Validation of Physical Model and Dual-Frequency Radar Retrieval Algorithm using SnowSAR Data

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ABSTRACT

In this paper we combine the bicontinuous dense media radiative transfer (Bic-DMRT) model with a radar retrieval algorithm of snow water equivalent (SWE). Both the Bic-DMRT model and the retrieval algorithm are validated using airborne SnowSAR data at X and Ku band. The retrieval algorithm is based on the absorption loss of the snowpack which is directly proportional to the SWE. In the algorithm, Bic-DMRT is first applied to generate the look-up table (LUT) of scattering properties of snow at X- and Ku-band. With the LUT, we plot the scatter diagram of the scattering albedo \( \omega_{Ku} \) VS. \( \omega_X \) and the optical thicknesses \( \tau_{Ku} \) VS. \( \tau_X \), respectively and derive regression formulas for \( \omega_{Ku} \) VS. \( \omega_X \) and \( \tau_{Ku} \) VS. \( \tau_X \) separately. Furthermore, regression formulas between multiple (volumetric) and single scattering at both bands are also derived. With these four regression formulas, we transform the volumetric scattering of a single snow layer at dual bands as functions of \( \omega_X \) and \( \tau_X \). The background scattering is then subtracted from the total scattering which gives the volume scattering of snow. Based on the obtained volume scattering, a cost function is established to find the solution. Performance of the retrieval algorithm was tested using SnowSAR data (the Finland SnowSAR1 and SnowSAR2, and the Canada SnowSAR campaigns). The retrieval algorithm achieves RSME smaller than 20 mm for all the SnowSAR data in this paper which meets the requirements for snow mass mission concept studies currently underway at the European Space Agency (ESA) and Canadian Space Agency (CSA).

Keywords: bicontinuous dense media radiative transfer (Bic-DMRT), retrieval algorithm, snow water equivalent (SWE), look-up table (LUT), regression formula, SnowSAR

ESTIMATION OF BACKGROUND SCATTERING

The radar observation consists of two parts, the volume scattering component from the snowpack and the background scattering component from the snow-free ground, as shown in Figure 1 (a). These two components are combined to give the expression of radar observation below:

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\[ \sigma_{pq}^{\text{vol}} = \sigma_{pq}^{\theta} \exp \left(- \frac{2\tau}{\cos \theta} \right) + \sigma_{pq}^{\text{snow}} \]  

where \( \sigma_{pq}^{\text{snow}} \) is the volume scattering component from the snowpack and \( \sigma_{pq}^{\theta} \) is the scattering from snow-free ground which is attenuated by the snow layer by a factor of \( \exp(-2\tau/\cos \theta) \). \( \tau \) is the optical thickness of the snow layer and \( \theta \) is the transmitted angle in the snow. Figure 1 (b) illustrates the data of SnowSAR measurements from the flights in Canada and the bicontinuous / DMRT model predictions which are derived within the range that bicontinuous / DMRT model predicts which means variabilities exhibited in Canada SnowSAR data are covered by the bicontinuous / DMRT LUT. The bicontinuous / DMRT works well in modeling the volume scattering for Canada SnowSAR data.

The surface backscattering at co- and cross-pol taken from a prebuilt lookup table based on NMM3D (Huang, 2010 and 2012) will be used in further studies, however, the table does not cover the full surface roughness range in our campaigns. Right now we apply an empirical model proposed by (Oh, 1992) to calculate the scattering from bare soil surfaces.

