

TRAINING
COURSE

**EUMETSAT/
ECMWF
NWP-SAF
satellite data
assimilation**



Background Errors for Satellite Data assimilation

Data Assimilation ...combining background information with observations

- Models give a complete description of the atmospheric, but **errors grow rapidly** in time
- Observations provide an **incomplete description** of the atmospheric state, but bring up to date information
- Data assimilation **combines** these two sources of information to produce an optimal (best) estimate of the atmospheric state
- This state (the *analysis*) is used as **initial conditions** for extended forecasts.

The cost function $J(\mathbf{X})$

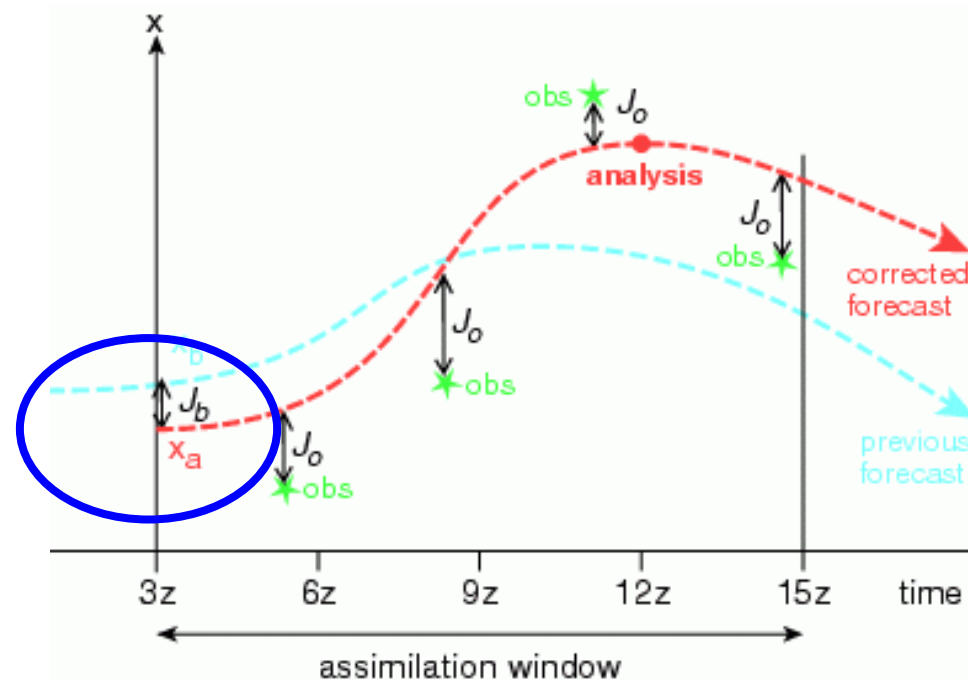
The diagram illustrates the cost function $J(x)$ with the following components and annotations:

- model state**: An arrow points from this label to the variable x in the first term of the equation.
- background error covariance**: An arrow points from this label to the matrix \mathbf{B}^{-1} in the first term.
- observations**: An arrow points from this label to the variable y in the second term.
- observation* error covariance**: An arrow points from this label to the matrix \mathbf{R}^{-1} in the second term.
- observation operator**: An arrow points from this label to the matrix \mathbf{H} in the second term. A sub-note below it states: "(maps the model state to the observation space)".

$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - \mathbf{H}[x])^T \mathbf{R}^{-1} (y - \mathbf{H}[x])$$

The 4D-Var Algorithm J_b

$$J(x) = \boxed{(x - x_b)^T \mathbf{B}^{-1} (x - x_b)} + (y - \mathbf{H}[x])^T \mathbf{R}^{-1} (y - \mathbf{H}[x])$$



**What do we want our
background errors to do ?**

What do we want our background errors to do ?

- Describe our confidence in the background estimate of the atmosphere X_b
- Describe how background errors are correlated with each other:
 - vertically (between different model levels)
 - spatially (between different grid points)
 - between variables (T / Q / O3 / wind)
 - impose balance (e.g. geostrophic)
- **They should be data and flow dependent!**

How do we determine background errors?

**Simply compare X_b to
the true state of the atmosphere ?**

...but we don't have the truth!

How do we estimate background errors?

How do we estimate background errors?

- Innovation departure statistics – i.e. comparison of X_b with **radiosondes** (best estimate of truth but limited coverage)
- comparison of forecasts differences e.g. 48hr and 24hr (so called **NMC method**)
- comparison of **ensembles** of analyses made using perturbed observations

None of these approaches are perfect!

How do we estimate background errors?

- **Innovation statistics:**

- ☺ The only direct method for diagnosing background error statistics.
- ☹ Provides statistics of background error in observation space.
- ☹ Statistics are not global, and do not cover all model levels.
- ☹ Requires a good uniform observing network.
- ☹ Statistics are biased towards data-dense areas.

- **Forecast Differences:**

- ☺ Generates global statistics of model variables at all levels.
- ☺ Inexpensive.
- ☹ Statistics are a mixture of analysis and background error.
- ☹ Not good in data-sparse regions.

- **Ensembles of Analyses:**

- ☹ Assumes statistics of observation error (and SST, etc.) are well known.
- ☺ Diagnoses the statistics of the actual analysis system.
- ☹ Danger of feedback. (Noisy analysis system => noisy stats => noisier system.)

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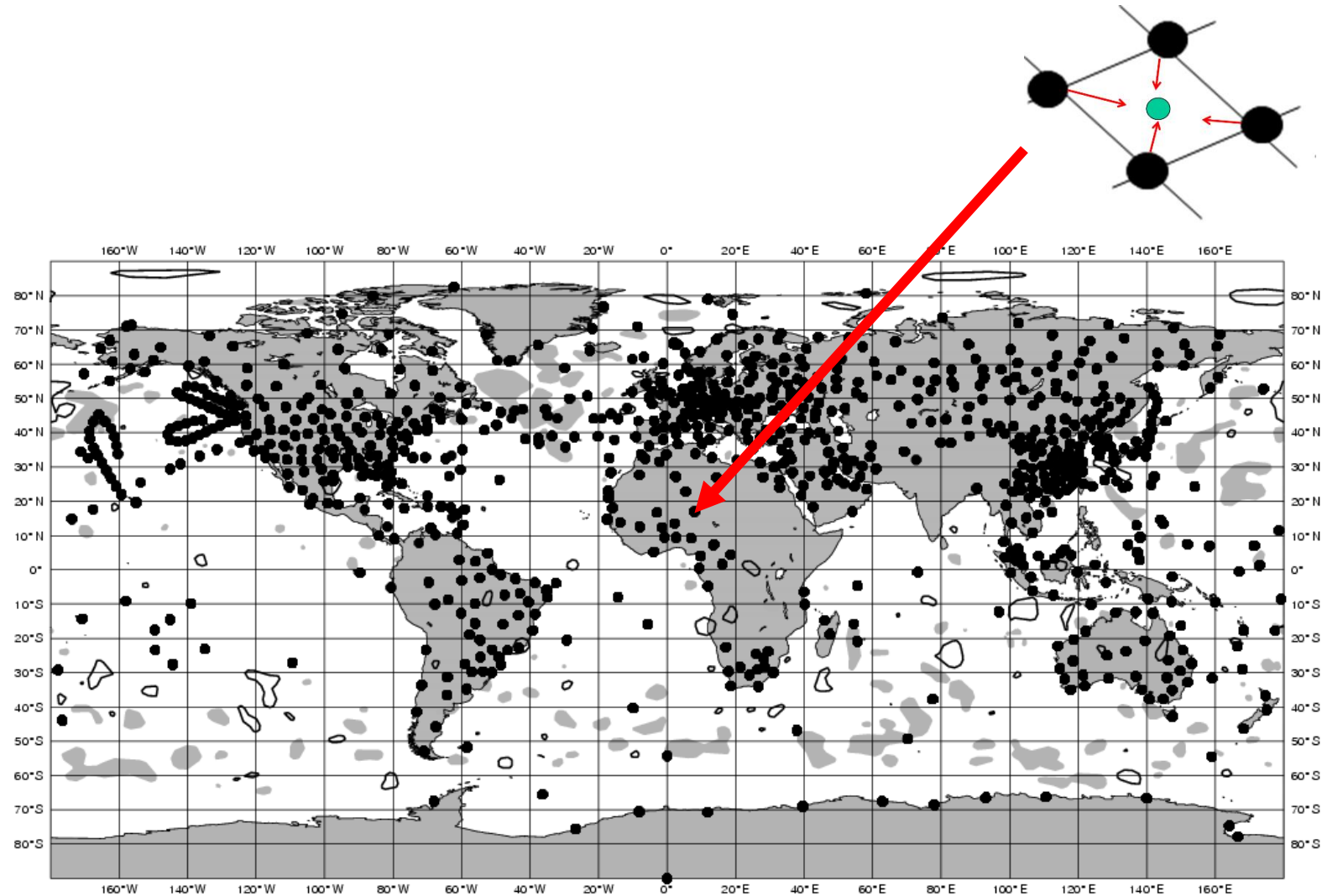
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Innovation statistics ...

e.g. compare X_b to radiosondes



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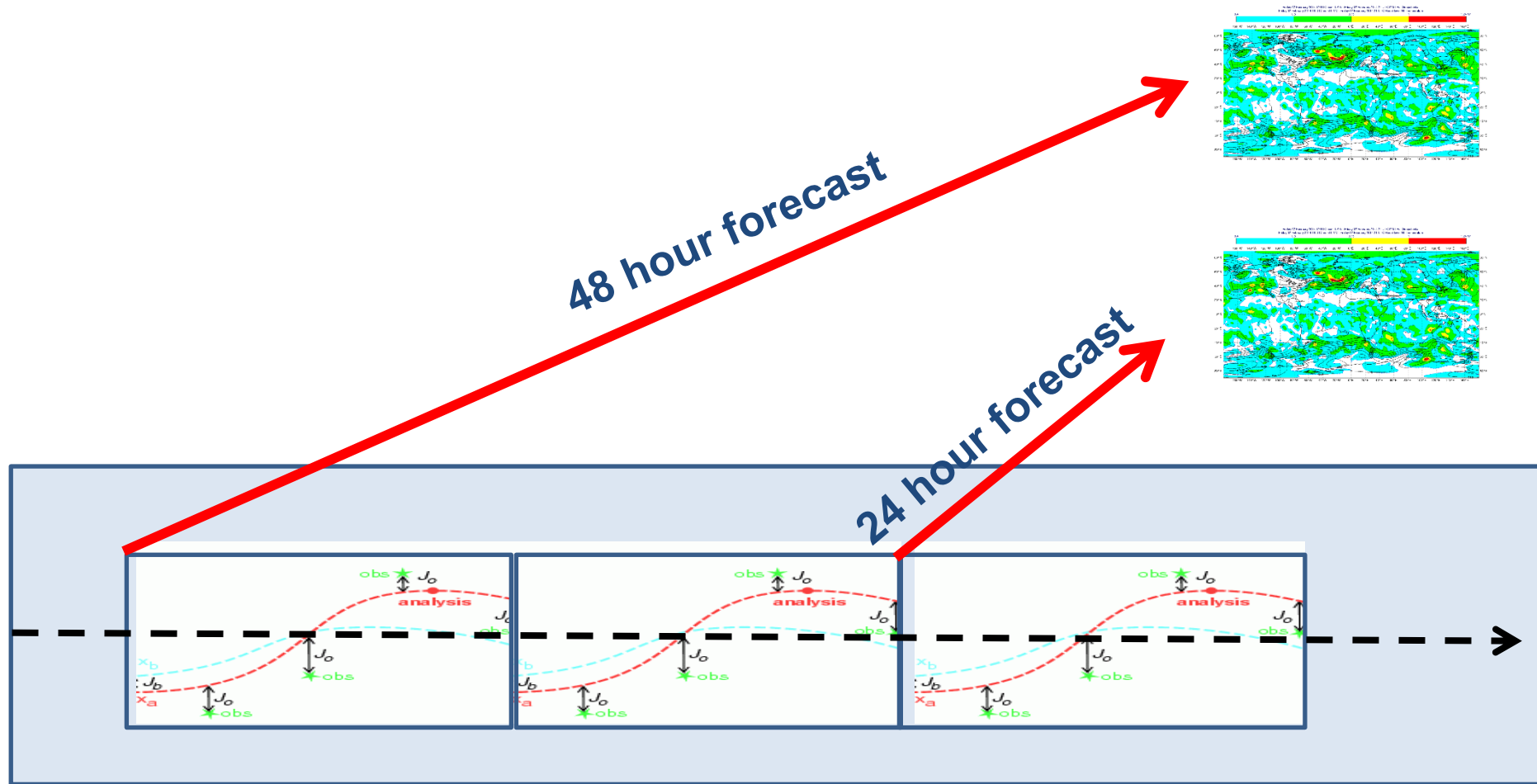
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Compare forecasts of the same state from different ranges



