Multidisciplinary Earth System Science and the Global Carbon Cycle

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Parishkar
Group of Institutions

Parishkar Group of Institutions, Jaipur (India)

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Department of Life Science & Department of Geography in Association with Internal Quality Assurance Cell (IQAC)

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Forrest M. Hoffman, Computational Earth System Scientist

- Group Leader for the ORNL Computational Earth Sciences Group
- 32 years at ORNL in Environmental Sciences Division, then Computer Science and Mathematics Division, and now Computational Sciences and Engineering Division
- Develop and apply Earth system models to study global biogeochemical cycles, including terrestrial & marine carbon cycle
- Investigate methods for reconciling uncertainties in carbon–climate feedbacks through comparison with observations
- Apply artificial intelligence methods (machine learning and data mining) to environmental characterization, simulation, & analysis
- Joint Faculty, University of Tennessee, Knoxville, Department of Civil & Environmental Engineering

Oak Ridge National Laboratory

The University of Tennessee Knoxville

Reducing Uncertainties in Biogeochemical Interactions through Synthesis and Computation (RUBISCO) Science Focus Area (SFA)

US Dept. of Energy’s RUBISCO Scientific Focus Area (SFA)

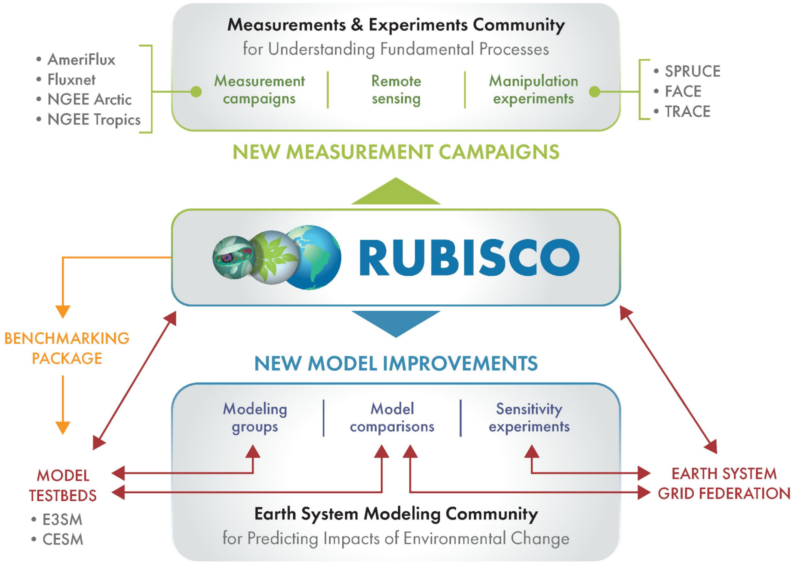
Forrest M. Hoffman (Laboratory Research Manager), William J. Riley (Senior Science Co-Lead), and James T. Randerson (Chief Scientist)

Research Goals

- Identify and quantify interactions between biogeochemical cycles and the Earth system
- Quantify and reduce uncertainties in Earth system models (ESMs) associated with interactions

Research Objectives

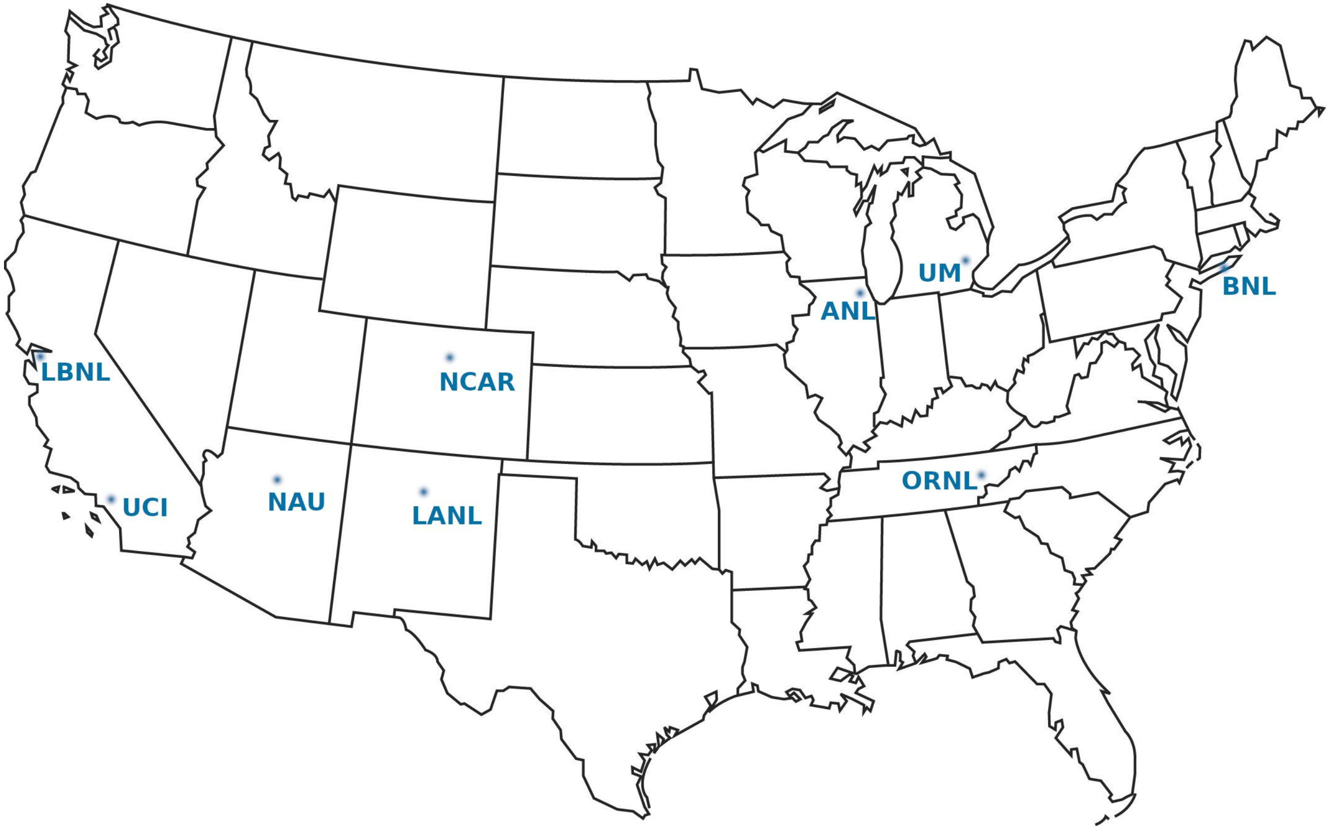
- Perform hypothesis-driven analysis of biogeochemical & hydrological processes and feedbacks in ESMs
- Synthesize in situ and remote sensing data and design metrics for assessing ESM performance
- Design, develop, and release the International Land Model Benchmarking (ILAMB) and International Ocean Model Benchmarking (IOMB) tools for systematic evaluation of model fidelity
- Conduct and evaluate CMIP6 experiments with ESMs



The RUBISCO SFA works with the measurements and the modeling communities to use best-available data to evaluate the fidelity of ESMs. RUBISCO identifies model gaps and weaknesses, informs new model development efforts, and suggests new measurements and field campaigns.

RUBISCO SFA Nine Partner Institutions

- **5 National Labs**
  - Argonne
  - Brookhaven
  - Los Alamos
  - Lawrence Berkeley
  - Oak Ridge
- **3 Universities**
  - UC Irvine
  - U. Michigan
  - N. Arizona U.
- **National Center for Atmospheric Research (NCAR)**



Soil Carbon Dynamics Working Group

RUBISCO

U.S. DEPARTMENT OF ENERGY

- Formed after community recommendation from the 2016 International Land Model Benchmarking (ILAMB) Workshop Report
- Objective is to apply data and models to improve predictive understanding
- June and September conference calls led to meeting at ORNL in October 2018

Data to Knowledge
Synthesize existing data from collaborative networks, archives, and publications

+

Knowledge to Data
Perform simulations to test hypotheses and characterize model structural uncertainties

→

Predictive Understanding
Design functional relationship metrics to confront models and apply data-driven approaches to model formulation

Global Data Synthesis Theme

- Combine field observations from collaborative sampling networks and databases, including International Soil Carbon Network (ISCN) and published literature
- Quantify vertical distribution of SOM and responses to controlling mechanisms

Model–Data Integration Theme

- Develop consistent datasets for initializing, forcing, and benchmarking microbially explicit soil carbon models
- Characterize model structural uncertainty through software frameworks to understand controlling mechanisms

For more information, see *2018 Fall Meeting Report* (June 26, 2019)

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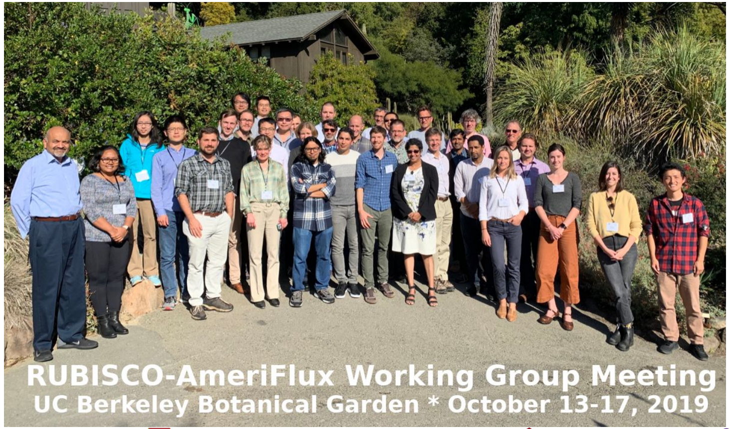
RUBISCO-AmeriFlux Working Group

- Formed after community recommendation from the 2016 International Land Model Benchmarking (ILAMB) Workshop Report
- Objective is to use AmeriFlux data to improve process understanding and to develop, parameterize, and test models
- Multiple conference calls led up to a meeting at the UC Berkeley Botanical Garden (outside LBNL) on October 15–17, 2019

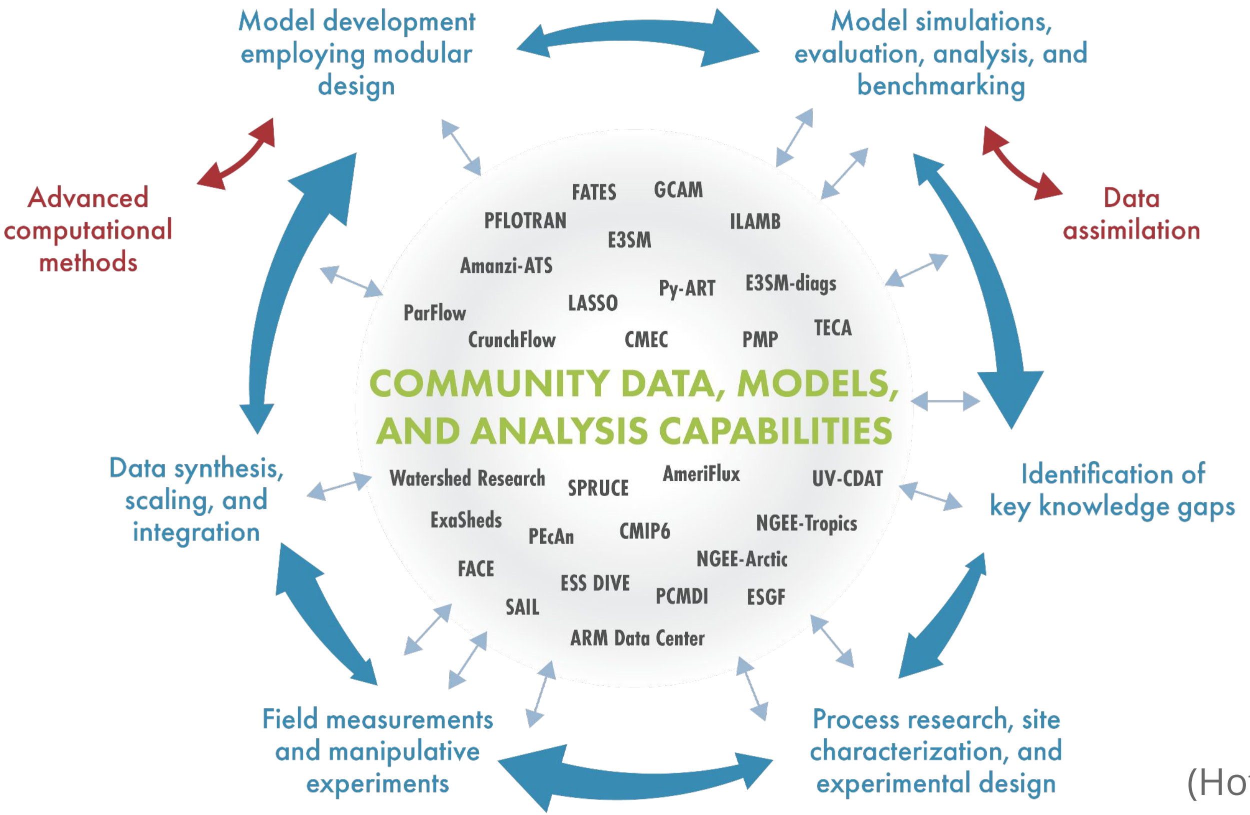


Four key areas of research emerged from the Working Group Meeting:

- **Ecosystem trend spotting** - employing long ecosystem carbon and water flux records to detect trends in ecosystem metabolism and to disentangle responses of ecosystems to elevated CO_2, climate change, and human disturbances
- **Ecosystem responses to extreme events** - use long-running AmeriFlux measurements, which include ecosystem responses to extreme weather conditions, to evaluate models
- **Untangling contributions to carbon exchange** - use complementary measurements of respiration fluxes and satellite-derived vegetation indices to improve partitioning methods for eddy covariance estimates of GPP and R_{eco}
- **Scaling up from sites to ecosystems** - combine bottom-up and top-down approaches for scaling fluxes across spatial scales

For more information, see [Measuring, Monitoring, and Modeling Ecosystem Cycling]() in *Eos Trans. AGU* (August 5, 2020)

DOE's Model-Data-Experiment Enterprise (aka MODEX)



(Hoffman et al., 2017)

Ensemble machine learning approach produces greater spatial prediction accuracy of soil carbon stocks

Objective: To identify accurate methods for SOC prediction and regions of higher uncertainty in the northern circumpolar permafrost region.

