

Influence of ECMWF background error covariances on the retrieval of temperature and humidity by the HAMP radiometer



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1. Introduction

Profiles of temperature and humidity are fundamental for weather forecasting, climate monitoring as well as the interpretation of remote sensing instrument measurements. The HALO (High Altitude Long range aircraft) remote sensing payload includes a 26 channel microwave radiometer, a 36 GHz Doppler cloud radar and a water vapor lidar. During the recent field campaign NARVAL-South (December 2013), HALO was flown over Tropical Atlantic with the aim of measuring tropical warm boundary layer clouds.

In this work we present a 1-D variational algorithm to retrieve profiles of temperature and humidity for the HAMP (HALO microwave package) radiometer.



Fig. 1: The HALO aircraft during the NARVAL-South campaign (left). NARVAL-South flight patterns for the 9 flights (right).

2. The HAMP radiometer

The HAMP instrument:

- 26 channel microwave radiometer
- Temperature and liquid: 60 and 118 GHz O₂ absorption lines
- Humidity, liquid and snow: 22 and 183 GHz H₂O lines
- Footprint at 13 km: from 1.2 km (K-band) to 0.6 km (183 GHz)

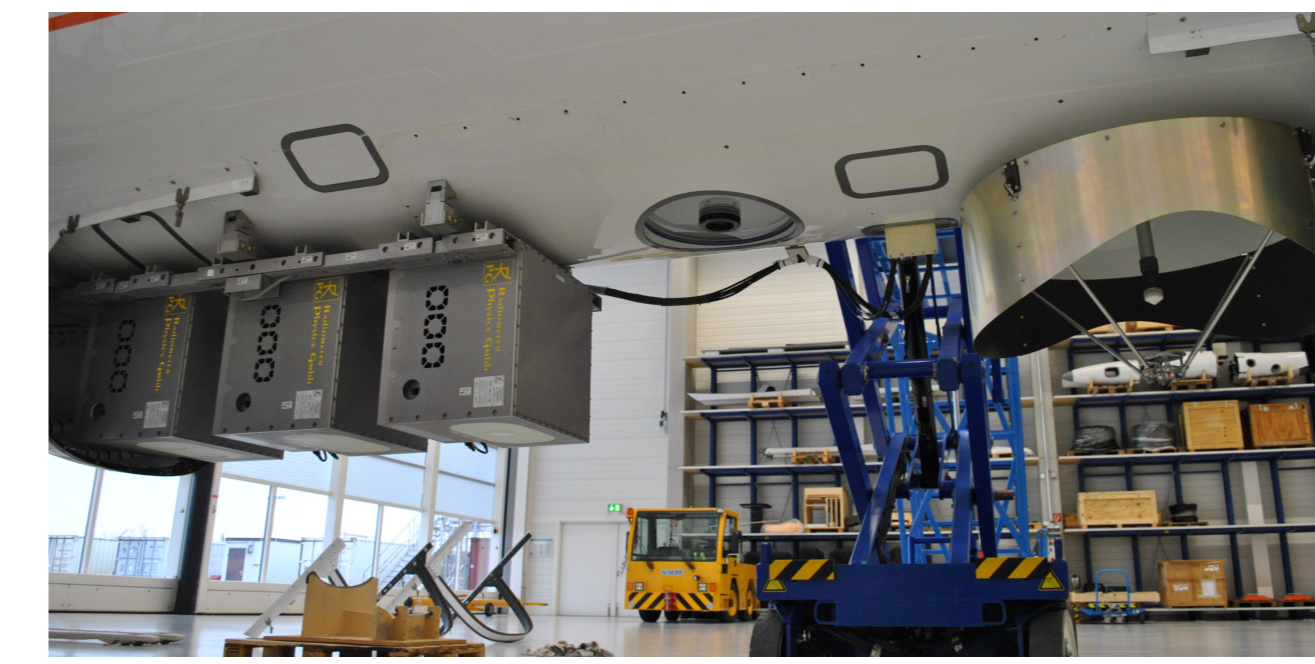


Fig. 2: Installation of the remote sensing suite on HALO. From left to right: radiometer boxes, lidar window and radar antenna.

