Fast and Slow Terrestrial Carbon Cycle Feedbacks
—or—
How I learned to stop worrying and love both simple and complex models

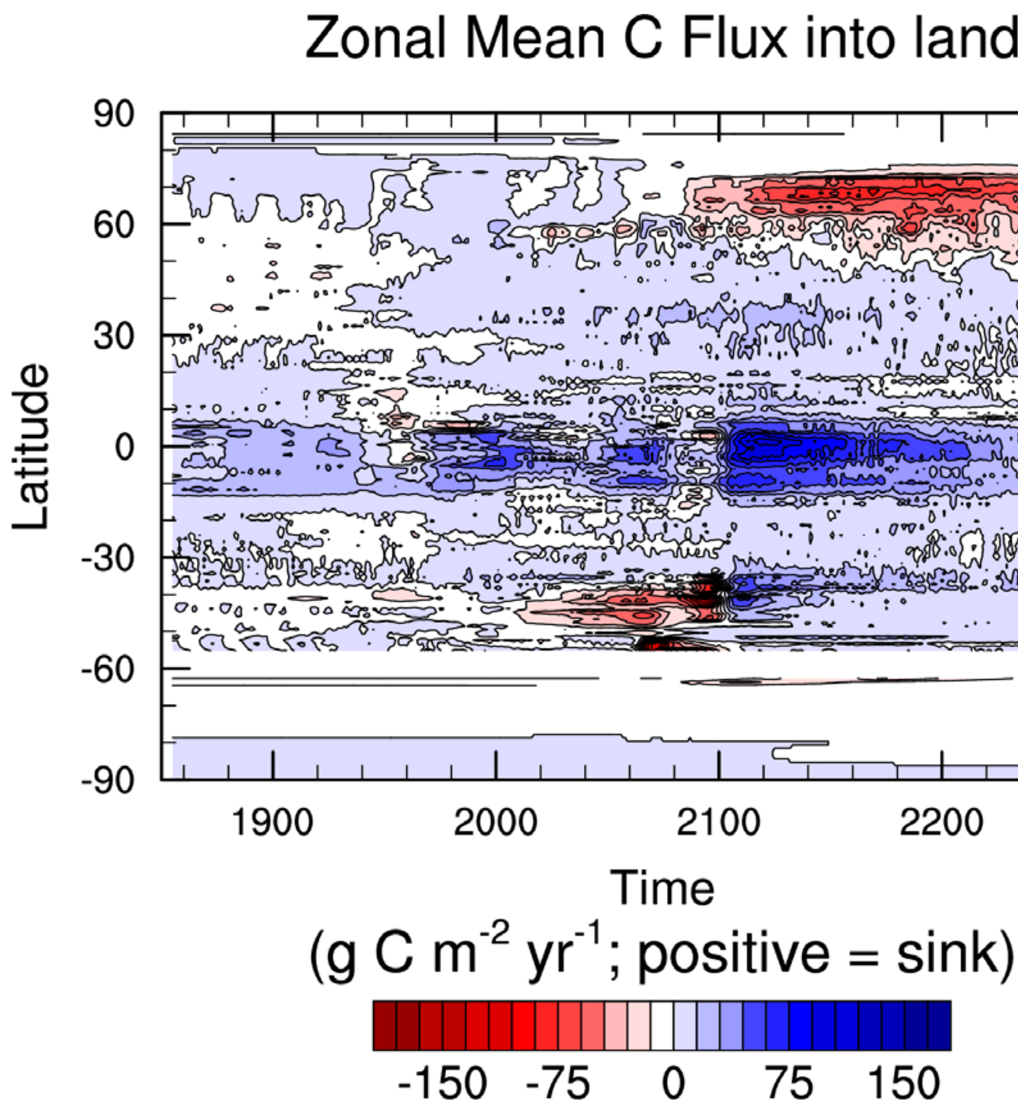
Charlie Koven

Lawrence Berkeley National Lab

With

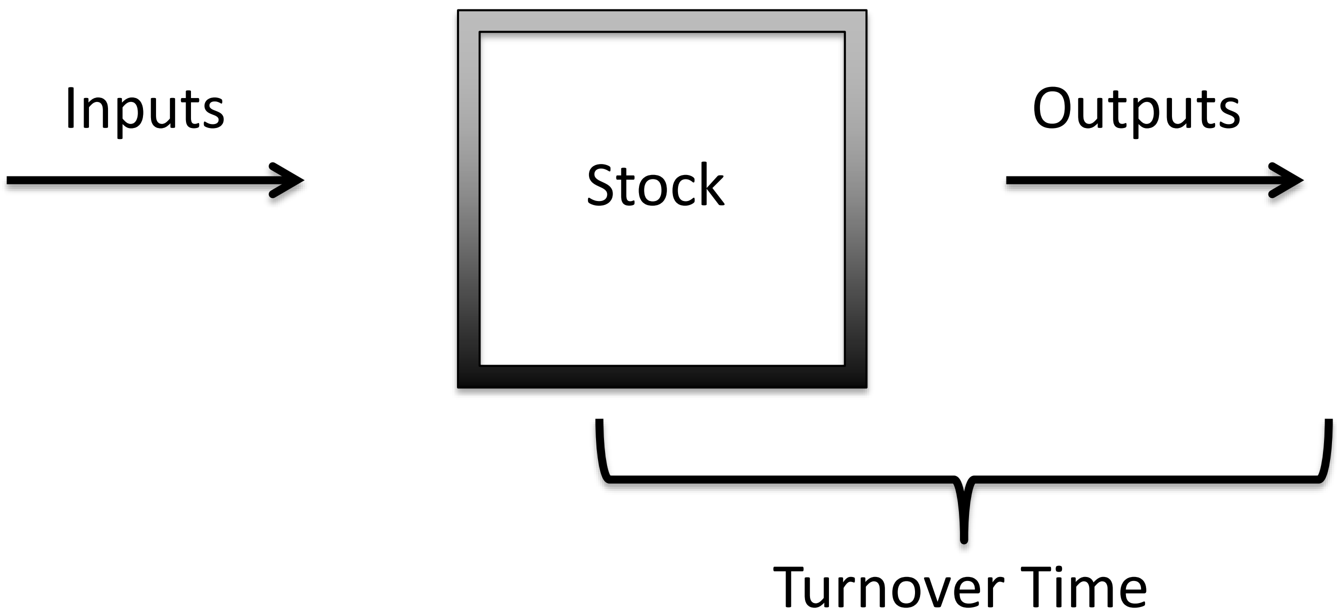
Rosie Fisher, Ryan Knox, David Lawrence, Gustaf Hugelius, Will Wieder, Bill Riley, Jeff Chambers, Robinson Negron-Juarez, Kat Georgiou, Lara Kueppers

What are the slow feedbacks?
(1) those, like permafrost, that seem to operate on the 100+ year timeframe



Koven et al., *PNAS*, 2015

What are the slow feedbacks?
(2) those that operate downstream of the fast, input driven feedbacks



Starting with CMIP5 ESMs: Disaggregate controls on C changes via a linear analysis of equilibrium C changes

$$C_t = C_l + C_d$$

Live C Pools

$$\frac{dC_l}{dt} = f_{npp} - \frac{C_l}{\tau_l}$$

$$\widehat{C_l} = f_{npp}\tau_l$$

$$\frac{d\widehat{C_l}}{dt} = \frac{df_{npp}}{dt}\tau_l + \frac{d\tau_l}{dt}f_{npp}$$

Productivity-driven live C change

Turnover-driven live C change

Dead C Pools

$$\frac{dC_d}{dt} = f_{l\rightarrow d} - \frac{C_d}{\tau_d}$$

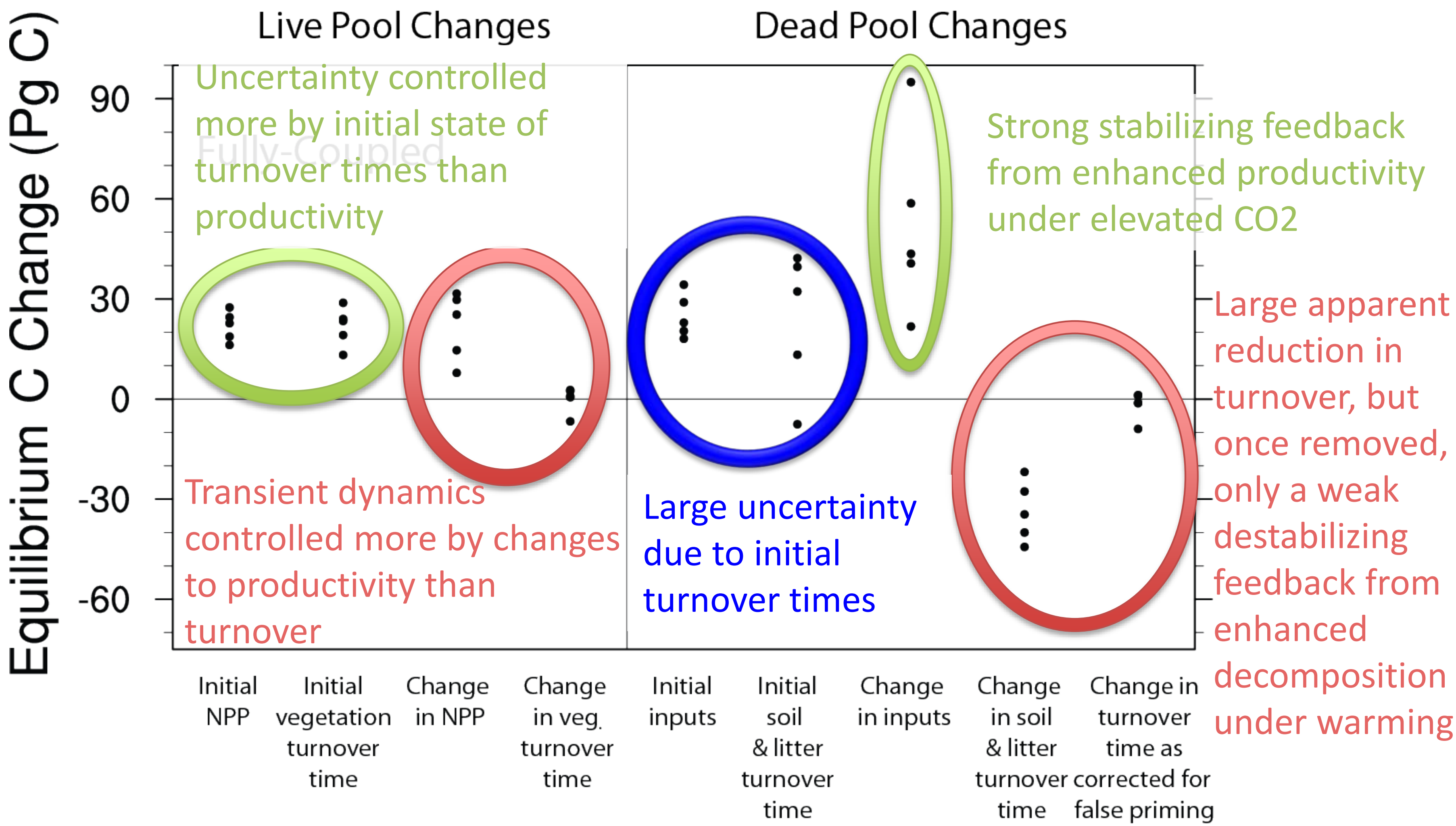
$$\widehat{C_d} = f_{l\rightarrow d}\tau_d$$

