



Forecast Sensitivity to Observations & Observation Impact

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WRFDA Tutorial – July 20-22 2011

- Introduction
- Implementation in WRF
- Applications
- Limitations
- Conclusions

Outline

➤ Introduction

➤ Implementation in WRF

➤ Applications

➤ Limitations

➤ Conclusions

Introduction

➤ What?

➤ Why?

➤ Who?

➤ How?

➤ How much?



Introduction

- What?
 - *A posteriori*, it is possible to evaluate the accuracy of NWP forecasts.
- Why?
 - Using an adjoint technique, we can trace it back to the observations used in the analysis.
- Who?
 - We can determine quantitatively which observations improved 😊 or degraded 😞 the forecast.
- How?
 - Forecast Sensitivity to Observations (FSO) is a diagnostic tool that complements traditional denial experiments (OSEs).
- How much?

Introduction

➤ What?

- Impact of each observation calculated simultaneously (less tedious than OSEs).

➤ Why?

- NWP centers use FSO routinely to monitor their Data Assimilation and Global Observing System

➤ Who?

- Can be used to tune Quality Control, Bias Correction, etc.

➤ How?

- Helps assess the impact of specific sensors for data providers.

➤ How much?

Introduction

➤ What?

- Naval Research Laboratory (Monterey, CA)

➤ Why?

- NASA/GMAO (Washington, DC)

- ECMWF (Reading, UK)

➤ Who?

- Environment Canada (Montreal, Canada)

➤ How?

- Meteo-France (Toulouse, France)

➤ How much?

- NCAR/MMM (Boulder, CO)

Introduction

➤ What?

➤ Why?

➤ Who?

➤ How?

➤ How much?

- Non-Linear (NL) forecast models can be linearized (with simplifications).
- The resulting **Tangent-Linear** (TL) represents the linear evolution of small **perturbations**.
- The mathematical transpose of the TL code is called the Adjoint (ADJ) and it transports **sensitivities** back in time.
- The ADJ of the Data Assimilation system is needed to compute the sensitivity to observations. It can be computed with various methods:
 - Ensemble (ETKF, Bishop *et al.* 2001)
 - Dual approach (PSAS, Baker and Daley 2000, Pellerin *et al.* 2007)
 - Exact ADJ calculation (Zhu and Gelaro 2007)
 - Hessian approximation (Cardinali 2006)
 - Lanczos minimization (Fisher 1997, Tremolet 2008)

Introduction

➤ What?

➤ Why?

➤ Who?

➤ How?

➤ How much?

- 2 runs of non-linear forecast model
- 2 runs of adjoint model
- 1 run of adjoint of analysis
- The computer cost is estimated to 10-15 times the cost of the forecast model.

➤ Introduction

➤ Implementation in WRF

➤ Applications

➤ Limitations

➤ Conclusions

Implementation in WRF

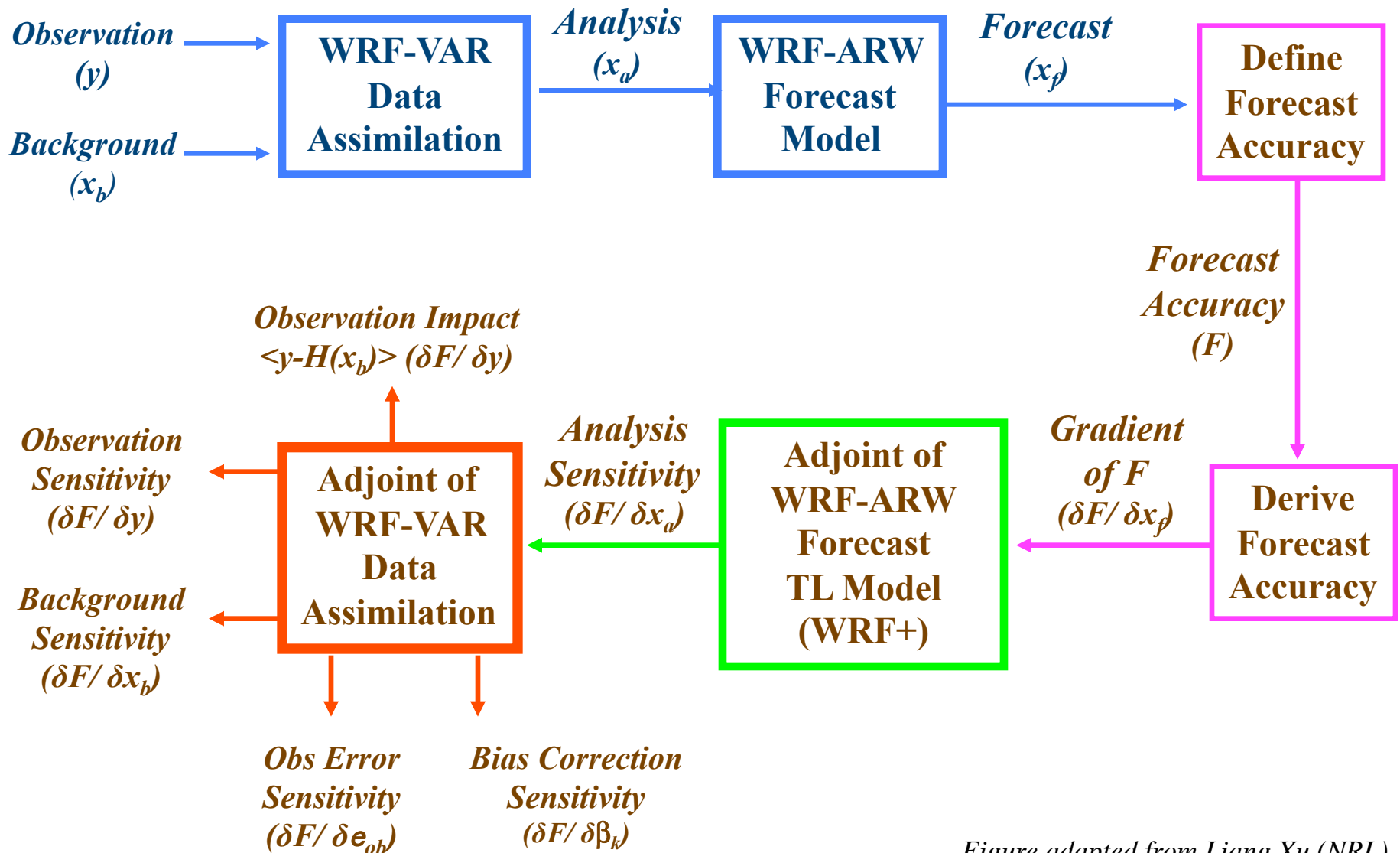
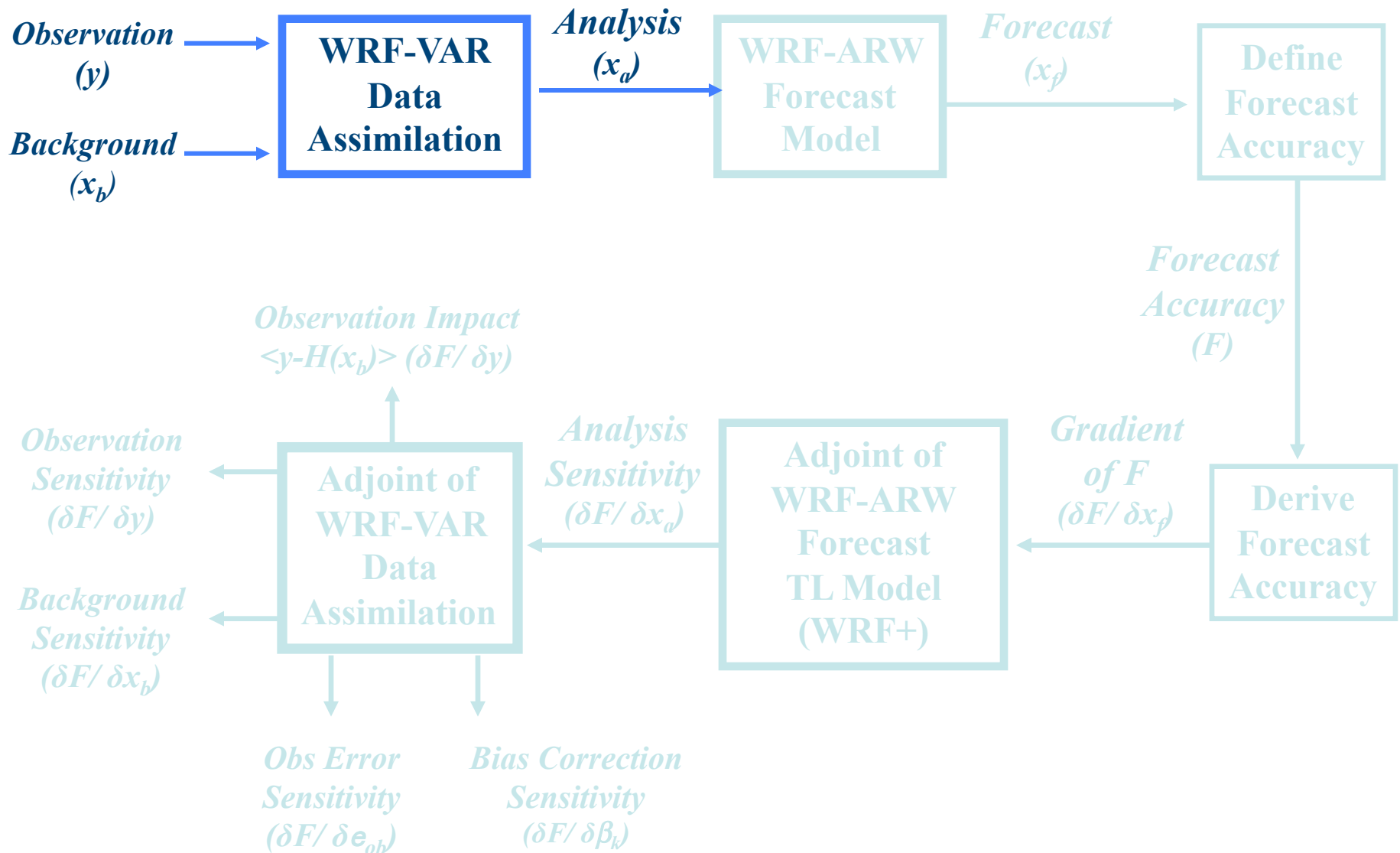
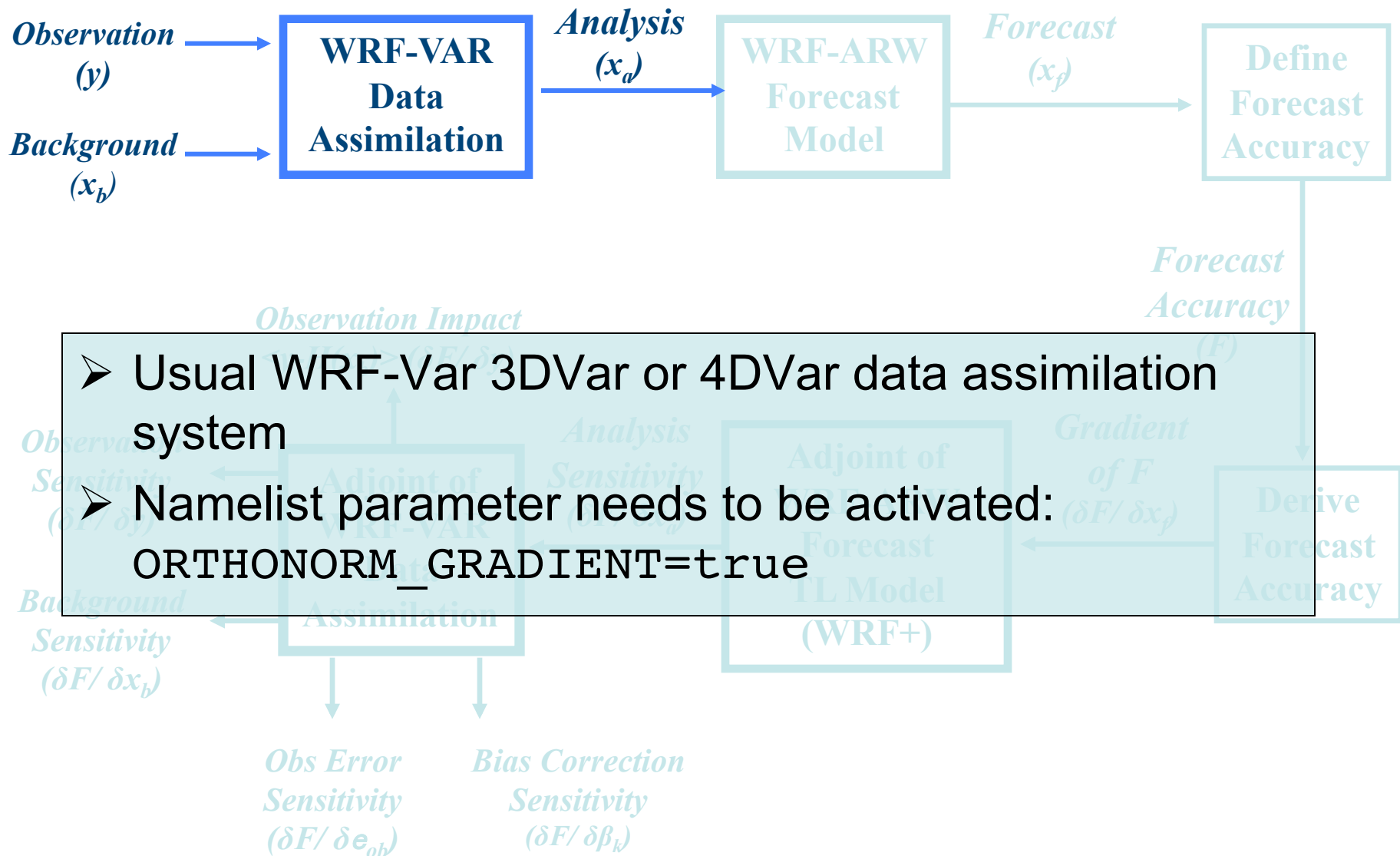


