ISS Perfect Model Experiments with CLM-DART

Andrew Fox[1,2], Tim Hoar[2], William Kolby-Smith[1], Jeffrey Anderson[2] , Mingjie Shi[3], David Schimel[3] & David Moore[1]

1. University of Arizona 2. National Center for Atmospheric Research 3. NASA Jet Propulsion Laboratory

Data
Assimilation
Research
Testbed

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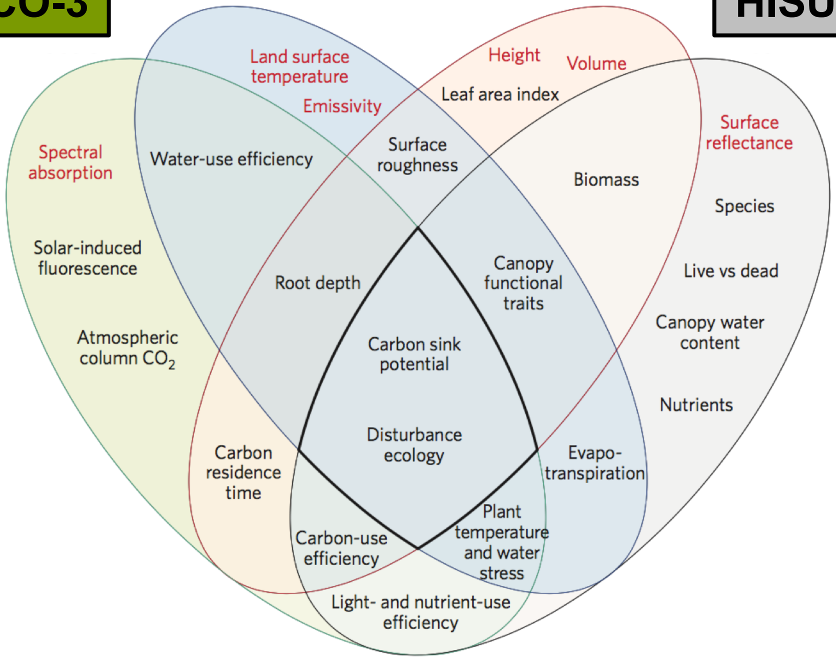
Integrating observations with a complex LSM

Early 2019 **OCO-3**

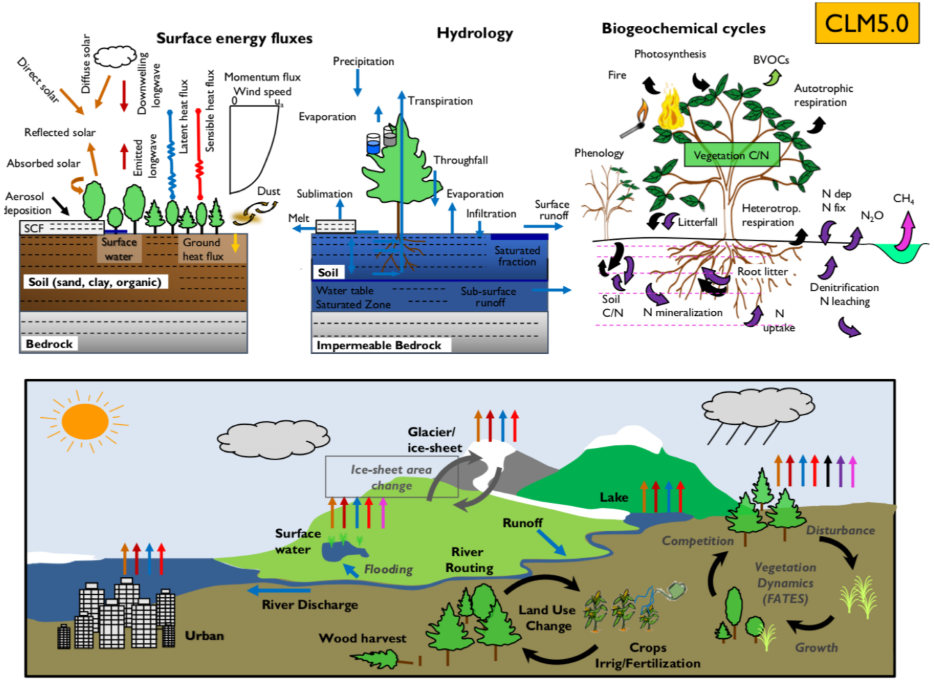
June 2018 **ECOSTRESS**

May 2019 **GEDI**

Early 2020 **HISUI**



Stavros et al. 2017



Lawrence et al. 2018

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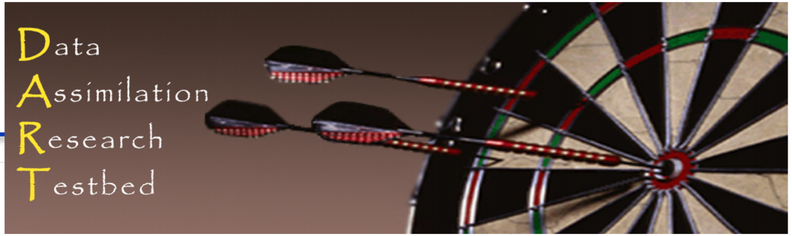
CLM-DART



Data
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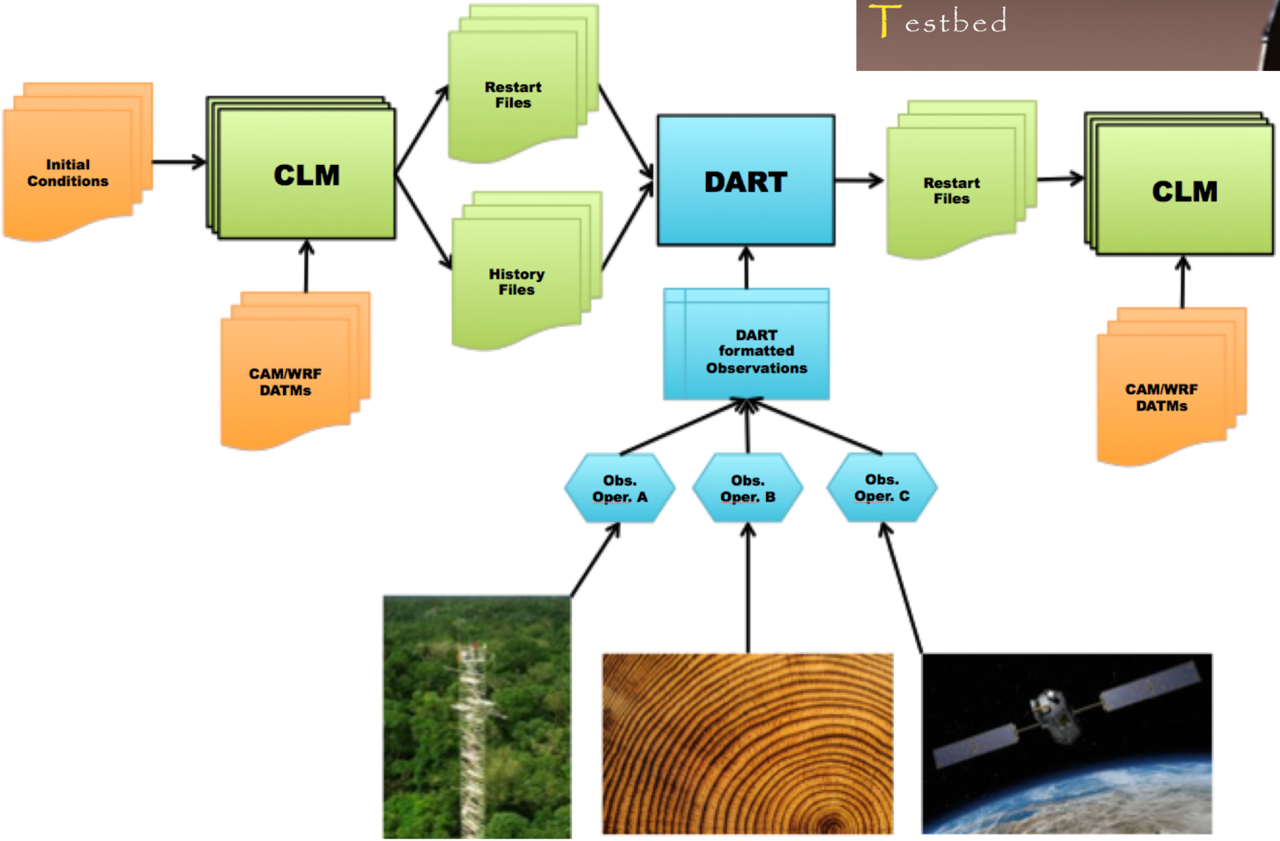
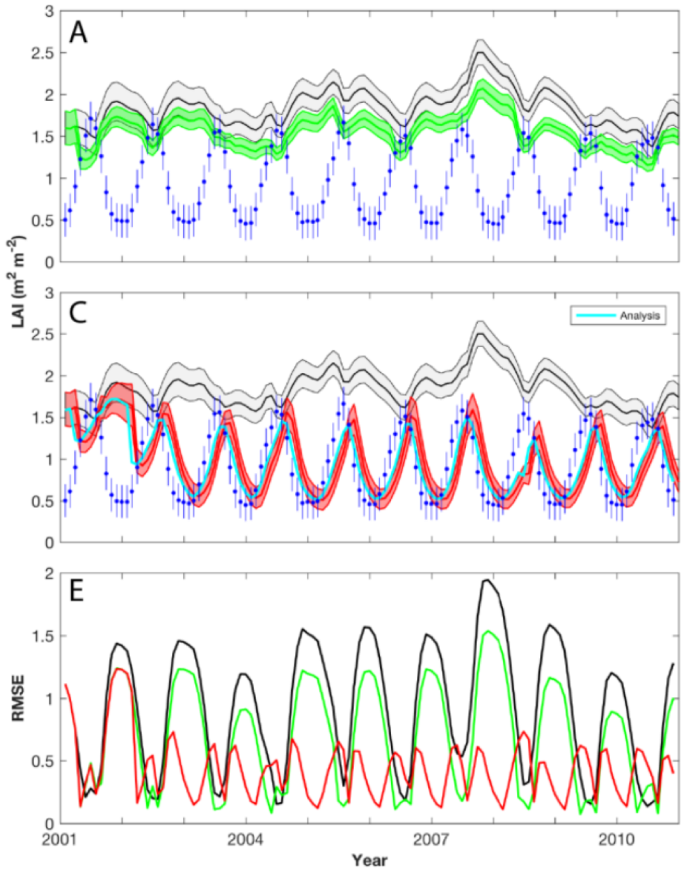


Initial Conditions
CLM
CAM/WRF DATMs
Restart Files
History Files
DART
DART formatted Observations
Obs. Oper. A
Obs. Oper. B
Obs. Oper. C
Restart Files
CLM
CAM/WRF DATMs

AGU100 ADVANCING EARTH AND SPACE SCIENCE

Journal of Advances in Modeling Earth Systems



RESEARCH ARTICLE

10.1029/2018MS001362

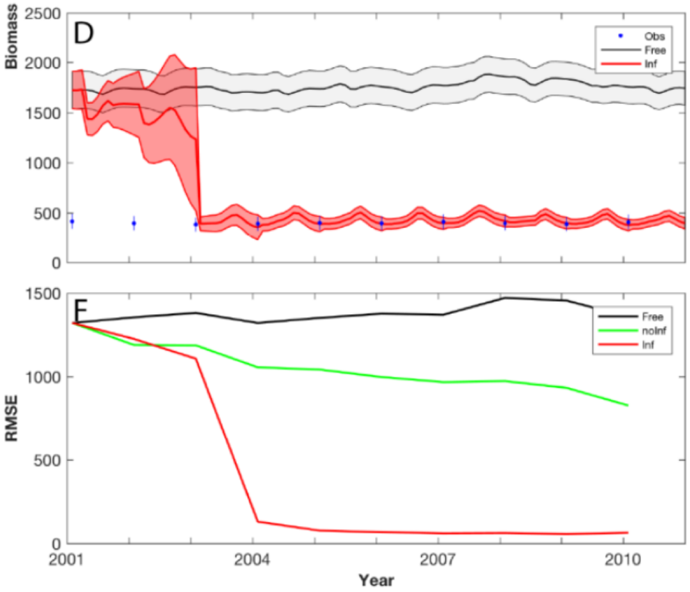
Key Points:

- Data assimilation was used to initialize biomass and leaf area in the Community Land Model
- Adaptive inflation was needed to give more weight to observations due to substantial discrepancies between model forecast and observations

Evaluation of a Data Assimilation System for Land Surface Models Using CLM4.5

Andrew M. Fox[1], Timothy J. Hoar[2], Jeffrey L. Anderson[2], Avelino F. Arellano[3], William K. Smith[1], Marcy E. Litvak[4], Natasha MacBean[1], David S. Schimel[5], and David J. P. Moore[1]

[1]School of Natural Resources and the Environment, University of Arizona, Tucson, AZ, USA, [2]National Center for Atmospheric Research, Boulder, CO, USA, [3]Hydrological and Atmospheric Sciences, University of Arizona, Tucson, AZ, USA, [4]Department of Biology, University of New Mexico, Albuquerque, NM, USA, [5]Jet Propulsion Laboratory, Pasadena, CA, USA