Approach: Combine large dataset of field observations and environmental factors to evaluate prediction accuracy of machine learning (ML) techniques in comparison to a widely used approach, regression kriging.

Results/Impacts: The ensemble ML approach provides greater spatial details and higher prediction accuracy in comparison to regression kriging and other individual ML approaches. Areas with high uncertainty in predicted SOC stocks were found in small patches in Southern Alaska and in larger areas of the Southern and Western Russian permafrost region.

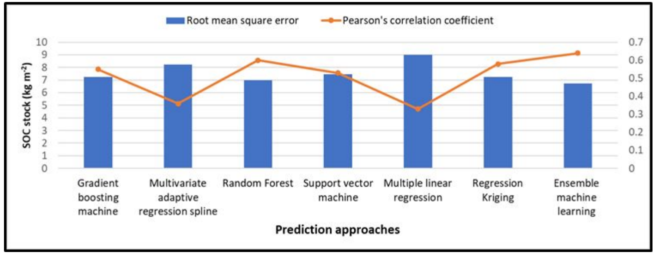


Figure 1: Prediction accuracy obtained from different machine learning approaches.

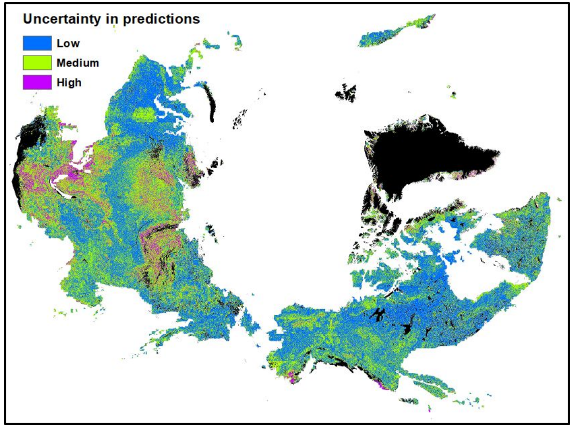
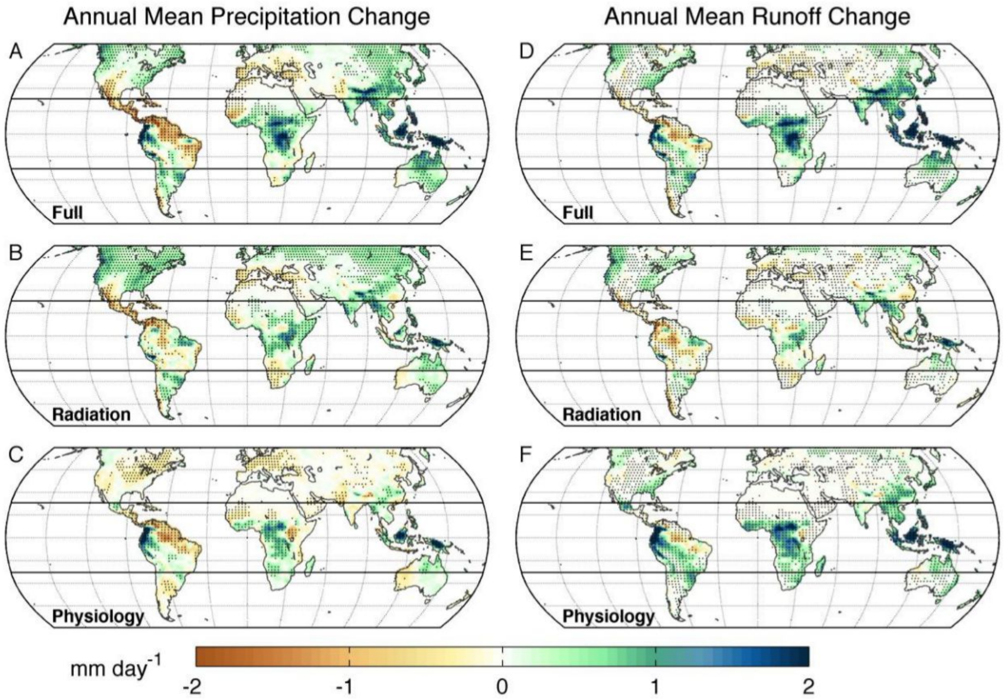


Figure 2: Uncertainties in surface SOC stocks in the northern circumpolar permafrost region.

Mishra, Umakant, **Sagar Gautam**, **William J. Riley**, and **Forrest M. Hoffman** (2020), Ensemble Machine Learning Approach Improves Predicted Spatial Variation of Surface Soil Organic Carbon Stocks in Data-Limited Northern Circumpolar Region, *Front. Big Data*, 3:40, doi:10.3389/fdata.2020.528441.

Plant-physiological responses to rising CO_2 increase tropical flood risk



- Assessments of future flood risk based only on precipitation changes ignore land processes
- Higher CO_2 may reduce stomatal conductance and transpiration
- We assessed relative impacts of plant-physiological and radiative- greenhouse effects on changes in daily runoff intensity over tropical continents using CESM
- Extreme percentile rates increase more than mean runoff
- Plant-physiological effects have a small impact on precipitation intensity, but are a dominant driver of runoff intensification

Kooperman, G. J., **M. D. Fowler**, **F. M. Hoffman**, **C. D. Koven**, K. Lindsay, M. S. Pritchard, A. L. S. Swann, and **J. T. Randerson** (2018), Plant-physiological responses to rising CO_2 modify simulated daily runoff intensity with implications for global-scale flood risk assessment, *Geophys. Res. Lett.*, 45(22):12,457–12,466. doi:10.1029/2018GL079901.

Soil moisture variability intensifies and prolongs eastern Amazon temperature and carbon cycle response to El Niño-Southern Oscillation

Objective: To understand how land–atmosphere coupling influences temperature and carbon cycle contrasts between El Niño and La Niña conditions in the Amazon.

Approach: Use the Energy Exascale Earth System Model (E3SM v0.3) to simulate land and atmosphere with observed SSTs during 1982–2016. Three simulations explored variability caused by full coupling (AMIP), sea surface temperatures only (SST_{var}), and soil moisture only (SM_{var}).

Results/Impacts: During the wet season (January–March), the contrast between El Niño and La Niña is driven by coupled ocean–atmospheric teleconnections. Soil moisture anomalies persist into the subsequent dry season in the eastern Amazon, strengthening and extending temperature and carbon cycle responses to forcing by ENSO.

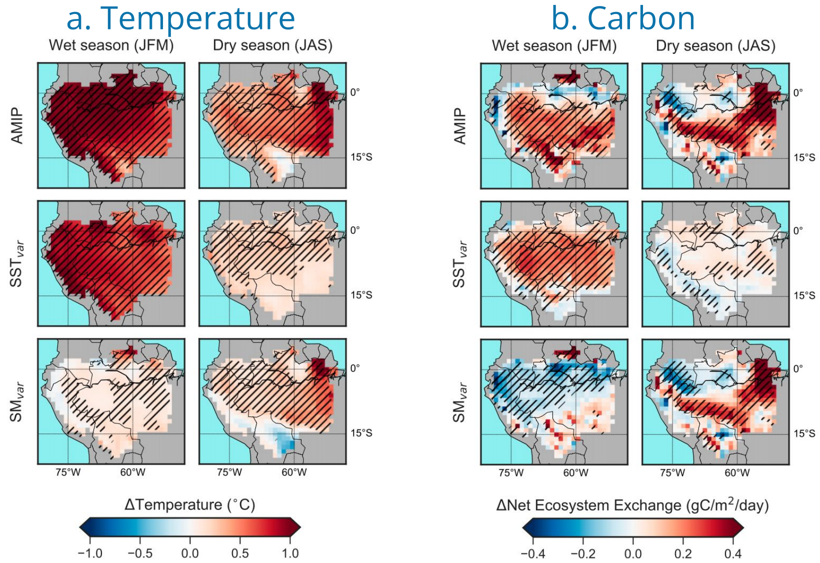


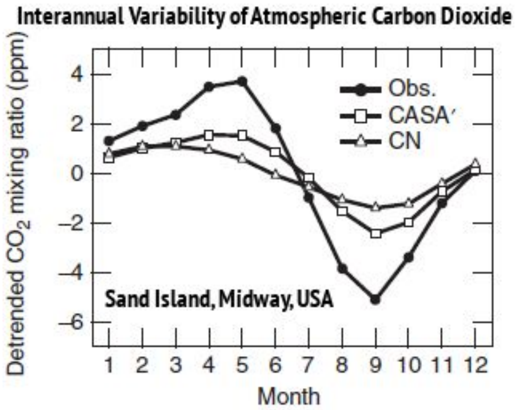
Figure: a. The difference between the mean temperature anomalies of El Niño years and those of La Niña years. Monthly anomalies are averaged across the wet season (JFM, left column) and dry season (JAS, right column). Each experiment (row) is described in the Approach section of the text. b. Same as a., but for monthly anomalies of net ecosystem exchange (positive is a flux to the atmosphere).

Levine, P. A., **J. T. Randerson**, **Y. Chen**, M. S. Pritchard, **M. Xu**, and **F. M. Hoffman** (2019), Soil moisture variability intensifies and prolongs eastern Amazon temperature and carbon cycle response to El Niño-Southern Oscillation, *J. Clim.*, 32(4):1273–1292, doi:10.1175/JCLI-D-18-0150.1.

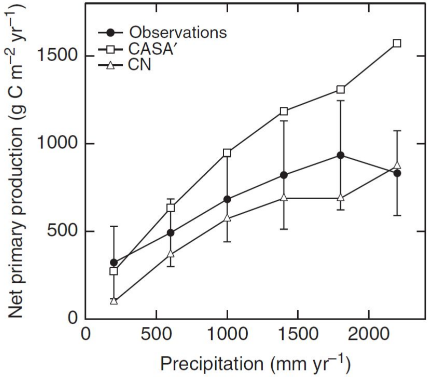
International Land Model Benchmarking (ILAMB)

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 a benchmark **is a necessary but not sufficient condition** for a fully functioning model
- **Functional relationship 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 at multiple scales



Models often fail to capture the amplitude of the seasonal cycle of atmospheric CO_2



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

(Randerson et al., 2009)

Why Benchmark Models?

- To **quantify and reduce uncertainties** in carbon cycle feedbacks to improve projections of future climate change (Eyring et al., 2019; Collier et al., 2018)
- To **quantitatively diagnose impacts of model development** on hydrological and carbon cycle process representations and their interactions
- To **guide synthesis efforts**, such as the Intergovernmental Panel on Climate Change (IPCC), by determining which models are broadly consistent with available observations (Eyring et al., 2019)
- To **increase scrutiny of key datasets** used for model evaluation
- To **identify gaps in existing observations** needed to inform model development
- To **accelerate delivery of new measurement datasets** for rapid and widespread use in model assessment

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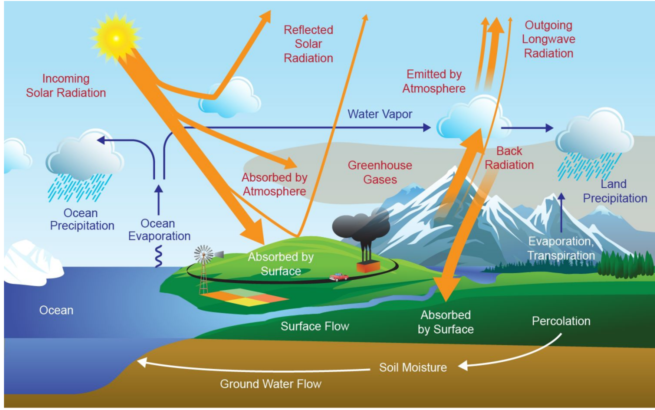
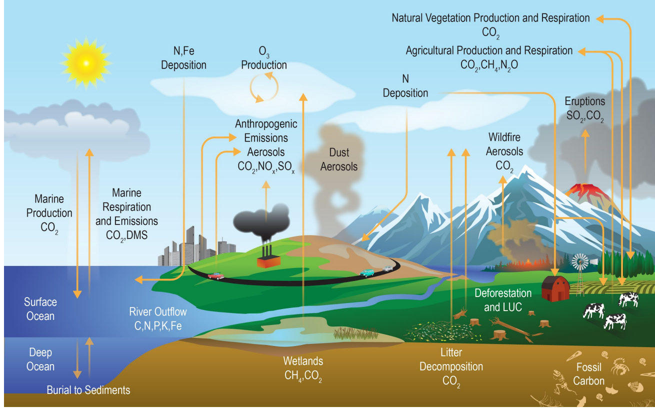
What is ILAMB?

