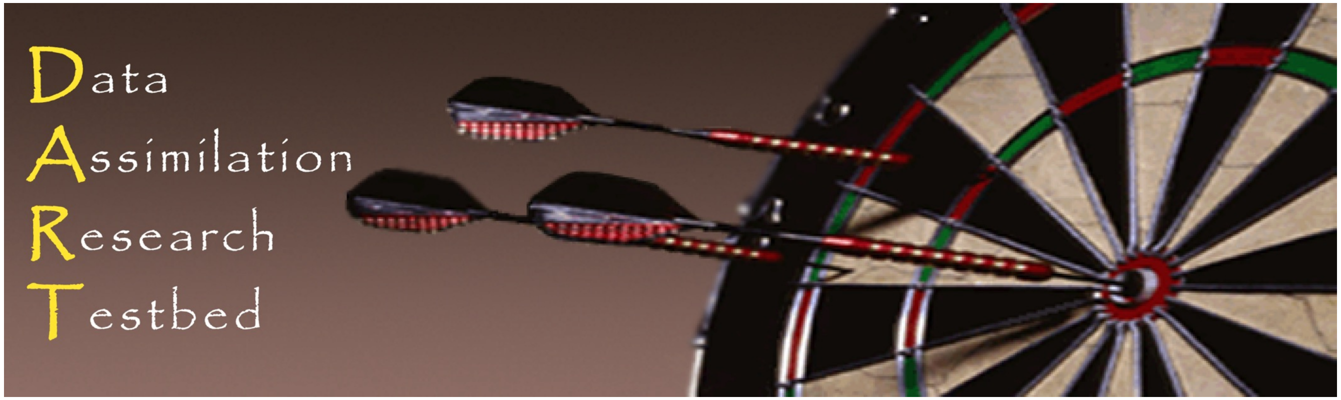
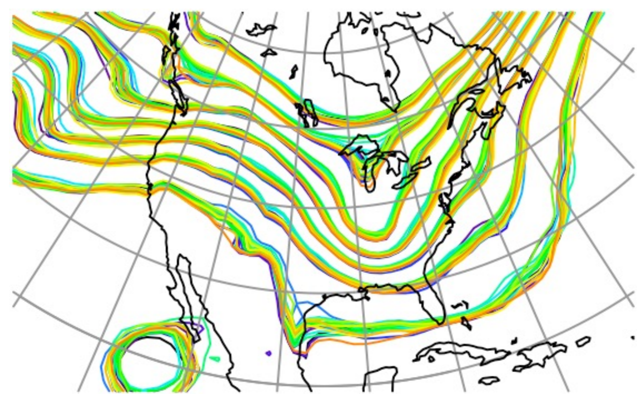


Land Data Assimilation using DART : Carbon cycling across the Western US

Brett Raczka, NCAR, Data Assimilation Research Section (DAReS)

THE UNIVERSITY OF UTAH



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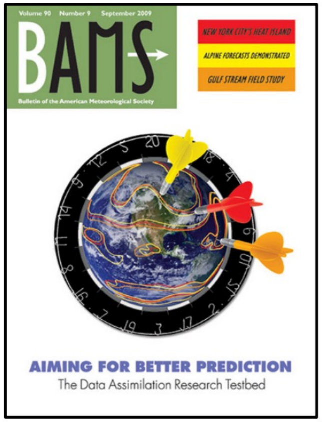
NCAR | National Center for
UCAR | Atmospheric Research

Example of DART workflow

Anderson et al.,2009



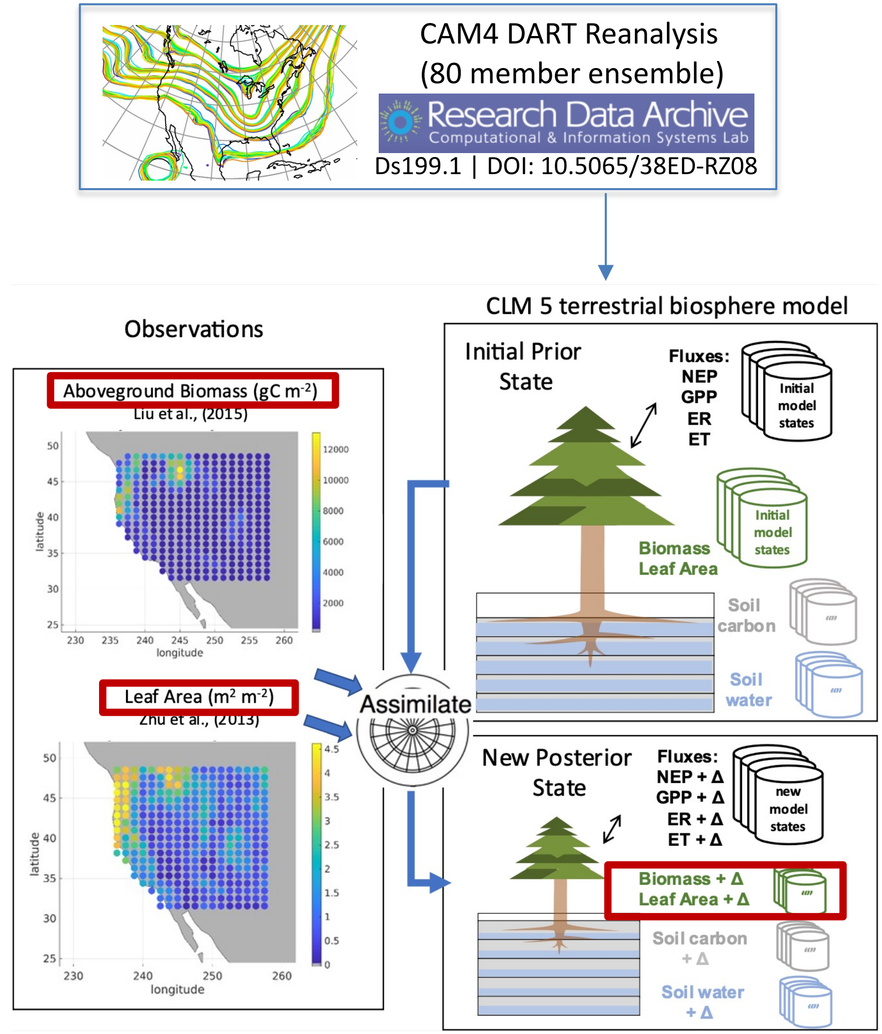
JAMES | Journal of Advances in Modeling Earth Systems

Research Article | Open Access

Improving CLM5.0 Biomass and Carbon Exchange Across the Western United States Using a Data Assimilation System

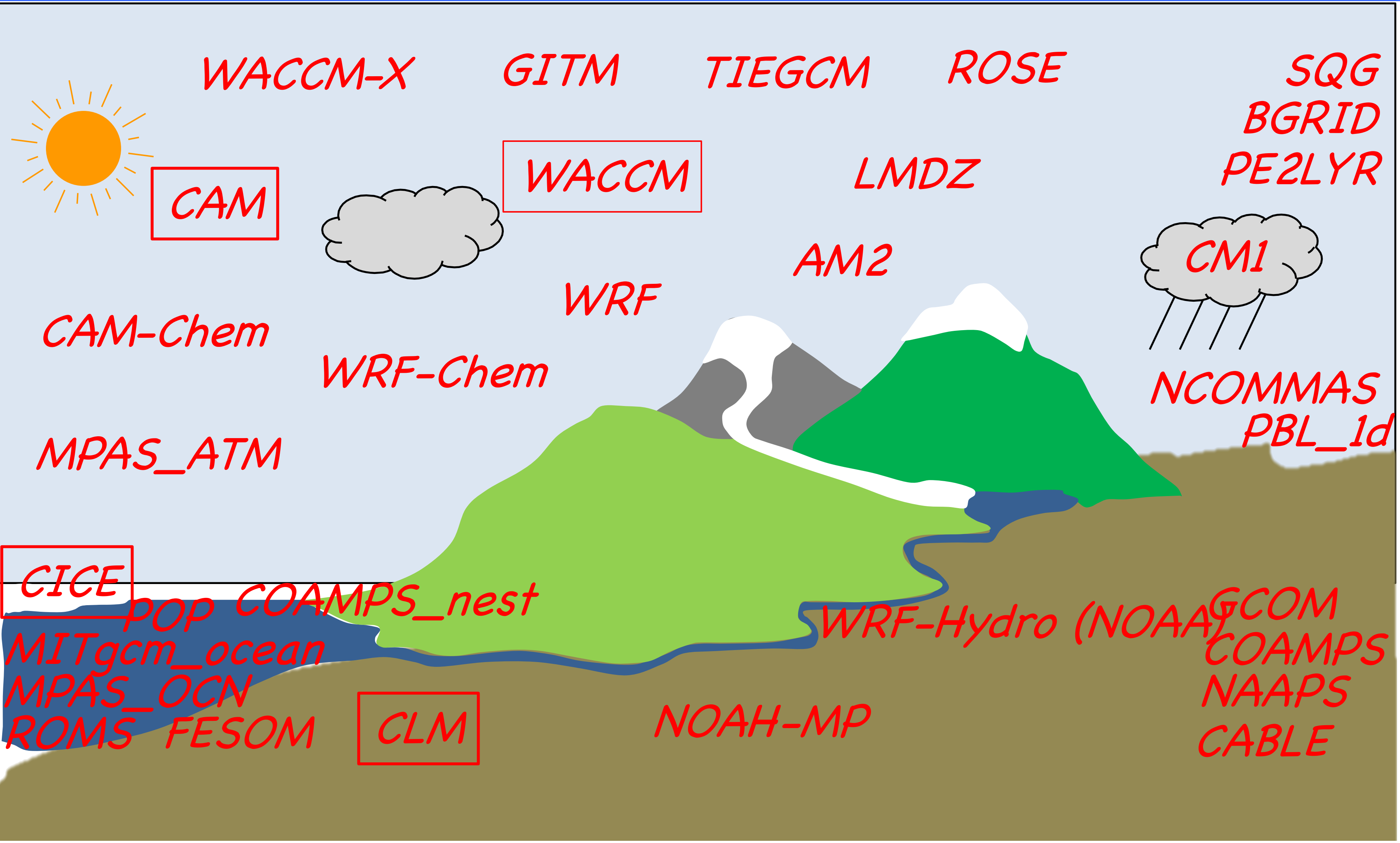
Brett Raczka, Timothy J. Hoar, Henrique F. Duarte, Andrew M. Fox, Jeffrey L. Anderson, David R. Bowling, John C. Lin,

