Combining L and X band SAR data for estimating biomass and soil moisture of agricultural fields

Simonetta Paloscia, Simone Pettinato and Emanuele Santi*

CNR-IFAC, via Madonna del Piano, 10 – 50019 Firenze (Italy)
*Corresponding author, e-mail address: E.Santi@ifac.cnr.it

Abstract
A method for retrieving both agricultural biomass and soil moisture starting from simultaneous observations at L and X band is described in this paper. The research was carried out within the framework of the SIASGE (Italian-Argentine System of Satellites for Emergency Management) project, funded by the Italian Space Agency (ASI), for the definition and development of X and L products oriented towards applications for risk and emergency management. SAR data at L (ALOS/PALSAR) and X (COSMO/SkyMed) bands were used for producing maps of Soil Moisture Content (SMC) and Plant Water Content (PWC) using inversion algorithms based on Artificial Neural Networks and on empirical relationships based on previous experiments. SMC obtained in an agricultural area in Lombardy showed average values in agreement with monthly rainfall. The corresponding maps of PWC were produced for the same area, and in this case the result was in agreement with the season, the classification, and the related agricultural practices.

Keywords: L and X-band SAR data, SIASGE project, vegetation biomass, soil moisture, Artificial Neural Networks.

Introduction
Within the framework of the SIASGE project (which is the Italy-Argentine Satellite System for the Management of Emergencies), the Italian Space Agency (ASI) has funded a study project for the definition, development, demonstration and promotion of X and X+L products, basic tools and prototypal software systems that can support applications in the field of Agriculture, National Security, and Land Planning. The aim of the project was to define a system oriented at applications for risk and emergency management using the synergy between the two constellations SAOCOM and COSMO-SkyMed constituting the SIASGE Joint X-L SAR band system. Particular attention was paid to generating products devoted to a pre-applicative level in certain test areas. The project leader was ACS (Advanced Computer Systems, spa), in Rome. The Microwave Remote Sensing Group (MRSG) of the Institute of Applied Physics of the National Research Council in Florence (CNR-IFAC) was involved in the Agriculture applications and investigated the capabilities of SAR data at L- (ALOS/PALSAR) and X (COSMO/SkyMed) band in producing thematic maps of soil and vegetation parameters (i.e. Soil Moisture Content, SMC, in %, and Plant Water Content, PWC, in kg/m², i.e. the total

European Journal of Remote Sensing - 2012, 45: 99-109
doi: 10.5721/EuJRS20124510
amount of water contained in vegetation per square meter), through inversion algorithms based on statistical or semi-empirical models. The SMC was estimated from an algorithm based on an Artificial Neural Network, which was trained with both experimental and model data, whereas the PWC was derived from experimental relationships, found in the course of past research, at both X and L bands.

Much research has been carried out since the 1990s concerning the capability of L- and X-band SAR in estimating soil and vegetation parameters. Many papers have been published within the framework of the MAC-Europe 1991 and the SIR-C/X-SAR campaigns, which have been the most meaningful experiments regarding the importance of SAR in measuring geophysical parameters [e.g. Engman and Chauhan, 1995; Shi et al., 1997; Baronti et al., 1995; Ferrazzoli et al., 1997; Macelloni et al., 1999]. An in-depth analysis of the capabilities of L- and X-band data in measuring SMC was also carried out by the IFAC MRSG, using all datasets of the experiments performed with AIRSAR and SIR-C/XSAR sensors in Tuscany, Italy, and in Southern France. In general, a remarkable sensitivity of the backscattering coefficient ($\sigma^o$) to SMC (especially at L band, in HH and HV polarizations) for bare soils characterized by moderate roughness was observed. On vegetated fields, the sensitivity lessened considerably, as expected [Ferrazzoli et al., 1997; Macelloni et al., 1999]. The same L-band backscattering exhibited a high sensitivity to vegetation biomass of crops characterized by large leaves (e.g. corn and sunflowers); whereas higher frequencies (C and X bands) showed good agreement with the development of plants with narrow leaves (e.g. wheat) [Ferrazzoli et al., 1997; Macelloni et al., 2001].

