# **ECMWF Data Assimilation**

# Contribution from many people



ECMWF DA System&Observations DA School Buenos Aires 2008



# Fundamental challenges of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance





# **Data assimilation system (4D-Var)**



- The observations are used to correct errors in the short forecast from the previous analysis time.
- Every 12 hours we assimilate 4 8,000,000 observations to correct the 100,000,000 variables that define the model's virtual atmosphere.
- This is done by a careful 4-dimensional interpolation in space and time of the available observations; this operation takes as much computer power as the 10-day forecast.



# **A few 4D-Var Characteristics**

All observations within a 12-hour period are used simultaneously in one global (iterative) estimation problem

- Observation minus model differences are computed <u>at the</u> <u>observation time</u> using the full forecast model at T799 (25km) resolution
- 4D-Var finds the 12-hour forecast evolution that optimally fits the available observations. A linearized forecast model is used in the minimization process based on the adjoint method
- It does so by adjusting surface pressure, the upper-air fields of temperature, wind, specific humidity and ozone
- The analysis vector consists of ~10<sup>8</sup>elements at T255 resolution (80km)



4

ECMWF

# Fundamental challenges of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance





## **4D Variational Data Assimilation**

- Model:  $\mathcal{M}$ ,
- Observations: y,
- Background:  $x_b$ ,
- Observation operator:  $\mathcal{H}$ ,
- Cost function to minimise:  $J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2}[y - \mathcal{H}(x)]^T R^{-1}[y - \mathcal{H}(x)] + J_c$
- In discrete form:

$$J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2} \sum_{i=0}^n [y_i - \mathcal{H}_i(\mathcal{M}_i(x))]^T R_i^{-1} [y_i - \mathcal{H}_i(\mathcal{M}_i(x))]$$

**ECMWF** (

# **Incremental 4D-Var**

- The cost function is expressed in terms of increments with respect to the background state  $\delta x = x x_b$ .
- $\mathcal{H}$  and  $\mathcal{M}$  are linearised around  $x_i = \mathcal{M}_i(x_0)$ .

$$J(\delta x) = \frac{1}{2} \delta x^T B^{-1} \delta x + \frac{1}{2} \sum_{i=0}^n (H_i M_i \delta x - d_i)^T R_i^{-1} (H_i M_i \delta x - d_i)$$

where

- $H_i$  and  $M_i$  are the linearised observation operator and model, -  $d_i = y_i - \mathcal{H}_i(\mathcal{M}_i(x_b))$  are the innovations.
- The innovations, which are the primary input to the assimilation, are always computed using the full observation operator and model to ensure the highest possible accuracy.



# **4D-Var incremental formulation** Courtier, Thépaut and Hollingsworth (1994)

In the <u>incremental</u> formulation the cost function *J* is expressed in terms of increments  $\delta \mathbf{x} = \mathbf{x} \cdot \mathbf{x}_{b}$  with respect to the background state at initial time.

 $H_i$  and  $M_i$  are the TL of  $\mathcal{H}_i$  and  $\mathcal{M}_i$  linearized around  $x(t_i) = \mathcal{M}_i(x_b(t_0))$ 

$$J(\delta x) = \delta x^T B^{-1} \delta x + \sum_{i=1}^N (H_i M_i \delta x - d_i)^T R^{-1} (H_i M_i \delta x - d_i)$$

The *i*-summation is over N=25

The <u>innovations</u>  $d_i$  are calculated using the

<sup>1</sup>/<sub>2</sub>-hour long <u>time slots</u> of the

12-hour assimilation period.

non-linear operators,  $\mathcal{H}_i$  and  $\mathcal{M}_i$ .

$$d_i = y_i - \mathcal{H}_i(\mathcal{M}_i(x_b(t_0)))$$

8

This ensures the highest possible <u>accuracy</u> for the calculation of the innovations  $d_i$  which are the primary input to the assimilation!



# **The Outer Iterations**

After each minimisation at inner level:

- x is updated:  $x_a^j = x_b + \delta x_j$ ,
- $H_i$  and  $M_i$  are re-linearised around  $x_i = \mathcal{M}_i(x_a^j)$ ,
- Innovations are re-calculated using the full nonlinear observation operator  $\mathcal{H}$  and model  $\mathcal{M}$ :

$$d_i^j = y_i - \mathcal{H}_i(\mathcal{M}_i(x_a^j))$$

- Superscript j represents the **outer iteration**.
- The nonlinear model  $\mathcal{M}$  remains at **T799** throughout.



