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SOIL MOISTURE ESTIMATE UNDER FOREST USING A SEMI-EMPIRICAL MODEL AT P-BAND

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1. INTRODUCTION

Soil moisture is a key parameter in the global warming context being part of water, energy and carbon cycles. In the past decades several remote sensing techniques have been developed to estimate the surface soil moisture. In most studies associated with radar sensing of soil moisture, the proposed algorithms are focused on bare or sparsely vegetated surfaces where the effect of vegetation can be ignored. At long wavelengths such as L-band, empirical [1] [2] [3] or physical models such as the Small Perturbation Model (SPM) [4] provide reasonable estimates of surface soil moisture at depths of 0-5cm. However for densely covered vegetated surfaces such as forests, the problem becomes more challenging because the vegetation canopy is a complex scattering environment. For this reason there have been only few studies focusing on retrieving soil moisture under vegetation canopy in the literature. Moghaddam et al. developed an algorithm to estimate soil moisture under a boreal forest using L- and P-band SAR data [5]. For their studied area, double-bounce between trunks and ground appear to be the most important scattering mechanism. Thereby, they implemented parametric models of radar backscatter for double-bounce using simulations of a numerical forest scattering model. Hajnsek et al. showed the potential of estimating the soil moisture under agricultural vegetation using L-band polarimetric SAR data [6] and using polarimetric-decomposition techniques to remove the vegetation layer. Here we use an approach based on physical formulation of dominant scattering mechanisms and three parameters that integrates the vegetation and soil effects at long wavelengths [7].

The underlying motivation for this study is the development of an operational soil moisture algorithm to be used for the recent NASA's First Earth Venture (EV-1) mission, AirMOSS (Airborne Microwave Observatory of Subcanopy and Subsurface) [8]. The AirMOSS system is a P-band fully-polarimetric synthetic aperture radar that operates at 435 MHz center frequency with approximately 20-40 MHz bandwidth. AirMOSS will provide high-resolution observations of soil moisture over nine representative regions of North America and will quantify the soil moisture variation on carbon fluxes estimate.

Here we present the result of a semi-empirical inversion model for soil moisture retrieval using the three backscattering coefficients: σ_{HH}, σ_{VV} and σ_{HV}. In this paper we focus on the soil moisture estimate and use the biomass as an ancillary parameter estimated automatically from the algorithm and used as a validation parameter.

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We will first remind the model analytical formulation. Then we will show some results obtained with real SAR data and compare them to ground estimates.

2. MODEL FROMULATION

We represent the total backscattering coefficients measured by a SAR system over a forest area by the following analytical formulation:

$$\sigma_{HH} = A_{HH} W^{\alpha_{HH}} \cos\theta \left(1 - e^{-B_{HH} W^{\beta_{HH}} / \cos\theta}\right) + C_{HH} \Gamma_{HH} W^{\delta_{HH}} \sin\theta e^{-B_{HH} W^{\beta_{HH}} / \cos\theta} + S_{HH} e^{-B_{HH} W^{\beta_{HH}} / \cos\theta}$$

$$\sigma_{VV} = A_{VV} W^{\alpha_{VV}} \cos\theta \left(1 - e^{-B_{VV} W^{\beta_{VV}} / \cos\theta}\right) + C_{VV} \Gamma_{VV} W^{\delta_{VV}} \sin\theta e^{-B_{VV} W^{\beta_{VV}} / \cos\theta} + S_{VV} e^{-B_{VV} W^{\beta_{VV}} / \cos\theta}$$

$$\sigma_{HV} = A_{HV} W^{\alpha_{HV}} \cos\theta \left(1 - e^{-B_{HV} W^{\beta_{HV}} / \cos\theta}\right) + C_{HV} \Gamma_{HV} W^{\delta_{HV}} \sin\theta e^{-B_{HV} W^{\beta_{HV}} / \cos\theta} + S_{HV} e^{-B_{HV} W^{\beta_{HV}} / \cos\theta}$$

