

Nonlinear Interactions between Climate and Carbon Dioxide Drivers of Marine and Terrestrial Carbon Cycle Changes

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OCB



**Ocean Carbon
& Biogeochemistry**

Ocean Carbon Uptake in CMIP6 Models Synthesis and Intercomparison Workshop



**December 8–9, 2018
Washington, DC, USA**



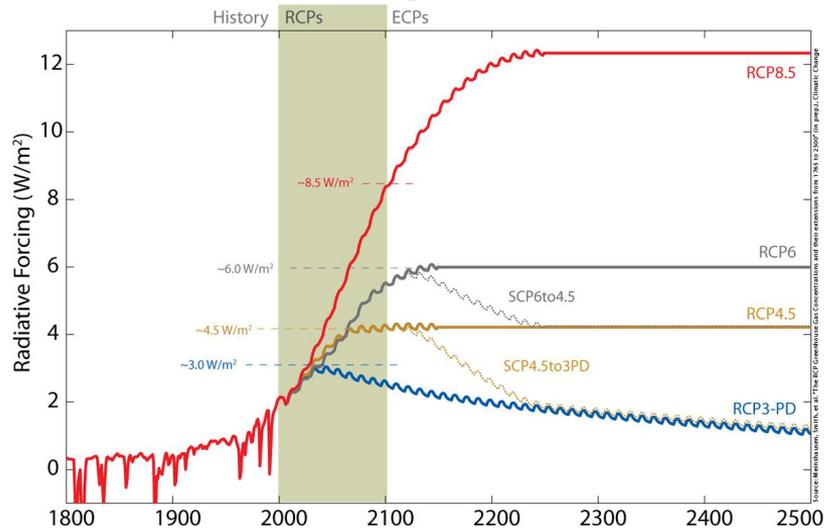
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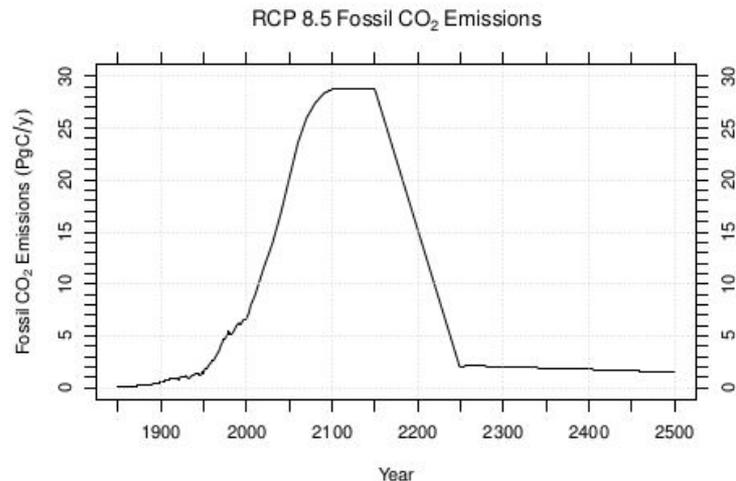
RUBISCO

Science Question: To what degree do the effects of climate change due to warming and CO₂ fertilization in isolation combine linearly?

Radiative Forcing for RCPs and ECPs



Meinshausen et al. (2011) extended RCP forcings out to 2500



Simulation Identifier	Radiative Coupling		Biogeochemical Coupling			Experiment Name
	CO ₂	Other GHG & aerosols	CO ₂	Nitrogen deposition	Land use	
RAD	✓	✓	—	—	—	bcrd
BGC	—	—	✓	✓	—	bdrds.pftcon
FC	✓	✓	✓	✓	—	bdrd.pftcon

- ✓ Transient anthropogenic forcing
- Constant pre-industrial (1850) forcing

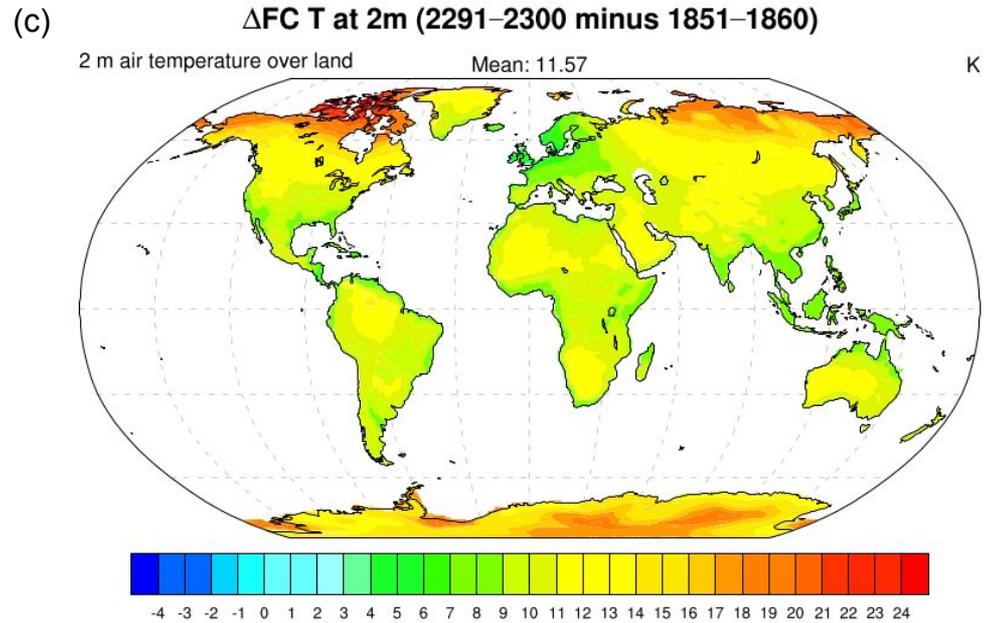
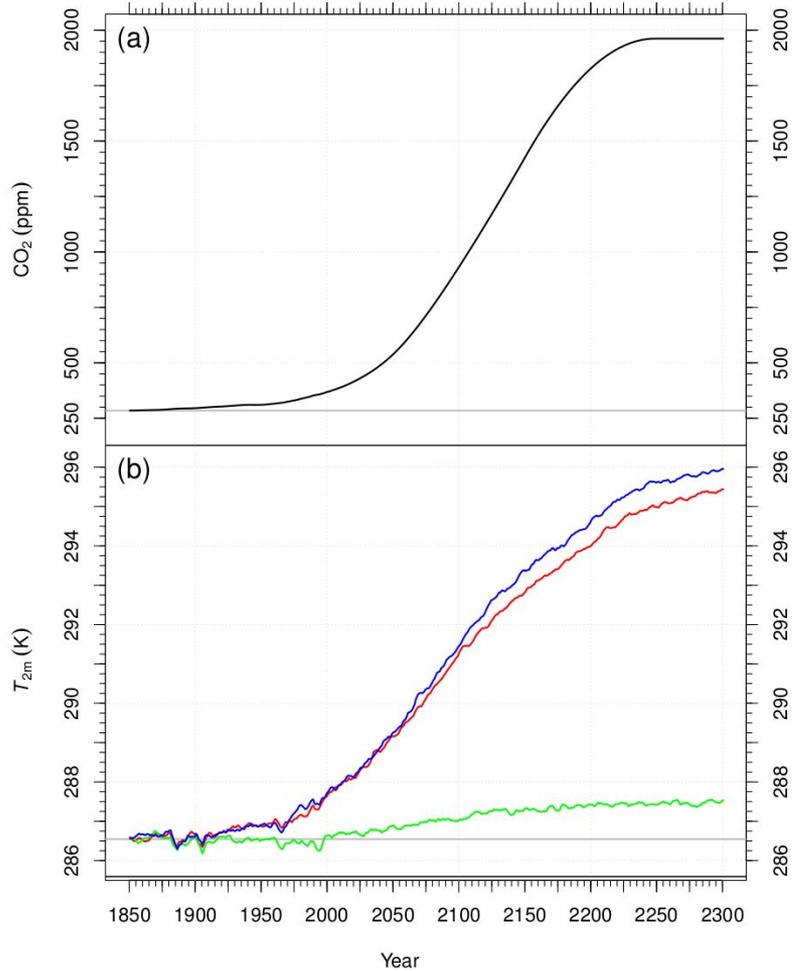
$$\Delta C_O = \beta_O \Delta \text{CO}_2 + \gamma_O \Delta T$$

