Comparison of different VARBC initialization approaches

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1. Introduction

The satellite radiance observations are important elements of any data assimilation systems, however, its systematic errors (i.e. biases) should be removed in order to not degrade the quality of analysis and of the related forecast. The variational bias correction (VARBC) aims to correct these observation biases in an adaptive manner and it is nested in the variational data assimilation. The VARBC approach was shown to be very efficient compared to other bias correction methods (e.g. static or offline) and is able to follow changes of the quality of satellite sensors and to distinguish between observation and NWP model biases (Auligne et al, 2007). On the other hand, it was studied more comprehensively in global data assimilation frameworks and due to different conditions of limited-area systems (data sample, asynoptic analyses, etc) the VARBC settings should be carefully revised. Even because of inappropriate settings the better performance of VARBC compared to more basic bias correction methods might not be necessarily true.
At the beginning of the LACE stay general questions have been raised regarding VARBC operation what we wanted to answer:

- *Which VARBC initialization approach provides more accurate bias information about currently used satellite sensors on a certain period (coldstart, warmstart, global, else)?*
- *How should the adaptivity parameter be set in passive and in active assimilation configurations for its proper use?*

However, during the first half of the LACE stay, few other questions were emerged too which we would be interested to answer as well:

- *What is the critical size of VARBC data sample which can provide reasonable estimation of the linear regression method in LAM?*
- *Which predictor(s) is(are) the most important one(s) in VARBC for each sensors and for each channels and how can the collinearity of the predictors be avoided?*
- *Can the VARBC be efficient for a LAM data assimilation system correcting only observation bias without the use of anchor and/or dense high quality observations?*
- *Can the Harris and Kelly method be implemented effectively in an operational LAM data assimilation system?*
- *Can we use different or mixed VARBC cycling strategy for different sensors and/or channels?*

In this report a set of experiments will be described which has been prepared to study VARBC behavior and to answer some of the above mentioned questions.

2. Experimental setup

During the experiments the configurations of the ALARO/CHMI operational NWP model has been used which has 4.7km horizontal resolution and uses 87 vertical levels up to 0.1 hPa. Its DA system includes an OI surface assimilation and a BlendVAR upper-air assimilation schemes (Bucanek et al, 2015). The operational assimilation system perform analyses 6 hourly i.e. 4 analyses in a day at 00, 06, 12 and 18UTC. Taking into account proper large-scale information, DF Blending technique (Brozkova et al, 2003) utilizes ARPEGE global analyses at each network times. The domain of the ALARO/CHMI can be seen on figure 1.

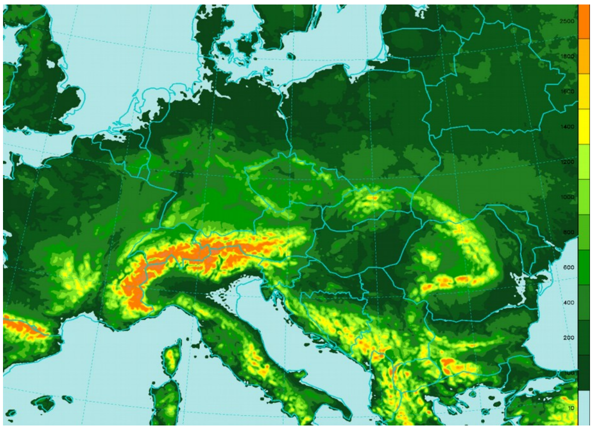


Figure 1. The orography of ALARO/CHMI model domain

For the investigation of VARBC, several passive assimilation experiments have been carried out with only the 3DVAR of the ALARO/CHMI system. The table 1. summarizes the different experiments and its configurations running on the period of 1^{st} of September and 20^{th} of October, 2015. The passive assimilation was started from 09UTC (and 06UTC) to get larger amount of observations from METOP (and NOAA satellites respectively) using 24h VARBC cycling. At 09UTC analysis time, the first-guess is used from the previous 3 hour forecast. The VARBC predictor selection in ALADIN is set consistently with the global model.

Name	**X94**	**X95**	X96	**X97**	**X98**
VARBC initialization	Coldstart	Warmstart	Cold+Warm	Harris and Kelly	Global
Observations at 09UTC	AMSU-A, MHS, HIRS, IASI (*METOP-A*, *METOP-B*), SEVIRI *Meteosat10*	AMSU-A, MHS, HIRS, IASI (*METOP-A*, *METOP-B*), SEVIRI *Meteosat10*	AMSU-A, MHS, HIRS, IASI (*METOP-A: COLD*, *METOP-B: WARM*), SEVIRI *Meteosat10: WARM*	AMSU-A, MHS, HIRS, IASI (*METOP-A*, *METOP-B*), SEVIRI *Meteosat10*	AMSU-A, MHS, HIRS, IASI (*METOP-A*, *METOP-B*)
Observations at 06UTC	AMSU-A, MHS, HIRS, IASI (*NOAA-18*, *NOAA-19*), SEVIRI *Meteosat10*	AMSU-A, MHS, HIRS, IASI (*NOAA-18*, *NOAA-19*), SEVIRI *Meteosat10*		AMSU-A, MHS, HIRS, IASI (*NOAA-18*, *NOAA-19*), SEVIRI *Meteosat10*	AMSU-A, MHS, HIRS, IASI (*NOAA-18*, *NOAA-19*)
NBG	Default	Default	Default	-	Default

Table 1. The list of experiments

In order to diagnose the efficiency and functionality of VARBC, the visualization of VARBC statistics have been executed for the evolution of bias parameters of various predictors, for the observation minus first-guess (OMG) biases (corrected and non-corrected) and for OMG standard deviations. Also the relevance of bias predictors were plotted where the predictors are normalized and therefore their importance in bias correction can be comparable (Auligne, 2007). The list of predictors can be seen on Table 2. The diagnostic and visualization tools are developed and provided by Patrik Benacek. In the following we will try to answer the above mentioned questions focusing only METOP-A satellite and its sensors. For the interest of NOAA satellites the analyses valid at 06UTC will be shortly discussed as well. In Appendix A and Appendix B the results of METOP-B and METEOSAT-10 satellites can be also seen respectively. In Appendix C short notes on the use of IASI sensor will be provided.

Predictor number	Predictor
0	constant
1	1000-300hPa thickness
2	200-50hPa thickness
3	skin temperature
4	total column water
5	10-1hPa thickness
6	50-5hPa thickness
8	nadir viewing angle
9	nadir view angle **2
10	nadir view angle **3
11	nadir view angle **4
15	land or sea ice mask
16	view angle (land)
17	view angle (land) **2
18	view angle (land) **3