A community coordination activity created to:

- **Develop internationally accepted benchmarks** for land model performance by drawing upon collaborative expertise
- **Promote the use of these benchmarks** for model intercomparison
- **Strengthen linkages between experimental, remote sensing, and Earth system modeling communities** in the design of new model tests and new measurement programs
- **Support the design and development of open source benchmarking tools**



Energy and Water Cycles



Carbon and Biogeochemical Cycles

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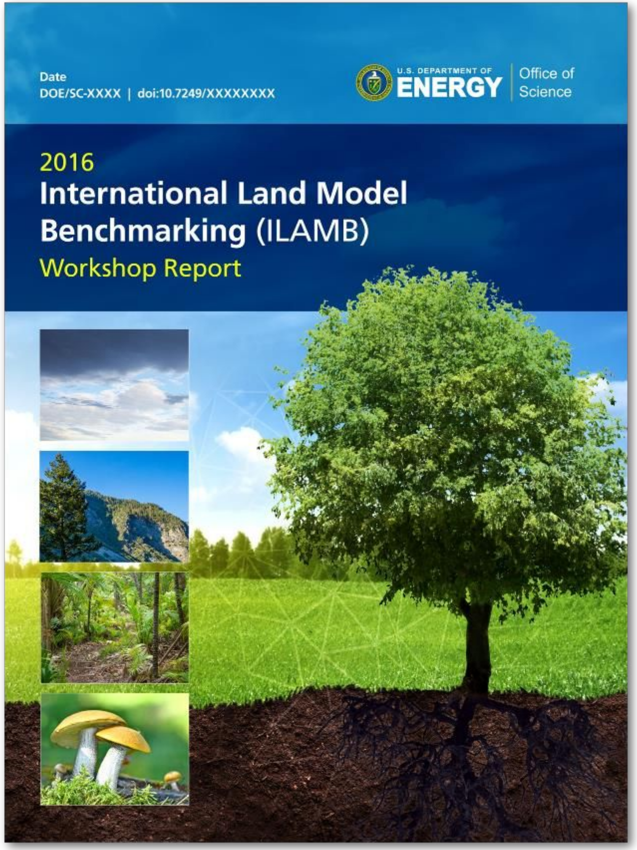
2016 International Land Model Benchmarking (ILAMB) Workshop
May 16–18, 2016, Washington, DC

Third ILAMB Workshop was held May 16–18, 2016

- Workshop Goals
  - Design of new metrics for model benchmarking
  - Model Intercomparison Project (MIP) evaluation needs
  - Model development, testbeds, and workflow processes
  - Observational datasets and needed measurements
- Workshop Attendance
  - 60+ participants from Australia, Japan, China, Germany, Sweden, Netherlands, UK, and US (10 modeling centers)
  - ~25 remote attendees at any time



(Hoffman et al., 2017)

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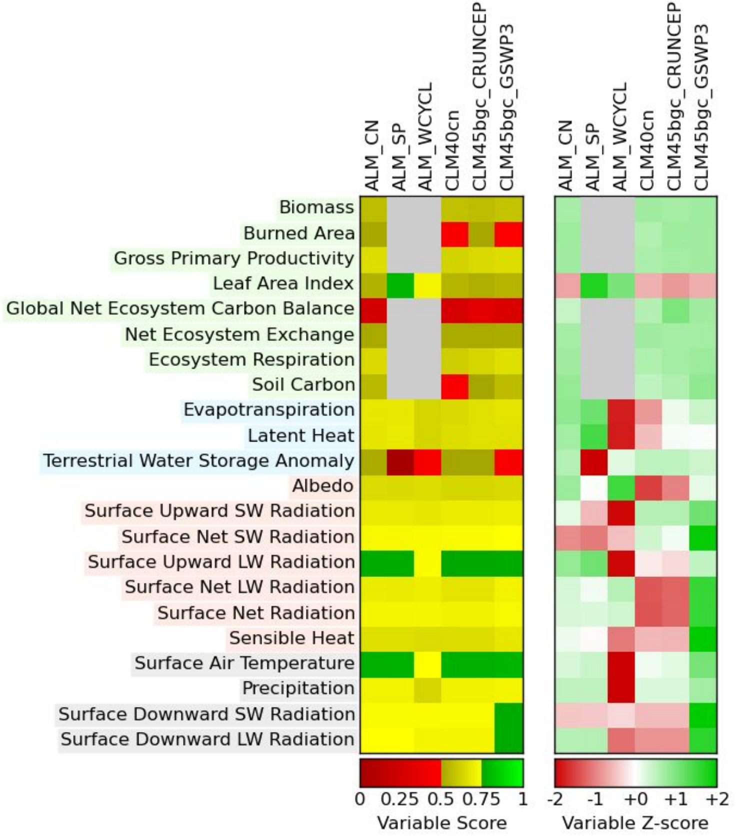
Development of ILAMB Packages

- **ILAMBv1** released at 2015 AGU Fall Meeting Town Hall, doi:10.18139/ILAMB.v001.00/1251597
- **ILAMBv2** released at 2016 ILAMB Workshop, doi:10.18139/ILAMB.v002.00/1251621
- **Open Source software** written in Python; **runs in parallel** on laptops, clusters, and supercomputers
- Routinely used for land model evaluation during development of ESMs, including the **E3SM Land Model** (Zhu et al., 2019) and the **CESM Community Land Model** (Lawrence et al., 2019)
- **Models are scored** based on statistical comparisons and functional response metrics



ILAMB Produces Diagnostics and Scores Models

- ILAMB generates a top-level **portrait plot** of models scores
- For every variable and dataset, ILAMB can automatically produce
  - **Tables** containing individual metrics and metric scores (when relevant to the data), including
    - Benchmark and model **period mean**
    - **Bias** and **bias score** (S_{bias})
    - **Root-mean-square error (RMSE)** and **RMSE score** (S_{rmse})
    - **Phase shift** and **seasonal cycle score** (S_{phase})
    - **Interannual coefficient of variation** and **IAV score** (S_{iav})
    - **Spatial distribution score** (S_{dist})
    - **Overall score** (S_{overall}) →

$$S_{\text{overall}} = \frac{S_{\text{bias}} + 2S_{\text{rmse}} + S_{\text{phase}} + S_{\text{iav}} + S_{\text{dist}}}{1+2+1+1+1}$$

  - **Graphical diagnostics**
    - Spatial contour maps
    - Time series line plots
    - Spatial Taylor diagrams (Taylor, 2001)
- Similar **tables** and **graphical diagnostics** for functional relationships

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ILAMBv2.6 Package Current Variables

- **Biogeochemistry:** Biomass (Contiguous US, Pan Tropical Forest), Burned area (GFED3), CO_2 (NOAA GMD, Mauna Loa), Gross primary production (Fluxnet, GBAF), Leaf area index (AVHRR, MODIS), Global net ecosystem carbon balance (GCP, Khatiwala/Hoffman), Net ecosystem exchange (Fluxnet, GBAF), Ecosystem Respiration (Fluxnet, GBAF), Soil C (HWSD, NCSCDv22, Koven)
- **Hydrology:** Evapotranspiration (GLEAM, MODIS), Evaporative fraction (GBAF), Latent heat (Fluxnet, GBAF, DOLCE), Runoff (Dai, LORA), Sensible heat (Fluxnet, GBAF), Terrestrial water storage anomaly (GRACE), Permafrost (NSIDC)
- **Energy:** Albedo (CERES, GEWEX.SRB), Surface upward and net SW/LW radiation (CERES, GEWEX.SRB, WRMC.BSRN), Surface net radiation (CERES, Fluxnet, GEWEX.SRB, WRMC.BSRN)
- **Forcing:** Surface air temperature (CRU, Fluxnet), Diurnal max/min/range temperature (CRU), Precipitation (CMAP, Fluxnet, GPCC, GPCP2), Surface relative humidity (ERA), Surface down SW/LW radiation (CERES, Fluxnet, GEWEX.SRB, WRMC.BSRN)

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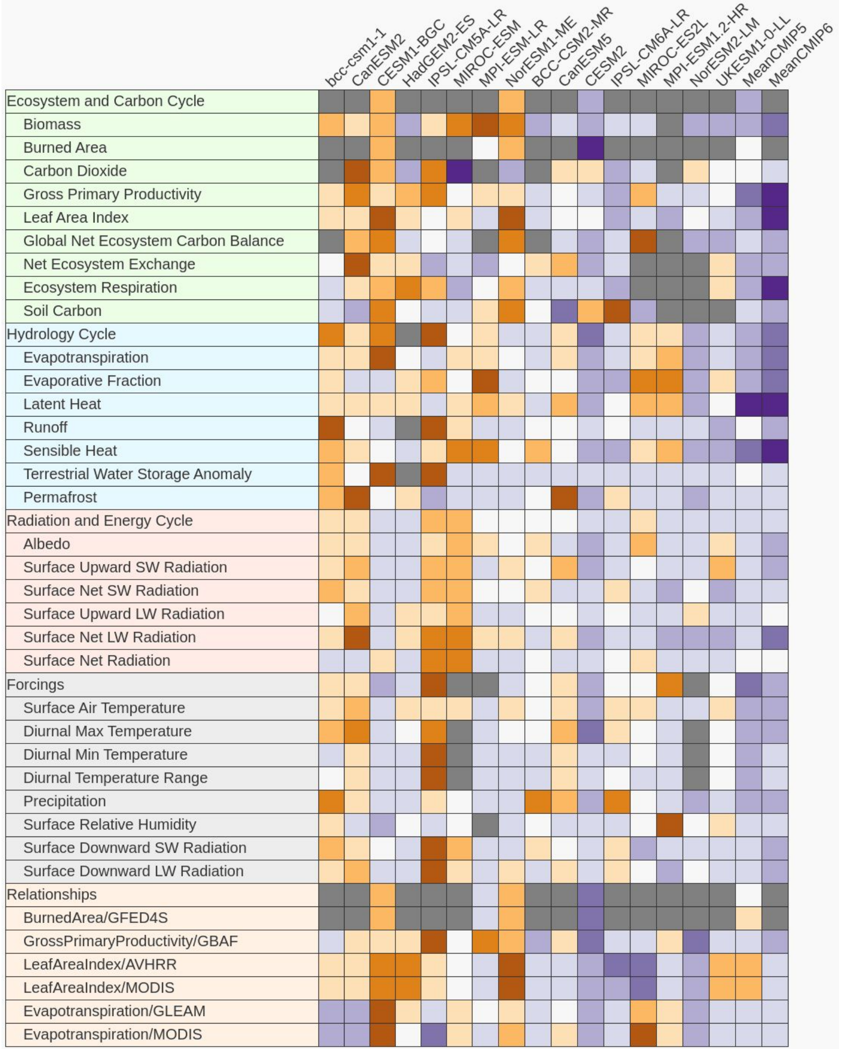
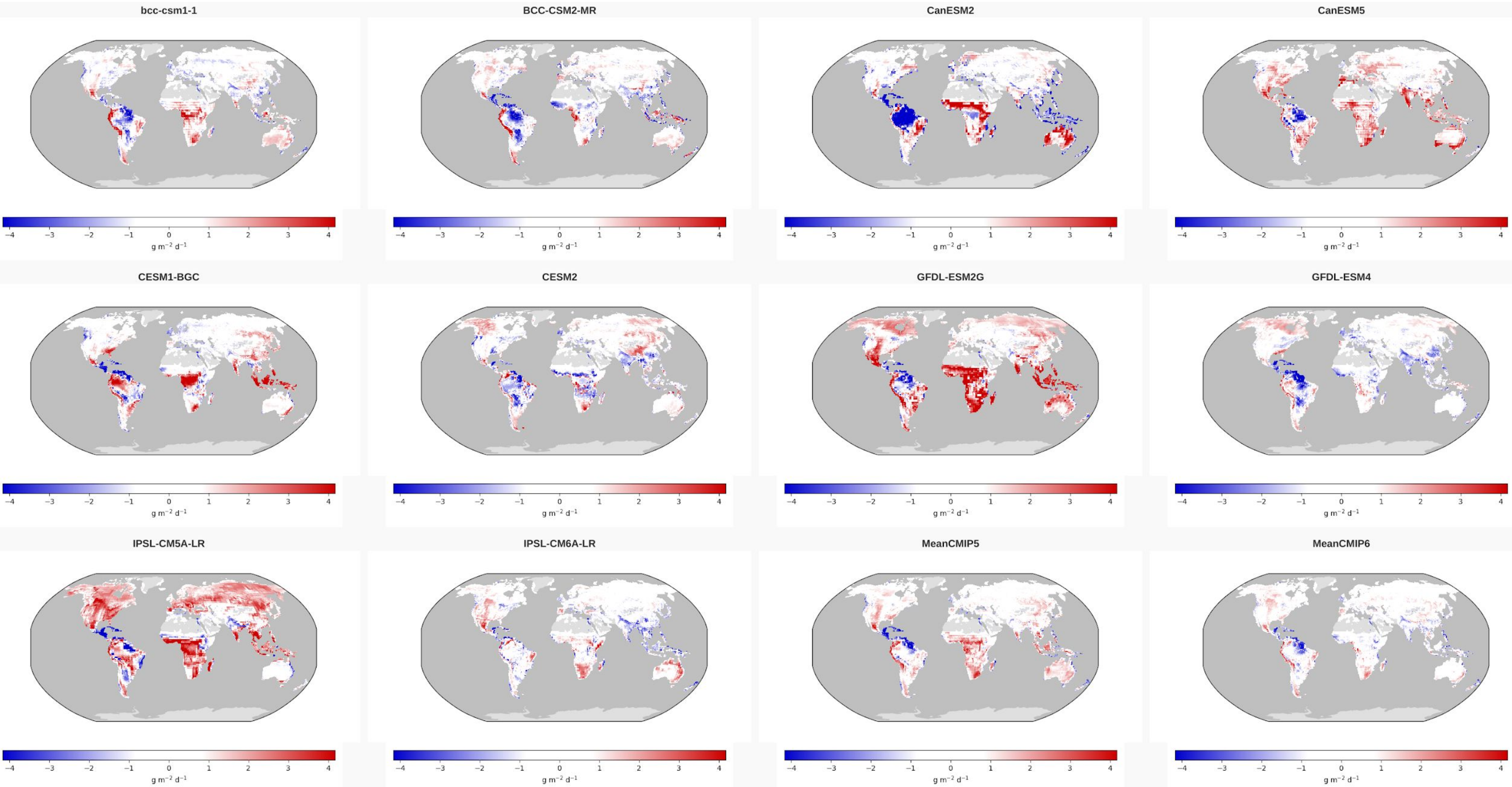
CMIP5 vs. CMIP6 Models

- The CMIP6 suite of land models (right) has improved over the CMIP5 suite of land models (left)
- The multi-model mean outperforms any single model for each suite of models
- The multi-model mean CMIP6 land model is the “best model” overall
- Why did CMIP6 land models improve?