$$\Delta C_L = \beta_L \Delta \text{CO}_2 + \gamma_L \Delta T$$

$$g = \frac{-\alpha(\gamma_O + \gamma_L)}{(m + \beta_O + \beta_L)}$$

From Friedlingstein et al. (2006).

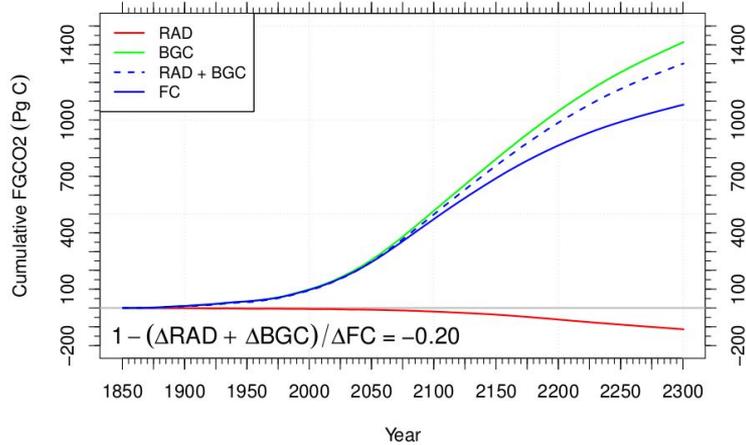
Climate–Carbon Cycle Drivers (1850–2300)



(a) Prescribed atmospheric CO₂ mole fraction was stabilized at 1962 ppm around 2250. (b) 2 m air temperature increased by 9.4°C in **FC**, 8.9°C in **RAD**, and 1.0°C in **BGC** simulations. (c) Mean air temperature over land increased by 11.6°C in the **FC** simulation and approached 25°C at high latitudes.

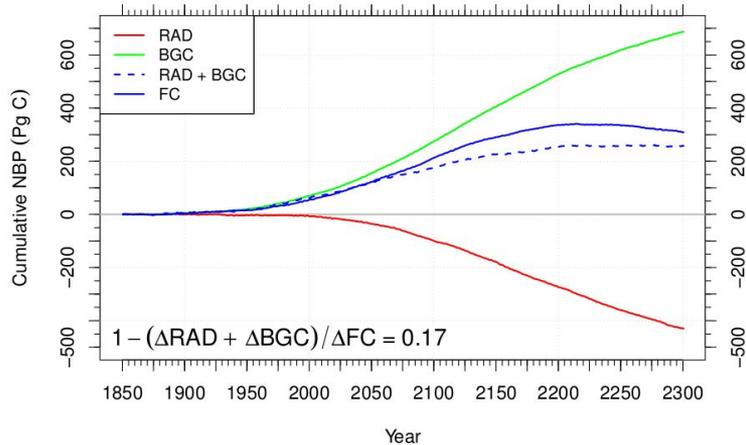
Net Ocean and Land Carbon Uptake (1850–2300)

net ocean carbon storage (1850–2300)



Net ocean carbon storage has a nonlinear response that Schwinger et al. (2014) attributed to surface stratification under climate change that restricted C penetration into intermediate and deep waters.

net land carbon storage (1850–2300)



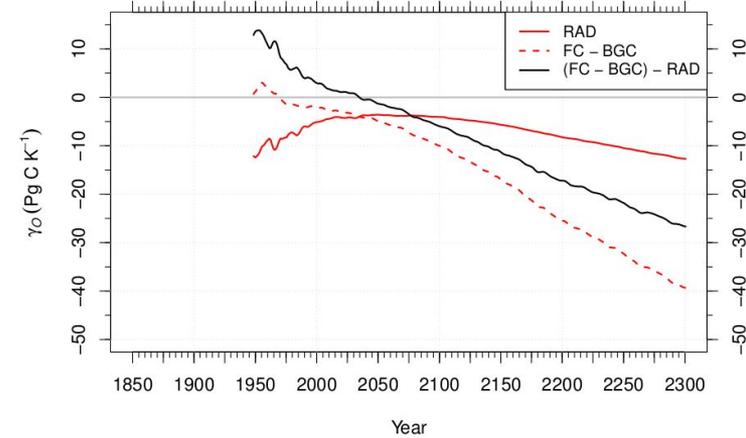
Net land carbon storage also has a nonlinear response, of opposite sign, that has not been explored in ESMs, although Zickfeld et al. (2011) explored similar nonlinear responses in an EMIC. It is driven by larger than expected productivity increases due to positive hydrological and nitrogen mineralization feedbacks.

Ocean and Land Climate–Carbon Sensitivities

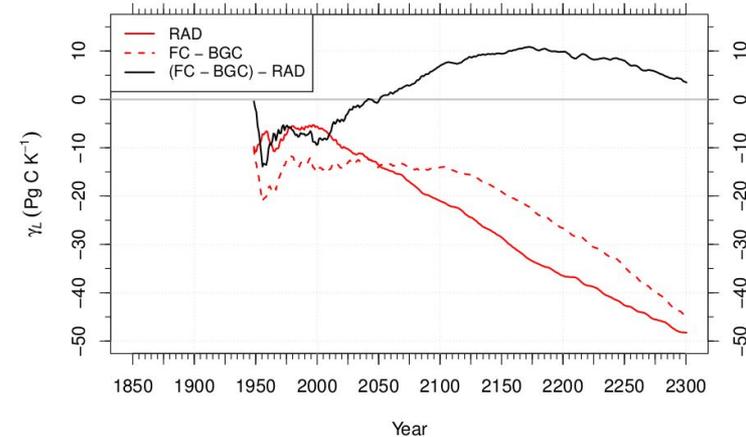
The difference between the net ocean carbon storage climate sensitivities, γ_o^{RAD} and $\gamma_o^{\text{FC-BGC}}$, was nearly -27 Pg C K^{-1} and continued to diverge at the end of the 23rd century.

