SENSITIVITY OF SAR SPECKLE FILTERING ON THE ASSESSMENT OF SURFACE ROUGHNESS AND SOIL MOISTURE CONTENT

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ABSTRACT: The assessment of soil moisture content and surface roughness from remotely sensed data is of primary importance for improving agricultural techniques of conservation farming such as yield forecasts, scheduling irrigations, fertilization. SAR (Synthetic Aperture Radar) remotely sensed data may provide a powerful tool for indirectly retrieving these agricultural surface parameters over large areas with frequent coverage. Nevertheless, one major source of error in the quantitative estimate of such geophysical parameters is the presence of the speckle within the scene. To overcome this difficulty many speckle filtering techniques have been developed for reducing this multiplicative noise. However, up to now, few works analyze the performance of these filters on the retrieval of spatially and physically accurate information useful for the estimates of these soil properties. In this context, this paper outlines the sensitivity of several speckle filtering methods on the assessment of these two agricultural surface parameters. Results stressed that depending on the speckle filtering method used, significant deviations were obtained on the estimates of soil properties.

INTRODUCTION

Soil moisture content and surface roughness play a critical role in the hydrological processes. They control the distribution of rainfall into runoff, evapo-transpiration, and infiltration, which must be considered in water and energy balance [1]. Thus these two soil parameters need to be measured consistently on a spatially distributed basis.

Remotely sensed SAR (Synthetic Aperture Radar) data have the potential to provide spatial and multitemporal estimates of these surface parameters, depending upon the sensor configuration and field condition. Nevertheless, the strong radiometric variability of extended surface targets within the SAR scene make the quantitative estimate of soil properties difficult. This variability is due to the presence of a signal-dependant multiplicative noise (so-called speckle), and directly results from the coherence of microwave radiations which induce unpredictable interference phenomena within SAR cell resolution.

Many techniques have been developed to attempt to reduce speckle within SAR images. The first category of filters, namely heuristic filters, does not consider the distribution of radar reflectivity within the scene (*e.g.*, median filter) and the second, the adaptive filters, (*e.g.*, Lee filter [2]) incorporate as A Priori knowledge statistical description of the scene and of the speckle. Both methods enhance radiometric resolution at the expense of spatial resolution. Recent more sophisticated filters (*e.g.*, Gamma-MAP filter [3], Wavelet filter [4]) try to preserve pertinent details and spatial resolution keeping a strong speckle reduction in homogenous area.

The Speckle filtering of SAR images is a primordial step in extracting the useful signal (*i.e.*, the underlying scene radar reflectivity or backscattering coefficient, σ^o) to be inverted for the retrieval of physical properties of the ground target. Although these filtering approaches have been tested with image processing criteria, such as the preservation of edge gradient value and the smoothing degree of homogeneous areas, a main issue is to know how these SAR filters influence spatially and physically the signal useful to the extraction of surface parameters.

In this paper, we attempted to reply to this question for a case study on an agricultural site in Normandy (France). This was conducted using RADARSAT-SGC time-series for which a set of filtering techniques (*i.e.*, 'box' and 'median' filters, and more sophisticated filters using wavelet representation and simulated annealing technique) was applied. Results stressed the significant impact of SAR filtering technique in the assessment of soil moisture content and surface roughness.

SPECKLE REDUCTION TECHNIQUES

Speckle filtering methods can be separated into two categories: the non-adaptive approaches (box filter, median, *etc.*) and adaptive techniques.

Speckle reduction can be achieved using a simple box filter which enhances radiometric resolution without any consideration on the target nature. Consequently, edges and other significant details are strongly degraded. The median filter allows to better preserve edge properties but with a possible bias in the radar reflectivity estimation.

