

1D-Var temperature retrievals from microwave radiometer and convective scale model

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ABSTRACT

This paper studies the potential of ground-based microwave radiometers (MWR) for providing accurate temperature retrievals by combining convective scale numerical models and brightness temperatures (BTs). A one-dimensional variational (1D-Var) retrieval technique has been tested to optimally combine MWR and 3-h forecasts from the French convective scale model AROME. A microwave profiler HATPRO (Humidity and Temperature PROfiler) was operated during 6 months at the meteorological station of Bordeaux (Météo France). MWR BTs were monitored against simulations from the Atmospheric Radiative Transfer Simulator 2 radiative transfer model. An overall good agreement was found between observations and simulations for opaque V-band channels but large errors were observed for channels the most affected by liquid water and water vapour emissions (51.26 and 52.28 GHz). 1D-Var temperature retrievals are performed in clear-sky and cloudy conditions using a screening procedure based on cloud base height retrieval from ceilometer observations, infrared radiometer temperature and liquid water path derived from the MWR observations. The 1D-Var retrievals were found to improve the AROME forecasts up to 2 km with a maximum gain of approximately 50 % in root-mean-square-errors (RMSE) below 500 m. They were also found to outperform neural network retrievals. A static bias correction was proposed to account for systematic instrumental errors. This correction was found to have a negligible impact on the 1D-Var retrievals. The use of low elevation angles improves the retrievals up to 12 % in RMSE in cloudy-sky in the first layers. The present implementation achieved a RMSE with respect to radiosondes within 1 K in clear-sky and 1.3 K in cloudy-sky conditions for temperature.

Keywords: remote sensing, radiative transfer, data assimilation, AROME

1. Introduction

Convective scale models are now key contributors to the forecast of severe weather events in most numerical weather prediction (NWP) centres. With their kilometre-size grid mesh, non-hydrostatic equations and multiple microphysics species and parametrisations, they enable a better modelling of precipitating events, turbulence and clouds. To that end, a better understanding and modelling of boundary layer (BL) processes are essential. These processes drive the formation of fog and low stratus clouds that can lead to dangerous air traffic conditions and also contribute to the initiation of convection. The study of BL processes in mountainous regions is also an active area of research due to the uncertainties in atmospheric dynamics

combining strong temperature inversions, anabatic/katabatic winds and complex wind circulation inside the valley (Whiteman, 2000; Rotach and Zardi, 2007). BL processes can also affect air quality by reinforcing the accumulation of pollutants in the atmosphere in case of very stable conditions (Lehner and Gohm, 2010). In order to improve BL parametrisations and NWP forecasts at local scale, it is crucial to increase the spatial density and temporal resolution of low-level atmospheric measurements. In fact, satellite data represent one of the major sources of data assimilated in NWP models but they do not resolve the BL very well and suffer from the rejection of surface-sensitive channels due to uncertainties in surface temperature and emissivity. In data assimilation systems, radiosonde measurements are a main contributor to the temperature and wind analysis but their poor temporal resolution (twice a day) reduces their impact on the analysis. The study of Brousseau et al. (2014) has shown that, for wind and temperature, radio-soundings are the main contributors to

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the variance reduction at 00 UTC, whereas on average over a day, the main contributors are aircraft measurements, surface level observations (2 m temperature and relative humidity, 10 m wind) and radar observations.

Ground-based microwave radiometers (MWR) are, on the contrary, able to automatically retrieve temperature and humidity profiles at a high frequency (from 1 s to few minutes depending on the scanning strategy). Strong efforts have been undertaken in the last decade to show the potential of MWR for the description of BL (both in terms of diurnal cycle and vertical inversions) and numerous meteorological services operate MWR in research mode (Cimini et al., 2006; Crewell and Löhnert, 2007; Löhnert et al., 2008; Cimini et al., 2011; Löhnert and Maier, 2012). The studies of Löhnert et al. (2004) and Löhnert et al. (2008) have demonstrated the good accuracy of atmospheric profile retrievals obtained through a one-dimensional variational (1D-Var) assimilation technique by combining different sensors: MWR, cloud radar, lidar ceilometer and radiosondes. From these studies, the so-called integrated profiling technique leads to root-mean-square-errors (RMSE) smaller than 1 K for temperature and 1 g m^{-3} for humidity. Even if this method has the advantage of accurately retrieving atmospheric profiles as well as liquid water content (LWC), it can only be operated in instrumented sites. Another approach relies on statistical inversions [neural network (NN) or regression methods] based on temperature, humidity and liquid cloud climatology usually derived from radiosonde measurements close to the observation site. The study of Löhnert and Maier (2012) has shown the potential of this method for an operational profiling of temperature. RMSE of 0.4–1.4 K in the lowest 2 km and 1.7 K at 4 km were obtained.

However, in order to provide temperature and humidity profiles in all locations by only using MWR measurements, the 1D-Var technique can be applied on short-term NWP forecasts (Cimini et al., 2006) instead of radiosonde data. Moreover, the 1D-Var retrieval technique was also found to perform better than statistical methods (Cimini et al., 2011) and is particularly useful to study the potential of operational data assimilation into NWP models. In fact, for operational purpose, it is preferred to directly assimilate raw measurements [brightness temperatures (BTs)] inside a global 4D-Var or 3D-Var system instead of using an already inverted variable (temperature, humidity, Geer et al., 2008). In this case, correlations between the atmospheric profile (considered as a ‘pseudo-observation’) and the background can be induced if the background was already used in the first stage to derive the atmospheric profile (like in a 1D + 3D-Var/4D-Var approach). However, these correlations are not taken into account in variational assimilation systems and they make difficult the definition of the observation-error covariance matrix. If different retrievals

from the same observation (like temperature and humidity) are also assimilated, correlations between observations are created but they cannot be handled by the assimilation system. This is why large thinning lengths are used in the assimilation of satellite data. Besides, in a 1D + 3D-Var approach, the model background has already influenced the retrieval. While assimilating this retrieval, the background is used a second time and influences the analysis. Thus, the weight given to the background is twice the one that would be used if BTs are directly assimilated. The direct use of BT also makes it possible to extract information on different variables (temperature, humidity, wind, clouds, etc.) from the measurement instead of limiting the information only on the previously retrieved variable (Bauer et al., 2010). By directly using the information from BT measurement, the 1D-Var stays close to the implementation that would be used in an operational 3D-Var or 4D-Var system. Thus, it is a useful tool to evaluate the capability of variational systems to assimilate observations from new instruments and it is a necessary first step before the inclusion of new observations inside a NWP model. Finally, the 1D-Var can be used as an additional step of quality control before assimilation into 3D-Var.

Recently, Météo France deployed a microwave profiler HATPRO manufactured by Radiometer Physics GmbH, Germany (RPG) at the National Meteorological Station of Bordeaux (LFBD) for a 6-month period (from April 2014 to October 2014) during the BRAHMS campaign (BT compared to AROME model with temperature and Humidity Measurement System). The goal of this experiment is to assess the potential of MWR BT measurements for contributing to operational data assimilation at convective scale. While previous studies have shown the performance of 1D-Var temperature and humidity retrievals from NWP forecasts at global scale (Cimini et al., 2010, 2011), this study goes further by answering the following questions:

- Do MWR BT measurements respect operational constraints of variational assimilation (Gaussian distribution of observation errors, unbiased observations)?
- Is a bias correction needed for an operational assimilation of MWR measurements?
- Can 1D-Var assimilation of MWR measurements improve NWP forecast from convective scale models (2.5 km grid mesh)?

This article begins with an overview of the instruments used in this study (Section 2), the French convective scale model AROME that provides the *a priori* profile (Section 3) and the 1D-Var system algorithm (Section 4). Statistics of the observation minus background departures as well as the distribution of observation errors are then described in

Section 5 before showing the results of 1D-Var retrievals (Section 6) in clear and cloudy conditions.

