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Sensitivity studies of reflectivity assimilation impact in ALARO with focus on the drying effect

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1 Introduction

The main focus of this stay is the assimilation of radar reflectivity data within ALARO CSC. During the previous stays in 2021, [5] and 2022 [6], impact studies were performed, evaluating different options in the 1D+3D-Var assimilation method proposed by Wattrelot et al. [2] and focusing on the observed drying effect.

So far, having an offset-ed fixed table of MDRF values for all radar sites showed the most promising results. During this stay, we explored if a table of OPERA-prescribed MDRF values would alleviate the drying effect in ALARO CSC. Additionally, the impact of dry observations (flgdyn=0) for each radar separately is evaluated in order to see if drying is more pronounced at shorter distances from the radar site. For this evaluation, an already existing set of experiments performed in 2022 was used.

New approach with inflation of errors for dry observations is explored. This method aims to reduce the impact of undetected observations, giving way to actual radar measurements (flgdyn=8). Additionally, the treatment of dry observations with zero reflectivity first guess departures is evaluated. Specifically, part of the inversion routine checks if the model reflectivity value is lower than the dry reflectivity observation value and then sets first guess departures of such cases to zero by modifying the background values. These values then pass the sign-check routine. Second proposal is to reject such observations.

Both methods showed a decrease in the drying effect. Section 4 and 5 contain descriptions and results of both approaches for the dry summer period. Section 6 explores the impact of both approaches in wet winter conditions.

2 Experiment with prescribed MDRF values from the OPERA files

During the last stay [6], it was explored if a fixed table of climatological minimum detectable reflectivity factors (MDRF) at 1km from radar sites would alleviate the drying problem. All MDRF values were calculated from the longer period TH data for every radar separately. Experiments showed that applying an offset to the MDRF value reduced the drying effect. While improvement was visible, an open question remained if this was a viable solution.

A small number of radar sites provide the MDRF value in OPERA files, under the key NEZ or a pair of keys NEZH/NEZV (horizontally- and vertically-polarized component) if the radar is double polarized. In order to explore if these prescribed values from the OPERA files would provide a good enough representation for the dry observation values, a small subset of radars that provide NEZ value was chosen. Radars chosen are five new Croatian radars (hrbil, hrgol, hrgra, hrdeb and hrulj), two Slovenian radars (silis and sipas) and two Czech radars (czbrd and czska).

For these nine radars, MDRF values were calculated from the longer period TH data and compared to the prescribed ones (except for Czech radars as they don't have prescribed MDRF values written in OPERA files, but they are known). Due to the usage of new Croatian radars (the newest radar set up on 25th November 2022.), the period chosen for the MDRF value calculation is 07.01.2023-25.01.2023. MDRF value is computed as a minimum of measured values for each radar and elevation separately during this period. Then, for each radar, the minimum of these values is used in the data assimilation process to apply to all dry observations. More details on how this is applied can be found in Panežić et al. [6]. During this period of 17 days, two radars (silis and czbrd) showed a drastic change in calculated MDRF values [Figure 1].

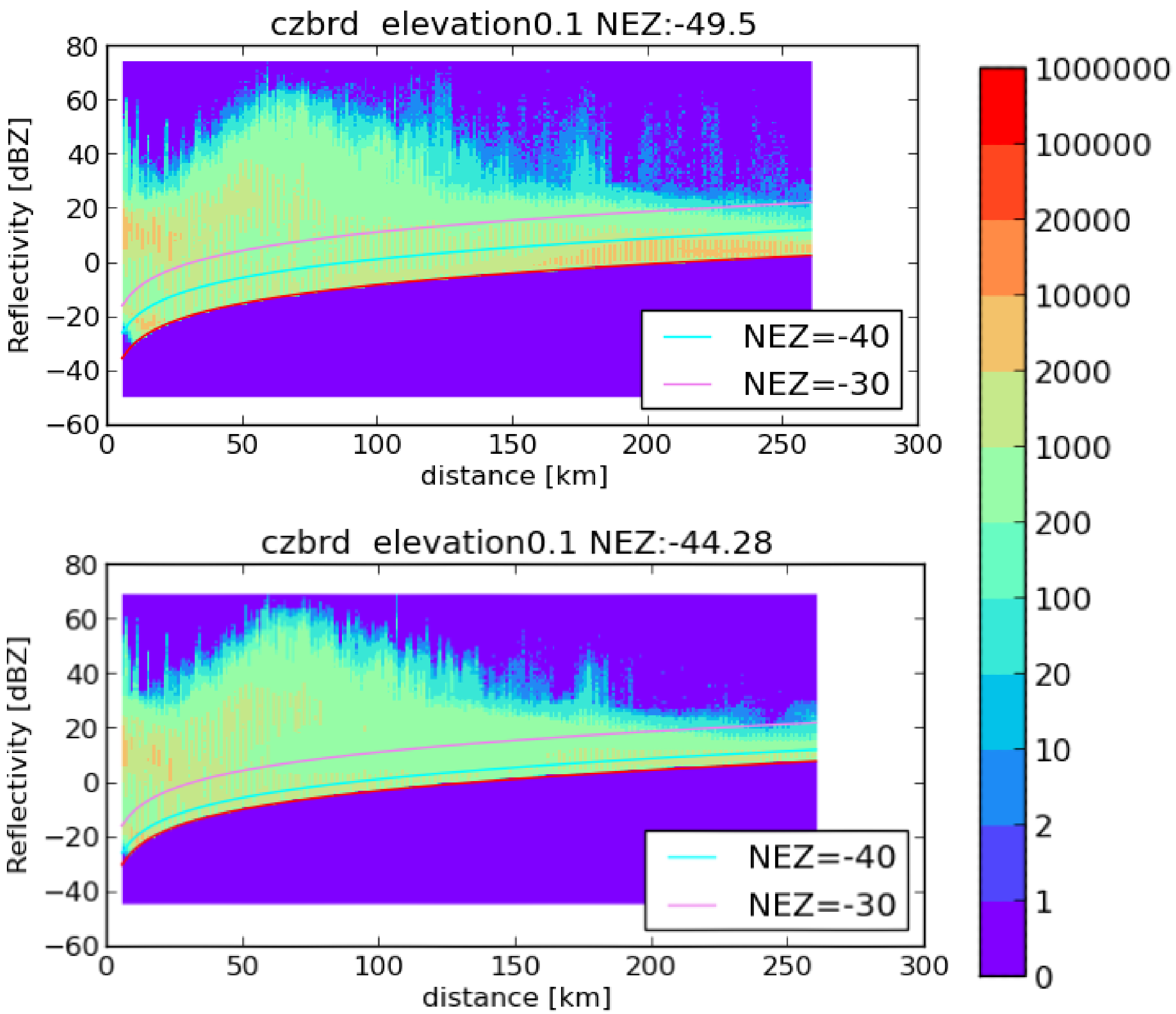

Figure 1: Radar czbrd 0.1 elevation TH data heatmap with calculated MDRF values (NEZ in OPERA files) for 09.01.2023 (upper picture; NEZ=-49.5) and 11.01.2023 (lower picture; NEZ=-44.28).

After investigation, it was confirmed that both radars were turned off for maintenance after which the MDRF value in OPERA files also changed. On top of that, radar czska had a hardware problem and was due to be repaired. It was explained that MDRF changes between two radar maintenance happen periodically, once or several times a year, depending on the meteo service [personal communication with Anton Zgonc]. For this reason, it would be very challenging to keep a fixed MDRF table up to date for operational use.

2.1 Experiment setup specification

In order to answer the question if prescribed MDRF values would solve the drying problem, a dry case was selected to be evaluated (1.1.2023-3.1.2023) and the radar subset was reduced further to Croatian and Slovenian radar network only [Figure 2]. This period showed no drastic changes in MDRF values for selected radars.

- AOS - reference without radar DA
- AUR - active radar DA with MDRF values diagnosed by BATOR
- AUM - active radar DA with MDRF values calculated from the raw data
- AUF - active radar DA with prescribed MDRF values from OPERA files

Values of MDRF used in AUM and AUF experiments can be found in Table 1. It can be seen that prescribed MDRF values are consistently higher than climatological (calculated) ones for a few decibels. The origin of these differences is still unclear and should be further explored.

Table 1: MDRF values for selected radars.

	hrbil	hrgol	hrgra	hrdeb	hrulj	silis	sipas
Calculated MDRF	-49.4800	-52.1000	-49.2000	-52.5000	-48.5700	-39.0000	-44.6300
Prescribed MDRF	-43.3750	-45.6875	-43.6875	-46.4375	-44.2500	-31.1875	-39.0625

2.2 Model setup specification

All experiments used the ALARO/CZ operational configuration with recently implemented prognostic graupels. The effect of prognostic graupels on the radar reflectivity observation operator was not investigated.

- Model: ALARO NH-v1B cy43t2ag_op1
- Domain: ALARO/CZ; $\Delta x = 2.3$ km; 1069x853 GP; 87 vertical levels; mean orography,
- Coupling: 3h space consistent coupling from ARPEGE; synchronous
- Upper air analysis: BlendVar scheme (DF blending, filtering at truncation E102x81) followed by 3D-Var; 6h Assimilation cycle; REDNMC=0.5, Ensemble data assimilation B matrix based on AEARP;
- Assimilated observation: SYNOP, TEMP, AMDAR, SEVIRI, Mode-S MRAR/Mode-S EHS, HR-AMV, wind profiler, ASCAT.

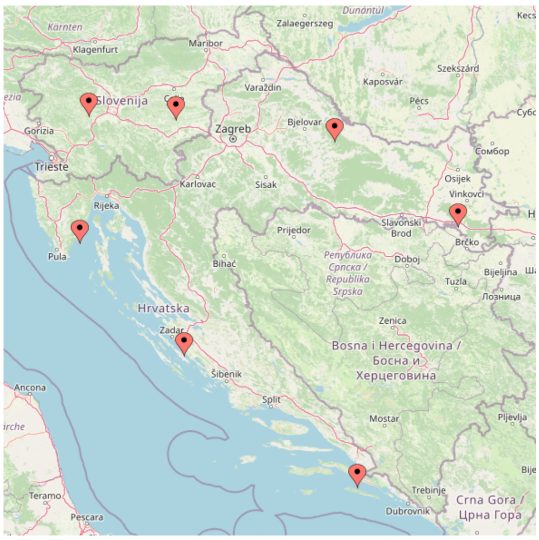

Figure 2: Radars used in the experiment

2.3 Results

For the purpose of this experiment, the verification domain was also reduced to the Croatian and Slovenian domain alone. A new whitelist, containing SYNOP and TEMP station id's, for VERAL tool was created from existing ECMA databases and was used for verification. Results showed a strong drying bias and increased standard deviation when calculated MDRF was used, but the difference in scores between prescribed MDRF and BATOR calculated one was rather minimal [Figure 3]. Since the model, in this case, is too wet and drying is preferred it can't be concluded that the drying effect was removed. The negligible difference between AUF and AUR experiments might also be due to a very small sample of radars or the shortness of the selected period, so no firm conclusion was made. This should be explored further.