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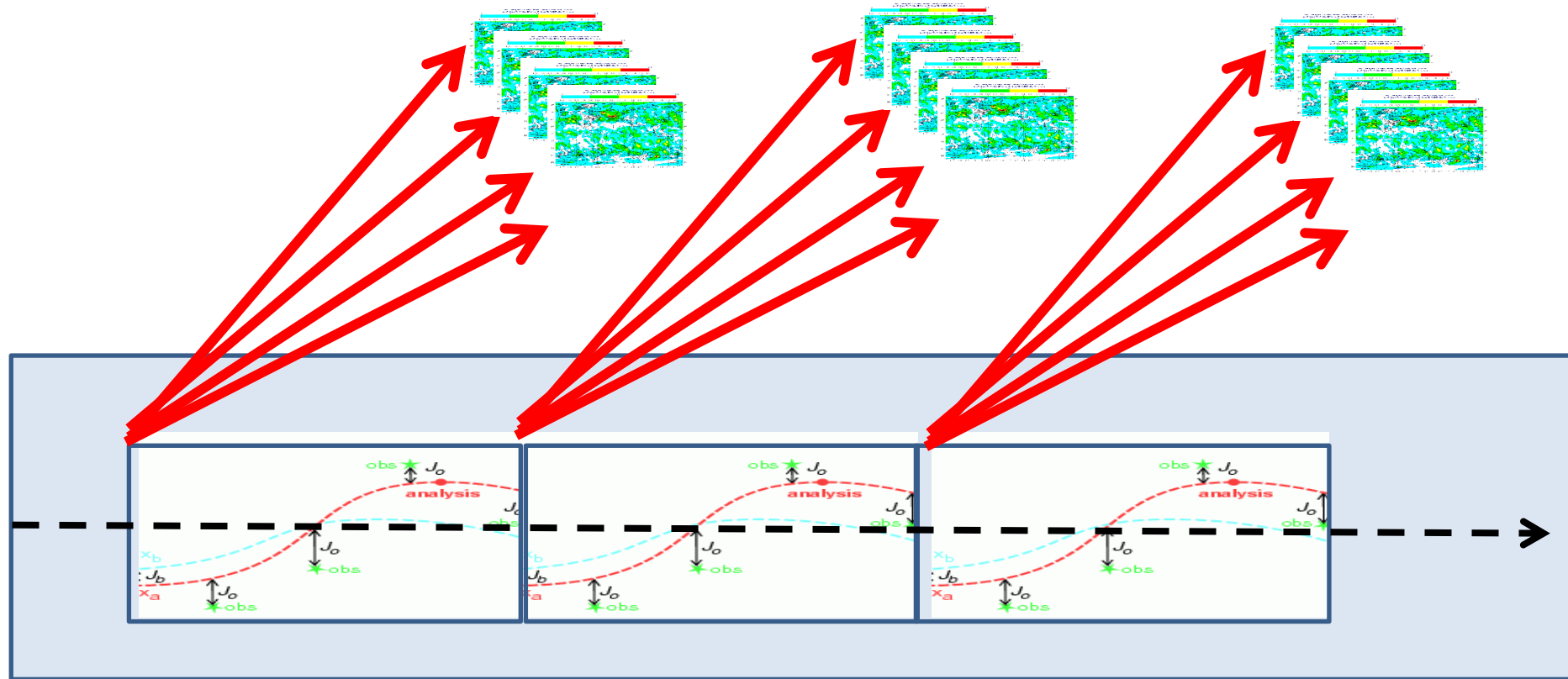
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- **Ensembles of Analyses:**

- ☹ Assumes statistics of observation error (and SST, etc.) are well known.
- ☺ Diagnoses the statistics of the actual analysis system.
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Perturb observations and physics to produce an ensemble of analyses



How do we estimate background errors?

- Innovation statistics:

- ☺ The only direct method for diagnosing background error.
- ☹ Provides statistics of background error.
- ☹ Statistics of background error are noisy.
- ☹ Feedback loop.

- Error analysis:

- ☺ Statistics of observation error (and SST, etc.) are well known.
- ☺ Diagnoses the statistics of the actual analysis system.
- ☹ Danger of feedback. (Noisy analysis system => noisy stats => noisier system.)

But! It is generally the case that where accurate background errors are most important we have the least information to estimate them!!

What do background errors look like?

...or at least what do we think they look like ?

What do background errors look like?

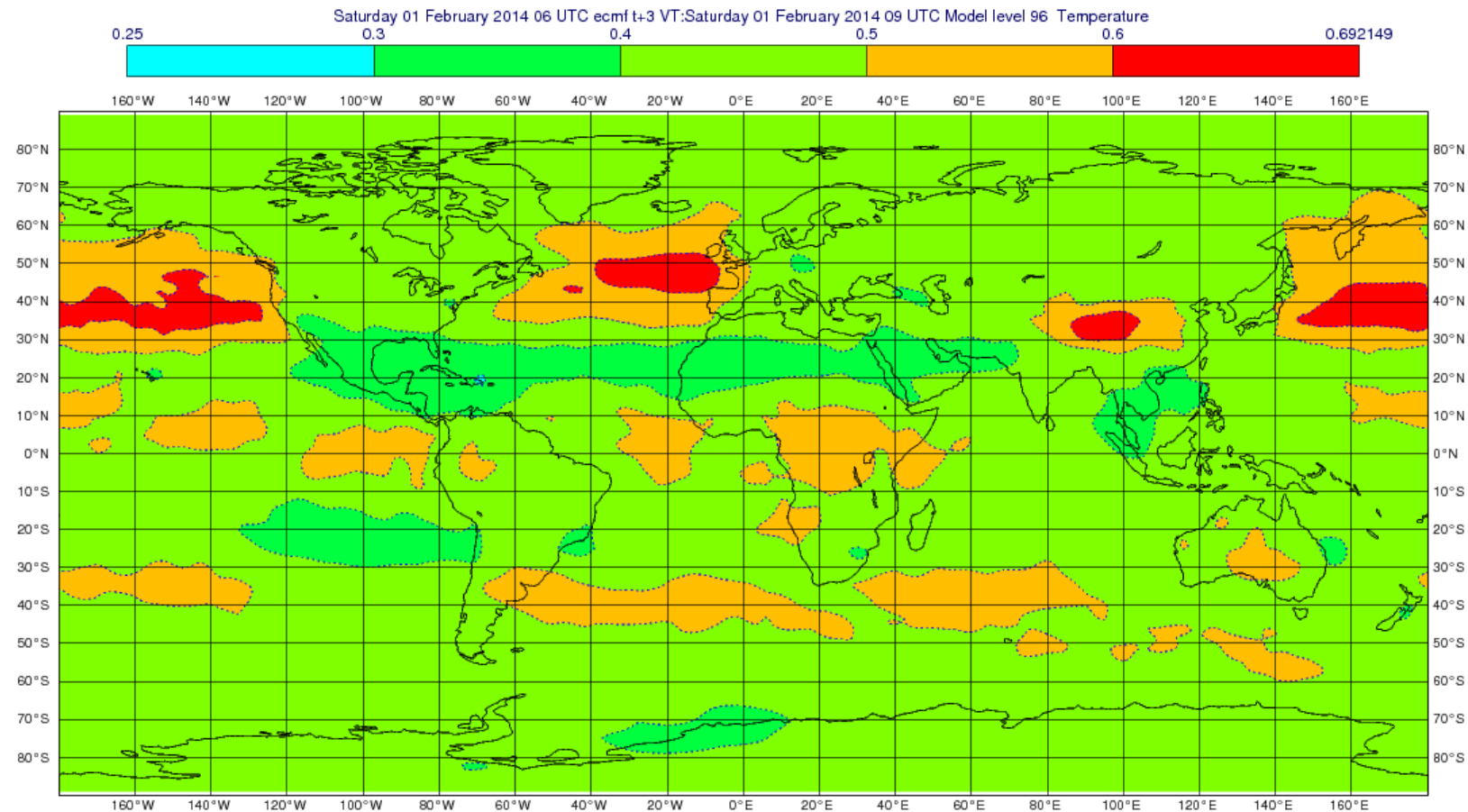
- **Error magnitude (variances)**
- **Spatial error correlations**
- **Vertical error correlations**

What do background errors look like?

- **Error magnitude (variances)**
- Spatial error correlations
- Vertical error correlations

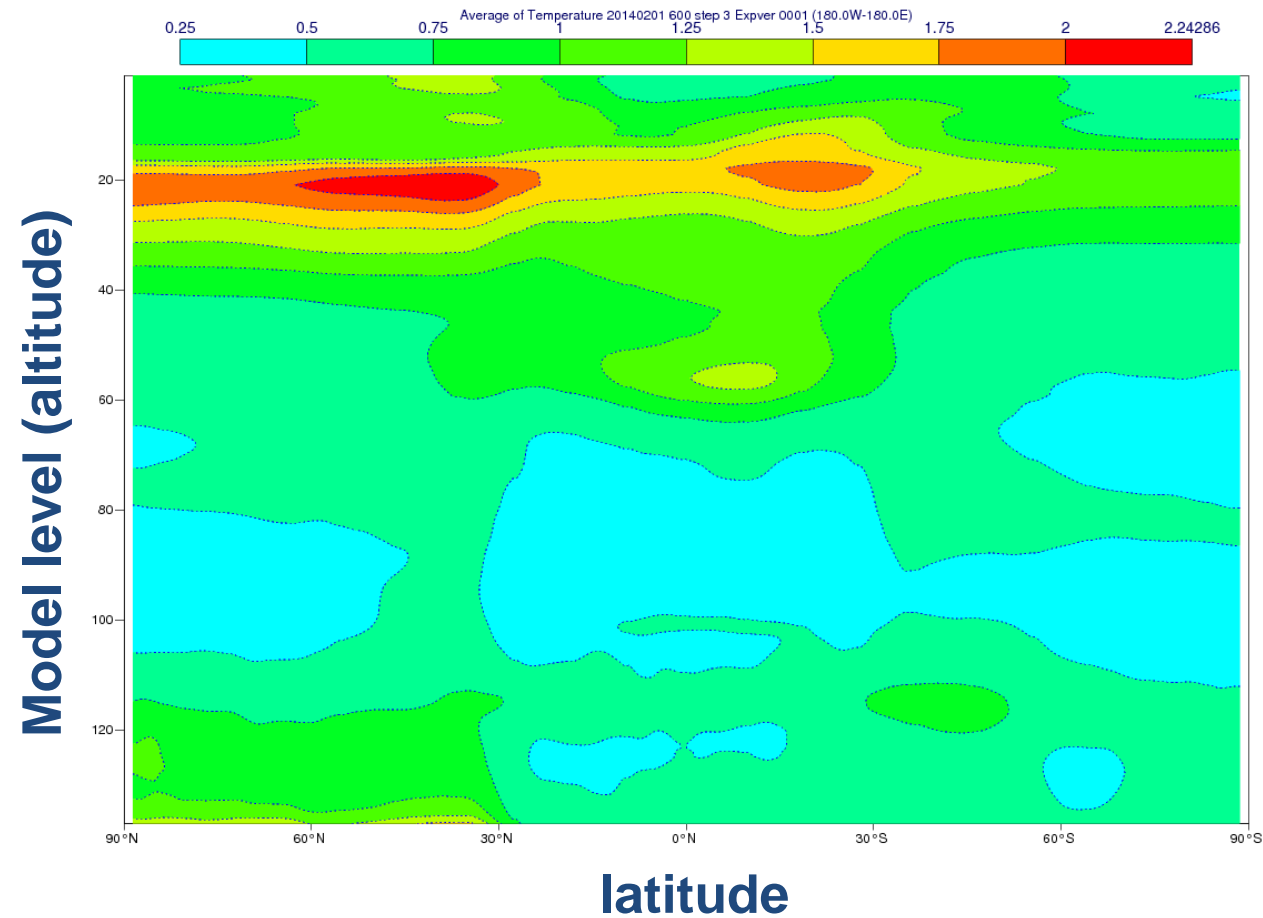
Magnitude of Background Errors

Monthly average of standard deviation of temperature error at 500hPa



Magnitude of Background Errors

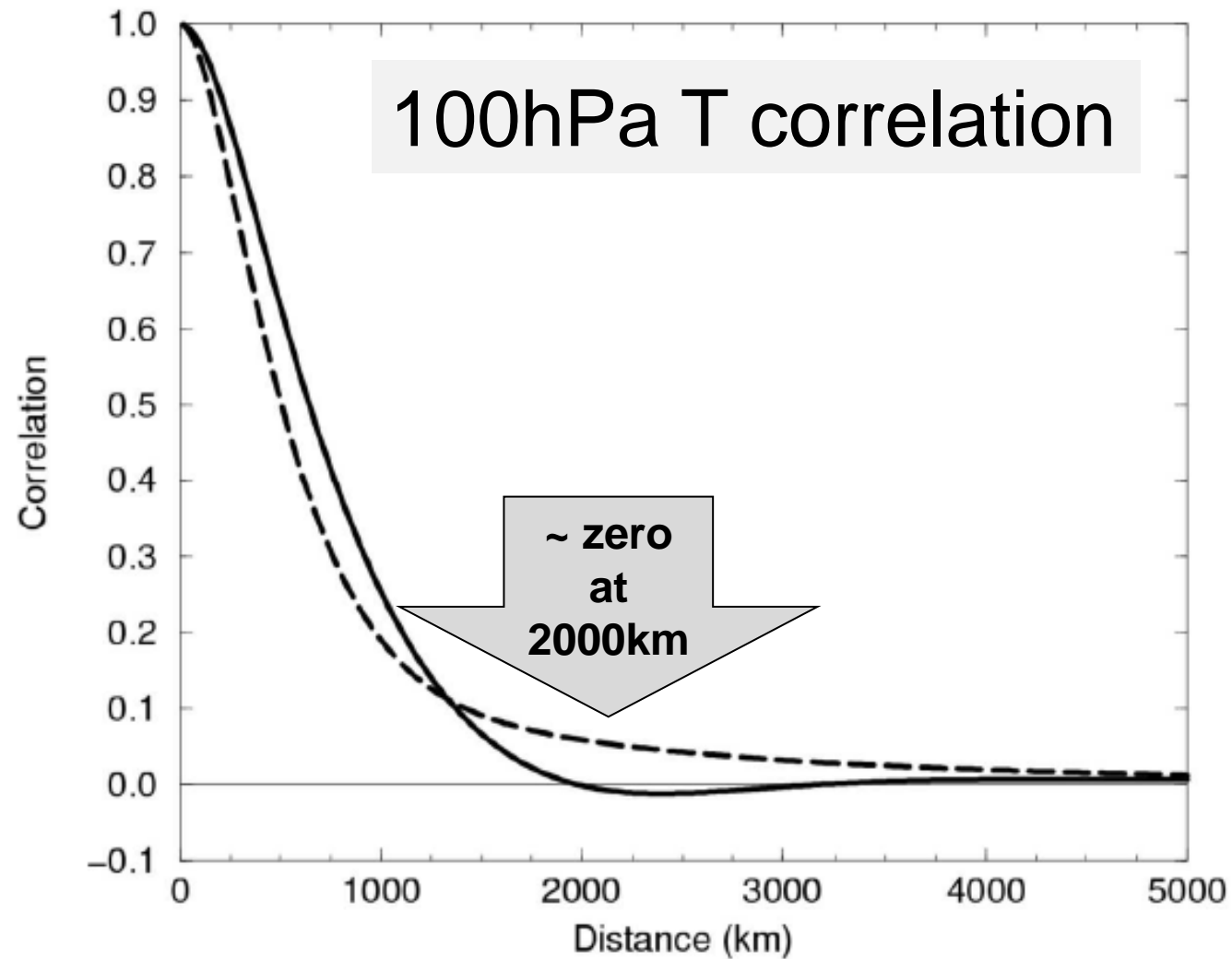
Monthly zonal average of standard deviation of temperature error at 500hPa



