

MAPPING OF SOIL MOISTURE USING TERRASAR-X DATA ACQUIRED OVER BARE AGRICULTURAL AREAS

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ABSTRACT: Soil moisture is one of the most important indicators for drought monitoring and is a key parameter in hydrology and natural risk assessment. Active-microwave remote-sensing techniques have already shown their potential for soil moisture mapping whatever the weather conditions. Most studies on soil moisture mapping were carried out using C-band SAR data. However, several drawbacks have been identified and were linked to the low temporal frequency of SAR acquisition, surface roughness vegetation-related signal corrections and the difficulty in transferring the approach to another study site. With its high sensitivity to soil moisture and low sensitivity to surface roughness, the TerraSAR-X sensor (X-band) has the potential to overcome some of the limitations mentioned above. Moreover, its high temporal and spatial resolutions are key features which facilitate the development of operational products.

The objective of the present study is to investigate the potential of TerraSAR-X mono polarization for bare soil detection and soil moisture mapping. This study was carried out on the Orgeval catchment (France) using images and in-situ measurements over bare agricultural plots in 2009 and 2010.

The soil moisture estimation algorithm has been developed for bare soils for two configurations of TerraSAR-X (HH-25°, HH-50°) using a database with a huge range of soil surface conditions (dry to wet and smooth to rough conditions) acquired in 2009. Then, the inversion algorithm was validated in using TerraSAR-X images acquired in 2010. To identify bare agricultural plots, the first TerraSAR-X image acquired in 2010 (March 1, HH-50°) was used in using a simple threshold on the mean backscattered signal. Results showed a good accuracy of bare soil mapping. Moreover, the comparison between soil moisture contents estimated from TerraSAR data and those measured from in situ campaigns shows good estimation of soil moisture, with a mapping accuracy (RMSE) of 3.2% and 4.3% for incidence angles of 25° and 50°, respectively.

1. INTRODUCTION

Managing agriculture or natural hazards requires access to spatial and temporal knowledge of soil surface characteristics as soil moisture (Wu & Wang, 2007). The knowledge of the spatial and temporal distribution of soil moisture at regional scale and at high spatial resolution is one of the most important issues in studies of the flood monitoring and crop yield forecast. This explains the continuing interest in developing methods to estimate and monitor this parameter from space. Active-microwave remote-sensing techniques have already shown their potential to determine the soil moisture of bare soil surfaces whatever the weather conditions.

The accuracy of soil moisture estimation from C- and L-band SAR measurements (over agricultural bare soil) depends both of the sensor configuration (polarization, incidence angle and radar wavelength) and of the knowledge of soil roughness. The first methodology developed were based on a linear relationship between soil moisture and SAR signal without knowledge of soil roughness, but the coefficients describing the linear relationship are often different from one watershed to another, and also from one year to the next. For this reason it is still very difficult to use this relationship for radar signal inversion without a time-consuming calibration work. To cope with soil roughness effects, many improvement have been achieved and some robust methodologies were developed based on incidence angle ratio (Low/high) (Zribi et al., 2005) or on times series (Kim Y., 2009; Wagner W. & Scipal K., 2000). Nevertheless, this field is still not fully operational due to the algorithm complexity of these methods and/or of the great number of data required (i.e. high repetitive pass). The new TerraSAR-X sensor has the potential to overcome the problem of roughness mentioned above due to the high sensitivity of radar signal at X-band to soil moisture and its low sensitivity to surface agricultural roughness (Aubert et al., 2011). Moreover, its high temporal and spatial resolutions are key features which facilitate the development of operational products.

Another main limitation for applications of soil moisture estimation over a watershed is the bare soil detection. Commonly, this preliminary process is conducted by using optical or in situ data. Nevertheless, recent studies

indicate that high-resolution TerraSAR-X imagery can be exploited for landuse/cover classification (Mahmoud and al., 2011; Breidenbach et al., 2010; Mróz and Mleczko, 2008). Thus, before the use of process for soil moisture estimation, TerraSAR-X data could provide a bare soil map. Therefore, TerraSAR-X sensor should provide valuable information for managing the soil moisture on an operational mode because X-band data could both permit to identify bare soil spatial extent and to estimate soil moisture content whatever the roughness conditions.

The present study aims to propose an operational methodology for soil moisture mapping over bare soils based only on TerraSAR-X data. Initially, a soil moisture estimation algorithm is developed using image and in-situ data acquired in 2009. The first acquisition of 2010 was used for mapping bare soils. Then, the soil moisture estimation algorithm based on 2009 database was used to estimate the soil moisture on the bare soil map for all data acquired on 2010. Finally, the mapping accuracy was carried out in using training plots by comparing soil moisture estimated from TerraSAR data and *in situ* measurements.

