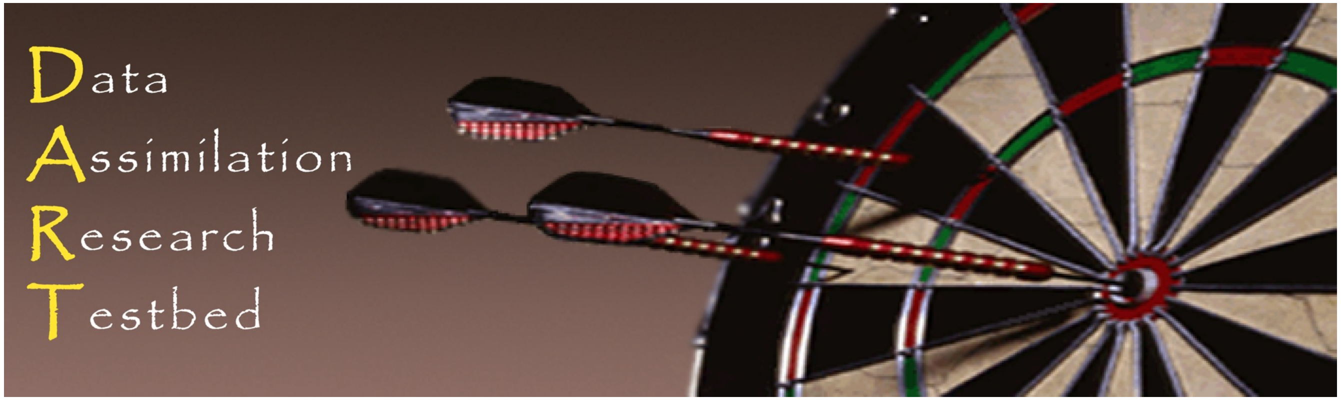
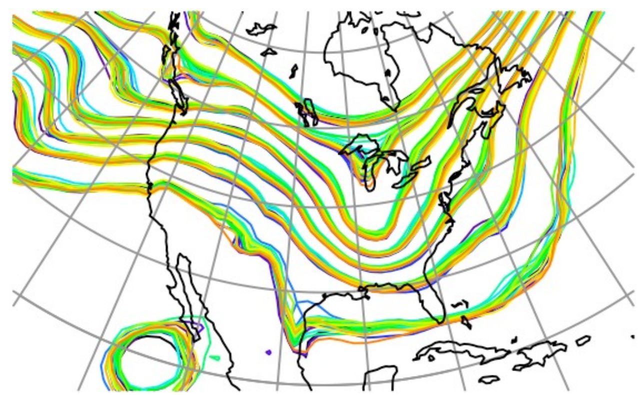


Improving Carbon Cycling using Land Data Assimilation: Progress and Challenges

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



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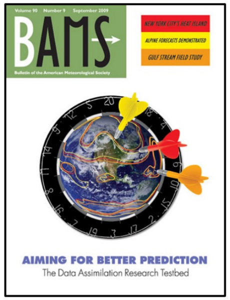
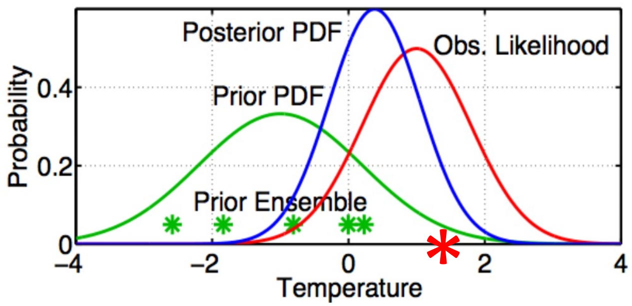
NCAR | National Center for
UCAR | Atmospheric Research

Overview

- Theory/Methods of
  EnKF Data Assimilation,
  Data Assimilation Research Testbed
  (DART)

Anderson et al.,2009

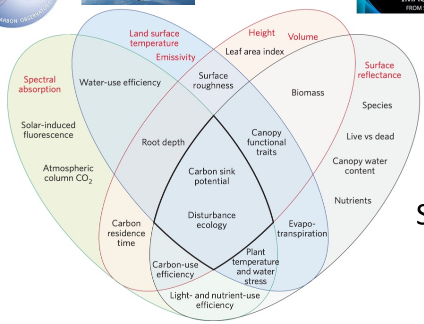




- Application of Data Assimilation to Western US Carbon Cycling

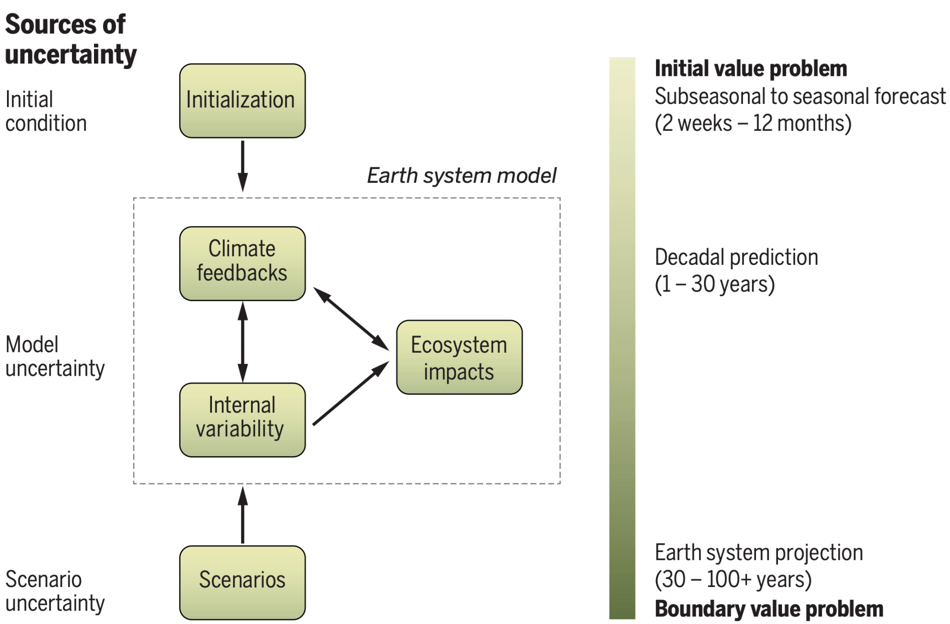
THE UNIVERSITY OF UTAH

- Future Directions: expanding satellite observations of land surface properties



Stavros et al., (2017)

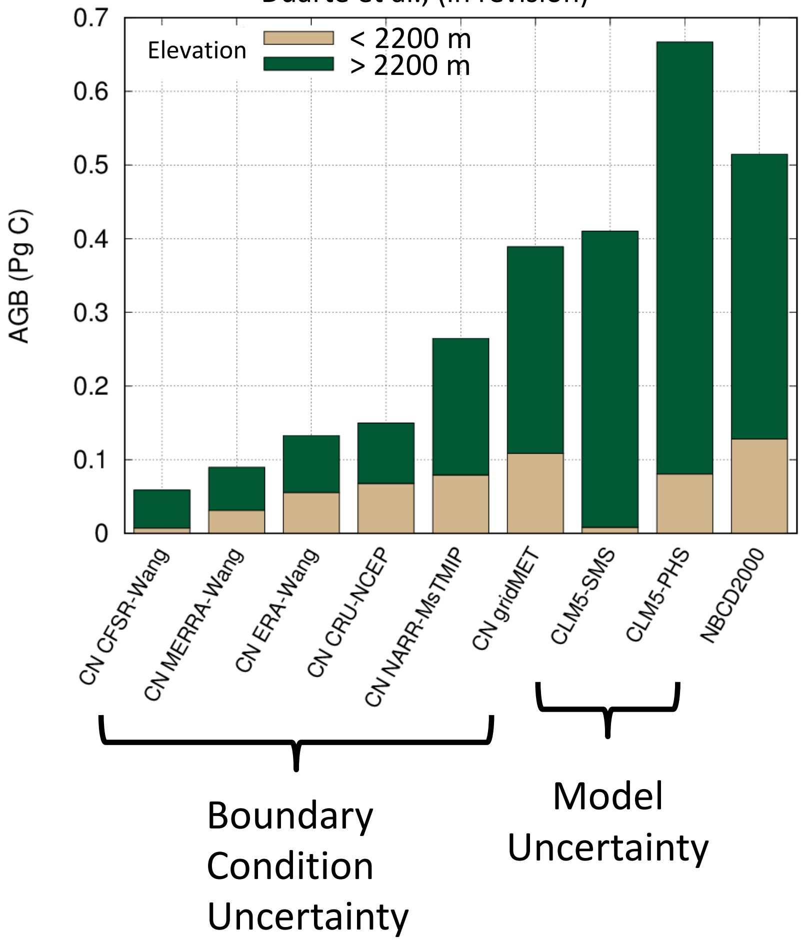
Motivation for DA in Earth System Models



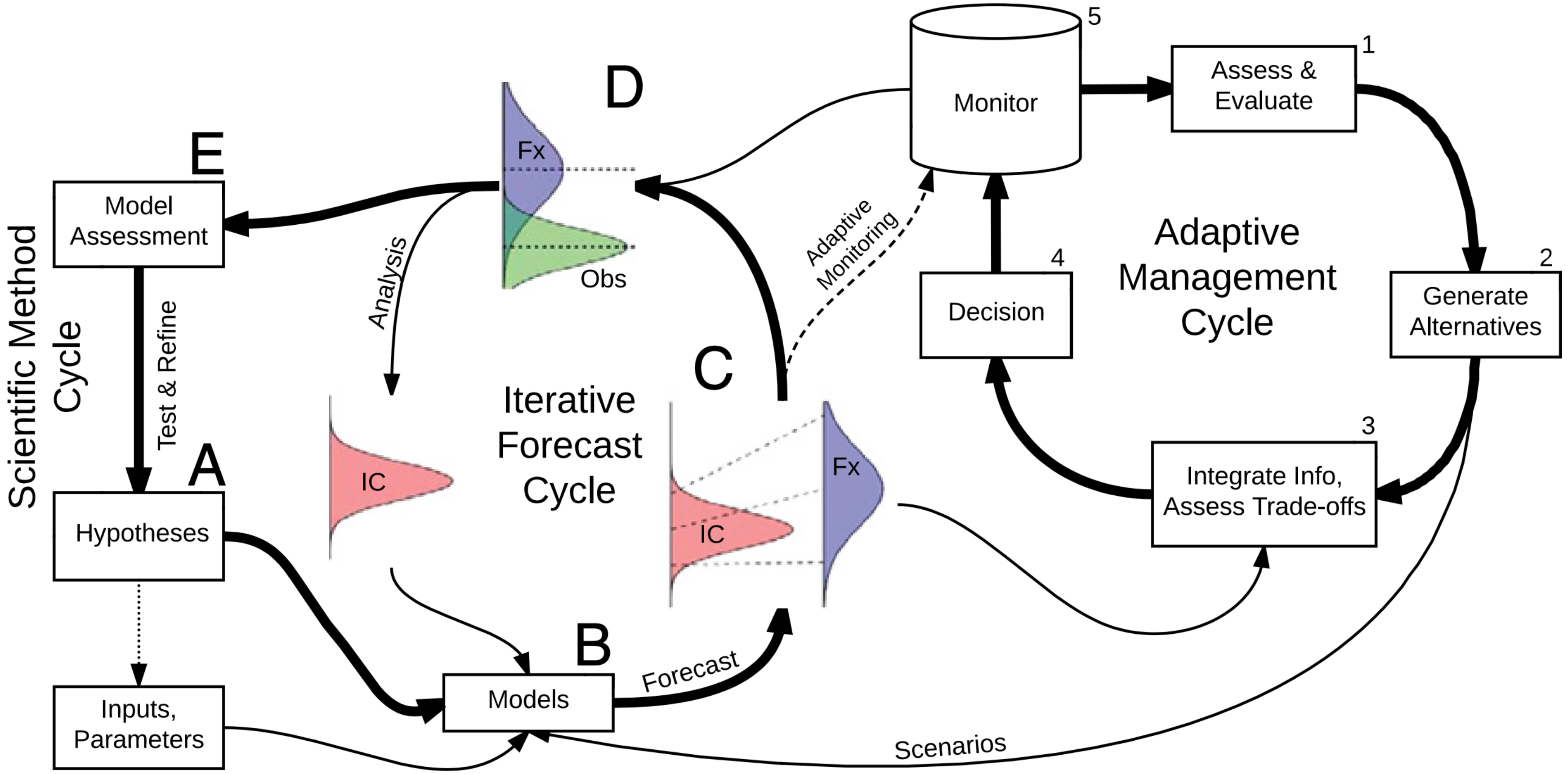
Bonan & Doney 2018

Simulated Biomass in Western US

Duarte et al., (in revision)



Motivation for DA in Earth System Models

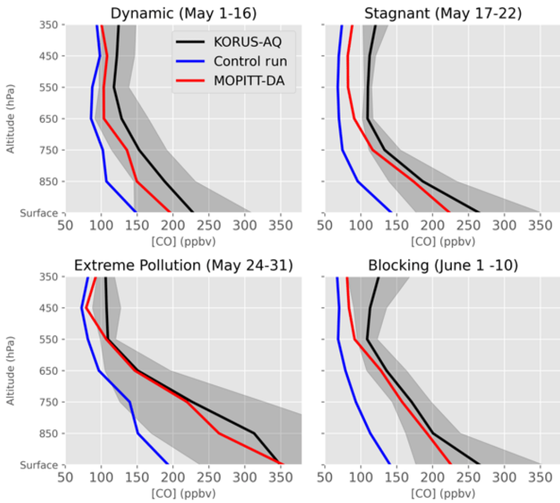


Dietze et al., 2018

Earth System DART applications

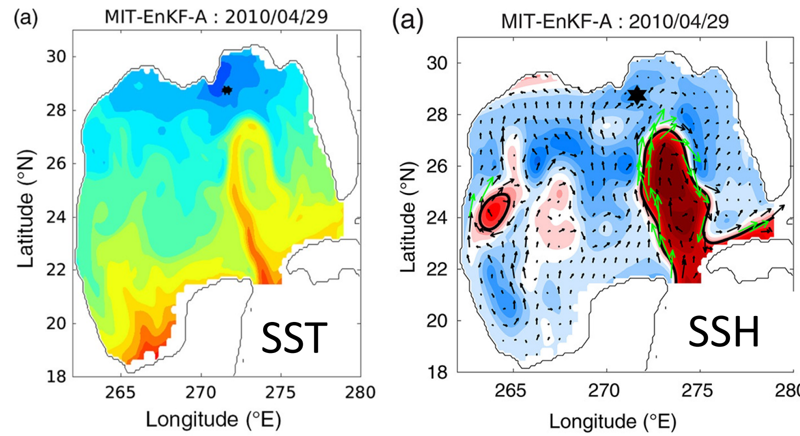
Atmosphere: CO w/ CAM-Chem

Gaubert et al., (2020)

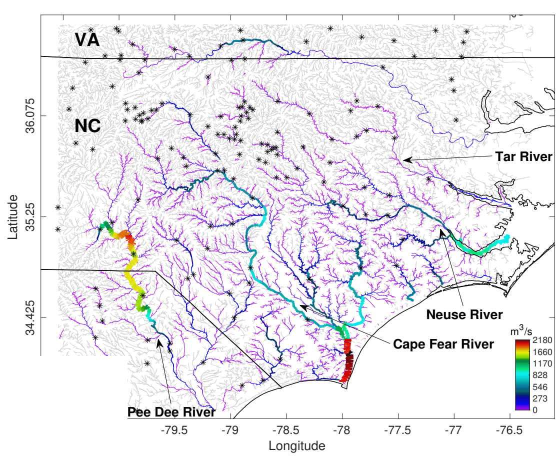


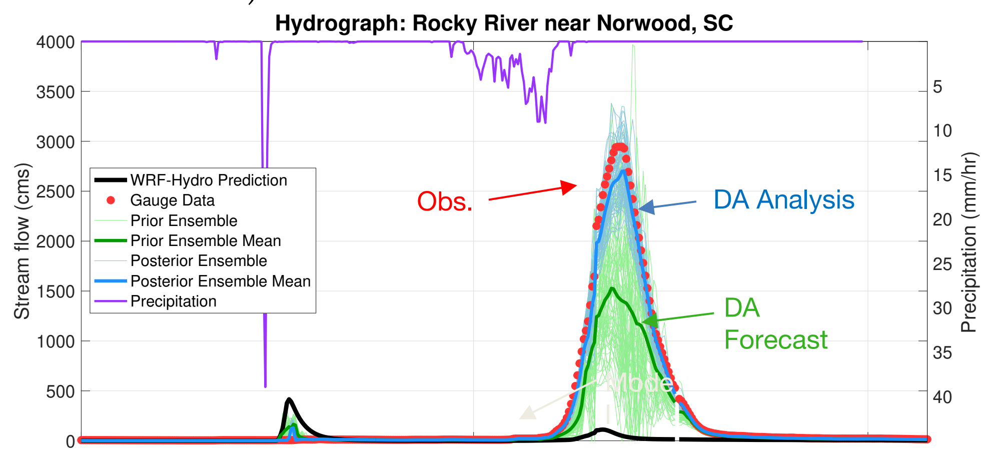
Ocean: Gulf Stream Eddy Dynamics (MITgcm)

