Environnement et Changement climatique Canada | Environment and Climate Change Canada

AN OVERVIEW OF ATMOSPHERIC DATA ASSIMILATION FOR OPERATIONAL NWP

Jean-François Caron
Numerical Modelling and Prediction Research Division
Environment and Climate Change Canada

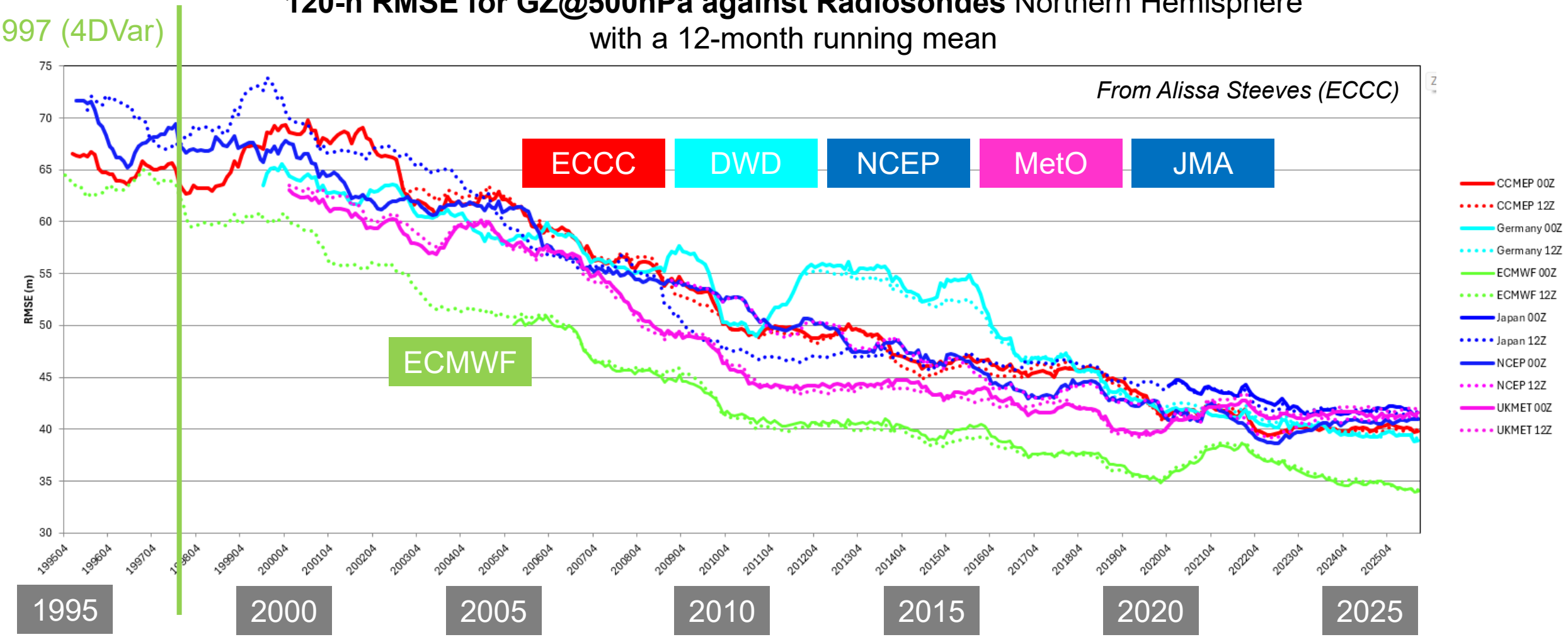
Thanks to Alain Beaulne (ECCC), Loïk Berre (Météo-France), Massimo Bonavita (ECMWF), Pierre Brousseau (Météo-France), Mark Buehner (ECCC), Marcin Chrust (ECMWF), Daniel Holdaway (NCEP), Daisuke Hotta (ECCC), Patrick Laloyaux (ECMWF), Sébastien Massart (ECMWF), Roland Potthast (DWD), David Simonin (Met Office) and Marek Wlasak (Met Office)

ECMWF Annual Seminar, Reading (UK), 14 September 2026

Canada

DA: A KEY INGREDIENT FOR NWP

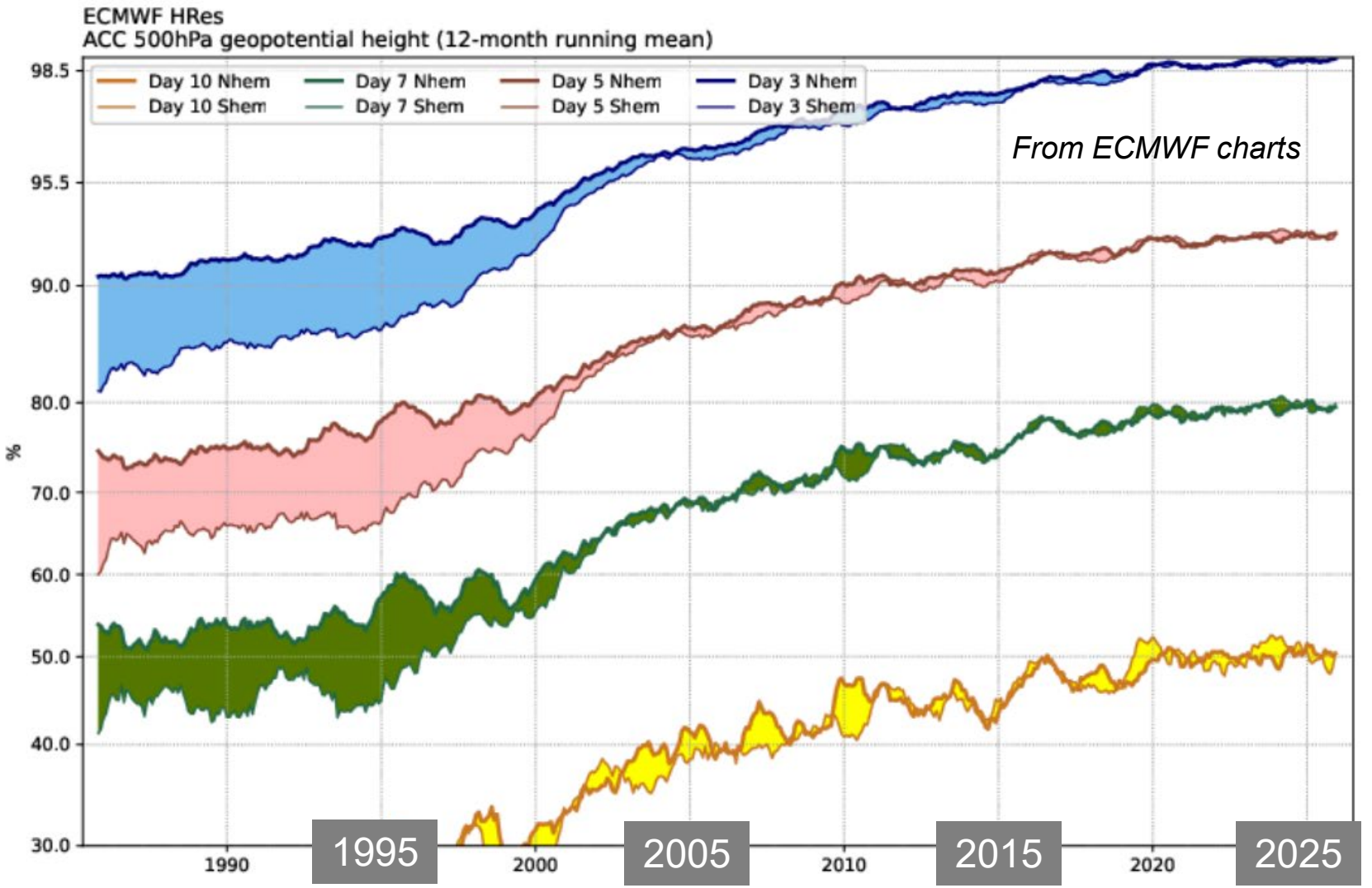
120-h RMSE for GZ@500hPa against Radiosondes Northern Hemisphere
with a 12-month running mean



DA: A KEY INGREDIENT FOR NWP

Anomaly Correlation Coefficients for GZ@500hPa in ECMWF HRES/CTL forecasts with a 12-month running mean

DA improvements allowed to close the forecast performance gap between Northern and Southern Hemispheres



CONTENTS

Current Operational Approaches

- DA and NWP systems
- Variational and LETKF algorithms
- **B**, **L** and **Q**
- **y**, **R**, BC and QC
- Handling nonlinearities
- Ensemble recentering
- Software frameworks

Looking forward

- Non-AI related: improving the old-world
- AI: from incremental changes to turning the tables

DWD

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ECMWF

気象庁
Japan Meteorological Agency

METEO FRANCE

Met Office

NCEP
NATIONAL CENTERS FOR ENVIRONMENTAL PREDICTION

Current operational approaches

DA AND NWP SYSTEMS IN A NUTSHELL

DA IN A NUTSHELL

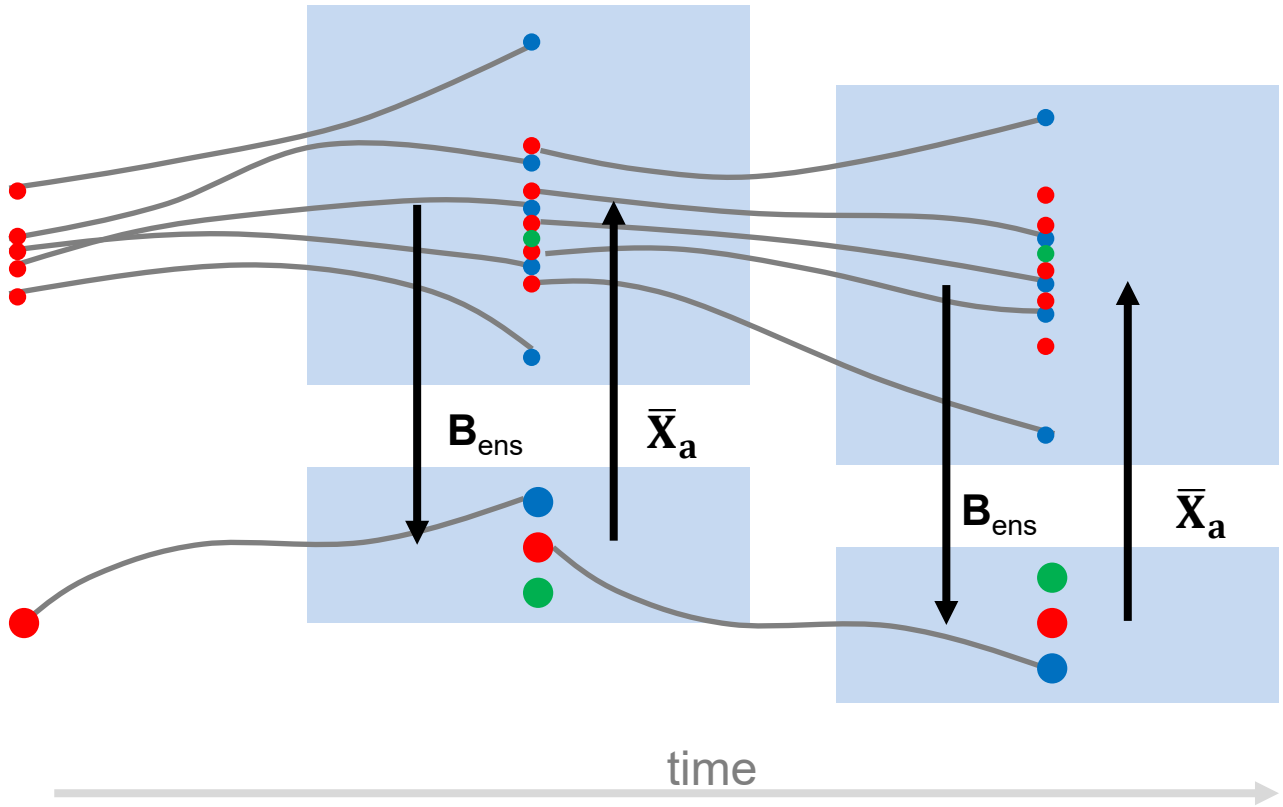
Data Assimilation goal is to correct a short-term forecast using information from all available observations

