Abstract—A multilayer formulation of snow hydrological processes implemented in an existing snow hydrology-emission model (MLSHM-ML) was applied in observing system simulation mode (OSS) to two very different climatic and physiographic regions (Valdai, Russia and Colorado, USA) for both wet and dry snow regimes, and over multiple years. The results were evaluated against ground-based observations of snowpack physical properties and microwave radiometric observations from scanning multichannel microwave radiometer (SMMR), special sensor microwave/imager (SSM/I), and advanced microwave scanning radiometer-EOS (AMSR-E) observations at 18–19-, 22–23-, and 36–37-GHz vertical and horizontal polarizations (V-pol and H-pol, respectively). Whereas snow water equivalent (SWE) results are similar to the results obtained with single-layer physics when the snow is dry, the multilayer physics have a better skill at capturing the overall temporal evolution of bulk density, snow temperature, and snow depth during the accumulation season, and at the onset and throughout the melting season. However, snow density profiles overestimate density at the bottom of the snowpack, consistent with the lack of an explicit representation of depth hoar in the rearrangement of mass and grain size distribution in the snowpack. Regarding the radiometric behavior, the multilayer SMMR OSS for Valdai shows improved results for nighttime simulations (descending SMMR paths, 11 P.M. LST) and H-pol (≈3–5 K decrease in error statistics), particularly at 37 GHz. For daytime simulations (ascending SMMR paths, 11 A.M. LST), there are modest improvements at 18 (≈1 K) and 37 GHz (≈2–3 K) for H-pol, and generally loss of skill for V-pol at all frequencies. Systematic improvements at nighttime but not during daytime suggest that surface heterogeneities, including subgrid scale variability of transient melting, play an important role on surface emissivity. This is the case for cold land process experiment in Colorado, where spatial variability in fractional forest cover, geology, and complex topography explains the modest differences between the single and multilayer SSM/I OSS for H-pol, whereas significant gains (≈4–8 K decrease in error statistics) were attained for V-pol at 37 GHz only. For AMSR-E, the multilayer OSS looses skill for H-pol, and only bias and mean absolute error improve for V-pol at all frequencies. These somewhat mixed results suggest that representation of snow stratigraphy alone is not sufficient to improve the OSS ability to describe the nonlinear interactions among hydrologic and electromagnetic processes. Chief among these are the temporal evolution of snow correlation length with depth and the representation of subgrid scale variability constrained by the spatial resolution and inherent uncertainty of the meteorological forcing. Nevertheless, the multilayer OSS improved performance at 37 GHz is an important finding toward reducing ambiguity in the sensitivity of 37-GHz H-pol brightness temperature to SWE in retrieval models.

Index Terms—Electromagnetic propagation in absorbing media, multi-layer, nonhomogeneous media, snow hydrology.

I. INTRODUCTION

KANG and Barros [1] presented a framework for monitoring snow water equivalent (SWE) and snowpack radiometric properties including microwave emissions that was developed by combining a snow hydrology model [24] with a microwave emission model [2], [3]. The idea is to rely on the radiometry of snow surfaces interpreted in the light of the snow physics to track the temporal evolution of snowpack microphysical and hydrologic properties, and consequently eliminate ambiguity in the interpretation of satellite observations. Generally, the ultimate goal is to map ice sheets, glaciers, and snowpack properties including snow-covered area, snow depth, snow wetness, and SWE particularly in regions of remote access, or inhospitable climate and terrain where ground-based measurements are not feasible and aircraft-based measurements are impractical. In addition to the role of snow cover extent and composition on albedo, and thus in the surface energy budget of the planet [5], snowpacks store precipitation temporarily during the cold season for release during the warm season, and therefore snow accumulation plays also a critical role in the water budgets and freshwater resources of vast regions of the world, such as the western U.S. [6].

Satellite-based remote sensing of snow originally relied on physically based empirical relationships between the difference in emission behavior at 37 GHz (V or H polarizations, the most sensitive frequency to changes in snow microstructure), and the emission behavior at a lower frequency (18 or 19 GHz), and snowpack properties namely snow depth and SWE on the other [7], [8]. Relevant sensors in this context include passive microwave radiometers such as scanning multichannel microwave radiometer (SMMR) [9], special sensor microwave/imager (SSM/I) [10], and advanced microwave scanning radiometer-EOS (AMSR-E) [11], respectively, on board of Nimbus-7 [12], defense meteorological satellite program [13], and AQUA [14] satellites. Prompted by the necessity to estimate snowpack properties at locations around the world with different terrain, soils, vegetation cover, air pollution, and

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overall climate, it became clear early that empirical models requiring place-based calibration based on local observations could not be used for reliable operational retrievals. Instead, dynamical calibration approaches relying on a mix of satellite and ground-based ancillary data were developed to produce global estimates of snow cover and snow depth [36]. To address this challenge, alternative approaches were developed based on physically based models that simulate the microwave emission of the snowpack as a function of its physical and electromagnetic properties. Specifically, multilayer snow hydrology models such as SNThERM [20], CROCUS [21], and SNOWPACK [22] have been coupled successfully to microwave emission model for multilayered Snowpacks (MEMLS) [2]–[4], [23].

Part 1 [1] describes the MLSHM, a hydrology-emission model that resulted from coupling an existing hydrology model, the LSHM [24], to MEMLS both using single and multilayer physics. The single-layer adaptation of MLSHM yielded consistently good performance statistics for observing system simulation (OSS) simulations of SMMR (six years simulation), SSM/I (1 year simulation), and AMSR-E (1 year simulation) with absolute bias during dry snow periods that does not exceed 4.5 K. Overall, error statistics presented by [1] throughout the snow season from accumulation through melt yield better or similar skill to previous emission modeling studies (e.g., [16]). Yet, the forward simulations of snowpack emissivity were significantly better for the vertical polarization than for horizontal polarization at all frequencies and for all sensors with differences in error statistics greater than 10 K. For instance, the bias at 37 GHz decreases from 19.25 K for H-pol to 4.53 K for V-pol in the Valdai case. Furthermore, an evaluation of the snowpack physical properties indicated that melting was taking place faster than observed, and density and snow depth tended to be, respectively, lower and higher during the late accumulation and ripening phases than those from snowpit observations during the cold land process field experiment (CLPX, [31]). Although some of these disparities may be the result of spatial scale discrepancies between model resolution and nominal sensor footprints, as well as subgrid scale variability associated with land use and land cover (e.g., fractional vegetation cover, [38]) and terrain complexity, it is hypothesized that a multilayer formulation of snow hydrology that can capture snowpack stratigraphy should have a positive impact on the representation of vertical gradients of temperature, compaction rates, and thus density. Better representation of snow density profiles should lead to more accurate estimates of snowpack radiometric properties (permittivity, absorption, and scattering coefficients) taking full advantage of the multilayer formulation of MEMLS.