By using adaptive filters a compromise exists between the radiometric enhancement in the homogeneous areas and the preservation of the spatial resolution within the heterogeneous areas (*i.e.*, the textural area or edges). Depending on the local heterogeneity degree of the target, pixels are weighted with a value ranging from the local mean to the raw intensity values. Filters differ from the local weight determination depending on the *A-Priori* hypothesis applied on the probability density function (pdf) of both speckle and radar reflectivity. Thus, filters can be distinguished by the estimation strategy used such as the Minimum Mean Square Error (MMSE) or the Maximum A Posteriori (MAP). As an example, whereas Lee's filter [2] assumes Gaussian pdf and apply a MMSE criterion, Gamma-MAP filter [3] assumes gamma pdf and uses a local MAP estimation. Oliver proposes a global MAP estimation based on the Metropolis algorithm [5]. Integration of both optimal target and edge detection with an adaptive size of window strategy can improve filtering results [2]. Wavelet filters are based on a multiscale representation of the image where high frequencies (Wavelet coefficients) are denoised using a MAP criterion and gamma pdf assumptions [4].

On the contrary, in the case of an agricultural parcel, a non adaptive filter will be to take the parcel mean as input for the assessment of the soil parameters.

DATA SET

RADARSAT-SGC time-series (4 dates) were acquired over an experimental agricultural site in Normandy (Blosseville, France) under several incidence angles (standard beam S4, S5, S6 and S7, which correspond to an incidence angle of 37°, 39°, 43.5° and 47°, respectively) during March 1998. These SAR data were over-sampled, reducing the 12.5 m nominal resolution to 25 m, with a number of looks around 4. Moreover, a SPOT-XS image from 1997 completed our remote sensing database.

METHODOLOGY

Speckle filtering methods

Five speckle reduction methods were applied on all the calibrated SAR images using the following specifications: (1) box filter (with a window size of 11x11 pixels); (2) median filter (5x5); (3) Gamma-MAP filter (11x11); (4) simulated annealing (ACMAP [5]) using 50 iterations and (5) wavelet filter (3 levels of decomposition) [4].

Co-registration of SAR images

Standard techniques were employed to extract control points in all images (30 points were found for both optic and SAR data) and, subsequently deduce bilinear polynomial transformations using standard image-processing techniques. Residuals were monitored in the process of selecting the polynomial degree: it was found that simple linear polynomials were sufficient to achieve residual (sub-pixel) levels and that these residuals were independent of the application of higher-order polynomials.

Parcel sampling

Samples (~ 300 relatively homogeneous parcels) were selected within the SPOT scene, thus allowing a better control of the sampling quality for the sensitivity study of filtering SAR data in the estimate of physical soil parameters.

SAR backscattering models

2 SAR backscattering models were used for retrieving surface roughness and soil moisture content over each of all selected parcels.

The first is a semi-empirical model from Dubois [6] which presents some built-in limitations (the imaginary part of the dielectric constant ε is not taken into account, no dependence on the surface correlation, *cf.* [7]). Angular dependence of the backscattering coefficient for HH polarization is given by :

$$\sigma^o_{hh} = 10^{-2.75} . \frac{\cos^{1.5}\theta}{\sin^5\theta} . 10^{0.028.\varepsilon.\tan\theta} . (\mathrm{k.h}) . \sin^{1.4}\theta . \lambda^{0.7} \quad (1)$$

where θ is the incidence angle, k the wave number, ε the real part of the dielectric constant, h the rms height of the surface (cm) and λ the wavelength (cm). The validity domain of this relationship corresponds to rms roughness ($k.h$) values within [0.3 ; 3] and incidence angles between 30° and 65°.

The second is the analytical integral equation model (IEM) specially adapted to roughness values typical of agricultural soil, and convenient for a large range soil status conditions [8]. The SAR backscattering coefficient (σ^0) is expressed as:

$$\begin{aligned}\sigma^0_{pp} = & \frac{k^2}{2}.|f_{pp}|^2.\exp(-4.K_0).\sum_{n=1}^{+\infty}\frac{(4.K_0)^n}{n!}.W^{(n)}(2.k.\sin\theta,0)\\ & + \frac{k^2}{2}.Re(f^*_{pp}.F_{pp}).\exp(-3.K_0).\sum_{n=1}^{+\infty}\frac{(2.K_0)^n}{n!}.W^{(n)}(2.k.\sin\theta,0)\\ & + \frac{k^2}{8}.|F_{pp}|^2.\exp(-2.K_0).\sum_{n=1}^{+\infty}\frac{(K_0)^n}{n!}.W^{(n)}(2.k.\sin\theta,0) \quad (2)\end{aligned}$$

