Computational Approaches for Model, Experiment, and Data Integration Supporting Site Characterization and Model Evaluation

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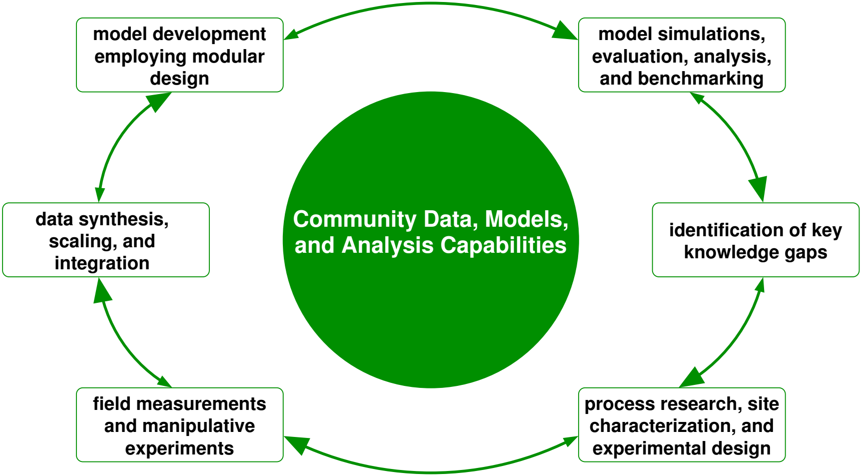
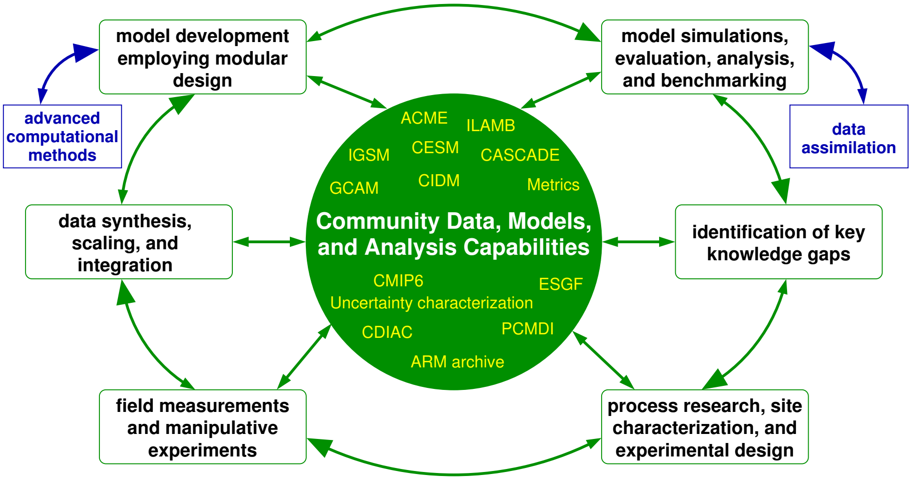
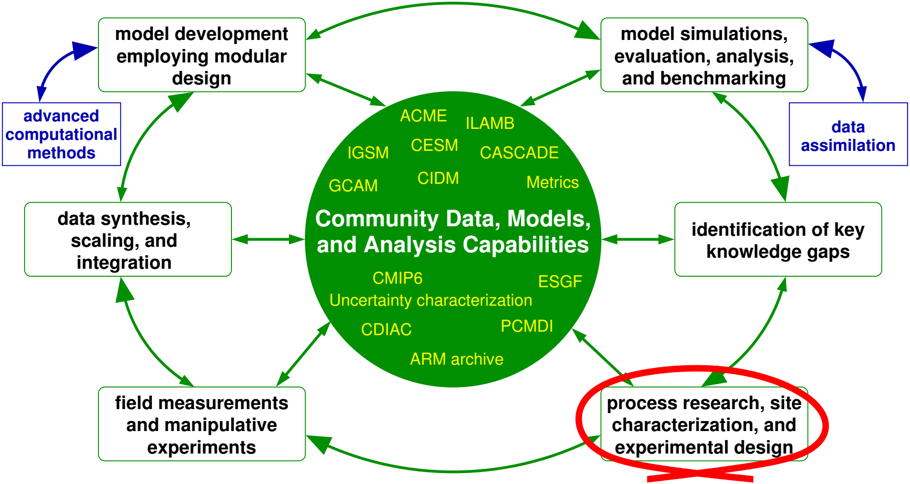
Model, Experiment, and Data Integration Strategy



Model, Experiment, and Data Integration Strategy

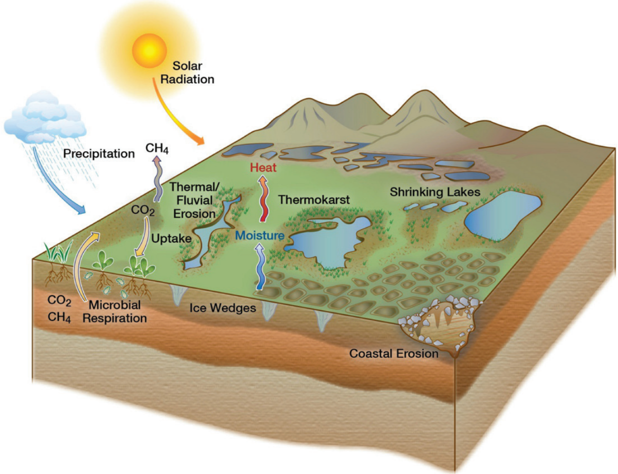


Model, Experiment, and Data Integration Strategy



Next-Generation Ecosystem Experiments (NGEE Arctic)

http://ngee.ornl.gov/



The Next-Generation Ecosystem Experiments (NGEE Arctic) project is supported by the Office of Biological and Environmental Research in the U.S. Department of Energy Office of Science.

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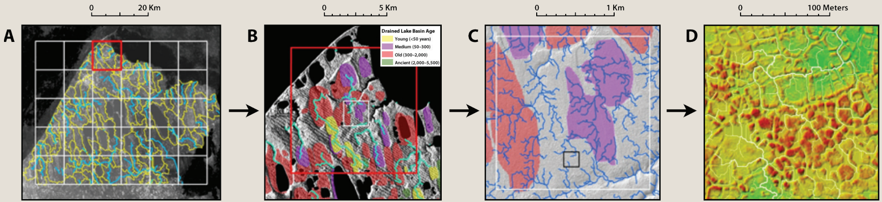
Integrating Across Scales

- NGEE Arctic process studies and observations are strongly linked to model development and application for improving process representation, initialization, calibration, and evaluation.
- A hierarchy of models will be deployed at fine, intermediate, and climate scales to connect observations to models and models to each other in a quantitative up-scaling and down-scaling framework.

Hydrologic and Geomorphic Features at Multiple Scales. *At the scale of (A) a high-resolution ESM, (B) a single ESM grid cell, (C) a 2 × 2 km domain of high-resolution Light Detection and Ranging (LiDAR) topographic data, and (D) polygonal ground. Yellow outlines in panel A show geomorphologically stable hydrologic basins, connected by stream channels (blue). Colored regions in panels B and C show multiple drained thaw lake basins within a single 10 × 10 km grid cell (B) or a 2 × 2 km domain (C), with progressively more detailed representation of stream channels (blue). Colors in panel D represent higher (red) to lower (green) surface elevations for a fine-scale subregion, with very fine drainage features (white). [Los Alamos National Laboratory, University of Alaska Fairbanks, and University of Texas at El Paso]*



Quantitative Sampling Network Design

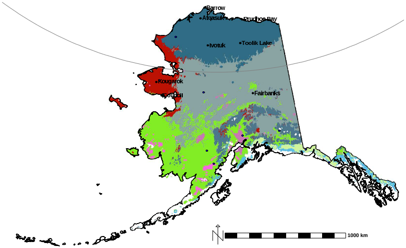
- Resource and logistical constraints limit the frequency and extent of observations, necessitating the development of a systematic sampling strategy that objectively represents environmental variability at the desired spatial scale.
- Required is a methodology that provides a quantitative framework 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 (Schimel et al., 2007; Keller et al., 2008).

Data Layers

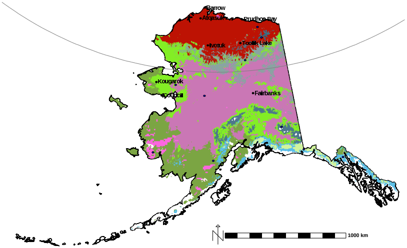
Table: 37 characteristics averaged for the present (2000–2009) and the future (2090–2099).

