Observations monitoring and related diagnostics

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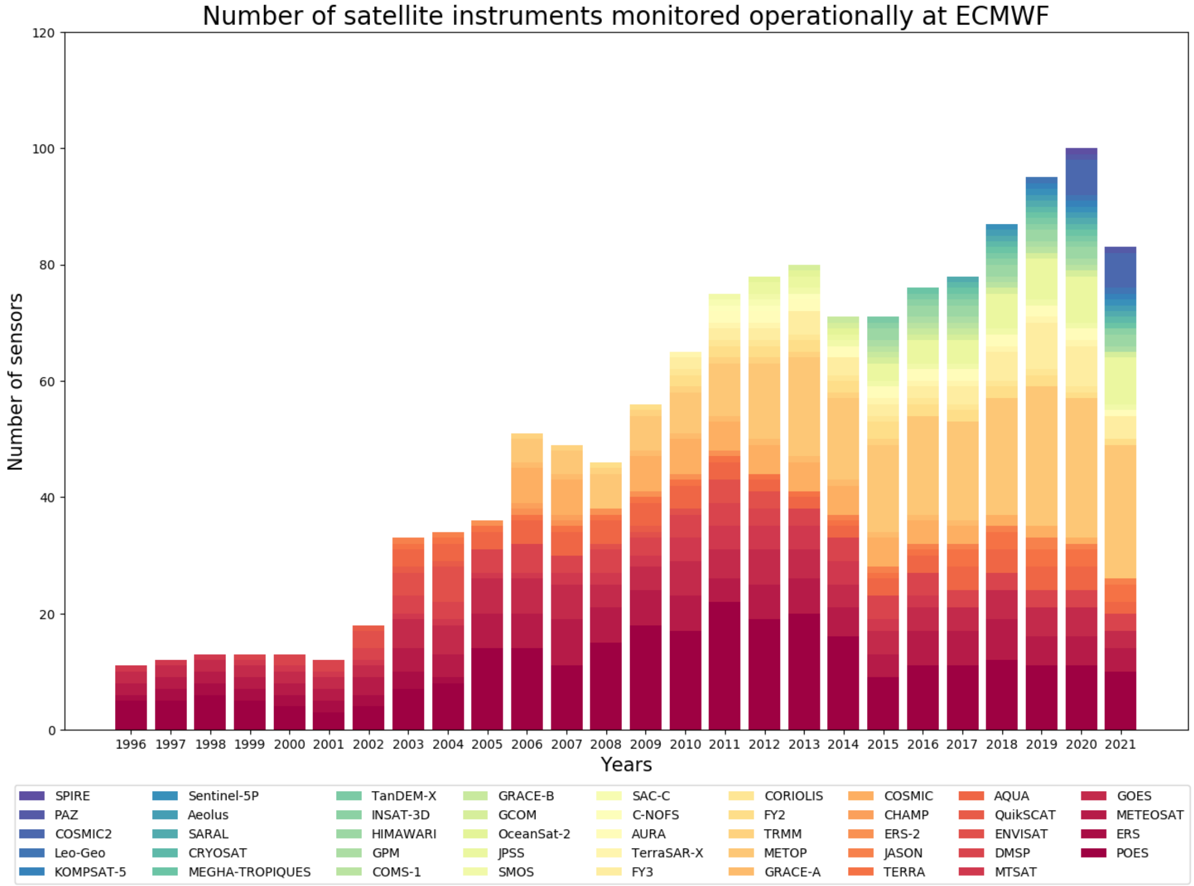
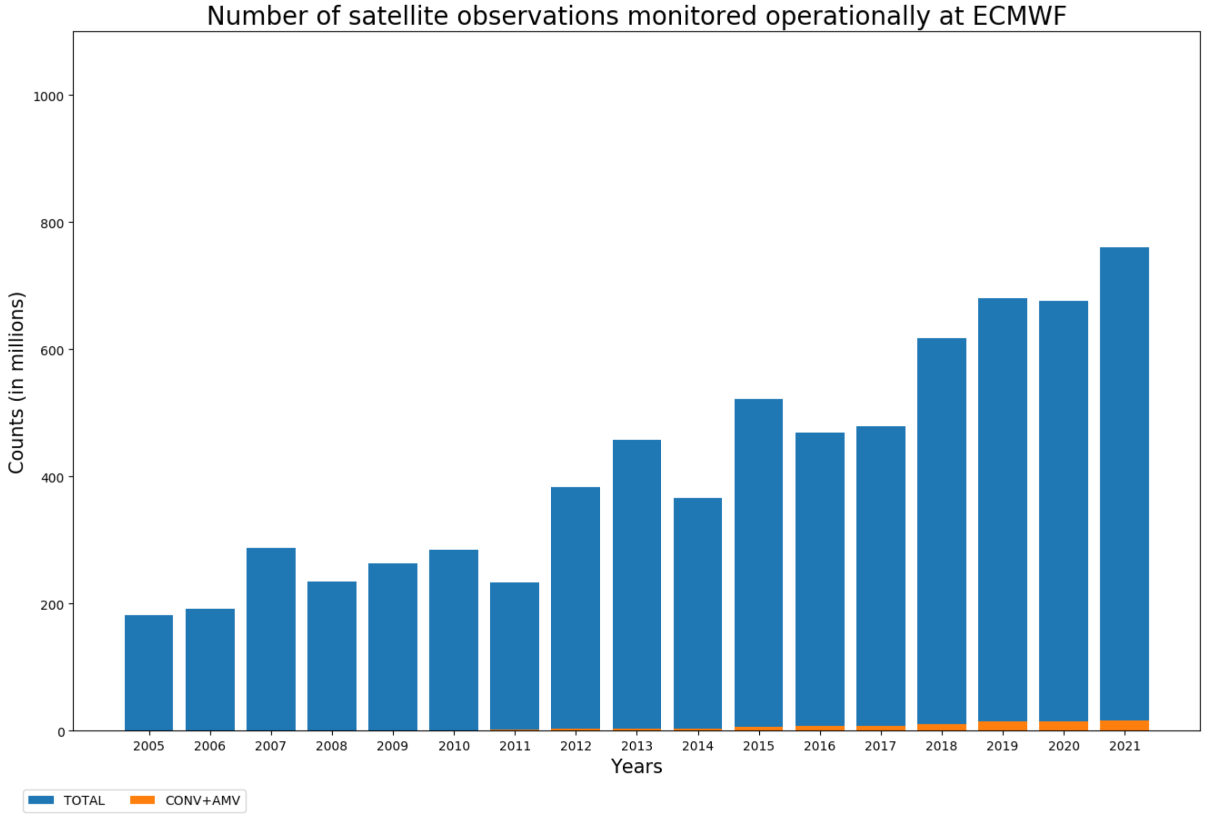
Outline

1. Monitoring of observations: Why and how ?
2. Observation monitoring capabilities
3. Observation based diagnostics
4. Conclusion

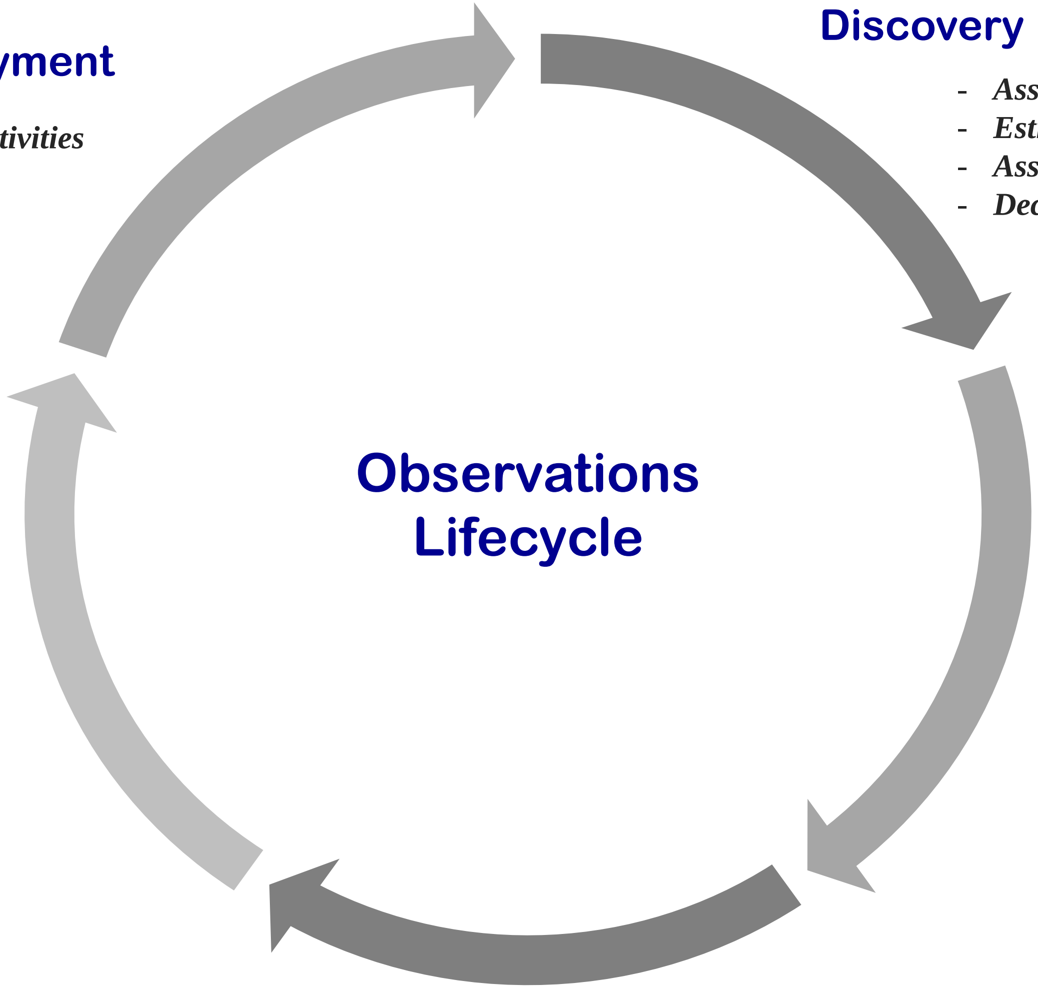
Evolution of data counts and diversity





- ~ 800 million pieces of observations received daily and ~60 millions active . A lot of potential
- Data characteristics are subject to variation with possible consequences on the data impact.

Monitoring of observations: Why ?



Discovery & evaluation

- *Assessment of quality*
- *Estimation of observation errors*
- *Assessment of impact*
- *Decision to use the data*

Use & Re-use

- *Continuous monitoring of quality and availability*
- *Blacklist/Re-activation when necessary*
- *Assessment of drifts*
- *Monitor data impact (FSOI)*
- *Improve the way the data are used*

End of life

Planning & design

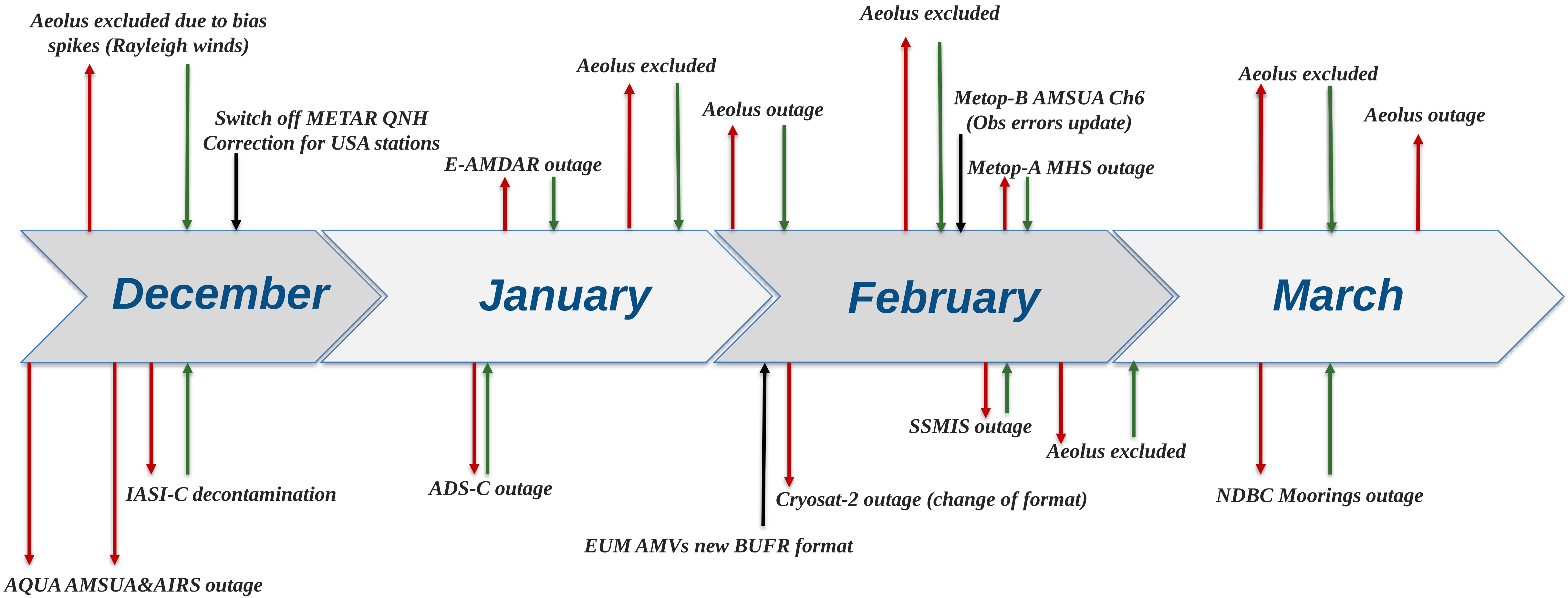
Monitoring statistics from similar or heritage data

Deployment

Feedback for Cal/Val activities

Monitoring of observations: Why ?

Data events (DJFM 2021)

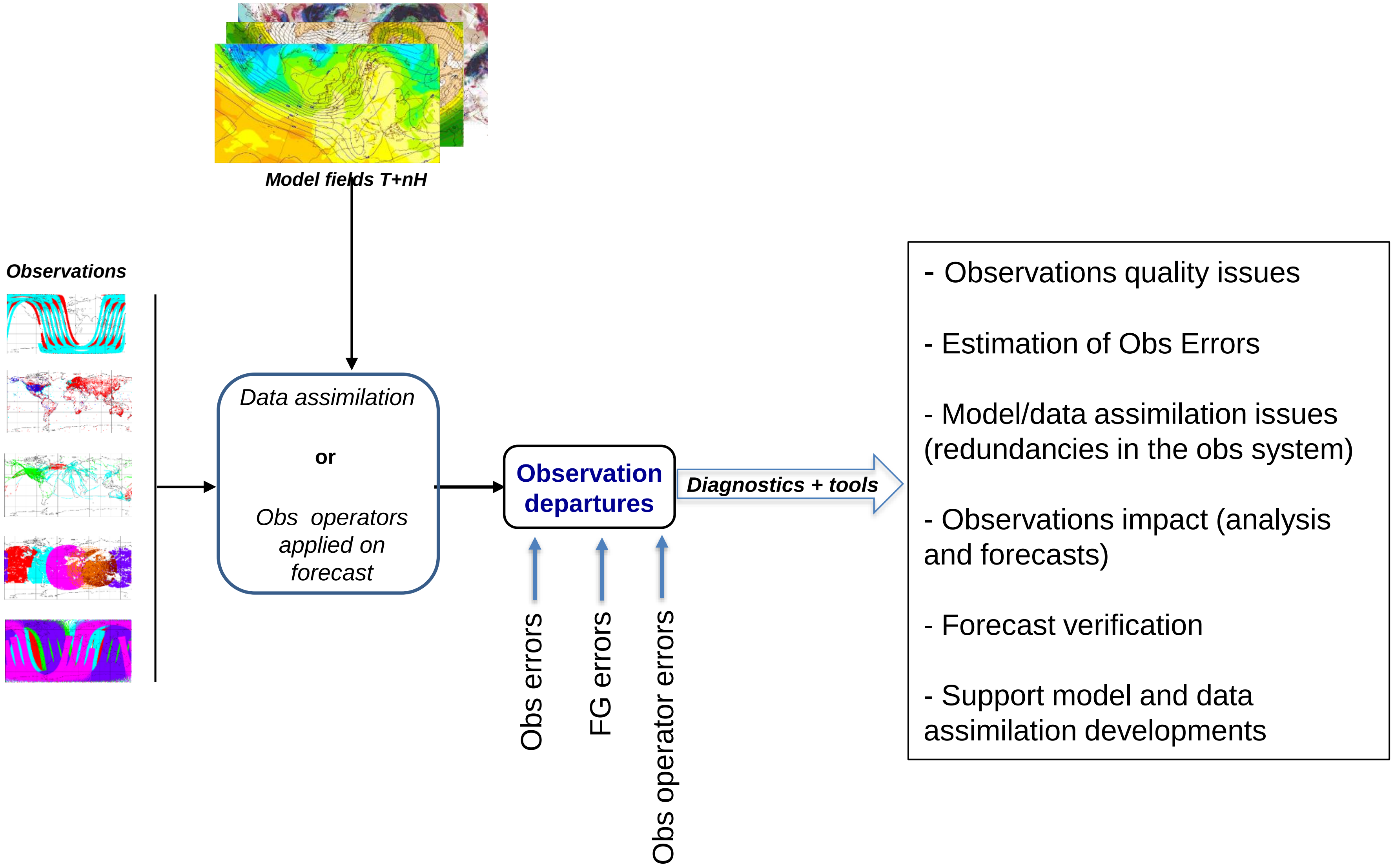


Monthly update of data selections (4D-VAR in-situ and LDAS)

ECMWF

https://confluence.ecmwf.int/display/FCST/Observations+data+events

Monitoring of observations: how ?



Observations monitoring: how ?

