Data assimilation of multilayer snowpack on Argentière glacier, using X-band SAR data, DMRT and a detailed snowpack model

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ABSTRACT: This study discuss the potential of using remote sensing data from Synthetic Aperture Radar (SAR), couple with Dense Media Radiative Transfer (DMRT) model, to constrain the snowpack's optical grain size and density calculated by the detailed snowpack model Crocus. A snowpack Electromagnetic Backscattering Model (EBM) based on DMRT compatible with X-band and Ku-band frequencies is developed from the previous one by Longépé et al., 2009. From measured or simulated snowpack stratigraphic profiles consisting of snow optical grain size, density, the model calculates the backscattering coefficient σ^0 for co-polarized channels (HH and VV). Next, from the EBM, the adjoint operator is developed and used in a variational assimilation scheme in order to minimize the discrepancies between simulations and SAR image data observations. A time series of TerraSAR-X acquisitions on Argentière glacier (Chamonix Mont Blanc, France) is used to test the proposed scheme.

KEYWORDS: Remote sensing, electromagnetic backscattering model, snow grain optical diameter, snow density, radar (SAR), data assimilation.

1 INTRODUCTION

Snowpack characterization has become a critical issue in the present context of climate change. Estimating some of the properties of a snowpack, like its density and grain diameter distribution will provide great benefit to snow forecasting, prevision of natural hazard, like snow avalanche warning, and economic arrangements related to tourism and winter sports. Due to its imaging capabilities over large areas, unaffected by weather and day-night conditions, Synthetic Aperture Radar (SAR) is an important tool for snowpack characterization in a natural environment. Moreover, the high penetration depth of radar electromagnetic waves allows us to retrieve the information inside the volume of the snowpack.

A new generation of X-band (8-12GHz) SAR systems, and in the near future K_u-band (12-18GHz), with high image resolution, short revisit time will provide improved information that might be used to characterize and monitor snowpack. In this context, it is necessary to develop a compatible Electromagnetic Backscattering Model (EBM) accounting for electromagnetic waves (EMW) propagation and scattering at high frequencies (X and K_u-bands) through a multilayer snowpack. Some backscattering models at L and C-band frequencies have been introduced by Longépé et al., 2009 and Koskinen et al., 2010. These models simulate the loss of EMW energy while propagating through dense media by solving the Radiative Transfer (RT) differential equation (Ulaby et al., 1981). In order to introduce coherent recombination effects in the RT coherent model, Wang. et al., 2000 applied the Strong Fluctuation Theory (SFT) introduced by Stogryn, 1984 to calculate the effective permittivity of each snow layer, in which the correlation among particles was taken into account.

In this paper, the snowpack backscattering model initially developed in Longépé et al., 2009 is adapted for X-band and higher frequencies, in the case of a dry snow medium. The adaptation consists of updating the Integral Equation Model (IEM) introduced by Fung et. al., 1992 by a newer version published in 2004, which allows the calculation of air-snow interface and snow-ground backscattering components for X-band and higher frequencies. The modeling of volume backscattering is based on solving the Vector Radiative Transfer equation and SFT and is compatible for X and Ku-bands. From the physical features of each snow layer (optical grain radius, density, thickness) and for given SAR acquisition conditions (frequency, incidence angle), the model calculates total backscattering coefficients σ_{pq} for different polarization channels and their vertical distribution within the snowpack. Next, snowpack profiles generated by the detailed snowpack model Crocus using

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downscaled meteorological fields from the SAFRAN analysis (Vionnet et al., 2012) are used to feed EBM simulations and the results are compared to SAR images. In this context, the number of backscattering coefficients, being much smaller than the number of unknown variables, i.e. the snow cover properties, classical estimation approaches based on the use of an inverse problem would reveal totally inefficient. Instead, an adjoint operator of the direct EBM is developed and used in an assimilation scheme. A variational assimilation method allows the integration of the observation data into a set of initial guess parameters through a direct model, and therefore can constrain these parameters without explicitly inverting the model. In our study, the three-dimensional variational analysis (3D-VAR) method (Courtier et al., 1998) is implemented. Finally, TerraSAR-X acquisitions over the French-Alps are used to evaluate the model and the data assimilation process. The Argentière glacier area (Chamonix Mont Blanc, France) has been chosen for this case study due to its large and rather uniformly snow-covered surface area.

