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Improvement of microwave emissivity parameterization of frozen Arctic soils using roughness measurements derived from photogrammetry

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4 **Improvement of microwave emissivity parameterization of frozen Arctic soils**
5 **using roughness measurements derived from photogrammetry**
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8 J. Meloche ^{ab*}, A. Royer ^{ab}, A. Langlois ^{ab}, N. Rutter ^c, and V. Sasseville ^{ab}
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10
11
12 *^aDépartement de Géomatique Appliquée, Université de Sherbrooke, Sherbrooke, Canada*

13 *^bCentre d'études nordiques, Québec, Canada*

14 *^cDepartment of Geography and Environmental Sciences, Northumbria University, Newcastle*
15 *upon Tyne, UK*
16

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21
22 *Corresponding author: Julien Meloche, julien.meloche@usherbrooke.ca
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Abstract

Soil emissivity of Arctic regions is a key parameter for assessing surface properties from microwave brightness temperature (T_b) measurements. Particularly in winter, frozen soil permittivity and roughness are two poorly characterized unknowns that must be considered. Here, we show that after removing snow, the 3D soil roughness can be accurately inferred from in-situ photogrammetry using Structure from Motion (SfM). We focus on using SfM techniques to provide accurate roughness measurements and improve emissivity models parametrization of frozen arctic soil for microwave applications. Validation was performed from ground-based radiometric measurements at 19 and 37 GHz using three different soil emission models: the Wegmüller and Mätzler (1999) model (Weg99), the Wang and Choudhury (1981) model (QNH), and a geometrical optics model (Geo Optics). Measured and simulated brightness temperatures over different tundra and rock sites in the Canadian High Arctic show that Weg99, parametrized with SfM-based roughness and optimized permittivity (ϵ), yielded a RMSE of 3.1 K ($R^2 = 0.71$) for all frequencies and polarizations. Our SfM based approach allowed us to measure roughness with 0.1 mm accuracy at 55 locations of different land cover type using a digital camera and metal plates of known dimensions.

Keywords: surface roughness; microwave remote sensing; frozen Arctic soil; SfM photogrammetry

1. Introduction

Most research on natural soil reflectivity focuses on soil moisture retrievals at L-band (reviewed by Wigneron et al., 2017) or higher frequencies (Njoku et al., 2003). Soil permittivity values are key parameters that allows retrieval of soil moisture using soil emissivity models such as those developed by Zhang et al. (2010) and Mironov et al. (2017). However, active and passive microwave dielectric sensitivity to soil moisture is strongly reduced by surface roughness that must be known or derived in the retrieval processing. During Arctic winter, surface parametrization is more difficult due to the presence of snow cover, and significant lingering uncertainties remain, specifically regarding required soil characteristics that are challenging to quantify in the Arctic.

Large scale monitoring of snow properties in the Canadian Arctic using both active and passive microwave has been conducted in the past (reviewed by Saberi et al., 2020 and Shi et al., 2016) using measurement inversions based on radiative transfer models (Picard et al. 2013; Royer et al. 2017). These models must consider contributions from both snow and ground to simulate total backscatter or emission, particularly over northern areas with shallow snow cover (Roy et al. 2013; Derksen et al. 2014; B. Montpetit et al. 2018). Several soil microwave models integrated into the Snow Microwave Radiative Transfer Model (SMRT) (Ghislain Picard, Sandells, and Löwe 2018) allow simulation of soil emissivity, but many uncertainties are associated with the permittivity and roughness of frozen ground (Montpetit et al. 2018). Models used for forward retrievals of soil parameters with satellite remote sensing are usually semi-empirical for the purposes of simplicity. For instance, the Soil Moisture Active and Passive mission (SMAP) retrieval algorithms use the QNH model, named for its parameters, Q, N, and H, to simulate surface reflectivity following Wang et al. (1983) and Wang and Choudhury (1981). More recently, the parameters in the

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3 QNH model were optimized by different studies (Wigneron et al. 2001; Lawrence et al.
4 2013; Montpetit et al. 2015). Of particular relevance, the roughness parameters needed for
5 the QNH model consist of effective parameters that were found to have smaller values than
6 the actual physical measurements (Tsang and Newton, 1982; Ulaby et al., 1982). Another
7 semi-empirical model (Wegmüller and Mätzler, 1999), developed for a wider range of
8 applications (1-100 GHz), was derived from the QNH model using a simpler Kirchhoff
9 approximation (Mo, Schumge, and Wang 1987). Montpetit et al. (2018) parametrized
10 permittivity and roughness using the Wegmüller and Mätzler (1999) semi-empirical model
11 by optimizing surface-based radiometer multi-angle measurements of frozen soils in a
12 subarctic environment in northern Québec, Canada, for higher frequencies (19 and 37 GHz)
13 needed for snow application. Theoretical permittivity can also be calculated using the two
14 models stated earlier: (Zhang et al., 2010 and Mironov et al., 2017).

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31 Surface reflectivity can be solved analytically using the Kirchhoff approximation
32 or the Small Perturbation Method (SPM) with its associated bi-static coefficient. However,
33 this requires a more detailed knowledge of the surface to determine which regime of
34 scattering is involved (e.g. rough surface with geometrical optics). Other analytical
35 solutions like Integral Equation Model (IEM or AIEM) (Fung, 1994) can be used to
36 simulate surface reflectivity. Finally, numerical methods solving Maxwell's equation using
37 the Finite Element Method (FEM) or Method of Moments (MoM) (Lawrence et al. 2011;
38 Tsang et al. 2013, 2017) can be used to calculate the scattered electric field from a rough
39 surface, but they are more complex and computationally intensive than the models
40 described above.
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3 Another issue in soil microwave modelling is how to measure the soil roughness and link
4 it to microwave sensitivity. The most common parameter used to describe roughness is
5 height standard deviation (σ_H), but it can also be described by horizontal correlation length
6 (l_c). Soil roughness parameters can be measured directly using a needle profiler (Trudel et
7 al. 2010) or indirectly with terrestrial laser approaches (Martinez-Agirre et al. 2019; Turner
8 et al. 2014; Zheng et al. 2014), which allow more complex 3D analysis. Recent studies
9 using Structure-from-Motion (SfM), a technique that couples photogrammetry with
10 artificial intelligence, have shown promising results in producing 3D models for various
11 geoscience applications (Bühler et al. 2017; Westoby et al. 2012; Lejot et al. 2007). This
12 method was recently tested over agricultural fields to provide roughness parameters
13 (Gharechelou, Tateishi, and Johnson 2018; Martinez-Agirre et al. 2019; Snapir, Hobbs, and
14 Waine 2014). Martinez-Agirre et al. (2019) showed that SfM photogrammetry can
15 accurately provide roughness measurement comparable to high precision terrestrial laser
16 scanner for agricultural fields. Also, it is common to see successful comparison of SfM
17 with LIDAR or laser scanner used as reference in various applications outside roughness
18 estimates (Nolan, Larsen, and Sturm 2015; Westoby et al. 2012; Murtiyoso et al.
19 2017). While the capabilities to measure “geometric roughness” was validated by these
20 experiments, we focused more on “radiometric” roughness. We hypothesize here that SfM
21 can deliver accurate roughness parameters to improve microwave radiative transfer
22 models, which is the central focus of this paper.