- Routine production and display of statistics over large data samples
- Statistics are generally computed for observation quantities related to the data assimilation: departures, bias correction, data counts, etc.
- Statistics are produced for various data selection criteria (crucial for data usage monitoring and quality assessment)
- Availability of statistical tools to generate products allowing the investigation of data from various perspectives: time, area, vertical, FOV, etc.
- Availability of tools allowing generic comparison of statistics from different data assimilation setups
- Tools Should be generic and future proof (easy to maintain) to support new instruments

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2. **Observation monitoring capabilities**
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Observations monitoring resources

- Operational monitoring suite: repository of generic monitoring statistics for almost all observations (internal and external use)

- Automatic detection of quality/availability issues

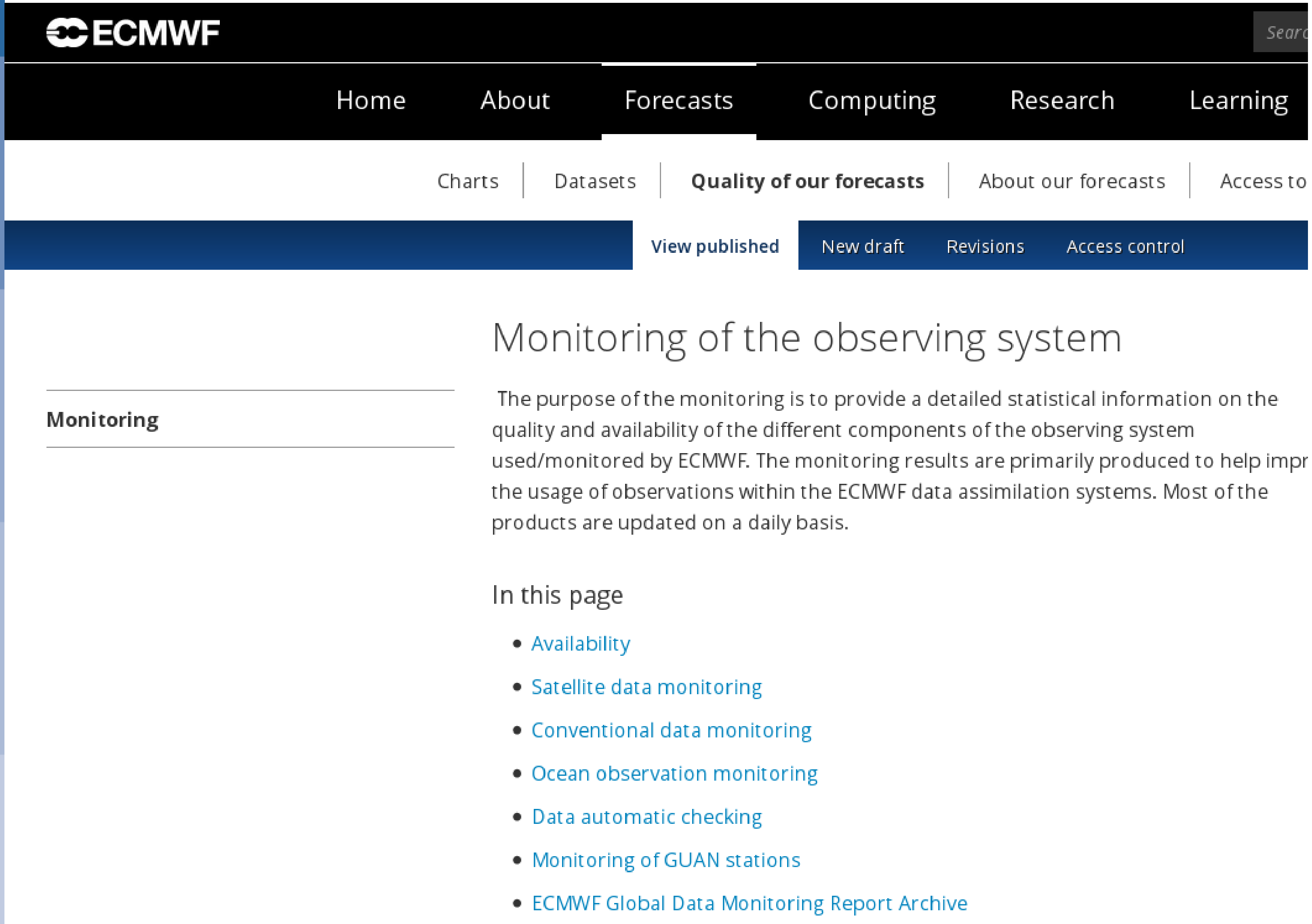
- Research monitoring suite: systematic for all experiments and allows inter-comparison (data impact on short ranges)

- Standalone monitoring tools: allow users to explore and investigate other aspects of data usage

- Other sources of information (data providers notifications, external monitoring resources, cross-activities monitoring, etc)

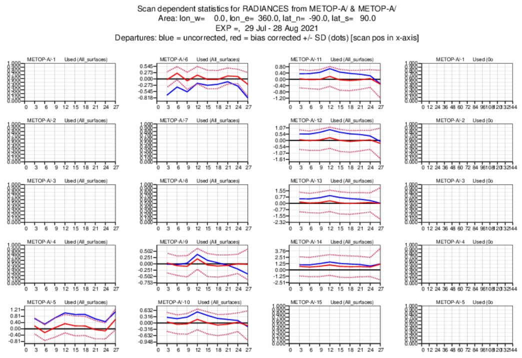
Operational monitoring

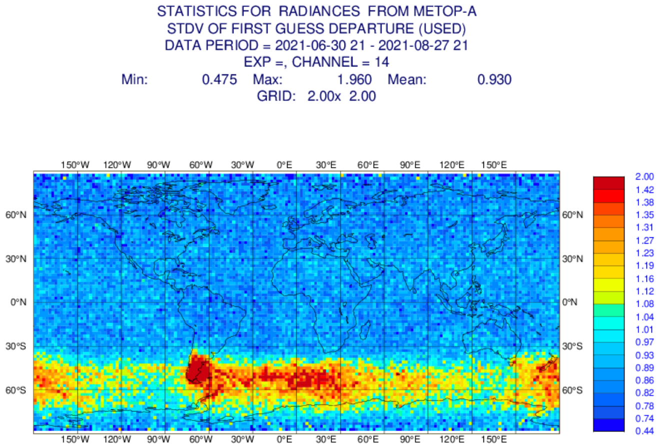
https://www.ecmwf.int/en/forecasts/quality-our-forecasts/monitoring-observing-system

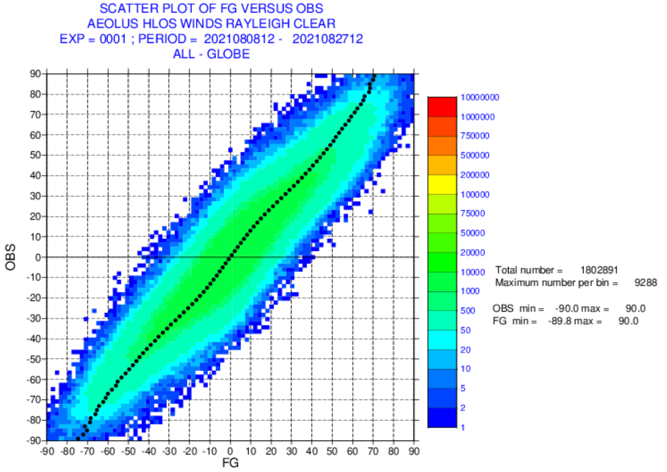


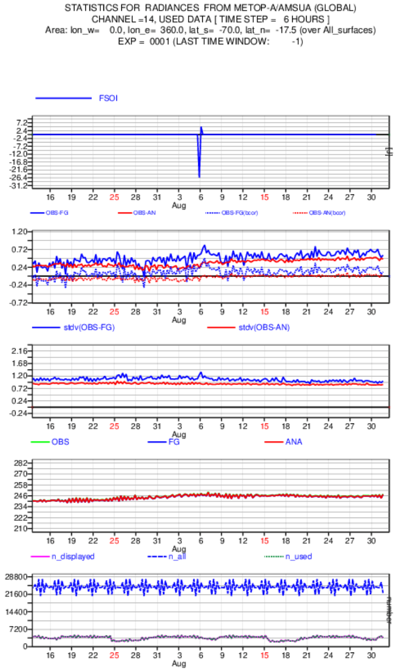
- Almost all earth system observations supported
- ~ 140000 plots updated daily or weekly
- Various types of plots for each data type
- Publicly accessible

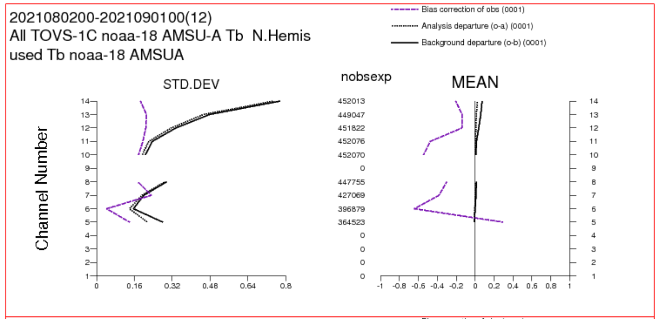
Selected monitoring products

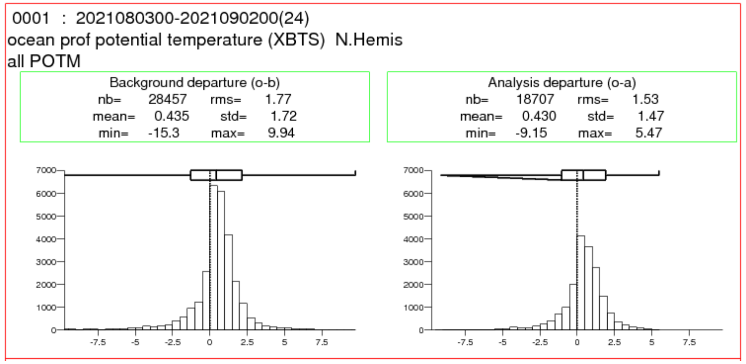


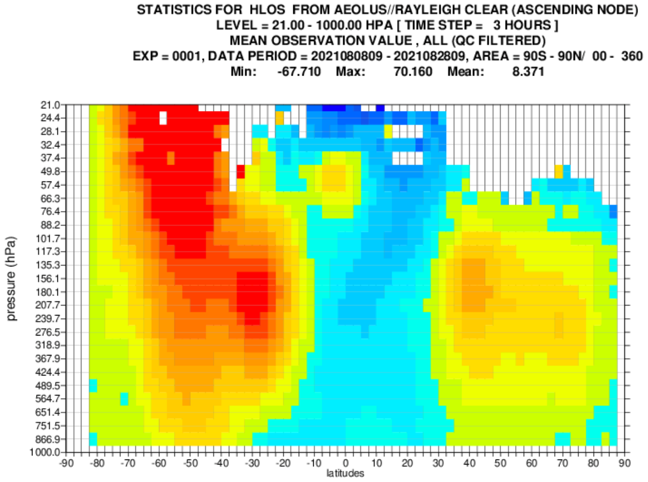


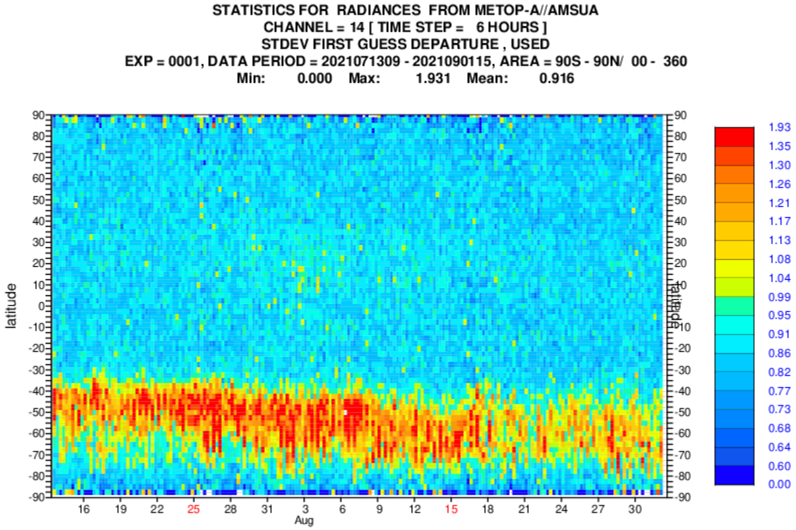




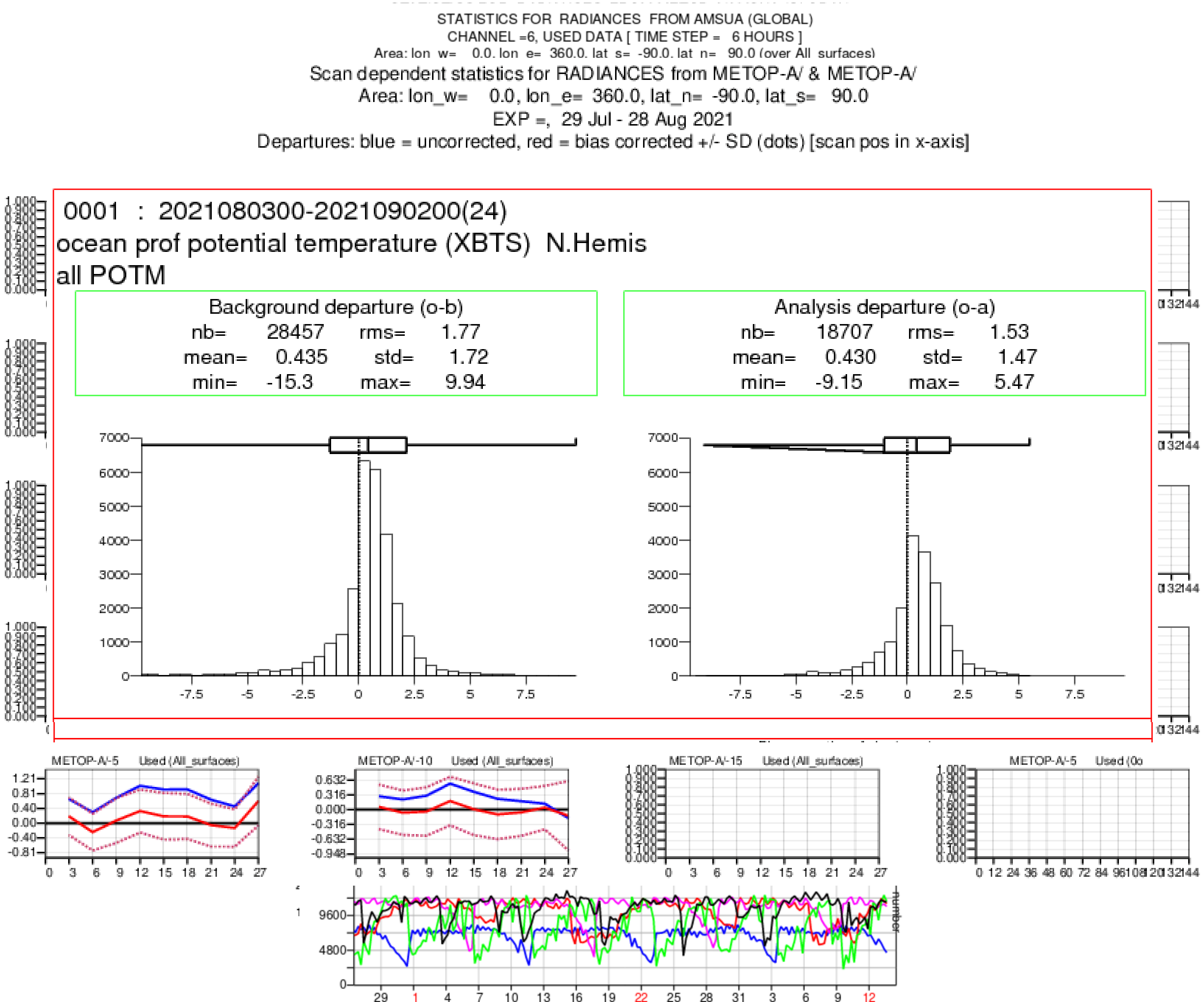








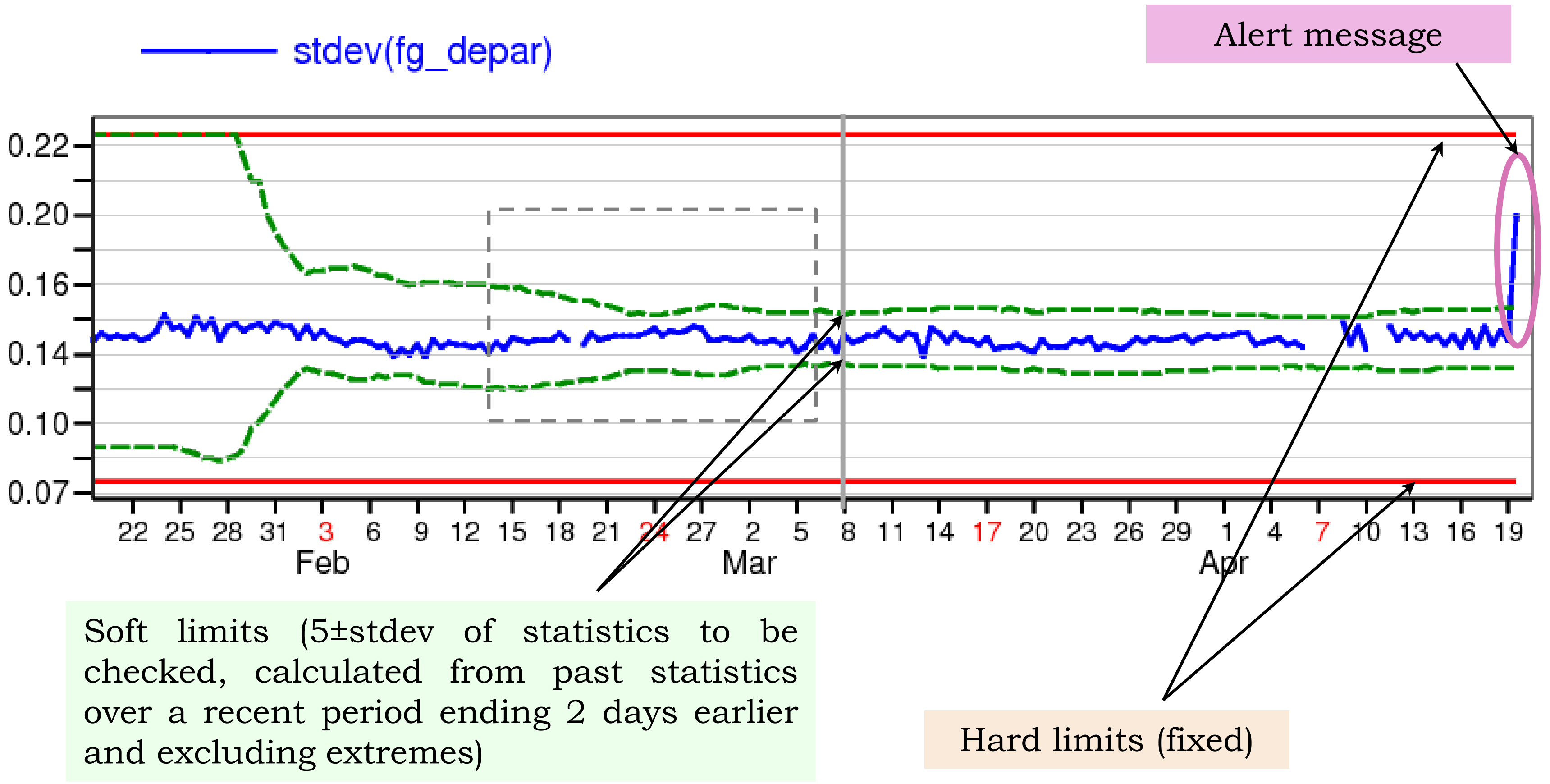
Selected monitoring products

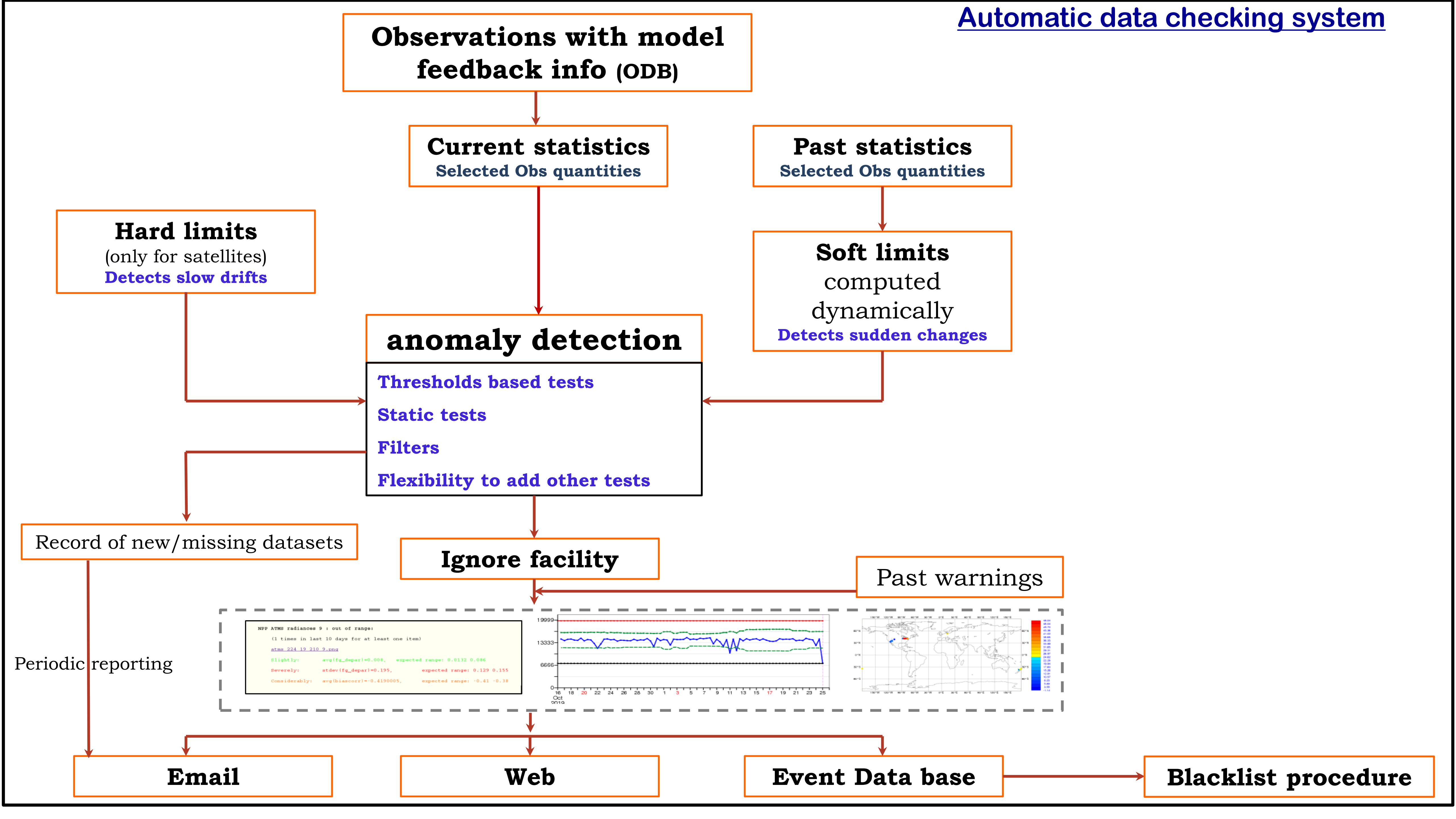


Automatic data checking system

- The large amount of active observations makes it difficult to timely detect availability/quality issues
- An automatic data checking system is implemented at ECMWF to continuously monitors satellite and in-situ data (main trigger for corrective actions). Warnings available to internal and selected external users, at user specified levels of detail
- The same system is used to detect improved in-situ data that are currently excluded (timely activation of improved observations
- Detects data problems but informs also when extreme events are taking place or in case of issues with the model/DA

