Monitoring of Observations and Data Assimilation System

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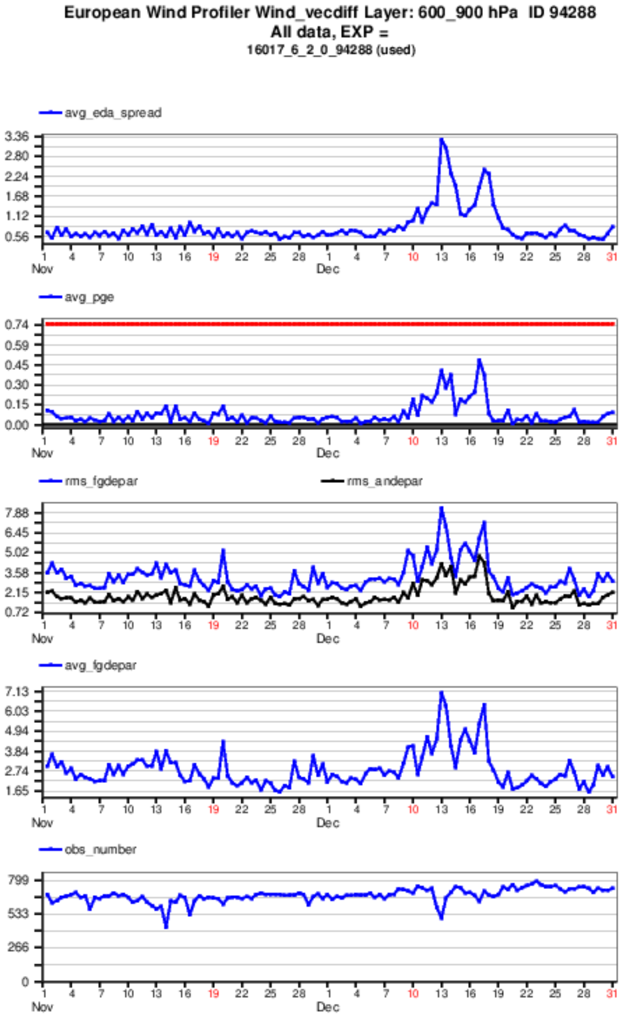
Outline

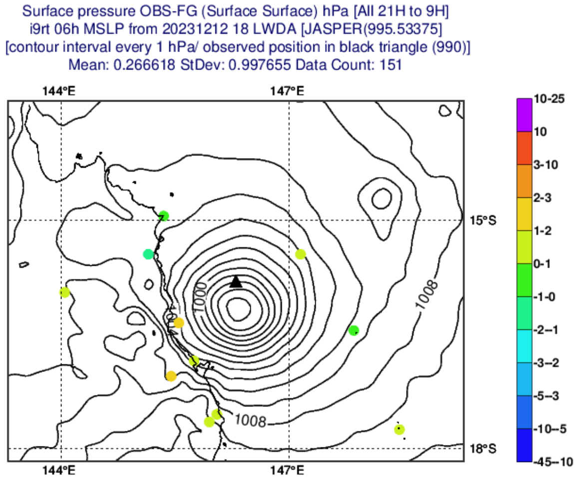
1. Monitoring of observations: Why and how ?
2. Observation monitoring capabilities
3. Machine learning for Anomaly detection and classification
4. Observation based diagnostics
5. Conclusion

TC JASPER (13/12/2023 00)

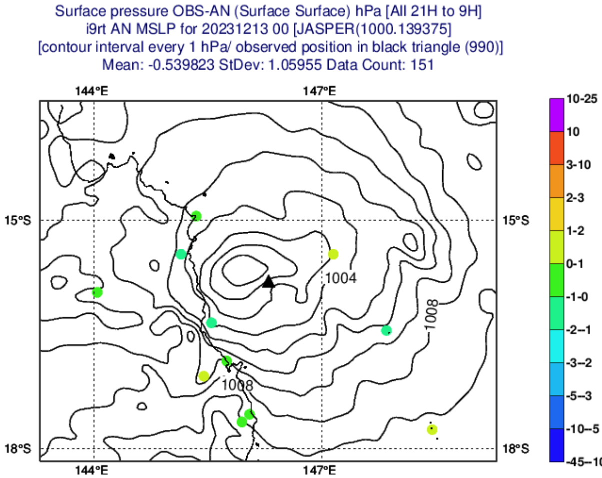
Profiler 94288



FG

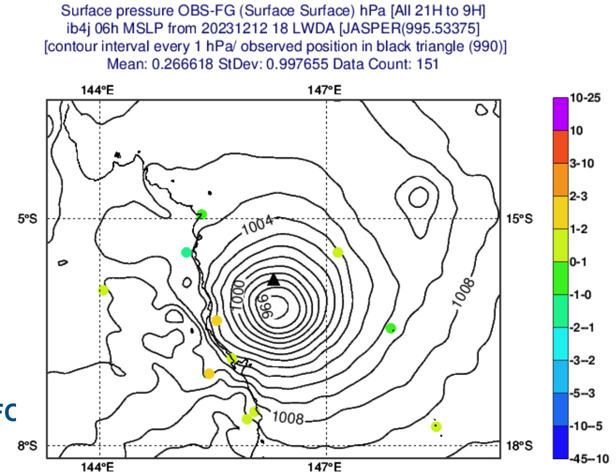


Analysis

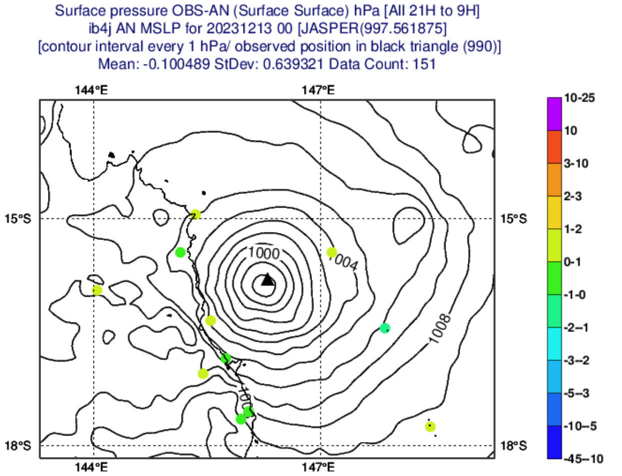


Remove profiler 94288 (ib4j)

FG

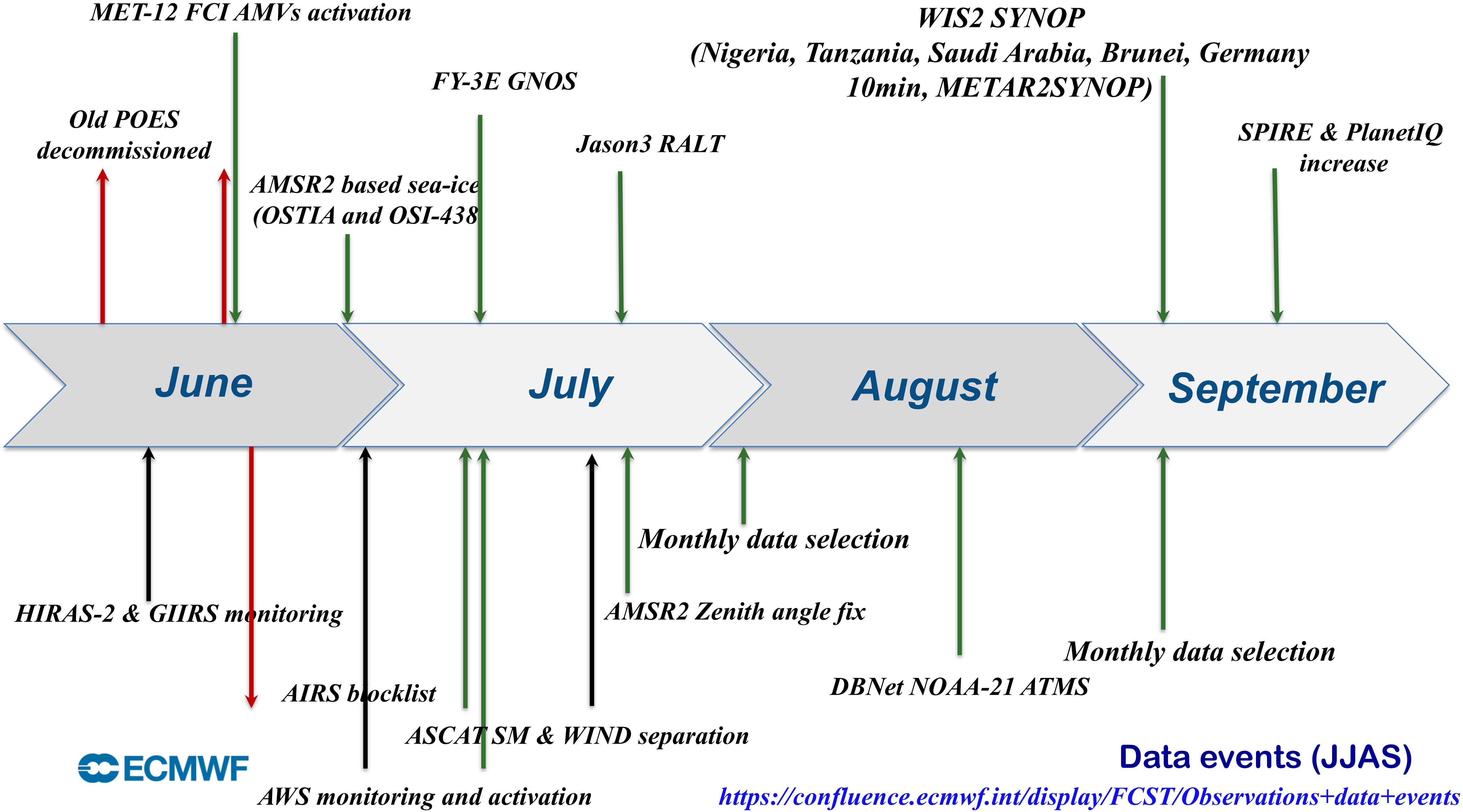


Analysis



ECMWF EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FC

Monitoring of observations: Why ?

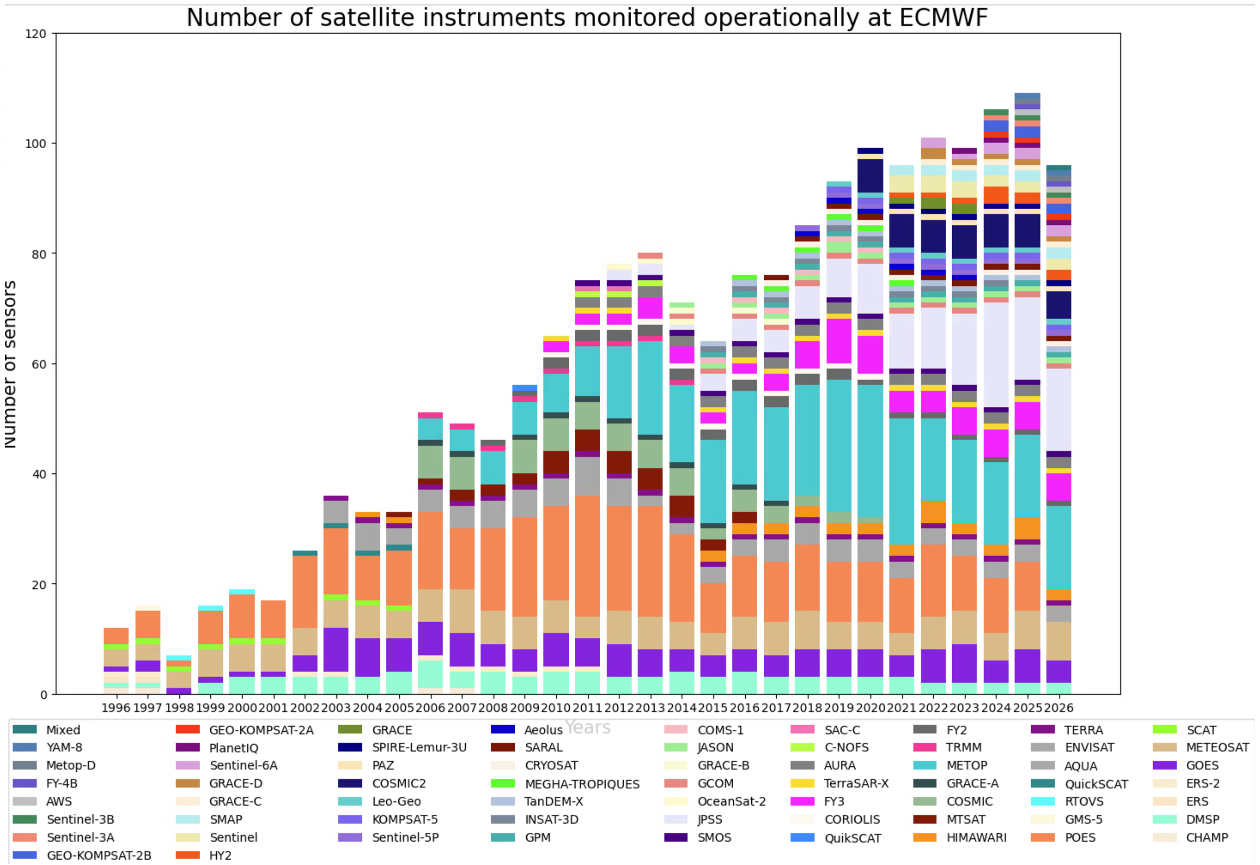


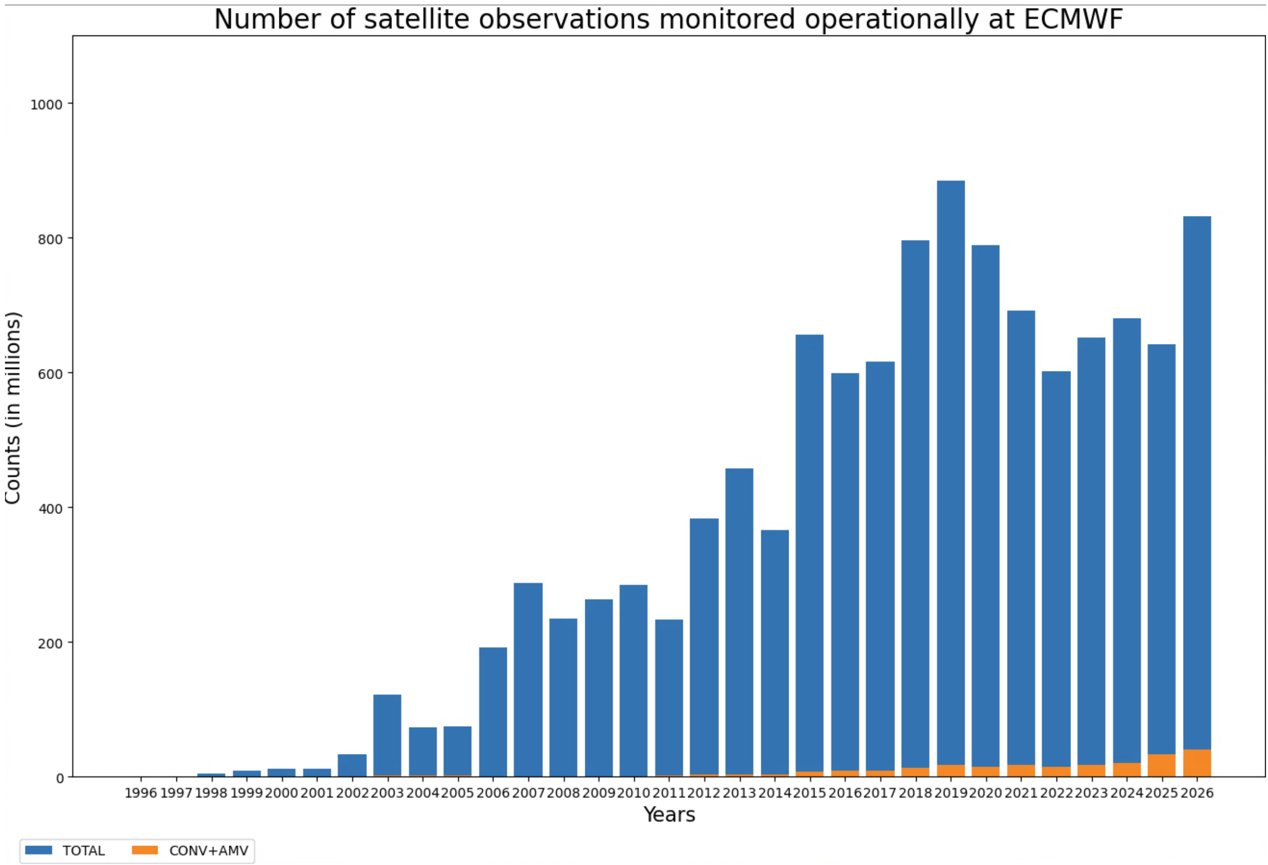
ECMWF

Data events (JJAS)

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

Evolution of data counts and diversity





- ~ 700 million pieces of observations received daily and ~40 millions active . A lot of potential
- Data characteristics are subject to variation with possible consequences on the data impact (statistical on scores or localised).

Current NWP Observing system

- Microwave observations
  - AMSR2
  - AWS
  - SSMIS
  - MWHS2
  - GMI
  - AMSUA
  - MHS
  - ATMS
  - SMAP
  - SMOS

- Ocean observations
  - Ocean profilers
    - ARGO
    - CTDs
    - mbuoy
    - MMAL
  - Sea Level Anomaly

- Scatterometer winds
  - Surface wind speed
    - HY-2B
    - HY-2C
    - METOP-B
    - METOP-C

- Infrared observations
  - AIRS
  - HIRAS
  - GIIRS
  - IASI
  - CRIS

- Satellite altimetry
  - Wave height
    - CRYOSAT2
    - JASON-3
    - SARAL
    - Sentinel-3A
    - Sentinel-3B
    - Sentinel-6A

- In-situ observations
  - SHIP
  - AMDAR
  - SYNOP
    - Automatic-Land-SYNOP
    - BUFR-LAND-SYNOP
    - Manual-Land-SYNOP
  - METAR
  - PILOT
  - TEMP_DESC
  - BUOY
  - PROF
  - TEMP
  - TEMP_SHIP

- GNSS Radio Occultation
  - GNSS-RO
    - COSMIC2-E1
    - COSMIC2-E2
    - COSMIC2-E4
    - COSMIC2-E5
    - COSMIC2-E6
    - FY-3D
    - FY-3E
    - GRACE-C
    - GRACE-D
    - KOMPSAT-5
    - METOP-B
    - METOP-C
    - Metop-D
    - PAZ
    - PlanetIQ
    - Sentinel-6A
    - SPIRE-Lemur-3U
    - TanDEM-X
    - TerraSAR-X
    - YAM-8

- Ozone
  - MLS
  - OMI
  - GOME-2
  - OMPS
  - OMPS-limb
  - OMPS-LP
- Satellite altimetry
- Scatterometer winds
- In-situ observations
- Ocean observations

- Atmopsheric Motion Vectors
  - Wind speed
    - AQUA
    - Dual-Metop
    - FY-2G
    - GEO-KOMPSAT-2A
    - GOES-18
    - GOES-19
    - HIMAWARI-9
    - Leo-Geo
    - METEOSAT-10
    - METEOSAT-11
    - METEOSAT-12
    - METEOSAT-9
    - METOP-B
    - METOP-C
    - NOAA-20
    - NOAA-21
    - NPP
    - TERRA

- Geostationary radiances
  - Geostationary radiances
    - GOES-18
    - GOES-19
    - HIMAWARI-9
    - METEOSAT-10
    - METEOSAT-12
    - METEOSAT-9

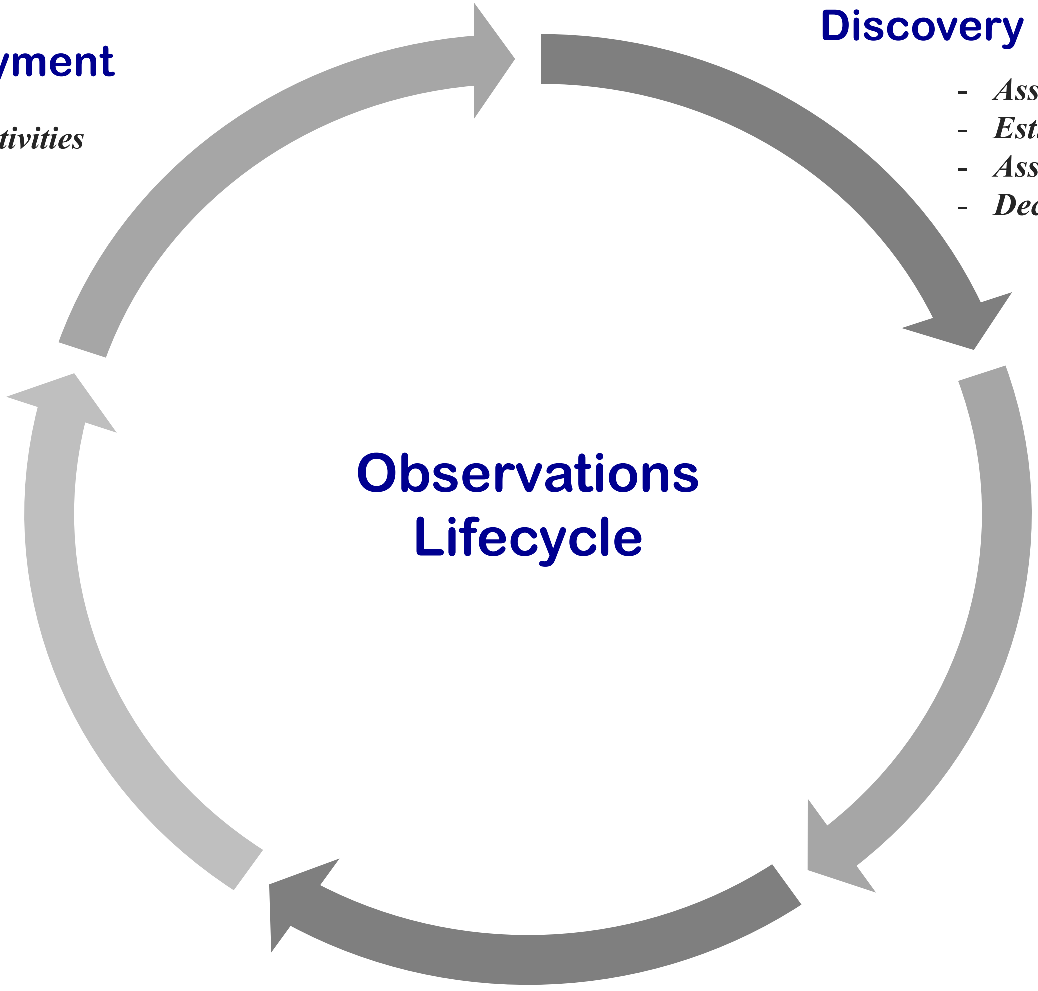
Monitoring of observations: Why ?