2. Instruments

The data used in this paper were collected by continuous MWR observations at the station of Bordeaux (latitude 44.49 °N, longitude 0.41 °E, elevation 49 m). At Bordeaux, radiosondes from the MODEM automated robotsonde (M10 sondes) of Météo France are launched twice a day (23 and 11 UTC). This system automatically launches balloons without any man power (www.meteomodem.com/Leaflet-ROBOTSONDE-Container-140704.pdf). The specifications for total measurement uncertainties are 0.5 °C for temperature, 1 hPa for pressure, 0.15 m s⁻¹ for wind speed and 5 % for relative humidity (www.meteomodem.com/Leaflet-M10-120217.pdf). The RPG MWR was deployed on the roof of the meteorological station at an altitude of 10 m above ground. The third generation of HATPRO MWR was used in this study with an integration time of 60 s for BT measurement at 90 °, and 10 s for low elevation angles. A BL scan is made of 10 elevation angles (see below). It is thus performed in 110 s and repeated every 10 min. Internal gain calibrations are performed every 5 min. The HATPRO MWR was designed as a network suitable instrument with accurate retrievals of liquid water path (LWP), humidity and temperature profiles (Rose et al., 2005). During the period, the MWR observed BTs in 14 channels and 10 elevation angles (90 °, 30 °, 19.2 °, 14.4 °, 11.4 °, 8.4 °, 6.6 °, 5.4 °, 4.8 ° and 4.2 °). The first band (K-band) contains seven channels close to the 22.235 GHz water vapour band at centre frequencies 22.24, 23.04, 23.84, 25.44, 26.24, 27.84 and 31.4 GHz, whereas the second band (V-band) contains seven channels close to the 60 GHz oxygen line at centre frequencies 51.26, 52.28, 53.86, 54.94, 56.66, 57.3 and 58 GHz. The first band contains information on atmospheric humidity and LWC while the second band brings information on the vertical profile of temperature due to the homogeneous mixing of O₂. The H₂O line at 22.235 GHz is optically thin and contains information from high atmospheric layers, whereas at 60 GHz most of the emission comes from layers near the surface. Further away from this line, the atmosphere becomes more transparent and more emission comes from higher atmospheric layers. The use of several elevation angles was found to significantly improve the accuracy of temperature profile retrievals in the BL (Crewell and Löhnert, 2007) when the atmosphere is supposed to be horizontally homogeneous in the vicinity of the MWR (≈ 3 km). For accurate measurements, the MWR V-band channels need to be calibrated approximately twice a year by using a liquid-nitrogen-cooled (LN₂) load that is considered as a black body at the boiling temperature of 77 K. This cold point calibration

was performed at the beginning of the campaign. An internal ambient black body is used together with the LN₂ load for the absolute calibration procedure (Löhnert and Maier, 2012).

3. The AROME model

AROME (Application of Research to Operations at MESoscale) is a limited area model with a 2.5 km grid covering Western Europe. It is hourly coupled with the ARPEGE (Action de Recherche Petite Echelle Grande Echelle) forecast on its lateral boundaries. The 60 unequally spaced vertical levels cover the troposphere and, more loosely, the stratosphere up to 1 hPa. AROME is based on the ALADIN (Aire Limitée, Adaptation Dynamique, Développement International) non-hydrostatic equations (Bubnová et al., 1995). A detailed parametrisation of cloud micro-physical processes considering five classes of hydrometeors (cloud liquid water and cloud ice, rain, snow and graupels) is used (Caniaux et al., 1994; Pinty and Jabouille, 1998). Rain, snow and graupel precipitate but it is also possible to activate the sedimentation of cloud ice and cloud liquid water to obtain a better simulation of cirrus and fog. Deep convection is explicitly resolved in AROME. These equations as well as the physical parametrisations are inherited the non-hydrostatic Meso-NH model (Lafore et al., 1998).

AROME has its own 3D variational data assimilation system based on that of ALADIN-FRANCE (Fischer et al., 2005). As described in Brousseau et al. (2011), the AROME background-error covariances are calibrated using a multivariate formulation (Berre, 2000) and a method based on an ensemble of perturbed assimilations which formalism can be found in Berre et al. (2006).

In the operational AROME 3D-Var, observations collected within a ± 1 h 30-min assimilation window are used to perform the analysis from which a 3-h forecast will serve as a background for the next cycle. For the analysis, the control vector is composed of vorticity, divergence, temperature, specific humidity and surface pressure. The other model variables that are not included in the control vector are held fixed from the background. All conventional observations are assimilated together with wind profilers, winds from space-borne measurements (Atmospheric Motion Vectors and scatterometers), Doppler winds (Montmerle and Faccani, 2009) and reflectivity (Caumont et al., 2010) from ground-based weather radars, satellite radiances as well as ground-based GPS measurements.

For this study, 3-h forecasts from the operational AROME model are used as background in the 1D-Var algorithm.

4. Retrieval method

4.1. 1D-Var framework

Usually, MWR retrievals use linear regressions, quadratic regressions or NNs. The 1D-Var algorithm used in this study is based on the Bayesian optimal estimation theory described in Rodgers (2000) by combining MWR measurements and *a priori* information from a short-term forecast. The best approximation of the true atmospheric vector $\mathbf{x}$ is thus a combination of the observation vector $\mathbf{y}$ and the background state $\mathbf{x}_b$ defined by the NWP forecast. An observation operator including interpolations from model space to observation space and a radiative transfer model is needed to compute the equivalent observation from the background. The statistically optimal state is then obtained through the minimisation of the cost function J :

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + \frac{1}{2}(\mathbf{y} - \mathbf{H}(\mathbf{x}))^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}(\mathbf{x})) \quad (1)$$

where $\mathbf{R}$ is the measurement error covariance matrix, $\mathbf{B}$ is the background-error covariance matrix, T is the transpose operator and -1 the inverse operator. During the minimisation process, a Levenberg–Marquardt descent algorithm is applied; this method was found to improve the convergence rate compared to the Gauss–Newton method by introducing a factor g that is adjusted after each iteration. If the cost function is not decreased with the new profile, the factor is multiplied by 10. The iterative solution that minimises the cost function J is given by

$$\mathbf{x}_{i+1} = \mathbf{x}_i + ((1 + \gamma)\mathbf{B}^{-1} + \mathbf{H}_i^T \mathbf{R}^{-1} \mathbf{H}_i)^{-1} \times (\mathbf{H}_i^T \mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}(\mathbf{x}_i)) - \mathbf{B}^{-1}(\mathbf{x}_i - \mathbf{x}_b)) \quad (2)$$

where $\mathbf{H}_i$ is the Jacobian matrix, which represents the sensitivity of the observation operator to changes in the control vector $\mathbf{x}$ ($\mathbf{H}_i = \partial \mathbf{H}(\mathbf{x}_i) / \partial \mathbf{x}_i$).

4.2. Settings

In our case, the control vector $\mathbf{x}$ consists of the temperature profile on the same 60 vertical levels as defined in the AROME model. These levels cover the atmospheric range from the ground up to approximately 50 km altitude. The vertical resolution decreases with altitude: 50–120 m below 1 km of altitude, 120–300 m from 1 to 5 km and $\simeq 500$ m on average from 5 to 10 km. The observation vector for temperature retrieval $\mathbf{y}$ consists of all V-band channels at 90 ° and the five optically thickest channels (53.86, 54.94, 56.66, 57.3 and 58 GHz) at low elevation angles to improve the retrieval accuracy in the BL. Nine elevation angles were defined by the RPG manufacturer from 4.2 ° to 30 °.

