THE DATA ASSIMILATION RESEARCH TESTBED

A Community Facility

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DART, developed and maintained at the National Center for Atmospheric Research, provides well-documented software tools for data assimilation education, research, and development.

Data assimilation combines observations with model forecasts to estimate the state of a physical system. Developed in the 1960s (Daley 1991; Kalnay 2003) to provide initial conditions for numerical weather prediction (NWP; Lynch 2006), data assimilation can do much more than initialize forecasts. Repeating the NWP process after the fact using all available observations and state-of-the-art data assimilation produces reanalyses, the best available estimate of the atmospheric state (Kistler et al. 2001; Uppala et al. 2005; Compo et al. 2006). Data assimilation can estimate the value of existing or hypothetical observations (Khare and Anderson 2006a; Zhang et al. 2004). Applications include predicting efficient flight paths for planes that release dropsondes (Bishop et al. 2001) and assessing the potential impact of a new satellite instrument before it is built or launched (Mourre et al. 2006). Data assimilation tools can also be used to evaluate forecast models, identifying quantities that are poorly predicted and comparing models to assess relative strengths and weaknesses. Data assimilation can guide model development by estimating values for model parameters that are most consistent with observations (Houtekamer et al. 1996; Aksoy et al. 2006). Assimilation is now used also for the ocean (Keppene and Rienecker 2002; Zhang et al. 2005), land surface (Reichle et al. 2002), cryosphere (Stark et al. 2008), biosphere (Williams et al. 2004), and chemical constituents (Constantinescu et al. 2007). Assimilation tools under different names are used in other areas of geophysics, engineering, economics, and social sciences.

The Data Assimilation Research Testbed (DART) is an open-source community facility that provides software tools for data assimilation research,

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development, and education. Using DART's carefully engineered ensemble data assimilation algorithms and diagnostic tools, atmospheric scientists, oceanographers, hydrologists, chemists, and other geophysicists can construct state-of-the-art data assimilation systems with unprecedented ease. A basic data assimilation system for a large model can be built in person-weeks, and comprehensive systems have been built in a few months. Incorporating new observation types only requires creating a forward operator that computes the expected value of an observation given a model's state.

DART includes interfaces to a number of large community atmospheric and oceanic models. For global NWP, DART produces ensemble mean analyses comparable to analyses from major centers along with initial conditions for ensemble predictions. Forward operators for standard, in situ observations and novel types, like GPS radio occultation soundings, are available. Tools to support applications like parameter estimation, sensitivity analysis, observing system design, and smoothing are also part of DART. The DART algorithms scale well on parallel computers, allowing large data assimilation problems to be studied. DART also includes many low-order models and an ensemble assimilation tutorial appropriate for undergraduate and graduate instruction.

Most operational NWP assimilation systems are based on variational calculus (Talagrand and Courtier 1987) and require enormous software development efforts with large amounts of computer code specific to a particular prediction model and observing system (Mahfouf and Rabier 2000; Okamoto and Derber 2006). For now, these costs preclude the development of variational assimilation systems by small research groups.

Ensemble filters like those provided by DART are an alternative assimilation methodology. An ensemble of forecasts is used every time data are assimilated. The forecasts are treated as a random draw from the probability distribution of the model's state given all previously used observations. The sample covariance between different state components determines how additional observations improve the ensemble estimate. Basic ensemble filters require only a prediction model and a forward operator to compute the expected value of an observation given a model state. By way of contrast, the most advanced variational assimilation methods also require linearized models and forward operators, their adjoints, and additional prior knowledge about the covariance between different model components (Kalnay et al. 2007).

DART takes advantage of the simplicity of ensemble methods to facilitate the use of data assimilation with new models and novel observation types. A small, well-defined set of interface routines is needed for a new model to be used with DART. Several comprehensive atmosphere and ocean general circulation models (GCMs) have been added to DART by modelers from outside the National Center for Atmospheric Research (NCAR; Table 1). Forward operators for new observation types also require a

Table 1. A list of large geophysical models that have been used with the DART system.

Model	Description	Lead institution
Simple advection	Tracer source/sink; low-order	NCAR/Institute for Mathematics Applied to Geosciences (IMAGe)
Two-layer primitive equation	Idealized GCM	NOAA/Earth System Research Laboratory (ESRL)
Bgrid dynamical core	Dynamical core of GCM	NOAA/Geophysical Fluid Dynamics Laboratory (GFDL)
MIT GCM annulus	Flow on rotating annulus	MIT
WRF	Regional/global prediction	NCAR/Mesoscale and Microscale Meteorology Division (MMM)
WRF-Mars	Martian GCM	Caltech
WRF 1D column	Column version of WRF	NCAR/Research and Applications Lab (RAL)
GFDL AM2	Climate prediction GCM	NOAA/GFDL NOAA/ESRL
CAM	Climate prediction GCM	NCAR/Climate and Global Dynamics (CGD)
CAM/Chem	Climate chemistry GCM	NCAR/Atmospheric Chemistry Division (ACD)
COAMPS	Short-range NWP	NRL Monterey
CMAQ	Regional air quality	University of Chicago
NCEP GFS (earlier version)	Global NWP model	NOAA/ESRL NOAA/NCEP
Rose	Middle-atmosphere GCM	NCAR/High Altitude Observatory (HAO)
MIT ocean GCM	Ocean prediction model	Scripps

small set of interface routines and can be created nearly independently of the forecast model.

DART provides a framework for developing, testing, and widely distributing advances in ensemble data assimilation. The DART software and documentation have been downloaded by more than 200 users during the last 2 yr from www.image.ucar.edu/DAReS/DART/. DART runs "out of the box" on a variety of compilers and hardware, including those listed in Table 2. In addition, DART can be customized for real-time applications that require efficient use of large computers.

Some capabilities of the DART tools are described here using a series of examples ranging from assimilation in toy models to global NWP, observing system design, and model improvement. Although the large model examples are for atmospheric applications, DART is also being used with models of the ocean and land surface, and for applications as diverse as economics and target tracking. The examples are followed by a description of the DART ensemble filter algorithms.

Table 2. DART runs on the compilers and hardware shown here. Linux indicates single processor or clusters.

Compiler	Hardware
Intel ifort	Linux, Mac Intel, SGI Altix
Absoft f90	Mac PowerPC/Intel
PGI pgf90	Linux, Mac PowerPC/Intel
gfortran	Linux, Mac PowerPC/Intel, cygwin
g95	Linux, Mac PowerPC
IBM xlf	IBM Power 5/6
Pathscale pathf90	Linux
Lahey lf95	Linux

SAMPLE DART APPLICATIONS.

