Rationale Behind an Optimal Field Experiment to Assess the Suitability of Soil Moisture Retrieval Algorithms for SAR Data

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Abstract—Validation of soil moisture products derived from synthetic aperture radar (SAR) remotely sensed observations involves a comparison against ground-truth data. This validation step helps one to state the performance of competing retrieval algorithms. Nevertheless, the design of a field experiment in the context of SAR retrieval is not straightforward. Ground-based measurements are affected by instrument errors due to both the physical limitations of the measurement technique and the uncertainties related to the spatial variability of the soil moisture. To properly assess the performance of the retrieved estimates, both of the mentioned sources of uncertainties should be considered in the ground-based sampling and in the subsequent error assessment analysis. This letter addresses the rationale behind an optimal field experiment designed to assess the suitability of soil moisture retrieval algorithms.

Index Terms—Ground-based sampling, remote sensing applications, surface soil moisture, synthetic aperture radar (SAR) estimates.

I. INTRODUCTION

WHEN using synthetic aperture radar (SAR) data to retrieve geophysical variables, a tradeoff between radiometric accuracy and spatial resolution is always present due to speckle noise. Usually, high accuracy in the observations is required in order to guarantee a given error in the retrieved estimate. On the other hand, high spatial resolution is desirable from the user's standpoint. In general, accurate SAR measurement over a homogeneous extended target can only be attained at the expense of spatial resolution.

This is particularly important in the context of soil moisture estimation from SAR data. In this case, several factors affect spatial variability of surface soil moisture content over bare soils, including precipitation, evaporation, soil texture, topography, soil management, etc. Each factor exerts a degree of spatial organization on the soil moisture distribution by introducing or removing water into/from the soil or by facilitating or ham-

pering soil water distribution [1]. Each of the previously listed factors can either enhance or reduce the spatial variability of soil moisture. For example, relative homogeneous land surface properties can act dissipatively to reduce soil moisture variability created by heterogeneous precipitation [2]. Finally, there is another very important process that determines the spatial variability of soil properties: soil management. Agricultural land is often divided into smaller fields, each one characterized by the same land management and land use over several growing seasons.

From the aforementioned considerations, it is natural to assume that fields are the larger agricultural extents in which land properties can be regarded as homogeneous. Therefore, a field-based retrieval scheme will guarantee the minimal possible soil heterogeneity compatible with the required radiometric uncertainties [3]. For this reason, SAR-based soil moisture estimates are best defined on a field basis. These estimates will be referred to as "field-based retrieved estimates" hereafter.

Validation of field-based retrieved estimates against ground-truth data should be done carefully, since different spatial scales are involved. On one hand, retrieved estimates represent mean soil moisture over a spatial domain defined by the outer limits of the field, typically ranging from 1 to 50 ha. On the other hand, soil moisture estimates derived from ground-based sampling involve a finite (and often small) number of point measurements (over an extent of 1 m $\times$ 1 m) performed with nonideal (i.e., with errors) instruments.

Since agricultural fields are regarded as the unit for retrieving purposes, field-intrinsic soil moisture variability should be taken into account. This variability cannot be measured from a high-resolution SAR image over the agricultural field, due to radiometric uncertainties from speckle noise. It only can be estimated by means of a field experiment (see, for example, [1]). This variability becomes critical at the moment of the design of a ground-based validation scheme. Despite this, in most calibration/validation (Cal/Val) experiments, errors in ground-based estimates are usually disregarded, even when these experiments should take into consideration the well-known spatial variability of soil moisture. As will be seen in the next sections, Cal/Val strategies can be defined by scaling considerations in SAR retrievals and the results shown in [1].

In this letter, the link between uncertainties in the ground-based estimates and uncertainties in the field-based estimates in the context of SAR soil moisture retrieval is addressed.

As will be shown, such a link becomes very relevant when designing dedicated field experiments to assess the performance of developing retrieval algorithms. The results shown here are directed toward the definition of a rationale, i.e., an optimized field experiment for soil moisture retrieval: How many field measurements are needed to achieve a good error assessment?

