



Diagnosics for Evaluating the Impact of Satellite Observations

Nancy L. Baker

Rolf Langland

Naval Research Laboratory

Monterey, CA USA

ECMWF Seminar on Recent Developments in the Use of Satellite Observations in Numerical Weather Prediction
3-7 September 2007; ECMWF; Reading UK



Adjoint-based Techniques for Evaluating Satellite Impact

- Motivation
- Data assimilation adjoint theory
- Exploration of observation adjoint sensitivity using idealized cases
- Assessing observation impact
 - Defining the cost function
 - Defining the observation impact function
- Applications
 - Channel selection
 - Justifying the continuation of observing stations
 - Identifying systematic observation errors
 - Identifying shortcomings with the data usage
- Future work



Motivation

- How can we improve our forecast skill?
- Short to medium-range forecast errors are mainly due to errors in the initial conditions
 - How can we improve the quality of the analysis in these regions?
- Original motivation was adaptive or targeted observations for FASTEX
 - How to identify and sample/observe regions where additional observations are most likely to have large positive impact on the forecast
 - Expectation is that the additional observations in the sensitive regions will decrease the analysis error and improve the forecast
- Improve the use of existing observations
 - Assimilate additional observations
 - Correct deficiencies in the observation pre-processing or data assimilation system



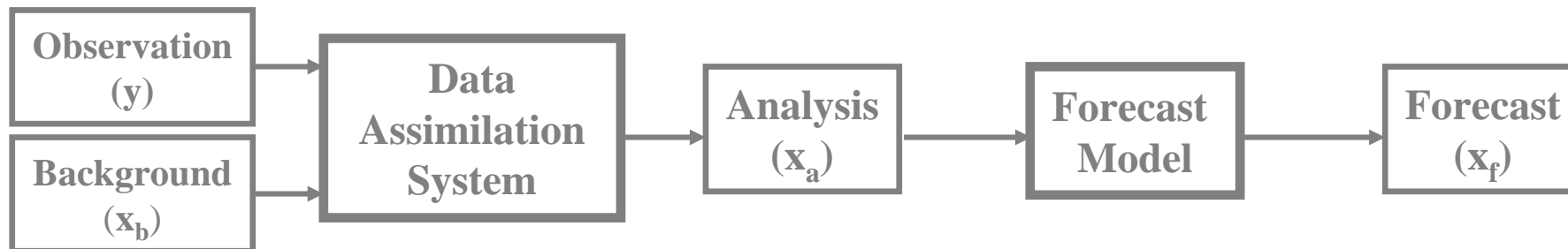
Classical Adjoint-based Targeting Methods

FASTEX 1997

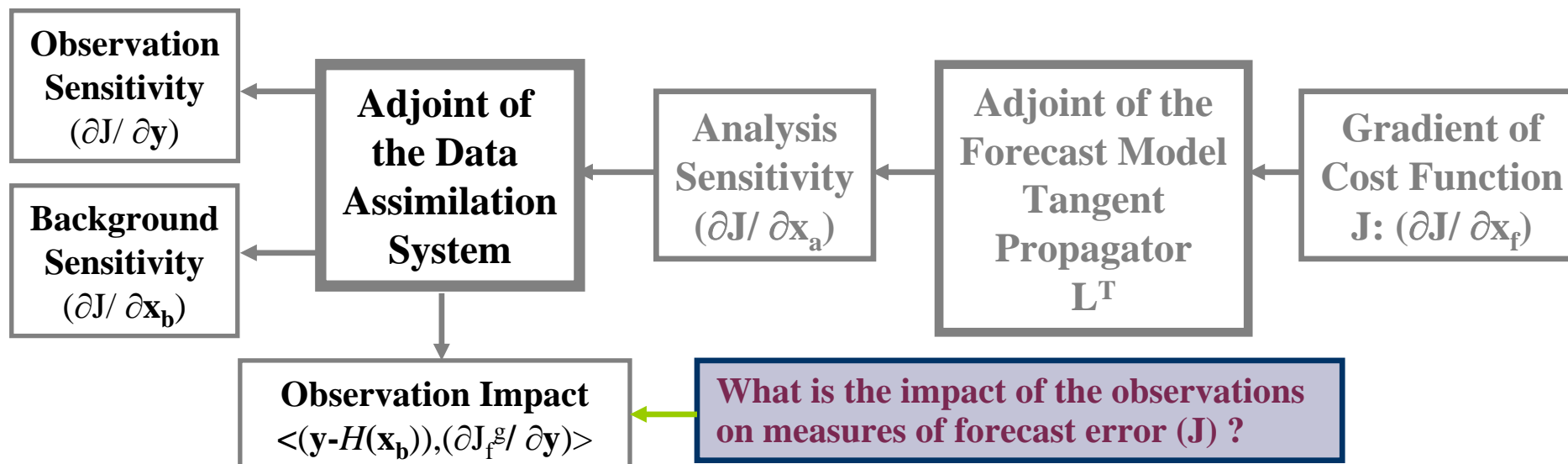
- The gradient sensitivity (GS) and singular vector (SV) targeting methods highlight areas that are highly sensitive to errors in the initial conditions
 - GS method uses the adjoint of the forecast model to calculate the sensitivity or gradient of J with respect to the initial conditions for the forecast.
 - SVs identify the possible error structures in the analysis field that grow most rapidly as they are propagated forward in time by the forecast model
- Assimilation of FASTEX special observations led to both improved and degraded forecasts
- Neither method takes into account how the data assimilation system will use the additional observations
 - the characteristics of the assimilating algorithm
 - the presence of other observations in the area
 - neither method provided guidance on where to place the adaptive observations
- Classical adjoint sensitivity represents only the first part of the complete adjoint NWP problem
- The complete sensitivity includes the adjoint of the data assimilation system



NAVDAS Analysis – NOGAPS Forecast System



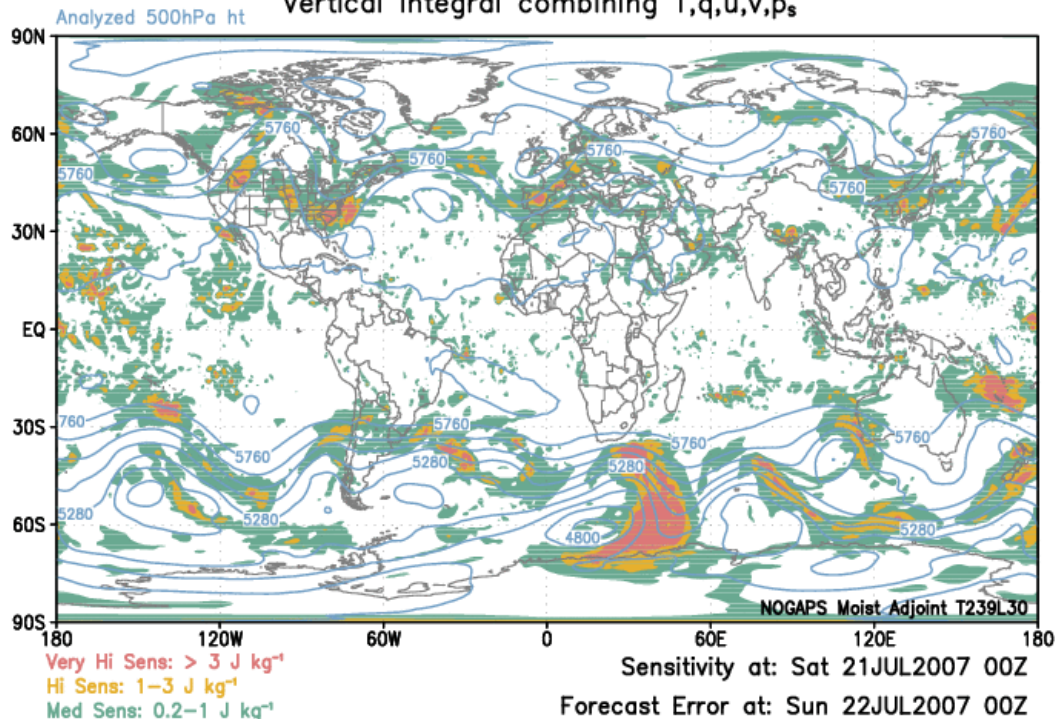
Adjoint System





Sensitivity of 24h Forecast Error to ICs

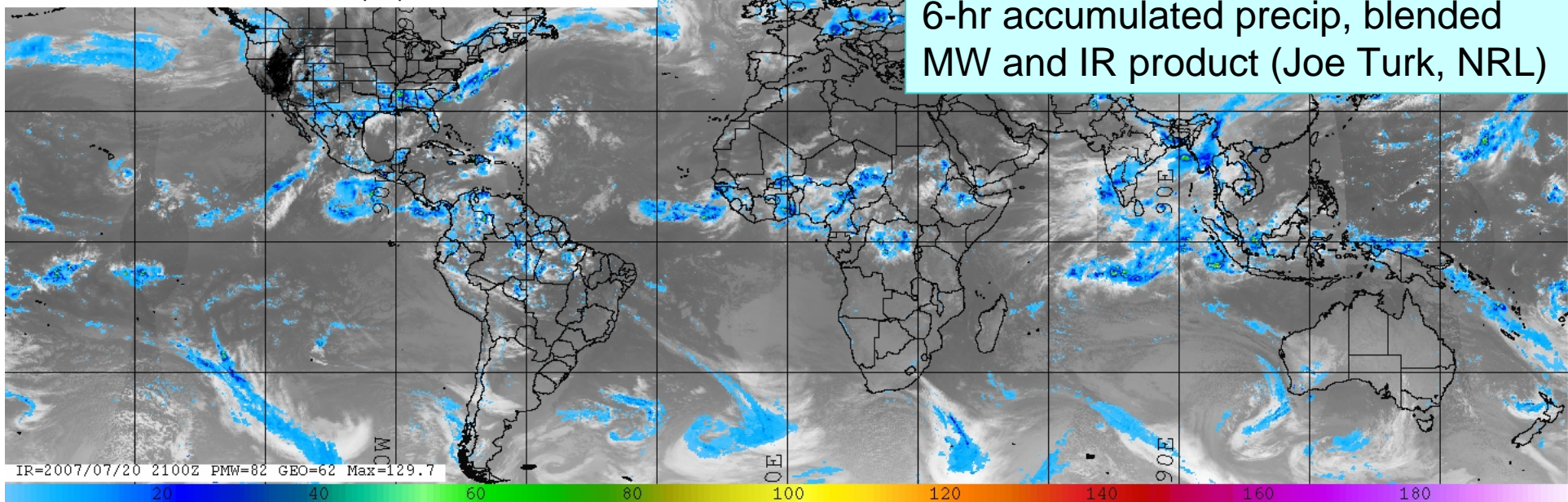
Vertical Integral combining T,q,u,v,p_s



J is the 24-hr vertically-integrated moist static energy error norm

$\partial J / \partial \mathbf{x}_a$ is the sensitivity of J with respect to the initial conditions

6-hr BLENDED accumulation (mm) 21-Jul-2007 0000z

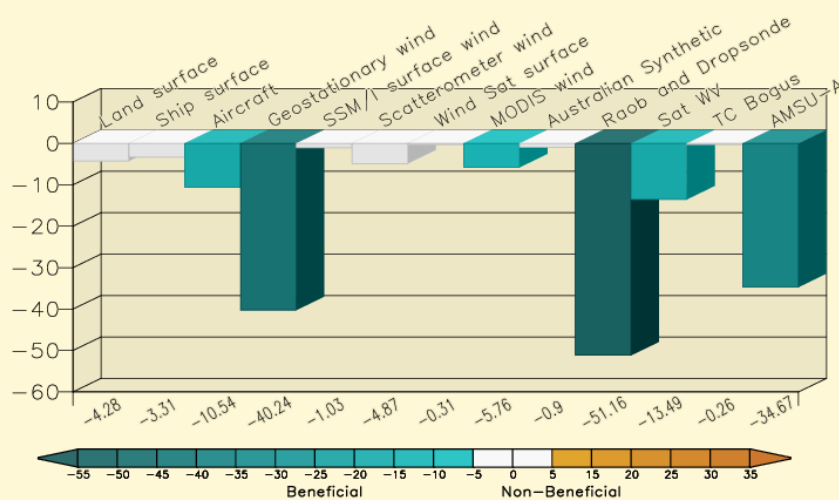




Assessing the Impact of 00UTC Observations for NAVDAS-NOGAPS

Impact Sum by Instrument Type

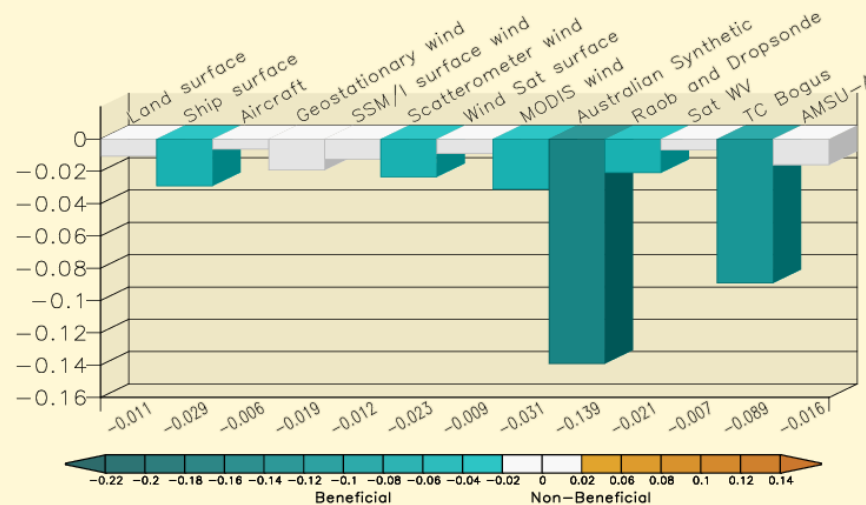
Impact of 00UTC observations on 24h global forecast error – moist total energy norm ($J\ kg^{-1}$)
30-days ending 22 Jul 2007