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49 This paper presents a comparison of three soil emissivity models using roughness
50 parameters derived from SfM: QNH, Wegmüller and Mätzler (1999), hereafter noted
51 Weg99, and the analytical solution of geometrical optics, hereafter noted Geo Optics. We
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3 first present an approach to measure surface roughness using photogrammetry (SfM) and
4 then evaluate the use of SfM roughness measurements with different permittivity values
5 and three radiative transfer models of frozen soil. Model results are then validated against
6 in-situ radiometric measurements over different land cover types in Cambridge Bay, NT,
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14 15 16 **2. Background**

17 The emissivity of a surface (e_p) can be calculated using reciprocity and energy
18 conservation concepts (Eq. 1). The brightness temperature of soil (T_{Bsoil}) (Eq. 2) is defined
19 by the product of e_p and the effective temperature of the surface (T_{soil}^{eff}). For T_{Bsoil} , the
20 downward atmospheric contribution ($T_{Batmo\downarrow}$) is taken into account for ground
21 observations only following:
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$$29 \quad e_p = 1 - \Gamma_p \quad \#(1)$$

$$30 \quad T_{Bsoil}(f,p) = (1 - \Gamma_{f,p})T_{soil}^{eff} + \Gamma_{f,p}T_{Batmo\downarrow} \quad \#(2)$$

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32 where the p and f indices are respectively for polarization and frequency and Γ_p the
33 reflectivity.
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38 **2.1. Permittivity model of Zhang et al. (2010)**

39 Emissivity calculation requires known permittivity or dielectric constant of the
40 medium. It can be calculated, for example, using the semi-empirical equation from Dobson
41 et al. (1985). Zhang et al. (2003;2010) adapted Dobson et al. (1985) equation for frozen
42 soil by adding ice fraction in soil with a transition between liquid to solid water as a
43 function of temperature. The inputs needed are frequency, soil moisture, temperature, dry
44 bulk density and soil composition described by percentage of clay, silt and sand.
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2.2. QNH model

The QNH reflectivity model is a semi-empirical model (Wang et al., 1983; Wang and Choudhury, 1981) that uses Fresnel reflectivity with a polarization ratio and a roughness attenuation factor to simulate the reflectivity of random rough surface Γ_p (Eq. 3-4) for both horizontal and vertical polarizations,

$$\Gamma_H = [(1 - Q_R)\Gamma_H^{Fresnel}(\theta, \epsilon) + Q_R\Gamma_V^{Fresnel}(\theta, \epsilon)]e^{-H_R \cos^{N_H}(\theta)} \#(3)$$

$$\Gamma_V = [(1 - Q_R)\Gamma_V^{Fresnel}(\theta, \epsilon) + Q_R\Gamma_H^{Fresnel}(\theta, \epsilon)]e^{-H_R \cos^{N_V}(\theta)} \#(4)$$

Multiple studies have optimized the original values for the parameters of the QNH model, Q_R , N_H , N_V and H_R , and provided different formulations of H_R (J.-P. Wigneron, Laguerre, and Kerr 2001; Lawrence et al. 2013). For instance, Montpetit et al. (2015) found values of Q_R , N_H , N_V , H_R for the frequency range 1-90 GHz based on PORTOS-93 dataset (J.-P. Wigneron, Laguerre, and Kerr 2001) because QNH is mostly used for L-band (1.4GHz) and not for higher frequencies (19 and 37 GHz). However, Montpetit et al. (2015) parameters were not used because high biases for H polarization in our simulations led us to use the value proposed by Wang et al. (1983). Therefore, we used the following: $N_H = N_V = 0$ and $Q_R = 0$ was changed to $Q_R = 0.9$ with the roughness parameter H_R from Eq. 5 proposed by (Choudhury et al. 1979) where k is the wavenumber, provided best fit with our observations.

$$H_R = (2k\sigma_H)^2 \#(5)$$

2.3. Weg99 model

The Weg99 model (Wegmüller and Mätzler, 1999) is semi-empirical and used over a wider range of applications in the 1-100 GHz frequency range. It mixes the functionality

and simplicity of the QNH model with a theoretical background from a parametrization based on Kirchhoff's approximation (Mo and Schmutge, 1987). Weg99 also uses Fresnel reflectivity of smooth surfaces and a polarization ratio (β_f) but a different roughness attenuation function based on the wavenumber (k), height standard deviation (σ_H) and incident angle (θ). Surface reflectivity in Weg99 is described by (Eq. 6) where the vertically polarized reflectivity is a function of the horizontal reflectivity (Eq. 7).

$$\Gamma_H = \Gamma_H^{Fresnel}(\theta, \varepsilon) e^{-(k\sigma_H)^{\sqrt{0.1\cos\theta}}} \quad \#(6)$$

$$\Gamma_V = \Gamma_H (\cos\theta)^{\beta_f} \quad \#(7)$$

Wegmüller and Mätzler (1999) originally proposed a single parameter $\beta_f = 0.655$ however, we followed the approach of Montpetit et al. (2018) who suggested using a β_f per frequency based on observations at 11, 19 and 37 GHz (see Table 3 for values). Eq. 6 and Eq. 7 are valid for $\theta \leq 60^\circ$, which is the case for this study.

2.4. Geo Optics solution

The analytical solution of emissivity at polarization q of a random rough surface can be solved by integrating the bi-static coefficient γ_{pq} over the upper hemisphere (Eq.8) (Tsang, Kong, and Ding 2000), where the bi-static coefficient under the Geo Optics solution is described by Eq. (9) (Kong and Tsang, 2001). Geo optics solution is characterized by a very rough surface yielding the coherent scattering component to vanish. The rough surface is described using a Gaussian autocorrelation function with a mean square slope ($m = 2\sigma_H^2/l_c^2$) where σ_H and correlation length l_c can both be measured by SfM photogrammetry.

$$e_q(\theta_i, \phi_i) = 1 - \Gamma_q = 1 - \frac{1}{4\pi} \sum_{p=p,q} \int_0^{\frac{\pi}{2}} d\theta \sin\theta \int_0^{2\pi} d\phi \gamma_{pq}(\theta, \phi, \theta_i, \phi_i) \#(8)$$

$$\gamma_{pq}(\hat{k}_i, \hat{k}_s) = \frac{|k_d|^4}{\cos\theta_i |\hat{k}_i \times \hat{k}_s|^4 k_{dz}^4 2m} e^{-\frac{k_{dx}^2 + k_{dy}^2}{2k_{dz}^2 m}} f_{pq} \#(9)$$

A more detailed description of f_{pq} , \hat{k}_i , \hat{k}_s , $k_d, k_{dx}, k_{dy}, k_{dz}$ can be found in Kong and Tsang (2001) where the k vectors relate to the geometry (i: incident wave, s: scattered wave, d: vector difference between incident and scattered wave) and f_{pq} , also a geometric term, is dependent of \hat{k}_i , \hat{k}_s and the Fresnel coefficients of both polarization p and q which depend on the permittivity of the medium.

The conditions for Geo Optics are $k\sigma_H \gg 1$ and $kl_c \gg 1$. The IEM model is not used in this paper since the model conditions, $k\sigma_H < 3$ and $k^2\sigma_H l_c < \sqrt{\varepsilon}$ where k is the wavenumber and ε the permittivity, are not met (Table 1). The Advanced Integral Equation Model (AIEM) is a modified version of IEM that was developed to increase the validity range of IEM (Chen et al. 2003). They showed that for a rough case ($k\sigma = 2.576$ and $kl_c = 8.356$), the emissivity modeled by AIEM and Geo optics converged to the Method of Moment (used as reference) while IEM still showed significant bias. Considering that in our case, the normalized roughness ($k\sigma = 6.4$ and $kl_c = 111.4$ at 19GHz) is higher, we decided that only the analytical solution of geometrical optics for rough surfaces will be used.

Table 1. Summary of conditions needed for Geo Optics and IEM. Permittivity from Montpetit et al. (2018) was used for calculation.

Frequency (GHz)	Geo Optics		IEM	
	$k\sigma_H \gg 1$	$kl_c \gg 1$	$k\sigma_H < 3$	$k^2\sigma_H l_c < \sqrt{\epsilon}$
19	6.4	111.4	6.4	709.4 > 1.73
37	12.4	217.0	12.4	2690.3 > 1.73

3. Data and methods

3.1. Study site

Field measurements were collected during spring 2019 in Cambridge Bay, Nunavut, Canada ($69^\circ 13' 05.66''$ N/ $104^\circ 56' 47.90''$ W). The study site is located inside Greiner Lake watershed in the arctic tundra spanning across various ecotypes (Figure 1).

