**ABSTRACT**

An inversion technique based on neural networks has been implemented to estimate surface roughness and soil moisture over bare fields using ERS and RADARSAT data. The neural networks were trained with a simulated data set generated from the Integral Equation Model. Later the networks were applied to a field data set spanning a wide range of surface roughness and soil moisture, with backscattering coefficients for three radar configurations (VV-23°, HH-39°, HH-47°). Approaches based on two and three radar image configurations were examined and tested. Although the three-image configuration produces slightly more accurate results, a two-image configuration gives results of comparable accuracy when a favourable combination of incidence angles is adopted. The introduction of a priori information on the range of soil moisture (mv) improves mv estimation. Soil moisture and surface roughness errors were estimated respectively at about 7.6% and 0.47 cm using the root mean square error (RMSE).

**RESUME**

Une technique d'inversion basée sur les réseaux de neurones a été mise en œuvre pour estimer, à partir d’images radar de type ERS et RADARSAT, la rugosité et l’humidité de surface des sols nus.
en zones agricoles. Les réseaux de neurones ont été entraînés sur une base de données simulées à partir du modèle de rétrodiffusion IEM (Integral Equation Model). Ensuite, les réseaux ont été appliqués sur des données réelles de rugosités, d'humidités, et des coefficients de rétrodiffusion issus de trois configurations radar (VV-23°, HH-39° et HH-47°). Des approches basées sur deux et trois configurations d'images radar ont été examinées. Bien que la configuration utilisant trois images produise des résultats légèrement plus précis, une configuration de deux images donne des résultats comparables quand une combinaison favorable des angles d'incidence est adoptée. L'introduction d'une information a priori sur l'humidité du sol (mv) améliore l'estimation de celle-ci.

Les deux paramètres de surface ont été estimés avec une erreur quadratique moyenne d'environ 7,6% pour l'humidité et 0,47 cm pour la rugosité.

1. INTRODUCTION

In many parts of the world, excessive runoff and soil erosion are amongst the major sources of damage. Monitoring tools at catchment scale are necessary for improving flood prediction and water-resource management. Surface runoff occurs when rainfall intensity exceeds soil infiltration capacity (Zobeck and Onstad, 1987; Boiffin et al., 1988; Le Bissonnais, 1990). In addition to vegetation, soil roughness also plays a role of trapping water in agricultural areas, which increases infiltration and in turn reduces downstream runoff. More specifically, it has been proved in loamy contexts that smooth soils are commonly crusted and have a poor infiltration capacity compared to rough soils (Le Bissonnais et al., 1998). Therefore, mapping of soil roughness states could offer a reliable key for assessing those surfaces that could potentially contribute to runoff in agricultural contexts.

One possible way of estimating surface roughness consists in using active microwave remote sensing. The backscattering signal, which depends on different radar parameters (incidence angle, frequency, polarization), is also correlated for bare soils to soil surface roughness and moisture content (Ulaby et al., 1986; Dobson and Ulaby, 1986; Oh et al., 1992; Fung, 1994; Rakotoarivony
Experimental results and studies using simulation models have shown that the radar signal is more sensitive to surface roughness at high incidence angles than at low incidence angles. In addition, the C-band at low-incidence angles is optimal for soil moisture estimation with a minimum influence of soil surface roughness (Ulaby et al., 1978; Autret et al., 1989). In the present study, we discuss the application of neural networks to retrieving the parameters of surface roughness (rms surface height) and soil moisture (mv).

2. DATA SETS
Two data sets were used. The first is a simulated data set generated from the Integral Equation Model (IEM) (Fung, 1994) and served to train the neural networks. The second is a field data set used to validate the inversion results.

2.1 Simulated data set
In order to test the performance of radar signal inversion using the neural networks technique, it is vital to have data spanning a wide range of surface roughness and soil moisture, as is encountered in agricultural contexts for bare soils. Because of the difficulty involved in establishing a field data set, which demands several SAR images, several study sites and numerous field measurements; we decided to use a backscattering digital model to simulate the radar signal according to various configurations of the SAR sensors and different soil characteristics.