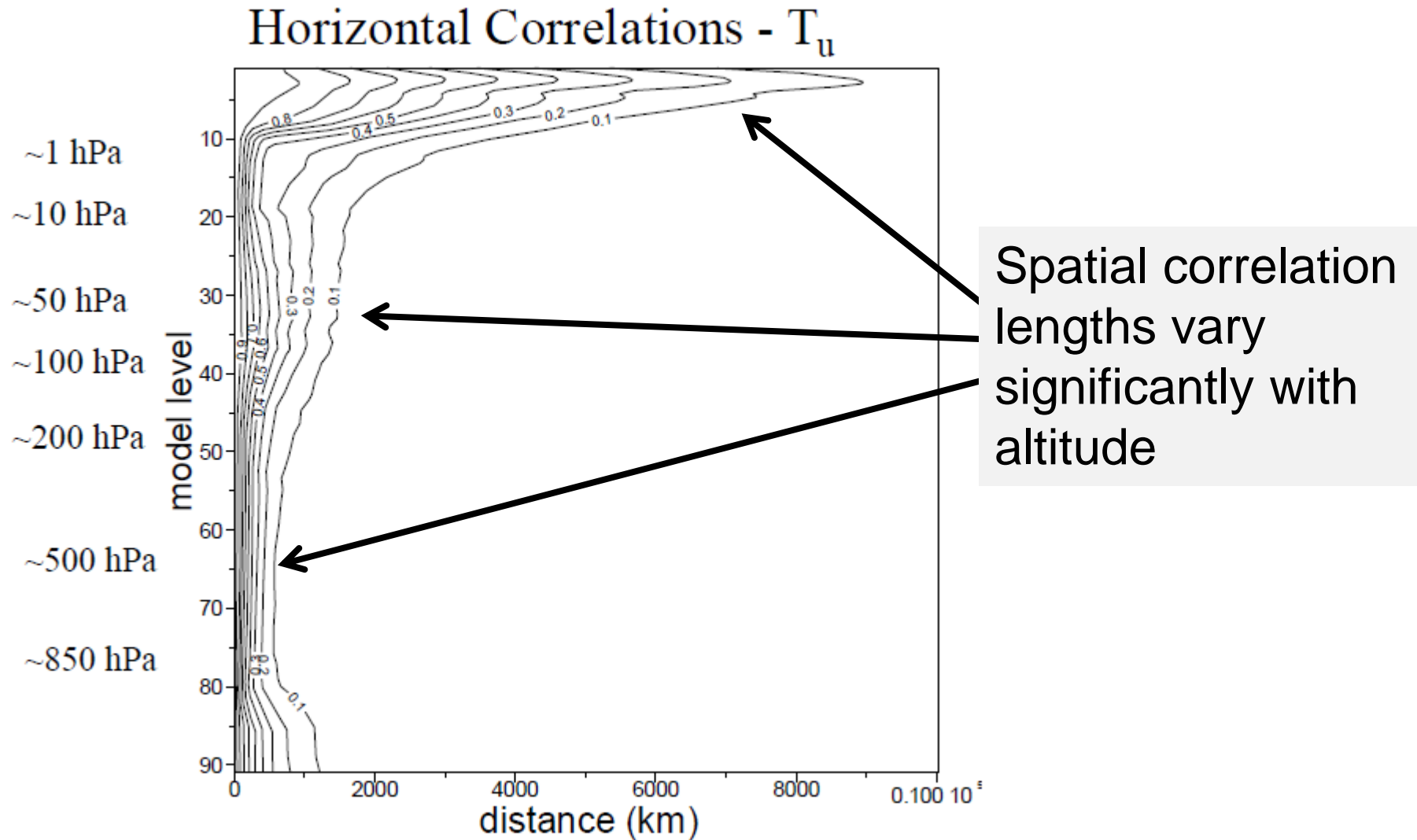
What do background errors look like?

- Error magnitude (variances)
- **Spatial error correlations**
- Vertical error correlations

Spatial Error Correlations



Spatial Error Correlations

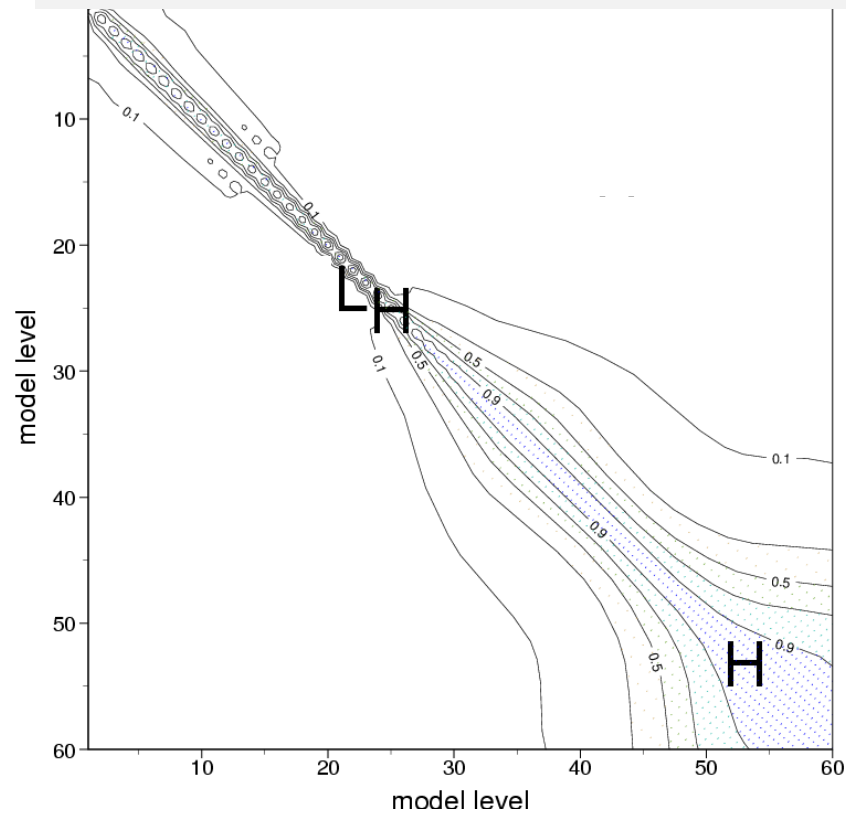


What do background errors look like?

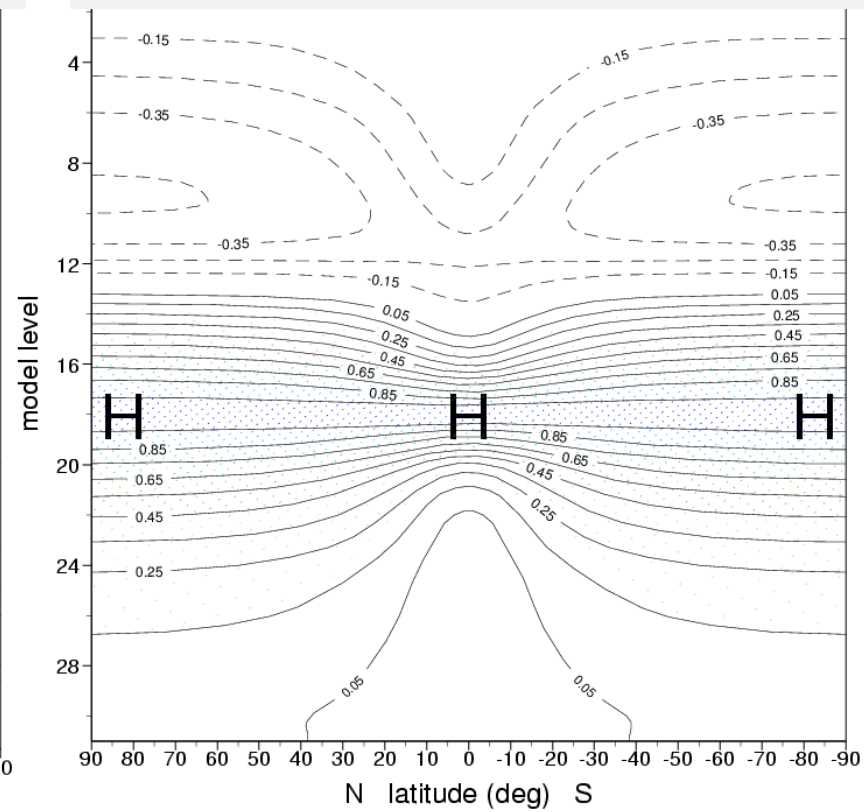
- Error magnitude (variances)
- Spatial error correlations
- **Vertical error correlations**

Vertical (inter-level) error correlations

Inter-level error vorticity correlations



Cross section of T error correlations



Background error dependencies

Background error dependencies

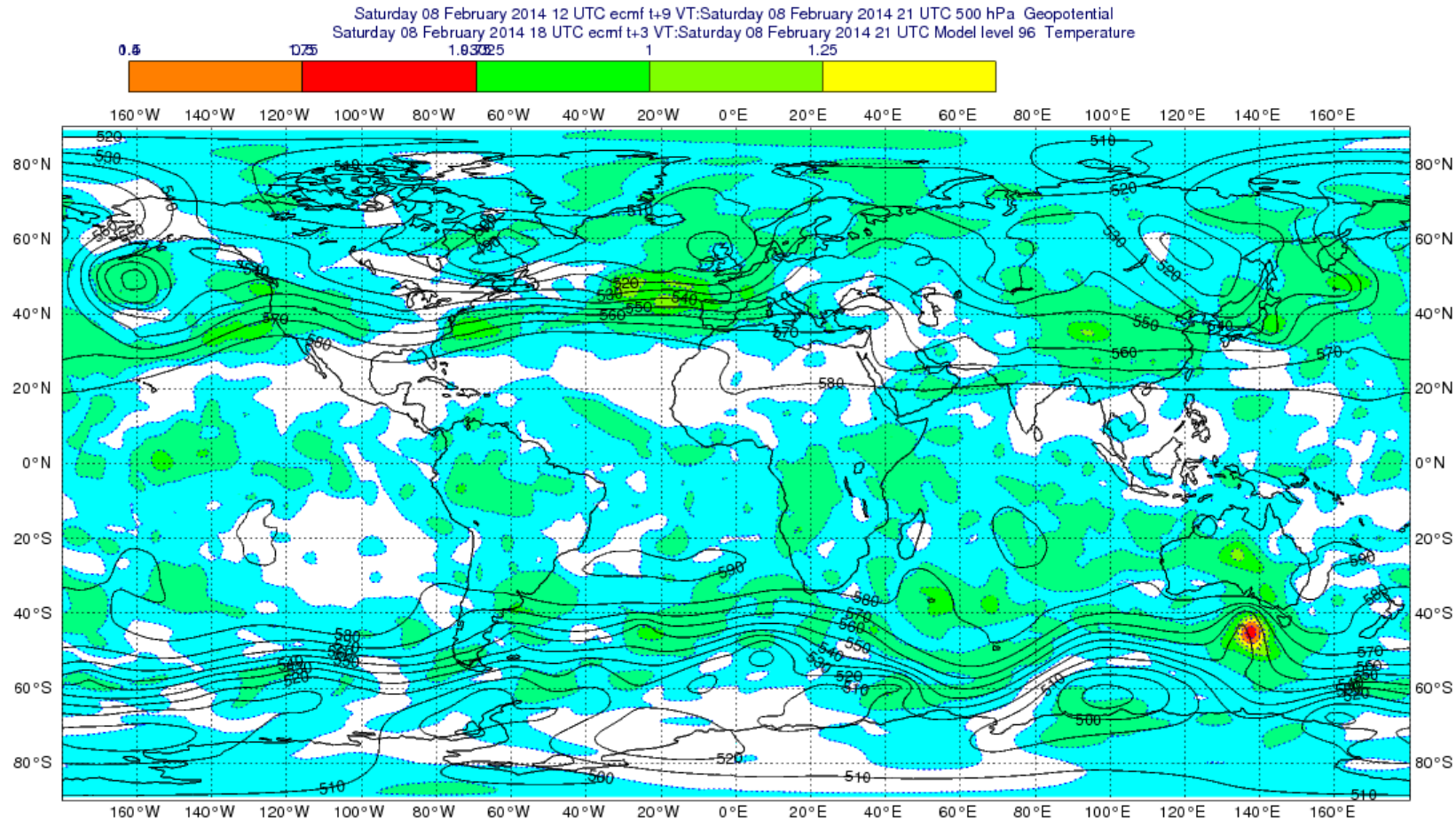
- **Flow / regime dependence**
- **Observation dependence**
- **Method dependence**