# **The Inner Iterations**

• Tangent Linear approximation:

 $\mathcal{M}(x + \delta x) \approx \mathcal{M}(x) + M\delta x$  and  $\mathcal{H}(x + \delta x) \approx \mathcal{H}(x) + H\delta x$ 

- Approximations to reduce cost: the tangent linear model (and its adjoint) is degraded with respect to the full model  $\mathcal{M}$ :
  - Lower resolution T255 instead of T799
  - Simplified physics (some processes are ignored),
  - Simpler dynamics (spectral instead of grid-point humidity).
- This results in shorter control vector and cheaper TL and
  AD models during the minimisation.



# **ECMWF 4D-Var procedure**

Use all data in a 12-hour window (0900-2100 UTC for 1200 UTC analysis)

- **1.** Group observations into 1/2 hour time slots
- 2. Run the T799 (25km) high resolution forecast from the previous analysis and compute "observation"- "model" differences
- 3. Adjust the model fields at the start of assimilation window (0900 UTC) so the 12-hour forecast better fits the observations. This is an iterative process using a lower resolution linearized model T95 (210km), T159 (125km) or T255 (80 km) and its adjoint model
- 4. Rerun the T799 high resolution model from the modified (improved) initial state and calculate new observation departures
- 5. The 3-4 loop in repeated three times to produce a good high resolution estimate of the atmospheric state the result is the ECMWF analysis



# Multi-incremental quadratic 4D-Var at ECMWF









## **4D-Var with three inner loop:** efficient, accurate and allows non-linearity

- M.Level 80 (900 hPa) temperature analysis increments for each of the three minimizations.
- Decreasing • amplitudes T95>T159>T255.
- Small corrections • added at T255 where data density is highest.
- Model and observ. operators are relinearized twice.



Add T95 increment to T799 BG and re-linearize M<sub>r</sub> H



Add T159 increment and re-linearize M<sub>r</sub> H



ECMWF DA System&Observations **DA School Buenos Aires 2008** 

# Fundamental challenges of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance





#### **ECMWF LINEARIZED PHYSICS**







# Fundamental challenges of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance









#### **Data extraction**

- Check out duplicate reports
- Ship tracks check
- Hydrostatic check

#### Thinning

 Data not used to avoid over-sampling and correlated errors

 Even so departures from background and analysis are generated and usage flags also

### Blacklisting

- Data skipped due to systematic bad performance or due to different considerations (e.g. data being assessed in passive mode)
- Departures and flags available for further assessment

#### Model/4D-Var dependent QC

**Analysis** 

23

ECMV

- First guess based rejections
- VarQC rejections



### **Observation data count for one 12h 4D-Var cycle** 0900-2100UTC 3 March 2008

	Screened		Ass	imilated	
• Synop:	450,000	0.3%	• Synop:	64,000	0.7%
Aircraft:	434,000	0.3%	Aircraft:	215,000	2.4%
Dribu:	24,000	0.02%	• Dribu:	7,000	0.1%
• Temp:	153,000	0.1%	• Temp:	76,000	0.8%
Pilot:	86,000	0.1%	• Pilot:	39,000	0.4%
• AMV's:	2,535,000	1.6%	• AMV's:	125,000	1.4%
Radiance dat	a: 150,663,000	96.9%	Radiance data:	8,207,000	91.0%
Scat:	835,000	0.5%	• Scat:	149,000	1.7%
•GPS radio oco	cult. 271,000	0.2%	•GPS radio occu	lt. 137,000	1.5%
TOTAL:	155,448,000	100.00%	TOTAL:	9,018,000	100.00%
99% of screened data is from satellites			96% of assimilated data is from satellites		



#### **Quality control: Good example**



In the quality control procedure all data from different data types are simultaneously checked. In this Australian example the presence of AIRCRAFT data has led to the rejection of a PILOT wind.



# Quality control: Bad example Tropical Cyclone

Observations of intense and small-scale features may be rejected although the measurements are correct.

The problem occurs when the resolution of the analysis system (as determined by the B-matrix) is insufficient.





### Quality control: Bad example Extreme event -The 'French Storm', 27 Dec 1999

Observations of intense and small-scale features may be rejected although the measurements are correct.