The difference between the net land carbon storage climate sensitivities, γ_L^{RAD} and $\gamma_L^{\text{FC-BGC}}$, peaked at about 10 Pg C K^{-1} around 2175 and ended at about 4 Pg C K^{-1} at 2300.

net ocean carbon storage climate sensitivity (1850–2300)

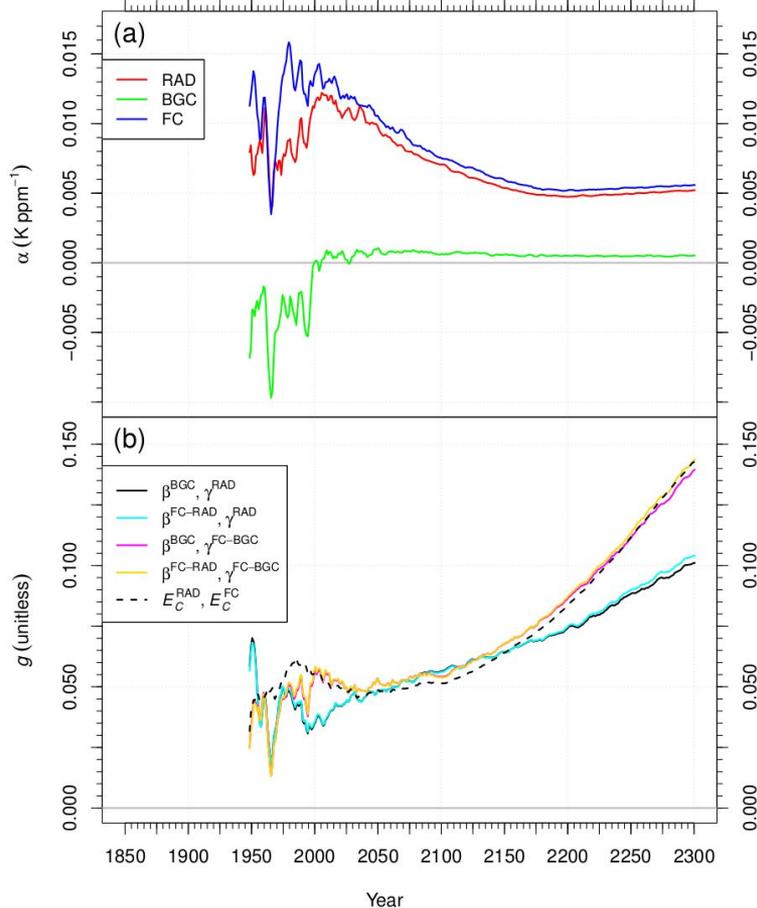


net land carbon storage climate sensitivity (1850–2300)



Climate Sensitivities and Climate–Carbon Cycle Gains

Climate Sensitivities and Feedback Gains (1850–2300)



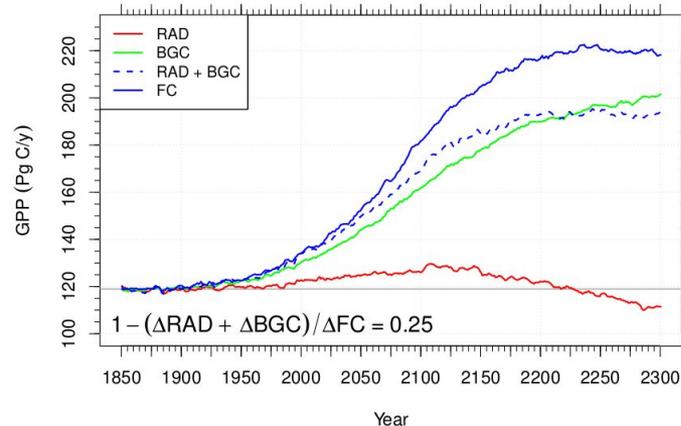
The climate sensitivity, α , for the **FC** simulation was about 0.0056 K ppm⁻¹ at the end of the 23rd century.

The climate–carbon cycle gain* (g) clustered around two different values, depending on the method and experiments used to calculate it, and at 2300 was 42% higher when estimated from sensitivity parameters derived from **(FC – BGC)** than from RAD.

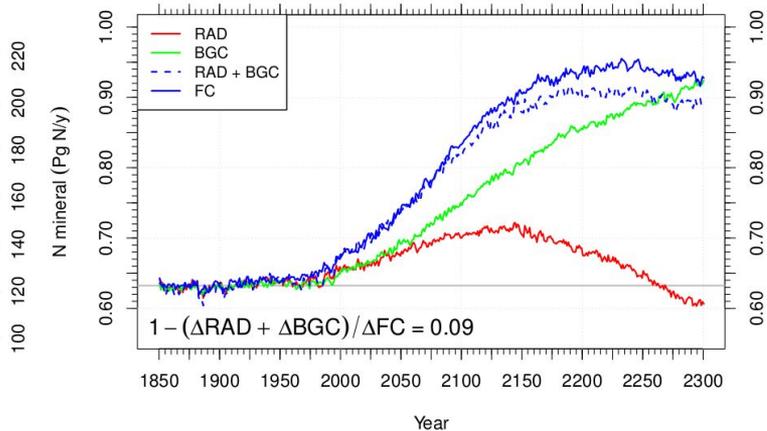
*This gain included effects of aerosols and other greenhouse gases.

Drivers of Nonlinear Terrestrial Uptake Responses

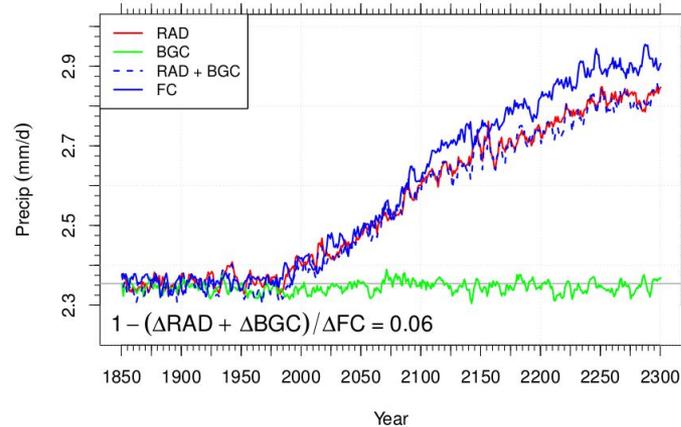
5 y mean gross primary production (1850–2300)



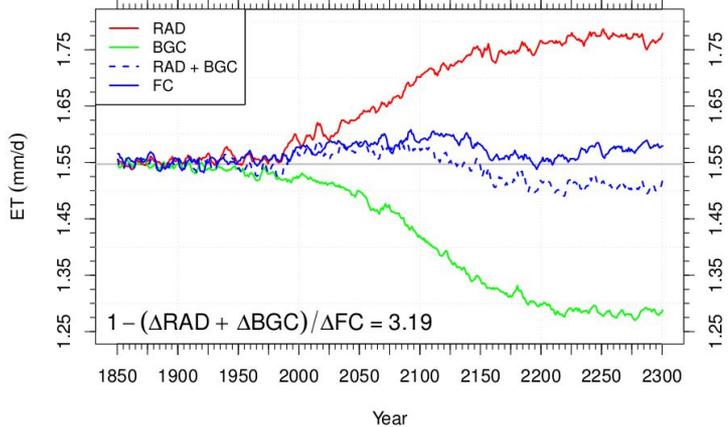
5 y mean nitrogen mineralization (1850–2300)



5 y mean total precipitation (1850–2300)

