

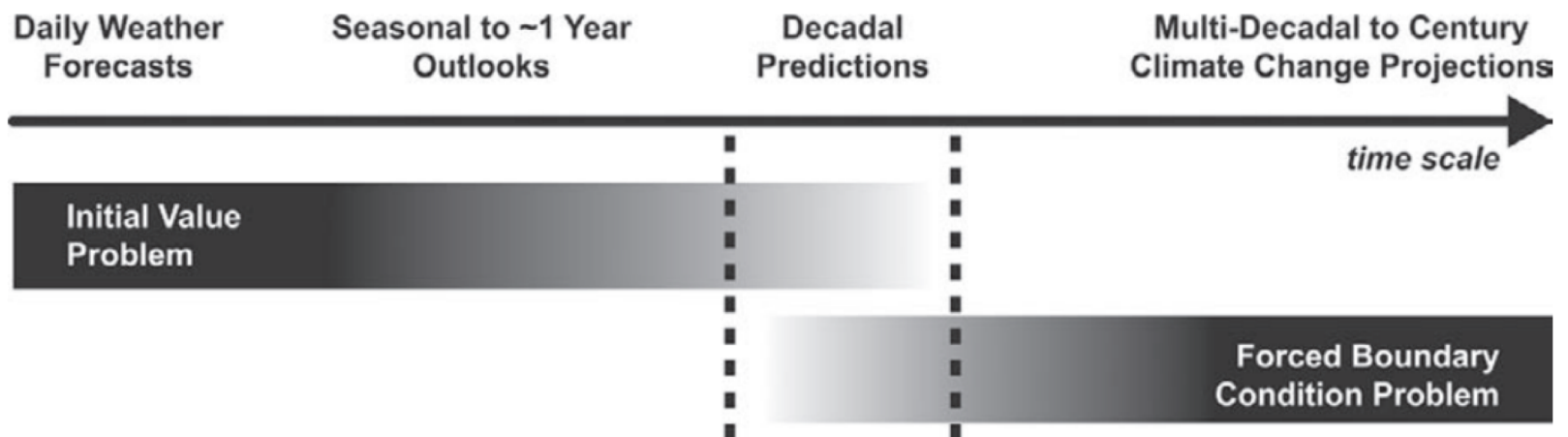
Initializing carbon cycle predictions from CLM by assimilating biomass and LAI observations

**Andrew Fox^{1,2}, Tim Hoar², William Kolby-Smith¹,
Jeffrey Anderson² & David Moore¹**

1. University of Arizona
2. National Center for Atmospheric Research

Forecasting the Carbon Cycle?

- Forecasting
 - Near-term, iterative, initialized prediction
- Potentially very useful because:
 - Can be verified
 - Provides information for decision support



(Meehl et al., 2009)

Sources of uncertainty (& their cure)

- Model Structure DEVELOPMENT
 - Model Parameters MCMC OPTIMIZATION
 - Initial Conditions
 - Spin Up
 - Climate forcing
- STATE DATA
ASSIMILATION

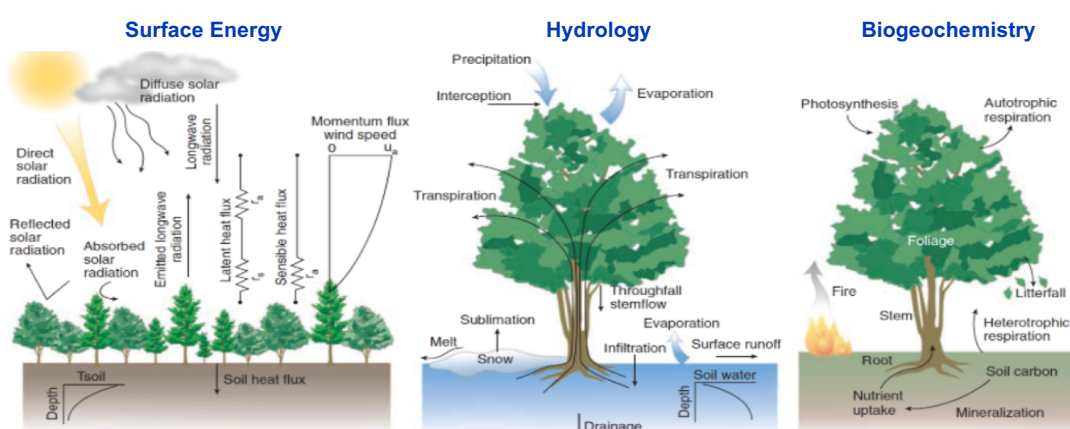
Sources of uncertainty (& their cure)

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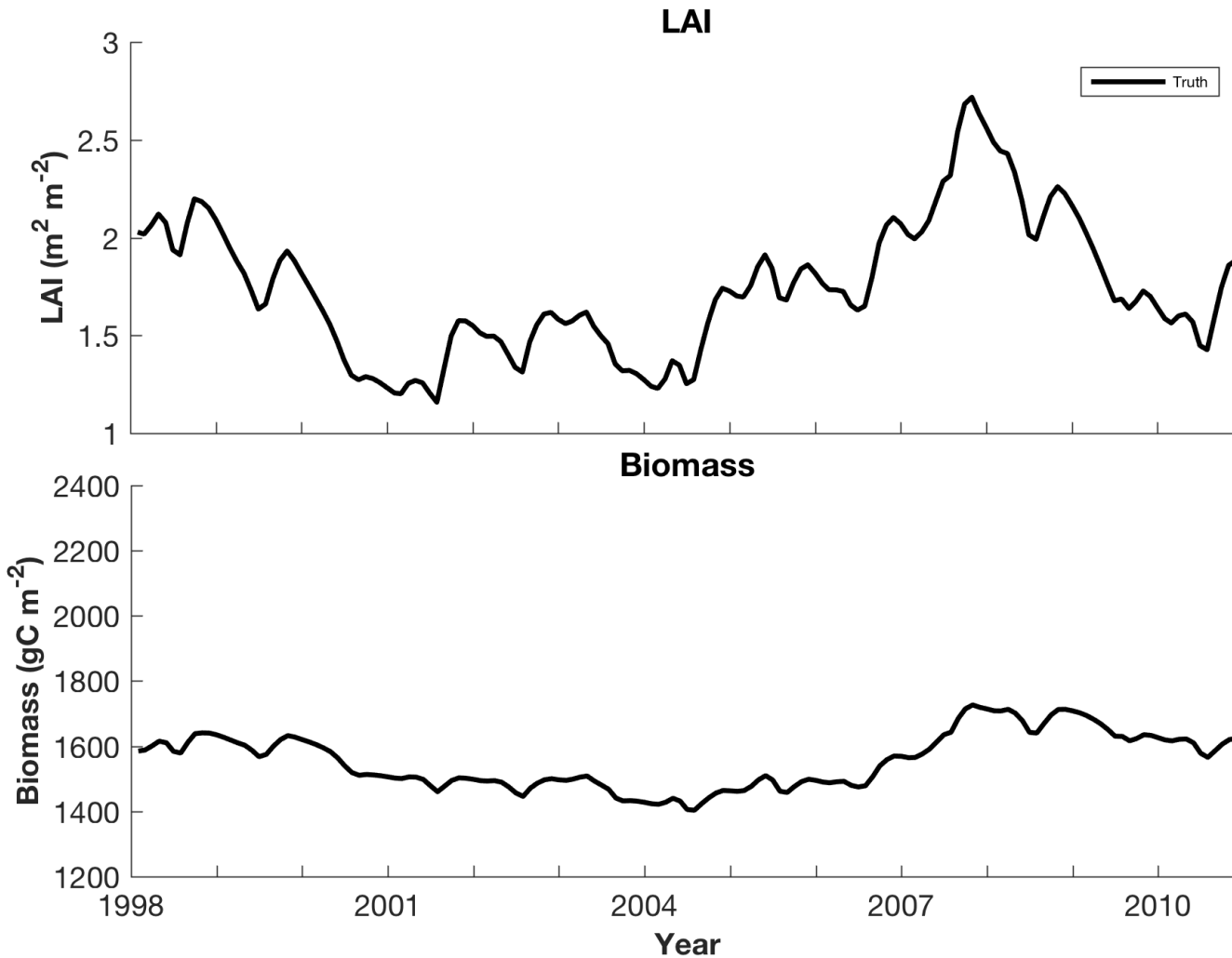
- Initial Conditions
 - Spin Up
 - Climate forcing
- STATE DATA
ASSIMILATION

Community Land Model set up

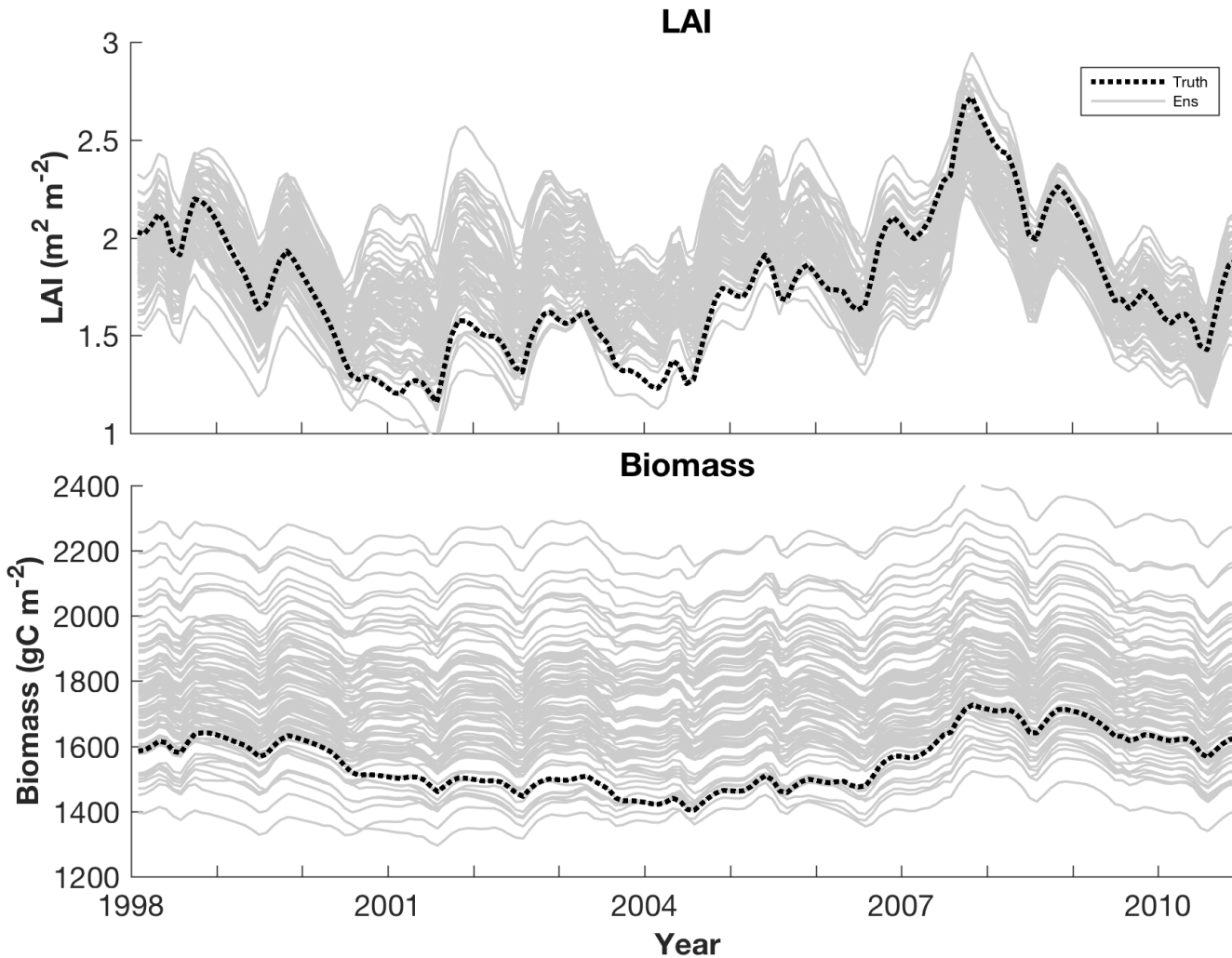
- Multi-instance CLM4.5 BGC set up for a location in central New Mexico, USA
- PFT fractions of Bare, C4 grass, shrub and Needleleaf Evergreen – Temperate
- Spun up by cycling 12 years of ensemble atmospheric reanalysis data



