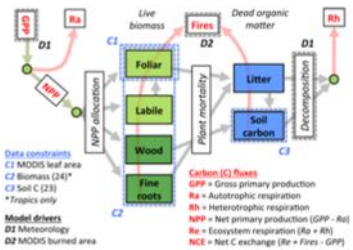

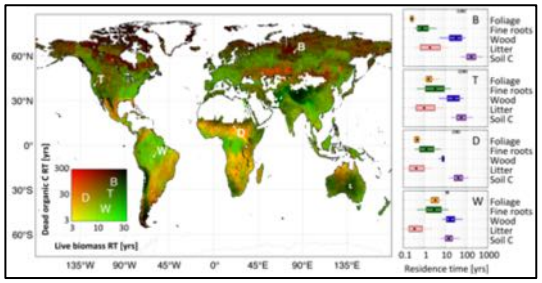

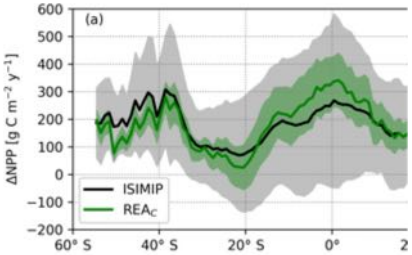

Opportunities and Challenges for Constraining Carbon Models with Global Biomass Data

