Predictability of a Data Assimilation / Prediction System

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Introduction:

I. Interesting predictability problems in assimilation / prediction systems

II. Consider assimilation / prediction system as dynamical system of interest

III. Examine predictability of this system

IV. Examine 'information content' of observational systems

V. Work here in perfect model world

Outline:

I. Introduce hierarchical ensemble filter

II. Look at predictability in Lorenz-96 low-order model

- A. As function of ensemble size (detail of assimilation system)
- B. As function of observational error

III. Moderate resolution idealized atmospheric GCM, surface pressure obs. only

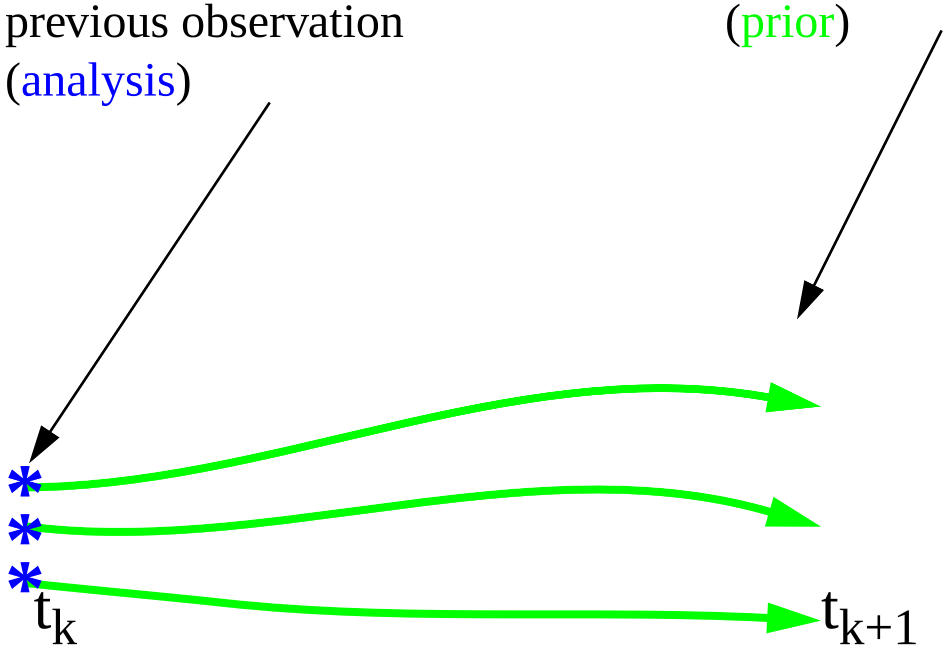
- A. Impact of observation frequency
- B. Impact of observation density
- C. A passing mention of 'balance' issues

How an Ensemble Filter Works

1. Use model to advance ensemble (3 members here) to time at which next observation becomes available

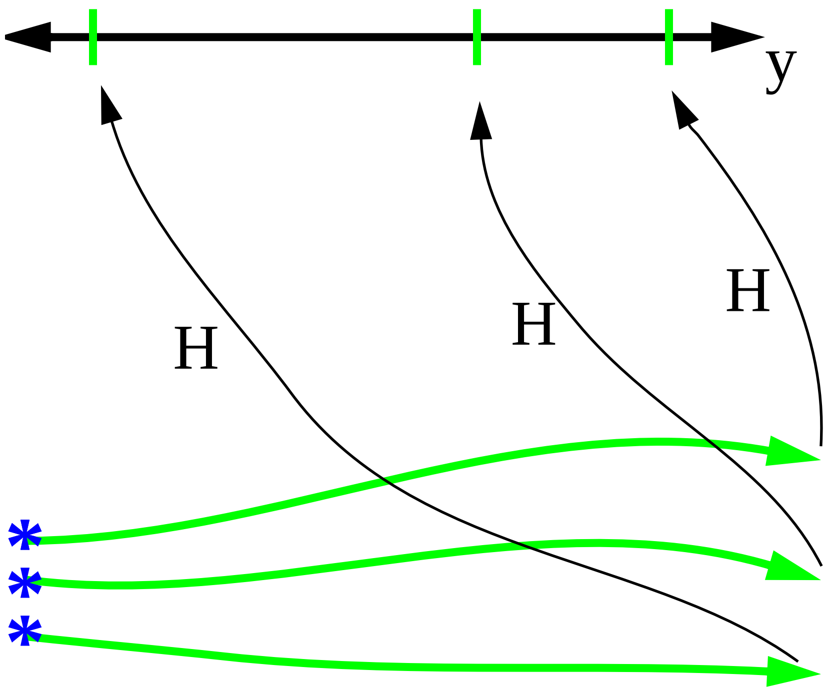
Ensemble state estimate after using previous observation (analysis)

Ensemble state at time of next observation (prior)



How an Ensemble Filter Works

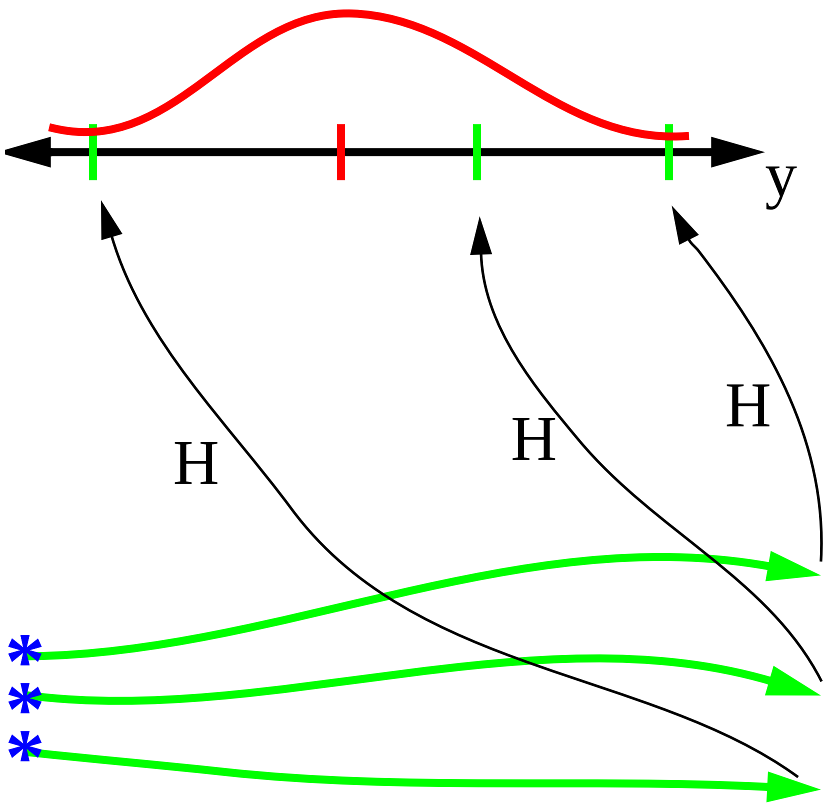
2. Get prior ensemble sample of observation, y=H(x), by applying forward operator H to each ensemble member



Theory: observations from instruments with uncorrelated errors can be done sequentially.

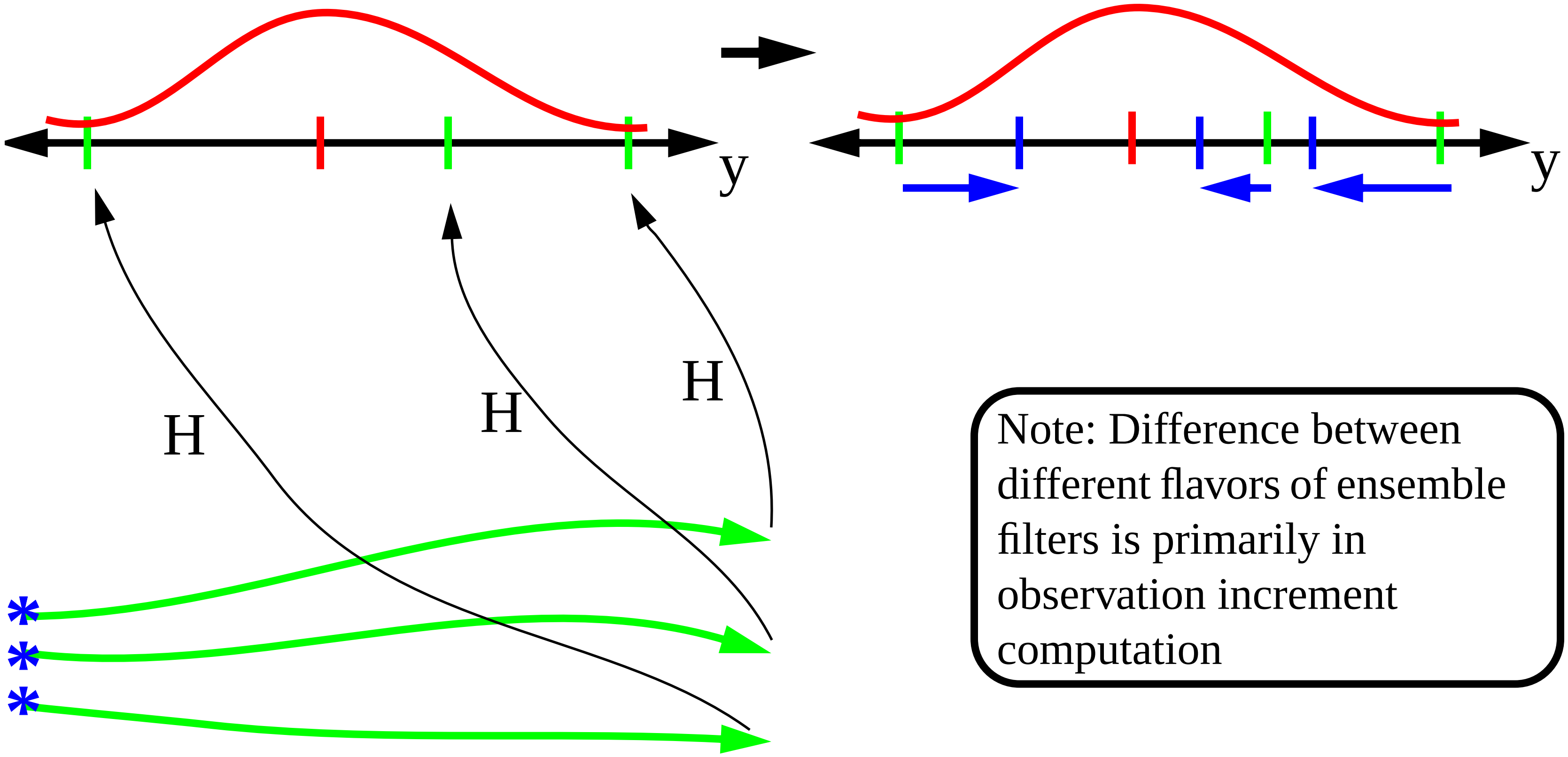
How an Ensemble Filter Works

3. Get observed value and observational error distribution from observing system



How an Ensemble Filter Works

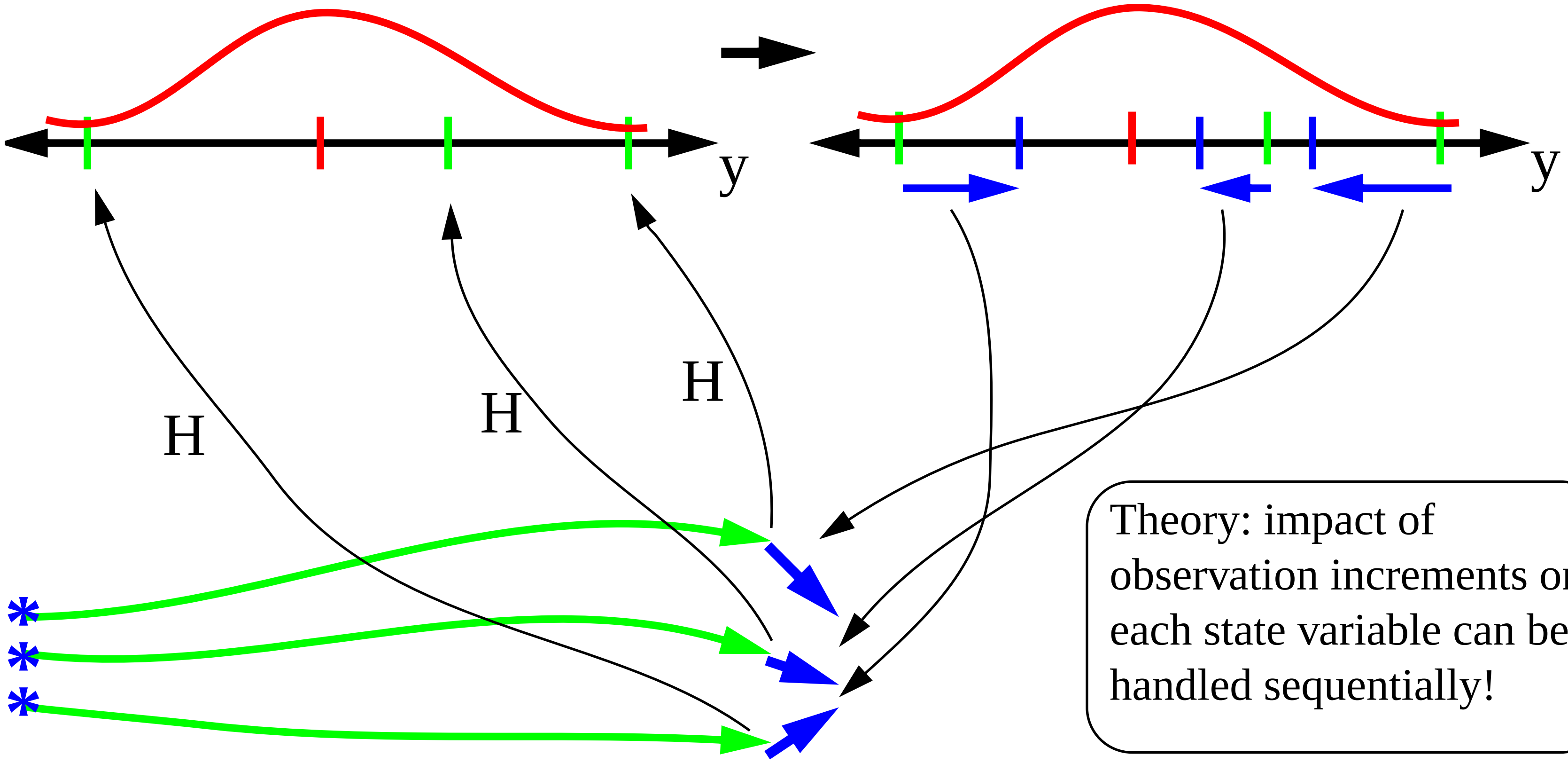
4. Find increment for each prior observation ensemble
(this is a scalar problem for uncorrelated observation errors)



Note: Difference between different flavors of ensemble filters is primarily in observation increment computation

How an Ensemble Filter Works

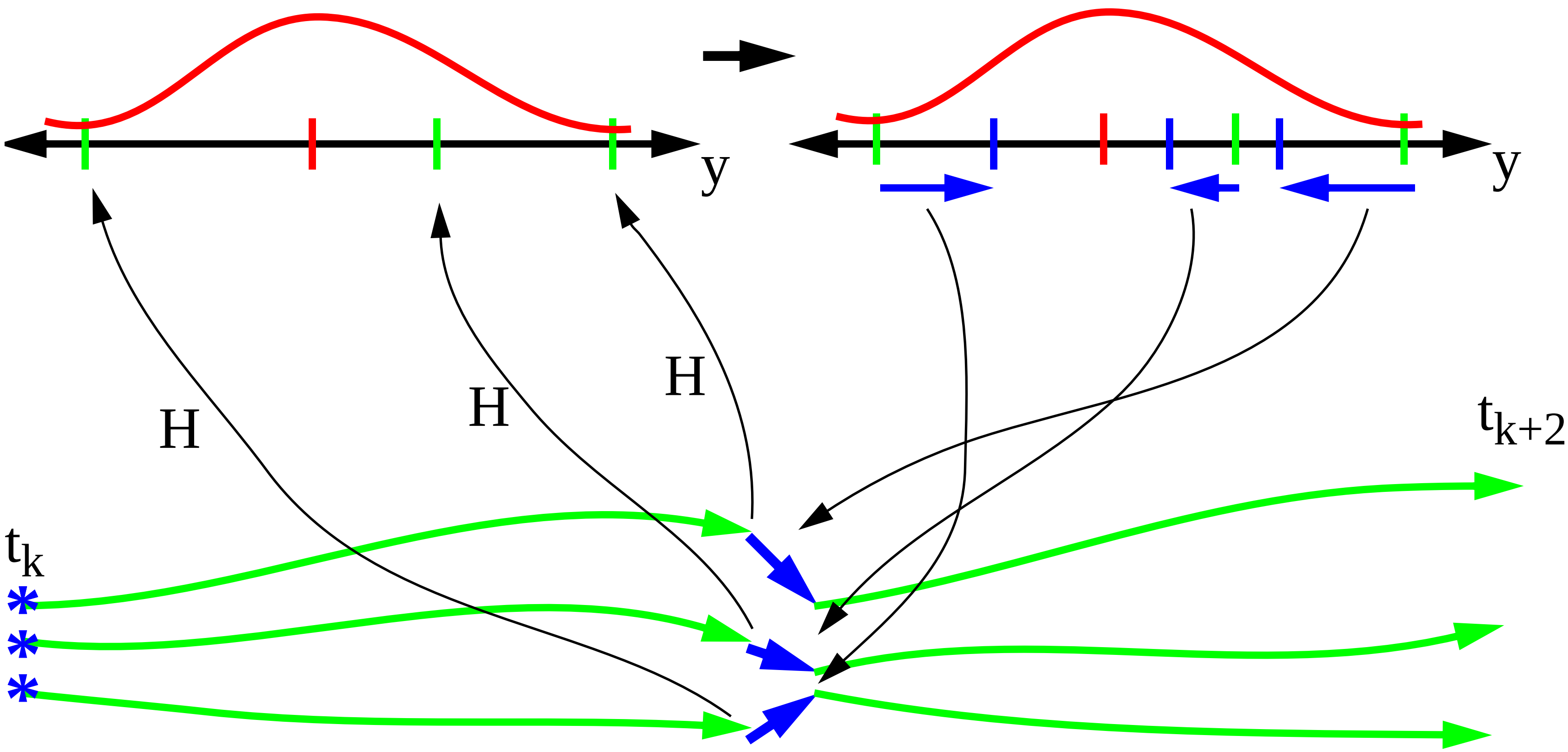
5. Use ensemble samples of y and each state variable to linearly regress observation increments onto state variable increments



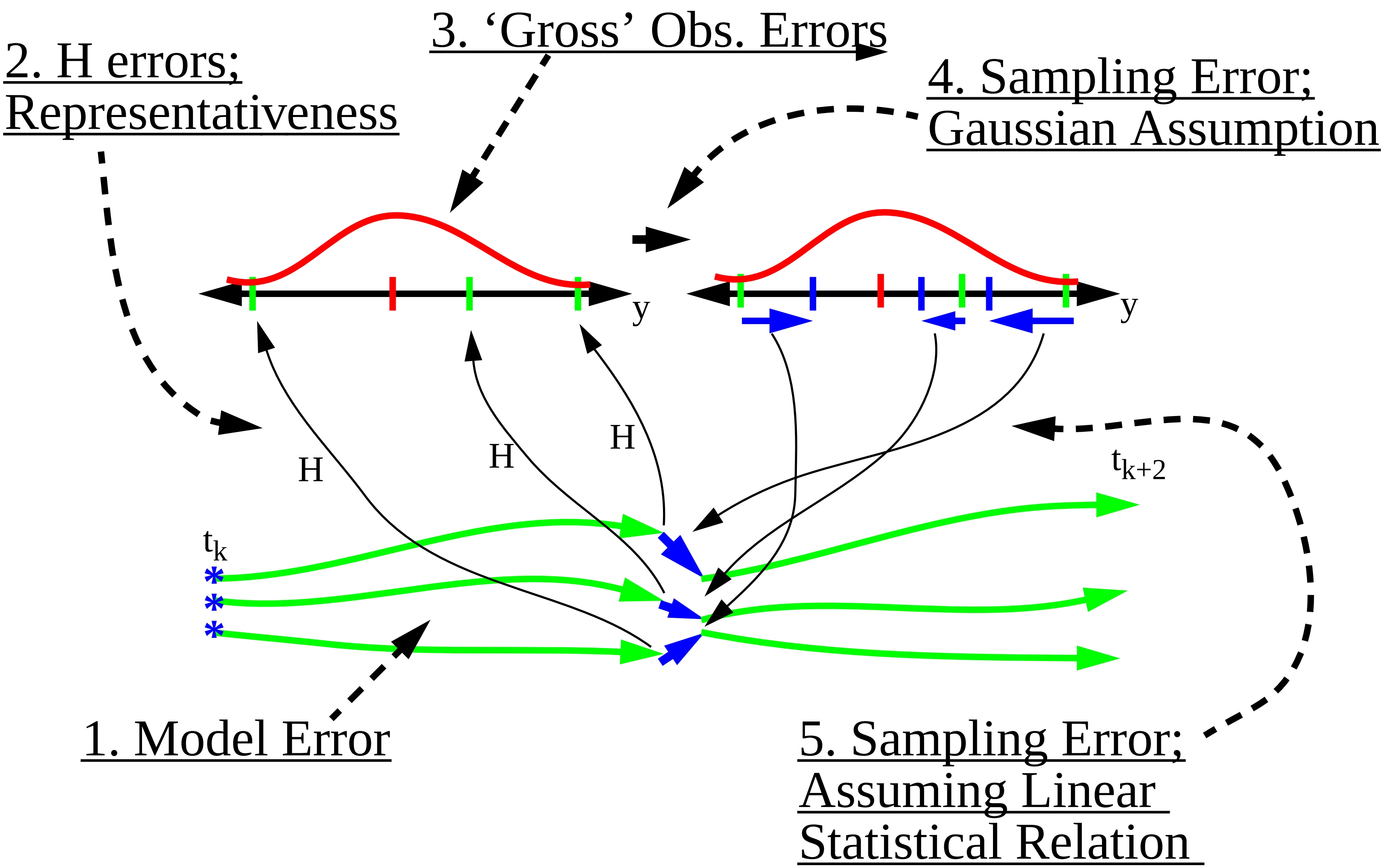
Theory: impact of observation increments on each state variable can be handled sequentially!

