An inverse dielectric mixing model at 50MHz that considers soil organic carbon

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Abstract. The prevalent soil moisture probe algorithms are based on a polynomial function that does not account for the variability in soil organic matter. Users are expected to choose a model before application: either a model for mineral soil or a model for organic-rich mineral soil. Both approaches inevitably suffer from limitations with respect to estimating the volumetric soil water content in soils
20 having a wide range of organic matter content. In this study, we propose a new algorithm based on the idea that the amount of soil organic matter (SOM) is related to major uncertainties in the in-situ soil moisture data obtained using soil probe instruments. To test this theory, we derived a multiphase inversion algorithm from a physically based dielectric mixing model capable of using the SOM amount, performed a selection process from the multiphase model outcomes, and tested whether this new
25 approach improves the accuracy of soil moisture (SM) data probes. The validation of the proposed new soil probe algorithm was performed using both gravimetric and dielectric data from the Soil Moisture Active Passive Validation Experiment in 2012 (SMAPVEX12). The new algorithm is more accurate than the previous soil-probe algorithm, resulting in a slightly improved correlation ($0.824 \rightarrow 0.848$), 12 % lower root mean square error (RMSE; $0.0824 \rightarrow 0.0725$ cm^3·cm^{-3}), and 90 % less bias (-0.0042
30 $\rightarrow 0.0004$ cm^3·cm^{-3}). These results suggest that applying the new dielectric mixing model together with global SOM estimates will result in more reliable soil moisture reference data for weather and climate models and satellite validation.

1. Introduction

Soil moisture (SM) plays a critical role in weather and climate by affecting atmospheric variables via
35 latent and sensible heat exchange. For example, near-surface air temperature can be affected by the

메모 포함[CP1]: We updated the list of our co-authors and the affiliation.

메모 포함[CP2]: Editor: The reviewer is concerned about the limited range of organic matter content in the soils you consider and objects to the term 'organic soil', which you use on multiple locations in the paper, including the abstract. I agree with the reviewer that the term 'organic soils' is usually reserved for peaty soils with limited mineral content. The reviewer also points out your results disagree with results reported in the literature for similar, relatively low, organic carbon contents. From you reply it appears you have confidence in your data and you are not prepared to do more experiments on soils with a higher organic carbon content. If I understand your reply correctly your position is that the focus on organic-rich mineral soils (e.g., not 'organic soil' per se) is important enough in and of itself to warrant the dedication of the paper to them. If that is the case, your paper would improve if you dedicate a bit more text to clarifying the contribution and relevance of your work, and avoid using the term 'organic soil', because this can create misunderstandings among readers.

Response: Thank you very much for your comments. We agreed with the reviewer's and the editor's opinion. The 'organic soil' used in our manuscript is not proper expression and might cause the confusion to readers. Therefore, according to the editor's comment, we replace the term 'organic soil' into 'organic-rich mineral soil' which is highlighted with cyan color in p.1, line 18; p.3, line 82; p.4, line 144; p.5, line 176; p.6, line 191; p8, line 214; p.11, line 308; p.12, line 330; p.15, line 389; p.18, line 481; p.19, line 507.

evapotranspiration of surface and root zone soil moisture. Therefore, its correlation with the near-surface temperature is usually considered an effective indicator of the coupling strength between the land surface and the atmosphere (Seneviratne et al., 2006; Koster et al., 2009; Seneviratne et al., 2010; Jaeger and Seneviratne, 2011; Seneviratne et al., 2013; Hirschi et al., 2014,?; Whan et al., 2015). In

40 particular, soil moisture anomalies in a dry regime have been reported as the main cause of strong land-atmosphere coupling, which can trigger drought and heat waves (Fischer et al., 2007; Zampieri et al., 2009; Hirschi et al., 2011; Miralles et al., 2011; Mueller and Seneviratne, 2012; Taylor et al., 2012; Guillod et al., 2015; Hauser et al., 2016; Seo et al., 2019). Soil moisture also influences precipitation formation and storm tracks by coupling with the atmosphere (Koster et al., 2004; Taylor et al., 2012;

45 Guillod et al., 2015; Santanello et al., 2018, 2019; Zhang et al., 2019). Consequently, inaccurate SM information in the land-surface-model hinders accurate predictions of extreme climate and weather because of unrealistic land-atmosphere interactions that result from uncertainties in air temperature, moisture, dynamics, cloud formation and precipitation.

High-quality in situ soil moisture data are an important reference for evaluating climate models (Yuan
50 and Quiring, 2017; Zhuo et al., 2019) and remote-sensed SM data (Entekhabi et al., 2010; Kerr et al., 2010). However, it is not practically possible to perform in situ SM measurements with high spatial and temporal coverage. Soil moisture networks based on cosmic ray neutron probes might be more manageable for long-term operation yet is still not more established than the dielectric based approach.

A practical alternative is to employ a portable soil probe that is calibrated using locally measured soil
55 moisture. In particular, portable dielectric sensors make use of the relationship between the dielectric constant and volumetric soil water content. However, such retrieval of the volumetric soil water content from dielectric measurements does not account for soil organic matter (SOM) and saturation conditions. A few studies have reported the relationship between the dielectric constant and the volumetric soil water content in organic-rich soils (Topp et al., 1980; Roth et al., 1992; Bircher et al., 2012). However,

60 the calibration functions derived from these studies have limitations for global-scale applications because they were developed using only a few specific sites and/or applicable only for the sites with a limited range of organic matter content. For the purpose of a global soil moisture probe observing system, using an inversion method of the existing physical dielectric mixing model can be a great alternative approach to incorporate the variability of organic matter into the probe algorithm beyond the

65 current empirical probe models.

With this background, this work provides a pathway for a physical model to consider soil organic matter. We developed an inverse dielectric mixing model for mineral soil derived from Park et al. (2017, 2019) to obtain more accurate volumetric soil moisture estimates from the dielectric constant. The proposed model reflects the damping effect and simulates the supersaturation of soil moisture over

70 soil porosity (when soil moisture occupied larger than porosity of dry compacted soil in the unit volume causing light weight clay swelling or starting existence of standing water or starting surface runoff due to the precipitation accumulation over soil surface faster than infiltration) so that we can capture the standing water and surface runoff during flood events, which has not been studied in other prevalent dielectric mixing models

75 The most recent high resolution SOM map (Hengl et al., 2014; Batjes, 2016) is only available as a static variable for the land model; therefore, the realism of the parameterization for surface runoff, infiltration,

메모 포함[cp3]: Editor: In the past decade or so, soil moisture sensor networks covering a few hectares have become quite popular. Keeping such networks running semi-permanently is not yet done I believe. Cosmic ray neutron probes may have potential for long-term operation but are not yet firmly established.
This is just my opinion, there is no need to react to this statement or modify the text in response in this phase.

Response: Thank you very much for your comments. We agreed with the reviewer's and the editor's opinion. The 'organic soil' used in our manuscript is not proper expression and might cause the confusion to readers. Therefore, according to the editor's comment, we replace the term 'organic soil' into 'organic-rich mineral soil' which is highlighted with cyan colour in line 18, p.1; line 82, p.3; line 144, p.4; line 176, p.5; line 191, p.6; line 214, p8; line 308, p.11; line 330, p.12; line 389, p.15; line 485, p.18; line 512, p.19.

evapotranspiration, and soil respiration is limited. Therefore, the other aim of this study is to provide a foundation for global SOM estimation using observations from a satellite, such as Soil Moisture Active Passive (SMAP), by developing a dielectric mixing model based on accurate in-situ SOM and

80 gravimetric soil moisture.