Gopalakrishnan et al., (2019)



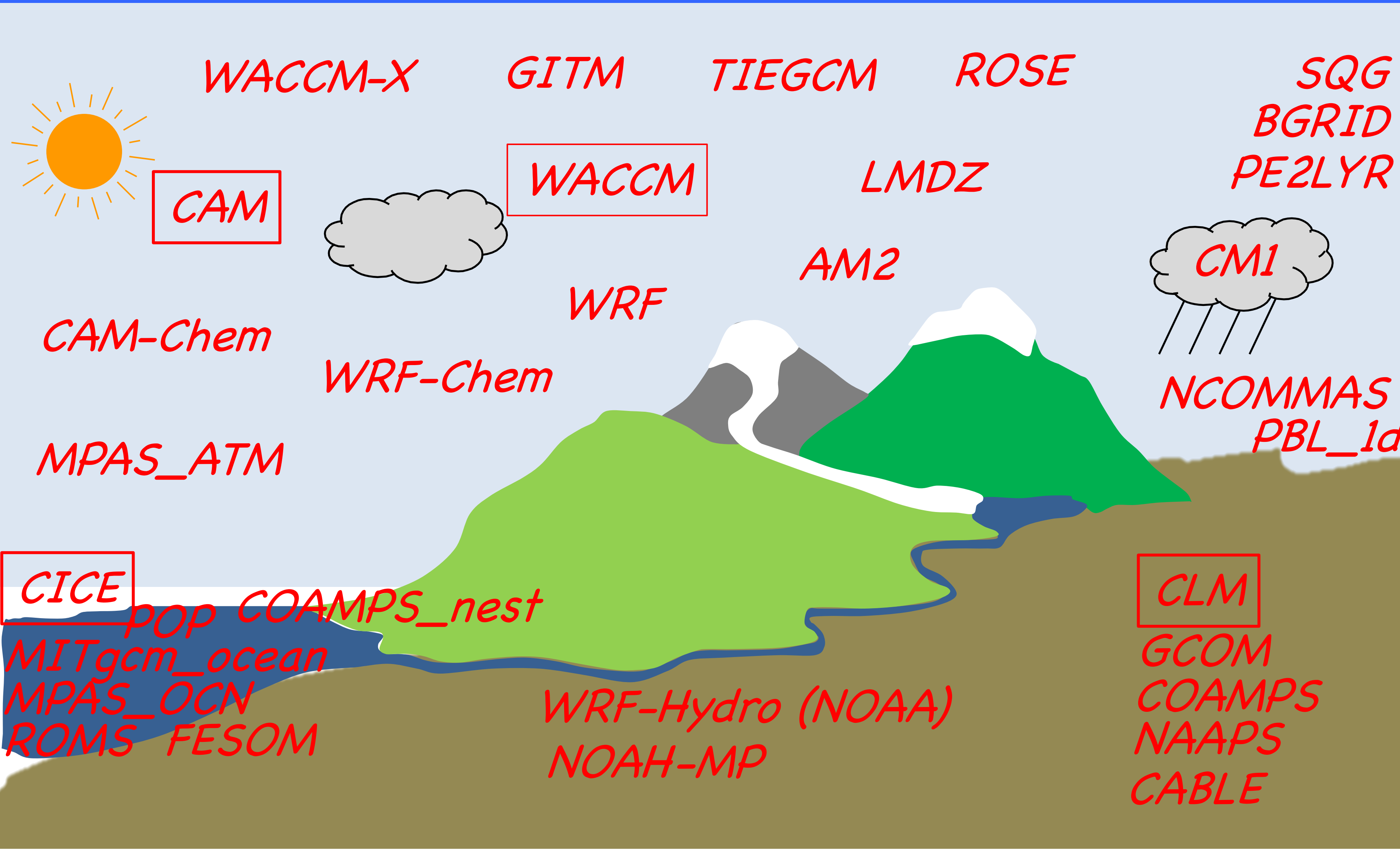
River Transport: StreamFlow in WRF-Hydro (Hurricane Florence)





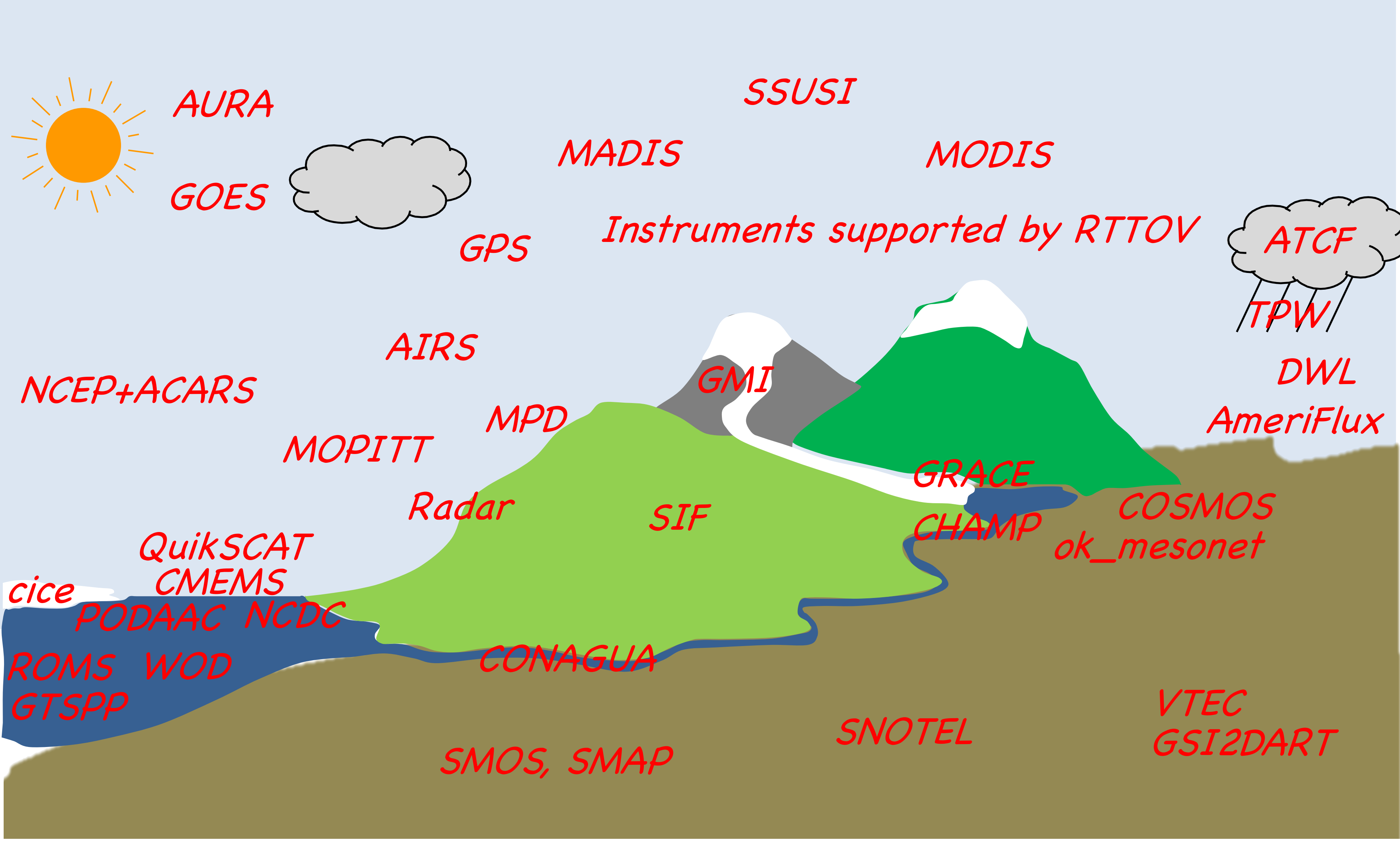
Gharamti et al., (2021)

Geophysical Models Interfaced to DART



Data
Assimilation
Research
Testbed

Earth System Observations (others available)

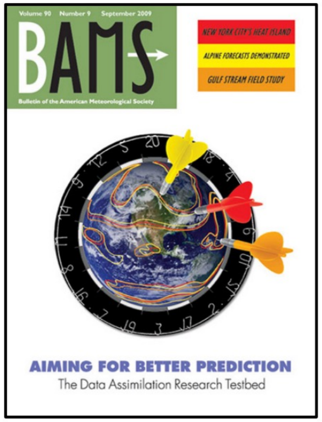


Data
Assimilation
Research
Testbed

Basics of EnKF Data Assimilation

- Observations combined with a model forecast to produce an improved forecast ('analysis').
- Typically adjust the system state, but also model parameters

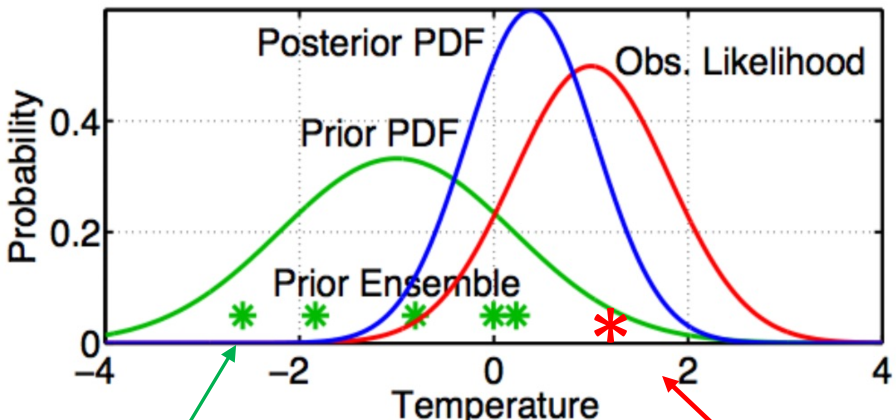
Anderson et al.,2009

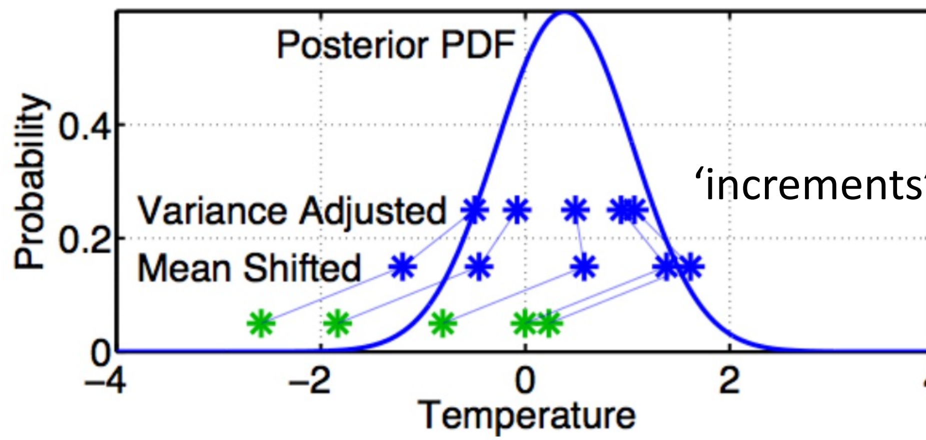


<u>Bayes Theorem</u>

Posterior ~ Prior · Observation Likelihood

'Update' or 'analysis'   Model generated   Earth System Observations





'increments'

5 prior model estimates of temperature

1 new observation of temperature

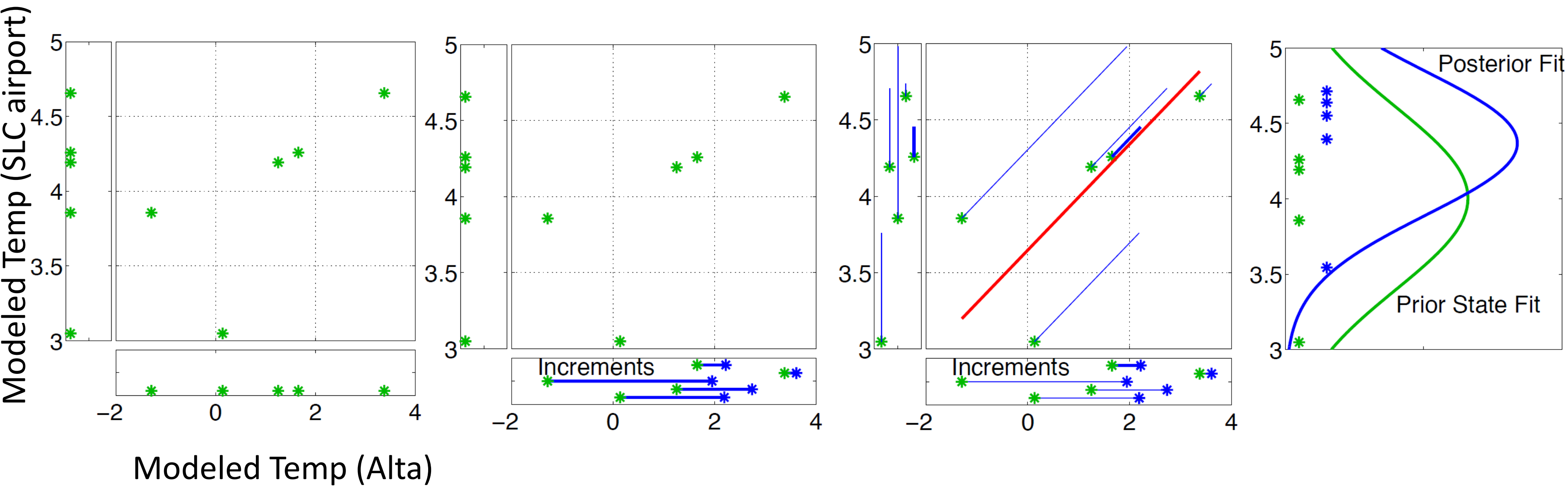
Data Assimilation Research Testbed

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/ observed temp | Apply correction to unobserved temp | Generate posterior



- This is a simple example, but in complex ESMs this can be applied across entire model state: both in physical space, and across different variables.

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

Data Assimilation Research Testbed

Expanding Earth System Observations

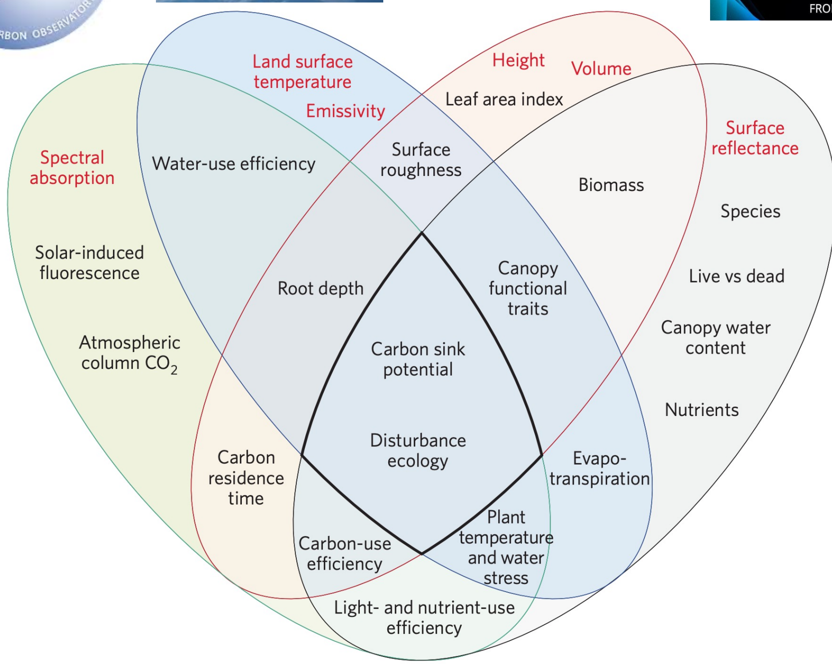
Remote Sensing Satellites

2019

2018

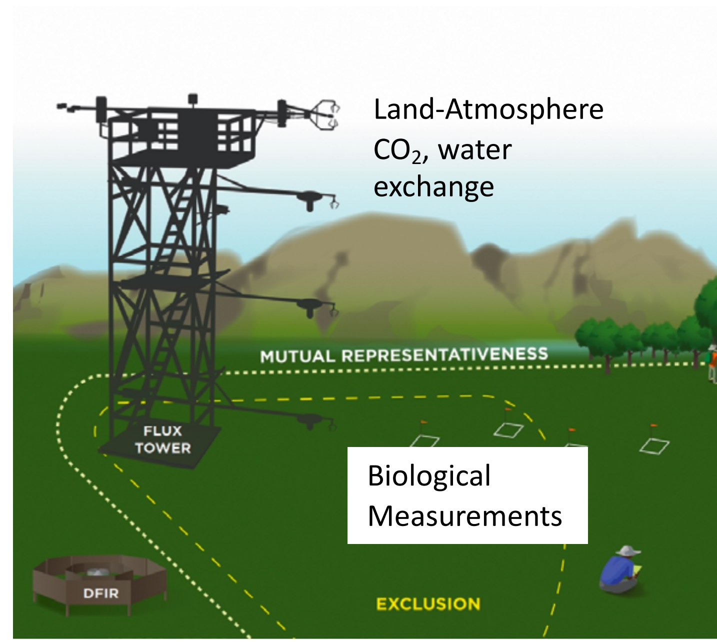
2018

2020



Stavros et al., (2017)