II. Soil Moisture Variability Across Scales: Famiglietti's Model

While remote sensing provides an effective methodology for mapping surface moisture content over large areas, it averages within-pixel variability, thereby masking the underlying heterogeneity observed at the land surface. This variability must be better understood in order to rigorously evaluate soil moisture estimation performance and to enhance the utility of the larger scale remotely sensed averages by quantifying the underlying variability that remote sensing cannot record explicitly.

In this respect, in [1], a study on the relationship of soil moisture standard deviation versus mean moisture content was conducted by analyzing over 36 000 ground-based soil moisture measurements on the top 6 cm of soil collected during a number of field campaigns. Results from that study relevant to this letter are as follows.

1) The variability of soil moisture, quantified as the standard deviation, generally increases with extent scale. The standard deviation increases from 0.036 cm^3/cm^3 at the 2.5-m scale to 0.071 cm^3/cm^3 at the 50-km scale.
2) The log standard deviation of soil moisture increases linearly with the log extent scale, from 16 m to 1.6 km, indicative of fractal scaling.
3) The soil moisture standard deviation versus mean moisture content exhibits a convex upward relationship at the 800-m and 50-km scales, with maximum values at mean moisture contents of roughly 0.17 and 0.19 cm^3/cm^3, respectively.

The third observation is indicative of a great variability in the middle range of soil moisture, and therefore, it is expected that mean moisture estimates will have larger errors.

The experimental observation made in item 2) can be modeled as

$$\text{Var}(X^S) = CS^D \quad (256 \text{ m}^2 < S < 2.56 \text{ km}^2) \qquad (1)$$

where C is a parameter, D is a fractal power ($D = 0.086$), S is the extent scale, and $\text{Var}(X^S)$ is the variance of soil moisture at S. Such a relationship can be used to estimate the average variance conditions at a particular scale.

III. Reformulation of Famiglietti's Model: Scaling Considerations in SAR Retrievals

Next, we will reformulate Famiglietti's model to adapt it to any retrieval scheme over agricultural lands using SAR images. Let the extent scale $S_{\text{rad}} = L_{\text{rg}} \times L_{\text{az}}$ be the smallest spatial scale on which it is feasible to retrieve biogeophysical variables using a remote sensing technique, where L_{rg} is the range pixel spacing and L_{az} is the azimuth pixel spacing of a ground-
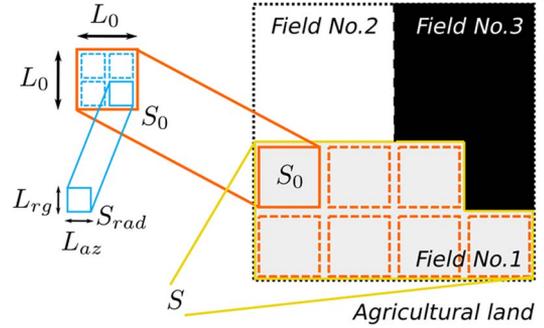
Fig. 1. Scaling involved in a ground validation of a spatially distributed geophysical variable as soil moisture. Scale S is related to the number of pixels n of the field. Famiglietti's model allows one to estimate the soil moisture standard deviation at the scale S.

projected image. Typically, S_{rad} is the pixel size projected on the ground for a square pixel image (Fig. 1). In addition, Famiglietti's model predicts how the variability of soil moisture increases from a unit scale $S_0 = L_0 \times L_0$ according to (1) (where $S_0 = 256 \text{ m}^2$, i.e., $L_0 = 16 \text{ m}$). Usually, for an airborne sensor (one-look image), $S_{\text{rad}} \ll S_0$, while for a satellite sensor (one-look image) $S_{\text{rad}} < S_0$. Let m be the number of times the radar scale S_{rad} fits into S_0; then

