistic emissions of dimethyl sulfide into the global troposphere. Observational data sets being drawn upon for validation include PANGAEA ecosystem structural tables and the LANA mixed layer trace gas collection (Figure 3). Relevant publications are now entering the AGU family of journals. The familiar dissolved organic carbon or DOC available in many biogeochemistry codes is now being segregated into its specific macromolecular composition. Lipids, proteins, and polysaccharides along with their phosphorylated, aminated and acidic variants, heteropolycondensates and humic substances are all distinguished for planetary scale surfactant mapping purposes. Under the present SFA we are creating our own data base, because no others are currently in existence. Results will be made available on the web under the acronym/name OCEANFILMS. This is a strong cross-laboratory collaboration involving LANL, PNNL and LLNL. Detailed parameterizations for bubble bursting and sea spray generation of aerosol organic mass will be comprehensively included. Influence of organic coverage on properties of the global microlayer will be studied, relative to greenhouse gas sea-air transfer.

Taken together, the COSIM reduced sulfur and DOC surfactant simulations provide the department with a complete capability to study marine biogenic aerosol precursors. Global indirect effect calculations thus become uniquely possible within the department systems model family. There is the potential to quantify feedbacks in the single most uncertain component of the present day climate system. Diffusion toward the international community has already begun, through agreements with our sister code CESM which remains under development at NCAR. Publications describing the overall research are appearing in ERL, ACP, Biogeochemistry and AGU journals plus one particularly high profile contribution has just been accepted at *Science Advances* (Figure 4). Both our

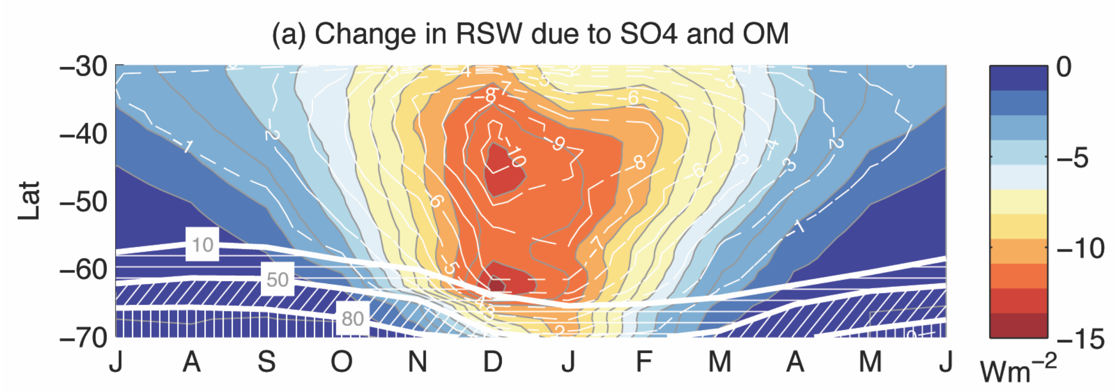


Figure 4: Feedbacks from specialized DOE geocycles to the marine atmosphere: Biogenic aerosol emissions operate on cloud droplet number concentrations over the Southern Ocean. In press, McCoy et al. (*Science Advances*). A multiple linear regression analysis superimposed on one dimensional radiation transfer is used to attribute almost two thirds of variability in reflected shortwave to biogeochemical aerosol sources. Biology thus controls between ten and twenty watts per meter squared during the critical summer period. This calculation includes both sulfate from DMS and macromolecular POA. Across the international community, the underlying simulations can only be performed in DOE model systems. The work represents an early application of the new OCEANFILMS database.

taxonomic structure papers and the Science work discuss aerosol-cloud-ecosystem feedback mechanisms which become accessible given our dynamic mechanisms. We will argue that the department is positioned to conduct super-CLAW ensembles for natural aerosol cycles.

COSIM Benchmarking scientists have also recently tested and incorporated the first global ice algal simulator, primarily for insertion into a biogeochemical CICE model, which figures prominently in plans for both ACME and DOE HiLAT. Emphasis will be placed upon pigment/energy deposition feedbacks leading to Arctic amplification. But simultaneously we will elucidate the role of detrital macromolecules in gel formation. Colloids forming from exopolymers injected into brine channels can dramatically alter the configuration of pack ice pore networks. Nutrient penetration, light absorption and crystalline matrix formation may all be affected. Relevant benchmarking has been supported entirely by the current project. Chlorophyll data from a variety polar campaigns are utilized as a primary basis for validation, but again the environmental organic chemistry turns out to be understudied and underorganized. Hence another independent d-basing effort must be undertaken. This will appear under a combined CICE-OCEANFILMS banner since the compounds involved exhibit ice-to-brine adsorption properties. Furthermore they bind the growth limiting trace metal iron tightly and internally within the pack. Thus we we will include ligand-chelation equilibrium constants in the data set. This effort is more recent than any of our other projects, so that most of publications are still in preparation. They will likely appear in AGU venues and the new code development format JAMES.

The DOE-side marine sciences benchmarking project is specialized at several levels, but it is nonetheless designed to be readily extensible. We anticipate connections with multiple, rapidly-approaching data base efforts distributing themselves across the community. CMIP type validation should move beyond standard GLODAP applications to include the new generation of automated biogeochemical float sensors/detectors. The SOCCOM experiments will be among the first to utilize such information. Hence DOE systems models are natural participants—alternative mechanisms and variable mesh resolution complement the peculiarities of Southern Ocean biogeochemistry. Ice edge and eddying processes will be representable along basin scale fronts and across circumpolar currents. Our aerosol flux and global organic chemistry work parallel the proposed EXPORTS and NASA (P)ACE campaigns. Such missions are high on the earth science recommendation lists of both the independent NRC and NAS. The acronym ACE in fact signifies marine Aerosol-, Cloud- and Eco- systems taken collectively. Department models clearly bring all the most appropriate mechanisms to the table. By the same token our benchmarking/benchmarked ice algal simulations complement recent nutrient, primary production and aerosol/trace gas experiments targeted to high latitudes. Examples include ARCSS and ACCACIA along with arctic PPARR intercomparisons. We are currently exploring and building collaborations in these highly interdisciplinary areas, with alternate international agencies.

This effort contributes directly to performance on Question E5.