Ground Based Ecological Observation Networks: NEON, Ameriflux

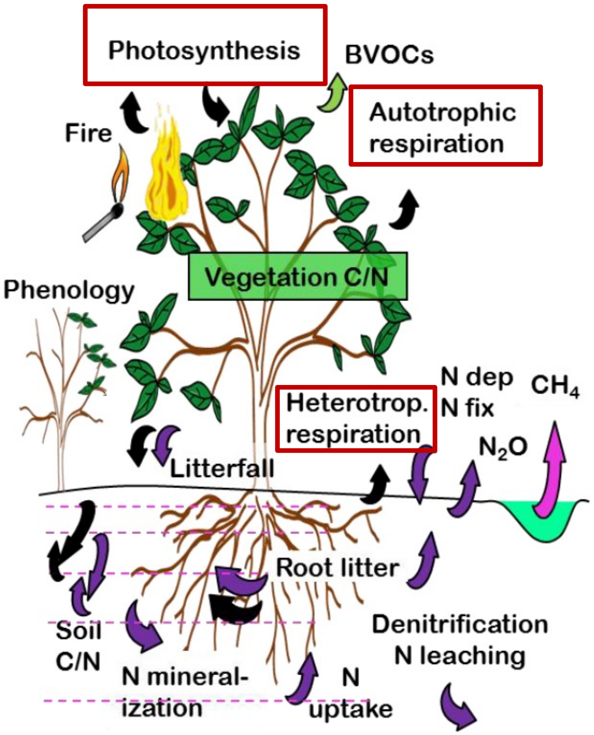


Metzger et al., (2019)

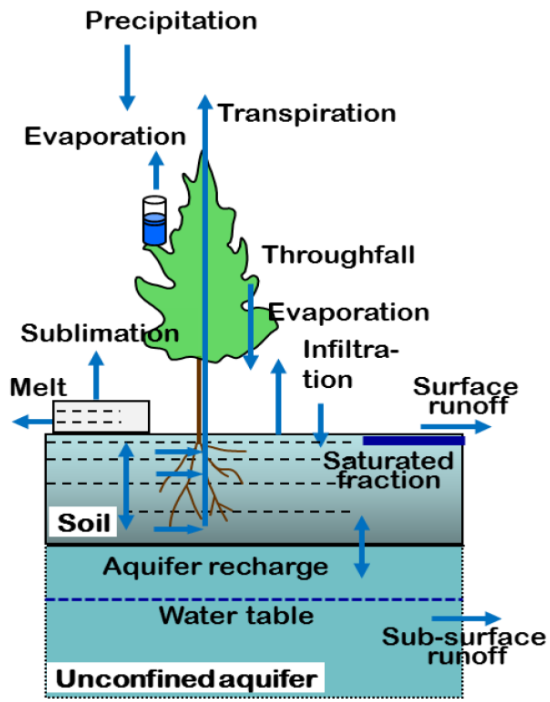
Data Assimilation Research Testbed

Components of a land surface model (CLM)

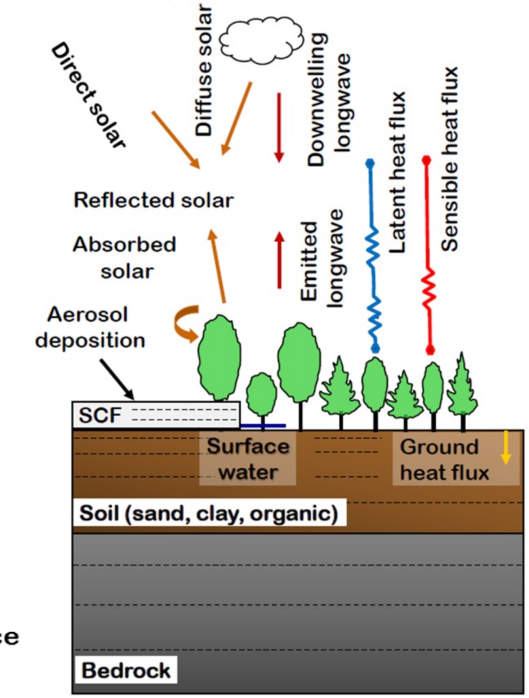
Carbon and nitrogen cycles



Hydrology



Energy balance



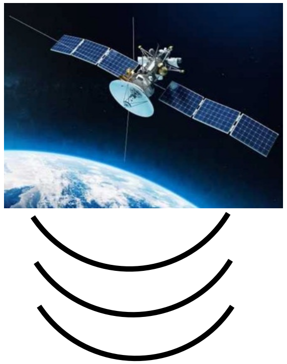
Gross Primary Productivity (GPP) Ecosystem Respiration (ER) Net Ecosystem Production (NEP) NEP = GPP – ER

- The carbon cycle is coupled to, and influenced by the nitrogen, water cycles and surface energy balance

Data Assimilation Research Testbed

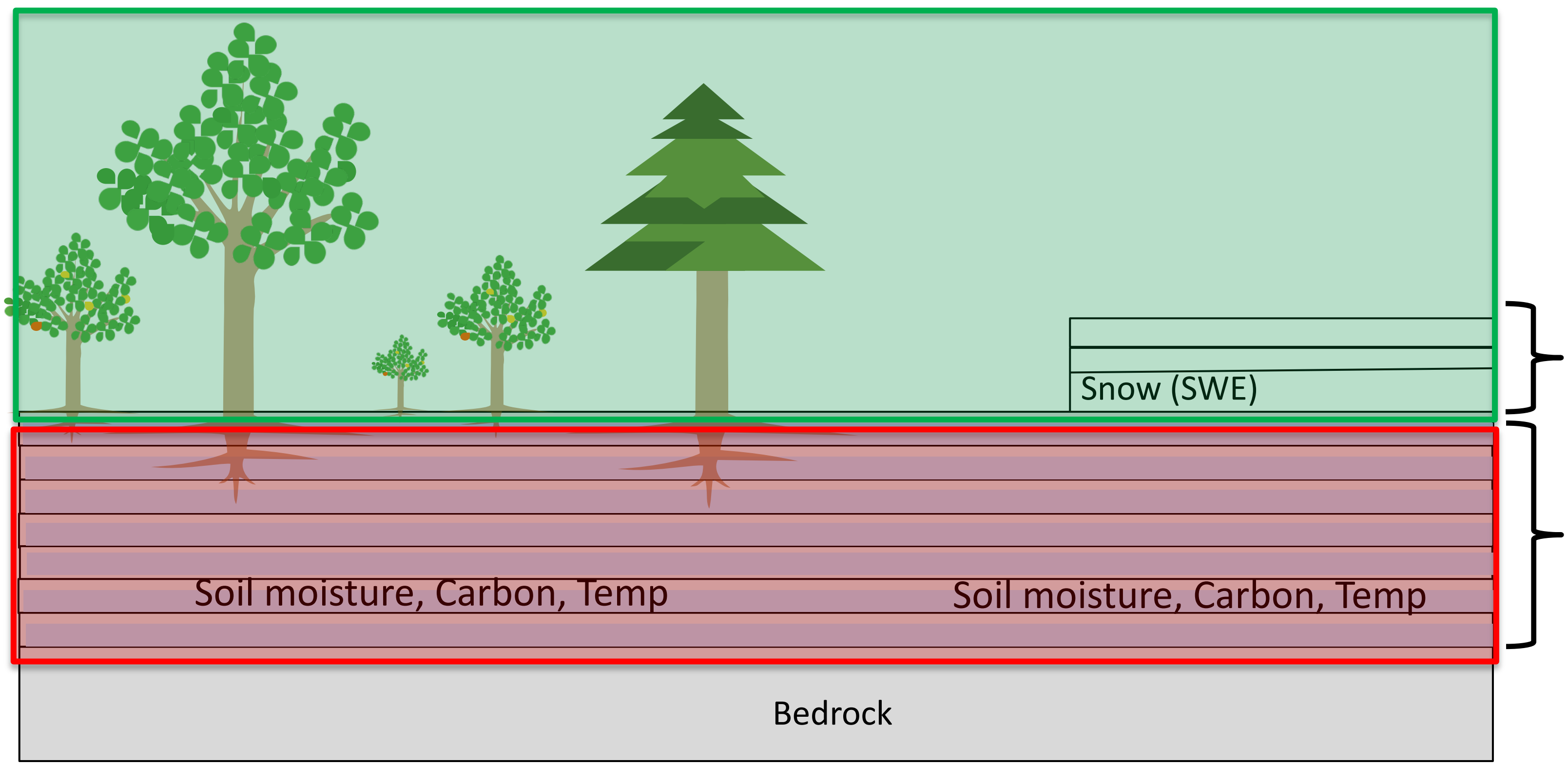
Limitations of remotely-sensed land observations

Leaf Area, Biomass, SIF



Soil Moisture, Temp, Snow

- Spatial Coverage
- Temporal Coverage
- Sub-surface Coverage

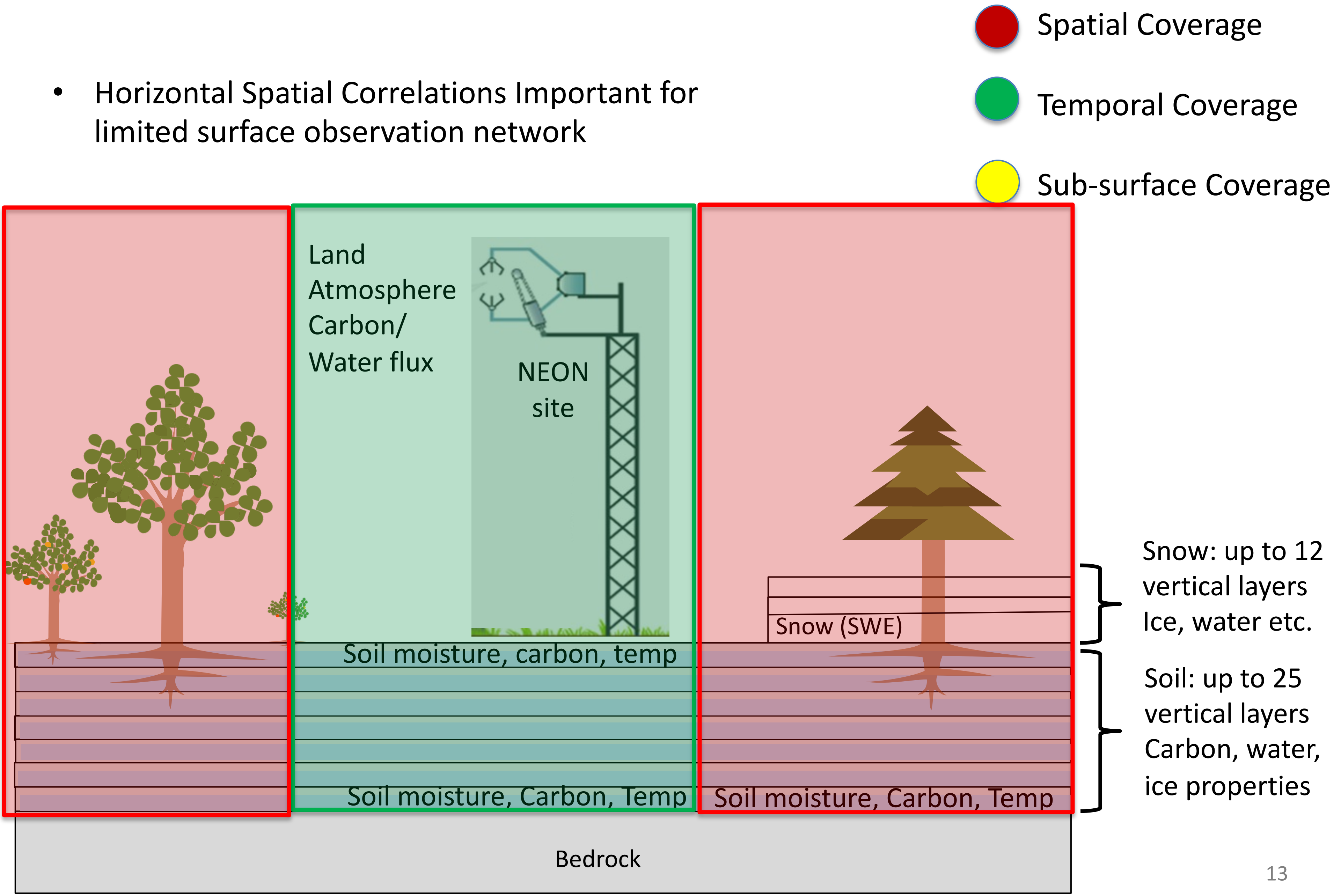


Snow: up to 12 vertical layers
Ice, water etc.

Soil: up to 25 vertical layers
Carbon, water, ice properties

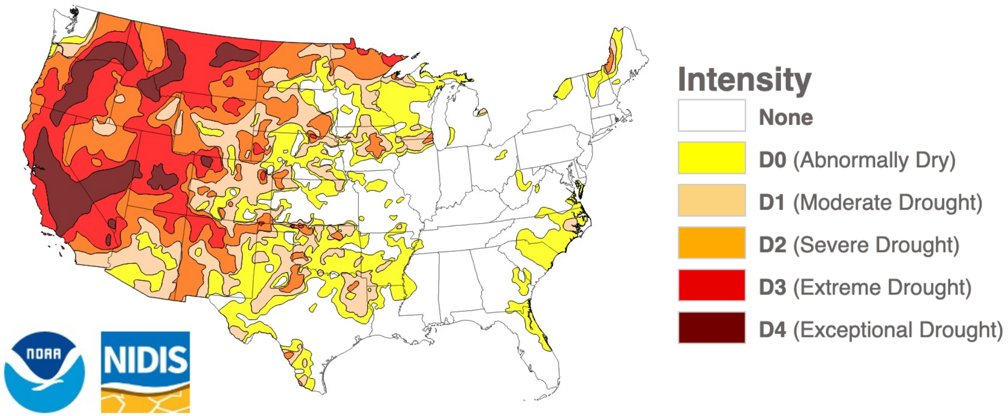
Limitations of ground-based land observations

- Horizontal Spatial Correlations Important for limited surface observation network

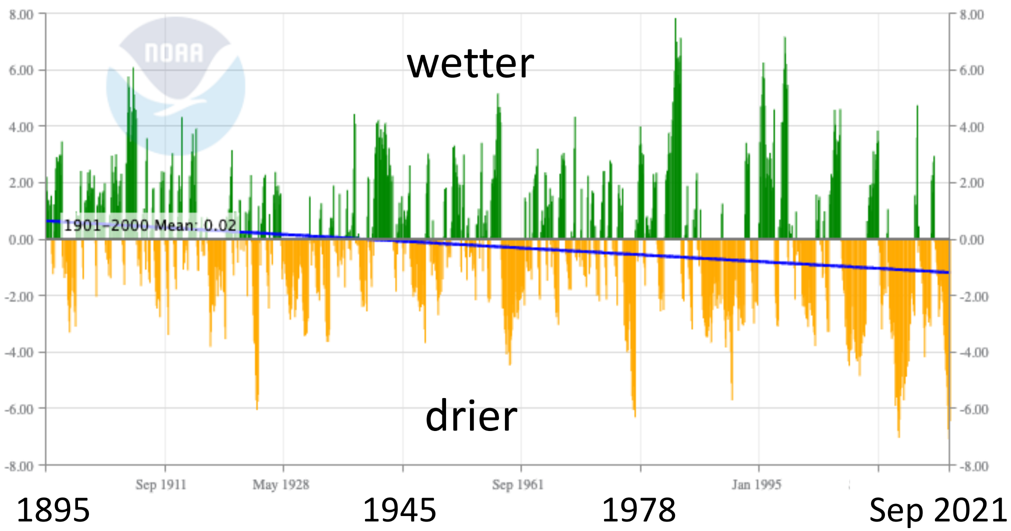


Carbon Monitoring Across Western US

US Drought Monitor,
Oct 26, 2021

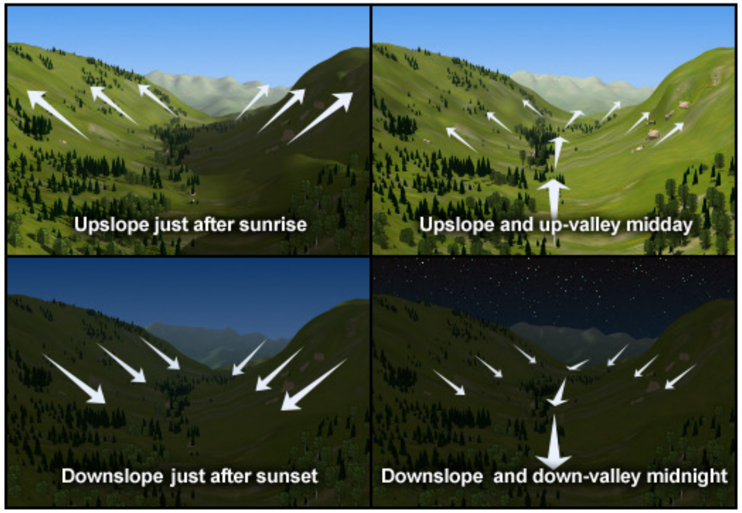


Palmer Drought Severity Index
(1895-present for California)



Carbon Monitoring Across Western US

- Complex terrain challenges traditional carbon monitoring, flux towers, atmospheric inversions