Where α_{pq}, β_{pq} and δ_{pq} are structural parameters related to branches, trunks and leaves. Note that α_{pq}, β_{pq} and δ_{pq} were estimated from 3-D model simulation for broadleaf, needle leaf, mixed forest and crops and are frequency dependent. These power terms may change depending on the forest type then should be re-calculated if we work with a non-tropical forest. A_{pq}, B_{pq} and C_{pq} are calibration parameters used to parameterize the forward model, W is the vegetation biomass in Mg/ha and gathers diameter at breast height, tree height and wood density information, θ is the local incidence angle, Γ_{pq} is the reflectivity coefficient and S_{pq} stands for the rough surface contribution from any rough surface model like Oh's model [1], Dubois's model [2] or SPM [4]. Γ_{pq} is defined as: $\Gamma_{pq} = R_p R_q^* \exp\left(-4k^2 s^2 \cos^2\theta\right)$ where R_p and R_q are the Fresnel reflection coefficients. The A_{pq}, B_{pq} and C_{pq} coefficients were fitted with tropical ground estimates assuming soil moisture equal to 50%, roughness equal to 4 cm and an incidence angle of 45°. The data used to get A_{pq}, B_{pq} and C_{pq} comes from studies in two different tropical forests: in Costa Rica [9] and in French Guiana [10]. The model predictions for the three backscattering coefficients versus the biomass for tropical forest are shown in Fig.1.

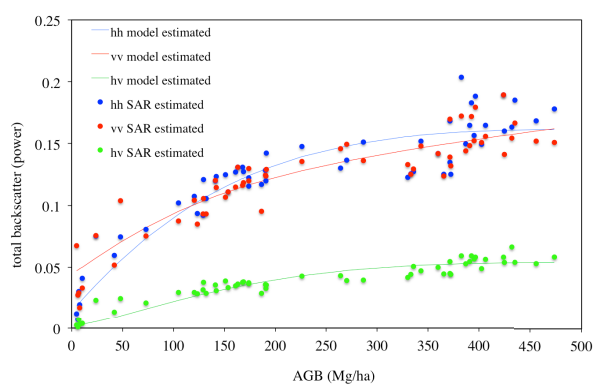

Fig. 1: Backscattering coefficients (in power) - σ_{HH}, σ_{VV} and σ_{HV} using AirSAR P-band data over tropical forest. Points are the ground estimates and lines are model predictions for σ_{HH} in blue, σ_{VV} in red and σ_{HV} in green.

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3. INVERSION RESULTS

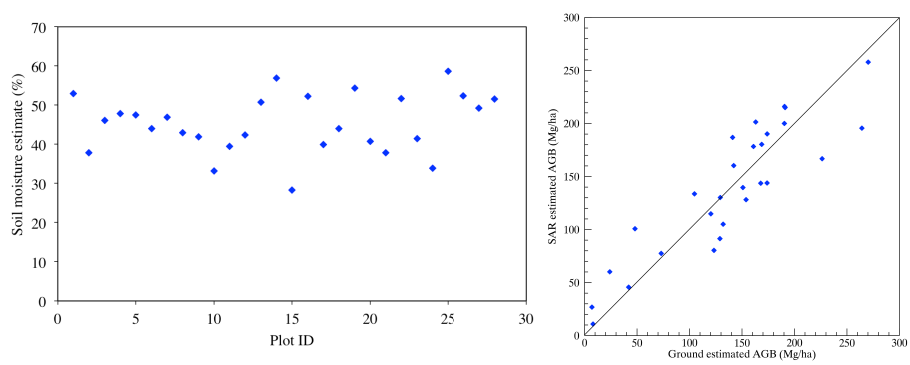
To validate our inversion process with real SAR data, we used P-band AirSAR data acquired over La Selva in Costa Rica on March 6th 2004. The swath width is 12 km and the incidence angle varies from 20º to 60º. The soil moisture ground estimates are located on the eighteen CARBONO plots and were recorded through the 2004 year at several days of interval. The biomass ground estimates cover different forest structures ranging from abandoned pastures to old-growth wet forests.

