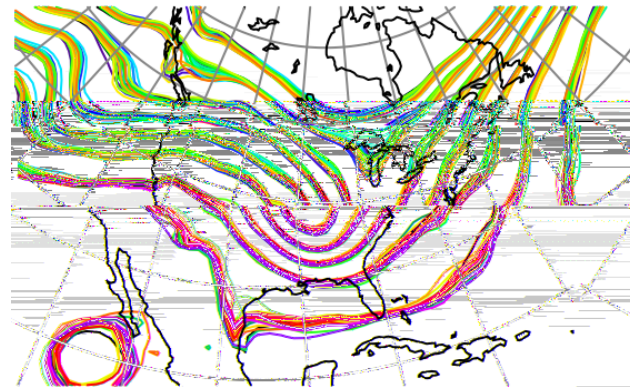


Data  
Assimilation  
Research  
Testbed



## 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  $w$ .

## **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.

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

$\sigma_{noise}$  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.

# 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  $i, t$ .

$\sigma_{noise}$  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  
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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