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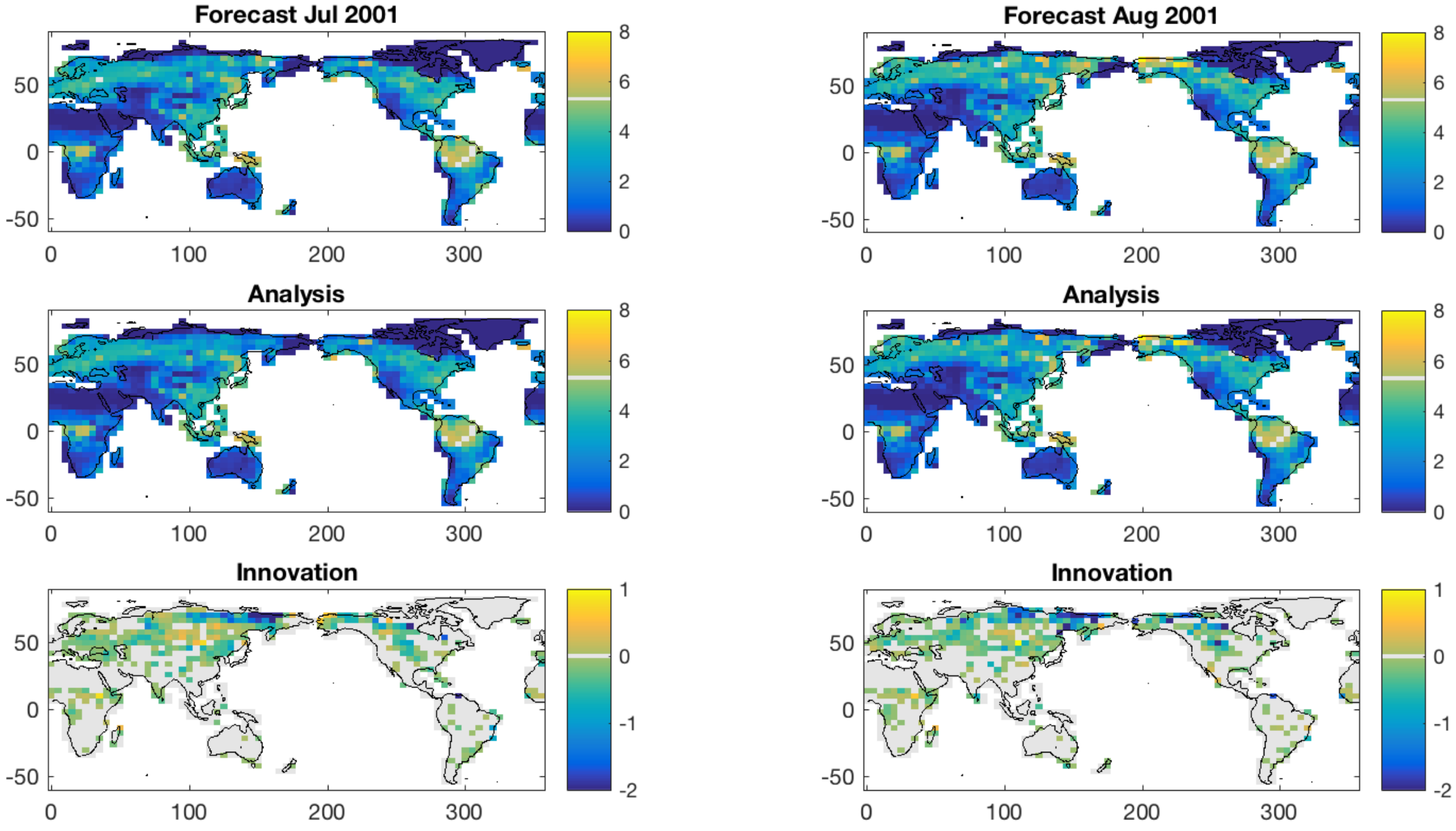
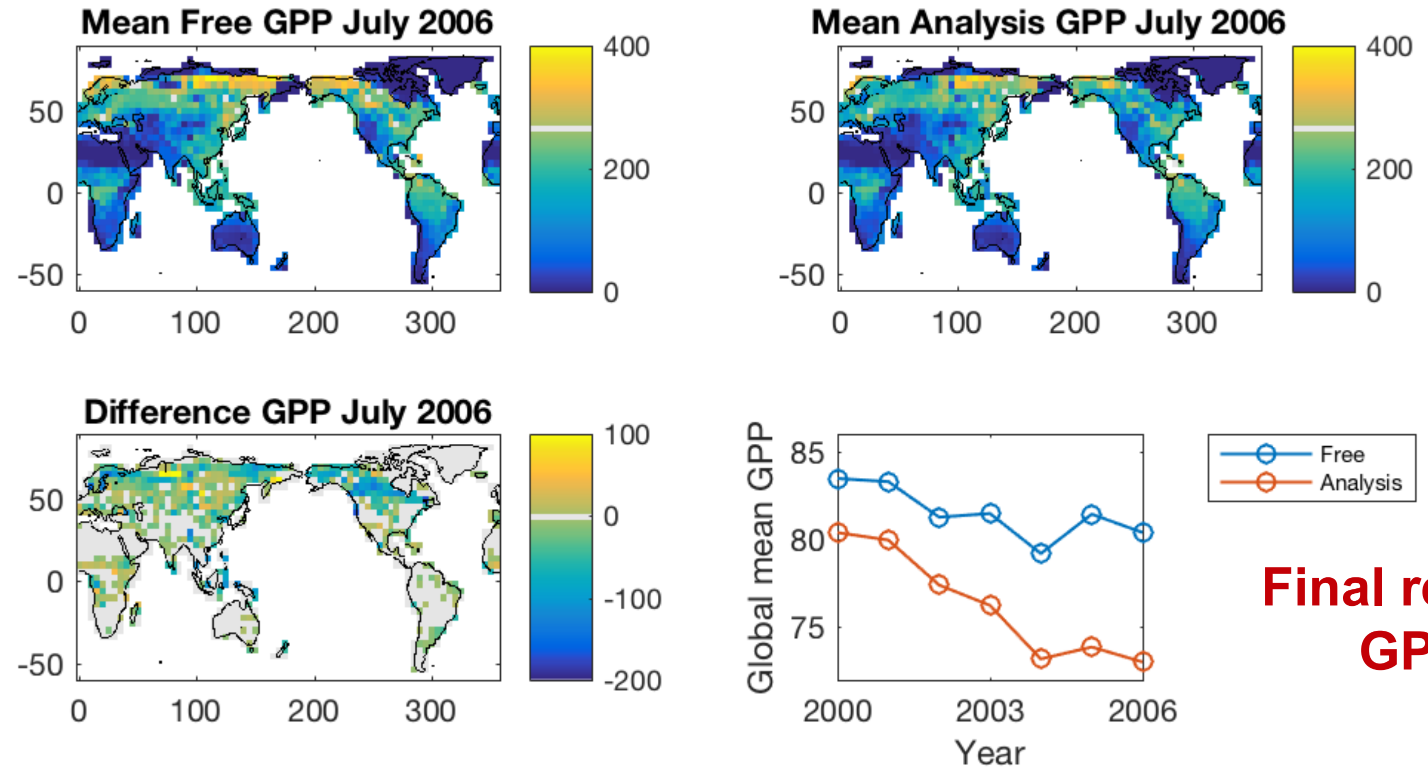
Increments in LAI, July & August 2001

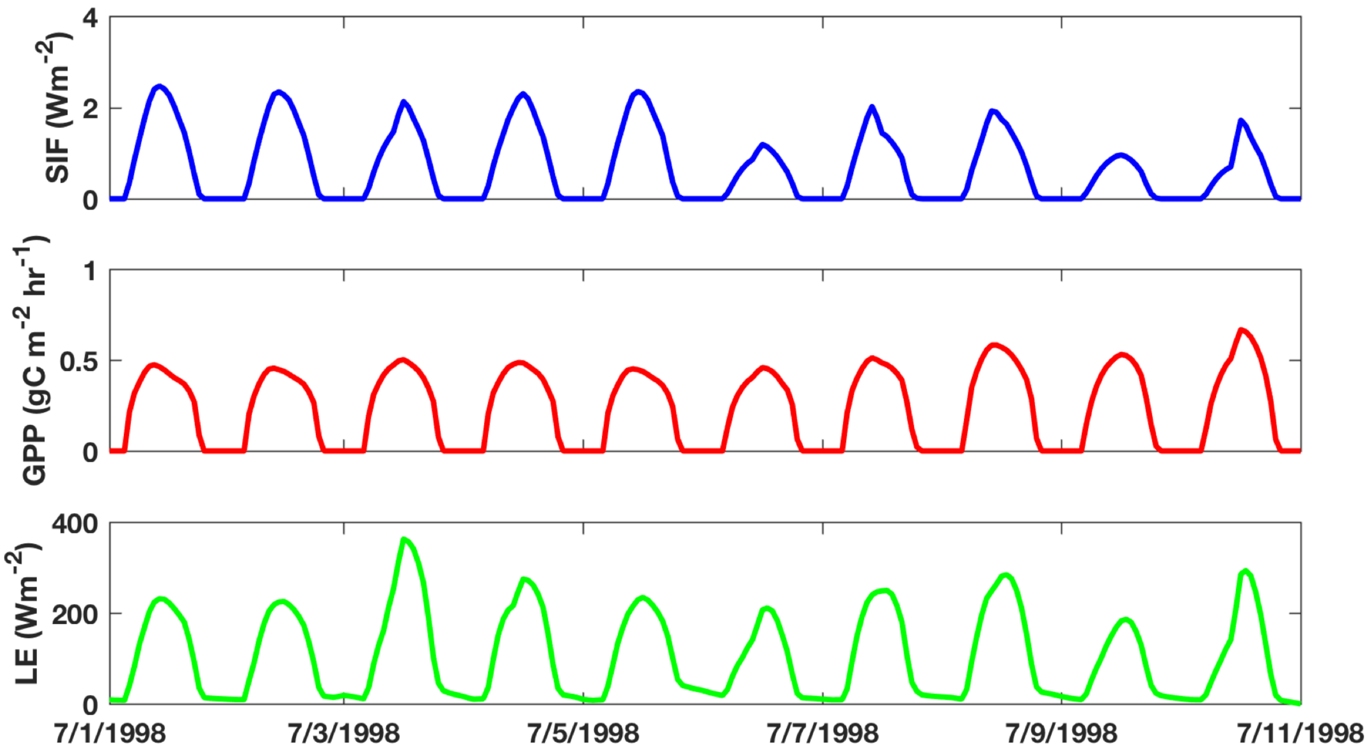


GPP compared to the Freerun, July 2006

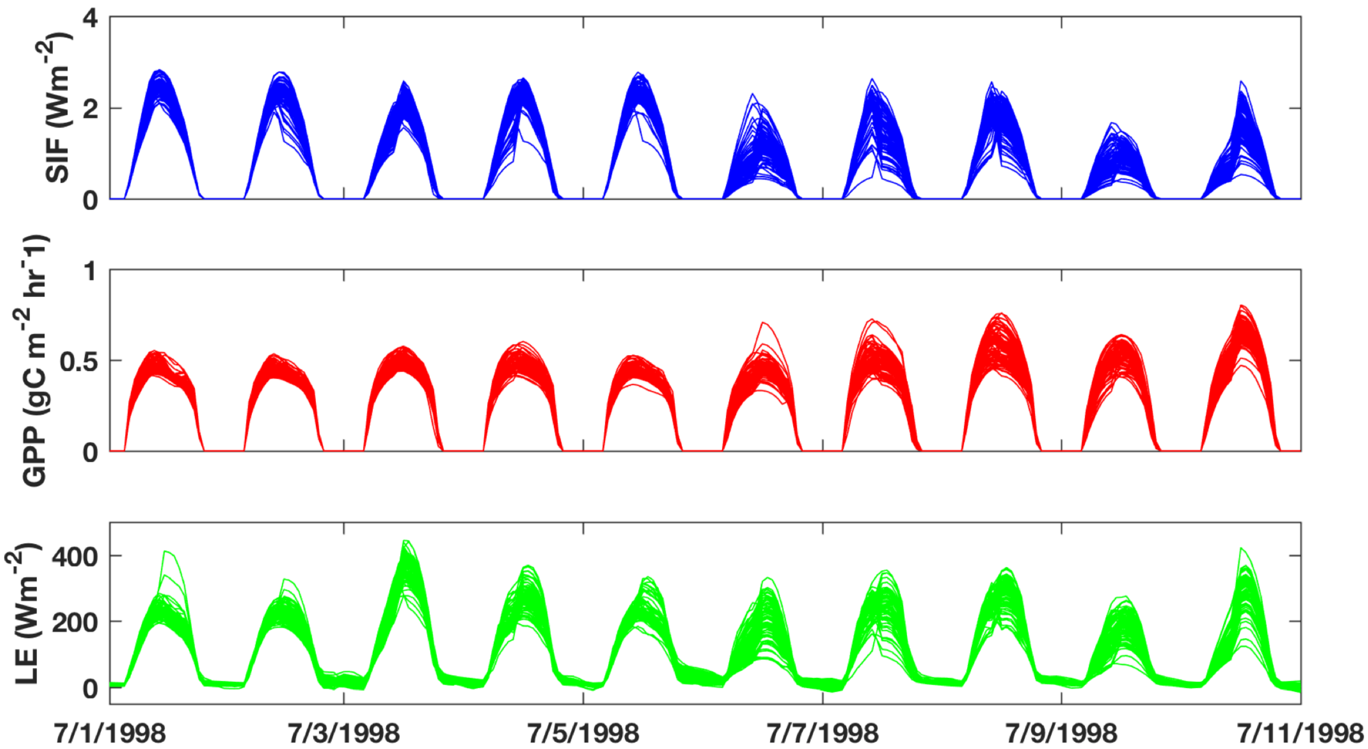


Final reduction in GPP = 9%

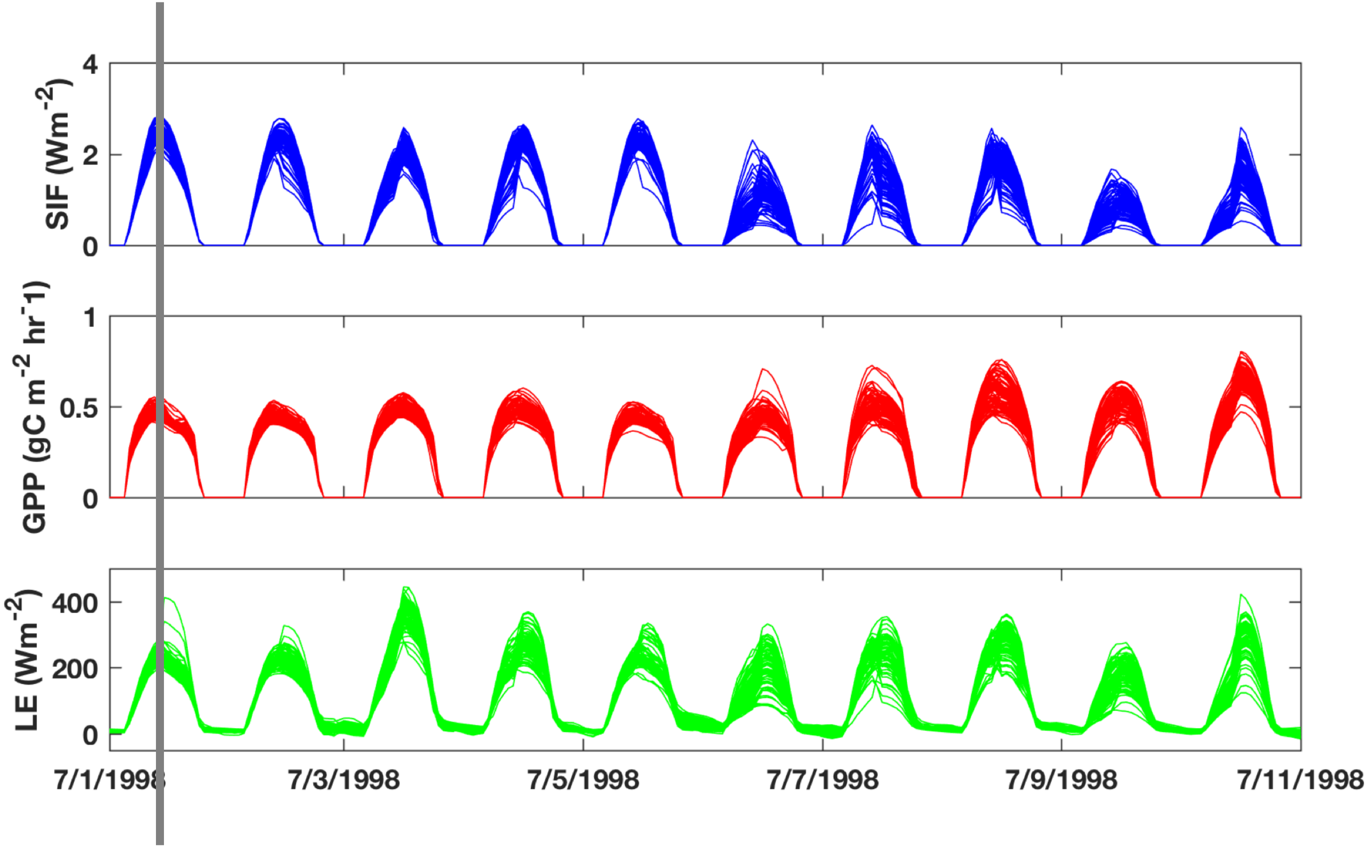
SIF simulated at Niwot Ridge over 10 days



