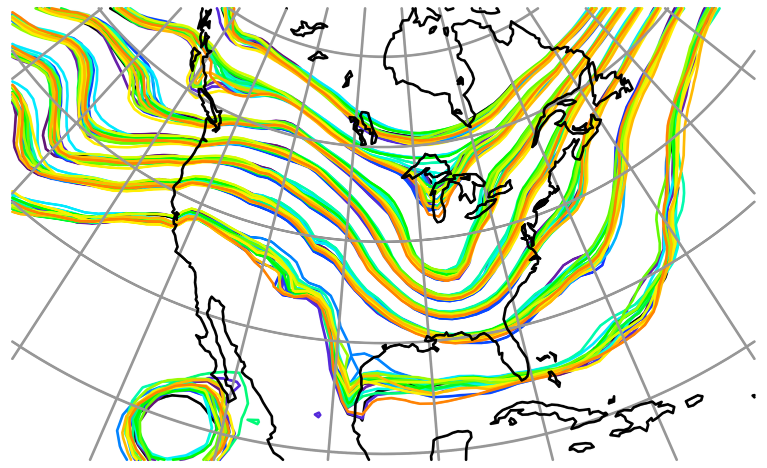

A General Purpose Data Assimilation Facility: DART

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1. Ensemble Data Assimilation

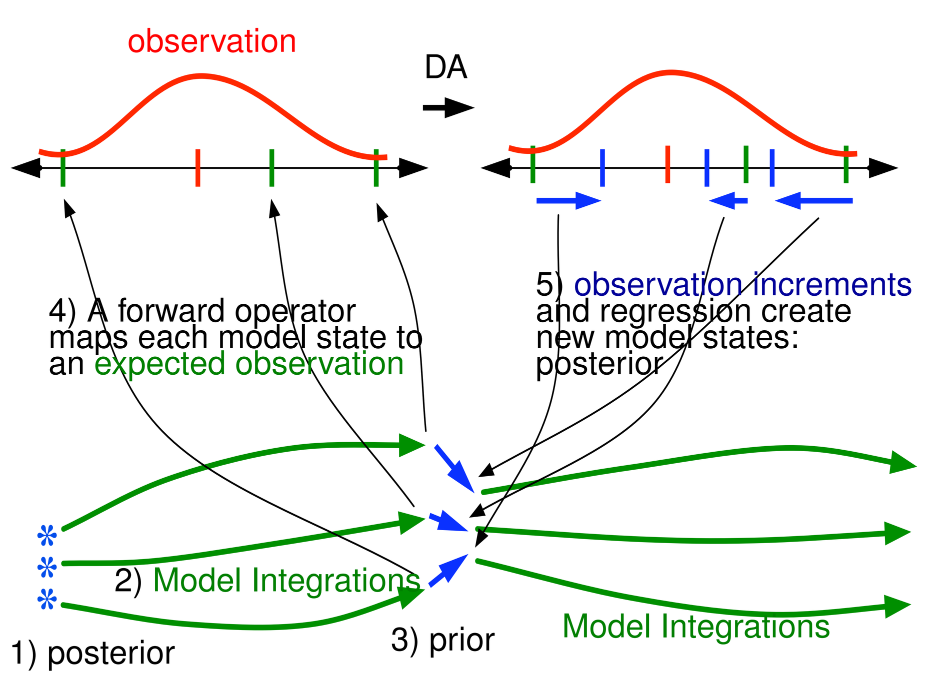
1.1 What is Data Assimilation?

Data Assimilation (DA) combines observations of a physical system with predictions from a numerical forecast model. DA can be used for many purposes, including:

+ constructing initial conditions for forecasts,
+ evaluating errors in the model and observations,
+ finding appropriate values for model parameters,
+ designing better observational systems.

The Data Assimilation Research Testbed (DART) is a community software facility that can be used for all the above purposes. DART provides a variety of ensemble filtering (EF) algorithms.

1.2 Sequential Ensemble Filtering



1.3 Geophysical applications require extensions

The basic EF algorithm does not work well when applied to large geophysical problems. Model error, sampling error from using affordable ensemble sizes, and violation of linear and Gaussian assumptions all lead to overconfidence in the ensemble priors. This can result in poor performance or filter divergence. DART has several self-tuning algorithms to address these problems that work for a wide variety of models and observations without the need for user expertise. Some of these are described in sections 3 and 4.

