Towards the improvement of the assimilation of cloudy IASI observations in Numerical Weather Prediction

Imane Farouk, Nadia Fourrié and Vincent Guidard
CNRM/ Météo-France & CNRS
Imane.farouk@meteo.fr

Abstract

Satellite data currently represent the vast majority of observations assimilated into NWP models. However, their exploitation remains suboptimal, less than 10% of the total volume is used operationally in assimilation. Furthermore, about 80% of the infrared data are affected by clouds and it is essential to develop the assimilation of satellite observations in cloudy areas. Météo-France NWP models have been using since February 2009 AIRS (Atmospheric Infra-Red Sounder) cloudy radiances and since 2012 IASI (Infrared Atmospheric Sounding Interferometer) cloudy radiances with a simple cloud modeling in addition to clear data. The exploitation of the infrared hyperspectral sounder IASI has already improved weather predictions, thanks to its precision and information content never equaled. Nevertheless, its use in storm areas remains very complex because of the strong non-linearity of cloud processes in the infrared spectrum. The method for the assimilation of cloudy radiances in the present research work is based on the use of a sophisticated radiative transfer model RTTOV-CLD, which takes into account the cloud scattering, in order to better simulate the brightness temperatures from the background in the data assimilation of the ARPEGE global model. Firstly, we were interested in the selection of homogeneous scenes using the information of AVHRR clusters to place in the most favorable cases. We used the homogeneity criteria derived from Martinet et al (2013) and Eresmaa (2014). The intercomparison between the two methods reveals a considerable number of divergences, either in the method of calculating the criteria or in the statistical results. Combining the two selection methods results in a new method, in which the last two AVHRR channels are used to define the homogeneity criteria in the brightness temperature space. This method has a positive impact on statistics of observations minus simulations, while keeping many of the observations (clear and cloudy) for the assimilation.

1 INTRODUCTION

Satellite observations are currently an important source of information, accounting for the three-quarters of all observations numerical weather prediction (NWP) systems. They are used together with in-situ observations through an essential component, the atmosphere analysis, which is a necessary step in the definition of the initial conditions of the forecast.

This analysis consists in finding a state of the atmosphere that is compatible with the different sources of observations, the dynamics of the atmosphere and an earlier state of the model. 70% of used observations comes from infrared hyperspectral sounders, where IASI fills a large part.

IASI was designed by CNES and firstly launched in October 2006, on-board the European satellites Metop A and B, which are polar orbiting satellites. This sounder, provides the measurement of temperature and / or humidity and through its window channels we can obtain the information about the land surface parameters in clear sky or cloudy parameters.

However, the wealth of information provided by this type of sensor with its large number of channels or radiances (8461 in the case of IASI) and its overall coverage with a horizontal resolution of 12 km at the nadir, is far from being fully exploited.

Indeed, the presence of clouds in the instrument's field of view, which affects the majority of observations, is one of the reasons why NWP centers use only a small amount of observations from these sounders. The NWP centers have begun to assimilate the radiances affected by clouds over the oceans since 10 years (Kelly and Thépaut (2007)). They use a simple radiative transfer model with a single layer cloud represented by its top pressure and effective cloud fraction.

The aim of this study is to develop an all sky data assimilation approach for IASI observations, which will allow to increase the amount of Infrared data assimilated in the ARPEGE forecast model at the global scale.

To achieve our principal objective, we made developments to better assimilate the cloudy IASI radiances using cloud microphysics in simulation and data assimilation. The first step consists in the identification of homogeneous situations using the AVHRR clusters. The homogeneity criteria derived from Martinet et al., (2013) and Eresmaa (2014) have been intercompared before detailing our proposed selection method. Finally, this paper concludes with a summary of the results and some perspectives.

2 METHODOLOGY

2.1 Radiatif transfert model RTTOV-CLOUD

In this research study, we have used the sophisticated radiative transfer model RTTOV-CLD (Hoking 2010), which takes into account the multi-layer clouds and the cloud scattering. This model allows the simulation of the infrared cloudy radiances from atmospheric profiles and cloudy microphysical parameters (liquid water content (ql), ice content (qi), cloud fraction), as illustrated in Figure 1.

