The Causes and Implications of Persistent Atmospheric Carbon Dioxide Biases in Earth System Models

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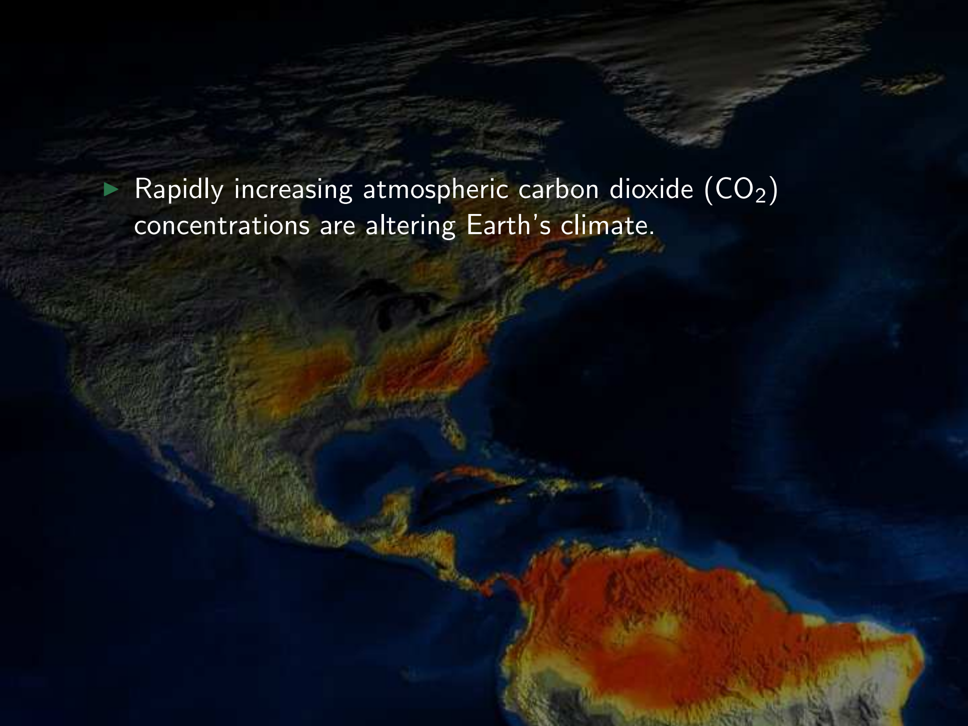

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- Climate-carbon cycle feedbacks are highly uncertain and potentially large.
- Prediction of feedbacks requires knowledge of mechanisms connecting carbon and nutrients with the climate system.

Research Objectives

Objective 1

Quantify climate-carbon cycle feedback responses in global models contributing to the Coupled Model Intercomparison Project Phase 5 (CMIP5) for the IPCC Fifth Assessment Report.

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Objective 2

Reduce the range of uncertainty in climate predictions by improving the model representation of feedbacks through comparisons with contemporary observations.

Feedback Analysis

- Friedlingstein et al. (2003, 2006) defined the climate-induced change in atmospheric CO_2 in terms of the change due to direct addition of CO_2,

$$\Delta C_A^c = \frac{1}{1-g} \Delta C_A^u, \tag{1}$$

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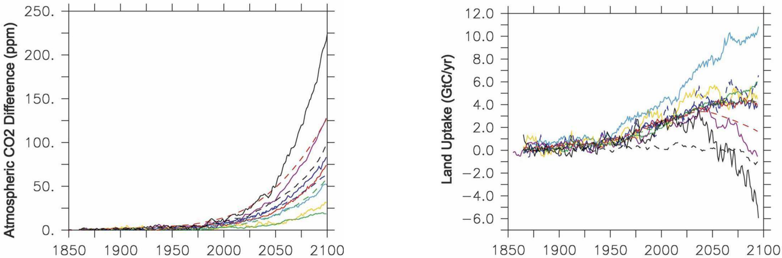
- The change in land carbon storage,

$$\Delta C_L^c = \beta_L \Delta CO_2^c + \gamma_L \Delta T^c, \tag{3}$$

  where β_L is the sensitivity to the change in CO_2, and γ_L is the sensitivity to climate change.

