

# Characterization and Handling of Errors of Satellite Radiances for km-scale Data Assimilation over Three Operational Domains

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## Consortium

- ACCORD research and development consortium consisting of 26 countries for convection-scale limited-area modelling.
- Sub-consortia of ALADIN, LACE and HIRLAM.
- HIRLAM flavour of common modelling framework is referred to as HARMONIE-AROME. It consists of by HIRLAM quality assured modelling framework containing source-code and scripts prepared for operational use.
- HARMONIE-AROME used by several operational centers, including MetCoOp, UWC-W and AEMET.



## Runs over three operational domains

Extensive data assimilation experiments have been carried out over three operational domains (see Figure to the right) and for four different seasons. The aim was to evaluate and tune the performance of the data assimilation system.

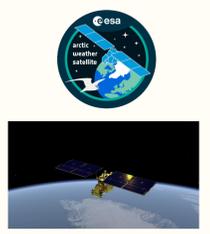
They have been run over a month period and with an observation usage roughly corresponding to operational use in each domain. These runs have formed the basis for results presented in this poster.



Model domains.

## Use of satellite radiances

- A clear-sky approach for operational assimilation of satellite radiances in the HARMONIE-AROME modelling system.
- RTTOV version 12.1.0.
- Micro-Wave radiances used resides from satellite-based instruments AMSU-A, MHS, ATMS, MWHS-2. To handle low-peaking channels we apply a dynamical emissivity approach.
- Infra-Red radiances resides from satellite-based instruments IASI and SEVIRI (as well as CRIS in preoperational model version).
- On-going preparations for FCI, AWS and MTG-IRS.



The Arctic Weather Satellite (AWS).

## First guess Check Rejection Limits

First-guess check to reject observations due to Gross errors

$$\{ |H(x_{b,i}) - y_i| \}^2 / \sigma_{b,i}^2 > L \times \lambda, (1)$$

where  $\lambda = 1 + \sigma_{o,i}^2 / \sigma_{b,i}^2$  L rejection limit and

$\sigma_{o,i}$  and  $\sigma_{b,i}$  - error standard deviations ( $\sigma_{b,i}$  from -file)

By default L=25  $\rightarrow$  reject obs if  $|y - Hx_b| > 5$  times  $\sqrt{\sigma_{b,i}^2 + \sigma_{o,i}^2}$

Tunable parameter: L

## Andersson&Järvinen TOOL to Diagnose Rejection Limits

Q. J. R. Meteorol. SOC. (1999). 125, pp. 691-122

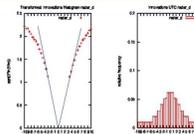
**AIM:** To select appropriate check limits (FgLim) for background check. Assumption is that observations with errors outside Gaussian distribution are affected by Gross errors and should be removed prior to the data assimilation.

**HOW:** Plots histograms and transformed histograms of innovations to identify when distribution starts to deviate from Gaussian and where to put rejection limit.

Transformation formula:

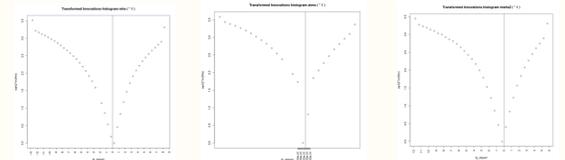
$$\hat{f} = \sqrt{-2 \ln(f / \max(f))}$$

Example for radial winds:



## Suggested changes of Rejection Limits

For radiances from MHS, ATMS and MWHS-2 instruments, diagnostics suggests a general reduction of L tunable value to 3. For data from the rest of the satellite sensors the currently used rejection limits are in accordance with diagnostics..



Transformed histograms for MHS, ATMS and MWHS-2 for MetCoOp domain.

## Thinning of satellite data

A thinning to alleviate effects of spatial observation error correlations not accounted for in the data assimilation. For each satellite instrument there is a horizontal thinning applied to minimize the effect of observations getting too close to each other. The thinning is applied in a step with multiple horizontal grid sizes with lengths RMIND (red dashed) and RFIND (black full), respectively. First one observation per finer size grid is chosen (larger grey dot) and then in a second final step one of those finer grid chosen observations per coarser resolution final grid is chosen (blue dot) and passed to the minimization.

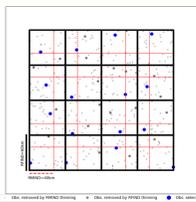


Illustration of thinning procedure

Tunable parameters: RFIND and RMIND

## Obstool TOOL to Diagnose the Thinning Distances

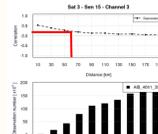
**AIM:** To set the thinning distances applied to high spatial density data in accordance with estimated observation error correlation length scales.

**HOW:** Based on DA feedback statistics files, innovations are separated into observation error correlations and background error correlations. From plots of the observation error correlation part, appropriate thinning distance is estimated with distance when the observation correlation drops to 0.2.

Derived observation error correlation as function of distance between data pairs.

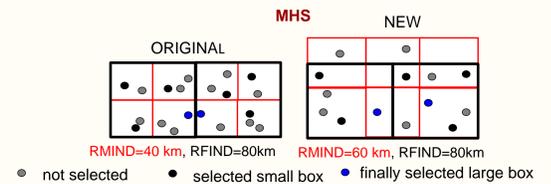
Example for satellite MHS channel 3 data

Number of data in each bin as function of distance between data pairs.