Total impact as a function of observing platform

Impact*1000 / Ob by Instrument Type

Impact of 00UTC observations on 24h global forecast error – moist total energy norm ($J\ kg^{-1}$)
30-days ending 22 Jul 2007



Total impact per observation

- Observation impact is routinely generated once per day at 00 UTC
 - Operational analyses and innovation vectors from NAVDAS / NOGAPS are used



Data Assimilation Adjoint Theory

Begin with the linear analysis equation

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x}_b)$$

where

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T (\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1}$$

The sensitivities of the analysis to the observations and background are

$$\frac{\partial \mathbf{x}_a}{\partial \mathbf{y}} = \mathbf{K}^T$$

$$\frac{\partial \mathbf{x}_a}{\partial \mathbf{x}_b} = (\mathbf{I} - \mathbf{H}\mathbf{K})^T$$

\mathbf{x}_a – analysis vector

\mathbf{x}_b – background

\mathbf{y} – observation vector

$\mathcal{H}(\mathbf{x}_b)$ – forward observation operator

\mathbf{H} – Jacobian or tangent linear approximation of $\mathcal{H}(\mathbf{x}_b)$

\mathbf{R} – observation error covariance

\mathbf{B} – background error covariance

\mathbf{K} – Kalman gain matrix

\mathbf{I} – identity matrix

Influence Matrix (Cardinali, 2004)

$$\hat{\mathbf{y}} = \mathbf{H}\mathbf{x}_a$$

$$\mathbf{S} = \frac{\partial \hat{\mathbf{y}}}{\partial \mathbf{y}} = \mathbf{K}^T \mathbf{H}^T$$

$$\frac{\partial \hat{\mathbf{y}}}{\partial (\mathbf{H}\mathbf{x}_b)} = \mathbf{I} - \mathbf{K}^T \mathbf{H}^T = \mathbf{I}_p - \mathbf{S}$$



Observation and Background Sensitivity

- Using the chain rule, the sensitivities of the forecast aspect J to the observations and background are

$$\frac{\partial J}{\partial \mathbf{y}} = \frac{\partial \mathbf{x}_a}{\partial \mathbf{y}} \frac{\partial J}{\partial \mathbf{x}_a} = \mathbf{K}^T \frac{\partial J}{\partial \mathbf{x}_a}$$

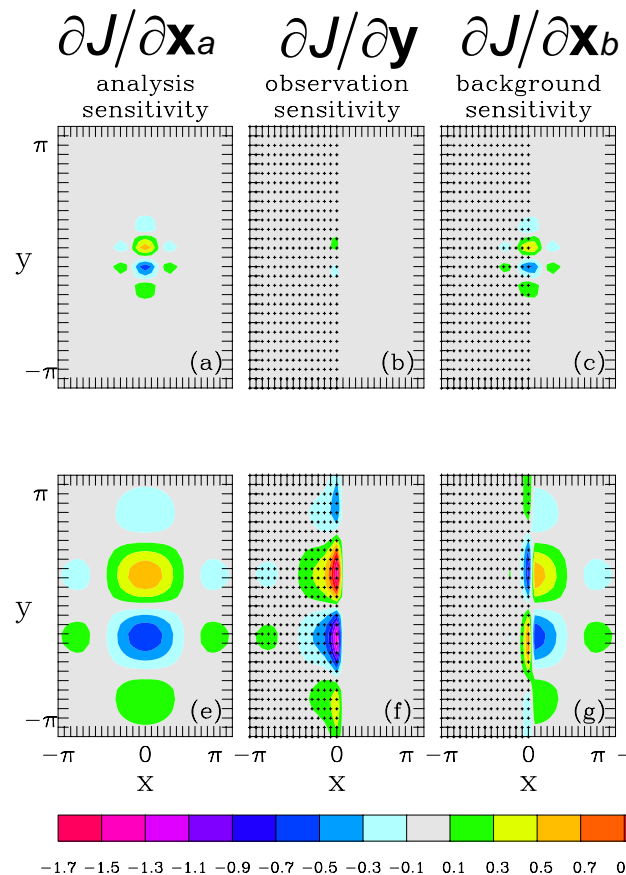
$$\frac{\partial J}{\partial \mathbf{x}_b} = \frac{\partial \mathbf{x}_a}{\partial \mathbf{x}_b} \frac{\partial J}{\partial \mathbf{x}_a} = (\mathbf{I} - \mathbf{H}^T \mathbf{K}^T) \frac{\partial J}{\partial \mathbf{x}_a}$$

$$\mathbf{K} = \mathbf{B} \mathbf{H}^T (\mathbf{H} \mathbf{B} \mathbf{H}^T + \mathbf{R})^{-1}$$

- Observation and background sensitivity depend upon
 - the structure of the background error correlation
 - assumed accuracy of the observations relative to the background ($\varepsilon_r / \varepsilon_b$)
 - forward and adjoint observation operators, \mathbf{H} and \mathbf{H}^T
 - the amplitude and spatial structure of the initial sensitivity $\partial J / \partial \mathbf{x}_a$
 - the distribution of the observations



Exploration of Observation Sensitivity using Idealized Cases

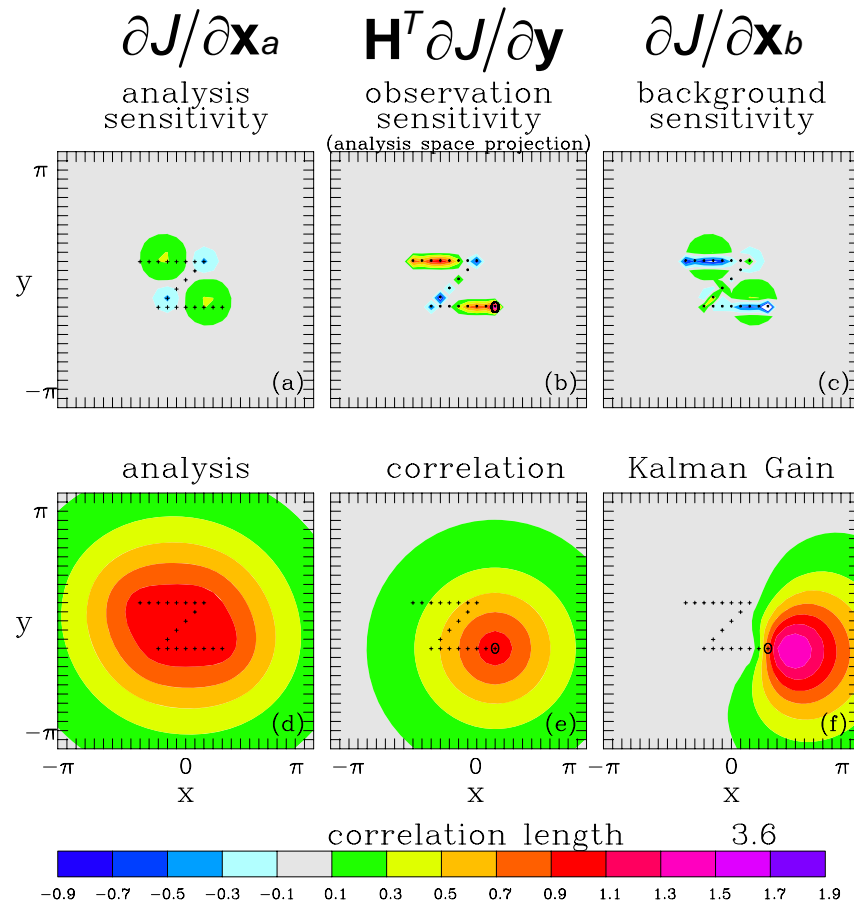


2D univariate height analysis
 Ob error = background error = 1.0,
 $L_b = 2.42dx$

- Observation sensitivity is greater for large-scale targets
- Observation sensitivity is greatest along the coastline where the observation density changes.
- In the well-observed interior,
 - Small-scale targets: background sensitivity = analysis sensitivity.
 - Large-scale targets: observation sensitivity = analysis sensitivity.
- Large values of L_b imply the background errors are primarily in the large scales, so the analysis uses the observations reduce the large-scale errors
- Observation sensitivity will be derived from the large targets



Observation Sensitivity for a Hypothetical Flight Path



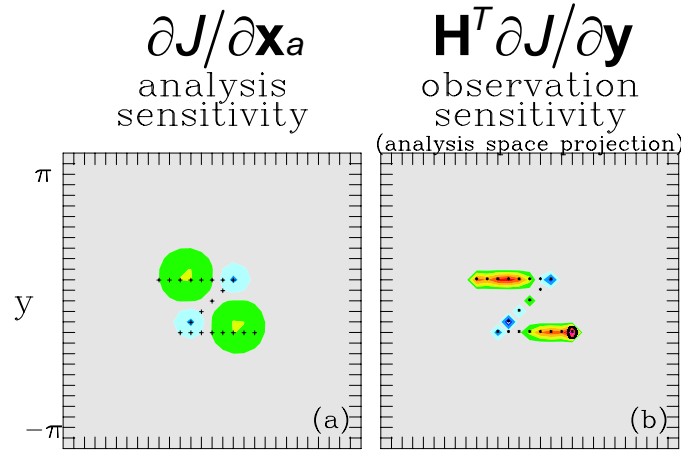
2D univariate height analysis
 Large and small-scale $\partial J / \partial \mathbf{x}_a$ patterns
 20 height obs with $\epsilon_r / \epsilon_b = 0.1$; $L_b = 3.6 dx$;
 innovation = 1.0

- Observation sensitivity is largest when changes in the observation density coincide with large-scale and amplitude analysis sensitivity gradients
- Observation sensitivity is maximized when the observation is strongly projected onto $\partial J / \partial \mathbf{x}_a$ by the adjoint of the assimilation operator \mathbf{K}^T
- Background sensitivity tends to be large (and of opposite sign) when the observation sensitivity is large

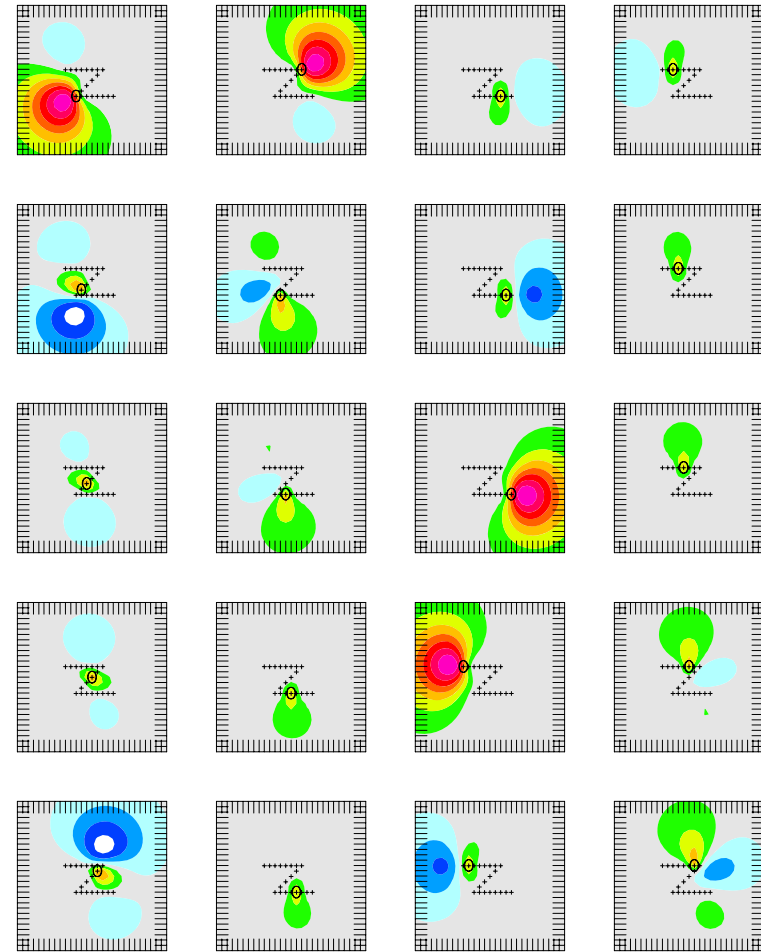
$$\begin{aligned} \partial J / \partial \mathbf{y} &= (\mathbf{H} \mathbf{B} \mathbf{H}^T + \mathbf{R})^{-1} \mathbf{H} \mathbf{B} \partial J / \partial \mathbf{x}_a \\ &= \mathbf{K}^T \partial J / \partial \mathbf{x}_a \\ \mathbf{H}^T \partial J / \partial \mathbf{y} &= \partial J / \partial \mathbf{x}_a - \partial J / \partial \mathbf{x}_b \end{aligned}$$



Understanding Observation Sensitivity



$$\frac{\partial J}{\partial \mathbf{y}} = \mathbf{K}^T \frac{\partial J}{\partial \mathbf{x}_a}$$



Row of \mathbf{K}^T for each observation

- For relatively isolated observations, \mathbf{K}^T is large in amplitude and spatial scale.
 - If \mathbf{K}^T projects strongly onto the analysis sensitivity, the potential change to the forecast aspect is large.
- For high density observations, \mathbf{K}^T is small in amplitude and spatial scale.
 - Projection of \mathbf{K}^T onto the analysis sensitivity is weaker, and the potential change to the forecast aspect is small.



