REPORT:

In this deliverable, we present the potential use for the C-band polarimetric SAR (Radar Synthetic Aperture) parameters to characterize the soil surface over bare agriculture fields. RADARSAT-2 data were analyzed to evaluate the polarimetric SAR parameters’ sensitivities to the soil moisture and surface roughness. Moreover, an approach was developed to estimate soil surface parameters from C-band polarimetric SAR data. An inversion technique based on Multi-Layer Perceptron (MLP) neural networks was introduced. The neural networks were trained and validated on a noisy simulated dataset generated from the Integral Equation Model (IEM) on a wide range of surface roughness and soil moisture, as is encountered in agricultural contexts for bare soils. The performances of neural networks in retrieving soil moisture and surface roughness were tested for several inversion cases in using or not a-priori knowledge on soil parameters. The inversion approach was then validated against a real dataset composed of RADARSAT-2 images in polarimetric mode.

1. Potential of polarimetric RADARSAT-2 for the bare agricultural soils characterization

1.1 Background

Soil surface characteristics, namely the soil moisture content and roughness, play an important role in different applications such as hydrology, agronomy or meteorology. Floods, excess runoff, and soil erosion are, among others, key factors controlled and influenced by soil surface conditions (Engman, 1991; Jackson et al., 1996; Le Bissonnais et al., 1998). Indeed, soil moisture and surface roughness affect numerous processes on the soil surface such as infiltration capacity, temporary surface storage, deposition or detachment of particles, etc. Numerous research studies that have been performed during the three last decades have shown that Synthetic Aperture Radar (SAR) sensors have a high potential to measure the surface soil moisture (e.g. Alvarez-Mozos et al., 2006; Baghdadi et al., 2002a-
It is well known that the SAR return signal over bare soil surfaces is affected by surface characteristics such as the soil’s roughness and dielectric constant. There is currently a great challenge to demonstrate an interest in the use of polarimetric parameters in order to estimate surface roughness and soil moisture. Only a few studies have analyzed the potential uses of polarimetric SAR data for the estimation of surface roughness and soil moisture over bare agricultural fields (Allain et al., 2003-2004-2006; Hajnsek et al., 2003). The potential of polarimetric parameters in the C-band was studied little and the available SAR studies use especially high radar wavelengths as the L-band. The main investigation in this study concerns the analysis of the dynamic of polarimetric parameters in the C-band according to soil moisture and surface roughness. The sensitivity of polarimetric parameters at the C-band to bare agricultural soil parameters (soil moisture and surface roughness) was studied. RADARSAT-2 images in the polarimetric mode were analyzed.

1.2 Polarimetric parameters

A polarimetric Synthetic Aperture Radar (SAR) measures the scattering matrix $S$ of a medium with quad polarizations. This matrix is constituted by the complex scattering coefficients $S_{pq}$, where $p$ is the transmitting polarization and $q$ is the receiving polarization ($p, q = H$ or $V$, where $H$ represents horizontal and $V$ represents vertical). The polarimetric information in the monostatic case can be represented by a coherency matrix $T$ which can be calculated from the complex target vector $k_p$ as follows (Cloude and Pottier, 1996):

$$T = \begin{pmatrix} k_p & k_p^T \end{pmatrix}$$

where the superscripts $^*$, $^T$ and $<>$ denote the complex conjugate, the matrix transpose, and the average operator, respectively.

Cloude and Pottier (1996) proposed a polarimetric decomposition theorem that is based on the eigenvector/value of the coherency matrix into elementary mechanisms (i.e. single, double and volume scattering) to identify the global mean scattering mechanism. The matrix $T$ can be defined as the non coherent sum of three orthogonal unitary matrices as follows:

$$T = \sum_{i=1}^{3} \lambda_i V_i V_i^{*T}$$

where $\lambda_i$ are the three eigenvalues of $T$, which are real and non-negative $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$. $V_i$ are the related orthogonal unitary eigenvectors.

Using the eigenvectors and eigenvalues, three main parameters are used to characterize the results of this decomposition: entropy ($H$), mean alpha angle ($\bar{\alpha}$), and anisotropy ($A$). The polarimetric scattering entropy $H$ is defined from the logarithmic sum of the eigenvalues of $T$ and represents the random behavior of the scattering phenomenon as follows:

$$H = -\sum_{i=1}^{3} P_i \cdot \log_2(P_i) , \quad 0 \leq H \leq 1$$

where $P_i$ are the normalised eigenvalues as follows:
\[ P_i = \frac{\lambda_i}{\sum_{j=1}^{3} \lambda_j} \]

The entropy \( H \) is a measure of the randomness of the scattering mechanisms. Low entropy \( (H \approx 0) \) indicates a single scattering mechanism (isotropic scattering) while high entropy \( (H \approx 1) \) indicates a totally random mixture of scattering mechanisms with equal probability and, therefore, a depolarizing target.

The mean scattering angle \( \bar{\alpha} \) represents the mean dominant scattering mechanism and it is calculated from the eigenvectors and eigenvalues of \( T \):

\[ \bar{\alpha} = \sum_{i=1}^{3} \alpha_i P_i \]

where \( \alpha_i \) are the scattering mechanisms that are represented by the three eigenvectors. \( \bar{\alpha} = 0^\circ \) indicates a surface scattering, \( \bar{\alpha} = 45^\circ \) indicates a dipole mechanism (volume scattering), and \( \bar{\alpha} = 90^\circ \) indicates a double bounce scattering from metallic surfaces (dihedral scatter).

The anisotropy \( A \) is defined as the relative importance of the secondary scattering mechanism and it is expressed as:

\[ A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3}, \quad 0 \leq A \leq 1 \]

where \( \lambda_2 \) and \( \lambda_3 \) are the two lowest eigenvalues. \( A \) becomes 0 if both of the scattering mechanisms are of equal proportion, while the larger values of \( A \) indicates the increasing amounts of anisotropic scattering.

The reflection symmetry hypothesis, which is valid for agricultural surfaces, allows the derivation from the coherency matrix \( T \) of the analytical expressions of the polarimetric parameters. In this case, the correlation between the co- and cross-polarized channels is assumed to be zero \( (<S_{HH}, S_{VV}^*> = <S_{HV}, S_{VH}^*> = 0) \) (Nghiem et al., 1992). The simplified expressions of the Non-Ordered in Size (NOS) eigenvalues are defined as follows (Van Zyl, 1992):

\[ \lambda_{1\text{NOS}} = \frac{1}{2} \left( |S_{hh}|^2 + |S_{vv}|^2 + \sqrt{\left( |S_{hh}|^2 - |S_{vv}|^2\right)^2 + 4 |S_{hh}S_{vv}^*|^2} \right) \]

\[ \lambda_{2\text{NOS}} = \frac{1}{2} \left( |S_{hh}|^2 + |S_{vv}|^2 - \sqrt{\left( |S_{hh}|^2 - |S_{vv}|^2\right)^2 + 4 |S_{hh}S_{vv}^*|^2} \right) \]

\[ \lambda_{3\text{NOS}} = 2 |S_{hh}|^2 \]

The eigenvectors can also be written analytically in the case of reflection symmetry hypothesis (Van Zyl, 1992).

Allain (2003) suggest the analysis of the alpha angle that corresponds to the first eigenvector \( (\alpha_1) \) rather than the mean scattering alpha \( (\bar{\alpha}) \) because \( \alpha_1 \) indicates the type of the scattering process that is associated with the first eigenvector and then with the dominating scattering process. A value of \( \alpha_1 \) that is lower than 45° corresponds to surface scattering. The \( \alpha_1 \) parameter is given by the following:

\[ \alpha_1 = \arctan \left( \frac{\sqrt{|v_1(2)|^2 + |v_1(3)|^2}}{|v_1(1)|^2} \right) \]
Where \( v_1(i) \) is the \( i \)th component of the first eigenvector \( v_1 \) and \( / / \) is the module.