How an Ensemble Filter Works

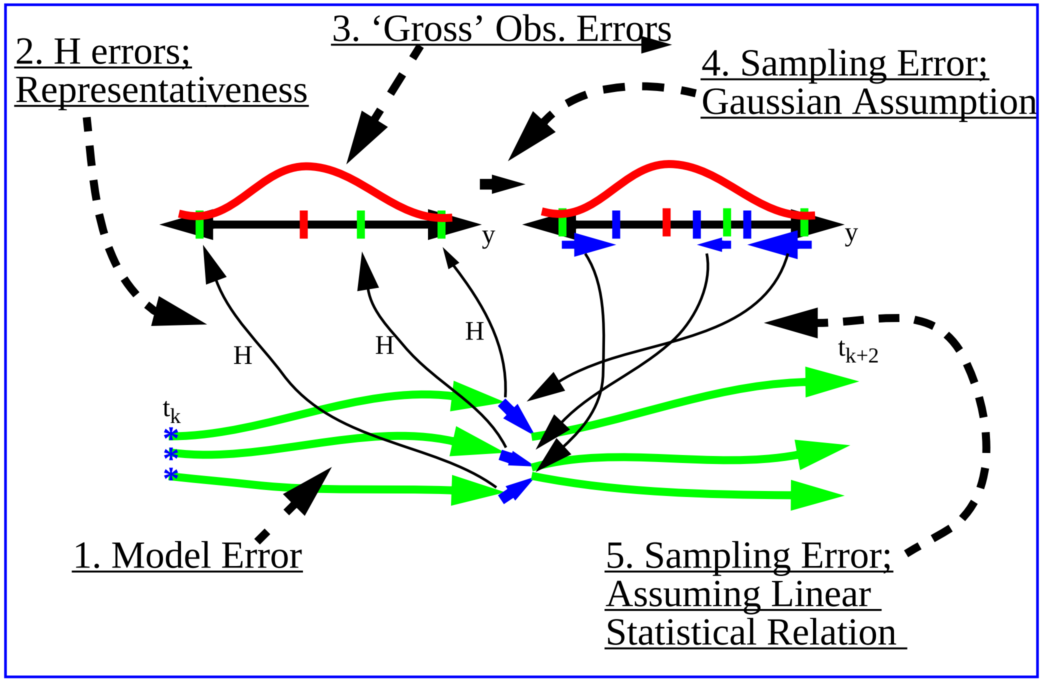
6. When all ensemble members for each state variable are updated, have a new analysis. Integrate to time of next observation...



Some Error Sources in Ensemble Filters



Dealing With Ensemble Filter Errors



Deal with 1, 2, 3 independently;
This is HARD but ongoing

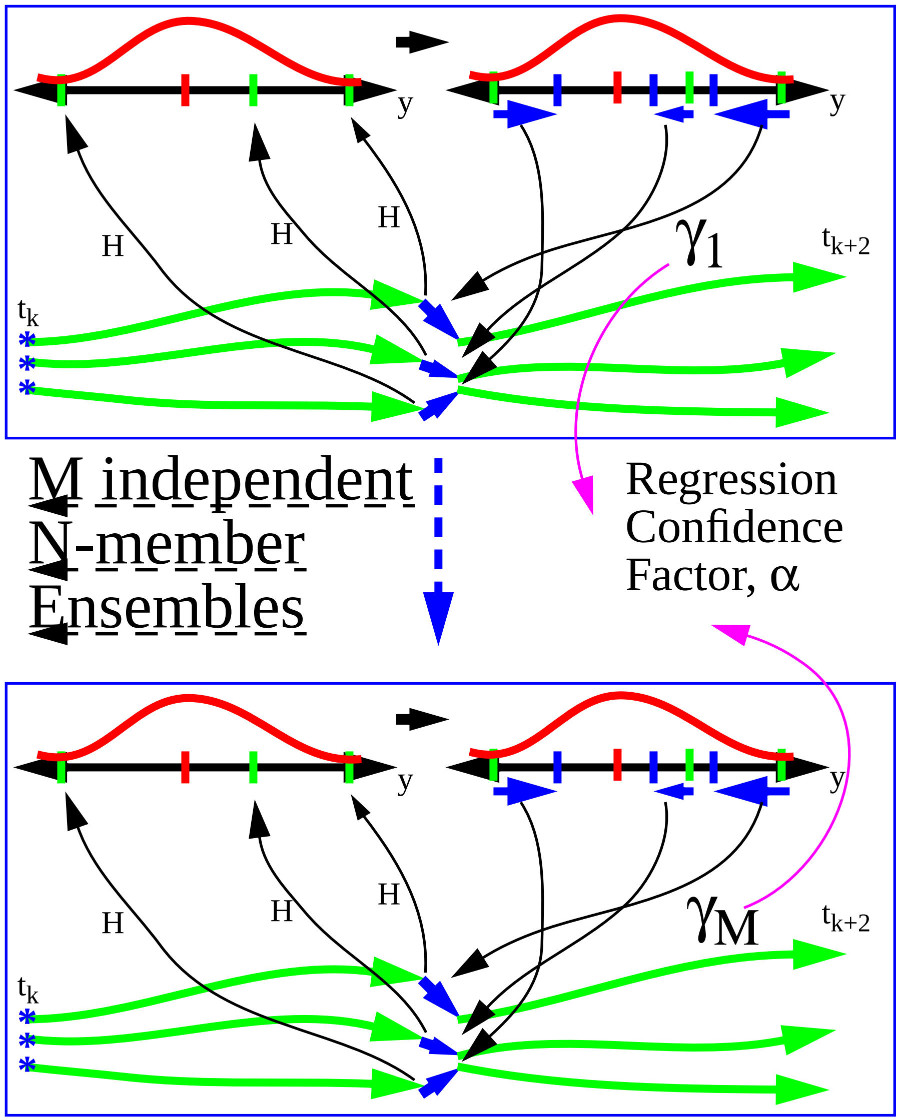
Traditionally, ensemble filters...

1-4: Covariance inflation,
Increase uncertainty in prior to give observations more impact

5. 'Localization': only let obs. impact a set of 'nearby' state variables

Often smoothly decrease impact to 0 as function of distance (Gaspari-Cohn)

Hierarchical Monte Carlo Filter



Replace 'localization' with second order Monte Carlo to deal with regression sampling errors

M groups of N-member ensembles

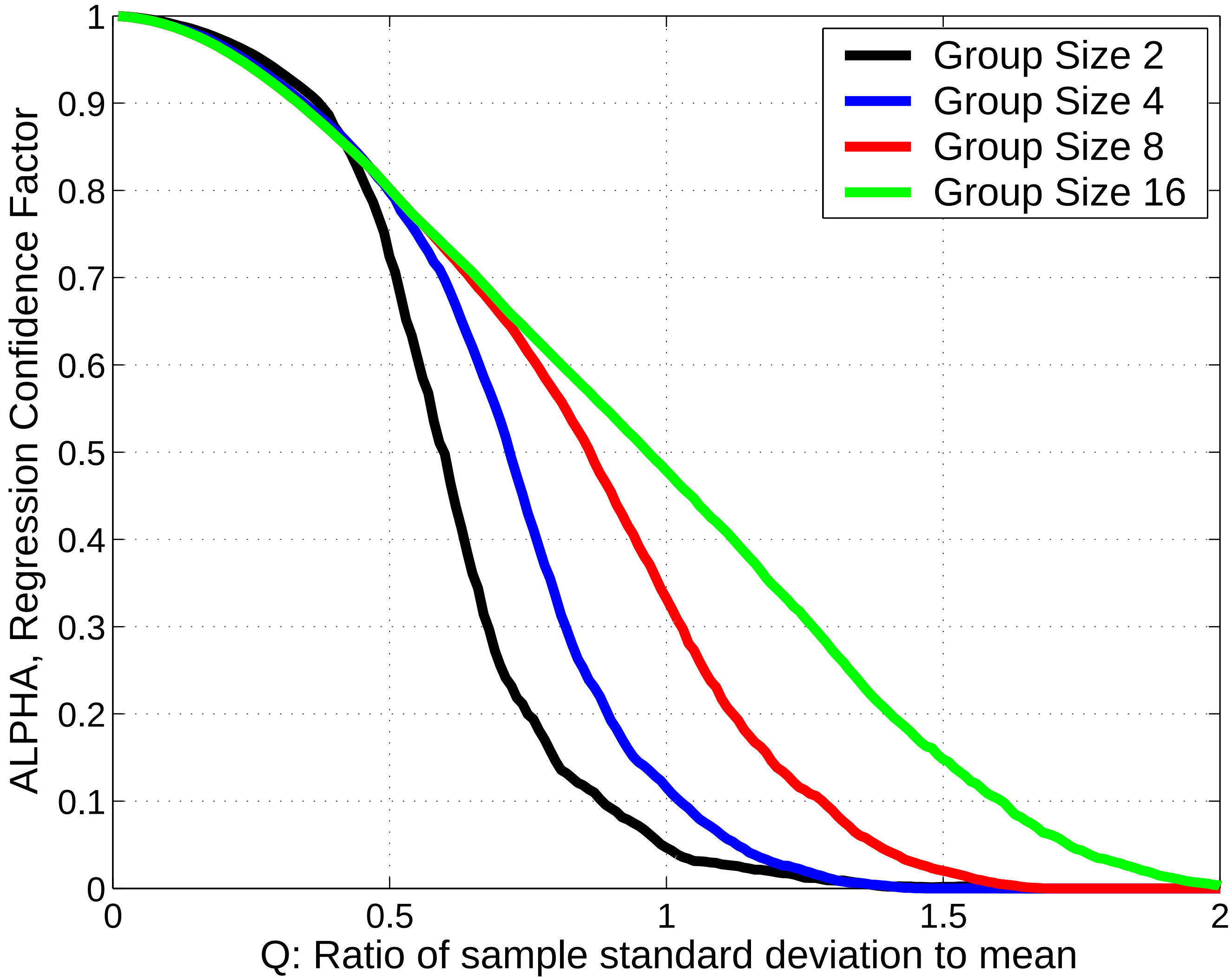
Compute obs. increments for each

For given obs. / state variable pair

1. Have M samples of regression coefficient, γ
2. Uncertainty in γ implies state variable increments should be reduced
3. Compute regression confidence factor, α

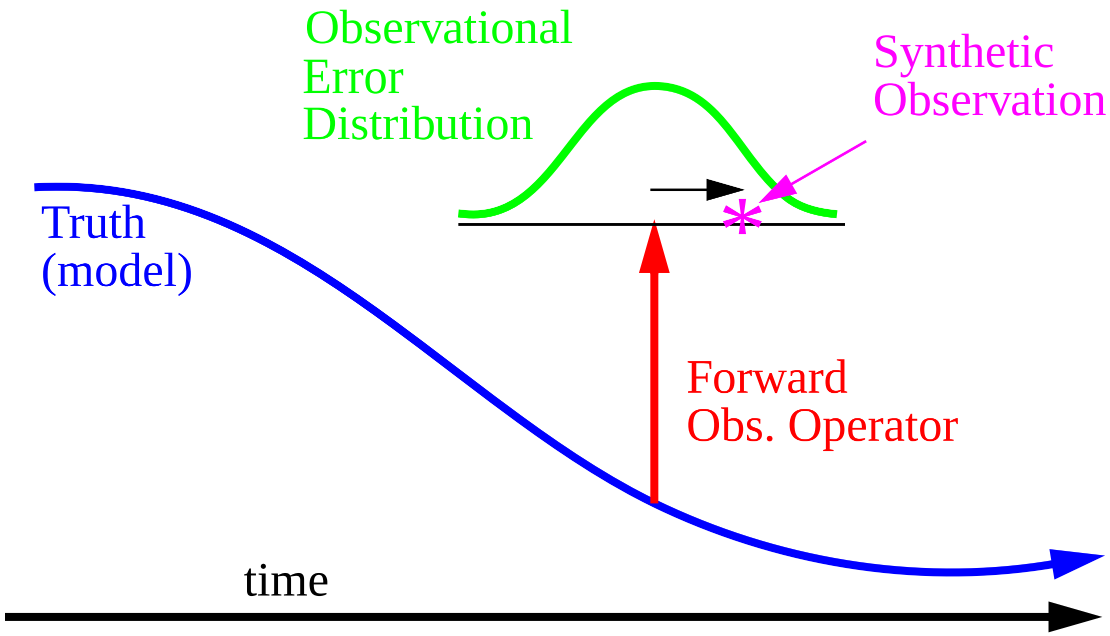
Hierarchical Monte Carlo Filter

Here, α is function of M, and $Q = \Sigma\gamma / \bar{\gamma}$ (ratio of sample S.D. to sample mean regression)



Perfect Model (Synthetic Observation) Experiments

'Truth' is generated by integrating model



'Synthetic' obs. by applying 'forward observation' operator to truth

(Here, this is generally just interpolating to a random horizontal location)

Instrument/representativeness error simulated:

Add draw from specified Gaussian distribution to the interpolated observation

All the assimilation algorithm ever sees is these simulated observations

Result of assimilation can be compared to 'truth'

Predictability in a Hierarchical Ensemble Filter: Lorenz-96 Model

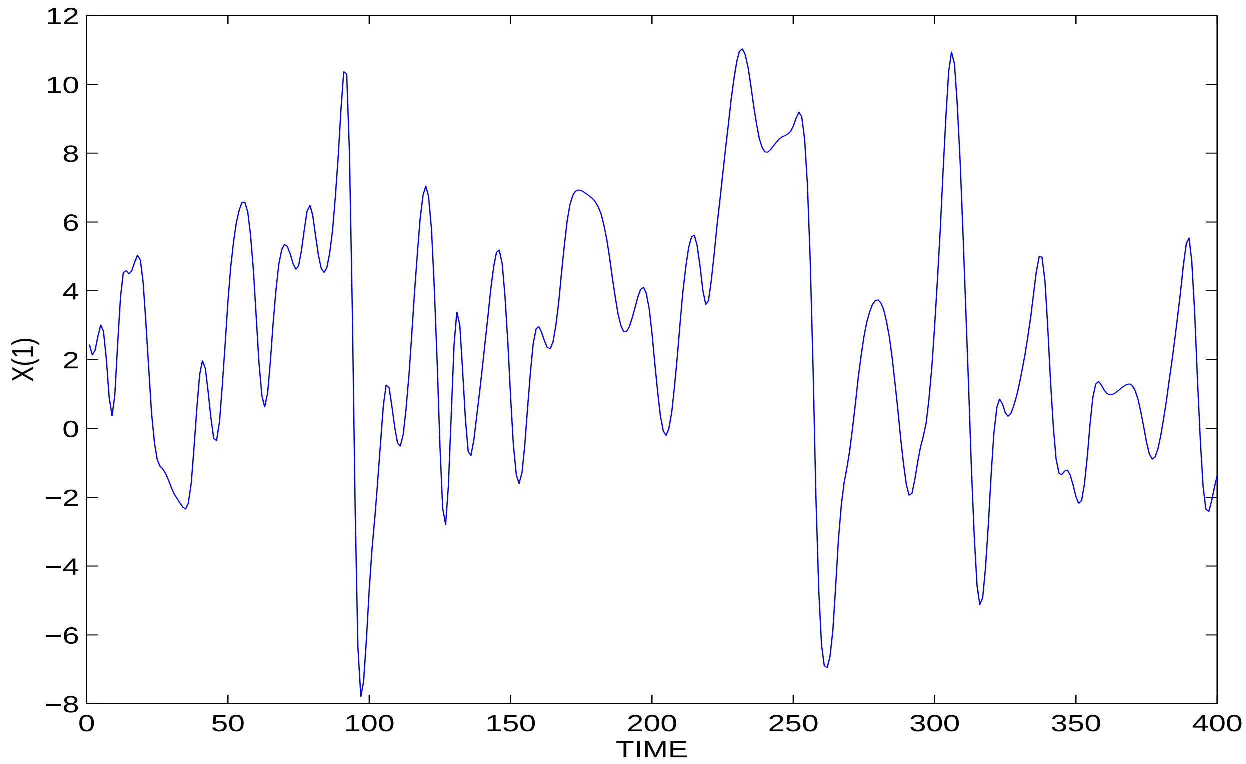
Variable size low-order dynamical system

N variables, X_1, X_2, ..., X_N

$dX_i / dt = (X_{i+1} - X_{i-2})X_{i-1} - X_i + F$;   i = 1, ..., N with cyclic indices

Use F = 8.0, 4th-order Runge-Kutta with dt=0.05

With 40 state variables (N = 40) ‘attractor dimension’ is 13



Time series of state variable from free L96 integration

Lorenz 96 Experimental Design

40 Randomly located observations fixed in time

Observed every time step

Initial ensemble members random draws from ‘climatology’

4000 step assimilations, results shown from second 2000 steps

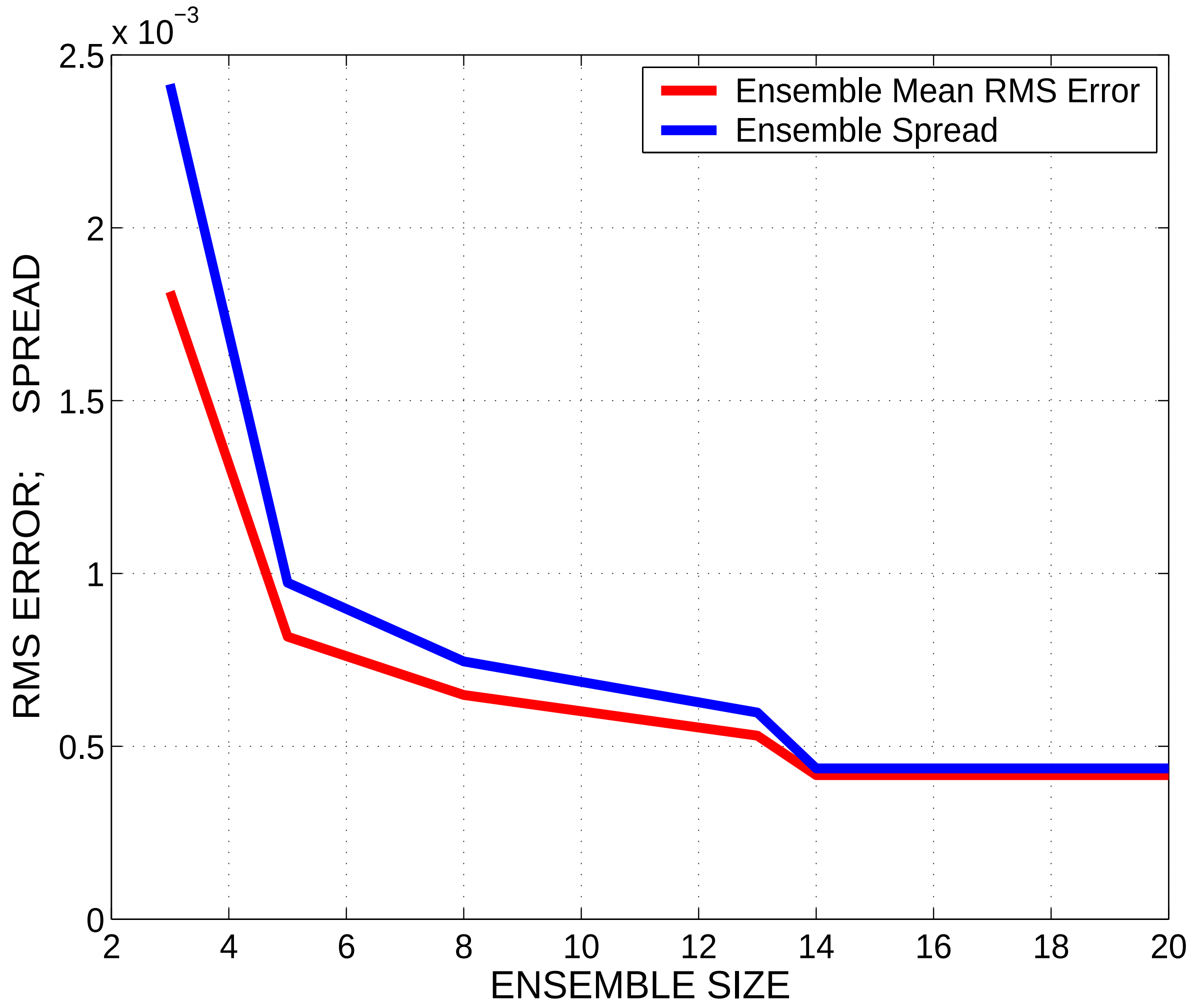
Covariance inflation tuned for minimum RMS

Note: Good ideas on getting rid of covariance inflation, too, but not today

4 groups of ensembles used

All results can be reproduced with traditional ensemble filters using time mean values of regression confidence factor to ‘localize’ observation impacts

Hierarchical Filter Predictability: Small Error Limit in L96



For ensembles size > 13 filter converges for any group size (no sampling error!)