Deployment

Feedback for Cal/Val activities

Discovery & evaluation

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



Planning & design

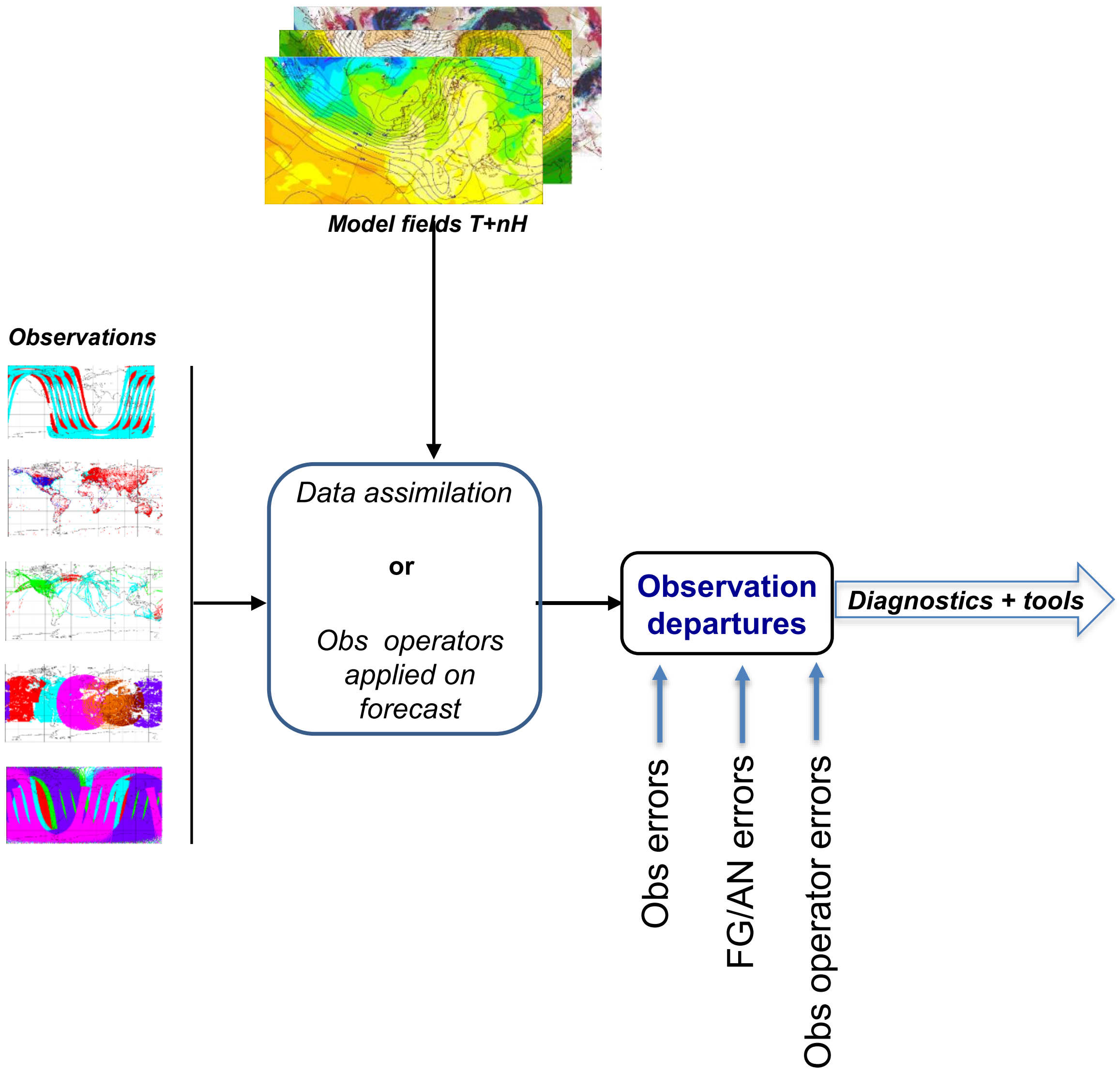
Monitoring statistics from similar or heritage data

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

Monitoring of observations: how ?



- Observations quality issues
- Estimation of Obs Errors
- Observations intercomparison (co-location)
- Model/data assimilation issues (redundancies in the obs system)
- Observations impact (analysis and forecasts)
- Forecast verification
- Support model and data assimilation developments

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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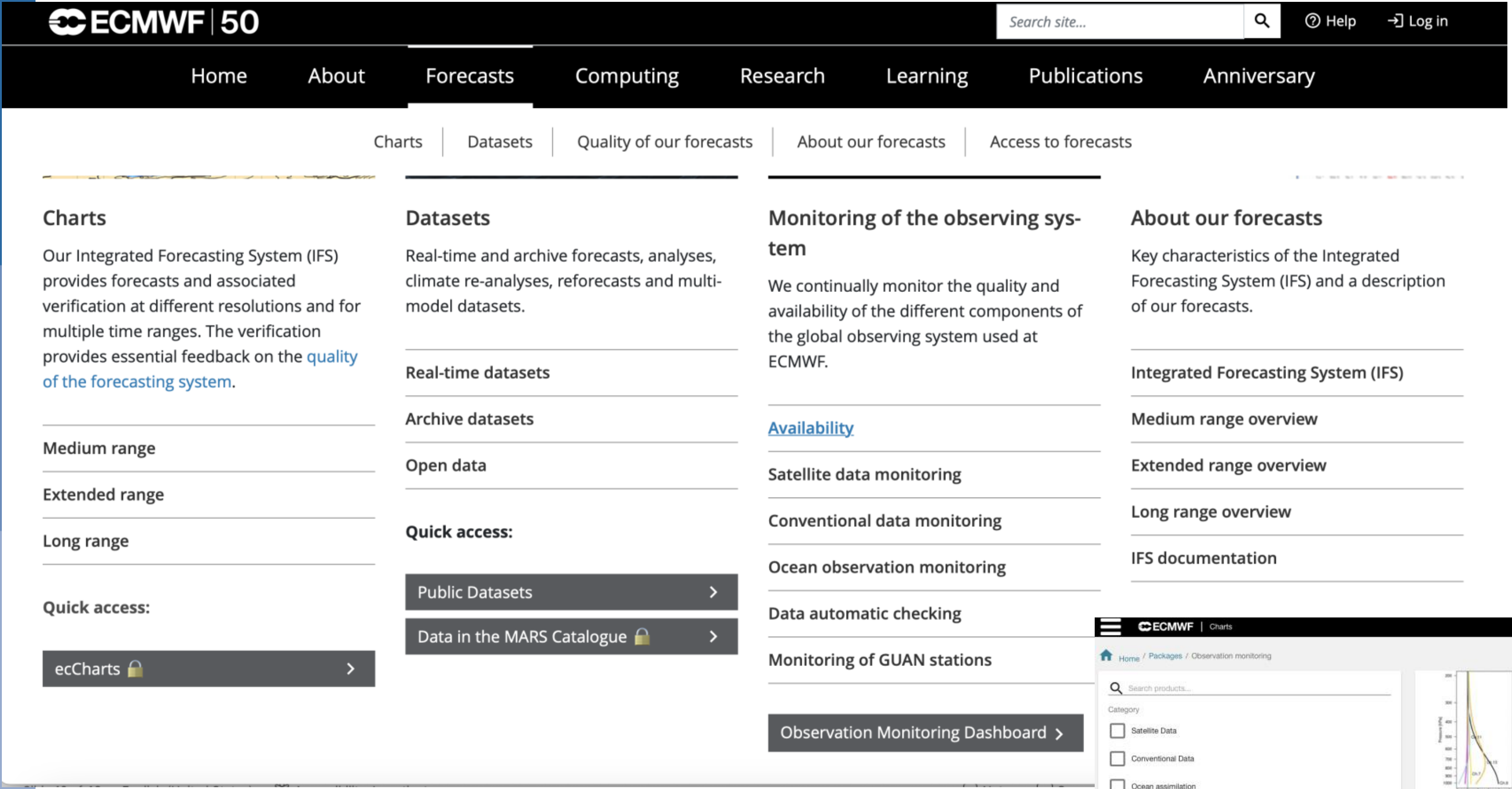
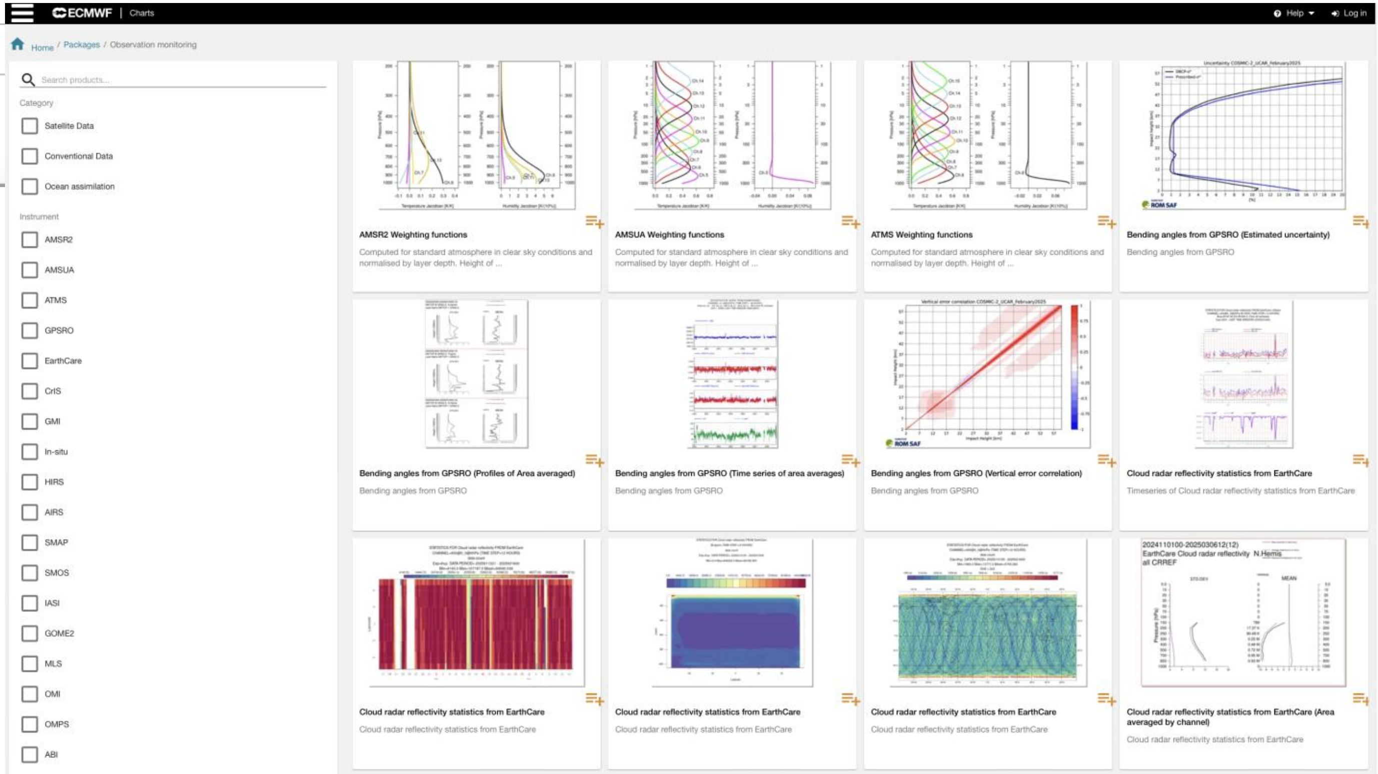
Observations monitoring resources

- 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)

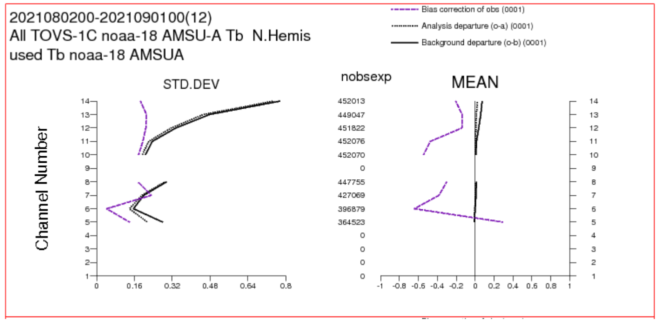


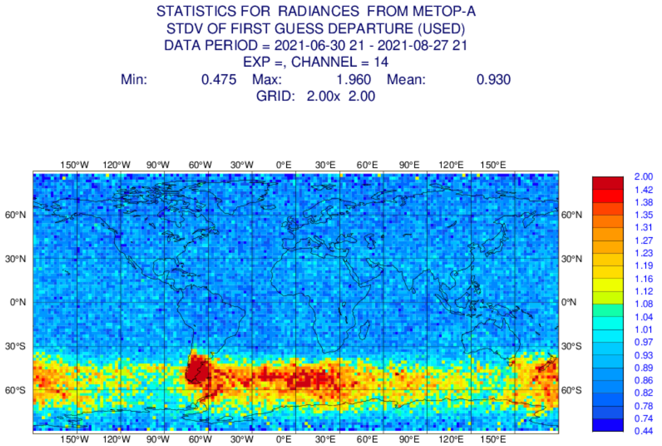
- Almost all earth system observations supported
- Various types of plots for each data type
- Public access

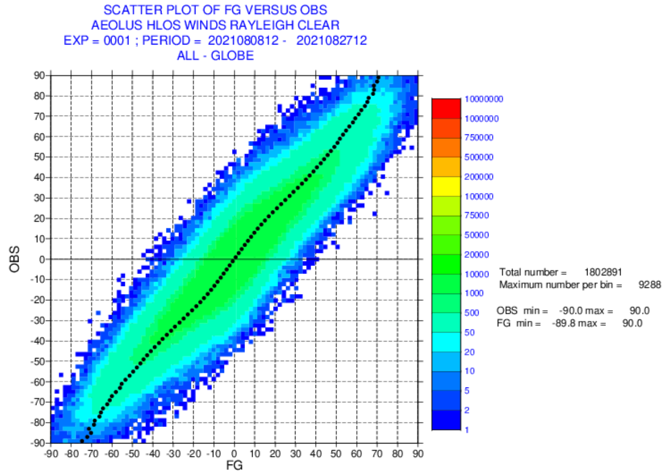


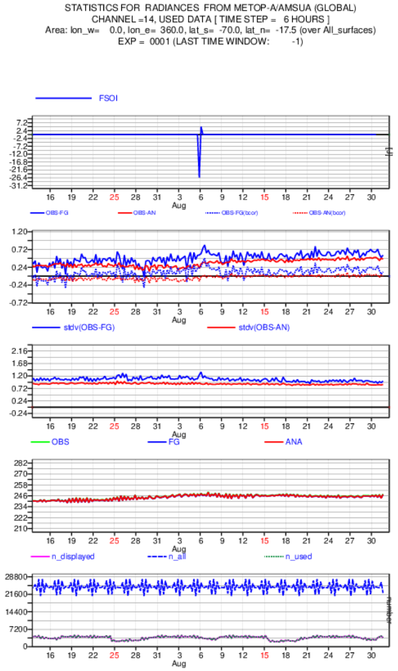
https://charts.ecmwf.int/catalogue/packages/obstat/

