Have Land Surface Processes in Earth System Models Improved Over Time?

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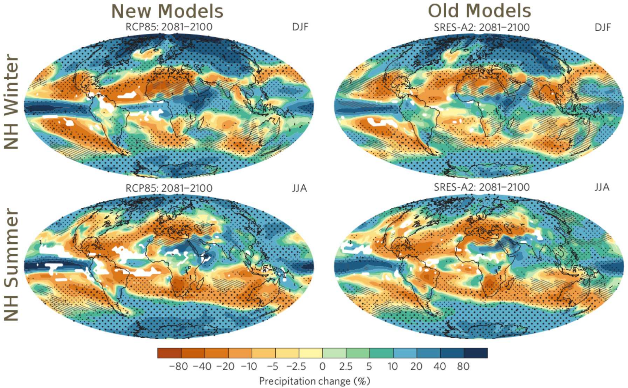
Problem: Model Uncertainty

Model uncertainty is one of the biggest challenges we face in Earth system science, yet comparatively little effort is devoted to fixing it (Carslaw et al., 2018)

- Model complexity is rapidly increasing as detailed process representations are added
- Evidence shows overall model uncertainty is reduced only slowly and is sometimes increased (Knutti and Sedláček, 2013)
- A balance must be struck between model "elaboration" and efforts to reduce model uncertainty



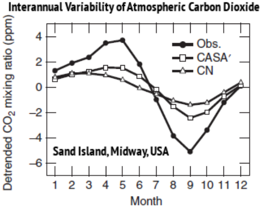
Patterns of precipitation change across two generations of models. Adapted from Knutti and Sedláček (2013).

Why is Reducing Uncertainty a Challenge?

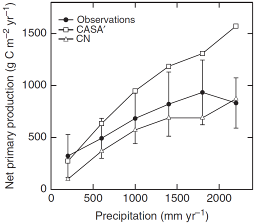
- Ecosystems have complex responses to a wide range of forcing factors in heterogeneous spatial environments, requiring a highly multivariate approach
- The focus is on adding complexity (e.g., more detailed representations of plant traits, photosynthesis, nutrient limitation, respiration), assuming more processes is better
- However, model uncertainty may increase, even as predictions of states and fluxes improve
- Rigorous confrontation of models with independent observations and large ensembles of simulations are required to reduce uncertainty
- Modeling centers have a limited capacity to conduct sensitivity experiments and systematically assess model fidelity, especially in fully coupled Earth system models
- Community-developed benchmarking tools are beginning to address part of the solution

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 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)

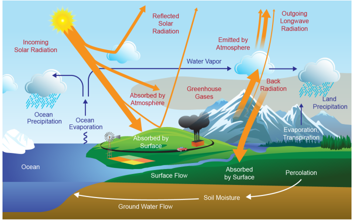
What is ILAMB?

Originally, ILAMB was a community activity designed to:

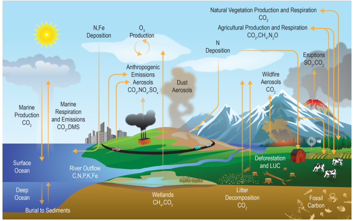
- **Develop internationally accepted benchmarks** for land model performance by drawing upon collaborative expertise
- **Promote the use of these benchmarks** for model intercomparison
- **Strengthen linkages between experimental, remote sensing, and climate modeling communities** in the design of new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

Now, ILAMB is a:

- **Community:** global group of modelers and scientists enthusiastic about benchmarking
- **Datasets:** curated collection of datasets formatted for easy data-model integration
- **Methods:** standard library of techniques for benchmarking models
- **Software:** an extensible open source Python package
- **Results:** an easy-to-use catalog of model-data comparisons



Energy and Water Cycles



Carbon and Biogeochemical Cycles

ILAMB Produces Diagnostics and Scores Models

- ILAMB generates a top-level **portrait plot** of model scores
- For every variable and dataset, ILAMB automatically produces
  - **Tables** containing individual metrics and metric scores (when relevant to the data), including
    - Reference 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})

