Quantification and Reduction of Uncertainties Associated with Carbon Cycle–Climate System Feedbacks

Forrest M. Hoffman

Computational Earth Sciences Group (CESG)
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Computational Earth Sciences Group Leader Interview

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Climate Change Science Institute
Oak Ridge National Laboratory

Oak Ridge National Laboratory

Forrest M. Hoffman: Computational Earth System Scientist at ORNL

- 31 years at ORNL; 26 years as staff in ESD, CSMD, and CSED
- B.S. (1991) and M.S. (2004) in Physics from University of Tennessee, Knoxville; M.S. (2012) and Ph.D. (2015) in Earth System Science from University of California, Irvine
- develop and apply Earth system models to study global biogeochemical cycles, including terrestrial & marine carbon cycle
- investigate methods for reconciling uncertainties in carbon cycle–climate feedbacks through comparison with observations
- apply artificial intelligence methods (machine learning and data mining) to environmental characterization, simulation, & analysis
- Joint Faculty Professor, University of Tennessee, Knoxville, Department of Civil & Environmental Engineering

Oak Ridge National Laboratory

The University of Tennessee Knoxville

Research Questions

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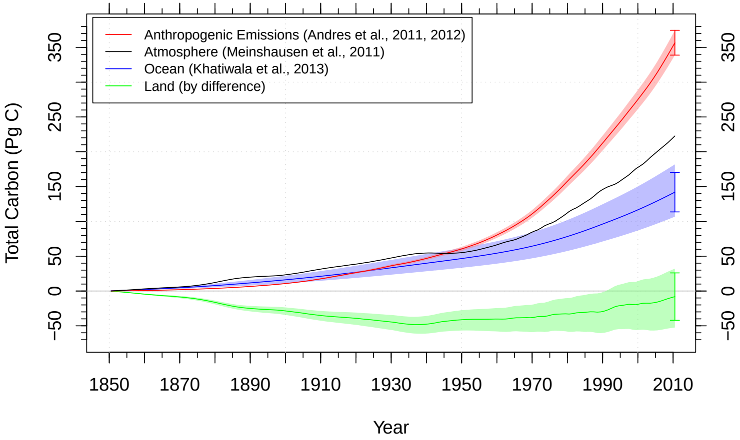
Community Model Benchmarking

Systematic assessment of model fidelity, employing best-available observational data, can identify model weaknesses and inspire new measurements.

Observed Carbon Accumulation Since 1850



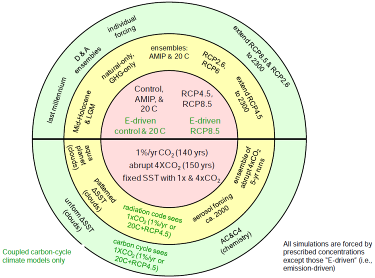
Observational estimates of anthropogenic carbon emissions (excluding land use change) and accumulation in atmosphere, ocean, and land reservoirs for 1850–2010. Atmosphere carbon is a fusion of Law Dome ice core CO_2 observations, the Keeling Mauna Loa record, and more recently the NOAA GMD global surface average, integrated for the purpose of forcing IPCC models. Total land flux is computed by mass balance as follows:

$$\Delta C_L = \sum_i F_i - \Delta C_A - \Delta C_O.$$

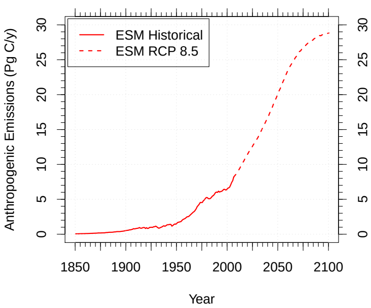
15 ESMs that performed CMIP5 emissions-forced simulations

Model	Modeling Center
BCC-CSM1.1	Beijing Climate Center, China Meteorological Administration, CHINA
BCC-CSM1.1(m)	Beijing Climate Center, China Meteorological Administration, CHINA
BNU-ESM	Beijing Normal University, CHINA
CanESM2	Canadian Centre for Climate Modelling and Analysis, CANADA
CESM1-BGC	Community Earth System Model Contributors, NSF-DOE-NCAR, USA
FGOALS-s2.0	LASG, Institute of Atmospheric Physics, CAS, CHINA
GFDL-ESM2g	NOAA Geophysical Fluid Dynamics Laboratory, USA
GFDL-ESM2m	NOAA Geophysical Fluid Dynamics Laboratory, USA
HadGEM2-ES	Met Office Hadley Centre, UNITED KINGDOM
INM-CM4	Institute for Numerical Mathematics, RUSSIA
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, FRANCE
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (University of Tokyo), and National Institute for Environmental Studies, JAPAN
MPI-ESM-LR	Max Planck Institute for Meteorology, GERMANY
MRI-ESM1	Meteorological Research Institute, JAPAN
NorESM1-ME	Norwegian Climate Centre, NORWAY

CMIP5 Long-Term Experiments

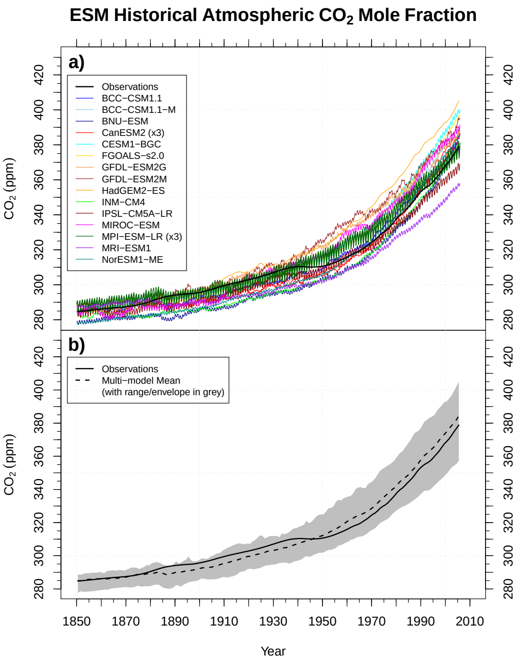


Emissions for Historical + RCP 8.5 Simulations



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

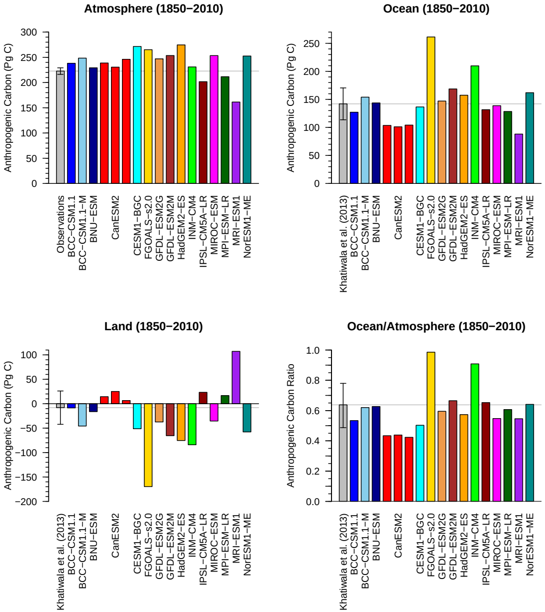
(b) The multi-model mean was biased high from 1946 throughout the 20th century, ending 5.6 ppm above the observed value of 378.8 ppm in 2005.