The proposed algorithm for the retrieval of SMC and PWC was based on the experimental relationships between L- and X-band backscattering coefficient and ground data, model simulations with the AIEM [Fung, 1994; Wu and Chen, 2004; Brogioni et al., 2010], and an Artificial Neural Network (ANN).

A preliminary separation into four land-use classes (i.e. urban areas, water bodies, forest, and agricultural fields) was carried out to identify the surfaces on which SMC and PWC could reasonably be estimated. After this phase, the algorithm for the parameter retrieval was applied. SMC maps, obtained in an agricultural area located in Lombardy (Northern Italy), close to Milan, in 2008, showed an average SMC value in agreement with the monthly rainfall recorded at a nearby meteorological station. Five SMC intervals from 5% to 40% could be identified. Two corresponding maps of PWC were also produced for the same area. The presence of wheat crops was evident, and also in this case the result was in agreement with the season and the corresponding agricultural practices. However, the necessity of using simultaneously acquired images of COSMO and ALOS satellites significantly reduced the number of available data. Thus, only two SMC and PWC maps could be generated.

**Description of the inversion algorithm**

The purpose of this research was to develop an algorithm for retrieving spatial and temporal variations in soil moisture and plant biomass from ALOS/PALSAR and COSMO/SkyMed data. First of all, an investigation of the sensitivity of $\sigma^o$ to SMC and PWC by using previous experimental data collected with different sensors at the same frequency, polarizations, and incidence angles as ALOS/PALSAR and COSMO-Skymed was made, and the most suitable models for describing the interaction mechanism between microwaves and land surfaces were selected. Subsequently, tests of the inversion approach and the implementation of the retrieval algorithm were carried out.
**Analysis of previous experimental data**

The analysis of data collected in Tuscany pointed out that the correlation between $\sigma^o$ at L-band (in both HH and VV polarizations and at an incidence angle of 25°) and the SMC of bare soils is remarkable, as can be noted from the following regression equations, which had already been reported in Ferrazzoli et al. [1997] and Macelloni et al. [1999]:

- $\sigma^o_{HH} = 0.77$SMC-23.0 (determination coefficient, $R^2=0.58$)
- $\sigma^o_{VV} = 0.91$SMC-25.1, ($R^2=0.62$)

At incidence angles $>25°$ and if also vegetated fields were taken into consideration, the sensitivity, as expected, decreased considerably. In this case, the regression line became: $\sigma^o_{HH} = 0.63$SMC-23.21, with $R^2 = 0.43$.

**Model Investigations**

In spite of their complexity, only theoretical models can yield a significant understanding of the interaction between electromagnetic waves and the Earth’s surface. However, the exact solution of equations governing rough surface scattering is difficult to find, and therefore several approximate methods have been developed with different ranges of validity. Due to the wider range of validity of the Advanced Integral Equation Method (AIEM) [Fung, 1994; Wu and Chen, 2004; Brogioni et al., 2010] with respect to other models, this model was selected for simulating backscattering from natural terrains. The model was implemented for simulating $\sigma^o$ at L-band as a function of SMC for different standard deviation values of the surface heights (Hstd, in cm), using a fixed exponential autocorrelation function and correlation length, (Lc=6 cm). Figure 1 shows simulated and measured $\sigma^o$ at L-band, HH pol., and an incidence angle equal to 35°, as a function of SMC for different values of surface Hstd (from 1 cm to 3 cm). Experimental points were subdivided into two classes of surface roughness: Hstd < 2cm and > 2cm. We can see that, although there was some saturation for high Hstd values, the model was able to follow the experimental data fairly well, at least up to a Hstd value of 2 cm. Experimental points with Hstd <2cm were indeed between the model lines of 1 and 1.5 cm and those with Hstd > 2cm were all above the 1.5-cm line.