Ensemble

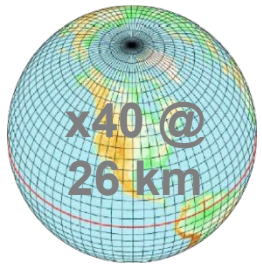
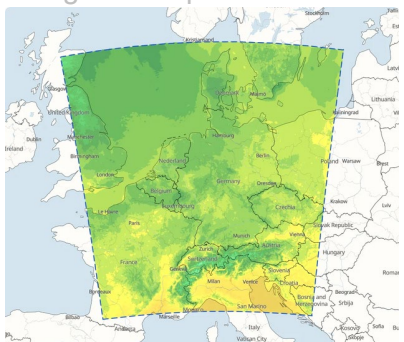
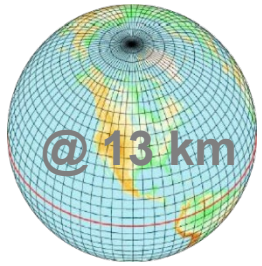
an **ensemble of forecast** is adjusted toward observations based on the ensemble forecast uncertainty to produce an **ensemble of analysis**

Deterministic

one forecast is adjusted toward observations to produce **one (optimal) analysis**



DWD

	Global (8x per day)		**Limited-Area** (24x per day)	
Ensemble	40-m @ 26km LETKF		40-m @ 2km LETKF	image from open-meteo.com  x40 / x20 @ 2 km
Deterministic	70 % B_{ens} 100% $\bar{X}_a$ 3DEnVar Δx_a= 26 km			
	DA	Model & Forecast	DA	Model & Forecast

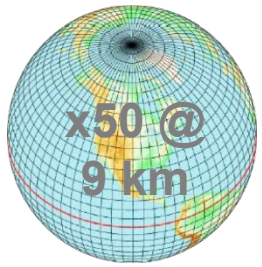
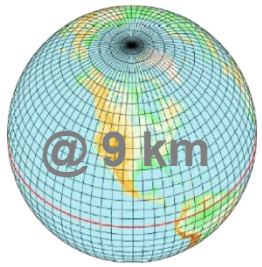
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ECCC

	Global (4x per day)		**Limited-Area** (4x per day)	
Ensemble	75% to 50% $\bar{X}_a$ 256-m @ 25km LETKF & 4DEnVar	x256 / x20 @ 25 km	Global ensemble perturbation recentering around global deterministic analysis	x20 @ 10 km
Deterministic	100% B_{ens} 4DEnVar Δx_a=25km	@ 15 km	4DEnVar Δx_a=25km	image from open-meteo.com @ 2.5 km
	DA	Model & Forecast	DA	Model & Forecast

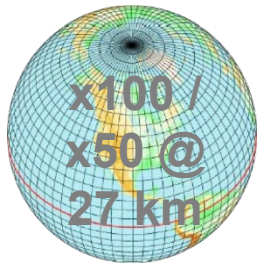
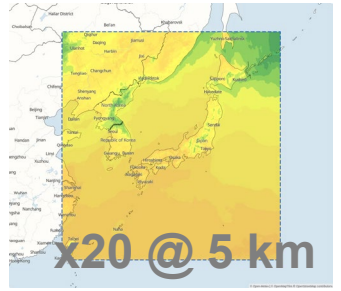
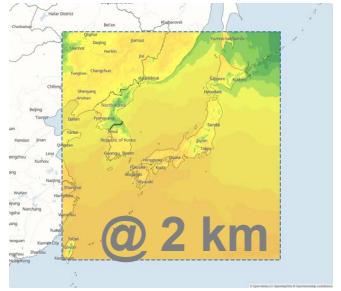
https://eccc-msc.github.io/open-data/msc-data/changelog_nwp_en/

ECMWF

	Global (2x per day)		**Limited-Area**	
Ensemble	50-m @ 9km $\Delta x_{a\text{-}CTL}$ = 80 / 50 / 40 km $\Delta x_{a\text{-}PERT}$ = 80 km Ens of 4DVar		member states	
Deterministic	100% **B**(σ_{ens}, **C**) 4DVar Δx_a = 80 / 65 / 50 / 40 km			
	DA	Model & Forecast	DA	Model & Forecast

https://www.ecmwf.int/en/elibrary/81732-ifs-documentation-cy50r1-part-2-data-assimilation

JMA

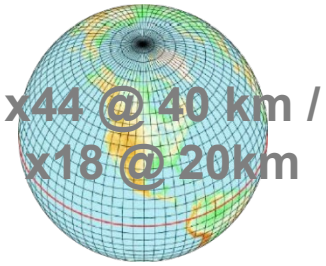
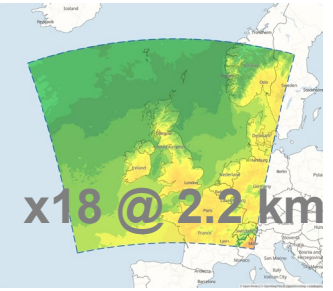
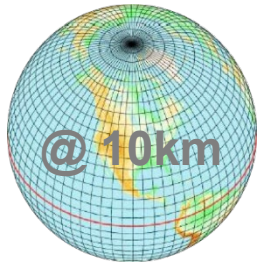
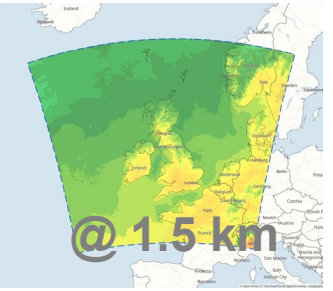
	Global (4x per day)		**Limited-Area** (24x per day)	
Ensemble	100-m @ 27km LETKF		4DVar + perturbations (SVs)	image from open-meteo.com 
Deterministic	50% B_{ens} / 100% $\bar{X}_a$ 4DVar Δx_a= 55 / 55 km		50% B_{ens}, 100m with lagging 3DEnVar	
	DA	Model & Forecast	DA	Model & Forecast

https://www.jma.go.jp/jma/jma-eng/jma-center/nwp/outline-latest-nwp/index.htm

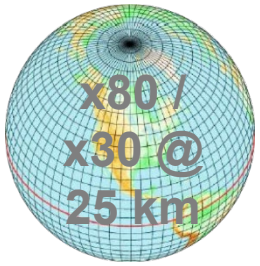
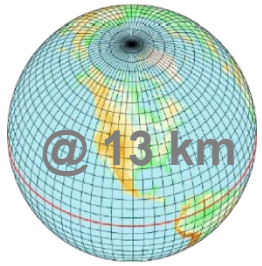
MÉTÉO-FRANCE

	Global (4x per day)		**Limited-Area** (8 or 24x per day)	
Ensemble	50-m @ 40km Δx_a= 40 km Ens of 4DVar	x50 @ 40 km / x34 @ 5-24km	50-m @ 3.2km Δx_a= 3.2 km Ens of 3DEnVar	image from open-meteo.com x50 @ 3.2km / x24 @ 1.3 km
Deterministic	50% B_{ens} 50% $B(\sigma_{ens}, C)$ 4DVar Δx_a= 40 / 40 km	@ 5-24km	100% B_{ens} 100% B_{ens} 4DEnVar Δx_a= 3.2 km	@ 1.3 km
	DA	Model & Forecast	DA	Model & Forecast

MET OFFICE

	Global (4x per day)		**Limited-Area** (24x per day)	
Ensemble	50-m @ 40km Δx_a= 40 km Ens of 4DEnVar 50% B_{ens} 264m with lagging & shifting		Global ensemble perturbation recentering around UKV analysis	image from open-meteo.com 
Deterministic	4DVar Δx_a= 40 km 50% $\bar{X}_a$		$\bar{X}_a$ 4DVar Δx_a= 4.5 km	
	DA	Model & Forecast	DA	Model & Forecast

NCEP

	Global (4x per day)		**Limited-Area** (24x per day)	
Ensemble	80-m @ 25km LETKF 87.5% B_{ens} ↓ ↑ 100% $\bar{X}_a$		30-m @ 25km LETKF 85 % B_{ens} ↓ ↑ 100% $\bar{X}_a$	 x30 / x6 @ 3 km
Deterministic	4DEnVar Δx_a= 25 km		3DEnVar	 @ 3 km
	DA — Model & Forecast		DA — Model & Forecast	

Current operational approaches

VARIATIONAL AND LETKF ALGORITHMS

4DVAR VS 4DENVAR

- In 4DVar the 3D analysis increment is evolved in time using the TL/AD forecast model (here included in $\mathbf{H}_{4D}$):

$$J(\Delta\mathbf{x}) = \frac{1}{2}(H_{4D}[\mathbf{x}_b] + \mathbf{H}_{4D}\Delta\mathbf{x} - \mathbf{y})^T \mathbf{R}^{-1}(H_{4D}[\mathbf{x}_b] + \mathbf{H}_{4D}\Delta\mathbf{x} - \mathbf{y}) + \frac{1}{2}\Delta\mathbf{x}^T\mathbf{B}^{-1}\Delta\mathbf{x}$$

J_o J_b

- In 4DEnVar, the background-error covariances and analyzed state are explicitly 4D, resulting in cost function:

$$J(\Delta\mathbf{x}_{4D}) = \frac{1}{2}(H_{4D}[\mathbf{x}_b] + \mathbf{H}\Delta\mathbf{x}_{4D} - \mathbf{y})^T \mathbf{R}^{-1}(H_{4D}[\mathbf{x}_b] + \mathbf{H}\Delta\mathbf{x}_{4D} - \mathbf{y}) + \frac{1}{2}\Delta\mathbf{x}_{4D}{}^T\mathbf{B}_{4D}^{-1}\Delta\mathbf{x}_{4D}$$

By making use of the 4D ensembles, 4DEnVar performs a 4D analysis without the need of the tangent-linear and adjoint of the forecast model

LETKF

- Proposed by Hunt et al. (2007) and considered well suited for parallelization on HPC
- A deterministic type of ensemble DA: no need to perturb the observations as in the EnKF.
- Assimilate all observations simultaneously to update each grid point independently whereas EnKF and others assimilate observations sequentially to update all grid points.
- Covariance localization applied by increasing the observation errors with increasing distance of a grid point instead of decreasing the background error covariances with distance as in other EnKF flavors.
- Majority of cost is in the calculation of a set of weights (like EnVar); application of weights to more variables is cheap, allowing:
  - output of 4D analyses and increments (for 4D-IAU)
  - output of analyses and increments of other model variables: clouds, precipitation, etc.