27

#### The Huber-norm –





#### **Comparing optimal observation weights Huber-norm (red) vs. Gaussian+flat (blue)**

#### North Hemisphere Temperature from Radiosonde





29

10<sup>5</sup>

104

 $10^{3}$ 

 $10^{2}$ 

 $10^{1}$ 

# Fundamental challenging of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance



### **Satellite observing system**



**ECMWF** 

31

ECMWF DA System&Observations DA School Buenos Aires 2008

# **Combined impact of all satellite data**





# Assimilation of rain-affected microwave radiances

SSM/I observational **\Delta Tb** 19v-19h [K]

20

-40

-60

-80

- Assimilation of rain-affected SSM/I radiances in 1D+4D-Var active since June 2005.
- Main difficulties: inaccurate moist physics parameterizations (location/intensity), formulation of observation errors, bias correction, linearity.
- Major improvements accomplished in 2007 and SSMIS, TMI, AMSR-E data included.
- Direct 4D-Var radiance assimilation envisaged for 2008.

#### 4D-Var first guess SSM/I ∆Tb 19v-19h [K]



#### **Forecast sensitivity to observations in analysis**

#### CY32R1, T511L60, 20070105-20070212

SSM/I clear-sky, winter

SSM/I clouds/rain, winter



Mean 36-12h precipitation forecast initialized at 12 UTC

[J/kg]



## **Advanced infrared sounders: AIRS and IASI**



500 hPa geopotential anomaly correlation (56 cases, spring 2007, normalized RMSE difference, own analysi

35



ECMWF 😷

# **Assimilation of GPS radio occultation data**

- COSMIC bending angles assimilated (both rising and setting occultations), CHAMP, GRACE as back-up, GRAS being monitored.
- GPSRO data reveals a warm bias of aircraft observations.
- Substantial improvement of stratospheric T-biases.
- METOP GRAS data assimilated since May 2008.
- COSMIC-2 follow-on?



#### Southern Hemisphere scores (normalized AC differences)



#### Improved fit to radiosonde data



36

ECMWF DA System&Observations DA School Buenos Aires 2008



# **Recent revisions to observation usage**

- Use AMSU-B on NOAA-16, 17 and 18, AMSU-A on NOAA-18 and 20
- Operational assimilation of 155 EOS-1/AIRS channels
- Operational assimilation of 168 METOP/IASI channels
- Radiances from Meteosat-5 (India), GOES-9 (Japan) and 12 (replaces GOES-8) and Meteosat-8
- Atmosp. feature track. winds from GOES-12, Meteosat-8, MTSAT-1R
- Use MODIS winds from AQUA satellite
- Use of SCIAMACHY and more SBUV ozone retrievals
- METAR surface pressure data active
- Increase use of radiosonde humidity in upper troposphere
- Use GPS radio occultation data (COSMIC)



# Recent revisions to the assimilation system

- Increased resolution from T511/T159 L60 to T799/T255 L91
- Now three outer loop: T799 outer with T95/T159/T255 inner loop
- Use grid-point humidity and ozone in 4D-Var analysis
- More advanced Tangent Linear physics scheme in 4D-Var
- Wavelet Jb formulation has been implemented
- Jb statistics from latest ensemble data assimilation
- New humidity analysis using a normalized control variable
- Assimilation of "Cloudy and rainy radiances"
- Variational bias correction of satellite radiances
- Adaptive bias correction for radiosondes and SYNOP pressure data



# Fundamental challenging of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance



#### **Model bias:**

#### upper-stratospheric model errors variation



ECMWF DA System&Observations DA School Buenos Aires 2008



### **Observation bias:** Radiosonde temperature observations



#### Bias changes due to change of equipment



### **Observation bias: Satellite radiances**

Monitoring the background departures (averaged in time and/or space):



Diurnal bias variation in a geostationary satellite

Air-mass dependent bias (AMSU-A channel 14)







#### Implications for data assimilation: The effect of model bias on trend estimates

Most assimilation systems assume unbiased models and unbiased data



#### Biases in models and/or data can induce spurious trends in the assimilatio



### Variational bias correction: The modified analysis problem

The original problem:

Dee 2004, 2005



J<sub>o</sub>: observation constraint

**44** 

The modified problem:





#### **Performance:**

#### **Adaptive bias correction of NOAA-17 HIRS Ch12**



ECMWF DA System&Observations DA School Buenos Aires 2008



#### **Performance:**

**NOAA-9 MSU channel 3 bias corrections (cosmic storm)** 



#### Weak-constraint 4D-Var

Include model error in the control vector:

$$J(x_0, \eta) = \frac{1}{2} \sum_{i=0}^{n} [\mathcal{H}(x_i) - y_i]^T R_i^{-1} [\mathcal{H}(x_i) - y_i] + \frac{1}{2} (x_0 - x_b)^T B^{-1} (x_0 - x_b) + \eta^T Q^{-1} \eta \text{ with } x_i = \mathcal{M}_i (x_{i-1}) + n_i.$$