Automatic data checking system



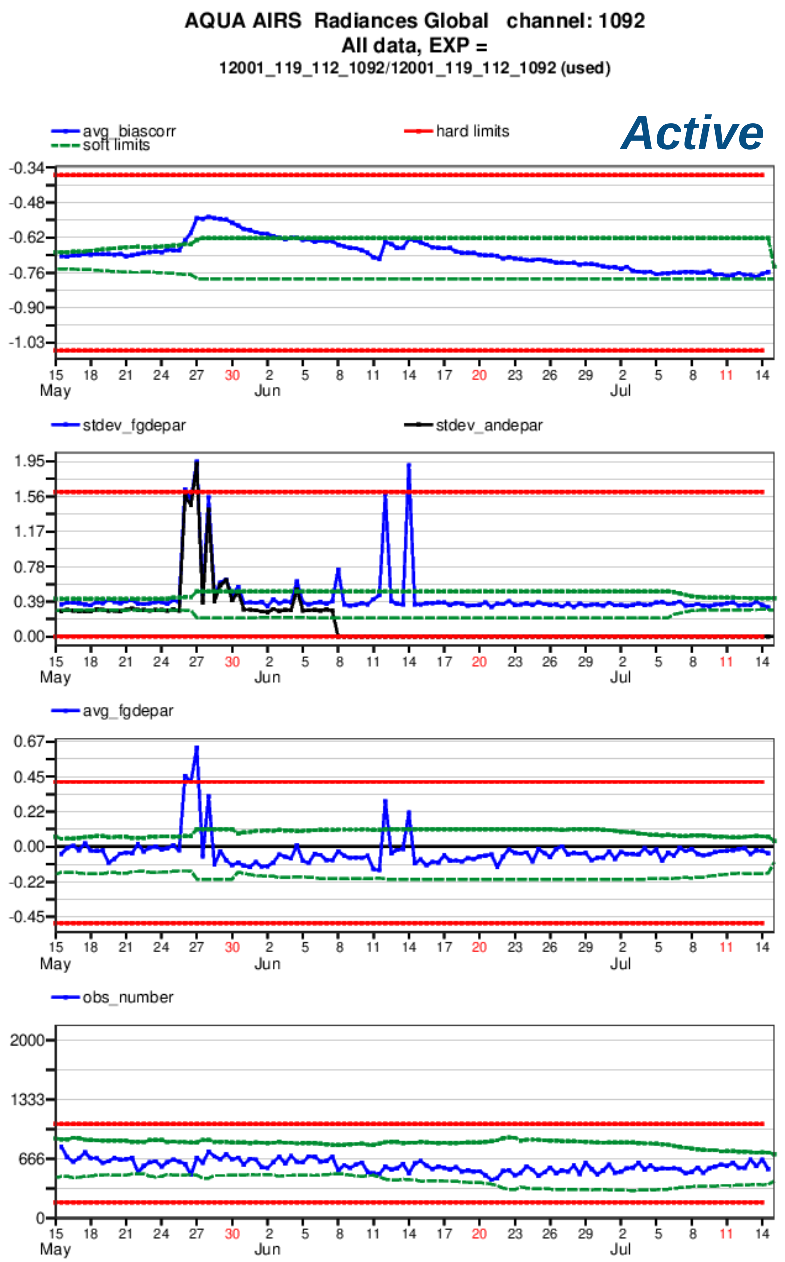

Automatic data checking system
Observations with model feedback info (ODB)
Current statistics
Selected Obs quantities
Past statistics
Selected Obs quantities
Hard limits
(only for satellites)
Detects slow drifts
Soft limits
computed dynamically
Detects sudden changes
anomaly detection
Thresholds based tests
Static tests
Filters
Flexibility to add other tests
Record of new/missing datasets
Ignore facility
Past warnings
Periodic reporting
Email
Web
Event Data base
Blacklist procedure

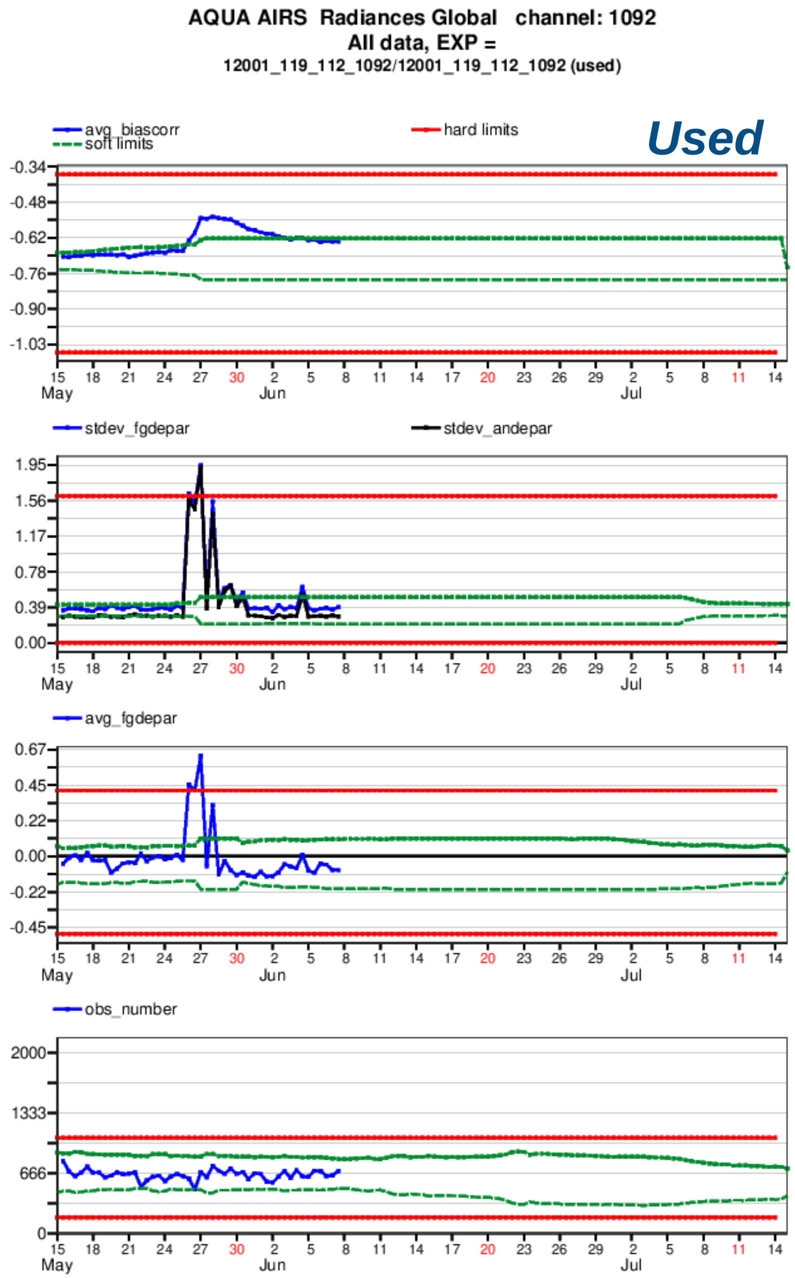
Automatic data checking system

Three-component system

All observations	*In-situ observations*	*In-situ observations*
Detects widespread availability and quality problems over selected areas	Detects severe quality problems affecting individual stations Detect stations persistently missing Detect new stations	Detects persistent quality improvements of "blacklisted" stations
Based on FG and Analysis departures, bias correction, data counts, etc	Based on FG departures and the IFS produced PGE	Based on an estimated PGE

Automatic data checking system (examples)



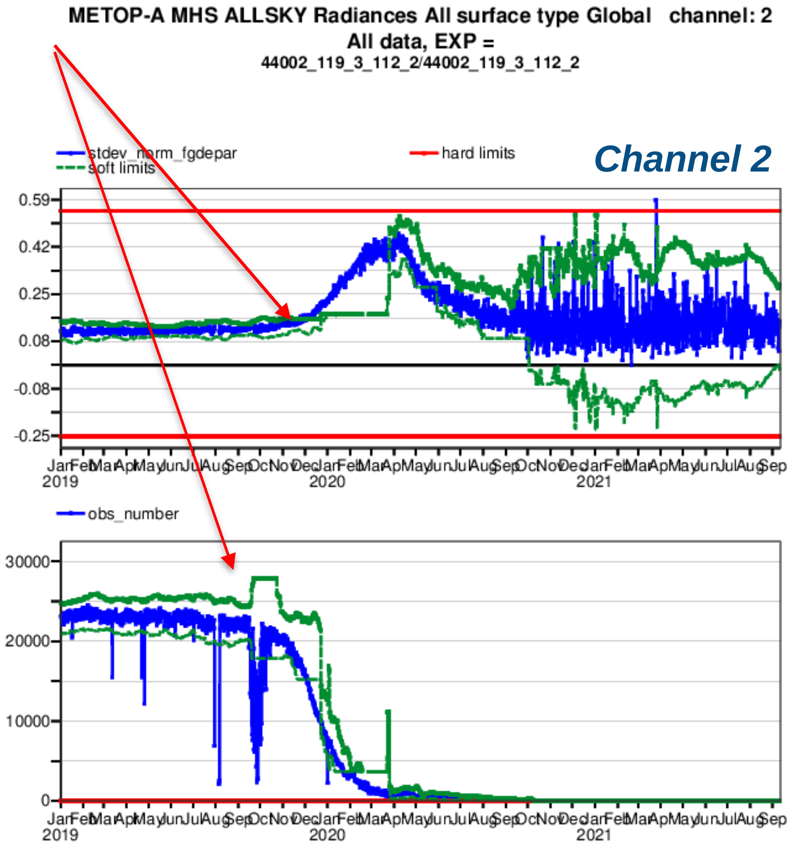


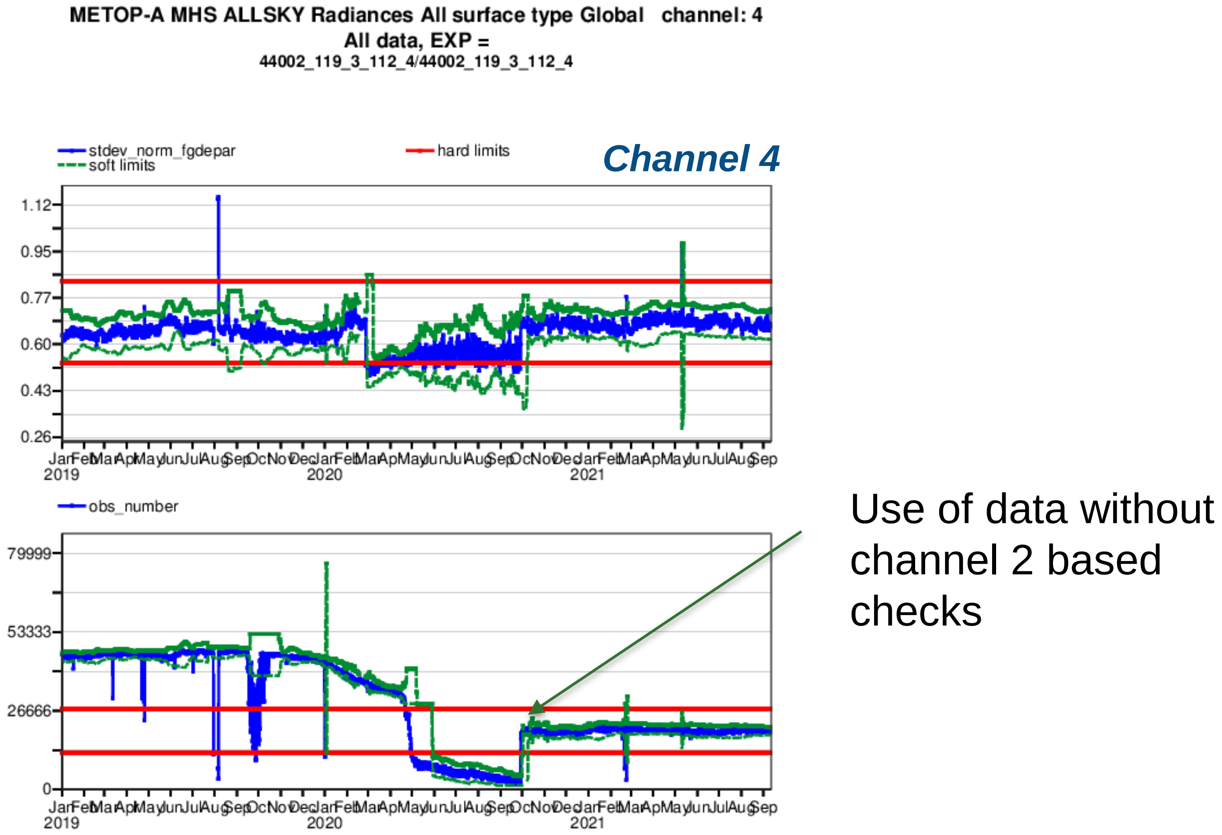
- AIRS channel 1092 erratic behaviour
- Data excluded after few bad cycles

Automatic data checking system (examples)

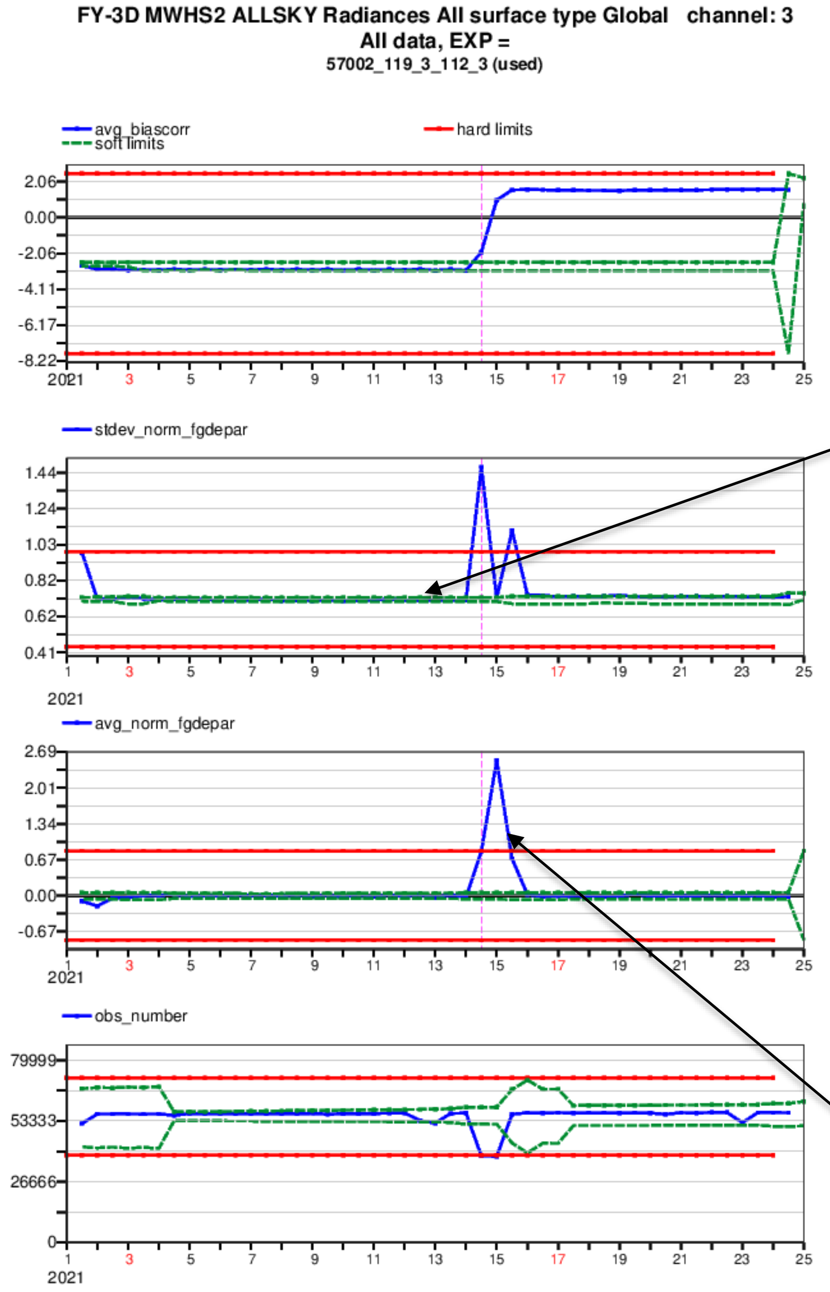
– METOP-A MHS channel 2 quality degradation resulting in the drop of counts below the processing thresholds and hence the reduction of data. Fixed by data provider

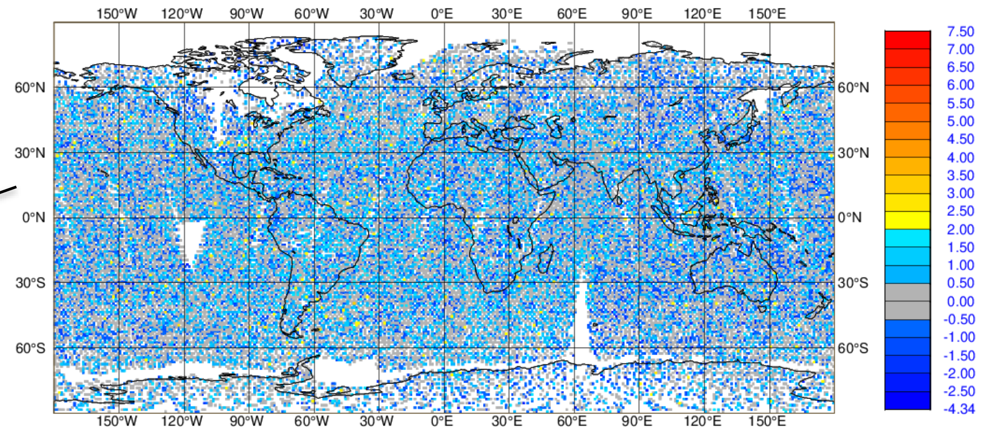
– METOP-A MHS channel 2 continued to behave badly. This had an impact on the use of other channels until we found a way to use the rest of data without checks based on channel 2

