A Case Study of Using a Multilayered Thermodynamical Snow Model for Radiance Assimilation
Ally M. Toure, Kalifa Goïta, Alain Royer, Edward J. Kim, Michael Durand, Steven A. Margulis, and Huizhong Lu

Abstract—A microwave radiance assimilation (RA) scheme for the retrieval of snow physical state variables requires a snowpack physical model (SM) coupled to a radiative transfer model. In order to assimilate microwave brightness temperatures (Tbs) at horizontal polarization (h-pol), an SM capable of resolving melt–refreeze crusts is required. To date, it has not been shown whether an RA scheme is tractable with the large number of state variables present in such an SM or whether melt-refreeze crust densities can be estimated. In this paper, an RA scheme is presented using the CROCUS SM which is capable of resolving melt-refreeze crusts. We assimilated both vertical (v) and horizontal (h) Tbs at 18.7 and 36.5 GHz. We found that assimilating Tb at both h-pol and vertical polarization (v-pol) into CROCUS dramatically improved snow depth estimates, with a bias of 1.4 cm compared to −7.3 cm reported by previous studies. Assimilation of both h-pol and v-pol led to more accurate results than assimilation of v-pol alone. The snow water equivalent (SWE) bias of the RA scheme was 0.4 cm, while the bias of the SWE estimated by an empirical retrieval algorithm was −2.9 cm. Characterization of melt-refreeze crusts via an RA scheme is demonstrated here for the first time; the RA scheme correctly identified the location of melt-refreeze crusts observed in situ.

Index Terms—Assimilation, melt–refreeze crusts, radiance, snow, snowpack model (SM).

I. INTRODUCTION

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EASONAL snow cover has a strong impact on climate, hydrological processes, and on human activities [1]. Snow is the frozen storage term in the water balance and is also a valuable resource. Monitoring snow physical variables (extent, water equivalent, and melting conditions) is essential for weather and hydrological forecasts in many regions and provides information for meteorological forecasts, hydropower generation, fresh water supply, river traffic, irrigation, runoff, and flood control [2].

Passive microwave-based estimates of terrestrial snow variables such as snow water equivalent (SWE) from satellite observations have so far been generated primarily by regression-based empirical methods. Snow variables retrieved by such methods are sometimes used in product-based data assimilation [3]–[5]. With this type of approach, the retrieval and the forward data assimilation do not necessarily have consistent physics or assumptions. Consistency is much easier to achieve when radiances are directly assimilated. This radiance assimilation (RA) approach has been used for years to retrieve atmospheric parameters by the operational weather forecasting community with great success [6]. This approach may also be an effective way to retrieve snow physical parameters such as snow depth and its water equivalent [7].

Snow RA requires accurate predictions of the brightness temperature (Tb) emitted by the snowpack. This imposes requirements on the key elements of the snow RA scheme: a snowpack model (SM), a radiative transfer model (RTM), and a data assimilation framework. In a previous study, Durand et al. [8] demonstrated that the microwave emission model for layered snowpacks (MEMLS) [9] has the ability to accurately predict the radiance when the snow layering structure and other state variables, such as grain-size correlation length, density, snow depth, liquid water, and temperature, are accurately represented. They also showed that the accuracy of RTMs particularly at horizontal polarization (h-pol) is highly sensitive to the stratigraphic representation of the snowpack and particularly to dense snow layers, such as melt–refreeze crusts.

Durand et al. [10] subsequently demonstrated the potential of snow RA using the simple snow-atmosphere-soil transfer model (SAST) [11] SM coupled to MEMLS. SAST is a simple three-layer energy-balance scheme. An improvement of the simulation of snow depth was achieved through the use of an ensemble Kalman smoother scheme at this local scale for a weeklong study [10]. However, limitations of SAST (three layers and no representation of melt-refreeze crusts) were evident. Indeed, only Tbs at vertical polarization (v-pol) could be assimilated due to the fact that SAST does not adequately represent the vertical stratigraphy of the snowpack. This is inherently suboptimal, as only half of the available information could be assimilated; the h-pol channels were ignored. Assimilation of
the h-pol channels thus requires an SM with higher vertical resolution. This is due to the fact that vertical variations in snow density lead to increased h-pol reflection coefficients at the layer interfaces within the snowpack; a melt-refreeze crust with a thickness of 1 cm can lead to a dramatic decrease in h-pol brightness [8]. While increasing the number of layers increases the fidelity of the RTM, it makes the assimilation problem much more difficult, however, as it increases the number of SM parameters that must be estimated using the assimilation scheme.