Table 2. The list of available predictors in VARBC

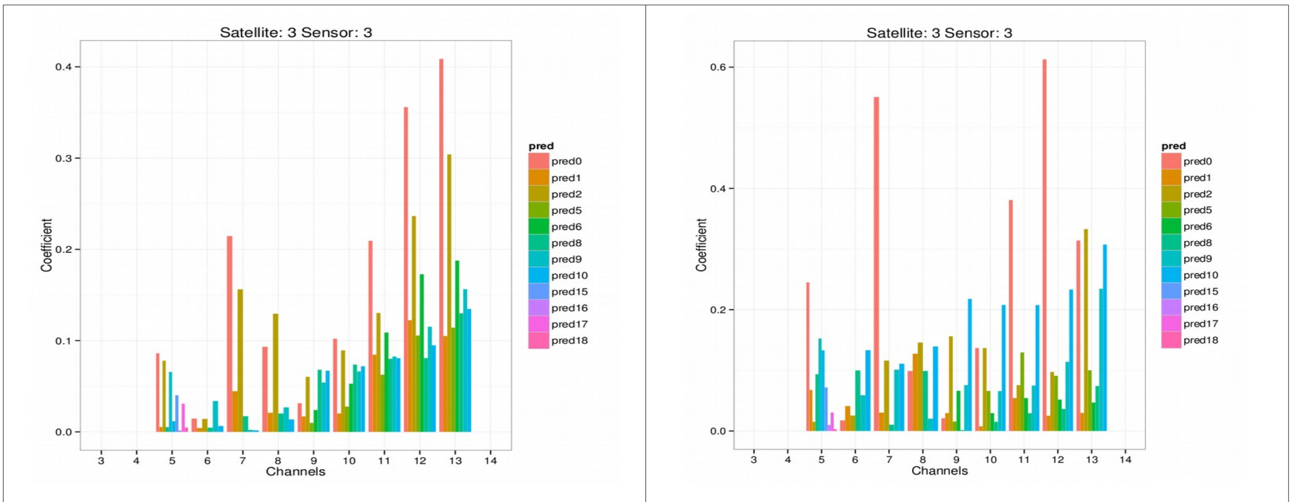
2.1. The references of the experiments

During the comparative study, two experiments as references were selected which provide good estimation of observation biases and draw “control” values to assess performance of VARBC initialization methods. The first one (x98) is the use of global VARBC coefficients in each consecutive analysis step from ARPEGE global model and the second one (x97) is the approach proposed by Harris and Kelly, 2000. In addition, this HK approach is based on observation-minus-analysis departures to provide regression coefficients that are less affected by a first-guess error. In case that the satellite bias does not change in time, both approaches should provide reasonably good information about observation bias what LAM VARBC should follow or should converge to during the 50 days of the initialization period.

2.2. METOP-A AMSU-A

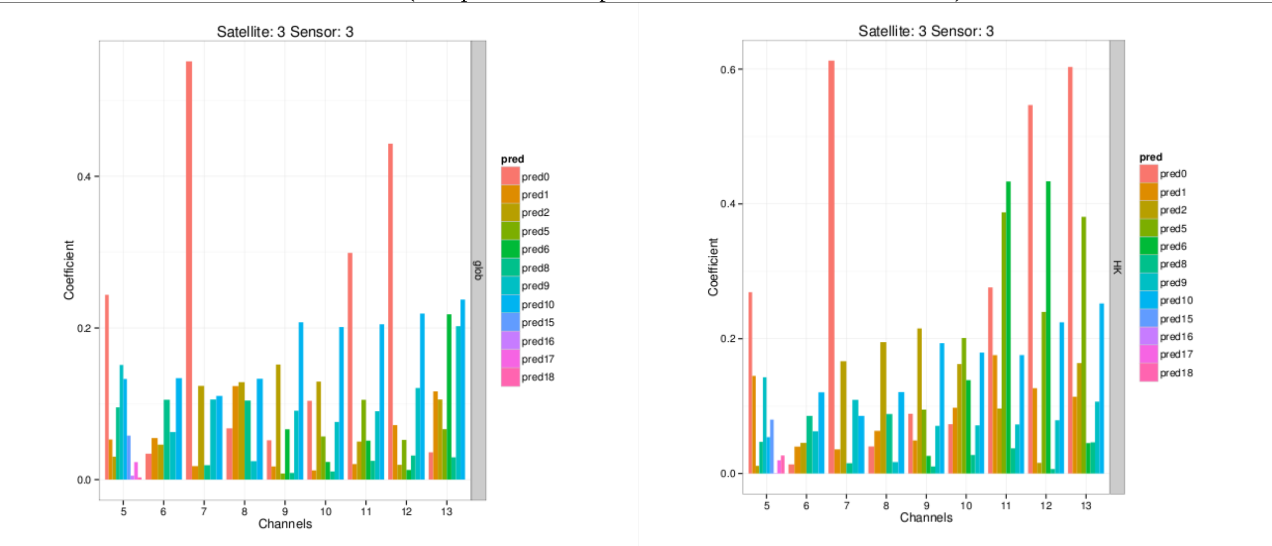
2.2.1. The importance of predictors

The figure 1. shows the importance of predictors in the bias correction for each AMSU-A channels which were used during the x94 and x95 experiments. In figure 2. the same diagram for the two references is plotted as well. It can be seen that some of the predictors are contributing in bias correction with larger amount than others. Also it is important to observe that the coldstart and the warmstart determine differently these contributions i.e. the relevance of predictors. Furthermore one can see also that in case of coldstart initialization for the AMSU-A sensor the strong collinearity of predictor 0 and predictor 2 is apparent and it is not presented in case of warmstart. The collinearity of predictors could be explained by a less observation sample providing unreasonable ranges of predictors. Due to the results of figure 1. we will focus on “the most important” predictors for different AMSU-A channels to study the functionality of the VARBC.



Coldstart Warmstart

Figure 1. The importance of VARBC predictors for cold and warmstart initialization using METOP-A satellite, AMSU-A sensor (computed on the period of 01/09/2015-20/10/2015).



Global Harris and Kelly

Figure 2. The importance of VARBC predictors for global and HK initialization using METOP-A satellite, AMSU-A sensor (computed on the period of 01/09/2015-20/10/2015).

2.2.2. Evaluation of VARBC diagnostics

In figure 3. the diagnostic results of AMSU-A channel 5 can be seen with the evolution of predictor 0 and predictor 9 comparing the different experiments. From the OMG statistics it is visible that certain bias exists and we can observe the specialties of the different VARBC initialization methods as well. Regarding the evolution of predictors, the warmstart starts from global information and tries to converge slowly towards the Harris and Kelly (HK or x97). The coldstart starts from zero and after 50 days, it is still far from references i.e. it would require even longer period with the current configuration to get reasonably good bias information with this approach.

In figure 4. the results of AMSU-A channel 7 are visualized with predictor 0 and predictor 8. Regarding the OMG statistics one can observe similar behavior than with channel 5 except the STD of OMG in case of coldstart is slightly larger compared to other runs. As relatively larger bias exists for this AMSU-A channel, coldstart is also not able to reach HK and global bias information during the test period. Note that even if the coldstart provide reasonable bias correction at the end of the period, the quality of bias correction is deteriorated probably due to underestimated limb-correction coefficients (for the predictors 8 to 10). The slow convergence and higher STD of the coldstart is not a good signal and require further investigations.