3.1. Soil moisture retrieval

Unfortunately, there are no ground estimates for the 6th of March but the closest day is the 3rd of March. For this date only two ground estimates were taken: m_1=47.4 % and m_2=48.8 %. The result of the inversion using the local optimization process is e_1=43.9 % and e_2=50.8 %. The first result shows an absolute error of 3.5% and the second has an absolute error of 2%. From ground estimates around March 3rd, the soil moisture values vary between 40% and 60% and the average from March 1st to March 3rd is 52.3% so the estimated values are in the ground estimates range. The soil moisture estimate over the twenty-eight plots where biomass *in-situ* data is available is shown in Fig. 2(a). The minimum value is 28.3%, the maximum value is 58.7% and the average is 45.2%. Even though it is not possible to assess these results with some ground estimates, the estimates are in the range of the ground estimates taken in the same period of time.

3.2. Biomass retrieval

Although we focus on soil moisture estimates, another important parameter in this inversion process is the biomass, which is used as a validation parameter. To show how well the vegetation parameter is then retrieved we display its inversion result compared to ground estimates in Fig. 2(b). Twenty-eight plots are used for this study where the biomass is up to 270 Mg/ha with an average of 138 Mg/ha. The estimates take values between 10 Mg/ha and 257 Mg/ha with an average of 138 Mg/ha. The root-mean-square error is 30.5 Mg/ha.



(a) (b)

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Fig. 2: (a) Soil moisture estimates over the 28 plots. (b) AGB model estimates (y-axis) versus ground estimates (x-axis) in Mg/ha over the plots in La Selva

11. REFERENCES

[1] Y. Oh, K. Sarabandi and F. T. Ulaby, "An Empirical model and an Inversion Technique for Radar Scattering from Bare Soil Surfaces", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 30, no. 2, pp. 370-381, March 1992.

[2] P. C. Dubois, J. van Zyl and T. Engman, "Measuring Soil Moisture with Imaging Radars", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 33, no. 4, pp. 915-926, July 1995.

[3] J. Shi, K. S. Chen, Q. Li, T. J. Jackson, P. E. O'Neill and L. Tsang, "A Parameterized Surface Reflectivity Model and Estimation of Bare-Surface Soil Moisture With L-band Radiometer", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 40, no. 12, pp. 2674-2686, December 2002.

[4] F. T. Ulaby, R. K. Moor and A. K. Fung, "Microwave Remote Sensing: Active and Passive", vol.2, Chap. 12, *Addison-Wesley Publishing Company*, 1982.

[5] M. Moghaddam, S. Saatchi and R. H. Cuenca, "Estimating subcanopy soil moisture with radar", *Journal of Geophysical Research*, vol. 105, no. D11, pp. 14899-14911, June 2000.

[6] I. Hajnsek, T. Jagdhuber, H. Schön and K. P. Papathanassiou, "Potential of Estimating Soil Moisture Under Vegetation Cover by Means of PolSAR", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 2, pp. 442-454, February 2009.

[7] M-L. Truong-Loï, S. Saatchi and S. Jaruwatanadilok, "A parameterized inversion model for soil moisture and biomass from polarimetric backscattering coefficients", *IGARSS'2012 Proceedings*, Munich, Germany, July 2012.

[8] E. Chapin, A. Chau, J. Chen, B. Heavey, S. Hensley, Y. Lou, R. Machuzak, and M. Moghaddam. "AirMOSS: An Airborne P-band SAR to Measure Root-Zone Soil Moisture." *Radar Conference (RADAR)*, IEEE, Atlanta, GA, 7-11 May 2012. Pages 693-698.

[9] S. S. Saatchi and K. C. McDonald, "Coherent Effects in Microwave Backscattering Models for Forest Canopies", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 35, no. 4, pp. 1032-1044, July 1997.

[10] P. C. Dubois-Fernandez, T. Le Toan, S. Daniel, H. Oriot, J. Chave, L. Blanc, L. Villard, M. W. J. Davidson and M. Petit, "The TropiSAR Airborne Campaign in French Guiana: Objectives, Description, and Observed Temporal Behavior of the Backscatter Signal," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 8, pp. 3228-3241, August 2012

12. ACKNOWLEDGMENTS

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