Figure adapted from Liang Xu (NRL)

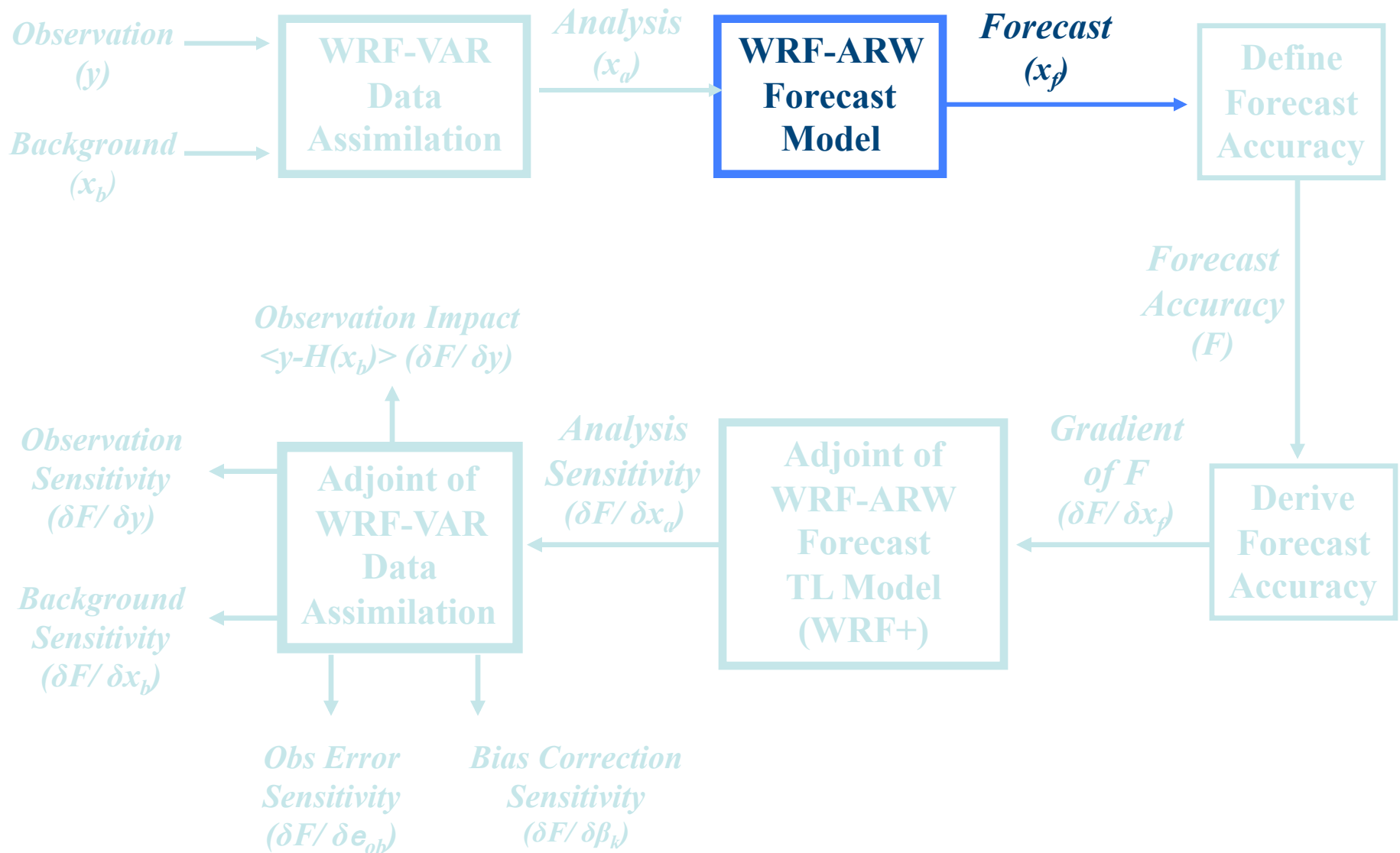
Implementation in WRF



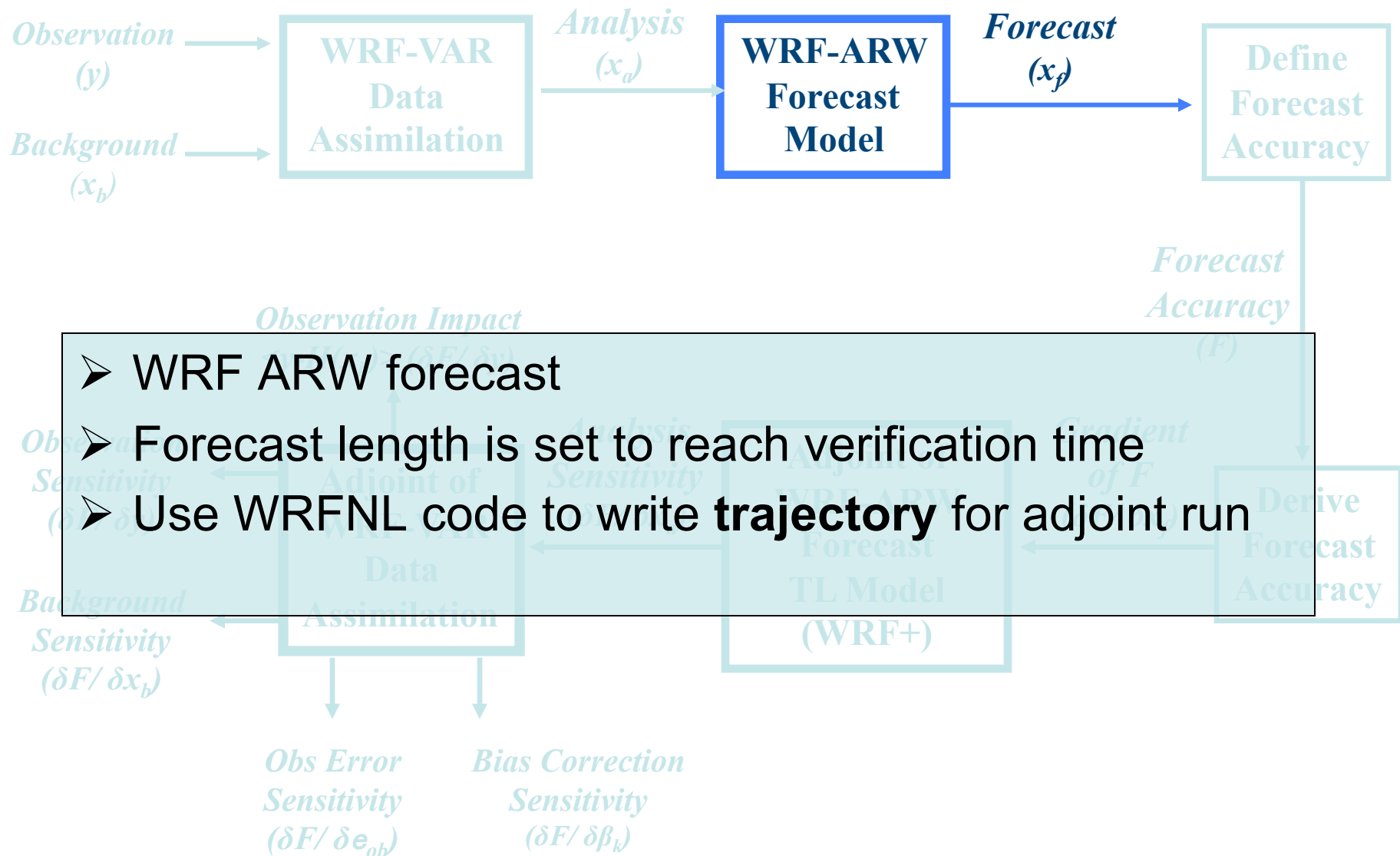
Implementation in WRF



Implementation in WRF

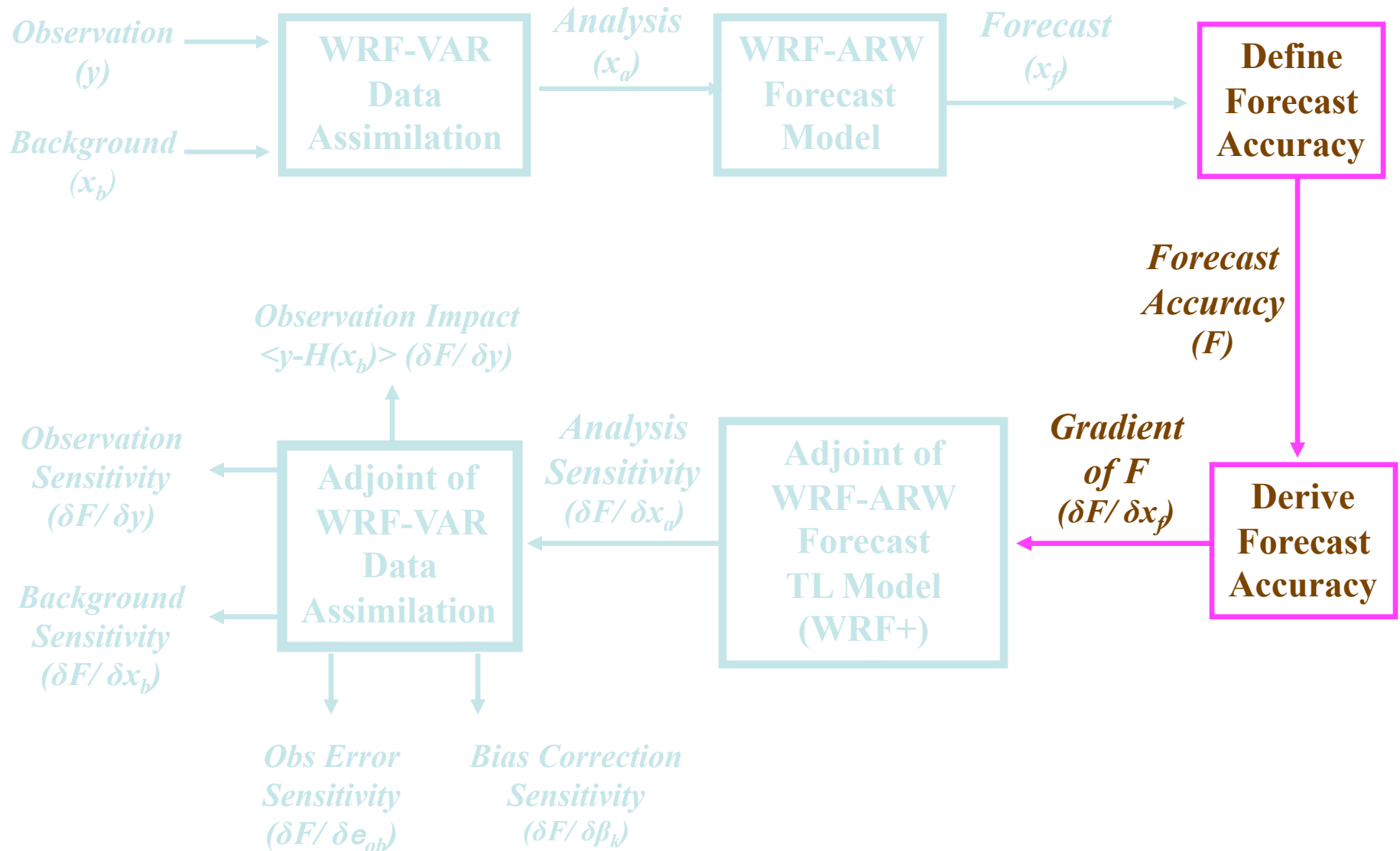


Implementation in WRF



- WRF ARW forecast
- Forecast length is set to reach verification time
- Use WRFNL code to write **trajectory** for adjoint run

Implementation in WRF



Implementation in WRF

➤ **Reference state:** Namelist ADJ_REF is defined as

- 1: X^t = Own (WRFVar) analysis
- 2: X^t = NCEP (global GSI) analysis
- 3: X^t = Observations

➤ **Forecast Aspect:** depends on reference state

- 1 and 2: Total Dry Energy

$$\langle \mathbf{x}, \mathbf{x} \rangle = \frac{1}{2} \iiint_{\Sigma} [u'^2 + v'^2 + \left(\frac{g}{N\bar{\theta}} \right)^2 \theta'^2 + \left(\frac{1}{\bar{\rho}c_s} \right)^2 p'^2] d\Sigma$$

- 3: WRFVar Observation Cost Function: J_o

