### **Tropical forests:**

Research questions, representation in models, and the ForestGEO plots

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### Importance of tropical forests

- Major role in global carbon cycle:
  - 1/3 of terrestrial GPP (gross primary productivity)
  - 2/3 of terrestrial biomass carbon stocks
  - Intact tropical forests ~ 1/2 of current terrestrial C sink
  - Uncertainty regarding tropical forest response to global change dominates uncertainty in future global C budget
- Majority of terrestrial species diversity
  - ~2/3 of tree species
  - ~3/4 of terrestrial vertebrate species



Tropical forests in global vegetation models

### What do the models try to capture? Everything needed to get the carbon budget right!



# What do global vegetation models need?

- Driver data:
  - Climate temperature, rainfall, solar radiation, lightning, fires, soil moisture
  - Topography, geology, geomorphology high resolution ground topography, insights into nutrient availability from hyperspectral
  - Human influences roads, timber extraction, fires, proximity to settlements
- For parameterization:
  - Plant functional trait data tree height and crown allometry, leaf traits, wood traits, root traits, carbon allocation rules
- For evaluation:
  - Forest structure tree size distributions, above-ground biomass
  - Forest dynamics productivity, mortality
  - Woody plant composition relative abundances of functional types, of different trait combinations
  - Plant "behavior" leaf phenology, leaf area index, sap flux, individual growth
  - Stand-level fluxes eddy covariance, evapotranspiration

# What questions can global vegetation models help with?

- Elucidating underlying mechanisms:
  - what is needed to reproduce observed patterns of spatial and temporal variation?
  - what is the relative importance of different processes and mechanisms?
- Predicting responses to novel future conditions
  - Only if the models capture the mechanisms sufficiently well!

### How well do the models do?

- Y axis: CMIP 5 model output, for the 4 models that provided these variables
- X axis: ground-based observations synthesized in Galbraith et al. 2013

These models fail to capture spatial variation in biomass stocks and fluxes in old-growth tropical forests.



Muller-Landau et al., in preparation, Tansley review for New Phytologist

Ground-based datasets for tropical forests

#### **Smithsonian ForestGEO**

(formerly known as the Center for Tropical Forest Science, CTFS) Large-scale forest census plots



6.4 million living trees, 10,000 species, 901 forest years 67 sites, 26 countries, >100 partner institutions

#### ForestGEO sites span global variation in forest type



Core tree censuses (plots mostly >16 ha)

- All trees > 1 cm diameter are
  - Tagged and mapped
  - Identified to species
  - Measured in diameter

#### Associated products

- Forest structure and biomass stocks
- Dynamics: mortality, recruitment, productivity
- Composition



### Ground-based data collection at ForestGEO plots



Near-surface remote sensing at ForestGEO

#### UAV imagery linked to tagged trees to track phenology, crown dynamics



Park et al., submitted Muller-Landau et al., in prep

### LiDAR for some plots & surrounding



For example, canopy height is greater on valleys than in ridges.

Detto et al., 2013, PLOS ONE

Canopy height (m)

Has resulted in new knowledge of spatial patterns in forest structure at landscape scale with respect to topography and geology.



## Promise of hyperspectral to map species and traits in tropical forests



Some tree species can be specifically identified and mapped.

Baldeck et al. 2015 Plos One mapped 3 species The more species, the harder to classify them individually.





Liana cover can be estimated across landscapes.

Marvin et al. 2016 Rem Sens Env Fig. 7. Classification analysis for 50 species from three sites, Parque Natural Metropolitano, Fort Sherman, and Chamela. Data were gathered in the 2003 wet season using the UniSpec. Mean test data error  $\pm 1$ SD was computed from 10000 classifications each per set of 5, 10, 15, 20, 25, 30, 35, 40, and 45 species. Sets of species were selected at random for each classification.

Castro-Esau et al. 2006 Am J Bot

# Lianas (woody vines) – important and difficult to study



#### Lianas reduce tree growth



200 400 600 800 1000 1200 1400 1600 1800 liana abundance (no. individuals ha<sup>-1</sup>)

## Some findings from ForestGEO

# Finding: Tree community composition varies strongly with topography and soils

(a) Barro Colorado Island





#### (b) Korup





Measured soil and topographical variables explain 13-39% of tree community variation at 20 m scales in eight large forest plots.

