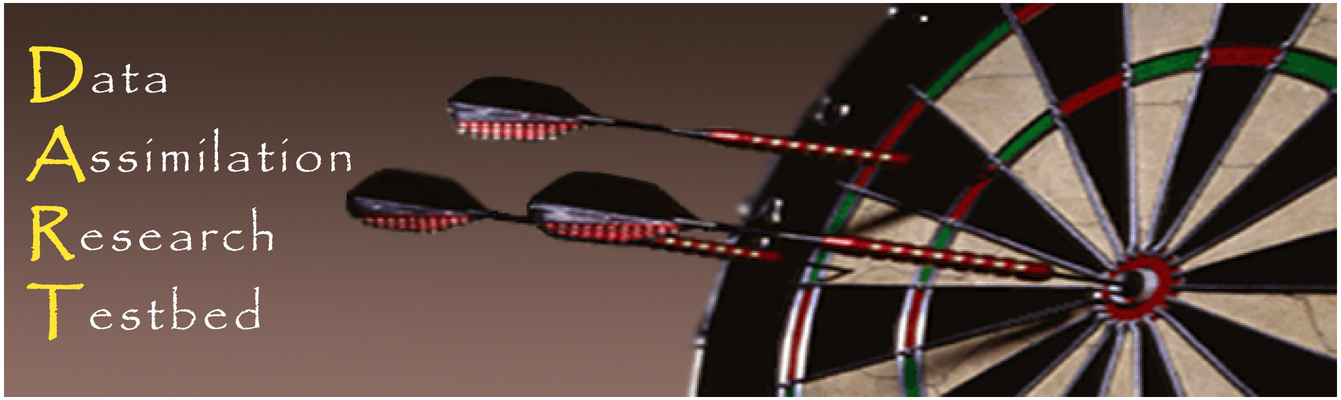
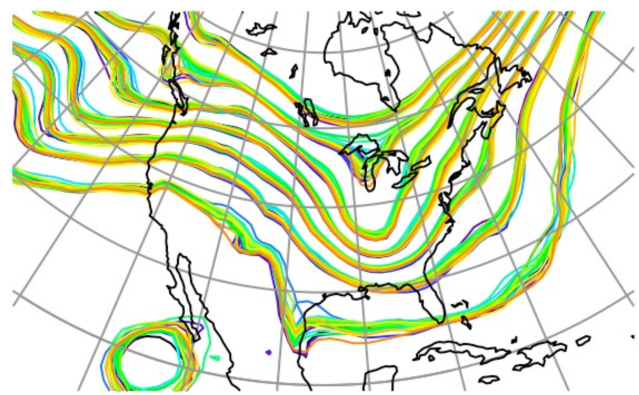


DART Tutorial Section 20: Model Parameter Estimation



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Model Parameter Estimation

Suppose a model is governed by a (stochastic) Difference Equation:

$$dx_t = f(x_t, t; u) + G(x_t, t; w)d\beta_t, \quad t \geq 0 \qquad (1)$$

where u and w are vectors of parameters. Also, suppose we really don't know the parameter values (very well). **Can we use observations with assimilation to help constrain these values?**

Rewrite (1) as:

$$dx_t^A = f^A(x_t^A, t) + G^A(x_t^A, t)d\beta_t, \quad t \geq 0 \qquad (2)$$

where the augmented state vector includes x_t, u, and w.

The model is modified so values of u and w can be changed by assimilation. The model might also introduce some time tendency for u and w.

Model Parameter Estimation

From the ensemble filter perspective:

Just add any parameters of interest to the model state vector;
Proceed to assimilate as before.

Possible difficulties:

1. Where are parameters 'located' for localization?
2. Parameters won't have any error growth in time (unless we add some): could lead to filter divergence.
3. Parameters may not be strongly correlated with any observations.

Testing Parameter Estimation in DART

DART includes a ***models/forced_lorenz_96*** directory.

Each state variable has a corresponding forcing variable, F_i.

$$dX_i / dt = \left(X_{i+1} - X_{i-2}\right) X_{i-1} - X_i + F_i \qquad (3)$$

Observational errors for obs. in set i independent of those in set j.

$$dF_i / dt = N\left(0, \sigma_{noise}\right) \qquad (4)$$

Can observations of some function of state variables constrain F?

Adding namelist control aspects required for experimentation:

models/forced_lorenz_96/work/

```
&model_nml
   num_state_vars     = 40
   forcing            = 8.0
   delta_t            = 0.05
   time_step_days     = 0
   time_step_seconds  = 3600
   reset_forcing      = .false.
   random_forcing_amplitude = 0.10
   /
```

If `reset_forcing = .true.`, F_i = *forcing* (also from namelist) for all i,t.

σ_{noise} for F_i time tendency, not used if `reset_forcing = .true.`

Using these, can create OSSE sets with fixed, global F value.

Assimilate these with filter, estimate state and forcing.

Get an ensemble sample of F_i at each time.

Random noise can be useful for avoiding filter divergence.

Assimilation in the forced Lorenz 96 model

```
cd models/forced_lorenz_96/work
./workshop_setup.sh
```

Use Matlab, etc. to examine output.

Same 40 randomly-located observations as in lorenz_96 cases.
Forcing was fixed at 8.0 in the perfect_model run.
Values of F_i are modified in the assimilation.
There was some noise (amplitude of 0.1) added to the time tendency.

Amazing Fact: *Best assimilations of state come when* F_i *varies, even better than when* F_i *is set to exact known value of 8.0!*

Contest: Given an observation set, what was the value of F?

In *models/forced_lorenz_96/work* edit *input.nml*

```
&filter_nml
   …
   obs_sequence_in_name = "obs_seq.out"
```

Change to "obs_seq.out.CONTEST"

Question: *What was the value of the forcing in the perfect_model run?*

You can try anything (ethical) you want.

Feel free to ask for help to try experiments you don't know how to do.

Remember: The Truth is NO LONGER KNOWN!

Consistent with the theme of the workshop … in the event of a tie, a random number generator will be used to decide the winner.

Honor, fame, and fabulous(?) prizes go to the winning team!!!

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