In this follow-on study, we explore RA using a much more sophisticated snow model, i.e., the CROCUS snowpack model [12], [13]. CROCUS has been used for operational avalanche forecasting in France since 1992. It simulates the physical snowpack processes and layering (stratigraphy) using up to 50 layers; CROCUS tracks layers that undergo melt-refreeze metamorphism. In the RA scheme proposed in this paper, we treat precipitation, grain-size evolution, and the density evolution of melt-refreeze crusts as uncertain within the context of the assimilation framework, and we estimate snow depth as well as grain size and density for each layer in the CROCUS model (i.e., on the order of 100 state variables at each model time step). We seek to answer the following two questions: 1) When on the order of 100 state variables are estimated simultaneously, will there be adequate information in the observations to accurately characterize snow depth? Previous snow RA studies have estimated less than ten state variables per model time step, e.g., [10]. To date, it has not been shown whether a snow RA scheme is tractable with on the order of 100 state variables per time step; and 2) Do the measurements contain enough information to simultaneously estimate the vertical structure of the snowpack grain size and melt-refreeze crusts, as well as the snow depth?

In this paper, we follow the convention in [14] and refer to snow layers resulting from partial melting and refreezing processes as “melt-refreeze crusts.” Note that melt-refreeze crusts so defined generally have densities lower than that of solid pure ice (\( \rho_{\text{ice}} = 917 \text{ kg} \cdot \text{m}^{-3} \)). In contrast to melt-refreeze crusts, pure ice has a glasslike appearance and is generally more homogeneous as melting has eliminated individual snow grains. Melt-refreeze crusts generally still consist of snow grains; some of which may have begun to adhere via melting/refreezing. We believe that this distinction may prove to be important for proper radiative transfer modeling; using an SM with more sophisticated representation of snow stratigraphy and melt-refreeze crusts should improve the accuracy of the prediction of the RA estimates.

II. MATERIAL AND METHODS

A. Experimental Data Set

Three types of in situ data were used in this paper: meteorological data to drive the SM, Tb data for assimilation within the RA scheme, and snowpit measurements for the validation of the RA estimates. We used meteorological, snowpit, and microwave radiance measurements collected during the National Aeronautics and Space Administration Cold Land Processes Field Experiment-1 (CLPX-1) [15], [16] in Colorado, USA. The CLPX-1 was a multisensor multiscale field campaign to provide a comprehensive data set for understanding fluxes, storage, and transformations of water and energy in cold land areas at regional and global scales. Intensive ground, airborne, and spaceborne observations were collected on a set of nested study areas, ranging from 1 ha to 160,000 km\(^2\), selected to cover a wide range of physiographic conditions and spatial scales (www.nohrsc.nws.gov/~cline/clpx.html). Our study area is the local scale observation site (LSOS). LSOS was a 1-ha study site located within the 1-km\(^2\)-CLPX-1 Fraser intensive study area, near the Fraser experimental forest headquarters facility (39°50′49″N, 105°54′40″W, 2780 m above sea level). Our period was the intensive observation period-3 (IOP3) on February 19–25, 2003. IOP3 was characterized by dry snow except on February 25 [8]. The snowpit data on February 25 revealed the presence of wet snow. The presence of liquid water in the layer generally leads to melt/refreeze metamorphism [17] which can result in the formation of large irregular clusters of rounded crystals held together by large ice-to-ice bonds (larger grains grow at the expense of smaller ones). Liquid water retained in snow pores can refreeze during the following cool night (under clear sky), and partial melting may occur subsequently. Consecutive melt/refreeze cycles lead to the formation of melt-refreeze crusts [2] and ultimately to layers of true ice.

1) Snowpit Data: There were seven days (February 19–25, 2003) on which both snowpit data and Tb were collected at the LSOS. Snowpit data included the snow depth, SWE, snow density, snow temperature, snow stratigraphy, and snow grain size. The average snow depth and SWE during the IOP3 were 92.7 and 197 mm, respectively [15]. The snowpit data were collected from two different snowpit locations within 10 m of the radiometer footprint: pit #1 (on February 20, 22, and 24) and pit #2 (on February 19, 21, 23, and 25). On February 19, the data were collected at 12:10 local time (LT); on February 20 at 15:30 LT; on February 21 at 11:30 LT; on February 22 at 11:00 LT; on February 23 at 11:00 LT; on February 24 at 13:30 LT; and on February 25 at 11:00 LT.