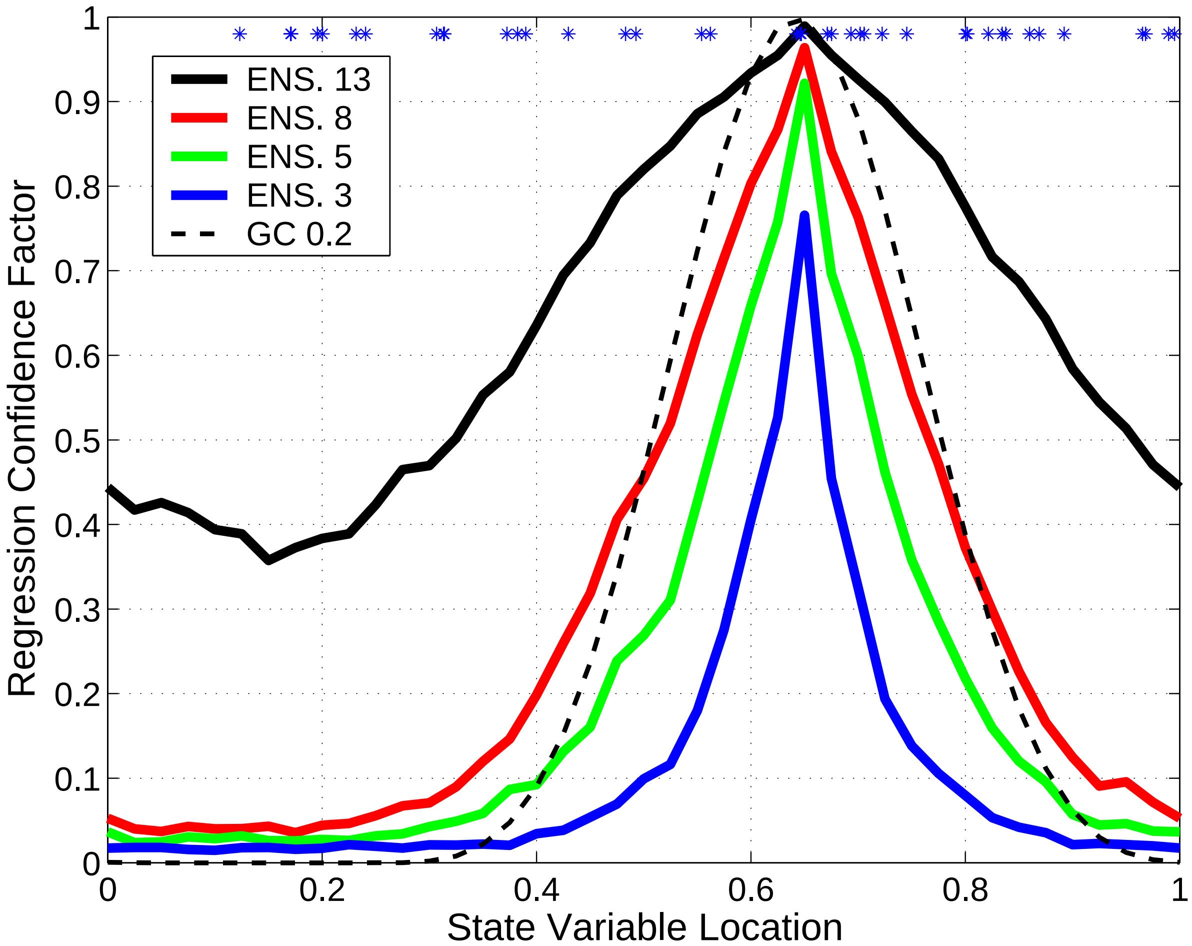
For smaller ensembles, error / spread increase

Prior RMS and Spread are measures of predictability of one step forecast

Posterior (analysis) error (not shown) is also a measure of predictability

Predictability is function of model, observational network, assimilation methodology

Hierarchical Filter Regression Confidence Factors



Regression confidence factor for observation at location 0.64 with all 40 state variables

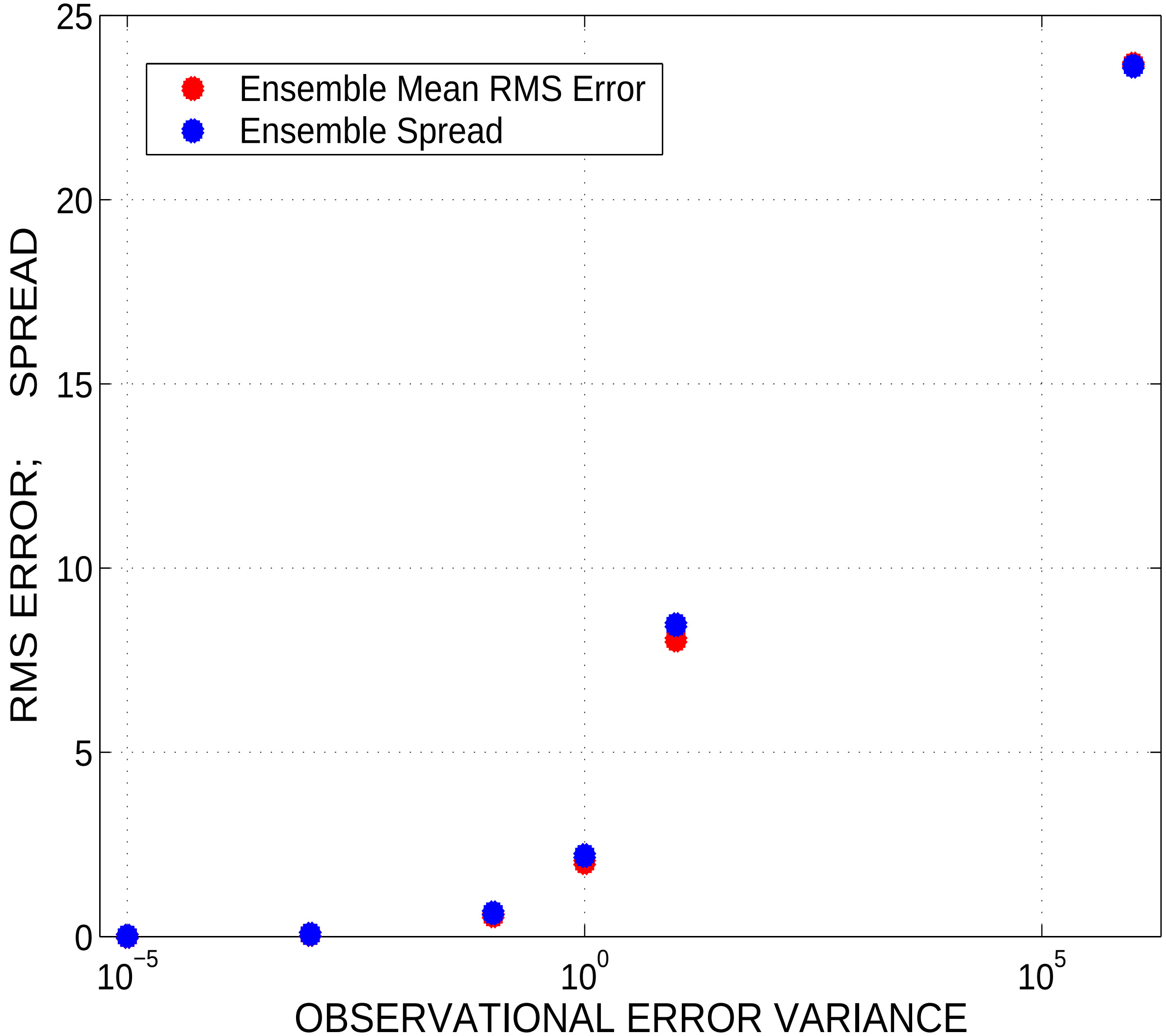
For ensemble size > 13, factor is 1 everywhere (no sampling error)

Observation impact increasingly localized as ensemble becomes more degenerate

Traditional Gaspari-Cohn localization with half-width 0.2 also shown

Shape is similar in this case

Hierarchical Filter Predictability: Varying Obs. Error Variance



Vary observational error variance from 1e-5 to 1e7

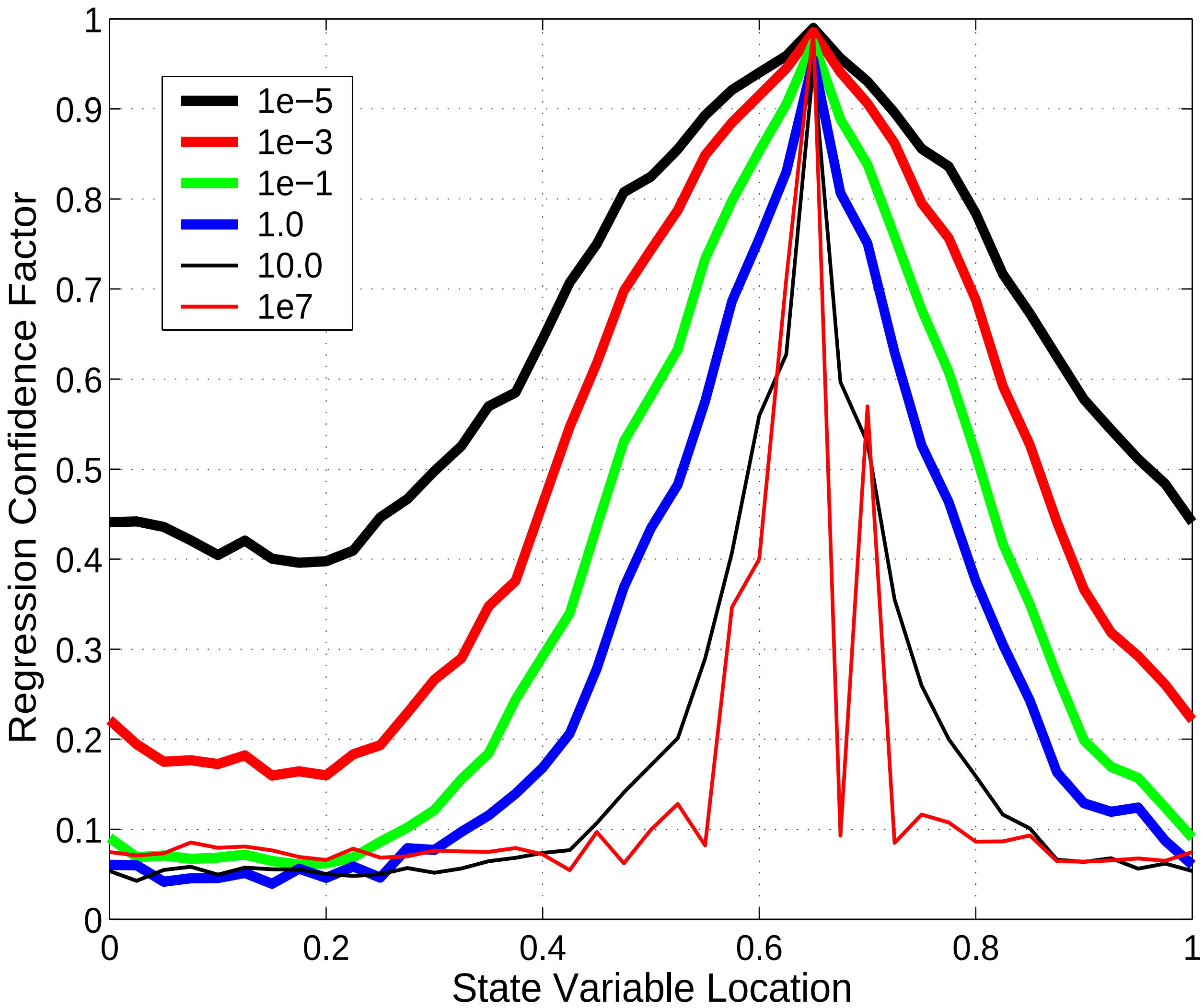
Largest case is just looking at ‘climate’

Error increases nearly linear for small errors

Exponential for intermediate errors

Then saturate for large errors

Hierarchical Filter Regression Confidence Factors



Obs. impact more localized as error increases

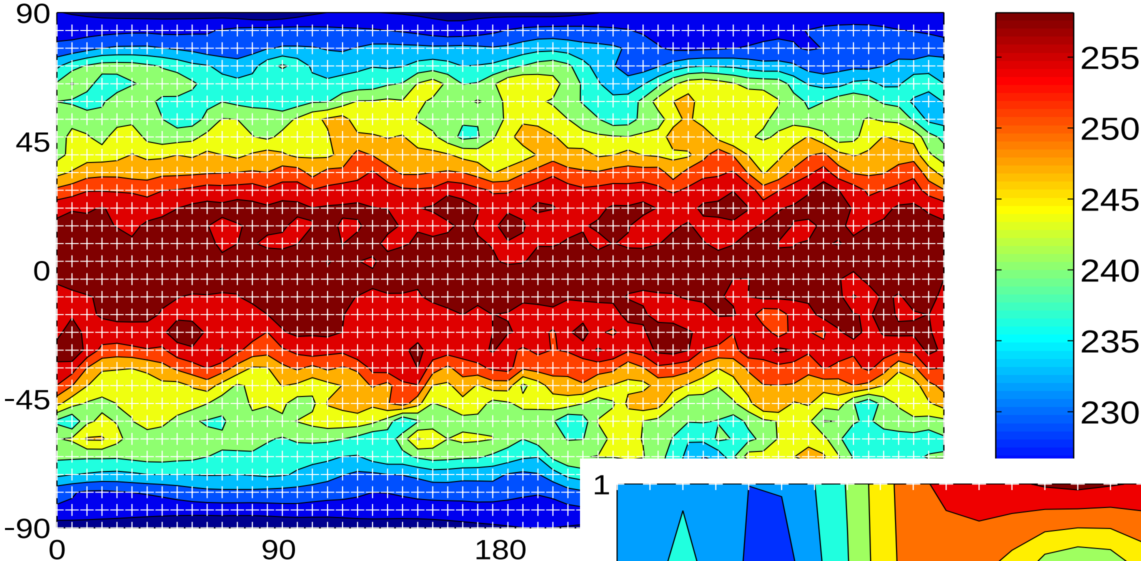
Climatological structure is two-peaked

Similar to coherence structure from climatological time series

Predictability in an Idealized AGCM: GFDL FMS B-Grid Dynamical Core (Havana)

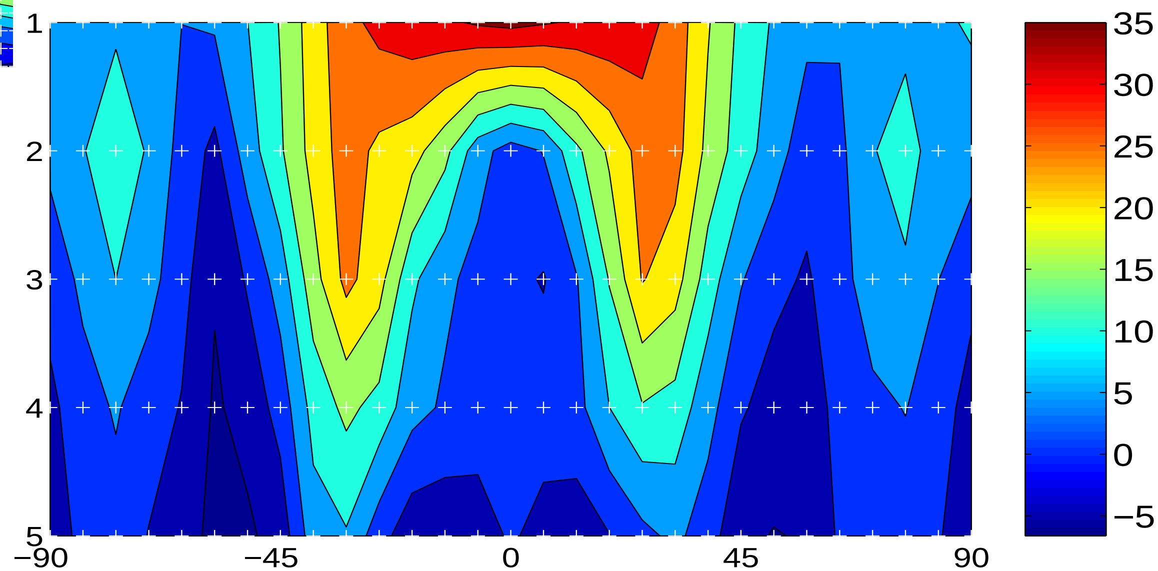
Held-Suarez Configuration (no zonal variation, fixed forcing)

Low-Resolution (60 lons, 30 lats, 5 levels); Timestep 1 hour (less for frequent observations)

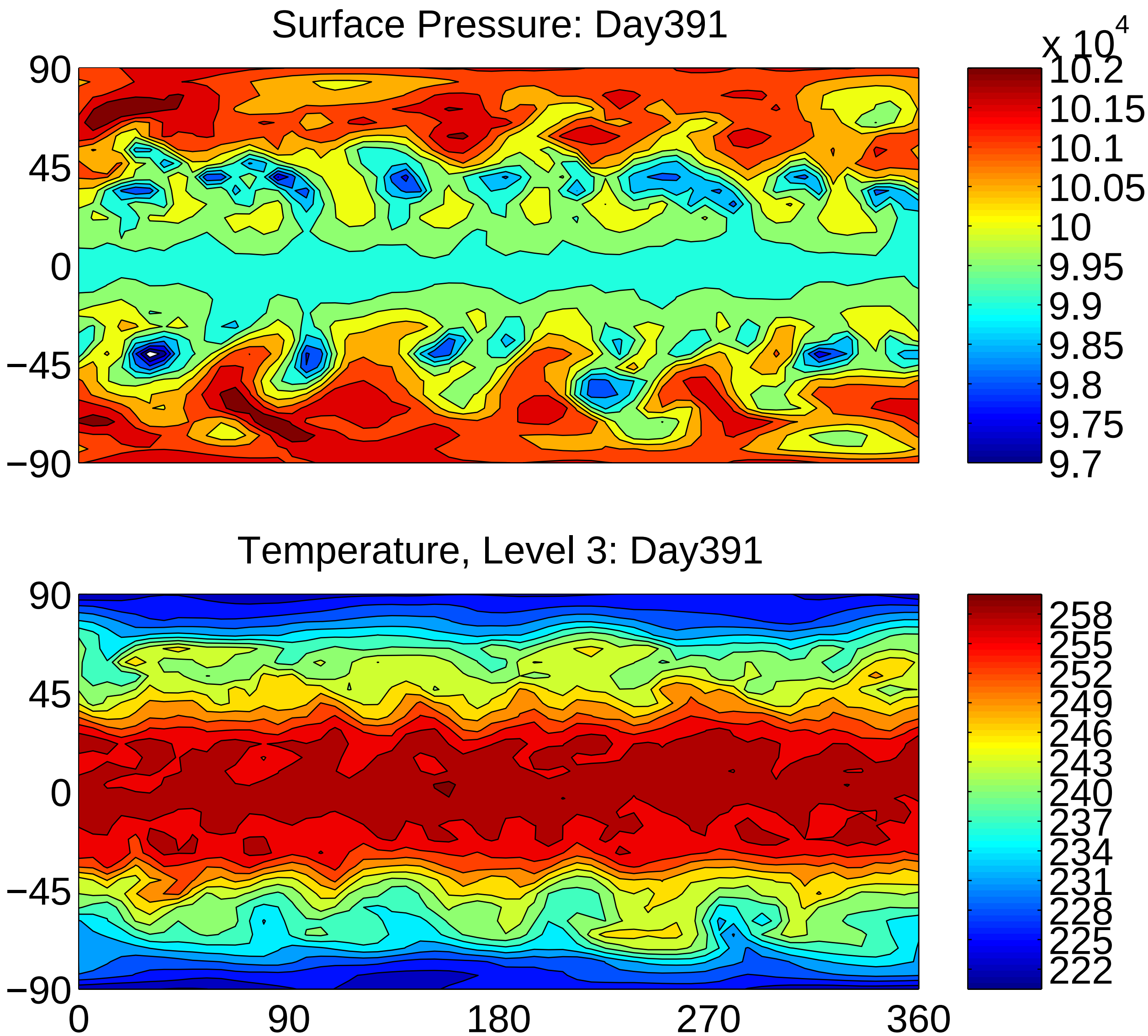


T at Level 3
(Middle of Atmosphere)