➤ **Geo. projection:** Script option for box (default = whole domain)
ADJ_ISTART, ADJ_IEND, ADJ_JSTART, ADJ_END,
ADJ_KSTART, ADJ_KEND

➤ **Forecast Accuracy Norm:** $\mathbf{e} = (\mathbf{x}^f - \mathbf{x}^t)^T \mathbf{C} (\mathbf{x}^f - \mathbf{x}^t)$

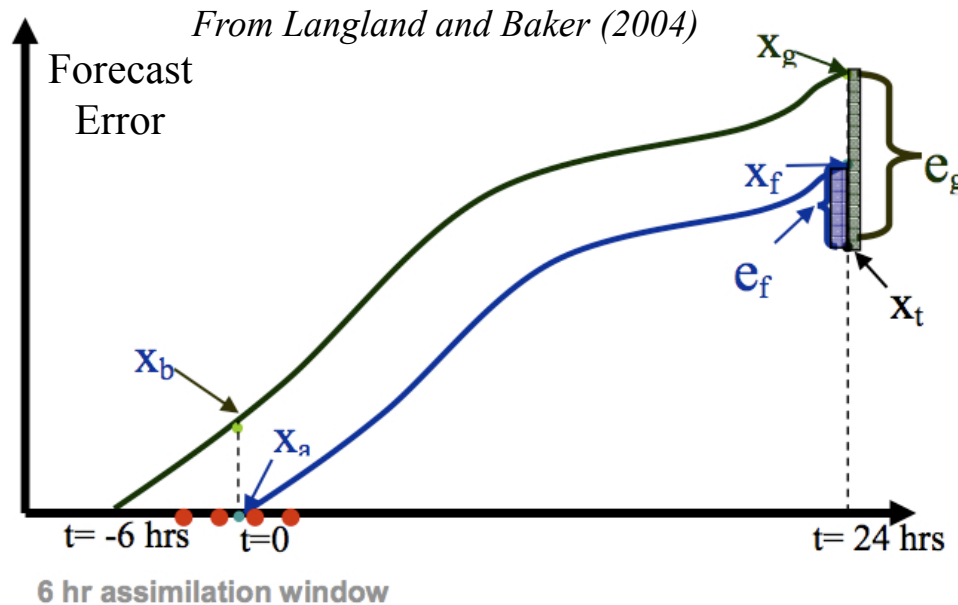
**Define
Forecast
Accuracy**

*Forecast
Accuracy
(F)*

*Gradient
of F
($\delta F / \delta x_p$)*

**Derive
Forecast
Accuracy**

Implementation in WRF



x^t is the true state, estimated by the analysis at the time of the forecast

x^f is the forecast from analysis x^a

x^g is the forecast from first-guess at the time of the analysis x^a

Impact of analysis: $F = De^{f,g} = e^f - e^g$

Products: $\delta F / \delta x_a^f = C(x_a^f - x^t)$
 $\delta F / \delta x_b^f = C(x_b^f - x^t)$

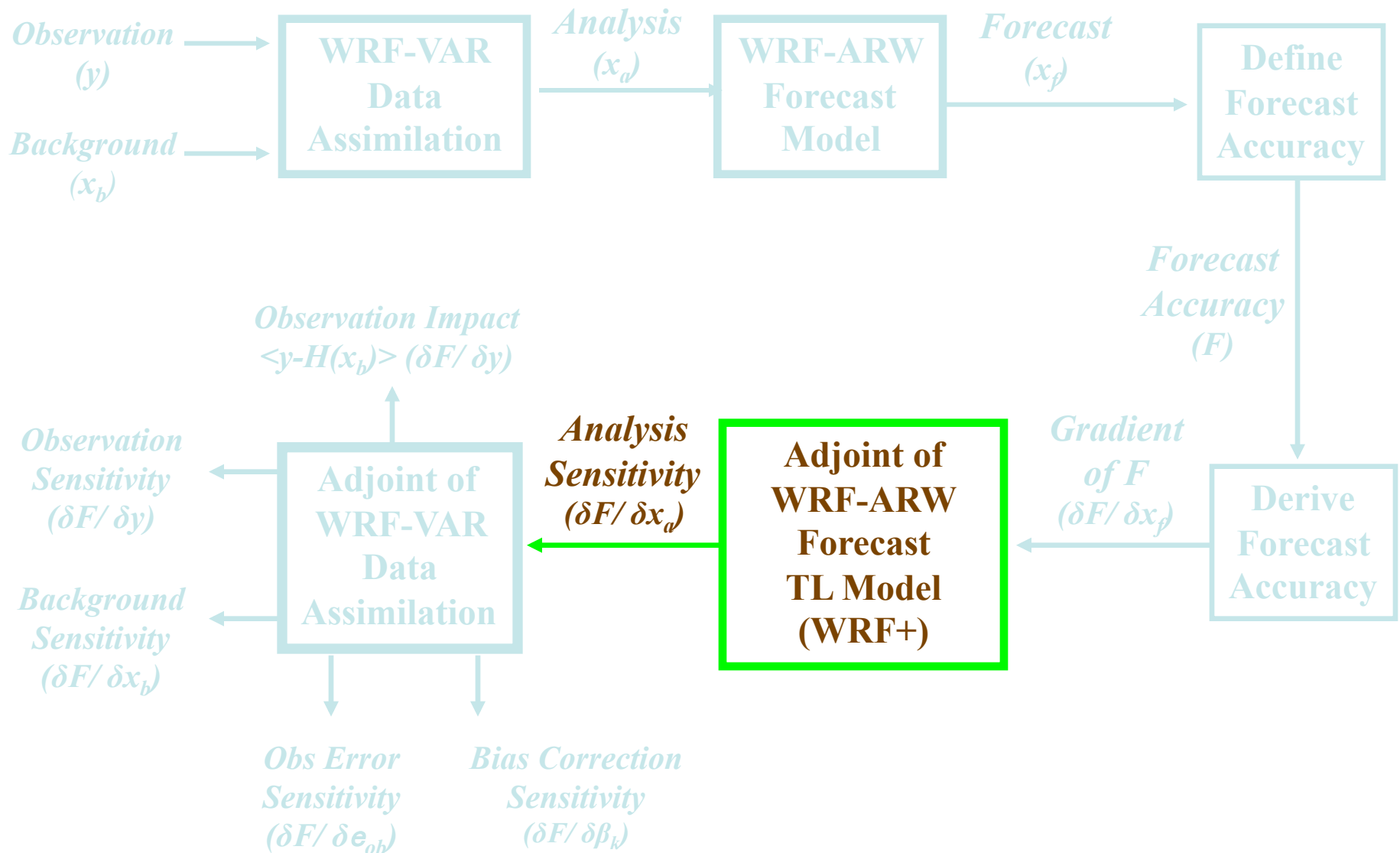
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Implementation in WRF



