Biophysical modulators of interannual variability in eddy-covariance data

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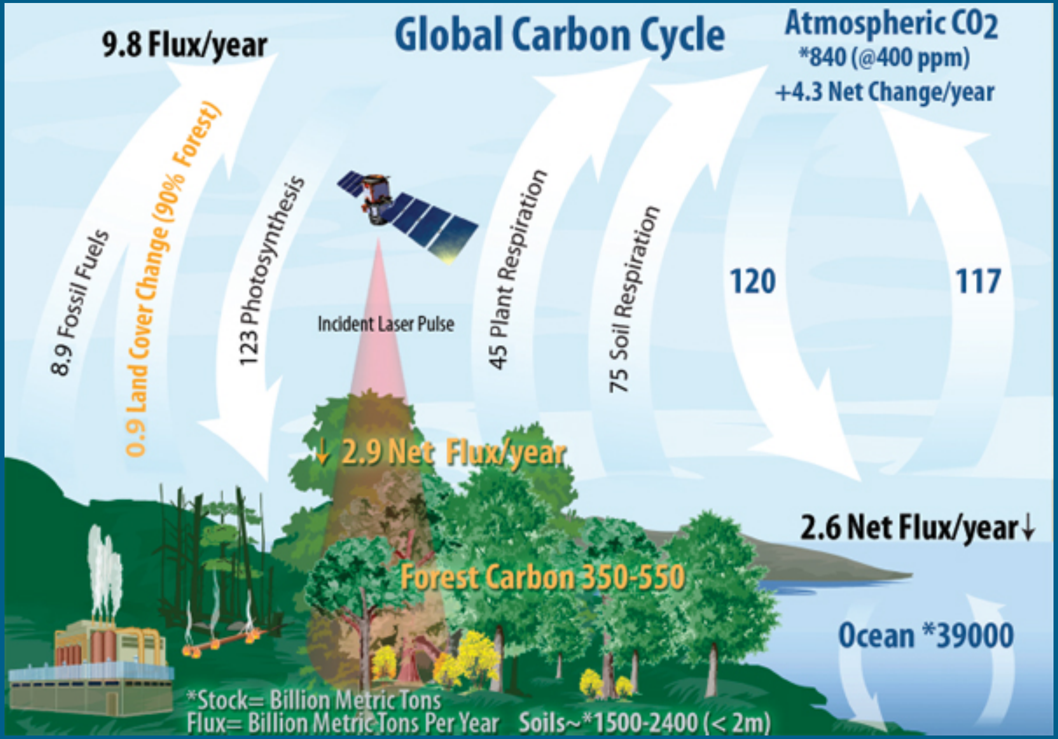
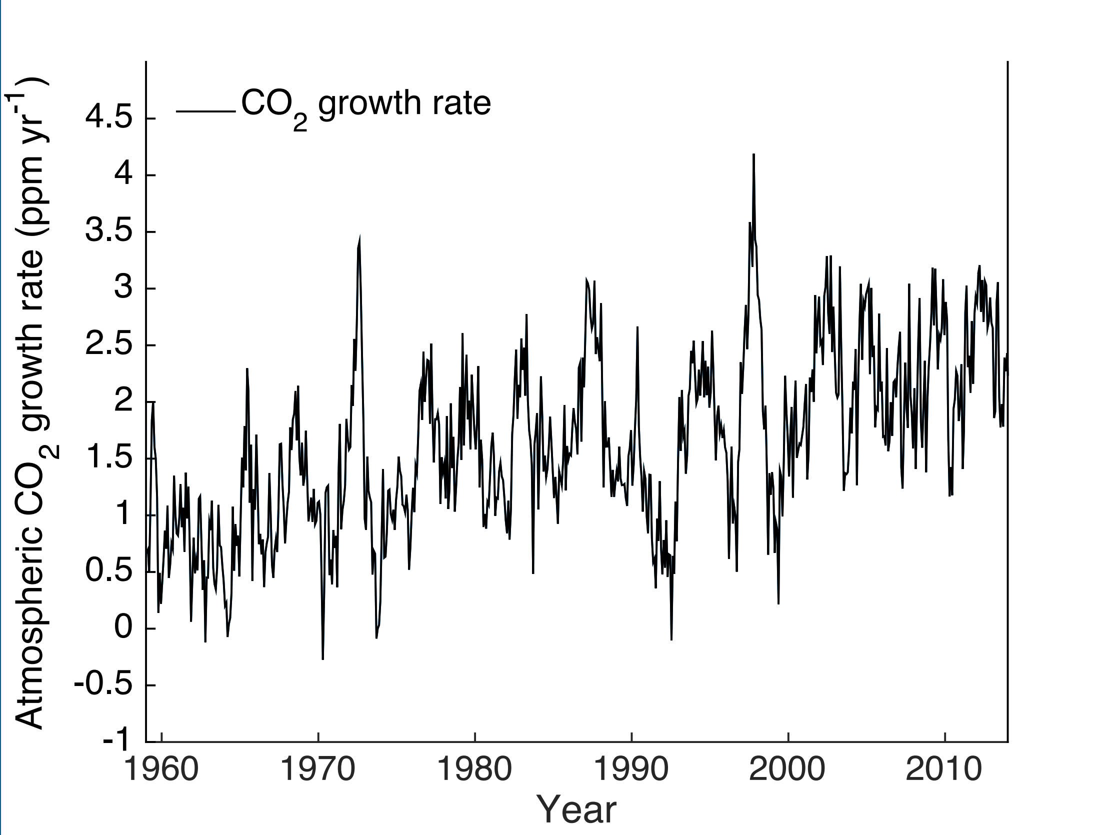
Variability in the growth rate of atmospheric CO_2