4.4 Marine biogeochemistry (carbon cycle feedbacks)

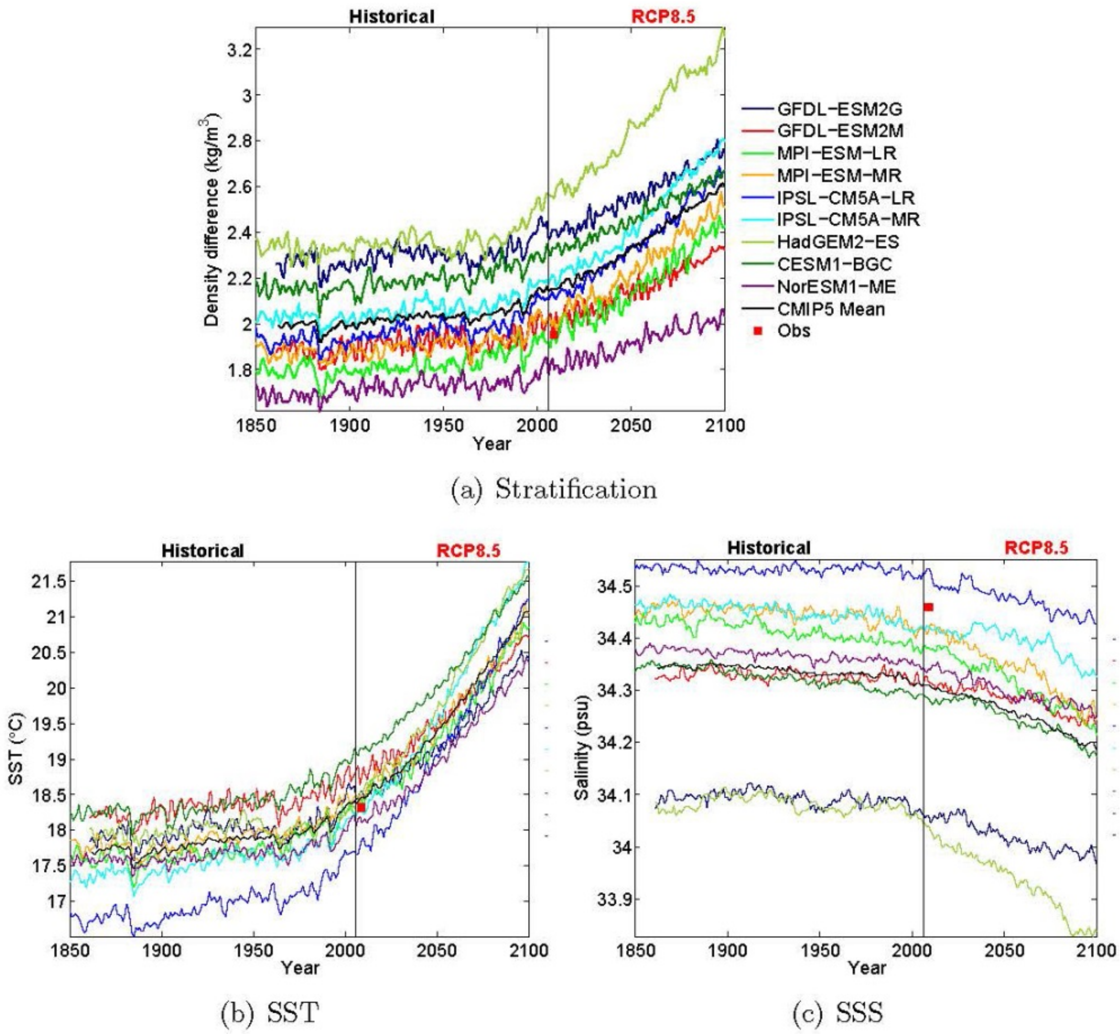
Work at UCI on the marine biogeochemistry side has focused on an inter-comparison of the CMIP5 ocean biogeochemical models. We find considerable model spread when comparing output from the models with observational estimates of key metrics from the current era, including global net primary production (NPP) and mean surface nutrient concentrations. The inherent export efficiency built into the models (and largely a function of the simulated phytoplankton and zooplankton community structure) drives the wide model spread in NPP. In terms of projections of NPP into the future, one group of models (CESM, IPSL, and GFDL) predicts larger declines in export production (EP, sinking carbon flux to ocean interior) than in NPP, because the community structure shifts in key regions. The other models have a simpler representation of the phytoplankton community and cannot capture these composition shifts. This class of models predicts larger declines in NPP. As part of this work we have also been developing analysis tools for looking across all the models that will be incorporated into the SFA benchmark system. A paper based on this work has recently been submitted to Biogeosciences Discusssions (Fu, Randerson, and Moore, submitted). Below we highlight some of the key results from this paper (all figures are from the submitted paper).

Surface Warming and Freshening Increases Stratification

As a consequence of high greenhouse gas emissions under Representative Concentration Pathway (RCP) 8.5, surface ocean waters warm strongly over the coming century in all the CMIP5 model simulations. There are also declines in the mean sea surface salinity. Both of these trends act to decrease the density of surface waters, and so to increase the stratification (defined as the density difference between 0 m and 200 m depth). Figure 5 shows the increasing mean sea surface temperatures (panel b), the decreasing mean sea surface salinity (panel c) and the resulting increasing stratification (panel a). Note that some models strongly overestimate the stratification for the current era (red square in panel a).

As stratification increases, surface nutrient concentrations decline

As stratification increases, the exchange of water between the surface ocean and sub-surface waters is reduced. Thus, the upward flux of nutrients to the surface that supports biological productivity decreases. This is seen in the generally declining trends in mean surface nitrate and phosphate in Figure 6. Note also the wide spread in simulated nutrient concentrations for the current era,

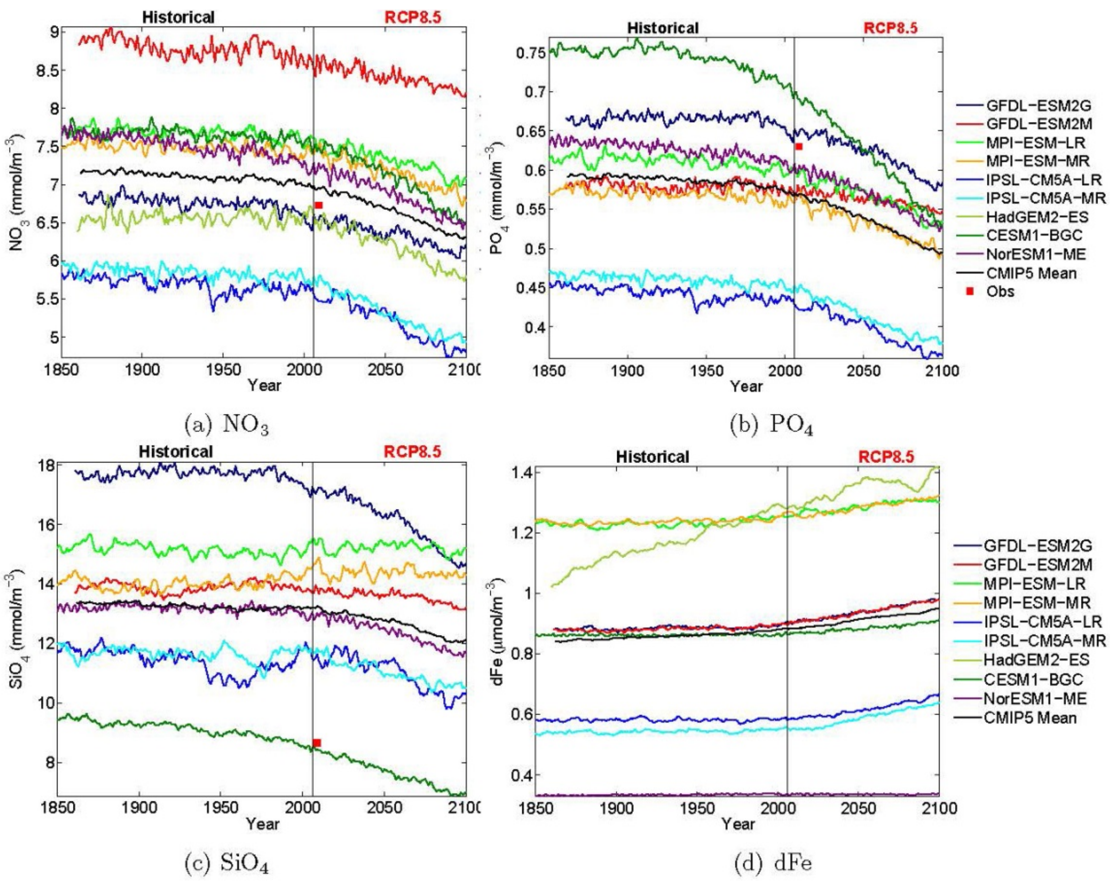


(a) Stratification

(b) SST

(c) SSS

Figure 5: Time series of global mean stratification, SST, and SSS for historical run and RCP 8.5 over 1850–2100. Stratification is defined as the density difference between 200 m and the surface. Red square indicates observations from the WOA2009 data.



(a) NO_3 (b) PO_4 (c) SiO_4 (d) dFe

Figure 6: Time series of mean nitrate (NO_3), phosphate (PO_4), silicate (SiO_4), and dissolved iron (dFe) concentrations (0–100 m) are shown for 1850–2100. Red square indicates WOA2009 global mean values.

relative to the observed values (red squares).

As surface nutrients decline, biological production decreases

The group of models that show smaller declines in NPP than in EP (CESM, GFDL, IPSL) are those that can capture a shift in phytoplankton community with increasing nutrient stress (fewer diatoms, more small phytoplankton) (Figure 7).

Current Era Stratification Biases and the Future Projections of NPP and EP

The group of models that show the strongest declines in NPP and EP, also show stronger increases in the mean ocean stratification. In general, we find a strong correlation between increasing stratification, and decreasing NPP ($r^2 = 0.73$) and with decreasing EP ($r^2 = 0.90$). However, the models which show the strongest increases in stratification with climate change also have strong positive biases in mean stratification for the current era (+20–35%). The models with better simulation of current era stratification (GFDL, IPSL, CESM1), show weaker increases in stratification with climate change (though still substantial), and show smaller declines in NPP and EP. This suggests the more biased models may be overestimating the productivity declines with climate change.

