**OBSERVATION ERROR - causes and solutions**

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- proper observation error screening often makes the difference between data assimilation success or failure
- requires substantial effort for remote-sensed data to be useful (about 1 year)
- need to prepare 'clean' observation databases with quality metadata
- need for real-time screening in operational applications
- the amplitude and complexity of obs error can restrict or prevent the use of new 'advanced' instruments
- obs error are as much a modelling as an instrumental issue.

OBSERVATION ERRORS - synopsis

- Introduction : semantics, to use or not to use an obs
- Sources of errors : conventional, remote sensing
- Data Monitoring : basic checks, consistency, buddy check
- Real-time quality control : sanity checks, background check, thinning, variational QC
- Estimation of obs error statistics : error budget, variational method, colocation
- Conclusion

## INTRODUCTION (1) : SEMANTICS

**Common sense definition :** an obs error is an unknown perturbation of the observed value that makes it inconsistent with reality.

**In an estimation context :** $x$ is the model state vector to estimate

$x^t$ its 'real' value (= a discretization of reality), not known (a PDF)

$y$ the vector of observed values, known

$H$ the observation operator **used** to compare model with obs as $y - H(x)$

$y - H(x^t)$ is the random vector of observation errors

**error bias** = average error, $\overline{y - H(x^t)}$ on an ensemble of homogeneous PDFs

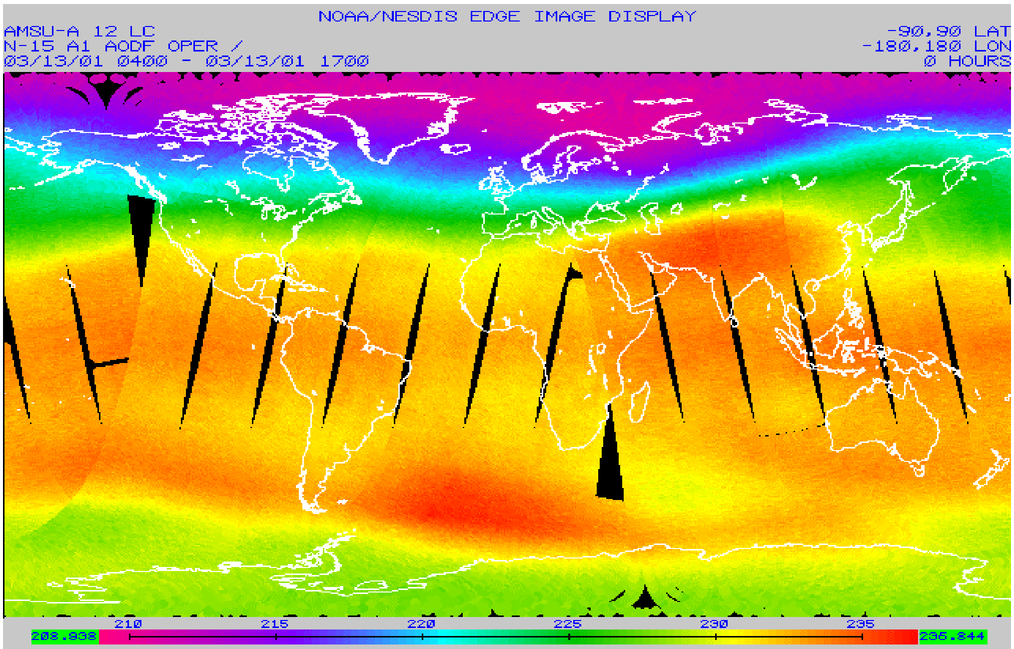
**error covariance** = $\overline{(y - H(x^t))(y - H(x^t))^T}$ matrix