GR_{CO2} = emissions (fossil fuels, land use change, cement production)



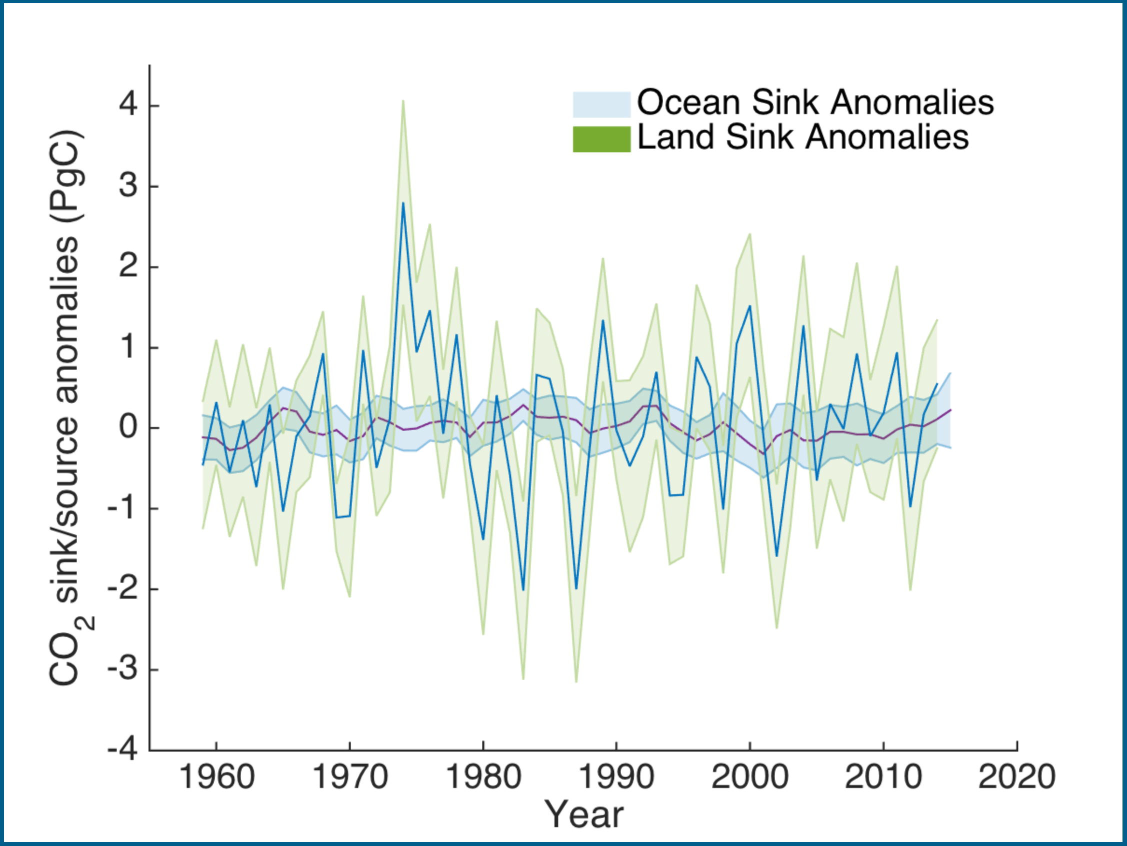
- Terrestrial CO_2 sinks
- Oceanic CO_2 sinks

