Characterizing Tropical Forest Representativeness for Optimizing Sampling Network Coverage

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Next Generation Ecosystem Experiments (NGEE Tropics)

- **Overarching Goal:** Determine if tropical forests will continue to act as a large net carbon sink throughout the 21st century.
- **Grand Deliverable:** A representative, process-rich tropical forest ecosystem model, extending from bedrock to the top of the vegetative canopy, in which the evolution and feedbacks of tropical ecosystems in a changing climate can be modeled at the scale/resolution of a next generation Earth System Model grid cell.
- **Key Science Questions:**
  - How do tropical forest ecosystems respond to changing temperature, precipitation, and atmospheric CO_2 concentration?
  - How do disturbance and landuse change in tropical forests affect carbon, water and energy fluxes?
  - How will the response of tropical forests to climate change be modulated by spatial and temporal heterogeneity in belowground processes?

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Next Generation Ecosystem Experiments (NGEE Tropics)

Incorporating Models and Experiments to Advance Knowledge

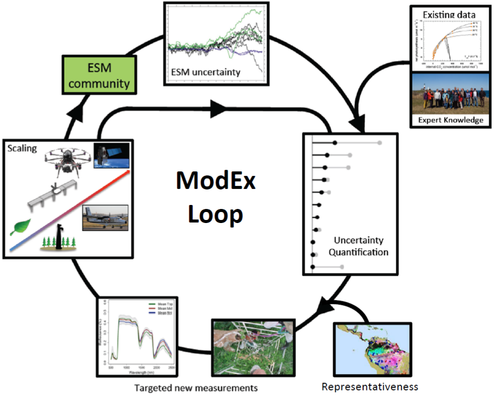
Develop Modeling Framework

Knowledge assessment
UQ, gap analysis, structural uncertainty

Prioritization
of knowledge gaps

Design and execute
ModEx loop
for priority gaps

Integrate
new model in Terrestrial Land Model

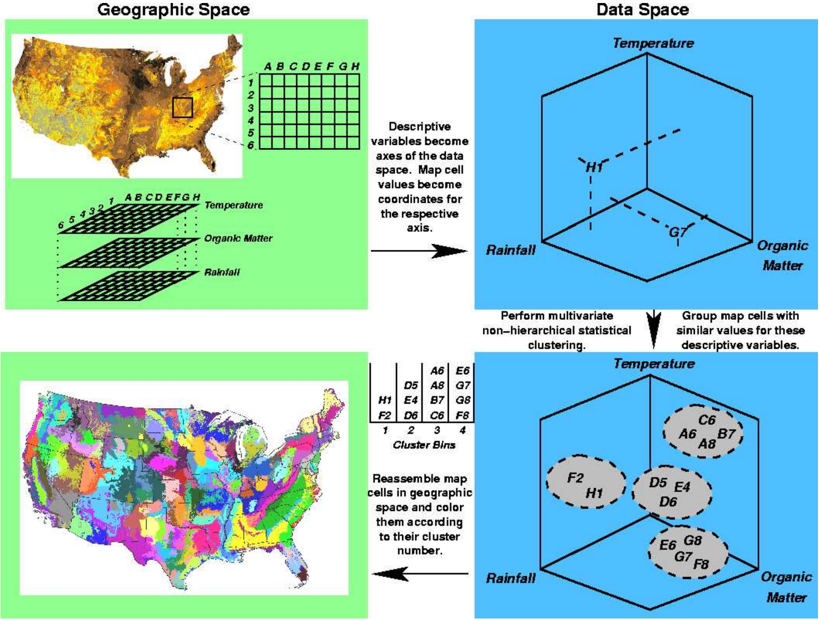


Understanding the representativeness of measurements helps to minimize sampling biases that may influence interpretation of observations.

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 desired spatial scales.
- 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 $\times$ 4 km) globally to demonstrate its utility for representativeness and scaling.
- Method recently used to quantify representativeness of candidate sampling sites for the State of Alaska (Hoffman et al., 2013).
- 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).