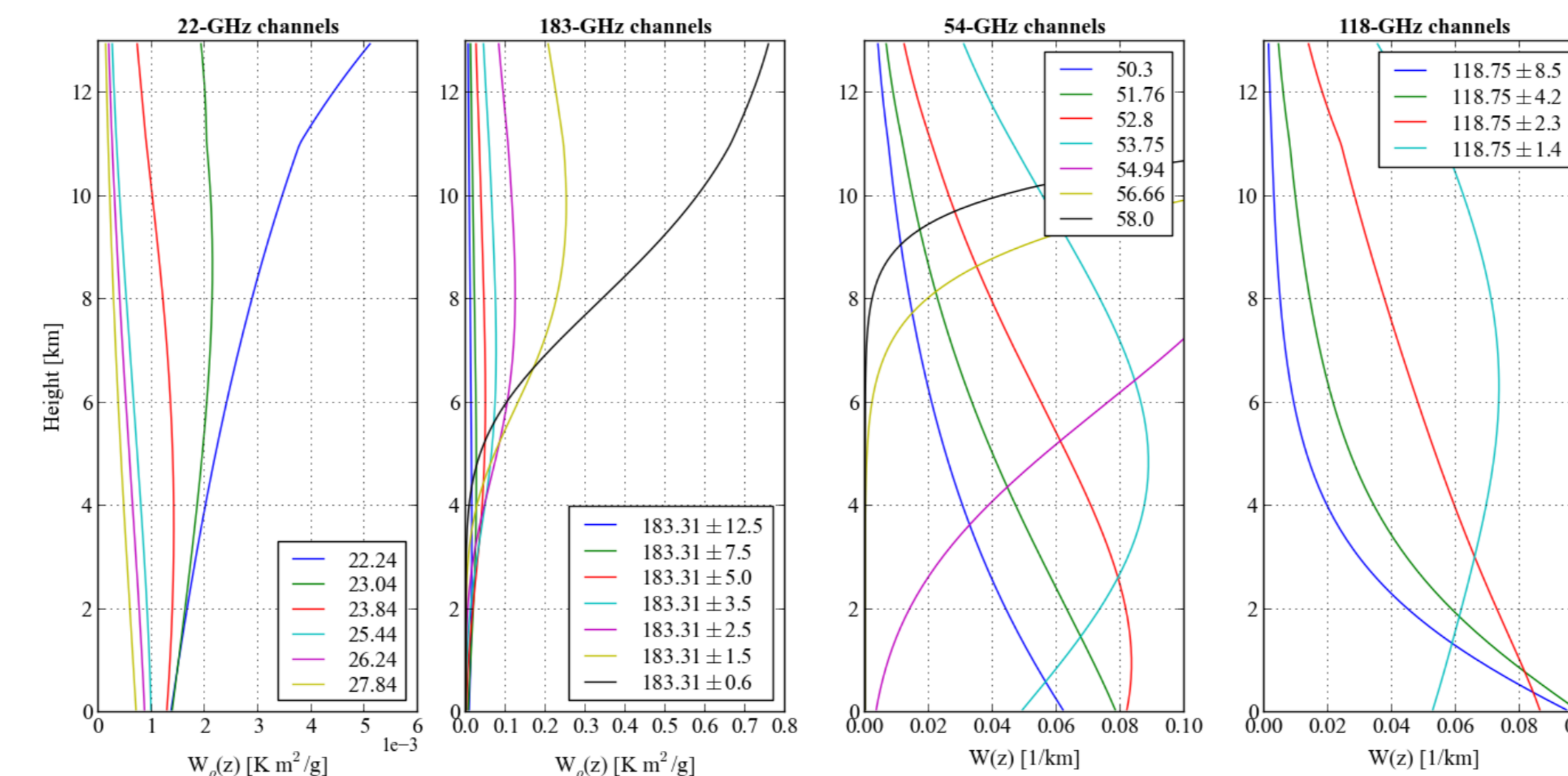


Fig. 3: HAMP radiometer clear-sky weighting functions at Nadir-viewing geometry at a ceiling height of 13 km. Mech et al. (2014)

3. 1-D variational retrieval algorithm

Optimal estimation equation:

$$\mathbf{x}_{i+1} = \mathbf{x}_i + (\mathbf{K}_i^T \mathbf{S}_e^{-1} \mathbf{K}_i + \mathbf{S}_a^{-1})^{-1} \times [\mathbf{K}_i^T \mathbf{S}_e^{-1} (\mathbf{y} - \mathbf{y}_i) + \mathbf{S}_a^{-1} (\mathbf{x}_a - \mathbf{x}_i)],$$