Several backscattering models, both empirical and physical, can provide us with backscattering coefficients ($\sigma^o$) based on the characteristics of the sensor (wavelength, incidence angle, and polarisation) and those of the target (statistical parameters of surface roughness, dielectric constants). The model used here is the Integral Equation Model (IEM) which is one of the most widely used models (Fung, 1994). Its success is partly due to its applicability to a wide range of surface roughness and soil moisture: $krms \leq 3$, where $k$ is the wave number ($\approx 1.11$ cm$^{-1}$ in C-band).

Over bare soils in agricultural areas, the expression of the backscattering coefficient of the surface contribution is:
\[\sigma_{pp} = \frac{k^2}{2} |f_{pp}|^2 e^{-4\text{rms}\nu_0^2 \cos^2 \theta} \sum_{n=1}^{\infty} \frac{(4\text{rms}^2 k^2 \cos^2 \theta)^n}{n!} W^{(n)} (2k \sin \theta, 0)\]

\[+ \frac{k^2}{2} \text{Re}(f_{pp}^* F_{pp}) e^{-3\text{rms}\nu_0^2 \cos^2 \theta} \sum_{n=1}^{\infty} \frac{(4\text{rms}^2 k^2 \cos^2 \theta)^n}{n!} W^{(n)} (2k \sin \theta, 0)\]

\[+ \frac{k^2}{8} |F_{pp}|^2 e^{-2\text{rms}\nu_0^2 \cos^2 \theta} \sum_{n=1}^{\infty} \frac{(\text{rms}^2 k^2 \cos^2 \theta)^n}{n!} W^{(n)} (2k \sin \theta, 0)\]

where:

\[f_{hh} = -\frac{2R_h}{\cos \theta}\]

\[f_{vv} = \frac{2R_v}{\cos \theta}\]

\[F_{hh} = 2 \frac{\sin^2 \theta}{\cos \theta} \left[ 4R_h - \left( 1 - \frac{1}{\varepsilon_r} \right) (1 + R_h)^2 \right]\]

\[F_{vv} = 2 \frac{\sin^2 \theta}{\cos \theta} \left[ \left( 1 - \frac{\varepsilon_r \cos^2 \theta}{\mu_r \varepsilon_r - \sin^2 \theta} \right) (1 - R_v)^2 + \left( 1 - \frac{1}{\varepsilon_r} \right) (1 + R_v)^2 \right]\]

\[R_h = \frac{\cos \theta - \sqrt{\varepsilon_r (1 - \sin^2 \theta)}}{\cos \theta + \sqrt{\varepsilon_r (1 - \sin^2 \theta)}}: \text{Fresnel coefficient at horizontal polarization}\]

\[R_v = \frac{\cos \theta - \frac{1}{\sqrt{\varepsilon_r}} (1 - \sin^2 \theta)}{\cos \theta + \frac{1}{\sqrt{\varepsilon_r}} (1 - \sin^2 \theta)}: \text{Fresnel coefficient at vertical polarization}\]

\[W^{(n)} (a,b) = \frac{1}{2\pi} \int \rho^n (x,y) e^{-i(ax+by)} dx dy\]

\(W^{(n)}\) is the Fourier transform of the nth power of the surface correlation coefficient.

\(\varepsilon_r\): dielectric constant, which is obtained on the basis of volumetric water content using the empirical model of Hallikainen et al. (1985).

\(\mu_r\): relative permittivity

\(\theta\): incidence angle

pp: co-polarization (pp = HH or VV)
Re: real part of the complex number

\[ f_{pp}^* \]: conjugate of the complex number \( f_{pp} \)

\( \rho(x, y) \): surface correlation function. Its distribution is exponential for low surface roughnesses and Gaussian for high surface roughnesses:

\[
\rho(x, y) = e^{-\frac{|x+y|}{L}} : \text{exponential}
\]

\[
= e^{-\frac{x^2+y^2}{2\sigma^2}} : \text{Gaussian}
\]