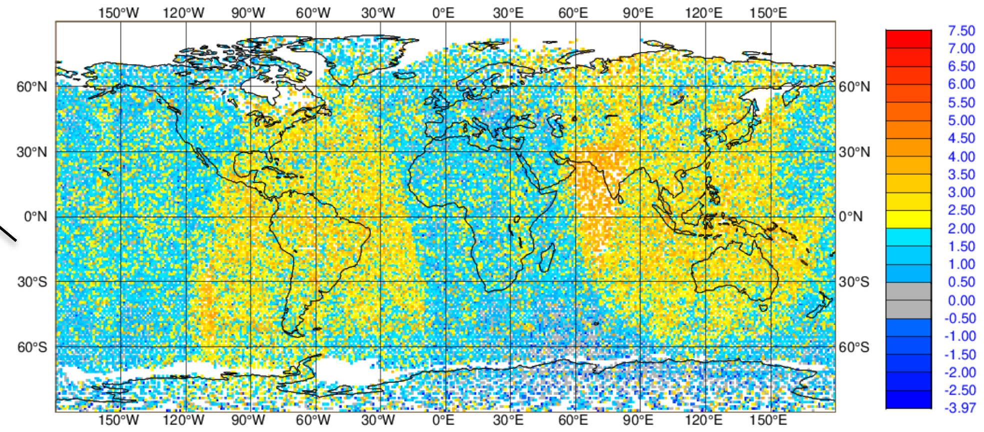




Automatic data checking system (examples)





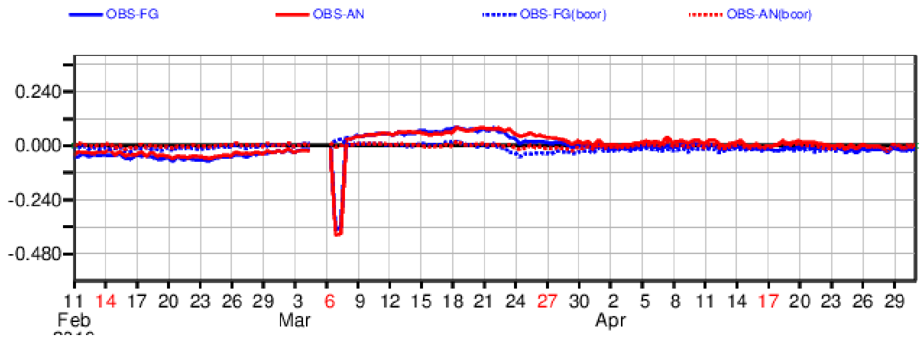


- FY-3D MWHS2 Ch3 sudden degradation
- Quick recovery (no action needed)

Earth system automatic warnings

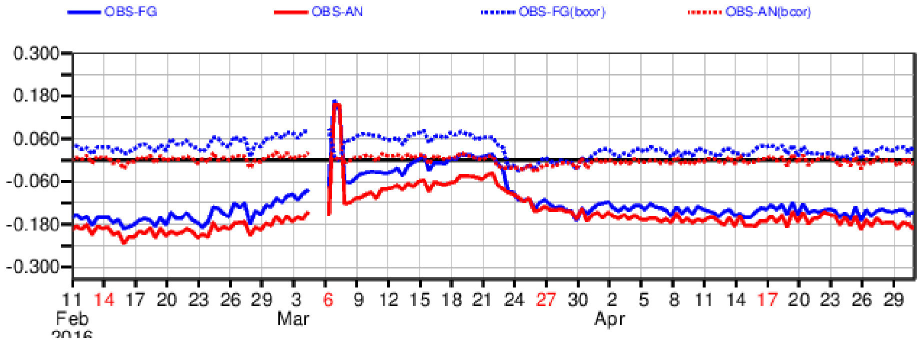
STATISTICS FOR CRIS FROM NPP/CRIS
CHANNEL =457, ACTIVE DATA [TIME STEP = 12 HOURS]
Area: lon_w= 0.0, lon_e= 360.0, lat_s= -90.0, lat_n= 90.0 (over All_surfaces)
EXP = 0001 (LAST TIME WINDOW: 2016043021)

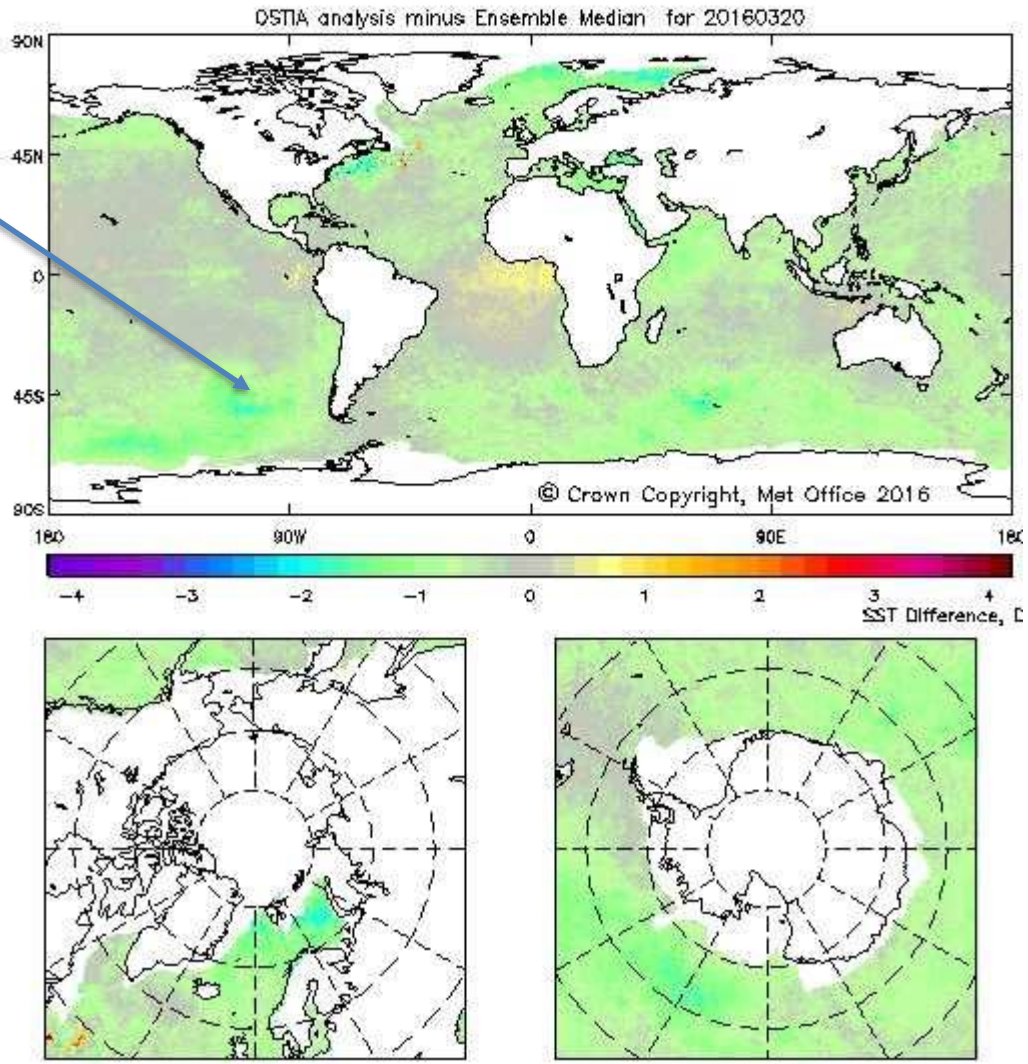
CrIS Ch 457



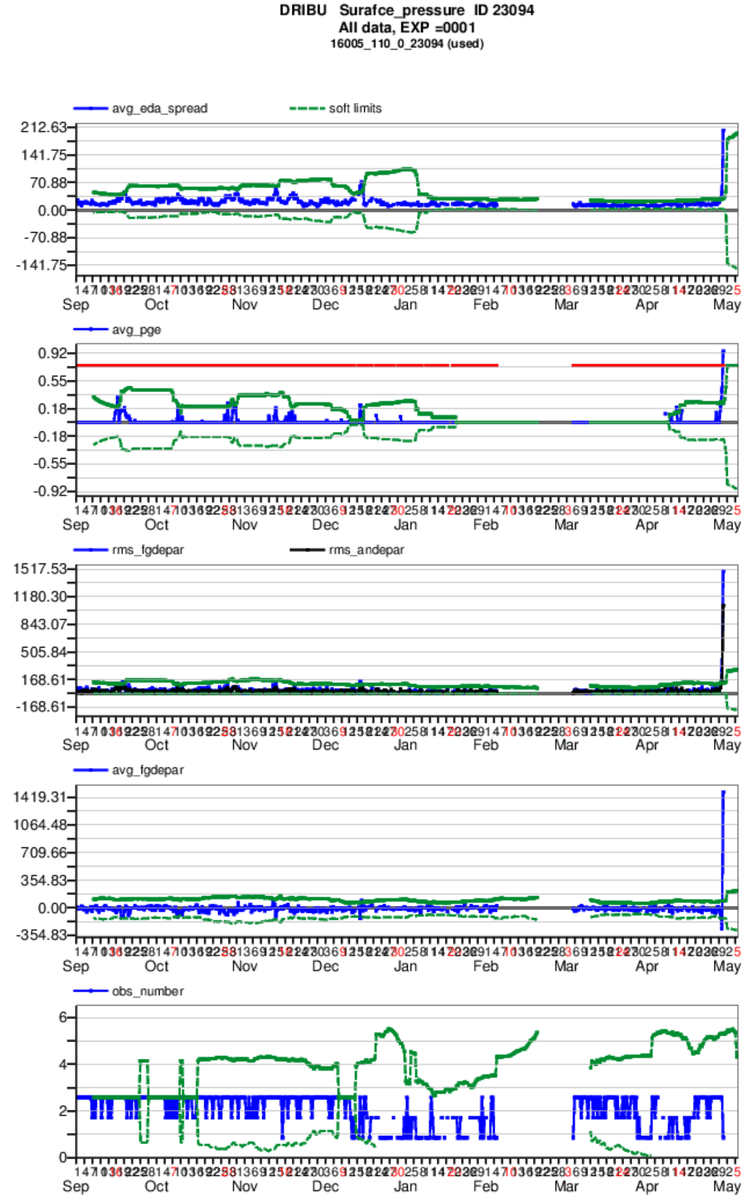
STATISTICS FOR RADIANCES FROM METOP-A/IASI
CHANNEL =1090, ACTIVE DATA [TIME STEP = 12 HOURS]
Area: lon_w= 0.0, lon_e= 360.0, lat_s= -90.0, lat_n= 90.0 (over All_surfaces)
EXP = 0001 (LAST TIME WINDOW: 2016043021)

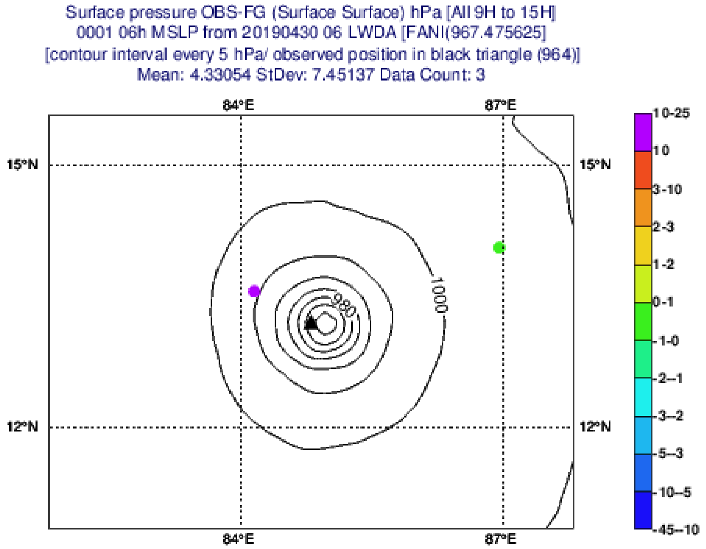
IASI Ch 1090

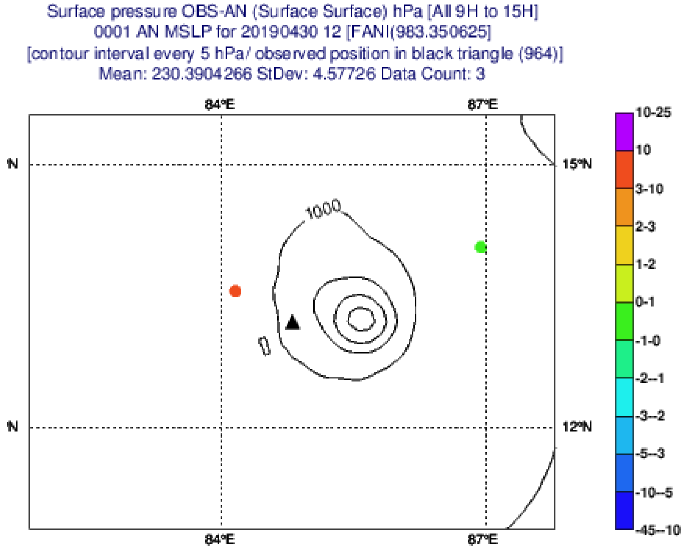




Automatic data checking system (examples)

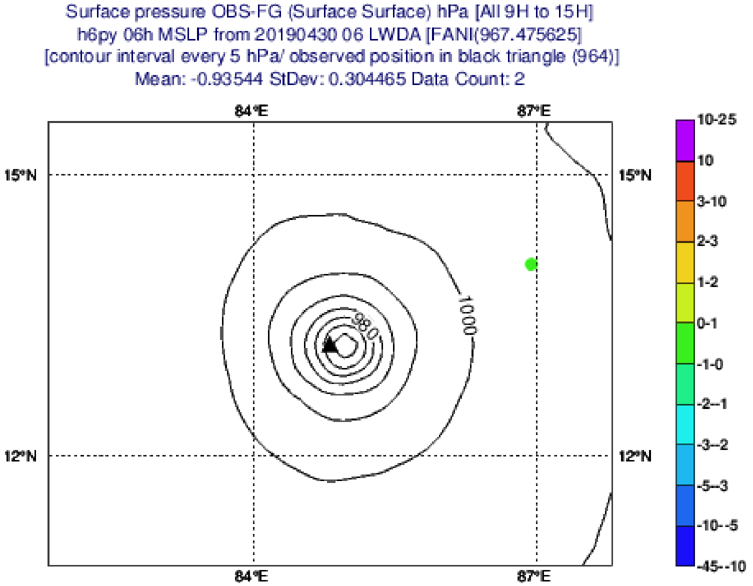


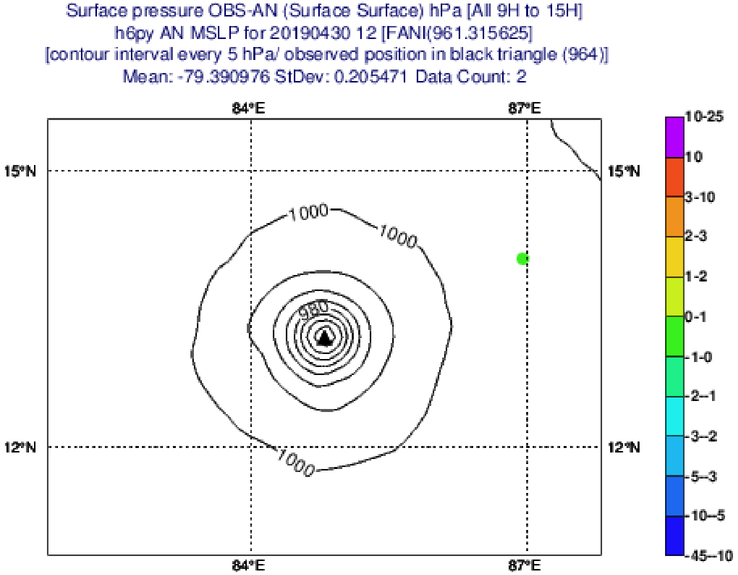




The forecast was also - impacted

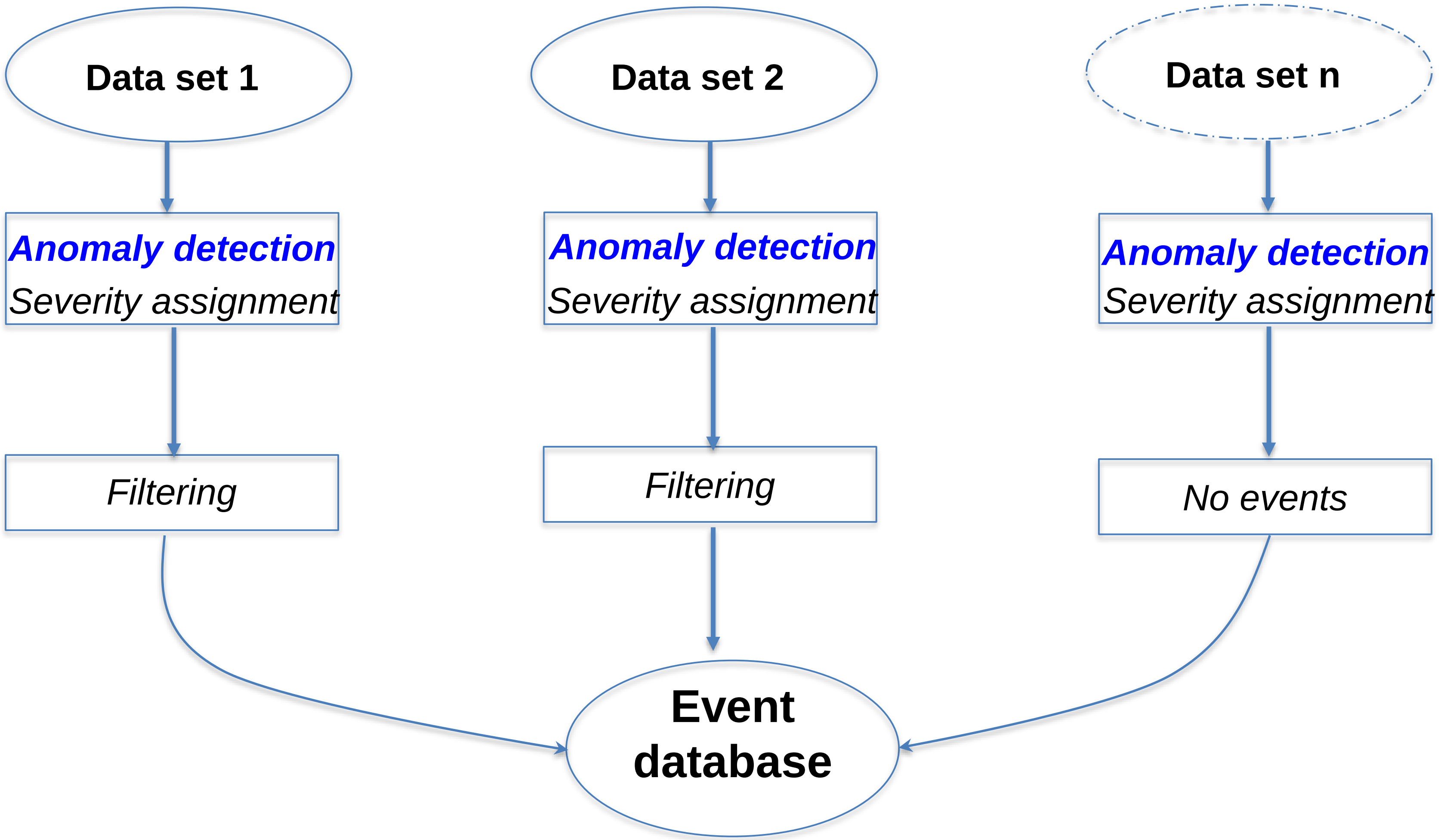
Denial of the buoy 23094





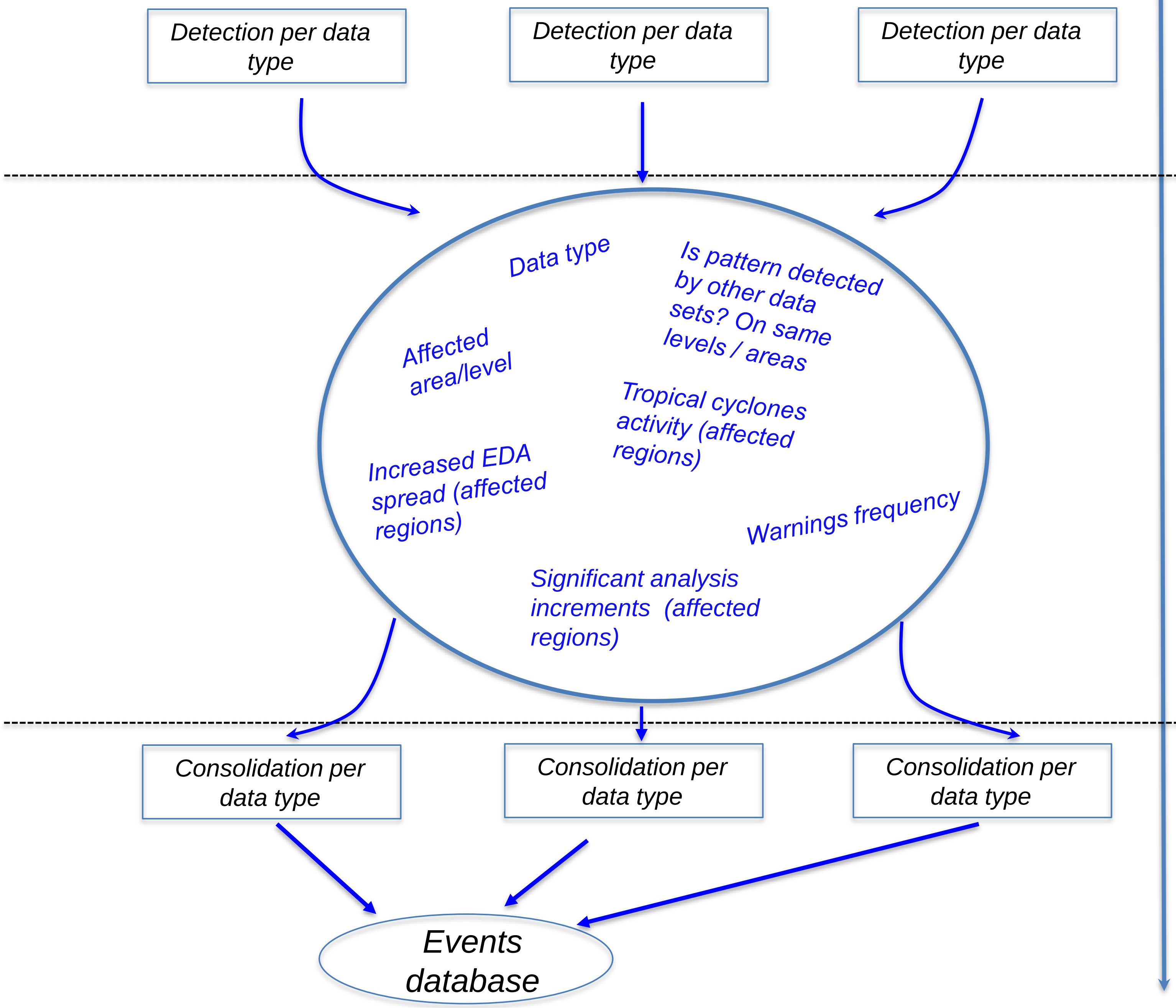
Earth system automatic warnings (ML approach)

Work in progress



- Current system works well but requires time and expert knowledge to distinguish data and model issues. Both important but require different actions

- Although false alarms are not common but many alarms do not require actions.