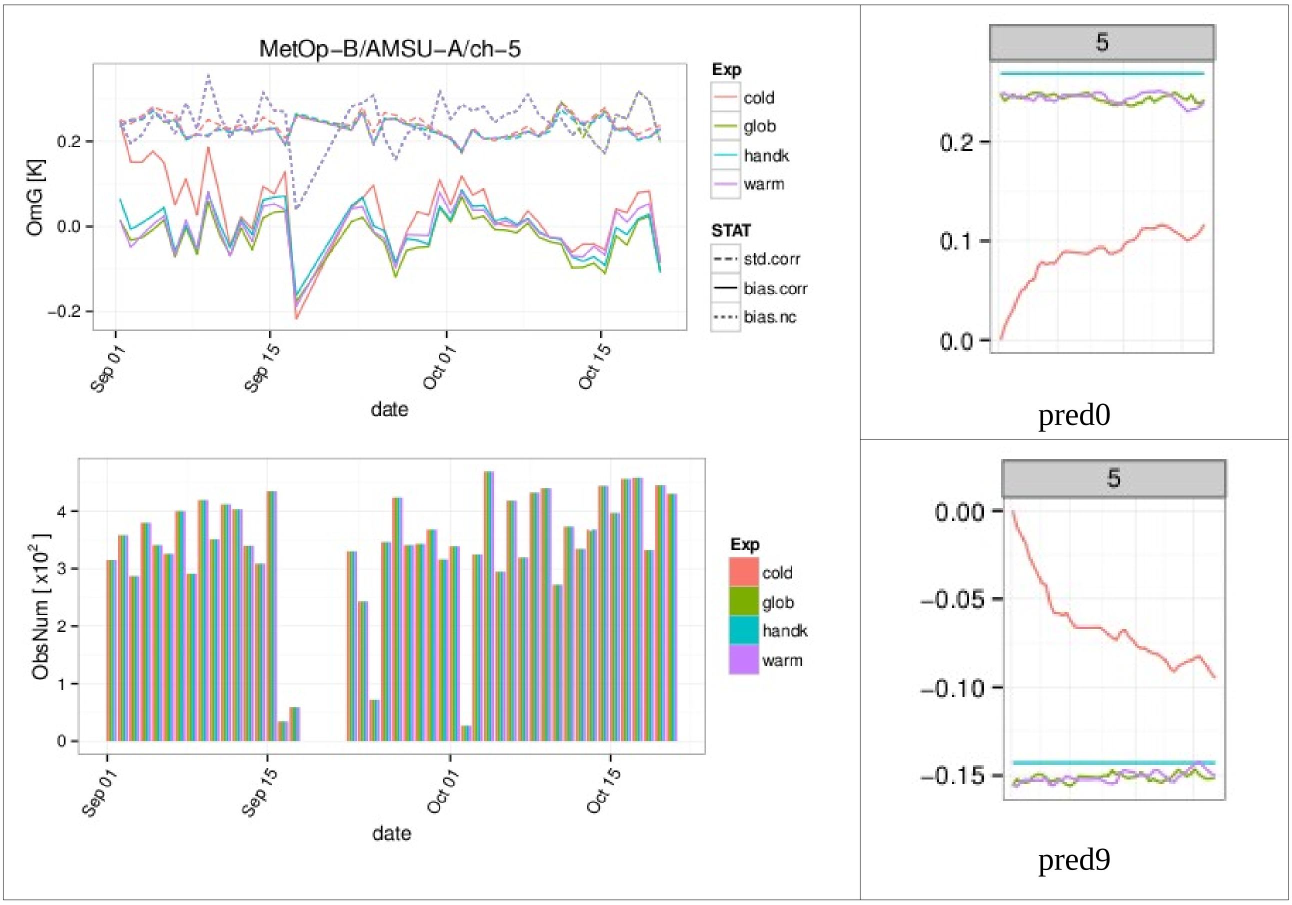


Figure 3. AMSU-A channel 5 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 9 on the right.

In figure 5. the statistics of AMSU-A channel 13 are plotted highlighting predictor 0 and 10 which were found to be the most important ones. Channel 13 is a higher peaking channel and one can see different behavior concerning the evolution of predictors than above mentioned channels. For this channel (and for ch11, ch12 as well which are not shown) the predictors have too adaptive evolution and the two different approaches (namely cold and warmstart) behave very similarly in term of OMG statistics as well (of course after a short spin-up period of coldstart). This stronger adaptivity could be explained mainly by a combination of a larger observation sample and a higher FG error in stratosphere. Supposing that the observation number determines the adaptivity of VARBC coefficients (IFS Documentation, part II), the higher-peaking channels, which have two times higher observation sample than the low-peaking channels, have also a larger response to the FG error.

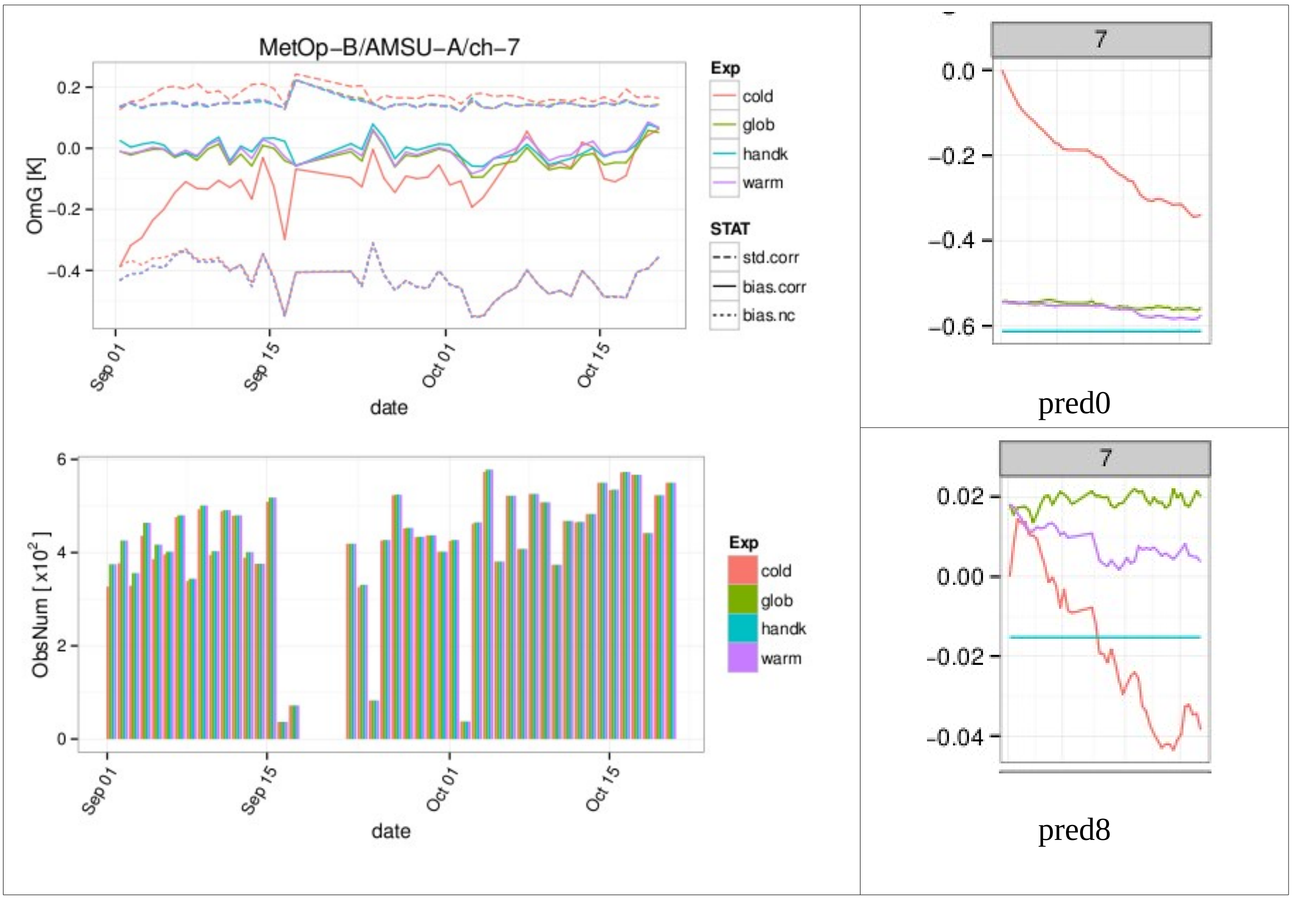


Figure 4. AMSU-A channel 7 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 8 on the right.

