

# Towards a diagnostic terrestrial C- H<sub>2</sub>O model-data fusion analysis and prediction framework

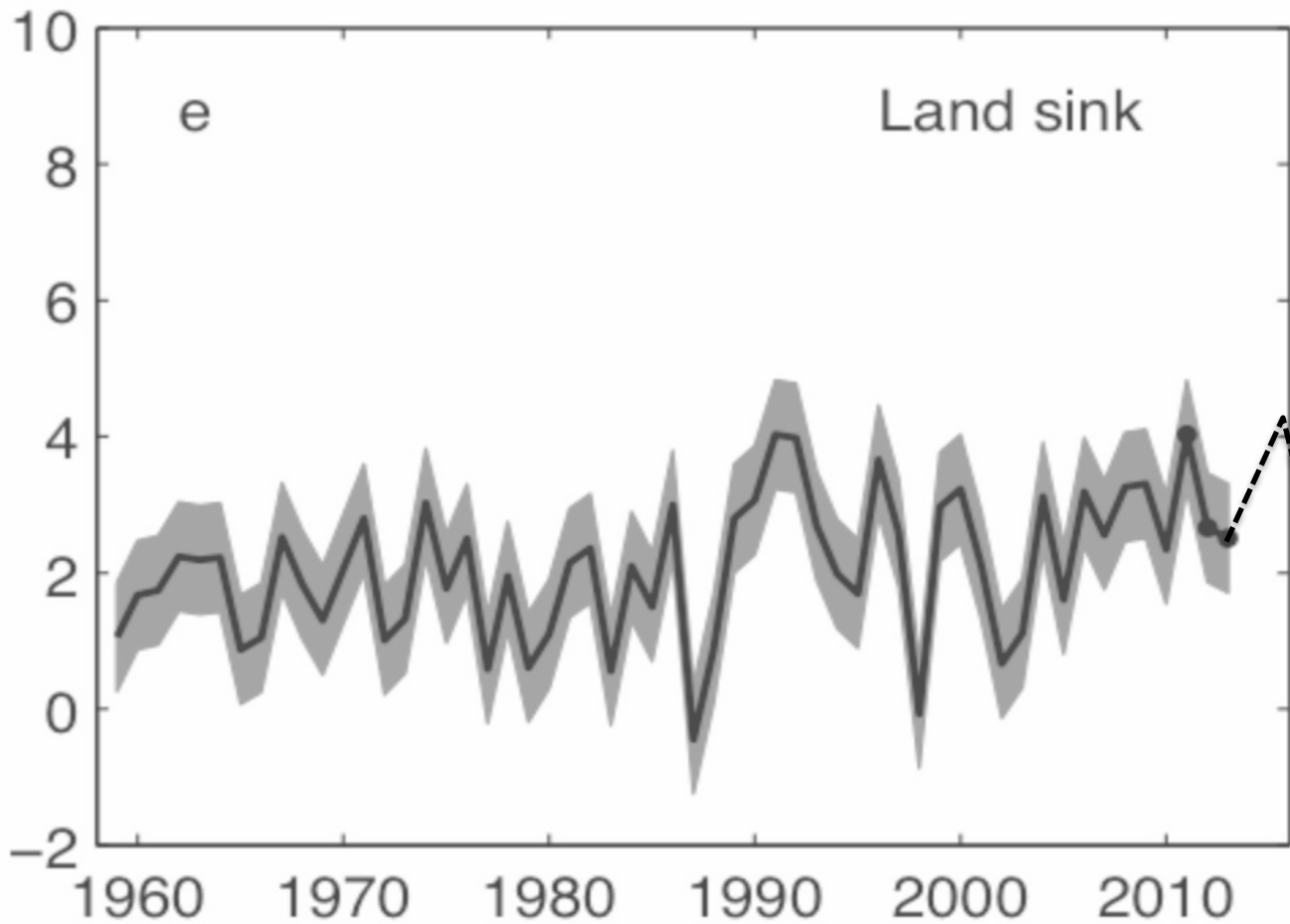
**A. Anthony Bloom<sup>\*1</sup>,**  
*ESM workshop Mar 27 2017*

*\*abloom@jpl.nasa.gov*

*Also: Junjie Liu<sup>1</sup>, Kevin Bowman<sup>1</sup>, Sassan Saatchi<sup>1</sup>, Michael Keller<sup>1</sup>, Alexandra Konings<sup>2</sup>, John Worden<sup>1</sup>, Meemong Lee<sup>1</sup>, David Schimel<sup>1</sup>, Mathew Williams<sup>3</sup>, Nicholas Parazoo<sup>1</sup>, John Reager<sup>1</sup>, others.*

*<sup>1</sup>Jet Propulsion Laboratory, California Institute of Technology, <sup>2</sup>Stanford University, <sup>3</sup>University of Edinburgh, UK, <sup>4</sup>California Institute of Technology*





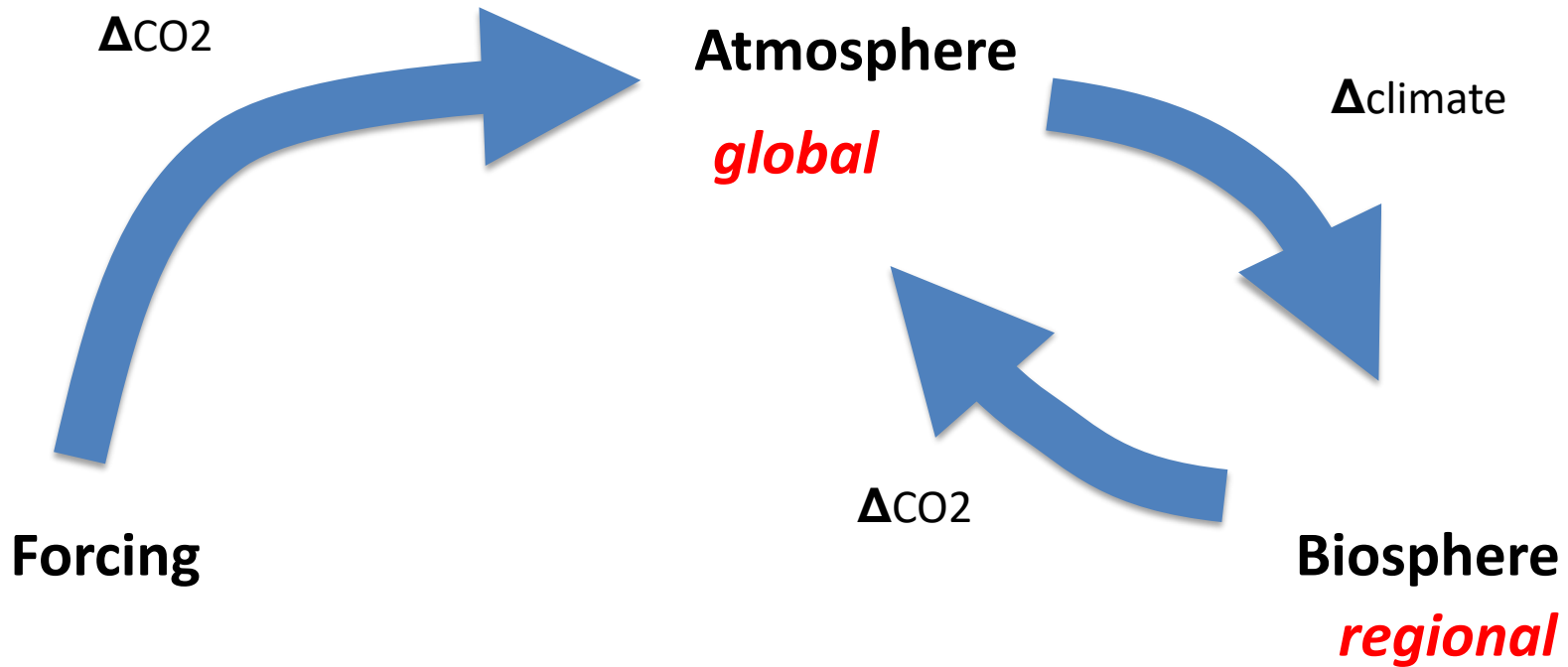
Le Quéré et al. (2015)

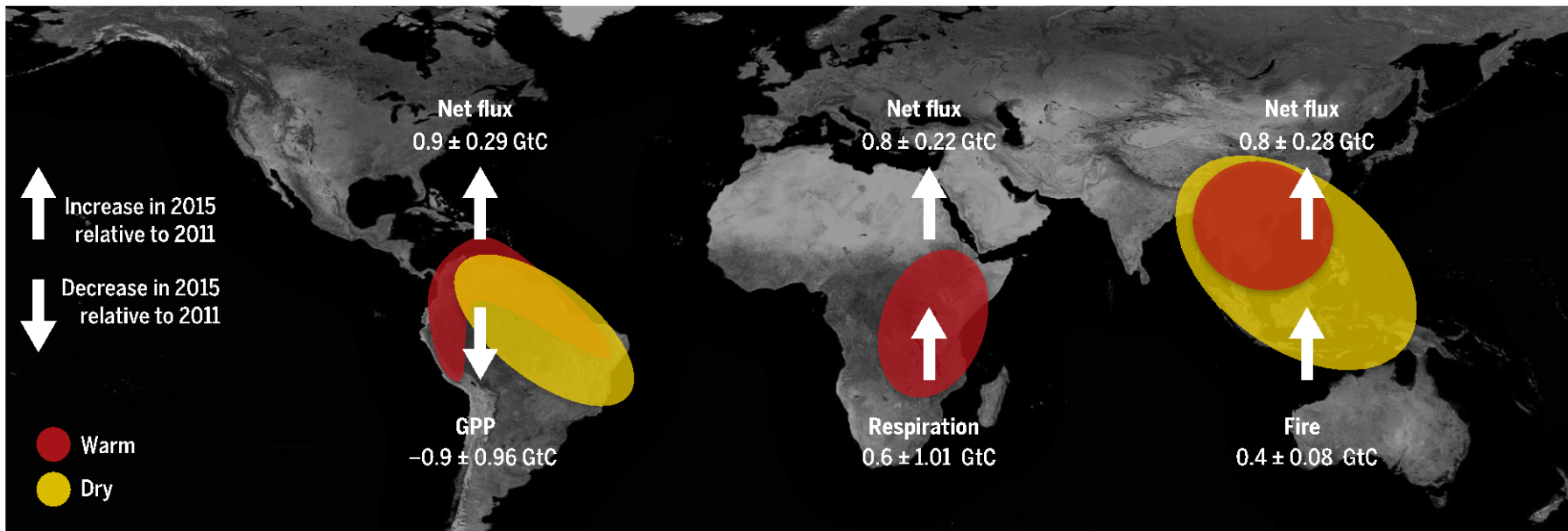
***Improving predictions depends on quantitatively understanding of present-day terrestrial C cycle dynamics:***

