On the Relationship Between Stickiness in DMRT Theory and Physical Parameters of Snowpack: Theoretical Formulation and Experimental Validation With SNOWPACK Snow Model and X-Band SAR Data

Simone Pilia, Fabrizio Baroni, Alessandro Lapini, Simonetta Paloscia, Fellow, IEEE, Simone Pettinato, Member, IEEE, Emanuele Santi, Senior Member, IEEE, Paolo Pampaloni, Life Fellow, IEEE, Mauro Valt, and Fabiano Monti

Abstract—This study aims at relating the stickiness parameter (τ) of the dense media radiative transfer theory in quasi-crystalline approximation of Mie scattering of densely packed sticky spheres (DMRT-QMS), to the physical parameters of the layered snowpack. A relationship has been derived to express τ, which modulates the attractive contact force between ice spheres, as a function of ice volume fraction (φ) and coordination number (n). Since τ is not a measurable parameter, this is a step forward with respect to what is commonly made in the literature, where τ is assumed as an arbitrary parameter, generally ranging between 0.1 and 0.3, to fit simulated backscattering data with those measured. As a first validation, DMRT-QMS was integrated with the SNOWPACK model to simulate backscattering at X-band (9.6 GHz) driven by nivo-meteorological data acquired on a test area located in Monti Alti di Ornela, Italy. The simulations were compared with Synthetic Aperture Radar COSMO-SkyMed (CSK) satellite observations. The results show a significant agreement (R² = 0.68), although for a limited dataset of eight points in a unique winter season.

Index Terms—Backscattering, coordination number, COSMO-SkyMed (CSK), dense media radiative transfer theory in quasi-crystalline approximation of Mie scattering of densely packed sticky spheres (DMRT-QMS), ice volume fraction, SNOWPACK, snowpack, stickiness, sticky hard sphere (SHS), X-band.

I. INTRODUCTION

Snow on Earth influences natural processes, such as global radiation balance, hydrological cycle, and glacier evolution, and human activities, such as tourism and infrastructure [1], [2]. In fact, the World Meteorological Organization indicates snow as an essential terrestrial climate variable in meteorological and climate trends [3]. Snow has higher values of albedo with respect to natural bodies, therefore reflecting high quantity of solar energy and lowering the surface temperature [4]. Consequently, a decrease in snowpack extension and duration leads to an increase of local warming and accelerate the snow melting and water runoff processes, causing avalanches and floods, in particular flash floods. In fact, several studies predicted that in several mountains of the European Alps, snow water equivalent (SWE) may be reduced significantly by 2100 and that they may become totally snow-free during the summer [5], [6]. This could lead to a point of no return in the management of water resources, energy balance, and winter tourism. Snow is important also in permafrost behavior, due to its thermal insulation characteristics. As a result of all these aspects, continuous monitoring of snowpack can be crucial and represent an important tool for water resources management [7].

From the physical point of view, snow can be considered as a mixture of air, ice grains, and, if present, liquid water. Since the ice grains occupy between 10% and 40% of the snow volume, snow can be studied as a dense medium with a high fractional volume of scatterers. Consequently, variations in the scatterers inside snowpack cause significant changes of the electromagnetic response. In the microwave range, a variety of radiative transfer model of snowpack has been proposed, such as MEMLS [8] and HUT [9], to simulate the scattering and emission of a layered snowpack. Among them, dense media radiative transfer theory in quasi-crystalline approximation of Mie scattering of densely packed sticky spheres (DMRT-QMS) [10], [11], [12], [13] considering the interactions of the electromagnetic waves scattered from the particles.

It is important to parameterize snow microstructure in a radiative transfer model of snowpack in microwave frequencies. In DMRT-QMS snow representation, grains are considered spherical particles of ice. The particles’ distribution...
is determined by a free dimensionless parameter called stickiness ($\tau$). This parameter modulates an adhesive force that pushes grains to form clusters; the higher $\tau$, the lower the attraction force among grains.

Different approaches for setting $\tau$ were proposed in the literature. In several applications, $\tau$ was set to 0.1 with single-layer [14], [15] or multilayer [16] snowpack, both in the active and passive electromagnetic cases [17], [18]. In other studies, $\tau$ was varied between a minimum and a maximum value, looking for the best value fitting experimental data [19], [20], [21], [22], [23]. In [24] and [25], a pair of values ($\tau$, $\alpha$), where $\alpha$ is the snow grain radius, were optimized in order to obtain the lowest root-mean-square error (RMSE) compared to experimental data.

Other approaches were followed to seek an adequate value of parameter $\tau$. In [26], the optimal values of $\tau$ can vary significantly according to different situations and, given the large sensitivity of the scattering coefficient ($k_s$) on $\tau$ [27], these variations have a significant impact on the electromagnetic response of snow. Furthermore, Löwe and Picard [26] concluded that the pragmatic approach of using the same $\tau$-value for the entire snowpack is questionable.

Notwithstanding, most scientific works have been carried out using a constant value of $\tau = 0.1$. There is no real physical motivation for this setting, however, as it was explained in [28]. In fact, as described in [29], “the case of sticky spheres is for the very sticky case of $\tau = 0.1$ because, for this case, it was shown that the extinction coefficient has a frequency dependence that is consistent with experimental measurements of extinction coefficient of snow.” Various studies analyzed possible relations between $\tau$ and the backscattering ($\sigma^b$) or snow parameters without analytic relationships but only using some experimental dependences [26], [27]. For instance, in [27] and [30], a relation between $\tau$ and the scattering coefficient $k_s$, was analyzed. The lower $\tau$ the higher $k_s$ was observed for the same grain size. This is likely due to the tendency of grains to cluster among them in the sticky hard sphere (SHS) model. In [31], some tests were carried out setting $\tau = 0.1$ and 0.5 and using the nonsticky case in both DMRT-quasi-crystalline approximation (QCA) and Monte Carlo methods. It was deduced that, at the same frequency, a lower $\tau$ leads to higher scattering ($k_s$) and extinction coefficient ($k_e$), resulting in a greater amount of scattered signal.

Due to the difficulties in correctly estimating the parameter $\tau$, sometimes, it was set a nonsticky problem ($\tau \rightarrow +\infty$) [32] and the grains’ dimension was changed by a scaling factor, which can be considered a surrogate of $\tau$. In this assumption, the grain size is considered monodisperse. Then, an equivalent optical radius ($R_0$) was generally used to characterize the different shape of grains present in snow layers, instead of using the real single grain radius $a$. This parameter, which cannot be measured empirically [33], can be analytically expressed as a function of snow density ($\rho$) and specific surface area (SSA) with $R_0 = 3 \times 10^3/(\rho \cdot \text{SSA})$ [34]. A scaling factor was sometimes used in order to tune the grains’ dimension to obtain a reasonable agreement between experimental and theoretical data. This value is not constant and depends on the considered model and the snow characteristics. The same results can be obtained using grain size in alternative to the equivalent optical grain radius, using a new scaling factor. In [35], it was described an interesting relationship between the grain size scaling factor and $\tau$ as $\rho$ varies, in order to obtain the same simulation results.

The surface roughness of snow was deemed macroscopically negligible, especially at X-band (9.6 GHz), since previous studies showed a small sensitivity of $\sigma^0$ with respect to surface roughness at this frequency [36]. This assumption is no more valid if the testing area extends over an area of a few meters, so-called small-scale area; in [37], a snow albedo variation between 1% and 3% was observed in midwinter, reaching 10% during the melting season due to local snow roughness. Likewise, in [38], an experiment carried out on a dry snowpack of about 2 m demonstrated that surface roughness and soil moisture under the snowpack cannot be negligible in backscattering computation. The study was carried out at 5.3 and 13 GHz from bistatic radar. The soil surface roughness contribution under the snow was described analytically and experimentally in a recent study using the statistical S-matrix wave propagation in spectral domain (SSWaP-SD) approach [39].

