AGU 100 ADVANCING EARTH AND SPACE SCIENCE

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Uncertainties characterization of troposphere profile retrievals by Bayesian inversion as compared to state-of-the-art ground-based microwave radiometry methods

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1.- Research Objectives

* Microwave radiometry has become a common tool for estimation of profiles of atmospheric parameters. With a high temporal resolution radiometers are an alternative to standard methods like radiosondes.

* However remote sensing radiometry requires the use of retrieval algorithms. Some state-of-the-art methods like linear-, quadratic-regression or Neural Network are widely used by manufactures [3].

The present study assessts the uncertainty of those methods. Additionally two alternative inversion techniques are used: Bayesian (BAY) and Maximum Likelihood (MLE) inversion. Uncertainties are estimated from state-of-the-art retrieval algorithms provided by the HATPRO radiometer (RPG) firmware version 8.78 [3].

To estimate the uncertainties resulting from the algorithms, synthetic radiometer data have been created by radiative transfer simulations using radiosonde profiles [4] as descriptor of atmospheric states. These synthetic observations are arranged to mimic radiometer's firmware binary files. Thus letting the radiometer performs retrievals as with real data, but with the advantage of knowing the original profile. Absolute errors were assesed from retrieval results relative to the input profile to characterize the algorithms.

2.- Retrieval methods

State-of-the-art retrieving methods by radiometer manufacturers are:

- Linear (k=1)/quadratic (k=2) regression as [3]:

$$RP_{out}(i) = a_0(i) + \sum_{f}^{freq} a_{fk}(i) * TB_f^k(\theta) + \sum_{h}^{sensor} b_h * SE_h$$

with TB_f measured brightness temperature at frequency f and angle θ and SE_h surface sensors. $RP_{out}(i)$ is the retrieved parameter.

- Neural Networks [3]:

$$\overrightarrow{RP}_{out} = \mathbf{IM} * \overrightarrow{TB}$$

where **IM** is the neural network coefficient matrix trained by the manufacturer.

This work developed alternative retrievals based on:

- Bayesian inversion [2,1]: PDF of atmospheric parameter $\vec{x}$ given the measurements matrix $\mathbf{TB}(f,\theta)$

$$P(\vec{x}|\mathbf{TB}) \sim P(\mathbf{TB}|\vec{x}) * P(\vec{x})$$

$$P(\mathbf{TB}|\vec{x}) = (2\pi)^{-\frac{1}{2}k}|\mathbf{\Sigma}|^{-\frac{1}{2}} exp(-\frac{1}{2}(\mathbf{TB}_{sim} - \mathbf{TB}_o)^T\mathbf{\Sigma}^{-1}(\mathbf{TB}_{sim} - \mathbf{TB}_o))$$

with TB_o, TB_{sim} and Σ the brightness temperature measured, simulated and covariance matrix. The estimated parameter is given by the expected value from the *posteriori* PDF

$$< \vec{x} > = \int P(\vec{x}|\mathbf{TB})\,\vec{x}\,d\vec{x} \quad \text{and,} \quad \sigma_{\vec{x}}^2 = \int P(\vec{x}|\mathbf{TB})[< \vec{x} > - \vec{x}]^2\,d\vec{x}$$

- The Maximum Likelihood [1]: given the log-likelihood function

$$\mathcal{L}(\mathbf{TB}|\vec{x}) = -log(|\mathbf{\Sigma}|) - (\mathbf{TB}_{sim} - \mathbf{TB}_o)^T\mathbf{\Sigma}^{-1}(\mathbf{TB}_{sim} - \mathbf{TB}_o) - k\,log(\pi)$$