2. What's in DART?

DART makes it easy to learn and apply EF data assimilation.

- Has an extensive tutorial and instruction set.
- Incorporating new models and new observation types requires only minimal coding of a small set of interface routines.
- Scales linearly to hundreds of processors. Parallel performance is independent of the forecast model. Even single-threaded models can be run in parallel.
- Includes many flavors of ensemble filters:
  1 EAKF; Ensemble Adjustment Kalman Filter,
  2 EnKF; Ensemble Kalman Filter,
  3 Kernal filter,
  4 particle filter,
  5 a fixed-lag ensemble Kalman smoother.
- Provides additional algorithms for improved performance:
  1 prior and posterior inflation,
  2 automatic adaptive inflation,
  3 horizontal, vertical, multivariate localization,
  4 hierarchical filter for adaptive localization,
  5 dynamic adjustment of localization cutoff radius,
  6 *a priori* sampling error correction.
- Output is in portable netCDF files and one custom-format observation file. Matlab© scripts are provided to investigate:
  1 rank histograms,
  2 bias and spread (by variable) as a function of height or time,
  3 ensemble trajectories, error, and spread,
  4 innovations,
  5 3D plots of observation densities and rejection attributes.

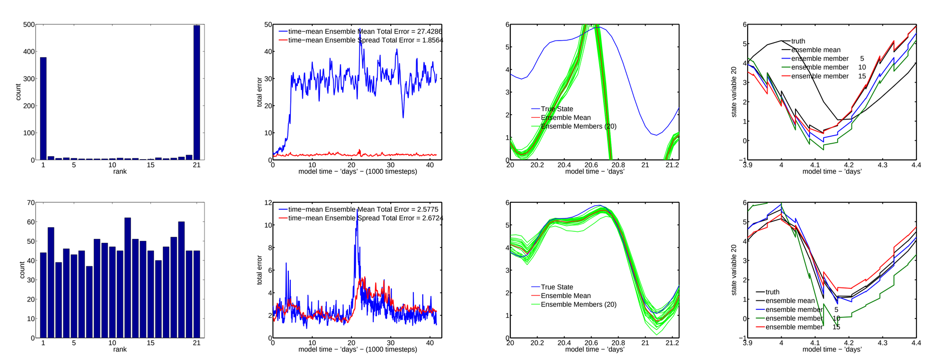


Figure 1: *Examples of some diagnostic plots which can be generated for any DART experiment, any model. These are 'perfect model' experiment results with the Lorenz 96 model. The top row of plots is from an experiment that exhibited filter divergence. The bottom row of plots used covariance inflation.*

- It is freely available via a web download using subversion, which provides for easy code upgrade paths and bug fixes.

Compliant Models and Observation Types

The distributed code includes a variety of low-order models and the following geophysical model interfaces:

1 CAM; Community Atmosphere Model (spectral, FV cores),
2 WRF; Weather and Research Forecast Model,
3 MIT; general circulation model; annulus,
4 ROSE; Middle atmosphere dynamics and chemistry,
5 GFDL; grid point GCM dynamical core,
6 Two-layer primitive equation model (NOAA/CDC),
7 Single column (WRF) model.

Observation types that have been used include:

1 upper air: radiosondes, ACARS, satellite drift winds,
2 surface: winds(10m), T and Q(2m), P_{surf},
3 scatterometer winds,
4 Doppler radial velocity and reflectivity,
5 GPS radio occultation, refractivity,
6 ground-based GPS.

3. Hierarchical Filter for Adaptive Localization

Sampling error from using small ensembles leads to spuriously large correlations among weakly-related observations and state variables. This results in systematic underestimation of posterior variance and can lead to filter divergence. Localizing the impact of an observation to nearby state variables has been the traditional solution. This requires expert knowledge and trial-and-error to get appropriate localizations. DART provides an algorithm to automatically compute localizations using a small group of ensembles.