First published: 19 June 2021 | https://doi.org/10.1029/2020MS002421



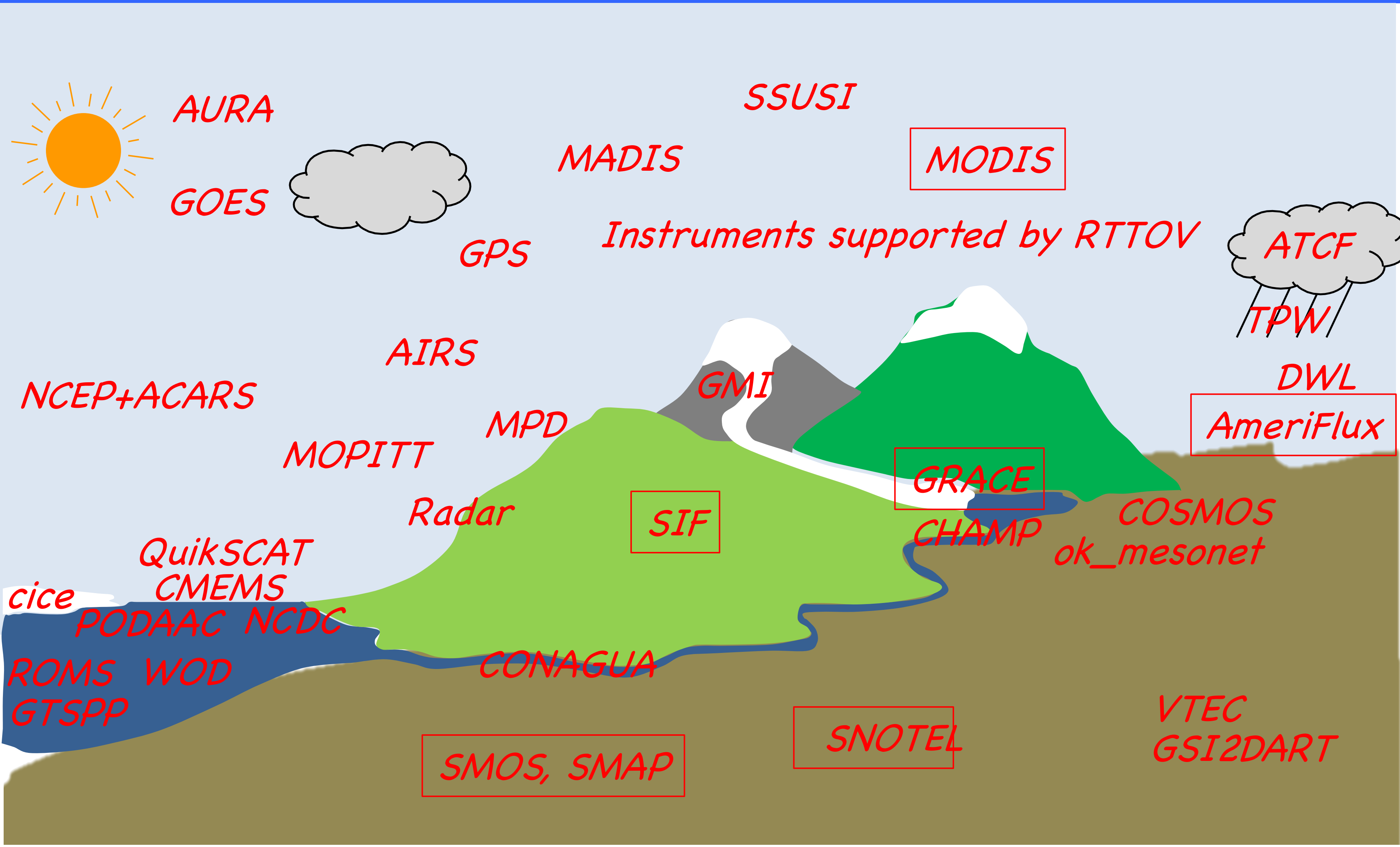
Data Assimilation Research Testbed

Geophysical Models Interfaced to DART



Data Assimilation Research Testbed

Earth System Observations (others available)



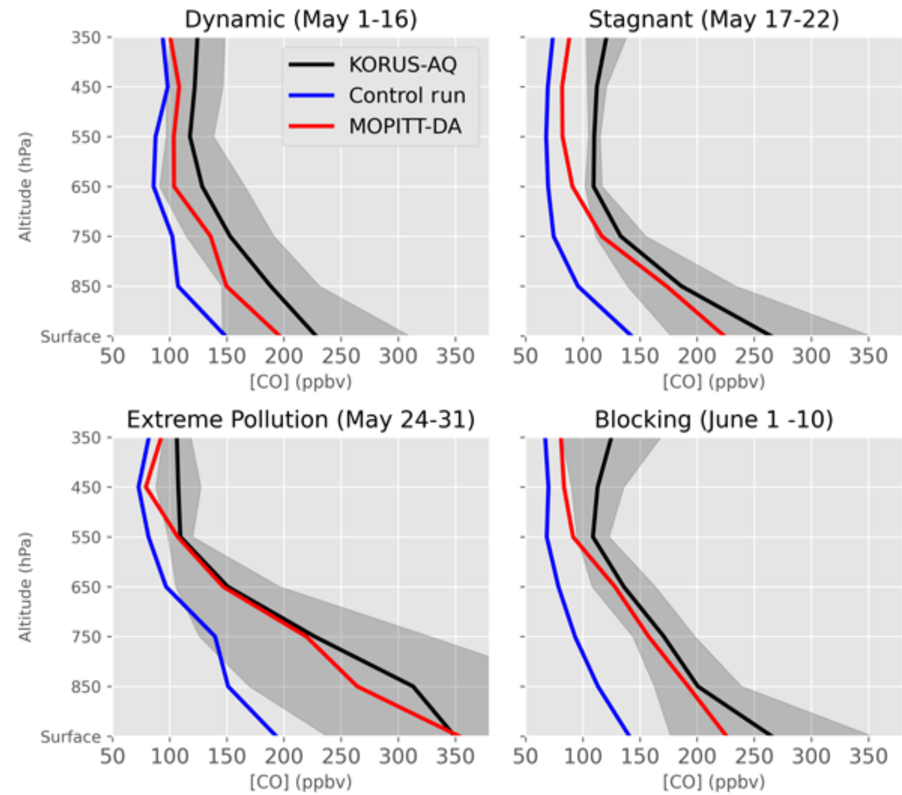
Data
Assimilation
Research
Testbed

Field Campaign and Satellite Data: Pollution Emission Estimation

- Assimilate atmospheric CO into CAM-Chem

Aircraft measurements from KORUS-AQ field study in Korea 2016
Satellite retrievals of CO from Terra/MOPITT
Chemistry modeling with CAM-Chem DART
Ensemble Kalman Filter with:
- Optimized CO initial conditions
- Optimized CO emissions

Inversion of MOPITT data updated emissions estimates, improved model performance
- Against the KORUS-AQ aircraft observations of CO (shown) and O_3, OH, HO_2
- Suggests underestimates of CO/VOCs in China



Lead; Benjamin Gaubert

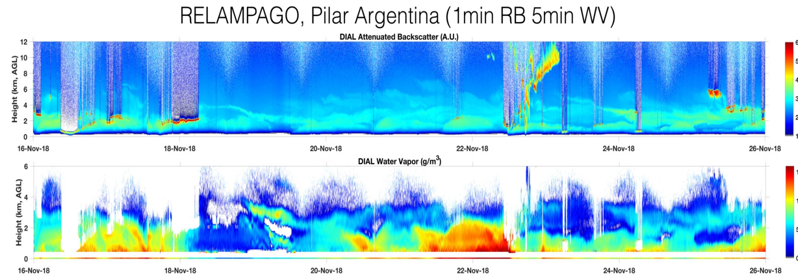
DA improves fit to NASA DC-8 aircraft CO measurements for all synoptic conditions:
DA closer to obs than no DA.

Data
Assimilation
Research
Testbed

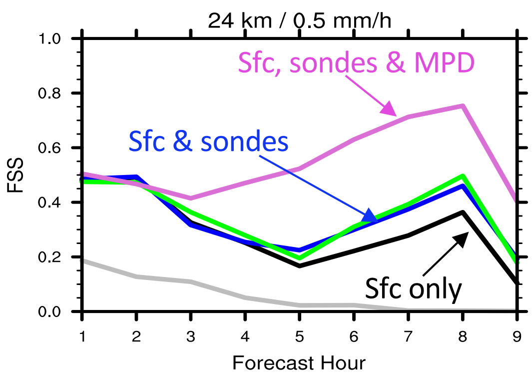
MPD Water Vapor Profile DA for Convective Weather Forecasts

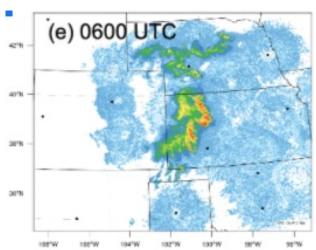
- Assimilate MPD Water Vapor into WRF

MicroPulse Differential absorption lidar (MPD) developed by Montana State University and EOL measures continuous relative backscatter and water vapor profiles.

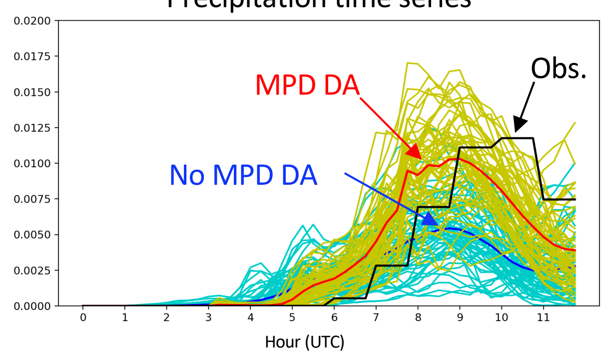


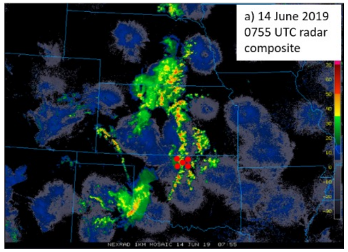
Observing System Simulation Experiment (OSSE)





Observing System Experiment (OSE)





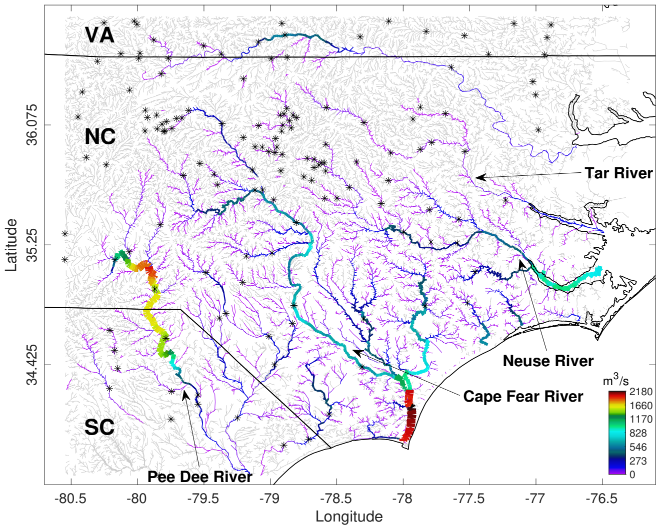
Lead: Tammy Weckwerth

WRF/DART DA of MPD improves short-term forecasts of convection initiation and evolution compared to assimilating conventional observations (in the OSSE) and no DA (in the OSE).

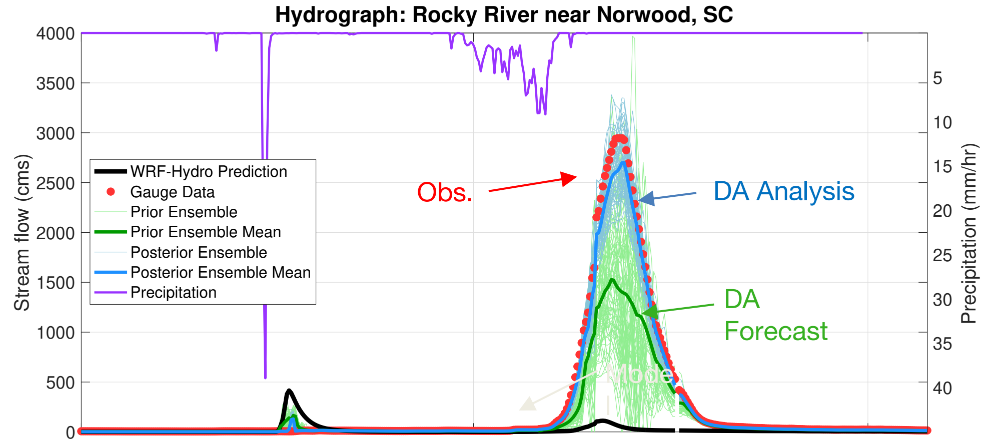
Data Assimilation Research Testbed

Flood Prediction: WRF-Hydro/DART for Hurricane Florence 2018

High-resolution stream network with USGS streamflow gauges.



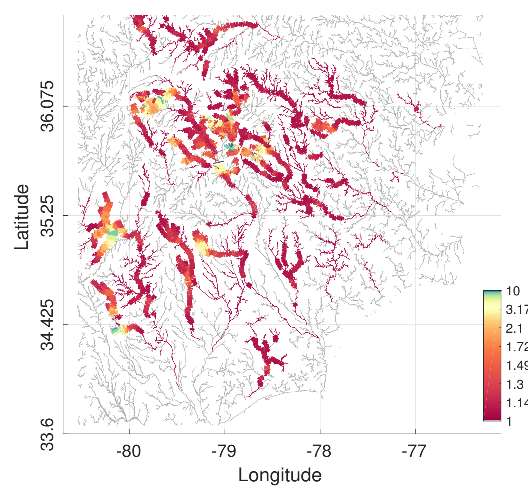
DA greatly improves analysis and forecasts of streamflow.