- Climate sensitivity of terrestrial C fluxes
- Ecosystem memory (lags, initial conditions, residence times)
- C cycle feedbacks and interactions with water, energy and nutrient cycles



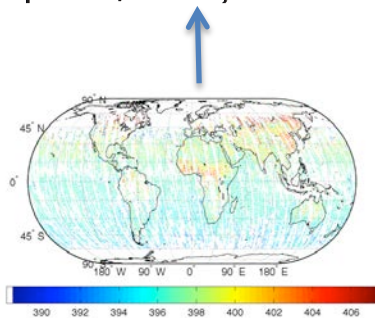
# Terrestrial carbon-climate feedbacks



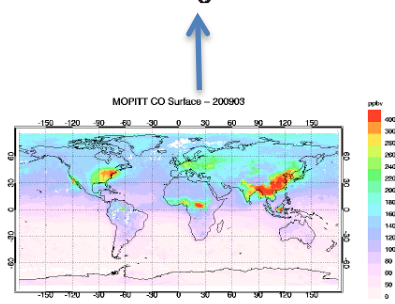


Diverse climate driver anomalies and carbon cycle responses to the 2015–2016 El Niño over the three tropical continents. Schematic of climate anomaly patterns over the three tropical continents and the anomalies of the net carbon flux and its dominant constituent flux (i.e., GPP, respiration, and fire) relative to the 2011 La Niña during the 2015–2016 El Niño. GtC, gigatons C.

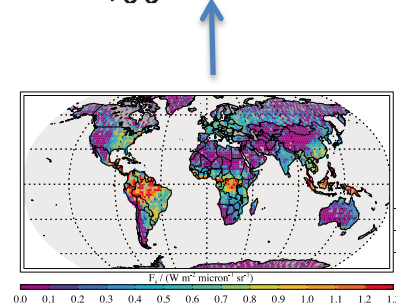
*Liu et al., 2017*



OCO-2 & GOSAT CO<sub>2</sub>



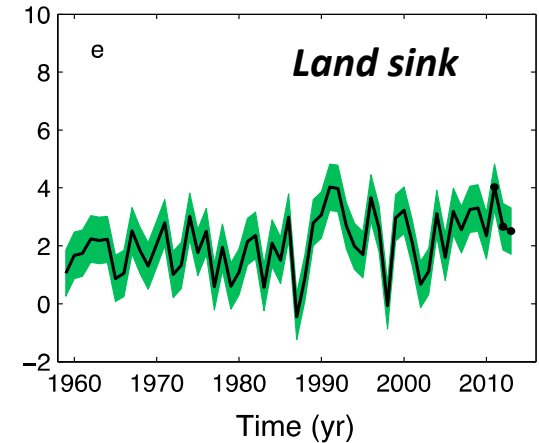
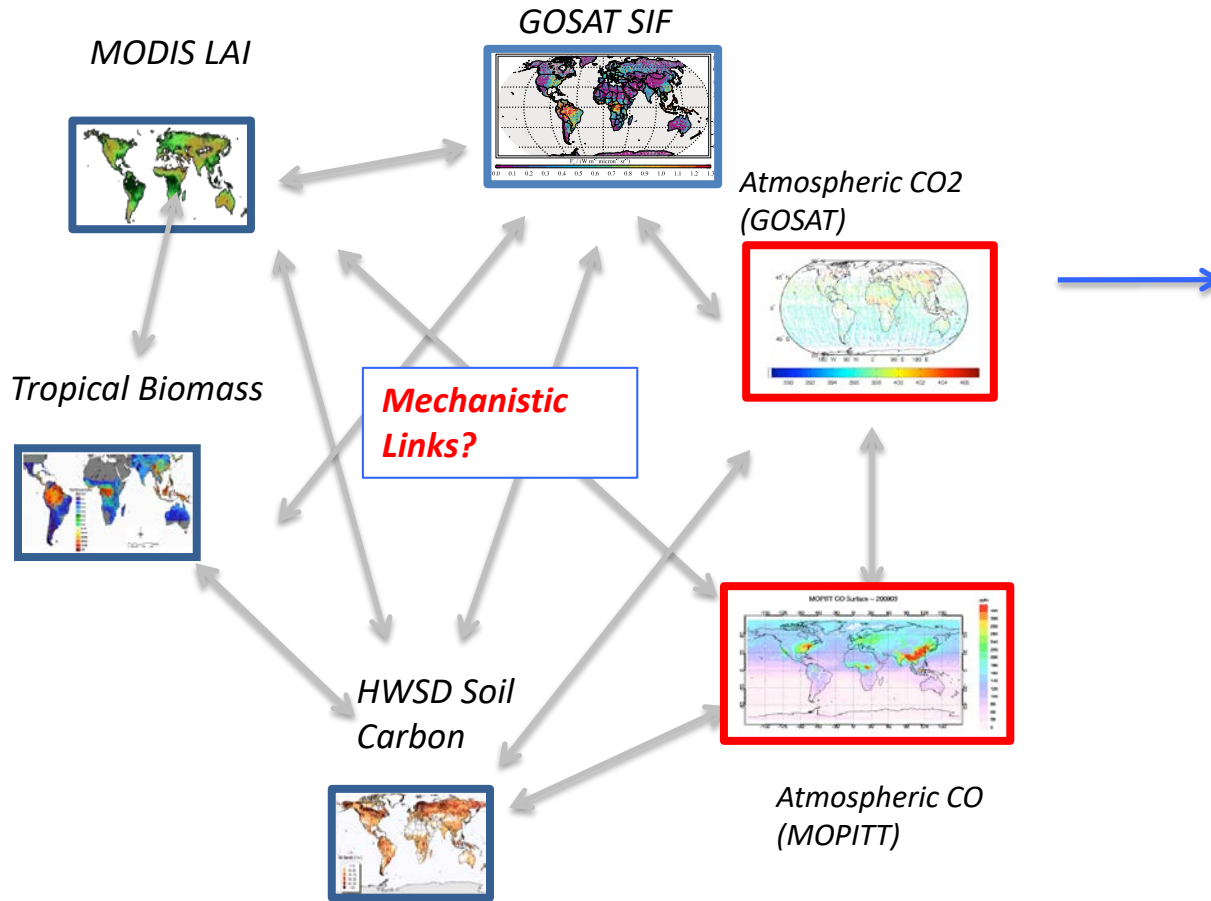
MOPITT CO



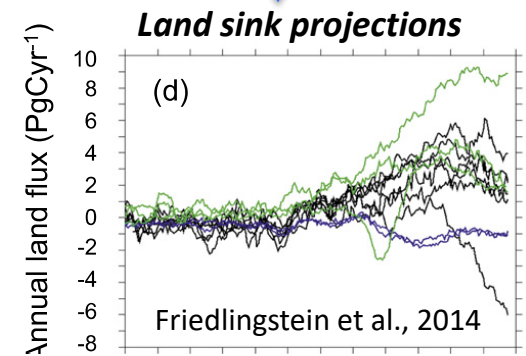
GOSAT SIF



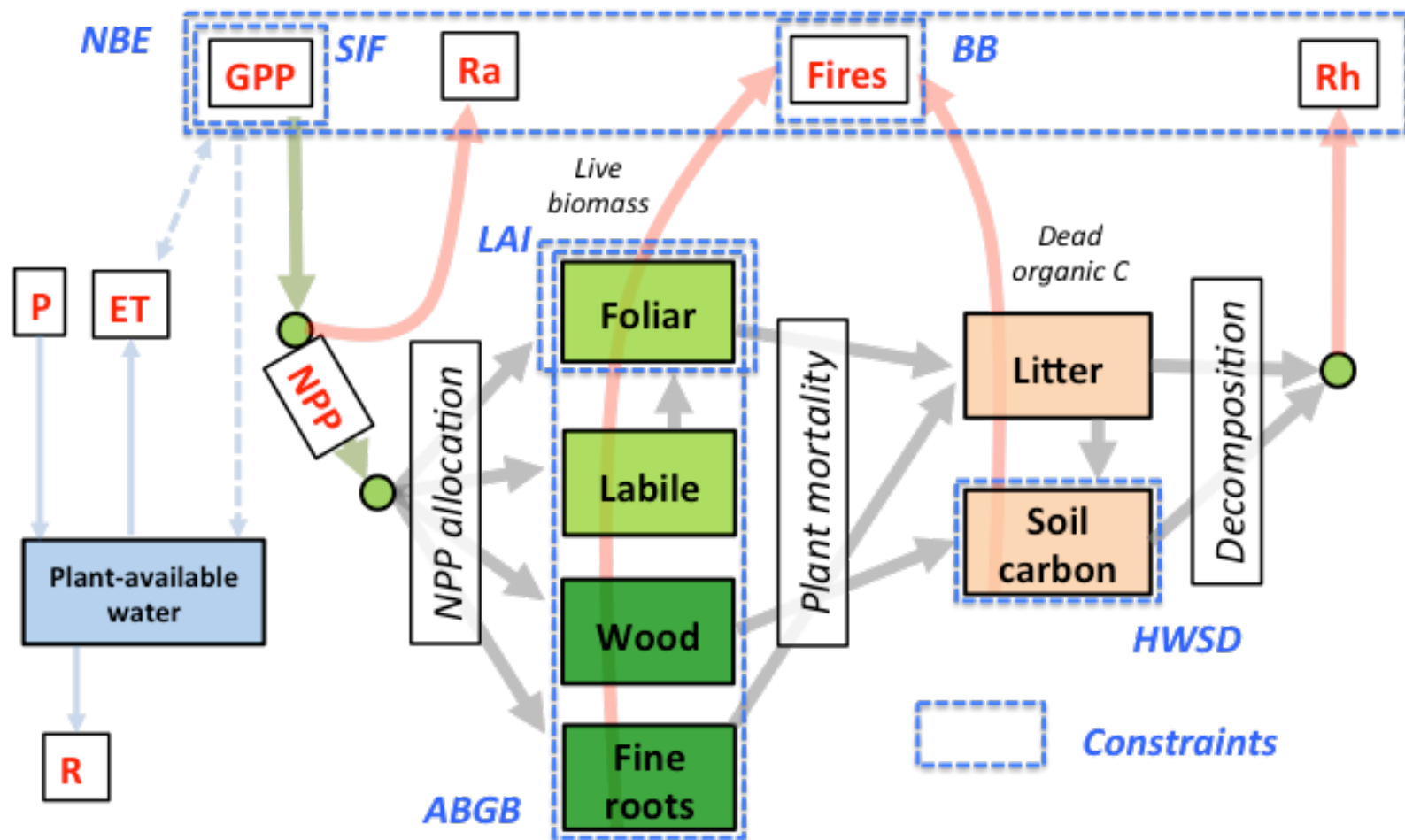
# Terrestrial C cycle: towards reducing process uncertainty.