Low-order models. DART includes a dozen low-order dynamical systems that are used in the tutorial as educational tools and by data assimilation scientists for testing novel assimilation techniques. Figure 1, from the DART tutorial, illustrates the operation of an ensemble filter in the Lorenz (1963, hereafter LOR) three-variable dynamical systems with its familiar butterfly attractor.

Ensemble analyses and uncertainty. DART algorithms and code identical to those used in LOR are applied to enormous models like atmosphere or ocean GCMs. Figure 2 shows a "spaghetti" plot produced by an 80-member ensemble filter using NCAR's Community Atmosphere Model (CAM) version 3.5 (Collins et al. 2006) and assimilating wind components and temperatures from radiosondes and aircraft and satellite cloud motion vectors every 6 h. Operational NWP centers like the National Centers for Environmental Prediction (NCEP) and the European Centre for Medium-Range Weather Forecasts (ECMWF) solve similar data assimilation problems with higher-resolution models, variational assimilation tools, and additional observations like satellite radiances. The figure shows the major winter storm that affected the 2007 American Meteorological

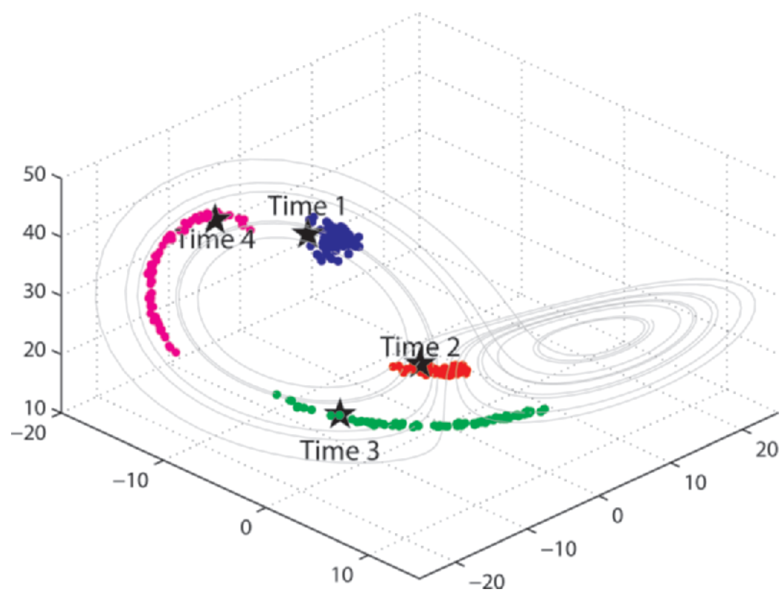

Fig. 1. The evolution of an ensemble Kalman filter assimilation system in the LOR model from the DART tutorial. Synthetic observations (black stars) are created by "observing" a long integration of the model and adding random noise to simulate observational error. The forecasts from an 80-member ensemble assimilation valid at four consecutive observing times are shown by colored dots; the background attractor is depicted by the thin gray curve resulting from the long integration. At time 1, the prior estimate is fairly compact. At time 2 the ensemble is passing through the bifurcating region, and the prior at time 3 is stretched out with members heading into each attractor lobe. The observation at time 3 is enough to compel all ensemble members into the correct lobe at time 4, but uncertainty is greater at this time.

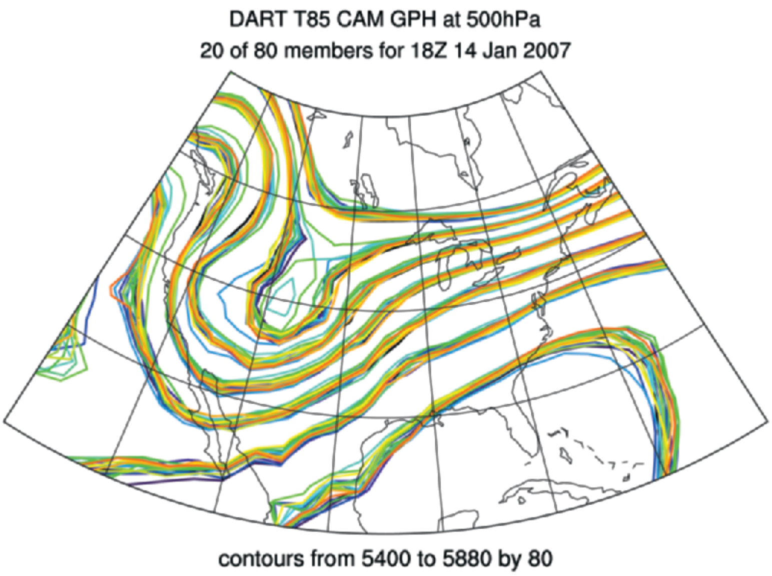

Fig. 2. A spaghetti plot of 6-h forecast 500-hPa height showing contours from 20 of 80 ensemble members in a DART assimilation using the CAM GCM. The forecasts are valid at 1800 UTC 14 Jan 2007. Forecasts are more certain where the contours are more similar and less certain where spread is greater.

Society annual meeting in San Antonio, Texas. The ensemble mean height contours (not shown) fit the observations as well as the NCEP Global Forecast System (GFS), but the ensemble system provides information about the forecast uncertainty. Variability is smallest along contours with parcels that have been in well-observed regions for a long time. Contours over the western United States and adjacent Pacific have more variability than those over the northeast United States. The position and tilt of the deep trough over the Rocky Mountains are uncertain. Quantifying uncertainty in analyses and forecasts is a distinct advantage of ensemble data assimilation over variational methods.

Global NWP. The most advanced variational assimilation systems are used for global NWP. Ensemble assimilation methods are competitive with three-dimensional variational assimilation algorithms (Houtekamer et al. 2005; Whitaker et al. 2008), while the relative capabilities of ensemble filters and four-dimensional variational methods are a topic of ongoing research (Kalnay et al. 2007). The DART algorithms out of the box compare favorably with operational systems for the global NWP problem.

Figure 3 shows the monthly-mean root-mean-square (RMS) error and bias of the ensemble mean for DART/CAM assimilations and 6-h forecasts for January 2007. The data are generated by applying forward operators to the ensemble members to compute estimated values of radiosonde temperature observations and comparing the ensemble mean to the observations. The 6-h forecast metrics are the most informative, since the analysis fits are compared to observations that have already been assimilated and overfitting is a possibility (in any data assimilation system). These results depend on the assimilation system, the model, and the observations. Despite a lower-resolution model and fewer observations, the DART results for January 2007 compare favorably with the operational GFS system at NCEP for this month (see http://wwwt.emc.ncep.noaa.gov/gmb/ssaha/ for comparison).