2. MATERIAL AND METHODS

2.1 Study site

The study site is the Orgeval watershed (104 km²), located to the east of Paris in France (Latitude: 48°51'; longitude 3°07'E; Figure 1). The main land use is arable farming intended for growing wheat and maize. It is flat and the topsoil composition is predominantly loamy (17% clay, 78% silt, and 5% sand). This soil composition promotes crust development, which increases soil sealing and causes runoff (Boiffin et al., 1990; Eimberck, 1990). The Orgeval watershed has been managed since 1962 as an experimental basin for hydrological research by the Agricultural and Environmental Engineering Research Center (CEMAGREF) research institute.



Figure 1. Location of the Orgeval watershed (central coordinates: 48°52'N, 3°06'E).

2.2 TerraSAR-X Data

Fourteen TerraSAR-X images were used in this study. They are acquired in spotlight mode (pixel spacing ~1m) between March 2009 and March 2010. Images were obtained with incidence angles of 25° and 50°, and at HH polarizations (Table 1).

SAR acquisition date dd/mm/yy	Incidence angle	In situ soil moisture (%) [Min; Max]
17/03/09	25°	[24.7; 32.3]
18/03/09	50°	[24.5; 29.8]
25/03/09	50°	[24.1; 31.0]
26/03/09	25°	[23.9; 32.7]
08/04/09	25°	[16.8; 27.5]
09/04/09	50°	[15.2; 26.3]
17/04/09	25°	[14.1; 16.4]
20/04/09	50°	[18.3; 23.9]
11/05/09	25°	[25.8; 31.3]
01/03/10	50°	[33.4; 39.8]
02/03/10	25°	[32.7; 39.0]
04/03/10	25°	[27.3; 34.3]
12/03/10	50°	[12.6; 29.0]
13/03/10	25°	[14.9; 26.3]

Table 1. Characteristics of TerraSAR-X images and in situ soil-moisture measurements.

First, SAR data were radiometrically calibrated, using the following equation (Eineder, 2011):

$$\sigma_{i,dB}^{\circ} = 10 \cdot \log_{10} (K_s \cdot DN_i^2 - NEBN) + 10 \cdot \log_{10} \sin(\theta_i) \quad (1)$$

This calibration permits to convert the digital numbers of each pixel (DN_i) into a backscattering coefficients (σ_i°) corrected for sensor noise (NEBN) on decibels scale. This calibration process takes into account the radar incidence angle (θ) and the calibration constant (K_s) provided in the image data.

Images were then co-registered using aerial orthophotos (50-cm spatial resolution) with a root mean square error of the control points of approximately one pixel (i.e. 1 m). This co-registration error was overcome by removing the

boundary pixels (two pixels wide) from each training plot relative to the limits defined by the GPS control points. All these calibration processes makes it possible to carry out multi-temporal analysis of different images.

In this study only radar signal from bare soil were used. Also, selected bare plots are identified and their mean signal calculated was used as the radar signature of each selected plot.

Finally, in complement of the TerraSAR-X data, a RapidEye image was also acquired on May 22, 2010 (resolution= 5m; band: Blue, Green, Red, Red Edge, Near IR). This optical data was used as reference to validate the bare soil mapping process and for digitized object boundaries for the segmentation process.

2.3. Experimental measurements

Simultaneously to TerraSAR-X acquisitions, ground measurements were performed in seven bare training plots in 2009 and six in 2010 (\pm three hours around the satellite overpass time) (Figure 2). All training plots were flat (slope $< 1\%$).

Gravimetric soil moisture samples (depth: 0-5 cm) were collected on our training plot. All gravimetric measurements were converted into volumetric moisture (mv) based on bulk density, and the location of each gravimetric measurement was recorded using a GPS device. Thus, soil moisture of each plot was assumed to be equal to the mean value estimated from the samples collected in each plot. The two field surveys in 2009 and 2010 covered a large range of soil moisture, between 12.6% and 39.8% (Table 1).