Snow temperature was measured at 10-cm vertical intervals. All snow layers were dry during IOP3 except on February 25 when wet snow was observed near the snow–air interface (surface temperature was between −0.2 °C and +0.5 °C). IOP3 snow-soil interface temperatures ranged from −0.2 °C to −0.5 °C [15].

Snow density was measured at 10-cm vertical intervals. The presence and location of melt-refreeze crusts was also identified and recorded, but melt-refreeze crust density was not measured in the field. Melt-refreeze crust density is generally lower than that of the pure ice (917 kg · m\(^{-3}\)), depending on the amount of pore space in the layer [18]. The details of the location of melt-refreeze crusts observed in IOP3 are presented in [8, Fig. 4]. Some of the melt-refreeze crusts are due to melt-refreeze metamorphism that has occurred earlier in the season, outside of our experiment period. Snowfall events on February 20, 22, and 25 increased snow depth by approximately 20 cm as the total.

Grain size was characterized by measuring the greatest spatial extension of the prevailing grains \( D_{\text{max}} \) using a microscope with 8 × 30 optics [14]. Newly fallen snow with grain sizes...
ranging from 0.1 to 1.5 mm was observed in the upper part of the snowpack. Depth hoar was observed at the bottom of the snowpack with $D_{\text{max}}$ between 1.5 and 2.4 mm (see [8, Fig. 4]). Between these boundaries, mixed grain shapes were observed with $D_{\text{max}}$ ranging between 0.7 and 1 mm. During IOP3, the presence of melt-refreeze crusts was noticed in each snowpit except on February 22. The locations of the melt-refreeze crusts are different for each snowpit (see [8, Fig. 4]). This can be attributed to the local spatial variability of the site because each snowpit was excavated in a slightly different location.

Fierz et al. [14] have defined snow grain size as the largest dimension (maximum diameter, $D_{\text{max}}$) of predominant snow grains. $D_{\text{max}}$ was measured in the field during the CLPX-1. Volume scattering of electromagnetic waves by a granular medium such as snow, however, does not depend upon $D_{\text{max}}$ [19], [20]. Physically meaningful structural parameters include the optical grain size ($D_0$), the snow specific area (SSA), and the correlation length ($P_{\text{ex}}$) [20]–[24]. We used the empirical formula developed in [8] to estimate the $P_{\text{ex}}$ from the CLPX-1 $D_{\text{max}}$ measurements.

2) Meteorological Data: The meteorological station used was located near the ground-based microwave radiometer (GBMR-7) instrument from the University of Tokyo [16]. The meteorological data were collected between October 1, 2002 and March 29, 2003 with a 10-min temporal resolution. The data collected include wind speed, wind direction, air temperature, relative humidity, downward long-wave radiation, downward shortwave radiation, and precipitation. Three other meteorological forcing parameters needed to run the CROCUS (i.e., the cloud cover, the type of precipitation, and the diffuse solar radiation) were not measured in the field but were estimated as a function of measured meteorological (downward long-wave radiation, air temperature, and relative humidity) data using the Simplified Simple Biosphere (SSiB) land surface model [25].

3) Radiometric Data: We used radiance observations from the GBMR-7 at 18.7 and 36.5 GHz at v- and h-pol from February 19 to February 25, 2003 (IOP3). The Tb observations were obtained between 12:30 and 15:30 LT on a daily basis [16]. Tbs were available for seven measurement times. We had four channels for a total number of 28 observations. The GBMR-7 was designed to withstand extreme outdoor conditions ($-30 \degree C \pm 40 \degree C$) [26]. The radiometer receiver electronics was encapsulated in a thermally stabilized container to ensure accurate measurements. The radiometers were calibrated before each scan using a combination of the cold/hot and Dicke switching techniques. An additional internal calibration was performed before each scan [16]. A mechanical positioner was used to vary the measurement incidence and azimuth angles. Two different snow measurement techniques were used: 1) azimuth scans of undisturbed total snow cover with varying azimuth (140°–210°) with a fixed incidence angle of 55°; and 2) angular scans with varying incidence angles (30°–70°) with fixed azimuth angle of 180° [16]. In this paper, we use the azimuth because the location of the footprint was closer to the IOP3 snowpits (in situ observation used to validate the RA) for a majority of the azimuth scans (see [8], Fig. 3). These observations were also the closest in time to the snowpit observations performed on the same day. Variations of several kelvins were observed within each azimuth scan [8]. Details of the viewing geometry of the instrument including the incidence angle and the azimuth can be found in [16] and in [8].

