Snow Data Assimilation: DART and CLM

Y. -F. Zhang[1], T. J. Hoar[2], W. J. Sacks[2], T. Craig[2], A. M. Fox[2], J. L. Anderson[2], Z.-L. Yang[1]

1. Jackson School of Geosciences, University of Texas at Austin, Austin, TX, United States.
2. The National Center for Atmospheric Research, Boulder, CO, United States.

(yongfei@utexas.edu)

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Introduction

✓ The Data Assimilation Research Testbed (DART) (http://www.image.ucar.edu/DAReS/DART/) is a comprehensive data assimilation software environment that can help modelers and observational scientists easily explore a variety of data assimilation methods and observations with different numerical models. DART is developed and well maintained by a group led by Jeff Anderson at the National Center for Atmospheric Research (NCAR). DART is being extended to support the Community Land Model (CLM4) to assimilate observations of land-based quantities such as snow cover, soil moisture, and soil temperature. This study represents the first effort linking DART and a land surface model.

✓ To obtain accurate estimate of snowpack is very important to the regions where people live on the snowmelt. Also, more precise snow information is significant to improve the predictability of climate models. As one of the state-of-art land surface models, CLM4 has a sophisticated snow parameterization, consisting of up to 5 layers depending on snow depth. One of the important motivations of this work is to improve the snow simulation of CLM4. The influence of the improved snow product on the predictability of climate models is equally important.

Philosophy of Linking DART and CLM4

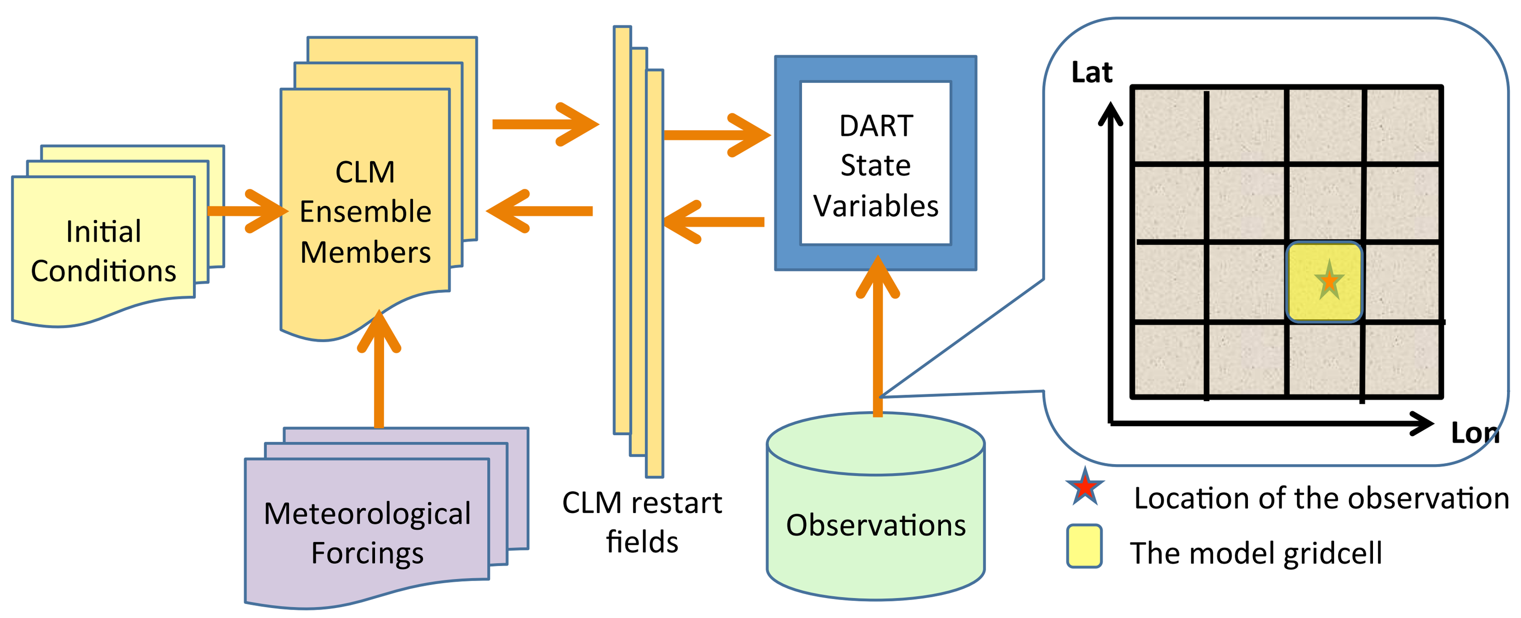

Fig.1 Flowchart of the coupling between DART and CLM

✓An ensemble set of CLM members starts with initial conditions and is driven by meteorological forcings of the same ensemble size, that is, each ensemble CLM member has a distinct meteorological forcing and initial condition. When new observations are available, all the members stop and send restart files to DART. DART will reshape the state variables in its own unique structure and combine the modeled state variables with the observations to produce analysis state variables. The updated state variables are then sent back to CLM to act as the restart variables for the next simulation period.