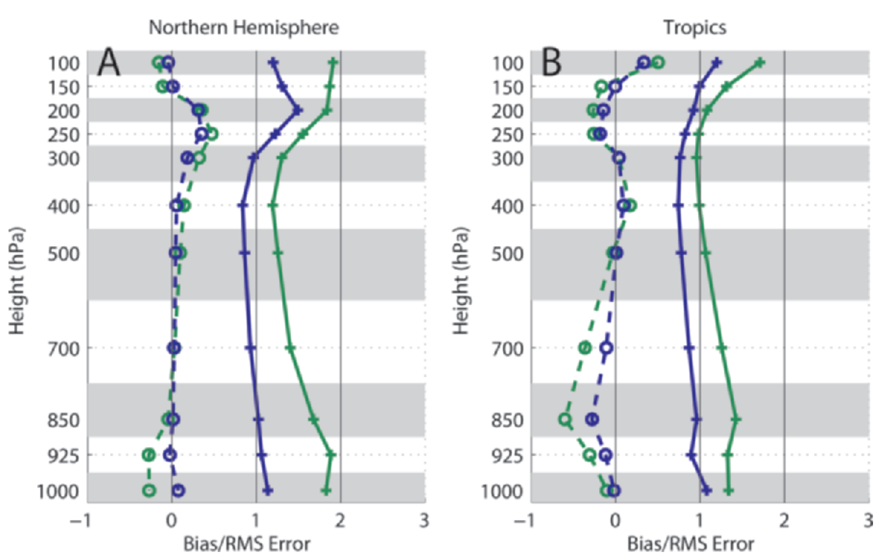

Fig. 3. Jan 2007 monthly mean bias (dashed) and RMSE (solid) for analyses (blue) and 6-h forecasts (green) of observed radiosonde temperatures averaged over different vertical bands indicated by shading. The forecasts are produced by an 80-member ensemble filter using the CAM model and assimilating radiosonde, ACARS, and cloud drift wind observations.

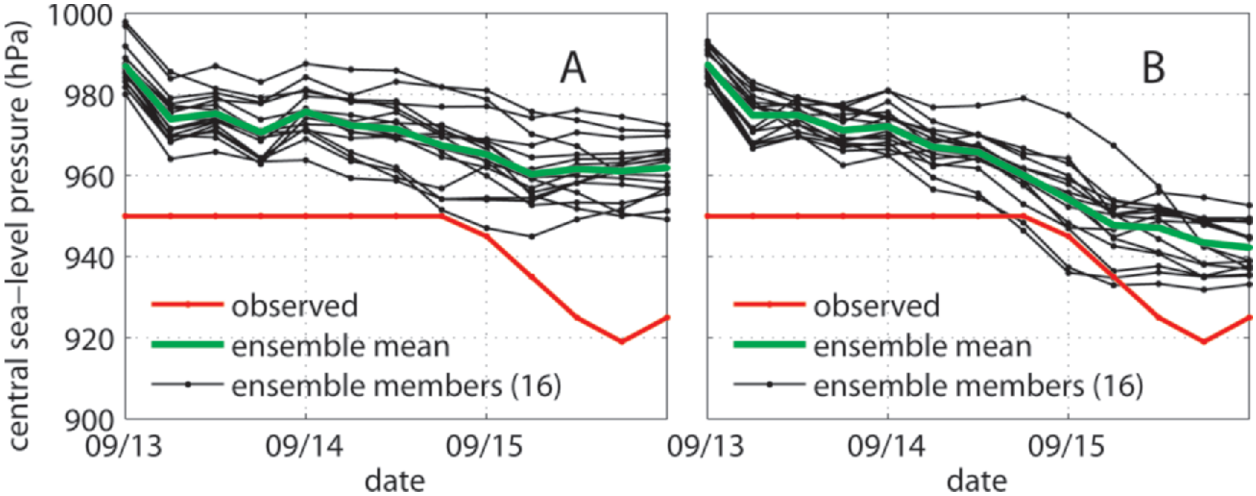

FIG. 4. The minimum sea level pressure of Typhoon Shanshan (2006) from an ensemble of 16 forecasts (black), the ensemble mean (green), and the best estimate of the observed (red). The forecasts are made with a 15-km grid WRF model while the initial conditions are 16 randomly chosen members of a 32-member ensemble analysis performed with a coarser 45-km WRF configuration. The assimilation uses (a) radiosondes, ACARS, cloud drift winds, QuikSCAT surface winds, and satellite thickness, and (b) all of the above as well as COSMIC radio occultation observations (Liu et al. 2008). About 100 COSMIC soundings per day are available in the region covered by the model.

Assimilating novel observation types. DART enables researchers to quantify the potential impact of new observation types on predictions of high-impact weather like tropical storms. Figures 4 and 5 show ensemble forecasts for Typhoon Shanshan in 2006 with initial conditions from DART with the Weather Research and Forecasting (WRF) regional prediction model (Skamarock et al. 2005). (DART has interfaces to all recent versions of the Advanced Research WRF model and works with both regional and global domains with nested higher-resolution subdomains.) Differences between the two ensembles of forecasts reflect the impact of assimilating GPS radio occultation measurements from the Constellation Observing System for Meteorology, Ionosphere and Climate (COSMIC) satellites (Rocken et al. 2000; Anthes et al. 2008). A local refractivity forward operator (Kuo et al. 2000) was used to map from the WRF state vector to the expected value of the observation. About 100 COSMIC soundings per day are available in the region covered by the model.