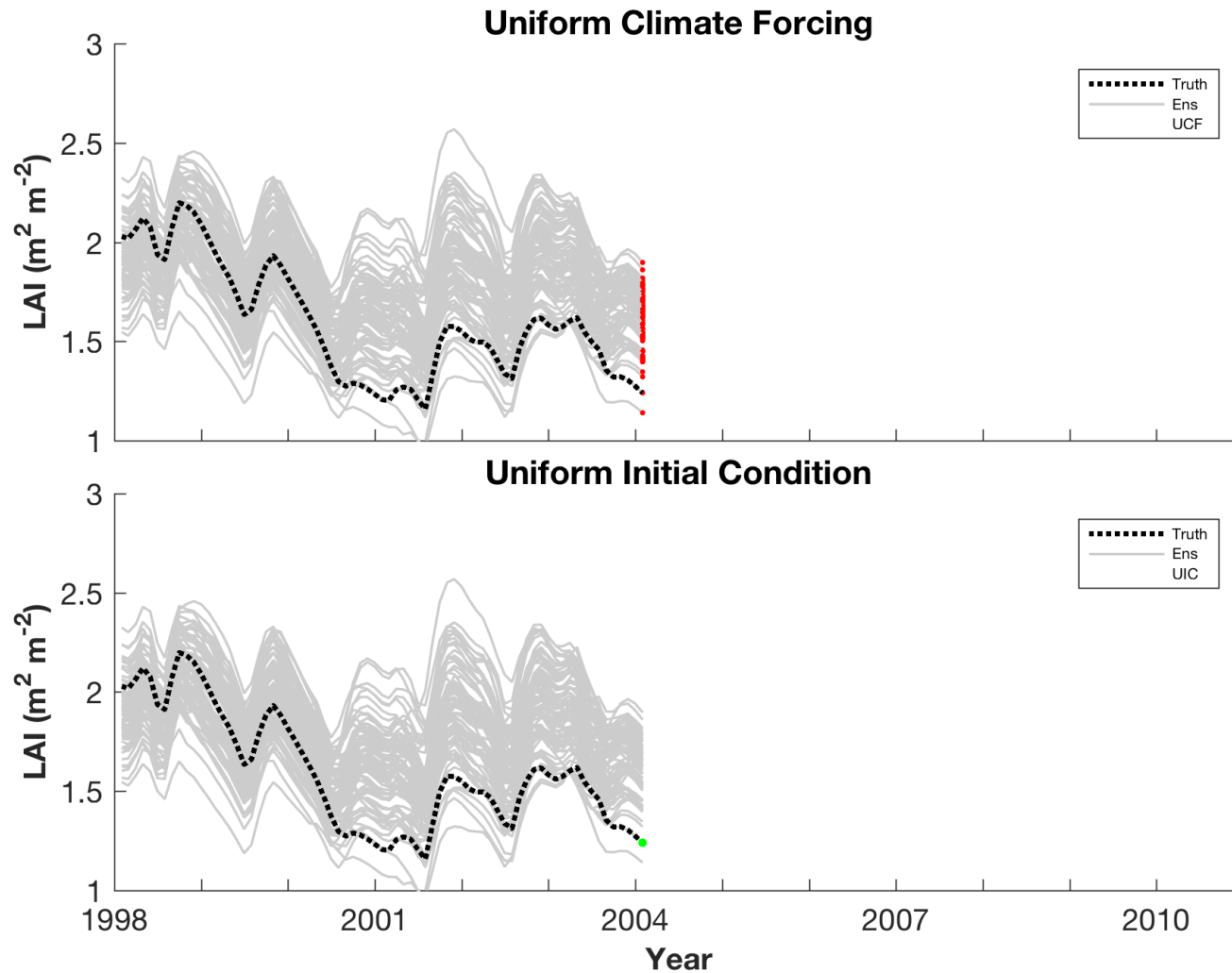
LAI and Biomass – single instance



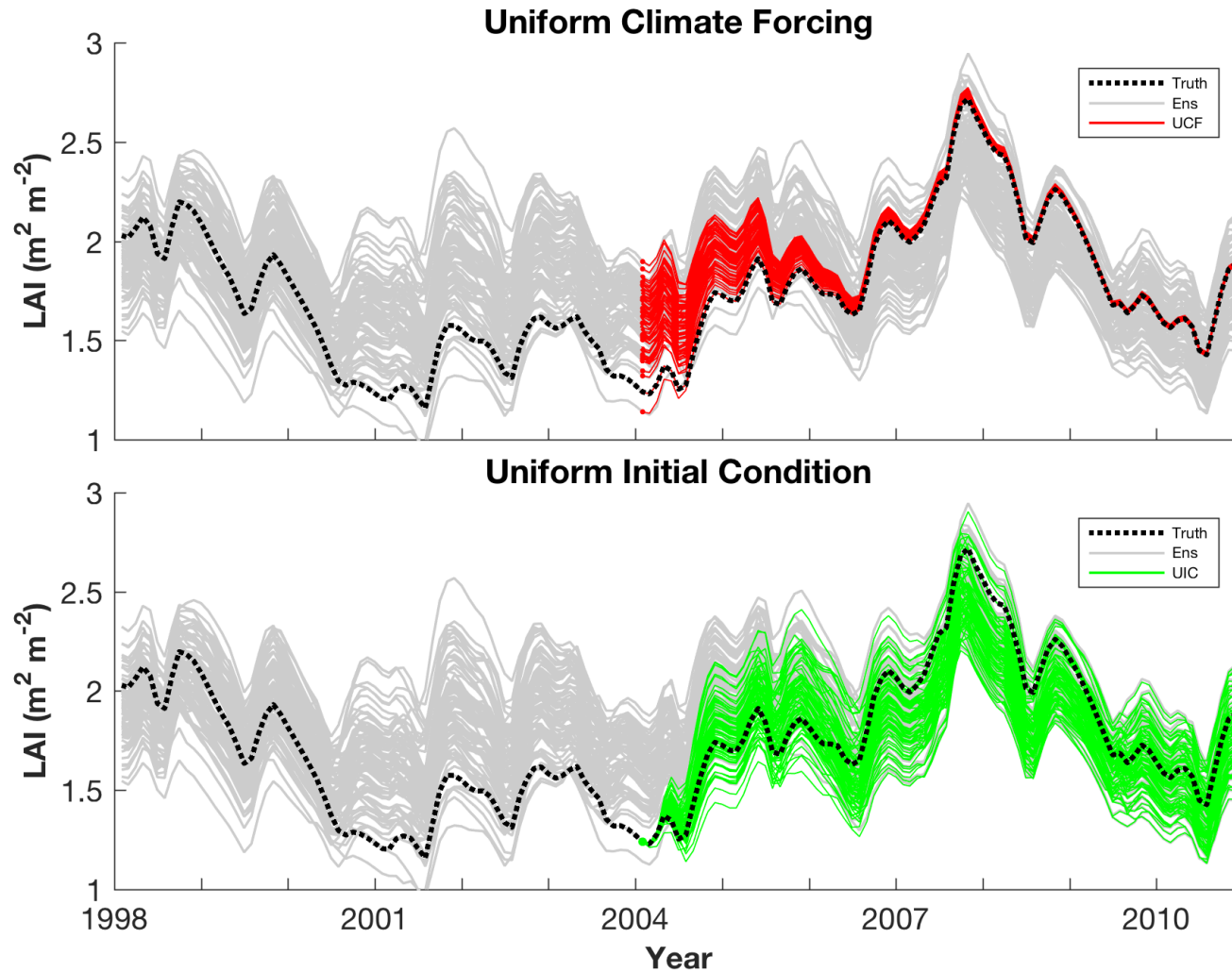
LAI and Biomass – multi-instance



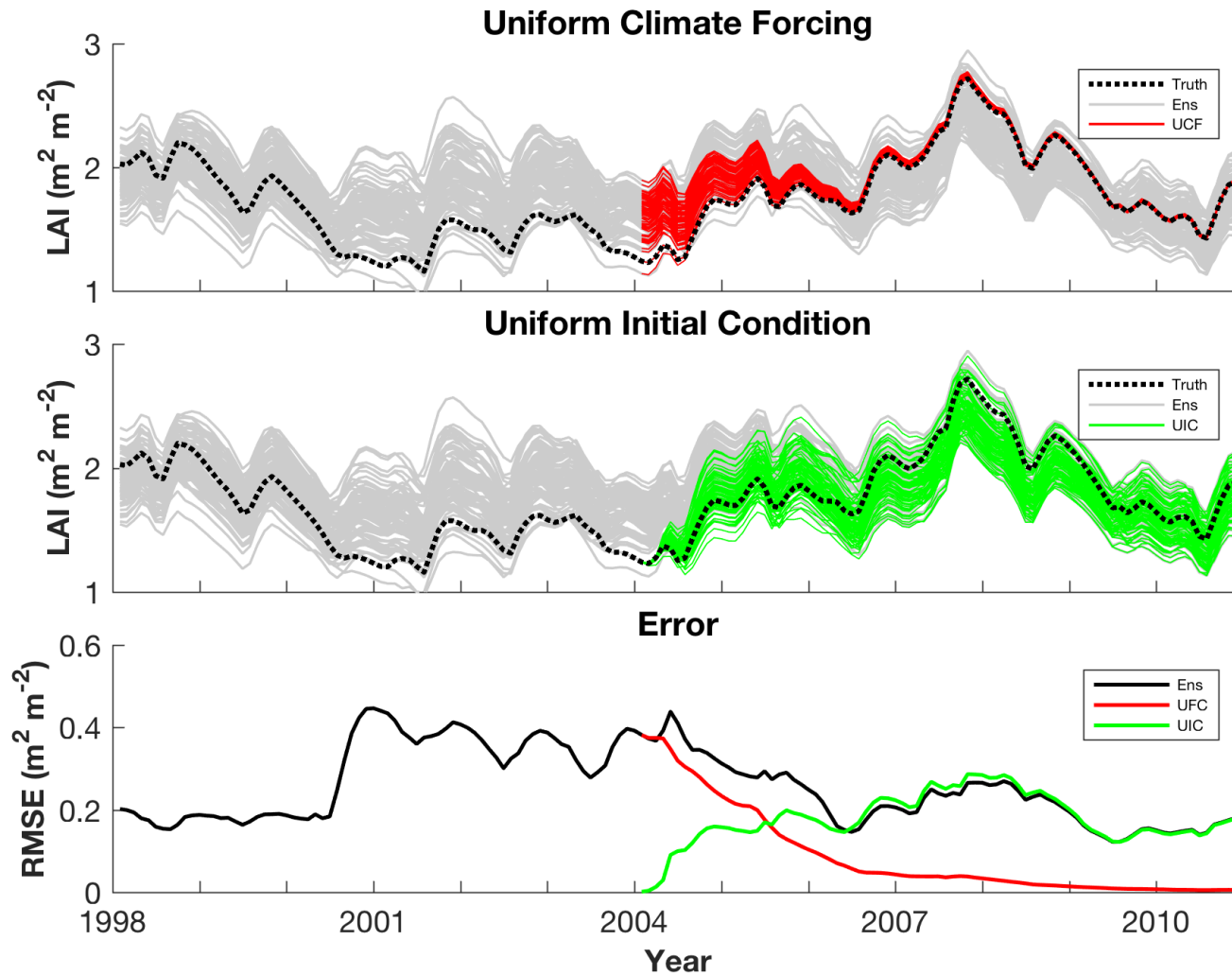
Uniform Climate Forcing v. Initial Conditions



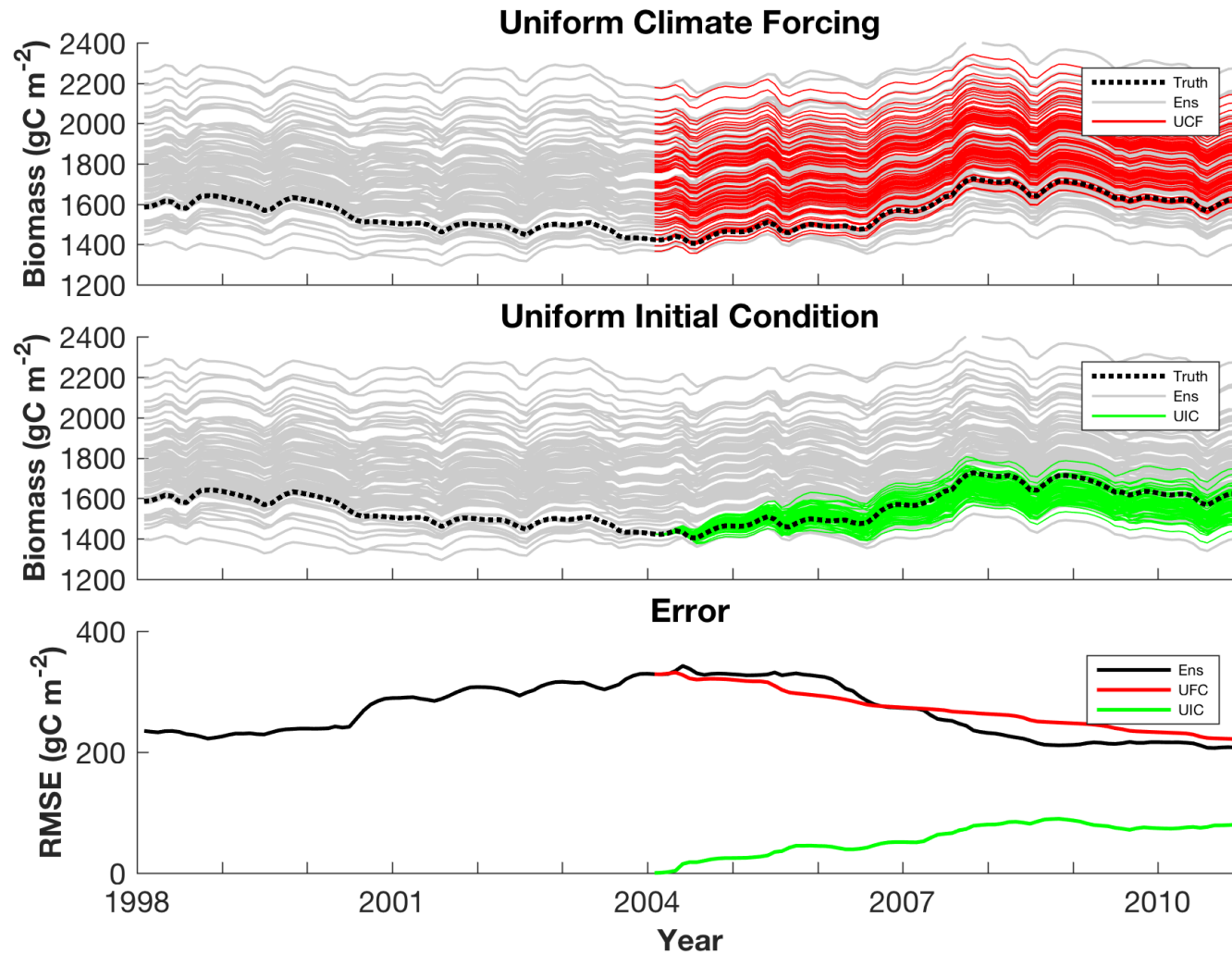
Uniform Climate Forcing v. Initial Conditions



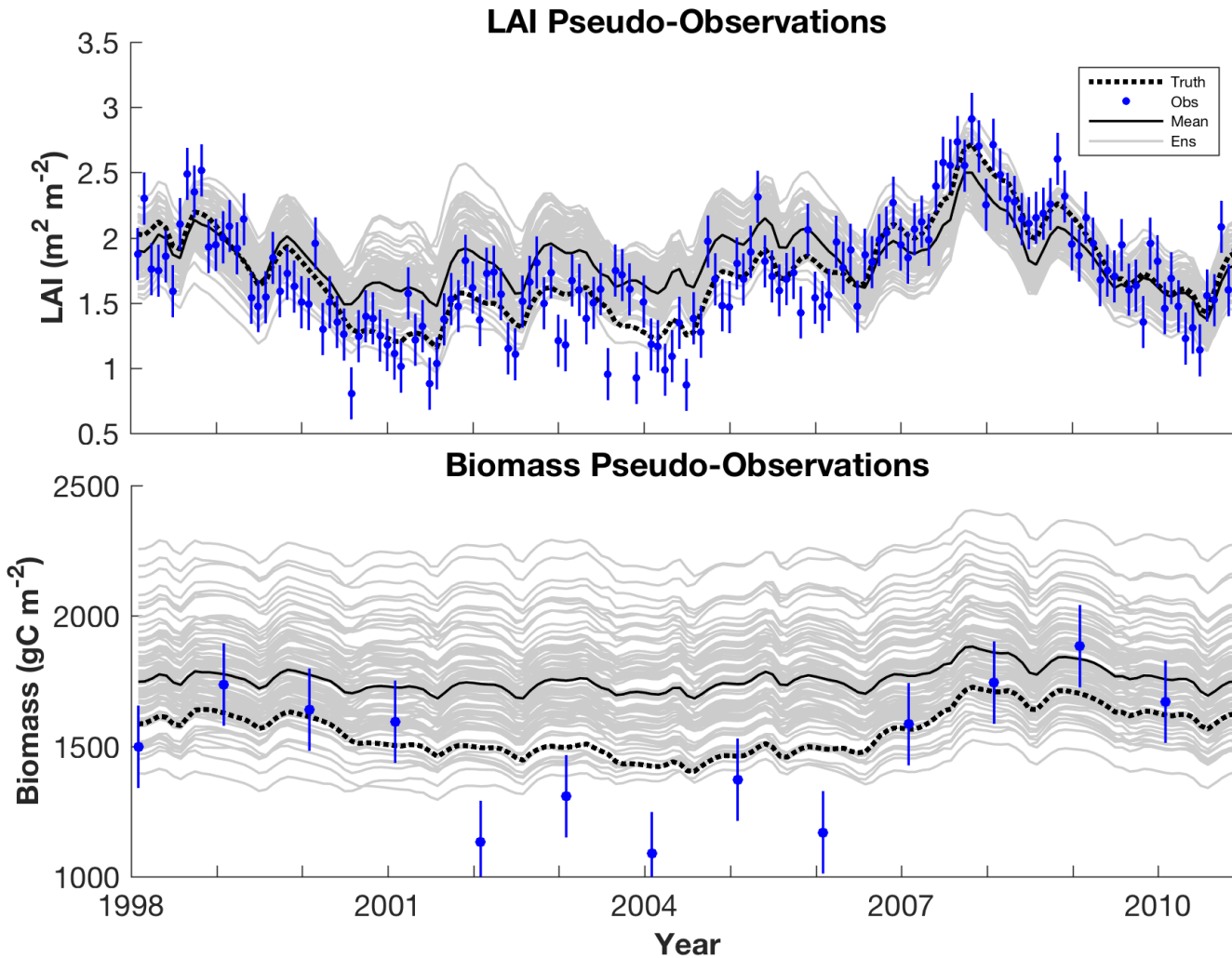
LAI – Error is reduced for 2.5 years



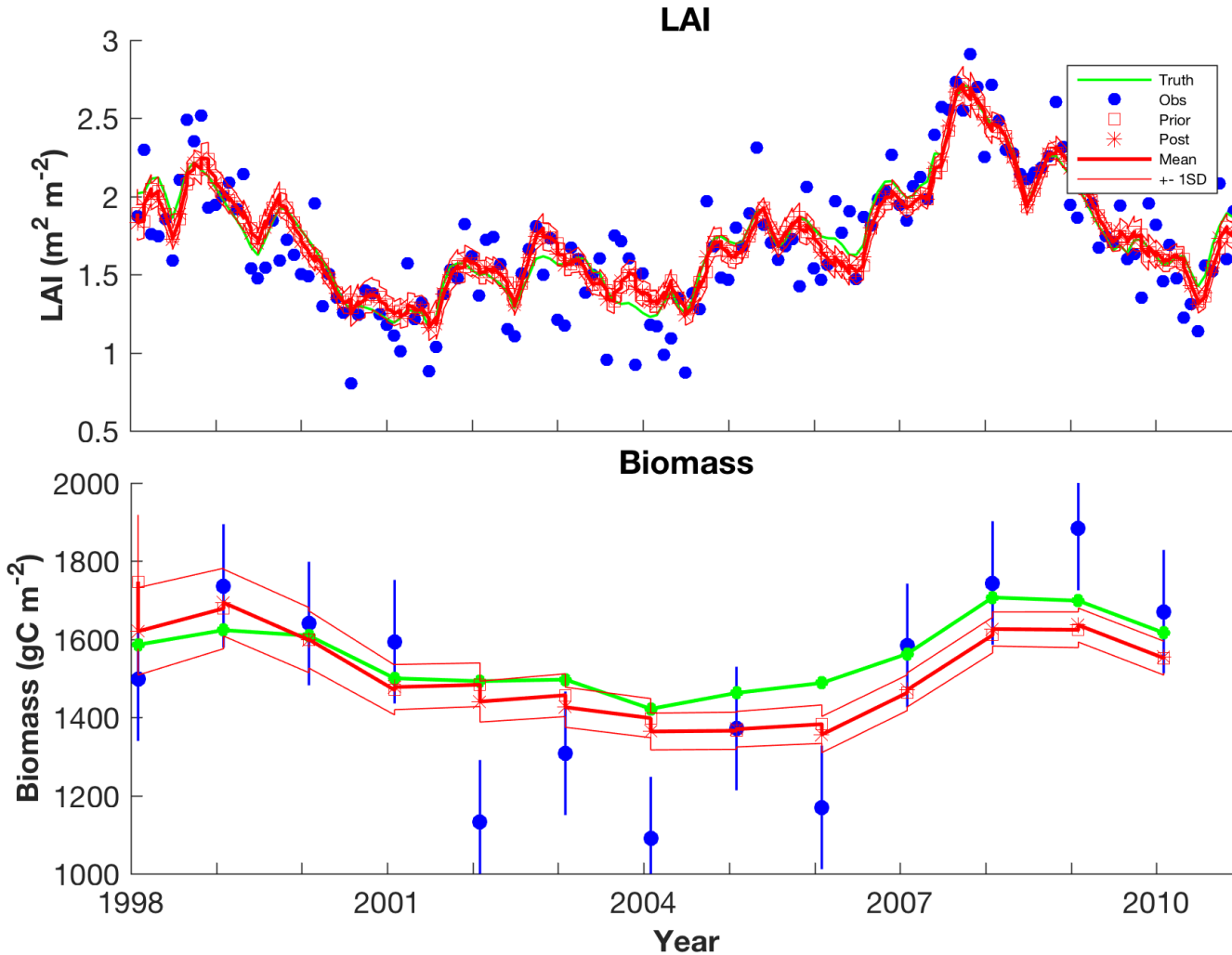
Biomass – Error is reduced for 5+ years



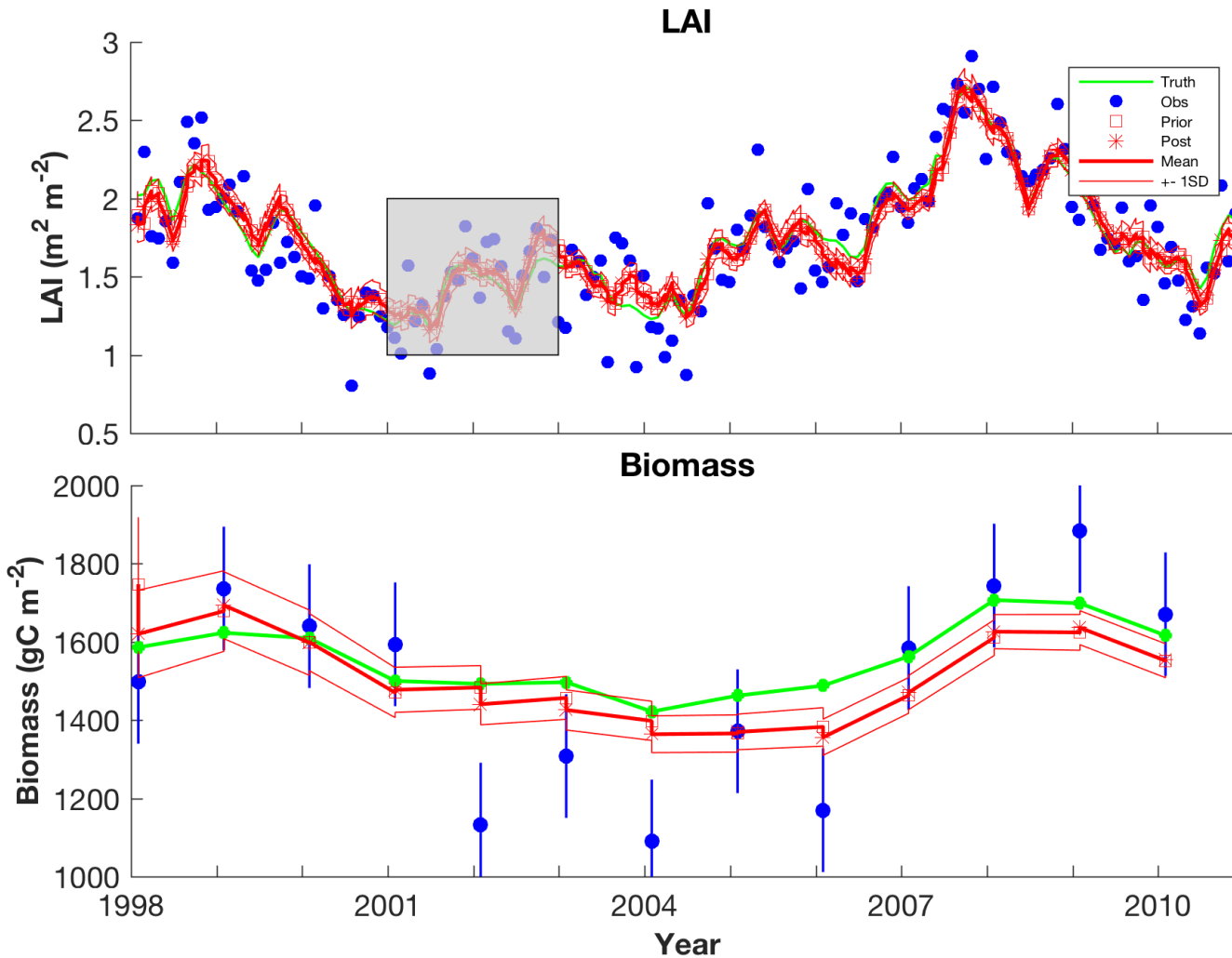
LAI and Biomass – observations of the “truth”