✓Given the location of an observation, DART will search its nearest grid cell, scale up the state variable from the CLM4's sub-grid level to the grid cell level.

Initial Conditions

✓The initial conditions are obtained by driving an ensemble of CLM members from Jan. 1st 1998 to Nov. 1st 2002. Again, each CLM member has a distinct meteorological forcing provided by CAM reanalysis data.

✓The largest variability among the ensemble members exist in Siberia, the Tibetan Plateau, Alaska, and Northern Canada. So we expect that it is in these regions with high variability that data assimilation will be influential.

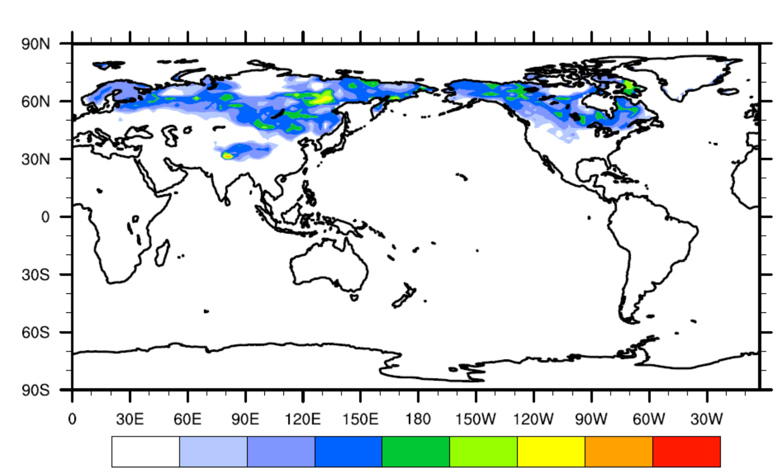

Fig.2 Snow cover fraction variability of the initial conditions for Oct. 2002

Meteorological Forcings

✓ A freely available ensemble of reanalysis data created by DART and the Community Atmospheric Model (CAM4) is used to drive the CLM ensemble members.

✓ The CAM4 reanalysis is similar to the NCEP reanalysis, except the former is an ensemble and a product of coupled DART and CAM4.

