4th Carbon from Space Workshop

Forrest M. Hoffman, Nathan Collier, Mingquan Mu, Min Xu, Gretchen Keppel-Aleks, David M. Lawrence, Charles D. Koven, Weiwei Fu, William J. Riley, James T. Randerson

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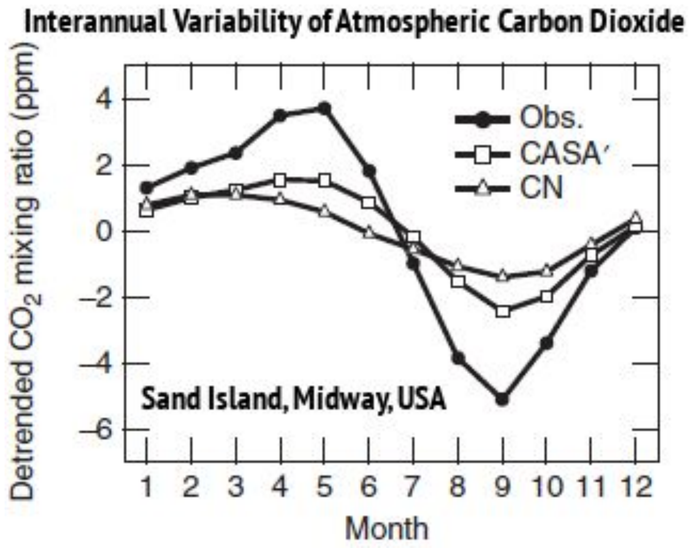
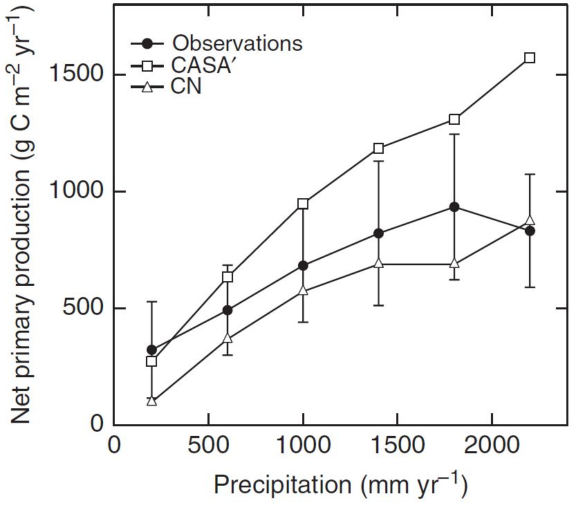
Evaluating Land Carbon Cycle Processes in Earth System Models: Have Models Improved Over Time?

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



(Randerson et al., 2009)

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

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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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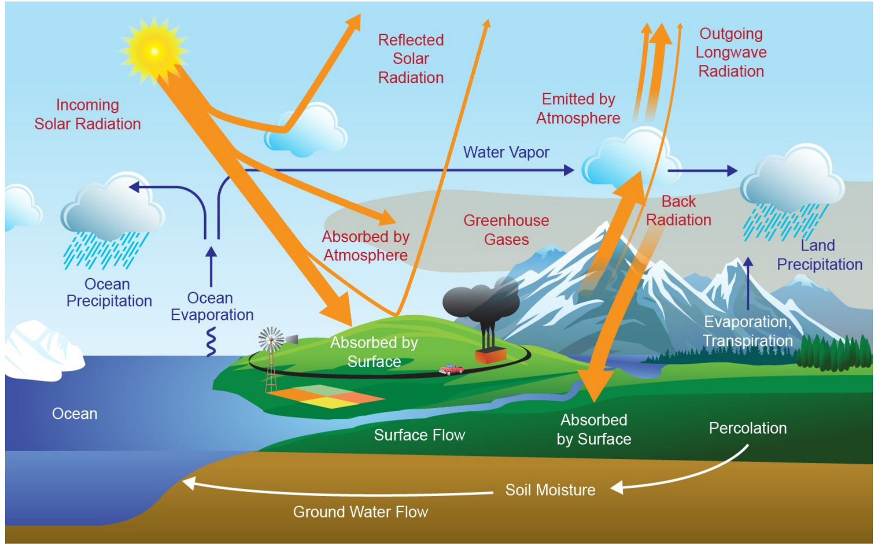
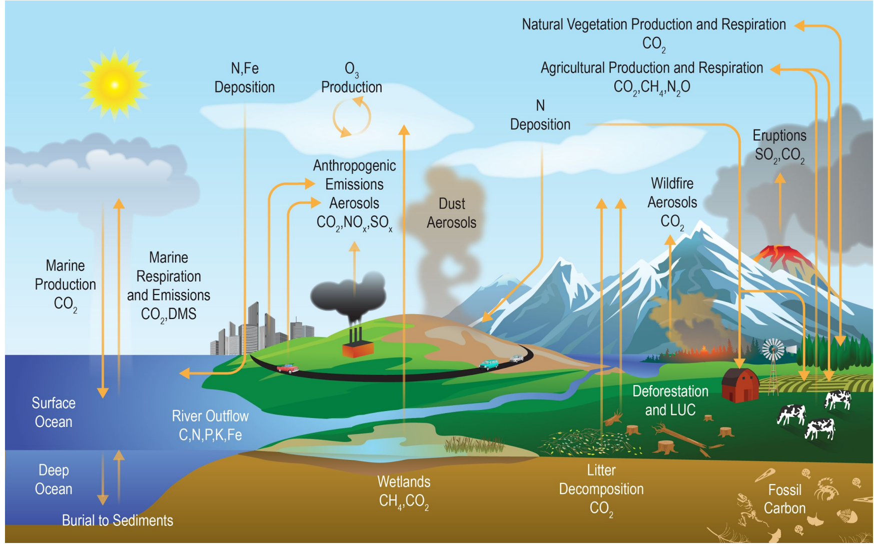
What is ILAMB?