The growth rate of atmospheric CO_2



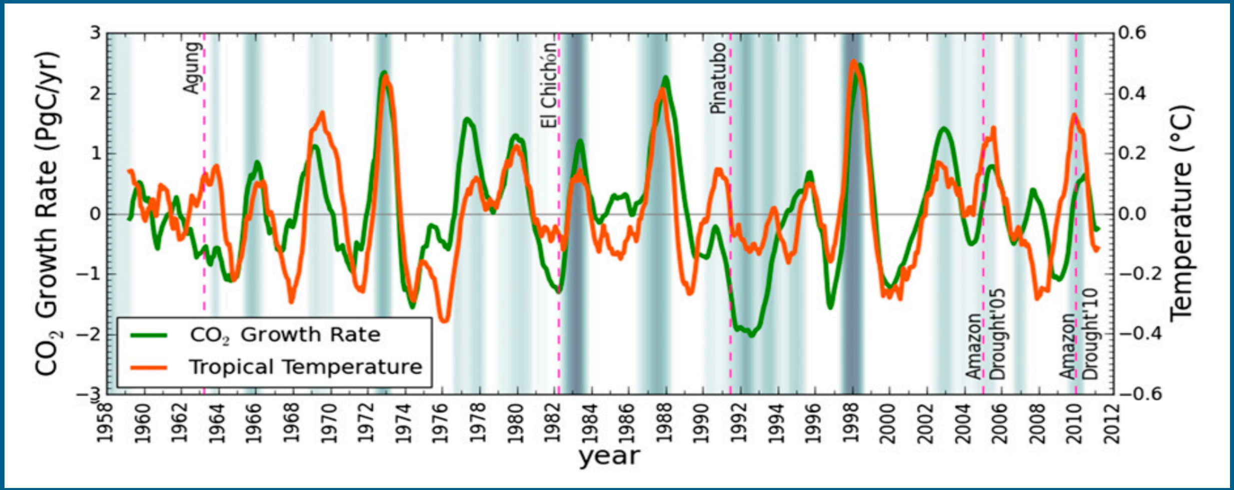
Data source: Scripps CO_2 program @ Mauna Loa

