

BIOGEOCHEMISTRY–CLIMATE FEEDBACKS: Quantifying Feedbacks and Uncertainties of Biogeochemical Processes in Earth System Models

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Biogeochemistry–Climate Feedbacks SFA Goals

- ▶ Terrestrial and ocean biogeochemical processes are poorly represented in current Earth system models (ESMs).
- ▶ Large uncertainties in the strengths of BGC–climate feedbacks motivates addition of new BGC mechanisms in ESMs.
- ▶ To advance understanding, comprehensive and multi-faceted evaluation, analysis, and diagnosis of ESM results are needed.
- ▶ We are performing systematic evaluation of ESMs, delivering diagnosis tools for informing model development, and engaging experimentalists in identifying model weaknesses and needed measurements.

BGC Feedbacks SFA Goals

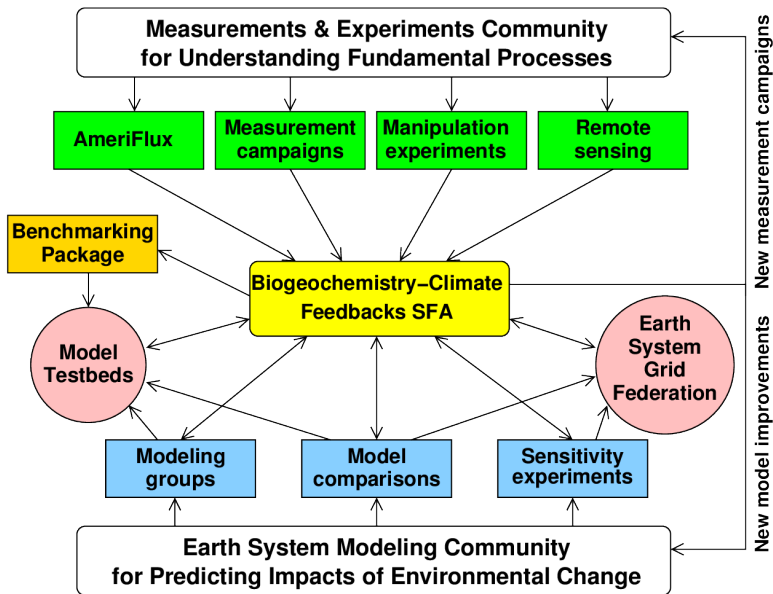
The overarching goals of the BGC Feedbacks SFA are to identify and quantify the feedbacks between biogeochemical cycles and the climate system, and to quantify and reduce the uncertainties in ESMs associated with those feedbacks.

Biogeochemistry–Climate Feedbacks SFA Objectives

We will achieve these goals through five objectives:

1. development of new hypothesis-driven approaches for evaluation of ESM biogeochemical process representation responses at site, regional and global scales;
2. investigation of the degree to which contemporary observations can be used to reduce uncertainties in future scenarios, using an “emergent constraint” approach;
3. development of 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;
4. evaluation of the performance of biogeochemical processes and feedbacks in different ESMs using the benchmarking software system; and
5. providing international leadership for biogeochemistry model evaluation and benchmarking.

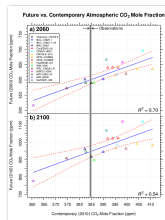
Biogeochemistry–Climate Feedbacks SFA Diagram



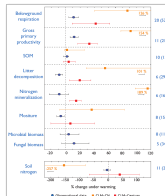
Biogeochemistry–Climate Feedbacks SFA Accomplishments

Accomplishments for 2015

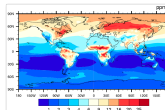
- ▶ Published 38 peer-reviewed papers since January 1, 2014.
- ▶ Randerson *et al.* *Global Biogeochemical Cycles* paper highlighted in *Nature* News and Views on June 18, 2015.
- ▶ J. Keith Moore received the 2015 CESM Distinguished Achievement Award on June 15, 2015 in Breckenridge.
- ▶ 2 of top 10 most-cited papers in *Biogeosciences* for 2014 (#1 by Todd-Brown *et al.* and #6 by Melton *et al.*).
- ▶ Negrón-Juárez paper was one of 10 highlighted for June 2015 by *Environmental Research Letters*.
- ▶ Demonstrated an ILAMB prototype package at DOE Germantown on September 8, 2014.
- ▶ Jinyun Tang won an Outstanding Publication Award from the Ecological Society of America in August 2014.
- ▶ Koven, Hoffman, and Randerson participating in C⁴MIP Committee for CMIP6.
- ▶ Lawrence participating in LUMIP Committee for CMIP6.
- ▶ Most DOE Lab participants are also contributing to ACME model development, verification, or simulations.
- ▶ Riley, Lawrence, and Randerson are CESM Working Group Co-chairs.