B. Models and the EnKF

1) Snow Physical Model: CROCUS is a 1-D multilayer SM designed to simulate the evolution of the vertical profile of the physical properties of the snowpack under given meteorological conditions [12], [13]. In contrast with simple SMs used in previous studies, CROCUS simulates up to 50 layers for snowpacks. CROCUS has a variable internal temporal resolution for evaluating mass and energy exchanges between the snowpack and the low-level atmosphere as functions of meteorological conditions [27]. The optimum time step is 15 min [13]. A smaller internal time step (for example, 5 min) yields more accurate results but requires more computation. Furthermore, a smaller internal time step leads to the formation of thin snow layers since the total precipitation for the time step decreases for the smaller time step. The meteorological forcing parameters include air temperature, wind speed, humidity, the amount and type of precipitation (rain or snow), direct downwelling shortwave radiation, downwelling long-wave radiation, diffuse solar radiation, and cloudiness.

CROCUS output parameters include the type and size of grains for each snowpack layer along with layer thickness, temperature, density, and liquid water content. Additionally, the model tracks a variable indicating whether liquid water or faceted crystals have been predicted [13]. In short, CROCUS has significantly greater physical fidelity compared to the SAST three-layer model used in the previous snow RA study. Snow grain metamorphism is described in CROCUS by the shape parameters, namely, dendricity and sphericity. Dendricity varies from one to zero and describes how much of the original precipitated crystal form is still present in the snow layer. Sphericity ranges from zero for completely faceted grain to one for rounded particles [13].

MEMLS and CROCUS do not have the same way of representing the grain size. MEMLS uses the correlation length [20], and CROCUS uses the dendricity and sphericity. Details of the relationship between the dendricity and sphericity with the snow $D_0$ can be seen in [13]. The $D_0$ is defined as the diameter of a sphere with the same total surface area and the same volume as the real distribution of snow grains in a given layer [19]. The SSA of a granular medium is the ratio of the surface area of the grains divided by their total volume [20]. According to [20] and [28], the relation between the $P_{\text{ex}}$, the SSA, and the $D_0$ (calculated by CROCUS) is as follows:

$$P_{\text{ex}} = \frac{4 (1 - f_\text{ice})}{\text{SSA}} = \frac{2}{3} (1 - f_\text{ice}) D_0$$

where $f_\text{ice} = \rho / \rho_\text{ice}$ is the volume fraction of the ice, $\rho$ is the density of the snow, and $\rho_\text{ice} = 917 \text{ kg} \cdot \text{m}^{-3}$ is the density of pure ice.

2) RTM: The MEMLS [9], [29] was developed for the frequency range from 5 to 100 GHz. It is based on an RTM which
takes multiple volume scattering and absorption into account. In this paper, the scattering coefficient is derived from snowslab experiments with dry winter snow [9] and using the improved Born approximation theory, [30] and the absorption coefficient, refraction, reflection at layer interfaces, and the effective permittivity are based on physical models and on measured ice and snow dielectric properties. MEMLS has been validated for both fine-grained snow [9] and for melt-refreeze crusts [30]. Because MEMLS has the ability to handle snow as a multilayered medium as well as calculate extinction coefficients for melt-refreeze crusts, it is ideal for this study. MEMLS requires the following inputs: thickness, density, temperature, liquid water content, and correlation length for each snow layer. MEMLS uses the correlation length $P_{\text{cor}}$ to compute the scattering coefficient.