Background error dependencies

- **Flow / regime dependence**
- Observation dependence
- Method dependence

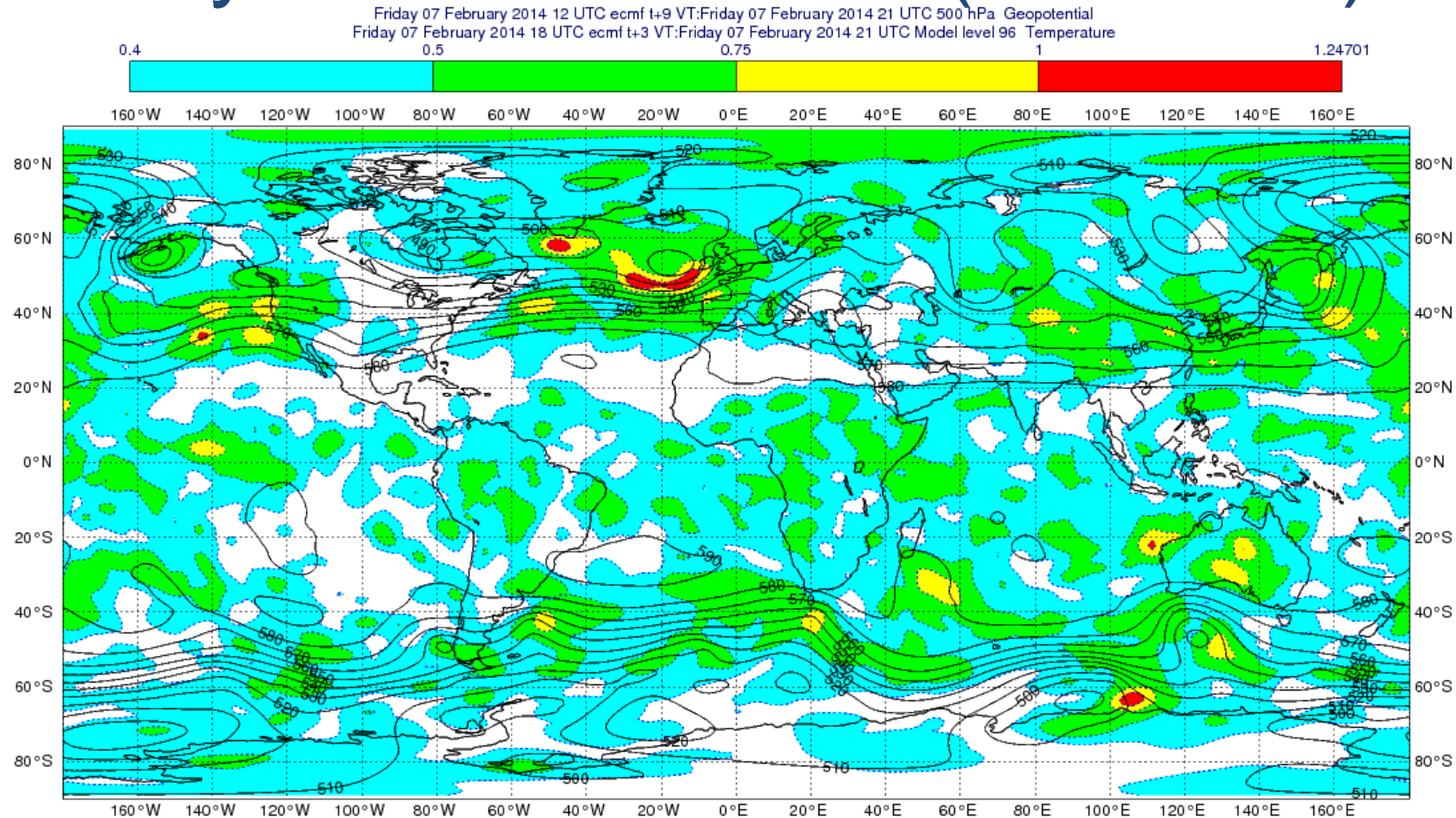
Flow / regime dependent background errors

Daily 500hPa T error (8/2/2014)



Flow / regime dependent background errors

Daily 500hPa T error (7/2/2014)

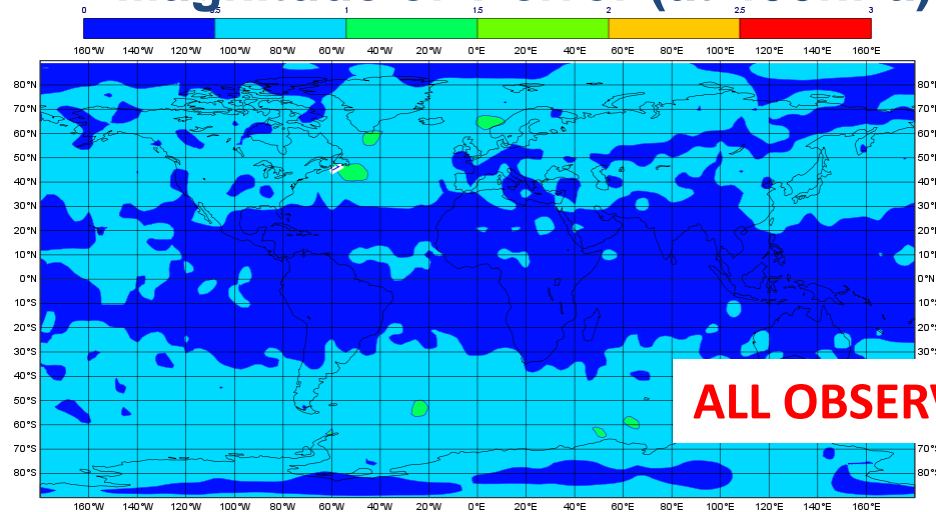


Background error dependencies

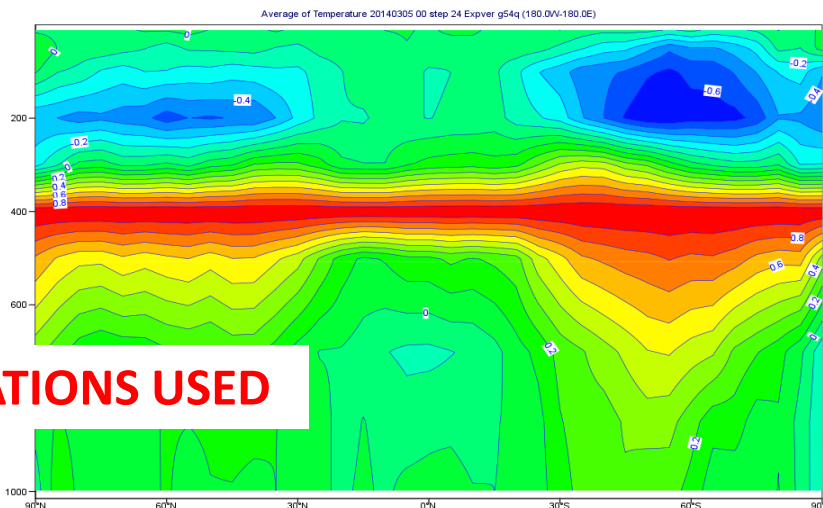
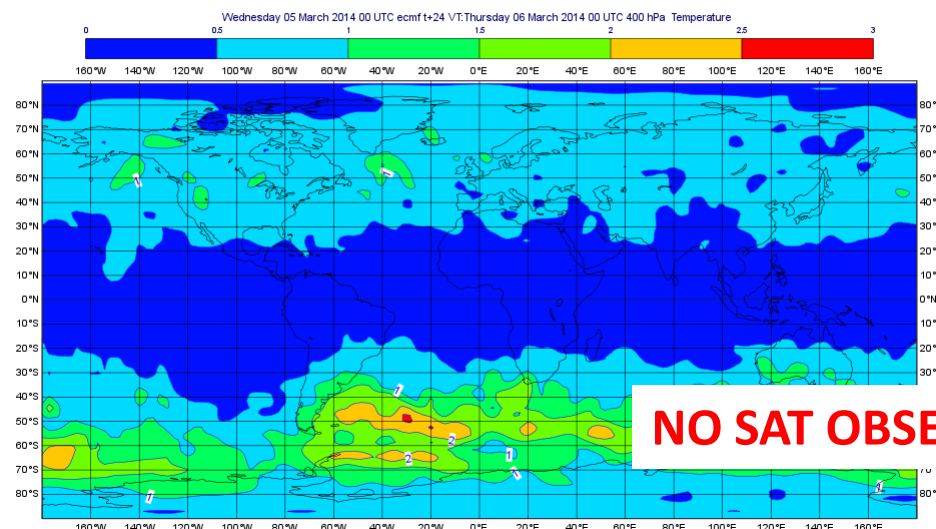
- Flow / regime dependence
- **Observation dependence**
- Method dependence

Background errors depend on which observations are assimilated in the system

Magnitude of T error (at 400hPa)



Correlation of T error (at 400hPa)

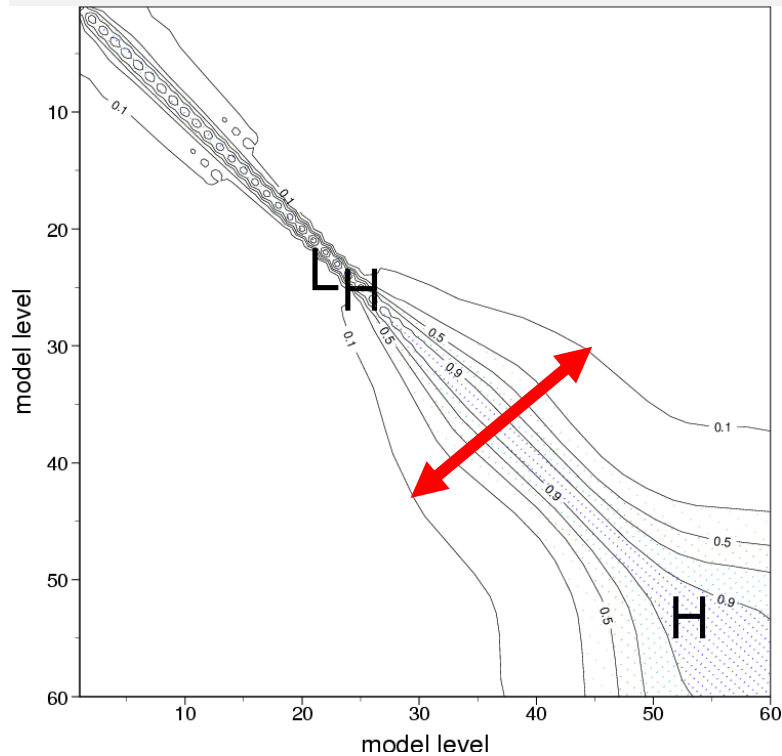


Background error dependencies

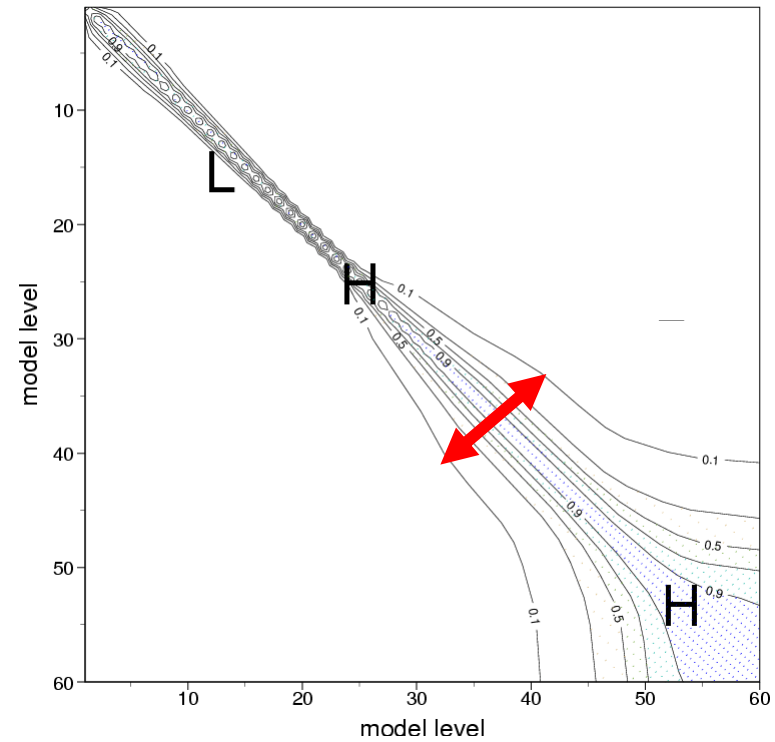
- Flow / regime dependence
- Observation dependence
- **Method dependence**

The background error estimates depends on the method you use!