The remainder of this paper is organized as follows: Section 2 introduces the inversion approach of dielectric mixing model to estimate soil moisture from organic-rich mineral soil using the probe. The data used in this study are described in Sect. 3. In Sect. 4, we evaluate the results using the soil moisture measured during SMAPVEX12. Finally, a summary and discussion for further applications are

85 provided in Sect. 5.

2. Method

The dielectric constant indicates a polarizability of materials at a certain wavelength. The dipole structure of water molecules is highly sensitive to a microwave electric field with very high dielectric constant (approximately 80). On the other hand, the dielectric constant of mineral soil at microwave

90 electric fields is rarely reacting, having only low value from 3 to 5. Therefore, an instrument which can measure the effective dielectric constant of soil medium such as Stevens Hydraprobe can provide an accurate estimate of water amount within soil (Jackson et al., 1982; Schmugge, 1983; Stafford, 1988). Also, from space, microwave satellite such as SMAP (Soil Moisture Active Passive) (Entekhabi et al., 2010), SMOS (Soil Moisture and Ocean Salinity) (Wigneron et al., 2007) and AMSR-E (Advanced

95 Microwave Scanning Radiometer for EOS) can effectively estimate soil moisture from the measured brightness temperature by relating the effective dielectric constant of land surface.

For the application of portable soil moisture probes, the in-situ soil moisture data are provided based on the empirical relationship between the measured dielectric constant and the volumetric soil moisture (Seyfried and Murdock, 2004; Bell et al., 2013) using the following equation:

100 $$w = 0.0838 \sqrt{\varepsilon_{\text{obs}}} - 0.0846 \tag{1}$$

where, ε_{obs} is the real part of the dielectric constant measured with the soil probe and w is the estimation of the volumetric soil moisture ($cm^3 \cdot cm^{-3}$). As apparent in Eq. (1), the dependence of ε_{obs} on SOM was not considered in the estimation of w.

105 To consider the SOM, we first derive Eqs. (2)–(4), based on Park et al. (2019).

If the observed real part of the dielectric constant measured with the soil probe is smaller than the real part of the dielectric constant at the wilting point, $\varepsilon_{\text{obs}} < \varepsilon_{\text{wp}}$, we obtain:

for $w < w_{\text{wp}}$

$$w = a\left((\varepsilon_{\text{obs}} - 1)H^{-1} + 1\right) + b \tag{2}$$

110 where,

$a = 1/(\varepsilon_{\text{bound}} - \varepsilon_{\text{air}})$

$b = -\dfrac{(1 - p)\varepsilon_{\text{soil}} + p\varepsilon_{\text{air}}}{\varepsilon_{\text{bound}} - \varepsilon_{\text{air}}}$

where, H is the damping factor (0.8), ε_{bound}, is the dielectric constant for bound water, ε_{free}, dielectric
115 constant for free water, ε_{air} is the dielectric constant for air (1).

If the observed real part of the dielectric constant measured with the soil probe is larger than the real
part of the dielectric constant at the wilting point and still smaller than the saturation point, $\varepsilon_{wp} <$
$\varepsilon_{obs} < \varepsilon_p$, we get:
120 for $w_{wp} < w < p$

$$w = \frac{-b + \sqrt{b^2 - 4a(c - (\varepsilon_{obs} - 1)H^{-1} - 1)}}{2a} \tag{3}$$

where,

$$a = \frac{\varepsilon_{free} - \varepsilon_{bound}}{p - w_{wp}}$$
125 $$b = \frac{p\varepsilon_{bound} - w_{wp}\varepsilon_{free}}{p - w_{wp}} - \varepsilon_{air}$$
$$c = (1 - p)\varepsilon_{soil} + p\varepsilon_{air}$$

Finally, for $\varepsilon_{obs} > \varepsilon_p$, we get:
for $p < w$
130 $$w = a\left((\varepsilon_{obs} - 1)H^{-1} + 1\right) + b \tag{4}$$

$$a = \frac{1}{\varepsilon_{free} - \varepsilon_{soil}}$$
$$b = -\frac{\varepsilon_{soil}}{\varepsilon_{free} - \varepsilon_{soil}}$$

135 According to Debye Relaxation, the dielectric constant of free water at less than 2GHz frequency has a
constant value of approximately 80. However, in the field measurements (Curtis, John O. et al., 1995;
Fal et al., 2016; Ishida, 2000; Mironov et al., 2013) it is found that in clay-rich soil, the real part of the
dielectric constant increases at lower frequencies, which occurs by the clay-ion-complex interaction
(Kelleners et al., 2005). Therefore, in this study for 50 MHz, the clay content and the real part of the
140 dielectric constant at 1.4GHz are empirically considered in the dielectric constant not only for free, but
also, for bound water Eq.(5,6).

$$\varepsilon_{free} = \varepsilon_{free_{1.4GHz}} + 65 \cdot v_{clay} \tag{5}$$
$$\varepsilon_{bound} = \varepsilon_{bound_{1.4GHz}} + 5 \cdot v_{clay} \tag{6}$$

Also, we proposed the formulation of the dielectric constant for the dried organic-rich mineral soil at 50
145 MHz, as shown in Eq. (7).

$$\varepsilon_{soil} = \left(\varepsilon_{clay} \cdot v_{clay} + \varepsilon_{sand} \cdot v_{sand} + \varepsilon_{silt} \cdot v_{silt}\right)(1 - v_{SOM}) + \varepsilon_{SOM} \cdot v_{SOM} \tag{7}$$

메모 포함[cp5]: RC1: Eq (5) and (6): it is confusing whether this applies to 50MHz, or any frequency ranging from 1.4GHz to 50MHz. Also please provide the original references for these two equations.

Response: Thank you for the comment. Our application is targeting for 50MHz sensor. To avoid the confusion, we corrected the paragraph (p.4, lines 135-141). Also, we added the relevant references for Eq.(5) and (6).

where, $\varepsilon_{\text{free 1.4GHz}}$ and $\varepsilon_{\text{bound 1.4GHz}}$ are the dielectric constant for free and bound water at 1.4GHz, respectively and v_{clay}, v_{silt} and v_{sand} are the volumetric ratios (cm^3·cm^{-3}) for clay, silt and sand, respectively.

The bulk density for organic-rich mineral soils can be computed with pure mineral and organic matter densities (Federer et al., 1993) or be expressed with their total volume and mass of these component (Liu et al., 2013; Jin et al., 2017). By relating these two formulas, we can derive the following volumetric ratio of organic matter (v_{SOM}, cm3·cm-3) (see appendix A for more details):

$$v_{\text{SOM}} = \left(\left(\frac{1}{\text{SOM}} - 1 \right) \frac{BD_{\text{SOM}}}{BD_{\text{MI}}} + 1 \right)^{-1} \tag{8}$$

where,

$$\text{SOM} = f_{oc} \cdot \frac{OC}{1000} \tag{9}$$

$$BD = 0.071 + 1.322 \cdot exp(-0.0071 \cdot OC) \tag{10}$$

SOM is expressed as organic carbon (OC) in the majority of global soil maps (Hugelius et al., 2013; Hengl et al., 2014; Batjes, 2016; Hengl et al., 2017; "Harmonized world soil database v1.2 | FAO SOILS PORTAL," 2020), as well as in the published units in the SMAPVEX 12 study (Manns and Berg, 2014). Organic carbon is the major component of SOM, and in order to convert OC to SOM, the conversion factor (f_{oc}) of 1.8 was used in Eq (9). The conventional OC-to-SOM conversion factor was proposed to be 1.724 by (Waksman and Stevens, 1930; Stenberg et al., 2010). However, it has been reported that the OC-to-SOM conversion factor can vary from 1.25 to 2.5, and the conventional value of 1.724 tends to overestimate the OC, as reported by Pribyl (2010). Instead of 1.724, 1.8 is a more appropriate value for a wide range of OC, as supported by various studies (Broadbent, 1953; Ranney, 1969; Manns and Berg, 2014). Therefore, in this study, we applied 1.8 for the conversion factor f_{oc} in Eq. (9). If a further effort in mapping conversion factors in global scale is made in a future study, the probe sensor algorithm might benefit in the improvement of its accuracy for soil moisture estimation in organic-rich mineral soils.