Le Quéré et al., 2016



# Carbon data-model framework (CARDAMOM)

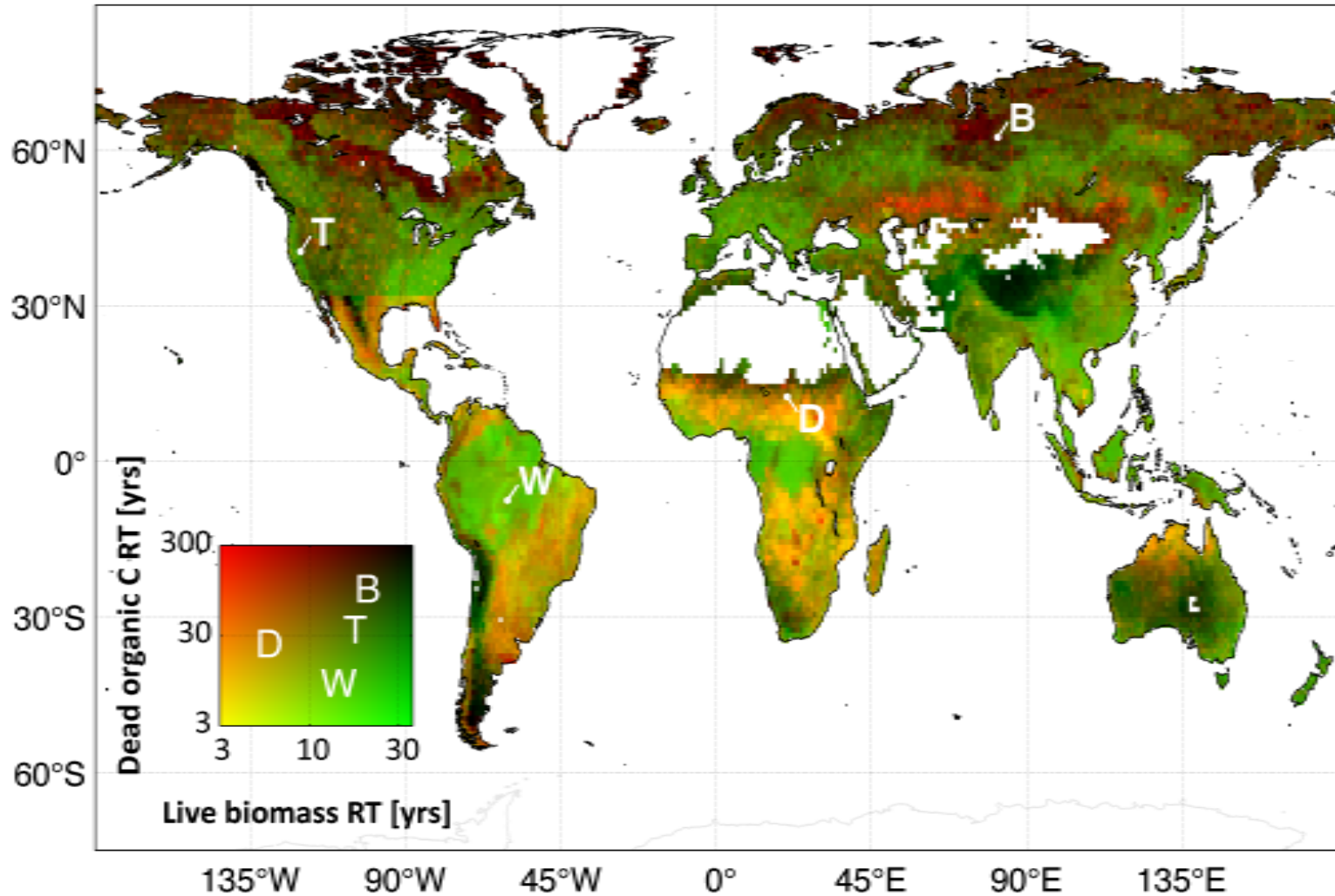


Spatially-explicit optimization of terrestrial C cycle parameters

Williams et al. (2005), Bloom & Williams (2015), Bloom et al. (2016)



# CARDAMOM: Terrestrial carbon cycle state and process variables

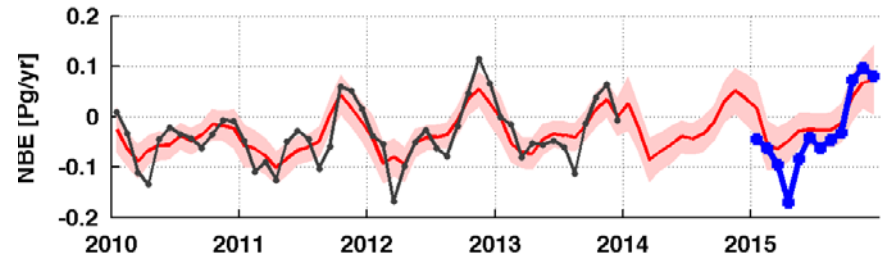
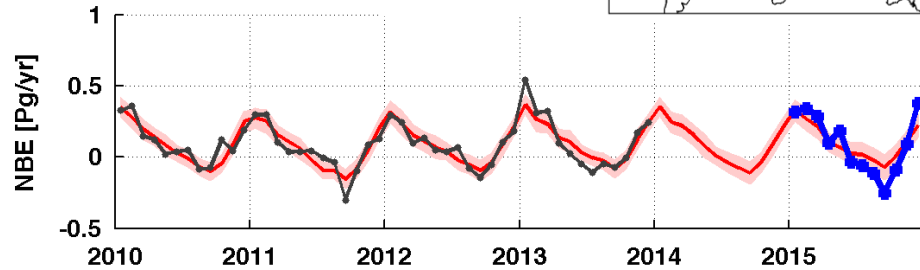