This work was devoted at assessing the relationship between $\tau$ and the physical parameters of the snowpack, by combining DMRT-QMS and SNOWPACK model simulations, COSMO-SkyMed (CSK) X-band synthetic aperture radar (SAR) acquisitions, and in situ data. Here, SNOWPACK is one of the multilayer snow hydrology models developed by the Swiss Federal Institute for Snow and Avalanche Research, SLF, Davos, Switzerland, for details see Section II-D. First, the $\tau$ dependence on physical snow parameters is analyzed based on SNOWPACK simulations, and the optimized $\tau$ is estimated by fitting the backscattering simulated by coupling SNOWPACK and DMRT-QMS ($\sigma^b_{\text{QMS}}$) with the CSK measurements ($\sigma^0_{\text{CSK}}$). The analysis pointed out a significant correlation between $\tau$, $\phi$, and $n_c$. Then, the theoretical relationship between $\tau$, ice volume fraction ($\phi$), and coordination number ($n_c$) valid in the SHS model is established. The relationship, which can be considered the main result of this work, is validated in the Monti Alti di Ormella test area, in the eastern Italian Alps, based on SNOWPACK simulations and CSK measurements collected on the area. The input nivometeorological data for SNOWPACK were provided by the automatic weather station (AWS) installed in the area.

This article is organized as follows. Test area, models, and satellite data are described in Section II. The empirical relationship between optimized $\tau$ and physical parameters is analyzed in Section III. The theoretical relationship between $\tau$, $\phi$, and $n_c$ is established in Section IV and the preliminary validation is described and discussed in Section IV-A.

II. MATERIALS AND METHODS

A. Test Area

The Monti Alti di Ormella AWS [see Fig. 1(b)] is located at 2227 m a.s.l. on the northern side of the Paduan group, a chain of volcanic rocks immediately north of Marmolada mountains in Dolomites Alps. The average annual temperature of the site
is +1.8 °C, the precipitation is about 970 mm (data referred to the nearby Passo Pordoi station, 2142 m), the seasonal accumulation of fresh snow is about 600 cm (data collected at the nearby station of Lago of Cavia, 2100 m), and the average height of the snowpack on ground, from November to April, is usually 92 cm.

**B. CSK Data**

CSK is a civil and defense end-to-end Earth observation system managed by the Italian Space Agency (ASI). It consists of a constellation of four low-Earth-orbit midsize satellites, each equipped with a multimode high-resolution SAR operating at X-band, with a sun-synchronous orbit at a 620 km height. The sensor operates in different observation modes. The four radars are currently in orbit to observe the Earth’s surface in single or double polarization and in a relatively wide range of incident angles. These features allow the system for a multiple-imaging opportunity over the same area in a very short time, with a full constellation revisit time of 12 h, although not with the same repeat pass geometry.

For this work, ten CSK images (for the dates, see Table IV) acquired in the Stripmap Himage mode and horizontal–horizontal (HH) polarization (the only one available) were processed. The Lee sigma filter [40] was applied to reduce the speckle effect. Given the complex orography, a correction for the local incidence angle (LIA) was introduced by using a digital elevation model (DEM) of the test area. The LIA values were about 26.5° and 40° depending on the pass geometry. The output of this processing was the calibrated and geocoded $\sigma^0$ at a spatial resolution of 10 m × 10 m and the corresponding LIA. The data have been extracted and averaged on an area of 50 m × 50 m centered in the AWS [see Fig. 1(a)], corresponding to 5 × 5 pixels in the CSK images.

**C. Snow and Meteorological Parameters**

The meteorological parameters are measured by the AWS of Monti Alti di Ornella every hour. They are those of Table I except ISWR (see Table I). Some data are not fully complete due to temporal gaps. These gaps are usually around 2–3 h.

**D. SNOWPACK Model**

SNOWPACK is developed by WSL, Swiss Federal Institute for Snow and Avalanche Research, SLF, Davos, Switzerland. It works synergistically using various models developed in several sciences branches. These models are described mathematically in detail in several scientific works [41], [42], [43], [44].

SNOWPACK is a ground surface model that simulates the evolution of the snowpack driven by nivometric-meteorological data and can be used in a variety of scenarios. It describes the snow microstructure and the layering of the snowpack. It illustrates how the snowpack interacts with its surroundings by simulating the key physical processes (mass and energy exchange) that take place between atmosphere, snow, and soil. It is a 1-D model and is based on the finite-element method for the solution of the differential equations.

Meteorological data obtained from a nearby AWS are used as inputs. Some of these input parameters are mandatory, while others are optional in order to run more accurate simulations with some ancillary information as ground slope angle [°], and date and time combined in the ISO 8601 format. The slope angle was 0° with an approximation within 5° after considering the local DEM. Some ancillary information is also necessary and consists of canopies information (if present), snow and soil initial conditions, as well as snow albedo value.

If some input parameters are missing, new data can be generated. In one case, the goal is to create new parameters as functions of other variables. In another situation, a statistical temporal interpolation is used when few isolated data failures are present (e.g., a not working sensor or a meteorological parameter that was not measured) [46]. In our case, ISWR was not available and therefore was generated from TA (see Table I) and RH (see Table I) corrected by cloudiness, if available [47].

**E. DMRT-QMS Model**

In synergy with SNOWPACK, an electromagnetic model was used to simulate the snow backscattering values. Among
TABLE I

| Parameter Description                              | Symbol | Unit |
|---------------------------------------------------|--------|------|
| Air temperature at 8 m over the ground            | $T_A$  | K    |
| Relative humidity at 8 m over the ground          | $RH$  |      |
| Snow ground temperature                            | $TSG$ | cm   |
| Vectorial average of the wind velocity at 10 m over the ground | $VW$  | m/s  |
| Snow height                                       | $HS$  |      |
| Incoming long wave radiation                      | $ILWR$ | W/m² |
| Outgoing long wave radiation                       | $OLWR$ | W/m² |
| Incoming short wave radiation                      | $ISWR$ | W/m² |
| Wind direction                                     | $DW$  |      |
| Snow surface temperature                           | $TSS$ | K    |

In many theoretical models, DMRT-QMS was chosen because it has been extensively used to study remote sensing of seasonal and perennial snow [48] and needs few parameters, as shown in Table II.

In DMRT-QMS, the particles of snow are modeled as spherical bodies attracted to each other [13], [49]. This attractive force is modulated by $\tau$ [32]. Then, the snowpack is depicted as densely packed spheres dependent on $\tau$. DMRT-QMS includes several models [13], [27], [49], [50] with a solid theoretical background. It can simulate both active and passive cases [17], [28], [30], [36], [51].

The MATLAB implementation of DMRT-QMS used in this study is freely available in [52].

It is worth mentioning that DMRT-QMS is also included in the snow microwave radiative transfer (SMRT) thermal emission and backscatter model [35] for simulating the active–passive electromagnetic properties of layered snow.

Some experiments were already carried out in the past [53], [54] in order to analyze possible relationships between simulated backscatter $\sigma^0$ at different frequencies and snow parameters, assuming both single-layer [15], [55], [56], [57], [58], [59] and multilayer [57], [59], [60], [61], [62] snow hypotheses. Some of these experiments have been carried out at X-band. At this wavelength, the snow can be penetrated significantly by the electromagnetic wave if it is dry or, however, not so much wet [54], [63], [64].

In DMRT-QMS, the contribution to the backscattering of soil surface roughness and volumetric soil moisture (mv) under the snow, assuming that the latter is not frozen, can be considered by using the Oh model [65] and providing roughness information such as correlation length, root mean square (rms) of ground peaks, and mv. Using this model, the roughness influence on backscatter does not depend on correlation length but only on the standard deviation of roughness profile, rms. Snow surface roughness was not considered because a very smooth snowpack can be considered a good approximation of the real situation [37].

*F. SHS Model*

It is integrated in DMRT-QMS and describes the ice spheres’ distribution to which apply the electromagnetic scattering rules. The SHS model is defined by a classical fluid of monodisperse hard spheres. The ice spheres are subject to an adhesive contact interaction modulated by stickiness $\tau$ belonging to the interval $[0, +\infty]$: the lower $\tau$, the stronger the interaction. The effect of the interaction is creating clusters of spheres. The nonsticky case is recovered for $\tau \to +\infty$. The SHS model has the advantage of requiring few parameters.

The scheme in Fig. 2 provides a depiction of the interaction among experimental data, model parameters, models, and model simulations. The AWS data were processed by SNOWPACK. Some of the outputs were used as inputs for DMRT-QMS with the addition of $\tau$, mv, and rms. The simulated backscatter was compared to the measured one by CSK.