Implications for the Forward Analysis Problem

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - \mathbf{H}\mathbf{x}_b)$$

- For a given observation, the row of \mathbf{K}^T and column of \mathbf{K} are equivalent.
- When the observation is relatively isolated, \mathbf{K} is large in amplitude and spatial scale.
 - The observation has more independent information
 - The observation will be given more weight in the analysis
 - Potential changes to the analysis due to the observation are large in amplitude and spatial scale
 - Use extra caution along edges of satellite swaths; endpoints of satellite overpasses; boundaries between ocean, and land or sea-ice
- This is not necessarily a good thing – assimilating more observations helps protect against outliers or incorrect specification of the background error covariances
- Observations with small innovations are still important – as they affect \mathbf{K} and \mathbf{K}^T



Observation Sensitivity Summary

- The observation sensitivity gives an estimate of the potential for an observation to make changes to the analysis with the amplitude and structure suggested by the analysis sensitivity gradient.
- Weak sensitivity implies that a single observation cannot resolve the small-scale structures
 - It does not imply that the analysis changes will be small, only that the changes will not be in the direction needed to effectively change the forecast aspect J
- Strong sensitivity implies that the single observation has the potential to change the analysis in the direction that will significantly change J
 - For a single observation, this occurs when the length scales of the analysis sensitivity and the background error correlations are similar
 - Targeting of large-scale features may be preferable



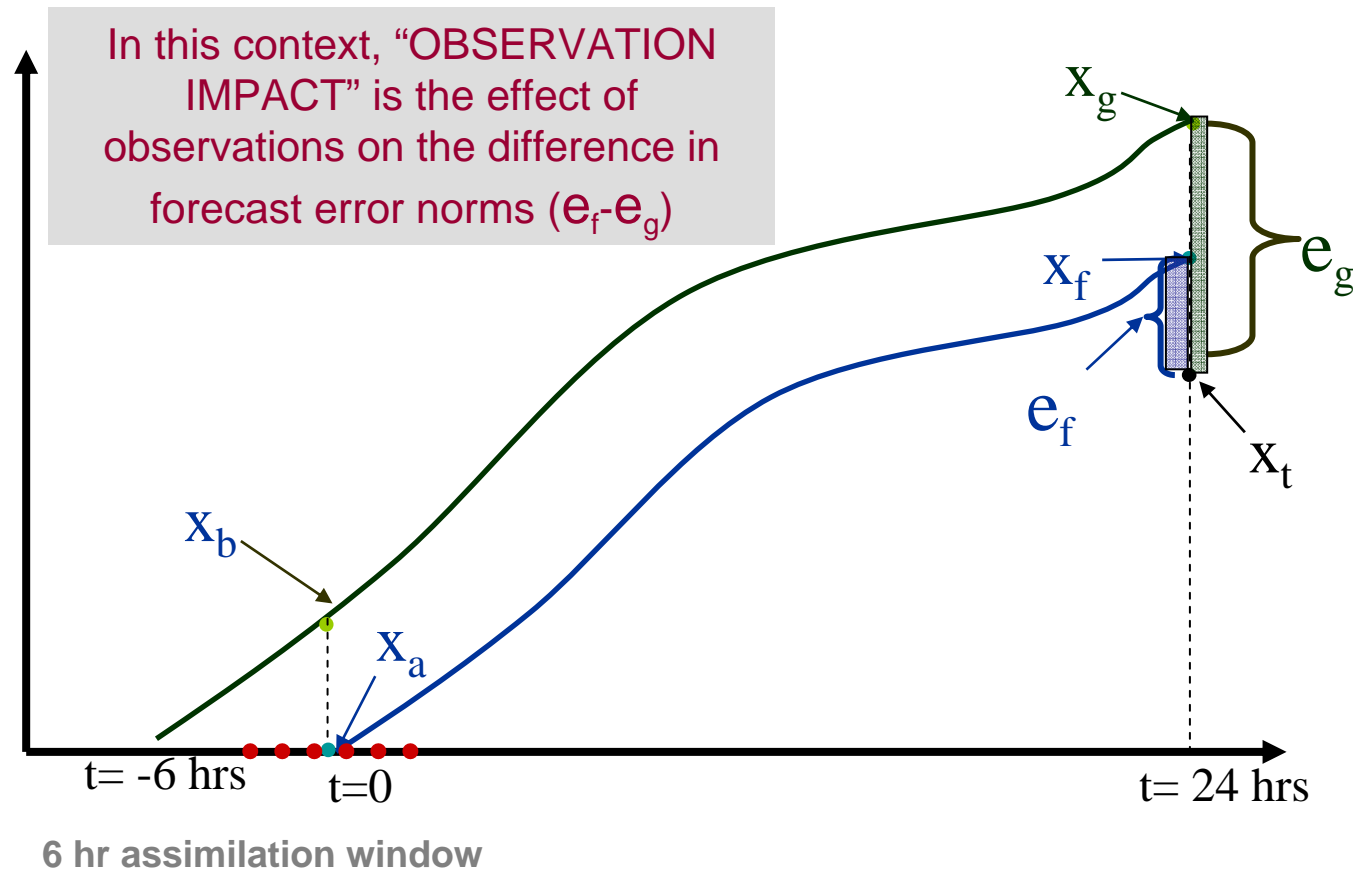
Application to Real Problems

- Define the cost function J or forecast aspect
 - Some function of the model forecast starting from the initial analysis
 - Tangent linear approximation limits the forecast length to 3 days or less
- Compute sensitivity of J with respect to the initial conditions (e.g. temperature, moisture, wind fields and surface pressure)
- Compute the observation sensitivity
- We really want to know whether a given set of observations improve or degrade the forecast?



NRL Approach to Observation Impact

Observations move the forecast from the **background trajectory** to the **trajectory starting from the new analysis**



Langland and Baker (Tellus, 2004), Gelaro et al (2007), Morneau et al. (2006)



Steps in Observation Impact Calculation

**NAVDAS analysis
and background**

FNMOC ops

\mathbf{x}_a (00UTC), \mathbf{x}_b (6h fcst from 18UTC)

**NOGAPS forecasts
& error norms**

T239L30, full physics

$$\mathbf{x}_{24} = \mathbf{M}(\mathbf{x}_a)$$

$$\mathbf{x}_{30} = \mathbf{M}(\mathbf{x}_b)$$

Forecast errors

NOGAPS adjoint

T239L30, includes large-scale precip

$$\partial e_{24} / \partial \mathbf{x}_a = \mathbf{L}^T \left[\mathbf{C}(\mathbf{x}_{24} - \mathbf{x}_t) \right]$$

$$\partial e_{30} / \partial \mathbf{x}_b = \mathbf{L}^T \left[\mathbf{C}(\mathbf{x}_{30} - \mathbf{x}_t) \right]$$

Sensitivity gradients in
model grid-point space



Observation Impact Equation

$$\delta e_f^g = \left\langle (\mathbf{y} - \mathbf{H}\mathbf{x}_b), \mathbf{K}^T \left\{ \frac{\partial e_f}{\partial \mathbf{x}_a} + \frac{\partial e_g}{\partial \mathbf{x}_b} \right\} \right\rangle = \left\langle (\mathbf{y} - \mathbf{H}\mathbf{x}_b), \left\{ \frac{\partial J_f^g}{\partial \mathbf{y}} \right\} \right\rangle$$

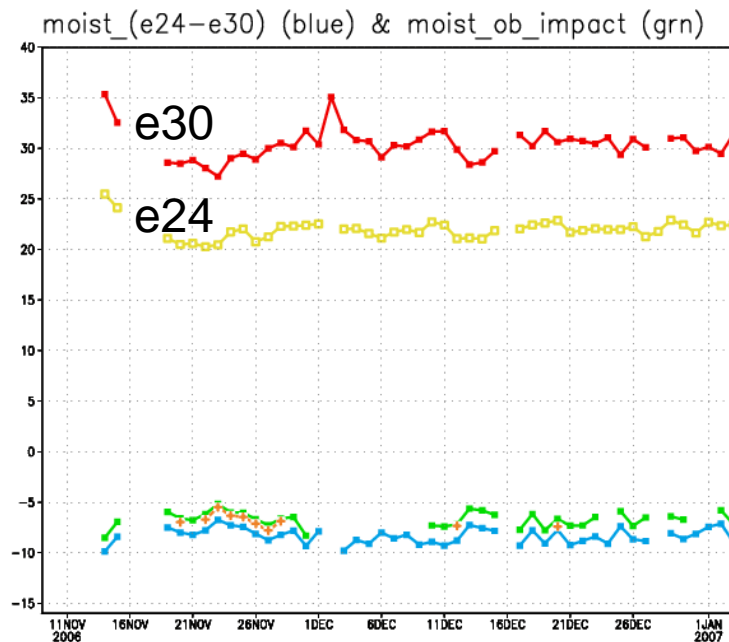
- The impact of observation subsets (e.g., separate channels, or separate satellites) can be easily quantified
- Computation always involves entire set of observations; changing properties of one observation changes the scalar measure for all other observations

$\delta e_f^g < 0.0$ the observation is BENEFICIAL

$\delta e_f^g > 0.0$ the observation is NON - BENEFICIAL



Nonlinear vs. adjoint estimates of forecast error



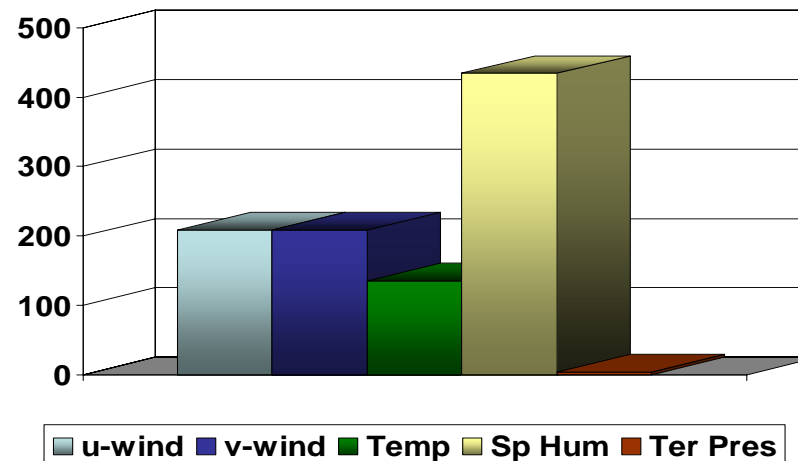
When summed over the entire innovation vector ...

$$\sum_n \delta e_{24}^{30} \text{ is an approximation of } e_{24} - e_{30}$$

Adjoint-based ob impact accounts for ~84% of **actual error** difference

Includes large-scale precip, no convection

Contributions to NOGAPS moist error norm e_{24}



Cost function is a quadratic measure of the vertically-integrated (sfc to 150 hPa) moist-energy weighted forecast error.
Units of e-norm = J / kg



Nonlinearity Considerations

- The NRL technique of combining linear adjoint sensitivity gradients on two trajectories (those of x_a and x_b) essentially gives **higher than first-order accuracy** in the estimation of the observation impact
- Gelaro et al. (2007) examined the effects of nonlinearity on the interpretation of the partial sums (observation impact binned by platform, station, channel, etc.)
 - Second and third order terms have dependence on innovations and trajectories starting from x_a
 - The dominant nonlinearity arises from the quadratic nature of the cost function
 - Higher than first-order accuracy is required to adequately capture the observation impact
 - The authors found “no obvious detrimental effects” on the estimated impact for the major observing systems.
- Recall that observation sensitivity/impact is always in the context of all other observations

Errico, 2007; Gelaro et al., 2007



Applications: Improving the observation quality and assimilation system

- Assessing the relative impact of observation platforms
- Diagnosing problems with observing systems
 - Sat winds example
 - Meta data such as Master Station Lists
 - Lihue raob station
- Justifying continuation of observing platforms
- Channel selection for high spectral resolution IR sounders
- Identifying problems with the assimilation system
- Cross-comparisons with other NWP centers
- *Optimal observation density for assimilation*