**Instrumental error :** $y - y^t$ where $y^t$ is a 'correct' observed value (usually unknown)

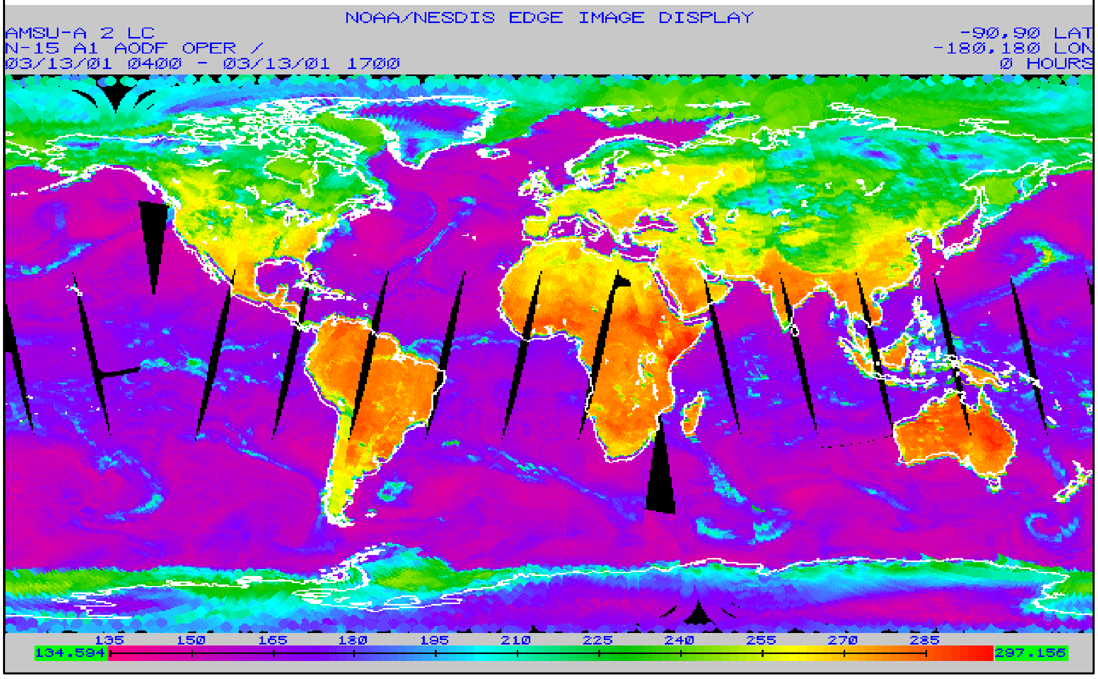
**Observation modelling errors :** in $H$, i.e. $[y^t - H(x^t)]$

**Representativeness errors :** in $H$, specifically linked to lack of model resolution (small clouds, orography...)

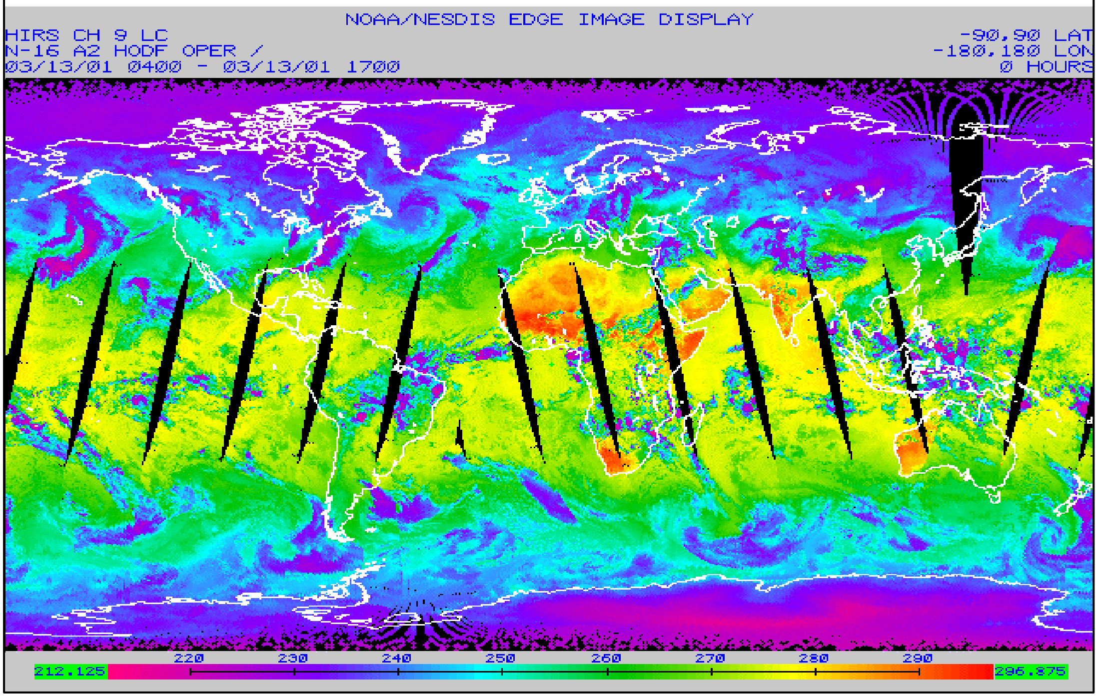
## obs errors : nice case 1



## obs errors : nice case ?




## obs errors : not so nice



INTRODUCTION (2) : TO USE OR NOT TO USE AN OBS

The basic dilemma of observation quality control :

- obs can be biased towards 'average' states : instrument response, model-dependent preprocessing, averaging processes in instrument...
- obs can also contain random errors : thermal/sampling noise, instrument drift, interference...
- we tend to mistrust 'unexpected' observations — but perhaps nature is trying to tell us something important ?
- typical example : intense storm development, ozone hole, etc.
- do you prefer large errors into the data assimilation, or a robust and uninteresting system ?
- rms scores and operational constraints favour a careful (cowardly ?) approach
- improving POD (probability of detection) is at the expense of FAR (false alarm rate). It is considered ok to reject a few % of observations of each type.