TensorFlow (LSTM + auto-encoders)

- Data de-seasonalised and normalised
- Models trained (once every quarter) on long data sets (> year)
- Models trained (every cycle) on short data sets (~60 days)
- Previous alarms excluded from training

ML classifier (random forests)

- Training based on labelled warnings populated from the operational alarm system)

- During the labelling process, decisions are made based on the data types, area of interest, etc.

- The classifier will adjust: Severity, likely cause of the problem (model, obs) and the need for action.

Consolidation

- Warnings are consolidated and processed for each data type

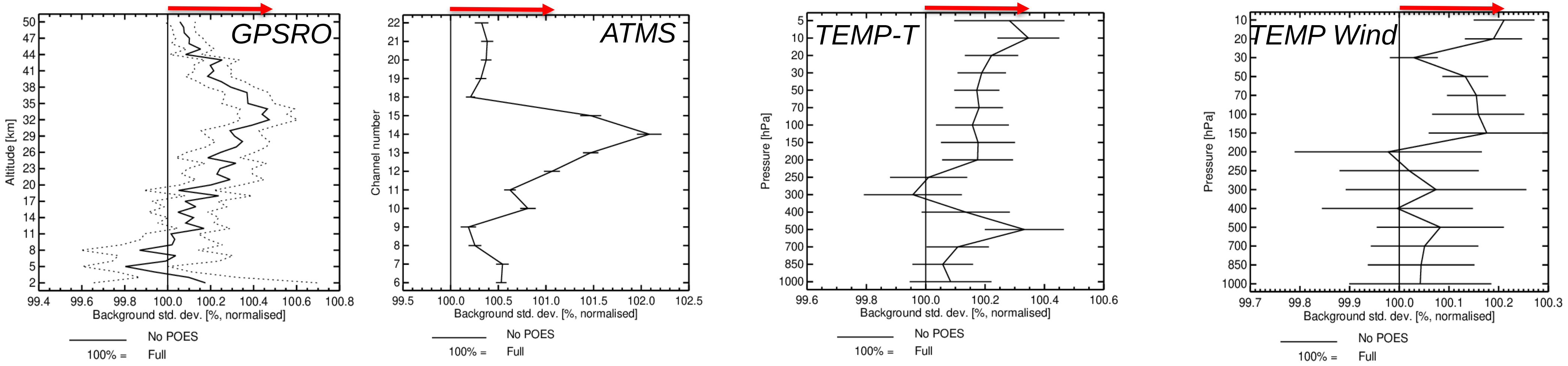
Research monitoring suite

- Generic statistics are computed systematically for all research experiments (used observations only)

- Quick comparison of data usage between experiments: Data counts, First guess and analysis fit to used observations

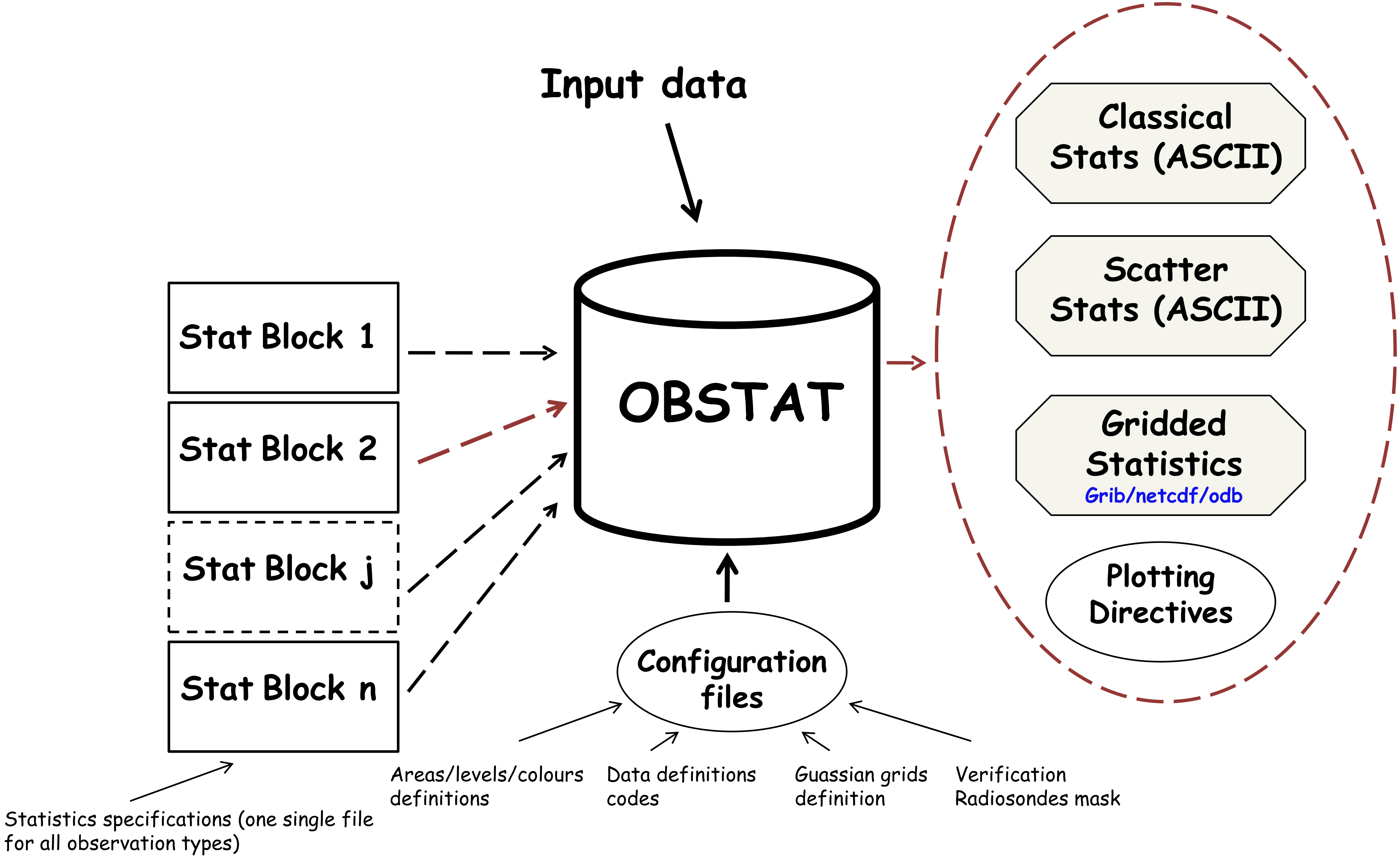
- Provides idea on data impact (for data denial experiments) and the impact of scientific changes

Degradation of short-range forecasts from losing the legacy POES satellites for temperature wind and humidity

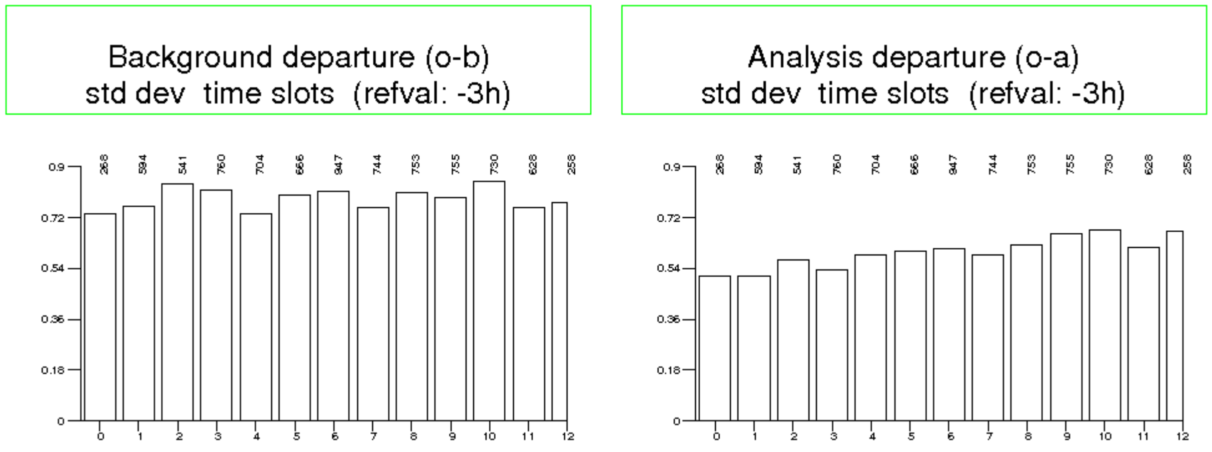


Standalone monitoring tools

- Designed to allow users to conduct special investigations of data usage (Beyond the default set of statistics)
- Allows users to compute statistics for various **diagnostics** (departures, bias correction, FSOI, etc.)
- Production of statistics from various perspective (time, vertical, latitudes, asc/desc, day/night, FOV, Lagrangian, scatterplots, time series for individual stations, etc.)
- Sufficiently generic to handle all data types
- Used to overlay results from different model versions
- Advanced functions such as co-colocation, Observation matching, etc
- At ECMWF the OBSTAT software is used as a standalone monitoring tool in addition to being the core of the operational and research monitoring suites.


Input data
Stat Block 1
Stat Block 2
Stat Block j
Stat Block n
OBSTAT
Classical Stats (ASCII)
Scatter Stats (ASCII)
Gridded Statistics
Grib/netcdf/odb
Plotting Directives
Configuration files
Statistics specifications (one single file for all observation types)
Areas/levels/colours definitions
Data definitions codes
Guassian grids definition
Verification Radiosondes mask

0001 /DCDA 2012032000-2012032012(12)
AIREP-T Tropics
used T

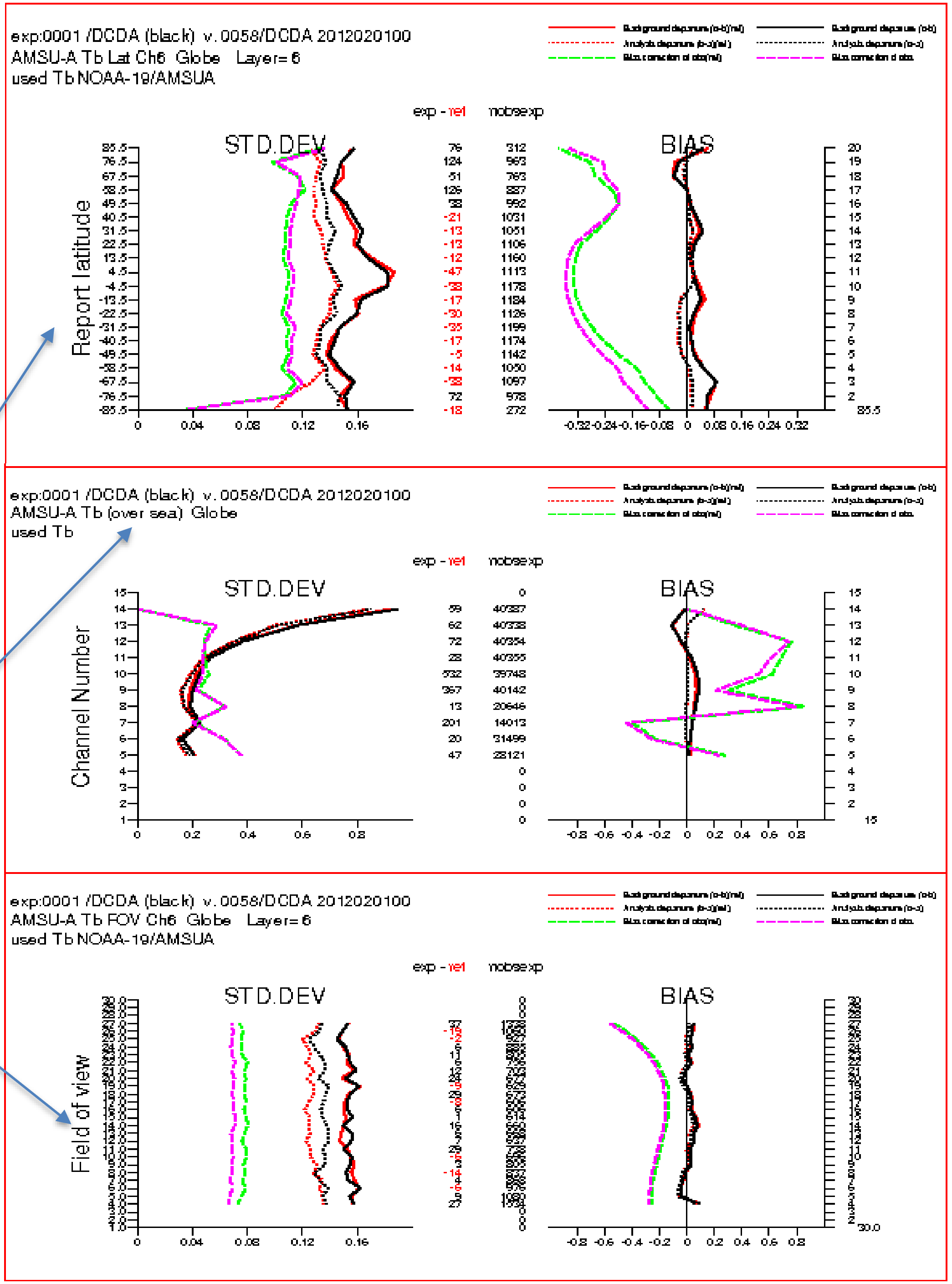


Data assimilation slots

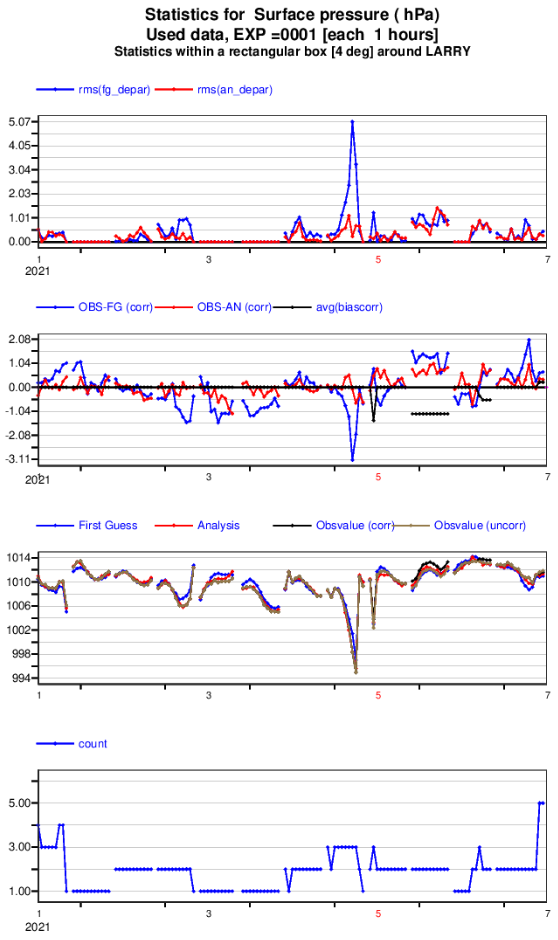
Latitude bands

Data over sea

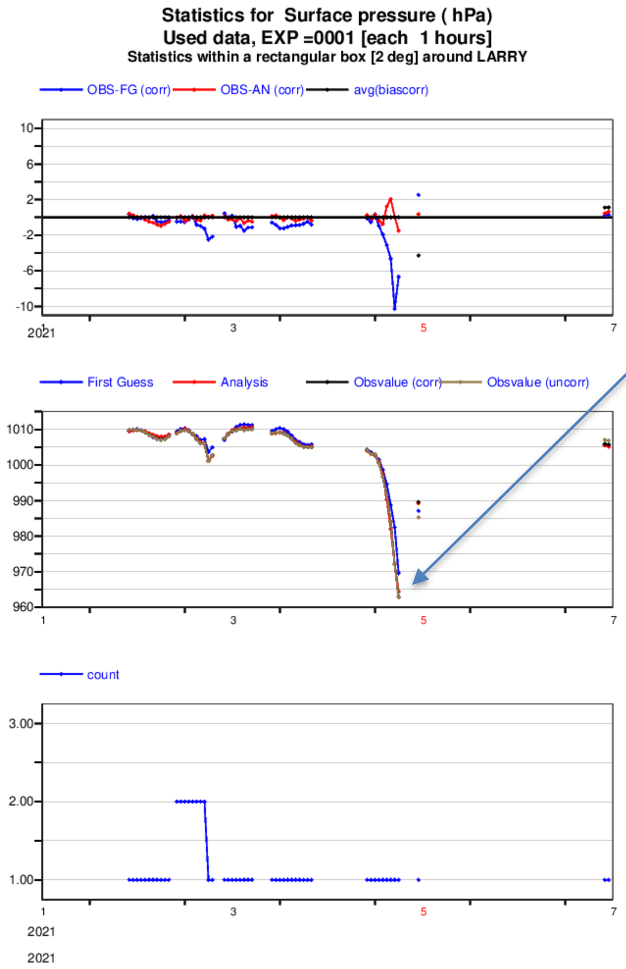
Field of view

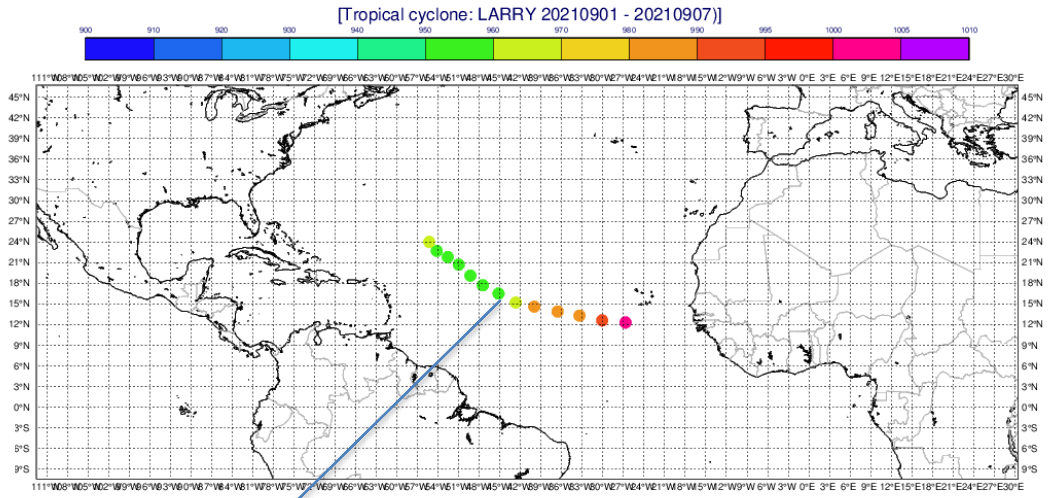


TC LARRY (4x4 degrees)