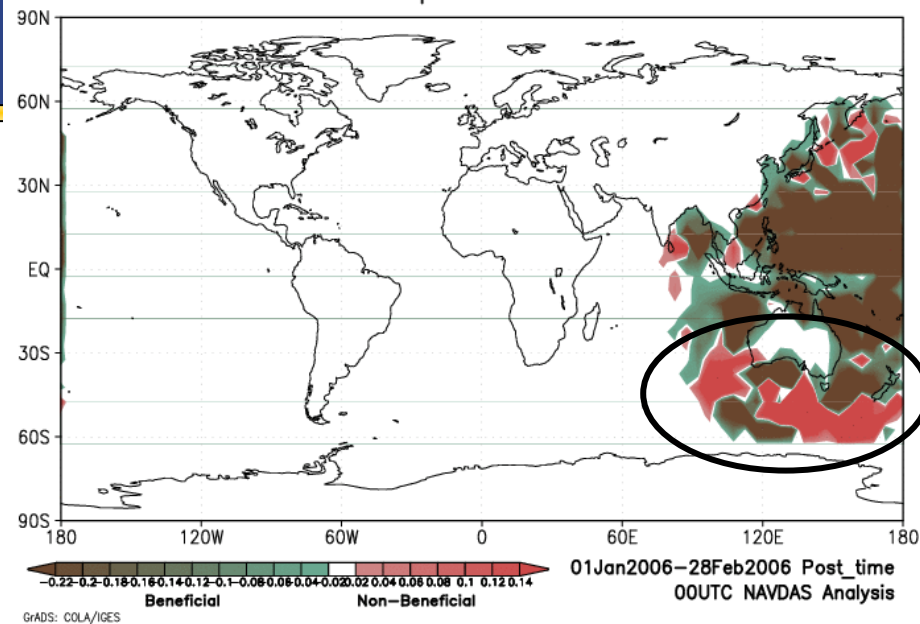
SATWIND data denial experiment

Date: Jan-Feb 2006

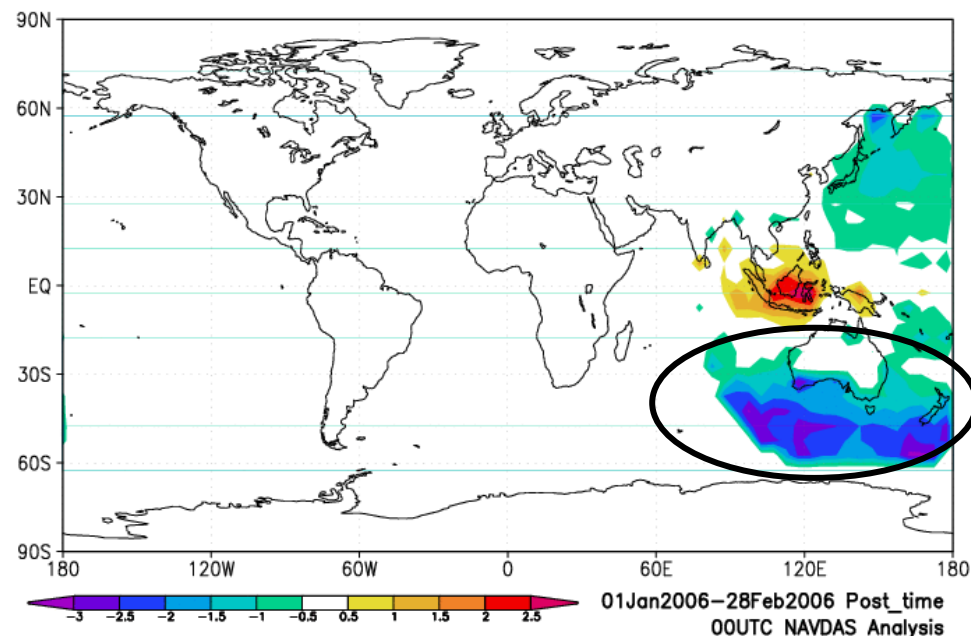
Issue: Large innovations and non-beneficial impact from satwinds at edge of coverage areas

Action Taken: Ob data removed if $> 39^\circ$ from satellite sub-point – gave 3-hr improvement in SHEM NOGAPS forecast skill

Type 58 SATWIND GMSC
Innovation Impact on 24h Fcst Error



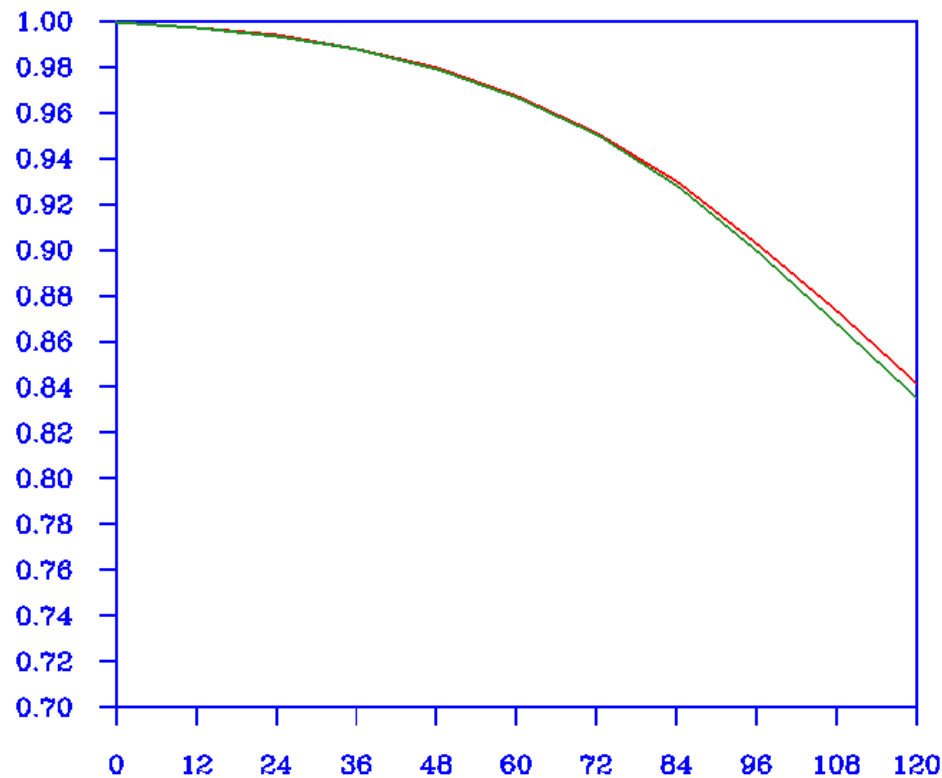
Mean Innovation – u-wind



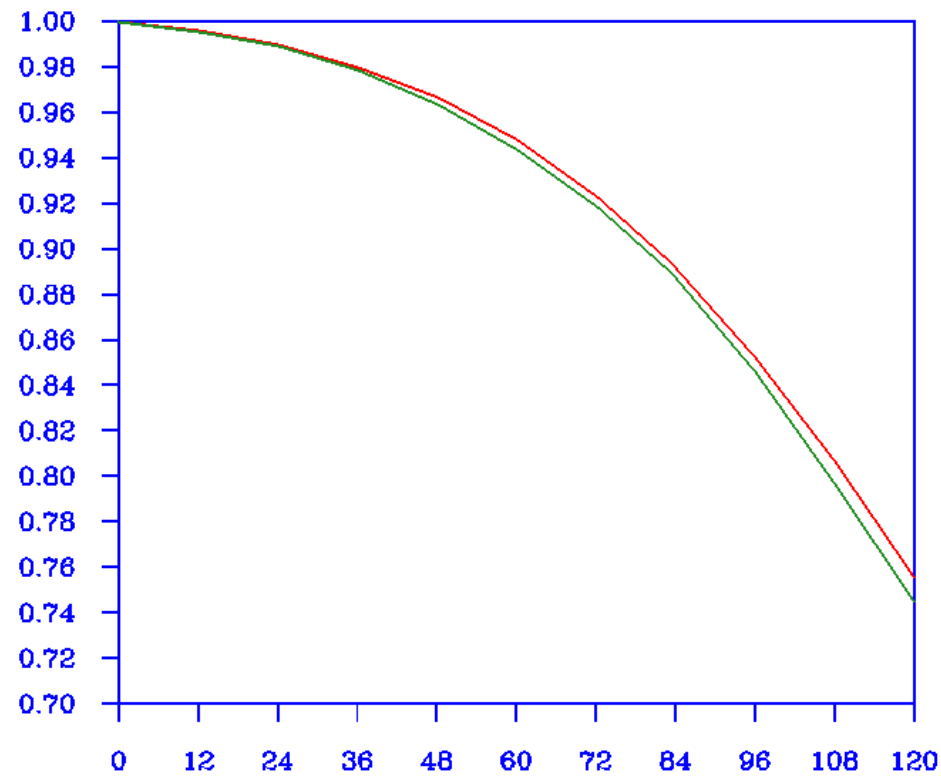


Restricting SSEC MTSAT Winds 500 mb Height Anomaly Correlation

Northern Hemisphere



Southern Hemisphere



Restricted Winds

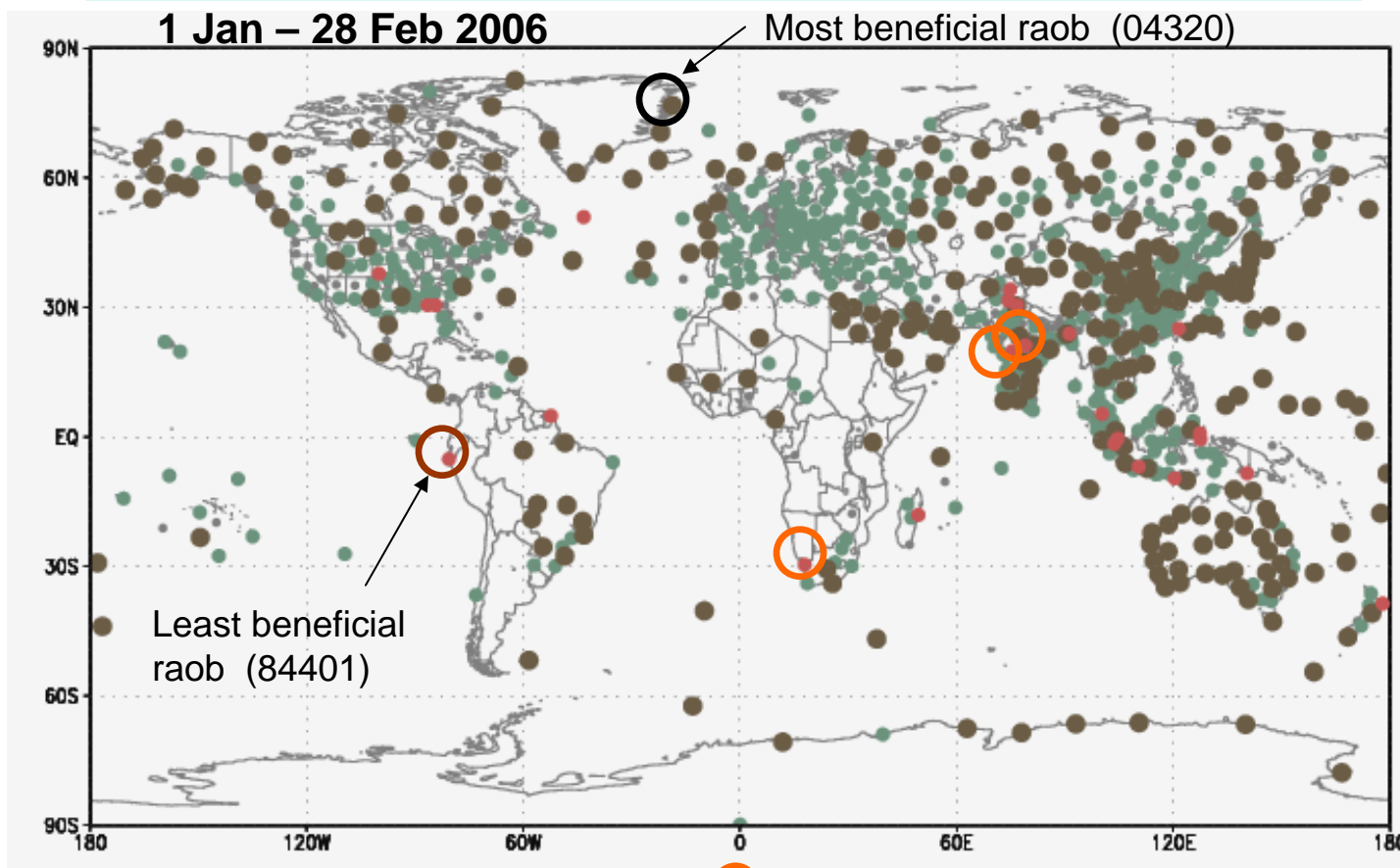
Control

February 16 – March 27, 2006



Radiosonde profile observation impact Justifying Continuation of Raob Stations

Diego Garcia, Thule AFB Greenland, Vandenberg AFB, US



- Most beneficial ($< -0.1 \text{ J kg}^{-1}$)
- Beneficial ($-0.01 \text{ to } -0.1 \text{ J kg}^{-1}$)
- Non-beneficial ($0.01 \text{ to } 0.1 \text{ J kg}^{-1}$)

○ On recent UKMO blacklist

Combines all separate temperature, wind, moisture, and height impacts at all levels of radiosonde profile



Channel Selection Methods

(Fourrié and Rabier, 2004; Ruston, Gelaro)

1. **Entropy-reduction** (iterative*; non-adjoint based; Rodgers, 1996; Rabier et al., 2002)

- Computationally efficient;

$$ER = \frac{1}{2} \log_2(1 + h^T \mathbf{B} h)$$

2. **Adjoint Sensitivity** (iterative*; adjoint; Baker and Daley, 2000; Doerenbecher and Bergot, 2001)

- Computationally expensive
- Chooses channel that maximizes the observation sensitivity

$$\partial J / \partial \mathbf{y} = \mathbf{K}^T \partial J / \partial \mathbf{x}_a$$

3. **Kalman Filter Sensitivity** (iterative*; adjoint; Bergot and Doerenbecher, 2002)

- Computationally efficient
- Chooses the channel that gives the maximum decrease in the error variance for J

$$(\delta \sigma)^2 = \partial J / \partial \mathbf{x}_a \mathbf{B} \mathbf{H} (\mathbf{R} + \mathbf{H} \mathbf{B} \mathbf{H}^T)^{-1} \mathbf{H}^T \mathbf{B} \partial J / \partial \mathbf{x}_a$$

4. **Observation Impact** (non-iterative; adjoint; Ruston, Gelaro)

- Computational cost proportional to one data assimilation cycle
- Computed in tandem with DA cycle

** Iterative – choose channel with most “value”, update analysis error covariance, which is used for B in the next iteration.