By applying Eq.(10) (Hossain et al., 2015), BD_{MI} (bulk density of "pure" mineral matter) and BD_{SOM} (bulk density of "pure" organic matter) in Eq.(8) are computed as 1.393 g·cm^{-3} with 0% OC (0g OC per 1kg soil) and 0.097 g·cm^{-3} with 56% OC (560g OC per 1kg soil) converted from 100% SOM with the conversion factor 1.8 by Eq.(9), respectively.

In a previous study, Eq. (11) was proposed as the wilting point, which is a function of SOM (kg·kg^{-1}) with the slope parameter of SOM modified from 0.786 to 0.6 (Park et al., 2019). In our study the porosity is suggested as a power law function according to the SOM variable, as shown in Eq. (12) (please see the result of simulation in all SOM and clay regions in Appendix B).

$$w_{wp} = 0.02982 + 0.089 \cdot v_{clay} + 0.65 \cdot \text{SOM} \tag{11}$$

메모 포함[cp6]: RC1: Eq. (8) does not seem correct to me. The correct equation should be: v_som = 1/((1/SOM-1)(BD_SOM/BD_soil)+1), where in the original equation, the BD_soil and BD_som should switch. The authors should also clearly define "BD_soil" and "BD_SOM". If "BD_soil" is the soil bulk density, it varies greatly based on the SOM concentration, and using a constant value is not proper. Rather, I think here "BD_soil" and "BD_SOM" should mean the specific density of "mineral" and "organic matter" part of the soil solids. Please double check this.

Response: Thank you very much for pointing out this error. The mineral and organic matter should be switched as shown in the corrected Eq.(8) (p.5, lines 152-156). Furthermore, we specified the BD_SOM and BD_MI are constant based on the Eq.(9) with assumption of 0 and 56% OC cases (p.5, lines 177-180) which are called as "pure mineral" and "pure organic matter". We also added the detailed derivation of Eq.(8) in the appendix A (p.18-19, lines 480-500).

메모 포함[CP7]: RC1: Eq. (9): if this equation is used to estimate the soil bulk density for organic soils, it is not applicable to highly organi soils. E.g. when SOM=1 (or OC=~0.58), BD_SOM>2 g/cm3. The original reference does not include data with OC > 20%. This is also a common problem in the empirical equations derived for organic soils or organic-rich soils.

Response: The bulk density function is used for the calculation of "pure" organic matter and "pure" mineral particles. As you mentioned for very high OC, the bulk density becomes unrealistically large. Therefore, we replaced it to more proper and well-known equation to estimate their pure density proposed by Hossain et al., 2015 as Eq.(10) (p.5, line 162) and further explained how to calculate BD_MI and BD_SOM using this equation (p.5, line 177-180).

메모 포함[cp8]: Editor : From the range you report a few lines above, it appears this can lead to substantial errors in specific locations. You really would like to have a map of the conversion factor.
This too is a statement you do not need to consider now, but you may want to address later on.

Response: We added new sentence of our wish about a benefit of possible study for the global conversion map in the future (lines 142-143, p. 5).

$$p = 0.194 + 0.26 \cdot v_{clay} + 0.5 \cdot \text{SOM}^{0.5} \tag{12}$$

By applying Eqs. (11) and (12), which require Eq. (8), Eqs. (2–4) can be used to compose the inverse
190 dielectric mixing model for organic-rich mineral soil (IDO). A detailed description of the parameters
used in the algorithm is provided in Table 1.

Table 1. Required physical properties to inverse the dielectric mixing model

Symbol	Physical property	Physical unit
ε_{obs}	Dielectric constant (real part) measured by TDR instrument	-
ε_{bound}	Dielectric constant (real part) of bound water at 50MHz	-
ε_{free}	Dielectric constant (real part) of free water at 50MHz	-
$\varepsilon_{bound\ 1.4GHz}$	Dielectric constant (real part) of bound water at 1.4GHz	-
$\varepsilon_{free\ 1.4GHz}$	Dielectric constant (real part) of free water at 1.4GHz	-
ε_{soil}	Dielectric constant (real part) of dry soil	-
ε_{air}	Dielectric constant (real part) of air	-
p	Dry porosity or saturation point	$cm^3 \cdot cm^{-3}$
w_{wp}	Wilting point [$cm^3 cm^{-3}$]	$cm^3 \cdot cm^{-3}$
H	Damping factor [-]	-
w	Volumetric soil water	$cm^3 \cdot cm^{-3}$
v_{clay}	Volumetric mixing ratio of clay	$cm^3 \cdot cm^{-3}$
v_{silt}	Volumetric mixing ratio of silt	$cm^3 \cdot cm^{-3}$
v_{sand}	Volumetric mixing ratio of sand	$cm^3 \cdot cm^{-3}$
v_{SOM}	Volumetric mixing ratio of soil organic matter	$cm^3 \cdot cm^{-3}$
OC	Organic carbon	$g \cdot kg^{-1}$
SOM	Organic matter	$kg \cdot kg^{-1}$
BD	Bulk density	$g \cdot cm^{-3}$

195 The IDO model is composed of bound, mixed, and free water models, as shown in Fig. 1(a–c),
respectively. The dielectric constant at the wilting point or porosity should be calculated first and then
compared to the measured data in order to determine which model should be used among the Eqs.2, 3,
or 4 for soil moisture estimation from the measured dielectric constant. The results of this selection for
soil moisture estimation from the measured dielectric constant is displayed as shown as red dots in Fig.
200 1(d).

The difference in the soil moisture estimation from the observed dielectric constant based on the Seyfried and IDO models is presented in Fig. 1(e). The IDO model provides larger SM values with high SOM input (purple curve) and lower SM values in low SOM input (orange curve) compared to the Seyfried model (black dotted curve). The factory setting (default probe algorithm) reflects the average SOM effect empirically in the generalized model. Even with medium-range SOM (red curve), a relatively small but more complex difference between the two approaches can be revealed in the SM estimation: lower SM estimation in wet soil and higher SM estimation in dry soil than the probe estimated (black dotted).