This effort contributes directly to performance on Questions H, J, E5, E7.

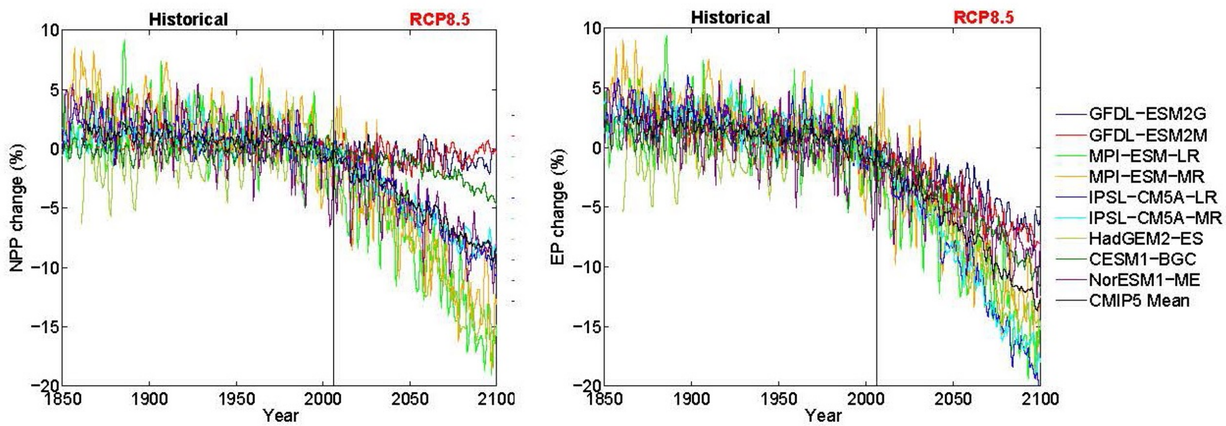


Figure 7: Time series of global mean change in net primary production (NPP) and export production (EP) for the historical run and RCP 8.5 over 1850–2100.

4.5 Permafrost carbon–climate feedback

As permafrost soils warm, the carbon that is currently locked in them is expected to decompose, increasing the concentrations of CO_2 and CH_4 in the atmosphere. This process, known as the permafrost carbon–climate feedback, is a potentially strong amplifier of global climate change. We have included the mechanistic basis for these processes within a land surface model, CLM4.5, the terrestrial component of the CESM Earth system model, and explore the roles of decomposition dynamics and their interactions with ecosystem processes that govern the magnitude of this process (Koven et al. 2015; *Proc. Nat. Acad. Sci.*). We find that magnitude of this effect is highly sensitive to how decomposition dynamics differ at depth from at the surface, and that deep soil processes therefore represent a critical uncertainty on projections of future climate change (Figure 8). Further, we include a model of nitrogen dynamics, which are expected to increase plant growth due to nitrogen released from thawing permafrost. However, we find that deep nitrogen pools are less effective at stimulating plant growth than surface soil pools, implying that the decomposition of deep permafrost soils is more likely to lead to net carbon losses—and therefore more climate change—than surface soils.

This effort contributes directly to performance on Questions D, E, F, E2.

4.6 Over-prediction of soil carbon–climate feedbacks

Accurately representing the temperature response of soil carbon decomposition is a prerequisite for credible predictions of soil carbon-climate feedbacks within Earth system models (ESMs). However, existing ESM soil biogeochemical models generally do not represent the large variability of this temperature sensitivity. Rather, this temperature sensitivity is usually represented with static functions or constant parameters (e.g., Q_{10} and microbial carbon use efficiency) and the concept of organic matter recalcitrance, all of which are challenged by many recent empirical measurements and experimental manipulations. To characterize these mechanisms and their impacts on carbon cycling, we developed a thermodynamically based microbe-explicit model that quantifies the interactions between microbes, enzymes, substrates, and mineral sorption reactions (Tang and Riley, 2015; *Nature Clim. Change*). We found that (1) Q_{10} spans a very large range; (2) microbial

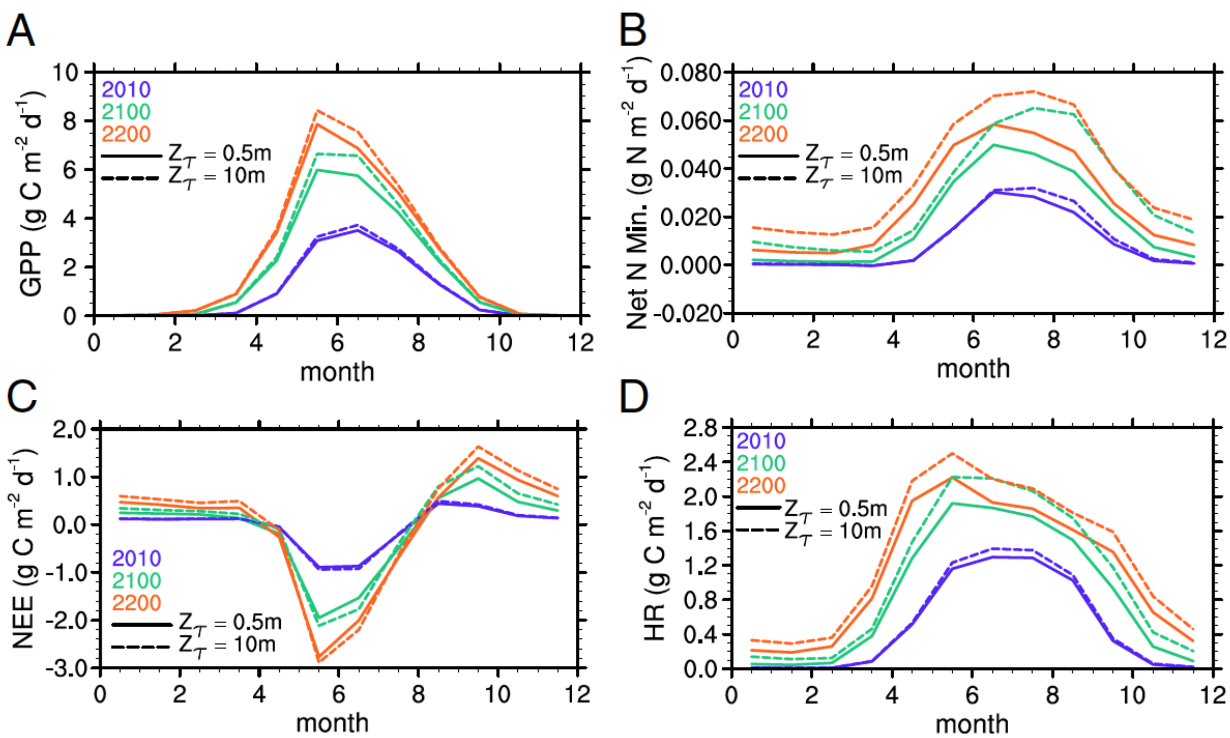


Figure 8: Mean annual cycles of key ecosystem fluxes for three time periods of the fully forced C–N case. (A) GPP, (B) net N mineralization, (C) net ecosystem exchange (NEE, positive = CO_2 source), and (D) heterotrophic respiration. Relative increase in GPP between experiments is smaller than proportional increase in N mineralization with deeper decomposition. Shift in N mineralization with enhanced deeper SOM decomposition toward autumn is due to longer decomposing than growing seasons, and phase lag of temperature in deep soils. The solid and dashed lines represent $Z_\tau = 0.5$ m and 10 m, respectively. All cases show the mean of the geographic region in which permafrost initially occurs in the model.