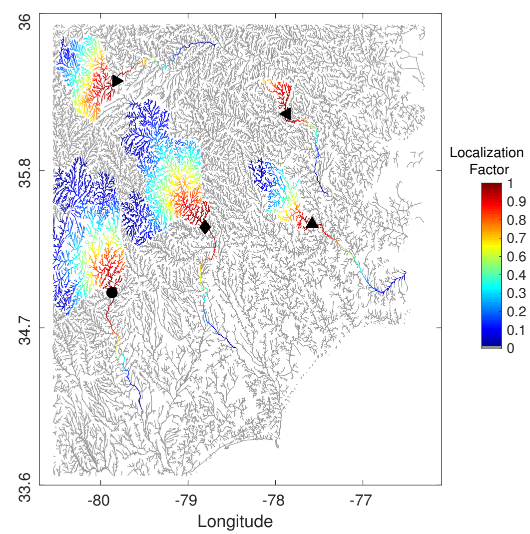
Lead; Moha el Gharamti

Novel Data Assimilation Science

1. Prior and Posterior Adaptive Covariance Inflation



2. Along-The-Stream (topology-based) Localization

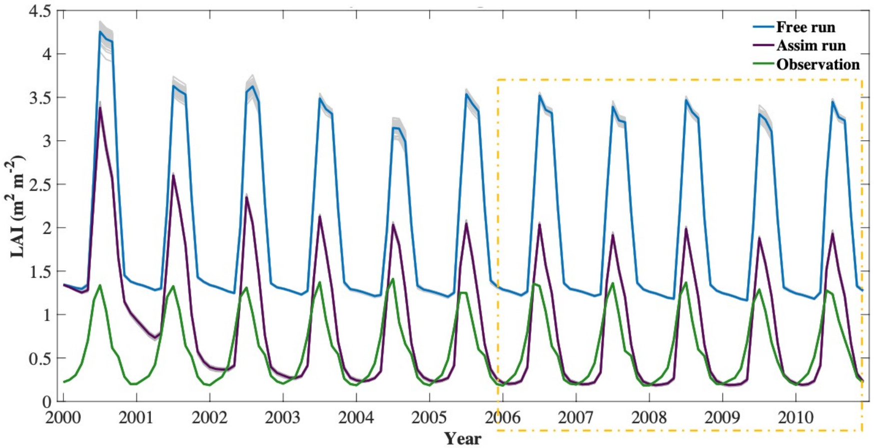


Data Assimilation Research Testbed

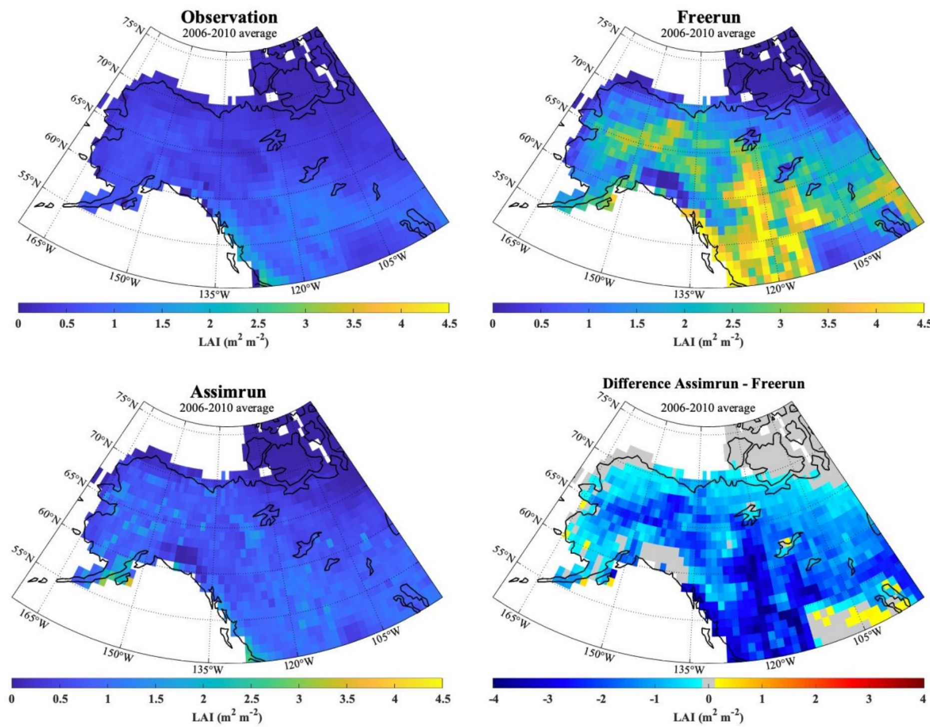
Current Land Data Assimilation (CLM-DART)

Assimilating Leaf Area Observations within Arctic Boreal Domain (ABoVE Project)
Led by: Xueli Huo, Andy Fox and others

Monthly Arctic Leaf Area



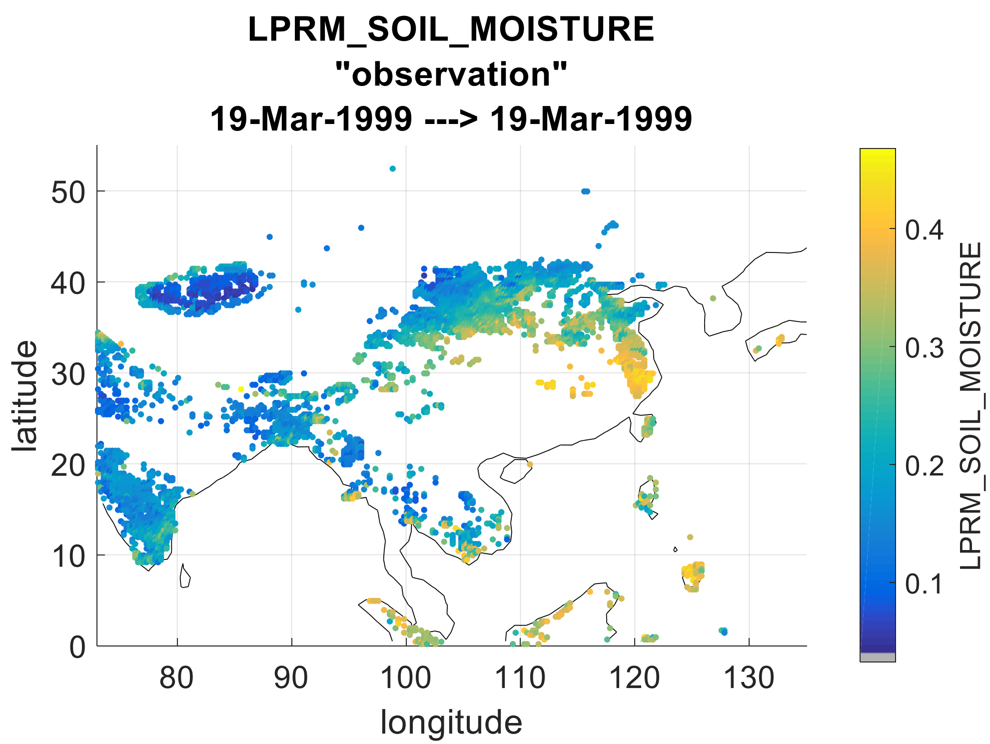
The mean annual LAI in the assimilation run decreased by **63.7%** compared with the free run.

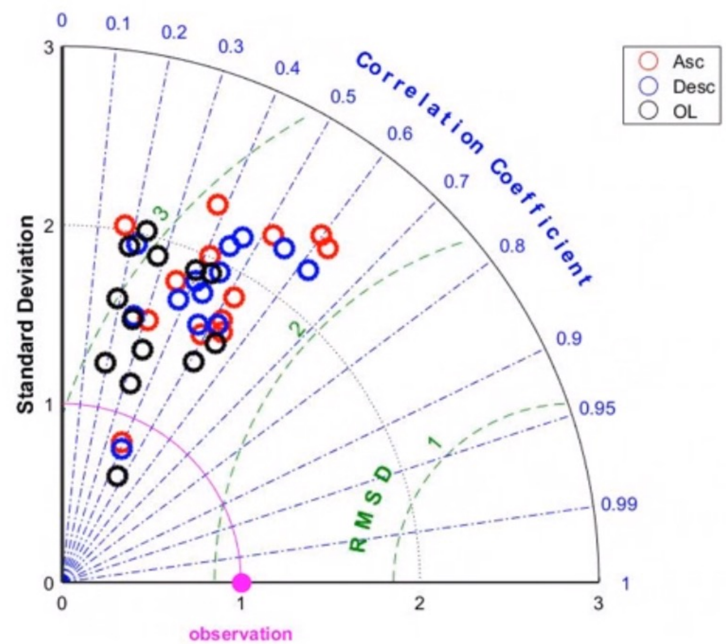


Data
Assimilation
Research
Testbed

Current Land Data Assimilation (CLM-DART)

Assimilating Surface Soil Moisture Observations (Passive/Active Microwave Bands)
Led by: Daniel Hagan





Basics of EnKF Data Assimilation

- Observations combined with a model forecast to produce an improved forecast ('analysis').
- Improving model state (e.g. temperature, biomass, soil carbon) not parameter optimization

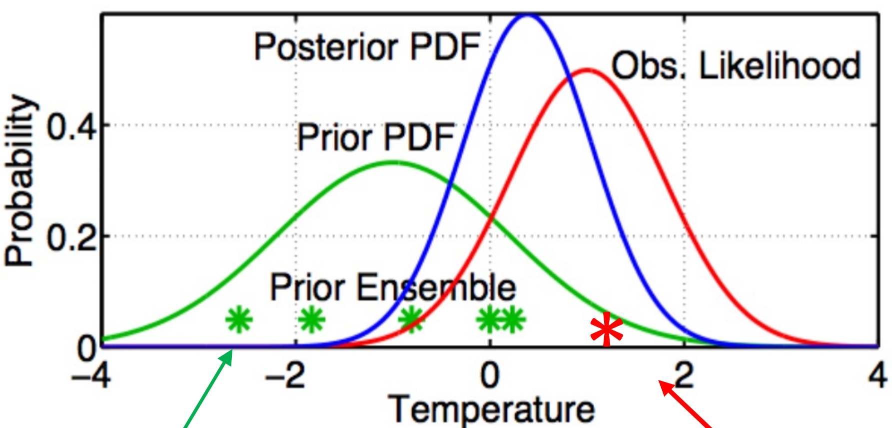
<u>Bayes Theorem</u>

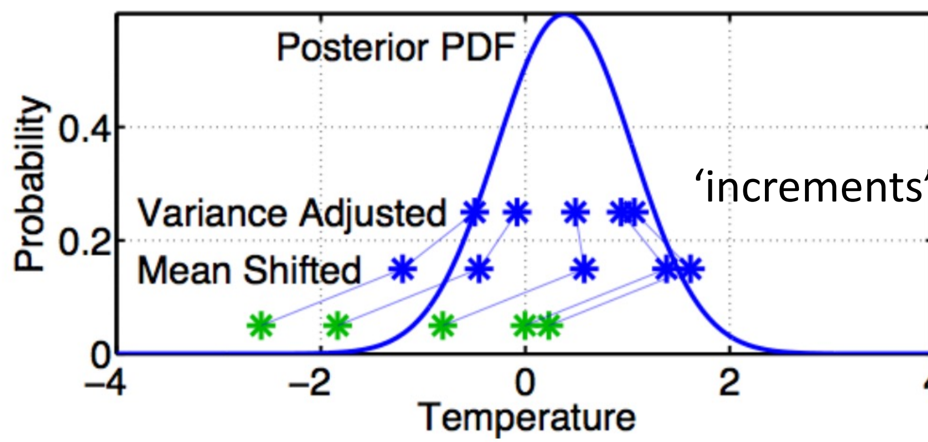
Posterior ~ Prior · Observation Likelihood

'Update' or 'analysis'

Model generated

Biosphere measurements





5 prior model estimates of temperature

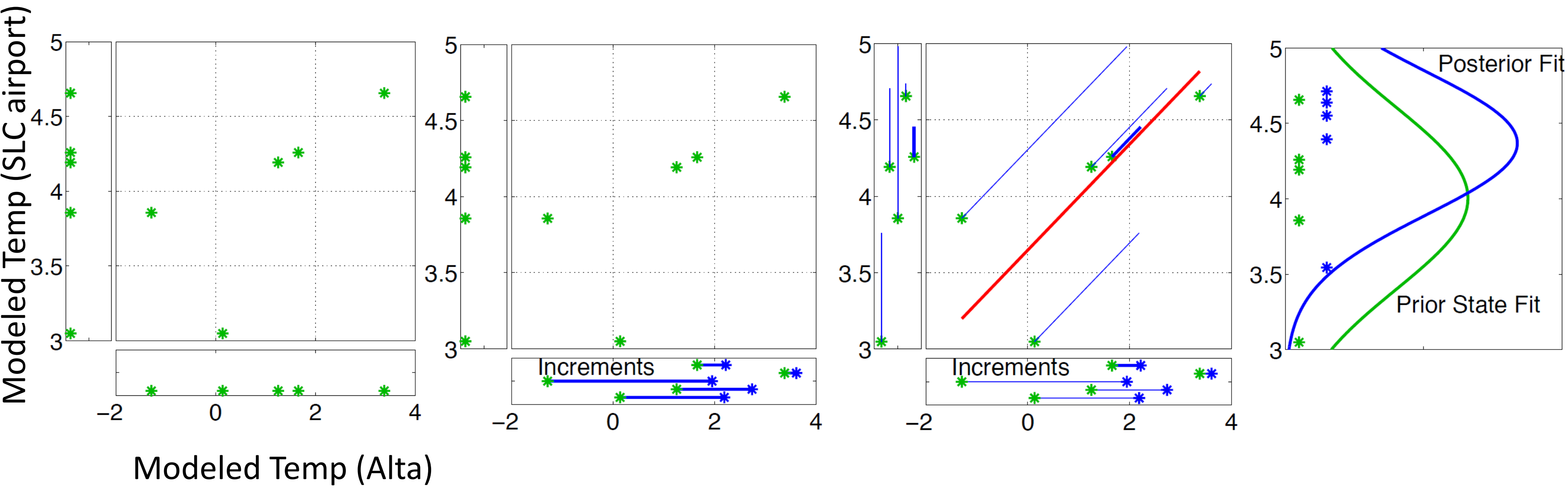
1 new observation of temperature

This is an 'observed' state variable, but what about 'unobserved' state variables?