Baldeck et al. 2012 Proc Roy Soc

Finding: Carbon stocks vary greatly among tropical forests *even very locally* – among 1-ha plots within a 16-50 ha plot



Réjou-Méchain, Muller-Landau et al. 2014

This heterogeneity means that calibration plots smaller than footprint area greatly increase uncertainty CV in AGB(%)



# Finding: Wood density predicts species demographic rates within and across sites

So changing functional composition is expected to affect demography.



## Finding: Old-growth tropical ForestGEO / CTFS sites are on average carbon sinks



# Finding: Functional composition is shifting over time within sites

Site	High Wood Density	Low Wood Density	Large Seeds	Small Seeds
BCI	0.18 [-0.36,0.66]	0.14 [-0.55,0.76]	0.15 [-0.55,0.75]	-0.01 [-0.64,0.55]
Edoro	0.17 [-0.38,0.72]	- <b>0.94</b> [-1.80,-0.23]	0.29 [-0.21,0.77]	- <b>0.66</b> [-1.26,-0.12]
Lenda	0.23 [-0.05,0.48]	0.4 [-0.17,0.89]	<b>0.3</b> [0.02,0.54]	0.15 [-0.50,0.68]
НКК	<b>0.31</b> [0.04,0.57]	-0.21 [-0.63,0.14]	0.16 [-0.11,0.40]	<b>0.62</b> [0.31,0.91]
Lambir	0.16 [-0.12,0.40]	0.22 [-0.08,0.48]	0.35 [0.06,0.62]	0.14 [-0.12,0.38]
La Planada	0.16 [-0.32,0.64]	<b>0.59</b> [0.28,0.90]	<b>0.51</b> [0.21,0.78]	<b>0.77</b> [0.10,1.36]
Palanan	<b>0.61</b> [0.14, 1.04]	- <b>0.88</b> [-1.83,-0.03]	-0.32 [-1.09,0.36]	<b>0.8</b> [0.27,1.28]
Pasoh	<b>0.56</b> [0.12,0.95]	0.07 [-0.55,0.60]	<b>0.53</b> [0.03,0.96]	<b>0.72</b> [0.32,1.03]
Sinharaja	- <b>3.67</b> [-4.97, -2.44]	<b>0.92</b> [0.56,1.29]	- <b>2.01</b> [-2.89,-1.16]	<b>0.89</b> [0.37,1.62]
Yasuni	0.03 [-0.42,0.46]	0.09 [-0.47,0.62]	0.1 [-0.28,0.45]	0.29 [-0.36,0.90]
Average	-0.12 [-0.30,0.04]	0.04 [-0.16,0.22]	0.01 [-0.17,0.16]	<b>0.37</b> [0.19,0.54]
Average	<b>0.27</b> [0.12,0.41]	-0.06 [-0.26,0.13]	<b>0.23</b> [0.07,0.37]	<b>0.31</b> [0.13,0.48]
(without Sinharaja)				
Luquillo <sup>a</sup>	-0.43 [-1.07,0.21]	-0.08 [-1.14,1.22]	0.47 [-0.58,1.43]	- <b>2.61</b> [-3.66,-1.64]
Mudumalai <sup>a</sup>	<b>0.60</b> [0.30,0.90]	- <b>2.82</b> [-3.98,-1.77]	<b>0.83</b> [0.61,1.05]	<b>1.49</b> [1.04,1.98]

Chave, Condit, Muller-Landau et al. 2008

Finding: The relationship of tree species richness to productivity and biomass varies with spatial scale.



Chisholm, Muller-Landau et al. 2013 J. Ecology

Finding: Tree species abundances are changing faster than can be explained by drift/chance alone



## Finding: Tree species abundances are changing faster than can be explained by drift/chance alone



But in all 12 tested sites!

Chisholm et al. 2014 Ecology Letters