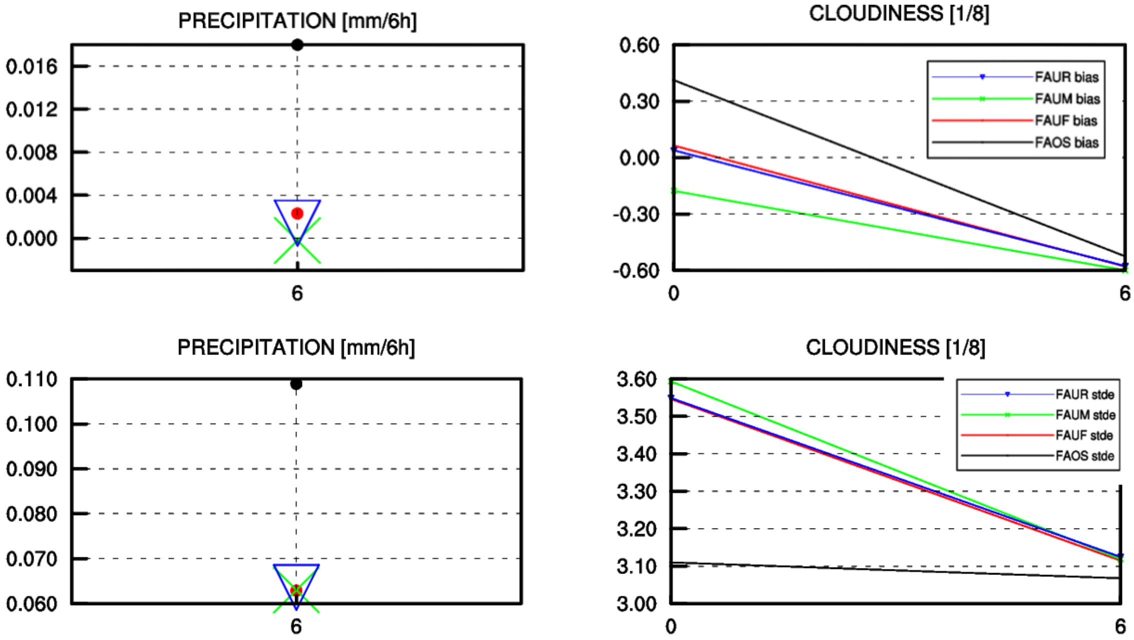

Figure 3: Bias and standard deviation of 6h precipitation (left) and cloudiness (right) for 1.1.2023-3.1.2023 period; experiments AOS, AUR, AUM and AUF

3 Evaluation of dry data impact

Having an already large set of experiments from the 2022 stay, no additional ones were performed for this evaluation. ODB statistics from the 2022 ASN experiment (default radar DA + MF BATOR code modification) were explored, as no dry observation treatment was applied to it yet. This experiment covers the period 20.6. - 30.6.2022 and includes several extreme precipitation events in the Czech Republic. An evaluation was performed on all data and only active data separately.

Idea was to see if any visible pattern as to where the drying effect occurs is present. Since near the radar site radar beam might not reach the base of the cloud it might underestimate the reflectivity values. Also, in case there is a larger number of dry observations near the radar, there was a possibility that strong drying might appear due to low reflectivity values applied to them. These values are given with a logarithmic function of distance [Figure 4] from the radar:

$$zthreshold(r) = MDRF + 20log_{10}(r) \tag{1}$$

where r is the distance from the radar site. What was explored is the dry observation impact and spread of first guess departures depending on the distance from the radar, for each radar site separately.

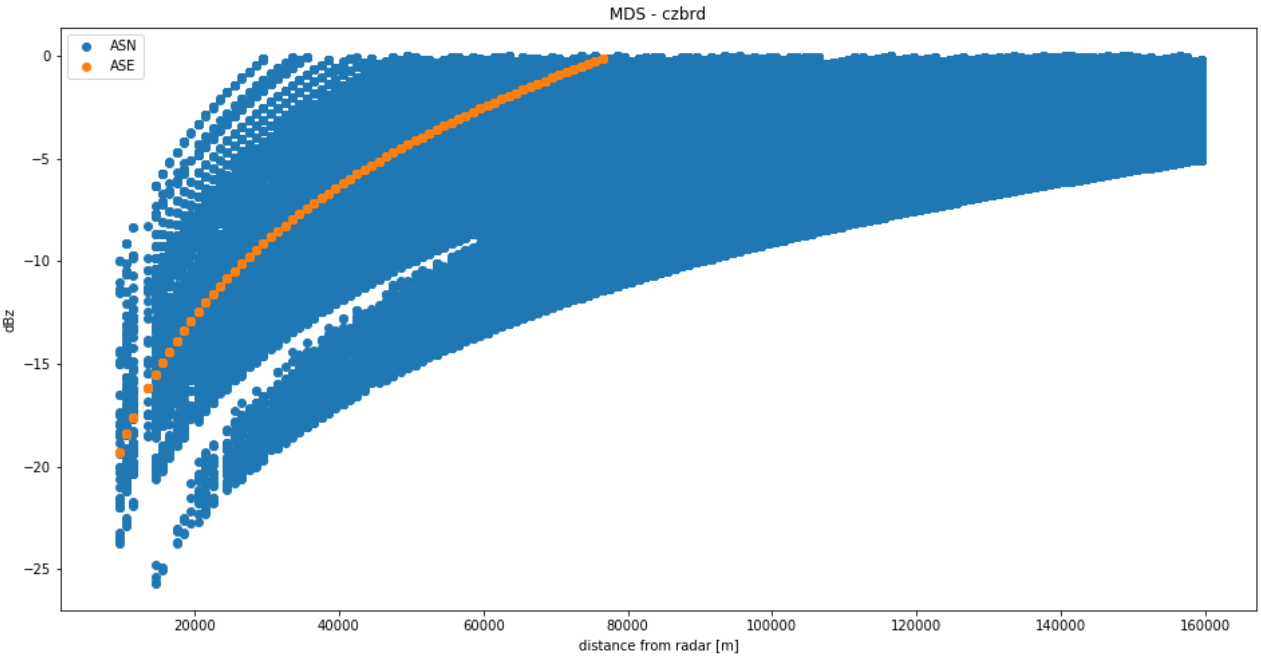

Figure 4: Radar czbrd - reflectivity values applied to the dry observations by BATOR (blue dots, ASN experiment) and when a fixed value (climatological with an offset) of MDRF is applied (orange dots, ASE experiment); picture from Panežić et al. 2022.

No significant drying near the radar site was observed during the evaluation. In fact, depending on the radar, there were very little or no dry observations at all near the radar site [Figure 5 and Figure 6]. On most radar sites, there was no dry observations on distances lower than 10 km, which is already enough to reject the idea that drying effect is directly linked to the dry observation values near the radar.

On average, most dry observations were situated at middle distances from the radar site. No obvious pattern in the dry observation first guess departure distribution was observed. Some radars showed increased drying on shorter distances [Figure 5], some on longer distances [Figure 6], while some showed consistent drying everywhere, etc.

What was apparent, though, was that the amount (red dashed line) of dry observations was significantly higher than the amount of wet ones. Also, for dry observation first guess departures can be as equally large or even larger than they are for the wet observations (blue box plots). Box plots show that both dry and wet observations can dry and moisten the atmosphere. But looking at the median (green line in box plots), we can say that dry observations mostly dry and wet observations mostly moisten the atmosphere.

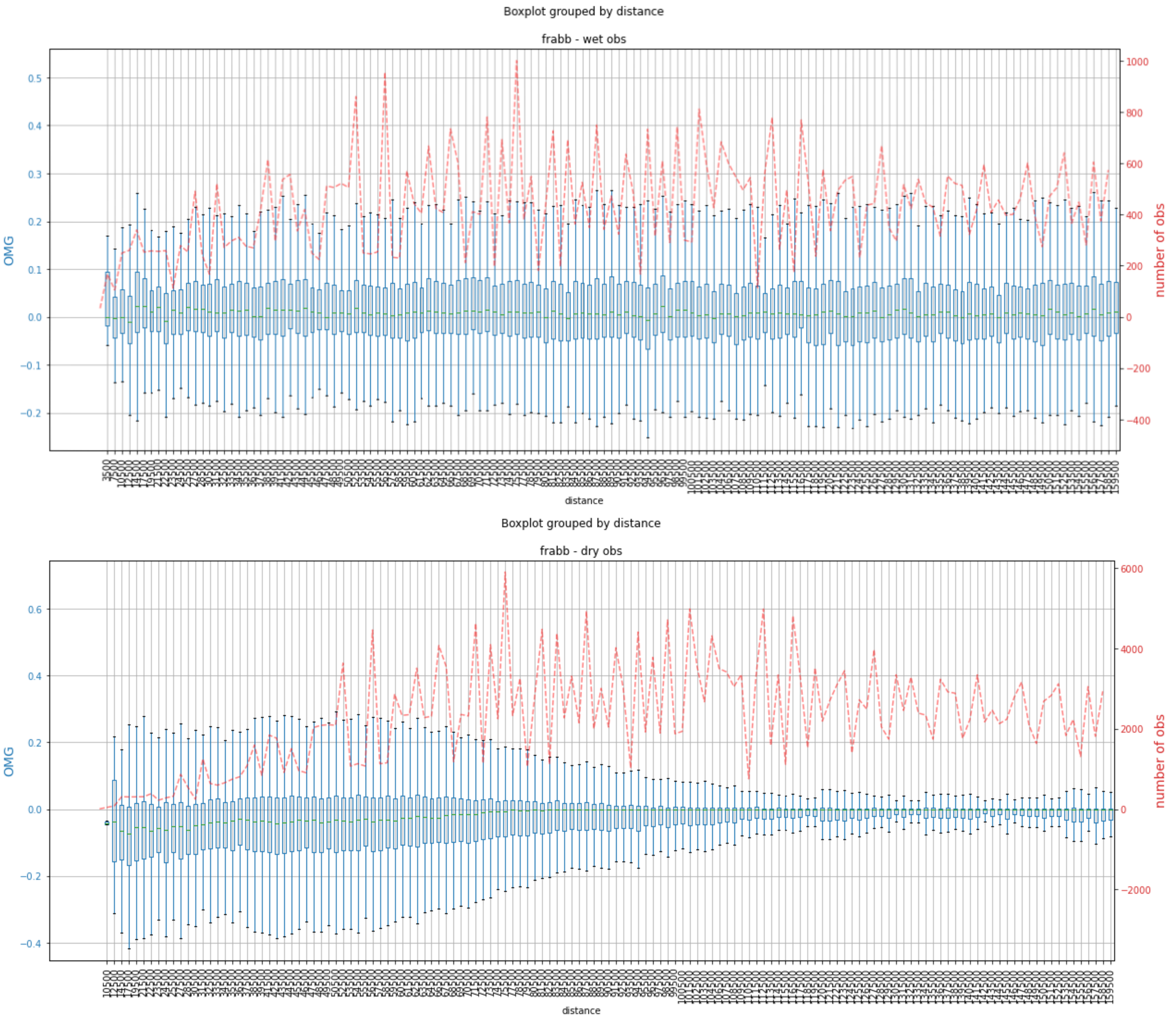

Figure 5: Radar frabb - boxplot of first guess departures grouped by distance from the radar (blue) and number of observations at the selected distance (red); split by type of radar observation data - wet (upper picture) and dry (lower picture).

Figure 6: Radar ndhl - boxplot of first guess departures grouped by distance from the radar (blue) and number of observations at the selected distance (red); split by type of radar observation data - wet (upper picture) and dry (lower picture).

Impact of relative humidity pseudo-observations during the data assimilation is also explored for the ASN experiment. 2D histograms of relative humidity values per height were created from the actively assimilated data (CCMA database) [Figure 7]. This means, that the model values were extracted from the first guess and analysis departures and compared to the observed ones. On the left are histograms of RH model values from the first guess for wet (upper pictures) and dry (lower pictures) observation locations. On the right are corresponding histograms with model values extracted from the analysis. Solid and dashed black lines represent medians for observation values and model values respectively. In a sense, this is a visualization of what happens during the radar reflectivity data assimilation.