solving for $\vec{x}$ that maximize $\mathcal{L}$ the retrieval is found by

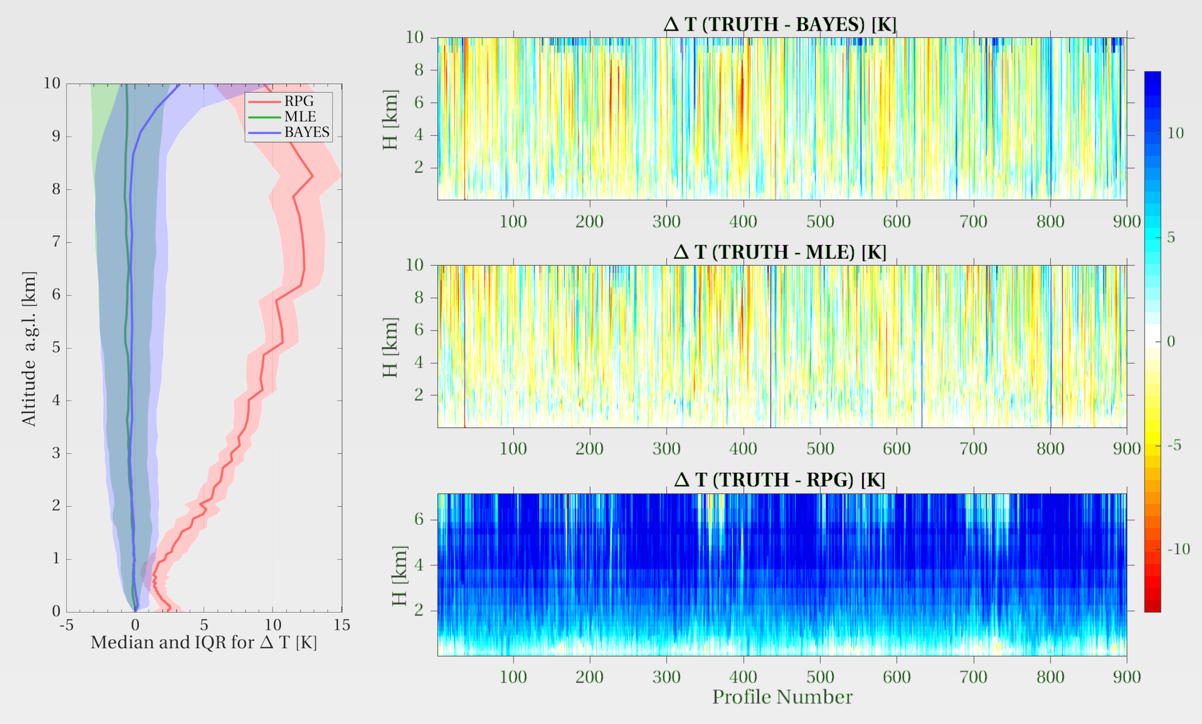
$$\frac{\partial}{\partial \mathbf{TB}}\mathcal{L}(\mathbf{TB}|\vec{x}_{max}) = 0$$

with $\vec{x}_{max}$ being the MLE for the parameter $\vec{x}$.

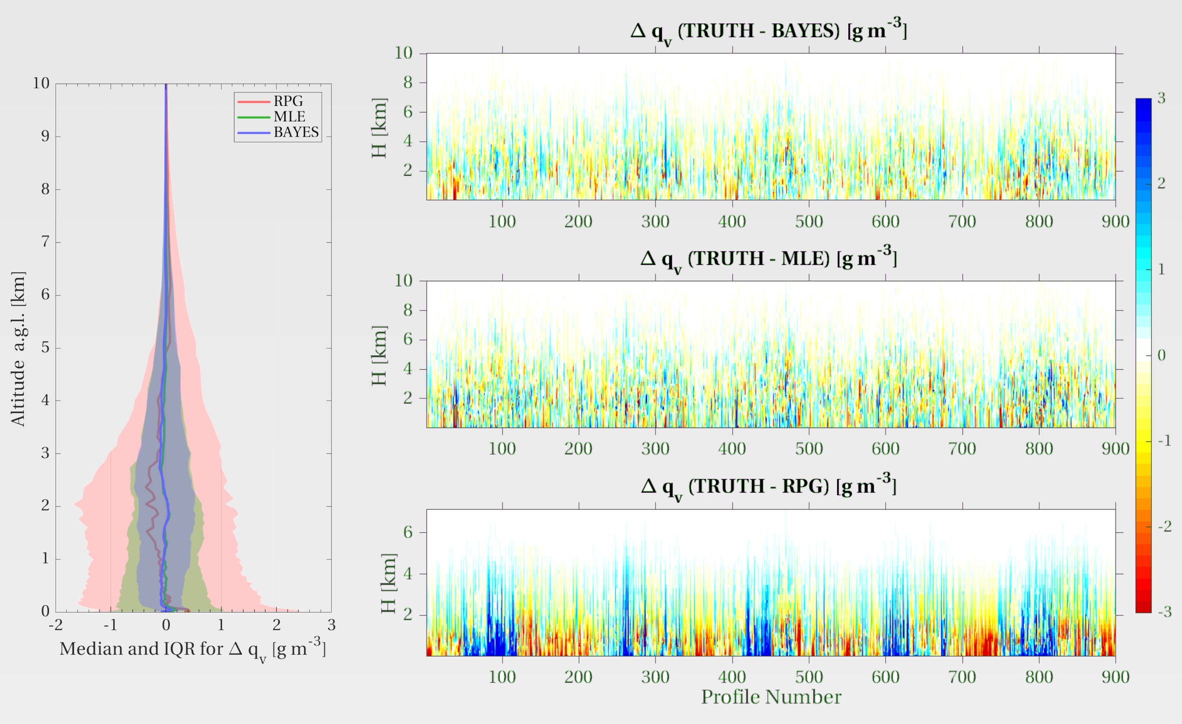
3.- Analysis of Retrieval Uncertainties for different methods