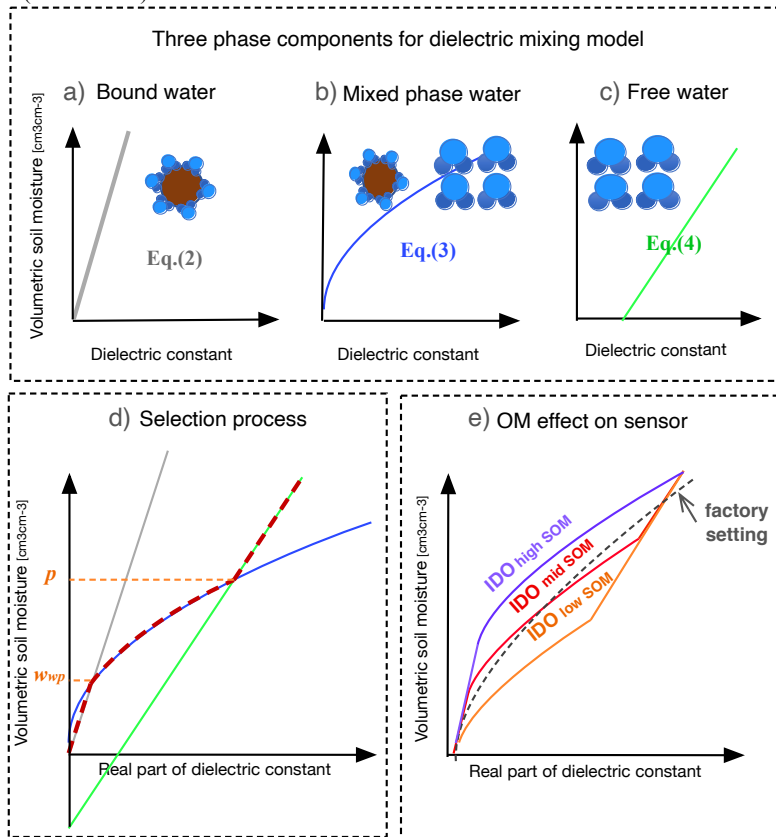



Figure 1: Single phase relationship between (a) dielectric constant and bound water, (b) bound and free water mixture, (c) free water, (d) soil moisture estimated among those models, and (e) comparison with the polynomial-based soil probe sensor algorithm proposed by Seyfried (Seyfried and Murdock, 2004) and for organic-rich mineral soils (IDO)

3. Data

First, it was necessary to determine whether including the organic matter parameter in the dielectric mixing model improves the accuracy of soil moisture estimation from the probed dielectric constant. Thus, we compared the results with the SM measured using the gravimetric method during SMAPVEX12. The SMAPVEX12 field campaign took place in 2012 (southwest of Winnipeg, Manitoba, Canada), and the SMAP SM retrieval algorithms were calibrated and validated before the launch of the SMAP satellite in 2015 (McNairn et al., 2015). During this field campaign, intensive data of the L-band brightness temperature and back-scattering albedo were collected using airborne sensors. The land surface type, crop type, soil texture (clay and sand contents), the real part of the dielectric constant from soil moisture probes with the field average of 16 sampling data obtained in every second day from June 6 to July 17, 2013. The sampling depth of the probe is established as the top 5cm of soil which layer is relevant to the brightness temperature emission depth detectable by SMOS and SMAP(Schmugge, 1983; Jackson et al., 1997) and gravimetrically determined volumetric soil moisture at the ground sites were measured on the ground by sampling soils with 4.7 cm diameter x 4.6 cm depth (Mann and Berg, 2013). For comparison with our new model, we used probe measurements (real dielectric constant) as the input and volumetric soil moisture data as references (Rowlandson et al., 2013), which were simultaneously archived with microwave brightness temperature measured from airborne NASA's L-band active-passive PALS instrument. The ancillary information for this function (soil texture information) was provided by (Bullock et al., 2014). At the SMAPVEX12 validation sites (Fig. 2a), the volumetric clay and sand mixing ratios for Eqs. 5, 6, 7, 11, and 12 are from the Agriculture and Agri-Food Canada (AAFC) Soil Landscapes of Canada database (Government of Canada, n.d.). The OC information was sampled from the SoilGrid250m database (Hengl et al., 2014, 2017) and compared to the field estimates of the OC put forth by Manns and Berg (2014). The field samples of the OC were processed by grinding oven dried soil samples, and igniting and burning off organic mass at 375 °C. The SOM was determined from the weight difference between before and after igniting the soil samples and divided by 1.8 to convert SOM to OC (Ball, 1964; Wang et al., 2011; Manns and Berg, 2014).

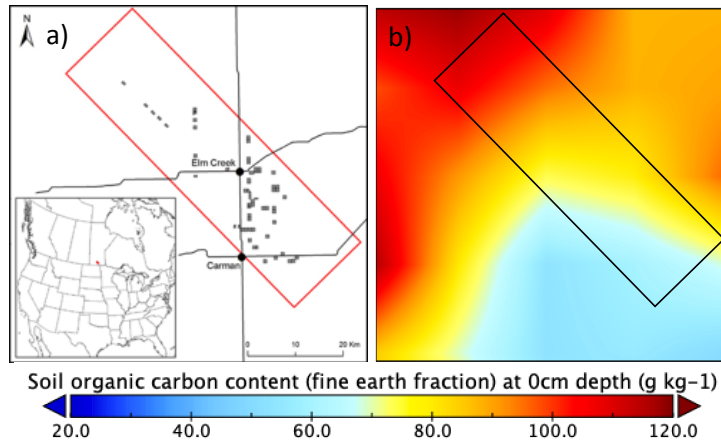



Figure 2: (a) SMAPVEX12 validation sites (adapted from (Rowlandson et al., 2013)) and (b) calculated distribution of soil organic matter in Canada based on the SoilGrid250m database.

There are significant range differences among the global soil organic carbon maps (Zhu et al., 2019), such as the HWSD ("Harmonized world soil database v1.2 | FAO SOILS PORTAL," 2020), SoilGrid250m (Hengl et al., 2014, 2017), WISE30sec (Batjes, 2016), and Northern Circumpolar Soil Carbon Database (NCSCD; Hugelius et al., 2013). Therefore, the reliability of the global soil organic maps used for local soil moisture estimation using soil probes is still unknown. To investigate the potential limitation of global OC maps (hereafter called the OC_map experiment), we performed a comparison of OC measurements obtained from each SMAPVEX12 site (Manns and Berg, 2014) with those retrieved from the SoilGrid205 map. As shown in Fig. 3(a), there is an offset between both datasets of ~ 50 g·kg^{-1}. The estimated OC from the map was greater and showed a wider OC range compared to the measured OC in the SMAPVEX12 sites (Fig. 3b). This means that the SoilGrid250m (Hengl et al., 2017) estimates are, on average, more than 100 % higher than the measured data. Thus, a potential limitation of the SoilGrid250m map exists not only in the spatial pattern, but also in the overall magnitude (74.4 g·kg^{-1} in average). In this study, we used OC from SoilGrid250m (without any scaling factor) for the OC_map experiment.

We investigated the OC accuracy using one type of OC input into the new soil probe algorithm (Eqs. 2–4) by performing two experiments: 1) OC entered using a SoilGrid250m map (OC_map experiment; blue in Fig. 3) and 2) SMAPVEX12 the OC in situ of SMAPVEX12 (red in Fig. 3).

