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Atmospheric Measurement Techniques
Discussions

Interactive comment on "Differential Absorption Radar Techniques: Water Vapor Retrievals" *by* Luis Millan et al.

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We thank the reviewer for his/her comments. Below are our responses in blue.

1 Reviewer 2 comments

Summary

In this work, water vapor retrieval from satellite-based radar measurements was first described and further demonstrated and investigated with simulations. The ideal is to exploit the differential water absorption from two distinct radar frequencies at

on and off the absorption line (183 GHz). As a result, the total column water vapor as well as water vapor profile can be estimated. The feasibility of the retrieval was investigated under different weather conditions including clear sky, cloudy, and rainy. It is also very valuable to assess the performance of different frequency combinations and contributions from various error sources. In summary, this is a well organized and written paper with significant scientific contribution to the community. I recommend to publish this work after those relatively minor comments/concerns in the following two sections are addressed.

General Comments

As pointed out by the authors, it is important to measure water vapor with adequate resolution, accuracy, and coverage to characterize the atmosphere. The proposed satellite-based retrieval method exploits differential absorption at two radar frequencies at around water vapor absorption. The overall structure of the paper is well organized and clear. However, there are some parts of the paper can be explained in a more clear way. For example, the theoretical basis is easy to understand. However, the forward model for simulation is not clearly explained. Even though the reference paper provided does not have enough detail to understand the basic idea of the simulation. I suggest to include a flow chart outlining the important steps in the simulation, which can be provided in the appendix. Specifically, what are the outputs of the simulations, reflectivity at two assigned frequencies? How are the reflectivity from each gate generated? When the noise is added, is it added in the dB scale or linear scale? Additionally, it is not clear to how the sensitivity of -30 dBZ, instrument precision of 0.16 dBZ, and spatial resolution were incorporated in the simulations, or were they ever incorporated in the simulation?
We consider adding a flowchart but we decided against it. We believe that the second paragraph of the radiometric model in conjunction with table 1, is sufficient. Besides

reviewer 1 did not found this to be problematic. The incorporation of the noise and the radar sensitivity will be discussed in an appendix describing the retrievals, see below.

Moreover, the retrieval of total CWV and profile of water vapor needs to be elaborated. For example, in line 21 page 5, it is stated that “The retrieval algorithm used was a linear least square fit ..." It is not clear what variables the least square fit are applied to. Do you mean reflectivity from multiple frequencies? In the profiling case, more detail for the optimal estimation algorithm is desired. Do you mean the problem is postulated as a constraint optimization? What is the mathematical representation of it and how exactly are the measurement and a priori information used in this method?

An appendix will be added describing the retrievals. The appendix is below.

Specific Comments

The comments here are relatively minor and mostly editorial.

1. Line 1, page 2 and line 27, page 3: change “asses" to ”assess". Ok

2. Line 3, page 2: change “retrieved" to ”retrieve" Ok

3. equation (6): need dr Correct thanks for spotting the omission.

4. Line 15, page 4: “same similar"? similar will be deleted

5. Line 23, page 5: change ”there" to “these" Ok

6. Line 26, page 5: need a space before ”Not only ..." Ok

7. Line 8, page 7: What is the role of these kernels? Please elaborate. This is also discuss in appendix.

A Least-Squares

In this study, the least-squares retrieval is used to estimate a total water vapor column, w. The measurement vector $\mathbf{y}$ is determined by the differences between surface radar returns at different frequencies, that is to say

$$\mathbf{y} = [dBZ(\nu_2, r_s) - dBZ(\nu_1, r_s), dBZ(\nu_3, r_s) - dBZ(\nu_1, r_s), \cdots] \tag{1}$$

For completeness, we present the theory for multiple radar tones even though in section 4 we only used a pair. The idea is to minimize the sum of the square differences — a least-squares approach— between the measurement vector $\mathbf{y}$ and the simulated measurements, given by:

$$\hat{\mathbf{y}}(\mathbf{x}) = [\mathbf{F}_{\nu_2,r_s}(\mathbf{x},\mathbf{b}) - \mathbf{F}_{\nu_1,r_s}(\mathbf{x},\mathbf{b}), \mathbf{F}_{\nu_3,r_s}(\mathbf{x},\mathbf{b}) - \mathbf{F}_{\nu_1,r_s}(\mathbf{x},\mathbf{b}), \cdots] \tag{2}$$

where $\mathbf{F}$ is the forward model described in section 3, $\mathbf{x}$ is a water vapor linearisation profile, and $\mathbf{b}$ is known as the forward model parameter and contains additional terms needed by the forward model but not being retrieved (such as profiles of temperature, pressure, ice water content, liquid water content, rain, snow, etc). In these simulations any reflectivity below the radar sensitivity is set to missing.