with: $f_{hh} = -\frac{2.R_{\perp}}{\cos\theta}$ $\qquad f_{vv} = \frac{2.R_{//}}{\cos\theta}$

$$F_{hh} = \gamma.\left[4.R_{\perp} - \left(1 - \frac{1}{\varepsilon_r}\right).(1+R_{\perp})^2\right],$$

$$F_{vv} = \gamma.\left[\left(1 - \frac{\varepsilon_r.\cos^2\theta}{\mu_r.\varepsilon_r - \sin^2\theta}\right).(1-R_{//})^2 + \left(1 - \frac{1}{\varepsilon_r}\right).(1+R_{//})^2\right],$$

and $K_0=(k.h)^2.\cos^2\theta$ $\qquad \gamma = 2.\frac{\sin^2\theta}{\cos\theta}$.

where *pp* stands for *HH* or *VV* polarization and $R_{//}$ and $R_{\perp}$ are the Fresnel reflection coefficients dependent on dielectric constant for vertically and horizontally polarized waves. *Re* means the real part of the complex number. $W^{(n)}(2.k.\sin\theta,0)$ characterizes the surface roughness spectrum [9], and is a function of the rms height *h* of the surface and of its correlation length *l* for a surface with an exponential-distributed roughness values.

For each of all selected samples a least-square fit to (1) was applied on the 4 corresponding angular SAR backscattering coefficients for estimating ε and $(k.h)$ values. The SAR multi-angular fit to (2) for retrieving $(k.h)$, $(k.l)$ and ε parameters relies on the optimized simplex method [10]. These 2 SAR multi-angular regression methods were performed on a pixel per pixel basis for each set of angular SAR data (*i.e.*, σ^o intensity resulting from parcel averages and σ^o estimated by each of 5 filtering techniques). ε is converted to volumetric soil moisture *m* through empirical curves [11].

Samples with a too small number of pixels (n<200) and for which the number of realistic estimates is lower than 75% were discarded from our analysis. A degree of heterogeneity level for each parcel (sample) was evaluated using the normalized standard deviation coefficient of the underlying radar reflectivity (C_R) [5]. The statistical validity of the regression is evaluated using the following probability:

$$P = \int_0^{\chi^2/2} \Gamma\left(\frac{N-2}{2},x\right)dx \qquad (4)$$

where χ^2 is the fit dispersion and N the number of observations. $P > 0.9$ means than the fit should be discarded. This probability will give us a level in confidence in the physical significance of the retrieved parameters.

To analyse the sensitivity of each speckle filtering methods on the assessment of agricultural surface parameters, we defined 2 filter performance indices, I_r and I_h for surface roughness and soil moisture content respectively, as follow:

$$I_h = \frac{\left|h_{filter} - h_{parcel}\right|}{h_{parcel}} \times \left(1 - \frac{P_{filter}}{P_{parcel}}\right) \qquad (5)$$

$$I_r = \frac{\left|r_{filter} - r_{parcel}\right|}{r_{parcel}} \times \left(1 - \frac{P_{filter}}{P_{parcel}}\right)$$

where h_{filter}, r_{filter}, h_{parcel}, r_{parcel} stands for humidity and roughness parameters derived from multi-angular regression on SAR data set filtered with *filter* and *parcel* methods respectively. These indices were computed for each pixel and thresholded in [-1;1]. They represent a relative deviation of the estimate on the surface parameter weighted by the relative deviation of the dispersion. If the analyzed filter gives better results on the estimate of the soil parameter than the parcel mean value then the filter performance index value *I* for this parameter will be greater than 1, on the contrary if the estimate is degraded then this value will be negative.

RESULTS

Figure 1 displays the RADARSAT Std Beam S4 image on which were superimposed ~300 field samples used in our SAR multi-angular regression.