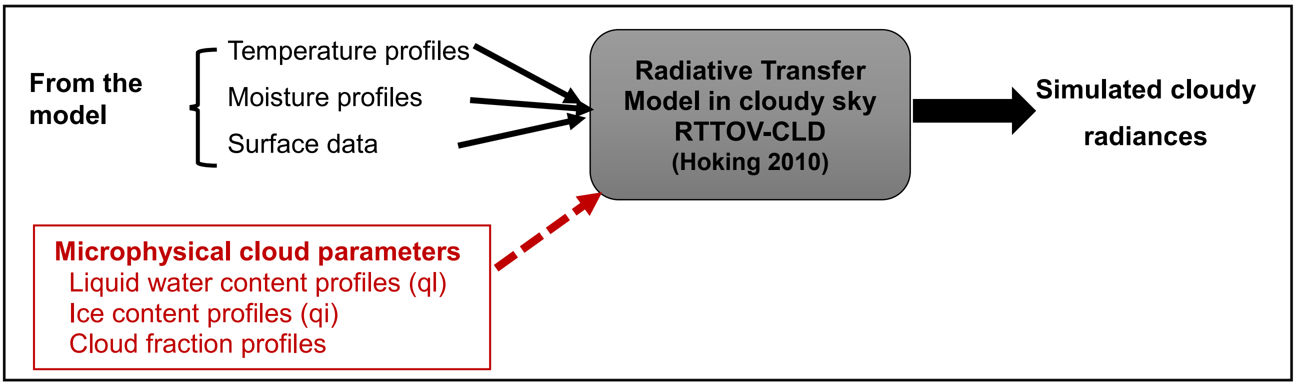


Figure 1: the inputs and the output of the radiative transfer model RTTOV-CLD

2.2 AVHRR Cluster

In this study, we have also used the information from the AVHRR imager, which is collocated with IASI on MetOp platforms. AVHRR measures in 5 channels, located in the visible, near-, middle-, and thermal-infrared spectrum, with a spatial resolution of 1km at the nadir. It provides the information on Cloud Cover and pixel homogeneity. We have used this information to select the homogeneous scenes using the AVHRR clusters (Cayla, 2001). This product gathers the AVHRR pixels of 1Km size in homogeneous classes inside each IASI pixel.

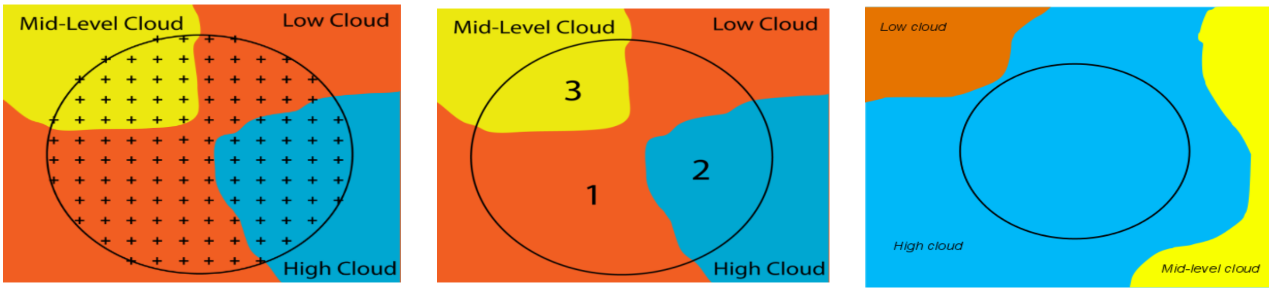


Figure 2: Illustration of the principle of clustering of AVHRR pixels (Martinet et al. 2013)

Figure 2 illustrates the clustering principle; the left panel shows the black circle representing the IASI pixel and the crosses representing the AVHRR pixels. AVHRR pixels are aggregated in homogeneous classes in the radiance space with visible and infrared channels using K-means clustering. In the middle panel, we have three clusters after the aggregation, which represent the low clouds, high clouds and mid-level cloud. In the right panel, we have a case where IASI contains just one cluster. For each cluster and each channel, we used the Average radiance, Standard deviation and cluster coverage in the IASI pixel.