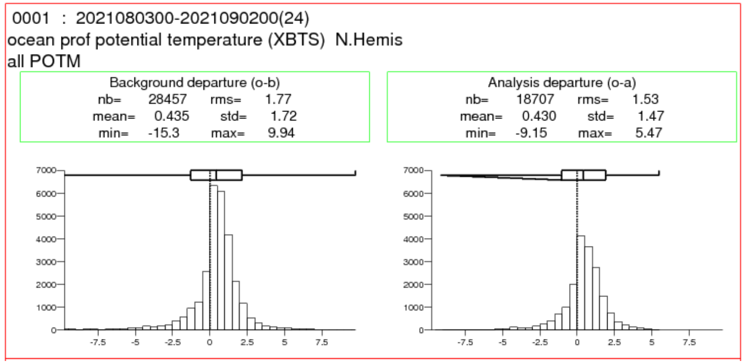
Selected monitoring products

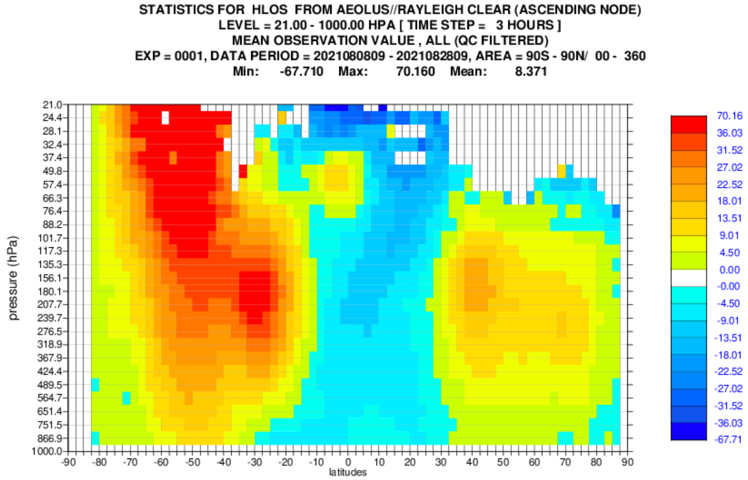


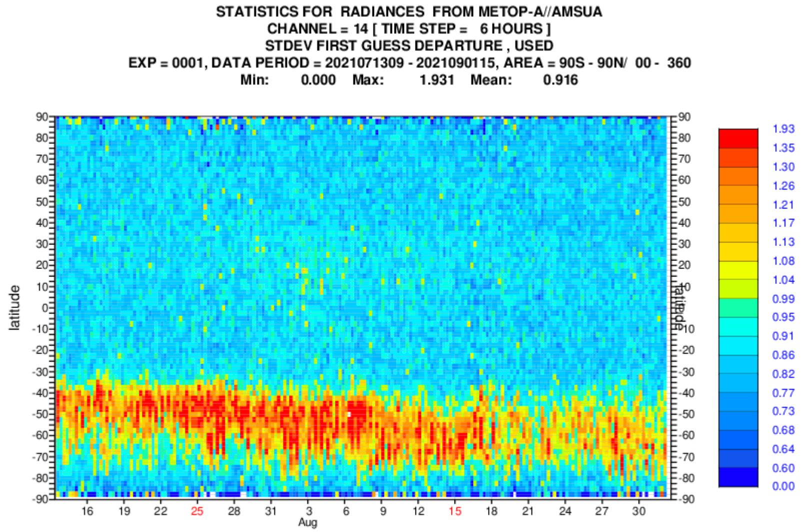




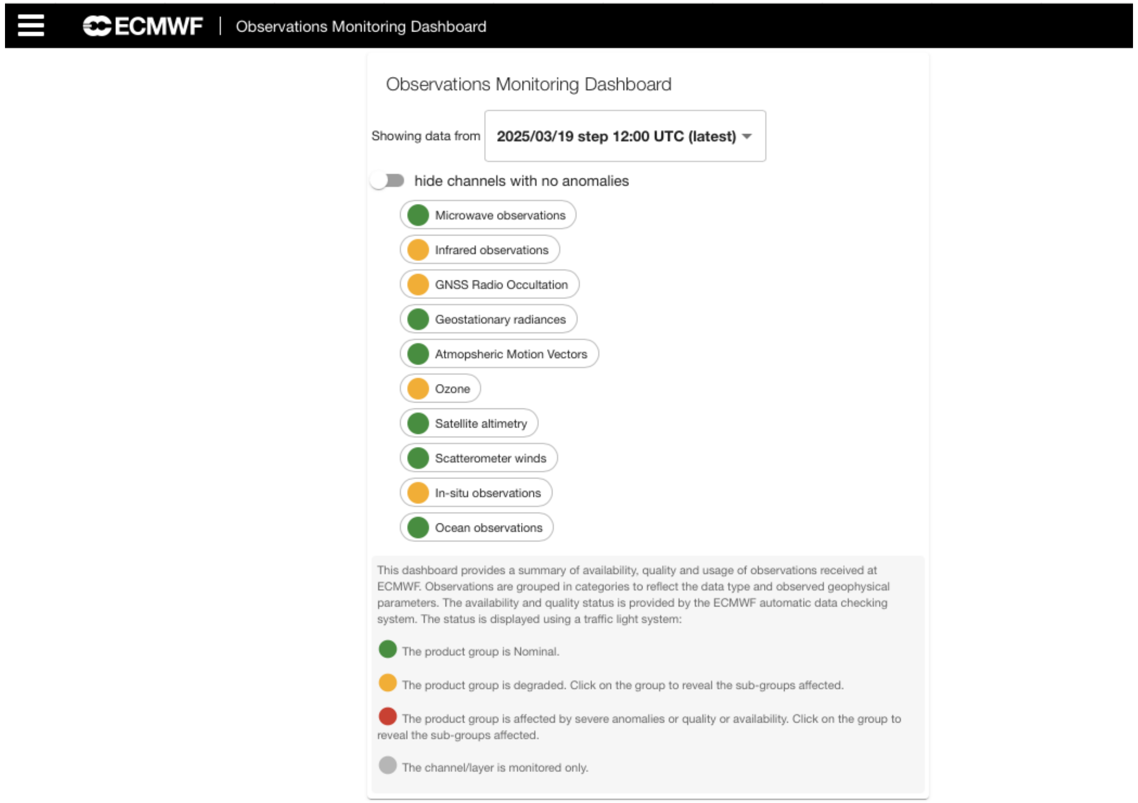


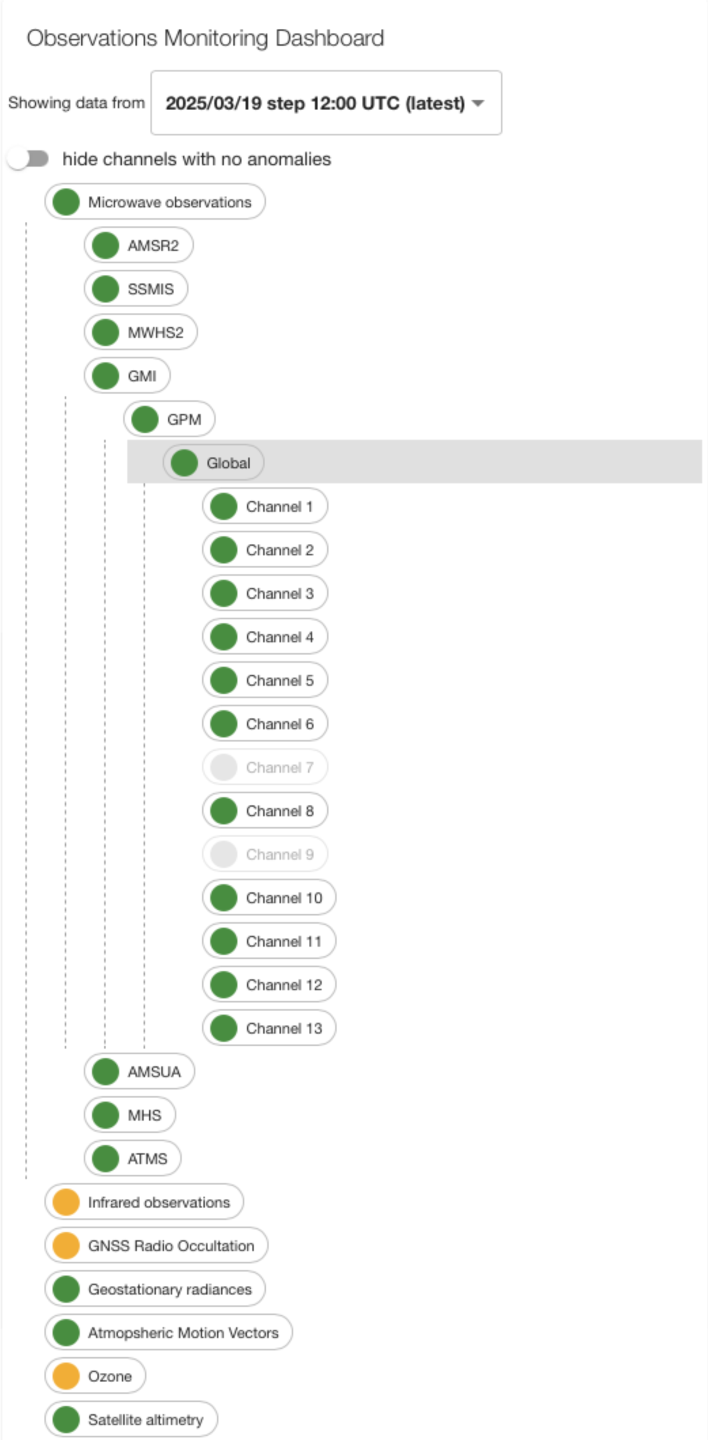






https://obsstatus.ecmwf.int/





Automatic data checking system

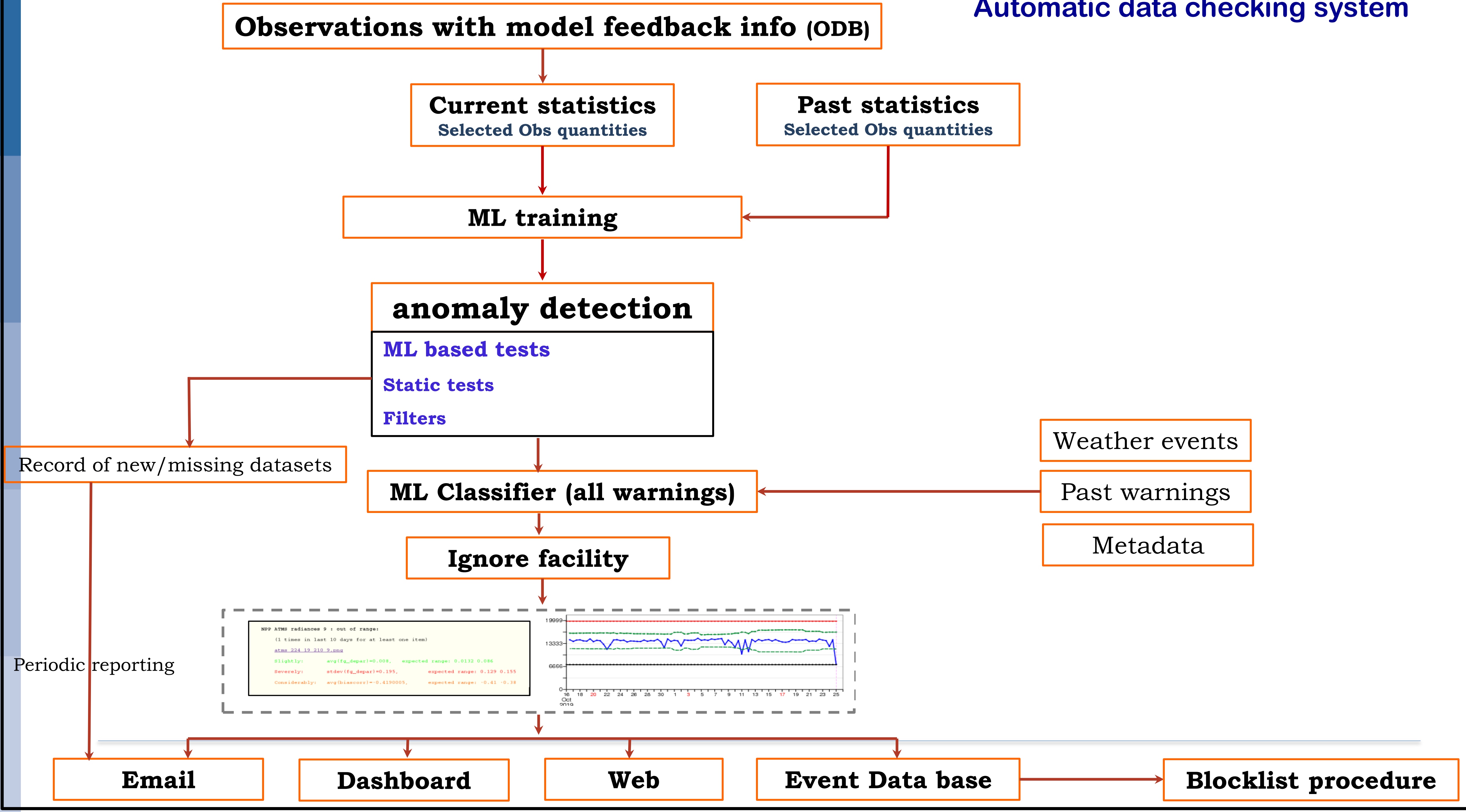
- The large amount, of active observations makes it difficult to timely detect availability/quality issues

- 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

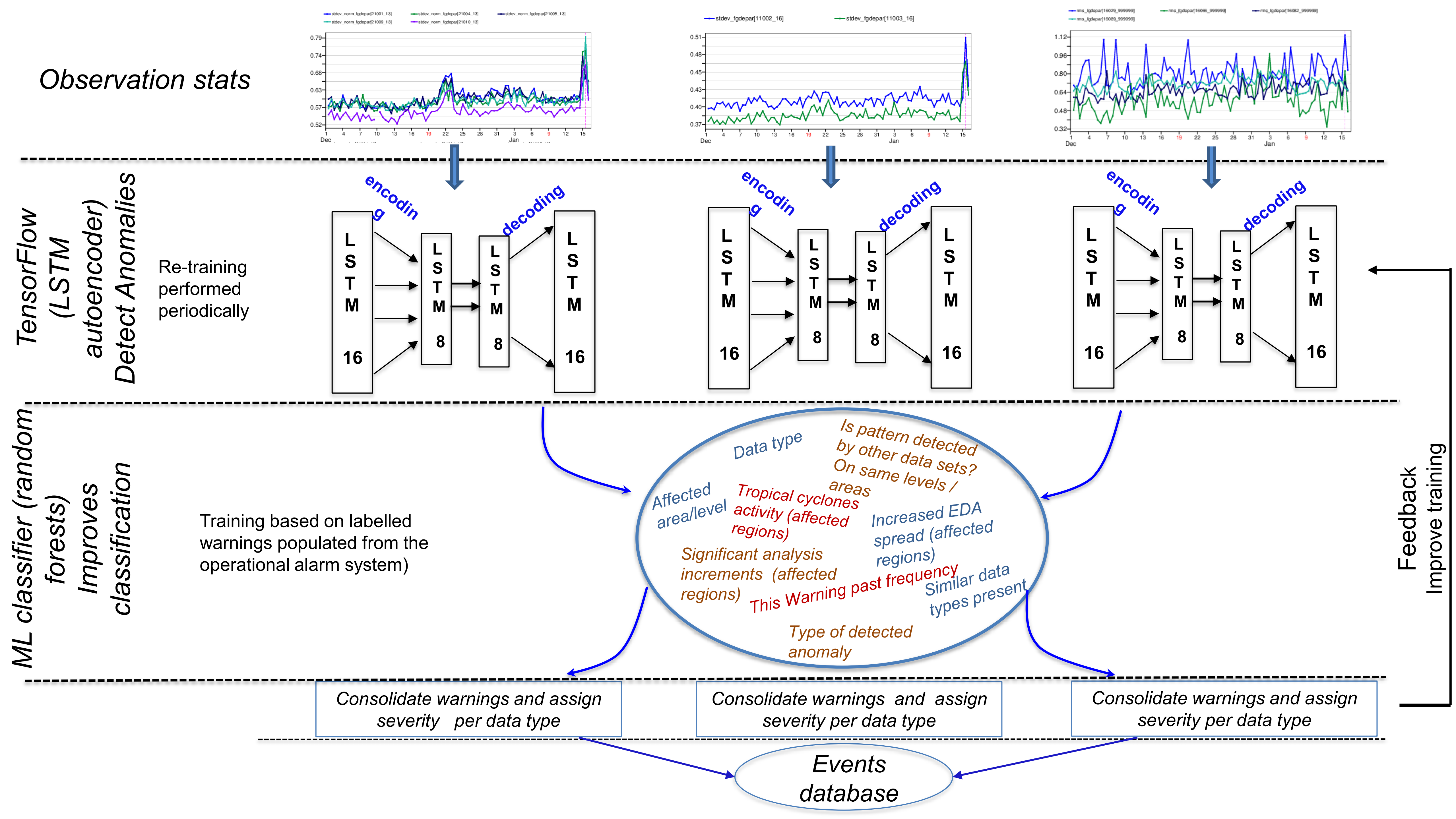
Three-component system

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

What ML can offer ?

- Perform anomaly detection from time series (unsupervised learning):
  - better handling of limits
  - Reduce false alarms
  - Learn from past events

- Improve classification of warnings (supervised learning): Severity, likely cause, need for action, etc
  - Cross-checking of warnings from all components of the observing system
  - Consider significant weather events (TC, areas of significant increments, strong winds, heavy rain, etc)
  - Understand patterns from Analysts judgment or simulations



Observation stats
TensorFlow (LSTM autoencoder) Detect Anomalies
Re-training performed periodically
encoding
decoding
LSTM 16
LSTM 8
LSTM 8
LSTM 16
ML classifier (random forests) Improves classification
Training based on labelled warnings populated from the operational alarm system)
Data type
Is pattern detected by other data sets? On same levels / areas
Affected area/level
Tropical cyclones activity (affected regions)
Increased EDA spread (affected regions)
Significant analysis increments (affected regions)
This Warning past frequency
Similar data types present
Type of detected anomaly
Consolidate warnings and assign severity per data type
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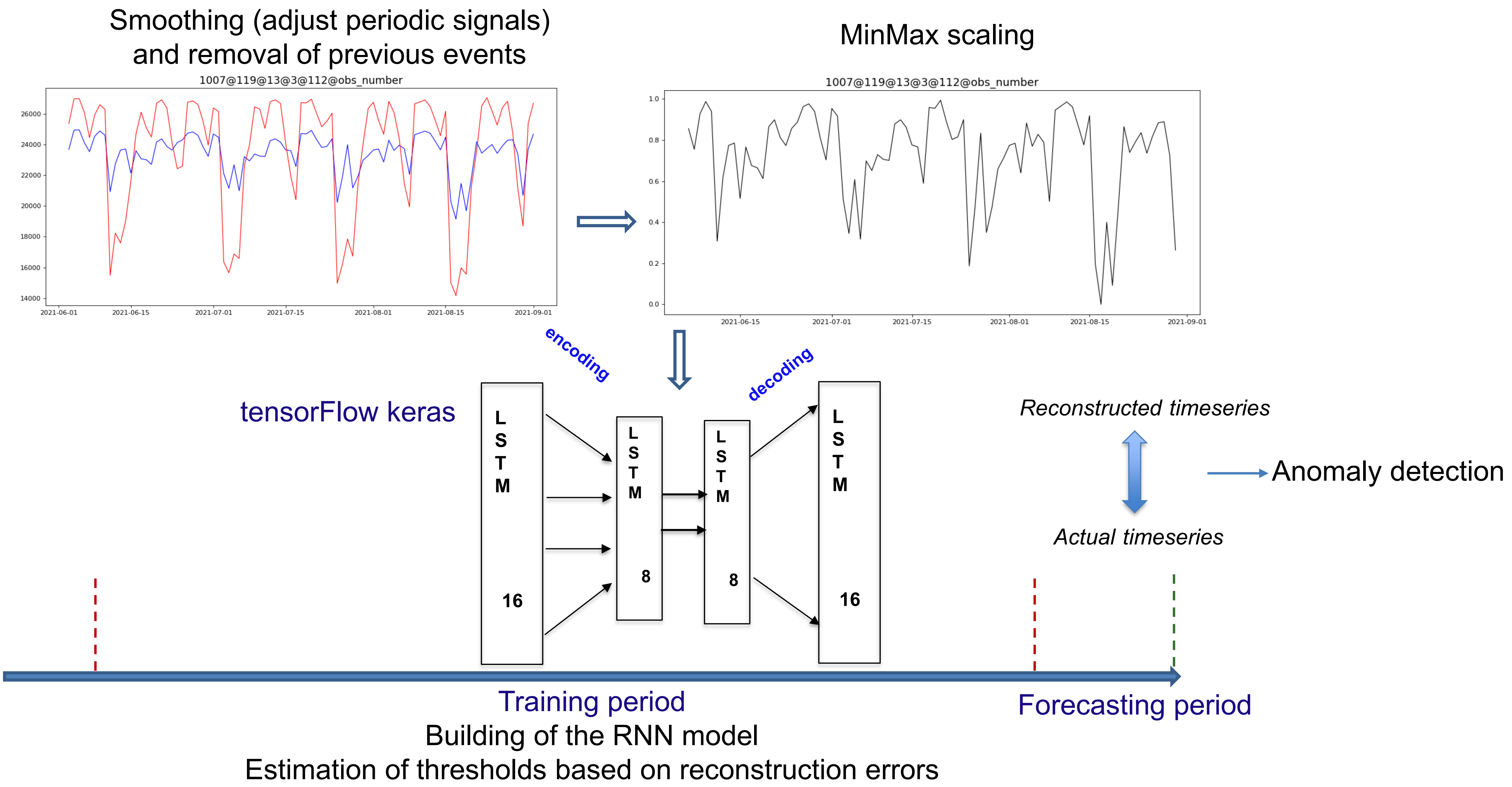
Consolidate warnings and assign severity per data type
Events database
Feedback
Improve training


Smoothing (adjust periodic signals)
and removal of previous events
1007@119@13@3@112@obs_number
MinMax scaling
1007@119@13@3@112@obs_number
encoding
decoding
tensorFlow keras
LSTM 16
LSTM 8
LSTM 8
LSTM 16
Reconstructed timeseries
Actual timeseries
Anomaly detection
Training period
Building of the RNN model
Estimation of thresholds based on reconstruction errors
Forecasting period

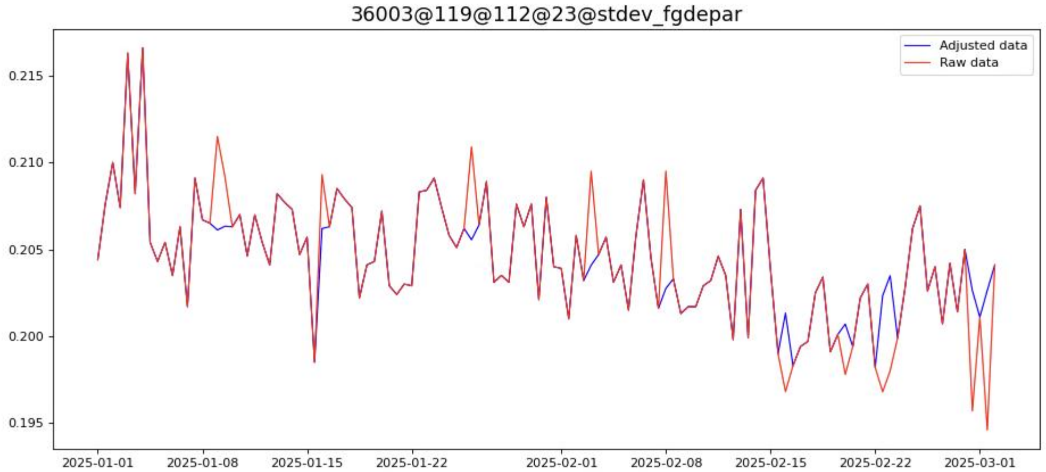
Anomaly detection (unsupervised learning)

For each data type two RNN models are trained on short (all data types) and long timeseries (satellite only):

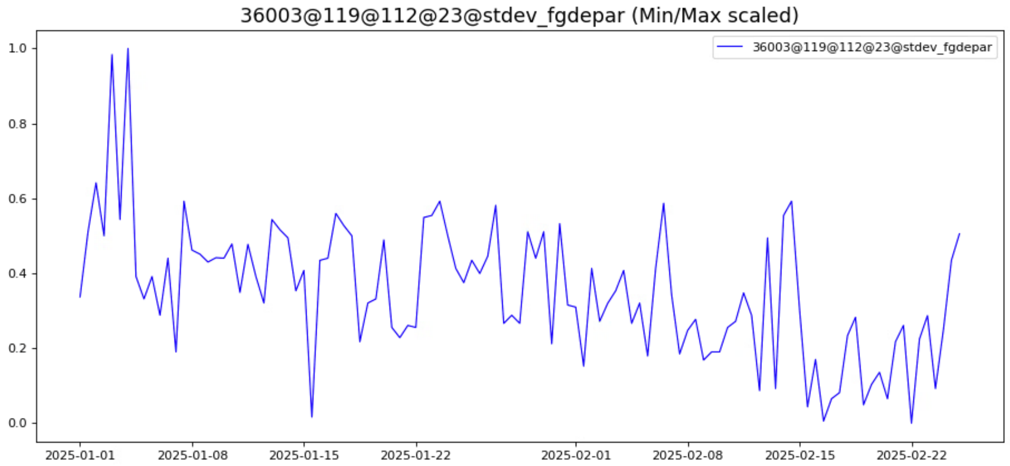
- RNN model trained on short timeseries (2 months):
  - Designed to detect sudden changes
  - staggered re-training schedule where each time series is updated once every 20 days.
  - Thresholds are estimated from the reconstruction loss distribution (from training dataset)
  - Periodicity adjustment applied to data counts only
  - A preliminary severity level is assigned based on how far the reconstruction error from thresholds (again based on loss distribution)

