The BGC Feedbacks Project

Quantifying Feedbacks and Uncertainties of Biogeochemical Processes in Earth System Models

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Biological and Environmental Research (BER)
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Scientific Focus Area (SFA) Annual Progress Report

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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).

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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 21 months in this Scientific Focus Area (SFA) and the prior four years of the preceding project, our team has pioneered the development and application of new diagnostic approaches, resulting in 90 published papers, plus 8 published early online papers, 16 manuscripts in review or revision, and additional papers in preparation. Of those papers, 24 have been published in issues and 8 have been published early online in the last 12 months (since July 1, 2015; see Appendix A). In addition, Appendix B contains a selected set of highlights generated by the SFA over the past 12 months. Most of these highlights have been posted on the Facebook, Twitter, Google+, and LinkedIn social media sites for public outreach.

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 BGC Feedbacks 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 are being 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 is 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). Our hypothesis-driven approach is focused on model evaluation and reduction in the spread of model predictions. In particular, our SFA has 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 Senior Science Co-Lead, and the Chief Scientist—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.

During the past year, David M. Lawrence from the National Center for Atmospheric Research (NCAR) was formally added to the project as a University Co-PI and Science Co-Lead through a subcontract. David previously collaborated with the project team using limited support through the NCAR Cooperative Agreement.

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						✓
Lawrence, David M.	NCAR					✓	✓
Mishra, Umakant	ANL				✓		
Moore, J. Keith	UCI						✓

†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.	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.	Lawrence, David M.	NCAR	✓		✓	Land Co-Lead
13.	Levine, Paul[2]	UCI	✓			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.	Shu, Shijie[2]	ORNL/UIUC	✓			Land Researcher
23.	Tang, Jinyun	LBNL	✓			Land Researcher
24.	Wang, Gangsheng	ORNL	✓			Land Researcher
25.	Wang, Shanlin[1]	LANL	✓			Ocean Researcher
26.	Xu, Min	ORNL	✓			Land Researcher
27.	Xu, Xiyan[1]	LBNL	✓			Land Researcher
28.	Yang, Cheng-En[2]	ORNL/UTK	✓			Land Researcher
29.	Yang, Xiaojuan	ORNL	✓			Land Researcher
30.	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 package development and workshops and tutorials, as well as 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 can be presented. Reported progress on development tasks and science questions is later summarized in Table 3.

4.1 ILAMB prototype software package (ILAMBv1)

As described in last year's progress report, 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. In the intervening period, additional metrics and capabilities have been added to this ILAMB prototype, which now stands at version 1.8.6. The ILAMB prototype, has been used at NCAR for testing the Community Land Model (CLM) as new process representations are being introduced, leading to CLM5, and within the DOE's Accelerated Climate Modeling for Energy (ACME) project for evaluating the performance of the ACME Land Model (ALM). Moreover, the ILAMB prototype was demonstrated and released to the public during the ILAMB Town Hall Meeting, convened by Dr. Renu Joseph and our SFA Team, in San Francisco in December 2015. Results from evaluating CMIP5 models, multiple CLM versions, and ALM using the ILAMB prototype were presented at the DOE-sponsored 2016 ILAMB Workshop—held in Washington, DC, in May—convened and hosted by our SFA Team. 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 CLM5 model, which is projected to be released before the end of calendar year 2016.

The released version of the ILAMBv1 package is available to the public from the project website and is citable as DOI: 10.18139/ILAMB.v001.00/1251597.

This effort contributes directly to performance on Tasks D1, D2, D4, and D5.

4.2 Next generation benchmarking software package (ILAMBv2)

Ahead of the proposal schedule, we have developed and distributed a next generation package, ILAMBv2, for performing model-data benchmarking activities. Released at the 2016 ILAMB Workshop in Washington, DC, in May 2016, this package is implemented in python and contains a small library (`ilamblib`) 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 that 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

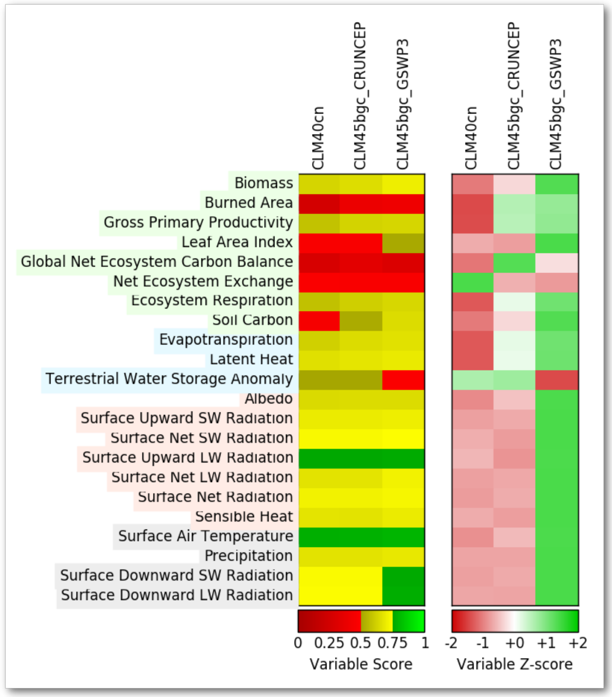

Figure 1: Summary graphic generated by the ILAMBv2 package depicting model performance across a wide variety of variables, emphasizing absolute performance (left) as well as relative performance (right).

model-confrontation pair is local. The ILAMBv2 package employs MPI (the Message Passing Interface) through `mpi4py` to provide both shared- and distributed-memory parallelism, dramatically speeding up processing and analysis.

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 generated by ILAMBv2. 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. Moreover, a device-friendly library is used for the HTML pages, enabling browsing of output on tablet and smartphone devices. The ILAMBv2 package is in use for evaluating the CESM2 and the ACME models, and it is presently being incorporated into the workflow packages of both of these modeling systems, so that it is run whenever land model output is generated.

The released version of the ILAMBv2 package is available to the public from the project website and is citable as DOI: 10.18139/ILAMB.v002.00/1251621.

This effort contributes directly to performance on Tasks D1, D3, D4, and D5.

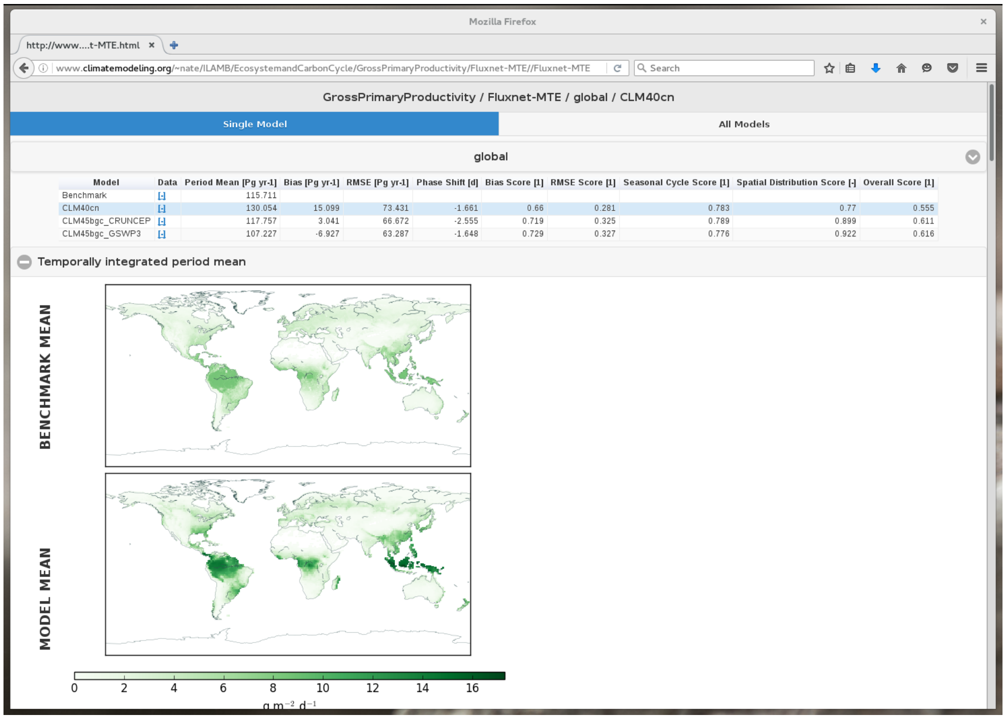

Figure 2: Sample output page from the ILAMBv2 python package.

4.3 ILAMB Town Hall at the AGU Fall Meeting in San Francisco, CA

The BGC Feedbacks SFA team organized a Town Hall meeting at the American Geophysical Union (AGU) Fall Meeting in San Francisco, CA, on December 14, 2015. The ILAMB Town Hall meeting started promptly at 6:15 p.m. with Renu Joseph presenting an overview of DOE-CESD, the RGCM Program, and the Biogeochemistry–Climate Feedbacks project. Forrest Hoffman provided background and history information about ILAMB and described the ILAMB prototype (ILAMBv1) system that is now available for download and general use. Following Forrest, Dave Lawrence discussed how the ILAMB prototype is being used as a part of Community Land Model (CLM) development, including some example diagnostics. Next, Jim Randerson presented results of the ILAMB analysis of 12 CMIP5 Earth system models. Finally, Gretchen Keppel-Aleks and Bill Riley conducted a question and answer session for 25 minutes. Between 70 and 80 people were in attendance, and questions and comments were received throughout the remainder of the available hour.