- Approaches to quantify regional land-atmosphere exchange of CO_2

Top-Down Modeling

Atmospheric CO_2

↓

Atm. Transport Model

↓

Land carbon exchange

Bottom-Up Modeling

Weather/Climate

↓

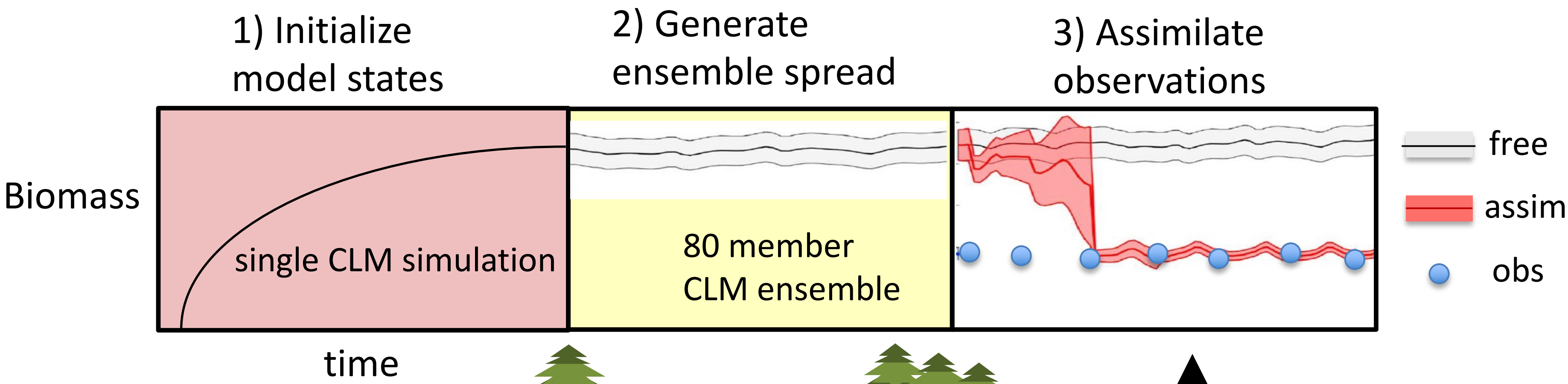
Land Surface Model (CLM)

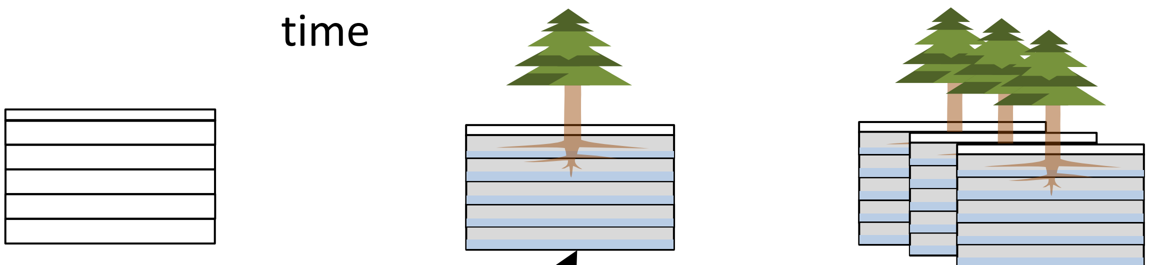
↓

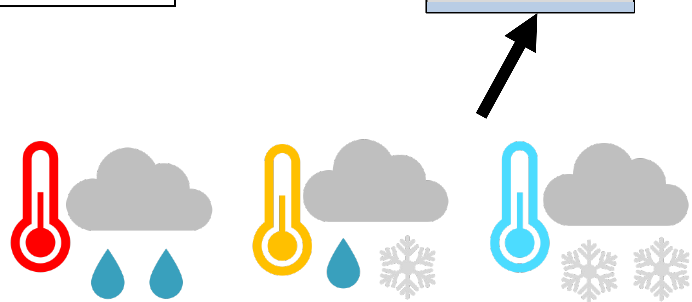
Land carbon exchange

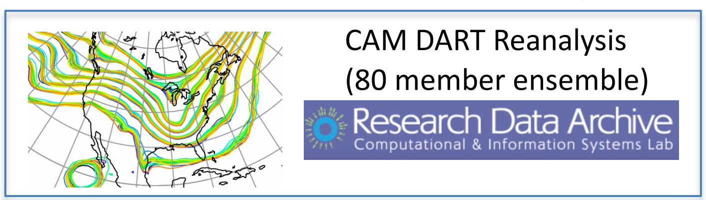
Data Assimilation Research Testbed

Generating an assimilation in CLM5-DART









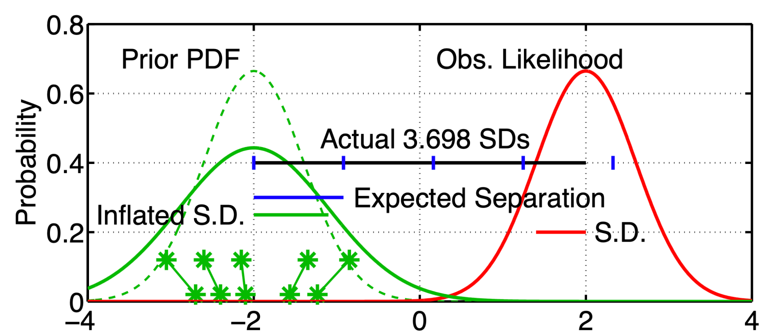
Raeder et al., (2012, 2021)

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

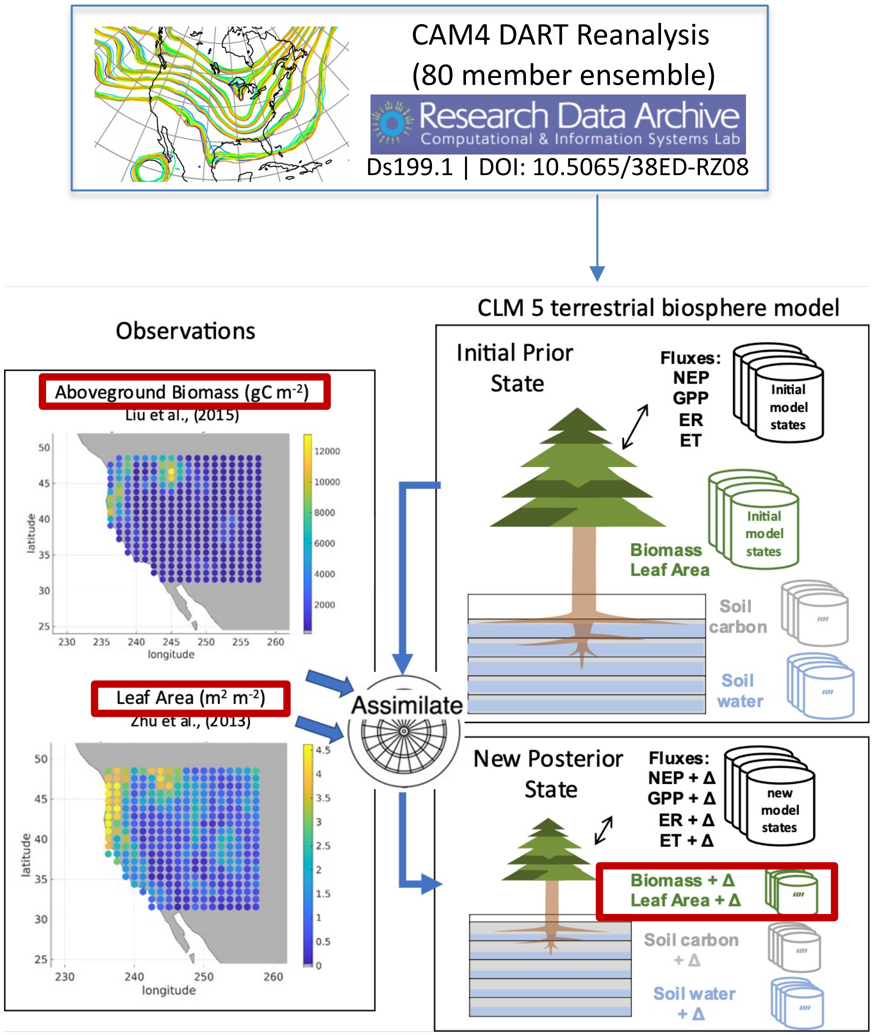
Ds199.1 | DOI: 10.5065/38ED-RZ08
Ds345.0 | DOI: 10.5065/JG1E-8525

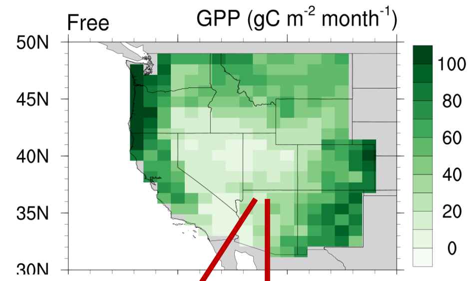
'Inflation' helps maintain ensemble spread

- Ensemble Sampling error
- Model vs. Observation Bias

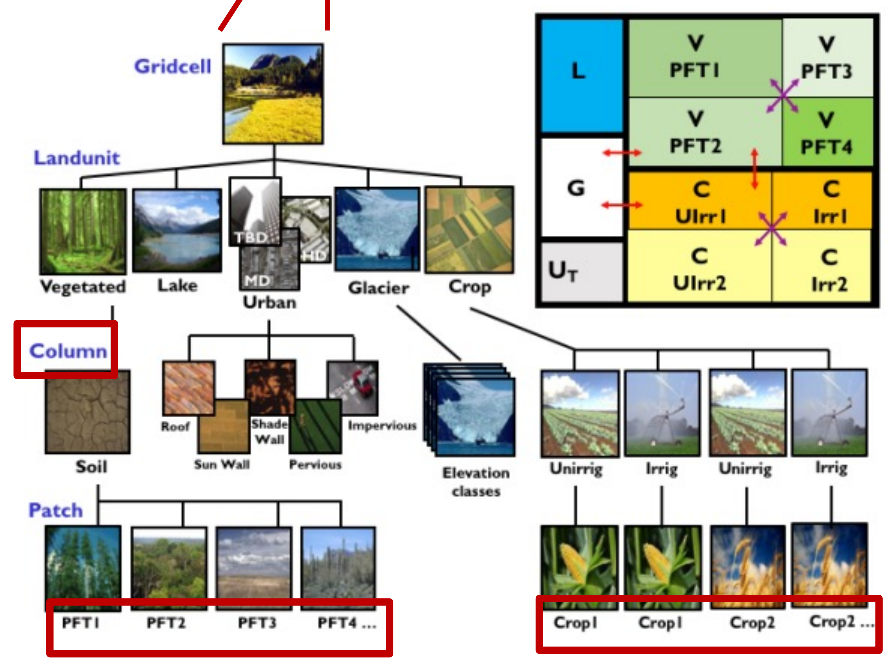


CLM5-DART Overview





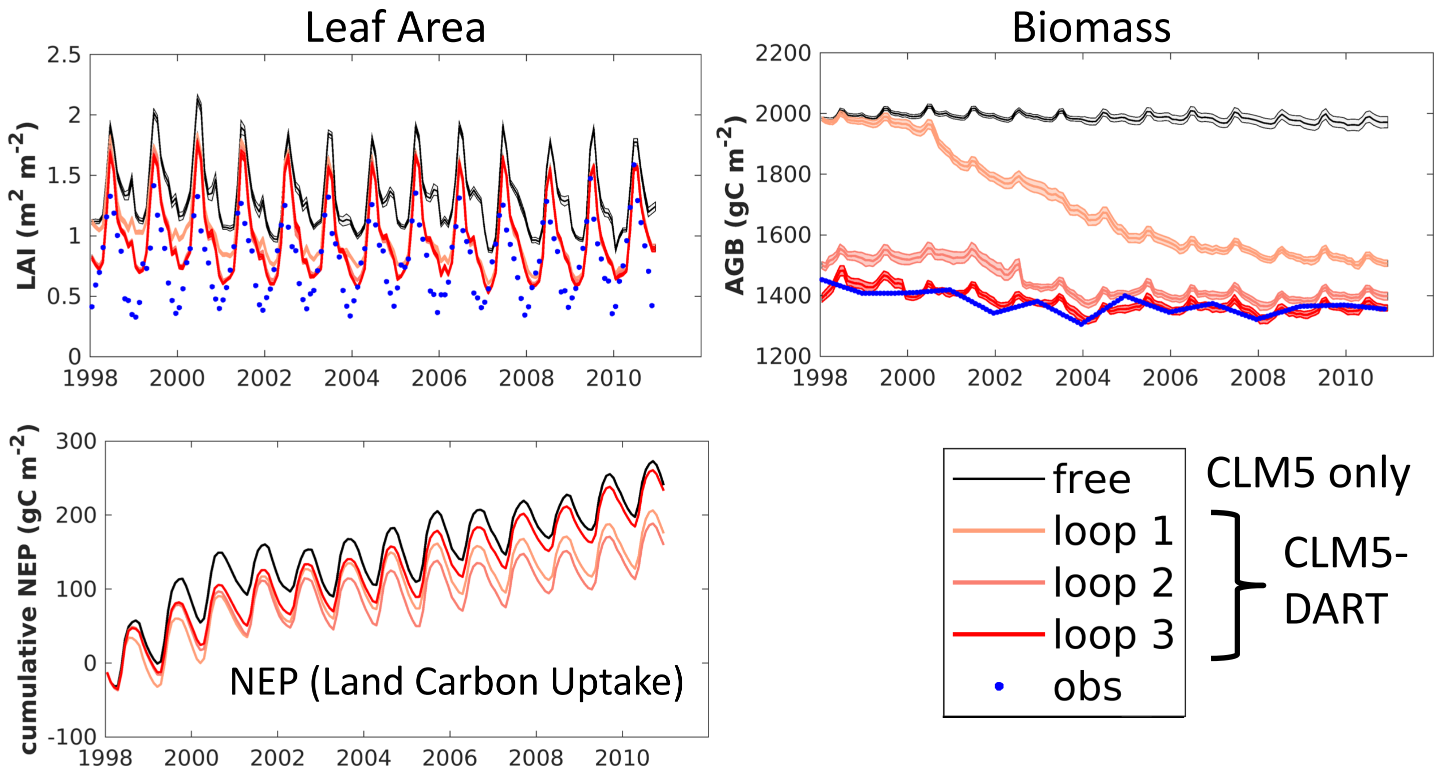
Grid Cell (~1°x1°)

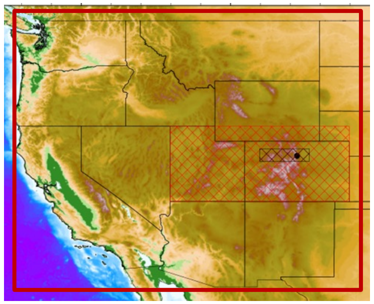


'Localized' the adjustments to biomass: 7 carbon and 7 nitrogen state variables

Observations reduce biomass/leaf area, net carbon flux steady

- ~30 % reduction in AGB and LAI respectively



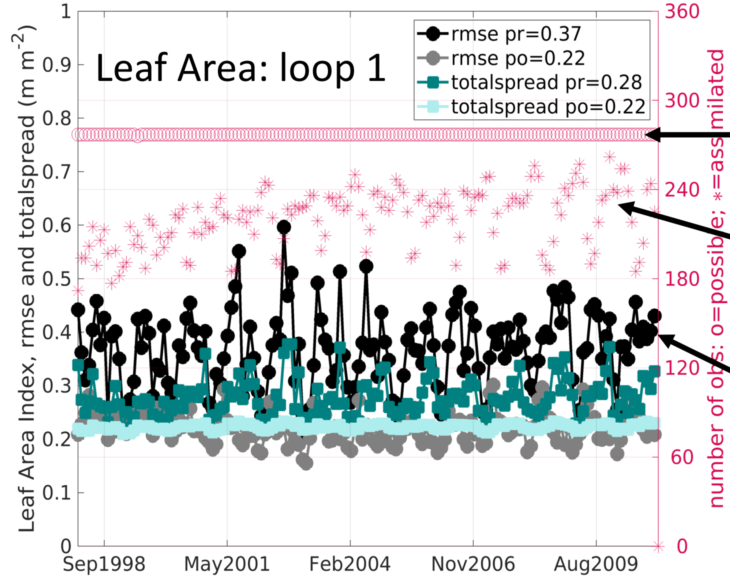


Simulation Name	AGB (kgC m^{-2})	LAI (m m^{-2})	GPP (gC m^{-2} month^{-1})	ER (gC m^{-2} month^{-1})	NEP (gC m^{-2} month^{-1})
Free	1.98	1.31	48.18	47.18	1.00
CLM5-DART	1.36	0.96	38.49	37.21	1.28