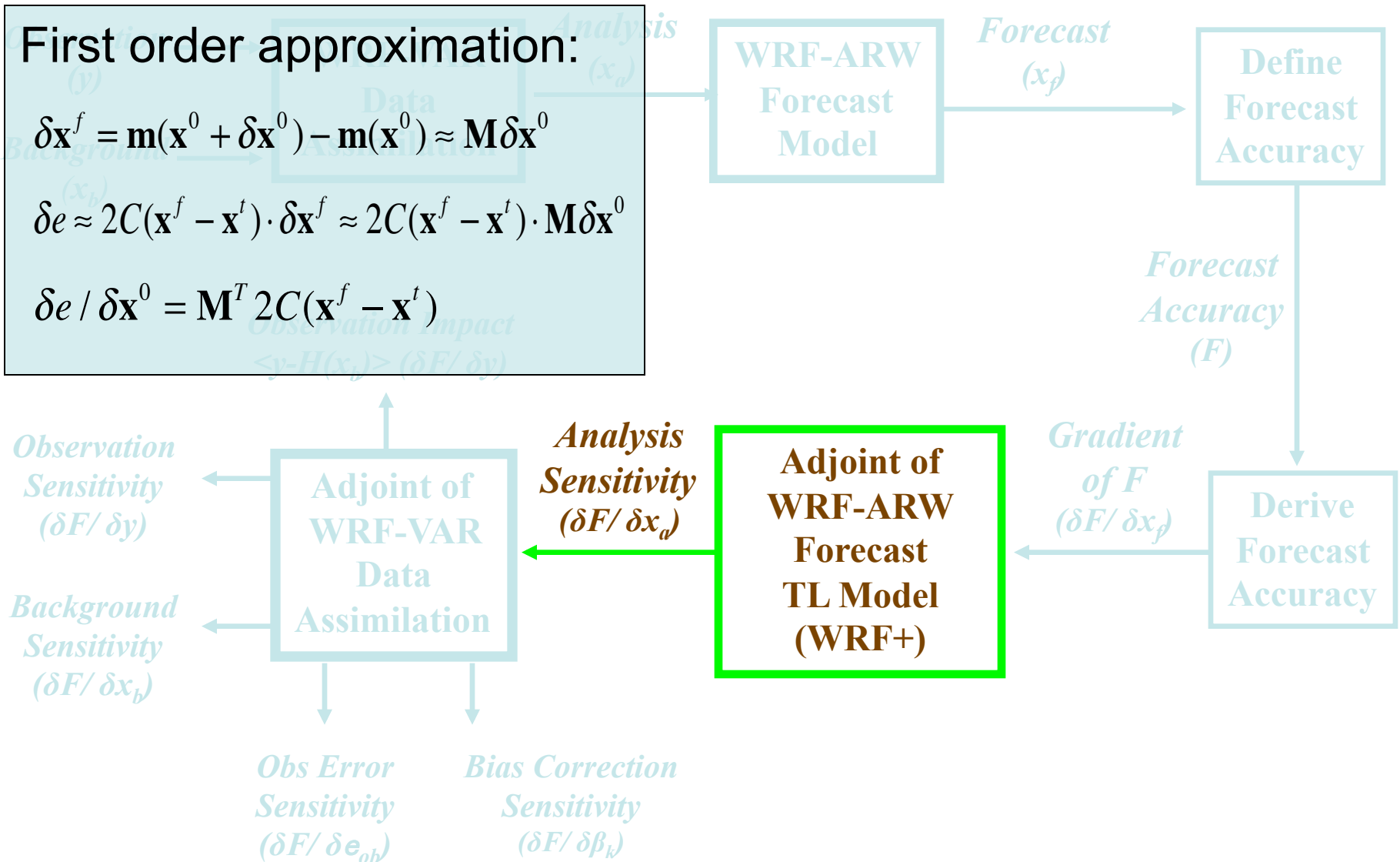
Implementation in WRF

First order approximation:

$$\delta \mathbf{x}^f = \mathbf{m}(\mathbf{x}^0 + \delta \mathbf{x}^0) - \mathbf{m}(\mathbf{x}^0) \approx \mathbf{M} \delta \mathbf{x}^0$$

$$\delta e \approx 2C(\mathbf{x}^f - \mathbf{x}^t) \cdot \delta \mathbf{x}^f \approx 2C(\mathbf{x}^f - \mathbf{x}^t) \cdot \mathbf{M} \delta \mathbf{x}^0$$

$$\delta e / \delta \mathbf{x}^0 = \mathbf{M}^T 2C(\mathbf{x}^f - \mathbf{x}^t)$$



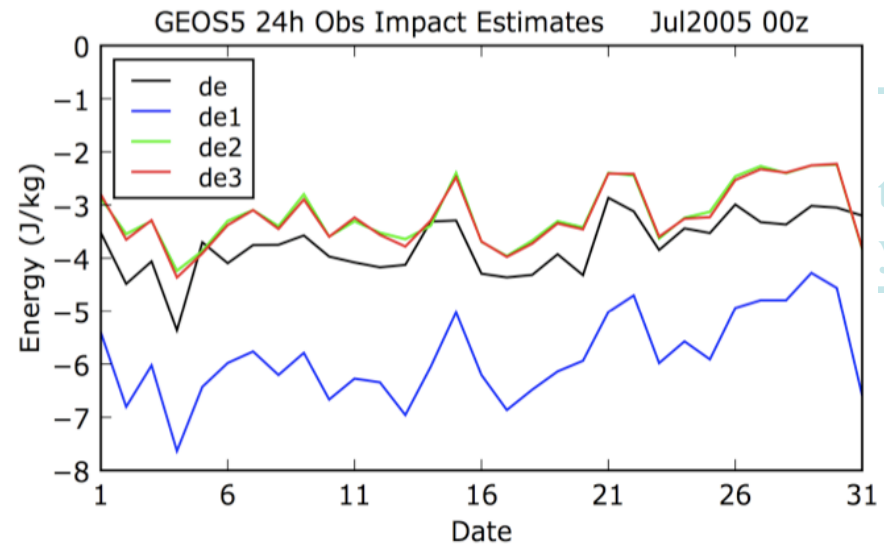
Implementation in WRF

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Gelaro et al. (2007)

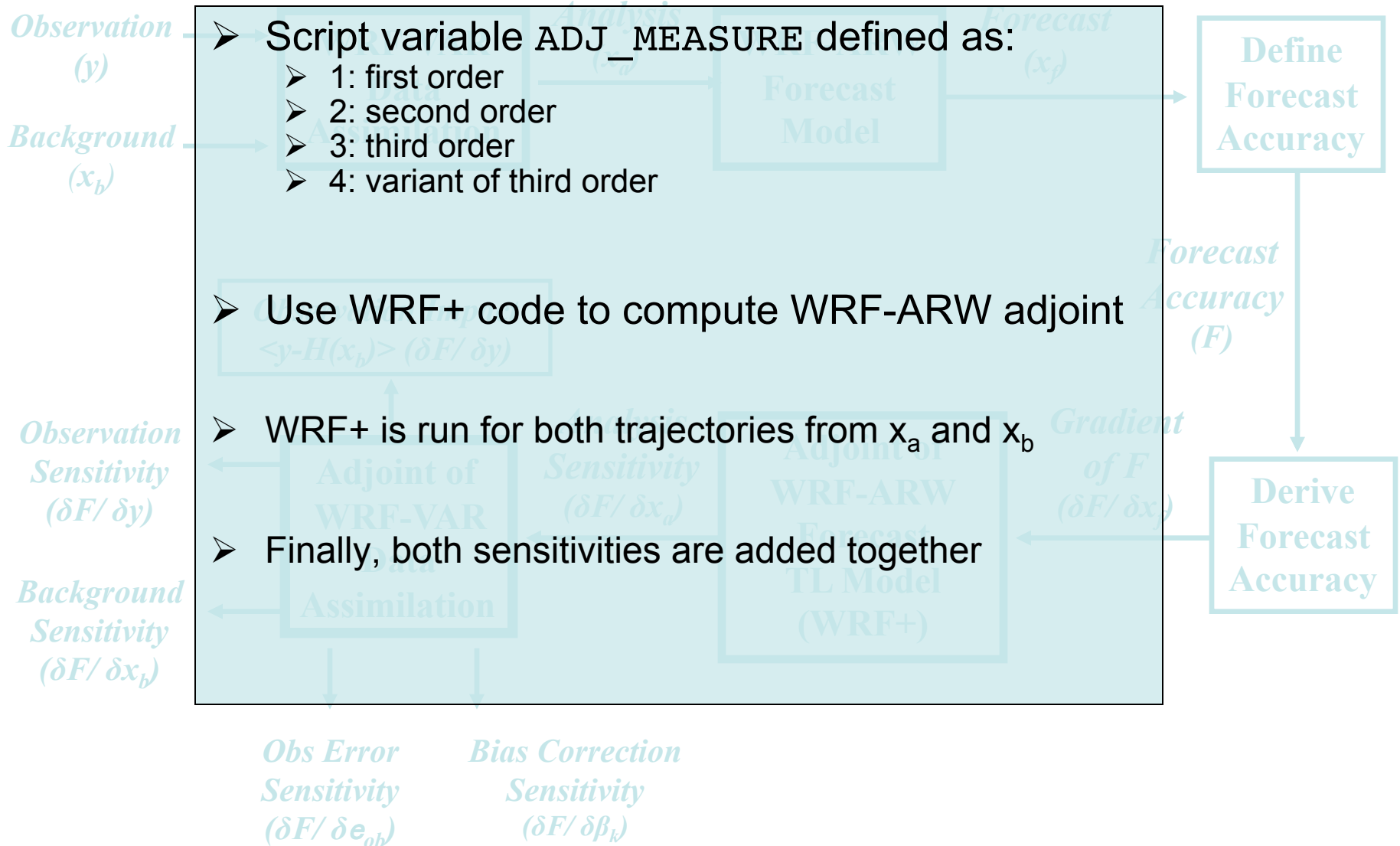
Relative error in WRF (linear vs. non-linear propagation of perturbation)

$$\delta e_1 = 2(\mathbf{x}_a - \mathbf{x}_b)^T \mathbf{M}_b^T C(\mathbf{x}_a^f - \mathbf{x}^t) \quad \text{-----} \rightarrow 62.25\%$$