VAR VS LETKF

- VAR is
  - More flexible (hybrid **B**, advanced localization, VarBC, VarQC, etc)
  - Can easily deal with non-local observations (e.g., radiances)
  - Can better handle non-linearities through outer loop iterations
  - More computationally expensive

- LETKF is
  - Computationally cheaper thus often favored to generate an ensemble of analyses

At ECCC, generating one 4DEnVar analysis is **3 times more computationally expensive*** than generating 256 analyses with the LETKF

* Cost = # of cores x wall clock time

Current operational approaches

B, L AND **Q**

B

The era where VAR was associated to only static background-error covariances ($\mathbf{B}_s$) belongs to the pass: All 7 centers use contributions from ensembled-derived **B** ($\mathbf{B}_{ens}$) for VAR

$$\mathbf{B} = \beta_{ens}\,\mathbf{B}_{ens} + \beta_s\,\mathbf{B}_s$$

	Global DA		LAM DA	
	β_{ens}	β_s	β_{ens}	β_s
DWD	0.7	0.3	LETKF only	
ECCC	1	0	1	0
JMA	0.5	0.5	0.5	0.5
Météo-France	0.5	0.5	1	0
Met Office	0.5	0.5	0	1
NCEP	0.875	0.125	0.85	0.15

$$\mathbf{B} = \mathrm{diag}(\sigma_{ens})\,\mathbf{C}_{wav}\,\mathrm{diag}(\sigma_{ens})$$

For global DA, ECMWF uses background-error standard deviations fully derived from ensembles of the day while relying on a mix of recent and past ensemble to derived somewhat non-homogeneous correlations based on wavelets

Météo-France uses the same approach to define $\mathbf{B}_s$ in the hybrid formulation

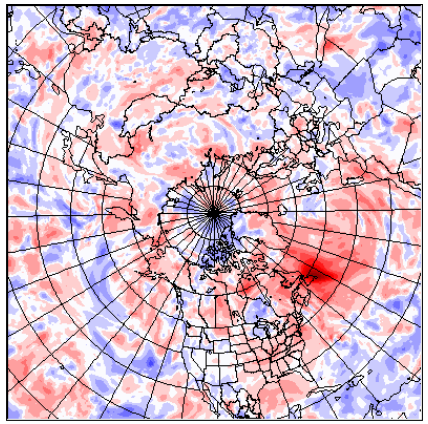
Note: In 4DEnVar, $\mathbf{B}_s$ is constant through the DA window while evolving in time with 4DVar

L

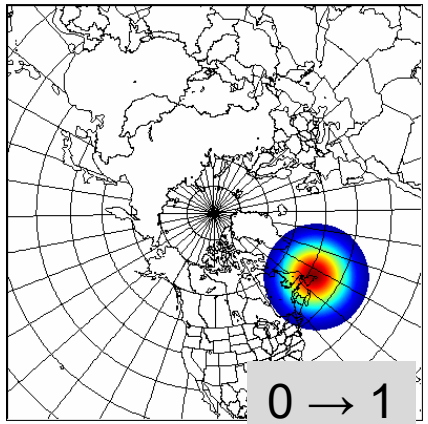
Spatial (horizontal and vertical) localization of ensemble-derived background-error covariances ($\mathbf{B}_{ens}$) is essential to both VAR and LETKF

Computed using 256 ensemble members

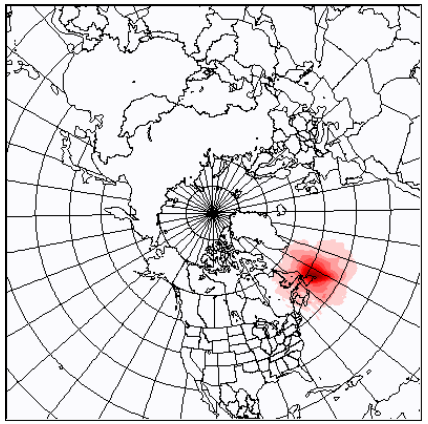
Raw ens covariances ($\mathbf{B}_{ens}$)



Localisation function ($\mathbf{L}$)



Localized covariances ($\mathbf{B}_L = \mathbf{B}_{ens} \circ \mathbf{L}$)



- Centers/applications use different localization functions
  Gaspari and Cohn (1999) 5th-order piecewise rational function likely the most common.
- Localization lenghtscales considerably vary based on ensemble resolution and sizes

Without localization, an assimilated observation over Australia (Canada) would influence the estimated atmospheric state over Canada (Australia), due to sampling error from the use of a “small” ensemble size

L

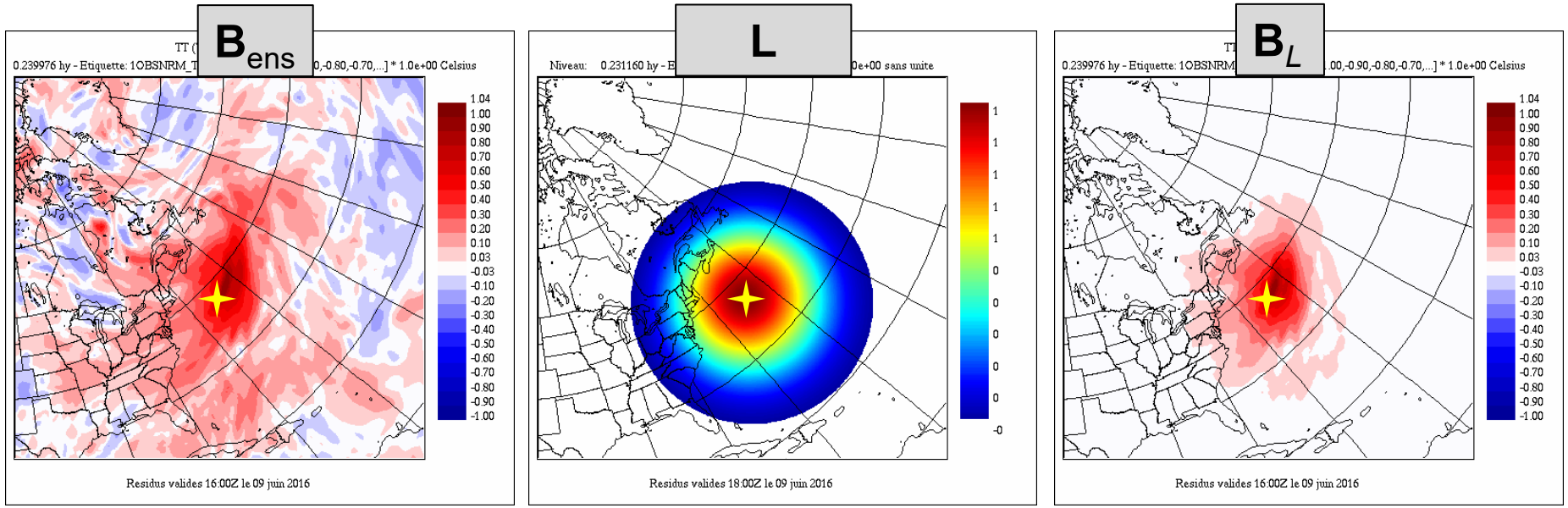
Different localization approaches used

- L_h varies only with vertical levels; L_v uniform
  ECCC-LETKF, NCEP-LEKTF, NCEP-EnVar-Global, MF-4DVar
- L_h uniform; L_v varies with vertical levels
  DWD
- L_h varies for some variables; L_v uniform
  JMA
- L_h varies with horizontal scales (Scale-Dependent Localization; SDL); L_v uniform
  ECCC-EnVar and MF-EnVar (based on Buehner and Shlyaeva 2015 formulation)
  Met Office (based on Buehner 2012 formulation)
- L_h varies with horizontal scales and variables; L_v uniform
  NCEP-EnVar-LAM

SDL in the horizontal leads to (implicit) vertical-level-dependent and variable-dependent horizontal localization. Significant benefits but computationally expensive.

L

In 4DEnVar and (4D) LETKF, spatial localization also imposes temporal localization

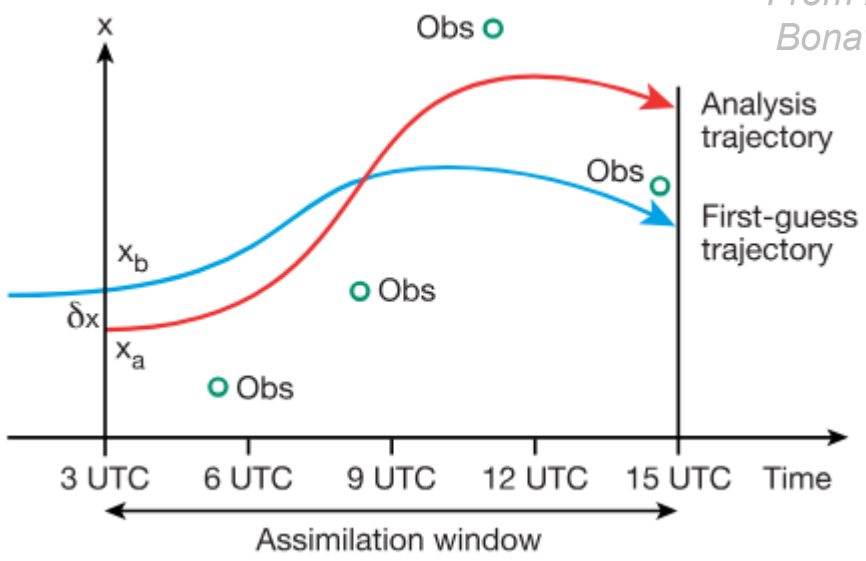


Although beneficial to limit spurious temporal covariances, this likely damps and crops some meaningful signal and potentially advantages 4DVar where localization is limited to the (3D) $\mathbf{B}_{ens}$ at the beginning of the DA window