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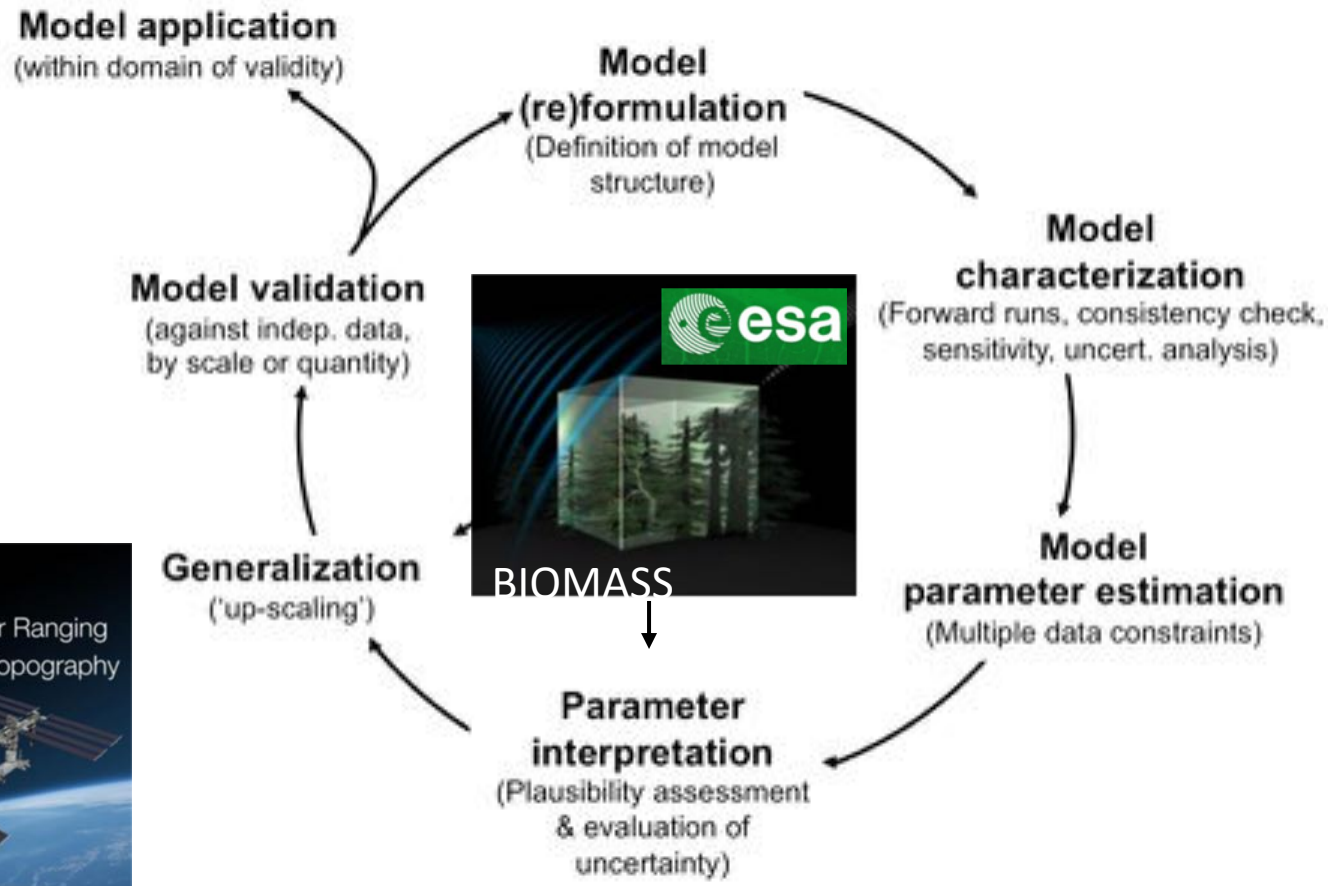