In total, the vector $\mathbf{y}$ consists of 52 BTs ($7 + 5 \times 9$). The forward model operator used in this study is the line-by-line Atmospheric Radiative Transfer Simulator 2 (ARTS, Eriksson et al., 2011) and 1D-Var experiments are performed using the Qpack2 package (Eriksson et al., 2005) provided with the ARTS software. For the radiative transfer simulations, the gaseous absorption is calculated according to Rosenkranz (1993) for O₂, Rosenkranz (1998) for water vapour and Liebe et al. (1993) for N₂. The LWC is also taken into account in the absorption model according to Liebe et al. (1993).

The observation-error covariance matrix $\mathbf{R}$ is assumed to be uncorrelated with a SD of 0.5 K for channels 8–9 and 0.2 K for channels 10–14. The observation error takes into account measurement error and forward model error. These values have been chosen empirically on the basis of previous studies by Löhnert et al. (2008) and Hewison (2007) and mainly represent the radiometric noise of the instrument. According to the study of Hewison (2007), the forward operator error is negligible for opaque channels but can be quite important for transparent channels at 51.26 and 52.28 GHz. In the future, an update of these measurement errors will be carried out to correspond to the specific HATPRO generation 3 used in this study and to the representativity errors, which depend on the NWP model used in the 1D-Var. It is important to note that the assumption of diagonal $\mathbf{R}$ matrix is probably wrong especially in the case of measurements made with the same frequency but at different elevation angles. However, the computation of a non-diagonal $\mathbf{R}$ matrix was beyond the scope of this study and it was decided to stay with a diagonal assumption to simplify these first retrievals. In the future, the potential benefit of using a correlated $\mathbf{R}$ matrix when different elevation angles are taken into account should be investigated.

In this work, the $\mathbf{B}$ matrix used operationally at Météo France for data assimilation purpose in the AROME model has been chosen. As described in Brousseau et al. (2011), the $\mathbf{B}$ matrix has been computed from an ensemble of perturbed assimilation cycles.

5. Evaluation of the observation operator

5.1. Observation minus background departure monitoring

In this section, we monitor observation minus simulation differences during the 6 months of the BRAHMS experiment (from April 2014 to mid-October 2014). The simulation is produced with the radiative transfer model ARTS. Temperature, humidity and pressure profiles are extracted from 3-h AROME forecasts. The mean profile of the four-model grid points closest to the MWR observations

is used as background $\mathbf{x}_b$. This monitoring is essential to point out some systematic errors that can come from the measurement itself, the radiative transfer model or the NWP forecast. Even if this monitoring is not able to differentiate the source of the systematic errors, it is widely used in the satellite data community. From this monitoring, a BT offset can be removed to unbiased the measurement to make sure that the assumption of unbiased observations, that is necessary for optimal estimation retrieval, is respected. To identify large BT differences that could come from the AROME background profile, and not from the measurement itself, these BT differences were also computed from collocated radiosonde measurements.

Figure 1 shows the observation minus background (O - B) departures computed from 3-h AROME forecasts. Biases (solid line) and SDs (dashed line) of the O - B are

shown in each figure for channels 8–14 (51.26–58 GHz) and six elevation angles: 5.4°, 11.4°, 14.4°, 19.2°, 30° and 90°. Departures computed in clear-sky cases (black line, 311 cases) are compared to those computed in cloudy conditions (red line, 334 cases). The distinction between clear and cloudy cases was performed by combining the information provided by different instruments: the cloud base height derived from a ceilometer deployed at the Bordeaux airport close by the MWR and temperature measurement by a 10.5 μm infrared radiometer included in the HATPRO platform. The last one is sensitive to the cloud base temperature and gives an information on the presence of a thick cloud when the infrared temperature is warm (almost no contribution from the clear-sky background above the cloud). To apply the most conservative methodology and to avoid any cloud contamination in the

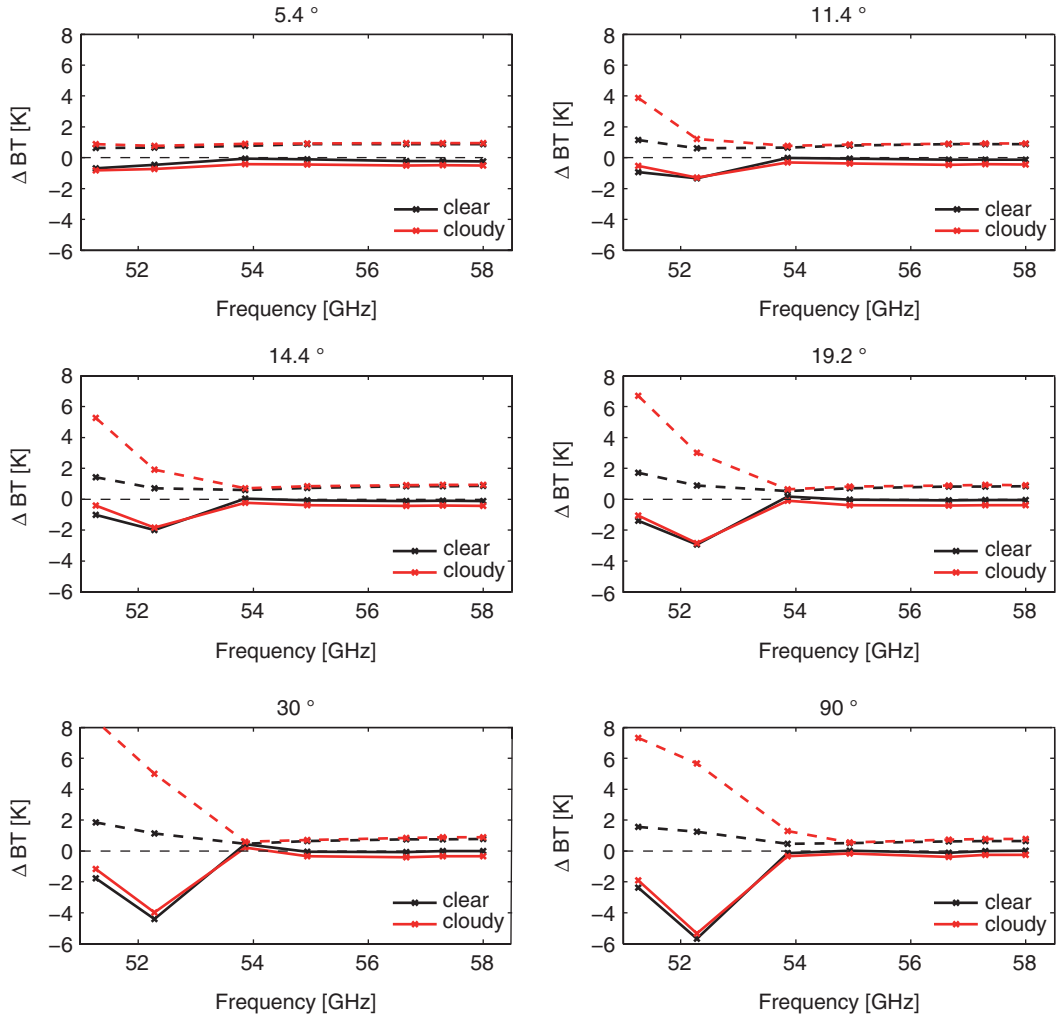


Fig. 1. Observation minus background (AROME forecast) departures for V-band channels (51–58 GHz) for different elevation angles from 5.4° to 90°. For each elevation angle, bias (solid line) and standard deviation (dashed line) are shown for clear-sky cases (black line, 311 cases) and cloudy cases (red line, 334 cases).

clear-sky sample, the SD of the LWP retrieved from the RPG manufacturer software through a NN retrieval was also used. As this product is retrieved with an integration time of 60 s, the SD over 20 min has been considered. Thresholds were then determined in order to have a good compromise between a sufficient data sample and the rejection of clouds in the clear-sky sample. Thus, an observation is considered as clear if it fulfils the three criteria:

- No cloud observed by the ceilometer (below 8 km altitude which corresponds to the limit of detection).
- Infrared radiometer temperature below -30°C (would reject thick clouds).
- SD of the LWP over 20 min smaller than 10 g m^{-2} .