Cross Section of
Zonal Mean U



Has Baroclinic Instability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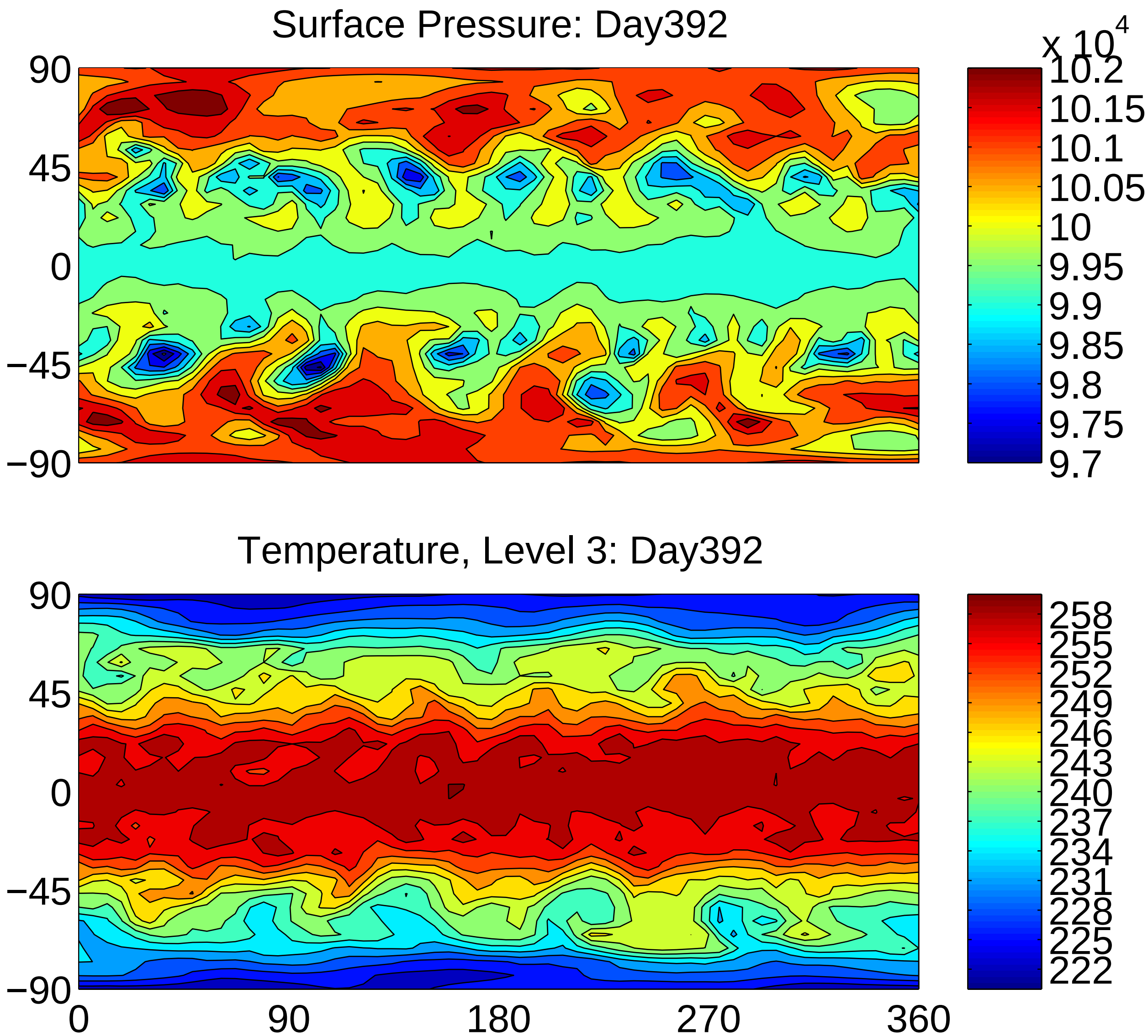
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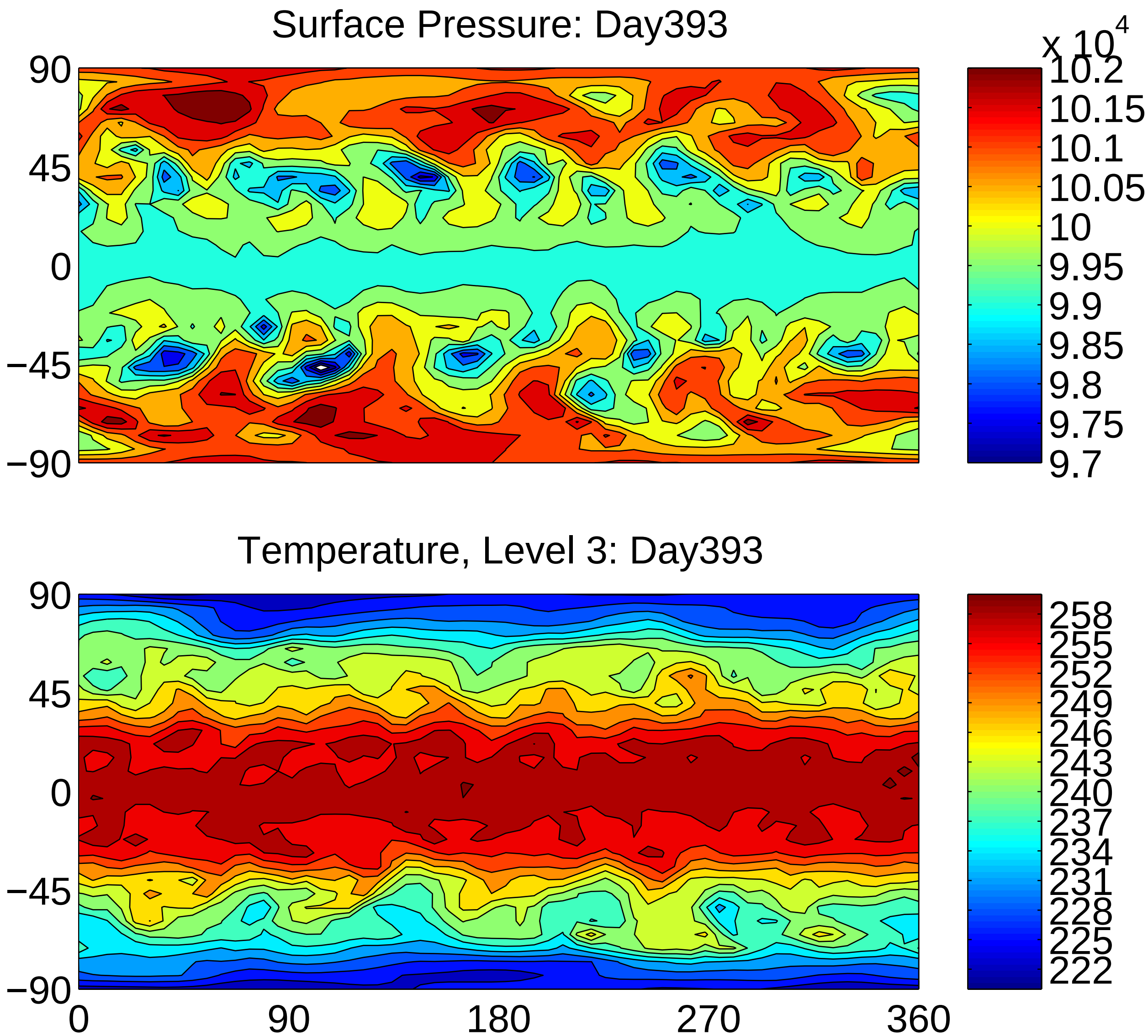
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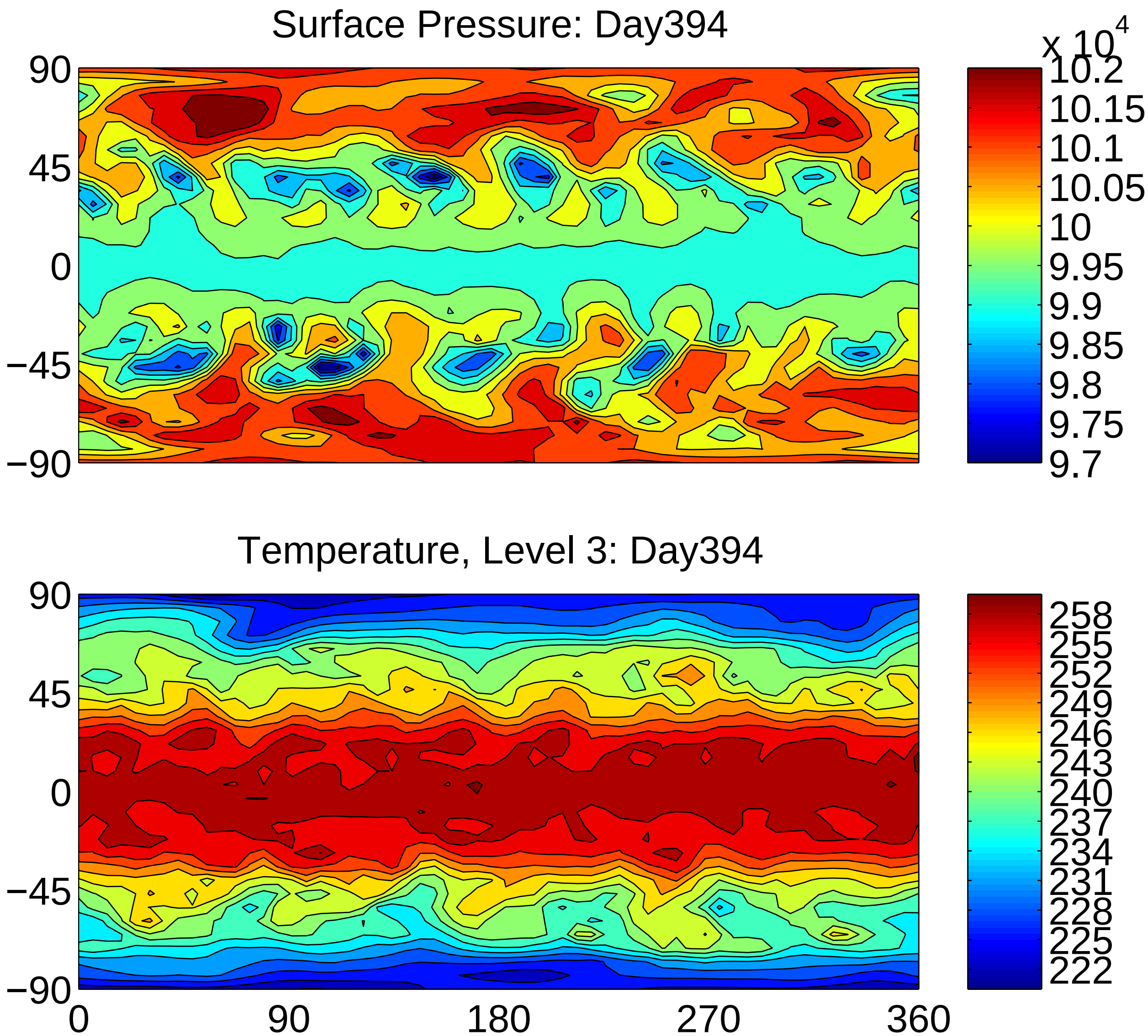
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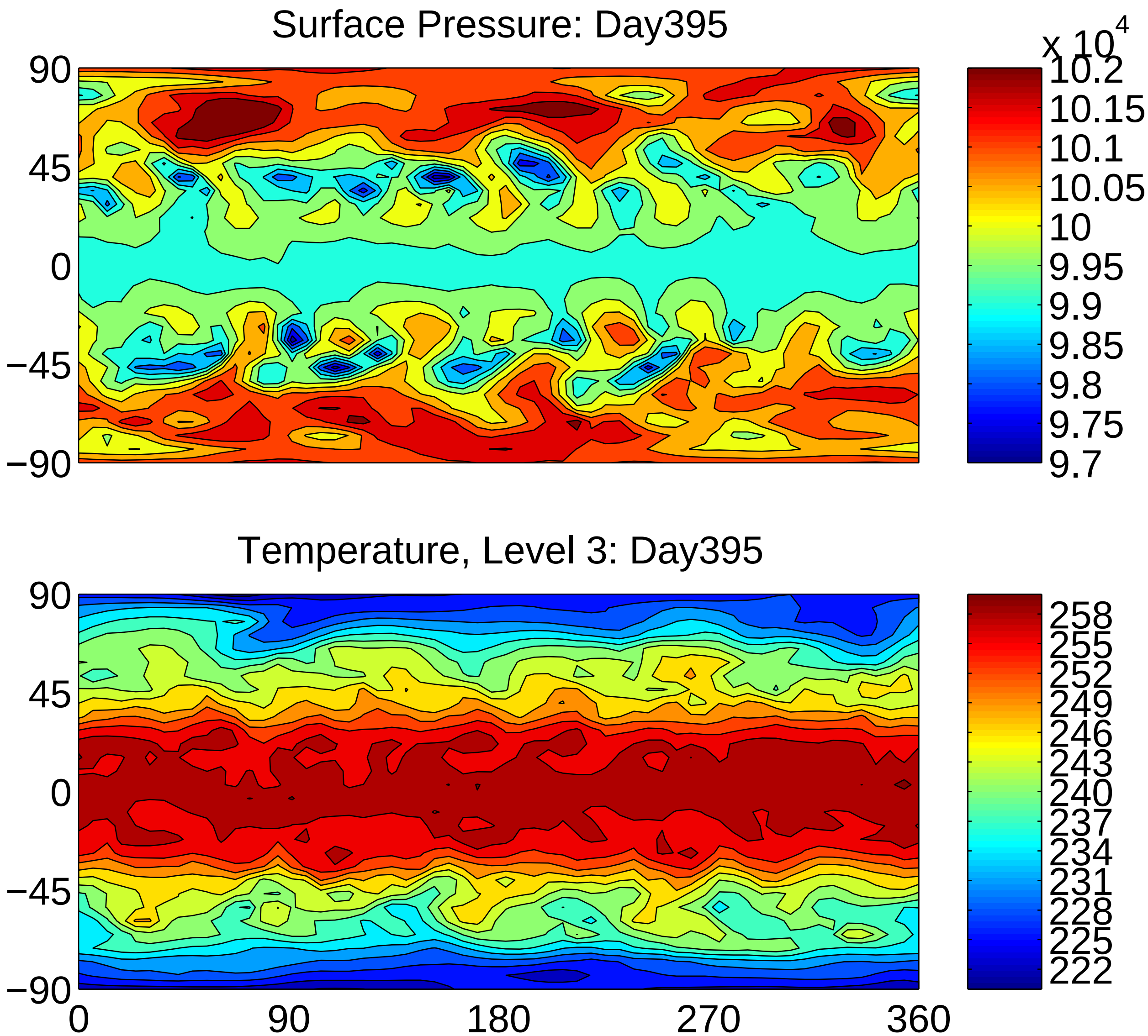
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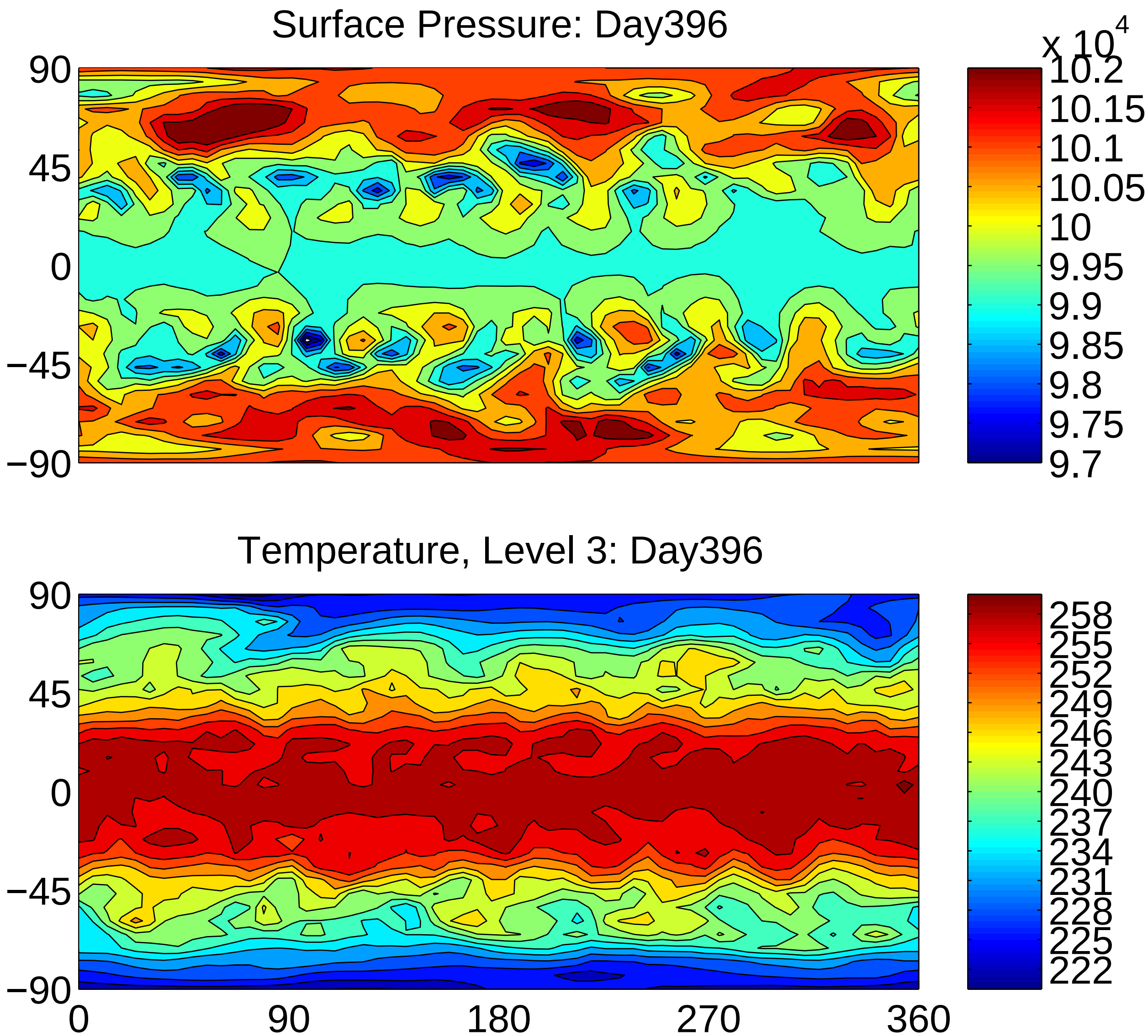
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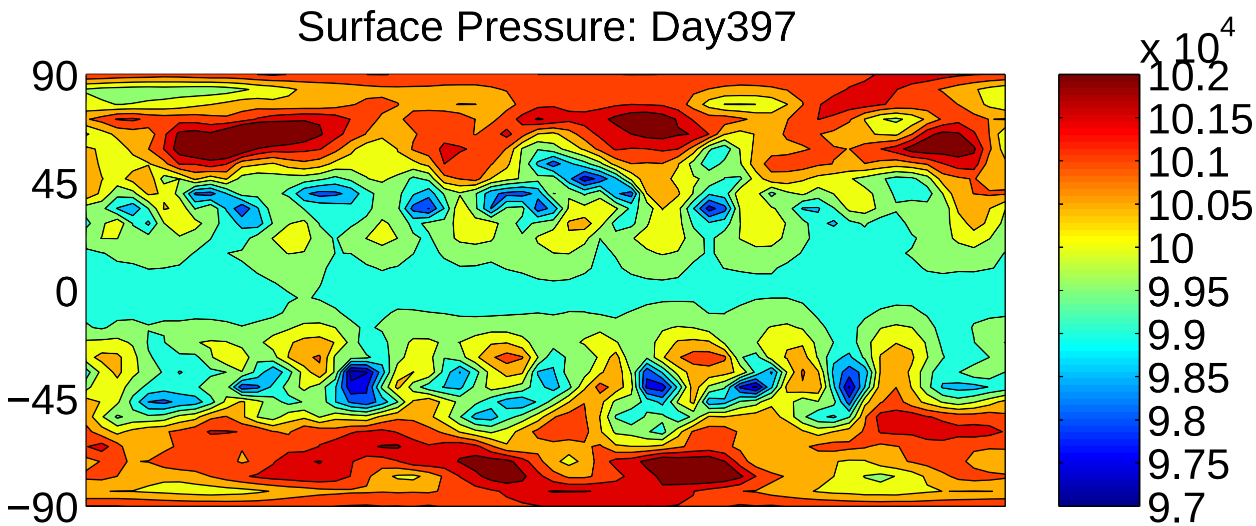
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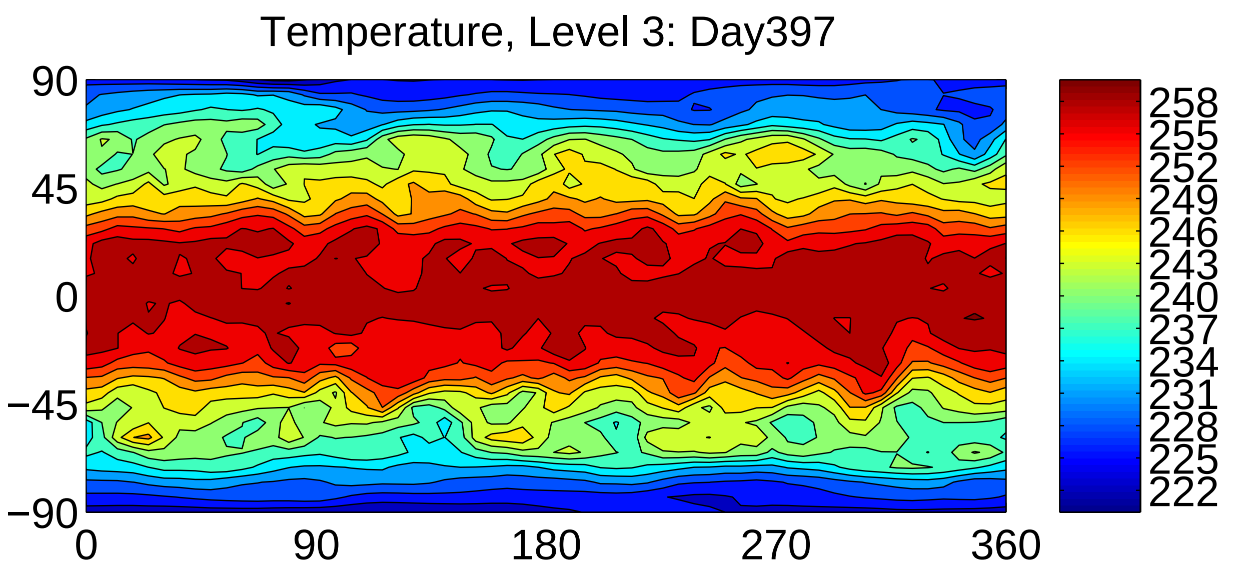
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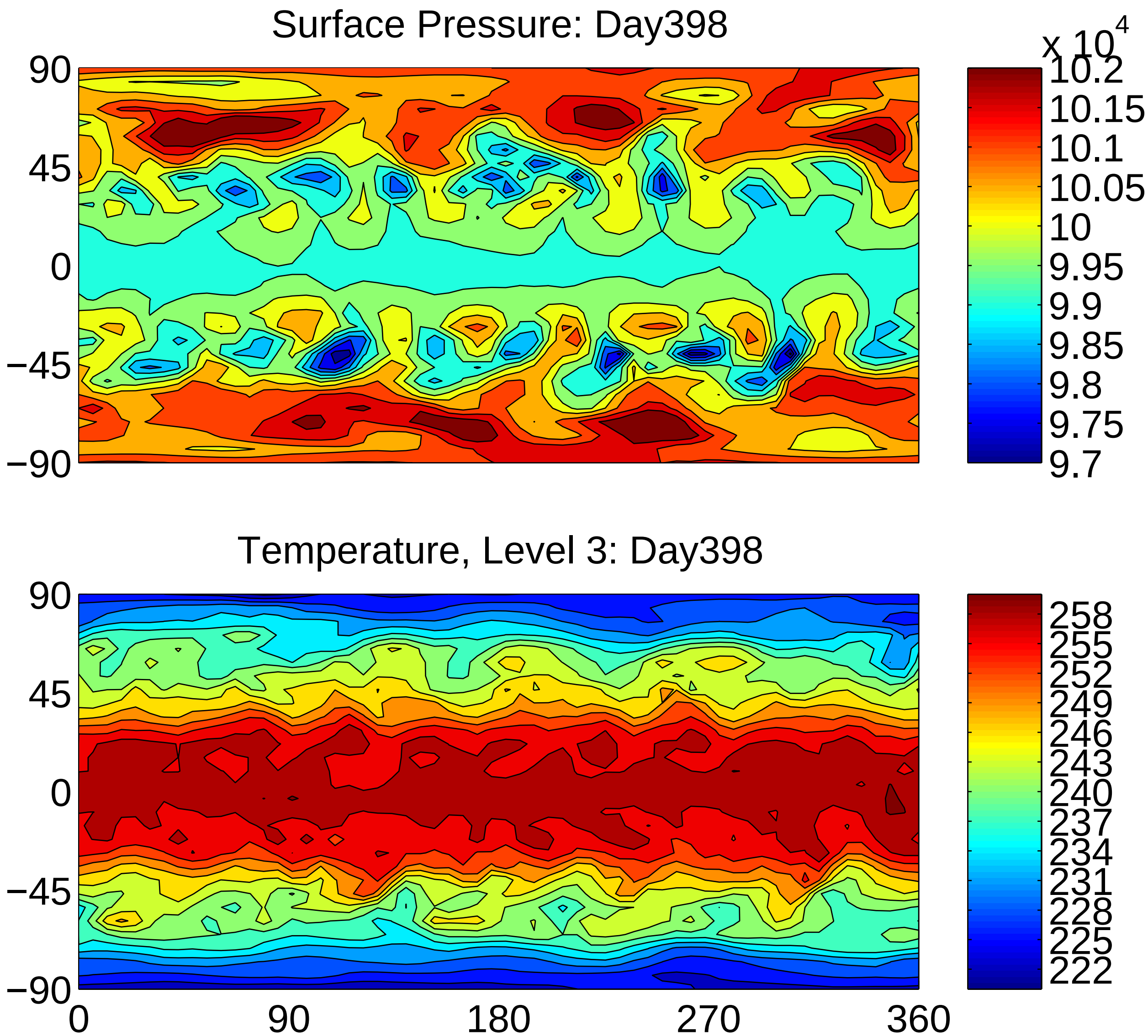
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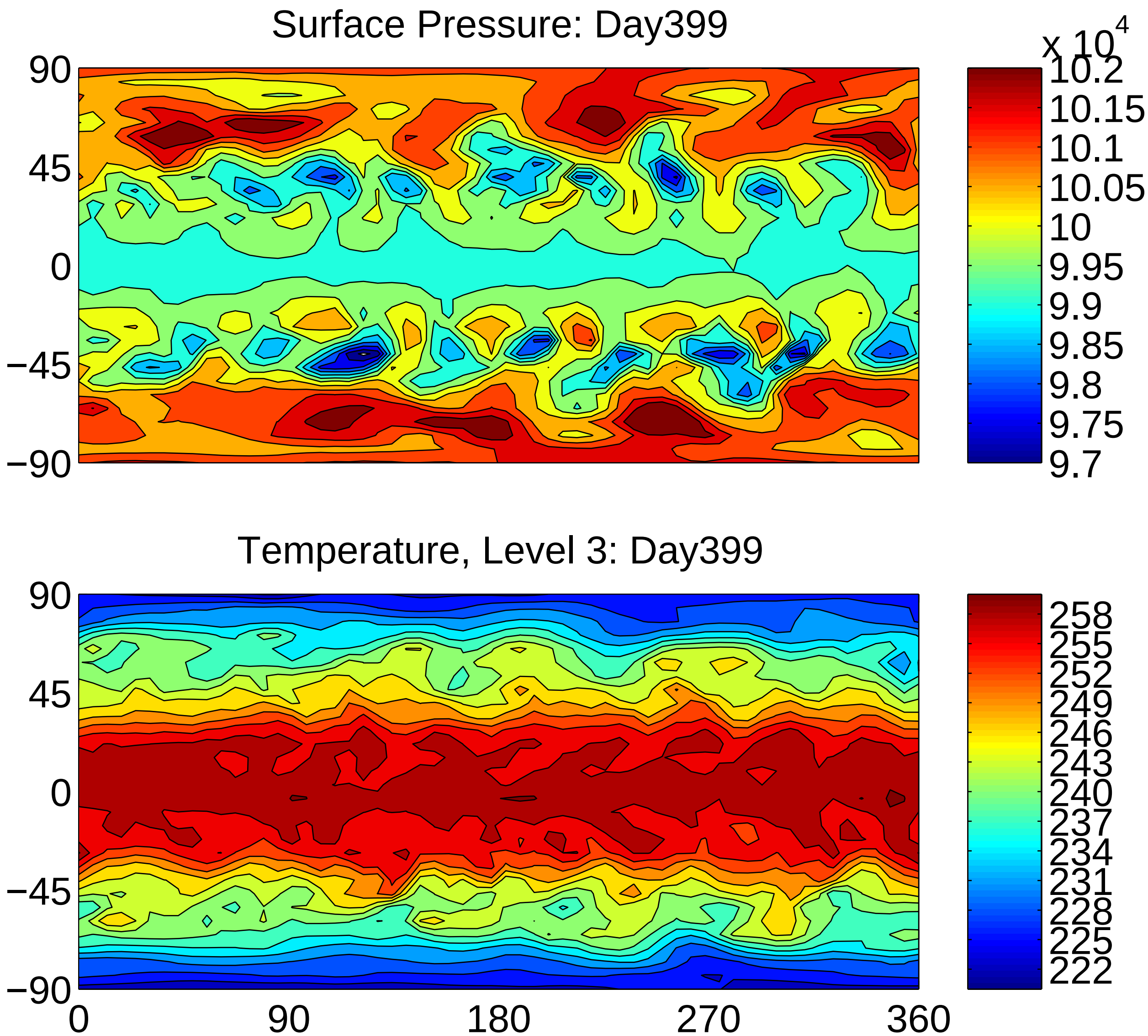
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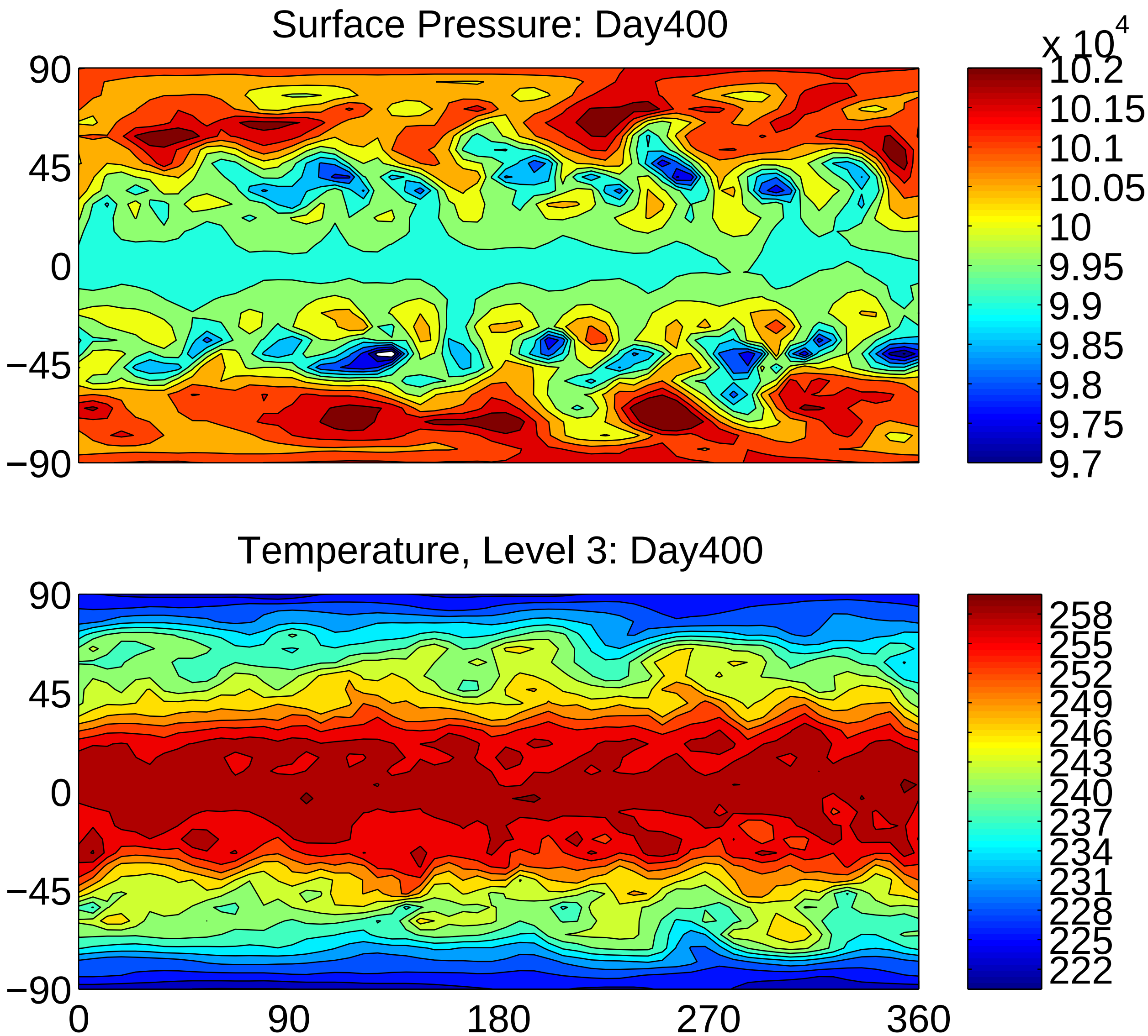
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Experimental Design Details: Bgrid AGCM