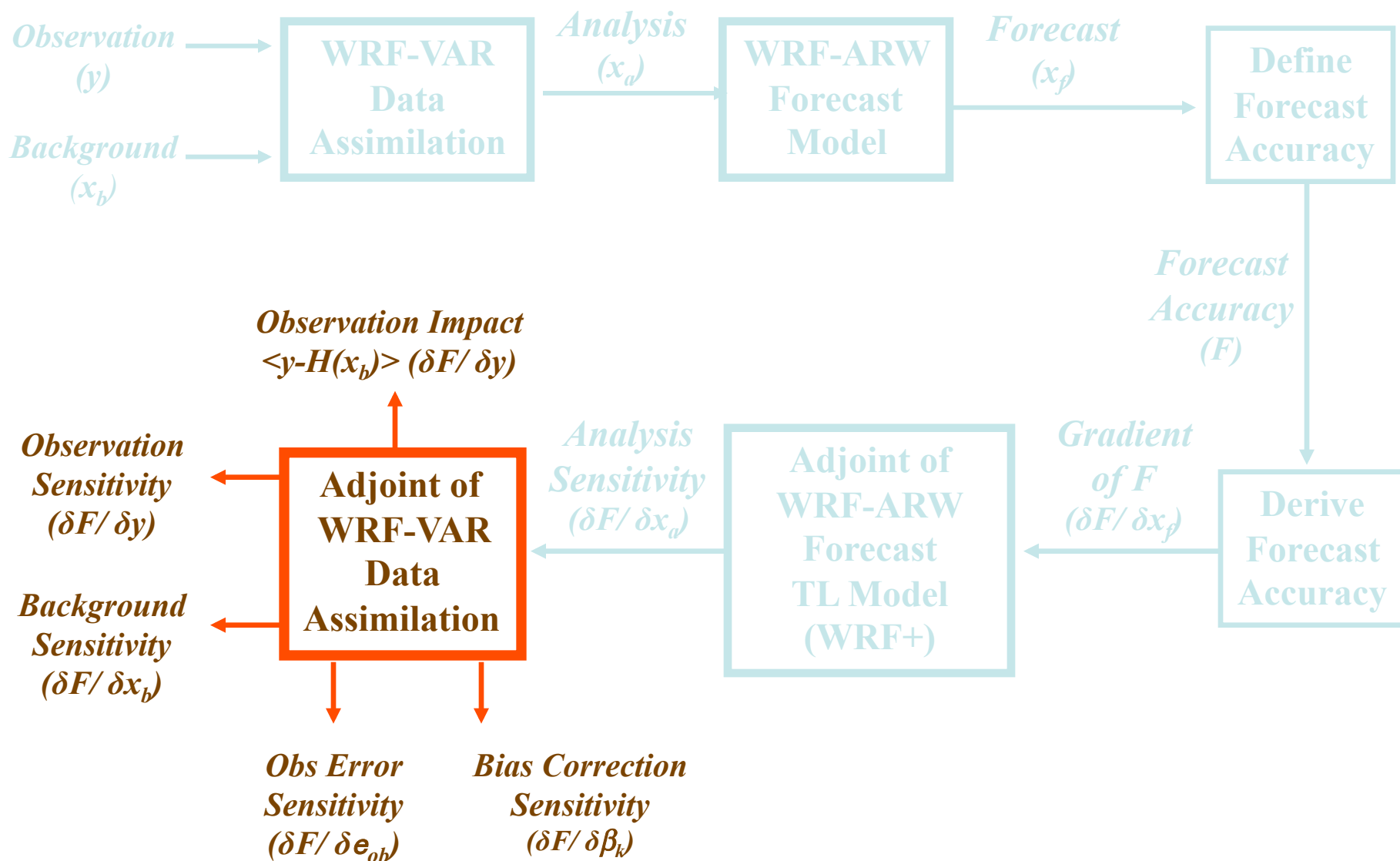
$$\delta e_2 = (\mathbf{x}_a - \mathbf{x}_b)^T [\mathbf{M}_b^T C(\mathbf{x}_a^f - \mathbf{x}^t) + \mathbf{M}_a^T C(\mathbf{x}_b^f - \mathbf{x}^t)] \quad \text{-----} \rightarrow 19.68\%$$

$$\delta e_3 = (\mathbf{x}_a - \mathbf{x}_b)^T [\mathbf{M}_b^T C(\mathbf{x}_b^f - \mathbf{x}^t) + \mathbf{M}_a^T C(\mathbf{x}_a^f - \mathbf{x}^t)] \quad \text{-----} \rightarrow 11.45\%$$

Results are consistent with Gelaro et al. (2007)

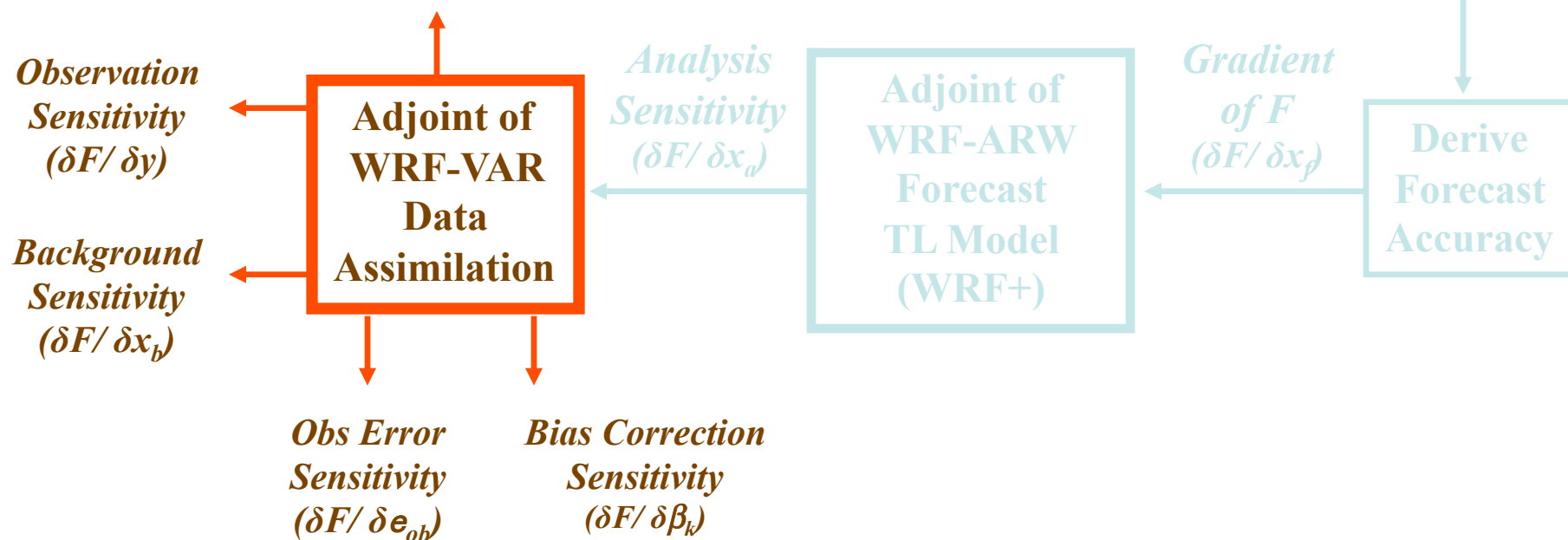


Implementation in WRF



Implementation in WRF

- Analysis increments: $\delta x = x_a - x_b = \mathbf{K} [y - H(x_b)] = \mathbf{K} d$
- Sensitivity of analysis to observations: $\delta x_a / \delta y = \mathbf{K}^T$
- Adjoint of the variational analysis: $\delta F / \delta y = \mathbf{K}^T \delta F / \delta x_a$
- New minimization package, activated with Namelist `USE_LANCZOS=true`