It should be considered that, since both moisture and surface roughness have the same effect of increasing the backscatter, in some particular cases the correlation with SMC can be enhanced when a simultaneous increase of both these parameters occurs. Although an increase in SMC due to rainfall is generally associated with a decrease in roughness, as pointed out in other papers [e.g. Escorihuela et al., 2007; Paloscia et al., 1993], the observed effect here was just the opposite. This was due to the fact that the agricultural fields of our experiment showed higher soil moisture contents in the fall, when the fields were ploughed and were then characterized by rather high surface roughness.

The relatively good agreement between experimental data and AIEM confirmed that this model could be chosen to implement the inversion algorithm.

As far as the sensitivity to vegetation biomass is concerned, the analysis of experimental data showed a different behaviour between backscatter and PWC, depending on the observation frequency, polarization, and plant type. In fact, if we examine Figure 2a, we can note that the direct relationship between $\sigma^o$ at L-band (HH pol.) and the PWC of broad-leaf crops (i.e. sunflower, corn and sorghum) shows a marked increasing trend, with a rather high determination coefficient ($R^2=0.66$). Instead, at X-band (VV pol.) the backscattering of...
narrow-leaf crops (i.e. wheat and alfalfa) decreases as the PWC increases, with a $R^2 > 0.6$ (Figure 2b) (Macelloni et al., 1999 and 2001). These relationships suggested the use of a simple inversion of the regression equations for estimating PWC.

![Figure 1](image_url)

**Figure 1** – $\sigma^0$ at L-band at HH pol. as a function of SMC of bare or slightly vegetated fields, for different values of Hstd (from 1 cm to 3 cm) and at an incidence angle of 35°. Curves represent the AIEM model computed for different values of Hstd (1 cm, 1.5 cm, 2 cm and 3 cm). Points represent experimental data collected during the MAC-Europe 1991 and SIR-C/X-SAR 1994 experiments and basically subdivided into two roughness classes: Hstd < 2cm and > 2cm.

**The retrieval algorithm**

The flow chart of the SMC and PWC algorithm is provided in Figure 3. The algorithm can be subdivided into two main modules:

- The first module performs a pre-processing of SAR images;
- The second module, split into two parts, provides an estimate of the SMC (SMC_ALGO) and PWC (PWC_ALGO).

In the pre-processing phase, SAR images were calibrated, and then geocoded using a DEM (Digital Elevation Model) with a resolution of 30m, so that the areas in which the SMC was extracted could be identified with the precision of a pixel. SAR images were also de-speckled by using a gamma filter.
Figure 2 - a) $\sigma^0$ at L-band (HH pol.) vs. the PWC of broad-leaf crops (i.e. sunflower, corn and sorghum). b) $\sigma^0$ at X-band (VV pol.) vs. the PWC of narrow-leaf crops (i.e. wheat and alfalfa). Lines represent the regression equations showing $R^2=0.66$ (a) and $R^2>0.6$ (b). Points represent experimental data collected during the MAC-Europe 1991 and SIR-C/X-SAR 1994 experiments.

Figure 3 – Algorithm flowchart.

The separation into classes was necessary in order to identify the surfaces on which SMC and PWC could be estimated, i.e. agricultural fields, bare soils, and naturally vegetated fields (grass, lawn). The areas in which the two parameters could not be estimated were masked on the output maps. A classification of the input image was obtained by using land-use maps, when available. Otherwise, a separation into 4 classes (urban areas, water bodies, forest, agricultural surfaces) was also obtained by using both X-band and L-band backscattering data.
The primary input data for the algorithm was provided by a stack of co-registered SLC COSMO/SkyMed (stripmap) and ALOS/PALSAR SAR images in a standard ENVI format. Mandatory auxiliary data were those relative to the terrain elevation DEM (Digital Elevation Map).