Details of the EBM equations and its physical and mathematical hypothesis are presented in section II. Introductions to the Crocus snowpack model and to the implementation of the 3D-VAR scheme are described in section III. Section IV shows a description of TerraSAR-X acquisition parameters, as well as results of the case study on the Argentière glacier.

2 EMW BACKSCATTERING MODEL

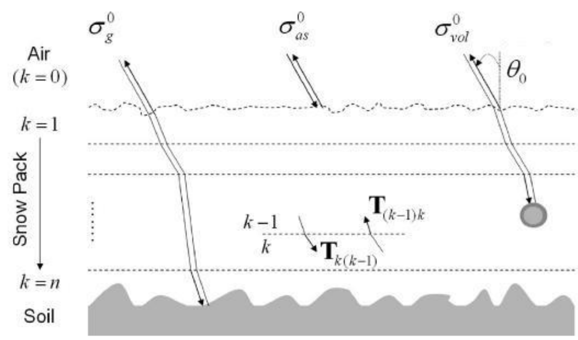

Figure 1. Main backscattering mechanisms occurring within a multilayer snowpack that can be simulated using the RT theory at order 1 (Longépé et al., 2009)

The solution of the RT equation at order 1 provides a total backscattered information from a snowpack that consists of a combination of five scattering mechanisms: reflection at the surface air-snow interface, volume scattering, volume-ground and ground-volume interactions, and reflection over the ground (Martini et al., 2003). Due to their small amplitude, the volume-ground and ground-volume contributions can be neglected (Floricioiu and Rott, 2001). The illustration of the three other mechanisms is shown in Figure 1. The expression of the total polarimetric backscattered information can be written as the sum of each backscattering mechanism:

$$\sigma_{tot}^0 = \sigma_{as}^0 + \sigma_{vol}^0 + \sigma_g^0 \qquad (1)$$

The air-snow interface and ground backscattering are modeled using the IEM introduced by Fung and Chen, 2004, whereas the volume contribution is calculated using the Vector Radiative Transfer equation.

3 3D-VAR DATA ASSIMILATION

3.1 The detailed snowpack model Crocus

Crocus is a one-dimensional numerical model simulating the thermodynamic balance of energy and mass of the snowpack. Its main objective is to describe in detail the evolution of internal snowpack properties based on the description of the evolution of morphological features of snow grains during their metamorphism. It takes as input the meteorological variables air temperature, relative air humidity, wind speed, solar radiation, long wave radiation, amount and phase of precipitation. When used in the French mountain ranges (Alps, Pyrenees and Corsica), these quantities are commonly provided by the SAFRAN system, which combines ground-based, radiosondes and remote sensing (cloudiness) observations with an *a priori* estimate of meteorological conditions from a numerical weather prediction (NWP) model (Durand et al., 1993). The output includes scalar physical properties of the snowpack (snow depth, snow water equivalent, surface temperature, albedo…) along with the internal physical properties for each layer (density, thickness, optical grain radius…). SAFRAN meteorological fields are assumed to be homogeneous within a given mountain range and provide a description of the altitude dependency of meteorological variables by steps of 300 m elevation (Durand et al., 2009).

This study uses the latest version of the detailed snowpack model Crocus, recently incorporated in the land surface scheme ISBA within the SURFEX interface (Vionnet et al., 2012). Among other advantages over previous versions of Crocus, this allows seamless coupling of the snowpack to the state of the underlying ground.

3.2 Introduction to the assimilation method

Variational assimilation aims to integrate observation data into guess variables through the use of an observation operator. It is widely used in meteorological studies in order to relate observations, measurements and modelling

(Dumont et al., 2012). The method concentrates on searching a solution that minimizes simultaneously the distance between observations and simulation results and the distance between initial guess variables and the analysed variables. A scheme of this process is presented in Figure 2.