On the contrary, the observation is considered as cloudy if a cloud is detected by the ceilometer and at least one of the two conditions on the infrared radiometer or the LWP is not fulfilled. The 3-h AROME forecasts used to compute the O - B statistics have been extracted from each assimilation cycle. From a total of 1592 AROME profiles, 917 are considered as non-rainy according to the MWR precipitation sensor and close enough to the MWR measurements (time delay $< 2\text{ h}$). From these 917 profiles, the process of selection leads to 334 profiles considered as cloudy (38 %) and 311 as clear (34 %). When comparing the retrieved profiles to the radiosondes that are launched only twice a day, the sample of clear-sky observations is reduced to 72 cases and the sample of cloudy-sky observations to 77 cases. More conservative thresholds would have led to too few selected cases and to avoid another reduction of the data set no constraint on the AROME cloudiness is used. Cloud discrepancies between observation and model can thus affect the O - B statistics for the most transparent channels.

Table 1 gives the bias and SD of the O - B departures computed at 90° from AROME forecasts in clear-sky and cloudy conditions. Figure 1 shows that large biases up to

Table 1. The bias and standard deviation of the observation minus background departures computed from AROME forecasts at 90° elevation angle

Frequency (GHz)	Bias (K) (clear/cloudy)	Standard deviation (K) (clear/cloudy)
51.26	-2.4/ -1.9	1.5/7.3
52.28	-5.7/ -5.3	1.2/5.7
53.86	-0.1/ -0.3	0.4/1.3
54.94	0.02/ -0.2	0.5/0.6
56.66	-0.11/ -0.4	0.6/0.7
57.3	-0.01/ -0.2	0.6/0.8
58	0.02/ -0.2	0.6/0.8

-5.7 K are observed in the most transparent V-band channels at 51.26 GHz and more especially at 52.28 GHz, whereas almost no bias is observed for the highest MWR frequencies above 53 GHz (smaller than 0.1 K). Transparent channels are influenced by uncertainties in both the water vapour continuum, the O_2 absorption model and are affected by liquid water emission. To evaluate the contribution of NWP forecast errors to O - B departures, these departures have also been computed from radiosonde profiles. In cloudy conditions, in order to take into account the liquid water emission, the LWC is calculated from a modified liquid adiabatic model based on an empirical correction accounting for entrainment (Karstens et al., 1994). Figure 2 shows the bias of the O - B departures computed either from AROME forecasts or from collocated radiosondes. Only AROME forecasts at the same time of the radiosondes are used to avoid discrepancies in the two biases that would be due to different atmospheric conditions or different MWR observations. Thus, each bias is computed on 72 clear-sky profiles and 77 cloudy-sky profiles. Almost the same bias (differences smaller than 1 K) is observed when the BT spectrum is simulated from a collocated radiosonde or from an AROME forecast in clear-sky condition suggesting a systematic error in the instrumental measurement. The differences between the two biases are smaller for opaque channels that are not affected by the water vapour and liquid water emissions. In cloudy-sky, large differences up to 4 K are observed at 51.26 GHz pointing out a smaller bias when the BT is computed from AROME. These differences come from the uncertainty in the LWC profile that strongly affects the 51.26 and 52.28 GHz channels and the empirical assumption used to derive this content from the radiosonde temperature and humidity profiles. Even if the LWC profile forecasted by AROME seems more accurate than the one derived from radiosondes, large errors in the forecast can also occur and impact the O - B departures. These channels are also influenced by the O_2 absorption band and are more difficult to simulate with large differences found when using different absorption models (Hewison et al., 2006). Note that these BT offsets at 51 and 52 GHz are also consistent with the ones derived in the study of Löhnert and Maier (2012).

We can also note that, for transparent V-band channels (51 and 52 GHz), the bias increases with higher elevation angles. Due to the decrease in optical depth when sensing, these channels are more affected by errors during the liquid nitrogen calibration (cold point calibration).

In order to evaluate if the SD of the O - B departures can be considered as small enough to apply a constant bias correction offset, the ratio of the SD to the mean BT spectrum is given in Table 2. We can note that SDs can be considered as small for clear-sky cases with absolute values

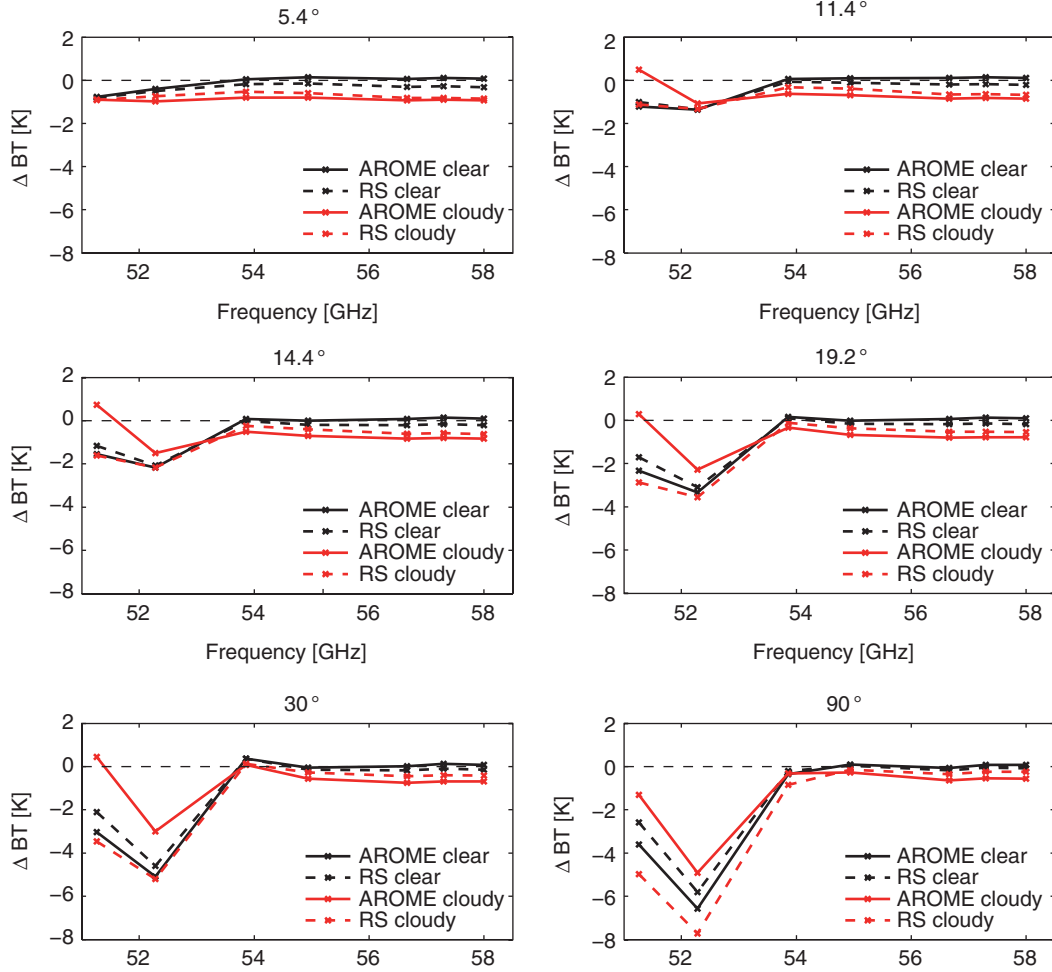


Fig. 2. Bias of the departures (observation minus background) computed either with AROME (solid line) or collocated radiosondes (dashed line). The differences are computed for different elevation angles from 5.4 ° to 90 ° in clear-sky cases (black line, 72 observations) and cloudy conditions (red line, 77 observations).