Basics of EnKF Data Assimilation

- Imagine you were modeling temperature across Salt Lake City but only had temperature observations at Alta Ski Resort

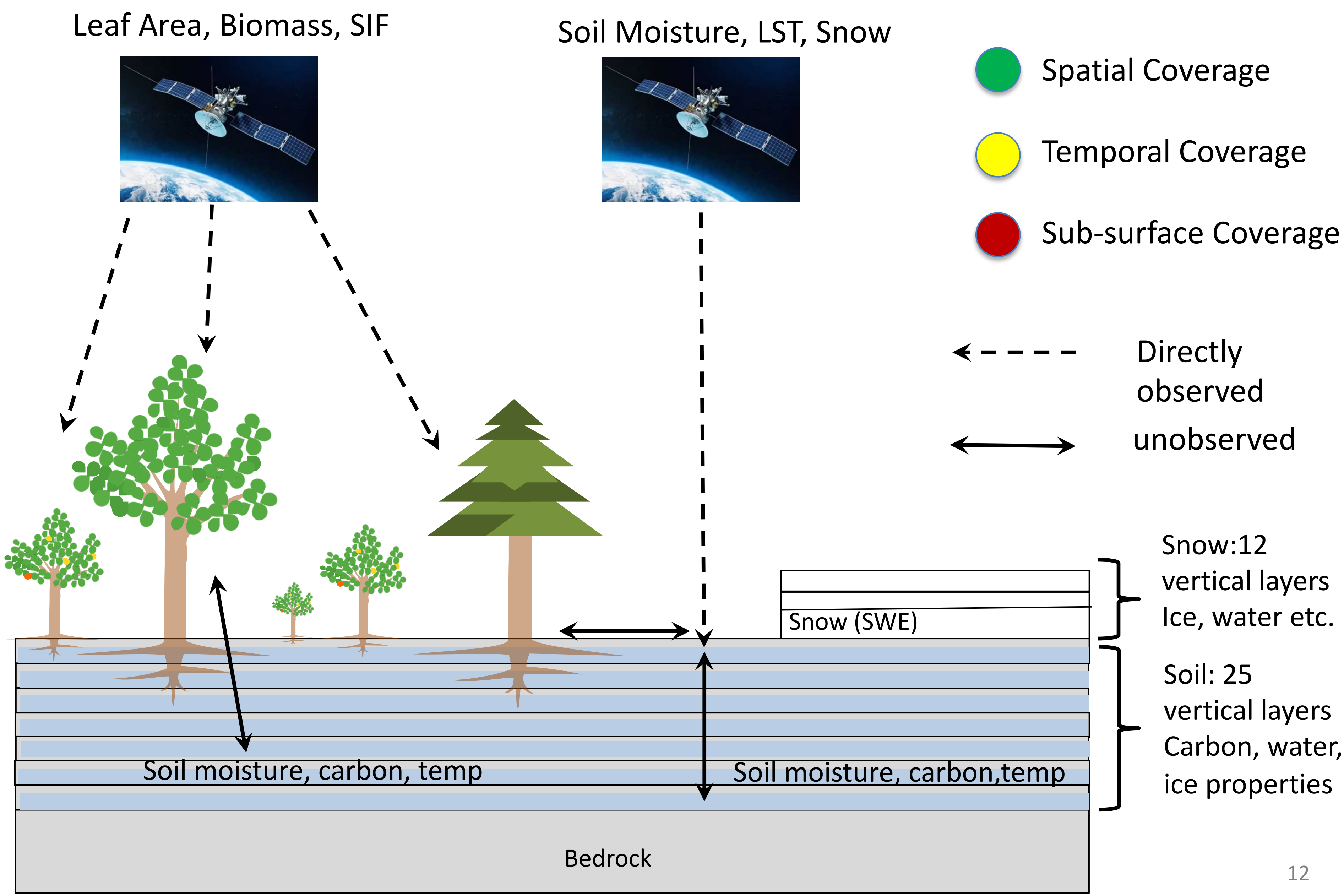
Ensemble of model generated temperatures | Apply correction to model w/ <u>observed</u> temp | Apply correction to <u>unobserved</u> temp | Generate posterior



- The correlation between states is based upon error covariance matrix generated from a model. Also observation uncertainty must be carefully quantified.

- How can we apply correlations to improve model performance for Land DA?

Limitations in remotely-sensed land observations



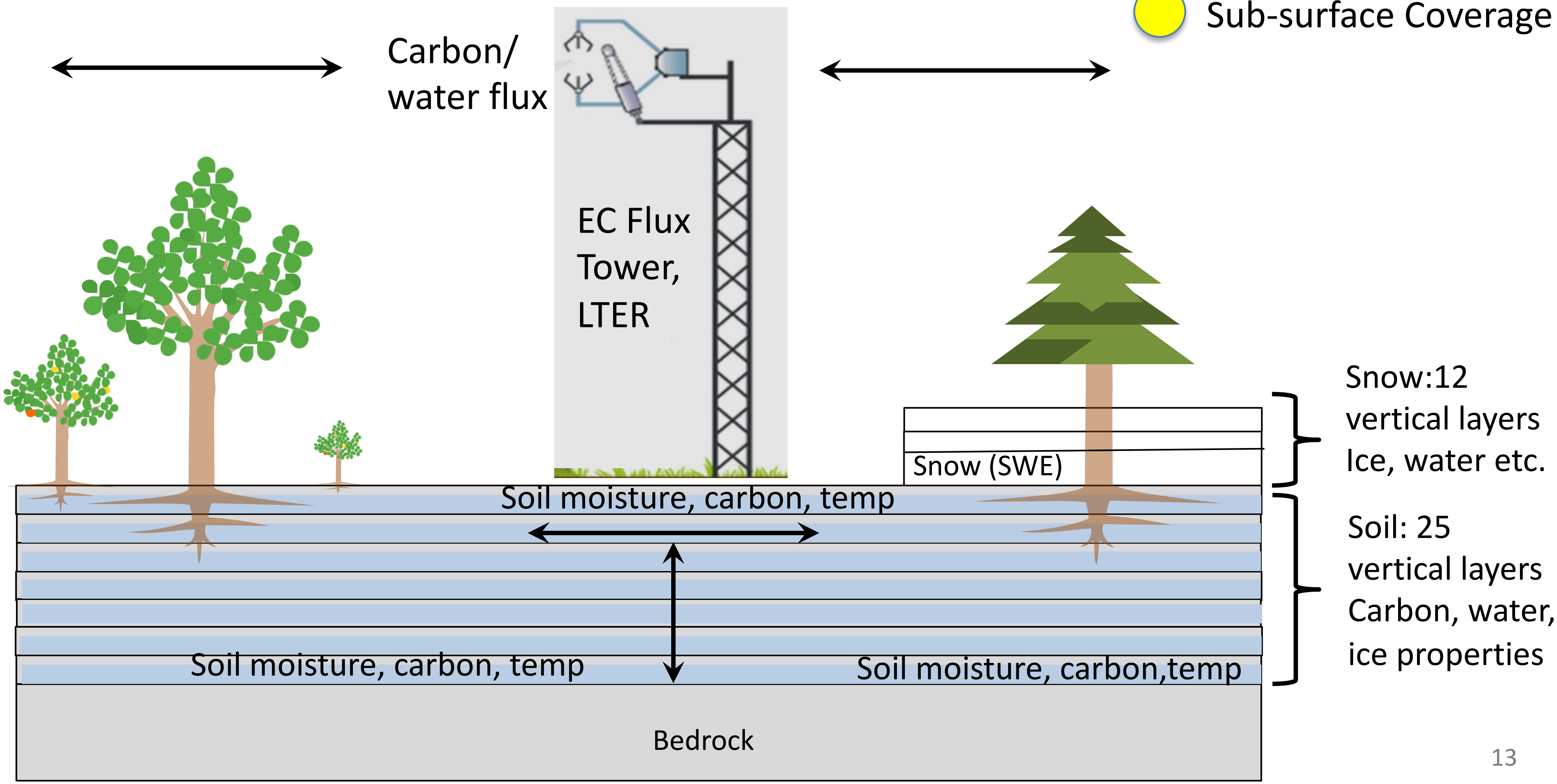
Limitations in ground-based land observations

- Horizontal/Vertical Spatial Correlations Important for limited surface observation network

Spatial Coverage

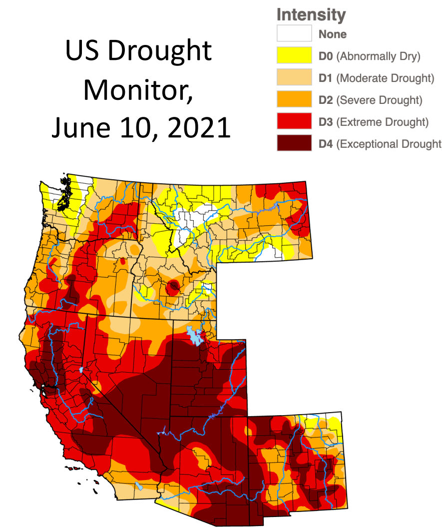
Temporal Coverage

Sub-surface Coverage



Carbon Monitoring Across Western US

US Drought Monitor, June 10, 2021



- Vulnerable carbon stocks create drastic change to landscape and ecosystem functioning
- Complex terrain challenges traditional carbon monitoring, flux towers, atmospheric inversions