Model inventory comparison with Khatiwala et al. (2013)

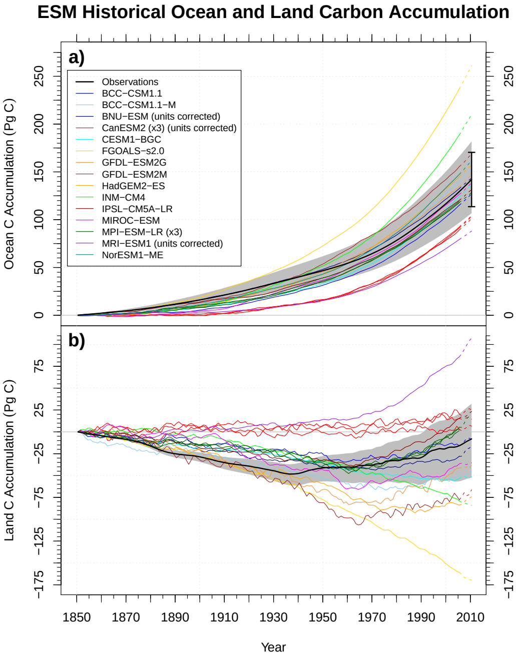
Once normalized by their atmospheric carbon inventories, most ESMs exhibited a low bias in anthropogenic ocean carbon accumulation through 2010.

The same pattern holds for the Sabine et al. (2004) inventory derived using the ΔC^* separation technique.



(a) Ocean inventory estimates had a fairly persistent ordering during the second half of the 20th century.

(b) ESMs exhibited a wide range of land carbon accumulation responses to increasing CO_2 and land use change, ranging from a net source of 170 Pg C to a sink of 107 Pg C in 2010.



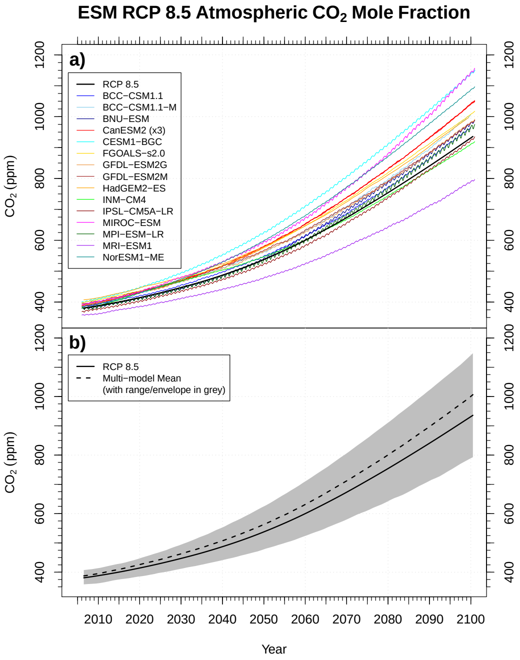
Question 1

How well do Earth System Models (ESMs) simulate the observed distribution of anthropogenic carbon in atmosphere, ocean, and land reservoirs?

- Most ESMs exhibited a high bias in predicted atmospheric CO_2 mole fraction, ranging from 357–405 ppm in 2005.
- The multi-model mean atmospheric CO_2 mole fraction was biased high from 1946 onward, ending 5.6 ppm above observations in 2005.
- Once normalized by atmospheric carbon accumulation, most ESMs exhibited a low bias in ocean accumulation in 2010.
- ESMs predicted a wide range of land carbon accumulation in response to increasing CO_2 and land use change, ranging from -170–107 Pg C in 2010.

Question 2

Can contemporary atmospheric CO_2 observations be used to constrain future CO_2 projections?



Reducing Uncertainties Using Observations

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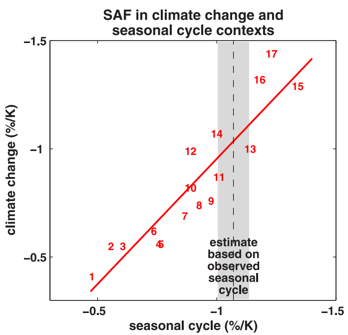
Example #1

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.



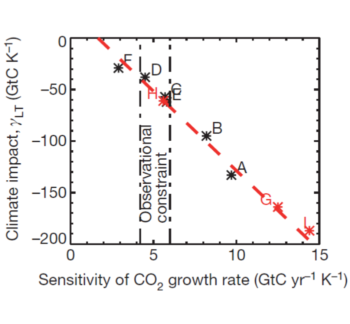
Reducing Uncertainties Using Observations

To reduce feedback uncertainties using contemporary observations,

1. there must be a relationship between contemporary variability and future trends on longer time scales within the model, and
2. it must be possible to constrain contemporary variability in the model using observations.

Example #2

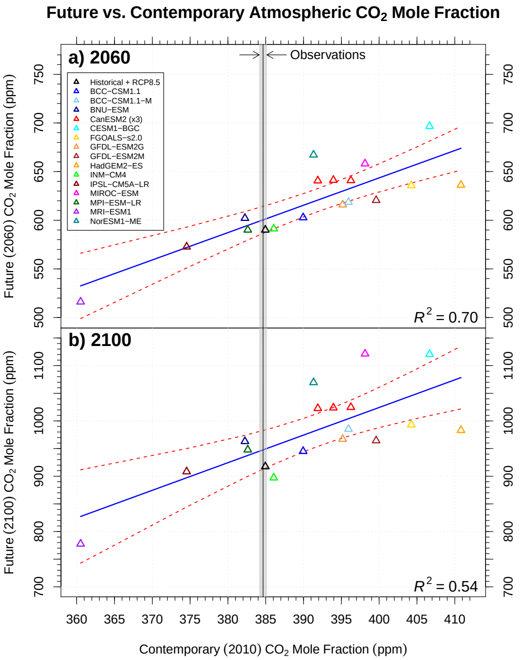
Cox et al. (2013) used the observed relationship between the CO_2 growth rate and tropical temperature as a constraint to reduce uncertainty in the land carbon storage sensitivity to climate change (γ_L) in the tropics using C^4MIP models.



I discovered a new emergent constraint based on carbon inventories.

A relationship exists between contemporary and future atmospheric CO_2 levels over decadal time scales because carbon model biases persist over decadal time scales.

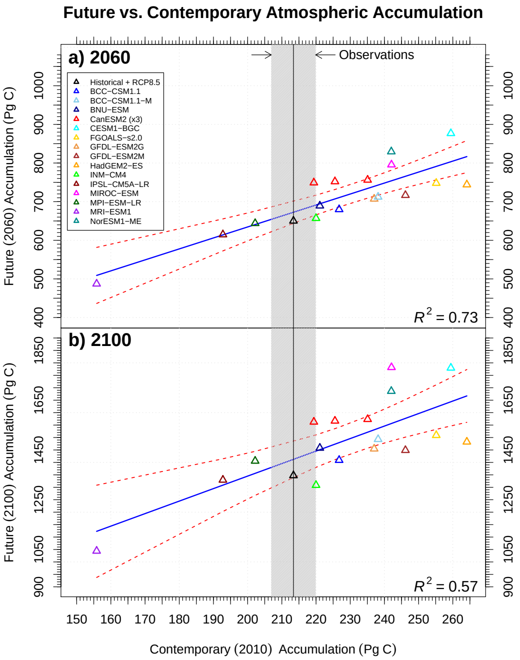
The observed contemporary atmospheric CO_2 mole fraction is represented by the vertical line at 384.6 ± 0.5 ppm.