Moreover, Allain et al. (2006) introduced two new parameters, which are called the Single-bounce Eigenvalue Relative Difference (SERD) and the Double-bounce Eigenvalue Relative Difference (DERD), to provide a better inversion of the geophysical parameters in the natural media:

\[
SERD = \frac{\lambda_S - \lambda_{3\text{NOS}}}{\lambda_S + \lambda_{3\text{NOS}}} \quad \text{and} \quad DERD = \frac{\lambda_D - \lambda_{3\text{NOS}}}{\lambda_D + \lambda_{3\text{NOS}}}
\]

\( \lambda_S \) is associated to the single reflection mechanism and \( \lambda_D \) is associated to the double reflection. For \( \alpha_1 < \pi/4 \), \( \alpha_2 \) is higher than \( \pi/4 \), then \( \lambda_S = \lambda_{1\text{NOS}} \) and \( \lambda_D = \lambda_{2\text{NOS}} \). If \( \alpha_1 > \pi/4 \implies \alpha_2 < \pi/4 \) then \( \lambda_S = \lambda_{2\text{NOS}} \) and \( \lambda_D = \lambda_{1\text{NOS}} \).

In this study, only the following polarimetric descriptors that were considered to be important for the characterisation of the soil surface parameters were analysed: the angle \( \alpha_1 \), the entropy (H), the anisotropy (A), and the eigenvalue relative differences (SERD and DERD). These polarimetric parameters are those resulting from the studies carried out with L-band polarimetric data over bare agriculture fields.

### 1.3 Database

Two RADARSAT-2 datasets and ground measurements over agricultural study sites were acquired in the framework of CLIMB project. The first dataset contains ten images acquired over the Thau basin (France; Table 1, Figure 1a). The second dataset was acquired over the Chiba basin (Tunisia; Table 1, Figure 1b).

The first study site is located on the Thau watershed near Montpellier in Southern France (43°26'N and 3°40'E). It is mostly composed of agricultural plots that are intended for growing cereals (wheat) and vineyards, natural vegetation (Garrigue=Mediterranean forest), and agricultural wasteland. The second study site is the Orgeval watershed, which is located to the east of Paris (48°51'N and 3°07'E). The Orgeval watershed is mostly composed of agricultural plots that are intended for growing wheat and maize. This site is flat and composed of loamy soils. The measurement campaigns of the soil moisture and surface roughness were conducted simultaneously with the SAR acquisitions on several bare training plots (with low local topography and at least one hectare in size). The soil composition is approximately 52% silt, 35% clay, and 12% sand.
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<th>Orbit</th>
<th>Number of training plots</th>
<th>Soil moisture (%) [min – mean – max]</th>
<th>Soil roughness (cm) [min – max]</th>
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Table 1. Primary characteristics of the data set that was used in the study sites of Thau and Orgeval (France), and Chiba (Tunisia): images characteristics, number of training plots, range of soil moisture, and soil surface roughness (s).

The Tunisian study site is located on the Chiba river basin (36°41’N and 10°48’E), in the North East of Tunisia (Cap-Bon). It covers approximately an area of 286 Km². The catchment is situated in the Mediterranean semi-arid bioclimatic region. The average annual precipitation is 450mm and average annual temperature of 19°C. The ratio between the minimum rainfall and the maximum is 4.4, confirming the high variability in precipitation. The Chiba catchment is principally drained by Chiba stream and numerous little streams. Its river flows from the mountain Sidi Abdel Rahman to the Mediterranean Sea. The Cap Bon has a remarkably rich flora with over 40% of Tunisia’s wild species. The Chiba catchment is mostly composed of agricultural plots that are intended for growing cereals (wheat), market garden, fruit trees plantations, olive trees, natural vegetation, and agricultural wasteland.
RADARSAT-2 data

The C-band SAR images were obtained from the RADARSAT-2 sensor in the polarimetric mode. The radar data are available in fine mode with a spatial resolution of approximately 10m and incidence angles of 34-36°, 40°, and 45-47° (Table 1), for the study sites in France, and of 32°, 37°, and 46-47° for the study site in Tunisia. The PolSARPro v4.2.0 software (http://earth.eo.esa.int/polsarpro/) was used to process the RADARSAT-2 images. The following polarimetric parameters that were considered to be important for the characterization of the soil surface parameters were generated: the angle $\alpha$, the entropy (H), the anisotropy (A) and the eigenvalue relative differences (SERD and DERD). Next, every generated data layer was geocoded using the MapReady 2.3 software (http://www.asf.alaska.edu/downloads/software_tools) and a Digital Elevation Model at a pixel spacing of 5m (Figure 2) for the study sites in France. For the Tunisian study site, a SRTM (NASA) Digital Elevation Model at a pixel spacing of 90m was used (Figure 3). The geocoding errors were calculated for each RADARSAT-2 image by using an aerial optical image that was acquired by the French National Geographic Institute in 2005 with a spatial resolution of 50cm. For the Tunisian study site, errors were calculated using “google maps” images (GeoEye satellite acquired in 2011). The errors slightly different between one image and another (from 55.9m to 62m in X and from 5.6m to 10.7m in Y) were corrected by a simple translation of the images.

Coherency matrices are commonly processed for speckle noise reduction by averaging several neighbouring pixels using a moving window. Lopez and Pottier (2005) and Lee et al. (2008) have shown that an insufficient number of looks produce an underestimation of entropy and an overestimation of anisotropy and alpha angle (for grass). For a correct retrieval of the physical information, reliable H, A and $\alpha$ values may be obtained with a minimum of 49 looks. For our RADARSAT-2 data, a 7x7 boxcar filter was applied to the single-look complex data. The average of the polarimetric parameters was then calculated for each training plot.
Figure 2. RADARSAT-2 Quad-Pol image (January 05, 2011) over Thau Basin (Pauli composition: RGB=HH+VV, HV, HH-VV). Size of RADARSAT-2 image: 33.745km x 32.336km; Central coordinates: Lat. 43°26.569'N and Long. 3°40.669'E
Figure 3. RADARSAT-2 Quad-Pol image (July 05, 2010) over Chiba Basin (RGB = HH, HV, HH). Central coordinates: Lat. 36°41'N and Long 10°48'E
In situ measurements

Simultaneously to the RADARSAT-2 acquisitions, ground measurements were performed in selected bare training plots (± three hours of the satellite overpass time). Between two and sixteen training plots were visited on each SAR acquisition date (Table 1) in the French study sites (ten to twelve training plots for six SAR acquisition dates for the Tunisian study site). Two soil-surface parameters were measured: the moisture content (at a 0-5-cm depth) and the surface roughness.

The soil moisture (m_v) of each training plot was assumed to be equal to the mean value that was measured from several samples (between 20 and 50 for the French study sites, and 5 measurements per plot for the Tunisian study site) that were collected from that plot in using a calibrated TDR (Time Domain Reflectometry) probe. The soil moistures range from 0.03 to 0.46 cm³/cm³.

The roughness measurements were made using needle profilometer (1m long and with 2cm sampling intervals). Ten roughness profiles along and across the direction of tillage (five parallel and five perpendicular) were established in each reference field. From these measurements, the two roughness parameters, which are root mean square (s) surface height and correlation length (L), were calculated using the mean of all of the correlation functions. The rms surface heights ranged from 0.5 cm to 4.4 cm. The correlation length (L) varied from 1.7 cm in the sown fields to 8.5 cm in the ploughed fields.

A good characterization of surface roughness is dependent on the roughness profile length, the number of roughness profiles measurements and the horizontal resolution (sampling interval) of profiles (Lievens et al., 2009; Verhoest et al., 2008; Callens et al., 2006; Oh and Kay, 1998). According to Oh and Kay (1998), the roughness profiles length should be at least 40L and 200L (where L is the correlation length) in order to obtain the s and the correlation length with a precision of 10%. Lievens et al. (2009) and Callens et al. (2006) have demonstrated that shorter profiles result in lower s and correlation length. The underestimation of roughness parameters is more significant for smooth surfaces than for rough surfaces. The number of averaged profiles that is required to obtain a standard deviation on s and L less than 10% is dependent of profile length. Lievens et al. (2009) demonstrated that less than 10 averaged profiles are required for 1 m profile to obtain a standard deviation of s lower than 10%, whereas the same accuracy (better than 10%) for correlation length only becomes feasible for at least 15 averaged profiles. The precision on the correlation length measurements should be about 15 to 20% for the range of correlation length measured within our bare agricultural fields. with 1m profile and 10 average profiles (higher standard deviation for large correlation length). The precision associated with the measurements of s and L, were also dependent on the horizontal spacing between height points (∆x). According to Lievens et al. (2009), an increase in horizontal spacing causes a decrease in s and an increase in correlation length, which are more pronounced for surfaces with small correlation length. Oh and Kay (1998) suggested that the surface should be sampled at a spacing no longer than 0.2L and no more than 0.5L for the same precision of about 5% on the correlation length and the s surface height, respectively. For our range of correlation length, the accuracy of roughness parameters with a spacing of 2 cm should be better than ± 10% for s and between ± 10% and ± 20% for large and small correlation lengths, respectively.