Top-Down Modeling

Atmospheric CO_2
↓
Atm. Transport Model
↓
Land carbon exchange

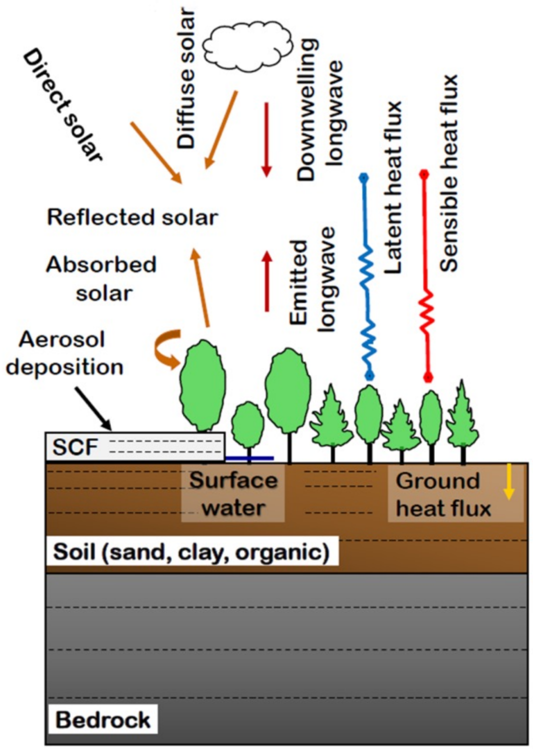
Bottom-Up Modeling

Weather/Climate
↓
Land Surface Model (CLM)
↓
Land carbon exchange

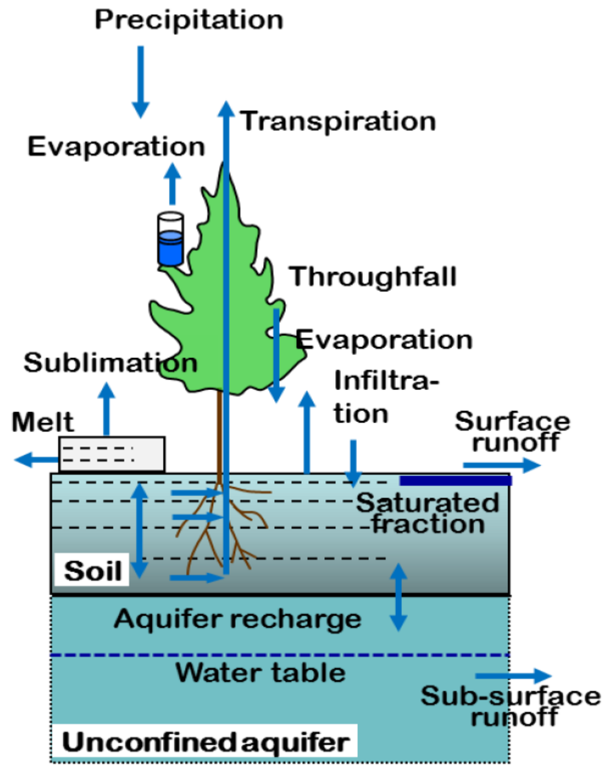
Data Assimilation Research Testbed

Components of a land surface model (CLM)

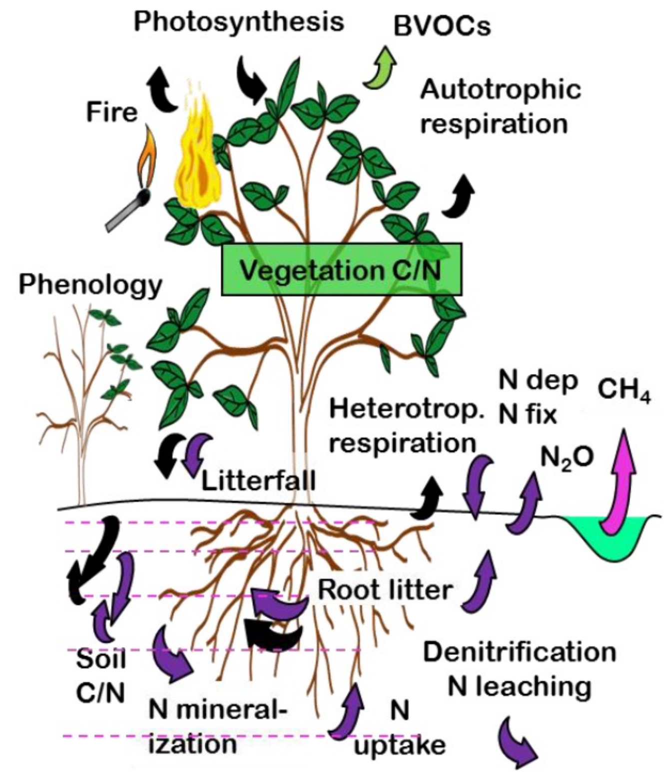
Energy balance



Hydrology

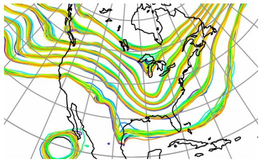


Carbon and nitrogen cycles



- The carbon cycle is coupled to, and limited by, the nitrogen and water cycles

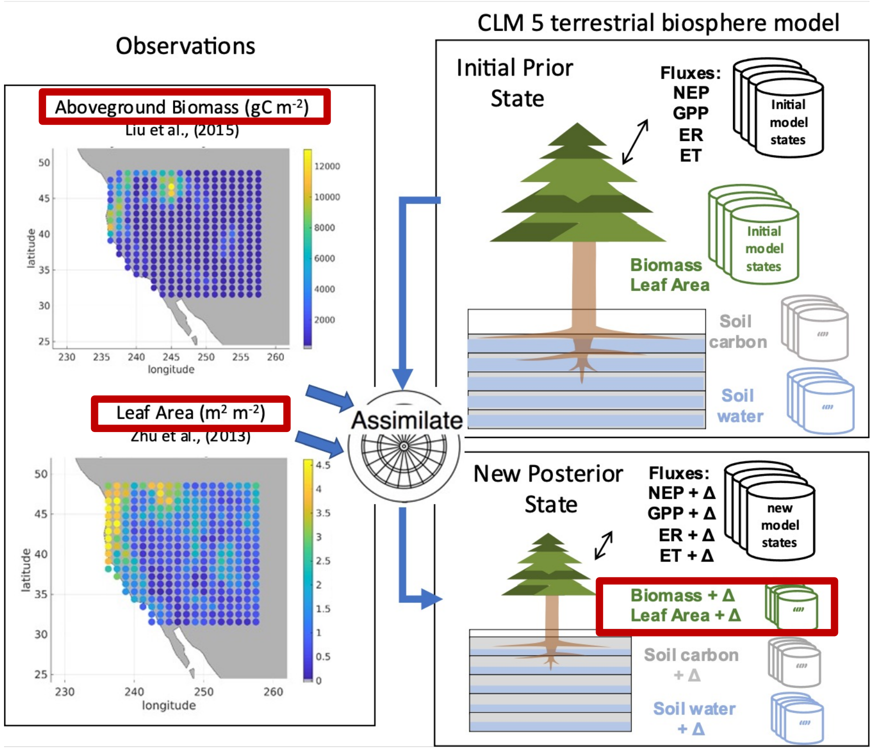
CLM5-DART Overview

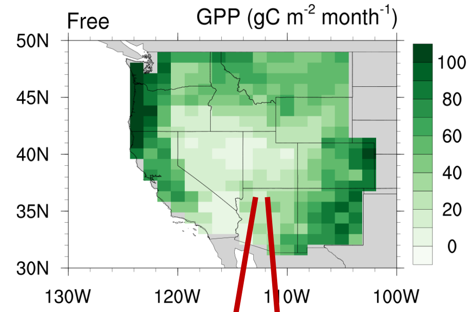


CAM4 DART Reanalysis
(80 member ensemble)

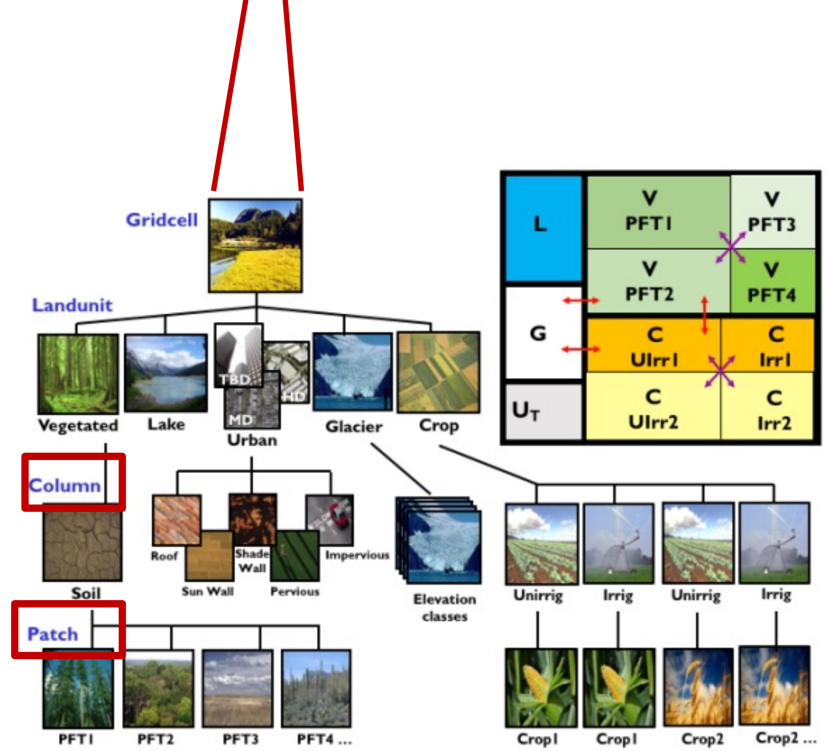
Research Data Archive
Computational & Information Systems Lab

Ds199.1 | DOI: 10.5065/38ED-RZ08



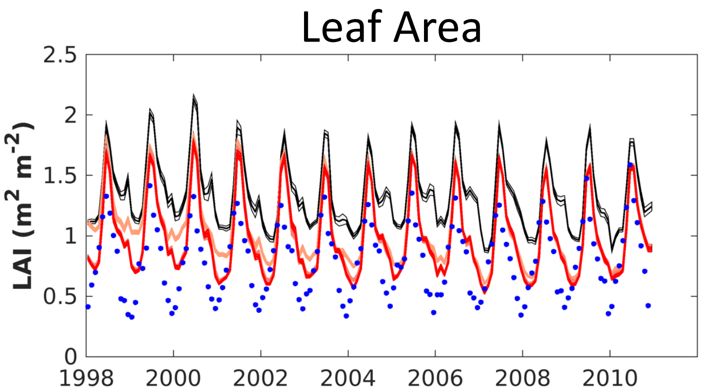


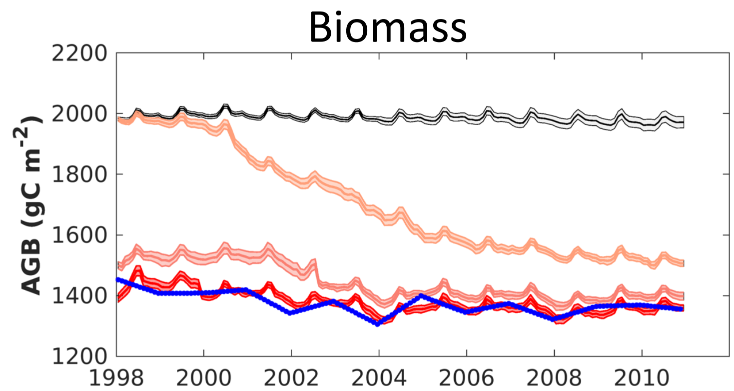
Grid Cell
(~1ºx1º)

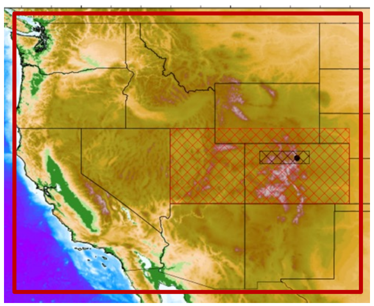


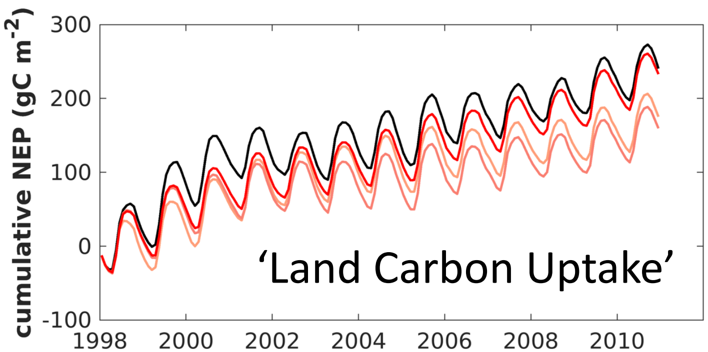
Observations reduce biomass/leaf area, net carbon flux steady

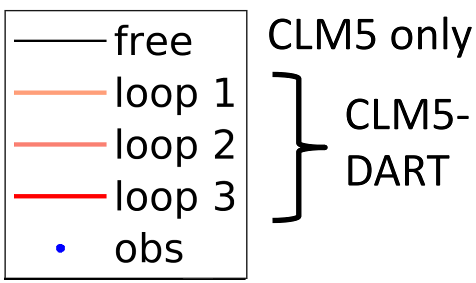
- ~30 % reduction in AGB and LAI respectively