TC LARRY (2x2 degrees)





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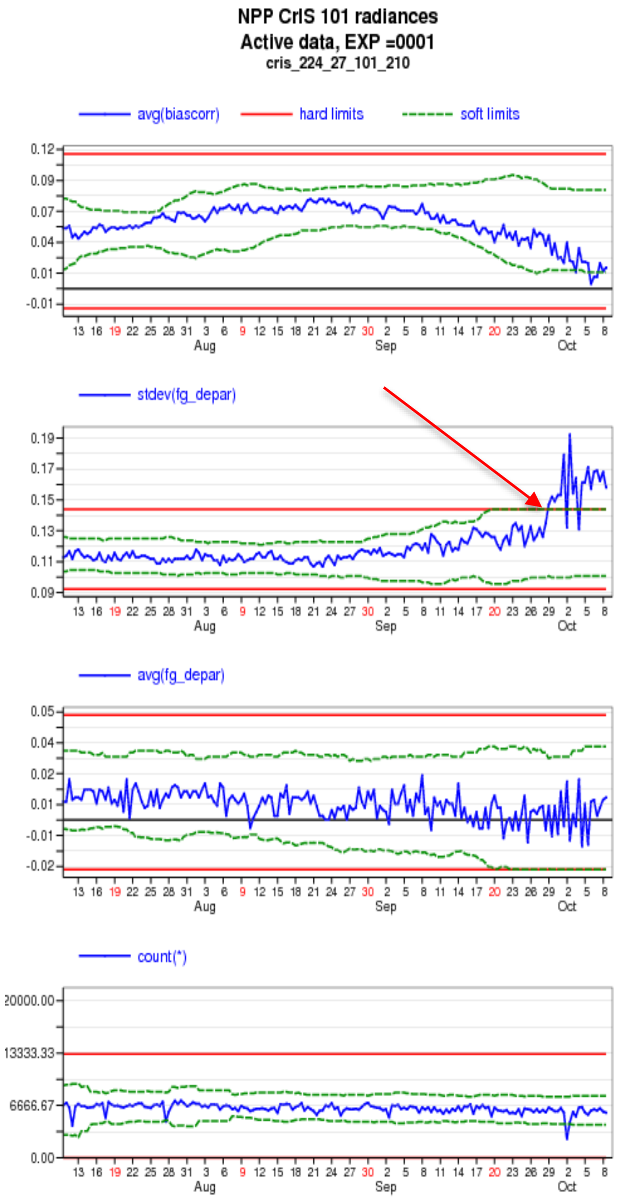
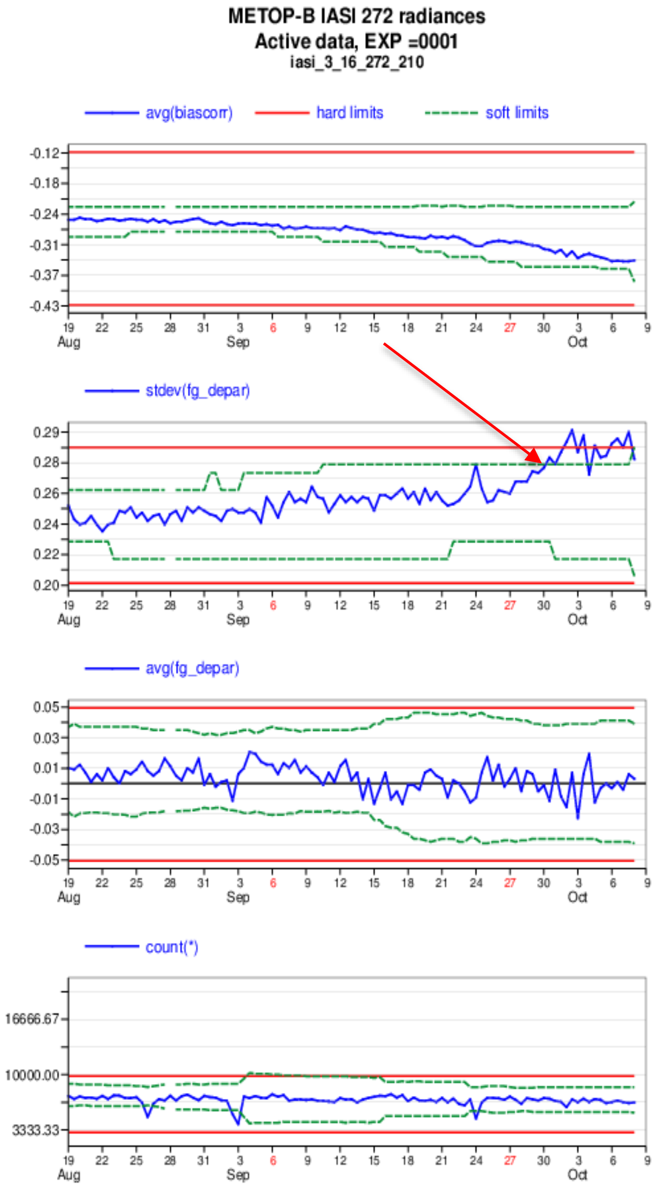
Observations related diagnostics

- Inference from redundancies in the observing system (supported by collocation when possible)
- Impact on departures from changes to the observing system or how the data are assimilated
- Diagnostics in observation space based on departures
- Diagnostics from the EDA
- Triple-collocation

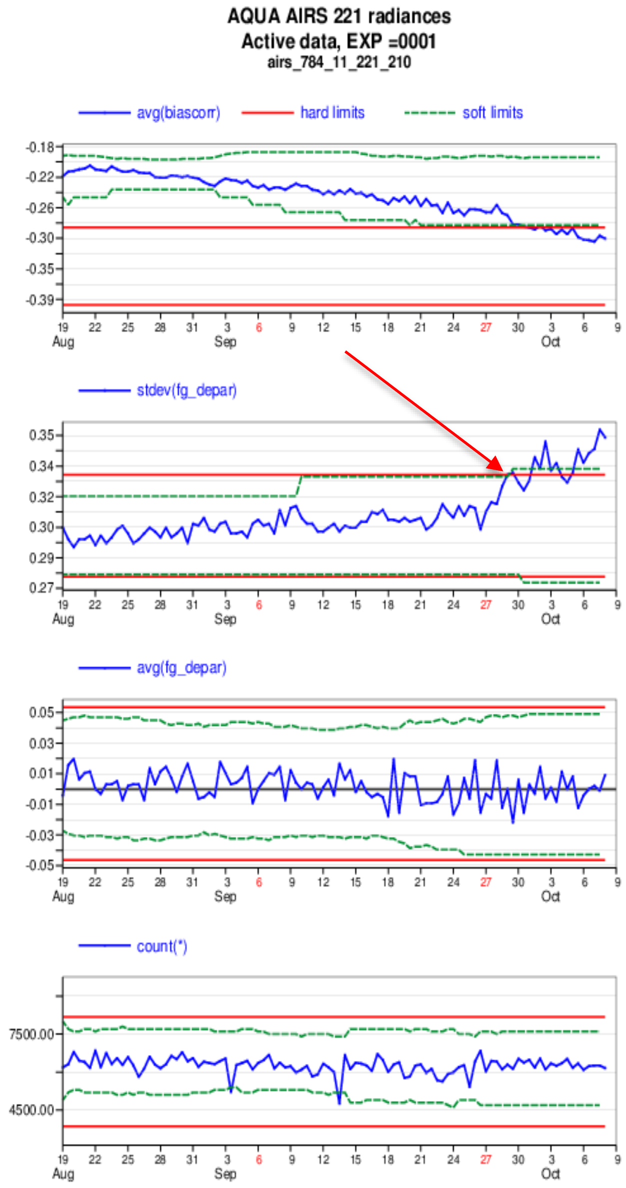
S-NPP CrIS Ch 101



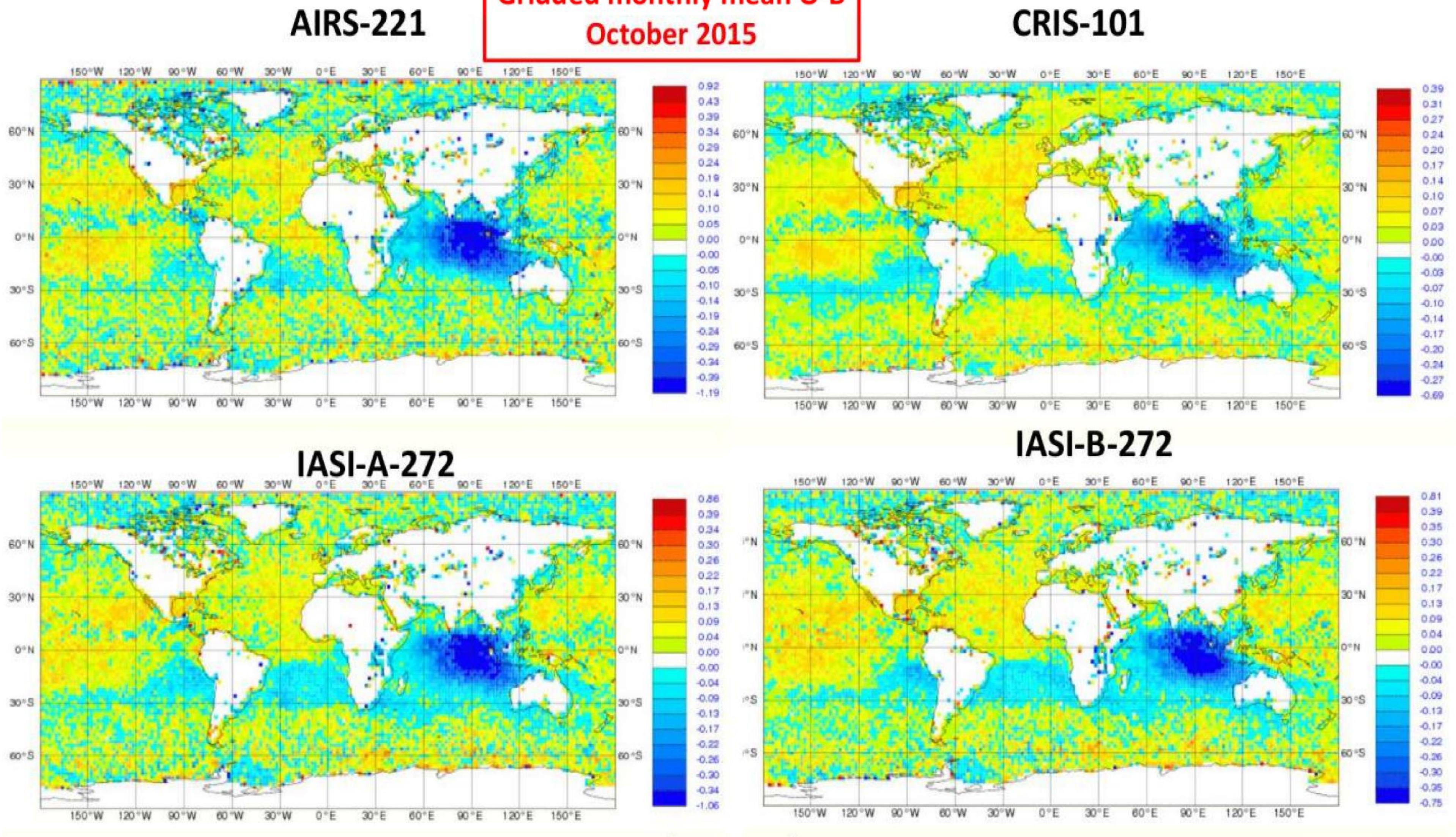
METOP-B IASI Ch 272



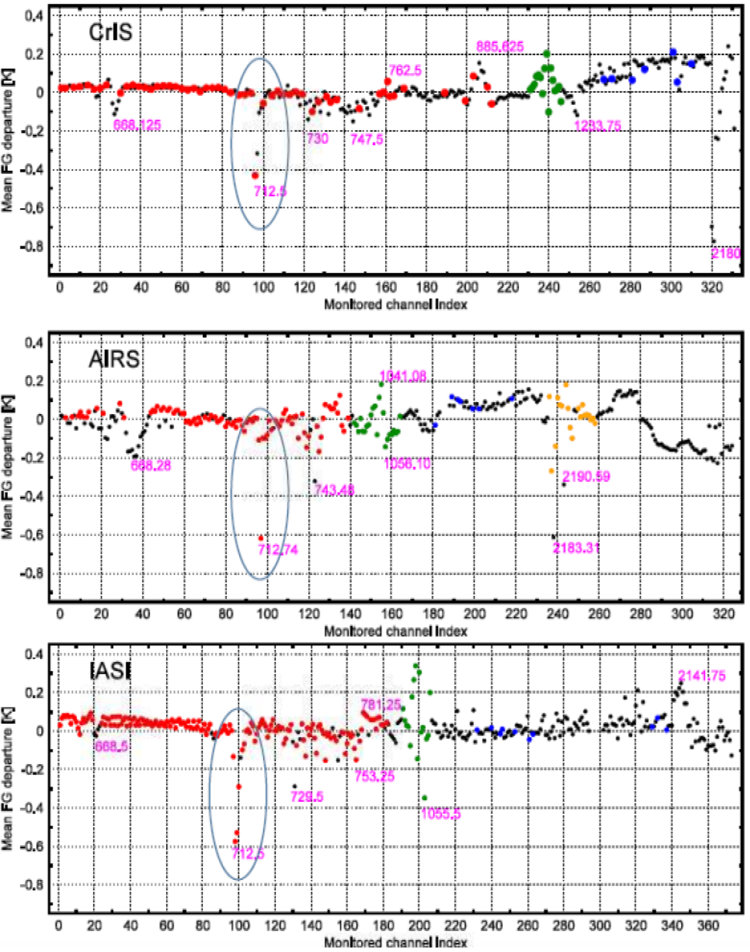
AQUA AIRS Ch 221



Gridded monthly mean O-B
October 2015



M. Matricardi



The mean O-B statistics in other IR channels shows that the anomaly can be seen in any IR channel sensing around 712 cm-1 (or 14 micron) from CrIS, AIRS and both IASI instruments (A and B)

However, there is no evidence of a similar contamination signal in the IR window channels indicating that the signal cannot be attributed to residual clouds or aerosols

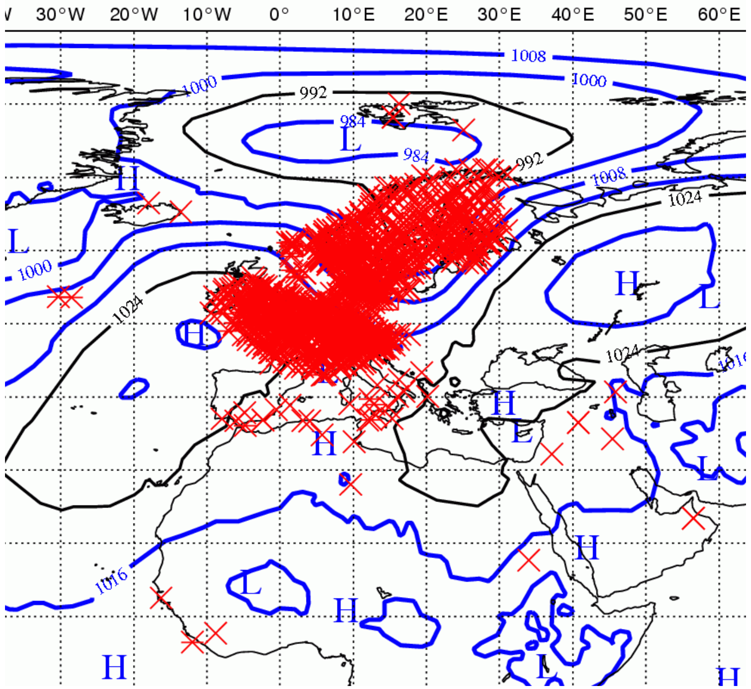
M. Matricardi

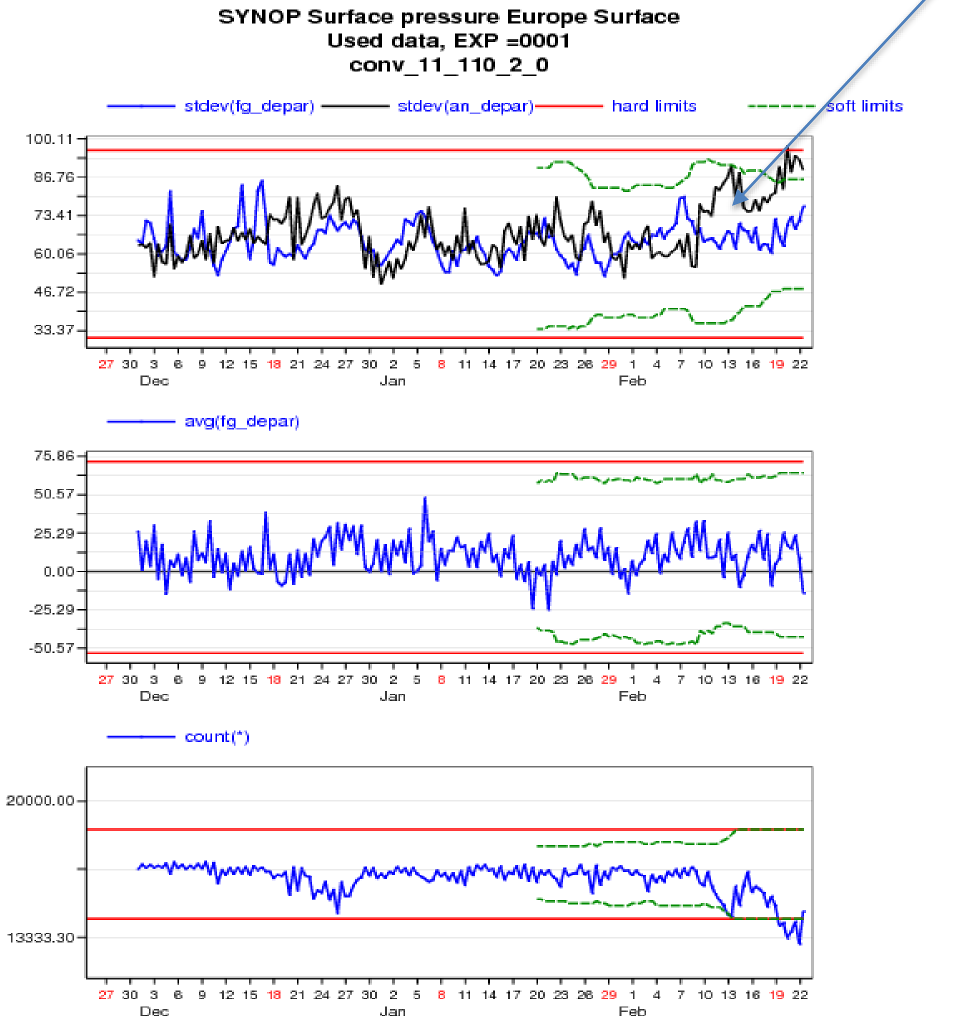
Decision to blacklist the affected channels (unwanted temperature increments)