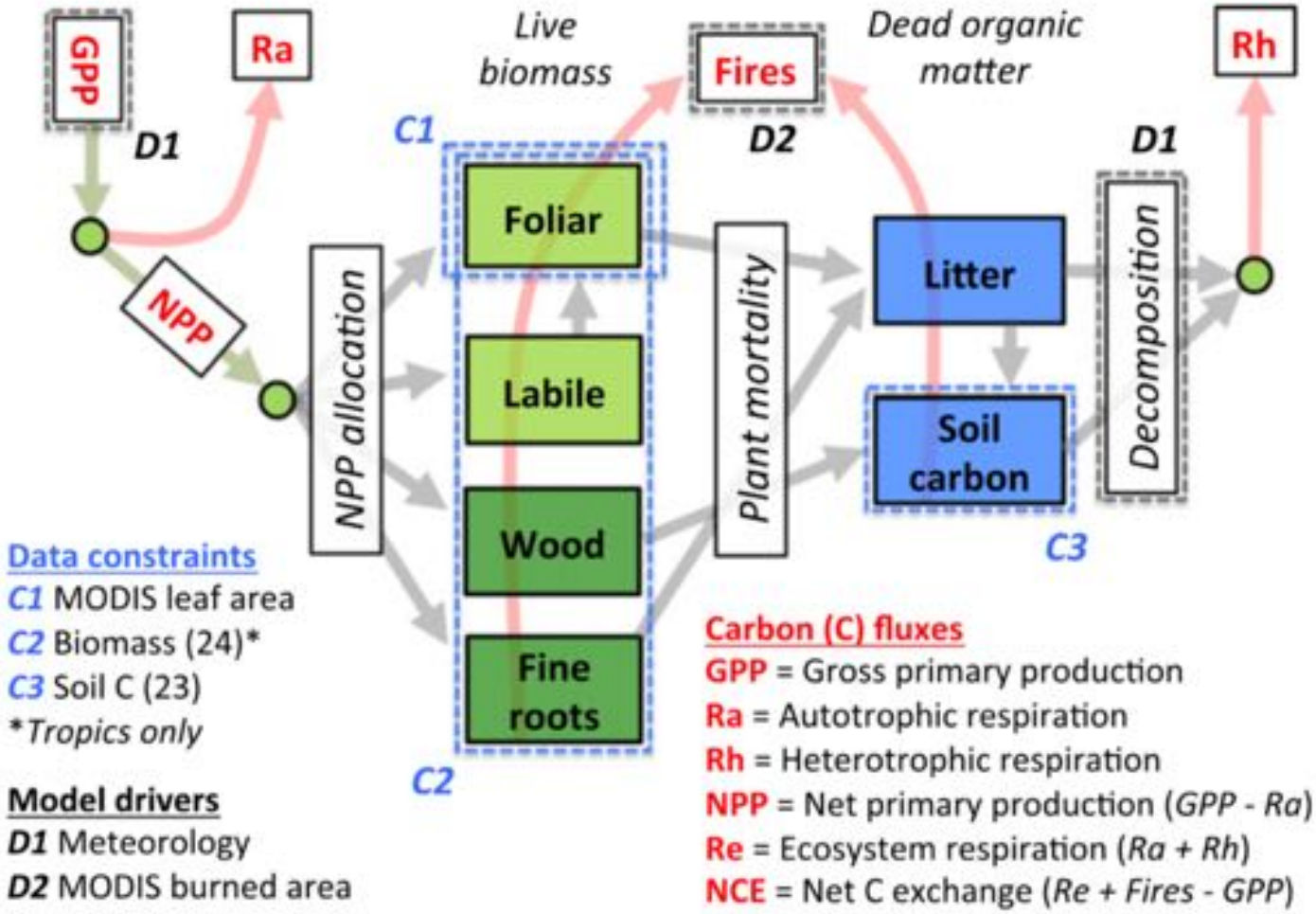
Improving process models with data