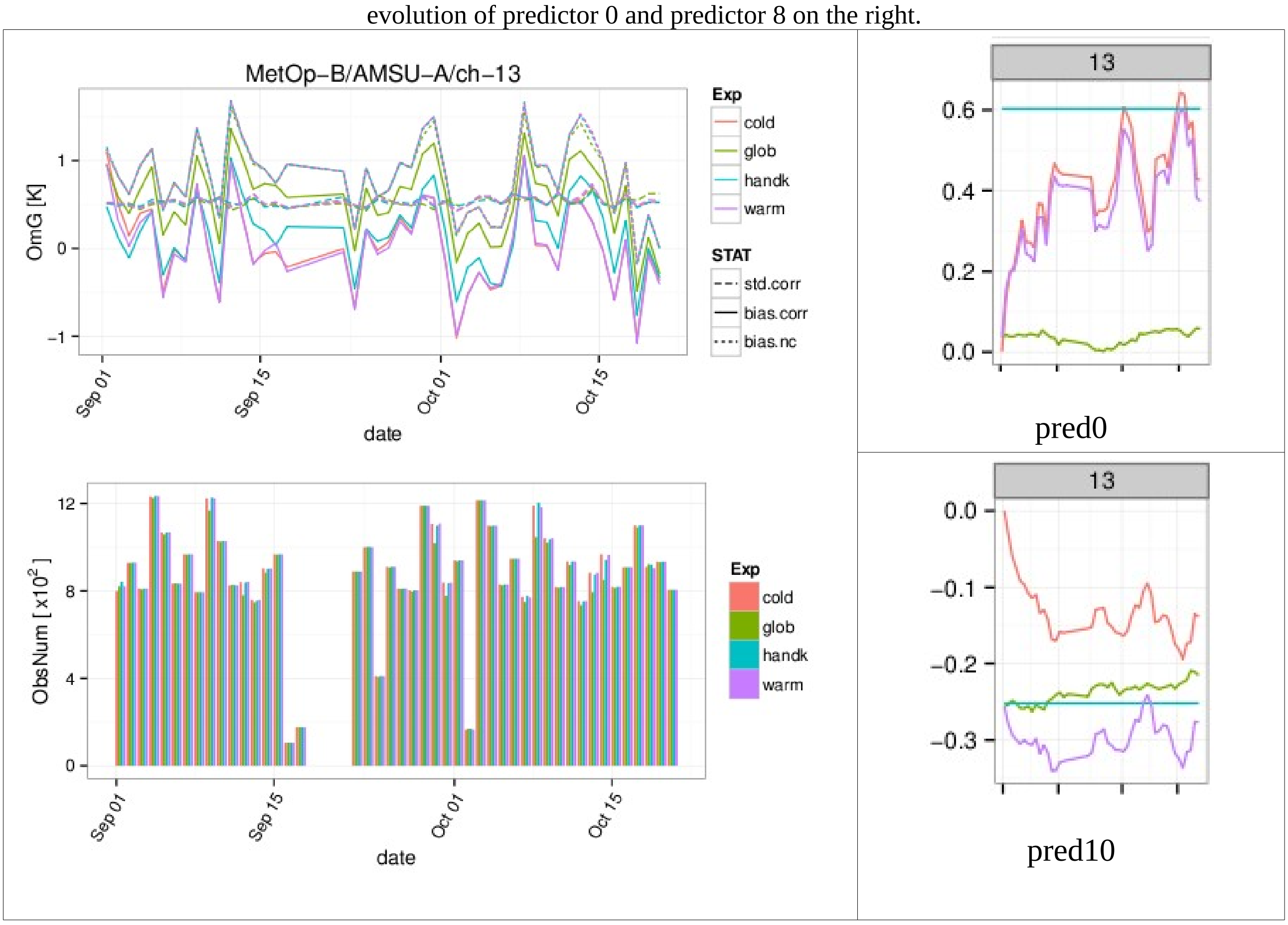


Figure 5. AMSU-A channel 13 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 10 on the right.

2.3. METOP-A MHS

2.3.1. The importance of predictors

Similarly for MHS sensor the figure 6. shows the importance of predictors in the bias correction for cold and warmstart (and figure 7. shows references). It can be seen again that the coldstart and the warmstart determine differently the relevance of predictors. Also it is visible that in case of coldstart VARBC initialization the predictor 0 and predictor 2 have clear collinearity which is not that obvious with warmstart. After the results of figure 5. we will pick up only two predictors for two MHS channels to verify the functionality of the VARBC. Supposing that the observation sample of MHS instrument is (in passive assimilation mode) around 7000, both the coldstart and warmstart VARBC approaches response strongly on a higher FG error.

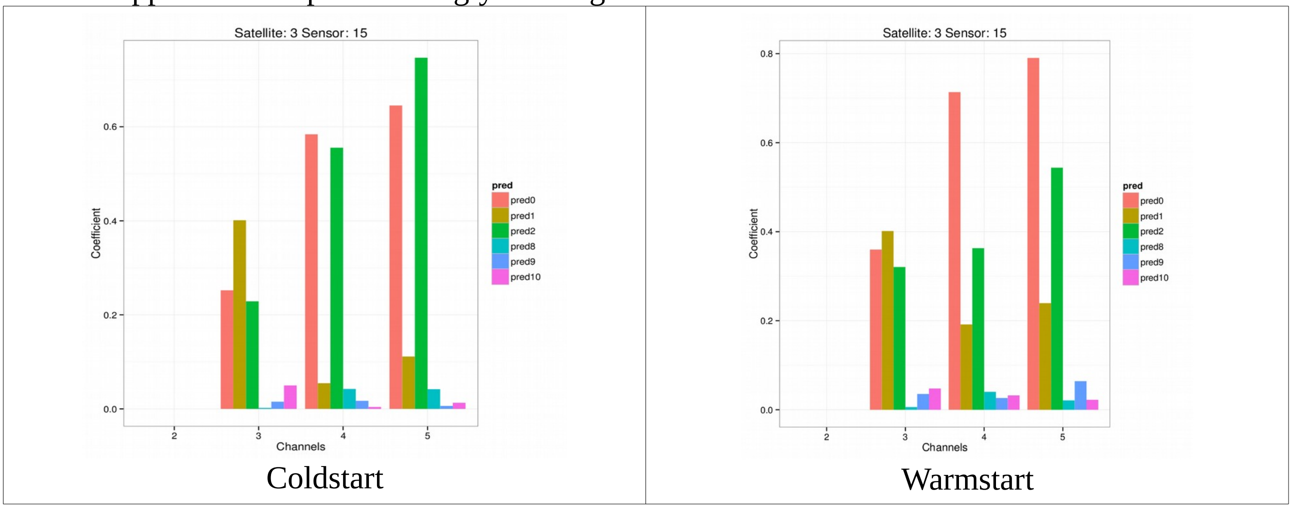


Figure 6. The importance of VARBC predictors for cold and warmstart initialization using METOP-A satellite, MHS sensor.