**SMC_ALGO**

The core of the algorithm devoted to the estimate of SMC is an Artificial Neural Network (ANN). For this study, feedforward multilayer perceptrons (MPL) ANNs, trained using the backpropagation learning rule, were considered [Hornik, 1989; Linden and Kinderman, 1989]. After several tests, a configuration with two hidden layers of five and ten perceptrons each, and a transfer function of a ‘tansig’ type, was chosen as the optimal one. The selected ANN configuration has three input parameters obtained from ALOS/PALSAR and COSMO/Skymed SAR: \( \sigma^o \) at L-band in HH pol., \( \sigma^o \) at X-band in VV pol., and the map of local incidence angles (LIA map). The output is the SMC (% vol.).

The training of the ANN was carried out by using the extended archives of backscattering data available at IFAC. The core of this archive was the SIR-C/X-SAR dataset, gathered on the supersite of Montespertoli in Tuscany, which also contains the ground data of SMC (measured at different depths, in both gravimetric and volumetric units), PWC (in Kg/m\(^2\)), soil surface roughness (Hstd and Lc, in cm), together with cartographic information, which was co-located with the satellite measurements at L- C- and X-bands. This dataset was collected under different conditions of agricultural vegetation. Since this dataset was not sufficient for training the ANN and completely defining the neuron and weight values, data simulated using the AIEM model [Fung, 1994; Wu and Chen, 2004; Brogioni, 2010] were included in the training set. Minimum and maximum values of the soil parameters measured during the experimental campaigns (SMC, Hstd and Lc) were considered in order to define the range of variability of each model input. This procedure was iterated 10,000 times in order to obtain a set of backscattering coefficients at L- and X-bands for each input vector of soil parameters. Although the AIEM model did not account for the effects of vegetation, the range of the input of surface roughness of the model was modulated according to the ground truth, in order to cover the range of the measured backscattering from the archives. By doing this, it was assumed that (low) vegetation effects were implicitly accounted for. These considerations are valid for low vegetation only, while dense vegetation and forests have been disregarded on the basis of land cover or ancillary information.

The consistency between these model simulations and the experimental data was verified before proceeding with the ANN training. Figure 4 represents an example of simulated and measured backscattering coefficients at L-band (HH pol.) as a function of SMC (% vol.) for various roughness conditions. The training of the ANN, which was carried out by using almost half of these data, produced the diagram of Figure 5, where SMC estimated by the algorithm is compared with the one simulated by the AIEM. The regression equation obtained was: \[ \text{SMC}_{est} = 0.89 \times \text{SMC}_{mod} + 2.54, \] with \( R^2 = 0.89 \).

**PWC_ALGO**

This second part of the algorithm refers to the estimate of plant water content (PWC, in kg/m\(^2\)) of agricultural crops from simultaneous observations from Cosmo Skymed and ALOS/PALSAR. Here, the algorithm computed PWC by using X band, VV pol., and L-band, HH pol., backscattering and by inverting the two semi-empirical relationships derived from the data of the IFAC archives for two types of agricultural crops, as already described in the previous section.
Figure 4 – $\sigma^0$ simulated by AIEM as a function of the SMC% and compared with experimental archival data at L-band.

Figure 5 – Training result of the ANN: SMC estimated by the algorithm was compared with the SMC produced by the AIEM model. The regression equation is SMCest=0.89 SMCmod+ 2.54 ($R^2 = 0.89$). Algorithm results.
SMC
The product of the algorithm consisted basically of the SMC maps and, as a secondary output, of a 4-class land-use classification map, which was used for masking. Validation of the algorithm was carried out by using 2 PALSAR images co-registered with 2 COSMO images of an area located in Northern Italy, close to Milan (central coordinates: Lat 45.44N; Lon 9.44E). The site was an agricultural area that included a portion of forest and a high percentage of urban and industrial buildings. SAR data were collected in April and August 2008 in a situation of moderately wet soils, even in August, due to frequent rainfall that had occurred during the summer. The images were masked for the presence of dense vegetation (forest), water bodies, and urban areas. All the non-valid values of the input images were masked as well. In Figure 6 the SMC maps obtained for April and August 2008 are shown, in which at least 5 SMC intervals from 5% to 40% can be identified. Unfortunately, the only available ground information for validating the maps was the meteorological data derived from the archives of CML (Meteorological Center of Lombardy: www.centrometeolombardo.com). The average SMC values of 25-30% obtained for the entire area in April and August (with Std= 9.23% and 8.92%, respectively) were in line with the monthly rainfall of 45mm recorded at the nearby meteorological station in Milan for both these months (Table 1).