Absolute error (Input TRUTH - RETRIEVAL) of retrieved profiles for three different inversion methods: Bayesian (top), Maximum Likelihood (middle), and Firmware Neural network (RPG)

- **Temperature**



- **Humidity**

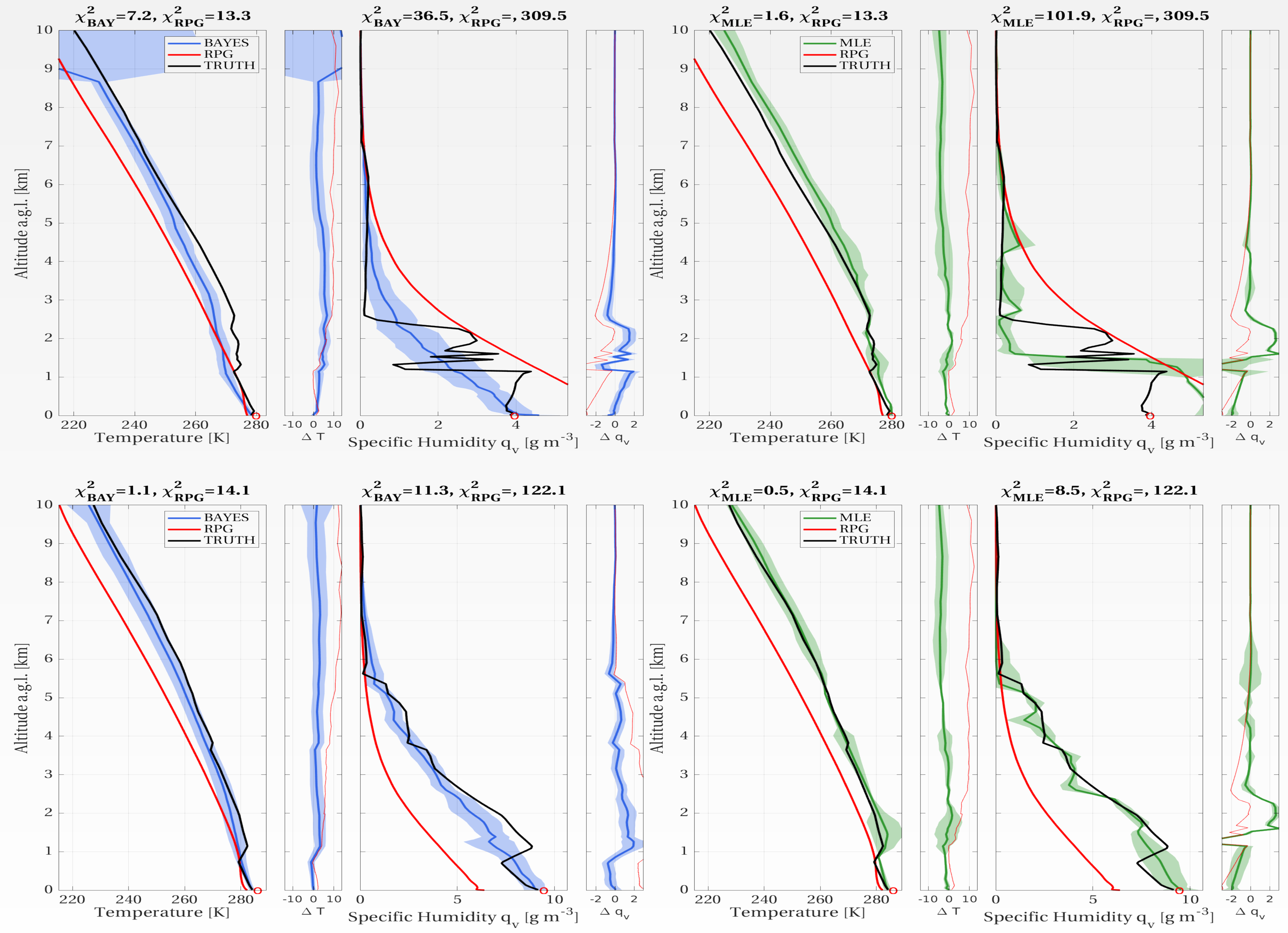


Performance for individual cases. Close-up to two profiles (200 and 600 in top figures) with comparison to TRUE (Radiosonde). The shaded-area represents the retrieval uncertainty provided by the Bayesian (light blue) and Maximum Likelihood (light green). RPG's firmware [3] does not provide any uncertainty.