In this paper, the multilayer implementation of the snow hydrology model [1], [2] coupled to MEMLS (MLSHM-ML) is applied in fully prognostic OSS mode to the two case studies described by [1]: first, a multiyear simulation in Valdai, Russia to be compared against SMMR observations; and second, an extended cold season simulation (October–May) in 2002–2003 encompassing accumulation, ripening, and melting phases during CLPX to be compared against SSM/I and AMSR-E brightness temperatures. In both cases, a suite of ground-based observations including SWE, snow density, and snow depth are available, which permit evaluation of the evolution of the snowpack physics concurrently.

Section II provides a short overview of key elements of the multilayer implementation of the coupled hydrology-emission model (MLSHM-ML). A more detailed model description can be found in [1]. Data used to force the coupled MLSHM-ML and to evaluate the model simulations are described in Section III. Section IV presents analysis of the results and discussion for Valdai, whereas the CLPX case study is presented in Section V. Synthesis and conclusion are presented in Section VI.

### II. Model Description

The basic structure of the coupled snow hydrology-emission model is the same as described in [1], except that the focus here is on the implementation of the multilayer coupled hydrology-emission model (MLSHM-ML). The snow layering algorithm treats the mass and energy balance and snow compaction equations on a layer-by-layer basis using first-order finite-difference approximations to describe vertical gradients. The number of layers is adaptive during the simulation depending on layer depth and volumetric liquid water content (LWC). The same atmospheric correction scheme described by [1] is applied here to the brightness temperatures as needed.

#### A. Multilayer Snowpack Hydrology

The multilayer snow hydrology model is already described in the companion paper (Part 1, [1]). In the snow layering algorithm, the layers are divided and compacted as the snow depth increases with precipitation, or decreases due to snowmelt. In addition, liquid water percolation between the snow layers and between the bottom snow layer and the upper soil layer is explicitly resolved. A schematic view of the stacked snowpack is shown in Fig. 1. Each snow layer is characterized by state variables such as layer thickness $h_i$, snow temperature $T_s$, SWE $s_w$, and volumetric LWC $l_w$ both expressed as a water depth [volume per unit area], and bulk density $\rho_s$. Snow layers begin to accumulate from the bottom (layer 1, Fig. 1) up to the top of the snowpack (layer n, Fig. 1). The mass flow exchange between layers below the top layer is governed by liquid water flow when melting occurs and during rain-on-snow events.

| $T_s^1$ | $h_s^1$ | $s_w^1$ | $l_w^1$ |
| $T_s^{n-1}$ | $h_s^{n-1}$ | $s_w^{n-1}$ | $l_w^{n-1}$ |
| $T_s^n$ | $h_s^n$ | $s_w^n$ | $l_w^n$ |

![Fig. 1. Schematic view of the multilayer snowpack containing snow temperature $T_s$, snow water equivalent ($SWE$) $s_w$, snow depth $h_s$, snow density $\rho_s$, and volumetric liquid water content ($LWC$) $l_w$ for each snow layer.](image-url)
Upon reaching the ground, snowflake morphology and snow grain size evolve fast initially, and then slower in time due to thermodynamic processes associated with vapor transport (diffusion and deposition) in the snowpack. This leads to rounding and coarsening of snow grain size distributions over time. In the MLSHM, the evolution of the size distribution is parameterized as a function of snow density following [32] and [34]. Depth hoar formation processes which become increasingly important with time and manifest themselves by a decrease of snow density in the lower (that is, deeper) layers of aged snowpacks and increase (by deposition) at mid-depths are not accounted for explicitly [45]. The mass balance equation of each layer is expressed by

\[ \frac{dh_j^{\text{wuc}}}{dt} = \frac{1}{\rho_w} \left( P_{sw}^j + xP_{r}^j \right) - \Phi_{sn}^j, \quad j = 1 \text{ to } n. \]  

Where \( \rho_w \) [kg/m\(^3\)] is the density of water, \( P_{sw} \) [kg/(sec m\(^2\))] is precipitation in the form of snow, and \( xP_{r} \) [kg/(sec m\(^2\))] is the accumulated precipitation from rain-on-snow events. \( P_{sw}^j \) and \( xP_{r}^j \) are zero when \( j \) is not equal to \( n \), and \( \Phi_{sn}^j \) [m/s] is the snowmelt flux toward the lower layer

\[ \Phi_{sn}^j = \rho_w \frac{dh_j^{\text{wuc}}}{dt}, \quad j = 1 \text{ to } n \]  

where \( h_j^{\text{wuc}} \) is the depth of liquid water from snowmelt or rainfall in layer \( j \). This is obtained from the energy balance equation. The maximum retention capacity of liquid water in each layer is 5%. Above this value, the liquid water is released to the lower layer below. Also, it is noted that intermittent melting is only triggered in the top layer due to diurnal solar forcing. Integrating from the bottom to the top of the \( n \) layers of thickness \( h_1^{\text{wuc}}(h_n^{\text{wuc}} = (\rho_w/\rho_{sn})h_1^{\text{wuc}}) \), volumetric LWC \( lw^j \), ice water content \( iw^j \), and snow density \( \rho_{sn}^j \) [kg/m\(^3\)], snowpack integral properties such as total snow depth \( h_{sd} \) [m], SWE [m], and snowpack volumetric LWC \( LWC \) [m] can be calculated.