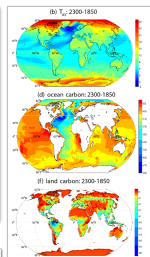
Hoffman *et al.* (2014)



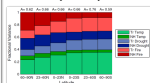
Bouskill *et al.* (2014)



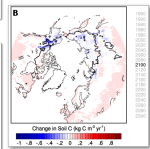
Lindsay *et al.* (2014)



Randerson *et al.* (2015)



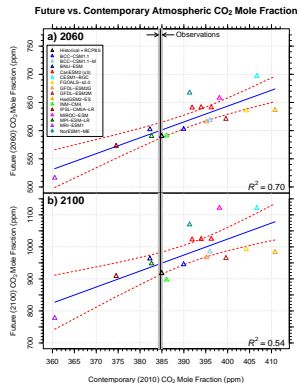
Keppel-Aleks *et al.* (2014)



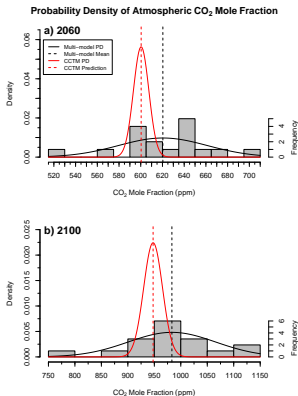
Koven *et al.* (2015)

Biogeochemistry–Climate Feedbacks SFA Highlights (1)

An emergent constraint based on carbon inventories was applied to constrain future atmospheric CO₂ projections from CMIP5 ESMs.



- ▶ Much of the model-to-model variation in projected CO₂ during the 21st century is tied to biases that existed during the observational era.
- ▶ Model differences in the representation of concentration–carbon feedbacks and other slowly changing carbon cycle processes appear to be the primary driver of this variability.
- ▶ Range of temperature increases at 2100 slightly reduced, from $5.1 \pm 2.2^\circ\text{C}$ for the full ensemble, to $5.0 \pm 1.9^\circ\text{C}$ after applying the emergent constraint.



Best estimate using Mauna Loa CO₂

- At 2060:** 600 ± 14 ppm, 21 ppm below the multi-model mean
- At 2100:** 947 ± 35 ppm, 32 ppm below the multi-model mean

Hoffman, Forrest M., James T. Randerson, Vivek K. Arora, Qing Bao, Patricia Cadule, Duoying Ji, Chris D. Jones, Michio Kawamiya, Samar Khattiwala, Keith Lindsay, Atsushi Obata, Elena Shevliakova, Katharina D. Six, Jerry F. Tjiputra, Evgeny M. Volodin, and Tongwen Wu. February 2014. "Causes and Implications of Persistent Atmospheric Carbon Dioxide Biases in Earth System Models." *J. Geophys. Res. Biogeosci.*, 119(2):141–162. doi:10.1002/2013JG002381. *Most downloaded JGR-B paper for February 2014!*

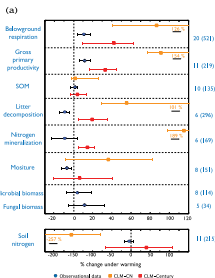
Biogeochemistry–Climate Feedbacks SFA Highlights (2)

Objective

We describe an observational and modeling meta-analysis to benchmark land models and identify needed improvement. We applied the method to CLM with two versions of belowground biogeochemistry (CN and Century).

Research

- We extracted benchmark metrics (e.g., belowground respiration, soil organic matter content) from 53 manipulation experiments studies across 17 high-latitude ecosystems.
- We calculated a response ratio of a metric relative to the control.
- We performed complimentary CLM4.5 simulation and analyzed discrepancies.



Carbon cycle responses to warming in observations (blue) and two versions of CLM. CLM performed poorly against many of these observations.

Impacts

- We identified poor representation of microbial activity, above- and belowground coupling, and nutrient cycling as the primary reasons for the discrepancies.
- Identifying deficiencies in the model structure can motivate future experiments and focus model development efforts.