NOAA-21 CrIS Channel 23

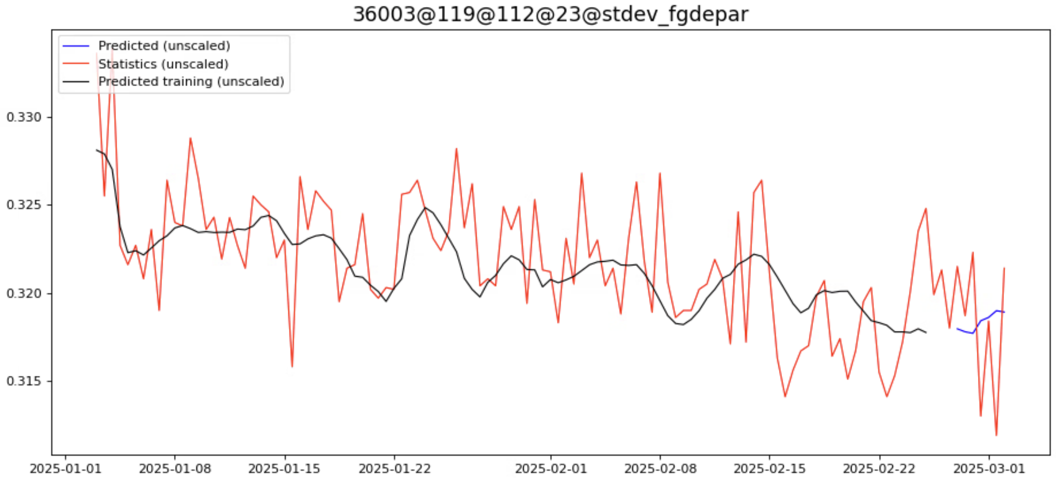
Raw and adjusted stats



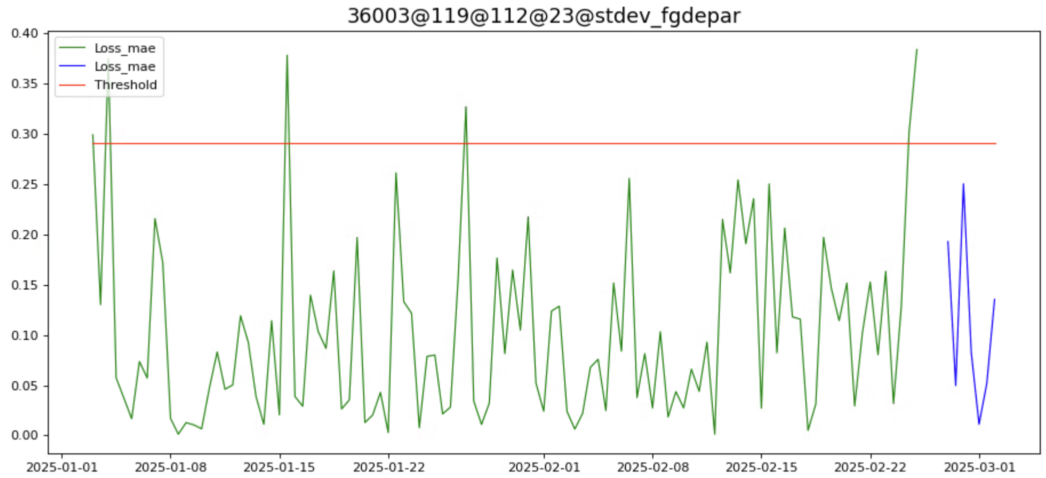
Scaled stats

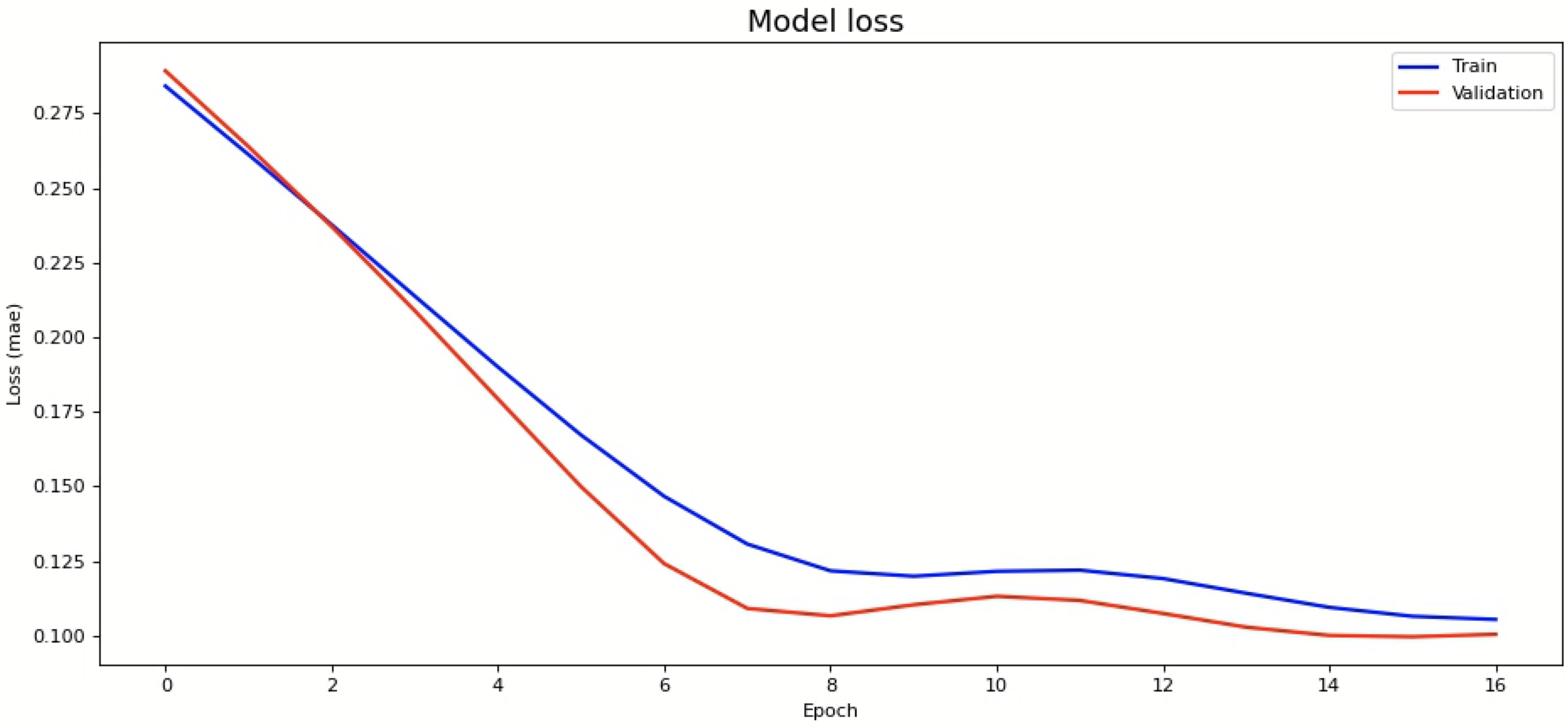


Predicted vs Observed stats



Detection step

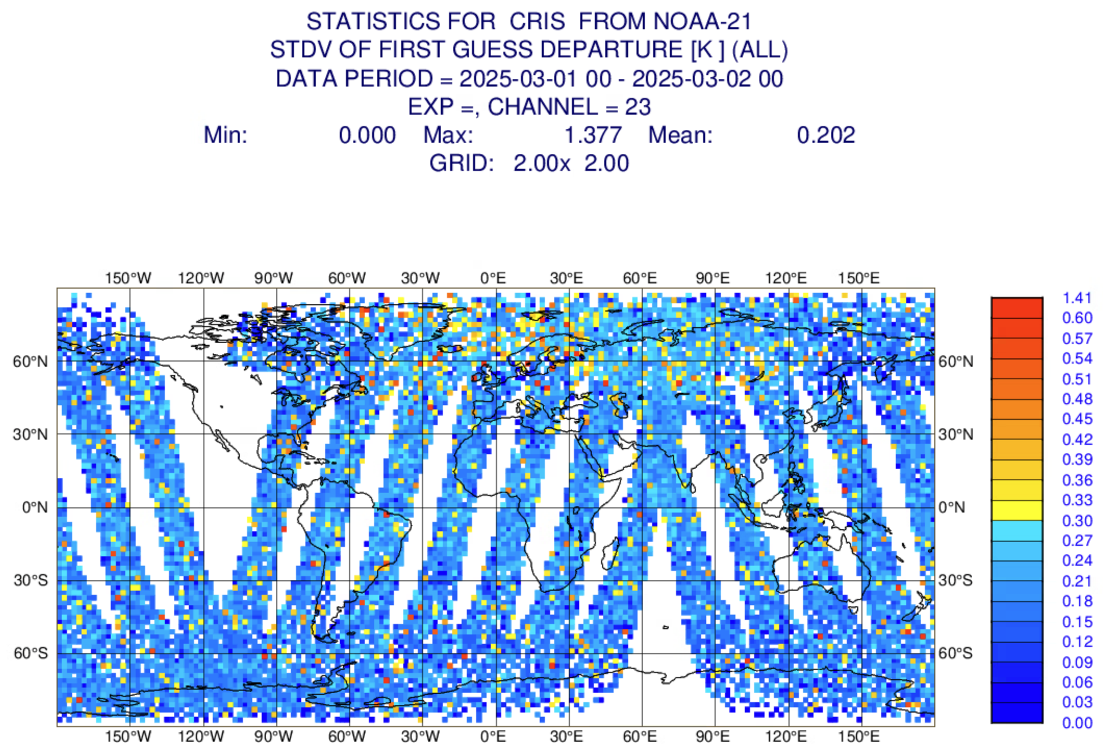




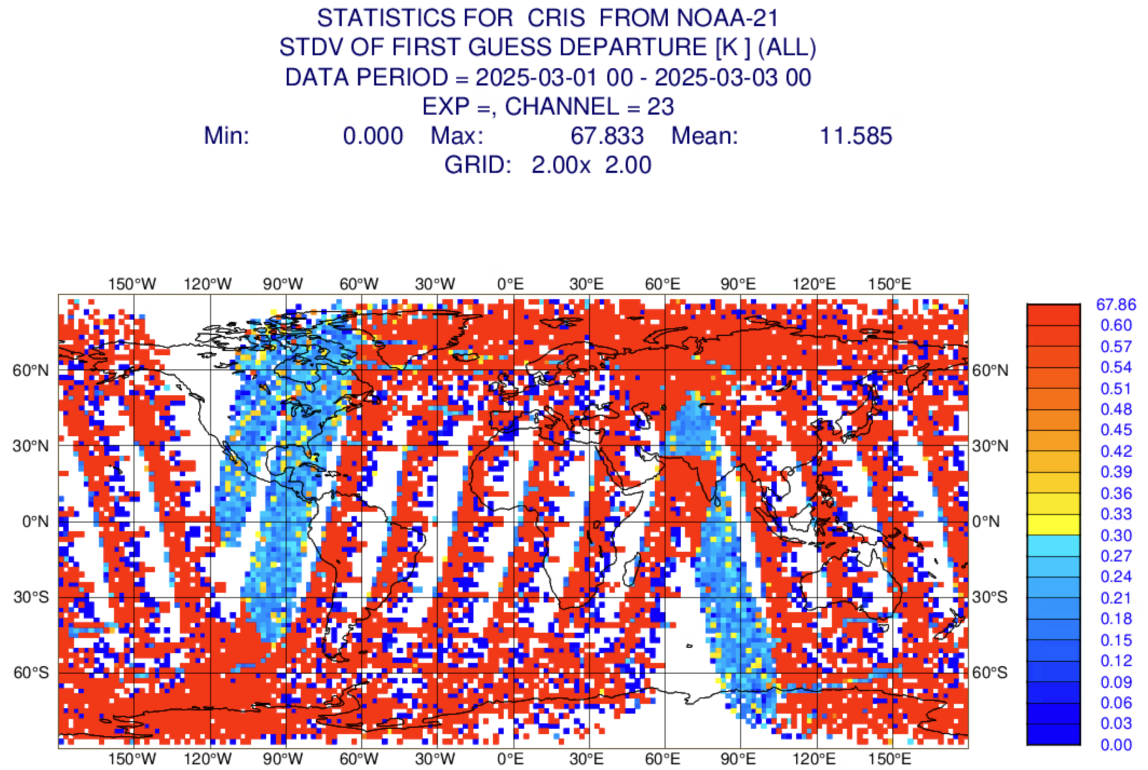
Model loss
Train
Validation
Loss (mae)
Epoch
0.275
0.250
0.225
0.200
0.175
0.150
0.125
0.100
0
2
4
6
8
10
12
14
16

NOAA-21 CrIS Channel 23

20250301 21 – 20250302 09

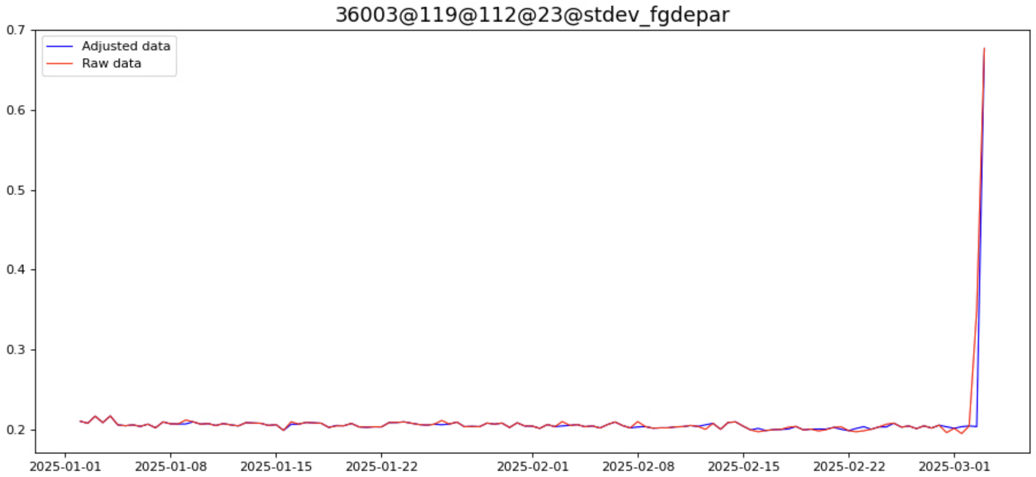


20250302 21 – 20250303 09

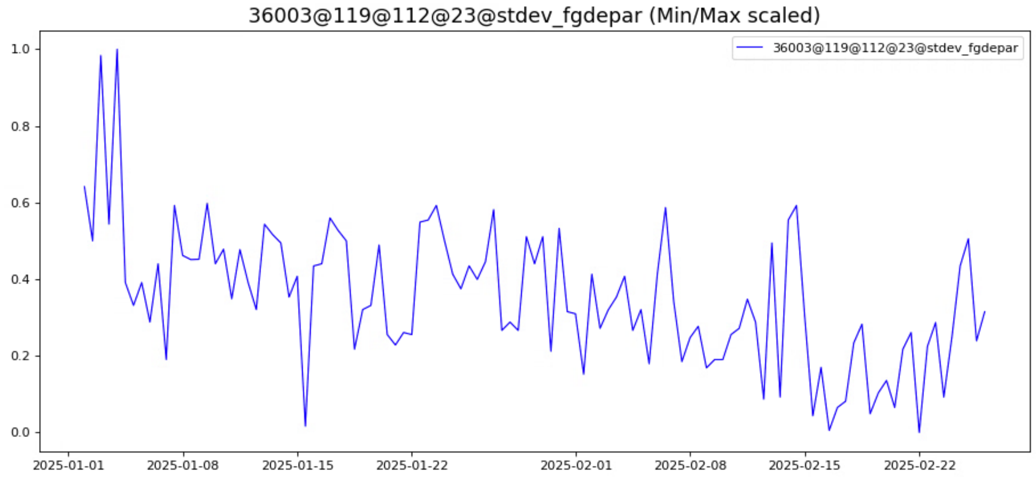


NOAA-21 CrIS Channel 23

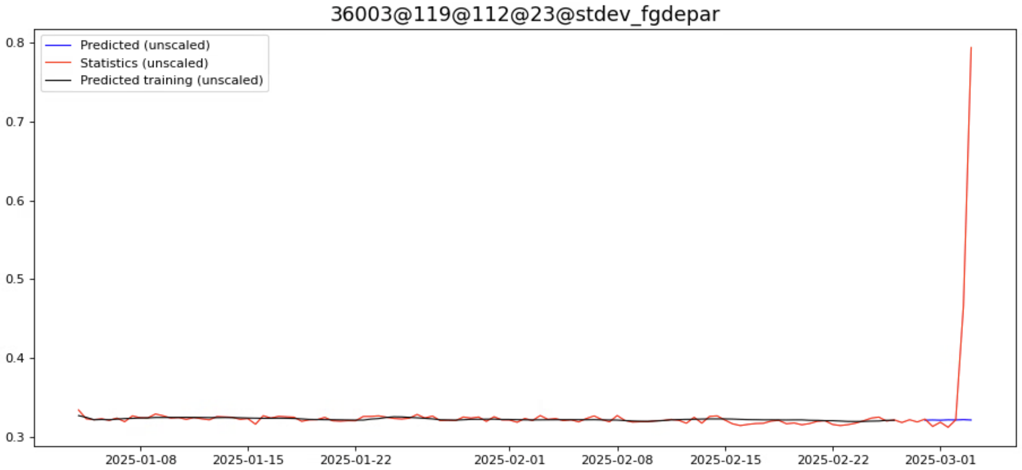
Raw and adjusted stats



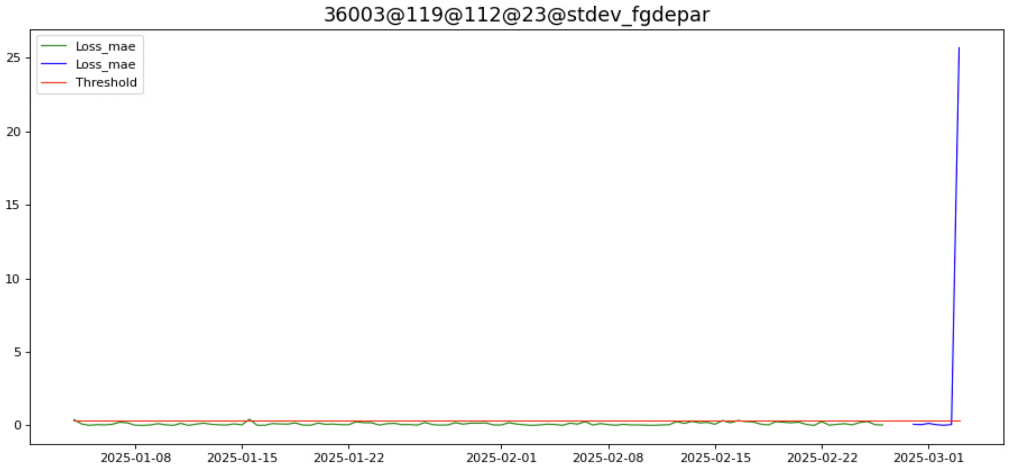
Scaled stats



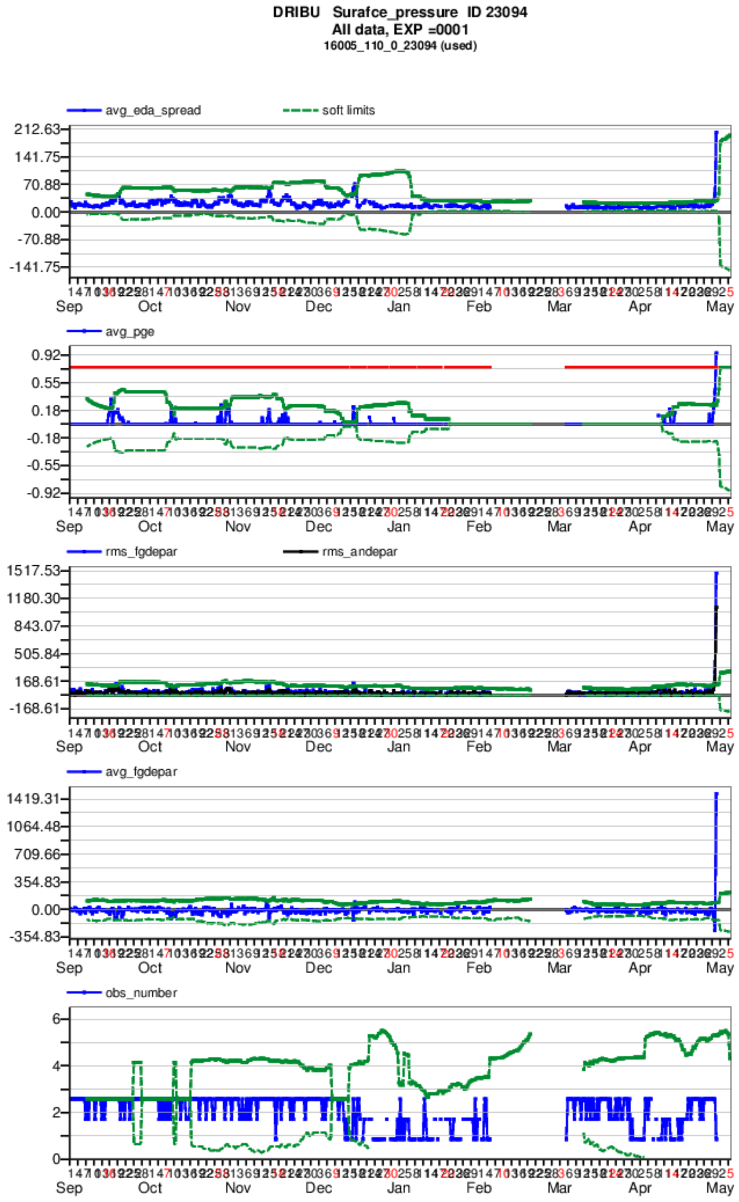
Predicted vs Observed stats

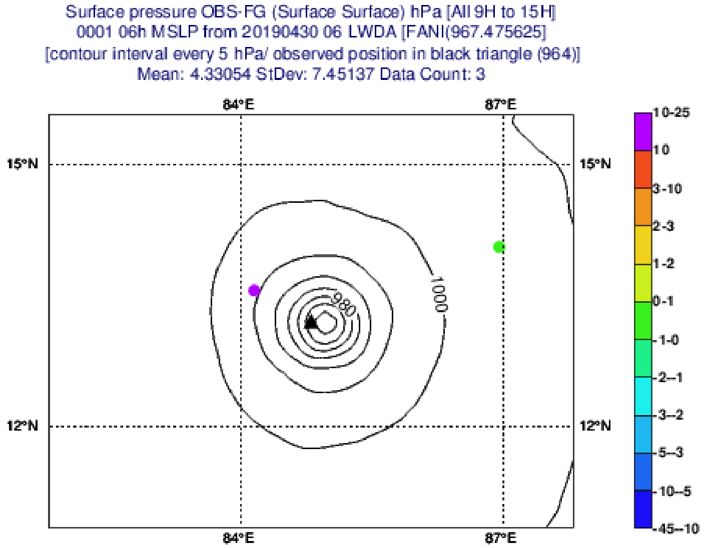


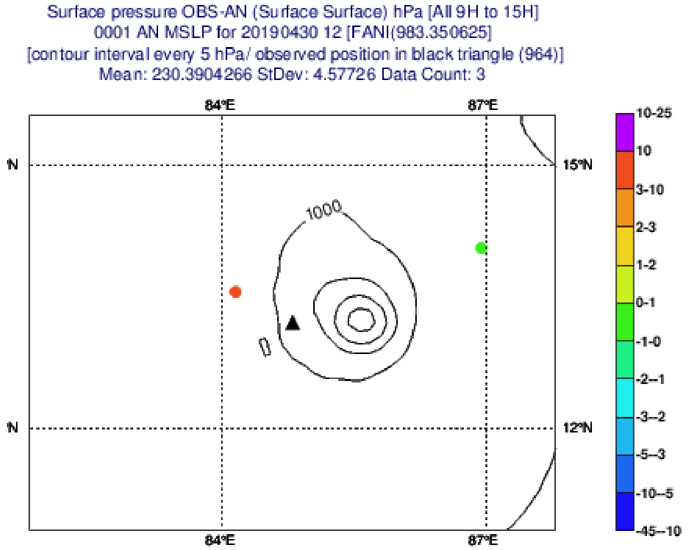
Detection step



Faulty moored buoy (23094)