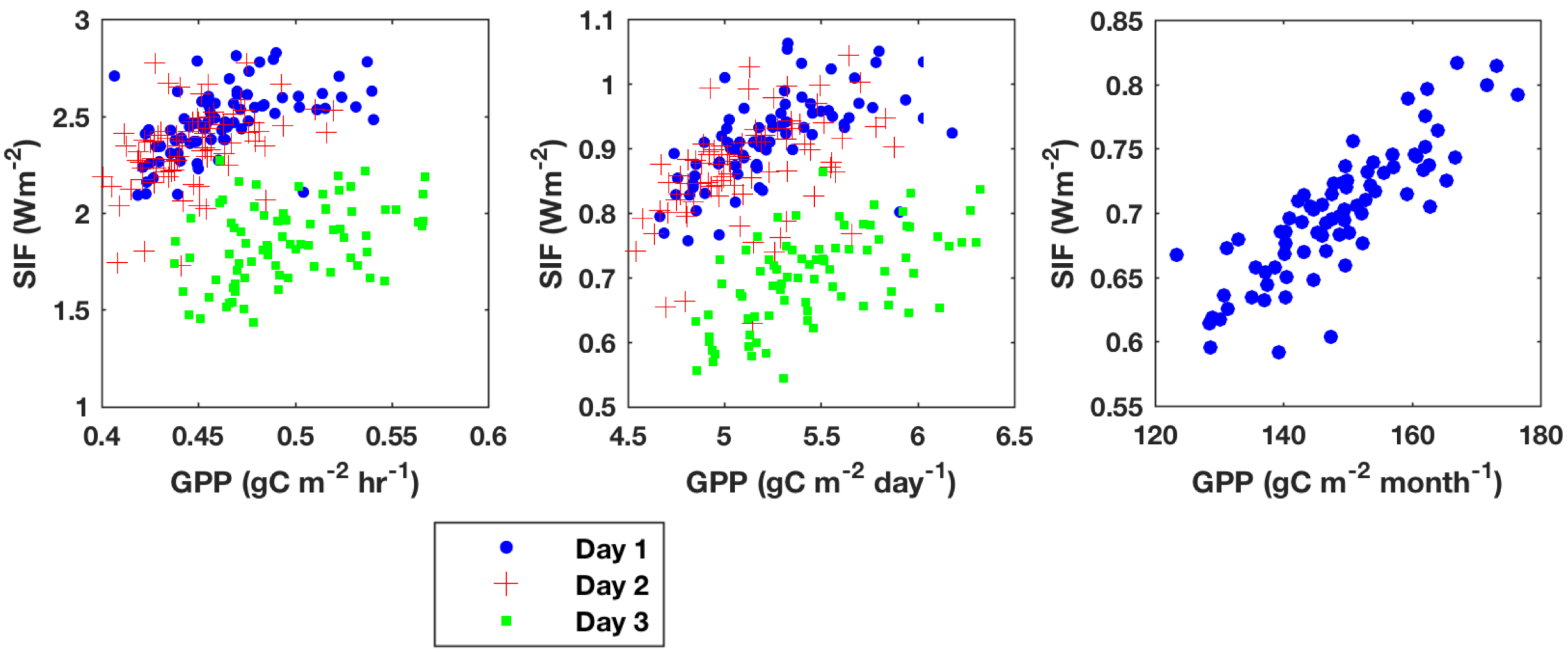
Using Atmospheric Forcing Ensemble



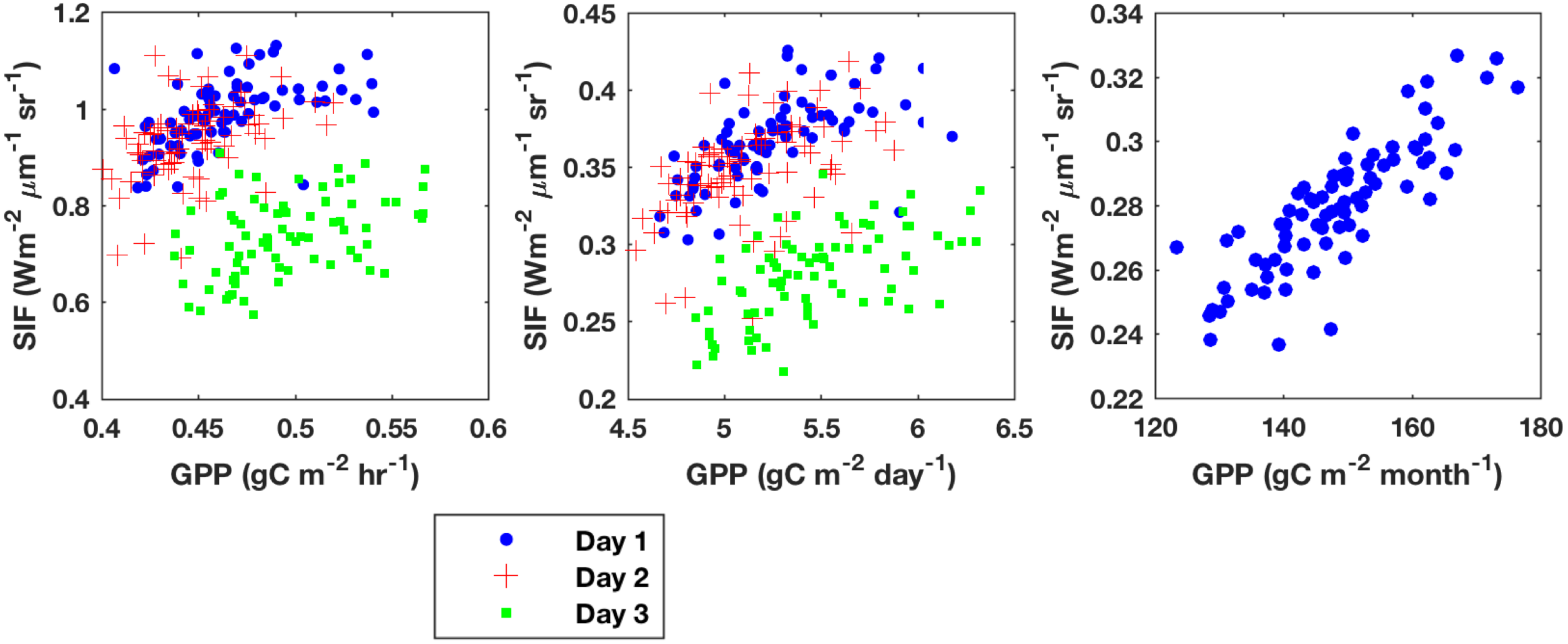
Using Atmospheric Forcing Ensemble



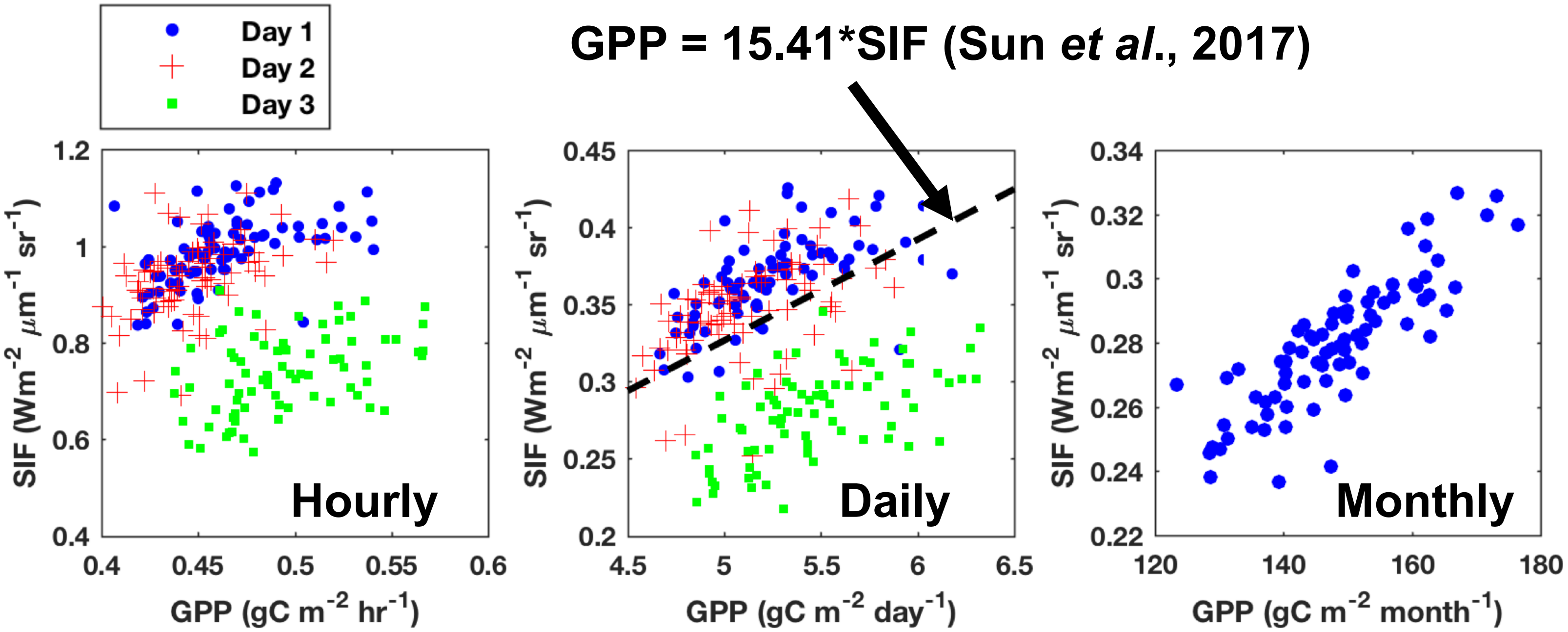
Relationship between SIF and GPPd



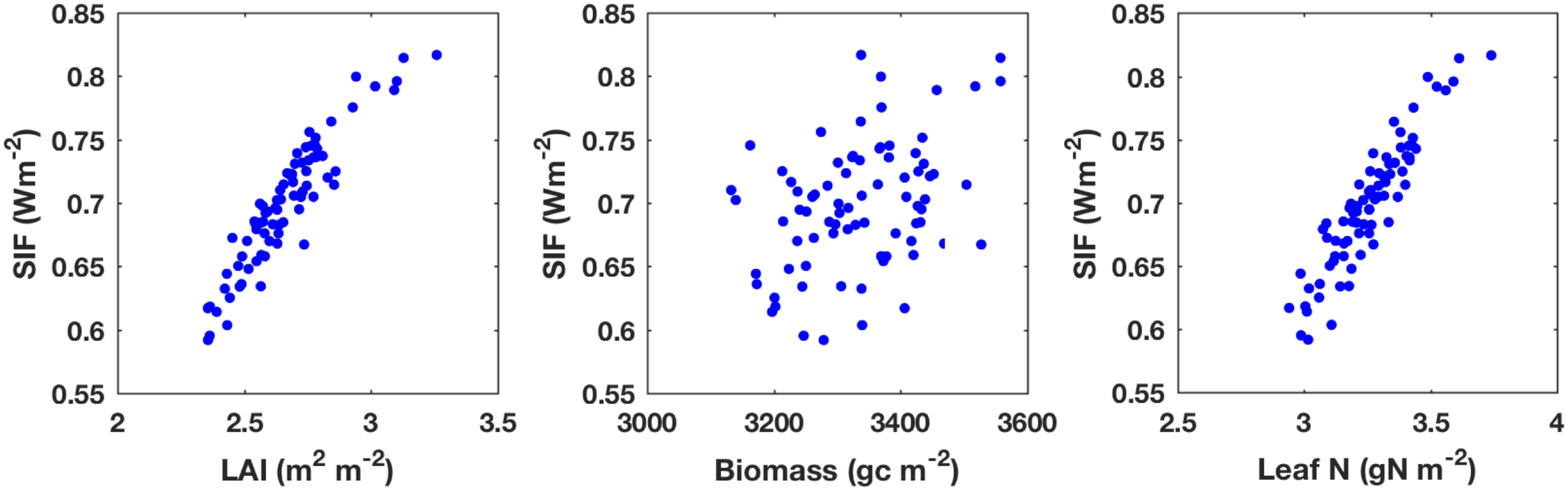
“Scaled” to the canopy



"Scaled" to the canopy



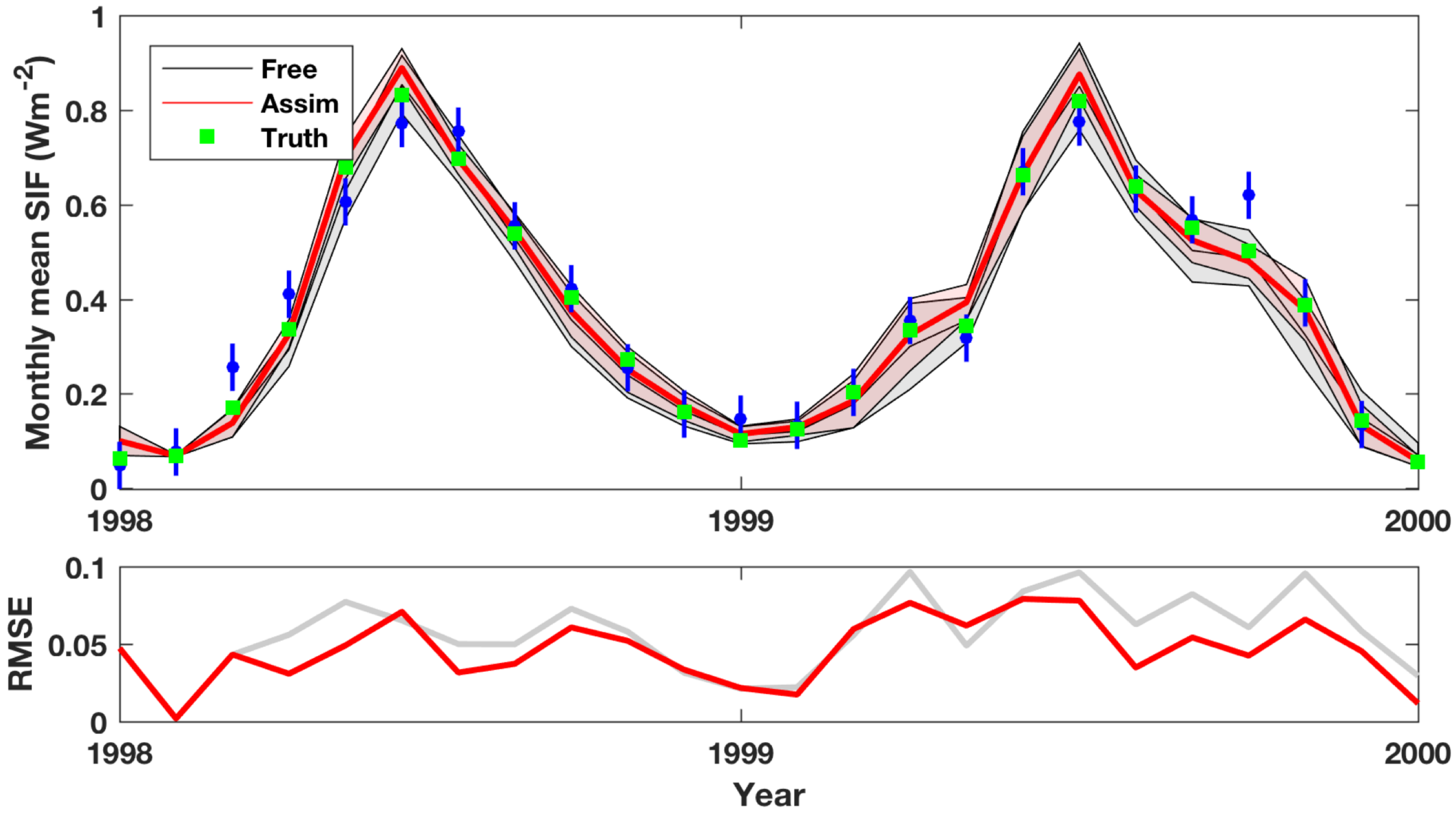
Between SIF and State Variables