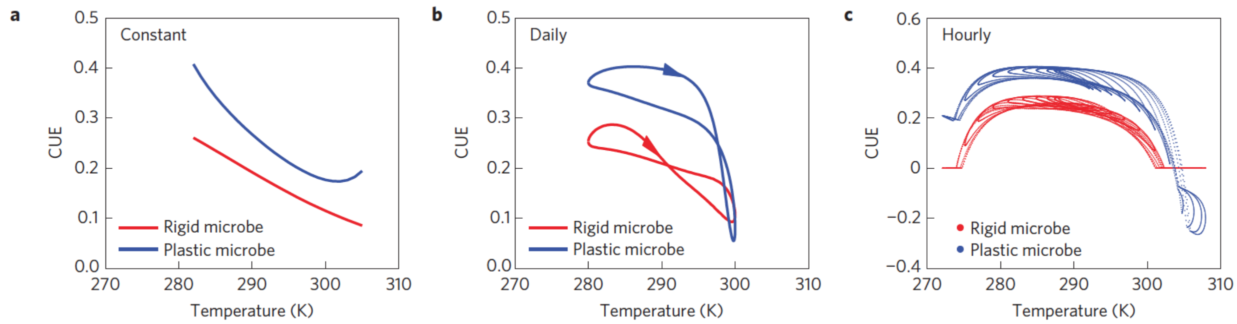


Figure 9: Predicted emergent responses as a function of temperature forcing of different temporal variability: (a) steady-state models forced with constant temperature; (b) transient models forced with seasonally varying, but daily constant, temperature; (c) transient models forced with seasonally varying, but hourly constant, temperature.

carbon use efficiency is a hysteretic function of temperature (Figure 9); and (3) the concept of empirically defined "labile" and "recalcitrant" substrates is flawed. We further showed that failing to represent the dynamic interactions between microbes, enzymes, substrates, and mineral sorption reactions, as most existing soil biogeochemical models do, may result in significant over-prediction of soil carbon-climate feedbacks and incorrect application of empirical experimental results to model development.

This effort contributes directly to performance on Questions D, F, E4.

4.7 Intercomparison of wetland emissions models over West Siberia

Wetlands are the world's largest natural source of methane, a powerful greenhouse gas. The strong sensitivity of methane emissions to environmental factors such as soil temperature and moisture has led to concerns about potential positive feedbacks to climate change. This risk is particularly relevant at high latitudes, which have experienced pronounced warming and where thawing permafrost could potentially liberate large amounts of labile carbon over the next 100 years. Recent intensive field campaigns across the West Siberian Lowland (WSL) make this an ideal region over which to assess the performance of large-scale process-based wetland models in a high-latitude environment. We assessed 21 models and 5 inversions over this domain in terms of total CH_4 emissions, simulated wetland areas, and CH_4 fluxes per unit wetland area and compared these results to an intensive in situ CH_4 flux data set, several wetland maps, and two satellite surface water products (Bohn et al. 2015; *Biogeosci.*). We found that (a) despite the large scatter of individual estimates, 12-year mean estimates of annual total emissions over the WSL from forward models (5.34 ± 0.54 Tg CH_4 yr^{-1}), inversions (6.06 ± 1.22 Tg CH_4 yr^{-1}), and in situ observations (3.91 ± 1.29 Tg CH_4 yr^{-1}) largely agreed; (b) forward models using surface water products alone to estimate wetland areas suffered from severe biases in CH_4 emissions; (c) the interannual time series of models that lacked either soil thermal physics appropriate to the high latitudes or realistic emissions from unsaturated peatlands tended to be dominated by a single environmental driver (inundation or air temperature), unlike those of inversions and more sophisticated forward models; (d) differences in biogeochemical schemes across models had relatively smaller influence over performance; and (e) multiyear or multi-decade observational records are crucial for evaluating models' responses to long-term climate change.

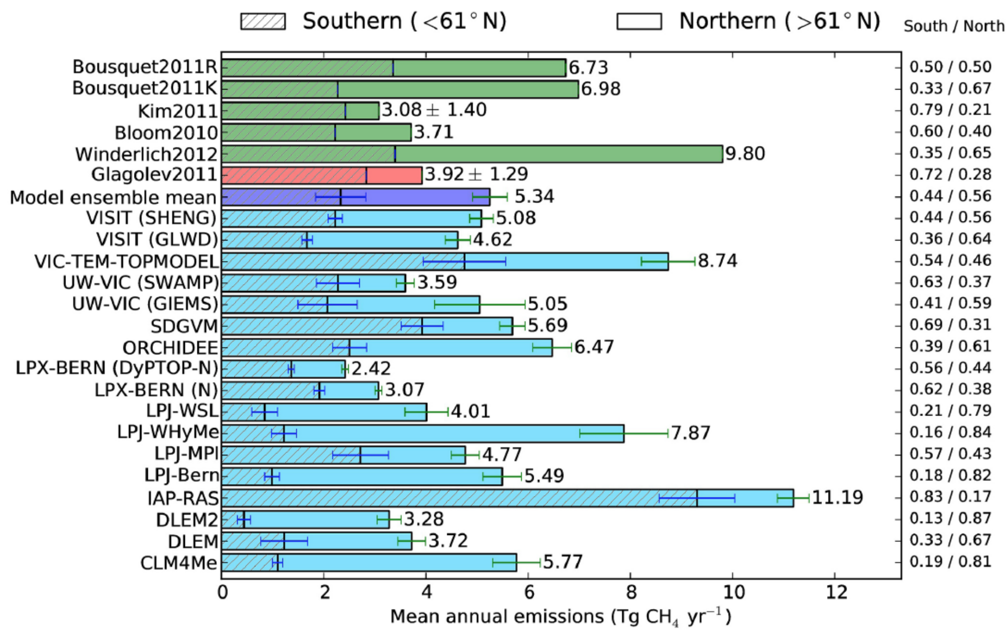


Figure 10: Mean annual emissions from the WSL (inversions in green, observation-based estimates in red, and forward models in blue).

This effort contributes directly to performance on Questions A, D, E, F, E4.

4.8 Representation of tropical forest productivity, biomass, and turnover times

A significant fraction of anthropogenic CO_2 emissions is assimilated by tropical forests and stored as biomass, reducing the rate of global warming. Because different plant tissues have different functional roles and turnover times, predictions of carbon balance of tropical forests depend on how Earth system models (ESMs) represent the dynamic allocation of productivity to different tree compartments. This study shows that observed allocation of productivity, biomass, and turnover times of the main tree compartments (leaves, wood, and roots) are not accurately represented in CMIP5 (Coupled Model Intercomparison Project Phase 5) ESMs (Negrón-Juárez et al. 2015; *Environ. Res. Lett.*). In particular, observations indicate that biomass saturates with increasing productivity, but most models predict continuous increases in biomass with increases in productivity (Figure 11). This bias may lead to an over-prediction of carbon uptake in response to CO_2 or climate-driven changes in productivity. Compartment-specific productivity and biomass are useful benchmarks to assess terrestrial ecosystem model performance. Improvements in the predicted allocation patterns and turnover times by ESMs will reduce uncertainties in climate predictions.

This effort contributes directly to performance on Questions C, D, E1, E4.

4.9 Growing feedback from ocean carbon to climate

Improved constraints on carbon cycle responses to climate change are needed to inform mitigation policy, yet our understanding of how these responses may evolve after 2100 remains highly uncertain. Using the Community Earth System Model (v1.0), we quantified climate-carbon feedbacks from

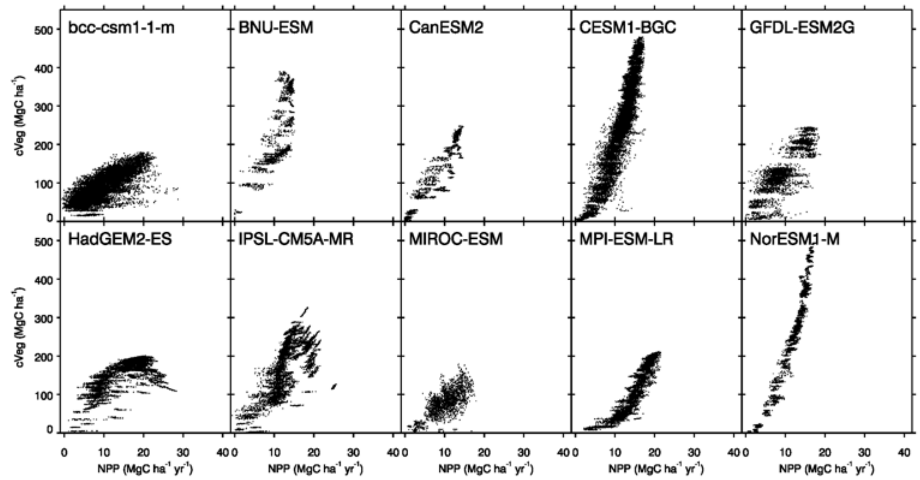


Figure 11: Relationship between productivity (NPP) and biomass (cVeg) over tropical forests using CMIP5 models. All models but one show continual increasing biomass as a function of NPP, while observations show a saturating response.