1.4 Data Analysis

In this section, we will analyze the potential of some of the polarimetric parameters for the soil surface characterization (soil moisture « m_v » and surface roughness « s »). The behavior of polarimetric parameters according to the soil moisture and surface roughness will be studied in using all SAR acquisitions (all data).

To provide a good interpretation of the polarimetric parameters α₁, entropy, anisotropy, SERD and DERD that were averaged from the RADARSAT-2 images of each training plot, the distribution of the standard deviations that were calculated in the training plots were analyzed (329 data points).

Figure 4 shows that the mean of the standard deviations was approximately 3°, 0.07, 0.09, 0.06, and 0.12 for α₁, H, A, SERD and DERD, respectively. As example, the standard deviation of α₁ vary
between 2° and 4° (for 90% of values) with a mean about 3°. The $\alpha_1$ parameter could thus be useful in the mapping of soil moisture or surface roughness if its dynamic is at least of 6°.

**Figure 4.** Histogram of the standard deviations of $\alpha_1$, H, A, SERD, and DERD. A database of 329 points was used. Each point corresponds to the standard deviation of a polarimetric parameter that was calculated from a given training plot.

### 1.4.1 Behavior of alpha angle of the first eigenvector ($\alpha_1$) according to mv and ks

The $\alpha_1$ parameter indicates the scattering mechanism that is associated with the first eigenvector. $\alpha_1$ values that are lower than 45° correspond to surface scattering. Figure 4 represents the behavior of $\alpha_1$ according to the soil moisture and ks for three incidence angles, 34°, 40°, and 46°. Each value represents the mean parameter of a training site, and it was determined by averaging the values of all of the pixels that belonged to the site.

For an incidence angle of 34°, $\alpha_1$ appeared to decrease with the soil moisture for the mv values that were lower than 10-15% and increase subsequently from 6° to 12° for the mv values that were between 15% and 40% (Figure 4a). This behavior seems to be the same when ks<1.5 and ks>1.5. Figure 4c shows that $\alpha_1$ decreases slightly with ks (a decrease of only few degrees for a ks between 1 and 4). Moreover, this decrease is slightly more important for the high mv values (mv>30%). For the incidence angles of 40 and 46°, the behavior of $\alpha_1$ was identical to that observed for $\theta$=34°. $\alpha_1$ decreased when mv<10-15%, was constant when mv was between 15% and 30%, and increased approximately 8° when mv was between 30% and 45% (Figure 4b). Figure 4d shows that $\alpha_1$ decreased slightly with ks for the incidence angles of 40-46° and an mv<30%, and this decrease was only important for the low values of ks (ks <1). Moreover, Figure 4d shows that the difference between $\alpha_1$ of the training plots where mv<30% and the training plots where mv>30% was higher for the high incidence angles (40-46° in comparison to 34°). Thus, this parameter could be used to identify the plots that have a high surface soil moisture (mv>30%).
1.4.2 Behavior of entropy (H) according to mv and ks

H seemed to decrease slightly with the soil moisture when mv was lower than 15-20%. However, H values of approximately 0.2 increased with mv when the mv values were between 20% and 45% (Figures 5a and 5b). Moreover, H decreased with ks when the mv values were higher than 30%, and H seemed to be constant when mv<30% (Figures 5c, 5d). The observed difference in the entropy values for mv<30% and mv>30% could be useful in the separation of these two soil moisture classes. However, it is difficult to note a clear behaviour of H according to ks except for when $\theta=34^\circ$ and $\text{mv}>30\%$; in this case, H decreased approximately 0.2 for ks between 1 and 2.4. When $\theta=40^\circ$, the entropy seemed to be constant with the ks when mv<30%.
1.4.3 Behavior of anisotropy (A) according to mv and ks

Anisotropy increased with mv for the mv values that were lower than 25% and $\theta=34^\circ$, and it decreased next (Figure 7a). When $\theta=46^\circ$, A was constant with mv (Figure 7b). Moreover, the anisotropy decreased with ks when the ks values were lower than 1 by approximately 0.2 for ks between 0.5 and 1 (Figure 7d). For the ks values that were higher than 1, A seemed to be independent of ks (Figures 7c and 7d). The anisotropy could be used to separate two soil roughness classes: ks<1 and ks>1.

Figure 6. Behavior of entropy from the RADARSAT-2 data as a function of the soil moisture and ks

Figure 7. Behavior of anisotropy from the RADARSAT-2 data as a function of the soil moisture and ks
1.4.4 Behavior of single-bounce Eigenvalue Relative Difference (SERD) according to mv and ks

When \( \theta \) was between 34° and 46°, the SERD parameter was independent of the incidence angle. The SERD was constant when the soil moisture was between 9% and 30%, and it decreased slightly by approximately 0.1 (Figures 8a, 8b). The SERD decreased with the ks when ks<1, and next, the SERD became constant (Figures 8c, 8d). This parameter has the same potential as the anisotropy to separate the smooth soils (ks<1) from the rough soils (ks>1). This parameter is slightly less disturbed than the anisotropy (low standard deviations were observed for the mean of SERD) (Figure 4).

In conclusion, this polarimetric parameter presents a weak potential in the discrimination of ks or mv classes.

![Figure 8](image)

Figure 8. Behavior of the SERD from the RADARSAT-2 data as a function of the soil moisture and ks

1.4.5 Behaviour of double-bounce Eigenvalue Relative Difference (DERD) according to mv and ks

The DERD parameter was independent of the incidence angle when \( \theta \) was between 34° and 46°. When \( \theta=34° \), the DERD parameter increased slightly for mv values that were between 9% and 30%, and it next decreased slightly (Figure 9a). Moreover, the DERD was constant with the soil moisture when \( \theta=46° \) (Figure 9b). The behavior of the DERD with the ks showed that the DERD decreased with ks for ks values that were lower than 1 and became constant next (Figures 9c, 9d).
1.6 Conclusions

The objective of this study was to analyze the potential use of the C-band polarimetric SAR to perform a surface soil characterization over bare agricultural areas. Indeed, few previous studies had investigated this potential and the available studies used especially high-radar wavelengths, such as the L-band. The present study utilized the RADARSAT-2 polarimetric data (C-band). The parameters that were chosen in this analysis correspond to the parameters that are frequently used in the literature and are as follows: $\alpha_1$, entropy, anisotropy, SERD and DERD. Simultaneously with the RADARSAT-2 acquisitions, field measurements of the soil moisture and surface roughness were performed on several bare soil training fields.

Although the studies in L-band facilitated the collection of polarimetric SAR data that could be used to estimate the soil parameters (characterization of soil parameters), this study shows that the polarimetric parameters in the C-band are not very relevant to the characterization of the soil surface over bare agricultural area. The high potential that was observed in the L-band is related to the low values of $ks$ and the high dynamics of some of the polarimetric parameters for the low values of $ks (<1)$.

A weak dynamic is often observed in the C-band between the polarimetric parameters and both the soil roughness and moisture content. This weak dynamic does not allow for the direct estimation of the soil parameters, but it could help to improve the inversion standard approaches of the soil parameters by adding a priori information regarding the value ranges for the soil parameters to be estimated (i.e., it could eliminate ambiguities). Indeed, the polarimetric parameter $\alpha_1$ could be used to discriminate two soil moisture classes (very wet soils, where mv>30% and the remainder, where mv<30%), while the anisotropy (A) could be used to separate the smooth soils ($\text{ks}<1$) from the other soils ($\text{ks}>1$).
2. Soil parameters estimation over bare agriculture areas from C-band polarimetric SAR data using neural networks

2.1 Background

The possibility of retrieving soil moisture and surface roughness is insufficiently investigated from C-band polarimetric SAR (Synthetic Aperture Radar) data. However, extensive studies have been conducted to retrieve soil moisture by using mono- or multi-polarization C-band SAR data (e.g. Alvarez-Mozos et al., 2006; Baghdadi et al., 2002a-2006a; Dubois et al., 1995; Rahman et al., 2008; Le Hégarat-Mascle et al., 2002; Lievens et al., 2011; Moran et al., 2004; Satalino et al., 2002; Srivastava et al., 2003; Weimann et al., 1998; Zribi and Deschambre, 2002). The availability of RADARSAT-2 data (C-band, ~5.3 GHz) should enable to improve and increase the ability to retrieve soil parameters, based on RADARDAT’s capability of providing images in full polarization.