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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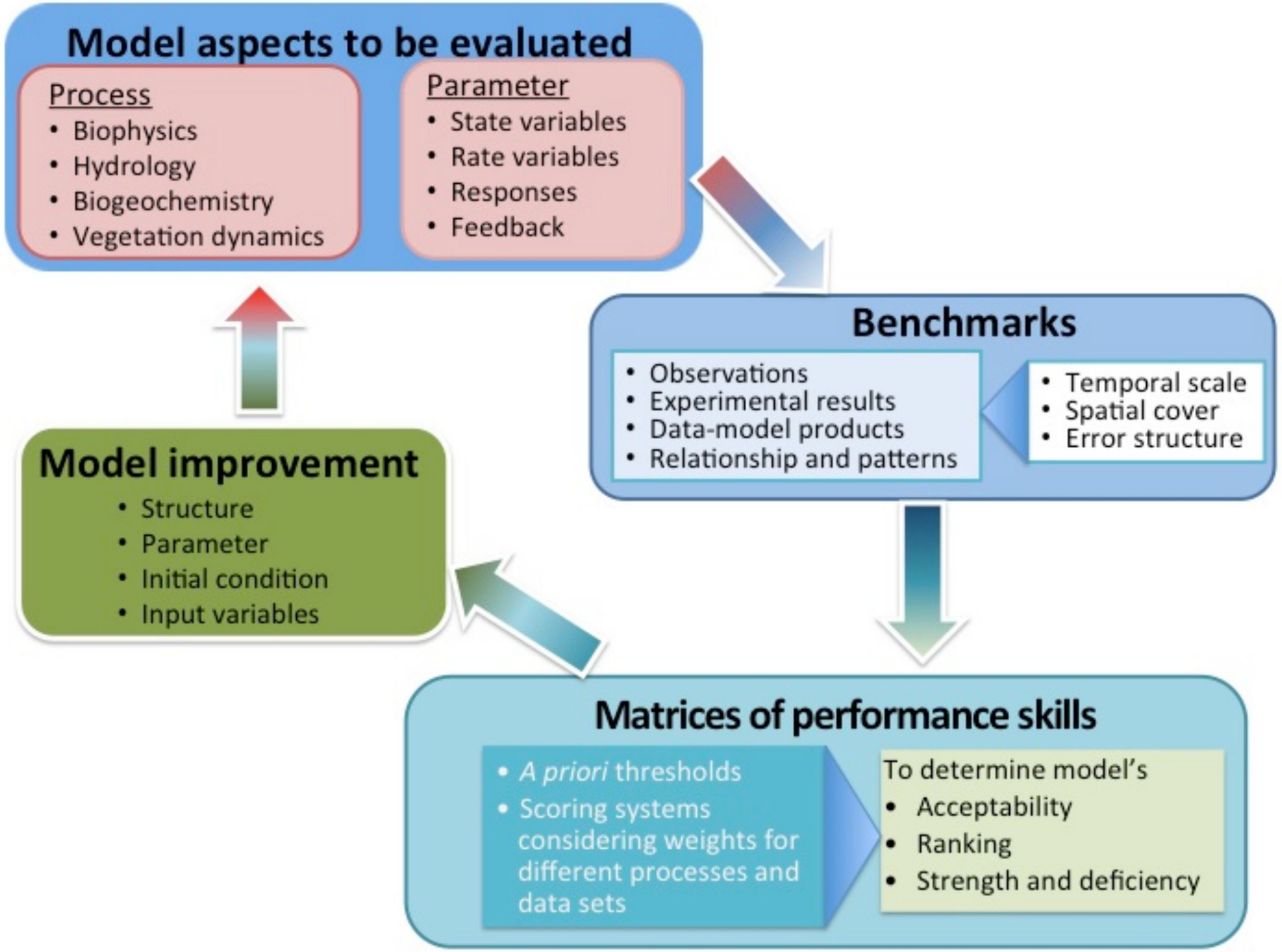
- **First ILAMB Workshop** was held in Exeter, UK, on June 22–24, 2009
- **Second ILAMB Workshop** was held in Irvine, CA, USA, on January 24–26, 2011
  - ~45 researchers participated from the US, Canada, UK, Netherlands, France, Germany, Switzerland, China, Japan, and Australia
  - Developed methodology for model-data comparison and baseline standard for performance of land model process representations (Luo et al., 2012)

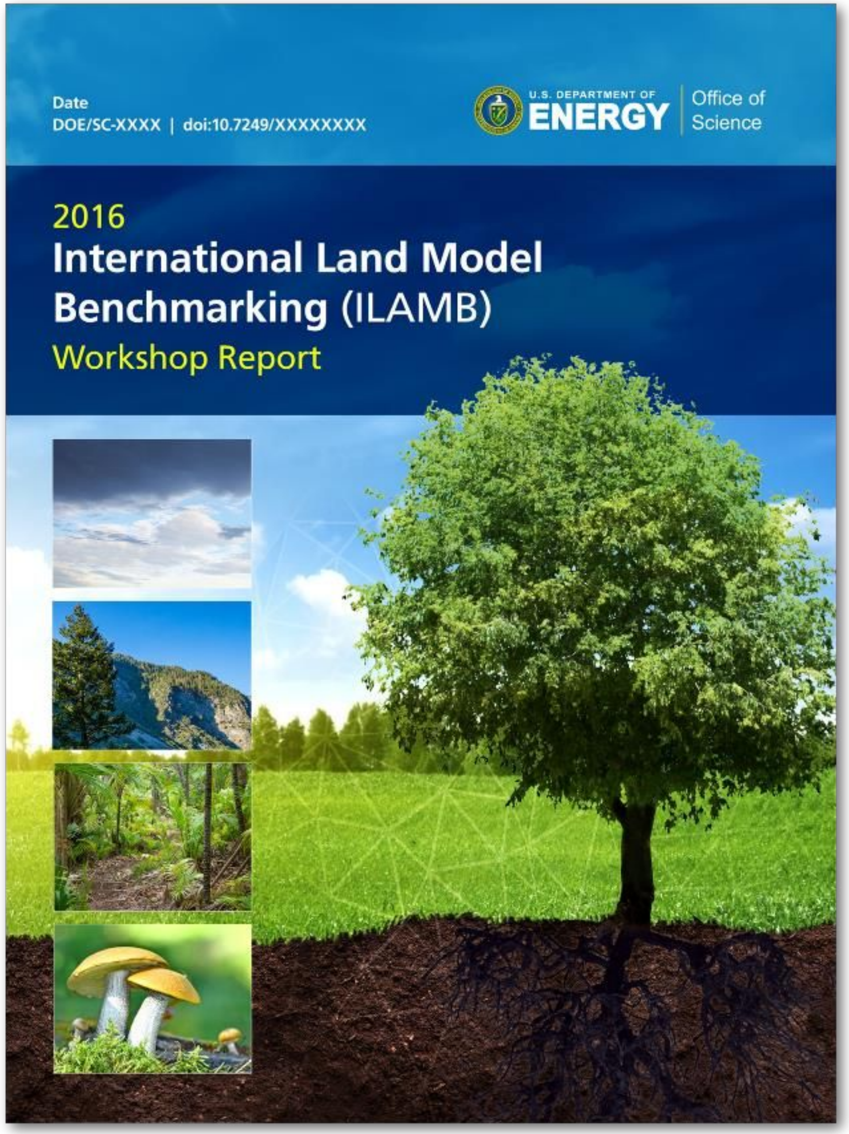
A Framework for Benchmarking Land Models

