

# Retrieving snow density from passive microwave measurements at L-band

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## Introduction

Snow cover and its physical parameters such as depth, density and water equivalent are important environmental parameters as they describe the stored freshwater in the snow pack, effect the energy exchange and control hydropower. The remote sensing of these parameters by space and airborne instruments have been conducted for decades. The passive microwave remote sensing has been traditionally used to retrieve the snow water equivalent, the amount of water stored in the snow pack. Typically the measurements from frequencies 19 GHz and 37 GHz have been used for this purpose. Previous studies [3] and [2] have shown that the observations from L-band (1 – 2 GHz) are sensitive to the snow density and furthermore demonstrated the possibility to retrieve the snow density from the multiangular passive microwave measurements at the L-band. Retrieval method proposed in [3] employs a physical forward model simulating the emitted microwave radiation from snow covered ground. Parameters of interest are retrieved from the observations by minizing a cost function between model predictions and observations. To understand the uncertainty of the retrieval, caused by the measurement and modelling errors, we write the retrieval problem as a Bayesian inference problem. The retrieval approach is applied to measurements from Finnish Meteorological Institutes Intense Observation Area (IOA) station, located in Sodankylä, Finland, during the years 2009-2015, which were also used in [2].

## Measurements

The ELBARA-II instrument shown in figure 1 measures the upwelling brightness temperature  $T_B(\theta, p)$  from two polarizations  $p = v, h$  and from incident angles  $\theta_k \in [0, \pi)$ . The instrument measures the total upwelling brightness temperature

$$T_B(\theta, p) = T_{B,e}(\theta, p) + T_{B,r}(\theta, p) \quad (1)$$

where  $T_{B,e}$  is the emitted and  $T_{B,r}$  the reflected brightness temperature from the scene. In particular, measurements from the winter 2011-2012 are considered here.



Figure 1: ELBARA-II measuring the upwelling brightness temperature at IOA site, located in Sodankylä, Finland. Photo: C. Mätzler, 2011

## Methods

The L-band emission model introduced in [3] is used in this study. The model gives the measured  $T_B(\theta, p)$  as a function of four parameters; the snow density  $\rho_s$ , ground permittivity  $\epsilon_g$ , ground temperature  $T_g$ , and empirical ground-snow surface roughness parameter  $z$ . The model assumes a homogeneous snow layer on top of a homogeneous ground layer. Volume scattering and absorption are neglected, which is a reasonable assumption at the L-band when the ground is fully frozen and the snow is dry. The measurements  $T_B(\theta_k, p)$  are represented by a vector

$$T_{B,obs} \in \mathbb{R}^{2n} \quad (2)$$

where  $n$  is the number of incident angles. The corresponding modelled observations are denoted by

$$T_B(x) \in \mathbb{R}^{2n} \quad (3)$$

where

$$x = [\rho_s, \epsilon_g, T_g, z]^T \in \mathbb{R}^4 \quad (4)$$

is the vector of unknowns. However, in this study we consider the ground temperature  $T_g$  and empirical roughness parameter  $z$  fixed, and only focus on retrieving the pair  $(\rho_s, \epsilon_g)$ . In particular the ground temperature  $T_g$  is fixed according to in-situ measured value. When modelled as random variables, the observation and unknown are connected by

$$T_{B,obs} = T_B(x) + \xi, \quad (5)$$

where the error  $\xi$  is assumed to be a normal distributed random variable with zero mean and covariance matrix  $C$

$$\xi \sim \mathcal{N}(0, C). \quad (6)$$

The covariance matrix is written as

$$C = \begin{bmatrix} \sigma_v^2 \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \sigma_h^2 \mathbf{I} \end{bmatrix} \quad (7)$$

where  $\sigma_v$  and  $\sigma_h$  correspond to the measurement channels  $p = v, h$ . Both  $\sigma_v$  and  $\sigma_h$  are unknown and also modelled as random variables. The retrieval problem is written as a Bayesian inference problem for the unknowns  $x = [\rho_s, \epsilon_g]^T$  and  $\sigma = [\sigma_v, \sigma_h]^T$  as

$$\begin{aligned} T_{B,obs} | x, \sigma &\sim \mathcal{N}(T_B(x), C) \\ x_k &\sim U(a_k, b_k), \quad k = 1, 2 \\ \sigma_p^{-2} &\sim \Gamma(\alpha, \beta), \quad p = v, h \end{aligned}$$