The Biogeochemistry–Climate Feedbacks Team was encouraged by the overwhelmingly positive response to the release of the ILAMB prototype (ILAMBv1) package, and were excited about the possibility of working closely with other research groups to extend ILAMB and to participate in regional and process-specific studies with the wider scientific community using the ILAMB framework.

This effort contributes directly to performance on Tasks D5 and D6.

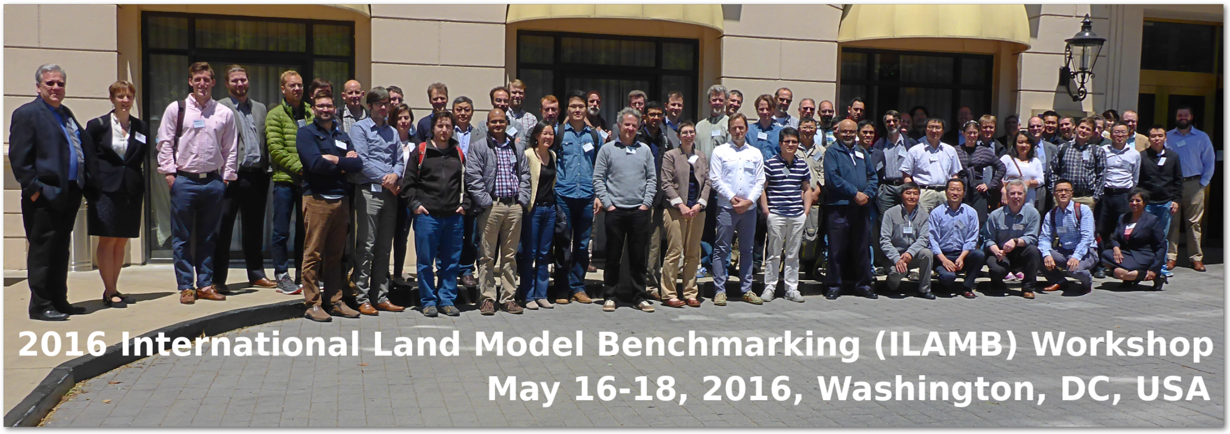

Figure 3: Some of the 60+ ILAMB Workshop participants posing for a group photo outside the DoubleTree by Hilton Hotel Washington DC on May 16, 2016.

4.4 ILAMB 2016 Workshop in Washington, DC

The BGC Feedbacks SFA team organized an international workshop focused on ILAMB, with sponsorship from both the RGCM and ESM Programs in DOE-BER, in Washington, DC, on May 16–18, 2016. The workshop drew more than 60 on-site participants, most of whom paid for their own travel costs and a registration fee. Attendees were from Australia, Japan, China, Germany, Sweden, Netherlands, UK, and all over the US. They represented 10 different major modeling centers. In addition, we had about 90 people sign up to attend remotely, although most people who do that do not end up attending. Nevertheless, we consistently had between 20 and 30 participants online via BlueJeans at any time during the plenary sessions, including additional DOE Program Managers (David Lesmes and Sally McFarlane), students and postdocs from various universities and Labs, and invitees unable to travel from Canada, China, etc. In addition, we had 24 posters presented on the evening of the first day.

Breakout session slides and draft whitepapers were prepared online in Google Slides and Docs a week before the workshop, and these were all made available for review and comment before the start of the workshop, which I think helped prepare participants for really productive discussions once everyone got in one room. Notes were taken and slides and whitepapers were updated during the sessions, and remote participants were able to comment on or edit the documents in real time, as were all other participants. We are continuing this crowdsourcing approach for preparation of the final workshop report, which we are targeting for completion on September 1. The workshop agenda and additional information is available at `http://www.ilamb.org/meetings/washington2016/`, and the presentations and documents are all on Google Drive at `https://drive.google.com/folderview?id=0B5CL4wjM7r4hU05aLVk5ZlpzY2M&usp=sharing`.

We handed out thumb drives with the ILAMBv2 code, observational data, and a couple of model output data sets, which was useful for some to run ILAMB right on their own laptops during the tutorials and to have a version they could all take home. The tutorials were well attended, and many stayed well past 6:00 p.m. Wednesday, an hour after the meeting had formally adjourned, to continue discussing and learning the ILAMBv2 system. The discussions were really useful, and we received many comments that people found the workshop was useful and rewarding for them.

This effort contributes directly to performance on Tasks D5 and D6.

4.5 ILAMB Tutorial at the 21st CESM Workshop in Breckenridge, CO

Because of the success of the tutorial sessions held at the ILAMB 2016 Workshop and interest expressed from NCAR and university researchers, we held another tutorial session on the use of the ILAMBv2 package at the 21st Annual CESM Workshop in Breckenridge, CO. The tutorial session was offered on Wednesday evening, following the Land Model Working Group and the Biogeochemistry Working Group Meetings earlier in the day, from 5:00 p.m. to 7:00 p.m. Approximately 25 people attended the tutorial for the entire time, even though it was at the end of a long day, and received a thumbdrive copy of the ILAMBv2 code and data. This session allowed us to engage more students, postdocs, and university and laboratory researchers to widen the use of our benchmarking system.

This effort contributes directly to performance on Tasks D5 and D6.

4.6 Marine biogeochemistry (organics and aerosols)

Organic macromolecules constitute a high percentage of remote sea spray. They enter the atmosphere through adsorption onto bubbles followed by bursting at the ocean surface, and go on to influence the chemistry of the fine mode aerosol. In a recent study, we presented a global estimate of mixed-layer macromolecular distributions, driven by offline marine systems model output (**Oluwaseun O. Ogunro** et al., 2015). The approach permits estimation of oceanic concentrations and bubble film surface coverages for several classes of organic compound. Mixed layer levels are computed from the output of a global ocean ecodynamics model by relating the macromolecules to standard biogeochemical tracers. Steady state is assumed for labile forms, and for longer-lived components we rely on ratios to existing transported variables. Adsorption is then represented through conventional Langmuir isotherms, with equilibria deduced from laboratory analogs. Open water concentrations locally exceed one micromolar carbon for the total of proteins, polysaccharides and refractory heteropolycondensates. The shorter-lived lipids remain confined to regions of strong biological activity. Results are evaluated against available measurements for all compound types, and agreement is generally well within an order of magnitude. Global distributions are further estimated for both fractional coverage of bubble films at the air–water interface and the two-dimensional concentration excess. Overall, we show that macromolecular mapping provides a novel tool for the comprehension of oceanic surfactant patterns. These results may prove useful in planning field experiments and assessing the potential response of surface chemical behaviors to global change.

This effort contributes directly to performance on Question E5.

4.7 Marine biogeochemistry (carbon cycle feedbacks)

Marine biogeochemistry work at UCI has focused on continued analysis of the CMIP5 ocean models, initial analysis of longer-term oxygen and marine biogeochemistry trends in the extended climate simulations to year 2300, and continued development of new diagnostics and observational constraints on marine biogeochemical cycling. One new dataset generated was compiled from the literature summarizing field-estimates of phytoplankton community growth rates at the global-scale. We have also created a number of new diagnostic routines for examining model output in comparison with the World Ocean Atlas oxygen and nutrient databases, and with new iron-related

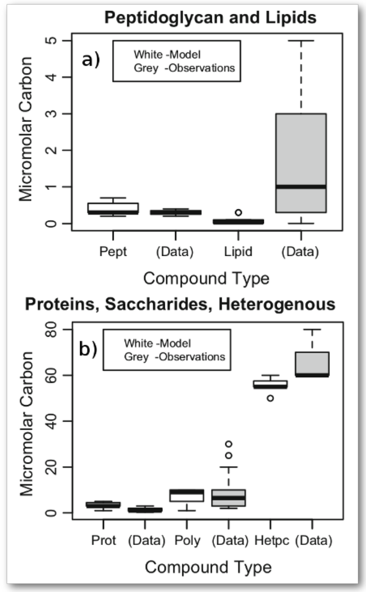

Figure 4: Comparisons of modeled versus measured global macromolecule concentrations.

observations from the GEOTRACES program. These new diagnostics and datasets are being incorporated into the ILAMB system ocean component. Two new publications have resulted, which are summarized below.

In a recent paper, we compiled and analyzed a new, global-scale dataset of field-based estimates of phytoplankton community growth rates (Sherman et al., 2016). This new dataset useful for climate model validation, was published in the supplementary materials section of the paper. We showed that the influence of temperature on community growth rates at the global scale was substantially weaker than previously thought (Q_{10} value of $\sim$1.5, rather than 2.0). For climate models to capture the biological response to the ongoing ocean warming, it is critical for them to accurately represent this observed empirical relation between temperature and community growth rates.

In another study, we examined a suite of CMIP5 ocean biogeochemical models to determine the key factors driving declining primary and export production across the models with strong warming under Representative Concentration Pathway (RCP) 8.5 (Fu et al., *Biogeosci.*, accepted). All of the models showed declining export production in response to increasing stratification (and an associated reduction in nutrient inputs to surface waters). However, the degree of stratification in the 1990s and the rates of increase during the 21$^{\mathrm{st}}$ century varied considerably across models. The models with the largest climate-driven increases in stratification and the largest relative declines in primary and export production, were those that also had the strongest stratification bias for the 1990s. This suggests the climate response may be overestimated in these models. We also show in this work that the response of Net Primary Production (NPP) to climate warming, is strongly dependent on ecosystem community structure within the phytoplankton. Models with multiple phytoplankton groups can capture a community shift towards smaller phytoplankton under the increasing nutrient stress associated with increasing stratification. The models show smaller relative declines in primary productivity.

