Dynamic Approaches for Snow Depth Retrieval From Spaceborne Microwave Brightness Temperature

Marco Tedesco, Rolf Reiche, Alexander Löw, Member, IEEE, Thorsten Markus, Member, IEEE, and James L. Foster

Abstract—Snow depth (SD) can be retrieved from spaceborne data through linear regression against the microwave brightness temperature difference between 19 and 37 GHz (or similar frequencies). Other methods use snow physical and/or snow electromagnetic (EM) models to estimate SD. Here, we introduce novel retrieval approaches that dynamically combine ancillary SD information (e.g., from snow physical models driven with surface meteorological data) with established algorithms based on regression or EM modeling. The basic idea is to recalibrate regression coefficients (or the effective grain size in the case of EM models) once per week in a simple data assimilation scheme. SD is retrieved from Special Sensor Microwave Imager brightness temperature data and evaluated against in situ observations from 37 stations throughout the Northern Hemisphere. As expected, the SD retrievals perform better with (weekly) ancillary SD inputs from in situ measurements (not used in validation) than with (weekly) ancillary SD inputs from snow physical modeling. The best results were obtained with the regression-based approach using dynamically recalibrated coefficients and ancillary SD inputs from in situ observations (rmse = 6 cm). The regression approach still performs better with the time average of the dynamic coefficients (rmse = 8 cm) than with standard literature values based on climatology (“REGR-CLIM”; rmse = 50 cm). For SD retrieval with an EM model, we obtain results comparable to REGR-CLIM (rmse = 44 cm). Driving the novel regression approaches with SD estimates from snow physical modeling still results in improvements over REGR-CLIM for all approaches (rmse = 15 cm). Comparable SD estimates are obtained from the snow physical model alone.

Index Terms—Microwave, remote sensing, snow.

I. INTRODUCTION AND MOTIVATION

Estimating snow depth (SD) and snow water equivalent (SWE) at large spatial scales, and consequently snow-covered area (SCA), is important for many applications. In many regions, snow represents a fundamental source of freshwater. The knowledge of how much water is stored within a snowpack supports estimates of water resources for hydropower energy production. Knowing SWE and SD can, for example, support the forecast of flooding that is due to the combination of melting snow and rain. With its high albedo, snow plays a major role in the Earth’s energy budget, affecting the amount of solar radiation redirected into the atmosphere.

The spatial resolution of satellite microwave data (on the order of tens of kilometers) is coarser than that of visible observations, but the large swath of passive microwave sensors and the weak sensitivity to atmospheric parameters allow collecting useful data over most of the globe on a daily basis. The retrieval of SD or SWE from microwave data is possible because the microwave observations are sensitive to processes occurring below the surface of the snowpack. The frequencies used for SD or SWE retrieval are near 19 GHz (K-band) and 37 GHz (Ka-band), with the radiation at 37 GHz being scattered more by the snow than that at 19 GHz. As snow deposits on the ground, it attenuates the relatively warmer signal emitted by the underlying soil, with the extinction increasing as the number of scatterers (e.g., snow grains) increases. The K- and Ka-band data are thus differently affected by snow parameters, with the latter being more sensitive to the presence and amount of snow. Therefore, when snow accumulates, the brightness temperature at the Ka-band decreases more than that at the K-band, and their difference is generally assumed to increase as SD increases.

Many approaches have been proposed in the literature, which exploit this sensitivity [1]–[6]. The approaches typically use a linear regression between SD and the brightness temperature difference at the K- and Ka-bands. The regression coefficient $R_c$ is often also referred to as the retrieval coefficient. Hereinafter, we refer to this class of methods as regression-based retrieval approaches.

Initially, $R_c$ was treated as a constant in space and time (e.g., [1], [3], and [4]). More recent studies [5], [6] have investigated the potential of regression-based approaches that use dynamic coefficients. For example, Foster et al. [5] use information on Sturm [7] snow classes and other climatological information to derive monthly retrieval coefficients for each snow class (Section II-B). Hereinafter, we refer to the approach of Foster et al. [5] as a regression-based algorithm with climatological retrieval coefficients or REGR-CLIM. This approach will also be used as a benchmark for the evaluation of the novel approaches that we will introduce later.

More sophisticated approaches use electromagnetic (EM) models to retrieve SD or SWE from satellite microwave brightness temperatures (e.g., [8]–[11]). In these methods, the retrieval is performed by minimizing the difference between the measured and modeled brightness temperatures through numerical techniques such as, for example, artificial neural networks or genetic algorithms. Hereinafter, we refer to these methods as EM-based approaches. Results have shown that, in general,
EM-based approaches can provide better results than regression methods (e.g., [8]–[11]).