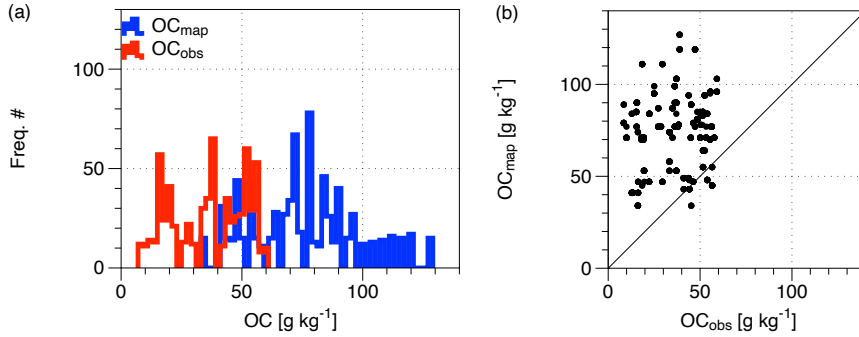



Figure 3: Comparison between organic carbon (OC) observation from SMAPVEX12 (red) and
data sampled from highly resolved SoilGrid250m map (Hengl et al., 2017) (blue) in: (a) in
histogram and (b) in scatter plot.

4. Calibration of portable soil-moisture sensors

The development of the calibration models is necessary for further campaigns or further extension of
the global soil moisture network based on a portable soil moisture sensor. For example, calibration
models (Rowlandson et al., 2013) were proposed by deriving the parameters A, B, and C of the
quadratic function between the effective dielectric constant and soil moisture for each SMAPVEX12
station.

$$\varepsilon_{obs} = Aw^2 + Bw + C$$
                        (13)

In each site a unique set of A, B and C was obtained to estimate w (volumetric soil moisture) from the
measured dielectric constant ε. It is important to verify whether these empirical models are transferable
to other field sites based on physical interpretation. Therefore, we compared them with those derived
from the dielectric mixing model, as shown in Table 2. The weighting function describing the
attenuation of signal on probe and satellite sensor can be an exponential form basically following Beer-
Lambert law where infinite attenuation of the electric field is allowed but negligible for the deeper than
sampling depth. On the other hand, a quadratic form can be considered as the weighting function based
on the assumption of linearly decreasing refractive index scheme (Wilheit, 1978) so that the emission
can be assumed to be zero from the deeper sampling depth. In this study, as shown in Table 2, we
assumed the Beer-Lambert law to consider the attenuation effect by applying the damping factor 0.8
applicable both for probe and satellite remote sensing. More detailed derivation associated with the
damping factor can be found in the previous study (Park et al., 2017).

Table 2. A, B, and C parameters of the relationship between the effective dielectric constant and soil moisture adapted from (Park et al., 2017) with damping factor H (0.8) ; dielectric constant for free (εfree), bound water (εbound) and soil mineral including organic matter (εsoil).

w range	A	B	C
$w < w_{\text{wp}}$	0	$(\varepsilon_{bound} - \varepsilon_{air})H$	$((1-p)\varepsilon_{soil} + p\varepsilon_{air} - 1)H + 1$
$w_{\text{wp}} < w < p$	$\dfrac{\varepsilon_{\text{free}} - \varepsilon_{\text{bound}}}{p - w_{\text{wp}}} H$	$\left(\dfrac{p\varepsilon_{\text{bound}} - w_{\text{wp}}\varepsilon_{\text{free}}}{p - w_{\text{wp}}} - \varepsilon_{air}\right)H$	$((1-p)\varepsilon_{soil} + p\varepsilon_{air} - 1)H + 1$
$p < w$	0	$(\varepsilon_{\text{free}} - \varepsilon_{\text{soil}}) \cdot H$	$\varepsilon_{\text{soil}} H - H + 1$

메모 포함[cp14]: Revised by the authors: The damping factor (H) had been applied all calculation and validation except Table 2. and Fig. 4. In this revision, we reflected the damping factor also in this table and Fig. 4.

We observed that when the wilting point and porosity increased with increasing OC [according to Eqs. (11–12)], A and B increased and decreased, respectively, as shown in Fig. 4. The results of this matching (Fig. 4) showed that A and B used in the quadratic function computed for SMAPVEX12 can be parameterized with soil texture, wilting point, porosity, and the bound and free water dielectric constants. Additionally, the C parameter indicates the effective dielectric constant of the mixture of dry organic matter (approximately 1.2 (Savin et al., 2020)) and solid mineral soil (3-5); ideally, the C parameter value should decrease with an increase in OC. Notably, the clay content was also positively correlated with an increase in OC in the SMAPVEX12. Therefore, owing to the simultaneous increase in clay content, which is characterized by a high dielectric constant, the sensitivity of the C parameter to OC variation (decreasing pattern in C) is nullified, as shown in Fig. 4(c). Furthermore, because C perfectly represents the dielectric constant of dry soil, it should be greater than 1, which is the real part of the dielectric constant of a vacuum. Based on this physical constraint, the previous C (gray points in Fig. 4) is unrealistically low (less than that of the vacuum state) in the higher SOM range. The minimum C is $(1-p)\varepsilon_{\text{soil}}$ among three w ranges [Eq. (4)] because the following order is always true [$(1-p)\varepsilon_{\text{soil}} < (1-p)\varepsilon_{\text{soil}} + p < \varepsilon_{\text{soil}}$] and it is larger than 2 as shown in Fig. 4 C. This shows that the proposed IDO computes a more realistic value of dielectric constant for organic-rich mineral soil.

310

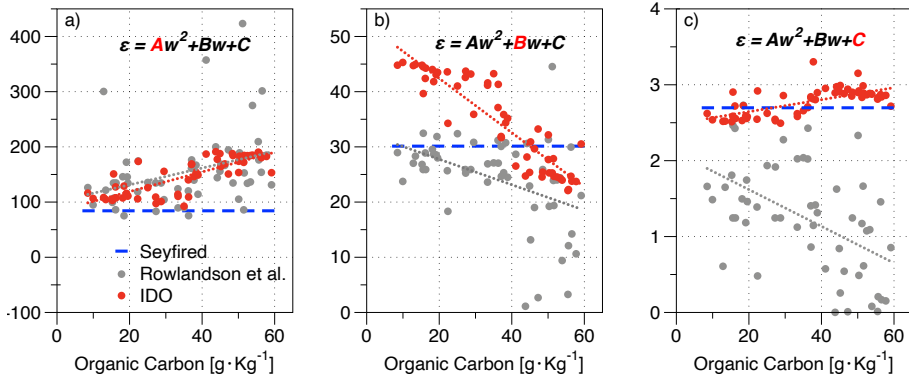



Figure 4: Relationship between soil organic carbon measurements (x-axis) and calibration parameters (*A*, *B* and *C*) (y-axis) relating between measured dielectric constant (*ε*) and volumetric soil moisture (*w*): (blue dash lines) *A*, *B*, *C* which are not sensitive to OC measurements (Seyfired
315 **approach); (gray dots) *A*, *B*, *C* which are empirically obtained (Rowlandson et al., 2013); (red dots) *A*, *B*, *C* which are physically simulated by proposed IDO which applies the wilting point and porosity as functions of sand and clay volumetric mixing ratios as well as soil organic carbon with the damping factor applied.**

5. Results

320   This study aimed to mitigate a significant discrepancy found between volumetric soil moisture estimated by soil probe sensor (considered as ground truth for the validation of land surface modelling and remote sensing) and the gravimetric soil moisture. Therefore, in this section, the new approach proposed in the section 2 investigated whether the accuracy of the new sensor algorithm can be improved compared to the existing probe algorithm. Firstly, looking at the Fig. 5(a) the current issue in
325   the probe SM estimates was well displayed in terms of the matching pattern of the gravimetric soil moisture with the measured dielectric constant. It showed that the existing probe soil moisture (red dots in Fig.5(a)) couldn't follow both features appeared in the measurements (the significant scattering degree and the distinct varying patterns in dry and wet condition). This is a fundamental limitation of the traditional polynomial function, the Seyfried model as well as a two-mode system (mineral or
330   organic-rich mineral soil), as proposed by Topp et al. (1980) or (Roth et al., 1992).