$$\frac{d\widehat{C_d}}{dt} = \frac{df_{l\rightarrow d}}{dt}\tau_d + \frac{d\tau_d}{dt}f_{l\rightarrow d}$$

Productivity-driven Dead C change

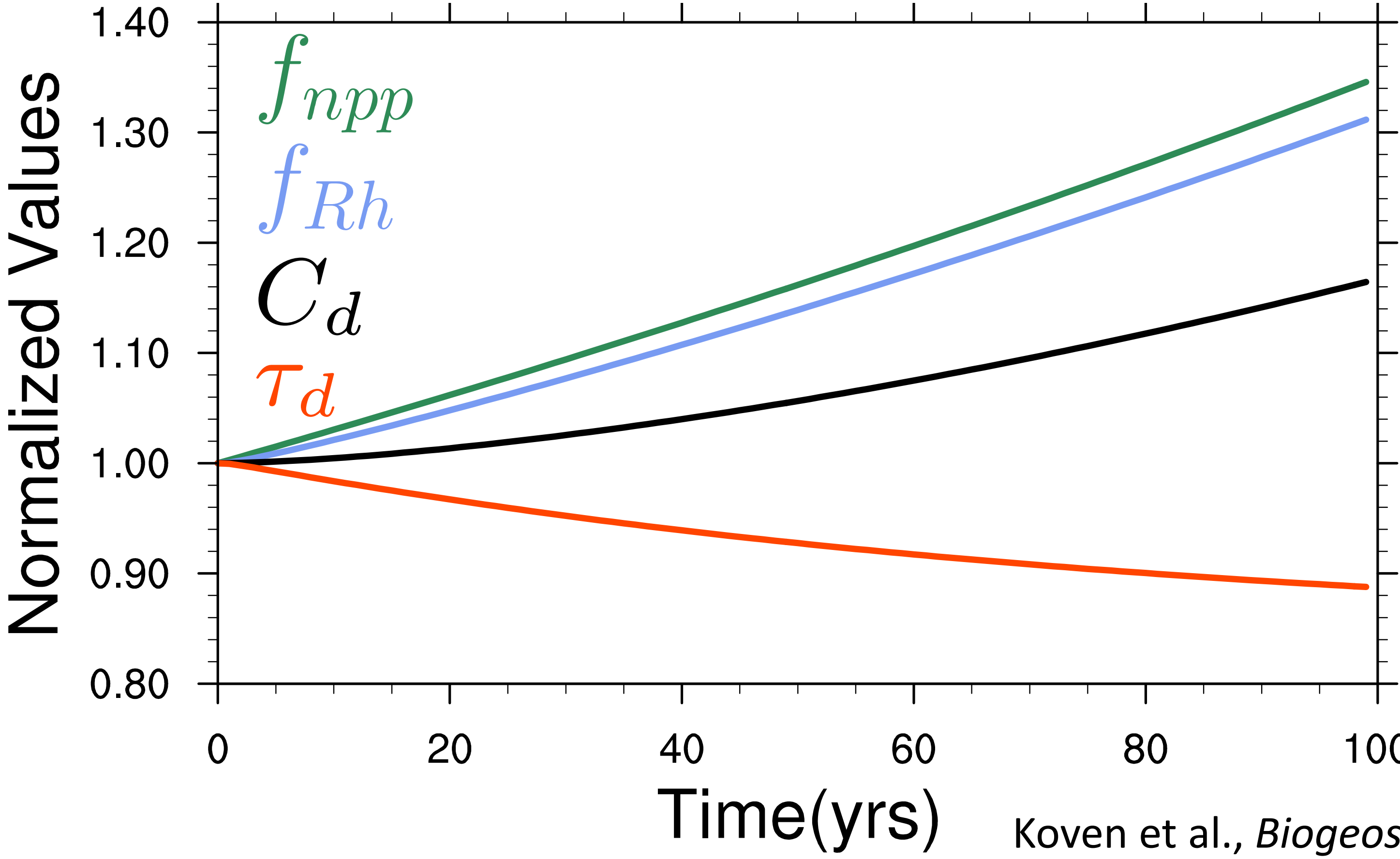
Turnover-driven Dead C change

What does it tell us to disaggregate the carbon feedbacks from CMIP5 ESMs?



Koven et al., *Biogeosciences*, 2015

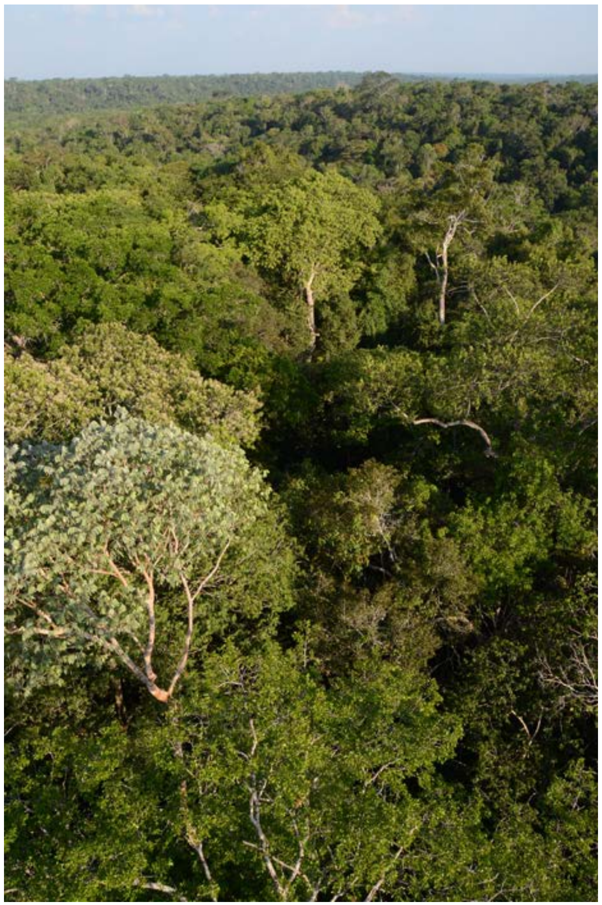
“False Priming”



Koven et al., *Biogeosciences*, 2015

Really simple model experiment: take a multi-pool model (here 3 pool) with fixed turnover times for each pool. Start from steady-state and increase the inputs. What happens to the bulk turnover time?

But: an ecosystem is not a box, even though it is sometimes useful to model it like one



