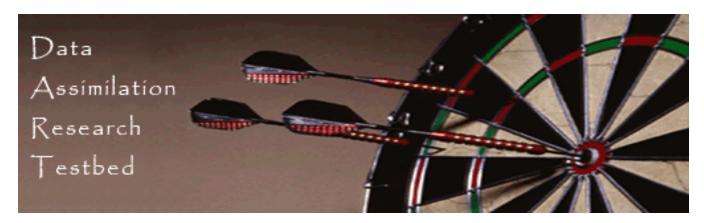




Ensemble data assimilation for soil-vegetation-atmosphere systems.



Tim Hoar: National Center for Atmospheric Research (NCAR) with a lot of help from:

Jeff Anderson: NCAR

Andrew Fox: National Ecological Observatory Network (NEON)

Yongfei Zhang: University of Texas Austin

Rafael Rosolem: University of Bristol/University of Arizona











Motivation

- 1. The ecological state of the planet is the result of an unknowable history.
- 2. Model spinup cannot be counted on to accurately recreate that history.
- 3. Data assimilation can put the model state more in line with the current state. With that, we can:
- Quantify ecological states
 - to establish a baseline
 - as a preface for ecological forecasting
- Better understand our models
- Improve our understanding of the underlying processes





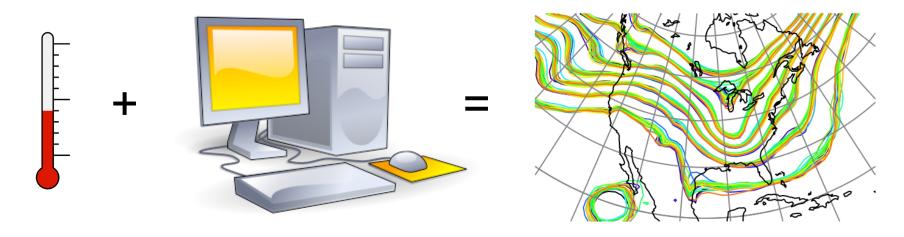






What is Data Assimilation?

Observations combined with a Model forecast...



dart@ucar.edu for more!

... to produce an analysis.

Overview article of the Data Assimilation Research Testbed (DART):

Anderson, Jeffrey, T. Hoar, K. Raeder, H. Liu, N. Collins, R. Torn, A. Arellano, 2009: The Data Assimilation Research Testbed: A Community Facility.

Bull. Amer. Meteor. Soc., 90, 1283-1296. doi:10.1175/2009BAMS2618.1











My difficulties with ensemble land DA:

- What parts of the model 'state' do we update?
- What is, and how do we get, a proper initial ensemble?
- Representing proper uncertainty in the forcing fields.
- Model/observation bias ... probably both wrong ...
- Can models tolerate new assimilated states? Silently fail?
- Snow (vegetation) ... depths, layers, characteristics, content.
 - Destroying easier than creating new
- Forward observation operators
 - many flux observations are over timescales that are inconvenient
 - need soil moisture from last month and now ... GRACE
- Impact of bounded quantities on ensemble spread
- Observation metadata usually insufficient or hard to use.
 - land cover type needed for accurate forward observation operators.

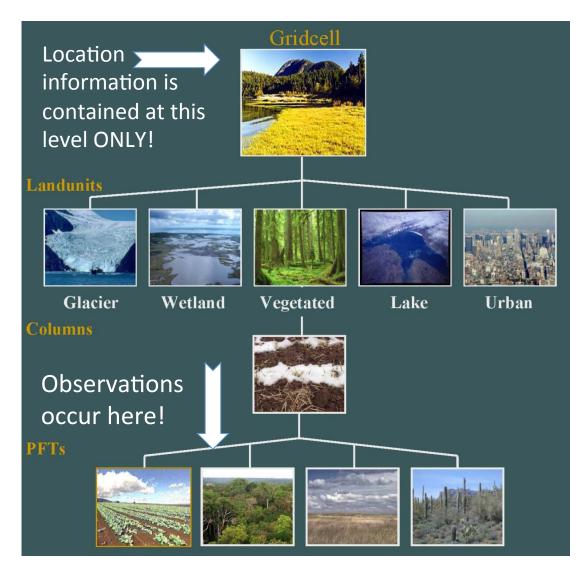












Models that abstract the gridcell into a "nested gridcell hiearchy of of multiple landunits, snow/soil columns, and Plant Function Types" are particularly troublesome when trying to convert the model state to the expected observation value.

Given a soil temperature observation at a specific lat/lon, which PFT did it come from? No way to know! Unless obs have more metadata!