SOURCES OF ERRORS : CONVENTIONAL

Conceptually simple, but not perfect : ground stations, radiosondes, aircraft, dropsondes, buoys, ships, rockets...

- conventional data = in situ sensors reporting at discrete points
- instrumental errors are normally uncorrelated in space and time
- exception 1 : radiative heating of sensors (radiosondes)
- exception 2 : inertia or corruption of humidity and temperature sensors
- exception 3 : degradation of non-maintained automatic stations e.g. buoys
- built-in random noise due to sensor technology (sensitivity, sampling volume, time filter, electronics...)
- frequent human errors in observing/reporting practice ('bad' stations)
- location errors (even for fixed stations !)
- representativeness errors are mainly due to lack of model resolution and local influences (valleys, coasts, ground heterogeneity, orography)

Typical standard errors : wind=0.5m/s, T=0.5K, humidity=10

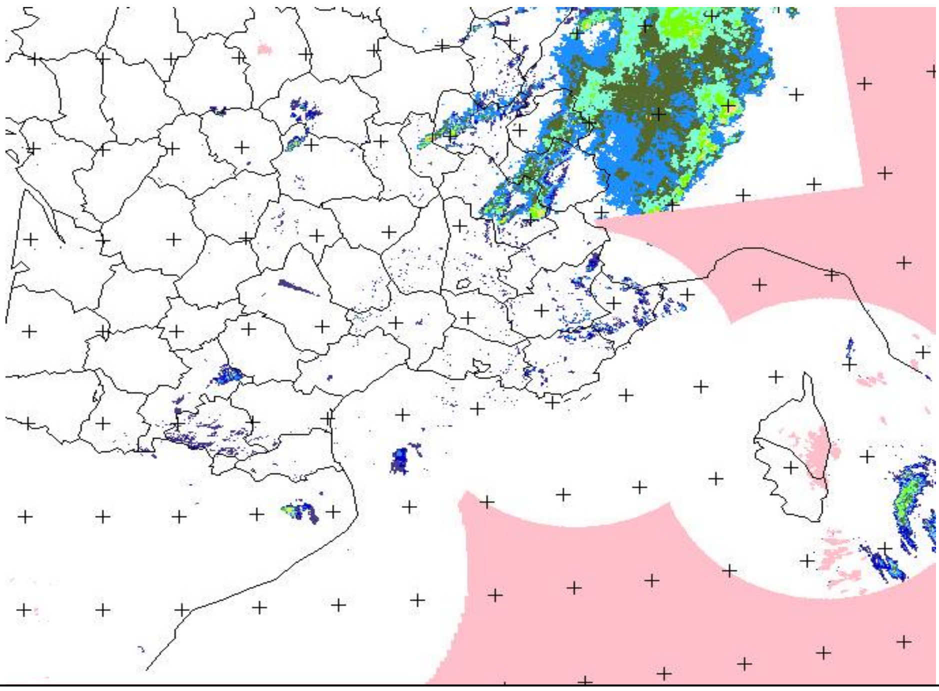
SOURCES OF ERROR : REMOTE SENSING

radars, radiometres, lidars, GPS, sodars...

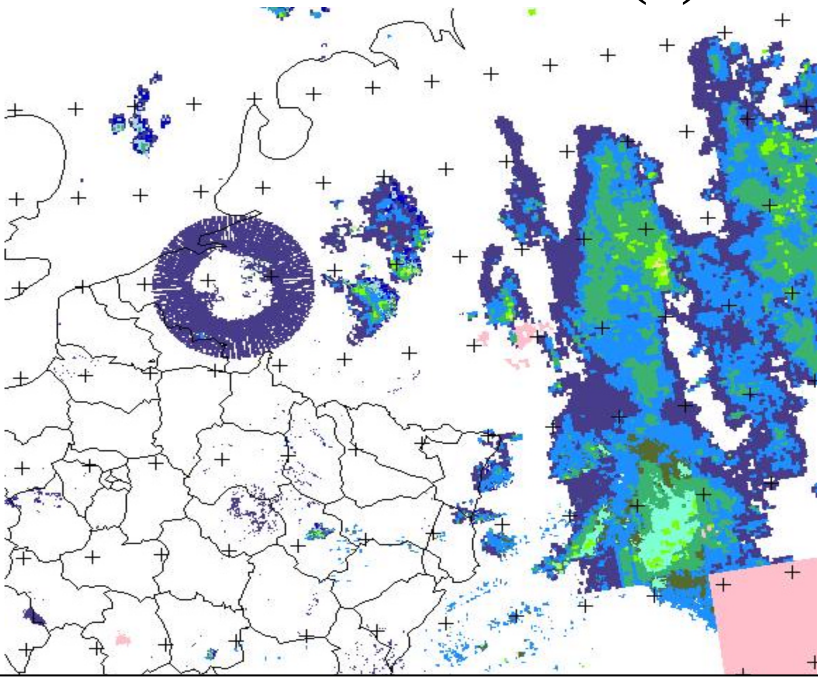
- technological limits : instrument noise, electronics, antenna function... e.g. Ne$\Delta$T
- drift in instrument characteristics : contamination, interference...
- location errors due to satellite navigation and radar propagation
- representativeness error linked to beam width and sensitivity functions (satellite sounders have poor along-the-beam resolution)
- complex and potentially large errors from observation modelling problems :
  - radiative transfer modelling (its physics and modelling)
  - appropriateness of underlying model (model top, not modelled fields...)
  - unknown forcings (surface, ashes, aerosols, insects, aircraft, cloud properties...)