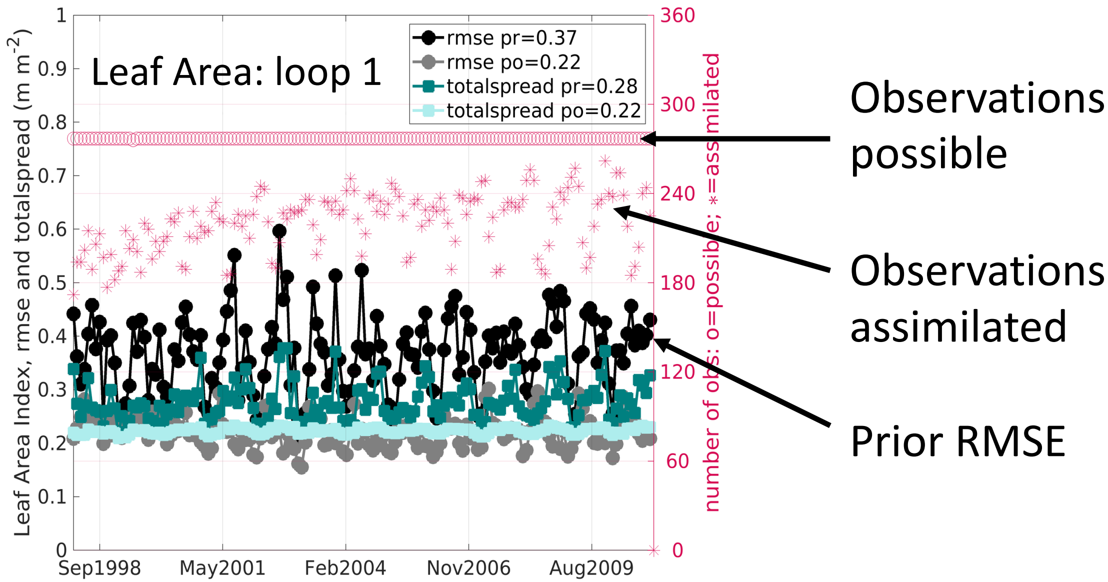


Simulation Name	AGB (kgC m^{-2})	LAI (m m^{-2})	GPP (gC m^{-2} month^{-1})	ER (gC m^{-2} month^{-1})	NEP (gC m^{-2} month^{-1})
Free	1.98	1.31	48.18	47.18	1.00
CLM5-DART	1.36	0.96	38.49	37.21	1.28

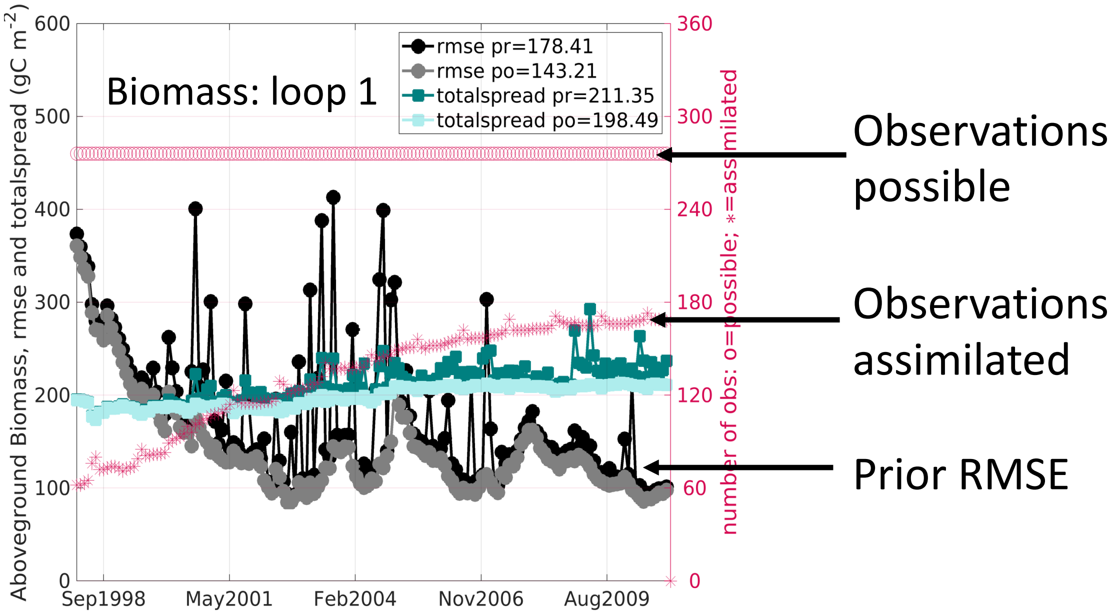
Data Assimilation Research Testbed

Diagnostics of LAI/AGB observation acceptance and RMSE

Leaf Area : steady acceptance rate (90%) seasonal dependence, RMSE steady

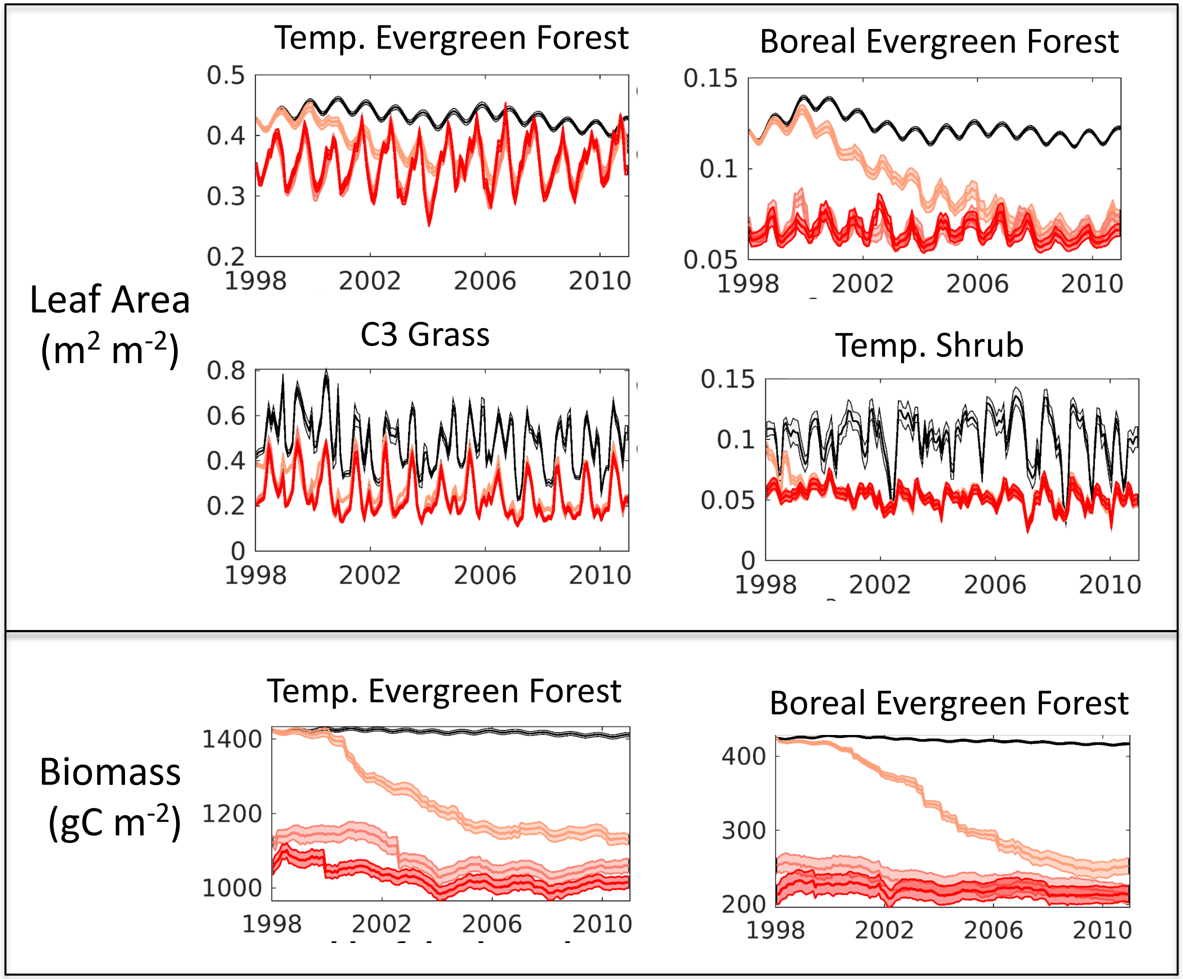


Biomass : increasing acceptance rate (75%), decreasing RMSE



Data Assimilation Research Testbed

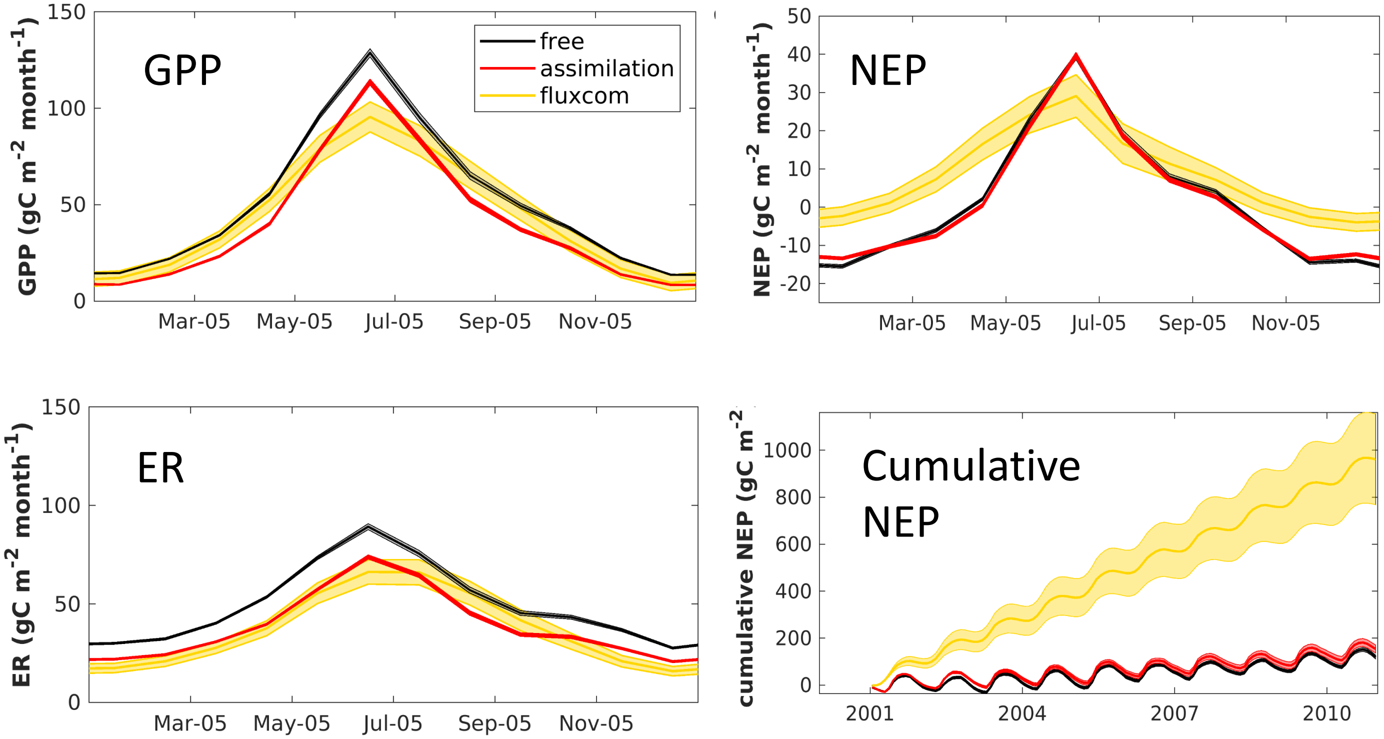
Behavior for dominant PFTs within domain