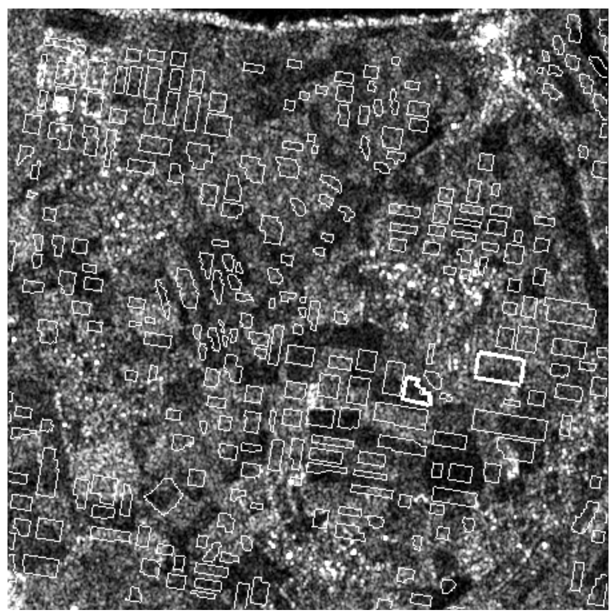
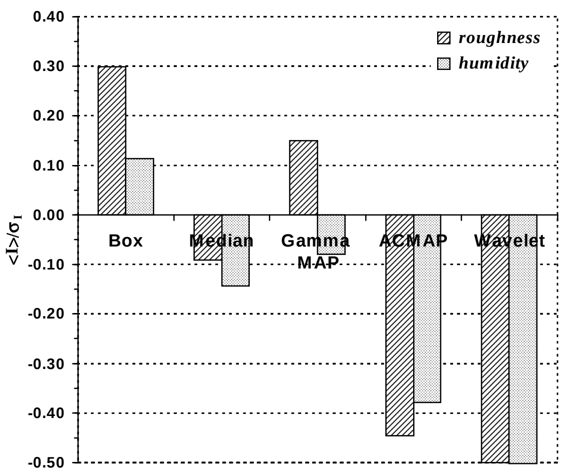


Fig. 1: *RADARSAT Std Beam S4 image acquired over Blosseville watershed (Normandy, France) in March 25, 1998. Area shown is 5.6 km x 5.6 km.*

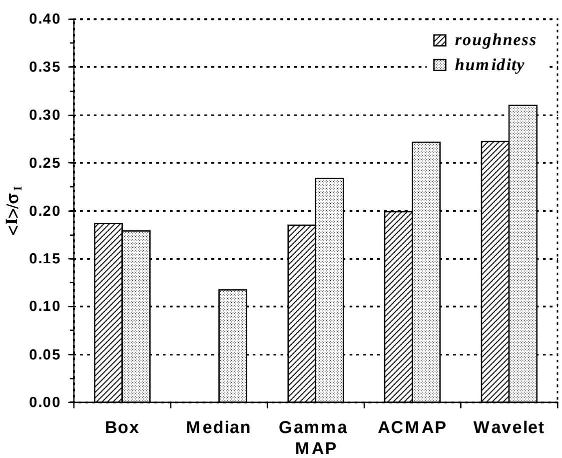
Once the 2 statistical criteria (mentioned above) applied to this set of samples, only 100 parcels remained for our filter sensitivity analysis. For each selected parcel and each speckle reduction techniques, 2 performance indices (I_h, I_r) were then computed for the soil moisture and surface roughness retrievals. Results indicated that 50% of parcels gave a better estimates of soil properties derived from IEM or Dubois'model for each of the 5 local filters (box, median, Gamma-MAP, ACMAP and Wavelet filters) than for the parcel average method. Among this 50%, the large positive values of I_h and I_r for heterogeneous parcels stressed the interest of use of these local filters for retrieving an useful signal to be inverted in a SAR backscattering model. Consequently, this means the parcel average method must be carefully applied even if the parcel seems to be homogeneous.