### III. Empirical Relationships Between Retrieved Stickiness and SNOWPACK Physical Parameters

Some of the nivo-meteorological parameters measured by the AWS were used as inputs to SNOWPACK to estimate the characteristics of the snowpack [66] in the winter season 2014–2015. The input data were measured every hour and the output data were generated every 15 min. The simulations of the snow type’s distribution inside the snowpack, the presence of liquid water content, SWE, and snow ground temperature (TSG) temporal evolution are shown in Fig. 3.

The winter season was characterized by some very mild days, i.e., 18/12/2014, 10/01/2015, and 11/02/2015 (DD/MM/YYYY, hereafter), in which the energy input in the snowpack was difficult to simulate, also considering the northern exposure of the site. This nivo-meteorological condition implies that small variations in the control parameters of the SNOWPACK model can determine the possibility of even different snowpack simulations. The one proposed in this article, although characterized by a snowpack a little colder than reality, finds a good match with the snowpack profiles carried out on the ground by the Veneto Regional Agency for Environmental Protection and Prevention (ARPAV), as shown in Fig. 3(d) for HS and SWE. The latter was measured in two different modes: “Stratigraphy SWE” was performed as explained in [67] and “Coring SWE” was performed as explained in [68]. About grain size, some papers have shown a good correspondence between SNOWPACK results and in situ observations, as, for example, in [69]. In our case, the comparison between the in situ measurements and the
Fig. 3. SNOWPACK simulation carried out for the test area during the winter season 2014–2015. The vertical lines in (a) and (d) correspond to the CSK satellite passes; for the dates, see Table IV. (a) Different snow types are characterized by different colors. PP: precipitation particle. DF: decomposing and fragmented precipitation particles. RG: rounded grain. FC: faceted crystal. DH: depth hoar. SH: surface hoar. MF: melt form. MFcr: melt forms melt-freeze crust. (b) Liquid water content. (c) TSG. (d) Comparison between SNOWPACK results and ARPA V measurements.

Simulations showed a good agreement for the rounded grains (RGs) and partly for the melt form (MF) grains, whereas there is a substantial difference in size in the faceted crystals (FCs) and depth hoar (DH) grains. SNOWPACK proposes for the size of grains the average size of the sphere that surrounds them in the prevailing average size, whereas the in situ observation method, for avalanche warning systems, observes the maximum size of the grains. These differences have also been illustrated in [70]. Therefore, the values of the grain sizes are not comparable, but, given the dimensions observed in the field, those of the model can be considered real and valid.

The backscattering simulated by DMRT-QMS ($\sigma_{0,SP/DMRT}$) also depends on the characteristics of the soil under the snowpack. To evaluate the sensitivity of $\sigma_{0,SP/DMRT}$ to $mv$, $rms$, and $\tau$, several simulations were carried out by varying them at the same time of the CSK passes. Furthermore, $\sigma_{0,SP/DMRT}$ with, and without, the presence of snow is shown in Table III.

We deduced that the soil under the snowpack was not frozen by the TSG values (see Fig. 3) and the knowledge of historical in situ measurements [71]. TSG ranged between 0 °C and −1 °C; only in a few cases, it dropped below −1 °C for very short time, probably due to measurement errors. This is an important assumption because, otherwise, the use of the Oh model would not give correct results. If the soil is completely frozen, i.e., there is no liquid water in it, it should be considered as dry, and therefore, the mv values should be assumed close to zero.

A strong variability of $\sigma_{0,SP/DMRT}$ as a function of $\tau$ can be observed in Fig. 4(a). This diagram demonstrates the importance of a careful choice of $\tau$. A significant variability of $\sigma_{0,SP/DMRT}$ versus $rms$ and $mv$ is also evident in
In order to investigate the relationships between $\tau$ and the physical parameters of the snowpack simulated by SNOWPACK, the optimized stickiness $\hat{\tau}$ was calculated. Specifically, $\hat{\tau}$ was obtained by minimizing the difference between $\sigma_{0}^{\text{SP/DMRT}}$ and $\sigma_{0}^{\text{CSK}}$. The results are shown in Table IV. The accuracy of $\sigma_{0}^{\text{SP/DMRT}}$ was set to $10^{-2}$ dB.

---

**Table IV**

| Date and time (UTC) | $\hat{\tau}$ |
|---------------------|--------------|
| 23/12/14 5:15 p.m.  | 0.117        |
| 04/01/15 4:45 a.m.  | 0.142        |
| 04/01/15 5:15 p.m.  | 0.153        |
| 05/02/15 4:45 a.m.  | 0.160        |
| 05/02/15 5:15 p.m.  | 0.158        |
| 21/02/15 5:15 p.m.  | 0.150        |
| 09/03/15 4:45 a.m.  | 0.158        |
| 09/03/15 5:15 p.m.  | 0.163        |
| 10/04/15 5:15 p.m.  | —            |
| 12/05/15 5:15 p.m.  | 0.179        |

---

The SNOWPACK simulations on 10/04/2015 and 12/05/2015 show that liquid water was present in the snowpack (see Fig. 5). In April, the snow melting started from the cover top, while in mid-May, the snow melting affected the whole snowpack. In this case, DMRT-QMS cannot predict reliable results. Due to this reason, these last two points were not considered in our simulations. Furthermore, on 10/04/2015, there is no $\hat{\tau}$ that reproduces $\sigma_{0}^{\text{CSK}}$, unless a lower $mv$ value is assumed.

Since the values of the snowpack parameters are not constant but depend on the number of layers, the following...
PILIA et al.: ON THE RELATIONSHIP BETWEEN STICKINESS IN DMRT THEORY AND PHYSICAL PARAMETERS 4305914

Fig. 6. (a) Optimized stickiness $\hat{\tau}$ versus weighted average ice volume fraction $\bar{\varsigma}$. $m v = 0.1 \text{cm}^3/\text{cm}^3$ and rms $= 0.5 \text{cm}$ were assumed. The regression line is $\hat{\tau} = 0.40\bar{\varsigma} + 0.054$ ($R^2 = 0.27$). (b) $\hat{\tau}$ versus weighted average coordination number $\bar{n}_c$. $\hat{\tau} = 0.054\bar{n}_c + 0.021$ is the regression line ($R^2 = 0.16$). (c) $\bar{\varsigma}$ versus $\bar{n}_c$.

weighted average was introduced:

$$\bar{\rho} = \frac{\sum_i l_i p_i}{\sum_i l_i}$$ (1)

where $i$ ranges from 1 to the total number of layers, $l_i$ is the thickness of the $i$th layer, $p$ stands for a generic parameter, and $p_i$ is the $p$-value on the $i$th layer.

In general, a weak correlation between $\hat{\tau}$ and the snow parameters was observed, except for density $\rho$, ice volume fraction $\phi$, and coordination number $n_c$ (see Fig. 6). We remark that $n_c$ is defined as the average number of bonds per snow grain. Since $\rho$ and $\phi$ are proportional quantities with good approximation, especially not in the presence of liquid water, only $\phi$ was considered. To simulate $n_c$, SNOWPACK implements the following function of $\rho$:

$$n_c(\rho) = \begin{cases} 0.0175\rho, & \rho \leq 100 \\ N_0 - N_1\rho + N_2\rho^2 - N_3\rho^3 + N_4\rho^4, & 100 < \rho < 670 \\ 10.5, & \rho \geq 670 \end{cases}$$ (2)

where $N_0 = 1.4153$, $N_1 = 7.5580 \times 10^{-5}$, $N_2 = 5.1495 \times 10^{-5}$, $N_3 = 1.7345 \times 10^{-7}$, and $N_4 = 1.8082 \times 10^{-10}$. This explains what can be observed in Fig. 6 where the correlation of $\hat{\tau}$ exists for both $\phi$ and $n_c$ and in Fig. 7 where $n_c$ is just a function of $\varsigma$.