The recent widespread availability of high-quality meteorological forcing data for land surface models opened up the possibility to combine forward EM modeling with sophisticated data assimilation methods. Preliminary attempts at assimilating SWE retrievals, however, did not yet provide satisfactory results [12]. More recent results [13], [14] show that it is possible to simulate ground-measured brightness temperatures by means of EM models driven with inputs derived from snow pit measurements. However, the translation of the encouraging results obtained at small spatial scales to large ones is not trivial. Approaches based on (inverse or forward) EM modeling require input parameters that are difficult to obtain at the global scale, face tremendous difficulties with modeling key processes such as grain size evolution, and require ample computing resources. Much work remains to be done before these approaches can be used successfully in global land data assimilation systems.

In this paper, we pursue an approach of intermediate complexity and explore whether the use of ancillary dynamic SD information can be used in retrieval algorithms that are based on regression or EM modeling. The basic idea is to recalibrate the regression coefficients (or the effective grain size in the case EM modeling) once every few days or weeks in a simple data assimilation scheme. For global applications, the ancillary SD information may be drawn from snow physical models driven with surface meteorological forcings. In particular, we address the following questions: At large spatial scales, how do these novel approaches perform when compared with the traditional regression approach based on climatological retrieval coefficients? Should an improvement be found in the novel approaches? What can we learn from the dynamic retrieval coefficients (or effective grain size) about the prospects of improving current global SD products? Answers to these questions will point to potential avenues for improving current global SD or SWE operational products.

To answer the aforementioned questions, we evaluate the novel approaches when ancillary SD information is provided through in situ observations and, separately, through snow physical modeling. As mentioned, for the remainder of this paper, we use the REGR-CLIM approach of Foster et al. [5] as the benchmark. For testing and validation, we use in situ quality-controlled observations collected during three snow seasons at 37 stations of the World Meteorological Organization (WMO) distributed over the Northern Hemisphere. We will refer to the snow season in 2001–2002 as year 1, to the snow season in 2002–2003 as year 2, and to the snow season in 2003–2004 as year 3. To our best knowledge, this is the first time that a comparison between the various methods is provided at a relatively large number of stations.

II. DATA AND METHODS

In this section, we report details on the data used in this paper as well as a description of the retrieval and modeling tools used.

A. Microwave Data

We use brightness temperatures collected by the Special Sensor Microwave Imager (SSM/I) radiometer flying on board the Defense Meteorological Satellite Program F13 satellite. The SSM/I is a seven-channel four-frequency (19.35, 22.235, 37, and 85.5 GHz) microwave radiometric system, with all channels operating in dual vertical (V) and horizontal (H) polarizations, except for the one at 22.235 GHz which operates at V polarization only. A detailed documentation about the SSM/I instrument is available in electronic format at http://www.ssmi.com/. Specifically, we make use of the NOAA/NASA Pathfinder Program SSM/I Level 3 Equal-Area Scalable Earth Grid Brightness Temperatures [15] at 19.35 and 37 GHz and vertical polarization. The gridded resolution is 25 km for both frequencies.

B. Benchmark Retrieval Approach

As mentioned earlier, regression-based approaches relate SD to the difference in brightness temperature \( T_B \) at 19 and 37 GHz (or similar frequencies)

\[
SD = Rc(T_B19 - T_B37) \equiv Rc\Delta T_B.
\]

Early versions of the algorithm used a constant coefficient of \( Rc = 1.59 \) to obtain SD in centimeters (or \( Rc = 4.8 \) to obtain SWE in millimeters) [1]. This approach was originally developed from ground measurements and EM modeling and was not calibrated for global retrievals. Foster et al. [2] later account for the presence of forest through a correction factor such that \( Rc = 1.59/(1-f) \), where \( f \) is the forest cover fraction within the satellite footprint. More recently, Foster et al. [5] proposed an approach in which \( Rc \) depends on monthly climatology and on the snow class (according to Sturm et al. [7])

Foster approach:

\[
Rc = \Gamma(\text{snow class}, \text{month}, \text{forest fraction})
\]

where \( \Gamma \) indicates a nonlinear operator that relates the climatological inputs (snow class, calendar month, and forest fraction) to the retrieval coefficient \( Rc \). Hereinafter, this approach will be named REGR-CLIM and will serve as the benchmark retrieval algorithm. Foster et al. [5] also quantify errors by taking into account various factors that impact passive microwave responses from snow in various climatic/geographic regions, such as snow morphology (crystal size), and errors related to brightness temperature calibration.