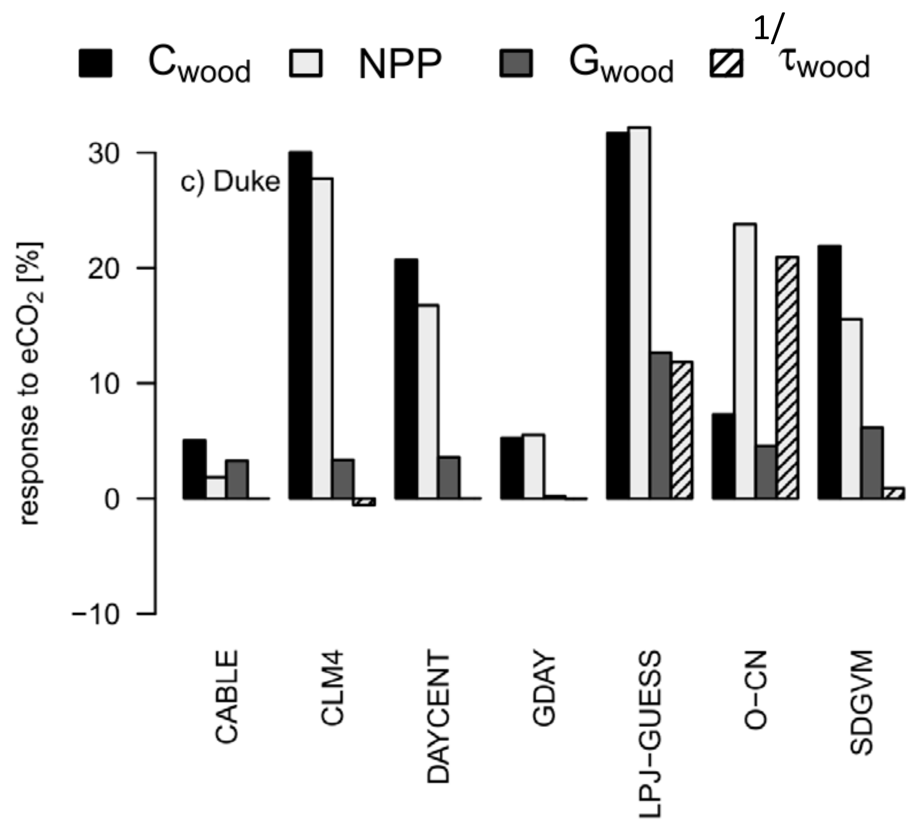
!=

The Actual Amazon

An Amazon Box

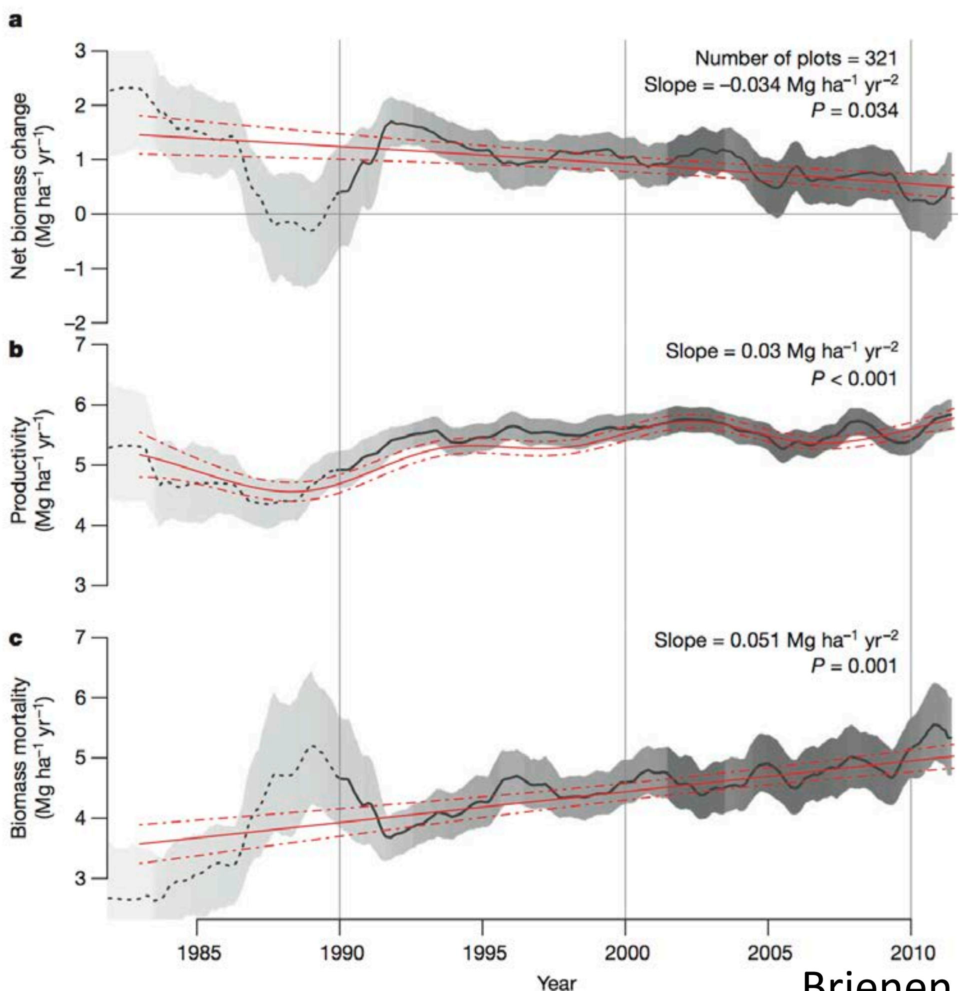
In models that resolve wood dynamics, changes to turnover under elevated CO2 lead to divergent carbon responses

Responses of wood carbon to CO2 fertilization at Duke FACE, and its drivers



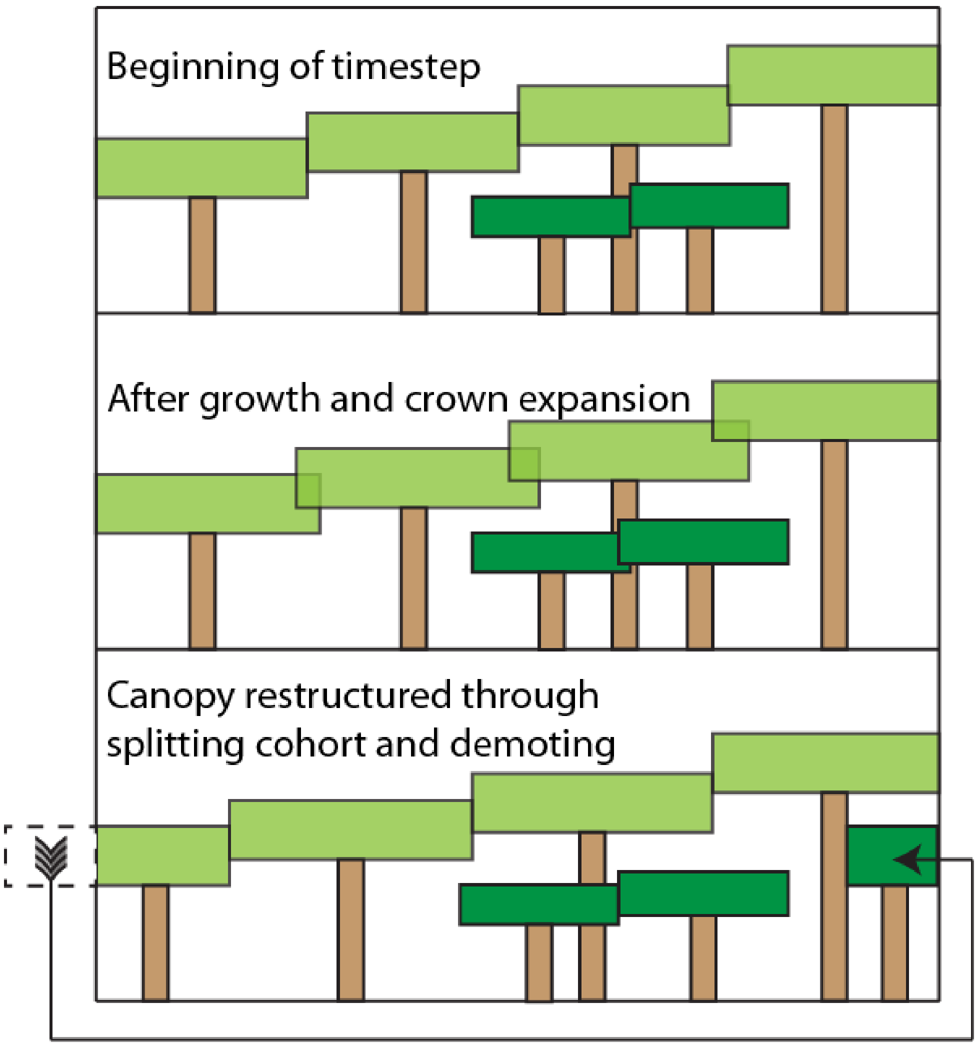
Walker et al., 2015

Productivity and mortality appear to both be rising. Are these opposing or related trends?



Brienen et al., 2015

Light Competition and the PPA



An emerging class of ESM land models resolve canopy growth and light competition.

The Perfect Plasticity Approximation (PPA) is one such approach: breaks forest into canopy layers with competition between trees to be in the upper level.

Light Competition and the PPA

An emerging class of ESM
olve
and light

ticity
(PPA) is
ach:
to canopy
petition
o be in

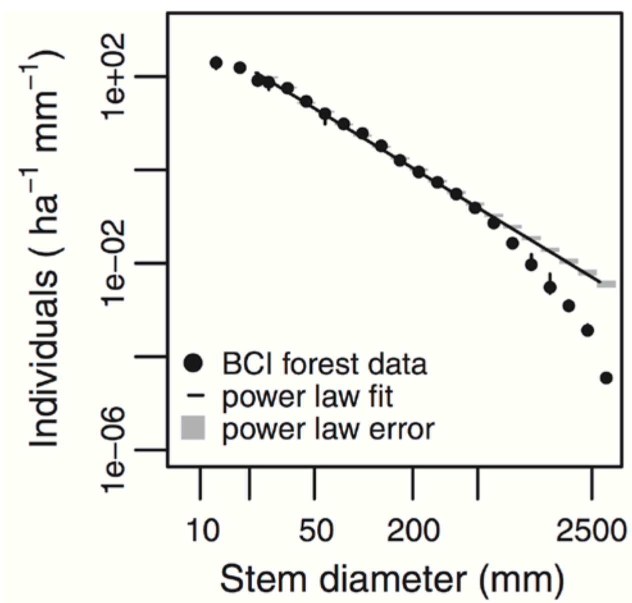
The combination of ED+PPA dynamics, on their own, are able to predict tropical forest tree size distributions: therefore a useful reduced-complexity model