Spectral signature of Hydrogen Cyanide (HCN)

HCN is a known pollutant associated with biomass burning and the alarms coincided with the Indonesian fires

Surface pressure from SYNOP @20120222

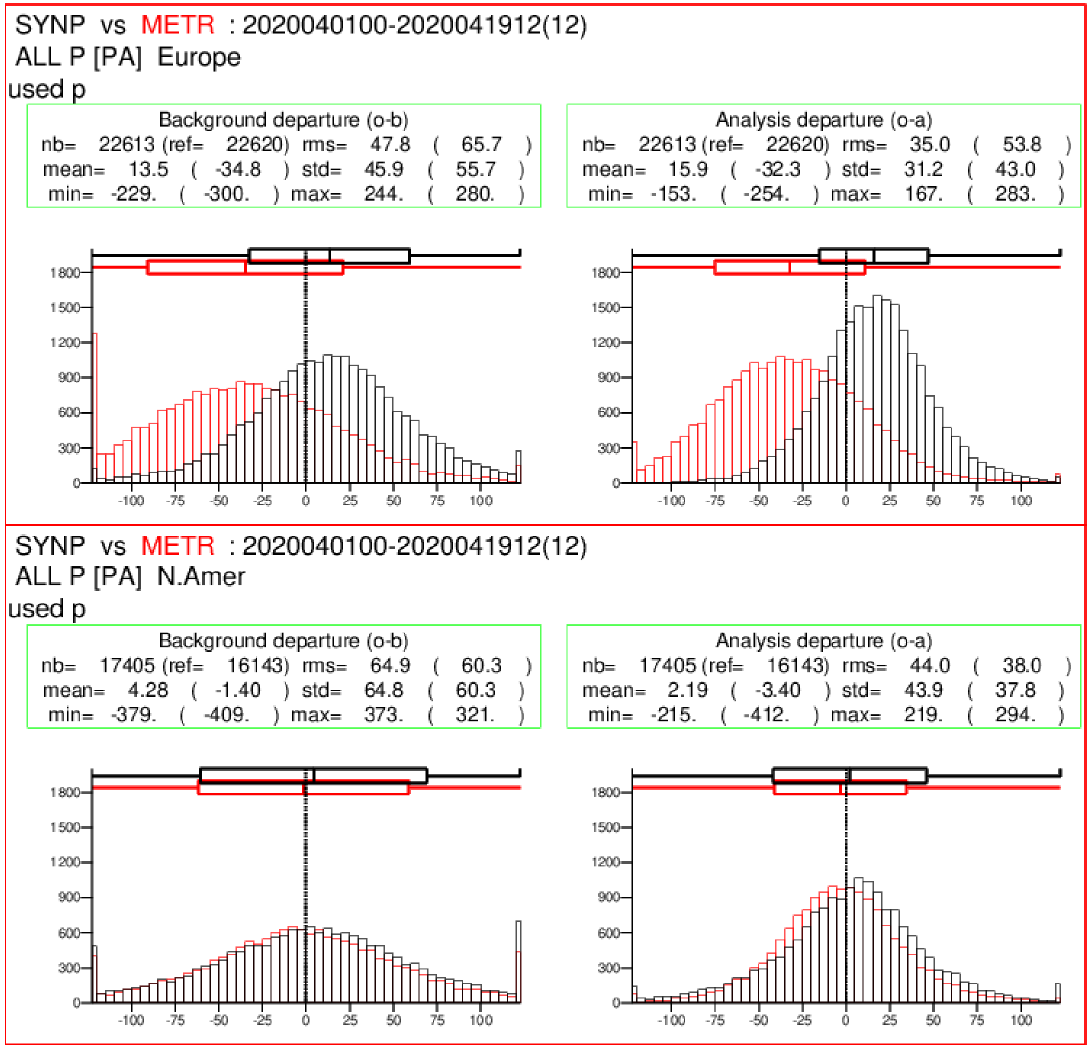




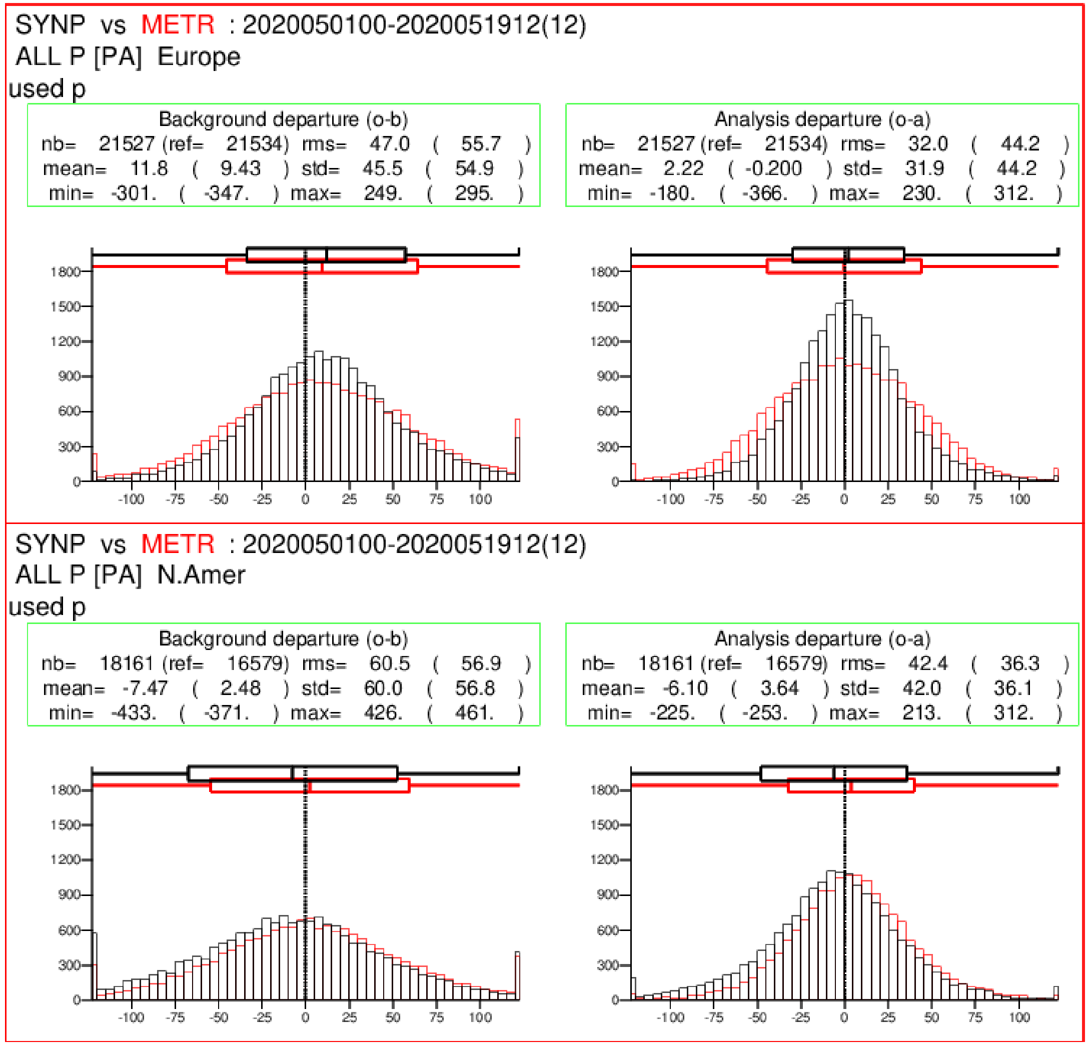
SYNOP Surface pressure Europe Surface : out of range:
(19 times in last 10 days for at least one item)
http://wedit.ecmwf.int/products/forecasts/satellite_check//do/get/satcheck/969/59315?showfile=true
Slightly: count(*)=13632, expected range: 14227.5(H) 18606.9(H)
Severely: stdev(fg_depar)=73.073 < stdev(an_depar)=88.41

SYNOP and METAR co-location

Before METAR QNH correction



After METAR QNH correction (Apr 2020)



Observation statistics and data impact

- Changing the data usage or the assimilation algorithms impact the fit of "used" observations to the background and analysis

- The change of fit is indicative of the (positive/negative/neutral) impact of the change being tested

- The availability of forecast departures (O-F computed similarly to O-B but for QC data and for longer ranges) allows verification against observations

Diagnostics in observation space based on departures

Consistency diagnostics on departures (Desroziers et al. 2005)

$$E[\mathbf{d}_b^o(\mathbf{d}_b^o)^T] = \mathbf{R} + \mathbf{HBH}^T$$ *Global consistency check*

$$E[\mathbf{d}_a^o(\mathbf{d}_b^o)^T] = \mathbf{R}$$ *Observation errors estimation*

$$E[\mathbf{d}_b^a(\mathbf{d}_b^o)^T] = \mathbf{HBH}^T$$ *Background errors check*

$$E[\mathbf{d}_b^a(\mathbf{d}_a^o)^T] = \mathbf{HAH}^T$$ *Analysis errors*

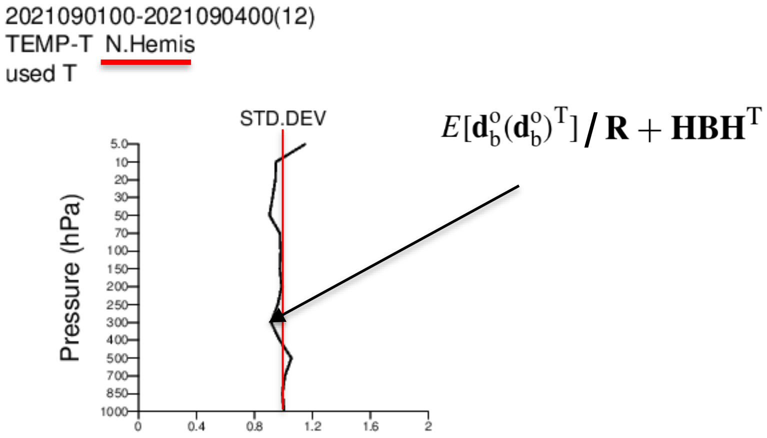
$\mathbf{d}_b^o$	**(O-B)**	Background departures
$\mathbf{d}_a^o$	**(O-A)**	Analysis departures
$\mathbf{d}_b^a$	**(A-B)**	Increments

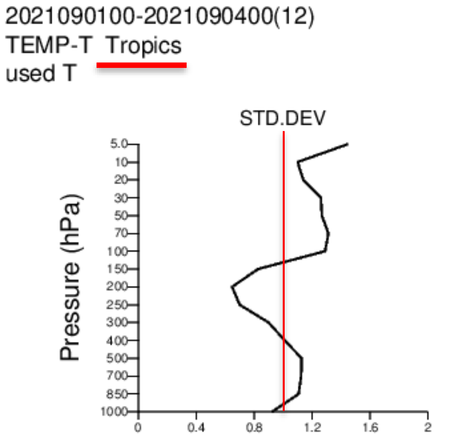
These diagnostics are easily computed by the monitoring system for cases without obs error correlations

$$E[\mathbf{d}_b^o(\mathbf{d}_b^o)^T] = \mathbf{R} + \mathbf{HBH}^T$$

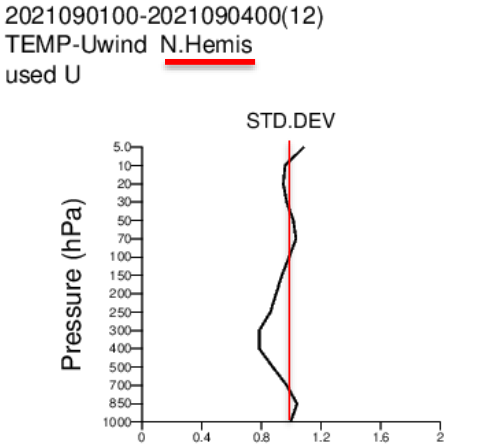
- Observation and background errors are assumed uncorrelated
- In a well tuned system this equation verifies
- Otherwise further tunning is needed for R, B or H

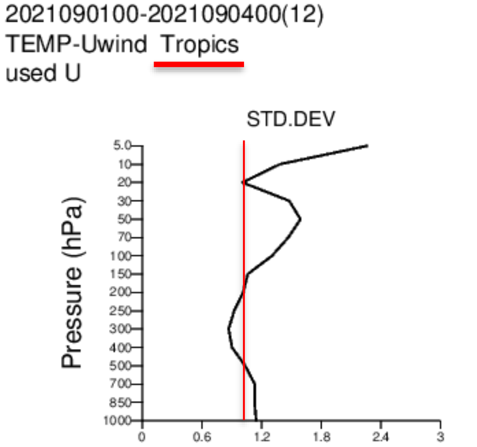
TEMP temperature



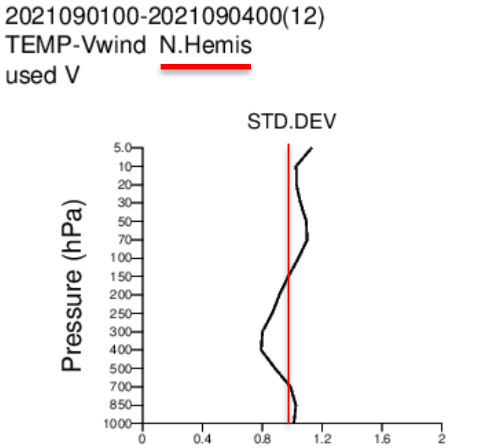


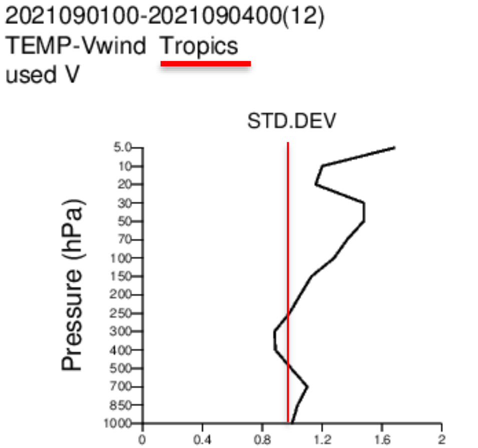
TEMP U-comp



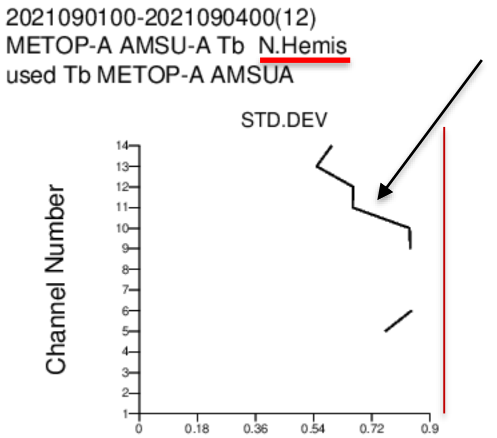


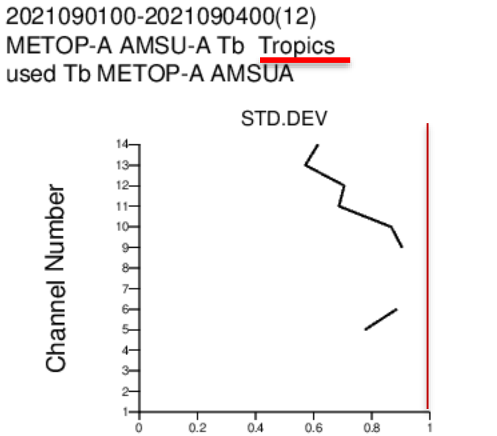
TEMP V-comp





METOP-A AMSUA

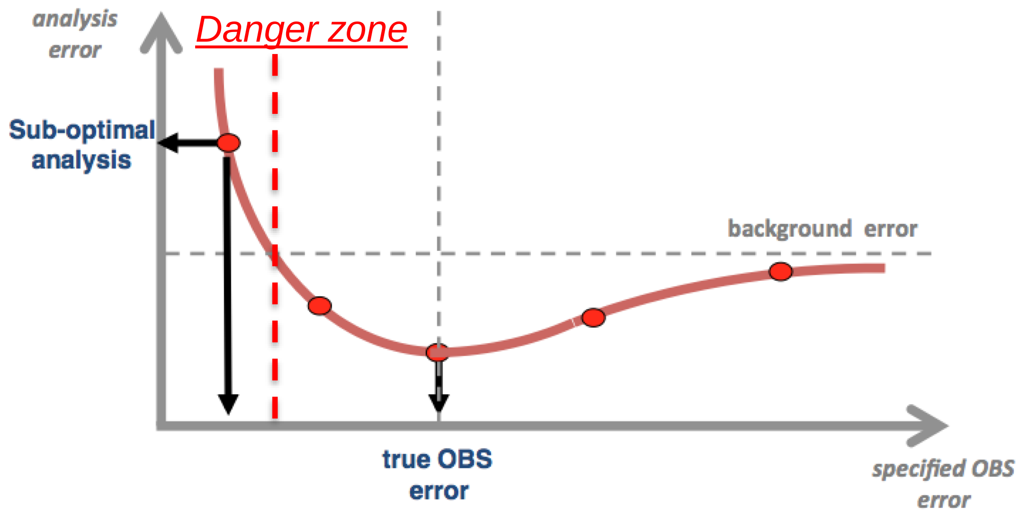




Diagnostics in observation space based on departures

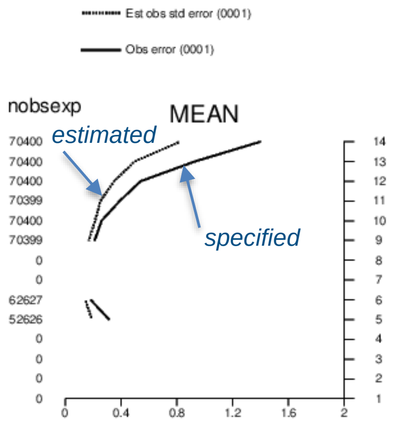
$$E[\mathbf{d}_a^o(\mathbf{d}_b^o)^T] = \mathbf{R}$$

$$E[\mathbf{d}_b^a(\mathbf{d}_b^o)^T] = \mathbf{HBH}^T$$

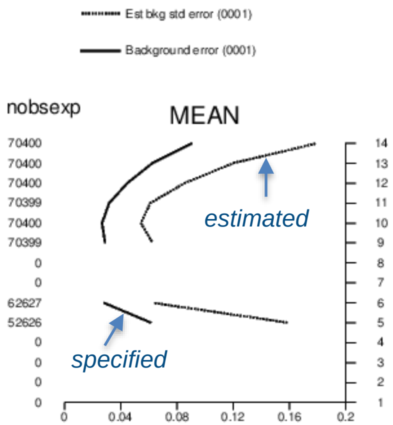


METOP-A/ AMSUA (01-04 Sep 2021)

Estimated and specified Obs errors

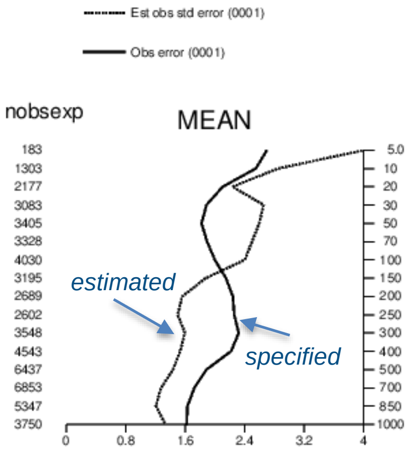


Estimated and specified FG errors

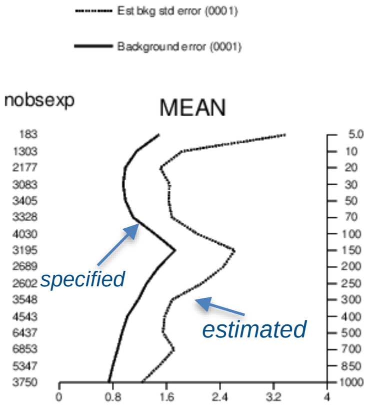


TEMP V-comp Tropics (01-04 Sep 2021)