In this study, we focused on IASI pixels that contain only one type of cluster, but we only have 2% of observations that contain a single cluster. In addition, this cluster is based on visible and infrared channels, but we want to focus on the IR spectrum.

Therefore, we have used the AVHRR clusters and AVHRR infrared channels, and we applied the homogeneity criteria that were inspired by the method of Martinet et al,.(2013) for cloudy observations in AROME and Eresmaa in (2014) to select the clear sky.

3 HOMOGENEITY CRITERIA DERIVED FROM MARTINET ET AL., (2013)

These homogeneity criteria are based on a single infrared channel AVHRR (11.5um), and define three tests of homogeneity in the radiance space (the two first tests are computed in the observation space and the third one in the model space):

Inter-cluster homogeneity: If this standard deviation is small, this means that all classes observe a very similar cloud scene in the channel.

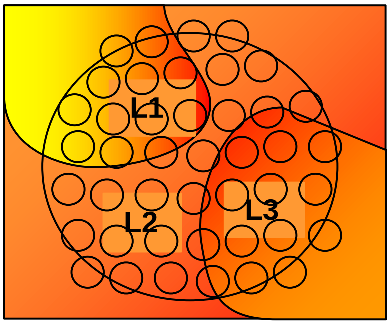


Figure 3: Illustration of the principle for calculating inter-cluster homogeneity

$$\sigma_{inter} = \sqrt{\frac{1}{\sum C_j}\sum_{j=1}^{N} C_j\left(L_{i,j} - L_{moy}\right)^2}$$

Where Lmoy is the weighted average, N is the number of clusters inside the IASI pixel, index j is the number of clusters in the IASI pixel, index i is the number of channel, Li,j is the average radiances, and Cj is the cloud fraction.

The Relationship between inter-class homogeneity and mean radiance < 8%

Intra-cluster homogeneity: this test checks the homogeneity within the same cluster.

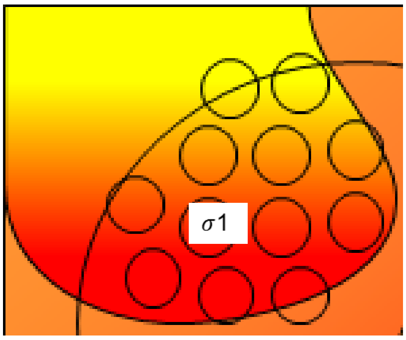


Figure 4: Illustration of the principle for calculating intra-cluster homogeneity

$$\sigma_{intra} = \sqrt{\frac{1}{\sum C_j}\sum_{j=1}^{N} C_j \sigma^2_{i,j}}$$

Where σi, j are the standard deviations of each class j calculated for the infrared channel i considered.

The Relationship between intra-class homogeneity and mean radiance < 4%

Background departure check: The homogeneous IASI observations are preserved if the difference between AVHRR observations and simulations are less than 7K.

4 HOMOGENEITY CRITERIA DERIVED FROM ERESMAA (2014)

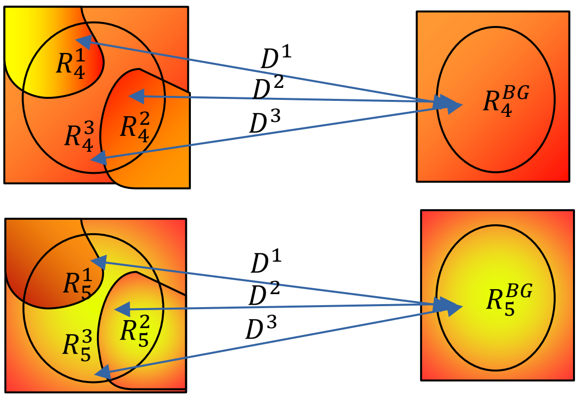
Eresmaa used this homogeneity criteria to select the clear pixels, but we tried to adapt them for the selection of homogeneous clear and cloudy pixels. In this criteria, we have used the two last infrared channels 10.5 µm and 11.5 µm and defined two tests of homogeneity in the brightness temperature space (the first one in the observation space and the second test in the model space):