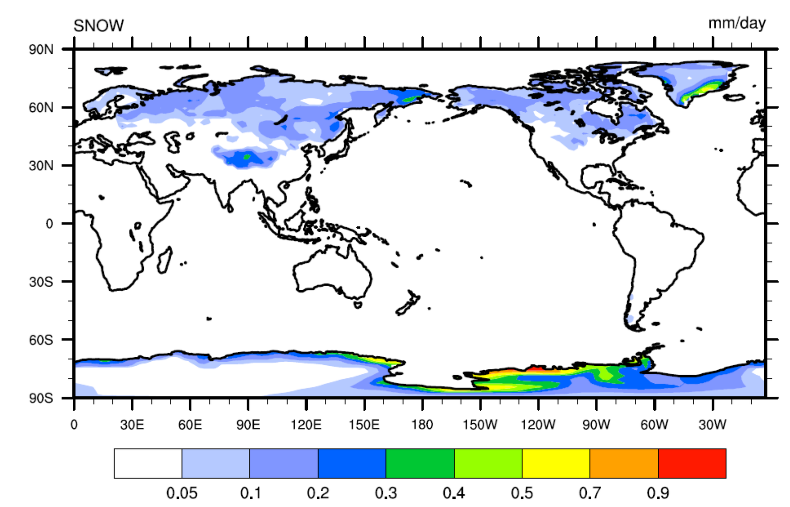

Fig.3 Snowfall rate variability of the CAM ensemble members for Dec., 2000

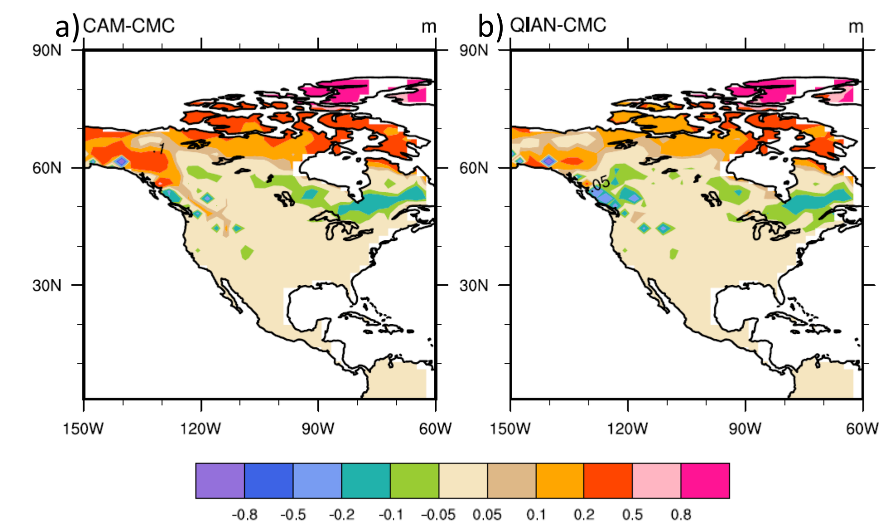

Fig. 4 Snow depth comparisons between the case driven by the default forcing (Qian et al., 2006) and that driven by the CAM forcing. Both are subtracted by the Canadian Meteorological Center (CMC) snow depth data.

✓ The ensemble of CAM reanalysis data provides a reasonable spread, which is critical to obtaining a good data assimilation result.

✓ The CAM reanalysis data may inherit systematic biases commonly found in climate models.

✓ CAM tends to have cold bias and excessive precipitation in the Arctic region (de Boer et al., 2011), which in part explain the deeper snow depth from the case driven by the CAM reanalysis forcing (Figure 4).

Case Setup

Data to be assimilated: MODIS Snow Cover Fraction Product

✓SCF product is retrieved using a normalized difference snow index (NDSI).

$$\text{NDSI} = \frac{\text{band 4} - \text{band 6}}{\text{band 4} + \text{band 6}}$$

Band 4: Satellite reflectance in 0.545—0.565μm visible band

Band 6: Satellite reflectance in 1.628—1.652μm near-infrared band

✓The fraction of snow cover within a MODIS pixel using this approach can be provided with a mean absolute error less than 0.1 over the range from 0.0 to 1.0 in fractional snow cover (Salomonson and Appel, 2003). In this case study, the error variance of the SCF product is set to be 0.1 universally.

Assimilation Method: Ensemble Adjustment Kalman Filter (EAKF)

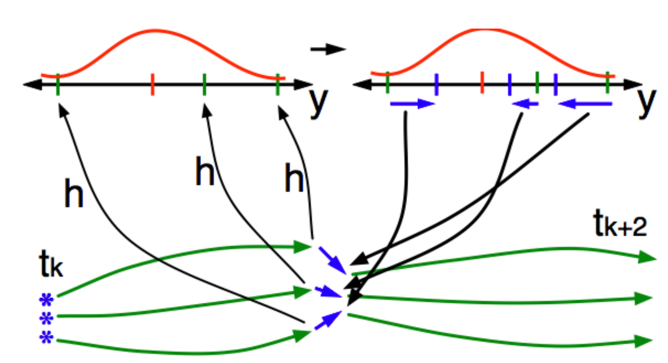

Fig.5 Diagram of the key steps of ensemble filters

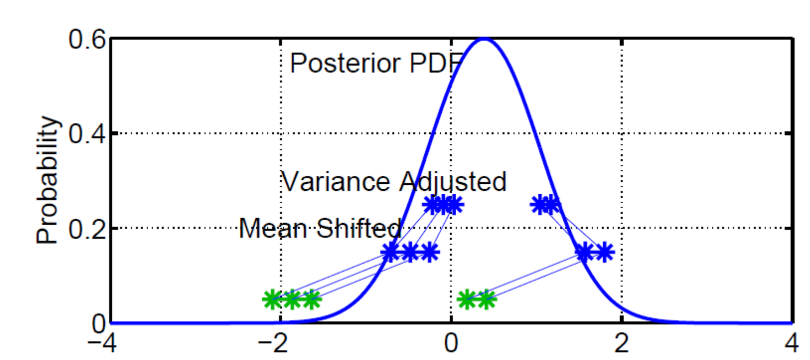

Fig.6 Diagram showing how EAKF updates the state variables after computing the posterior PDF

✓The EAKF is a deterministic ensemble filter that computes a linear operator that is applied to the prior ensemble estimate of the state, resulting in an updated ensemble whose mean and covariance are consistent with the theory (Anderson, 2001).