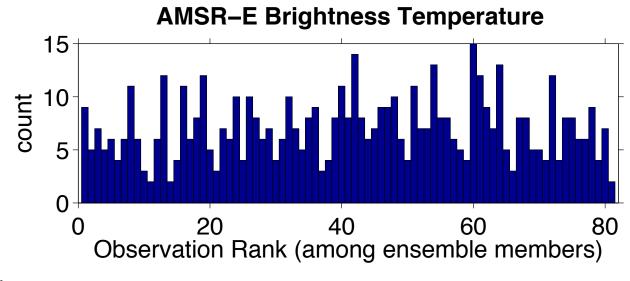




Observations: AMSR-E Tb

In collaboration with Ally Toure, NASA





These are synthetic results.

The only way the rank histogram looks this good is if there is no **bias** between the obs and the ensemble. **Real life interferes here** ...

Real observation converter complete, but ... DENSE observations. Superob? Correlated? h() depends on land cover?

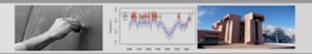
Innovations in Snow Cover Fraction 0.05 0.00 220 240 260 280 300 Longitude











Martinelli Subnivean

Saddle

In collaboration with Andy Fox (NEON): An experiment at Niwot Ridge



- C-1 is located in a Subalpine Forest
- (40° 02' 09" N; 105° 32' 09" W; 3021 m)
- One column of Community Land Model (CLM)
 - Spun up for 1500 years with site-specific information.
- 64 ensemble members
- Forcing from the DART/CAM reanalysis,
- Assimilating tower fluxes of latent heat (LE), sensible heat (H), and net ecosystem production (NEP).
- Impacts CLM variables: LEAFC, LIVEROOTC, LIVESTEMC, DEADSTEMC, LITR1C, LITR2C, SOIL1C, SOIL2C, SOILLIQ ... all of these are *unobserved*.





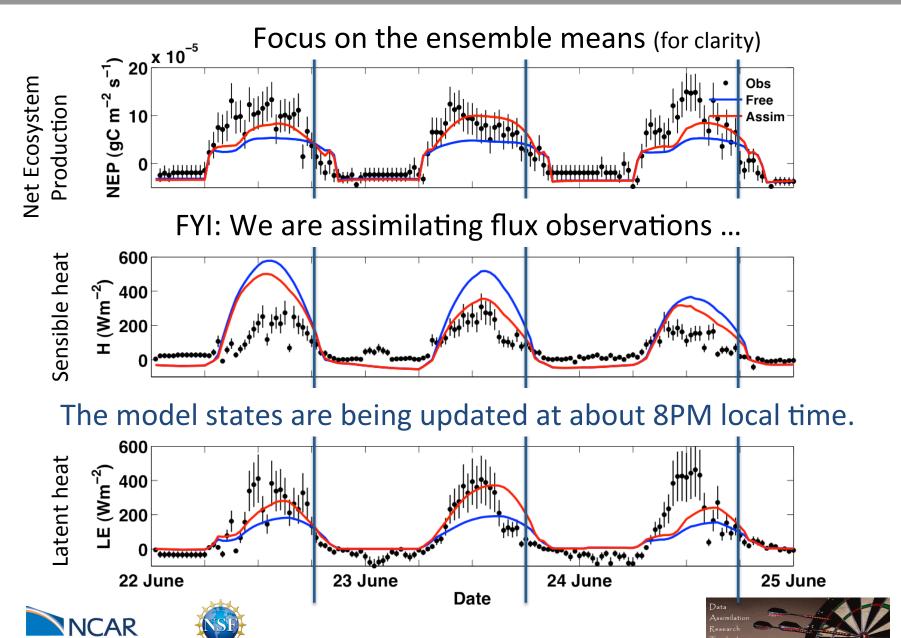


Denvei

COLOR/ADO



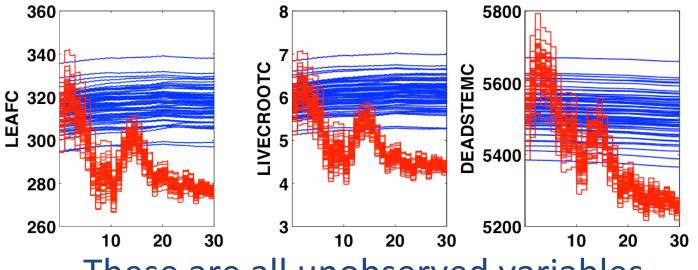




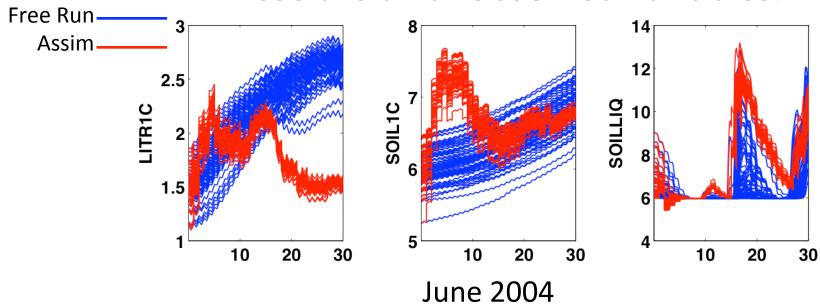
TJH AMS 2014 pg 8







These are all unobserved variables.