S_e: measurement error covariance. Diagonal, 1K error for all channels

K: Linearized radiative transfer model

X_a, S_a: a-priori profile and error covariance

Y: measurement vector

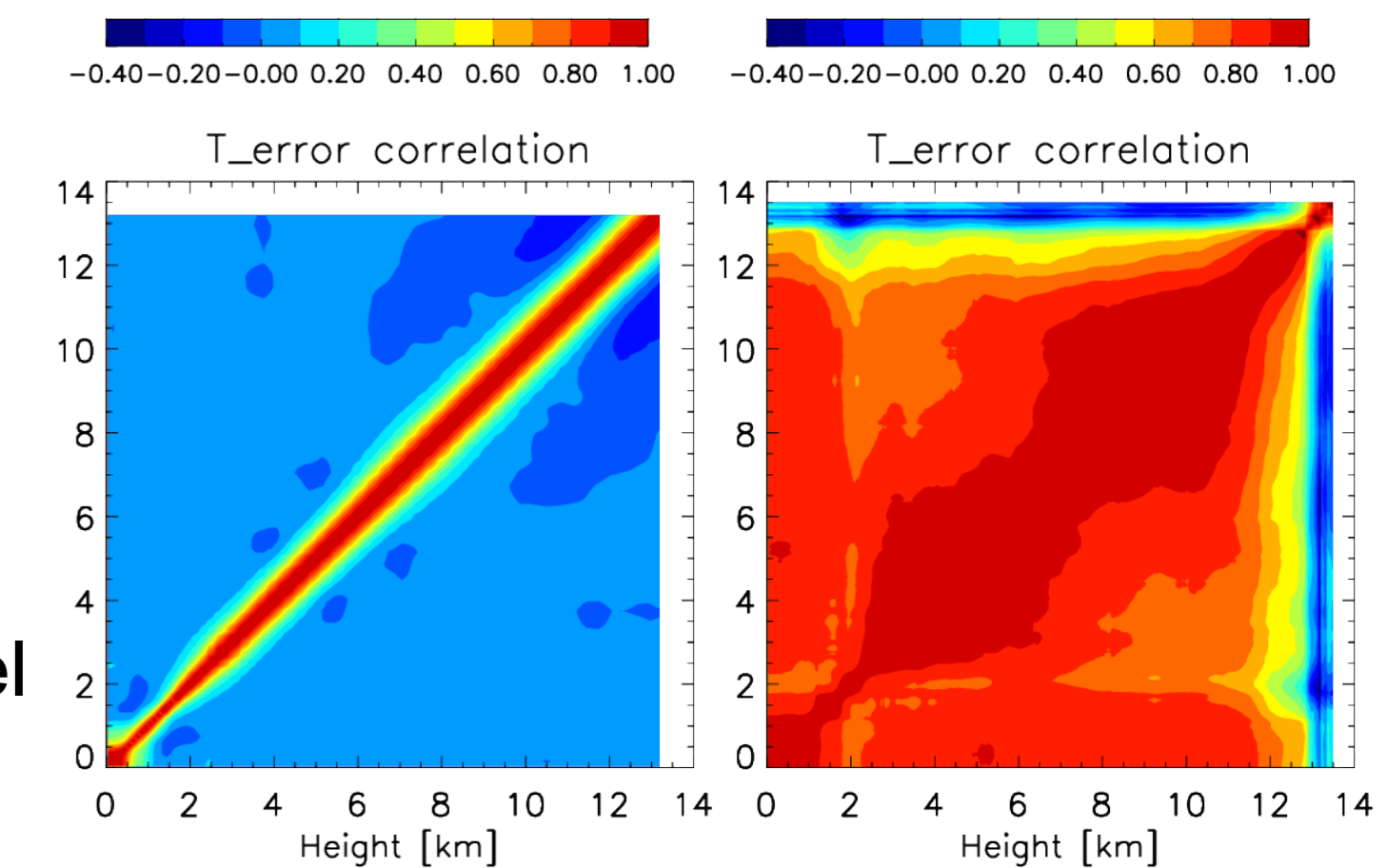


Fig. 4: Temperature profiles a-priori error covariance matrices, from the ECMWF forecasting system (left) and from dropsonde climatology (right).

A-priori profiles, errors and covariances:

Dropsonde climatology

75 dropsondes, launched during NARVAL-South, have been used to derive **X_a** and **S_a**.

ECMWF

Delayed cut-off forecast (T639) at 3 to 12-hour is used as **X_a**. 1-D background error covariances **S_a** are extracted (E. Holm, 2012) from 3-D ones used for data assimilation in the ECMWF forecast system.