Williams et al. 2009

DALEC



Bloom et al 2016

CARDAMOM: Terrestrial ecosystem carbon cycle analysis

Posterior DALEC Parameter Probability
1° x 1° Pixel scale parameter, flux & carbon pool estimates

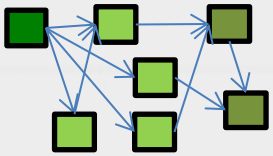
C state likelihood function = observation likelihood & parameter priors
No spin-up
No PFTs
No Steady state

Biometric Data Constraints

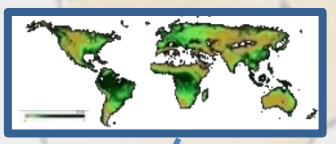
Drivers:

ERA-interim 1° x 1° resolution 8-day time-step 2001-2010

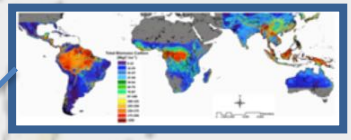
DALEC



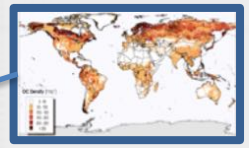
MODIS LAI



Pan-Tropical Biomass



HWSD Soil Organic C



$$p(x|c) \propto p(c|x)\, p(x)$$

Parameter probability **p(x|c)** at each pixel derived using a Metropolis-Hastings MCMC algorithm

C_{eff} constraint:
100 Gt/yr < Global GPP <150 Gt/yr

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Bloom et al., PNAS, 2016.

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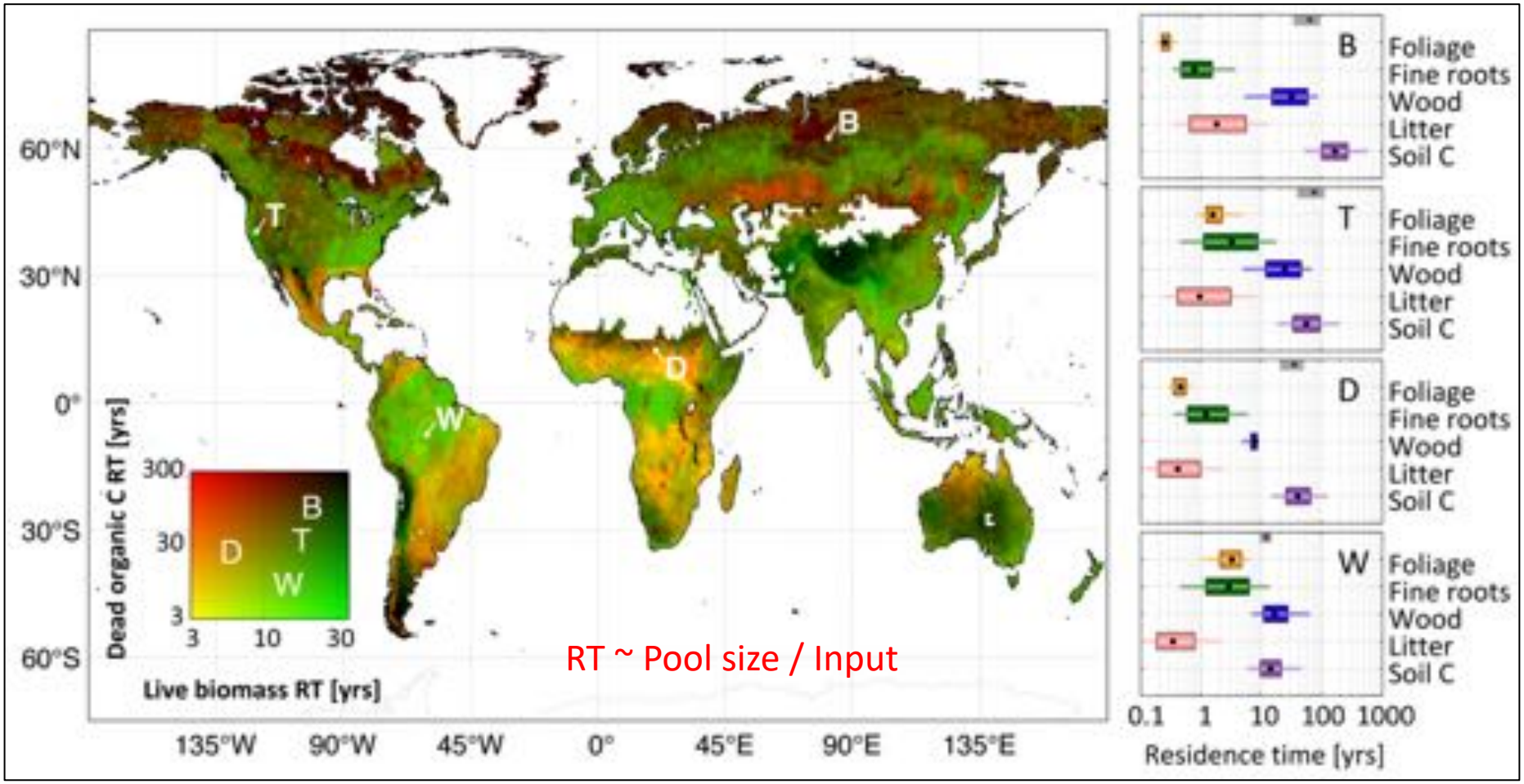
Global retrievals of carbon residence times