Tremolet 2007

Constraint is determined by Q

Lindskog 2008



# SSU Ch3 mean radiance departures – Aug 1993



ECMWF DA System&Observations DA School Buenos Aires 2008



# Fundamental challenging of ECMWF 4D-Var Assimilation System

- Incremental 4D-Var
- Linearized Physics
- Observation handling
- Assimilation of satellite data
- Model and Observation Bias
- Modelling Background Covariance



# **Importance of Background Covariances**

- The formulation of the J<sub>b</sub> term of the cost function is <u>crucial</u> to the performance of current analysis systems.
- To see why, suppose we have a <u>single observation</u> of the value of a <u>model field</u> at <u>one gridpoint</u>.
- For this simple case, the observation operator is:

H = (0, ..., 0, 1, 0, ..., 0).

• The gradient of the 3dVar cost function is:

 $\nabla J = B^{-1}(x-x_b) + H^{T}R^{-1}(Hx-y) = 0$ 

• Multiply through by B and rearrange a bit:

 $x - x_b = B H^T R^{-1}(y - Hx)$ 

• But, for this simple case, R<sup>-1</sup>(y-Hx) is a scalar



## **Importance of Background Covariances**

- So, we have:  $\mathbf{X} \mathbf{X}_h \propto \mathbf{B} \mathbf{H}^{\mathrm{T}}$
- But, H = ( 0,...,0,1,0,...,0)
- => The analysis increment is proportional to a column of B.
- The role of B is:
  - 1. To spread out the information from the observations.
  - 2. To provide statistically consistent increments at the neighbouring gridpoints and levels of the model.
  - 3. To ensure that observations of one model variable (e.g. temperature) produce dynamically consistent increments in the other model variables (e.g. vorticity and divergence).



# Estimating Background Error Statistics from Ensembles of Analyses



### The ECMWF J<sub>b</sub> Formulation – the balance operator

- The most obvious correlation in the background errors is the balance between mass errors and wind errors in the extra-tropics.
- We therefore define our change of variable as:

 $L = KB_{u}^{1/2}$ 

- where K accounts for all the correlation <u>between</u> variables (e.g. between the mass and wind fields).
- The matrix B<sub>u</sub> is a covariance matrix for variables that are uncorrelated with each other.



### The ECMWF J<sub>b</sub> Formulation – The balance operator

$$\begin{pmatrix} \zeta \\ \mathbf{D} \\ (\mathbf{T}, \mathbf{p}_{s}) \\ \mathbf{q} \end{pmatrix} = \begin{pmatrix} \mathbf{I} & 0 & 0 & 0 \\ \mathbf{M} & \mathbf{I} & 0 & 0 \\ \mathbf{N} & \mathbf{P} & \mathbf{I} & 0 \\ 0 & 0 & 0 & \mathbf{I} \end{pmatrix} \begin{pmatrix} \zeta \\ \mathbf{D}_{u} \\ (\mathbf{T}, \mathbf{p}_{s})_{u} \\ \mathbf{q} \end{pmatrix}$$

- The most important part of the balance operator is the sub-matrix N, which calculates a balanced part of (T,p<sub>s</sub>), determined from the vorticity.
- N is implemented in 2 parts:
  - 1. A balanced "geopotential" is calculated from  $\zeta$ .
  - 2. Balanced  $(T,p_s)$  are calculated using statistical regression between  $(T,p_s)$  and geopotential.



#### **Increments from a single observation**



ECMWF DA System&Observations DA School Buenos Aires 2008



# Increments for a single observation of geopotential height at 1000hPa





#### **NSCAT wind information vertically propagated and impact on other variables**



# **Ensembles of data assimilations**

- Run an ensemble of analyses with randomly perturbed observations, peturbed SST field and stochastic physics perturbations.
- Compute the variance of the short-range forecast fields
- The spread will have the statistical characteristics of short-range forecast error and it will be flow dependent



850 hPa U-Comp 1-Month EnDA Mean Spread of 3-hour forecast

ECMWF DA System&Observations DA School Buenos Aires 2008



# Reanalysis

- ERA-Interim is current ECMWF reanalysis project following ERA-15 & 40.
- 2006 model cycle, 4D-Var, variational bias-correction, more data (rain assimilation, GPSRO); 1989-1998 period available, 1998-

