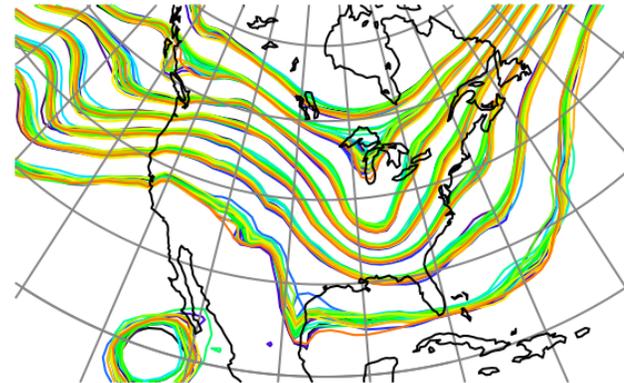


Data
Assimilation
Research
Testbed



DART Tutorial Section 20: Model Parameter Estimation



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Model Parameter Estimation

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

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

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:

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

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 .

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

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

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

Can observations of some function of state variables constrain F ?

Adding namelist control aspects required for experimentation:

1. `reset_forcing`

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

2. `random_forcing_amplitude`

σ_{noise} for F_i time tendency,

not used if `reset_forcing` is *.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  
csh workshop_setup.csh
```

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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