The 11 C^4MIP models varied by a factor of

- 8 in the gain of the carbon cycle feedback (g),
- 9 in the climate sensitivity of land storage (γ_L), and
- 14 in the concentration sensitivity of land storage (β_L).



Spread in the projected atmospheric CO_2 increase due to feedbacks (left) and total land carbon uptake (right) from 11 models participating in the C^4MIP Experiment. From Friedlingstein et al. (2006, Figure 1).

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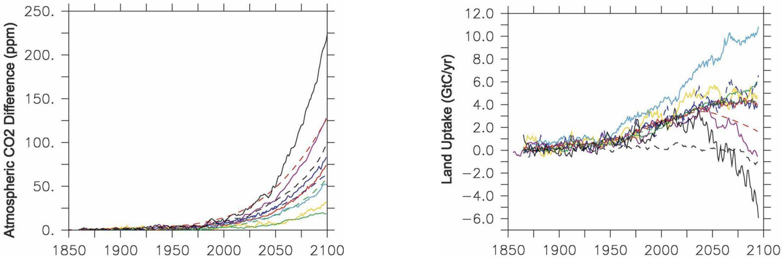

Spread in the projected atmospheric CO_2 increase due to feedbacks (left) and total land carbon uptake (right) from 11 models participating in the C^4MIP Experiment. From Friedlingstein et al. (2006, Figure 1).

No comparisons were made with observations.
This is the next crucial step for reducing uncertainties!

Reducing Uncertainties Using Observations

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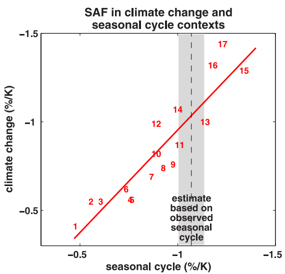
Example

Hall and Qu (2006) evaluated the strength of the springtime snow albedo feedback (SAF; $\Delta\alpha_s/\Delta T_s$) from 17 models used for the IPCC AR4 and compared them with the observed springtime SAF from ISCCP and ERA-40 reanalysis.



Persistence of Atmospheric CO_2 Biases

Objective: Quantify and diagnose persistence of atmospheric CO_2 biases in Earth System Model (ESMs).

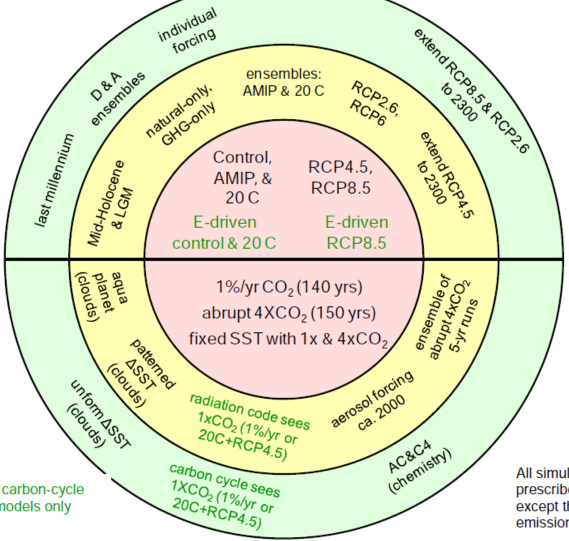
Hypothesis

Biases in prognostic atmospheric CO_2 are persistent on decadal time scales because carbon-concentration feedbacks in ESMs (β_L and β_O) are related to processes that do not change rapidly.