Multivariate Spatiotemporal Clustering (MSTC)



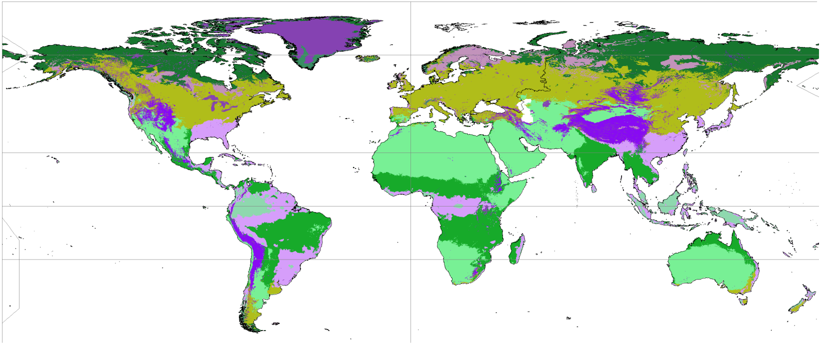
(Hargrove and Hoffman, 2004)

17 Data Layers

Variable Description	Units
Bioclimatic Variables	
Precipitation during the hottest quarter	mm
Precipitation during the coldest quarter	mm
Precipitation during the driest quarter	mm
Precipitation during the wettest quarter	mm
Ratio of precipitation to potential evapotranspiration	unitless
Temperature during the coldest quarter	$^\circ$C
Temperature during the hottest quarter	$^\circ$C
Day/night diurnal temperature difference	$^\circ$C
Sum of monthly T_{avg} where $T_{\text{avg}} \geq 5^\circ$C	$^\circ$C
Integer number of consecutive months where $T_{\text{avg}} \geq 5^\circ$C	unitless
Edaphic Variables	
Available water holding capacity of soil	unitless
Bulk density of soil	g/cm^3
Carbon content of soil	g/cm^2
Nitrogen content of soil	g/cm^2
Topographic Variables	
Compound topographic index (relative wetness)	unitless
Solar interception	kW/m^2
Elevation	m

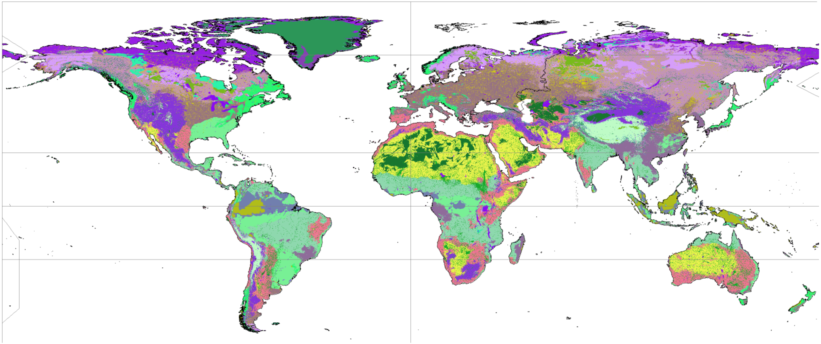
(Potter and Hargrove, 2013)

10 Global Ecoregions, Random Colors



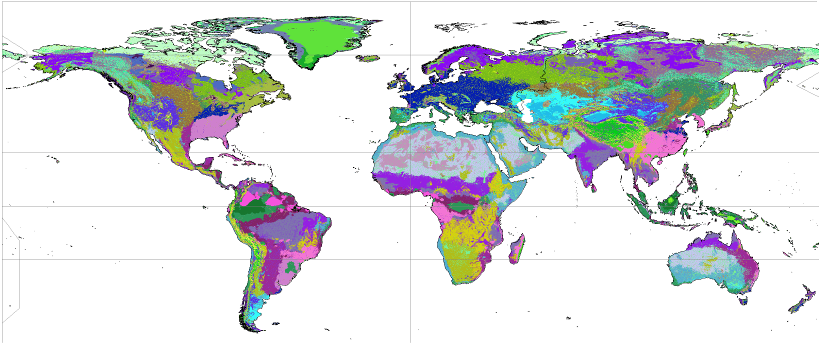
The 10 most different ecoregions globally are shown in random colors. Notice that areas with similar environmental characteristics are colored the same no matter where they occur on Earth.

25 Global Ecoregions, Random Colors



The 25 most different ecoregions globally are shown in random colors. Notice that areas with similar environmental characteristics are colored the same no matter where they occur on Earth.