1850 to 2300 for the Representative Concentration Pathway 8.5 and its extension (Randerson et al., 2015). In three simulations, land and ocean biogeochemical processes were exposed to the same trajectory of increasing atmospheric CO_2. Each simulation had a different degree of radiative coupling for CO_2 and other greenhouse gases and aerosols, enabling diagnosis of feedbacks. In a fully coupled simulation, global mean surface air temperature increased by 9.3 K from 1850 to 2300, with 4.4 K of this warming occurring after 2100. Excluding CO_2, warming from other greenhouse gases and aerosols was 1.6 K by 2300, near a 2 K target needed to avoid dangerous anthropogenic interference with the climate system. Ocean contributions to the climate-carbon feedback increased considerably over time, and exceeded contributions from land after 2100. The sensitivity of ocean carbon to climate change was found to be proportional to cumulative ocean heat uptake, as a consequence of this heat modifying transport pathways for anthropogenic CO_2 inflow and solubility of dissolved inorganic carbon. By 2300 climate change reduced cumulative ocean uptake by 330 Pg C, from 1410 Pg C to 1080 Pg C. Land fluxes similarly diverged over time, with climate change reducing stocks by 232 Pg C. Regional influence of climate change on carbon stocks was largest in the North Atlantic Ocean and tropical forests of South America. Our analysis suggests that after 2100, oceans may become as important as terrestrial ecosystems in regulating the magnitude of climate–carbon feedbacks.

This effort contributes directly to performance on Questions J, E1, E5.

4.10 Separating the influence of temperature, drought, and fire on the interannual variability of atmospheric CO_2

Quantifying contributions of known drivers of interannual variability in the growth rate of atmospheric carbon dioxide is important for improving the representation of terrestrial ecosystem processes in ESMs. Several recent studies have identified the temperature dependence of tropical net ecosystem exchange (NEE) as a primary driver of this variability by analyzing a single, globally averaged time series of CO_2 anomalies. We examined how the temporal evolution of CO_2 in

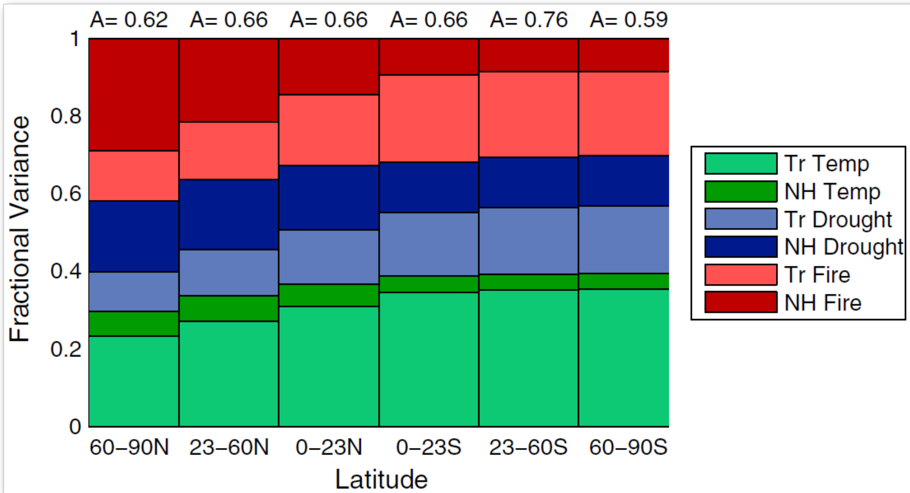


Figure 12: Relative contributions to the simulated variability in atmospheric CO_2 in different latitude bands (x axis) from net ecosystem exchange responses to temperature, drought stress, and fire emissions originating from the tropics and Northern Hemisphere.

different latitude bands may be used to separate contributions from temperature stress, drought stress, and fire emissions to CO_2 variability. We developed atmospheric CO_2 patterns from each of these mechanisms during 1997–2011 using the GEOS-Chem atmospheric transport model. NEE responses to temperature, NEE responses to drought, and fire emissions all contributed significantly to CO_2 variability in each latitude band, suggesting that no single mechanism was the dominant driver (Figure 12. We found that the sum of drought and fire contributions to CO_2 variability exceeded direct NEE responses to temperature in both the Northern and Southern Hemispheres. Additional sensitivity tests revealed that these contributions are masked by temporal and spatial smoothing of CO_2 observations. Accounting for fires, the sensitivity of tropical NEE to temperature stress decreased by 25% to 2.9 ± 0.4 $\mathrm{Pg\,C\,yr^{-1}\,K^{-1}}$. These results underscore the need for accurate attribution of the drivers of CO_2 variability prior to using contemporary observations to constrain long-term ESM responses, and will inform approaches for developing functional response benchmarks in the ILAMB system under development.

This effort contributes directly to performance on Questions A, B, E, E1.

4.11 Environmental controls and spatial heterogeneity of SOC depend on spatial scale

Spatial heterogeneity of land surface affects energy, moisture, and greenhouse gas exchanges with the atmosphere. However, representing heterogeneity of terrestrial hydrological and biogeochemical processes in Earth system models (ESMs) remains a critical scientific challenge. DOE/BER-funded researchers used soil profile observations, environmental factors (topography, climate, land cover types, and surficial geology), and geospatial modeling to study the impact of spatial scaling on environmental controls, spatial structure, and statistical properties of soil organic carbon (SOC) stocks. Authors found different environmental factors as significant predictors of SOC stocks at different spatial scales. Only elevation, temperature, potential evapotranspiration, and scrub land cover types were significant predictors at all investigated scales. The strengths of control of these

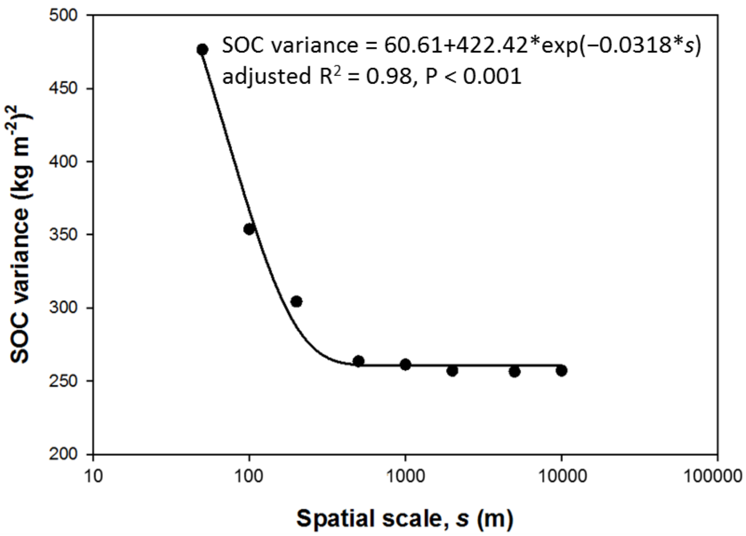


Figure 13: The spatial heterogeneity of soil organic carbon (SOC) stocks decreased with spatial scale between 50 and 500 m, and remained constant at larger scaled.

four environmental variables on SOC stocks decreased with increasing scale and were accurately represented using different mathematical functions ($R^2 = 0.83$–0.97). The spatial structure of SOC stocks also changed with scale. The spatial heterogeneity of predicted SOC stocks decreased with spatial scale over the range of 50 m to ∼500 m, and remained constant beyond this scale. The fitted exponential function accounted for 98% of variability in the variance of SOC stocks. Moderately-accurate linear relationships were found between mean and other statistical properties of predicted SOC stocks ($R^2 \approx 0.55$–0.63). Current ESMs operate at coarse spatial scales (50–100 km), and are therefore unable to represent environmental controllers and spatial heterogeneity of high-latitude SOC stocks consistent with observations. Improved knowledge of the scaling behavior of environmental controls and statistical properties of SOC stocks will improve ESM land model benchmarking and perhaps allow representation of spatial heterogeneity of biogeochemistry at scales finer than those currently resolved by ESMs.