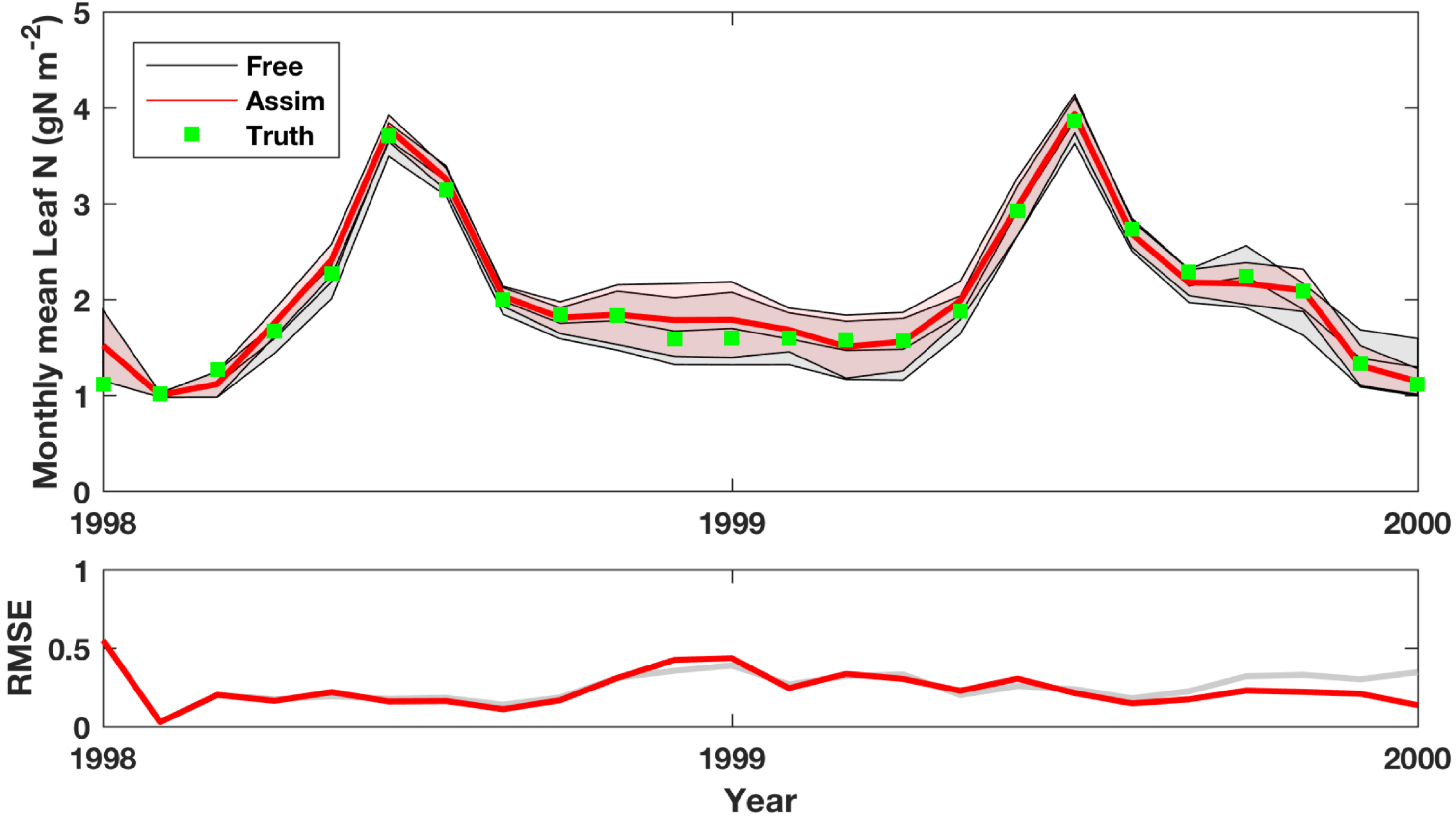
"Perfect Model" Experiments

1) Merging multiple types of RS observations

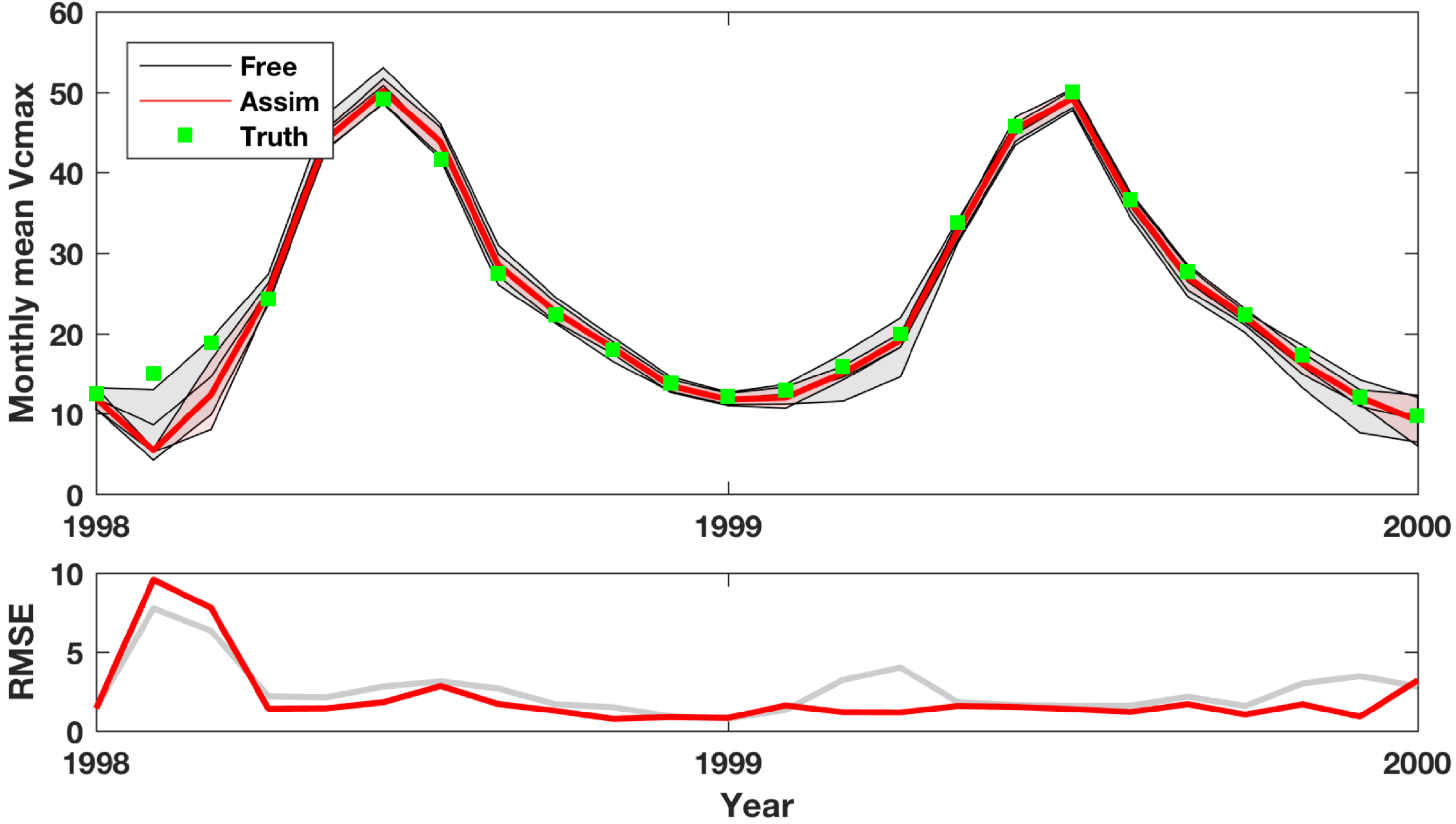
“Perfect Model” Experiments - SIF



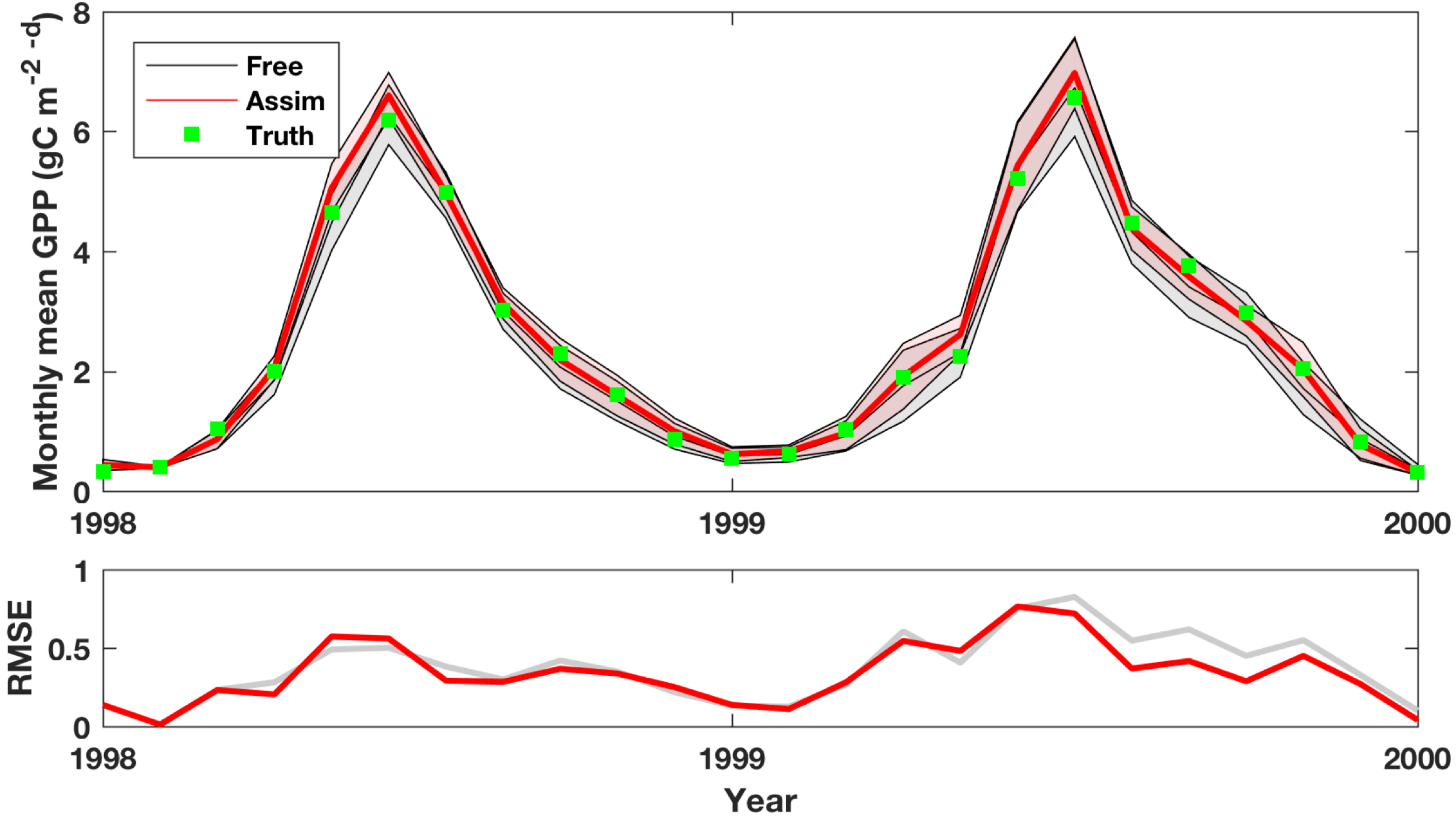
Modest impact on Leaf N



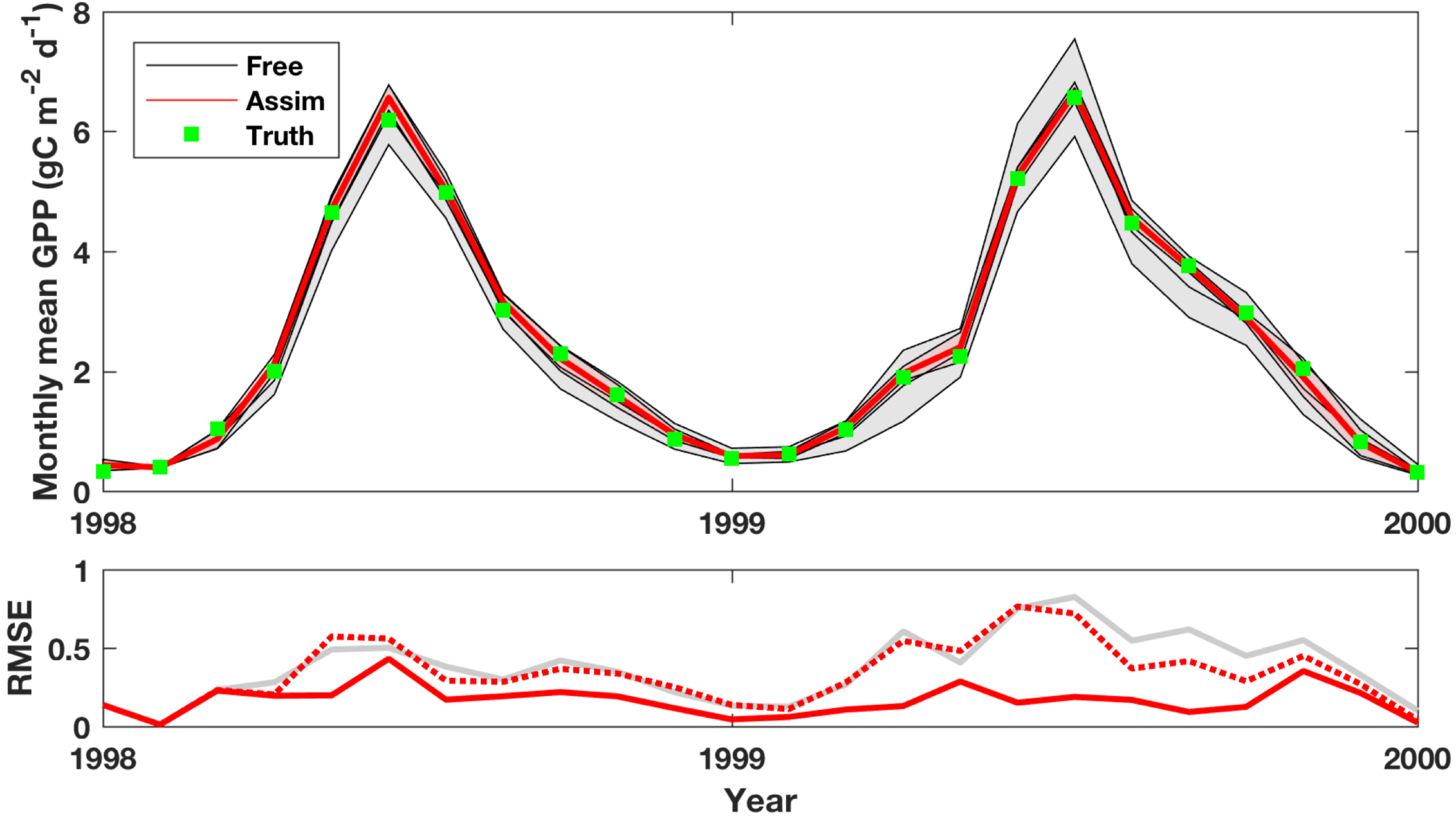
Constrains V_{cmax} very well



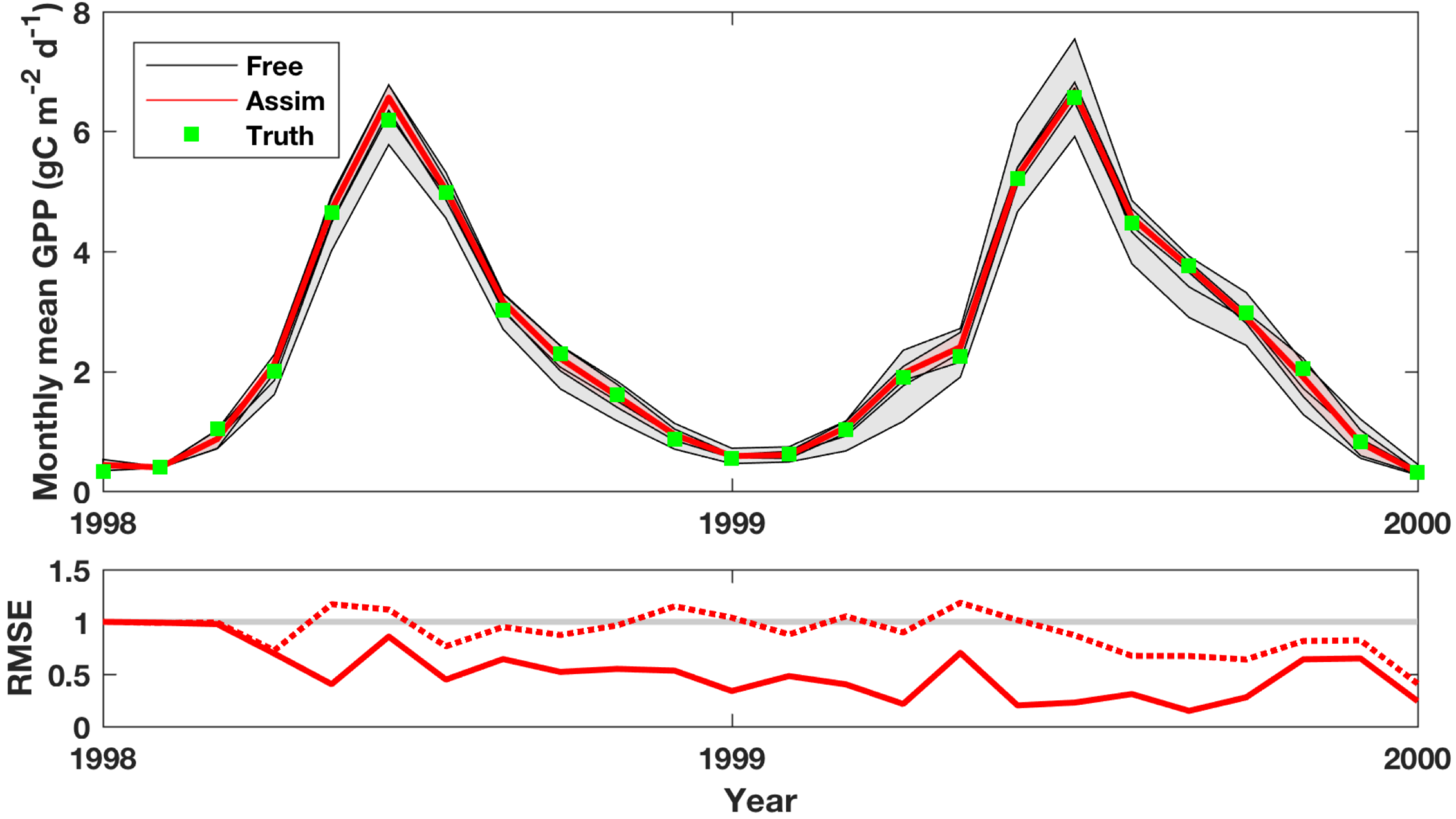
Really start to see impact on GPP in year 2