(Hoffman et al., in prep)

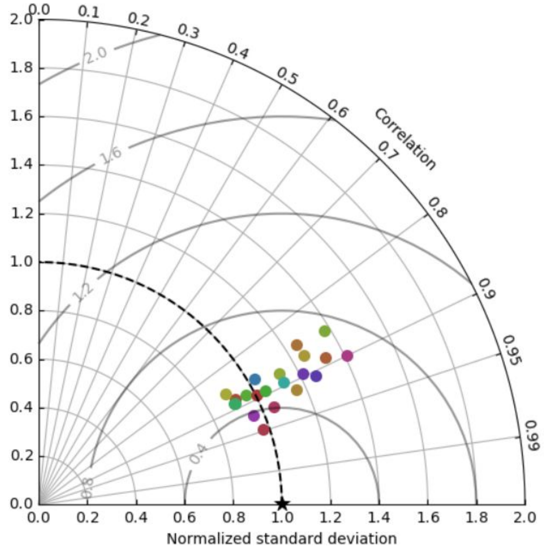

bcc-csm1-1
BCC-CSM2-MR
CanESM2
CanESM5
CESM1-BGC
CESM2
GFDL-ESM2G
GFDL-ESM4
IPSL-CM5A-LR
IPSL-CM6A-LR
MeanCMIP5
MeanCMIP6
−4 −3 −2 −1 0 1 2 3 4
g m^{-2} d^{-1}

Gross Primary Productivity

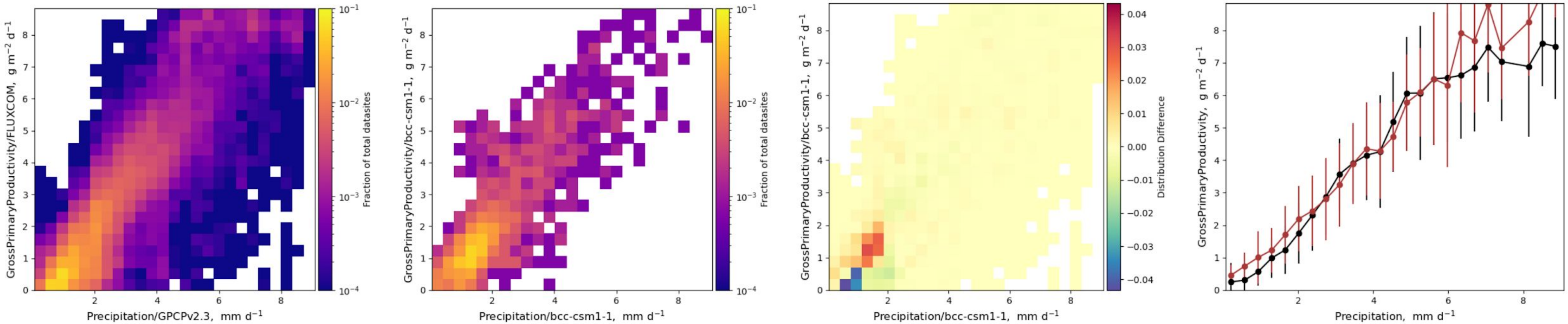
	Download Data	Period Mean (original grids) [Pg yr-1]	Model Period Mean (intersection) [Pg yr-1]	Benchmark Period Mean (intersection) [Pg yr-1]	Model Period Mean (complement) [Pg yr-1]	Benchmark Period Mean (complement) [Pg yr-1]	Bias [g m-2 d-1]	RMSE [g m-2 d-1]	Phase Shift [months]	Bias Score [1]	RMSE Score [1]	Seasonal Cycle Score [1]	Spatial Distribution Score [1]	Overall Score [1]
Benchmark	[-]	114.												
bcc-csm1-1	[-]	123.	112.	114.	8.79	0.0945	0.238	1.51	1.01	0.484	0.435	0.830	0.955	0.628
BCC-CSM2-MR	[-]	114.	107.	113.	5.88	0.671	-0.0233	1.52	1.11	0.479	0.447	0.817	0.941	0.626
CanESM2	[-]	129.	117.	114.	9.54		0.0601	2.31	2.00	0.388	0.437	0.650	0.836	0.549
CanESM5	[-]	141.	128.	114.	10.1		0.730	1.87	1.60	0.449	0.418	0.710	0.948	0.589
CESM1-BGC	[-]	129.	123.	113.	5.55	0.660	0.379	1.66	1.20	0.426	0.468	0.765	0.889	0.603
CESM2	[-]	110.	104.	113.	5.57	0.642	-0.0542	1.62	1.32	0.458	0.466	0.774	0.933	0.619
GFDL-ESM2G	[-]	167.	152.	114.	12.4		1.26	2.78	1.38	0.377	0.288	0.735	0.897	0.517
GFDL-ESM4	[-]	105.	99.0	114.	6.18		-0.177	1.59	1.49	0.495	0.403	0.702	0.939	0.588
IPSL-CM5A-LR	[-]	165.	150.	113.	11.7	0.515	1.18	2.68	1.20	0.327	0.352	0.781	0.896	0.542
IPSL-CM6A-LR	[-]	115.	109.	113.	5.27	0.708	0.111	1.39	1.14	0.547	0.477	0.790	0.961	0.650
MeanCMIP5	[-]	121.	115.	114.	6.65		0.574	1.41	0.981	0.494	0.502	0.799	0.965	0.652
MeanCMIP6	[-]	116.	110.	114.	6.26		0.129	1.17	0.931	0.572	0.522	0.826	0.956	0.679
MIROC-ESM	[-]	129.	118.	102.	9.04	11.4	0.396	1.90	1.27	0.463	0.435	0.767	0.920	0.604
MIROC-ESM2L	[-]	116.	104.	113.	9.90	0.119	-0.0111	1.95	1.99	0.409	0.379	0.628	0.920	0.543
MPI-ESM-LR	[-]	169.	159.	104.	8.91	9.81	1.36	2.36	1.29	0.402	0.371	0.715	0.930	0.558
MPI-ESM1.2-LR	[-]	141.	133.	104.	6.89	9.81	0.725	2.06	1.13	0.409	0.393	0.769	0.925	0.578
NorESM1-ME	[-]	129.	120.	114.	7.82		0.386	1.86	1.25	0.387	0.456	0.761	0.856	0.583
NorESM2-LM	[-]	107.	97.5	114.	7.59		-0.0828	1.63	1.31	0.443	0.472	0.791	0.938	0.623
UK-HadGEM2-ES	[-]	137.	130.	113.	6.93	0.848	0.602	2.01	1.10	0.389	0.388	0.820	0.855	0.568
UKESM1-0-LL	[-]	126.	119.	113.	7.06	0.825	0.387	1.77	1.16	0.436	0.419	0.791	0.924	0.598

- Multimodel GPP is compared with global seasonal GBAF estimates
- We can see Improvements across generations of models (e.g., CESM1 vs. CESM2, IPSL-CM5A vs. 6A)
- The mean CMIP6 and CMIP5 models perform best