$$S_0 = mS_{\text{rad}} \qquad (2)$$

where m is referred to as "the scale factor for a certain scale S_{rad}" (where S_{rad} depends on the sensor characteristics). As an example, let us assume a SAR acquisition over the agricultural site shown in Fig. 1, which consists of three different fields of bare soil. An estimate of the mean moisture standard deviation σ^S at S corresponding to Field No.1 can be computed considering it as composed of n fundamental units S_{rad}, with n as the number of pixels. (Recall that the retrieval scheme in this letter is a field-based one, with the field being the smallest ground unit on which it is feasible to retrieve biogeophysical variables via a remote sensor.) Thus

$$S = nS_{\text{rad}} = \frac{n}{m}S_0 \qquad (3)$$

where n is the number of pixels associated to a field of scale S and m is the ratio S_0/S_{rad} depending only on the sensor. In the right side of (3), (2) was used to express the scale S in terms of S_0. Expression (3) allows one to decompose a SAR-imaged field in terms of fundamental units S_0. With S on hand, it can be combined with (1), which is reformulated as follows:

$$\sigma(X^S) = \sqrt{CS^D} = \left(\frac{L}{X_0}\right)^D \qquad (4)$$

where L is the side of S (assumed square) computed from (3) as $L = \sqrt{S} = \sqrt{nS_0/m} = \sqrt{(n/m)}L_0$. $X_0 = C^{-(1/2D)}$ replaces C in (1), $X_0 = 2.879 \times 10^{17}$ m. The standard deviation allowed by (4) has a dynamic range of 0.040 cm^3/cm^3 for the spatial scale $S = 256 \text{ m}^2$ to 0.059 cm^3/cm^3 for the spatial scale $S = 2.56 \text{ km}^2$. Expressions (4) and (3) allow one to estimate the expected spatial variability of soil moisture, quantified by the standard deviation, for a field imaged by a

TABLE I
MAIN FEATURES OF SAR SYSTEMS (AIRBORNE AND SATELLITE-BORNE)
REGARDING FIELD ESTIMATES

Sensor	Space Agency/ Country	Pixel size $L_{rg} \times L_{az}$ [m²]	S_{rad} [m²]	m
SARAT†	CONAE/Argentina	5.28×5.28‡	27.9	9.18
UAVSAR†	NASA-JPL/USA	5.00×7.20‡	36.0	7.11
RADARSAT-2	CSA/Canada	3.125×3.125	9.77	26.2
Sentinel-1	ESA/Europe	4.00×4.00‡	16.0	16.0
ALOS-2	JAXA/Japan	5.1×4.3	21.9	11.7
SMAP	NASA-JPL/USA	1000×1000ᵃ	10^6	2.56×10^{-4}
SAOCOM 1A	CONAE/Argentina	10×10	100	2.56

The scale factor m is a feature of each sensor. †Airborne systems.
‡Multilooked images. ªLevel 1C High Resolution Radar Product.

SAR sensor. Table I summarizes the scale factor m for a number of relevant airborne and satellite-borne SAR sensors. The scale factor m relates a SAR n-pixel image over an agricultural area with the soil moisture variability by means of the reformulated Famiglietti's model.

IV. INSTRUMENT ERROR

The commonly used gravimetric (oven-dry) method relies on measuring the gravimetric moisture m_g of a wet sample as $m_g = ((x - t)/(y - t)) - 1$, where x and y are the wet and dry weights, respectively, and t is the tare weight of the sample holder [4, Ch. 21]. The volumetric moisture is obtained from the bulk ρ_b and water ρ_w density as

$$m_v = \frac{\rho_b}{\rho_w} m_g. \tag{5}$$

Assuming independence between $(x - t)$ and $(y - t)$ and that the variances of the three weighings are likely to be nearly the same ($\sigma_x^2 \approx \sigma_y^2 \approx \sigma_t^2 \approx \sigma_{bal}^2$, where σ_{bal} is the weighing precision of the balance), the variance of the volumetric moisture estimator is [4]