- A **benchmarking framework for evaluating land models** emerged and included (1) defining model aspects to be evaluated, (2) selecting benchmarks as standardized references, (3) developing a scoring system to measure model performance, and (4) stimulating model improvement
- Based on this methodology and prior work on the **Carbon-LAnd Model Intercomparison Project (C-LAMP)** (Randerson et al., 2009), a prototype model benchmarking package was developed for ILAMB



(Luo et al., 2012)

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



(Hoffman et al., 2017)

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

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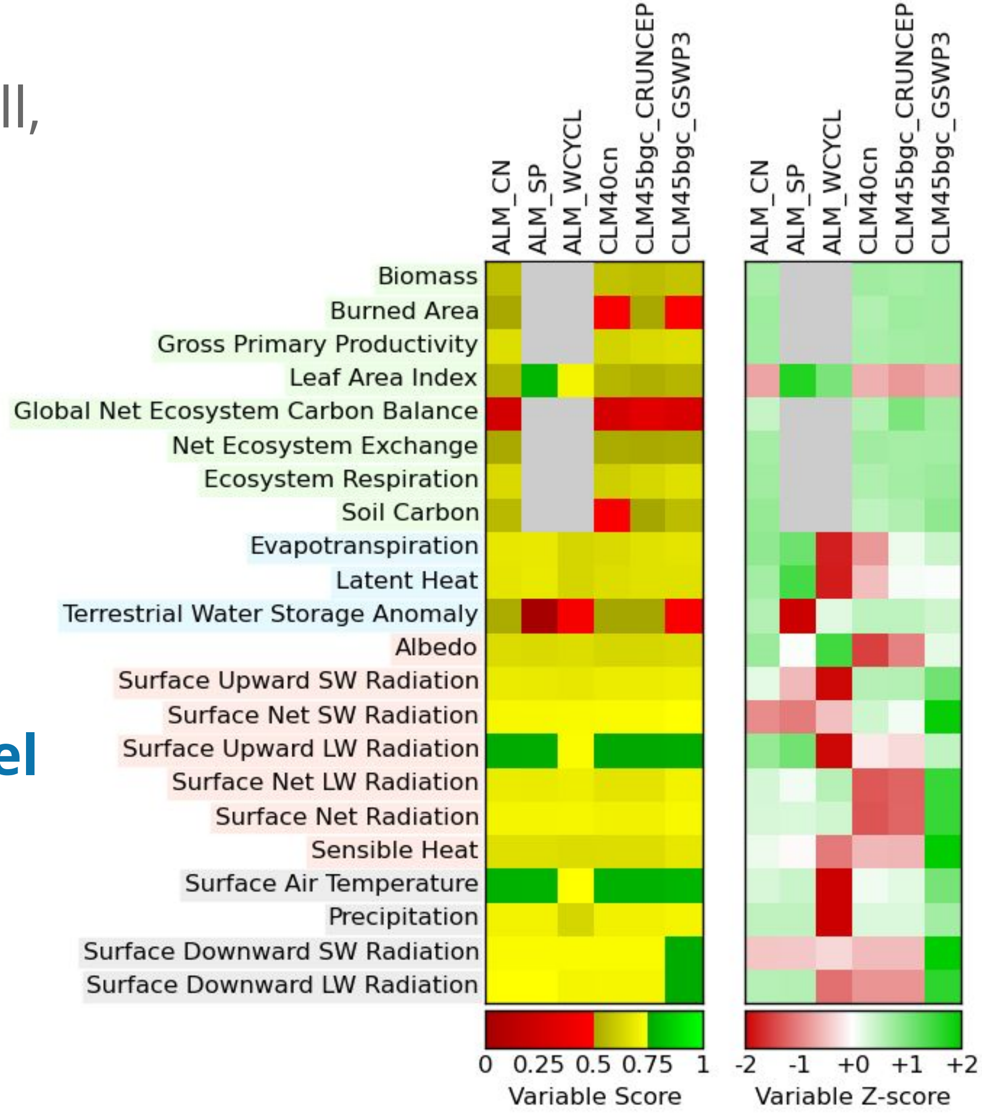
Development of ILAMB Packages

- **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}) →

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

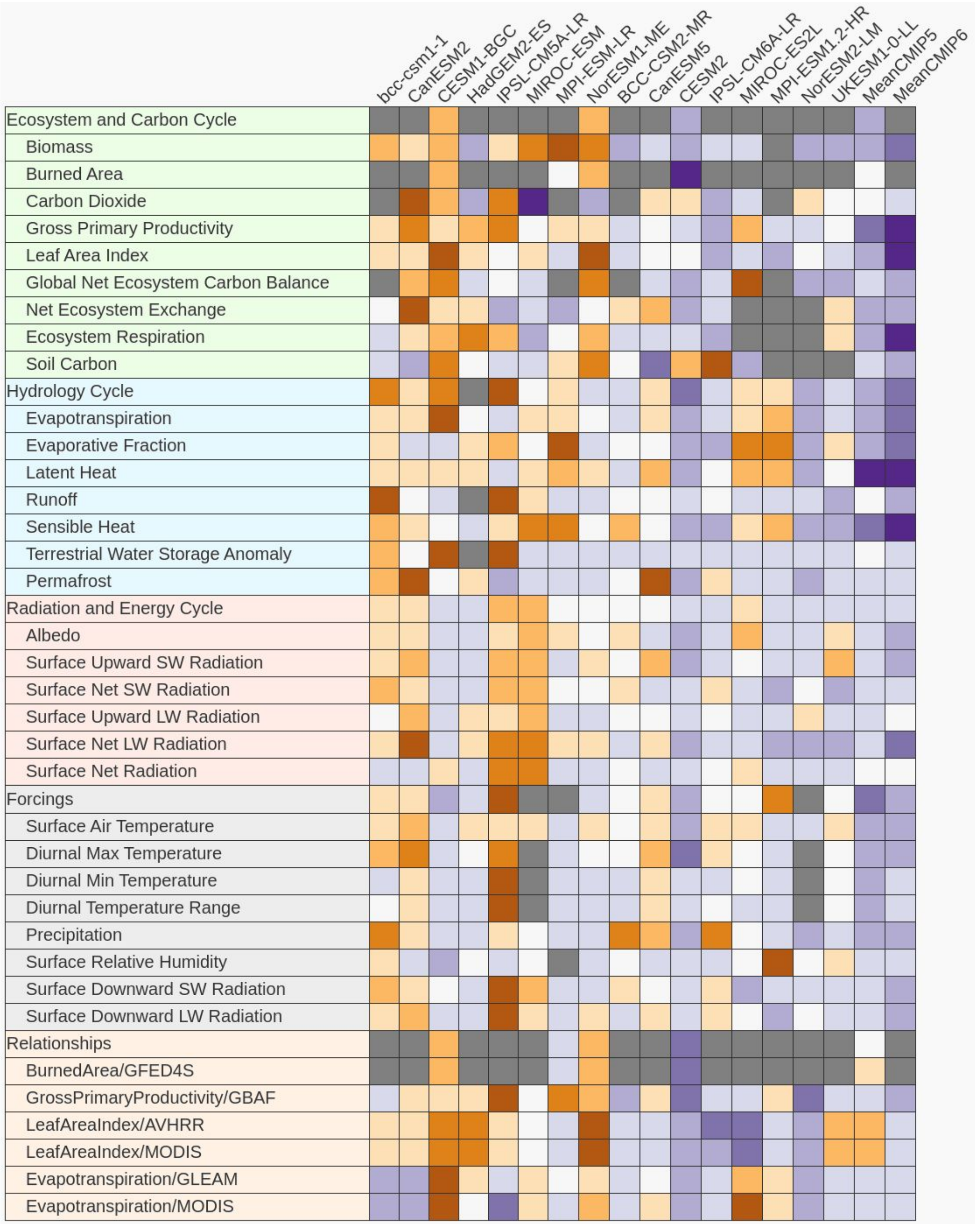
  - **Graphical diagnostics**
    - Spatial contour maps
    - Time series line plots
    - Spatial Taylor diagrams (Taylor, 2001)
- Similar **tables** and **graphical diagnostics** for functional relationships