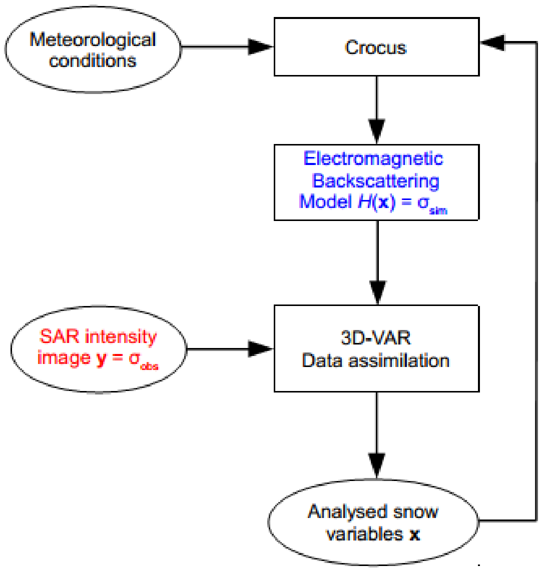

Figure 2. Global scheme of the data analysis used in this study

The 3D-VAR algorithm (Courtier et al., 1998) is based on the minimization of a cost function $J(\boldsymbol{x})$, defined as:

$$J(\boldsymbol{x}) = \left(\boldsymbol{x} - \boldsymbol{x_g}\right)^t \boldsymbol{B}^{-1}\left(\boldsymbol{x} - \boldsymbol{x_g}\right) + \left(\boldsymbol{y_{obs}} - \boldsymbol{H_{ebm}}(\boldsymbol{x})\right)^t \boldsymbol{R}^{-1}\left(\boldsymbol{y_{obs}} - \boldsymbol{H_{ebm}}(\boldsymbol{x})\right) \quad (2)$$

where $\boldsymbol{x}$ is called the state vector, and can be modified after each iteration of the minimization, $\boldsymbol{x_g}$ is the initial guess of the state vector and remains constant during the whole process. Therefore $\left|\boldsymbol{x} - \boldsymbol{x_g}\right|^2$ serves as a distance between the modified profile and the starting point. The observed polarimetric response, $\boldsymbol{y_{obs}}$, contains calibrated values of the backscattering coefficients σ^0 for different polarimetric channels. $|\boldsymbol{y_{obs}} - \boldsymbol{H_{ebm}}(\boldsymbol{x})|^2$ hence represents the distance between simulated and observed radiometric quantities. The process also requires the estimation of the error covariance matrices of observations/simulations $\boldsymbol{R}$ and the guess error variance $\boldsymbol{B}$.

3.3 Adjoint operator and minimization algorithm

In order to minimize the cost function J, one needs to calculate its gradient:

$$\nabla J(\boldsymbol{x}) = 2\boldsymbol{B}^{-1}\left(\boldsymbol{x} - \boldsymbol{x_g}\right) - 2\nabla \boldsymbol{H}_{\boldsymbol{ebm}}^{t}(\boldsymbol{x})\boldsymbol{R}^{-1}(\boldsymbol{y_{obs}} - \boldsymbol{H_{ebm}}(\boldsymbol{x}) \quad (3)$$

If the model is denoted $\boldsymbol{H_{ebm}}: \mathrm{B} \rightarrow \mathrm{R}$, with B and R are the domain of definition of $\boldsymbol{x}$ and $\boldsymbol{y_{obs}}$, then the function $\nabla \boldsymbol{H}_{\boldsymbol{ebm}}^{t}$ satisfying: $\forall \boldsymbol{x}, \boldsymbol{y_{obs}}, \langle \nabla \boldsymbol{H}_{\boldsymbol{ebm}}^{t} \boldsymbol{y}, \boldsymbol{x} \rangle_{\mathrm{B}} = \langle \boldsymbol{y}, \nabla \boldsymbol{H}_{\boldsymbol{ebm}}^{t} \boldsymbol{x} \rangle_{\mathrm{R}}$ is the adjoint operator of $\boldsymbol{H_{ebm}}$.