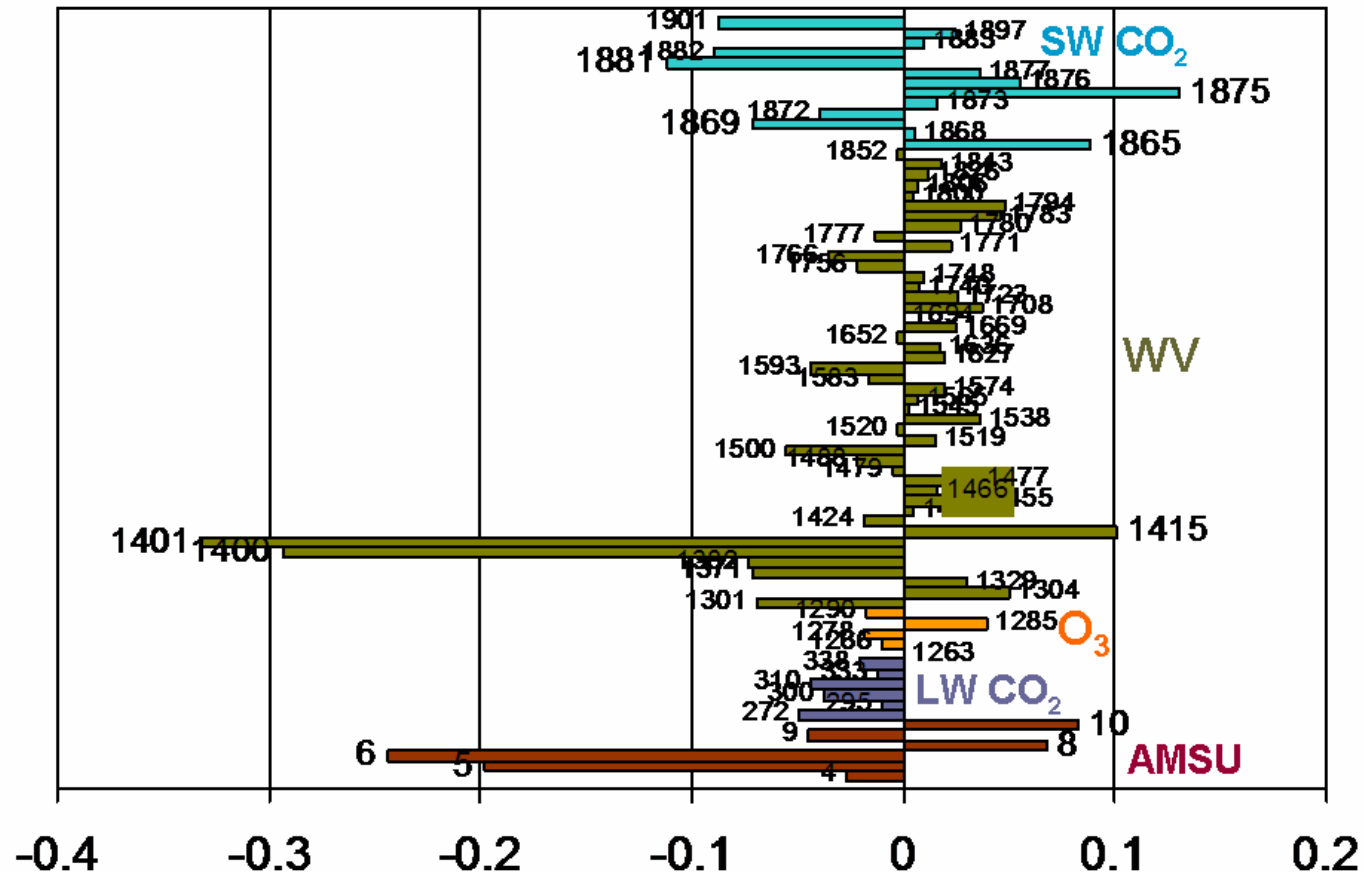


Channel Selection Methods

- Compute Degrees of Freedom for the Signal (DFS) for #1-3
- Results for methods #1-3:
 - Comparable results, even though channels selected are not the same
 - Adjoint-based methods tend to favor information in sensitive areas (lower troposphere)
 - Approach #1 also includes information for upper troposphere
 - A large part of the AMSU and AIRS information comes from the stratosphere (Rabier, 2006)
 - A constant channel set works well too

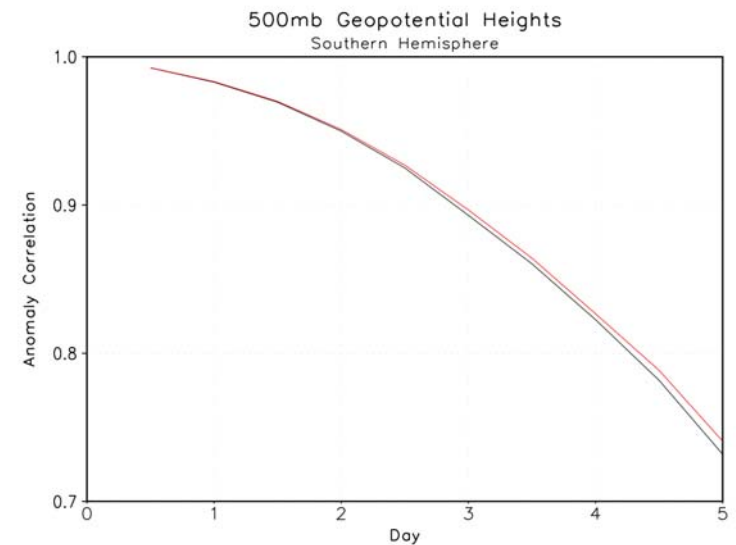
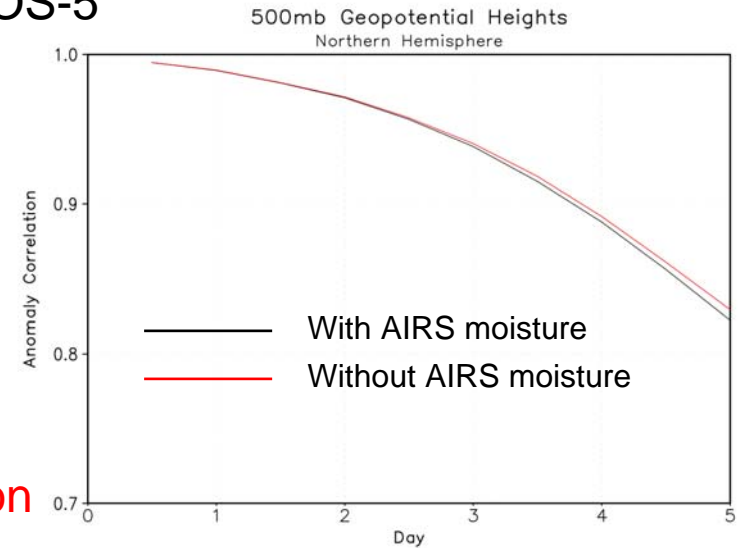
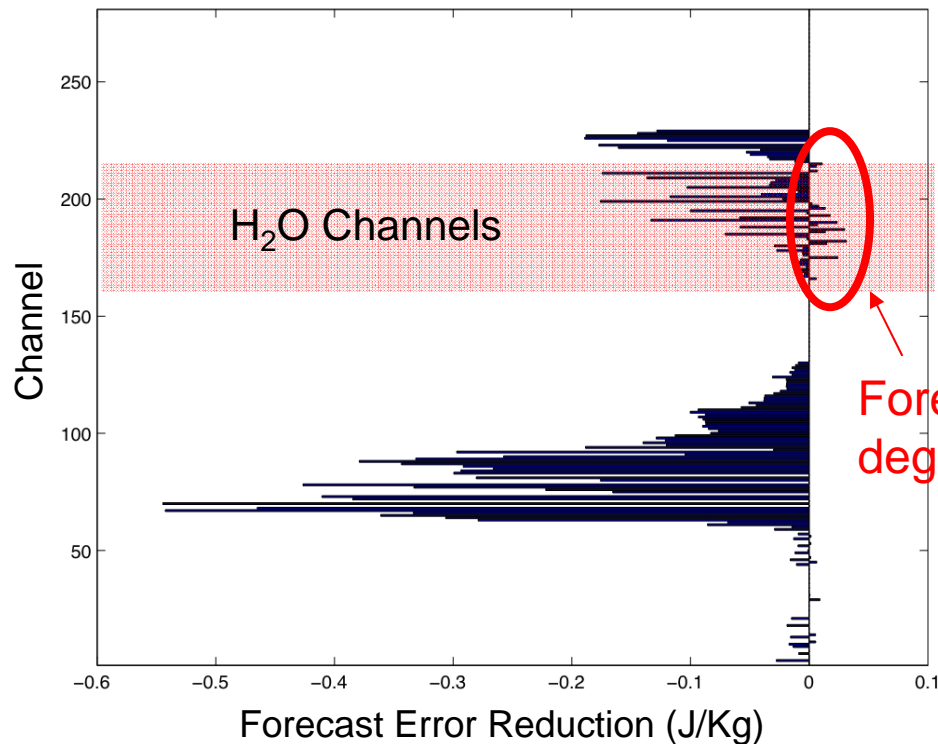


NRL AIRS Observation Impact



Adjoint-based data selection and QC decisions

NASA/GMAO GEOS-5



- Adjoint results show that the some AIRS moisture channels degrade the 24h forecast
- Observing system experiments (OSE) corroborate that skills are increased when AIRS moisture channels are excluded
...investigation of problem is underway...

Slide courtesy of Ron Gelaro, GMAO

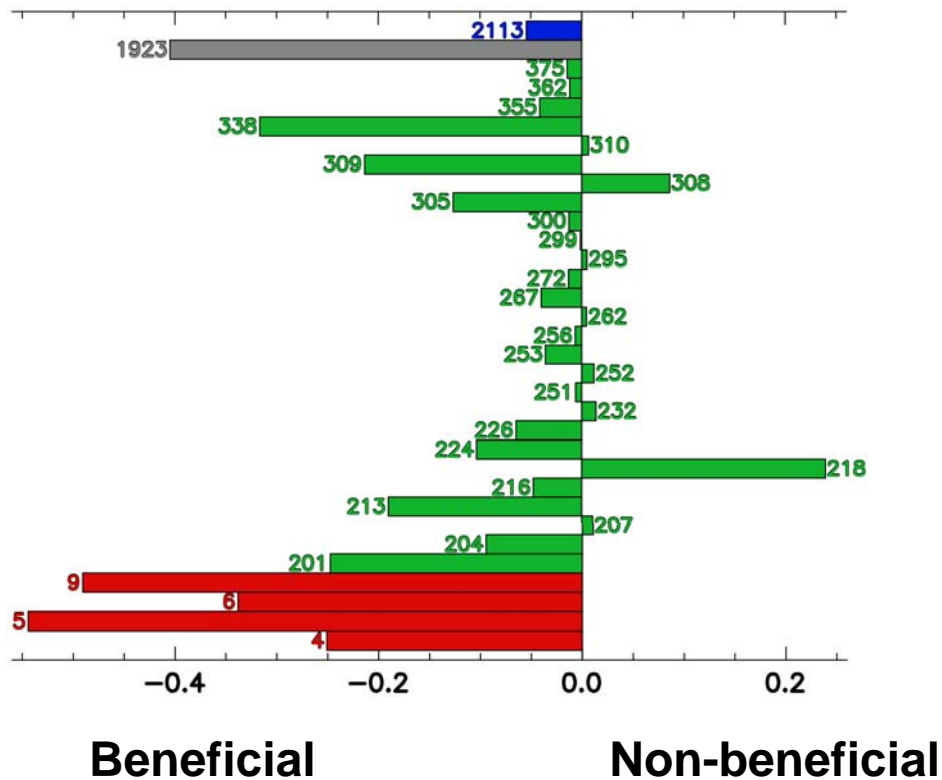


Data Assimilation

Use of NAVDAS Adjoint

Assessment of AQUA sensors
AMSU/A, AIRS longwave 14-13 μ m,
AIRS shortwave 4.474 μ m, **AIRS shortwave 4.180 μ m**