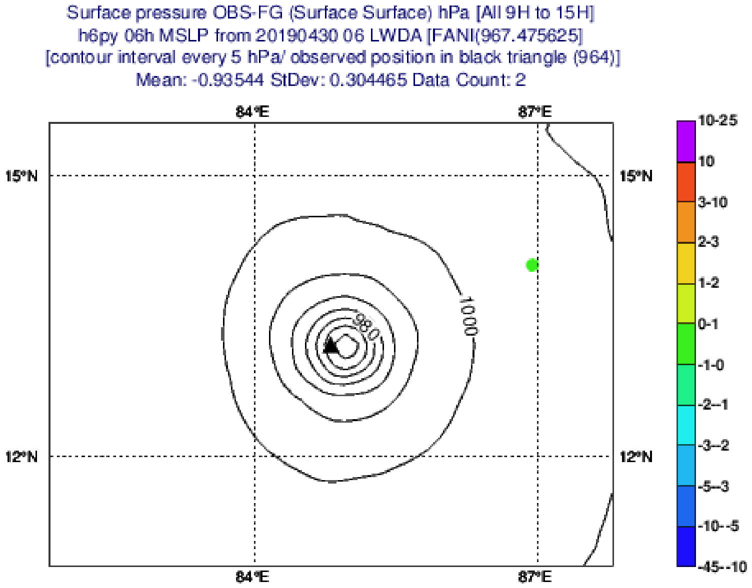


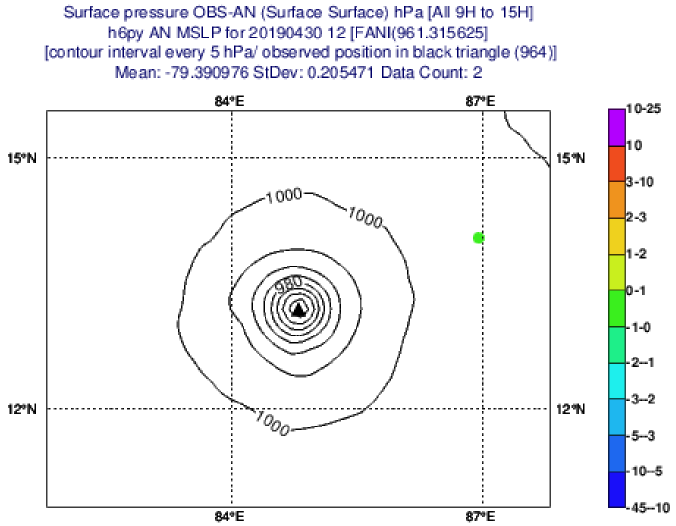




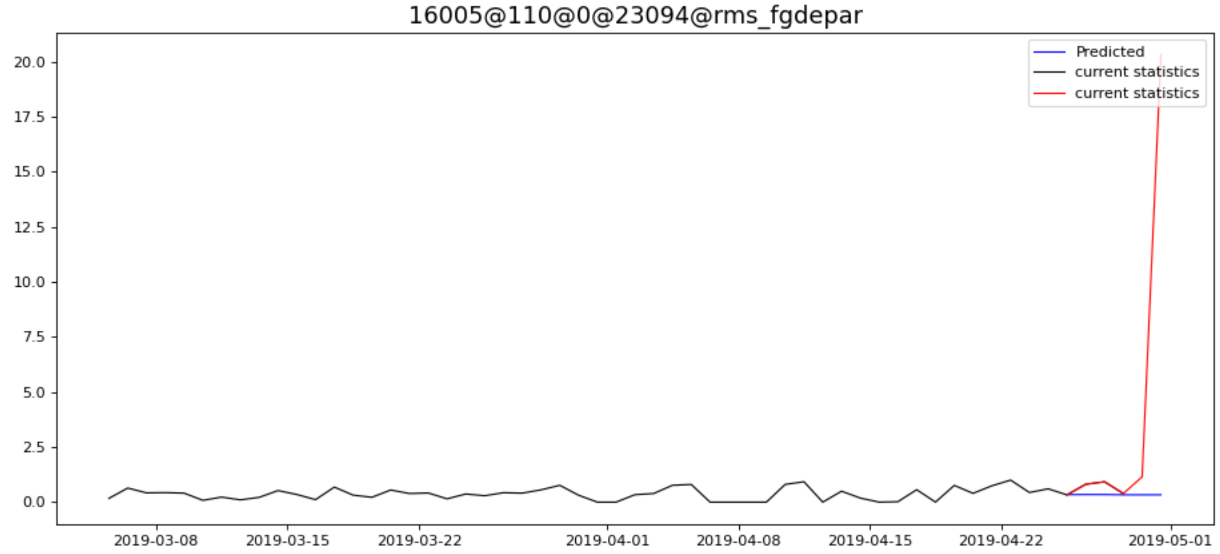
The forecast was also - impacted

Denial of the buoy 23094

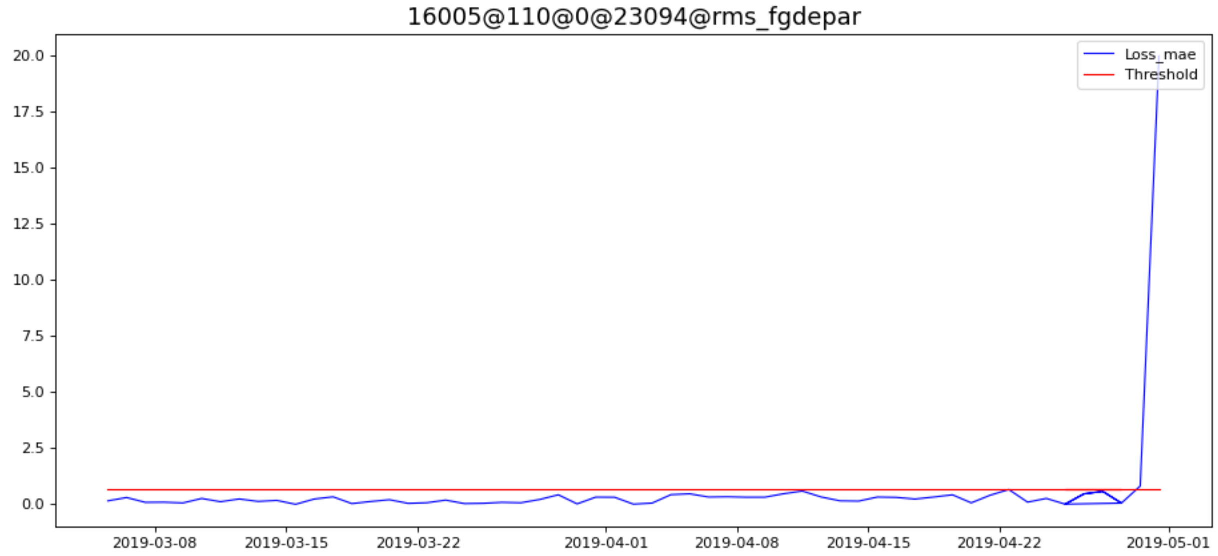




Predicted and current stats (short timeseries)



Re-construction error (short timeseries)

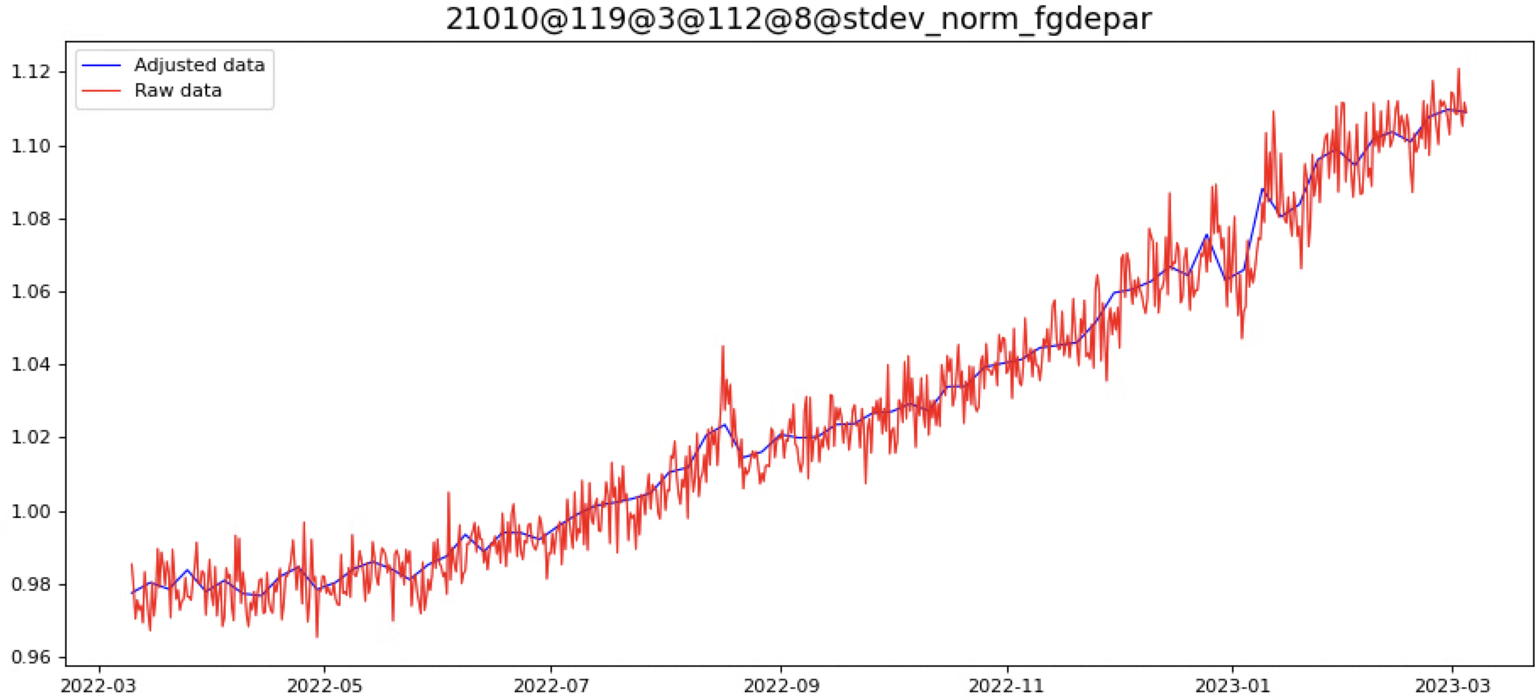


Anomaly detection (unsupervised learning)

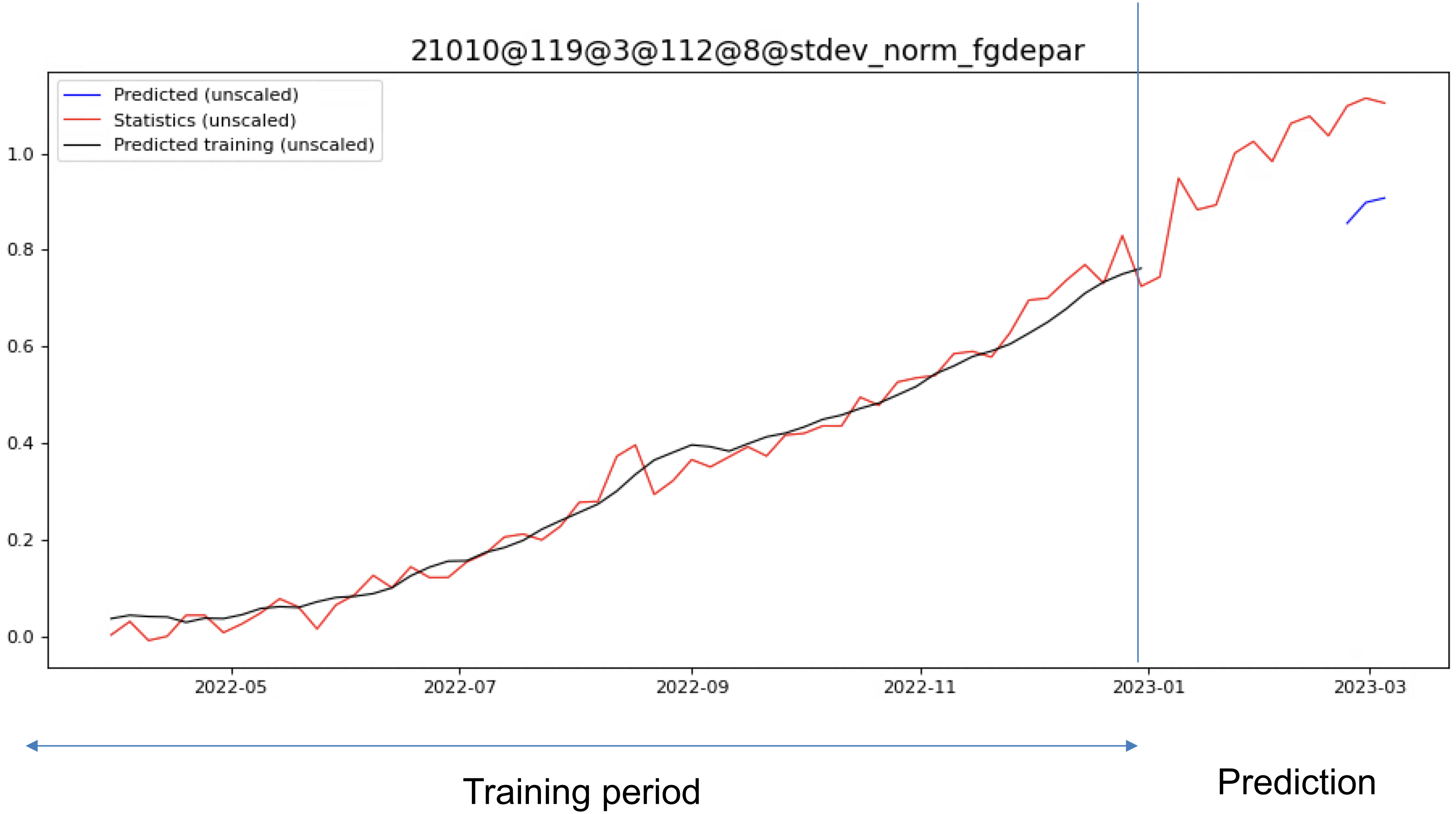
For each data type (satellite only) two RNN models are trained on short and long timeseries:

- RNN model trained on long timeseries (12 months when available):
  - Designed to detect slow changes
  - Model re-trained every week.
  - Thresholds are estimated from the reconstruction loss distribution (from training dataset)
  - Standard deviation of background departures and bias correction are pre-processed to remove periodic signals
  - If an exceedance is flagged, then an additional test is performed to see if a monotonic trend is dominating the period. If the trend test fails (many changing slopes) and if no sudden change is detected (based on short time series) then the event is ignored.

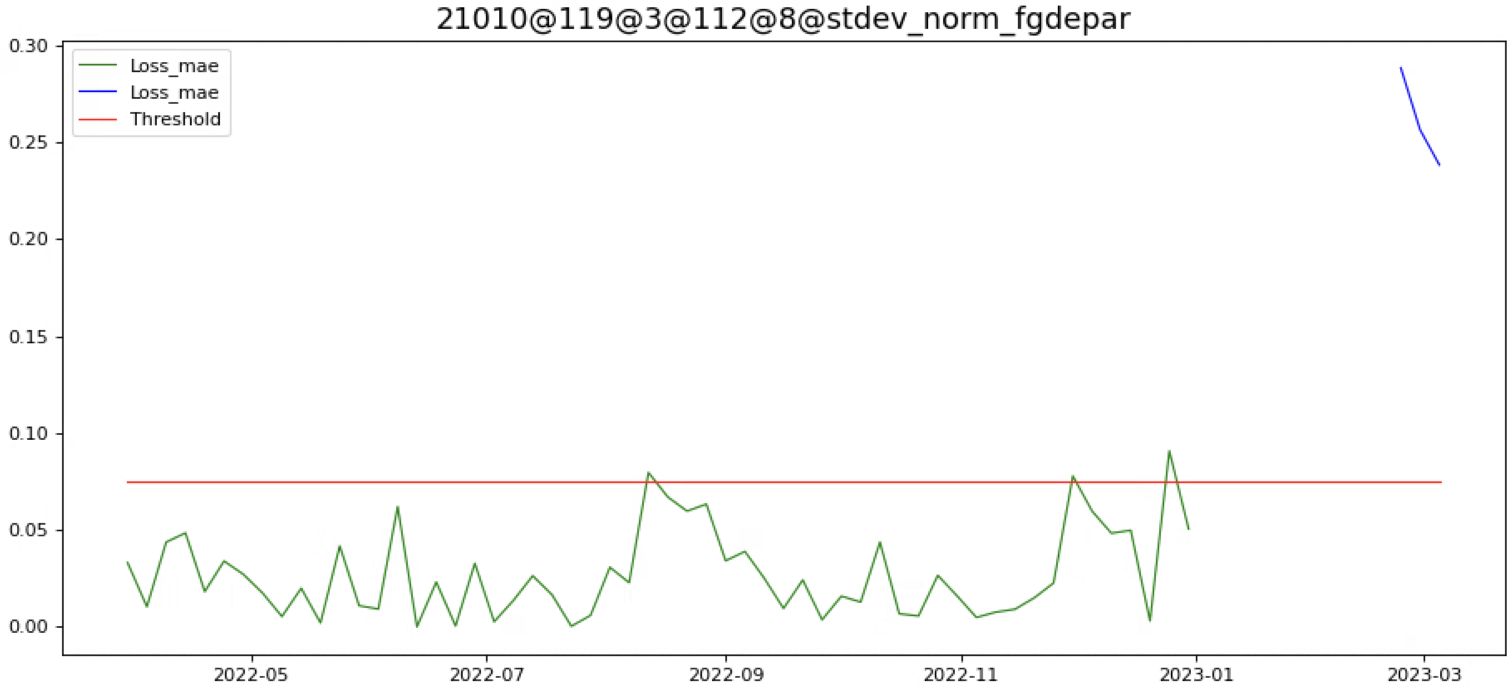
Metop-B AMSUA Channel 8



Metop-B AMSUA Channel 8



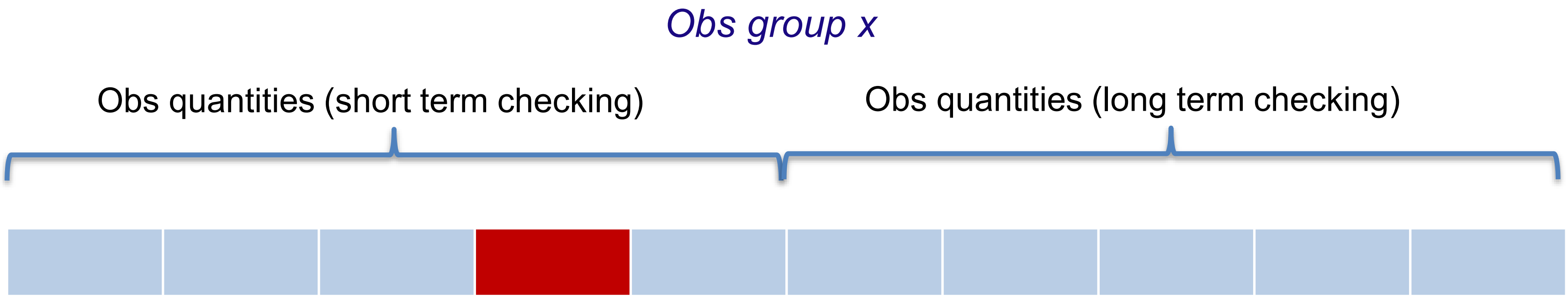
Metop-B AMSUA Channel 8



Test of monotonic trend confirmed: warning of drift issued

Anomaly detection (unsupervised learning)

All flagged cases are recorded (bitfields) in the data files and excluded from subsequent training (positive feedback)



In future evolution of the system the recorded information can be potentially used by the DA to reject data. Allow the screening to take advantage of the past behaviour of the data.

- Additional tests (mainly for in-situ data):
  - Detect metadata changes (position movement, speed, land sea mask change)
  - Departures exceeding static limits
  - VarQC exceeding static limit

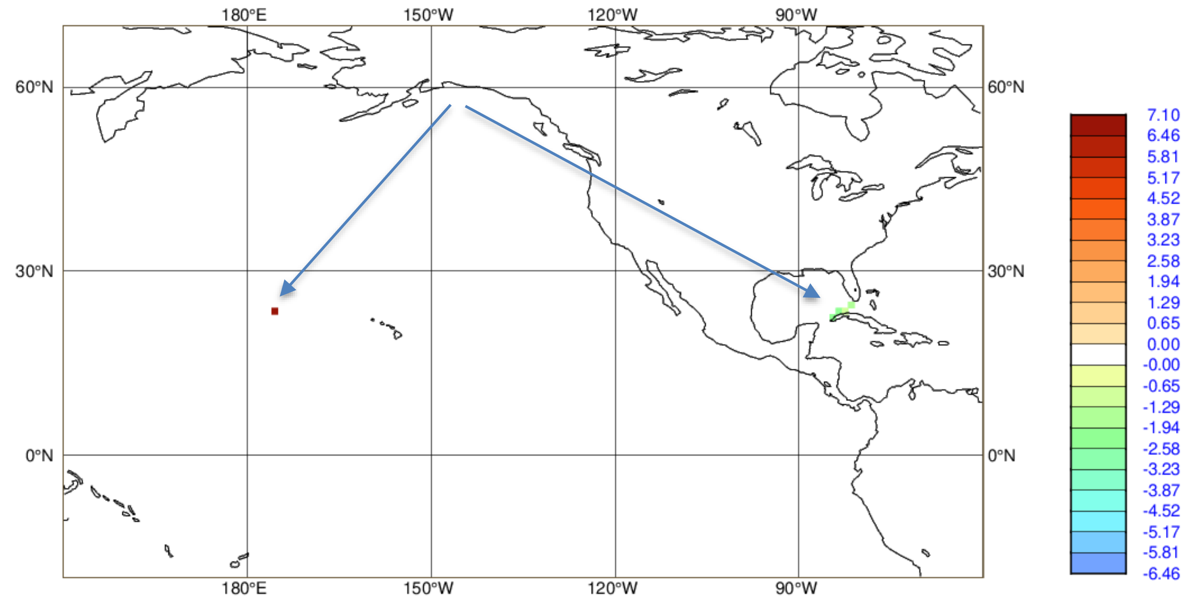
Metadata changes

- Several reports of in-situ stations affected by unexpected metadata changes
- Most of issues remain silent during fair weather but can potentially degrade the forecast
- Changes affecting remote areas are more worrisome
- Build timeseries of metadata indicators

Changes of position (history)	Speed of movement (within DA)	Change of land sea mask (history)	Warm conditions (snow) (history)
SYNOP PILOT METAR TEMP TAC PROF TEMP-BUFR (Near surface) MOORED	SHIP DRIFTER TEMP-BUFR TEMP-MOBILE	SYNOP METAR PILOT TEMP TAC PROF MOORED	SNOW

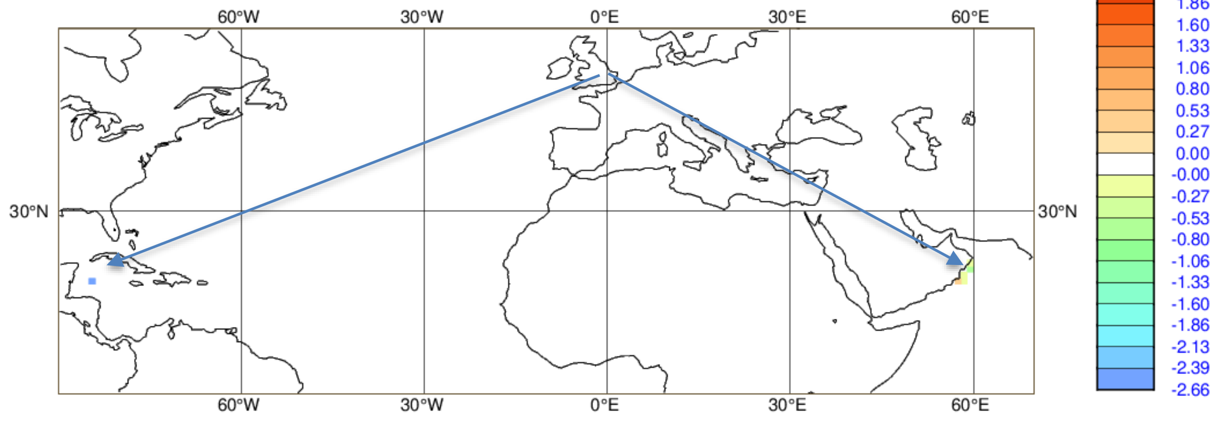
SHIP CFFW9

SURFACE PRESSURE (HPA) FROM C6FW9
MEAN FIRST GUESS DEPARTURE (OBS-FG) [HPA] (ACTIVE)
DATA PERIOD: 2022120809 - 2022120821
ACTIVE-LAYER:5.-1100 HPA-AREA:N:70,S:-20,W:150,E:-60
Min: -2.218 Max: 6.457 Mean: -0.519
GRID: 1.00x 1.00