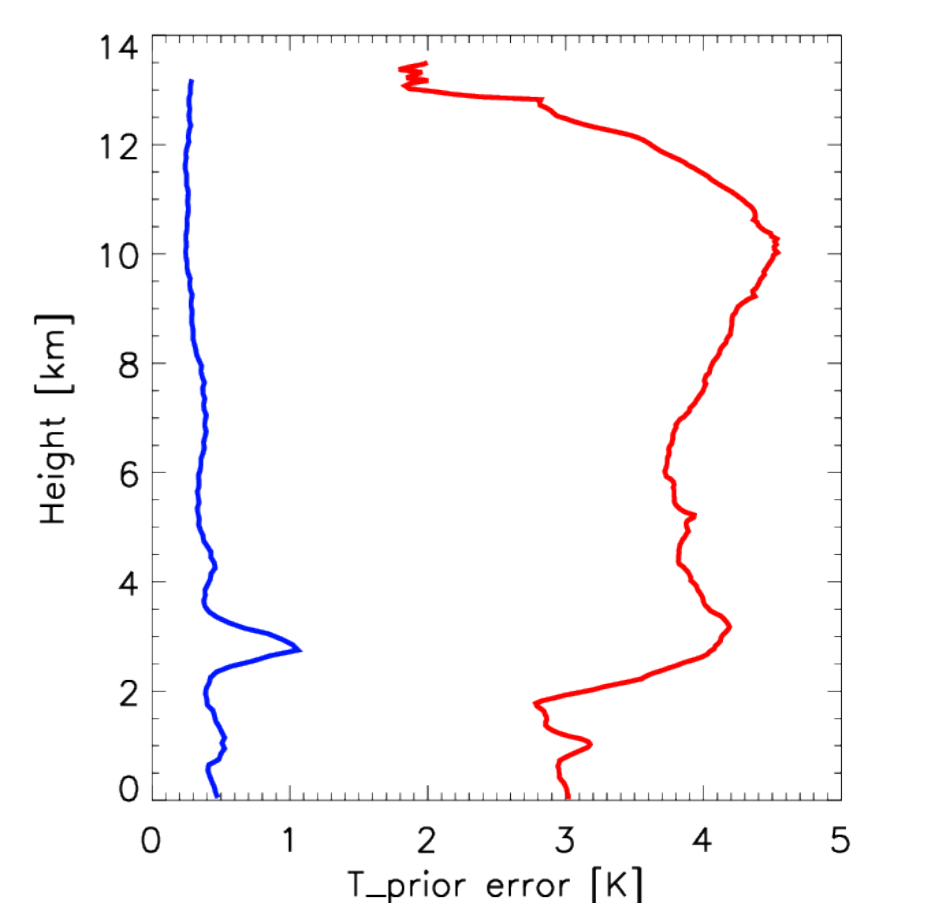


Fig. 5: Temperature profiles a-priori errors, from the ECMWF forecasting system (blue) and from dropsonde climatology (red).

4. Case study

- HALO crossed the Atlantic from Barbados to the coast of Portugal
- 8 dropsondes were released and used to assess the quality of the retrieved profiles
- ECMWF profiles mean RMS is 1.2 K
- Use of HAMP measurements to reduce the error

Fig. 6: Difference between ECMWF temperature profiles and 8 dropsondes.