Approach:

- Quantify CO_2 biases in emissions-forced CMIP5 historical (esmHistorical) and future (esmrcp85) simulation results.
- Use observationally based estimates of ocean carbon inventories from Sabine et al. (2004) and Khatiwala et al. (2009, 2012) to diagnose causes of biases.
- Use model results to develop an atmospheric CO_2 trajectory with reduced bias and uncertainty range.

Schematic Summary of CMIP5 Long-Term Experiments

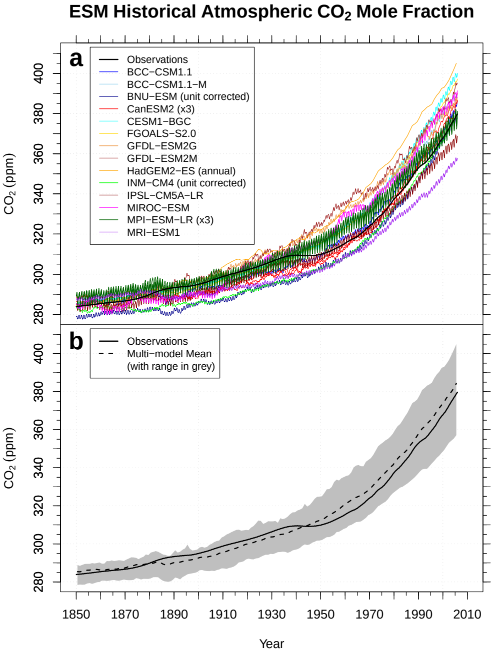


Coupled carbon-cycle climate models only

All simulations are forced by prescribed concentrations except those "E-driven" (i.e., emission-driven)

(a) Most ESMs exhibit a high bias in predicted atmospheric CO_2 mole fraction, which ranges from 357–405 ppm at the end of the historical period (1850–2005).

(b) The multi-model mean is biased high from 1945 throughout the 20th century, ending 5.3 ppm above observations in 2005.



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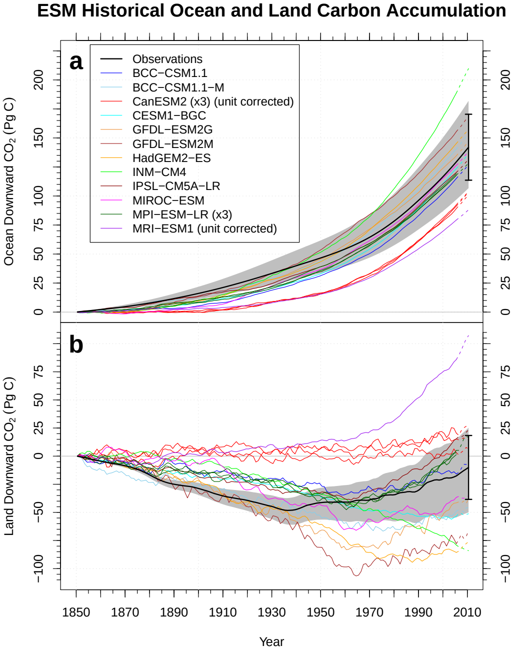
(a) Most ESMs exhibit a low bias in ocean carbon accumulation from 1870–1970 as compared with adjusted estimates from Khatiwala et al. (2012).

(b) ESMs have a wide range of land carbon accumulation responses to increasing CO_2 and land use change, ranging from a net source of 85 Pg C to a sink of 110 Pg C in 2010.