Table 1 - Monthly rainfall data recorded at the Milan meteorological station.

| METEO STATION | DATE     | MONTHLY RAINFALL |
|---------------|----------|------------------|
| Milan         | April 2008 | 44 mm            |
|               | August 2008 | 45 mm            |
PWC

The product of the PWC Algorithm consisted of the PWC maps. As for the case of SMC, it also produced classification maps capable of identifying 4 basic classes of land use. The validation of the algorithm was carried out with the same images used for validating the SMC product, namely ALOS and COSMO collected in April and August 2008. For PWC retrieval, two different relationships at L and X bands have to be used for broad-leaf crops, such as corn, sunflower, and sugar beet, and narrow-leaf crops (wheat, barley, and so on), and this implies an a priori classification. However, since narrow- and broad-leaf crops usually show different and sometimes complementary growth cycles, the decision as to which relationship should be used can be made on the basis of the season. In April, in fact, only wheat crops were present, since broad-leaf crops have not yet been seeded; in this case, only the regression for narrow-leaf crops was used. From the analysis of the April image, it can be observed that in Figure 7 (left) the presence of narrow-leaf crops is correctly pointed out by the algorithm. In April, in fact, wheat (or similar cereals) was most likely at an early growth stage (with a crop height of about 30-40 cm), corresponding to a range of PWC between 1 and 3 kg/m². Fields corresponding to lower values of PWC (between 0 and 1 kg/m²) were most probably bare fields prepared for spring sowing. In August, instead, both crop types present in the area in May-July were completely ripe or already harvested; thus, the output of the algorithm correctly indicated negligible PWC values (Figure 7, right). In this case, the regression for broad-leaf crops was used, since these, although ripe, were the only crops in the fields. In total, five levels of PWC were identified in both images.

![Figure 7 - PWC maps for April (left) and August (right) 2008. Colors represent masking (Violet=urban areas, Blue=water bodies) and different levels of PWC: Red=0-0.5 kg/m², Orange=0.5-1 kg/m², Yellow=1-2 kg/m², Light green=2-3 kg/m², Dark green=3-4 kg/m².](image)

Summary

This research was carried out within the framework of the SIASGE project funded by ASI for the definition and development of remote sensing products, to be used in risk and emergency management. In particular, the study was aimed at developing an algorithm capable of producing maps of Soil Moisture Content (SMC) and Plant Water Content (PWC) from X- and L- band SAR data. The part of the algorithm for generating soil moisture maps of bare soils and scarcely vegetated soils was based on an ANN trained by using simulations obtained from the AIEM model. Instead, the part concerning the estimate of vegetation biomass used empirical
relationships between the backscattering coefficient at L- and X-band and the plant water content of two types of agricultural vegetation types (narrow and broad leaf crops) obtained from experimental archive data.

SMC maps obtained in an agricultural area in Lombardy (northern Italy) in April and August 2008 showed average SMC values that were basically in agreement with the meteorological conditions and made possible the identification of five SMC classes. On the same area, the presence of wheat crops was well pointed out in April, with a range of PWC values that were in agreement with the season and with the agricultural practices. In August, both wheat and broad-leaf crops were completely ripe or harvested. The algorithm showed reasonable low PWC values.

In general, the method applied for the retrieval seems to be suitable for the retrieval of both SMC and PWC. Unfortunately, the dataset available for the test showed strong limitations (few images and in extremely urbanized areas). Further investigations and a refinement of the algorithm, especially for the PWC estimate, would be desirable.

Acknowledgments
This research was partially supported by the Italian Space Agency (ASI) through the ASI/SIASGE project.