Data Assimilation Research Testbed

Diagnostics of LAI/AGB observation acceptance and RMSE

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

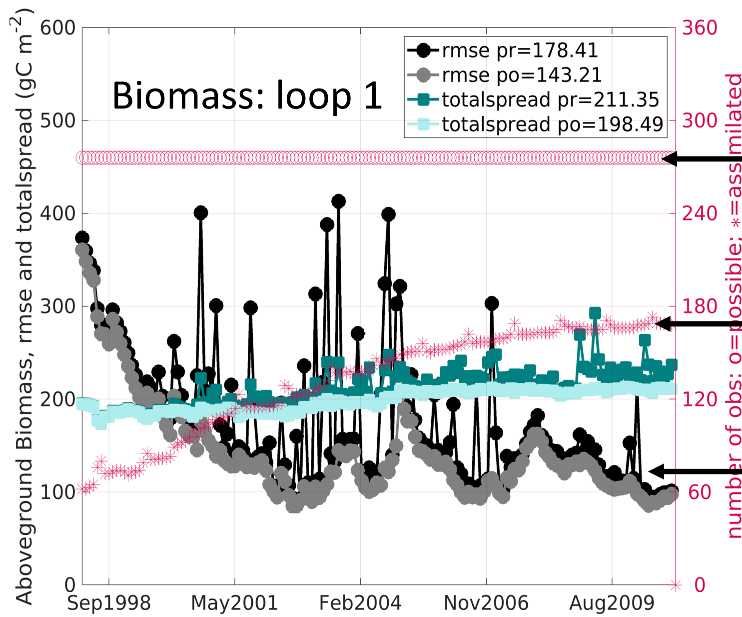


Observations possible

Observations assimilated

Prior RMSE

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



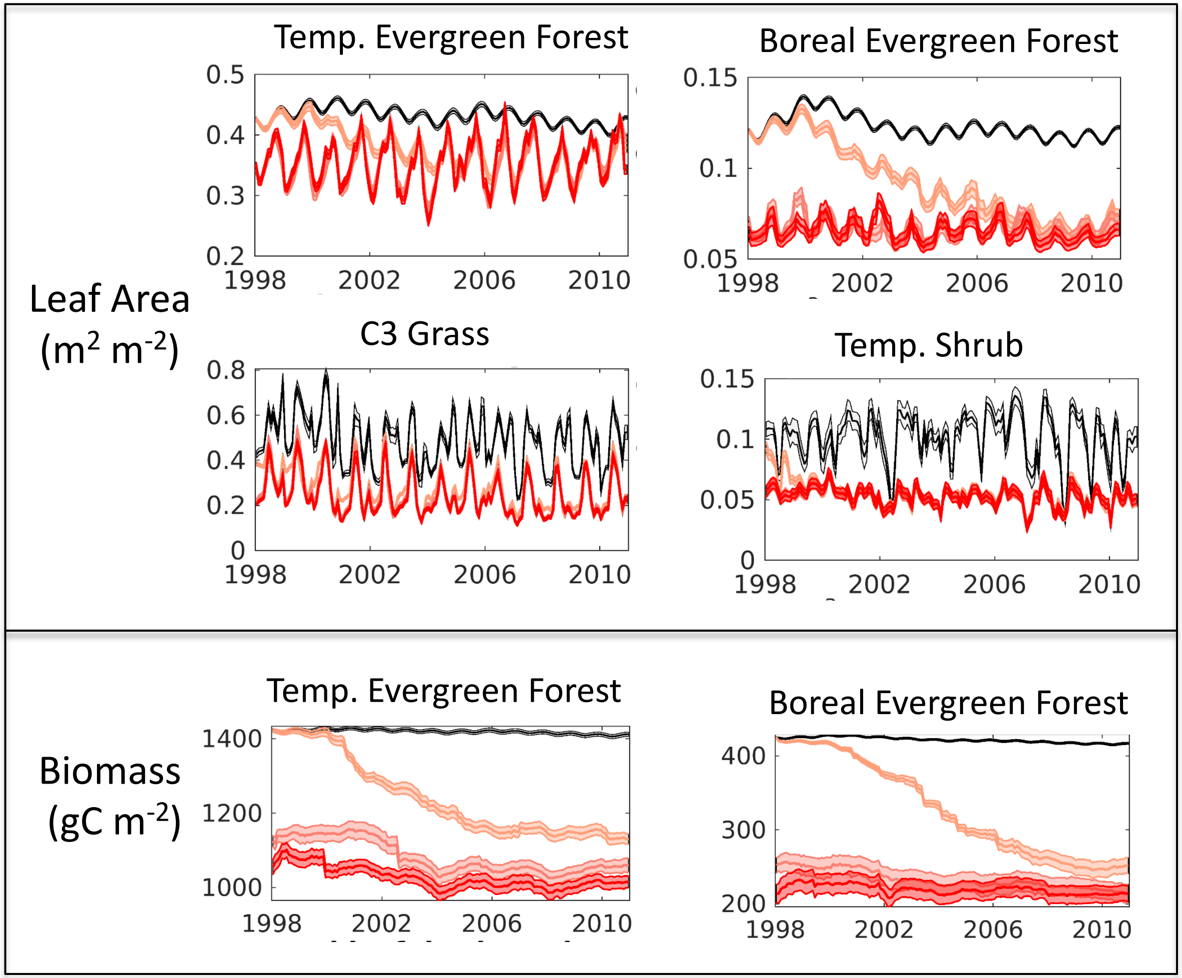
Observations possible

Observations assimilated

Prior RMSE

Data Assimilation Research Testbed

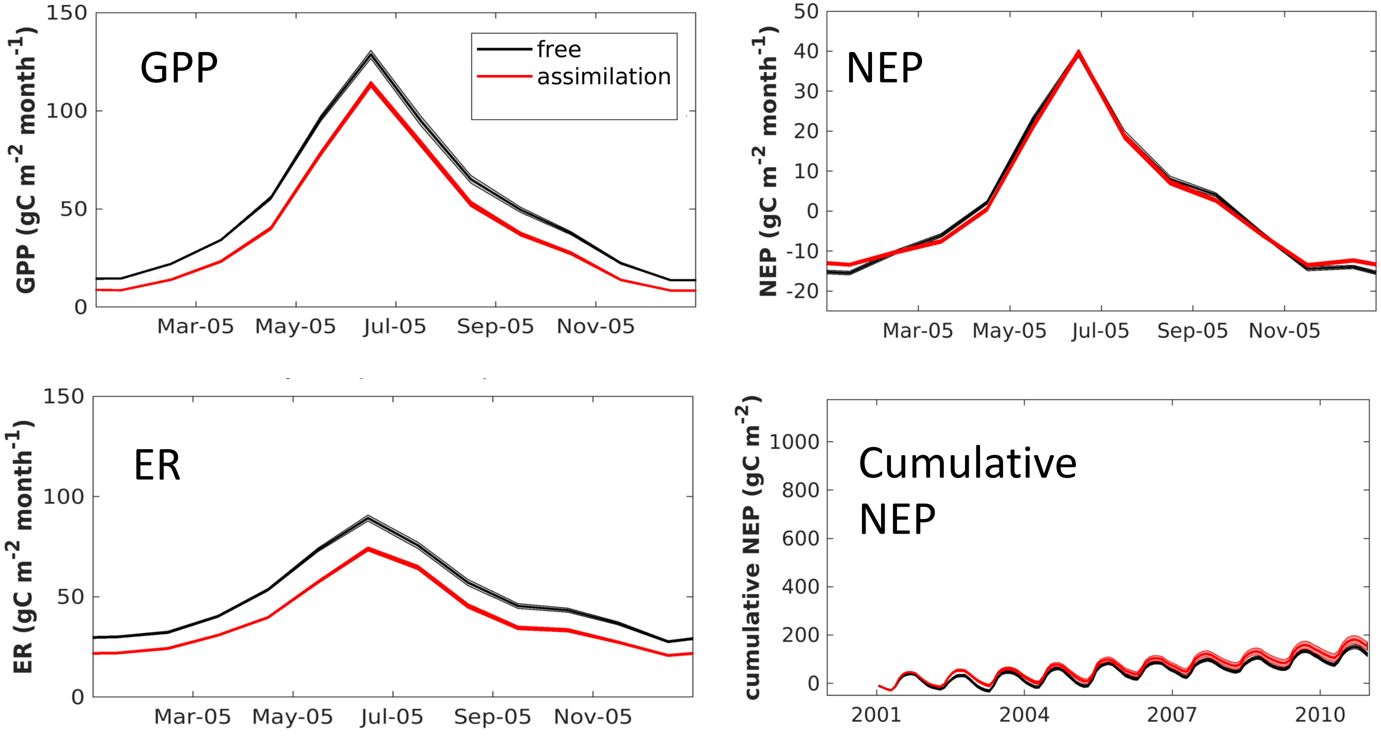
Behavior for dominant Plant Functional Types



Data
Assimilation
Research
Testbed

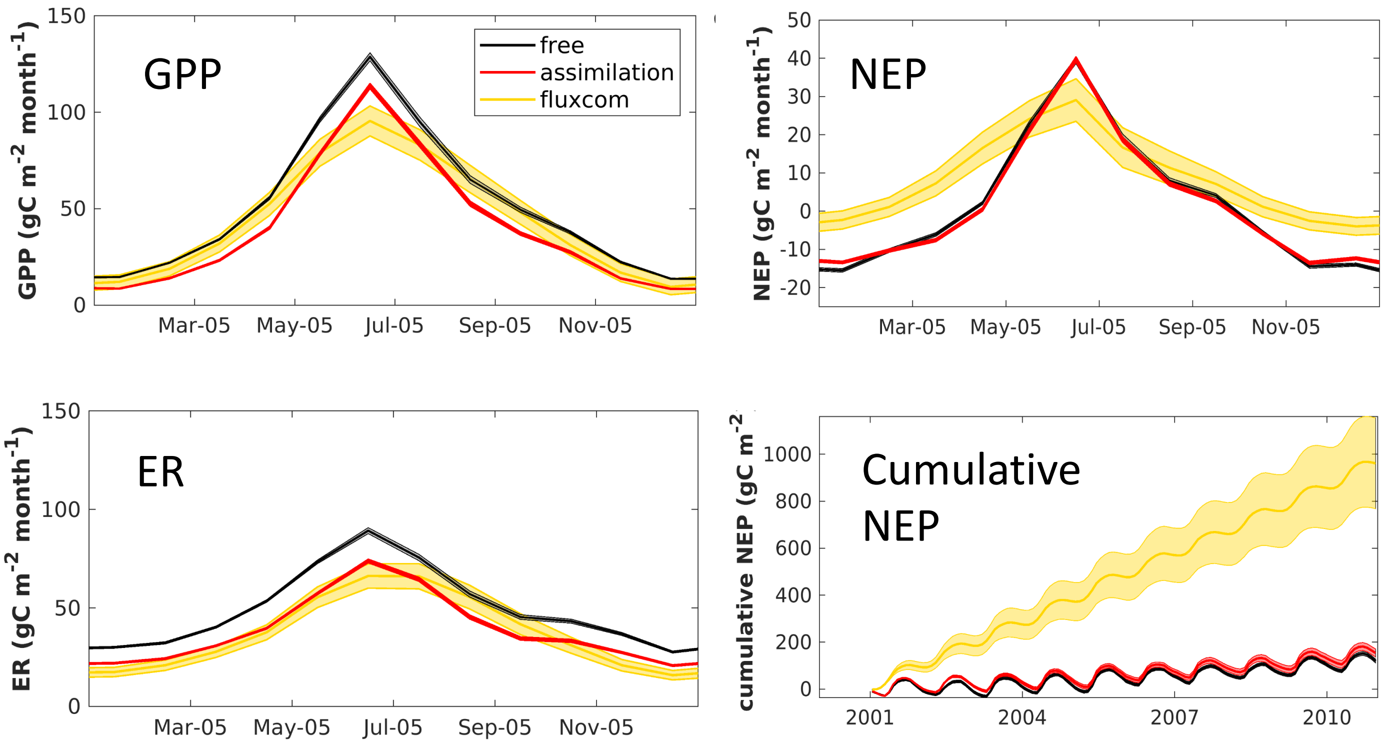
CLM5-DART simulates weak carbon sink compared to FLUXCOM

- CLM5-DART (red) reduces biomass states create offsetting reductions in GPP and ER compared to free run



CLM5-DART simulates weak carbon sink compared to FLUXCOM

- CLM5-DART (red) reduces biomass states create <u>offsetting</u> reductions in GPP and ER compared to free run
- FLUXCOM (yellow): Machine learning approach that trains satellite data and meteorology to flux tower data to generate a carbon flux product Jung et al., (2020).



<u>CLM5-DART:</u>

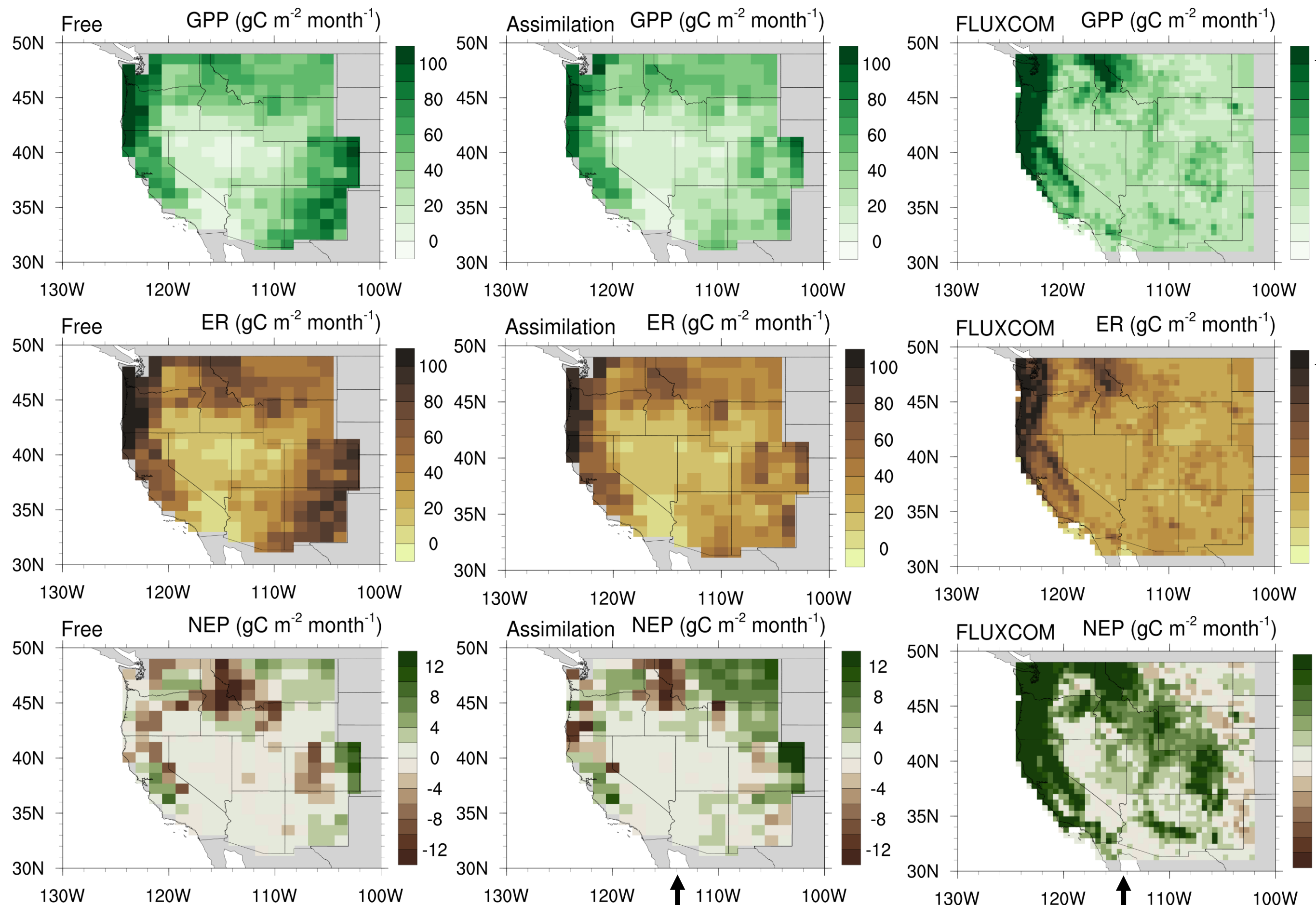
- Strength: more explicit disturbance history, not dependent on flux tower CO_2 data
- Weakness: limited adjusted variables (biomass)