Once the adjoint operator is developed, the minimization of J can be achieved using a gradient descent algorithm. Each iteration consists of modifying the vector $\boldsymbol{x}$ according to the Newton method:

$$\boldsymbol{x_{n+1}} = \boldsymbol{x_n} - \nabla J(\boldsymbol{x_n}) / \nabla^2 J(\boldsymbol{x_n}) \quad (4)$$

where $\nabla^2 J(\boldsymbol{x_n})$ is the gradient of second order (Hessian) of J:

$$\nabla^2 J = 2\boldsymbol{B}^{-1} + 2\nabla \boldsymbol{H}_{\boldsymbol{ebm}}^{t} \boldsymbol{R}^{-1} \nabla \boldsymbol{H_{ebm}} \quad (5)$$

3.4 Comments on the assimilation method

In general, modelling techniques are used to establish the relations between the physical properties of natural environment and observations measured by specific equipment (such as SAR or optical sensors). An inverse approach may then be developed to characterize the environment using the observations. However, such problems often require solving an underdetermined system, with a number of unknown quantities higher than the number of equations.

In our case, the length of the input state vector $\boldsymbol{x}$ can reach 100 (in the case of snowpack with 50 layers, frequently generated by Crocus), whereas the output of the model only consists of backscattering coefficients corresponding to the polarimetric channels of SAR data. Therefore the realization of an inverse model is theoretically impossible.

Data analysis methods, on the other hand, require a vector of guess variables relatively close to the actual values, allowing adding *a priori* information. The snowpack variables calculated by Crocus are used as guess in our assimilation scheme. The fundamental goal is to modify the initial guess variables, while balancing the errors of guess, modelling and measurements. It should be noted that, as the problem remains underdetermined, the analysis scheme only serves as a method to improve the initial guess variables using the new observations from SAR data. The quality of improvement is based on the estimation of the initial guess vector $\boldsymbol{x_g}$ and on the precision of the EBM.

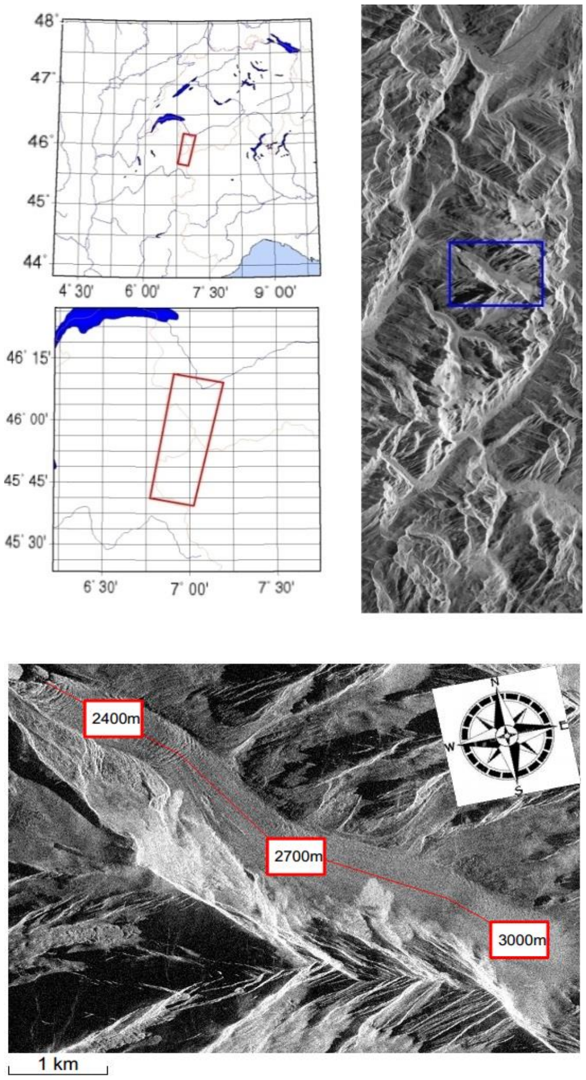

Figure 3. (Top) Location of TerraSAR-X acquisition in the French Alps. (Bottom) Zoom on the Argentière glacier area. Approximate positions of different altitudes over the glacier: 2400m, 2700m and 3000m are shown. The red line indicates the continuous trail on the glacier where SAR data are sampled in the case study.