Ensemble size is 20 for ALL cases here

Each assimilation case is run for 400 days; starting from climatological distribution

Summary results are from last 200 days

No bias correction steps taken (no covariance inflation)

Bgrid: Experimental Sets

1. Impact of spatial density of observations:
   150, 300, 450, 900, 1800, 3600, 7200, 14400, 28800 PS obs
   Every 24 hours
   PS observational error standard deviation 1.0 mb

2. Impact of frequency of observations
   1800 PS observations
   Every 24, 12, 6, 4, 3, 2, and 1 hours, 30, 15, and 5 minutes
   PS observational error standard deviation 1.0 mb

3. Information content of different observation types
   1800 observations of PS, or low-level T, or low-level U/V
   Every 24 hours
   PS observational error SD 2.0 and 1.0 mb
   T observational error SD 1.0 and 0.5 K
   U/V observational error SD 2.0 and 1.0 m/s, U, V errors independent

Bgrid: Experimental Sets

4. What happens if observations are confined to limited spatial domain
   450 PS obs, only in N. Hemisphere between 90 and 270 deg. longitude
   Every 24 hours
   PS observational error standard deviation 1.0 mb

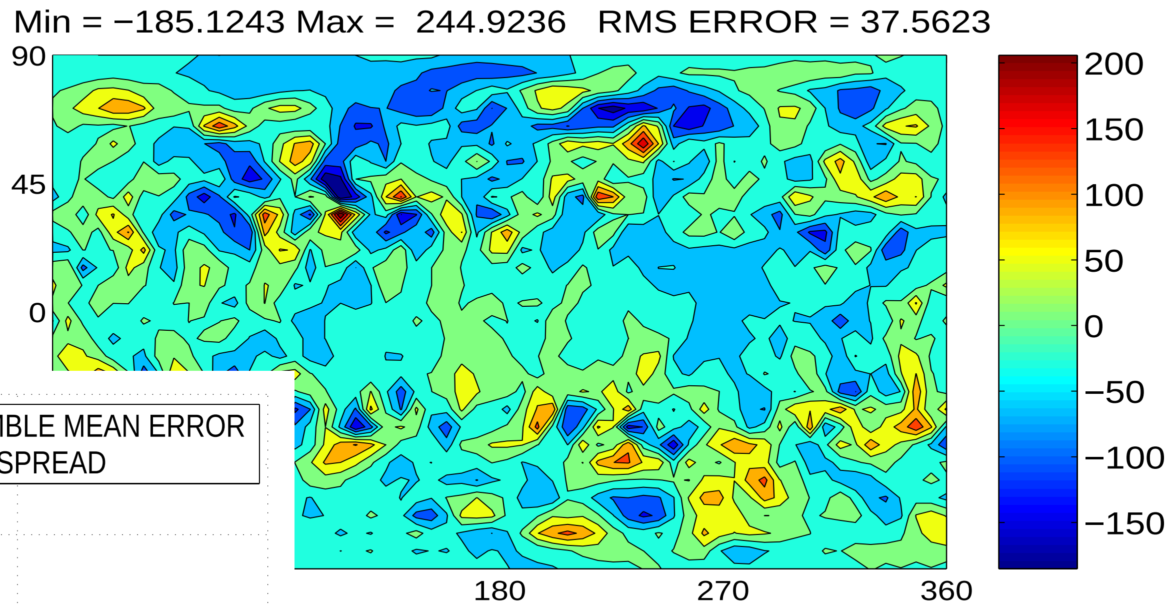
5. Impact of increased vertical resolution
   1800 PS obs
   Every 24 hours
   PS observational error standard deviation 1.0 mb
   5 and 18 vertical levels

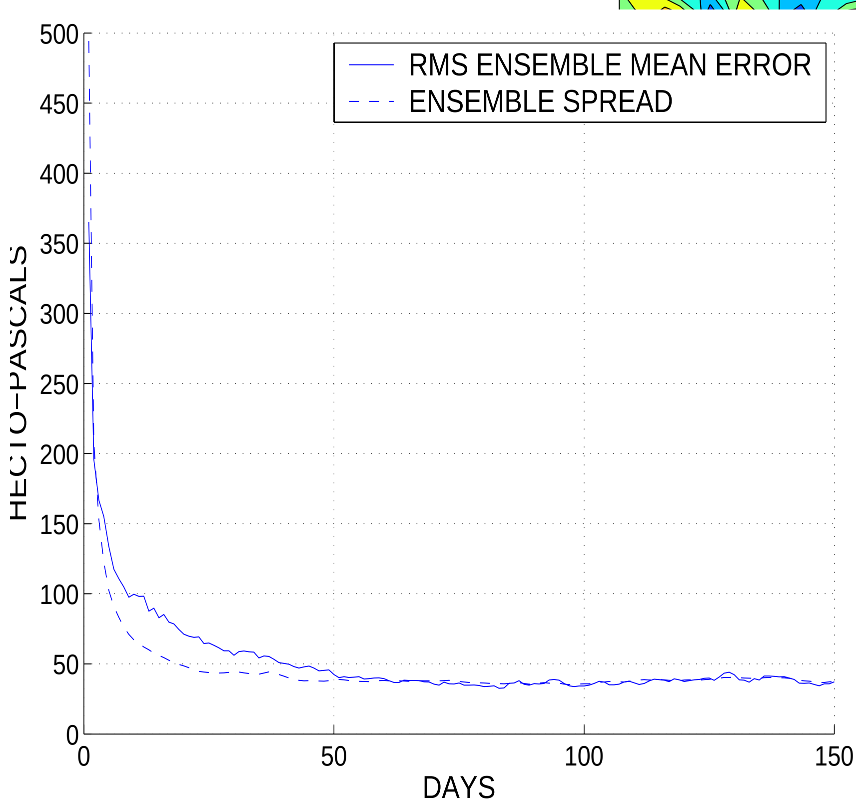
6. Impact of adding stochastic 'sub-grid scale' noise
   1800 PS obs, Every 24 hours
   PS observational error standard deviation 1.0

Temperature time tendency noise standard deviation 0, 10%, 40%

Baseline Case: 1800 PS Obs every 24 hours

Largest error in mid-latitudes, ‘synoptic’ scales after 400 days





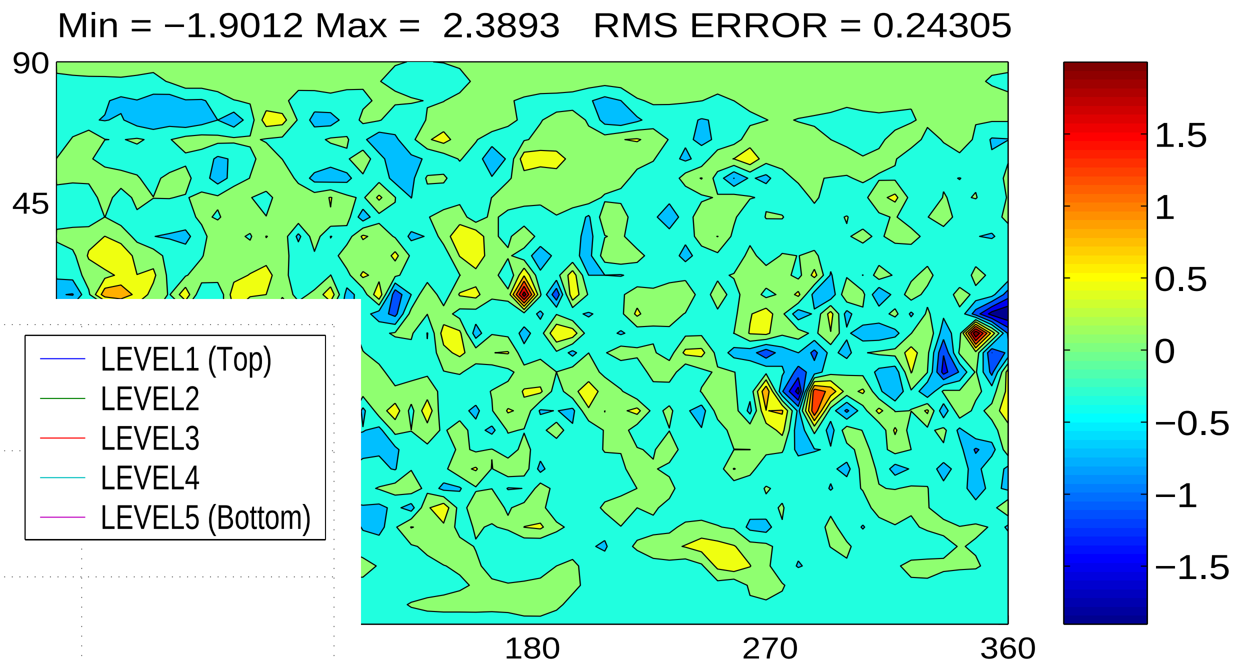
PS Error Reduces by about factor of 10

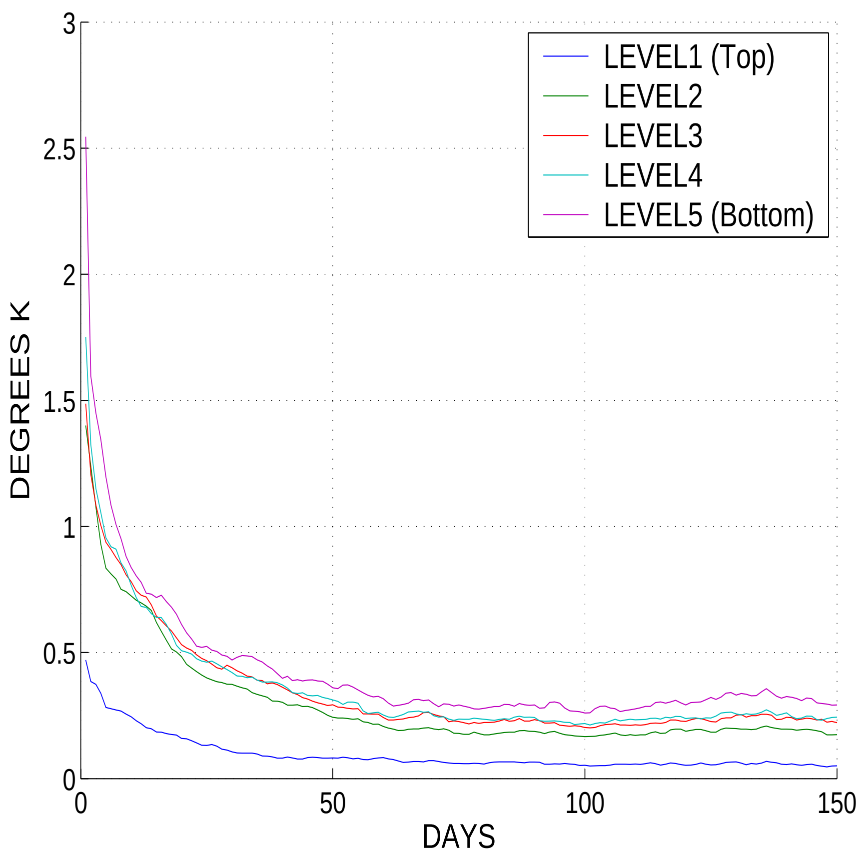
Asymptotes after about 50 days

Ensemble spread is approximately correlated with RMS error

Baseline Case: 1800 PS Obs every 24 hours

Largest T error in tropics for interior levels (level 3, day 400 shown)