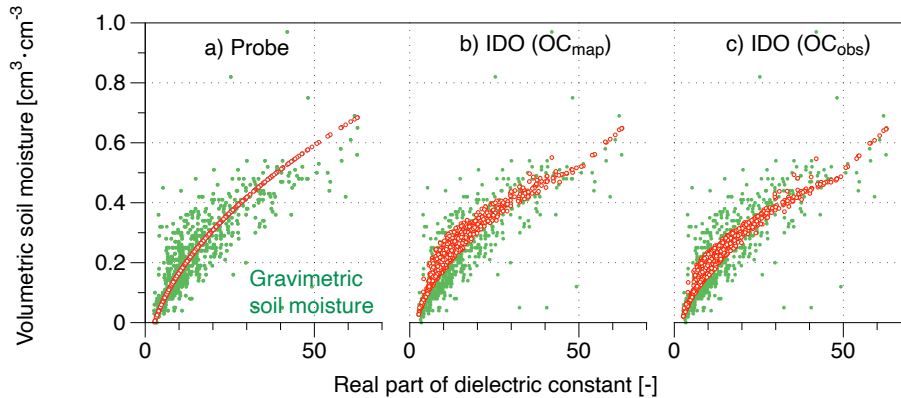
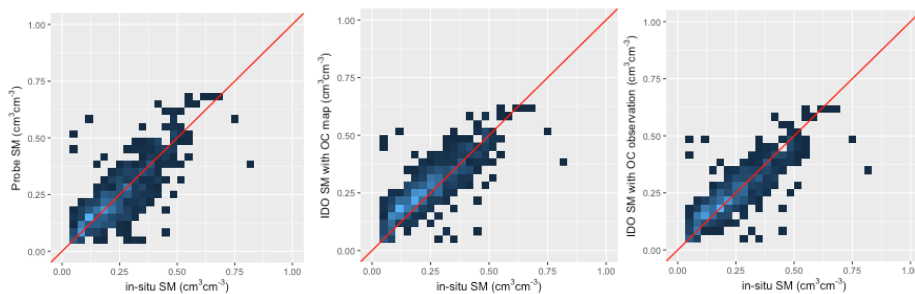



Figure 5: Scatter plot between probe measurements of the real part of the dielectric constant (x-axis) and volumetric soil moisture (y-axis) measured by gravimetric method (green dots in a, b, c), Seyfried model (red dots in a), IDO with SOM taken from SoilGrid250m (Hengl et al., 2017) (red dots in b) and IDO using OC measured during SMAPVEX12 (Manns and Berg, 2014) (red dots in c).

On the other hand, the IDO, with soil organic carbon considered, allowed us to compute SM with similar scattering pattern comparable to that measured by gravimetric method. It means that soil organic carbon is a critical factor for the application of the soil moisture sensors from portable to satellite based. In regards to the shape appearing in the scattering pattern, IDO captured the distinctively curved edge in the low and high-end points close to the values of 12 and 50, respectively, in the x-axis for the real part of the dielectric constant. Only difference between b) and c) at Fig.5 is OC input, originated from SoilGrid250m or from in-situ obtained during SMAPVEX12, respectively, with the same input of clay and sand mixing ratio from SMAPVEX 12. This pattern is probably related to the transition moments from bound to mixed (a to b in Fig. 1) and from mixed to free water states (b to c in Fig.1), which is very interesting evidence indicating that soil probes can detect critical soil parameters such as wilting point and soil porosity based on the accumulated dielectric measurements of certain sites.

Even though the shape of SM scattering estimated from the measured dielectric data (x-axis) became similar to the one appearing in the gravimetric soil moisture, it is also required to investigate whether the actual improvement in the SM accuracy has been achieved via the point-by-point comparison with the gravimetric data. This analysis was illustrated in the Q-Q plot in Fig.6. It displayed that the scattered uncertainty shown in Fig. 6(a) of the current soil probe algorithm can be reduced by IDO approach as (b) and (c). The scatter error shown in Fig.6(a) slightly converged into a 1:1 line when the IDO adapted the OC map as input (b) and further improved with a narrower scattered error pattern with OC in situ (c). This result further supported that the OC variability with the proposed model can mitigate the uncertainty in SM estimation of the current dielectric-based soil moisture sensor network.

360 **Figure 6:** **Performance of soil moisture probe algorithms in terms of scattering degree to the gravimetric measurements (x-axis); soil moisture estimates (y-axis) using a) 3rd order polynomial approach (Bell et al., 2013; Seyfried and Murdock, 2004), b) the proposed inverse dielectric mixing model (IDO) with the variational soil organic matter (SOM) sampled from the SoilGrid250m map (Hengl et al., 2017) and c) the same algorithm but with SOM measured from**
365 **SMAPVEX12 (Manns and Berg, 2014).**

In Fig. 7, we investigated more characteristics of SM uncertainty: how the biases of SM estimated by the conventional probe algorithm are related to the in-situ OC and whether they can be mitigated by the proposed algorithm with the OC measurements. Fig. 7(a) shows that both negative and positive biases
370 are affected by the IDO. Fig. 7(b), obtained by spreading out the histogram according to the degree of SOM, provides an in-depth analysis on how these biases are distributed according to the measured SOM. This shows that the negative bias in the high SOM range was reduced because the polynomial function of the conventional probe algorithm presented in Fig. 1(e) tends to overestimate the SM in the cases of lower SOM and underestimate the SM in cases of higher SOM (as compared to the proposed
375 multiphase model).

메모 포함[cp17]: RC1: Fig.6 & 7: the reduction of the uncertainty in SM estimates is relatively limited. It may be partly due to a narrow range and also a low amount of SOM in the soil samples in the study area. Therefore, it needs additional investigation whether this method applies to highly organic soil (e.g. SOM>30%), prevalent in the boreal and Arctic region, and how it performs if it is applicable. I would think this method is more general and has a high potnetial applicable to those conditions. However, the parameterization (including the witling point, porosity) needs additional improvement. It will be also helpful if the authors can compare their results with the previous methods that particularly incorporates organic carbon content. For example, in Bircher et al. 2016, the data do not show substantially dielectric differences in soils with SOM<30%, while this study shows even a small amount of SOM (SOM<~10-11%) can make a significant difference in the relationship between SM and dielectric constant.

Response: I agreed with you about your comments that in the low or medium OC range, the previous study (Bircher) was hard to demonstrate the improvement by OC consideration and we made the significant difference as you mentioned in the last comment. Therefore, I believe the improvement is meaningful without further experiments.
Furthermore, the direct comparison with the Bircher's study is difficult for this study because of two different conditions; 1) the OC measurements (the OC measurements of Bircher's study is obtained from soils highly covered with moss, which show very different characteristics from the one obtained from our SMAPVEX12 agricultural soil and 2) the dielectric measurements (Bircher's study used the theta probe which the frequency used in is 100MHz). Therefore, we decided to investigate the possibility of further improvement for higher OC regions in the future study.