C. SD Data

Daily SD and air/surface temperature are measured by stations of the WMO and obtained through the NOAA National Climate Data Center Web site (http://www.ncdc.noaa.gov). Table I shows, for each station, the WMO identification number, the station coordinates, the forest cover fraction (also shown in Fig. 1), and the associated snow classes. SD retrieval using microwave frequencies fails when snow is wet because of the high absorption coefficient of wet snow induced by the presence of liquid water (e.g., [16] and [17]). We therefore consider only data collected when the surface/air temperature is less than or equal to \(-5 \, ^\circ C\) to minimize the number of days when wet snow is present.

Fig. 2 shows the average (light gray) and maximum (dark gray) SD values measured at the different WMO stations for the three considered snow seasons. The average SD ranges
between ~0.2 and ~0.8 m, with maximum values of up to 2 m. The maximum SD to which microwave data at the K- and Ka-bands is sensitive is a function of several snow parameters and frequency [18]. The maximum penetration depth at 19.35 GHz can exceed 1 m, whereas at 37 GHz, it generally does not exceed 0.6–0.8 m, depending on snow conditions [18]. While the average values of SD for the different stations are lower than the maximum penetration depth at 37 GHz, some of the maximum SD values are greater than 0.6–0.8 m, with the consequence that, in these cases, SD is underestimated by the retrieval algorithms. Fig. 2 shows, in fact, that, during the three study periods in 23, 15, and 20 stations, the maximum SD was greater than 0.8 m; this is, on average, more than 50% of the stations. Note that, because of the saturation effect that is

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<th>Lon. [deg]</th>
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<th>Sturm snow class</th>
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TABLE I
LIST OF WMO STATIONS. COUNTRIES OR U.S. STATE ARE SWD (SWEDEN), RUS (RUSSIA), FIN (FINLAND), AK (ALASKA), AND CAN (CANADA). ALSO SHOWN ARE FOREST FRACTION, STURM CLASS, THE NUMBER OF SAMPLES USED FOR VALIDATION, AND TIME SERIES MEAN AND STANDARD DEVIATION OF THE RETRIEVAL COEFFICIENTS FROM THE REGR-DYN APPROACH WHEN DRIVEN WITH WEEKLY ANCILLARY IN SITU OBSERVATIONS FROM WMO STATIONS.
TABLE I

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Consequent to intrinsic physical limitations, no improvement is expected when using input SDs above this threshold. Fig. 3 shows the number of samples used for each station and year. Snow measurements were not performed every day for all stations, thereby further limiting the number of samples (in addition to the air temperature threshold of −5 °C). Moreover, for some cases, the minimization procedure of the EM modeling approach (Section II-G) yielded effective grain size estimates outside of the physical range allowed by the EM model, potentially because of the ill-posed nature of the inversion problem [9]. As a result, the number of samples used for each station differs from year to year, and for some stations, a few samples could be used for the analysis.

D. Surface Meteorological Forcing Data

The surface meteorological forcing data are used to run the land model (Section II-F) which, in turn, is used to generate inputs to the EM model and the novel approaches when driven with model-simulated SD values (Section II-G). Surface meteorological forcing data are from the Global Land Data Assimilation Systems (GLDAS) project [19] (http://ldas.gsfc.nasa.gov) and were provided at three hourly
time steps and at 2° and 2.5° resolution in the latitude and longitude, respectively. The data stream provided by GLDAS is based on outputs from the global atmospheric data assimilation system at the NASA Global Modeling and Assimilation Office [20]. Important corrections were applied by GLDAS using observations of precipitation from the Climate Prediction Center Merged Analysis of Precipitation (CMAP) (http://www.cdc.noaa.gov/cdc/data.cmap.html). The CMAP data used for corrections are merged satellite-gauge pentad data on a 2.5° global grid. Moreover, corrections to the radiation fields were applied by GLDAS using daily observations from the Air Force Weather Agency Agricultural Meteorology modeling system based on a 23-km satellite cloud product. Together, the observation-based corrections ensure that the forcing data and, hence, the snow estimates from the model are as close to reality as possible.

E. EM Model

We used the Helsinki University of Technology model (formerly known as HUT but now referred to as TKK) in simulating microwave brightness temperatures in the EM-based approach...
TKK is based on the radiative transfer theory, and it treats the snowpack as a single homogeneous layer. General inputs to the model are SD, snow density, snow particle size, snow temperature, and, in the wet snow case, surface roughness of the air/snow boundary and snow wetness. Soil inputs (reflectivity between the soil and snow, and soil temperature) must be also provided. The fundamental assumption in the TKK model is that scattering is mostly concentrated in the forward direction. The extinction coefficient $k_e$ is modeled by means of the equation reported by Hallikainen et al. [21] as a function of the frequency and mean grain size. Recently, a new expression for the extinction coefficient has been proposed [22], extending the validity range to large particle sizes. However, in this paper, we adopted the original formula proposed in [21] as it has been widely tested in the literature. Ice permittivity is computed by means of an empirical formula [23]. The real part of snow permittivity is calculated by means of the formula proposed in [23], where the imaginary part is calculated by means of the Polder–Van Santen mixing formula [24]. The absorption coefficient is calculated from the imaginary part of the dielectric constant of snow.