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)

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?



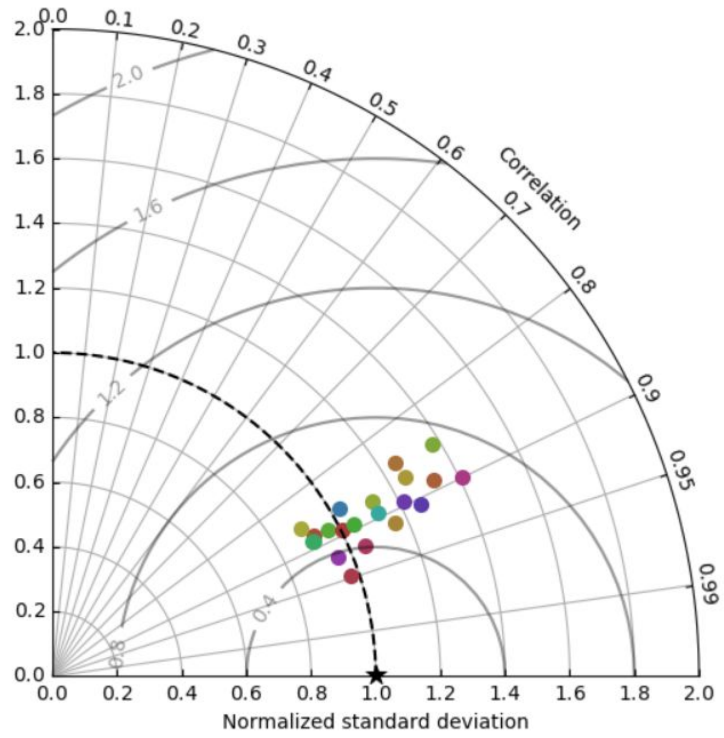
(Hoffman et al., in prep)

Gross Primary Productivity

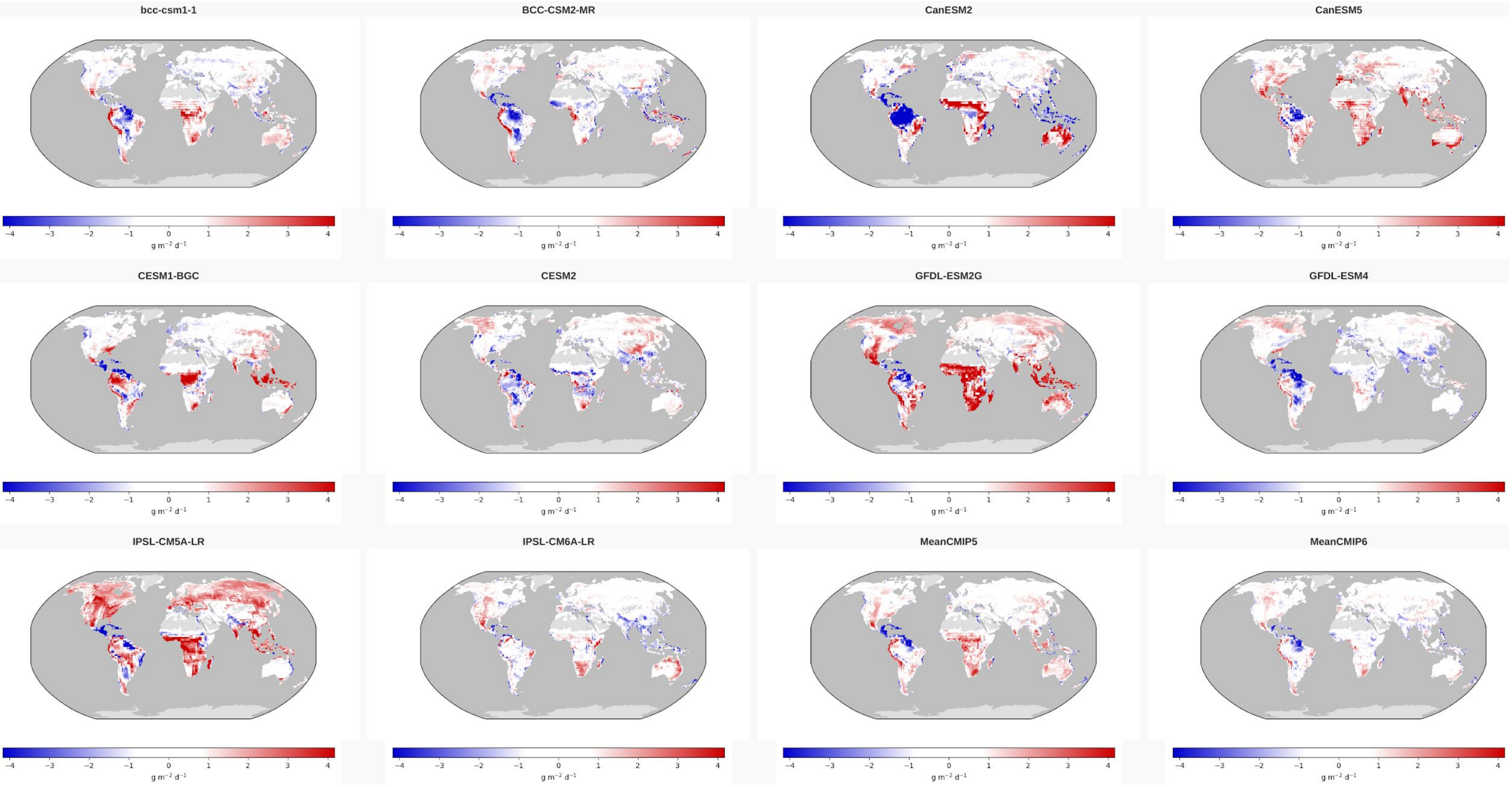
	Download Data	Period Mean (original grids) [Pg yr-1]	Model Period Mean (intersection) [Pg yr-1]	Benchmark Period Mean (intersection) [Pg yr-1]	Model Period Mean (complement) [Pg yr-1]	Benchmark Period Mean (complement) [Pg yr-1]	Bias [g m-2 d-1]	RMSE [g m-2 d-1]	Phase Shift [months]	Bias Score [1]	RMSE 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