IV. GENERAL RESULT: ANALYTIC RELATIONSHIP BETWEEN STICKINESS, ICE VOLUME FRACTION, AND COORDINATION NUMBER IN SHS MODEL

In this section, we derive an analytic relationship among $\varsigma$, $\phi$, and $n_c$ holding in the SHS model. In general, the problem of knowing the position of the scatterers to which apply the scattering rules of DMRT has been addressed in two ways. In the first, which we do not adopt in this work, polydisperse scatterers are considered, i.e., the spheres’ diameters are randomly distributed according to a specific probability distribution. In the second, according to the SHS model, monodisperse scatterers are considered. The scatterers are subject to the action of an attractive contact interaction modulated by $\tau$. The effect of $\tau$ is the tendency of the scatterers to form clusters, the larger they are, the lower $\tau$ is. The case of random distribution is recovered for $\tau \to +\infty$.

In order to compute the scattering from many particles, the classical theory assumes independent scattering and the scattering intensity is set equal to the sum of scattering intensities from each particle [72], [73]. The classical approach ignores the coherent wave interaction among the particles. To consider the collective scattering effects, QCA can be used
in the Dyson equation for the coherent field, and the correlated ladder approximation is used for the Bethe–Salpeter equation for the incoherent field [51], [49]. The QCA and correlated ladder analytic approximations lead to the DMRT theory.

The pair distribution functions of the Percus–Yevick (PY) approximation [49], [74], [75] of the SHS model are used to describe the correlations of particle positions. An advantage of the sticky particle model is that it requires few parameters. The SHS model is defined by a classical fluid of monodisperse hard spheres with diameter $D$ interacting via a pair of central potential

$$V(r) = \begin{cases} \frac{12r\rho}{D + \delta}, & r \leq D + \delta \\ 0, & r > D + \delta \end{cases}$$

where $k_B$ is Boltzmann’s constant and $T$ is the temperature. The potential consists in a hard-core repulsion, which prevents particles from overlap at distances smaller than the sphere diameter $D$, and a square well attraction, which tends to a contact adhesion force in the limit $\delta \to 0$. The strength of the adhesion is proportional to the inverse of $\tau$.

Thermodynamic and configurational properties of SHS can be investigated within the PY approximation, giving rise to closed-form expressions in terms of $\phi$ and $\tau$. Despite well-known shortcomings [76], we show an overview of the PY phase diagram in the $(\phi, \tau)$-plane in Fig. 8. The SHS system exhibits rich microstructural variability above the coexistence line $\tau_{\text{coex}}(\phi)$ (the continuous line in Fig. 8)

$$\tau_{\text{coex}}(\phi) = \frac{1}{12} \frac{14\phi^2 - 4\phi - 1}{2\phi^2 - \phi - 1}$$

where the attractive forces lead to a percolation transition in the high-stickiness region. The region under the coexistence black line has no physical meaning. In particular, the maximum of $\tau_{\text{coex}}(\phi)$ results to be $(2 - \sqrt{2})/6 \simeq 0.0976$ [75]. The percolation transition is defined by $\tau_{\text{perc}}(\phi)$ (the dashed line in Fig. 8)

$$\tau_{\text{perc}}(\phi) = \frac{1}{12} \frac{19\phi^2 - 2\phi + 1}{(1 - \phi)^2}$$

The region above $\tau_{\text{perc}}(\phi)$ is defined as the nonpercolating phase, while the region under $\tau_{\text{perc}}(\phi)$ is defined as the percolating phase. In the percolating phase, particle clusters with average size tending to infinity (system-spanning clusters) exist. This is reflected by the behavior of the average $n_c$ of SHS, which is well described by PY, and is the average number of spheres that is in contact with a given one. For given $\phi$ and $\phi$, $n_c$ is given by [75]

$$n_c = 2\phi \lambda(\phi, \tau)$$

where $\lambda(\phi, \tau)$ is the smallest solution of the quadratic equation

$$\frac{\phi^2}{12\lambda^2} - \left(\tau + \frac{\phi}{1 - \phi}\right)\lambda + \frac{1 + \phi/2}{(1 - \phi)^2} = 0$$

under the additional condition [26], [77]

$$\lambda(\phi, \tau) < \frac{(1 + 2\phi)}{\phi(1 - \phi)}.$$

A contour plot of the average $n_c$ is added in Fig. 8. This indicates that the locus of the percolation points $\tau_{\text{perc}}(\phi)$ in the $(\phi, \tau)$-plane, originally identified with the divergence of the mean cluster size, corresponds to $n_c = 2$, as a mean-field condition of minimum connectivity.

Starting from (6) and (7), we can derive $\phi$ as a function of $n_c$ and $\phi$

$$\tau(\phi, n_c) = -\frac{\phi}{1 - \phi} + \frac{2\phi(1 + \phi/2)}{n_c(1 - \phi)^2} + \frac{n_c}{24}$$

with the condition

$$n_c < \frac{4(3\phi(1 + \phi/2))^{1/2}}{(1 - \phi)}$$

see Fig. 7 for a plot. The last condition is a consequence of the fact that only the smallest solution of (7) is acceptable, and it is obtained by setting equal to zero the partial derivative with respect to $n_c$ in (9).

A. Validation With SNOWPACK Simulations

Following the suggestion given by Lüöe and Picard [26], we can identify $n_c$ and $\phi$ of the SHS model with those derived from SNOWPACK simulations. In this way, due to (9), $\tau$ is no longer a free parameter of DMRT-QMS, but a consequence of the snowpack microstructure simulated by SNOWPACK. This model uses four primary independent parameters to describe the microstructure of the snowpack: sphericity, dendricity, grain size, and bond size [42]. All other microstructure parameters of SNOWPACK can be derived from other parameters. In particular, the coordination number $n_c$ is derived from snow density $\rho$ by means of (2) [42]. This is the average number of bonds per grain and it determines the interconnectivity of the ice matrix.

Before considering the pair $(\phi, n_c)$ generated by SNOWPACK as valid arguments for determining $\phi$, it is necessary

![Fig. 8. Phase diagram in the $(\phi, \tau)$-plane of the SHS model in the PY approximation. The continuous line is (4) and the dashed one is (5). The colored lines are the level curves at constant $n_c$. Circles and crosses correspond to the layers of two SNOWPACK simulations in different periods of the year. The triangles are $f$ of Section III, as a function of $\phi$ already shown in Fig. 6.](image-url)
to verify that \( n_c \) is actually the smaller of the two values associated with the same \( \tau \)-value. This is equivalent to fulfill (10). Another condition to be satisfied is (8) with \( \lambda \) replaced by (6). Fig. 7 shows that both conditions are fulfilled for two examples of SNOWPACK data.

The identification between \( n_c \) generated by SNOWPACK with that one of SHS does not guarantee that the snowpack characteristics simulated by SHS are the same as those simulated by SNOWPACK. Indeed, there are two substantial differences. First, the attractive interaction between ice grains in SHS is modeled as an attractive contact force, whereas in SNOWPACK, it is given by an additional ice structure (bond) that bonds two grains. The latter is more similar to what occurs in physical reality. The presence of bonds alters the scattering properties of grain aggregates. The second difference is that scatterers are spheres in SHS, whereas SNOWPACK uses two dimensionless parameters (dendricity and sphericity) to model the deviance from the spherical shape.

This opens to the general problem of relating the equivalent spheres diameter \( D \), to be used as input for DMRT-QMS, to the actual grain dimensions. In our simulations, we used the grain size \( G \) and the equivalent optical diameter \( D_0 \) [69]. Our results showed a significant decrease of \( \sigma_0^0 \) when we used \( D_0 \) instead of \( G \) because the former is on average smaller than the latter. This agrees with the behavior of DMRT-QMS according to which the \( \sigma_0^0 \) increases, while \( D \) increases [60]. Our simulations highlighted that the use of \( D_0 \) led to worse results with respect to the grain size \( G \).

Table V shows an example of input data for DMRT-QMS with \( \phi \) calculated according to (9). We note that \( \tau \) mainly ranges between 0.1 and 0.3 in agreement with the values commonly used in the literature and tends to increase as the snow depth increases due to the increase of snow density \( \rho \).

In Fig. 8, two datasets corresponding to the layers of two SNOWPACK simulations in different periods of the year have been inserted. Note that the oldest snow layers have higher \( n_c \)’s. This is because, according to (2), \( n_c \) is a function of snow density \( \rho \) alone, which is, in turn, a function of \( \phi \) with good approximation. It can be observed in Fig. 7, where two different SNOWPACK simulations have the same \( n_c \) values related to the same \( \phi \)-values. Since \( \phi \) increases as the snow ages, \( n_c \) is an increasing monotone function of \( \phi \), from which the conclusion follows. Almost all points fall into the percolating phase where the clusters have infinite size. This is consistent with the fact that the snowpack layers are self-supporting against gravity. Nevertheless, some points of the most recent part of the snowfall are outside the percolating phase. This may be because the demarcation line of the percolating phase is derived in the PY approximation, which involves some deviations with respect to the real case [77], [78]. In [26], a similar result was obtained when almost all the data fall in the percolating phase.