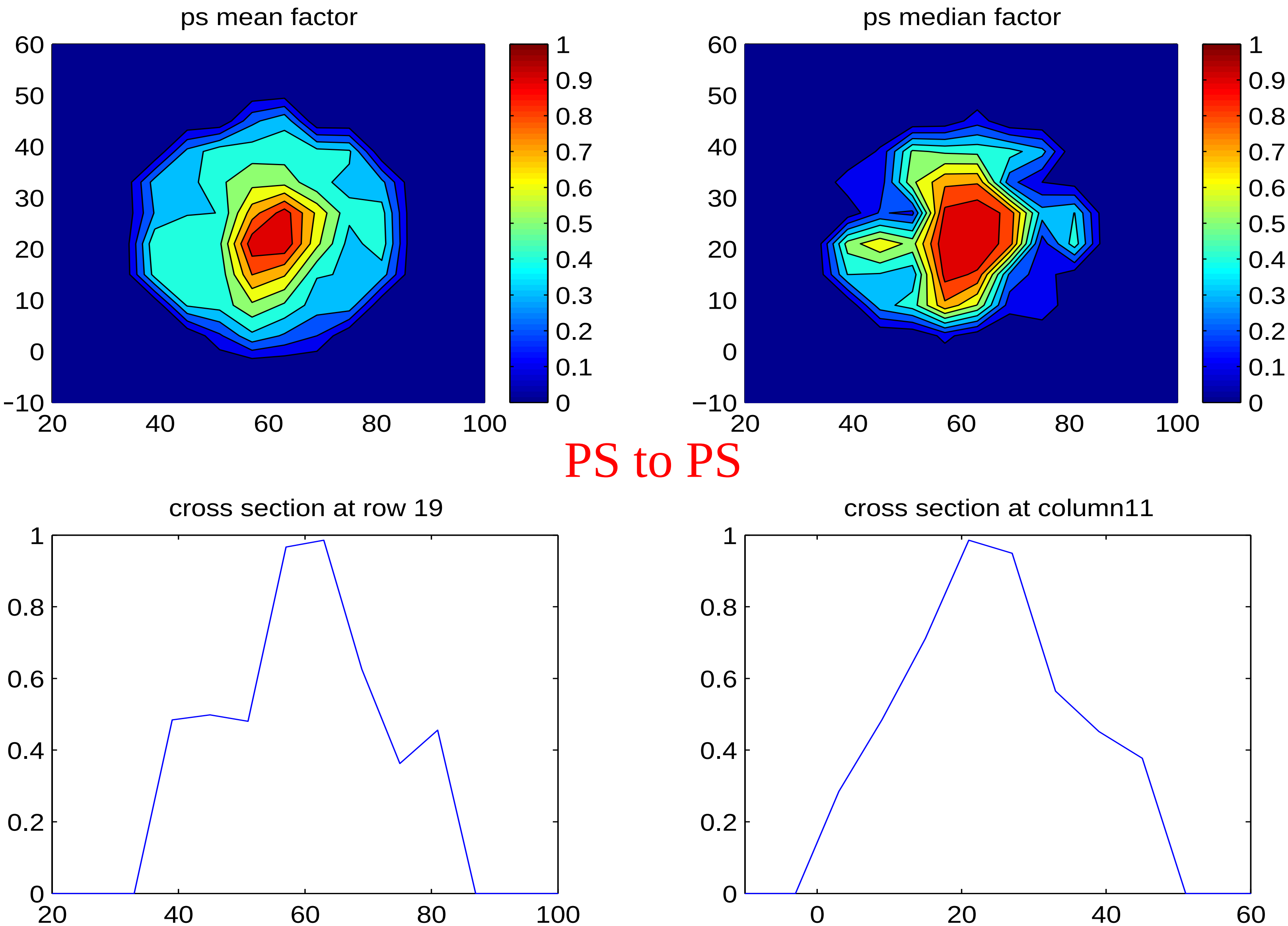


T Error also reduced by about factor of 10

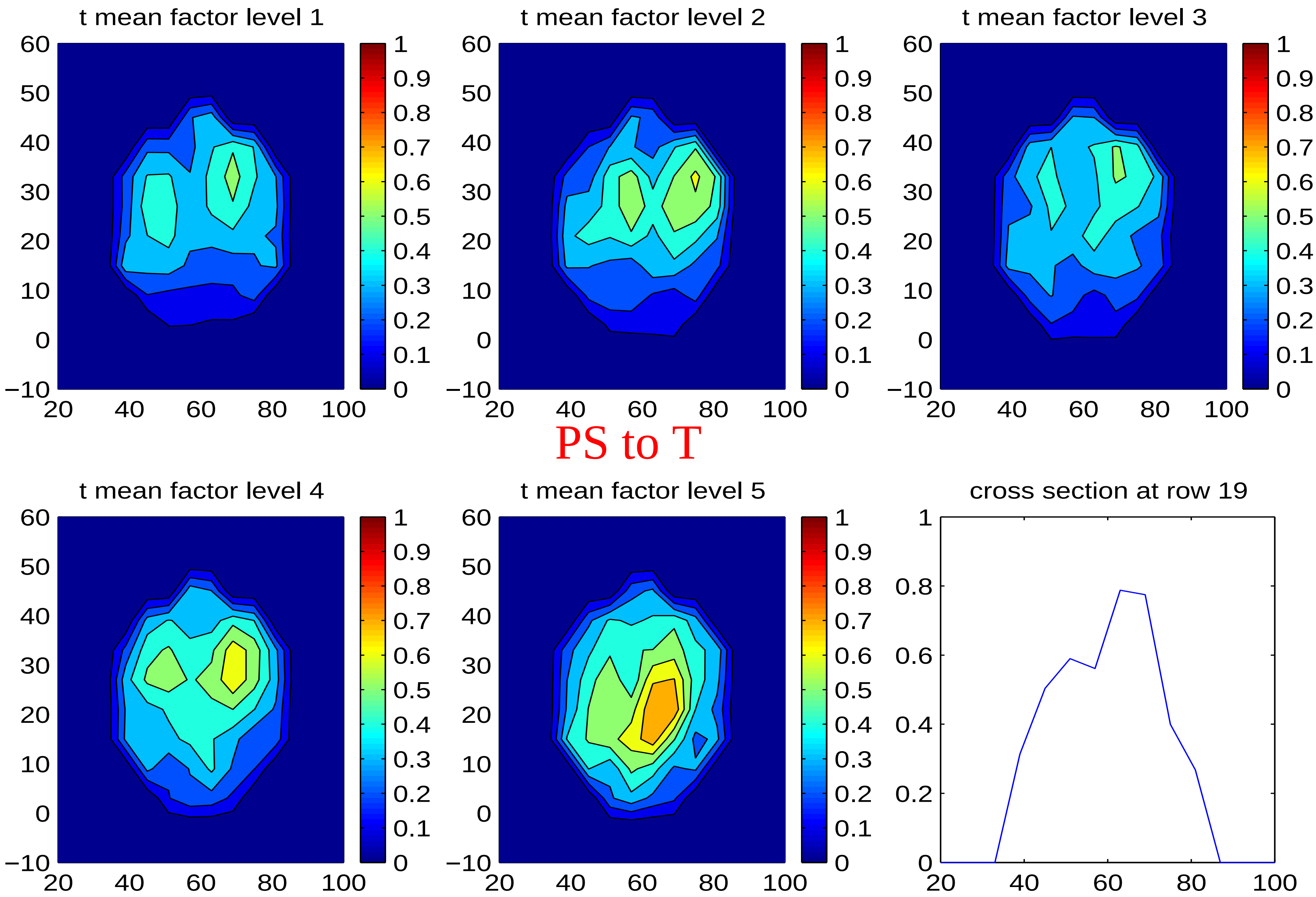
Asymptotes about day 70

Final error about 0.25 K for interior levels

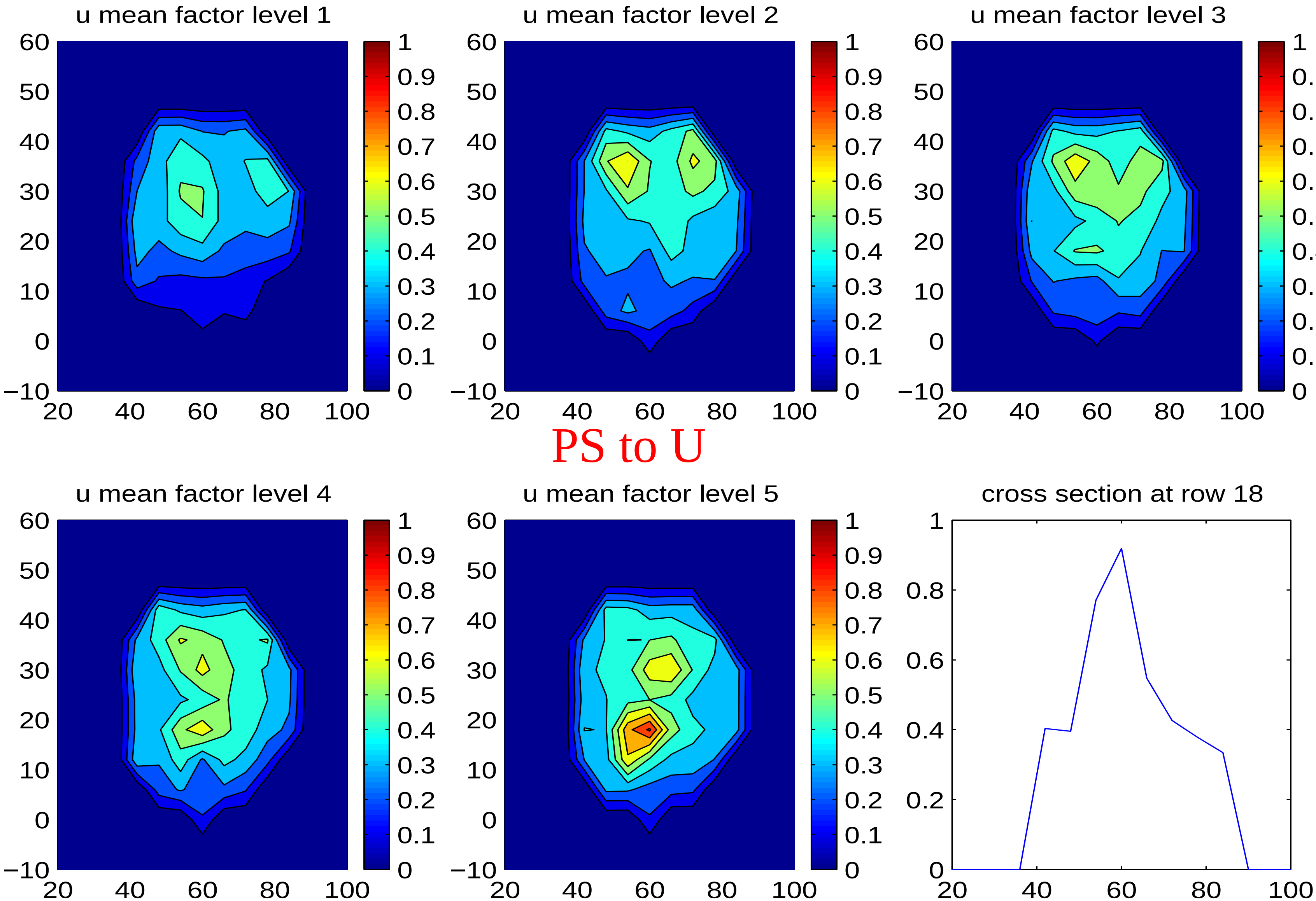
Hierarchical Filter Regression Confidence Factors: PS Obs. at 20N, 60E



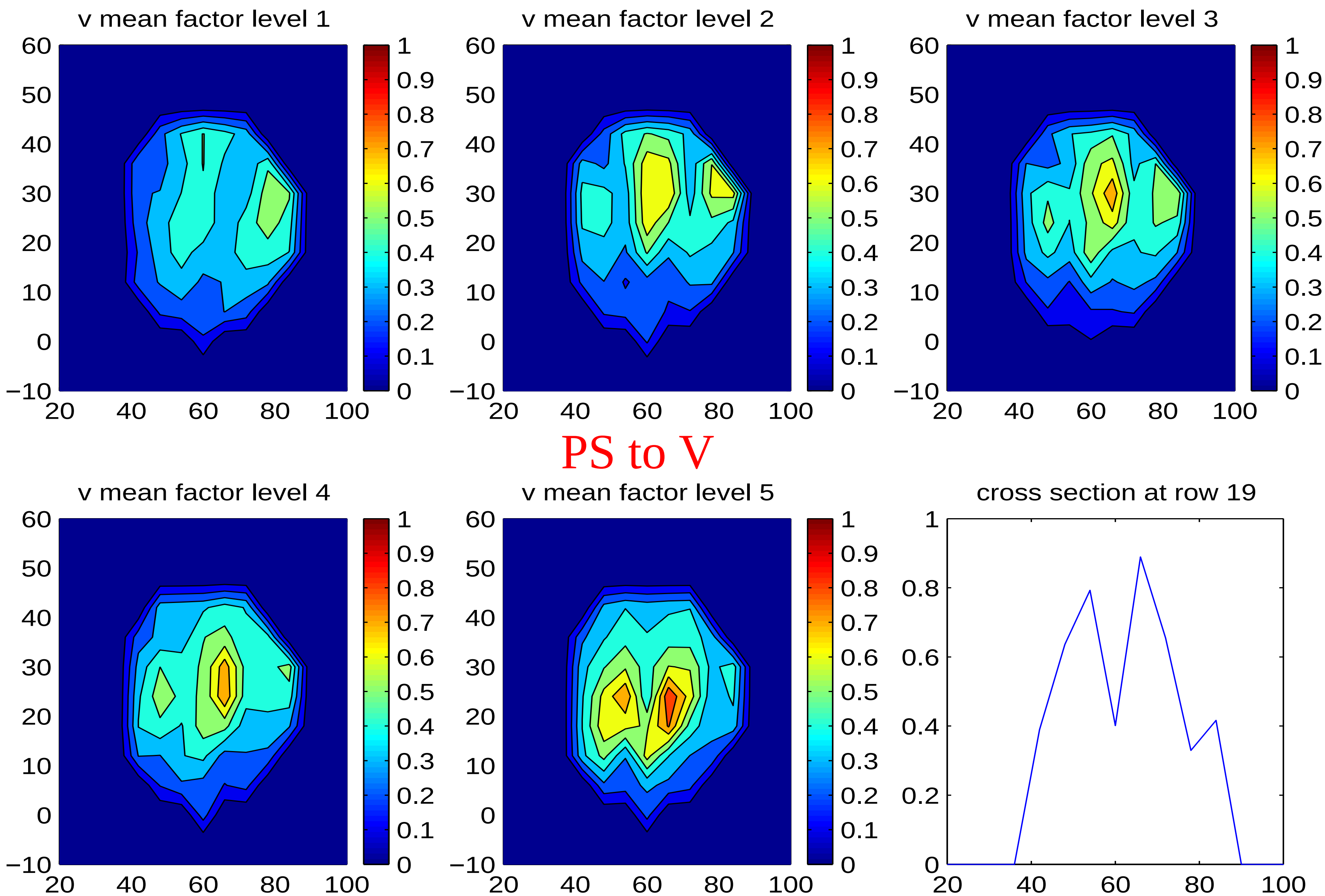
Hierarchical Filter Regression Confidence Factors: PS Obs. at 20N, 60E



Hierarchical Filter Regression Confidence Factors: PS Obs. at 20N, 60E



Hierarchical Filter Regression Confidence Factors: PS Obs. at 20N, 60E



Impacts of spatial density of PS obs

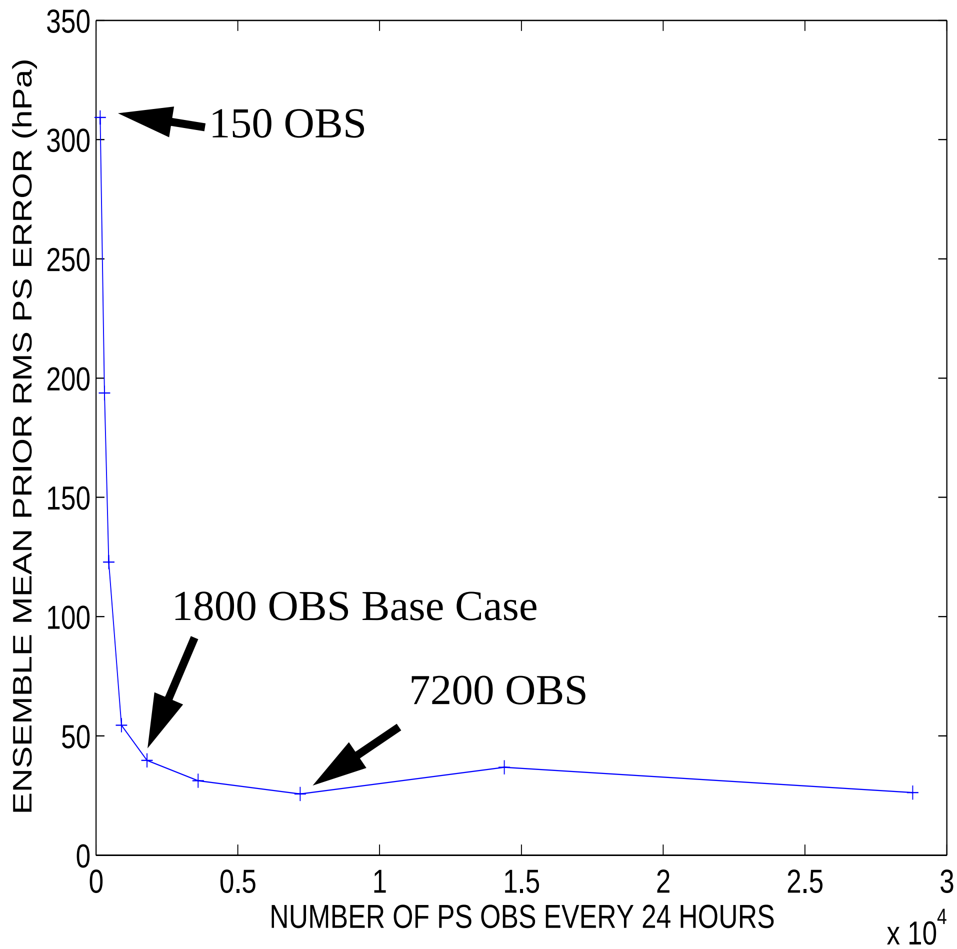
150, 300, 450, 900, 1800, 3600, 7200, 14400 and 28,800 every 24 hours

PS error reduces to about 0.3 mb

150 obs reduces clima-tological error by less than half

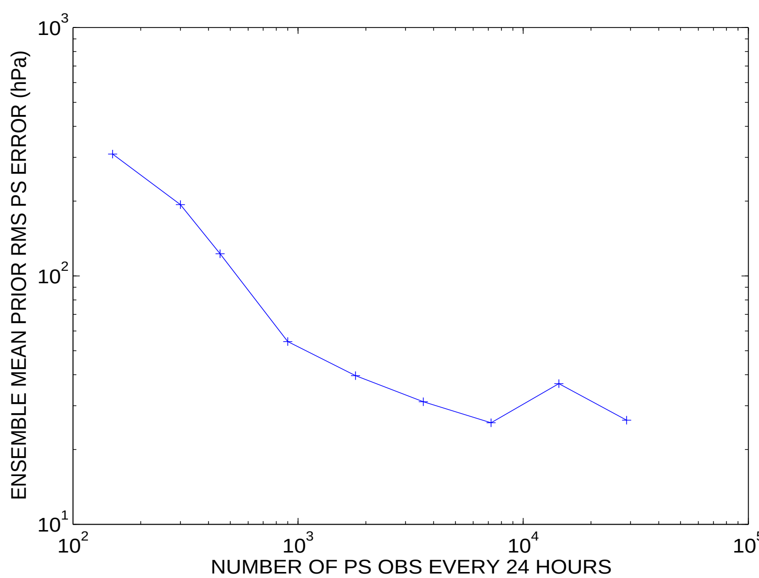
More than 7200 obs appears superfluous

Why is 14,400 worse? No clue.



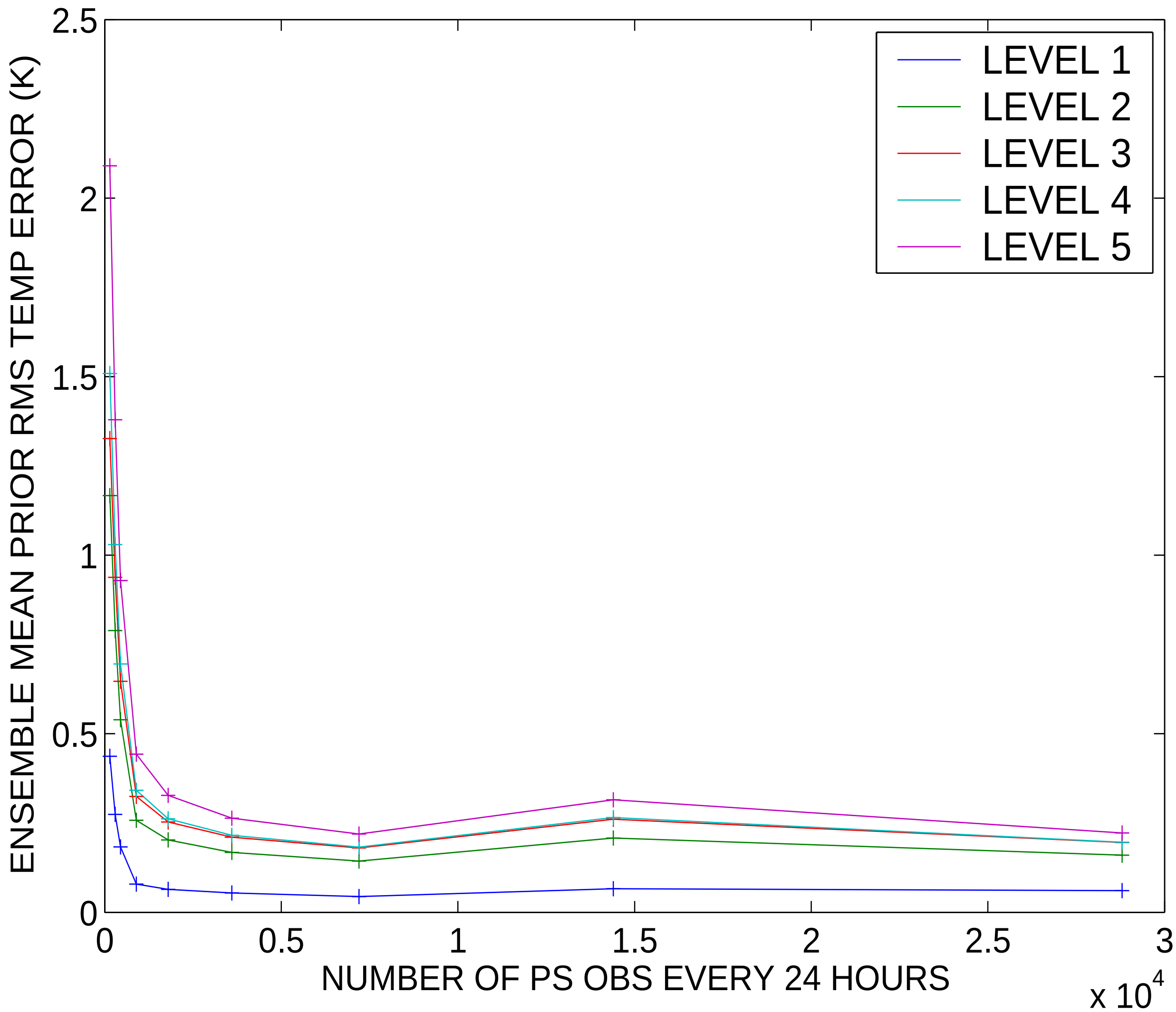
Plotting log /log of RMS shows approx. linear decrease from 150 to 7200 obs

Behavior for very large numbers of obs clearly different



Impacts of spatial density of PS obs on Temperature RMS

150, 300, 450, 900, 1800, 3600, 7200, 14400 and 28,800 every 24 hours



Behavior for Temperature (and U, V not shown) similar to that for PS
Best results for 7200 PS observations
Interior level mean T RMS of about 0.25 K for best case

Impacts of frequency of PS obs

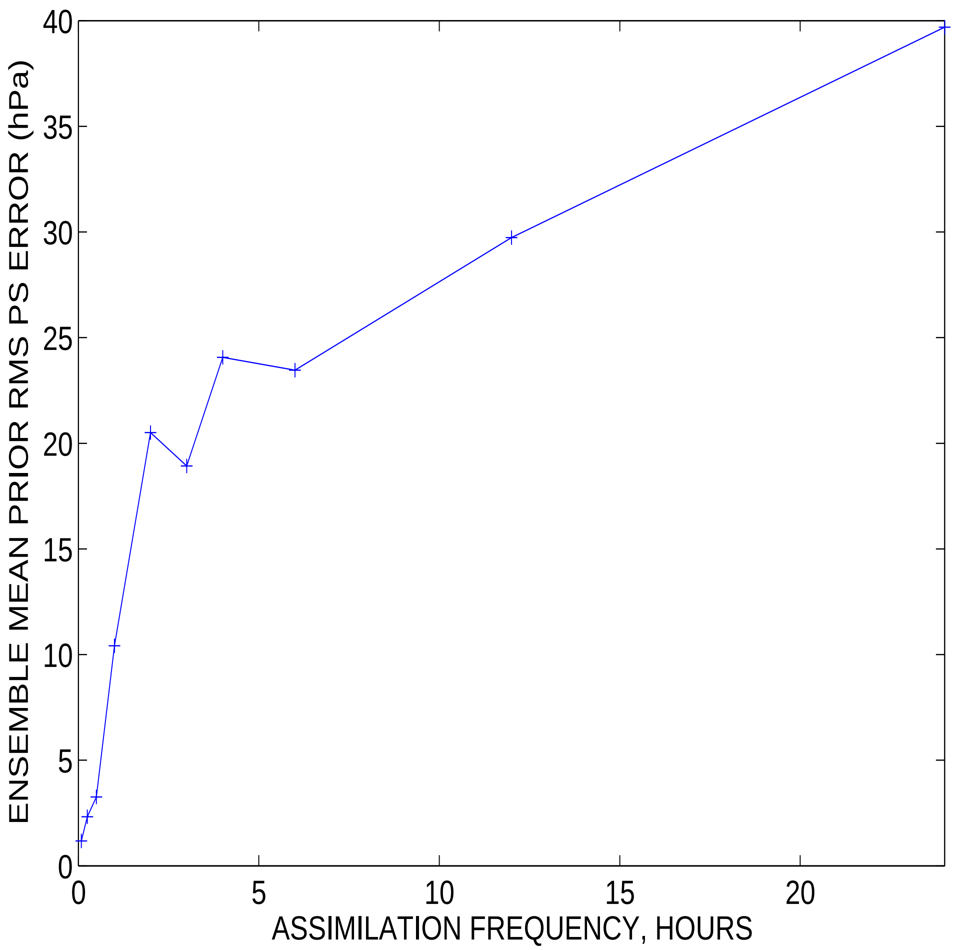
24, 12, 6, 4, 3, 2, 1 hours; 30, 15, 5 minutes; 1800 obs.