3) EnKF: The SM is used to develop a priori estimates of the snowpack states or the state forecast vector $y_i^f$ for replicate (an individual model realization using one unique set of perturbations) $i$ at time $t$. This is expressed mathematically by

$$y_{i,t}^f = F(y_{i,0}, u_{i,t}, \beta_i)$$

where $F()$ is the SM operator (CROCUS in our case; the forecasting model), $y_{i,0}$ is the state initial condition, $u_{i,t}$ is the meteorological forcing data for replicate $i$, and $\beta_i$ represents the unknown parameters controlling grain size and melt-refreeze crust evolution (described in the following section). Note that vectors and matrices are marked by boldface characters and the scalars by ordinary italics. The a posteriori state estimate or analysis vector $y_i^a$ is computed as a linear combination of the a priori estimate $y_i^f$ and a weighted difference between the actual measurement $z_{\text{obs}}$ and the measurement prediction $M(y_i^f)$ as (time subscripts are omitted)

$$y_i^a = y_i^f + K \left( [z_{\text{obs}} - \mu_i] - M(y_i^f) \right)$$

where $\mu_i$ is the random measurement error that prevents the introduction of correlations among the replicates [31] and $K$ is the Kalman gain calculated from the error covariances provided by the ensemble (see [7]).

C. Experimental Setup

Our RA scheme consists of three components: 1) A snow physical model (CROCUS) prognoses snowpack structure and is driven by meteorological data; 2) An RTM (MEMLS) simulates Tb using the predicted snowpack state variables predicted by CROCUS; and 3) The Ensemble Kalman Filter (EnKF) updates the predicted snowpack state variables. While the data and EnKF framework are consistent with previous work [10], the CROCUS SM used in this paper resolves the snowpack in far greater detail. The more sophisticated SM used herein fundamentally changes the estimation problem because of the following: 1) The horizontal Tb was not assimilated in [10], since the SM used in that study was not capable of resolving melt-refreeze crusts and therefore not capable of simulating horizontal Tb; and (2) the number of snowpack state variables for the three-layered SM used in previous work is far less than the number of state variables simulated by CROCUS, which increases the complexity of the estimation problem.

Using the models described earlier, we performed an RA experiment. In order to have a benchmark by which the performance of the RA can be evaluated, CROCUS was run using the measured precipitation data and without assimilating GBMR-7 measurements. These results are referred to as the “open-loop” run hereafter. An “open-loop” simulation is defined as a forward model run without implementing/enacting the RA procedure [7]. In this paper, the “open-loop” run was a single model run performed using the nominal model inputs.

The ensemble was constructed by perturbing the CROCUS inputs as follows: We assumed that, for modeling snow physics during the accumulation season, the three dominant sources of uncertainty in the SM run are: 1) the precipitation measurements; 2) the grain-size parameterization (grain-size physics models are still under development [7]); and 3) the modeling of the melt-refreeze crusts. These three sources of uncertainty are taken into account in the RA by treating key variables in the model inputs as random variables. The measured precipitation forcing data were perturbed with a multiplicative time-correlated lognormal forcing error with an assumed coefficient of variation of 0.25, based on the value used in previous work [10]. The coefficients of growth of the grain-size parameters (see [13]) were randomly perturbed. The coefficient of variation is assumed to be 0.5 for the grain-size growth parameter. We also treated the parameter controlling density evolution for melt-refreeze crusts as an uncertain random variable and applied a multiplicative lognormal random perturbation.

Fifty combinations of perturbed random input variables were used in the RA. For each ensemble member realization of meteorological data and model parameters, CROCUS was run to obtain an a priori estimate. The a posteriori estimate was obtained by assimilating GBMR-7 Tb using the EnKF technique. In this paper, we performed two assimilation experiments. First, we followed previous studies and assimilated only Tb at v-pol (TbV). Second, we experimented with assimilating both TbV and Tb at h-pol (TbH). Based on [8], we know that TbH is very sensitive to melt-refreeze crusts. By modeling melt-refreeze crusts and treating them as random variables, we allow for the possibility of using the TbH channels, effectively doubling the number of measurements that can be assimilated. Doing this is only possible with a physical SM such as CROCUS that has enough vertical resolution (up to 50 layers) and snow physics to model melt-refreeze crusts, particularly the melt-refreeze crusts noted at LSOS snowpits [15].

III. RESULTS AND DISCUSSION

In this section, we present the results of the two RA experiments described earlier. In the first experiment, only TbV is assimilated; in the second experiment, both TbV and TbH are assimilated. RA estimates of snow depth, SWE, snow grain size, and snow density are compared with in situ measurements and with the open-loop model run. Additionally, the RA snow depth estimates are compared with the results obtained in [10] in previous work. Finally, the RA SWE estimates are compared
with empirical algorithm SWE estimates derived directly from
the observations. In all of the comparisons hereinafter, the
mean across the a posteriori ensemble is used to represent the
RA-derived estimate of the snow state variables.