More to come in Patrick Laloyaux's talk

Q

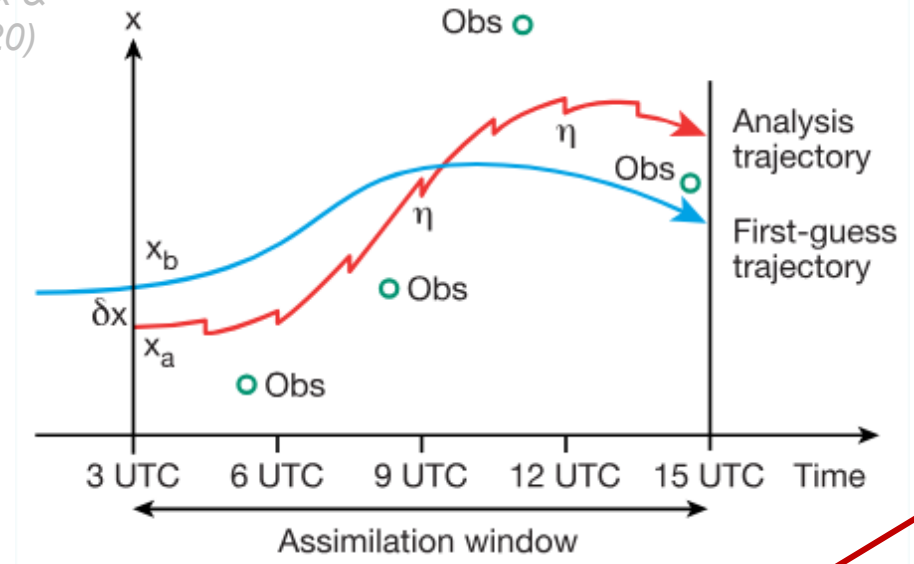
Strong-constraint DA
The trajectory can be changed only by modifying the initial conditions



DWD, ECCC, JMA, Météo-France, Met Office & NCEP

From Laloyaux & Bonavita (2020)

Weak-constraint DA
A model-error forcing estimated from the minimization reduce the biases in the trajectory



$$J_{\mathrm{WC}}(\mathbf{x}_0,\boldsymbol{\eta}) = \frac{1}{2}\left(\mathbf{x}_0-\mathbf{x}_0^{\mathrm{b}}\right)^{\mathrm{T}}\mathbf{B}^{-1}\left(\mathbf{x}_0-\mathbf{x}_0^{\mathrm{b}}\right) + \frac{1}{2}\sum_{k=0}^{N}\left(\mathcal{H}_k(\mathbf{x}_k)-\mathbf{y}_k\right)^{\mathrm{T}}\mathbf{R}_k^{-1}\left(\mathcal{H}_k(\mathbf{x}_k)-\mathbf{y}_k\right) + \frac{1}{2}\left(\boldsymbol{\eta}-\boldsymbol{\eta}^{\mathrm{b}}\right)^{\mathrm{T}}\mathbf{Q}^{-1}\left(\boldsymbol{\eta}-\boldsymbol{\eta}^{\mathrm{b}}\right),$$

ECMWF

Q-matrix estimated from timeseries of model errors derived from Q estimated from SPPT-induced ensemble perturbations.

Active only in the stratosphere, the boundary layer as well as for surface pressure and skin temperature

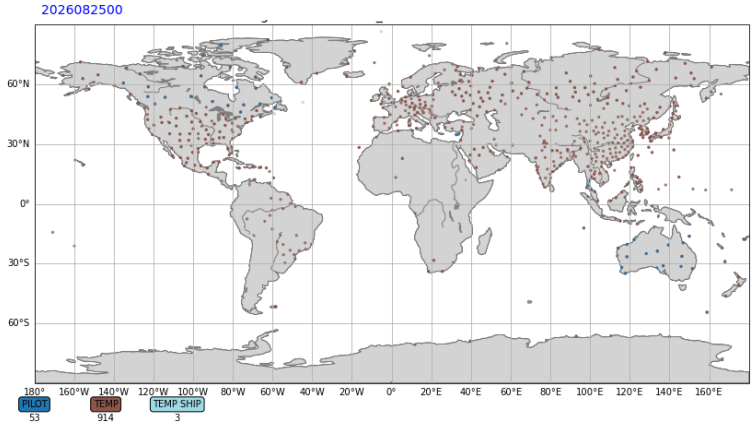
Current operational approaches

y, R AND QC

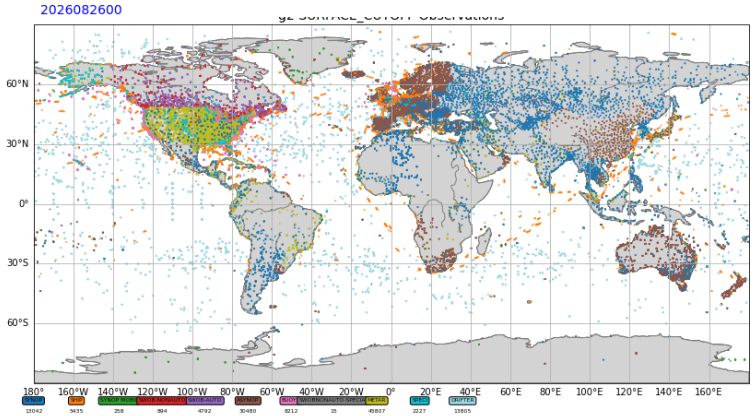
y

Distribution of some observations used for NWP

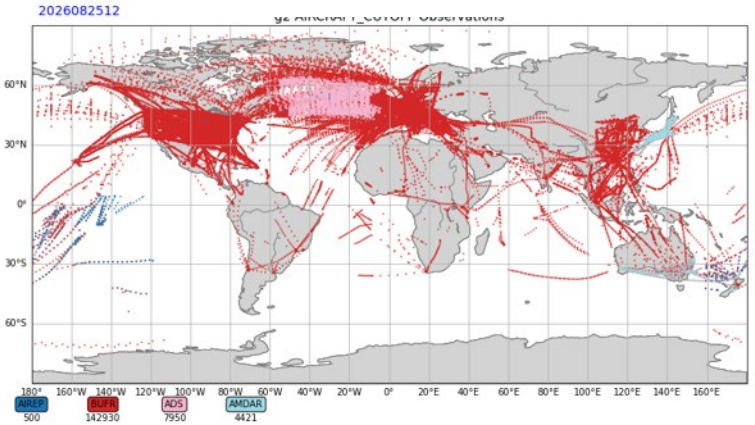
Radiosondes



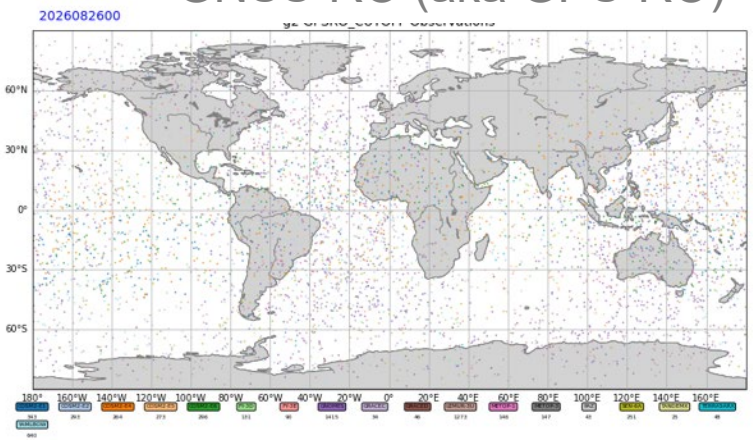
Surface



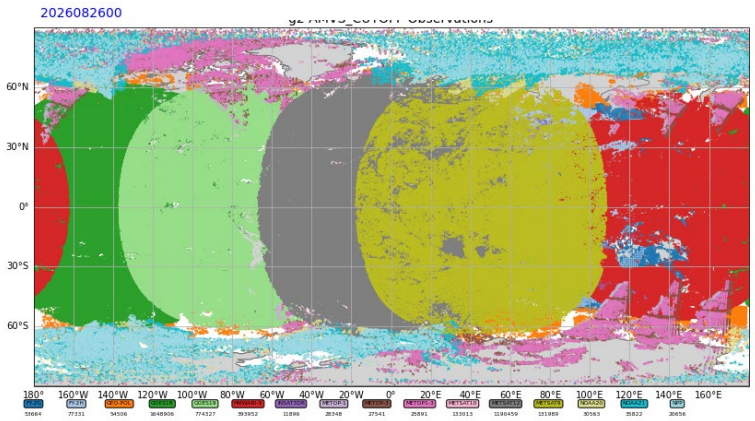
Aircrafts



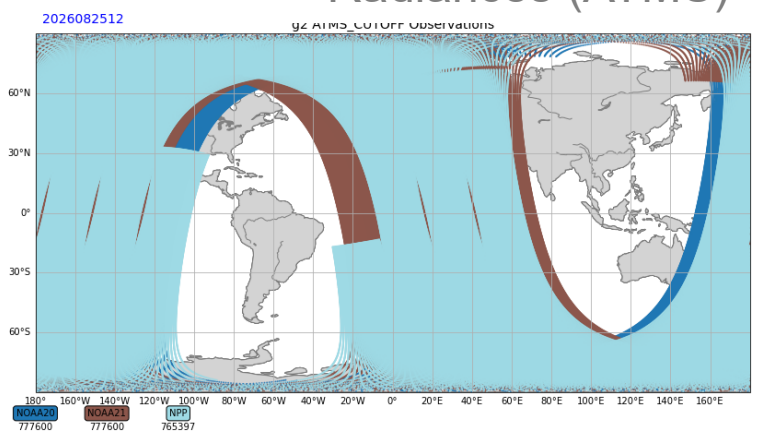
GNSS-RO (aka GPS-RO)