**PARAMETERIZATION AND REGRESSION TRAINING**

With the snowpack parameters, we utilize the bicontinuous / DMRT model to generate a look-up table (LUT) (Tan, 2015). We tabulate 6 bicontinuous / DMRT outputs, including four parameters which are the scattering albedo \( \omega_X, \omega_Ku \) and the optical thicknesses \( \tau_X, \tau_Ku \) at X and Ku band and two observations \( \sigma_{VV}^X, \sigma_{VV}^{Ku} \) which are the VV polarization backscatter of snowpack at dual bands. With the LUT, we derive regression formulas from the scattering albedo \( \omega_Ku \) vs. \( \omega_X \) and the optical thicknesses \( \tau_Ku \) vs. \( \tau_X \) separately, as shown in Figure 2. Next, given the single scattering solution which only depends on \( \omega \) and \( \tau \), the regression formulas between single and multiple scattering are derived to transform \( \sigma_{VV}^X \) as a function of \( \omega_X, \tau_X \) and \( \sigma_{VV}^{Ku} \) as a function of \( \omega_Ku, \tau_Ku \), as illustrated in Figure 3. We then reduce the number of unknowns by utilizing the regression formulas of \( \omega_Ku \) vs. \( \omega_X \) and \( \tau_Ku \) vs. \( \tau_X \). Finally, both \( \sigma_{VV}^X, \sigma_{VV}^{Ku} \) only depend on \( \omega_X, \tau_X \) resulting in 2 observations and 2 unknowns (Cui, 2016).

\[
\begin{align*}
\sigma_{VV}^X (dB) &= -3.3841481 + 0.92035737 \times 10 \log_{10} \left\{ 0.75 \cos \theta \omega_X \left[ 1 - \exp \left( -2\tau_X / \cos \theta \right) \right] \right\} \\
\sigma_{VV}^{Ku} (dB) &= -0.24752984 + 1.1091572 \times \\
&\quad \left\{ 0.75 \cos \theta \left( \frac{\omega_X}{0.58352316 \omega_X + 0.43973192} \right) \times \right. \\
&\quad \left. \left[ 1 - \exp \left( -2 \exp \left( 1.3760377 + 0.96250819 \ln \left( -\tau_X / \cos \theta \right) \right) \right) \right] \right\}
\end{align*}
\]

Originally there are four snowpack parameters in the bicontinuous / DMRT model. After parameterization, we reduce the number of unknowns to two. The parameterized model only depends on \( \omega_X, \tau_X \). Furthermore, the parameterized model provides with an effective equivalent single layer description for the multi-layer snow. With such characterization of snowpack, we directly retrieve \( \omega_X \) and \( \tau_X \) in the retrieval algorithm. The retrieved \( \omega_X \) and \( \tau_X \) give the absorption...
VALIDATION OF THE PARAMETERIZED MODEL AND PERFORMANCE OF THE RADAR RETRIEVAL ALGORITHM USING EXISTING SNOWSAR DATA

Three SnowSAR datasets have been used for validation of the algorithm:

a) SnowSAR1 airborne campaign has been carried out in the Lappish region of Finland from March 12th to 19th, 2011 and mostly focused on the area close to the town of Sodankylä. In the CoReH2O, a dual frequency, X- and Ku-bands, dual polarization (V&H) mini-SAR airborne system (SnowSAR) has been deployed (CoReH2O, 2010).

b) SnowSAR2 airborne campaign is the continuous campaign of SnowSAR1, which was also performed around Sodankyla, Finland, from December 19th, 2011 to March 24th, 2012 (Cohen, 2015).

c) The Canadian SnowSAR campaign is another airborne campaign with SnowSAR instrument performed within the Track Valley Creek (TVC), the Northwest Territories, Canada, during winter 2013. Two sets of polarimetric SAR images operating at X- and Ku-bands were obtained (King, 2017).

Figure 4 depicts that the results of parameterized model agrees well with the Canada SnowSAR data at both X- and Ku-band. The root-mean-square error (RMSE) between model and Canada SnowSAR data is ~0.3dB and their correlation coefficient is above 0.94. It indicates that the model predicts the backscattering of snowpack accurately provided reasonable physical parameters of the snowpack.

We apply a statistical method to search for the solution. In practice, a priori constrained least-squares algorithm is used to fit the model predictions into radar observations at dual bands, which was also the case in the CoReH2O SWE retrieval (Cui, 2016 and CoReH2O, 2010). The cost function is defined as:

$$F = \text{MIN}_{\omega_x, \tau_x} \left\{ \frac{\left( \sigma_{VV}^{X,\text{obs}} - \sigma_{VV}^{X,\text{mod}}(\omega_x, \tau_x) \right)^2}{2s_x^2} + \frac{\left( \sigma_{UU}^{Ku,\text{obs}} - \sigma_{UU}^{Ku,\text{mod}}(\omega_x, \tau_x) \right)^2}{2s_{Ku}^2} + \frac{\left( \omega_x - \omega_x^* \right)^2}{2s_{\omega_x}^2} \right\}$$