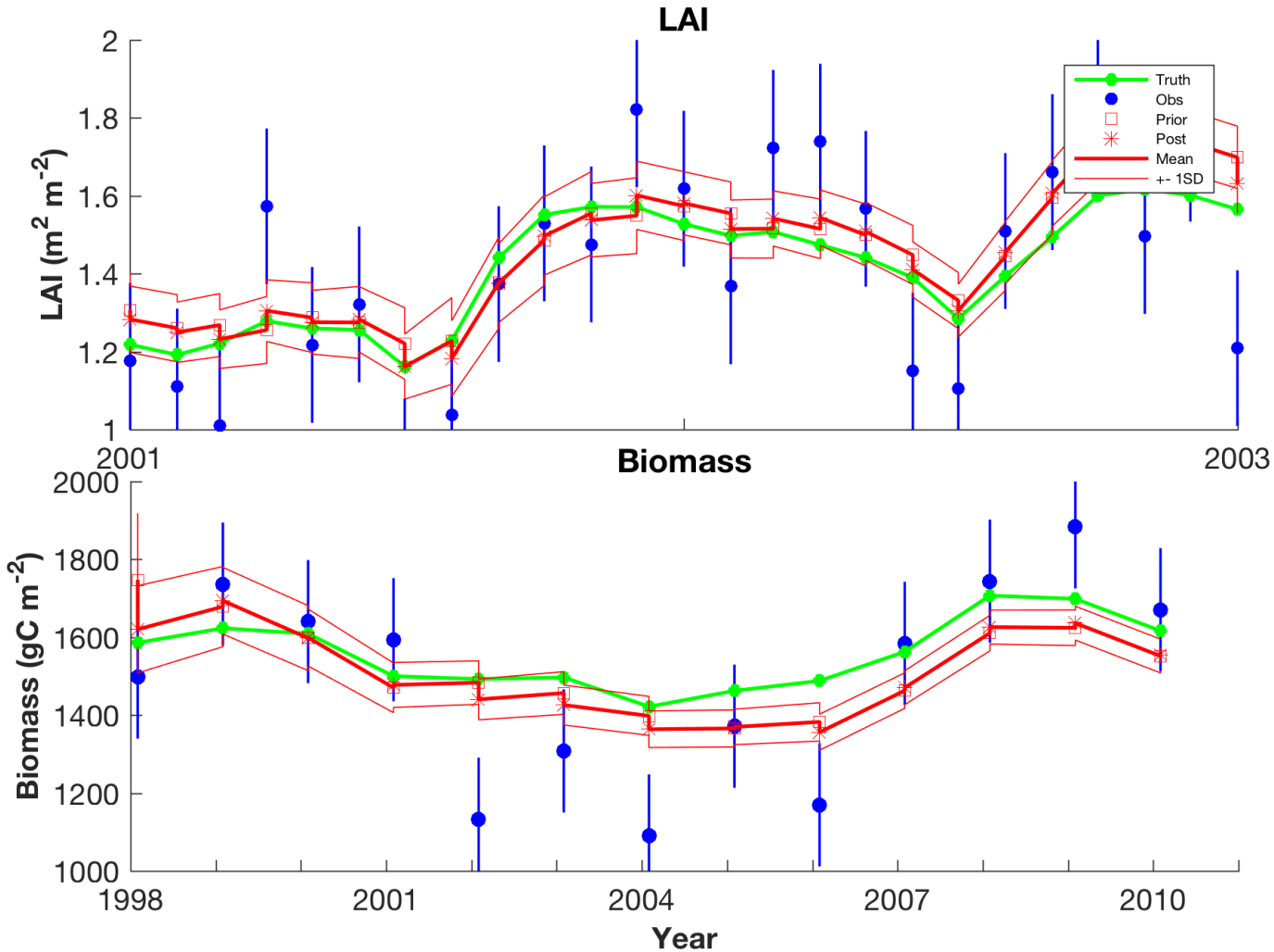
Ensemble is updated at observation time



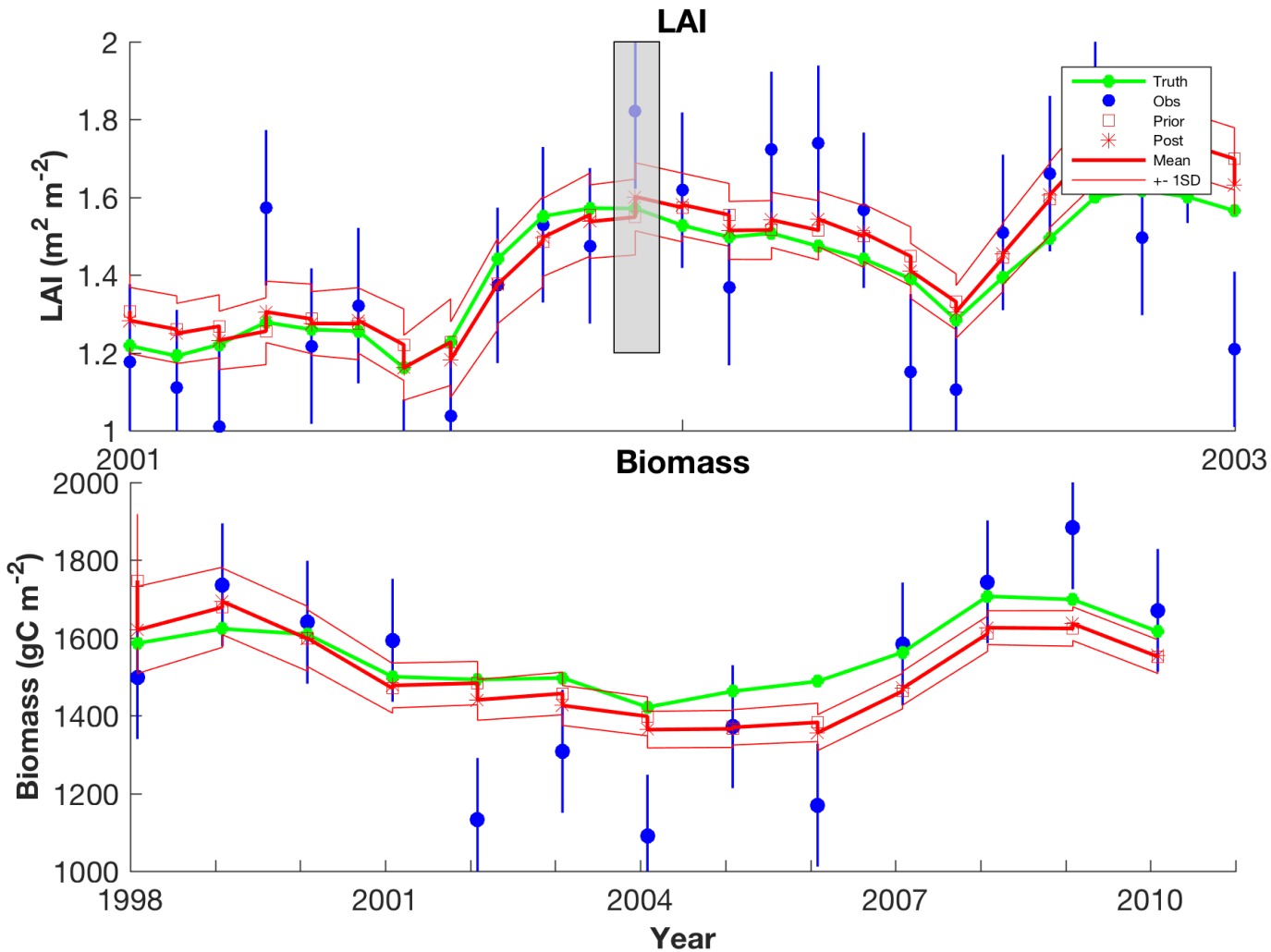
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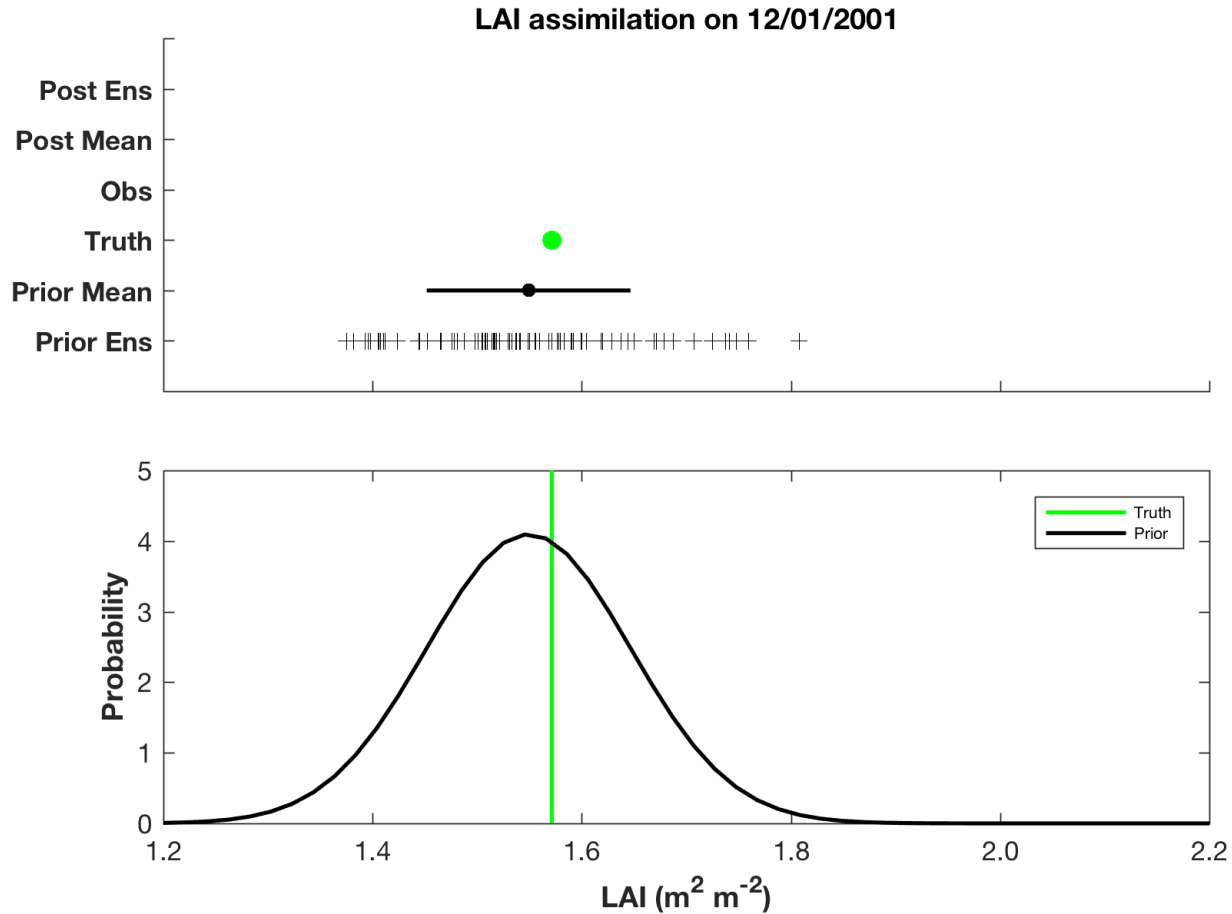
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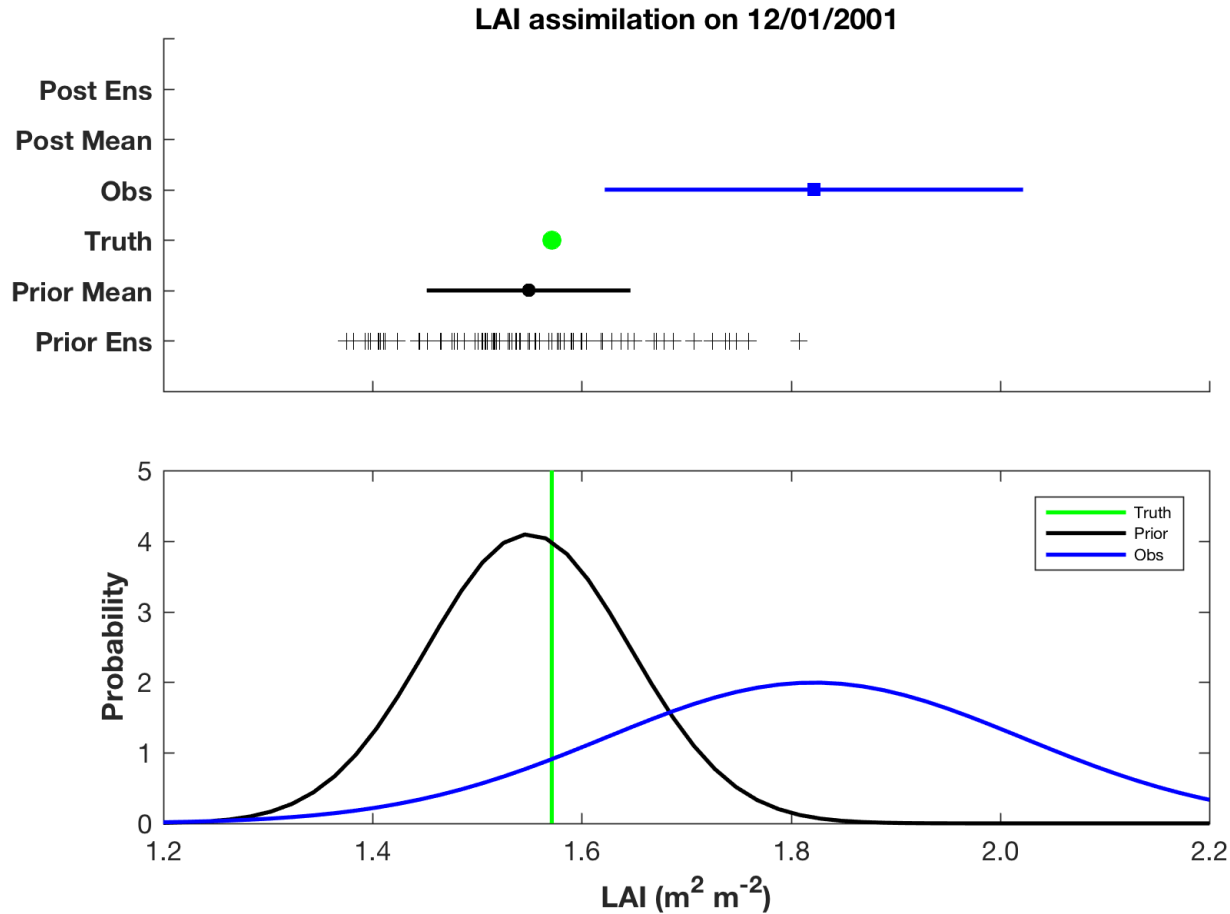
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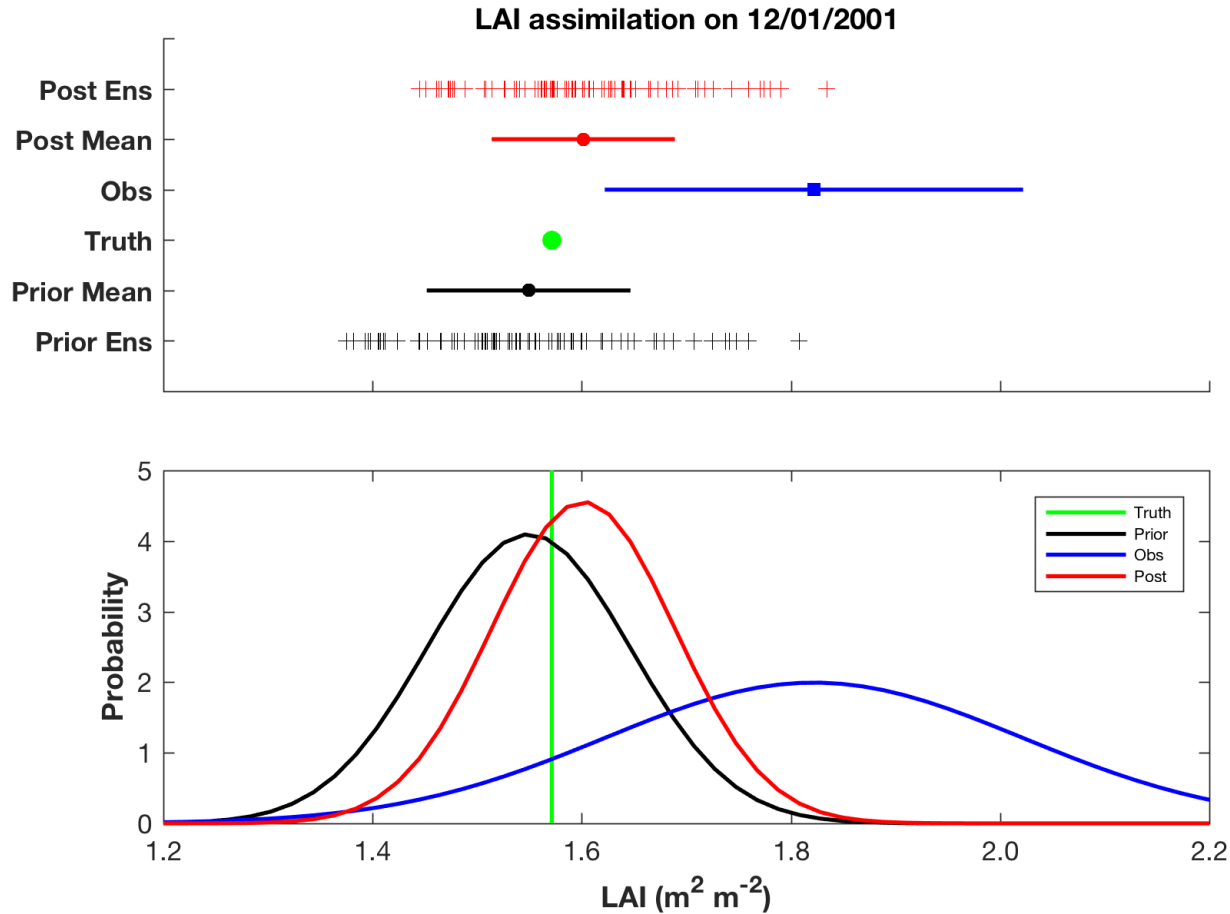
LAI updated by Ens. Adjustment Kalman Filter