For a detailed analysis of the performance of these 5 filters two fields are selected within the test site. These two parcels are delimited by a white thick line in the right bottom side of Fig.1. The largest from these two parcels is relatively homogenous with a SAR intensity coefficient variation (C_I) of 0.56, and an area of 10 ha. Surface roughness (*k.h*) and soil moisture content (*m*) derived from the parcel average method are 0.42 and 0.53, respectively. The other parcel, with a smaller size (area of 3.5 ha), is heterogeneous (C_I=0.61) with an estimated *k.h* and *m* of 0.15 and 0.56, respectively.

Figure 2 displays $<I>/\sigma_I$ values for each of the 5 speckle filtering methods on the assessment of soil properties for these two selected fields.



(a)

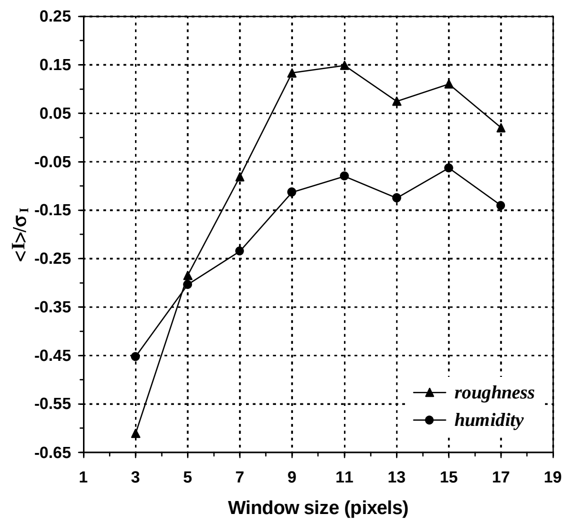


(b)

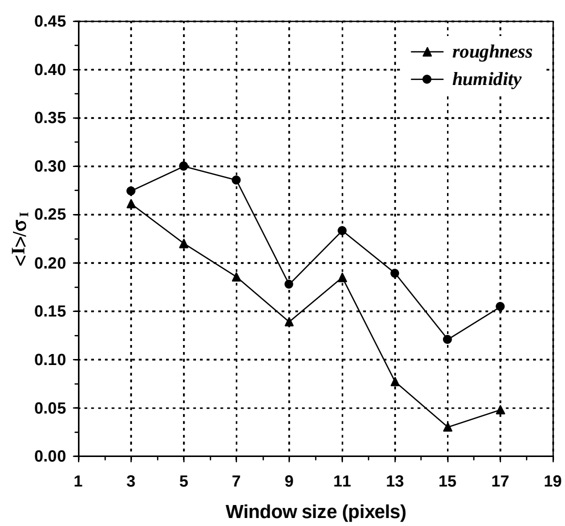
Fig. 2: *$<I>/\sigma_I$ values for surface roughness and soil moisture estimates, and for each of 5 speckle filtering methods: (a) homogeneous field, and (b) heterogeneous field.*

Results confirm the smoothing filters (Box, Median) are more efficient than the adaptive filters (ACMAP, Wavelet) for the homogeneous parcel (Fig.2a) whereas all the 5 filters are better than the parcel average method for the heterogeneous parcel (Fig.2b). It can be noted that the Gamma-MAP filter realized the best compromise for these two fields.

Figure 3 depicts $<I>/\sigma_I$ values for the 2 soil parameters estimates as function of the window size of the Gamma-MAP filter. For the homogeneous parcel (Fig.3a), it clearly appears an optimal size of windows (*i.e.*, 11x11 pixels) for estimating surface roughness estimates whereas smaller window sizes are better for the case of the heterogeneous parcel (Fig.3b).