When the snow depth at layer \( j \), \( h_j \), is less than a specified minimum criterion, \( h_0 \) (0.14 m in CLPX and 0.12 m in Valdai based on the local climatology of annual snowfall), all related mass terms such as \( h_1^{\text{wuc}} \) and \( h_2^{\text{wuc}} \) are combined, whereas \( T_j \) and the layer density \( \rho_{sn}^j \) are depth averaged using as weights the snow layer thickness at the previous and current time steps similar to [20]

\[ T_{s \text{comb}} = \frac{h_{sn}^{m} \cdot T_{s}^{m} + h_{sn}^{m-1} \cdot T_{s}^{m-1}}{h_{sn}^{m} + h_{sn}^{m-1}}, \]
\[ h_{s \text{comb}}^{m} = \frac{h_{sn}^{m} + h_{sn}^{m-1}}{h_{sn}^{m} + h_{sn}^{m-1}}, \]
\[ \rho_{s \text{comb}}^{m} = \frac{h_{sn}^{m} \cdot \rho_{sn}^{m} + h_{sn}^{m-1} \cdot \rho_{sn}^{m-1}}{h_{sn}^{m} + h_{sn}^{m-1}}. \]

\section*{B. Microwave Emission Model of Layered Snowpacks (MEMLS)}

While the bulk layer approach only considers simulation of single-layer emissions, the multilayer model has \( n \) horizontal layers, which therefore enables taking advantage of the detailed volume scattering calculations in MEMLS (see [1]–[3]).

Considering layer \( j \) (\( j = 1, n \)) in the multilayered snowpack, the outgoing radiation from the snowpack to the layer above and the layer beneath can be expressed as follows (Fig. 2):

\[ A_j = r_j B_j + t_j C_j + e_j T_j, \]
\[ D_j = t_j B_j + r_j C_j + e_j T_j. \]

In the MEMLS multilayer formulation, the brightness temperature, \( T_b \) of each layer is \( B_{j+1} + s_{j+1} A_{j+1} + (1 - s_{j+1}) D_{j+1} \), \( A_j \) is the downwelling brightness temperature and \( s_j \) is the reflectivity at the interface of adjacent layers, and between the snow surface and the atmosphere at the top of the snowpack.

Equations (8) and (9) form a system of coupled linear equations for the brightness temperatures \( A_j \) and \( D_j \)

\[ A_j = r_j \left[ s_{j-1} A_j + (1 - s_{j-1}) D_{j-1} \right] + t_j \left[ (1 - s_j) A_{j+1} + s_j D_{j+1} \right] + e_j T_j \]
\[ D_j = t_j \left[ s_{j-1} A_j + (1 - s_{j-1}) D_{j-1} \right] + r_j \left[ (1 - s_j) A_{j+1} + s_j D_{j+1} \right] + e_j T_j. \]

In matrix formation, the equations above can be rewritten

\[ A = M_1 \cdot A + M_2 \cdot D + E \]
\[ D = M_3 \cdot A + M_4 \cdot D + E. \]

Where \( A \) and \( D \) account for the brightness temperatures of \( n \) layers, \( M_j \) to \( M_4 \) are \( n \) by \( n \) matrices containing \( r, t, e \), and \( E \) and \( F \) are the \( n \) vectors with brightness temperatures at the boundaries including \( T_{sky} \) and \( T_{soil} \). Using linear algebra, the final solution is

\[ D = (I - M_3)^{-1} \cdot [M_3 \cdot (I - M_1)^{-1} \cdot E + F] \]

where

\[ M_5 = M_3 \cdot [I - M_1]^{-1} \cdot M_2 + M_4. \]

After determining \( D_n \), the outgoing brightness temperature from the snow surface is given by \( B_2 \) which is \( T_b \)

\[ T_b = B_2 = s_n T_{sky} + (1 - s_n) D_n. \]
scattering coefficients are estimated for each frequency based on snow density \( \rho \) and snow correlation length \( \rho_c \) (m), a measure of surface-to-volume ratio of an electromagnetically equivalent distribution of spherical particles equivalent to the heterogeneous snow grain size distribution of the real snowpack [32], [34]. Specifically, the classification presented in Table I of [34] was used to estimate the snow correlation length for each layer based on the temporal evolution of layer snow density.

### III. Data Description

As detailed in Part I [1], PILPS standard forcing and RUC40 MM5 meteorological data \((40 \times 40 \text{ km}^2)\) are used to force the coupled modeling system at regional scale, respectively for Valdai and CLPX 2002–2003 studies. For the evaluation of simulated emissions, microwave brightness temperatures from SMMR, SSM/I, and AMSR-E are used in the same way as in Part I. Note that, despite common SMMR heritage, the frequencies are slightly different (2–3% difference) for SSM/I and AMSR-E. Accordingly, the exact sensor-specific frequencies are used in the MEMLS OSS. Even though brightness temperature products are resampled and projected on equal Area Scalable Earth (EASE)-grid at \(25 \times 25 \text{ km}^2\), the nominal footprint spatial resolutions of each sensor at different frequencies are very different (e.g., coarser for SMMR and SSM/I and finer for AMSR-E roughly on a 1 : 3 ratio). In addition to the spatial scale gaps between atmospheric forcing, and consequently MLSHM resolution, satellite observations, and ground-based observations, it is important to acknowledge that even at their nominal scale, there is uncertainty in the RUC40 and the ERA40 data sets, which can vary from day to day depending on weather conditions and availability of observations for data assimilation (e.g., [27]). The atmospheric corrections follow [1] closely.