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

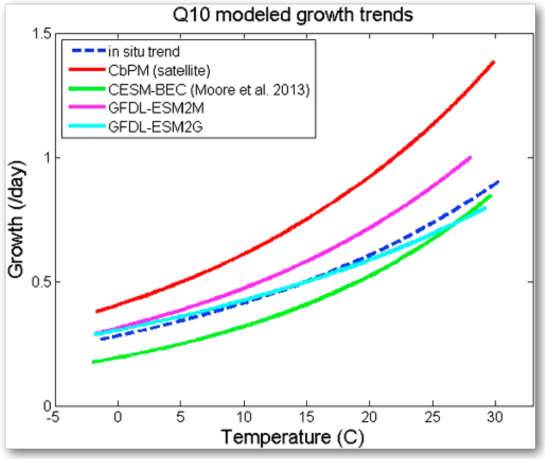

Figure 5: Apparent Q_{10} modeled growth trends plotted against temperature for CESM-BEC, GFDL-ESM2M, and GFDL-ESM2G as compared with CbPM (satellite) estimates.

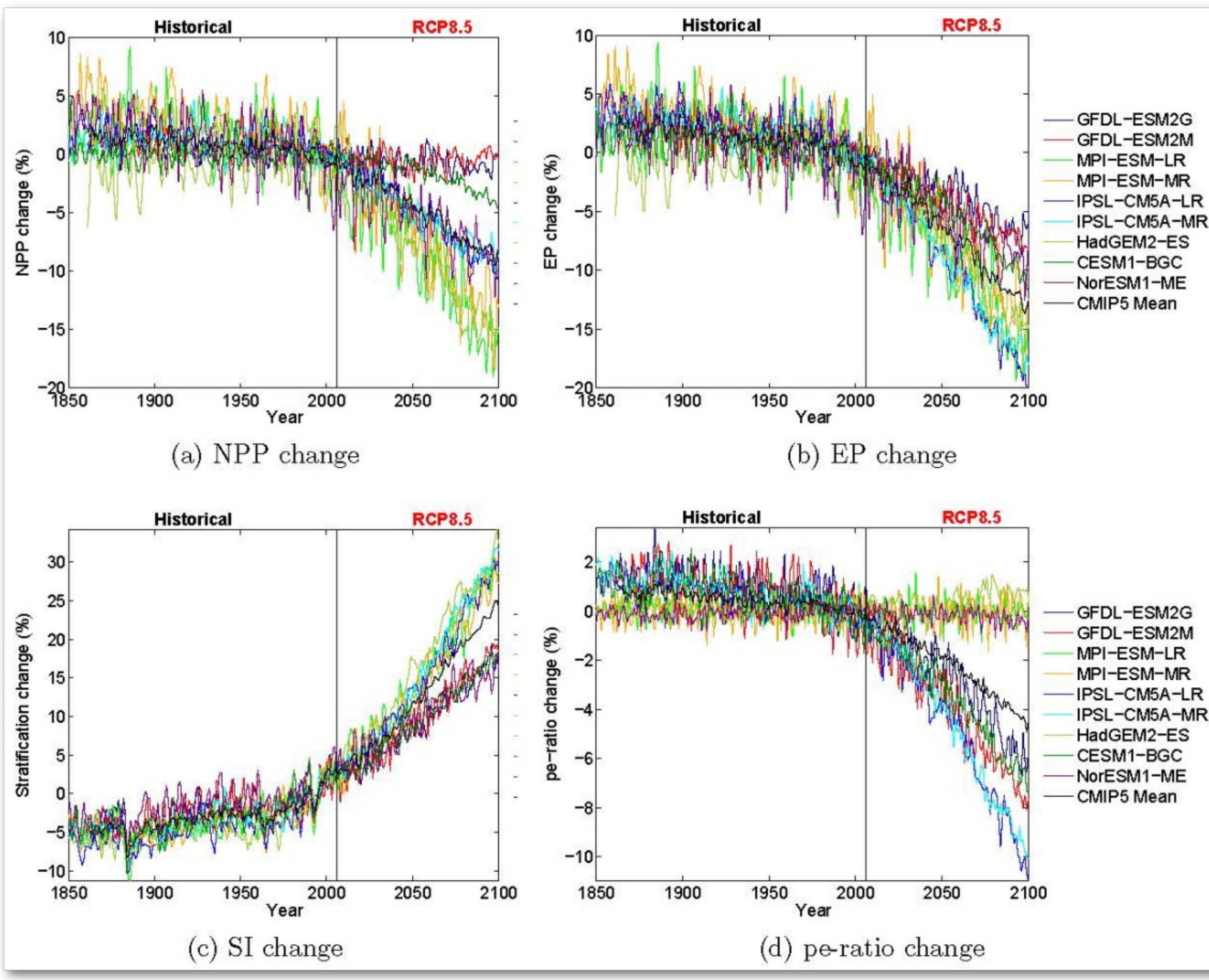

Figure 6: Displayed are time series for the percent changes in NPP, EP, pe-ratio, and stratification over ther period 1850–2100 for a collection of CMIP5 models (each relative to the 1990s means).

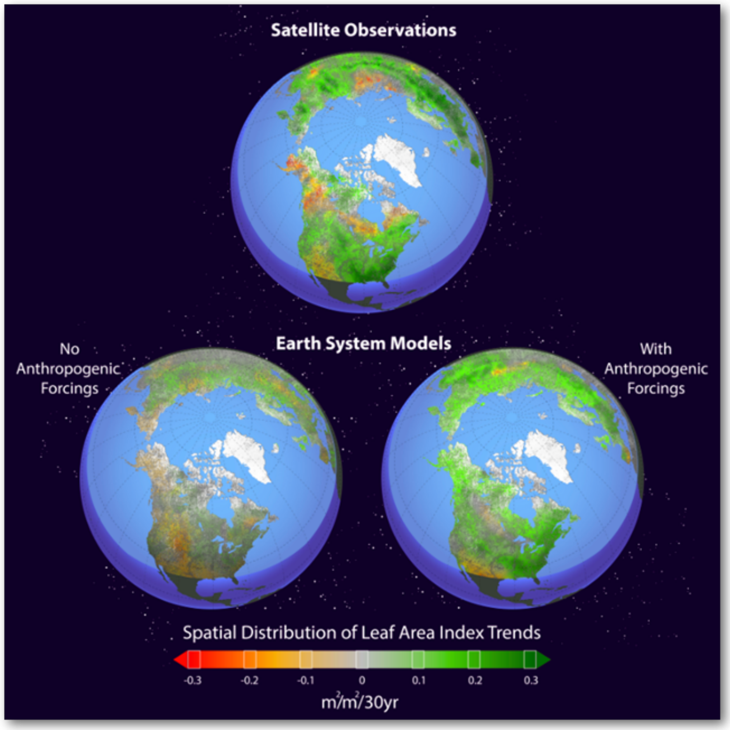

Figure 7: Spatial distribution of LAI trends observed by satellite and simulated by CMIP5 models over the period 1982–2011.

4.8 Human-induced greening of the northern extratropical land surface

Significant land greening in the northern extratropical land (NEL) has been documented through satellite observations during the past three decades. This enhanced vegetation growth has broad implications for surface energy, water and carbon budgets, and ecosystem services across multiple scales. Discernable human impacts on the Earth's climate system have been revealed by using statistical frameworks of detection and attribution. These impacts, however, were not previously identified on the NEL greening signal, due to the lack of long-term observational records, possible bias of satellite data, different algorithms used to calculate vegetation greenness, and the lack of suitable simulations from coupled Earth system models (ESMs). In a recent study, we have overcome these challenges in order to attribute recent changes in NEL vegetation activity (Mao et al., 2016). We used two 30-year-long remote-sensing-based LAI datasets, simulations from 19 coupled ESMs with interactive vegetation, and a formal detection and attribution algorithm. Our findings reveal that the observed greening record is consistent with an assumption of anthropogenic forcings, where greenhouse gases play a dominant role, but is not consistent with simulations that include only natural forcings and internal climate variability. Given the strong evidence provided here of historical human-induced greening in the northern extratropics, society should consider both intended and unintended consequences of its interactions with terrestrial ecosystems and the climate system. This work demonstrates the first clear evidence of a discernible human fingerprint on NEL physiological vegetation changes and proposes new investigations which could use detection and attribution methods to study broad-scale terrestrial ecosystem dynamics.

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

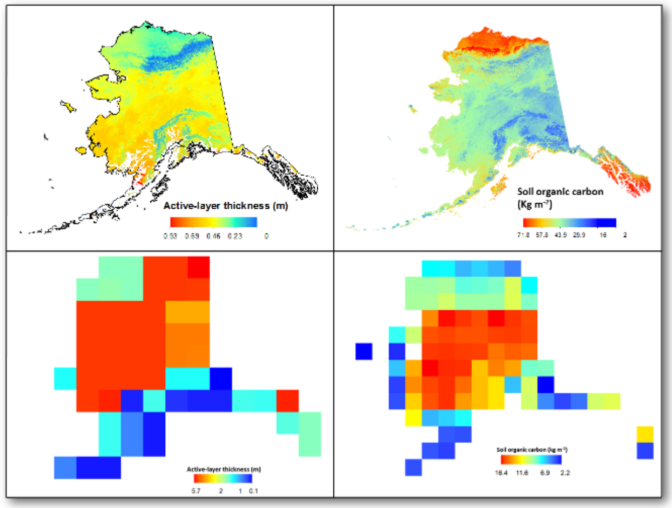

Figure 8: Spatial distribution of active-layer thickness (left) and soil organic carbon stocks to 1-m depth (right) across Alaska (upper figures) compared with those represented in the average of four CMIP5 Earth system models (lower figures).