## Suggested changes on Thinning Distances after Diagnosis

For radiances from MHS maintain RFIND value but change RMIND value from 40 to 60km. We thereby reduce risk of close observations. For data from all other satellite instruments, diagnostics suggests to maintain both currently used RFIND and RMIND values.



not selected • selected small box • finally selected large box

## Background and Observation error scaling

Relative weight of background and observations in minimisation of J:

$$J = J_b + J_o = \frac{1}{2} \delta x^T B^{-1} \delta x + \frac{1}{2} (H \delta x + H \delta y - y)^T R^{-1} (H \delta x + H \delta y - y)$$

Tunable parameter: REDNMC

Tunable parameter: SIGMAO\_COEFF

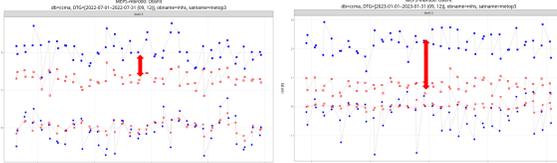
$\sigma_{o,i}$  and  $\sigma_{b,i}$  in different spaces (unbalanced temperature, humidity relative to radiance)

## MetCoOp operational observation monitoring

Metop C MHS channel 3 observation fit statistics time-series

Summer (July 2022)

Winter (January 2023)



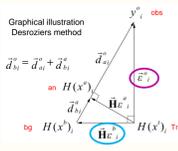
More weight to MHS observations during winter than during summer!

## DESROZIER'S TOOL to Diagnose the Background and Observation errors

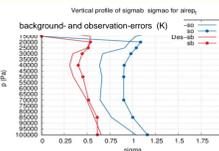
Q. J. R. Meteorol. Soc. (2005), 999, pp. 1-999

**AIM:** To compare used background- and observation-error standard deviations with theoretical ones calculated by Desroziers method and exploit if revisions needed

**HOW:** Use data assimilation feedback statistics of residuals and innovations from parallel experiments. Investigate plots of the current prescribed and the by Desroziers method suggested observation and background error standard deviation values.



Example for ABO temperatures



## BGOS TOOL to calculate Background errors in observation space

Application developed in the OOPS framework to compute background error standard deviation in observation space:

$$\sigma_{bg}^2 = \frac{1}{N} \sum_{i=1}^N (H U x_i)^2$$

where  $\sigma_{bg}^2$  bg error std in obs space  
N sample size

U is the series of transform applied to get a unit B matrix in minimization, H is the observation operator ( $(x_i, 1)$ ) and  $\delta$  is the control vector (containing Gaussian errors) for the individual member i.  
( $\delta x = U x$   $J_b = \frac{1}{2} \delta x^T B^{-1} \delta x = \frac{1}{2} x^T X$ )

## Main findings

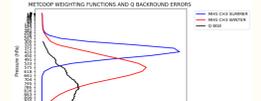
Analysis indicated that no change of observation error standard deviations for neither temperature nor humidity sensitive channels were needed for any instrument. Application of BGOS revealed **strong spatial and seasonal variation** for **humidity sensitive satellite radiances** background errors in observation space (despite background errors in model space constant). See example below for MHS radiances.



Background errors in MHS channel 3-4 observation space with standard operational MetCoOp B matrix. Black curve observation error, Blue winter background error in MHS ch 3-4 space and Red summer background error in MHS ch 3,4 space.

## The reason for spatial and seasonal variation for MHS

MHS channel 3 summer condition weighting functions  
MHS channel 3 winter condition weighting functions  
MetCoOp vertical profile of seasonally and spatially averaged used vertical profile of unbalanced background error specific humidity profile.



In cold and dry conditions (winter-time) the radiative transfer weighting function peak lower in the atmosphere and where the seasonally averaged humidity standard deviations are larger. Then, in cold conditions/winter-time we have larger background errors in observation space and therefore larger impact of observations.

## General Conclusions

- HARMONIE-AROME Cycle 46 has been subject to an extensive evaluation of tunable settings of data assimilation for three operational domains.
- Many tools to diagnose the performance of the data assimilation of satellite data have been adapted and developed for all kind of sensors and are made available in ACCORD to be used by the different countries.
- After a detailed analysis, just some minor revisions were proposed for rejection limits, thinning distances and observation and background errors values applied in the data assimilation of satellite observations.
- The application of BGOS revealed a weaknesses in our current handling of humidity sensitive channels in data assimilation.

## How to improve data assimilation of humidity sensitive channels?

- Introduce seasonally dependent background error statistics.
- Also change of humidity control variable in data assimilation or application of flow dependent data assimilation techniques would improve the handling.

Introducing seasonally dependent background error statistics

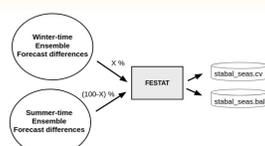


Figure C1. Illustration of proposed mix of seasonal input data for F2ESTAT. Winter: X=100 and seas=win, Summer X=0 and seas=sum, Autumn, Spring: X=50 and seas=aut, spr.

## Future work

- Continue experiments with revised tunable settings.
- Performs extended experiments with seasonally dependent background error statistics.
- Application diagnostics to new satellite instruments, such as AWS, FCI and MTG-IRS.
- Extend diagnostics to include all-sky.

## Acknowledgements

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