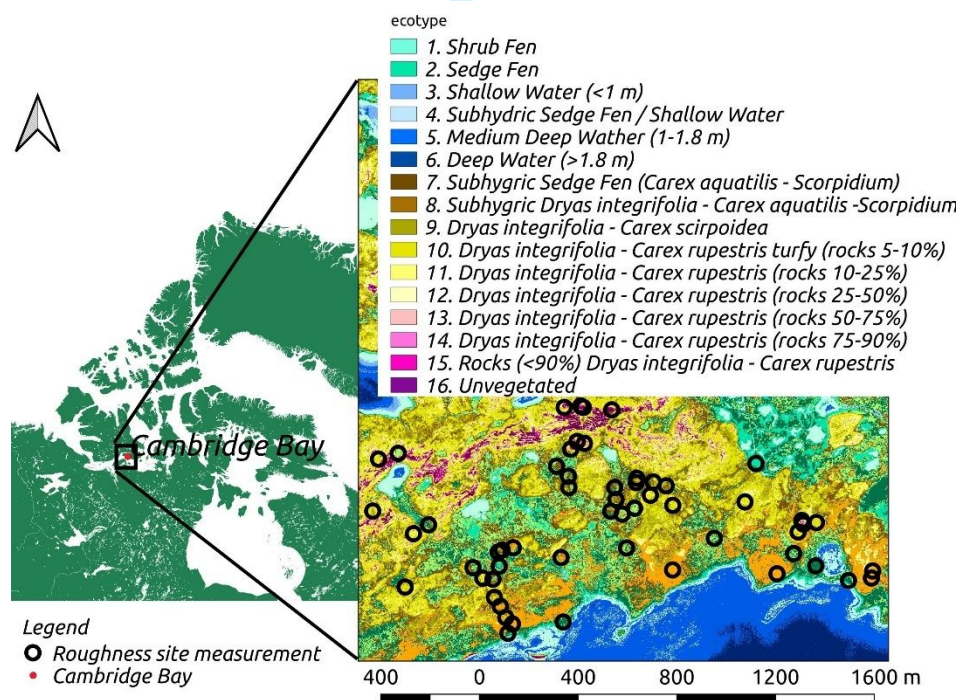


Figure 1. Study site in Greiner Lake watershed, Nunavut, Canada.

The ecotypes described in Figure 1 were determined using an ecosystem mapping approach (Ponomarenko et al. 2019) based on an ecosystem classification (McLennan et

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3 al. 2018). In total, 55 sites were used to create 3D point clouds for roughness
4 measurements. These sites were classified in four different ecosystem types derived from
5 the 15 classes displayed in Figure 1: 1) sedge/shrub, classes 1,2 and 7; 2) organic soil (rock
6 < 10%), classes 8, 9 and 10; 3) organic soil (rock < 75%), classes 11, 12 and 13; 4) rock >
7 75%, classes 14 and 15. It should be noted that for the sedge/shrub type, the roughness
8 measurements were not of actual shrubs but rather of the area surrounding small vegetation.
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19 **3.2. Data**

20 **3.2.1. Roughness measurements**

21 At each site, after sweeping the snow off without damaging the surface,
22 approximately 30 downward facing photographs of the ground were taken using a standard
23 compact camera (Canon Powershot Elph 160 5.0 mm). All sites were batch processed with
24 Agisoft Metashape software using the same parameters for point cloud filtering
25 (Normalized criterion for filtering: Reprojection error = 0.2, Reconstruction Uncertainty =
26 10.0, Projection Accuracy = 10.0), producing 3D models yielding approximately 2-4
27 million points each (Figure 2). Once a 3D point cloud is produced from 2D pictures, there
28 is no scale to real world dimension. The relative distance between every point is accurate
29 but lacks an absolute relationship. Known dimensions are then used to scale the 3D model.
30 Using the software, we can define on the images the plate's length so that these known
31 dimensions can be used for optimization. Three metal plates of 50 cm each were used to
32 scale the model where two were used for optimization of camera and position parameters
33 and a third for validation yielding a precision of 0.1 mm by estimating the length of the
34 third plates using optimization from first two plates. The plates need to be within as many
35 pictures as possible without the radiometers field of view (FOV) becoming obstructed
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(after a radiometer measurement) so roughness can be measured. Light condition is also critical when doing photogrammetry, shadowing of half the surface could add uncertainty in reconstruction so constant illumination condition for every surface produced is desirable. Shadowing can be avoided while taking pictures by not going full circle around the sites, $\frac{3}{4}$ of a circle is sufficient for SfM to reconstruct the scene. This technique is fast and efficient in the field, producing reliable and precise measurements with only a standard digital camera and metal plates of known dimensions. These plates allow 3D models to be scaled without using a differential GPS unit with ground control points (GCP), e.g. Martinez-Agirre et al. (2019). The area covered for each 3D model ranged approximately from 0.25 to 0.6 m². Dimensions can be seen for one site on Figure 2.

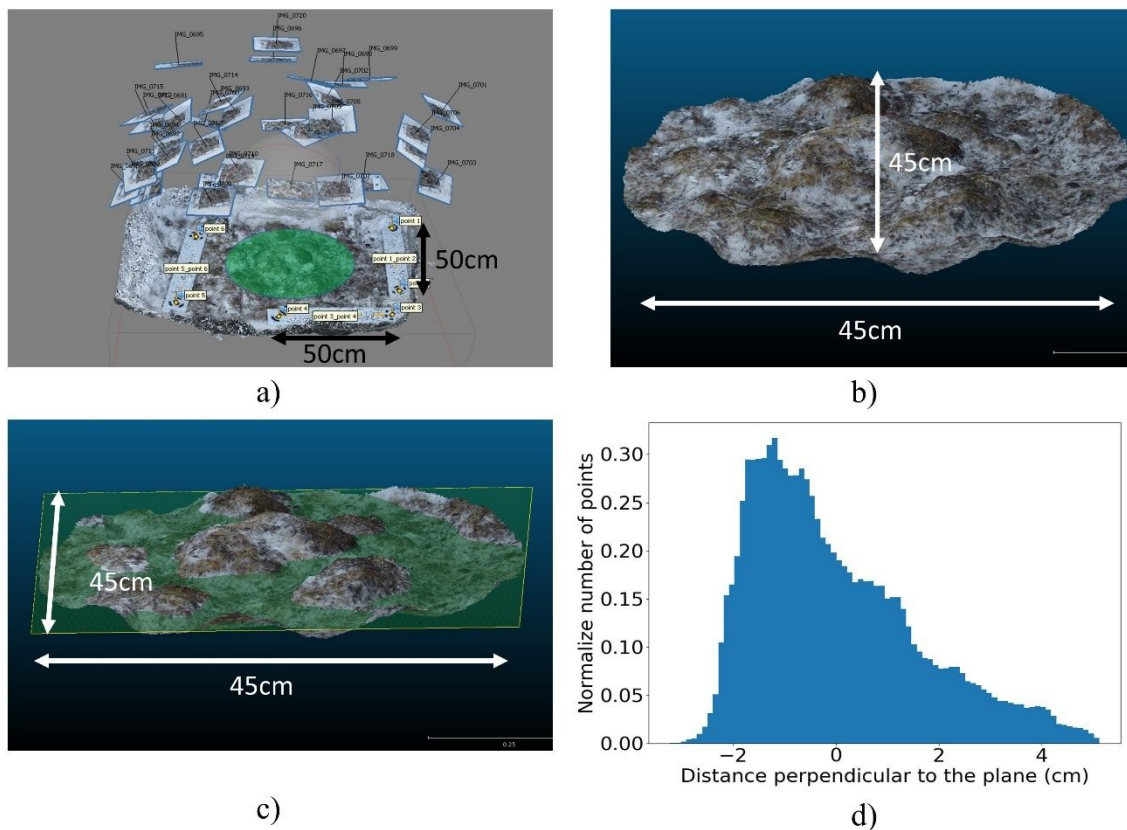


Figure 2. a) 3D point cloud creation, b) clipped 3D model to field of view of radiometer, c) fitted plane to 3D surface and d) histogram of perpendicular distances to plane, with $\sigma_H = 1.3\text{cm}$ and 2 787 233 points.