Soil roughness measurements were also carried out, using ten profile of a 1 m long profilometer with a 2 cm sampling interval. The surface roughness of a given bare soil is defined statistically by the standard deviation of surface height (rms), and the correlation length (L). The $Hrms$ values of the plots obtained during the two field surveys (March to May 2009 and March 2010) varied between 0.4 and 3.9 cm. The lower values (0.4 to 1.5 cm) corresponded to sown plots, whereas the higher values (above 1.5 cm) corresponded to fallow and recently ploughed plots. The correlation length (L) varies from 2.3 cm in sown plots to 9.3 cm in ploughed plots.

Finally, meteorological data (precipitation and temperature) were also obtained from five meteorological stations installed in the basin. No precipitations were recorded during the 2010 field campaign.



Figure 2. Subset of a TerraSAR-X image (March 17, 2009) acquired over the Orgeval watershed. Plot A to G are the training plots investigated in 2009 field survey, plots H to M are those of 2010.

Thus, data collected between 2009 and 2010 covered a huge range of soil surface conditions (dry to wet and smooth to rough conditions). The database of 2009 was used to develop algorithm of signal inversion in term of soil moisture. The database of 2010 was used to test its applicability.

3. RESULTS

3.1. Relationship between soil moisture and TerraSAR-X signal

In several previous studies, the inversion of radar signal was based on a simple linear relationship between the mean signal at one incidence angle (σ°) and the mean soil surface moisture (mv):

$$\sigma^\circ(\text{dB}) = a \text{ mv } (\%) + b \quad (2)$$

In this simplified relationship the coefficient a is dependent on both incidence angle and polarization. The coefficient b is primarily controlled by incidence angle, polarization and surface roughness. At the plot scale in X-band, it is possible to neglect the effect of soil surface roughness variation because for agricultural bare plots, the effects of soil roughness on the TerraSAR-X signal are small (Aubert et al., 2011).

The coefficients a and b of the equation (2) were calculated using the large database of 2009 for two TerraSAR configurations (HH-25°, HH-50°; Figure 4). Results showed that the sensitivity of the TerraSAR-X signal to soil moisture is slightly higher for low incidence angles (0.433 dB/% at 25°) than at high incidence angle (0.291 dB/% at 50°), but the moisture mapping is possible whatever the incidence angle.

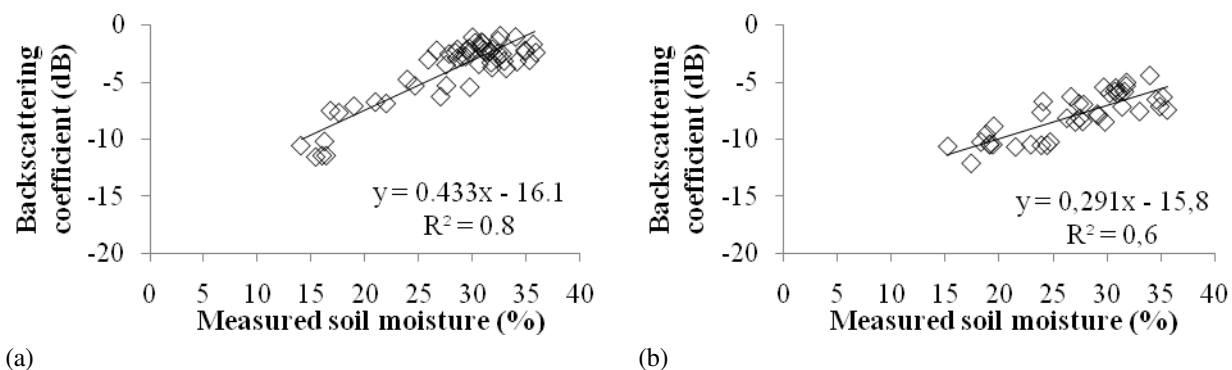


Figure 4. Sensitivity of TerraSAR-X signal (HH polarization) to soil moisture in the top 0–5-cm soil layer for incidence angles of 25° (a) and 50° (b). Each point corresponds to one training plot. The black line corresponds to the best fitting and the dotted line to the confidence interval at 95%.

3.2. Soil moisture mapping

The inversion procedure of TerraSAR-X signal described previously was applied for soil moisture mapping in using the TerraSAR time serie acquired in 2010 (HH-25°; HH-50°). In a first step, the map of bare soils was created using the first TerraSAR-X image acquired the March, 1 2010 (HH-50°). Then soil moisture were estimated on each TerraSAR-X acquisition and compared to in situ soil moisture measurements.