### F. Land Surface Model

Estimates of SD can be obtained through snow physical modeling. Here, estimates of snow conditions are obtained from integrations of the NASA Catchment Land Surface Model (hereinafter referred to as the Catchment model or CLSM [25], [26]). The Catchment model’s basic computational unit is the hydrological catchment (or watershed). The global land surface is divided into catchments (excluding inland water and ice-covered areas) with a mean linear scale of around 50 km (ranging from a few kilometers to 250 km). In each catchment, a total of nine prognostic variables (three for each of the three layers) describe the evolution of SWE, SD, and snow heat content in response to surface meteorological forcings and snow compaction. The time step for the model integration is 20 min. The salient feature of the land model integration is that it uses meteorological forcing inputs that rely on observed data as much as possible at global scales (Section II-D).

### G. Novel Retrieval Approaches

Table II summarizes the approaches used for SD estimation. In addition to SD estimates from CLSM (Section II-F) and the benchmark regression approach REGR-CLIM (Section II-D), we obtain SD from three novel methods. Two of the novel approaches are based on regression (REGR-DYN and REGR-AVG), and one is based on EM modeling (EM-TKK, to indicate that it is based on the TKK model). The novel approaches require ancillary SD inputs which are taken either from in situ WMO observations or from CLSM estimates.

The key unknown parameter of a regression-based SD retrieval algorithm is naturally the retrieval coefficient $R_c$. For an approach that relies on EM modeling, the key unknown parameter is the effective snow grain size $S_{\text{eff}}$. The basic idea of the novel REGR-DYN and EM-TKK algorithm is shown in Fig. 4. The novel approaches recalculate the key unknown algorithm parameter at prespecified update times $t_u$, typically once every few days or weeks. At such update times, ancillary SD values are combined with satellite observations of the brightness temperature difference $\Delta T_B$ in order to recalibrate the retrieval coefficients (in the case of REGR-DYN) or the effective grain size (in the case of EM-TKK). More specifically, the retrieval coefficient is computed by dividing the ancillary SD input by the observed $\Delta T_B$. In the EM-TKK approach, the ancillary SD is used (at time $t_u$) as input to the EM model, together with the remaining necessary snow parameters simulated by the CLSM (snow density and temperature), and the effective grain size is computed by minimizing the difference between the modeled and observed brightness temperatures.

After an update step, the recalibrated parameters are held constant for a period of time ($\Delta \tau$ days) and are repeatedly used with satellite $\Delta T_B$ to retrieve daily SD until the recalibration is due at the next update time $t_u$. In the case of REGR-DYN, SD is therefore obtained by multiplying the updated retrieval coefficient with the observed satellite $\Delta T_B$. In the EM-TKK approach, SD is a fitting parameter obtained by minimizing the difference between the modeled and observed brightness temperatures, given the daily snow density and temperature from CLSM and the effective grain size computed at the previous update time.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
<th>Main inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLSM</td>
<td>Land model driven with surface meteorological data</td>
<td>Surface meteorological data</td>
</tr>
<tr>
<td>REGR-CLIM</td>
<td>Regression of $\Delta T_B$ using coefficients based on climatology</td>
<td>Daily SSM/I $T_B$</td>
</tr>
<tr>
<td>REGR-DYN</td>
<td>Regression of $\Delta T_B$ using dynamically derived coefficients</td>
<td>Daily SSM/I $T_B$ + weekly SD</td>
</tr>
<tr>
<td>REGR-AVG</td>
<td>Regression of $\Delta T_B$ using seasonally averaged coefficients of REGR_DYN</td>
<td>Daily SSM/I $T_B$ + seasonally averaged coefficients of REGR_DYN</td>
</tr>
<tr>
<td>EM-TKK</td>
<td>Use of electromagnetic (radiative transfer) model with fitted snow grain size</td>
<td>Daily SSM/I $T_B$ + weekly SD</td>
</tr>
</tbody>
</table>

**Table II** Overview of SD Retrieval Methods

![Fig. 4. Flow diagram for novel SD retrieval approaches REGR-DYN and EM-TKK.](image)
The REGR-DYN and EM-TKK approaches can be viewed as very simple data assimilation schemes because they merge SD ancillary information (e.g., from land models) with relevant satellite observations and because of the sequence of update and retrieval steps that is typical of filtering methods. It must be stressed, however, that the REGR-DYN and EM-TKK approaches do not consider uncertainty estimates of the input data sources in the merger. In this respect, the novel algorithms can, at best, be considered as “poor man’s” data assimilation schemes. More sophisticated methods that include error modeling as an integral part of the algorithm [34] might yield better results but are beyond the scope of this paper.