Data
Assimilation
Research
Testbed

CLM5-DART simulates weak carbon sink compared to FLUXCOM

1998-2011 Average Fluxes

Free CLM5 | CLM5-DART | FLUXCOM



GPP

ER

NEP

Weak, neutral uptake

Strong uptake

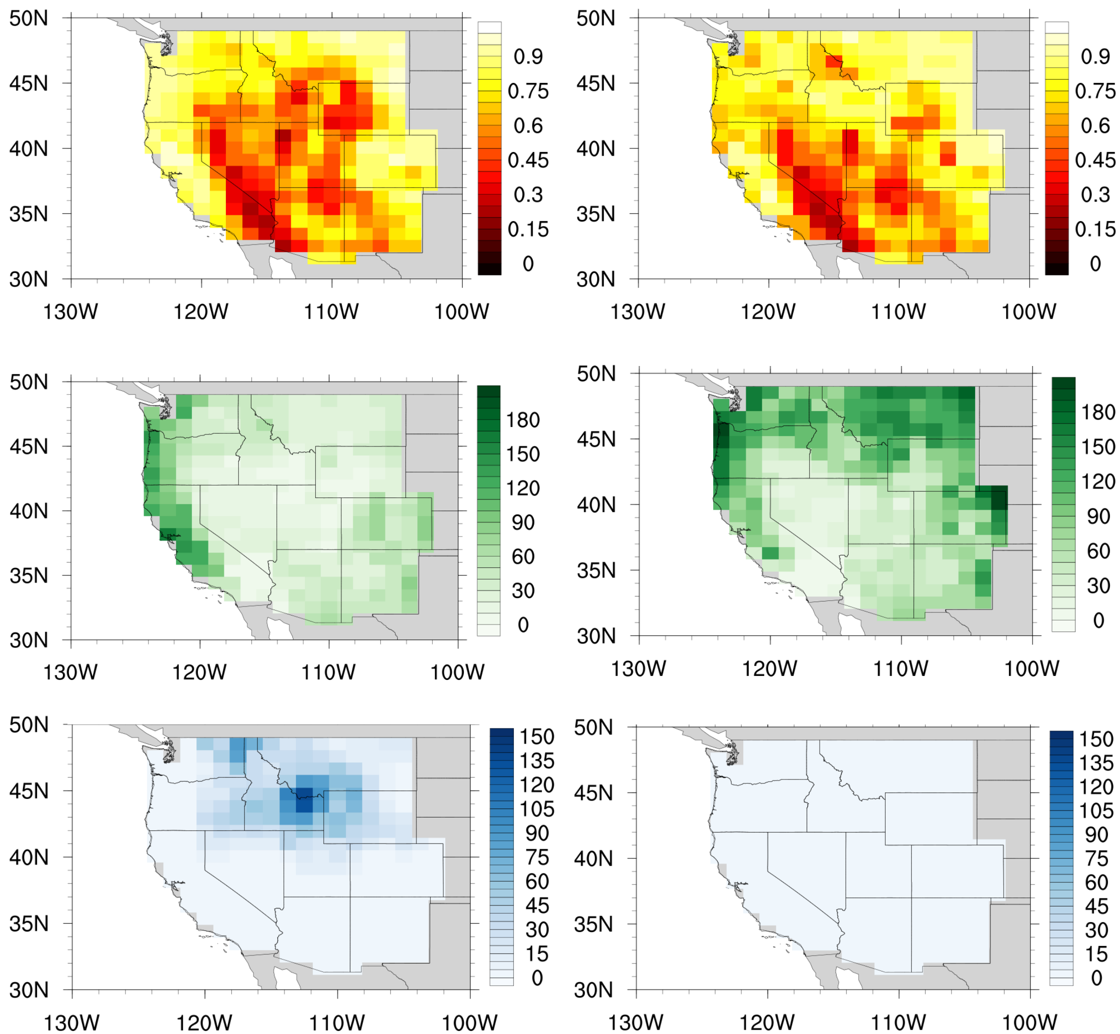
Water limitation shapes carbon uptake pattern

Spring (1998-2011) Summer (1998-2011)

Soil moisture limitation (0-1)

GPP (gC m^{-2} mth^{-1})

Snow water equivalent (mm)



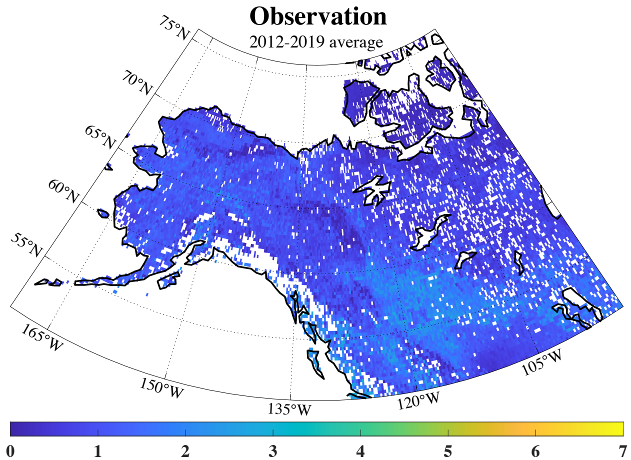
- Soil moisture limitation and GPP highly correlated (spring: R=0.64; summer: R=0.67)
- Simulated snow has low bias

Data Assimilation Research Testbed

Current Land Data Assimilation: Arctic

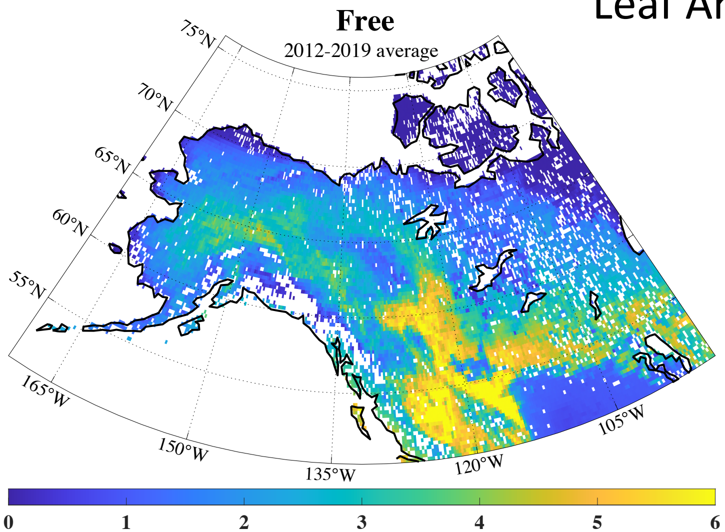
Arctic Boreal Domain (ABoVE Project), Led by: Xueli Huo, Andy Fox

Leaf Area Index (LAI)

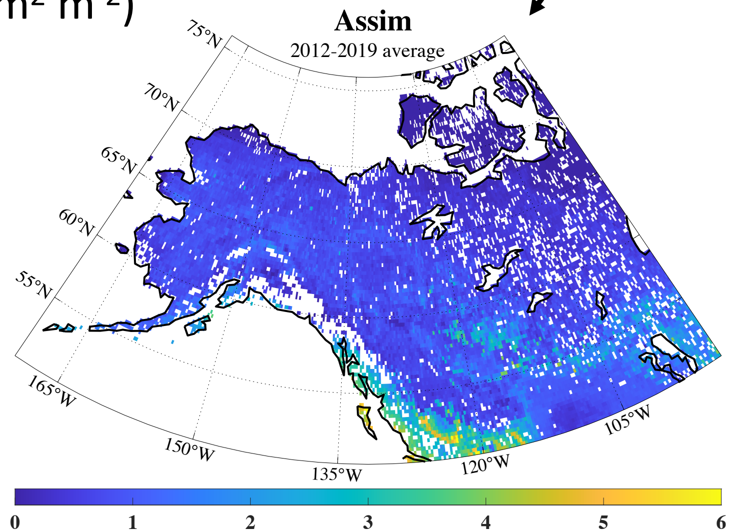


Leaf Area (m^2 m^{-2})

- 30 % reduction in Leaf Area



Leaf Area (m^2 m^{-2})

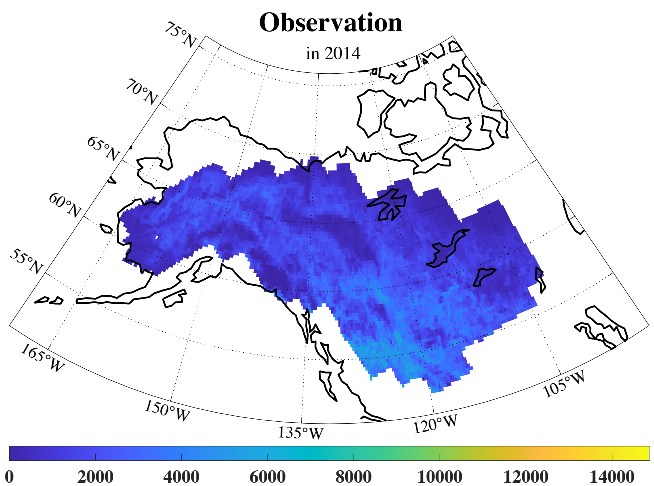


Leaf Area (m^2 m^{-2})

Current Land Data Assimilation: Arctic

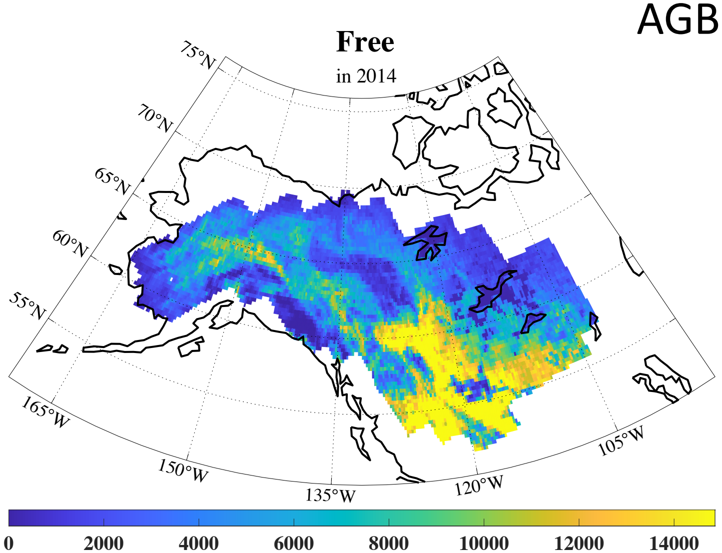
Arctic Boreal Domain (ABoVE Project), Led by: Xueli Huo, Andy Fox

Aboveground Biomass (AGB) (gC m^{-2})

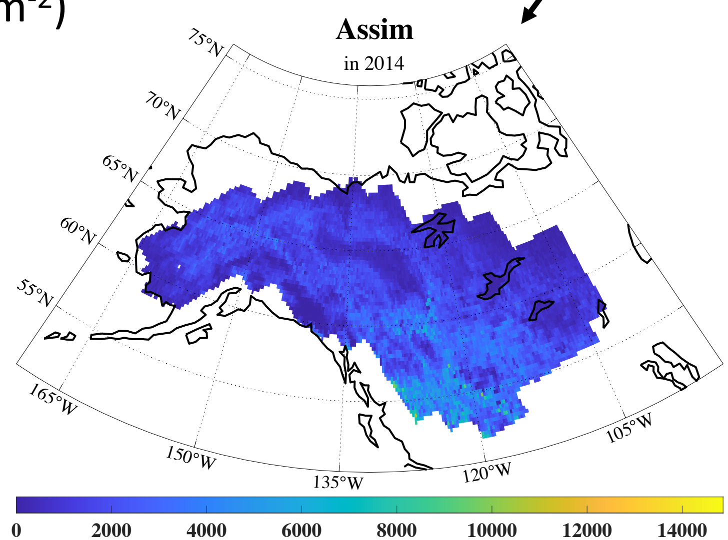


AGB (gC m^{-2})

- 70 % reduction in AGB



AGB (gC m^{-2})



AGB (gC m^{-2})

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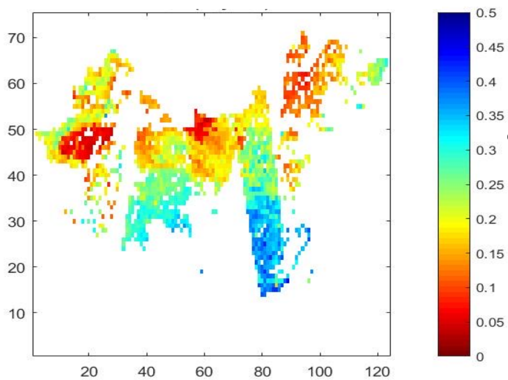
Current Land Data Assimilation: Soil Moisture

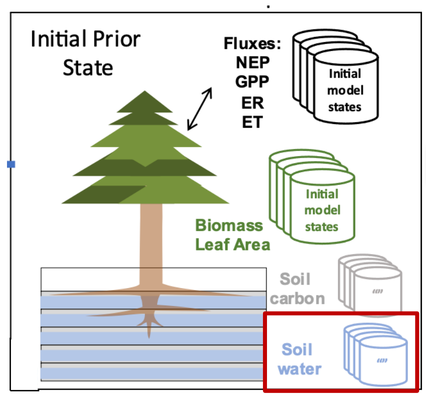
- Gap-Filling Soil moisture products across China
- European Space Agency Climate Change Initiative Essential Climate Variable (ECV)

ECV Soil Moisture Product ($m^3\ m^{-3}$)



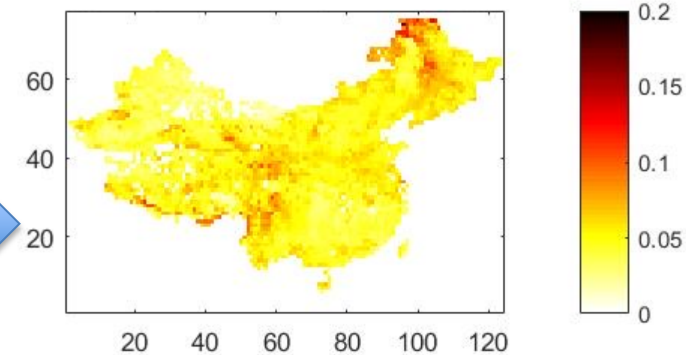
+

CLM-DART

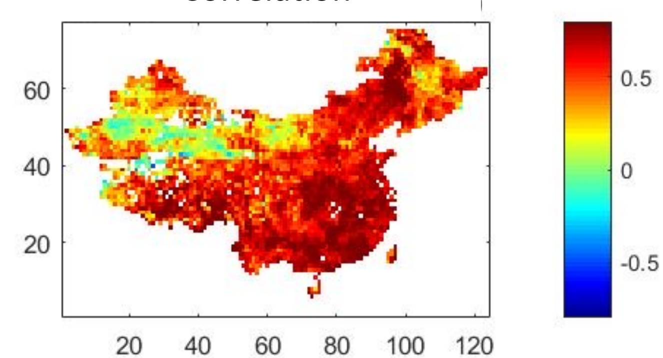


Compares favorably to GLEAM Soil Moisture Data Product (1998)

Unbiased RMSD ($m^3\ m^{-3}$)



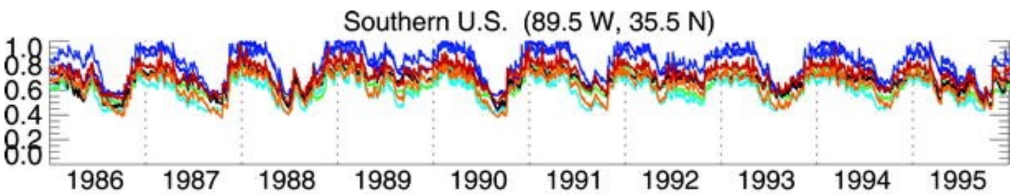
Correlation



Led by: Daniel Hagan, Nanjing University of Information Science & Technology

Challenges in Land DA : Soil Moisture

- Soil moisture data are prone to systemic bias in magnitude

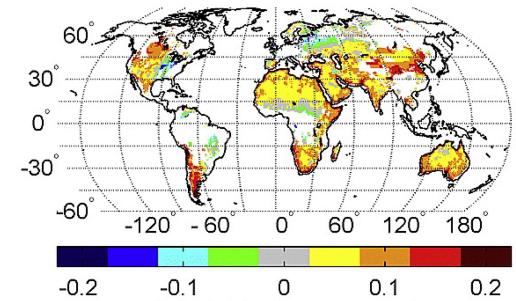


volumetric soil moisture (mm^3/mm^3); Koster et al., 2009

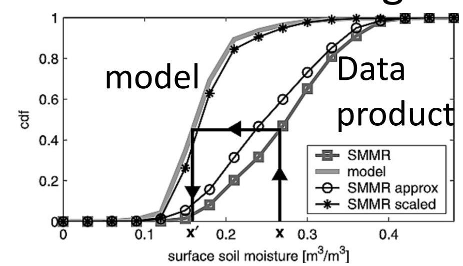
- Model/Data product bias is challenging to address

- The trends and patterns in the data are useful. Cumulative Distribution Function (CDF) matching re-scales data products to match the magnitude and variation of model

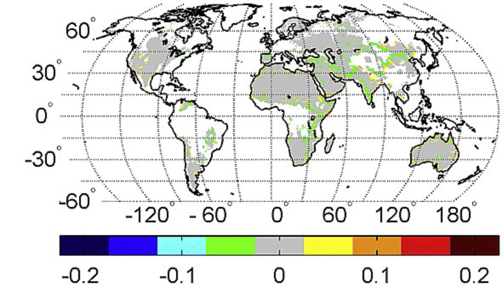
(Model) – (Data Product), Before



CDF Matching



(Model) – (Data Product), After



Reichle & Koster 2004 (GRL)

Current challenges in Land DA : Snow

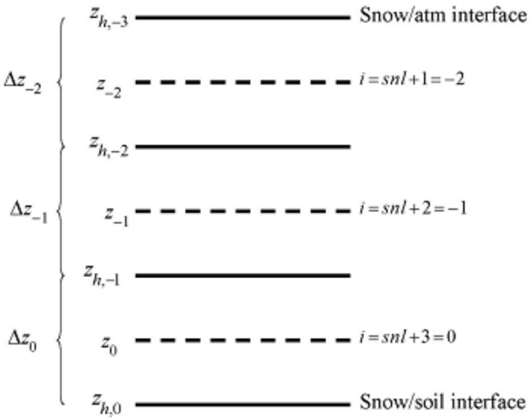
<u>Snow Hydrology</u>: Snow Water Equivalent