A. Snow Depth Comparisons

As expected, the open-loop model run underestimates the
measured snow depth significantly [7], [10] (Fig. 1). The open-
loop bias is 28.2 cm, and the root mean square error (RMSE) is
28.5 cm. This large bias of the open-loop case was also noticed
in [10], using the SAST land surface model and is attributed
primarily to the precipitation undercatch at the meteorological
station. The open-loop model runs form one baseline against
which to evaluate the EnKF. While a calibrated model might
perform better, we would argue that, in general, snow precipi-
tation undercatch remains a significant problem; our goal is to
determine whether the RA scheme can correct both for these
precipitation errors and for the grain size and melt-refreeze
crust prediction errors.

In the first RA experiment, only the TbV measurements were
assimilated using the EnKF. The results of this experiment are
shown in Table I. The estimate of snow depth is improved as
compared with the open loop, with a bias of −3.10 cm and an
RMSE of 5.10 cm. The RMSE is thus reduced by 82.1%, and the
absolute value of the bias is reduced by 89% as compared
to the open loop. In the second experiment, both TbV and TbH
were assimilated. The results of this experiment are shown in
Fig. 1(a). The snow depth estimates in this case show additional
improvement (see Table I). The bias is reduced to 1.4 cm
and the RMSE to 4.5 cm, demonstrating an improvement of
54.8% and 11.8%, respectively, compared with assimilation of
only TbV. These results indicate that significant improvement
in snowpack estimates can be obtained by utilizing both the
h- and v-pol channels. In order to utilize the TbH channels,
however, the SM must have the capability to resolve melt-
refreeze crusts. For both experiments, these results show sig-
nificant improvement compared to the 7.3-cm bias found in
[10] obtained by assimilating the GBMR-7 TbV into SAST.
Since, here, we used the exact same forcing and the same
RTM with the same EnKF assimilation technique, only the
SM was different. Fig. 1(a) shows the posterior and open-loop
snow depth calculated during IOP3. These results suggest that
the use of the more sophisticated CROCUS model permits
higher fidelity snowpack modeling leading to smaller bias in
the characterization of snow depth.
TABLE II
Daily Error and RMSE of the SWE Estimate (in Centimeter) Based on Assimilation of TbV and TbH (SWE Retrieved) Compared to Errors of the SWE Open Loop and SWE Retrieval Using the CHANG et al. [32] Retrieval Formula. Values in Parenthesis Represent the Ratio (in Percent) of the RMSE Divided by the Average IOP3 SWE

<table>
<thead>
<tr>
<th>Date</th>
<th>SWE Retrieved</th>
<th>Open-loop error</th>
<th>SWE[Chang et al., 1987]</th>
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</thead>
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<tr>
<td>19 Feb</td>
<td>1.04</td>
<td>8.97</td>
<td>-5.7</td>
</tr>
<tr>
<td>20 Feb</td>
<td>1.5</td>
<td>9.68</td>
<td>-6.85</td>
</tr>
<tr>
<td>21 Feb</td>
<td>-2.1</td>
<td>6.41</td>
<td>-7.21</td>
</tr>
<tr>
<td>22 Feb</td>
<td>0.8</td>
<td>9.92</td>
<td>-1.1</td>
</tr>
<tr>
<td>23 Feb</td>
<td>-0.16</td>
<td>9.5</td>
<td>-0.08</td>
</tr>
<tr>
<td>24 Feb</td>
<td>0.22</td>
<td>11.64</td>
<td>0.10</td>
</tr>
<tr>
<td>25 Feb</td>
<td>-0.16</td>
<td>9.42</td>
<td>0.52</td>
</tr>
<tr>
<td>Mean</td>
<td>0.44</td>
<td>9.47</td>
<td>-2.87</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.4</td>
<td>(7.10%)</td>
<td>(48.1%)</td>
</tr>
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<td></td>
<td></td>
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<td>(21.8%)</td>
</tr>
</tbody>
</table>

Fig. 2. IOP3 in situ snow (a), (c), (e) optical grain size and (b), (c), (f) density vertical profiles compared to the open-loop simulation and RA from February 19, 2003 to February 21, 2003. The snow depth is normalized to one.