4.9 Spatial representation of organic carbon and active-layer thickness of high latitude soils in CMIP5 Earth system models

Soil properties such as soil organic carbon (SOC) stocks and active-layer thickness are used in Earth system models (ESMs) to predict anthropogenic and climatic impacts on soil carbon dynamics, future changes in atmospheric greenhouse gas concentrations, and associated climate changes in the permafrost regions. Accurate representation of spatial and vertical distribution of these soil properties in ESMs is a prerequisite for reducing existing uncertainty in predicting carbon–climate feedbacks. In our recent work, we compared the spatial representation of SOC stocks and active-layer thicknesses predicted by the coupled Model Intercomparison Project Phase 5 (CMIP5) ESMs with those predicted from geospatial predictions, based on observation data for the state of Alaska, USA (Mishra et al., *Geoderma*, in press). For the geospatial modeling, we used soil profile observations (585 for SOC stocks and 153 for active-layer thickness) and environmental variables (climate, topography, land cover, and surficial geology types) and generated fine-resolution (50-m spatial resolution) predictions of SOC stocks (to 1-m depth) and active-layer thickness across Alaska. We found large inter-quartile range (2.5–5.5 m) in predicted active-layer thickness of CMIP5 modeled results and small inter-quartile range (11.5–22 $\mathrm{kg\,m^{-2}}$) in predicted SOC stocks. The spatial coefficient of variability of active-layer thickness and SOC stocks were lower in CMIP5 predictions compared to our geospatial estimates when gridded at similar spatial resolutions (24.7 compared to 30% and 29 compared to 38%, respectively). However, prediction errors, when calculated for independent validation sites, were several times larger in ESM predictions compared to geospatial predictions. Primary factors leading to observed differences were (1) lack of spatial heterogeneity in ESM predictions, (2) differences in assumptions concerning environmental controls, and (3) the absence of pedogenic processes in ESM model structures. Our results suggest that efforts to incorporate these factors in ESMs should reduce current uncertainties associated with ESM predictions of carbon–climate feedbacks.

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

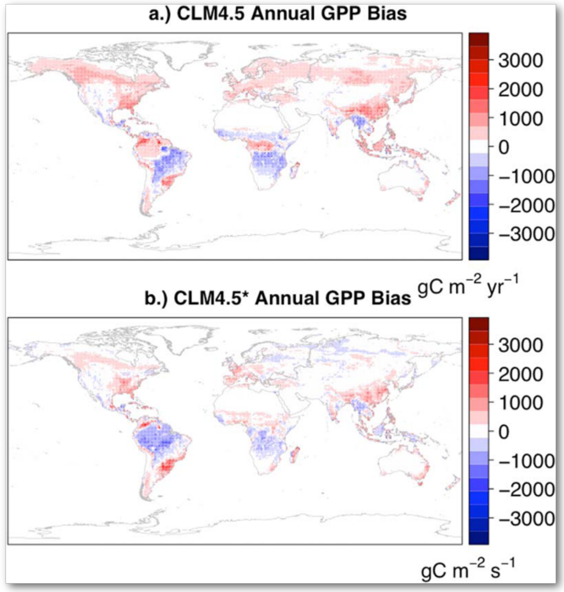

Figure 9: Spatial distribution of the annual GPP bias (model − reference) for (a) default version of CLM4.5 (CLM4.5) and (b) modified version of CLM4.5 (CLM4.5*) aggregated across 1995–2004. Predictions of CLM4.5* exhibited lower GPP bias compared to FLUXNET-MTE estimates than did CLM4.5, especially in higher latitudes.

4.10 Representing leaf and root physiological traits in CLM improves global carbon and nitrogen cycling predictions

In many ecosystems, nitrogen is the most limiting nutrient for plant growth and productivity. However, current Earth system models (ESMs) do not mechanistically represent functional nitrogen allocation for photosynthesis or the linkage between nitrogen uptake and root traits. The current version of the Community Land Model (CLM4.5) links nitrogen availability and plant productivity via (1) an instantaneous downregulation of potential photosynthesis rates based on soil mineral nitrogen availability, and (2) apportionment of soil nitrogen between plants and competing nitrogen consumers assumed to be proportional to their relative N demands. However, plants do not photosynthesize at potential rates and then downregulate; instead photosynthesis rates are governed by nitrogen that has been allocated to the physiological processes underpinning photosynthesis. Furthermore, the role of plant roots in nutrient acquisition has also been largely ignored in ESMs. We therefore presented a new plant nitrogen model for CLM4.5 with (1) improved representations of linkages between leaf nitrogen and plant productivity based on observed relationships in a global plant trait database and (2) plant nitrogen uptake based on root-scale Michaelis-Menten uptake kinetics (Ghimire et al., *J. Adv. Model. Earth Syst.*, in press). Our model improvements led to a global bias reduction in GPP, LAI, and biomass of 70%, 11%, and 49%, respectively. Furthermore, water use efficiency predictions were improved conceptually, qualitatively, and in magnitude. The new model's GPP responses to nitrogen deposition, CO_2 fertilization, and climate also differed from the baseline model. The mechanistic representation of leaf-level nitrogen allocation and a theoretically consistent treatment of competition with belowground consumers led to overall improvements in global carbon cycling predictions.

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

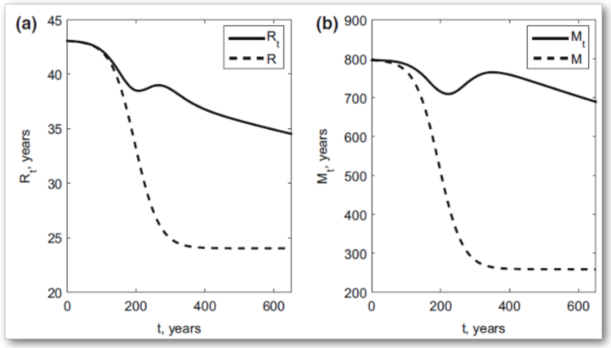

Figure 10: Using our nonautonomous theory for representing a nine-pool terrestrial carbon cycle model, we showed an order of magnitude difference in the absolute values of mean transit time, R_t, and mean age, M_t. Moreover, significant differences were shown between these nonautonomous properties and the instantaneous quantities, R and M, which represent the autonomous model.

4.11 Modeling the carbon cycle as a nonautonomous system

The terrestrial carbon cycle, like many biological systems, is commonly represented by compartmental models. Key metrics of the dynamics of such systems are transit time and mean age, which need not be the same. Under equilibrium, parameters describing the dynamics are constant in time, leading to models in the form of autonomous linear differential equations. With parameters and inputs that depend on time (e.g., under climate change), the compartmental models of interest are nonautonomous and are special cases of linear nonautonomous differential equations. We developed a theory for transit times and mean ages as nonautonomous compartmental systems. In recent research within an NIMBioS Working Group led by Yiqi Luo, we employed the McKendrick-von Förster equation to show the mean age of mass in a compartmental system satisfies a linear nonautonomous ordinary differential equation that is exponentially stable (Rasmussen et al., *J. Math. Biol.*, in press). We applied this theory to study a nine-dimensional nonautonomous compartmental system modeling the terrestrial carbon cycle based on a modification of the Carnegie–Ames–Stanford Approach (CASA) model. We demonstrated that the nonautonomous versions of transit time and mean age differ significantly from the autonomous quantities when calculated for that model. For the nine-pool carbon model, results indicate that the average age of carbon stored on land is much larger than the average age of carbon leaving the land. We further showed that our nonautonomous theory generalizes the autonomous case.

This effort contributes directly to performance on Questions D and E.