A detailed description of CLPX is provided by the National Snow and Ice Data Center (NSIDC) CLPX website (http://nsidc.org/data/clpx/) and [31]. Within the Fraser mesoscale study area (MSA), snowpit measurements at various times were conducted at the location of the ground-based passive microwave radiometer No. 7 (GBMR-7), and within the three intense study areas (Alpine, St. Louis Creek, and Fool Creek). CLPX snowpit observation profiles are used to evaluate the multilayer formulation of the snow physics in the MLSHM-ML. Snowpits are trenches that allow one-time mapping of the vertical profiles of density and temperature in the snowpack, as well as stratigraphic analysis. Note that snowpit measurements are destructive, and once excavated, it is not possible to sample the same location again. This contrasts with nondestructive monitoring such as proposed by [44] for example. Again, there is a large gap in spatial scales between the snowpit data (point scale, near instantaneous) and the scale of the RUC40 grid cell (40 km, hourly) that is used to force the MLSHM-ML. Thus, the simulated emissions represent the average electromagnetic behavior at the RUC40 scale, which can be interpreted as a regional mean. By comparing the MLSHM-ML profile predictions against several snowpit profiles, it is possible to characterize the uncertainty associated with surface heterogeneity at the subgrid scale. The data sets are available at http://nsidc.org/data/clpx/clpx_pits.gd.html for the intensive study areas (ISAs), and for GBMR-7 at http://nsidc.org/data/docs/daac/nsidc0165_clpx_gbmr/index.html [50], [51].

### IV. Results and Discussion: Valdai

#### A. Snow Physics

Fig. 3(a)–(c) show the inter-annual variability of SWE, snow depth, and snow density simulated by the MLSHM using both single and multilayer formulations. The two formulations yield very similar SWE results, consistent with the mass balance constraint in the model and with the phase of precipitation forcing (all precipitation is specified in terms of water equivalent of rain, and when temperature is below freezing, then rainfall is accumulated as snow). Slight differences from one year to another reflect different types of precipitation. For example, percolation of liquid water deep into the snowpack during rain-on-snow events is described differently in single and multilayer formulations. In addition, surface melting takes place at a faster rate in the multilayer simulation, because the uppermost layer that interacts with the atmospheric boundary is shallower than the single-layer model, the vertical temperature gradient is captured with better fidelity, and thus it warms faster for the same energy forcing (radiation, turbulent heat fluxes).

Snow depth in the multilayer simulation is significantly larger than in the single-layer case, and consequently the bulk snow density is lower. This difference is because the bulk snow density in the multilayer snowpack increases more slowly than the density of the single layer. The parameterization of

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### Table I

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Parameters</th>
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<tbody>
<tr>
<td>18.0 GHz H</td>
<td>( \beta = 0.9465/0.9245 \text{ neper, } \phi = 0.009/0.0062 \text{ neper/mm, } \zeta = 0.0819/0.0819 \text{ neper/mm} )</td>
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<td>( \beta = 1.3255/1.1915 \text{ neper, } \phi = 0.0083/0.00274 \text{ neper/mm, } \zeta = 0.0819/0.0819 \text{ neper/mm} )</td>
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<td>( \beta = 0.8017/0.8399 \text{ neper, } \phi = 0.0152/0.0119 \text{ neper/mm, } \zeta = 0.0819/0.0819 \text{ neper/mm} )</td>
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<td>( \beta = 0.4957/0.5143 \text{ neper, } \phi = 0.0062/0.0062 \text{ neper/mm, } \zeta = 0.0819/0.0819 \text{ neper/mm} )</td>
</tr>
</tbody>
</table>
compaction rate (see [1] and [20]) is very sensitive to the thickness of the layers considered to account for overburden effects: the integral of the density profile over a stack of very thin layers (Fig. 4) leads to lower bulk density than that for the single-layer snowpack.

Fig. 3. MLSHM simulations in Valdai compared with ground-truth observations as available. (a) Snow water equivalent, SWE. (b) Snow depth. (c) Snow density.

Fig. 4. Temporal evolution of the number of snow layers in the MLSHM-ML simulation for the Valdai simulations.

Fig. 5. SMMR (red circle) and MLSHM-ML (blue dot) corrected brightness temperatures ($T_{\text{appm}}$) at 37 GHz (top: H-pol. bottom: V-pol.)

Fig. 6. SMMR (red circle) and MLSHM-ML (blue dot) corrected brightness temperatures ($T_{\text{appm}}$) at 21 GHz. (top: H-pol. bottom: V-pol.)

B. Microwave Emissions

Figs. 5–7 show the time series of MLSHM-ML simulations after applying local atmospheric correction ($T_{\text{appm}}$, [1]) compared against SMMR observations from 1978 to 1983 at 37, 21, and 18 GHz, for horizontal and vertical polarizations (H-pol and V-pol). Table II shows the summary error statistics between SMMR and multilayer and single-layer MLSHM simulations after atmospheric correction ($T_{\text{appm}}$) for ascending (11:00 A.M. LST) and descending (11:00 P.M. LST) paths. The same atmospheric correction scheme with parameters optimized locally as described by [1] was used here (Table I). Because these parameters lead to larger atmospheric transmissivity values for
temperatures simulated value (RMSE), and bias were calculated by comparing the MLSHM and dry winter conditions.

H-pol than V-pol, and despite lower snowpack emissivities for H-pol, there is a significant increase in the corrected brightness temperatures in H-pol relative to V-pol, particularly during cold and dry winter conditions.

The mean absolute error (ME), root mean squared error (RMSE), and bias were calculated by comparing the MLSHM simulated value $\hat{y}$ against the corresponding SMMR observation $y$ at the same frequency and polarization

$$\text{ME} = \frac{\sum |y - \hat{y}|}{n} \quad (17)$$

$$\text{RMSE} = \sqrt{\frac{\sum (y - \hat{y})^2}{n}} \quad (18)$$

$$\text{Bias} = \frac{\sum y - \hat{y}}{n} \quad (19)$$

The MLSHM-ML SMMR OSS for V-pol exhibits neutral to modest improvements in error statistics at all frequencies for descending (nighttime) paths as compared to the single-layer formulation for V-pol, except with regard to bias at 37 GHz which decreases ($\sim 3$ K). There is no improvement for ascending (daytime) paths. However, in the case of H-pol, the error statistics improve dramatically at 18 and 37 GHz for both ascending and descending paths ($\sim 1$–1.5 K at 18 GHz, and 2–3.5 K at 37 GHz), corresponding to a decrease of up to 30% in the difference between V-pol and H-pol as compared to single layer. Similar behavior can be found at 21 GHz for descending though not ascending paths. Thus, the multilayer formulation does improve significantly the SMMR OSS performance for horizontal polarization, but results are somewhat neutral or mixed for vertical polarization during the day. In empirical retrieval algorithms (e.g., [7]), H-pol is used to estimate SWE, whereas V-polarization is an indicator of snowpack internal structure, and thus volume scattering. Thus, the results suggest that the multilayer representation of the snowpack, if not accompanied by an improvement in the representations of the vertical distributions of nonlinear interactions between snow hydrologic states and electromagnetic properties, is not sufficient to describe the impact of snowpack stratigraphy, and specifically the vertical structure of snow density, on emissions. On the other hand, significant improvements in H-pol simulations with the MLSHM-ML, and particularly at 37 GHz for both ascending and descending paths, suggest that there is great potential for SWE monitoring from space.