4 CASE STUDY: ARGENTIERE GLACIER

4.1 TerraSAR-X data

For this study, TerraSAR-X descending acquisitions on the region of Chamonix Mont-Blanc, France performed over March 2nd, March 13th and March, 24th 2009 are available. Table 1 shows the main features of the TerraSAR-X datasets. The area of interest covers the Argentière glacier (Altitude: 2771m, 45.94628°N, 7.00456° E). The size of the domain is approximately 5km x 6km. Figure 3 shows the location and the intensity image of the glacier captured on March 2nd, 2009.

Meteorological forcing data provided by SAFRAN from 2400m to 3000 m altitude on horizontal terrain were used to drive the detailed snowpack model Crocus throughout the whole season 2008-2009 (starting on August 1st 2008).

4.2 Evaluation of the EBM

Crocus snow stratigraphic profiles have been computed for 7 different altitudes over the Argentière glacier, from 2400m to 3000m. The level of liquid water content per volume at the time and location of measurement is 0%, therefore the condition of dry snow is satisfied. Figure 3 shows the approximate locations of each study area on the glacier.

The agreement between TerraSAR-X reflectivity and the output of EBM using Crocus simulated profiles can be observed in Figure 4. The EBM is able to follow important changes like those between the altitudes 2500m and 2900m. Scattering coefficient values corresponding to some altitude (on 2400m altitude and from 2500 to 2600m) are not represented given scattering for such locations are affected by glacier crevasses. There is a considerable increase of reflectivity at the altitude of 3000m, due to firn, which accounts for very high range of density.

4.3 3D-VAR data assimilation

Figure 4 shows that the gap between the TerraSAR-X backscattering coefficient and the simulation result of analysed snow parameters is reduced with respect to the initial simulations. This shows that after the modification made by the 3D-VAR assimilation scheme, the assimilated snowpack stratigraphic profiles lead to simulated results that are closer to the backscattering value observed from radar.

Figure 5 shows detailed analysis of the modifications of the snowpack profiles done by the data assimilation process. The input parameters consist of the snow grain optical diameter and the density of each snow layer. We have selected two snowpack profiles which are significantly modified by the assimilation algorithm (March 2nd 2009 at 2600m and March 24th at 2900m). It can be observed that the assimilated profiles show considerable changes especially in the lower layers. The algorithm tends to densify the snowpack more slowly in these layers in order to adapt the backscattering coefficient to TerraSAR-X reflectivity. It can also be noted that the snow depth of the assimilation profiles is a bit less than the original open-loop Crocus one on March 24th (about 280cm vs. 295cm). This is due to the accumulation of assimilation made on previous dates that modify the Crocus snow depth. This shows the ability to propagate the effects of assimilation over time so that the previous modifications are not “forgotten” in the process.