When using only one radar channel (one incidence angle and one polarization), a better estimate of soil moisture is obtained for a SAR configuration that minimizes the effects of surface roughness (low incidence angle) (Baghdadi et al., 2006a; Zribi and Deschambre, 2002). Moreover, Baghdadi et al. (2006a) have shown that the accuracy of the soil moisture estimate does not improve significantly (<0.01 cm³/cm³) when two polarizations (HH and HV, C-band) are used instead of only one polarization. Several studies have shown that the best estimates of soil moisture for one polarization and one radar wavelength are obtained with SAR images acquired at both low and high incidence angles. Indeed, the use of two incidence angles (20° and 40° for example) allows estimating both soil moisture and surface roughness (e.g. Baghdadi et al.; 2006a; Srivastava et al., 2003; Zribi and Deschambre, 2002).

Soil moisture and surface roughness can be estimated from SAR images by using physical or statistical models (e.g. Baghdadi et al., 2002a; Merzouki et al., 2011, Rahman et al., 2008). The most known physical model is the Integral Equation Model (IEM) developed by Fung (1994). It simulates the radar backscattering coefficients from SAR and soil parameters (radar wavelength, polarization, incidence angle, surface roughness and soil dielectric constant). The validity domain of IEM in C-band covers the range of roughness values that are commonly encountered for agricultural surfaces (k.rms≤3, where rms is the root mean square surface height and k the radar wave number ~1.11 cm⁻¹ for a frequency in C-band of 5.3 GHz). Typical rms values of agricultural bare soils ranges from 0.5 to 4 cm. The discrepancies observed between the IEM and the SAR data had encouraged Baghdadi et al. (2006b; 2011) to propose an empirical calibration of IEM model. As the correlation length is the least accurate of the parameters required in the IEM model, Baghdadi et al. (2006b; 2011) proposed to replace the measured correlation length, for each SAR configuration (radar wavelength, incidence angle, and polarization), by a fitting parameter (Lopt), so that the IEM model reproduce better the radar backscattering coefficient. The fitting parameter replaces inaccurate correlation length measurement and compensates for the inaccuracy of the IEM model. Statistical models based on experimental measurements are also often used in soil moisture estimation. For bare soils, the most popular statistical model is that developed by Oh et al. (1992; 2002) and Oh (2004) which uses an inversion diagram based on either the cross-polarized backscattering coefficient σ°HV and the copolarized ratio (σ°HH/σ°VV) or the copolarized ratio (σ°VV/σ°VV) and the cross-polarized ratio (σ°VV/σ°VV).

Due to the importance for numerous hydrologic and agronomic applications, the development of inversion approaches to estimate soil moisture from SAR images remains a great challenge. The estimation of such variables is often a complex and nonlinear process, making it suitable for Artificial Neural Networks (ANN) application. While extensive work has been done on the use of neural networks for processing remotely sensed data, only few studies had investigated the potential of neural networks for soil parameters estimation (e.g. Baghdadi et al., 2002a; Notarnicola et al., 2008; Paloscia et al., 2002; Santi et al., 2004).

An inversion technique based on neural networks was developed to estimate soil surface parameters (moisture content and roughness) over bare agricultural areas from fully polarimetric RADARSAT-2 C-band SAR data. The training of the neural networks is performed by using simulated radar backscattering coefficients through the Integral Equation Model (IEM). First, soil parameters retrieval
from polarimetric data is accomplished by using neural networks applied to a simulated dataset from the IEM model. In order to make the IEM simulation realistic, SAR measurement errors are added to the simulated backscattering coefficients. Next, the approach is validated using RADARSAT-2 data. The performance of the inversion technique is studied in introducing a priori information on the soil moisture and/or the surface roughness. This work enables to evaluate the potential of polarimetric SAR sensors at C-band for retrieving surface soil parameters.

### 2.2 Material and Methods

#### 2.2.1 Synthetic dataset

The Integral Equation Model (IEM; Fung, 1994) is used in order to generate a reference dataset for the inversion of SAR data by a neural network technique. The backscattering IEM model is capable to reproduce the radar signal at HH, HV and VV from SAR parameters (incidence angle and radar wavelength) and soil surface characteristics (dielectric constant and surface roughness). The empirical model developed by Hallikainen et al. (1985) is used to link the volumetric water content (mv) to the corresponding complex dielectric constant. This model uses the sand and clay composition of the soil. The description of surface roughness on bare soils in the IEM is currently based on three parameters (Fung, 1994): the correlation function, the correlation length, and the standard deviation of heights (rms).

Many studies have revealed a poor agreement between IEM simulations and measured data (e.g. Baghdadi et al., 2004-2006b-2011; Rakotoarivony et al., 1996; Zribi et al., 1997), with deviations of several decibels which renders the inversion results inaccurate. Baghdadi et al. (2006b-2011) proposed a semi-empirical calibration of the IEM to improve its performance at C-band. A large experimental database composed of SAR images and ground measurements of soil moisture and surface roughness was used. The discrepancy observed between the simulated and measured backscattering coefficients was 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. The approach consisted of replacing the measured correlation length, for each SAR configuration (incidence angle, and polarization), by a fitting/calibration parameter (Lopt), so that the IEM model reproduce better the radar backscattering coefficient. It replaces the inaccurate correlation length and empirically calibrates the model. The calibration parameter is found dependent on rms surface height, polarization, and incidence angle $\theta$ (for a given radar wavelength). The validity domain of the calibrated version of IEM at C-band covers a wide range of soil surface conditions and incidence angles: 0.05 cm$^3$/cm$^3$ < mv < 0.45 cm$^3$/cm$^3$, 0.3 cm < rms < 5 cm for HH and VV, 0.5 cm < rms < 3.8 cm for HV, and 25° < $\theta$ < 45°. The use of Gaussian correlation function ensures correct physical behavior of IEM. In Baghdadi et al. (2006b-2011) the expressions of Lopt for each polarization were given as a function of rms surface height and incidence angle. These expressions were improved in using additional SAR datasets:

$$Lopt (rms, \theta, HH) = 0.162 + 3.006 (\sin 1.23 \theta)^{-1.494} \text{ rms}$$

$$Lopt (rms, \theta, HV) = 0.9157 + 1.2289 (\sin 0.1543 \theta)^{-0.3139} \text{ rms}$$

$$Lopt (rms, \theta, VV) = 1.281 + 0.134 (\sin 0.19 \theta)^{-1.59} \text{ rms}$$

The coefficient of determination $R^2$ is 0.98 for HH, and 0.96 for both HV and VV.

A realistic dataset 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 network technique. We considered a total of 268110 elements (C-band, HH, HV and VV) corresponding to 331 surface roughness values (rms between 0.3 and 3.6 cm with a step of 0.01 cm), 90 soil moisture values (mv between 0.005 cm$^3$/cm$^3$ and 0.45 cm$^3$/cm$^3$ with a step of 0.005 cm$^3$/cm$^3$), 9 radar incidence angles ($\theta$ between 25° and 45° with a step of 2.5°). In order to make
the IEM simulations more realistic, the SAR measurement error which includes both calibration errors and measurements precision errors is added to the simulated backscattering coefficients. Realistic values of measurements errors are between 0.5 and 1dB (Satalino et al., 2002). To better simulate an experimental dataset, the synthetic dataset is then obtained by adding a zero mean Gaussian random noise with a standard deviation of ±0.5 and ±1 dB to the simulated backscattering coefficients (in dB scale). In order to obtain a statistically significant dataset, 100 noise samples are generated for each couple of mv and rms.

2.2.2 RADARSAT-2 dataset

The performance of the inversion technique is studied in using two RADARSAT-2 datasets acquired in the framework of CLIMB project. The first dataset contains ten images acquired over the Thau basin (France; Table 1, Figure 1a, section 1.3). The second dataset was acquired over the Chiba basin (Tunisia; Table 1, Figure 1b).