Bloom et al. 2016, PNAS



A. Anthony Bloom, ESM workshop, Mar 2018

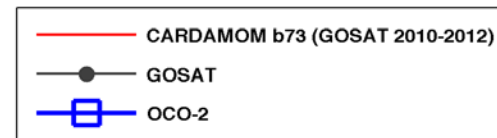
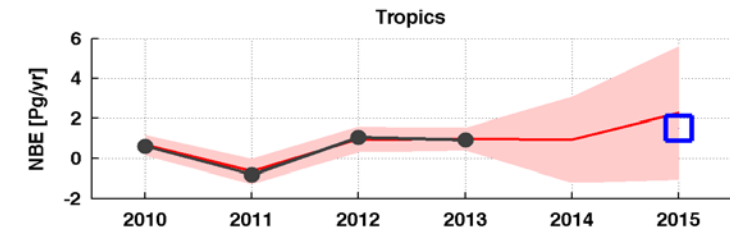
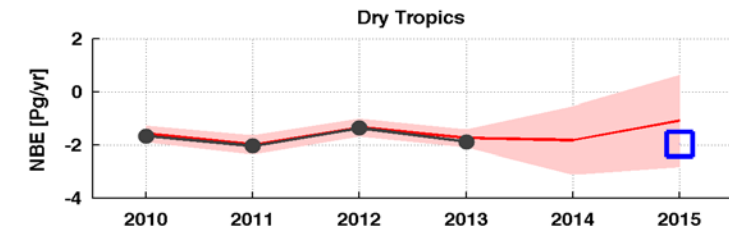
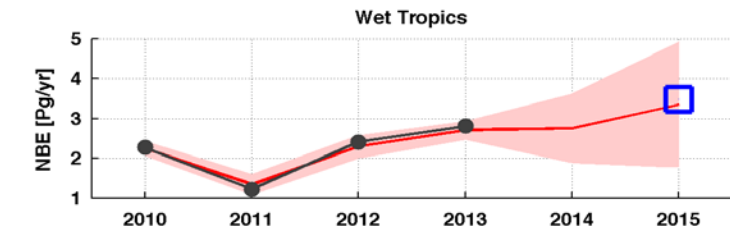
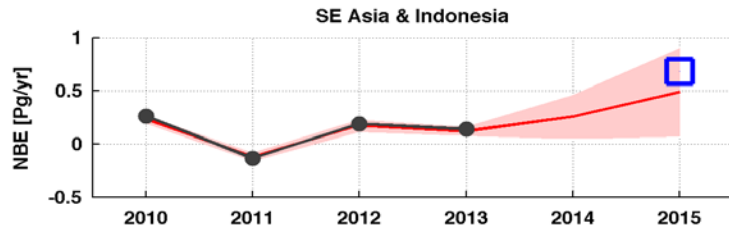
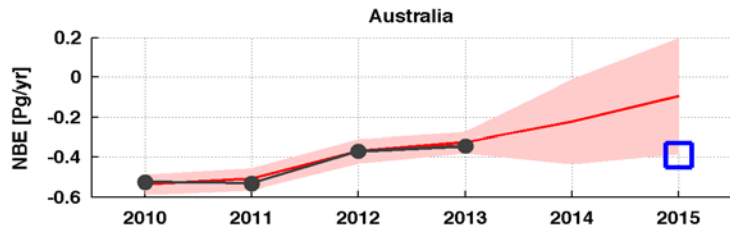
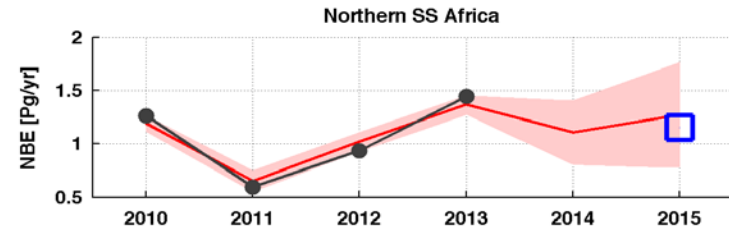
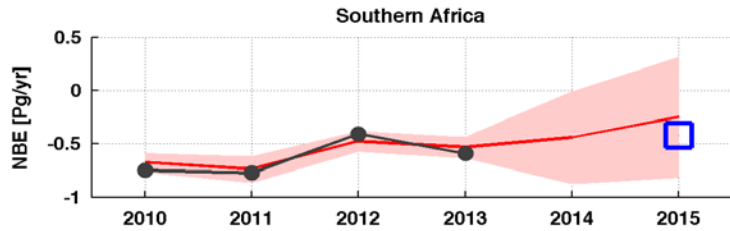
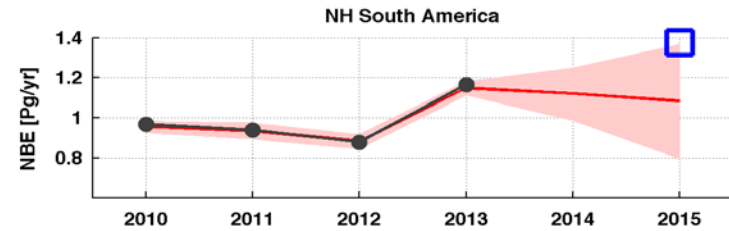
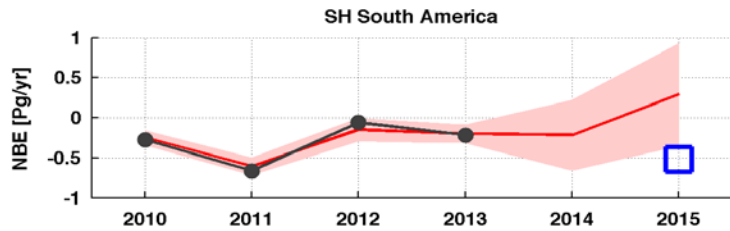
# GOSAT and OCO-2 NBE – assimilation & prediction



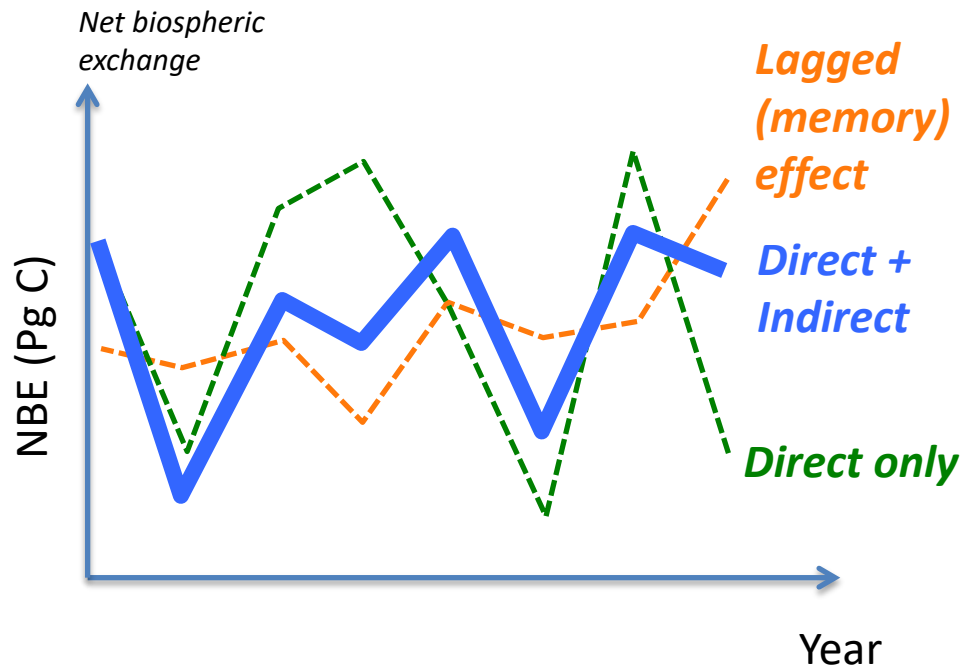
**Red = CARDAMOM mean**  
**Pink = CARDAMOM  $1\sigma$**

**Black = GOSAT-derived NBE (assimilated into CARDAMOM)**  
**Blue = OCO-2 derived NBE (withheld for validation)**





# Do memory effects contribute to NBE IAV?

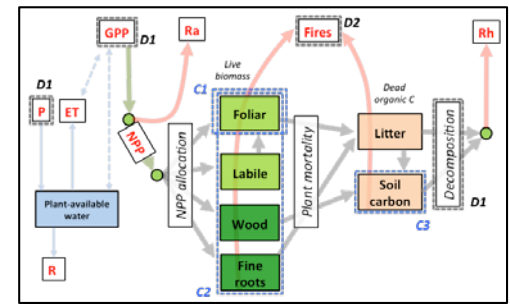


**Lagged effect:** attributable to ecosystem memory effects

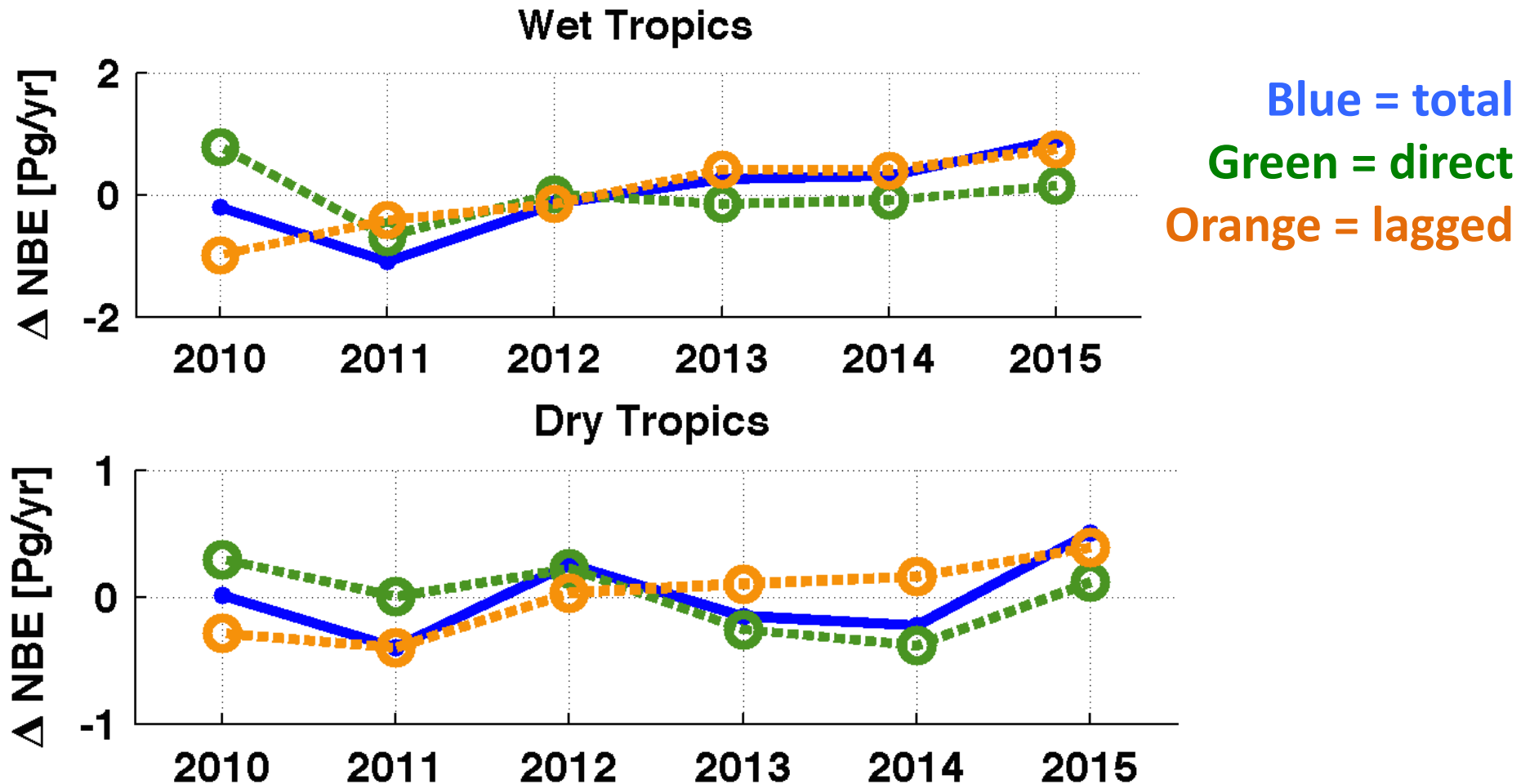
**Direct effect:** attributable to instantaneous met. forcings