The solution of such system may be found by minimizing the cost function,

$$\chi^2 = [\mathbf{y} - \hat{\mathbf{y}}(\mathbf{x})]^T \mathbf{S}_y^{-1} [\mathbf{y} - \hat{\mathbf{y}}(\mathbf{x})] \tag{3}$$

where $\mathbf{S}_y$ is the matrix describing the noise covariance of the measurements.

Following Rodgers (2000), the iterative least-squares fit solution is given by,

$$w_{i+1} = w_i + \left[\mathbf{K}^T\mathbf{S}_y^{-1}\mathbf{K}\right]^{-1} \mathbf{K}^T\mathbf{S}_y^{-1} [\mathbf{y} - \hat{\mathbf{y}}(\mathbf{x})_i)] \tag{4}$$

where the total water vapor column, w_i, is computed by suitably integrating the vertical profile $\mathbf{x}_i$ and

$$\mathbf{K} = \frac{\partial \hat{\mathbf{y}}(\mathbf{x})}{\partial w}|_{\mathbf{x}=\mathbf{x}_i} \tag{5}$$

is the Jacobian matrix evaluated by finite differences perturbing the entire profile by 1%. Note that after each iteration $\mathbf{x}_{i+1}$ is computed following

$$\mathbf{x}_{i+1} = \frac{w_{i+1}}{w_i}\mathbf{x}_i \tag{6}$$

.

This technique estimates the uncertainties (the precision) in the retrieved total column water vapor, w, according to:

$$\mathbf{S}_w = \left(\mathbf{K}^T\mathbf{S}_y^{-1}\mathbf{K}\right)^{-1} \tag{7}$$

where $\mathbf{S}_w$ is the covariance matrix of the estimated total column water w_{i+1}.

So, to test the total column water vapor retrieval four parameters are needed: (1) the measurements $\mathbf{y}$, (2) the initial guess x_0, (3) the forward model parameters $\mathbf{b}$, and (4) the measurement covariance matrix $\mathbf{S}_y$. The measurements are CloudSat-driven simulations. The initial guess, that is to say the water vapor profile used in the first iteration, is a climatological water profile. The forward model parameters needed are: IWC, LWC, rain, snow, temperature and pressure. All of them were taken from the CloudSat retrieval products. The hydrometeor PSDs used were listed in table 1, which are the same ones employed to compute the synthetic measurements. Lastly, the measurement covariance matrix was assumed to be a diagonal matrix with the variances of the elements of the measurement vector. That is to say,

$$\sigma^2 = \left(\sqrt{2\delta_Z}\right)^2 \tag{8}$$

where δ_Z is the radar precision, in this study assumed to be 0.16 dBZ, and the expression within the brackets is just the addition in quadrature of the uncorrelated radar tones precision.

While finding the solution of the retrieval problem is the central part of operational retrieval algorithms, it is not the main focus of this study. This study quantifies the theoretical capabilities of such measurements, and therefore, the precision and accuracy of the solution w reached by the iterative process. As already mentioned, the uncertainty in the retrieved state due to the measurement noise (the precision) is described by the diagonal elements of the covariance matrix $\mathbf{S}_w$. To compute the accuracy impacts of various sources of systematic uncertainties were investigated. These errors were estimated using end-to-end retrieval simulations. First, for each systematic error a perturbed set of measurements were generated and ran through the retrieval algorithm. These perturbed measurements were computed following,

$$\mathbf{y}' = \mathbf{F}(\mathbf{x}_T, \mathbf{b}') \tag{9}$$

where $\mathbf{x}_T$ is the true water vapor state as provided by the CloudSat-ECMWF product, and where $\mathbf{b}'$ is the perturbed forward model parameter. Note that in $\mathbf{b}'$ only one of the parameters is perturbed at a time; for instance, when computing the systematic uncertainty related to temperature, only the temperature values are perturbed, while the rest (IWC, LWC, Rain, Snow, PSDs, etc) are left unperturbed. Then, the retrieval results using the perturbed measurements were compared to the retrieved values from an unperturbed run, i.e. where the measurements were,

$$\mathbf{y} = \mathbf{F}(\mathbf{x}_T, \mathbf{b}) \tag{10}$$

and the difference between the two was a measure of the impact of a given systematic error source. Table 2 summarizes the perturbation used.