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

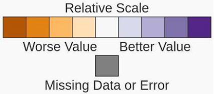
  - **Graphical diagnostics**
    - Spatial contour maps
    - Time series line plots
    - Spatial Taylor diagrams (Taylor, 2001)
- Similar **tables** and **graphical diagnostics** for functional relationships
- ILAMB design, theory, and implementation are described in Collier et al. (2018)

ILAMBv2.5 Package Current Variables

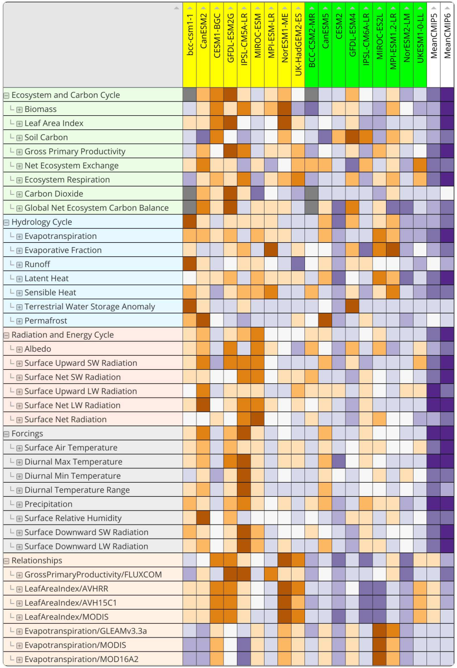
- **Biogeochemistry:** Biomass (Contiguous US, Pan Tropical Forest), Burned area (GFED4.1s), CO_2 (NOAA GMD, Mauna Loa), Gross primary production (Fluxnet, FLUXCOM), Leaf area index (AVHRR, MODIS), Global net ecosystem carbon flux (GCP, Khatiwala/Hoffman), Net ecosystem exchange (Fluxnet, FLUXCOM), Ecosystem respiration (Fluxnet, FLUXCOM), Soil C (HWSD, NCSCDv2, Koven)
- **Hydrology:** Evapotranspiration (GLEAM, MODIS), Evaporative fraction (FLUXCOM), Latent heat (Fluxnet, FLUXCOM, DOLCE), Permafrost (NSIDC), Runoff (Dai, LORA), Sensible heat (Fluxnet, FLUXCOM), Terrestrial water storage anomaly (GRACE)
- **Energy:** Albedo (CERES, GEWEX.SRB), Surface upward and net SW/LW radiation (CERES, GEWEX.SRB, WRMC.BSRN), Surface net radiation (CERES, GEWEX.SRB, WRMC.BSRN)
- **Forcing:** Surface air temperature (CRU, Fluxnet), Dirunal max/min/range temperature (CRU), Precipitation (CMAP, Fluxnet, GPCC, GPCP2), Surface relative humidity (ERA), Surface down SW/LW radiation (Fluxnet, CERES, GEWEX.SRB, WRMC.BSRN)

CMIP5 vs. CMIP6 Land Models

- The performance of the CMIP6 suite of land models (on right with green headings) has improved over that of the CMIP5 suite of land models (on left with yellow headings)
- The multi-model mean (on far right with white headings) 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 over their CMIP5 progenitors?