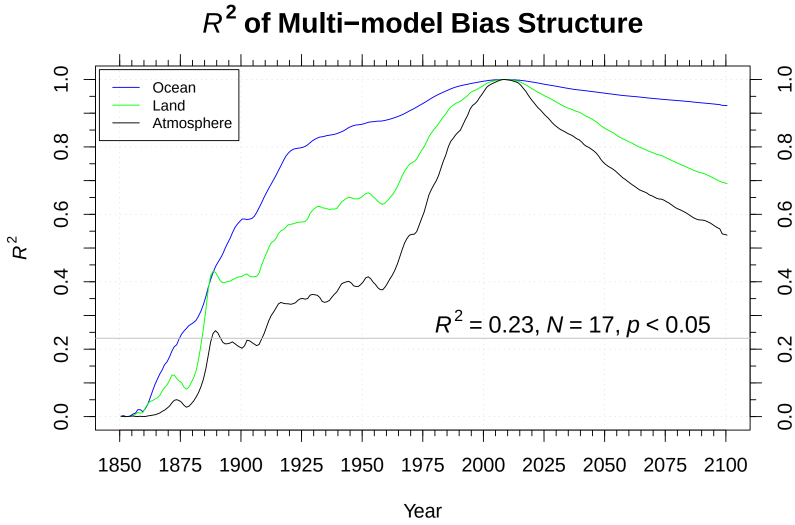


Removing pre-industrial CO_2 mole fraction biases from models, I found the relationship held, confirming the robustness of the result.

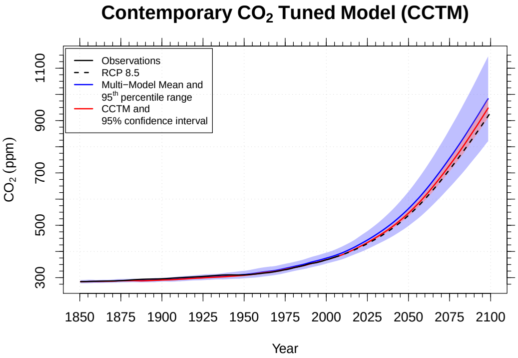
Observed contemporary anthropogenic atmospheric carbon inventory is represented by the vertical line at 213.4 ± 6.5 Pg C, which incorporates 1850 CO_2 mole fraction uncertainties.

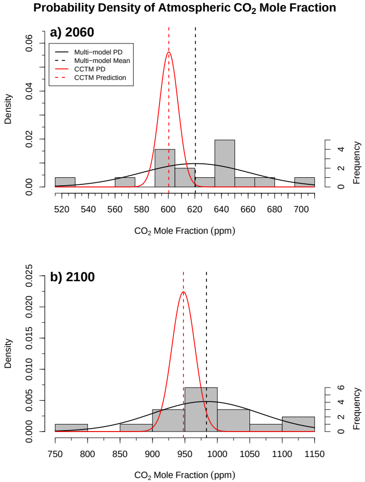
Adding uncertainties from fossil fuel emissions increased the uncertainty to ± 12.7 Pg C.





The coefficients of determination (R^2) for the multi-model bias structure relative to the set of CMIP5 model atmospheric CO_2 mole fractions (black), and oceanic (blue) and land (green) anthropogenic carbon inventories in 2010. Atmospheric CO_2 mole fractions are statistically significant for 1910–2100. Bias persistence was highest for the ocean, followed by land, and then by the atmosphere.





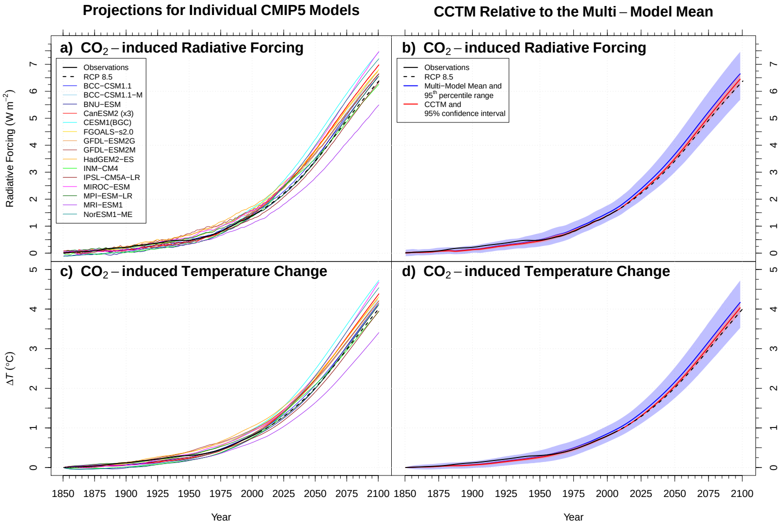
I used this regression to create a contemporary CO_2 tuned model (CCTM) estimate of the atmospheric CO_2 trajectory for the 21st century.

- Peak probability densities of CO_2 mole fraction predictions were lower for the CCTM than the multi-model means.
- The ranges of uncertainty were smaller by almost a factor of 6 at 2060 and almost a factor of 5 at 2100.

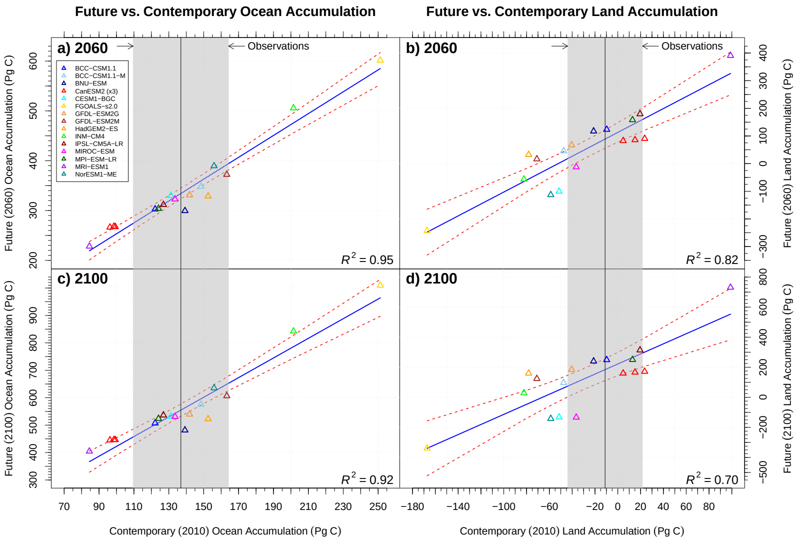
Best estimate using Mauna Loa CO_2

At 2060: 600 ± 14 ppm, 21 ppm below the multi-model mean

At 2100: 947 ± 35 ppm, 32 ppm below the multi-model mean



I calculated the CO_2 radiative forcing and used an impulse response function (tuned to the mean transient climate response of CMIP5 models) to equitably compute the resulting CO_2-induced temperature change (ΔT_{CO_2}) for models and the CCTM. The CO_2 biases for individual models contributed to ΔT_{CO_2} biases of $-0.7°C$ to $+0.6°C$ by 2100, relative to the CCTM estimate.



I also developed a multi-model constraint on the evolution of ocean and land anthropogenic inventories. Since observational uncertainties are higher for ocean and land, uncertainties in future estimates cannot be reduced as much as for atmospheric CO_2.

Question 2

Can we use contemporary CO_2 observations to constrain future CO_2 projections?

- Yes.
- I developed a new emergent constraint from anthropogenic carbon inventories in atmosphere, ocean, and land reservoirs.
- Land and ocean processes contributing to contemporary carbon cycle biases persist over decadal timescales.
- I used the relationship between contemporary and future atmospheric CO_2 levels to create a contemporary CO_2 tuned model (CCTM) estimate for the 21st century.
  - At 2060: 600 ± 14 ppm, 21 ppm below the multi-model mean.
  - At 2100: 947 ± 35 ppm, 32 ppm below the multi-model mean.
- Uncertainties in future climate predictions may be reduced by improving models to match the long-term time series of CO_2 from Mauna Loa and other monitoring stations.