FOREST ECOLOGY

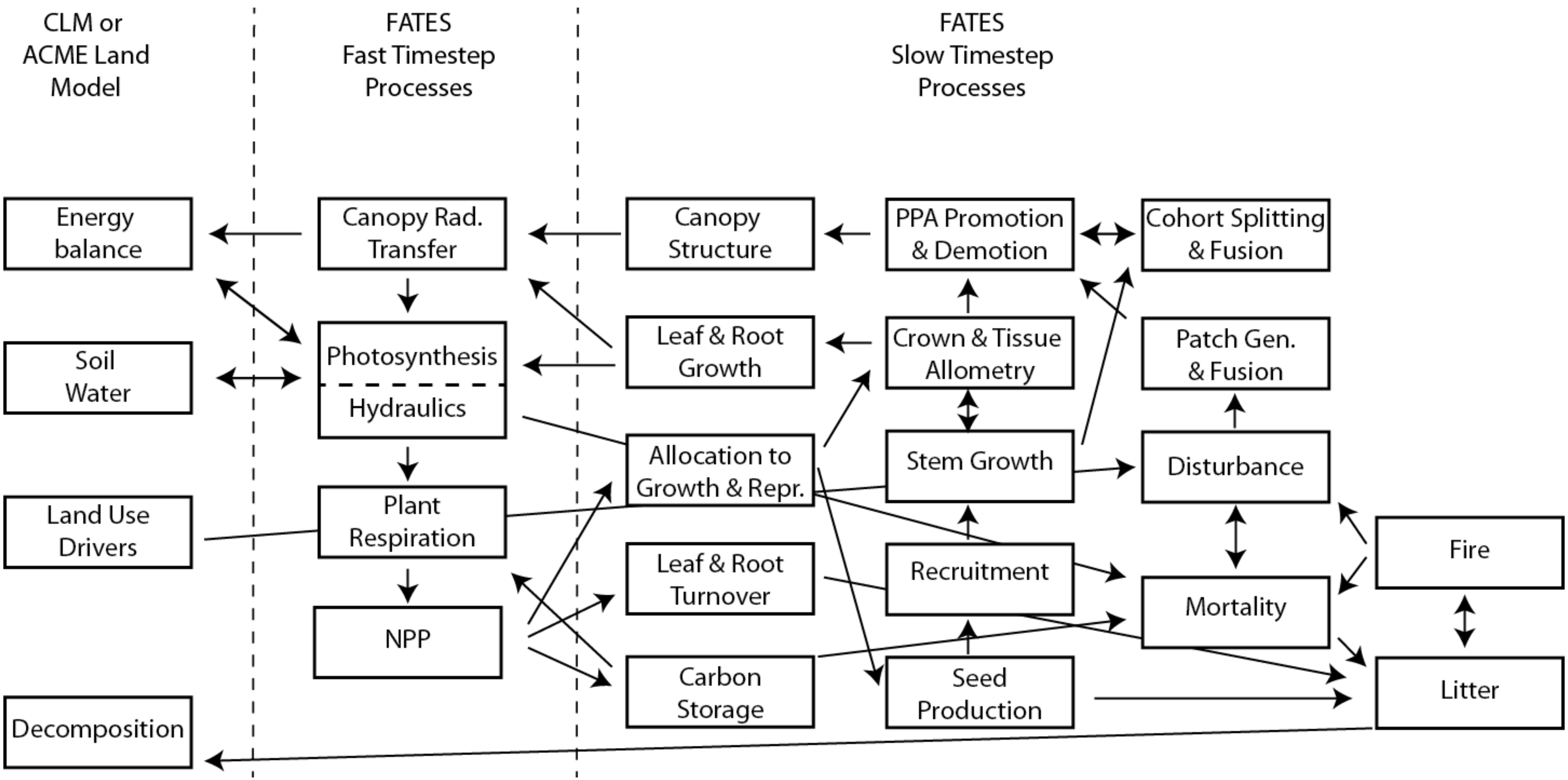
Dominance of the suppressed: Power-law size structure in tropical forests

C. E. Farrior,[1,2*] S. A. Bohlman,[3,4] S. Hubbell,[4,5] S. W. Pacala[6]

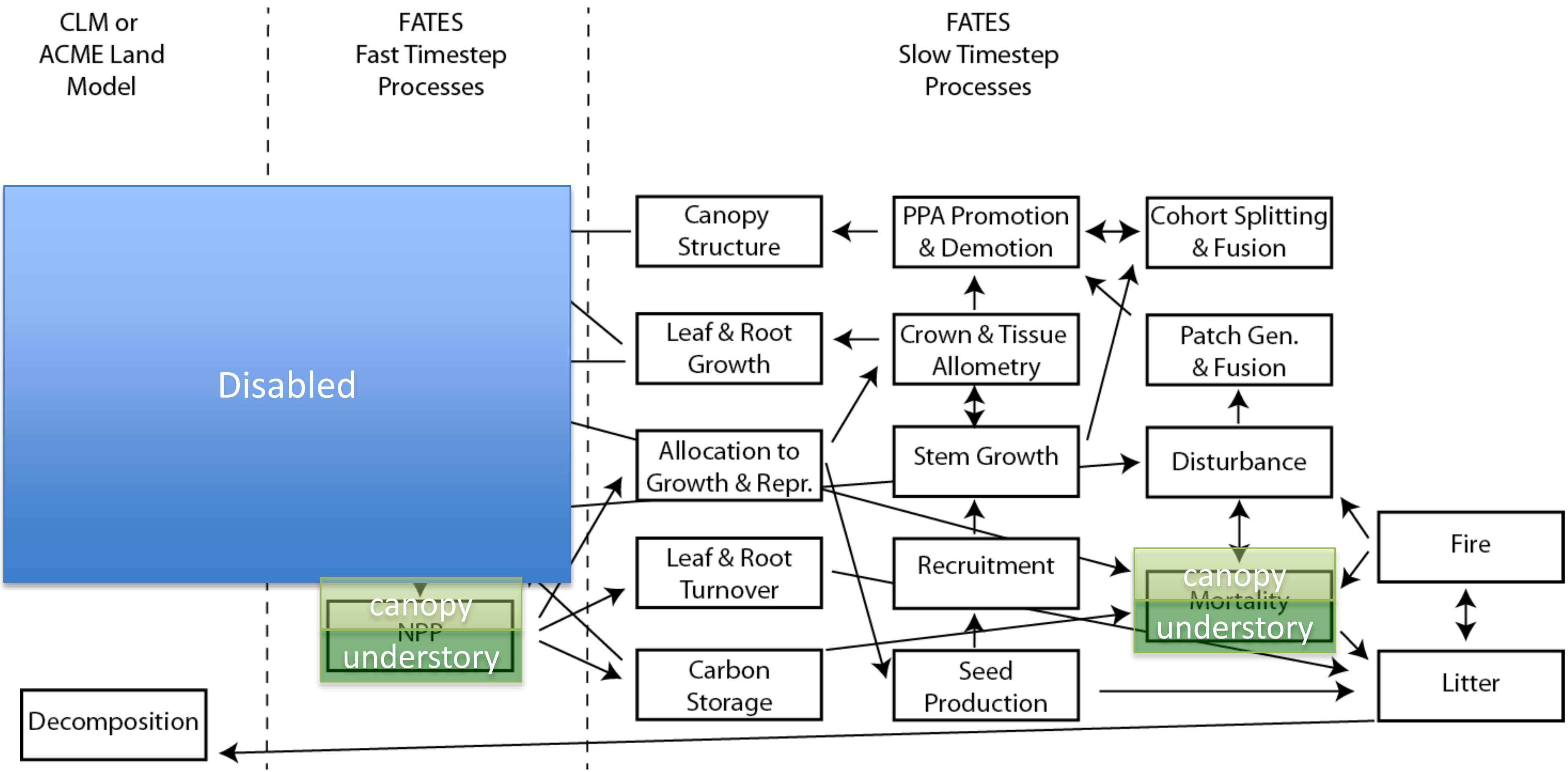
Tropical tree size distributions are remarkably consistent despite differences in the environments that support them. With data analysis and theory, we found a simple and biologically intuitive hypothesis to explain this property, which is the foundation of forest dynamics modeling and carbon storage estimates. After a disturbance, new individuals in the forest gap grow quickly in full sun until they begin to overtop one another. The two-dimensional space-filling of the growing crowns of the tallest individuals relegates a group of losing, slow-growing individuals to the understory. Those left in the understory follow a power-law size distribution, the scaling of which depends on only the crown area–to–diameter allometry exponent: a well-conserved value across tropical forests.