In a third approach, we first compute the time average of the REGR-DYN retrieval coefficient for each snow season and each station and then use those values with the regression equation throughout the corresponding snow season. This third approach, termed REGR-AVG, is still informed by the ancillary SD inputs that are specific to each location, although only in terms of a seasonal average. In other words, the retrieval coefficients of REGR-AVG are allowed to vary from snow season to snow season but are constant throughout the season (being the average of that particular season). Therefore, the retrieval coefficients of REGR-AVG only account for interannual variability and are mainly affected by the spatial features and annual cumulative meteorological trends.

**H. Performance Metrics and Error Sources**

All SD retrievals are validated against in situ WMO observations (excluding the measurements that were used as ancillary data inputs to the novel retrieval approaches). The results obtained with the different approaches are evaluated in terms of the root-mean-square error (rmse), the average relative percentage error (defined here as $100 \cdot |SD_{meas} - SD_{ret}|/SD_{meas}$, averaged over the total number of samples), and the correlation coefficient ($R$) between the in situ observations and the corresponding retrieved values.

As is typical when validating large-scale satellite estimates with in situ data, it is important to consider that the in situ measurements are collected at point scale, whereas satellite data represent a spatial scale of tens of kilometers. For the cases considered in this paper, each satellite pixel contains exactly one point measurement. Obviously, this is a source of error that cannot be avoided for lack of a denser in situ observation network.

Besides spatial scaling issues, factors such as vegetation and atmospheric effects are also sources of error. Overforested areas, measured brightness temperature can be approximated as a linear combination of forested and unforested brightness temperatures (e.g., [27]), $T_B = f \cdot T_{B\text{-forest}} + (1 - f) \cdot T_{B\text{-snow}}$, where $T_{B\text{-forest}}$ and $T_{B\text{-snow}}$ are the forest and snow brightness temperatures, respectively. The actual brightness temperature to be used to derive SD should thus be $T_{B\text{-snow}}$. Recent studies also show that atmospheric effects should also be taken into account [28]–[30]. However, the information necessary to correct these effects is generally not available. As discussed in Section II-B, the REGR-CLIM approach accounts for forest cover fraction through the correction factor $1/(1 - f)$. By contrast, the novel approaches implicitly account for vegetation and atmospheric effects through the updated retrieval coefficient (in the case of REGR-DYN) and the updated effective grain size parameter (in the case of EM-TKK).

**III. Results**

In this section, we discuss the results of applying the SD retrieval algorithms to SSM/I satellite observations (Section II). Results in Section III-A are characterized by using in situ WMO observations of SD as ancillary inputs to the novel retrieval approaches. With this, we demonstrate the maximum potential improvements that can be obtained with the novel approaches. Since in situ SD measurements are not available everywhere, we obviously cannot derive dynamic retrieval coefficients (or effective grain size parameters) at the global scale from in situ measurements. We therefore also evaluate the performance of the novel approaches when, instead of using WMO measured SD data, we use weekly SD simulated by CLSM as ancillary inputs (Section III-B). Obviously, in this case, the skill of SD retrievals is also affected by the skill of ancillary SD from CLSM.

A. Updating Dynamic Approaches Using WMO SD

We first report results obtained when using ancillary SD from in situ WMO observations. Fig. 5 shows the performance of SD retrievals derived with the novel approaches (REGR-AVG, REGR-DYN, and EM-TKK) expressed as relative rmse improvement over the benchmark (REGR-CLIM) algorithm [e.g., $100 \cdot (\text{rms}_{\text{REGR-CLIM}} - \text{rms}_{\text{REGR-DYN}})/\text{rms}_{\text{REGR-CLIM}}$] for the different stations and averaged over the three years. Positive values signify improvement over the benchmark; negative values imply a worse performance.

In Fig. 5, we observe that, in general, the biggest improvements (and thus the lowest rmse values) are obtained with the REGR-DYN and REGR-AVG approaches. Improvements typically range from 50% to 90%. The EM-TKK algorithm still offers improvements over the benchmark at most stations, albeit somewhat lower than those of the novel regression-based approaches. This is not surprising, of course, because weekly in situ WMO measurements are used as inputs to the algorithms whose outputs are again evaluated against in situ WMO measurement (excluding in situ measurements at times and locations that were used as algorithm inputs).