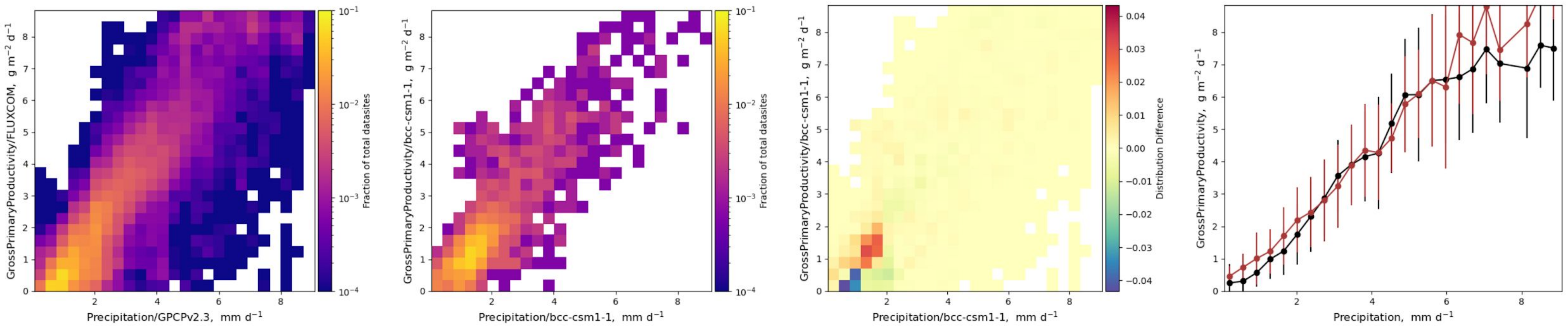


Biases in GPP by Model



Functional Relationship Metrics (GPP vs. Precipitation, Temperature)