Land variability dominates the growth rate



Data source: Global Carbon Project

Linking the growth rate to the land

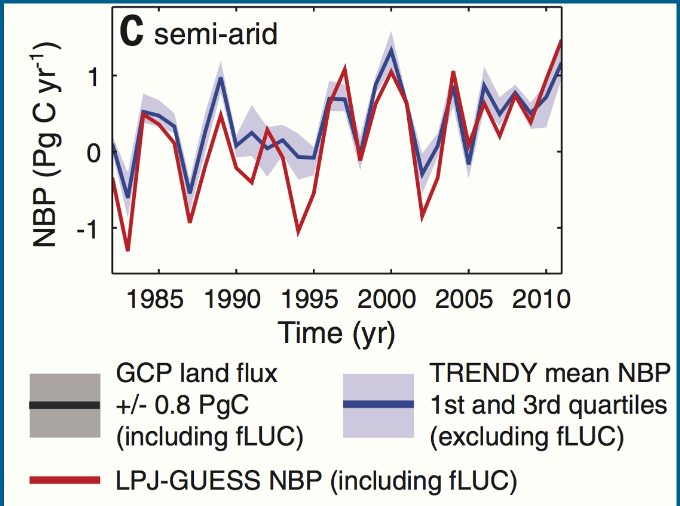


Weile Wang et al. (2013) PNAS

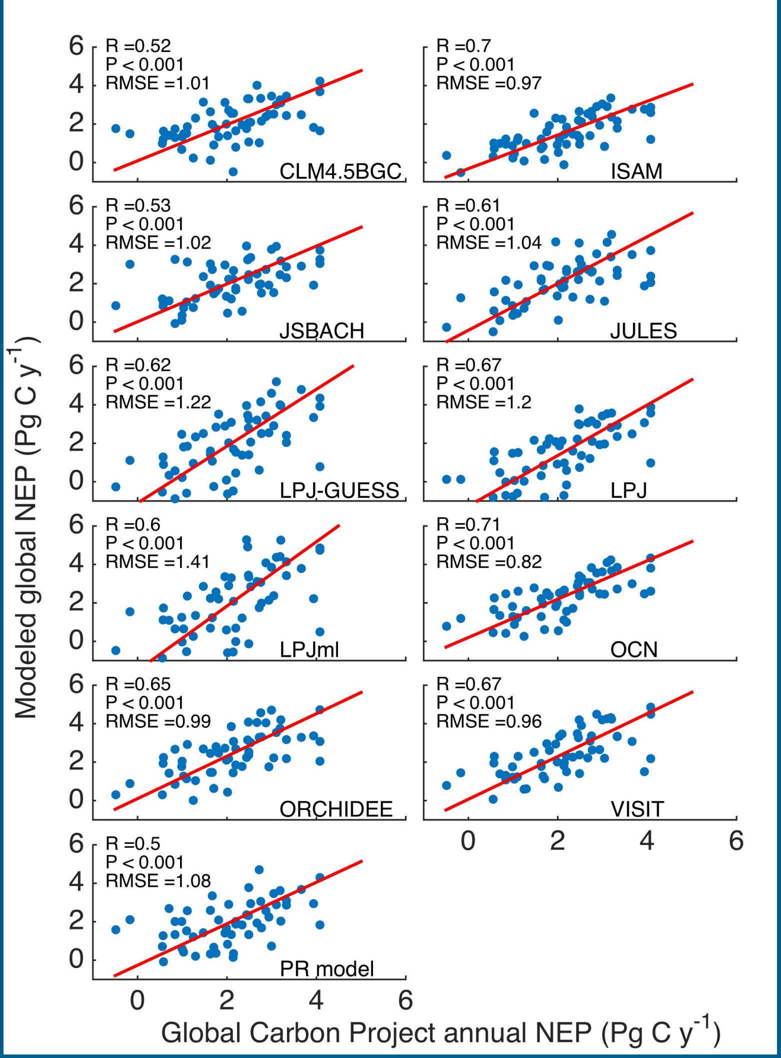
Ahlström et al. (2015); Poulter et al. (2015)

Variation in the growth rate tightly coupled to tropical temperatures.

Semi-arid regions also play an important role.

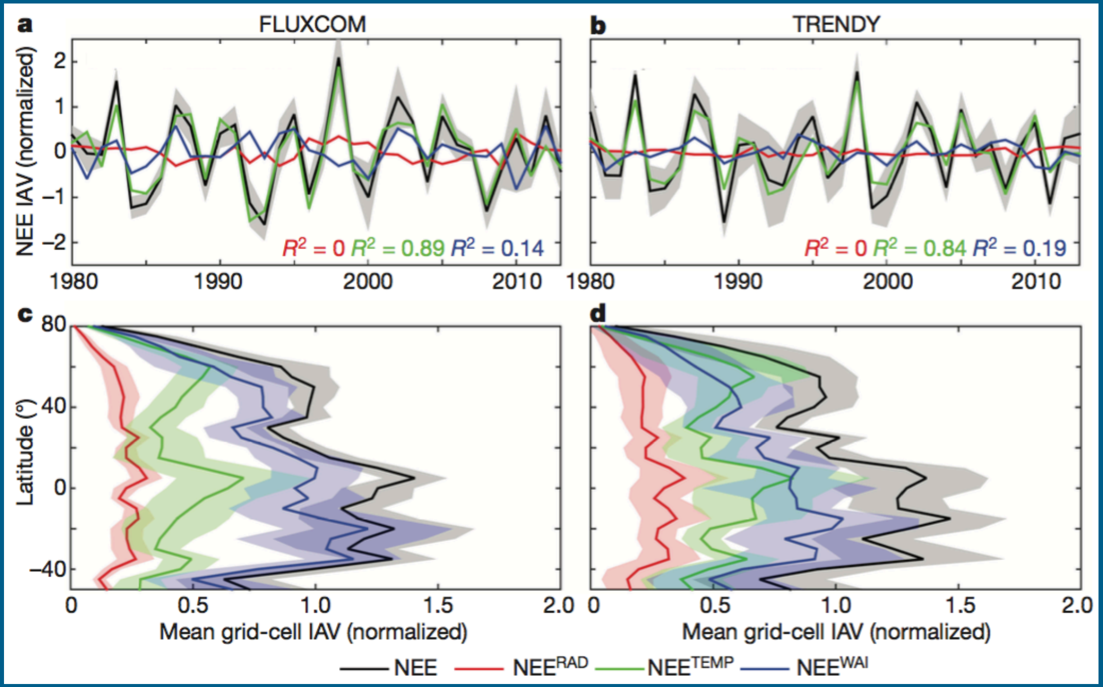


Global scale model performance – good enough?