Direct & lagged NBE  
Attribution approach:  
meteorological forcing  
sensitivity of optimized  
CARDAMOM NBE

$$\Delta NBE_{total} = \Delta NBE_{direct} + \Delta NBE_{lagged}$$



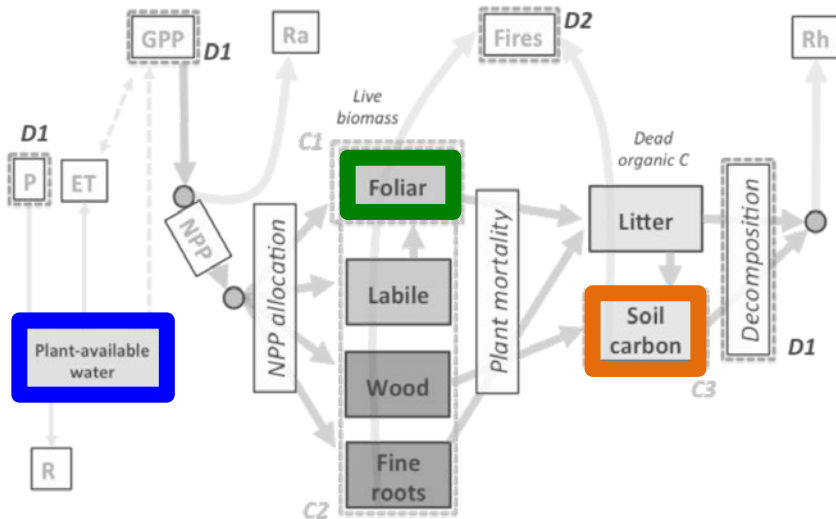
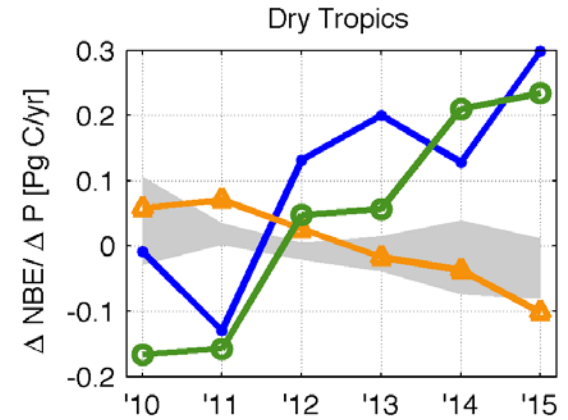
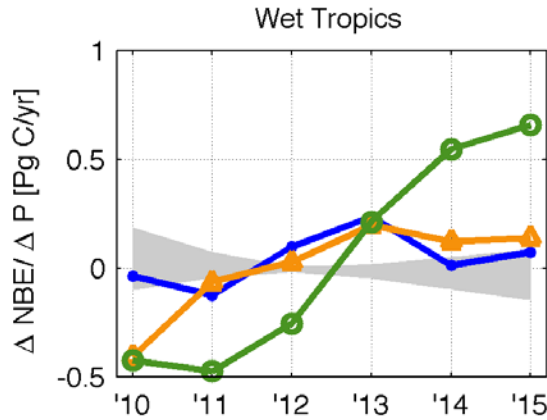
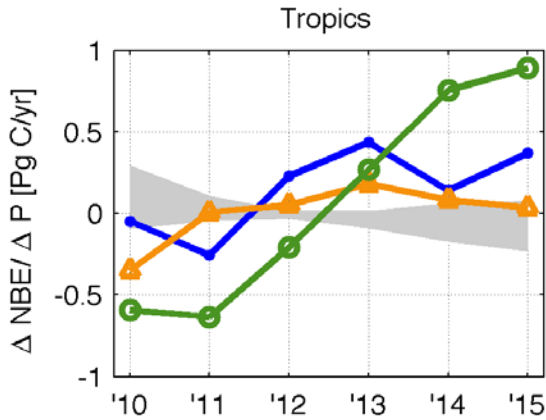
# Ecosystem memory in tropical ecosystems



*Bloom et al. (2018, in prep.)*



# Why?



**Blue = Plant-available H<sub>2</sub>O**

**Green = Foliar C**

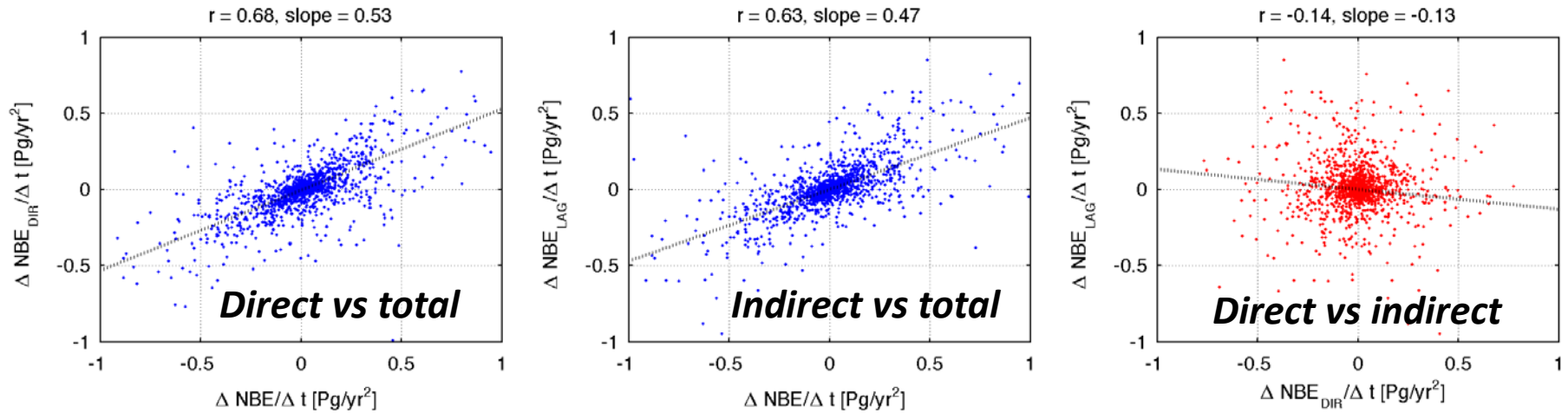
**Orange = Soil C**

*IAV and trajectories of plant-available H<sub>2</sub>O, canopy C and soil C stocks influence NBE responses to climate variability.*

*Bloom et al. (2018, in prep.)*

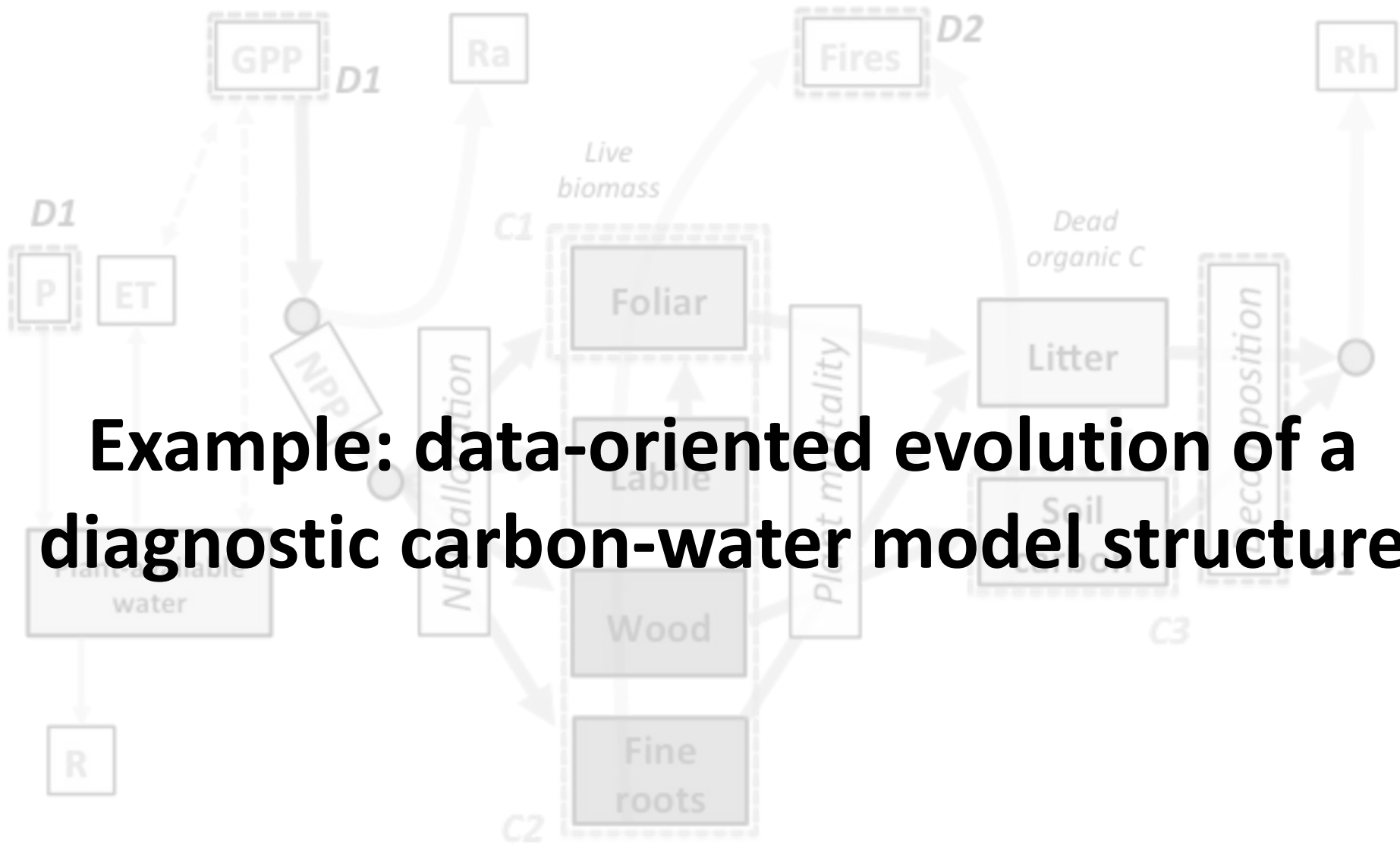


# Memory effects on tropical NBE IAV



- Memory effects account for  $\sim 50\%$  of tropical NBE IAV
- Quantitative knowledge of NBE legacy effects is necessary to predict the evolution of the terrestrial C balance.
- Process-oriented diagnostic model central to advancing mechanistic understanding of terrestrial C cycling.