C. Coupled Hydrology-Emission Behavior

The lack of improvement for V-pol in ascending paths is attributed to excessive warming of the brightness temperatures and degradation of the OSS skill particularly at the peak of the accumulation and ripening phases in the daytime (Table II). Fig. 8 shows the temporal evolution of SWE, integrated volumetric LWC, 37-GHz H-pol simulated brightness temperatures with optimal atmospheric correction ($T_{\text{appm}}$, [1]) for the 1982–1982 snow season, and the corresponding SMMR observations. The brightness temperature reaches a minimum before the maximum SWE accumulation in Fig. 8, and thus there is an increase in internal energy before melting starts, the so-called “ripening” phase of the snowpack during which temperatures increase until they reach 273.15 K. The lack of sensitivity of the microwave emission as SWE increases above 100 mm is similar to the saturation behavior identified by [47] for SWE values above the 150–200 mm range. Since significant changes of correlation length and density with depth to account for depth hoar and other microphysical changes are not explicitly described by the model and the parameterization of correlation length as a function of snow density is based on limited empirical data [32], [34], this study indicates that a more parsimonious parameterization of the temporal evolution of snow microphysics (metamorphic processes) with depth is required to improve the OSS simulations for V-pol using the MLSHM-ML as compared to the MLSHM-SL in Valdai. That is, better understanding of the temporal evolution of snow correlation length with density is necessary.

The simulated density and temperature profiles at three times corresponding to accumulation $A^1$, ripening $A^2$, and melting $A^3$ phases (Fig. 8) are shown in Fig. 9. Consistent with the compaction model described in Section II, snow density increases from the top to the bottom layer. However, note how the temperature of the top snow layer decreases between February ($A^1$) and March ($A^2$), and then rapidly increases between March ($A^3$) and April. $A^3$ exhibits a strong inversion with the upper layer significantly warmer than the lower layers, an indication that the melting phase is underway toward March 23rd. The yellow marker in Fig. 8 marks March 21st 1983 at the beginning of the melt season. On this date, there was significant daytime superficial melt resulting in high LWC both in the multi- and single-layer simulations. Fig. 10(a) shows that the brightness temperature from the multilayer model increases during the afternoon while that from single layer is
TABLE II

<table>
<thead>
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<th>H-pol [K]</th>
<th>V-pol [K]</th>
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<td></td>
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<td>13.59/19.25</td>
<td>10.49/15.72</td>
</tr>
<tr>
<td>$ME$</td>
<td>14.07/19.44</td>
<td>11.57/16.04</td>
</tr>
</tbody>
</table>

Fig. 8. MLSHM-ML simulated brightness temperatures with atmospheric correction ($T_{\text{appm}}$, 37 GHz, H-pol) and snowpack hydrology during the 1982 to 1983 snow season at Valdai. A$^1$: Feb. 5th, A$^2$: Mar. 15th, A$^3$: Mar. 23rd, and Yellow Circle: March 21st.

relatively constant. The brightness temperature is determined by two terms in (16) [Fig. 10(a)–(c)]: 1- outgoing radiation, $D_n$, and 2- surface transmissivity ($1 - s_{n+1} = r + t$). Compared to changes in $D_n$, the change of surface transmissivity between single- and multilayer formulations is negligible. The surface emission is influenced by the surface emissivity, the complementary of the summation of reflectivity and transmissivity. Fig. 10(d) shows that $(r + t)$ sharply decreases after 16:00 LST leading to significantly higher brightness temperatures in the multilayer snow simulation. This increase is explained by the increase in volumetric LWC inside the snowpack during the afternoon shown in Fig. 10(e). First, superficial melting around noon increased the LWC of the multilayer snowpack, lower internal reflectivity and transmissivity, and rapid increase of the outgoing radiation $D_n$. Second, rainfall at the end of the day further increases the LWC. As previously pointed out by [1] using the single-layer formulation, increases in LWC “warm” the snowpack and lead to an increase in outgoing radiation $D_n$.

The representation of the combined effects of intermittent surficial melting and other surface heterogeneities such as complex topography and heterogeneous land use and land cover can only be described by improved spatial resolution of the model, which in turn depends strongly on the meteorological forcing.
V. RESULTS AND DISCUSSION: CLPX
A. Snow Physics

Fig. 11 shows the SWE [Fig. 11(a)], snow depth [Fig. 11(b)], and bulk snow density [Fig. 11(c)] evolution for the multilayer and the single-layer MLSHM simulations against snowpit observations at GBMR-7 in the local scale observation station (LSOS) within the Fraser MSA (for location, see Fig. 2 of Part 1 [1]). The results show that during accumulation and beginning of ripening phases, the two formulations lead to similar results, whereas there are significant differences during late ripening and melting phases. Melting is faster in the single-layer case, and, based on snowpit observations, melting is faster in both model formulations as compared to observations. The simulated snowpack never reaches the high density values observed in mid-May, and presumably the densification of the snowpack in March–May, particularly at mid-depths is underestimated though there are no snowpit observations in that period to test this hypothesis. Note that the model results correspond to the grid cell that contains the entire Fraser MSA using RUC40 forcing; the GBMR-7 data in Fig. 11 are presented for reference purposes only, and therefore some variability is expected around the observed values. One important result for modeling microwave signatures is that in both formulations, and better so in the multilayer case, the overall changes in snow density profile during the accumulation season appear to be well captured by the model. Fig. 12 shows the evolution of the number of snow layers in the model increasing up to 14 during the peak accumulation season.