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5 After the 3D reconstruction, the point cloud was clipped and a plane fitted by
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7 minimizing the mean perpendicular distance to zero. The height standard deviation was
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9 calculated with the perpendicular distance of every point to the plane and correlation length
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11 estimated using a variogram with x-y coordinates and height (z) from a randomly selected
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13 sub data set within point cloud (5000 points) where the fitted plane serves as the new x-y
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15 plane for the correlation in z. Several point clouds were tested (pairwise correlations
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17 calculations using up to 10 000 points) selected randomly from the entire point cloud. The
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19 correlation length converged on similar values irrespective of whether 5000 or 10 000
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21 points were used. Therefore 5000 points was used for batch processing. Soil roughness is
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23 described at each site by the height standard deviation and correlation length. A fixed
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25 roughness parameter applicable to all sites was estimated with the mean of roughness
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27 parameters for all 55 sites. First the roughness value per site is used and then the mean
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29 roughness was tested for all simulations.
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37 **3.2.2. Radiometric data**

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39 Brightness temperatures were measured at all sites (March and May 2019) with
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41 surface-based radiometers (SBR) at 19 and 37 GHz mounted on a mobile sled measuring
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43 both vertical and horizontal polarizations. Snow was removed so as to measure only soil
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45 brightness temperature, and effective surface temperatures were recorded within the soil
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47 surface (2-3cm) shielded from the sun using a probe thermometer with an accuracy of \pm
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49 0.5°C at five different locations within the field of view of the radiometers. Among the 55
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51 roughness sites analyzed, 21 radiometric measurements at 55° from nadir were recorded
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53 and calibrated using cold and warm targets (Asmus and Grant, 1999) yielding an accuracy
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for radiometers of 2 K. Downward atmospheric contribution ($T_{B_{Atmo\downarrow}}$) was estimated for each frequency using the amount of precipitable water in the 29 atmospheric layers from the North America Regional Reanalysis model (NARR) (Roy et al. 2012) within 32 x 32 km pixels. All sites are within the same pixel, thus variations in atmospheric contribution by date only represent changes in the atmosphere (see Table 2). Angular emissivity was also simulated ($e_H = 1 - \Gamma_H$ and $e_V = 1 - \Gamma_V$ derived from Eq. 6 and 7) using the Weg99 model (for incident angles between 0 and 60°) to analyze angular dependency. Using averaged measurements of soil temperature and atmospheric contribution of all sites, the mean measured emissivity at 55° (from Eq. 1 and 2) was calculated with standard variation (± 0.009).

Table 2. Summary of radiometric observations and modeled downward atmospheric contributions.

Date	Number of sites	Mean Tsoil (°C)	Mean height std (cm)	Mean T_B (K)				$T_{B_{atmo\downarrow}}$ (K)	
				19H	19V	37H	37V	19	37
2019-04-30	1	-17	1.6	235.5	239.8	240.4	244.4	12.5	25.5
2019-05-02	7	-14.1	1.4	244.6	251.2	247.7	252.3	13.5	26.1
2019-05-03	2	-14.8	2.1	242.8	252.1	247.6	253.0	11.7	24.9
2019-05-10	6	-10.1	2.4	248.5	249.4	250.1	252.4	14.9	27.1
2019-05-11	4	-9.6	1.9	254.2	256.1	256.4	258.2	15.5	27.5

Montpetit et al. (2018), hereafter noted Mont18, parametrized frozen sub-arctic tundra soil using multi-angular microwave observations. Based on Weg99 model retrieval, the Mont18 effective parameters shown in Table 3 are from a different site but can serve as a comparison in this study given that they were found from passive observations at 19 and 37 GHz such as conducted in our experiment. King et al. (2018a) measured a permittivity of $4+0.5i$ also in a sub-Arctic environment in NWT, Canada. The retrieved permittivity values ($\epsilon'_f - \epsilon''_f i$) are in agreement with simulated permittivity using the soil radiative transfer model of Zhang et al., (2010) for frozen Arctic sites ($-15^\circ\text{C} < T < -10^\circ\text{C}$). The

simulated values range from dry (wet) conditions: $3.13 - 0.0081i$ ($4.63 - 0.0067i$) and $3.11 - 0.0043i$ ($4.61 - 0.0036i$) respectively at 19 and 37 GHz (Table 3) with a sub-arctic soil composition (Clay = 9.66%, Sand = 50.73%, Silt = 39.61%). The values from Zhang et al. (2010) theoretical model (hereafter Zhang10) with a Volumetric Moisture Content (VMC) = 0.05 will be used as a reference value for the permittivity. The permittivity will then be optimized for all models to allow deviations from theoretical values to reflect the assumptions presented here.

Table 3. Parameters (Mont18) from optimization in Montpetit et al. (2018) with different soil moisture permittivity from model of Zhang et al., (2010). VMC stands for volumetric moisture content.

Frequency (GHz)		ϵ	β_f	σ_H (cm)
Montpetit et al. (2018) optimization				
19		3.42-0.005i	0.72	0.19
37	Retrieved	4.47-0.033i	0.42	
Zhang et al. (2010) model				
19	dry (VMC=0.05)	3.13-0.008i		
	wet (VMC=0.6)	4.63-0.007i		
37	dry (VMC=0.05)	3.11-0.004i		
	wet (VMC=0.6)	4.61-0.004i		

4. Results

4.1. Roughness measurements

Table 4 presents the results of all 55 sites, where both height standard deviation (σ_H) and correlation length (l_c) were measured for each ecotype. The average σ_H was 1.65 cm with l_c of 39.5 cm.

Table 4. Mean value of roughness parameters measured with SfM photogrammetry.

Ecotype	Number of sites		mean σ_H (cm)	std σ_H (cm)	mean l_c (cm)	std l_c (cm)
	Roughness	Radiometric				
Sedge/shrub	6	3	1.57	0.29	29.4	12.5
Organic soil (rock < 10%)	25	8	1.91	0.59	37.9	25.1
Organic soil (rock < 75%)	14	7	1.46	0.72	52.2	38.6
Rock > 75%	8	2	1.50	0.95	33.0	16.5
Total	55	20	1.65	0.71	39.5	28.3

Measured σ_H greatly differs from Mont18 ($\sigma_{eff} = 0.19$ cm), which was derived from a microwave optimization approach using Weg99. Effective roughness optimized in Mont18 using Weg99 yielded lower roughness values than the actual physical measurement. This point is examined in the discussion.

4.2. Brightness temperature simulation

Three soil emission models were tested using different roughness parameters and permittivity values as inputs in Eq. (2). Model performances are shown in Fig. 3 and summarized in Table 5. Simulated brightness temperatures from two semi-empirical models, QNH and Weg99, using dry permittivity from Zhang et al. (2010) model ($\epsilon_{19}' = 3.13$ and $\epsilon_{37}' = 3.11$, Table 3) and roughness derived from SfM, were compared to SBR measurements (Fig. 3a and b). The final model used was the Geo Optics (Fig. 3c) analytical approach, which required two roughness parameters (σ_H and l_c) measured with SfM photogrammetry. Table 5 summarizes the root mean square errors (RMSE) and correlation (R^2) between observed and simulated brightness temperatures shown in Figure 3 for all three models and parameters used. Results are first presented for all sites and for all sites

without rocks (excluding two sites with rock > 75%), as they exhibit particular clusters. At rock-free sites: Sedge/shrub and Organic soil (rock < 10% and rock < 75%), Weg99 with σ_H derived from SfM and permittivity from Zhang10 has one of the lowest RMSE with 3.3 K and highest R^2 of 0.71. RMSE for horizontal polarization (H pol) were generally higher than for V pol (high model dependency to the polarization ratio).