Reference: Bouskill NJ, Riley WJ, Tang J (2014) Meta-analysis of high-latitude nitrogen-addition and warming studies implies ecological mechanisms overlooked by land models. *Biogeosciences*. 11:1-15.

Biogeochemistry–Climate Feedbacks SFA Highlights (3)

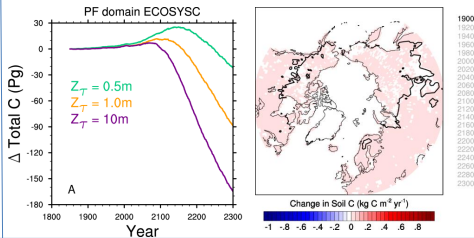
Objective:

Quantify the carbon cycle dynamics of the permafrost region under a warming climate, and understand the roles of deep C lability and carbon–nitrogen interactions in determining the magnitude of the permafrost carbon–climate feedback.

Research:

Use CLM4.5-BGC, which allows for interactions between thawing permafrost, mineralization of C and N from decomposing permafrost soil and vegetation feedbacks, under a transient, offline, RCP 8.5 warming experiment to 2300. Identify N controls by comparing C–N and C-only versions of the model; and quantify role of deep C dynamics by varying a parameter that controls role of depth on decomposition.

Reference: Koven, C. D., D. M. Lawrence, and W. J. Riley (2014), 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, doi:10.1073/pnas.1415123112.



Impact:

Permafrost soils are a potentially large component of the terrestrial carbon cycle response to warming, which are only recently available for understanding their dynamics in ESMs. Including these processes allows CLM4.5-BGC to predict the magnitude of the permafrost carbon–climate feedback, which is a potentially large fraction of global feedbacks on long timescales.

Biogeochemistry–Climate Feedbacks SFA Highlights (4)

Objective:

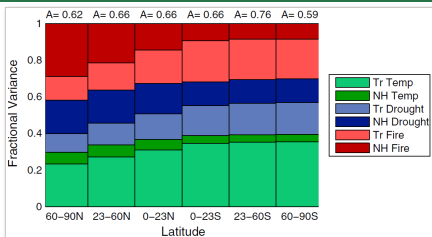
Quantify the contributions of known drivers of interannual variability in the growth rate of atmospheric carbon dioxide (CO_2).

Approach:

We examined how the temporal evolution of CO_2 in different latitude bands may be used to separate contributions from temperature stress, drought stress, and fire emissions to CO_2 variability.

Results/Impacts:

- ▶ Net ecosystem exchange (NEE) responses to temperature, drought, and fire emissions all contributed significantly to CO_2 variability; no single mechanism was dominant.
- ▶ Combined, drought and fire contributions to CO_2 variability exceeded direct NEE responses to temperature in both the Northern and Southern Hemispheres.
- ▶ Accounting for fires, the sensitivity of tropical NEE to temperature stress decreased by 25% to $2.9 \pm 0.4 \text{ Pg C yr}^{-1} \text{ K}^{-1}$.
- ▶ Results will inform the improvement of the representation of terrestrial ecosystem processes in Earth system models.



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.

Keppel-Aleks, Gretchen, Aaron S. Wolf, Mingquan Mu, Scott C. Doney, Douglas C. Morton, Prasad S. Kasibhatla, John B. Miller, Edward J. Dlugokencky, and James T. Randerson (2014), Separating the Influence of Temperature, Drought, and Fire on Interannual Variability in Atmospheric CO_2 . *Global Biogeochem. Cycles*, 28(11):1295–1310. doi:10.1002/2014GB004890.

Biogeochemistry–Climate Feedbacks SFA Highlights (5)

Objective:

Understand how land and ocean contributions to climate–carbon feedbacks evolve over time from 1850 to 2300.

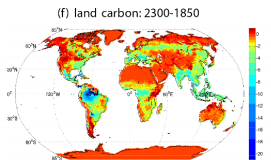
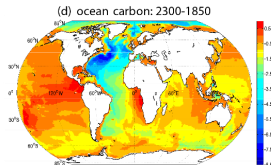
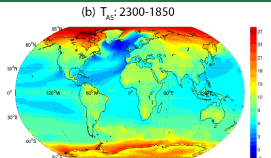
Research:

- Use CESM1(BGC) to assess carbon cycle dynamics for the Representative Concentration Pathway 8.5 and its extension.
- Three simulations with different levels of radiative coupling allowed us to diagnose parameters describing the gain of the climate–carbon feedback.