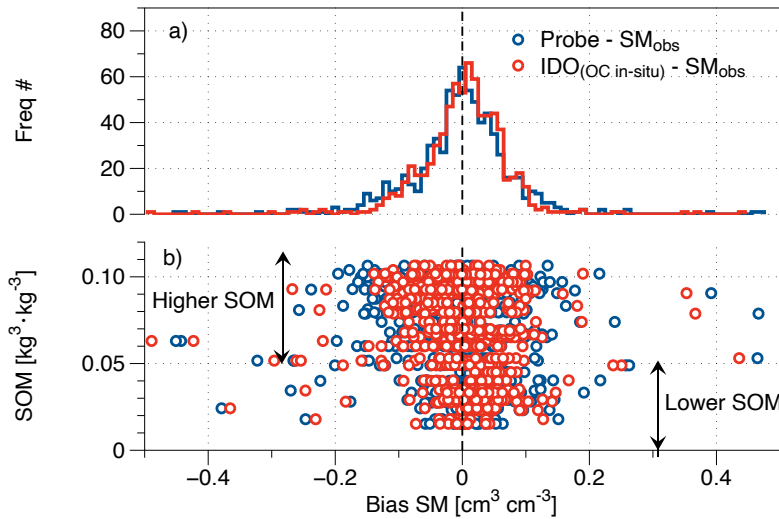



Figure 7: (a) Histogram of soil moisture (SM) bias and (b) its scatter relationship according to soil organic matter (SOM) converted from in-situ organic carbon (OC)

The importance of accurate and highly resolved organic carbon data in soil moisture estimation from portable soil sensors is highly evident from the statistical validation presented in Table 3. The results confirmed that the IDO performs better than the traditional probe algorithm based on a 3rd order polynomial function specially with the OC measured in the SMAPVEX12 field campaign (with a maintained spatial variability); RMSE = 0.0727 cm^3·cm^{-3}, correlation of 0.848, and bias of 0.0001 cm^3·cm^{-3}.

Table 3. Validation of soil moisture obtained from Probe (Probe SM), organic-rich mineral soil based on SoilGrid250m organic carbon map (IDOmap), and SMAPVEX12 OC in situ observation (IDO$_{obs}$)

	Bias	RMSE	Correlation
Probe	-0.0042	0.0824	0.824
Proposed algorithm with organic carbon map (IDO$_{map}$)	0.0222	0.0789	0.835
Proposed algorithm with in situ organic carbon (IDO$_{obs}$)	0.0001	0.0727	0.848

메모 포함[CP18]: RC1: I would think this method is more general and has a high potential applicable to those conditions. However, the parameterization (including the witling point, porosity) needs additional improvement.

After improving the wp and p function based on your previous comment (p.5-6, lines 186-188), we could update the validation score properly in the table 3 (p.15, line 392).

The results in this section demonstrated that the wilting point and porosity which emerged in paring the gravimetric soil moisture and the dielectric measurements, could be detected also by the new model. Also, it is proven that the volumetric soil moisture could be estimated from the sensor more accurately in terms of bias, RMSE and correlation analysis. It means that our approach can provide more accurate soil moisture probe algorithm than currently used in various soil moisture networks such as USCRN (US Surface Climate Observing Reference Networks) and the SMAPVEX field campaigns. In the boreal forest and Alaska Tundra region with abundant SOM, our study can deliver a significant effect to the validation and conclusion of the previous studies in land surface modelling and microwave satellite remote sensing, which used the probe soil moisture as a reference data.

6. Summary and discussion

In this study, we proposed an inverse dielectric mixing model for a 50-MHz soil sensor for agricultural organic-rich mineral soil. The 50MHz sensor is a prevalent frequency band for soil moisture probes. (Cosh et al., 2021) found that in North America soil sensors using this waveband occupied 40% of the soil moisture networks (10 of 25 including USCRN) and 53% of sensors (1021 of 1923 locations). Therefore, the proposed algorithm has potential to contribute significantly to the accuracy of the soil moisture estimates derived from current in situ soil moisture measurements. Furthermore, since the SMAPVEX also used 50 MHz sensors, it is anticipated that the accuracy of the calibration and validation of the SMAP related soil moisture algorithms will be increased. The proposed model is composed of three nonlinear functions that are mathematically capable of describing the physical behaviour, including the effect of the organic matter content. In this model, we proposed a physical mixing approach of organic matter in dry soil and improved the wilting point and saturation point. This derivation also can be applied to other bands for Capacitance sensors (5TE (70MHz), Wet (20MHz), Time-Domain-Reflectometry (TDR) (TDR100/200 (1450MHz), SoilVUE-10 (1450MHz) and satellite sensors SMAP (L-band) and SMOS (L-band) (AMSR-E (JAXA) X/C, Sentinel-1 (ESA) (C)). It is also noticed that the applied organic matter carbon data sampled from SMAPVEX12 sites (36 g·kg⁻¹) was half that of the OC map (74 g·kg⁻¹). The validation results demonstrated a higher performance of the new model. Regardless of the small amount of OC, its effect improved the performance of the SM estimation, which was demonstrated via the IDO proposed in this study. We compared the obtained soil-moisture retrievals with improved RMSE (13% ↓), slightly stronger correlation (3%↑), and lower bias (90%↓) using the new model and gravimetric soil moisture data. But still the coverage of the simulated pattern over the measured points was smaller. Therefore, we sought out a potential further improvement based on the additional experiment designed with SOM varying within the proposed model. The simulation based on the conventional polynomial function (red curve in the Fig. 8 (a)) could not reduce the innate uncertainties and the IDO proposed in this study could resolve this issue. However, the red dots simulated with IDO (Fig. 8(b)) covered over the measured green dots insufficiently. Therefore, in order to activate this weak pattern, we performed the experiments to impose a more dynamic OC estimate to investigate whether greater or less SOM can cover a similar boundary of the measured distribution through the IDO model. The results showed that the piecewise pattern of

메모 포함[CP19]: Editor: Your reply already points to the relevance of your work to some degree, so you appear to be developing a suitable line of argumentation that you can include in the revised text.

Response: We emphasized the importance of our study relating to the current soil moisture probe network in the discussion. For example, the improvement by our study can be anticipated on over 50% locations of the current sensors installed in the United States (page 16, lines 404-410). Furthermore, we discussed that the proposed mixing approach for dry organic soil is applicable to the other soil probe sensors in the different range of frequencies (p.16, lines 404-410).

SM simulated with the proposed approach well covered the measured pattern with imposing lower (1 %) to higher (30 %) SOM.