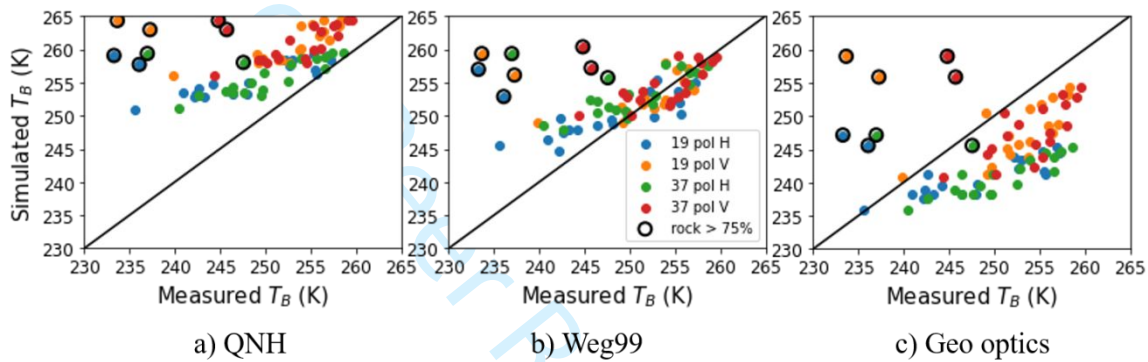


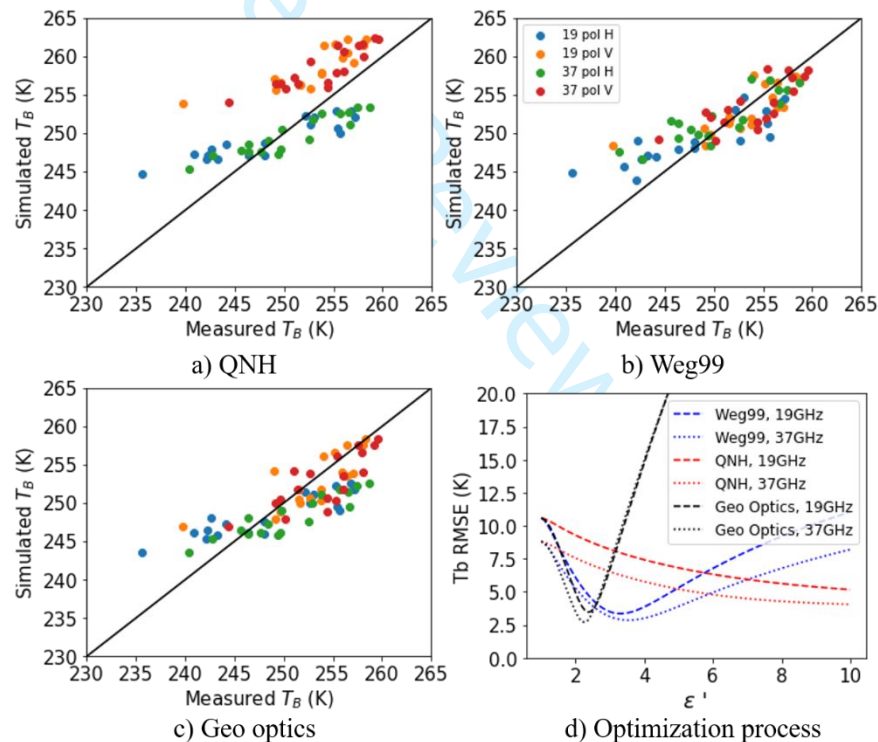
Figure 3. Simulations using Weg99, QNH and Geo optics models based on roughness estimates from SfM. Permittivity from Zhang10 was used. Polarization ratio (β_f) used for Weg99 are ($\beta_{f19} = 0.72$, $\beta_{f37} = 0.42$) (Table 3) and parameters for QNH defined in section 2.2.

Table 5. Simulation results using roughness parameters from SfM and permittivity from Zhan10 model (dry: VMC = 0.05).

Model	roughness	ϵ	RMSE (K)				Total	R^2
			19H	19V	37H	37V		
QNH	SfM	Zhang10	10.8	11.8	7.9	8.7	9.8	0.23
Weg99	SfM	Zhang10	7.3	7.4	5.5	4.9	6.3	0.13
Geo optics	SfM	Zhang10	9.2	9.3	10.1	7.9	9.1	0.07
No rock								
QNH	SfM	Zhang10	8.2	8.0	5.9	6.9	7.2	0.68
Weg99	SfM	Zhang10	4.2	2.8	3.7	2.6	3.3	0.71
Geo optics	SfM	Zhang10	8.8	6.4	10.2	7.2	8.2	0.55

To investigate permittivity further and see if optimized values for every model would converge, each model using parameters from Table 5 without rock sites, were

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3 optimized from (1-10) for ϵ' and are shown in Figure 4 and Table 6. While QNH was
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5 optimized to lower RMSE, the value had no physical meaning since the permittivities are
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7 too high for frozen soil as optimization did not reach a minimum ($\epsilon'_{19} = 10.0$, $\epsilon'_{37} = 10.0$).
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9 Weg99 and geo optics reached a minimum and indicating a low volumetric moisture
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11 content if we refer to Zhang et al. (2010) model values from Table 3. The Geo Optics
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13 model also shows a lower RMSE with 3.3 K when the permittivity is optimized ($\epsilon'_{19} =$
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15 2.4, $\epsilon'_{37} = 2.3$). The permittivity is outside Zhang et al. (2010) moisture interval presented
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17 in Table 3 however, there is uncertainty linked to the composition of soil type chosen.
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48 Figure 4: Simulated vs measured brightness temperatures for all models with optimized
49 permittivity in a), b), and c) and optimization results in d).
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52 Table 6. Results from optimization of permittivity.
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Model	ϵ'		RMSE (K)				Total	R^2
	19	37	19H	19V	37H	37V		

QNH	10.0	10.0	4.3	6.0	3.1	5.0	4.6	0.51
Weg99	3.3	3.6	4.0	2.7	3.2	2.6	3.1	0.71
Geo optics	2.4	2.3	4.2	2.7	3.7	2.8	3.4	0.66

4.3. Analysis of rock sites

The two rocky sites (rock >75%) had high biases in simulated brightness temperatures (Figure 3, and Table 5). It is difficult to precisely attribute the observed bias to only one factor (permittivity, temperature, structure of piled stones, see Figure 5a). Part of the deviation can result from the difference in permittivity between rocks and the mainly frozen organic soil at all the other sites. The ‘rocks’ found in the Greiner Watershed study site are in fact a loose part of a limestone bedrock emerging to the surface at the top of a hill (McLennan et al. 2018). The dielectric constant (ϵ') of limestone was measured from 0.5 to 4.5 GHz in the recent study by Wang et al. (2019), giving values ranging from 8 to 8.5 at room temperature ($\sim 20\text{-}25^\circ\text{C}$), and without trend within the range of frequency used. Even though this study is at higher frequencies and at lower temperatures ($\sim -10^\circ\text{C}$), this permittivity differs greatly from the Mont18 values used in this paper. Moreover, the five temperature measurements taken per site after snow removal and radiometric measurement yielded a mean temperature of $-9.4 \pm 1.4^\circ\text{C}$ for both rock sites, while the mean rock temperature at the snow–rock interface was at -14°C and the air temperature was between -8 and -6°C during the experiments. Rock warming during the delay between the radiometric and temperature measurements might explain the observed difference in T_B if we recall Eq. 2, effective soil temperature is major component in T_B calculation. Also, it is more difficult to measure rock temperature than organic soil with a probe thermometer. To investigate the potential impact of temperature differences, a sensitivity analysis was

performed on the brightness temperature as a function of permittivity and temperature changes for the rock sites (Figure 5a).