50 Global Ecoregions, Random Colors



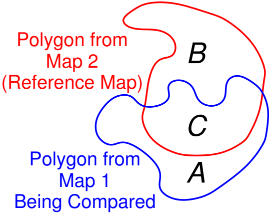
The 50 most different ecoregions globally are shown in random colors. Notice that areas with similar environmental characteristics are colored the same no matter where they occur on Earth.

Automated Supervision for Unsupervised Classification

- Clustering is an unsupervised classification technique, so ecoregions have no descriptive labels (e.g., **Eastern Deciduous Forest Biome**).
- **Label stealing** allows us to perform automated “supervision” by “stealing” the best corresponding human-created descriptive labels to assign to ecoregions.
- We employ a tool called **Mapcurves** to select the best ecoregion labels from ecoregionalizations delineated by human experts.
- We consider an entire library of ecoregion and land cover maps, and choose the label with the highest **goodness-of-fit (GOF)** score for every ecoregions polygon.

Mapcurves: A Method for Comparing Categorical Maps

- Hargrove et al. (2006) developed a method for quantitatively comparing categorical maps that is
  - independent of differences in resolution,
  - independent of the number of categories in maps, and
  - independent of the directionality of comparison.

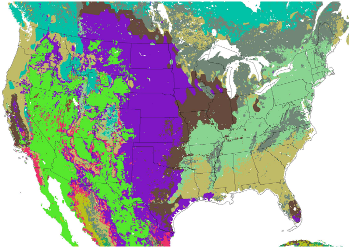


Goodness of Fit (GOF) is a unitless measure of spatial overlap between map categories:

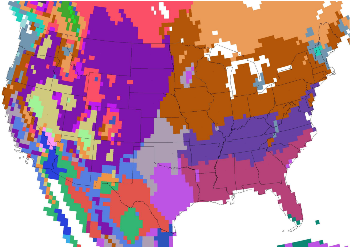
$$\text{GOF} = \sum_{\text{polygons}} \frac{C}{B+C} \times \frac{C}{A+C}$$

- GOF provides "credit" for the area of overlap, but also "debit" for the area of non-overlap.
- Mapcurves comparisons allow us to reclassify any map in terms of any other map (*i.e.*, color Map 2 like Map 1).
- A greyscale GOF map shows the degree of correspondence between two maps based on the highest GOF score.

Expert-Derived Land Cover/Vegetation Type Maps



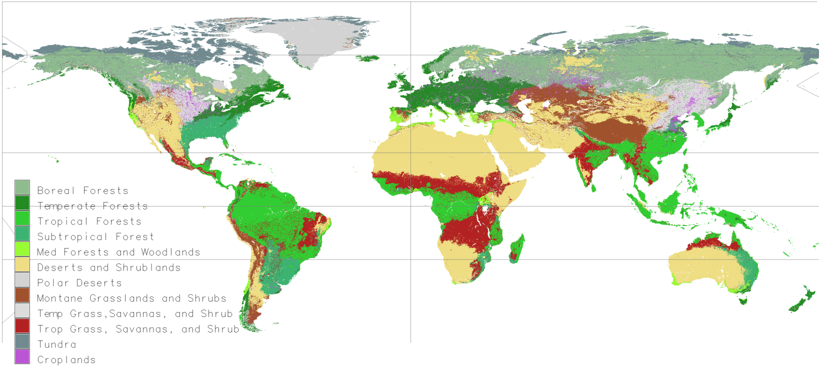
Foley Land Cover



Holdridge Life Zones

	Expert Map	# Cats
1.	DeFries UMd Vegetation	12
2.	Foley Land Cover	14
3.	Fedorova, Volkova, and Varlyguin World Vegetation Cover	31
4.	GAP National Land Cover	578
5.	Holdridge Life Zones	25
6.	Küchler Types	117
7.	BATS Land Cover	17
8.	IGBP Land Cover	16
9.	Olson Global Ecoregions	49
10.	Seasonal Land Cover Regions	194
11.	USGS Land Cover	24
12.	Leemans-Holdridge Life Zones	26
13.	Matthews Vegetation Types	19
14.	Major Land Resource Areas	197
15.	National Land Cover Database 2006	16
16.	Wilson, Henderson, & Sellers Primary Vegetation Types	23
17.	Landfire Vegetation Types	443
18.	ESA Global Land Cover	23

50 Ecoregions Reclassified by Label Stealing



The 50 quantitatively derived global ecoregions are reduced to 12 broadly defined land cover classes through the Label Stealing process.