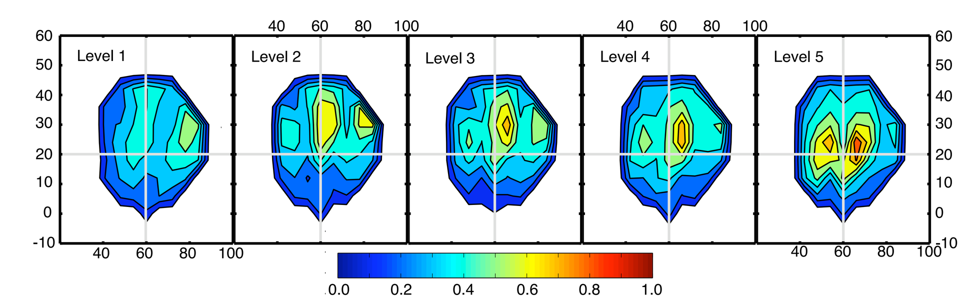


Figure 2: *Adaptive localization for a surface pressure (PS) observation on the zonal wind (V) at 5 model levels as determined from 4 groups of 20 members. The location of the PS observation is indicated by the crosshairs. Note the asymmetry! The model is the GFDL dynamical core.*

4. Adaptive Inflation

Model error and violation of linear and Gaussian assumptions are additional sources of insufficient variance in the ensemble priors. This can be ameliorated by 'inflation': where the ensemble spread is increased while maintaining the mean and sample correlations among all prior variables. Traditionally, all variables at all locations have been 'inflated' by a constant value, chosen by the user to optimize performance in some region or timespan. This tuning takes time and computer resources and can never be optimal for the entire domain. Often, a value of inflation that works well in one region will lead to uncontrolled growth of variance in another. DART has an adaptive inflation algorithm that uses the set of observations affecting a state variable to determine the best value of inflation for that variable.

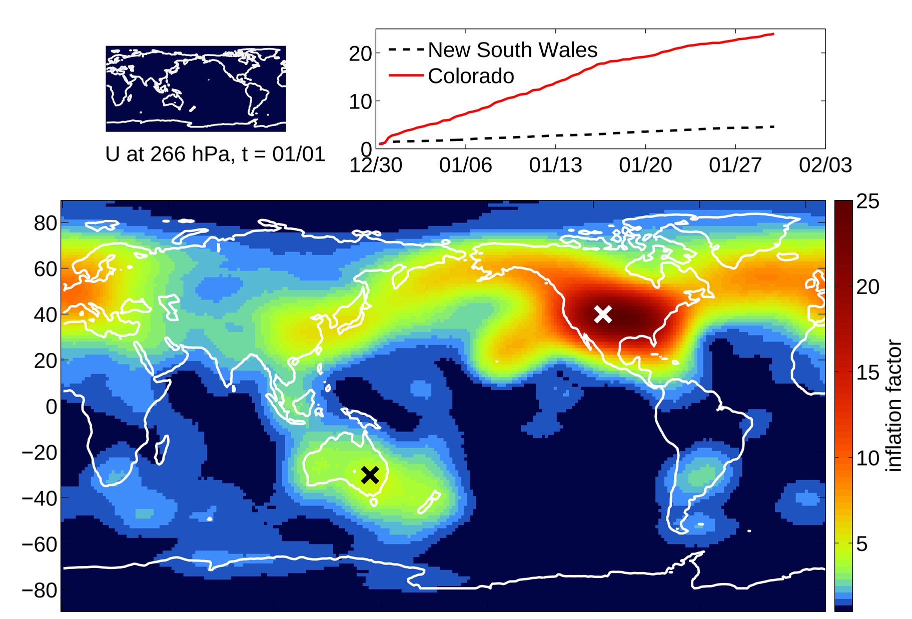


Figure 3: *Illustration of the adaptive spatial inflation and its evolution over time at a pair of locations. CAM T85 U winds at level 15 (≈ 266 hPa) at the end of one month of assimilating observations every 6 hours. The field started off with a uniform value of 1.0.*