This effort contributes directly to performance on Question E.

4.12 Honors and Awards

A June 18$^{\text{th}}$ News & Views article, titled "Global warming: Growing feedback from ocean carbon to climate," appeared in *Nature*, describing Jim Randerson's recent paper highlighting significant ocean carbon cycle feedbacks in long-term simulations. See doi:10.1038/522295a.

J. Keith Moore (UCI) received the 2015 CESM Distinguished Achievement Award at the 20$^{\text{th}}$ Annual CESM Workshop in Breckenridge, Colorado, on June 15, 2015. Keith was cited for his contributions to the first version of the biogeochemistry component of the ocean model.

At the Ecological Society of America's annual meeting in Sacramento, California, in August 2014, Jinyun Tang (LBNL) received honorable mention for the Gene E. Likens Junior Scientist Outstanding Publication Award for his *Biogeosciences* paper proposing an "equilibrium chemistry" approach to problems classically represented using Michaelis-Menten (or MM) kinetics.

Table 3: Major Project Deliverables and Science Questions

Task or Question	Section
Task D1: Initial design document for benchmarking package	4.1, 4.2
Task D2: Alpha prototype of benchmarking package	4.1
Task D3: Beta prototype of benchmarking package	4.2
Task D4: Friendly-user testing of benchmarking package	
Task D5: Delivery of initial benchmarking package to community	
Task D6: First benchmarking workshop	
Task D7: Second benchmarking workshop	
Question A: How well can ESMs capture observed changes in the amplitude and phase of the seasonal cycle of atmospheric CO_2 and CH_4?	4.7, 4.10
Question B: How well can ESMs simulate observed linkages between growing season onset and mid-summer drought stress?	4.10
Question C: How well can ESMs capture the abundance and spatial variability of leaf area regionally and globally?	4.8
Question D: How do comparisons between observed and modeled functional responses inform whether models (1) include the appropriate mechanisms; (2) have accurate parameterizations of those mechanisms; and (3) produce reasonable estimates of biogeochemical feedbacks?	4.5, 4.6, 4.7, 4.8
Question E: How do carbon stocks, ecosystem processes, and surface biophysics vary across ecotones?	4.5, 4.7, 4.10, 4.11
Question F: How will C-nutrient interactions regulate terrestrial carbon cycle responses to changes in atmospheric CO_2 and climate?	4.5, 4.6, 4.7
Question G: How can ecosystem manipulations serve to constrain long-term model responses?	
Question H: What factors control spatial and temporal differences in the patterns of ocean net primary production and export production among ESMs?	4.4
Question I: What factors control the size and distribution of the ocean oxygen minimum zones currently, and what are the potential climate feedbacks from OMZ expansion?	
Question J: How well do ESM ocean models capture the magnitude and spatio-temporal patterns of anthropogenic CO_2 uptake and storage in the oceans? What are the climate feedbacks of this CO_2 uptake and the resulting ocean acidification?	4.4, 4.9
Question E1: Can observed variability in the CO_2 growth rate be used as a constraint on the long-term (21st century) sensitivity of tropical carbon stocks to warming and drought?	4.8, 4.10, 4.9
Question E2: Do models that overestimate snow albedo feedbacks underestimate permafrost loss during the 21st century?	4.5
Question E3: How have plant functional type distributions changed over the past several decades, and can these changes be used to infer rates of future spatial shifts?	
Question E4: Can the strength of the carbon-concentration feedbacks in terrestrial ecosystems be constrained using observations?	4.6, 4.7, 4.8
Question E5: Is the weakening of the ocean biological pump over the 21st century linked to biases in current-era nutrient distributions, carbon flux observations, and/or tracers of ocean physical processes?	4.3, 4.4, 4.9
Question E6: Are variations in the future expansion of oxygen minimum zones across different models tied to existing O_2 and/or CFC biases?	
Question E7: How strongly are the spatial and temporal trends in anthropogenic CO_2 and ocean acidification over the 21st century linked to current-era biases in the ocean anthropogenic CO_2 distributions?	4.4

A Publications

In Review and Revision

Koven, C. D., J. Q. Chambers, K. Georgiou, R. Knox, R. Negrón-Juárez, W. J. Riley, V. K. Arora, V. Brovkin, P. Friedlingstein, and C. D. Jones. 2015. "Controls on Terrestrial Carbon Feedbacks by Productivity vs. Turnover in the CMIP5 Earth System Models." *Biogeosci. Discuss.*, 12:5757–5801. doi:10.5194/bgd-12-5757-2015. (In revision)

Koven, C. D., E. A. G. Schuur, C. Schädel, T. J. Bohn, E. J. Burke, G. Chen, X. Chen, P. Ciais, G. Grosse, J. W. Harden, D. J. Hayes, G. Hugelius, E. E. Jafarov, G. Krinner, P. Kuhry, **D. M. Lawrence**, A. H. MacDougall, S. S. Marchenko, A. D. McGuire, S. M. Natali, D. J. Nicolsky, D. Olefeldt, S. Peng, V. E. Romanovsky, K. M. Schaefer, J. Strauss, C. C. Treat, M. Turetsky. 2015. "A Simplified, Data-constrained Approach to Estimate the Permafrost Carbon–Climate Feedback." *Phil. Trans. R. Soc. A*, Special issue on Climate Feedbacks in the Earth System. (Accepted with minor revisions)

Negrón-Juárez, R. I., **W. J. Riley**, **C. D. Koven**, R. G. Knox, P. G. Taylor, J. Q. Chambers. 2015. "The Rainfall Sensitivity of Tropical Net Primary Production in CMIP5 20^{th} and 21^{st} Century Simulations." *J. Clim.* (Accepted with minor revisions)

Mishra, U., and **W. J. Riley**. 2015. "Scaling Impacts on Environmental Controls and Spatial Heterogeneity of Soil Organic Carbon Stocks." *Biogeosci.* (In review)

Yang, X., **P. Thornton**. D. Ricciuto, and **F. Hoffman**. 2015. "Phosphorus Feedbacks May Constrain Tropical Ecosystem Responses to Changes in Atmospheric CO_2 and Climate." *Geophys. Res. Lett.* (Submitted)

Fu, Weiwei, **James T. Randerson**, and **J. Keith Moore**. 2015. "Climate Change Impacts on Net Primary Production (NPP) and Export Production (EP) Regulated by Increasing Stratification and Phytoplankton Community Structure in CMIP5 Models. *Biogeosci.* (Submitted)

In Press

[68] McCoy, D., with S. Burrows, **S. Elliott** and 5 others. 2015. Natural Aerosols Explain Seasonal and Spatial Patterns of Southern Ocean Cloud Albedo. *Science Advances.*

[67] **Randerson, James T.**, Keith Lindsay, Ernesto Munoz, **Weiwei Fu**, **J**. Keith Moore, **Forrest M. Hoffman**, Natalie M. Mahowald, and Scott C. Doney. 2015. "Multicentury Changes in Ocean and Land Contributions to the Climate Carbon Feedback." *Global Biogeochem. Cycles*, doi:10.1002/2014GB005079.

[66] Sasha C. Reed, **Xiaojuan Yang**, and **Peter E. Thornton**. 2015. "Incorporating Phosphorus Cycling into Global Modeling Efforts: A Worthwhile, Tractable Endeavor." *New Phytol.* doi:10.1111/nph.13521.

[65] Wang Shusen, Ming Pan, Qiaozhen Mu, **Xiaoying Shi**, **Jiafu Mao**, Christian Brümmer, Rachhpal S. Jassal, Praveena Krishnan, Junhua Li and T. Andrew Black. 2015. "Assessing Evapotranspiration from Eddy Covariance Measurements, Water Budgets, Remote Sensing, and Land Surface Models over Canada." *J. Hydrometeor.*, doi:10.1175/JHM-D-14-0189.1.

2015

[64] **Robinson I. Negrón-Juárez**, **Charles D. Koven**, **William J. Riley**, R. G. Knox, and J. Q. Chambers. Observed allocations of productivity and biomass, and turnover times in tropical forests are not accurately represented in CMIP5 Earth system models. *Environ. Res. Lett.*, 10 (6):064017, June 2015. doi:10.1088/1748-9326/10/6/064017.