References
Baronti S., Del Frate F., Ferrazzoli P., Paloscia S., Pampaloni P., Schiavon (1995) - SAR polarimetric features of agricultural areas. International Journal of Remote Sensing, 16, 14:2639-2656. doi: http://dx.doi.org/10.1080/01431169508954581.

Brogioni M., Pettinato S., Macelloni G., Paloscia S., Pampaloni P., Pierdicca N., Ticconi F., (2010) - Sensitivity of Bistatic Scattering to Soil Moisture and Surface Roughness of Bare Soils. International Journal of Remote Sensing, 31, 15: 4227 - 4255. doi: http://dx.doi.org/10.1080/01431160903232808.

Engman E.T., Narinder Chauhan (1995) - Status of microwave soil moisture measurements with remote sensing. Remote Sensing of Environment, 51, 1: 189-198. doi: http://dx.doi.org/10.1016/0034-4257(94)90074-W.

Escorihuela M.J., Kerr Y., de Rosnay P., Wigneron J.P., Calvet J.C., Lemaître F. (2007) - A Simple Model of the Bare Soil Microwave Emission at L-band. IEEE Transactions on Geoscience and Remote Sensing, 45, 7:1978-1987. doi: http://dx.doi.org/10.1109/TGRS.2007.894935.

Ferrazzoli P., Paloscia S., Pampaloni P., Schiavon G., Sigismondi S., Solimini D. (1997) - The potential of multifrequency polarimetric SAR in assessing agricultural and arboreous biomass. IEEE Trans. on Geosci. and Remote Sensing, 35, 1: 5-17. doi: http://dx.doi.org/10.1109/36.551929.

Fung, A. K. (1994), Microwave scattering and emission models and their applications. Norwood, MA: Artech House.

Hornik K. (1989) - Multilayer feed forward network are universal approximators. Neural Networks, 2, 5: 359-366. doi: http://dx.doi.org/10.1016/0893-6080(89)90020-8.

Linden, Kinderman J. (1989) - Inversion of multi-layer nets” in Proc. Int. Joint Conf. Neural Networks, II: 425-43.
Macelloni G., Paloscia S., Pampaloni P., Sigismondi S., de Mattheis P., Ferrazzoli P., Schiavon G., Solimini D. (1999) - The SIR-C/X-SAR experiment on Montespertoli: sensitivity to hydrological parameters. International Journal of Remote Sensing, 20, 13:2597-2612. doi: http://dx.doi.org/10.1080/014311699211958.

Macelloni G., Macelloni G., Paloscia S., Pampaloni P., Marliani F., Gai M. (2001) - The relationship between the backscattering coefficient and the biomass of narrow and broad leaf crops. IEEE Trans. on Geosci. and Remote Sensing, 39, 4:873-884. doi: http://dx.doi.org/10.1109/36.917914.

Paloscia S., Pampaloni P., Chiarantini L., Coppo P., Gagliani S., Luzi G. (1993) - Multifrequency passive microwave remote sensing of soil moisture and roughness. International Journal of Remote Sensing, 14, 3:467-483. doi: http://dx.doi.org/10.1080/01431169308904351.

Shi Jianchen, Wang J., Hsu A.Y., O’Neill P.E., Engman E.T. (1997) - Estimation of bare surface soil moisture and surface roughness parameter using L-band SAR image data. IEEE Transactions on Geoscience and Remote Sensing, 35, 5: 1254 - 1266. doi: http://dx.doi.org/10.1109/36.628792.

Ulaby F. T., Dubois P. C., Van Zyl J. (1996) - Radar mapping of surface soil moisture. Journal of Hydrology, 184: 57-84, 1996. doi: http://dx.doi.org/10.1016/0022-1694(95)02968-0.

Wu T.D. and Chen K.S. (2004) - A Reappraisal of the Validity of the IEM Model for Backscattering From Rough Surfaces. IEEE Transactions on Geoscience and Remote Sensing, 42, 4:743-753. doi: http://dx.doi.org/10.1109/TGRS.2003.815405.

Received 17/02/2011, accepted 03/10/2011

© 2012 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).