smaller than 1 K and relative values smaller than 1.4 % for all channels. This result suggests that a constant offset applied to the BT measurements might be adequate to unbiased the observations in clear-sky conditions. In cloudy-sky conditions, large values from 3 to 7 K are observed at

elevation angles higher than 8 ° at 51.26 GHz and 19 ° at 52.28 GHz. At zenith, the SD reaches 6 and 4 % of the mean BT spectrum at 51.26 and 52.28 GHz, respectively. The O - B departures are thus spread over a large range around the mean mainly due to cloud discrepancy between

Table 2. Relative standard deviation (ratio of the standard deviation to the mean brightness temperature) of the observation minus background departures computed from clear-sky AROME forecasts at different elevation angles

Angle/(GHz)	51.26	52.28	53.86	54.94	56.66	57.3	58
5.4 °	0.2 (0.3)	0.2 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)
11.4 °	0.4 (1.4)	0.2 (0.4)	0.2 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)
14.4 °	0.6 (2.1)	0.3 (0.7)	0.2 (0.2)	0.2 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)
19.2 °	0.8 (3.0)	0.3 (1.2)	0.2 (0.2)	0.2 (0.3)	0.3 (0.3)	0.3 (0.3)	0.3 (0.3)
30 °	1 (4.6)	0.6 (2.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.3)	0.3 (0.3)	0.3 (0.3)
90 °	1.4 (6.3)	0.8 (3.7)	0.2 (0.5)	0.2 (0.2)	0.2 (0.2)	0.2 (0.3)	0.2 (0.3)

Relative standard deviations computed in cloudy conditions are given in brackets. Unit: %.

the background and the observation. However, the relative SDs are smaller than 0.5 % at frequency above 53 GHz showing a small dispersion of the O - B departures at these frequencies. Thus, in cloudy conditions a constant bias correction might be adequate at least for channels above 53 GHz.

5.2. Frequency distribution of the observation minus background departures

The optimal estimation technique is based on two assumptions on the observation vector y : observations are supposed to be unbiased and the distribution of observation errors should follow a Gaussian law. Previously, it has been shown that a constant BT offset can be applied to MWR measurements to respect the first condition in clear-sky cases for all V-band channels and in cloudy-sky for frequency above 53 GHz. In this section, we investigate whether the second criterion is met by studying the frequency distribution of the departures of the AROME background profiles from the MWR measurements.

Figure 3 shows the frequency distribution of the O - B departures for three V-band channels: 52.28, 54.94 and 58 GHz at 90 ° elevation angle. Top panels show the distributions computed with clear-sky cases, whereas bottom panels show the distributions computed with cloudy cases. In each panel, the median, skewness, excess kurtosis (kurtosis coefficient minus 3), full width at half maximum

and result of a Kolmogorov–Smirnov test is mentioned. For comparison with the equivalent Gaussian distribution, the width of the Gaussian is also specified. For clear-sky cases, the departures are characterised by a near-symmetric distribution for channels above 53 GHz and, from a qualitative point of view, are close to the Gaussian distribution with the same mean and SD (full widths at half maximum are very similar for all channels). On the contrary, the distribution at 52.28 GHz is slightly asymmetric with a negative skewness of -1.89 and has a large kurtosis (10.2). Comparable results were found at 51.26 GHz (not shown). The distributions are almost centred on zero except the 52.28 GHz channel for which we observe a median of -5.5 K. A Kolmogorov–Smirnov test approves the hypothesis that the O - B departures come from a Gaussian distribution at the 5 % significance level for channels above 53 GHz but this hypothesis is rejected at 51.26 and 52.28 GHz.

In cloudy-sky, clouds have a strong impact on the statistics at 52.28 GHz which is affected by both the water vapour continuum and the liquid water emission (Hewison et al., 2006). For this channel (bottom left panel), the distribution in cloudy conditions is asymmetric with positive skewness (1.1), large kurtosis (12.7) and far from the equivalent Gaussian distribution with a width 10 times smaller than the corresponding Gaussian distribution. Again a Kolmogorov–Smirnov test rejects the hypothesis that the O - B departures at 52.28 GHz come from a Gaussian distribution, whereas it is still valid for the most opaque channels (> 54 GHz) that are not affected by clouds.

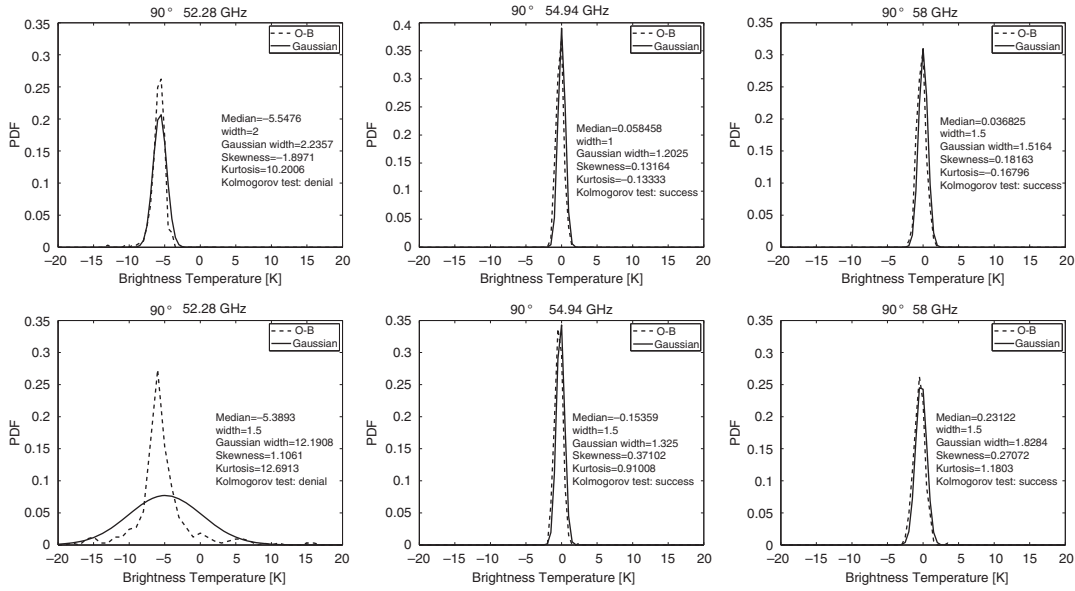


Fig. 3. Relative frequency distribution of brightness temperature differences between observation and background at 90 ° elevation angle for three channels: 52.28 GHz (left panel), 54.94 GHz (middle panel) and 58 GHz (right panel). The frequency distributions are shown for clear-sky cases (311 observations) on top panels and cloudy cases (334 observations) on bottom panels. The Gaussian distributions with the same error characteristics are also shown in solid line.

The last two sections have shown the potential of the ARTS model to simulate MWR observations from 3-h AROME forecasts with reasonable O - B departures. The possibility of applying a constant bias correction to correct systematic errors that could affect the retrievals was investigated. According to the O - B departures and their frequency distributions, a constant BT offset seems adequate in clear-sky conditions for all channels and in cloudy-sky for channels above 53 GHz. The study of the O - B distributions showed that O - B departures do not follow a Gaussian distribution for channels 51.26 and 52.28 GHz in clear-sky conditions and channels 51.26–53.86 GHz in cloudy-sky conditions. In the following sections, 1D-Var retrievals performed in all-weather conditions are presented with a channel selection in agreement with these results.