Ensemble size: 80

Variable to be updated: Snow Water Equivalent (SWE)

Cutoff: 0.03 (in radians), approximately 200 km, which means DART will only allow the observation to influence its projected grid cell only.

Results

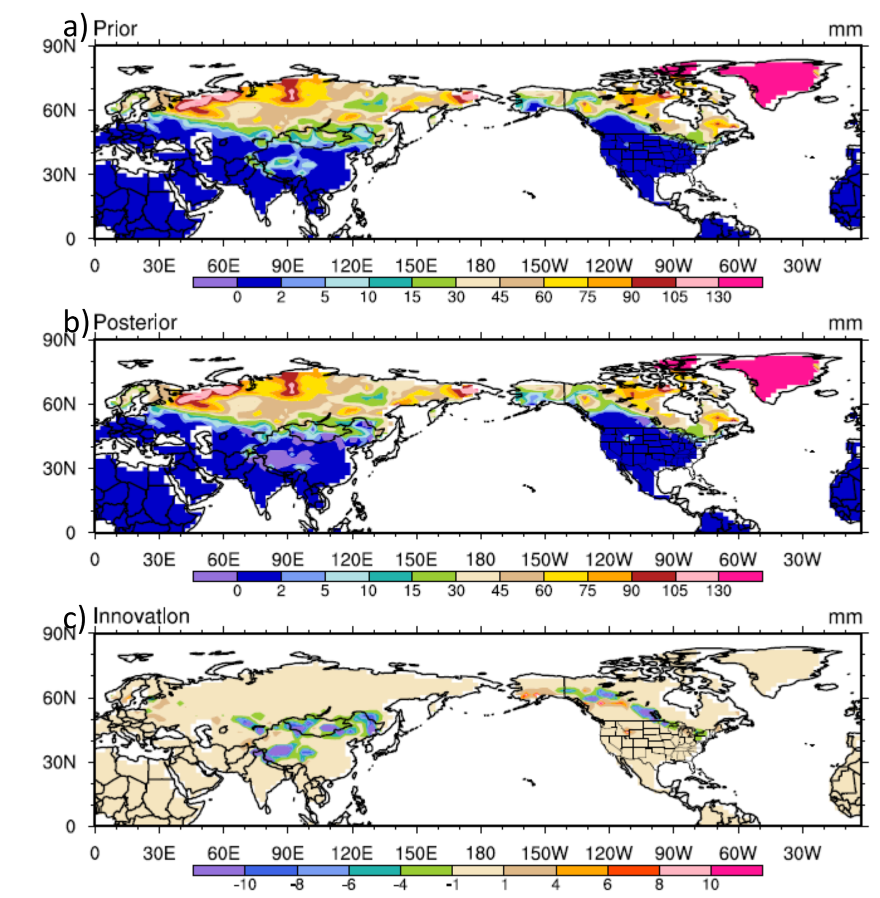

Fig.7 The ensemble mean Snow Water Equivalent a) prior; b) posterior; and c) innovation (Posterior-Prior) for Nov. 30, 2002