L: correlation length

However, much work has revealed a poor agreement between IEM simulations and measured data (Baghdadi et al., 2002; Zribi et al., 1997; Rakotoarivony et al., 1996), deviations as much as several decibels have been found, which renders the inversion results inaccurate. Baghdadi et al., (2002) proposed a semi-empirical calibration of the IEM to improve its performance, with consideration of only three radar configurations (VV-23°, HH-39°, HH-47°). The discrepancy between the measured and simulated backscattering coefficients is assumed to be directly related to the poor accuracy of the correlation length measurements, considering that the other IEM input parameters (rms surface height, soil moisture and incidence angle) are relatively accurate. Baghdadi et al., (2002) thus proposed an empirical calibration parameter (\( L_{opt} \)) which integrates the true correlation length as well as the imperfections of the IEM (the shape for the correlation function is considered as exponential). This parameter depends on rms surface height and radar configuration (frequency, polarization and incidence angle). The results reveal two trends for the behaviour of \( L_{opt} \): the first is characterized by lower rms heights and an approximately constant \( L_{opt} \), and the second by higher rms heights and an \( L_{opt} \) that increases with rms height according to an exponential relationship (Baghdadi et al., 2002).

A realistic data set combining a wide range of soil variables (rms surface height “rms” and soil moisture “mv”) and corresponding backscattering coefficients was generated from the calibrated IEM to evaluate the performance of the neural networks. We considered a total of 5376 elements corresponding to 56 surface roughness values (rms between 0.25 and 3 cm with a step of 0.05 cm),
24 soil moisture values (mv between 4% and 50% with a step of 2%), and three radar configurations (VV-23°, HH-39°, HH-47°). The only radar configurations used are the three for which the IEM was calibrated. The data set was contaminated by a zero mean Gaussian random noise to assimilate it to a measured data set (Satalino et al., 2000). A noise level of 1 dB, corresponding to the calibration errors of satellite images, was selected for the backscattering coefficient.

2.2 Field data set

The field measurements were collected within the framework of the European FLOODGEN campaign of 1998 (Baghdadi et al., 2002; King, 2001) in the Pays de Caux region of northern France (long. 0°50’ W and lat. 49°47’ N, Figure 1). The site consists mainly of flat agricultural fields on low-relief plateaux with homogeneous soil composed of about 67% loam, 13% clay and 17% sand.

One ERS image (VV-23°) and two RADARSAT images (Standard S5: HH-39° and Fine F5: HH-47°) were acquired on 8, 9 and 23 February 1998, respectively. Absolute calibration of the ERS and RADARSAT images was carried out, which enabled the derivation of backscattering coefficients ($\sigma^0$) using algorithms developed by the Canadian and European Space Agencies (Laur, 1992; Shepherd, 1997).

A field survey was conducted, at the same time as the satellite overpasses, on crop-sowing fields (wheat, sunflower and corn) with a low vegetation density (<20%) and on ploughed fields in order to measure the soil characteristics. The data set contains a total of 28 measurements of surface roughness and soil moisture. These fields have a homogeneous area of 16 hectares or more.

Roughness measurements were carried out using a 1-m long needle profilometer with a 2-cm sampling interval. Eight roughness profiles were sampled for each training field. On the basis of these measurements, we calculated the standard deviation of rms surface height using the mean of the autocorrelation function. The rms values fluctuate between 3 mm and 3 cm; the lower ones correspond mainly to wheat-sowing fields and the higher ones to recently ploughed fields.
The volumetric water content at field scale was assumed to be equal to the mean value estimated from several samples (4 to 15 per field) collected from the top 10 cm of soil using a Time Domain Reflectometry (TDR) probe. The soil moisture contents range from 30% to 40% with a standard deviation of about 5%. However, for certain fields, we measured soil moisture content at a depth of 5 cm (penetration depth of C-band SAR) in addition to the 10-cm-deep measurements. The soil moisture content at a depth of 10 cm is slightly higher than at 5 cm (about 1.2%), but the 10-cm-deep measurements are more consistent at field scale than the 5-cm-deep measurements. This 1.2% difference, which generates only a minor overestimation of the backscattering coefficient (<0.4 dB), is so little at this time of the year because the soil is saturated and solar evaporation is low.