In Section III, we showed that, using the Oh model integrated in DMRT-QMS, \( \text{rms} \), and in particular \( mv \), has a strong influence on \( \sigma_{0/DMRT}^0 \) [79]. Therefore, we assumed a reasonable value of \( \text{rms} \) equal to 0.5 cm and carried out a series of simulations for \( mv \) ranging from 0.01 to 0.3 cm³/cm³. We excluded greater \( mv \) values because they are not reasonable for the soil type of the test area. The simulations with the best agreement with \( \sigma_{CSK}^0 \) were for \( mv = 0.1–0.15 \text{ cm}^3/\text{cm}^3 \).

| \( lt \) | \( \rho \) | \( \phi \) | \( T \) | \( G \) | \( \tau(\phi, n_c) \) | \( (n_c) \) |
|---|---|---|---|---|---|---|
| cm | g/cm³ | | K | cm | | |
| 0.35 | 0.0414 | 0.05 | 245.67 | 0.136 | 0.139 | 0.7 |
| 0.39 | 0.0603 | 0.07 | 246.83 | 0.128 | 0.123 | 1.1 |
| 0.65 | 0.1070 | 0.12 | 248.22 | 0.096 | 0.121 | 1.8 |
| 0.45 | 0.0726 | 0.08 | 249.77 | 0.137 | 0.118 | 1.3 |
| 1.23 | 0.0804 | 0.09 | 252.11 | 0.124 | 0.122 | 1.4 |
| 2.40 | 0.0963 | 0.11 | 256.07 | 0.112 | 0.120 | 1.7 |
| 1.56 | 0.1153 | 0.13 | 259.63 | 0.101 | 0.122 | 1.9 |
| 1.38 | 0.1274 | 0.14 | 261.70 | 0.118 | 0.130 | 1.9 |
| 0.41 | 0.2485 | 0.27 | 262.72 | 0.085 | 0.181 | 2.6 |
| 1.85 | 0.1304 | 0.14 | 263.67 | 0.134 | 0.130 | 1.9 |
| 1.30 | 0.2002 | 0.22 | 264.84 | 0.101 | 0.152 | 2.4 |
| 1.42 | 0.1453 | 0.16 | 265.56 | 0.125 | 0.138 | 2.0 |
| 1.73 | 0.1659 | 0.18 | 266.20 | 0.120 | 0.137 | 2.2 |
| 2.40 | 0.1671 | 0.18 | 266.81 | 0.119 | 0.137 | 2.2 |
| 1.52 | 0.1708 | 0.19 | 267.26 | 0.126 | 0.145 | 2.2 |
| 2.38 | 0.1816 | 0.20 | 267.61 | 0.123 | 0.145 | 2.3 |
| 2.43 | 0.2022 | 0.22 | 268.00 | 0.111 | 0.152 | 2.4 |
| 0.93 | 0.2003 | 0.22 | 268.26 | 0.123 | 0.152 | 2.4 |
| 1.86 | 0.2050 | 0.22 | 268.49 | 0.128 | 0.152 | 2.4 |
| 1.89 | 0.2201 | 0.24 | 268.80 | 0.117 | 0.161 | 2.5 |
| 0.62 | 0.2466 | 0.27 | 269.02 | 0.120 | 0.181 | 2.6 |
| 0.42 | 0.2012 | 0.22 | 269.12 | 0.171 | 0.152 | 2.4 |
| 0.37 | 0.3091 | 0.34 | 269.19 | 0.116 | 0.254 | 2.8 |
| 0.55 | 0.2013 | 0.22 | 269.27 | 0.212 | 0.152 | 2.4 |
| 0.69 | 0.2858 | 0.31 | 269.36 | 0.177 | 0.205 | 2.8 |
| 0.78 | 0.2062 | 0.22 | 269.47 | 0.213 | 0.152 | 2.4 |
| 1.95 | 0.2111 | 0.23 | 269.73 | 0.197 | 0.162 | 2.4 |
| 2.57 | 0.2227 | 0.25 | 270.17 | 0.172 | 0.171 | 2.5 |
| 2.26 | 0.2423 | 0.26 | 270.67 | 0.153 | 0.170 | 2.6 |
| 1.72 | 0.2501 | 0.27 | 271.07 | 0.152 | 0.181 | 2.6 |
| 1.20 | 0.2569 | 0.28 | 271.37 | 0.150 | 0.193 | 2.6 |
| 2.16 | 0.2685 | 0.29 | 271.70 | 0.144 | 0.192 | 2.7 |
| 1.27 | 0.2820 | 0.31 | 272.04 | 0.134 | 0.220 | 2.7 |
| 1.84 | 0.2891 | 0.32 | 272.33 | 0.135 | 0.219 | 2.8 |
| 1.02 | 0.3469 | 0.38 | 272.59 | 0.122 | 0.296 | 3.0 |
| 0.95 | 0.3142 | 0.34 | 272.76 | 0.127 | 0.235 | 2.9 |
Fig. 9. (a) $n_c$ as a function of snow height HS for two SNOWPACK simulations. (b) $\phi$ as a function of snow height HS for two SNOWPACK simulations. (c) $\phi$ as a function of snow height HS for two SNOWPACK simulations.

The result is reported in Fig. 10(a). The experimental curve falls within those simulated for $mv$ values between 0.1 and 0.15 cm$^3$/cm$^3$. The RMSE between simulations and experimental values results to be 0.79 and 0.72 dB for $mv = 0.1$ and 0.15 cm$^3$/cm$^3$, respectively. These values are reasonable for the soil type of the test area. Fig. 10(b) shows the scatter plot of CSK acquisitions versus simulated $\sigma_0$ for $mv = 0.125$ cm$^3$/cm$^3$. The regression line is $\sigma_0^{\text{SP/DMRT}} = 0.68\sigma_0^{\text{CSK}} - 3.3$ ($R^2 = 0.68$).

Using the SHS model, we found a significant relation between $\tau$ and two parameters, which can be generated by the SNOWPACK model, namely, the ice volume fraction $\varsigma$ and the coordination number $n_c$. The latter, in turn, is a function of $\phi$ in SNOWPACK. It follows that $\tau$ is mainly a function of $\phi$ only (Fig. 8). This seems to be in contrast with results achieved by de Gregorio et al. [21] who found a more disperse relation between $\tau$ and $\phi$ to the point that the authors declare that $\phi$ cannot depend mainly on $\phi$ alone. However, our values of $\tau$ derived from SNOWPACK as a function of $\phi$ fit well the average value of data determined experimentally by those authors.

Leppänen et al. [69] compared the predictions of SNOWPACK with measurements in a taiga snowpack. The results show that SNOWPACK tends, in some cases, to underestimate the grain size $G$ by a factor ranging between 1 and 2. Considering that the larger the diameter of the scatterers $D$ of DMRT-QMS, the higher the simulated backscattering, and the results of Section III on the dependence of backscattering on $mv$, we can deduce that an underestimation of $G$ can lead to an overestimation of the $mv$ values assumed in this work. However, we cannot verify whether the results in [69] can also be applied to the snow type of our test area located in Monti Alti di Ornella [80].

V. CONCLUSION

In this study, the stickiness parameter $\tau$ in the SHS model is related to the physical properties of snowpack by establishing an analytical relationship between $\tau$, the ice volume fraction $\phi$, and the coordination number $n_c$. This relationship led
to have a different $\tau$ value for each snowpack layer. This is an important step in improving the simulation accuracy of microwave observations of snowpack, by overcoming the limits of the common and physically not based practice of imposing constant $\tau$ values for all the snowpack layers. The relationship was limited but well validated by comparing the backscattering values simulated using SNOWPACK integrated with DMRT-QMS, $\sigma^0_{\text{DMRT}}$, with the X-band SAR measurements, $\sigma^0_{\text{CSK}}$ on a test area located in North Italy. The obtained determination coefficient was encouraging ($R^2 = 0.68$), even though optimizing some unmeasured parameters such as $\text{m}$ and $\text{rms}$.