Spatial Taylor Diagram



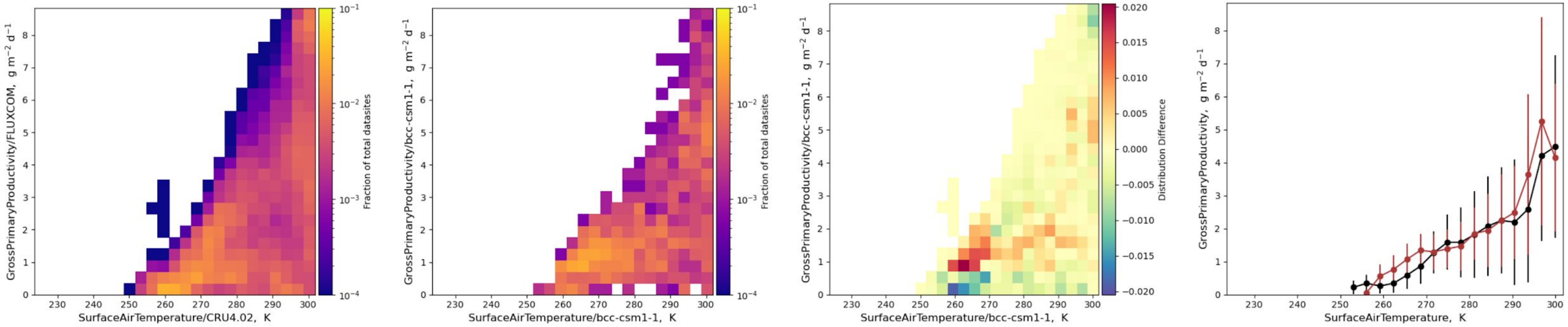
Precipitation/GPCPv2.3



SurfaceDownwardSWRadiation/CERESed4.1

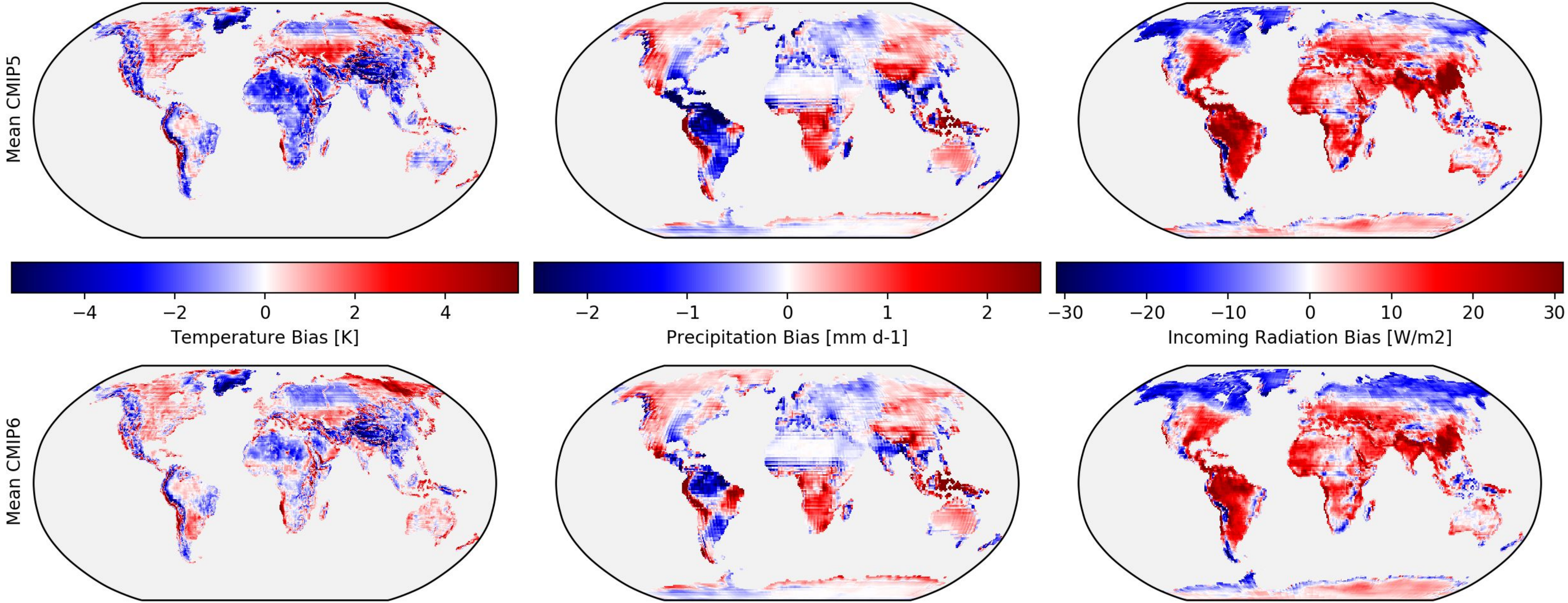
SurfaceNetSWRadiation/CERESed4.1

SurfaceAirTemperature/CRU4.02



Reasons for Land Model Improvements

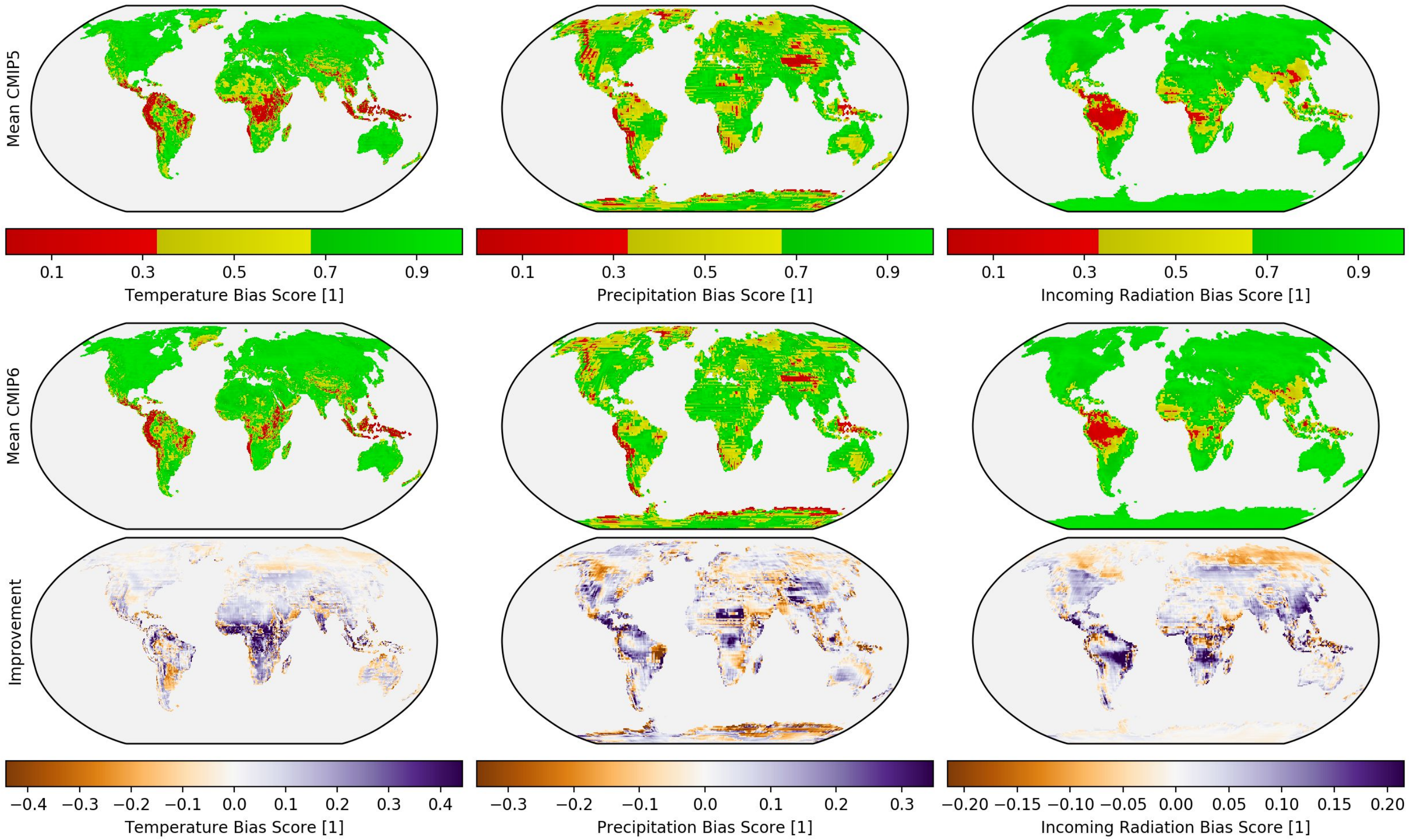
ESM improvements in climate forcings (temperature, precipitation, radiation) likely partially drove improvements exhibited by land carbon cycle models



(Hoffman et al., in prep)

Reasons for Land Model Improvements

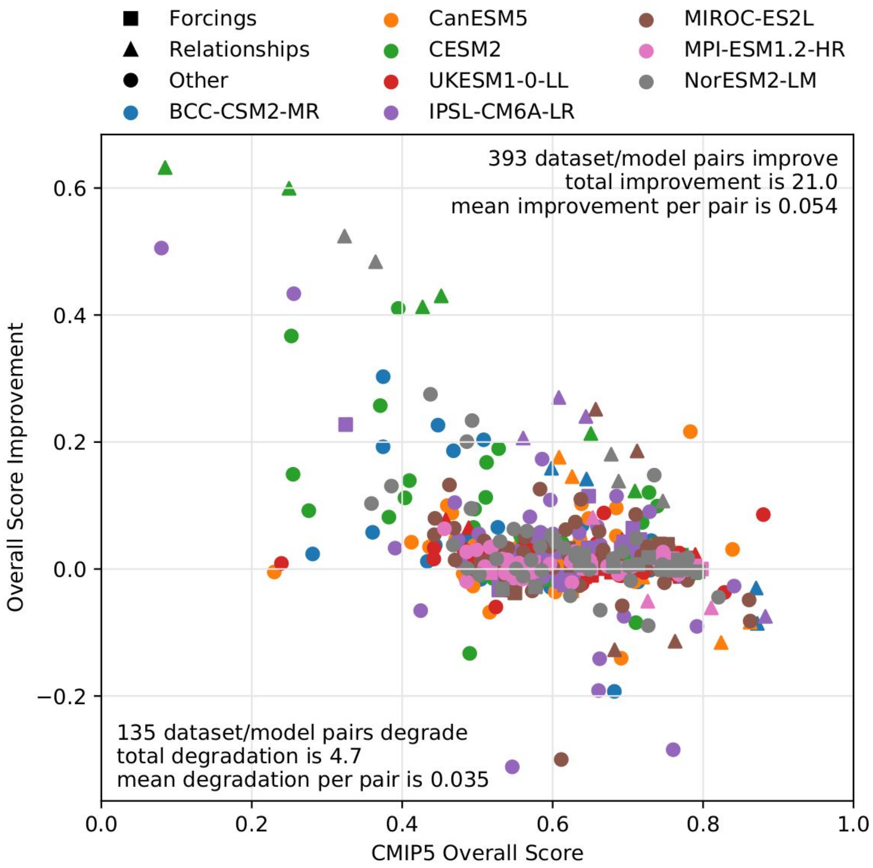
Differences in bias scores for temperature, precipitation, and incoming radiation were primarily positive, further indicating more realistic climate representation



(Hoffman et al., in prep)

Reasons for Land Model Improvements

While forcings got better, the largest improvements were in **variable-to-variable relationships**, suggesting that increased land model complexity was also partially responsible for higher CMIP6 model scores



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ILAMB & IOMB CMIP5 vs 6 Evaluation

- (a) ILAMB and (b) IOMB have been used to evaluate how land and ocean model performance has changed from CMIP5 to CMIP6
- Model fidelity is assessed through comparison of historical simulations with a wide variety of contemporary observational datasets
- The UN's Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) from Working Group 1 (WG1) Chapter 5 contains the full ILAMB/IOMB evaluation as Figure 5.22

	CMIP5 ESMs									CMIP6 ESMs										
	bcc-csm1-1	CanESM2	CESM1-BGC	GFDL-ESM2G	IPSL-CM5A-LR	MIROC-ESM	MPI-ESM-LR	NorESM1-ME	HadGEM2-ES	BCC-CSM2-MR	CanESM5	CESM2	GFDL-ESM4	IPSL-CM6A-LR	MIROC-ES2L	MPI-ESM1.2-LR	NorESM2-LM	UKESM1-0-LL	Mean CMIP5	Mean CMIP6
(a) Land Benchmarking Results																				
Land Ecosystem & Carbon Cycle	-0.72	-0.93	-1.55	-1.51	-0.13	0.60	-0.43	-1.31	0.19	-0.43	0.66	0.48	-1.09	0.22	0.60	-0.07	1.00	0.49	1.63	2.30
Biomass	0.20	-0.45	-1.52	-0.40	-1.26	-0.26	-1.07	-1.77	0.92	1.39	0.74	-0.20	-0.54	0.16	0.93	-0.96	-0.01	1.04	1.23	1.82
Burned Area			-0.87				0.10	-0.83				1.60								
Leaf Area Index	-0.20	-0.64	-1.30	-2.53	-0.01	0.30	0.01	-1.85	-0.16	0.27	0.08	0.34	-0.70	1.19	0.82	0.46	0.37	0.69	1.04	1.81
Soil Carbon	0.27	1.26	-1.46	0.07	0.75	0.47	-0.03	-1.14	0.07	0.23	1.35	-0.99	-2.04	-1.55	0.90	-0.75	-0.17	0.24	1.01	1.48
Gross Primary Productivity	0.59	-1.23	0.01	-1.81	-1.40	0.29	-0.53	-0.24	-1.04	0.77	0.04	0.59	-0.38	1.17	-1.02	-0.37	0.73	0.09	1.51	2.22
Net Ecosystem Exchange	-0.42	-1.81	-0.21	-0.65	1.10	-0.24	0.80	0.02	-1.03	-1.02	-1.19	0.59	1.69	-0.42	0.63	-0.21	1.08	-1.43	1.28	1.43
Ecosystem Respiration	0.90	-0.56	-0.86	-0.24	-1.35	0.99	-0.01	-0.94	-1.54	0.81	0.59	0.51	-0.79	0.90	-0.21	-1.24	0.43	-0.94	1.34	2.21
Carbon Dioxide		-1.54	-0.36	-2.92	-0.74	1.53	-0.00	0.37	0.85		0.42	0.26	0.39	0.59	1.10	-0.87	0.21	0.69	0.09	-0.07
Global Net Carbon Balance		-1.64	-0.88	-1.13	0.17	-0.31	-0.38	-0.50	0.24		-0.23	1.34	-1.70	0.17	-0.74	1.45	1.56	0.26	0.92	1.40
Land Hydrology Cycle	-2.65	-0.42	0.44	-0.18	-0.49	-0.52	-0.57	0.17	0.70	0.15	-0.47	1.51	-1.24	0.58	-0.72	-0.83	0.97	0.87	1.00	1.70
Evapotranspiration	-0.82	-0.99	-0.27	-1.02	0.64	-1.14	-0.62	-0.60	0.28	0.39	-1.08	1.09	0.65	0.43	-1.40	-1.01	0.82	1.05	1.41	2.20
Evaporative Fraction	-0.34	0.74	0.74	-0.14	-0.85	0.21	-1.98	0.22	-0.34	0.10	0.11	1.25	-0.88	1.29	-1.65	-1.81	1.11	-0.06	0.98	1.29
...																				
Terrestrial Water Storage Anomaly	-2.79	-0.45	0.47	0.50	-0.38	0.34	0.35	0.43	0.58	0.15	-0.08	0.95	-2.91	0.43	0.37	0.15	0.39	0.51	0.49	0.50
Permafrost	-0.88	-2.26	0.01	0.13	0.83	0.69	0.56	0.69	-0.56	-0.11	-3.02	0.83	0.74	-0.18	0.49	0.42	0.89	0.43	0.06	0.23
(b) Ocean Benchmarking Results																				
Ocean Ecosystems			2.18	0.20	-0.20		0.04		0.22		-0.37	0.83	-0.37	-0.26	-0.91	-0.67	-1.93	0.27	0.30	0.67
Chlorophyll		-1.50	2.15	0.44	1.02		0.49		0.56		-0.67	0.88	-0.21	0.10	-1.02	-0.41	-2.19	0.18	0.13	0.04
Oxygen, surface			0.73	-0.13	-1.98		-0.53	-1.53	-0.29		0.73	0.34	-0.09	-0.41	0.35	-0.30	0.40	0.49	0.64	1.57
Ocean Nutrients			-0.84	-0.10	0.91		-0.80	-1.25				-0.02	1.00	1.88		-0.90	-1.14	-0.17	-0.16	1.60
Nitrate, surface		0.21	-1.63	0.67	1.22		-0.18	-1.70	0.82		1.21	-0.90	0.29	1.21	1.02	0.39	-1.78	-0.56	-0.47	0.18
Phosphate, surface			-0.69	-0.04	0.04		-0.45	-0.43				0.39	-0.14	0.17	-0.41	-0.98	0.00	0.02	0.88	1.63
Silicate, surface			0.44	-0.71	0.24		-0.81	-0.20	-2.16			0.50	1.24	1.60		-1.21	-0.19	0.18	-0.29	1.37
Ocean Carbon											1.24	-0.23	-0.62	-0.69	-1.08	-1.12	1.31			1.19
TAlk, surface		-0.27	1.01	0.12	0.19		0.32	-2.31	-0.22		0.06	-0.36	0.85	-0.42	0.29	-2.40	1.27	0.06	1.27	0.54
...																				
Salinity, 700m	0.44	-0.35	-1.06	-0.54	0.70	0.46	-0.46	-0.80	0.32	0.36	0.25	-1.16	-0.47	0.54	0.33	-0.39	-0.87	-0.54	1.58	1.64
Ocean Relationships			-1.86	-0.36	-0.29		1.50	-0.43	0.68		-0.02	0.72	1.20	0.17	-1.86	0.02		-1.12	0.39	1.25
Oxygen, surface/WOA2018			0.27	0.23	-0.63		-0.26	-0.12	-0.38		0.29	-0.21	0.19	0.18	0.14	-0.07		0.03	-0.23	0.53
Nitrate, surface/WOA2018		-2.41	-1.38	-0.18	0.06		1.41	-0.16	0.78		0.09	0.79	1.07	0.26	-1.35	0.20		-0.74	0.52	1.04

Relative Scale

Worse Value — Better Value

Missing Data or Error

Summary

- **Model benchmarking** is increasingly important as model complexity increases
- Systematic model benchmarking is useful for
  - **Verification** – during model development to confirm that new model code improves performance in a targeted area without degrading performance in another area
  - **Validation** – when comparing performance of one model or model version to observations and to other models or other model versions
- The **ILAMB package** employs a suite of in situ, remote sensing, and reanalysis datasets to comprehensively evaluate and score land model performance, *irrespective of any model structure or set of process representations*
- ILAMB is **Open Source**, is written in **Python**, **runs in parallel** on laptops to supercomputers, and has been **adopted in most modeling centers**
- *Usefulness* of ILAMB depends on the quality of incorporated observational data, characterization of uncertainty, and selection of relevant metrics