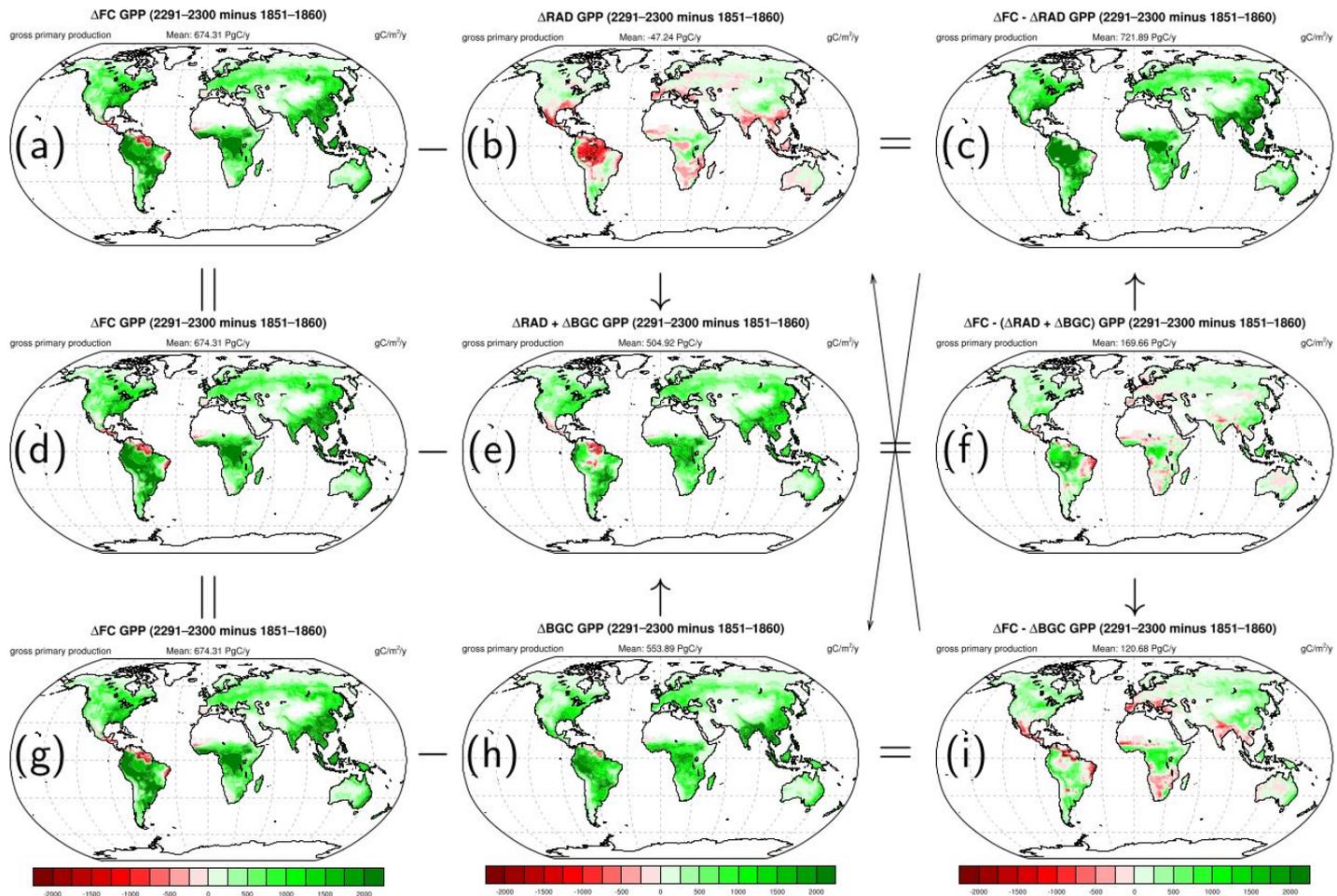


5 y mean evapotranspiration (1850–2300)

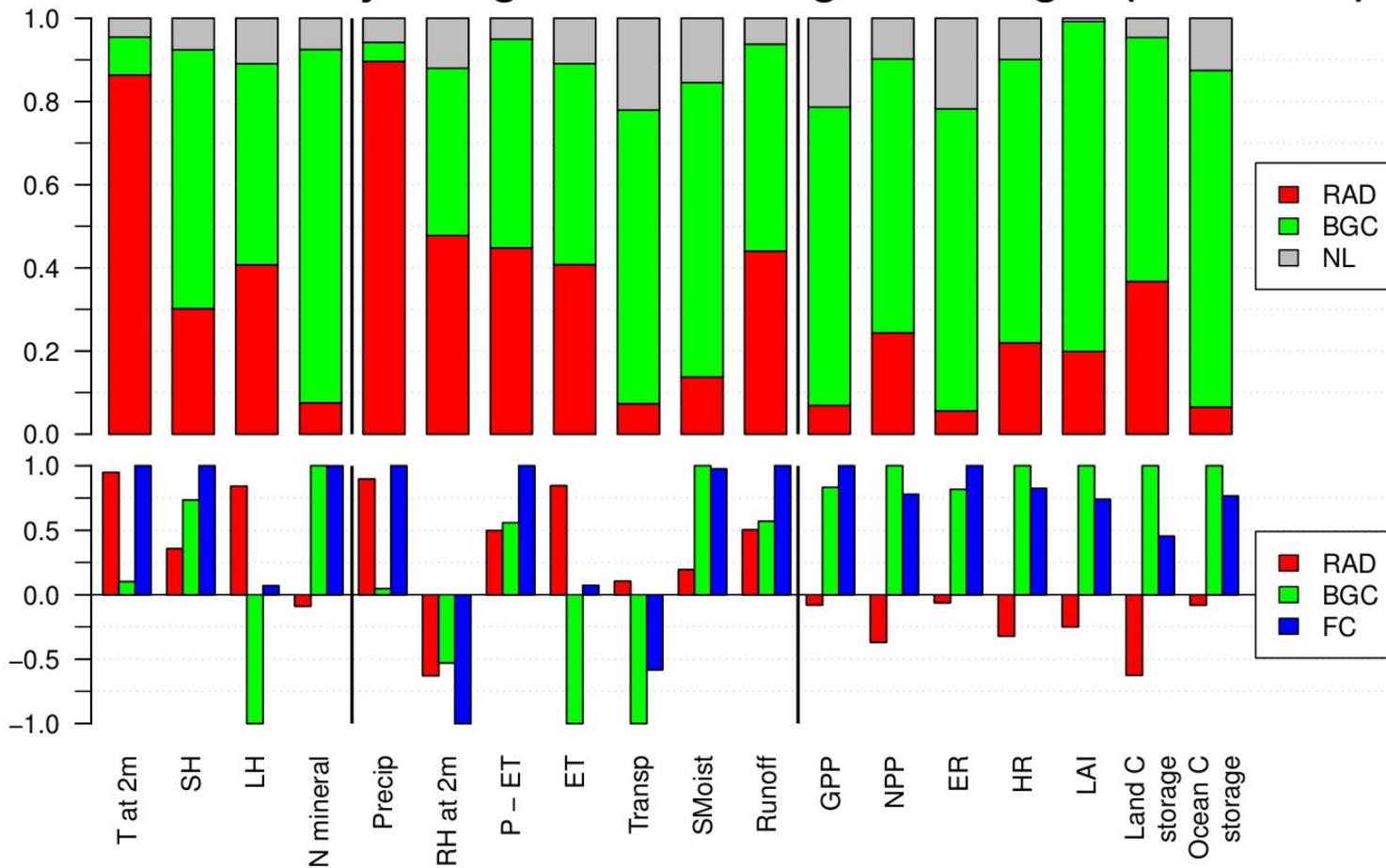


Enhanced gross primary production (GPP) and higher rates of N mineralization, driven by excess precipitation increases and reduced evapotranspiration, led to the nonlinear C uptake response on land under simultaneous climate change and elevated CO₂ levels.