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

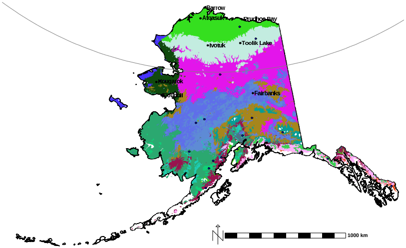


2090–2099

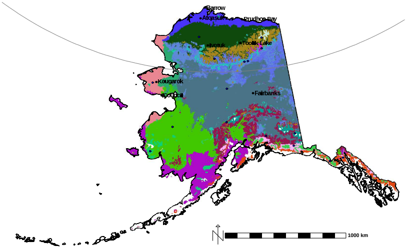
(Hoffman et al., 2013)

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

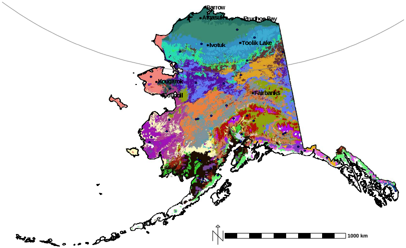


2090–2099

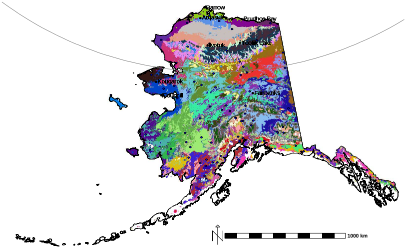
(Hoffman et al., 2013)

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.

50 and 100 Alaska Ecoregions, Present



$k = 50$, 2000–2009



$k = 100$, 2000–2009

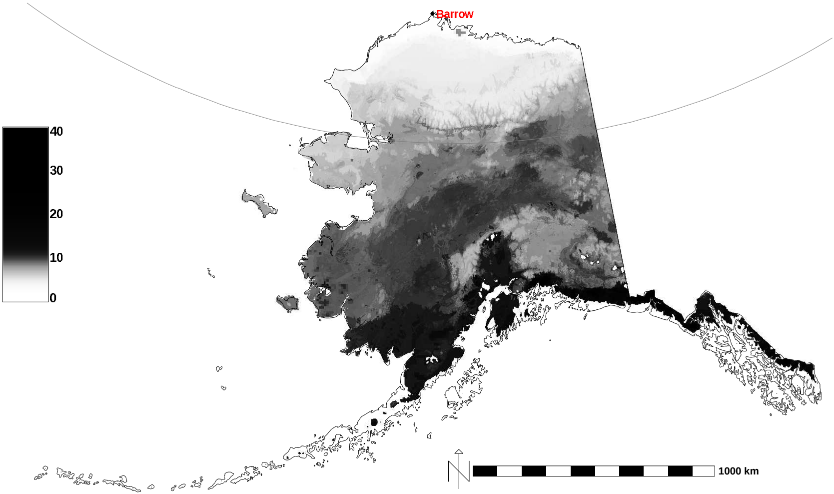
(Hoffman et al., 2013)

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 high levels of division, some regions vanish between the present and future while other region representing new combinations of environmental conditions come into existence.

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.

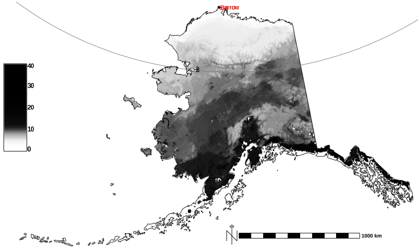
Present Representativeness of Barrow or "Barrow-ness"



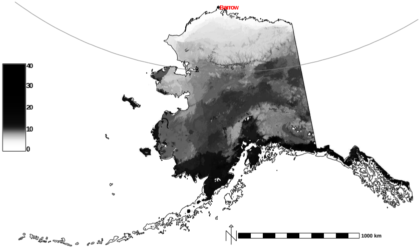
(Hoffman et al., 2013)

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

Present vs. Future Barrow-ness



2000–2009

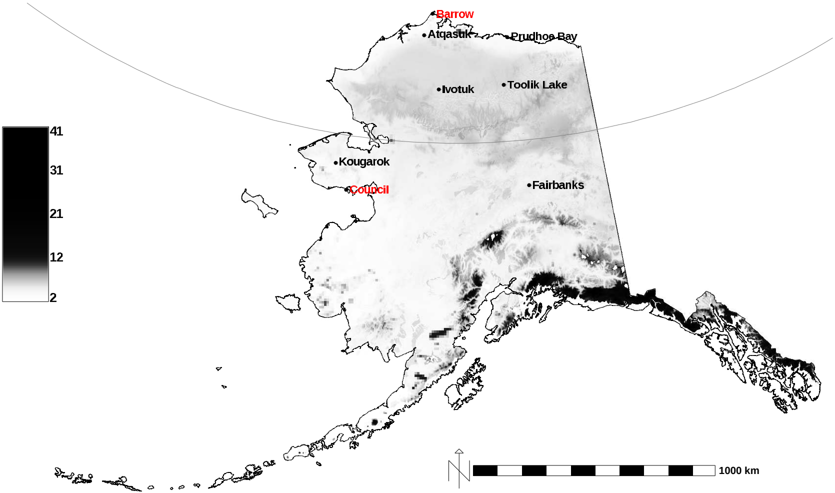


2090–2099

(Hoffman et al., 2013)

As environmental conditions change, due primarily to increasing temperatures, climate gradients shift and the representativeness of Barrow will be reduced in the future.

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

(Hoffman et al., 2013)

State Space Dissimilarities: 8 Sites, Present and Future

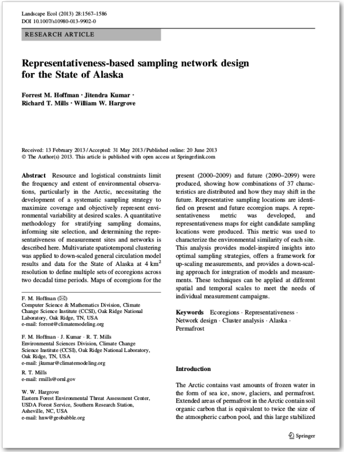
Table: Site state space dissimilarities between the present (2000–2009) and the future (2090–2099).

		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

(Hoffman et al., 2013)

Representativeness: A Quantitative Approach for Scaling

- 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
DOI 10.1007/s10980-013-9902-0

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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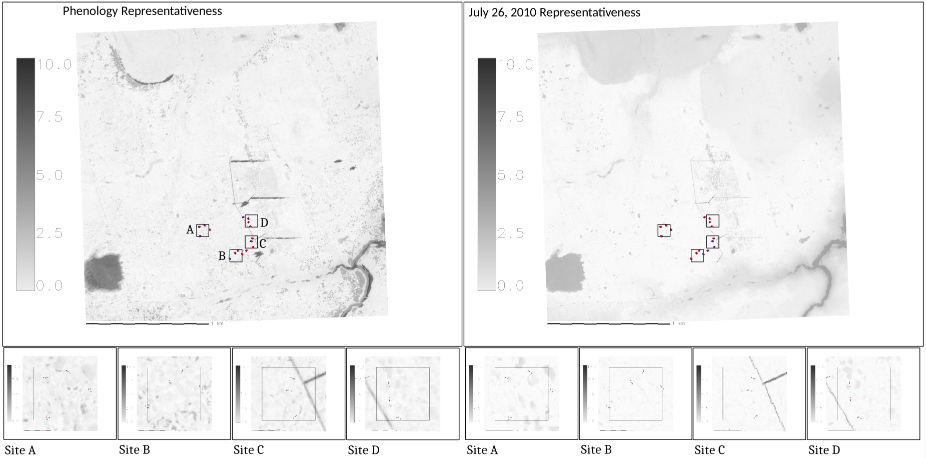
Introduction

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

Springer

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.

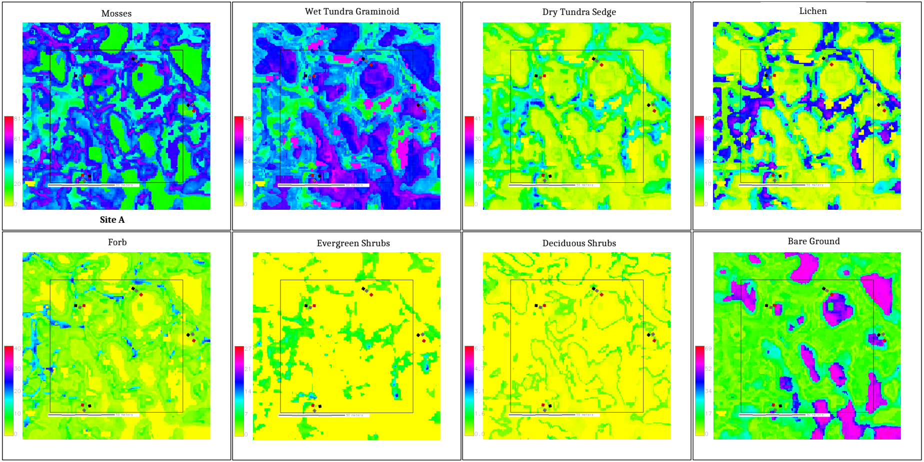
Barrow Environmental Observatory (BEO)



(Langford et al., in review)

Representativeness map for vegetation sampling points in A, B, C, and D sampling area with phenology (left) and without (right), based on WorldView2 satellite images for the year 2010 and LiDAR data.