This validation has to be considered a promising first step toward a general validation that could involve different sensors and techniques.

Beside SNOWPACK, other equivalent snow models or experimental measurements can be used to simulate the physical properties of snowpack. Furthermore, given the capability of DMRT-QMS to simulate the microwave emission, the relationship could also be validated against radiometric data by using higher frequencies, such as the Ku- and Ka-bands, which are more suitable for snowpack monitoring applications. This could be achieved by using not only satellite acquisitions that are limited by the coarse ground resolution but also aircraft or ground installations [71].

The possibility of simulating the backscattering with sufficient accuracy is relevant for SWE retrieval applications from SAR or radiometric data since it allows generating spatially distributed datasets that could be used for training algorithms based on machine learning, as those proposed in [22], [58], and [81]. This approach would be especially appealing when insufficient satellite data are available. It should be noticed, however, that generating spatially distributed datasets of simulated backscattering from punctual acquisitions at some AWSs would imply using 3-D models combined with SNOWPACK, which would be very demanding in terms of computational resources.

ACKNOWLEDGMENT

The authors would like to thank Prof. Michael Lehning and Dr. Edoardo Raparelli for their useful discussions and suggestions.

REFERENCES

[1] M. Beniston, F. Keller, B. Koffi, and S. Goyette, “Estimates of snow accumulation and volume in the Swiss Alps under changing climatic conditions,” Theor. Appl. Climatol., vol. 76, nos. 3–4, pp. 125–140, Dec. 2003.
[2] R. L. Armstrong and E. Brun, Eds., Snow and Climate: Physical Processes, Surface Energy Exchange and Modeling. Cambridge, U.K.: Cambridge Univ. Press, 2008.
[3] W. M. O. Goss, Systematic Observation Requirements for Satellite-BASED Data Products for Climate, document 154, 2011.
[4] J. Dozier, R. O. Green, A. W. Nolin, and T. H. Painter, “Interpretation of snow properties from imaging spectrometry,” Remote Sens. Environ., vol. 113, pp. S25–S37, Sep. 2009.
[5] E. Schmucki, C. Marty, C. Fierz, and M. Lehning, “Simulations of 21st century snow response to climate change in Switzerland from a set of RCMs,” Int. J. Climatol., vol. 35, no. 11, pp. 3262–3273, Sep. 2015.
[6] J. Magnusson, T. Jonas, I. López-Moreno, and M. Lehning, “Snow cover response to climate change in a high Alpine and middle-glacierized basin in Switzerland,” Hydrol. Res., vol. 41, nos. 3–4, pp. 230–240, Jun. 2010.
[7] Y.-L. S. Tsai, A. Dietz, N. Oppelt, and C. Kuenzer, “Remote sensing of snow cover using spaceborne SAR: A review,” Remote Sens., vol. 11, no. 12, pp. 1456, Jun. 2019.
[8] A. Wiesmann and C. Mätzler, “Microwave emission model of layered snowpacks,” Remote Sens. Envir., vol. 70, pp. 307–316, Dec. 1999.
[9] J. T. Pulliainen, J. Grandell, and M. T. Hallikainen, “HUT snow emission model and its applicability to snow water equivalent retrieval,” IEEE Trans. Geosci. Remote Sens., vol. 37, no. 3, pp. 1378–1390, May 1999.
[10] V. Twersky, “Coherent electromagnetic waves in pair-correlated random distributions of aligned scatterers,” J. Math. Phys., vol. 19, no. 1, pp. 215–230, 1978.
[11] L. Tsang and J. A. Kong, “Effective propagation constants for coherent electromagnetic wave propagation in media embedded with dielectric layers,” J. Appl. Phys., vol. 55, no. 11, pp. 7162–7173, Nov. 1982.
[12] L. Tsang, J. A. Kong, and R. Shin, Theory of Microwave Remote Sensing. New York, NY, USA: Wiley, 1985.
[13] L. Tsang, J. Pan, D. Liang, Z. Li, D. W. Cline, and Y. Tan, “Modeling active microwave remote sensing of snow using dense media radiative transfer (DMRT) theory with multiple-scattering effects,” IEEE Trans. Geosci. Remote Sens., vol. 45, no. 4, pp. 990–1004, Mar. 2007.
[14] C.-T. Chen, J. Guo, L. Tsang, A. T. C. Chang, and K.-H. Din, “Analytical and numerical methods for the scattering by dense media,” Int. J. Remote Sens., vol. 26, no. 11, pp. 2337–2361, Apr. 2005.
[15] J. Shi and J. Dozier, “Estimation of snow water equivalent using SIR-C/X-SAR data,” Remote Sens. Environ., vol. 61, no. 12, pp. 157–167, Jun. 1998.
[16] Y. T. Pulliainen, J. Grandell, and M. T. Hallikainen, “HUT snow emission model and its applicability to snow water equivalent retrieval,” IEEE Trans. Geosci. Remote Sens., vol. 37, no. 3, pp. 1378–1390, May 1999.
[17] L. Tsang and J. A. Kong, “Effective propagation constants for coherent electromagnetic wave propagation in media embedded with dielectric layers,” J. Appl. Phys., vol. 55, no. 11, pp. 7162–7173, Nov. 1982.
[18] L. Tsang, J. Kong, and R. Shin, Theory of Microwave Remote Sensing. New York, NY, USA: Wiley, 1985.
[19] C. Mätzler, “Improved born approximation for scattering by dense media,” J. Appl. Phys., vol. 83, no. 11, pp. 6111–6117, Jun. 1998.
[20] J. Shi and J. Dozier, “Estimation of snow water equivalence using SIR-C/X-SAR. II. Inferring snow 697 depth and particle size,” IEEE Trans. Geosci. Remote Sens., vol. 38, no. 6, pp. 2475–2488, 2000.
[21] L. Grigorioupolos et al., “SWE retrieval by exploiting COSMO-SkyMed X-band SAR imagery and ground data through a machine learning approach,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 12, pp. 8245–8257, Dec. 2015.
[22] E. Santi et al., “SWE retrieval in Alpine areas with high-resolution COSMO-SkyMed X-band SAR data using artificial neural networks and support vector regression techniques,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 12, pp. 8245–8257, Dec. 2015.
[23] C. Xiong, “Model investigation of time-series ground based SAR and microwave radiometer experimental data of snow-covered soil,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 9, pp. 5247–5268, Sep. 2015.
[24] D. Tapete et al., “Development of algorithms for the estimation of hydrological parameters combining co-skymed and sentinel time series with in situ measurements,” in Proc. Medit. Middle-East Geosci. Remote Sens. Symp. (MERSYS), Mar. 2020, pp. 53–56.
[25] C. Xiong et al., “Model investigation of time-series ground based SAR and microwave radiometer experimental data of snow-covered soil,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 9, pp. 5247–5268, Sep. 2015.
[26] H. Löwe and G. Picard, “Microwave scattering coefficient of snow in a granular medium,” IEEE Trans. Geosci. Remote Sens., vol. 37, no. 3, pp. 1378–1390, May 1999.
[27] L. Tsang, J. A. Kong, and R. Shin, “Effective propagation constants for coherent electromagnetic wave propagation in media embedded with dielectric layers,” J. Appl. Phys., vol. 55, no. 11, pp. 7162–7173, Nov. 1982.
[28] L. Tsang, J. A. Kong, and R. Shin, “Modeling active microwave remote sensing of snow using dense media radiative transfer (DMRT) theory with multiple-scattering effects,” IEEE Trans. Geosci. Remote Sens., vol. 45, no. 4, pp. 990–1004, Mar. 2007.
Scattering of Electromagnetic Waves:

- L. Brucker, G. Picard, and M. Fily, “Snow grain-size profiles deduced from microwave snow emissivities in Antarctica,” *IEEE Trans. Geosci. Remote Sens.*, vol. 35, no. 3, pp. 731–749, May/Jun. 2000.

- S. Tan and L. Tsang, *Available Researc Resources*. [Online]. Available: http://web.eecs.umich.edu/~leutsang/Available%20Resources.html

- W. H. Stiles and F. T. Ulaby, “The active and passive microwave response to snow parameters,” *J. Geophys. Res.*, Oceans, vol. 85, no. C2, pp. 1037–1044, 1980.