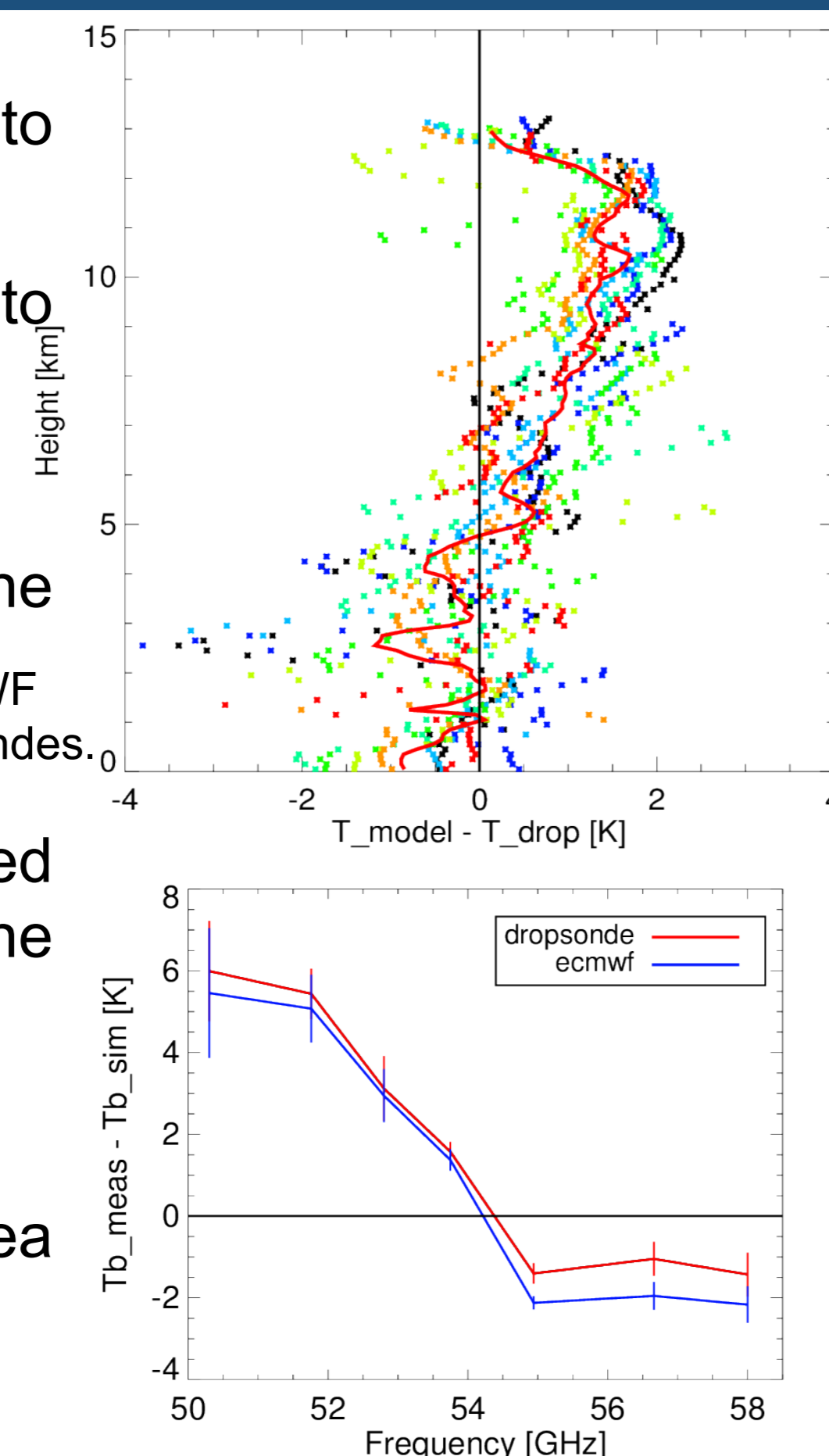


Figure 7 shows the difference between simulated and measured brightness temperature (T_b). The discrepancies can be due to:

- radiometer calibration
- uncertainty of oxygen absorption
- modelling of surface emissivity (wind, sea surface temperature)

Mean bias was subtracted from simulated T_b.

Fig. 7: Mean difference between measured and simulated T_b using ECMWF profiles (blue) and dropsondes (red). Vertical bars indicate max and min bias for the 8 dropsondes.

5. Sensitivity to a-priori covariance matrix

Mean RMS over the retrieved profile and degrees of freedom for signal (DFS) have been calculated and averaged for the 8 dropsondes. Figure 8 shows the DFS and RMS sensitivity to the a-priori covariance matrix **S_a**. On the left hand side of the plot **S_a** estimated using the dropsonde database has been used, on the right the background error covariance matrix from ECMWF has been used.

$$\mathbf{S}_a = \mathbf{S}_{a_{ECMWF}} * \text{weight} + (1 - \text{weight}) * \mathbf{S}_{a_{drop}}$$

X_a a-priori profile	S_a covariance	Retrieval RMS [K]
Dropsonde climatology	Dropsonde climatology	1.51
ECMWF	ECMWF	1.11
ECMWF	Dropsonde climatology	0.89