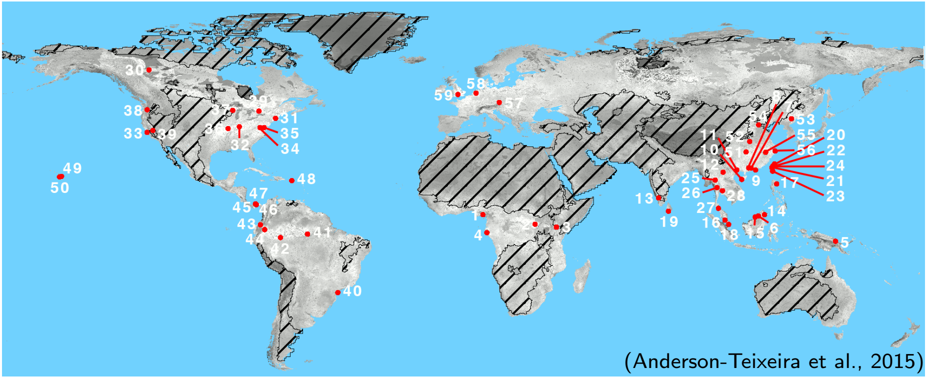
Barrow Environmental Observatory (BEO)



(Langford et al., in review)

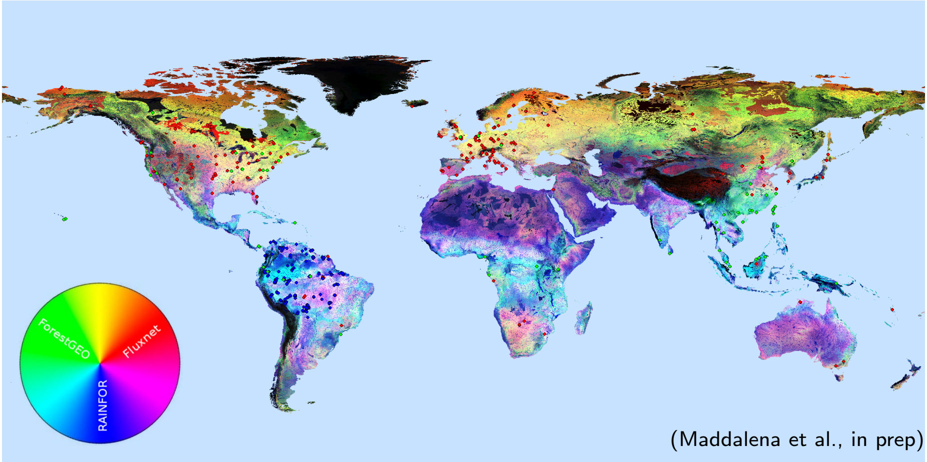
Example plant functional type (PFT) distributions scaled up from vegetation sampling locations.

ForestGEO Network Global Representativeness



Map illustrating ForestGEO network representation of 17 bioclimatic, edaphic, and topographic conditions globally. Light-colored regions are well represented and dark-colored regions are poorly represented by the ForestGEO sampling network. Stippling covers non-forest areas.

Triple-Network Global Representativeness



Map indicates which sampling network offers the most representative coverage at any location. Every location is made up of a combination of three primary colors from Fluxnet (red), ForestGEO (green), and RAINFOR (blue).

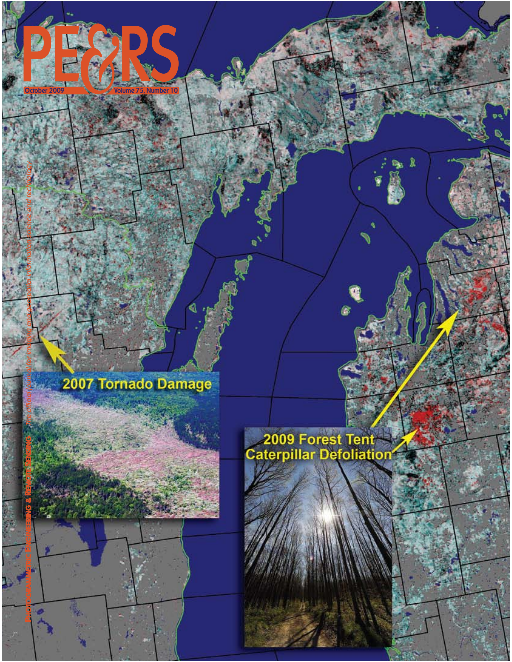
The USDA Forest Service, NASA Stennis Space Center, DOE Oak Ridge National Laboratory, and DOI Eros Data Center have created a system to monitor threats to U.S. forests and wildlands:

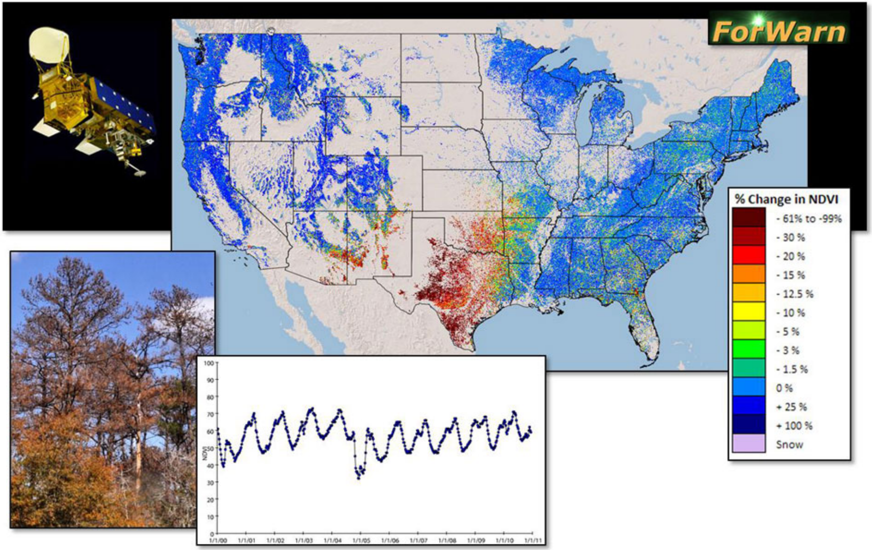
- Tier 1: Strategic — The *ForWarn* system that routinely monitors wide areas at coarser resolution, repeated frequently — a *change detection system* to produce alerts or warnings for particular locations may be of interest
- Tier 2: Tactical — Finer resolution airborne overflights and ground inspections of areas of potential interest — *Aerial Detection Survey (ADS)* monitoring to determine if such warnings become alarms

Tier 2 was in place and managed by the USDA Forest Service, but Tier 1 was needed to optimally direct its labor-intensive efforts and discover new threats sooner.

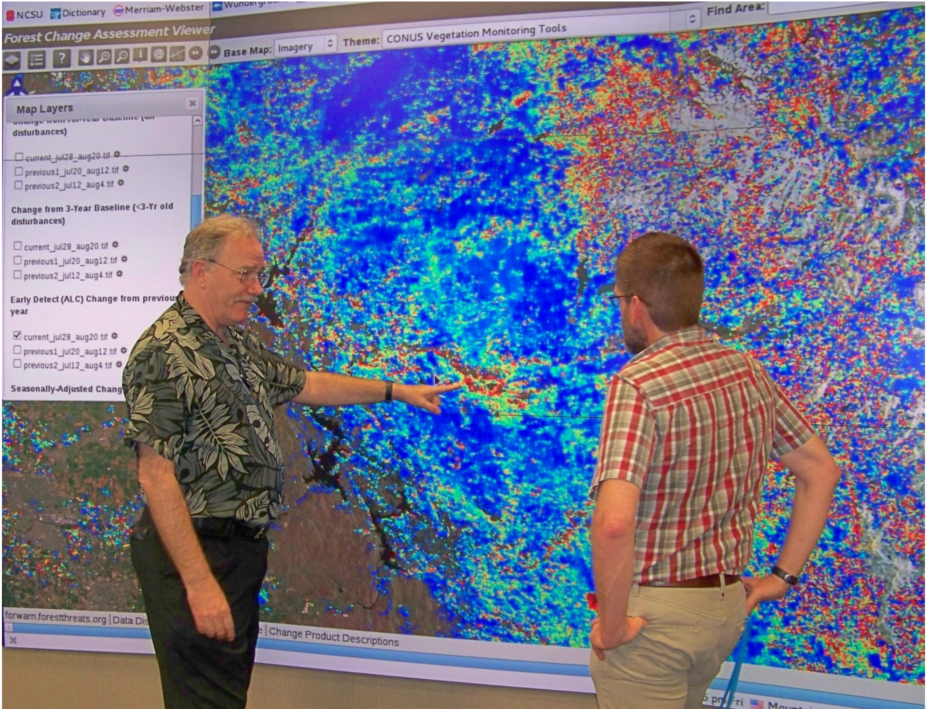
- To detect vegetation disturbances, the current NDVI measurement is compared with the normal, expected baseline for the same location.
- Substantial decreases from the baseline represent potential disturbances.
- Any increases over the baseline may represent vegetation recovery.
- Maximum, mean, or median NDVI may provide a suitable baseline value.

June 10–23, 2009, NDVI is loaded into blue and green; maximum NDVI from 2001–2006 is loaded into red (Hargrove et al., 2009).