Impact:

- We found that the gain of the climate–carbon feedback increased almost 3-fold from 2100 to 2300.
- Ocean carbon sensitivity to climate change was proportional to increases in heat content.
- Climate influence on carbon largest in the Atlantic Ocean and in Central and South American forests.

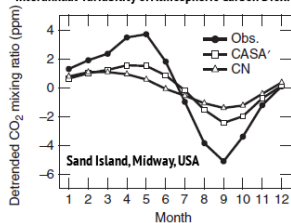
Reference: Randerson, J. T., K. Lindsay, E. Munoz, W. Fu, J. K. Moore, F. M. Hoffman, N. M. Mahowald, and S. C. Doney (2015), Multicentury Changes in Ocean and Land Contributions to Climate–Carbon Feedbacks, *Global Biogeochem. Cycles*, 29(6):744–759, doi:10.1002/2014GB005079.



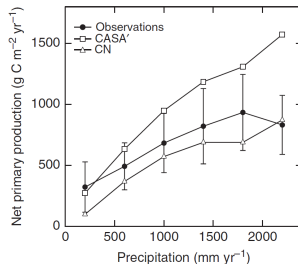
What is a Benchmark?

- ▶ A **Benchmark** is a quantitative test of model function achieved through comparison of model results with observational data.
- ▶ Acceptable performance on benchmarks **is a necessary but not sufficient condition** for a fully functioning model.
- ▶ **Functional benchmarks** offer tests of model responses to forcings and yield insights into ecosystem processes.
- ▶ Effective benchmarks must draw upon a broad set of independent observations to evaluate model performance on **multiple temporal and spatial scales.**

Interannual Variability of Atmospheric Carbon Dioxide



Models often fail to capture the amplitude of the seasonal cycle of atmospheric CO₂.



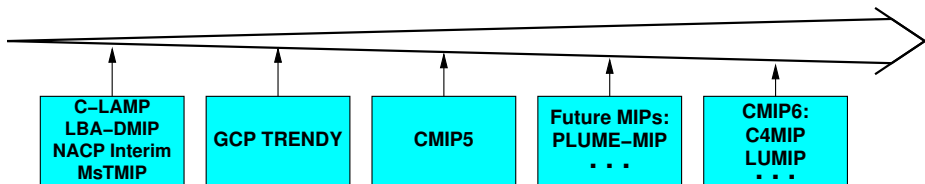
Models may reproduce correct responses over only a limited range of forcing variables.

(Randerson et al., 2009)

Why Benchmark?

- ▶ to demonstrate to the science community and public that the representation of coupled climate and biogeochemical cycles in Earth system models (ESMs) is improving;
- ▶ to quantitatively diagnose impacts of model development in related fields on carbon cycle processes;
- ▶ to guide synthesis efforts, such as the Intergovernmental Panel on Climate Change (IPCC), in the review of mechanisms of global change in models that are broadly consistent with available contemporary observations;
- ▶ to increase scrutiny of key datasets used for model evaluation;
- ▶ to identify gaps in existing observations needed for model validation;
- ▶ to accelerate incorporation of new measurements for rapid and widespread use in model assessment;
- ▶ to provide a quantitative, application-specific set of minimum criteria for participation in model intercomparison projects (MIPs).

An Open Source Benchmarking Software System



- ▶ Human capital costs of making rigorous model-data comparisons is considerable and constrains the scope of individual MIPs.
- ▶ Many MIPs spend resources “reinventing the wheel” in terms of variable naming conventions, model simulation protocols, and analysis software.
- ▶ **Need for ILAMB:** Each new MIP has access to the model-data comparison modules from past MIPs through ILAMB (e.g., MIPs use one common modular software system). Standardized international naming conventions also increase MIP efficiency.



International Land Model Benchmarking (ILAMB) Meeting The Beckman Center, Irvine, CA, USA January 24-26, 2011