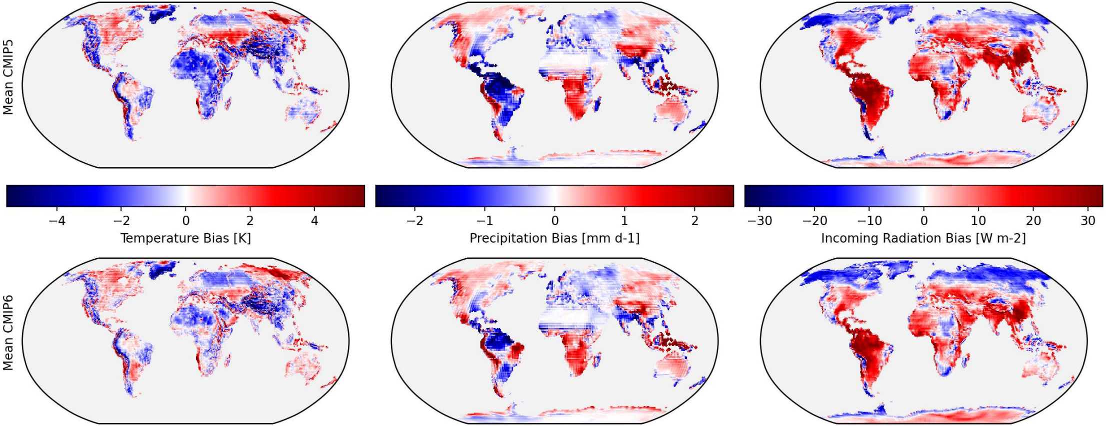


(Hoffman et al., in prep.)



Reasons for Land Model Improvements

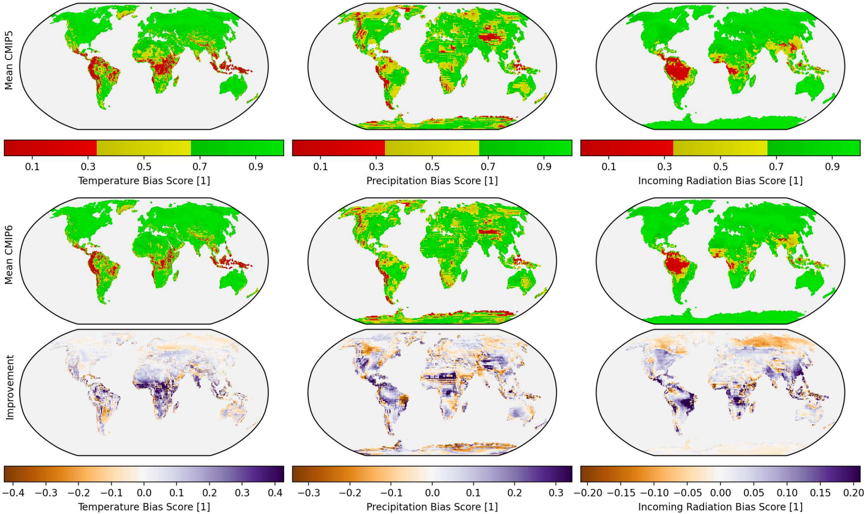
ESM improvements in climate forcings (temperature, precipitation, radiation) likely partially drove improvements exhibited by land carbon cycle models



(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 by the fully coupled ESMs



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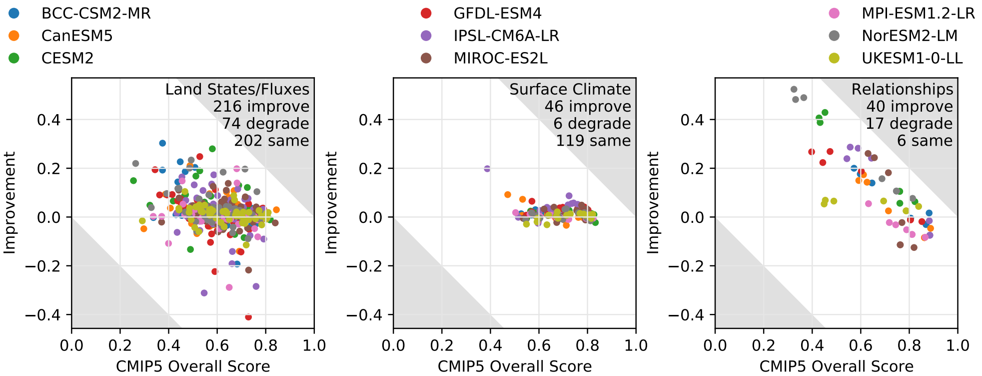
Reasons for Land Model Improvements