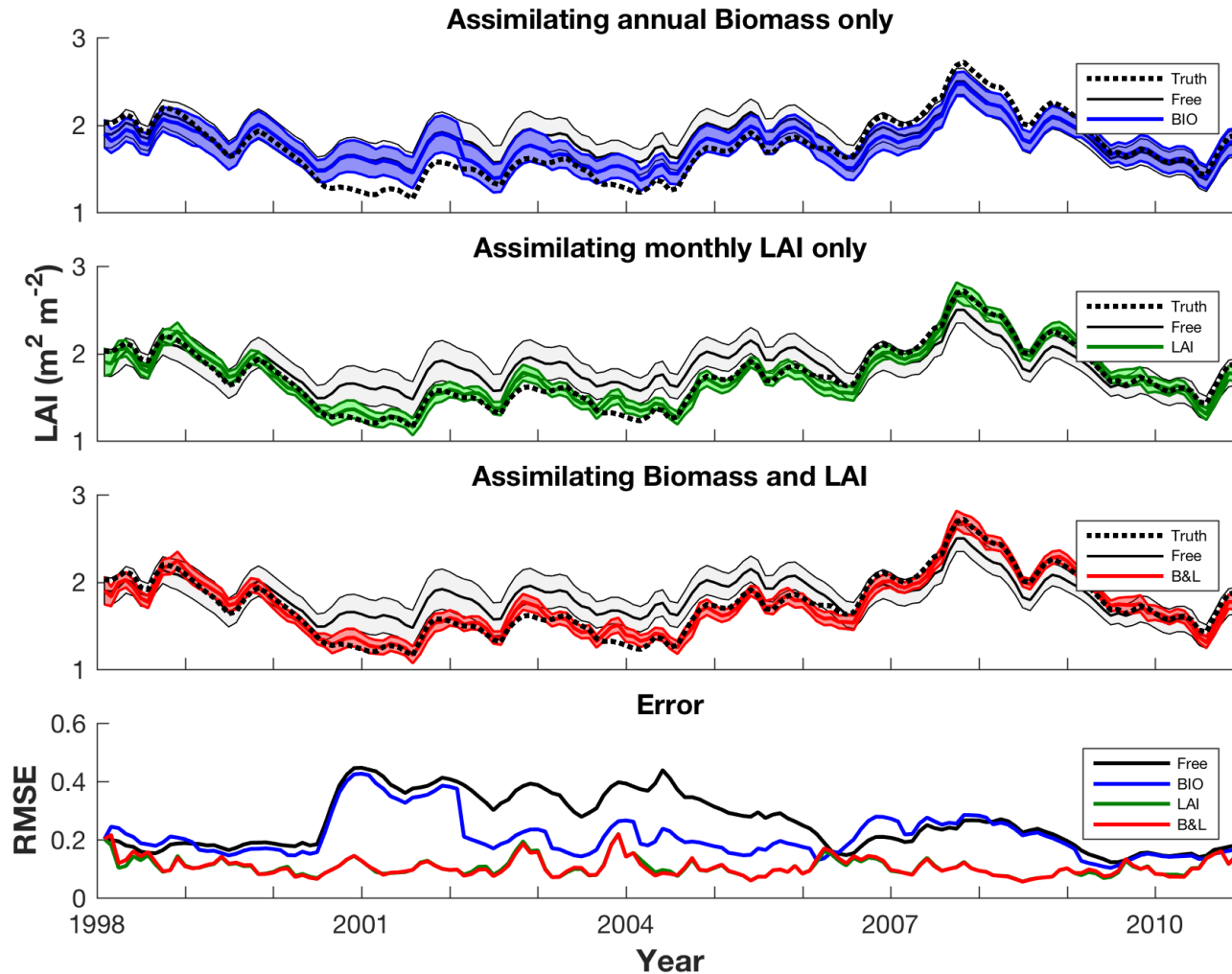
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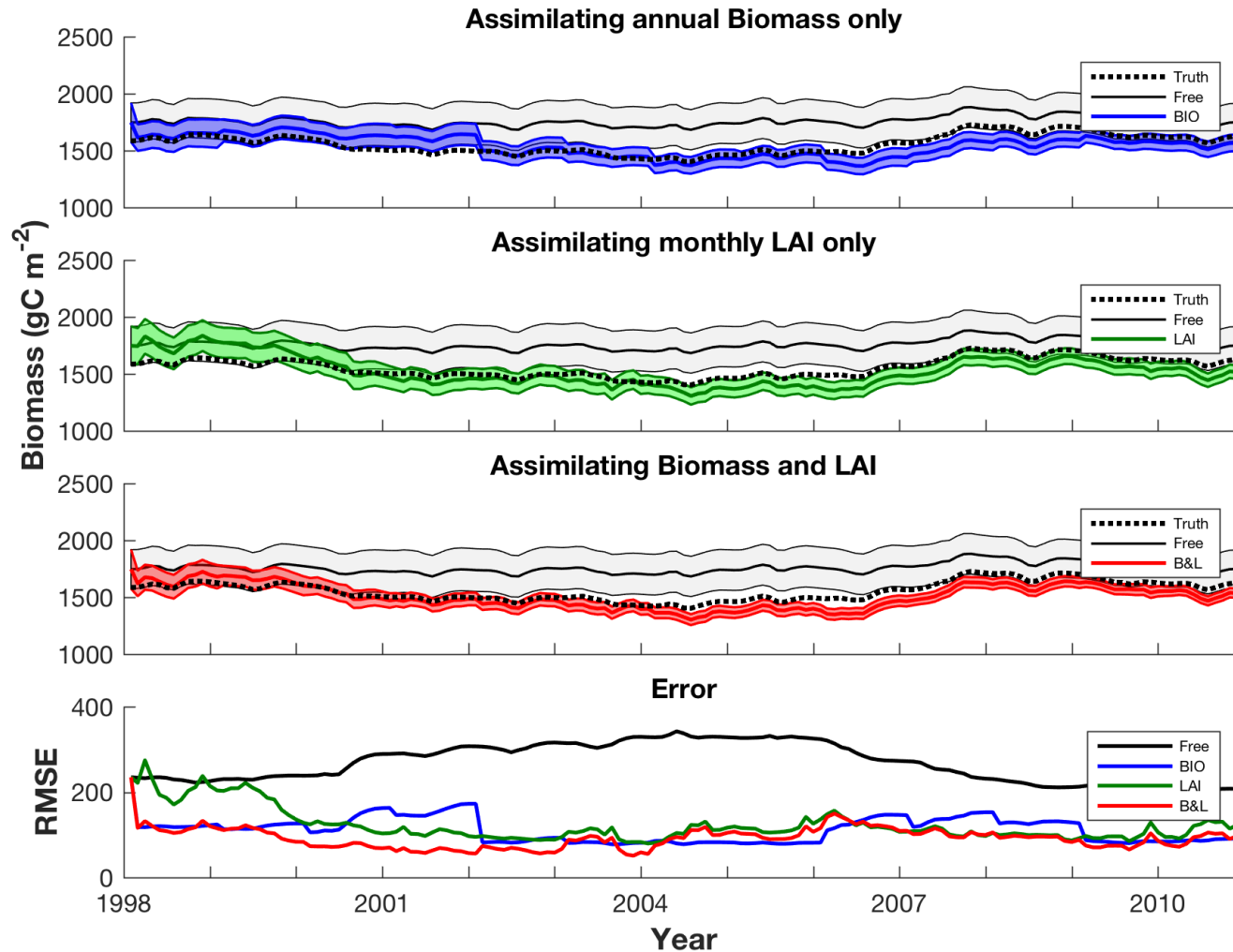
LAI updated by Ens. Adjustment Kalman Filter



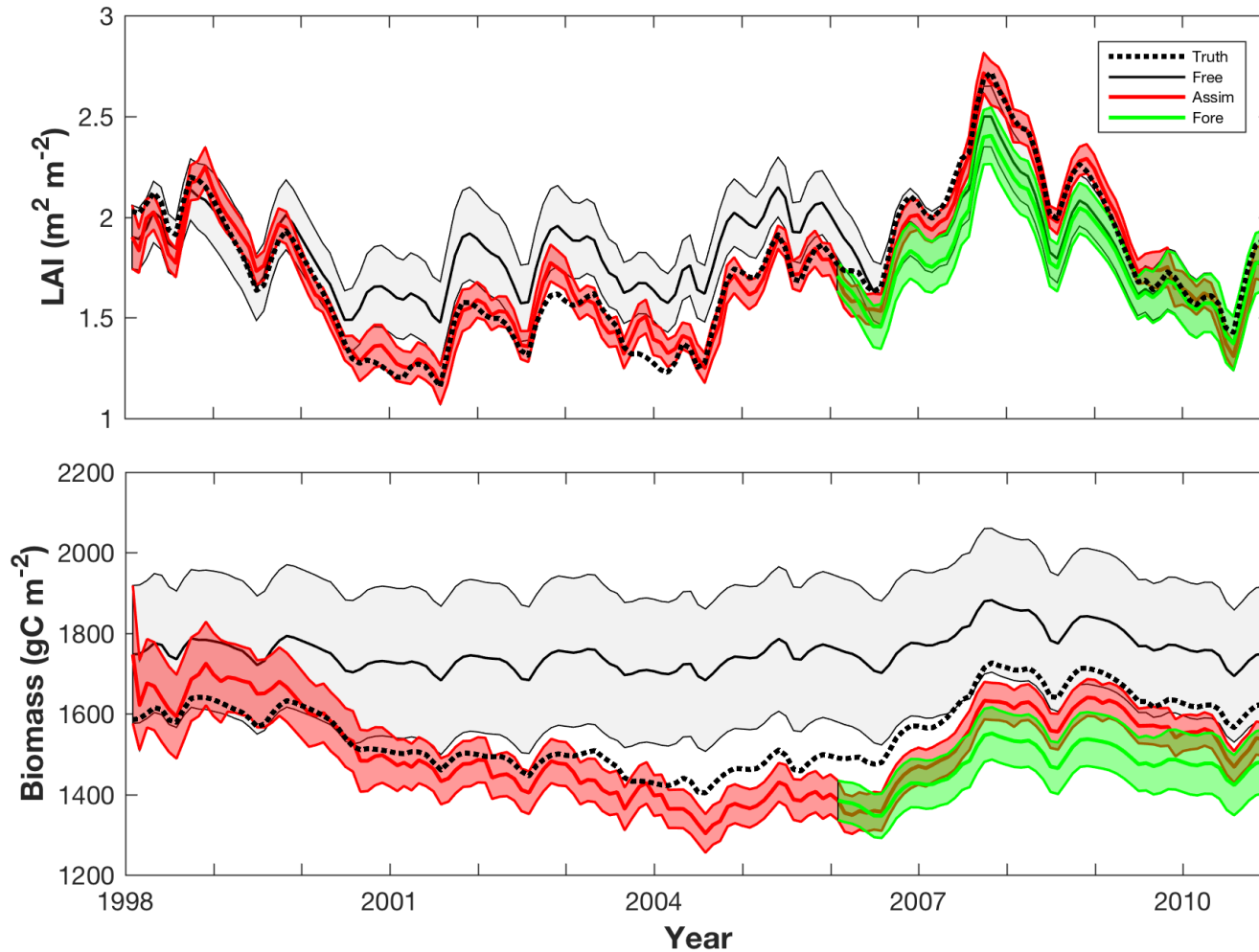
Impact of assimilating LAI, Biomass and both



Impact of assimilating LAI, Biomass and both



Impact on Forecast



LAI and Biomass – “real” observations

0.5° Aggregated MODIS LAI Observations

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 112, G01023, doi:10.1029/2006JG000168, 2007

Representing a new MODIS consistent land surface in the Community Land Model (CLM 3.0)

Peter J. Lawrence¹ and Thomas N. Chase¹

Received 27 January 2006; revised 3 October 2006; accepted 14 November 2006; published 17 March 2007.

0.25° Vegetation Optical Depth Biomass Observations

nature
climate change

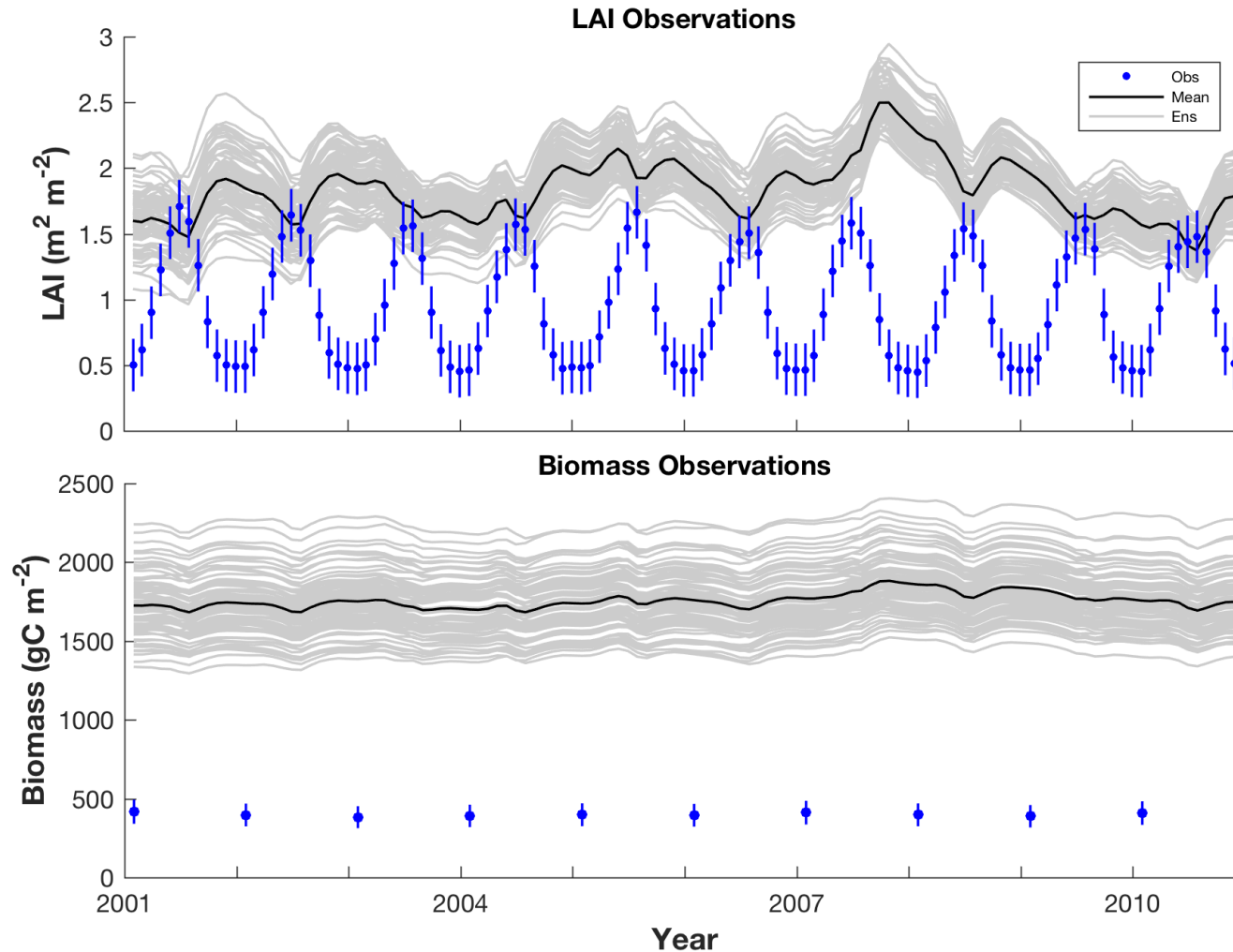
LETTERS

PUBLISHED ONLINE: 30 MARCH 2015 | DOI: 10.1038/NCLIMATE2581

Recent reversal in loss of global terrestrial biomass

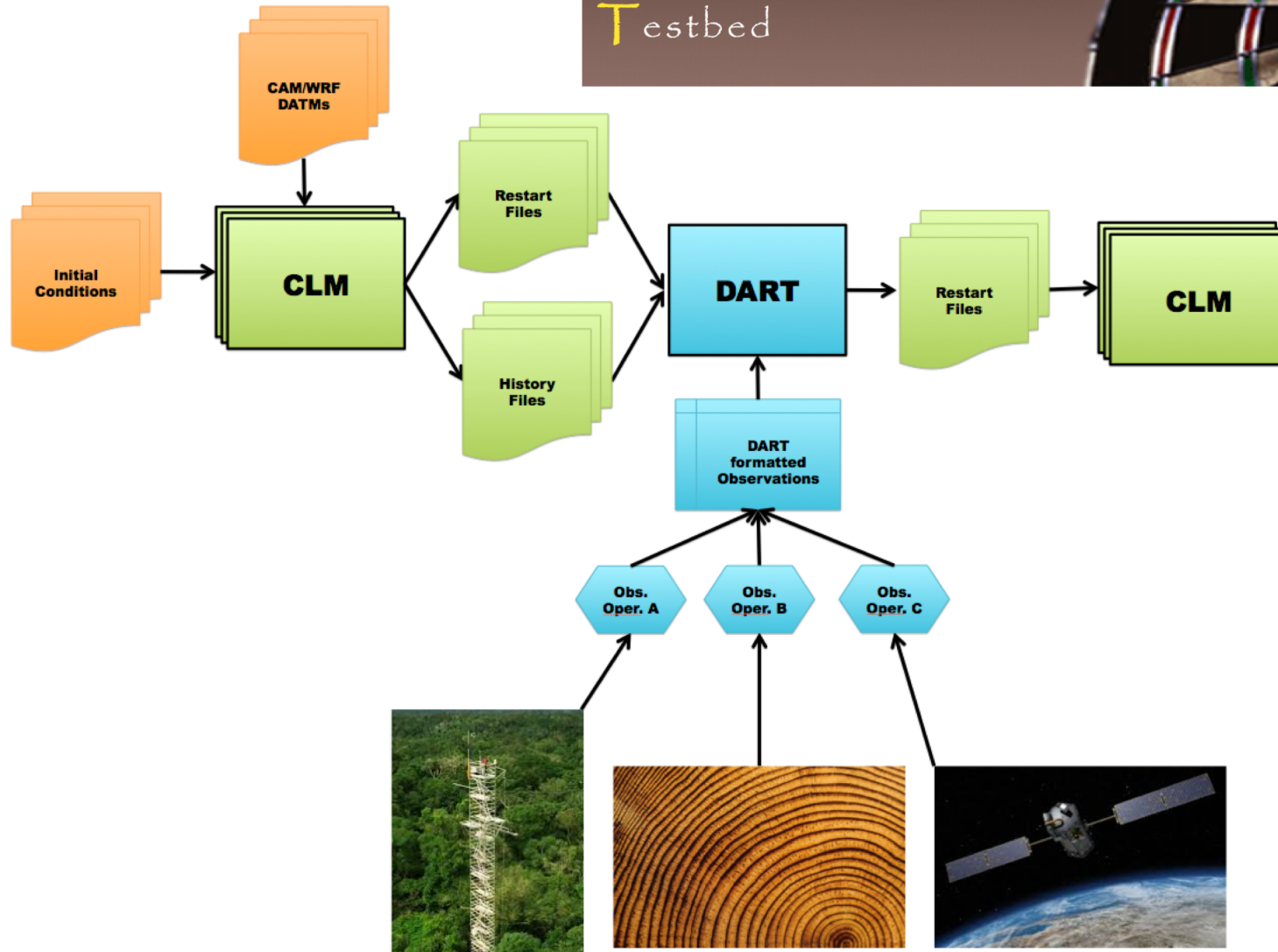
Yi Y. Liu^{1,2*}, Albert I. J. M. van Dijk^{3,4}, Richard A. M. de Jeu⁵, Josep G. Canadell⁶, Matthew F. McCabe⁷, Jason P. Evans¹ and Guojie Wang⁸