Forecast Differences (NMC method)



Analysis Ensembles (EDA method)

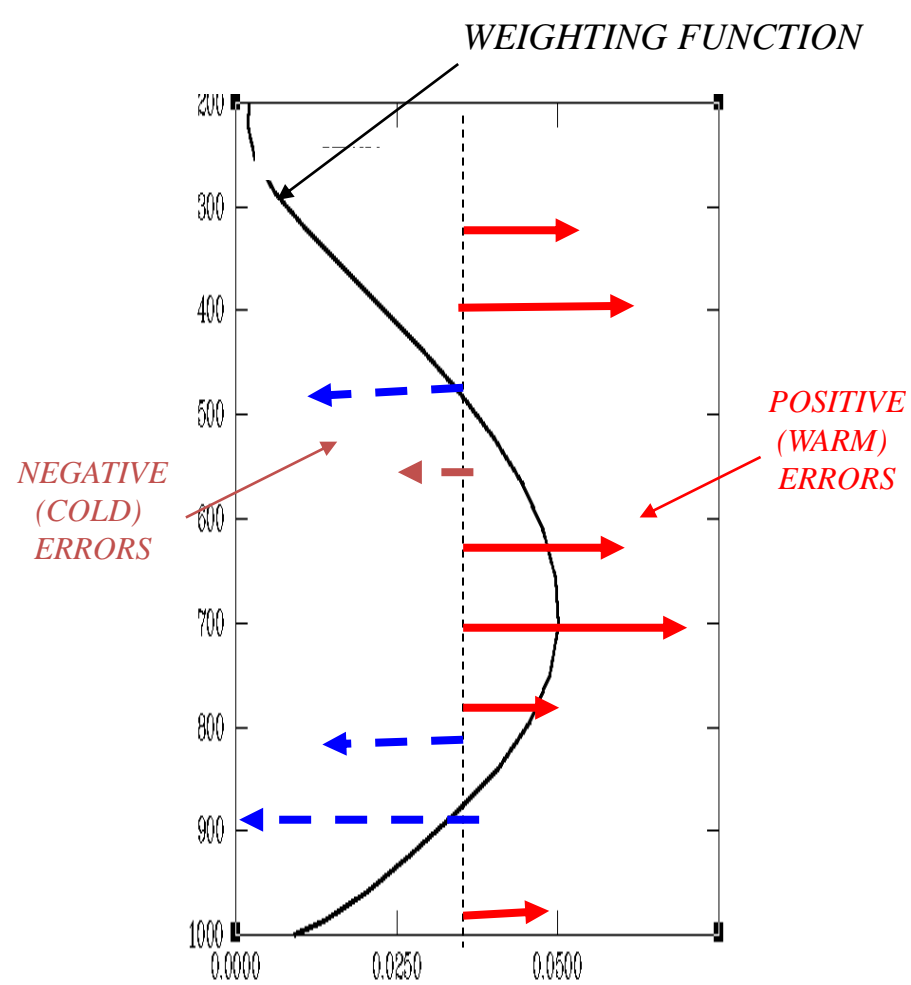


Background errors and radiance assimilation

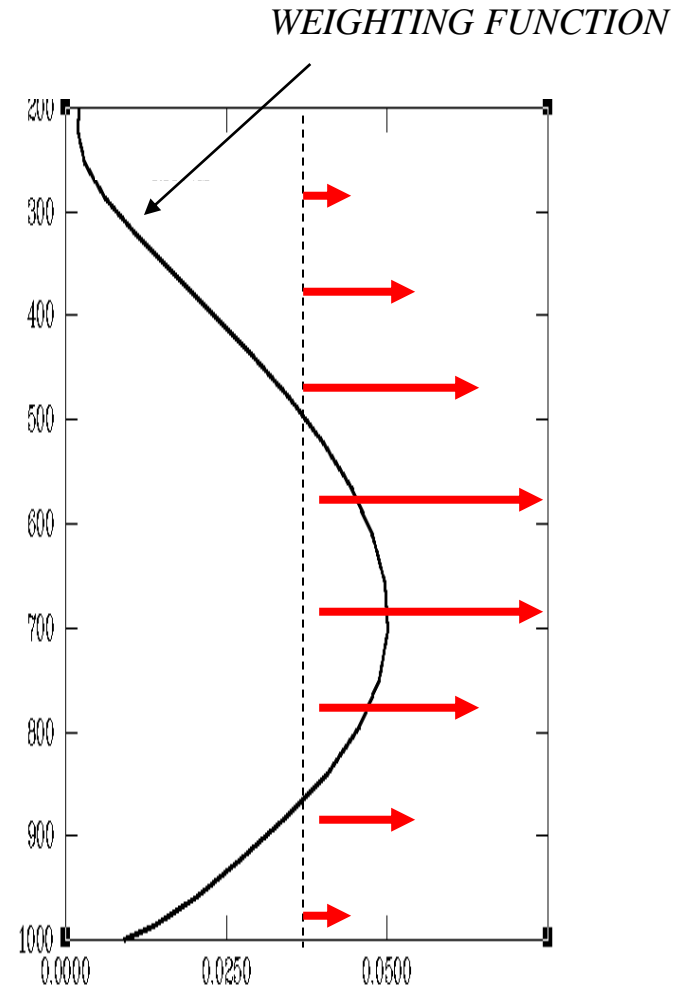
Background errors and radiance assimilation

- The physics of radiative transfer mean that radiances measured by downward looking satellite sounders have very **poor vertical resolution** (they are broad vertical averages)
- If we wish to **correct errors in the background** with radiance observations (in DA) the vertical structure of these errors is very important.
- This structure is described by the **vertical correlations in the background error covariance**

Background errors (and vertical resolution)



“Difficult” to correct



“Easy” to correct

Can we quantify the impact of vertical background error correlations on analysis accuracy ?

...a helpful linear analogue ...

model state

background error covariance

$$J(x) = (x - x_b)^T \mathbf{B}^{-1} (x - x_b) + (y - H[x])^T \mathbf{R}^{-1} (y - H[x])$$

observations

observation* error covariance

observation operator
(maps the model state to the observation space)

...when we minimise $J(x)$...

...we correct background errors

It can be shown that the state that minimizes the cost function is equivalent to a linear **correction** of the background using the observations:

$$x_a = x_b + \underbrace{[\mathbf{HB}]^T}_{\text{Kalman gain}} \underbrace{[\mathbf{HBH}^T + \mathbf{R}]^{-1}}_{\text{innovation}} (y - \mathbf{H}x_b)$$

...where the **correction** is the Kalman Gain Matrix multiplied by the innovation vector (observation minus radiances simulated from the background)

$$\text{correction term} = \underbrace{[\mathbf{HB}]^T}_{\text{Kalman gain}} \underbrace{[\mathbf{HBH}^T + \mathbf{R}]^{-1}}_{\text{innovation}} (y - \mathbf{H}x_b)$$

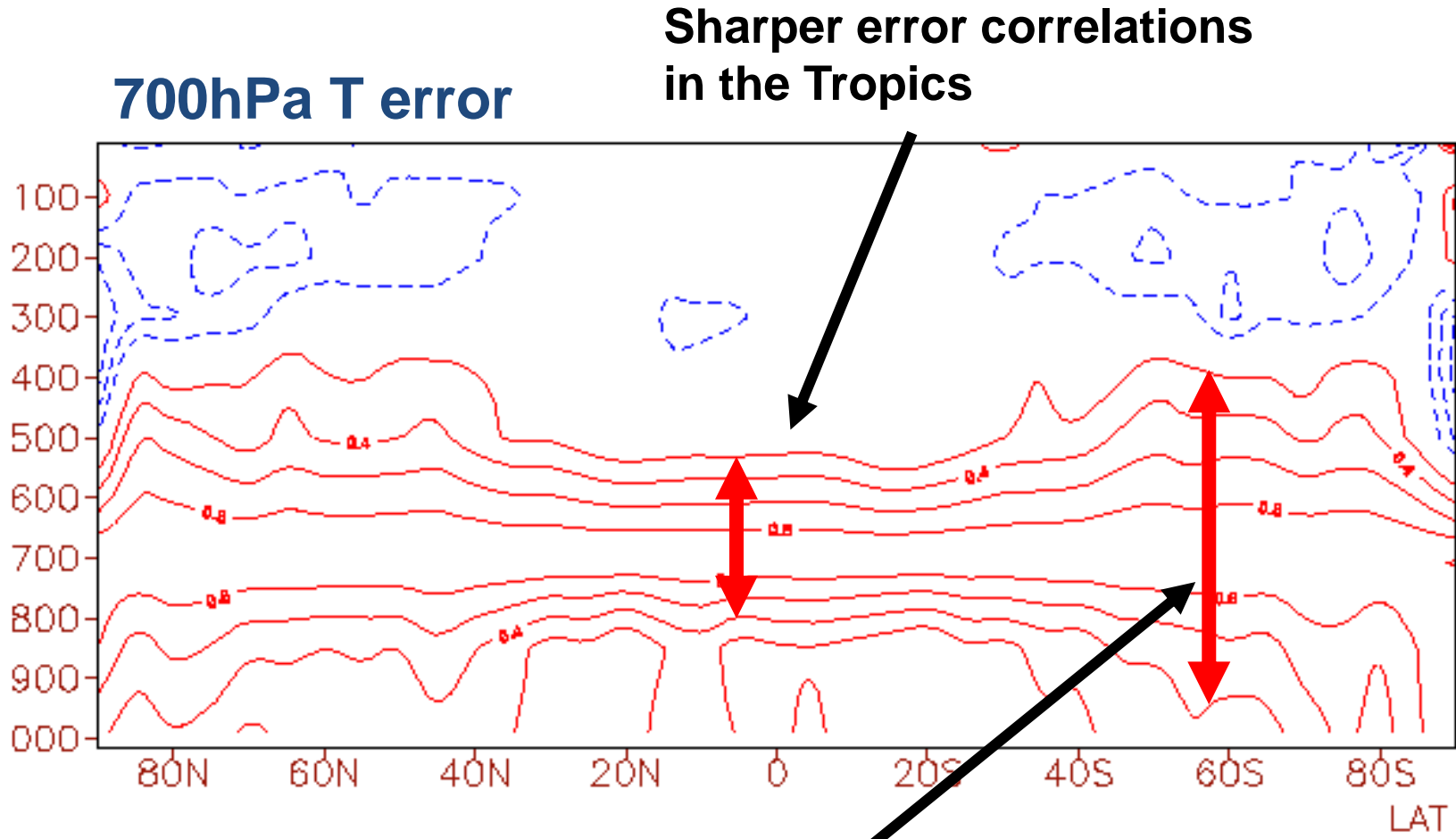
...and reduce the error ...

Furthermore when we apply this **correction** we produce a state (the analysis) that is more accurate than the background. We can compute the improvement as an **error reduction** of the analysis error (**A**) compared to the error in the background (**B**) ...

$$\mathbf{A} = \mathbf{B} - \frac{[\mathbf{HB}]^T [\mathbf{HBH}^T + \mathbf{R}]^{-1} \mathbf{HB}}{\text{error reduction}}$$

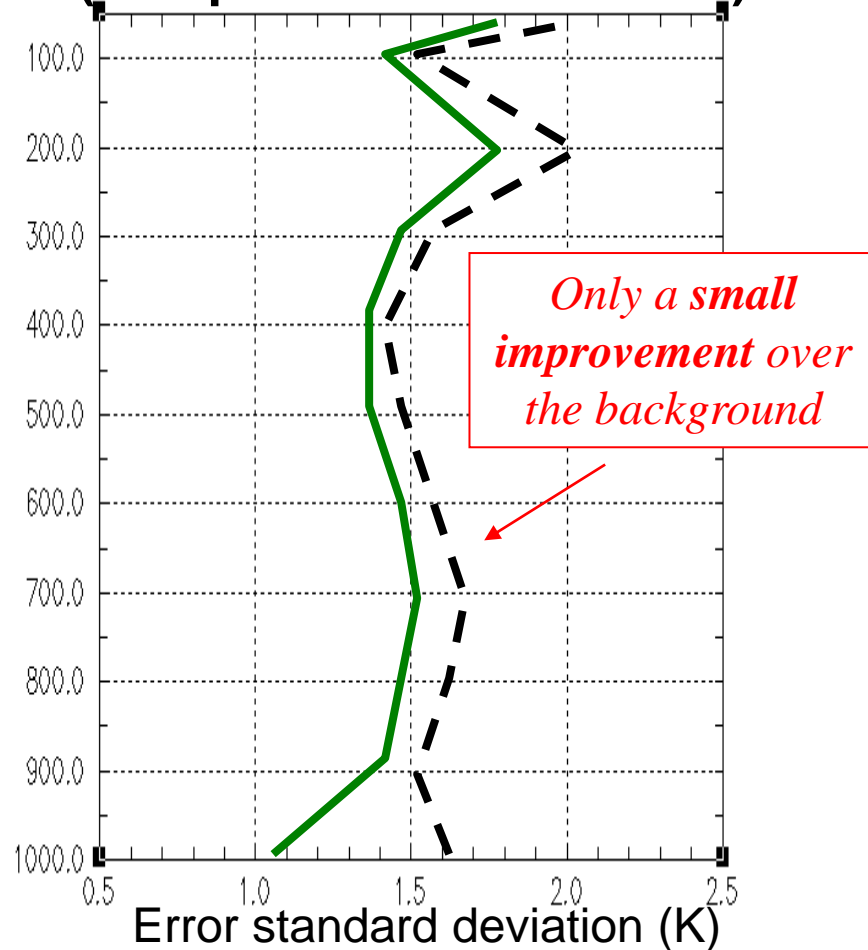
So we can look at how **A** performs for two different types of vertical correlation present in **B** (for example using **8461 IASI channels** correct background errors in the analysis)