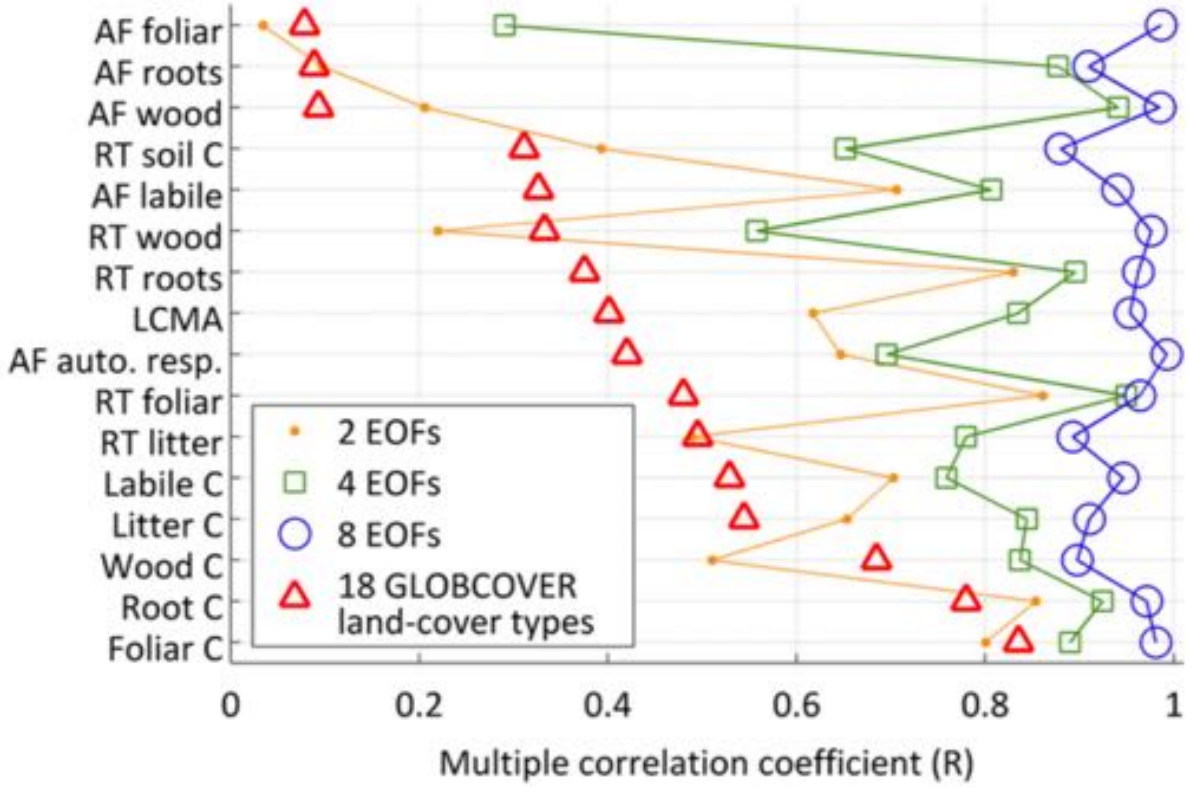


Bloom et al., PNAS 2016

Land cover classifications do not match parameter mappings

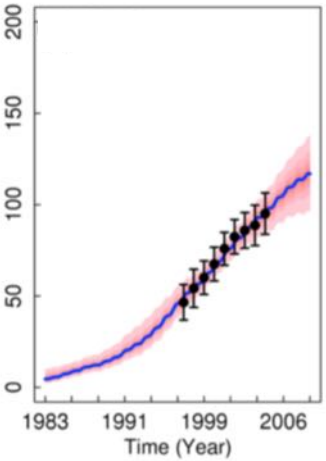
AF – allocation fraction
RT - residence time

Retrieved C state and process variables are largely explained by eight modes of spatial variability



Constraining local dynamics

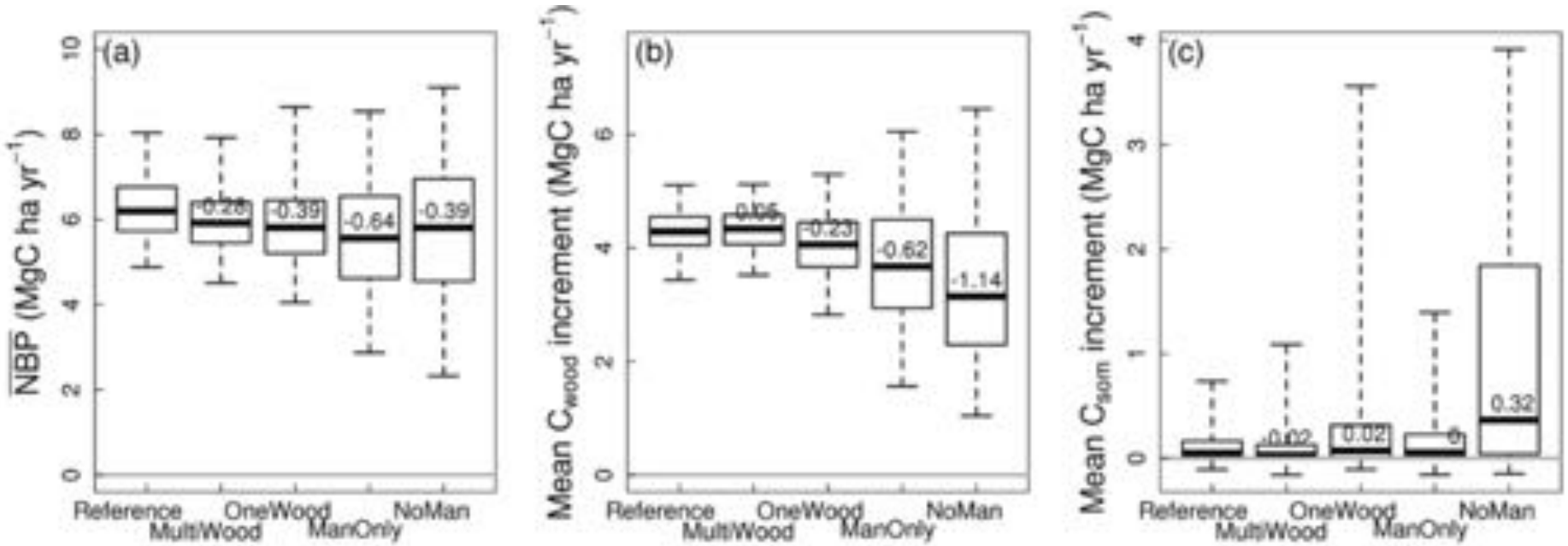
- Coarse resolution quasi steady state analyses are tractable
- At finer scale dynamical processes (disturbance and aggradation) provide a modelling challenge
  - Aggrading forest, non steady-state
  - Duke Forest, NC (Loblolly Pine planted in 1983)
  - What information is required to constrain model parameters?