We can see that model and observation medians for dry observations come closer together than they do for wet observations. This would imply that the process is not very balanced and that there is a larger impact of dry observations on the analysis.

4 Inflation of the dry observation error

Given the larger influence of dry observations, a new approach was explored. Since dry observations are not actual measurements but values applied to unobserved data, their credibility is questionable. In order to reduce the influence of more numerous dry observations and to favor wet observations that are true measurements, it is proposed to increase the error of dry observations.

By default, observation error of the relative humidity pseudo-observations is given as a function of distance from the radar as per Wattrelot et al. [2]:

$$\sigma_o^{RH} = 0.15 + \frac{0.25 \times r}{160} \tag{2}$$

where r is the distance from the radar. The values of observation error applied during the data assimilation process are the same for both dry and wet observations (no distinction is made) and vary between 15% and 40%, according to the distance from the radar. The proposed approach splits the observation error values on dry and wet. Observation error for wet observation remains as is defined in formula 2, while for the dry observations an offset is applied:

$$\sigma_o^{RH} = 0.15 + \frac{0.25 \times r}{160} + offset \tag{3}$$

In the case of a 10% dry observation error increase, we will get values of 25% to 50% applied to dry pseudo-observations, depending on the distance from the radar. For wet observations, values of 15% and 40% will remain [Figure 8].

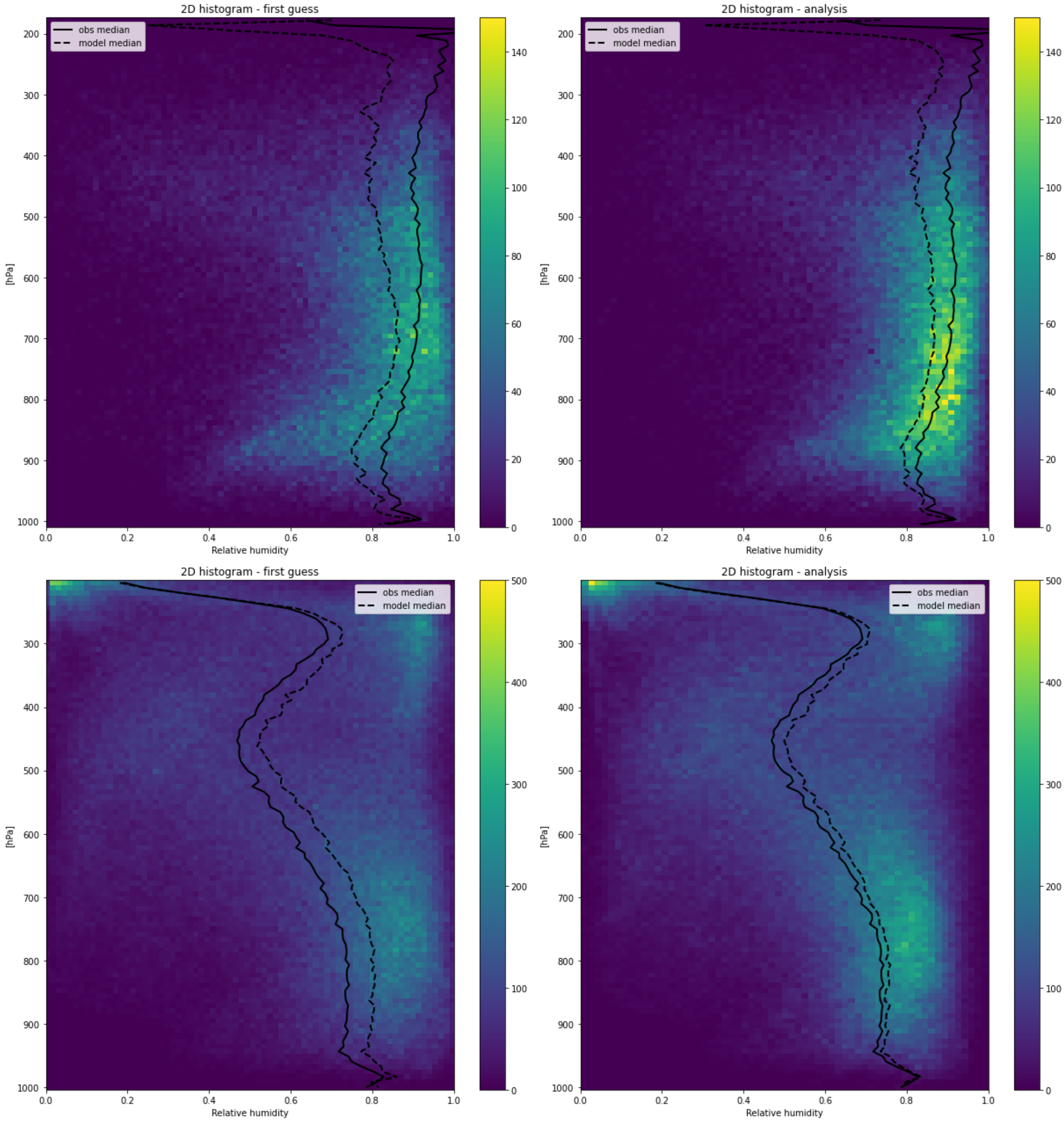

Figure 7: 2D histogram of RH model values at observation locations for period of 20-30 June 2022. The relative humidity per height for ASN experiment first guess (left pictures) and analysis (right pictures); split by type of observation: wet (up) and dry (down).

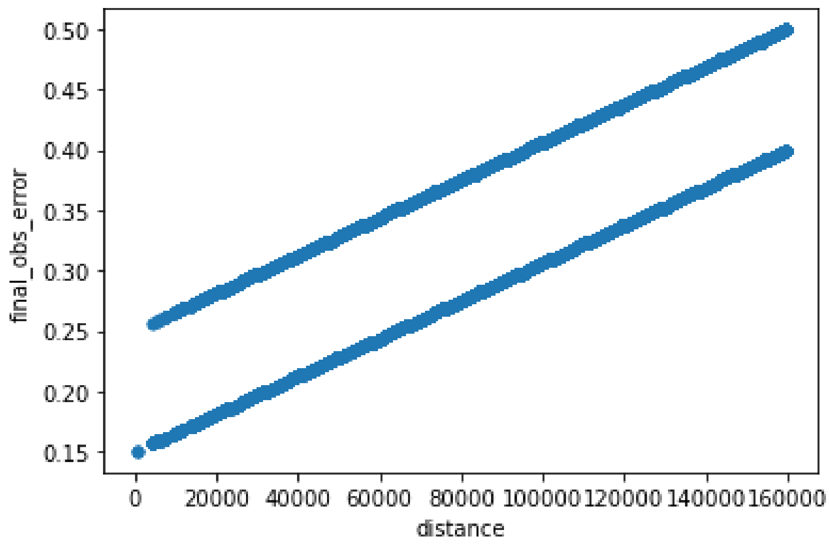

Figure 8: Separation of dry (upper line) and wet (lower line) observation error applied to the relative humidity pseudo-observations, taken from CCMA database.

Modified sources:

`Odb/pandor/module/bator_ecritures_mod.F90`

New BATOR related logical keys and variables:

- LINFLERRDRY - logical key that separates RH pseudo-observation observation errors to dry and wet; default value is FALSE
- ZERRDRYOFFSET - variable that defines the value of the offset in formula 3; default value is 0.0

In order to explore sensitivity to the dry observation error inflation, several experiments were created:

- AOP - no radar data assimilation, reference experiment
- ASN - active radar DA with MF BATOR code modifications (no dry data above 0dBz)
- AIE - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), 10% dry observation error increase
- AI3 - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), 30% dry observation error increase
- AI5 - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), 50% dry observation error increase
- AI7 - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), 70% dry observation error increase

Experiments were performed during the same period and with the same model setup that was analyzed in Panežić et al. 2022. All experiments were using BATOR-calculated MDRF values, equivalent to ASN experiments. The radar data assimilation was set to use the model profile selection box size of 100km and the reflectivity observation error $\sigma = 0.2$. Experiments were carried out over the period 20.6.2022 - 30.6.2022 containing several extreme precipitation events in the Czech Republic. As the impact of data assimilation in LAM is usually prominent in the forecast up to 6 -12 hours, only 6 hourly data assimilation cycle was performed and evaluated.

2D histograms of relative humidity values per height for AI3 experiment show less impact of the dry observations, while the impact of wet observations increases [Figure 9]. When compared to the ASN experiment 2D histograms [Figure 7], it appears there is now more balance between dry and wet observation impact.

Verification showed a clear reduction of the drying effect with the dry observation error increase. Vertical verification scores also show better agreement of the analysis with respect to TEMP observations. The forecast shows a decrease in bias as well, with scores worse than the operational setup between 300 and 500 hPa [Figure 10]. It is also visible that increasing the error above 50% no longer gave any significant benefit, while the standard deviation of the 6h precipitation accumulation largely increased [Figure 11].

Spatial verification, using useful fraction skill score, also shows improvement of the precipitation fields for all experiments [Figure 12]. The same can be observed by looking at the precipitation fields themselves [Figure 13], showing the increase in the precipitation amount and the improvement in spatial structure. But it is also obvious that increasing the dry observation error by 50% produces too large maximums in the convective system [Figure 14]. This implies that such an increase in dry observation error might now be suppressing dry observations too much. From these results, it can be assumed that the point of degradation is somewhere between 30% and 50% dry observation error increase.