ForWarn is a forest change recognition and tracking system that uses high-frequency, moderate resolution satellite data to provide near real-time forest change maps for the continental United States that are updated every eight days. Maps and data products are available in the **Forest Change Assessment Viewer** at `http://forwarn.forestthreats.org/fcav/`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Dictionary
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Find Area:
Forest Change Assessment Viewer
Base Map: Imagery
Theme: CONUS Vegetation Monitoring Tools
Map Layers
disturbances)
current_jul28_aug20.tif
previous1_jul20_aug12.tif
previous2_jul12_aug4.tif
Change from 3-Year Baseline (<3-Yr old disturbances)
current_jul28_aug20.tif
previous1_jul20_aug12.tif
previous2_jul12_aug4.tif
Early Detect (ALC) Change from previou
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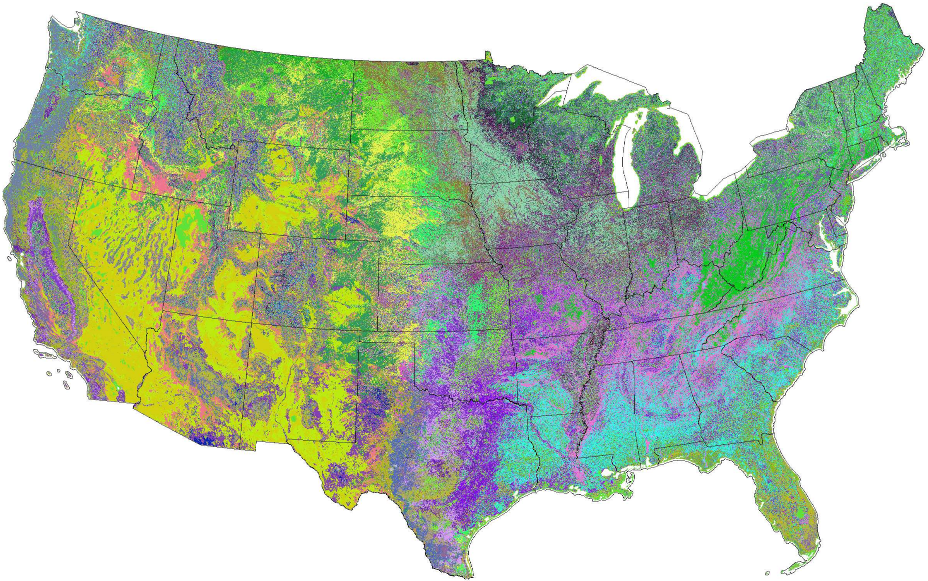
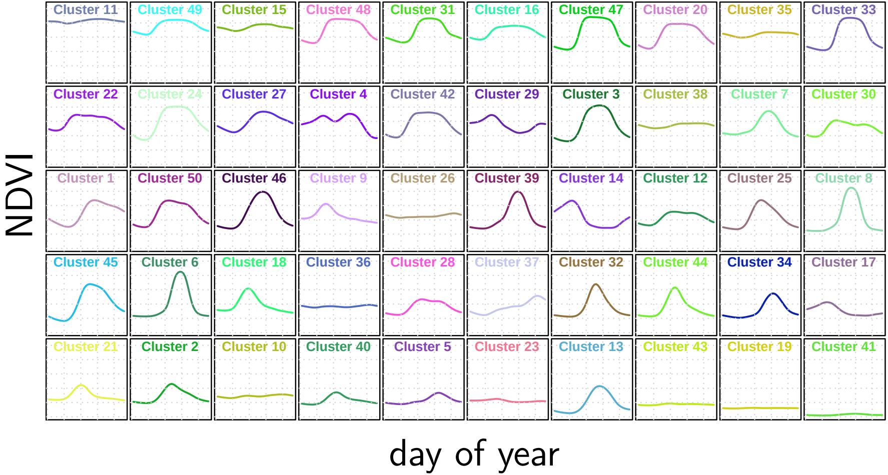
Clustering MODIS NDVI to Produce Phenoregions

- Hoffman and Hargrove previously used *k*-means clustering to detect brine scars from hyperspectral data (Hoffman, 2004) and to classify phenologies from monthly climatology and 17 years of 8 km NDVI from AVHRR (White et al., 2005).
- This data mining approach requires high performance computing to analyze the entire body of the high resolution MODIS NDVI record for the continental U.S.
- $>$101B NDVI values, consisting of $\sim$146.4M cells for the CONUS at 250 m resolution with 46 maps per year for 15 years (2000–2014), analyzed using *k*-means clustering.
- The annual traces of NDVI for every year and map cell are combined into one 395 GB single-precision binary data set of 46-dimensional observation vectors.
- Clustering yields 15 phenoregion maps in which each cell is classified into one of *k* phenoclasses that represent prototype annual NDVI traces.

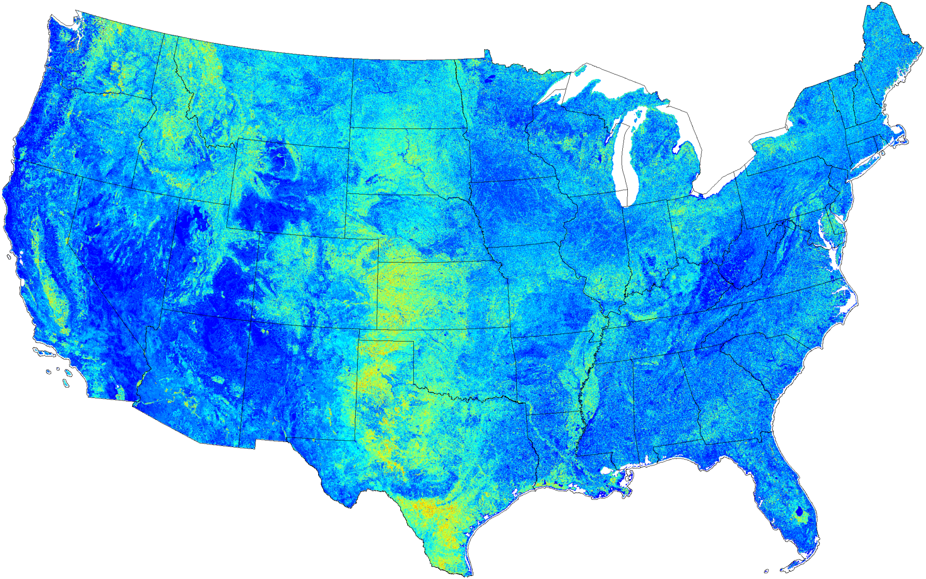
50 Phenoregions for year 2012 (Random Colors)



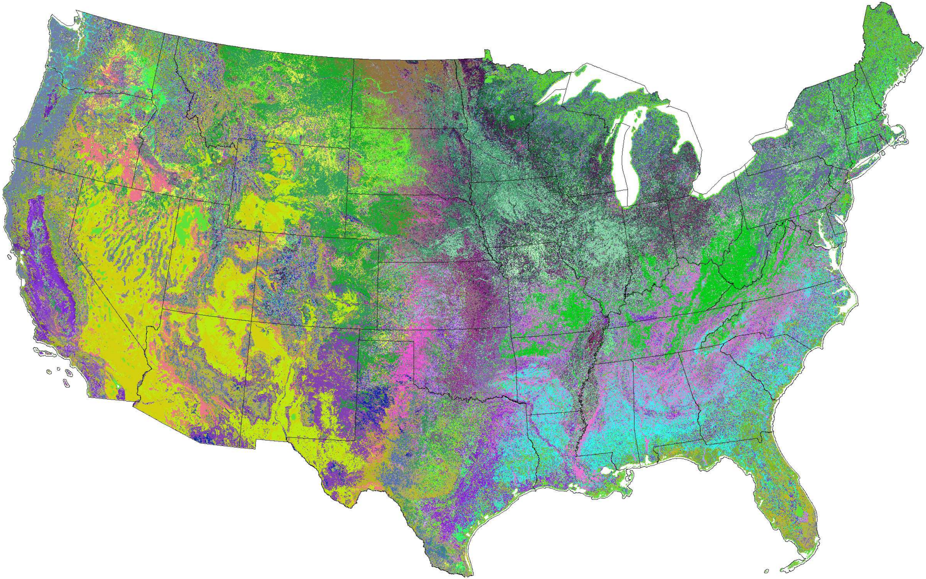
50 Phenoregion Prototypes (Random Colors)