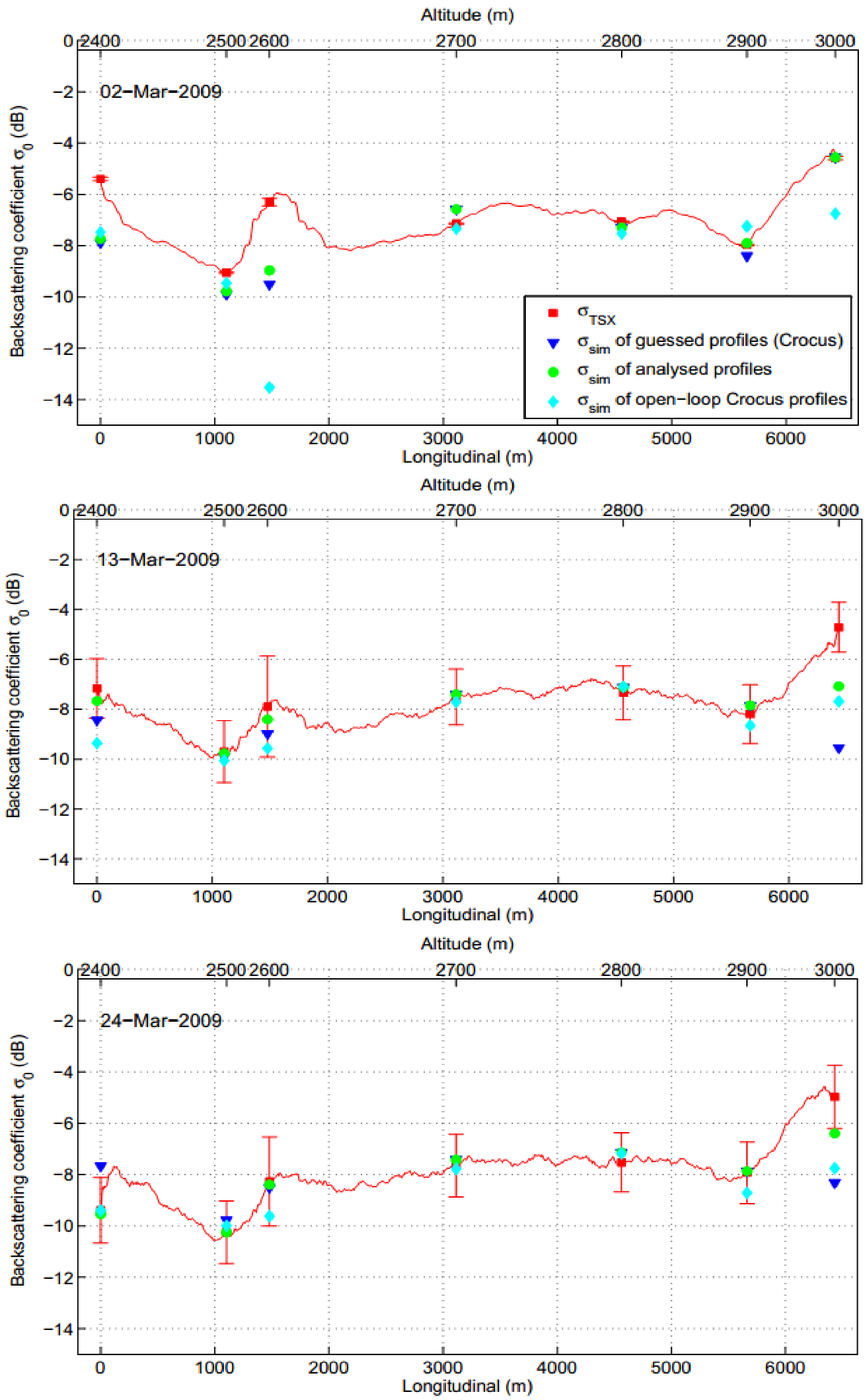

Figure 4. Results of simulation and assimilation using TerraSAR-X acquisitions. σ_{TSX}(red) represent mean values obtained from the SAR images over Argentière glacier (corresponding to the red line of Figure 3). σ_{sim}(blue) represents the output of simulations using Crocus snowpack variables as input. Simulations obtained after data analysis are shown in green. Error bars represent the standard deviation of measured reflectivity.