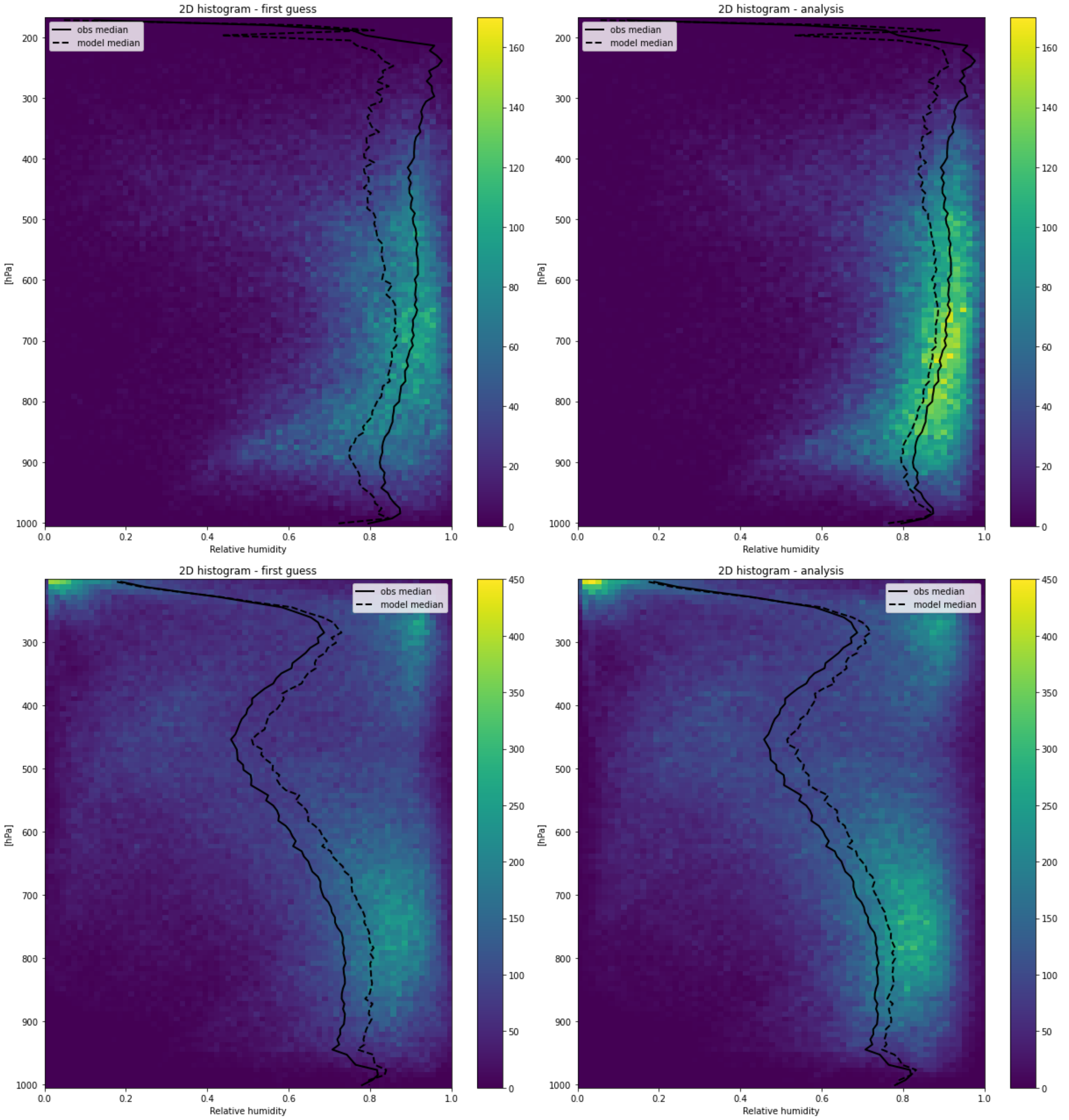

Figure 9: 2D histogram of RH model values at observation locations for a period of 20-30 June 2022. The relative humidity per height for AI3 experiment first guess (left pictures) and analysis (right pictures); split by type of observation: wet (upper pictures) and dry (lower pictures).

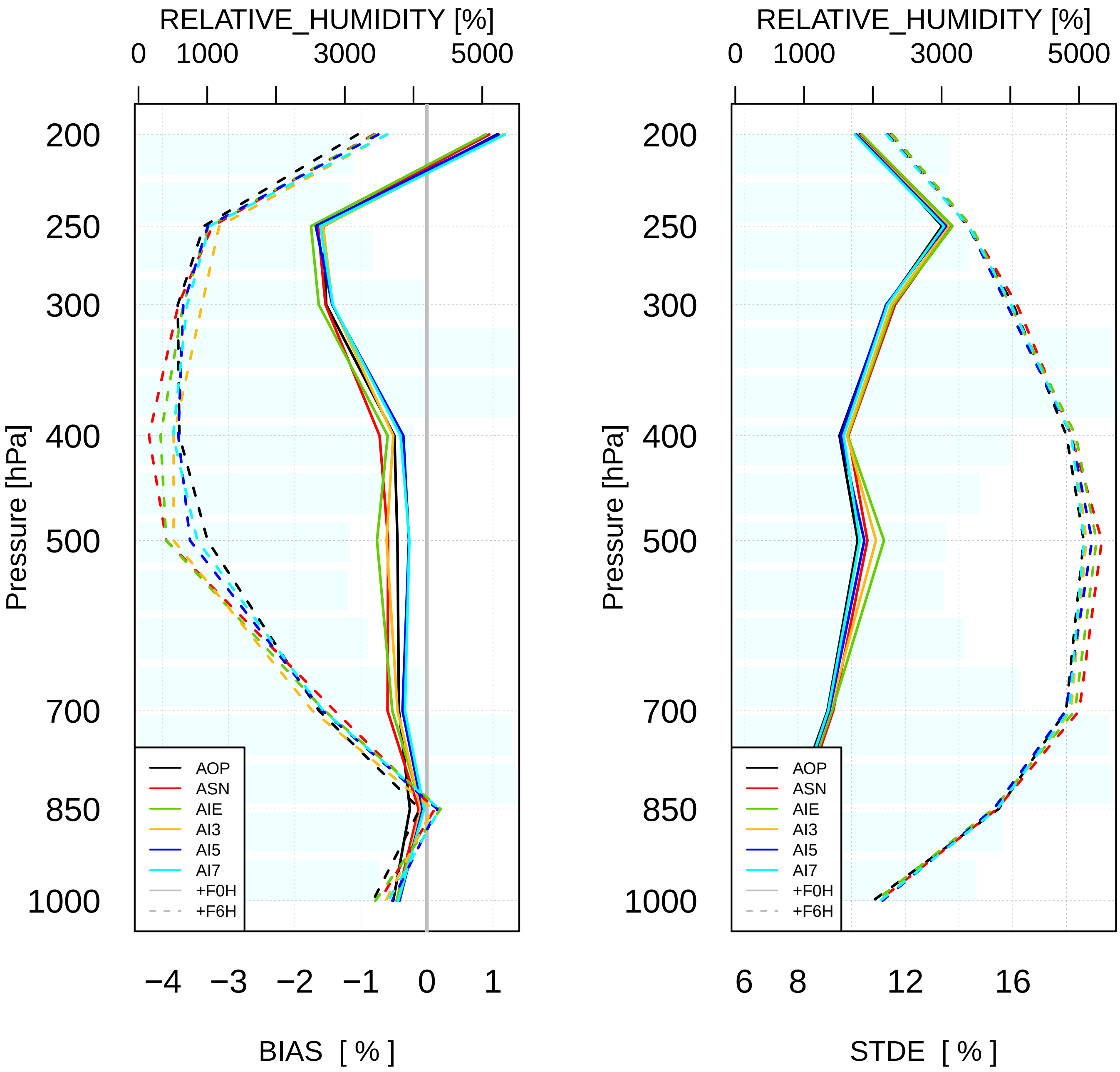

Figure 10: BIAS (left) and STDE (right) of relative humidity for reference experiment AOP and radar experiments ASN, AIE, AI3, AI5 and AI7 over the assimilation period of 20-30 June 2022 for all network times (00, 06, 12 and 18 UTC).

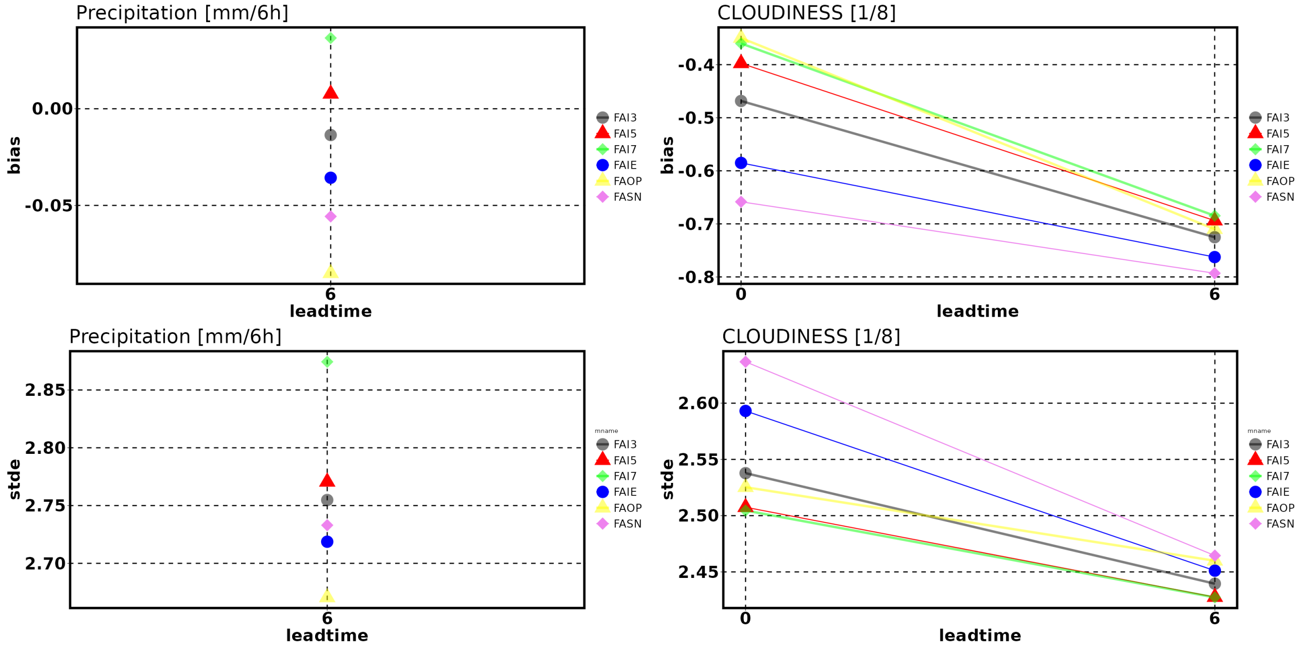

Figure 11: BIAS (upper pictures) and STDE (lower pictures) of the 6h precipitation accumulation and cloudiness for reference experiment AOP and radar experiments ASN,AIE, AI3, AI5, and AI7 over the assimilation period of 20-30 June 2022 for all network times (00, 06, 12 and 18 UTC).

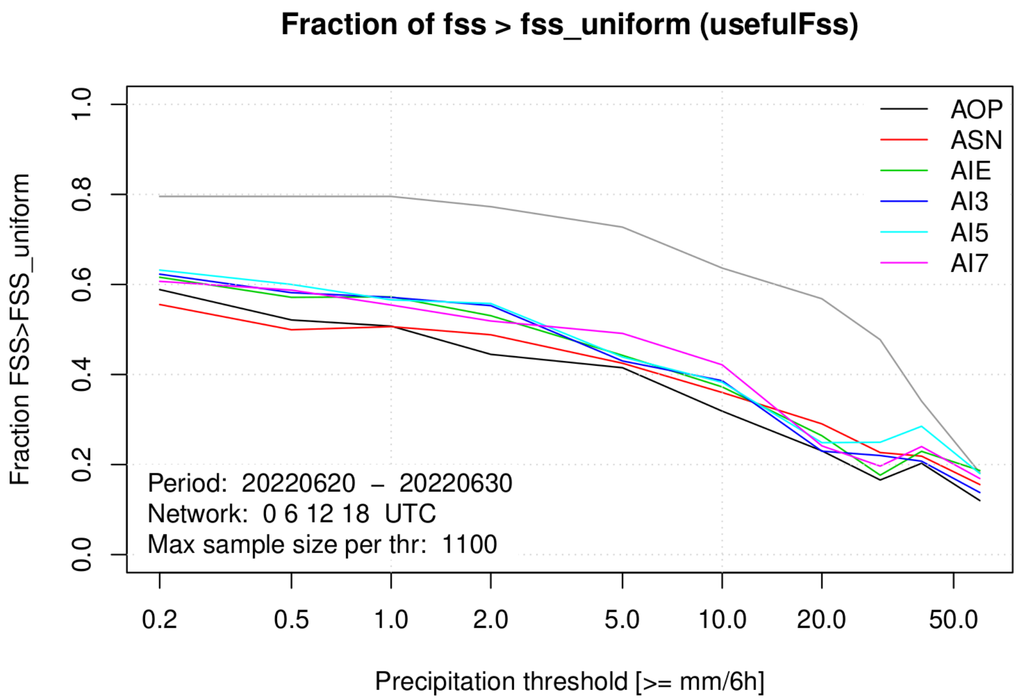

Figure 12: The fraction of forecasts which are useful (FSS > FSS_uniform). The grey line shows the percentage of cases when both observed and forecasted precipitations exceed the defined threshold at least at one point.