The homogeneity check: this test makes use of the standard deviation of infrared brightness temperature, as computed over all clusters occupying the IASI FOV. The IASI pixel is suggested homogenous if the two standard deviations (one for each channel) both less than their predetermined threshold values (**0.75K and 0.8K, respectively)**.

The background departure check: we compute a test quantity as a fraction-weighted mean of the squared-summed background departures.

$$D_{mean} = \sum_{j=1}^{N} f^j D^j$$

where N is the number of clusters in the IASI FOV and $f^j$is the fractional coverage of cluster j, and $D^j$is the distance to the background $R_i^{BG}$is computed for each cluster j as :



$$D^j = \sum_{i=4}^{5} \left(R_i^j - R_i^{BG}\right)^2$$

Figure 5: Illustration of the principle for calculating background departure check

The IASI pixel is considered homogeneous if Dmean less than 49K²

INTER-COMPARISON OF SELECTION CRITERIA

In this paper, we evaluated results for daytime over sea of January 30, 2017. Before applying our homogeneity criteria, we calculated our statistics on all the datasets. Figure 6.a represents the bias and the standard deviation of the observations minus simulations of the 314 channels of IASI which are routinely monitored at Météo-France, but we are interested in channels sensitive to the surface temperature and the presence of the clouds (650-1000cm^1). This part presents a mean standard deviation of 7.5 K and a Bias of 0.5 K and the correlation coefficient between the observations and the simulations of 0.79.

By applying derived Martinet's homogeneity criteria (figure 6.b), we obtained a standard deviation reduced to 3.5 K with a bias of 0.21K, and a correlation coefficient of 0.98.

Then, we apply the modified Eresma's criteria (figure 6.c) we have obtained a standard deviation of 0.17K and a bias of 1.30K with 0.98 of the correlation coefficient. This different homogeneity criteria not only improve our statics but also impact the number of observations. By applying the homogeneity criteria derived from Martinet, we keep 54% of observations, with 19% of observations totally covered by clouds and 10% of clear observations. The homogeneity criteria derived from Eresmaa keep 22% of observations, with 10% of clear pixels and 6% of the cloudy pixels.