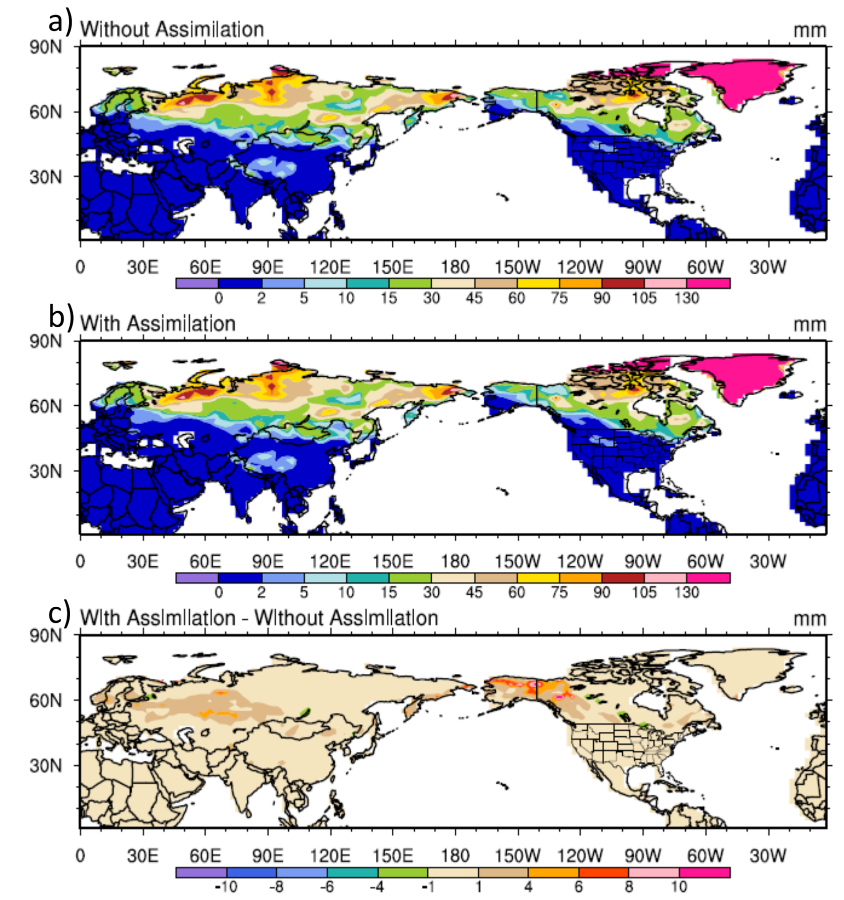

Fig.8 The monthly averaged ensemble mean Snow Water Equivalent a) without assimilation; b) with assimilation; and c) their differences for Nov., 2002

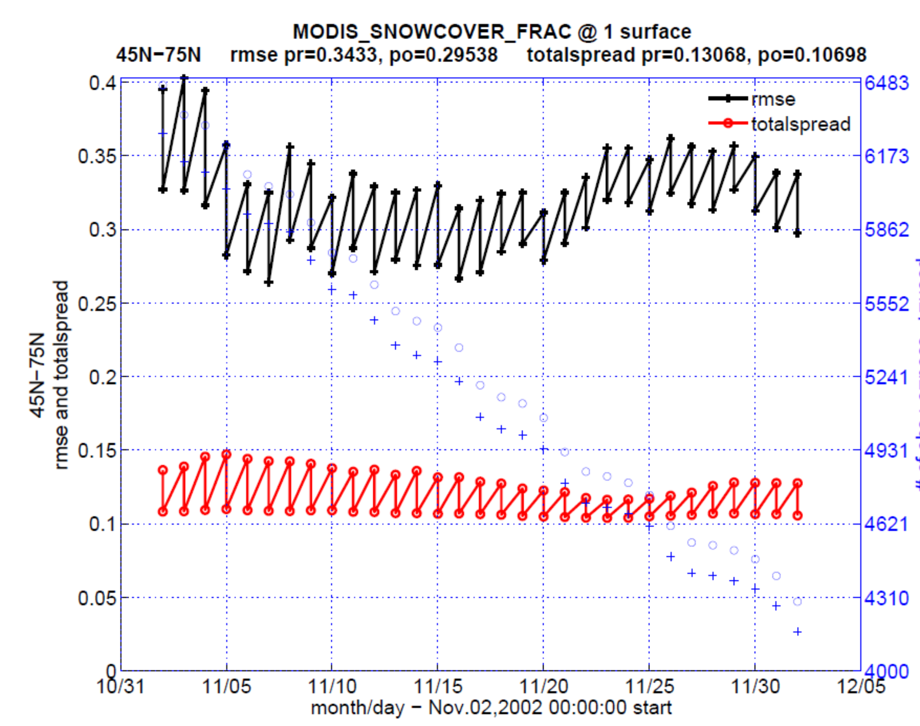

Fig.9 The evolution of the RMSE and total spread of the 80-member ensemble. The quantities are calculated relative to the observations in the band 45°N to 75°N. The total spread is defined as the square root of the ensemble variance and the observation error variance. The number of observations to be assimilated is represented by a blue 'o', the number successfully assimilated is represented by a blue '+'.

Conclusions and Future Work

✓The assimilation with DART and CLM is properly reducing the RMSE (Figure 9) at each assimilation step.

✓We'll examine the assimilation work on longer time scales, for example, the seasonal cycle. To see how the improved snow product affects the simulation of climate model is also our interest.

References

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Acknowledgement

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