There are, however, a number stations at which EM-TKK performs considerably worse than the benchmark algorithm. Some of the inputs to the EM model, such as soil temperature and permittivity, are kept fixed for all stations and during the whole snow season (with $T_{\text{soil}} = -10$ °C and $\varepsilon_{\text{soil}} = 3.5 + i \ast 0.1$), as they cannot be derived from WMO data. These values were suggested by previous studies [8], [9], [11]. This can present a source of error as changes in the EM properties of soil can occur during the snow season (although these changes might not strongly affect the results) and from site to site (with these changes more likely affecting the results). While CLSM can simulate soil properties, they are not used in this paper (so as to maintain a consistent comparison between the cases with ancillary SD data inputs from WMO and CLSM). Another potential source of error with the EM-TKK approach lies in the assumption of modeling the snowpack as a single layer of scatterers. In nature, snow is typically vertically stratified. Nevertheless, we observe that the EM-TKK approach is,
in most cases, able to retrieve SD values that are closer to the in situ measurements than the benchmark retrievals. Finally, the EM-TKK approach also relies on snow density and temperature estimates from CLSM, which may be inconsistent with the SD inputs from the WMO in situ observations.

The highest absolute rmse values in the benchmark REGR-CLIM approach are obtained for station numbers 247380, 249440, and 719340. Interestingly, high values of forest cover fraction occur for the same stations, exceeding 80%. An analysis of the behavior of rmse versus forest cover fraction (not shown) suggests that the rmse is gently increasing with forest cover fraction up to 70%. Thereafter, the rmse increases drastically with increasing forest cover fraction. For the same three stations (numbers 247380, 249440, and 719340), the rmse obtained with the novel approaches is smaller, arguably because the vegetation effects are implicitly accounted for when the algorithm parameters are updated. We also observe that in the case of station numbers 247380 and 249440, the maximum SDs recorded during year 1 are 1.38 and 1.12 m, respectively, and are therefore above the maximum value to which the microwave data are sensitive. This aspect, together with the dense forest covering the area, likely contributes to the high rmse values.

Fig. 6 compares the time-averaged values of retrieval coefficients for each year (that are used in the REGR-AVG approach) with corresponding time averages of the climatological values (that are used in the REGR-CLIM approach). The REGR-AVG coefficients obviously differ from the climatological values used in the REGR-CLIM approach for some stations considerably. The spatial variability that is evident in Fig. 6 is a consequence of the different spatial features (for example, vegetation and topography) of each site. The results suggest that it is important to consider the local variability even within the same snow or vegetation classes. The REGR-AVG coefficients also vary from year to year as a consequence of interannual differences in the evolution of the snowpack in response to meteorological forcing. The REGR-CLIM coefficients might not be sensitive enough to changes in snow parameters at weather time scales, leading to problems with SD retrieval at large scales. Table I reports the time average (and standard deviation) of the coefficients obtained from the REGR-DYN approach, when driven with weekly ancillary in situ observations from WMO stations. The variability of even the time averages of these calibrated coefficients suggests that regression coefficients that are solely based on climatology (as in REGR-CLIM) lack location-specific information.

B. Updating the Dynamic Approaches With CLSM Outputs

Results discussed in the previous section are derived by using the WMO measured SD for updating either the retrieval coefficients or the effective grain size values in the novel approaches. In situ measurements cannot be used for global-scale applications, however, because of the lack of complete spatial coverage. Therefore, we also investigated using SD estimates from CLSM as inputs to the updating procedure. Since surface meteorological forcing data are available over the entire globe (e.g., from the Numerical Weather Prediction systems), the novel approaches, if successful, could be used for the generation of a global SD retrieval product.

Table III reports average (over all three years and all stations) values of rmse, percentage error, and correlation coefficient (versus in situ WMO observations) for SD estimates from CLSM, REGR-CLIM, and the three novel approaches (REGR-DYN, REGR-AVG, and EM-TKK) when updated either with WMO observations or CLSM estimates once every seven days.

All novel approaches perform significantly better than the standard regression-based approach that uses climatological retrieval coefficients (REGR-CLIM). For reference, SD estimates from REGR-CLIM have an rmse of 50 cm, an average percentage error of 56.7%, and an average correlation coefficient of 0.60. As expected from the earlier discussion, the best results for rmse and relative error are obtained with the REGR-DYN algorithm, updated with WMO measurements, with an average rmse of 6 cm, an average percentage error of 5.3%, and an average correlation coefficient of 0.82. The second best approach is REGR-AVG, again when using WMO measurements, with an rmse of 8 cm, a percentage error of 7.3%, and a correlation of 0.66. In both cases, the SD retrievals clearly outperform the benchmark REGR-CLIM and the CLSM estimates. In terms of the correlation coefficient, however, CLSM estimates of SD outperform all other approaches. Presumably, the use of satellite brightness temperatures in all retrieval methods other than CLSM introduces high-frequency noise. Surface temperature fluctuations and spatial heterogeneity within the satellite footprint may contribute to spurious changes in the