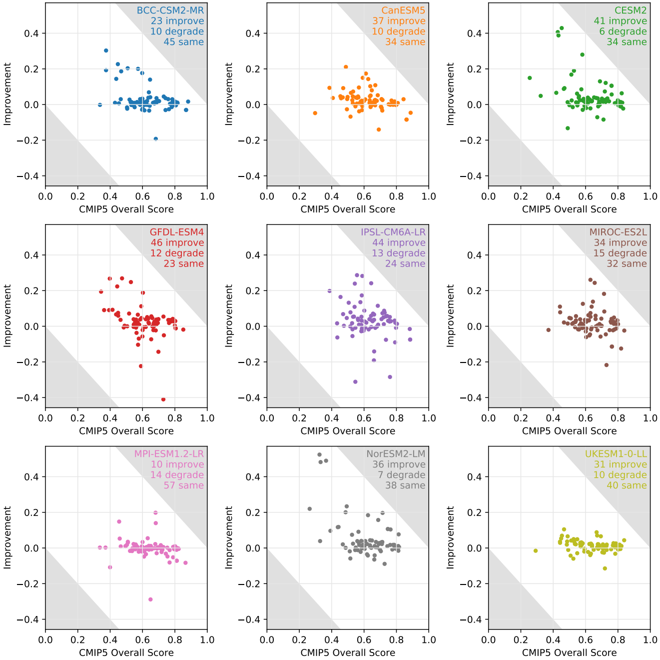


(Hoffman et al., in prep.)

Across all land models, scores for most state and flux variables improved (216) or remained nearly the same (202), although some were degraded (74). While atmospheric forcings from CMIP6 ESMs were improved over those from CMIP5 ESMs, the largest improvements were in land model **variable-to-variable relationships**, suggesting that increased land model development was also partially responsible for higher CMIP6 land model scores.

Improvements by Land Model

- Experience indicates that improvements in some model aspects will lead to degradation in some other aspects
- Here, all models except MPI-ESM1.2-LR showed more improvements than degredations
- CESM2 and NorESM2-LM had the largest ratio of improvements to degradations
- UKESM1-0-LL exhibited the smallest variation in scores between CMIP5 and CMIP6



(Hoffman et al., in prep.)

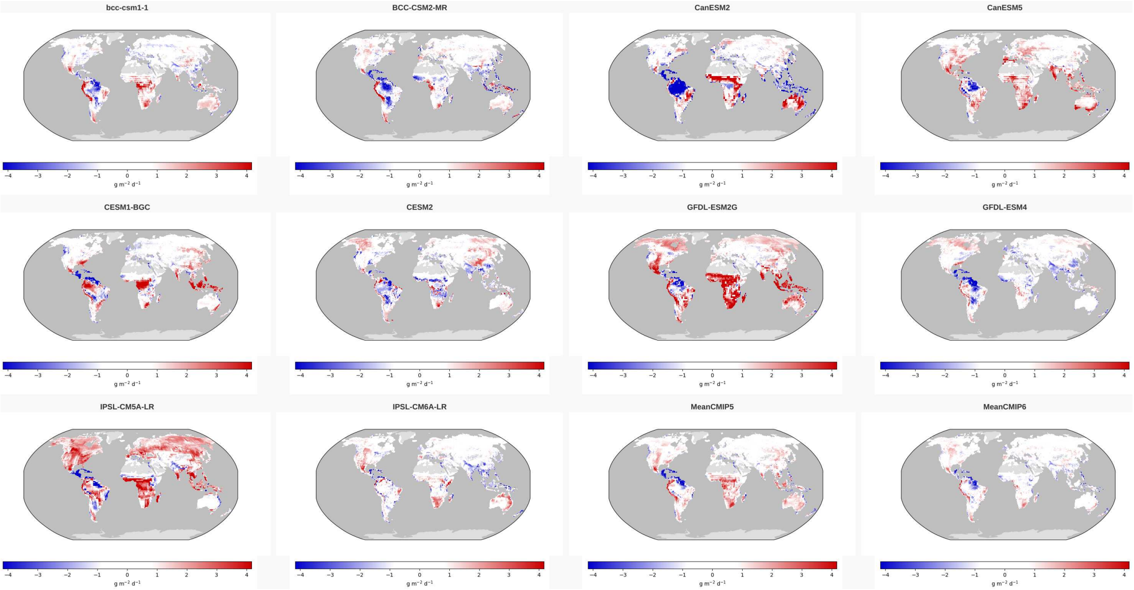
CMIP5 and CMIP6 Land Model Global GPP

	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

- Most models of the same lineage improved in various characteristics between CMIP5 and CMIP6
- The MeanCMIP5 and MeanCMIP6 models perform the best