4.12 Multiple soil nutrient competition between plants, microbes, and mineral surfaces

Soil is a complex system where biotic (e.g., plant roots, micro-organisms) and abiotic (e.g., mineral surfaces) consumers compete for resources necessary for life (e.g., nitrogen, phosphorus). This competition is ecologically significant, since it regulates the dynamics of soil nutrients and controls aboveground plant productivity. In our recent research, we developed, calibrated and tested a nutrient competition model that accounts for multiple soil nutrients interacting with multiple biotic and abiotic consumers (**Qing Zhu** et al., 2016). When applied for tropical forests, the Nutri-

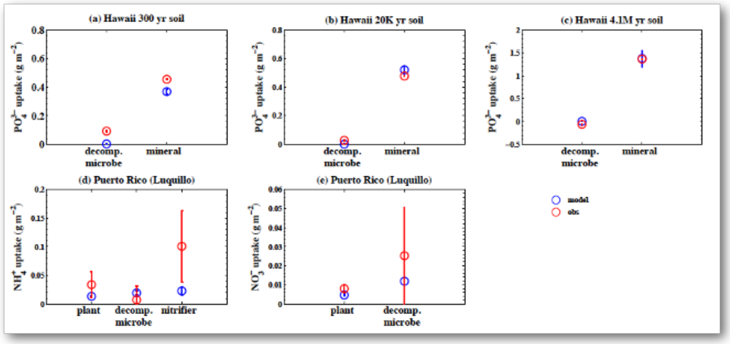

Figure 11: Model perturbation experiments compared with nitrogen and phosphorus fertilization field experimental data. The blue dots show the difference between control and perturbed simulations, which mean how much newly added nutrient each consumer takes up. The red circles are recovered isotopically labeled nutrient within each consumer. Since plants phosphorus uptake was not measured at Hawaii sites, we did not include the plants in the perturbation study.

ent COMpetition model (N-COM) included three primary soil nutrients (NH_4^+, $NO{+}3^-$ and PO_x; representing the sum of PO_4^{3-}, HPO_4^{2-} and $H_2PO_4^-$) and five potential competitors (plant roots, decomposing microbes, nitrifiers, denitrifiers and mineral surfaces). The competition was formulated with a quasi-steady-state chemical equilibrium approximation to account for substrate (multiple substrates share one consumer) and consumer (multiple consumers compete for one substrate) effects. N-COM successfully reproduced observed soil heterotrophic respiration, N_2O emissions, free phosphorus, sorbed phosphorus and NH_4^+ pools at a tropical forest site (Tapajos). The overall model uncertainty was moderately well constrained. Our sensitivity analysis revealed that soil nutrient competition was primarily regulated by consumer–substrate affinity rather than environmental factors such as soil temperature or soil moisture. Our results also imply that under strong nutrient limitation, relative competitiveness depends strongly on the competitor functional traits (affinity and nutrient carrier enzyme abundance). We then applied the N-COM model to analyze field nitrogen and phosphorus perturbation experiments in two tropical forest sites (in Hawaii and Puerto Rico) not used in model development or calibration. Under soil inorganic nitrogen and phosphorus elevated conditions, the model accurately replicated the experimentally observed competition among nutrient consumers. Although we used as many observations as we could obtain, more nutrient addition experiments in tropical systems would greatly benefit model testing and calibration. In summary, the N-COM model provides an ecologically consistent representation of nutrient competition appropriate for land BGC models integrated in Earth system models.

This effort contributes directly to performance on Questions C, D, E, F, and G.

4.13 How can we most directly combine datasets to estimate the magnitude of the permafrost carbon–climate feedback?

Enormous stocks of carbon exist in permafrost soils, which are vulnerable to loss with warming. Earth system models (ESMs) are beginning to include the processes that govern this feedback, but they show large uncertainties for permafrost processes. Working as part of the Permafrost Carbon Network (PCN), we built a synthesis of syntheses that combines meta-analyses of permafrost incubation data, Panarctic soil C maps, and Intercomparison of soil thermal models for the permafrost

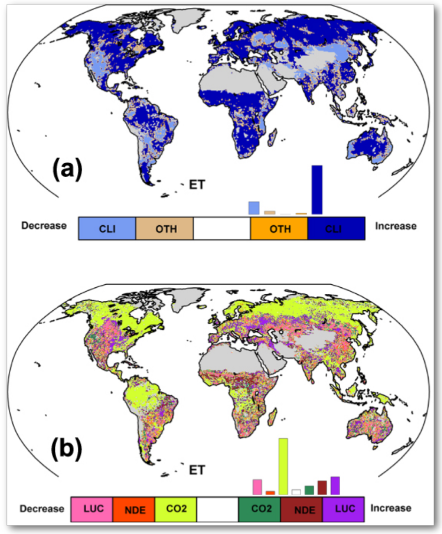

Figure 12: Spatial distribution of the dominant drivers for the ET. (a) Dominant drivers for the natural and human-induced ET, and (b) dominant drivers for the human-induced ET. CLI: the impact from historical climate only, OTH: all anthropogenic impacts, CO_2: the historical CO_2 impact only, NDE: the historical nitrogen deposition impact only, LUC: the historical land use/land cover change impact only.

region to create the PCN Incubation–Panarctic Thermal (PInc–PanTher) scaling approach. The results of this approach are that carbon losses are roughly linear with warming, with a permafrost carbon–climate feedback parameter of -14 to -19 Pg C °C^{-1}, which is still substantial but smaller than some earlier estimates. We identified key processes that are not included in this approach as a guide for further research directions on understanding the permafrost carbon–climate feedbacks.

This effort contributes directly to performance on Questions D, E2, and E4.

4.14 Disentangling climatic and anthropogenic controls on global terrestrial evapotranspiration trends

We examined natural and anthropogenic controls on terrestrial evapotranspiration (ET) changes from 1982 to 2010 using multiple estimates from remote sensing-based datasets and process-oriented land surface models (**Jiafu Mao** et al., 2015). A significant increasing trend of ET in each hemisphere was consistently revealed by observationally-constrained data and multi-model ensembles that considered historic natural and anthropogenic drivers. The climate impacts were simulated to determine the spatiotemporal variations in ET. Globally, rising CO_2 ranked second in these models after the predominant climatic influences, and yielded decreasing trends in canopy transpiration and ET, especially for tropical forests and high-latitude shrub land. Increasing nitrogen deposition slightly amplified global ET via enhanced plant growth. Land-use-induced ET responses, albeit with substantial uncertainties across the factorial analysis, were minor globally, but pronounced locally, particularly over regions with intensive land-cover changes. Our study highlights the importance of employing multi-stream ET and ET-component estimates to quantify the strengthening anthropogenic fingerprint in the global hydrologic cycle.

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

4.15 Plant responses to increasing CO_2 reduce estimates of climate impacts on drought severity

The demand for water by the atmosphere is widely predicted to increase due to climate change. While it is commonly assumed that this will cause droughts to become more widespread and severe, many recent studies, ignore the impact of rising atmospheric CO_2 on stomatal conductance and plant water use. In our recent research, we show that prediction of future drought stress is greatly reduced by plant physiological responses to CO_2 and that this is captured by using plant-centric rather than atmosphere-centric drought metrics from Earth system models (ESMs) (Swann et al., *Proc. Nat. Acad. Sci.*, in review). The atmosphere-centric Palmer Drought Severity Index (PDSI) predicts future increases in drought stress for more than 70% of global land area. This area drops to 37% with the use of precipitation minus evapotranspiration ($P - E$), a measure that represents the water flux available for use by humans and downstream ecosystems. Projections of future climate made with Earth system models already include the response of plants to increasing CO_2. We show the sensitivity of widely-used drought metrics to radiative and physiological drivers is highly variable, and that incomplete representation of plant transpiration responses to CO_2 contributes to recent divergent reports of changing drought stress. More effective use of drought indices that fully integrate the influence of plants on evapotranspiration, including direct use of $P - E$, soil moisture and runoff variables from ESMs, is needed to reduce uncertainties associated with future assessment of changing drought stress.

This effort contributes directly to performance on Questions B and E1.

4.16 Evaluating the strength of the land–atmosphere moisture feedback in Earth system models using satellite observations

The relationship between terrestrial water storage (TWS) and atmospheric processes has important implications for predictability of climatic extremes and projection of future climate change. In places where moisture availability limits evapotranspiration (ET), variability in TWS has the potential to influence surface energy fluxes and atmospheric conditions. Where atmospheric conditions, in turn, influence moisture availability, a full feedback loop exists. In a recent study, we developed a novel approach for measuring the strength of both components of this feedback loop, i.e., the forcing of the atmosphere by variability in TWS and the response of TWS to atmospheric variability, using satellite observations of TWS, precipitation, solar radiation, and vapor pressure deficit during 2002–2015 (Levine et al., *Hydrol. Earth Syst. Sci. Discuss.*, in review). Metrics derived from the satellite data were used to evaluate the strength of the feedback loop in 38 members of the Community Earth System Model (CESM) Large Ensemble (LENS) and in six models that contributed simulations to Phase 5 of the Coupled Model Intercomparison Project (CMIP5). We found that both forcing and response limbs of the feedback loop in LENS were stronger than in the satellite observations in tropical and temperate regions. Feedbacks in the selected CMIP5 models were not as strong as those found in LENS, but were still generally stronger than those estimated from the satellite measurements. Consistent with previous studies conducted across different spatial and temporal scales, our analysis suggests that models may overestimate the strength of the feedbacks between the land surface and the atmosphere. We describe several possible mechanisms that may contribute to this bias, and discuss pathways through which models may overestimate ET or overestimate the sensitivity of ET to TWS.

This effort contributes directly to performance on Questions D and E.