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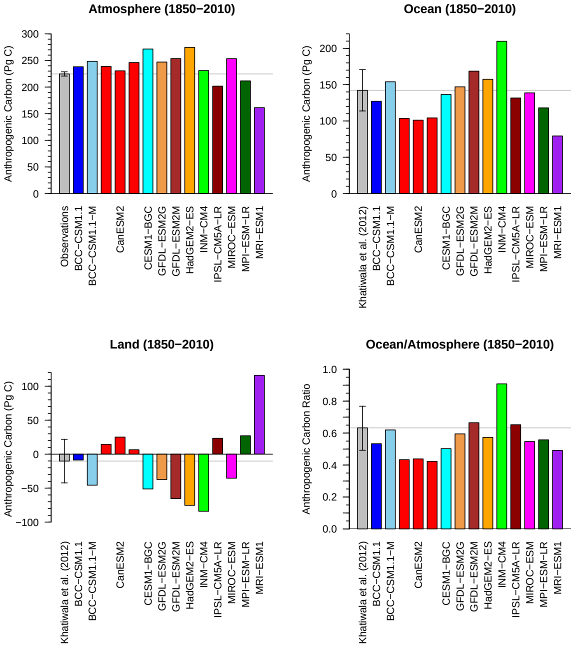
Once normalized for high atmospheric CO_2 mole fraction biases, most ESMs exhibit a low bias in ocean carbon accumulation.



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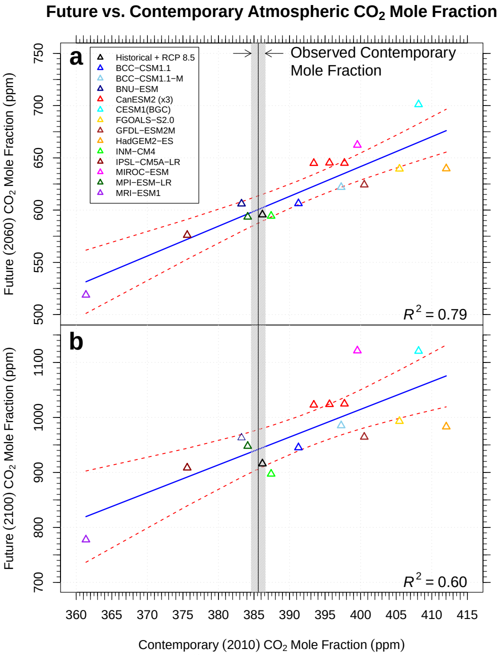
A relationship exists between contemporary and future CO_2 over decadal time scales, so carbon model biases persist over decadal time scales.

The (a) 2060 vs. 2010 and (b) 2100 vs. 2010 atmospheric CO_2 mole fraction fit for CMIP5 emissions-forced simulations of RCP 8.5. Observed atmospheric CO_2 mole fraction is represented by the vertical line at 385.6 ± 2 ppm.



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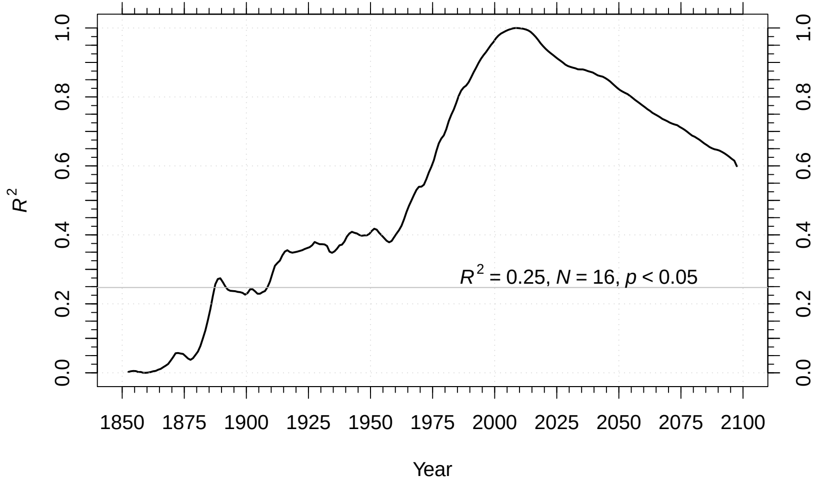
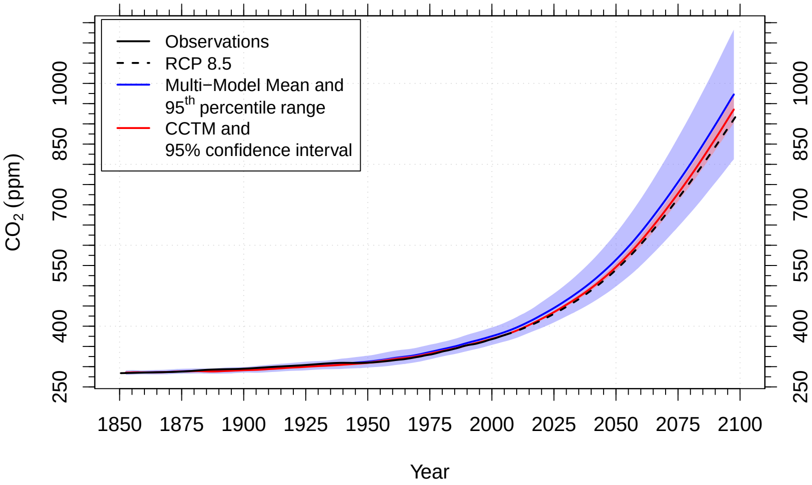
R^2 of Multi−model Bias Structure



