Data Assimilation

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Special acknowledgements to Lars Isaksen, Mohamed Dahoui, Tony McNally, Patricia de Rosnay, Fernando Prates, Stephen English, Patrick Laloyaux, Alan Geer, Mike Rennie, Bruce Ingleby, Florence Rabier, Erland Källen and Jean-Noël Thépaut

Overview of talk

- What is data assimilation?
- How does data assimilation work?
- Observations used by the data assimilation system at ECMWF
- How to use observations in data assimilation
- Four dimensional variational data assimilation (4D-Var)
- Recent improvements of the data assimilation system
- Future challenges

Data Assimilation

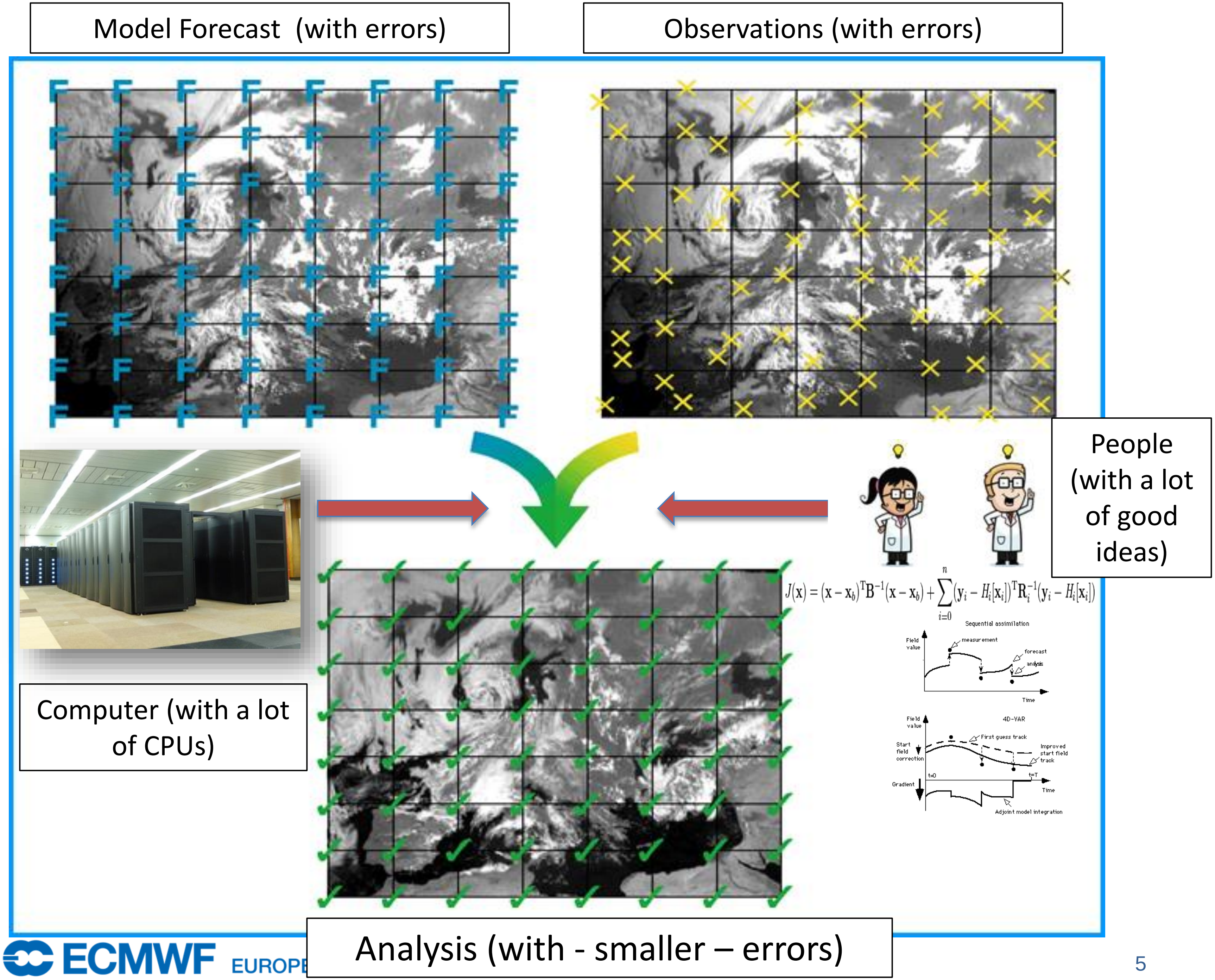
NWP definition: Process by which “optimal” initial conditions for numerical forecasts are defined.

- The best analysis (initial conditions) is the analysis that leads to the best forecast
- Do it quickly – typically in less than 45 minutes on a large high performance computer

Data Assimilation

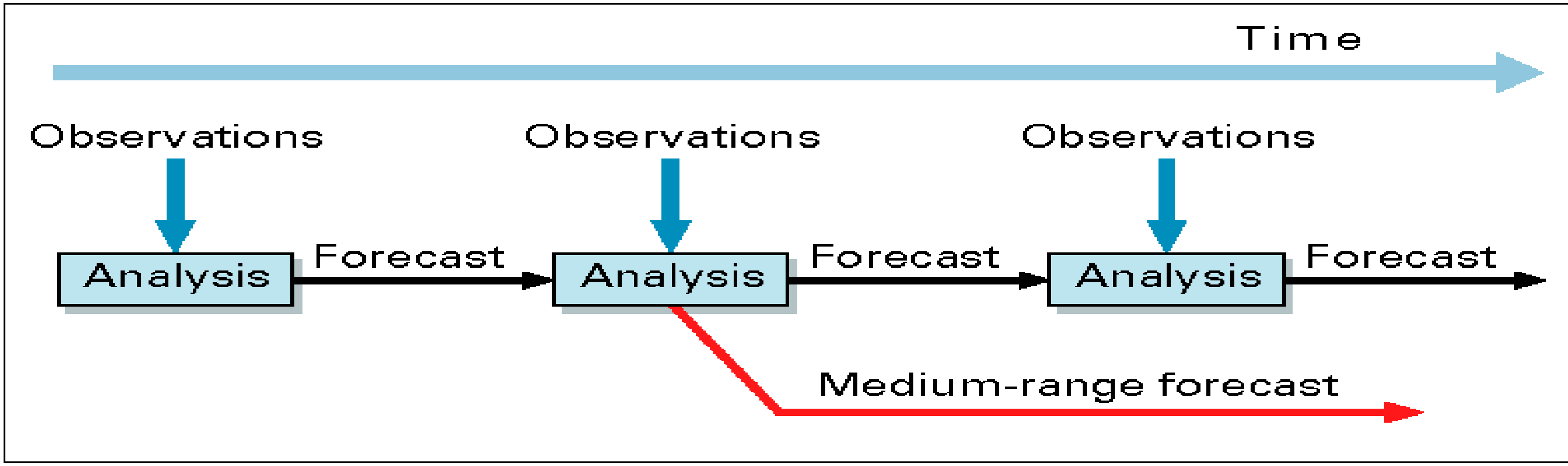
Data Assimilation has two main goals:

- Make the best estimate of the initial state of the atmosphere-land-ocean system out of all available information (model + observations)
- Quantify the uncertainty of our estimate of the initial state (this is necessary to be able to initialise an ensemble forecast!)



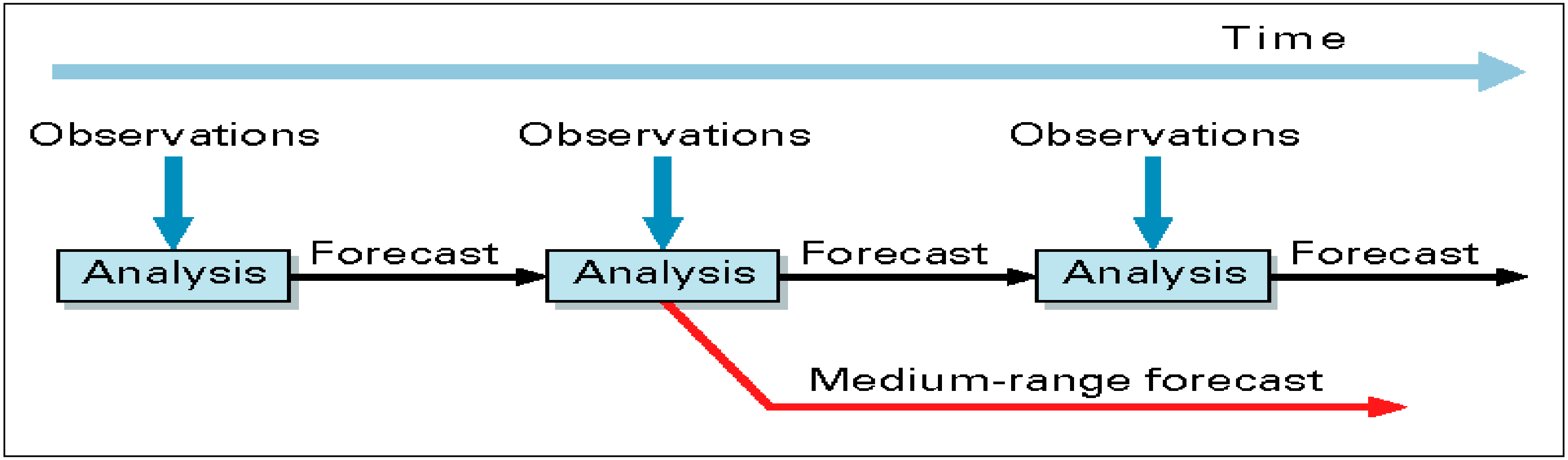
Model Forecast (with errors)
Observations (with errors)
People (with a lot of good ideas)
Computer (with a lot of CPUs)
$J(\mathrm{x}) = (\mathrm{x}-\mathrm{x}_b)^{\mathrm{T}}\mathrm{B}^{-1}(\mathrm{x}-\mathrm{x}_b) + \sum_{i=0}^{n}(\mathrm{y}_i - H_i[\mathrm{x}_i])^{\mathrm{T}}\mathrm{R}_i^{-1}(\mathrm{y}_i - H_i[\mathrm{x}_i])$
Sequential assimilation
Field value
measurement
forecast
analysis
Time
4D-VAR
Field value
First guess track
Start field correction
Improved start field track
t=0
t=T
Gradient
Time
Adjoint model integration
Analysis (with - smaller – errors)

The Data assimilation cycle



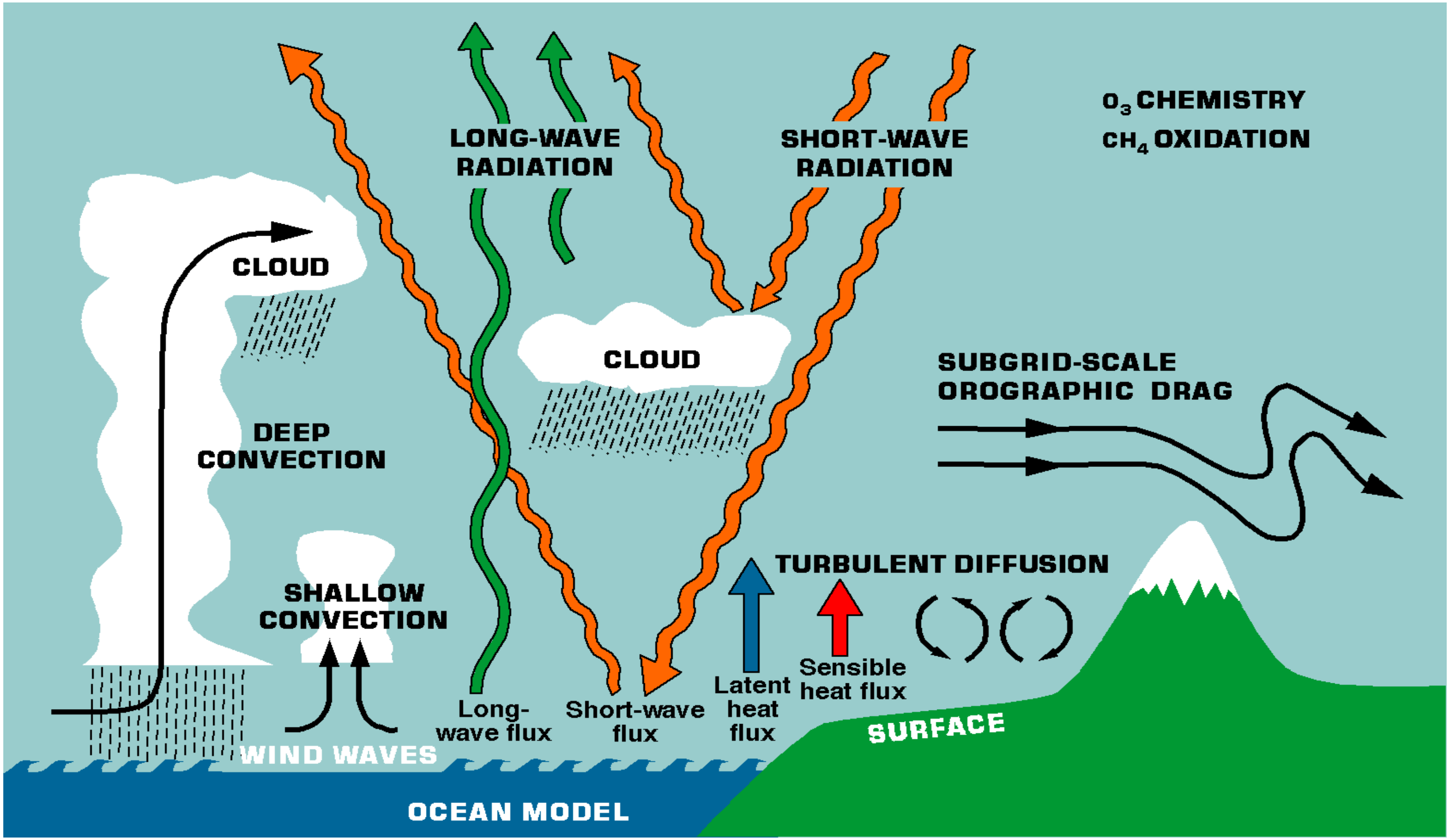
- An analysis is not produced by observations alone!
- The observations are used to correct errors in the short forecast from the previous analysis time (every 12 hours at ECMWF; more frequently for higher resolution, local area models).
- The short range forecast carries information from past observations into the current analysis

The Data assimilation cycle



- At ECMWF, twice a day about 20,000,000 observations are used to correct the 80,000,000 variables that define the model's virtual atmosphere.
- This is at ECMWF done by a 4-dimensional adjustment in space and time based on the available observations (4D-Var); this operation takes as much computer power as the 10-day forecast.

The forecast model is a very important part of the data assimilation system



Most important physical processes in the ECMWF model

ECMWF EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

The forecast model is a very important part of the data assimilation system

- The short range forecast carries information from past observations into the current analysis (this is called "the background"): we need a good model to do this job
- A good model starting from accurate previous analysis will produce an accurate background ⇨ the analysis will make only small corrections to the background
- In fact when the analysis makes large corrections to the background state should alert the forecaster that something interesting is happening… (e.g., rapid development not present in the forecast; suspect observations)
- In modern data assimilation methods (4D-Var, EnKF) the analysed state is constructed so as to respect the physical and dynamical balances of the model ⇨ the model is an integral part of the analysis algorithm

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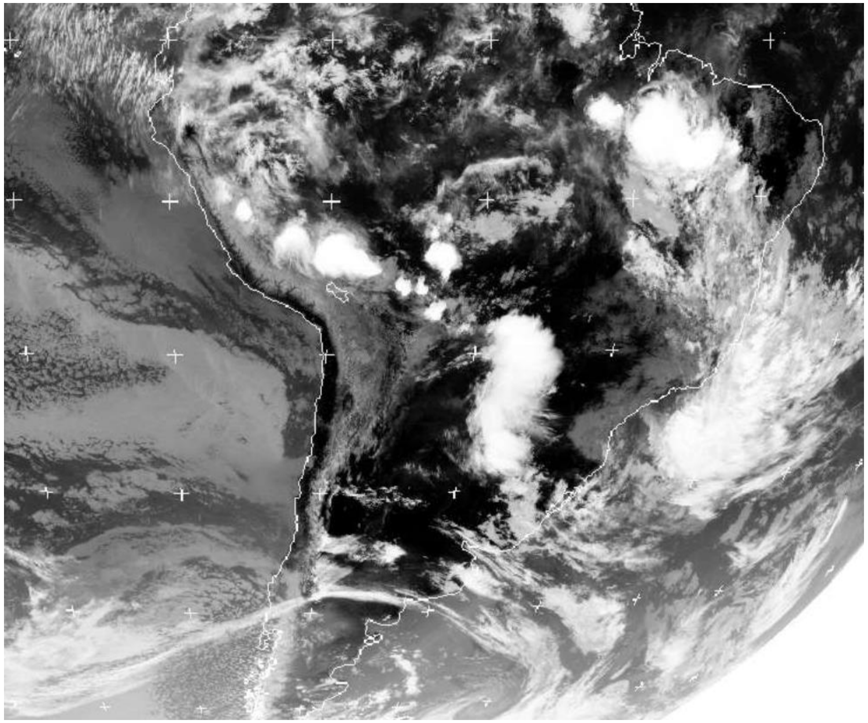
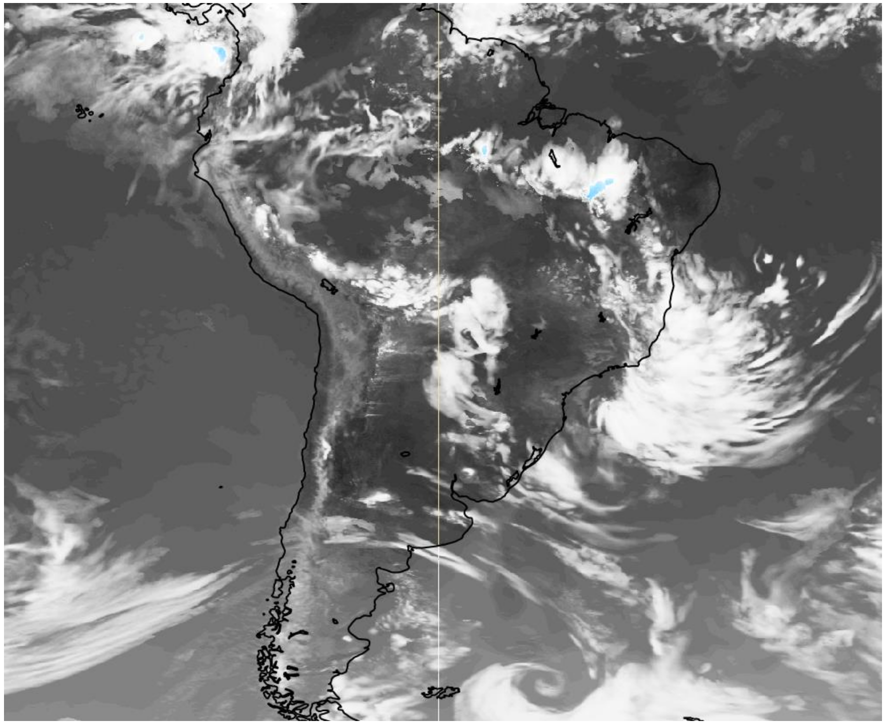
Large analysis increments