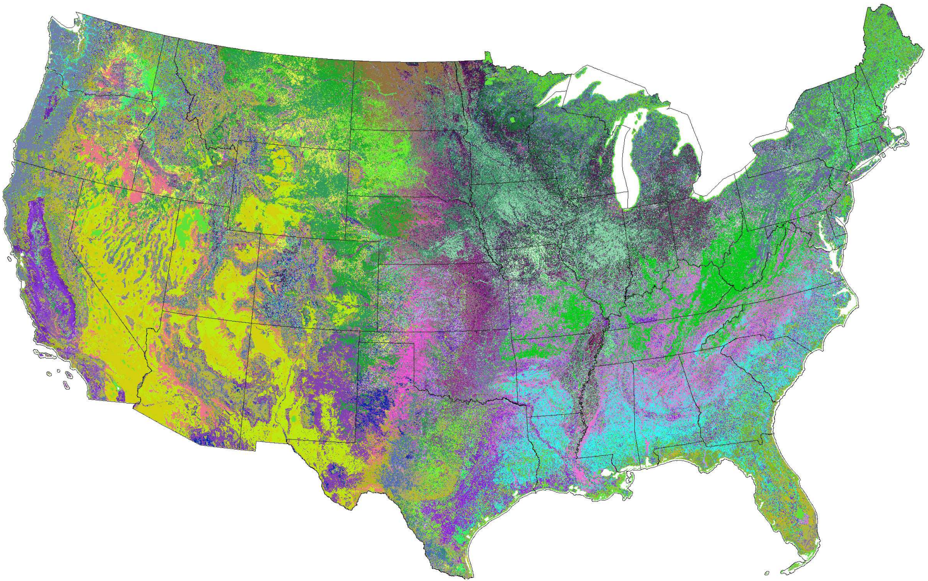
50 Phenoregions Persistence



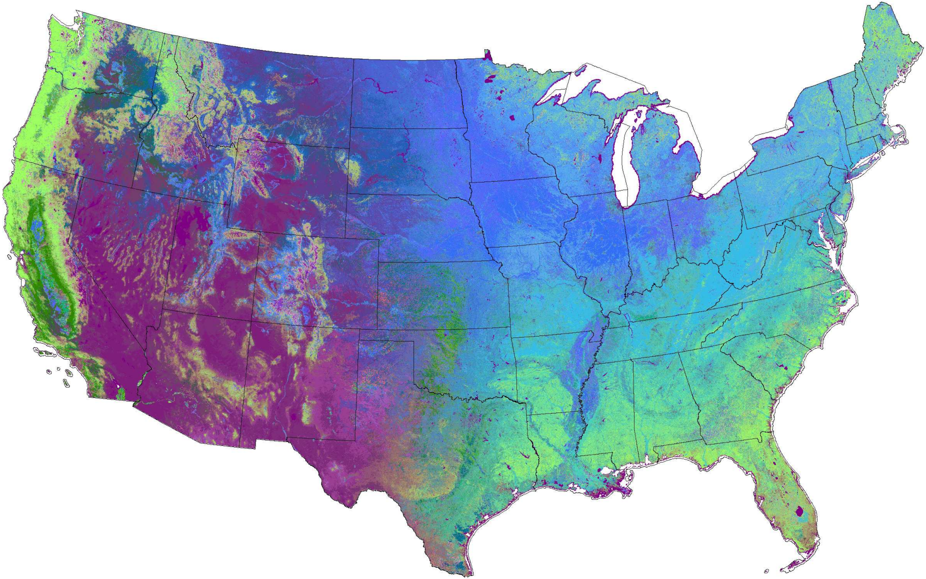
50 Phenoregions Mode (Random Colors)



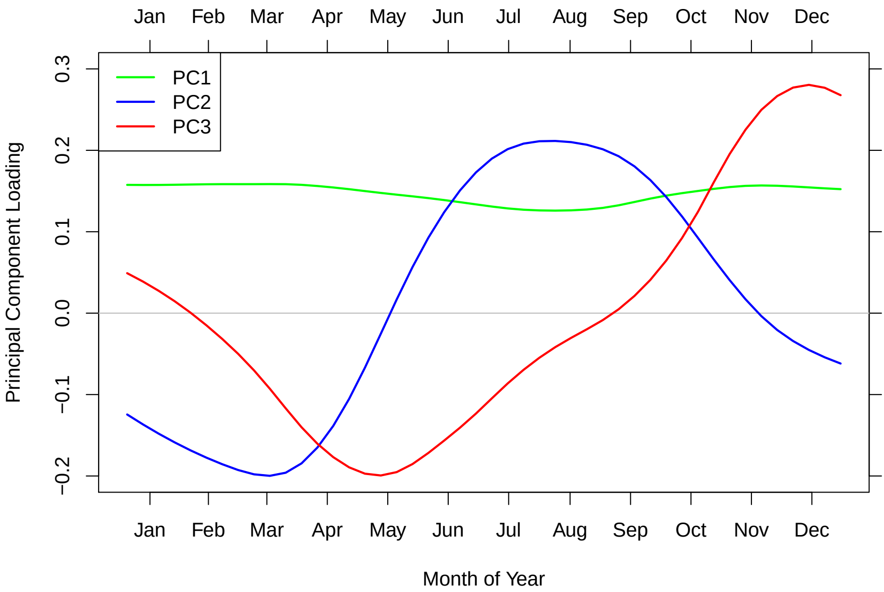
50 Phenoregions Max Mode (Random Colors)



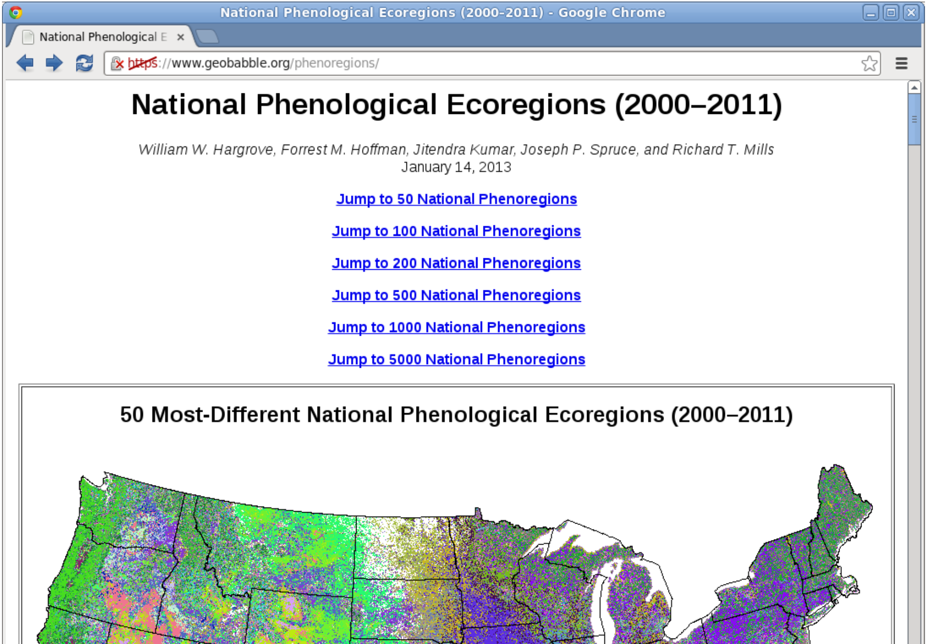
50 Phenoregions Max Mode (Similarity Colors)



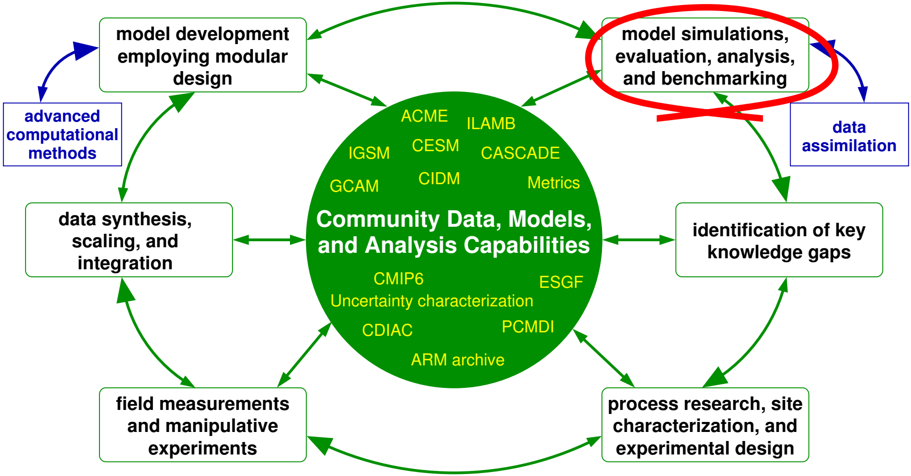
50 Phenoregions Max Mode (Similarity Colors Legend)