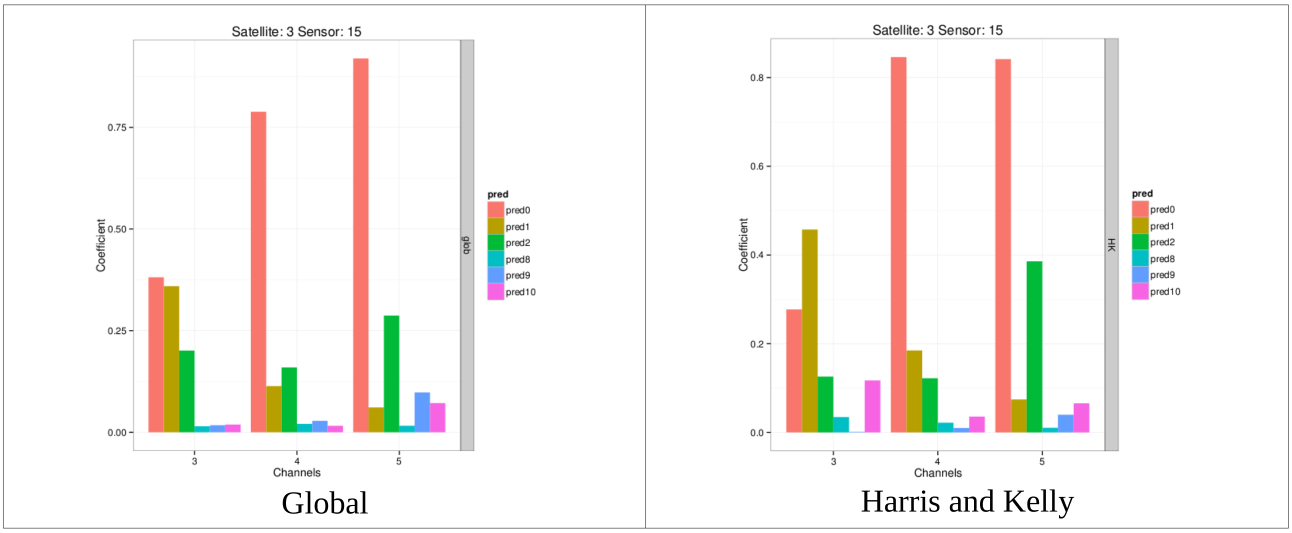


Figure 7. The importance of VARBC predictors for global and HK initialization using METOP-A satellite, MHS sensor.

2.3.2. Evaluation of VARBC diagnostics

In figure 8. and in figure 9. the MHS channel numbers 4 and 5 are shown respectively and their VARBC diagnostics. The OMG STD of the different experiments are matching around the value of 1.3. The corrected OMG biases of the cold and warmstart behave similarly as it was pointed out for AMSU-A channel 13 as well. Furthermore in the evolution of the different predictors larger adaptivity can be identified and the warmstart (together with the cold) is usually not able to follow the references and difficult to see any convergence during the 50 days period.

Figure 8. MHS channel 4 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 2 on the right.

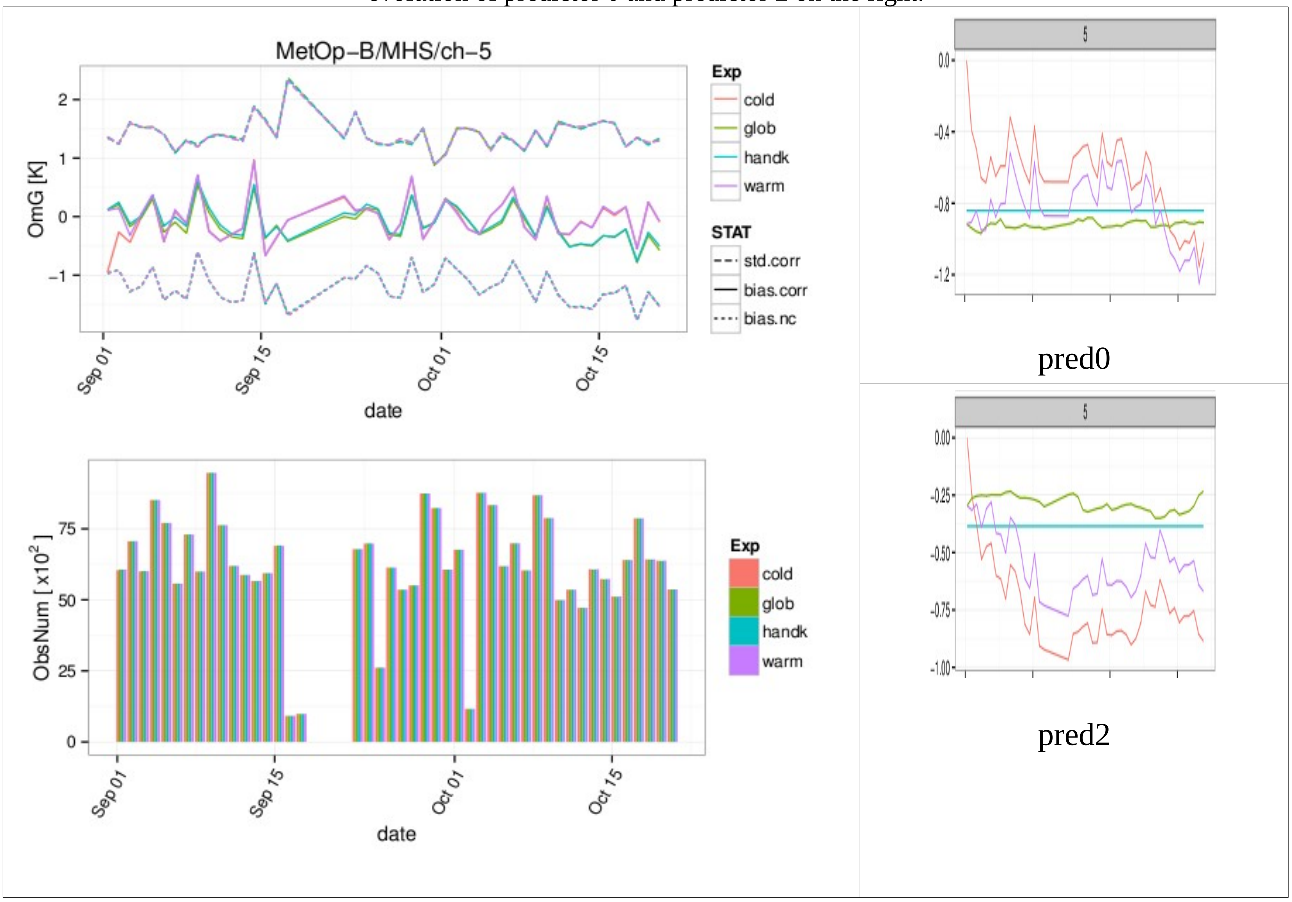


Figure 9. MHS channel 5 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 2 on the right.

2.4. METOP-A IASI

2.4.1. The importance of predictors

Due the large number of IASI channels, only selected ones were considered and will be shown for this investigation. One CO2 channel (ch242) was taken which is sensitive around the tropopause and another which is a humidity sensitive channel (ch3653) of the IASI sensor. Here in figure 10. and in figure 11. the importance of predictors are presented for more (selected) channels. For channel 242 the predictor 1, predictor 6 and for channel 3653 the predictor 0 and 6 can be considered for cold and warmstart.