FATES schematic: lots of process complexity



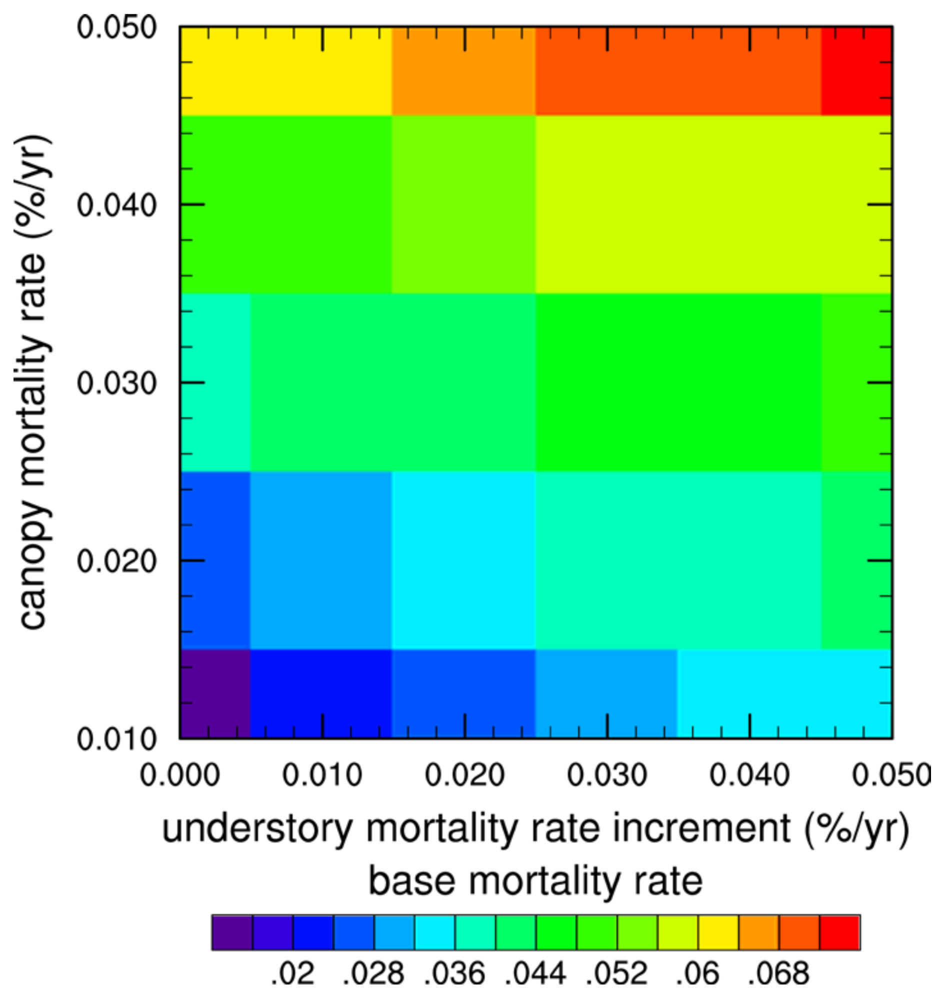
A reduced-complexity FATES: "Prescribed Physiology Mode" Blue: disabled; Green: Prescribed



Allows efficient sampling of rates that directly govern outcomes

How changes in productivity and turnover relate in reduced-complexity FATES system: 1 mean state

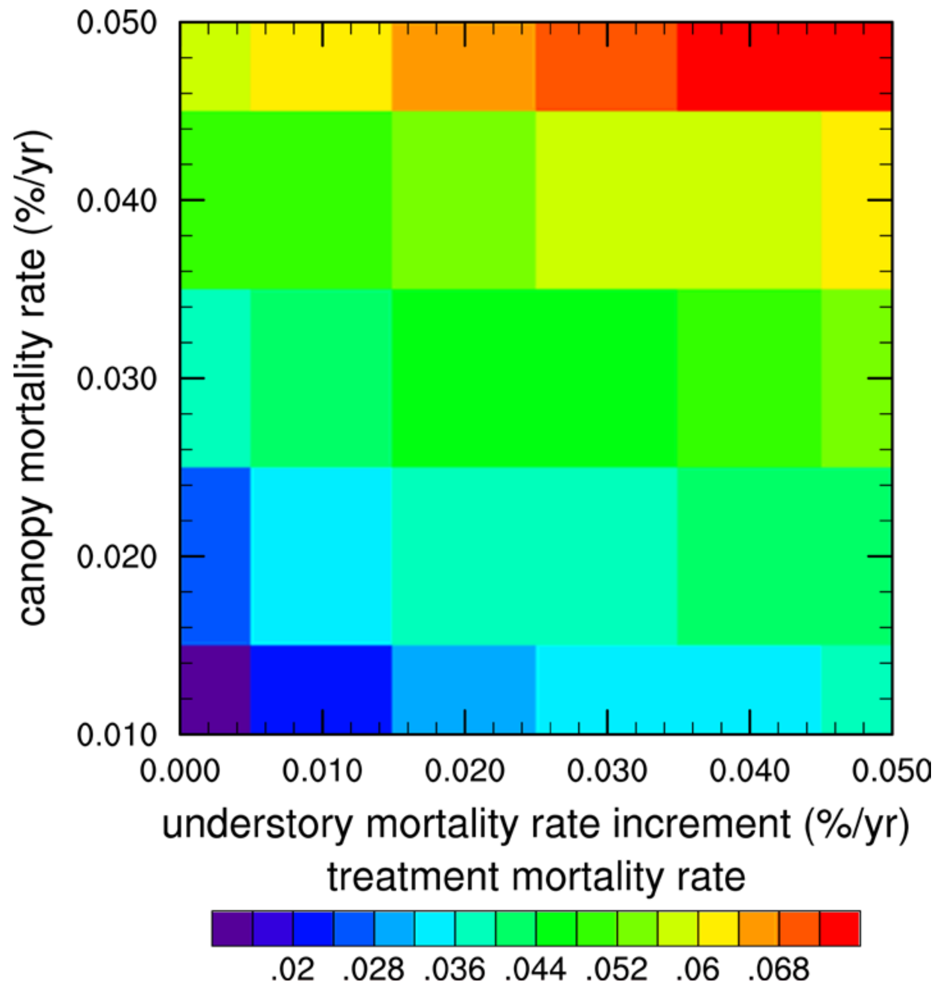
Use FATES model, which combined ED and PPA logic, in a reduced-complexity mode where growth and mortality rates in the canopy and understory can be set as parameters. Explore a 2-D parameter surface varying the mortality rates in canopy and understory, with fixed productivity.



How changes in productivity and turnover relate in reduced-complexity FATES system: 2 increased productivity

Now increase productivity by 25% (as if by CO_2 fertilization), holding mortality rates within each layer constant.

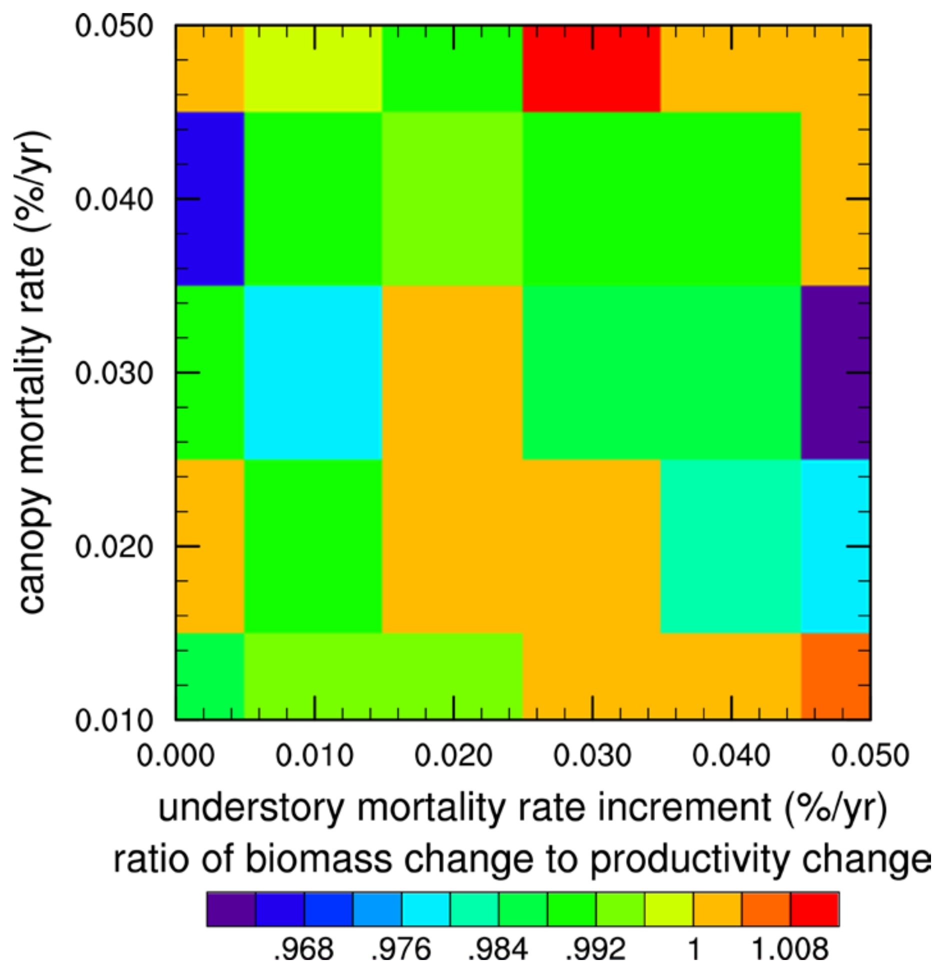
Ecosystem mortality rate increases because plants are pushed into understory faster where they die more quickly.



How changes in productivity and turnover relate in reduced-complexity FATES system: 3 Net C Response

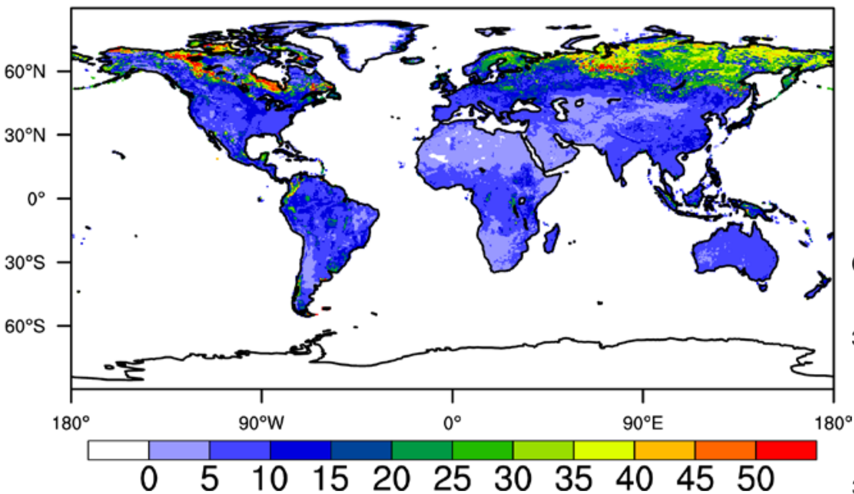
But ΔBiomass/ΔNPP stays close to 1 despite increased mortality, because of a counteracting effect: shift to larger tree size => more carbon per unit crown area of a tree due to allometric relationships.