B. SWE Comparison

Fig. 1(b) shows the estimated SWE compared to the open-loop case and the in situ data. The open-loop underestimates the in situ SWE. The bias is 9.4 cm, and the RMSE is 9.5 cm. When the TbV and TbH were assimilated in CROCUS, the SWE estimate is improved, the bias is 0.44 cm, and the RMSE is 1.4 cm (see Table II). We compared the results of RA to that of the snapshot retrieval formula used in [32], referred to as the “Chang” retrieval hereafter. The bias of Chang SWE is −2.87 cm. The formula was originally derived to estimate snow depth using the difference of the TbH at 18 and 36 GHz scaled by a time static coefficient (based on homogeneous grain-size radius of 0.3 mm and a constant density of 300 kg · m$^{-3}$). The comparison shows that RA using CROCUS performs better than the empirical model because it is able to provide detailed and time-varying snow a priori information.

C. Grain-Size Comparison

Snow optical grain size was calculated using the equations established by Brun et al. [13]. These equations relate the optical grain size to the dendricity and the sphericity simulated by CROCUS. We plotted the optical grain-size profiles for the seven days of the IOP3. Figs. 2(a), (c), (e), 3(a), (c), (e), and 4(a) are the representations of the optical grain-size vertical profiles...
Fig. 3. IOP3 in situ snow (a), (c), (e) optical grain size and (b), (c), (f) density vertical profiles compared to the open-loop simulation and RA from February 22, 2003 to February 24, 2003. The snow depth is normalized to one.

Fig. 4. IOP3 in situ snow (a) optical grain size and (b) density vertical profiles compared to the open-loop simulation and RA on February 25, 2003. The snow depth is normalized to one.

for the seven days of the IOP3. The figures showed that there are systematic underestimates of grain size in the open loop when compared with the in situ, and that, those underestimates are corrected by the posterior. The grain size of the bottom layer (i.e., the snow layer that is in contact with the ground) was low for the first three days of the RA. For the last three days, the grain size increased dramatically to values ranging between 2 and 3.7 mm. Predicting grain growth during melt/refreeze metamorphism responsible for the formation of coarse snow grain size is a complex task, and the theories used by CROCUS are yet to be extensively validated. However, it is very significant that the assimilation scheme predicts large grain-size values in the bottom of the snowpack. For most of the snowpits, melt-refreeze crusts were observed near the bottom of the snowpack (see [8], Fig. 4). The values of the grain size predicted by the RA scheme in Figs. 2–4 are in the range measured in [33] for
melt-refreeze crusts. The open-loop grain size lower in the pack is qualitatively too low to belong to melt-refreeze crusts. While the melt-refreeze crust grain size was not measured during IOP3, the aforementioned analysis gives qualitative support for the hypothesis that the RA scheme is adjusting grain size in a way that is consistent with what is known about snow during IOP3 and the grain size of melt-refreeze crusts.

D. Density Comparison

Figs. 2(b), (d), (f), 3(b), (d), (f), and 4(b) show the density vertical profiles for all the IOP3. The figures show that the open-loop snow density profiles underestimate the snow density. The EnKF estimate is much closer to the in situ average density expected at the bottom of the profile and for normalized snow depths at around 0.4 and 0.6 for the first three days and for depth around 0.4 for the last four days.

The CROCUS historical index of the bottom layer for the entire IOP3 is five which indicates that the layers underwent multiple wet metamorphisms (see earlier discussion for model details). Despite this, the open-loop density value is rather low, approximately 200 kg m\(^{-3}\). The reason for this may point to an issue with the melt-refreeze crust evolution in the CROCUS model. Within the RA scheme, however, the melt-refreeze crust prognostic scheme is treated as uncertain, which allows the EnKF to prescribe a large update to the melt-refreeze crust density. On the 19th and the 20th, the a posteriori density of the melt-refreeze crusts at the bottom of the pack is around 650 kg m\(^{-3}\). From the 21st to the 25th, the density increased to reach values between 850 kg m\(^{-3}\) and 900 kg m\(^{-3}\). Because the density of the melt-refreeze crusts was not measured in situ, it is impossible to validate these estimates. However, there is no doubt from the in situ snowpit observations that melt-refreeze crusts were observed in the bottom of the snowpack. Moreover, literature values for the density of melt-refreeze crusts [33], [34] range from 440 to 950 kg m\(^{-3}\). Clearly, the melt-refreeze crust densities estimated by the RA scheme are in the range of those reported in the literature, while the open-loop densities are less than the literature values.