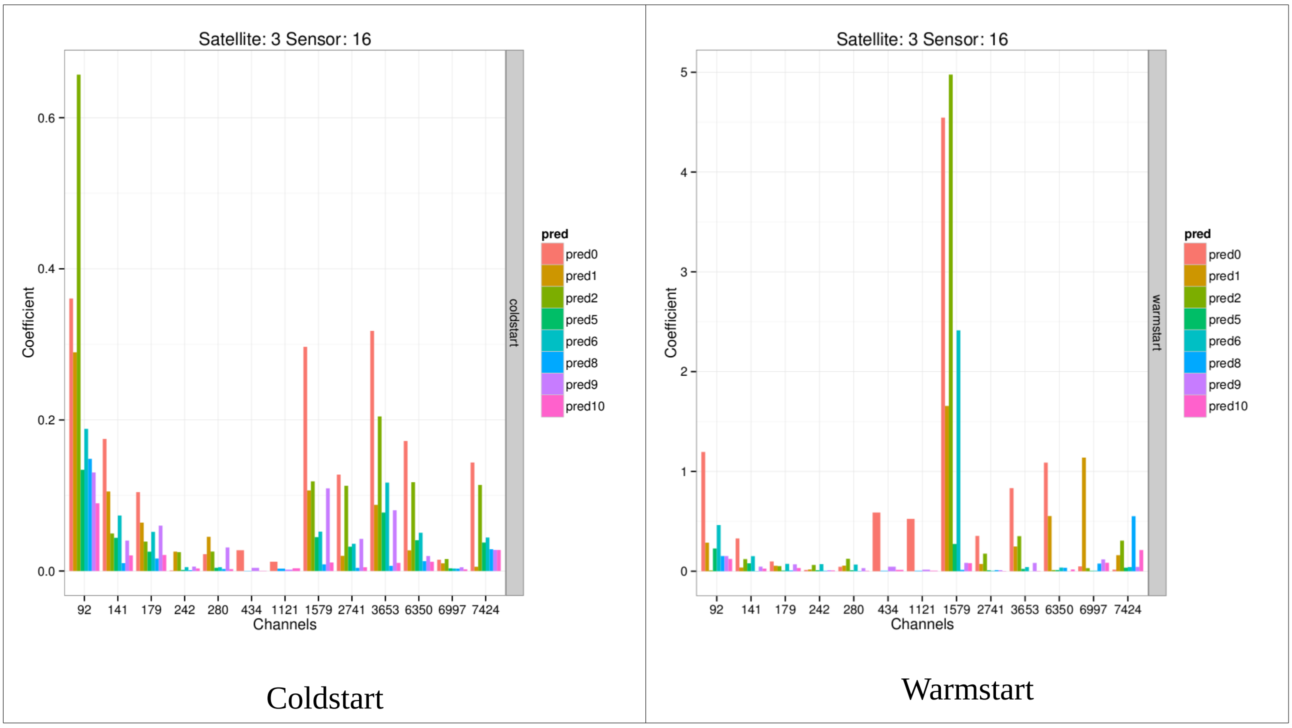


Figure 10. The importance of VARBC predictors for cold and warmstart initialization using METOP-A satellite, IASI sensor (computed on the period of 01/09/2015-20/10/2015).

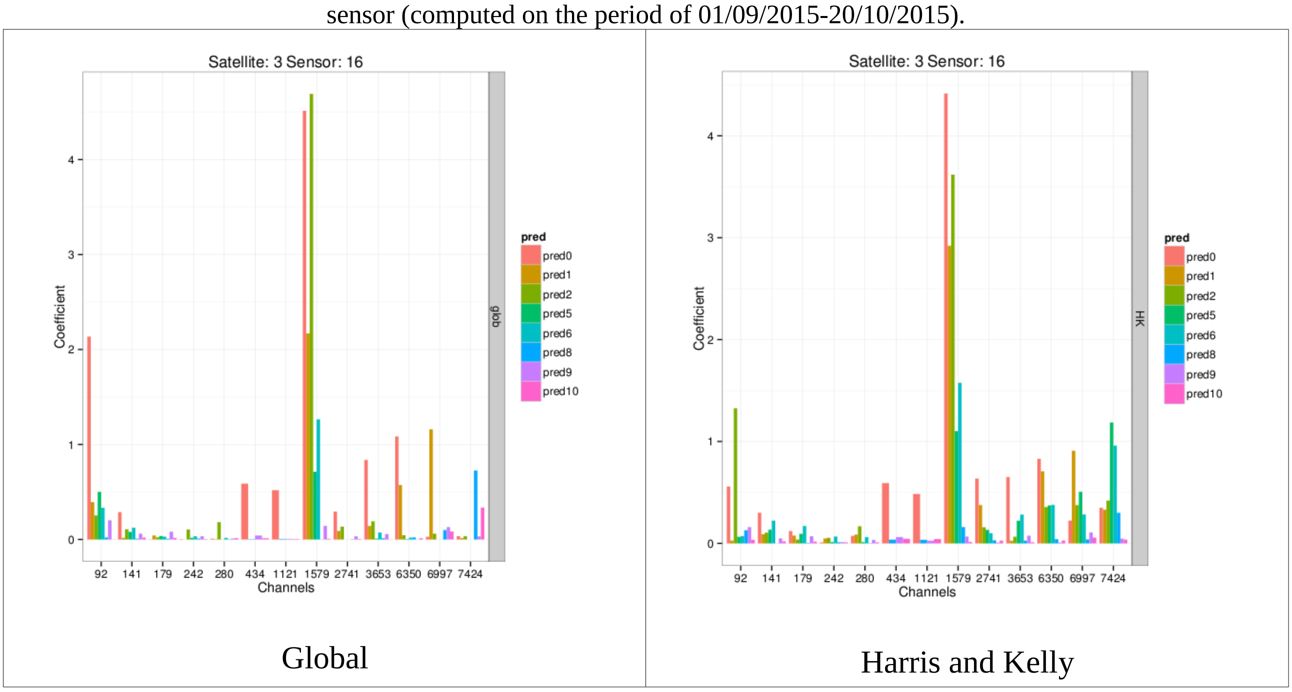


Figure 11. The importance of VARBC predictors for global and HK initialization using METOP-A satellite, IASI sensor (computed on the period of 01/09/2015-20/10/2015).

2.4.2. Evaluation of VARBC diagnostics

The IASI channel 242 (in figure 12.) has in general smaller bias which can be seen from OMG stats and from the bias parameters. Due to this the coldstart (together with warmstart) is able to give reasonable bias correction during the 50 days. The evolution of the predictor 0 is comparable for the two initialization approaches and it is a general comment that coldstart (in LAM context and with default settings) is able to give appropriate bias correction in case of smaller observation bias. Another example for this is the METOP-A AMSU-A channel 6 which is not shown here.

In figure 13. the stats of IASI humidity channel (ch3653) are visualized. For this channel larger observation bias can be detected and regarding the evolution of the selected predictors, one can see that warmstart and coldstart behave differently and furthermore warmstart hardly moves towards the reference HK solution in case of pred 6. The HK coefficients for predictor 5 and 6 are overestimated for this method (see Figure 11.) This might be due to inadequate range of predictors 5 and 6 within the linear regression model. At the same time, the adaptivity of the bias parameters (for both methods) looks correct with the defaults VARBC settings.