Sharp and broad vertical correlation

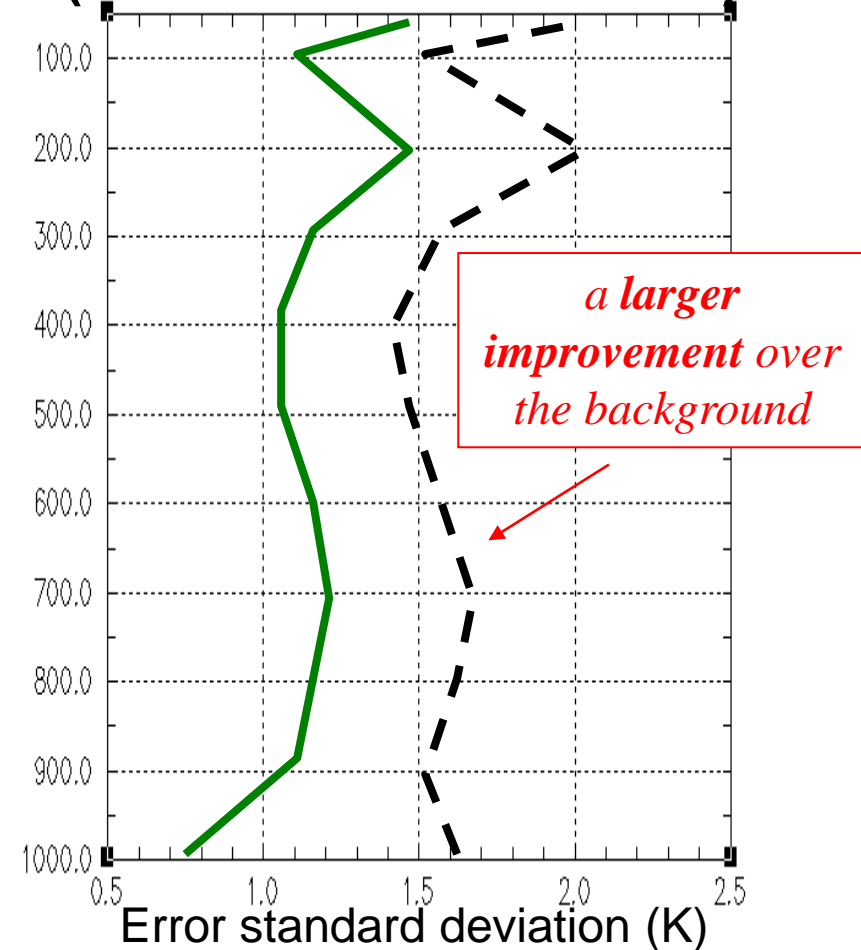


Sharp and broad vertical correlation

**Tropical background errors
(sharp vertical correlation)**



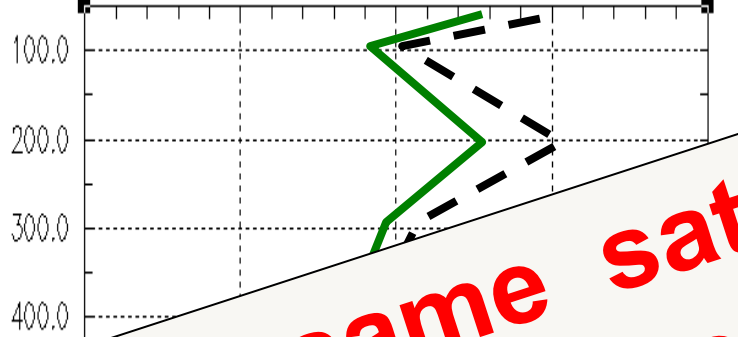
**Mid-Lat background errors
(broad vertical correlation)**



background error ---- Analysis error —

Sharp and broad vertical correlation

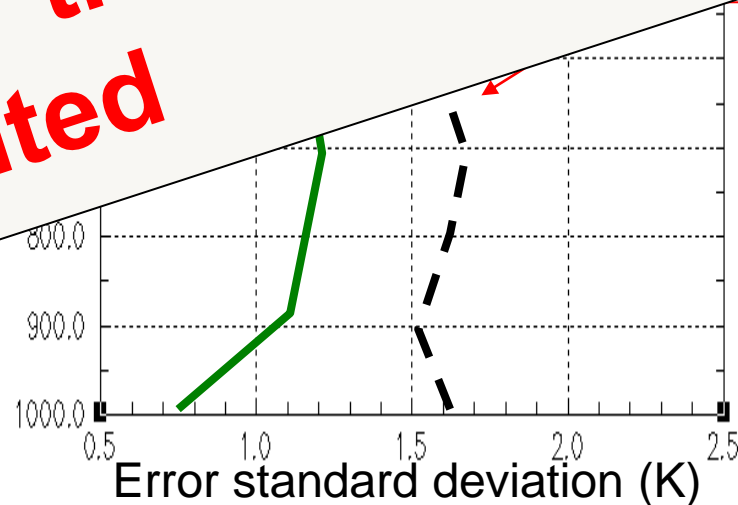
Tropical background errors
(sharp vertical correlation)



Mid-Lat background
(broad vertical correlation)



So the same satellite can have a big impact or small impact depending on how the background errors are distributed



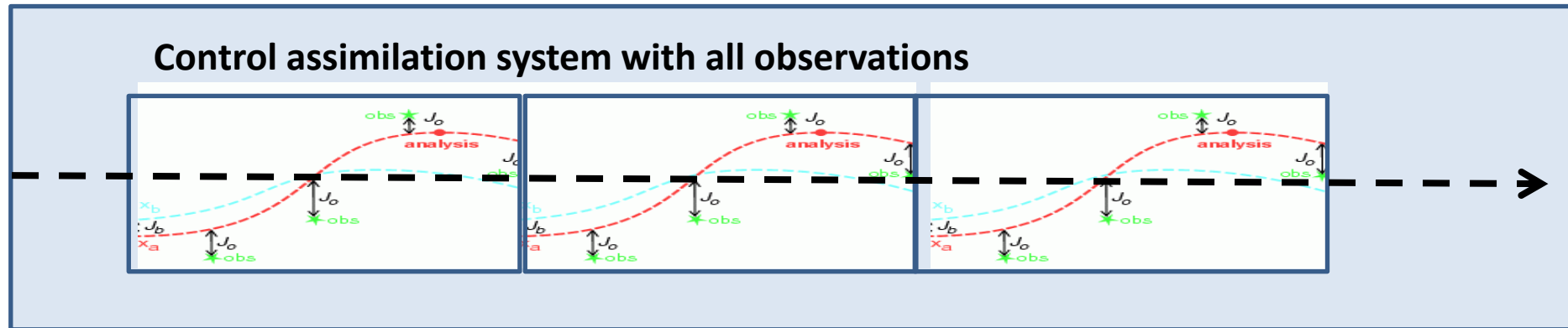
background error ---- Analysis error —

Background error specification in Observing System Experiments (OSE)

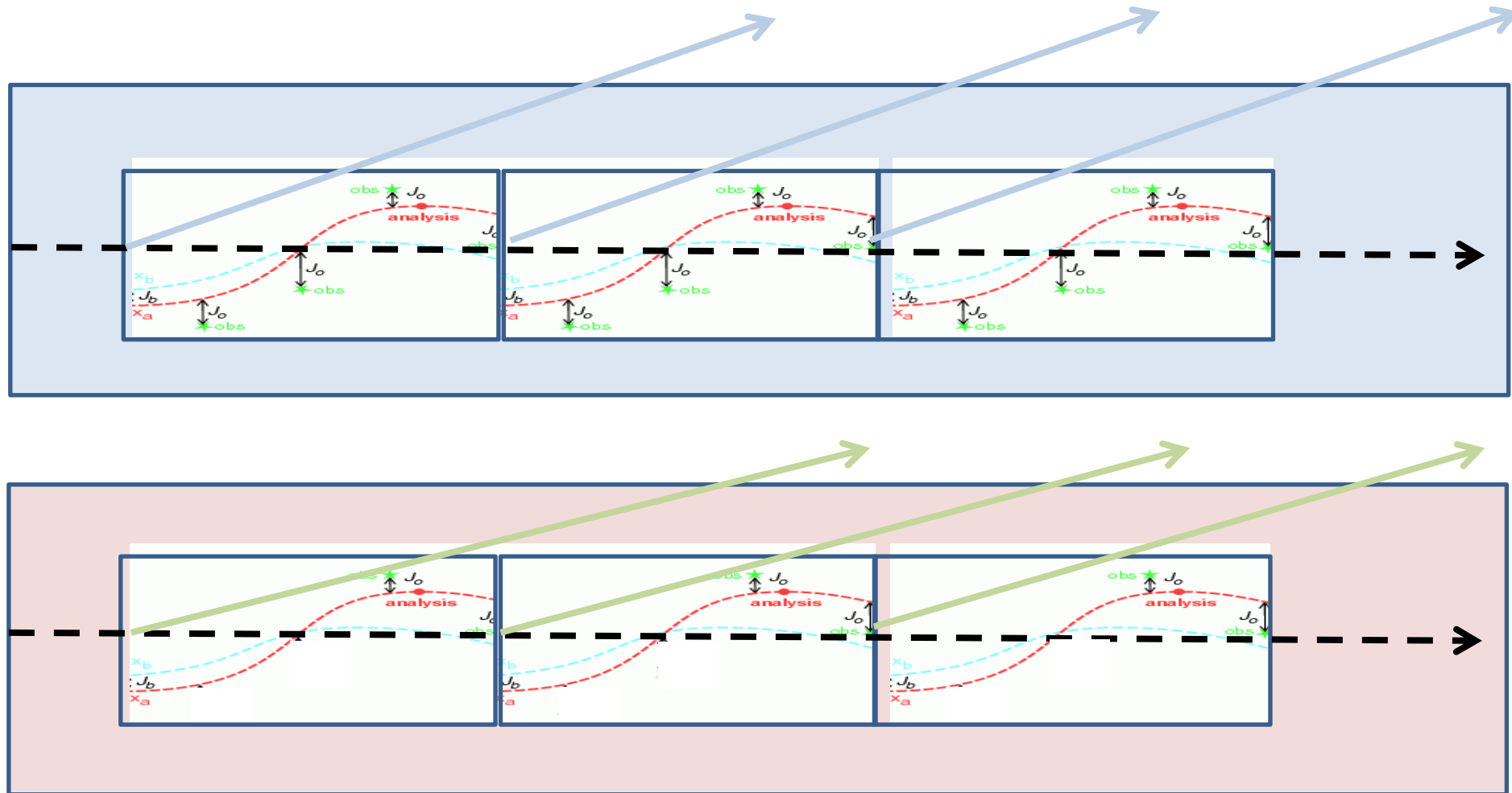
For example.....

**Evaluating the impact of Satellite
Observations with denial experiments**

Control assimilation



We run forecasts from each assimilation



Impact of removing satellite observations

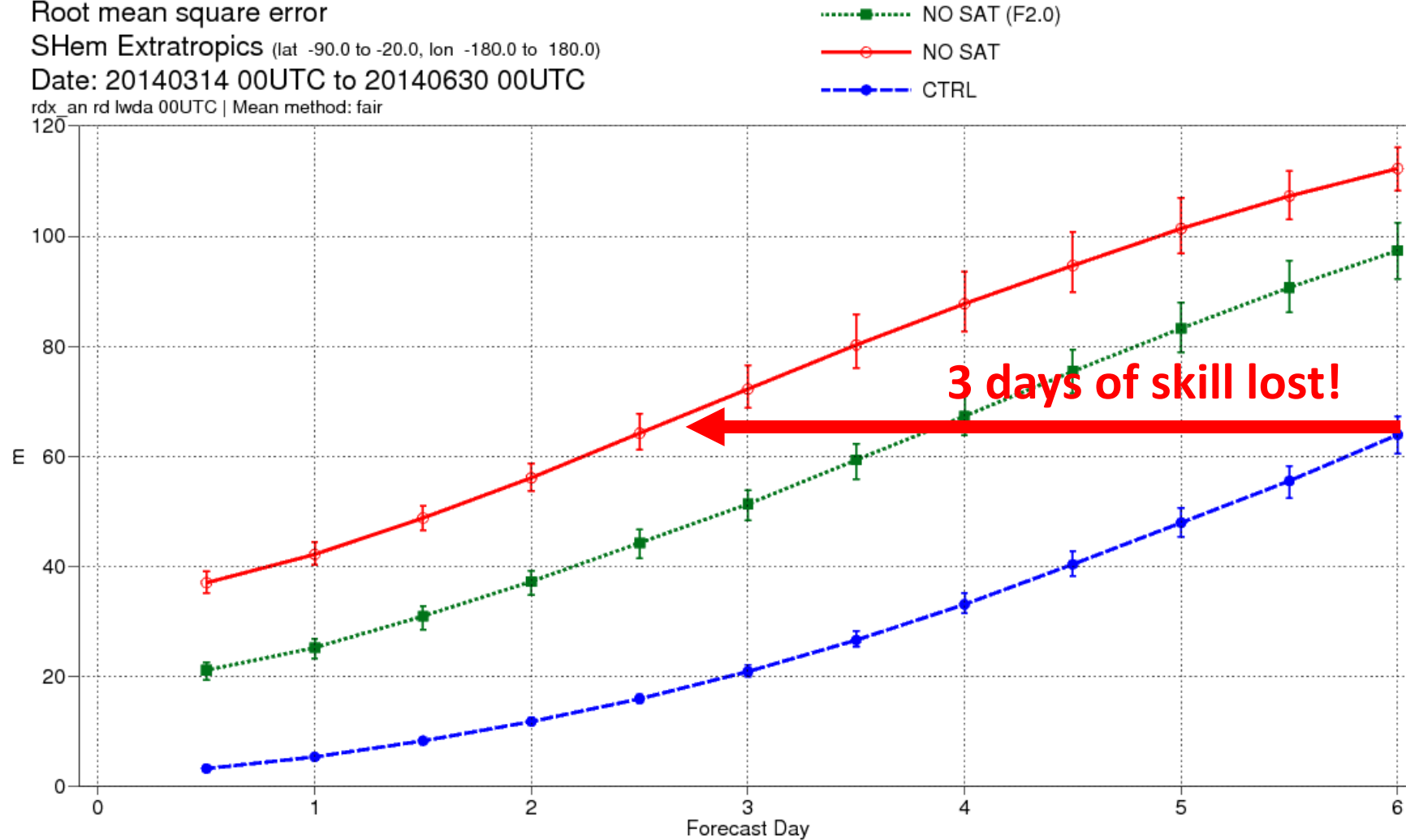
500hPa geopotential

Root mean square error

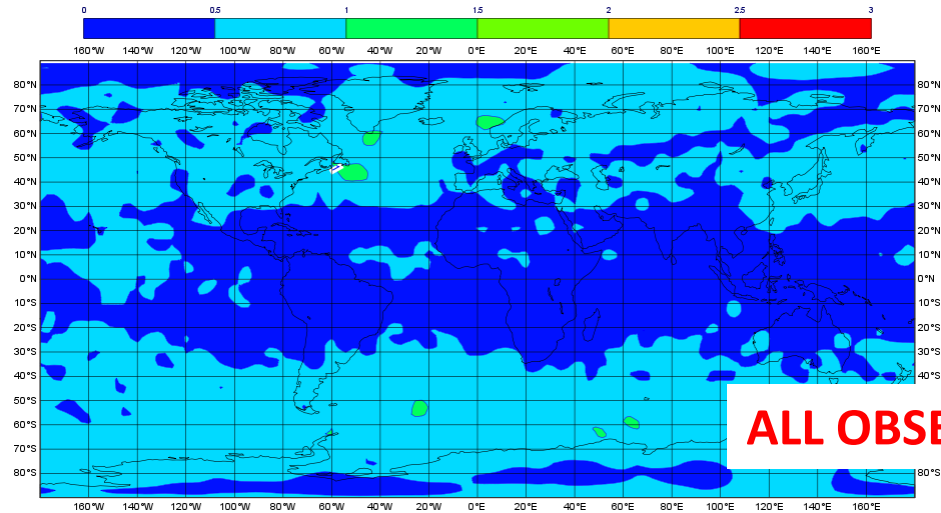
SHEM Extratropics (lat -90.0 to -20.0, lon -180.0 to 180.0)