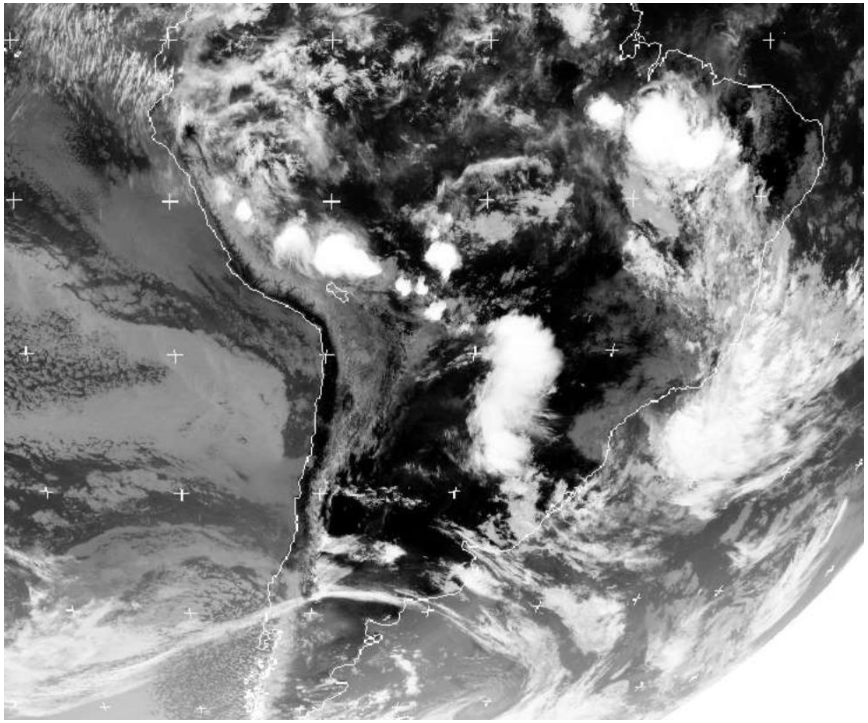


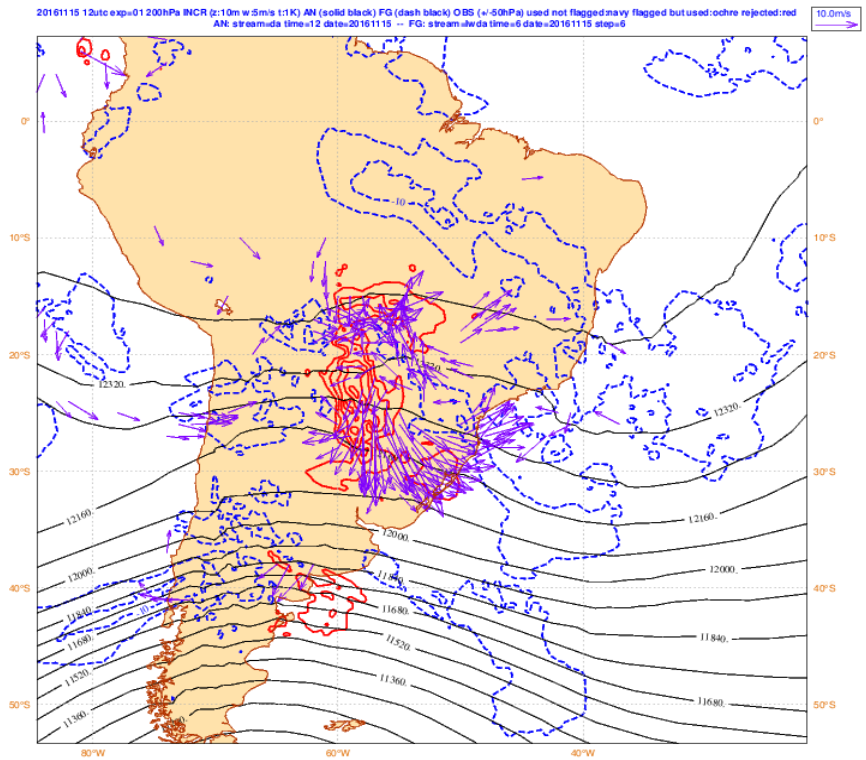
IR GOES EAST
2016-11-15 12UTC



Simulated IR GOES EAST from background forecast
2016-11-15 12UTC

Large analysis increments

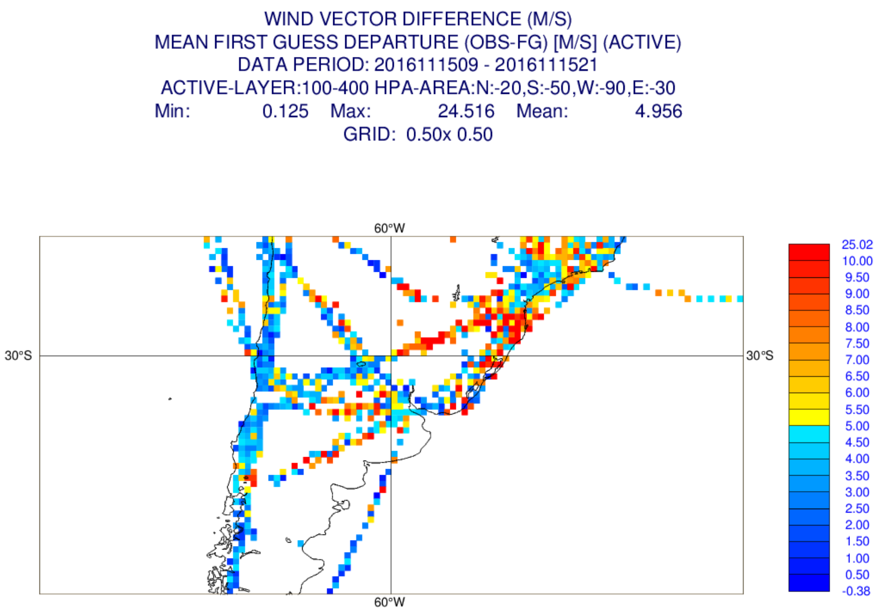


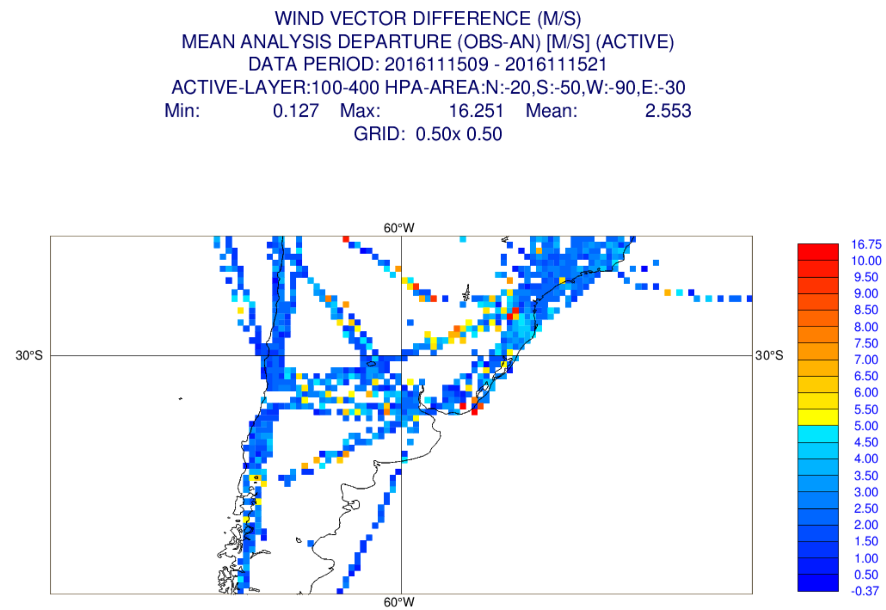


IR GOES EAST
2016-11-15 12UTC

Height and wind analysis increments
200 hPa, 2016-11-15 12UTC

Large analysis increments

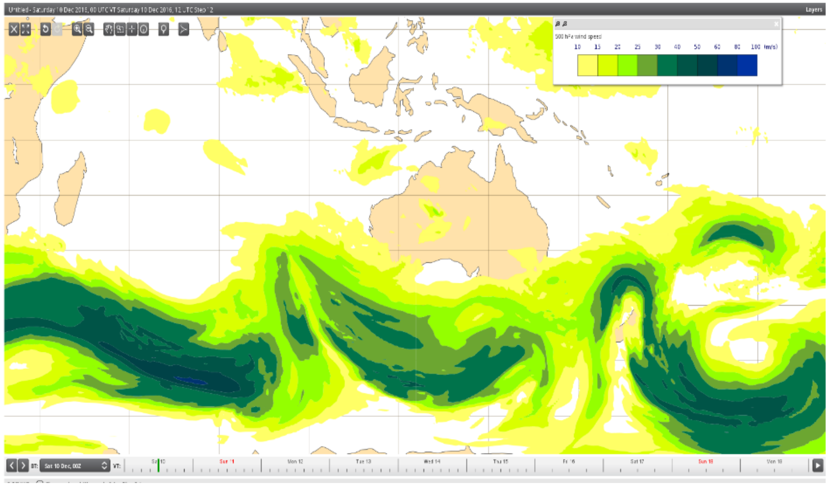


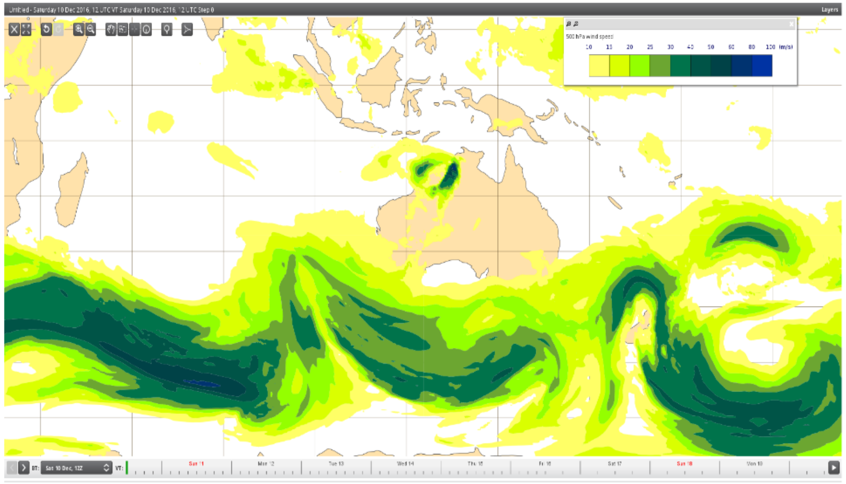


Obs-background difference
Aircraft Winds
2016-11-15 12UTC

Obs-analysis difference
Aircraft Winds
2016-11-15 12UTC

Large analysis increments

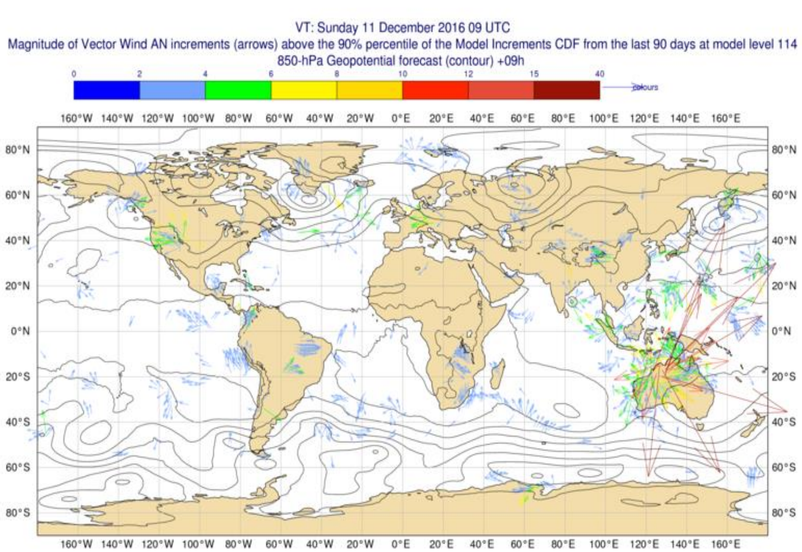




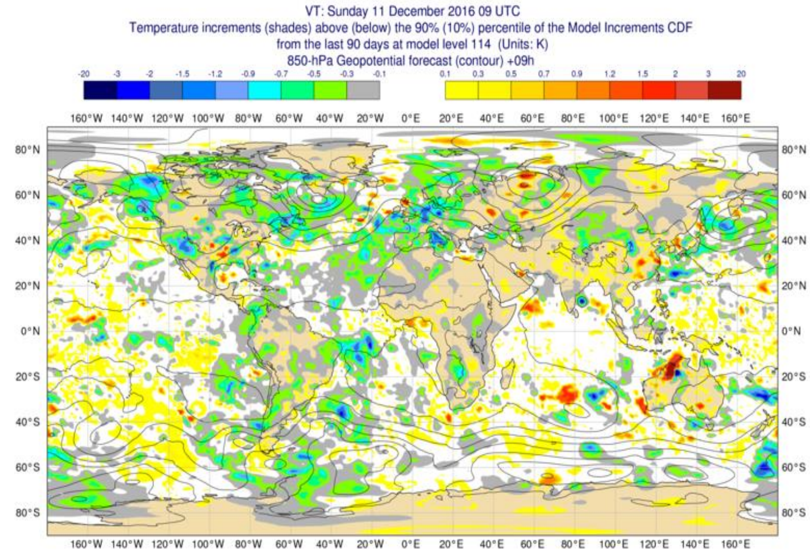
Background forecast of 500 hPa
Wind speed
2016-12-12 12UTC