The initial minimum surface pressure of the typhoon is significantly too weak (Fig. 4), in part because of the coarse 45-km WRF used in the assimilation. A quantitative assessment of significance can be made by comparing the ensemble

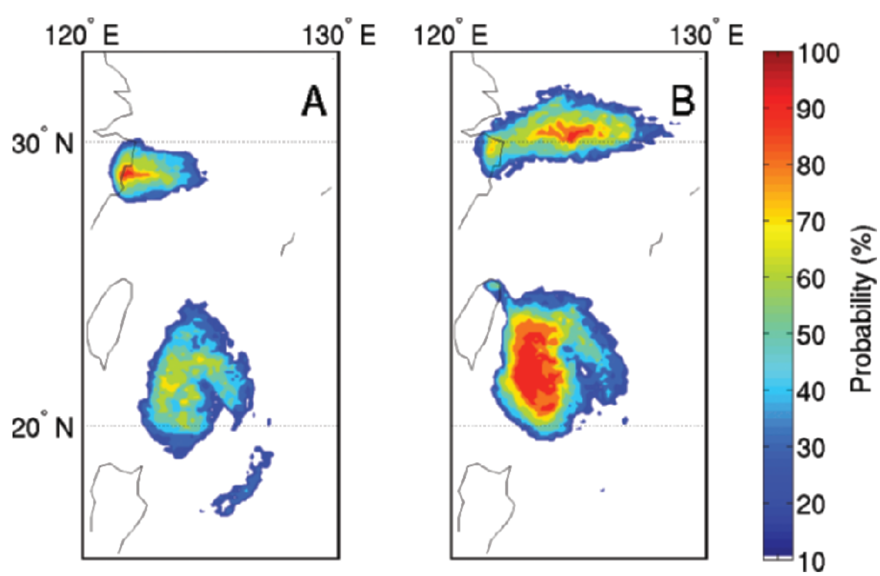

FIG. 5. Forecasts of the estimated probability that rainfall will exceed 60 mm during the period from 1200 UTC 14 Sep to 1200 UTC 15 Sep 2007 initiated 36 h before the start of the period. The probability at each grid point is computed by dividing the number of forecast members that predicted excessive precipitation by 16, the total number of forecasts. As in Fig. 4, the assimilations producing the forecasts were made both (b) with and (a) without COSMIC radio occultation observations.

samples for the two cases. As the 15-km forecasts advance, the predicted storms intensify but the forecasts from the analyses with COSMIC are significantly stronger. Even the forecasts with COSMIC are too weak in general, suggesting that further model improvements and additional observations are needed for better predictions.

Figure 5 demonstrates another ensemble capability, estimating the probability of occurrence of an event. Ensemble forecasts starting from analyses using COSMIC observations indicate larger probabilities of excessive precipitation and are more consistent with observations of heavy rainfall over northern Taiwan.

Adding the ability to assimilate a new type of observation like GPS radio occultation to DART only requires coding the forward operator function that maps from the model state to the expected observed value. No adjoints, linear tangents, or prior estimates of error covariances between the observation and state components are required. The same forward operator can be used with many models. For instance, the COSMIC forward operator is also used with CAM, the AM2 atmospheric GCM from the National Oceanic and Atmospheric Administration's (NOAA's) Geophysical Fluid Dynamics Laboratory, and versions of NCEP's GFS global model. DART has two radio occultation forward operators, one using local and another using nonlocal refractivity (Sokolovskiy et al. 2005).

Data assimilation support for field experiments. DART assimilations with NCAR's Community Atmosphere Model with Chemistry (CAM-Chem) model provided real-time predictions for the 2008 Arctic Research of the Composition of the Troposphere from Aircraft and Satellites (ARCTAS) field experiment. This required incorporating an extended version of CAM and new observations into DART and running the system in real time. Ensemble-mean analyses of carbon monoxide (CO) concentration for a case used to prototype the real-time data assimilation system are shown in Fig. 6. Assimilations of the standard observations used in the CAM NWP experiments (Fig. 6a) are compared to a case that also assimilates observations from the Measurements of Pollution in the Troposphere (MOPITT) instrument on the National Aeronautics and Space Administration's (NASA's) Earth Observing System (EOS) *Terra* satellite (Fig. 6b). The MOPITT observations modify the CO analysis to be more consistent with independent aircraft observations (Arellano et al. 2007). Because ensemble data assimilation provides estimates of the prior covariance between any model state component and any observation, incorporating additional state variables like chemical tracers into existing DART-compliant models is straightforward and can lead to improved estimates of all model variables.

Observing system design. As part of the ARCTAS campaign, forecasts from several models and assimilation systems were used to make flight plans for aircraft taking special observations. Ensemble assimilations and forecasts provide estimates of the sensitivity of analyzed and predicted state components to additional observations. Questions like where an additional observation of CO concentration must be taken 6 h from the present to give the best possible

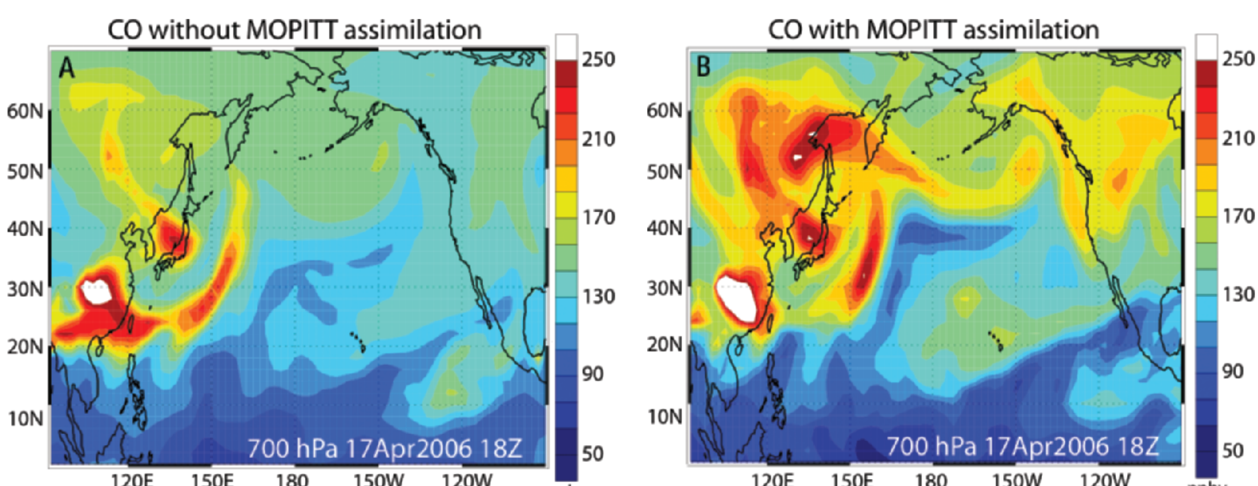

Fig. 6. Ensemble-mean concentration of carbon monoxide at 700 hPa at 1800 UTC 17 Apr 2006 produced by 20-member ensemble assimilations with the CAM/CHEM model. (a) Radiosondes, ACARS, and satellite cloud drift winds were assimilated; (b) same as (a), but augmented by observations of CO retrieved from MOPITT.

forecast of concentrations at a given point 24 h further in the future can be answered quantitatively. Related experiments called Observation System Simulation Experiments (OSSEs) can assess the value of existing or planned observations. In an OSSE, a long time series from a model integration is treated as a proxy for the physical system. This model time series is referred to as the "truth" or a "nature run." Synthetic observations are generated by computing the value of the observed quantities given the model's state and adding random draws from the prescribed observational error distribution. The synthetic observations are then assimilated to investigate how they reduce differences between an analysis and the "true" model state. DART provides tools to do a variety of evaluations of planned observations or enhanced observing system (Khare and Anderson 2006b).