Bayesian Retrieval (BAY) **Maximum Likelihood (MLE)**

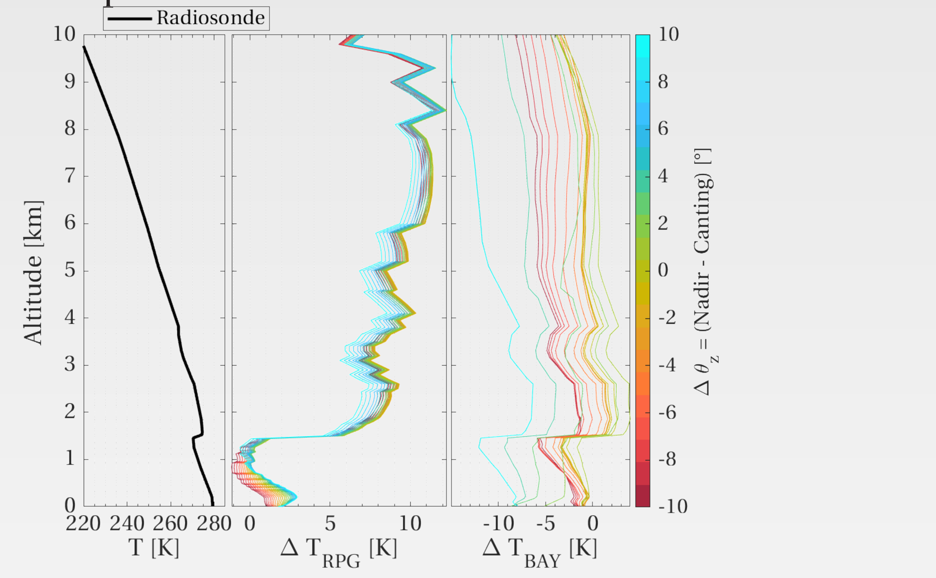
- Profile number 200: Where the Bayesian and RPG methods retrieve close to truth only till ~1 km then the temperature inversion is not captured by Bayesian. The right-most graph shows that MLE retrives the inversion better. While Bayesian profile estimates humidity closer to the real Radiosonde profile.

- Profile number 600: Temperature inversion at ~0.8 km where the MLE method retrieves the profile better fitted than the Bayesian. On the other hand, Bayesian humidity retrieval matches closer the Radiosonde profile.

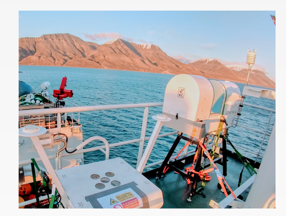


4.- Application

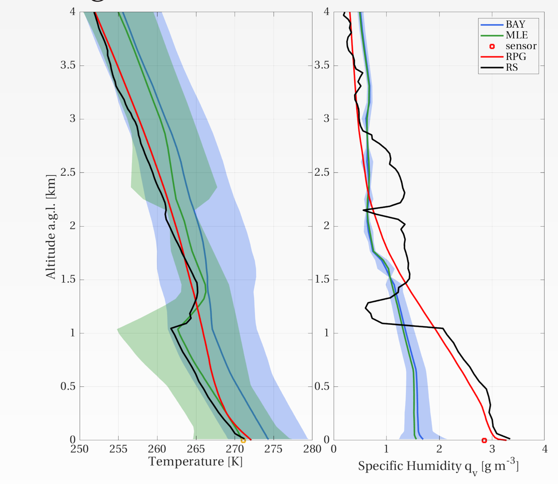
Retrievals by Radiometers operating in remote location suffer from unrepresentative neural network training dataset. Such the case for off-shore measurements on floating platforms, research vessels. Waves change the effective instrument elevation angle but the Firmware retrievals has no compensation for that.



Retrievals absolute error as a function of Radiometer's canting angle from i.e. floating platform. A $\Delta\theta_z$ = +10° means the Radiometer was observing -10° at every elevation angle.



During the Nansen Legacy Cruise in September 2018, the HATPRO Radiometer measured on the *Kronprins Haakon* Research vessel.



Retrievals from 20th Sept. 2018.

Special care must be taken on analysis the data due to wave-forcing changes on elevation angle and effects on retrievals.

5.- Conclusions

Advantages of Bayesian and Likelihood inversion:

* To customize an *a-priori* dataset suited for specific climatologies [4],
* BAY and MLE use the same *a-priori* to perform retrievals simultaneously,
* Synergistic observations from other instruments can be included to increase retrieval capabilities.

The retrievals performance are based on synthetic brightness temperatures, hence instrument calibration/systematic errors are not considered.

We found the MLE method better to retrieve temperature while BAY is better for humidity profiles. However Bayesian is found to be more sensitive to observation line-of-sight misalignments, where the RPG firmware shows to be less affected.

6.- References / Acknowledges

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5. Bayes Retrieval Toolbox: http://www.github.com/pablosaa/TROPROS_prof

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