AMVs



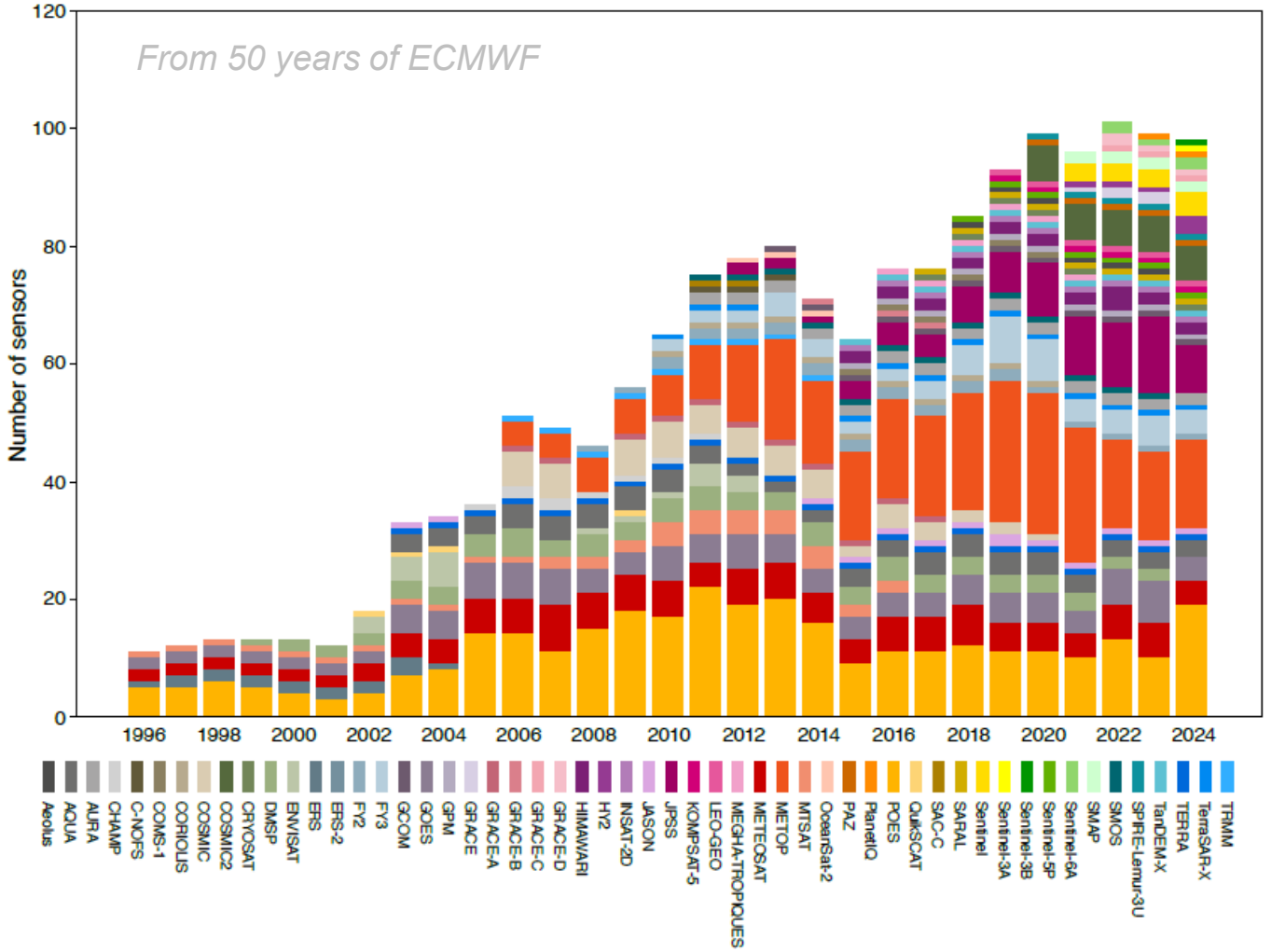
Radiances (ATMS)



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Growth of satellite-based observations

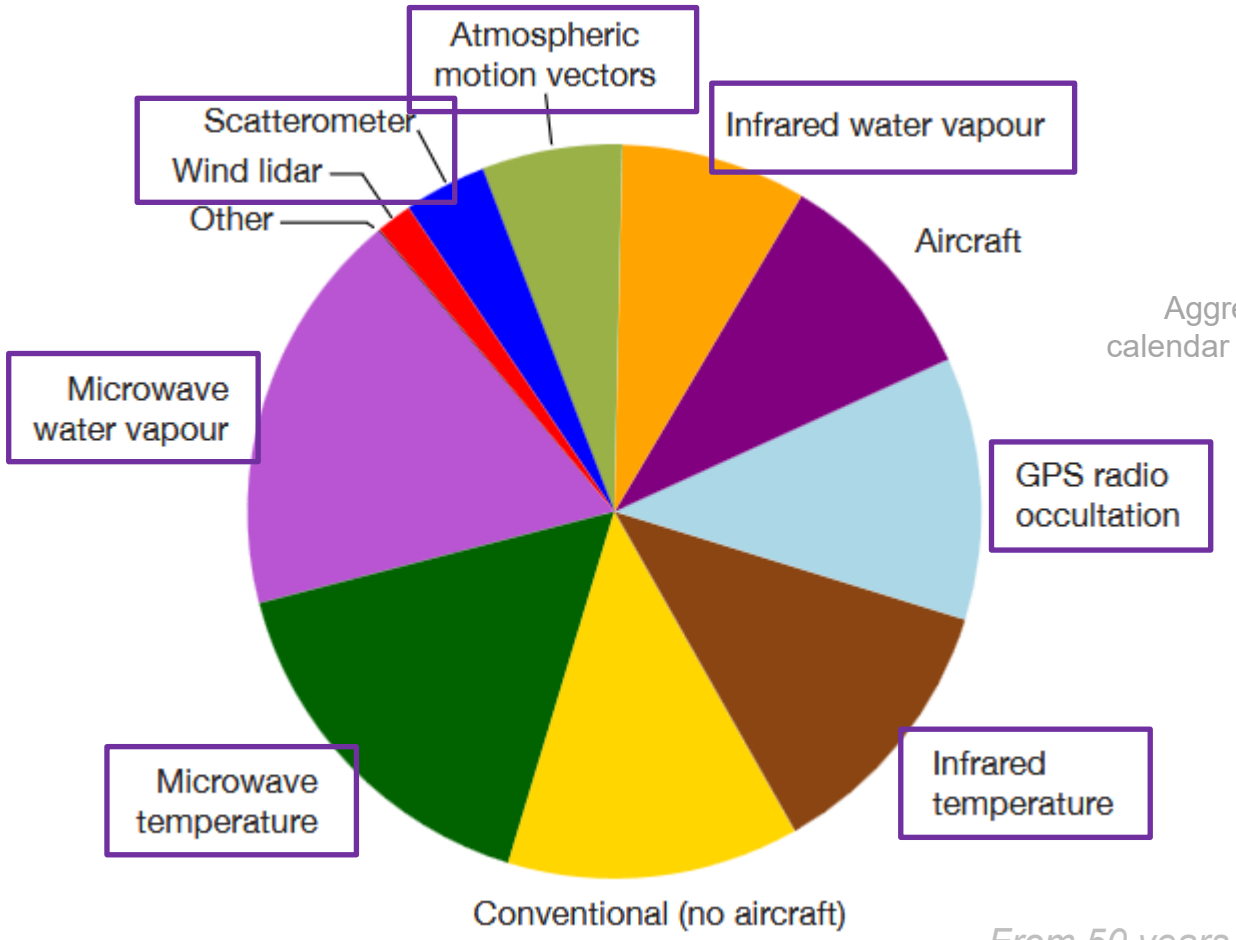
- **10x** increase in satellite sensors monitored at ECMWF between 1996 to 2024.
- The volume increase is much bigger since most modern sensors measure more wavelengths than before (hyperspectral)



y

Relative impact of observation families on the quality of 24-h forecast at ECMWF estimated from the FSOI technique (Forecast Sensitivity to Observation Impact)

Satellite-based observations dominate!

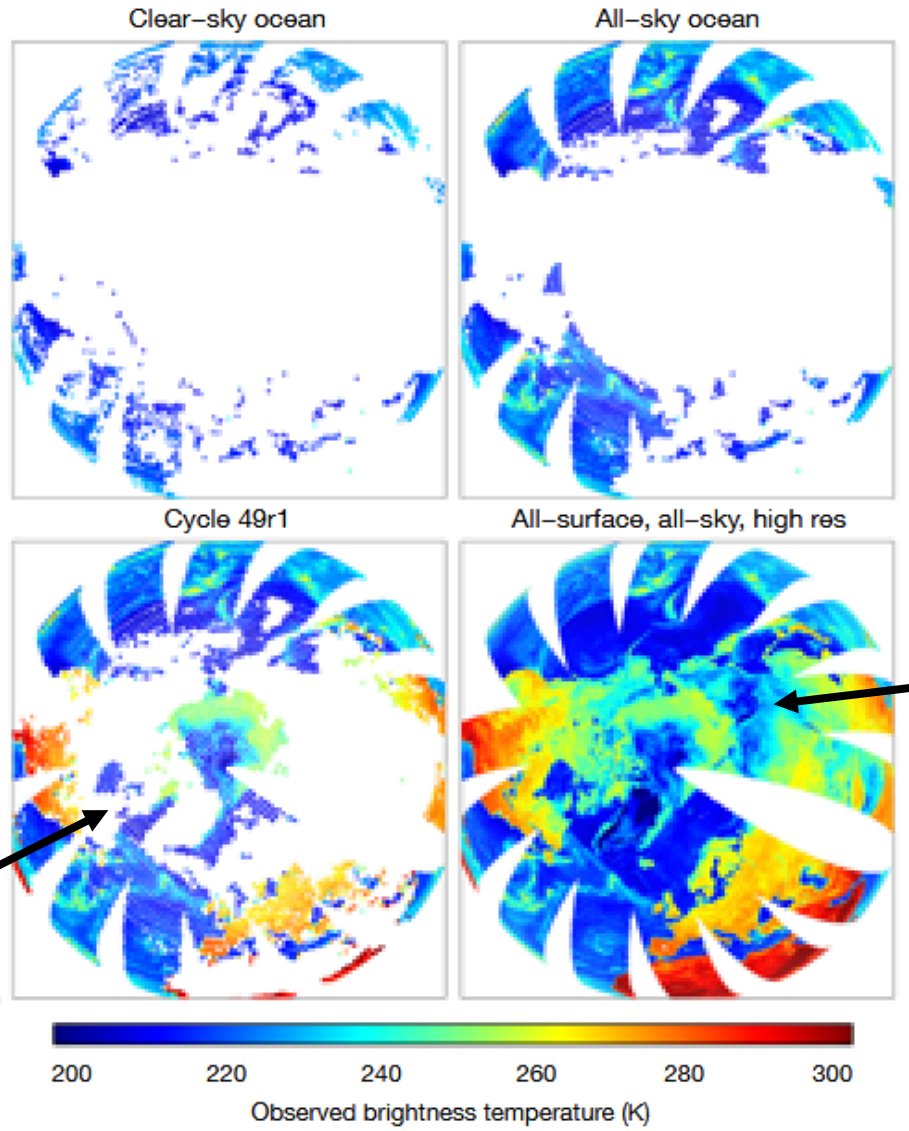


Aggregated over the calendar years 2020 to 2024

From 50 years of ECMWF

y

- Only a few % (up to ~5%) of all satellite radiances are assimilated in global operational DA systems
  - Important data thinning is still applied (~100 km spacing between obs)
  - Several radiances sensitive to hydrometeors and land surface are still not assimilated