Sensitivity analysis. Sensitivity analysis evaluates how a forecast is affected by changes to its initial conditions. DART ensemble analyses and forecasts can be used for sensitivity analysis to learn more about the impact of observations and the data assimilation system on forecasts and to increase understanding of model dynamics (Ancell and Hakim 2007; Torn and Hakim 2008). Ensemble sensitivity is similar to adjoint and singular vector sensitivity (Baker and Daley 2000; Langley et al. 2002) from variational assimilation systems but requires little additional computation given the ensemble analyses and forecasts. Figure 7 displays the sensitivity of a 48-h forecast of Hurricane Katrina's longitude to the initial conditions for the deep layer mean (850–250 hPa) zonal wind. The longitude forecast is sensitive to Katrina's initial position and to the wind in the Gulf of Mexico. When a storm is farther east or easterly winds in the Gulf are weaker, the forecast storm is farther east.

Improving prediction models. Ensemble data assimilation is a powerful tool for improving prediction models, particularly climate models that are not normally confronted by high-frequency observations. Investigating the source of distinctive gridpoint noise along 67°N in an ensemble mean analysis of 266-hPa meridional wind (Fig. 8a) revealed an incorrect implementation of the polar filter in an earlier version of the finite-volume CAM dynamical core. Figure 8b shows results from a reanalysis with a corrected polar filter. Subsequent examination revealed this noise in climate integrations of CAM. More subtle problems

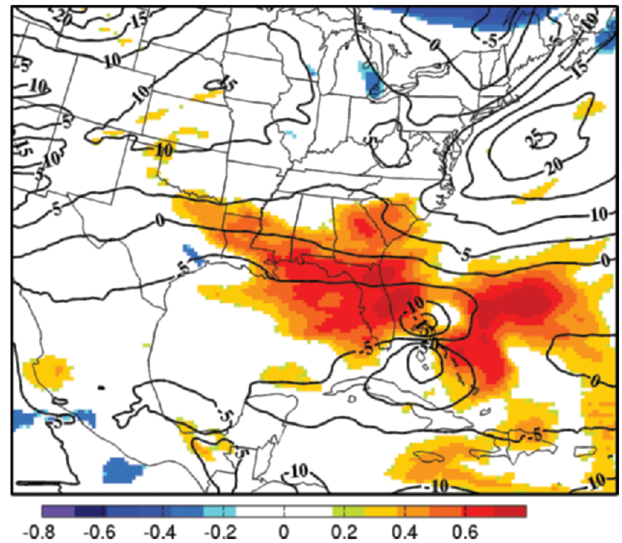

Fig. 7. The shading shows the sensitivity of a 48-h forecast of Hurricane Katrina's longitude to the value of the analyzed 850–250-hPa-layer mean zonal wind. Units for the sensitivity are degrees of change per each standard deviation change in the analysis value. The contours are the analyzed ensemble-mean, layer-mean zonal wind (m s^{-1}). The results are produced using forecasts initialized from a 96-member DART assimilation with a 27-km grid WRF model.

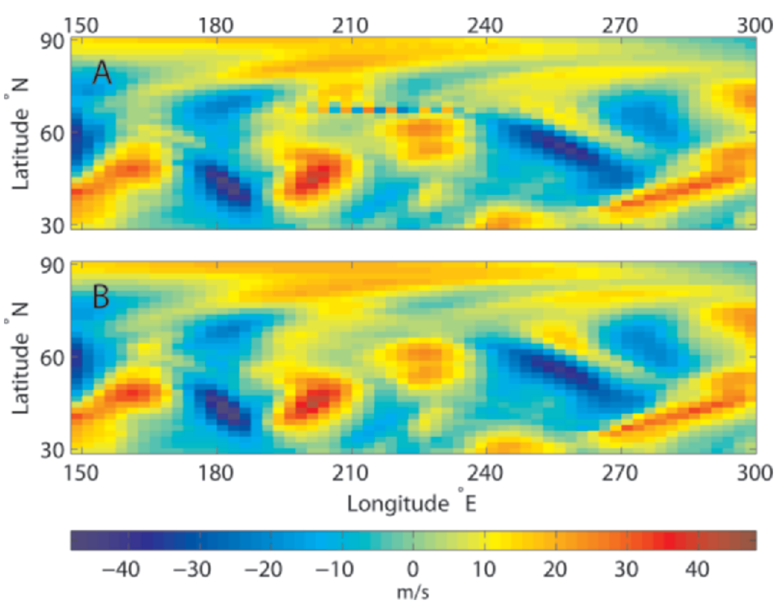

Fig. 8. The ensemble-mean 266-hPa meridional wind for 0000 UTC 25 Sep 2006 from an 80-member DART assimilation with (a) an early version of CAM 3.5 and (b) a later version in which problems with the polar filter have been corrected.

with the CAM dynamics were also detected with DART/CAM, catalyzing an on-going effort to improve the numerical diffusion in the model.

Ensemble data assimilation can also tune model parameters directly to make predictions that are as consistent with observations as possible. Model parameters are recast as additional state variables so that each ensemble has its own estimate of each parameter. Parameter estimates are updated by observations just like the regular state variables (Aksoy et al. 2006). For instance, parameters from the gravity wave drag scheme in CAM were added to the state vector, and the resulting predictions fit observations better than the baseline DART/CAM. Parameter tuning remains a challenging statistical and numerical research problem that can be attacked with tools in DART.