Figure 2 shows, for each radar configuration (HH-47°, HH-39° and VV-23°), the relationship between the backscattering coefficient ($\sigma^o$) and the surface height (rms).

3. THE INVERSION TECHNIQUE

3.1 Method

A technique based on neural networks was developed to estimate surface roughness and soil moisture from SAR data (Kohonen, 1988; Atkinson and Tatnall, 1997). Retrieval of soil moisture and surface roughness parameters needs at least two SAR configurations. The neural network most commonly encountered in remote sensing is of the feed-forward back-propagation multi-layer perceptron (MLP) type (Rumelhart et al., 1986). The MLP neural network consists of one input layer, one output layer, and one or more hidden layers in between. The input vector contains the measurements ($\sigma^o$-values), and the output vector contains the quantity to be retrieved from these (rms surface height and soil moisture).

The simulated data set was divided randomly into a training set (2688 elements) and a validation set (2688 elements). The training phase is carried out with the training set and the optimum network is defined. This minimises the error (SSE: Sum Square Error) in the validation set between the measured backscattering values and those predicted by the network. For the training set, the overall
error decreases with the training, approaching a value of convergence. Conversely, the error on the validation set reaches a minimum value, after which it starts to increase if training is continued; the training phase is interrupted at this point. Later, the performance of the neural network was evaluated using the field data set.

Two cases are considered in this study:

- Input to the network is a set of two or three $\sigma^\circ$-values: (VV-23°; HH-39°), (VV-23°; HH-47°), (HH-39°; HH-47°), and (VV-23°; HH-39°; HH-47°). Output is rms surface height and soil moisture (mv).

- In order to reduce ambiguity in the retrieval problem, a constraint on the soil moisture conditions is introduced: slightly moist soil or very moist soil. The two moisture classes are: mv <20% for dry to slightly moist soils and mv ≥20% for wet soils. It is possible for certain study sites to estimate the degree of moisture from weather forecasts and field knowledge. We decided to include this information in the inversion process as this constrains the range of possible moisture values and thus lead to a better estimation of our two surface parameters. The cases of two and three images were examined.

### 3.2 Results and Discussion

A MLP neural network with one hidden layer of twenty nodes was found to best model the relationship between the soil parameters (rms surface height and soil moisture) and the backscattering coefficients without overfitting (Keiner and Yan, 1997). These characteristics are the result of a compromise between accuracy and computation time.

The inversion performance of the neural network model is evaluated to show the robustness of the presented technique. As suggested by Willmott (1992), three statistical indexes were used:

- Mean Absolute Error:

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |Pi - Oi|
\]
- Root Mean Square Error:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Pi - Oi)^2}
\]

- Index of agreement:

\[
d = 1 - \left[ \frac{\sum_{i=1}^{N} (Pi - Oi)^2}{\sum_{i=1}^{N} \left( |Pi - \frac{1}{N} \sum_{i=1}^{N} Oi| + |Oi - \frac{1}{N} \sum_{i=1}^{N} Oi| \right)^2} \right], \quad 0 \leq d \leq 1
\]

Where P is the field or simulated variable, O the estimated variable, and N the data number. MAE and RMSE are expressed in centimetres for surface roughness and % for soil moisture, while d is dimensionless.

### 3.2.1 Simulated data

All three statistical indexes were computed for the schemes under consideration. Table 1 shows the inversion results for the no-noise condition. Where two radar images are used, one must have a high incidence angle for a better estimation of rms surface height, and the other a low incidence angle for a better estimation of soil moisture. The combination of HH-47° and VV-23° seems to be the optimal two-image configuration with an RMSE of about 0.21 cm for rms and 1.46% for mv (no-noise condition). The introduction of an mv constraint only improves mv estimation when the images used are not optimal: RMSE is reduced from 5.69% to 2.30% for dry to slightly moist soils (average of 4.05% when the wet soils are taken into consideration) for HH-47° and HH-39°, and from 4.66% to 1.86% for dry to slightly wet soils and 2.51% for wet soils for HH-39° and VV-23°.