Nonlinear GPP Responses Across Model Experiments



Drivers of Hydrological and Ecological Changes (1850–2300)



Energy & N

Water

Carbon

Science Question: To what degree do the effects of climate change due to warming and CO₂ fertilization in isolation combine linearly?

- **RAD** simulations yielded a net ocean carbon storage climate sensitivity (γ_O) that was weaker and a net land carbon storage sensitivity (γ_L) that was stronger than those diagnosed from **FC** and **BGC** simulations.
 - For the ocean, the nonlinearity was associated with warming-induced weakening of ocean circulation and mixing, which limited exchange of dissolved inorganic carbon between surface and deeper water masses.
 - For the land, the nonlinearity was associated with strong gains in gross primary production in the **FC** simulation, driven by enhancements in the hydrological cycle and increased nutrient availability.
- The feedback gain* (g) at 2300 was 42% higher when estimated from sensitivity parameters derived from (**FC** – **BGC**) than from **RAD**.
- We recommend deriving $\gamma_O^{\text{FC-BGC}}$ and $\gamma_L^{\text{FC-BGC}}$ in future studies.

*This gain included effects of aerosols and other greenhouse gases.

Sustained Warming Drives Declining Marine Biological Productivity

Objective: To study climate change impacts on marine biogeochemistry and productivity over multi-century timescales.

Approach: Analyze Community Earth System Model (CESMv1.0) simulation to year 2300 with RCP8.5/ECP8.5 scenario (atmospheric CO₂ exceeds 1960 ppm).

Results/Impacts: Increasing biological production and export around Antarctica “traps” nutrients. This drives a net transfer of nutrients to the deep ocean, reducing net primary production (NPP) globally. Declining productivity reduces potential global fishery catch by 20%, with declines of nearly 60% in the North Atlantic.

Moore, J. K., W. Fu, F. Primeau, G. L. Britten, K. Lindsay, M. Long, S. C. Doney, N. Mahowald, F. M. Hoffman, J. T. Randerson (2018), Sustained climate warming drives declining marine biological productivity, *Science*, 359(6380): 1139–1143, doi:[10.1126/science.aao6379](https://doi.org/10.1126/science.aao6379).

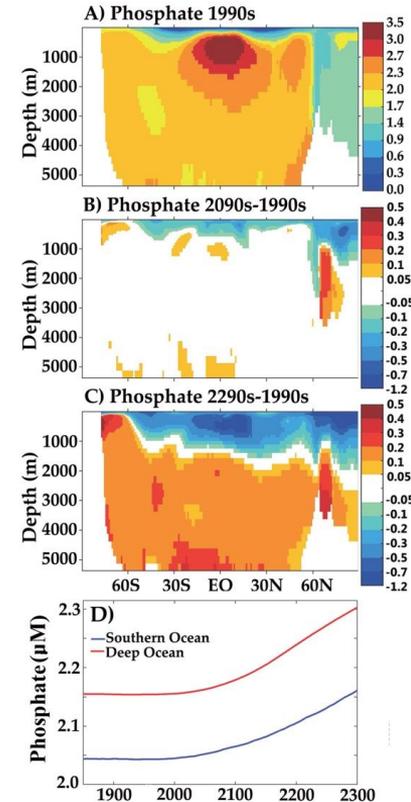


Figure: Antarctic trapping increases nutrient transfer to the deep ocean.



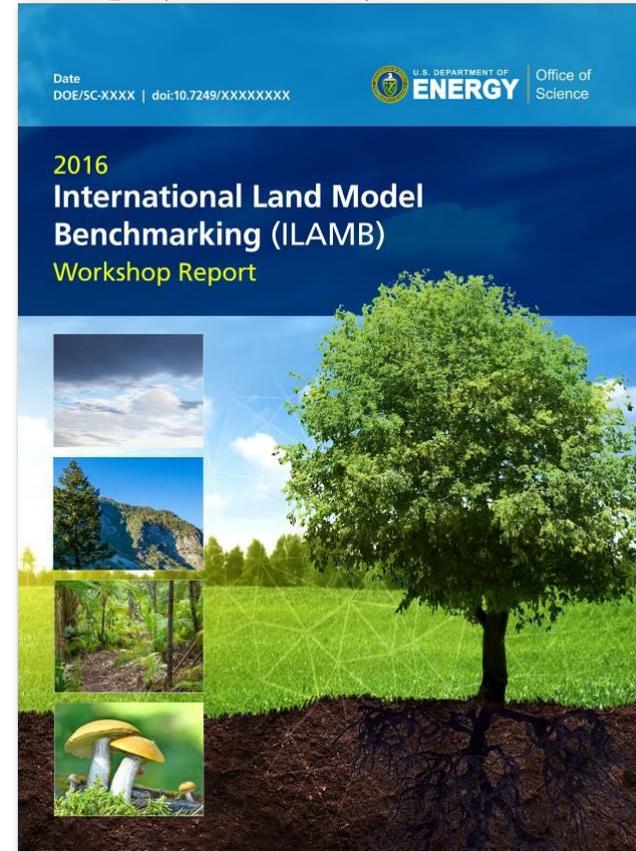
International Land Model Benchmarking (ILAMB)

ILAMB is a community coordination activity to

- Develop internationally accepted benchmarks
- Promote the use of these benchmarks
- Strengthen linkages between experimental, remote sensing, and climate modeling communities
- Support the design and development of open source benchmarking tools

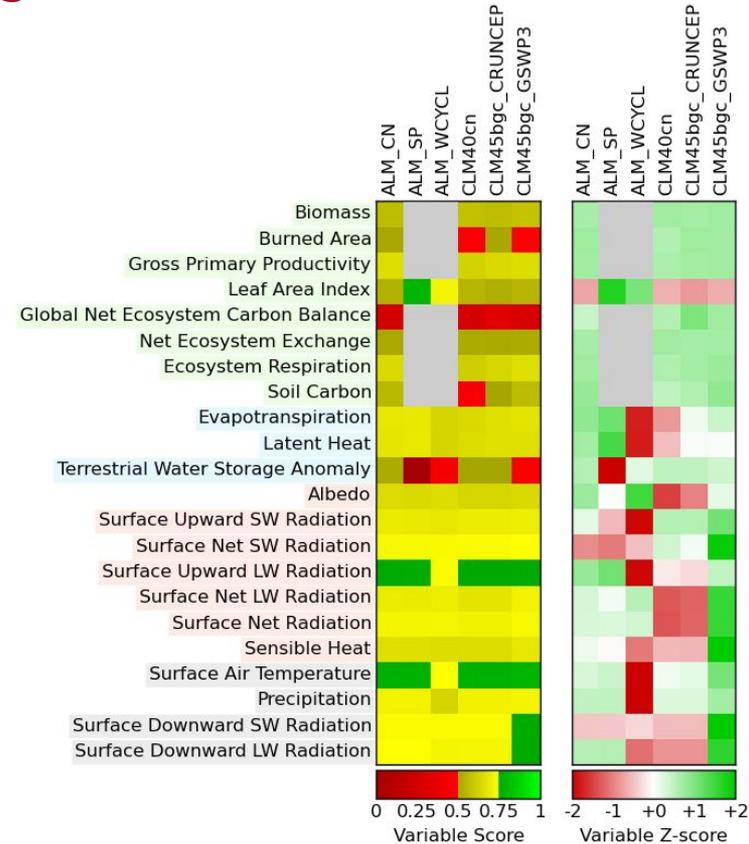
Second US ILAMB Workshop, May 16–18, 2016