Analysis of 500 hPa
Wind speed
2016-12-12 12UTC

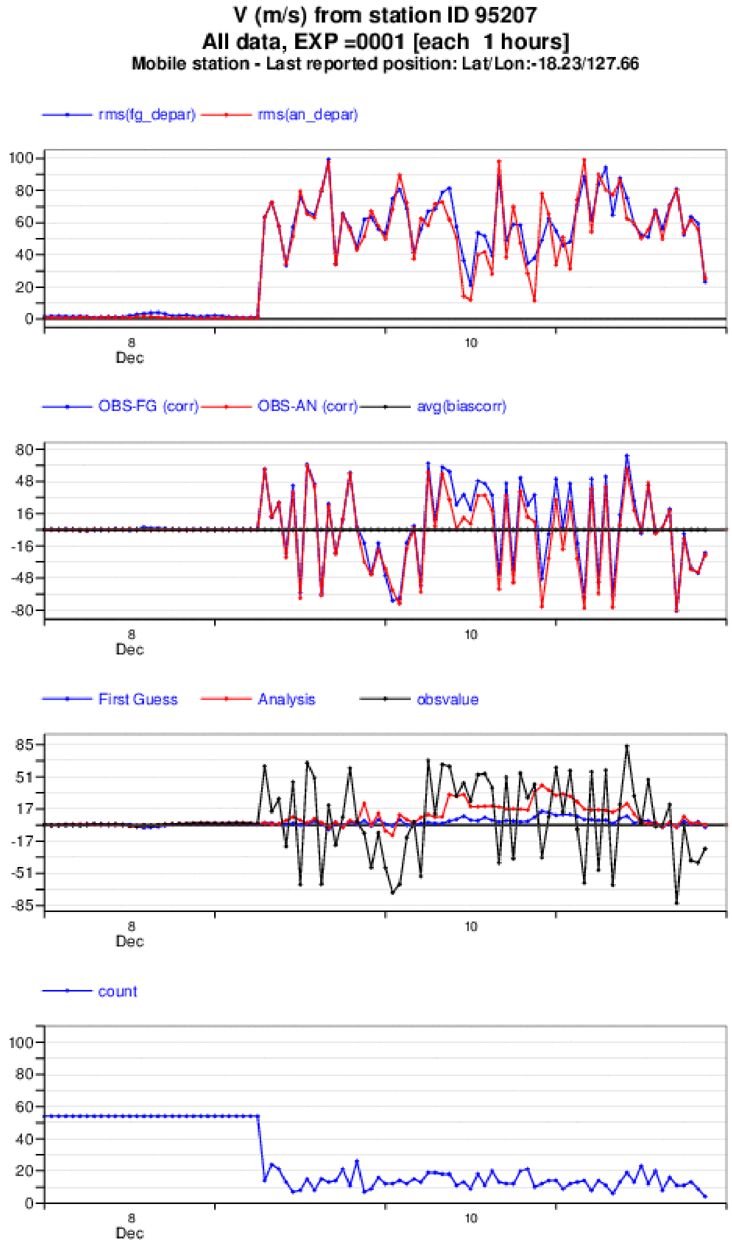
Large analysis increments



Wind vector analysis increments
850 hPa, 2016-12-11 12UTC



Temperature analysis increments
850 hPa, 2016-12-11 12UTC

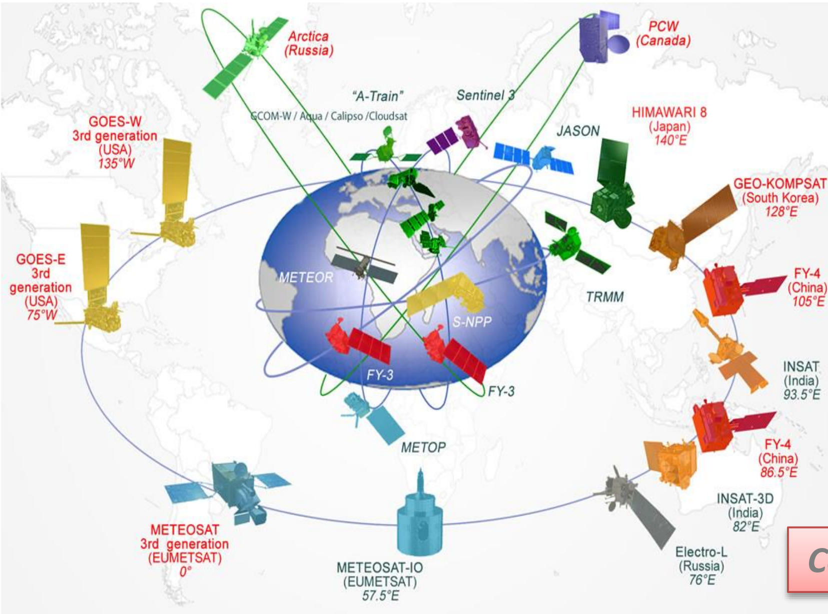


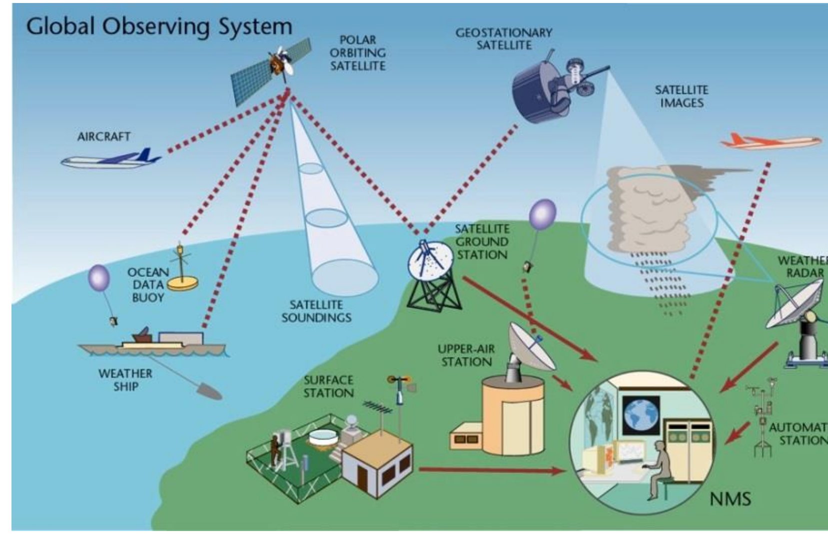
Observation statistics for v-wind component of wind profiler 95207 (Northern Australia)
8-11 Dec. 2016

Wind profiler 95207 was blacklisted on 13 Dec. 2016

Observations used by the data assimilation system at ECMWF

WMO Integrated Global Observing System





Courtesy: WMO

ECMWF Preview – DTS

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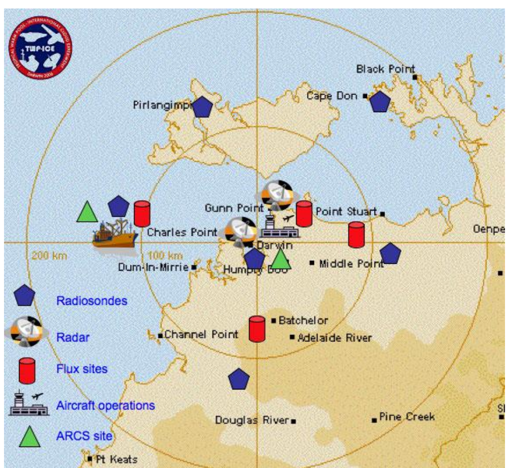
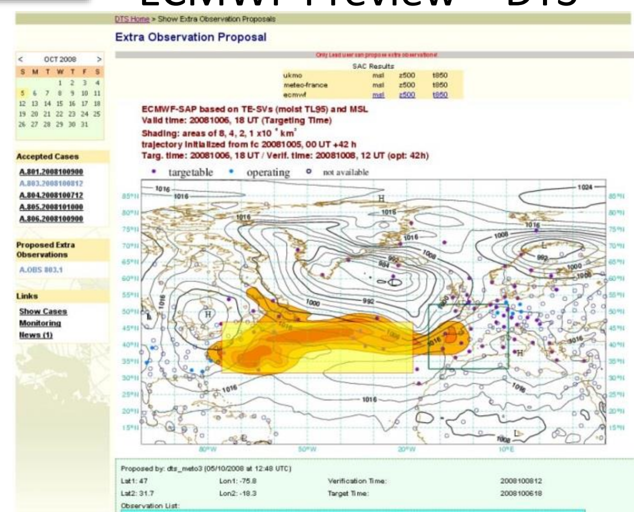
C
E



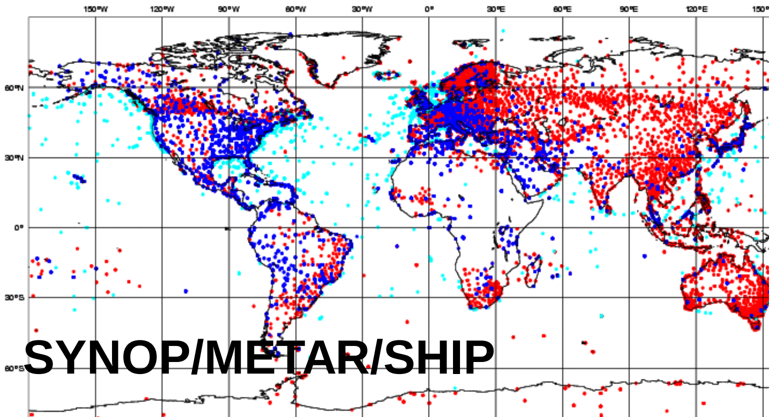
Supported by field campaign experiments, Data targeting studies, etc.

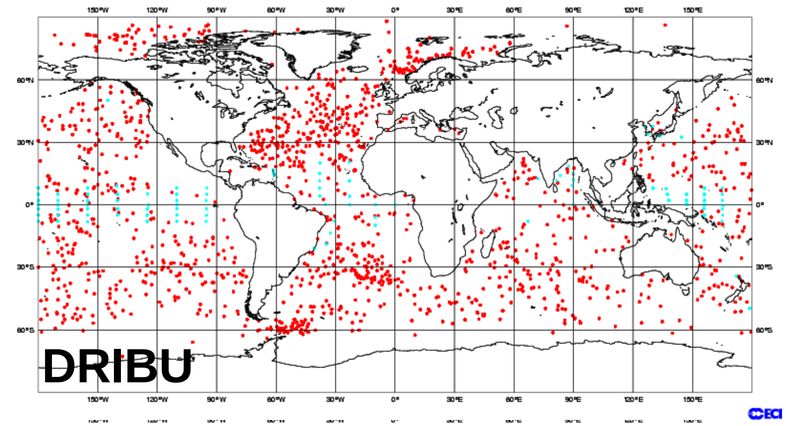


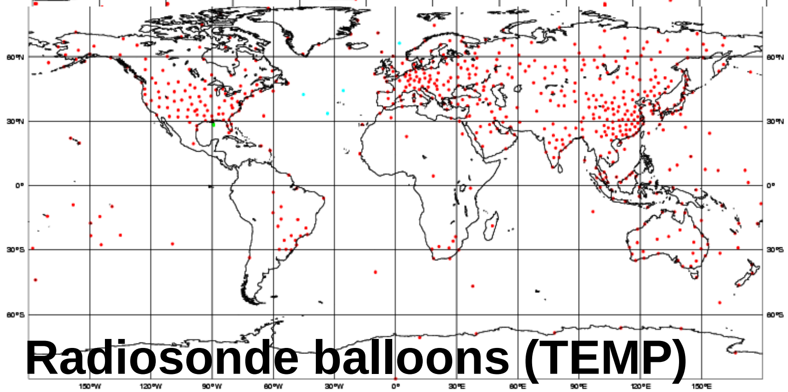
In situ (Conventional) observations

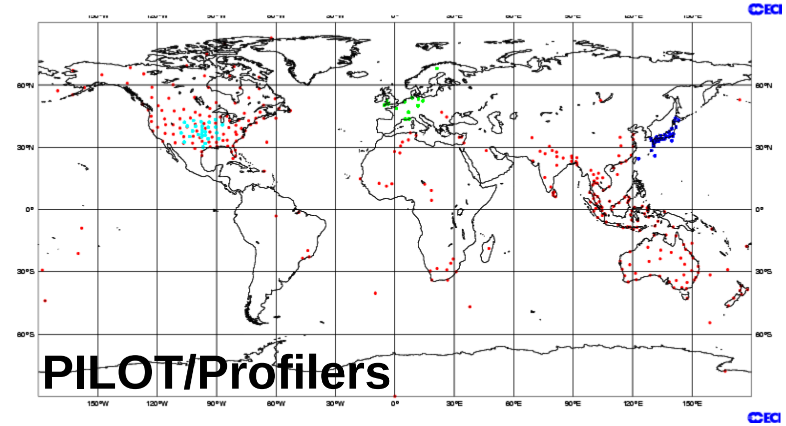
Instrument	Parameters	Height
SYNOP **SHIP** **METAR**	Pressure, temperature, dew-point (wind)	Land: 2m, ships: 25m
BUOYS	temperature, pressure, wind	2m
TEMP **TEMPSHIP** **DROPSONDES**	temperature, humidity, pressure, wind	Profiles
PROFILERS	wind	Profiles
Aircraft	temperature, pressure wind	Profiles Flight level data

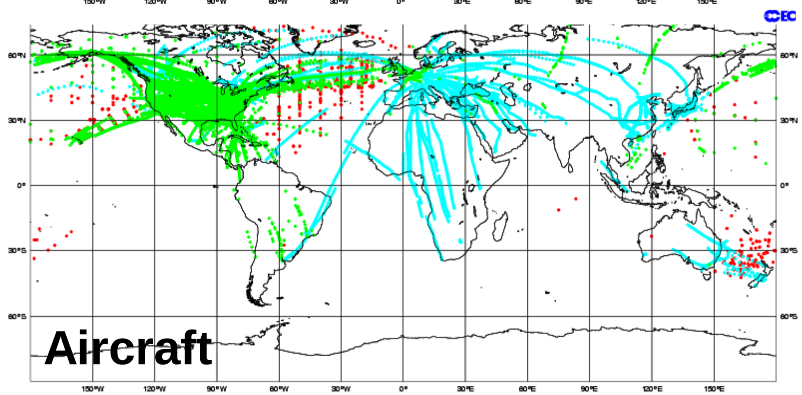
Distribution of in situ observations











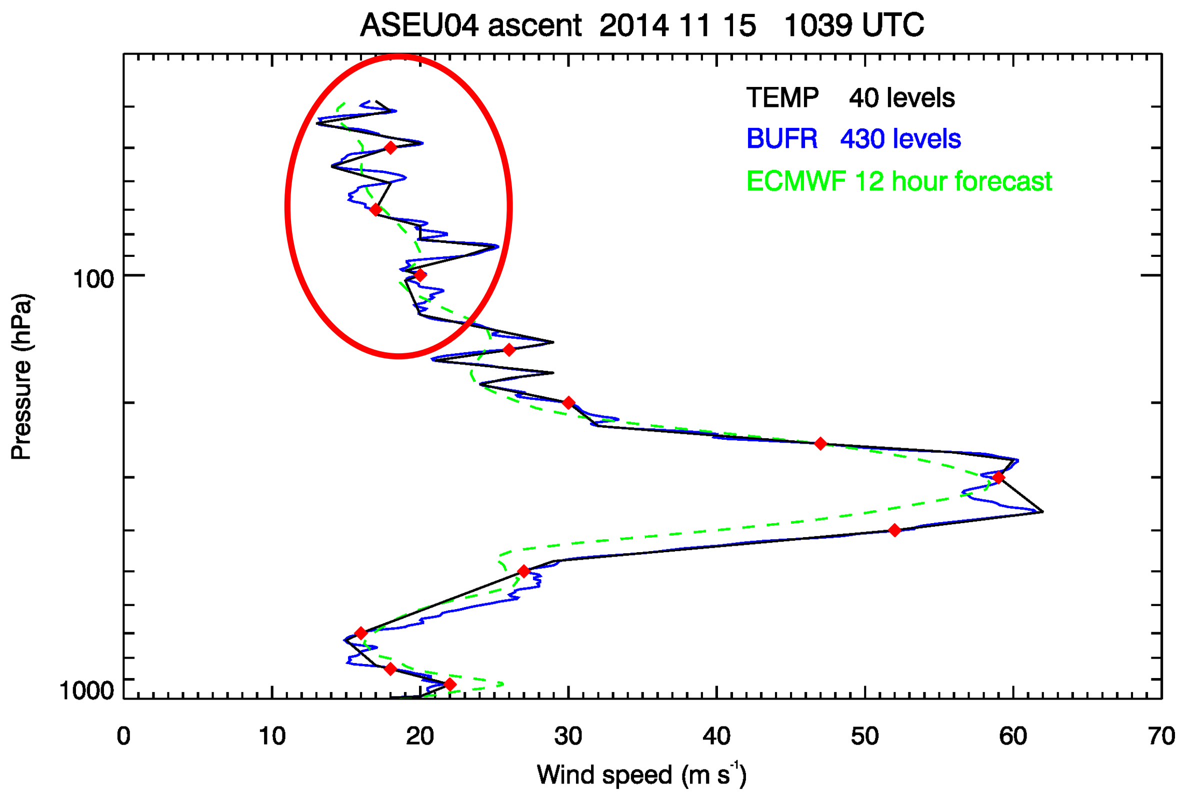
Conventional data issues

- Biases, duplicates, incorrect locations.
- Representativity error….if we measure temperature here at ECMWF is it representative of model grid resolution?
- Data voids.
- Data quality – some radiosondes are good quality, others less so; absolute calibration can vary with age.
- Sampling e.g. significant levels in radiosonde vs full resolution data (Old alphanumeric codes -> BUFR).

But, they are a direct, in situ measurement.

Interpretation is usually more straightforward than remotely sensed data.