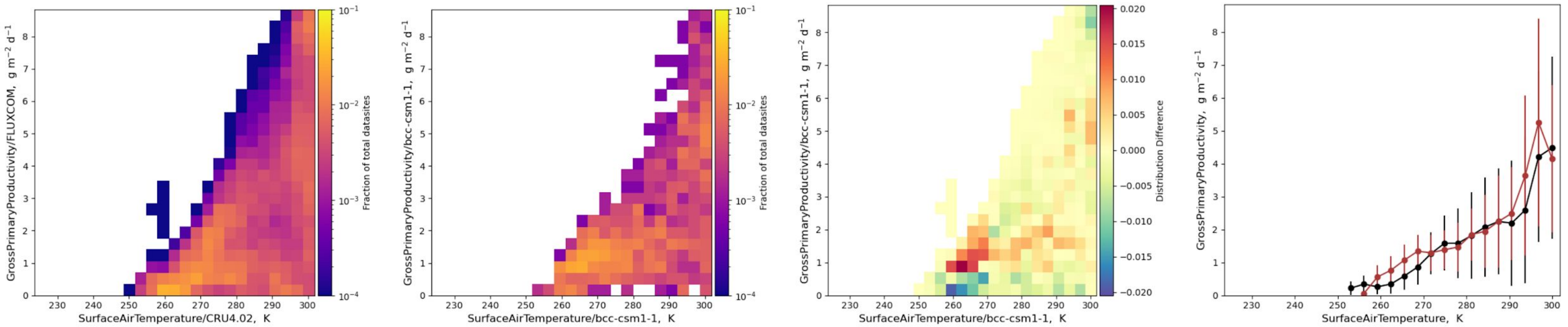
Precipitation/GPCPv2.3



SurfaceDownwardSWRadiation/CERESed4.1

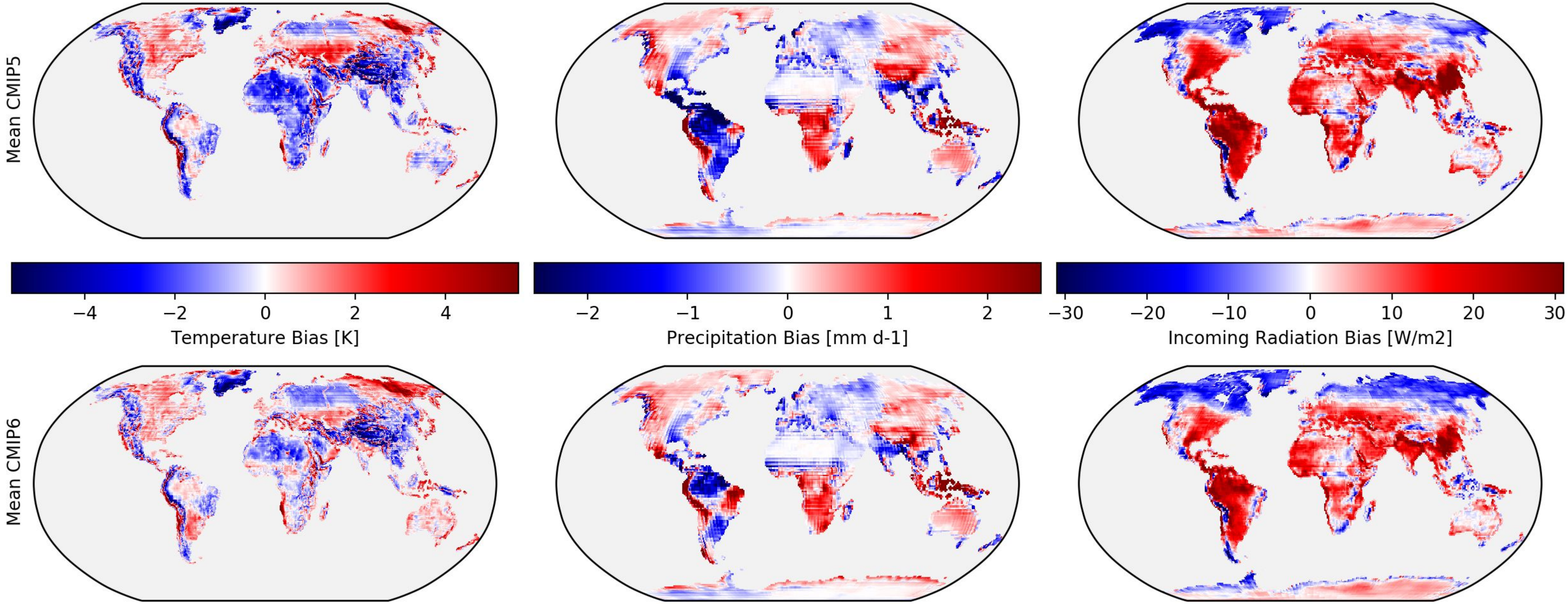
SurfaceNetSWRadiation/CERESed4.1

SurfaceAirTemperature/CRU4.02



Reasons for Land Model Improvements

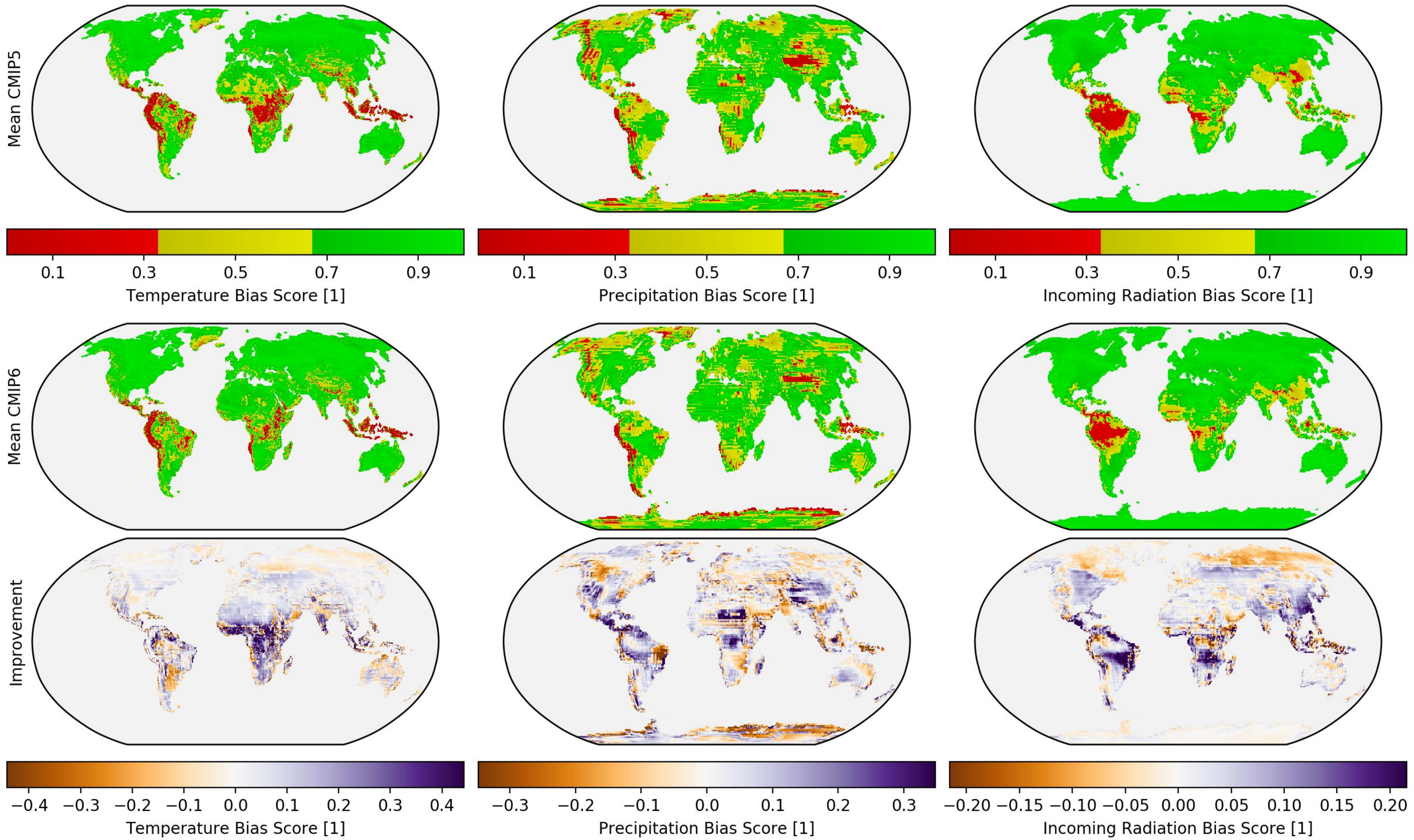
ESM improvements in **climate forcings** (temperature, precipitation, radiation) likely **partially drove improvements** exhibited by land carbon cycle models