(a)



(b)

Fig. 3: *Variation of $<I>/\sigma_I$ values for surface roughness and soil moisture estimates as function of the window size of the Gamma-MAP filter: (a) homogeneous field, and (b) heterogeneous field.*

Figure 4 depicts the spatial variability of the performance indices of the Gamma-MAP filter (Fig.4a & 4b) and the Box filter (Fig.4c & 4b) relative to surface roughness and soil moisture content within the homogeneous field, and the corresponding spatial map for each of two agricultural parameters derived from our multi-angular SAR regression with Dubois' model. Window size of both two filters are 11x11 pixels. This parcel comprises two distinguished areas with different SAR reflectivities (Fig.1). The adaptive filter performs well better than the heuristic approach by preserving this fluctuation. The window size used in speckle filtering appears to be optimal (as observed in Fig.3a), due to the fact that it keeps local statistics unmixed between these two kinds of ground target. For window size larger than 11x11 pixels, we noted a decreasing of the spatial Gamma-MAP performance indices which stresses that many local statistics are not within an homogenous target. This behaviour was observed for the 4 other filters, but also with the soil properties derived from the IEM model.

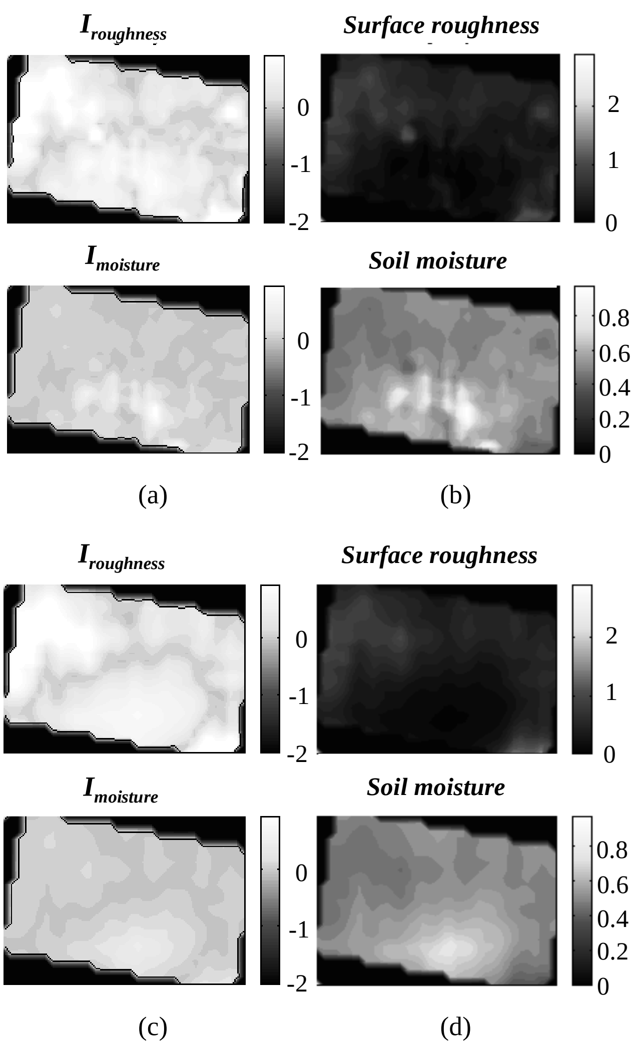


Fig. 4: Filter performance indices relative to 'roughness' and 'soil moisture' estimates for the homogeneous field, and parameter maps derived from our multi-angular SAR regression with Dubois' model: Gamma-MAP filter (11x11) [a, b], and Box filter (11x11) [c, d].

Figure 5 is similar to Fig.4 but with performance indices of the Gamma-MAP filter 3x3 (Fig.5a, 5b) and the Wavelet filter (Fig.5c, 5d), for the heterogeneous parcel. This is a an illustration case where thin detail preservation strategy of the adaptive filter can improve the performance indices. Gamma-MAP 3x3 and Wavelet filter well perform whereas the Gamma-MAP 17x17 (Fig.6) is inappropriate due to the polluted local statistics.