2.2.3 Artificial Neural Networks (ANN)

Multi-Layer Perceptron (MLP) neural networks is developed in this study to estimate the soil parameters over bare agricultural soils (moisture content and surface roughness) (Atkinson and Tatnall, 1997; Fine, 1999; Ripley, 1996). Neural networks are trained with the Levenberg-Marquart algorithm (Marquardt, 1963). The network architecture for the estimation of soil moisture and surface roughness has a three-dimensional input vector representing the backscattering coefficients in HH, HV and VV polarizations. The two dimensional output vector contains soil moisture and surface roughness. The soil roughness to be estimated corresponds to the soil standard deviation of height rms. The neural network has only one hidden layer. The number of neurons associated with the hidden layer is determined by training the networks. 20 hidden neurons give a good estimate of parameters while keeping a reasonable computing time. To develop a neural network, it is necessary to train the network with training dataset composed of input and output vectors. Training is accomplished to minimize the mean square error between the predicted ANN outputs and the reference values. The ANN models were developed using Matlab® software.

2.2.4 Methodological overview

The synthetic dataset of IEM simulations is divided into equal amounts, where 50% of the synthetic dataset is used for the training of the neural networks, and the remaining 50% is used for the validation of networks. The neural networks are first trained on a IEM simulation dataset using the fitting/calibration parameter (Lopt) (section 2.1). The outputs of the network are compared with synthetic and, ultimately, real (RADARSAT-2) data.

In order to improve the soil moisture estimates, a priori knowledge about soil moisture and/or surface roughness is introduced. Indeed, the polarimetric parameters $\alpha_1$ and anisotropy ($A$) can be used to provide thresholds on the possible values of mv and rms, respectively. Baghdadi et al. (2011) showed that the use of $\alpha_1$ allows to separate the very wet soils ($\alpha_1 \geq 10^\circ$) from the rest with a threshold on mv of 0.30 cm$^3$/cm$^2$. Moreover, the anisotropy can be used to discriminate two surface roughness classes, smooth soils with $krms<1.5$ ($A<0.3$) from the rest. Moreover, it is possible to determine the degree of the soil moisture from weather forecasts and field knowledge (e.g. soil type) in order to integrate in the inversion process the a priori knowledge on the soil moisture range: dry to wet soils (mv<0.3 cm$^3$/cm$^2$) or very wet soils (mv$\geq$0.3 cm$^3$/cm$^2$). The integration of a priori information constrains the range of possible soil parameter values and thus leads to a better estimation of soil parameters.

Neural networks are built in either using or neglecting a priori information on soil parameters. Four cases were defined:

- Case 1: No a priori information on mv and rms
Case 2: A priori information on $m_v$. For this case, two neural networks were developed, one for dry to wet soils and one for very wet soils. An overlapping of $0.05 \, \text{cm}^3/\text{cm}^3$ on $m_v$ was used between the datasets used for the training of these two networks. For dry to wet soils, soil moisture values range from $0.005$ to $0.35 \, \text{cm}^3/\text{cm}^3$ (the $m_v$ minimum and the threshold plus $0.05 \, \text{cm}^3/\text{cm}^3$, respectively). In the case of very wet soils, the $m_v$ values vary between $0.25$ and $0.45 \, \text{cm}^3/\text{cm}^3$ (the threshold minus $0.05 \, \text{cm}^3/\text{cm}^3$ and the $m_v$ maximum, respectively).

Case 3: A priori information on $r_m$. Two neural networks were developed, one for smooth soils and one for rough soils. An overlapping of $0.5 \, \text{cm}$ on $r_m$ was used for the training of these two networks. For smooth soils, surface roughness values vary between $0.3$ and $2 \, \text{cm}$ (the $r_m$ minimum and the threshold plus $0.5 \, \text{cm}$, respectively). In the case of rough soils, $r_m$ was between $1$ and $3.6 \, \text{cm}$ (the threshold minus $0.5 \, \text{cm}$ and the $r_m$ maximum, respectively).

Case 4: A priori information on $m_v$ and $r_m$. Four networks were developed, one for dry to wet soils and smooth areas, one for dry to wet soils and rough areas, one for very wet soils and smooth areas, one for very wet soils and rough areas. The $m_v$ and $r_m$ values of each network are the same as those defined in cases 2 and 3.

For each inversion configuration, two standard deviations of the measurement error are used: $\pm 0.5$ and $\pm 1 \, \text{dB}$ (same measurement error in the training and validation phases). The inversion performance is evaluated in using two statistical indexes, the bias (estimated - measured) and the Root Mean Square Error.

2.3 Evaluation of the inversion approach

The neural networks developed above have been tested for the evaluation of the precision on soil moisture and surface roughness estimates. Two datasets were used, synthetic (IEM simulations) and real datasets (RADARSAT-2 data). The soil parameters estimated in using the networks developed above were compared with the reference data.

2.3.1 Synthetic dataset

The inversion approach was first tested on synthetic data in order to study its performance for a large range of soil characteristics ($r_m$ and $m_v$) and sensor configurations ($\theta$). In this paper, three incidence angles were studied in detail: $25^\circ$, $35^\circ$, and $45^\circ$. These incidences are selected to cover the range of incidence angles available on the satellite SARs.

All statistical indexes were computed to evaluate the performance of the inversion procedure and to determine the retrieval errors on $m_v$ and $r_m$. Table 2 shows the inversion results for the $\pm 0.5$ and $\pm 1 \, \text{dB}$ noise conditions. The three incidence angles analyzed in this study ($25^\circ$, $35^\circ$, and $45^\circ$) showed similar performance on the soil moisture estimation. As example, in the case of neural networks with a priori information on $m_v$, the RMSE on the $m_v$ estimates vary between $0.036 \, \text{cm}^3/\text{cm}^3$ ($\theta=25^\circ$ and $45^\circ$) and $0.044 \, \text{cm}^3/\text{cm}^3$ ($35^\circ$) for $\pm 0.5 \, \text{dB}$ noise condition and between $0.045 \, \text{cm}^3/\text{cm}^3$ ($\theta=25^\circ$ and $45^\circ$) and $0.049 \, \text{cm}^3/\text{cm}^3$ ($\theta=35^\circ$) for $\pm 1 \, \text{dB}$ noise condition. The performance of the algorithm is slightly behind at incidence angle of $35^\circ$. This could be explained by the fact that the sensitivity of radar signal to $m_v$ and $r_m$ is the strongest for the incidence angles of $25^\circ$ and $45^\circ$ respectively (for incidences between $25^\circ$ and $45^\circ$), whereas the incidence of $35^\circ$ allows an intermediate sensitivity of the radar signal with $m_v$ and $r_m$. Table 2 also shows that the inversion algorithm provides un-biased soil moisture estimates.

The introduction of a priori information on one or two soil parameters ($m_v$, $r_m$, or $m_v$ and $r_m$) improves the $m_v$ estimates. This improvement reaches $0.02 \, \text{cm}^3/\text{cm}^3$ (RMSE) for a noise on the radar backscattering coefficients of $\pm 0.5 \, \text{dB}$, and $0.03 \, \text{cm}^3/\text{cm}^3$ for a noise of $\pm 1 \, \text{dB}$. For a noise of $\pm 0.5 \, \text{dB}$, the improvement observed on the $m_v$ estimates is of the same order in the case of a priori information on $m_v$ or $r_m$. For a higher noise ($\pm 1 \, \text{dB}$), results show better estimations of $m_v$ in the case of a priori information on $m_v$ than in the case of a priori information on $r_m$. Moreover, the results from simulated dataset show that the introduction of a priori information on both $m_v$ and $r_m$ provides similar accuracy
on the mv estimates than the case with a priori information on mv alone (difference lower than 0.005 cm$^3$/cm$^3$). Consequently, the improvement gained by the a priori information on rms is minor.