Radiosonde wind speed compared to ECMWF 12-h forecast

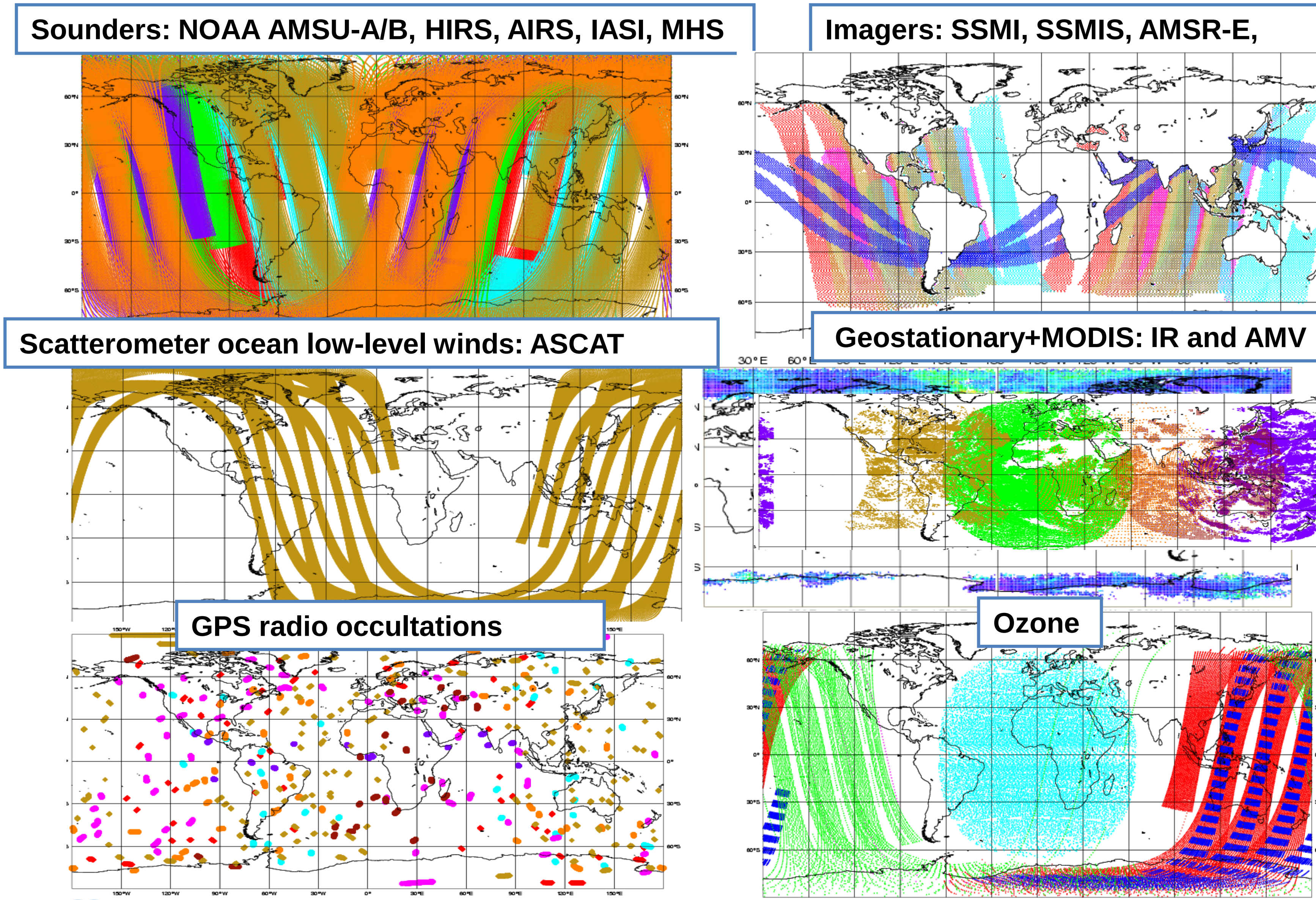


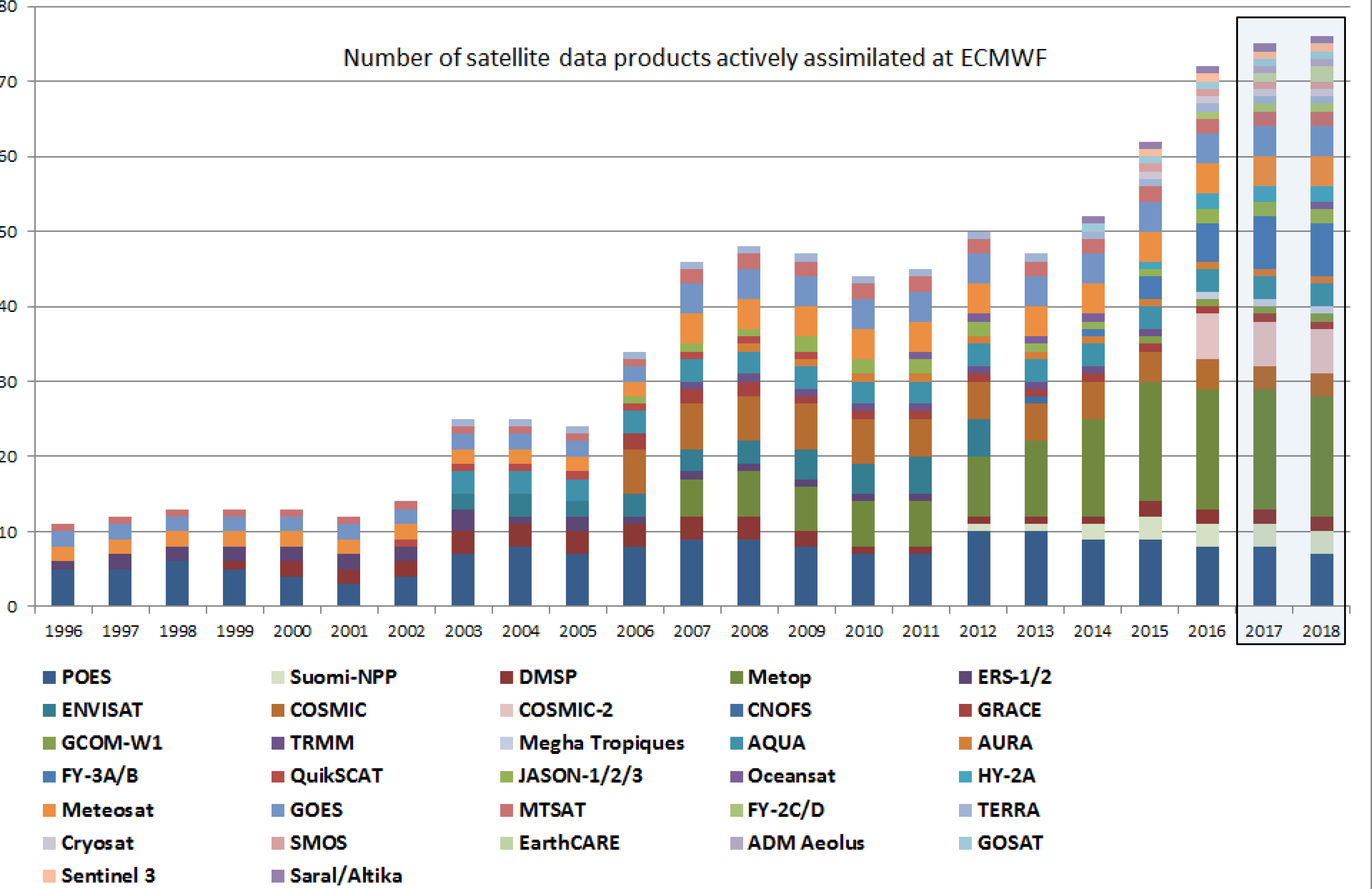
Bruce Ingleby, ECMWF

Satellite observations

Instrument Class	Parameters	Height
Microwave and IR Sounders (AMSU, HIRS, IASI, CRIS,…)	Brightness temperature (sensitive to atmospheric temperature and humidity)	Atmospheric layers
Microwave Imagers (SSMI-S, GMI, TMI,…)	Brightness temperature (sensitive to surface properties, WV, cloud, precipitation)	Surface, troposphere
Scatterometers (ASCAT, QuikScat, SeaWInds,…)	Ocean winds	Surface
Radio Occultation (GRAS, COSMIC, TerraSAR, GRACE,…)	Bending angles (sensitive to temperature, tropospheric humidity)	Profiles
Atmospheric motion vectors	Tropospheric winds	Pressure levels

Satellite data sources used by ECMWF's analysis





Number of satellite data products actively assimilated at ECMWF
80
70
60
50
40
30
20
10
0
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
POES
Suomi-NPP
DMSP
Metop
ERS-1/2
ENVISAT
COSMIC
COSMIC-2
CNOFS
GRACE
GCOM-W1
TRMM
Megha Tropiques
AQUA
AURA
FY-3A/B
QuikSCAT
JASON-1/2/3
Oceansat
HY-2A
Meteosat
GOES
MTSAT
FY-2C/D
TERRA
Cryosat
SMOS
EarthCARE
ADM Aeolus
GOSAT
Sentinel 3
Saral/Altika

Satellite data issues

- An indirect measurement
- Poor vertical resolution for sounding channels.
- Long term drifts, observation biases.
- Data quality – whilst most remotely sensed observations are of very high quality, this can change suddenly.

- They provide global coverage – often for years or even decades.
- They now account for ~95% of the total observation volume

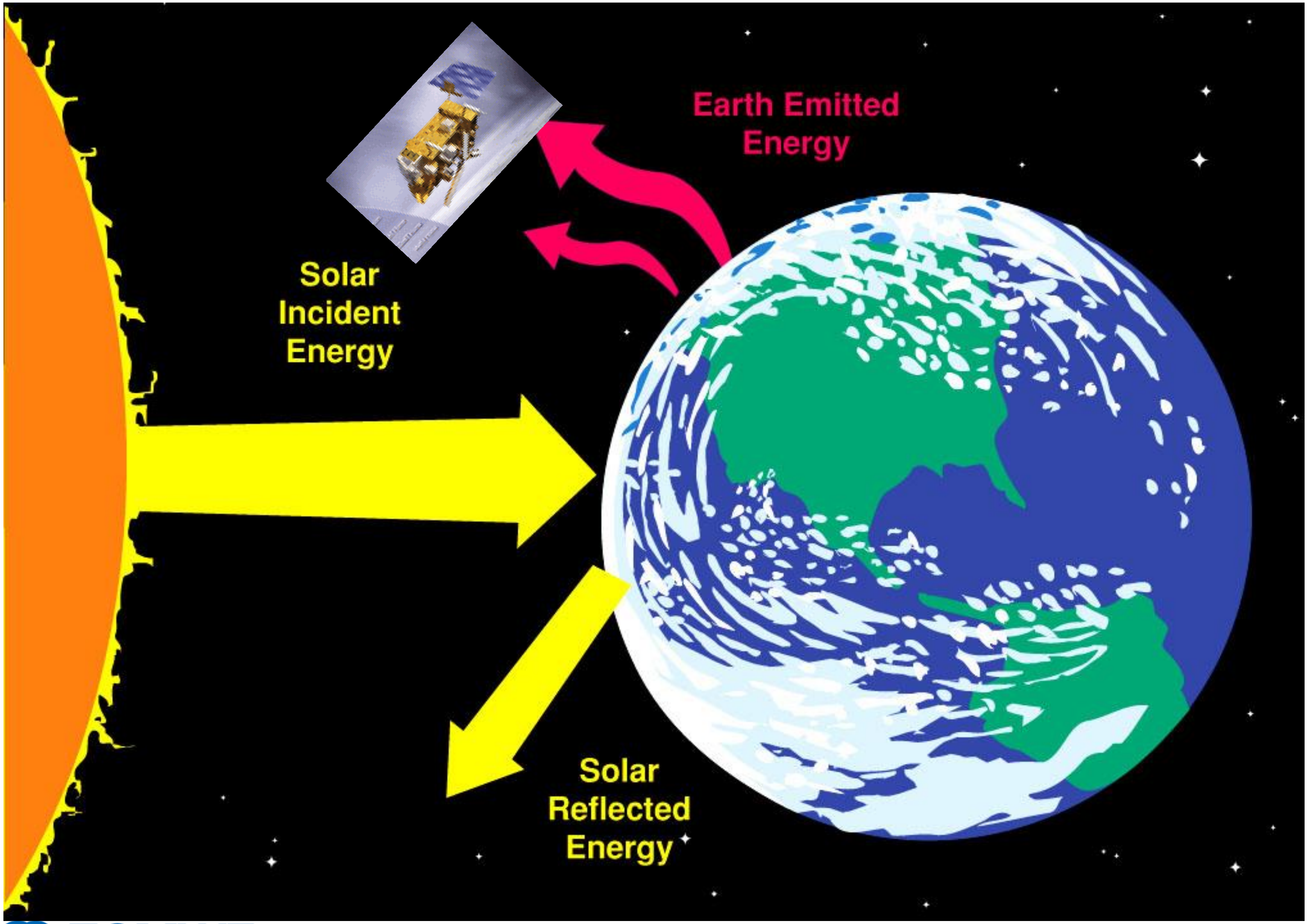
Satellite data issues

- An indirect measurement

To initialise the model we would ideally like to measure temperature, wind and humidity at every grid point.

However satellite observations measure something else…

SATELLITES CAN ONLY MEASURE OUTGOING THERMAL RADIATION FROM THE ATMOSPHERE



T. McNally

What do satellite instruments measure?

Satellite instruments measure the radiance *L* that reaches the top of the atmosphere at given frequency *v* .

The measured radiance is related to geophysical atmospheric variables (T,Q,O_3, clouds etc…) by the

Radiative Transfer Equation

measured by the satellite

Our description of the atmosphere

$$L(\nu) = \int_0^{\infty} B(\nu, T(z)) \left[\frac{d\tau(\nu)}{dz} \right] dz + \text{Surface emission} + \text{Surface reflection/ scattering} + \text{Cloud/rain contribution} + \ldots$$

Planck source term depending on temperature of the atmosphere

Absorption in the atmosphere

Other contributions to the measured radiances

Satellite data issues

- An indirect measurement

To initialise the model we would ideally like to measure temperature, wind and humidity at every grid point.

However satellite observations measure something else…

- Poor vertical resolution for sounding channels

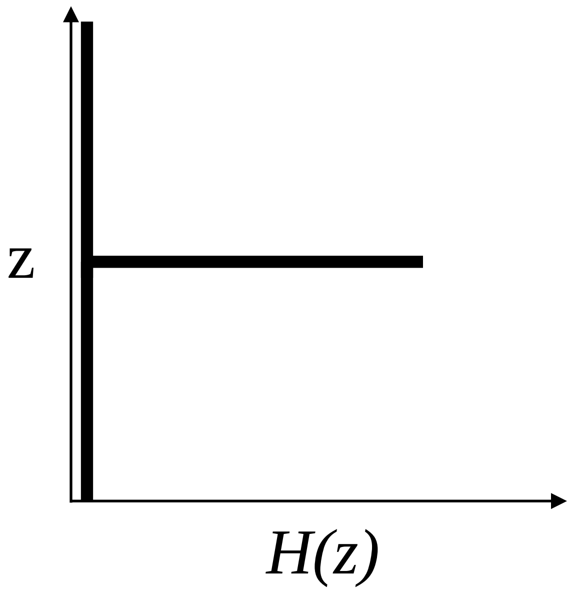
ATMOSPHERIC SOUNDING CHANNELS

For atmospheric sounding channels the measured radiance is essentially a weighted average of the atmospheric temperature profile:

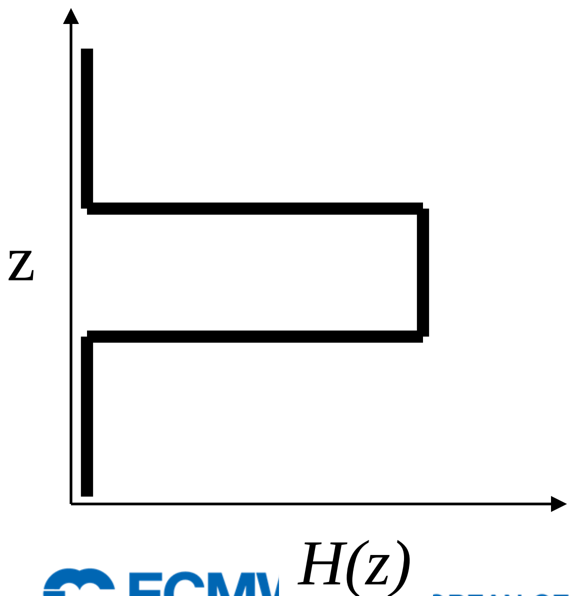
$$L(\nu) = \int_0^\infty B(\nu, T(z))\; H(z)\,dz$$

The function *H(z)* that defines this vertical average is known as a WEIGHTING FUNCTION

IDEAL WEIGHTING FUNCTIONS



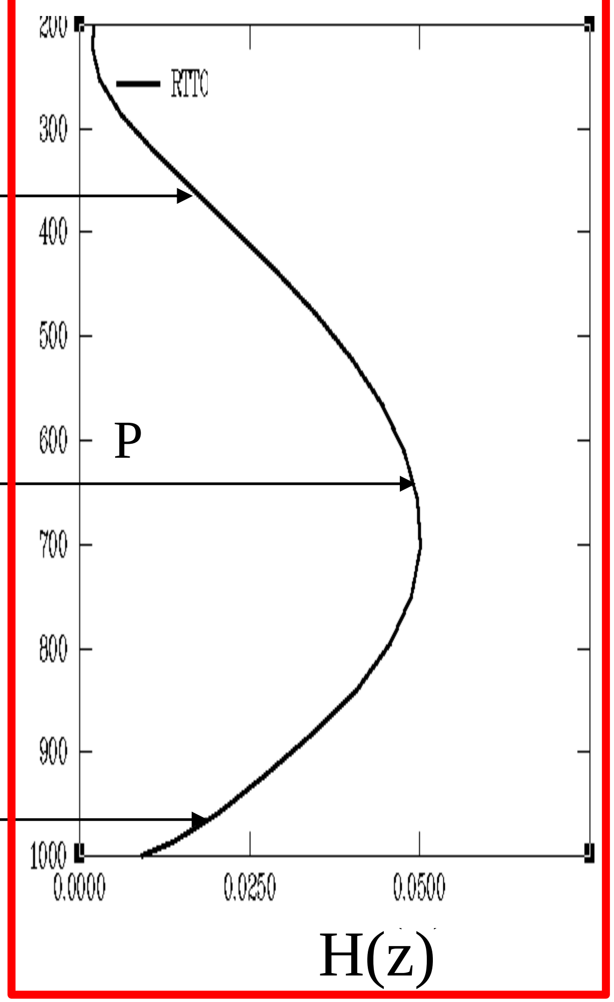
If the weighting function was a delta-function - this would mean that the measured radiance in a given channel is sensitive to the temperature at a single level in the atmosphere.