Fig. 13 shows the snow temperature and snow density profiles at three different times corresponding to the points marked with \( C_1 \) (12/19/2002), \( C_2 \) (2/21/2003), and \( C_3 \) (3/26/2003) in Fig. 11(a) from left to right, respectively. The number of layers varies with time as per Fig. 12. The results are compared against the snowpit data from three ISAs in the Fraser MSA: Fool Creek, St. Louis Creek, and Alpine, as well as LSOS (GBMR-7). Because the RUC40 meteorological forcing forecasts are used to drive the MLSHM at spatial resolution close to the scale of the entire Fraser MSA, snowpit observations from very distinct locations within Fraser provide a good measure of the spatial variability of the snow physical condition against the simulated area averages over time. At \( C_1 \), the temperature of
Fig. 11. MLSHM simulations of snowpack evolution in the Fraser MSA using RUC40 forcing. GBMR-7 integrated snowpit observations are shown for reference. (a) Snow water equivalent, SWE. (b) Snow depth. (c) Snow density. \( C^1, C^2, \) and \( C^3 \) correspond to selected dates for further analysis: 12/19/2002, 2/21/2003, and 3/26/2003, respectively; the red filled circle with cross hairs in part (a) the end of the accumulation season proper.

The top layer is well below freezing at 257 K, while the layers underneath display increasing temperatures up to the melting point both in the observations and in the simulations. This illustrates the typical heat insulating effect due to sensible heat fluxes [33]: even though the ambient temperature is cold, the internal layers adjacent to the soil maintain higher snowpack temperatures at the bottom. At \( C^2 \), there is an increase of snow density from the top to bottom layers due to overburden effects, while some observed density profiles have lower density in the bottom layers which can be attributed to depth hoar effects. Despite differences in snowpack density at \( C^2 \), the temperature profiles agree well particularly considering that the different profiles were obtained at far apart snowpit locations within the Fraser MSA (see Fig. 2 in Part1) encompassing different landforms, orientation with respect to solar forcing, and heterogeneous surface characteristics. The increase in density in the uppermost layers of the snowpit observations at \( C^3 \) accompanied by the nearly uniform temperature profiles suggests the presence of refrozen liquid water that percolated down from surface layer melting. During the accumulation season, the model consistently underestimates the top layer temperature by as much as 5 K on average. In particular, by the end of March, the temperatures of the upper layers in the model are still below freezing and the density profile exhibits a steep monotonic slope with depth that contrasts with the complex profiles from snowpit observations with uniform density at mid-depth. This can be addressed in part by increasing the number of layers at the top of the snowpack to better represent numerically the strong temperature gradient at the snow–atmosphere interface in solving the heat transfer equations. Note that different layers in the MLSHM do not need to have different physical or electromagnetic properties, as they are specified based on thickness alone.

Fig. 12. Temporal evolution of the number of snow layers in the MLSHM-ML simulation of snowpack for the Fraser MSA in the 2002–2003 season during CLPX.

Profiles of snow temperature and density profiles from three different snowpits at three distinct locations within the Fraser MSA (Alpine, Fool Creek, and St. Louise Creek) at 9:00, 12:00, and 15:00 LST on the same day, Feb. 20th, are shown in Fig. 14 to examine the diurnal cycle during the accumulation season. Note the increase in top layer temperature during the day and the effect of spatiotemporal variability in the propagation of the heat flux from the top to the bottom of the snowpack, whereas
Fig. 13. MLSHM-ML simulation of snow temperature and density profiles against snowpit observations at three ISAs (Fig. 4, [1]) throughout the Fraser MSA corresponding to dates $C^1$, $C^2$, and $C^3$ in Fig. 11: 12/19/2002, 2/21/2003, and 3/26/2003, respectively.

<table>
<thead>
<tr>
<th>[RMSE]</th>
<th>$C^1$</th>
<th>$C^2$</th>
<th>$C^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow temperature [K]</td>
<td>1.56</td>
<td>2.25</td>
<td>7</td>
</tr>
<tr>
<td>Snow density [kg/m$^3$]</td>
<td>66.25</td>
<td>77.25</td>
<td>94.35</td>
</tr>
</tbody>
</table>

Fig. 14. MLSHM-ML simulations of the diurnal cycle of the vertical profiles of snow temperature and density on Feb. 20th 2003 using RUC40 forcing against snowpit observations at the three ISAs (Fig. 4, [1]) within the Fraser MSA. From left to right: 9:00, 12:00, and 15:00 LST, respectively.

the density profiles do not change significantly. The snowpit data at the Alpine site at 12 P.M. show densification at mid-depths due to the presence of the liquid water. By mid-afternoon (15:00 P.M.), the temperature profiles both in the measurements and in the simulation show a linear increase of temperature at the top layer in response to solar forcing, and they are in good agreement, though the model underestimates the temperatures on average by about 3–5 K. The top layer exhibits therefore a marked diurnal cycle, and more so at St. Louis Creek. St. Louis Creek is located in the valley below 3000 m a.s.l., while the other two locations are above 3000 m on the slopes, and thus topographic effects should be important in terms of exposure for example as well as snow redistribution by boundary layer winds, which cannot be captured by the model.
Figure 15. (a) Temporal evolution of the simulated difference in brightness temperature ($\Delta T_b = T_b^{19H} - T_b^{37H}$) and simulated snow water equivalent (SWE), (b) same as (a) but for AMSR-E and SSM/I observations.

Furthermore, Fig. 14 shows that in the dry snow regime, during the accumulation phase, the model and the observations come close to agreement below the top layer before the end of February. Snowfall rarely occurs during the first three weeks of February, and the air temperature does not exceed the melting point of 273.15 K (not shown), which implies that the microwave behavior in February is controlled by radiative forcing at the air–snowpack interface and internal processes within the snowpack.