Estimated and specified Obs errors



Estimated and specified FG errors



Consistency check for observation errors but can also be used to estimate them. Works well if B is properly specified

Diagnostics from the EDA

Monitoring of EDA spread

$$E[\mathbf{d}_\mathrm{b}^\mathrm{o}(\mathbf{d}_\mathrm{b}^\mathrm{o})^\mathrm{T}] = \mathbf{R} + \mathbf{HBH}^\mathrm{T}$$

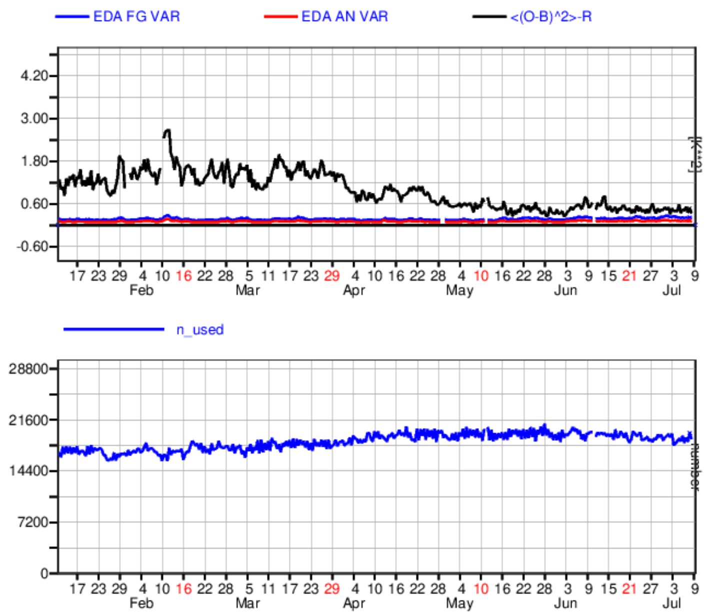
If($\mathbf{R}$ and $\mathbf{HBH}^\mathrm{T}$ are correctly specified)

EDA control (Variance of FG departures)

Computed from EDA members (variance of FG in obs points)

- Check the consistency of EDA spread with what is expected
- Monitor the evolution of EDA spread (including seasonal variations and model upgraded)

Temperature from Radiosondes
0 – 100 hPa
North Hemi Extra-tropics



Diagnostics from the EDA

(Cardinali et al. 2004, Liu and Kalnay 2008)

Observations influence on the analysis

$$\mathbf{S}^o = \frac{\partial \hat{\mathbf{y}}^a}{\partial \mathbf{y}^o} = \mathbf{K}^T\mathbf{H}^T = \mathbf{R}^{-1}\mathbf{H}\mathbf{P}^a\mathbf{H}^T = \frac{1}{n-1}\mathbf{R}^{-1}(\mathbf{H}\mathbf{X}^a)(\mathbf{H}\mathbf{X}^a)^T$$

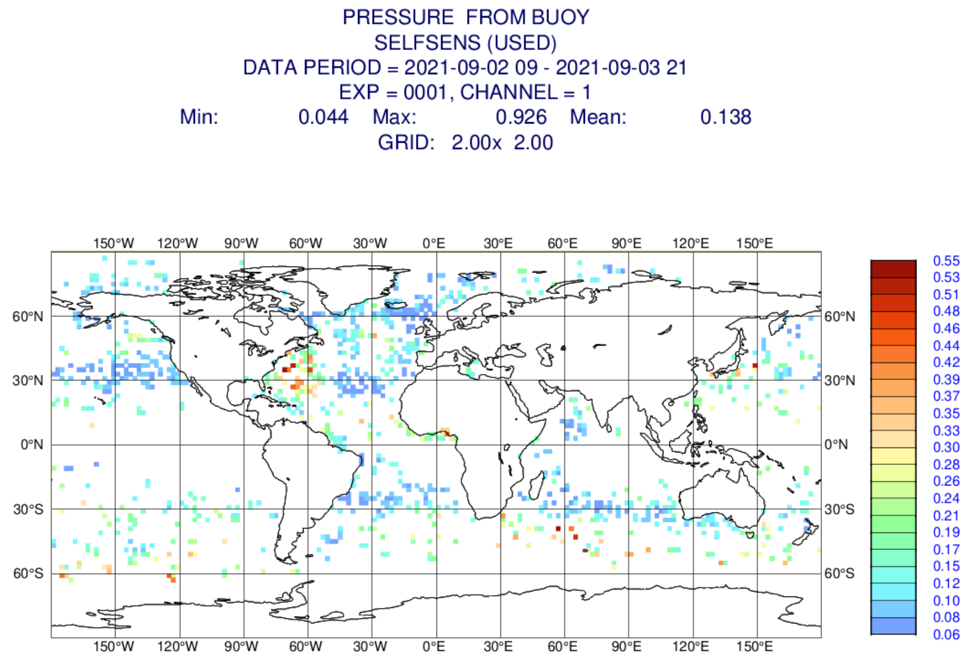
$$S^o_{jj} = \frac{\partial \hat{\mathbf{y}}^a_j}{\partial \mathbf{y}^o_j} = \left(\frac{1}{n-1}\right)\frac{1}{\sigma_j^2}\sum_{i=1}^{n}(\mathbf{H}\mathbf{X}^{ai})_j \times (\mathbf{H}\mathbf{X}^{ai})_j$$

Self-sensitivity

Assumed obs errors

EDA analyses in obs space

$$\mathbf{H}\mathbf{X}^{ai} \cong h(\mathbf{x}^{ai}) - \frac{1}{n}\sum_{i=1}^{n} h(\mathbf{x}^{ai})$$



- Input information readily available (No computation time)
- The computation assumes no observation error correlations (true for most data types)
- Less expensive way to monitor the impact of observations on analysis (weather related) and has the potential to flag data with gross errors (unusual influence)
- This diagnostics needs to be assessed against other implementations of self-sensitivity (Cardinali 2013)

Random Error estimations using Triple-colocation

S. Abdalla et al 2017

- Xi (3 or more) should be independent and measure the same parameter at the *same* location and time (triple collocation criteria)

- Each measurement $\boldsymbol{X_i}$ consists of a unknown truth T (calibrated with $\boldsymbol{\beta_i}$) and an unknown error $\boldsymbol{e_i}$ ($\boldsymbol{X_i} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_i}\ \boldsymbol{T_i} + \boldsymbol{e_i}$)

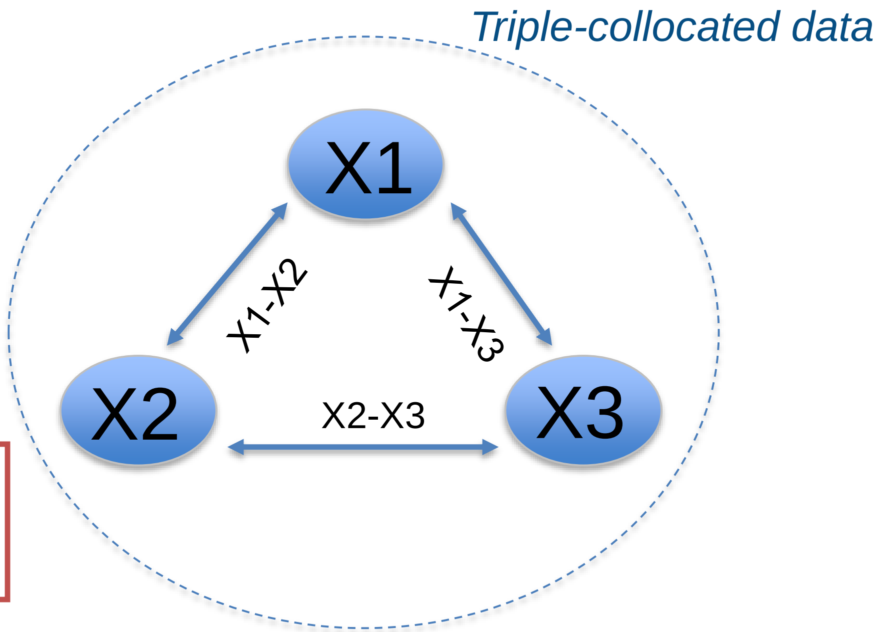
- The unknown error variance can be written as:

$$\langle e_p^2 \rangle = 0.5\left[\langle (X_p - X_{p1})^2 \rangle + \langle (X_p - X_{p2})^2 \rangle - \langle (X_{p1} - X_{p2})^2 \rangle\right]$$

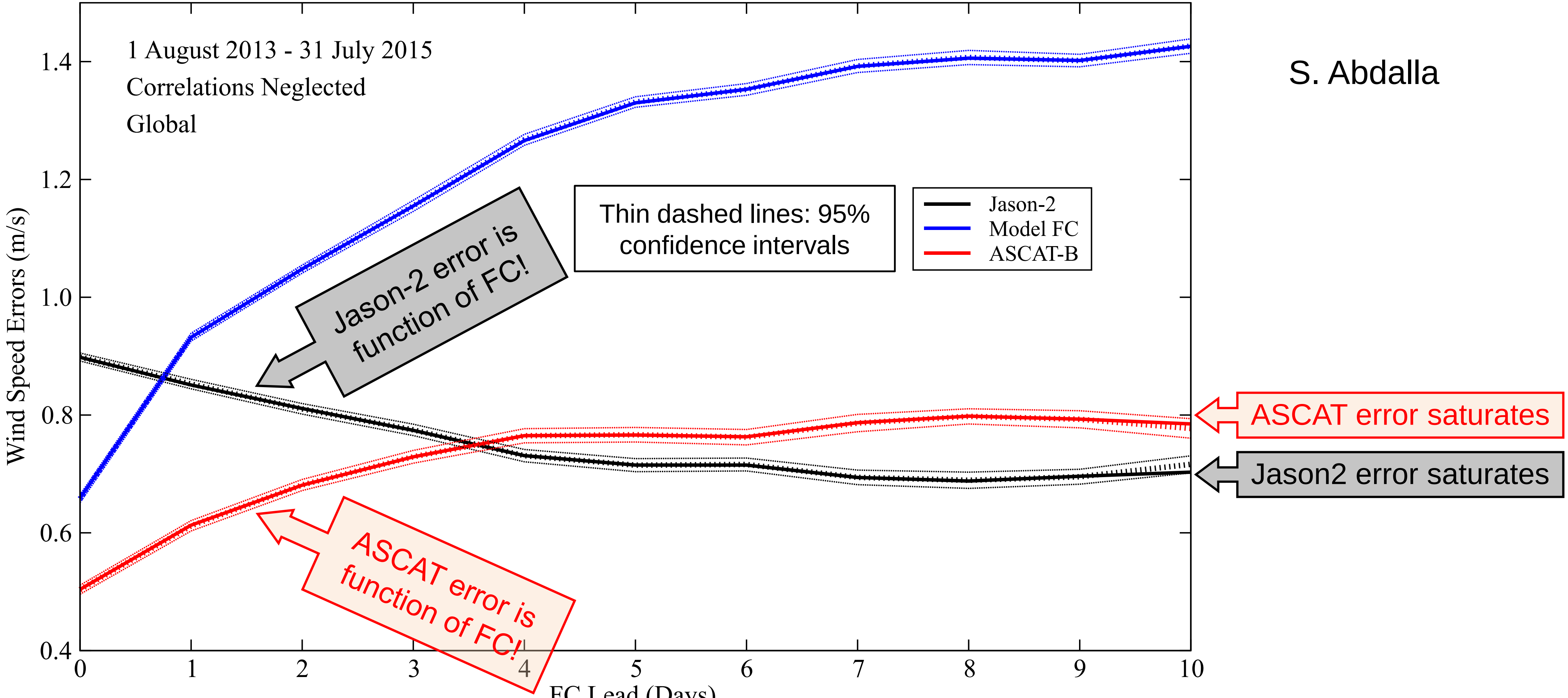
<..> is the average, p1&p2 refer to the other 2 systems.

- This assumes there is ***no correlation between the errors*** in the triplets. Calibration constants, βp , are found by iteration.

- The third dataset is usually the model (analysis and forecasts at various ranges). Forecast departures are potentially correlated with ***used*** datasets but the correlations tend to fade with forecast range



Initially the Errors estimated by ignoring the correlations

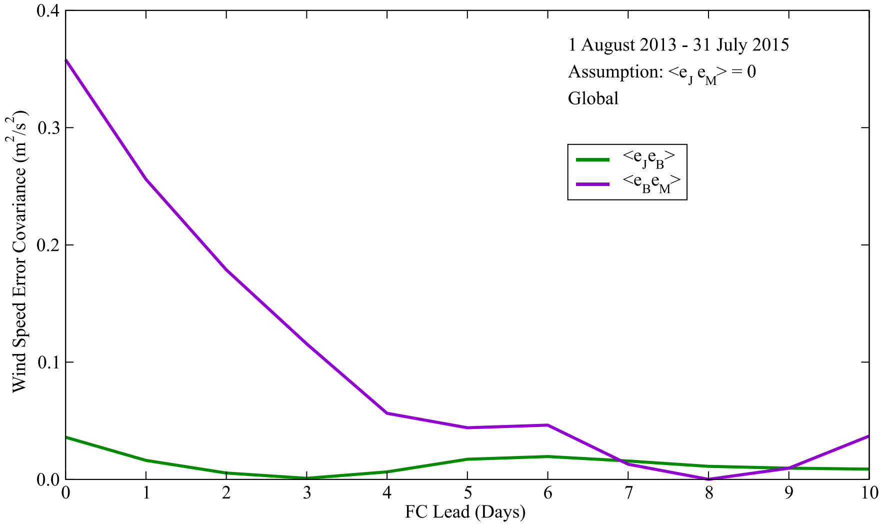


S. Abdalla

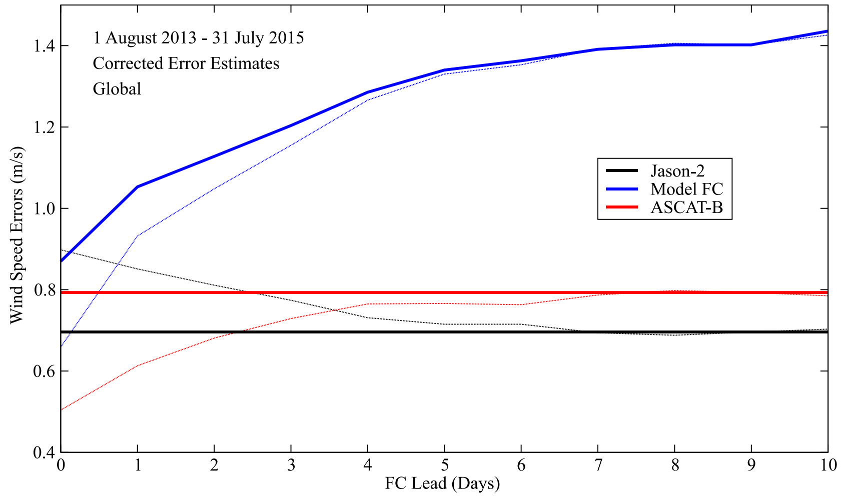
We can estimate the correlations (2 out of 3 only) and correct the error estimates.

S. Abdalla

Estimation of correlations (covariances)

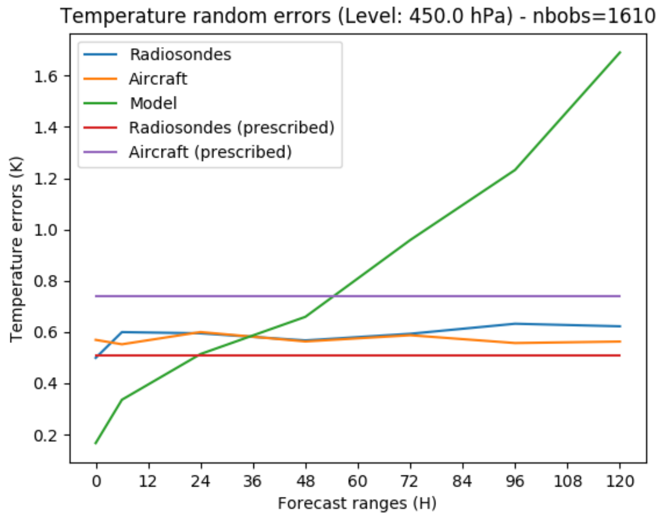


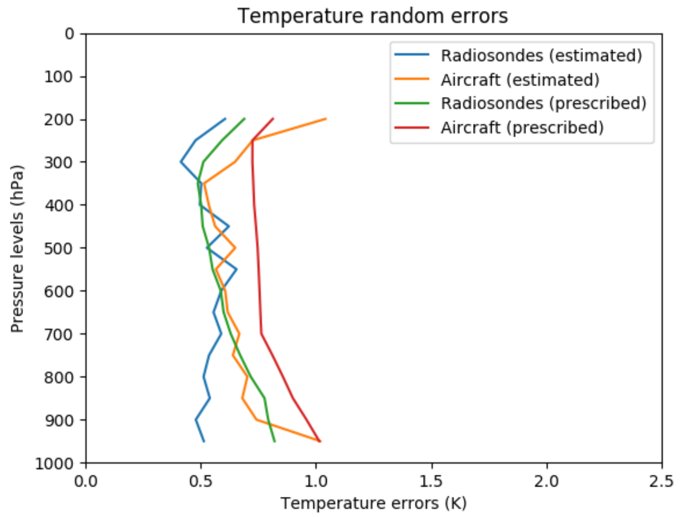
Errors corrected for correlations

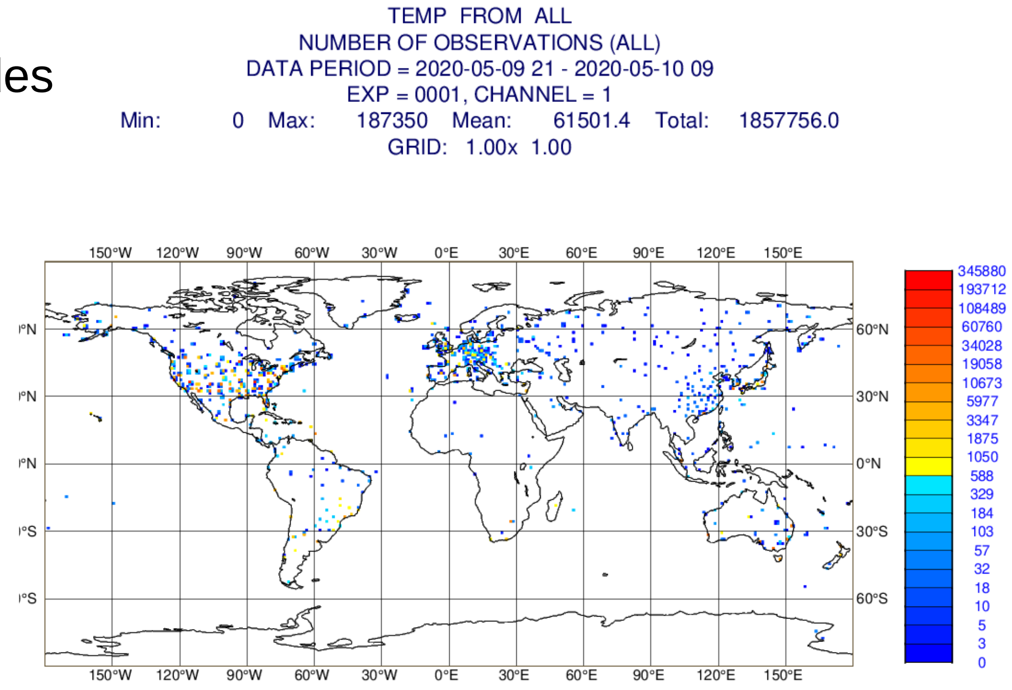


Radiosonde/Aircraft/Model (temperature and wind in the troposphere)

Co-located aircraft and radiosondes







Conclusions

- Observations monitoring activities are a key component of the data assimilation diagnostics
- An integrated monitoring system improves the data usage by assisting operational and research activities
- Monitoring activities benefits from a wide range of resources (internal and external). Collaboration and timely sharing of information is vital
- Various diagnostics are available to check the consistency of the DA system and to suggest estimates of errors