Requires assistance from specialist communities (e.g. RTTOV) and substantial investigation work in relation with the model.

## rain radar artifacts (1)



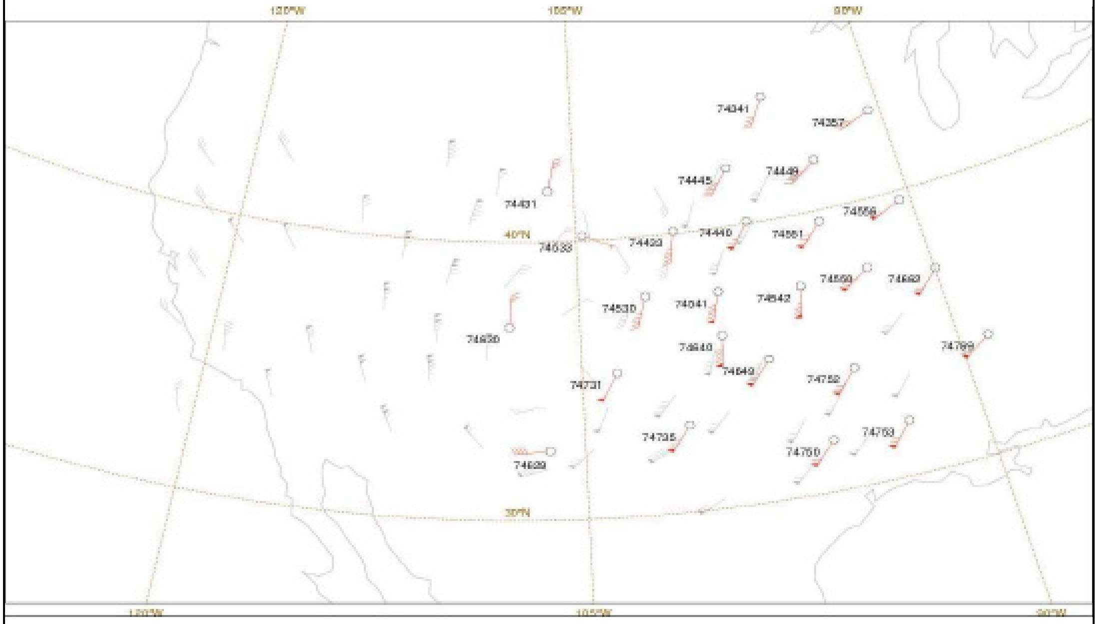
## rain radar artifacts (2)