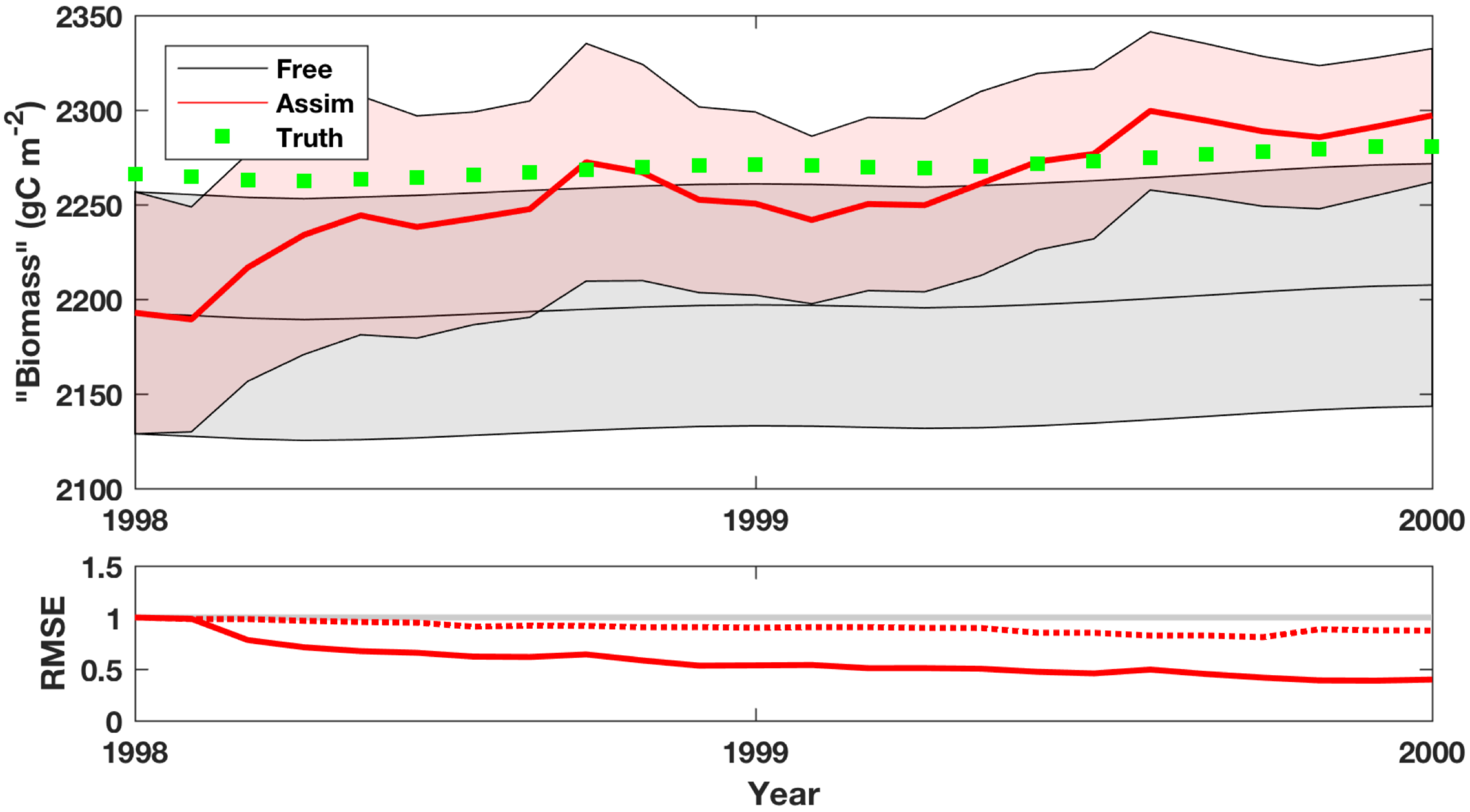
Assimilating SIF, ET, Leaf N and Biomass



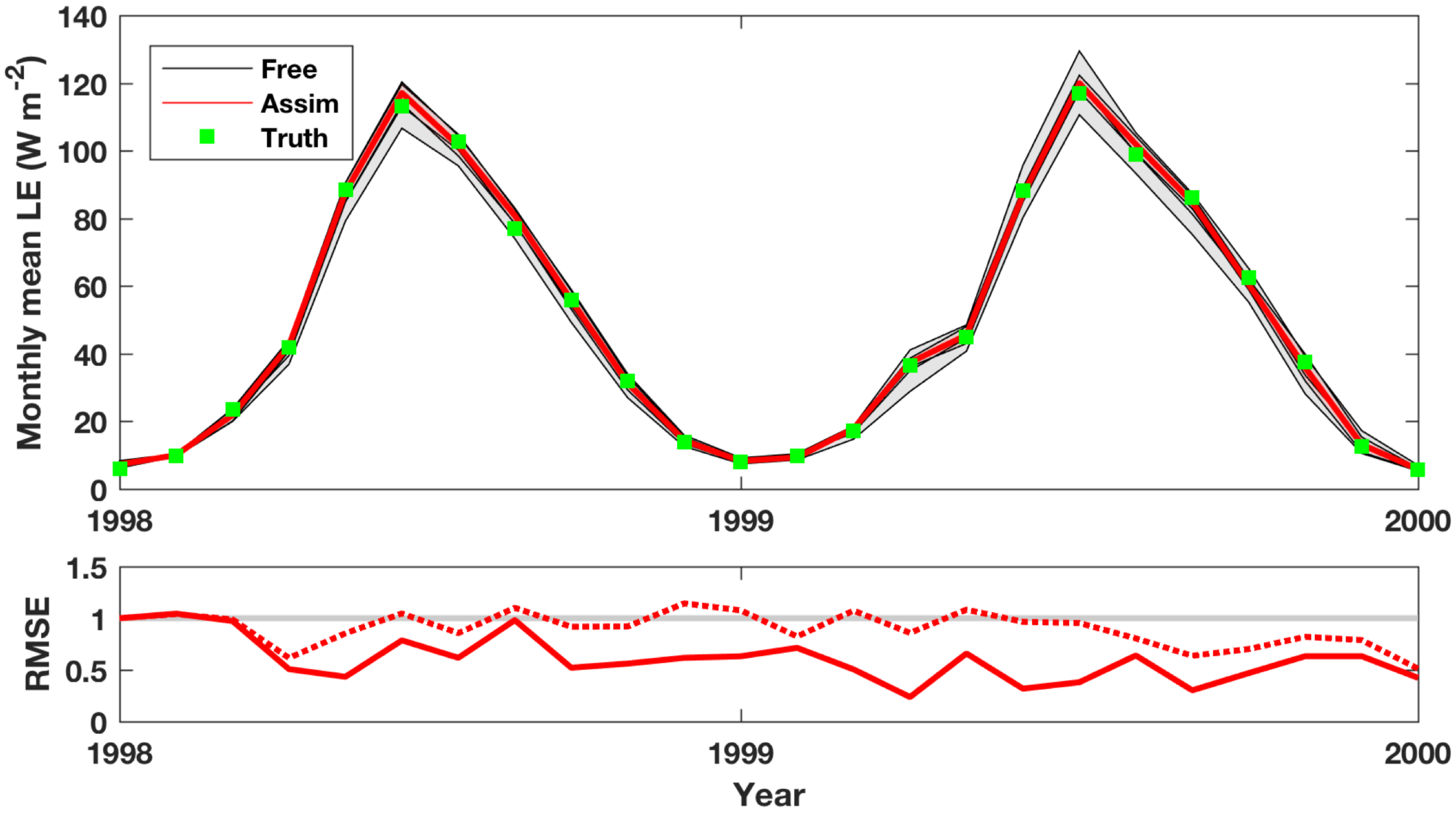
Large reductions in error relative to Freerun