Data
Assimilation
Research
Testbed

CLM5-DART simulates weak carbon sink compared to FLUXCOM

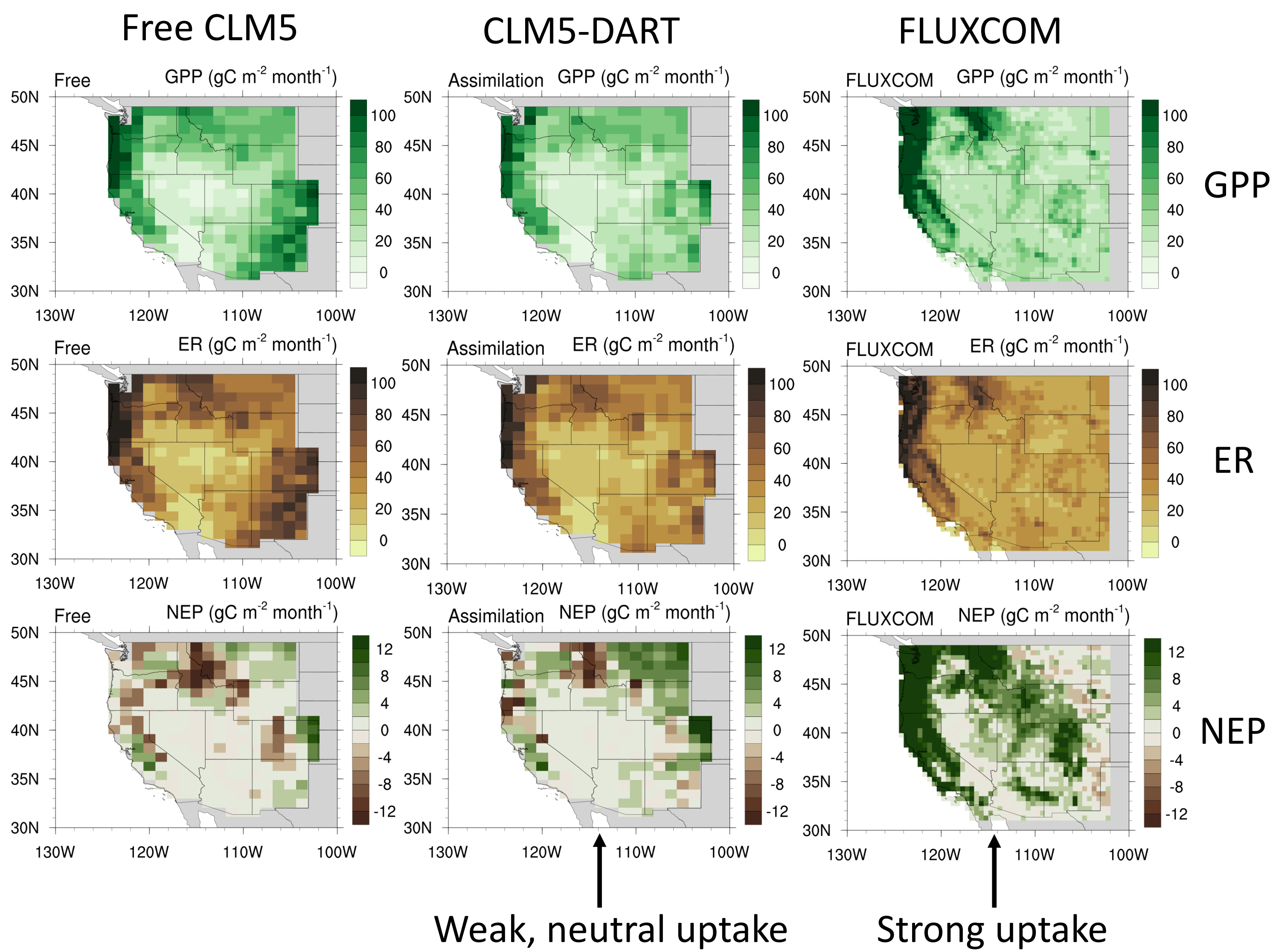
- CLM5-DART (red) reduces biomass states create offsetting reductions in GPP and ER compared to free run
- FLUXCOM (yellow): Machine learning approach that uses flux tower data, satellite data and meteorology as explanatory variables for carbon cycling data product Jung et al., (2020).



- Difference due to disturbance history?
- Need more adjusted variables in CLM5-DART?

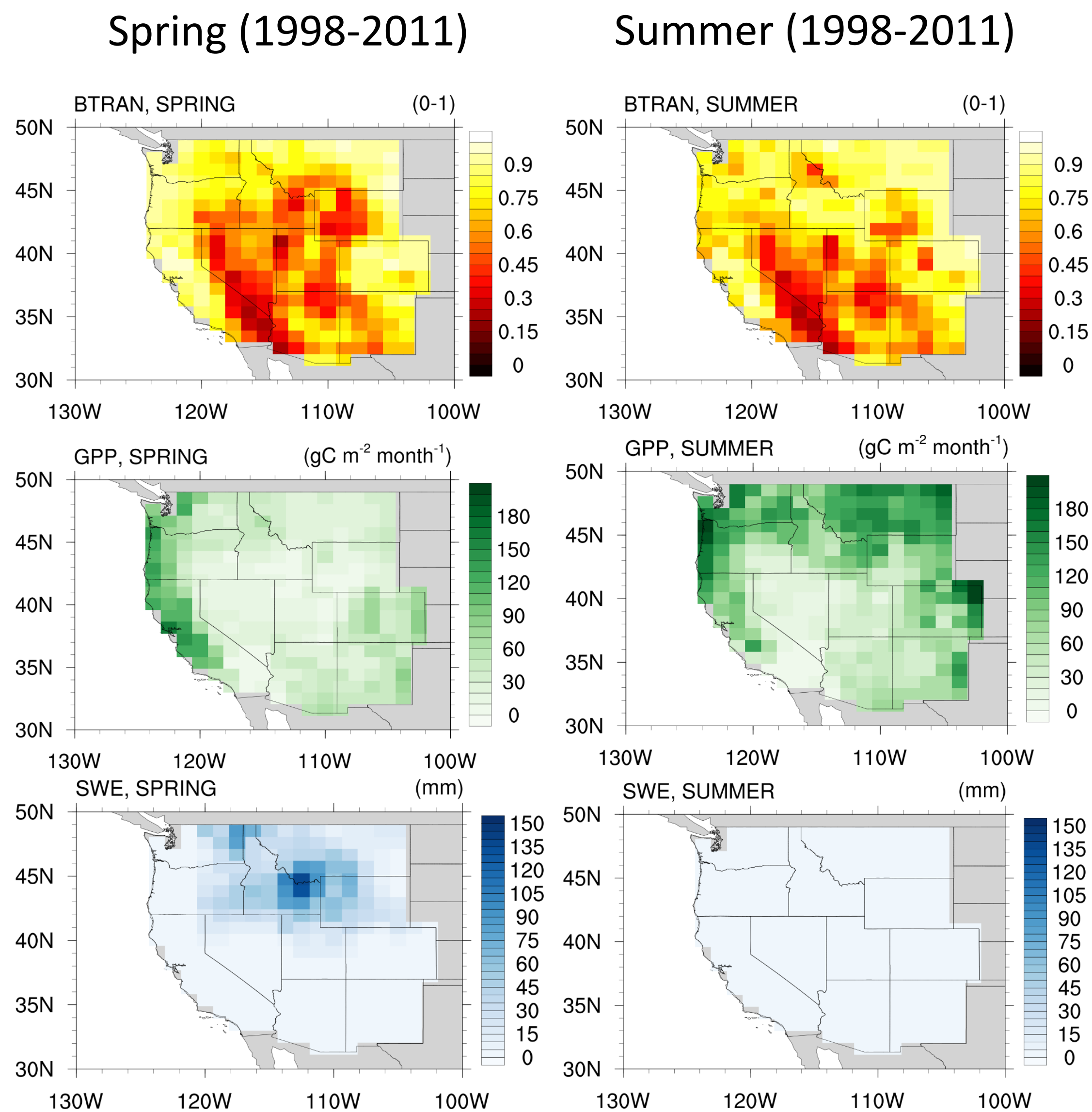
CLM5-DART simulates weak carbon sink compared to FLUXCOM

1998-2011
Average
Fluxes



Water limitation shapes carbon uptake pattern

- Soil moisture limitation and GPP highly correlated (spring: R=0.64; summer: R=0.67)



Soil moisture limitation

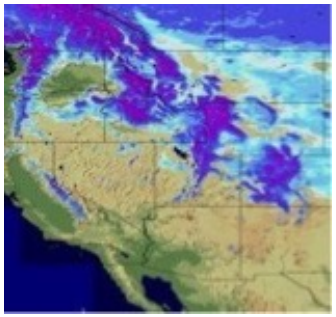
GPP

Snow water equivalent

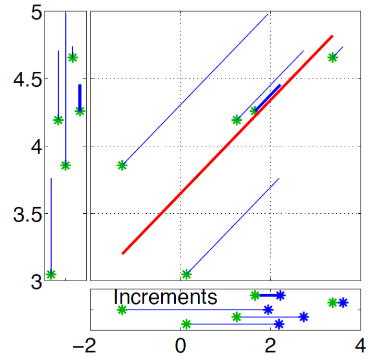
- Simulated snow has low bias

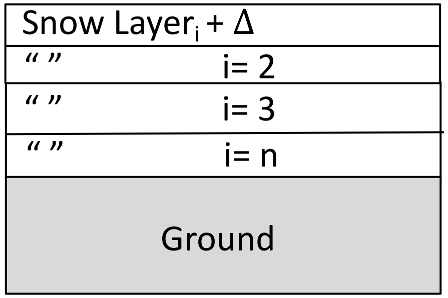
Current challenges in Land DA : Snow

Snow (SWE) Observations



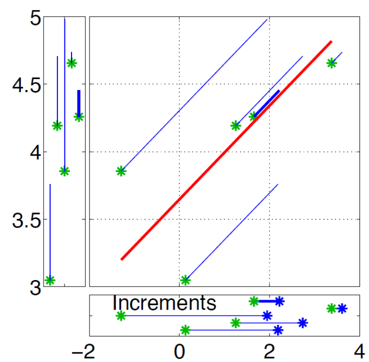
Snow Layer $_{i = n}$



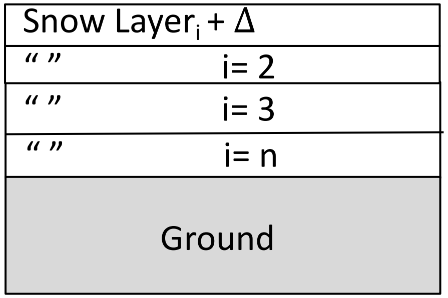


Δ Total SWE ≠ Σ(ΔLayers) ✗

Total SWE

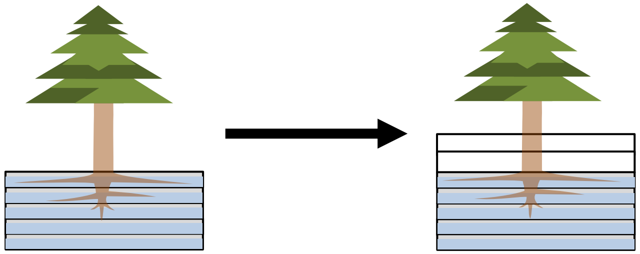


Repartition Algorithm

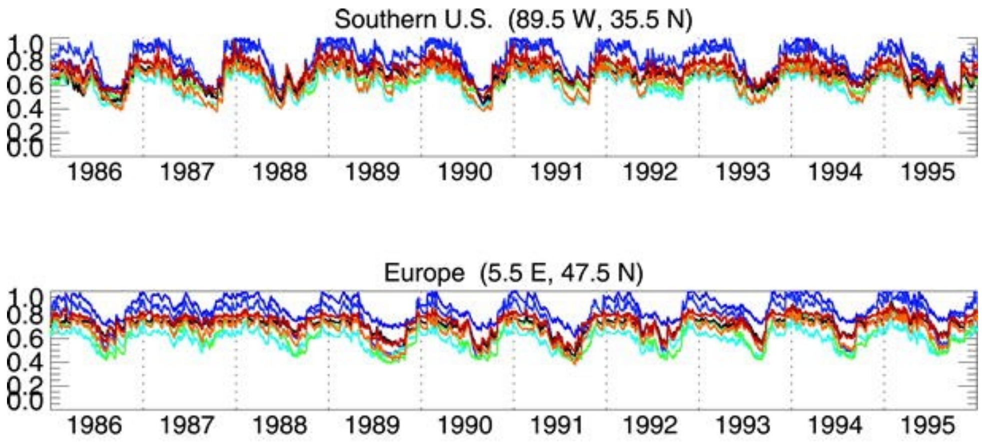


Δ Total SWE = Σ(Δ Layers) √

- Generating Snow ??