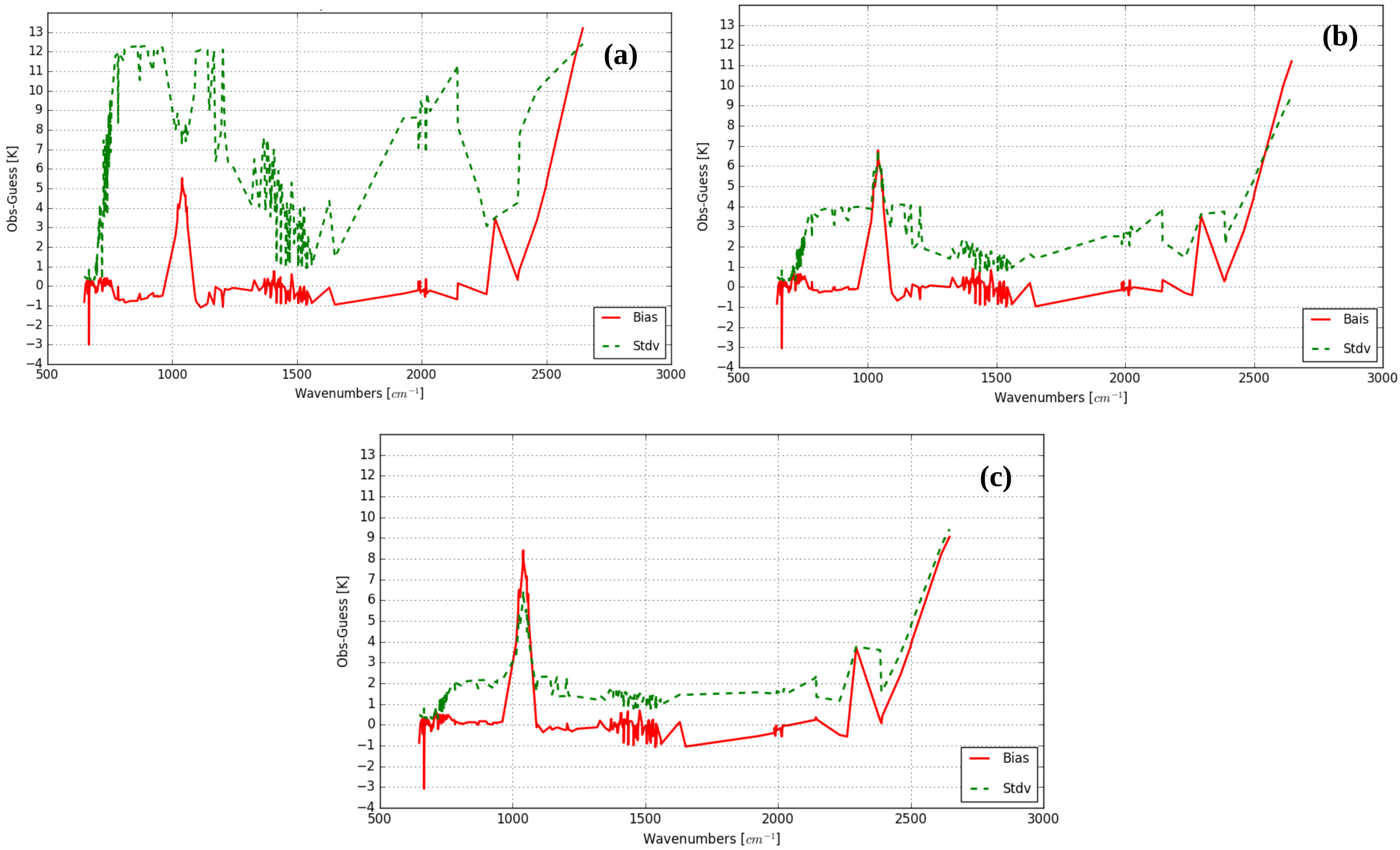


Figure 6. Bias (red solid line) and standard deviation (Stdv) (green dashed line) of the differences between background simulations and the IASI observations : (a) for all datasets, (b) after applying the homogeneity criteria derived from Martinet et al. (2013), (c) after applying the homogeneity criteria derived from Eresmaa (2014).

5 SELECTED HOMOGENEITY CRITERIA

Based on the obtained results, we observed that the departure statistics are improved, but the number of observations is reduced. Hence, we developed a third method which proposes a compromise between both methods presented above. In this selection method, we used the last two infrared channels of AVHRR (10.5 µm and 11.5 µm), and we defined two homogeneity criteria in the brightness temperature space.

Inter-cluster homogeneity: In the observation space this test makes use of the standard deviation of the infrared brightness temperature, calculated on all clusters occupying the IASI FOV, using the following formula:

$$\sigma_{inter} = \sqrt{\frac{1}{\sum C_j} \sum_{j=1}^{N} C_j (TB_{i,j} - TB_{mean})^2}$$

Where :

$TB_{i,j}$ is the mean brightness temperature of cluster j on channel i, TBmean represents the weighted average, N is the number of classes in the IASI pixel, and Cj is the cloud fraction.

Background departure check

In the model space we used D_{mean} (presented in section 3)

We decided to select an observation if it fulfills two criteria:

- Relationship between intercluster homogeneity and mean radiance for two AVHRR IR channels (10.5µm and 11.5 µm) < 0.8%.
- The sum of the average distances between each cluster and the background departure < $49K^2$

The population selected by this new selection method gives a bias of 0.18K and a standard deviation of 1.4K for channels sensitive to the presence of clouds (channels between 650-1000 cm^{-1}).