<table>
<thead>
<tr>
<th>Inversion with measurement errors of $\pm0.5$ / $\pm1$ dB</th>
<th>Soil moisture (mv)</th>
<th>Surface roughness (rms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No a priori information on mv and rms</td>
<td>Bias (cm$^3$/cm$^3$)</td>
<td>RMSE (cm$^3$/cm$^3$)</td>
</tr>
<tr>
<td>0=25°</td>
<td>0 / 0</td>
<td>0.044 / 0.063</td>
</tr>
<tr>
<td>0=35°</td>
<td>0 / 0</td>
<td>0.058 / 0.071</td>
</tr>
<tr>
<td>0=45°</td>
<td>0 / 0</td>
<td>0.046 / 0.064</td>
</tr>
<tr>
<td>A priori information on mv</td>
<td>0 / 0</td>
<td>0.037 / 0.046</td>
</tr>
<tr>
<td>0=25°</td>
<td>0 / 0</td>
<td>0.044 / 0.049</td>
</tr>
<tr>
<td>0=35°</td>
<td>0 / 0</td>
<td>0.036 / 0.045</td>
</tr>
<tr>
<td>0=45°</td>
<td>0 / 0</td>
<td>0.039 / 0.055</td>
</tr>
<tr>
<td>A priori information on rms</td>
<td>0 / 0</td>
<td>-0.04 / -0.07</td>
</tr>
<tr>
<td>0=25°</td>
<td>0 / 0</td>
<td>0.044 / 0.058</td>
</tr>
<tr>
<td>0=35°</td>
<td>0 / 0</td>
<td>0.036 / 0.052</td>
</tr>
<tr>
<td>0=45°</td>
<td>0 / 0</td>
<td>-0.03 / -0.06</td>
</tr>
<tr>
<td>A priori information on mv and rms</td>
<td>0 / 0</td>
<td>-0.04 / -0.06</td>
</tr>
<tr>
<td>0=25°</td>
<td>0 / 0</td>
<td>0.035 / 0.043</td>
</tr>
<tr>
<td>0=35°</td>
<td>0 / 0</td>
<td>0.036 / 0.043</td>
</tr>
<tr>
<td>0=45°</td>
<td>0 / 0</td>
<td>0.031 / 0.041</td>
</tr>
</tbody>
</table>

Table 2. Inversion approach results for simulated data with measurement errors of $\pm0.5$ and $\pm1$ dB. Statistics are given for the estimation of soil moisture (mv) and surface roughness (rms). The format of results is “a/b” with “a” corresponds to statistics in using a noise of $\pm 0.5$ dB, and “b” corresponds to statistics in using a noise of $\pm 1.0$ dB.

Moreover, the performances of the neural networks were analyzed as a function of the rms and mv values (Figures 10 and 11). For a noise of $\pm1$ dB, results showed that for a given rms between 1.0 cm and 3.6 cm, the RMSE on the mv estimates is of the same order for incidence angles between 20° and 45°. Results show that the RMSE on mv varies slightly with the rms for rms between 1.0 cm and 3.6 cm (between 0.05 and 0.07 cm$^3$/cm$^3$ in the case of no a priori information on mv and rms). For rms lower than 1.0 cm, the RMSE increases with the incidence angle in the case of no a priori information on mv and rms (from 0.075 cm$^3$/cm$^3$ to 0.12 cm$^3$/cm$^3$ for rms=0.5 cm) and decreases when the rms increases (for rms between 0.5 and 1 cm). As example for an incidence angle of 45°, RMSE on mv is of 0.12 cm$^3$/cm$^3$ for rms = 0.5 cm and of 0.06 cm$^3$/cm$^3$ for rms = 0.9 cm). In the case of a priori information on rms, the same behaviour is revealed with slightly lower RMSE values. In using the neural network developed with a priori information on mv alone or with a priori information on both mv and rms, the RMSE on mv shows values between 0.04 cm$^3$/cm$^3$ (for high rms) and 0.06 cm$^3$/cm$^3$ (for low rms) for incidence angles between 20° and 45°, and rms between 0.5 and 3.6 cm.

Concerning the dependence between the RMSE on the mv estimates and the reference value of mv, results indicate that for a noise of $\pm1$ dB the RMSE is about 0.02 cm$^3$/cm$^3$ for mv=0.05 cm$^3$/cm$^3$ with or without a priori information on the soil parameters. Moreover, weak dependence is observed between the RMSE on the mv estimates and the reference values of mv for mv between 0.05 and 0.35 cm$^3$/cm$^3$. The RMSE is about 0.06 cm$^3$/cm$^3$ in the case of no a priori information on the soil parameters, 0.05 cm$^3$/cm$^3$ in the case of a priori information on mv, 0.04 cm$^3$/cm$^3$ in the case of information a priori on rms alone or on both mv and rms. For mv between 0.35 and 0.45 cm$^3$/cm$^3$, the RMSE is about 0.09...
cm³/cm³ in the case of no information a priori on the soil parameters, 0.075 cm³/cm³ in the case of a priori information on mv, 0.06 cm³/cm³ in the case of information a priori on rms alone or on both mv and rms.

The difference between the estimated and reference mv shows that the neural networks over-estimates the mv for high rms-values (>1.1 cm) and underestimates it for low rms-values (<1.1 cm). Indeed, in our inversion procedure of radar signals, the NN estimates the rms parameter in the range 0.3 to 3.6 cm. To estimate the rms in the case of smooth soils, the NN will propose for rms only estimated values higher than 0.3 cm and thus sometimes an estimate which could be higher than the optimal value. This overestimate of rms will lead to an underestimate of mv. The opposite phenomenon occurs for the estimate of high values of rms, where an over-estimate of mv is observed.

For a given rms between 1.1 cm and 3.6 cm, the bias is of the same order for incidence angles between 25° and 45°. Moreover, the bias on the mv estimates increases with rms for rms-values between 1.1 and 3.5 cm. For lower rms (<1.1 cm) and a noise of ±1dB, the bias increases when the incidence angle increases and decreases when the rms increases between 0.5 and 1.1 cm. The use of a priori information on mv reduces clearly the bias. It varies of -0.08 to +0.04 cm³/cm³ in the case of no a priori information on the soil parameters and of -0.02 to +0.02 cm³/cm³ in the case of a priori information on both mv and rms. Underestimations between –0.06 and -0.04 cm³/cm³ on mv are also observed for high mv (>0.4 cm³/cm³) without or with a priori information on the soil parameters. For mv between 0.05 and 0.4 cm³/cm³, overestimations on mv could reach 0.04 cm³/cm³.

Moreover, the results reveal a great difficulty of estimating correctly the soil roughness. Similar accuracies on the rms estimates were obtained in the cases 1 (no a priori information on the soil parameters) and 2 (a priori information on mv), or in the cases 3 (a priori information on rms) and 4 (a priori information rms and mv). However, the accuracy is slightly better if a priori information on the rms is available (cases 3 and 4). In using the most favourable cases (3 and 4), the mean RMSE on the rms estimates is about 0.45 cm for a noise of ±0.5 dB and 0.5 cm for a noise of ±1 dB. The bias between the estimated rms and the reference rms was low for all the four studied cases (between 0 and -0.07 cm).
Figure 10. Box plots of soil moisture estimates (cm$^3$/cm$^3$) retrieved from the synthetic dataset. Training and validation datasets correspond to a noise on the backscattering coefficients of ± 1 dB. Four rms and four mv values were plotted: rms=0.5, 1, 2, 3.5 cm; mv=0.05, 0.15, 0.25, 0.40 cm$^3$/cm$^3$.
Figure 11. Box plots of surface roughness estimates (cm) from the synthetic dataset. Training and validation datasets correspond to a noise on the backscattering coefficients of ±1 dB. Four rms and four mv values were plotted: rms=0.5, 1, 2, 3.5 cm; mv=0.05, 0.15, 0.25, 0.40 cm³/cm³.
The neural networks underestimate the rms estimates for the high values of reference rms (>2.5 cm) and overestimate it for low and medium surface roughness (<2.5 cm). The use of a priori information on rms allows reducing very clearly the bias and the RMSE on rms for low reference rms values whereas the bias and the RMSE on rms stay unchanged for the high values of rms. With a priori information on rms, the bias on the rms estimates does not exceed the ±0.5 cm for reference rms values between 0.5 and 3.1 cm and is about -1 cm for reference rms values about 3.6 cm. The RMSE on the rms estimates is lower than 0.5 cm for reference rms lower than 3.1 cm and is about 1.1 cm for reference rms values about 3.5 cm. The analysis of rms estimates as a function of reference mv values shows also that the difference between the estimated and the reference rms is unchanged with the incidence angle for a given mv. Moreover, the networks underestimate the rms estimates for mv lower than 0.25 cm³/cm³ and overestimate for mv higher than 0.25 cm³/cm³. The RMSE on the rms estimates increases slightly with the incidence angle for a given reference mv value when no a priori information on the rms was considered (from 0.6 cm at 25° to 0.85 cm at 45°). With a priori information on rms, the RMSE is of the same order for all incidence angles and reference mv values (about 0.5 cm).