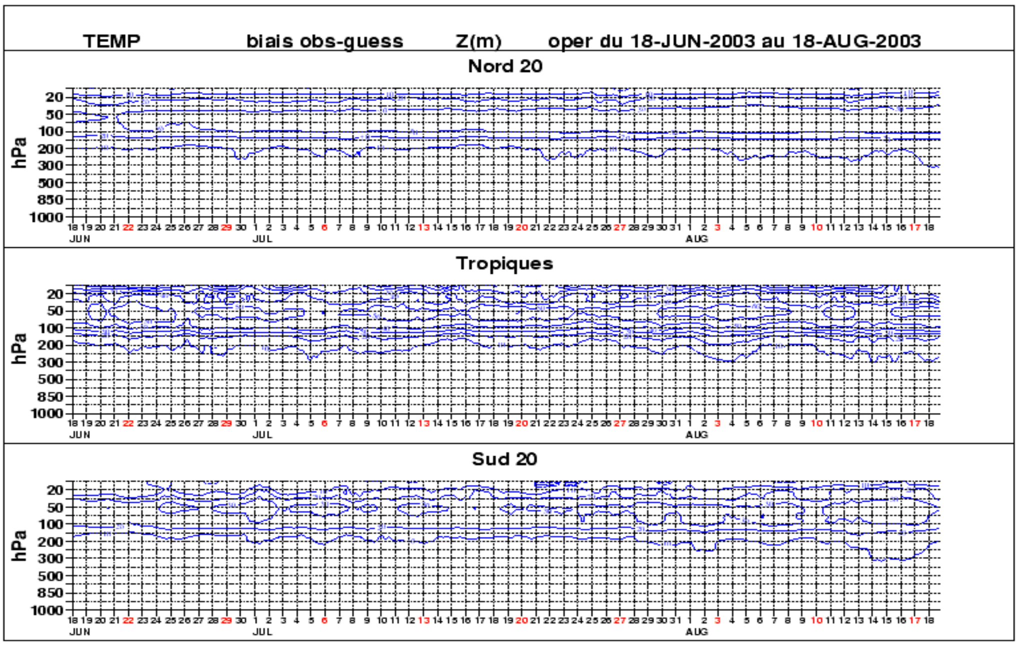
MONITORING : BASIC CHECKS

- stability and variability of averages and variances (self-consistency is reassuring)
- location (compare with station catalogues and expected platform trajectories)
- duplicates (sometimes disguised under several IDs and encodings)
- consistency with climatological limits (if reliable)
- physical impossibilities (ship over land, station under the ground...)
- in non-real time : consistency with known weather and independent data sources (human reports, imagery, research instruments...) e.g. rain with no clouds...