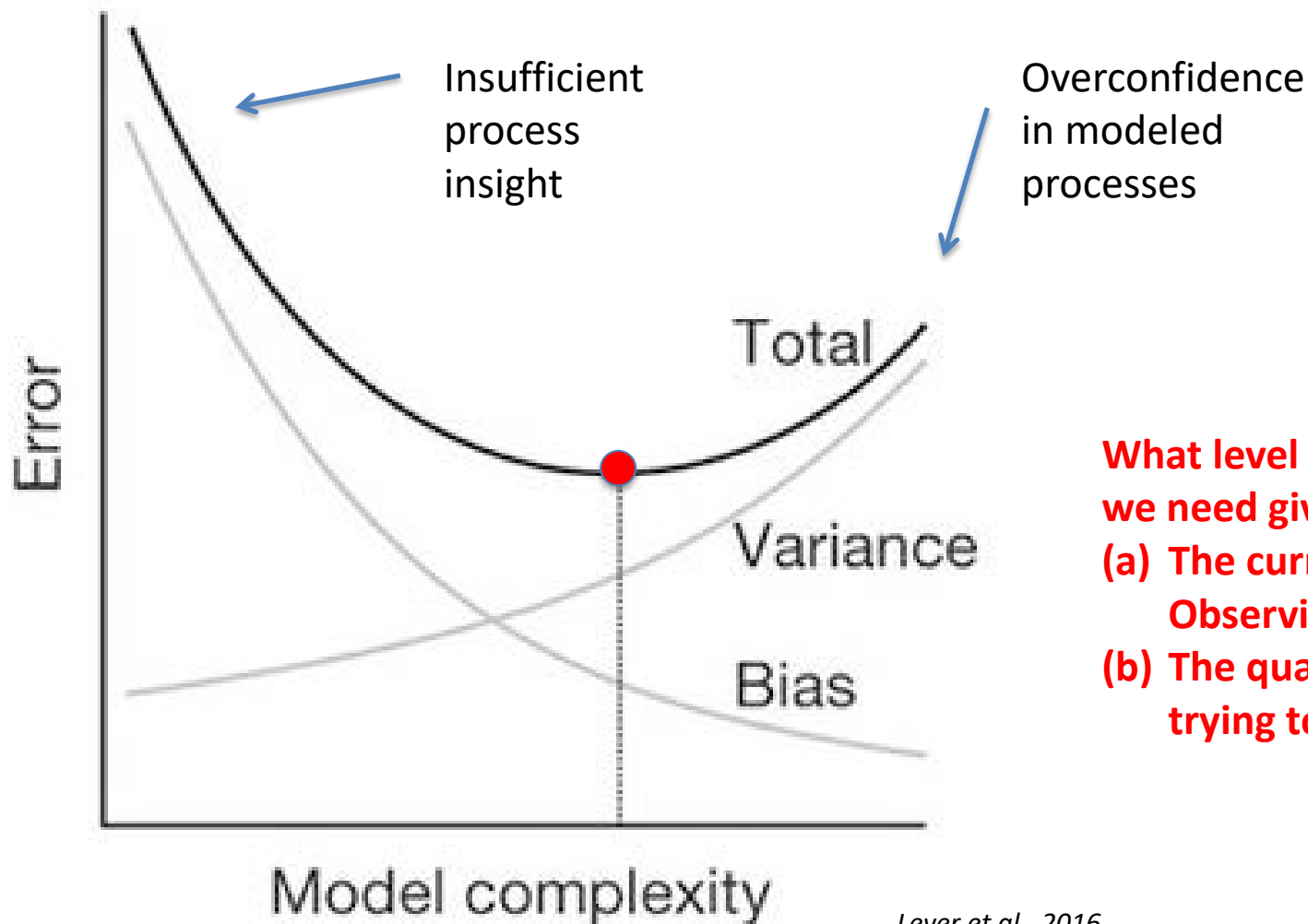




# Example: data-oriented evolution of a diagnostic carbon-water model structure



# Prediction error vs model complexity



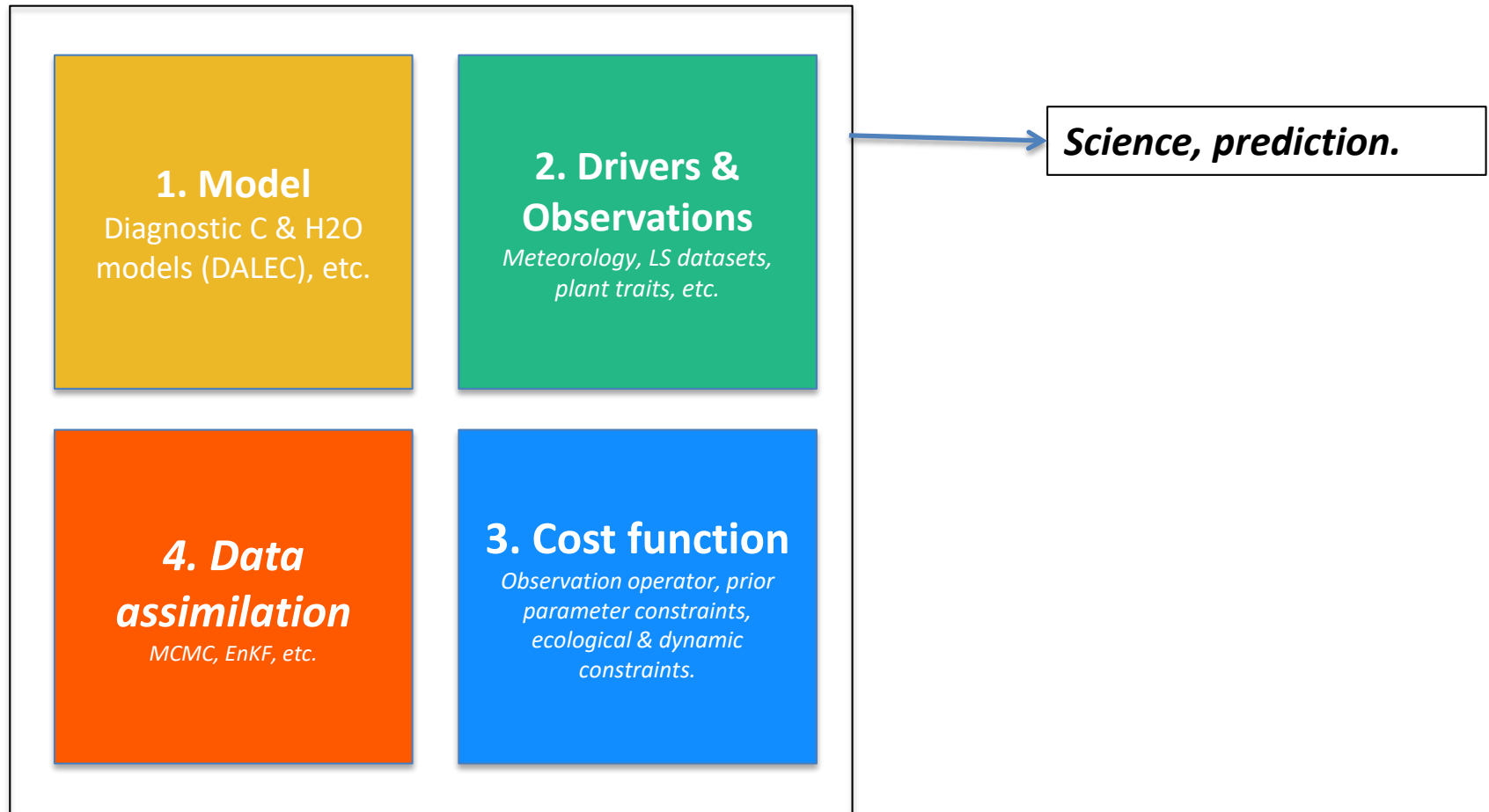
**What level of complexity do we need given:**

- (a) The current Earth-Observing system**
- (b) The quantities we're trying to predict?**