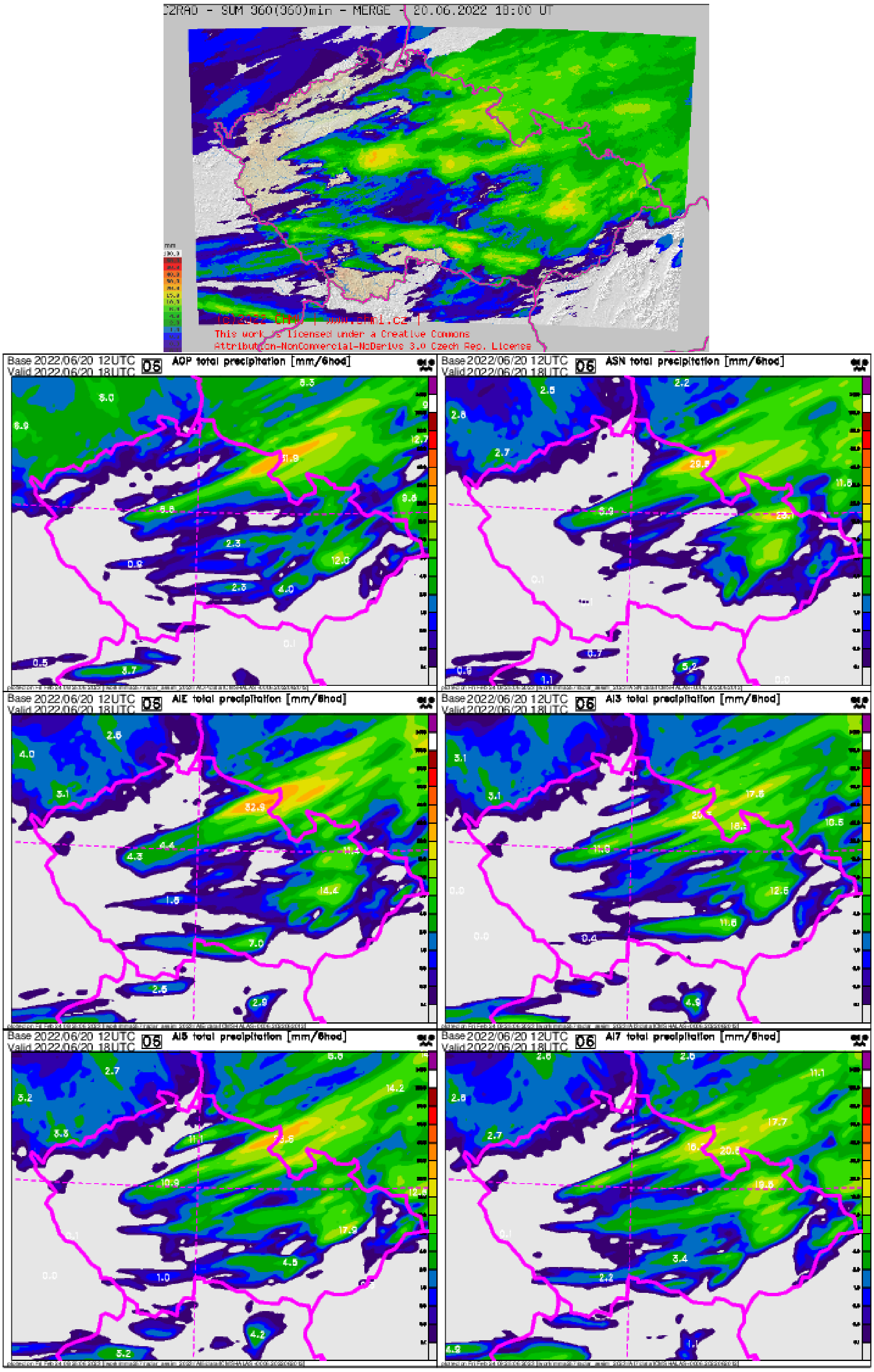

Figure 13: The 6h precipitation forecast for 20 June 2022 12UTC for lead time of +06h for experiments AOP, ASN, AIE, AI3, AI5 and AI7 and observations – radar and rain gauges based quantitative precipitation estimate (top).

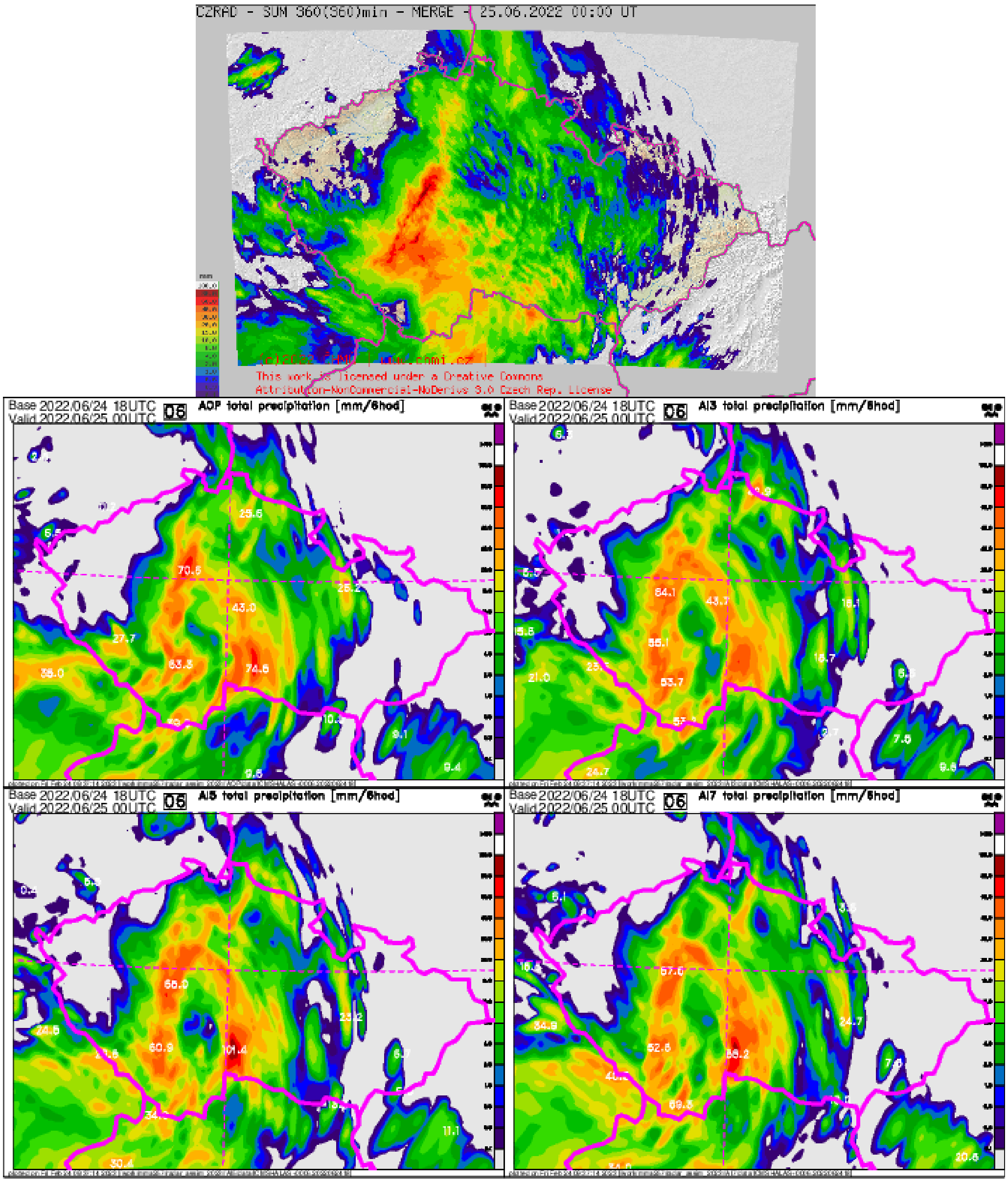

Figure 14: The 6h precipitation forecast for 24 June 2022 18UTC for lead time of +06h for experiments AOP, AI3, AI5 and AI7 and observations – radar and rain gauges based quantitative precipitation estimate (top).

5 Additional removal of dry observations

Independently of the previous suggestion of observation error inflation, Antonín Bučánek (personal communication) proposed removing dry observations with flipped signs to combat the drying effect. This approach was analyzed separately and when combined with the observation error inflation. Specifically, part of the inversion routine checks if the model reflectivity value is lower than the dry reflectivity observation value and then sets first guess departures of such cases to zero by modifying the background values ($REFL_M = REFL_O$):

```
Arp/op_obs/inv_refl1dstat.F90

IF (SATBODY%DATA(IIBODY,SATBODY%FLGDYN_AT_RADAR_BODY) == 0 .AND.
PREFL2D(JLEN,JJCOUNT,JPROF) < ROBODY%DATA(IIBODY,ROBODY%OBSVALUE_AT_BODY)) THEN
    PREFL2D(JLEN,JJCOUNT,JPROF) = ROBODY%DATA(IIBODY,ROBODY%OBSVALUE_AT_BODY)
ENDIF
```

Later in the code, there is a check of signs between reflectivity observations and their relative humidity pseudo-observation counterparts:

```
Arp/obs_preproc/flgtst.F90

LLMDBOMF_REFL=(ROBODY(IPOS,MDBOMF) > 0)
    IF ( (LLMDBOMF_REFL .AND. (ROBODY(IPOS+1,MDBOMF) < 0)) .OR. &
    & ((ROBODY(IPOS,MDBOMF) < 0) .AND. (ROBODY(IPOS+1,MDBOMF) > 0))) THEN
        ROBODY(IPOS+1,MDBDSTA) = ZCHSTAT_REJECT(ROBODY(IPOS+1,MDBDSTA))
        ROBODY(IPOS,MDBDSTA) = ZCHSTAT_REJECT(ROBODY(IPOS,MDBDSTA))
    ELSE
        ROBODY(IPOS,MDBDSTA) = ROBODY(IPOS+1,MDBDSTA)
    ENDIF
```

This part of the routine checks signs between first guess departures. If reflectivity observation implies that the model is too dry, then the relative humidity counterpart should moisten the model (and another way around). In cases where the sign of relative humidity first guess departures flips (as opposed to reflectivity ones), such observations should be rejected.

But this part of the routine doesn't check the cases where first guess departures are equal to zero, such as from the inv_refl1dstat.F90 routine. The proposed modification is to include such cases in the sign check routine. The idea is that if the model is already drier than the dry observation, then we should not dry the model further through the relative humidity counterpart of the inversion routine (Antonín Bučánek personal communication).

Modified sources:

```
Arp/obs_preproc/flgtst.F90
```

New SCREENING related logical keys and variables:

- LFGDEP0FIX - logical key that includes zero first guess departures of reflectivity for a sign check; default value is FALSE

The list of sensitivity experiments is as follows:

- AOP - no radar data assimilation, reference experiment
- ATN - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), check sign modification
- AT3 - same as ATN, with 30% dry observation error increase
- AI3 - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), with 30% dry observation error increase

From the ODB statistics [Figure 15] and 2D histogram of relative humidity [Figure 16], it can be seen that a large number of dry observations was removed by including zero first guess departures to the sign check routine (experiment ATN and AT3). Consequently, the impact of dry observations in the upper atmosphere has now turned toward moistening the atmosphere.