Information content of observations

Data	Reference	Multi Wood	One Wood	Man Only	No Man
Foliar C/LAI	In situ	MODIS	MODIS	MODIS	MODIS
Root C	In situ	-	-	-	-
Wood C	In situ	annual	one	age	-
Soil C	In situ	HWSD	DWSD	HWSD	HWSD
Concept	*Field site*	*BIOMASS*	*Avitabile*	*LC history*	*Baseline*

Biomass information can constrain NBP, soil dynamics



NBP

Wood increment

SOM increment

More assimilated information

Smallman et al., (2017)

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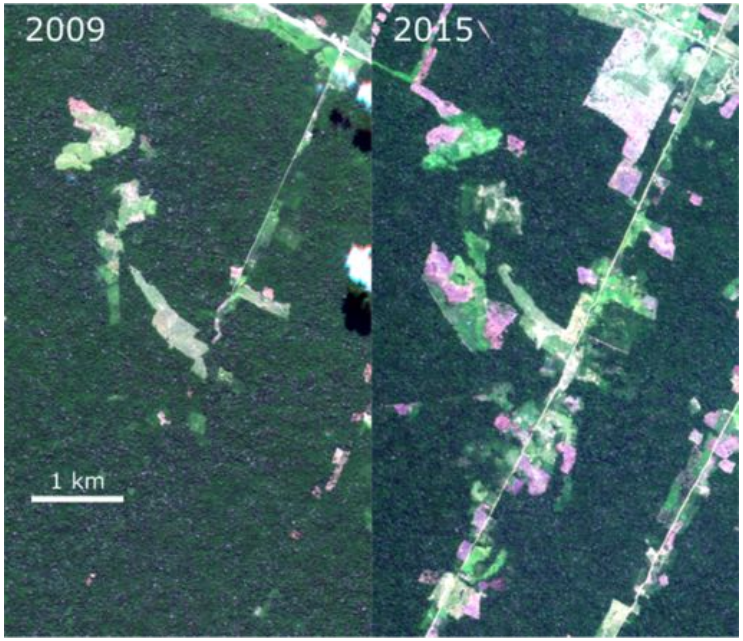
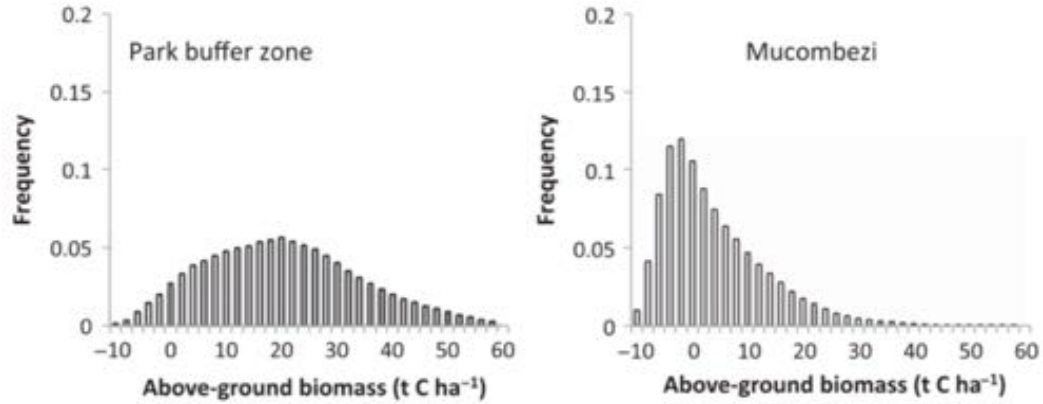
Challenges for high resolution

RapidEye images, Brazil



Milodowski et al. 2017

ALOS-PALSAR biomass estimates, Mozambique



Williams et al. 2013

How can models represent real landscapes, at observed scales?

- Fragmentation, edge effects, degradation, fire, windthrow
- Secondary forests, regrowth
- Does **pattern** of change carry process information?

Challenges for high resolution DA

- Understanding dynamic, patterned landscapes
- Resolving spatially variable processes – e.g. management, disturbance, edge effects, regrowth
- Add value of additional constraints (e.g. traits, SIF, LUC, soil moisture)
- Robust error propagation

Summary

- C cycle data is growing exponentially, higher spatial/temporal resolution, more diverse
- Huge opportunity to calibrate and evaluate process models
- Massive challenge to maximise data value and develop knowledge
- Combined efforts of biogeochemical, ecological, remote sensing, data science, modelling communities required

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NASA MODIS team, Saatchi et al., Avitabile et al., Duke Forest team, Biomass MAG, HWSD team, FLUXCOM partners

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