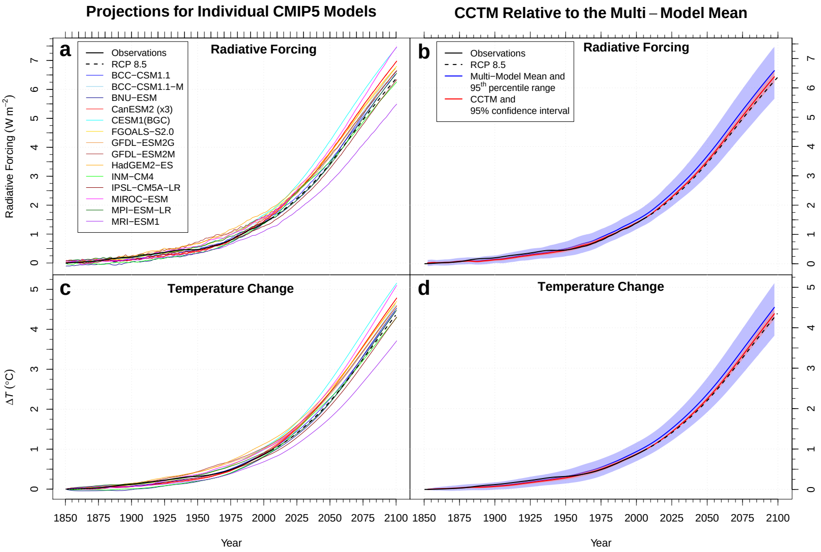
The coefficient of determination, R^2, of the multi-model bias structure relative to the model CO_2 predictions for 2010 is statistically significant for 1910–2100.

Contemporary CO_2 Tuned Model (CCTM)



Multi-model estimates and contemporary observations can be used to reduce uncertainties in future scenarios.

Implications for Radiative Forcing and Temperature



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Implications for CO_2, Radiative Forcing, and Temperature