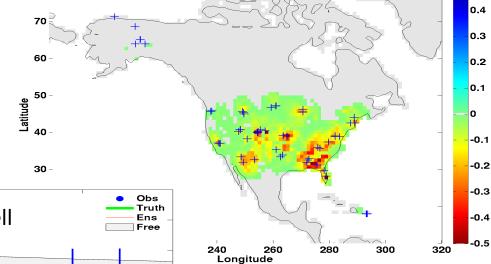
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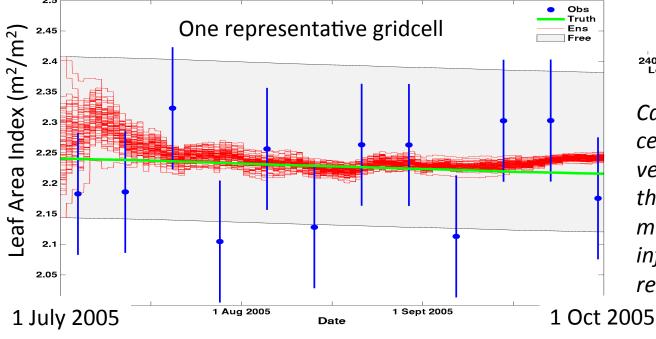


Leaf Area Index

This is the result of a synthetic experiment. Experiments with MODIS LAI observations are in progress.



Carbon pools from all grid cells are in the DART state vector, and are updated through the covariance matrix, propagating information from sites to regions.