All of above for a 1-PFT system; unclear if it holds for early/late successional 2-PFT system, or across uncertainty of allometry.

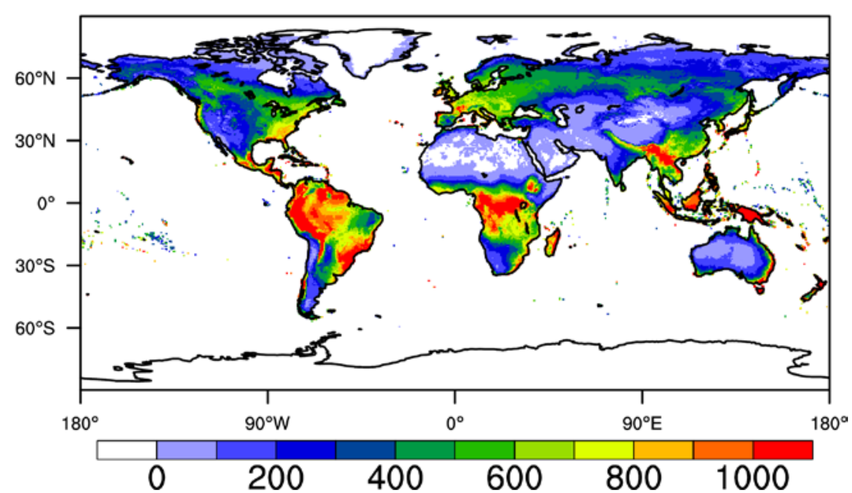


What about soil carbon turnover, and its response (or lack in CMIP5) to warming?

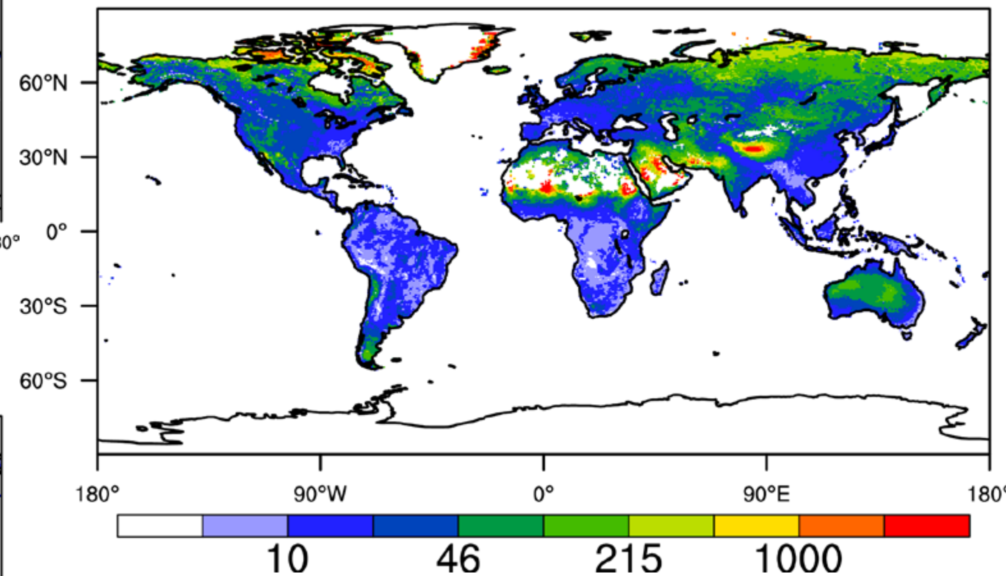
HWSD & NCSCD Soil C to 1m (kg m^{-2})



MODIS NPP (g C m^{-2} y^{-1})

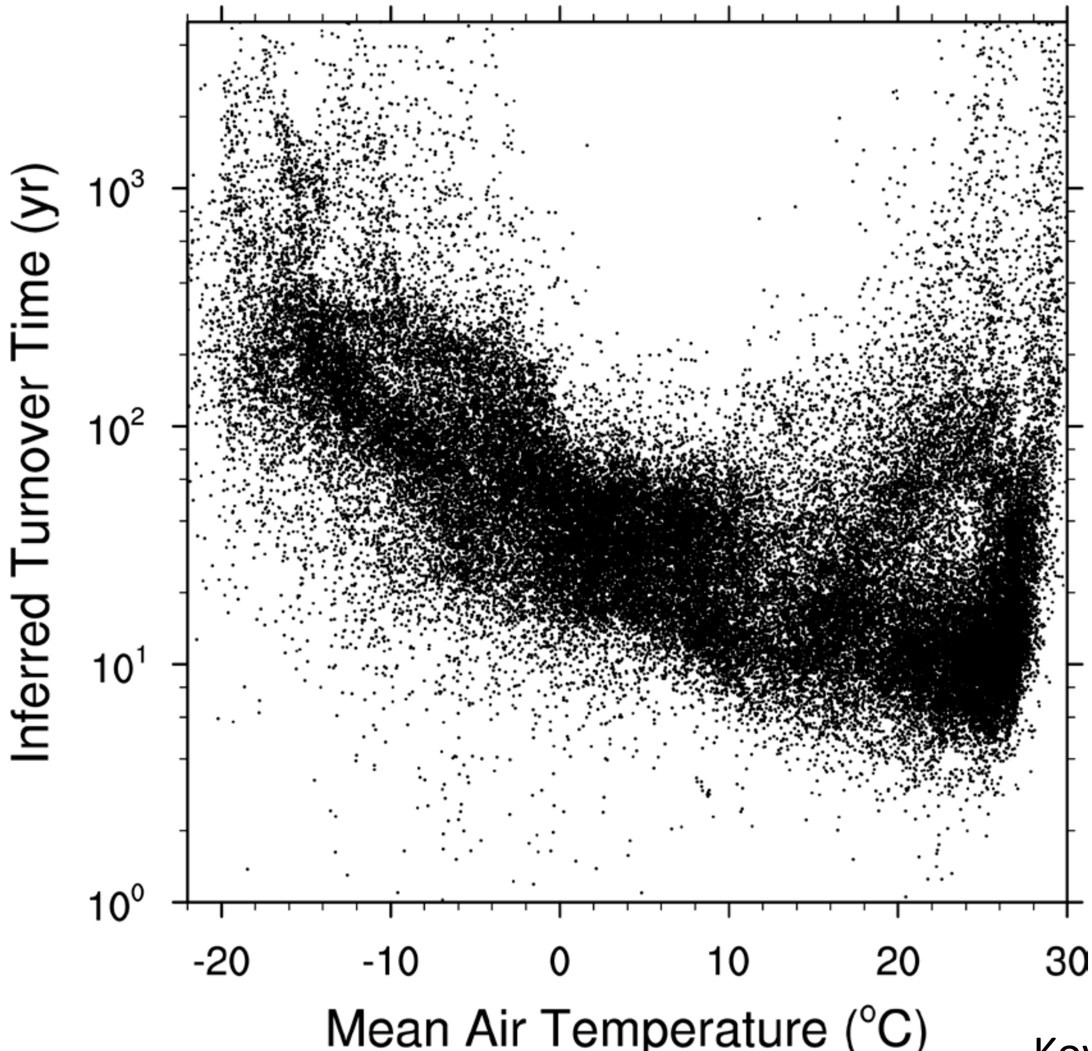


Soil C Turnover Time (y)