Implications of CO_2 Biases in ESMs

- Most of the model-to-model variability of CO_2 in the 21st century was traced to biases that existed at the end of the observational record.
- Future fossil fuel emissions targets designed to stabilize CO_2 levels would be too low if estimated from the multi-model mean of ESMs.
- Models could be improved through **extensive comparison with sustained observations** and **community model benchmarking**.

AGU PUBLICATIONS

JGR

Journal of Geophysical Research: Biogeosciences

RESEARCH ARTICLE

10.1002/2013JG002381

Key Points:

- We analyzed emission-driven simulations from 15 Earth System Models (ESMs)
- Most ESMs had a small positive bias in contemporary atmospheric CO_2 predictions
- We used a linear relationship to create a trajectory of future atmospheric CO_2

Supporting Information:

- Readme
- Supplementary Materials

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Causes and implications of persistent atmospheric carbon dioxide biases in Earth System Models

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Abstract The strength of feedbacks between a changing climate and future CO_2 concentrations is uncertain and difficult to predict using Earth System Models (ESMs). We analyzed emission-driven simulations—in which atmospheric CO_2 levels were computed prognostically—for historical (1850–2005) and future periods (Representative Concentration Pathway (RCP) 8.5 for 2006–2100) produced by 15 ESMs for the Fifth Phase of the Coupled Model Intercomparison Project (CMIP5). Comparison of ESM prognostic atmospheric CO_2 over the historical period with observations indicated that ESMs, on average, had a small positive bias in predictions of contemporary atmospheric CO_2. Weak ocean carbon uptake in many ESMs contributed to this bias, based on comparisons with observations of ocean and atmospheric anthropogenic carbon inventories. We found a significant linear relationship between contemporary atmospheric CO_2 biases and future CO_2 levels for the multimodel ensemble. We used this relationship to create a contemporary CO_2 tuned model (CCTM) estimate of the atmospheric CO_2 trajectory for the 21st century. The CCTM yielded CO_2 estimates of 600 ± 14 ppm at 2060 and 947 ± 35 ppm at 2100, which were 21 ppm and 32 ppm below the multimodel mean during these two time periods. Using this emergent constraint approach, the likely ranges of future atmospheric CO_2, CO_2-induced radiative forcing, and CO_2-induced temperature increases for the RCP 8.5 scenario were considerably narrowed compared to estimates from the full ESM ensemble. Our analysis provided evidence that much of the model-to-model variation in projected CO_2 during the 21st century was tied to biases that existed during the observational era and that model differences in the representation of concentration-carbon feedbacks and other slowly changing carbon cycle processes appear to be the primary driver of this variability. By improving models to more closely match the long-term time series of CO_2 from Mauna Loa, our analysis suggests that uncertainties in future climate projections can be reduced.

1. Introduction

Anthropogenic emissions of radiatively active greenhouse gases into the atmosphere, especially carbon dioxide (CO_2), are rapidly increasing the burden of these gases and altering the Earth's climate [*IPCC*, 2007; *Raupach and J. G. Canadell*, 2010]. This perturbation of the global carbon cycle is expected to induce feedbacks from the terrestrial biosphere and oceans on future CO_2 concentrations and the climate system. These climate–carbon cycle feedbacks are highly uncertain, difficult to predict, and potentially large [*Denman et al.*, 2007]. Understanding and predicting the strength and direction of feedbacks is critically important

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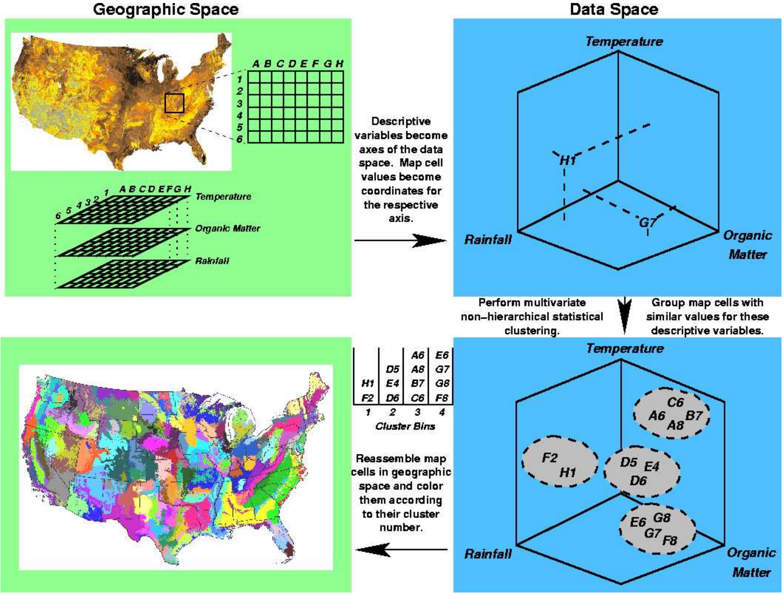
Hoffman, Forrest M., James T. Randerson, Vivek K. Arora, Qing Bao, Patricia Cadule, Duoying Ji, Chris D. Jones, Michio Kawamiya, Samar Khatiwala, Keith Lindsay, Atsushi Obata, Elena Shevliakova, Katharina D. Six, Jerry F. Tjiputra, Evgeny M. Volodin, and Tongwen Wu (2014), Causes and Implications of Persistent Atmospheric Carbon Dioxide Biases in Earth System Models, *J. Geophys. Res. Biogeosci.*, 119(2):141–162, doi:10.1002/2013JG002381.

Question 3

Can we design a strategy for objectively sampling diverse environmental gradients using models and measurements?

- Resource and logistical constraints limit the frequency and extent of observations, necessitating the development of a systematic sampling strategy that objectively represents environmental variability at the desired spatial scale.
- Required is a methodology that provides a quantitative framework for informing site selection and determining the representativeness of measurements.
- Multivariate spatiotemporal clustering (MSTC) was applied at the landscape scale (4 km^2) for the State of Alaska to demonstrate its utility for representativeness and scaling.
- An extension of the method applied by Hargrove and Hoffman for design of National Science Foundation's (NSF's) National Ecological Observatory Network (NEON) domains.

Multivariate Spatiotemporal Clustering (MSTC)

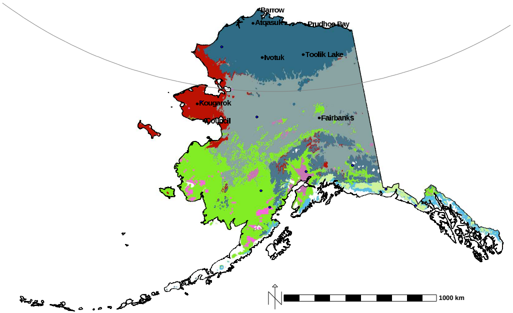


Data Layers

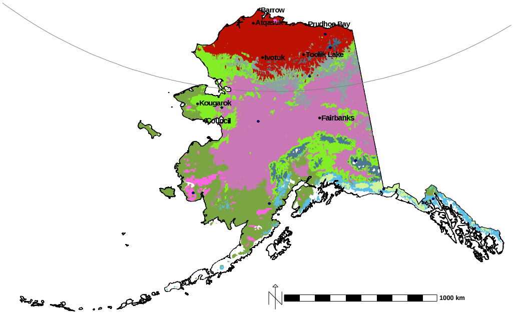
Table: 37 characteristics averaged for the present (2000–2009) and the future (2090–2099).