Model	CO_2 Mole Fraction (ppm)			Radiative Forcing ($W\,m^{-2}$)			Cumulative ΔT (°C)			ΔT Bias (°C)		
	2010	2060	2100	2010	2060	2100	2010	2060	2100	2010	2060	2100
BCC-CSM1.1	390	603	945	1.70	4.03	6.43	1.06	2.60	4.38	0.03	0.02	0.06
BCC-CSM1.1-M	396	619	985	1.78	4.16	6.65	1.14	2.71	4.54	0.11	0.13	0.22
BNU-ESM	382	602	963	1.59	4.02	6.53	0.98	2.54	4.44	−0.05	−0.04	0.12
CanESM2 r1	394	641	1024	1.75	4.36	6.86	1.07	2.80	4.69	0.04	0.22	0.37
CanESM2 r2	392	641	1023	1.72	4.35	6.85	1.06	2.79	4.69	0.03	0.21	0.37
CanESM2 r3	396	641	1025	1.78	4.35	6.87	1.10	2.80	4.69	0.07	0.22	0.37
CESM1-BGC	407	697	1121	1.92	4.80	7.34	1.21	3.10	5.06	0.18	0.52	0.74
FGOALS-S2.0	404	636	993	1.89	4.31	6.70	1.19	2.79	4.62	0.16	0.21	0.30
GFDL-ESM2G	395	616	967	1.77	4.14	6.56	1.14	2.70	4.50	0.11	0.12	0.18
GFDL-ESM2M	400	621	964	1.83	4.18	6.54	1.18	2.74	4.50	0.15	0.16	0.18
HadGEM2-ES	411	636	983	1.98	4.31	6.64	1.28	2.83	4.58	0.25	0.25	0.26
INM-CM4	386	591	897	1.64	3.92	6.15	1.00	2.57	4.21	−0.03	−0.01	−0.11
IPSL-CM5A-LR	375	573	908	1.48	3.75	6.22	0.93	2.40	4.22	−0.10	−0.18	−0.10
MIROC-ESM	398	658	1121	1.81	4.50	7.35	1.15	2.90	5.00	0.12	0.32	0.68
MPI-ESM-LR	383	590	948	1.60	3.91	6.45	1.04	2.51	4.39	0.01	−0.07	0.07
MRI-ESM1	361	516	778	1.28	3.20	5.39	0.81	2.05	3.63	−0.22	−0.53	−0.69
Multi-model Mean	393	621	968	1.74	4.19	6.56	1.10	2.71	4.48	0.07	0.13	0.16
CCTM Estimate	386	600	931	1.64	4.00	6.35	1.03	2.58	4.32	—	—	—
Historical + RCP 8.5	385	592	916	1.63	3.93	6.26	1.02	2.53	4.28	−0.01	−0.05	−0.04

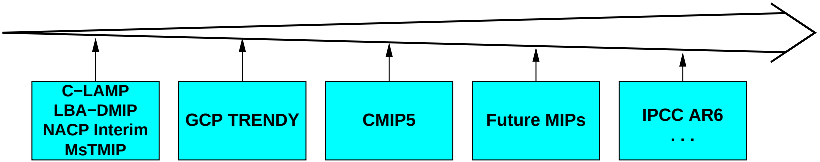
Discussion and Conclusions

- Ordering among model predictions of atmospheric CO_2 persisted on the order of several decades.
- Underestimate of ocean CO_2 uptake likely contributes to a persistent and growing atmospheric CO_2 bias in most ESMs.
- Similar deficiencies in land models—including the response of GPP to CO_2 concentration, allocation to woody pools, nutrient limitation, response of heterotrophic respiration to temperature, and land use change—further contribute to an atmospheric CO_2 bias.
- Future fossil fuel emissions targets designed to stabilize CO_2 levels would be too low if estimated from the multi-model mean of ESMs.
- Value in tuning models: The CCTM projection provided a 6-fold reduction in uncertainty at 2060 and a 5-fold reduction at 2100.
- Models could be improved through extensive comparison with observations using a community benchmarking system like planned for the International Land Model Benchmarking (ILAMB) project.

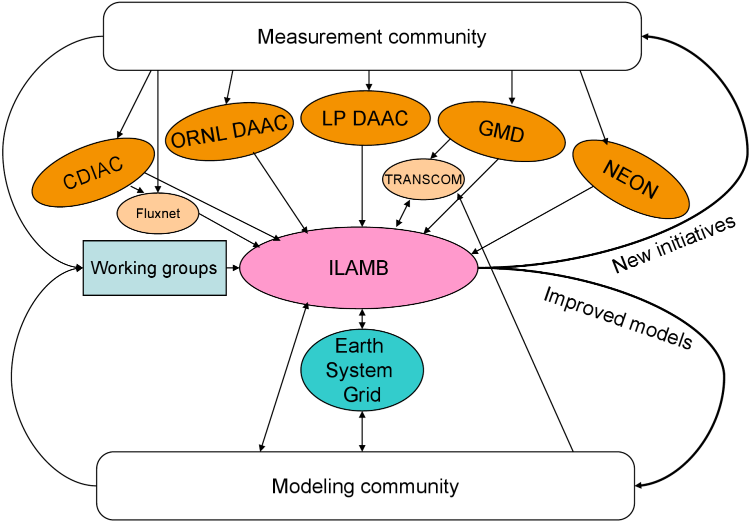
Why Benchmark?