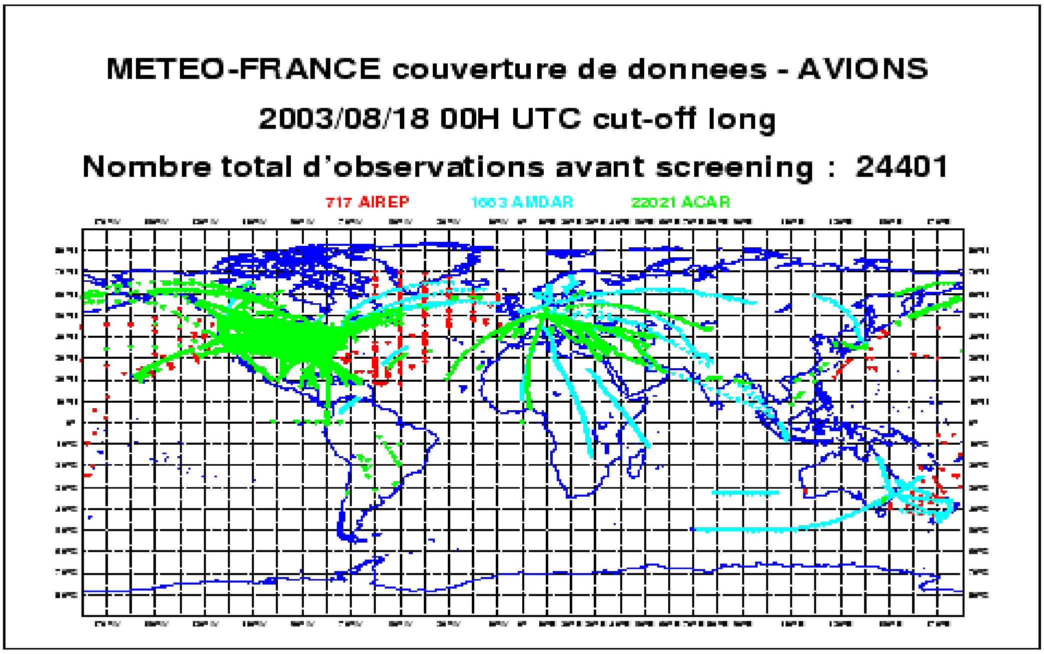
## obs visual checking



## monitoring statistics

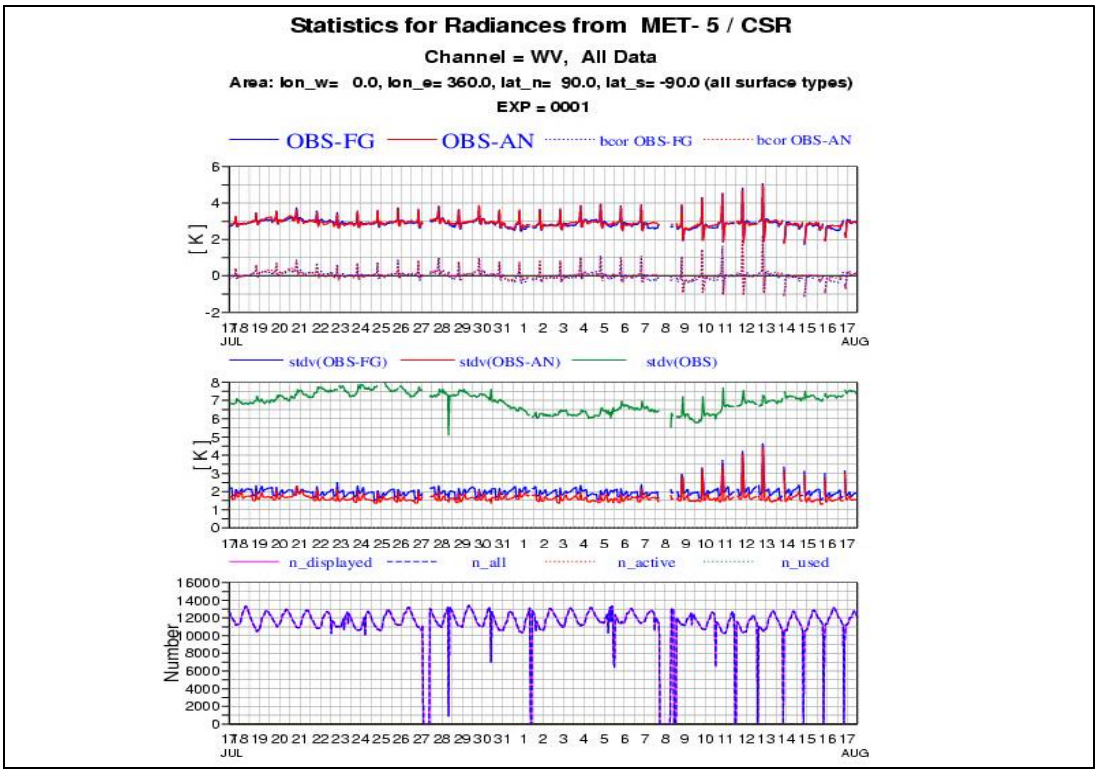


# monitoring aicraft trajectories

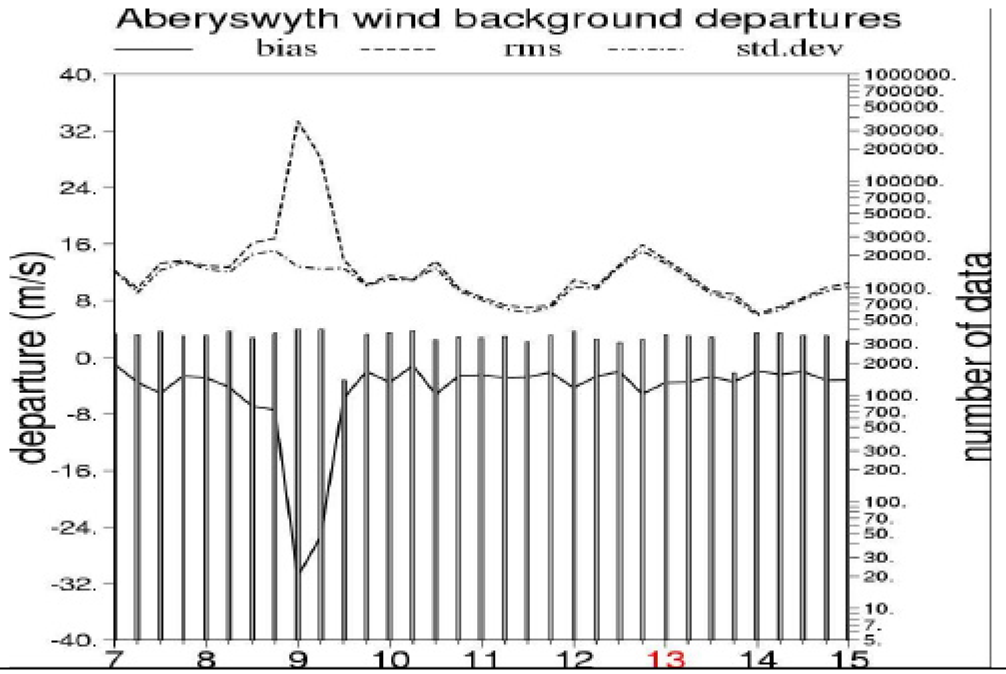



MONITORING : CONSISTENCY

- rarely reporting stations are scary (basic checks are difficult) and probably not useful (low weight in analysis)
- check compatibility of timeseries/spatial distributions with known possible variability in space and time
- compare with analyses if possible : the obs/analysis departures should be self-consistent (even if they are not perfect)
- e.g. satellite radiance bias and std.dev. monitoring vs models clearly shows biases and instrument failures (and model changes !)