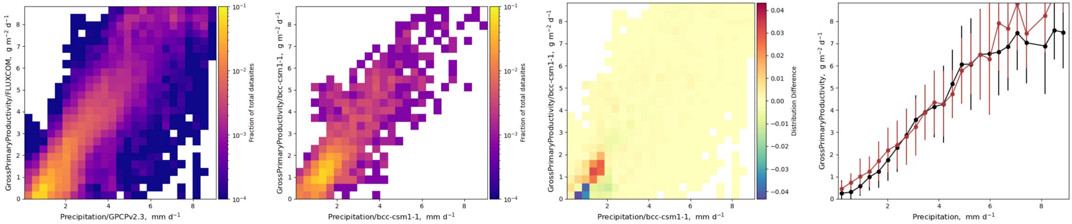
(Hoffman et al., in prep.)

Spatial Distribution of Global GPP Biases



Relationships of Global GPP with Precipitation and Temperature

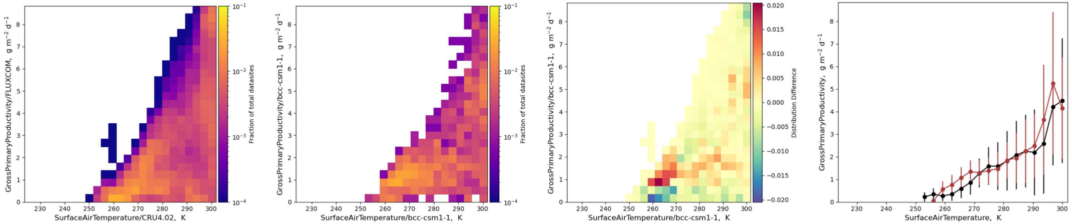
Precipitation/GPCPv2.3



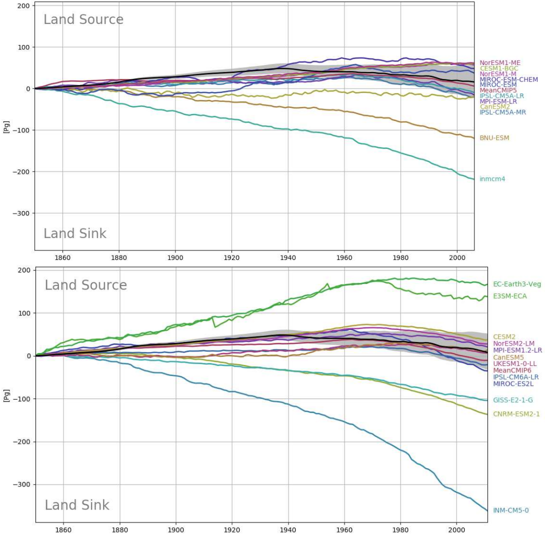
SurfaceDownwardSWRadiation/CERESed4.1

SurfaceNetSWRadiation/CERESed4.1

SurfaceAirTemperature/CRU4.02



Land Model Spread in Net Ecosystem Carbon Balance



- The spread in the net ecosystem carbon balance increased between CMIP5 and CMIP6
  - CMIP5 at 2005: -215 Pg to 75 Pg $\rightarrow$ 290 Pg
  - CMIP6 at 2010: -360 Pg to 175 Pg $\rightarrow$ 535 Pg
- However, the range from most multi-generation models was reduced

(Hoffman et al., in prep.)

Conclusions and Future Research

- CMIP6 land models performed better than CMIP5 land models due to **(1) improved climate forcing from fully coupled ESMs** and **(2) improved process representation**
- **Variable-to-variable relationships** exhibited the largest improvements for some models
- CMIP6 model results are more valuable for impact and adaptation/mitigation analysis
- Model improvements in mean states and fluxes may not result in reduced uncertainty or projected model spread
- Upon further examination, will improved multi-model performance result in reduced spread in feedback sensitivities, projected land carbon storage, and future climate change?
- Can ILAMB scores be used to weight contributions to multi-model means to reduce contemporary biases, reduce projected uncertainties, or alter expected mitigation targets?

Acknowledgments

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