Implementation in WRF

- Analysis increments: $\delta x = x_a - x_b = \mathbf{K} [y - H(x_b)] = \mathbf{K} d$
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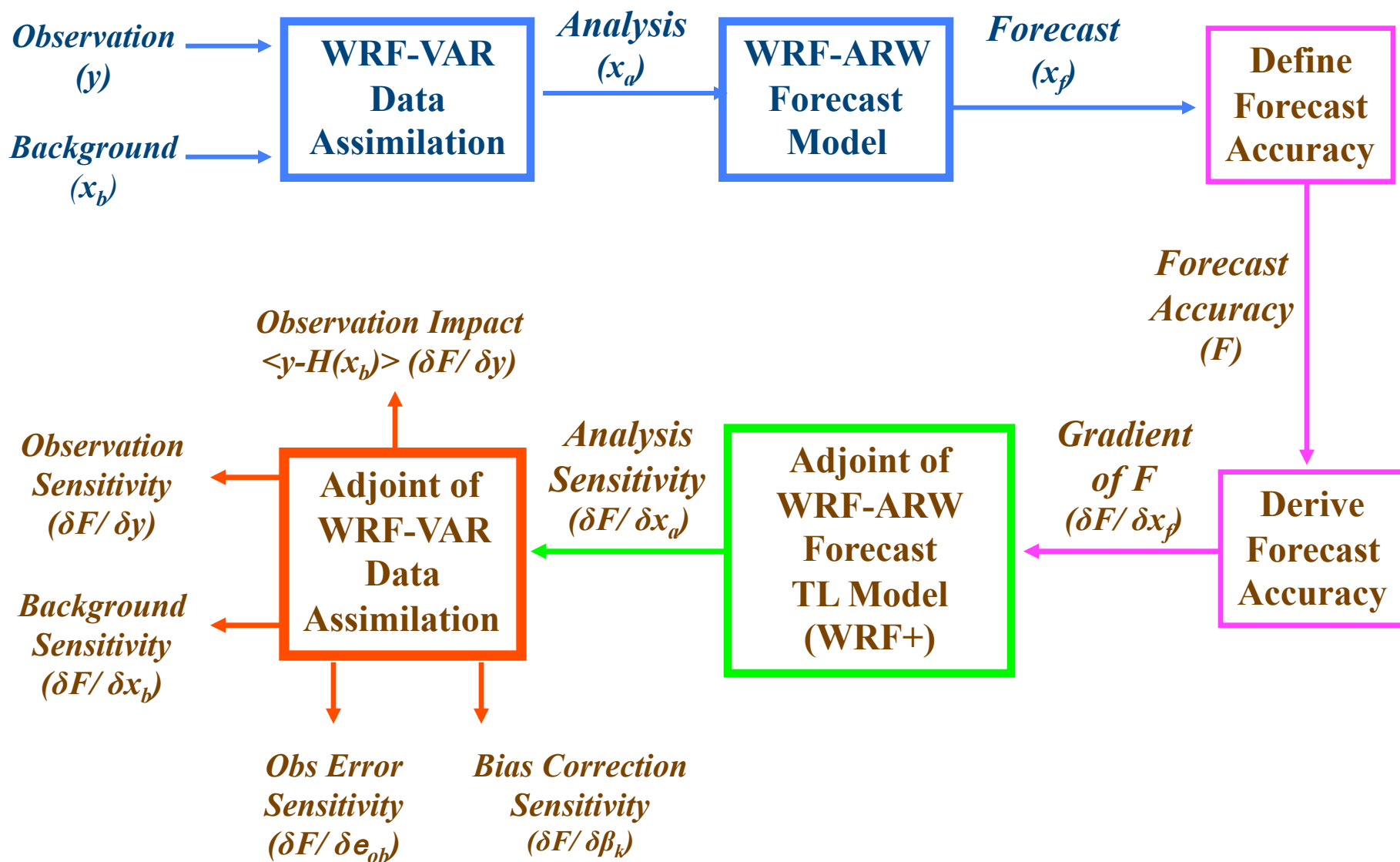
- Cost Function and Gradient are IDENTICAL to Conjugate Gradient
- Lanczos estimates the Hessian = Inverse of Analysis error $\mathbf{A}^{-1}$

➤ $\mathbf{K}^T = \mathbf{R}^{-1} \mathbf{H} \mathbf{A}^{-1}$

- We calculate the **EXACT** adjoint of analysis gain: $\mathbf{K}^T$

$\langle \delta x, \delta x \rangle = \langle \delta x, \mathbf{K} d \rangle$ compared to $\langle \mathbf{K}^T \delta x, d \rangle \rightarrow 10^{-13}$ relative error

Implementation in WRF



- Scripts:
- **Analysis Experiment**
 - WRF-Var with Namelist ORTHONORM_GRADIENT=true
 - **Trajectories**
 - WRFNL from X_a and from X_b
 - **Forecast Accuracy**
 - ADJ_REF to choose reference for forecast accuracy
 - ADJ_ISTART, ADJ_IEND, *etc* to define a box
 - **Adjoint of Model**
 - ADJ_MEASURE to select order of Taylor expansion
 - WRF+ (Adjoint mode)
 - **Adjoint of Analysis**
 - RUN_OBS_IMPACT=true launches WRF-Var with Lanczos

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➤ **Applications**

➤ Limitations

➤ Conclusions

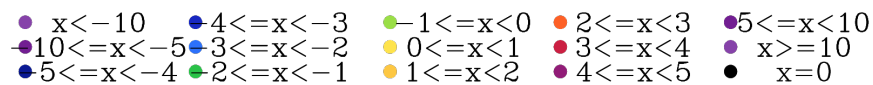
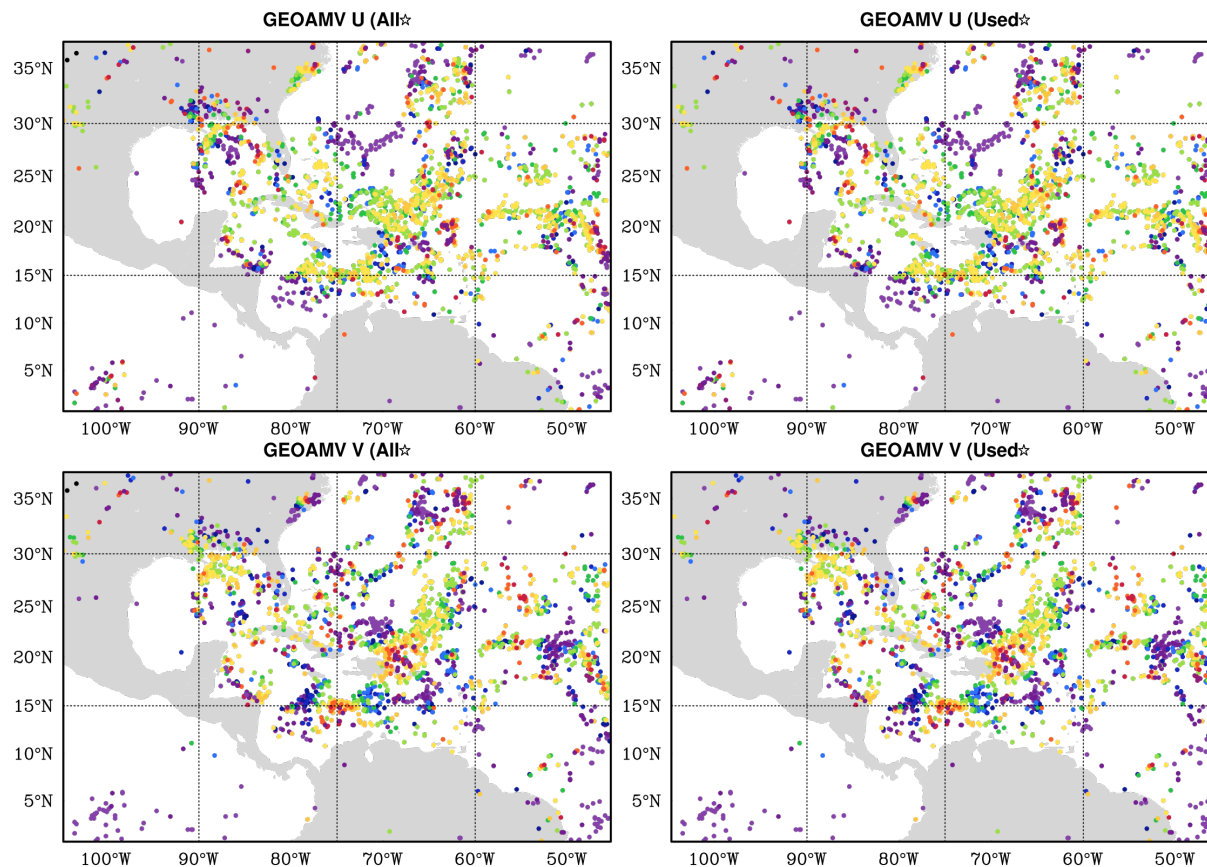


One-month 6-hr cycling experiment (20070815 – 20070915)

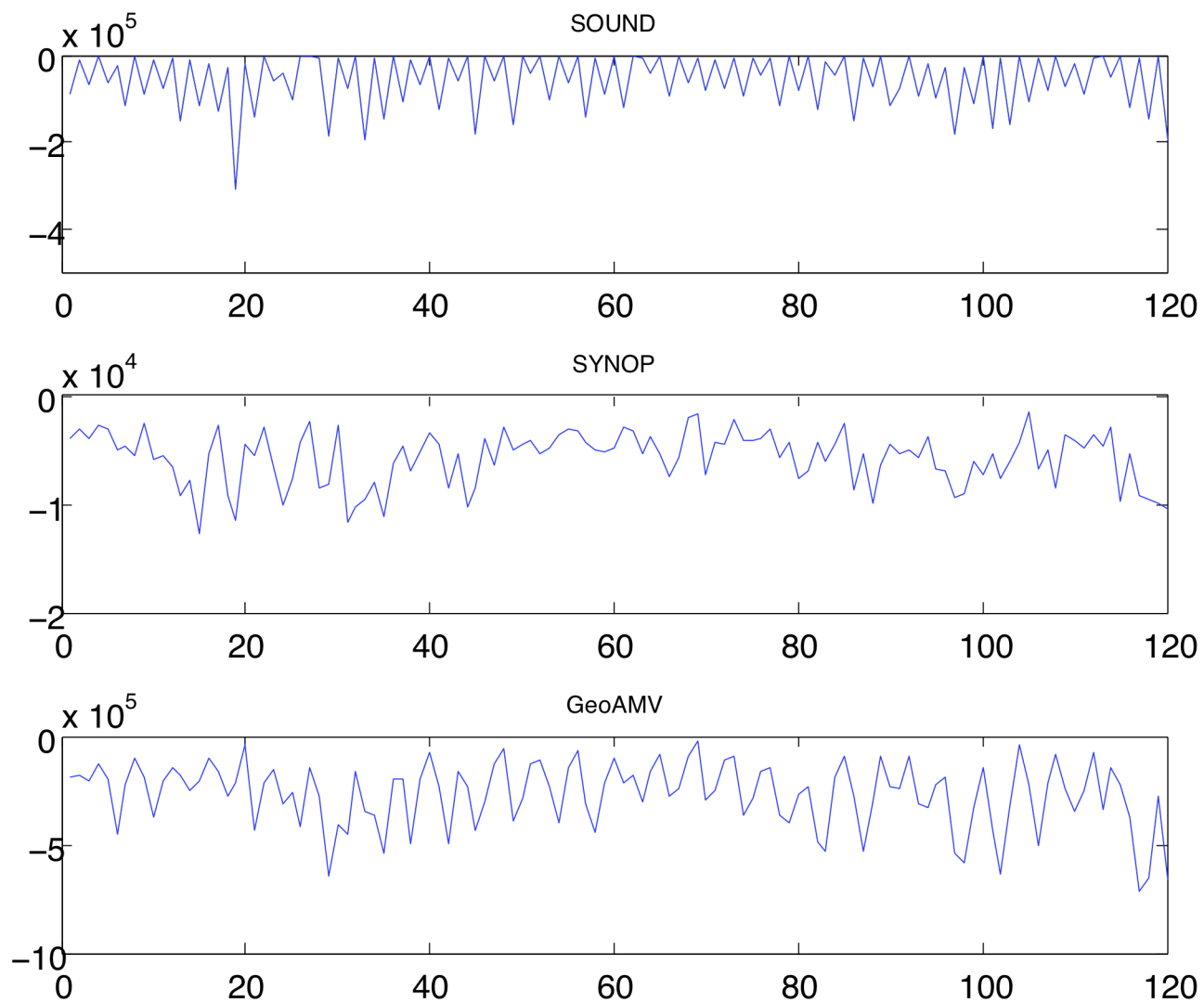
Impact evaluated for 6hr forecast in d02 domain