Ice content
Water content

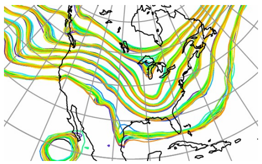
<u>Snow Albedo</u>: Surface Energy Balance

Black/organic carbon
Dust
Snow Grain radius

- CLM snow will compact and subdivide into layers depending upon layer thickness
- This creates unique snow properties for each layer
- This presents challenges for DA systems

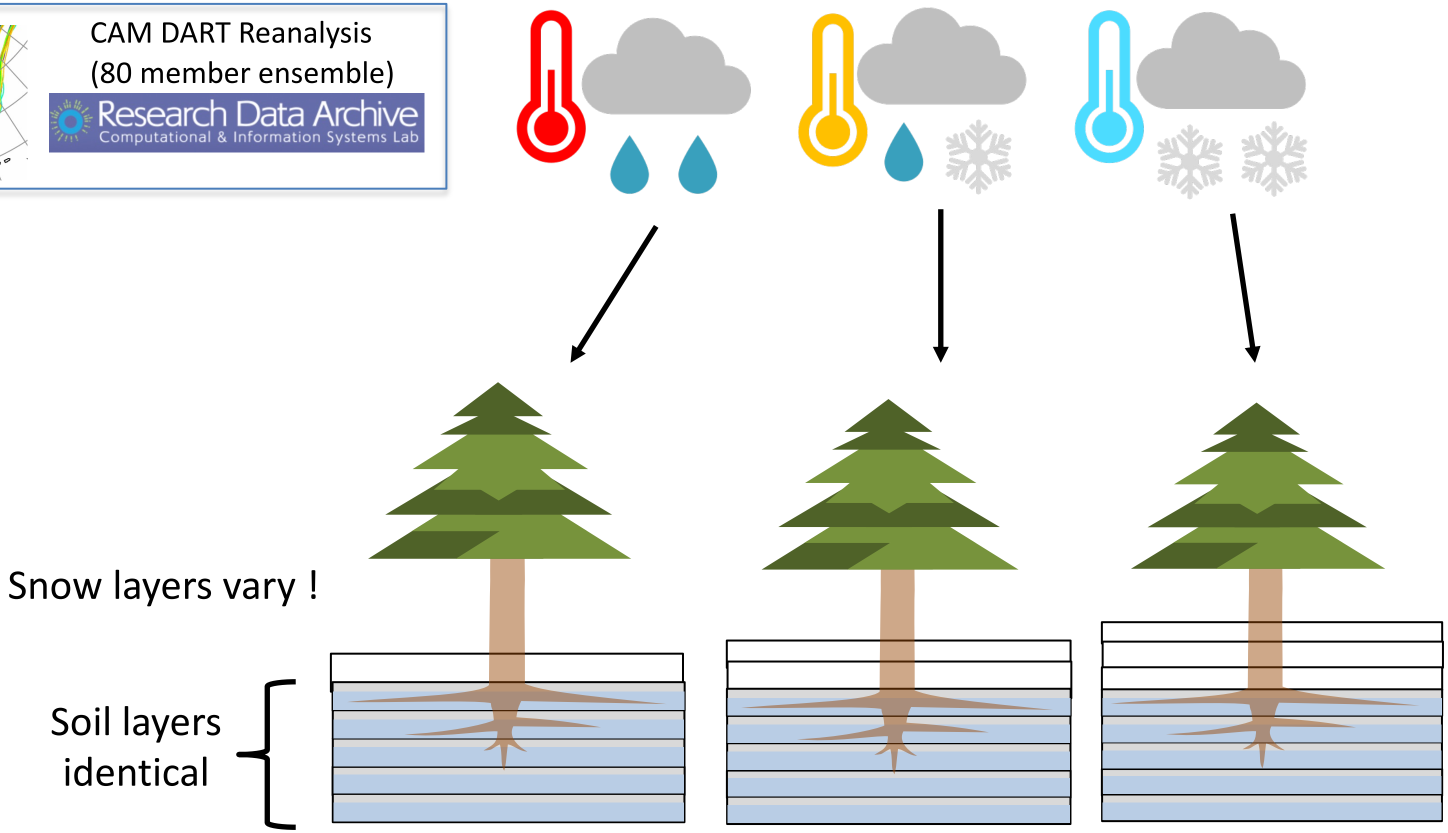


Current challenges in Land DA : Snow



CAM DART Reanalysis
(80 member ensemble)

Research Data Archive
Computational & Information Systems Lab



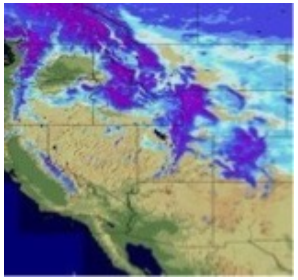
- Standard implementation of DART regression and update step will not work if layer (and property) does not exist for all ensemble members

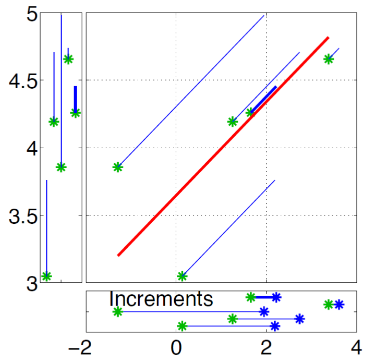
Data Assimilation Research Testbed

Current challenges in Land DA : Snow

Standard Approach

Snow (SWE) Observations





Model Estimated SWE

Snow Layer Property $_{i = n}$

Snow Layer$_i$ + Δ	
" " + Δ	i= 2
" " + Δ	i= 3
" " + Δ	i= n
Ground	

✕ Snow updates not internally consistent

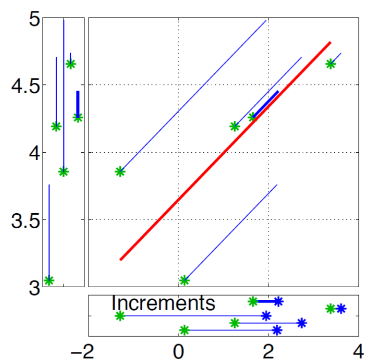
Δ Total SWE ≠ Σ(ΔLayers)

Δ Total Ice ≠ Σ(ΔLayers)

Δ Total Liquid ≠ Σ(ΔLayers)

Δ Total Depth ≠ Σ(ΔLayers)

Added Snow re-partitioning algorithm



Model Estimated SWE

Column SWE

Repartitioning Algorithm

Snow Layer$_i$ + Δ	
" "	i= 2
" "	i= 3
" "	i= n
Ground	

√ Snow updates are internally consistent

Δ Total SWE = Σ(ΔLayers)

Δ Total Ice = Σ(ΔLayers)

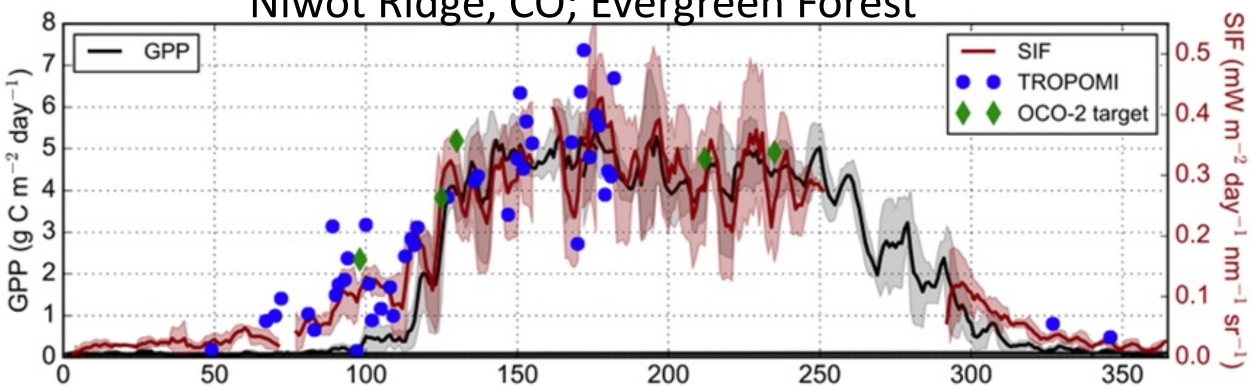
Δ Total Liquid = Σ(ΔLayers)

Δ Total Depth = Σ(ΔLayers)

Data Assimilation Research Testbed

Challenges in Land DA: Solar-Induced Fluorescence

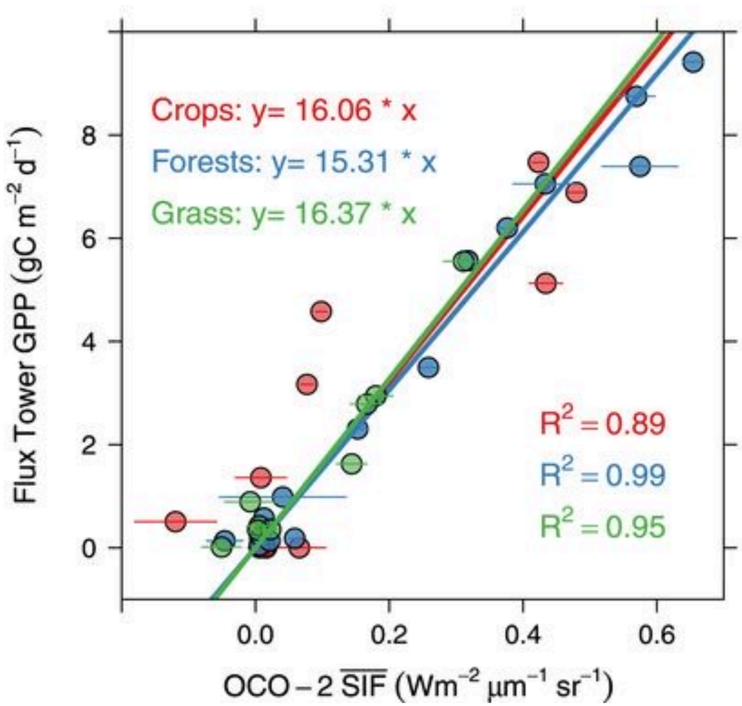
- SIF is a useful indicator of timing/magnitude of photosynthesis (GPP)



Day of Year

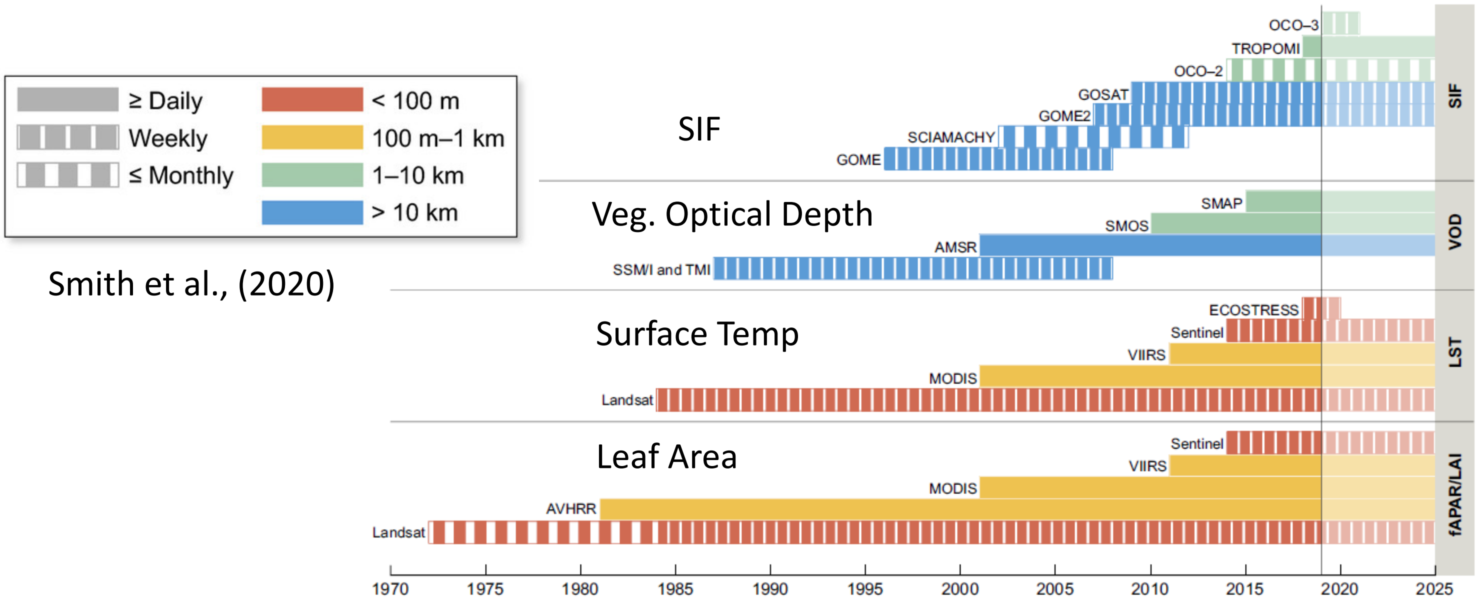
Magney et al., (2019)

- Strong SIF-GPP relationship across many vegetation types



Sun et al., (2018)

Advancing observations & models together

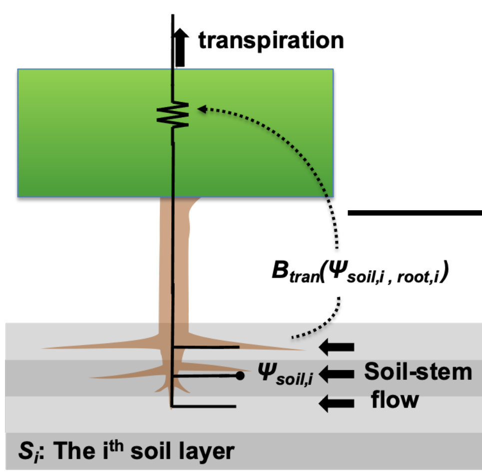


Smith et al., (2020)

Expanding satellite observation network

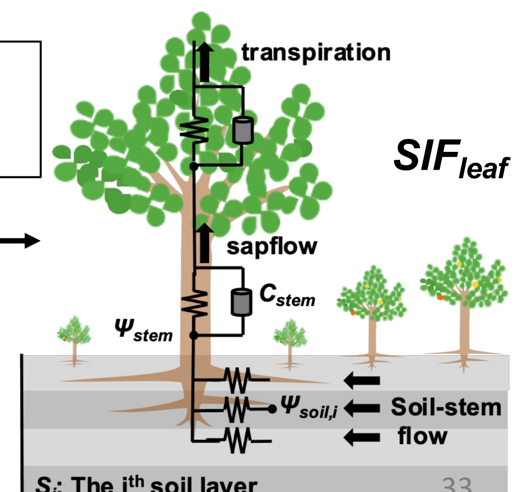
(Leaf water potential) Ψ_{leaf} SIF_{canopy}

CLM 4.5
(Soil Moisture Stress Formulation)



Increasing model complexity

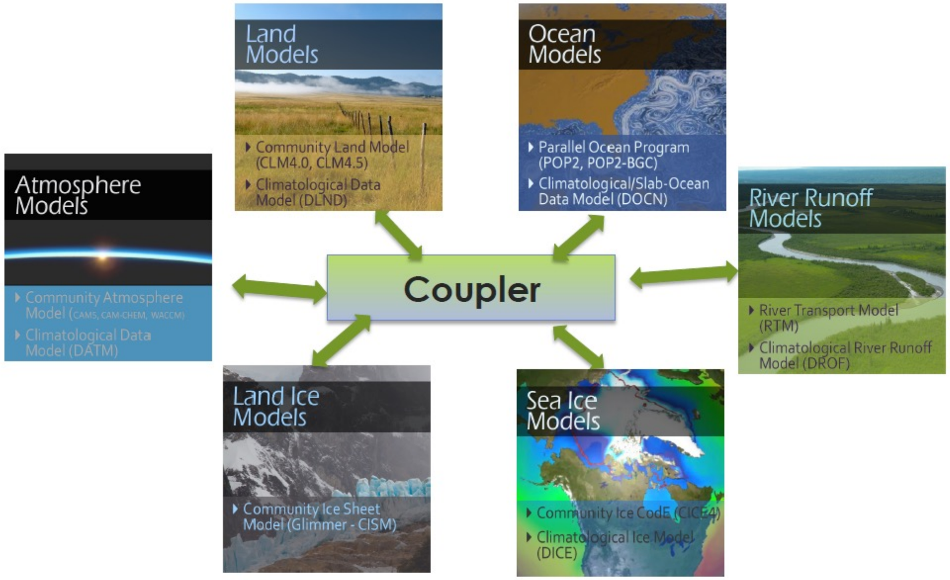
Current: CLM 5.0
Added Hydraulic Stress & SIF



SIF_{leaf}

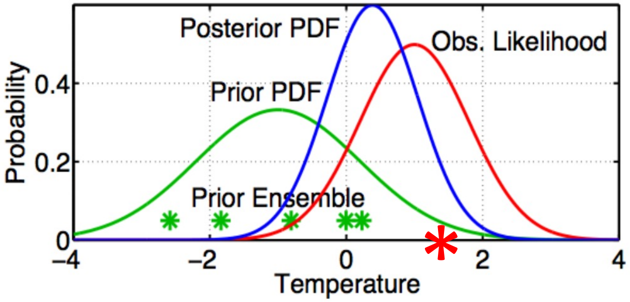
Advances in DART

- Increased emphasis on coupled Earth System assimilations (e.g. land-atmosphere coupling)