Speckle noise, due to the coherent interference of waves reflected from many elementary scatterers, is present on SAR images and makes the pixel-by-pixel interpretation of TerraSAR images extremely difficult. First, it seems appropriate to segment the image into objects with similar properties (such as agricultural plot, forest area, urban area and open water) and then to classify these objects. Dean and Smith (2003) have shown that the plot scale was the most appropriate for mapping agricultural area because of the inherent plot structure (Dean and Smith, 2003). Moreover, some previous studies on SAR classification used the existing parcels-data (digital) or generated it for current and further studies (Wu et al., 2007, Mahmoud, et al., 2011). In the current study, objects boundaries were digitized from the RapidEye image. Then, for each digitized object (mainly agricultural plot, forest area, urban area and open water) several statistical parameters such as the mean backscattering coefficient, the standard deviation, the brightness and the skewness were calculated on the first TerraSAR-X image (March, 1, 2010). The results showed that the mean of the backscattered signal was better suited to separate the bare soil objects (including some thin herbaceous areas with vegetation height < 5cm) from other classes of land cover (forests, developed culture, urban and open water). Also, each object which had a mean backscattered signal lower than -11 dB was classified on bare soil. The performance of the classifier was recorded in the confusion matrix as shown in Table 2. The confusion matrix between bare soil mapped and bare soil observed (by visual interpretation) on the RapidEye image gives an overall accuracy of 94.3% and a kappa value of 0.86 (Table 2). Thus, the map obtained with the first image acquired by Terrasar-X (HH-50°) has a good level of accuracy.

User \ Reference Class	Bare soil	Other	Sum
Bare soil	568856	18644644	19213500
Other	7085202	960424	8045626
Sum	7654058	19605068	
Kappa per class	0.894	0.834	
Overall Accuracy		0.943	
Kappa		0.863	

Table 2: Confusion matrix and Kappa statistic of bare soil classification.

Based on single TerraSAR image (one polarization and one incidence), a simple procedure was used for mapping the surface soil moisture over the selected bare soils (equation 2). For each image of the TerraSAR time serie acquired in 2010, the mean backscattered signal is calculated for each bare plot defined previously on the bare soil map. Then, the relationship $\sigma_{dB}(m_v)$ corresponding to the same radar configuration (incidence) was used (equation (2), Figure 4) to invert the backscattered signal into soil moisture (Figure 5).

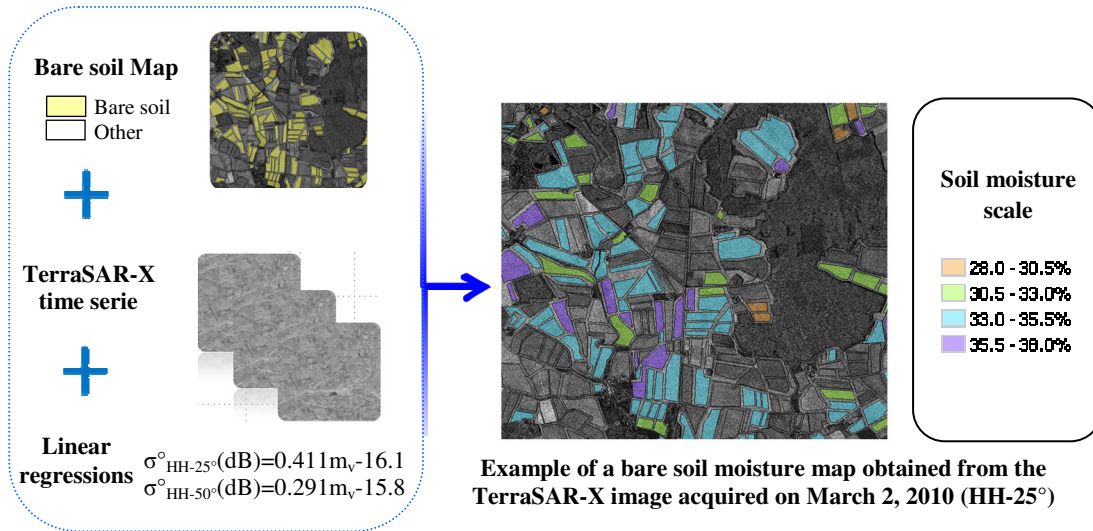


Figure 5. Procedure for mapping soil moisture over bare soils in using TerraSAR images. A bare soil moisture map was obtained from a TerraSAR-X image. The class denominated “other” includes forests, soils covered with vegetation, etc.

The inversion performance of radar signal for retrieving soil moisture is evaluated to show the robustness of the presented technique. The comparison between soil moisture contents estimated from TerraSAR images of 2010 and gravimetric soil moistures shows a good agreement between estimated and measured soil moistures (Figure 6).