A three-image configuration provides a better estimation of the two soil parameters rms and mv: the RMSE between the retrievals and the references is small: 0.01 cm for rms and 0.27% for mv. The estimation of rms is not affected by the introduction of a constraint on mv. Figure 3 shows, for the three radar image configurations, the retrieval of rms surface height and soil moisture versus their corresponding references under no-noise conditions.
The results obtained using backscattering coefficients contaminated by a Gaussian noise with a standard deviation of 1 dB show that beyond a certain rms threshold, which depends on the images used and ranges from 1.5 cm to 2 cm, the neural network has great difficulty in retrieving the parameter rms (Figure 4a). For data beneath this threshold, rms estimation is good despite a slight bias, whereas for data above this threshold, estimation is poor with a considerable bias for all configurations (two or three radar images). For all points with an rms between 1.5 cm and 3 cm, the network yields an rms of approximately 1.75 cm. This is because the radar at C-band (5.3GHz) is not highly sensitive to changes in rms at high rms ranges (threshold dependent on the angle of incidence). For mv values between 4% and 35%, we note an overestimation of about 5%, and for mv values above 35%, the network underestimates soil moisture (Figure 4b). Table 2 shows the inversion results for the simulated data set. When no constraint on mv is introduced, the use of the two-image configuration HH-47° and VV-23° seems to give optimal results for rms and mv estimation. An accuracy comparable to that obtained with this optimal configuration (HH-47° and VV-23°) is also noted for rms estimation using the HH-47° and HH-39° configuration (RMSE about 0.6 cm), and for mv estimation using the HH-39° and VV-23° configuration (RMSE about 9.4%). The results also show a slight improvement in retrieval of both surface roughness and soil moisture (by 0.6 mm for rms and 0.4% for mv) when three radar images are used rather than two radar images.

The RMSE on mv is reduced by a third when a constraint on mv is introduced. In the case of a network based on three radar images, the RMSE drops from 8.9% without the constraint on mv to 6.1% with the constraint on mv (average for the entire data set). The introduction of a constraint on mv only slightly improves the rms results (cf. Table 2).

3.2.2 Field data

The retrieval capacity of neural networks trained by theoretical backscattering coefficients generated by the IEM model was then tested using the field data set. The networks used are those
obtained using data contaminated with a Gaussian noise with a standard deviation of 1 dB (simulated data). The resulting networks, one without constraint on mv and the other with, were then analysed. Considering that the elements of the field data set have a moisture corresponding to what we call ‘wet soils’ (mv >20%), we applied the neural networks developed using the simulated data set with the constraint on mv. Table 3 gives the statistical results obtained for the estimation of rms and mv according to the two- and three-image configurations considered. The estimations of surface roughness (rms) and soil moisture (mv) are illustrated in Figures 5 and 6.

The introduction of a constraint on mv provides a good agreement between the estimated and measured soil moisture, with a significant decrease of the bias and the RMSE on the estimation of mv. This decrease varies according to the images used, with an average improvement of some 5% for the bias and 4% for the RMSE. The results obtained for rms estimation are practically the same with or without the constraint on mv. The best rms and mv estimation results were obtained with a combination of three radar configurations. Nevertheless, the use of two images, one high incidence (47°) and the other low incidence (23°), provides results of comparable accuracy because VV-23° yields less errors in the mv estimation while HH-47° yields less errors in the rms estimation. The network based on the HH-47°, HH39° and VV-23° configuration for input gives an RMSE of 0.47 cm for rms and 7.6% for mv, whereas the network based on the HH-47° and VV-23° configuration gives an RMSE of 0.48 cm for rms and 8.6% for mv. With the introduction of a constraint on mv, the residual bias is less than 0.1 cm for rms estimation and less than 1.5% for mv estimation if we adopt optimal image configurations. We also note an overestimation of rms surface height in low roughness regions (rms ≤1.5 cm) and an underestimation in high roughness regions (rms >1.5 cm).