GLOBAL
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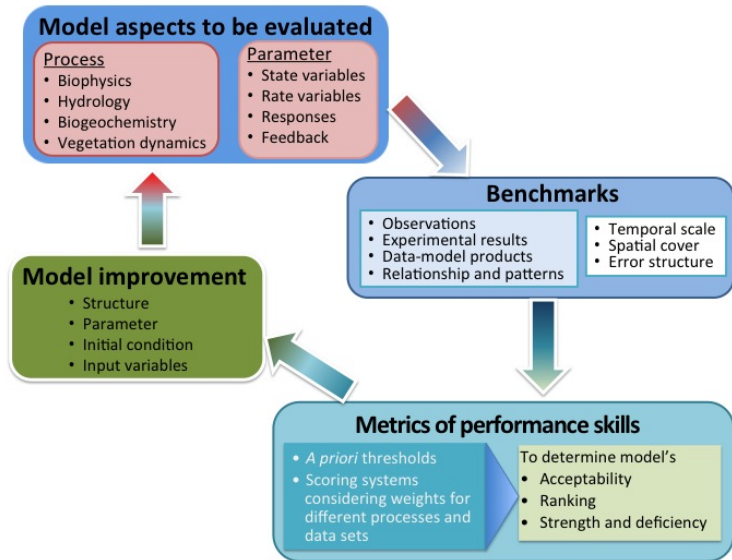


DEPARTMENT OF EARTH SYSTEM SCIENCE
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- ▶ We co-organized inaugural meeting and ~45 researchers participated from the United States, Canada, the United Kingdom, the Netherlands, France, Germany, Switzerland, China, Japan, and Australia.
- ▶ **ILAMB Goals:** Develop internationally accepted benchmarks for model performance, advocate for design of open-source software system, and strengthen linkages between experimental, monitoring, remote sensing, and climate modeling communities. *Initial focus on CMIP5 models.*
- ▶ Provides methodology for model–data comparison and baseline standard for performance of land model process representations (Luo et al., 2012).



General Benchmarking Procedure



(Luo et al., 2012)

Example Benchmark Score Sheet from C-LAMP

Models →

BGC Datasets

Metric	Metric components	Uncertainty of obs.	Scaling mismatch	Total score	Sub-score	CASA'	CN
LAI	Matching MODIS observations			15.0		13.5	12.0
	• Phase (assessed using the month of maximum LAI)	Low	Low		6.0	5.1	4.2
	• Maximum (derived separately for major biome classes)	Moderate	Low		5.0	4.6	4.3
	• Mean (derived separately for major biome classes)	Moderate	Low		4.0	3.8	3.5
NPP	Comparisons with field observations and satellite products			10.0		8.0	8.2
	• Matching EMDI Net Primary Production observations	High	High		2.0	1.5	1.6
	• EMDI comparison, normalized by precipitation	Moderate	Moderate		4.0	3.0	3.4
	• Correlation with MODIS (r^2)	High	Low		2.0	1.6	1.4
	• Latitudinal profile comparison with MODIS (r^2)	High	Low		2.0	1.9	1.8
CO ₂ annual cycle	Matching phase and amplitude at Globalview flash sites			15.0		10.4	7.7
	• 60°–90°N	Low	Low		6.0	4.1	2.8
	• 30°–60°N	Low	Low		6.0	4.2	3.2
	• 0°–30°N	Moderate	Low		3.0	2.1	1.7
Energy & CO ₂ fluxes	Matching eddy covariance monthly mean observations			30.0		17.2	16.6
	• Net ecosystem exchange	Low	High		6.0	2.5	2.1
	• Gross primary production	Moderate	Moderate		6.0	3.4	3.5
	• Latent heat	Low	Moderate		9.0	6.4	6.4
	• Sensible heat	Low	Moderate		9.0	4.9	4.6
Transient dynamics	Evaluating model processes that regulate carbon exchange on decadal to century timescales			30.0		16.8	13.8
	• Aboveground live biomass within the Amazon Basin	Moderate	Moderate		10.0	5.3	5.0
	• Sensitivity of NPP to elevated levels of CO ₂ : comparison to temperate forest FACE sites	Low	Moderate		10.0	7.9	4.1
	• Interannual variability of global carbon fluxes: comparison with TRANSCOM	High	Low		5.0	3.6	3.0
	• Regional and global fire emissions: comparison to GFEDv2	High	Low		5.0	0.0	1.7
				Total:	100.0	65.9	58.3

(Randerson et al., 2009)

ILAMB Prototype Diagnostics System

An initial ILAMB prototype has been developed by Mingquan Mu at UCI.

