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Enhancing remotely-sensed soil moisture estimations using in-situ ancillary information

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Developing algorithms used to generate soil moisture maps of agricultural, bare soils from synthetic aperture radar systems benefits from including ancillary information within a Bayesian retrieval scheme.

Soil moisture is a key variable related to crop development and yield. Too much or too little moisture can have each devastating effects: persistently dry soil renders plants to wilt and diminishes their ability to transpire and grow. By contrast, excess moisture results in poor seed germination, inadequate nutrient uptake, and soil compaction. Consequently, the early assessment of soil moisture reserves, and monitoring moisture changes, is particularly important prior to—and throughout—the seeding season.

In response to this demand for information, a systematic effort has been made to develop maps of soil moisture over agricultural areas. Orbiting microwave synthetic aperture radar (SAR) systems offer the opportunity to monitor moisture content at different scales and under almost any weather condition. SAR systems leverage the known sensitivity that the backscattered signal (which originated in the sensor and was scattered by the target) exhibits to soil parameters, including soil moisture and soil roughness.[1] However, the relationship between the backscattered signal and soil parameters is not straightforward and, consequently, no operational SAR-derived soil moisture maps are yet available.

The major obstacles to developing such maps include the difficulty in modeling the scattering processes that relate backscattering to soil properties (moisture and roughness),[2] the speckle noise[3] and the difficulty in measuring soil roughness in the field. The former two mainly relate to the SAR imaging system, whereas the latter relates to soil heterogeneity.[4,5] Moreover, several combinations of surface parameters can usually produce the same SAR observation. As a consequence, the retrieval of soil parameters remains challenging, and soil-moisture maps derived

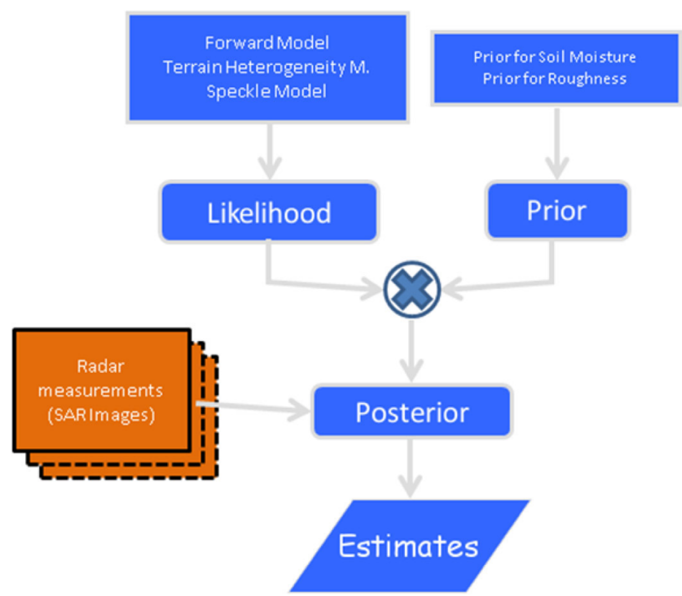

Figure 1. *Diagram showing the block elements comprising the Bayesian retrieval algorithm for soil parameters. SAR: synthetic aperture radar. M: Model.*

from remotely-sensed SAR data remain fairly inaccurate.

Many approaches have been explored to develop retrieval methodologies to infer soil condition, for example, change-detection procedures[6–8] and radar backscatter modeling (theoretical and semi-empirical).[2,9–11] Change-detection methods exploit the availability of temporal series of SAR acquisitions whereby variations in surface backscatter are expected to reflect changes in soil moisture, because other parameters affecting radar backscatter can be considered fairly constant. Radar backscatter modeling deals with the dependency of soil parameters to backscattered signal from a deterministic, physical point of view. By contrast, only Bayesian approaches[12–14] are

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able to incorporate ancillary information about the soil in a systematic, natural way. We have been working on such a kind of Bayesian approach, whereby better performance is reached against a 'blind' (i.e., without ancillary data) estimation.

Roughly speaking, given a set of measured SAR backscattering coefficients, one tries to assign the best set of soil parameters (i.e., soil moisture and roughness) that account for those measurements. A Bayesian inference scheme for soil parameters is shown in Figure 1. Typically, the scheme comprises both the forward and error model (or 'likelihood' in Bayes' jargon), ancillary information ('prior') and output (or 'posterior'). The likelihood measures the degree of compatibility between a certain SAR measurement and certain soil parameters constrained to some given forward model. The higher the values of the likelihood, the more likely that the SAR measurement comes from that specific combination of soil parameters. The prior involves all the information available about the soil parameters and can originate from historical or cadastral records, estimation from other sensors, in-situ data, and/or contextual information. The point-by-point multiplication of the likelihood by the prior leads to the posterior. For this reason, the posterior is a 'modulated' version of the likelihood function owing to the prior envelope. Finally, estimates of soil parameters are computed from the posterior in a number of ways (e.g., the mean or maximum).

We recently modeled speckle noise and terrain heterogeneity within a Bayesian retrieval methodology.[15] As a natural advantage of the Bayesian approach, prior information about soil condition can be easily included, enhancing the performance of the

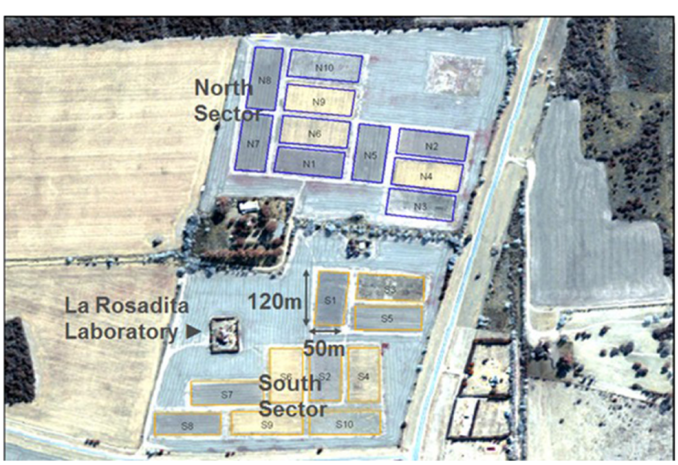

Figure 2. *Optical image from the study area. Plots are labeled as north (N) or south (S) followed by a site number (1–10). Image courtesy of the Argentine Microwaves Observation Satellite (SAOCOM) Mission, Argentine Space Agency (CONAE).*

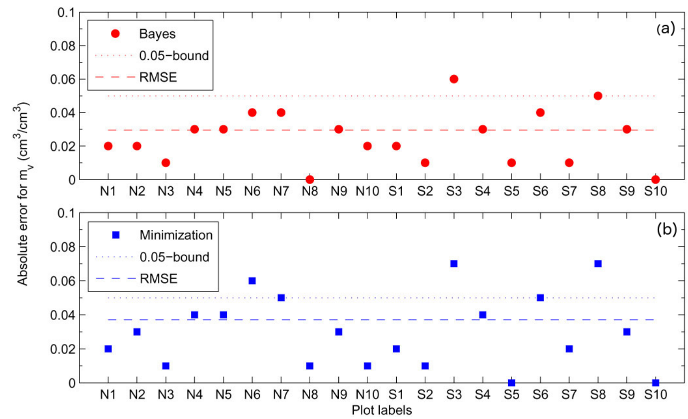

Figure 3. *Absolute difference between estimated soil moisture and in-situ measurements using (a) our Bayesian approach and (b) the minimization approach. Dotted lines indicate a 'desirable' 0.05-error bound (a measure of the desired maximum error) RMSE: Root mean squared error.*

retrieval. Also, the results indicate that the Bayesian model enlarges the validity region of a standard minimization-based procedure.

With this model in hand, we carried out an experimental study to assess the performance of the Bayesian approach against a traditional minimization procedure, estimates from which can be compared to in-situ measurements. The study area consisted of a set of 20, 120 × 50m agricultural plots in Centro Espacial Teófilo Tabanera (CETT), near Falda del Carmen, Córdoba, Argentina (see Figure 2). The test site belongs to the Argentinean Space Agency (CONAE). Tillage treatments are presented on the plots, leading to different roughness conditions and, therefore, to 'expected' roughness (prior information). Over the study site, 16 plots were no-tillage whereas only four were ploughed. Prior information for roughness was collected on a previous field campaign using a bi-dimensional laser profiler.[16] The hydrological soil condition was dry, with a cumulative rainfall of 3.4mm in the 60-day period preceding the field work. Soil moisture was retrieved from a full polarimetric L-band (wavelength of 23cm) image from CONAE's airborne SAR system SARAT over the 20 plots.

The forward model employed in this study is a semiempirical one developed by Oh.[11] After decorrelating the pixels to diminish the speckle noise, the mean values of the backscattered signal are computed on each plot and used as inputs to the retrieval algorithm. Thus, 20 soil moisture estimates (with their associated errors) can be computed and then compared with in-

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situ data. Figure 3 shows the absolute difference between the estimated soil moisture and in-situ measurements. Both retrieval approaches are shown: Bayesian—see Figure 3(a)—and minimization: see Figure 3(b). Correspondence between our Bayesian model and in-situ measurements was achieved with a root mean squared error (RMSE) of $0.03\text{cm}^3/\text{cm}^3$ and a maximum absolute error (MAE) of $0.06\text{cm}^3/\text{cm}^3$. For the minimization procedure, the RMSE was calculated at $\sim 0.04\text{cm}^3/\text{cm}^3$ with a MAE of $0.07\text{cm}^3/\text{cm}^3$. Between the models, the Bayesian one performs better with less spread of the errors.

In summary, rendering quantitative soil moisture maps is of critical relevance for the management of the agricultural sector. Such maps are feasible using SAR images acquired by satellites or airborne systems. A Bayesian retrieval scheme can deal with the speckle noise introduced by the imaging system and the heterogeneity of the soil parameters. A remarkable feature of the Bayesian approach is that it includes information ancillary to the retrieval algorithm to enhance the output estimates. Our next step will be to assess the errors in the output estimates caused by the heterogeneity of the soil parameters.

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