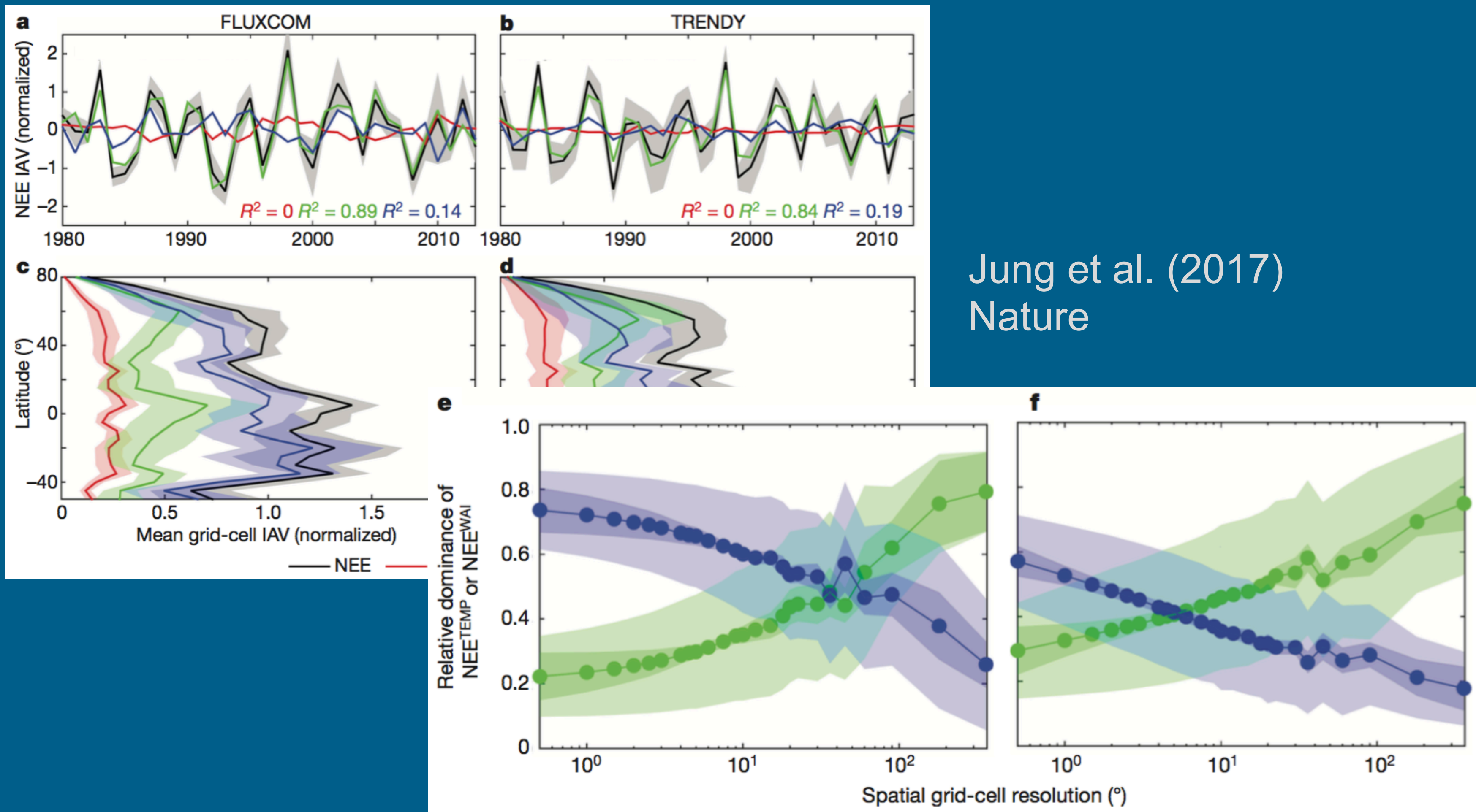
Keenan et al. (2016) Nat. Comms.

A question of scale...



Jung et al. (2017) Nature

A question of scale...



Jung et al. (2017) Nature

at the site scale...