Steady RMS decrease as frequency increases

Much smaller RMS than for high density low frequency obs

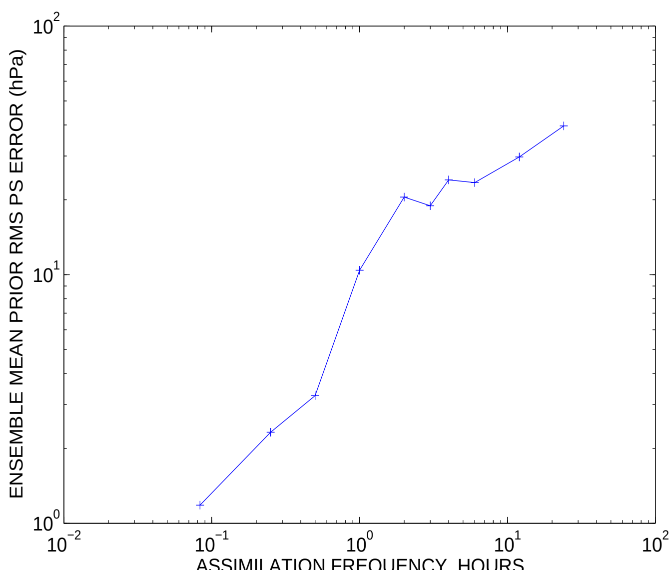
RMS < 0.02mb for 5 minutes

Strange behavior between 1 and 6 hour frequency



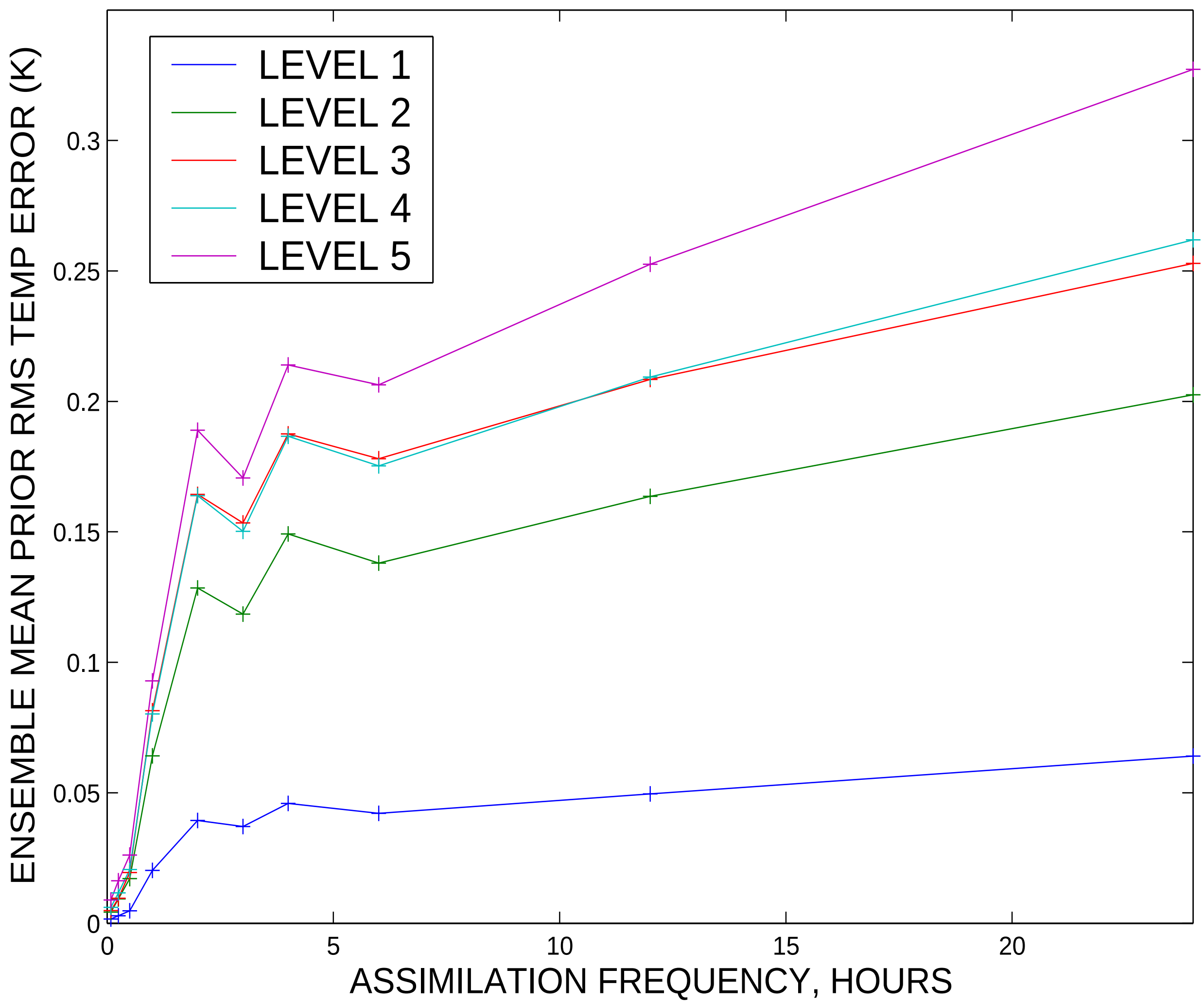
Plotting log /log of RMS shows approx. linear increase with a bump

What's going on in the middle?



Impacts of frequency of PS obs

24, 12, 6, 4, 3, 2, 1 hours; 30, 15, 5 minutes; 1800 obs.



Temperature (and U and V, not shown) similar to PS
Consistent decrease in RMS with increased obs frequency
Errors at 5 minute frequency less than 0.01 K !!!
How low can you go?

What’s going on at moderate obs frequencies?

Equilibrated model has very low gravity wave amplitude
When perturbed, ‘off-attractor’ gravity waves can result
Noise in observations can project off attractor

Ensemble members pulled in same direction; get phased gravity waves

Gravity wave period varies: approximately 4 hours
Gravity waves heavily damped; quickly reduced in amplitude

Low frequency (> 12 hours): gravity waves damped before next obs time

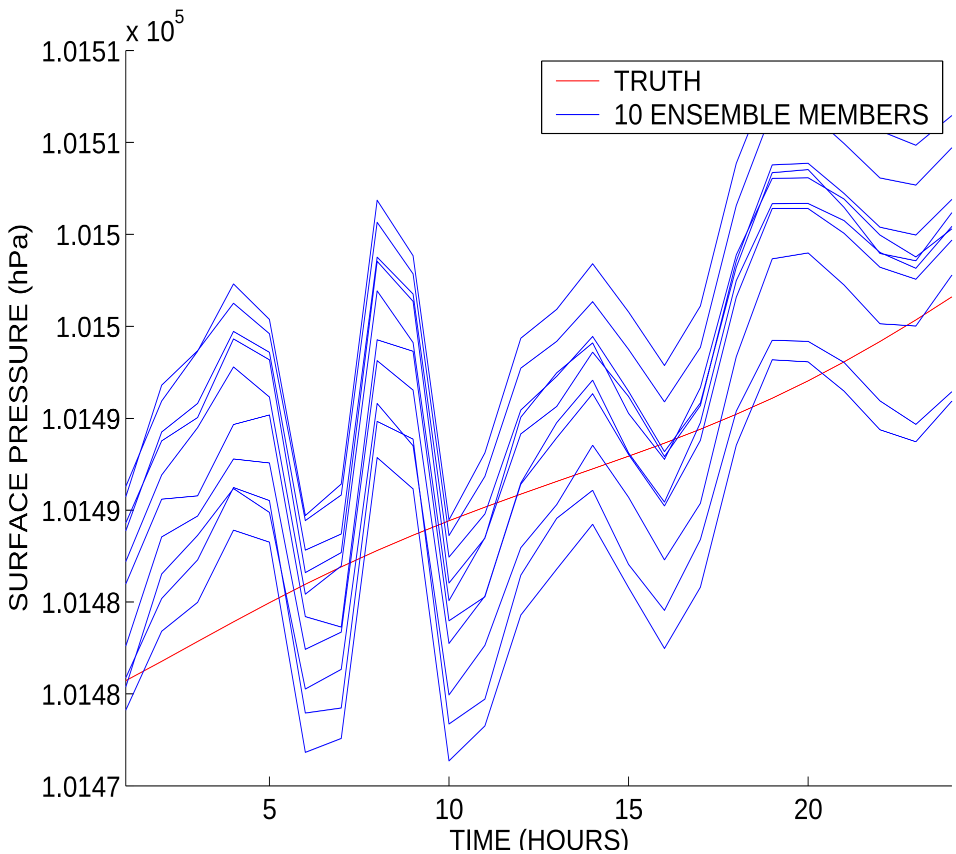
High frequency (< 1 hour): enough obs per period to control amplitude

Moderate frequency (~ 4 hours): get phased gravity waves in ensemble;
large bias; increased assimilation error

Time series of 10 out of 20 ensemble members at mid-latitude PS point.

Forecast initiated from end of 1800 PS obs every 4 hours

(Extreme example)



<u>Why does increasing frequency do more than increasing density?</u>

>>1. Temporal has more ‘independent’ correlation estimates

Can better eliminate sampling noise

>>2. Temporal sees observations at more ‘phases’ of wavelike structures

>>3. Large ensemble size could help to distinguish this by reducing sampling noise

These are yet to be done

>>4. Historically, high frequency obs were hard to acquire

Modern technology changes this

Exploring use of high frequency obs is planned

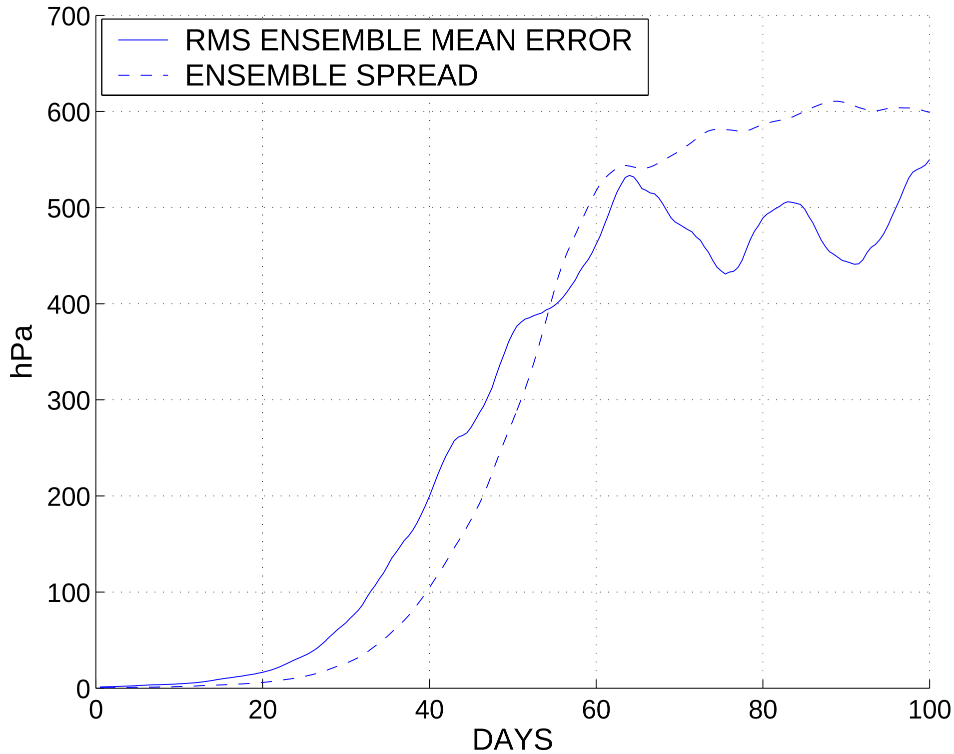
Need to demonstrate model has error growth

Free integration (forecast) at end of 1800 PS obs every 5 minutes

Error saturates at climatological values after about 60 days

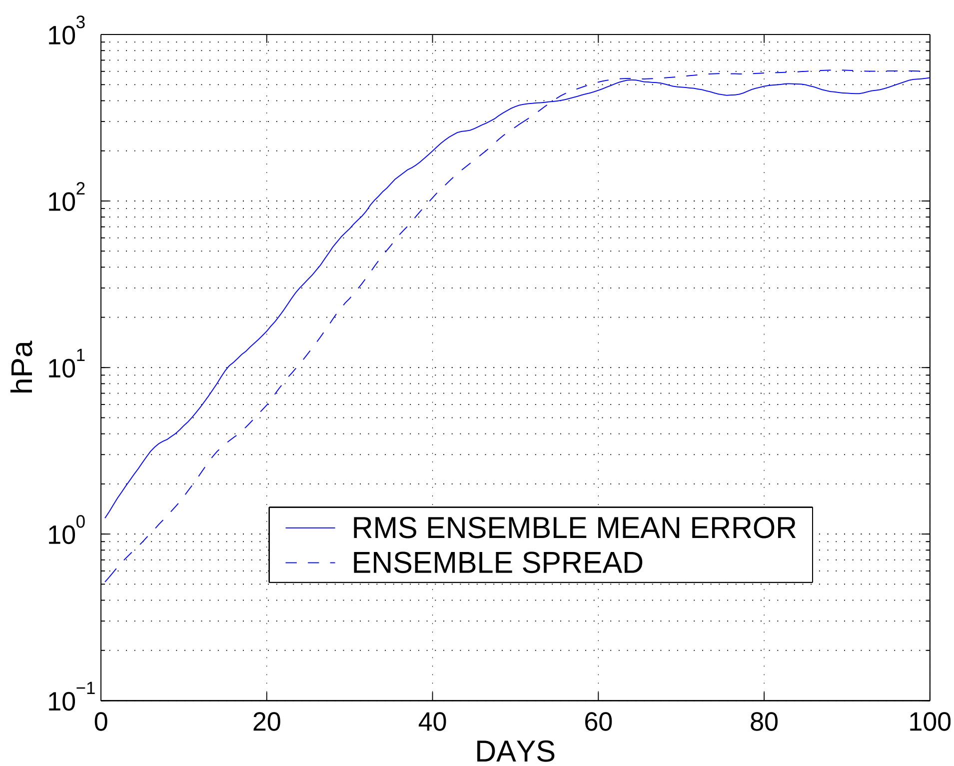
Error doubling time about 7 days

Considerably slower than real atmosphere



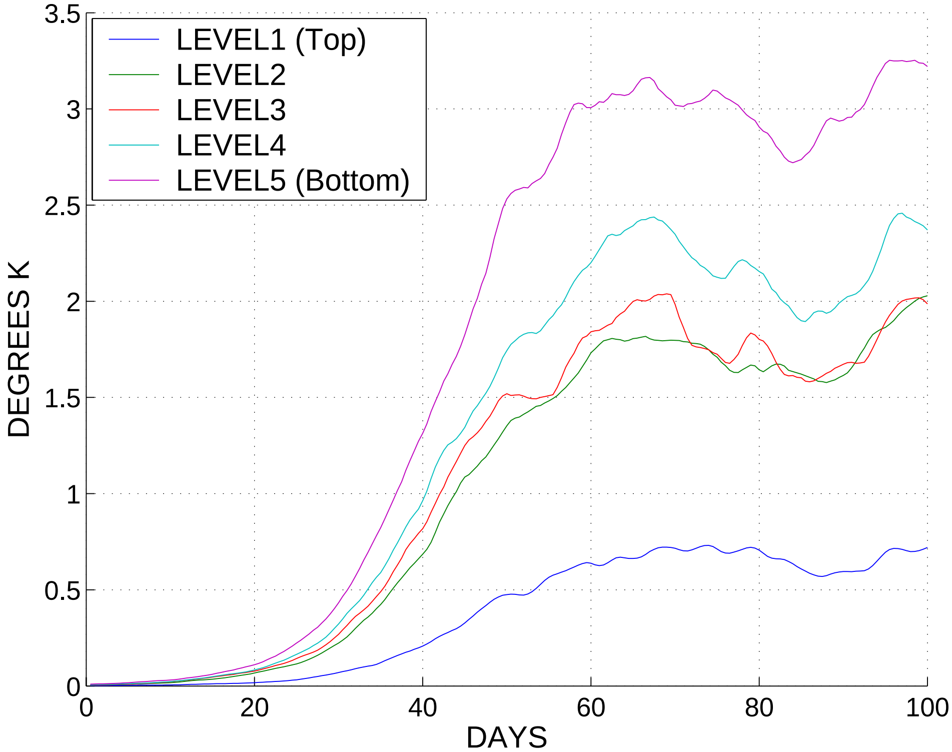
Error growth very nearly linear in log plot

Growth is almost purely exponential to saturation

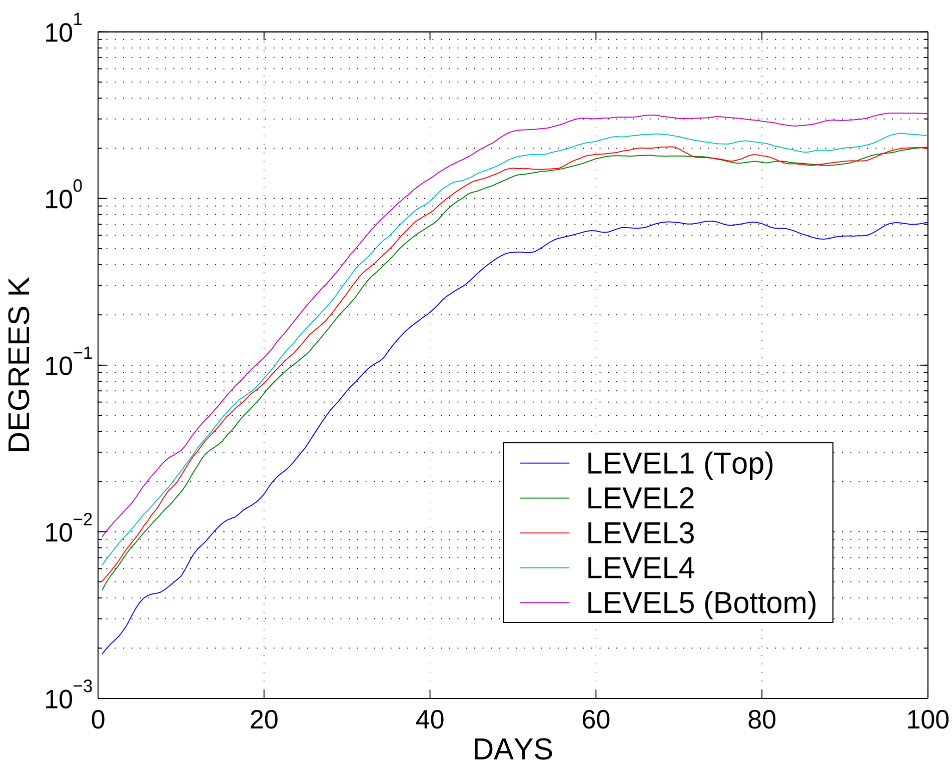


Error growth of other fields similar to PS

T (and U and V not shown) also saturate at about 60 days



Growth is very nearly exponential throughout

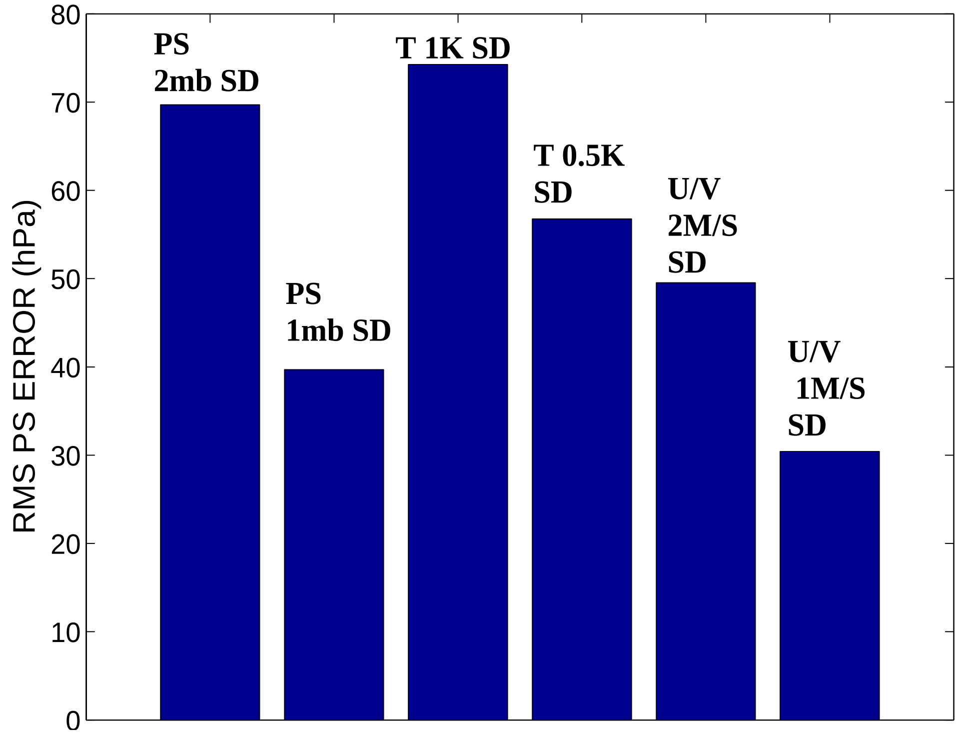


Relative Information Content of Various Surface Obs

Compare PS with T and U/V obs from lowest level

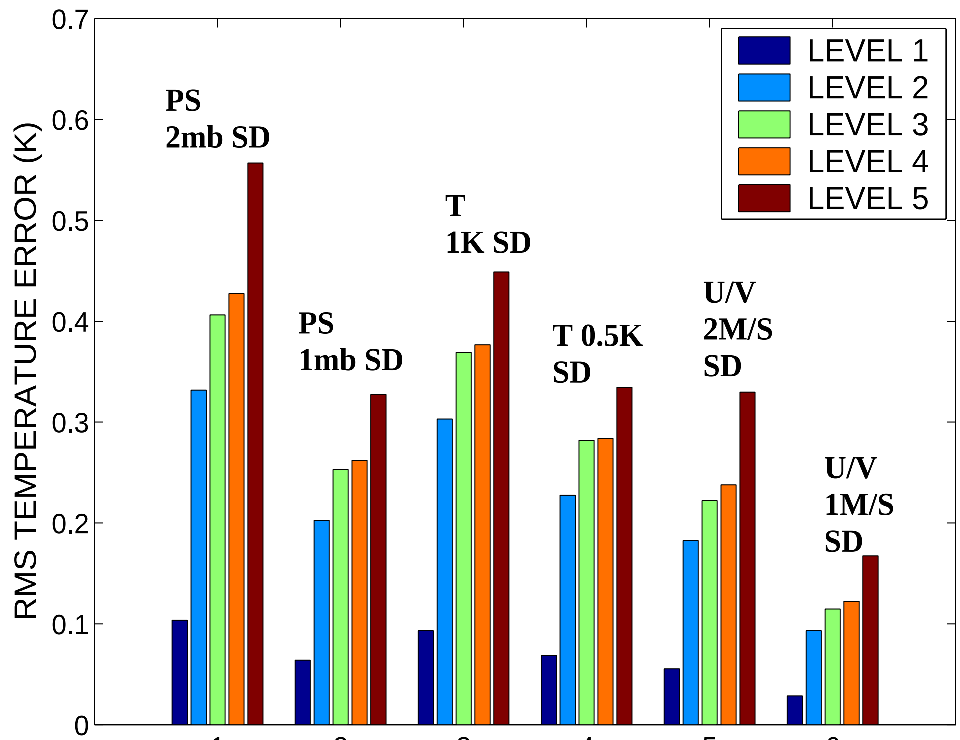
RMS error of PS prior assimilation when assimilating 1800 PS, T, or U and V wind components every 24 hours.

Two specified error SDs are checked for each.



RMS error of T for same cases.

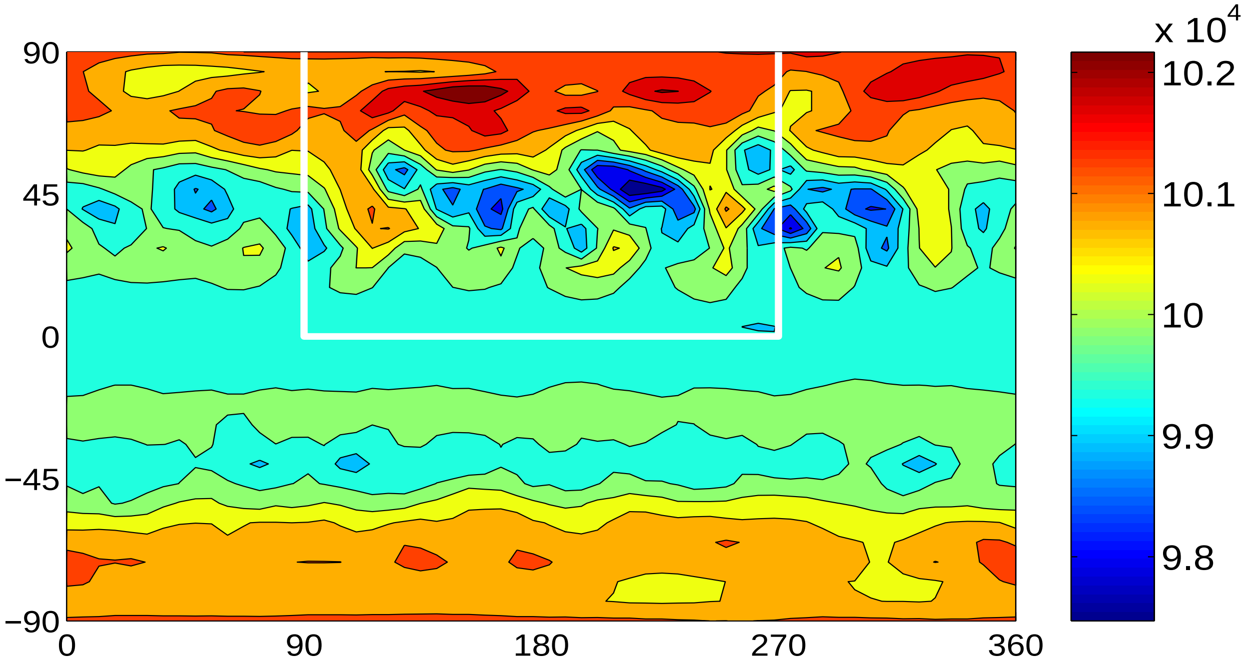
Very roughly, U/V obs with 2M/S SD have same information content as PS with 1mb SD or T with 0.5K SD.