6. 1D-Var retrievals

6.1. Expected accuracy

The expected errors of the 1D-Var retrievals can be determined through the computation of the analysis-error covariance matrix $\mathbf{A}$:

$$\mathbf{A}^{-1} = (\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}) \quad (3)$$

The $\mathbf{A}$ matrix depends on the background-error covariance matrix $\mathbf{B}$, the observation-error covariance matrix $\mathbf{R}$ and the Jacobian matrix $\mathbf{H}$. This matrix gives an estimate of the uncertainty on retrieved profiles assuming that the problem respects the constraints of optimal estimation (linearity of the observation operator, unbiased observations, Gaussian distributions of background and observation errors, etc.). The $\mathbf{A}$ matrix has been computed on the set of clear-sky MWR observations. Figure 4 compares the square-root of the diagonal elements of $\mathbf{A}$ with those of $\mathbf{B}$ (left panel). We can see that the estimated error on the temperature profile

retrieved from MWR is expected to approach 0.2 K near the surface and increases with height up to 0.5 K. We observe a large improvement over the background in the first 2 km showing the potential of MWR for BL to 3 km profiling. A maximum improvement of 80 % of the analysis over the background is observed near the surface. The analysis is able to improve the temperature background profiles up to 5 km but the improvement is small above 3 km. Fig. 4 also shows the temperature Jacobians used in the 1D-Var to compute and minimise the cost function (right panel). The average temperature Jacobians over all the MWR clear-sky observations used in the 1D-Var are shown. We can note a peak of the Jacobians for channels 56.66–58 GHz at around 500 m above ground. Channels 54.94 and 53.86 bring information around 1 km above ground with a peak less pronounced than the one observed for the most opaque channels. The sensitivity to temperature changes decreases to very small values for the most transparent channels. From these figures, we can expect the background to be improved by the analysis essentially below 2 km altitude but some improvements might be observed upper in the atmosphere due to the sensitivity of the temperature Jacobians at 53.86 GHz.

6.2. 1D-Var retrievals

The 1D-Var technique and the settings described in the previous sections were applied to MWR measurements collected during the BRAHMS campaign. Background profiles were extracted from 3-h AROME forecasts from the 9 and 21 UTC analysis cycles. The MWR measurement the closest in time with the radiosonde ascent was used in the retrieval (11 UTC for daytime radiosonde and 23 UTC for nighttime radiosonde). This configuration was chosen to be as close as possible to the operational 3D-Var assimilation

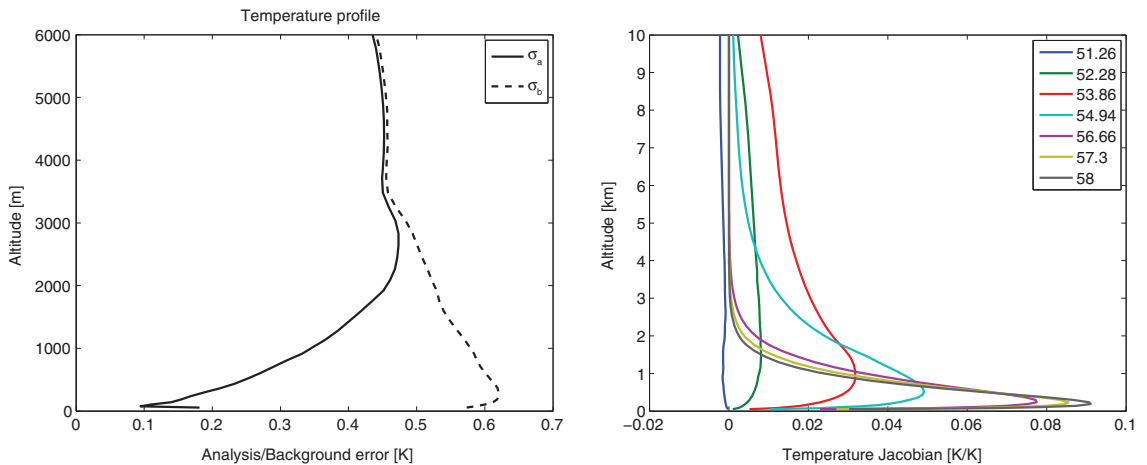


Fig. 4. Left panel: temperature analysis error (solid line) and background error (dashed line). Right panel: temperature Jacobians.

system of the AROME model. In cloudy conditions, the LWC from the AROME forecast is taken into account in the 1D-Var as a sink variable. Thus, it is used to simulate the background BT and kept constant during the minimisation. As large cloud discrepancies can occur between observation and model, channels 51.26 and 52.28 GHz should be used only if the LWC is retrieved simultaneously with temperature to avoid unphysical temperature increments to adjust the BT of transparent V-band channels. The inclusion of liquid water as a new control variable requires a careful specification of background errors and cross-correlations (Martinet et al., 2013) and is beyond the scope of this study. A good bias correction of transparent channels is also needed and results of Sections 5.1 and 5.2 have shown the complexity of using them efficiently. As a result only channels 10–14 (53.86–58 GHz) were used for clear-sky retrievals and channels 11–14 (54.94–58 GHz) for cloudy-sky retrievals. According to Section 5.1, a constant bias offset, dependent on the atmospheric scenario (clear or cloudy) is removed from the channels used in the retrieval. Thus, it was chosen to use a bias correction depending on the air mass: clear-sky bias correction for clear observations and cloudy-sky bias correction for cloudy observations. The background-error statistics were derived from an AROME ensemble assimilation that considers explicit observation perturbations coupled with operational ensemble assimilation at global scale.

Figure 5 shows the bias and SD of the O - B departures compared to those of the observation minus analysis (O - A) innovations after 1D-Var retrievals using all elevation angles. The O - B departures after bias correction (black line) are also compared to those before bias correction (red line). The proposed bias correction does not have a significant impact on the O - B departures in clear-sky but

a decrease from -0.6 to -0.3 K is observed in cloudy-sky. After the retrievals, the O - A are very close to zero and much smaller than the O - B departures for the most opaque channels of frequency higher than 54.94 GHz both in clear-sky and cloudy-sky conditions. For these channels, the O - A innovations do not exceed 0.01 K while the O - B departures reach -0.30 K. This result confirms the sensitivity of BT measurements to temperature in the lowest layers. The analysis is also able to slightly improve the O - B departures at 53.86 GHz in clear-sky conditions with a final O - A bias of -0.20 K instead of -0.35 K for the background. We can also note that the SD of the O - A innovations do not exceed 0.2 K compared to 1 K for the O - B departures except at 53.86 GHz in clear-sky where it reaches 0.4 K. This decrease of the SD after the analysis is observed both in clear and cloudy-sky conditions for opaque channels.