Fig. 5. Relative percentage improvement in SD rmse over the Foster approach for (gray bars) REGR-DYN, (black bars) REGR-AVG, and (white bars) EM-TKK approaches, computed, for example, as 100 - \( \frac{\text{rmse}_{\text{REGR-CLIM}} - \text{rmse}_{\text{REGR-DYN}}}{\text{rmse}_{\text{REGR-DYN}}} \) averaged over the three years.
We have evaluated a variety of regression-based approaches and a method based on an EM model (TKK model) for the retrieval of SD from spaceborne microwave brightness temperature. In the regression-based approaches, the SD is proportional to the difference of the brightness temperature at two different frequencies. Even though we are focusing on SD, we evaluated the sensitivity of the physically based approach to snow density. Density is indeed used in deriving SWE from SD, and therefore, it is important to assess the sensitivity of the retrieval approaches to snow density. To this aim, we considered a retrieval scheme in which snow density is kept fixed at 0.3 g/cm³, instead of being derived from land model outputs. The value of 0.3 g/cm³ was selected because it was used in the original Chang algorithm [1]. Results (not reported here) show that the rmse obtained with a fixed snow density is lower than or comparable to the rmse obtained when using a variable snow density. We conclude that the error introduced either in modeling snow density by the CLSM (ranging between 0.15 to 0.5 g/cm³) or in accounting for density variations in the EM model can play a considerable role and needs to be further investigated. Note also that, although CLSM simulates three snow layers, the TKK EM model idealizes the snowpack as a single layer of scatterers. It is possible that using vertically averaged density values from the CLSM model might generate errors because the value of density to which microwave data are sensitive depends on the penetration depth, which, in turn, is a function of snow conditions.

The sensitivity of the novel approaches to the update interval ∆τ is investigated by considering several values for ∆τ. In particular, Figs. 7 and 8 show the rmse and percentage error when ∆τ is equal to 7, 14, 21, and 28 days, respectively, for the cases of the the following: 1) REGR-DYN; 2) REGR-AVG; and 3) EM-TKK approaches (all using ancillary SD observations from WMO at the specified update intervals). The figures show that the rmse almost doubles when ∆τ increases from 7 to 14 days and slightly increases when ∆τ exceeds 14 days. The percentage error also increases from values below or around 10% to values around 50%–60% when ∆τ increases from 7 to 14 days. In the remaining cases of ∆τ, the already high values of percentage error are not significantly affected by a further increase in ∆τ. The results suggest that ancillary estimates of SD should be ingested at least once every seven days to obtain the best performance.

IV. CONCLUSION AND RECOMMENDATIONS

The use of physical models in the EM-TKK retrieval algorithm makes it possible to test the sensitivity of retrieval performance to snow parameters. Even though we are focusing on SD, we evaluated the sensitivity of the physically based approach to snow density. Density is indeed used in deriving SWE from SD, and therefore, it is important to assess the sensitivity of the retrieval approaches to snow density. To this aim, we considered a retrieval scheme in which snow density is kept fixed at 0.3 g/cm³, instead of being derived from land model outputs. The value of 0.3 g/cm³ was selected because it was used in the original Chang algorithm [1]. Results (not reported here) show that the rmse obtained with a fixed snow density is lower than or comparable to the rmse obtained when using a variable snow density. We conclude that the error introduced either in modeling snow density by the CLSM (ranging between 0.15 to 0.5 g/cm³) or in accounting for density variations in the EM model can play a considerable role and needs to be further investigated. Note also that, although CLSM simulates three snow layers, the TKK EM model idealizes the snowpack as a single layer of scatterers. It is possible that using vertically averaged density values from the CLSM model might generate errors because the value of density to which microwave data are sensitive depends on the penetration depth, which, in turn, is a function of snow conditions.

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IV. CONCLUSION AND RECOMMENDATIONS

We have evaluated a variety of regression-based approaches and a method based on an EM model (TKK model) for the retrieval of SD from spaceborne microwave brightness temperature. In the regression-based approaches, the SD is proportional to the difference of the brightness temperature at two different
Fig. 7. RMSE for different values of $\Delta \tau$ in the case of (a) dynamic–WMO, (b) modified climatological–WMO, and (c) HUT–WMO approaches.