$$\sigma_{m_v}^2 = 4 \left(m_v^2 + \frac{\rho_b}{\rho_w} m_v + \frac{\rho_b^2}{\rho_w^2} \right) \frac{\sigma_{bal}^2}{\rho_b^2 V^2} + m_v^2 \frac{\sigma_V^2}{V^2} + m_v^2 \frac{\sigma_{\rho_w}^2}{\rho_w^2} \tag{6}$$

where V is the volume of the sample holder with uncertainty σ_V, ρ_b ($= (y - t)/V$) is the bulk density of the soil sample, and ρ_w is the density of water with uncertainty σ_{ρ_w}. The standard (one-sigma) error σ_{m_v} is then computed from (6). For typical values ($m_v = 0.20$ cm³/cm³, $\rho_b = 1.10$ g/cm³, $\sigma_{bal} = 0.5$ g, $V = 100$ cm³, and $\sigma_V = 10$ cm³), the second term contributes with around 76% of the total variance, since it involves the uncertainty in V, from which the bulk density is computed. The first term, related to the balance precision and the weighing of the sample (since $\rho_b V$ is the dry weight), contributes with around 23%. The term related to the density of water is negligible. The impact of the uncertainty σ_V and the weighing precision σ_{bal} on σ_{m_v}, for typical values of V and ρ_b, is depicted in Fig. 2.

Portable impedance probes serve as a valuable alternative to destructive gravimetric sampling. These probes measure the dielectric properties of the soil–water–air mixture from which the volumetric soil moisture can be inferred. Typical
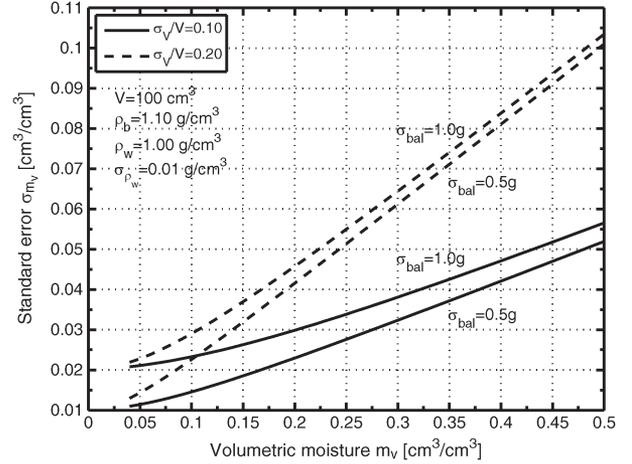
Fig. 2. Standard error for volumetric soil moisture at two weighing precisions (taken as the standard deviation σ_{bal} of the balance) 0.5 and 1.0 g. V is the volume of the sample with uncertainty σ_V, ρ_b is the bulk density, and ρ_w is the density of water with uncertainty σ_{ρ_w}.

accuracies reported by the manufacturers are 0.030 cm³/cm³ with a precision on the order of 0.003 cm³/cm³ [5] for the factory generalized calibration. Field-specific calibration improves performance since a root-mean-square error (rmse) of 0.040 cm³/cm³ and a negligible bias (< 0.001 cm³/cm³) are attained [6]. The instrument error is then

$$\varepsilon_{inst} = \sqrt{\left(\varepsilon_{inst}^{syst}\right)^2 + \left(\varepsilon_{inst}^{stat}\right)^2} \tag{7}$$

where $\varepsilon_{inst}^{syst}$ is the systematic error given by the accuracy and $\varepsilon_{inst}^{stat}$ is the statistical error given by the precision. In the case of a field-specific calibration, the former is given by the bias, and the latter is given by the rmse.