- 60+ participants from Australia, Japan, China, Germany, Sweden, Netherlands, UK, and US
- 10 modeling centers represented
- ~25 remote attendees at any time
- Workshop report identifies priorities and approaches

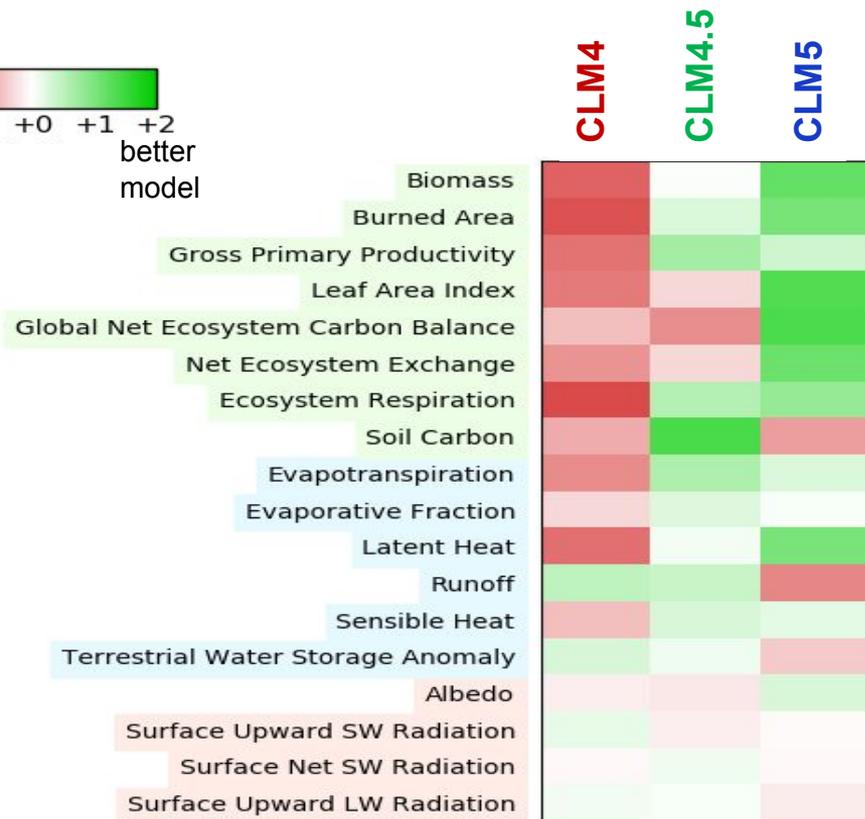
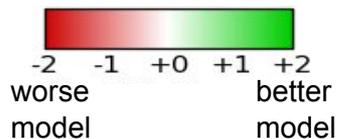


Development of ILAMB Packages

- **ILAMBv1** released at 2015 AGU Fall Meeting Town Hall,
doi:[10.18139/ILAMB.v001.00/1251597](https://doi.org/10.18139/ILAMB.v001.00/1251597)
- **ILAMBv2** released at 2016 ILAMB Workshop,
doi:[10.18139/ILAMB.v002.00/1251621](https://doi.org/10.18139/ILAMB.v002.00/1251621)
- Actively being used for E3SM and CESM evaluation during development
- Employed to evaluate CMIP5 models
- Models are scored based on statistical comparisons (bias, RMS error, phase, amplitude, spatial distribution, Taylor scores)
- Functional response metrics



ILAMB Assessing several generations of CLM



- Improvements in mechanistic treatment of hydrology, ecology, and land use with many more moving parts
- Simulation improved even with enhanced complexity
- Observational datasets not always self-consistent
- Forcing uncertainty confounds assessment of model development (not shown)

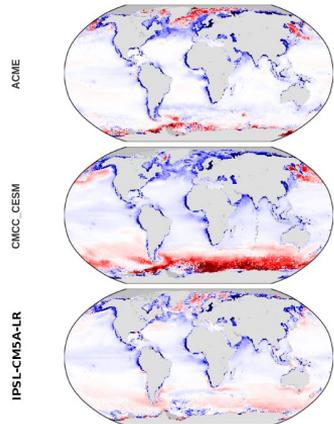
Lawrence et al., in prep

International Ocean Model Benchmarking (IOMB) Package

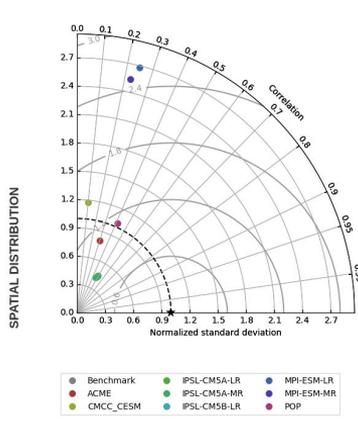
- Evaluates ocean biogeochemistry results compared with observations (global, point, ship tracks)
- Scores model performance across a wide range of independent benchmark data
- Leverages ILAMB code base, also runs in parallel
- Built on python and open standards
- Is open source and available for download

Chlorophyll / SeaWiFS

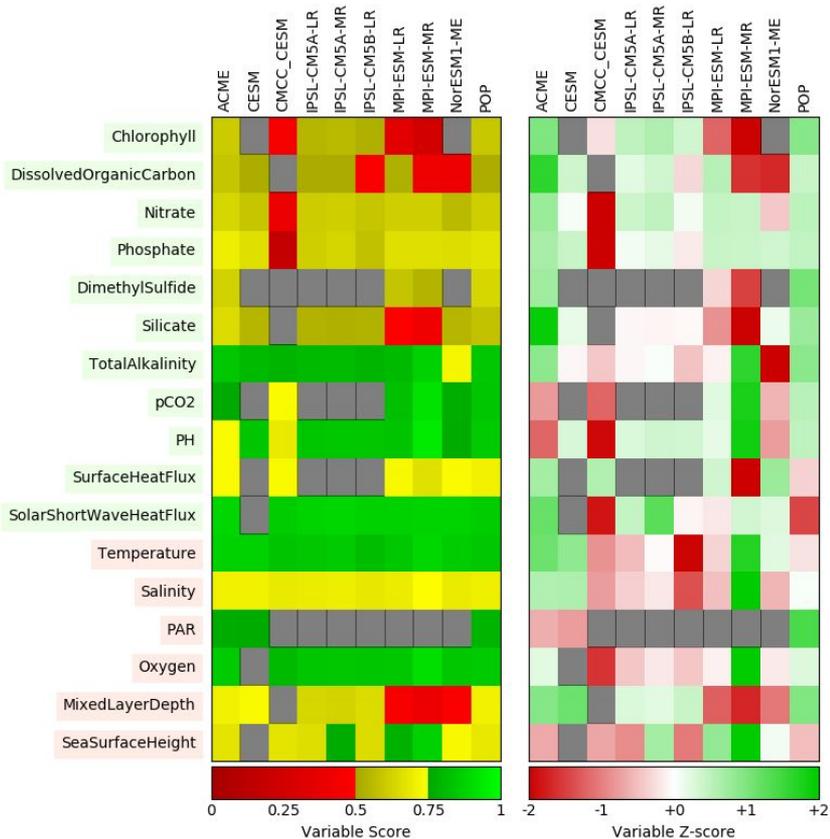
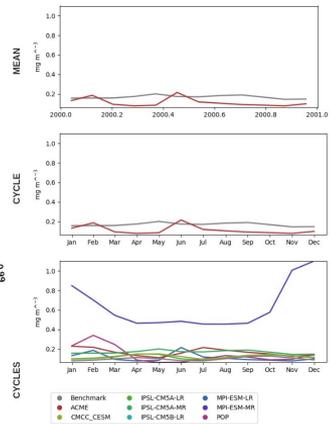
Bias