Applications

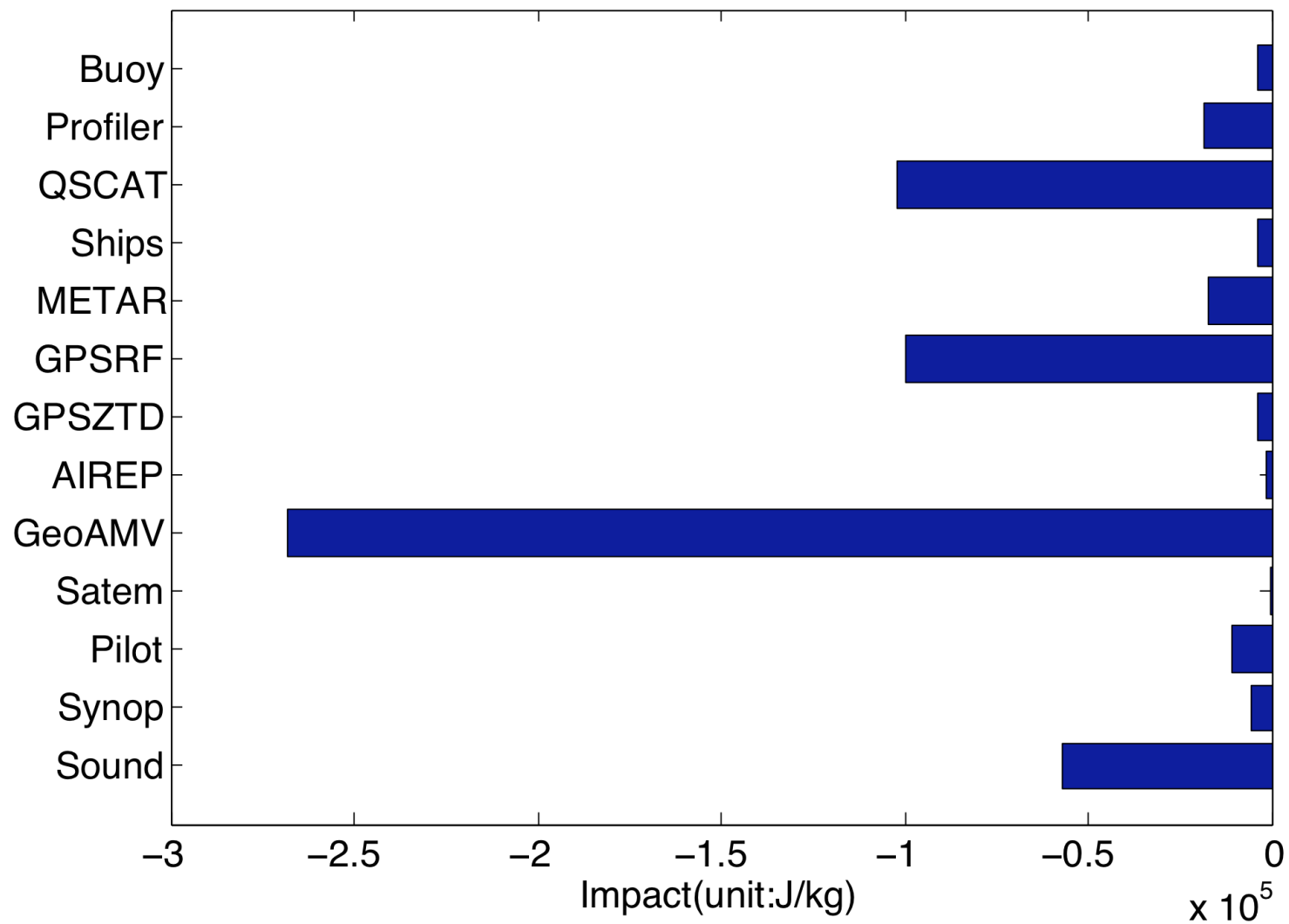
2007081618 GEOAMV 85500 Pa – 84500 Pa



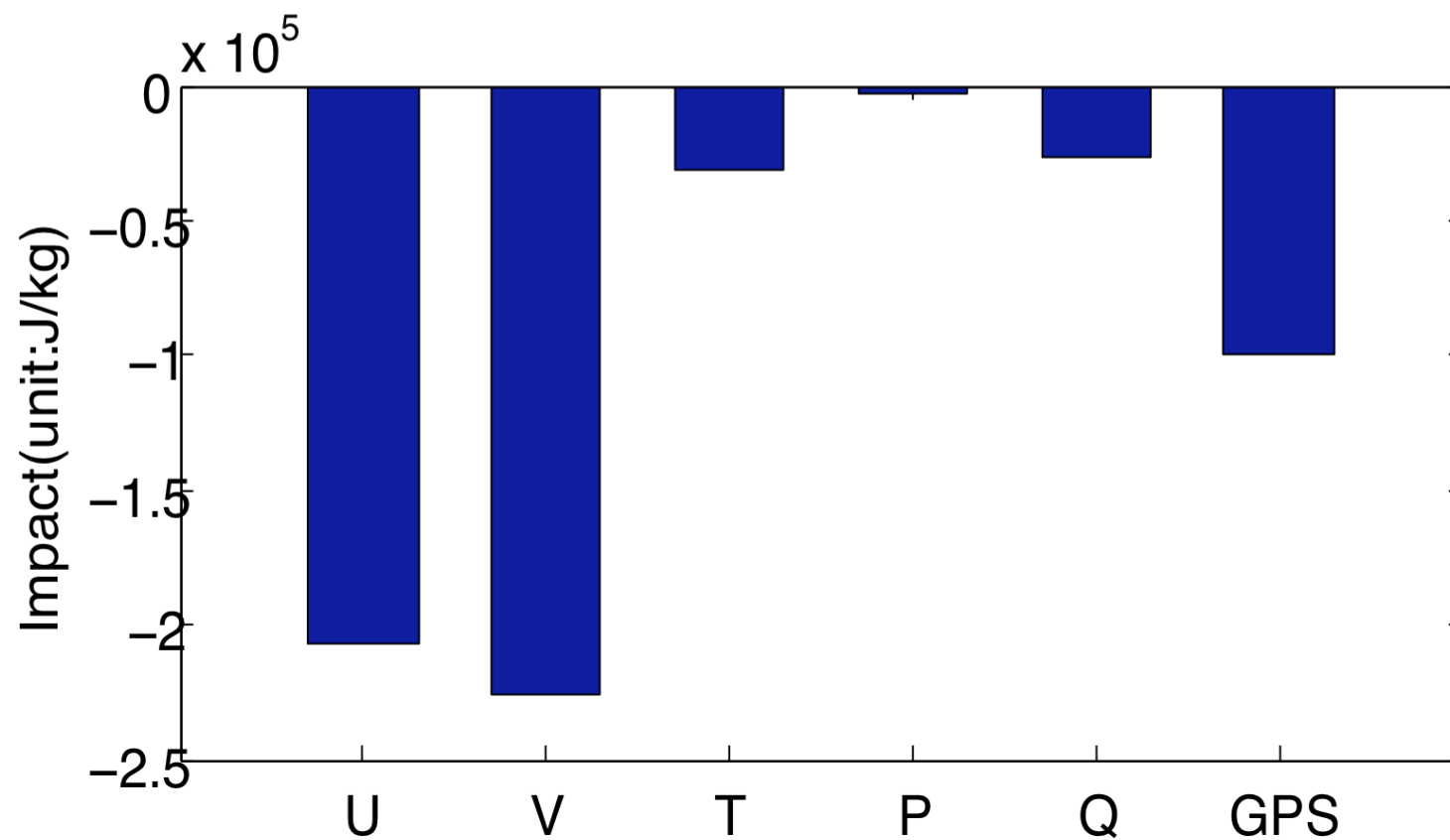
Applications



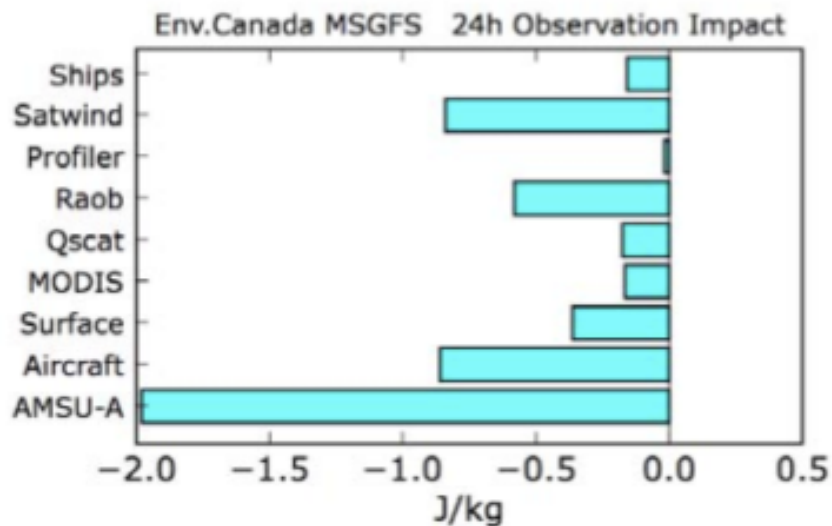
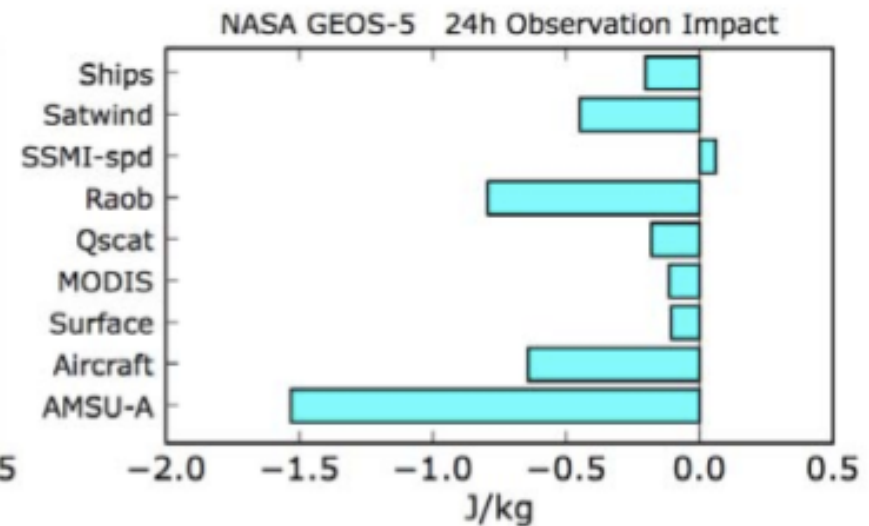
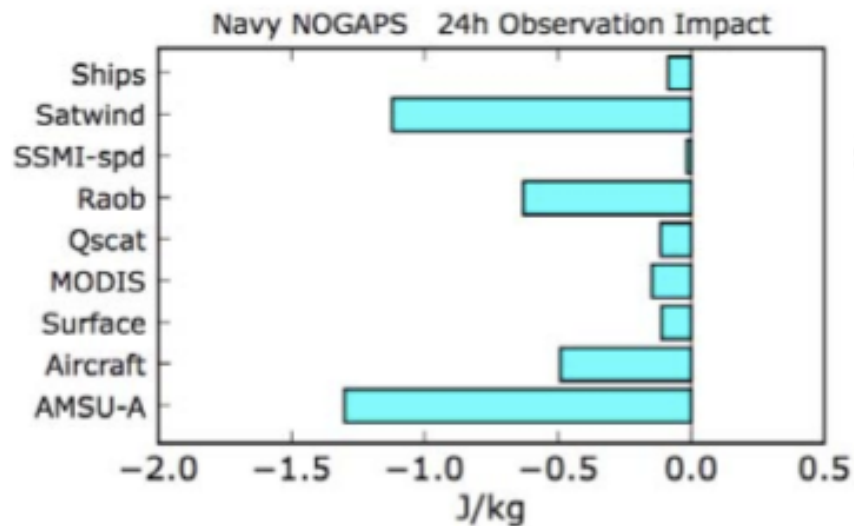
Applications