Description	Number/Name	Units	Source
Monthly mean air temperature	12	°C	GCM
Monthly mean precipitation	12	mm	GCM
Day of freeze	mean	day of year	GCM
	standard deviation	days	
Day of thaw	mean	day of year	GCM
	standard deviation	days	
Length of growing season	mean	days	GCM
	standard deviation	days	
Maximum active layer thickness	1	m	GIPL
Warming effect of snow	1	°C	GIPL
Mean annual ground temperature at bottom of active layer	1	°C	GIPL
Mean annual ground surface temperature	1	°C	GIPL
Thermal offset	1	°C	GIPL
Limnicity	1	%	NHD
Elevation	1	m	SRTM

10 Alaska Ecoregions, Present and Future



2000–2009



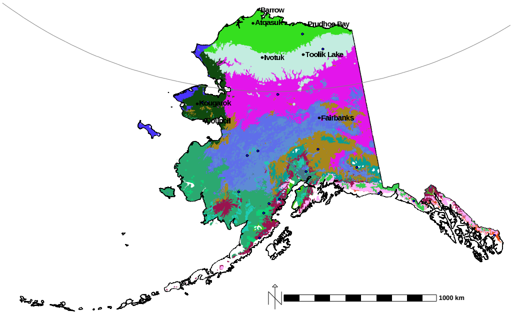
2090–2099

(Hoffman et al., 2013)

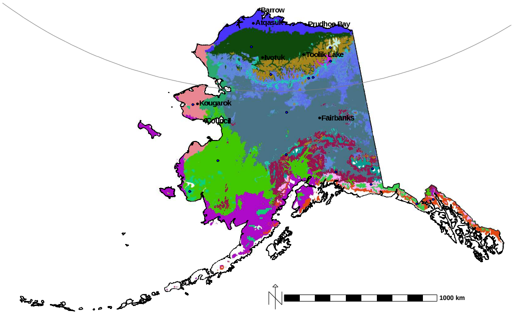
Since the random colors are the same in both maps, a change in color represents an environmental change between the present and the future.

At this level of division, the conditions in the large boreal forest become compressed onto the Brooks Range and the conditions on the Seward Peninsula “migrate” to the North Slope.

20 Alaska Ecoregions, Present and Future



2000–2009



2090–2099

(Hoffman et al., 2013)

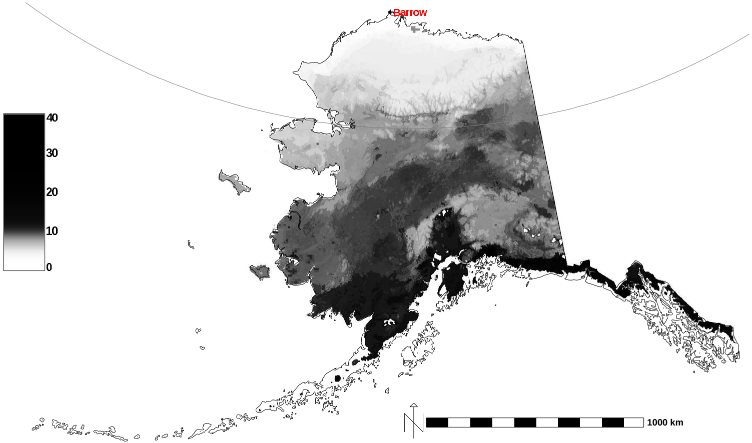
Since the random colors are the same in both maps, a change in color represents an environmental change between the present and the future.

At this level of division, the two primary regions of the Seward Peninsula and that of the northern boreal forest replace the two regions on the North Slope almost entirely.

NGEE Arctic Site Representativeness

- This representativeness analysis uses the standardized n-dimensional data space formed from all input data layers.
- In this data space, the Euclidean distance between a sampling location (like Barrow) and every other point is calculated.
- These data space distances are then used to generate grayscale maps showing the similarity, or lack thereof, of every location to the sampling location.
- In the subsequent maps, white areas are well represented by the sampling location or network, while dark and black areas as poorly represented by the sampling location or network.
- This analysis assumes that the climate surrogates maintain their predictive power and that no significant biological adaptation occurs in the future.

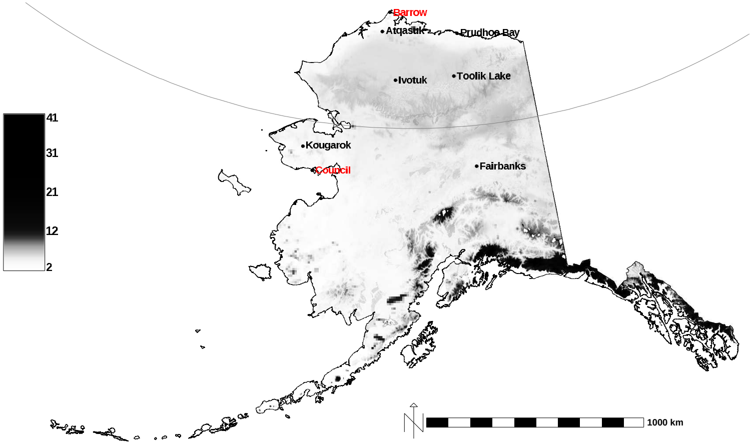
Present Representativeness of Barrow or "Barrow-ness"



(Hoffman et al., 2013)

Light-colored regions are well represented and dark-colored regions are poorly represented by the sampling location listed in **red**.

Network Representativeness: Barrow + Council



(Hoffman et al., 2013)

Light-colored regions are well represented and dark-colored regions are poorly represented by the sampling location listed in **red**.

State Space Dissimilarities: 8 Sites, Present (2000–2009)

Table: Site state space dissimilarities for the present (2000–2009).

Sites	Council	Atqasuk	Ivotuk	Toolik Lake	Kougarok	Prudhoe Bay	Fairbanks
Barrow	9.13	4.53	5.90	5.87	7.98	3.57	12.16
Council		8.69	6.37	7.00	2.28	8.15	5.05
Atqasuk			5.18	5.23	7.79	1.74	10.66
Ivotuk				1.81	5.83	4.48	7.90
Toolik Lake					6.47	4.65	8.70
Kougarok						7.25	5.57
Prudhoe Bay							10.38

State Space Dissimilarities: 8 Sites, Present and Future

Table: Site state space dissimilarities between the present (2000–2009) and the future (2090–2099).

		Future (2090–2099)							
	Sites	Barrow	Council	Atqasuk	Ivotuk	Toolik Lake	Kougarok	Prudhoe Bay	Fairbanks
Present (2000–2009)	Barrow	3.31	9.67	4.63	6.05	5.75	9.02	3.69	11.67
	Council	8.38	1.65	8.10	5.91	6.87	3.10	7.45	5.38
	Atqasuk	6.01	9.33	2.42	5.46	5.26	8.97	2.63	10.13
	Ivotuk	7.06	7.17	5.83	1.53	2.05	7.25	4.87	7.40
	Toolik Lake	7.19	7.67	6.07	2.48	1.25	7.70	5.23	8.16
	Kougarok	7.29	3.05	6.92	5.57	6.31	2.51	6.54	5.75
	Prudhoe Bay	5.29	8.80	3.07	4.75	4.69	8.48	1.94	9.81
	Fairbanks	12.02	5.49	10.36	7.83	8.74	6.24	10.10	1.96

Question 3

Can we design a strategy for objectively sampling diverse environmental gradients using models and measurements?