(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**

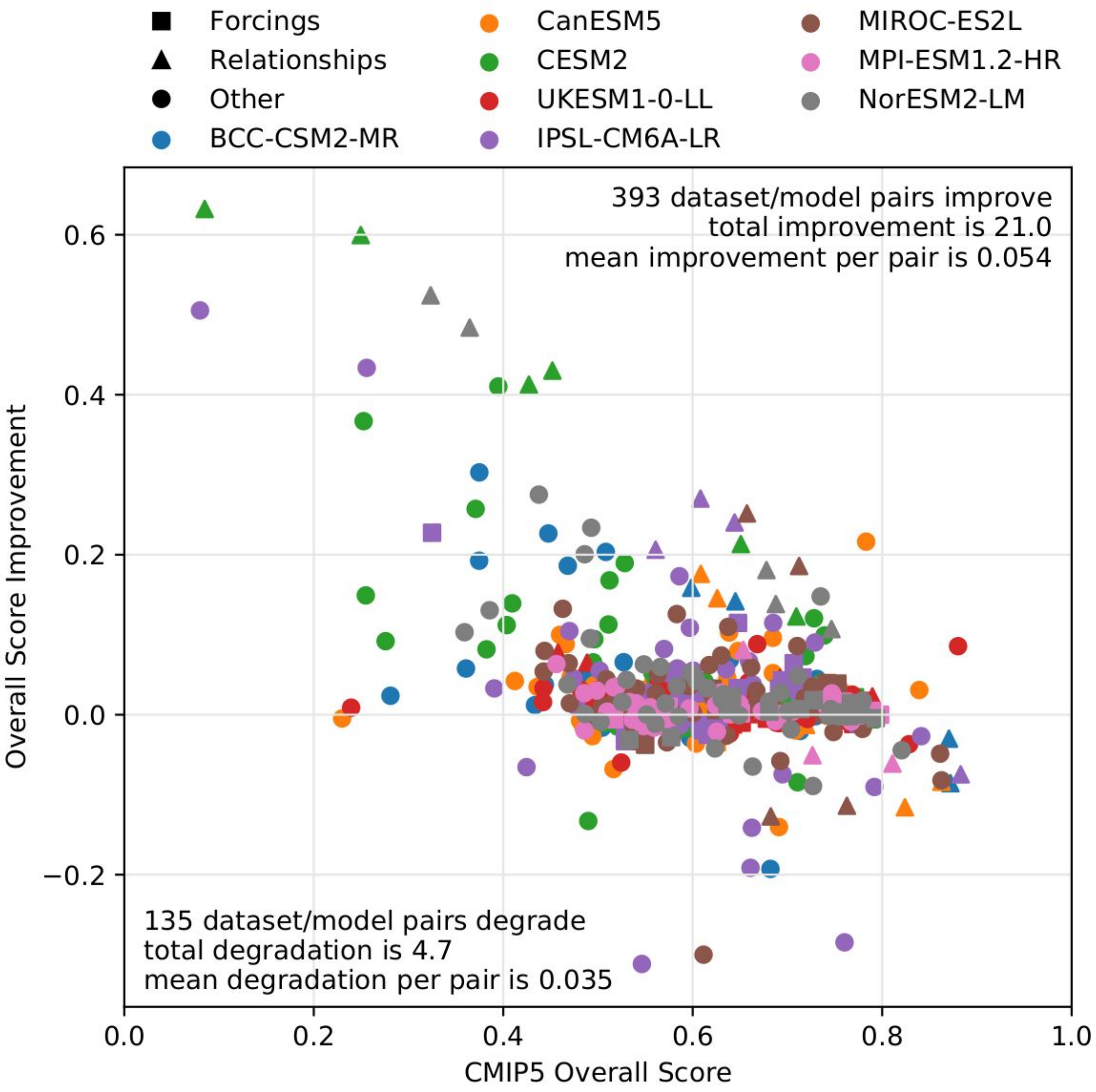


(Hoffman et al., in prep)

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

- These results suggest that **rigorous model evaluation & benchmarking** with tools like ILAMB and IOMB can lead to model improvements



(Hoffman et al., in prep)

CMIP5 vs. CMIP6 Evaluation

- (a) **International Land Model Benchmarking (ILAMB)** and (b) **International Ocean Model Benchmarking (IOMB)** tools were used to evaluate how land and ocean model performance 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