- to show the broader science community and the public that the representation of the carbon cycle in climate models is improving;
- to provide a means, in Earth System models, to quantitatively diagnose impacts of model development in related fields on carbon cycle and land surface 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 provide a quantitative, application-specific set of minimum criteria for participation in model intercomparison projects (MIPs);
- to provide an optional weighting system for multi-model mean estimates of future changes in the carbon cycle.

An Open Source Benchmarking Software System



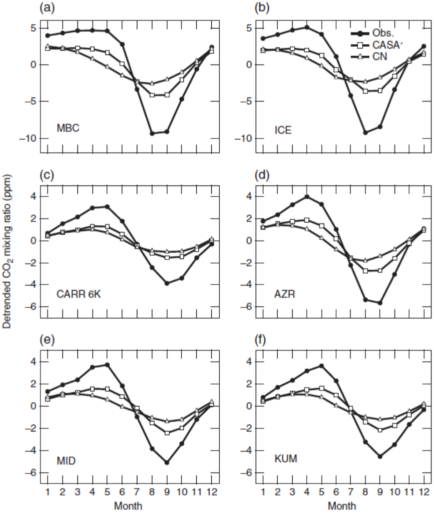
- Human capital costs of making rigorous model-data comparisons is considerable and constrains the scope of individual MIPs.
- Many MIPs spend resources "reinventing the wheel" in terms of variable naming conventions, model simulation protocols, and analysis software.
- **Need for ILAMB:** Each new MIP 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 project and diagnostic system

What is a Benchmark?

- A benchmark is a quantitative test of model function, for which the uncertainties associated with the observations can be quantified.
- Acceptable performance on benchmarks **is a necessary but not sufficient condition** for a fully functioning model.
- Since all datasets have strengths and weaknesses, an effective benchmark is one that draws upon a broad set of independent observations to evaluate model performance on multiple temporal and spatial scales.



(Randerson et al., 2009)

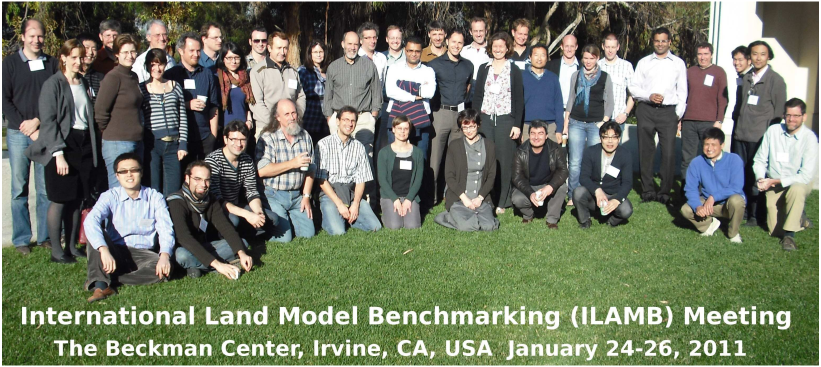
Example Benchmark Score Sheet from C-LAMP