- Yes, MSTC provides a quantitative framework for stratifying sampling domains, informing site selection, and determining representativeness of measurements.
- Representativeness analysis provides a systematic approach for up-scaling point measurements to larger domains.

Landscape Ecol (2013) 28:1567–1586
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RESEARCH ARTICLE

Representativeness-based sampling network design for the State of Alaska

Forrest M. Hoffman · Jitendra Kumar · Richard T. Mills · William W. Hargrove

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Abstract Resource and logistical constraints limit the frequency and extent of environmental observations, particularly in the Arctic, necessitating the development of a systematic sampling strategy to maximize coverage and objectively represent environmental variability at desired scales. A quantitative methodology for stratifying sampling domains, informing site selection, and determining the representativeness of measurement sites and networks is described here. Multivariate spatiotemporal clustering was applied to down-scaled general circulation model results and data for the State of Alaska at 4 km^2 resolution to define multiple sets of ecoregions across two decadal time periods. Maps of ecoregions for the present (2000–2009) and future (2090–2099) were produced, showing how combinations of 37 characteristics are distributed and how they may shift in the future. Representative sampling locations are identified on present and future ecoregion maps. A representativeness metric was developed, and representativeness maps for eight candidate sampling locations were produced. This metric was used to characterize the environmental similarity of each site. This analysis provides model-inspired insights into optimal sampling strategies, offers a framework for up-scaling measurements, and provides a down-scaling approach for integration of models and measurements. These techniques can be applied at different spatial and temporal scales to meet the needs of individual measurement campaigns.

Keywords Ecoregions · Representativeness · Network design · Cluster analysis · Alaska · Permafrost

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Introduction

The Arctic contains vast amounts of frozen water in the form of sea ice, snow, glaciers, and permafrost. Extended areas of permafrost in the Arctic contain soil organic carbon that is equivalent to twice the size of the atmospheric carbon pool, and this large stabilized

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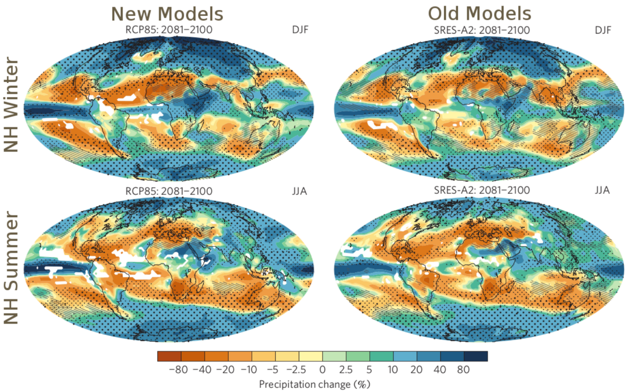
Hoffman, F. M., J. Kumar, R. T. Mills, and W. W. Hargrove (2013), Representativeness-Based Sampling Network Design for the State of Alaska, *Landscape Ecol.*, 28(8):1567–1586, doi:10.1007/s10980-013-9902-0.

Received US-IALE's 2014 Outstanding Paper in Landscape Ecology Award!

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 sometimes increased (Knutti and Sedláček, 2013)
- 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 Addressing Uncertainty a Challenge?

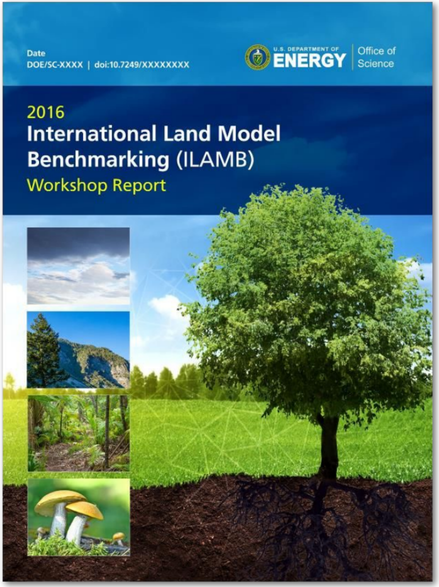
- Ecosystems have complex responses to a wide range of forcing factors in heterogeneous spatial environments, requiring highly multivariate approach
- Model uncertainty may increase, even as predictions of states and fluxes improves
- Rigorous confrontation of models with independent observations and hundreds of simulations are required to reduce uncertainty
- Modeling centers have a limited capacity to conduct sensitivity experiments, especially in fully coupled Earth system models, and rely primarily on homegrown methods and tools
- Focus is on adding complexity (e.g., more detailed representations of plant traits, photosynthesis, nutrient limitation, respiration)

We are working on an ORNL LDRD-supported DRD Project to develop a Land Model Testbed (LMT) to advance our capabilities in running large ensembles and evaluating model performance with a suite of tools.

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

The **International Land Model Benchmarking (ILAMB)** community coordination activity was designed to

- Develop internationally accepted benchmarks
- Promote the use of these benchmarks
- Strengthen linkages between experimental, remote sensing, and modeling communities
- Support the design and development of open source benchmarking tools (Luo et al., 2012), like the **ILAMB Package** (Collier et al., 2018)



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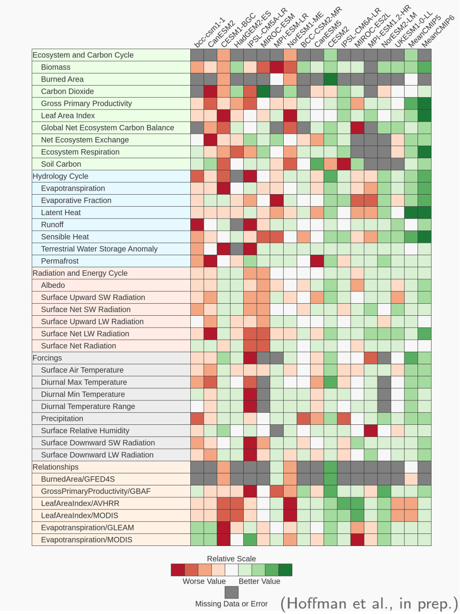
CMIP5 vs. CMIP6 Models

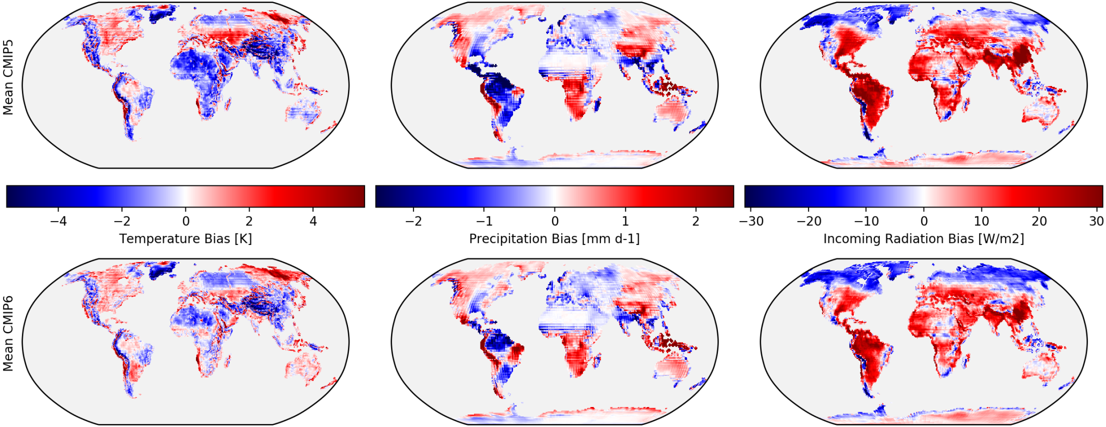
- The CMIP6 suite of land models (right) has improved over the CMIP5 suite of land models (left)
- The multi-model mean outperforms any single model for each suite of models
- The multi-model mean CMIP6 land model is the “best model” overall
- Why did CMIP6 land models improve?