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	4.1, 4.2
Task D5: Delivery of initial benchmarking package to community	4.1, 4.2, 4.3, 4.4, 4.5
Task D6: First benchmarking workshop	4.3, 4.4, 4.5
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?	4.14
Question B: How well can ESMs simulate observed linkages between growing season onset and mid-summer drought stress?	4.15
Question C: How well can ESMs capture the abundance and spatial variability of leaf area regionally and globally?	4.8, 4.10, 4.12
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?	4.9, 4.10, 4.11, 4.12, 4.13, 4.14, 4.16
Question E: How do carbon stocks, ecosystem processes, and surface biophysics vary across ecotones?	4.9, 4.10, 4.11, 4.12, 4.14, 4.16
Question F: How will C-nutrient interactions regulate terrestrial carbon cycle responses to changes in atmospheric CO_2 and climate?	4.8, 4.10, 4.12
Question G: How can ecosystem manipulations serve to constrain long-term model responses?	4.12
Question H: What factors control spatial and temporal differences in the patterns of ocean net primary production and export production among ESMs?	4.7
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?	4.7
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?	4.15
Question E2: Do models that overestimate snow albedo feedbacks underestimate permafrost loss during the 21st century?	4.13
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?	4.8, 4.9, 4.10, 4.13, 4.14
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?	4.6, 4.7
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?	4.7

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In Review, Revision, Press, or Published Early Online

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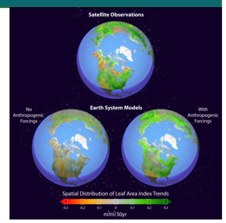
B Highlights

The following highlight slides have been submitted to DOE over the past year and are available on the project website at `http://www.bgc-feedbacks.org/research/highlights/`.

Human-induced greening of the northern extratropical land surface

Objective:
Two long-term satellite leaf area index (LAI) datasets, 19 coupled Earth system models (ESMs) and a formal detection and attribution algorithm were used to attribute changes of vegetation activity in the northern-extratropical latitudes (NELs) for the period 1982–2011.

Approach:
- Significant land greening in NELs was captured by satellite observations and ESM simulations with historical anthropogenic and natural forcings.
- The trend of strengthened northern vegetation greening is clearly distinguishable from both internal climate variability and the response to natural forcings alone.
- The observed greening record can be rigorously attributed to anthropogenic forcings, particularly to rising atmospheric concentrations of greenhouse gases.



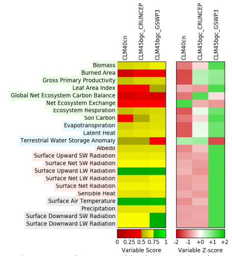
Spatial distribution of LAI trends observed by satellite and simulated by CMIP5 models over the period 1982–2011.

Results/Impacts:
- We clarified mechanisms driving NEL vegetation dynamics for the past 3 decades.
- We demonstrated the first clear evidence of a discernible human fingerprint on physiological vegetation changes other than phenology and range shifts.
- We proposed new areas for detecting and attributing terrestrial ecosystem dynamics across scales.

Mao, Jiafu, Aurélien Ribes, Binyan Yan, **Xiaoying Shi**, **Peter E. Thornton**, Roland Séférian, Philippe Ciais, Ranga B. Myneni, Hervé Douville, Shilong Piao, Zaichun Zhu, Robert E. Dickinson, Yongjiu Dai, Daniel M. Ricciuto, Mingzhou Jin, **Forrest M. Hoffman**, Bin Wang, Mengtian Huang, and Xu Lian (2016), Human-induced greening of the northern extratropical land surface, *Nature Clim. Change*, doi:10.1038/nclimate3056.

BGC Feedbacks

The ILAMB Benchmarking System (v2) Release



Summary graphic generated by the ILAMBv2 package depicting model performance across a wide variety of variables, emphasizing absolute performance (left) as well as relative performance (right).

Collier, N. et al. (2016), The ILAMB Benchmarking System, doi:10.18139/ILAMB.v002.00/1251621.

Objective:
Research and disseminate benchmarking procedures and datasets which improve land model fidelity.

Approach:
- Software framework written in python that compares model outputs to benchmark observational datasets in parallel on leadership-class supercomputers.
- Provides the community a means to comprehensively and routinely assess land model fidelity through comparison of 24 variables with 60 observational datasets.

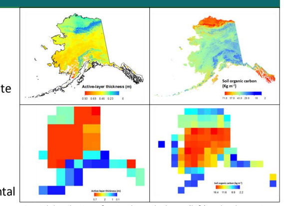
Results/Impacts:
- Framework provides an abstraction that allows groups to develop plugins to extend its functionality.
- New datasets and comparisons are easily added, encouraging routine use by modeling centers across the globe.
- Package is currently used by ACME and CESM to evaluate new model developments.

BGC Feedbacks

Spatial Representation of High Latitude Soil Properties in CMIP5 ESMs

Objective:
Accurate representation of spatial and vertical distribution of soil carbon stocks and active-layer thickness in earth system models for reducing uncertainty in predicting permafrost carbon–climate feedbacks.

Approach:
Employ observations, spatial statistics, uncertainty analysis, and data–model intercomparison.


Spatial distribution of active-layer thickness (left) and soil organic carbon stocks to 1-m depth (right) across Alaska (upper figures) compared with those represented in average of four CMIP5 earth system models (lower figures).

Results/Impacts:
- Different spatial heterogeneity and environmental controls of soil carbon stocks and active-layer thickness were observed in model projections in comparison to observations.
- Magnitude and spatial distribution of uncertainties in model projections were not consistent with uncertainties in observations.
- As ESM spatial resolution increases and important ecosystem processes are added to include critical soil dynamics of permafrost regions, our study provides a spatial benchmark to evaluate ESM outputs of permafrost affected systems.

Mishra, Umakant, Beth Drewniak, Julie D. Jastrow, Roser M. Matamala, and U. W. A. Vitharana (2016), Spatial representation of organic carbon and active-layer thickness of high latitude soils in CMIP5 earth system models, *Geoderma*, doi:10.1016/j.geoderma.2016.04.017.

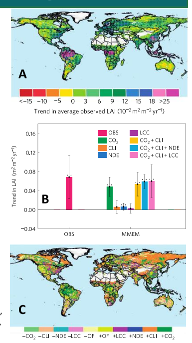
BGC Feedbacks

Greening of the Earth and Responsible Driving Mechanisms

Objective:
Understand how dynamics of terrestrial vegetation are responding to global environmental change.

Approach:
We applied three long-term satellite leaf area index (LAI) records and ten global ecosystem models for the period 1982–2009.

Results/Impacts:
- We identified a persistent and widespread increase of growing season integrated LAI (GSILAI) (greening) over 25–50% of the global vegetated area, whereas less than 4% of the globe shows decreasing GSILAI (browning) (Fig. A).
- Model-based interpretations of these data demonstrated significant correlation with CO_2 fertilization (70%), nitrogen deposition (9%), climate change (8%) and land cover change (LCC; 4%) (Figs. B and C).
- CO_2 fertilization effects dominated in the tropics, whereas climate change was the dominant driver in the Tibetan Plateau. LCC contributed most to regional greening in southeast China and the eastern United States (Fig. C).



Zhu, Z., S. Piao, R. B. Myneni, M. Huang, Z. Zeng, J. G. Canadell, P. Ciais, S. Sitch, P. Friedlingstein, A. Arneth, C. Cao, L. Cheng, E. Kato, **C. D. Koven**, Y. Li, X. Lian, Y. Liu, R. Liu, **J. Mao**, Y. Pan, S. Peng, J. Peñuelas, B. Poulter, T. A. M. Pugh, B. D. Stocker, N. Viovy, X. Wang, Y.-P. Wang, Z. Xiao, H. Yang, S. Zaehle, and N. Zeng (2016), Greening of the Earth and its drivers, *Nature Clim. Change*, doi:10.1038/nclimate3004.

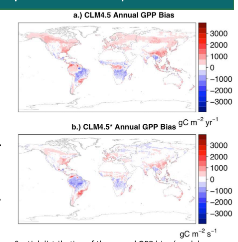
BGC Feedbacks

Can representing leaf and root traits improve model predictions?

Objective:
Understand if a more mechanistic representation of nitrogen limitation and root-scale uptake kinetics can reduce model biases.

Approach:
We developed a new plant nitrogen model for CLM4.5 that links leaf nitrogen and plant productivity and represents root-scale Michaelis-Menten uptake kinetics.

Results/Impacts:
- Model improvements led to global bias reductions in gross primary production (GPP), leaf area index (LAI), and biomass by 70%, 11%, and 49%, respectively.
- Water use efficiency predictions were similarly improved.
- Mechanistic representation of leaf-level nitrogen allocation and consistent treatment of competition led to global carbon cycle prediction improvements.



Spatial distribution of the annual GPP bias (model – reference) for (a) default version of CLM4.5 (CLM4.5) and (b) modified version of CLM4.5 (CLM4.5*) aggregated across 1995–2004. Predictions of CLM4.5* exhibited lower GPP bias compared to FLUXNET-MTE estimates than did CLM4.5, especially in higher latitudes.

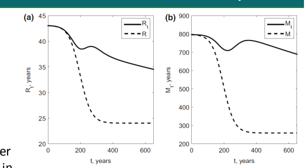
Ghimire, B., **W. J. Riley**, **C. D. Koven**, **M. Mu**, and **J. T. Randerson** (2016), Representing leaf and root physiological traits in CLM improves global carbon and nitrogen cycling predictions, *J. Adv. Model. Earth Syst.*, 8, doi:10.1002/2015MS000538.

BGC Feedbacks

Modeling the Carbon Cycle as a Nonautonomous System

Objective:
To understand transit time and mean age dynamics of terrestrial carbon storage with time-dependent parameters and inputs.

Approach:
- We developed a theory for transit times and mean ages within nonautonomous compartmental systems.
- We employed the McKendrick-von Förster equation to show the mean age of mass in a compartmental system satisfies a linear nonautonomous ordinary differential equation that is exponentially stable.



Using our nonautonomous theory for representing a nine-pool terrestrial carbon cycle model, we showed an order of magnitude difference in the absolute values of mean transit time, R_t, and mean age, M_t. Moreover, significant differences were shown between these nonautonomous properties and the instantaneous quantities, *R* and *M*, which represent the autonomous model.