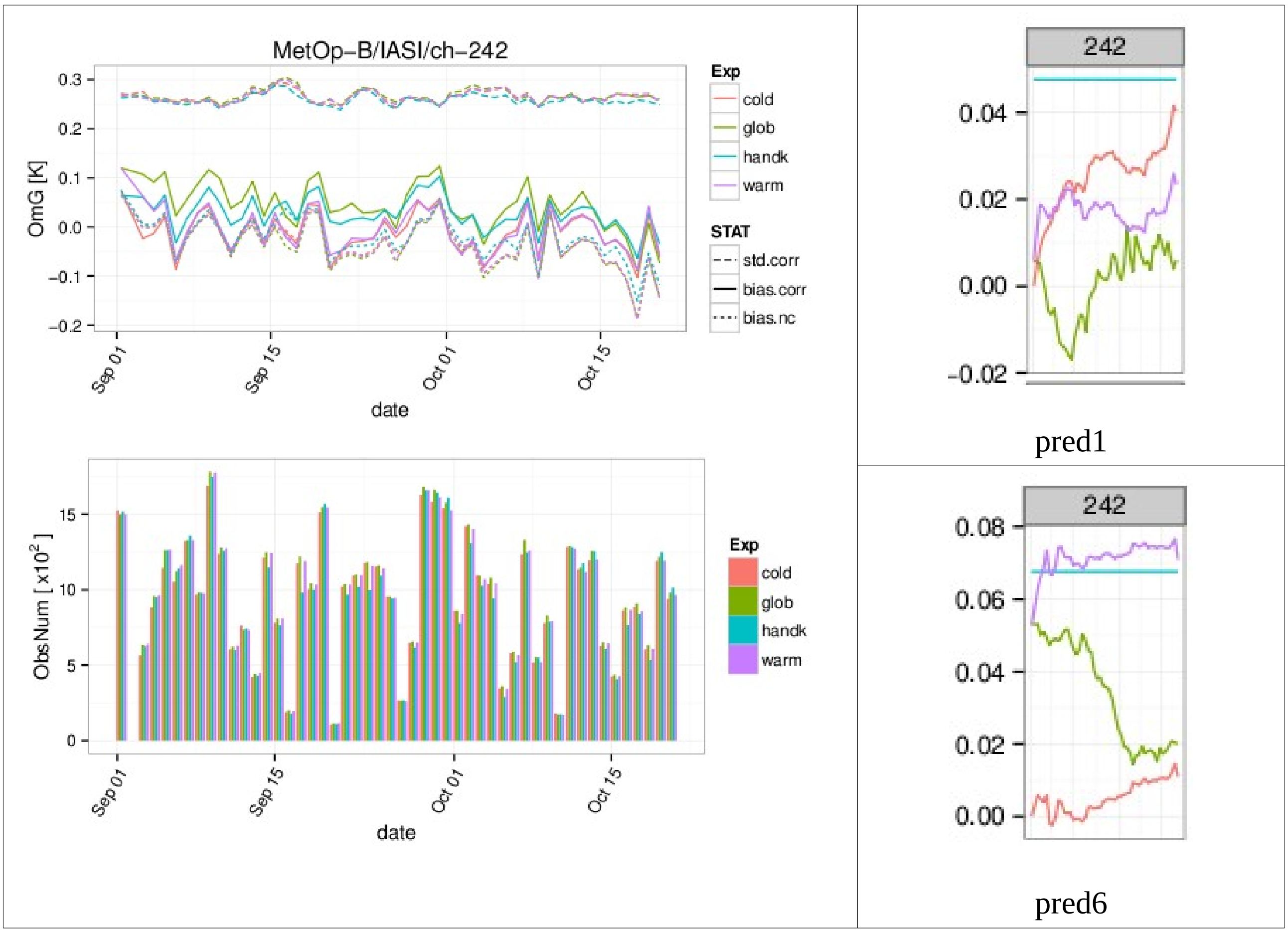


Figure 12. IASI channel 242 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 1 and predictor 6 on the right.

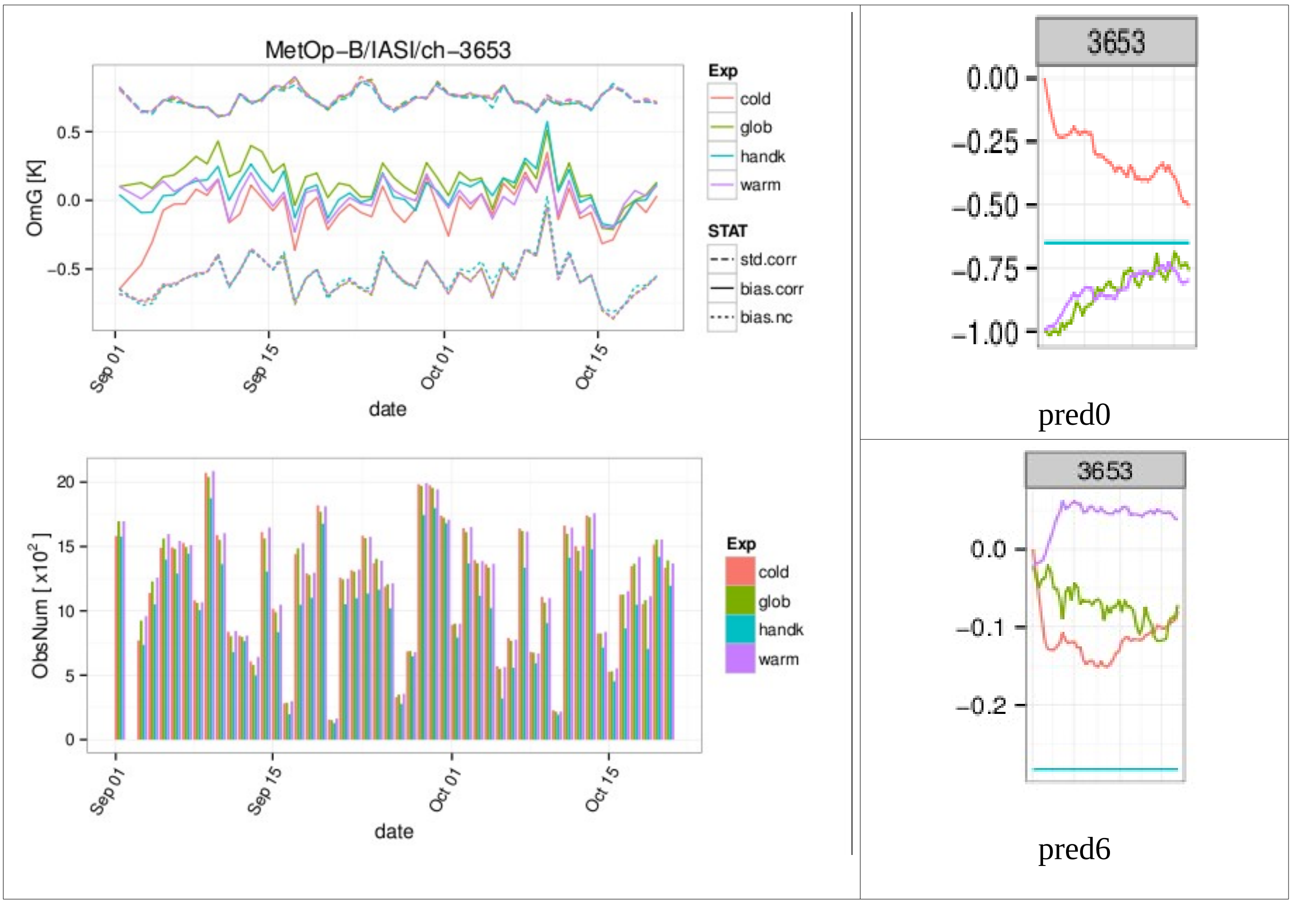


Figure 13. IASI channel 3653 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 6 on the right.

2.5. NOAA-18

Similarly to 09UTC experiments, passive assimilation experiments for 06UTC network time (in daily VARBC cycling) have been prepared to study radiance observations from NOAA satellites as well. In this section only NOAA-18 AMSU-A sensor will be highlighted. Due to the quality of this sensor has been changed during the selected period and it is interesting to verify the different VARBC initializations and its performances.

For a selected AMSU-A channel (number 7.) the most important predictors are the predictor 0 and predictor 9 for both the cold and the warmstart (not shown). In the figure 14. the non-corrected OMG statistics show clear signal of this change in the quality of AMSU-A sensor for this channel. Probably this is the reason for higher bias and higher standard deviation at the beginning of the examined period in case of coldstart initialization. In the time evolution of predictor 0 this change is also visible in the shift of global coefficients. Cold and warmstart are trying to follow this drift. It is important to note that Harris and Kelly approach in such case is not able to follow the change in sensor quality without the recomputation of “static” bias information. Therefore the advantage of adaptive VARBC correction is crucial in this kind of situation.