Assimilating PS over limited domains

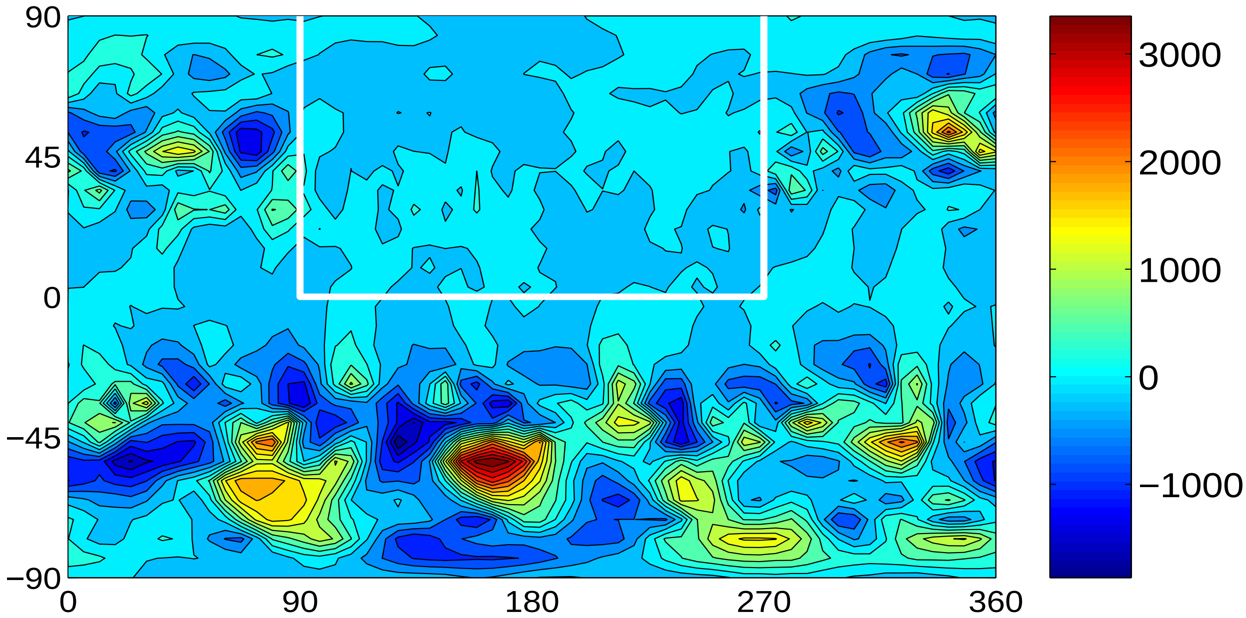
450 PS obs every 24 hours over 1/4 of surface

Ensemble mean prior assimilation for PS at 400 days
Approaches zonal climatology with no obs information



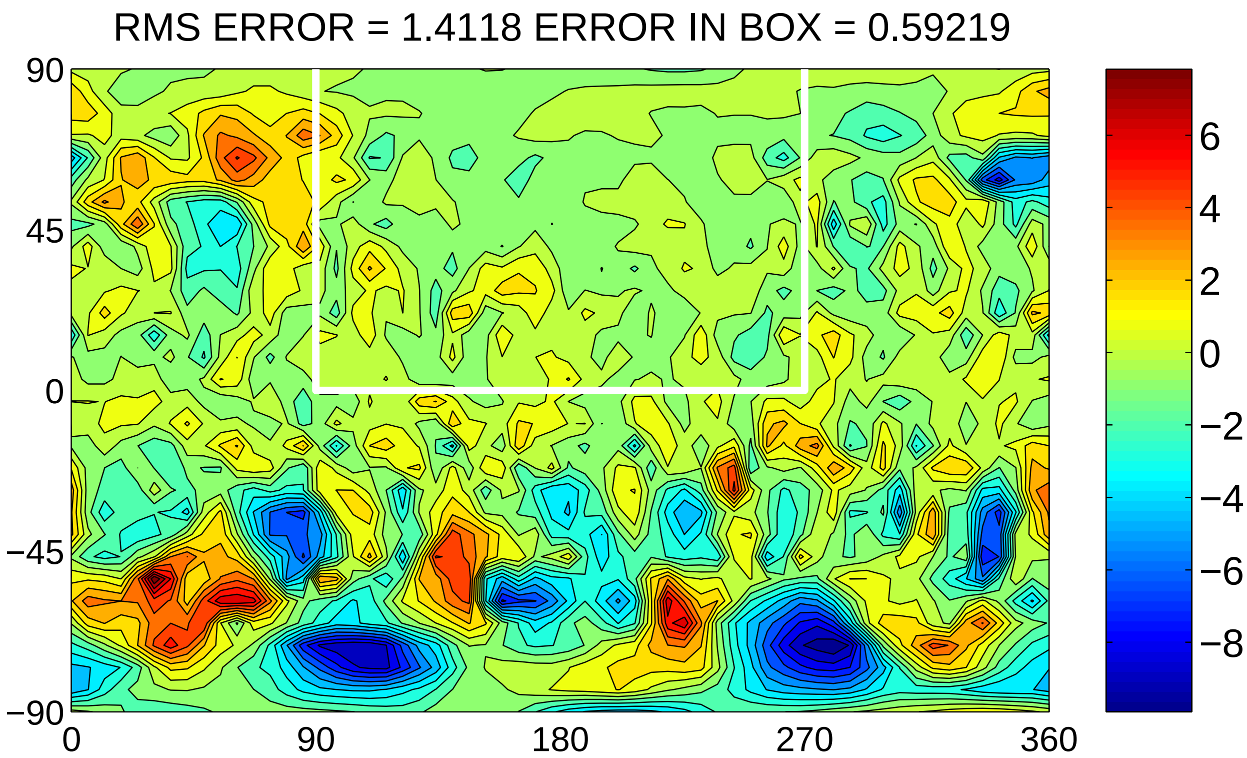
RMS Error for PS at 400 days
Error in box about twice the value for 1800 global obs

RMS ERROR = 320.2063 ERROR IN BOX = 84.584



Assimilating PS over limited domain

RMS error for T at day 400;



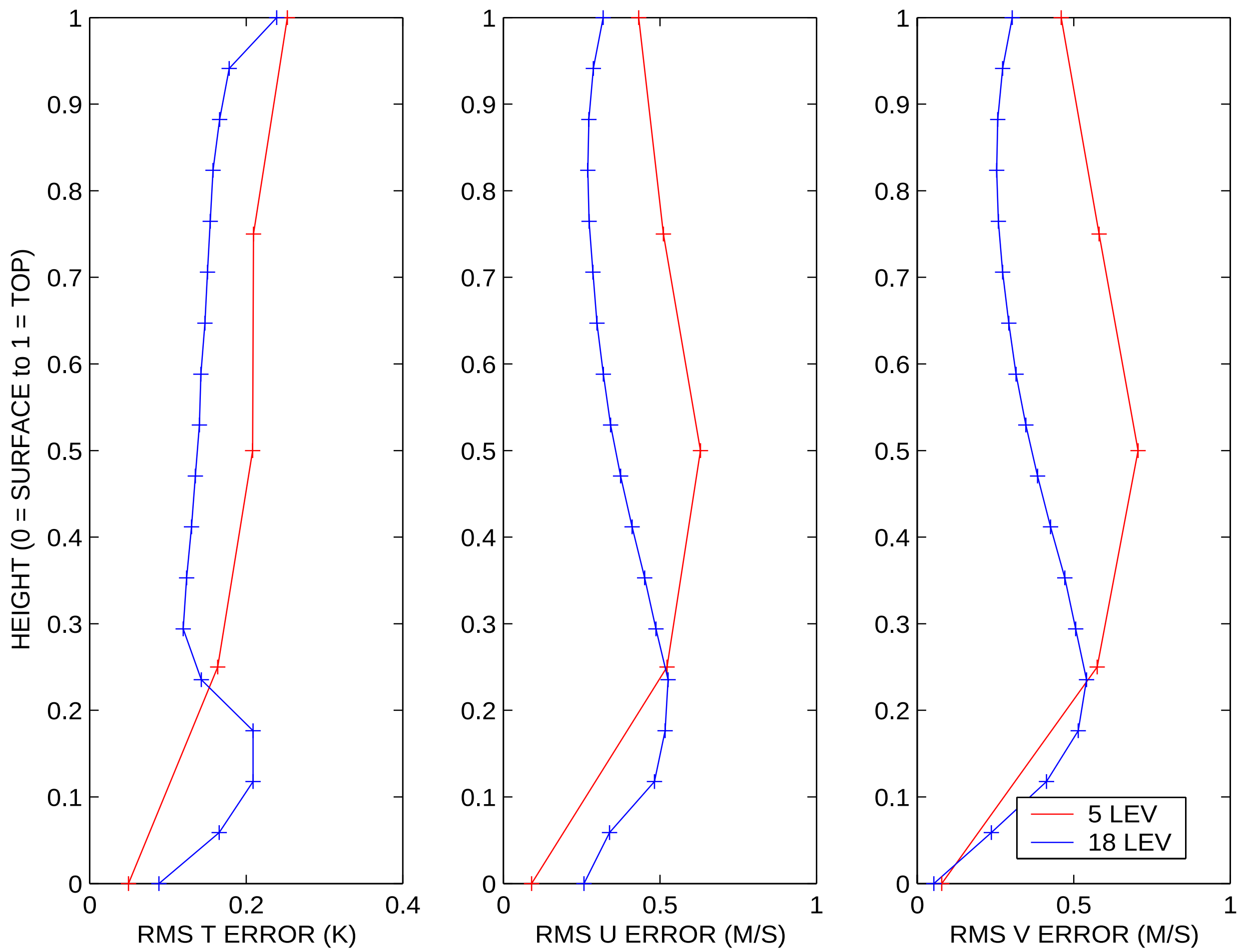
Error in box about twice that for 1800 global obs

Information is advected out of the box (to the east in mid-latitudes)

Method handles low information propagating in from upstream

Implications for regional and nested model filter data assimilation

What happens with increased resolution?



Comparison of 1800 PS obs for 5 and 18 level model
Tricky comparison, diffusion, etc. are identical
Error in upper levels of 18-level actually less

Horizontal resolution, water vapor, and more comprehensive physics:
First results in NCAR CAM at 2 degree resolution appear consistent
Results by Whitaker and Hamill with PS obs in NCEP model are good

Predictability and stochastic sub-grid scale parameterizations

Models don't resolve all spatial scales and processes

Normally parameterized (usually by column physics)

In prediction models, physics is usually deterministic

In reality, best we can hope for is to know probability distribution for impact of unresolved processes

Can simulate this in perfect model by adding random noise to model

Here, add noise factor to temperature tendency computation

At each gridpoint, let dT/dt = MODEL * (1 + N(0, R))
N(0, R) is random number with mean 0 and standard deviation R

Independent noise at each point in current implementation

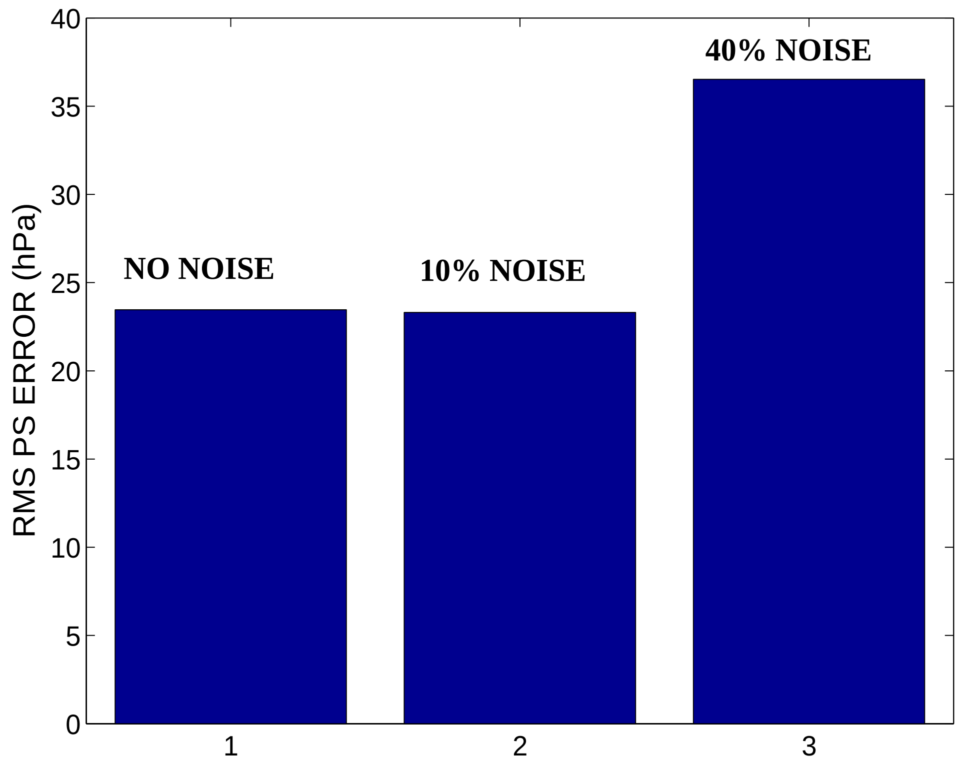
Ran cases with R = 0.1, 0.4

1800 PS obs every 6 hours (moderate gravity wave amplitude)

Impacts of sub-grid noise on Assimilation Error

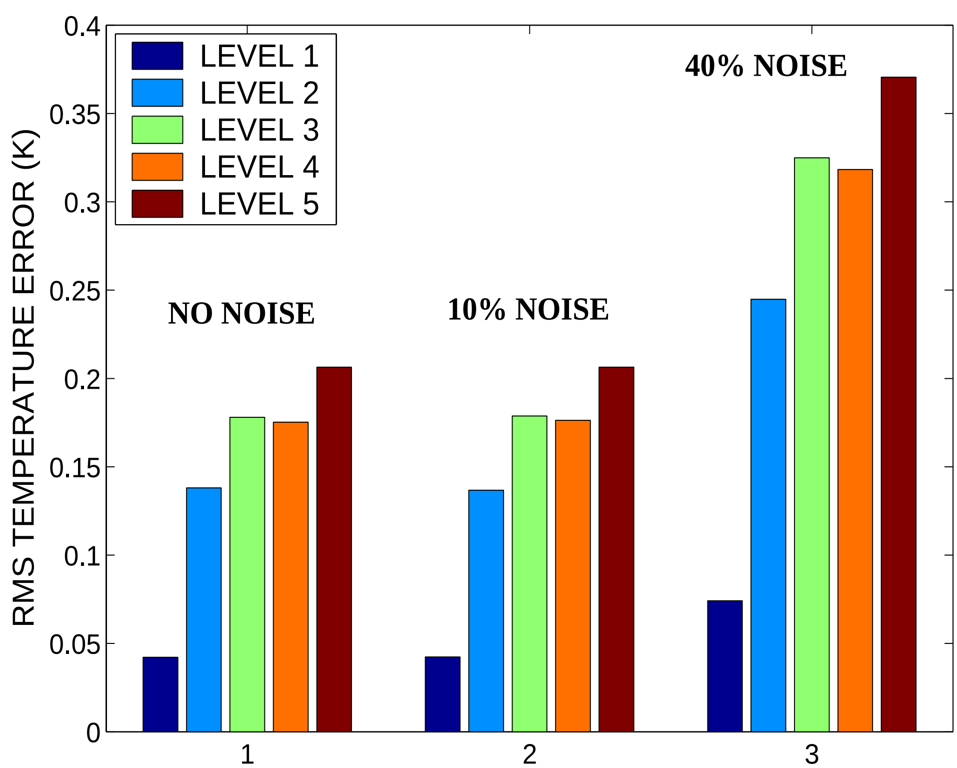
For 10%, error is slightly reduced

Adding noise in right proportions can solve gravity wave problem?



T results similar.

40% case has much increased error.

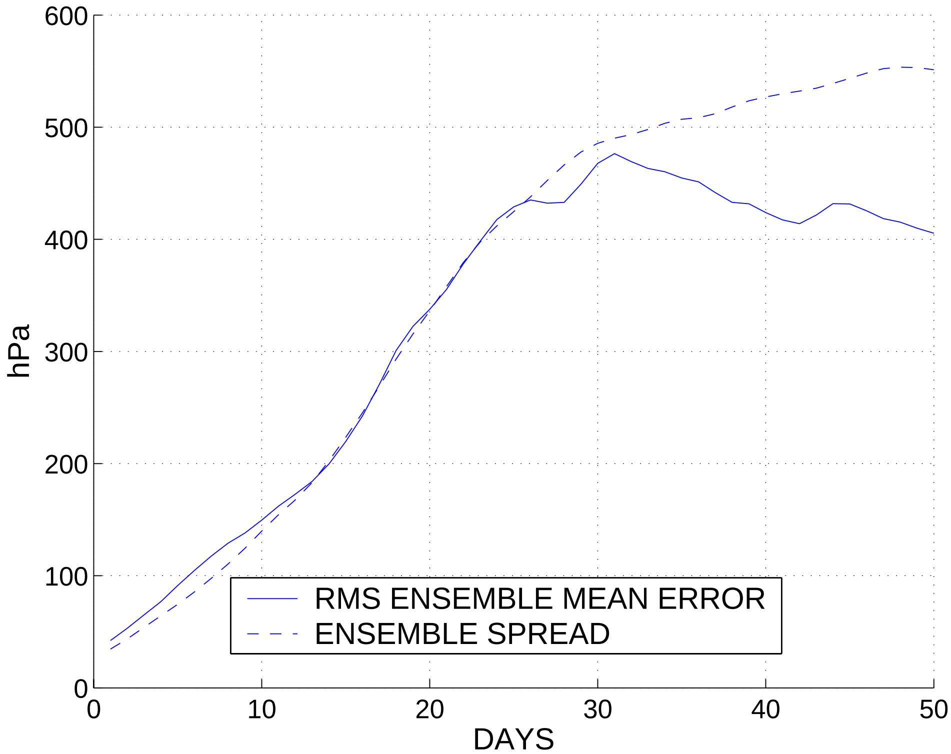


Error growth and predictability with sub-grid scale noise

PS error growth is mostly linear at first.

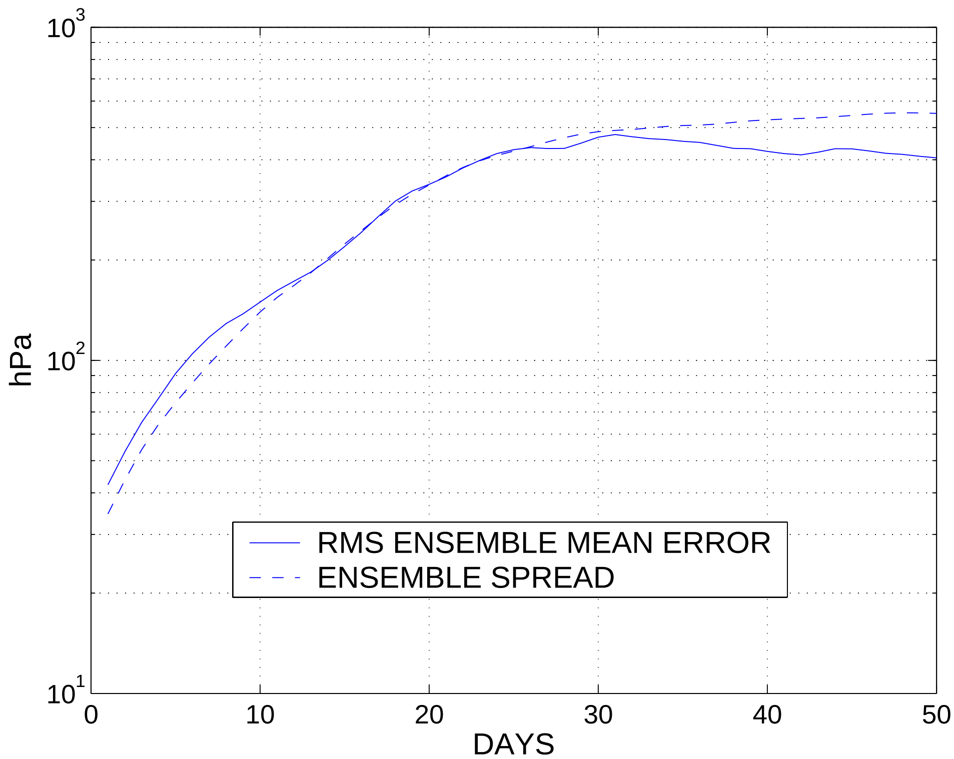
Then hint of exponential after day 15?

Saturates by day 25.



Should expect error growth in real systems to look like this.

Operational systems do not at this point?



Conclusions

1. Interesting 'Predictability' questions in assimilation / prediction systems

2. Need to account for details of assimilation

3. Some parameter ranges look ripe for useful analysis (small errors in this presentation for instance)

4. Assessing information content of observations very useful

5. Leads to rational design of observing systems

6. (Small) ensemble filter can extract lots of information

7. Increasing temporal density of obs may be very effective

8. Bias, bias, and bias are key remaining problems

9. Predictability studies must be done in assimilation / prediction context with stochastic sub-grid scale parameterizations

Dealing with bias in ensembles is remaining problem

Bayesian Theory supporting filters excludes bias

But, we know there are many violations of the Gaussian assumptions we make for implementation

Need to build an additional a priori model of bias

Covariance inflation and related tricks are one simple model
Have some advantage by retaining correlation structure
Simply States that there is an additional Gaussian component of error that is not accounted for by the model

Can we do more sophisticated, adaptive models?

With ensemble and known observation error distribution, can determine expected value of sum of model and observation bias for any observation

In other words, is the distance between the prior obs estimates and the obs inconsistent?

Can aggregate these statistics in time, or space or both

Need to partition unaccounted error into one of three bins:
1. Model first moment bias (error)
2. Model second moment bias (error)
3. Observation bias (error)

Dealing with bias in ensemble filters (cont.)

May be easy to partition between 3 and combined (1, 2)
- Similar to buddy checks
- Are observations in same ‘area’ not consistently inconsistent
- If so, much more inconsistent obs should have large bias

Tricky problem, how to partition bias between first and second moment in model

If it’s first moment, just let observation be more compelling

If it’s second, need to reduce decrement in spread

Initial results playing with this have been very successful in very large bias systems

Need to try out in a real setting

Note: this should eventually replace a part of quality control