To complete our statistics, it is important to study the Probability Density Function (PDF) of the O-G errors. Three channels were assessed: window channel 1271 (962.5 cm^{-1},weighting function peaks around 1000 hPa), mid-tropospheric water vapour channel 2701 (1320 cm^{-1}, weighting function peaks around 400 hPa) and low tropospheric water vapour channel 5403 (1955 cm^{-1}, weighting function peaks around 900 hPa). The PDF of the observations minus simulations (O-G) are illustrated in Figure 7.

The distribution asymmetry is relatively small for water vapour channels. The impact of clouds is bvious on the window channel, with differences ranging from -90 to 64 K (top panels).

By applying the proposed homogeneity criteria, the histograms shown are symmetrical (and Gaussian) around zero for all channels, with a significant improvement of the window channel, with a difference from -7 to 9K (bottom panels).

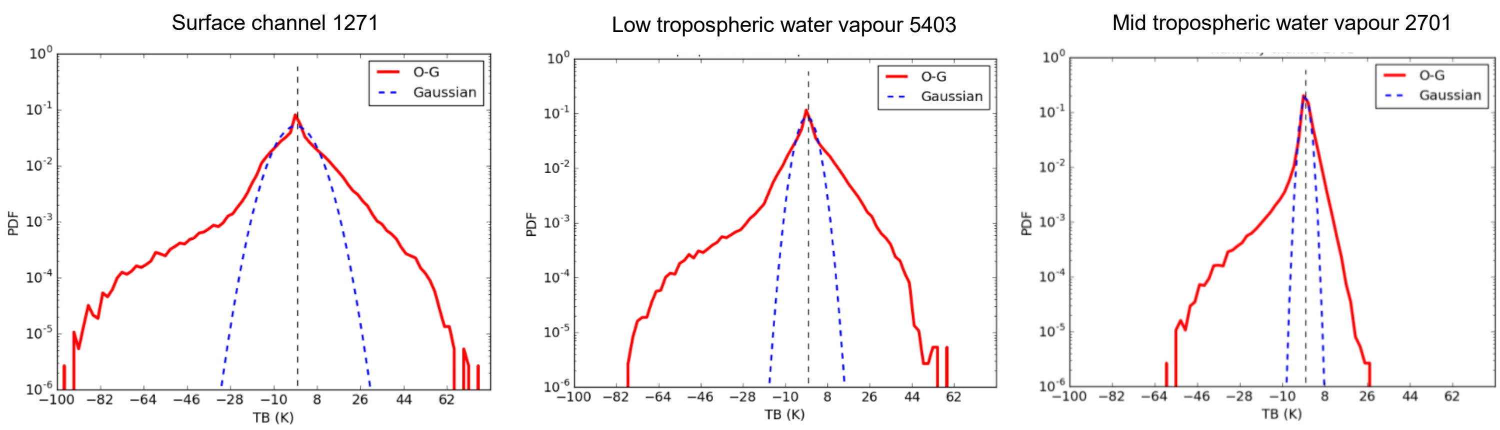
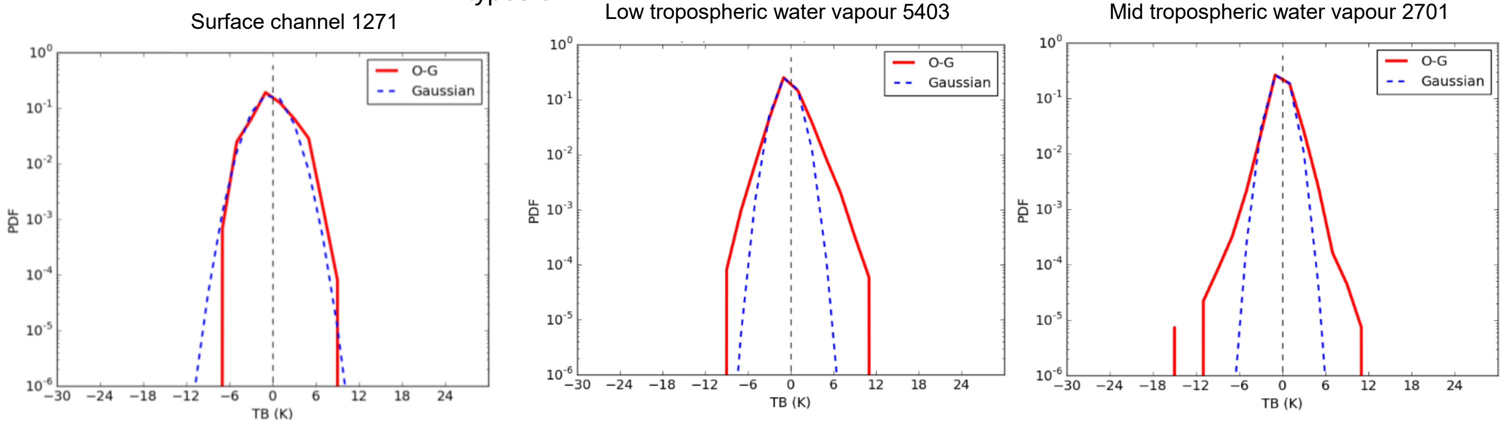
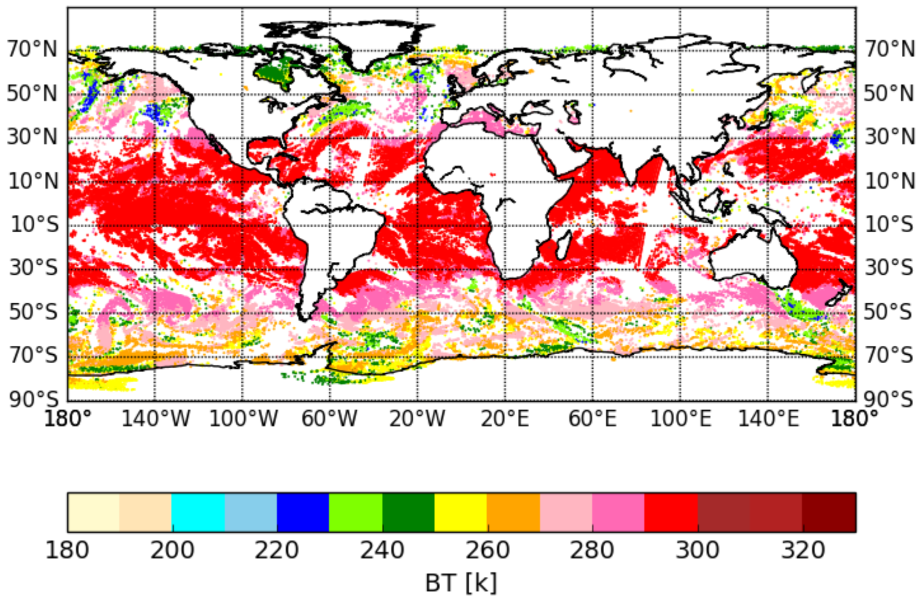