If the weighting function was a box-car function, this would mean that the measured radiance in a given channel was only sensitive to the temperature between two discrete atmospheric levels

REAL ATMOSPHERIC WEIGHTING FUNCTIONS

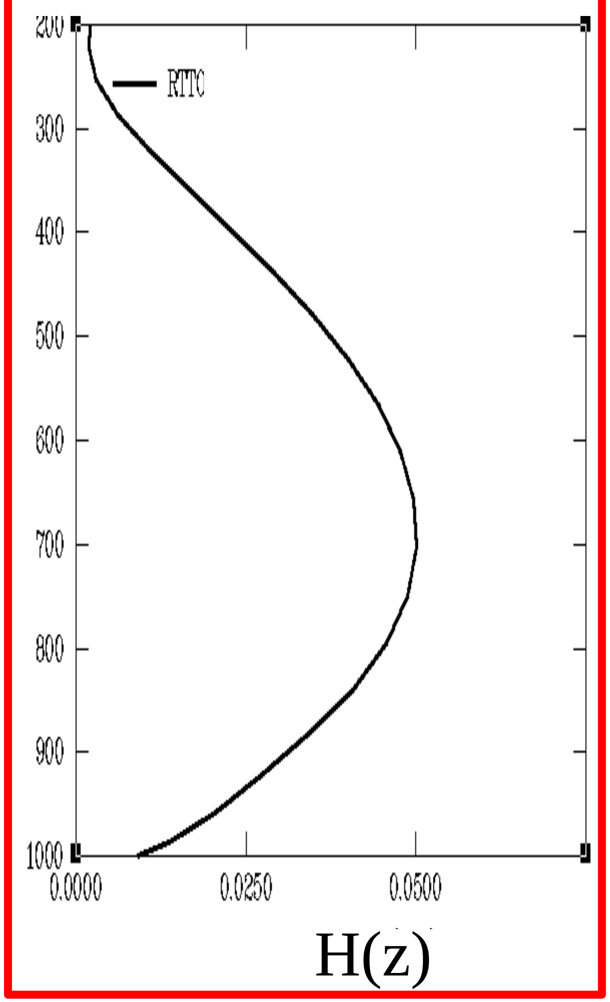
Satellite sounding radiances are broad vertical averages of the atmospheric temperature structure

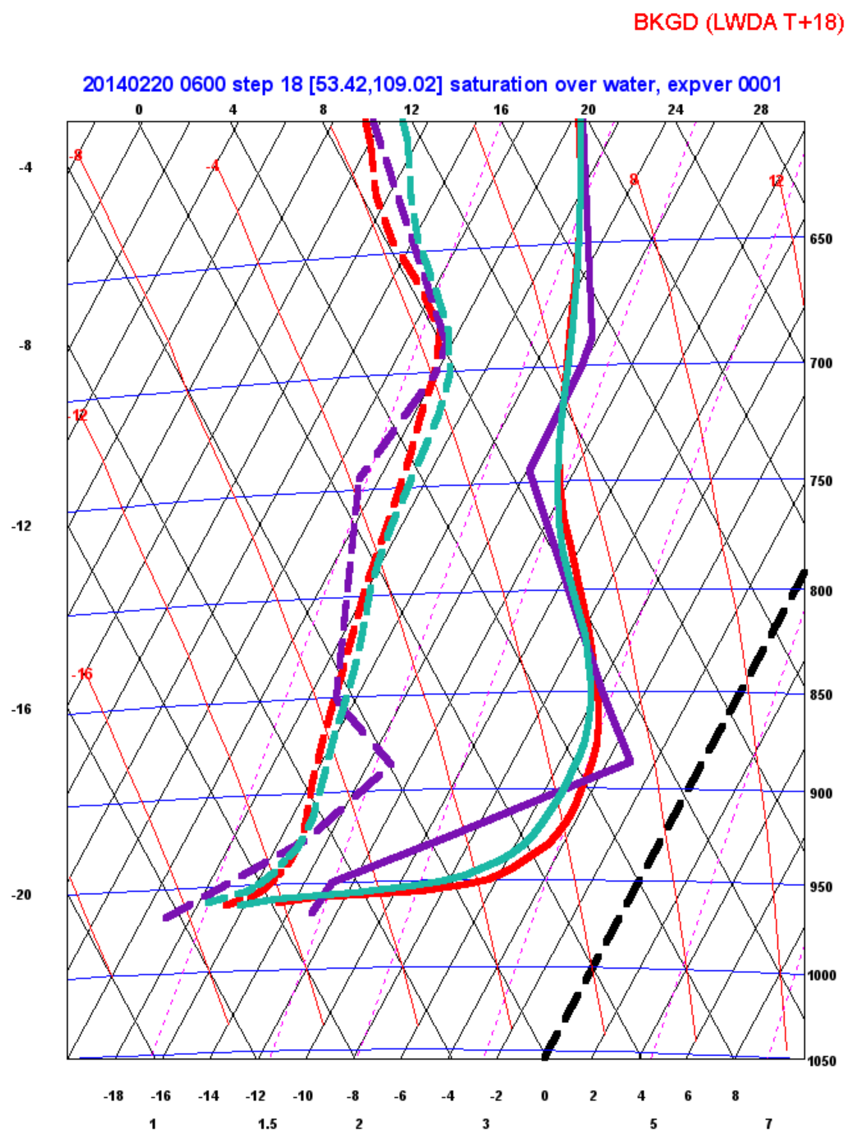


T. McNally

REAL ATMOSPHERIC WEIGHTING FUNCTIONS

- As a consequence, satellite sounding observations can not resolve sharp vertical structures (e.g., boundary layer inversions)
- Detailed vertical structures visible in analyses comes mainly from conventional observations (if available!), the model forecast and its error characteristics
- Limited vertical model resolution limits amount of detail visible in analysed profiles (the analysis is “smoother” than obs)
- Similar considerations apply to meteorological structures with sharp horizontal structures (e.g., frontal systems, tropical cyclones,…)





Station 30635 (Ust Barguzin, 53.4N 109.0E)
2014-02-21 00UTC

Observed profile
Background
Analysis

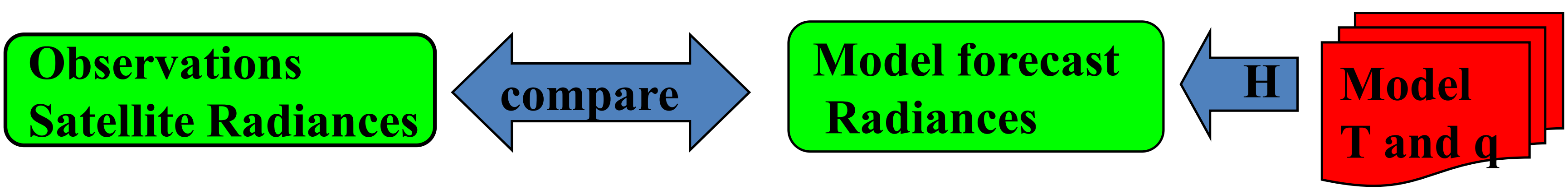
How we use observations in the analysis

- Observations are not made at model grid points.
- Satellites measure radiances, NOT temperature and humidity.

1) For conventional observations we interpolate model forecast values to the location and time of the observations.

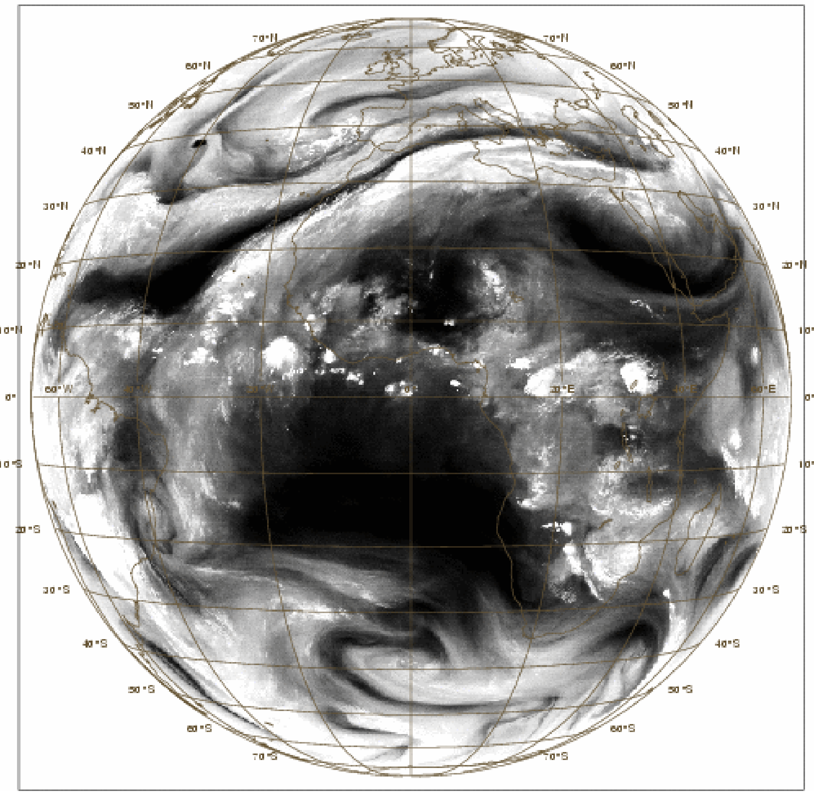
2) For satellite observations we additionally calculate a model radiance estimate of the radiance measurement from the interpolated model forecast fields.

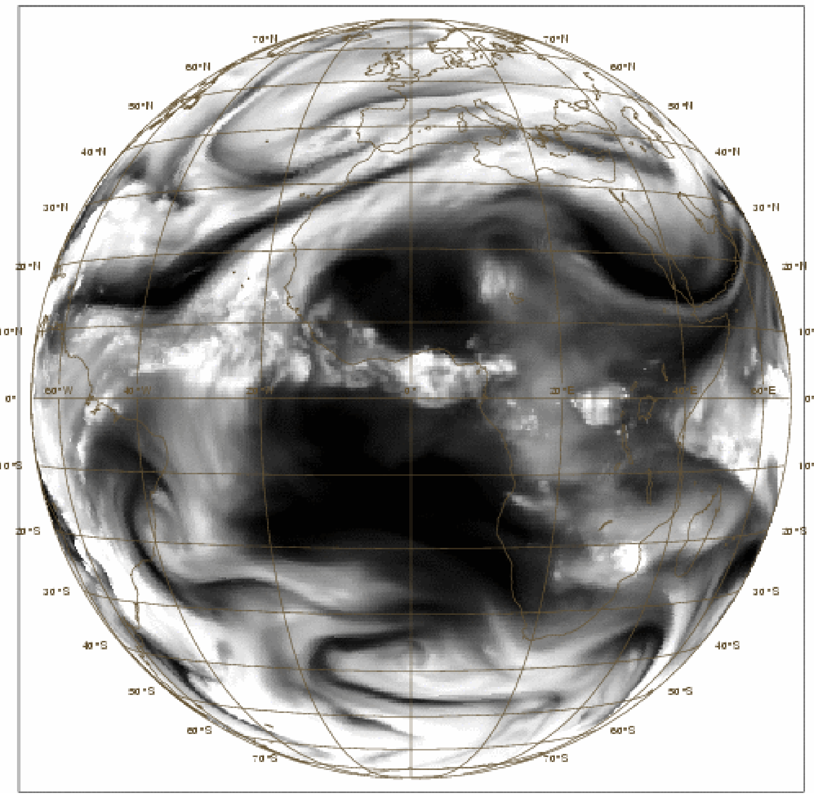
- Steps 1 and 2 define the observation operator (H).
- After Steps 1 and 2 the model forecast estimate can be compared with the observation.



Accurate radiative transfer models allows comparison of model and observed radiances

Observations Satellite Radiances ⟵ **compare** ⟶ **Model Radiances** ⟵ **H** ⟵ **Model T and q**



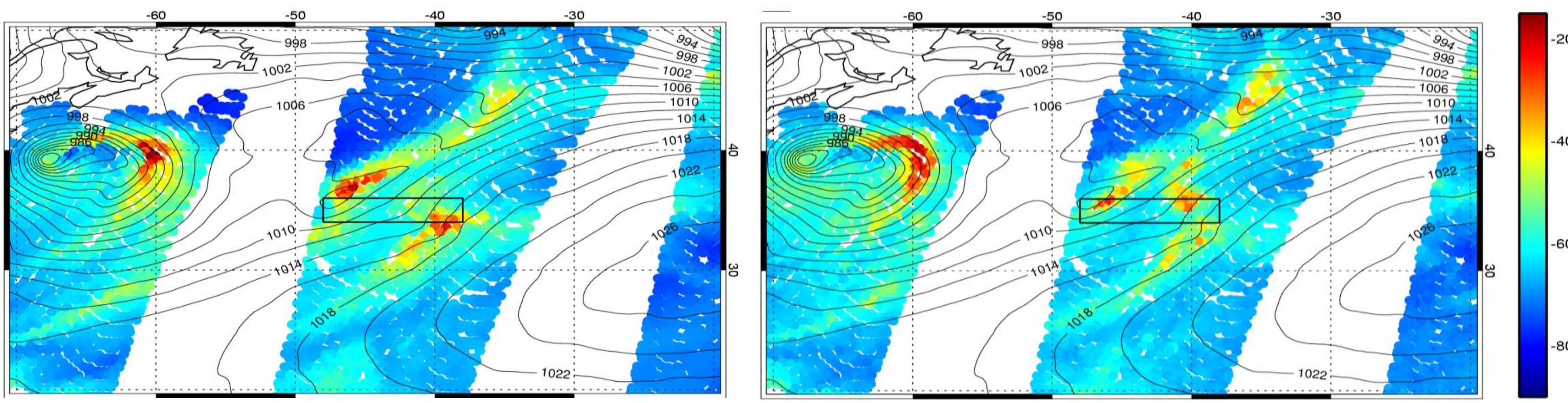


Assimilation of rain-affected microwave observations

Assimilation of rain-affected radiances has benefited from the increased realism and accuracy of models and observation operators

4D-Var first guess SSM/I ΔTb 19v-19h [K]

SSM/I observational ΔTb 19v-19h [K]



A. Geer

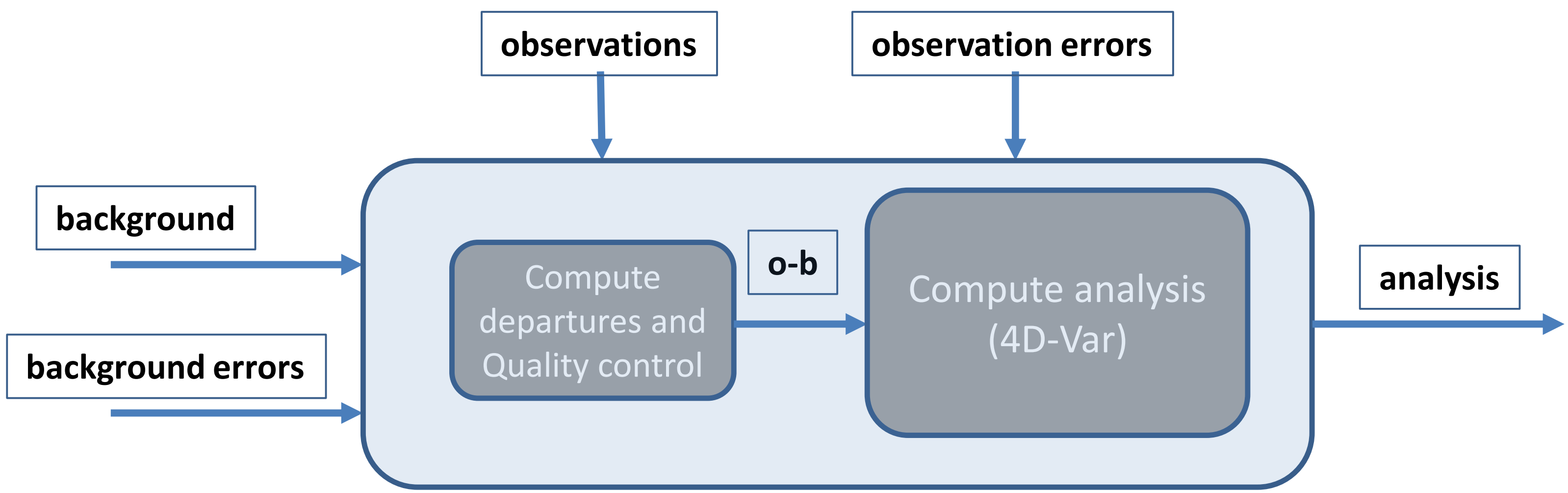
Comparing model and observations

The forecast model provides the background (or *prior*) information to the analysis

Observation operators (H) allow observations and model background to be compared

The differences are called background departures or innovations ("o-b")

The background departures provide the observation information that corrects the background model fields to construct a new analysis

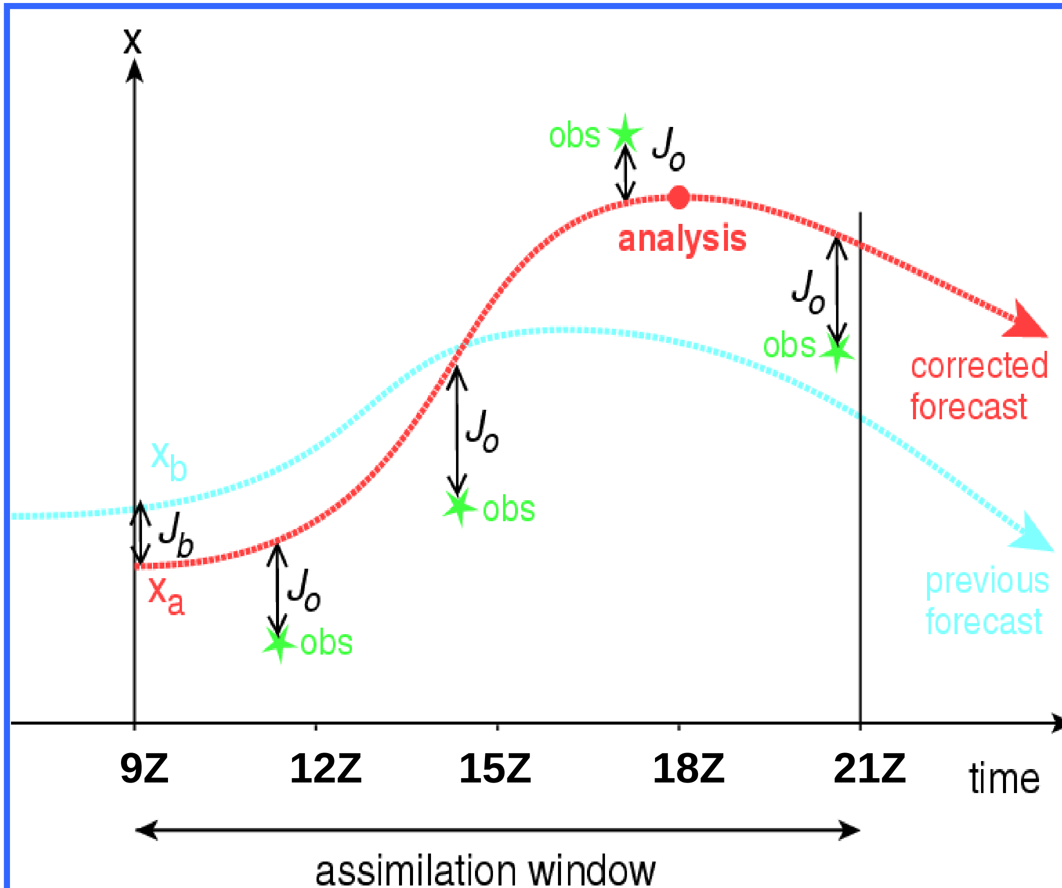


Four dimensional variational data assimilation (4D-Var)

ECMWF use a 4D Variational (4D-Var) Data Assimilation method

Around 20,000,000 observations within a 12-hour period are used simultaneously in one global (iterative) estimation problem