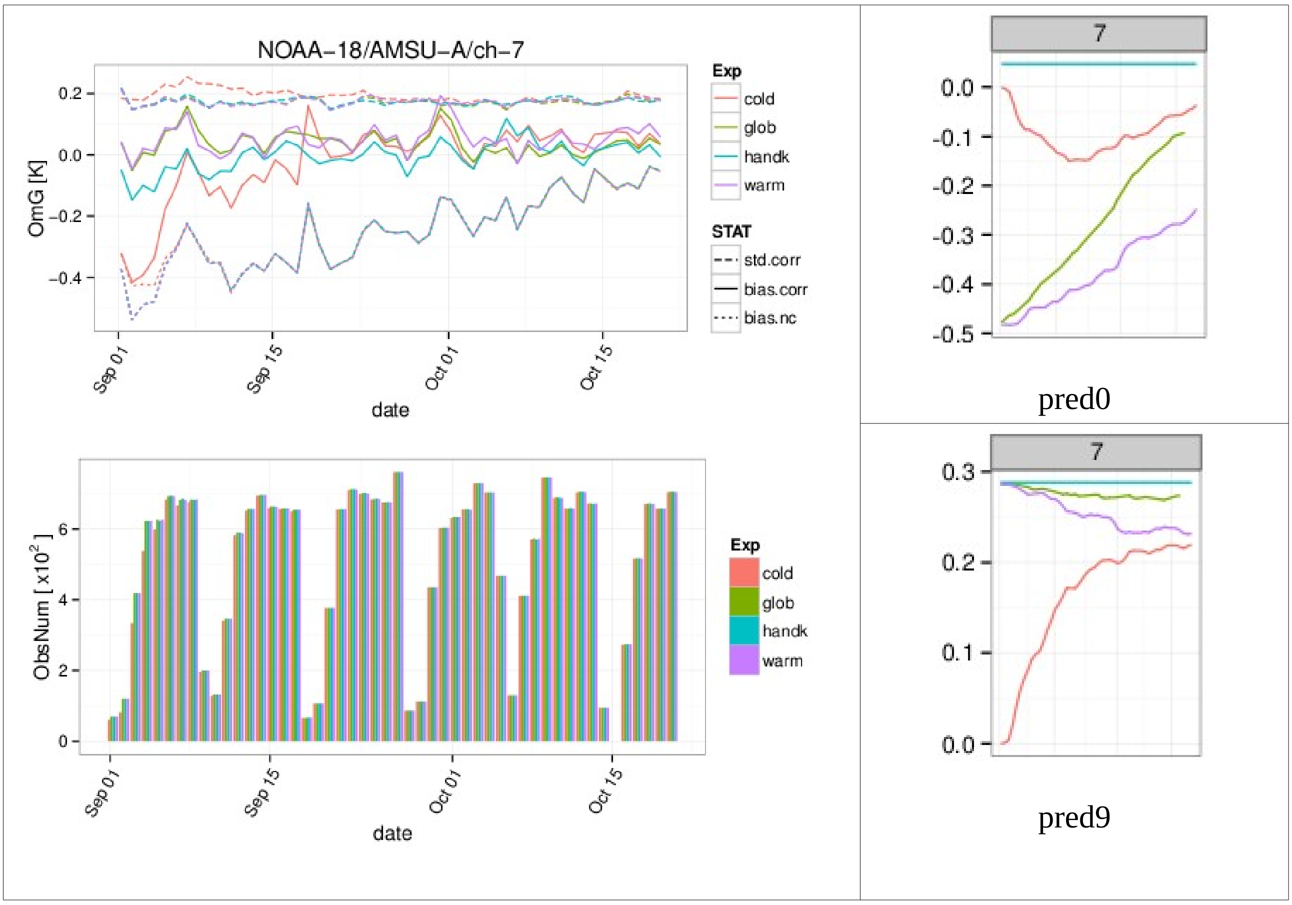


Figure 14. AMSU-A channel 7 OMG bias (corrected and non-corrected), OMG standard deviation on the left and the evolution of predictor 0 and predictor 6 on the right.

3. Conclusions and Summary

Two VARBC initialization methods in comparison with two different references were taken into account in order to determine their functionality using its default settings. During the study the following conclusions can be drawn.

- Regarding the importance of VARBC predictors, the issue of collinearity should be avoided. (More details about the collinearity can be read in Auligne, 2007)
- The preliminary conclusions about the coldstart initialization method:
  - It is not able to produce, spin-up bias information in case of small observation sample, especially for AMSU-A channel 5 to 7.
  - Some of the bias coefficients are not reasonable with respect to global coefficients (e.g. underestimation of limb-correction predictors channel 8 to 10).
  - The observed STD of the corrected OMG departures is sometimes larger than with the other approaches.
- Warmstart initialization (x95) for AMSU-A lower peaking channels provides plausible bias correction with the default settings.
- Warmstart approach (x95) together with coldstart for AMSU-A higher peaking channels shows too adaptive evolution of bias parameters. The fluctuation of VARBC coefficients in time could be explained by a combination of a larger observation sample and a higher FG error. Supposing that the observation number determines the adaptivity of VARBC coefficients (IFS Documentation, part II), the instrument channels providing a higher observation sample tend to adapt the bias coefficients to OmG strongly. Moreover, if there is a higher FG error, which is characteristics for stratosphere (temperature sensitive channels) or humidity-sensitive channels, the bias coefficients are more affected by the FG error

changes.

- For sensor MHS, both coldstart and warmstart behave similarly and provide too adaptive VARBC bias parameters.

At the introduction few questions have been raised and after the first results the following conclusions can be collected:

- *Which VARBC initialization approach provides more accurate bias information about currently used satellite sensors on a certain period (coldstart, warmstart, global, else)?*
  - The speed of convergence depends on the instrument observation sample in each analysis. Less observation sample means slower convergence in VARBC coefficients. The coldstart is able to correct the satellite bias for the MHS, IASI instruments (as well as the AMSU-A high-peaking channels) providing that there is a large observation sample (see Fig.5, 8, 9, 13). However, the quality of the coldstart bias coefficients is affected by the FG error that could be significant for the stratospheric and humidity channels. The benefit of the warmstart method is twofold: i) the shorter spin-up period for the channels with less observation sample (e.g. AMSU-A low-peaking channels) ii) more reasonable bias coefficients. The use of global VARBC coefficients directly in LAM requires more investigations.
- *How should the adaptivity parameter be set in passive and in active assimilation configurations?*
  - (not studied yet)

- *What is the critical size of VARBC data sample which can provide reasonable estimation of the linear regression method in LAM?*
  - From the first results this question cannot be answered. However the size of the data sample is the most critical issue about the success of VARBC. As a next step Harris and Kelly method will be calculated with different sample size in order to determine this limit experimentally. Furthermore the adaptivity issue of higher peaking channels requires also more study due to more observations should be used from these channels.
- *Which predictor(s) is(are) the most important one(s) in VARBC for each sensors and for each channels and how can the collinearity of the predictors be avoided?*
  - For the importance of predictors, diagnostic tool was used. During the first results it was found that with the use of warmstart the collinearity of the predictors can be avoided and there is no need to switch off one of them as it should be done in case of coldstart.
- *Can the VARBC be efficient for a LAM data assimilation system correcting only observation bias without the use of anchor and/or dense high quality observations?*
  - (not studied yet)
- *Can the Harris and Kelly method be implemented effectively in an operational LAM data assimilation system?*
  - (not studied yet)
- *Can we use different or mixed VARBC cycling strategy for different sensors and/or channels?*
  - (not studied yet)

References

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