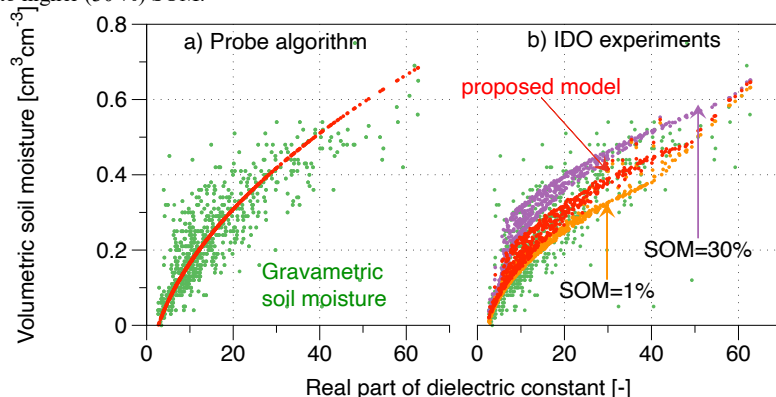



Figure 8: Investigation of the similarity of the scatter pattern between the measured dielectric
435 **constant and the soil moisture: (a) obtained from the gravimetric measurements and (b) experimentally simulated with extreme soil organic matter (SOM) from 0 % to 30 %.**

Because the SOM is translated from OC with a conversion factor (1.8) in this study, the improvement might have been not sufficient. A realistic estimation of the conversion factor (f_{oc}) in Eq. (10) varying
440 from 1.25 up to 2.5 might be a possible solution for this. In addition, the IDO is a model able to replace the calibration factors A, B, and C of Eq. (13) with the soil properties presented in Table.2. Overall, the proposed more physics based IDO can replace the current soil probe sensor algorithm, which does not incorporate the importance of organic matter variability.
A significant improvement could not be shown probably due to two reasons: the instrumental error in
445 measuring OC from soil sample or the constant OC to SOM conversion factor (1.8 for all soil samples). In addition, uncertainty can be suspected from other sources, such as clay or sand contents or soil salinity (assumed to be 0 % in this study) used in the IDO. These effects on the dielectric measurements and their uncertainties probably served as the limitation of further improvement by the IDO. Nevertheless, the results regarding the adaptation of in-situ OC in our study demonstrated that the
450 accuracy of the SOM input for IDO is critical for the accuracy of SM estimation from the probe sensor. In previous studies (Topp et al., 1980; Roth et al., 1992; Bircher et al., 2016), in the organic mode or the peat soil, the dielectric constant and soil moisture relationship is calibrated to be able to simulate the dielectric constant lower than mineral soil with given soil moisture. These results are consistent with our study, which showed decreasing dielectric constant value in higher SOM by increasing bound water
455 fraction due to higher wilting point (wp). Therefore, if we have more information about the dielectric constant of perfectly dried peat soil and a more accurate model for the wilting point and porosity of this soil, our model will be able to cover soils from mineral to peat regions to obtain more accurate global

메모 포함**[CP20]:** Editor: It will also help if you can expand the discussion of your results in view of earlier findings reported by others.

Response: In the discussion, we investigated about whether the results presented in our study is consistent to the previous studies (Topp et al., 1980; Roth et al., 1992; Bircher et al., 2016) (p.17-18, lines 451-460). As a result, our estimation of soil moisture from the dielectric constant showed the similar pattern with the one estimated by previous results, and it could be explained by the bound water fraction of organic soil in our study.

메모 포함**[CP21]:** RC1; It will be also helpful if the authors can compare their results with the previous methods that particularly incorporates organic carbon content. For example, in Bircher et al. 2016, the data do not show substantially dielectric differences in soils with SOM<30%, while this study shows even a small amount of SOM (SOM<~10-11%) can make a significant difference in relationship between SM and dielectric constant.

Response: As the reviewer's suggestion, the comparison to the study (Bircher et al. 2016) will be very helpful to demonstrate the benefit of our approach for 50MHz soil moisture sensor. However, as mentioned in above response, in the current study it is not directly applicable due to the difference in the type of organic soil and in the frequency of the soil probe sensor. I agreed with you about your comments that in the low or medium OC range, the previous study (Bircher) was hard to demonstrate the improvement by OC consideration and in our study, we made the significant difference as you mentioned in the reviewer's last comment. Therefore, I believe the improvement is meaningful without further experiments. We decided to investigate the possibility of further improvement for higher OC regions in the future study.

soil moisture. In addition, if we improve this model toward a frequency dependent model in the future study, the existing and future probe measurements obtained in various frequencies will be able to contribute more extensively for the calibration and validation of satellite and model.

Author contributions:
CHP developed the algorithm. CHP, AB, MHC, AC and HM designed the study. HM collected the soil organic carbon in-situ data. RZ provided the mathematical corrections. CHP conducted the validation and the analysis. JH, AB, JL and VW provided guidance on the research direction. CHP wrote the manuscript. All authors reviewed the manuscript.

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Declaration of Interest: The authors declare that they have no conflict of interest.

Appendix A

Based on the computation of the bulk density for organic-rich mineral soils, the volumetric mixing ratio of soil organic matter can be derived as shown in Eqs. (13)-(19).

$$BD_{soil} = \frac{M_{MI}+M_{SOM}}{V_{MI}+V_{SOM}} = \frac{BD_{MI} \times BD_{SOM}}{(1-SOM) \times BD_{SOM}+SOM \times BD_{MI}} \tag{13}$$

$$\frac{V_{SOM}}{V_{MI}+V_{SOM}} \frac{M_{MI}+M_{SOM}}{V_{SOM}} = \frac{BD_{MI} \times BD_{SOM}}{(1-SOM) \times BD_{SOM}+SOM \times BD_{MI}} \tag{14}$$

$$v_{SOM} = \frac{V_{SOM}}{M_{MI}+M_{SOM}} \times \frac{BD_{MI} \times BD_{SOM}}{(1-SOM) \times BD_{SOM}+SOM \times BD_{MI}} \tag{15}$$

$$v_{SOM} = \frac{M_{SOM}}{M_{MI}+M_{SOM}} \frac{V_{SOM}}{M_{SOM}} \times \frac{BD_{MI} \times BD_{SOM}}{(1-SOM) \times BD_{SOM}+SOM \times BD_{MI}} \tag{16}$$

$$v_{SOM} = \frac{SOM}{BD_{SOM}} \times \frac{BD_{MI} \times BD_{SOM}}{(1-SOM) \times BD_{SOM}+SOM \times BD_{MI}} \tag{17}$$

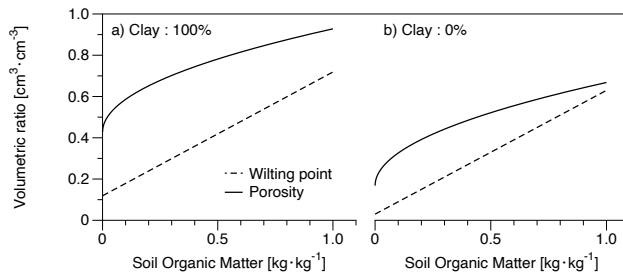
$$v_{SOM} = \frac{BD_{MI}}{\frac{(1-SOM)}{SOM} \times BD_{SOM}+BD_{MI}} \tag{18}$$

$$v_{SOM} = \cfrac{1}{\left(\cfrac{1}{SOM}-1\right)\times\cfrac{BD_{SOM}}{BD_{MI}}+1}$$

495

(19)

where, M_{MI} [kg] and M_{SOM} [kg] are mass of mineral and soil organic matter; V_{MI}, [cm^3] and V_{SOM} [cm^3] are volume of mineral soil and soil organic matter; v_{SOM} [cm^3 ·cm^{-3}] and SOM [kg·kg^{-1}] are volume and mass mixing ratio; and BD_{MI} [kg·cm^{-3}] and BD_{SOM} [kg·cm^{-3}] are bulk density of mineral and organic
500 matters, respectively.

Appendix B

505 **Figure. 9 Simulations of wilting point, Eq.(11) improved of Park et al., 2019 and porosity, Eq.(12), proposed in this study which are function of soil organic matter at extreme case a) volumetric clay mixing ratio 100% and b) 0% of the total mineral within organic-rich mineral soil**

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