LAI and Biomass – “real” observations

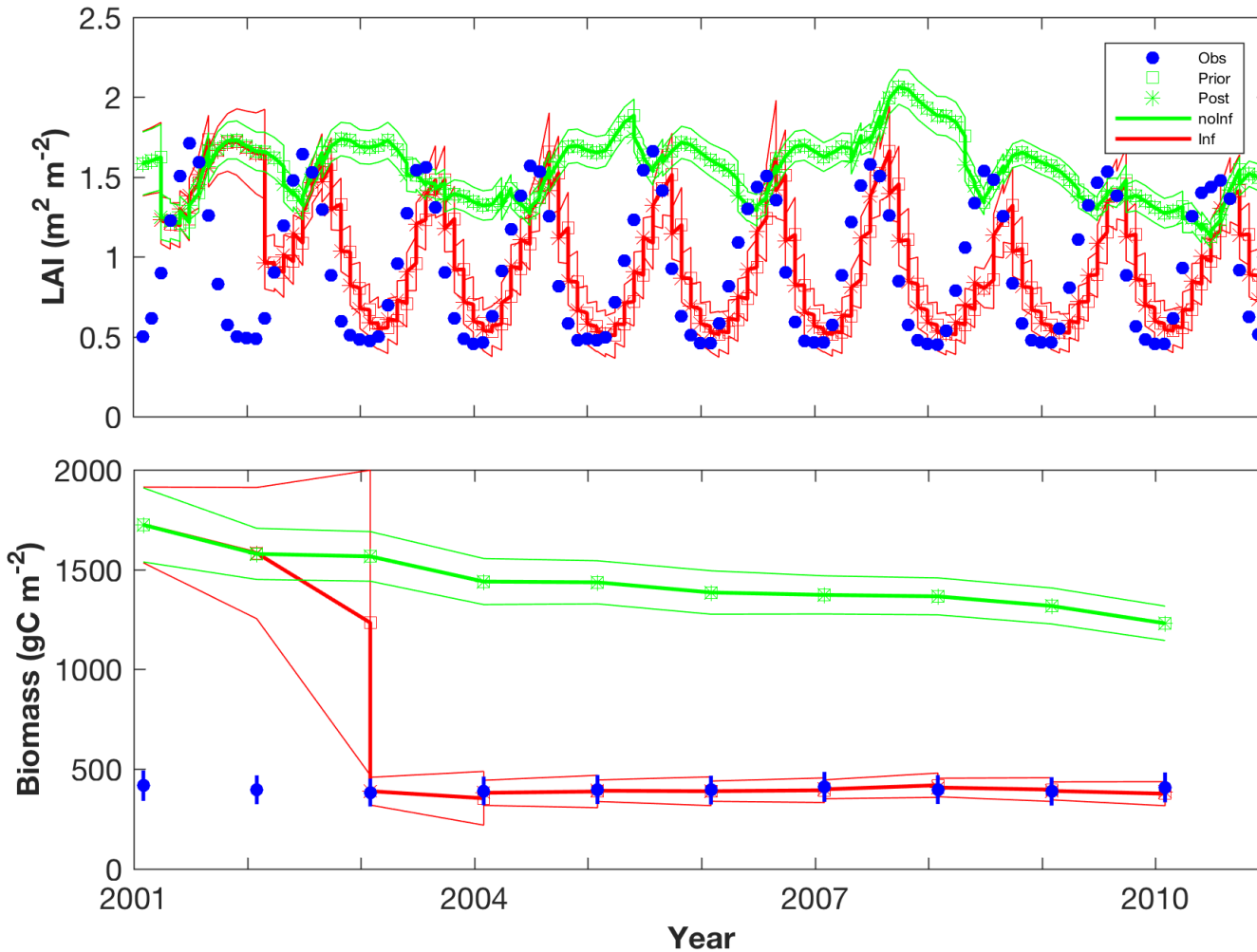


CLM-DART

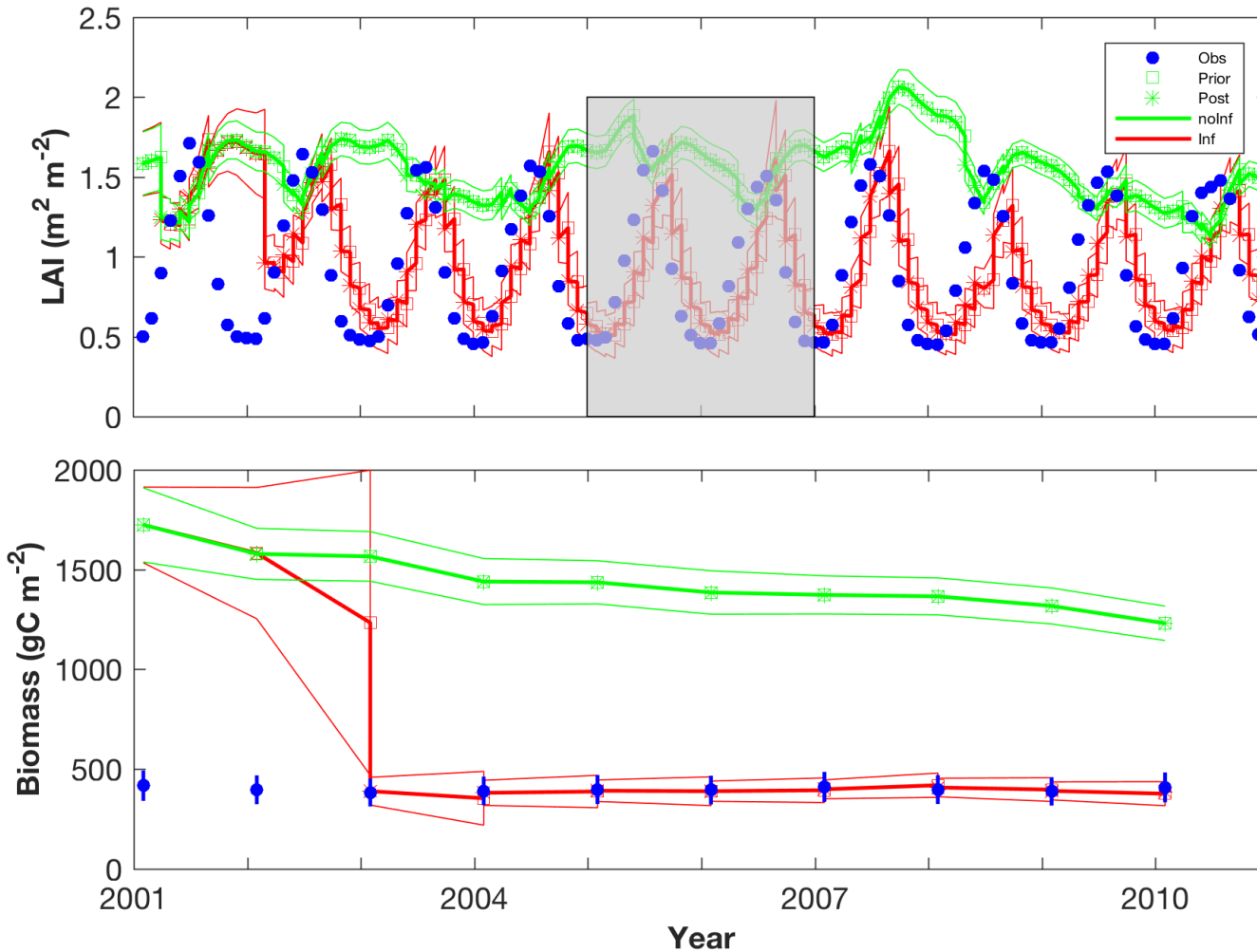
Data
Assimilation
Research
Testbed



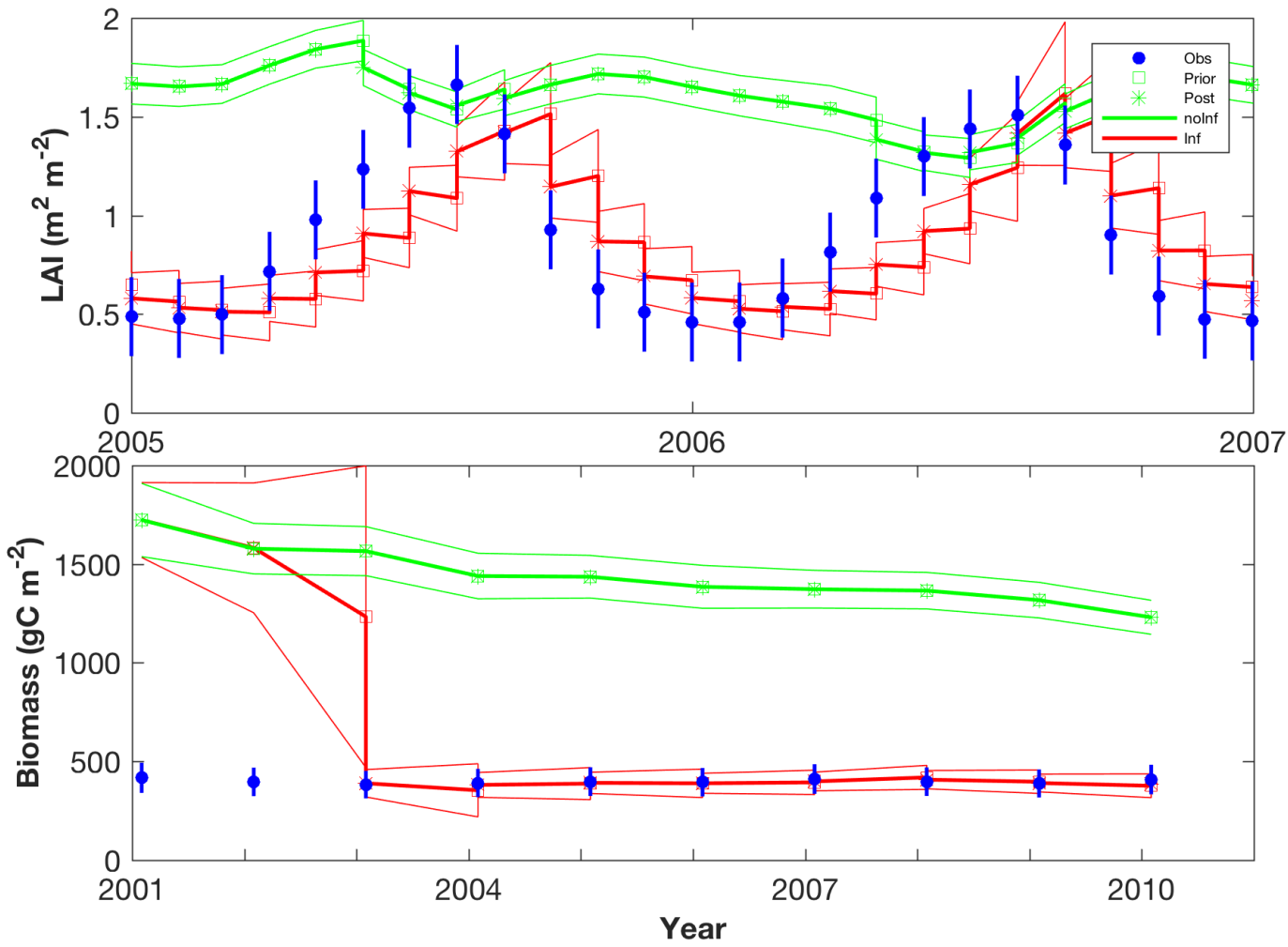
Ensemble is updated at observation time



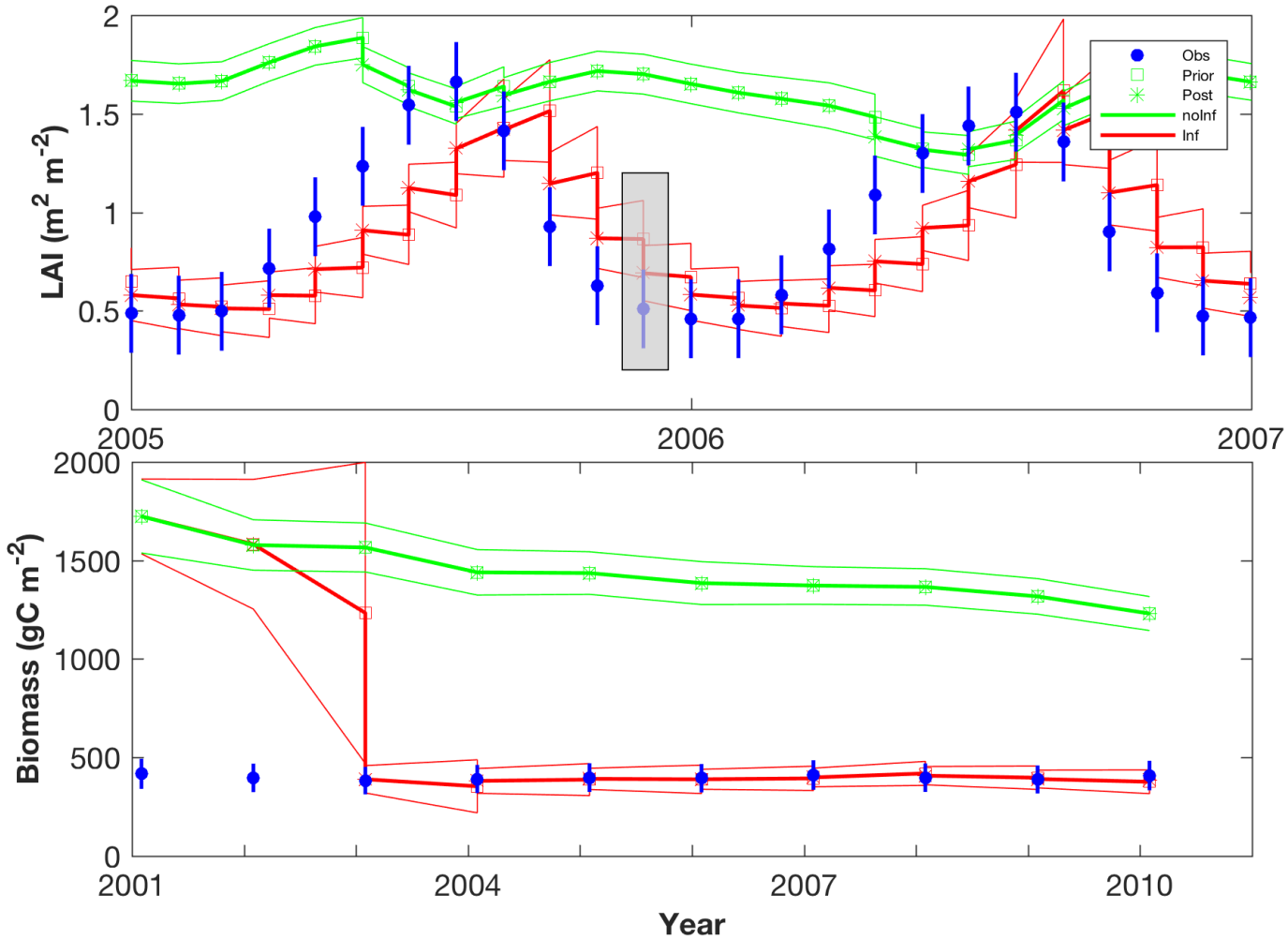
Ensemble is updated at observation time



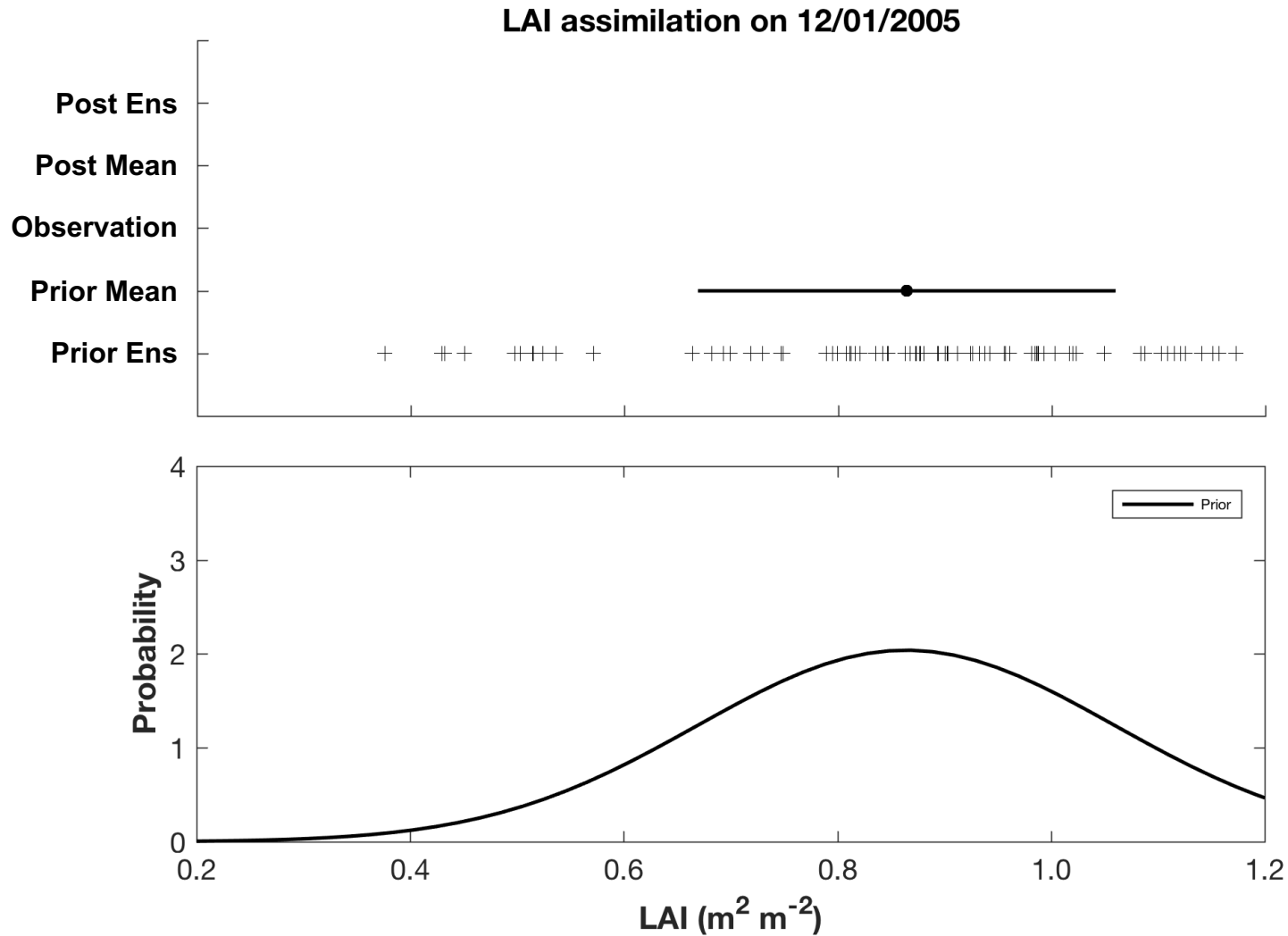
Adaptive inflation compensates for model error



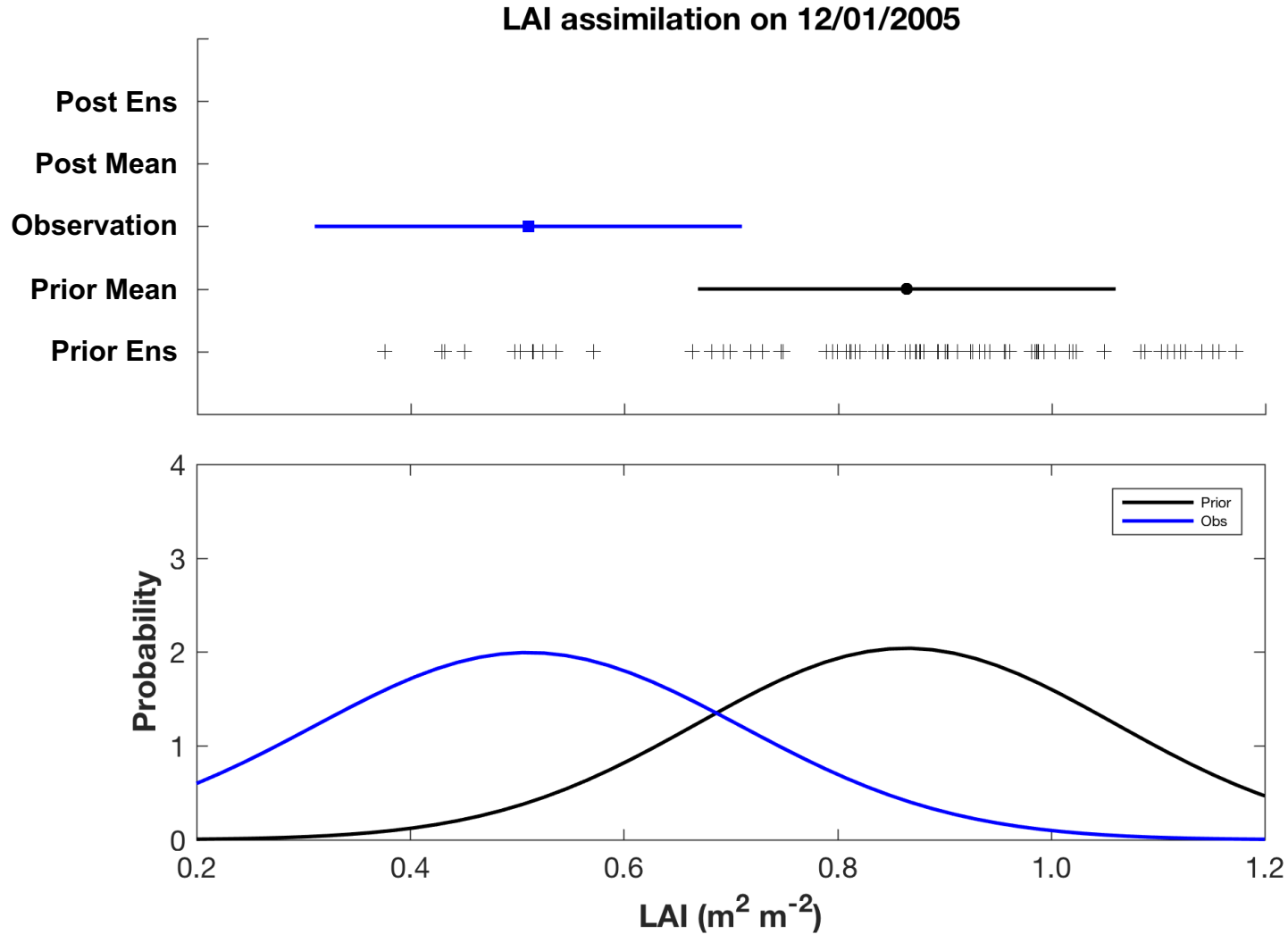
Ensemble is updated at observation time



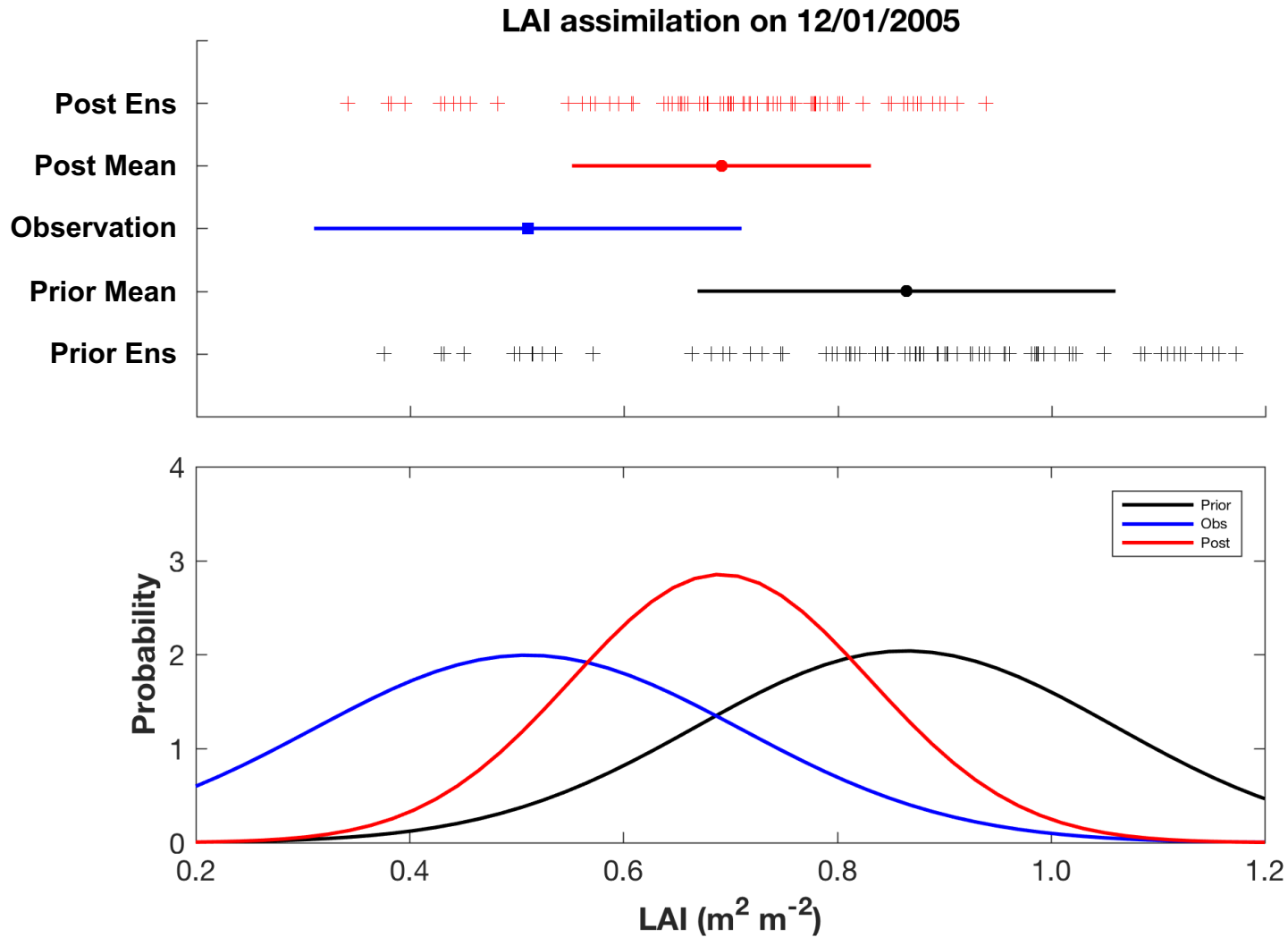
LAI updated by Ens. Adjustment Kalman Filter