- F. T. Ulaby and W. H. Stiles, “The active and passive microwave response to snow parameters: 2. Water equivalent of dry snow,” *J. Geophys. Res.*, Oceans, vol. 85, no. C2, pp. 1045–1049, 1980.

- S. Palosci, S. Pettinato, E. Santi, and M. Valt, “COSMO-SkyMed image investigation of snow features in Alpine environment,” *Sensors*, vol. 17, no. 1, p. 84, Jan. 2017.

- S. Palosci, S. Pettinato, E. Santi, and E. Palchetti, “Sentinel-1 and COSMO-SkyMed image comparison on Alpine environment for snow feature investigation,” in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Jul. 2016, pp. 7053–7056.

- M. Brogioni et al., “The effects of multilayering structure of snow on backscattering from snow covered soils,” in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, Jul. 2013, pp. 1198–1201.

- S. Pettinato, E. Santi, M. Brogioni, S. Palosci, E. Palchetti, and C. Xiong, “The potential of COSMO-SkyMed SAR images in monitoring snow cover characteristics,” *IEEE Geosci. Remote Sens. Lett.*, vol. 10, no. 1, pp. 9–13, Jan. 2013.

- S. Palosci, P. Pampaloni, E. Santi, Pettinato X. Chuan, and M. Brogioni, “Multi-layer model simulations of backscattering and emission from snow covered soils,” in *Proc. XXXIth URSI Gen. Assem. Scientific Symp. (URSI GASS)*, Aug. 2014, pp. 1–4.

- M. Brogioni, C. Xiong, P. Pampaloni, S. Pettinato, S. Palosci, and J. Shi, “Model analysis and experimental investigations of X-band backscattering sensitivity to snowpack characteristics,” in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, Jul. 2012, pp. 1254–1257.

- M. Brogioni et al., “Model investigations of backscatter for snow profiles related to avalanche risk,” in *Proc. IEEE Geosci. Remote Sens. Symp.*, Jul. 2014, pp. 2415–2418.

- M. Brogioni et al., “Sensitivity analysis of microwave backscattering and emission to snow water equivalent: Synergy of dual sensor observations,” in *Proc. XXXIth URSI Gen. Assem. Sensors Conf. Abstr.*. 2017, pp. 7053–7056.

- F. T. Ulaby, W. H. Stiles, and M. Abdelrazik, “Snowcover influence on backscattering from terrain,” *IEEE Trans. Geosci. Remote Sens.*, vols. GE-22, no. 2, pp. 126–133, Mar. 1984.

- T. Nagler and H. Rott, “Retrieval of wet snow by means of multitemporal SAR data,” *IEEE Trans. Geosci. Remote Sens.*, vol. 38, no. 2, pp. 754–765, Mar. 2000.

- Y. Oh, K. Saraband, and F. T. Ulaby, “An empirical model and an inversion technique for radar scattering from bare soil surfaces,” *IEEE Trans. Geosci. Remote Sens.*, vol. 30, no. 2, pp. 370–381, Mar. 1992.

- C. Fierz et al., “The international classification for seasonal snow on the ground,” *IHP-VII Tech. Documents Hydrol.*, Tech. Rep. 83, IACS Contribution no. 1, UNESCO-IHP, Paris, France, 2009.

- A. Cagnati, “Strumenti di misura e metodi di osservazione nivometeorologici: Manuale per i rilevatori dei servizi di previsione valanghe,” AINEVA, Trento, Italy, 2003.

- A. Berni and E. Giancanelli, “La campagna di rilievi nivometrici effettuata dall’ENEL nel periodo febbraio-giugno 1966 energia elettrica,” Tech. Rep. 9, 1966, pp. 533–542.

- L. Leppänen, A. Kontu, J. Vehviläinen, J. Lemmettyinen, and J. Pulli- ainen, “Comparison of traditional and optical grain-size field measure- ments with SNOWPACK simulations in a Taiga snowpack,” *J. Glaciol.*, vol. 64, no. 225, pp. 151–162, 2018.

- M. Valt, F. Monti, P. Cianfarani, and D. Moro, “Physical properties of snow cover in Alps: Insight from the Davos area (Switzerland) and Veneto-Friuli Venezia Giulia regions (Italy),” in *Proc. EGU Gen. Assem. Conf. Abstr.*, Apr. 2012, p. 12471.

- E. Santi et al., “Analysis of microwave emission and related indices over snow using experimental data and a multilayer electromagnetic model,” *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 4, pp. 2097–2110, Apr. 2017.

- S. Chandrasekhar, *Radiative Transfer*. Chelmsford, MA, USA: Courier Corporation, 2013.

- A. Ishimaru, *Wave Propagation and Scattering in Random Media*. New York, NY, USA: Academic, 1978.
Simone Pilia received the M.Sc. degree in telecommunication engineering from the University of Florence, Florence, Italy, in 2016. He is currently pursuing the Ph.D. degree with the University of Basilicata, Potenza, Italy.

In 2018, he has been with the National Research Council (CNR), Florence. His research interests are primarily focused on signal and image processing, particularly in the field of remote sensing and biomedical imaging, acoustics, and active noise control.

Fabiolo Baroni received the M.S. and Ph.D. degrees in physics from the University of Florence, Florence, Italy, in 2007, respectively.

In the past, he was active in quantum mechanics, statistical mechanics, and teaching. He is currently with the Microwave Remote Sensing Group, Institute of Applied Physics “Nello Carrara” (IFAC), National Research Council (CNR), Florence. His research interests are in modeling of snowpack, soil, and vegetation and application to retrieval of physical parameters by active and passive microwave remote sensing.

Dr. Baroni received the Giampietro Puppi Award for his doctoral thesis in physics and astrophysics in 2009. He is a referee for several international journals.

Alessandro Lapini received the M.S. degree (cum laude) in telecommunications engineering and the Ph.D. degree in computer science, systems and telecommunications from the University of Florence, Florence, Italy, in 2010 and 2014, respectively.

Since 2014, he has been a Research Assistant with the University of Florence, where he has been initially with the Department of Information Engineering and then with the Department of Industrial Engineering since 2015. From 2016 to 2018, he was a Research Fellow with the Department of Industrial Engineering, University of Florence. Since 2019, he has been with the Microwave Remote Sensing Group, Institute of Applied Physics Nello Carrara (IFAC), Consiglio Nazionale delle Ricerche (CNR), Florence. His research interests are mainly focused on signal and image processing, particularly in the field of remote sensing and biomedical imaging, acoustics, and active noise control.

Simone Palosco (Fellow, IEEE) has been with the National Research Council (CNR), Florence, Italy, since 1984, where she worked in agrometeorology and microwave remote sensing studies concerning natural surfaces. Her research currently concerns the study of microwave emission and scattering of soil (bare and snow covered) and vegetation. Since 2001, after winning a national competition, she has been a Senior Scientist at the Institute for Applied Physics–National Research Council (IFAC-CNR), Florence, where she has been the Research Director since 2010. Since 2004, she has been a scientific responsible for the Microwave Remote Sensing Group, IFAC-CNR, and the research line “Microwave Remote Sensing of natural surfaces.” in the EO Project of CNR. She was a Principal Investigator and a Co-Principal Investigator of many national and international projects (ASI, EC, ESA, and JAXA). Since 1996, she has been a Principal Investigator in the JAXA Science Team of AQUA/AMS-R and GCOM/AMS-R for algorithms’ development of soil moisture and vegetation biomass retrieval. She is a member of the SMAP JPL/NASA Science Team. She had a temporary teaching contract of “Microwave Remote Sensing Applications” for the Professional Master “Geomatics and Natural Resources Evaluation” at the “Istituto Agronomico per l’Oltremare” of the Ministry of Foreign Affairs in Florence from 1994 to 2010. Her H-index is 34 (SCOPUS) with over 3910 citations. She is the author and the coauthor of more than 100 works published on international journals and books, of more than 200 articles published on proceedings of international meetings.