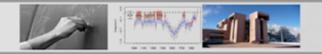






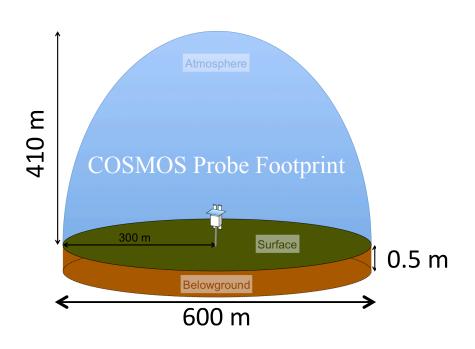


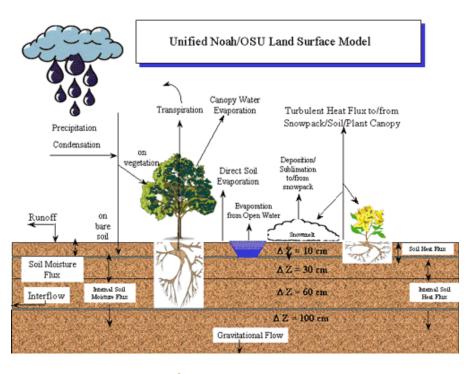




Cosmic Ray-Derived Soil Moisture

Rafael Rosolem, U. of Arizona, U. of Bristol











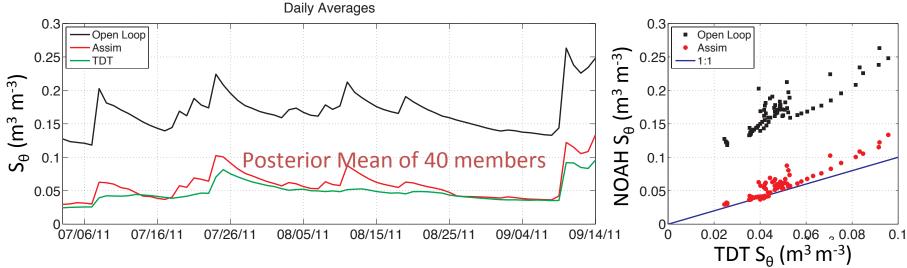


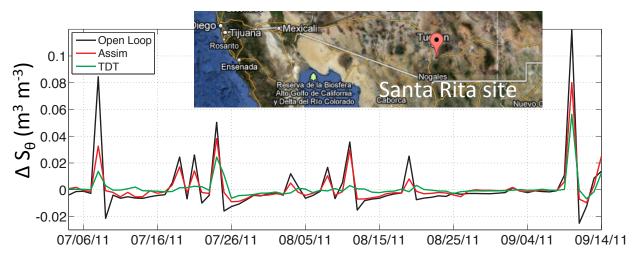






NOAH-DART Integrated Soil Moisture



















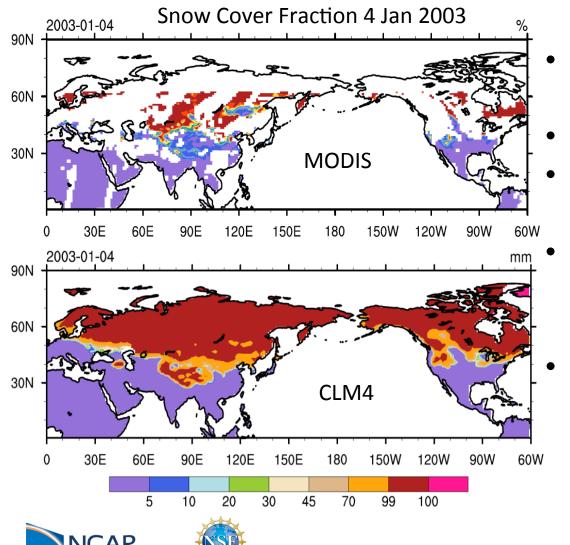
Assimilation of the MODIS Snow Cover Fraction Dataset through the Coupled Data Assimilation Research Testbed (DART) and the Community Land Model (CLM4)







Assimilation of MODIS snow cover fraction

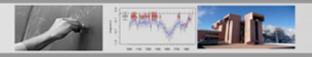


- 80 member ensemble for onset of NH winter
- assimilate once per day
- Level 3 MODIS regridded to a daily 1 degree grid
- Observations can impact state variables within 200km
- CLM variable to be updated is the snow water equivalent "H205N0"

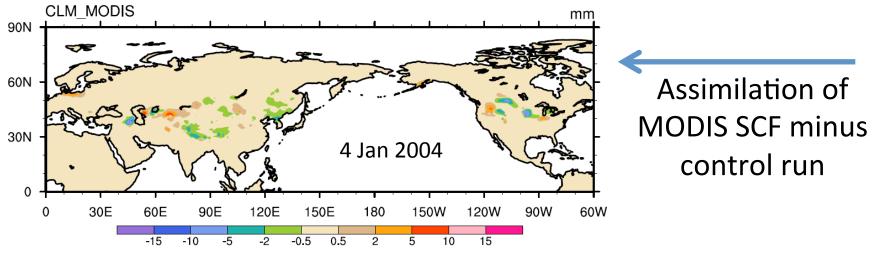




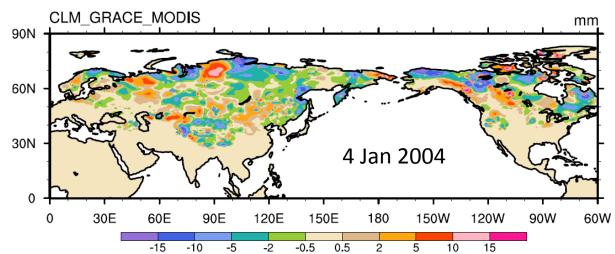




Impact on Snow Water Equivalent



TEASER: Assimilation of *GRACE Total Water Storage* & MODIS SCF minus control run

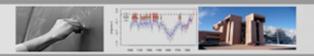












The HARD part is: What do we do when SOME (or none!) of the ensembles have [snow,leaves,precipitation, ...] and the observations indicate otherwise?

Corn Snow?

New Snow?

Sugar Snow?

CONFUSED

UNSURE

PERPLEXED

Wet Snow?

"Champagne Powder"?

Slushy Snow?

Dirty Snow?

Early Season Snow?

Snow Density?

Dry Snow?

Crusty Snow?

Old Snow?

Packed Snow?

Snow Albedo?



The ensemble must have some uncertainty, it cannot use the same value for all. The model expert must provide guidance. It's even worse for the hundreds of carbon-based quantities!







DISORIENTED BEWILDERED





We are attacking the problem of data assimilation for soil-vegetation-atmosphere systems with many tools.

- Eddy Covariance fluxes
- Leaf Area Index
- snow cover fraction
- Soil moisture
- Cosmic ray neutron counts
- Water table depth
- Total water storage (i.e. GRACE)











CAM

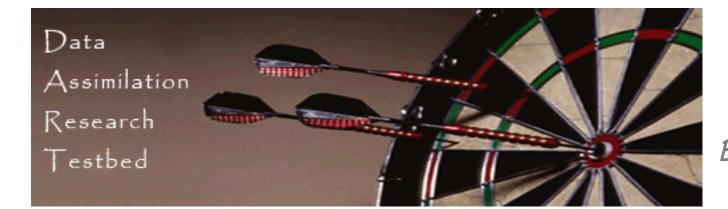
For more information:

GITM

WRF

CLM

AM2



POP

BGRID

www.image.ucar.edu/DAReS/DART

NOAH

MITqcm_ocean

dart@ucar.edu

MPAS_ATM

COAMPS_nest

SQG

NAAPS MPAS_OCN

TIEGCM

PBL_1d

NCOMMAS

PE2LYR