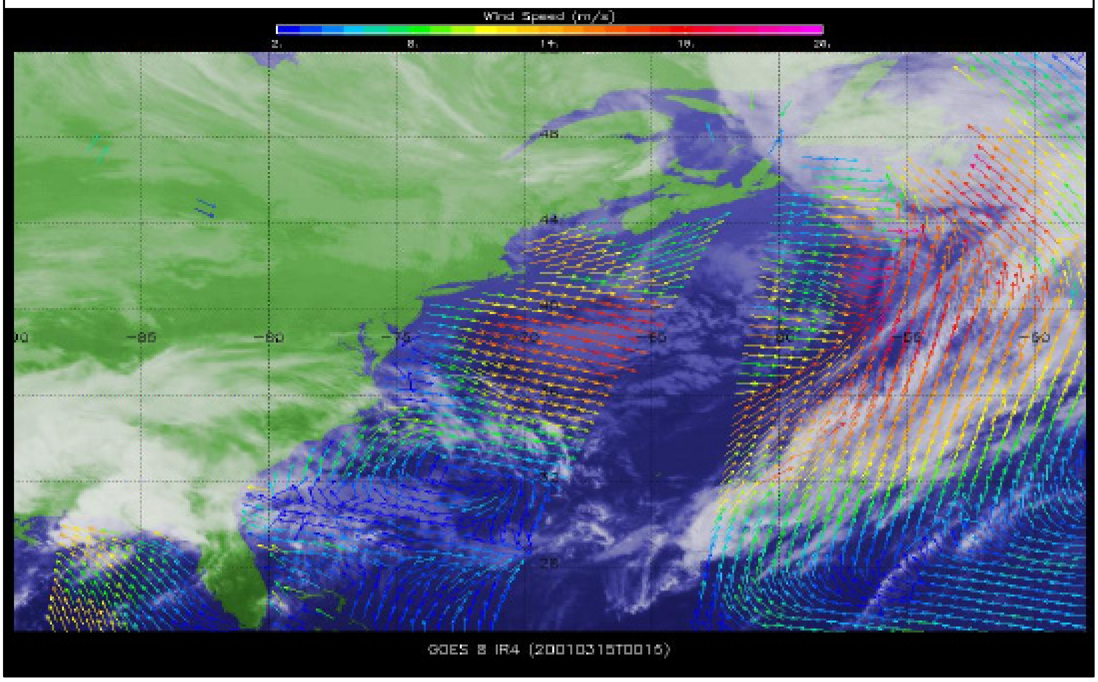

# Monitoring profilers



## MONITORING : BUDDY CHECK

- an observation consistent with its neighbours is probably right, but...
- ...several obs from the same sensor may contain correlated instrument errors !
- consistency is not always true in nature (fronts, cloud boundaries)
- often use for ambiguous data dealiasing (scatterometer or Doppler wind)

## Quikscat data (ambiguous winds)



## REAL-TIME QUALITY CONTROL : BASIC CHECKS

- check right/dubious/wrong status from monitoring process
- record QC decisions for debugging
- background check : an obs must not be TOO inconsistent with the model background
- expected obs-bg departure = background + obs standard errors
- several correlated obs may conspire to lead the model astray (e.g. creeping stratospheric biases)
- obs preprocessing may already create spurious obs-model correlations
- too strict bg check means obs/background error correlation = will prevent correction of wrong model features.

## REAL-TIME QUALITY CONTROL : THINNING

thinning= reduction of the observation density in space and time

- thinning discards some observed data
- different from obs averaging (superobbing)
- pragmatic justification : avoid overwhelming assimilation CPU/memory/disk with excessive data amounts (e.g satellites, aircraft)
- correct justification : remove local obs error correlation (due to instrument, representativeness or interpolation error) by sampling at uncorrelated frequencies.
- thinning should avoid retaining wrong data, but remain random (do not take the obs closest to the model !)

REAL-TIME QUALITY CONTROL : VARIATIONAL QC

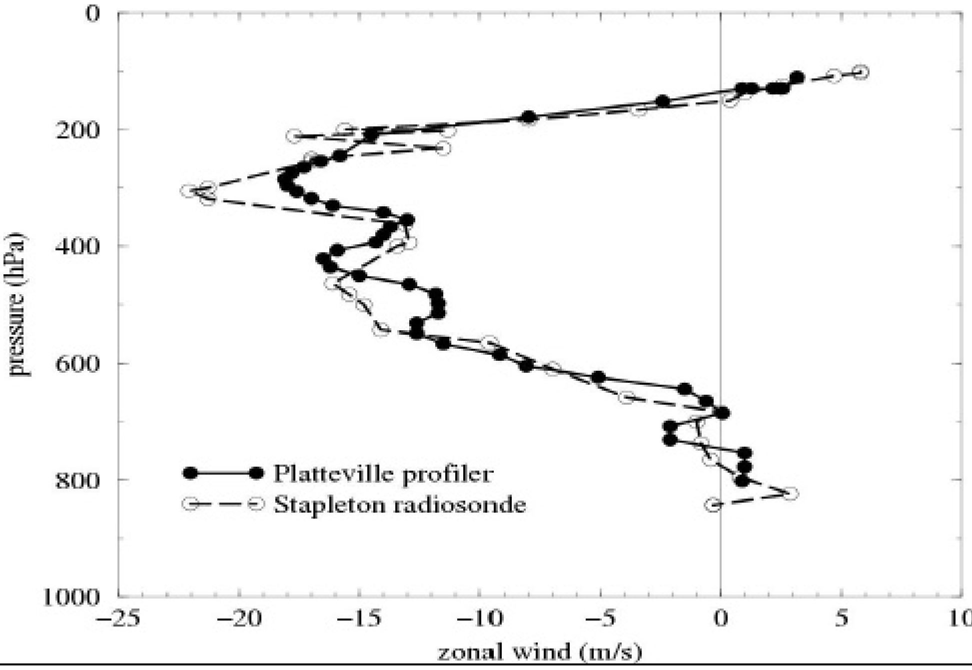
- a clean mathematical for obs quality control based on Bayesian PDFs
- allows gradual rejection of suspect observations
- primarily rejects obs that disagree with the analysis = a kind of buddy check
- used at ECMWF with small positive impact

OBS ERROR STATISTICS ESTIMATION : COLOCATION

How do we measure obs errors if observations are in error ?