Global Change Biology

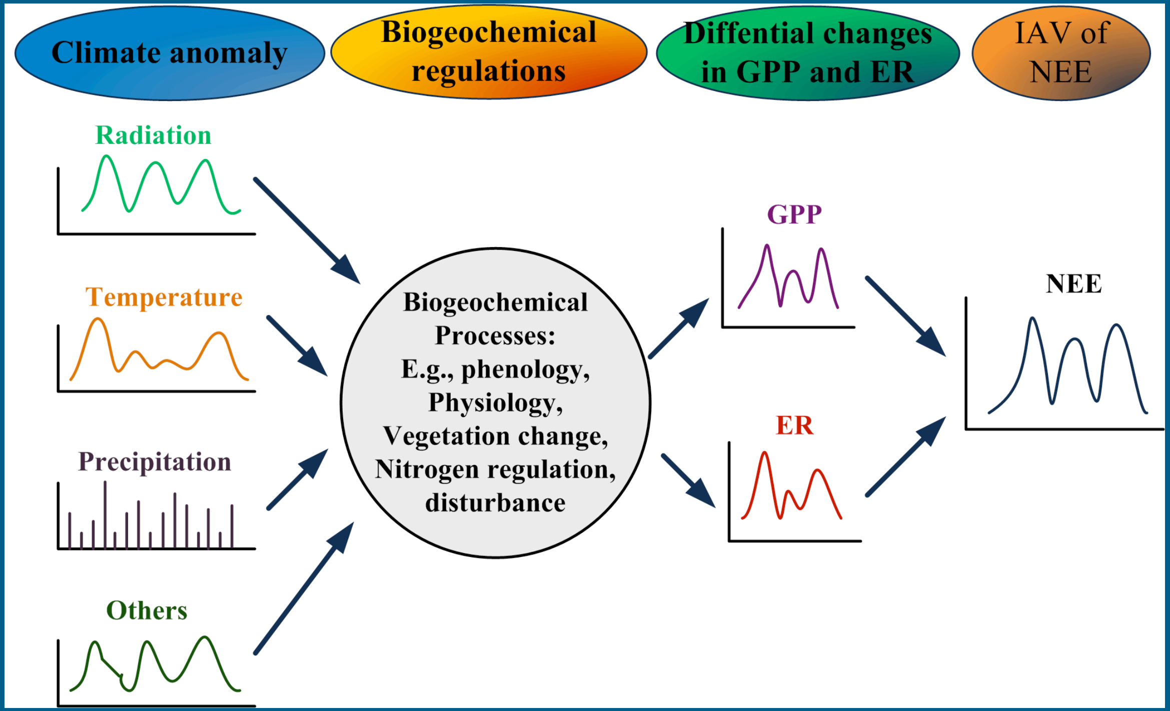
Global Change Biology (2012) **18**, 1971–1987, doi: 10.1111/j.1365-2486.2012.02678.x

Terrestrial biosphere model performance for inter-annual variability of land-atmosphere CO_2 exchange

Keenan et al. (2012)

- At the site level, models perform terribly
- 16 models and 3 satellite products, 11 forested sites
- None of the models fell within measurement uncertainty
- Systematic errors, common to all included models:
  - Underrepresentation of variability in soil thaw, snowpack melting, and canopy phenology
  - Difficulties in reproducing the lagged response to extreme climatic events