Date: 20140314 00UTC to 20140630 00UTC

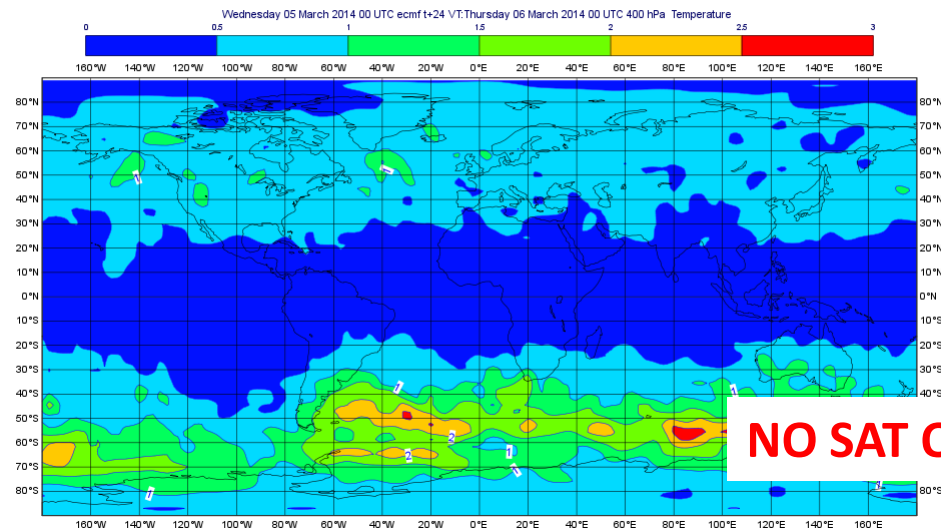
rdx_an rd lwd a 00UTC | Mean method: fair



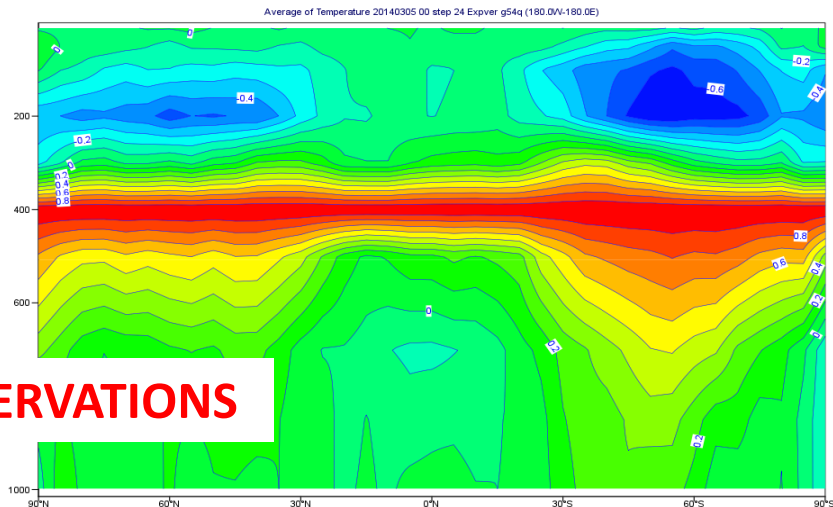
But we should retune the background errors!



ALL OBSERVATIONS



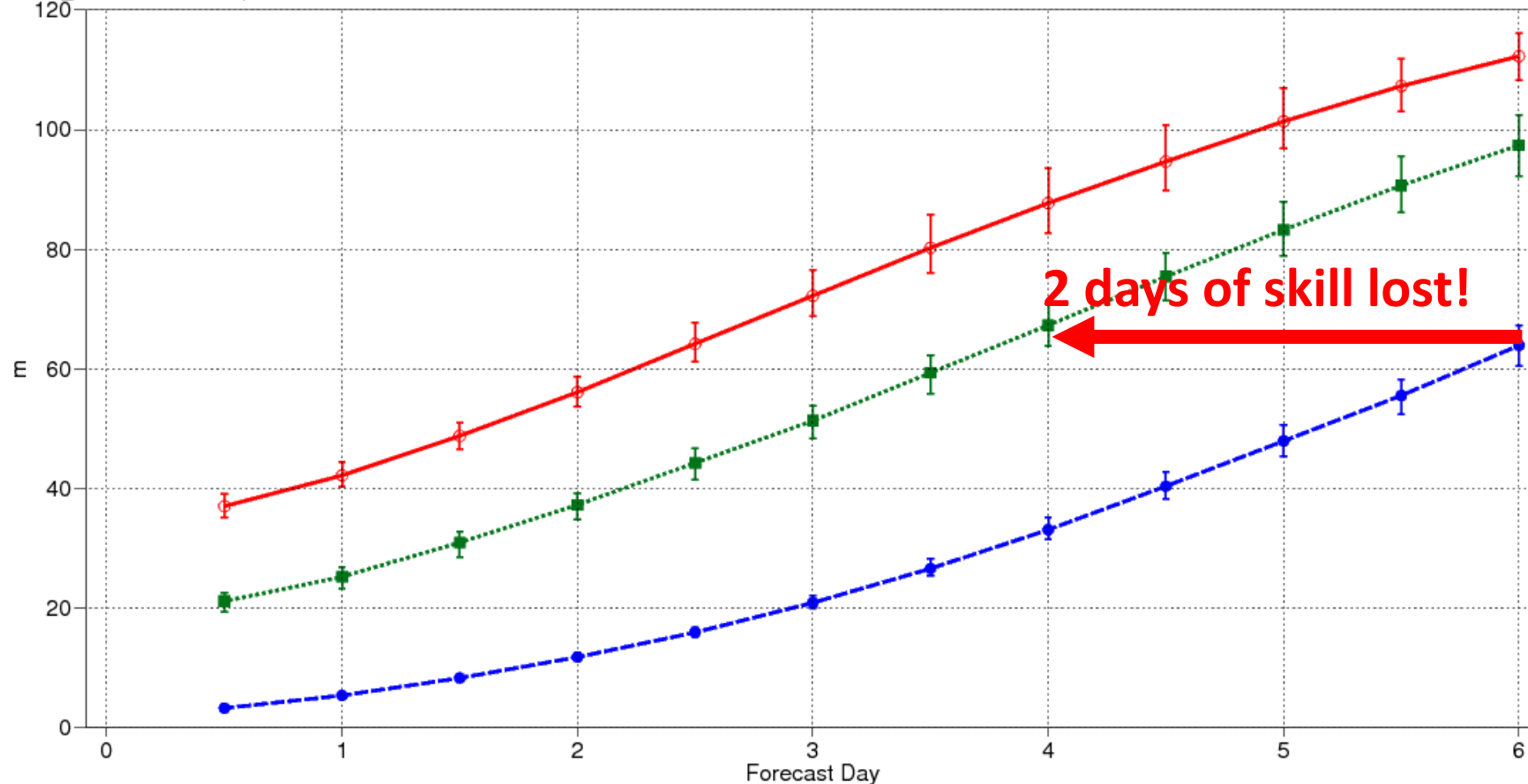
NO SAT OBSERVATIONS



Satellite Impact with retuned (larger) background errors

500hPa geopotential
Root mean square error
SHEM Extratropics (lat -90.0 to -20.0, lon -180.0 to 180.0)
Date: 20140314 00UTC to 20140630 00UTC
rdx_an rd lwda 00UTC | Mean method: fair