Spatial Distribution

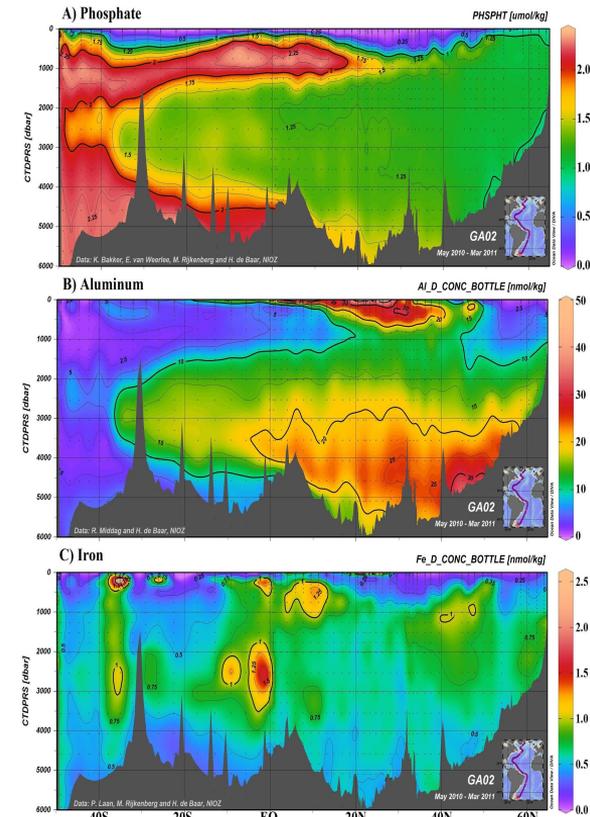


Annual & Seasonal Cycles



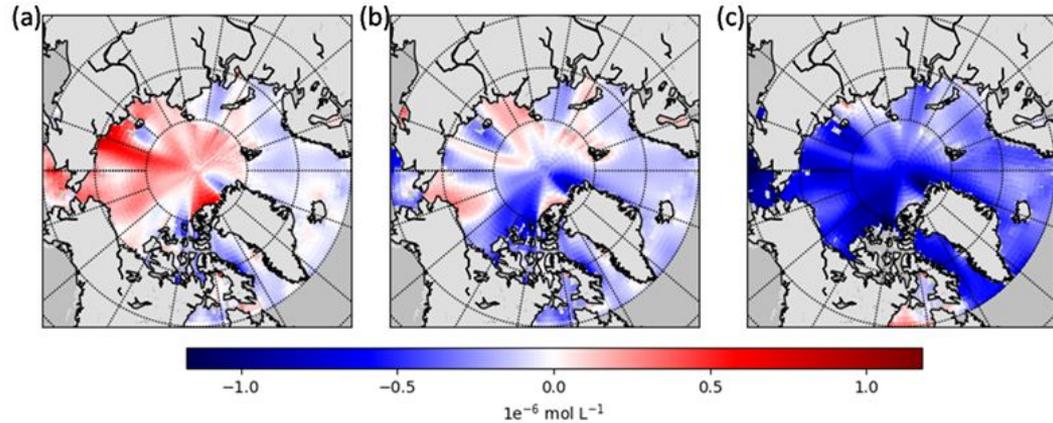
Unique Features of Ocean Model Benchmarks

- Observations are sparse and irregular, often coming from ships of opportunity
- Most variables are 4-dimensional (time, latitude, longitude, and depth)
- Synthesized data require climatological time scale encoding
- Analysis requires integration of physical circulation and biogeochemical variables

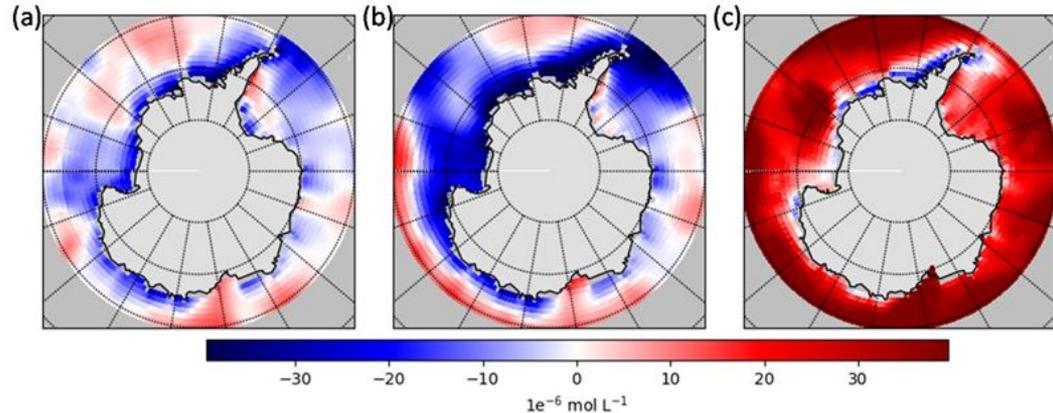


Nutrient Distributions in the Arctic and Southern Ocean

Temporal integrated mean bias of **phosphate** distribution for the year 2000 for (a) E3SM - BEC, (b) CESM - BEC, and (c) IPSL - PISCES



Temporal integrated mean bias of **silicate** distribution for the year 2000 for (a) E3SM - BEC, (b) CESM - BEC, and (c) IPSL - PISCES





Science Prospects for IOMB

- Explore Earth system feedbacks associated with the ocean carbon cycle
- Evaluate CMIP6 model responses to warming and rising atmospheric CO₂
- Partner with E3SM to assess MPAS-MARBL performance, CESM for MOM-MARBL fidelity, and RASM for high resolution Arctic ecosystems
- Extend the diagnostics framework for model-model intercomparison and identifying sources of largest uncertainties for observational community
- Evaluate circulation with tracers and decadal variability
- Evaluate the impact of land use change on ocean uptake carbon and subsequent implications for marine biogeochemistry
- Develop new benchmarking data sets from synthesis of observations with future working groups



New Marine Biogeochemistry Benchmarks for ESMs

We plan to move beyond mean satellite chlorophyll and nutrient climatologies:

New Satellite Products (not typically applied to ESMs)

- Chlorophyll over weekly to decadal timescales
- Calcite concentration (CaCO_3 – tied to particular plankton groups)
- Phytoplankton community composition from pigments
- Diazotroph biomass (important N fixing plankton group)
- Phytoplankton C, carbon/chlorophyll ratio, community growth rate