AMSR2 observed brightness temperatures in the 37 GHz v-polarised channel for the 12-hour DA window around 12 UTC, 17 November 2024

ECMWF in 2025

The dream

From 50 years of ECMWF

y

Thanks to Alain Beaulne (ECCC), ITWG and WMO's GODEX

Satellite-based data usage comparison for global NWP

	Missions	Instruments	Channels	Thinning (km)	**Obs (M/day)**
DWD	(17)	(21)	(240)	(160)	**6 (5)**
ECCC	26 (11)	46 (17)	(600)	(150)	**12 (10)**
ECMWF	27 (19)	51 (25)	(1150)	(70-140)	**41 (36)**
Météo-France	31 (17)	51 (22)	(470)	(100-140)	**28 (25)**
Met Office	(12)	(18)	(780)	(80-154)	**21 (16)**
NCEP	(13)	(19)	(590)	(145)	**32 (16)**

() radiances only, excluding RO, AMVs and Scatterometers

More to come in Sarah Dance's talk

R

- The observation error covariances (**R**; random error component) are still mostly considered to be diagonal, forcing important data thinning for several observing networks
  - Inter-channel error correlations (thus spatially collocated) are now taken into account in all centers for at least some space-based sensors.
  - The Met Office is the only center, so far, to take **spatial correlations,** but only in the assimilation of radial winds from ground-based radar (Simonin et al., 2019)
- The DBCP method (Desroziers et al., 2005) is often used to diagnosed the diagonal and off-diagonal components of **R**

IF

- Linear estimation theory holds; error covariances in observation and background uncorrelated
- **B** and **R** are already close to true observation and background error covariances and their correlations are different from each other.

$$\mathbf{R} = Cov[\mathbf{d}_a, \mathbf{d}_b]$$

$$\mathbf{d}_a = \mathbf{y} - H(\mathbf{x}_a)$$

$$\mathbf{d}_b = \mathbf{y} - H(\mathbf{x}_b)$$

More to come in Sarah Dance's talk

BC

- Observations ($\mathbf{y}$) are biased to different degree. Removing important systematic errors ($\mathbf{b}$) is important given that Var and LETKF approaches assume that observations errors are unbiased.

$$\mathbf{y}_{bc} = \mathbf{y} - \mathbf{b} \quad , \ \mathbf{b} = f(\boldsymbol{\beta}) \quad , \text{ where } \beta \text{ represents the bias correction coefficients}$$

Online: VarBC

Extends the control vector in 4DVar and EnVar to compute β during the minimization:

$$J(\delta\mathbf{x}, \boldsymbol{\beta}) = \boldsymbol{J_b} + \boldsymbol{J_o} + \frac{1}{2}(\boldsymbol{\beta} - \boldsymbol{\beta}_b)^T \mathbf{B}_{vbc}^{-1}(\boldsymbol{\beta} - \boldsymbol{\beta}_b)$$

ECMWF, JMA, Météo-France, Met Office & NCEP

Offline

Compute β based on recent past innovations (d) and linear regressions.

DWD $\quad \mathbf{d} = \mathbf{y} - H(\mathbf{x}_b)$

ECCC $\quad \mathbf{d} = \mathbf{y} - H(\mathbf{x}_{a_anchor})$,

where $\mathbf{x}_{a_anchor}$ is a separate EnVar analysis that assimilates only observations that are deemed less prone to biases: 1) GNSS-RO, 2) radiosondes, 3) AMVs and 4) surface reports.

QC

- Observation quality control is usually done in two parts based on $C = \frac{(y - H[x_b])^2}{\sigma_o^2 + \sigma_b^2}$

1 Pass or fail approach to identify gross errors

if C > $C_{crit\text{-}1}$, reject *y*

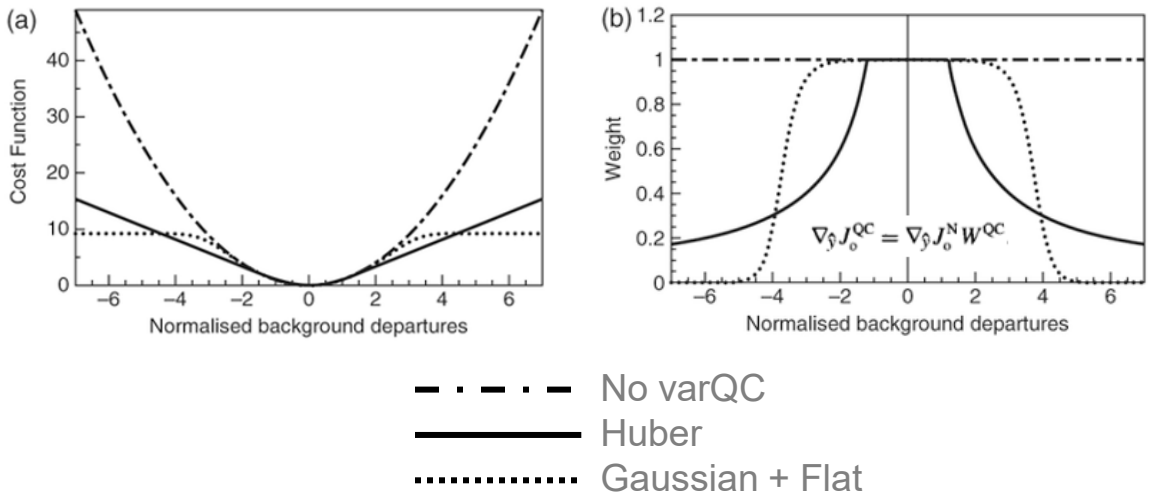
2a Inflation of observation errors

If C > $C_{crit\text{-}2a}$, inflate σ_o^2

ECMWF (for dropsondes) and ECCC-LETKF

2b VarQC (in Var of all centers for at least some *y*)

If C > $C_{crit\text{-}2b}$, reduces the cost function contribution of *y* (equivalent to inflating the observation errors)



Current operational approaches

Handling nonlinearities

OUTER LOOP ITERATIONS

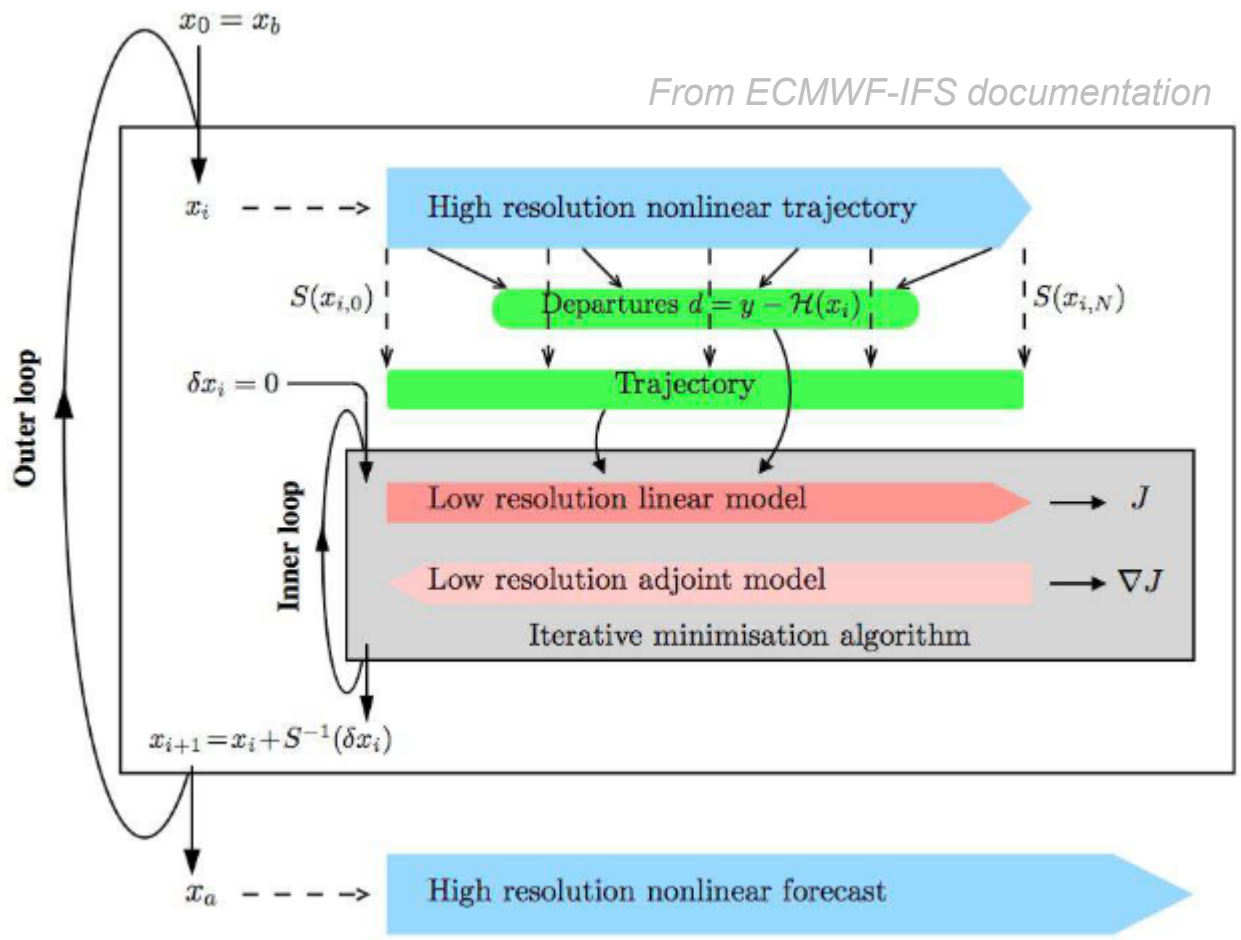
In 4DVar, outer loop iterations enable to include non-linear effects, the influence of which increases with resolution and DA window length.