AQUA sensitivity specified by channel number: Aug 15-26, 2006





Inter-comparison between NWP Centers

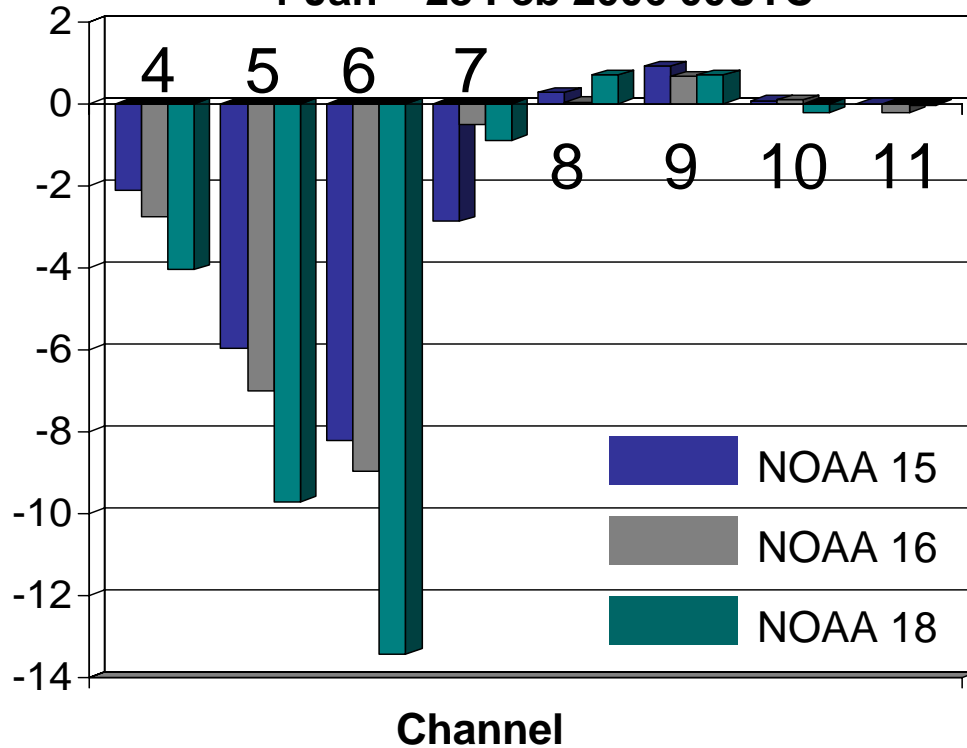
- NRL (NAVDAS and NOGAPS)
 - Adjoint constructed using (observation space) analysis operators
- GMAO (GEOS-5 – GSI and FVM)
 - Exact line by line adjoint of the GSI code
- Environment Canada (GEM and 3D/4D-Var)
 - 4D-Var dual (PSAS; observation space)
 - 3D-Var in observation space
 - Adjoint constructed using analysis operators
- ECMWF
 - Influence-matrix diagnostics (Cardinali, 2004)



Comparison of Forecast Impact for AMSU-A

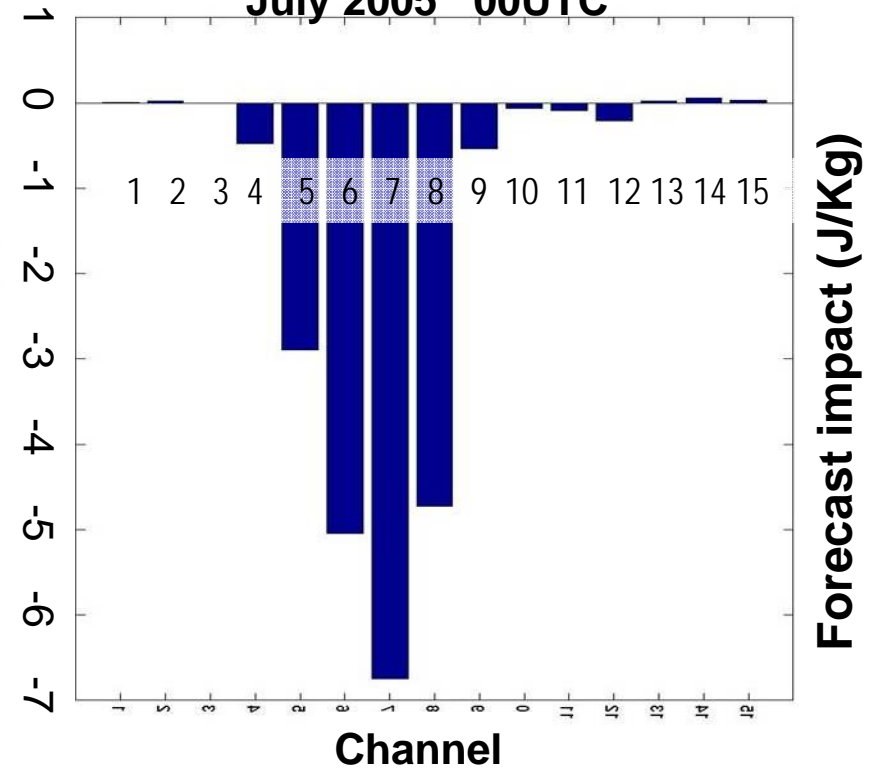
NRL NAVDAS/NOGAPS

1 Jan – 28 Feb 2006 00UTC



NASA/GMAO GEOS-5

July 2005 00UTC



Forecast impact (J/Kg)

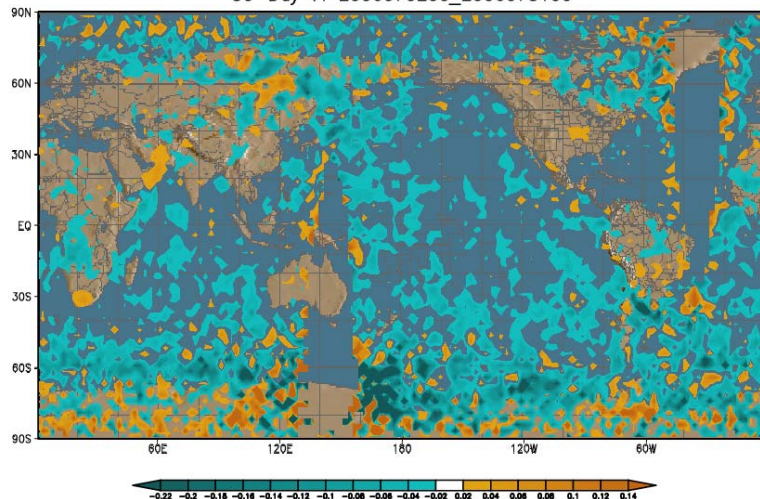
NRL results suggest a problem with assimilation of ch 8 and 9
Likely sources are the operational bias correction and insufficient model and analysis resolution
Much of the non-beneficial impact for ch 9 is in the tropics!



AMSU-A Impact Comparison

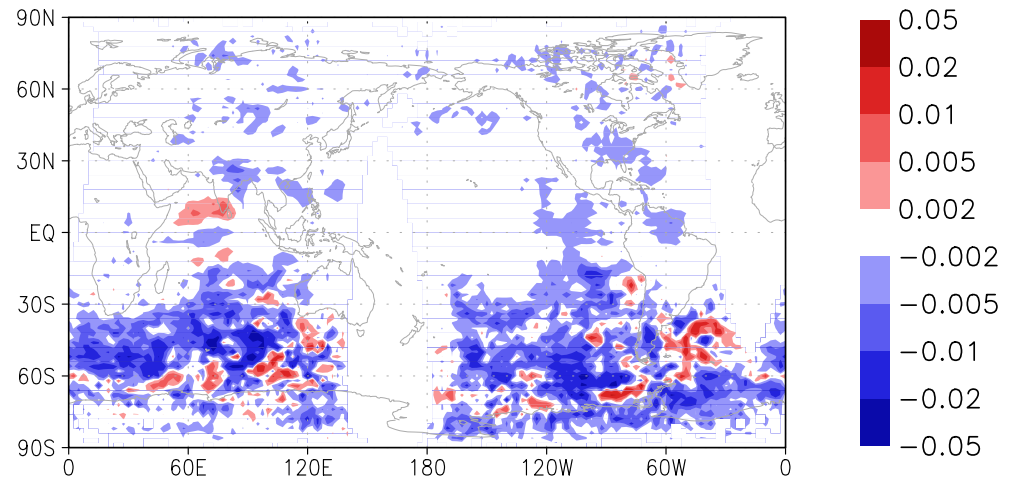
NAVDAS-NOGAPS

NAVDAS_ADJ AMSU_TB Mean Observation Impact [*1000] All NOAA, All chan
Min, Max: -2.09 , 2.110 , Mean: -0.01658, SDEV: 0.437, Sum: -33.3616
30-Day VT 2006070200_2006073100



Error reduction Error increase

GEOS-5



Largest impacts occur in SHEM mid-latitudes in both systems.

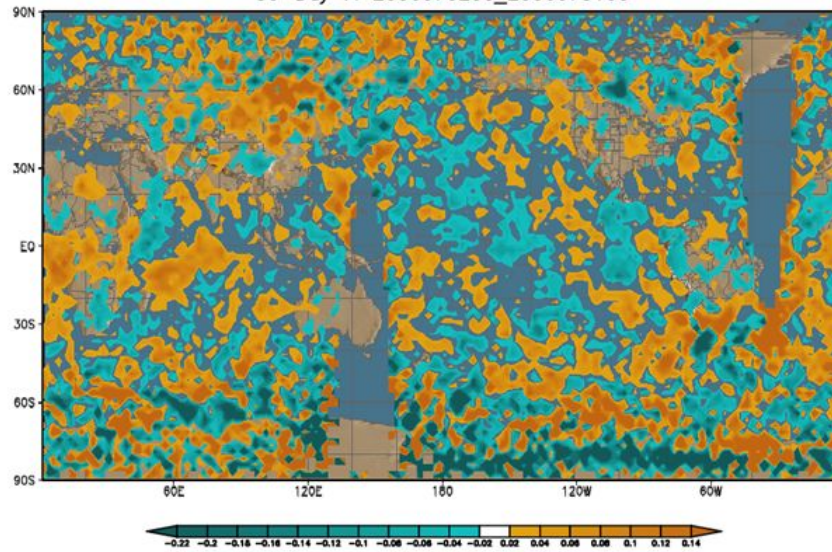
However, AMSU-A has more impact in high latitudes for NOGAPS, compared to GEOS-5



AMSU-A Ch 8 Impact Comparison

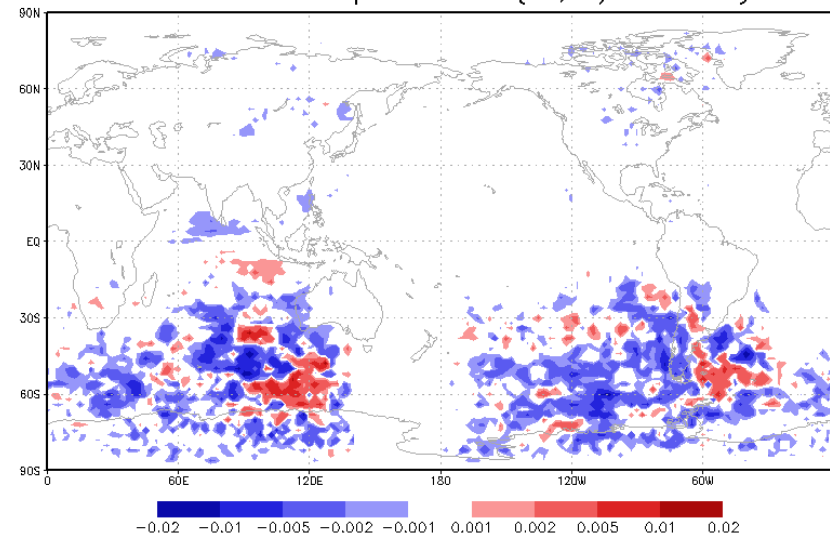
NAVDAS-NOGAPS

NAVDAS_ADJ AMSU TB Mean Observation Impact [*1000] All NOAA, chan 8
Min, Max: -2.80 , 2.669 , Mean: -0.00071, SDEV: 0.411, Sum: -0.22199
30-Day VT 2006070200_2006073100