Models →

BGC Datasets ↓

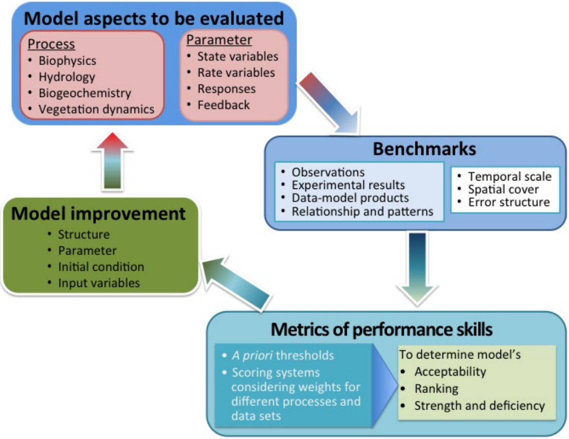
Metric	Metric components	Uncertainty of obs.	Scaling mismatch	Total score	Sub-score	CASA′	CN
LAI	Matching MODIS observations			15.0		13.5	12.0
	• Phase (assessed using the month of maximum LAI)	Low	Low		6.0	5.1	4.2
	• Maximum (derived separately for major biome classes)	Moderate	Low		5.0	4.6	4.3
	• Mean (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)



- Meeting Co-organized by Forrest Hoffman (UC-Irvine and ORNL), Chris Jones (UK Met Office), Pierre Friedlingstein (U. Exeter and IPSL-LSCE), and Jim Randerson (UC-Irvine).
- About 45 researchers participated from the United States, Canada, the United Kingdom, the Netherlands, France, Germany, Switzerland, China, Japan, and Australia.

General Benchmarking Procedure



(Luo et al., 2012)

ILAMB 1.0 Benchmarks Now Under Development

	Annual Mean	Seasonal Cycle	Interannual Variability	Trend	Data Source
Atmospheric CO_2					
Flask/conc. + transport		✓	✓	✓	NOAA, SIO, CSIRO
TCCON + transport		✓	✓	✓	Caltech
Fluxnet					
GPP, NEE, TER, LE, H, RN	✓	✓	✓		Fluxnet, MAST-DC
Gridded: GPP	✓	✓	?		MPI-BGC
Hydrology/Energy					
runoff ratio (R/P) ~~river flow~~	✓		✓		GRDC, Dai, GFDL
global runoff/ocean balance	✓				Syed/Famiglietti
albedo (multi-band)		✓	✓		MODIS, CERES
soil moisture		✓	✓		de Jeur, SMAP
column water		✓	✓		GRACE
snow cover	✓	✓	✓	✓	AVHRR, GlobSnow
snow depth/SWE	✓	✓	✓	✓	CMC (N. America)
T_{air} & P	✓	✓	✓	✓	CRU, GPCP and TRMM
Gridded: LE, H	✓	✓			MPI-BGC, dedicated ET
Ecosystem Processes & State					
soil C, N	✓				HWSD, MPI-BGC
litter C, N	✓				LIDET
soil respiration	✓	✓	✓	✓	Bond-Lamberty
FAPAR	✓	✓			MODIS, SeaWIFS
biomass & change	✓			✓	Saatchi, Pan, Blackard
canopy height	✓				Lefsky, Fisher
NPP	✓				EMDI, Luyssaert
Vegetation Dynamics					
fire — burned area	✓	✓	✓		GFED3
wood harvest	✓			✓	Hurtt
land cover	✓				MODIS PFT fraction

Summary

- Our international collaboration has made significant progress on development of metrics and diagnostics for ILAMB 1.0.
- As CMIP5 papers come out, we need to collect cost functions and algorithms for integration into an ILAMB 1.0 package.
- Much more work is needed on
  - diagnostics for full suite of variables and time scales,
  - combining metrics into model skill scores,
  - applying skill scores to weight models for multi-model statistics, and
  - writing papers.
- Greater participation is welcome!
- ILAMB Meeting in 2013? With ICDC-9 or GLASS/GSWP?

International Land Model Benchmarking (ILAMB) Project
http://www.ilamb.org/

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