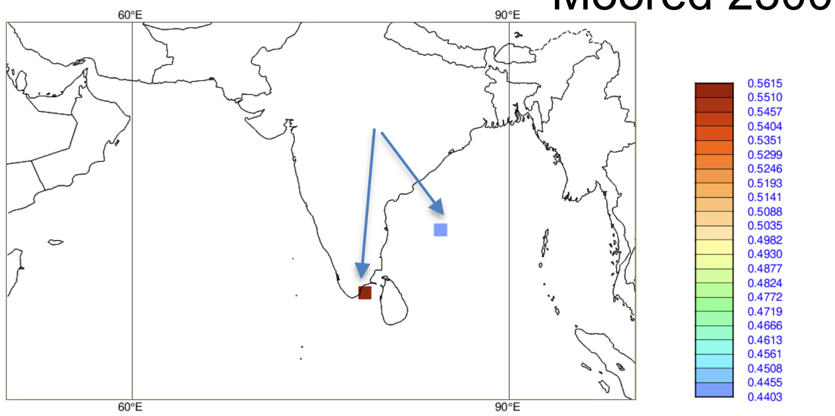
SURFACE PRESSURE (HPA) FROM WSEP
MEAN FIRST GUESS DEPARTURE (OBS-FG) [HPA] (ACTIVE)
DATA PERIOD: 2022120809 - 2022120821
ACTIVE-LAYER:5.-1100 HPA-AREA:N:60,S:0,W:-90,E:70
Min: -2.661 Max: 0.396 Mean: -0.538
GRID: 1.00x 1.00

SHIP WSEP



SURFACE PRESSURE (HPA) FROM 2300094
STDV OF FIRST GUESS DEPARTURE [HPA] (ACTIVE)
DATA PERIOD: 2025031912 - 2025051812
ACTIVE-LAYER:5.-1100 HPA-AREA:N:30,S:0,W:50,E:100
Min: 0.440 Max: 0.556 Mean: 0.447
GRID: 1.00x 1.00

Moored 2300094



In-situ observations (individual stations)

RMS departures

Warn about the event

Static limit 3

Watch event but not report until persistent

Static limit 2

Warn of analysis misfit
(rms(andepar)>rms(fgdepar)

Static limit 5

biases

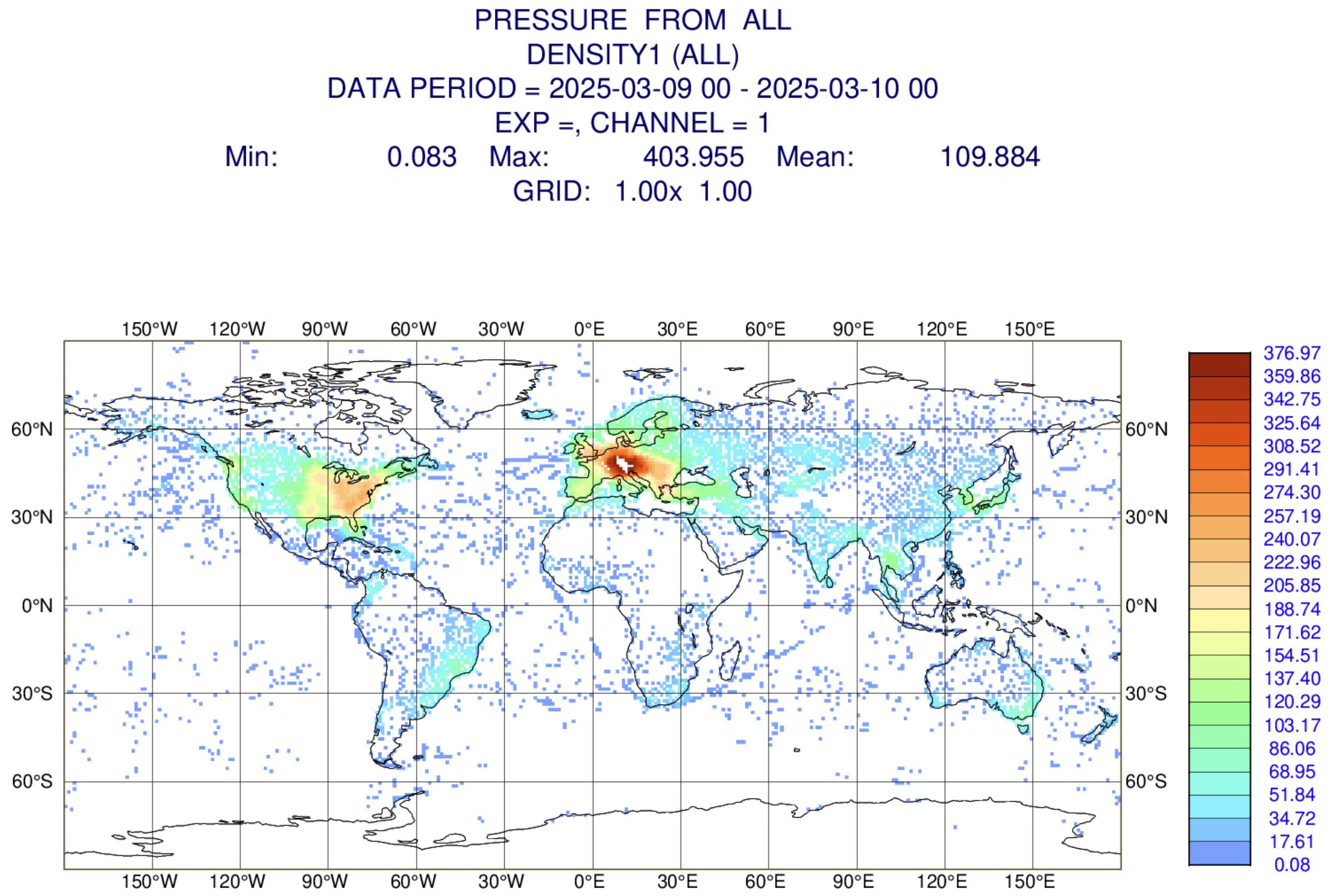
ml_alarm_settings.py

Warn if significance test

Static limit 1

Ignore event

Observations density and automatic detection

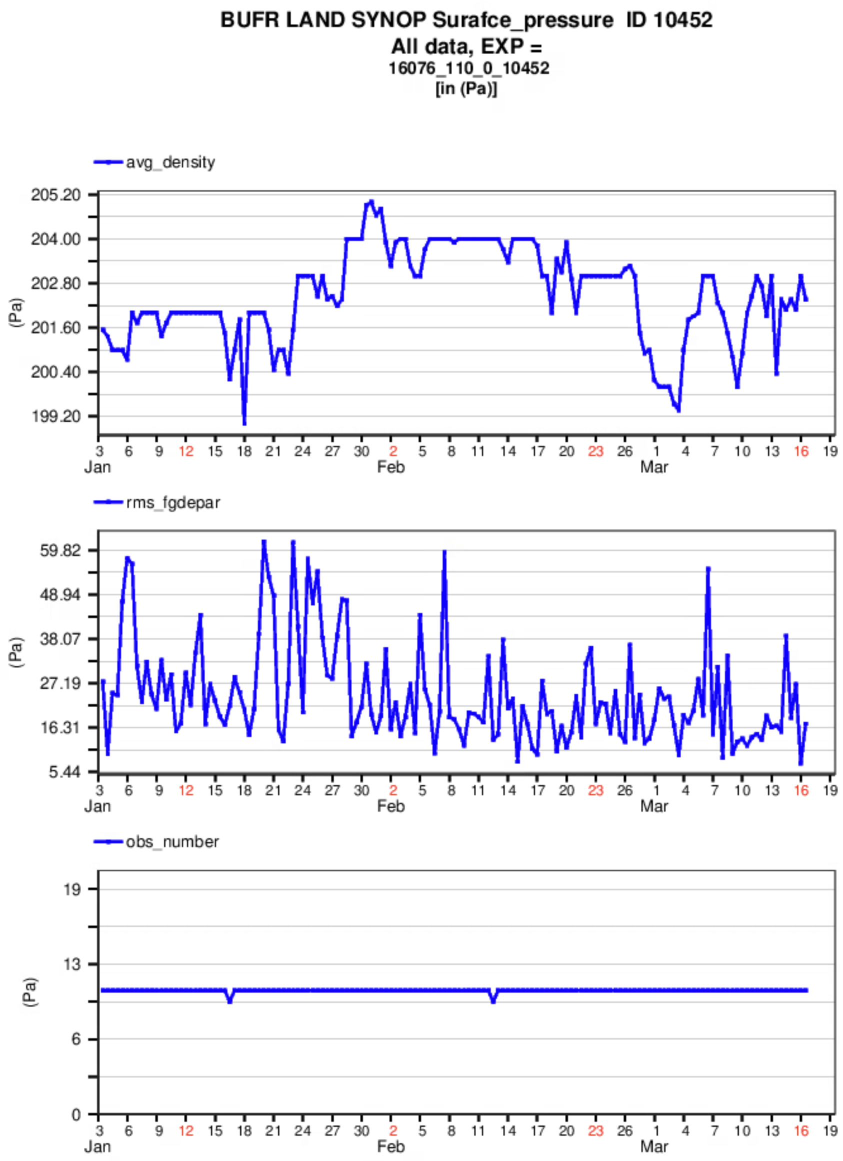


- *Monitoring of the number of surrounding observations (same variable number) regardless of data types: **4** and **8** degrees*

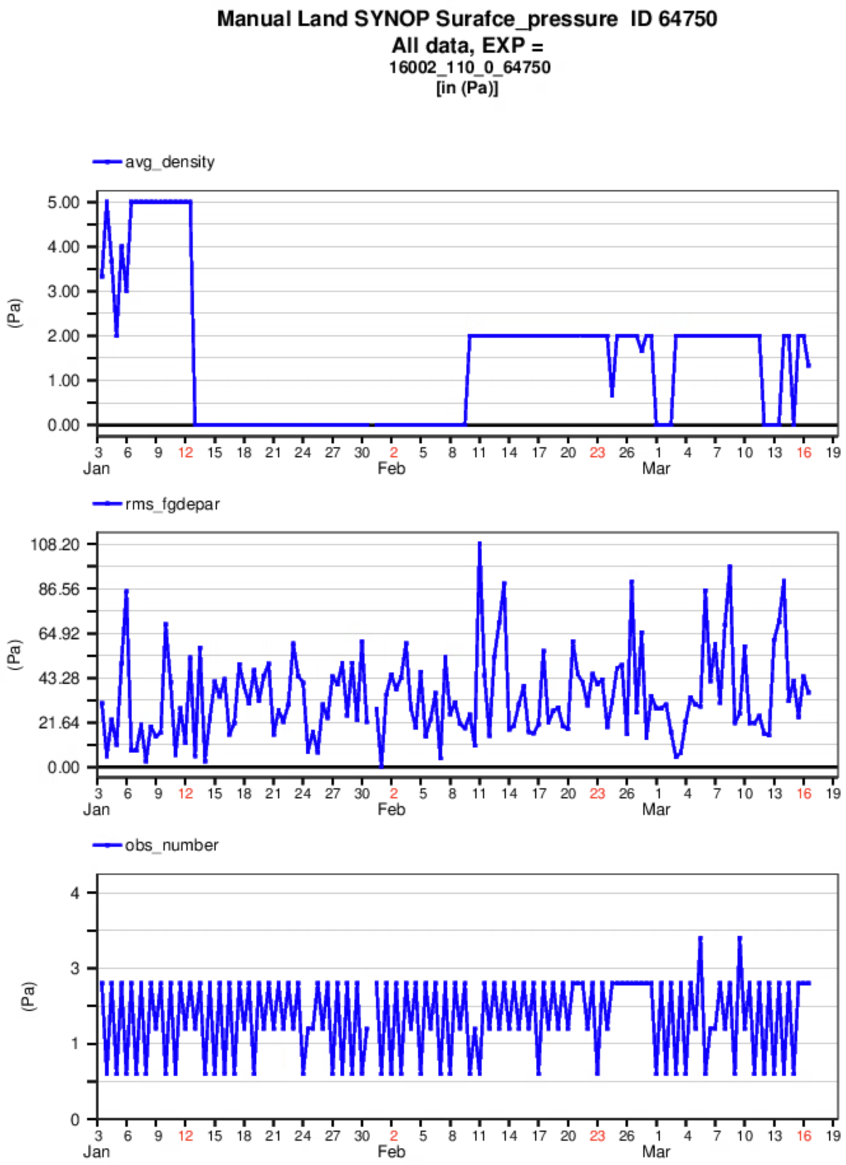
- *The density will be used to change priorities of actions.*

  - *Stations with many neighbouring stations will have low priority*
  - *Stations with few neighbouring stations will have high priority (monitoring counts, reporting, etc)*
  - *Warnings affecting many neighbouring stations should trigger immediate action if not weather related (issue with the data provider or potential hacking)*

10452 (Germany)



64750 (Chad)



Improve classification of warnings (supervised learning)

- Improve the system to distinguish data and DA/model issues (can have consequence when we select data to be blocklisted).

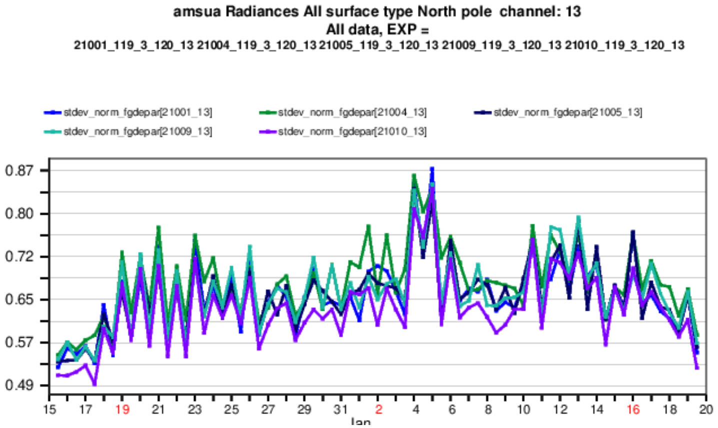
- Improved severity assignment of warnings (Severe, considerable, slight, false alarm)

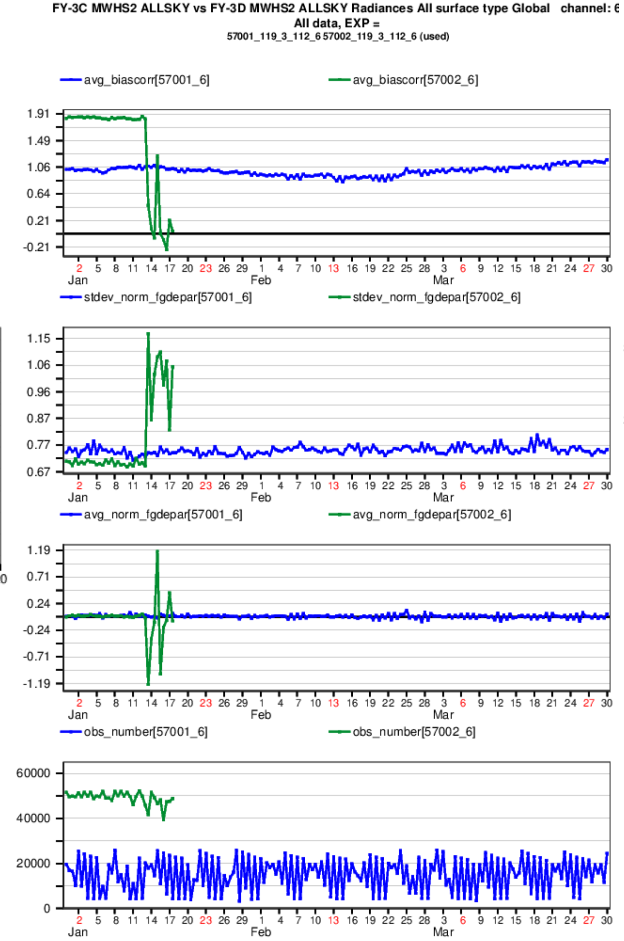
- Suggest if an action is needed

- Pattern extraction from analysts/scientist continuous labelling.

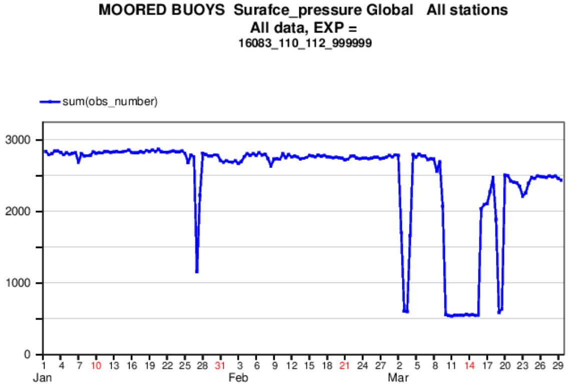
MWHS2 Ch 6 Global

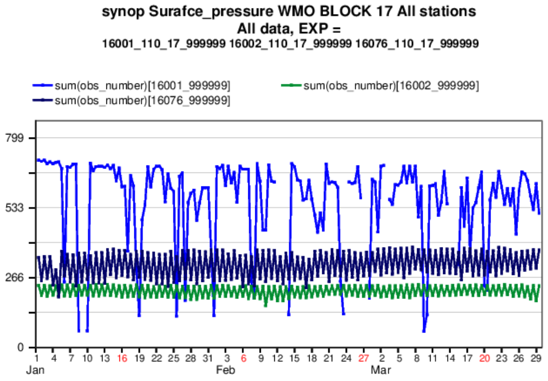
AMSUA Ch 13 N-Pole





Moored buoys





- Warnings affected many satellites (not a data issue)
- Severity: Considerable
- Cause: Atmospheric variability
- No need for action

- Warnings affected only one satellite Severity: Severe
- Cause: Data issue
- Action needed (stop using the data)

- Moored buoys reduced (important dataset)
- Severity: Severe
- Cause: Data outage
- Action needed (contact data provider)

- Automatic synop data intermittent over Turkey (Other datasets present)
- Severity: Considerable
- Cause: Data outage
- Action needed (monitor)

Event database

Population of Past events From the current system: Each Warning is augmented with info from the other warnings

Weather events

- *Tropical cyclones*
- *Areas with large increments (surface, Z500 and Z200)*
- *Areas with strong precipitation or wind gusts*

Static metadata

- *Weighting functions for satellite data (incomplete)*
- *Pressure levels for in-situ data*
- *Gridded position of in-situ stations*

Labelling: Performed using a decision tree BUT should be done manually to better reflect scientific judgment and allow better classification

Occasional annotation by analysts and scientists

Perform simulations (data tampering for instance) to learn patterns

training

Trained model (random forest)

All preliminary warnings

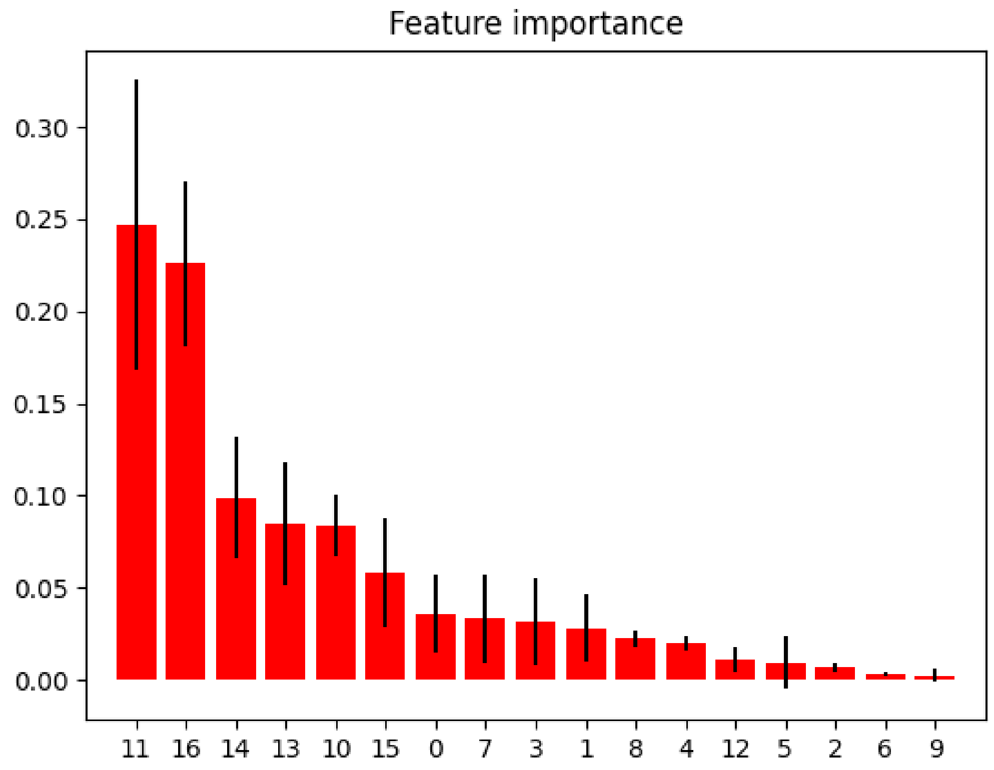
- Data category (satellite, conv, ocean, ostia)
- location or area
- Type of event (missing, out of range)
- Observation quantity
- Frequency of similar incidents
- Severity of deviation
- Other similar datasets present in the area and how many affected ?
- EDA spread increased ?
- Severe weather events in the area
- All levels/channels affected ?
- How many areas affected ?
- parameters affected ?
- Data counts
- Usage status (satellite data)

Random forest classifier

- False alarm (yes/no)
- Slight (yes/no)
- Considerable (yes/no)
- Severe (yes/no)
- Cause (data/other)
- Action required (data/other)