B Optimal Estimation

In this study, optimal estimation retrievals are used to estimate water vapor profiles, $\mathbf{x}$. In these retrievals the problem is ill-conditioned and to find a meaningful solution an *a*

priori constraint is added to the retrieval problem. Each element in the measurement vector, also denoted by $\mathbf{y}$, is determined by

$$y_{jk} = \frac{dBZ(\nu_2, r_k) - dBZ(\nu_2, z_{k-1})}{\partial r} - \frac{dBZ(\nu_1, r_k) - dBZ(\nu_1, r_{k-1})}{\partial r} \tag{11}$$

where j is the frequency counter (excluding the reference frequency), k is the range gate counter, and ∂r is the vertical resolution. In a similar manner, the elements of the forward model are given by

$$\hat{y}_{jk} = \frac{\mathbf{F}_{\nu_2, r_k}(\mathbf{x}, \mathbf{b}) - \mathbf{F}_{\nu_2, r_{k-1}}(\mathbf{x}, \mathbf{b})}{\partial r} - \frac{\mathbf{F}_{\nu_1, r_k}(\mathbf{x}, \mathbf{b}) - \mathbf{F}_{\nu_1, r_{k-1}}(\mathbf{x}, \mathbf{b})}{\partial r}. \tag{12}$$

The solution of such system may be found by minimizing the cost function,

$$\chi^2 = [\mathbf{y} - \hat{\mathbf{y}}(\mathbf{x})]^T \mathbf{S}_y^{-1} [\mathbf{y} - \hat{\mathbf{y}}(\mathbf{x})] + [\mathbf{x}$$

-$\mathbf{a}^T \mathbf{S}_a^{-1}$ [$\mathbf{x}$-$\mathbf{a}$(13)where $\mathbf{a}$ is the *a priori* estimate with covariance $\mathbf{S}_a$. As mention before, the *a priori* used is the mean profile of 100 adjacent CloudSat ECMWF-aux water vapor values smoothed by with a boxcar average of 4 vertical level and the uncertainties in this *a priori* are assumed to be 100%. In this case, the diagonal elements of S_y are given by

$$\sigma^2 = \left(\sqrt{4\delta_Z}/\partial r\right)^2 \tag{14}$$

because each element in the measurement vector involves four reflectivity measurements.

Following Rodgers (2000), the iterative solution is given by,

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \left[\mathbf{K}^T \mathbf{S}_y^{-1} \mathbf{K} + \mathbf{S}_a^{-1}\right]^{-1} \left\{\mathbf{K}^T \mathbf{S}_y^{-1} [\mathbf{y} - \hat{\mathbf{y}}(\mathbf{x}_i)] + \mathbf{S}_a^{-1} [a - x_i]\right\} \tag{15}$$

where in this case, the Jacobian matrix is given by

$$\mathbf{K} = \frac{\partial \hat{\mathbf{y}}(\mathbf{x})}{\partial x}\Big|_{\mathbf{x}=\mathbf{x}_i} \tag{16}$$

This technique gives an estimate of the precision in the water vapor profiles according to,

$$\mathbf{S}_x = \left(\mathbf{K}^T \mathbf{S}_y^{-1} \mathbf{K} + \mathbf{S}_a^{-1}\right)^{-1} \tag{17}$$

Another important quantity used to diagnose the retrieval performance is the "Averaging Kernel" matrix, given by

$$A = \frac{\partial \mathbf{x}}{\partial \mathbf{x}_T} = \left(\mathbf{K}^T \mathbf{S}_y^{-1} \mathbf{K} + \mathbf{S}_a^{-1}\right)^{-1} \mathbf{K}^T \mathbf{S}_y^{-1} \mathbf{K} \tag{18}$$

where $\mathbf{x}_T$ is the true state of the atmosphere and $\mathbf{x}$ is the retrieved state obtained in the last iteration of equation 15. The rows of this matrix are the averaging kernels and they map the true state into the retrieval space, that is to say, they describe how the elements of the true state influenced the retrieved state. The width of the kernel is a measure of retrieval resolution.

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