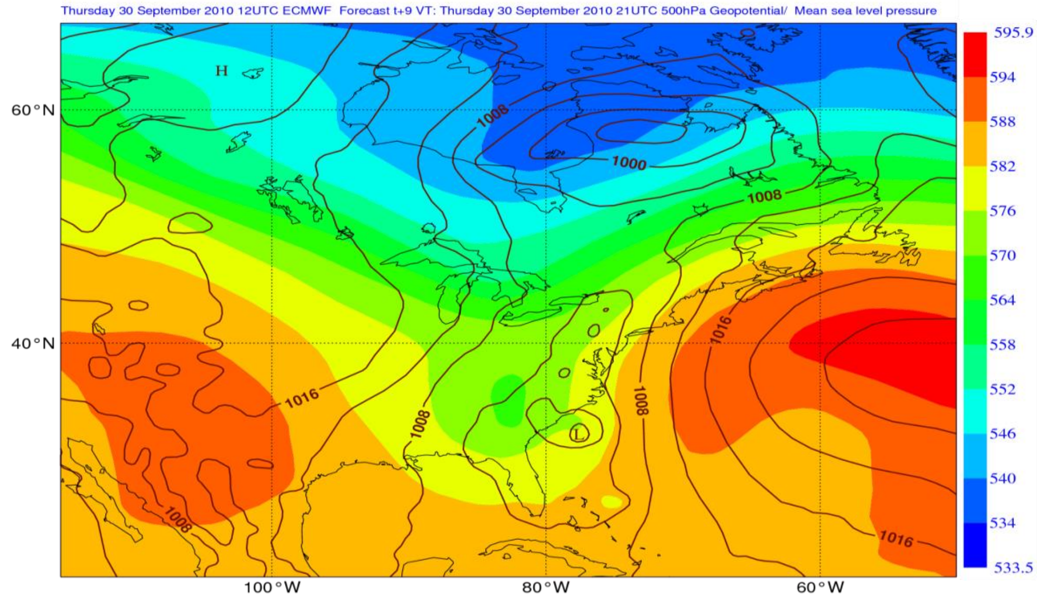
- "Observation – model" values are computed at the observation time at high resolution: 9 km
- 4D-Var finds the 12-hour forecast that takes account of the observations in a dynamically consistent way
- Based on a tangent linear and adjoint forecast models, used in the minimization process at lower resolution
- 80,000,000 model variables (surface pressure, temperature, wind, specific humidity and ozone) are adjusted



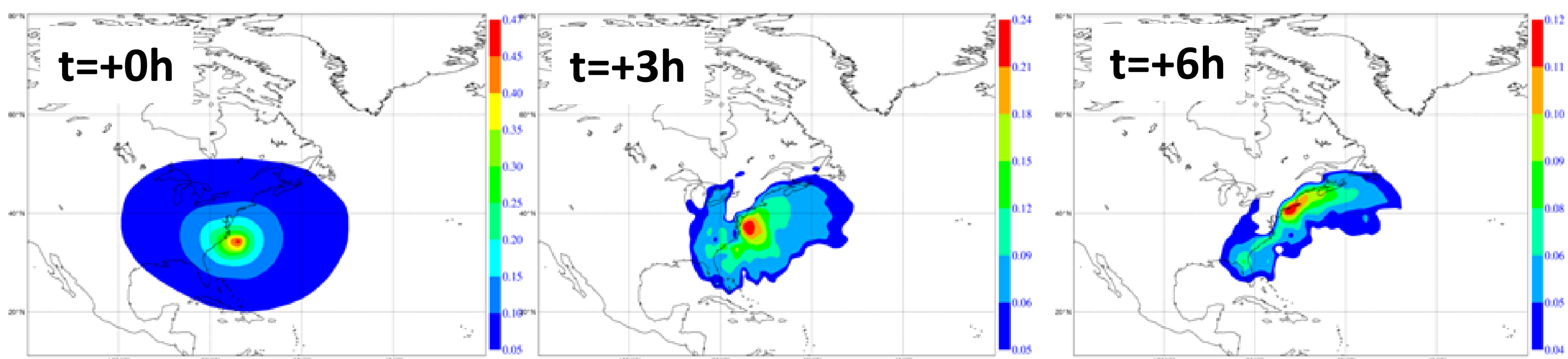
Incremental 4DVar

MSLP (contours) and 500 hPa geopotential height (shaded) background fields

Analysis change by adding an observation at the start of the assimilation window

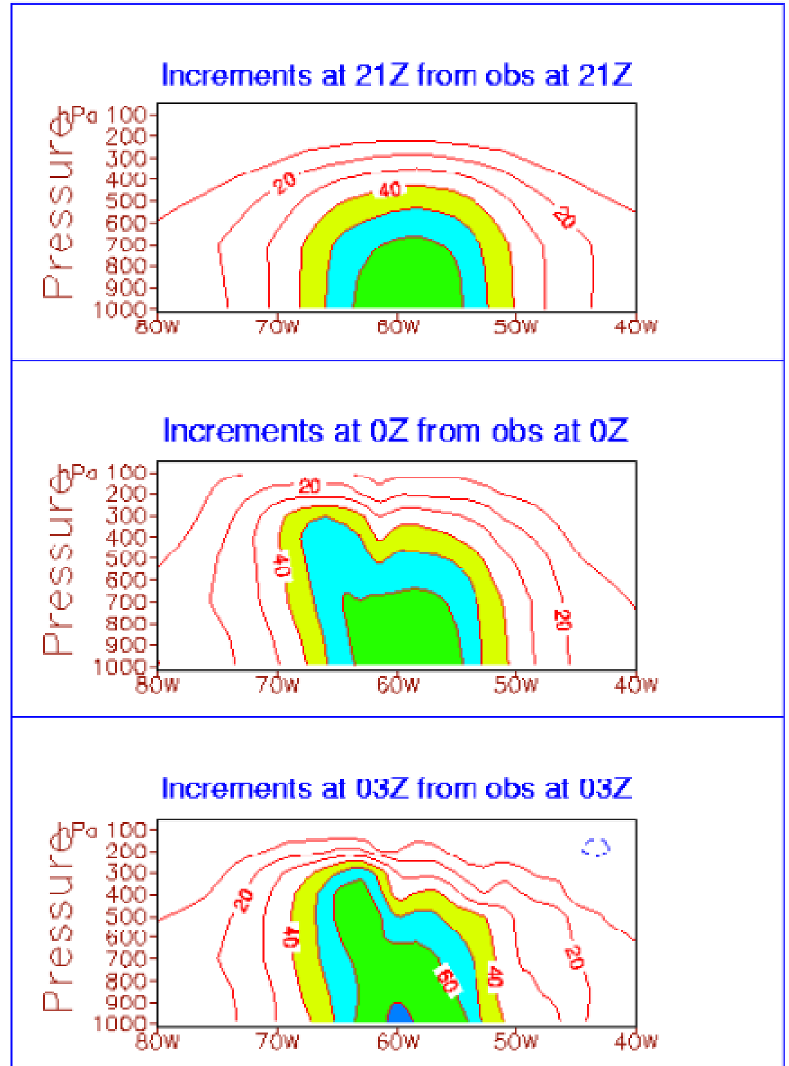


Temperature analysis increments for a single temperature observation at the start of the assimilation window: $x^a(t)-x^b(t) \approx MBM^TH^T(y-Hx)/(\sigma_b^2 + \sigma_o^2)$



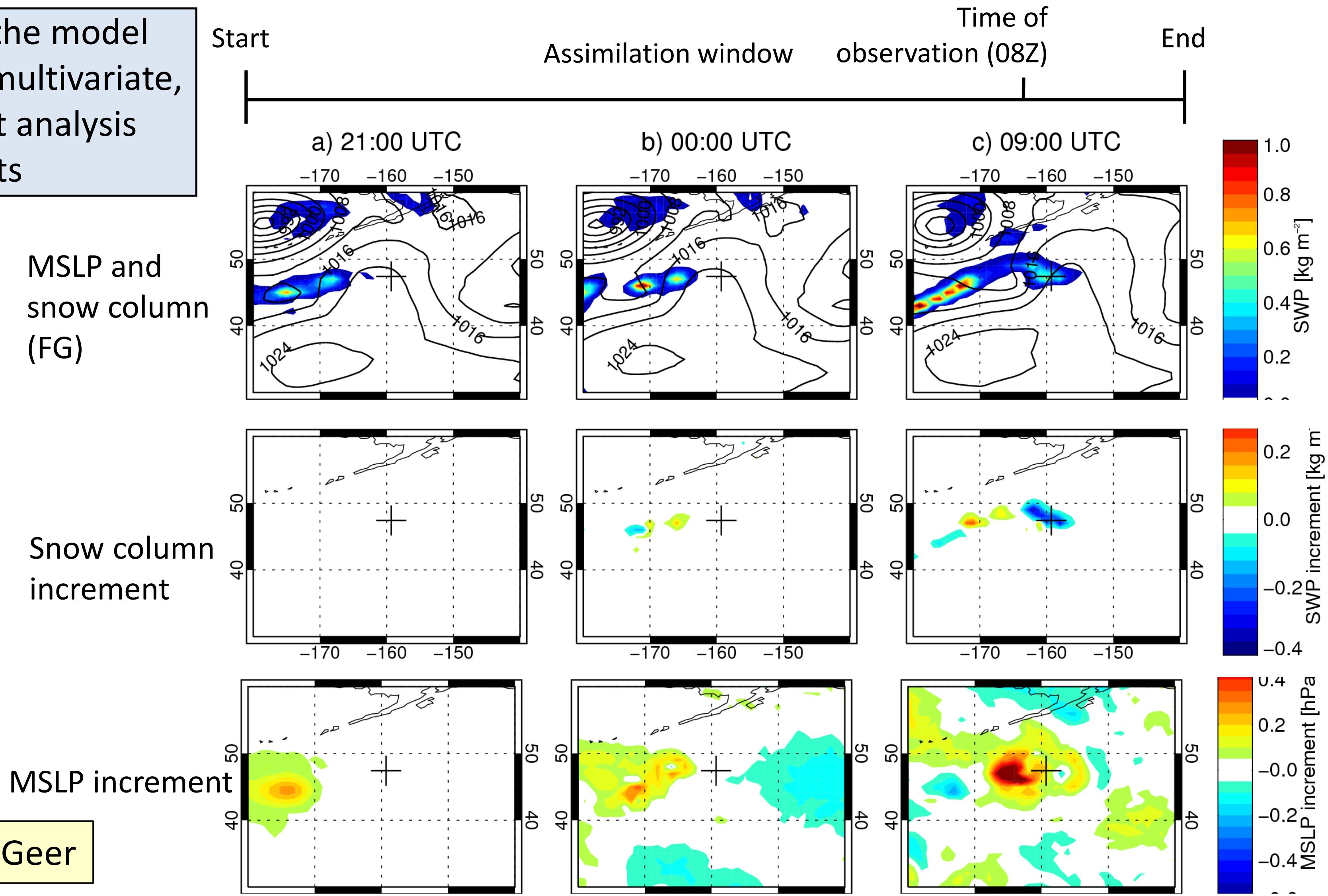
Incremental 4DVar

In 4DVar the model dynamics changes the shape of the analysis increments



Incremental 4DVar

In 4DVar the model produce multivariate, consistent analysis increments



A. Geer

Recent improvements of the data assimilation system

Ensemble of Data Assimilations (EDA)

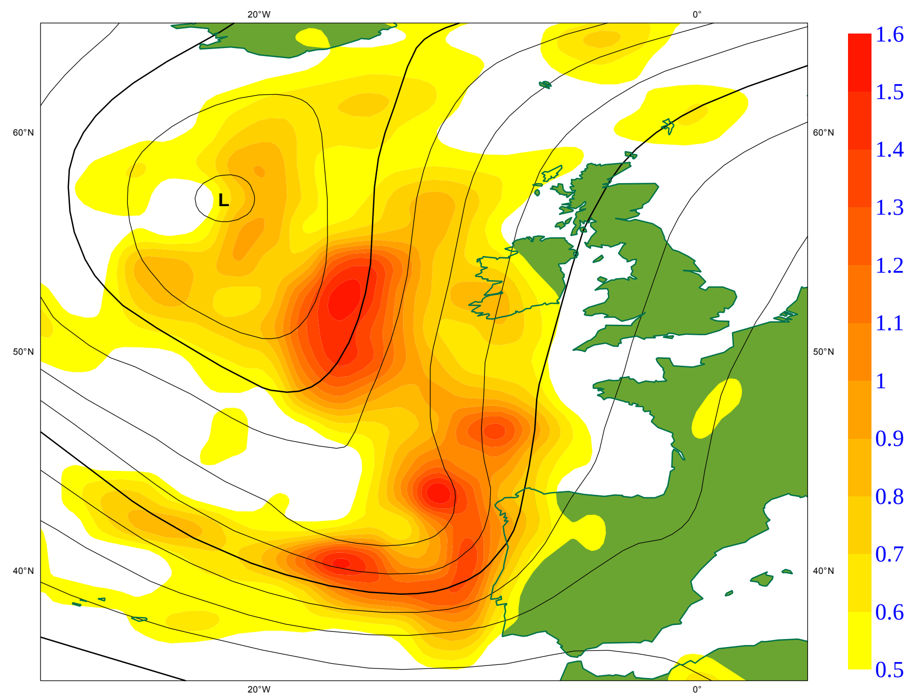
Run an ensemble of independent analyses with perturbed observations, model physics and Sea Surface Temperature fields.

25 EDA members plus a control at lower resolution.

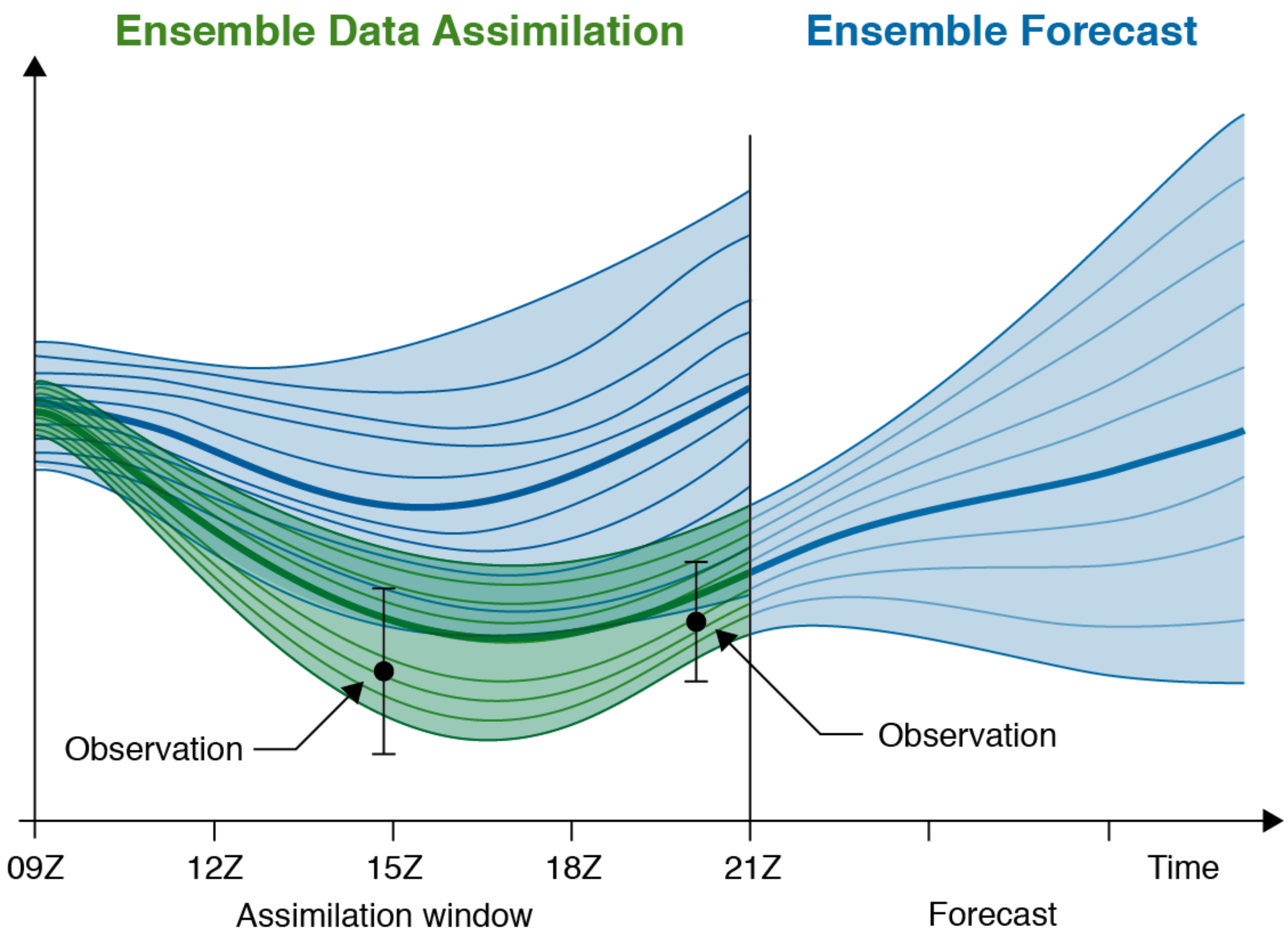
Form differences between pairs of analyses (and short-range forecasts).

These differences estimates the statistical characteristics of analysis (and background) errors.

Yellow shading where the short-range forecast is uncertain → give observations more weight in these regions.