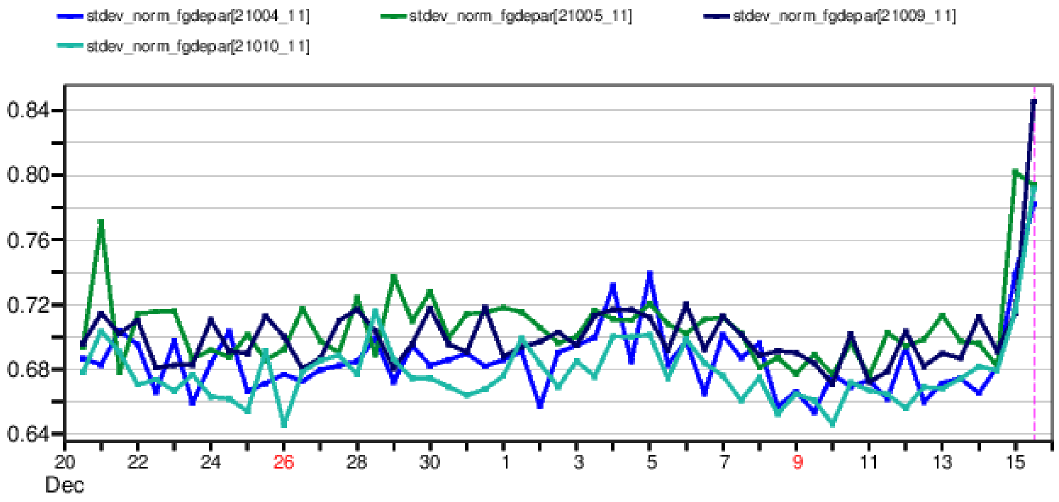
– Training dataset populated from *labelled* warnings (from the event database). Dataset is balanced before training
– The labelling process allows classification based on the context of the warnings
– The labelling process was largely semi-automated but will be further improved.
– Continuous labelling is an option (cases to be added occasionally when relevant)

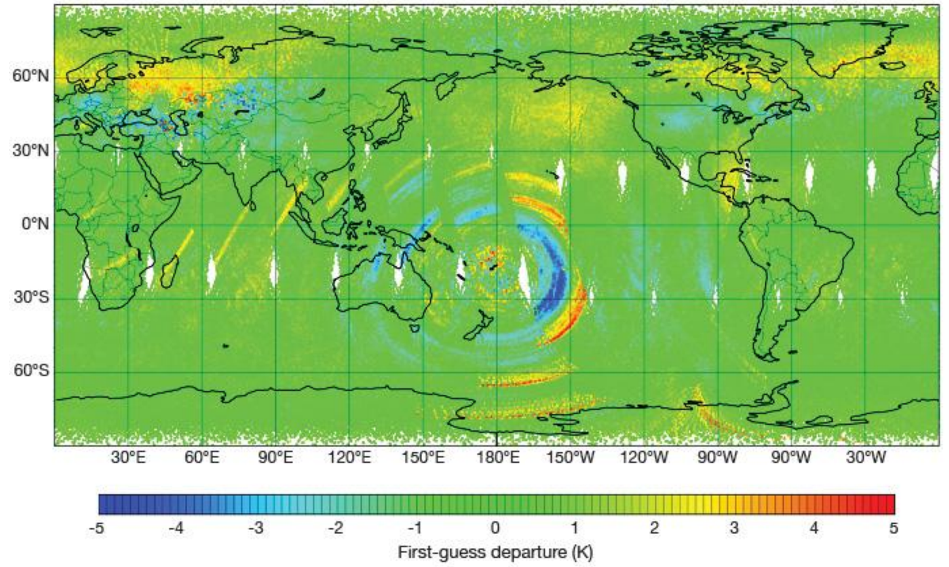
Feature ranking (target feature: cause)




```
Feature ranking:
1. feature 11 Eda_spread (0.246750)
2. feature 16 nbr_weather_events (0.226029)
3. feature 14 nbr_similar_wmoblock (0.098864)
4. feature 13 nbr_similar_reportypes_with_alarms (0.084890)
5. feature 10 nbr_similar_past_events (0.083562)
6. feature 15 nbr_similar_nearby (0.057817)
7. feature 0 Data_type (0.035918)
8. feature 7 varno (0.033076)
9. feature 3 Area (0.031896)
10. feature 1 Vertcol (0.027735)
11. feature 8 AlarmGroup (0.022424)
12. feature 4 Obs_quantity (0.019720)
13. feature 12 nbr_areas (0.010633)
14. feature 5 Severity (0.009229)
15. feature 2 vertco_type (0.006515)
16. feature 6 Type_event (0.002668)
17. feature 9 usage (0.002275)
```

AMSU-A Ch 14 – South Hemisphere (Hunga-Tonga eruption)





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AMSUA

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NOAA-19 AMSUA ALL SKY Radiances (5.0 channels affected - channel 14 shown) SHem ExtTrop: out of range:

http://apps.ecmwf.int/satellite-alerts/image//?image=2022011512_LWDA_0001_amsua1_21005_119_14_3_119.png

Severe (Likely not a data issue): stdev_norm_fgdepar=0.67765, expected range:0.5289 0.6064

Classifier re-training

– mechanism in place for analysts and RD scientists (on best effort basis and in ad-hoc manner) to annotate the warnings they receive

– On-demand re-training of the classifier → increased reliability of the system and more feedback for the diagnostics when the DA is struggling

– Continuous evaluation of the system reliability → might lead to automatic targeted data selection decisions (Enhance the QC algorithms of the IFS with an info from the past behaviour of data sources)

Research monitoring suite

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

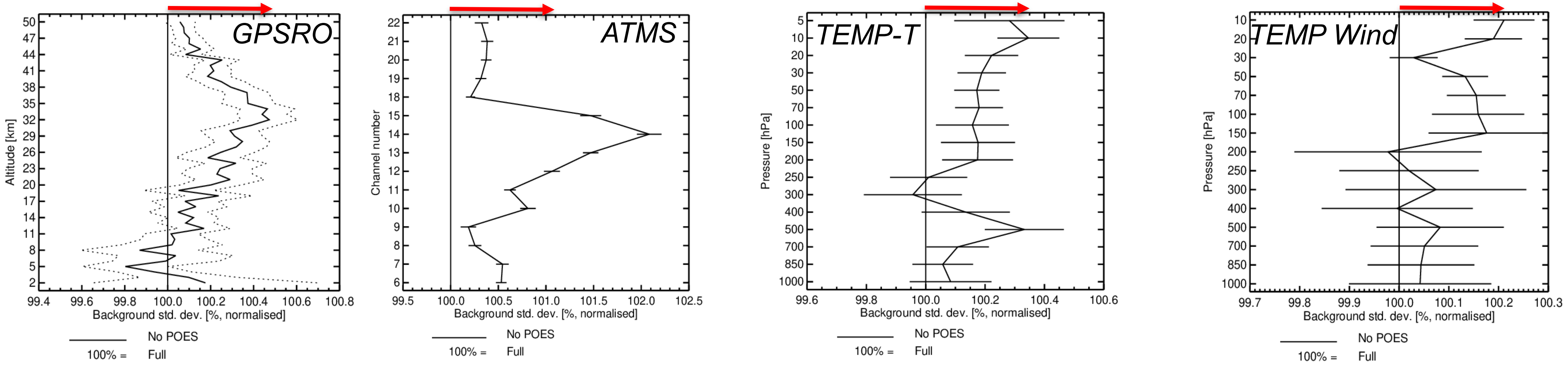
- The change of fit is indicative of the (positive/negative/neutral) impact of the change being tested