► Current variables:

Aboveground live biomass (Contiguous US, Pan Tropical Forest), Burned area (GFED3), CO₂ (NOAA GMD, Mauna Loa), Gross primary production (Fluxnet, MTE), Leaf area index (AVHRR, MODIS), Global net land flux (GCP, Khatiwala/Hoffman), Net ecosystem exchange (Fluxnet, GBA), Ecosystem Respiration (Fluxnet, GBA), Soil C (HWSD, NCSCDv2), Evapotranspiration (GLEAM, MODIS), Latent heat (Fluxnet, MTE), Soil moisture (ESA), Terrestrial water storage anomaly (GRACE), Albedo (CERES, GEWEX, MODIS), Surface up SW/LW radiation (CERES, GEWEX.SRB, WRMC.BSRN), Sensible heat (Fluxnet, GBA), Surface air temperature (CRU, Fluxnet), Precipitation (Fluxnet, GPCP, GPCP2), Surface down SW/LW radiation (Fluxnet, CERES, GEWEX.SRB, WRMC.BSRN),

► Graphics and scoring systems:

- Annual mean, Bias, RMSE, seasonal cycle, spatial distribution, interannual coeff. of variation and variability, long-term trend scores
- Global maps, variable to variable, and time series comparisons

► Software:

Freely distributed, designed to be user friendly and to enable easy addition of new variables (Mu, Hoffman, Riley, Koven, Lawrence, Randerson)

ILAMB Prototype Layout: Global Variables

Global Variables ([Info](#) for Weightings)

	MeanModel	bcc-csm1-1-m	BNU-ESM	CanESM2	CESM1-BGC	GFDL-ESM2G	HadGEM2-ES
<u>Aboveground Live Biomass</u>	0.71	0.55	0.43	0.65	0.60	0.58	0.67
<u>Burned Area</u>	0.38	-	-	-	0.37	-	-
<u>Carbon Dioxide</u>	0.80	-	0.71	0.69	0.75	0.69	-
<u>Gross Primary Productivity</u>	0.77	0.72	0.73	0.64	0.71	0.67	0.69
<u>Leaf Area Index</u>	0.67	0.67	0.40	0.60	0.55	0.50	0.60
<u>Global Net Ecosystem Carbon Balance</u>	0.52	-	0.18	0.25	0.36	0.20	0.30
<u>Net Ecosystem Exchange</u>	0.49	0.48	0.45	0.39	0.48	0.48	0.47
<u>Ecosystem Respiration</u>	0.74	0.72	0.73	0.65	0.67	0.71	0.66
<u>Soil Carbon</u>	0.55	0.50	0.43	0.56	0.38	0.51	0.51
Summary	0.63	0.60	0.51	0.55	0.54	0.54	0.55
<u>Evapotranspiration</u>	0.75	0.73	0.72	0.72	0.73	0.70	0.74
<u>Latent Heat</u>	0.80	0.76	0.75	0.77	0.78	0.75	0.77
<u>Terrestrial Water Storage Anomaly</u>	0.53	0.46	0.37	0.54	0.48	0.43	0.44
Summary	0.69	0.65	0.61	0.67	0.66	0.63	0.65
<u>Albedo</u>	0.72	0.71	0.62	0.71	0.73	0.69	0.74
<u>Surface Upward SW Radiation</u>	0.77	0.73	0.66	0.74	0.76	0.74	0.76

ILAMB Prototype Layout: Variable to Variable

Variable to Variable Relationships ([Info](#) for Weightings)

	Relationship	Benchmark	MeanModel	bcc-csm1-1-m	BNU-ESM	CanESM2	CESM1-BGC	GFDL-ESM2G	HadGEM2-ES	i
Evapotranspiration vs. Gross Primary Productivity	function_bar	1	0.82	0.79	0.62	0.85	0.73	0.89	0.83	
Precipitation vs. Burned Area	function_bar	1	0.44	-	-	-	0.46	-	-	
Precipitation vs. Evapotranspiration	function_bar	1	0.71	0.81	0.78	0.80	0.69	0.75	0.68	
Precipitation vs. Gross Primary Productivity	function_bar	1	0.89	0.90	0.73	0.77	0.86	0.78	0.74	
Precipitation vs. Leaf Area Index	function_bar	1	0.63	0.68	0.34	0.58	0.56	0.43	0.50	
Surface Downward SW Radiation vs. Gross Primary Productivity	function_bar	1	0.74	0.79	0.77	0.65	0.72	0.59	0.68	
Surface Net SW Radiation vs. Gross Primary Productivity	function_bar	1	0.77	0.82	0.62	0.68	0.76	0.66	0.78	
Surface Air Temperature vs. Burned Area	function_bar	1	0.41	-	-	-	0.43	-	-	
Surface Air Temperature vs. Evapotranspiration	function_bar	1	0.68	0.75	0.63	0.83	0.64	0.66	0.65	
Surface Air Temperature vs. Gross Primary Productivity	function_bar	1	0.78	0.76	0.67	0.73	0.69	0.68	0.75	
Overall			0.70	0.65	0.54	0.62	0.66	0.58	0.59	