B. Microwave Emissions

Fig. 15(a) shows the temporal evolution of the difference in brightness temperatures $\Delta T_b$ between 19-GHz and 37-GHz H-pol along with the temporal evolution of SWE for multilayer and single layer MLSHM simulations. The objective here is to examine the relationship between SWE and $\Delta T_b$ used in empirical retrieval algorithms (e.g., [7]). As the snow accumulates, volume scattering effects during the ripening phase in late April and early May are quite different in the multilayer and single-layer simulations. When melting initiates in mid-May, the multilayer results exhibit more sensitivity than the single layer for which the difference between 19 and 37 H-pol brightness temperatures abruptly collapses. Similarly, Fig. 15(b) presents $\Delta T_b$ calculated from AMSR-E and SSM/I observations at their nominal frequencies, respectively, 19.35- and 37-GHz H-pol for SSM/I, and 18.7- and 36.5-GHz H-pol for AMSR-E. The difference between 19- and 37-GHz H-pol brightness temperatures ($\Delta T_b$) increases during the snow accumulation phase, though the magnitude is 10 K smaller in the satellite-based observations as compared to the MLSHM simulations. That is, the range of the simulations is larger than that of the satellite observations. The convex shape of the observations is not captured by the model during the accumulation phase, though the timing and magnitude of the rapid transition from dry to wet snow regime in mid-March is present in both simulations and observations. The difference in the accumulation phase is tentatively attributed to the compaction rate parameterization and, as discussed earlier, the lack of an explicit parameterization of depth hoar effects which have a strong impact on density profiles, vertical structure of snow grain size distribution, and ultimately volume scattering.

Note that SWE peaks in May, whereas $\Delta T_b$ in both simulations and observations reaches a maximum in early March [Fig. 15(a) and (b)]. This phase shift between the peak of the accumulation season in the dry snow regime and the peak in the wet snow regime (ripe snowpack) explains the ambiguity in the relationship between SWE and $\Delta T_b$ in retrieval algorithms. The profound effect of increased density as well as depth hoar on brightness temperatures at 37 GHz was addressed by [35] who pointed out differences on the order of 20 to 40 K at 37-H GHz depending on layer thickness for dry snowpacks, and addressed by [41] in the context of very dense snow samples. The relationship between the difference in brightness temperatures and snow depth is more sensitive at higher frequencies (e.g., 37 GHz) because of the significant attenuation within the snowpack as expressed by the relationship between $\gamma_a$ and $\varepsilon''$. To help address this problem with empirical retrieval models, [36] implemented dynamical calibration of the relationship between $\Delta T_b$ and snow depth, and [8] explored various empirical retrieval models and found that incorporating explicit dependencies on elevation, land-cover categories, and atmospheric conditions decreased ambiguity and improved performance. An alternative approach to address the challenge of ambiguity in retrieval is to develop an algorithm that optimally derives the snow physical properties from the observations using a model such as MLSHM and a Bayesian approach [40], or for example using the MLSHM results to constrain a dynamically calibrated empirical model such as [36].

Finally, the panels in Fig. 16 show the brightness temperature responses near 19-, 23-, and 37-GHz V-pol and H-pol, respectively, against AMSR-E observations for the entire period of simulation. MLSHM-ML SSM/I OSS results are not shown, but error statistics are included in Table IV. The results capture well the seasonal cycle, particularly in the melting season and for 37-GHz H-pol. In the accumulation season between December and early March, during which the model is consistently warmer than the observations, the typical concave shape corresponding to increasingly lower temperatures before the onset of melt is not captured for AMSR-E at 36.5-GHz V-pol not unlike the behavior reported by [1]. This is attributed in part to errors in the vertical density profile, and thus the vertical structure of the snow correlation length. As discussed previously, the model underestimates density particularly at mid-depths, and overestimates density near the bottom of the snowpack due to the lack of a depth hoar and vapor diffusion and deposition parameterizations during dry periods in the accumulation phase [35]. Nevertheless, spatial scale differences between sensors’
footprint resolutions, re-gridded products, and the effective scale of MLSHM simulations that are in this case determined by the meteorological forcing are also expected to contribute to the discrepancies.

Table IV shows a summary of error statistics including results from [38] as a reference. [38] used a version of the HUT model as well as DMRT and MEMLS coupled to VIC for simulations at two sites within the Fraser MSA, February–May 2003, thus including both dry and wet snow regimes over a four-month period. Overall, there are very small differences in error statistics between the single- and the multilayer simulations (measurement uncertainty alone is in the range of 0.5–1 K for SSM/I and AMSR-E). Results show clear gains in OSS skill only for SSM/I at 37 GHz, in particular V-pol. This is in contrast with the results obtained for Valdai, which suggests that snow stratigraphy is more complex in CLPX where the weather is more variable and orographic effects are important as compared to the northern (drier) latitudes and flatter topography of Valdai, and there is significant subgrid-scale variability in terms of land cover and landform. The improvement of error statistics of the multilayer OSS for V-pol in CLPX is better than for H-pol, even more so in the case of AMSR-E. Although the simulation period in this study is longer than previous studies (8 months versus weeks up to 4 months) and no surface observations were used to specify snowpack properties or model parameters, that is the model was run in full prognostic forward OSS mode from snow hydrology to emissions, the errors statistics are competitive. This suggests that the MLSHM meets operational readiness requirements.

In summary, because the CLPX multilayer results do not significantly improve for horizontal polarization as compared to Valdai, further analysis is required with regard to: 1) improvement of the representation of snow densification processes, particularly the effect of metamorphosis on compaction rate, and separate parameterization of correlation length for layers that undergo intermittent melting and freezing leading to the formation of ice occlusions for example (i.e., ice lenses, [49]); 2) explicit parameterization of depth hoar effects; and 3) sensitivity analysis of the horizontal and vertical scattering coefficients to grain size correlation length and density on a layer-by-layer basis. Another critical aspect that must be accounted for is the role of subgrid scale variability of the topography as well as land cover, specifically vegetation (e.g., [48]).