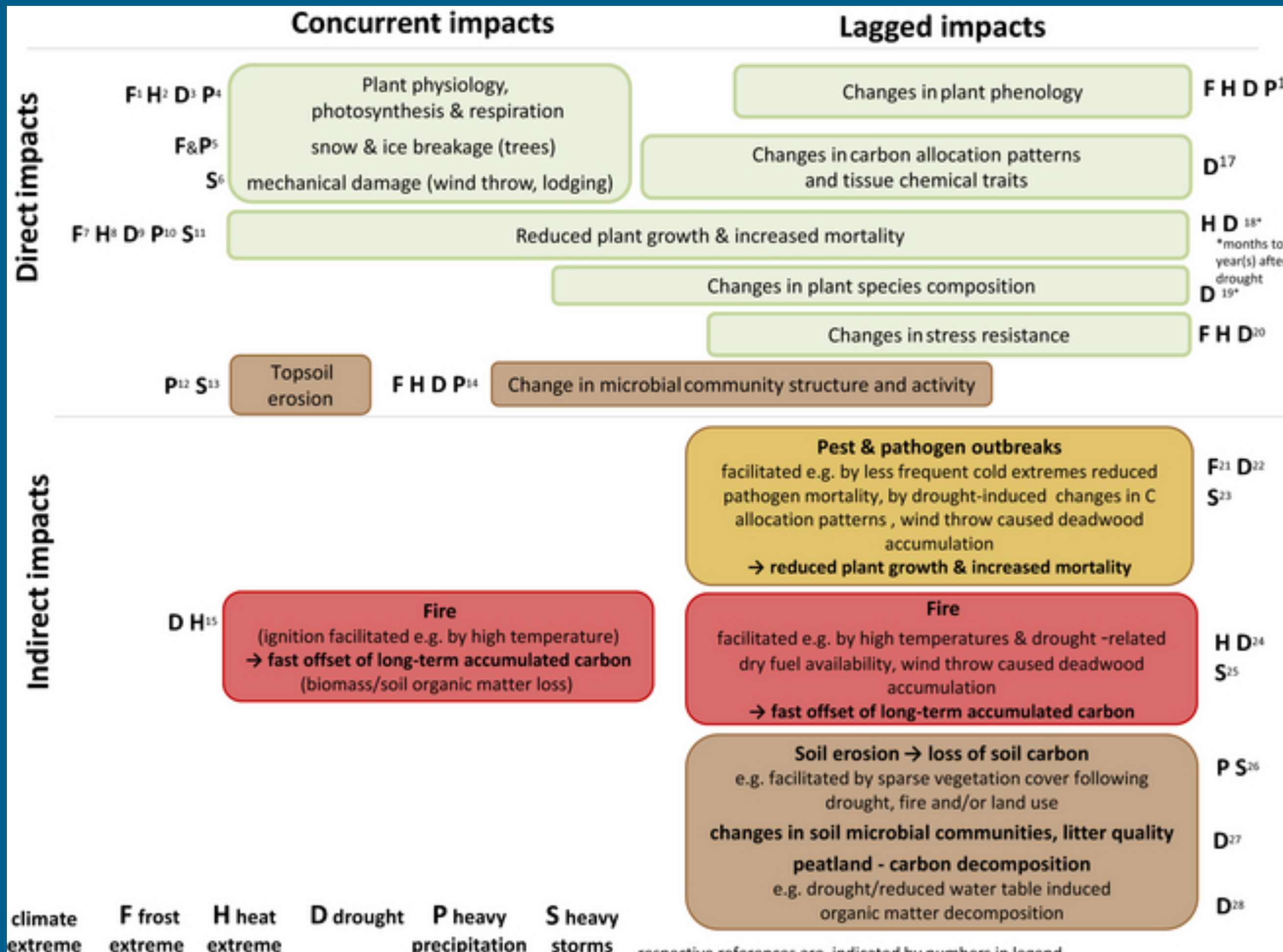
Biophysical Control



Niu et al. (in review)

Shao et al. 2015 AFM: 50/50 share between direct and indirect effects.

Direct and indirect pathways of influence



Frank et al. (2015)

Concurrent impacts

Lagged impacts

Concurrent impacts	
State Changes	
Changes in phenology from warming	
Changes in canopy structure from ice-storms/wind-throw	
Forest mortality due to drought	
Defoliation events (insect/wind/frost)	
Leaf/canopy temperature	
Trait Changes	
Acclimation	
Rate Changes	
Response of photosynthesis and respiration to environmental drivers	

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State Changes	
Canopy development	
Regrowth from disturbance	
Litter layer dynamics	
Non-structural carbohydrate pool dynamics	
Hydrology	
Trait Changes	
Acclimation	
Rate Changes	
All of the above!	

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Expected response depends on the duration, intensity and co-variation of anomalous forcings.

Way forward?

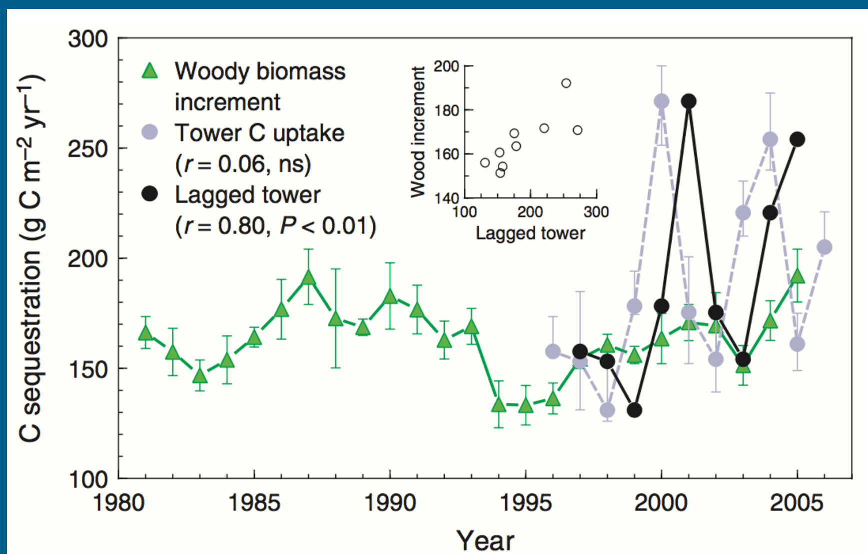
- Better data
  - with well characterized uncertainties
- Different data
  - BADM, remote sensing observations
- More sites
  - working on it!
- Longer datasets
  - F17 now has 10's of sites with >7 years
- Better techniques
  - Model-data integration
  - Data mining/Machine learning (incl. deep learning)
  - Causal inference approaches (e.g., Granger)