Support for education. Many universities use the DART tutorial to introduce undergraduate and graduate students to ensemble data assimilation. DART can also be adapted to provide examples and exercises for particular applications. For instance, conveners of a workshop on carbon data assimilation at NCAR

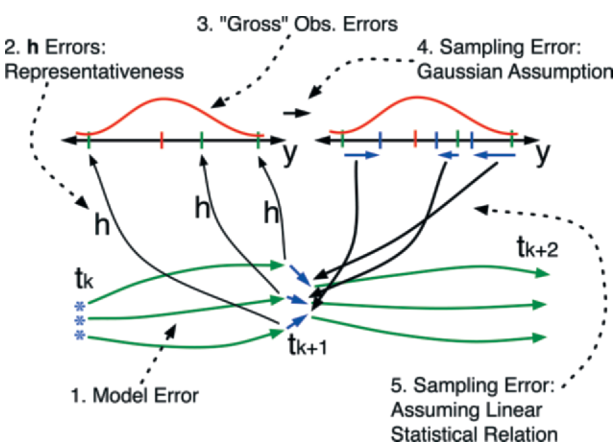

FIG. 9. Idealized operation of an ensemble Kalman filter with major error sources indicated for each step. A three-member estimate of the model state at time t_k (blue asterisks) is advanced to time t_{k+1} by a forecast model (green vectors). A forward observation operator, *h*, is applied to each state vector to obtain three estimates of an observation (green ticks on upper axes). The observed value (red tick) and the observation likelihood (red curve) are combined with the prior ensemble estimate to obtain an updated ensemble estimate (blue ticks) and increments (blue vector below top right axis). The increments to the observation ensemble are regressed onto each state vector component independently to generate increments (blue vectors on end of green vectors). The model is then used to advance the updated state estimates to time t_{k+2} when the next observation becomes available.

in July 2007 developed a low-order model of tracer production, transport, and destruction to investigate the relative value of observations of meteorological quantities and tracer concentration. The DART ensemble smoother (Evensen and van Leeuwen 2000) estimated tracer sources using only observations in the free "atmosphere." This low-order model was incorporated into DART in less than a day.

SEQUENTIAL ENSEMBLE DATA ASSIMILATION.

Figure 9 illustrates the assimilation algorithms used in DART starting with a three-member (20 or more are needed for real applications) ensemble of model state vectors at time t_k. A model produces ensemble forecasts for time t_{k+1} when the next observation is taken. Assuming that observational error distributions for all pairs of observations are independent (which can be relaxed using more advanced algorithms), means observations can be assimilated sequentially (Anderson 2003). Therefore, the assimilation algorithm can be described for a single observation without loss of generality.

A forward observation operator *h* is applied to each state vector to give prior estimates of the observation *y*. The observed value comes from the instrument while the observation likelihood depends on the instrument's error characteristics. The likelihood is the probability that the instrument would have observed what it did if *y* were the true value of the observed quantity.

An ensemble filter combines the prior ensemble, the observation, and the likelihood to compute an updated ensemble estimate and corresponding increments to the prior ensemble. Most differences between ensemble filter algorithms in the geophysical literature (Evensen 2003; Pham 2001; Whitaker and Hamill 2002; Ott et al. 2004) are associated with computing the updated ensemble for the observed quantity.

DART includes a variety of algorithms for computing the updated observation ensemble including the perturbed observation ensemble Kalman filter (EnKF; Burgers et al. 1998) and the ensemble adjustment Kalman filter (EAKF; Anderson 2001). The EnKF is a true Monte Carlo algorithm with a random number generator producing draws from the observation likelihood distribution, whereas the EAKF is a deterministic ensemble square root filter (Tippett et al. 2003).

The EAKF computes the updated ensemble for the observation as illustrated in Fig. 10. A normal distribution with the sample mean and standard deviation of a five-member prior is plotted. The observed likelihood is assumed to be normal; the mean of the likelihood, 1.0 in this case, is the observed value from the instrument. The Bayes theorem, the foundation of all data assimilation algorithms, indicates that the posterior distribution is the product of the prior distribution and the likelihood. The product of the prior normal and the normal likelihood is itself normal (after having its amplitude modified so that it is a probability distribution), with a standard deviation smaller than that of either the prior or the likelihood. The EAKF creates an updated ensemble by shifting the prior ensemble to have the same mean as the continuous posterior and then linearly contracting around the posterior mean so that the ensemble standard deviation is the same as that of the continuous posterior (Fig. 10b). For a simple problem with the linear forecast model, linear observation operators, normal observational errors, and an ensemble bigger than the model state vector, the EAKF is simply an algorithm for computing the Kalman filter (Kalman and Bucy 1961). Nevertheless, the EAKF does retain some nonnormal characteristics of the prior ensemble sample in the posterior sample. This can affect assimilations for applications like the LOR example shown in Fig. 1, where the apparent bimodality in the prior ensemble is maintained in the posterior ensemble.

Finally, increments for each component of the prior state vector are computed from the observation increments by linear regression. Figure 11 illustrates the joint prior distribution of an observed quantity and a state vector component (they have a positive correlation of about 0.6), the corresponding marginal distribution for the observation prior ensemble, and the updated ensemble computed as described in the previous paragraph. For the regression, the observation increments are projected onto the least squares line in the joint distribution. The increments from the joint distribution are projected onto the marginal distribution for the state vector component. The updated mean of the state component is larger than the prior, as one would intuitively expect given the positive correlation with the observed quantity.

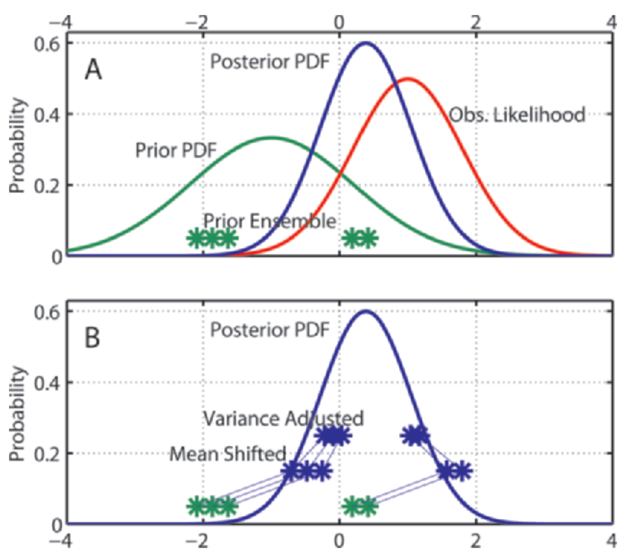

Fig. 10 (top). A five-member ensemble of prior estimates of an observed variable (green asterisks) has been obtained by applying a forward operator, *h*, to each ensemble state vector. It is illustrated (a) how the ensemble adjustment Kalman filter takes the product of a normal with the sample mean and variance of the ensemble (green curve) and a normal observation likelihood (red curve), resulting in a normal continuous posterior distribution (blue curve) and (b) how the posterior ensemble is generated by first shifting the prior ensemble to have the same mean as the continuous posterior (blue curve) and then linearly contracting the ensemble so that it has the same variance as the continuous posterior.