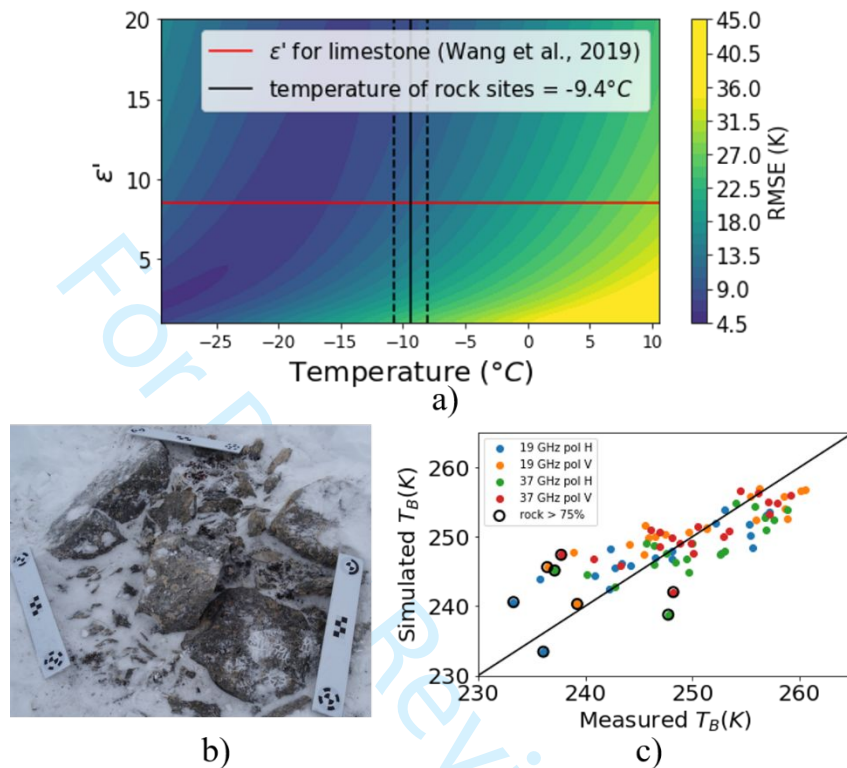


Figure 5. a) Representation of RMSE as function of permittivity and bias in effective temperature of the rock > 75% sites with Weg99 model and roughness SfM. b) Image of one of the rock sites. c) Simulation with modification of $\epsilon'=8.3$ and a change in temperature of -8°C (from -9.4°C to -17°C) on Fig. 5a for rock sites.

Figure 5b shows the RMSE associated with rock sites as a function of ϵ' and effective temperature compared to mean T_B measurements at 19 and 37 GHz. Assuming ϵ' from Wang et al. (2019) (red line in Fig. 5b), a low RMSE is reached with a change in temperature of -8°C (from -9.4°C to -17°C on Fig. 5a) from the measured temperature (black line). Soil temperature are presented in Table 2 with $T_{soil} = -17^\circ\text{C}$ for 2019-04-30, for which values are colder than air temperature given the fact that measurements occurred earlier during the Spring season. Figure 5c shows measured and simulated results when a

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3 fixed optimized temperature using Wang's permittivity (8.3) is used for rock sites, giving
4 a total RMSE of 3.8 K. Improvements are significant in the range of data uncertainties.
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10 **5. Sensitivity analysis and Discussion**

11 This discussion analyzes two points. We first examine the sensitivity of the considered
12 soil emission model to the roughness variability at the 55 studied sites in the same tundra
13 environment. Can a single value of roughness metrics be used to simulate emissivity of
14 frozen arctic soil for global scale applications? We then discuss the observed differences
15 between the measured physical roughness (by SfM) and the previously retrieved effective
16 microwave roughness by Mont18.
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25 We now explore the performance of a single roughness parameter applicable to all sites.
26 The mean of roughness parameters was calculated for all 55 sites and then used as a
27 reference value for all simulations (Table 7). Only Weg99 and Geo Optics models are
28 presented as they had the lowest RMSE and highest R^2 values in Table 6. The mean value
29 of σ_H for Weg99 and the mean value of σ_H and l_c with $\varepsilon =$ Table 6 were then applied as a
30 fixed roughness metric in both models. Results in Table 7 show that the mean RMSE
31 remains very similar to Table 5 and 6 (for Weg99, SfM, without rocks), suggesting that
32 average roughness can be satisfactorily applied, despite the observed spatial variability
33 (Table 4, 43% of variation coefficient). This offers confidence in using a single parameter
34 for different sites (or roughness) as uncertainty due to local roughness variability may
35 average out at larger scale.
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53 Table 7. Summary of simulation with a fixed SfM value of roughness for all sites without
54 rock.
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RMSE

		σ_H (cm)	l_c (cm)	19H	19V	37H	37V	Total	R^2
Weg99	mean	1.65		4.3	2.6	3.0	2.8	3.2	0.77
Geo Optics	mean	1.65	39.5	4.2	2.7	3.9	2.7	3.4	0.71

The physical surface roughness measured by SfM differs greatly from the effective roughness parameter found at a different site by inverse modelling of 0.19 cm (Montpetit et al., 2018). This difference is consistent with conclusions from Tsang and Newton (1982) and Ulaby et al. (1982) that found discrepancy when using the QNH model. As such, the difference observed in our study when using Weg99 can also be attributed to the mix of QNH and the parametrization from Mo and Schmugge (1987). This explains the observed discrepancy between our measured roughness and the effective roughness found by Mont18.

Also, in this study, all measurements were performed at 55° while multiple angles were used by Montpetit et al. (2018). The angular sensitivity of roughness is evaluated in Figure 6 for both frequencies and polarizations. All other factors being constant (soil moisture-permittivity in particular), roughness shows a stronger influence on emissivity at higher incidence angles ($> 50^\circ$), particularly for horizontal polarization. In other words, e_p around and over 50° is more sensitive to roughness. This could be one of the reasons why multi-angular retrieved effective roughness does not match physically measured roughness (of the order of 2 cm, instead of 0.2 cm from Mont18). Other factors are also involved like the frequency dependency between 19 and 37 GHz. This greater sensitivity of emissivity at higher viewing angles was shown in the pioneering works of Wang et al., (1983) and Singh et al., (1995), which concluded that the best fit angle for satellite-borne surface roughness observations is near 50° for both polarizations.

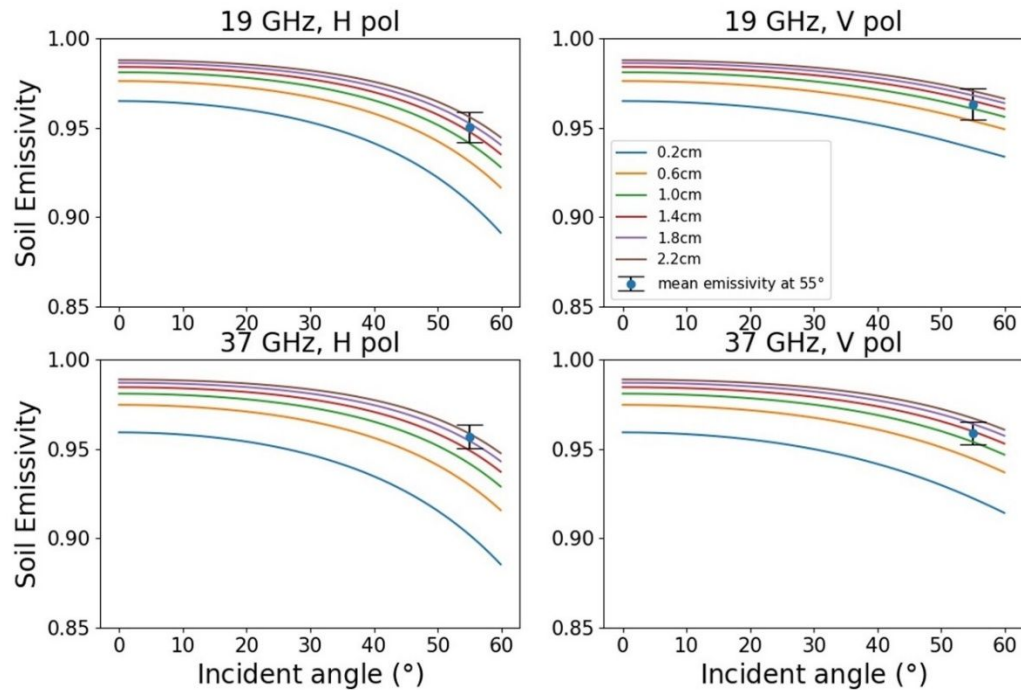


Figure 7. Sensitivity analysis on angular dependency of emission with different roughness values, for 19 and 37 GHz with horizontal and vertical polarization.

Our results are also in agreement with results from King et al., (2018), who studied similar types of tundra environment. Using airborne dual band SAR radar measurements at 9.6 and 17.2 GHz, they found an optimized effective roughness of 1.3 cm at an incident angle of 40°.