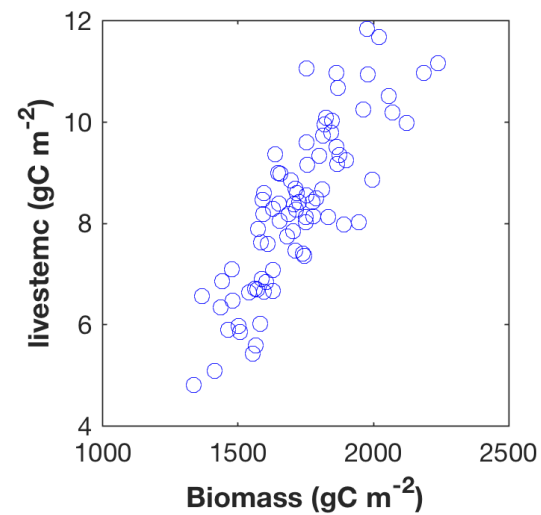
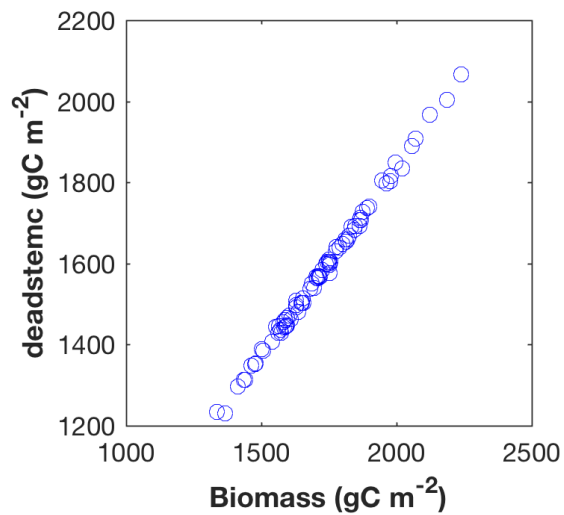
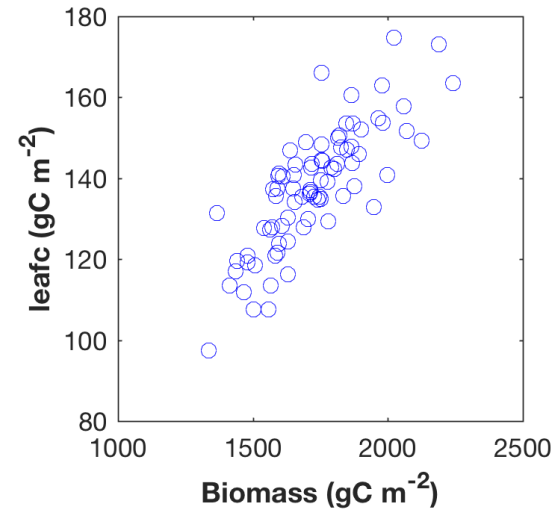
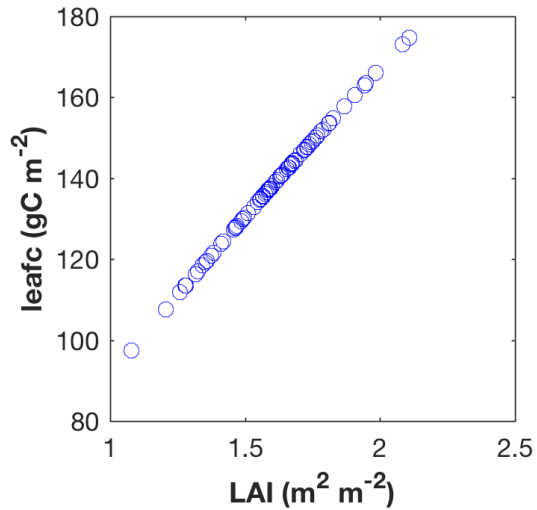
LAI updated by Ens. Adjustment Kalman Filter



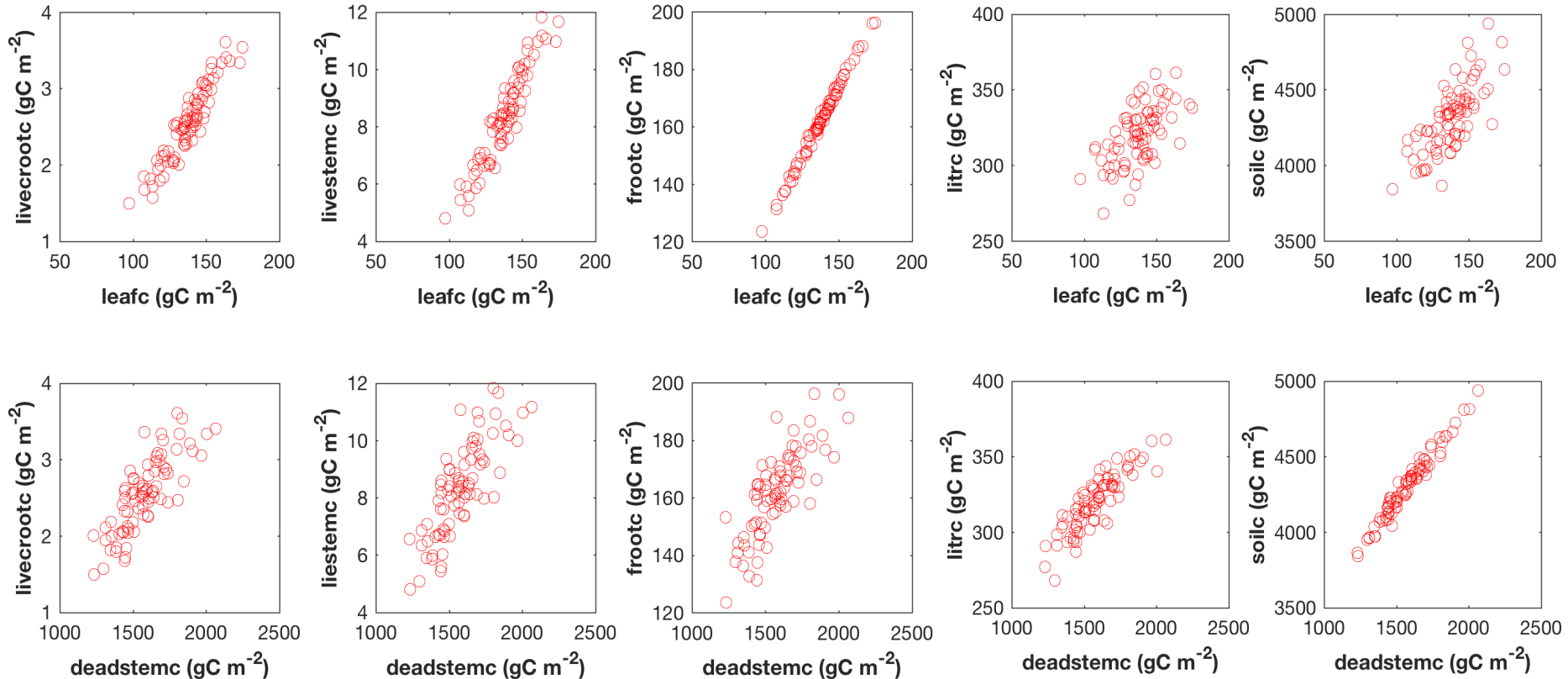
LAI updated by Ens. Adjustment Kalman Filter



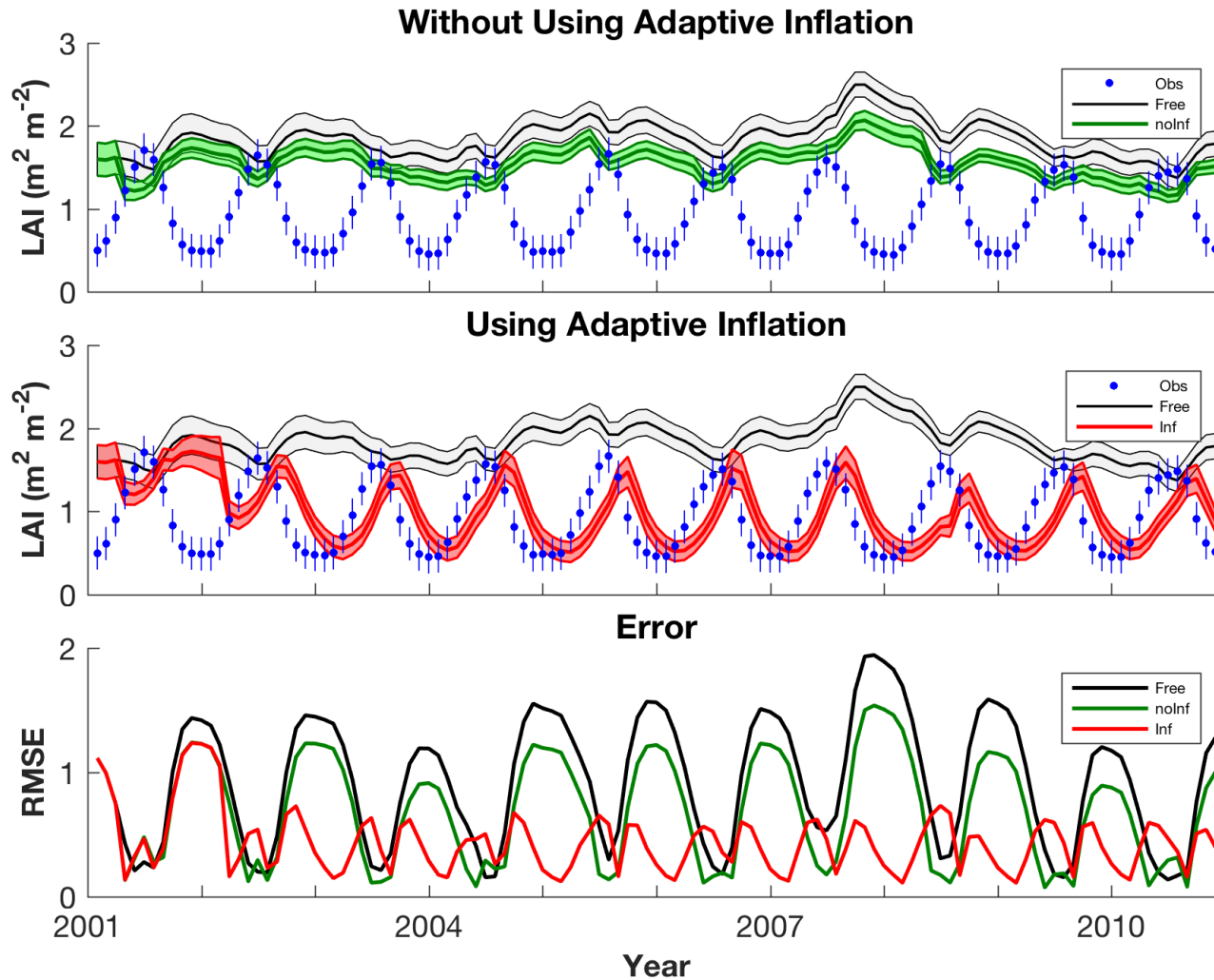
Model state correlations with observations



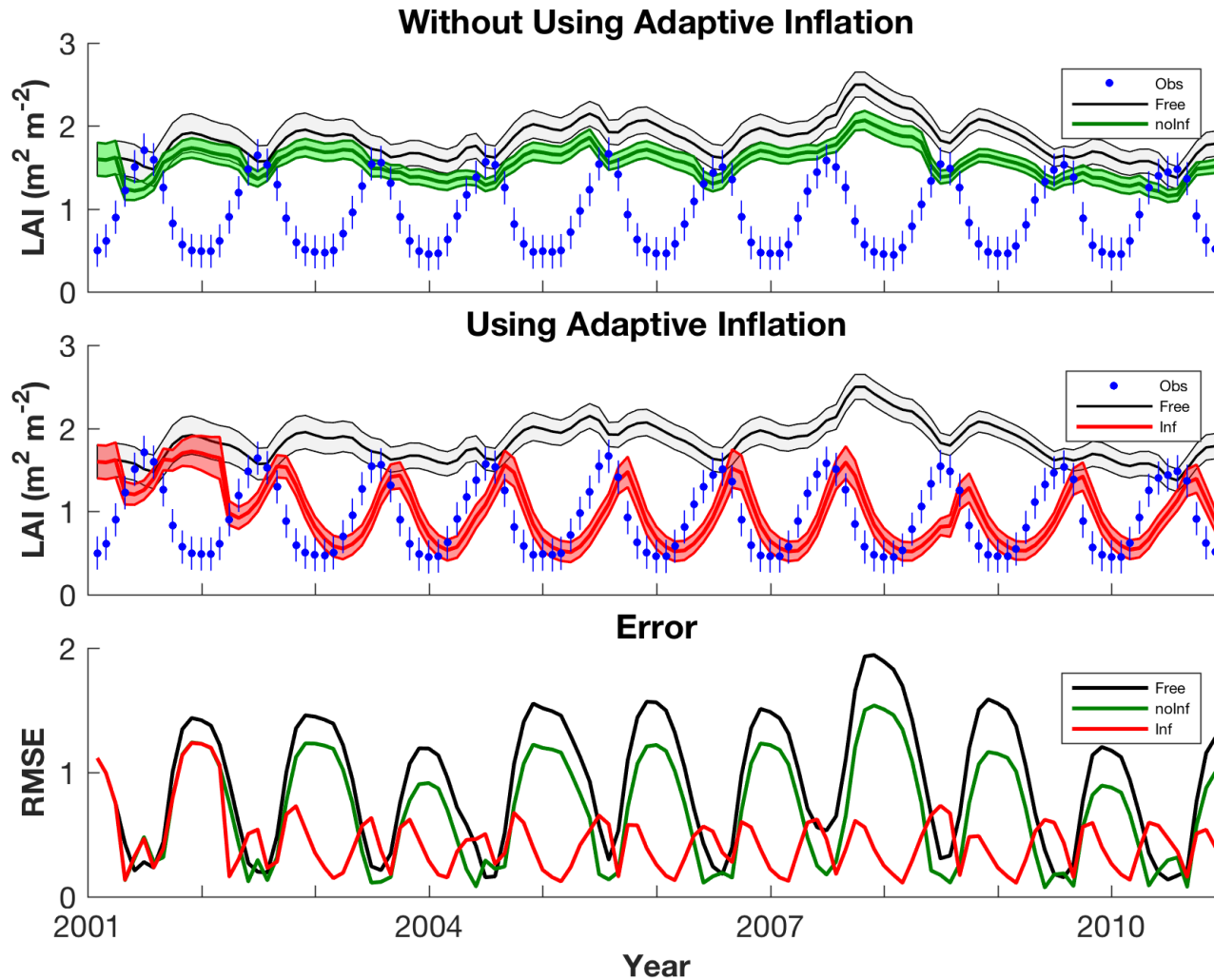
Observed and unobserved states



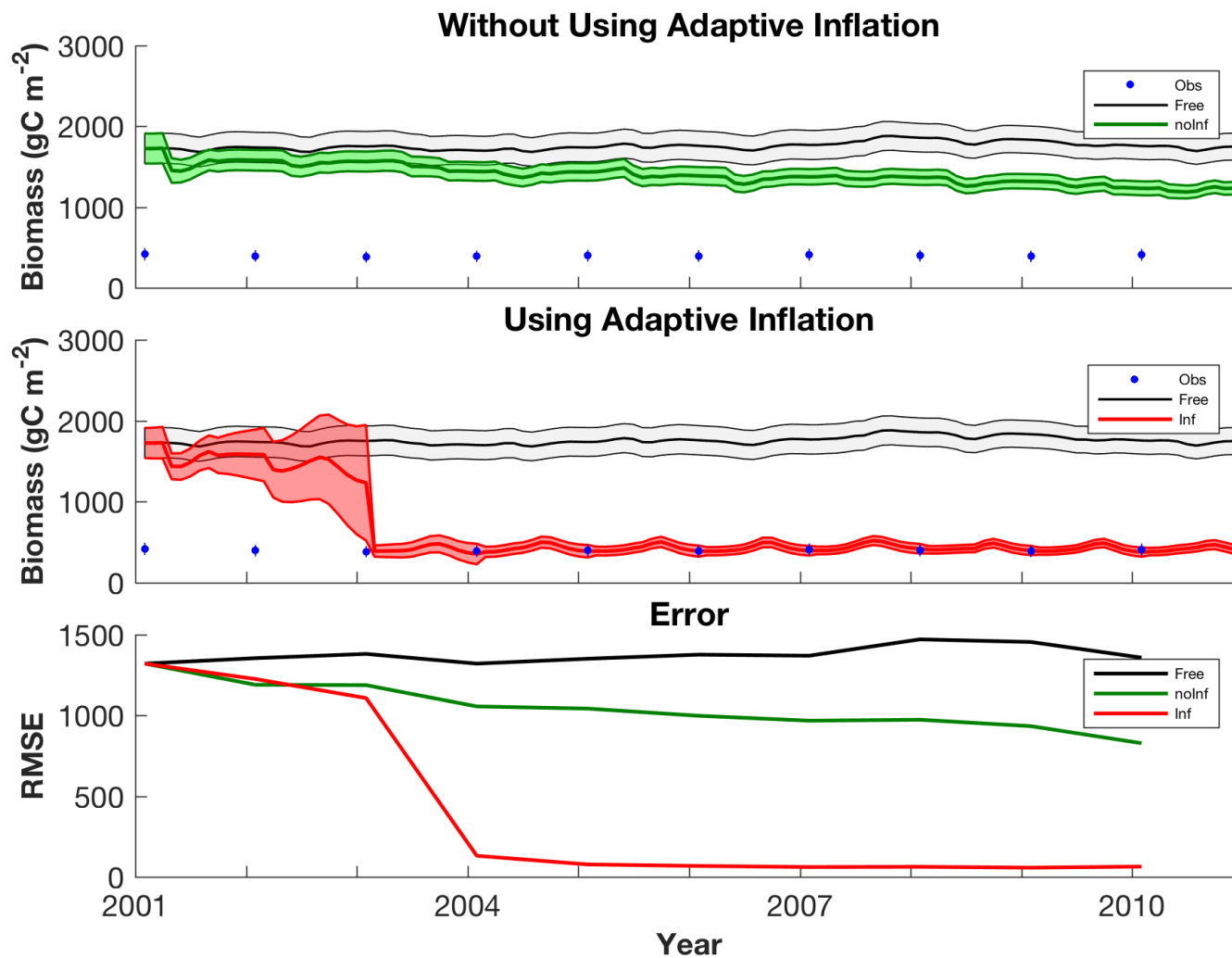
Assimilating LAI requires adaptive inflation