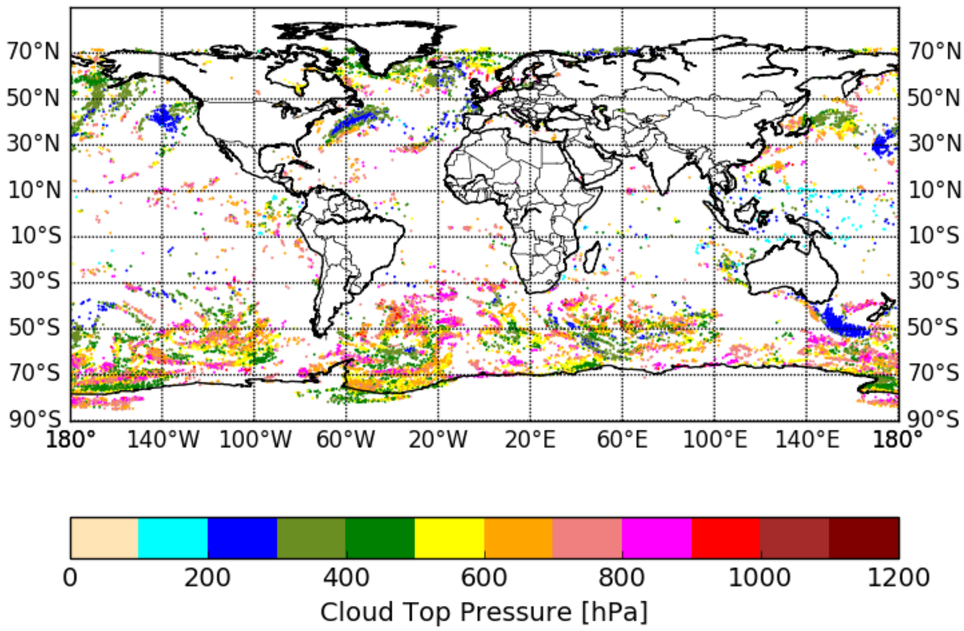
Figure 7. Frequency distribution of brightness temperature difference between observation and background (O-G) for all observations (top panels), after applying the selected homogeneity criteria (bottom panels). The PDF is presented for three channels: (Surface channel 1271, low tropospheric water vapour channel 5403, and mid tropospheric water vapour channel 2701)). The Gaussian distributions with the same error characteristics are also shown in the blue dashed Lines.

The shape of this distribution and the statistics obtained are close to that found with the criteria derived from Eresmaa. In our new selection, not only the statistics are well improved, but also a good amount of observations, 36% is kept (10% are totally clear and 11% are totally covered by clouds), which are distributed in different parts of the globe (Figure 8.a). Although, we have been able to retain different types of clouds, and it is important to note that we have kept high clouds even in the tropics areas (Figure 8.b).





(a)



(b)

Figure 8 : Map of IASI brightness temperature observations after applying the selected homogeneity criteria for surface channel (1271, 962.5 cm^{-1}) (a), Cloud-top pressure distributions retrieved from a CO2-slicing algorithm applied on IASI (b) for 30 Janvier 2017 Daytime over sea.

CONCLUSION

As our main objective was the identification of situations well simulated by RTTOV cloud and potentially usable in the data assimilation, we compared the two methods of selecting homogeneous IASI observations using AVHRR clusters, as a source of information. The first method is derived from Martinet et al., (2013). The observations minus simulations bias were improved to 3.5K with a standard deviation of 0.21K but these scores are not very satisfactory for use in assimilation, as we keep 24% of heterogeneous observations. The second method derived from Eresmaa (2014), improves well the statistics with a Bias of 0.17 and a standard deviation of 1.3K but this method results in a considerable reduction in the count of IASI observations.

The method suggested by this study is a compromise between the first two methods tested; the new feature is that the selection criteria use the two AVHRR channels in the space of brightness temperature. This restriction has enabled us to keep significantly 36% of observations and decrease the bias and standard deviations to 0.18K and 1.4K respectively, with a Gaussian distribution of brightness temperature difference between observation and background (O-B).

The radiance of a co-located AVHRR imager within each IASI field of vision and applying our new selection criteria were useful in quantifying the degree of homogeneity of the scene.

FUTURE WORK

As a perspective for future work, the next step toward the all-sky assimilation will consist in the definition of the observation errors before testing some assimilation methods for the initialization of the ARPEGE model as the variational method, only the cloud profiles are used for the direct simulation and we adjust just temperature and moisture.

The second one is the Bayesian method (1D + 4Dvar), in which we transform the information ql qi and cloud fraction in moisture that is assimilated in 4D-Var following the method by Caumont et al (2010).

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