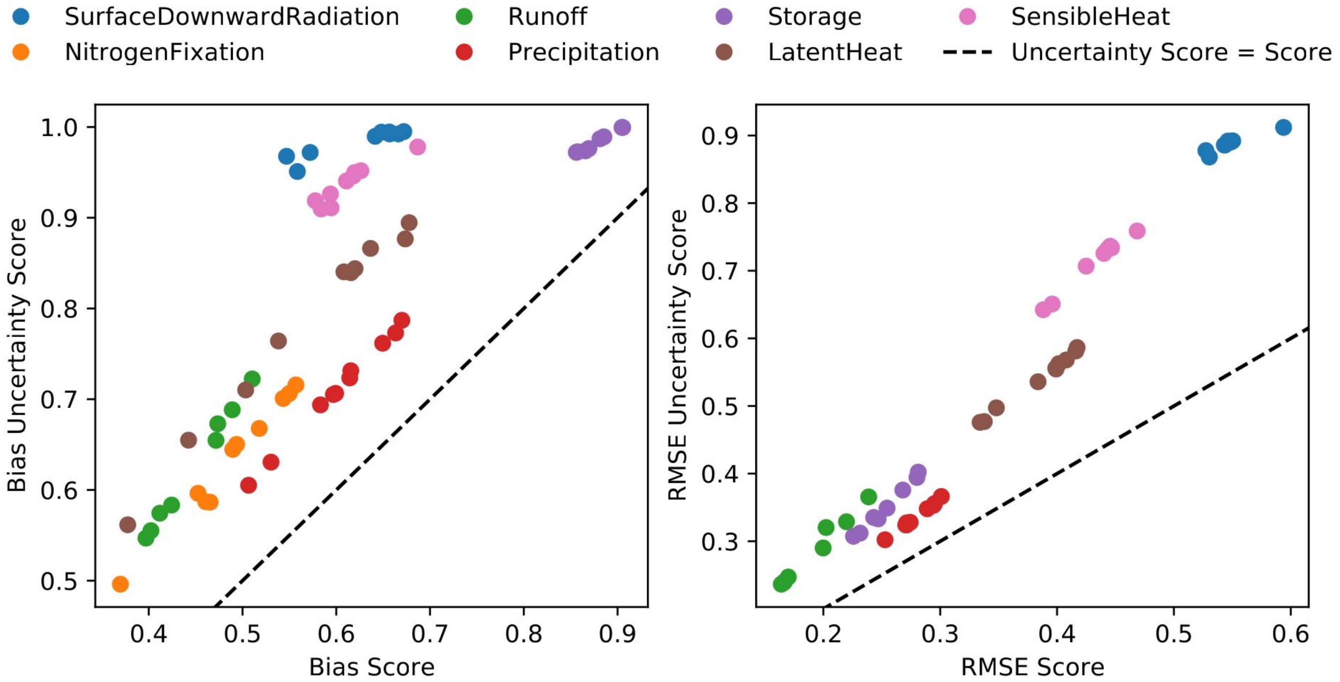
Relative Scale

Worse Value — Better Value

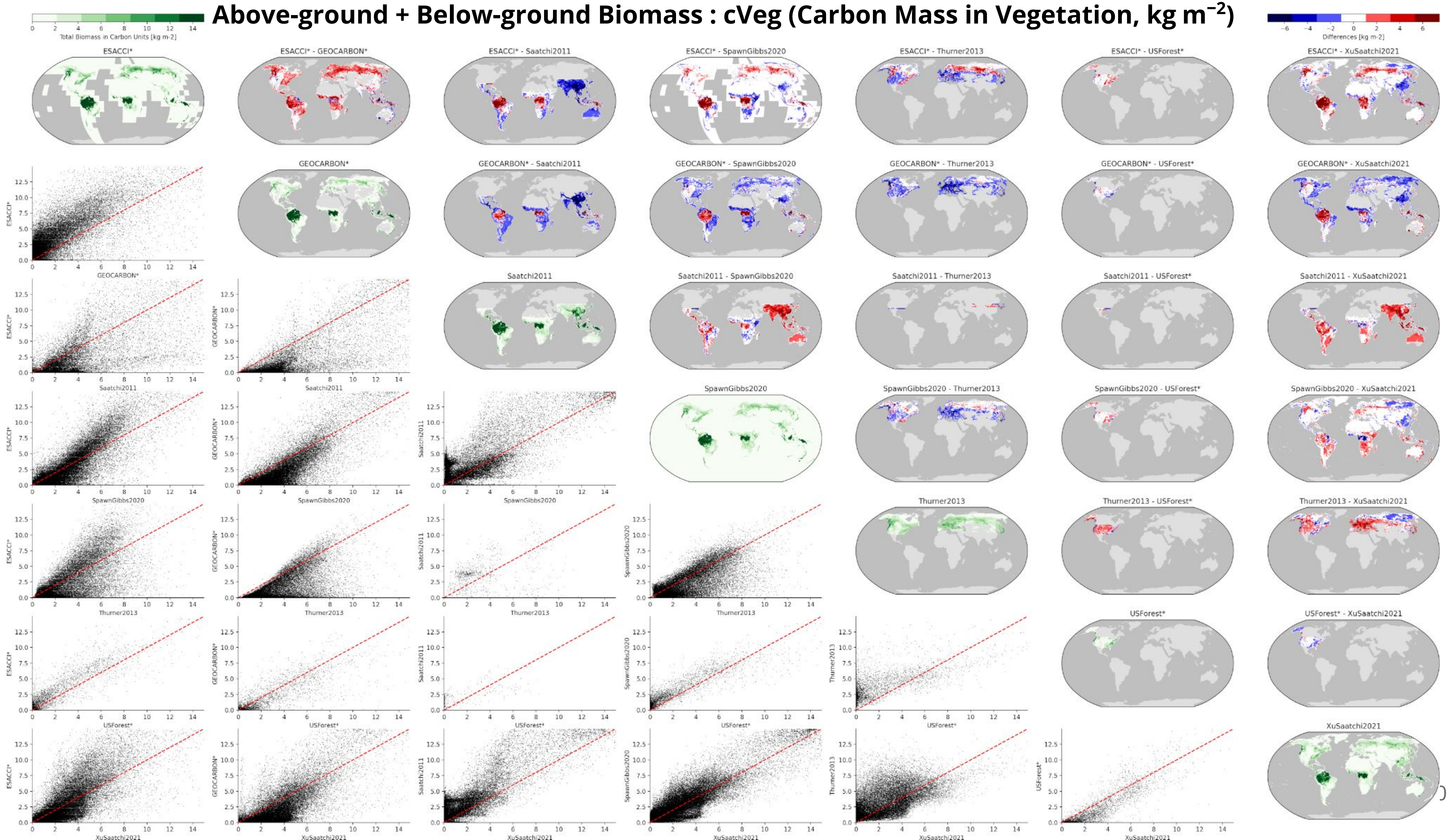
Missing Data or Error

Addressing Observational Uncertainty

- Few observational datasets provide complete uncertainties, but some are appearing
- ILAMB uses multiple datasets for most variables and allows users to weight them according to a rubric of uncertainty, scale mismatch, etc.
- ILAMB can also use:
  - Full spatial/temporal uncertainties provided with the data
  - Fixed, expert-derived uncertainty for a dataset
  - Uncertainties derived from combining multiple datasets
- Experiments with self-consistent CLASS data (Hobeichi et al. 2020) and Barnard's nitrogen fixation data demonstrate that while scores shift, including uncertainty rarely alters the rank ordering of models (figure)



Above-ground + Below-ground Biomass : cVeg (Carbon Mass in Vegetation, kg m^{-2})



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

Model Evaluation Perspective on Recommendations

- We need better **characterization of uncertainties** in observational and remote sensing data products
  - Do the data help distinguish models from each other?
  - Do the data help inform us about which combination of process representations are important?
- We need to better characterize and understand the **representativeness** of observations
  - Are in situ measurements representative of the data pixels / model grid cells?
  - What additional data are useful for quantifying representativeness and can this inform or direct measurement campaigns or sampling strategies (Matthias' talk, for example)?
- We need to better understand **how processes scale** across space and through time
  - How do we use measurements from stomata to leaves to organisms to inform process representations at the scales of cohorts to canopies to ecosystems to landscapes to watersheds?
  - Can we maintain a constellation of observational systems that produce data at relevant scales over long time periods as the climate changes?
- We need to characterize **plant traits, ecosystem community dynamics, and land use & land cover change** to inform demographic models
  - Do the data help us understand important plant traits and cohort behavior?
  - Can we capture enough data to inform / constrain models of disturbance and recovery?

Questions for the Modeling Community

- **How many different models** or model configurations are needed to answer science questions?
  - Are models designed to develop mechanistic understanding or address societally relevant questions?
  - What evaluation metrics should be used for models designed for different purposes?
- How can we **combine multisensor observational data** to better inform process representations in models?
  - Can we use AI/ML to derive synthesized or assimilated data products to constrain models?
  - Can we use data-driven AI/ML approaches to produce online parameterizations, hybrid models, surrogate models, and digital twins?
- How can we best **evaluate long timescale processes** with relatively short timescale remote sensing?
  - Can we trade space for time from representativeness analyses with model ensembles?
  - Does contemporary bias removal reduce future model spread?
  - Can we weight models based on ILAMB scores?
- How can we better **organize our communities** to build better (not more?) models, address uncertainties, engage observational community, prepare for CMIP7, 8, 9?
  - **1st Land Surface Modeling Summit** in Oxford (11–15 Sep 2022), Eleanor Blythe & Dave Lawrence
  - **4th Carbon from Space Workshop** in Frascati (25–28 Oct 2022), ESA & NASA
  - **4th ILAMB Workshop** in USA (Late 2023?)