- 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



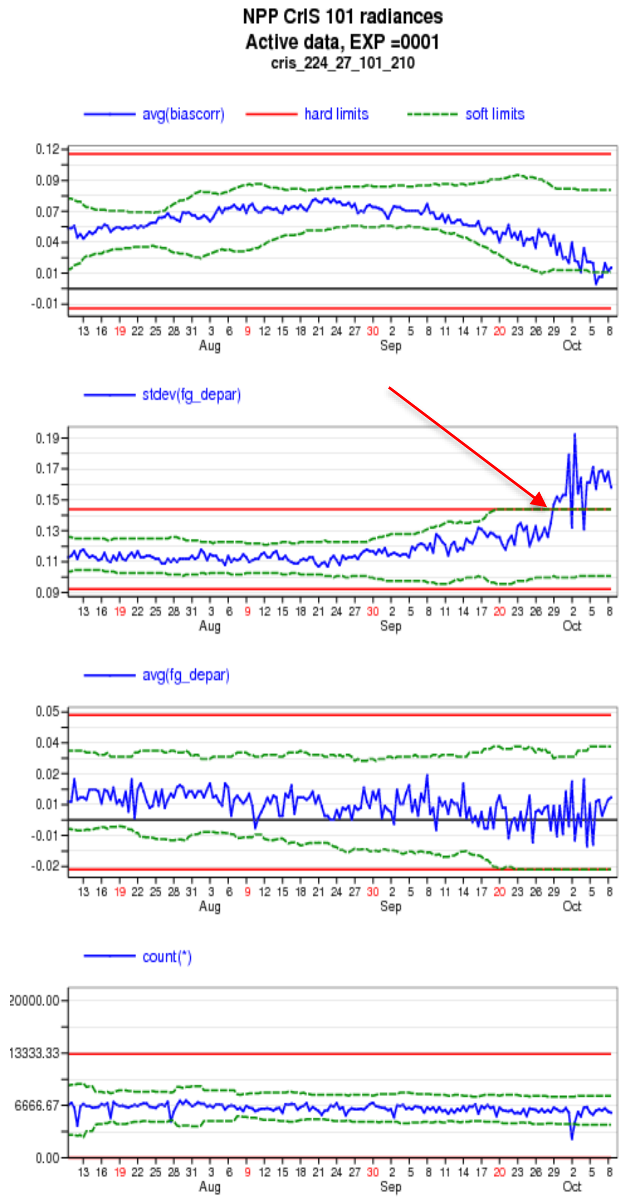
Outline

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

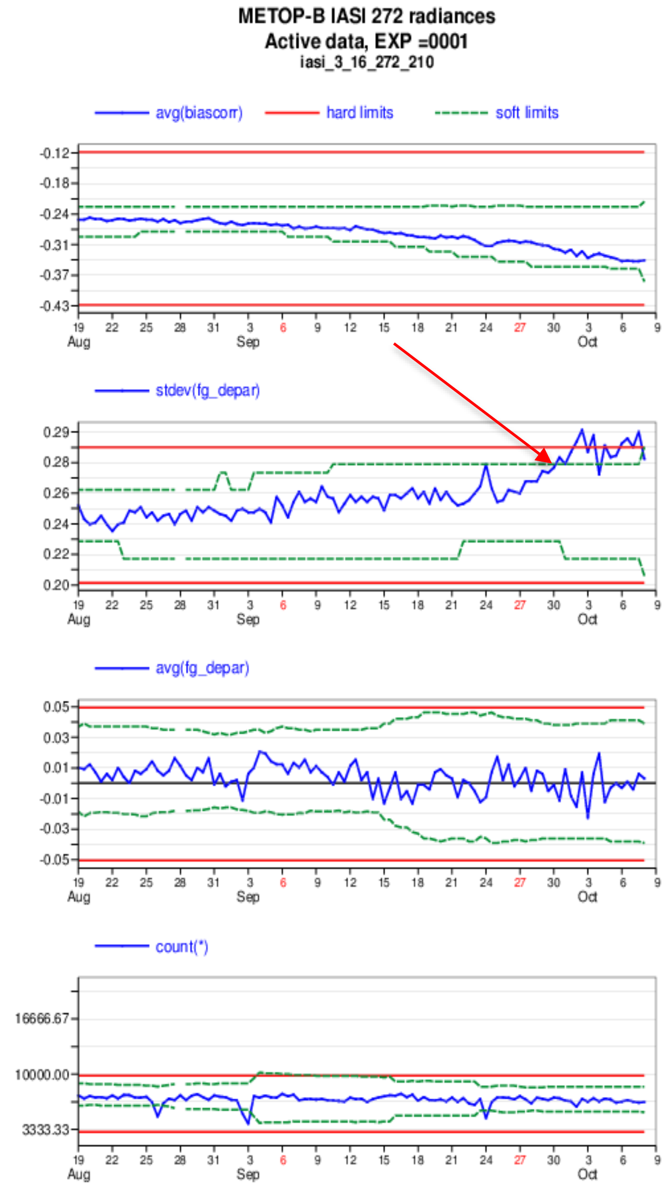
Observations related diagnostics

- 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

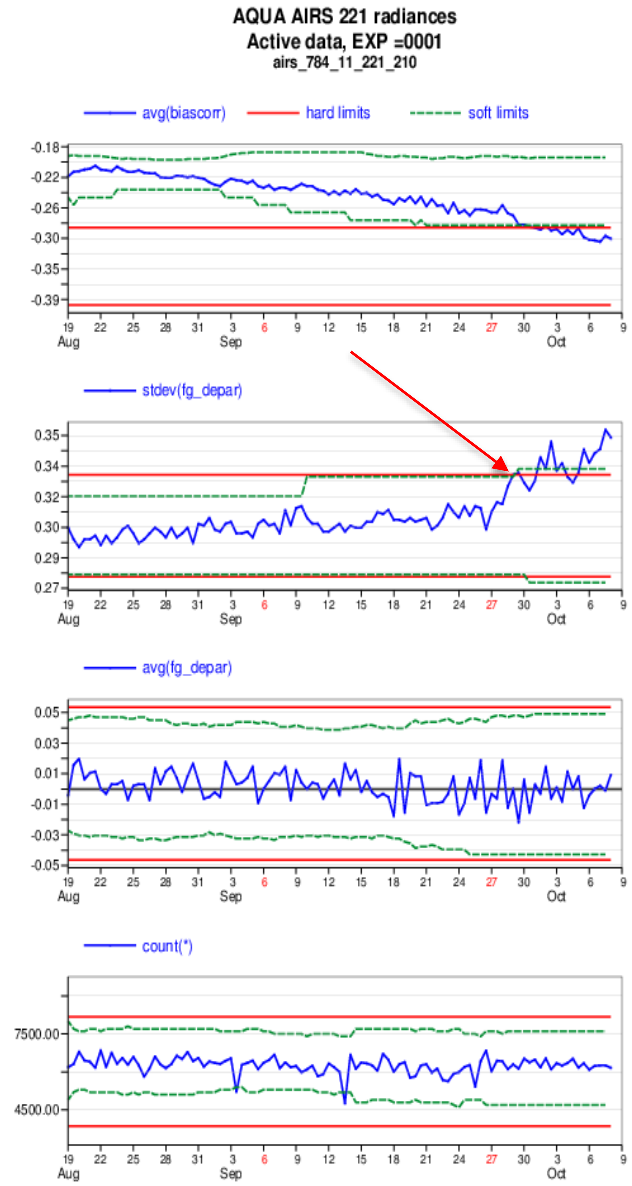
S-NPP CrIS Ch 101



METOP-B IASI Ch 272

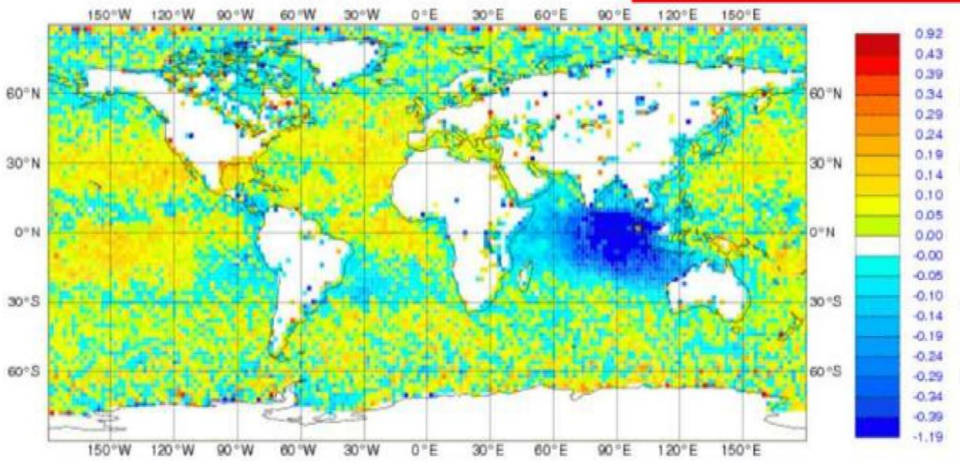


AQUA AIRS Ch 221

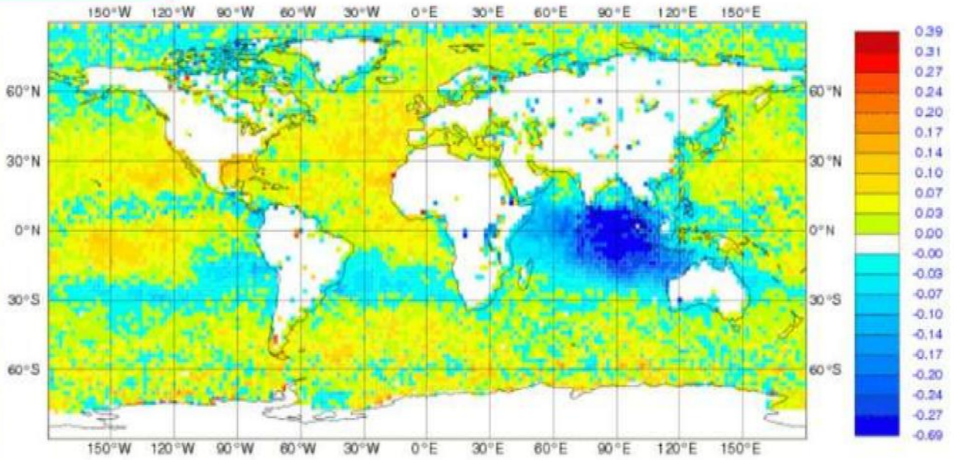


Gridded monthly mean O-B
October 2015

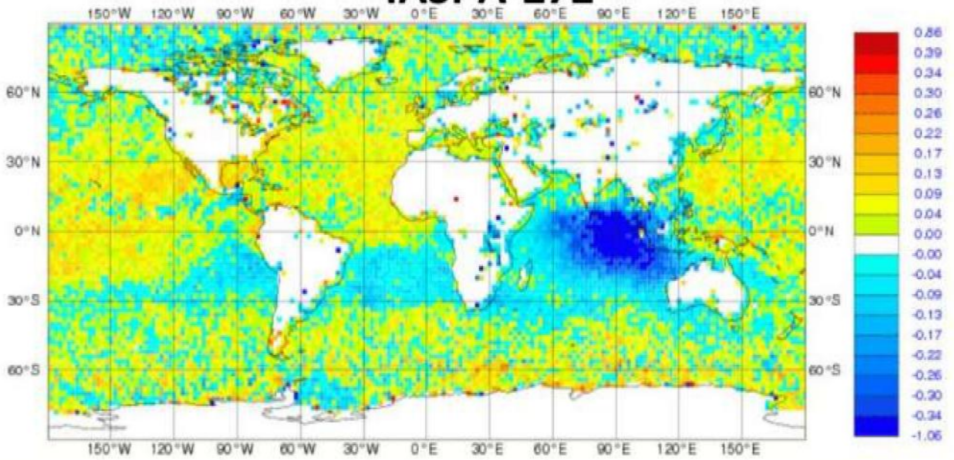
AIRS-221



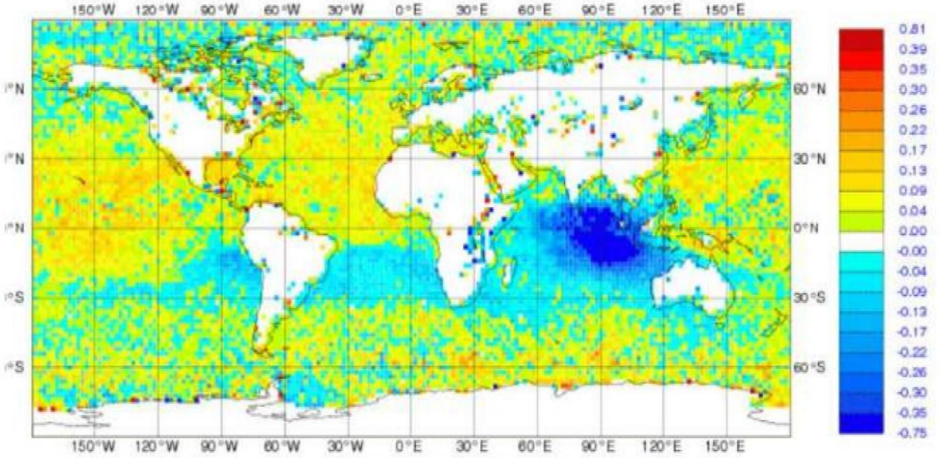
CRIS-101



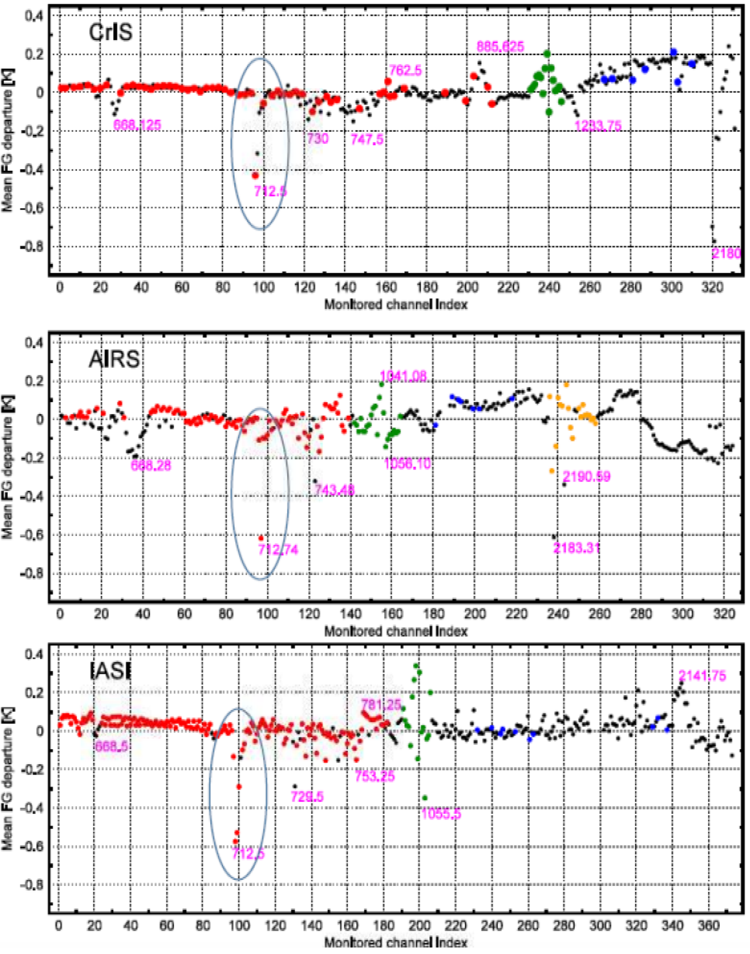
IASI-A-272



IASI-B-272



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

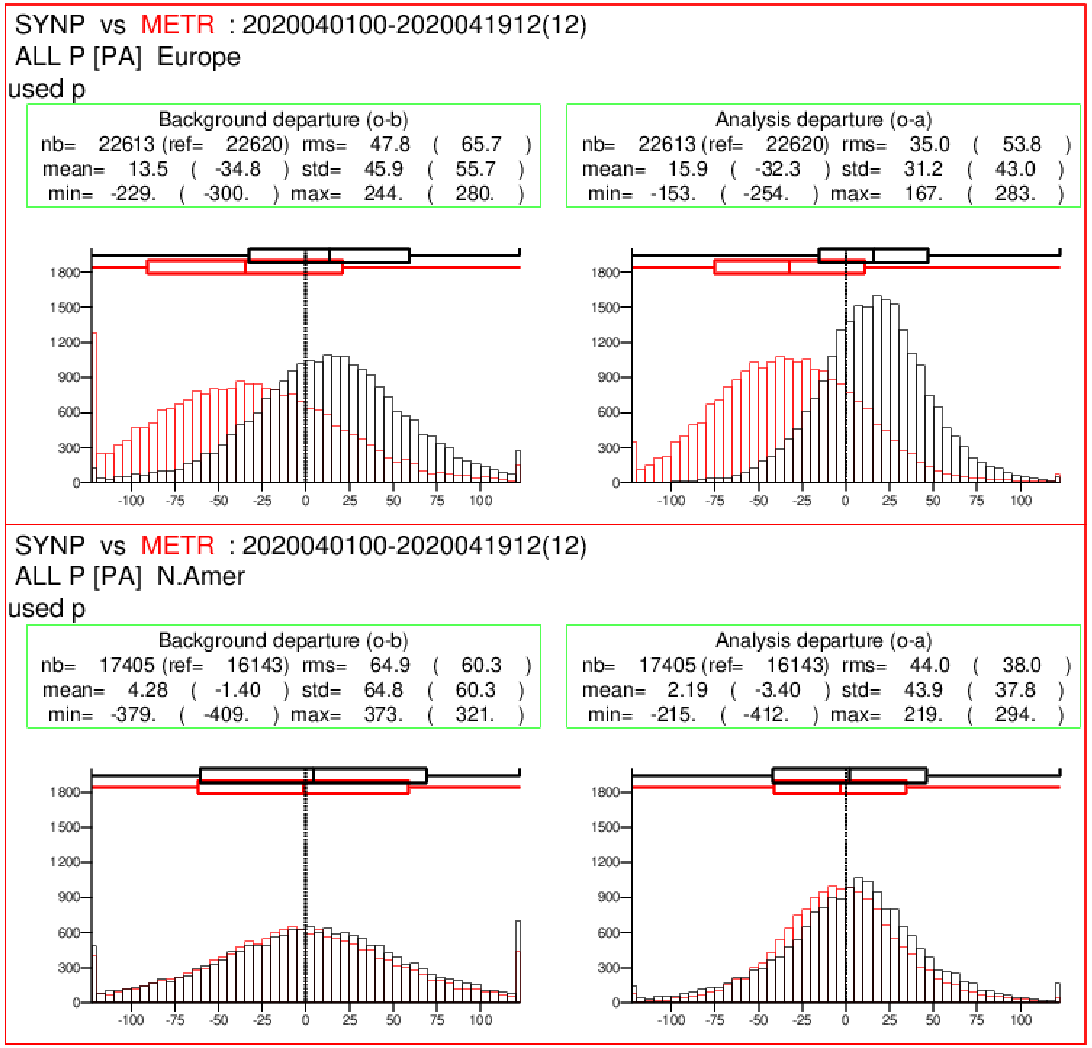
Decision to blacklist the affected channels (unwanted temperature increments)

Spectral signature of Hydrogen Cyanide (HCN)

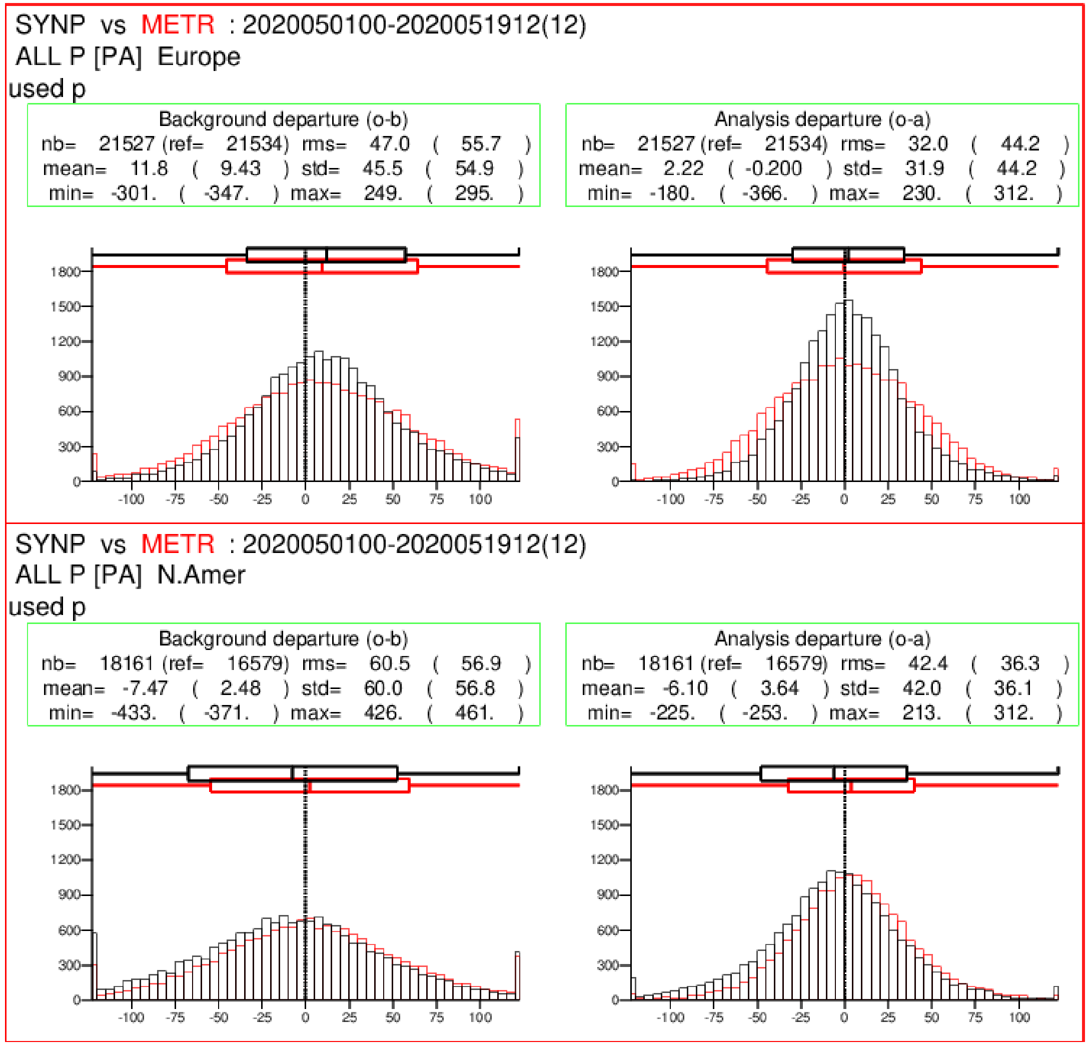
HCN is a known pollutant associated with biomass burning and the alarms coincided with the Indonesian fires

SYNOP and METAR co-location

Before METAR QNH correction



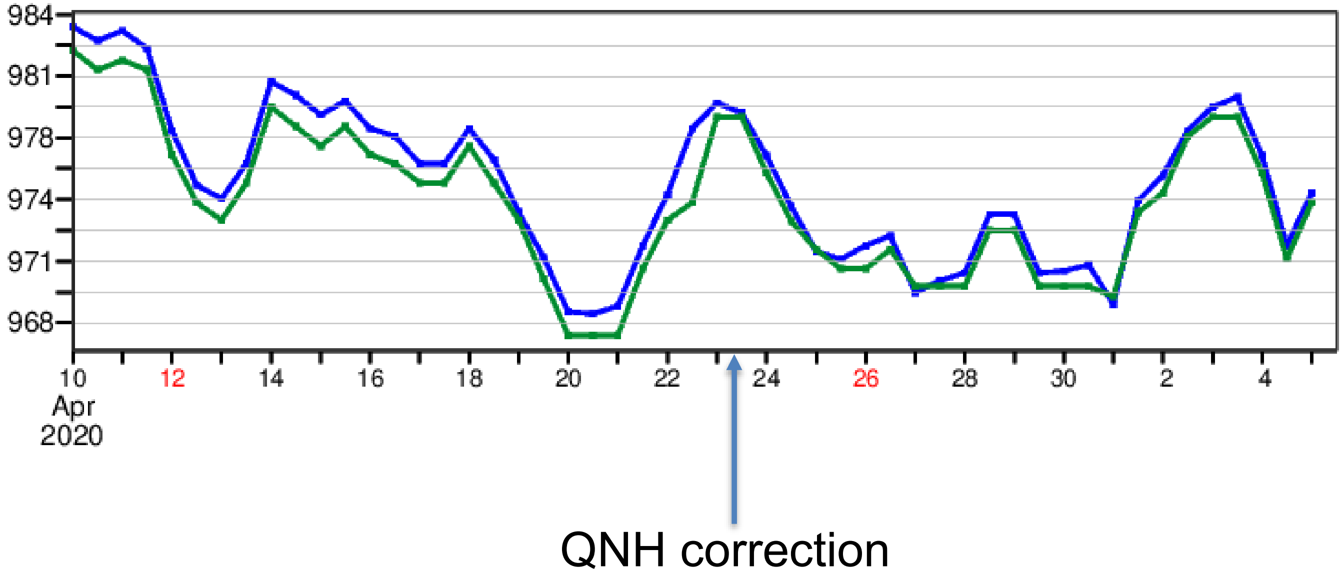
After METAR QNH correction (Apr 2020)



QNH correction

Observed surface pressure: Metar LFLC (green) and Synop 07460 (blue)

Clermant-Ferrant (France)



- METAR pressure measurements are rounded down to the nearest whole hPa in Europe (poor precision) and rounded down to hundredth inch of Mercury for American METAR data.
- METARs and SYNOPs are both available and used from most airports causing inconsistencies and slight degradation (against observations)
- The slight differences in position and frequency makes the duplicate check difficult to implement
- The solution was to implement a correction (at the level of SAPP): 0.5 hPa for stations reporting in hPa and 0.169 hPa for stations reporting in inches of mercury

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

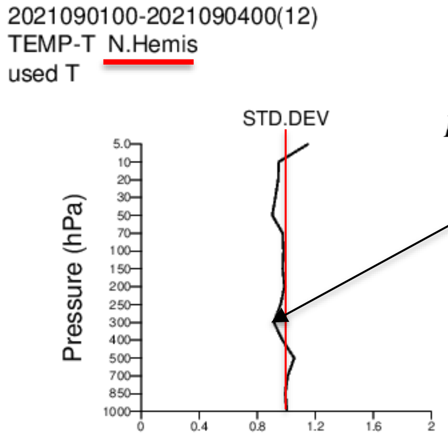
$\mathbf{d}_b^a$ **(A-B)** Increments

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

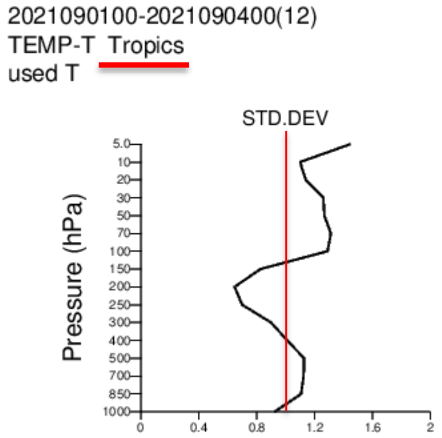
$$E[\mathbf{d}_b^o(\mathbf{d}_b^o)^T] = \mathbf{R} + \mathbf{HBH}^T$$

- 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

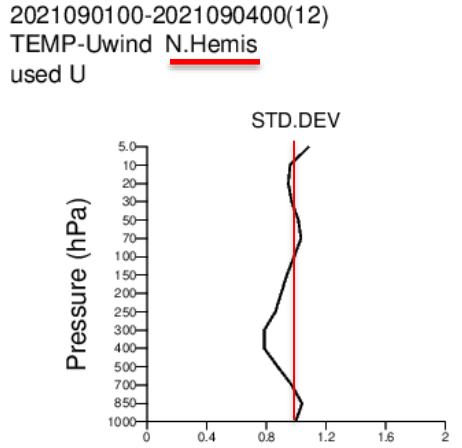
TEMP temperature

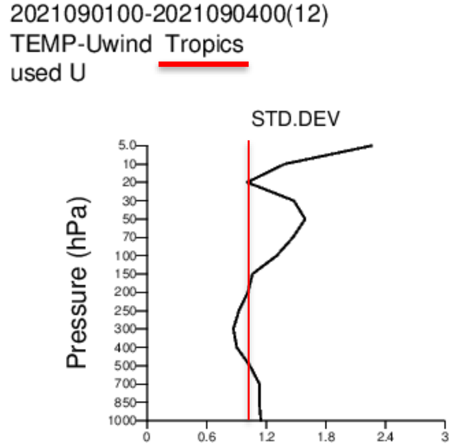


$E[\mathbf{d}_b^o(\mathbf{d}_b^o)^T] / \mathbf{R} + \mathbf{HBH}^T$

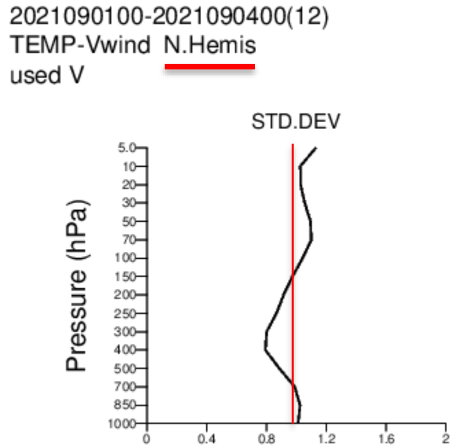


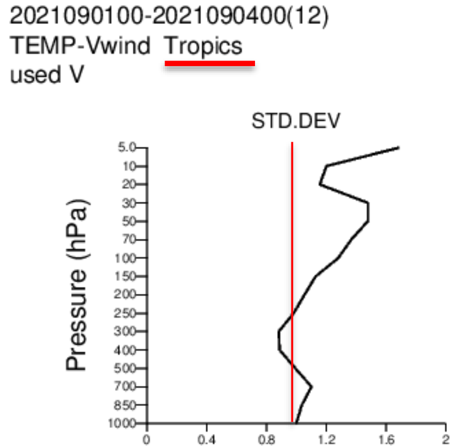
TEMP U-comp



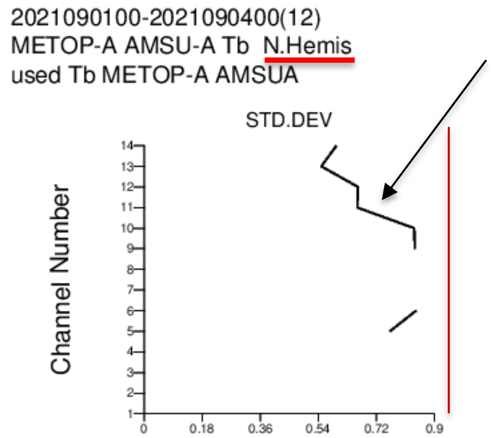


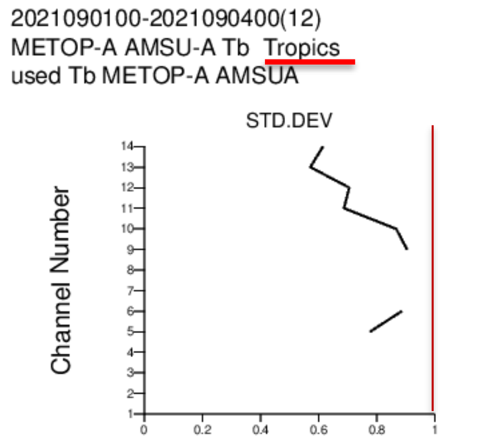
TEMP V-comp





METOP-A AMSUA

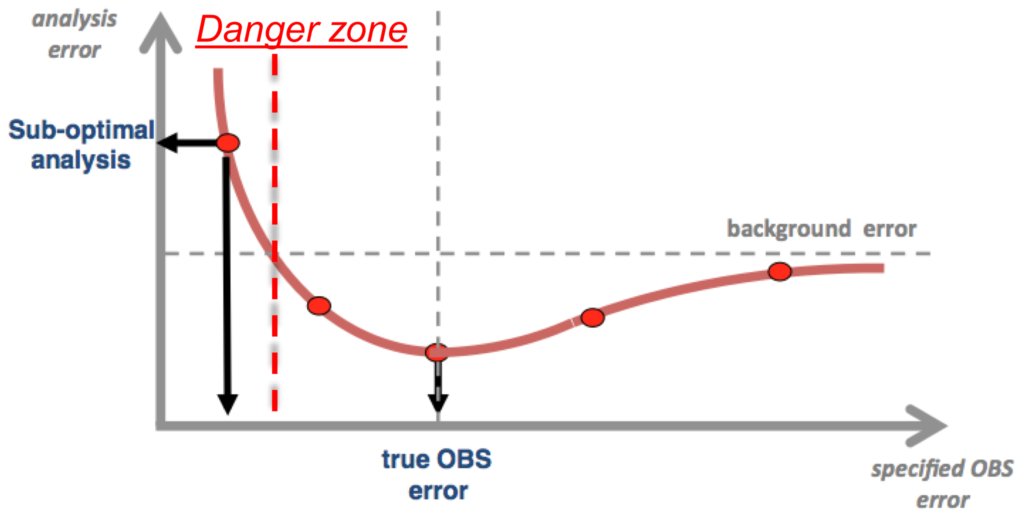




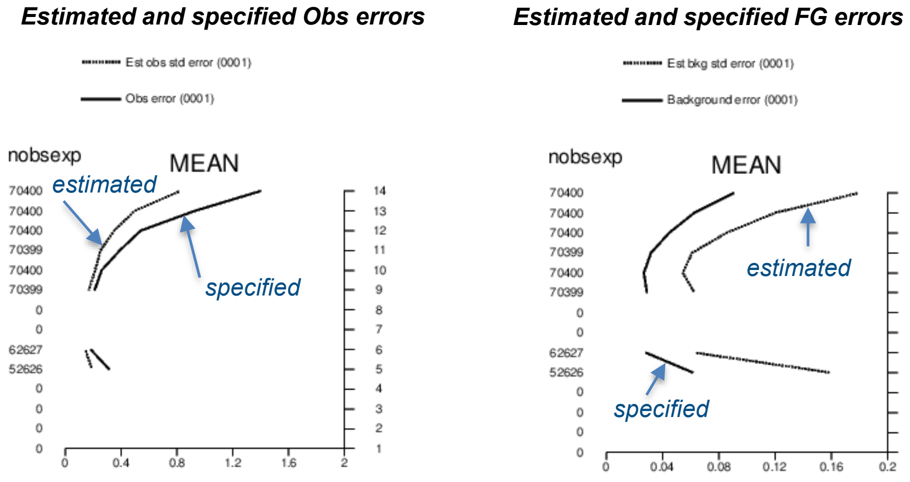
Diagnostics in observation space based on departures

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

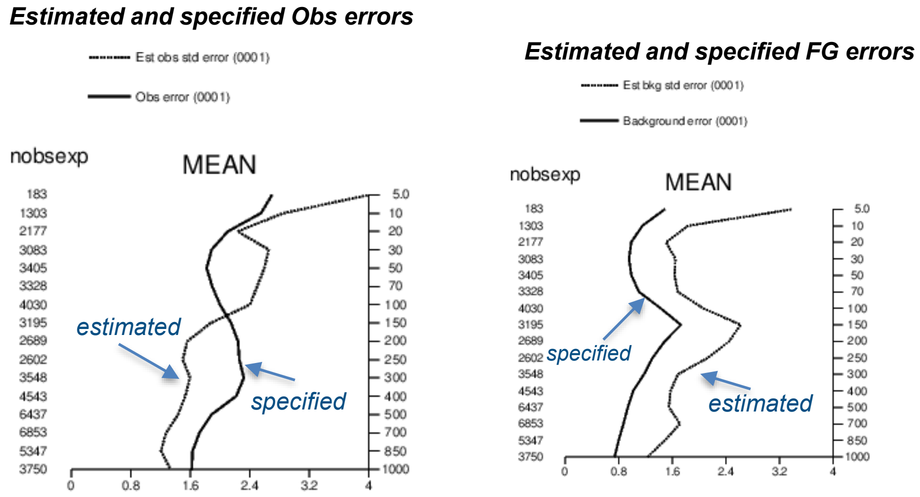
$$E[\mathbf{d}_b^a(\mathbf{d}_b^o)^T] = \mathbf{HBH}^T$$



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



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



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

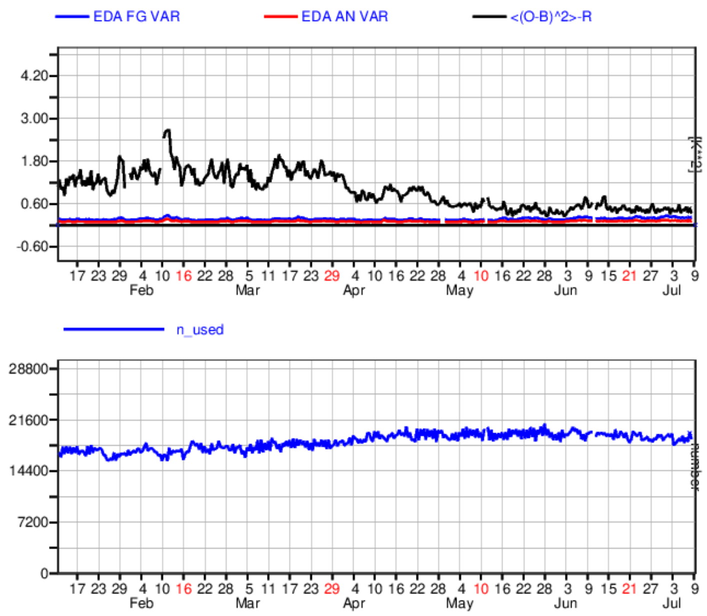
$$E[\mathbf{d}_{\mathrm{b}}^{\mathrm{o}}(\mathbf{d}_{\mathrm{b}}^{\mathrm{o}})^{\mathrm{T}}] = \mathbf{R} + \mathbf{HBH}^{\mathrm{T}}$$

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)

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



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

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