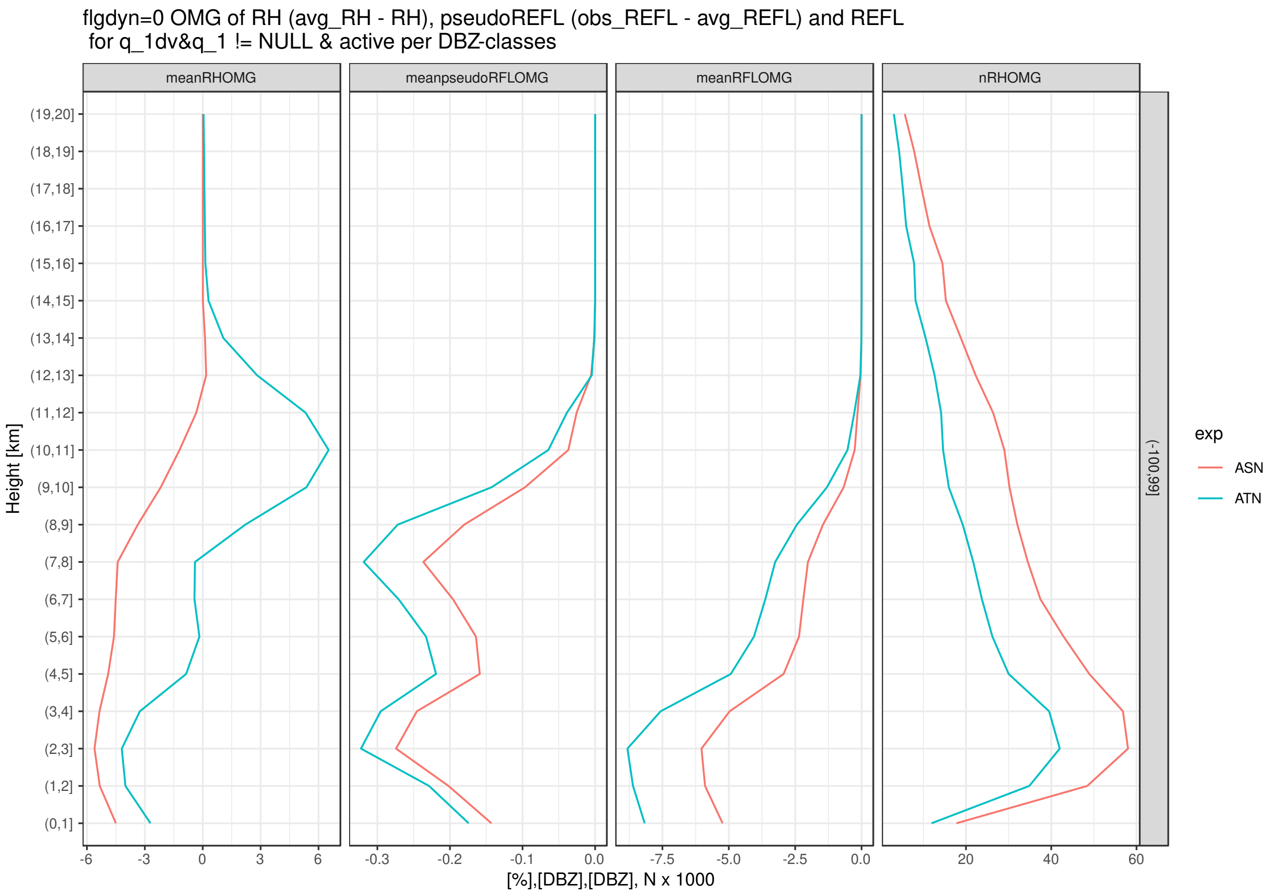

Figure 15: BIAS of departures for pseudo-observed RH, pseudo-observed reflectivity and simulated reflectivity and their count for dry observations in ASN and ATN experiments; calculated for the period of 20-30 June 2022.

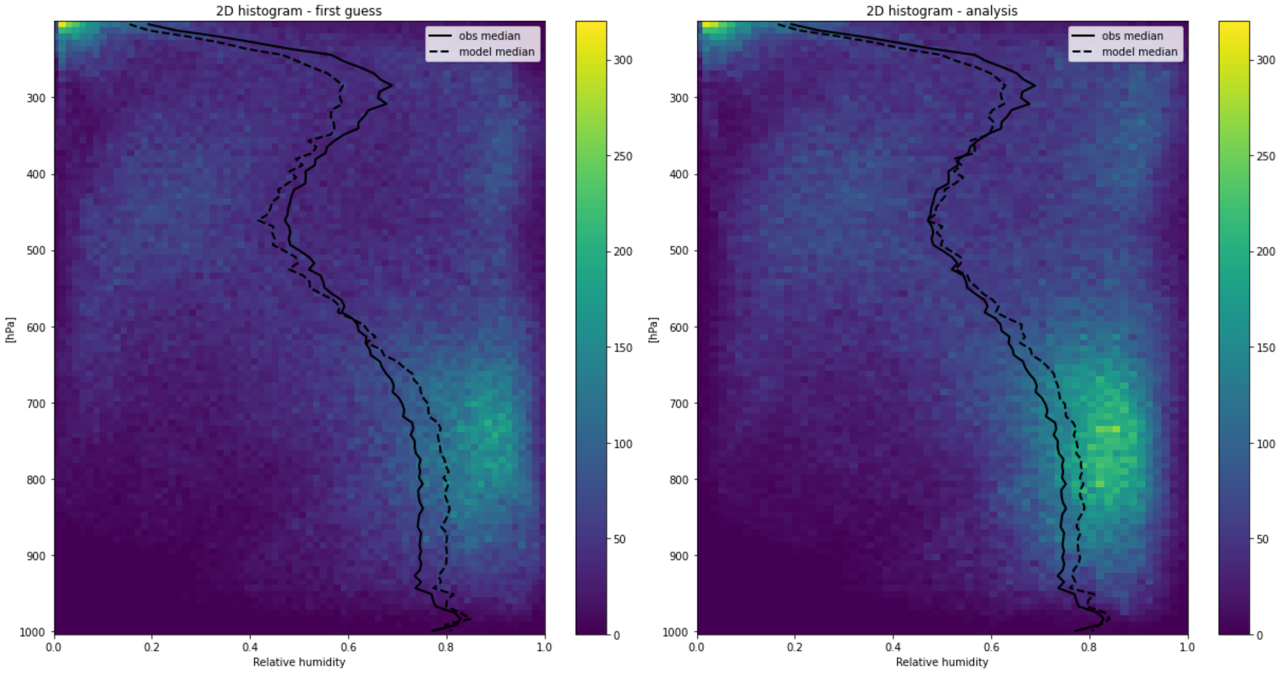

Figure 16: 2D histogram of RH model values at observation locations for period of 20-30 June 2022. The relative humidity per height for AT3 experiment first guess (left pictures) and analysis (right pictures) for dry observation.

While this modification alone (ATN) shows a significant removal of the drying effect in both cloudiness and relative humidity biases [Figure 18 and Figure 17], it also shows the increase in the precipitation amount and spread of the case of severe convection (threshold above 60 mm) [Figure 20]. Further tests are needed to evaluate if this code modification is now adding too much moisture into the atmosphere.

Experiment AT3 shows that reducing the dry observation impact (by inflating the dry observation error) on top of modifications made in ATN experiment reduces the appearance of such increased precipitating maximums [Figure 20]. Reduction of upper air moisture can be seen in the vertical profile bias [Figure 17] as well. From the same picture, it is visible that AT3 shows the best agreement (from all experiments) with the TEMP measurements at the analysis time (VERAL scores were verified against TEMP measurements) up until 400 hPa. It also reduces the bias and standard deviation of cloudiness, creating better scores than even the operational reference experiment [Figure 18].

AT3 experiment also shows more consistent behavior in useful fss scores, than both AI3 and ATN experiments [Figure 19].

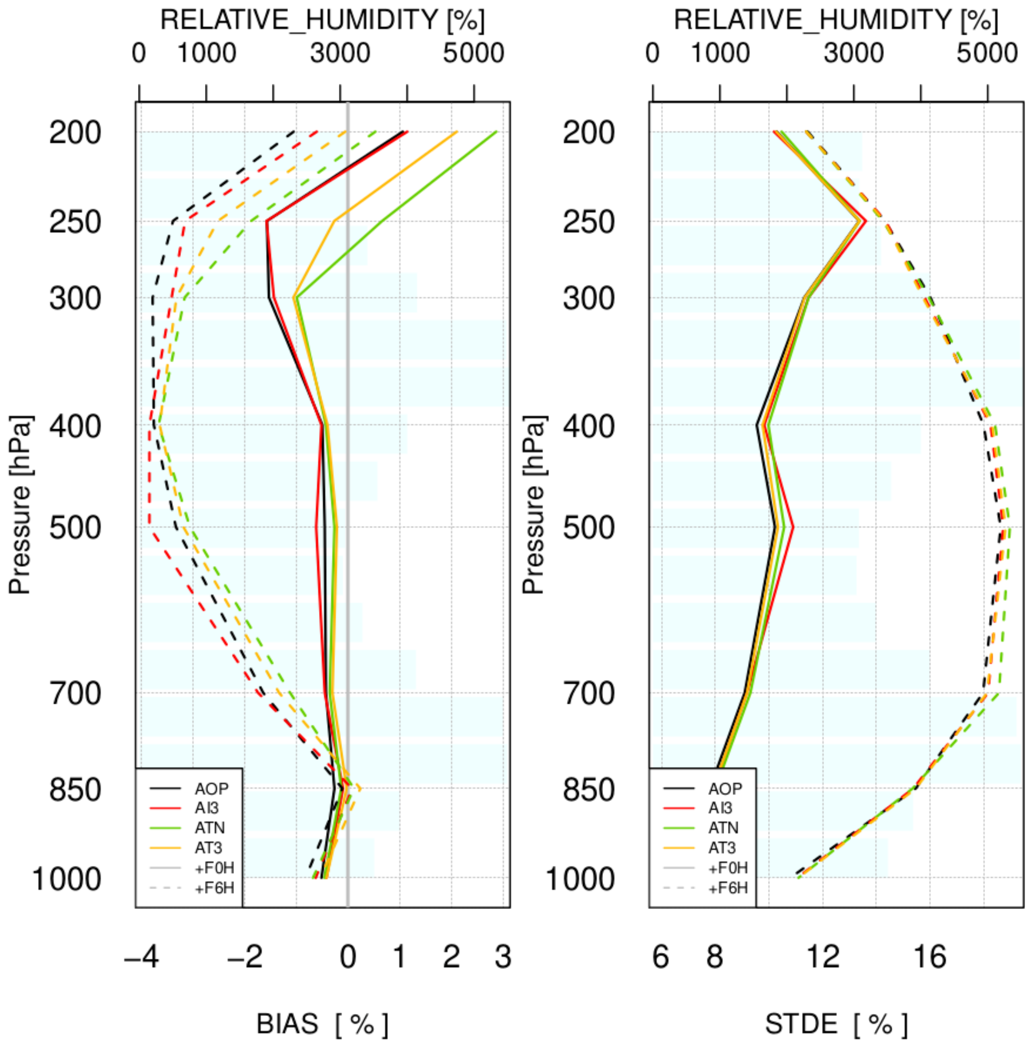

Figure 17: BIAS (left) and STDE (right) of relative humidity for reference experiment AOP and radar experiments ATN, AT3 and AI3 over the assimilation period of 20-30 June 2022 for all network times (00, 06, 12 and 18 UTC).