The prior distributions of  $x$  and  $\sigma$  are assumed to be independent. The joint posterior distribution of  $x$  and  $\sigma$  given the measurement  $T_{B,obs}$  is written according to Bayes formula as

$$\pi(x, \sigma | T_{B,obs}) \propto \pi_{\text{likelihood}}(T_{B,obs} | x, \sigma) \pi_{\text{prior}}(x) \pi_{\text{prior}}(\sigma). \quad (8)$$

This is sampled by Metropolis-Hastings algorithm.

## Results

The sampled values of the pair  $(\rho_s, \epsilon_g)$  are compared against in-situ measured reference values. We show two retrievals to demonstrate the performance of this setup for the retrieval problem. The figure 2 shows an example of two parameter retrieval with good match with the reference value. The figure 3 on the other hand shows an example where the match between the retrieval and the reference value is not satisfactory.

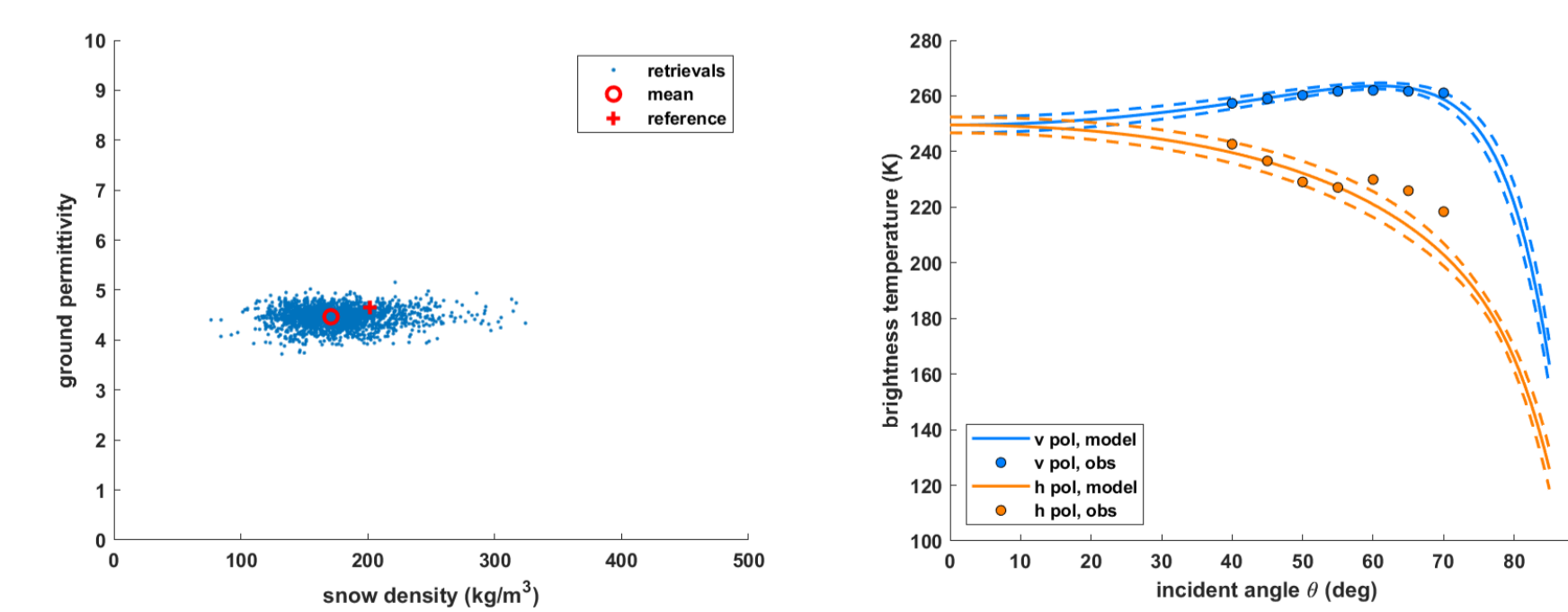


Figure 2: An example of good retrieval. Retrieval vs. reference (left) and model vs. observations (right).