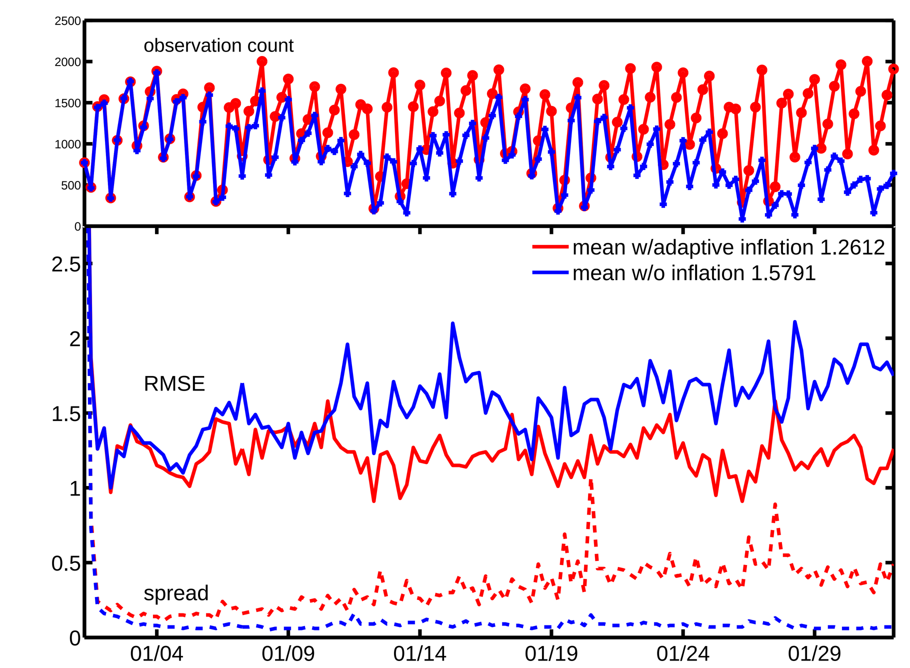


Figure 4: *Six hour forecast ensemble mean RMS error and spread of ACARS 500 hPa temperature observations for CAM T85 assimilations with and without adaptive inflation. The assimilation with adaptive inflation has reduced RMS error and more consistent spread. The upper panel also shows that fewer observations are being rejected by the assimilation using inflation.*

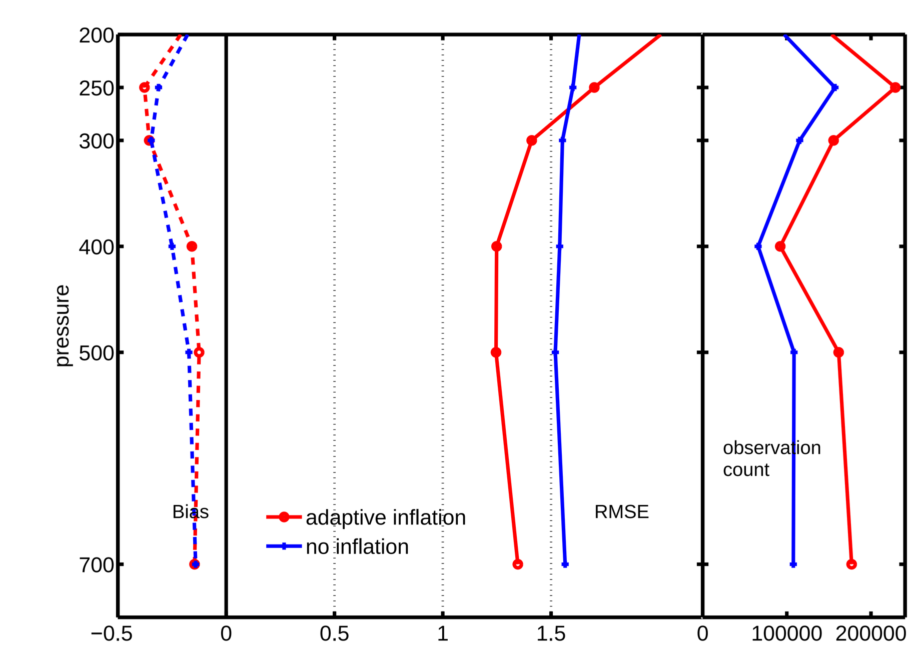


Figure 5: *The effect of adaptive inflation using ACARS temperature observations over North America represented in a vertical profile in observation-space. The dashed pair of curves represents the bias, the other pair is the RMSE. The number of observations assimilated are on the right. The inflation case rejects fewer observations and still (generally) results in a lower RMSE and better bias.*