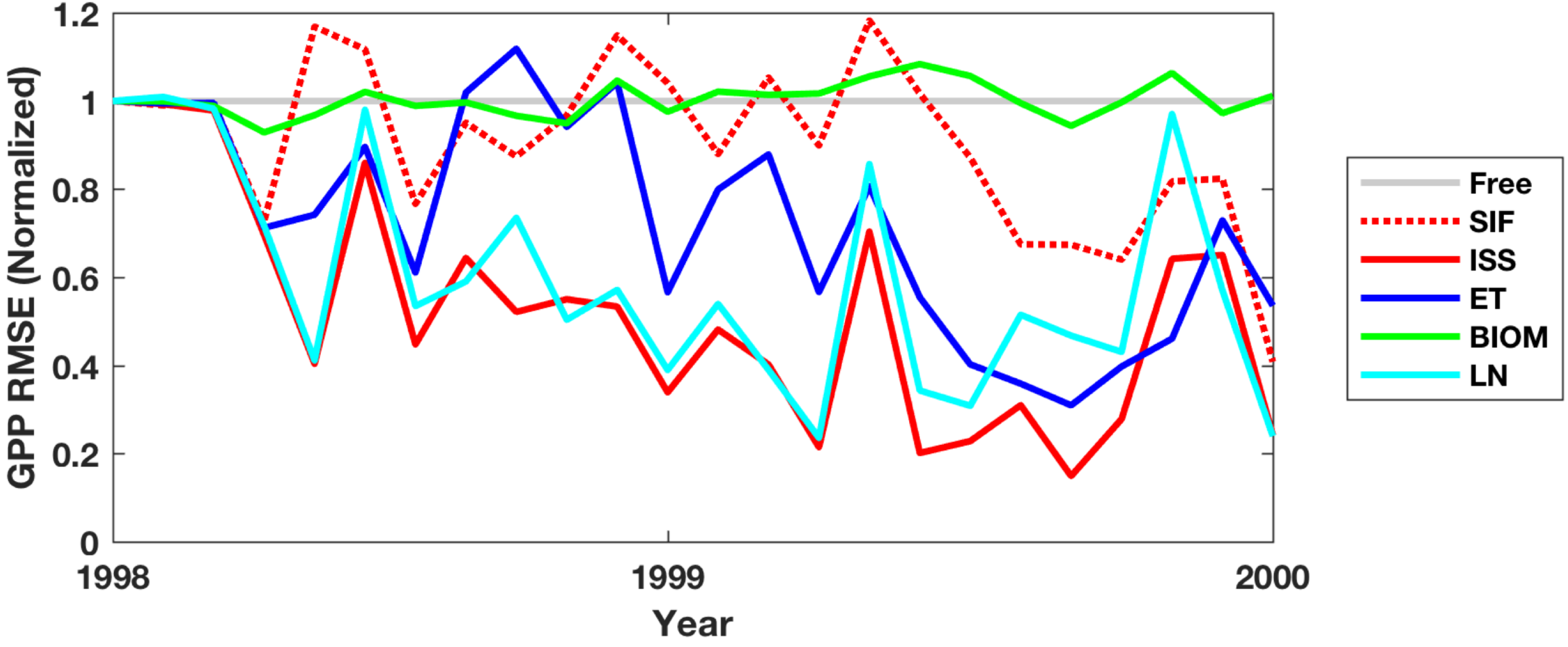
Clearly see large changes in Biomass



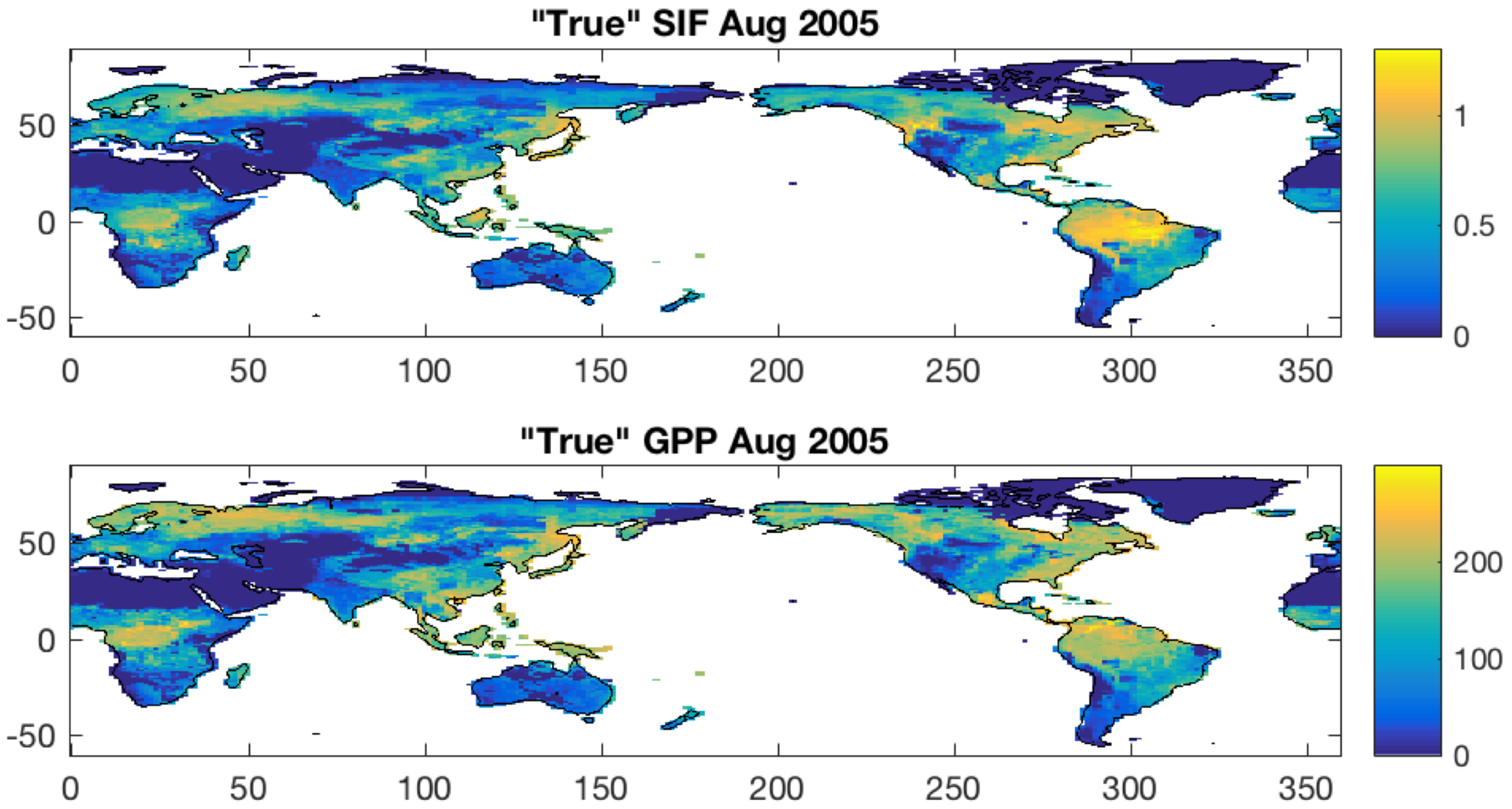
LE is well constrained



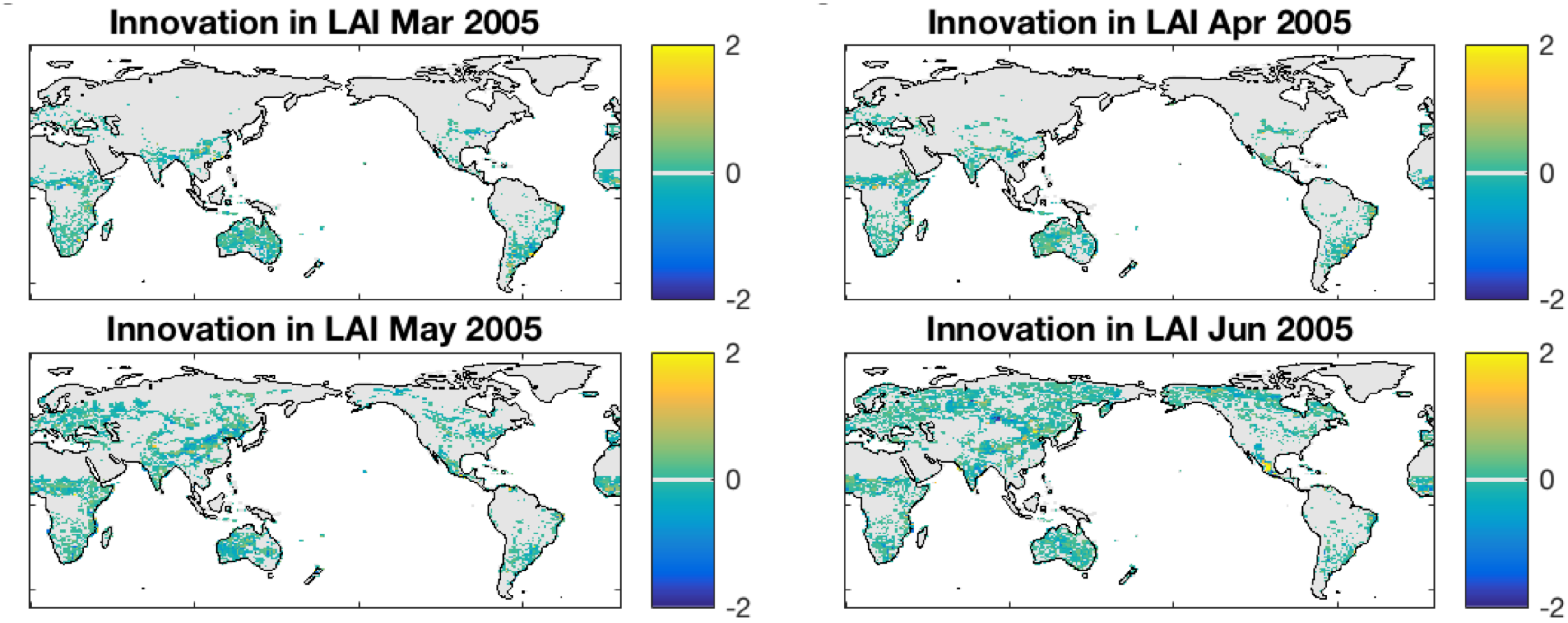
Combining all obs types reduces error the most



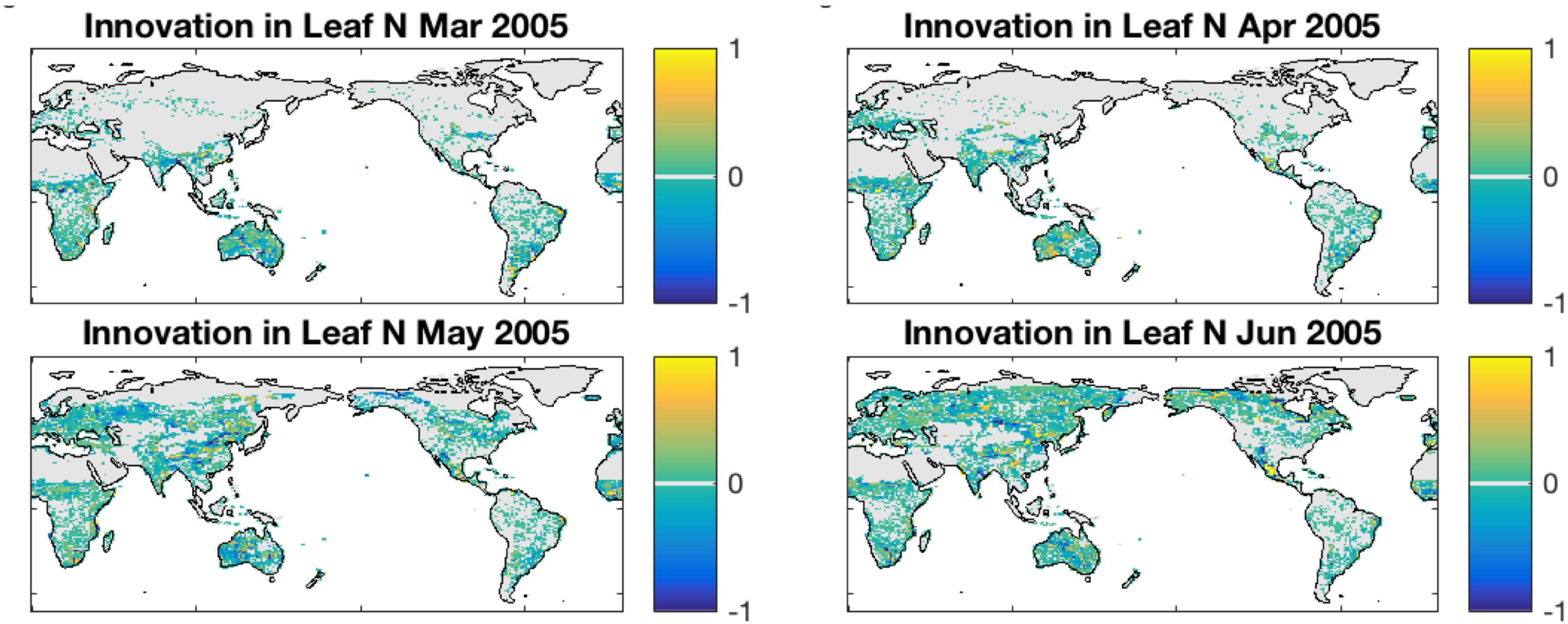
What happens when we go global?