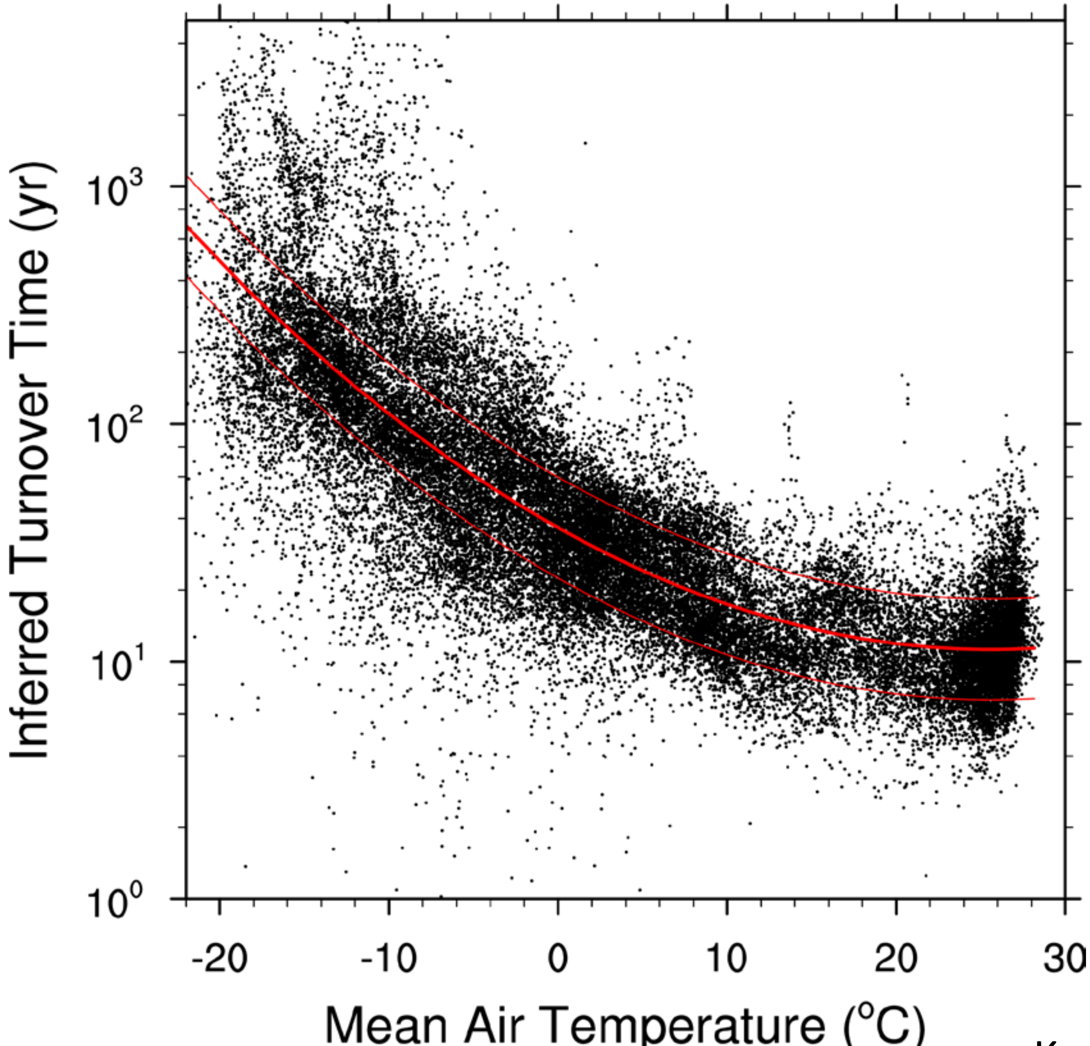
Koven et al., *2017*

Plot turnover as function of mean annual air temperature



Koven et al., *2017*

Isolate temperature from moisture effects by ignoring gridcells that are either too wet or too dry



Koven et al., *2017*

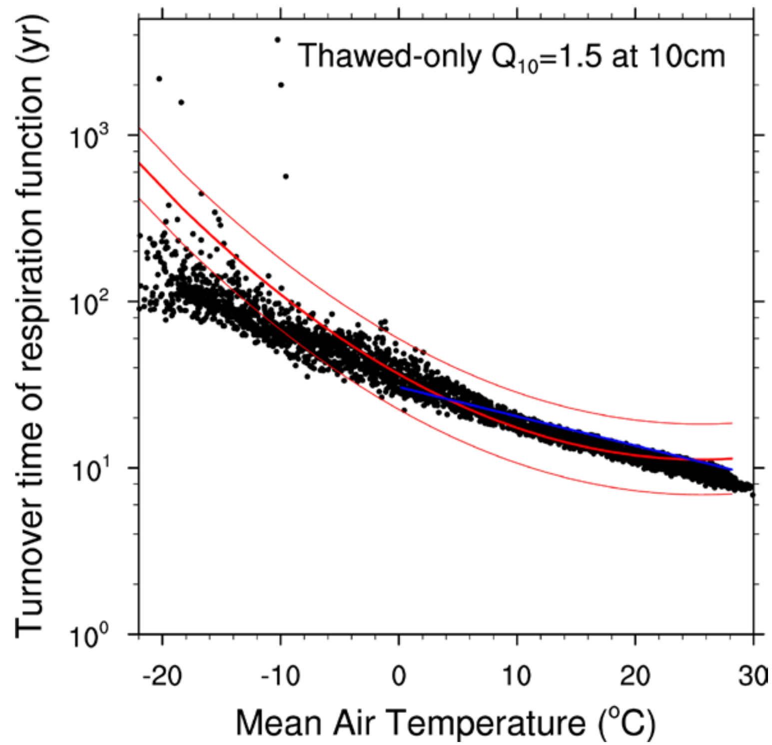
A simple scaling theory for why temperature sensitivity is high in cold climates

Using daily soil temperatures and mean annual air temperatures from a land surface model:

$$k = f(T)$$

$$\tau = 1/\overline{k}$$

1-Layer approach: Q_{10} = 1.5 when thawed, *k = 0* when frozen, using 10cm soil temperatures



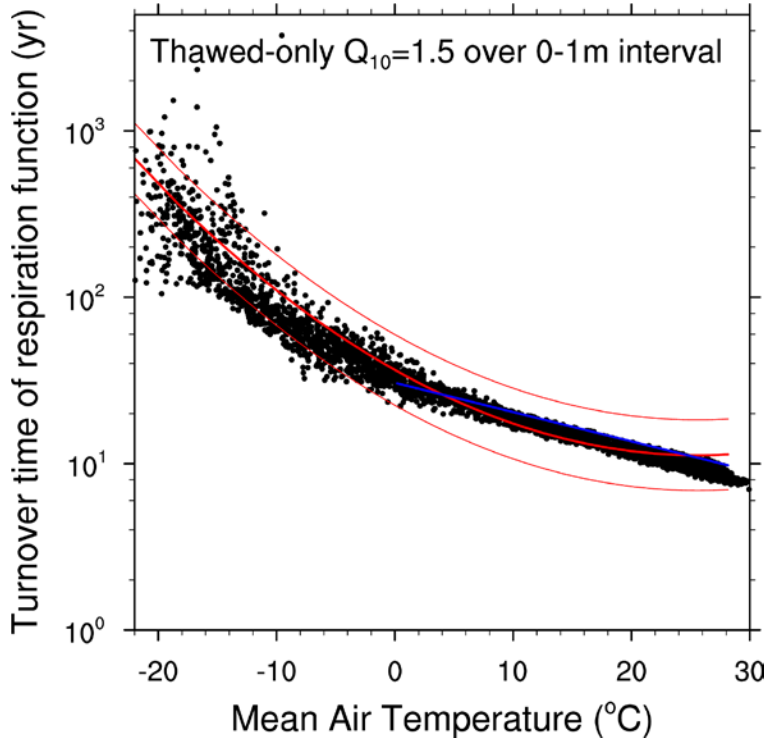
Koven et al., *2017*

A simple scaling theory for why temperature sensitivity is high in cold climates

Using daily soil temperatures and mean annual air temperatures from a land surface model:

$$k = f(T)$$

$$\tau = 1/\overline{k}$$



Koven et al., *2017*

Many-layer approach: Q_{10} = 1.5 when thawed, *k = 0* when frozen, using soil temperatures at each level, and then calculate mean k across 0-1m interval

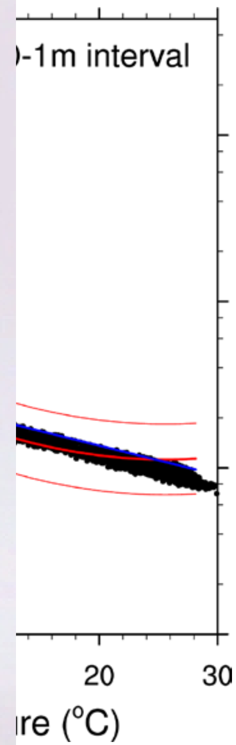
Implication: Properly representing the scaling of freeze/thaw in both volume and time is essential to understanding temperature controls on soil carbon cycling

A simple sc   perature
sensi   tes

Using daily soil
temperatures and m
annual air temperatu
from a land surface

$$k = f(T)$$

$$\tau = 1/\overline{k}$$

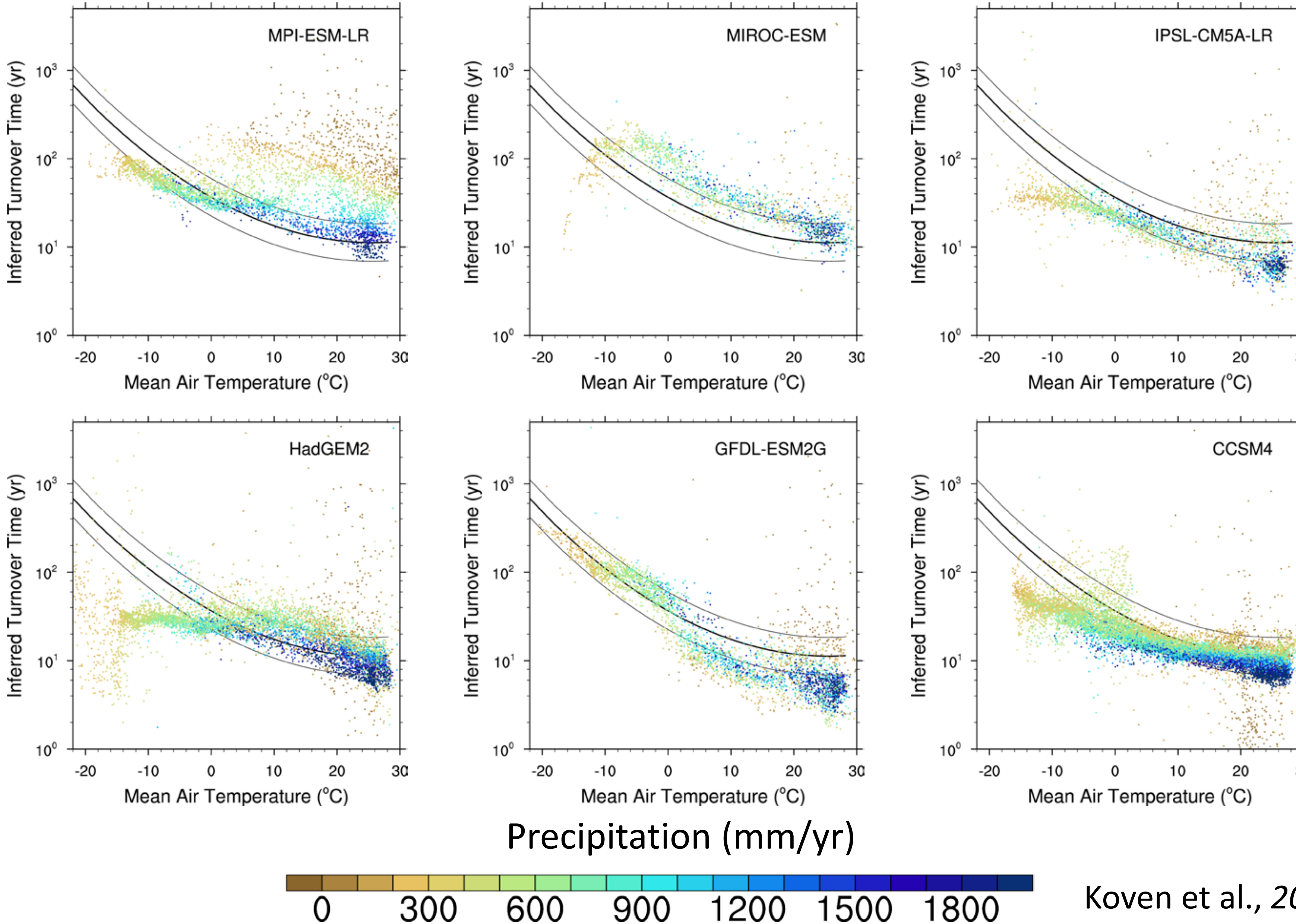


Koven et al., *2017*

Many-layer approach:
when thawed, *k = 0* wh
using soil temperature
level, and then calcula
across 0-1m interval