5. Parallel Scaling

Scaling runs were done using a state-of-the-art global atmospheric climate model (CAM) at low and medium resolutions on a commodity Intel-based Linux cluster from Aspen Systems, an Intel-based Linux cluster from IBM, and a Power 5+ AIX system with a high-speed switch. The following timing results are from the Aspen Systems cluster, and are representative of the results obtained on the other systems.

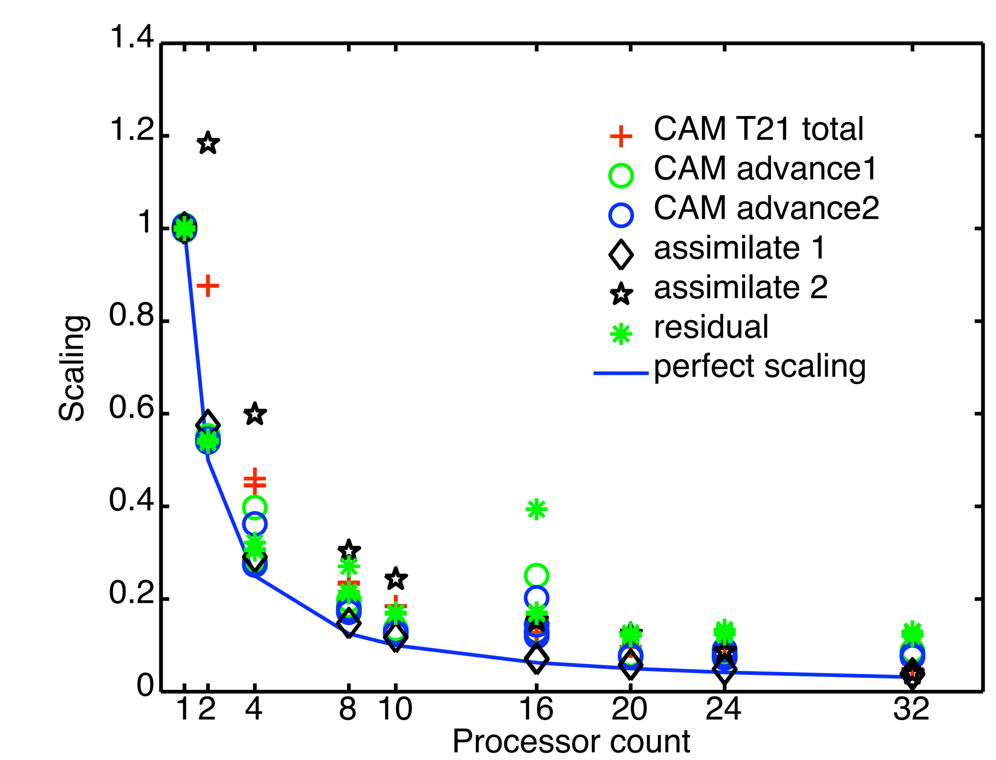


Figure 6: *Scaling on a 16-node Aspen Systems Linux cluster. Each node is a dual-processor, 3.2GHz, IA-32 EM64T with 4GB shared memory. The times are for a 20 member CAM T21 data assimilation (state vector length ≈ 320,000) with two 6-hour model advances, assimilating about 210,000 observations.*

6. Try this at home!

Our DART web site is: http://www.image.ucar.edu/DAReS/DART
There you will find information about how to download the latest version of DART from our subversion server, information on a full DART tutorial (included with the distribution), and contact information for the DART development group.

References

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[2] Anderson, J., *An adaptive covariance inflation error correction algorithm for ensemble filters. Tellus A,*, **59 (2)**, 210-224.

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[4] Anderson, J., Collins, N., *Scalable Implementations of Ensemble Filter Algorithms for Data Assimilation.* To appear in *Journal of Atmospheric and Oceanic Technology.*

AGU Joint Assembly, 22 May 2007, Acapulco, Mexico