*Lever et al., 2016*



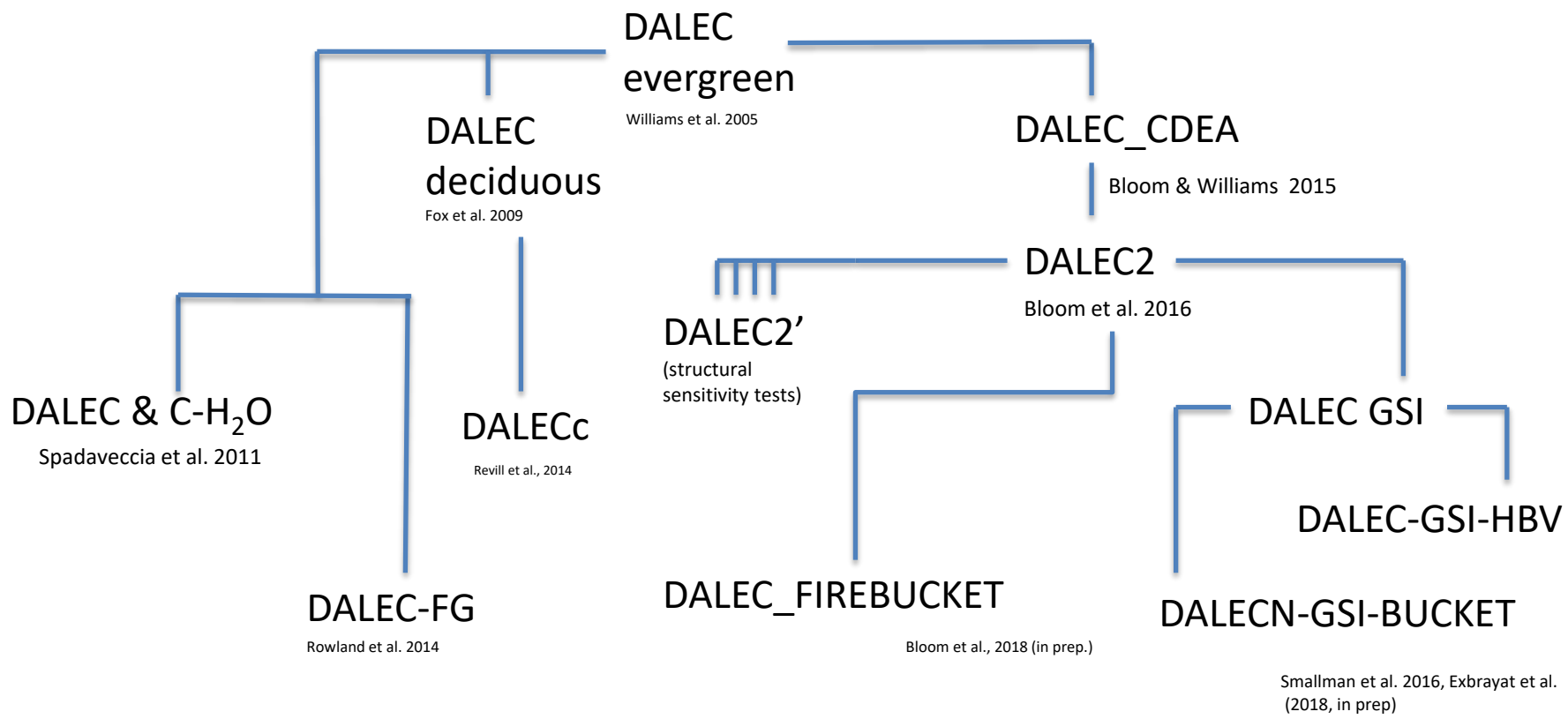
# CARDAMOM modular structure





# DALEC genealogy: data & hypothesis driven evolution

Data & hypothesis driven model development



# Carbon-water feedbacks

*Change in terrestrial  
water balance*

*Precip.*

*Evaporation + plant  
transpiration*

*Runoff*

$$dW/dt = P - ET - R$$

*Hydraulic constraints*

*Water use efficiency*

*Soil moisture + other*

*Land-use change*

*Change in terrestrial  
carbon balance*

$$dC/dt = GPP - R_{eco} - D$$

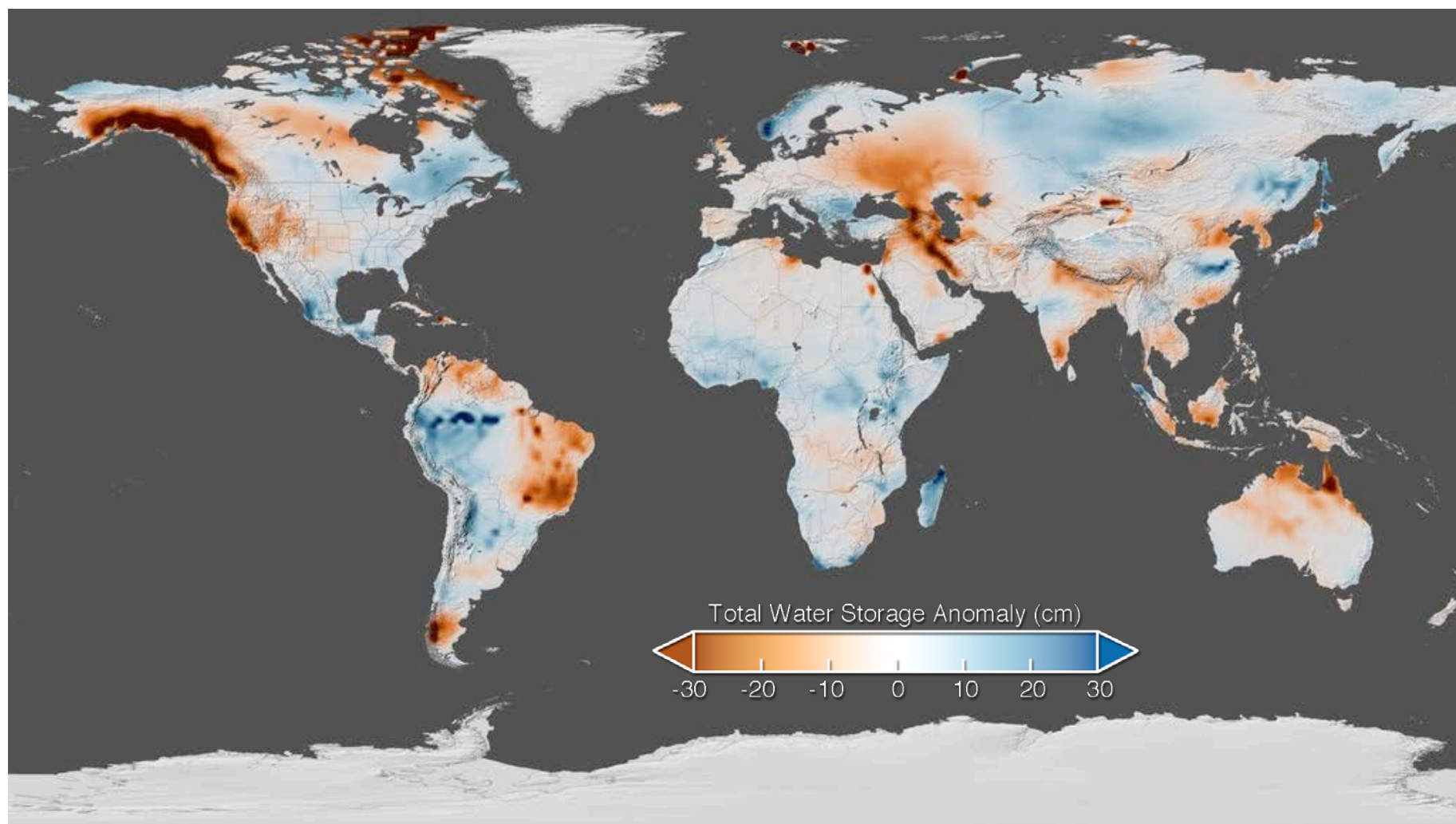
*Gross primary  
production*

*Ecosystem  
respiration*

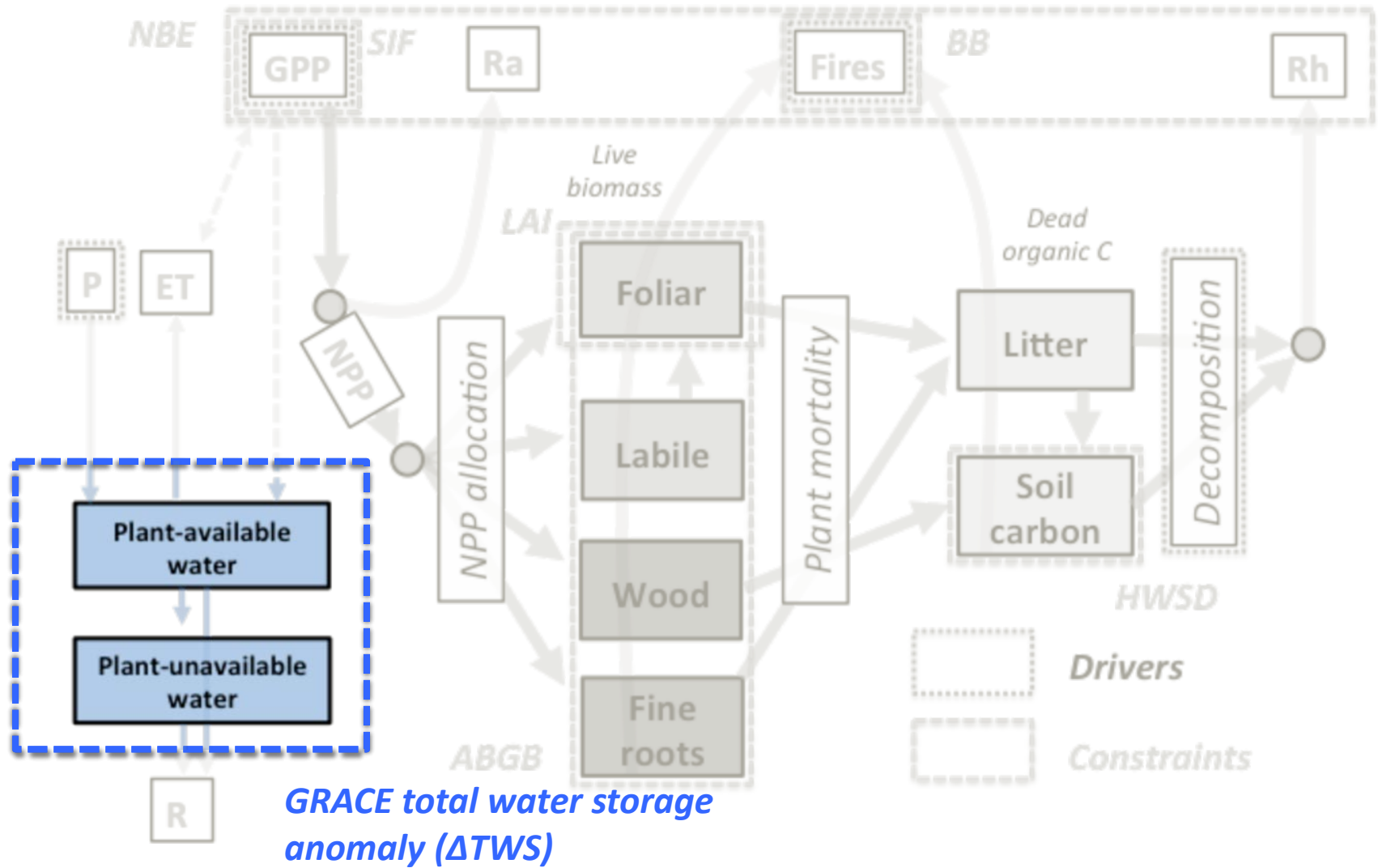
*Disturbances*



# Gravity recovery and climate experiment (GRACE)

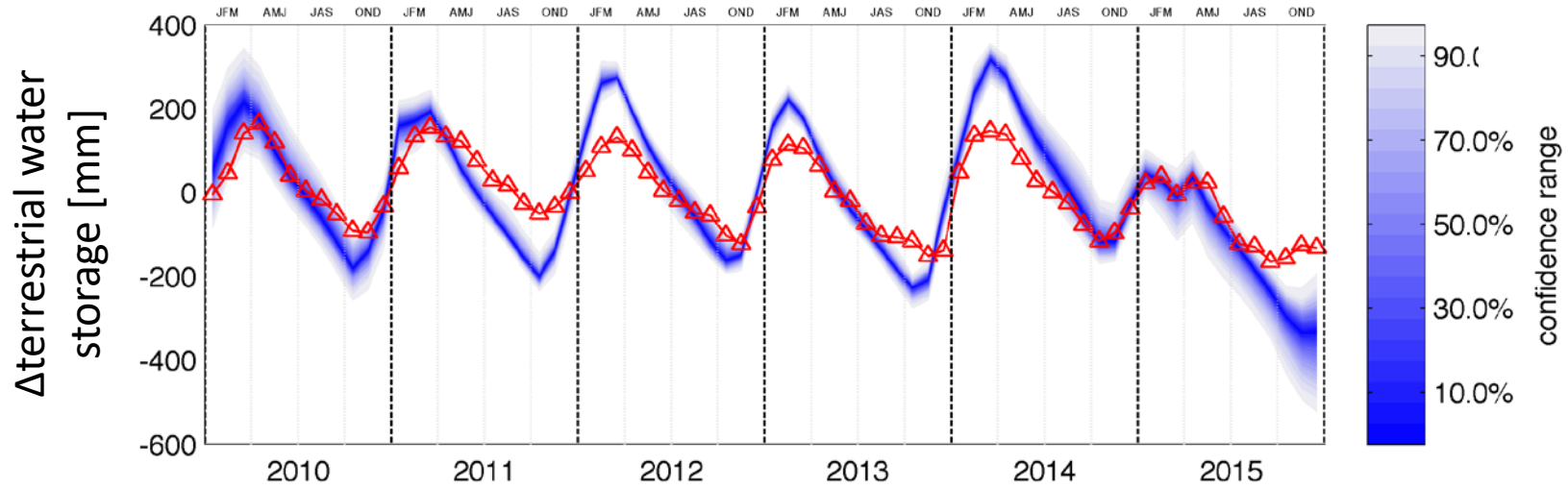


# Example: data-driven model structure evolution

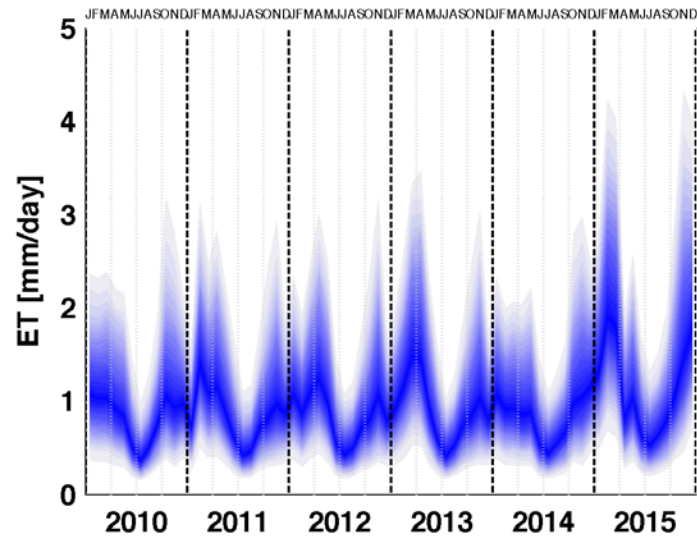
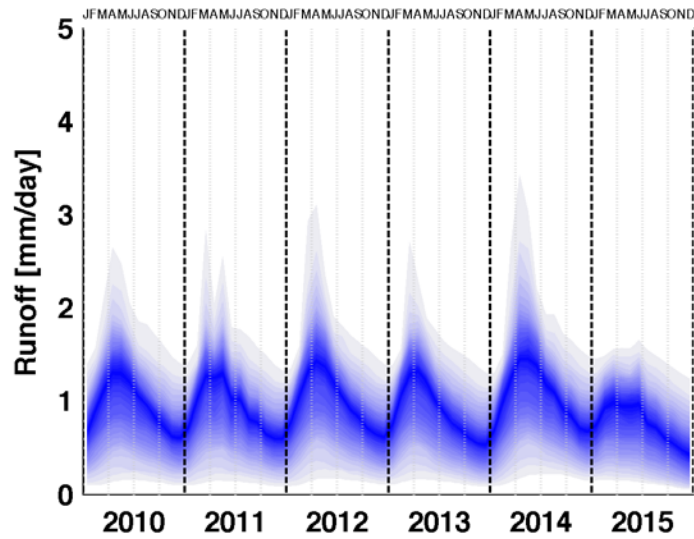


Blue = CARDAMOM

Red = GRACE (withheld)