Very few values of estimated effective roughness at high frequencies have been validated against in-situ roughness estimates. One reason is that previous techniques, such as those that use pin profilometers, are time consuming and best for point values, while modern techniques, such as laser scanning and SfM (Martinez-Agirre et al. 2019), are relatively easy to use and efficient for large-scale studies. Rahman et al. (2008) showed that the effective bare soil roughness at C-band (5.3 GHz) retrieved from radar

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3 measurements using the IEM model is of 2.19 ± 0.49 cm, while in-situ pin profilometer
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5 measurements gave a significantly lower soil roughness value of 0.79 ± 0.29 cm.
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8 Our results also show permittivity values that are representative of spatial variability
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10 and permittivity fluctuations within studied soil types, as multiple landcovers were part of
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12 the in-situ validation. In the literature, in-situ permittivity values and roughness for frozen
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14 soils are currently rare, our study offers measured roughness values with permittivity and
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16 soil moisture that are valid with assumptions made within the Zhang et al., (2010) model.
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18 Results from this study could be generalized spatially, for example on a catchment scale,
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20 by linking in-situ results (roughness and permittivity) to the types of land cover.
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22 Increasingly, it is possible to derive centimeter scale roughness information from UAVs
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24 that characterize different hydrological response units within catchments. In addition,
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26 topographic and ecological land-cover classes can be derived from very high-resolution
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28 optical satellite images (such as WORLDVIEW-3 images), which opens opportunities for
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30 application of roughness to land cover classes over larger pan-Arctic scales.
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36 **6. Conclusion**

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38 In this study, we applied an effective and relatively simple method to measure soil
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40 roughness at multiple Arctic sites using the Structure-from-Motion (SfM) technique.
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42 Measurements of surface roughness over 55 sites across 4 Arctic tundra ecotypes had an
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44 average RMS height (σ_H) of 1.65 cm and mean 2 $D_{x,y}$ correlation length (l_c) of 39.5 cm.
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46 The observed variability appears relatively low for σ_H but high for l_c . For the first time, we
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48 tested three different rough surface reflectivity models (QNH, Weg99 and Geo Optics) at
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50 19 and 37 GHz over frozen ground conditions and compared simulations to ground-based
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52 radiometer observations. Results show best performance with the Weg99 model
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3 parametrized with SfM-based roughness (1.65 cm) and frozen organic soil permittivity (ϵ)
4 from theoretical model by Zhang et al. (2010). When permittivity is optimized, Weg99 still
5 best fit observations. Accuracy considering fixed permittivity and measured roughness at
6 each site for Tb simulations yielded similar results indicating a fixed value could be used
7 for large scale application. The Geo Optics model also shows good results if the
8 permittivity is optimized (see Table 6).
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17 A fixed value for roughness (σ_H) for all the sites gives similar modelling performance
18 even though variability of σ_H between sites was observed. The mean roughness value of σ_H
19 = 1.65 cm and ϵ given in Table 6 using the Weg99 model appears to be representative of
20 Arctic tundra land cover, mainly characterized by sedge/shrub with organic soil and rock
21 between 10% to 75%.
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29 Analysis of particular rock sites with limestone composition and similar roughness to
30 organic soils revealed different behavior in radiometric measurements, suggesting a need
31 to consider specific rock permittivity and a colder effective temperature to match
32 simulations and observations. This is an important finding as rock surfaces cover up to 8%
33 of terrestrial high Arctic areas (Ponomarenko et al. 2019). Because of the large difference
34 in permittivity between rocks and soil, future studies may consider a mixed model that
35 takes into account the fraction of rocks in each land cover or geological class. This could
36 be useful in inversion of parameters for remote sensing planetary surfaces.
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47 This study thus offers surface roughness values that can be used on a larger scale in a
48 satellite retrieval algorithm for global Arctic monitoring by remote sensing. Using
49 inversion algorithm to retrieve surface parameters is difficult because both backscattering
50 coefficient and brightness temperature are strongly affected in the same way by several
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3 factors including roughness, soil moisture, vegetation or snow cover (e.g. Moradzadeh and
4 Saradjian, 2016; Wigneron et al., 2017). The reduction in microwave dielectric sensitivity
5 to soil moisture caused by surface roughness is a well-known problem. In addition,
6 estimating these parameters remains challenging, as shown in numerous studies (e.g. Du et
7 al., 2010, with active radiometry; Roy et al., 2016, Shi et al., 2016, with passive
8 radiometry). For example, surface roughness change linked to land cover change, such as
9 observed shrub expansion in the Arctic, could be an important source of uncertainties for
10 modelling active and passive microwave signals. The photogrammetry method presented
11 in this paper offers an effective and low-cost way to reliably measure soil roughness when
12 performing ground-based validation of passive/active microwave data while allowing us to
13 gain a better understanding of geophysical properties of frozen soil.
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33 **Data availability:**

34 All brightness temperatures and emissivity values will be available on request.
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47 overall guidance.
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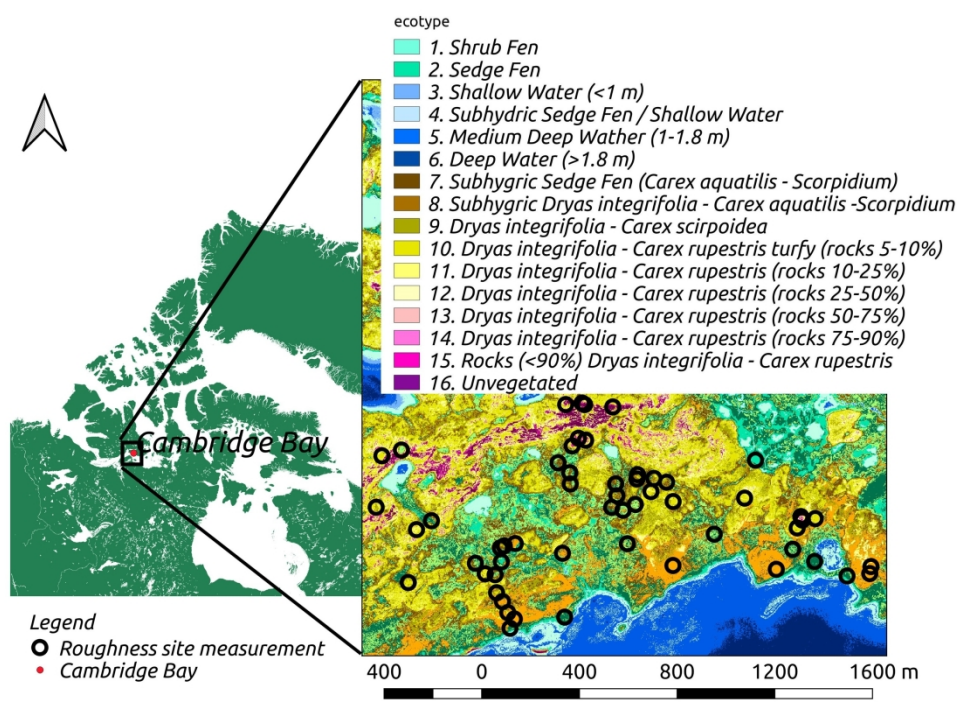
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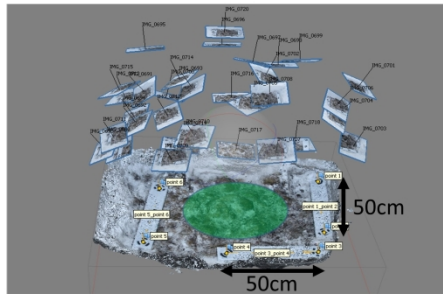
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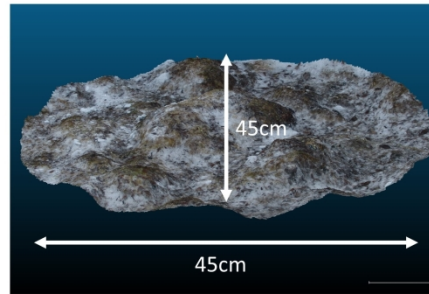