2.3.2 RADARSAT-2 dataset
The retrieval capacity of ANN is then analyzed using the RADARSAT-2 dataset. Tables 3 and 4 give the statistical results obtained for the estimation of mv and rms according to inversion configurations 1, 2, and 4:

- No a priori information on mv and rms
- With a priori information on mv given expert knowledge (dry to wet soils or very wet soils)
- With a priori information on mv and rms in using the thresholds on the polarimetric parameters $\alpha_1$ and A ($\alpha_1<10^\circ$ and A<0.3 for dry to wet soils and smooth areas; $\alpha_1<10^\circ$ and A$\geq$0.3 for dry to wet soils and rough areas; $\alpha_1\geq10^\circ$ and A<0.3 for very wet soils and smooth areas; $\alpha_1\geq10^\circ$ and A$\geq$0.3 for very wet soils and smooth areas).

Thau Basin
The estimations of soil moisture (mv) and surface roughness (rms) are illustrated in Figures 10 and 11. Results show that the precision on the estimates of soil moisture is better in using the neural networks trained on simulated data when ±1 dB noise is added than in using the networks trained with data at ±0.5 dB. This is probably due to the noise of RADARSAT-2 data which is closer to ±1 dB than to ±0.5 dB (Table 3). Indeed, without the use of a priori information on mv and rms, the RMSE decreases from 0.145 cm³/cm³ (noise 0.5 dB) to 0.098 cm³/cm³ (noise ±1 dB). The introduction of a constraint on mv provides better agreement between the estimated and measured soil moisture, with a significant decrease of the bias and the RMSE on the estimation of mv. In the case of a priori information on mv, the RMSE decreases from 0.107 cm³/cm³ (noise ±0.5 dB) to 0.065 cm³/cm³ (noise ±1 dB) (Table 3). In using the a priori information on mv and rms from the polarimetric parameters $\alpha_1$ and A, and adding noise of ±1 dB, the RMSE on the mv estimates slightly decreased from 0.098 cm³/cm³ without a constraint on mv and rms to 0.083 cm³/cm³ with a constraint on mv and rms. In conclusion, the use of expert knowledge on mv seems to be more relevant than applying the polarimetric parameters $\alpha_1$ and A. The weak improvement of mv and rms estimates in using the polarimetric parameters in the inversion process can be explained by low dynamics of $\alpha_1$ and A in C-band (Baghdadi et al., 2012). However, the bias is reduced by using a priori information on the soil parameters mv and rms (in using $\alpha_1$ and A). The bias was about -0.02 cm³/cm³ for the case without a constraint on mv and rms and +0.003 cm³/cm³ with a priori information on mv (expert knowledge) with a noise of ±1 dB (Table 3).
For the estimation of surface roughness, the use of neural networks built with a noise of ± 1 dB again provides better results in comparison to networks trained with a noise of ± 0.5 dB (Table 3). With a noise of ± 1 dB, the results obtained for the rms estimates are practically the same for the three studied cases with a RMSE about 0.70 cm (Table 3). Figure 11 shows also that the estimation of rms is very difficult for high surface roughness values (rms>2 cm). Indeed, the radar signal in C-band is very sensitive to the soil roughness only for rms values lower than 2 cm. Beyond this threshold, the radar signal increases very slightly with the rms. In Baghdadi et al. (2002b), the mean difference between the σ° values for rms=2 cm and rms=4 cm reaches a maximum of 1 dB. For surface roughness lower than 2 cm, the precision on the soil roughness estimates is better with a RMSE about 0.5 cm and a difference between estimated and measured rms smaller than 0.2 cm on average.

<table>
<thead>
<tr>
<th>Without a priori information on mv and rms</th>
<th>Soil moisture (mv)</th>
<th>Surface roughness (rms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias (cm³/cm³)</td>
<td>RMSE (cm³/cm³)</td>
<td>Bias (cm)</td>
</tr>
<tr>
<td>0.029 / -0.018</td>
<td>0.145 / 0.098</td>
<td>-0.41 / 0.05</td>
</tr>
<tr>
<td>With a priori information on mv (expert knowledge)</td>
<td>0.031 / 0.003</td>
<td>0.107 / 0.065</td>
</tr>
<tr>
<td>With a priori information on mv and rms in using α₁ and anisotropy</td>
<td>-0.012 / -0.015</td>
<td>0.101 / 0.083</td>
</tr>
</tbody>
</table>

Table 3. Inversion approach results for RADARSAT-2 data (Thau basin). The format of results is “a/b” with “a” corresponds to statistics in using a noise of ± 0.5 dB, and “b” corresponds to statistics in using a noise of ± 1.0 dB
Figure 12. Retrieved soil moisture versus in situ measurements. (a,b): without a constraint on $m_v$ and $rms$; (c,d): with a constraint on $m_v$ (expert knowledge); (e,f): use of $\alpha_1$ and anisotropy to determine the possible values of $m_v$ and $rms$. Each point corresponds to one training plot (using the mean backscattering coefficient of all pixels of the reference plot). The reference plots are at the outside of the RADARSAT-2 image of January 11, 2011.
Figure 13. Retrieved $rms$ surface height versus in situ measurements. (a,b): without a constraint on $mv$ and $rms$; (c,d): with a constraint on $mv$ (expert knowledge); (e,f): use of $\alpha_1$ and anisotropy to determine the possible values of $mv$ and $rms$. Each point corresponds to one training plot (using the mean backscattering coefficient of all pixels of reference plot).
Chiba Basin

The estimations of soil moisture (mv) are illustrated in Figure 14. With a priori information on mv (expert), the RMSE decreases slightly from 5.6 cm$^3$/cm$^3$ without a priori information to 5.1 cm$^3$/cm$^3$ with information given by an expert on the soil moisture level (Table 4). In using the a priori information on mv and rms from the polarimetric parameters $\alpha_1$ and $A$, the RMSE on the mv estimates increased strongly from 5.6 cm$^3$/cm$^3$ without a constraint on mv to 14.2 cm$^3$/cm$^3$. In conclusion, the soil moisture was estimated with a good accuracy on the Chiba basin (about 0.05 cm$^3$/cm$^3$).

![Figure 14](image.png)

**Figure 14.** Retrieved soil moisture versus in situ measurements. (a): without a constraint on mv and rms; (b): with a constraint on mv (expert knowledge); (c): use of $\alpha_1$ and anisotropy to determine the possible values of mv and rms. Each point corresponds to one training plot (using the mean backscattering coefficient of all pixels of the reference plot)
Table 4. Inversion approach results for RADARSAT-2 data (Chiba basin)

<table>
<thead>
<tr>
<th>Without a priori information on (mv) and (rms)</th>
<th>Bias ((cm^3/cm^3))</th>
<th>RMSE ((cm^3/cm^3))</th>
</tr>
</thead>
<tbody>
<tr>
<td>With a priori information on (mv) (expert knowledge)</td>
<td>+0.014</td>
<td>0.056</td>
</tr>
<tr>
<td>With a priori information on (mv) and (rms) in using (\alpha_1) and anisotropy</td>
<td>-0.003</td>
<td>0.051</td>
</tr>
<tr>
<td>With a priori information on (mv) and (rms) in using (\alpha_1) and anisotropy</td>
<td>+0.108</td>
<td>0.142</td>
</tr>
</tbody>
</table>

2.3.3 Operational mapping of soil moisture using RADARSAT-2 images

Surface soil moisture mapping was carried out over Thau and Chiba basins in using RADARSAT-2 images acquired between November 2010 and March 2011 for Thau and between July and March for Chiba (Table 1). Based on polarimetric SAR images (HH, HV and VV polarizations), the neural networks developed from IEM simulated data are used for mapping the surface soil moisture over bare soils. The networks trained with a noise of \(\pm 1dB\) are selected due to the better correspondence with the noise level in RADARSAT-2 imagery.

Soil moisture estimates are obtained for several mapping scales: an estimate for each bare agricultural field, an average estimate on the basin, and an estimate for each cell of a predefined grid. For mapping at the field scale, the radar signal is averaged for each field. The estimation of mean soil moisture on the basin scale uses the mean backscattering coefficient of all bare soil pixels present in the basin. For mapping soil moisture on grid cells of \(N\) meters by \(M\) meters each, the basin is subdivided in a regular grid and the mean backscattering coefficient for each grid cell is determined from averaging the values of all bare soil pixels within each grid cell.

The estimation of soil moisture is performed only on bare soils or soils with thin vegetation layer.