V. TOTAL ERROR IN FIELD VALIDATION

Let us consider the ground validation stage of a field-based retrieved magnitude X_{ret}^S against ground-truth data. Roughly speaking, ground-sampling campaigns involve a set of N ground-based samples $X_1, X_2, \ldots, X_N$ at the scale S performed with an instrument or measurement method that contains an uncertainty ε_{inst}. Usually, those N measurements are carried out over a regular grid covering the entire agricultural field, naming sites to each grid intersection (see Fig. 3). A common practice is to perform a set of M measurement replicates $X_1^k, X_2^k, \ldots, X_M^k$ on the kth site to diminish the statistical error of the measurement technique (by a factor of $1/\sqrt{M}$ if replicates are regarded as independent). From that set of M replicates, the site mean μ^k can be computed, since it is assumed that, at each site, X has a definite value and, therefore, variance comes only from the measurement technique. An estimate on the ground μ_{grd} for the true field-mean soil moisture μ at the scale S is then obtained by averaging μ^k ($k = 1, \ldots, N$). Instrument errors for μ_{grd} accordingly to the techniques described earlier are summarized in Table II.

In addition to instrument errors, a second error source comes from the spatial extent of the magnitude X. An error estimate
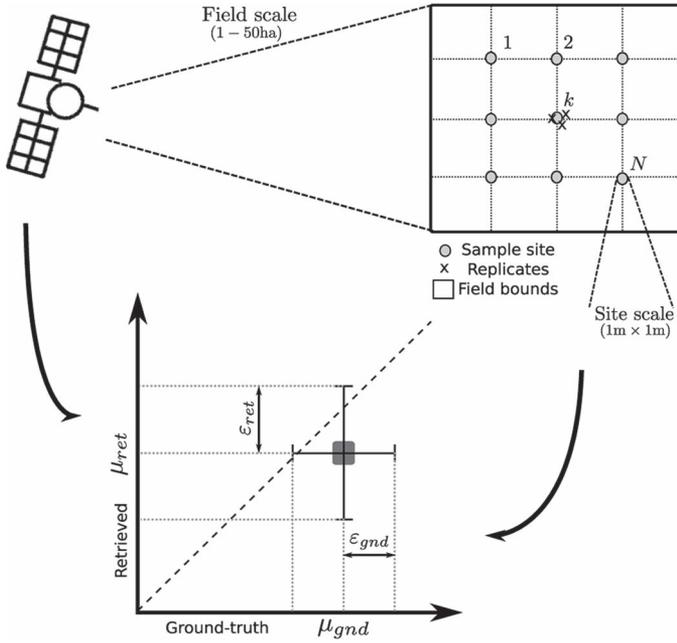
Fig. 3. General sketch for an assessment of a retrieved estimate μ_{ret} against a field-mean estimate μ_{grd} measured on ground. A sound assessment is attained when error bars in site-scale (1 m × 1 m) and field-scale estimators are stated. Performance metrics are used to measure how successful is the estimator to represent the ground truth.

TABLE II

CONTRIBUTIONS OF INSTRUMENT AND EXTENT ERRORS TO THE TOTAL
UNCERTAINTY ASSOCIATED TO A GROUND-BASED SOIL MOISTURE
ESTIMATE FOR GRAVIMETRIC (OVEN-DRY) AND
DIELECTRIC PROBING TECHNIQUES

Technique	Total Error Terms in cm^3/cm^3	
	Instrument (site scale) ε_{inst}	Extent (scale S) σ_{grd}
Gravimetric	Standard error $\frac{\sigma_{m_v}}{\sqrt{M}}$ (see 6)	Famiglietti modified
Dielectric Probe	0.030 (syst) + $\frac{0.003}{\sqrt{M}}$ (stat) †	$\frac{\sigma(X^S)}{\sqrt{N}}t_{\frac{\alpha}{2},N-1}$ (see 8)
	or 0.001 (bias) + $\frac{0.040}{\sqrt{M}}$ (rmse) ‡	

M is the number of replicates within each site. N is the number of sites. $t_{p,q}$ is the inverse of the Student's t distribution for a probability p with degrees of freedom q. †Generalized calibration (manufacturer). ‡Field specific calibration.

for μ_{grd} computed from N sparse site measurements over the field extent is given by [7, Ch. 7]

$$\sigma_{grd} = \frac{\sigma(X^S)}{\sqrt{N}}t_{\frac{\alpha}{2},N-1} \qquad (8)$$

where $t_{(\alpha/2),N-1}$ is the α quantile of the student's t distribution with $N-1$ degrees of freedom. Expression (8) defines a $100\alpha\%$ confidence region for the true value μ.