Results/Impacts:
- We applied the theory to a nine-dimensional terrestrial carbon cycle model.
- We demonstrated the nonautonomous versions of transit time and mean age differ significantly from the autonomous quantities when calculated for that model.
- Results indicated the average age of carbon stored on land is much larger than the average age of carbon leaving the land.

Rasmussen, M., A. Hastings, M. J. Smith, F. B. Agusto, B. M. Chen-Charpentier, **F. M. Hoffman**, J. Jiang, K. E. O. Todd-Brown, Y. Wang, Y.-P. Wang, and Y. Luo (2016), Transit times and mean ages for nonautonomous and autonomous compartmental systems, *J. Math. Biol.*, doi:10.1007/s00285-016-0990-8.

BGC Feedbacks

Predicting biomass of hyperdiverse and structurally complex central Amazonian forests – A virtual approach using extensive field data

Objective:
Reliable biomass estimates require the inclusion of predictors that express inherent variations in species architecture.

Approach:
Old-growth forests are highly heterogeneous in structure and species composition. Therefore, generic global or pantropical biomass estimation models can lead to strong biases (Fig. 1).

Results/Impacts:
Generic aboveground biomass (AGB) models applicable across species were applied across six scenarios (Fig. 2) of data from 727 trees (DBH > 5 cm) from 101 genera, and 135 species harvested near Manaus, Brazil.

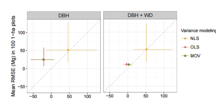


Fig 1. Performance of 12 aboveground tree estimation models along six forest scenarios composed of 100 1 ha plots. Models' predictors: diameter at breast height (DBH) (cm), wood density (WD) (g cm⁻³). NLS: nonlinear least square. OLS: ordinary least square with log-linear regression. MOV: nonlinear with modeled variance (MOV).

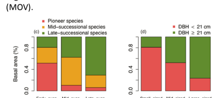


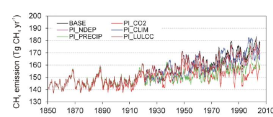
Fig 2. Sampling schemes applied to six forest scenarios designed to reflect changes in floristic composition and size distribution of trees, typical of central Amazonian terra firme forests.

Magnabosco Marra, Daniel, Niro Higuchi, Susan E. Trumbore, Gabriel H. P. M. Ribeiro, Joaquim dos Santos, Vilany M. C. Carneiro, Adriano J. N. Lima, Jeffrey Q. Chambers, **Robinson I. Negrón-Juárez**, Frederic Holzwarth, Björn Reu, and Christian Wirth (2016), Predicting biomass of hyperdiverse and structurally complex central Amazonian forests — A virtual approach using extensive field data, *Biogeosci.*, 13(5):1553–1570, doi:10.5194/bg-13-1553-2016.

BGC Feedbacks

Attribution of Changes in Global Wetland Methane Emissions from Pre-Industrial to Present Using CLM4.5-BGC

Objective:
- Understanding the factors controlling CH_4 emissions from natural wetlands is important to accurately project future atmospheric concentrations.
- Results inform needed observations to improve CH_4 models.



CH_4 emissions since 1850 separated into controls from N deposition, precipitation, CO_2, climate, and land use.

Approach:
- We examined contributions of precipitation, T, CO_2, N deposition, inundation, and land-use on changes in wetland CH_4 emissions from 1850–2005.
- We used the CH_4 model integrated in CLM4.5 (identical to that in ALMv1).

Results/Impacts:
- Preindustrial CH_4 emissions were higher by 10% than present-day.
- Changes in CH_4 substrate production and the areal extent and seasonality of wetlands led to the largest sensitivity in predicted emissions.

Paudel, Rajendra, Natalie M. Mahowald, Peter G. M. Hess, Lei Meng, and **William J. Riley** (2016), Attribution of changes in global wetland methane emissions from pre-industrial to present using CLM4.5-BGC, *Environ. Res. Lett.*, 11(3):034020, doi:10.1088/1748-9326/11/3/034020.

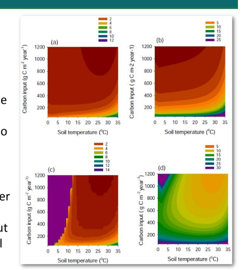
BGC Feedbacks

Responses of two nonlinear microbial models to warming and increased carbon input

Objective:
Improve understanding of significance of soil microbial processes in soil carbon responses to climate change.

Approach:
- Compared two nonlinear microbial models: one based on reverse Michaelis–Menton kinetics (model A) and the other on regular Michaelis–Menton kinetics (model B).
- Used analytic approximations and numerical solutions to test CO_2 efflux of both models.

Results/Impacts:
- We found oscillatory responses of C pools to small perturbations in initial pool sizes, which dampened faster in model A than in model B.
- Soil warming always decreased C storage in model A, but in model B it predominantly decreased C storage in cool regions and increased C in warm regions.
- Sensitivity of maximum CO_2 efflux to increased C input increased with soil temperature in model A but decreased with increased soil temperature in model B.

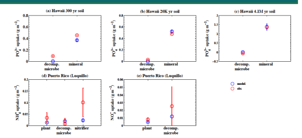


Half-life (a, b) and period (c, d) in units of year for model A (a, c) and B (b, d). The purple region represents non-oscillatory region for model A in (c), and a period greater than 30 years for model B in (d).

Wang, Y. P., J. Jiang, B. Chen-Charpentier, F. B. Agusto, A. Hastings, **Forrest M. Hoffman**, M. Rasmussen, M. J. Smith, K. Todd-Brown, Y. Wang, X. Xu, and Y. Q. Luo (2016), Responses of two nonlinear microbial models to warming and increased carbon input, *Biogeosci.*, 13(4):887–902. doi:10.5194/bg-13-887-2016.

BGC Feedbacks

Multiple soil nutrient competition between plants, microbes, and mineral surfaces



Objective:
- Develop, calibrate, and test a nutrient competition model that accounts for multiple soil nutrients and abiotic consumers.
- Calibrate and test model against N and P fertilization experiments.
- Predict dynamic competitive regimes.

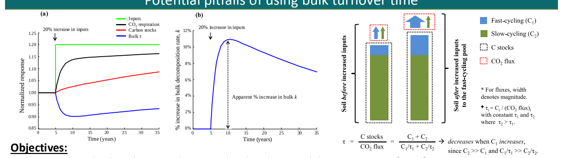
Approach:
- Model includes three primary soil nutrients (NH_4^+, NO_3^-, PO_x) and five competitors (plant roots, decomposing microbes, nitrifiers, denitrifiers, and mineral surfaces).
- Competition modeled with the Equilibrium Chemistry Approximation (ECA).
- Calibrated at a tropical forest site (Tapajos) and tested at two other tropical forest sites (Hawaii and Puerto Rico).

Results/Impacts:
- Model accurately replicated the experimentally manipulated forest responses that were not used in model calibration.
- Relative competitiveness of consumers was dynamic. For NH_4, nitrifiers and decomposers were comparably competitive and out-competed roots.
- These mechanisms are being integrated in ALM and tested against >80 field studies.

Zhu, Q., **W. J. Riley**, **J. Y. Tang**, and **C. D. Koven** (2016), Multiple soil nutrient competition between plants, microbes, and mineral surfaces: Model development, parameterization, and example applications in several tropical forests, *Biogeosci.*, 13(1):341–363, doi:10.5194/bg-13-341-2016.

BGC Feedbacks

Toward improved model structures for analyzing priming: Potential pitfalls of using bulk turnover time



Objectives:
- Determine whether the typical one-pool soil carbon model is appropriate for inferring changes in decomposition rate constants in response to elevated CO_2 and plant inputs (i.e., priming).
- Suggest model structures and observational constraints necessary for projections of the priming effect.

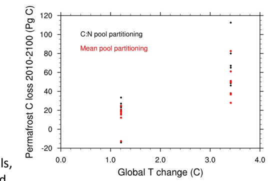
Approach:
Using a multi-pool soil carbon model, we show that changes in carbon flows that would be attributed to priming in a one-pool model can be explained without a change in decomposition rate constants of individual pools. Therefore, the typically applied one-pool approach is not adequate to infer priming.

Results/Impacts:
- Our study challenges the analytical framework used to quantify stimulated decomposition of soil carbon in response to increased plant inputs (i.e., priming).
- We explain the limitations of using simple soil carbon models and suggest solutions for incorporating priming in earth system models for projections of global change.

Georgiou, Katerina, **Charles D. Koven**, **William J. Riley**, and Margaret S. Torn (2015), Toward improved model structures for analyzing priming: Potential pitfalls of using bulk turnover time, *Glob. Change Biol.*, 21(12):4298–4302, doi:10.1111/gcb.13039.

BGC Feedbacks

Developing a simplified, data-constrained model of permafrost C feedback



Objective:
Estimate the magnitude of the carbon-climate feedback from permafrost soils, by synthesizing data on soil C stocks, decomposability, and combining these with model estimates of permafrost warming.

Approach:
A "synthesis of syntheses" to combine meta-analyses of permafrost incubation data, an intercomparison of permafrost soil thermal models, and pan-Arctic soil C maps to generate a simplified and data constrained approach for estimating the permafrost carbon–climate feedback.