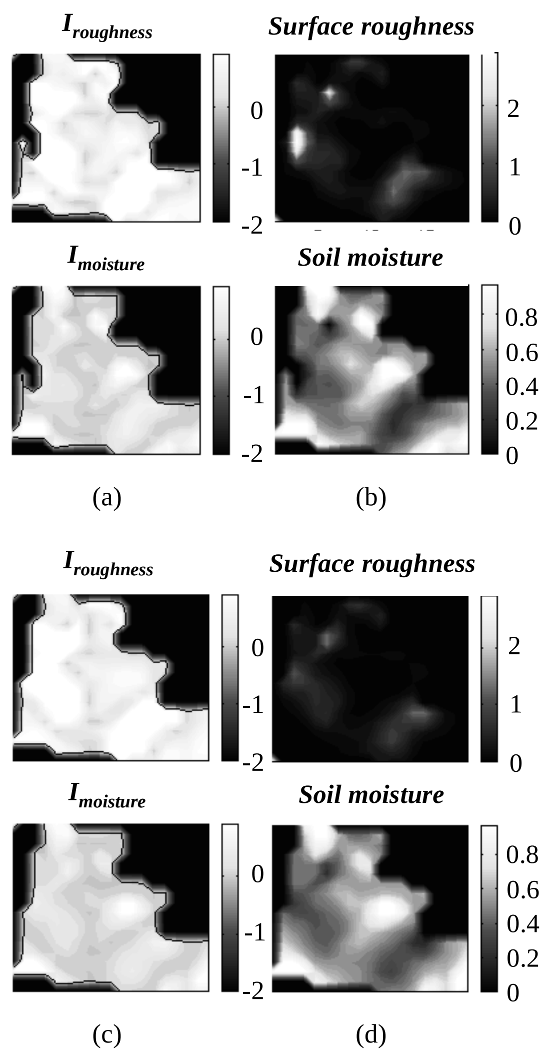


Fig. 5: Filter performance indices relative to 'roughness' and 'soil moisture' estimates for the heterogeneous field, and parameter maps derived from our multi-angular SAR regression with Dubois' model: Gamma-MAP filter(3x3) [a, b], and Wavelet filter [c, d].

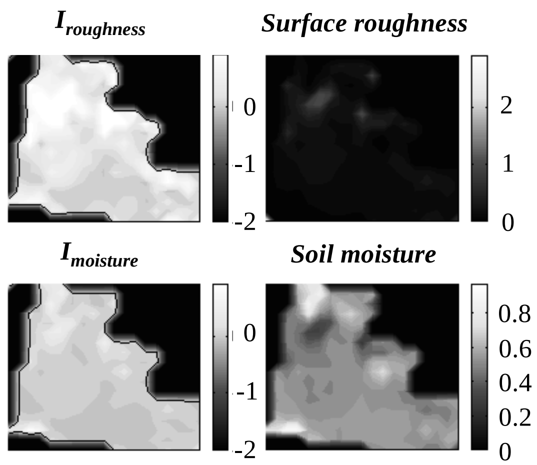


Fig. 6: Same legend as Fig.5 but for Gamma-MAP filter(17x17).

CONCLUDING REMARKS

Results derived from this study stressed the importance of the choice of the SAR filtering technique for extracting the useful signal to be inverted for accessing information about soil dielectric constant and surface roughness. Depending on the speckle reduction method applied to raw intensity images, significant deviations were obtained on the estimated soil parameters in comparison with the commonly used parcel average method. The soil roughness is much more sensitive to the employed SAR filtering method. In fact, estimates of such a parameter using the parcel average method or non-adaptive filtering approach result from a too large smoothing of SAR intensity fluctuations within the parcel which seems physically significant for soil moisture and surface roughness retrieval.

For a parcel with an uniform radar reflectivity without any discontinuities, a global mean is statistically more efficient than an adaptive filter. However almost all parcels are composed with heterogeneous targets, adaptive local filter seems to be more appropriate because of the visual result they give but also because physical models provide better results. For an heterogeneous parcel, we established that there is an optimal size for the local window which maximized the parameter retrieval. One further step would be to select this window size for each pixel according to the model response.

In short, statistical based filter hypothesis seems to be confirmed by the behavior of the physical models. However, due to the lake of in-situ measurements, we could not validate this result and go thoroughly into the discussion. Consequently, this work needs to be confirmed with another campaign.

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