The 1D-Var retrieved profiles are now compared with NN retrievals. These retrievals are generated by the RPG-HATPRO software (R2CH version 8.46) with NN coefficients produced by RPG. These retrievals were compared to automated MODEM radiosondes launched twice a day in Bordeaux. During the BRAHMS campaign, a total of 314 observations in which both radiosondes and MWR measurements were available have been collected. From these 314 observations, 88 were rejected due to the detection of rain on the MWR sensor. The remaining observations were screened into 72 clear-sky observations and 77 cloudy observations. During the BRAHMS campaign, the HATPRO MWR was deployed on the 10 m roof of the meteorological station. The automated robotsondes suffer from a loss of GPS signal after going out from the robot (personal communication). Due to this loss of GPS signal, no radiosonde measurements are performed between the ground and

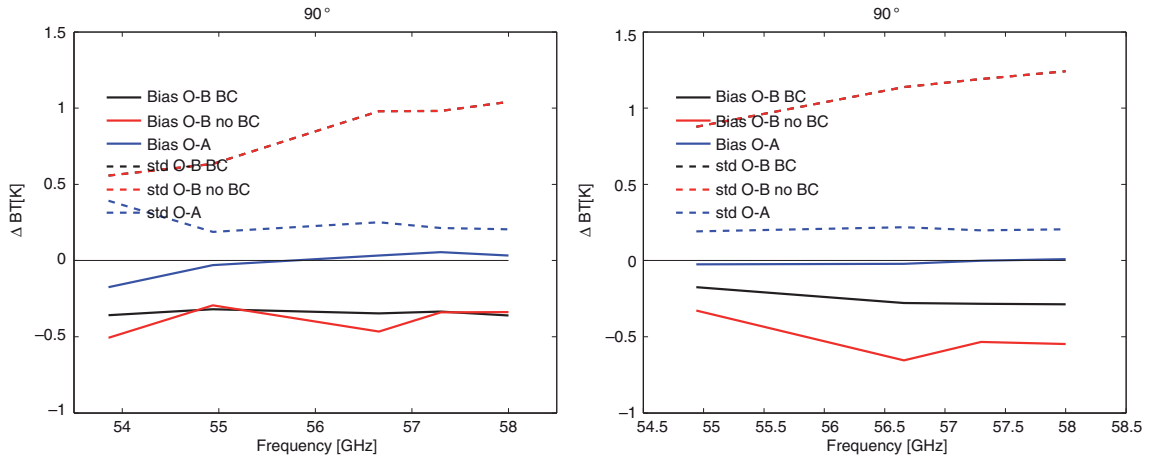


Fig. 5. Bias (solid line) and standard deviation (dashed line) of observation minus background departures after bias correction (O - B, black line) compared to those of observation minus background departures without bias correction (O - B, red line) and observation minus analysis innovations (O - A, blue line). Statistics computed on 51 clear-sky cases (left panel) and 69 cloudy-sky cases (right panel).

approximately 80 m of altitude. Consequently, MWR retrievals were compared to radiosonde measurements at the first AROME level for which both measurements are available. Fig. 6 evaluates the temperature retrieval accuracy in terms of bias (left panel), SD (middle panel) and (RMSE, right panel) of the retrieval minus radiosonde profile differences by focussing on clear-sky measurements. 1D-Var retrievals (blue lines) are compared to the accuracy of the AROME background profile (black line) and to the RPG NN retrievals (magenta). To evaluate the impact of the proposed bias correction, NN retrievals are performed on both brute measurements and bias-corrected observations. On average, the rate of convergence reaches 96 % in cloudy-sky and 90 % in clear-sky but it decreases to 82 % in clear-sky when only zenith angle observations are used. To compare the different configurations between each other, only the atmospheric profiles that converged in all experiments are considered in the statistics computation. The comparison is thus made on 51 profiles common to all the different experiments. We focus on the 0–6 km range that contains most of the information from the observation (see Section 6.1). We can note that AROME backgrounds present a positive bias below 3 km altitude and a slight negative bias above. The maximum is found near the surface with 0.5 K bias. This bias is slightly reduced by 1D-Var retrievals at the first level (0.2 K). The NN method presents a negative bias under 600 m that turns into a large positive bias of 1.5 K at 1.5 km altitude before decreasing again with altitude. Similar values were found by Cimini et al. (2006) and probably come from spectroscopic bias in absorption

models (Hewison et al., 2006). This large 1.5 K bias is significantly decreased when the bias correction is applied to the BTs before computing the NN retrievals. After bias correction, the NN bias does not exceed -0.6 K. In terms of SD and RMSE, under 300 m, 1D-Var and NN retrievals show similar performance and are both able to improve the AROME forecast except for the first atmospheric level (1.5 K RMSE instead of 1.1 K). However, above 400 m the 1D-Var shows the best retrieval accuracy, which stays within 1 K RMSE for heights up to 6 km. The AROME background is significantly improved below 1.5 km up to 40 % in RMSE. On the contrary, a RMSE of 1.8 K is observed at 1.5 km altitude if NN retrievals are applied to the raw measurements corresponding to a significant degradation of the background profiles due to the large bias. After bias correction, the NN RMSE is decreased to 1.2 K but is still larger than the one obtained with the background (0.9 K). The 1D-Var retrievals are thus able to provide the best estimate of the atmosphere by combining background information and ground-based observations. As the MWR observations do not contain information to unambiguously reconstruct the full atmospheric column, the 1D-Var retrieval strongly depends on the background above 2 km. Thus, the AROME model brings most of the information in the upper troposphere whereas it is well corrected in the lower few kilometres to get closer to the MWR measurement. The best improvement of the analysis over the background is found at 500 m. This is consistent with the estimated analysis-error covariance matrix **A**.

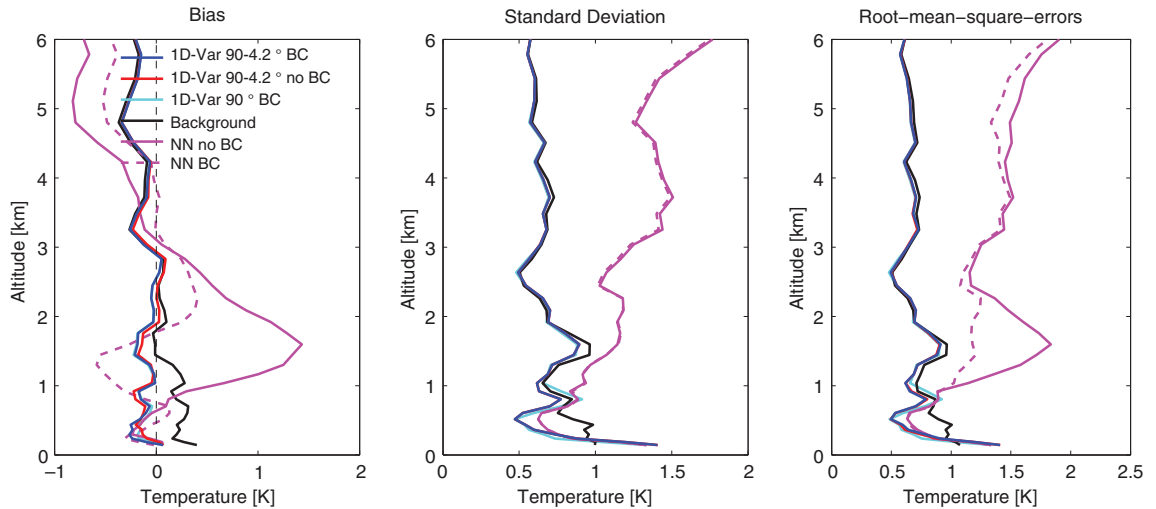


Fig. 6. Vertical profiles of bias (left panel), standard deviation (middle panel) and root-mean-square-errors (right panel) of the AROME background (black line) and MWR retrievals against radiosondes. The performance of neural network retrievals is displayed in magenta whereas all the other colours refer to 1D-Var retrievals for different settings: using all elevation angles and applying a BT offset correction (blue), using all elevation angles without bias correction (red) and using only observations at zenith angle (cyan). NN retrievals before bias correction are shown in solid line (magenta), whereas retrievals after bias correction are shown in dashed line (magenta). Results computed on 51 clear-sky temperature retrievals.

Figure 6 also compares the 1D-Var retrieval accuracy when MWR observations are not bias-corrected (red line). This bias correction does not impact the 1D-Var retrievals. However, the value of the bias offset is only significant for the first two channels that were not used in the retrievals, whereas it does not exceed 0.1 K for opaque channels (see Table 1). The same comparison was done for NN retrievals. The bias correction does not impact the retrievals below 1 km altitude as, similarly to the 1D-Var, the information mostly comes from opaque channels that are almost unbiased. However, a clear improvement of NN retrievals are observed in the troposphere, essentially between 1 and 3 km altitude, where transparent channels bring most of the information. NN retrievals probably give a larger weight to these channels that are not used in the 1D-Var making significant the impact of the bias correction on the accuracy. 1D-Var retrievals using only zenith observations were also compared to the retrievals performed with all elevation angles. The use of different elevation angles improves the retrievals only from 600 m to 1 km with a maximum gain of 20 % in RMSE at 1 km altitude.