ILAMB Prototype Metrics Documentation

B. Root Mean Square Error Metric

For different variables, we use 2 different methods to calculate their global mean RMSE scores. For above ground biomass (biomass), burned area (burnarea), evapotranspiration (et), gross primary production (gpp), lead area index (lai), latent heat (lc), net ecosystem exchange (nee), precipitation (pr), ecosystem respiration (reco), sensible heat (sh) and soil carbon (soilc), we use mass weighting (B3.1). For other variables, we use area weighting (B3.2).

$$M_i = 1 - \frac{RMSE_i}{\Phi_{obs,i}} \quad (B1)$$

$$M_i = e^{-RMSE_i} \quad (B2)$$

Mass weighting to calculate global mean RMSE score:

$$M = \frac{\sum_i M_i \times A_i \times |AM_{obs,i}|}{\sum_i A_i \times |AM_{obs,i}|} \quad (B3.1)$$

Area weighting to calculate global mean RMSE score:

$$M = \frac{\sum_i M_i \times A_i}{\sum_i A_i} \quad (B3.2)$$

We use Eqs. B1-2 and Eq. B3.1 or B3.2 to calculate root mean square error metric score M_i at grid cell or site i and its global mean M , respectively. Where $\Phi_{obs,i}$ is the root mean square for monthly mean annual cycle of the observation at grid cell i (for grid data) or site i (for site observation), and $RMSE_i$ is the root mean square error between model and observation. $AM_{obs,i}$ is annual mean of the observation at grid cell or site i . $|AM_{obs,i}|$ is to calculate its absolute value. A_i is the area for grid cell or site i . n_{cells} is the number of all land grid cells or sites where observation data is available. If the observation is site data, we set A_i equal to 1 (Ref: David Lawrence's personal Communication). This metric is used to compare magnitude and phase difference of the monthly mean annual cycle between the model and the observation.

C. Spatial Distribution Metric

$$M = \frac{4(1+R)}{(\sigma_j + 1/\sigma_j)^2(1+R_0)} \quad (C)$$

2

We use Eq. C to calculate spatial distribution metric score M . R is the spatial correlation coefficient of the annual mean between model and observation. R_0 is their ideal maximum correlation. Here, we set R_0 equal to 1 for all models. σ_j is ratio for standard deviation of model to that of observation (Ref: Taylor, J. Geophys. Res., 106, 2001). This metric is used to compare magnitude and spatial pattern of annual mean of model with observation.

D. Seasonal Cycle Phase Metric

For different variables, we use 2 different methods to calculate their global mean phase scores. For above ground biomass (biomass), burned area (burnarea), evapotranspiration (et), gross primary production (gpp), lead area index (lai), latent heat (lc), net ecosystem exchange (nee), precipitation (pr), ecosystem respiration (reco), sensible heat (sh) and soil carbon (soilc), we use mass weighting (D2.1). For other variables, we use area weighting (D2.2).

$$M_i = (1 + \cos \theta_i) / 2 \quad (D1)$$

Mass weighting to calculate global mean phase score:

$$M = \frac{\sum_i M_i \times A_i \times |AM_{obs,i}|}{\sum_i A_i \times |AM_{obs,i}|} \quad (D2.1)$$

Area weighting to calculate global mean phase score:

$$M = \frac{\sum_i M_i \times A_i}{\sum_i A_i} \quad (D2.2)$$

We use Eqs. D1 and D2.1 or D2.2 to calculate seasonal cycle phase metric score M_i at grid cell or site i and its global mean M , respectively. θ_i is the difference of the angle between the month of the maximum value for the model and that for the observation at grid cell i (for the grid data) or site i (for the site data). $AM_{obs,i}$ is annual mean of the observation at grid cell or site i . $|AM_{obs,i}|$ is to calculate its absolute value. A_i is the area for grid cell or site i . n_{cells} is the number of all land grid cells or sites where observation data is available. If the observation is site data, we set A_i equal to 1 (Ref: Prentice, et al., GBC, 25, 2011). This metric is used to compare phase difference of the monthly mean annual cycle between the model and the observation.

