Characterizing Tropical Forest Representativeness for Optimizing Sampling Network Coverage National Laboratory

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• 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).

Ecoregions

Table 1: 17 data layers used for this analysis (Potter and Hargrove, 2013).

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 $T_{avg} \ge 5^{\circ}C$	$^{\circ}$ C
Integer number of consecutive months where $T_{avg} \ge 5^{\circ}C$	unitless
Edaphic Variables	
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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) Solar interception Elevation	unitless kW/m ² m

• 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:



• GOF provides "credit" for area of overlap, but also "debit" for 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 grayscale GOF map shows the degree of correspondence between two maps based on the highest GOF score.

Expert-Derived Land Cover/Vegetation Type Maps



Cats Expert Map 1. DeFries UMd Vegetation 12 2. Foley Land Cover 14 3. Fedorova, Volkova, and Varlyguin

578

25

117

17

16

49

194

24

26

19

197

16

23

443

23



(Anderson-Teixeira et al., 2015)

Figure 4: Map of ForestGEO network representation. Stippling covers non-forest areas as determined by Label Stealing.

Triple-Network Global Representativeness



Figure 5: 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).

10 Global Ecoregions, Random Colors



Figure 1: 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.

50 Global Ecoregions, Random Colors



Holdridge Life Zones

50 Ecoregions Reclassified by Label Stealing



Conclusions and Next Steps

• 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.

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 levels 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.

References

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Figure 2: 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.

Temp Grass,Savannas, and Shrub 🐲 rop Grass, Savannas, and Shrut

roplands

Figure 3: The 50 quantitatively derived global ecoregions are reduced to 12 broadly defined land cover classes through the Label Stealing process.

Representativeness

Global Forest Site Representativeness

- Representativeness analysis uses the standardized *n*-dimensional data space formed from all 17 input data layers shown in Table 1.
- In this data space, the Euclidean distance between a sampling location (like Manaus, Brazil) and every other point is calculated.
- Data space distances are used to generate grayscale maps showing the degree of similarity, or lack thereof, of every location to the sampling location.

• Below, 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.

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Acknowledgments

This research was partially supported by the Biogeochemistry Feedbacks Scientific Focus Area (SFA), which is sponsored by the Regional and Global Climate Modeling (RGCM) Program, and the Next Generation Ecosystem Experiments (NGEE) Tropics Project, which is sponsored by the Terrestria Ecosystem Science (TES) Program. Both programs are part of the Climate and Environmental Sciences Division (CESD) of the Biological and Environmental Research (BER) Program in the U.S. Department of Energy Office of Science. Additional support was provided by the National Science Foundation (AGS-1048890). This research used resources of the Oak Ridge Leadership Computing Facility (OLCF) at Oak Ridge National Laboratory (ORNL), which is managed by UT-Battelle, LLC, for the U.S. Department of Energy under Contract No. DE-AC05-00OR22725.