Outer loop iterations used in operational systems

	Global
ECMWF	4
JMA	2
Météo-France	2

In the Met Office 4DVar, **H** is updated / relinearized every 10 iterations

From ECMWF-IFS documentation

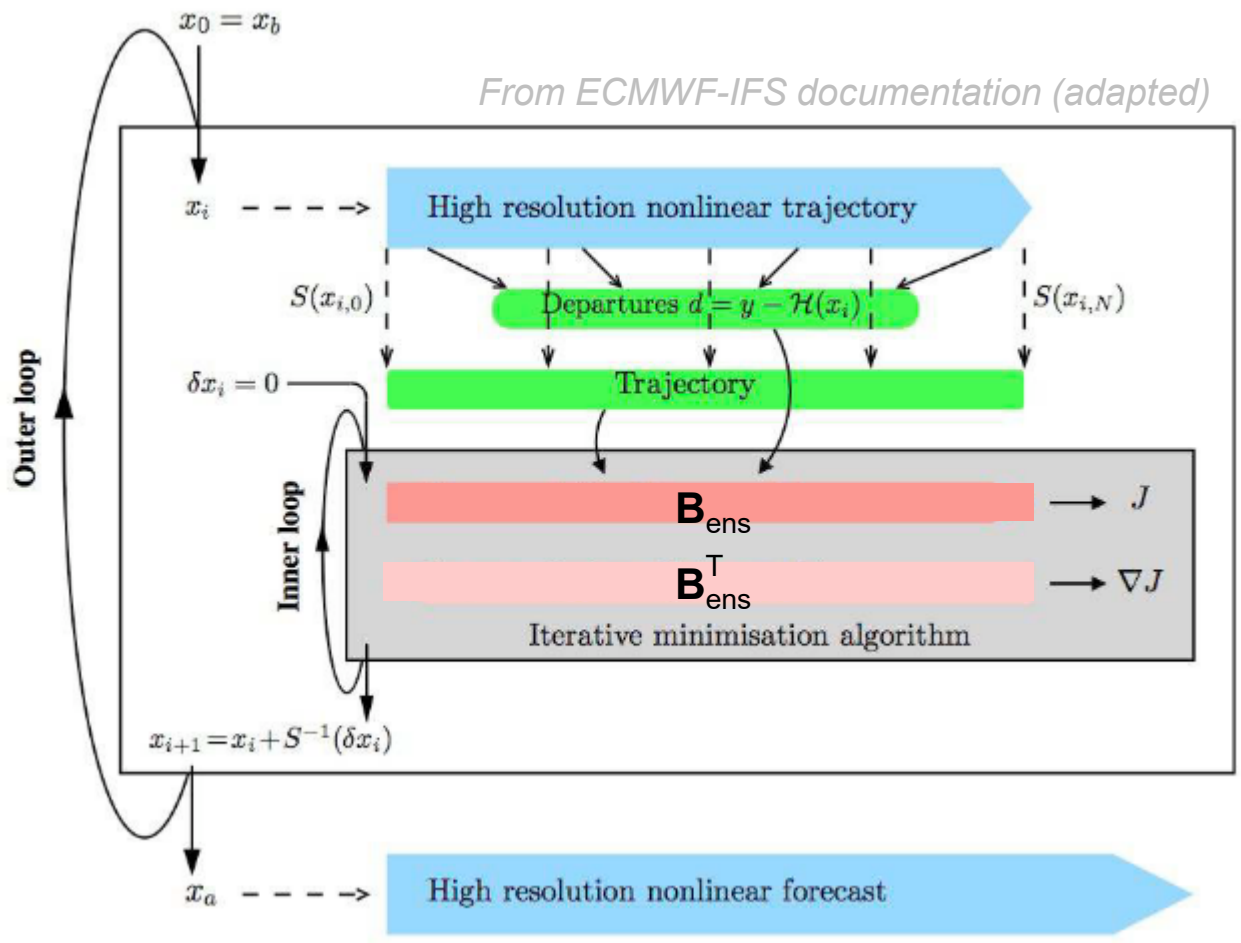


OUTER LOOP ITERATIONS

In 4DEnVar, outer loop iterations is (theoretically) possible but…

- Updating **H** is straightforward (planned at ECCC)
- Updating the nonlinear trajectory is tricky when the initialization rely on IAU (Incremental Analysis Update)
- Since the time evolution of **B** (and $\delta\mathbf{x}$) is controlled by an ensemble and not the model TL/AD, updating **B** demands **rerunning the ensemble** after recentering it around the updated initial state (at the start of the DA window)

From ECMWF-IFS documentation (adapted)



Current operational approaches

Ensemble recentering

ENSEMBLE RECENTERING

- EnKF-based algorithms like the LETKF struggle to assimilate as much observations and as efficiently as variational approaches, which explains the advantages of recentering the ensemble around a variational analysis.

$$\overline{\mathbf{x}^a} = \overline{\mathbf{x}^a_{\mathrm{LETKF}}} + \gamma \left(\mathbf{x}^a_{\mathrm{var}} - \overline{\mathbf{x}^a_{\mathrm{LETKF}}} \right)$$

$$\mathbf{x}^a_i = \mathbf{x}^a_{i,\mathrm{LETKF}} + \gamma \left(\mathbf{x}^a_{\mathrm{var}} - \overline{\mathbf{x}^a_{\mathrm{LETKF}}} \right)$$

0 means no recentering
1 means full recentering

	γ	
	Global	LAM
DWD	1	0
ECCC	0.75 – 0.5	n/a
JMA	1	0
NCEP	1	1

Soft recentering at ECMWF

Approximate the results of two outer loop iterations in the perturbed members at half the cost.

1. The perturbed members are fully recentered (γ=1) on the analysis obtained after the first outer loop iteration of the control member.

2. Single minimizations of the perturbed members start from the control vector increment of the control member (after the first outer loop iteration)

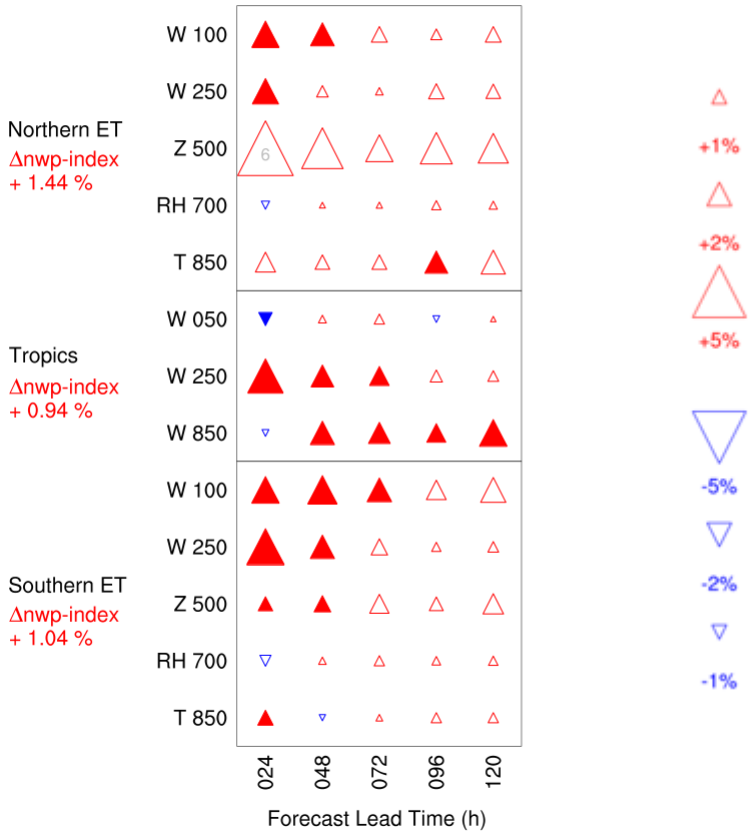
ENSEMBLE RECENTERING @ECCC

Impact of recentering on the **control member RMSE relative changes**

Red means with recentering is better

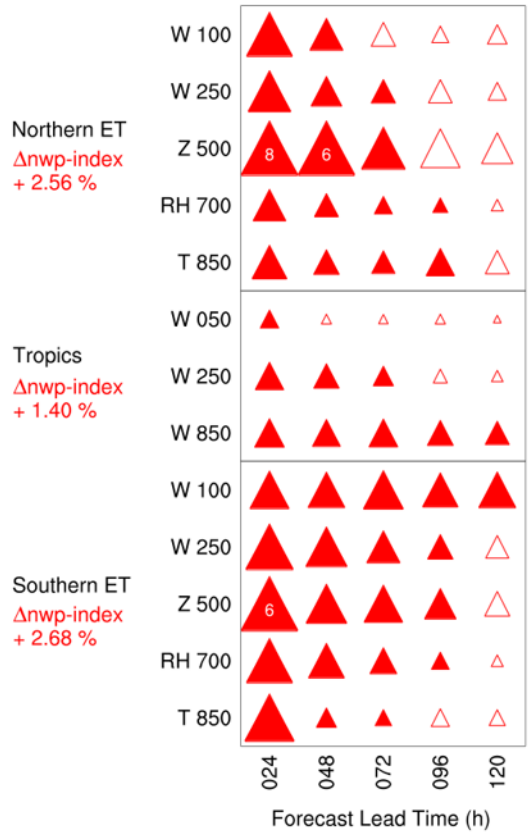
Blue means no recentering is better

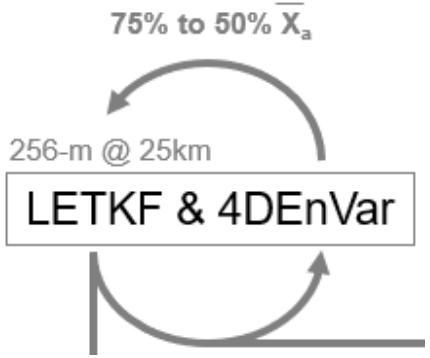
Recentering around a deterministic analysis



Using the ensemble mean as the background for the recentering analysis

Operational approach





Winter (Dec 2021 – Feb 2022)