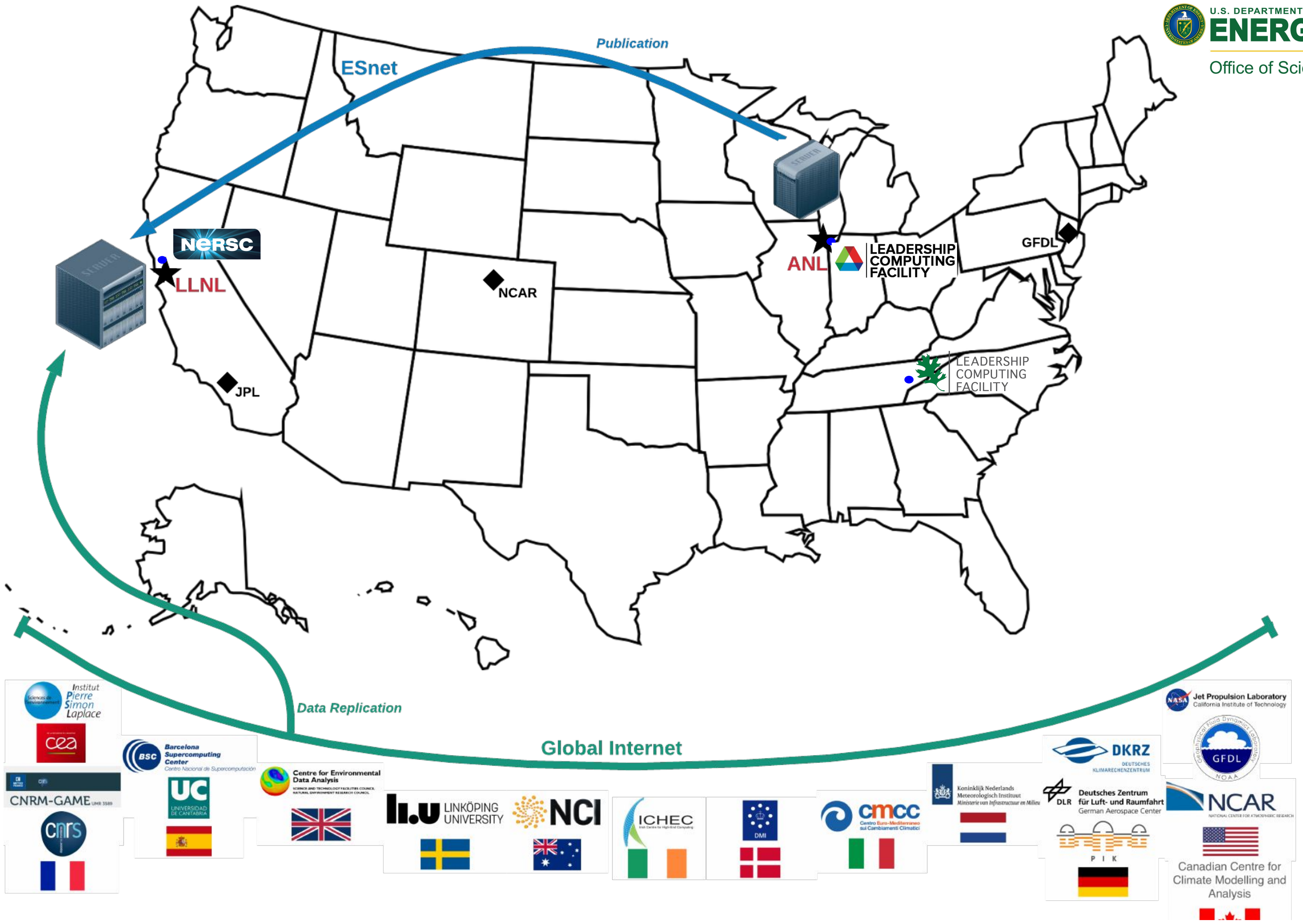
Earth System Grid Federation (ESGF)

ESGF2

U.S. DEPARTMENT OF ENERGY
Office of Science

DOE's Current Earth System Grid Federation

- Primary server at LLNL
- Replicating data from the global Federation
- Independent data node at ANL

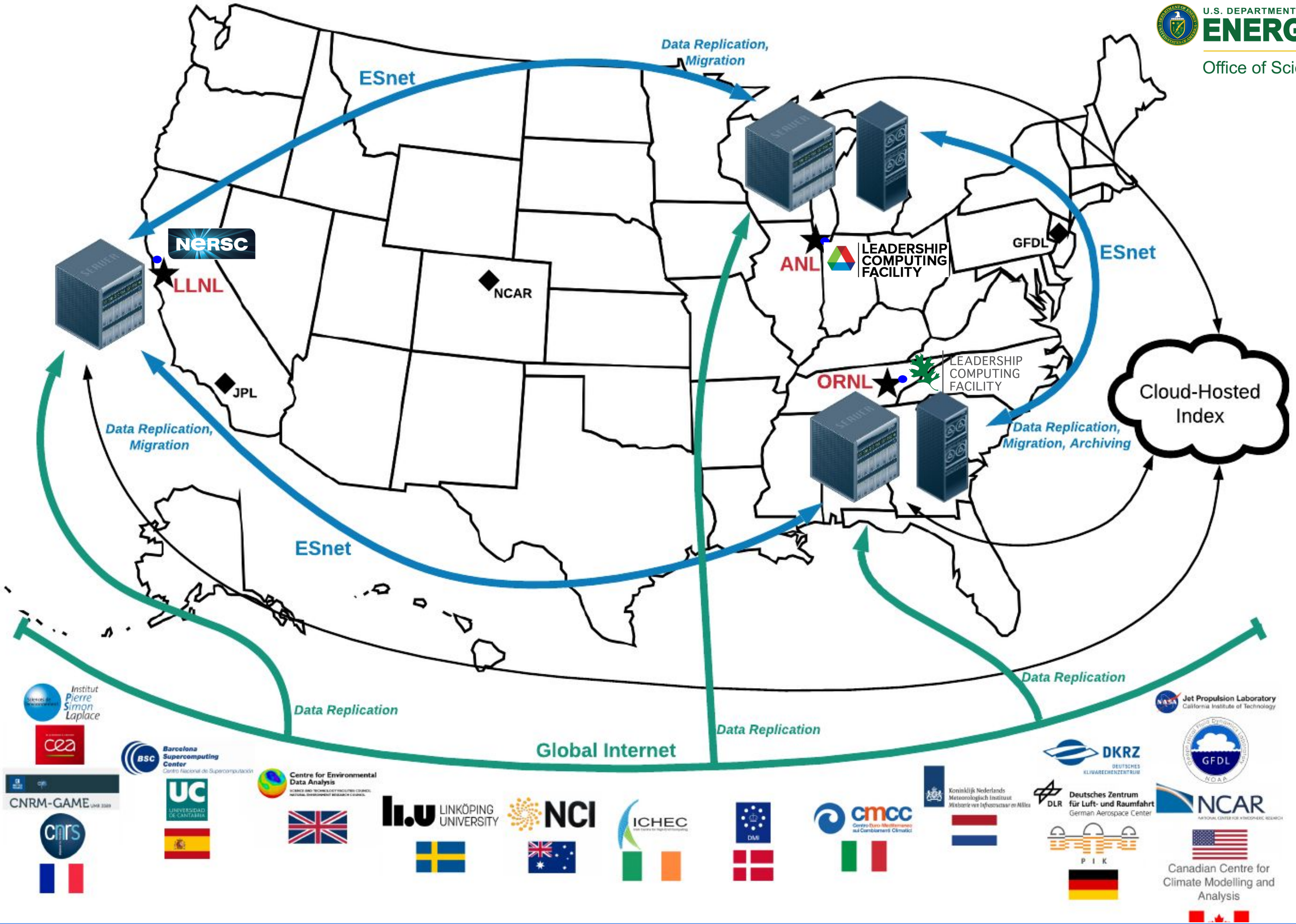


ESGF2

U.S. DEPARTMENT OF ENERGY
Office of Science

DOE’s Next Generation Earth System Grid Federation

- Co-located at all three of DOE’s major computing facilities
- Replicating data from the global Federation
- Providing cloud indexing, automated migration, and tape archiving



Design and implementation principles

- **Open architecture and protocols**
  - Enable substitution of alternative implementations
- Leverage **highly available and scalable** central services
  - Reduce complexity, increase reliability, provide economies of scale
- Use proven, modern **security technologies and practices**
  - Integrated access control; protect against attacks and intrusions
- **Use case approach** to design, implementation, and evaluation
  - Ensure that solutions meet real user needs
- Integrated **instrumentation**
  - Metrics drive data management, data access features, capability development
- Focus on **performance** to deal with big data
  - High-speed data transfer, search, server-side processing