GEOS-5

GEOS-5 Observation Impact AMSUA(15,16) Ch.8 July 2005

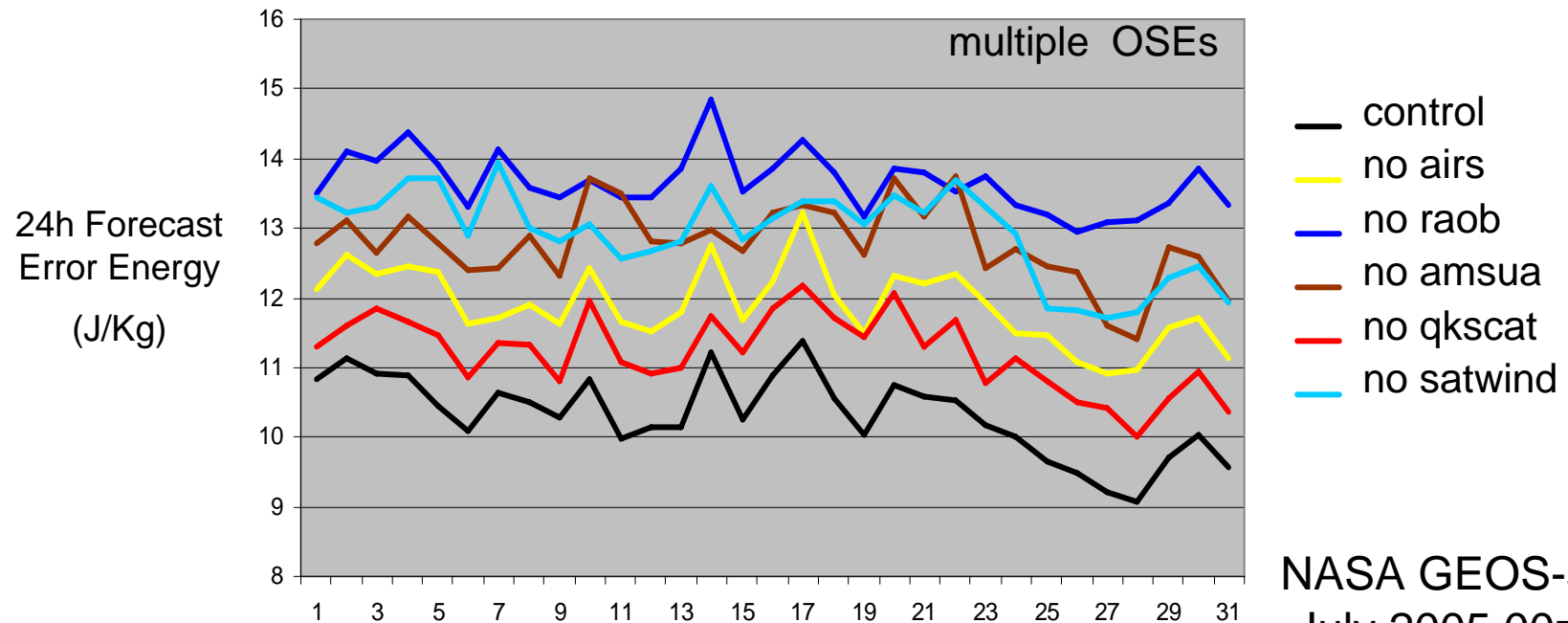




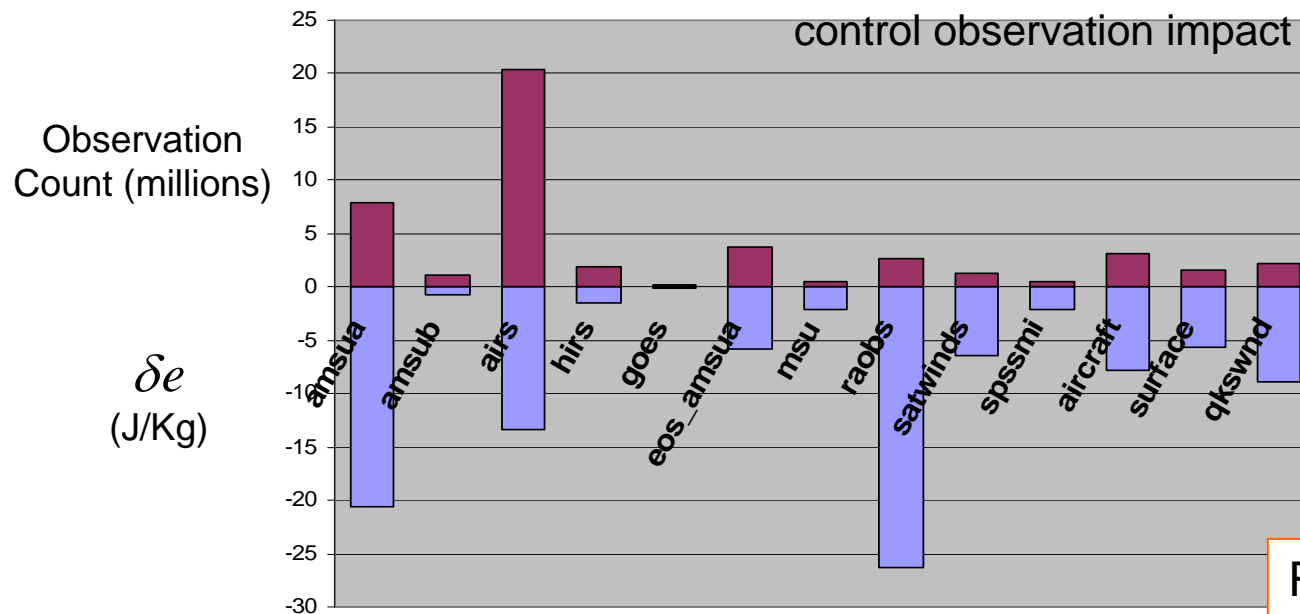
Validation of Adjoint Approach with OSEs

- GMAO performed a series of OSEs, each observing type was systematically removed from assimilation system
- Observation adjoint impact was determined from the control run
- The adjoint approach gives observation impact in the context of all other observations
- The OSE approach gives impact relative to control when an observing system is removed from the assimilation.
- The adjoint approach gives an assessment of the complementary information in observations

Comparison of adjoint observation impact with OSEs



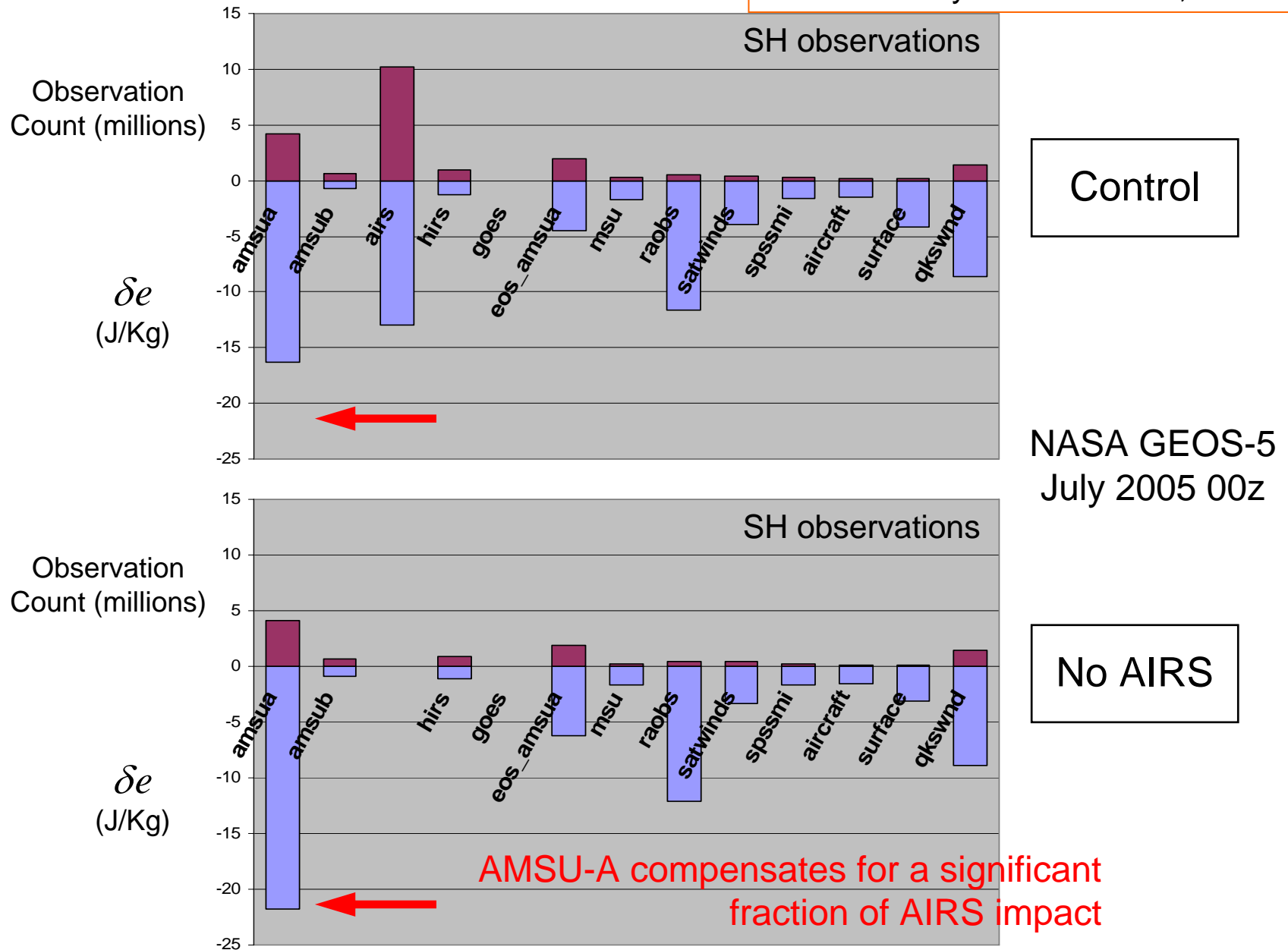
NASA GEOS-5
July 2005 00z



Ron Gelaro, GMAO

Adjoint system as complement to OSEs

Slide courtesy of Ron Gelaro, GMAO



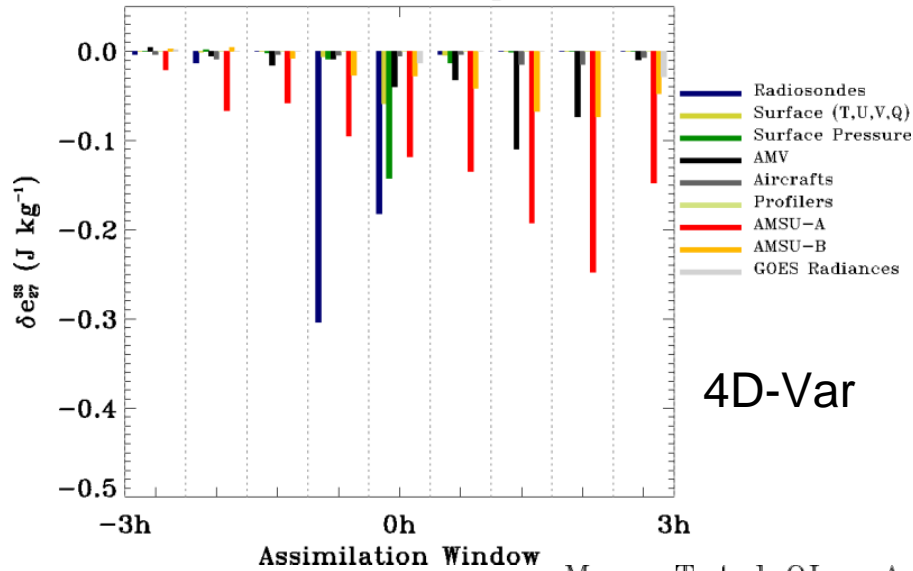


Influence-matrix Approach

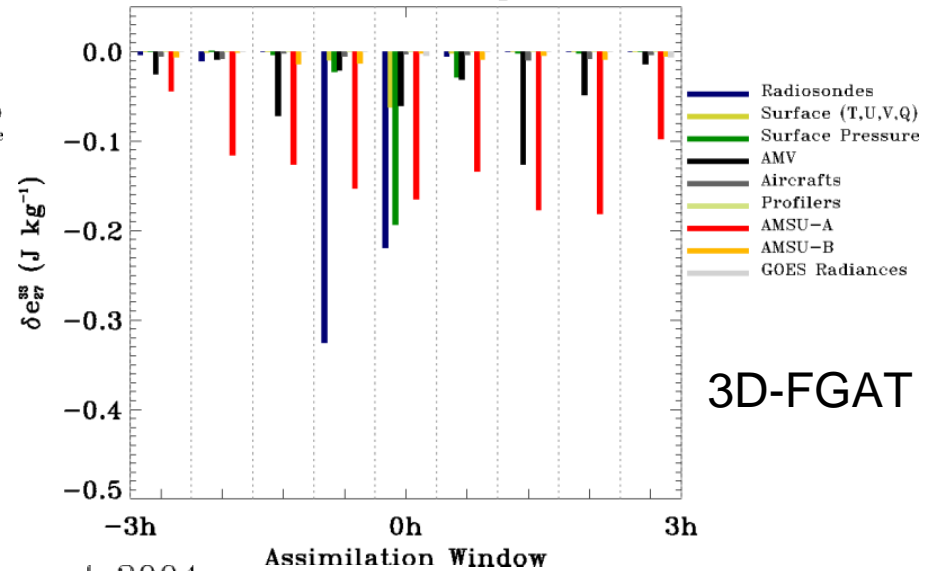
- Compute the influence on the analysis due to the assimilated observations
- Flow-dependence is gained through the evolved background error covariance
- NH spring 2003
 - 15% of the global influence is due to the assimilated observations and 85% is due to the background
- Ranking of information
 - AMSU-A (22%)
 - HIRS(17%)
 - SSMI(13%)
 - AIREP, QuikSCAT, raob, geo winds (6-8% each)