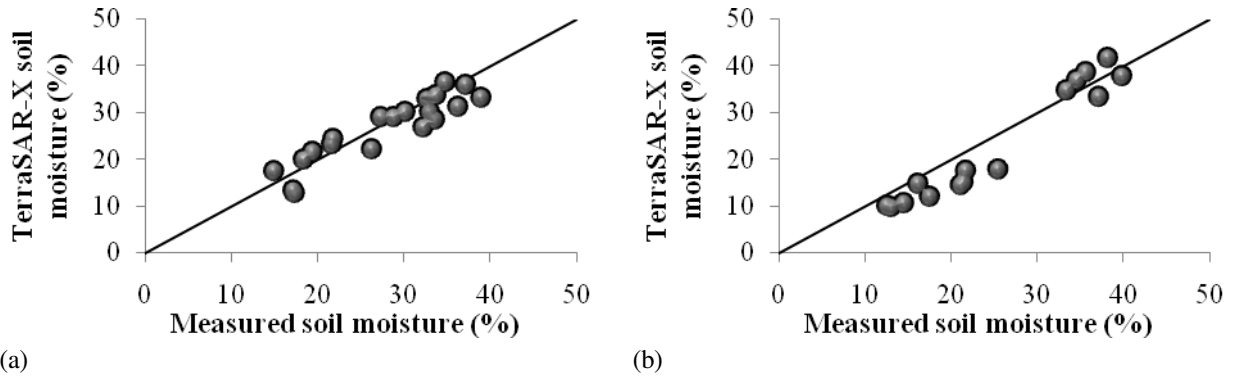


Figure 6. Comparison between soil moisture estimated by TerraSAR images acquired in 2010 and soil moisture measured in situ (at the training plot scale) for 25° incidence angle (a) and 50° incidence angle (b).

Moreover, as suggested by Willmott (Willmott, 1982), three statistical indexes were used to compare estimated and measured soil moistures:

$$\text{Mean Absolute Error: MAE} = \frac{1}{N} \sum_{i=1}^N |P_i - O_i|$$

$$\text{Root Mean Square Error: RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2}$$

$$\text{Index of agreement: } d = \left[\frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N |P_i - \frac{1}{N} \sum_{i=1}^N O_i| + |O_i - \frac{1}{N} \sum_{i=1}^N P_i|} \right]$$

In these relations P is the in situ soil moisture, O the estimated soil moisture, and N the data number. MAE and RMSE are expressed in percent, while d is dimensionless.

The statistical indexes values showed that the relationships between radar signal and soil moisture are robust and that the two incidence angles (25° and 50°) give good and similar performances (Table 3).

Statistical indexes	HH-25°	HH-50°
Bias	-1,5	-2,5
MAE	2,7	2,8
RMSE	3,2	4,3
d	0,95	0,96

Table 3: Values of statistical indexes calculated on training plots of the 2010 dataset (22 doublets of backscattering coefficients and soil moisture for HH-25° and 15 for HH-50°).

4. CONCLUSION

This study analyzes the potential of TerraSAR-X sensor (X-band) for monitoring soil moisture over bare agricultural plots. Due to a low sensitivity to agricultural roughness and a high sensitivity to soil moisture (0.433 dB/% at 25°, 0.291 dB/% at 50°) TerraSAR-X imagery is well adapted for estimating soil moisture and for overcoming the problem of roughness.

The bare soil map was obtained from a simple threshold on the first TerraSAR-X acquisition (HH-50°) with a good accuracy (94.3%). Nevertheless this threshold couldn't be used on other acquisition because it depends of the radar configuration and the condition of SAR acquisition (watershed moisture). Therefore, one of the future issues is to determine a parameter (such as textural parameters) which can be used whatever the TerraSAR-X acquisition.

Soil moisture estimates obtained from TerraSAR acquisitions were compared to those obtained by in situ measurements. The comparison between radar soil moisture and in situ measurements shows a RMSE for the soil moisture estimate of 3.2% and 4.3% for 25° and 50°, respectively (in comparison with gravimetric moistures of 2010). Other TerraSAR images of another watershed must be used to better validate the linear regressions established between signal and soil moisture. Nevertheless, these first results appear promising for the use of simplified algorithms for retrieving soil moisture from TerraSAR data, and for monitoring multi-temporal moisture changes. Thus, in further studies assimilation of soil moisture data estimated from TerraSAR-X time series could be used as calibration data to improve the forecast models.

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