The same evaluation was performed in cloudy-sky on 69 profiles (Fig. 7). As observed in clear-sky conditions, there is a positive bias of the background in the lowest levels and a slight negative bias above. This bias is well decreased by the 1D-Var below 1 km altitude when a bias correction is applied. RMSEs are slightly larger than observed in clear-sky but 1D-Var retrievals still perform the best with RMSE within 1.3 K except at 900 m altitude where the NN

retrievals are slightly better (0.9 K RMSE instead of 1.1 K for 1D-Var). As observed in clear-sky, NN retrievals degrade the background above 1 km but this degradation is reduced after bias correction. The 1D-Var improvement of the background reaches 56 % in RMSE at 250 m. Even if this improvement decreases with altitude, the RMSE is still improved by 12 % at 1.5 km altitude and is, on average, larger than the one observed in clear-sky. In fact, an improvement in the background is observed up to 2.5 km in cloudy-sky, whereas it is mainly observed below 1.5 km in clear-sky. The use of a bias correction has a neutral impact on the retrievals. The use of low elevation angles improves the retrieval up to 1.5 km with a maximum of 15 % in RMSE in the first levels.

7. Discussion and conclusion

This paper has studied the feasibility of combining NWP forecasts from convective scale models with ground-based MWR observations through a 1D-Var technique. 1D-Var temperature retrievals were performed during a 6-month period at Bordeaux. 1D-Var retrievals have been compared to MWR NN retrievals, collocated radiosondes and 3-hour forecasts from the convective scale model AROME. 1D-Var retrievals were found to outperform NN retrievals both in clear-sky and cloudy-sky conditions above 400 m.

The first part of this study has evaluated the capability of the ARTS radiative transfer model to simulate MWR observations from 3-h AROME forecasts. For V-band

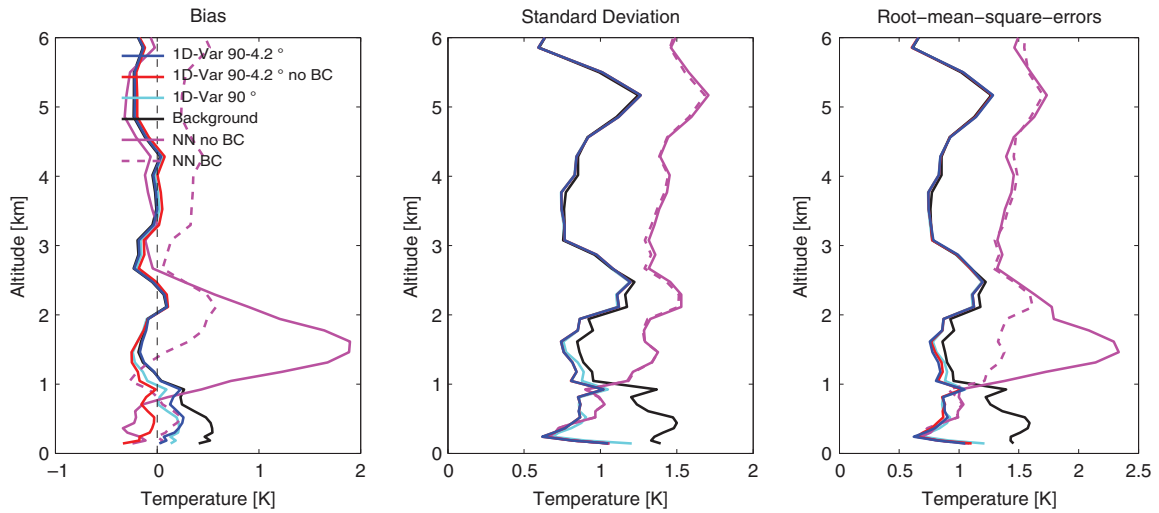


Fig. 7. Vertical profiles of bias (left panel), standard deviation (middle panel) and root-mean-square-errors (right panel) of the AROME background (black line) and MWR retrievals against radiosondes. The performance of neural network retrievals is displayed in magenta, whereas all the other colours refer to 1D-Var retrievals for different settings: using all elevation angles and applying a BT offset correction (blue), using all elevation angles without bias correction (red) and using only observations at zenith angle (cyan). NN retrievals before bias correction are shown in solid line (magenta), whereas retrievals after bias correction are shown in dashed line (magenta). Results computed on 69 cloudy-sky temperature retrievals.

channels, almost no bias was observed on the most opaque channels (53.86–58 GHz) with small SDs (<0.6 K). However, the most transparent channels present a negative bias up to -5.6 K at 52.28 GHz even in clear-sky conditions. The distribution of observation errors was then studied. They were found to follow a Gaussian distribution except the most transparent channels (51 and 52 GHz in clear-sky and up to 53.86 GHz in cloudy conditions) that are affected by water vapour and liquid cloud emissions. After this study, it was decided to remove transparent channels from the retrievals. From this monitoring a constant bias correction was proposed for all channels depending on the meteorological situation. It is important to remind that the proposed bias correction is specific to the period of measurements (April–October 2014), to the specific HATPRO instrument used in this study and to the ARTS radiative transfer model.

The second part of this study has evaluated 1D-Var retrievals in terms of bias and RMSE against collocated radiosondes. First of all, the O - B departures were found to be well decreased by the analysis for channels above 54.94 GHz. The decrease of the O - B departures at 53.86 was found to be smaller than the one observed for opaque channels. In terms of RMSE, the 1D-Var retrievals based on AROME forecasts improve the background up to 2 km with a maximum gain of approximately 50 % in RMSE below 500 m altitude. With the present implementation, we achieved a RMSE within 1.3 K for temperature in all-sky conditions. The bias correction was found to have a negligible impact on the 1D-Var retrievals but significantly improved NN retrievals between 1 and 2 km altitude. The use of low elevation angles was found to improve the retrievals up to 20 % in RMSE in clear-sky at 1 km altitude and 15 % in cloudy-sky for the first level. In the future, a screening procedure to select cases where the NWP model forecasts a cloud when it is also observed by the MWR will be tested. This screening procedure should help identifying valuable cases for cloudy-sky assimilation where humidity and liquid water content will be retrieved. The latter can be useful to improve short-term forecasts in cloudy-conditions by the initialisation of hydrometeors (Martinet et al., 2014).

The results shown in this study are encouraging and show the potential for moving to an operational assimilation of MWR measurements in convective scale models but we should keep in mind that they only represent a small number of cases. Variational bias correction (Auligné et al., 2007) could probably be adapted to ground-based microwave sensors to correct systematic measurement errors but more efforts have to be done to evaluate the impact of these data in a full assimilation system. However, the use of only opaque channels was found to already improve the AROME background in the BL and are less affected by errors during the cold point calibration. To progress

towards an operational assimilation of these instruments efforts will be made to develop a fast radiative transfer model that meets operational requirements. While the high accuracy of the line-by-line ARTS model must be pointed out, the computation of the equivalent BT from the NWP forecast is still too time consuming for an operational prospect. The development of a fast radiative transfer model for ground-based sensors will be undertaken in the framework of the COST action ES1303 TOPROF (Towards operational ground-based profiling with ceilometers, Doppler lidars and MWR for improving weather forecasts; www.toprof.imaa.cnr.it/). Improvement in the definition of the **R** matrix will also be carried out.

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