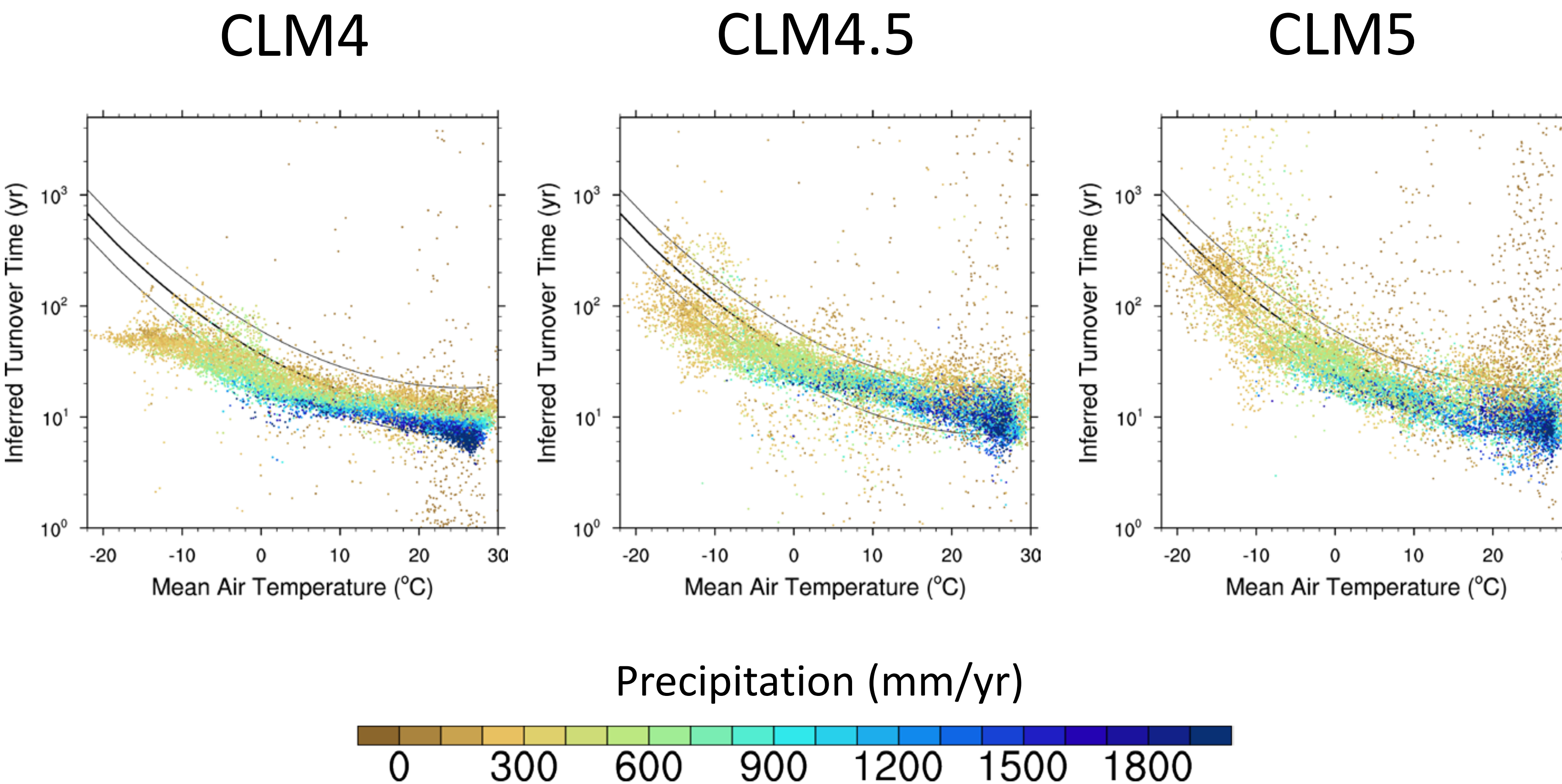
Implication: Properly   th volume and time
is essential to   arbon cycling

How do CMIP5 ESMs compare to soil turnover benchmark?



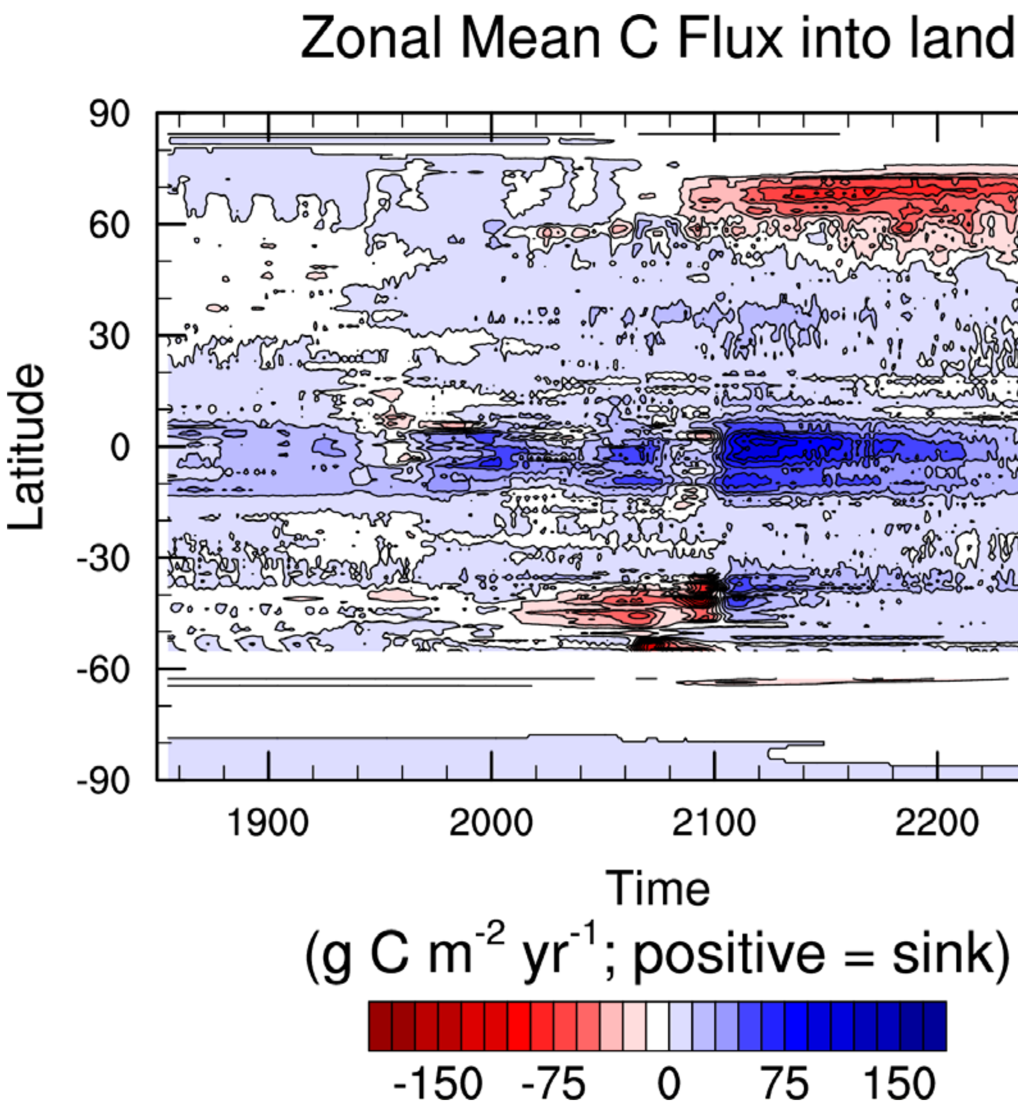
Koven et al., *2017*

Focus on scaling of sensitivity of decomposition to temperature and moisture, and learning from simple model, improves complex model performance against benchmark



Lawrence et al *in prep*

Including the better scaling allows the model to show more complex behavior such as the permafrost carbon feedback.



Koven et al., *PNAS*, 2015

Conclusions

- If we are to learn from our models, we need to be constantly building and traversing hierarchies of complexity in them.
- The processes that are downstream of photosynthesis—growth, mortality, competition, decomposition—are particularly uncertain because (a) dynamic observations of them are so scarce, and (b) because we are still trying to figure out the basic structures of how to model them.
- Hence the need for both simple and complex but flexibly structured models to make progress.

Thanks!