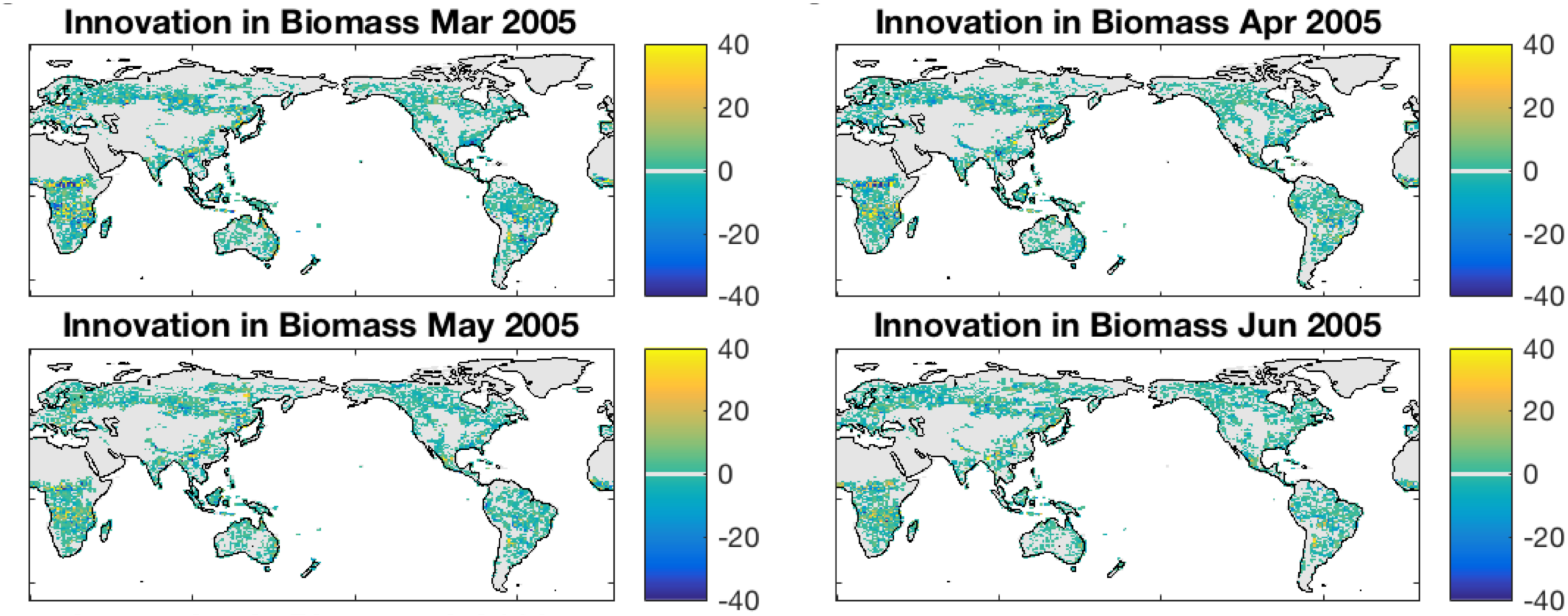
Monthly innovations in Leaf Area Index



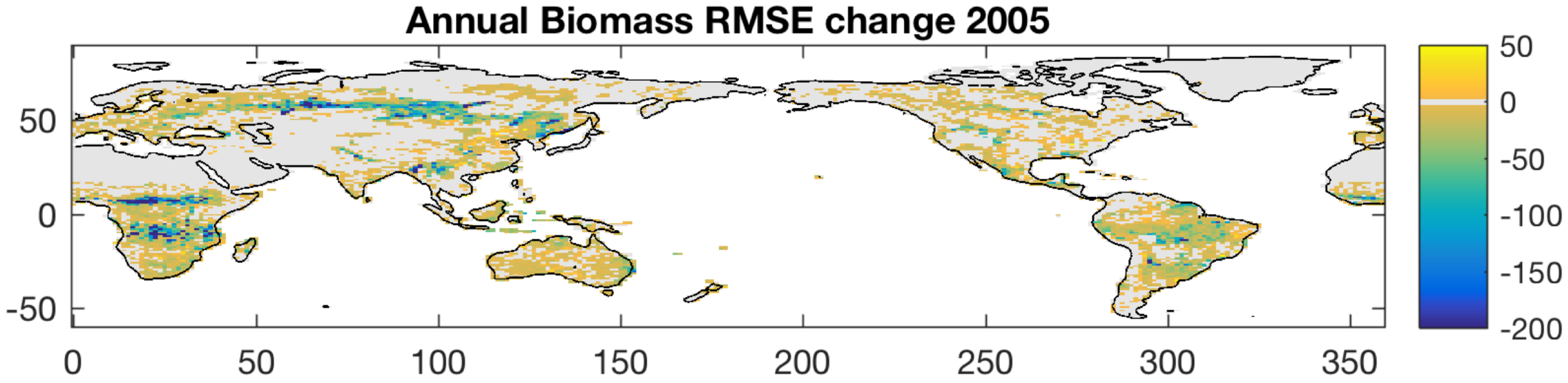
Monthly innovations in Leaf Nitrogen

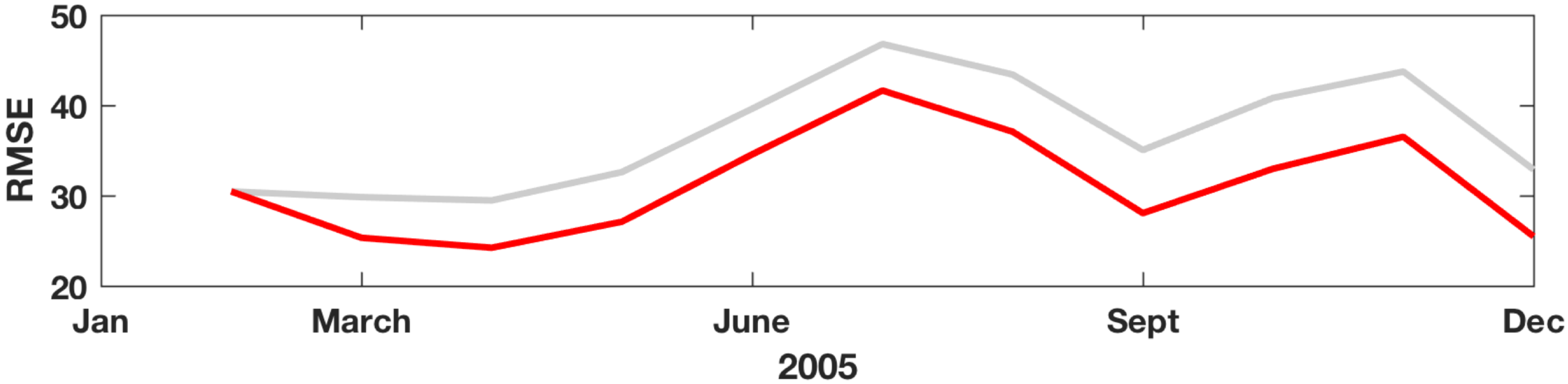


Monthly innovations in Biomass

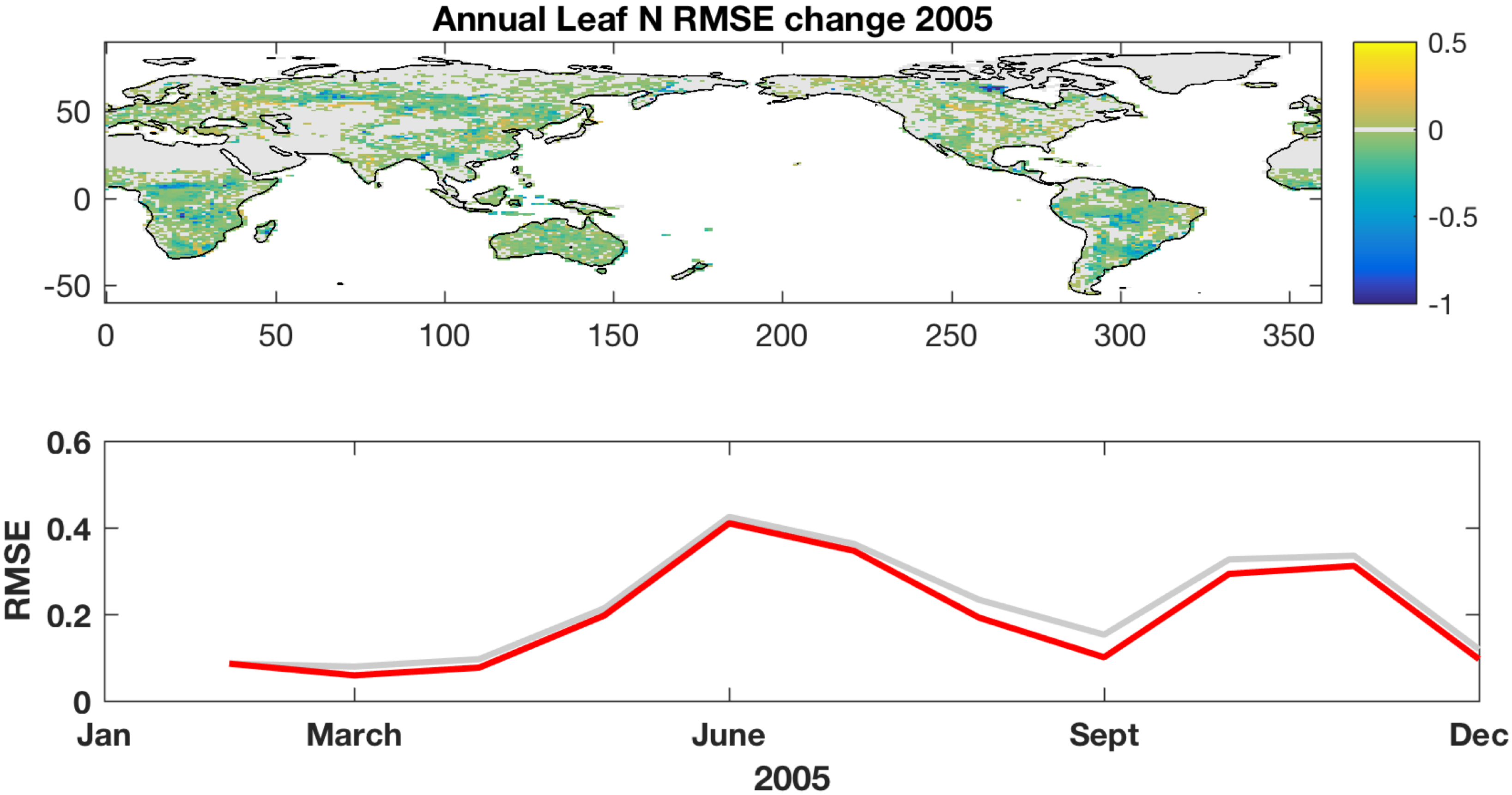


Large reduction in Biomass Error

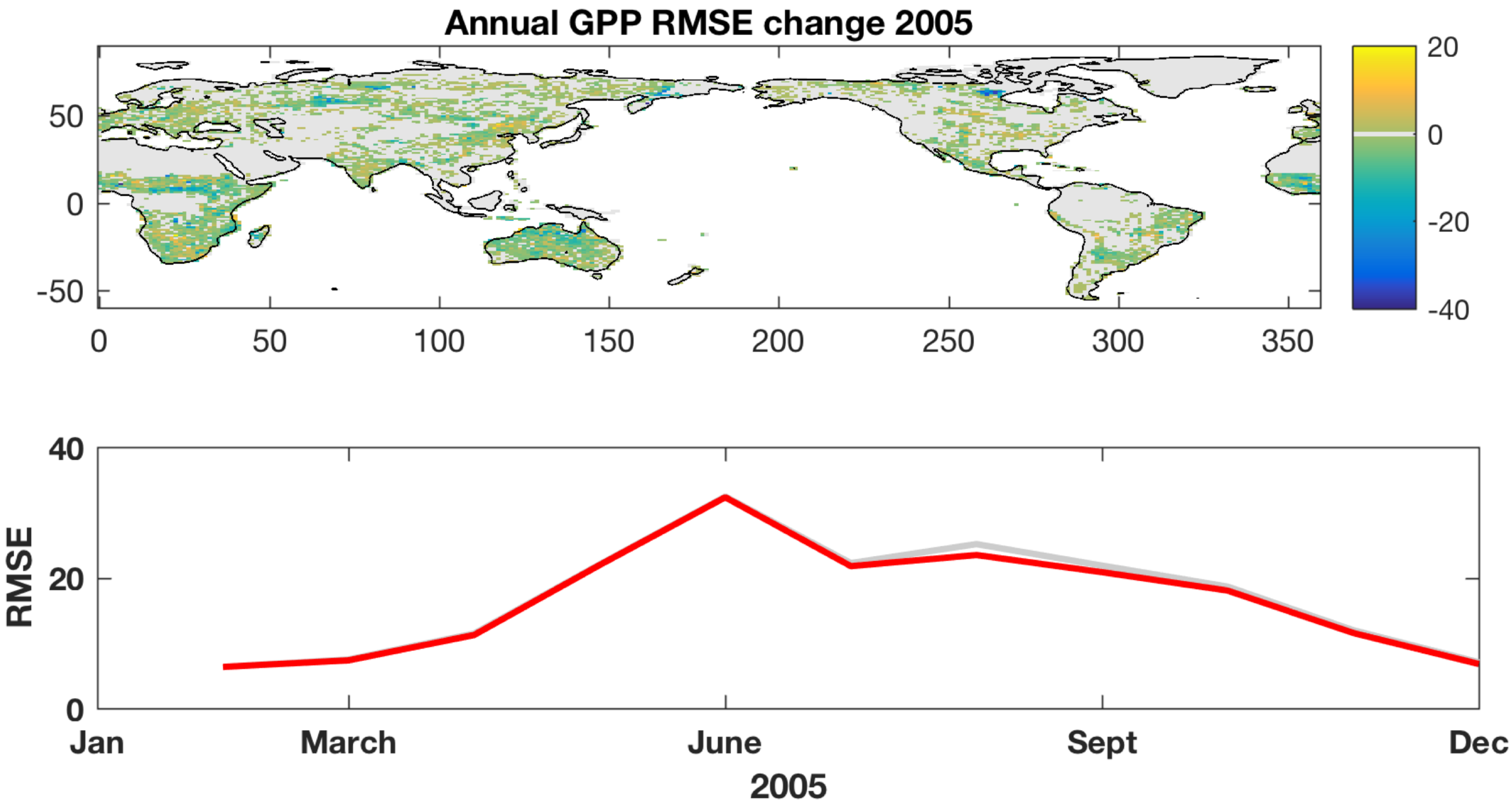




Modest impact on Leaf N Error



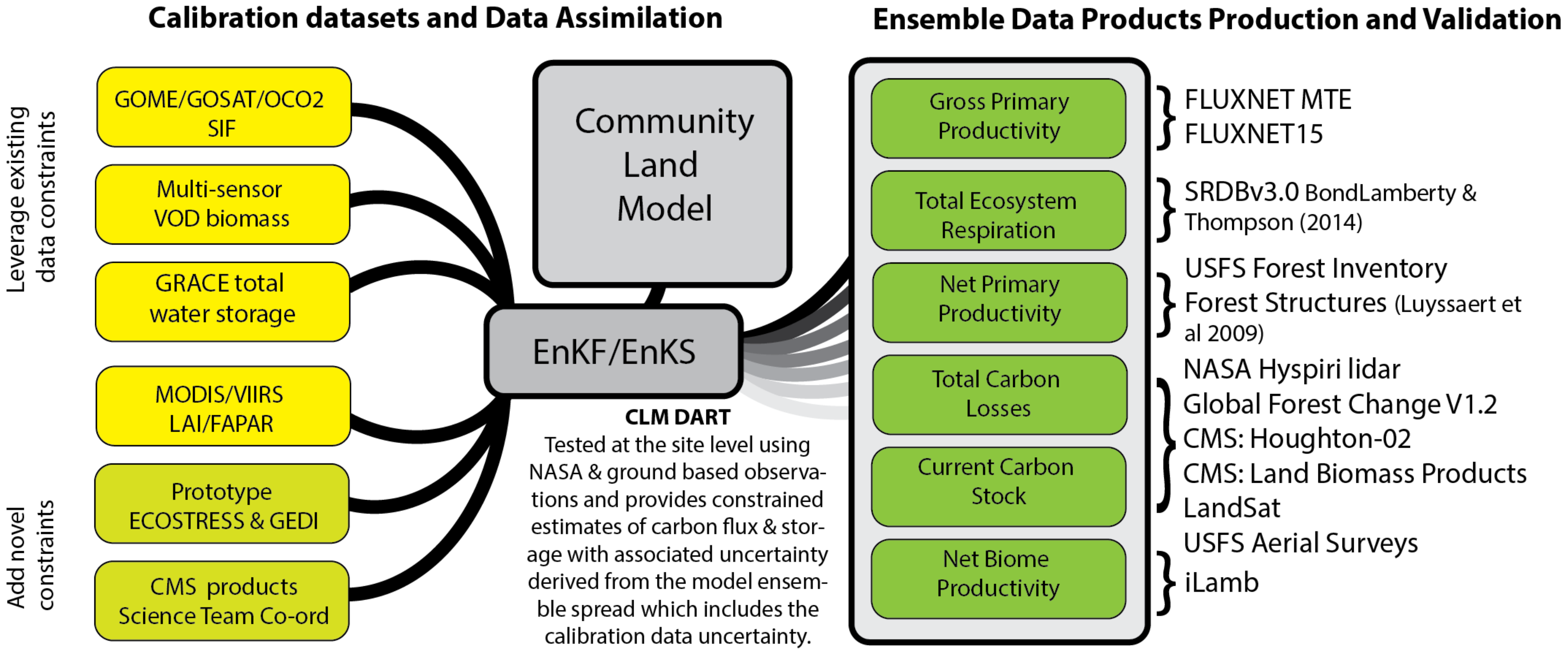
Mixed results for GPP Error



Take Home Points

1) Merging multiple types of RS observations

Merging RS data and models - Carbon



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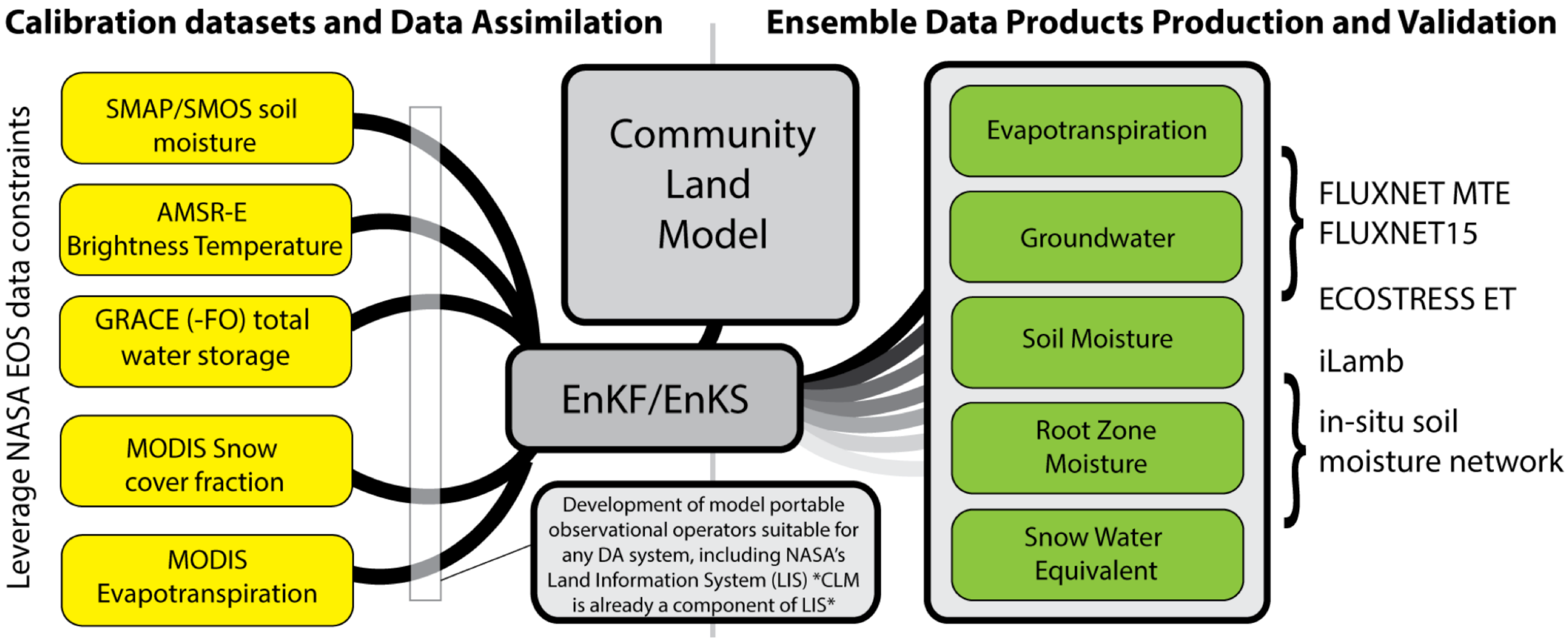
Merging RS data and models – Water



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Future Directions

1) Merging multiple types of RS observations
2) Working with new observations

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Future Directions

1) Merging multiple types of RS observations
2) Working with new observations
3) Moving from data products to “raw observations”

ECOSTRESS Level-3 Evapotranspiration ATBD

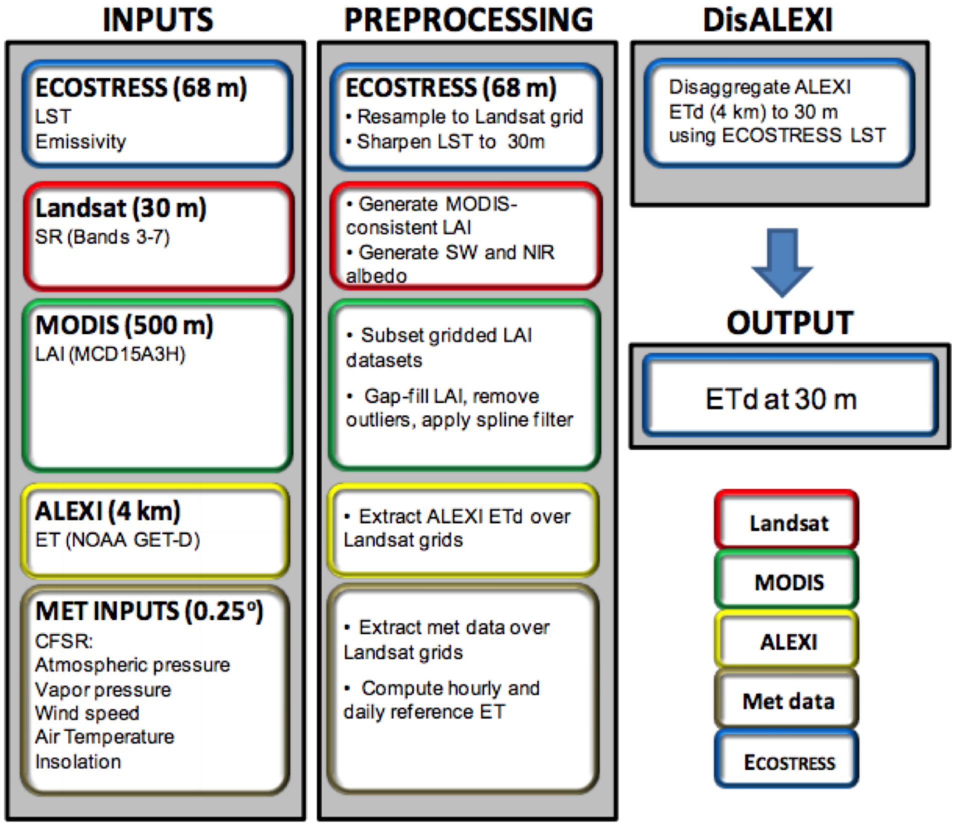

Figure 4. Conceptual diagram describing computation of L-3(ALEXI_ET) evapotranspiration.

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Future Directions

1) Merging multiple types of RS observations
2) Working with new observations
3) Moving from data products to “raw observations”
4) “Parameter” estimation

   (Often more like special state variables...)