Results/Impacts:
Estimated permafrost carbon losses are roughly linear with warming, supporting the idea of a permafrost carbon–climate feedback strength. Magnitude of this feedback on the 100-year timescale is substantial, though smaller than some earlier estimates. Identify key processes that are not included, and how they may influence results.

Koven, C. D., . 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, and M. Turetsky (2015), A simplified, data-constrained approach to estimate the permafrost carbon–climate feedback. *Phil. Trans. R. Soc. A*, 373(2054):20140423. doi:10.1098/rsta.2014.0423.

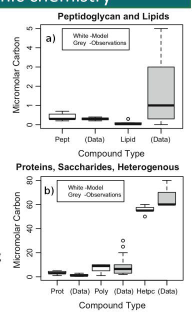
BGC Feedbacks

Global distribution and surface activity of macromolecules in offline simulations of marine organic chemistry

Objective:
Characterize the global distribution and activity of organic macromolecules at the ocean surface using a mechanistic marine systems model.

Approach:
- We conducted offline simulations of the Parallel Ocean Program (POP) with the Biogeochemistry-Ecosystem-Circulation (BEC) package to obtain ecodynamic tracer fields.
- Seasonal surface concentration distributions of organic macromolecules were calculated from these tracers.
- Fractional surfactant coverages and surface excess concentrations were also estimated.

Results/Impacts:
- Distribution estimates were found to agree with available measurements within an order of magnitude.
- Results can be used for planning field experiments and assessing potential response of surface chemical behaviors to global change.



Comparisons of modeled versus measured global macromolecule concentrations.

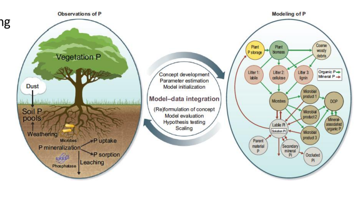
Ogunro, Oluwaseun O., Susannah M. Burrows, **Scott Elliott**, Amanda A. Frossard, **Forrest M. Hoffman**, Robert T. Letscher, **J.Keith Moore**, Lynn M. Russell, **Shanlin Wang**, and Oliver W. Wingenter (2015), Global distribution and surface activity of macromolecules in offline simulations of marine organic chemistry, *Biogeochemistry*, 126(1–2):25–56. doi:10.1007/s10533-015-0136-x.

BGC Feedbacks

Incorporating phosphorus cycling into global scale modeling efforts: A worthwhile tractable endeavor

Objective:
Provide guidance for effectively including phosphorus cycling into Earth system models.

Approach:
- We used empirical and modeling perspectives to synthesize the current understanding of phosphorus cycling processes, discussing existing challenges and opportunities.
- Model–data integration was demonstrated as the way forward and we provide key processes and parameters for modeling phosphorus.



Results/Impacts:
This paper brings attention to the need for including phosphorus for accurate predictions of future climate, and provides a road map for how to move forward.

Reed, Sasha C., **Xiaojuan Yang**, and **Peter E. Thornton** (2015), Incorporating phosphorus cycling into global scale modeling efforts: A worthwhile tractable endeavor, *New Phyt.*, 208(2):324–329, Invited Tansley Insight, doi:10.1111/nph.13521.

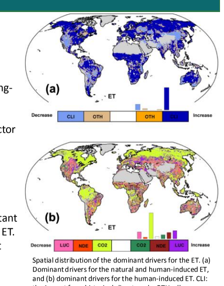
BGC Feedbacks

Disentangling climatic and anthropogenic controls on terrestrial ET trends

Objective:
Examine natural and anthropogenic controls on terrestrial evapotranspiration (ET) changes from 1982 to 2010.

Approach:
- We created a diagnostic tool combining ET information from 11 long-term datasets. All input datasets were based on extensive in situ observations, satellite retrievals, or both.
- We used this diagnostic tool to evaluate single-factor and multi-factor simulations from the Multi-Scale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP).

Results/Impacts:
- Changing climate was assessed to be the dominant control on spatiotemporal variations in ET.
- Rising atmospheric CO_2 concentration was the second most important factor influencing ET, with higher CO_2 driving a decreasing trend in ET.
- Nitrogen deposition slightly amplified global ET via enhanced plant growth. Land-use-induced ET responses were minor globally but pronounced locally.
- Multi-stream datasets and multi-modeling frameworks help to quantify the strengthening anthropogenic fingerprint on the global hydrologic cycle.



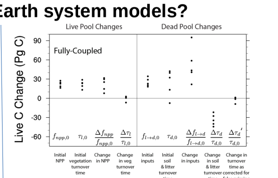
Spatial distribution of the dominant drivers for the ET. (a) Dominant drivers for the natural and human-induced ET, and (b) dominant drivers for the human-induced ET. CLI: the impact from historical climate only, OTH: all anthropogenic impacts, CO_2: the historical CO_2 impact only, NDE: the historical nitrogen deposition impact only, LUC: the historical land use/land cover change impact only.

Mao, Jiafu, et al. (2015), Disentangling climatic and anthropogenic controls on global terrestrial evapotranspiration trends, *Environ. Res. Lett.*, 10(9):094008, doi:10.1088/1748-9326/10/9/094008.

BGC Feedbacks

What processes most strongly govern terrestrial carbon cycle feedbacks in Earth system models?

Objective:
Better understand what processes control terrestrial carbon cycle feedbacks by separating carbon changes driven by changing inputs from those driven by changing outputs.



Research:
We developed a theoretical framework for separating inputs and outputs, and applied it to CMIP5 ESMs. We identified key areas where these terms interact, in particular identifying a process that we call "false priming" that is an apparent interaction between productivity and soil decomposition, and quantified processes that most strongly govern uncertainty in carbon cycle feedbacks.

Impact:
This research identified the key carbon cycle processes governing model uncertainty and the processes on which models agree. This allows us to focus efforts on reducing uncertainty in processes responsible for the largest spread, as well as to assess whether model agreement is due to well founded process representations or due to a shared lack of realism.

Reference: C. D. Koven, J. Q. Chambers, K. Georgiou, R. Knox, R. I. Negron-Juarez, W. J. Riley, V. Arora, V. Brovkin, P. Friedlingstein, and C. D. Jones (2015), Controls on terrestrial carbon feedbacks by productivity versus turnover in the CMIP5 Earth System Models, *Biogeosci.*, 12(17):5211–5228, doi:10.5194/bg-12-5211-2015.

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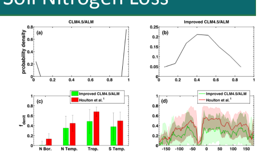
Improved Modeling of Soil Nitrogen Loss

Objective:
- Improve prediction of soil nitrogen losses via advection (i.e., nitrate) and gaseous emissions (i.e., N_2O and N_2).
- Improve the ACME Land Model (ALM) numerical representation of nutrient competition coupled with abiotic processes.



Approach:
- We modified the ALM nitrogen competition module with the Equilibrium Chemistry Approximation (ECA) approach that represents the multi-substrate, multi-consumer environment
- Advective nitrate losses and competition with biotic consumers (e.g., plants) were more realistically represented.

Results/Impacts:
- As shown in the upper left panel, the current versions of ALM and CLM4.5 poorly represent the gaseous proportion on nitrogen losses (f_{denit}).
- The bottom two panels show the dramatic improvements in partitioning of N losses with our ECA and advection changes.
- We are integrating these concepts into ALMv1.

Zhu, Q., and **W. J. Riley** (2015), Improved modelling of soil nitrogen losses, *Nature Clim. Change*, 5(8):705–706, doi:10.1038/nclimate2696.

BGC Feedbacks

Spatial scaling changes environmental controls and spatial heterogeneity of soil carbon stocks

Motivation

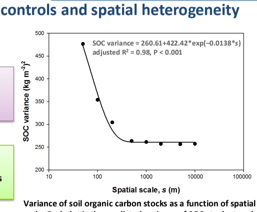
Spatial heterogeneity of the land surface affects energy, moisture, and greenhouse gas exchanges with the atmosphere. However representing the heterogeneity of terrestrial biogeochemical processes in earth system models is a critical scientific challenge.

Approach

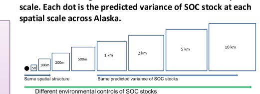
We used soil profile observations, environmental factors, and geospatial modeling to study the impact of spatial scaling on environmental controls, spatial structure, and statistical properties of soil carbon stocks, with a focus on permafrost regions in Alaska.

Results/Impacts

- **The strengths of environmental controls on soil carbon stocks decreased with increasing scale and were accurately represented using mathematical functions (R^2 = 0.83–0.97).**
- **The variance of predicted SOC stocks decreased with spatial scale over the range of 50 m to ~500 m, and remained constant beyond 500 m.**
- **Improved understanding of the scaling behavior of environmental controls and spatial heterogeneity of soil carbon stocks could improve land model benchmarking and allow representation of spatial heterogeneity of biogeochemistry at scales finer than those currently resolved by Earth system models.**



Variance of soil organic carbon stocks as a function of spatial scale. Each dot is the predicted variance of SOC stock at each spatial scale across Alaska.



Spatial structure of soil organic carbon stocks remains consistent with observations only up to 100 m.

Mishra, U., and W.J. Riley (2015), Scaling impacts on environmental controls and spatial heterogeneity of soil organic carbon stocks, *Biogeosci.*, 12(13):3993–4004, doi:10.5194/bg-12-3993-2015.

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