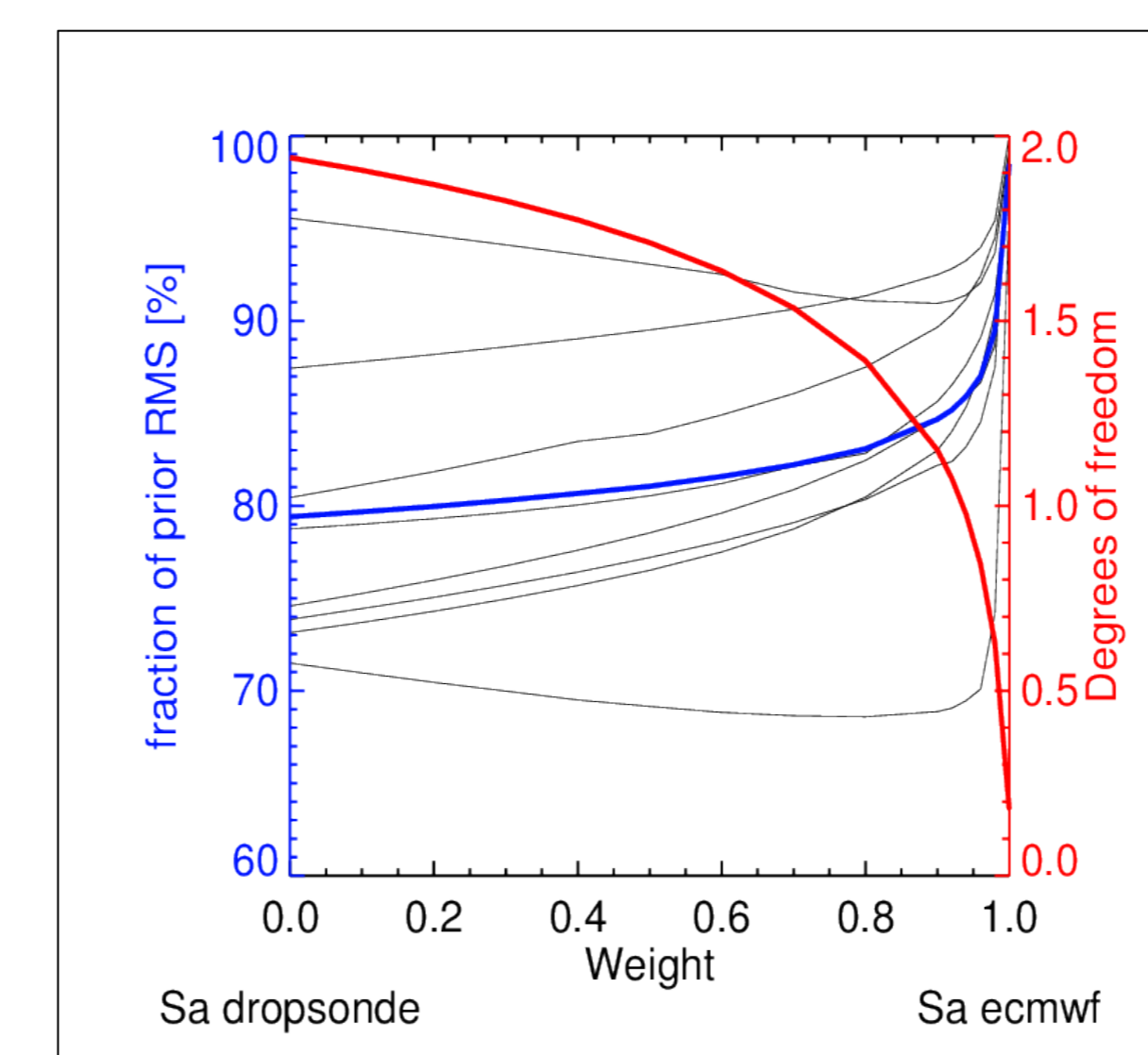


Fig. 8: Fraction of a-priori RMS (mean: blue, each dropsonde: black) and degrees of freedom for signal (red) as a function of the **S_a** matrix.

6. Conclusion and future work

- A 1-D variational algorithm for temperature profile retrieval in clear-sky has been developed for the HAMP radiometer.
- A-priori knowledge from climatology or from the ECMWF forecast system can be used.
- Small amount of information can be extracted from the measurements when ECMWF pure background errors are used.
- Best results (mean RMS < 1K) with ECMWF profiles as a-priori and blended **S_a**.
- Extend the retrieval to all HAMP channels, including water vapour.
- Extend the analysis to the whole campaign.

7. Bibliography

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- M. Mech et al, HAMP – the microwave package on the High Altitude and Long Range research aircraft HALO, Atmos. Meas. Tech, submitted.