Parameter estimation with EAKF

AGU PUBLICATIONS

JGR

Journal of Geophysical Research: Biogeosciences

RESEARCH ARTICLE

10.1002/2015JG003297

Key Points:
- The CLM parameters, estimated separately for four plant functional types, correlated with initial carbon-nitrogen pools

Estimation of Community Land Model parameters for an improved assessment of net carbon fluxes at European sites

Hanna Post[1,2,3], Jasper A. Vrugt[2,4,5], Andrew Fox[6], Harry Vereecken[2,3], and Harrie-Jan Hendricks Franssen[2,3]

MCMC

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Advances in Water Resources 28 (2005) 135–147

Advances in Water Resources

www.elsevier.com/locate/advwatres

Dual state–parameter estimation of hydrological models using ensemble Kalman filter

Hamid Moradkhani [a,*], Soroosh Sorooshian [a], Hoshin V. Gupta [b], Paul R. Houser [c]

JOURNAL OF ADVANCES IN MODELING EARTH SYSTEMS, VOL. 5, 58–70, doi:10.1029/2012MS000167, 2013

Parameter estimation using data assimilation in an atmospheric general circulation model: From a perfect toward the real world

Sebastian Schirber,[1] Daniel Klocke,[2] Robert Pincus,[3] Johannes Quaas,[4] and Jeffrey L. Anderson[5]

Check for updates

MONTHLY WEATHER REVIEW VOLUME 143

Parameter Estimation Using Ensemble-Based Data Assimilation in the Presence of Model Error

JUAN RUIZ

Centro de Investigaciones del Mar y la Atmósfera (CIMA/CONICET-UBA), DCAO/FCEyN-Universidad de Buenos Aires, UMI-IFAECI/CNRS, Buenos Aires, Argentina, and AICS/RIKEN, Kobe, Japan

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Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE

10.1002/2017MS001222

Key Points:

The ensemble data assimilation method can potentially be used to

Estimating Convection Parameters in the GFDL CM2.1 Model Using Ensemble Data Assimilation

Shan Li[1,2], Shaoqing Zhang[3,4], Zhengyu Liu[5], Lv Lu[6], Jiang Zhu[2], Xuefeng Zhang[7], Xinrong Wu[7], Ming Zhao[8], Gabriel A. Vecchi[9], Rong-Hua Zhang[4,10], and Xiaopei Lin[3,4]

Additional Points

1) Need CAM ensemble atmospheric forcing to present (20m core-hr task)
2) Need high resolution atmospheric forcing from additional sources
3) Uniformity of land cover descriptors (and discretization) across models
4) Trade off between resolution and complexity of observation operator

Georgia O’Keeffe – “Black Mesa Landscape”

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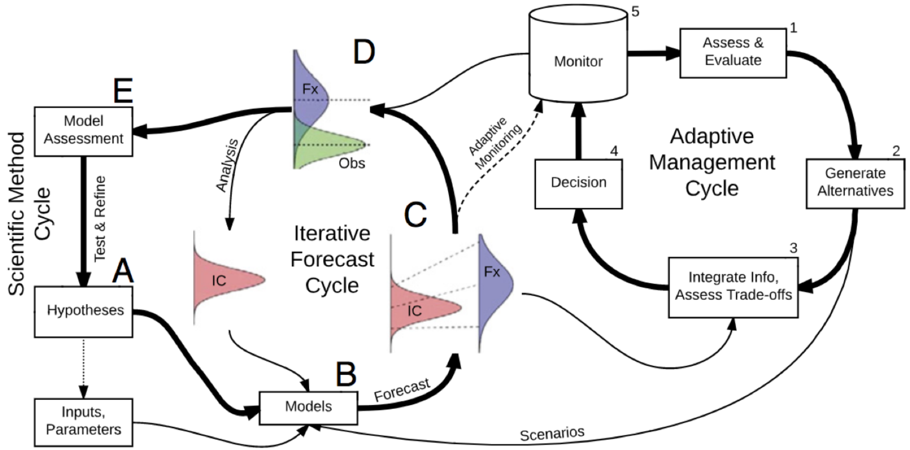
Why do we need a DA system for the CTSM?

PNAS

Iterative near-term ecological forecasting: Needs, opportunities, and challenges

Michael C. Dietze[a,1], Andrew Fox[b], Lindsay M. Beck-Johnson[c], Julio L. Betancourt[d], Mevin B. Hooten[e,f,g], Catherine S. Jarnevich[h], Timothy H. Keitt[i], Melissa A. Kenney[j], Christine M. Laney[k], Laurel G. Larsen[l], Henry W. Loescher[k,m], Claire K. Lunch[k], Bryan C. Pijanowski[n], James T. Randerson[o], Emily K. Read[p], Andrew T. Tredennick[q,r], Rodrigo Vargas[s], Kathleen C. Weathers[t], and Ethan P. White[u,v,w]

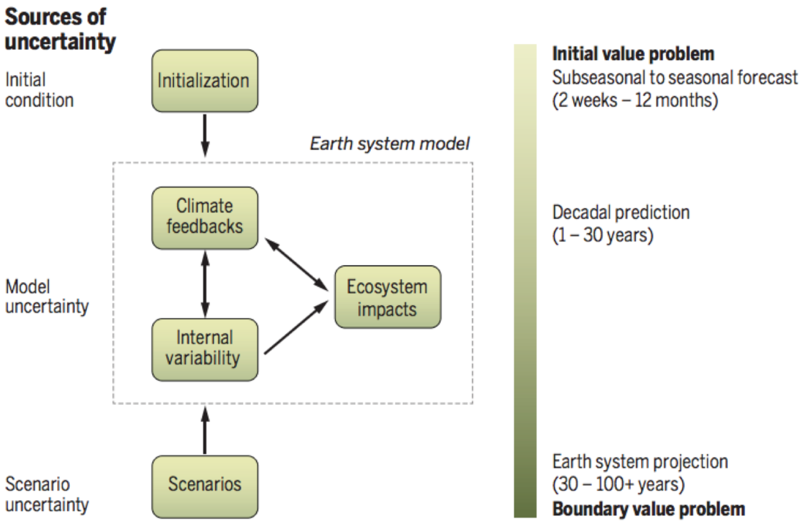


REVIEW

EARTH SYSTEMS

Climate, ecosystems, and planetary futures: The challenge to predict life in Earth system models

Gordon B. Bonan[1]* and Scott C. Doney[2]*



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New observations from the ISS

Early 2019 **OCO-3**

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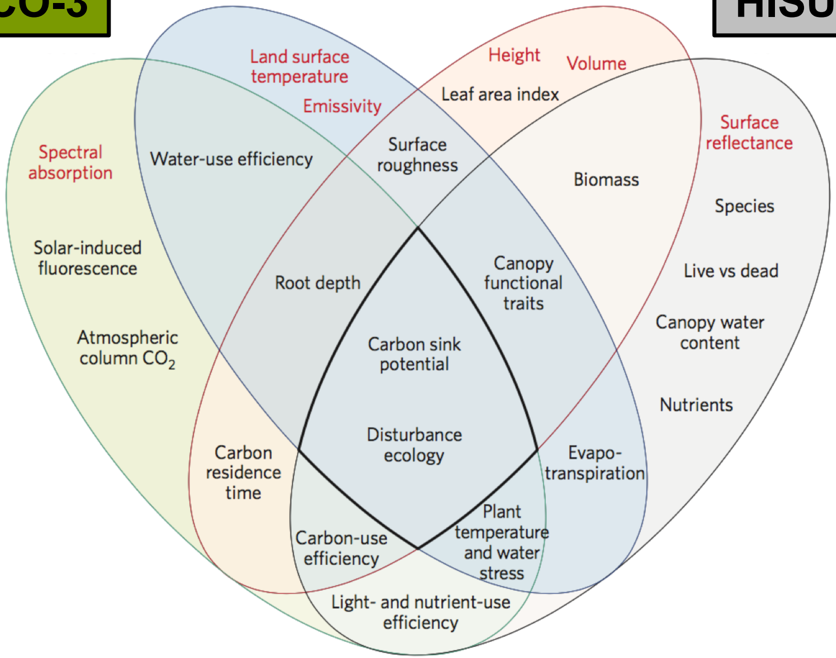
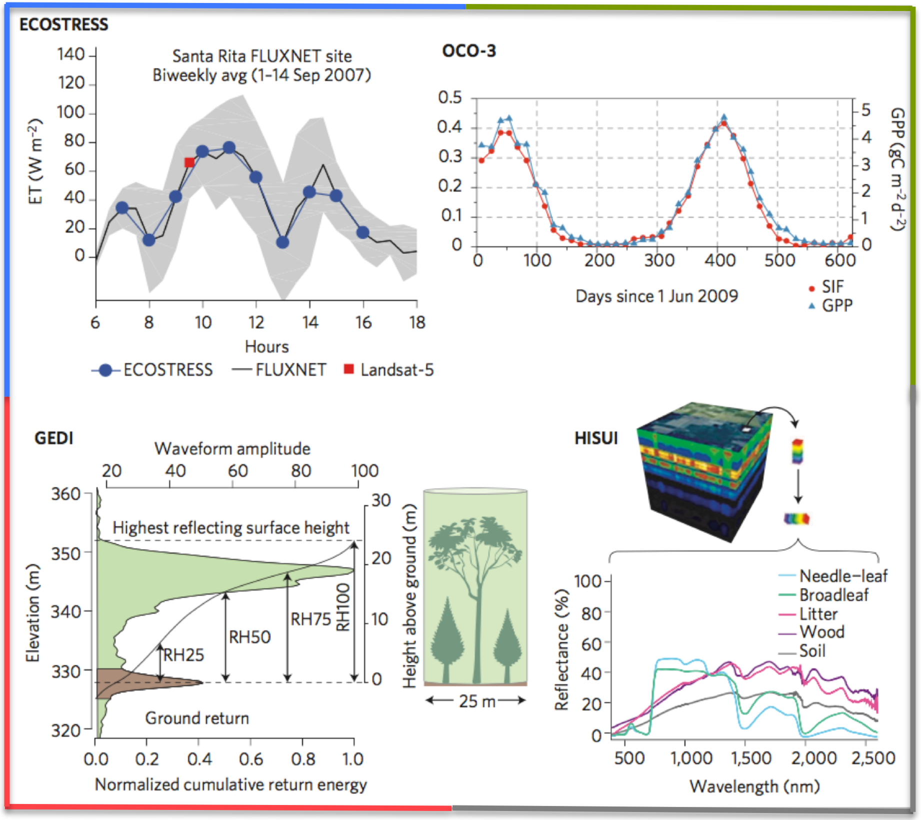
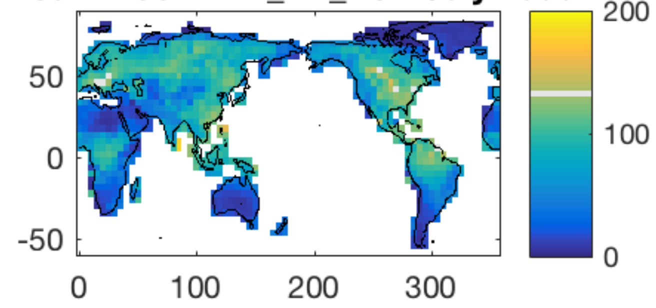
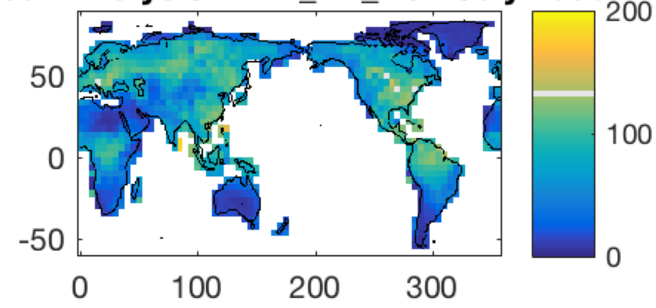


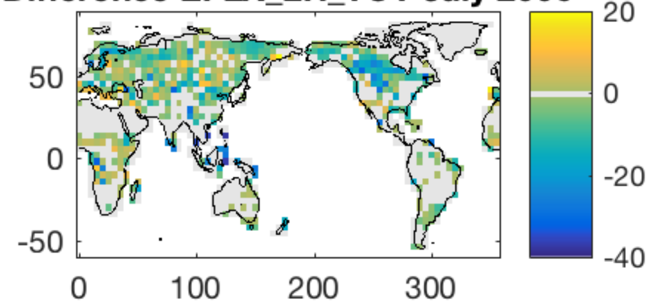
Stavros et al. 2017

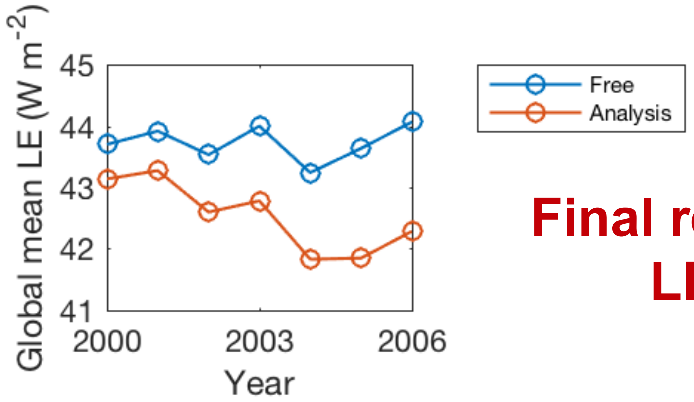


LE compared to the Freerun, July 2006



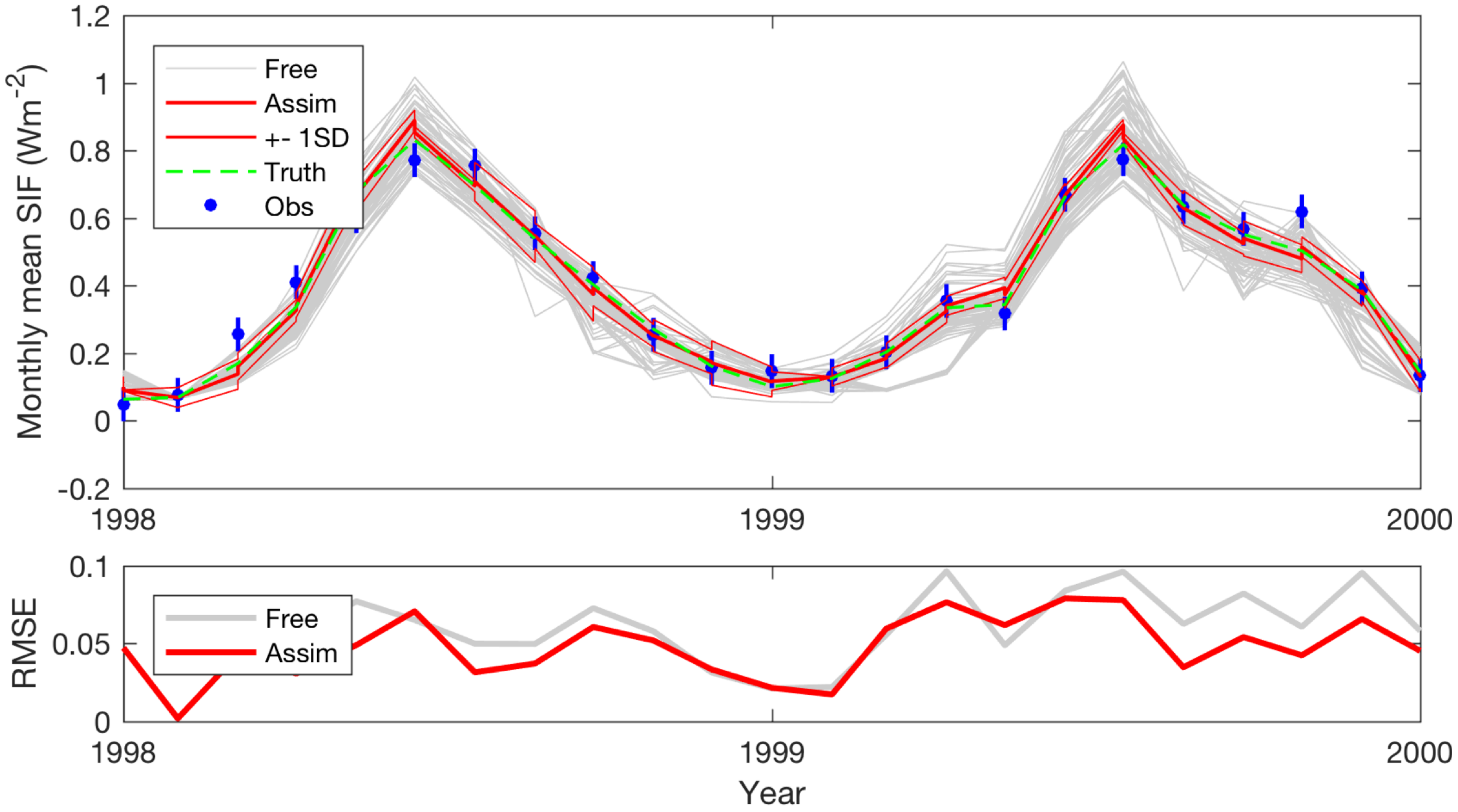






Final reduction in LE = 4%

“Perfect Model” Experiments



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