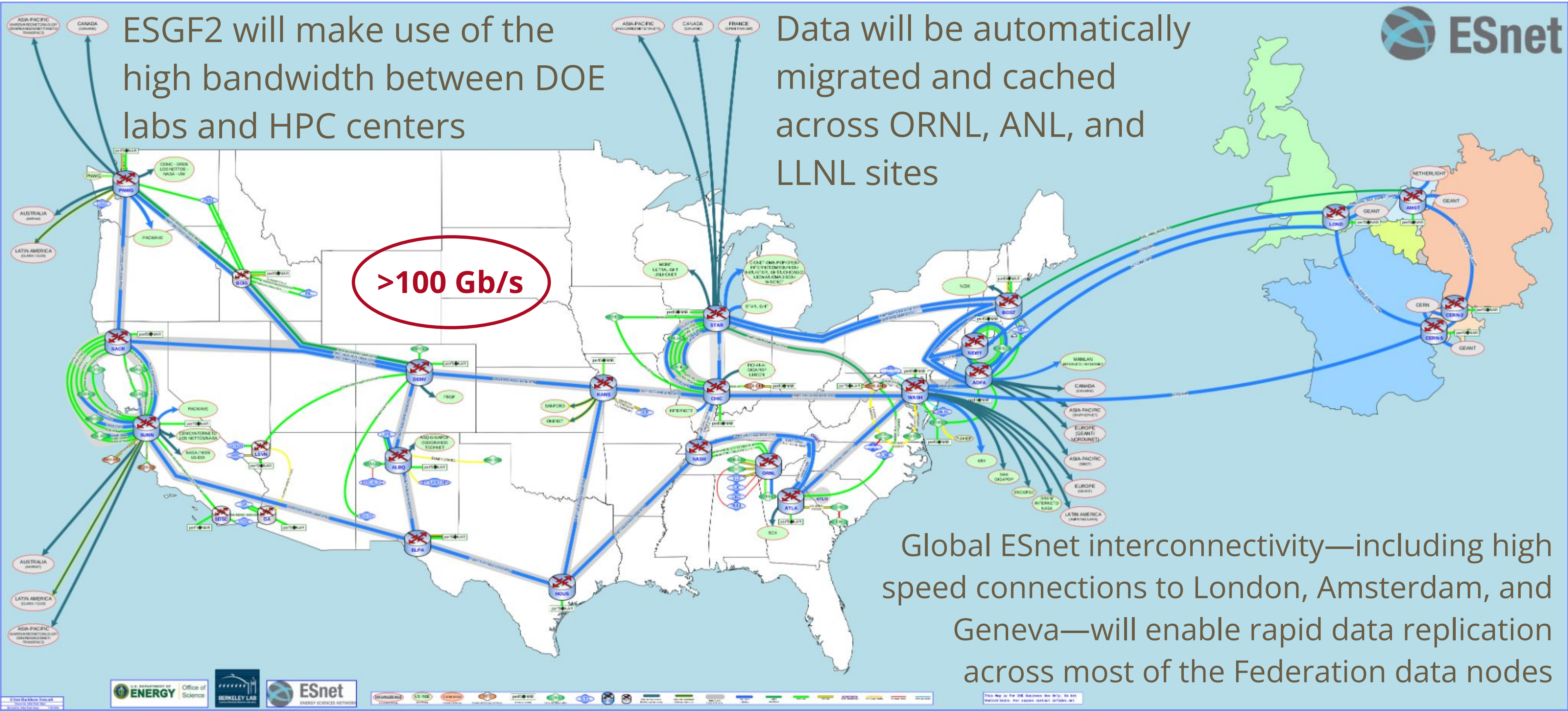
ESGF2 ESnet Global Connectivity

ESnet representative, Eli Dart, is part of our Resource & Project Liaisons group

ESnet
ENERGY SCIENCES NETWORK

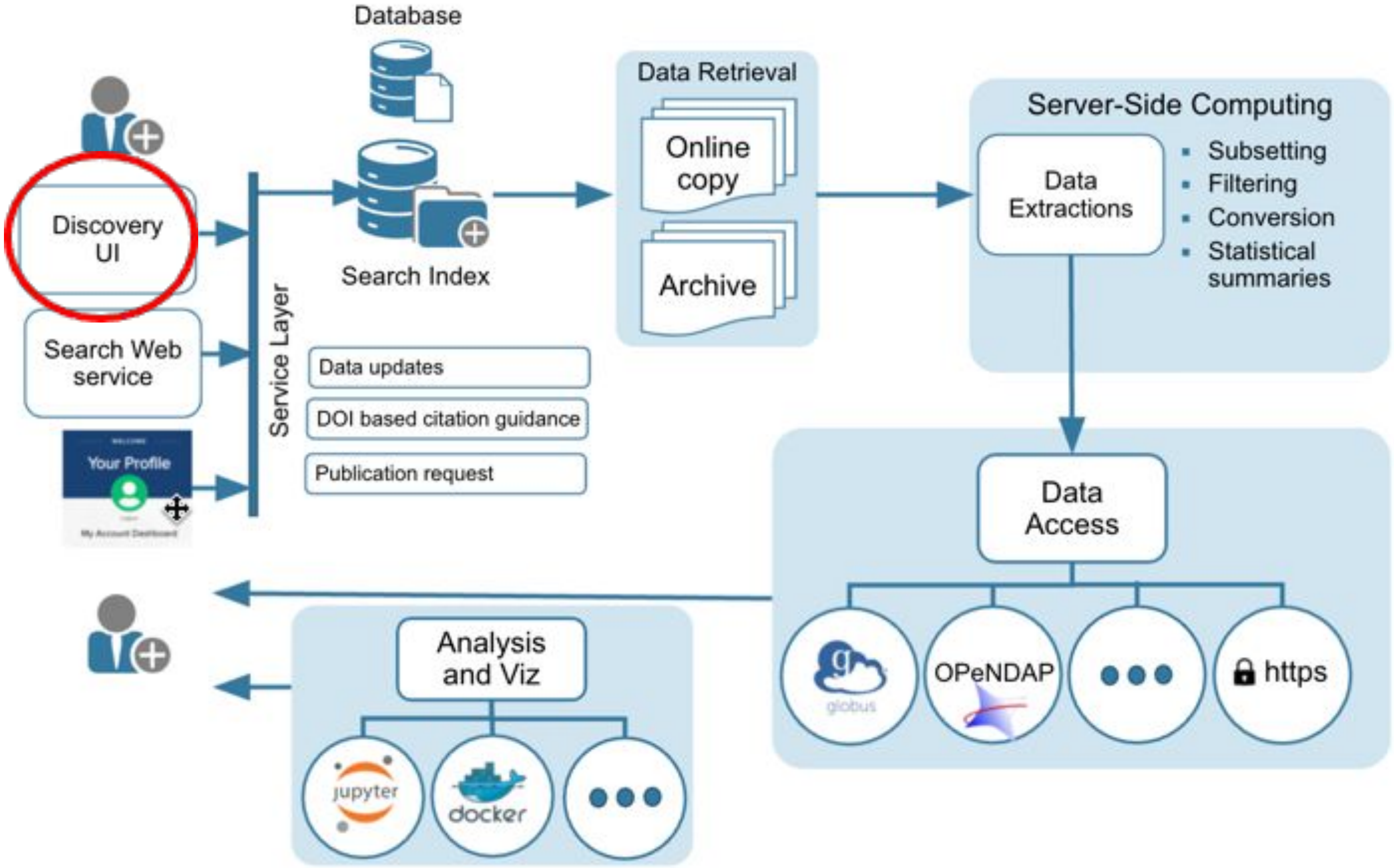
ESGF2 will make use of the high bandwidth between DOE labs and HPC centers

Data will be automatically migrated and cached across ORNL, ANL, and LLNL sites



Global ESnet interconnectivity—including high speed connections to London, Amsterdam, and Geneva—will enable rapid data replication across most of the Federation data nodes

ESGF2 Data Discovery Platform: Architecture



ESGF2 Outreach Activities

- Organize Webinars, Tutorials, and ESGF2 Bootcamps
  - Data management lessons learned
  - Ingest best practices
  - Data discovery and access
- Hackathons and Workshops
  - Data standards
  - Data node deployment
  - User compute resources
  - Hold at large relevant conferences, e.g.,
    AGU Fall Meeting, EGU, and AMS Annual Meeting
- Organize and host an annual
  ESGF Developer and User Conference

Artificial Intelligence for Earth System Predictability (AI4ESP)

https://ai4esp.org/ https://ai4esp.slack.com/

AI4ESP | Artificial Intelligence for Earth System Predictability

A multi-lab initiative working with the Earth and Environmental Systems Science Division (EESSD) of the Office of Biological and Environmental Research (BER) to develop a new paradigm for Earth system predictability focused on enabling artificial intelligence across field, lab, modeling, and analysis activities.

White papers were solicited for development and application of AI methods in areas relevant to EESSD research with an emphasis on quantifying and improving Earth system predictability, particularly related to the integrative water cycle and extreme events.

> ***How can DOE directly leverage artificial intelligence (AI) to engineer a substantial (paradigm-changing) improvement in Earth System Predictability?***

156 white papers were received and read to plan the organization of a workshop in Fall 2021.

AI4ESP Workshop: Oct 25–Dec 3, 2021

Earth System Predictability Sessions

- Atmospheric Modeling
- Land Modeling
- Human Systems & Dynamics
- Hydrology
- Watershed Science
- Ecohydrology
- Aerosols & Clouds
- Climate Variability & Extremes
- Coastal Dynamics, Oceans & Ice

Cross-Cut Sessions

- Data Acquisition
- Neural Networks
- Surrogate models and emulators
- Knowledge-Informed Machine Learning
- Hybrid Modeling
- Explainable/Interpretable/Trustworthy AI
- Knowledge Discovery & Statistical Learning

Oak Ridge National Laboratory (ORNL)
and the
Computational Earth Sciences Group

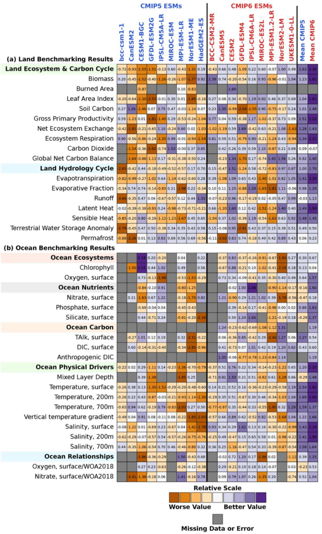
Summit at Oak Ridge National Laboratory, #2 fastest supercomputer on the [TOP500](TOP500) List (November 2021).

Computational Earth Sciences Group

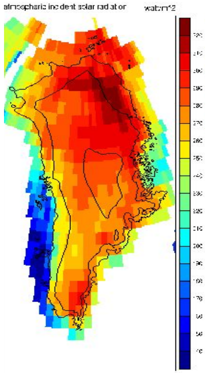
Forrest M. Hoffman
Group Leader

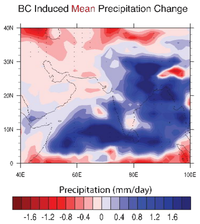
The **Computational Earth Sciences Group (CESG)** improves process understanding of the global Earth system by developing and applying models, machine learning, and computational tools at scale; integrating observational data; and quantifying Earth system predictability and uncertainty associated with interactions between water, energy, biogeochemical cycles, and aerosols.

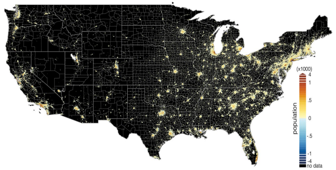
- Advances predictive understanding and simulation of atmospheric, terrestrial, cryospheric, and marine coupled systems
- Quantifies interactions and feedbacks within and between the Earth system and terrestrial, marine, and subsurface biogeochemical cycles
- Develops and applies methods and tools, including AI and machine learning, for quantitative assessment and benchmarking of coupled, multiscale Earth system models at global and regional scales
- Provides metrics for stakeholders through projects that connect to integrated and vulnerability assessment and adaptation projects



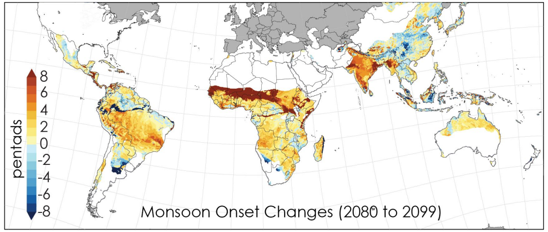
(IPCC AR6 WG1, 2021, Figure 5.22)







(Batibeniz et al., *Earth's Future*, 2020)



(Ashfaq et al., *Clim. Dyn.*, 2020)

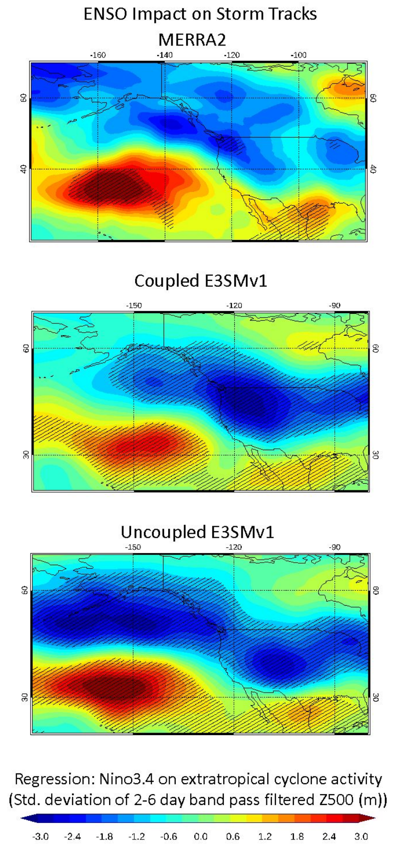
Sensitivity of ENSO Teleconnection to Extremes: Model Resolution and Air-sea Coupling

Objective: Evaluate representation of ENSO teleconnection to precipitation extremes over North America in DOE E3SM historical simulations.

New Science: Extreme value analysis reveals that high resolution models generally improve the simulation of precipitation extremes over North America. However, the improvement in ENSO teleconnection to precipitation extremes is marginal. Model bias over Western North America and Southeastern US is associated with a stronger and more widespread reduction of extratropical cyclone activity during El Nino years than observed. Air-sea coupling enhances this behavior as evident from prescribed SST simulations.

Results/Impacts: The deficiencies in the simulation of ENSO teleconnection to precipitation extremes appears to be due to ENSO associated large scale atmospheric drivers of precipitation extremes. Improving mid-latitude atmosphere-ocean coupled response to ENSO events in models could alleviate these biases.

Mahajan, Salil, Q. Tang, N. Keen, C. Golaz, L. Van-Roekel (2020), Sensitivity of the simulation of ENSO teleconnections to precipitation extremes over North America in an ESM: Model resolution and air-sea coupling, *Journal of Climate (in preparation).*



ENSO impacts on extra-tropical cyclone (storm track) activity in MERRA2 reanalysis product (1980-2018), and low-resolution (1-degree) E3SM v1 coupled and prescribed SST (uncoupled) historical ensembles (1979-2015).

Revisiting Recent U.S. Heat Waves in a Warmer and More Humid Climate

Contact: Deeksha Rastogi, E-mail: rastogid@ornl.gov

Objective: Investigate the characteristics of temperature-based (dry) and temperature-humidity-based (humid) temporally compounded heat waves in present and a warmer climate across the United States using a pair of high resolution spectrally nudged numerical model simulations.

New Science:

1) We show that humidity exacerbated the geographical footprint of heat waves more for some years (e.g. higher humidity impacts were identified during 2010 as compared to 2012 over the Southeast).
2) In a warmer climate, dry heat waves are projected to become drier, while humid heat waves remain humid. However, the overall increase in daily maximum temperature intensifies the heat stress during both future humid and dry heat waves across all regions.

Significance: There is a projected increase in apparent (or feels like) temperature and human exposure to extreme heat by the 21st century. This study utilized a set of high-resolution numerical simulations with large-scale circulation constrained, to emphasize the importance of thermodynamic drivers in determining future heat wave characteristics.

Citation - Rastogi, D., Lehner, F., & Ashfaq, M. Revisiting Recent U.S. Heat Waves in a Warmer and More Humid Climate. *Geophysical Research Letters*, 47, e2019GL086736, **https://doi.org/10.1029/2019GL086736**

Humid versus Dry Heat Wave Characteristics over the Southeast U.S. during 2010 and 2012 Summers

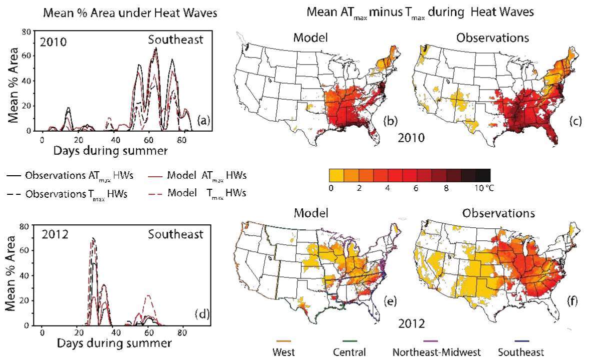


Figure: Daily maximum temperature (T_{max}) and daily maximum apparent temperature (AT_{max}) heatwaves during 2010 and 2012 summer over the southeast United States. Line plots show mean percentage area under heatwaves over the Southeast United States for summer (June-July-August) during (a) 2010 (d) 2012. Spatial maps show average differences between AT_{max} and T_{max} during the heatwave days in 2010 for (b) model (WRF) and (l) observations (PRISM) and 2012 for (m) model and (n) observations.

Funding:

Energy Exascale Earth System Model (E3SM), US DOE, Office of Science, Office of Biological and Environmental Research (BER)

Advance Study Program fellowship awarded by Graduate Visitor Program at National Center for Atmospheric Research (NCAR).

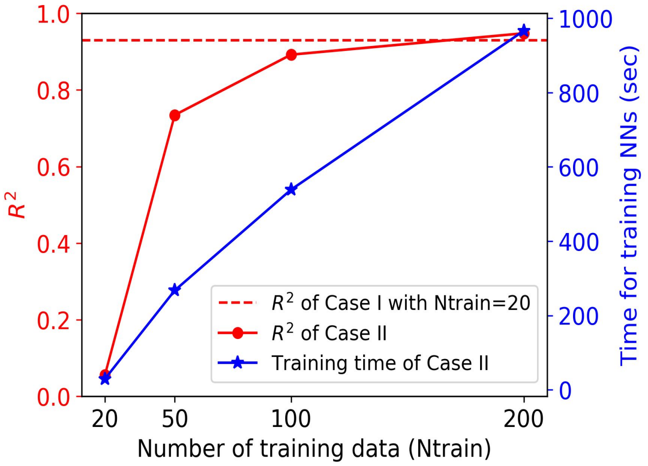
Support for data storage and analysis is provided by Computational Information Systems Laboratory at National Center for Atmospheric Research, Boulder, CO.