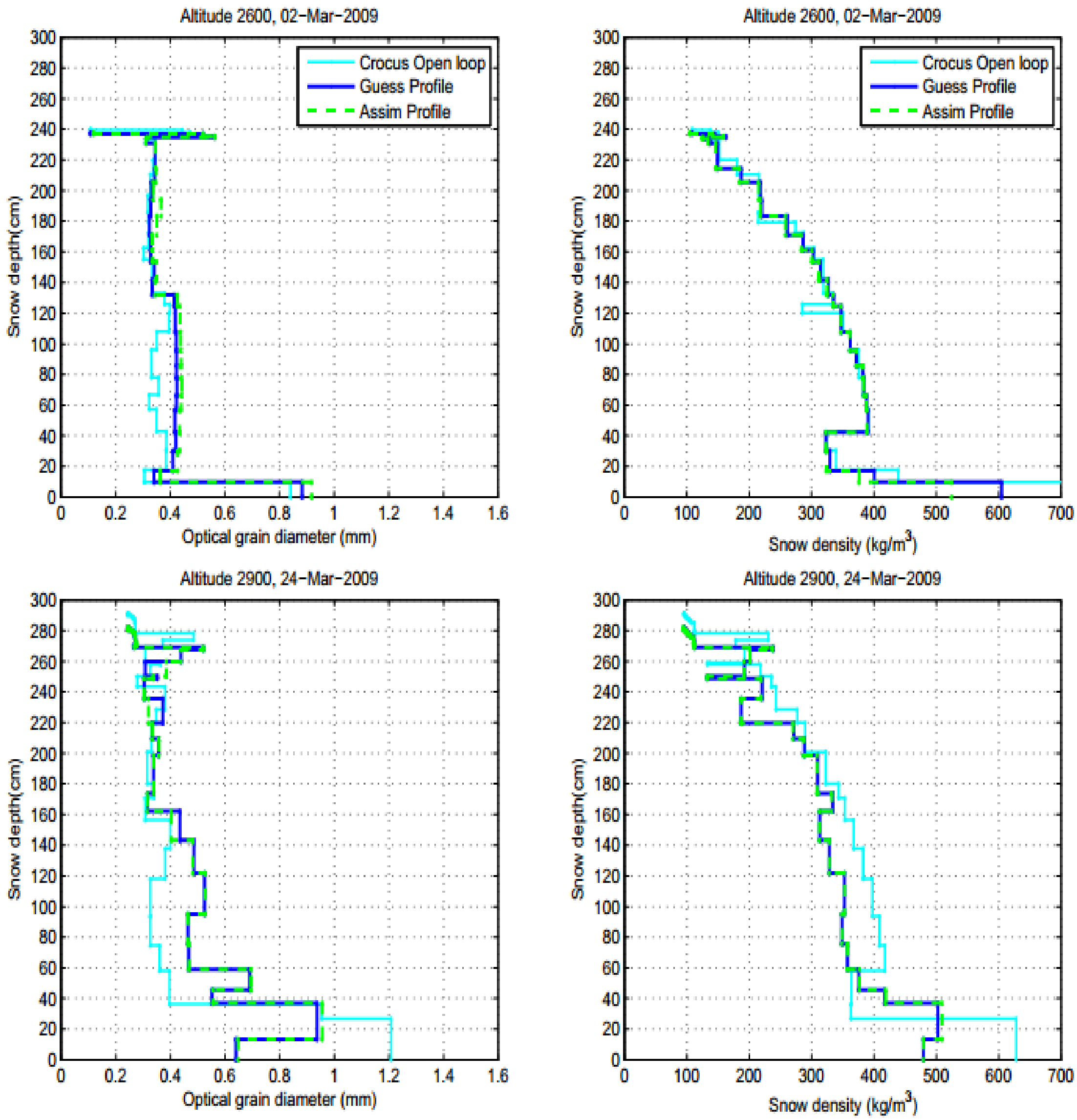

Figure 5. The results of data assimilation on Crocus profiles, which show changes made by the algorithm to the stratigraphy of snowpack.

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5 CONCLUSION

The results of this study show the potential of using SAR and meteorological data together with a multilayer snowpack backscattering model based on the radiative transfer theory in order to improve the snowpack detailed simulation. The new backscattering model adapted to X-band and higher frequencies enables the calculation of EMW losses in each layer of the snowpack more accurately. Through the use of 3D-VAR data analysis based on the linear tangent and adjoint operator of the forward model, we have the possibility to modify and improve the snowpack profiles calculated by the detailed snowpack model Crocus. The output of this process shows that the discrepancies between the simulated profile and the in situ measurements are smaller after assimilation, and therefore could be further developed and used in real application such as snow cover area monitoring on massif scale or snowpack evolution through a period of time using series of space borne SAR images.

Future studies will be concentrated on final evaluation of the assimilation process. This requires a number of in-situ measurements of snowpack properties, which can be used to validate the accuracy of the assimilated snow profiles. It also requires that the optical grain diameter becomes a prognostic variable of Crocus (currently it is a quantity diagnosed from several semi-empirical microstructure properties (see

Vionnet et al., 2012), which is currently under development.

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