Ms. Palosco was a member of organizing and steering committees of international meetings (Specialist Meeting on Microwave Radiometry and IGARSS). She is also a member of the permanent Steering Committee of MicroRad Meeting. She is a fellow of the Union Radio-Scientifique Internationale (URSI) and the Electromagnetics Academy, Cambridge, MA, USA. She was the General Co-Chair of the MicroRad 1999 and 2008 and URSI-F 2010 Meetings organized in Florence. She is an Associate Editor of the International Journal of Remote Sensing, IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, and European Journal of Remote Sensing. She was nominated the Vice-Chair of URSI Commission F in 2006; she was the chair from 2011 to 2014. Since 2013, she has been a member of the Evaluator Committee for Fellow, IEEE/GRSS candidates, where she has been the Chair since 2020. She is included in the list of Top 2% Scientists by Stanford University. In 2010, she was nominated the Head of Research at the National Research Council.

Simone Pettinato (Member, IEEE) was born in Florence, Italy, in 1972. He received the M.S. degree in telecommunications engineering from the University of Florence, Florence, in 2002, and the Ph.D. degree in “methods and technologies for environmental monitoring” from the University of Basilicata, Potenza, Italy, in 2007.

In the end of 2013, he has got a permanent position. Since 2003, he worked at the Microwave Remote Sensing Group, Institute for Applied Physics–National Research Council (IFAC-CNR), as a Scientist. The objective of his research consists mainly in the investigation of the natural surfaces by means of active and passive microwave sensors in order to retrieve information of geophysical parameters related to the hydrological cycle (soil moisture, snow, and vegetation). He participated, as a co-investigator, in different national and international scientific projects funded by the European Community (FLOODMAN and ENVISN ow) and European Space Agency (GRASS, LEIMON, CORE-H2O, DOMEX-2, DOMEX-3, GPS-SIDS, and GNSS-BIO). In 2009, 2010, and 2012, he was involved in three Antarctic expeditions in order to allow the execution of the DOMEX-2, DOMEX-3, and GPS-SIDS projects, respectively. He was involved in Italian Space Agency (ASI) projects for floods forecast (PROSA: Satellite Observation Products for Meteorological Alert), COSMO-SkyMed applications (Hydro-Cosmo: the retrieval and monitoring of Land Hydrological parameters for Risk and Water Resources Management), Cap and Trade Assessment by Remote Sensing Investigation (CATARSI), and SIASGE (Definition of products at X and X bands for SIASGE support). Actually, he is a co-investigator in a regional project (Hydrocontroller) for the monitoring of hydrologic risk and in an international project for sustainable water management for the economic growth and sustainability.
of the Mediterranean region (OPTIMED-WATER) in the frame of FP7 of European Union. Actually, he is also involved in the ASI project METEMW that aims to develop innovative algorithms for the retrieval of hydrological parameters and CRIOSAR for hydrological hazards. He is the author or the coauthor of 100 papers published on international peer-reviewed journals and conference proceedings.

Emanuele Santi (Senior Member, IEEE) received the M.S. degree in electronic engineering from the University of Florence, Florence, Italy, in 1997, and the Ph.D. degree in Earth's remote sensing techniques from the University of Basilicata, Potenza, Italy, in 2005.

Since 1998, he has been a Researcher with the Microwave Remote Sensing Group, Institute of Applied Physics, National Research Council, Florence. He was and is currently involved in many national and international projects funded by the Italian Space Agency (ASI), the European Community (EC), the European Space Agency (ESA), and the Japanese Aerospace Exploration Agency (JAXA), acting as a Team Leader, a WP Leader, and a Co-Investigator. He has authored or coauthored 168 articles and has published on ISI journals and books and conference proceedings (source Scopus). His research interests include the development and validation of models and inversion algorithms based on machine learning for estimating the geophysical parameters of soil, sea, snow, and vegetation from microwave emission and scattering.

Dr. Santi is a member of the “Centro di Telerilevamento a Microonde” (Microwave Remote Sensing Center), the Vice-Chair of the IEEE GRSS Chapter CNI-29, and the Conference Chair of the SPIE Europe Remote Sensing conference RS-106. In 2020, he served as the Chair for the 16th Symposium on Microwave Radiometry MicroRad. In 2018, he received the IEEE GRSS J-STARS Prize Paper Award for the best paper published in the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing in 2017.

Paolo Pampaloni (Life Fellow, IEEE) was the Head (retired) of Research of the Institute of Applied Physics–Italian National Research Council (IFAC-CNR), Florence, Italy. His research deals with active and passive microwave remote sensing of land surfaces (from the mid-1970s). From 1966 to 1979, he was involved in radio astronomy and solar physics with the Arcetri Astrophysical Observatory, Florence. Since 1980, he has been with CNR. From 1983 to 1996, he was a Consultant of the European Space Agency (ESA) for microwave radiometry as a member of various working and Advisory Groups (LAWG, MIMR, and EOAC). He was an X-SAR Project Scientist and the Deputy Team Leader of the XSAR/SIR-C (NASA, ASI, and DLR) project and a coordinator of numerous national and international research programs.

Mr. Pampaloni was the Italian Official Member of the Union Radio-Scientifique Internationale (URSI) Commission F from 2005 to 2013, the President of the Microwave Remote Sensing Center from 1993 to 2011, the Chairperson of the IEEE Central and South Italy Section from 2002 to 2005 and the unified IEEE Section in 2006, and a member of the IEEE Major Award Committee from 2008 to 2017. He was a recipient of the 2004 IEEE GRSS Distinguished Achievements Award, the 2019 IEEE GRSS Outstanding Service Award, and the 2020 CcTeM-IEEE GRSS Honorary Award. He has served as the General Chairperson for the 2nd and 6th MICRO-RAD (Specialist Meetings on Microwave Radiometry and Remote Sensing, Florence, in 1988 and 1999) and the 15th International Symposium on Geoscience and Remote Sensing (IGARSS) in 1995. He is an Associate Editor of the IEEE Transactions on Geoscience and Remote Sensing.

Mauro Valt was born in Falcade, Italy, in 1963. He holds the Diploma of Chief Mining Technician and specialization in the use of explosives and in geotechnics.

Since 1987, he has been working at the Avalanche Center of Arabba (ARPV Environmental Agency), Arabba, Italy. From 1987 to 1992, he was involved in the study of avalanche dynamics. At the same time, he began training in the field of avalanche forecasting. He is currently a Senior Avalanche Forecaster at the Arabba Avalanche Center and AINEVA, Trento, Italy. In 1996, it was the first participation in the scientific expedition to Antarctica in the context of the PNRA, followed by the 1998 expedition again in the field of international projects related to remote sensing. In 2005, the third scientific expedition was on the Antarctic plateau for the study of mega snow dunes. In Artico, at the Italian base Dirigibile Italia, Ny-Ålesund (Svalbard), Italy, he continued his scientific research in the field of snowpack classification with multispectral signatures, participating in the creation of the SISpec and Snowcrystals.it database. Since 2004, he has been involved in the operational development of the SNOWPACK model of the snowpack with the SLF, Davos, Switzerland, and AlpSolut s.r.l., Livigno, Italy. Since 2015, he has been dealing with snow water equivalent of estimating water resources for large basins (PO, Piave, Brenta) through the use of MODIS images and ground monitoring networks. He has been a lecturer in snow, avalanche, and snow slope stability courses in the courses of AINEVA, of the Italian Alpine Club and since 2002, professional training courses for ski instructors and mountain guides. Since 2000, he has been a member of the Editorial Board of “Neve e Valanghe” magazine. From 2005 to 2013, he was the representative of Italy in the international meetings of EAWS. He is the author or the coauthor of 50 articles published in peer-reviewed international journals, 150 articles in Italian trade journals, and over 700 citations.

Fabiano Monti received the master’s degree in environmental science from Insubria University, Varese, Italy, in 2008, with a thesis on SNOWPACK MODEL, and the Ph.D. degree in environmental science with a thesis on snow stability with the snow cover model SNOWPACK from the WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland, in 2014.

He has been part of two Antarctic expeditions: the Institute of Applied Physics–Italian National Research Council (IFAC-CNR), Florence, Italy, and ESA projects. He has been the Organizer and a Lecturer at Insubria University for the “Course on security in the winter mountain environment” since 2016. He is the CEO and a Charter Member of AlpSolut s.r.l., Livigno, Italy, a startup company operating in snow and hydropower sector.