CLIMATE CHANGE SCIENCE INSTITUTE
OAK RIDGE NATIONAL LABORATORY

Advancing a predictive understanding of large-scale earth systems through machine learning

Objective	• Use limited expensive earth system model simulation data to build a fast-to-evaluate surrogate model for accurate predictions in large-scale earth systems.
New science	• Advanced singular value decomposition method has been developed to produce a simple neural network (NN) surrogate model which greatly reduces the number of required training data. • Efficient Bayesian optimization algorithm has been developed to generate an accurate NN surrogate.
Significance	• An accurate and fast-to-evaluate surrogate enables efficient model-data integration in earth system modeling. • Advanced application of machine learning techniques for Earth and environmental systems sciences.

Lu, D. and D. Ricciuto, Efficient surrogate modeling methods for large-scale Earth system models based on machine learning techniques. https://doi.org/10.5194/gmd-2018-327



The resulted simple and optimized NN enables only 20 training data to produce accurate predictions of regional GPPs otherwise 200 data are needed for the similar accuracy.

OAK RIDGE National Laboratory

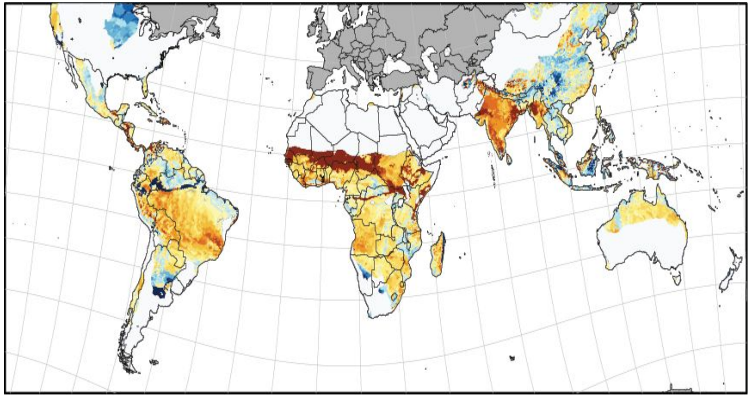
Monsoon seasons will shift and shrink at the higher levels of radiative forcing

Objective: Quantification of future changes in the global monsoons at various levels of radiative forcing.

New Science:

- For the first time, a global view of changes in monsoon characteristics using an unprecedented ensemble of high-resolution regional climate model experiments for two different radiative forcing scenarios.
- A spatially robust delay in the start of global monsoons and shrinking of monsoon seasons at higher levels of radiative forcing.
- Deeper boundary layer and reduced atmospheric saturation during pre-monsoons suppress convective precipitation, which weakens atmospheric diabatic heating and delays the transitioning of monsoon regions into deep convective states.
- No significant changes in monsoons at lower radiative forcing levels.

Significance: Two-thirds of global population relies on monsoons precipitation. Projected changes in the global monsoons will impact energy, health, agricultural and water resource sectors and has the potential to disrupt global economic supply chains. The possibility that a major change in global monsoons can be avoided at lower levels of radiative forcing highlights the urgent need for steps towards emissions stabilization.



Delay in the start of global monsoons at higher radiative forcing levels

Part of the climate model simulations, analyses, and data storage were supported by the OLCF resources.

Ashfaq, Moetasim, T. Cavazos, M. S. Reboita, J. A. Torres-Alavez, E.-S. Im, C. F. Olusegun, L. Alves, **Kesondra Key**, M. O. Adeniyi, M. Tall, M. Bamba Sylla, **Shahid Mehmood**, Q. Zafar, S. Das, I. Diallo, E. Coppola, and F. Giorgi (2020), Robust late twenty-first century shift in the regional monsoons in RegCM-CORDEX simulations, *Clim. Dyn.*, doi:10.1007/s00382-020-05306-2.

The Earth Has Humans, So Why Don't Our Climate Models?

RUBISCO

Objective: To inspire an interdisciplinary effort to couple models of human behavior and social systems with climate models to overcome deficiencies in representing feedbacks.

Approach: A multi-model approach that considers a range of theories and representations of human perception and behavior, driven by a suite of social factors, is proposed.

Results/Impacts: We describe the importance of linking social factors with climate processes and identify four priorities for advancing the development of coupled social-climate models: 1) evaluate an array of behavioral theories, 2) identify regional climate impacts on humans, 3) incorporate influence of diverse social systems, and 4) improve representation of how perceptions and behavior influence greenhouse gas emissions.

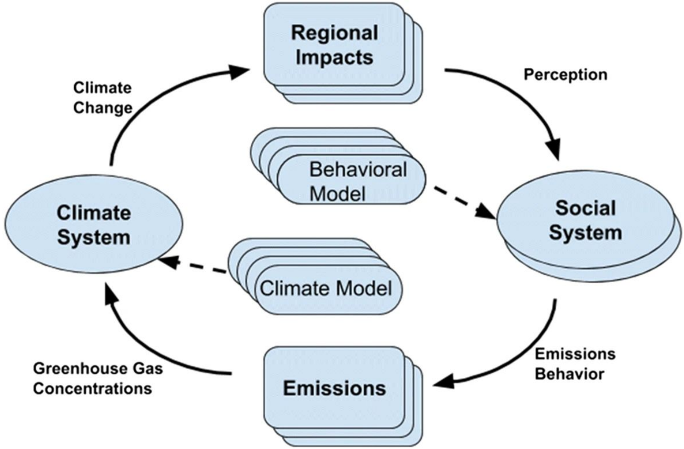


Figure: Schematic diagram demonstrating a strategy for coupling social models with climate models.

Beckage, B., K. Lacasse, J. M. Winter, L. J. Gross, N. Fefferman, **Forrest M. Hoffman**, S. S. Metcalf, T. Franck, E. Carr, A. Zia, and A. Kinzig (2020), The Earth Has Humans, So Why Don't Our Climate Models? *Clim. Change*, doi:[10.1007/s10584-020-02897-x](https://doi.org/10.1007/s10584-020-02897-x).

Argonne National Laboratory · Brookhaven National Laboratory · Berkeley Lab · Los Alamos National Laboratory · NCAR National Center for Atmospheric Research · Oak Ridge National Laboratory · UCI · Michigan

A Semi-implicit Barotropic Mode Solver for the E3SM Ocean Model Enables Faster and More Stable Ocean Simulations

Objective: To solve the barotropic mode in the E3SM ocean model more efficiently and stably as a competitor of an existing scheme.

Approach: Implement the semi-implicit method for the barotropic mode using a more scalable iterative method with an optimized preconditioner.

Results/Impacts: Several numerical experiments demonstrate that the semi-implicit barotropic mode solver has almost the same accuracy and better parallel scalability compared with the existing scheme while allowing faster and more stable simulations. The semi-implicit solver accelerates the barotropic mode up to 2.9 faster than the existing scheme on 16,320 processors. In addition, this semi-implicit solver provides a more flexible choice of a time step size to model users.

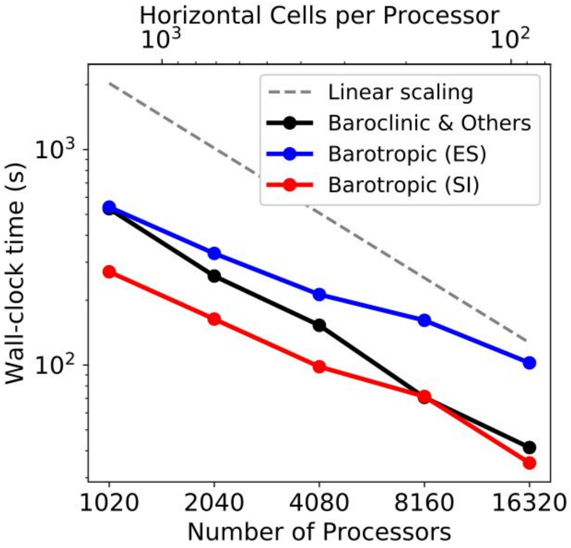


Figure: Strong scaling results for the barotropic mode solved by the explicit-subcycling scheme (ES, the existing scheme) and the semi-implicit method (SI). The MPAS-O model was run on the National Energy Research Scientific Computing Center's Cori supercomputer.

Kang, H.-G., **K. J. Evans**, M. R. Petersen, and P. W. Jones (2020), A scalable barotropic mode solver for the MPAS-Ocean, *J. Adv. Model Earth Sy.*, in preparation.

Oak Ridge National Laboratory · Los Alamos National Laboratory · E3SM Energy Exascale Earth System Model

Geoengineering Increases the Global Land Carbon Sink

Objective: To examine stratospheric aerosol intervention (SAI) impacts on plant productivity and terrestrial biogeochemistry.

Approach: Analyze and compare simulation results from the Stratospheric Aerosol Geoengineering Large Ensemble (GLENS) project from 2010 to 2097 under RCP8.5 with and without SAI.

Results/Impacts: In this scenario, SAI causes terrestrial ecosystems to store an additional 79 Pg C globally as a result of lower ecosystem respiration and diminished disturbance effects by the end of the 21st century, yielding as much as a 4% reduction in atmospheric CO_2 mole fraction that progressively reduces the SAI effort required to stabilize surface temperature.

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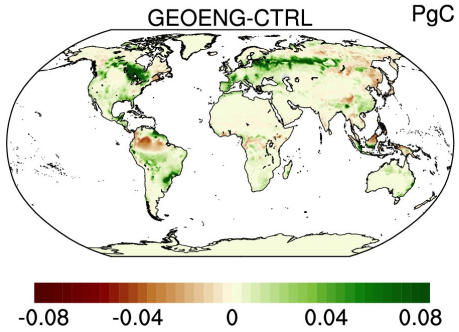

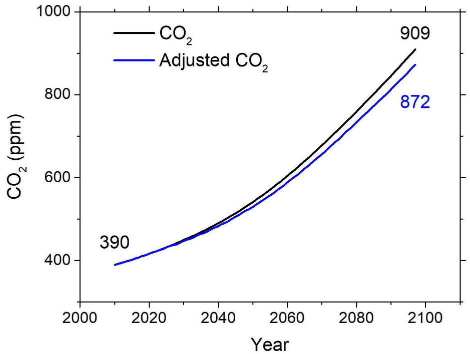

Figure: The larger sink under SAI increased land C storage by 79 Pg C by 2097, which would reduce the projected atmospheric CO_2 level.

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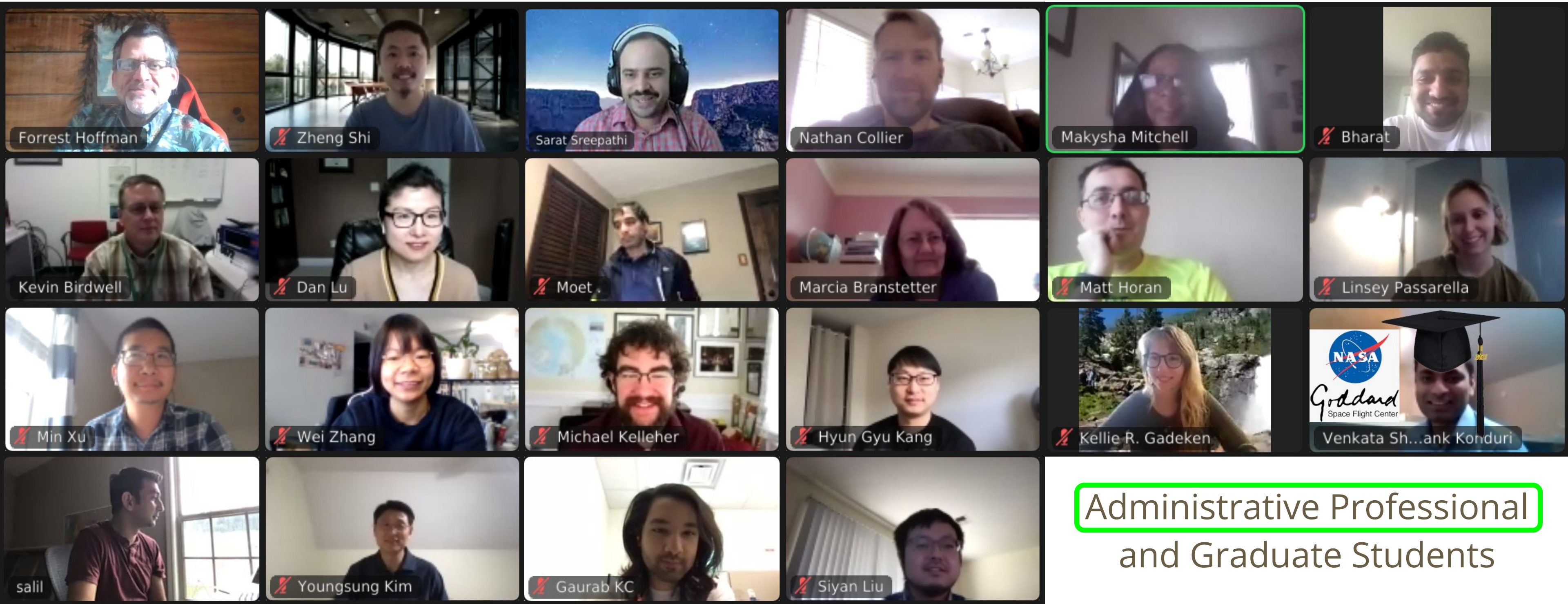

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Questions?

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