C. Coupled Hydrology-Emission Behavior

The challenge of space-time intermittency in snowpack radiometric properties is examined next focusing on surficial
TABLE IV

MODEL ERROR STATISTICS [MULTILAYER (SINGLE-LAYER)] AND CHANGE ∆ INTERCOMPARISON USING THE CORRELATION LENGTH \( p_{cc} \) BASED ON THE CLASSIFICATION BY [34] FOR THE FRASER MSA DURING CLPX: SSM/I, AMSR-E, AND [38]. SINGLE-LAYER SIMULATION RESULTS ARE FROM [1]

<table>
<thead>
<tr>
<th></th>
<th>H-pol [K]</th>
<th>V-pol [K]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SSM/I</td>
<td>AMSR-E</td>
</tr>
<tr>
<td></td>
<td>∆</td>
<td>∆</td>
</tr>
<tr>
<td>Bias</td>
<td>-10.76(-10.58)</td>
<td>-0.18</td>
</tr>
<tr>
<td>ME</td>
<td>10.96(10.78)</td>
<td>-0.18</td>
</tr>
<tr>
<td>18–19GHz RMSE</td>
<td>12.93(13.54)</td>
<td>0.39</td>
</tr>
<tr>
<td>Bias</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>ME</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>22–23GHz RMSE</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Bias</td>
<td>-3.97(-3.99)</td>
<td>0.02</td>
</tr>
<tr>
<td>ME</td>
<td>6.71(7.71)</td>
<td>1.0</td>
</tr>
<tr>
<td>36–37GHz RMSE</td>
<td>8.54(10.56)</td>
<td>2.02</td>
</tr>
</tbody>
</table>

Fig. 17. Sensitivity analysis of brightness temperature affected by volumetric liquid water content \( lw_n \) and \( lw_{n-1} \) in the two uppermost layers from 6 P.M. LST on May 14th through 6 A.M. on May 18th 2003 during CLPX. Note the nocturnal freezing of volumetric liquid water in the top layer after midnight LST.

snowpack melting. When it occurs, the liquid water moves downward from the top layer to the adjacent lower layers before it refreezes. This begs the question of which layer will contribute more to the microwave emission from the snowpack surface. Fig. 17 shows the temporal evolution of volumetric LWC \( lw \) in the two uppermost layers along with brightness temperature at 37-GHz H-pol for a short window from 6 P.M. LST on May 14th through 6 A.M. on 20th 2003 in the Fraser MSA during CLPX. Note the convergence of brightness temperatures to the physical snowpack temperature in response to afternoon warming and transient melting induced by solar forcing. There is very strong correlation between the top layer LWC and the surface brightness temperature, whereas changes in volumetric LWC in the second layer do not show a significant impact on the brightness temperature. That is, the top layer controls the radiometric signature of the snowpack when there is surficial melting. Combined with spatial heterogeneity, the occurrence of intermittent surface melting and subsequent refreezing at the scale of the MLSHM simulations could be a leading cause of the drop of OSS skill during daytime (e.g., SSMR in Valdai), as well as the mixed error statistics for H-pol and V-pol during the ripening and early melting phases in CLPX.

VI. CONCLUSION

The MLSHM-ML leads to improved results particularly in the case of horizontal polarization for the SMMR OSS in Valdai compared with the single-layer physics [1]. In the case of CLPX, performance was generally neutral as compared to the MLSHM-SL except for SSM/I at 37-GHz H-pol and V-pol, and for AMSR-E at all frequencies in V-pol. General improvement of the OSS performance at 37 GHz for all three sensors (SMMR, SSM/I, and AMSR-E) indicates there is value in the multilayer physics, particularly given the well-documented sensitivity of snowpack emissions to snow physical properties at this frequency ([23], [26], [32] among others). The multilayer formulation further facilitates physically-based inquiry into the processes that govern the coupled snow hydrology and radiometric behaviors by focusing on vertical structure. Comparison against snowpit data show that the model captures the overall evolution of the snowpack throughout the entire 2002–2003 cold season in Colorado within the range of uncertainty determined by the spatial variability of the snowpit observations, including the vertical structure of snow temperature and snow density, particularly for dry snow conditions across the Fraser MSA, and despite spatial scale differences. A cold bias of (3–5 K) was quantified for the top snow layers during the accumulation season, which does not persist after the onset of ripening and melting processes as compared to observations.
Finally, the results obtained with the coupled multilayer MLSHM-ML for CLPX without calibration are competitive with results obtained from emissivity models supplied by direct observations of snowpack characteristics (e.g., [18], [38], and [39]). Nevertheless, the results show that a multilayer representation of snow physics does not necessarily improve results as compared to the single-layer model, if the key governing processes that map the snowpack layers to snow stratigraphy, in the MLSHM-ML via the snow density profile, are not well described and, or parameterized in the model. Note that, as discussed in [1], fractional vegetation cover effects were neglected in this study, but even if the values are very small, an explicit representation should improve the results particularly for V-pol [52]–[54].

There are three types of physical processes that require improved model parameterizations: 1) densification and the representation of snow metamorphic processes, and particularly the formation of depth hoar in dry cold climates during the winter season, which has implications for both snow density and snow grain size distribution, and has long been recognized as a major challenge [35], [55], [56]; 2) the simulation of the snowpack energy balance, and specifically the diurnal cycle of snowpack surface temperature, and snowpack–canopy interactions; and 3) explicit representation of intermittent surficial melting in MEMLs. Furthermore, water percolation processes associated with the effect of abrupt and intermittent melting in early spring need to be further investigated [39]. During the fast melting snow season, as the melting water percolates through the layered snowpack, multidirectional routing of liquid water within the snowpack over complex terrain should also be accounted for, including outflow through intermediate layers as well as lateral redistribution of liquid water, and the underlying matrix beneath the snowpack needs to be considered such as ice lenses or lakes [46].

Finally, and independent of model physics, the two studies show that the utility of the MLSHM is ultimately determined by the spatial resolution of the model, and the uncertainty associated with the representation of subgrid scale variability. The differences between Valdai and CLPX, and separately between the SSM/I and AMSR-E OSS within CLPX suggest that even though all satellite-based observations are used at the same EASE-grid resolution, the influence of the original nominal footprint resolution carries through the resampling and projection: for H-pol, improvements (losses) in the MLSHM-ML simulation skills are much smaller (larger) for the higher resolution AMSR-E frequencies than for SSM/I. On the other hand, use of meteorological forcing from the local tower at the GMR-7 location greatly improves the simulations at the local scale. Because the spatial resolution of the MLSHM is only limited by the spatial resolution of the meteorological forcing, there is great potential in improving performance and operational utility in remote regions using high-resolution numerical weather prediction forecasts.

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REFERENCES


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