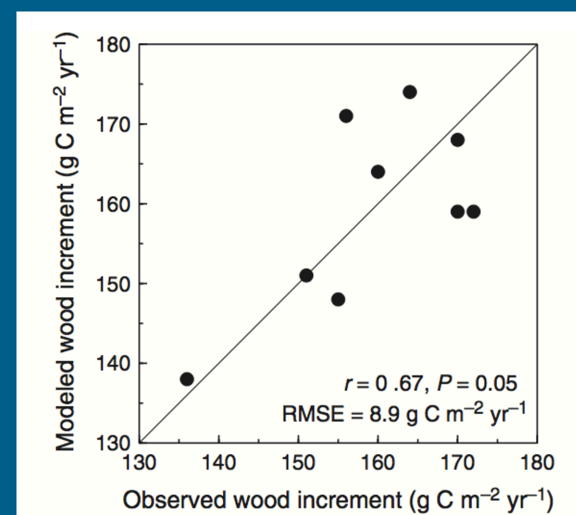
Model-data integration

Seasonal dynamics and age of stemwood nonstructural carbohydrates in temperate forest trees

Andrew D. Richardson[1], Mariah S. Carbone[2], Trevor F. Keenan[1], Claudia I. Czimczik[3], David Y. Hollinger[4], Paula Murakami[5], Paul G. Schaberg[5] and Xiaomei Xu[3]

New Phytologist (2013)



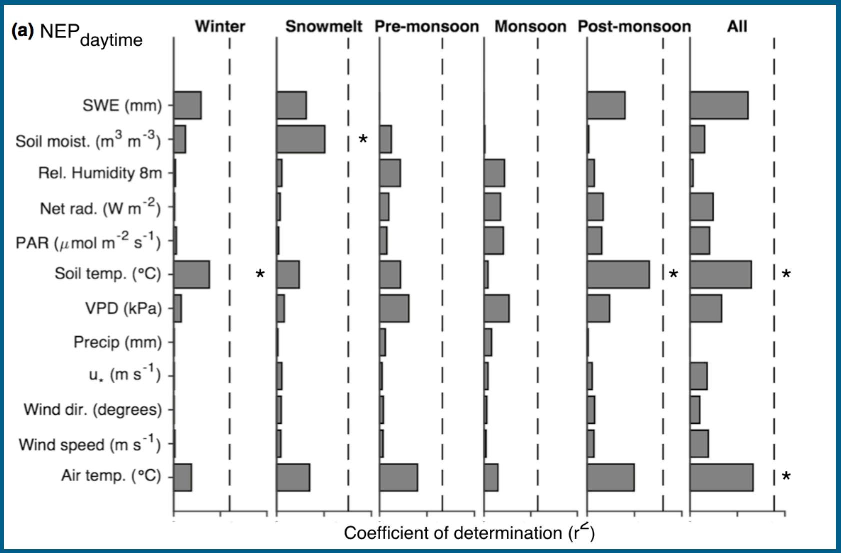


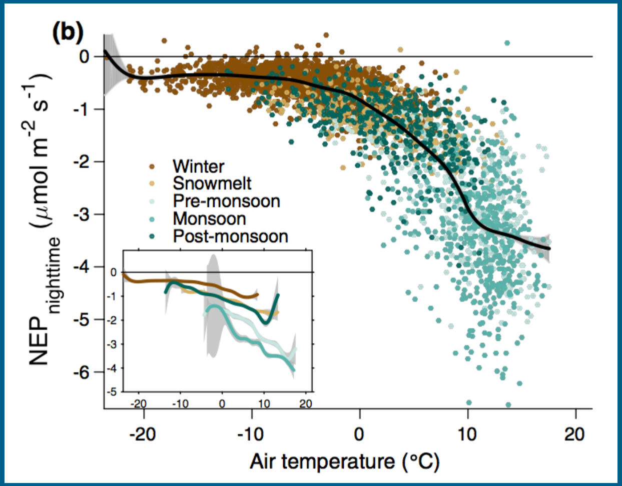
Machine Learning

Climate controls over ecosystem metabolism: insights from a fifteen-year inductive artificial neural network synthesis for a subalpine forest

Loren P. Albert[1] · Trevor F. Keenan[2] · Sean P. Burns[3,4] · Travis E. Huxman[5] · Russell K. Monson[1,6]

Oecologia (2017)





Take home messages:

1. Our understanding and ability to reproduce interannual variability is limited
2. Models have lots of room for improvement, but not known why
3. Lagged effects are important
4. More data than ever before
5. Better data than ever before
6. Wider array of quantitative techniques
7. We can do it!

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Thank you!

DOE, NOAA, FLUXNET scientists

GCP, TRENDY modeling teams