It is expected that σ_{grd} is similar to the one reported in [1] when N is large enough at the corresponding scale S. For all practical purposes, it will be assumed that $\sigma_{grd} = \sigma(X^S)$, where $\sigma(X^S)$ is computed from (4). Finally, the total error ε_{grd} in the ground estimate is

$$\varepsilon_{grd} = \sqrt{\varepsilon_{inst}^2 + \sigma_{grd}^2} \qquad (9)$$
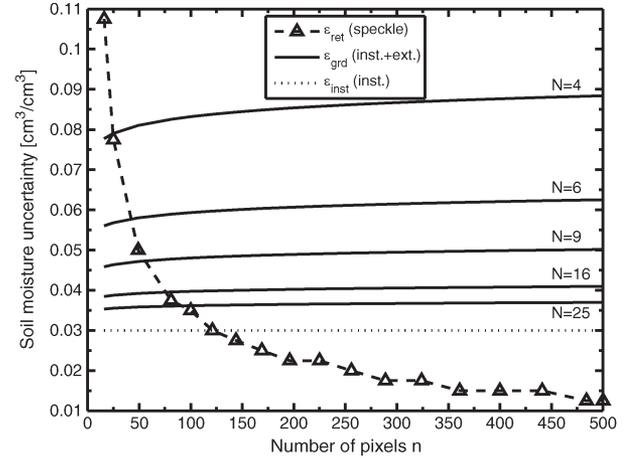
Fig. 4. Soil moisture uncertainties due to speckle noise, extent scale, and instrument errors. N is the number of measurement sites. Only instrument error remains when $N \gg 1$. $M = 3$ replicates are taken. An optimized number of measurements N can be computed from a given soil moisture uncertainty, i.e., 0.040 cm^3/cm^3, and under $\varepsilon_{ret} \sim \varepsilon_{grd}$ provides a suitable condition for assessment purposes.

where ε_{inst} is the total instrument error and σ_{grd} is the uncertainty related to the spatial variability of the magnitude under consideration.

The validation stage is performed by comparing field-based retrieved estimates against measured ground-truth data, along with their error bars, as shown at the bottom part of Fig. 3. Error bars in ground-truth data consist of two terms, as summarized in Table II. To quantitatively determine, although not uniquely, agreement of the field-based estimate with that of the ground truth, a set of error metrics can be defined (for instance, see [8]). It is worth noting that the spatial scale of a remotely sensed estimator (> 100 m × 100 m) is significantly larger than the scale involved in a point measurement (1 m × 1 m).

VI. OPTIMAL GROUND-SAMPLING SETUP FOR CAL/VAL

Cal/Val experiments are critical to developing and testing soil moisture retrieval algorithms from microwave remote sensing platforms. Ground sampling must be optimally designed to minimize sources of error during data collection.

In order to estimate the uncertainty in soil moisture coming from an uncertainty in σ^0 due to speckle noise, the copolarized ratio $(HH/VV) = u(m_v, \mathrm{ks}; \theta_i)$ is chosen as forward model, whose dependence on the volumetric soil moisture m_v, normalized roughness parameter ks, and beam incidence angle θ_i is explicitly stated in [9]. A sample of u is generated using the distribution P_U for the ratio $U = HH/VV$ of two intensity coefficients [10] and a standard Monte Carlo technique. The distribution $P_U(u; \tau, \rho, n)$ depends on the number of independent (one-look) pixels n used to compute the true ratio $\tau = E[HH/VV]$ and the correlation ρ between HH and VV. The standard deviation from that sample is then mapped to an uncertainty in soil moisture by numerically inverting the forward model $u(m_v, \mathrm{ks}; \theta_i)$. In this way, field-based retrieved soil moisture uncertainty ε_{ret} due to speckle noise is computed for a number of pixels.