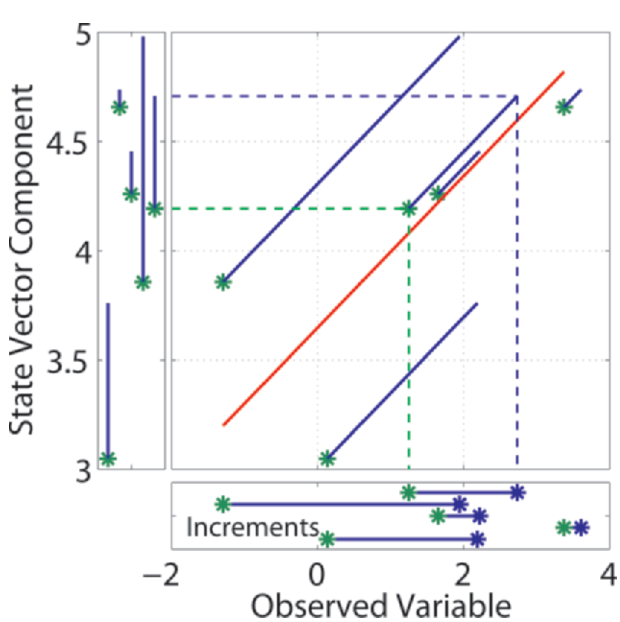

Fig. 11 (bottom). The large plot is the joint prior distribution of a five-member ensemble for an observed quantity and a state vector component (green asterisks) with a least-square fit shown in red. The lower plot shows the marginal distributions for the observed variable; the ensemble prior (green asterisks), the ensemble posterior obtained by an ensemble adjustment Kalman filter (blue asterisks), and the increments (blue segments). These increments are projected onto the joint distribution using the least-squares line (blue segments in central panel) and these are in turn projected onto the marginal distribution for the state variable to give the state increments (left panel, blue segments).

ADVANCED ASSIMILATION TOOLS. The simplicity of the basic ensemble filter algorithm has encouraged geophysicists to code their own implementations, but challenges to using ensemble data assimilation for geophysical applications remain. Figure 9 identifies potential error sources in each step of the assimilation process.

The computational expense of large geophysical prediction models compels the use of small ensembles that lead to large sampling error. DART provides tools to reduce sampling error in the regression step (step 5, Fig. 9) using localization of observation impact (Houtekamer and Mitchell 2001; Hamill et al. 2001). The expected error in the regression is larger when the absolute value of the correlation between an observed quantity and a state variable component is small. When the two are uncorrelated, the observation should not impact the state variable, but a small ensemble can have spurious large correlations due to sampling error. This leads to an erroneous increase in ensemble confidence and random errors in the mean. Regression sampling error can be limited by reducing the impact of an observation on weakly correlated state vector components. The regression coefficient is multiplied by a localization factor that decreases from 1 to 0 as the physical distance between an observation and a state vector component increases. Defining effective localization factors for a given ensemble size, forecast model, and observational network requires extensive expert knowledge. To circumvent this requirement, DART includes a group filter that computes appropriate localizations automatically (Anderson 2007a). This tool uses a small "group" of ensembles during a training period to estimate localization factors that minimize expected sampling error.

Model error (unavoidable and often dominant in geophysics applications) and the other error sources noted in Fig. 9 also lead to ensemble estimates that are too confident (Baek et al. 2006). In the worst case, the prior estimates become so confident that observations are mostly ignored, resulting in filter divergence. Inflation (Anderson and Anderson 1999) increases uncertainty in the ensemble estimate by linearly expanding the distance between each ensemble member and the ensemble mean. Whereas localization tries to eliminate the loss of variance due to sampling error, inflation treats the insufficient variance symptom caused by all error sources.

For some applications, a single value of inflation for each state vector component is effective in reducing the ensemble mean RMS error and increasing ensemble variance to appropriate values. However, a single inflation value can be problematic for large geophysical applications (Hamill and Whitaker 2005). For instance, a fixed inflation of 1.5 in an 80-member CAM assimilation with the observations used in earlier sections leads to significantly better ensemble-mean fits to observations over North America during the first week of an assimilation than a case with no inflation. However, ensemble variance in the Southern Hemisphere gradually increases until some model forecasts fail in the second week due to unrealistically strong winds. In the Southern Hemisphere, observations are sparse, and the fixed inflation required to ameliorate sampling error over densely observed North America leads to unconstrained growth of ensemble variance.

Inflation values must vary spatially to produce improved analyses and forecasts globally. Inflation that varies temporally as weather patterns or observation density vary in time is also useful. DART includes tools that allow ensemble data assimilation to automatically compute a temporally and spatially varying inflation (Anderson 2007b, 2009) as part of the assimilation. For each observation, the expected difference between the observed value and the prior ensemble mean estimate is computed from the prior ensemble, the observation, and the observation likelihood. If the observation is farther from the ensemble mean than expected, more inflation is indicated; if it is closer, less is needed. Bayes's theorem is used as in the basic ensemble assimilation to update the value of inflation for each component of the state vector.

We performed CAM assimilations for August 2006 with no inflation and with DART's most advanced damped adaptive inflation algorithm. The assimilations start from identical climatological ensembles. In 6-h forecasts of 500-hPa radiosonde temperature observations for these two assimilations, the spread (standard deviation) of the inflation case is larger and the RMS error is smaller. Monthly-mean RMS error is 0.99 for no inflation and 0.75 with inflation (Fig. 12, bottom). Like operational assimilation systems, DART includes quality control algorithms to automatically detect and discard observations that are too far away from the prior ensemble. Observations that are many standard deviations farther away from the prior ensemble mean than would be expected given the prior variance and the observational error are discarded.

As the assimilation without inflation proceeds, the reduced ensemble variance and increased error leads to a gradual increase in the number of observations that are discarded, further degrading the assimilation (Fig. 12, top).