Thau Basin

A land use/land cover map was produced for the Thau basin in using remote sensing data and ground observations (2010-2011). First, only agricultural fields intended for growing cereals (wheat) and market gardens were selected. Next, the Normalized Difference Vegetation Index (NDVI) was computed using Landsat-5 optical images (December 2010, February and March 2011), and a NDVI value under an empirical threshold of 0.25 was found for mapping bare soils and areas with thin vegetation cover. For each SAR image, the bare soil map used corresponds to the one obtained from the optical image with the closest acquisition date.

Figure 15 shows the temporal variation of soil moisture estimated by RADARSAT-2 for four different dates (November 18 and December 04, 2011; March 15 and 18, 2012).
Figure 15. Examples of soil moisture maps over bare agricultural areas for four different dates (Thau site). The estimation of soil moisture was carried out for each bare agricultural parcel in using expert knowledge on $mv$ (EK), or a priori information on $mv$ and $rms$ from $a_1$ and anisotropy ($a_1A$).

The estimation of soil moisture was carried out for each bare agricultural field in using a priori information on $mv$ based on expert knowledge or polarimetric parameters $a_1$ and $A$. Based on the meteorological data over the basin (Figure 16), a priori information of very wet soils was provided for March 15 and 18 acquisitions whereas an information of dry to wet soils was given for the other images. The comparison between soil moistures estimated from SAR images and in situ moistures shows good agreement. For example, on November 18, 2010, dry soil was observed over the basin, with a low average moisture content of around 0.16 cm$^3$/cm$^3$ (with expert knowledge on $mv$). Indeed, no rainfall was recorded during the eight days preceding the acquisition of this satellite image. The weak precipitation on November 30, 2010 (5.4 mm) maintained the same moisture content on December 04 as on November 18 (about 0.19 cm$^3$/cm$^3$). After significant precipitation between March 12 and March 15, 2011 (85 mm), the radar soil moisture increased from 0.19 cm$^3$/cm$^3$ on February 22, 2011 to 0.36 cm$^3$/cm$^3$ on March 15, 2011. Radar soil moistures estimated on March 18, 2011 were lower (0.34 cm$^3$/cm$^3$) than those of March 15, 2011. This tendency is completely coherent because there no was no precipitation recorded between the two dates and the soil has thus started to dry off. The air temperature during the SAR acquisitions was higher than 5°C.
Figure 16 Soil moisture contents from in situ measurements according to RADARSAT-2 acquisition dates, and meteorological data (daily precipitation and mean daily temperature) (Thau basin). Precipitation and air temperature were taken from a meteorological station installed in the basin (near Sète Town).

Figure 17 compares the soil moisture estimates averaged on all reference plots and the corresponding in situ measurements. Results show a better precision on the soil moisture estimates when a scale larger than the plot was used (mean of about 10 plots for each SAR date). For each image date, the soil moisture was estimated in using the mean backscattering coefficient of all pixels present in the reference plots. The difference between soil moisture estimates and in situ soil moistures is on average near to zero. The RMSE is about 0.056 cm³/cm³ with no a priori information on soil parameters, 0.032 cm³/cm³ with expert knowledge on mv, and 0.035 cm³/cm³ in using $\alpha_1$ and A.

Figure 17 Comparison between the estimated mv-values and those measured (Thau Basin). The error bars on the measured and estimated soil moisture values correspond to one standard deviation. Each point corresponds to the mean of soil moisture values of a given image date in using all reference plots.
Chiba Basin

A land use/land cover map (only two classes: bare soils and vegetated areas) was produced over the Chiba basin for each RADARSAT-2 image acquisition date using selected polarimetric parameters (Figure 18). A spectral signature was calculated from the July 2010 RADARSAT-2 image (polarimetric parameters: alpha angle, anisotropy and entropy). Training sites were selected over a polarimetric RADARSAT-2 image with the help of a NDVI calculated from a Landsat TM7 image (acquisition date: 2010-07-03). This spectral signature was applied to all RADARSAT-2 images. Results were validated using others NDVI-Landsat TM7 available for some acquisition dates.
Figure 18. Chiba catchment in yellow line, from top to bottom: 1) NDVI from Landsat TM7 image (2010-07-03) in grey scale and selected training areas (brown polygons naked soils, green polygons vegetated areas), 2) RADARSAT-2 Quad-Pol image (2010-07-05) RGB with polarimetric parameters alpha angle, anisotropy and entropy, and the same training areas, and 3) RADARSAT-2 image land cover classification using spectral signatures from the same polarimetric parameters listed before.

Figure 19 shows the temporal variation of soil moisture estimated by RADARSAT-2 for four different dates (July 05, 2010; November 26, 2010; March 02, 2011; March 26, 2011). The estimation of soil moisture was carried out for each soil unit in using a priori information on mv based on expert knowledge. Based on the meteorological data over the basin (Figure 20), a priori information of dry to wet soils was given for all images. The comparison between soil moistures estimated from SAR images and in situ moistures shows good agreement.

For example, on July 05, 2010, dry soil was observed over the basin, with a low average moisture content of around 0.073 cm$^3$/cm$^3$ (with expert knowledge on mv). After significant precipitation in October, the soil moisture was 0.219 on November 26, 2010. The radar soil moistures estimated on March 02, 2011 about 0.245 cm$^3$/cm$^3$ correspond to important precipitations during the three days preceding the acquisition of the radar image (21mm). Radar soil moistures estimated on March 26,
2011 were lower (0.141 cm³/cm³) than those of March 02, 2011. This tendency is completely coherent because there was no precipitation recorded between the two dates and the soil has thus started to dry off. The air temperature during the SAR acquisitions was higher than 16°C.

**Figure 19.** Examples of soil moisture maps over bare agricultural areas for six different dates. The estimation of soil moisture was carried out for each soil unit in using expert knowledge on mv.
2.4. Conclusions

The capacity of estimating soil moisture over bare agricultural areas using C-band polarimetric SAR was assessed. An inversion technique based on the Multi-Layer Perceptron neural network was developed to estimate soil surface parameters from SAR data. Neural networks (NNs) were trained with radar backscattering coefficients generated from the Integral Equation Model. The backscattering coefficients in HH, HV and VV polarizations were simulated in using the IEM model for a wide range of radar incidence angle, soil moisture (mv), and surface roughness (rms). The NNs were then applied to another simulated dataset and a real dataset composed of ten RADARSAT-2 images in polarimetric mode to validate the inversion technique and to determine the precision on the soil moisture and surface roughness estimates.

The best mv estimation results were obtained when a priori information was given to mv. The a priori information on mv can be provided by an expert in using meteorological data (precipitations, temperature ...) and terrain knowledge (soil type ...). The expert chooses among two simple configurations. The soils are supposed very wet if the SAR image is acquired after an intense rainy episode. In this case, the soil moisture contents will be in general estimated between 0.25 and 0.45 cm$^3$/cm$^3$. For a SAR image acquired far of a rainy episode or in a context of a fast drying of soil (high temperatures), the expert assumes dry or wet soils with moisture contents which will be estimated lower than 0.35 cm$^3$/cm$^3$. Moreover, the use of polarimetric parameters in the inversion procedure was tested. The polarimetric parameter $\alpha_1$ was used to discriminate two soil moisture classes (very wet soils, and dry to wet soils) and the anisotropy parameter A to separate two soil roughness (smooth with $\text{krms}<1.5$ and rough with $\text{krms}\geq 1.5$). The inversion errors obtained with the RADARSAT-2 images on the mv estimates is about 0.065 cm$^3$/cm$^3$ with a priori information on mv compared with 0.098 cm$^3$/cm$^3$ without a priori information on the soil parameters. The use of polarimetric parameters slightly improves the soil moisture estimates in comparison to the case without a priori information on the soil parameters (0.083 as compared to 0.098 cm$^3$/cm$^3$). This is due to the weak dynamics of the polarimetric parameters with the soil parameters for the C-band.
Results show also that the estimation of soil surface roughness (rms) is possible with an accuracy around 0.5 cm (RMSE). The estimation is better for rms lower than 2 cm. For higher rms, the NNs under-estimate the surface roughness.

The results indicate that the inversion technique using data generated by the electromagnetic model IEM are able to retrieve the soil moisture and surface roughness with acceptable accuracy. These inversion results are encouraging and indicate good potential for applying a neural network for soil parameters estimation. Nevertheless, we note that the introduction of a constraint of pre-information on soil moisture improves mv estimation. The quality of the estimation of soil moisture is probably not correlated to the incidence angle of SAR images (tested between 25° and 45°).

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References