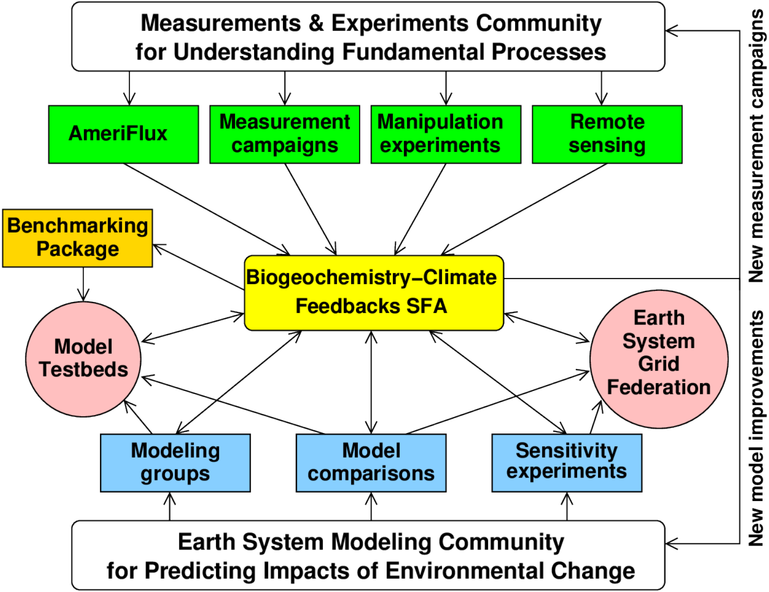
Phenoregions Clearinghouse



Model, Experiment, and Data Integration Strategy

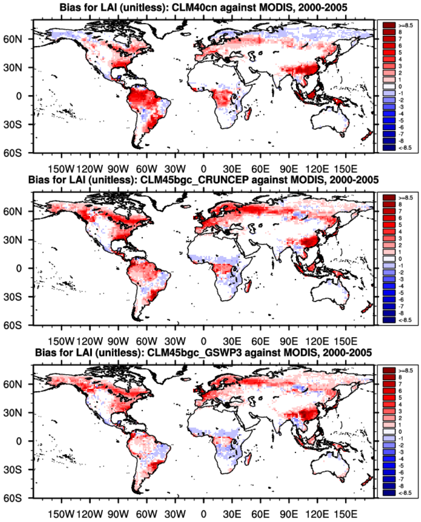


Biogeochemistry–Climate Feedbacks SFA Diagram

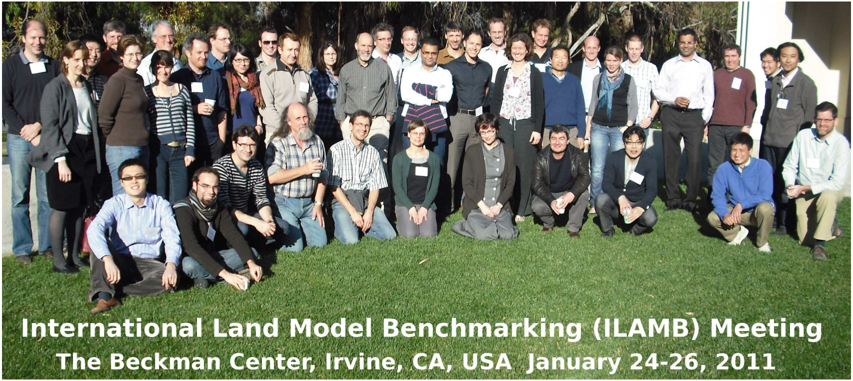


What is ILAMB?

- The **International Land Model Benchmarking (ILAMB)** project seeks to develop internationally accepted standards for land model evaluation.
- Model **benchmarking** can diagnose impacts of model development and guide synthesis efforts like IPCC.
- **Effective benchmarks** must draw upon a broad set of independent observations to evaluate model performance on multiple temporal and spatial scales.
- A free, **open source analysis and diagnostics software package** for community use will enhance model intercomparison projects.



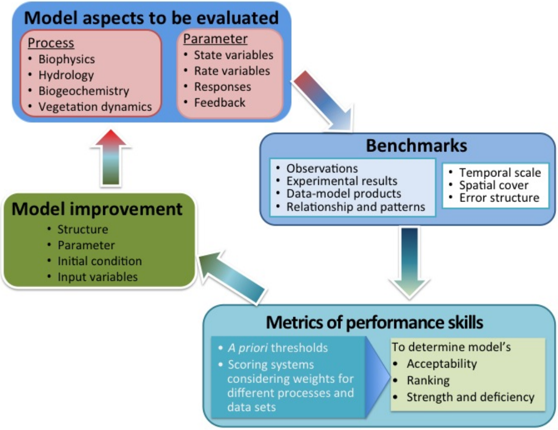
Bias in mean annual leaf area index from comparison of three versions CLM with MODIS.



- We co-organized inaugural meeting and ∼45 researchers participated from the United States, Canada, the United Kingdom, the Netherlands, France, Germany, Switzerland, China, Japan, and Australia.
- **ILAMB Goals:** Develop internationally accepted benchmarks for model performance, advocate for design of open-source software system, and strengthen linkages between experimental, monitoring, remote sensing, and climate modeling communities.
- Methodology for model–data comparison and baseline standard for performance of land model process representations (Luo et al., 2012).

Benchmarking Metholdology (Luo et al., 2012)

- Based on this methodology and prior work in C-LAMP, we developed a new model benchmarking package for ILAMB.
- Prototype is ready for use in NCL and a new version is under development using python.



(Luo et al., 2012)

ILAMB Prototype developed by Mingquan Mu at UCI

- Assesses 24 variables in 4 categories frm ∼45 datasets
  - aboveground live biomass, burned area, carbon dioxide, gross primary production, leaf area index, global net ecosystem carbon balance, net ecosystem exchange, ecosystem respiration, soil carbon
  - evapotranspiration, latent heat, terrestrial water storage anomaly
  - albedo, surface upward SW radiation, surface net SW radiation, surface upward LW radiation, surface net LW radiation, surface net radiation, sensible heat
  - surface air temperature, precipitation, surface relative humidity, surface downward SW radiation, surface downward LW radiation
- Graphics and scoring system
  - annual mean, bias, RMSE, seasonal cycle, spatial distribution, interannual coefficient of variation, spatial distribution, long-term trend
- Software is available at `http://redwood.ess.uci.edu/mingquan/www/ILAMB/index.html`

ILAMB Prototype: Global Variables for 12 Models

Global Variables (Info for Weightings)

	MeanModel	bcc-csm1-1-m	BNU-ESM	CanESM2	CESM1-BGC	GFDL-ESM2G	HadGEM2-ES	inmcm4	IPSL-CM5A-LR	MIROC-ESM	MPI-ESM-LR	MRI-ESM1	NorESM1-ME
Aboveground Live Biomass	0.68	0.52	0.50	0.61	0.65	0.58	0.67	0.54	0.68	0.52	0.51	0.67	0.65
Burned Area	0.38	-	-	-	0.37	-	-	-	-	-	0.38	-	0.38
Carbon Dioxide	0.85	-	0.65	0.65	0.78	0.65	-	-	-	0.79	0.68	0.68	0.75
Gross Primary Productivity	0.77	0.72	0.73	0.64	0.70	0.67	0.68	0.70	0.67	0.69	0.69	0.53	0.70
Leaf Area Index	0.66	0.66	0.41	0.60	0.53	0.49	0.59	0.68	0.66	0.62	0.68	0.43	0.50
Global Net Ecosystem Carbon Balance	0.58	-	0.38	0.27	0.38	0.18	-	0.46	0.25	0.38	0.42	0.27	0.40
Net Ecosystem Exchange	0.49	0.47	0.47	0.39	0.48	0.49	0.46	0.44	0.53	0.48	0.50	0.48	0.48
Ecosystem Respiration	0.75	0.72	0.72	0.65	0.67	0.71	0.66	0.70	0.67	0.68	0.68	0.47	0.66
Soil Carbon	0.55	0.50	0.42	0.56	0.38	0.51	0.51	0.53	0.57	0.53	0.41	0.53	0.39
Summary	0.64	0.59	0.54	0.54	0.55	0.53	0.59	0.57	0.57	0.58	0.54	0.51	0.55
Evapotranspiration	0.75	0.73	0.72	0.72	0.73	0.70	0.74	0.69	0.75	0.70	0.73	0.73	0.72
Latent Heat	0.80	0.76	0.77	0.77	0.78	0.74	0.77	0.72	0.77	0.75	0.76	0.78	0.76
Terrestrial Water Storage Anomaly	0.53	0.45	0.35	0.54	0.48	0.43	-	0.52	0.45	0.52	0.55	0.47	0.45
Summary	0.69	0.65	0.61	0.68	0.66	0.62	0.75	0.64	0.65	0.66	0.68	0.66	0.64
Albedo	0.72	0.71	0.61	0.71	0.73	0.69	0.74	0.67	0.71	0.67	0.73	0.64	0.72
Surface Upward SW Radiation	0.78	0.73	0.67	0.74	0.78	0.74	0.77	0.74	0.74	0.72	0.78	0.67	0.76
Surface Net SW Radiation	0.84	0.86	0.84	0.85	0.85	0.86	0.85	0.84	0.82	0.83	0.87	0.85	0.85
Surface Upward LW Radiation	0.90	0.91	0.91	0.91	0.92	0.91	0.92	0.89	0.90	0.91	0.92	0.92	0.92
Surface Net LW Radiation	0.81	0.82	0.81	0.79	0.82	0.81	0.83	0.79	0.78	0.78	0.81	0.82	0.81
Surface Net Radiation	0.78	0.79	0.76	0.80	0.80	0.80	0.79	0.74	0.77	0.76	0.80	0.78	0.80
Sensible Heat	0.76	0.69	0.70	0.71	0.75	0.69	0.75	0.66	0.69	0.69	0.69	0.72	0.72
Summary	0.79	0.78	0.75	0.78	0.80	0.78	0.80	0.75	0.76	0.76	0.79	0.77	0.79
Surface Air Temperature	0.87	0.87	0.85	0.85	0.88	0.85	0.87	0.85	0.87	0.85	0.88	0.88	0.87
Precipitation	0.70	0.67	0.66	0.67	0.70	0.68	0.72	0.68	0.68	0.68	0.70	0.69	0.69
Surface Relative Humidity	0.81	-	0.80	0.76	0.82	-	-	0.79	0.82	-	-	0.83	0.81
Surface Downward SW Radiation	0.86	0.88	0.87	0.87	0.88	0.87	0.87	0.87	0.83	0.86	0.88	0.86	0.88
Surface Downward LW Radiation	0.90	0.92	0.91	0.91	0.92	0.92	0.92	0.90	0.89	0.91	0.93	0.91	0.91
Summary	0.82	0.82	0.81	0.80	0.83	0.82	0.84	0.81	0.81	0.81	0.84	0.83	0.82
Overall	0.69	0.51	0.59	0.60	0.64	0.56	0.49	0.57	0.57	0.59	0.61	0.59	0.63