Average Total Ob Impact vs. Time in Analysis Window

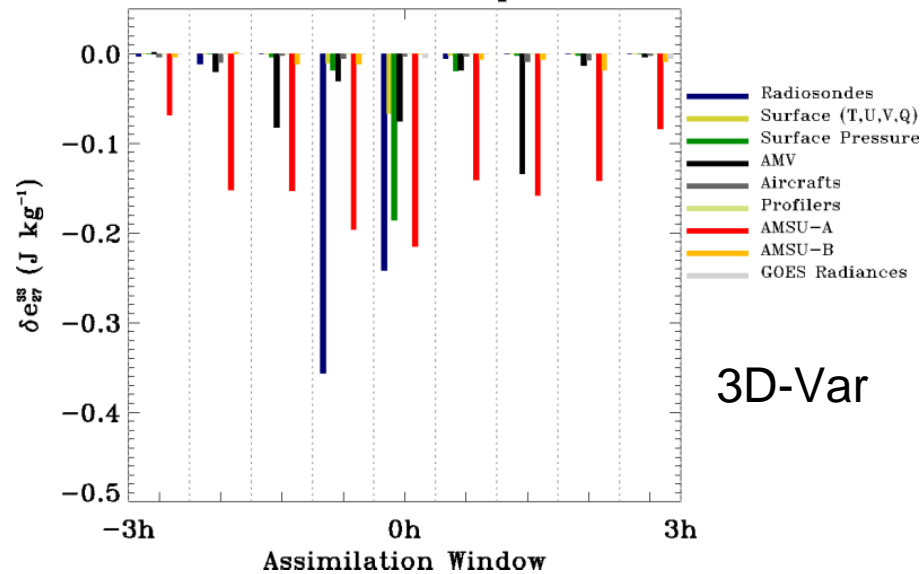
Mean Total OI – August 2004
Southern Hemisphere



Mean Total OI – August 2004
Southern Hemisphere



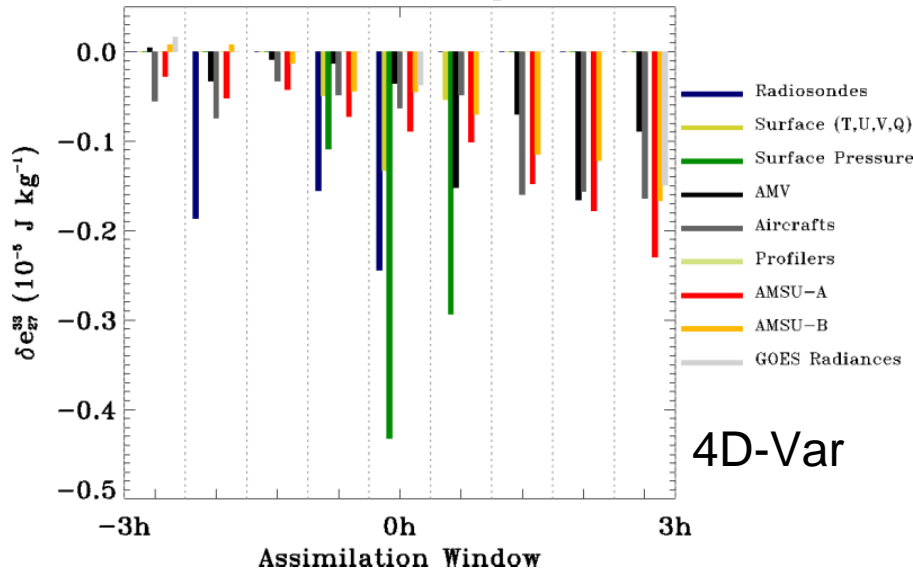
Mean Total OI – August 2004
Southern Hemisphere



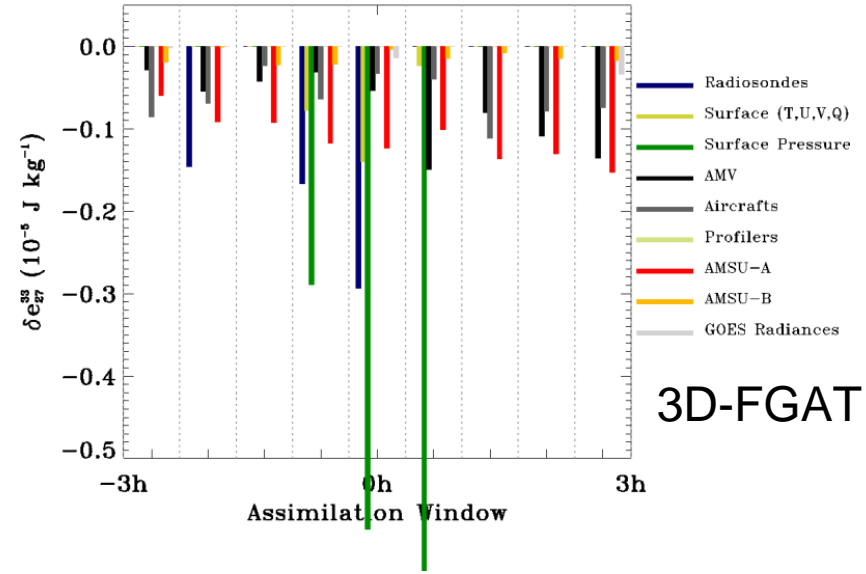
Environment
Canada
(Simon Pellerin
Stéphane Laroche,
Josée Morneau,
Monique Tanguay)

Average Ob Impact per data: Southern Hemisphere

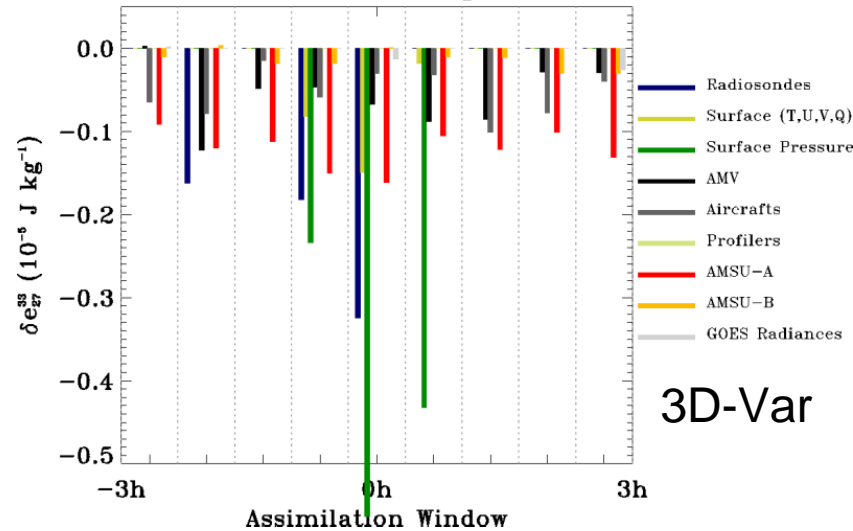
Mean OI per data – August 2004
Southern Hemisphere



Mean OI per data – August 2004
Southern Hemisphere



Mean OI per data – August 2004
Southern Hemisphere



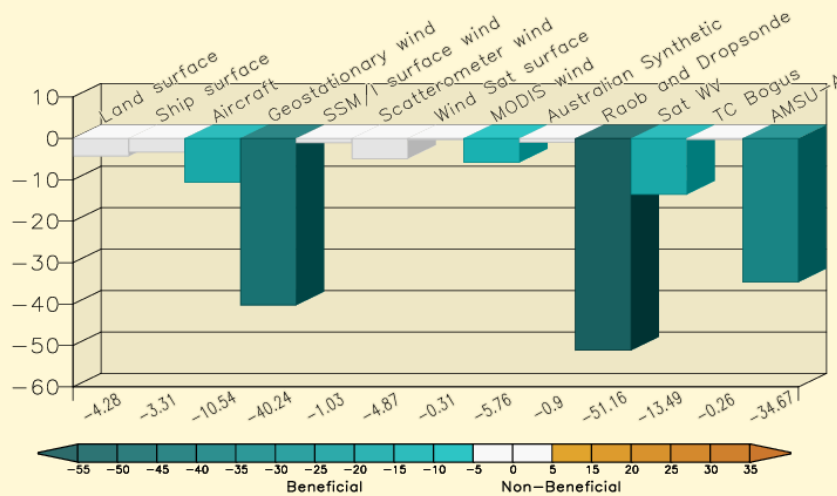
Environment
Canada
(Simon Pellerin
Stéphane Laroche,
Josée Morneau,
Monique Tanguay)



Assessing the Impact of 00UTC Observations for NAVDAS-NOGAPS

Impact Sum by Instrument Type

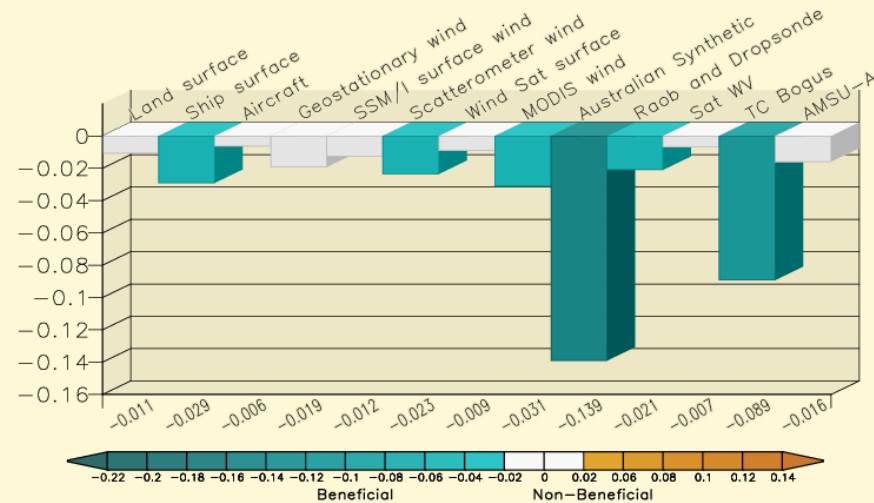
Impact of 00UTC observations on 24h global forecast error – moist total energy norm ($J\ kg^{-1}$)
30-days ending 22 Jul 2007



Total impact as a function of observing platform

Impact*1000 / Ob by Instrument Type

Impact of 00UTC observations on 24h global forecast error – moist total energy norm ($J\ kg^{-1}$)
30-days ending 22 Jul 2007



Total impact per observation

- Observation impact is routinely generated once per day at 00 UTC
 - Operational analyses and innovation vectors from NAVDAS / NOGAPS are used



Summary – Future Work

- Continue monitoring of observation impact in regular operational and beta assimilation
 - Identify problems with current observations
 - Identify problems with the assimilation system
 - AIRS and IASI channel selection
- Inter-comparison study: NAVDAS-GEOS5-Canadian observation impact



The End !





Selected References

- Baker, N.L., 2000: Observation adjoint sensitivity and the adaptive observation-targeting problem. Ph.D. dissertation, Naval Postgraduate School, 265 pp. [Available from the Naval Research Laboratory, Monterey, CA 93943.]
- Baker, N.L. and R. Daley, 2000: Observation and background adjoint sensitivity in the adaptive observation-targeting problem. *Q. J. R. Meteorol. Soc.*, **126**, 1431-1454.
- Bergot, T and A. Doerenbecher, 2002: A study of the optimization of the deployment of target observations using adjoint-based Methods. *Q.J.R. Meteorol. Soc.*, **128**, 1689-1712.
- Cardinali, C., 2004: Influence-matrix diagnostic of a data assimilation system. *Q. J. R. Meteor. Soc.*, **130**, 2767-2786.
- Doerenbecher, A. and T. Bergot, 2001: Sensitivity to observations applied to FASTEX cases. *Nonlinear. Proc. Geophys.*, **8**, 467-481.
- Errico, R., 2007: Interpretation of ad adjoint-derived observational impact measure. *Tellus*, in press.
- Fourrié, N.A., A. Doerenbecher, T. Bergot, and A. Joly, 2002: Adjoint sensitivity of the forecast to TOVS observations. *Q.J.R. Meteor. Soc.*, **128**, 2759-2777.
- Fourrié, N.A, and F. Rabier, 2004: Cloud characteristics and channel selection for IASI radiances in meteorologically sensitive areas. *Q. J. R. Meteor. Soc.*, **130**, 1839-1856.
- Gelaro, R., Y. Zhu and R. Errico, 2007: Examination of various-order adjoint-based approximations of observation impact. Submitted to *Meteorologische Zeitschrift*.
- Langland, R.H. and N.L. Baker, 2004: Estimation of observation impact using the NRL atmospheric variational data assimilation adjoint system. *Tellus*, 56A, 189-201.
- Ruston, B., C. Blankenship, W. Campbell, R. Langland and N. Baker, 2006: Assimilation of AIRS data at NRL. *15th International TOVS Study Conference*, Maratea, IT, 4-10 Oct., 2006.
- Xu, L., R. Langland, N. Baker and T. Rosmond, 2006: Development of the NRL 4D-Var data assimilation adjoint system. Operational Numerical Weather Prediction and Data Assimilation, European Geosciences Union, General Assembly 2006, Vienna, Austria, 02 – 07 April 2006.
- Zhu, Y. and R. Gelaro, 2007: Observation sensitivity calculations using the adjoint of the Gridpoint Statistical Interpolation (GSI) analysis system. *Accepted for publication in Monthly Weather Review*.