# CARDAMOM: C constrains only





# Conclusions & questions

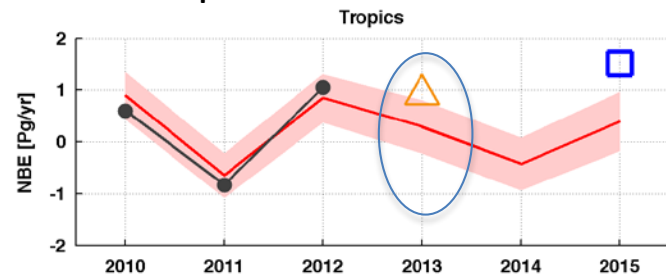
- Joint understanding of climate sensitivity and ecosystem memory effects on present-day NBE IAV necessary for prediction.
- Observational constraints on both carbon and water cycle dynamics are central to building a land-surface predictive ability.
- How do we bring and test process-based model knowledge in a diagnostic C-H<sub>2</sub>O-energy model-data framework?
- What is the optimum balance between process fidelity and data consistency for decadal-to-centennial predictions?



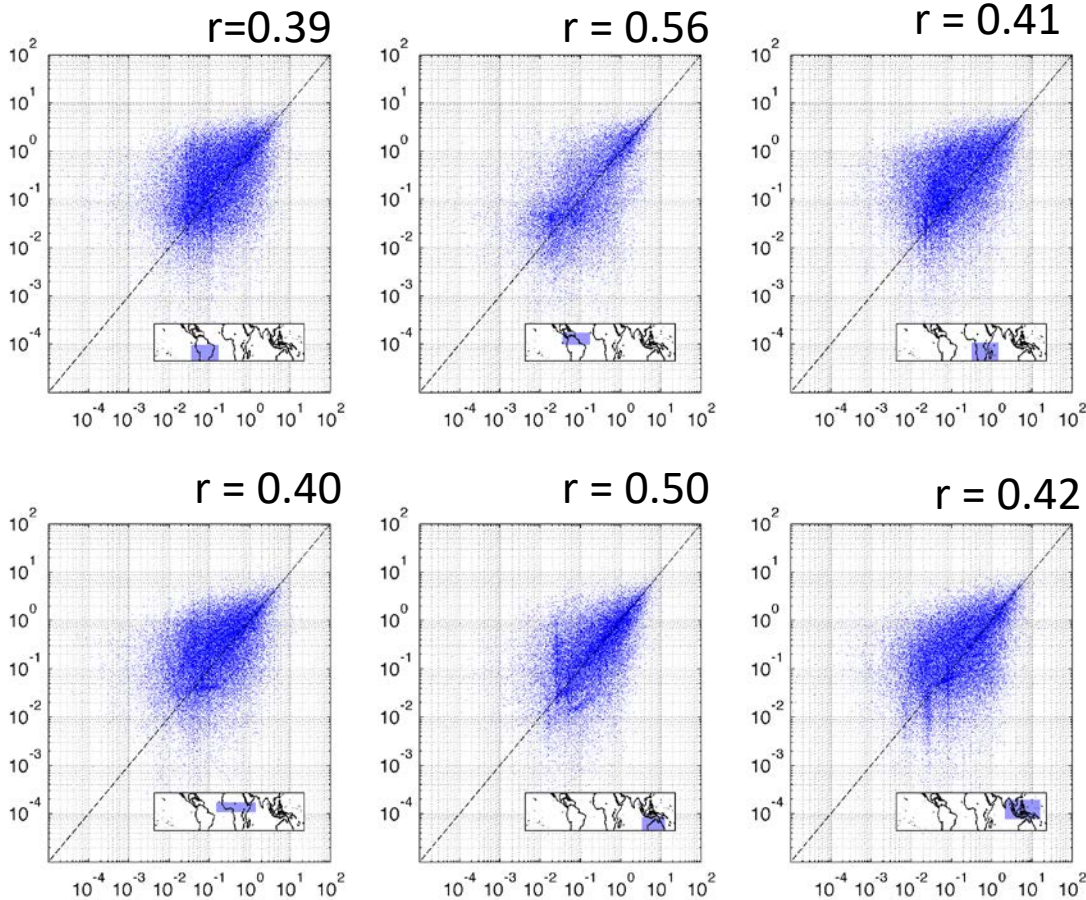


# Do ecosystem memory effects matter for NBE IAV prediction?

Example: 2013 NBE mismatch

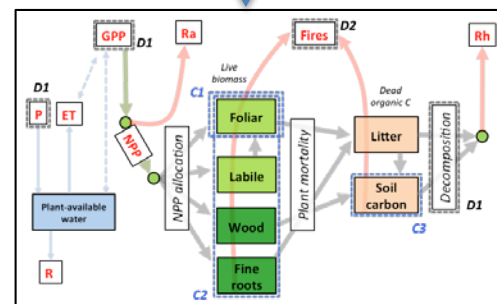


| $\delta$  2013 NBEI [normalized]



----- 1:1 | $\delta$  Lagged effect contribution| [normalized]

Random perturbations ( $\delta x$ ) on optimized CARDAMOM parameters ( $x$ )



Optimized CARDAMOM parameters and state variables.

CARDAMOM ( $x + \delta x$ )