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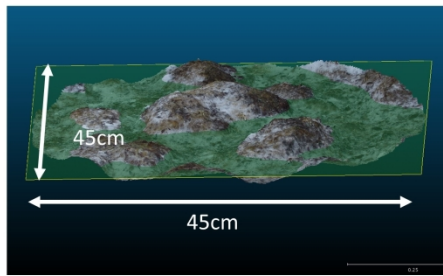
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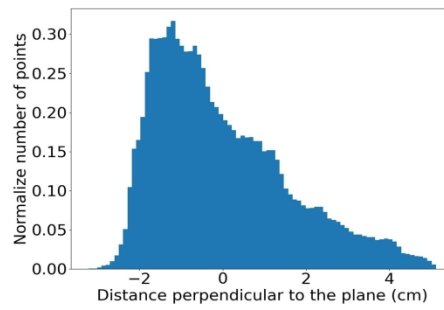
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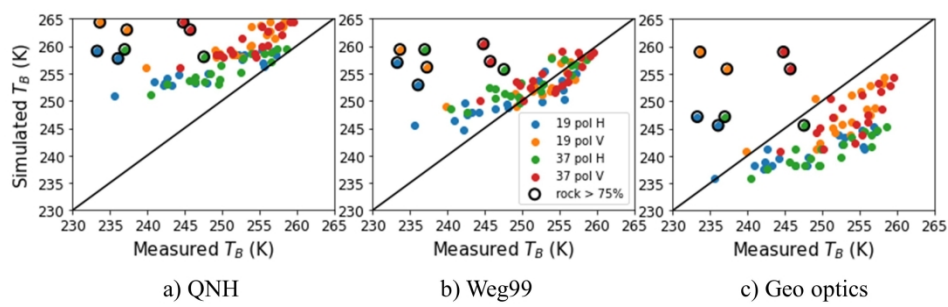
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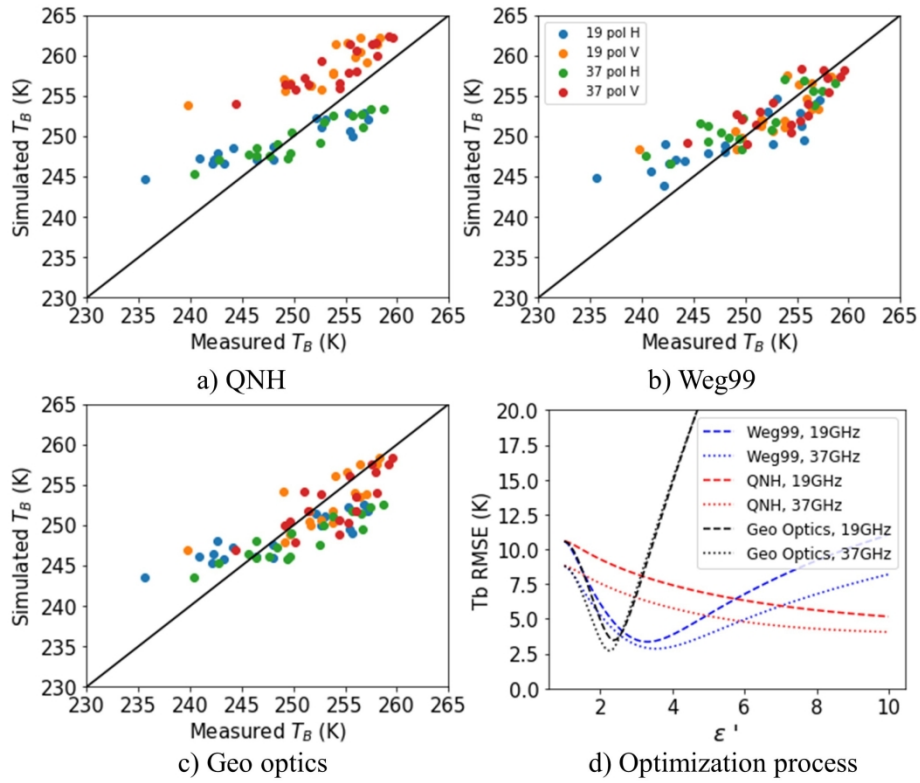
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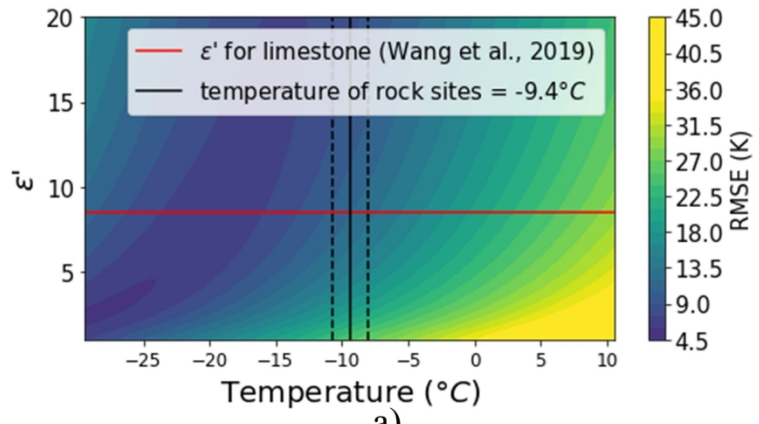


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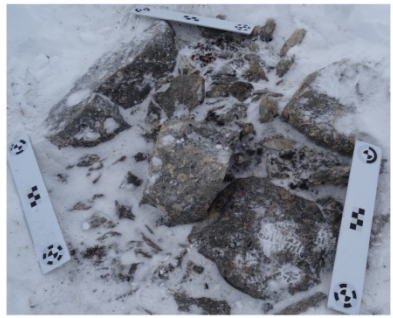


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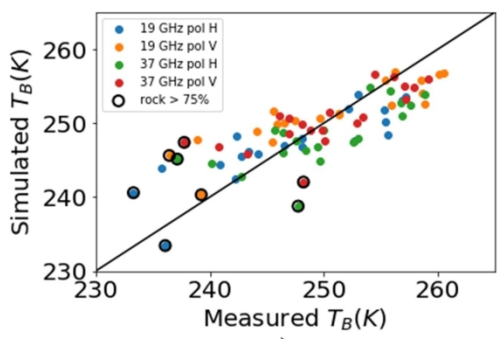
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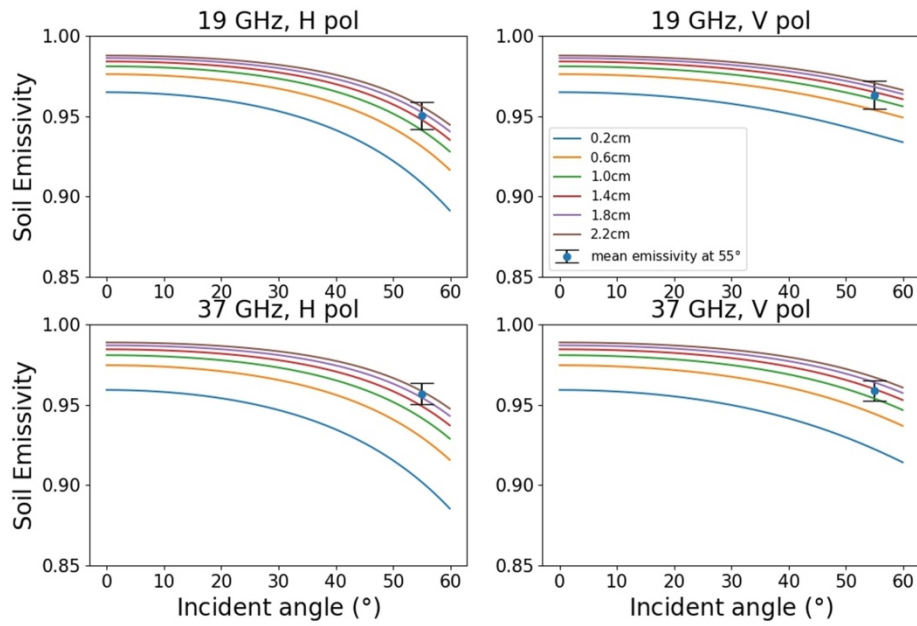


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705x592mm (96 x 96 DPI)



878x593mm (96 x 96 DPI)