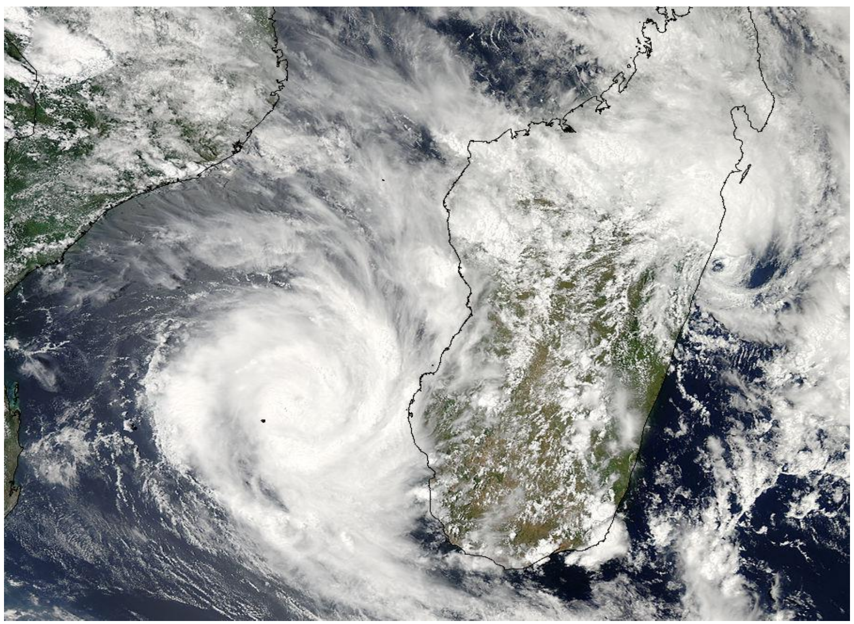
Data Assimilation



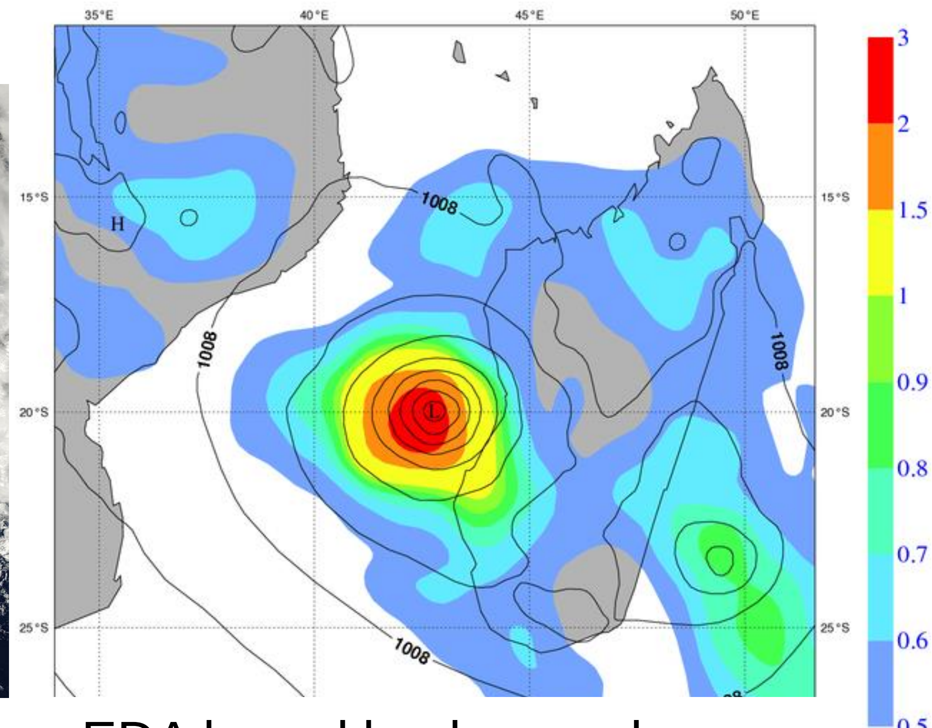
(E. Källén)

The EDA provides analysis and background uncertainty estimates

- To improve the initial perturbations in the Ensemble Prediction
- To estimate flow-dependent background error covariances in 4D-Var
- To improve QC decisions and improve the use of observations in 4D-Var



Hurricane Fanele, 20 January 2009

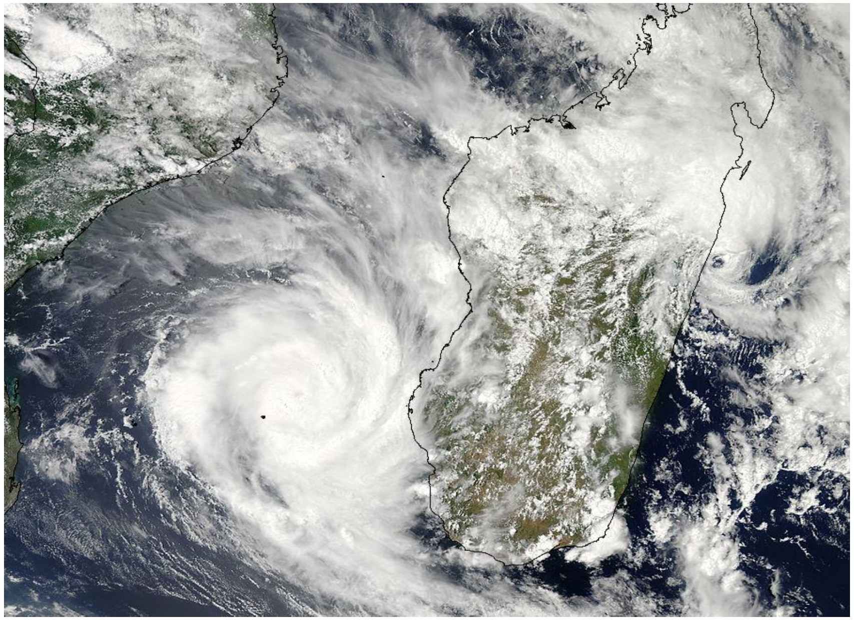


EDA based background error variance for Surface pressure

hPa

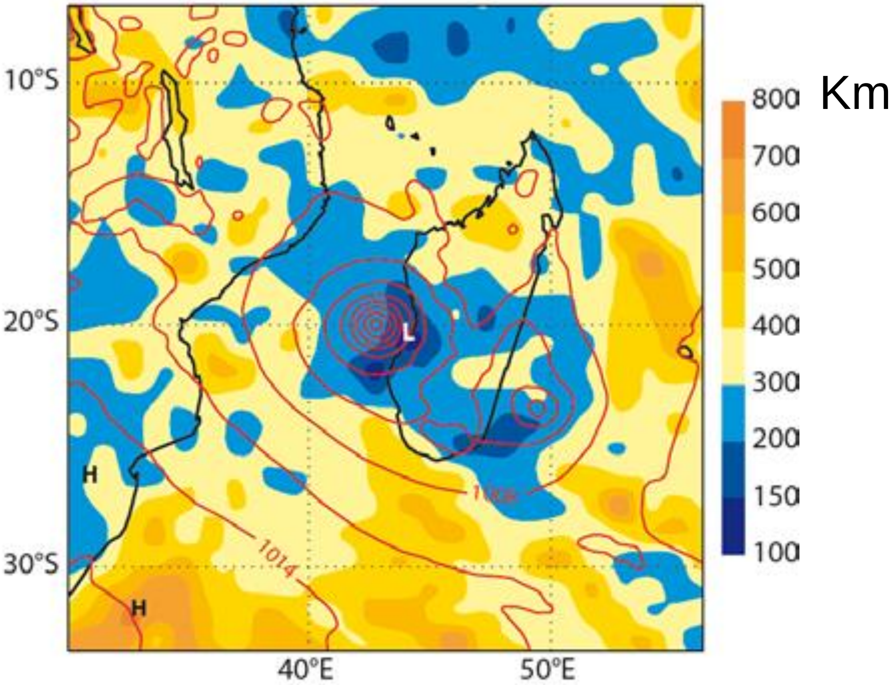
In November 2013 ECMWF will implement EDA based flow-dependent background error covariances in 4D-Var

The 25-member EDA has been used to estimate the background error covariance in 4D-Var.



Hurricane Fanele, 20 January 2009

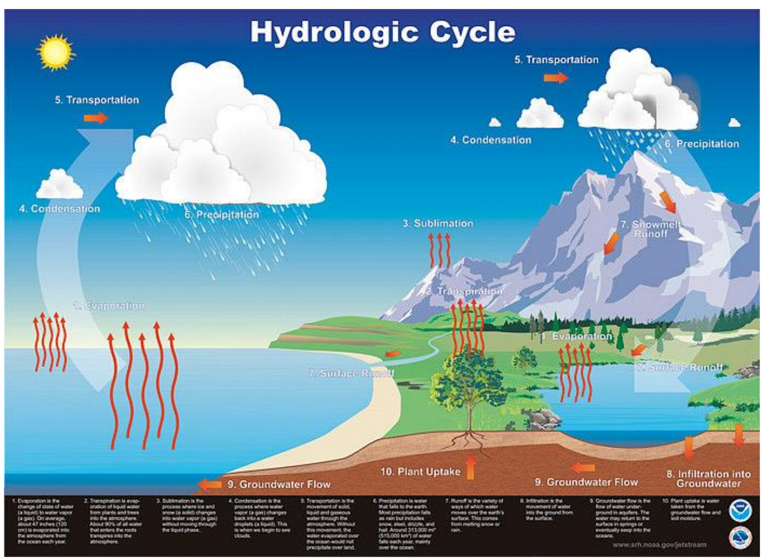
EDA based background error covariance length scale for Surface pressure



Land Data Assimilation

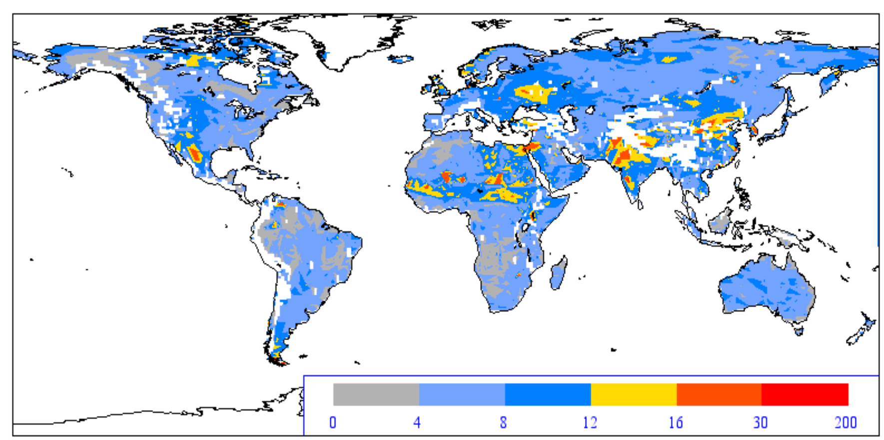
- Land surfaces: heterogeneities, range of spatial and time scales controlling the processes, reservoirs and fluxes.

- The Land Data Assimilation Systems (LDAS) make use of:
  - Processes and feedbacks represented with coupled land-atmosphere models (extension to carbon cycle available)
  - Data assimilation schemes, such as nudging, OI, EKF, EnKF, that update models states variables and/or surface parameters for NWP and climate applications
  - Routine Near Real Time observations with high information content about land surface variables (in-situ, SMOS, ASCAT, SMAP, etc.)



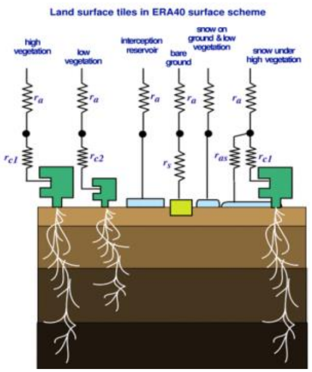
SMOS TB First Guess Departure (K) July 2012, RMSD=6.7K

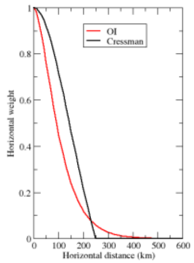
RMSE SMOSmatched_monthly CMEM TB JUL5months WaWsWi xx at angle 40

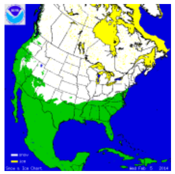


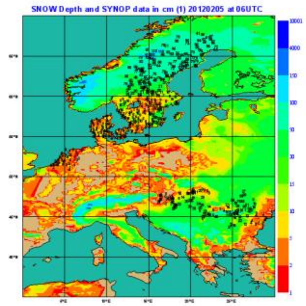
Snow in the ECMWF Data Assimilation System

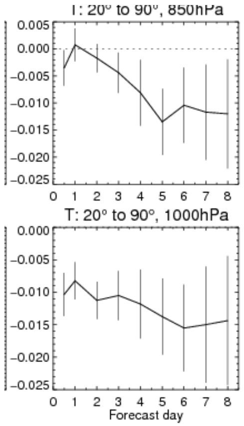
2009 2010 2011 2012 2013 2014 …











Snow Model

. Liquid Water
. Density
. Albedo
. Fraction

Snow Obs and DA

. Optimum Interpolation
. 4km IMS snow data
. Obs Quality Control
. IMS latency/acquisition

. Additional in situ obs
. WMO/SnowWatch action
. IMS data assimilation
. obs error revision

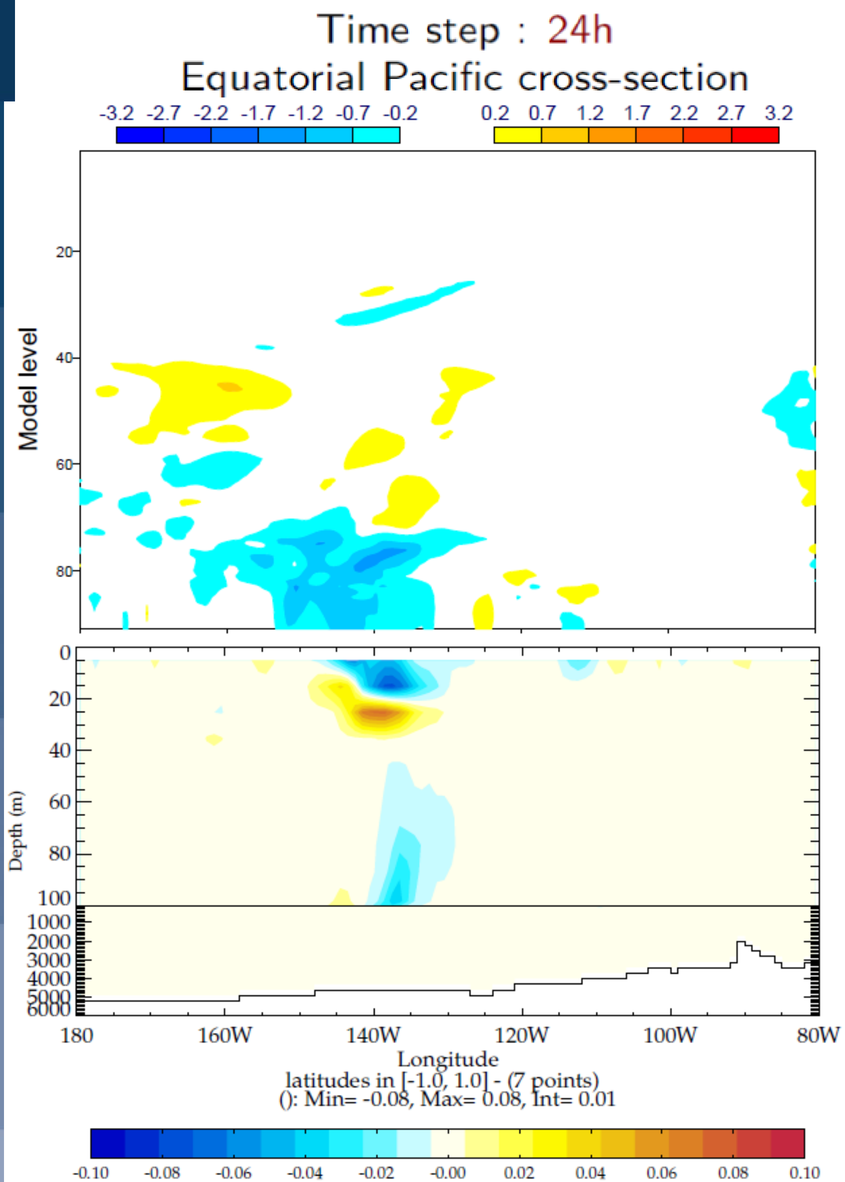
Snow Model & DA

. Multi-layer model
. Snow cover Fract
. BUFR SYNOP
. RT modelling
. Snow COST action

ECMWF Land Data Assimilation System:
https://software.ecmwf.int/wiki/display/LDAS/LDAS+Home

Future challenges

Coupled data assimilation



Atmosphere-ocean cross-section (wind and temperature)

Atmospheric wind increment (one station with hourly measurements of a 10m/s westward wind) spreads in the ocean as a temperature increment during the model integration (outer loop)

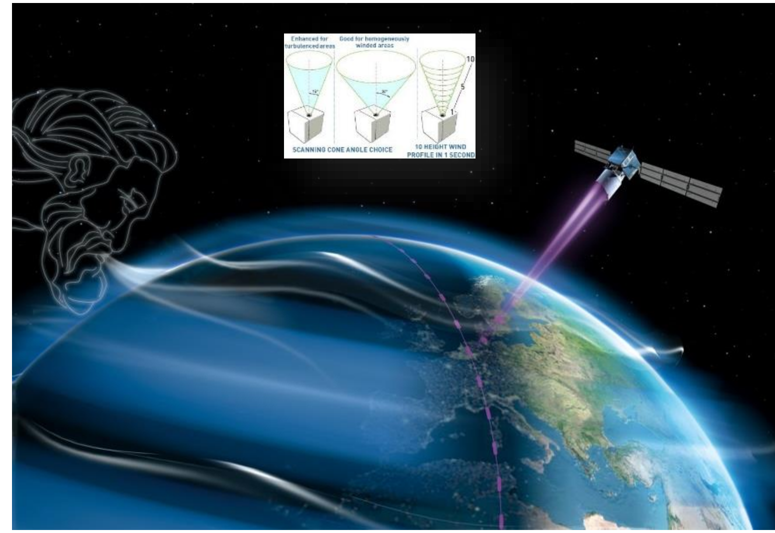
Ocean-atmosphere correlations are generated within the CERA incremental variational coupled DA

P. Laloyaux

ADM-AEOLUS: An important wind profiling mission

An ESA Earth-explorer mission

Doppler wind lidar
Measures Doppler shift (due to wind) of backscattered UV laser light from the atmosphere