Results show that, not surprisingly, the novel regression-based approaches (REGR-DYN and REGR-AVG) using in situ ancillary SD observations yield the best results. These approaches use a subset of the in situ observations against which the performance is evaluated (excluding the observations that were used in the algorithm). SD estimates from REGR-DYN have an average rmse of 6 cm, an average percentage error of 5.3%, and an average correlation coefficient of 0.82. SD estimates from the REGR-AVG algorithm have an rmse of 8 cm, a percentage error of 7.3%, and a correlation of 0.66, suggesting the potential use of averaged coefficients to improve current satellite-based retrieval of SWE and SD. The EM-TKK approach with in situ ancillary SD observations produced an average rmse of 44 cm, a percentage error of 54.9%, and a correlation of 0.54. Besides SD, the EM-TKK approach uses CLSM snow density and temperature. The higher values of the rmse and percentage error of the EM-TKK approach (relative to REGR-DYN and REGR-AVG) are likely related to either errors in the land model, most likely errors in snow density modeling, or errors in the EM model formulation. All novel approaches perform significantly better than the standard regression-based approach that uses climatological retrieval coefficients (REGR-CLIM). For reference, SD estimates from REGR-CLIM have an average rmse of 50 cm, an average percentage error of 56.7%, and an average correlation coefficient of 0.60.

Even when driven with the SD estimates from the land surface model (CLSM), the regression-based novel approaches
still outperform the benchmark retrieval approach (REGR-CLIM). The rmse, percentage error, and correlation coefficient value (averaged over the three seasons) of the REGR-DYN algorithm driven with ancillary SD estimates from CLSM are 15 cm, 27.2%, and 0.75, respectively. For the REGR-AVG approach, the numbers are comparable, and similar numbers are again obtained for the EM-TKK method (with ancillary SD inputs from CLSM). It is worth noting that the EM-TKK performs better with the CLSM-derived ancillary SD input than with observations. Taken together, the results suggest that there may be a benefit in producing maps of seasonally averaged coefficients or even coefficients sensitive to shorter time scales at global scale.

It must also be noted that the novel retrieval approaches, when driven with (weekly) ancillary SD estimates from CLSM, do not outperform SD estimates from the land surface model alone (CLSM). The relatively high skill of SD estimates from land modeling (when compared to the satellite retrievals) may also be related to the relatively complex formulation of the snow physical model, particularly when compared to the very simple satellite retrieval algorithms. The information contribution of the SSM/I brightness temperatures to SD estimates is thus much less than that of the snow physical model and its associated surface meteorological forcing data, even when the latter is available only at very coarse scales. In this paper, the resolution of the surface meteorological data was 2° in latitude and 2.5° in longitude.

Finally, the sensitivity of the novel approaches to the update time was investigated. Results suggest that performances of all approaches deteriorate considerably when \( \Delta \tau \) increases from 7 to 14 days. A further increase in \( \Delta \tau \) did not significantly affect the results. The results suggest that the novel algorithms require ancillary SD estimates at least once every seven days.

A deficiency in comparing the results from the different methods is the lack of information on the uncertainty of the in situ WMO SD measurements. It is difficult to assess how representative WMO observations are of the conditions in the area observed by the microwave sensor, and this depends on many factors and pixel-inherent features. The number of samples required to accurately represent SD of a large field depends on the spatial variability of SD within the large field and accuracy requirements [31]. The number of samples \( n \) required to be 95% confident that the true mean is within plus and minus \( L \) of the estimated mean can be written as \( n = (1.96 \sigma/L)^2 \) [32]. For example, 16 point-scale measurements would be necessary within a grid cell to measure the mean SD to within \( L = 10 \) cm, given a natural variability \( \langle \sigma \rangle \) of 20 cm. Even though the number of stations used in this paper is higher than that used in most of the studies reported in the literature, only one station falls within each satellite data cell. This is a common problem even when considering a larger number of stations (e.g., [33]). Therefore, while more stations could be analyzed, the underlying scale mismatch remains between point-scale in situ observations and coarse-scale satellite and land model estimates. In any case, our findings do indicate a general improvement in rmse through the use of the novel algorithms, as well as an improvement in the correlation between retrieved and measured SDs.
Finally, the results strictly apply only to our particular choice of EM and land surface models. Nevertheless, the models used here are standard approaches for global-scale modeling, and presumably, the use of more complex models, if computationally affordable, should only enhance the skill of SD estimates derived with our novel approaches. Despite their limitations, our results indicate possible avenues for improving existing satellite SD or SWE data operational products. The combined use of a snow physical model and spaceborne microwave measurements offers an opportunity in improving the retrieval not only of SD but also of other parameters (not inherently related to snow physical properties, such as the effective grain size) containing information on the evolution of the snowpack. Still, the difficulty in developing more robust approaches for SD/SWE retrieval at global scale and assessing their uncertainty mirrors the challenge of understanding the suite of processes affecting the EM response of a snowpack and the large spatio-temporal dynamics of snow processes.

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