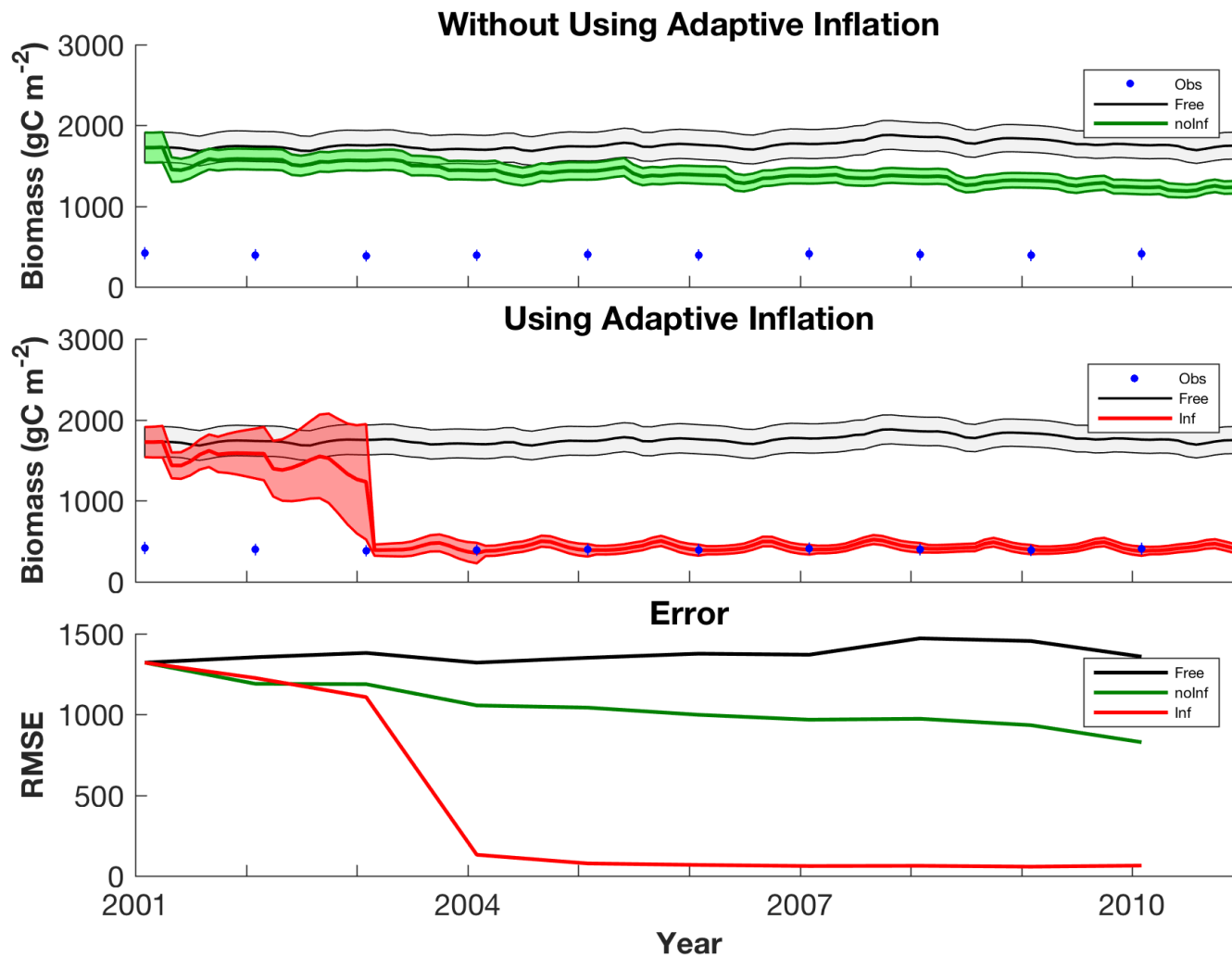
Assimilating LAI requires adaptive inflation