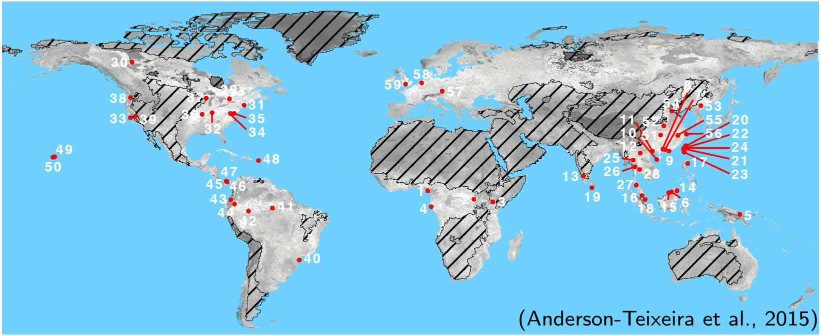
Global Forest Site Representativeness

- This representativeness analysis uses the standardized *n*-dimensional data space formed from all 17 input data layers.
- In this data space, the Euclidean distance between a sampling location (like Manaus, Brazil) 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.

Site Representativeness: CTFS-ForestGEO, Mpala, Kenya

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

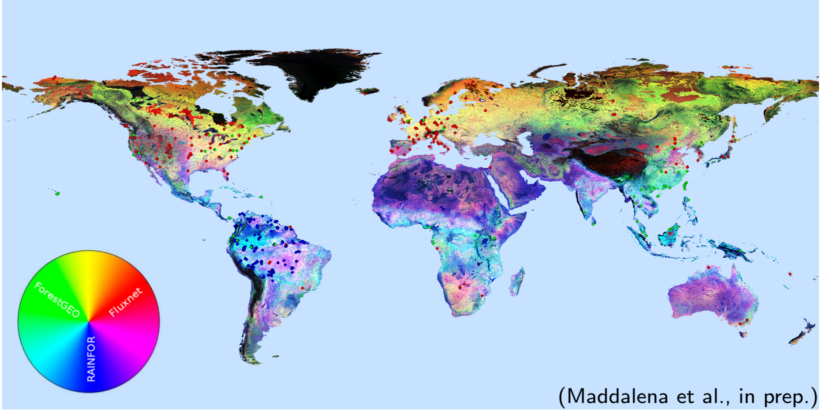
ForestGEO Network Global Representativeness



(Anderson-Teixeira et al., 2015)

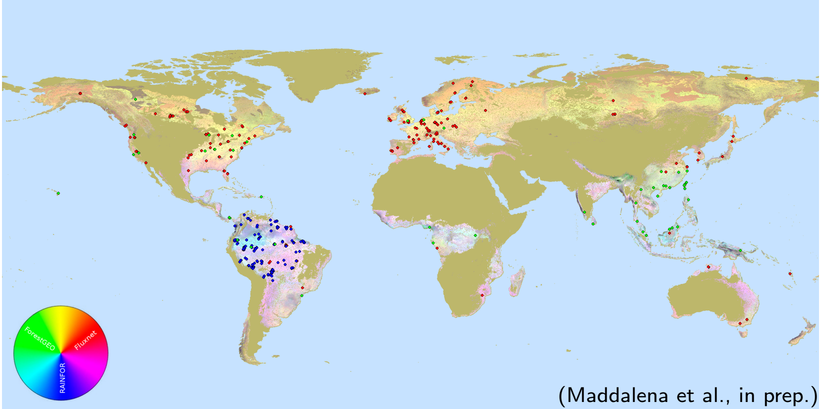
Map illustrating ForestGEO network representation of 17 bioclimatic, edaphic, and topographic conditions globally. Light-colored regions are well represented and dark-colored regions are poorly represented by the ForestGEO sampling network. Stippling covers non-forest areas.

Triple-Network Global Representativeness



Map indicates the sampling networks that offer the most representative coverage for any location. Every location is made up of a combination of three primary colors from Fluxnet (red), ForestGEO (green), and RAINFOR (blue).