[63] **Forrest M. Hoffman**. *Quantification and Reduction of Uncertainties Associated with Carbon Cycle–Climate System Feedbacks.* PhD thesis, University of California - Irvine, Department of Earth System Science, Irvine, California, USA, June 2015.

[62] T. J. Bohn, J. R. Melton, A. Ito, T. Kleinen, R. Spahni, B. D. Stocker, B. Zhang, X. Zhu, R. Schroeder, M. V. Glagolev, S. Maksyutov, V. Brovkin, G. Chen, S. N. Denisov, A. V. Eliseev, A. Gallego-Sala, K. C. McDonald, M. Rawlins, **W. J. Riley**, Z. M. Subin, H. Tian, Q. Zhuang, and J. O. Kaplan. WETCHIMP-WSL: Intercomparison of wetland methane emissions models over West Siberia. *Biogeosci.*, 12(11):3321–3349, June 2015. doi:10.5194/bg-12-3321-2015.

[61] C. Le Quéré, R. Moriarty, R. M. Andrew, G. P. Peters, P. Ciais, P. Friedlingstein, S. D. Jones, S. Sitch, P. Tans, A. Arneth, T. A. Boden, L. Bopp, Y. Bozec, J. G. Canadell, L. P. Chini, F. Chevallier, C. E. Cosca, I. Harris, M. Hoppema, R. A. Houghton, J. I. House, A. K. Jain, T. Johannessen, E. Kato, R. F. Keeling, V. Kitidis, K. Klein Goldewijk, **C. Koven**, C. S. Landa, P. Landschützer, A. Lenton, I. D. Lima, G. Marland, J. T. Mathis, N. Metzl, Y. Nojiri, A. Olsen, T. Ono, S. Peng, W. Peters, B. Pfeil, B. Poulter, M. R. Raupach, P. Regnier, C. Rödenbeck, S. Saito, J. E. Salisbury, U. Schuster, J. Schwinger, R. Séférian, J. Segschneider, T. Steinhoff, B. D. Stocker, A. J. Sutton, T. Takahashi, B. Tilbrook, G. R. van der Werf, N. Viovy, Y.-P. Wang, R. Wanninkhof, A. Wiltshire, and N. Zeng. Global carbon budget 2014. *Earth Syst. Sci. Data*, 7(1):47–85, May 2015. doi:10.5194/essd-7-47-2015.

[60] E. A. G. Schuur, A. D. McGuire, C. Schadel, G. Grosse, J. W. Harden, D. J. Hayes, G. Hugelius, **C. D. Koven**, P. Kuhry, **D. M. Lawrence**, S. M. Natali, D. Olefeldt, V. E. Romanovsky, K. Schaefer, M. R. Turetsky, C. C. Treat, and J. E. Vonk. Climate change and the permafrost carbon feedback. *Nature*, 520(7546):171–179, Apr. 2015. doi:10.1038/nature14338.

[59] S. Peng, P. Ciais, G. Krinner, T. Wang, I. Gouttevin, A. D. McGuire, **D. Lawrence**, E. Burke, X. Chen, C. Delire, **C. Koven**, A. MacDougall, A. Rinke, K. Saito, W. Zhang, R. Alkama, T. J. Bohn, B. Decharme, T. Hajima, D. Ji, D. P. Lettenmaier, P. A. Miller, J. C. Moore, B. Smith, and T. Sueyoshi. Simulated high-latitude soil thermal dynamics during the past four decades. *The Cryosphere Discuss.*, 9:2301–2337, Apr. 2015. doi:10.5194/tcd-9-2301-2015.

[58] S. Piao, G. Yin, J. Tan, L. Cheng, M. Huang, Y. Li, R. Liu, **Jiafu Mao**, R. B. Myneni, S. Peng, B. Poulter, **Xiaoying Shi**, Z. Xiao, N. Zeng, Z. Zeng, and Y. Wang. Detection and attribution of vegetation greening trend in China over the last 30 years. *Global Change Biol.*, 21 (4):1601–1609, Apr. 2015. doi:10.1111/gcb.12795.

[57] **Charles D. Koven**, **David M. Lawrence**, and **William J. Riley**. Permafrost carbon–climate feedback is sensitive to deep soil carbon decomposability but not deep soil nitrogen dynamics. *Proc. Nat. Acad. Sci.*, 112(12):3752–3757, Mar. 2015. doi:10.1073/pnas.1415123112.

[56] M. A. Rawlins, A. D. McGuire, J. K. Kimball, P. Dass, **D. Lawrence**, E. Burke, X. Chen, C. Delire, **C. Koven**, A. MacDougall, S. Peng, A. Rinke, K. Saito, W. Zhang, R. Alkama, T. J. Bohn, P. Ciais, B. Decharme, I. Gouttevin, T. Hajima, D. Ji, G. Krinner, D. P. Lettenmaier,

P. Miller, J. C. Moore, B. Smith, and T. Sueyoshi. Assessment of model estimates of land–atmosphere co_2 exchange across Northern Eurasia. *Biogeosci. Discuss.*, 12(3):2257–2305, Feb. 2015. doi:10.5194/bgd-12-2257-2015.

[55] K. J. Anderson-Teixeira, S. J. Davies, A. C. Bennett, E. B. Gonzalez-Akre, H. C. Muller-Landau, S. J. Wright, K. Abu Salim, A. M. Almeyda Zambrano, A. Alonso, J. L. Baltzer, Y. Basset, N. A. Bourg, E. N. Broadbent, W. Y. Brockelman, S. Bunyavejchewin, D. F. R. P. Burslem, N. Butt, M. Cao, D. Cardenas, G. B. Chuyong, K. Clay, S. Cordell, H. S. Dattaraja, X. Deng, M. Detto, X. Du, A. Duque, D. L. Erikson, C. E. N. Ewango, G. A. Fischer, C. Fletcher, R. B. Foster, C. P. Giardina, G. S. Gilbert, N. Gunatilleke, S. Gunatilleke, Z. Hao, W. W. Hargrove, T. B. Hart, B. C. H. Hau, F. He, **Forrest M. Hoffman**, R. W. Howe, S. P. Hubbell, F. M. Inman-Narahari, P. A. Jansen, M. Jiang, D. J. Johnson, M. Kanzaki, A. R. Kassim, D. Kenfack, S. Kibet, M. F. Kinnaird, L. Korte, K. Kral, **Jitendra Kumar**, A. J. Larson, Y. Li, X. Li, S. Liu, S. K. Y. Lum, J. A. Lutz, K. Ma, **Damian M. Maddalena**, J.-R. Makana, Y. Malhi, T. Marthews, R. Mat Serudin, S. M. McMahon, W. J. McShea, H. R. Memiaghe, X. Mi, T. Mizuno, M. Morecroft, J. A. Myers, V. Novotny, A. A. de Oliveira, P. S. Ong, D. A. Orwig, R. Ostertag, J. den Ouden, G. G. Parker, R. P. Phillips, L. Sack, M. N. Sainge, W. Sang, K. Sri-ngernyuang, R. Sukumar, I.-F. Sun, W. Sungpalee, H. S. Suresh, S. Tan, S. C. Thomas, D. W. Thomas, J. Thompson, B. L. Turner, M. Uriarte, R. Valencia, M. I. Vallejo, A. Vicentini, T. Vrška, X. Wang, X. Wang, G. Weiblen, A. Wolf, H. Xu, S. Yap, and J. Zimmerman. CTFS-ForestGEO: A worldwide network monitoring forests in an era of global change. *Global Change Biol.*, 21(2):528–549, Feb. 2015. doi:10.1111/gcb.12712.

[54] J. Tan, S. Piao, A. Chen, Z. Zeng, P. Ciais, I. A. Janssens, **Jiafu Mao**, R. B. Myneni, S. Peng, J. Peñuelas, **Xiaoying Shi**, and S. Vicca. Seasonally different response of photosynthetic activity to daytime and night-time warming in the Northern Hemisphere. *Global Change Biol.*, 21(1): 377–387, Jan. 2015. doi:10.1111/gcb.12724.

[53] **Jinyun Tang** and **William J. Riley**. Weaker soil carbon–climate feedbacks resulting from microbial and abiotic interactions. *Nature Clim. Change*, 5(1):56–60, Jan. 2015. doi: 10.1038/nclimate2438.