Applications



Applications



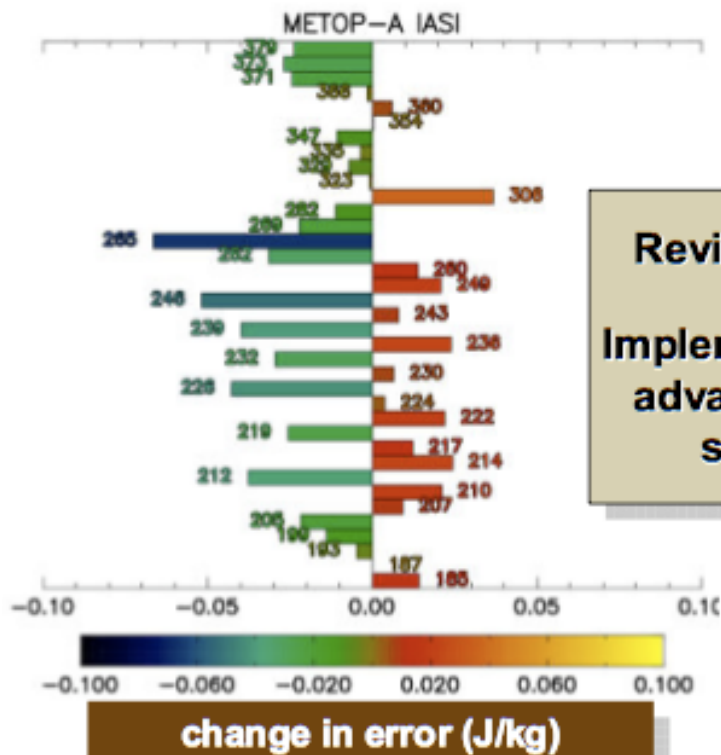
***AMSU-A Observations
Have the Greatest
Benefit at all Three
Centers.***

from Gelaro et al. 2009

Applications

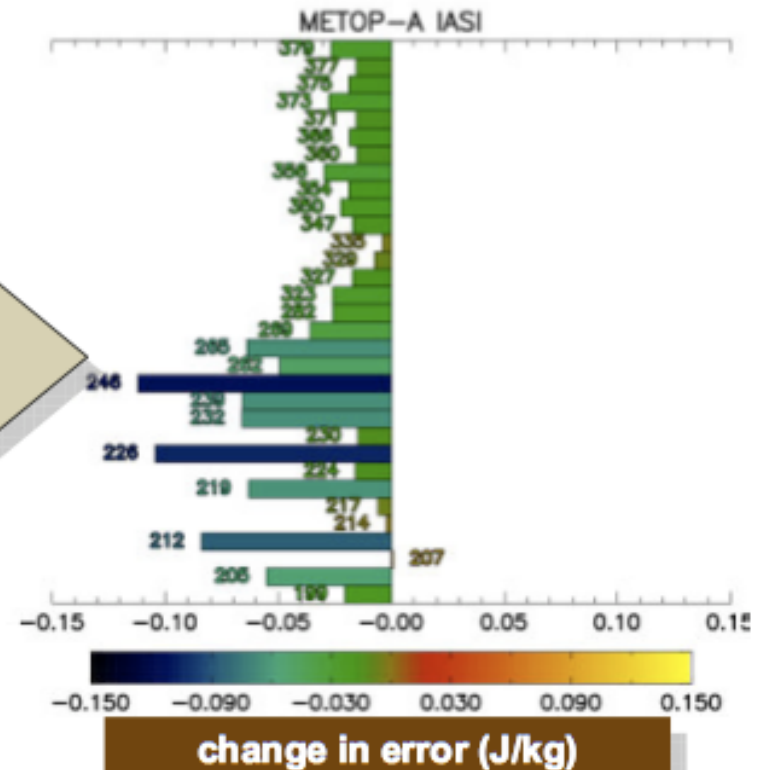
NAVDAS-AR Results

Aug27-Sep02, 2008



Revise channels
&
Implement ECMWF
advanced cloud
screening

Sep16-Sep22, 2008



from Langland 2009

Applications

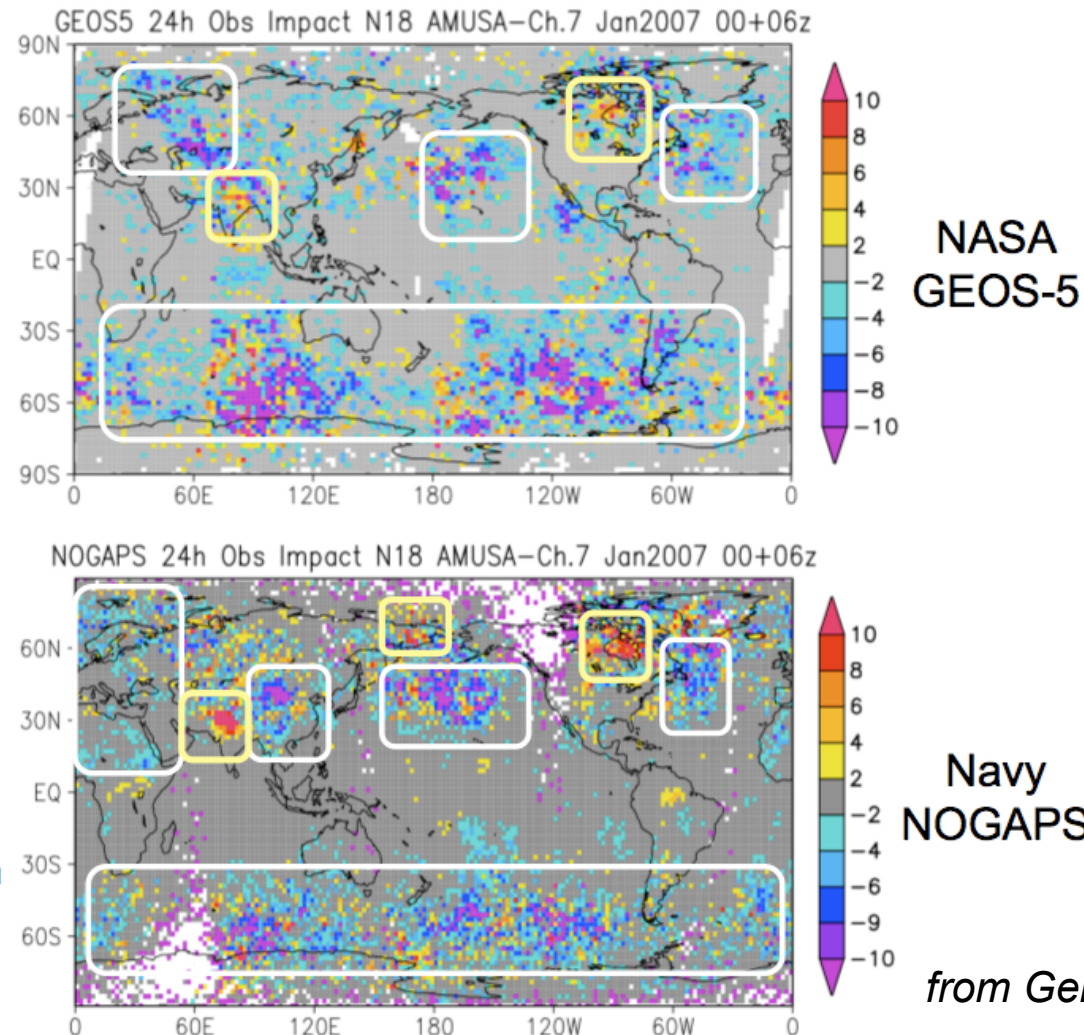
Observation Impacts for NOAA-18 AMSU-A Ch. 7

Observations that
produce large
forecast error
reductions

Observations that
produce forecast
error increases in
both models

Land or ice surface
contamination of
radiance data?

Baseline Intercomparison
Jan 2007 00+06 UTC



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Limitations

- Uncertainties are difficult to estimate
 - The reference for the calculation of forecast accuracy is NOT perfect and often correlated with the initial analysis.
 - The adjoint model is not an accurate representation of the NL model behavior (linearization, simplification, dry physics). Langland (2009) proposes a method to mitigate these errors.
 - For higher than first-order approximation of δe , nonlinear dependence on δy , which complicates the separation of observation impact (Errico 2007). These errors are small for the calculation of average impact (Gelaro et al. 2007).

Limitations

- Results are strongly dependent on the norm chosen to define forecast accuracy.
- The interpretation of information and application is not always straightforward.

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Conclusions

- All code and scripts for FSO are available in current WRF public release
- Testing package & User's Guide available on demand



Due to lack of funding,
no support is to be expected ;-(

- Have fun!