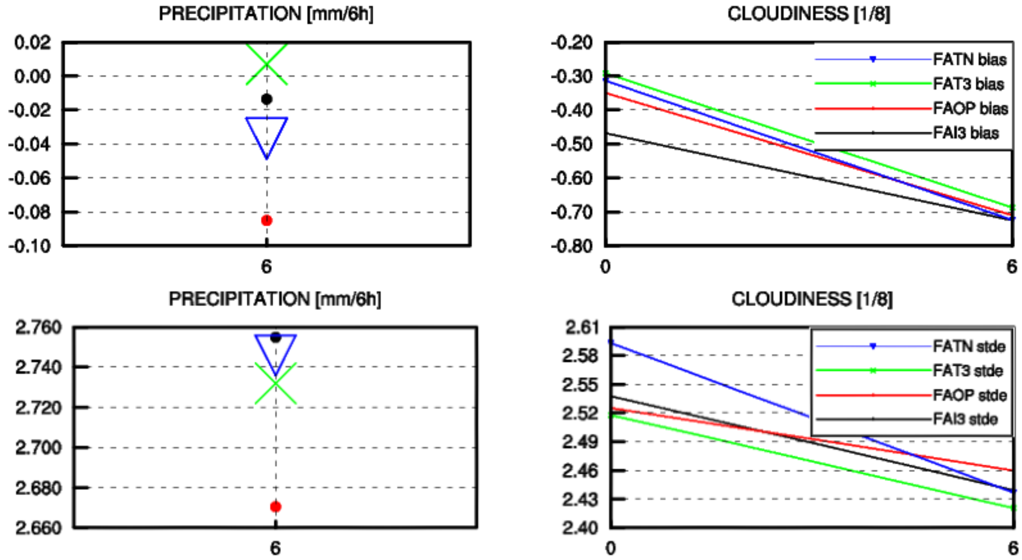

Figure 18: BIAS (upper pictures) and STDE (lower pictures) of the 6h precipitation accumulation and cloudiness for reference experiment AOP and radar experiments ATN, AT3 and AI3 over the assimilation period of 20-30 June 2022 for all network times (00, 06, 12 and 18 UTC).

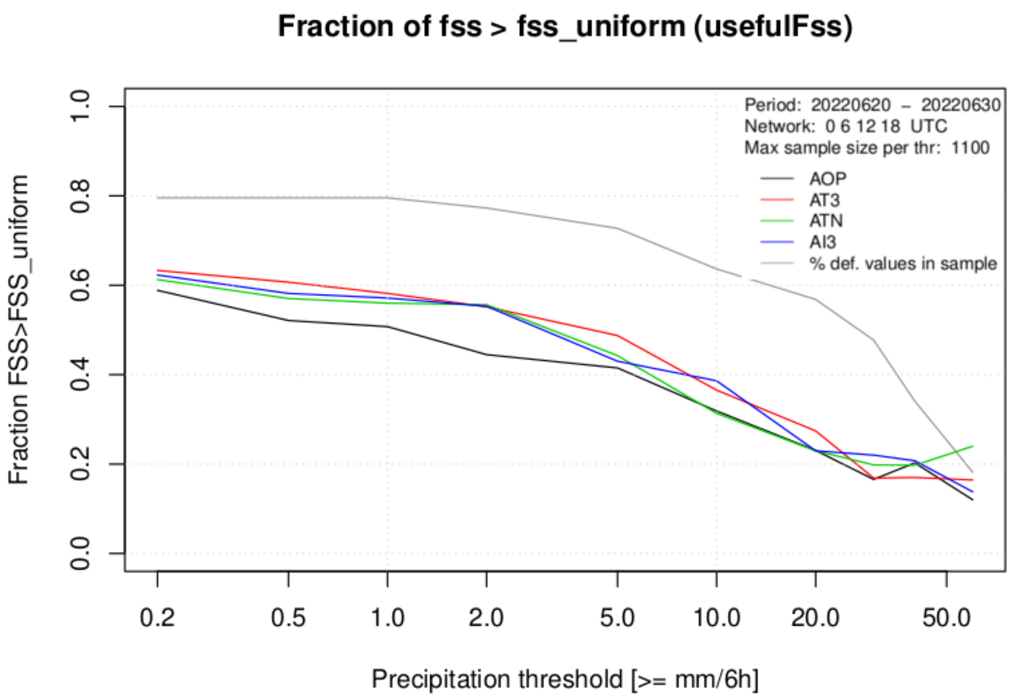

Figure 19: The fraction of forecasts which are useful (FSS > FSS_uniform). The grey line shows the percentage of cases when both observed and forecasted precipitations exceed the defined threshold at least at one point.

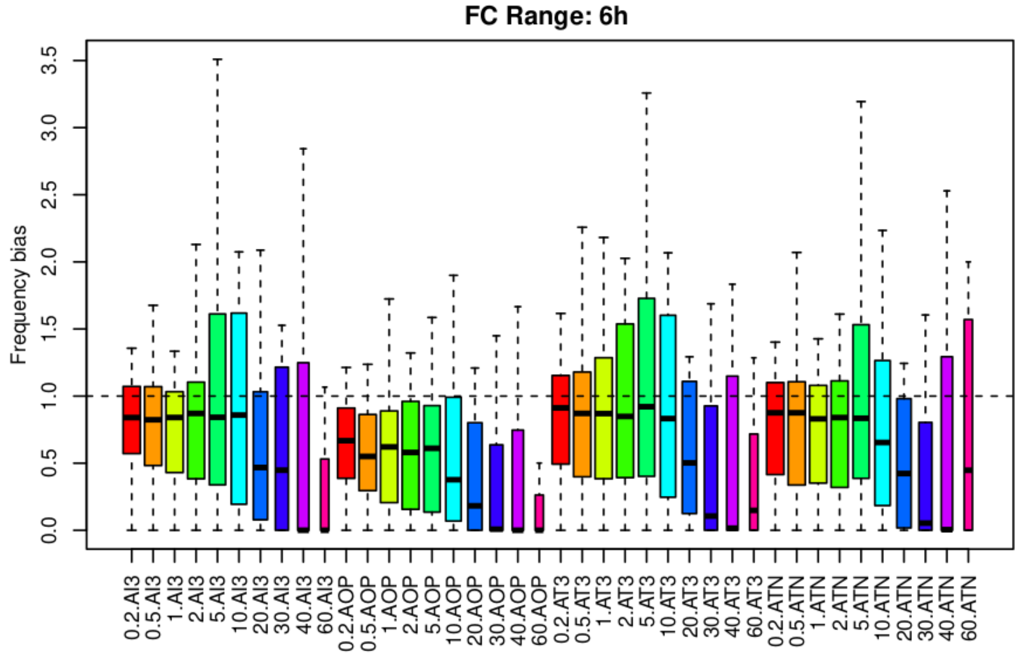

Figure 20: Box plot diagram of frequency bias per FC ranges (20-30 June 2022), per category, for all ranges: AOS, ATN, AT3 and AI3 experiments

6 Winter case

Since both approaches (inflation of observation error and removal of drying observations) add more moisture into the atmosphere, an additional period was chosen to be explored. Aim was to examine the behavior of both methods (and their combination) within the period where the model was already too wet. In case the dry observations were now too suppressed, it should be observed as an increase of an already too-large positive bias in cloudiness scores. Since we already found such a period while exploring the validity of prescribed MDRF values from the OPERA files (Section 2), the period of 08.01.2023 - 18.01.2023 was used for this test.

The list of sensitivity experiments has not changed and is as follows:

- AOS - no radar data assimilation, reference experiment
- ATN - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), check sign modification
- AT3 - same as ATN, with 30% dry observation error increase
- AI3 - active radar DA with MF BATOR code modifications (no dry data above 0dBZ), with 30% dry observation error increase

VERAL bias scores for cloudiness showed no additional moistening for any of the experiments. While AI3 experiment showed the best bias score at the analysis time, it also showed the worst standard deviation score for both analysis and forecast. AT3 experiment showed consistency in behaving better than both ATN and AI3 experiments for the winter period as well, but STDE was no longer better than the operational reference experiment [Figure 21].

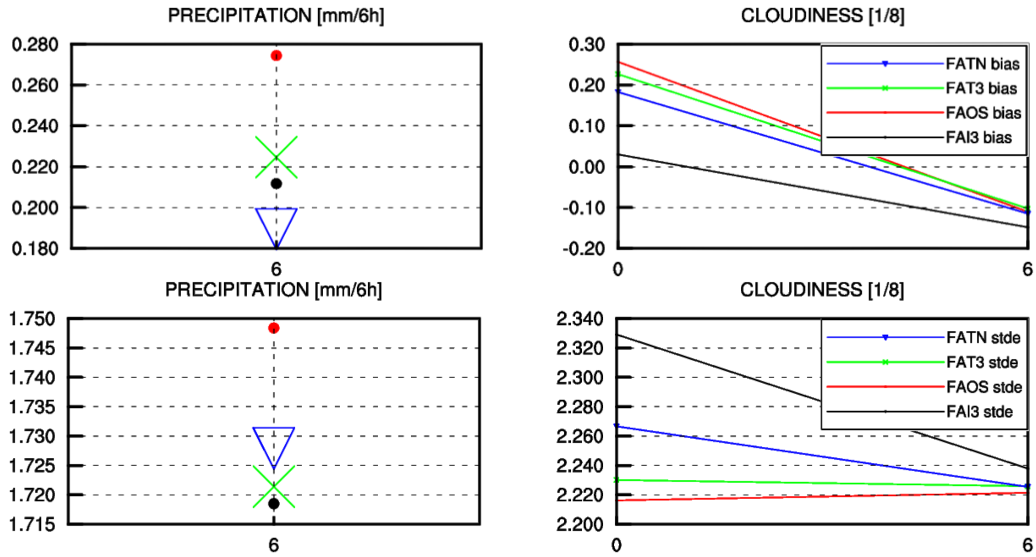

Figure 21: BIAS (upper pictures) and STDE (lower pictures) of the 6h precipitation accumulation and cloudiness for reference experiment AOP and radar experiments ATN, AT3 and AI3 over the assimilation period of 8-18 January 2023 for all network times (00, 06, 12 and 18 UTC).

Vertical VERAL bias scores of relative humidity profiles no longer showed better agreement with TEMP observations at analysis time when compared to an operational reference. At the same time, bias of the 6h forecast showed a consistent reduction of dry bias. STDE shows consistent behavior as was observed in the summer period [Figure 22].

Usefull FSS scores show improvement (for all experiments) in spatial representation of precipitation fields for all thresholds [Figure 24]. Box plot diagram of frequency bias shows that all experiments successfully remove excessive precipitation in the operational reference experiment AOS [Figure 23].

The combination of increased dry observation error and additional removal of flipped sign dry observations shows certain robustness in dealing with the drying effect. It also shows that their combination reduces the problematic behavior of both approaches. As such, it would be worth exploring if the results can be further improved by fine-tuning the offset of the dry observation error inflation approach. Also, if the shown robustness would still hold for a longer period of verification.