2014

[52] J. Zscheischler, M. Reichstein, J. von Buttlar, **Mingquan Mu**, **James T. Randerson**, and M. D. Mahecha. Carbon cycle extremes during the 21^{st} century in CMIP5 models: Future evolution and attribution to climatic drivers. *Geophys. Res. Lett.*, 41(24):8853–8861, Dec. 2014. doi:10.1002/2014GL062409.

[51] S. M. Burrows, O. Ogunro, A. A. Frossard, L. M. Russell, P. J. Rasch, and **S. M. Elliott**. A physically based framework for modeling the organic fractionation of sea spray aerosol from bubble film Langmuir equilibria. *Atmos. Chem. Phys.*, 14(24):13601–13629, Dec. 2014. doi: 10.5194/acp-14-13601-2014.

[50] K. Lindsay, G. B. Bonan, S. C. Doney, **Forrest M. Hoffman**, **David M. Lawrence**, M. C. Long, N. M. Mahowald, **J. Keith Moore**, **James T. Randerson**, and **Peter E. Thornton**. Preindustrial-control and twentieth-century carbon cycle experiments with the Earth system model CESM1(BGC). *J. Clim.*, 27(24):8981–9005, Dec. 2014. doi:10.1175/JCLI-D-12-00565.1.

[49] **Nicholas J. Bouskill**, **William J. Riley**, and **Jinyun Tang**. Meta-analysis of high-latitude nitrogen-addition and warming studies implies ecological mechanisms overlooked by land models. *Biogeosci.*, 11(23):6969–6983, Dec. 2014. doi:10.5194/bg-11-6969-2014.

[48] A. A. Frossard, L. M. Russell, S. M. Burrows, **Scott M. Elliott**, T. S. Bates, and P. K. Quinn. Sources and composition of submicron organic mass in marine aerosol particles. *J. Geophys. Res. Atmos.*, 119(22):12,977–13,003, Nov. 2014. doi:10.1002/2014JD021913.

[47] **Gretchen Keppel-Aleks**, A. S. Wolf, **Mingquan Mu**, S. C. Doney, D. C. Morton, P. S. Kasibhatla, J. B. Miller, E. J. Dlugokencky, and **James T. Randerson**. Separating the influence of temperature, drought, and fire on interannual variability in atmospheric CO_2. *Global Biogeochem. Cycles*, 28(11):1295–1310, Nov. 2014. doi:10.1002/2014GB004890.

[46] Y. Sun, L. Gu, R. E. Dickinson, R. J. Norby, S. G. Pallardy, and **Forrest M. Hoffman**. Impact of mesophyll diffusion on estimated global land CO_2 fertilization. *Proc. Nat. Acad. Sci.*, 111(44):15774–15779, Nov. 2014. doi:10.1073/pnas.1418075111.

[45] S. Piao, H. Nan, C. Huntingford, P. Ciais, P. Friedlingstein, S. Sitch, S. Peng, A. Ahlstrm, J. G. Canadell, N. Cong, S. Levis, P. E. Levy, L. Liu, M. R. Lomas, **Jiafu Mao**, R. B. Myneni, P. Peylin, B. Poulter, **Xiaoying Shi**, G. Yin, N. Viovy, T. Wang, X. Wang, S. Zaehle, N. Zeng, Z. Zeng, and A. Chen. Evidence for a weakening relationship between interannual temperature variability and northern vegetation activity. *Nat. Commun.*, 5, Oct. 2014. doi:10.1038/ncomms6018.

[44] N. Carvalhais, M. Forkel, M. Khomik, J. Bellarby, M. Jung, M. Migliavacca, **Mingquan Mu**, S. Saatchi, M. Santoro, M. Thurner, U. Weber, B. Ahrens, C. Beer, A. Cescatti, **James T. Randerson**, and M. Reichstein. Global covariation of carbon turnover times with climate in terrestrial ecosystems. *Nature*, 514(7521):213–217, Oct. 2014. doi:10.1038/nature13731.

[43] **Umakant Mishra** and **William J. Riley**. Active-layer thickness across Alaska: Comparing observation-based estimates with CMIP5 Earth system model predictions. *Soil Sci. Soc. Am. J.*, 78(3):894–902, June 2014. doi:10.2136/sssaj2013.11.0484.

[42] **S. Elliott**, S. M. Burrows, C. Deal, X. Liu, M. Long, O. Ogunro, L. M. Russell, and O. Wingenter. Prospects for simulating macromolecular surfactant chemistry at the ocean–atmosphere boundary. *Environ. Res. Lett.*, 9(6):064012, June 2014. doi:10.1088/1748-9326/9/6/064012.

[41] C. J. Deal, N. Steiner, J. Christian, J. Clement Kinney, K. L. Denman, **Scott M. Elliott**, G. Gibson, M. Jin, D. Lavoie, S. H. Lee, W. Lee, W. Maslowski, J. Wang, and E. Watanabe. Progress and challenges in biogeochemical modeling of the Pacific Arctic Region. In J. M. Grebmeier and W. Maslowski, editors, *The Pacific Arctic Region*, pages 393–445. Springer Netherlands, Apr. 2014. ISBN 978-94-017-8862-5. doi:10.1007/978-94-017-8863-2_12.

[40] **K. E. O. Todd-Brown**, **J. T. Randerson**, **F. Hopkins**, V. Arora, T. Hajima, C. Jones, E. Shevliakova, J. Tjiputra, E. Volodin, T. Wu, Q. Zhang, and S. D. Allison. Changes in soil organic carbon storage predicted by Earth system models during the 21st century. *Biogeosci.*, 11 (8):2341–2356, Apr. 2014. doi:10.5194/bg-11-2341-2014.

[39] Y. P. Wang, B. C. Chen, W. R. Wieder, M. Leite, B. E. Medlyn, M. Rasmussen, M. J. Smith, F. B. Agusto, **F. M. Hoffman**, and Y. Q. Luo. Oscillatory behavior of two nonlinear microbial models of soil carbon decomposition. *Biogeosci.*, 11(7):1817–1831, Apr. 2014. doi:10.5194/bg-11-1817-2014.

[38] Z. Zeng, T. Wang, F. Zhou, P. Ciais, **Jiafu Mao**, **Xiaoying Shi**, and S. Piao. A worldwide analysis of spatiotemporal changes in water balance-based evapotranspiration from 1982 to 2009. *J. Geophys. Res. Atmos.*, 119(3):1186–1202, Feb. 2014. doi:10.1002/2013JD020941.

[37] **Forrest M. Hoffman**, **James T. Randerson**, V. K. Arora, Q. Bao, P. Cadule, D. Ji, C. D. Jones, M. Kawamiya, S. Khatiwala, K. Lindsay, A. Obata, E. Shevliakova, K. D. Six, J. F. Tjiputra, E. M. Volodin, and T. Wu. Causes and implications of persistent atmospheric carbon dioxide biases in Earth System Models. *J. Geophys. Res. Biogeosci.*, 119(2):141–162, Feb. 2014. doi:10.1002/2013JG002381.

[36] M. M. Loranty, L. T. Berner, S. J. Goetz, Y. Jin, and **James T. Randerson**. Vegetation controls on northern high latitude snow-albedo feedback: Observations and CMIP5 model simulations. *Global Change Biol.*, 20(2):594–606, Feb. 2014. doi:10.1111/gcb.12391.

[35] **Jinyun Tang** and **William J. Riley**. Technical Note: Simple formulations and solutions of the dual-phase diffusive transport for biogeochemical modeling. *Biogeosci.*, 11(14):3721–3728, Jan. 2014. doi:10.5194/bg-11-3721-2014.

[34] N. Buenning, D. Noone, **James T. Randerson**, **William J. Riley**, and C. Still. The response of the $^{18}O/^{16}O$ composition of atmospheric CO_2 to changes in environmental conditions. *J. Geophys. Res. Biogeosci.*, 119(1):55–79, Jan. 2014. doi:10.1002/2013JG002312.

Support for this work was provided through the Regional & Global Climate Modeling Program funded by the U.S. Department of Energy, Office of Science, Biological and Environmental Research.

This document has been authored by UT-Battelle, LLC, under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy.