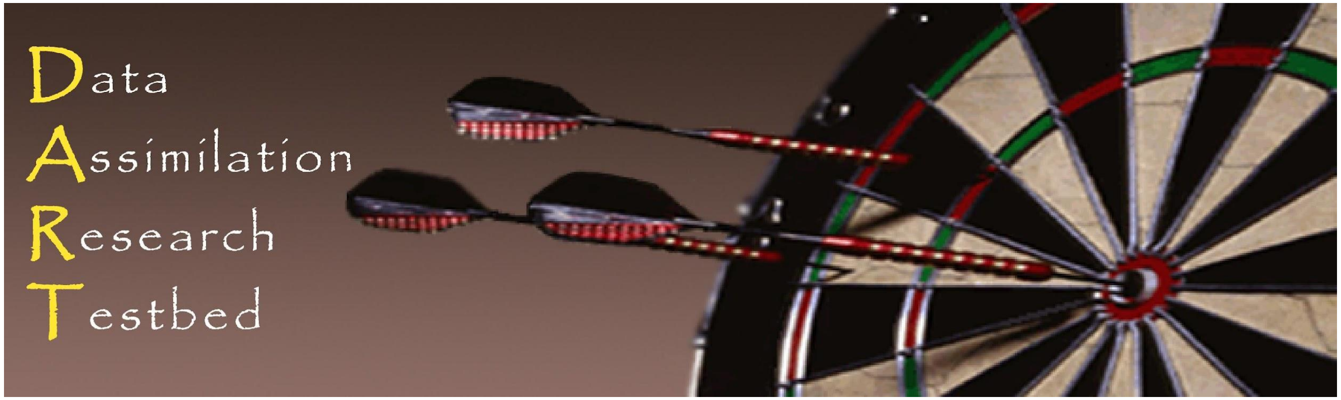


Improving Forecasts of Land Surface Processes using CLM-DART (Data Assimilation Research Testbed)

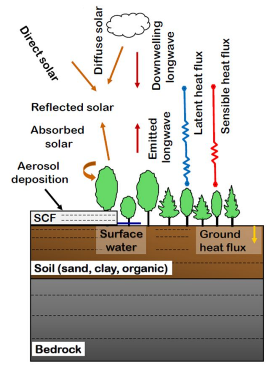
Brett Raczka[1], Xueli Huo[2], Lewis Kunik[2], John C. Lin[2] Daniel Hagan[3], Jiameng Lai[4], Zhenqi Luo[4], Ying Sun[4], Moha Gharamti[1], Kevin Raeder[1], Jeffrey Anderson[1]

[1]NSF National Center for Atmospheric Research, [2]University of Utah, [3]Ghent University, [4]Cornell University

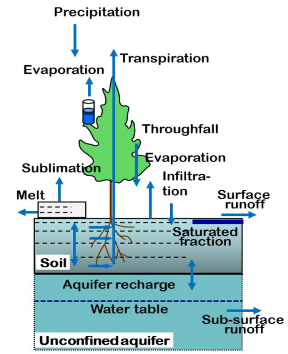
CESM Land Model and Biogeochemistry Working Group Meeting
February 29th, 2024

Approaches to implementing CLM

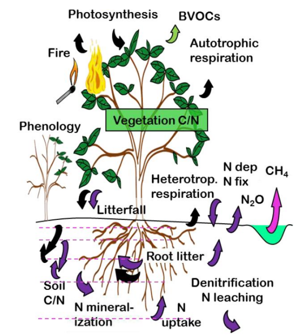
Energy balance



Hydrology



Carbon and nitrogen cycles

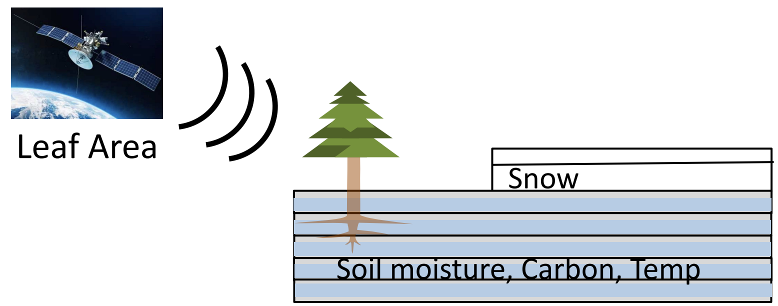


CLM-BGC (Biogeochemistry)

- Initial & boundary conditions
- Parameters/compsets
- No external constraints

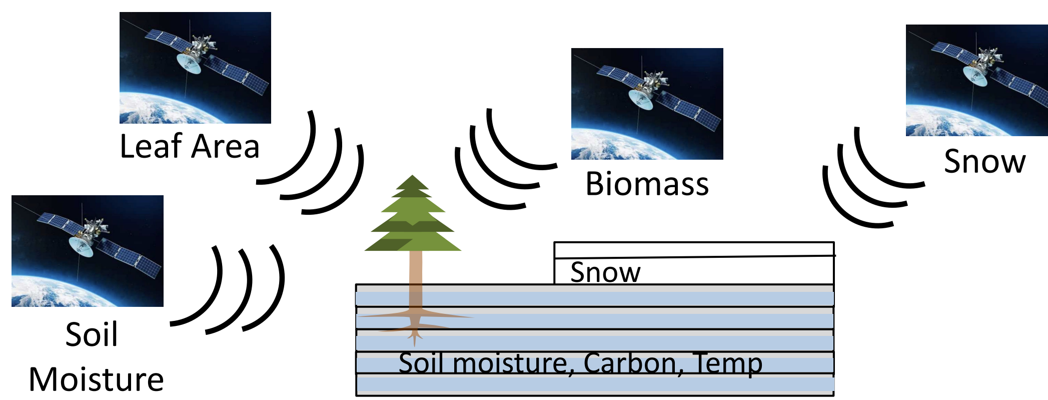
CLM-SP (Satellite Phenology)

- Prescribed Leaf Area

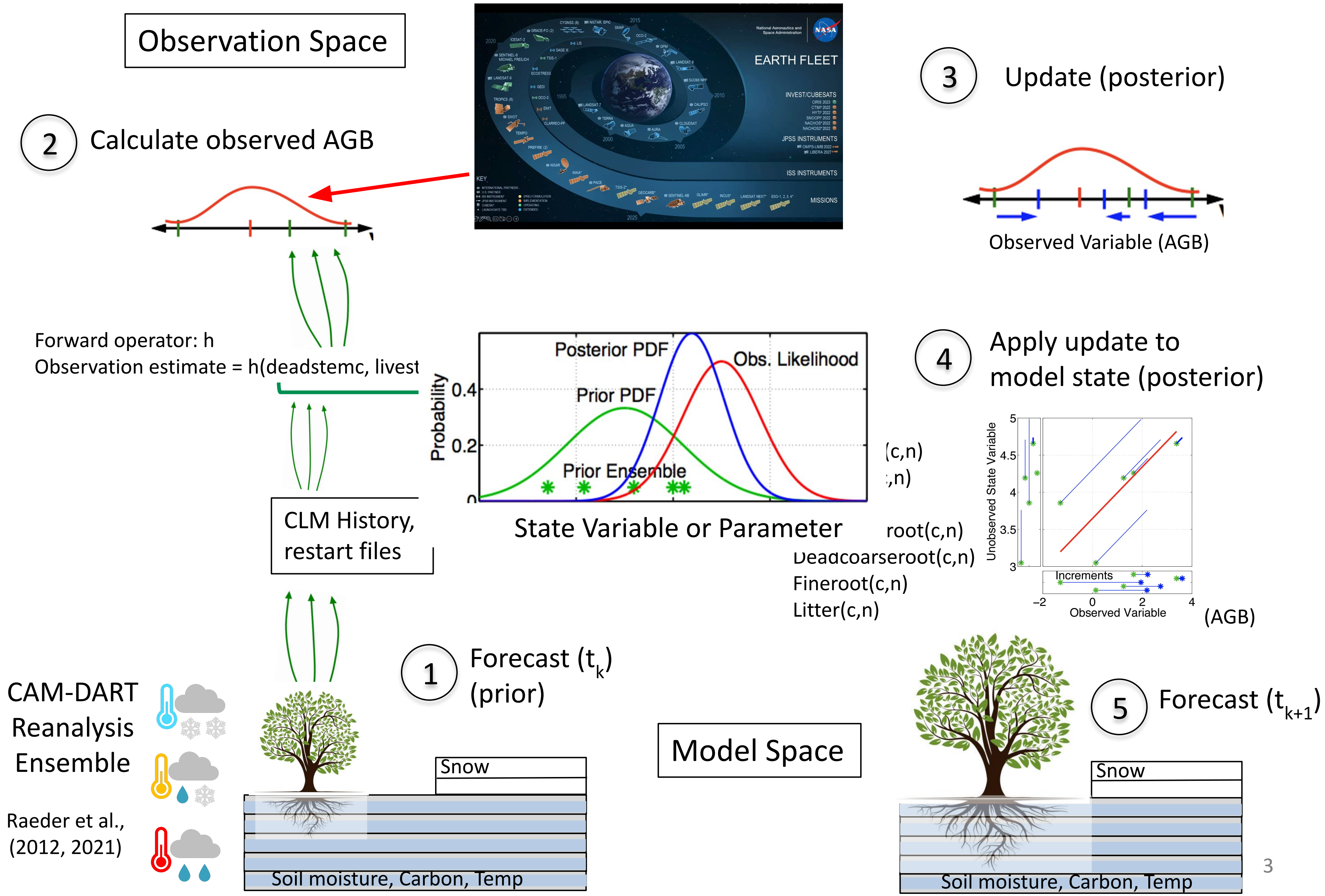


CLM-DART

- Observed and unobserved land surface properties
- Bayesian (prior retained)
- Uncertainty quantification

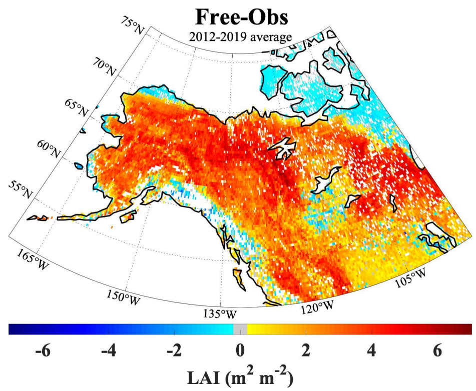


Overview of CLM-DART assimilation steps (biomass example)

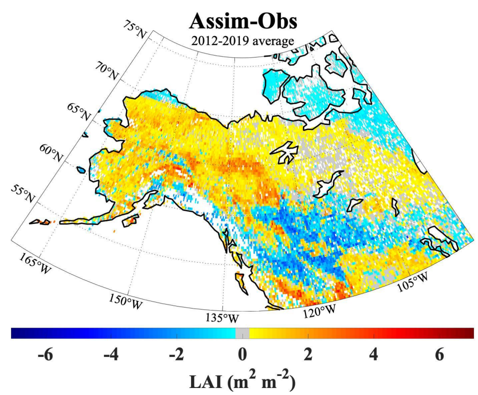


Arctic Ecosystems: Assimilating biomass has cascade effect

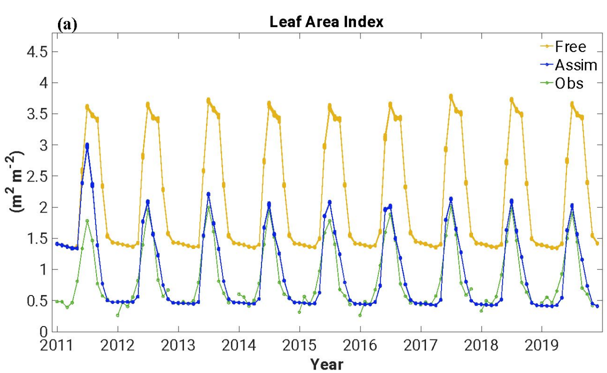
- Free run overestimates leaf area and biomass



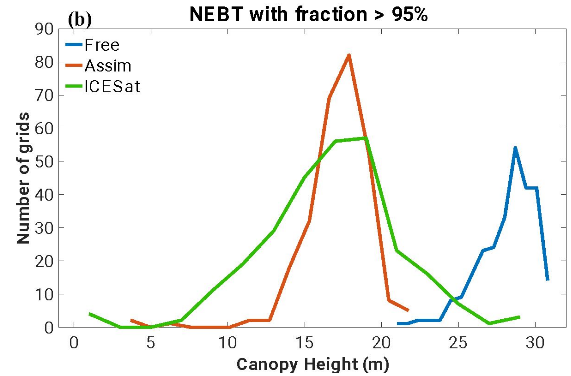
- CLM-DART removes this bias



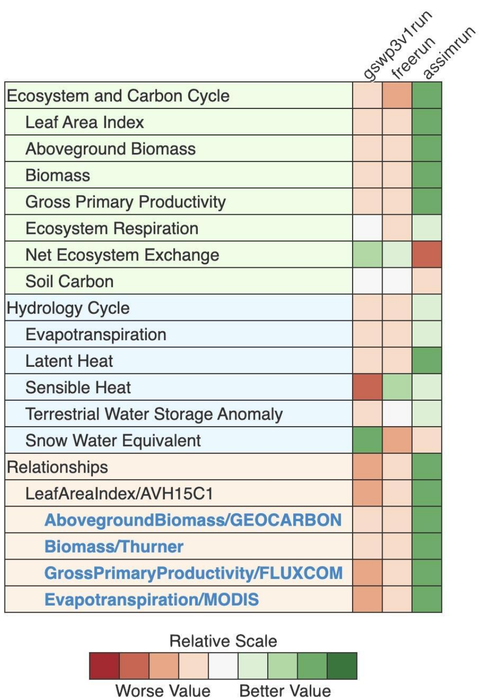
- Seasonal timing of leaf area (phenology) improved



- Forest height improved compared to ICEsat observations



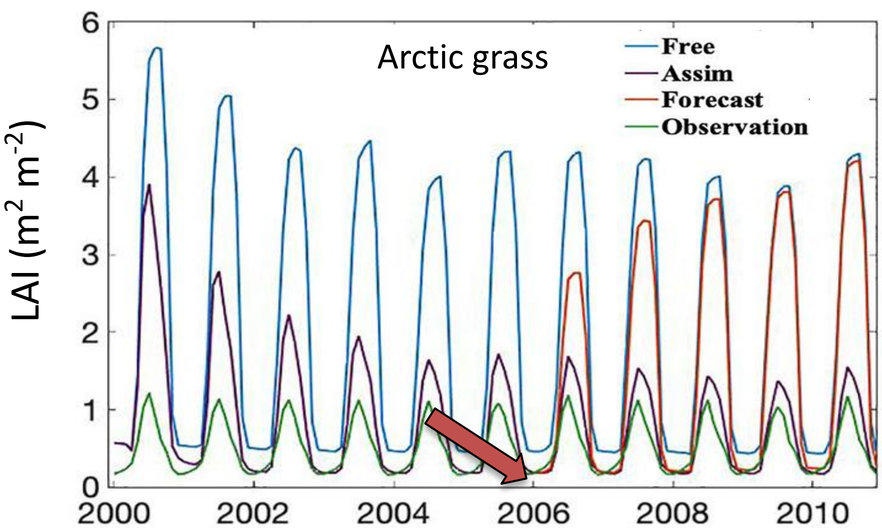
- Most carbon, water and energy fluxes improved; (ILAMB benchmark)



X. Huo et al.,
(JGR-Biogesciences, submitted)

Arctic Ecosystems: Enhance forecasting skill with parameter updates

- Global CLM simulation, w/ leaf area observations



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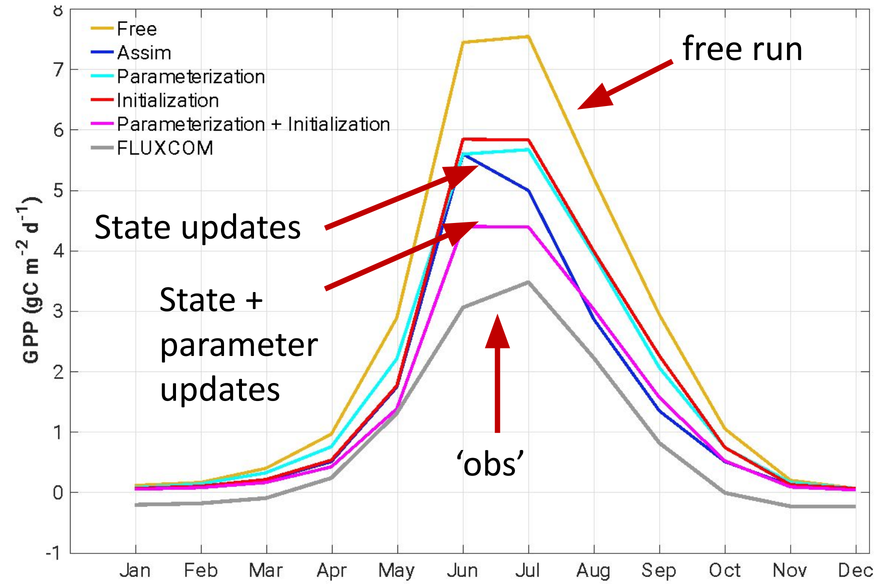
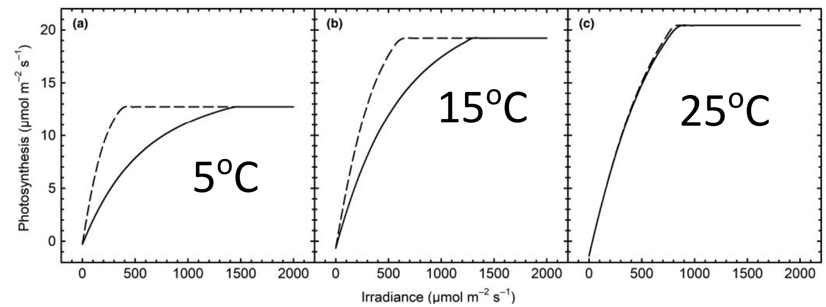
Fox et al., (2022)

- ABoVE (Arctic domain), CLM seasonal cycle of GPP





- Model 'state' updates reduce initial condition error, but some structural/parametric model error remain

- The simulated LAI extended forecast (starting at yr 2006) returns to the free simulation

- Including structural/parameter updates enhances forecasting (hindcasting) skill

THE UNIVERSITY OF UTAH

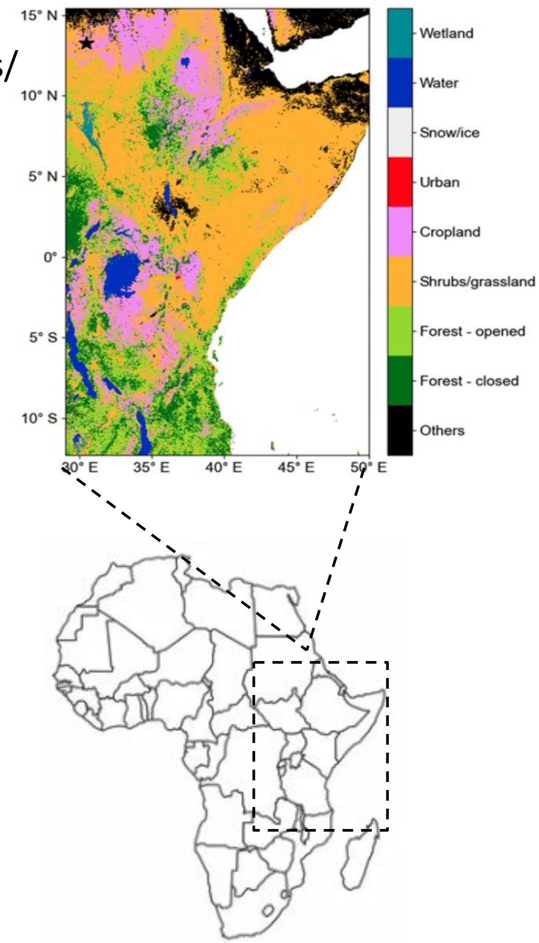
THE UNIVERSITY OF ARIZONA

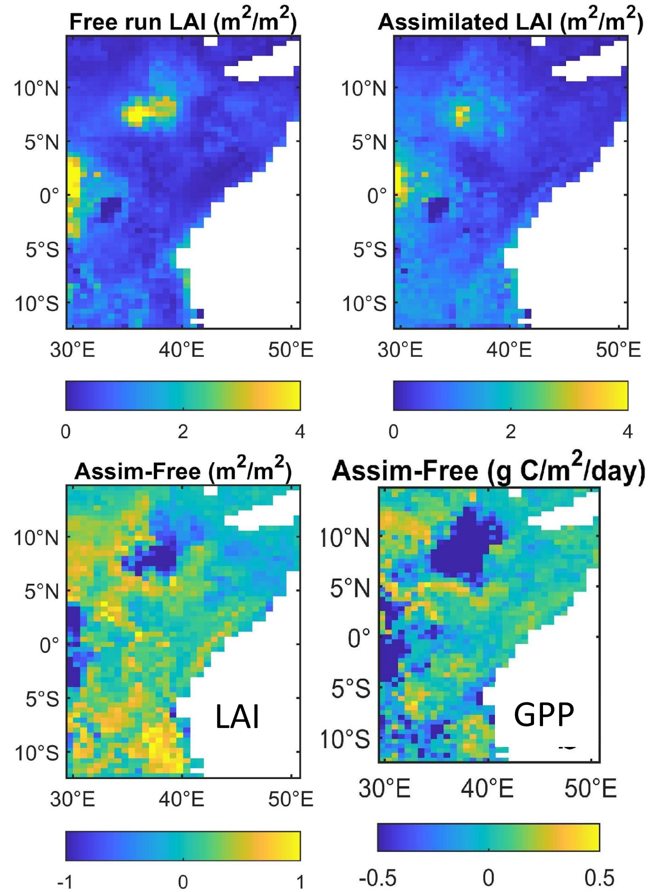
X. Huo et al., (JGR-Biogeosciences, submitted)

Sub-Saharan East Africa: Verifying forest restoration practices

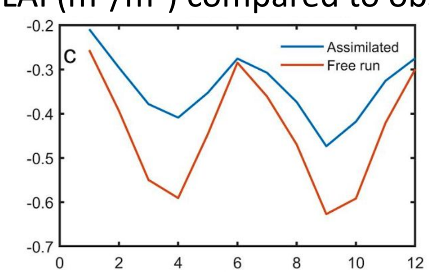
Shrubs/ grass

Forest





LAI (m^2/m^2) compared to obs



2011-2020 monthly average

- Observations increase average LAI and GPP
- PFT performance?

<u>Next steps</u>

- Increase ensemble size to 60
- Add observations of SMAP and SIF
- Expand to African continent

Constraining hydrologic cycle: Soil moisture observations

<u>Methodology</u>:

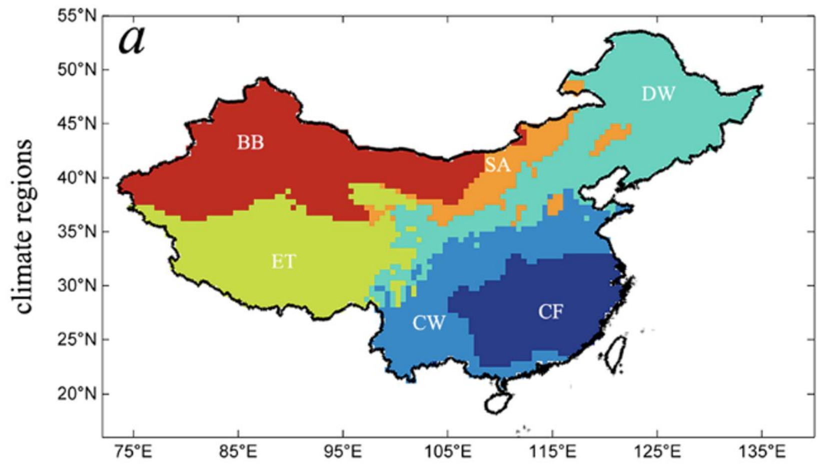
CLM 4.5 w/ satellite phenology
0.5^o spatial resolution

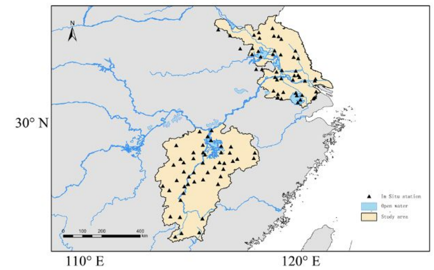
<u>Observations</u>:

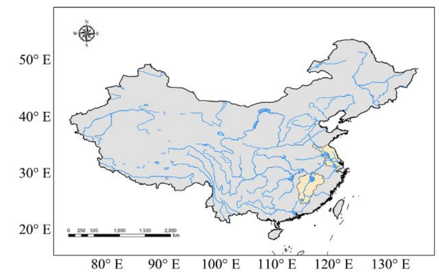
- ESA CCI ECV combined soil moisture (~ 5 cm depth)
- Re-scaled against GLDAS-NOAH climatology
- Frozen soil data not included

<u>Benchmark Data</u>

- ERA5 Land soil moisture
- Subsurface site level – insitu







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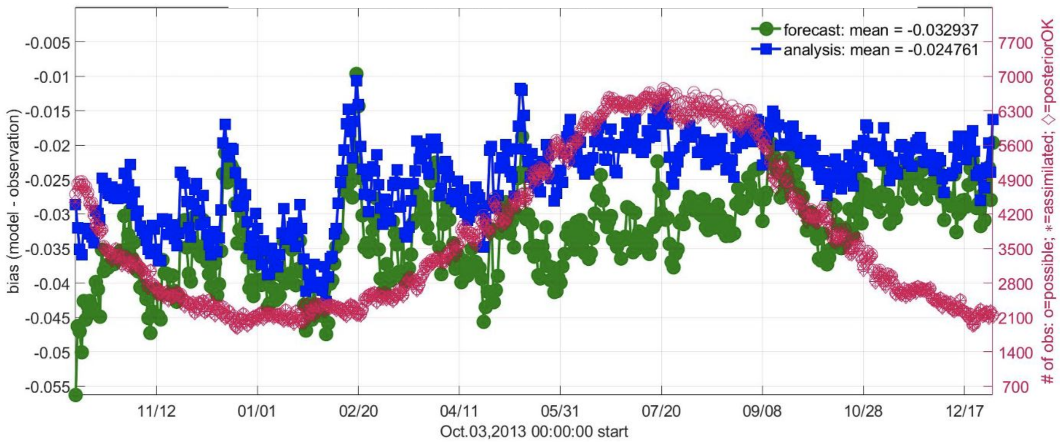
Hagan et al., (in prep)

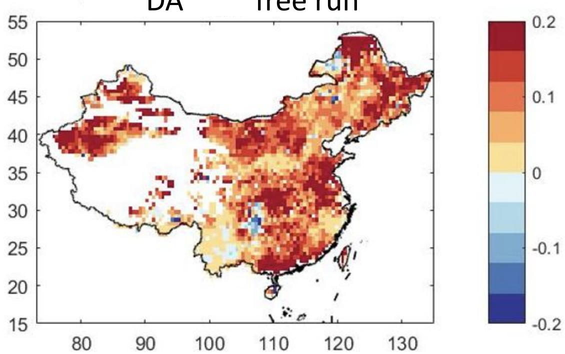
Constraining hydrologic cycle: Soil moisture observations

CLM Soil Moisture Bias (m^3/m^3)



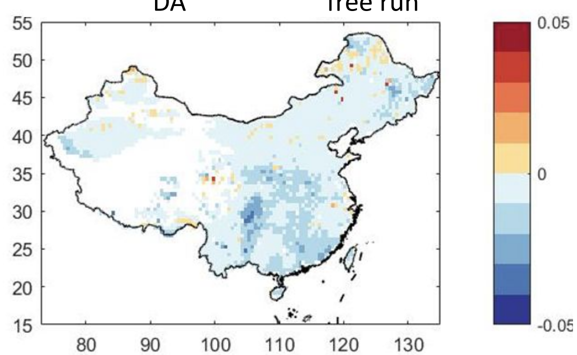
- >90% observations are assimilated, forecast and analysis bias reduced by ~50%

$R_{DA} - R_{free\ run}$



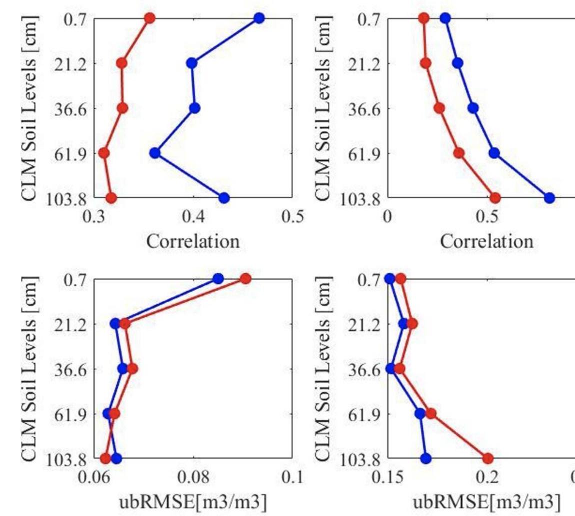
Red-> higher R for DA

$RMSE_{DA} - RMSE_{free\ run}$



blue-> lower RMSE for DA

CLM (free run) CLM-DART (DA)



- Surface soil moisture statistics improve for DA

- Influence of surface obs extends down to ~ 1 meter (100 cm shown here)

GHENT UNIVERSITY

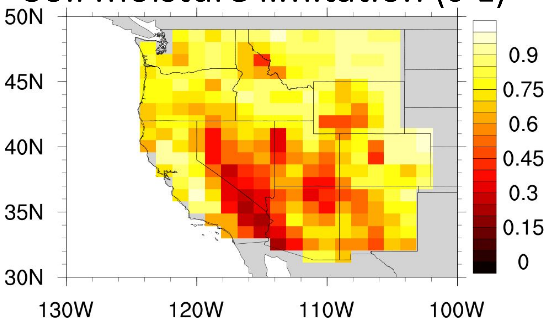
Hagan et al., (in prep)

Snow dependent systems: SWE observations (Western US)

- Snow and soil moisture is a strong limitation upon carbon uptake

Summer (1998-2011)

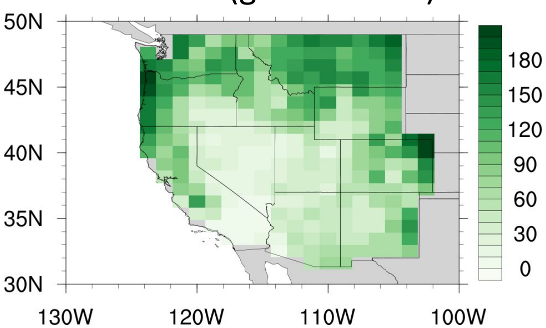
Soil moisture limitation (0-1)



low limitation

high limitation

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



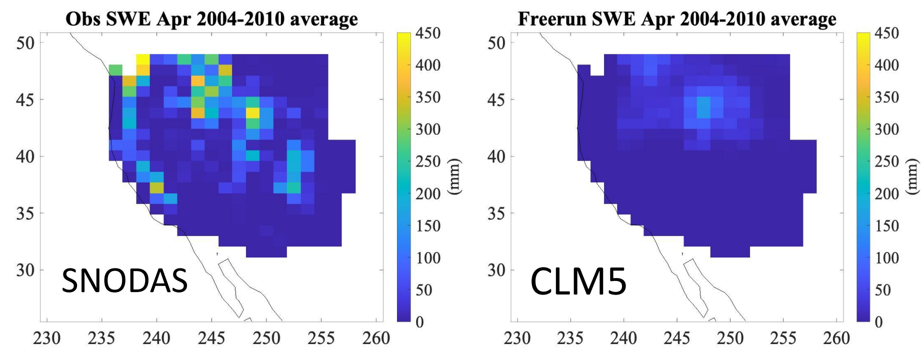
high carbon uptake

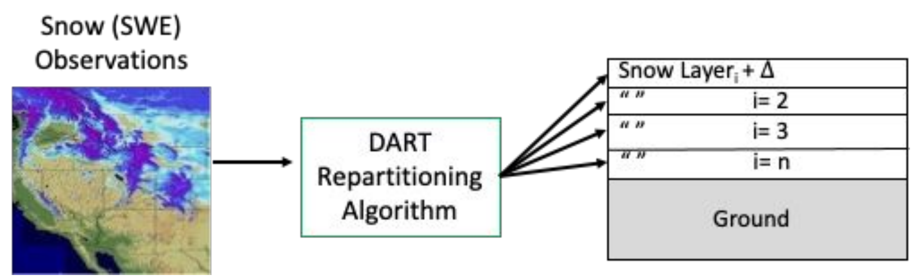
low carbon uptake

Raczka et al., (2021)

- CLM underestimates snow water equivalent (SWE), motivating snow and soil moisture DA

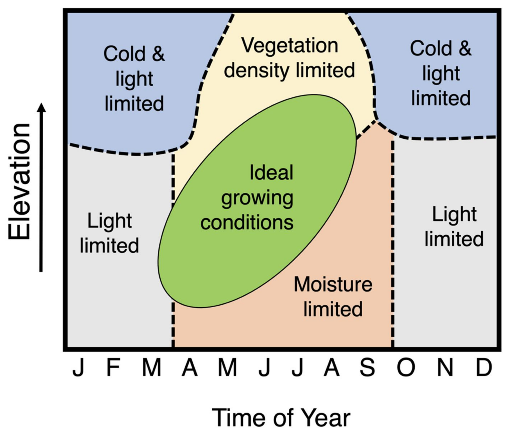
CLM simulated SWE

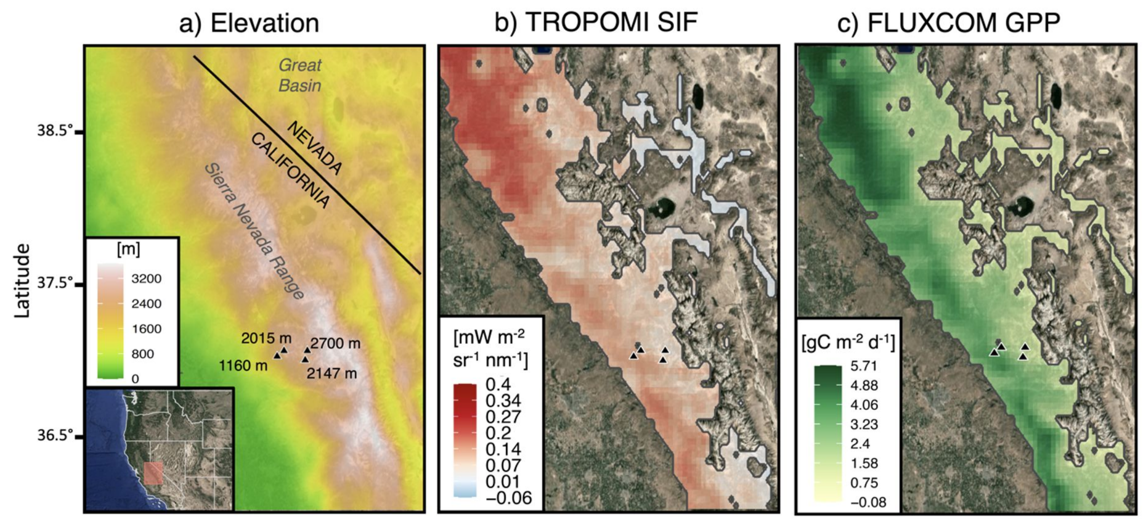




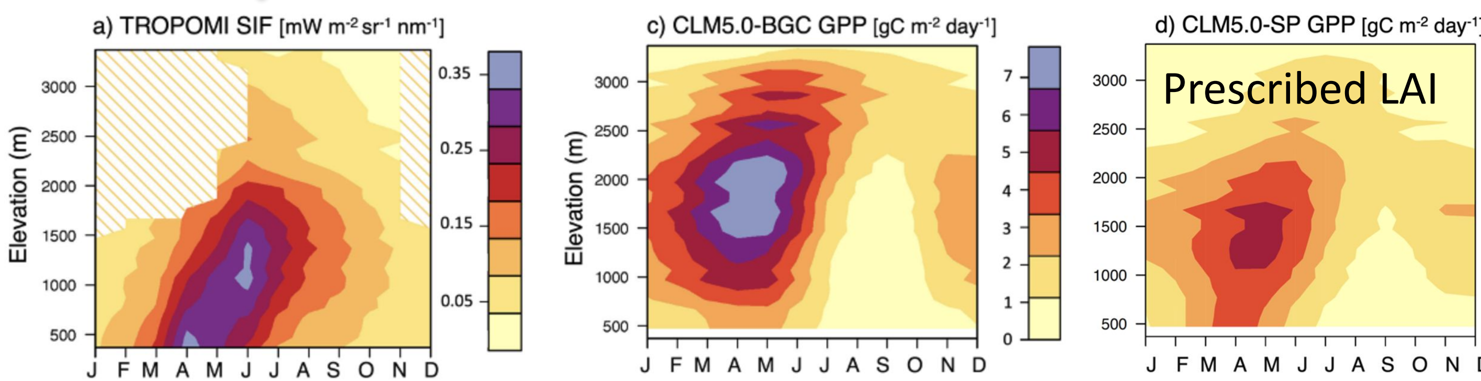
Solar Induced Fluorescence (SIF)

- SIF observations can capture both elevational and seasonal variation on carbon uptake across complex terrain (Sierra Nevada Mountains)





Yrs: 2018-2020



CLM Open loop

CLM + LAI observations

CLM + SIF observations:

- Leaf Area
- Moisture
- Nutrients

Ongoing work

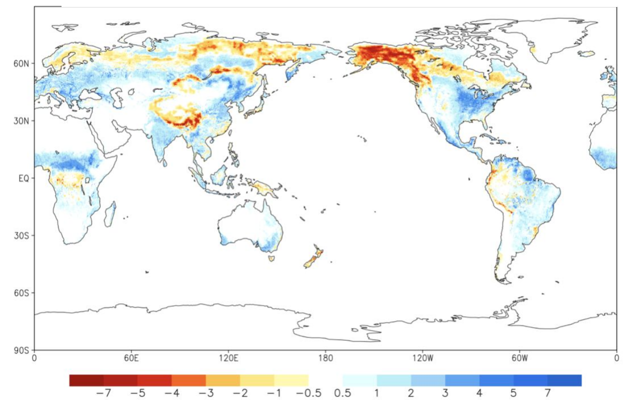
Kunik et al, (2024) ERL. https://doi.org/10.1088/1748-9326/ad07b4

Land-atmosphere interactions: Seasonal Forecasting

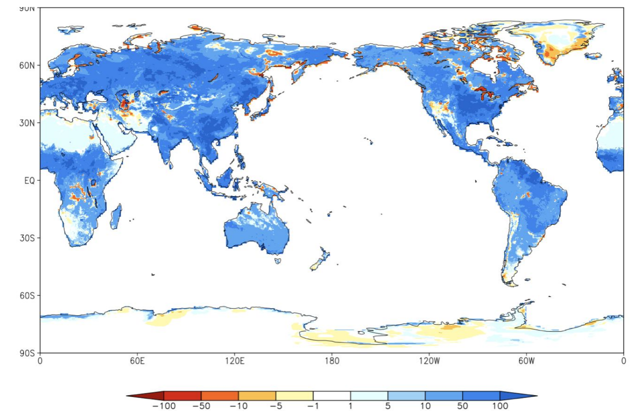
<u>Objective</u>: Use CLM and observations of LAI, AGB, snow and soil moisture to initialize the land surface (LDAS-SPREADS) for seasonal atmospheric forecasts

- Assimilation of LAI observation product (GLASS) shifts LAI and latent heat flux distributions

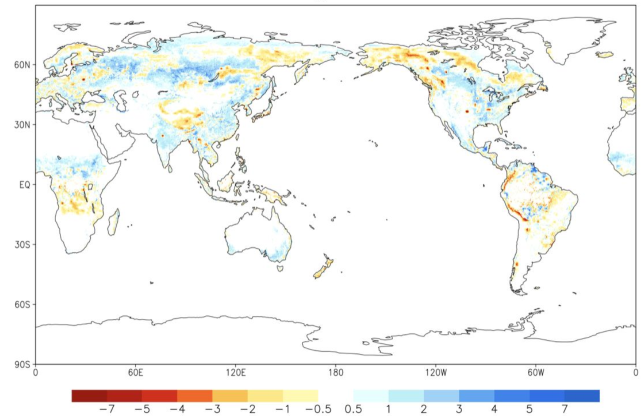
LAI ($m^2\ m^{-2}$), (obs – free run)



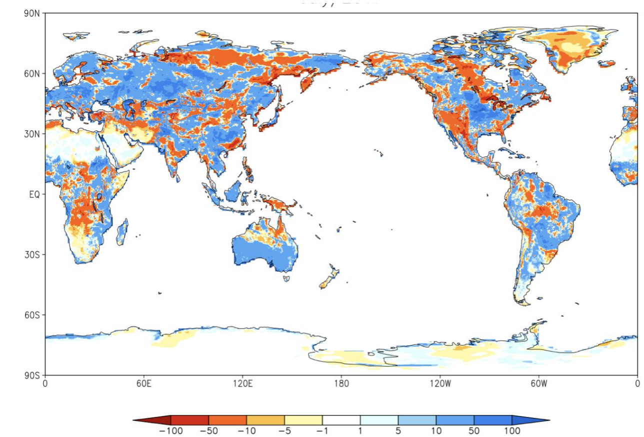
Latent Heat ($W\ m^{-2}$), (ERA5 – free run)



LAI ($m^2\ m^{-2}$), (obs – assimilation)



Latent Heat ($W\ m^{-2}$), (ERA5 – assimilation)



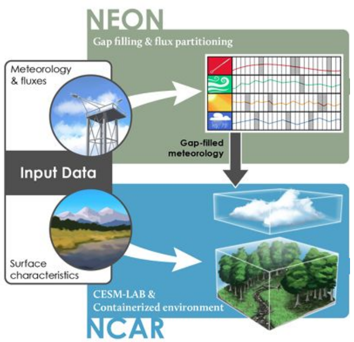
cmcc Centro Euro-Mediterraneo sui Cambiamenti Climatici

Provided by Luis Gustavo Goncalves

Incorporating site level data into CLM-DART

CLM site generation tools:

'run_neon'



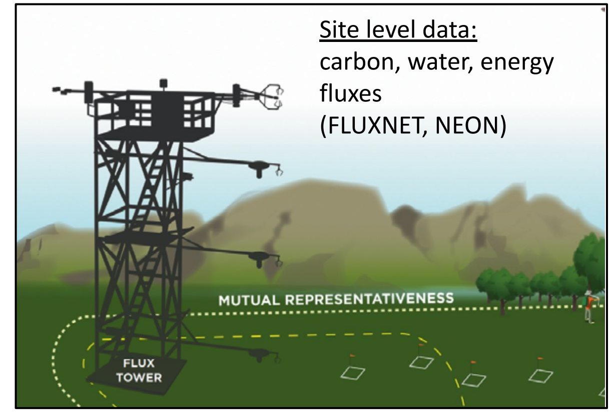
NCAR-NEON system

Generalizing to 'run_tower' for Ameriflux & PLUMBER2 sites

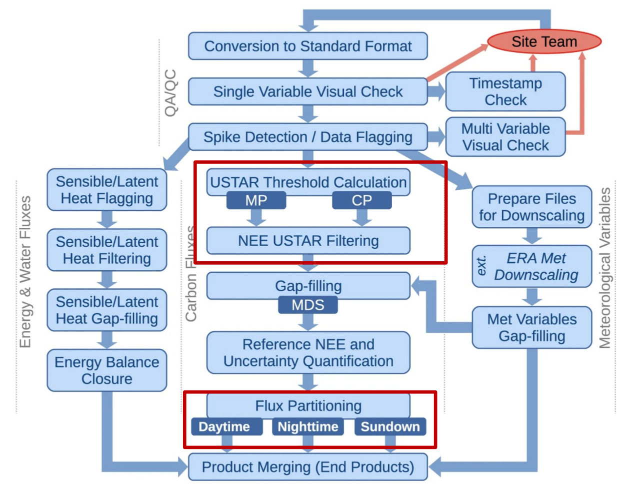
GitHub
/NCAR/DART

Oneflux observation converter

Site-Level Met Forcing Ensemble Generator



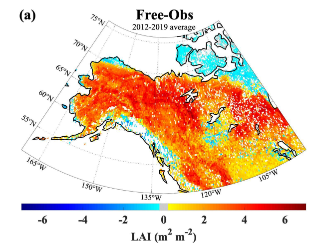
ONEFLUX Processed Data



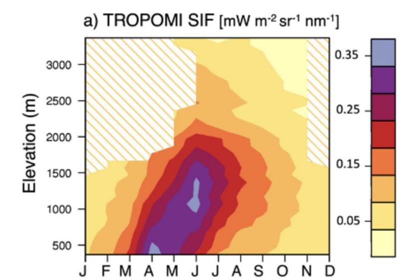
Pastorello et al., (2020)

Conclusions

- Leaf area and biomass observations improves the model state, with downstream effects on carbon, water and energy fluxes



- Water limitation can be addressed with snow and soil moisture observations, but presents methodological challenges

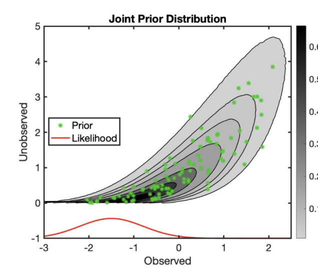


- Solar induced fluorescence shows promise to inform all limiting factors for carbon uptake (GPP)

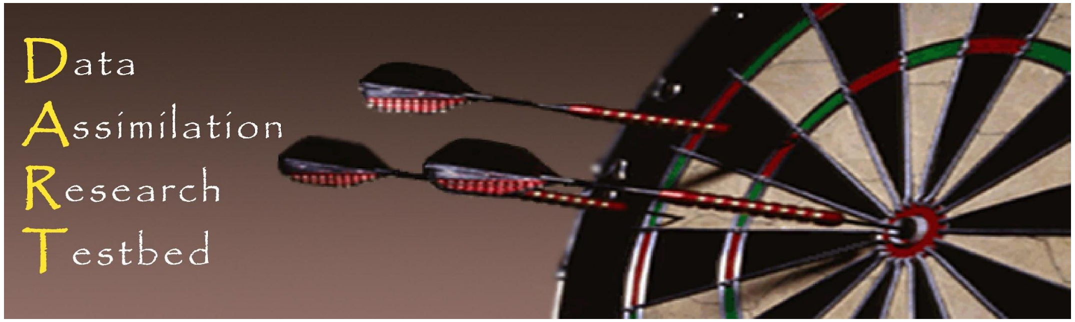
<u>Addressing Other Challenges</u>:

- State augmentation approach can be applied to fields for ensemble DA parameter estimation

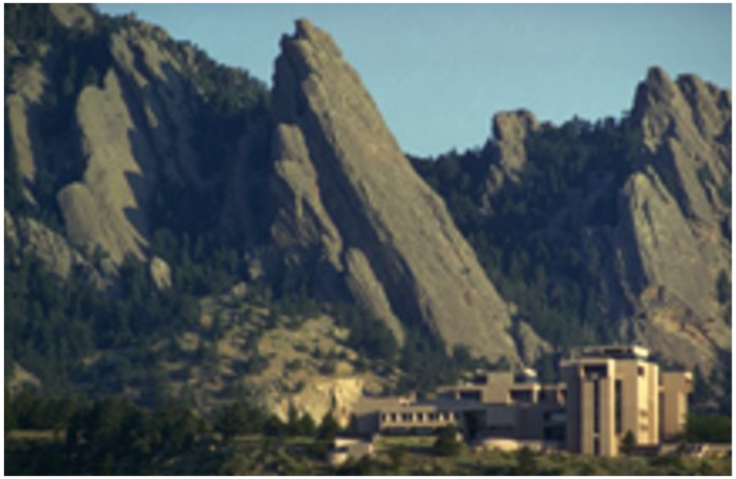
- New Quantile Conserving Filter (QCEFF) in DART addresses non-linear and non-gaussian applications for updating bounded quantities



For more information:



https://dart.ucar.edu/



Thank You !