Triple-Network Global Representativeness of Forests



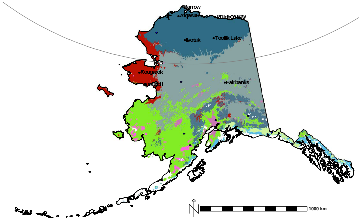
Map indicates the sampling networks that offer the most representative coverage at any forest location. *Only sites within forests were included and forest area was determined by Label Stealing.* Every location is made up of a combination of three primary colors from Fluxnet (red), ForestGEO (green), and RAINFOR (blue).

Data Layers for State of Alaska Climate Change Analysis

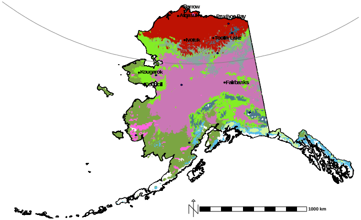
Table: 37 characteristics averaged for the present (2000–2009) and the future (2090–2099).

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



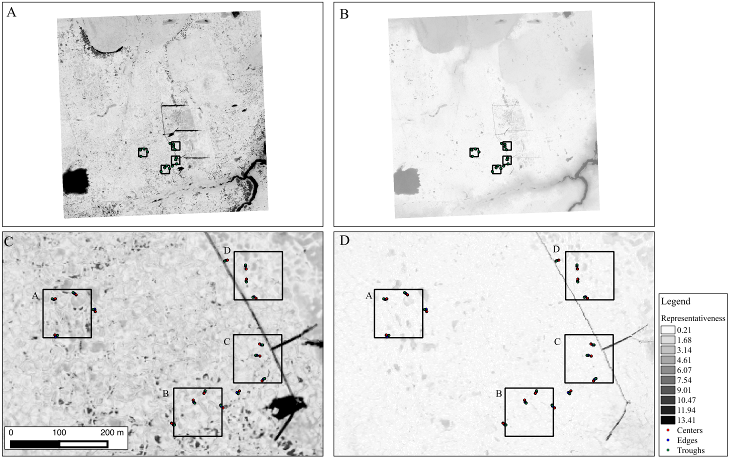
2090–2099

(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.

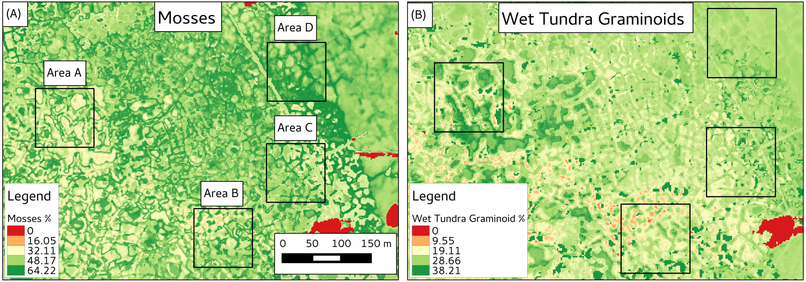
Barrow Environmental Observatory (BEO)



(Langford et al., in prep.)

Representativeness map for vegetation sampling points in A, B, C, and D sampling area including phenology (left) and for a single date (right), based on WorldView2 satellite images for the year 2010 and LiDAR data.

Barrow Environmental Observatory (BEO)



(Langford et al., in prep.)

Mosses and wet tundra graminoids PFT % for Areas A, B, C, D.

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

Conclusions

- **Multivariate Spatiotemporal Clustering (MSTC)** provides a quantitative framework for stratifying sampling domains, informing site selection, and determining representativeness of measurements.
- **Label Stealing** offers a useful means for interpreting and understanding ecoregion or sampling domain delineation.
- **Representativeness Analysis** provides a systematic approach for up-scaling point measurements to larger domains.
- Methodology is *independent of resolution and surrogate data*, thus can be applied from site/plot scale to landscape/global scale with site measurements, remote sensing, and models.
- Paper describing analysis method:

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.

Next Steps for Tropical Site Selection

- Input data layers must be selected to capture important environmental gradients related to carbon cycle drivers.
- A more careful analysis of existing sampling sites should consider type, frequency, and protocol of measurements.
- Observation data may be paired with projected changes in climate and atmospheric CO_2 to estimate how ecoregions may reorganize in the future.
- Method will be used to develop an optimized network of tropical forest sampling sites to answer key science questions.

For more information or to contribute ideas, please contact:

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