ILAMB Prototype: Global Variables for 12 Models

Global Variables (Info for Weightings)

	MeanModel	bcc-csm1-1-m	BNU-ESM	CanESM2	CESM1-BGC	GFDL-ESM2G	HadGE
Aboveground Live Biomass	0.68	0.52	0.50	0.61	0.65	0.58	0.6
Burned Area	0.38	-	-	-	0.37	-	-
Carbon Dioxide	0.85	-	0.65	0.65	0.78	0.65	-
Gross Primary Productivity	0.77	0.72	0.73	0.64	0.70	0.67	0.6
Leaf Area Index	0.66	0.66	0.41	0.60	0.53	0.49	0.5
Global Net Ecosystem Carbon Balance	0.58	-	0.38	0.27	0.38	0.18	-
Net Ecosystem Exchange	0.49	0.47	0.47	0.39	0.48	0.49	0.4
Ecosystem Respiration	0.75	0.72	0.72	0.65	0.67	0.71	0.6
Soil Carbon	0.55	0.50	0.42	0.56	0.38	0.51	0.5
Summary	0.64	0.59	0.54	0.54	0.55	0.53	0.5
Evapotranspiration	0.75	0.73	0.72	0.72	0.73	0.70	0.7
Latent Heat	0.80	0.76	0.77	0.77	0.78	0.74	0.7
Terrestrial Water Storage Anomaly	0.53	0.45	0.35	0.54	0.48	0.43	-
Summary	0.69	0.65	0.61	0.68	0.66	0.62	0.7
Albedo	0.72	0.71	0.61	0.71	0.73	0.69	0.7
Surface Upward SW Radiation	0.78	0.73	0.67	0.74	0.78	0.74	0.7
Surface Net SW	0.84	0.86	0.84	0.85	0.85	0.86	0.8

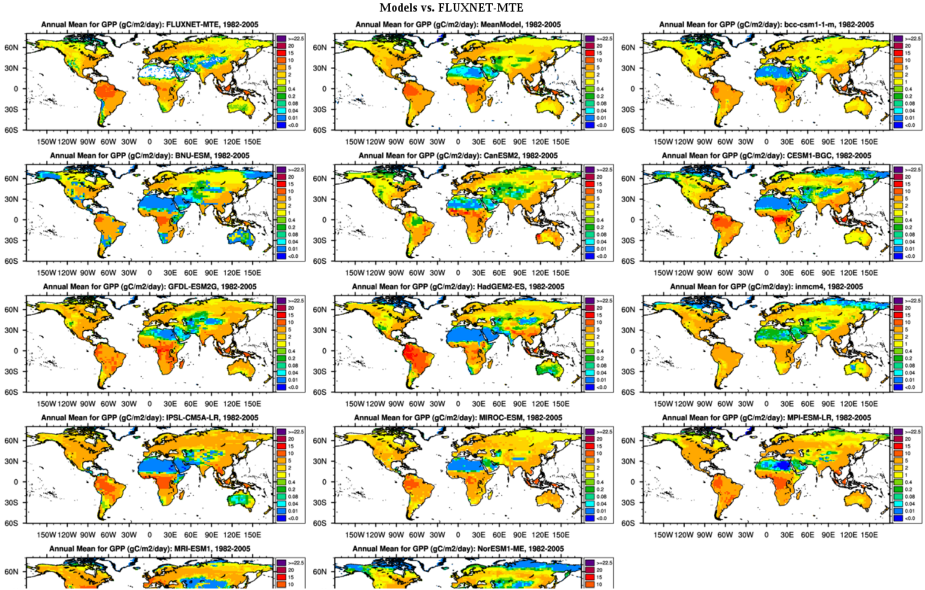
Scoring for Global GPP from Fluxnet-MTE

Diagnostic Summary for Gross Primary Productivity: Model vs. FLUXNET-MTE

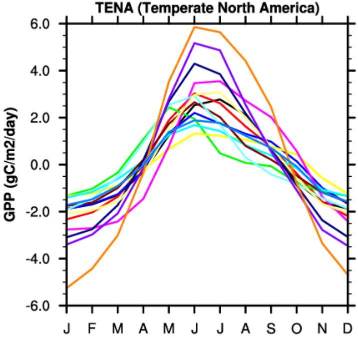
	Global Patterns				Regional and Seasonal Patterns	Scoring (Info)				
	Annual Mean (PgC/yr)	Bias (PgC/yr)	RMSE (PgC/mon)	Phase Difference (months)	Regional Means	Global Bias	RMSE	Seasonal Cycle	Spatial Distribution	Overall
Benchmark [Jung et al. (2009)]	118.4	-	-	0.0	access to plots	-	-	-	-	-
MeanModel	145.3	26.9	4.7	0.6	access to plots	0.77	0.73	0.78	0.94	0.79
bcc-csm1-1-m	114.4	-4.0	6.0	-0.2	access to plots	0.72	0.64	0.80	0.89	0.74
BNU-ESM	102.0	-16.4	6.2	0.1	access to plots	0.69	0.66	0.78	0.84	0.73
CanESM2	129.2	10.8	7.3	0.8	access to plots	0.64	0.60	0.68	0.70	0.64
CESM1-BGC	130.3	11.9	5.8	0.5	access to plots	0.69	0.65	0.76	0.87	0.72
GFDL-ESM2G	175.1	56.7	9.8	0.5	access to plots	0.66	0.54	0.73	0.83	0.66
HadGEM2-ES	145.9	27.5	7.4	0.3	access to plots	0.65	0.58	0.78	0.79	0.68
inmcm4	111.4	-7.0	5.6	0.3	access to plots	0.71	0.66	0.78	0.83	0.73
IPSL-CM5A-LR	166.6	48.2	8.8	0.4	access to plots	0.63	0.56	0.77	0.84	0.67
MIROC-ESM	131.7	13.3	6.2	0.2	access to plots	0.72	0.66	0.74	0.86	0.73
MPI-ESM-LR	169.9	51.5	7.4	0.3	access to plots	0.67	0.62	0.70	0.89	0.70
MRI-ESM1	236.1	117.7	12.5	0.2	access to plots	0.45	0.43	0.79	0.59	0.54
NorESM1-ME	130.4	12.0	6.5	0.5	access to plots	0.66	0.62	0.76	0.84	0.70

Notes: In calculating overall score, rmse score contributes double in comparison with all other scores.

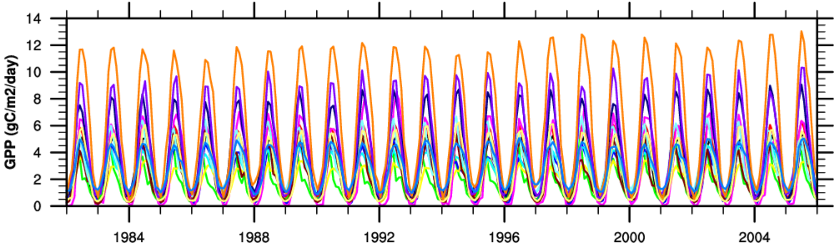
Annual Mean Global GPP

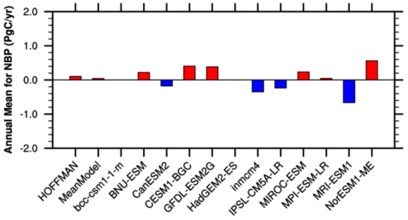


Seasonal Cycle of Regional GPP



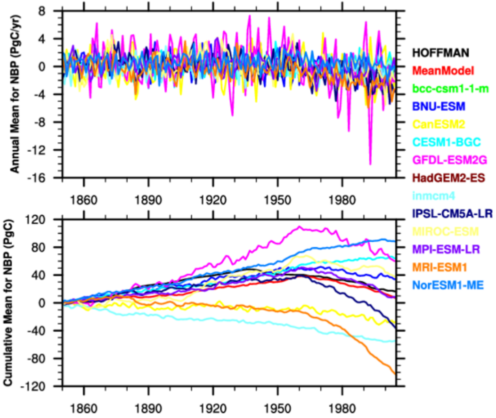
Model	Annual	Bias	RMSE
FLUXNET-MTE	2.36	-999.00	-999.00
MeanModel	2.99	0.63	0.74
bcc-csm1-1-m	1.82	-0.54	1.31
BNU-ESM	2.17	-0.19	0.62
CanESM2	1.76	-0.60	1.08
CESM1-BGC	2.45	0.08	0.78
GFDL-ESM2G	2.85	0.49	1.16
HadGEM2-ES	2.12	-0.24	0.72
inmcm4	3.06	0.70	1.20
IPSL-CM5A-LR	3.95	1.59	1.90
MIROC-ESM	2.48	0.12	0.35
MPI-ESM-LR	4.27	1.91	2.38
MRI-ESM1	6.13	3.76	4.46
NorESM1-ME	2.84	0.48	0.74