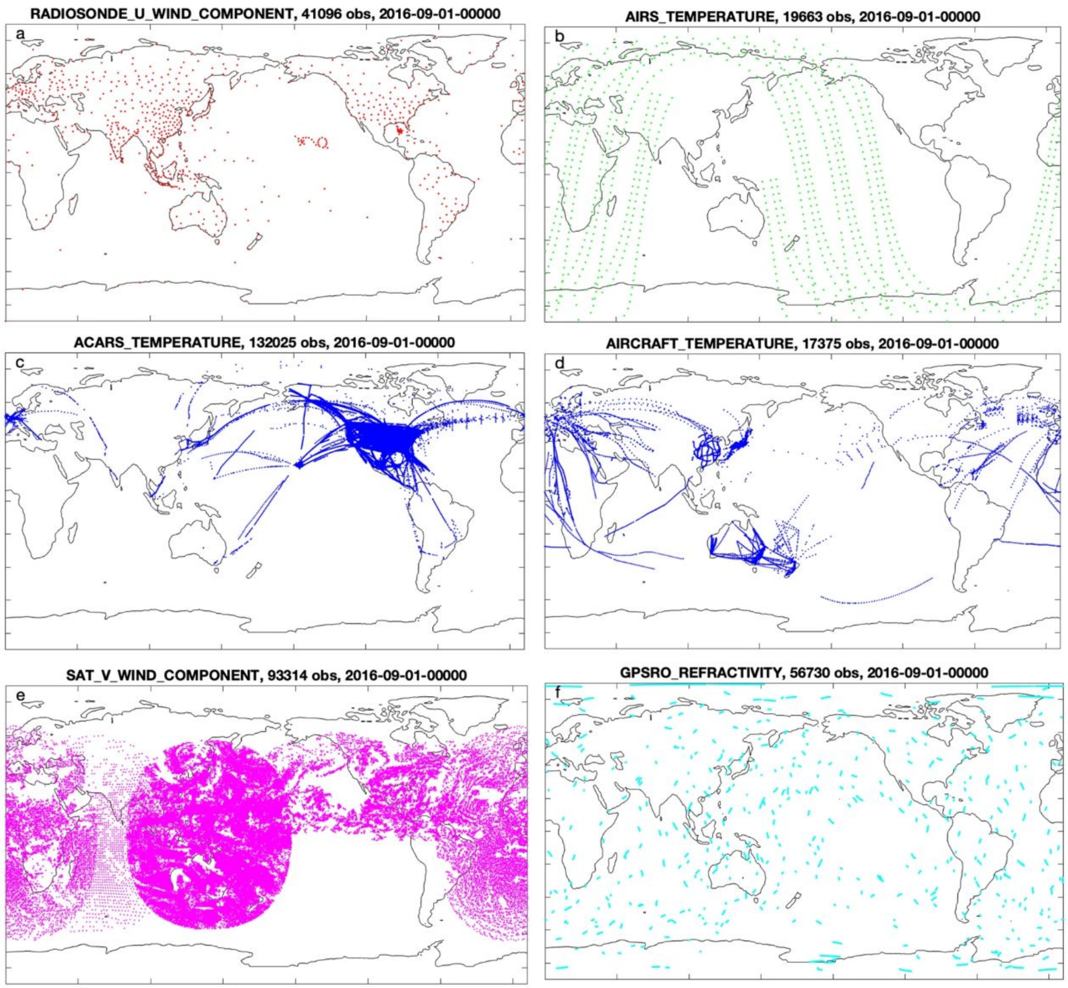
Questions ?

CISL
Computational & Information Sy

We would like to acknowledge high-performance computing support from Cheyenne (doi:10.5065/D6RX99HX) provided by NCAR's Computational and Information Systems Laboratory, sponsored by the National Science Foundation.

Coupling CLM to DART: Generating ensemble spread

- To generate ensemble spread in the CLM-DART simulations, we use an ensemble met forcing product (CAM6-DART Reanalysis Ensemble, 80 members).



(Kevin Raeder et al., 2021)

- Density of observation in time/space reduce CAM6 model biases

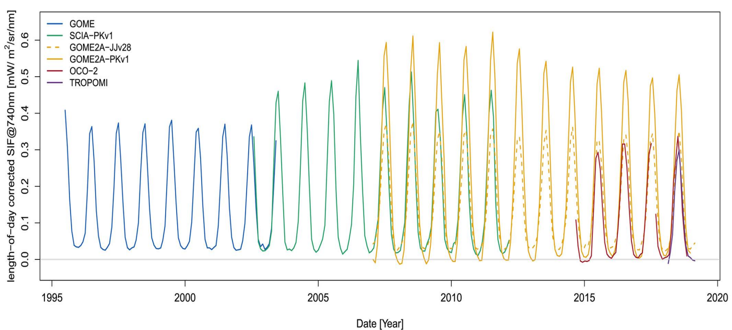
Observations: > 300,000 obs per 6 hour time step (yrs 2011-2021)

- Radiosondes: Surface balloon launches
- ACARS: aircraft
- AIRS: IR Soundings
- CDW: Cloud Drift Winds (satellites)
- GPS Refractivity: atmospheric density

Challenge: Addressing Observation and Model biases

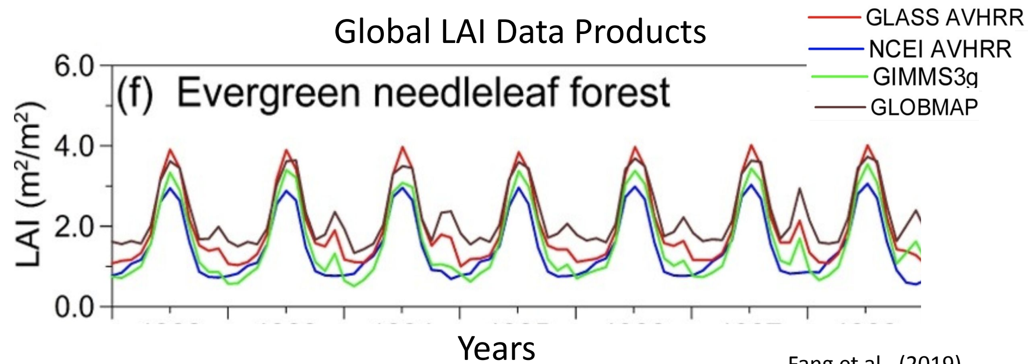
Remotely sensed land surface products are subject to systematic biases :

Solar Induced Fluorescence Data Products



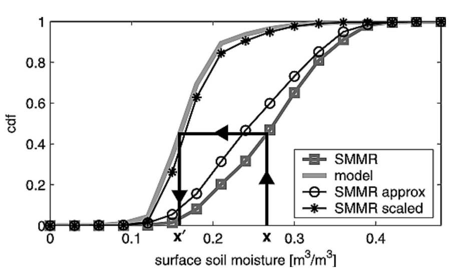
Parazoo et al., (2019)

Global LAI Data Products



Fang et al., (2019)

- Adaptive inflation can address systematic biases if data product is trusted
- If not, CDF matching re-scales data products to remove model-data bias and retain variability



Reichle & Koster 2004 (GRL)

- CDF matched soil moisture product removes systematic bias