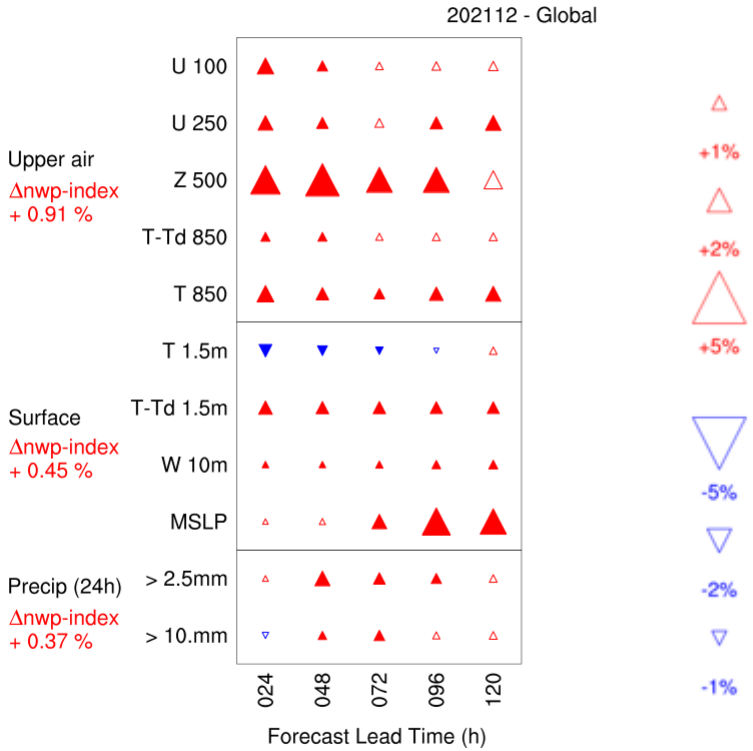
ENSEMBLE RECENTERING @ECCC

Impact of recentering on the **ensemble CRPS relative changes**

Red means with recentering is better

Blue means no recentering is better

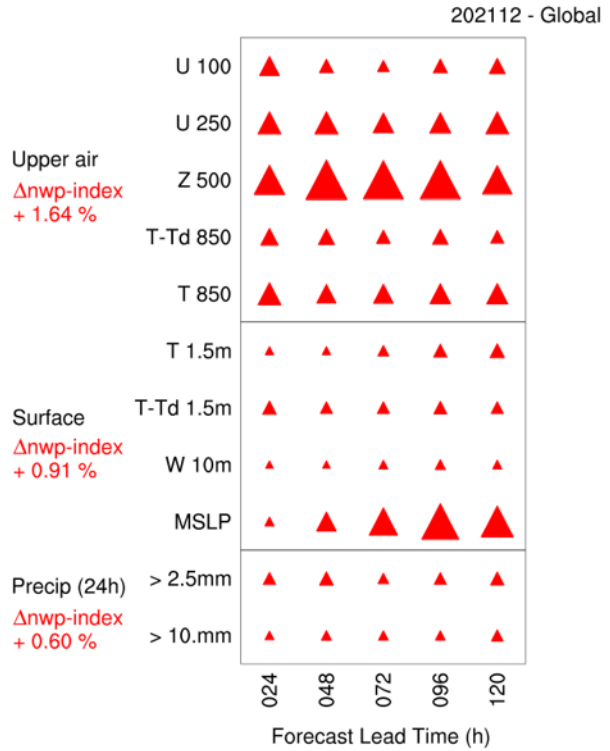
Recentering around a deterministic analysis



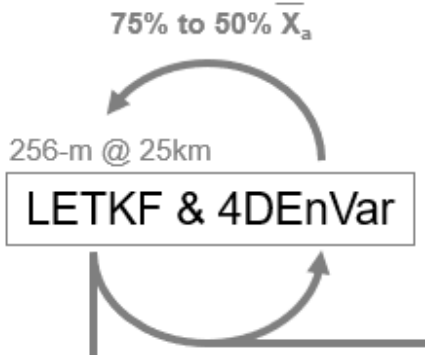
Observations used: radiosondes and SYNOP

Using the ensemble mean as the background for the recentering analysis

Operational approach



Observations used: radiosondes and SYNOP



Winter (Dec 2021 – Feb 2022)

Current operational approaches

Software frameworks

SOFTWARE FRAMEWORKS

- Developing computationally efficient software, avoiding redundant coding and easing code maintenance is key to foster data assimilation innovations in an operational environment.
- Operational centers have therefore favored the development of integrated code supporting different DA applications, a key to enable strongly coupled DA.

<table>
<tr><th></th><th>Name</th><th>Language</th><th>GPU compatible</th><th>Radiative transfer model</th></tr>
<tr><td>DWD</td><td>DACE</td><td>Fortran</td><td>No</td><td rowspan="6">RTTOV</td></tr>
<tr><td>ECCC</td><td>MIDAS</td><td>Fortran</td><td>No</td></tr>
<tr><td>JMA</td><td>multiple codes</td><td>Fortran</td><td>No</td></tr>
<tr><td>ECMWF</td><td rowspan="2">OOPS/IFS</td><td rowspan="2">C++ for OOPS,
Fortran for IFS</td><td rowspan="2">No</td></tr>
<tr><td>Météo-France</td></tr>
<tr><td>Met Office</td><td rowspan="2">JEDI*</td><td rowspan="2">Mostly C++ with
some Fortran</td><td rowspan="2">Many components</td></tr>
<tr><td>NCEP</td><td>CRTM</td></tr>
</table>

* Most operational deployment of JEDI is planed over the next year

Looking forward

Non-AI related: improving the old-world

IMPROVING THE OLD-WORLD

Improving **B** by extracting more info from ensembles

- Higher model resolution
- More ensemble members and better localization techniques
- Deriving hydrometeor covariances from ensembles

Improving observation related components

- Take spatial error correlations into account directly (similar to the Met Office) or indirectly (by augmenting the observation vector with spatial derivatives of the observations in addition to the observations themselves)
- Assimilate more land-surface and ice sensitive radiances
- Improving obs selection in the computation of the LETKF's weights

Nonlinear DA (e.g. particle filter)

Adapting (legacy) software frameworks to the upcoming supercomputer architectures

- Getting ready for GPUs and mixed CPUs-GPUs platforms and living in an age where memory is expensive

Moving towards strongly coupled atmosphere, ocean and land surface DA

- Make better use of interface observations and improve initialization of coupled models

Looking forward

AI: from incremental changes to turning the tables

AI & MODELING

Pure physics-based model

The end is near…

$$\frac{d\vec{V}}{dt} = -\alpha\vec{\nabla}p - \vec{\nabla}\Phi + \vec{F} - 2\Omega\times\vec{V}$$

$$\frac{\partial\rho}{\partial t} = -\vec{\nabla}\cdot\left(\rho\vec{V}\right)$$

$$p\alpha = RT$$

$$Q = C_p\frac{dT}{dt} - \alpha\frac{dp}{dt}$$

$$\frac{\partial\rho q}{\partial t} = -\vec{\nabla}\cdot\left(\rho\vec{V}q\right) + \rho(E-C)$$

Hybrid

The (upcoming) new standard

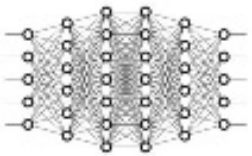
$$\frac{d\vec{V}}{dt} = -\alpha\vec{\nabla}p - \vec{\nabla}\Phi + \vec{F} - 2\Omega\times\vec{V} +$$

$$\frac{\partial\rho}{\partial t} = -\vec{\nabla}\cdot\left(\rho\vec{V}\right)$$

$$p\alpha = RT$$

$$Q = C_p\frac{dT}{dt} - \alpha\frac{dp}{dt} +$$

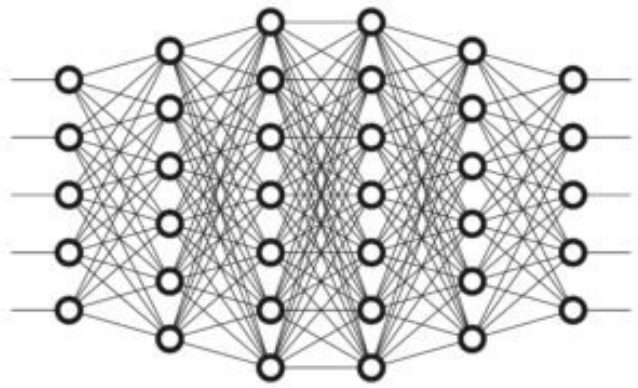
$$\frac{\partial\rho q}{\partial t} = -\vec{\nabla}\cdot\left(\rho\vec{V}q\right) + \rho(E-C)$$



- Operational for global deterministic forecasting at ECCC since May 2026
- In experimental mode at ECMWF for both HRES/CTL and ENS

Pure AI-based model

The challenger that won't go away



DWD-AICON, ECCC-GEML, ECMWF-AIFS, JMA-GraphCast, Met-Office-FastNet, NCEP-EAGLE

AI & DA

A land of experimentations

Substituting / adding components in the DA system

- Correct systematic observation and model errors
- Speed-up observation operators (e.g., RTTOV-MFASIS-NN; used at DWD) or learn complex observation operators (e.g., sea-ice)
- Compute **B** from forecasts generated by AI-based models (no promising results so far)
- Reduce the size of the control vector (e.g., latent-space DA)
- Speeding-up 4DVar/4DEnVar minimization

Replacing / emulating the whole DA step

- Learn the mapping from forecast and observations to analysis (e.g. DWD-AIDA)

End-to-end observation driven NWP (aka DOP)

- Integration of DA and forecasting into a single algorithm using observations for initialization

ECMWF-GraphDOP, ECMWF-AIFS-DOP, NCEP-OCELOT, ECCC-Paradis-DOP

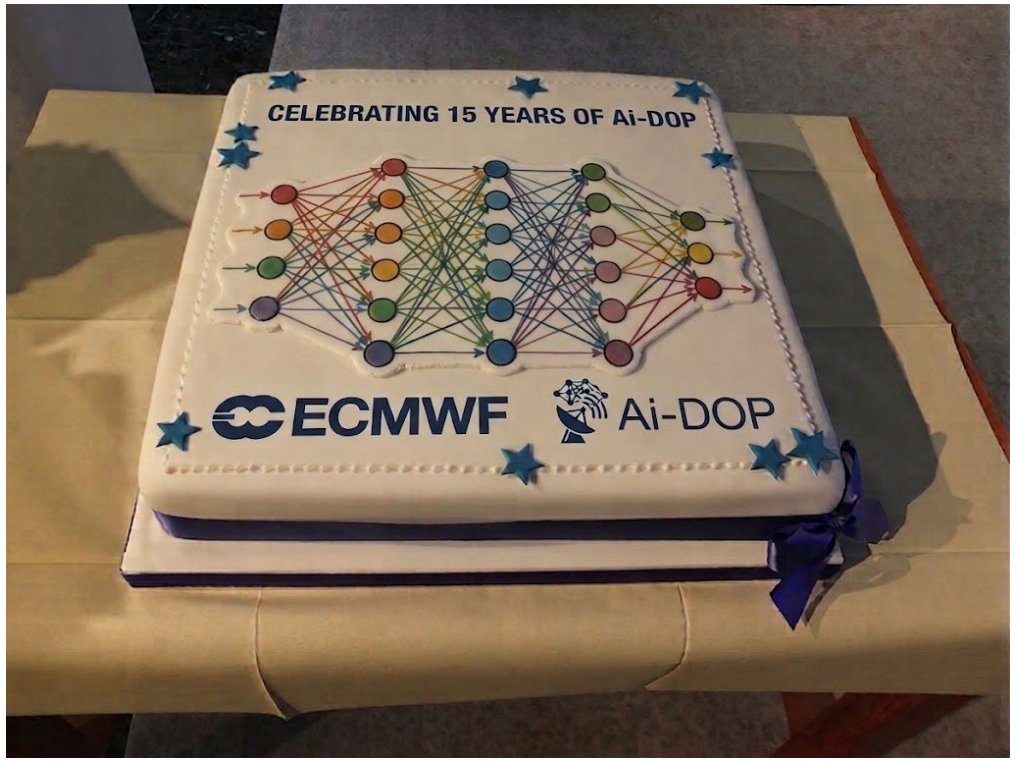


2047




50 YEARS OF 4D-VAR
ECMWF

or


CELEBRATING 15 YEARS OF Ai-DOP
ECMWF
Ai-DOP