## Information

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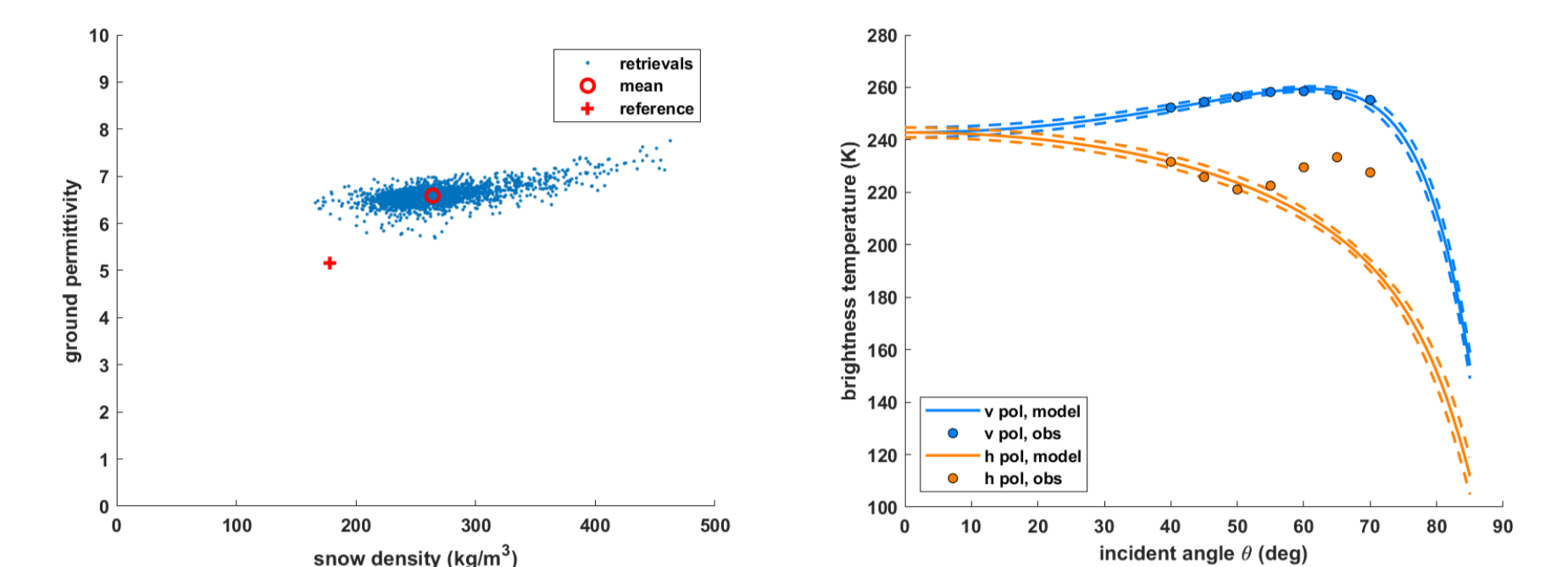


Figure 3: An example of bad retrieval. Retrieval vs. reference (left) and model vs. observations (right).

## Conclusions

The failure of the retrieval is primarily connected to the modelling error. In figure 3 the model is unable to explain the measurements which causes the decrease in the retrieval quality. This type of examples lead to believe that the modelling error plays a big part in this retrieval problem. An appropriate choice for the error term  $\xi$  in equation (5) is believed to mitigate this problem. A particular choice given by (6) and (7) is applied to the retrieval problem. The appropriate choice of error term  $\xi$  or the covariance matrix  $C$  is a central problem in the on going work on this problem.

## References

- [1] Poster template. <https://www.latextemplates.com/template/a0poster-landscape-poster>.
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- [4] A. Gelman, J.B. Carlin, H.S. Stern, and D.B. Rubin. *Bayesian Data Analysis, Second Edition*. Chapman & Hall/CRC Texts in Statistical Science. Taylor & Francis, 2003.

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