To study the impact of the correction of melt-refreeze crust density by the RA on the simulated Tb, we used the posterior estimates of snow characteristic as input to MEMLS to simulate the Tb. Table III shows bias and RMSE between the modeled and the measured GBMR-7 Tb for each of the seven days and for each of the four measurement channels. The update of the melt-refreeze crust density leads to an accurate simulation of the TbH. This is not surprising, of course, because the EnKF scheme is designed to minimize the differences between the observed and predicted Tb. Nonetheless, this comparison is valuable because it provides an additional check that the CROCUS+MEMLS simulations have been made consistent with the GBMR-7 observations.

In Durand et al. [10], only the TbV was used in the RA, and only the snow depth and grain size were retrieved. Here, we have used RA to adjust the melt-refreeze crust density for a better prediction of TbH. In doing so, we anticipate that assimilating the TbH in addition to the TbV can help retrieve the snow depth with at least the same accuracy as in [10] and also the SWE. Although we do not have ground truth data for the melt-refreeze crust density, we note that the depth and SWE estimates are improved when TbH is assimilated, and that, the melt-refreeze crust density and grain-size values from the RA scheme are consistent with the values reported in the literature, while the open-loop values of grain size and density of the melt-refreeze crusts are less than the literature values. Moreover, the RA scheme effectively increased melt-refreeze crust densities in a way that is completely consistent with the known location of melt-refreeze crusts from the snowpits. This is the first time that RA has been used to adjust the density of melt-refreeze crusts for a better retrieval of snow depth and SWE.

The fact that RA using a more sophisticated SM is able to retrieve snow density and optical grain-size profiles illustrates a crucial point: There is adequate information in the microwave signal, if applied within the RA framework, to extract the vertical structure of the grain size and density profiles with greater fidelity than when using a three-layered SM, at least at the point scale. The many-to-one problem of the SWE–Tb relationship can be overcome by assimilation, even when the density and grain-size profiles vary significantly with depth.

The ability of CROCUS to model melt-refreeze crusts is clearly imperfect. Indeed, when run outside the assimilation framework, CROCUS does not adequately model melt-refreeze crusts: The modeled densities are far less than those typical for melt-refreeze crusts. It is only when the densification is treated as a random process and the radiance measurements are utilized within the assimilation scheme that the melt-refreeze crust densities are identified. Thus, radiance assimilation schemes must incorporate uncertainty in the densification processes that lead to melt-refreeze crusts. If they are neglected, then only v-polarization channels should be utilized. If h-polarization channels are utilized and uncertainty in the melt-refreeze crusts is neglected, then errors in SWE or depth can be quite significant.
IV. CONCLUSION

Experiments have been performed to evaluate the accuracy of RA to estimate the snow physical parameters using a more realistic SM (CROCUS) versus earlier snow RA studies. Precipitation and CROCUS model parameters controlling grain-size growth and melt-refreeze crust density evolution were treated as uncertain. The RA scheme treated the snow depth, density, and grain size as the state variables and assimilated ground-based Tb at 18.7 and 36.5 GHz. We have compared results from assimilating only TbV and from assimilating both TbH and TbV. We have found that the RA scheme accurately characterized the snow depth and SWE, and that assimilation of both TbH and TbV improved the retrieval of the snow depth and SWE compared with assimilating only one polarization. The a posteriori bias from the RA scheme was reduced to 1.4 cm and the RMSE to 4.5 cm compared with an open-loop bias and RMSE of 28.2 and 28.5 cm, respectively. The snow depth bias obtained here is significantly less than that reported in a previous RA study [10], suggesting that the use of the more sophisticated CROCUS model permits higher fidelity snowpack modeling leading to smaller bias in the characterization of snow depth.

We have hypothesized that the improvement in snow depth and SWE over previous studies is due in part to the use of the TbH channels, which is made possible by the CROCUS and RA characterization of melt-refreeze crust densities. The RA scheme correctly identified the location of melt-refreeze crusts observed in situ. Moreover, the melt-refreeze crust densities estimated by the RA scheme are in the range of those reported in the literature, while the open-loop densities are less than the literature values. These improvements suggest that using a more sophisticated model such as CROCUS, RA is also able to update melt-refreeze crust density, which may lead to an improvement of the estimation of snow depth and SWE under more complex snow conditions than previously considered.

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