- need for at least one reliable reference : instrument specifications, instrumented sites
- two colocated observations : $var(o_1 - o_2) = var(o_1) + var(o_2)$ if their errors are uncorrelated
- an obs and a model : $var(o-m) = var(o)+var(m)$ if the model error $var(m)$ is precisely known (rare) and obs/model are uncorrelated i.e. the obs has not been assimilated into the model
- BEWARE of biases or correlation that will corrupt the computation.

## profiler/radiosonde colocation




## OBS ERROR STATISTICS ESTIMATION : COMMON SENSE

What to do about data from a brand new instrument ?

- get builder specifications of min expected noise levels $Ne\Delta T$
- get specialists' opinion on observation operator errors (radiative transfer modelling, interpolation error, sensitivity to unknown input parameters)
- plot space/time distributions and watch out for gross errors (location, unphysical variations)
- compare with other similar instruments of known quality (they will not be perfect, either)
- compare with model fields if their quality is known
- test their impact in data analysis and assimilation : do they improve the fit to other data ? do they improve model forecasts ?
- some empirical tuning of rejection thresholds and error variances is always recommended.

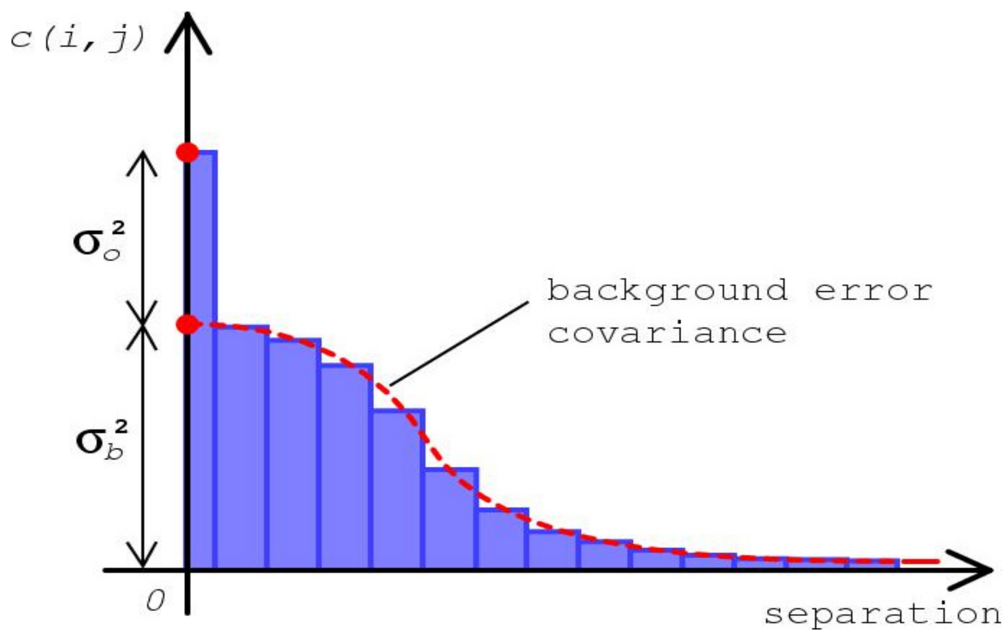
OBS ERROR STATISTICS ESTIMATION : OBSERVATIONAL METHOD

Applicable for large homogeneous sets of (obs,model) intercomparisons with similar error statistics.

- assuming no obs/model error correlation, homogeneous isotropic errors, mutually uncorrelated obs errors
- consider variogram : $cov(o_i - m_i, o_j - m_j) = f(d_{ij})$ where $d_{ij}$ is a measure of distance between points $i, j$
- $f(0) = var(o) + var(m)$ i.e. obs/model colocation
- $f(0 + \varepsilon) = var(m)$ because there is no spatial obs intercorrelation
- $f(d)$ for $d > 0$ is the model error autocovariance as a function of distance.
- usually applied for model background fields with tens of thousands of values.
- sensitive to statistical inhomogeneities, biases, correlated obs errors.

Yields the model and observation error variances.

## observational method



CONCLUSION

- 'observation errors' combine instrumental problems, effect of preprocessing, gross errors and unavoidable noise
- data with large errors must be deleted
- consistency with the model is not always a good thing
- data with smaller errors must be used with relevant weight in the analysis
- cross-validation data is rarely perfect, either.

It is necessary to consider all factors that might affect the good use of the observation.

Data with seemingly low quality may still be useful if it is abundant : a well-tuned data assimilation will filter out most of the errors.

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