Current challenges in Land DA : Soil Moisture

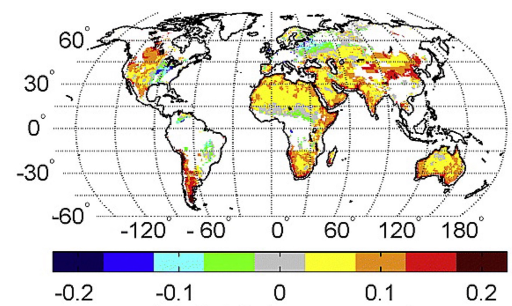


volumetric soil moisture (mm^3/mm^3)

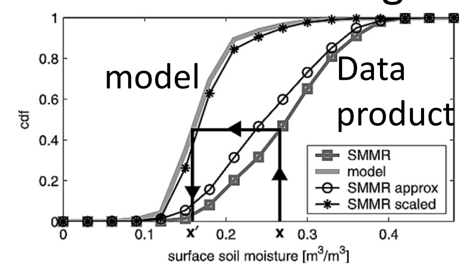
- Soil moisture (SIF, LAI) data are prone to systemic bias in magnitude and variability, but have useful information to assimilate
- CDF matching re-scales data products to match the bias and variability of a model

Koster et al., 2009
(J. of Climate)

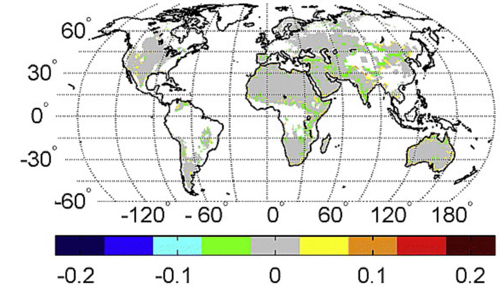
(Model) – (Data Product), Before



CDF Matching



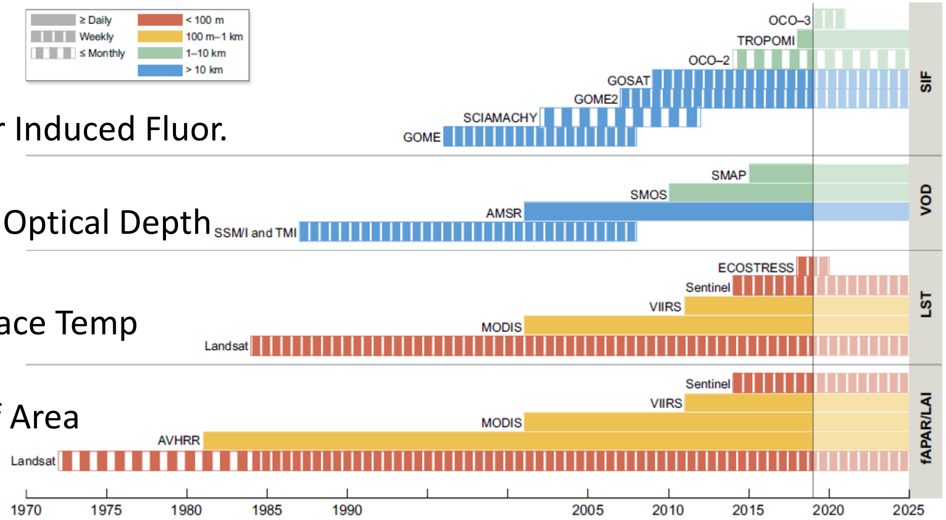
(Model) – (Data Product), After



Reichle & Koster 2004 (GRL)

Advancing models & observations together

Expanding land surface properties



Expanding satellite network

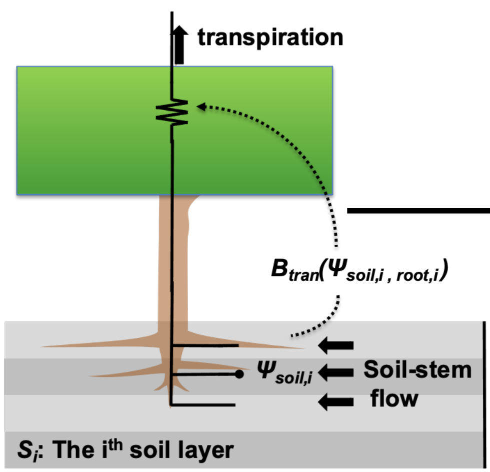
New Phytologist

Constraining estimates of terrestrial carbon uptake: new opportunities using long-term satellite observations and data assimilation

William K. Smith[1], Andrew M. Fox[1], Natasha MacBean[2], David J. P. Moore[1] and Nicholas C. Parazoo[3]

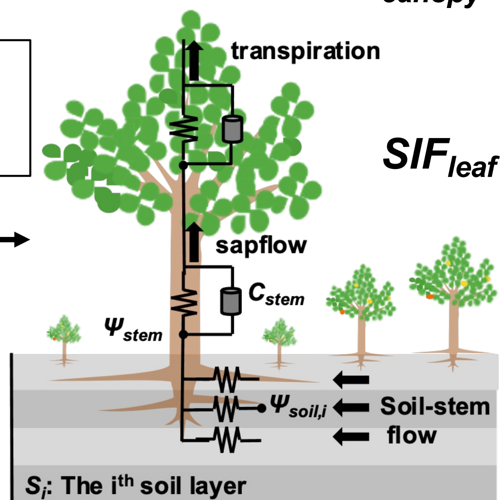
(Leaf water potential) Ψ_{leaf} SIF_{canopy}

CLM 4.5
(Soil Moisture Stress Formulation)



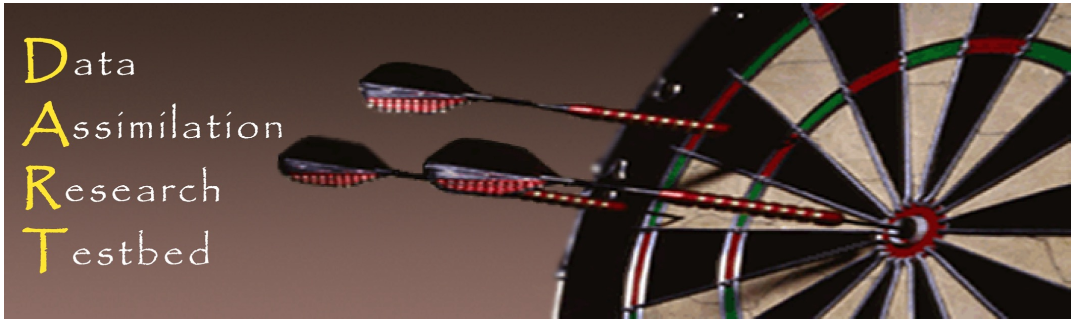
Increasing model complexity

Current: CLM 5.0
Added Hydraulic Stress & SIF



Data Assimilation Research Testbed

For more information:



https://dart.ucar.edu

https://docs.dart.ucar.edu

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CISL
Computational & Information Systems Lab

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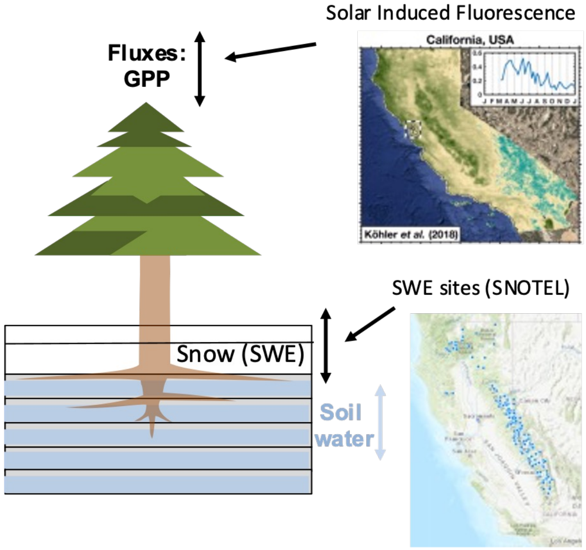
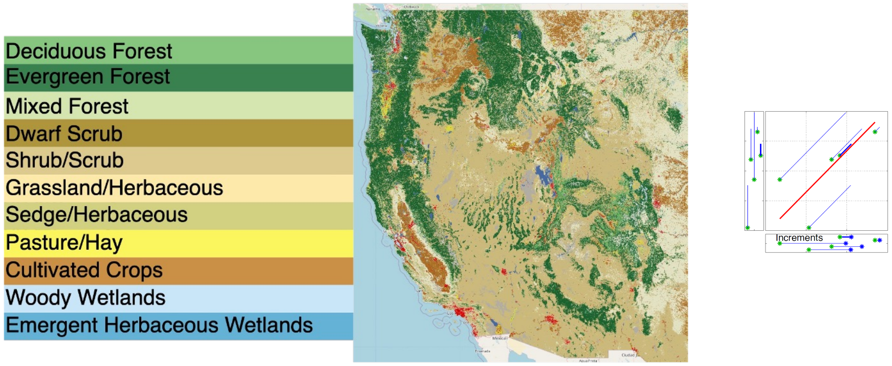
Future Directions

Additional data streams help constrain carbon cycling



Using high res land cover maps for improved forward operators (PFT specific).



Finer Spatial Resolution?

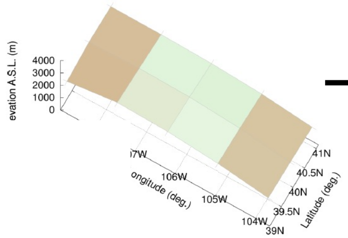
Atmosphere:

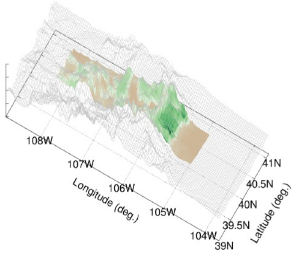
CAM4 Reanalysis (~2°) → CAM6 Reanalysis (~1°)

Ds199.1 | DOI: 10.5065/38ED-RZ08

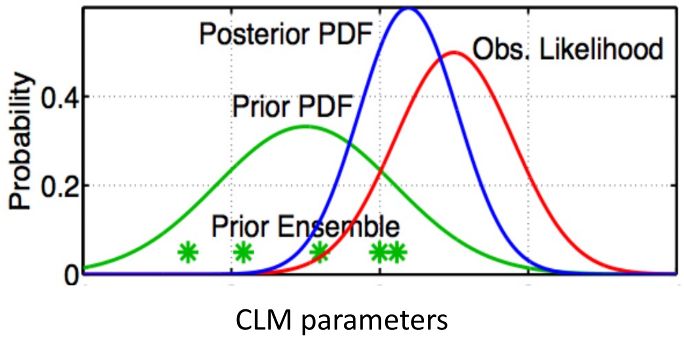
Ds345.0 | DOI: 10.5065/JG1E-8525

Land surface:





Parameter Estimation



CLM5-DART Methods/Terminology

- Remotely Sensed ‘Observations’: (1.25°x0.95°)
  Averaged to match model spatial resolution (reduces representation error)

- Observation Rejection Threshold (3 sigma): Reduces impact of systematic errors

- Adaptive ‘Inflation’ : Improve sampling of model error

- Spatial Localization:
  Horizontal range: ~100 km

- State Space Localization:
  Select most important variables for carbon cycling

‘Standard’ Adjusted State Variables (Biomass C, N)

Leaf carbon	Leaf nitrogen
Live stem carbon	Fine root nitrogen
Dead stem carbon	Live coarse root nitrogen
Leaf area index	Dead coarse root nitrogen
Fine root carbon	Live stem nitrogen
Live coarse root carbon	Dead stem nitrogen
Dead coarse root carbon	

Extra Slides/Ideas

"Meeting in the middle manuscript"

Alexei Shiklamanov

Parameter estimation

Look for Tim Hoar poster for other land data assimilation work.

Add now slide from Zhang to introduce concept.

Andy Fox Slide.

Slide components of an assimilation, where spread?

Sensitivity to met forcing, an model types, H. Duarte.

Slide 1 & 2 : (Advances in modeling and data assimilation) : Including explicit representation of slope/aspect on surface energy balance. Meeting in the middle manuscript.

Slide 3: Systemic biases between model and observations (leaf area rejection)

- Inflation
- Pre-processing of observations, CDF
- Meteorological Forcing → Err on side of over-productivity (snow)