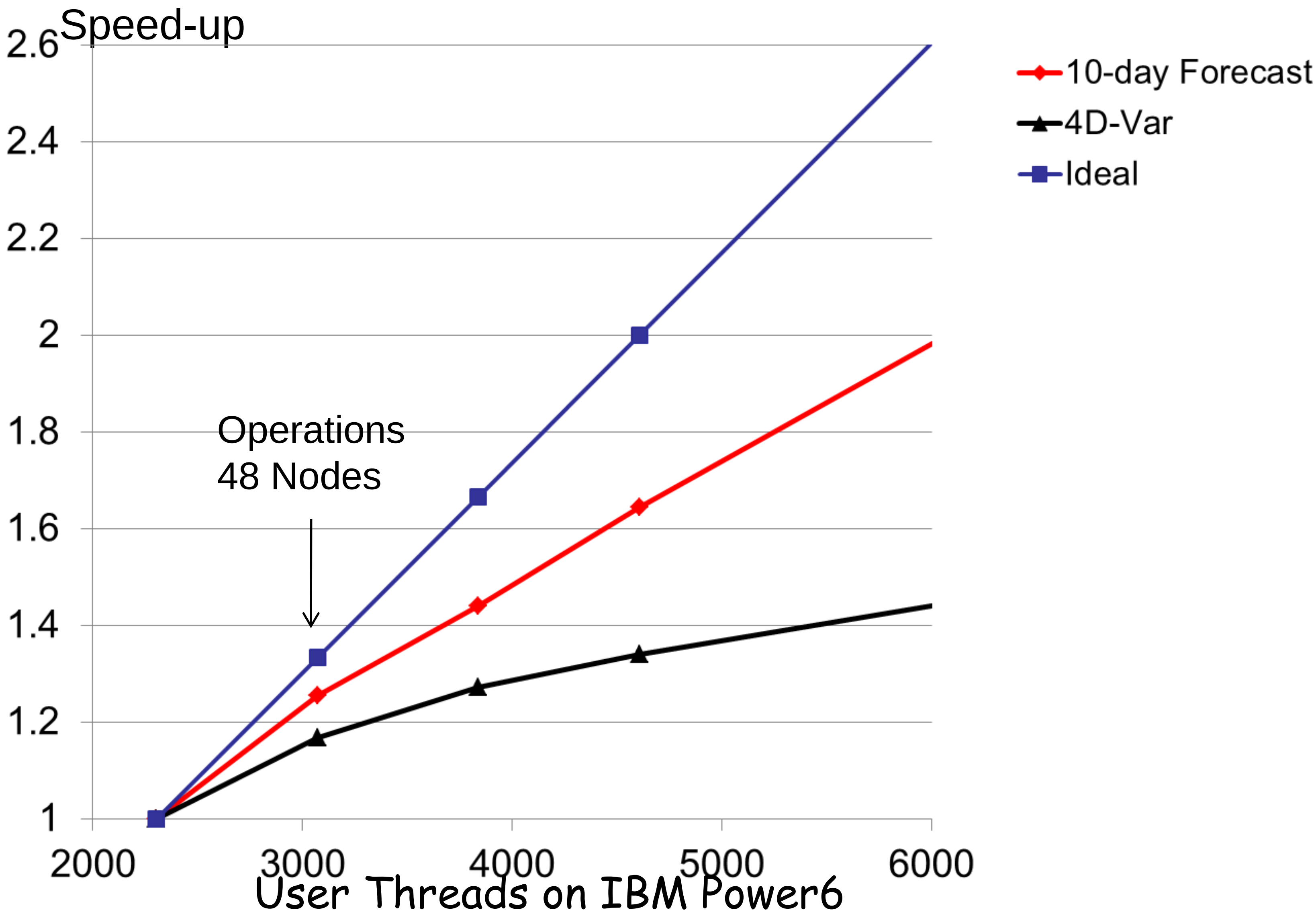
Courtesy: ESA

Main application is to improve global analyses and forecasts
Profiles of horizontal line-of-sight (HLOS) wind components

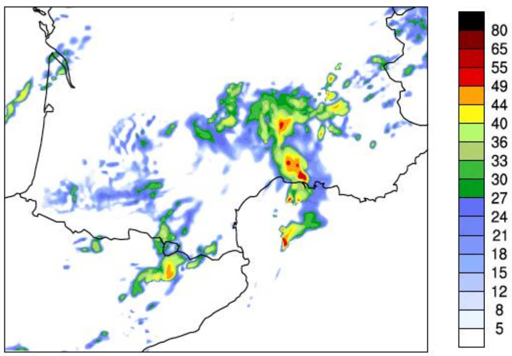
Launch expected end 2017

More wind profiles would greatly benefit the Global Observing System

Scalability of T1279 Forecast and 4D-Var

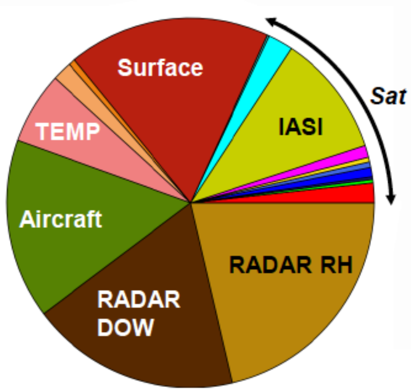


Challenges with Meso-scale Data Assimilation



Radar reflectivity simulated by AROME

Source: Thibaut Montmerle, Météo-France



Active obs in AROME for one rainy day

General

- Quick evolving processes
- Rapid updates requires (hourly or sub-hourly)
- Uncertainties and predictability

Remote sensing observations

- More timely use of information from GEO satellites
- Novel observations for convective scale DA
- Assimilate cloud-affected radiances
- Non-linear observation operators
- Accuracy and efficiency of radiative transfer in all-sky

Covariance modeling

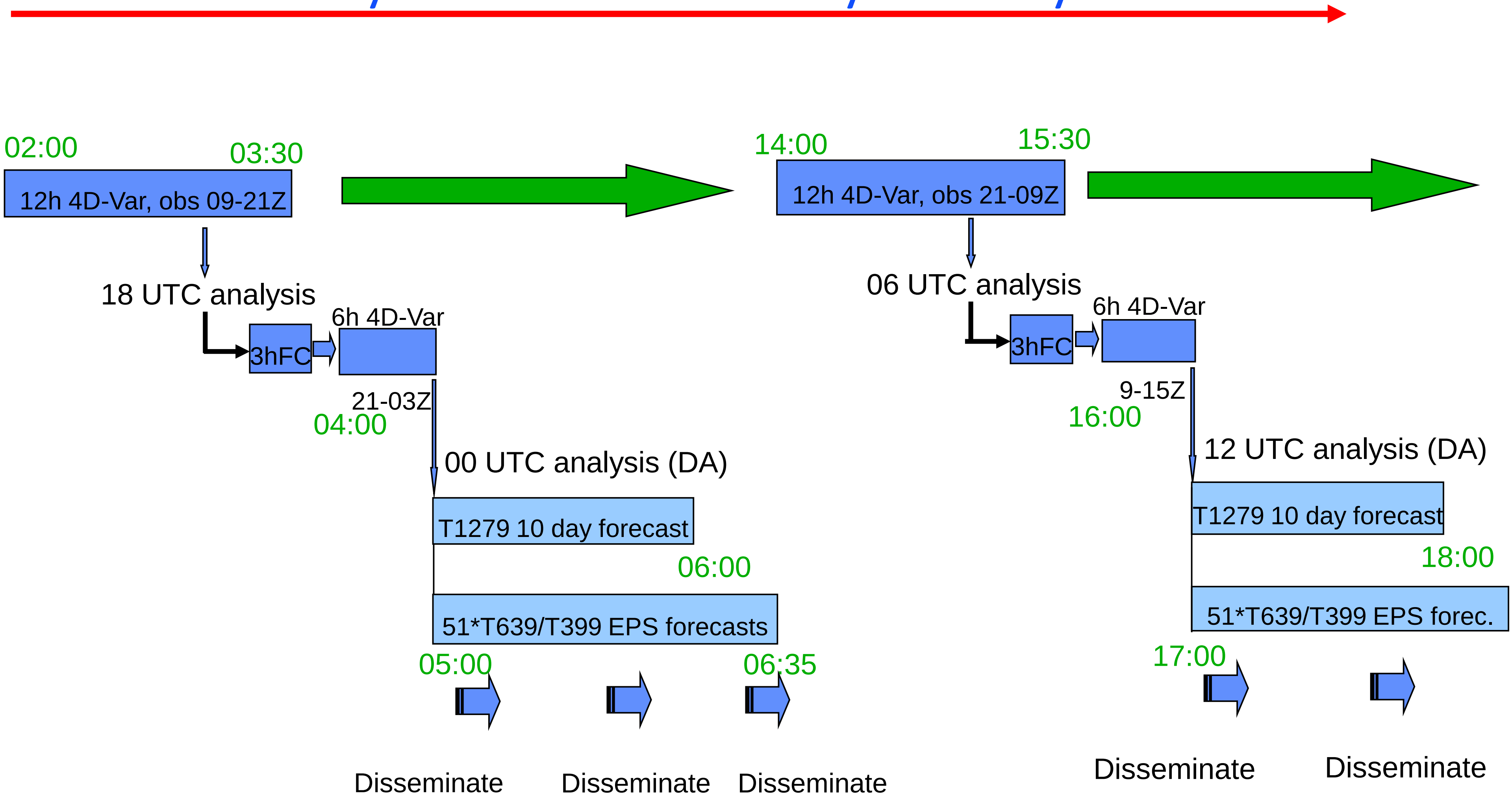
- Traditional balance (e.g. geostrophic & hydrostatic) not applicable at high-resolution
- Impact on ensemble size
- Complex, non-linear, flow-dependent relationship between model variables
- Significant model error (in phase and amplitude)

Conclusions

- Prospects of reducing further initial condition errors are great (improved models, observations and methods)
- Data assimilation is the natural vehicle to confront models and observations, and contribute to a seamless quantification of uncertainty estimation
- Observations are essential for data assimilation
- The best data assimilation systems today are using hybrid variational and ensemble methods
- Efficiency on future HPCs will be a fundamental driver
- Specific challenges and opportunities for coupled and meso-scale data assimilation

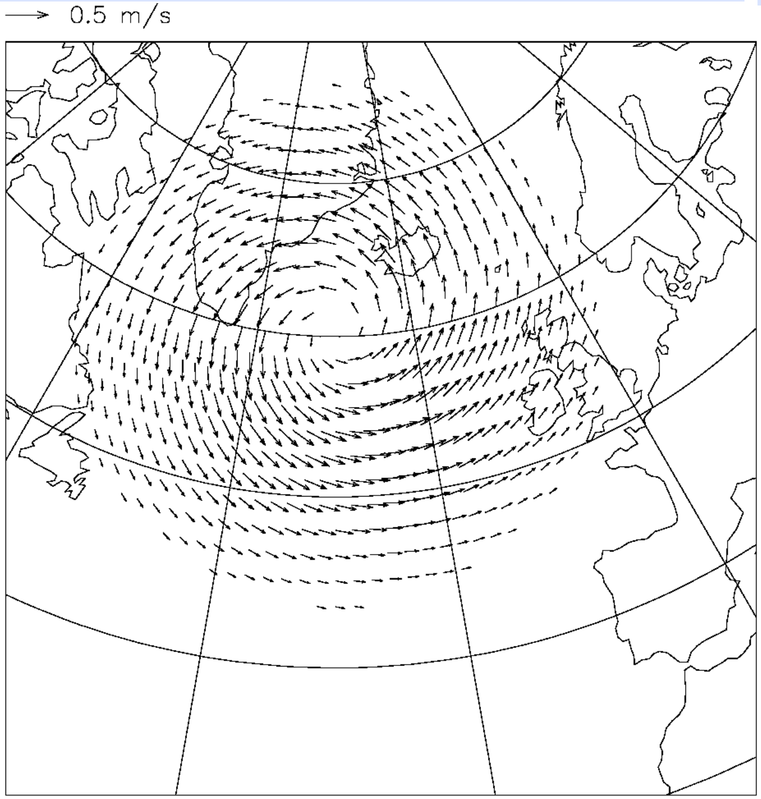
Thank You!

Operational schedule
Delayed Cut Off and Early Delivery suites

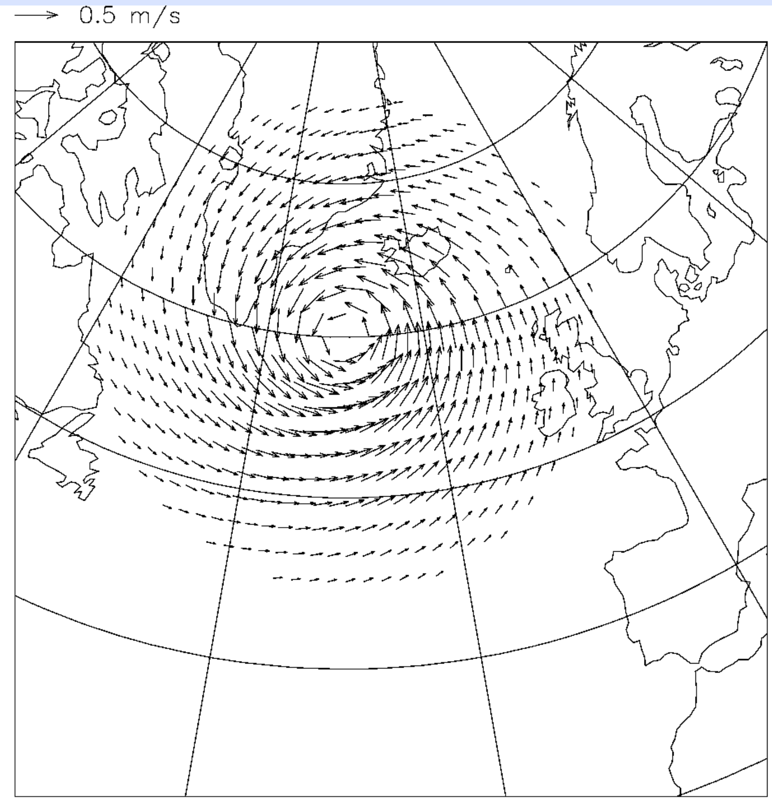


The Balance Operator ensures height/wind field approx. balance is retained in the extra-tropics

wind increments at 300hPa



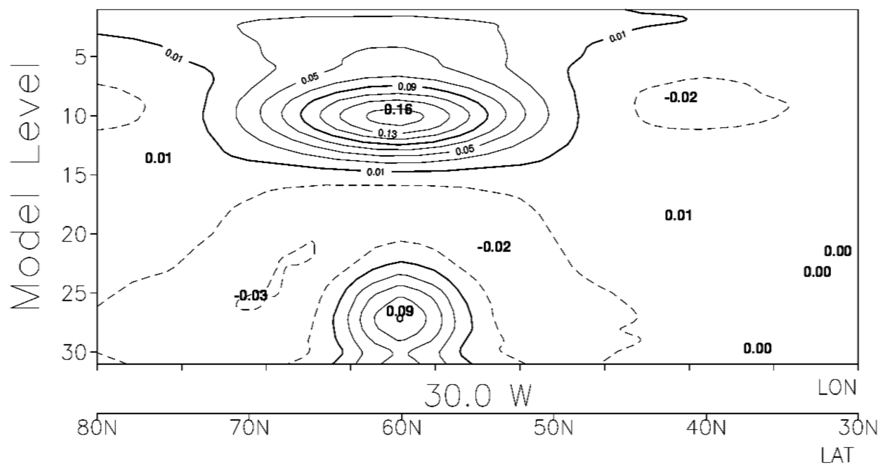
wind increments 150 metre above surface



Wind increments obtained from a single surface pressure observation

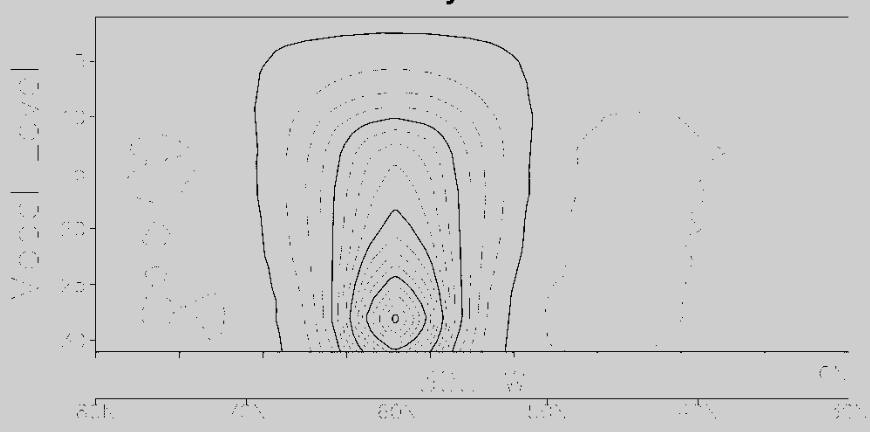
J_b: Ensures that the model fields are adjusted meteorologically consistently in the region close to the observation location

z1000 obs - temperature increments

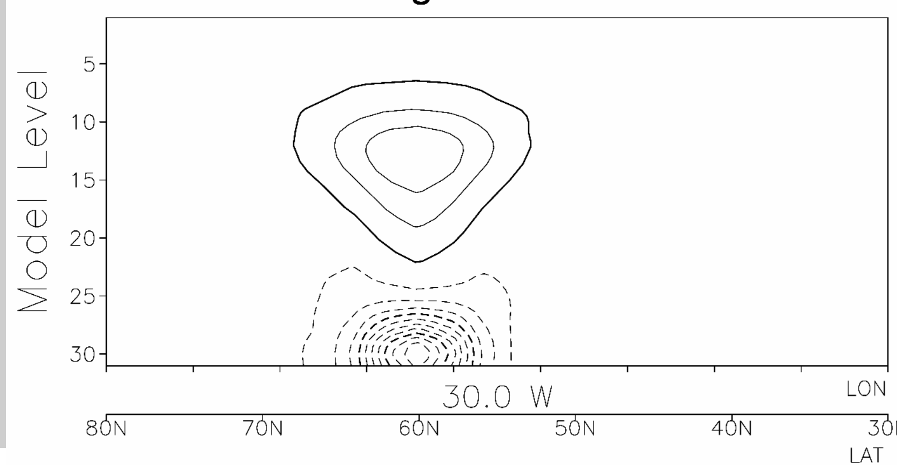


Increments due to a single observation of geopotential height at 1000hPa at 60N with value 10m below the background.

z1000 obs - vorticity increments



z1000 obs - divergence increments



Quality control of observations is very important

Data extraction

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

Thinning

- Some data is not used to avoid over-sampling and correlated errors
- Departures and flags are still calculated for further assessment

Blacklisting

- Data skipped due to systematic bad performance or due to different considerations (e.g. data being assessed in passive mode)

Model/4D-Var dependent QC

- First guess based rejections
- VarQC rejections

Used data → Innovations

Analysis