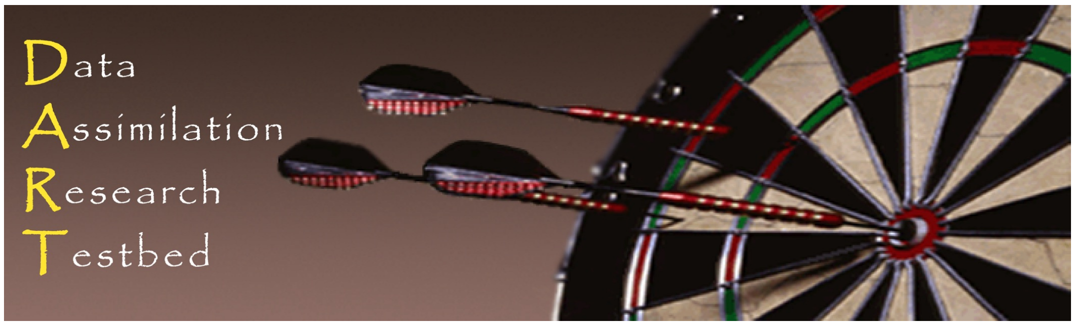


- Addressing Bounded Quantities:

  General Ensemble Filtering Framework Using Quantiles (GEFFQ) – Jeff Anderson



For more information:



https://dart.ucar.edu

https://docs.dart.ucar.edu

dart@ucar.edu

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Computational & Information Systems Lab

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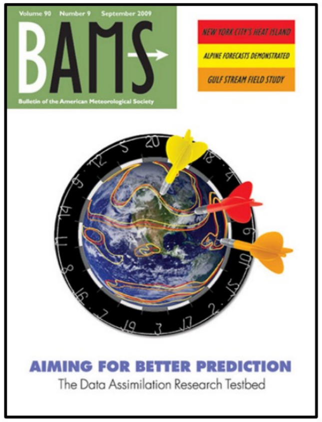
Example of DART workflow

Anderson et al.,2009



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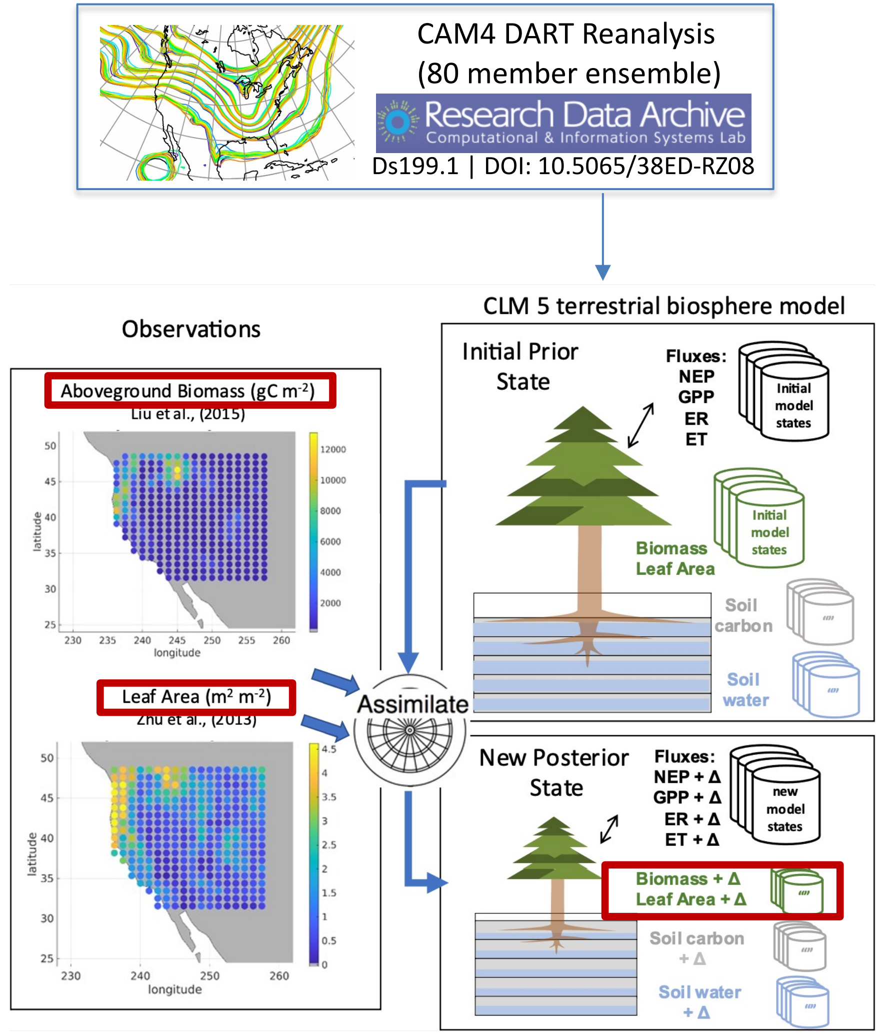
Improving CLM5.0 Biomass and Carbon Exchange Across the Western United States Using a Data Assimilation System

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

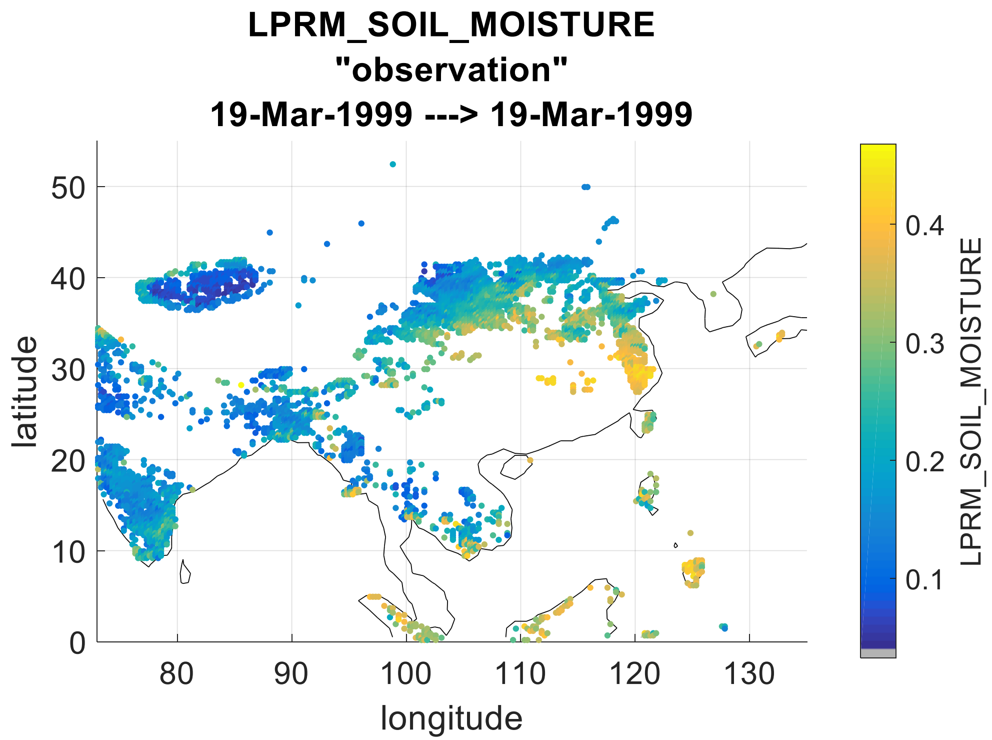
First published: 19 June 2021 | https://doi.org/10.1029/2020MS002421

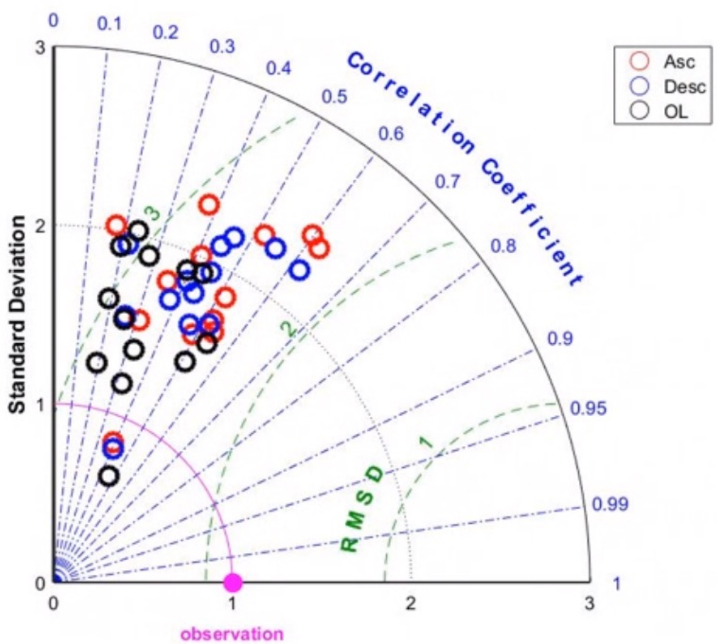


Data Assimilation Research Testbed

Current Land Data Assimilation: Soil Moisture

Assimilating Surface Soil Moisture Observations (Passive/Active Microwave Bands)
Led by: Daniel Hagan, Nanjing University of Information Science & Technology

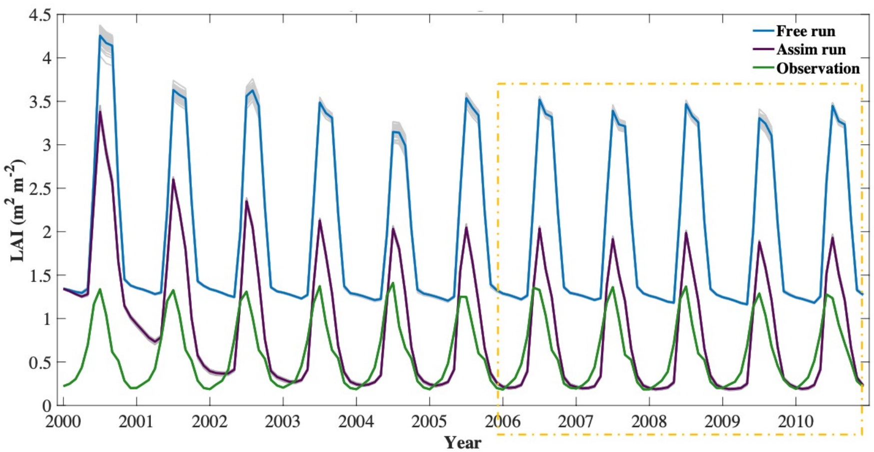


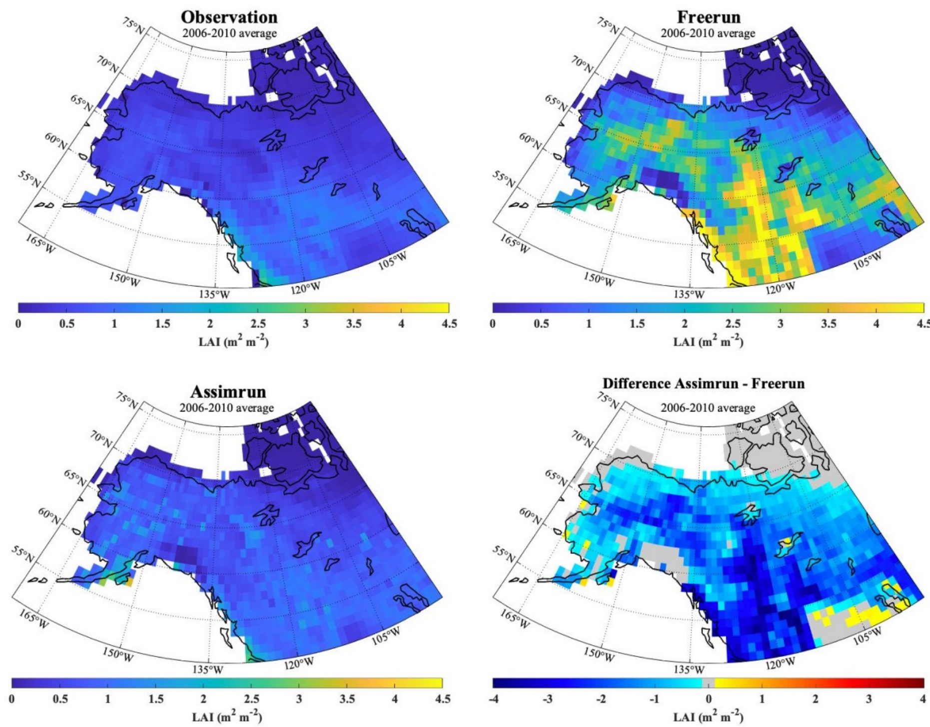


Current Land Data Assimilation: Arctic

Arctic Boreal Domain (ABoVE Project)
Led by: Xueli Huo, Andy Fox and others

Leaf Area (Monthly)

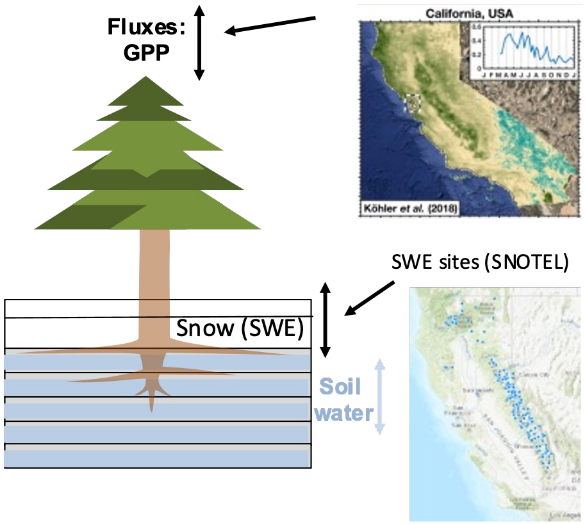




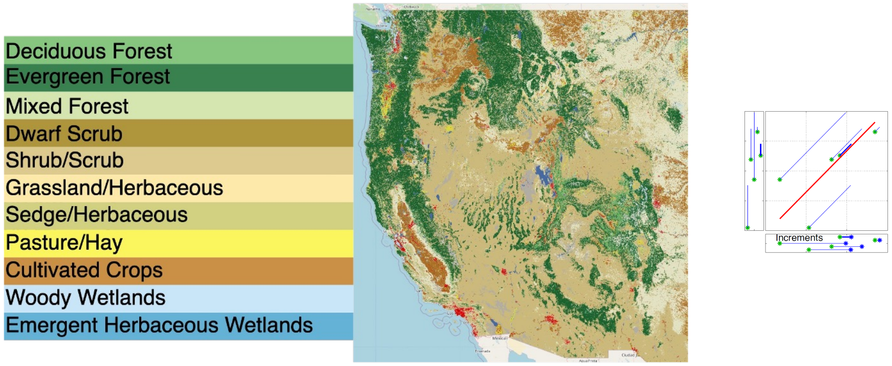
The mean annual LAI in the assimilation run decreased by **63.7%** compared with the free run.

Future Directions

Additional data streams help constrain carbon cycling



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



Finer Spatial Resolution?

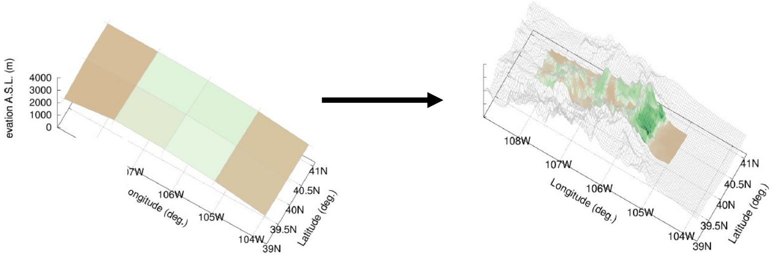
Atmosphere:

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

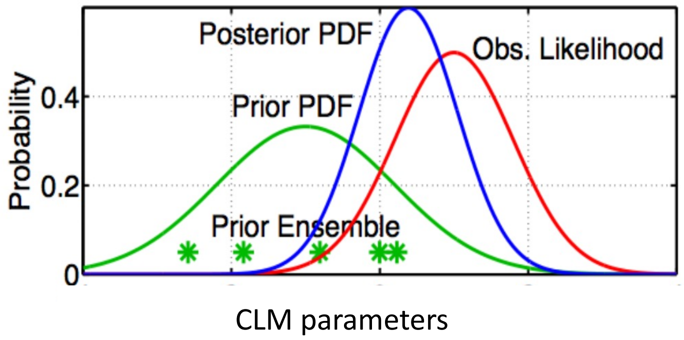
Ds199.1 | DOI: 10.5065/38ED-RZ08

Ds345.0 | DOI: 10.5065/JG1E-8525

Land surface:



Parameter Estimation



Bring models & observations closer together

“Meeting in the middle manuscript”

Alexei Shiklomanov

→Soil moisture/ vegetation optical depth/ radiative transfer characteristics For leaf properties←

Add SIF here as well leaf to canopy level SIF getting closer to observations

Data Assimilation Research Testbed