4. CONCLUSIONS

The objective of this study was to assess the capacity of estimating surface roughness and soil moisture over bare fields using SAR data. An inversion technique based on neural networks was implemented. A calibrated IEM model was used to generate a data set for training of the neural
networks. These networks were later applied to ERS and RADARSAT measurements (VV-23°, HH-39° and HH-47°) to estimate surface roughness and soil moisture. The results of this study indicate that neural networks trained with data generated by the electromagnetic model IEM are able to retrieve the parameters of surface roughness and soil moisture with acceptable accuracy. Nevertheless, we note that the introduction of a constraint of pre-information on soil moisture improves mv estimation. The relationship between the inversion results and the radar configurations adopted has also been explored. The inversion errors obtained with the three-image configurations were slightly less than with the two-image configuration. The retrieval errors on the field data set were 0.47 cm for rms and 7.6% for mv. The best estimation of soil moisture occurred when the multi-configuration measurements of backscattering coefficients included an image with a low incidence angle (23°). Inversion of the surface roughness parameter gives a more accurate result with a high incidence angle (47°). Inversion of surface roughness, however, revealed that the technique is limited to values greater than approximately 1.75 cm.

Future studies should have more in situ samples and radar configurations for the validation of this technique.

Acknowledgements

This work has been financed by the European project FLOODGEN (ENV4-CT96-0368) and the BRGM research programme PRD316. The authors would like to thank Marie Weiss and Thierry Fourty for their support concerning neural networks.

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<table>
<thead>
<tr>
<th>No noise on $\sigma_0$</th>
<th>Surface height (rms)</th>
<th>Soil moisture (mv)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Without constraint on mv</strong></td>
<td>MAE (cm)</td>
<td>RMSE (cm)</td>
</tr>
<tr>
<td>HH 47° and HH 39°</td>
<td>0.22</td>
<td>0.41</td>
</tr>
<tr>
<td>HH 47° and VV 23°</td>
<td>0.11</td>
<td>0.21</td>
</tr>
<tr>
<td>HH 39° and VV 23°</td>
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<td>0.08</td>
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<td>0.01</td>
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<td><strong>With constraint on mv</strong></td>
<td>MAE (cm)</td>
<td>RMSE (cm)</td>
</tr>
<tr>
<td><strong>Dry to slightly moist soils (mv ≤20%)</strong></td>
<td></td>
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<td><strong>Wet soils (mv &gt;20%)</strong></td>
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<td>RMSE (cm)</td>
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Table 1: Statistics for the estimation of surface height (rms) and soil moisture (mv) for no-noise conditions. The cases without and with a constraint on mv are presented.

<table>
<thead>
<tr>
<th>Noise on $\sigma_0=1$ dB</th>
<th>Surface height (rms)</th>
<th>Soil moisture (mv)</th>
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<td>RMSE (cm)</td>
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Table 2: Statistics for the estimation of surface height (rms) and soil moisture (mv) for 1-dB noise conditions. The cases without and with a constraint on mv are presented.
### Field data

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<td>With constraint on mv</td>
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</tr>
</tbody>
</table>

Table 3: Statistics for the estimation of surface height (rms) and soil moisture (mv) using the field data set. The cases without and with a constraint on mv are presented.
Figure 1: Location map of study site (long. 0°50' W and lat. 49°47' N).
Figure 2: Variation of the backscattering coefficient $\sigma^o$ as a function of surface height (rms) for the three radar configurations: RADARSAT 47°, RADARSAT 39°, and ERS 23°. The backscattering coefficient $\sigma^o$ was plotted for all data independently of row direction and soil moisture. The line represents the best fit of the experimental points.
Figure 3: Comparison between the estimated and measured values of (a) rms surface height and (b) soil moisture for the three radar images and no-noise conditions.
Figure 4: Comparison between the estimated and measured values of (a) rms surface height and (b) soil moisture for the three radar images and 1dB-noise conditions.
Figure 5: Retrieved rms surface height and soil moisture by neural network versus in situ measurements (without a constraint on mv).
Figure 6: Retrieved rms surface height and soil moisture by neural network versus in situ measurements (with a constraint of wet soils on mv).