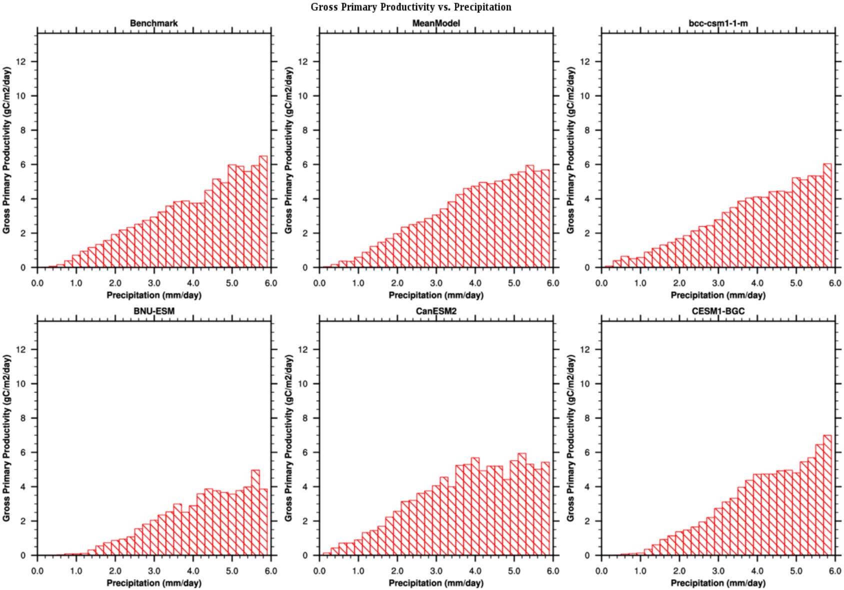


Global Net Ecosystem Carbon Balance

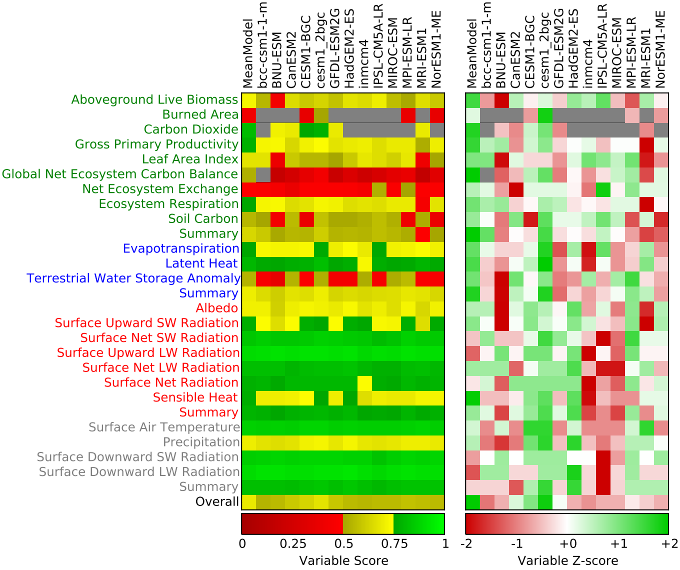
Long term carbon storage



Functional Relationships: GPP vs. Precipitation



ILAMB Model Scoring by Variable



ILAMB Next Generation Layout

Ecosystem and Carbon Cycle

	bcc-csm1-1	bcc-csm1-1-m	BNU-ESM	CanESM2	CCSM4	CESM1-BGC	GFDL-ESM2G	HadGEM2-CC	HadGEM2-ES	inmcm4	IPSL-CM5A-LR	IPSL-CM5A-MR	MIROC-ESM	MIROC-ESM-CHEM	MPI-ESM-LR	MRI-ESM1	NorESM1-M	NorESM1-ME	
Biomass	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Burned Area	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Carbon Dioxide	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Gross Primary Productivity	0.53	0.57	0.52	0.47	0.52	0.52	0.52	0.51	0.51	0.05	0.50	0.52	0.55	0.55	0.55	0.45	0.54	0.54	▼
Leaf Area Index	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Global Net Ecosystem Carbon Balance	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Net Ecosystem Exchange	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Ecosystem Respiration	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Soil Carbon	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼

Hydrology Cycle

	bcc-csm1-1	bcc-csm1-1-m	BNU-ESM	CanESM2	CCSM4	CESM1-BGC	GFDL-ESM2G	HadGEM2-CC	HadGEM2-ES	inmcm4	IPSL-CM5A-LR	IPSL-CM5A-MR	MIROC-ESM	MIROC-ESM-CHEM	MPI-ESM-LR	MRI-ESM1	NorESM1-M	NorESM1-ME	
Evapotranspiration	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Latent Heat	0.39	0.39	0.43	0.36	0.44	0.44	0.41	0.42	0.42	0.40	0.44	0.42	0.43	0.43	0.40	0.41	0.45	0.45	▲
Fluxnet-MTE (75.0%)	0.27	0.26	0.31	0.28	0.31	0.31	0.29	0.28	0.28	0.28	0.31	0.30	0.34	0.34	0.28	0.27	0.34	0.33	
Fluxnet (25.0%)	0.77	0.76	0.78	0.60	0.83	0.83	0.78	0.86	0.85	0.77	0.83	0.78	0.71	0.71	0.76	0.82	0.79	0.78	
Terrestrial Water Storage Anomaly	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼

Radiation and Energy Cycle

	bcc-csm1-1	bcc-csm1-1-m	BNU-ESM	CanESM2	CCSM4	CESM1-BGC	GFDL-ESM2G	HadGEM2-CC	HadGEM2-ES	inmcm4	IPSL-CM5A-LR	IPSL-CM5A-MR	MIROC-ESM	MIROC-ESM-CHEM	MPI-ESM-LR	MRI-ESM1	NorESM1-M	NorESM1-ME	
Albedo	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Surface Upward SW Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Surface Net SW Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Surface Upward LW Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Surface Net LW Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Surface Net Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Sensible Heat	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼

Forcings

	bcc-csm1-1	bcc-csm1-1-m	BNU-ESM	CanESM2	CCSM4	CESM1-BGC	GFDL-ESM2G	HadGEM2-CC	HadGEM2-ES	inmcm4	IPSL-CM5A-LR	IPSL-CM5A-MR	MIROC-ESM	MIROC-ESM-CHEM	MPI-ESM-LR	MRI-ESM1	NorESM1-M	NorESM1-ME	
Surface Air Temperature	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Precipitation	0.36	0.35	0.36	0.36	0.37	0.37	0.35	0.36	0.36	0.34	0.35	0.35	0.36	0.36	0.35	0.35	0.36	0.36	▼
Surface Downward SW Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼
Surface Downward LW Radiation	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	~	▼

ILAMB Next Generation Layout

GrossPrimaryProductivity / Fluxnet−MTE / global − Google Chrome

GrossPrimaryProduc ×

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www.climatemodeling.org/~nate/ILAMB/EcosystemandCarbonCycle/GrossPrimaryProductivity/Fluxnet-MTE//Fluxnet-MTE.html

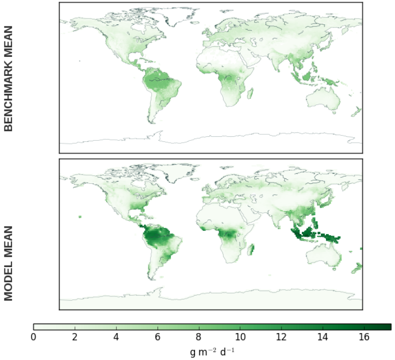
GrossPrimaryProductivity / Fluxnet-MTE / global

Single Model | All Models

global

Model	Data	Period Mean [Pg yr-1]	Bias [Pg yr-1]	RMSE [Pg yr-1]	Phase Shift [d]	Bias Score [-]	RMSE Score [-]	Phase Score [-]	Interannual Variability Score [-]	Spatial Distribution Score [-]	Overall Score [-]
Benchmark	[-]	118.895									
CLM40cn	[-]	134.761	20.969	0.31	22.039	0.402	0.178	0.775	0.333	0.81	0.81
CLM45bgc	[-]	119.838	5.809	0.27	21.843	0.435	0.152	0.788	0.355	0.902	0.902
CLM45bgc_GSWP3	[-]	111.456	-2.765	0.269	21.804	0.423	0.152	0.783	0.331	0.903	0.903

Temporally integrated period mean



Future ILAMB Development and Application

- Current ILAMB Prototype was applied to:
  - Model development of the Community Land Model (CLM)
  - CMIP5 Historical and esmHistorical simulations
  - ACME Land Model evaluation
- Within U.S. Department of Energy projects:
  - NGEE Arctic, NGEE Tropics, and SPRUCE are adopting the framework for evaluating process parameterizations & integrating field observations
  - ACME is developing metrics for evaluation of new land model features
  - BGC Feedbacks is developing the framework and benchmarking MIPs
- Future projects where we hope to apply ILAMB:
  - CMIP6, including C^4MIP, LS3MIP, and LUMIP
  - TRENDY
  - PLUME-MIP
- We will host a second ILAMB Workshop in the U.S. in the Washington, DC area May 16–18, 2016

Acknowledgements

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