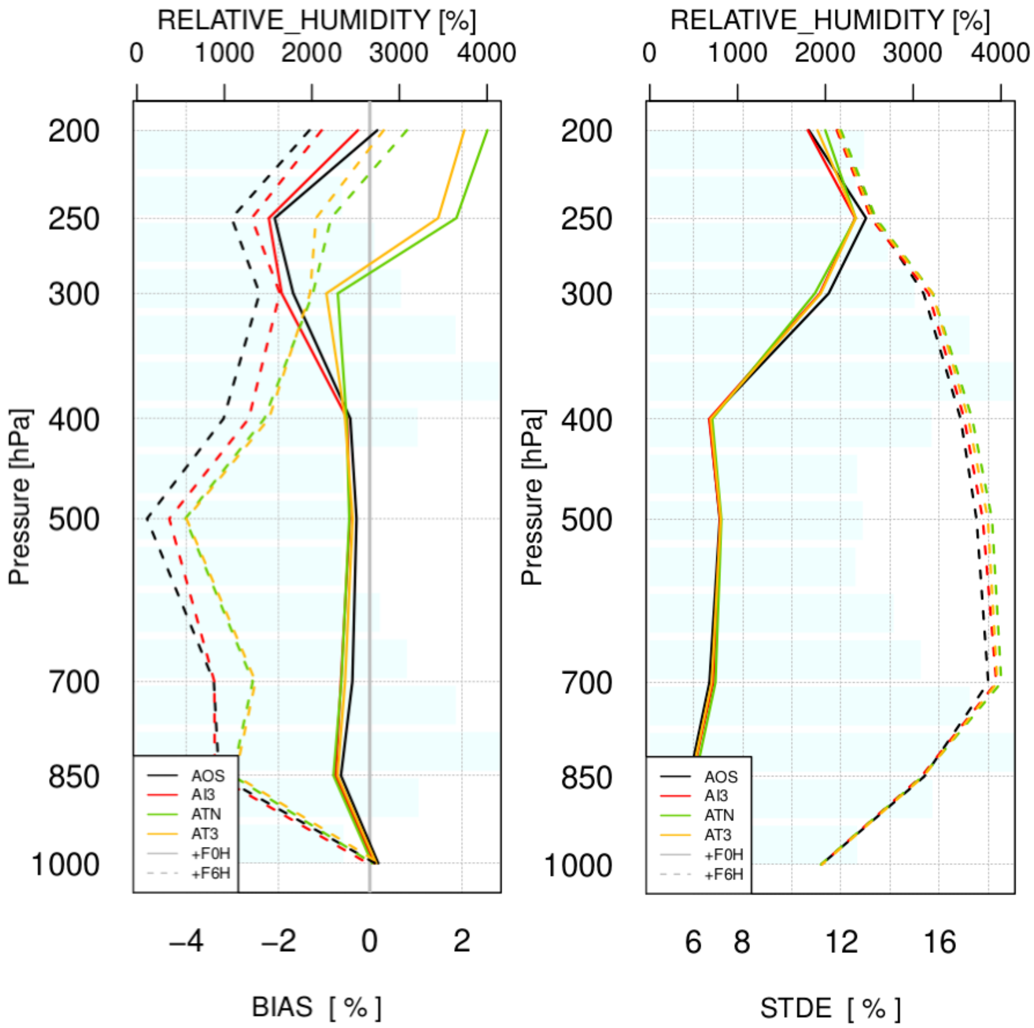

Figure 22: BIAS (left) and STDE (right) of relative humidity for reference experiment AOP and radar experiments ATN, AT3 and AI3 over the assimilation period of 8-18 January 2023 for all network times (00, 06, 12 and 18 UTC).

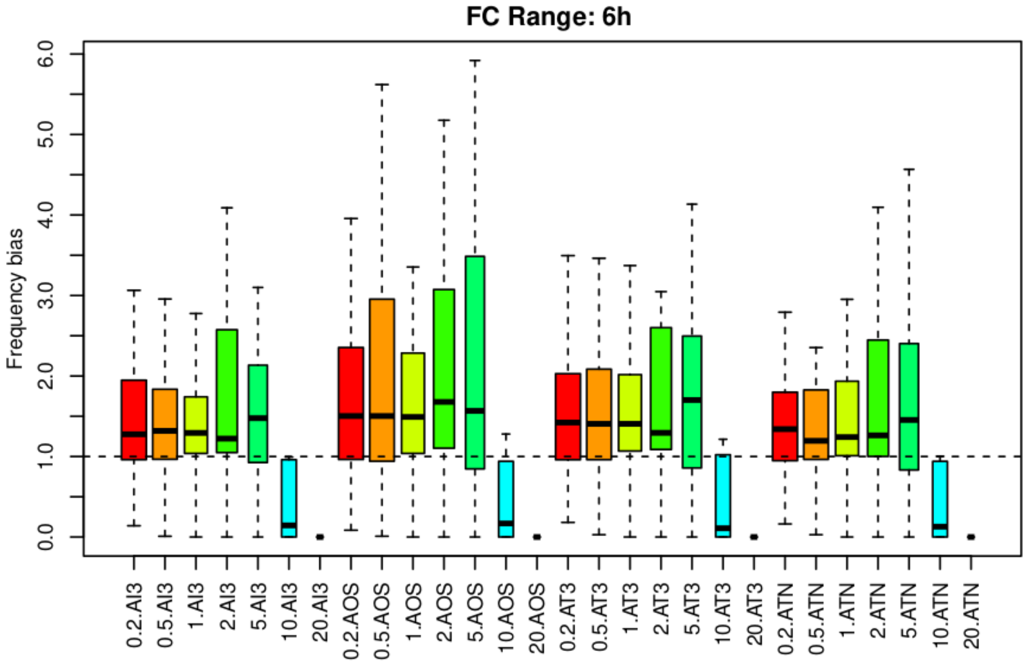

Figure 23: Box plot diagram of frequency bias per FC ranges (8-18 January 2023), per category, for all ranges: AOS, ATN, AT3 and AI3 experiments.

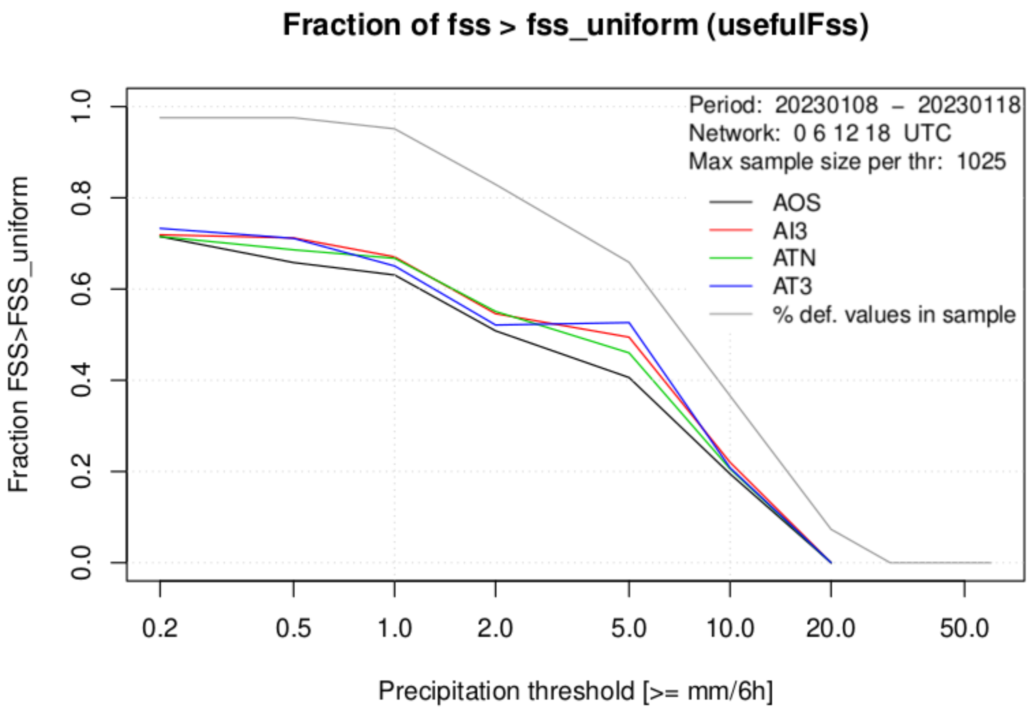

Figure 24: The fraction of forecasts which are useful (FSS > FSS_uniform). The grey line shows the percentage of cases when both observed and forecasted precipitations exceed the defined threshold at least at one point.

7 Conclusions

It was explored if a fixed table of MDRF values, using the OPERA-prescribed ones, would alleviate the drying effect in ALARO CSC. A period of 18 days during January 2023 was selected, along with 9 radars where a prescribed MDRF value was known. Even with such a low sample of radars during a short period, it was shown that keeping an up-to-date fixed table of MDRF values for operational purposes would be very challenging. It was explained that MDRF changes between two radar maintenance happen periodically, once or several times a year, depending on the meteo service. The same happened to two of the selected radars during this period. A shorter period where no MDRF values changed was selected, but no firm conclusion was made.

First guess departures per distance and height were explored. The aim was to see if any visible pattern as to where the drying effect occurs is present. No drying near the radar site was observed during the evaluation. In fact, depending on the radar, there were very little or no dry observations at all near the radar site. On most radar sites, there were no dry observations on distances lower than 10 km, which is already enough to reject the idea that the drying effect is directly linked to the dry observation values near the radar. Furthermore, the impact of active relative humidity pseudo-observations during the data assimilation was explored. It showed that dry observations have a larger impact on analysis than wet ones.

The new proposal of increasing the observation error for the dry relative humidity pseudo-observations was explored. It was shown that the increase in the observation error was followed by a decrease in the drying effect. Cloudiness and precipitation fields also improved. An increase of 50% in observation error showed signs of degradation by the appearance of too large maximums in the precipitation fields. From these results, it can be assumed that the point of degradation is positioned somewhere between 30% and 50% dry observation error increase.

Another approach of removing the flipped sign dry observations was explored. While this modification alone showed a significant removal of the drying effect in both cloudiness and relative humidity biases, it also showed an increase in the severe convective precipitation appearance (threshold above 60 mm). Further tests are needed to evaluate the impact on extreme precipitation events.

The combination of increased dry observation error and additional removal of flipped sign dry observations showed certain robustness (for both dry and wet periods) in dealing with the drying effect. It also shows that their combination reduces the problematic behavior of both approaches. As such, it would be worth exploring if the results can be further improved by fine-tuning the offset of the dry observation error inflation approach. Also, if the shown robustness would still hold for a longer period of verification.

References

[1] Olivier Caumont, Véronique Ducrocq, Éric Wattrelot, Geneviéve Jaubert and Stéphanie Pradier-Vabre; *1D+3DVar assimilation of radar reflectivity data: a proof of concept;* Tellus A: Dynamic Meteorology and Oceanography, vol. 62, issue 2, pp. 173-187, 2010.

[2] Éric Wattrelot, Olivier Caumont, and Jean-François Mahfouf; *Operational Implementation of the 1D+3D-Var Assimilation Method of Radar Reflectivity Data in the AROME Model;* Monthly Weather Review, vol. 142, issue 5, pp. 1852–1873 , 2014.

[3] Antonín Bučánek; *Processing of radar reflectivities in screening;* 2020., 10 pp

[4] Alena Trojáková; *ALARO tests of radar observation operator;* 2020., 16 pp

[5] Suzana Panežić, Alena Trojáková, and Antonín Bučánek; *Impact studies with OPERA reflectivity observations;* 2021., 26 pp

[6] Suzana Panežić, Alena Trojáková, and Antonín Bučánek; *Further sensitivity studies with radar reflectivity data assimilation;* 2022., 29 pp

8 Technical details

8.1 Source code modifications

Executables were based on the local model release CY43t2ag_op1. The modified sources can be found on kazi:

```
/work/mma257/radar_assim_2023/build_CY43t2ag_op1radar_ab_bs_flgtst_inflerr
```

8.2 Experiments

Scripts and namelists related to all experiments can be found on kazi:

```
/home/mma257/radar_assim_2023
```

Results are stored on archive in directory:

```
~mma257/exp/
```

Pictures can be found in:

```
/work/mma257/radar_assim_2023/pics/
```