Fig. 4 depicts the uncertainty ε_{ret} due to speckle in the retrieved soil moisture as a function of the number of pixels

n, for model parameters $m_v = 0.200$ cm^3/cm^3, ks $= 0.3$, and $\theta_i = 40°$. The true ratio is $\tau = u(m_v, \text{ks}; \theta_i)$, and $\rho = 0.7$. Pixels are assumed to be independent. Overlaid uncertainty curves ε_{grd} related to the ground-based field-mean soil moisture, given by (9), for several site measurements N are plotted. These curves depict the scaling behavior of the soil moisture variability (plus a constant level given by the instrument error) with the extent scale S. The instrument error is set to $\varepsilon_{\text{inst}} = (0.030 + (0.003/\sqrt{M}))$cm^3/cm^3, corresponding to a dielectric probe with M replicates per measurement site. For airborne sensors, where ground range images are already multilooked, the uncertainty ε_{ret} shown is an upper bound for the estimate error. The same applies for Sentinel-1 sensor, where the pixel spacing of 4.00 m $\times$ 4.00 m has a nominal number of looks of four [11].

For assessment purposes, an error in the retrieved estimate ε_{ret} similar to that of the ground estimate ε_{grd} is desired, i.e., horizontal and vertical error bars in Fig. 3 might be equal in length. Too large horizontal error bars imply a suboptimal experimental setup. On the other hand, horizontal error bars much smaller than the vertical ones suggest a considerable waste of efforts in the field experimental setup. The intersection points in Fig. 4 define the condition $\varepsilon_{\text{ret}} \sim \varepsilon_{\text{grd}}$ for certain n and N.

For example, let the desired field-based retrieved estimate error be $\varepsilon_{\text{ret}} = 0.040$ cm^3/cm^3. Therefore, from Fig. 4, this implies a ground-sampling design of about $N = 16$ site measurements over a field encompassing at least $n = 75$ pixels. For SARAT, $n = 75$ yields a field size of $S = nS_0/m = 2092$ m^2 or 0.21 ha. This is the minimum field size in which an error of at most 0.040 cm^3/cm^3 is reached for the retrieved estimate with a ground-sampling scheme involving $N = 16$ site measurements and under the assessment condition $\varepsilon_{\text{ret}} \sim \varepsilon_{\text{grd}}$. Likewise, let the typical field size be $S = 1$ ha, and let a given error be $\varepsilon_{\text{ret}} = 0.050$ cm^3/cm^3. For SAOCOM 1A ($m = 2.56$), this leads to $n = mS/S_0 = 100$ pixels, which, in turn, implies $N \sim 9$ site measurements accordingly to the predefined error. For this case, the better achievable error would be 0.035 cm^3/cm^3 with $N = 25$ at the intersection point around $n = 100$. Such an analysis can be done for any SAR sensor, provided the scale factor m is known for that sensor.

VII. DISCUSSION

This letter has explored the rationale behind an optimal field experiment designed to assess the suitability of soil moisture retrieval algorithms for SAR instruments. Assessment studies related to the retrieval of surface soil moisture from SAR imagery involve comparison of estimates at two very different scales: site scale (1 m $\times$ 1 m) for the ground estimates and field scale (> 100 m $\times$ 100 m) for the remotely sensed retrieved estimates. The possibility of establishing the impact of the uncertainties in those estimates is of great importance for selecting among different retrieval strategies. The total error in the ground-based estimates of soil moisture is composed of two parts: an instrument error having to do with the measurement technique (gravimetric or probing) and an error associated to the marked spatial variability observed in the field at the spatial scale of the soil moisture retrieved estimates. In this letter, both errors have been addressed, and a methodology to estimate them in the field has also been provided. Using a standard semiempirical model as case study, the analysis shown is useful as a guide to the design of field experiments for Cal/Val purposes. In applications constrained by a predefined error bound, the minimum field size can be derived from this study. In applications driven by high-resolution estimates, smaller errors are achievable provided a large number of sample sites are deployed in ground.

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