(Hoffman et al., in prep.)

Reasons for Land Model Improvements

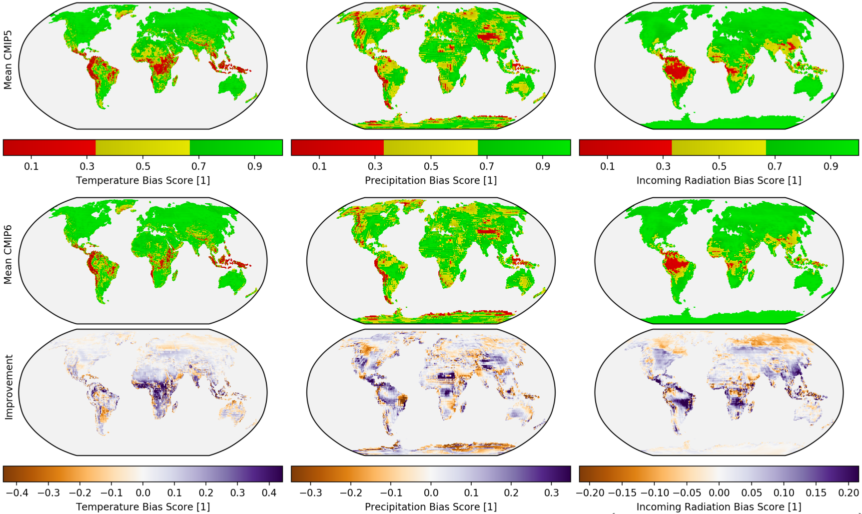
ESM improvements in climate forcings (temperature, precipitation, radiation) likely partially drove improvements exhibited by land carbon cycle models



(Hoffman et al., in prep.)

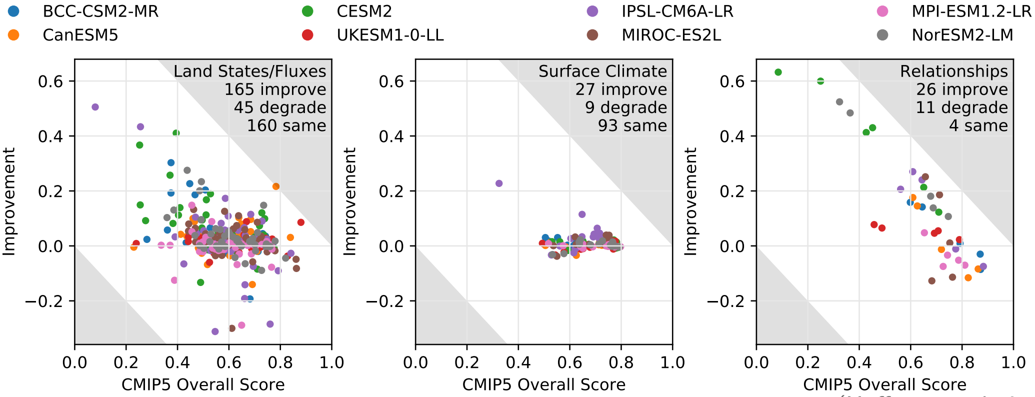
Reasons for Land Model Improvements

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



(Hoffman et al., in prep.)

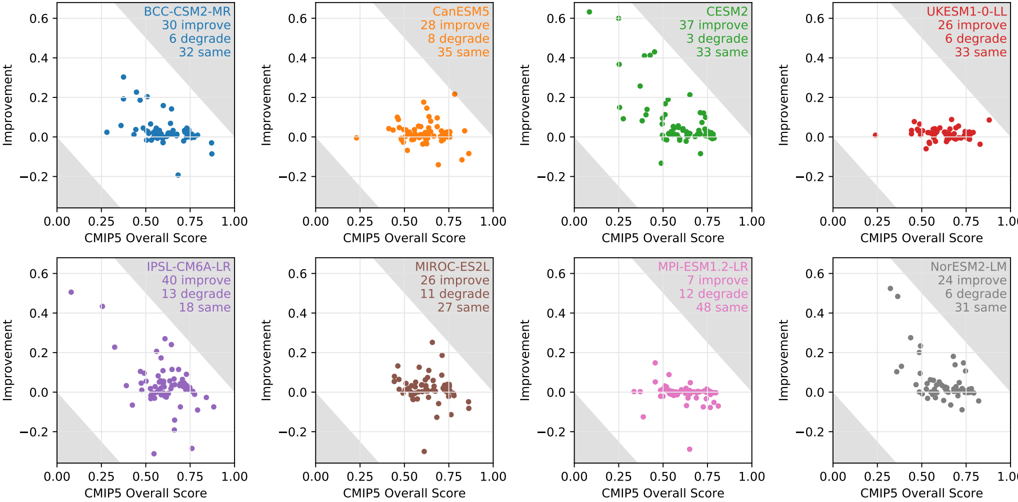
Reasons for Land Model Improvements



(Hoffman et al., in prep.)

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

Improvements by Land Model



(Hoffman et al., in prep.)

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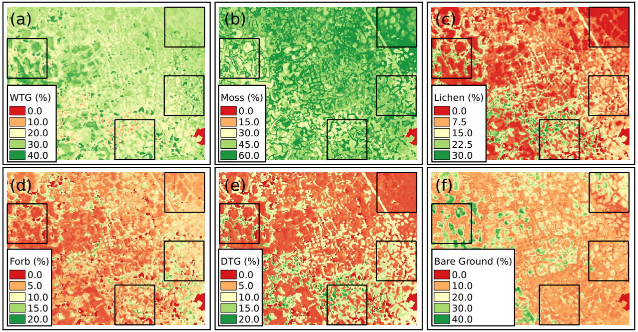
Recent and Ongoing Student Research

High Resolution Vegetation Maps for the BEO

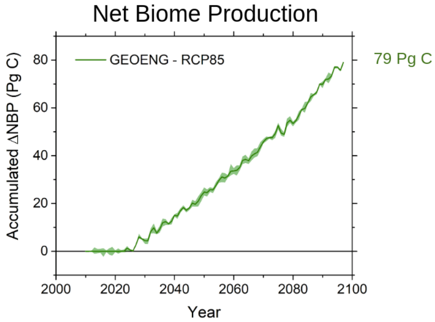
We combined high resolution multi-spectral remote sensing and digital elevation models and vegetation community data to develop machine learning models and produce high resolution maps of vegetation community distributions. Capturing vegetation phenology from repeat imagery exploits variations in the timing of green up for different vegetation types, allowing improved accuracy in resulting data products.

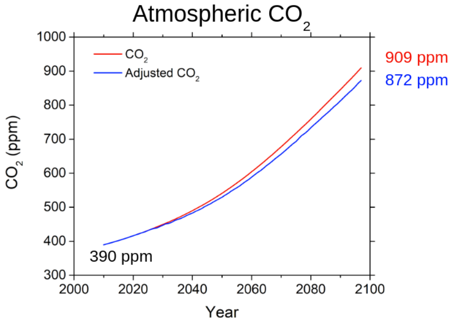


High resolution vegetation maps captures vegetation community and distribution across polygon types

Langford, Z. L., J. Kumar, F. M. Hoffman, R. J. Norby, S. D. Wullschleger, V. L. Sloan, and C. M. Iversen (2016), Mapping Arctic Plant Functional Type Distributions in the Barrow Environmental Observatory Using WorldView-2 and LiDAR Datasets, *Remote Sens.*, 8(9):733, doi:10.3390/rs8090733.