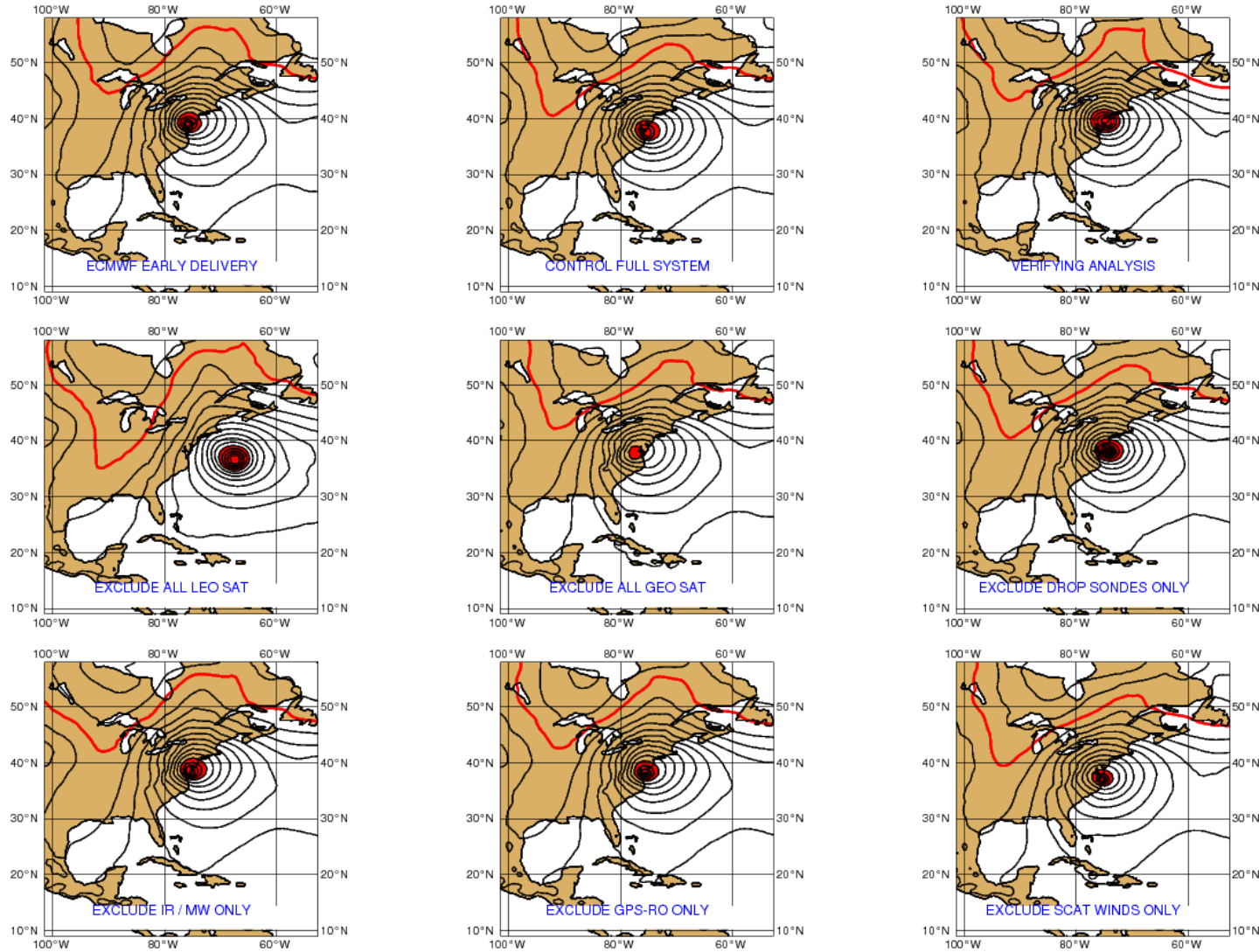
- NO SAT (F2.0)
- NO SAT
- CTRL



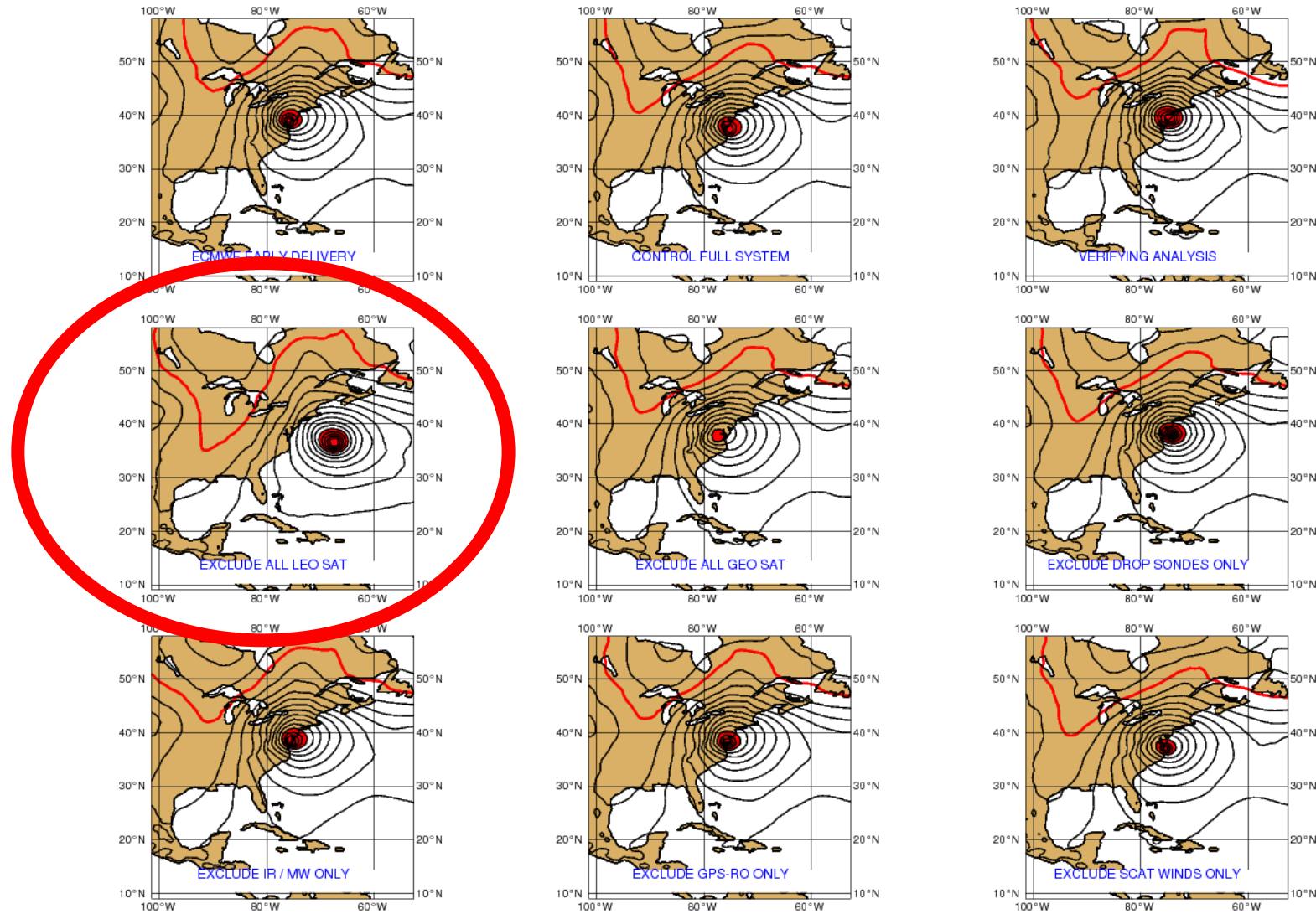


Hurricane Sandy

Data denial experiments

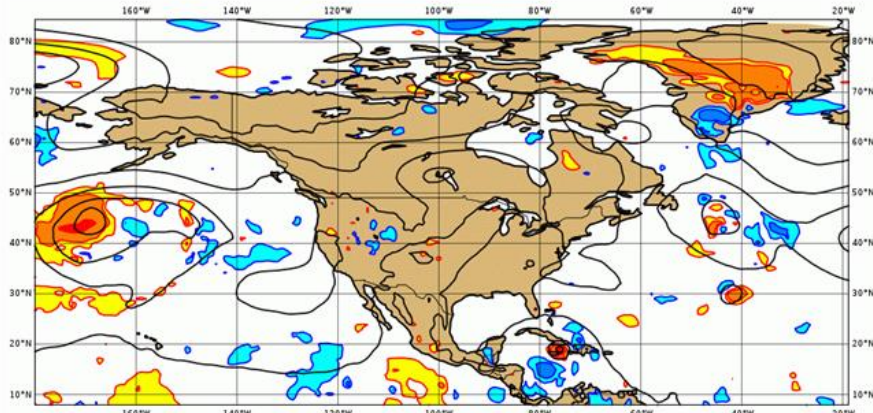
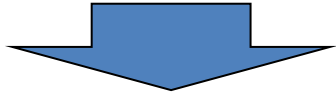


Data denial experiments

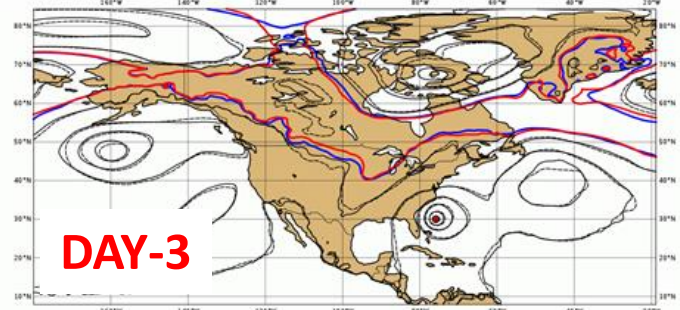
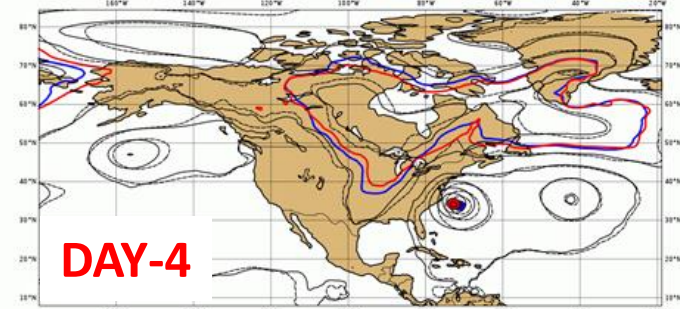
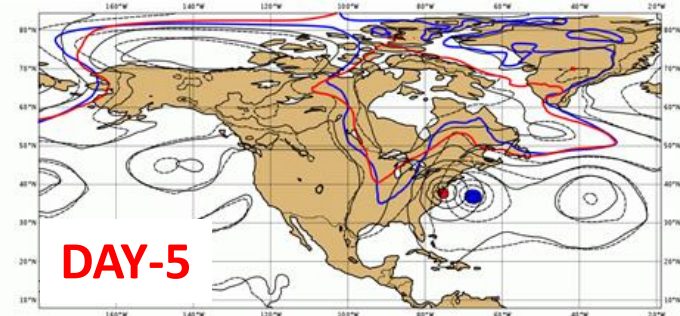
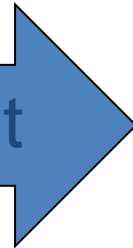


Data denial experiments (no LEO satellites)

Changes to the analysis
(2012-10-25) when all LEO
satellite observations are
removed



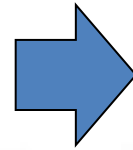
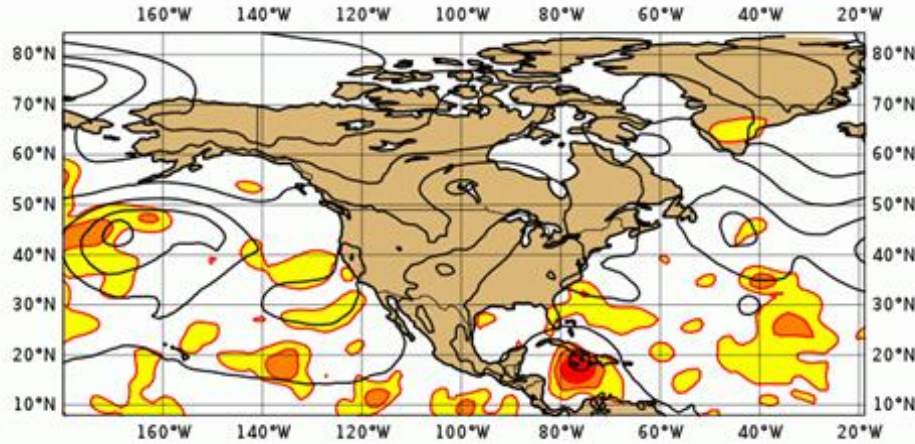
Changed the forecast



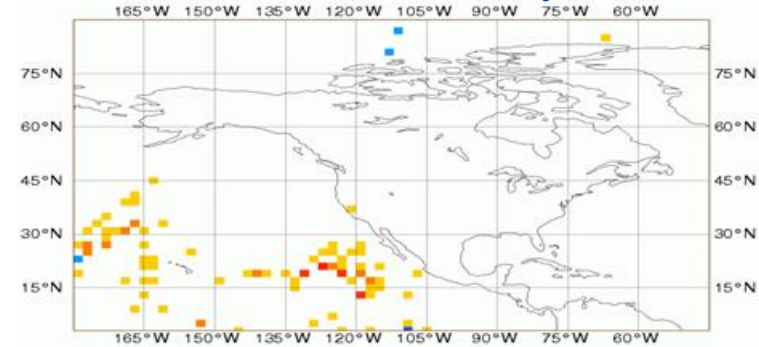
Re-calibrate (inflate) background errors

(to account for the LEO data being removed)

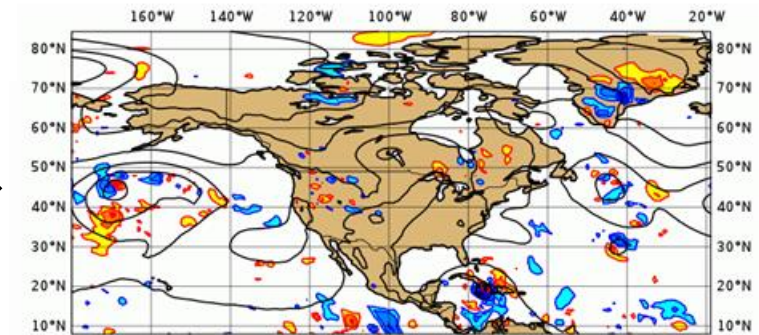
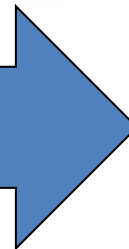
Inflated background errors



More weight to other OBS kept in the assimilation system

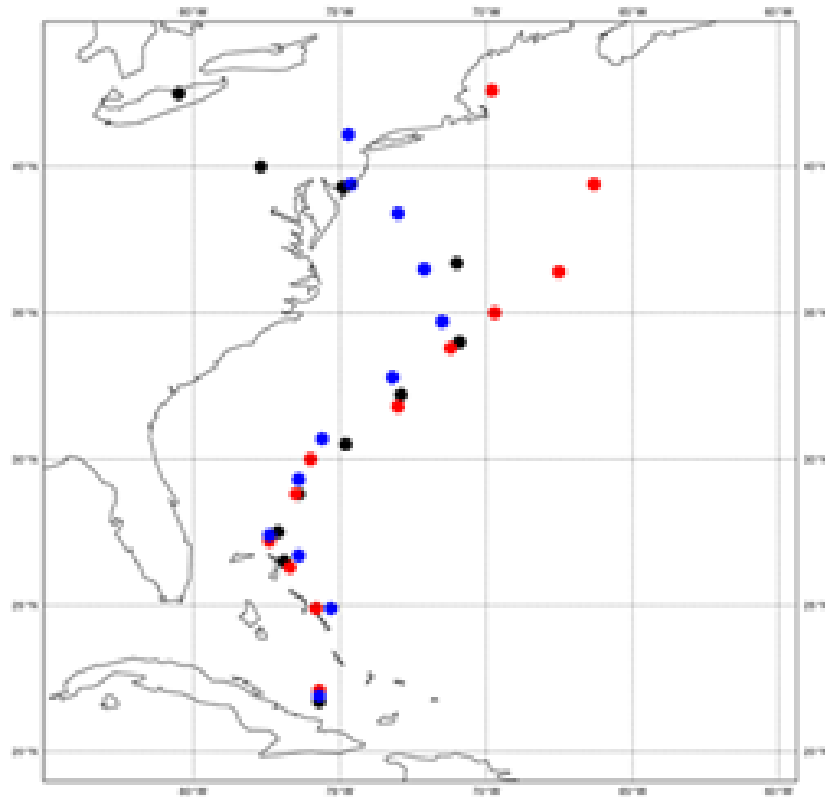


Changes to the analysis

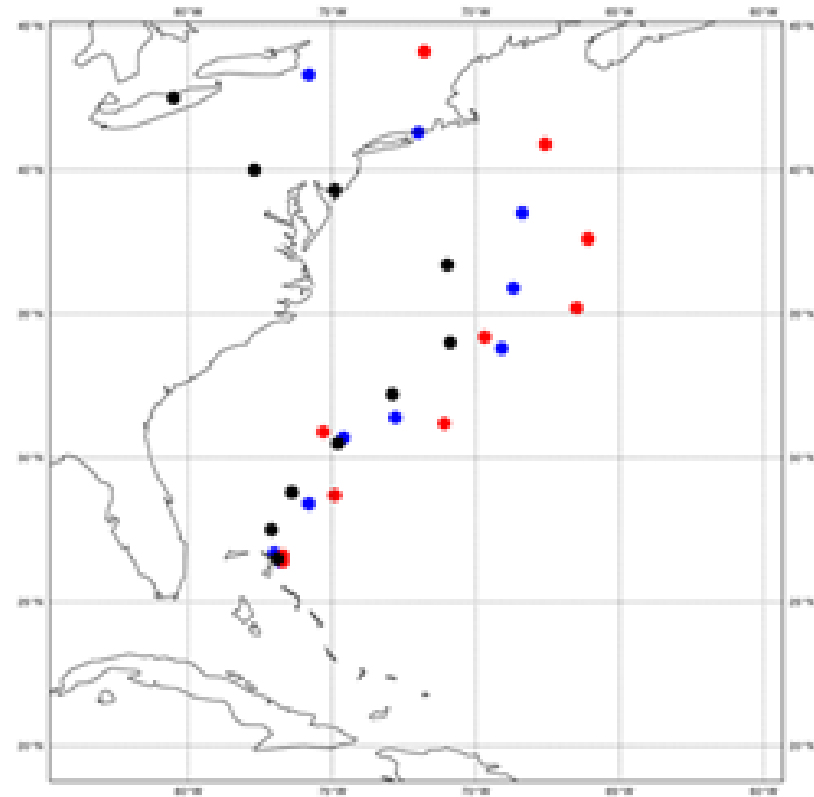


Re-calibrated background errors change the hurricane forecast!

Day 5 from 2012-10-25



Day 4 from 2012-10-26



Summary

- **Background errors are a crucial element of any data assimilation system and particularly important for radiance observations (due to their poor vertical resolution)**
- **Background errors are flow-dependent, but also depend on the observations in the system and even the method used to evaluate them!**
- **The impact of satellite observations depends on the characteristics of the background errors we are attempting to correct with the data**
- **Great care must be taken in evaluating satellite impact with observing system experiments**

Questions ?

You may want to impose additional constraints