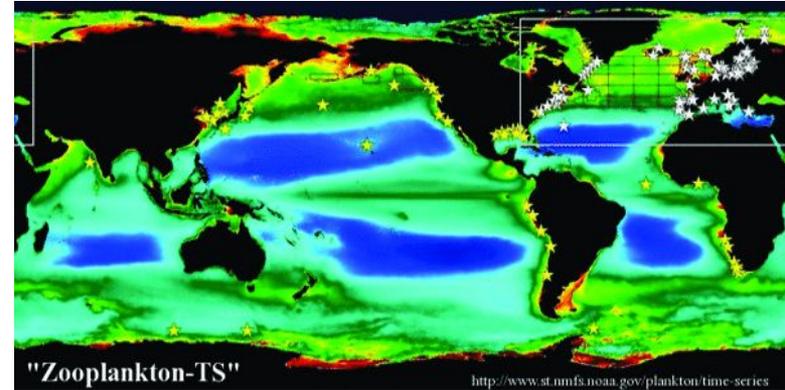
New Global-Scale Gridded Observational Data Compilations

- Plankton groups biomass, anthropogenic CO_2 distributions
- Sinking flux of particulate organic carbon, dissolved Fe distributions
- Field estimates of phytoplankton community growth rates
- Utilize site-level time series data for oxygen and nutrients in key regions

New Ocean Physics Benchmarks Relevant for Ocean Biogeochemistry

- Seasonal mixed layer depth, formation rates for the water masses that drive anthropogenic CO_2 uptake and ventilation of oxygen minimum zones, upwelling
- Tracers of ocean circulation and mixing (CFCs, ^{14}C , Ideal Age, Oxygen), sea ice

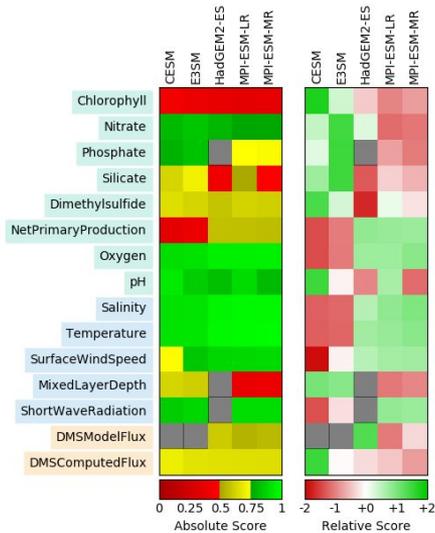
Link to projects (MAREMIP, GEOTRACES, JGOFS, CLIVAR) & data centers (NASA, NSF, NOAA, BCO-DMO)



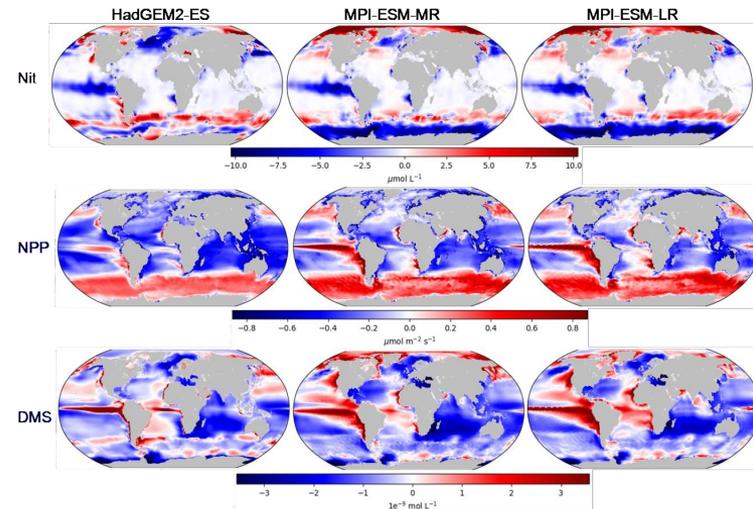
Evaluating Uncertainties in Marine Biogeochemical Models

Objective: To demonstrate the application of International Ocean Model Benchmarking (IOMB) package in evaluating marine biogeochemical models.

Approach: Used IOMB to analyze ESMs skill sets in predicting marine biogeochemical variables plus surface ocean concentrations and sea-air fluxes of dimethylsulfide.



Results/Impacts: Models over-predict the surface concentrations of DMS at the eastern tropical Pacific by a factor of two and the concentrations at the marine boundary layer by a factor of three. This could bias the aerosol indirect effect in models.



Nitrate (Nit), net primary production (NPP), and dimethylsulfide (DMS) surface mean bias.

Benchmarking results showing absolute score (S) and relative score (Z-score), computed between five ESMs and various observational datasets

Ogunro, O. O., S. M. Elliott, O. W. Wingenter, C. Deal, W. Fu, N. Collier, F. M. Hoffman (2018), Evaluating Uncertainties in Marine Biogeochemical Models: Benchmarking Aerosol Precursors, *Atmos.*, 9(5), 184, doi:[10.3390/atmos9050184](https://doi.org/10.3390/atmos9050184).



ILAMB/IOMB Tutorial

- Software tutorial at <https://www.ilamb.org/doc/>
- Supplementary details specific to ocean models will be added soon





Acknowledgements



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References

P. Friedlingstein, P. M. Cox, R. A. Betts, L. Bopp, W. von Bloh, V. Brovkin, S. C. Doney, M. Eby, I. Fung, B. Govindasamy, J. John, C. D. Jones, F. Joos, T. Kato, M. Kawamiya, W. Knorr, K. Lindsay, H. D. Matthews, T. Raddatz, P. Rayner, C. Reick, E. Roeckner, K.-G. Schnitzler, R. Schnur, K. Strassmann, S. Thompson, A. J. Weaver, C. Yoshikawa, and N. Zeng. Climate-carbon cycle feedback analysis, results from the C⁴MIP model intercomparison. *J. Clim.*, 19(14):3373–3353, July 2006. doi:10.1175/JCLI3800.1.

M. Meinshausen, S. Smith, K. Calvin, J. Daniel, M. Kainuma, J.-F. Lamarque, K. Matsumoto, S. Montzka, S. Raper, K. Riahi, A. Thomson, G. Velders, and D. P. van Vuuren. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Clim. Change*, 109(1):213–241, Nov. 2011. doi:10.1007/s10584-011-0156-z.

J. K. Moore, W. Fu, F. Primeau, G. L. Britten, K. Lindsay, M. Long, S. C. Doney, N. Mahowald, F. M. Hoffman, and J. T. Randerson. Sustained climate warming drives declining marine biological productivity. *Science*, 359(6380):1139–1143, Mar. 2018. doi:10.1126/science.aao6379.

O. O. Ogunro, S. M. Elliott, O. W. Wingenter, C. Deal, W. Fu, N. Collier, and F. M. Hoffman. Evaluating Uncertainties in Marine Biogeochemical Models: Benchmarking Aerosol Precursors. *Atmos.*, 9(5), 184, May 2018. doi:10.3390/atmos9050184.

J. Schwinger, J. F. Tjiputra, C. Heinze, L. Bopp, J. R. Christian, M. Gehlen, T. Ilyina, C. D. Jones, D. Salas-Méla, J. Segschneider, R. Séférian, and I. Totterdell. Nonlinearity of ocean carbon cycle feedbacks in CMIP5 Earth system models. *J. Clim.*, 27(11):3869–3888, June 2014. doi:10.1175/JCLI-D-13-00452.1.

K. Zickfeld, M. Eby, H. D. Matthews, A. Schmittner, and A. J. Weaver. Nonlinearity of carbon cycle feedbacks. *J. Clim.*, 24(16):4255–4275, Aug. 2011. doi:10.1175/2011JCLI3898.1.