Terrestrial Feedbacks in a Geoengineered Climate



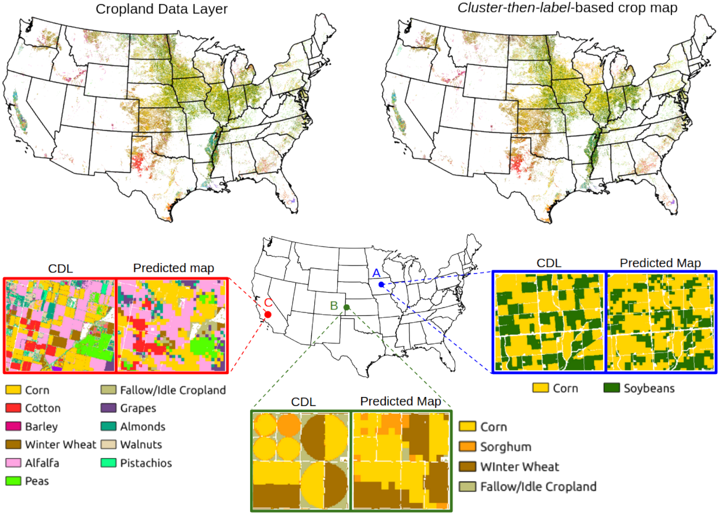


- Reduced ecosystem respiration and small increases in vegetation productivity under geoengineering resulted in an additional 79 Pg C sink by the end of the 21st century in comparison with RCP 8.5
- Increase in atmospheric CO_2 should have been reduced by 4% at 2097 due to the terrestrial carbon feedback ($\Delta[CO_2]_{atm} = 37$ ppm), but marine feedbacks will also influence these results

Yang, Cheng-En, Forrest M. Hoffman, Simone Tilmes, Douglas G. MacMartin, Lili Xia, Jadwiga H. Richter, Ben Kravitz, Michael J. Mills, and Joshua S. Fu (2019), Assessing Terrestrial Biogeochemical Feedbacks in a Strategically Geoengineered Climate, submitted to *Environ. Res. Lett.*

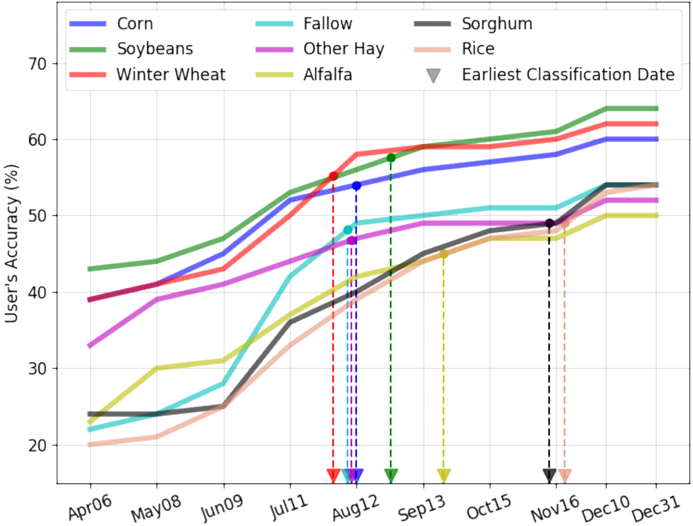
Continental-scale Monitoring of Croplands using Remote Sensing Data and Machine Learning Methods

- Continuous mapping (and monitoring) of crops in near real time – *what is growing?*
- Estimate fractional crop cover in every pixel and predict crop acreage – *where is it growing?*
- Impact of mean and extreme weather on crop yield – *what is the expected yield given growing conditions?*



(Konduri et al., submitted)

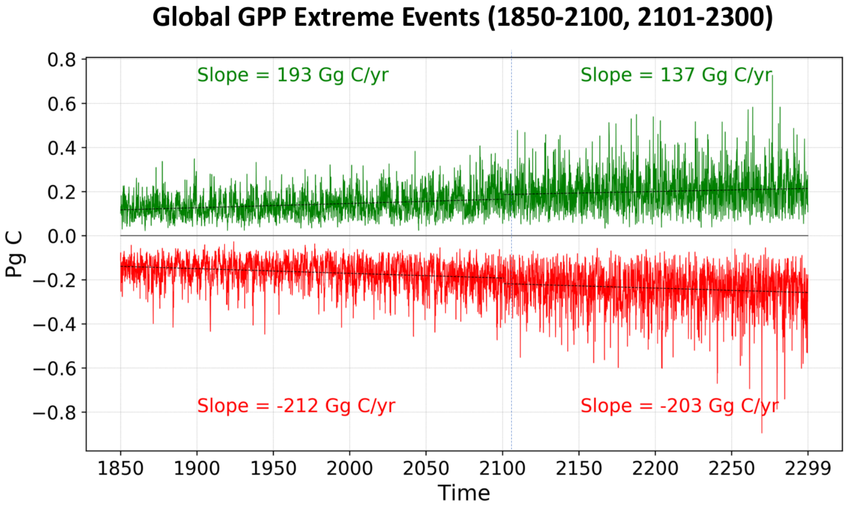
Earliest Date for Crop Type Classification

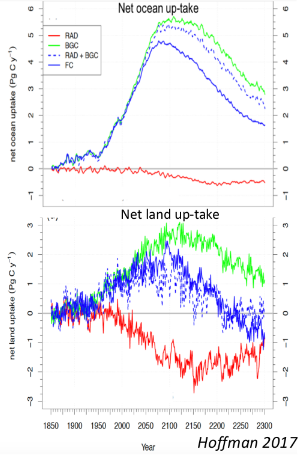


(Konduri et al., submitted)

Konduri, Venkata Shashank, Jitendra Kumar, William W. Hargrove, Forrest M. Hoffman, and Auroop R. Ganguly (2020), Mapping Crops Within the Growing Season Across the United States, submitted to *Remote Sens. Environ.*

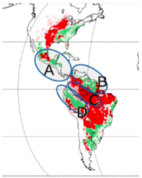
Carbon Cycle Extremes in Multi-Century Simulations





(Sharma et al., in prep.)

Changing Spatial Distribution of Negative Extremes

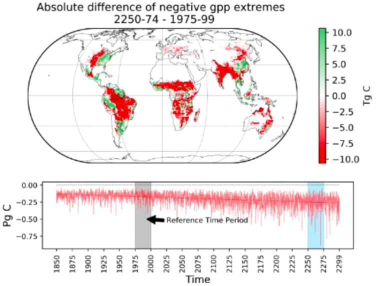


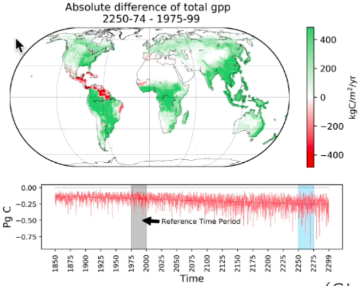
A : Central America

B : North of the South American Tropics

C : Central Amazon Basin

D : Southwest Amazon Basin





(Sharma et al., in prep.)

Sharma, Bharat D., Forrest M. Hoffman, Jitendra Kumar, Nathan Collier, and Auroop R. Ganguly (2020), Quantifying the Changes in Carbon Cycle Extremes with Land Use Change and Attribution to Climate Drivers through Year 2300, in preparation.

Acknowledgments

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