(2)

where $\sigma_{VV}^{X,\text{obs}}, \sigma_{UU}^{Ku,\text{obs}}$ are the radar observations at dual bands including surface scattering from the bottom ground and volume scattering from the snowpack, $\sigma_{VV}^{X,\text{mod}}, \sigma_{UU}^{Ku,\text{mod}}$ are the backscattering predictions from the regression forward model, $\omega_x$ is the a priori value for albedo. $s_x^2, s_{Ku}^2$ are the expected error standard deviation of the measurements which is also regarded as the variance of speckle in a SAR image, and $s_{\omega_x}^2$ act as the variance of the priori constraint. The contribution from each term in cost function is normalized by assuming a Gaussian distribution. $\omega_x, \tau_x$ are the two parameters we need to solve from this equation. With cost function, we find the best fit $\omega_x, \tau_x$ for each set of $\sigma_{VV}^{X,\text{obs}}, \sigma_{UU}^{Ku,\text{obs}}$.

We have validated the radar retrieval algorithm by applying the SnowSAR data. We set $s_x = 0.5, s_{Ku} = 0.6$ (Cui, 2016). Based on the error standard deviation of the measurements which is also regarded as the variance of speckle in a SAR image. And we set the variance of the priori constraint as $s_{\omega_x} = 0.1, s_{\tau_x} = 0.01$ based on the variance of $\omega_x, \tau_x$. The priori parameter $\omega_x$ for each data points of SnowSAR was taken from its corresponding matched dataset in LUT in the forward model validation. $\tau_x$ is uniformly sampled in a range which is determined by datasets who have the same $\omega_x$. The retrieval results are illustrated in Figure 5, Figure 6, and Figure 7, for the Finland SnowSAR1, the Finland SnowSAR2, and the Canada SnowSAR, respectively. These results meet the requirement defined in SCLP (the NASA Snow and Cold Land process). SCLP requires that the RMSE of SWE retrieval be less than 20mm for shallow snowpack with SWE less than 200mm and the RMSE be less than 10% of the total SWE when the SWE is larger than 200mm.

loss of the snowpack, which is proportional to SWE. In addition, it is also easy to obtain the priori information for the retrieval by using the parameterized model.
In Figure 5 of the results of the Finland SnowSAR1 dataset, both the RMSE and the bias are small. The relatively large correlation coefficient indicates that the retrieval results reflect the variation of the measurements. The fact that the range of the retrieval results is slightly larger than that of the observed SWE is possibly due to the inaccurate guess of the scattering from soil and vegetation. Meanwhile, the correlation in Figure 6 for the Finland SnowSAR2, and the bias and correlation in Figure 7 for the Canada SnowSAR datasets are better than that of SnowSAR1 in Figure 5. In Figure 6, and Figure 7, the correlation coefficient is approaching 1 and the ratio of retrieval and measurement data is almost 1:1, indicating excellent retrieval performance. The reason is that for SnowSAR2 and Cananda SnowSAR data we have selected data points located in open areas and the guess of the ground scattering is much better which improves the performance of the algorithm. The achieved RMSE and the correlation coefficient are 15.22 mm and 0.739 for the Finland SnowSAR1 dataset, 19.07 mm and 0.782 for the Finland SnowSAR2 dataset, and 15.89 mm and 0.916 for the Canada SnowSAR dataset, respectively.

Figure 1. (a, left) Illustration of volume scattering and surface scattering; (b, right) surface scattering affects the total scatter more in X- than in Ku-band.

Figure 2. Comparison of scattering parameters between simulation and regression results: optical thickness (a, left) and scattering albedos (b, right).
Figure 3. Comparison of volume scattering and first order regression at X-band (a, left) and Ku-band (b, right).

Figure 4. Validation of parameterized model Canada SnowSAR data at X-band (a, left) and Ku-band (b, right).

Figure 5. Comparison of SWE retrieved with SWE measured for SnowSAR1 data.
Figure 6. Comparison of SWE retrieved with SWE measured for SnowSAR2 data.

Figure 7. Comparison of SWE retrieved with SWE measured for Canada SnowSAR data.

REFERENCES:


