BAYESIAN COMBINED ACTIVE/PASSIVE (B-CAP) SOIL MOISTURE RETRIEVAL ALGORITHM: A RIGOROUS RETRIEVAL SCHEME FOR SMAP MISSION

Matias Barber, Cintia Bruscantini, Francisco Grings, and Haydee Karszenbaum

Institute for Astronomy and Space Physics, Quantitative Remote Sensing Group, Buenos Aires, Argentina.

1. INTRODUCTION

On-going and near-future Synthetic Aperture Radar (SAR) satellite missions are expected to provide meaningful and timely information about soil condition over vast agricultural lands such as those of Argentina (Pampas Plain) and of the mid-western United States (corn-belt), leading to actual economic benefits regarding to seeding dates, irrigation strategies and crop yield forecasting. NASA's Soil Moisture Active and Passive (SMAP) [1] and Argentinean SAOCOM (www.conae.gov.ar) missions have been specifically designed to develop surface soil moisture products and they are scheduled for launch in January 2015 and late 2015, respectively. These missions will exploit microwave radar at L-band ($\lambda = 23$cm) as sensing wavelength, which demonstrated to be less sensitive to residue cover over soil's surface and to be more accurate on retrieving soil moisture than other bands.

In addition to microwave radar, microwave radiometry is also a well-established technique for remote sensing of soil moisture. Combining passive and active observations provides complementary information contained in the surface emissivity and backscatter signatures, both correlated to soil dielectric properties. When active and passive microwave information are available at the same resolution, a Bayesian merging technique can be used to retrieve enhanced, combined active passive soil moisture estimations from remotely-sensed microwave observations.

We present here a Bayesian active/passive methodology in which soil moisture estimations from passive microwave data is used to constrain the estimation from active radar ones through a preliminary soil moisture guess, provided active and passive observations are made at the same resolution. This methodology exploits outstanding, rigorous IEM2M as forward model [2] to describe radar rough-surface scattering of bare or sparsely-vegetated soils and can be regarded as a benchmark to test SMAP active/passive soil moisture product over agricultural lands. The capability of passive microwave measurements to improve radar soil moisture predictions is demonstrated in this paper with in-situ and airborne observations from Soil Moisture Active Passive Validation Experiment 2012 (SMAPVEx12) field campaign.

2. COMBINED ACTIVE/PASSIVE BAYESIAN APPROACH

2.1. Bayesian theorem in the context of SAR products

The Bayesian approach presented here is based on the bivariate version of the Bayes' theorem. An expression for the conditional ("posterior") probability of measuring a certain set of soil parameters (ε and s) given measurements of backscattering coefficients z_1 and z_2 can be obtained from Bayes' theorem

$$P(\varepsilon, s|z_1, z_2) = \frac{P_{Z_1Z_2}(z_1, z_2|\varepsilon, s)P_{ES}(\varepsilon, s)}{P_{Z_1Z_2}(z_1, z_2)}, \tag{1}$$

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where $P_{Z_1 Z_2}(z_1, z_2|\varepsilon, s)$ is the probability of measuring a certain set (z_1,z_2) of backscattering coefficients given measurements of soil dielectric constant ε and RMS height s (the "likelihood function"), P_{ES} is the prior joint density function of ε and s and $P(z_1, z_2)$ (the "evidence") is a global normalizing factor and it is the probability of a certain set (z_1,z_2) to be measured. With the likelihood and the prior at hand, the posterior is computed by a point-by-point product of them.

Then, providing the conditional density function (1) is exact, the optimal unbiased estimator for the mean value of ε that has the minimum variance is the mean of (1),

$$\varepsilon^{bay} = \iint_D \varepsilon P(\varepsilon, s|z_1, z_2) d\varepsilon ds \tag{2}$$

and similarly the squared standard deviation $std[\cdot]$ of this estimator is:

$$std[\varepsilon^{bay}]^2 = \iint_D (\varepsilon - \varepsilon^{bay})^2 P(\varepsilon, s|z_1, z_2) d\varepsilon ds \tag{3}$$

where an explicit expression for (1) must be found in order to calculate ε^{bay} and its standard deviation. The integration domain D in (2) and (3) spans the same validity range than the forward model with respect to (ε, s). The standard deviation $std[\varepsilon^{bay}]$ can be used as a measure of the error e_{est} of the retrieved estimate ε^{bay}, so that $e_{est} = std[\varepsilon^{bay}]$. A number of error metrics will be used to assess the performance of the retrieved estimates against ground-truth data [3].

2.2. Description of the methodology

A flowchart of the procedure adopted in this paper is shown in Fig. 1. An electromagnetic forward model is able to describe, at a certain level of accuracy, the interaction of the radar pulse with the soil and predicts how this amount of energy is modified by the dielectric and geometric properties of the target in his way back to the sensor. This depends on soil and system parameters. The Integral Equation Model with multiple scattering at second order, named as IEM2M [2], is the rigorous forward model adopted in this paper. An initial grid of dielectric constant ε and RMS height s is used to generate outputs for HH and VV copolarized intensity images. The Bayesian approach includes a model for speckle noise and therefore can deal with the residuary speckle noise after multilooking in a systematic way. The statistical properties of two multilooked polarimetric intensity images is described by a bivariate gamma $P_{Z_1 Z_2}(z_1, z_2|C_{11}, C_{22}, n, \rho_c)$ ([4, Eq. 30]), where C_{11} and C_{22} are the predicted (expected) values of the forward model, n is the number of looks and ρ_c is the correlation between Z_1 and Z_2. The likelihood function is then constructed on evaluating the distribution $P_{Z_1 Z_2}$ on the measured backscattering coefficient hh_m and vv_m after multilooking, i.e. $P_{HHVV}(hh_m, vv_m|C_{11}, C_{22}, n, \rho_c)$.

The prior distribution describes the possible values of soil dielectric constant ε and RMS height s *before* SAR acquisition takes place. In what follows, it will be assumed independence between ε and s, i.e. $P_{ES}(\varepsilon, s) = P_E(\varepsilon)P_S(s)$. Two kind of priors are taken into account (Fig. 1). If passive microwave-based soil moisture guess is not available, an uniform prior $P_E \sim U(3, 30)$ for ε is used instead. A normal distribution is used to describe the uncertainty around a mean value μ_s of the ground-based estimate s. Mathematically, $P_S \sim N(\mu_s, \sigma_s)$. The uncertainty σ_s is arbitrarily set to $0.20\mu_s$. Passive microwave observations enable the use of soil moisture estimations from the brightness temperature of the soil. The zero order radiative transfer model RT-0 [5], is a rather simple physical model used to link the observed brightness temperature (Tb) with surface dielectric and geometric properties. The RT-0 is readily invertible by means of the Single Channel Algorithm (SCA) [6]. Thus, the estimated soil moisture from passive V-polarized microwave measurement T_{bV} is used to center a normal pdf into the prior. Finally, the posterior is built as the product of the likelihood function by the prior distribution. Dielectric constant estimates are computed from the posterior distribution as above mentioned, and then converted into soil moisture using an empirical relationship from [7].

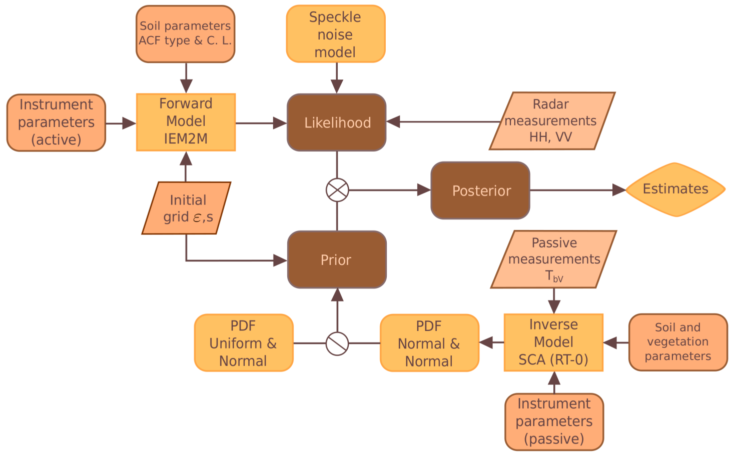


Fig. 1. Flowchart for Bayesian Combined Active/Passive retrieval scheme. Symbol of a cross mark encircled indicates product operation. Single line encircled indicates an 'Or' statement.

3. RESULTS

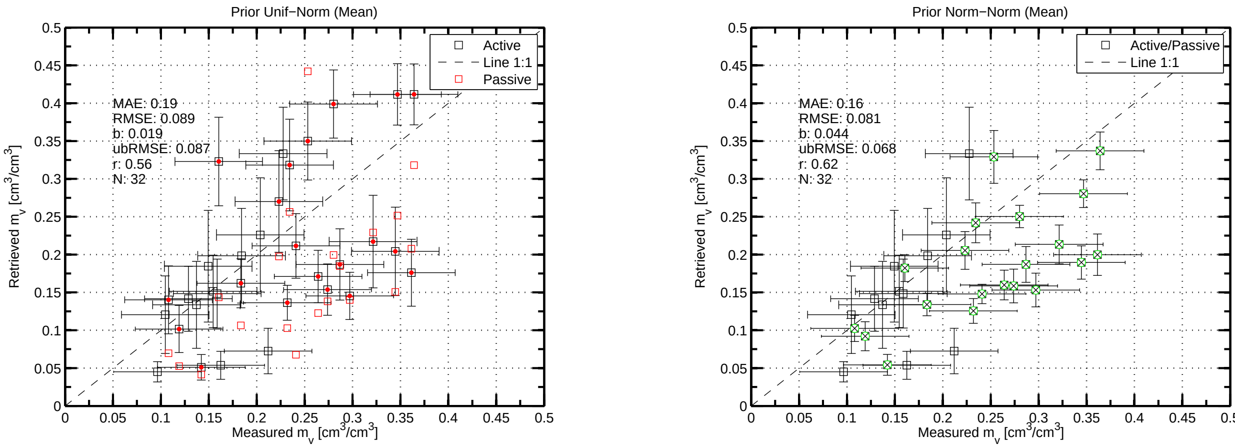
The active dataset is from NASA/JPL's full polarimetric L-band UAVSAR imagery acquired over southwest of Winnipeg, Manitoba, Canada, during a 6-week period in June and July 2012 in the context of the Soil Moisture Active Passive Validation Experiment (SMAPVEx) field campaign. The passive microwave data comes from the Passive Active L-band Sensor (PALS). Coincident with the acquisitions, several agricultural soils with a variety of soil textures were sampled. The reader is referred to [8] for a complete description of the dedicated field campaign.

Retrieved estimates for volumetric soil moisture m_v against measured ground-truth data are shown in Fig. 2. On the left, black squares are the estimates from the radar (active) HH- and VV-measurements using priors Uniform and Normal for ε and s, respectively. Red squares indicates estimates from passive microwave data independently of the radar estimation. (Brightness temperature were partly available for the entire radar dataset.) Red points within black markers indicate that passive microwave-based soil moisture guess is available. Error bars in ground-truth data are computed from instrumental (probe) error and ground-based soil moisture variability following [9].

On the right of Fig. 2, the combined active/passive estimates are shown. Crosses indicate radar estimates enhanced by passive measurements, in the sense of replacing the Uniform prior by a Normal one with mean value given by the dielectric constant estimate from SCA. The combined active/passive estimation shows an overall well agreement with an $RMSE = 0.081\text{cm}^3/\text{cm}^3$ and a higher sensitivity with correlation coefficient $r = 0.62$. An increase of the bias in the combined estimates is also observed, since PALS instrument may introduce a calibration bias. In anyway, the unbiased RMSE (ubRMSE) shows an improvement from $0.087\text{cm}^3/\text{cm}^3$ (only active) to $0.068\text{cm}^3/\text{cm}^3$ (combined).

4. CONCLUSION

When remotely-sensed active and passive microwave observations are available at the same resolution, a Bayesian merging technique can be used to retrieve radar soil moisture estimations enhanced by a preliminary soil moisture guess from passive microwave observations. Based on a field experiment over bare and/or sparsely-vegetated soils ($VWC < 0.72kg/m^2$), an overall improvement of the radar prediction is achieved on including information from passive microwave. Thus, active/passive synergy is expected to produce an enhanced soil moisture product, with a better performance than each one separately. This methodology can be used as a benchmark to test global surface soil moisture estimates over agricultural lands prior to –and throughout– the seeding season.



(a) Only active

(b) Combined active/passive

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Fig. 2. Retrieved estimates for volumetric soil moisture m_v against measured ground-truth data for bare or sparsely-vegetated soil ($VWC < 0.72kg/m^2$). (a) Uniform prior $P_\varepsilon \sim U(3, 30)$ for dielectric constant ε and Normal prior $P_S \sim N(\mu_s, \sigma_s)$ for RMS height s, with the mean μ_s determined by the ground-truth data. (b) Normal prior for ε with μ_ε given by the SCA retrieval algorithm.

5. REFERENCES

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