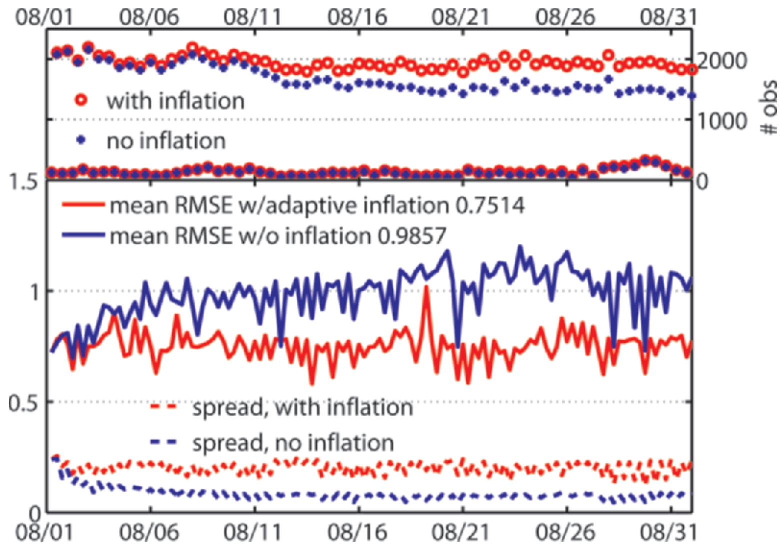

Fig. 12. (bottom) The RMSE of the ensemble mean (solid) and the ensemble spread (dashed) for 6-h forecasts of observed 500-hPa radiosonde temperatures for Aug 2006 over the Northern Hemisphere. The forecasts are generated by 80-member ensemble filters using the CAM model without any inflation (blue) and using the DART damped adaptive inflation (red). (top) The number of observations used by the two assimilations at each assimilation time; the lower points are for 0600 and 1800 UTC assimilations while the upper points are for 0000 and 1200 UTC when radiosondes are more plentiful.

The adaptive inflation fields that result in high-quality assimilations can have complex structures in space and time. Figure 13 shows the inflation pattern for 266-hPa zonal winds at the end of August. Inflation values vary from 1.0 (no inflation) to nearly 14. The largest values are associated with areas with the highest density of Aircraft Communication Addressing and Reporting System (ACARS) observations from commercial aircraft. Large inflation is needed to account for model error in regions where dense observations reduce ensemble spread the most. Adaptive inflation facilitates the use of ensemble data assimilation in the presence of errors without the need for extensive tuning and assimilation expertise.

DART includes a parallel version of the sequential ensemble filter using the message passing interface (MPI) programming model. The scaling characteristics of the algorithm are designed to be independent of the model and observations being assimilated (Anderson and Collins 2007). For sufficiently large models, the algorithm scales to an arbitrary number of processors. DART algorithms developed using low-order models can be applied to the largest geophysical models on large scalable computers.

The low-order model examples provided with DART can be run in seconds on a modern laptop. However, data assimilation with large models requires significant computational resources. For example, a 20-member assimilation for a 1-month period uses a total of 20 months of model forecasts. At least 20 ensemble members are needed for good results in atmospheric applications.

The chemical assimilation shown in Figure 6 uses 20 members, the typhoon results shown in Fig. 5 use 32 members, and the global NWP in Fig. 2 uses 80 members. In all three cases, the cost of assimilating the available observations is approximately equal to the cost of advancing the model. Details of the cost depend on the density of observations and the localization used, but a rough estimate of cost is twice that of advancing the ensemble forecasts over the assimilation period. Large model runs are typically configured on a supercomputer or Linux cluster with one MPI task for each ensemble member. As an example, the CAM NWP case requires approximately one wall-clock day on 80 processors of an IBM POWER6 system to assimilate a month of data with roughly half a million observations per model day. More details of the expected computational costs can be found in Anderson and Collins (2007).

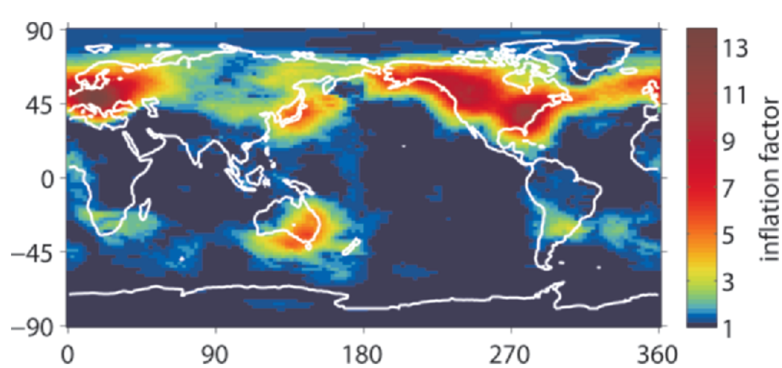

Fig. 13. The inflation field at 1800 UTC 31 Aug 2006 from the 80-member ensemble Kalman filter using CAM and the DART damped adaptive inflation. Large values of inflation are needed to compensate for model error in areas where dense ACARS observations from aircraft lead to small ensemble spread.

The basic DART algorithms are coded in Fortran 90 and controlled by namelist interfaces. Diagnostic output files describing model variables are in Network Common Data Form (NetCDF) whereas observation input and diagnostic files are in a special DART format. DART includes tools to convert common observational datasets, for instance NCEP PREPBUFR files, into this format. A suite of MATLAB scripts is included to produce plots from the diagnostic files. All figures shown here were produced by these scripts.

The Data Assimilation Research Section (DAReS) at NCAR provides limited support to users of DART. Comprehensive support is provided for the incorporation of new models, observations, or assimilation algorithms that are of broad community interest. For instance, DAReS has actively supported the incorporation of new models like the Community Multiscale Air Quality (CMAQ) model, the Massachusetts Institute of Technology (MIT) Ocean Model, and the Coupled Ocean–Atmosphere Mesoscale Prediction System (COAMPS). Scientists with interesting new data assimilation challenges are encouraged to seek collaborations with the DAReS staff.

SUMMARY. The DART community ensemble data assimilation facility provides students, educators, and scientists with unprecedented access to free, state-of-the-art assimilation tools. DART's comprehensive tutorial, low-order models, and examples can introduce students to ensemble data assimilation on their laptops. The same tools can produce analyses using 10-million-variable climate system models, novel remote sensing observations, and the newest supercomputers. This enables students to advance quickly from basic understanding to meaningful research projects. DART can also accelerate scientific progress by modelers and observational researchers who do not have resources to develop their own assimilation systems.

Future DART releases will include enhanced parallel methods that scale for thousands of processors, novel algorithms to deal with nonlinearity and non-Gaussianity in ensembles, and carefully documented MATLAB versions of the core DART algorithms for students. DART users are also contributing new models, observation types, and algorithms. By providing a nexus for a growing community of data assimilation users and experts, DART can provide an increasingly powerful and flexible set of tools for ensemble data assimilation.

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