Assimilating Biomass using adaptive inflation



Assimilating Biomass using adaptive inflation



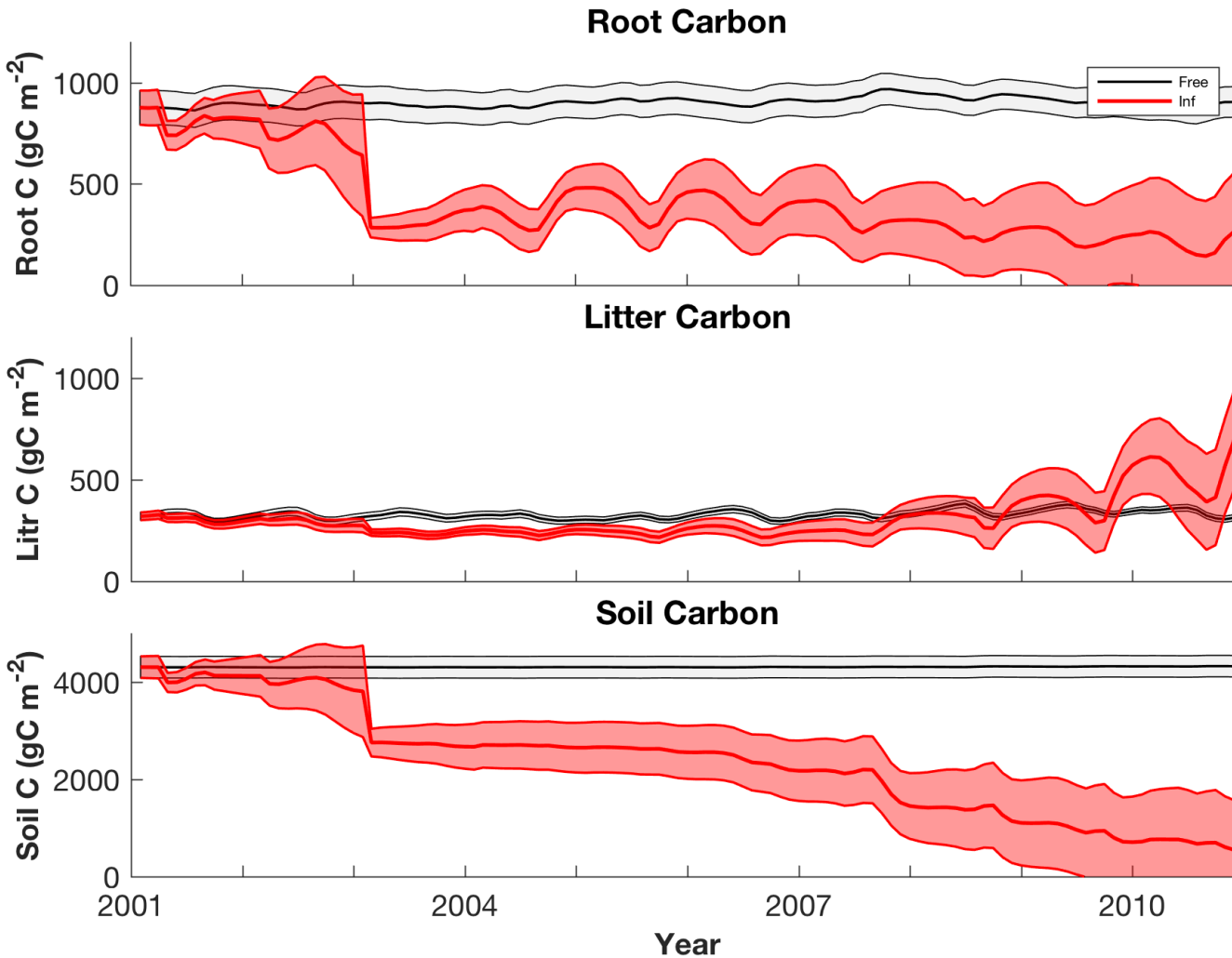
RMSE

1376

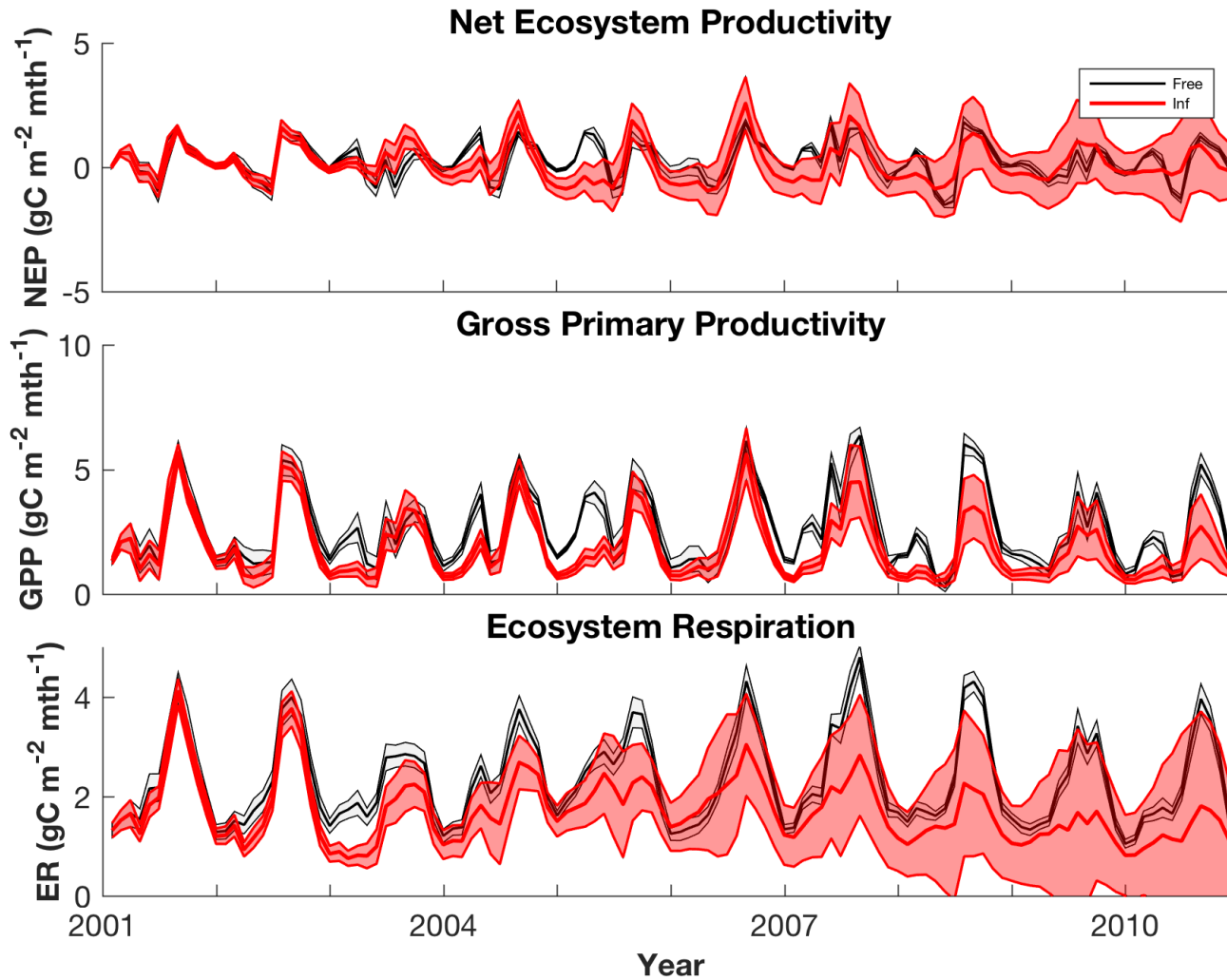
1049

417

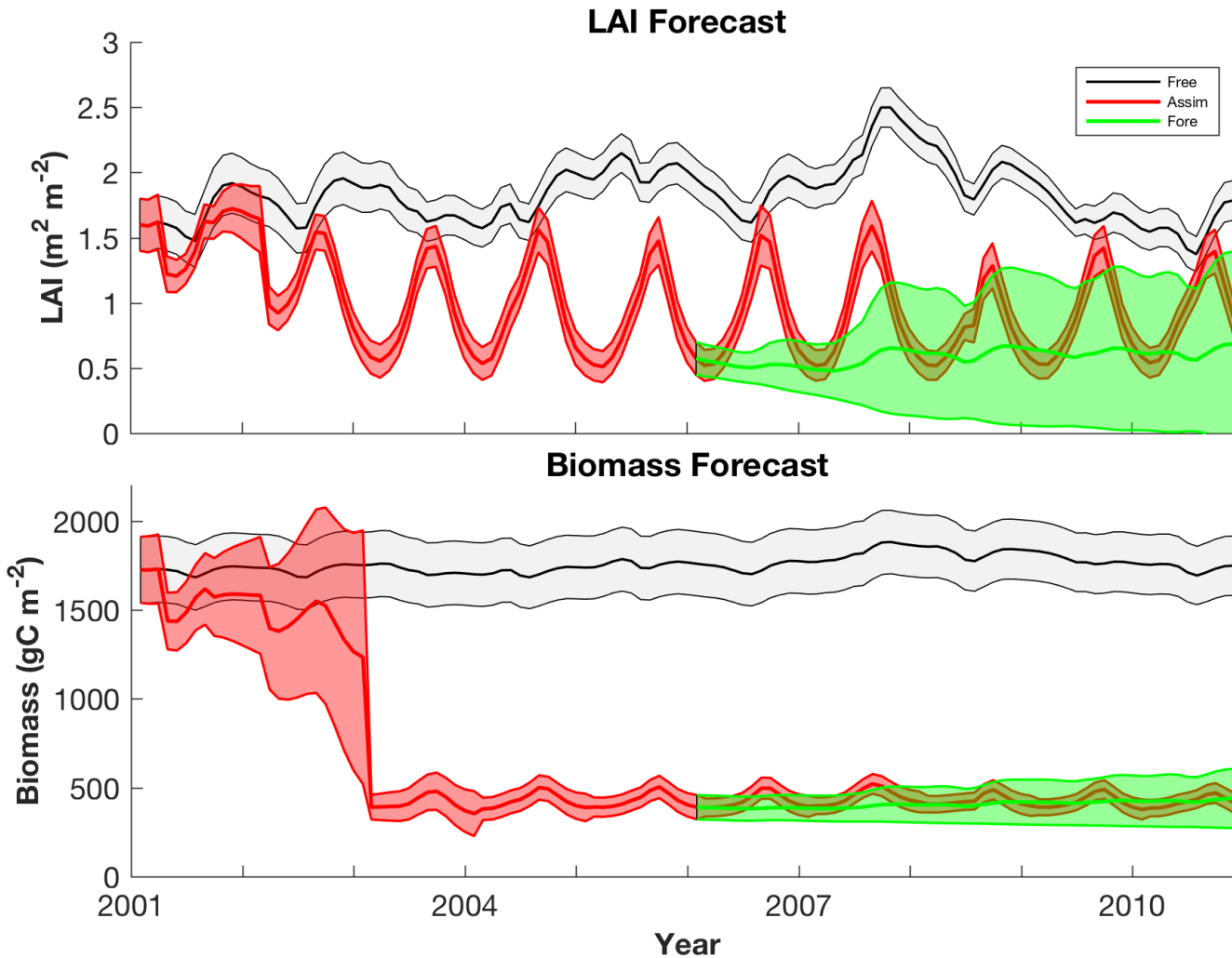
Unobserved State variables



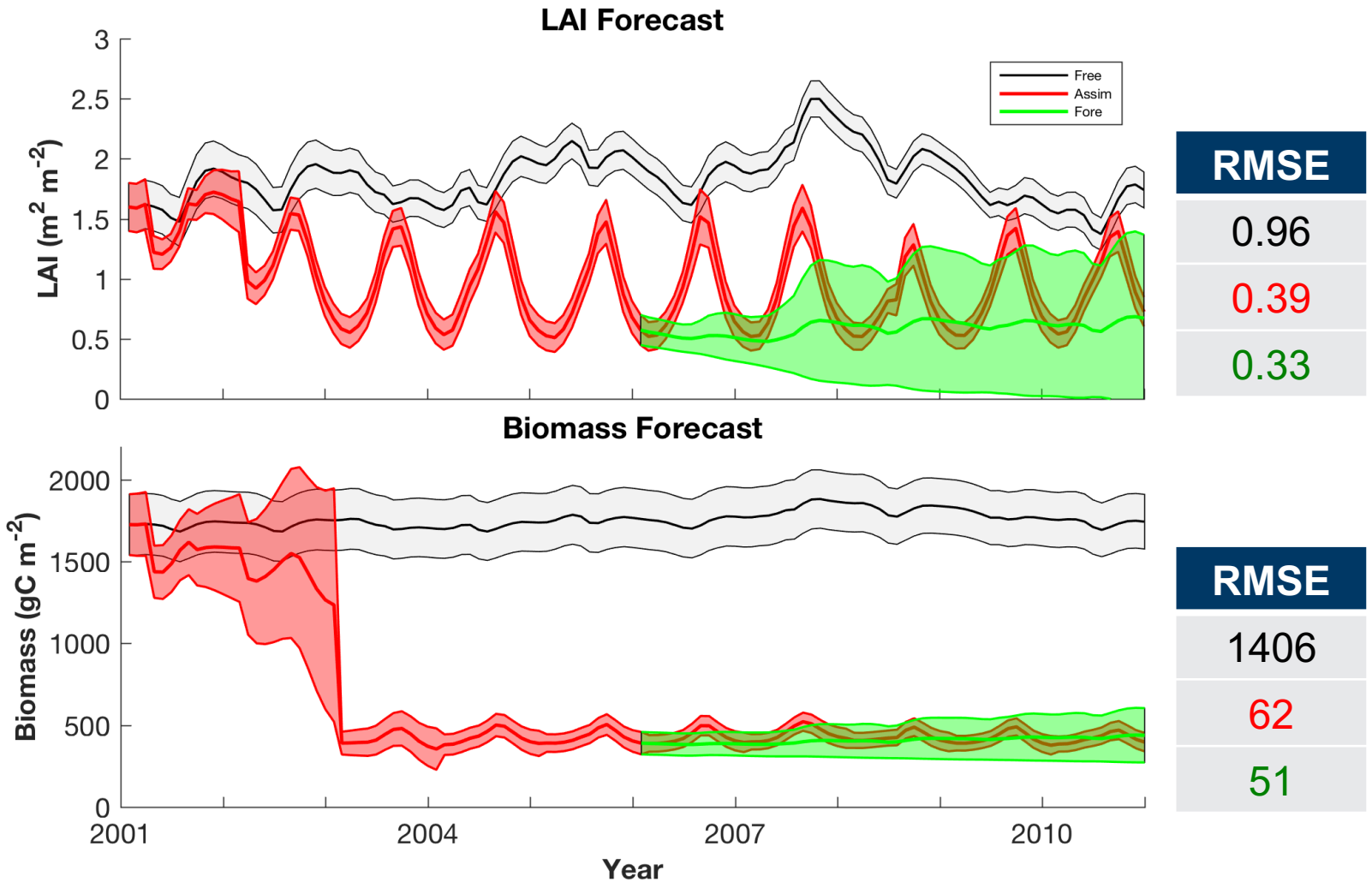
Carbon fluxes



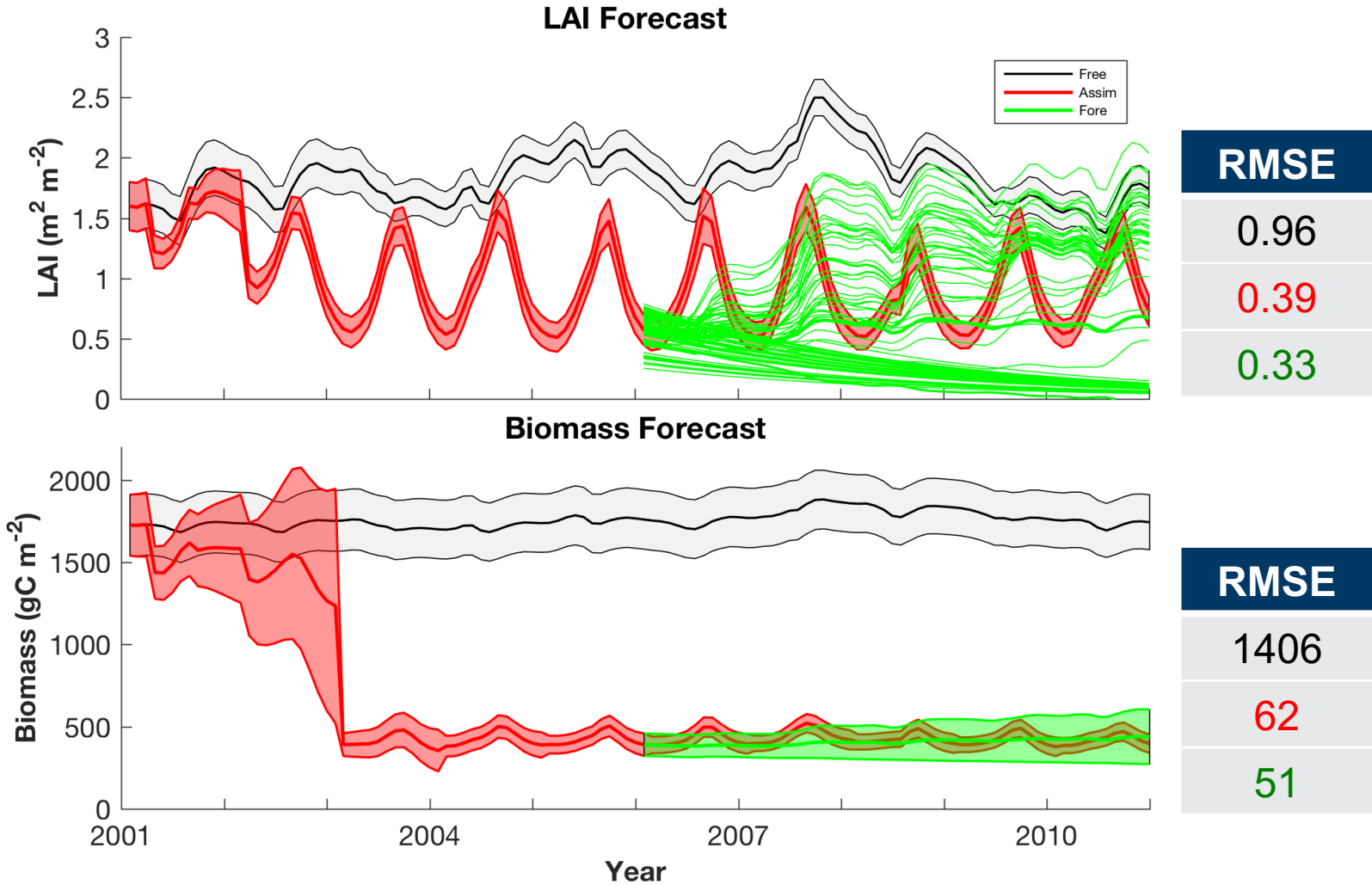
Long-term Forecasts



Long-term Forecasts



Long-term Forecasts



Reductions in RMSE during assimilation

		LAI (m² m⁻²)			
		<i>Free</i>	<i>No Inf.</i>	<i>Inflation</i>	<i>Forecast</i>
RMSE	<i>2001-2010</i>	0.93	0.70	0.44	-
	<i>2006-2010</i>	0.96	0.69	0.39	0.33
		Biomass (gC m⁻²)			
		<i>Free</i>	<i>No Inf.</i>	<i>Inflation</i>	<i>Forecast</i>
RMSE	<i>2001-2010</i>	1376.2	1049.9	417.7	-
	<i>2006-2010</i>	1406.3	940.29	62.8	51.4

Reductions in RMSE during forecast

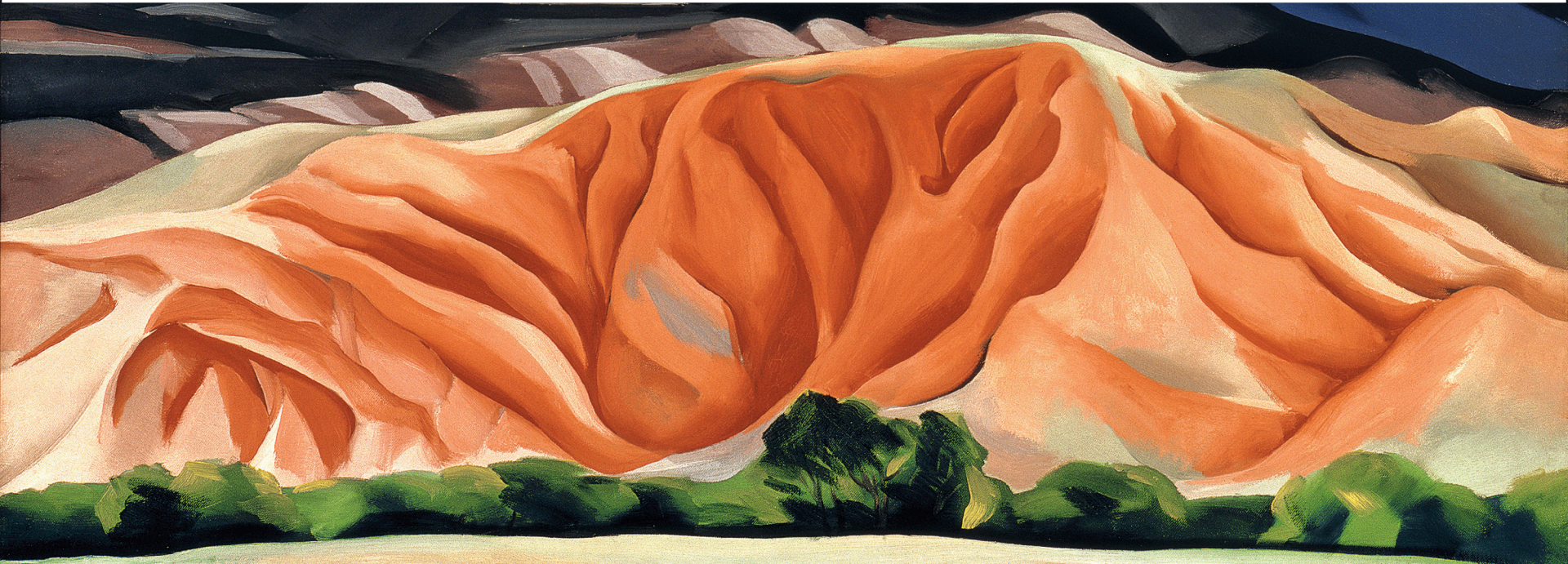
		LAI (m ² m ⁻²)			
		<i>Free</i>	<i>No Inf.</i>	<i>Inflation</i>	<i>Forecast</i>
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Key Points

- 1) Forecasts benefit from accurate initial conditions
- 2) Impact persists from years to decades for different C pools
- 3) Spun-up model had too high biomass, and inaccurate seasonal cycle in LAI
- 4) Large reductions in error during assimilation and forecast periods
- 5) Adaptive inflation is required to account for large model error
- 6) Impact on C fluxes is immediate



 U.S. DEPARTMENT OF **ENERGY** | Office of Science This work is funded by DOE Regional and Global Climate Modeling DE-SC0016011



Georgia O'Keeffe – “Black Mesa Landscape”

Data Assimilation Research Testbed (DART)

A Forecasting Challenge

- Deterministic knowledge of complex processes and feedbacks = complex models
- Present day stocks and fluxes are very dependent on disturbance history
- Actually disturbance history is “unknowable” – replace this by updating states based on observations
- Ensemble data assimilation can account for uncertainties in model and observations
- Provides probabilistic estimates of future states

AND THEN WHAT?

IAV from Semi-arid Ecosystems?

LETTER

doi:10.1038/nature13376

Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle

Benjamin Poulter^{1,2}, David Frank^{3,4}, Philippe Ciais², Ranga B. Myneni⁵, Niels Andela⁶, Jian Bi⁵, Gregoire Broquet⁷, Josep G. Canadell⁷, Frederic Chevallier², Yi Y. Liu⁸, Steven W. Running⁹, Stephen Sitch¹⁰ & Guido R. van der Werf⁶

CARBON CYCLE

The dominant role of semi-arid ecosystems in the trend and variability of the land CO₂ sink

Anders Ahlström,^{1,2*} Michael R. Raupach,^{3†} Guy Schurgers,⁴ Benjamin Smith,¹ Almut Arneth,⁵ Martin Jung,⁶ Markus Reichstein,⁶ Josep G. Canadell,⁷ Pierre Friedlingstein,⁸ Atul K. Jain,⁹ Etsushi Kato,¹⁰ Benjamin Poulter,¹¹ Stephen Sitch,¹² Benjamin D. Stocker,^{13,14} Nicolas Viovy,¹⁵ Ying Ping Wang,¹⁶ Andy Wiltshire,¹⁷ Sönke Zaehle,⁶ Ning Zeng¹⁸

LETTER

doi:10.1038/nature20780

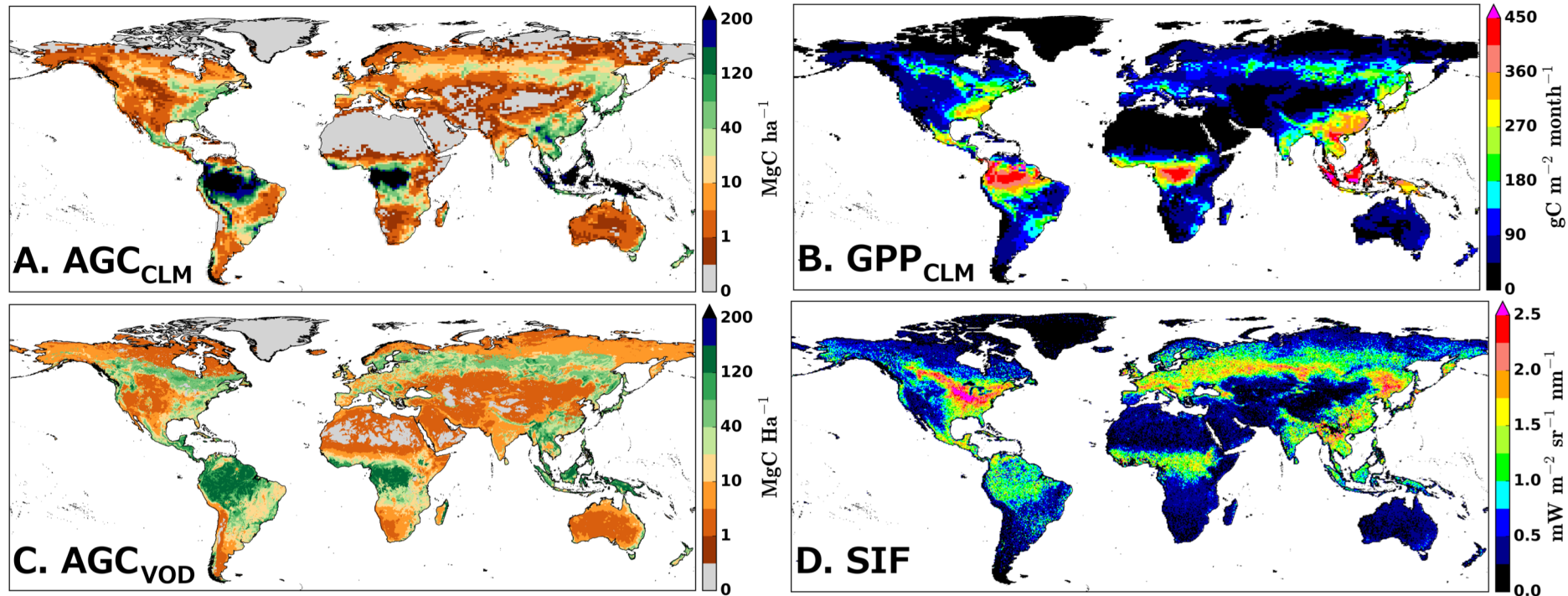
Compensatory water effects link yearly global land CO₂ sink changes to temperature

Martin Jung¹, Markus Reichstein^{1,2}, Christopher R. Schwalm³, Chris Huntingford⁴, Stephen Sitch⁵, Anders Ahlström^{6,7}, Almut Arneth⁸, Gustau Camps-Valls⁹, Philippe Ciais¹⁰, Pierre Friedlingstein¹¹, Fabian Gans¹, Kazuhito Ichii^{12,13}, Atul K. Jain¹⁴, Etsushi Kato¹⁵, Dario Papale¹⁶, Ben Poulter¹⁷, Botond Raduly^{16,18}, Christian Rödenbeck¹⁹, Gianluca Tramontana¹⁶, Nicolas Viovy¹⁰, Ying-Ping Wang²⁰, Ulrich Weber¹, Sönke Zaehle^{1,2} & Ning Zeng^{21,22}

Sources of Uncertainty

- Model Structure
- Model Parameter
- Initial Conditions/Model States
- Spin Up
- Boundary Conditions

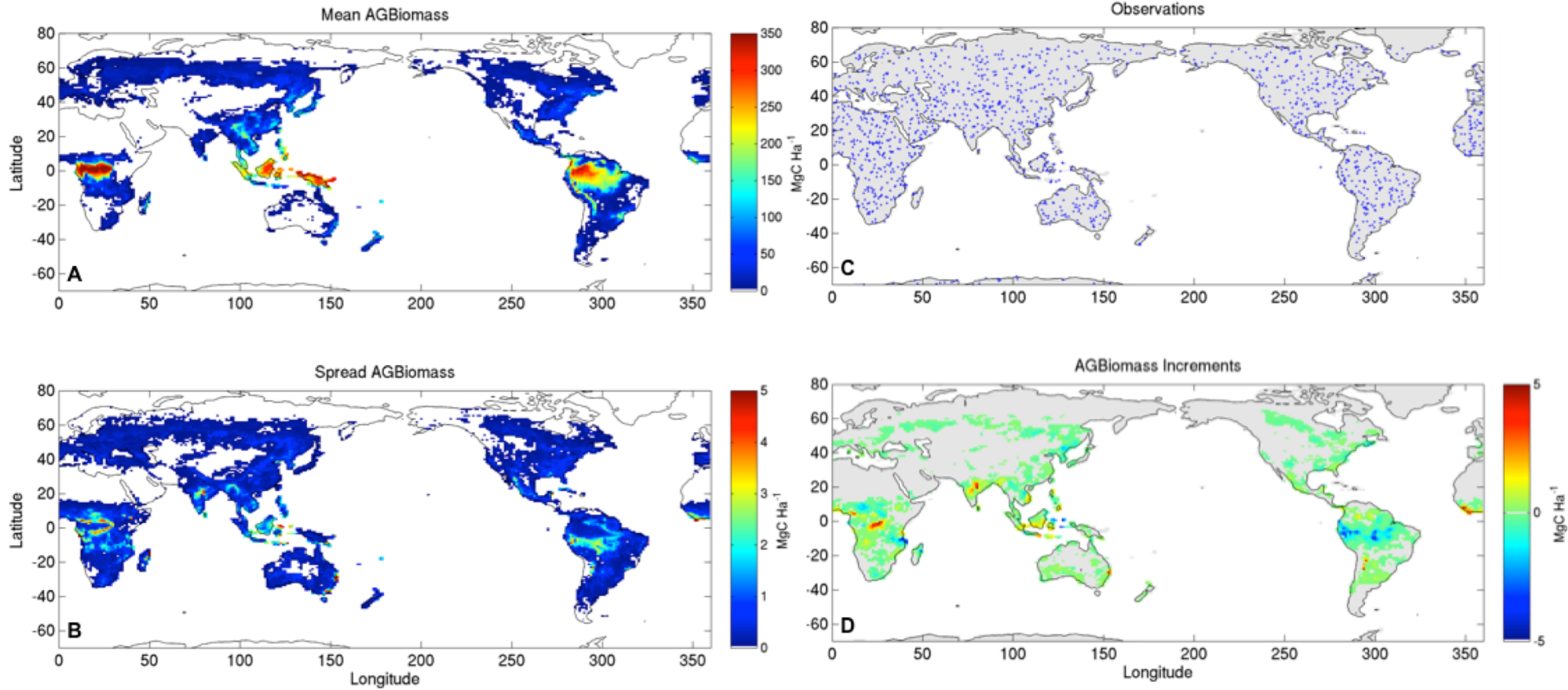
Vegetation Optical Depth and SIF



Courtesy Bill Kolby-Smith, UA

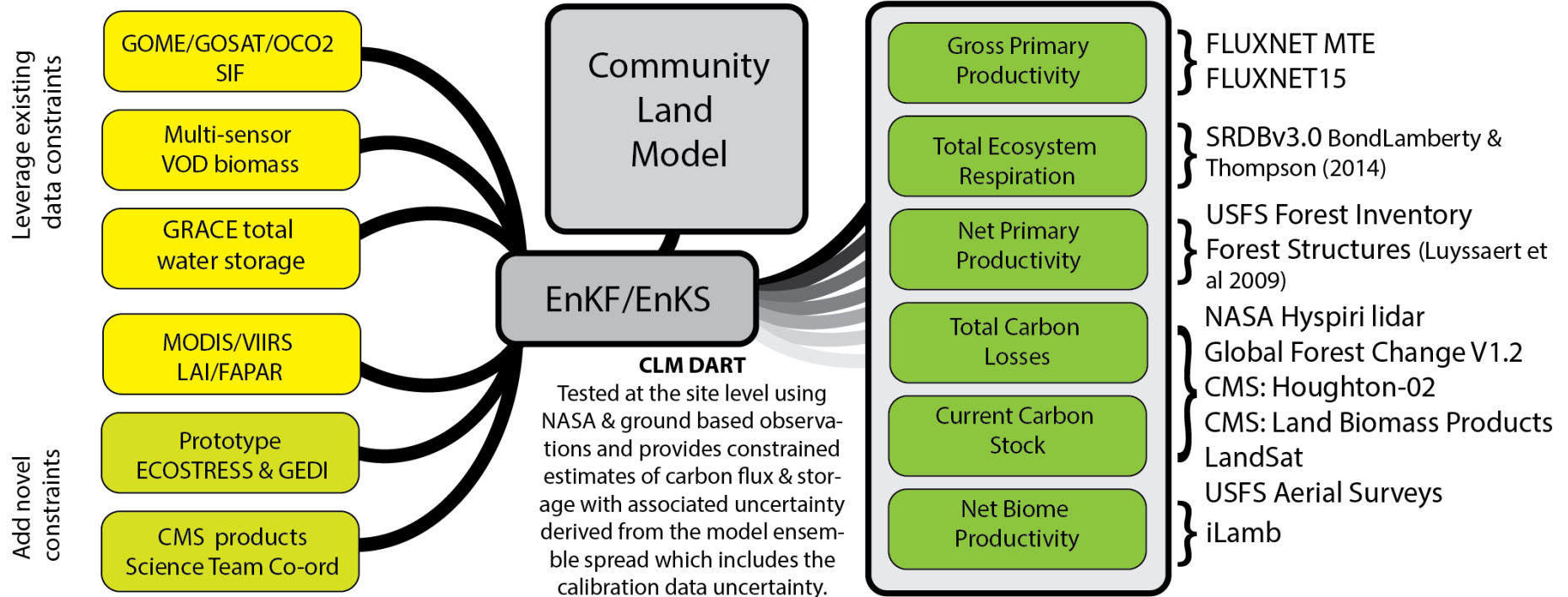


Global Biomass OSSE



Calibration datasets and Data Assimilation

Ensemble Data Products Production and Validation



Community Land Model set up

- Multi-instance CLM4.5 BGC set up for a location in central New Mexico, USA
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