E. Interannual Variability Metric

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Near-Term Goals

- ▶ Our international collaboration has made significant progress on development of metrics in the ILAMB prototype.
- ▶ Our **BGC-Feedbacks Project** is developing new model–data analysis studies for terrestrial and now marine biogeochemistry (see <http://www.bgc-feedbacks.org/>).
- ▶ We have proposed an **ILAMB Town Hall** at the upcoming American Geophysical Union (AGU) Fall Meeting in December.
- ▶ We are planning another community-wide meeting on model metrics and diagnostics in Washington, DC, USA in spring 2016.

5 Year Goals

- ▶ Fully fund and integrate marine and sea ice BGC benchmarking.
- ▶ Extend community engagement through Town Halls, community workshops, model–data intercomparison projects, and tutorials.
- ▶ Build new forcing and evaluation datasets, including from NGEA Arctic/Tropics, SPRUCE, Fluxnet, and satellites.
- ▶ Evaluate CMIP6, lead land and ocean BGC MIPs for CMIP7.

10 Year Goals

- ▶ Build a benchmarking system that evaluates all ESM processes.
- ▶ Build a multi-agency-sponsored ESM Assessment Center, support synthesis working groups.
- ▶ Integrate models and data to develop state-of-the-carbon-cycle data, incorporate a flexible data assimilation system.
- ▶ Perform and evaluate CMIP7 experiments.

Biogeochemistry–Climate Feedbacks SFA 10 Year Vision

	Phase 1 (2014–2017)	Phase 2 (2017–2020)	Phase 3 (2020–2024)
ILAMB and Benchmark Tools	ILAMB prototype and second generation system, integrate C cycle metrics into ESGF	Ocean benchmark integration, full integration into ESGF	Server-side benchmarking and offline transport / runoff model integration
Community Engagement and Leadership	AGU Town Hall, ILAMB community workshops, ILAMB tutorial	AGU and AGU Ocean Town Halls, land / ocean community workshops, benchmarking tutorials	Build multi-agency ESM Center, land and ocean community workshops, synthesis working groups
Metrics Development	Develop and test emergent constraint approach, land / ocean C cycles, OMZs, atm C distribution	DOC in sea ice, ocean organics and aerosols, land VOCs and SOAs, soil types, plant traits, atm chemistry	Coastal / estuarine processes, riverine nutrients, bi-directional canopy fluxes
Forcing Data Development	Evaluation land model sensitivity to forcing, test alternative forcing data	Contribute to development of new forcing data for land and ocean models	Develop state of the carbon cycle data / initial conditions through assimilation
Evaluation Data Development	Global carbon, water, energy data, high lat soil C, AmeriFlux, FACE / N addition / warming experiments	NGEE Arctic / Tropics and SPRUCE data, Fluxnet, LiDAR / hyperspectral, OCO-2, add uncertainty data	Synthesis / analytics for combining data, new in situ data from drivers / drones
MIP Experiment Development and Analysis	C ⁴ MIP and LUMIP for CMIP6, TRENDY for Global Carbon Project, PLUME-MIP	Evaluate CMIP6, lead land / ocean / atm biogeochemistry MIPs for CMIP7, other MIPs	Perform CMIP7 experiments, evaluate CMIP7

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References

- Y. Q. Luo, J. T. Randerson, G. Abramowitz, C. Bacour, E. Blyth, N. Carvalhais, P. Ciais, D. Dalmonech, J. B. Fisher, R. Fisher, P. Friedlingstein, K. Hibbard, F. Hoffman, D. Huntzinger, C. D. Jones, C. Koven, D. Lawrence, D. J. Li, M. Mahecha, S. L. Niu, R. Norby, S. L. Piao, X. Qi, P. Peylin, I. C. Prentice, W. Riley, M. Reichstein, C. Schwalm, Y. P. Wang, J. Y. Xia, S. Zaehle, and X. H. Zhou. A framework for benchmarking land models. *Biogeosci.*, 9(10):3857–3874, Oct. 2012. doi:10.5194/bg-9-3857-2012.
- J. T. Randerson, F. M. Hoffman, P. E. Thornton, N. M. Mahowald, K. Lindsay, Y.-H. Lee, C. D. Nevison, S. C. Doney, G. Bonan, R. Stöckli, C. Covey, S. W. Running, and I. Y. Fung. Systematic assessment of terrestrial biogeochemistry in coupled climate-carbon models. *Global Change Biol.*, 15(9):2462–2484, Sept. 2009. doi:10.1111/j.1365-2486.2009.01912.x.