Multitemporal Soil Moisture Retrieval from Three-Day Repeat ERS/SAR Data

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Abstract

The Sentinel-1 mission will offer the opportunity to obtain C-band radar data characterized by short revisit time, thus allowing the generation of frequent soil moisture maps through the application of multitemporal retrieval algorithms. Exploiting the availability of some archived ERS SAR data with a short revisit time, this paper compares the estimates obtained by applying a multitemporal algorithm, developed in a previous work, to moisture provided by a land surface model and in situ data, as well as to soil moisture products derived from low resolution satellite data (ASCAT and SMOS). Results indicate the multitemporal algorithm produces soil moisture estimates that agree with model and in situ data at watershed scale. At finer scale, SAR presents better performance than other satellite instruments when compared to in situ data, although the correlation is not very high.

1 Introduction

Soil moisture is a key environmental variable for a large number of disciplines. It plays an important role for monitoring the effects of global climate change (e.g. droughts), so that it has very important implications for agriculture, ecology, and public health. It controls the partition of rainfall between land and the atmosphere, thus representing a key parameter in land surface hydrology.

It is well-known that satellite microwave remote sensing allows obtaining frequent measurements of soil moisture (SM) with global coverage, thus representing a fundamental complement to in situ observing networks, which are sparse and expensive to maintain, and to physical models, which generally cover a limited spatial domain. At microwave bands, the dielectric constant of soils is sensitive to SM, and sensors operating in the low-frequency portion of the microwave spectrum (L-, C- and even X-band) are able to measure SM within a suitable depth (~ 5 cm or shorter), although their measurements (especially those at C- and X-bands) are affected by the presence of vegetation.

Both active and passive microwave remote sensing data are used for soil moisture estimation. Microwave radiometers (such as the L-band Soil Moisture and Ocean Salinity SMOS satellite) and scatterometers (as the C-band Advanced Scatterometer ASCAT on-board METOP), generally offer a temporal resolution which allows fulfilling the observing cycle requirement for soil moisture [1]. However, they do not always fulfill the spatial resolution requirement, since the spatial resolution of these instruments generally ranges between 20 and 50 km. Conversely, the use of Synthetic Aperture Radar (SAR) systems to retrieve SM allows for the generation of soil moisture products with resolution varying from hundreds of meters to 1 km, but SAR temporal resolution was generally considered as a critical aspect for soil moisture applications, so far. However, the forthcoming European Space Agency (ESA) Sentinel-1 (S-1) mission (the launch of the first satellite is planned in April 2014) will provide C-band radar data characterized by short revisit time (the two-satellite constellation will offer six days repeat, or less over Europe and Canada [2]). This kind of data give also the opportunity to deal with the well-known ill-posedness of the problem of SM retrieval using SAR data, thus increasing the capability to produce reliable SM maps. This improvement can be achieved by applying multitemporal inversion techniques which assume that the temporal scale of variation of soil roughness and vegetation is considerably slower than that of soil moisture [3].

Some SAR data with short revisit time are available from past missions. In fact, during an early stage of the ESA ERS-1 mission (1994), and during the last months of ERS-2 activity (in 2011), the orbit of the satellites was set in order to have a repeat cycle and thus an acquisition of radar images every three days. This repre-
The approach to retrieve presents a unique opportunity to apply a multitemporal approach to retrieve SM.

In this work, a multitemporal algorithm (hereafter denoted as MLTA) specifically developed to map SM from S-1 data [1] is applied to two series of three-day repeat ERS/SAR data. In particular, the ERS-1 data acquired over Central Italy in Winter/Spring 1994 and the ERS-2 observations performed, over Denmark, throughout May and June 2011 are used. Central Italy has been selected since a well-established hydrological model predicting soil moisture has been set up, namely the Soil Water Balance (SWB) model developed by Research Institute for Geo-Hydrological Protection, National Research Council (IRPI-CNR). Denmark has been chosen since, in the area imaged by ERS-2, ground stations measuring SM and belonging to the International Soil Moisture Network (ISMN) are present.

The outcomes of the comparison between ERS-derived estimates, in situ data and model outputs are presented. To provide further insights on SM retrievals from satellite microwave data, SAR and ISMN data over Denmark are also compared with the estimates provided by ASCAT and SMOS.

2 The MLTA algorithm

The MLTA algorithm was designed in the framework of the “GMES Sentinel-1 Soil Moisture Algorithm Development” project funded by the European Space Agency. It assumes the availability of a time series of SAR images and is based on the hypothesis that a statistical relation exists among the soil conditions at the different times of the series (i.e., among some of the geophysical parameters involved in the problem). In particular, it is assumed that, considering a specific temporal interval in which a number of SAR images are available, the average characteristics of surface roughness do not substantially change in time, as opposed to soil moisture, whose temporal scale of variation is shorter than that of roughness.

The temporal series of radar data, possibly corrected for the vegetation effects, is integrated within the retrieval algorithm that is based on the Bayesian maximum posterior probability (MAP) statistical criterion. The MAP estimator maximizes the probability density function (pdf) \( p(\Theta | Z) \) of the vector of soil parameters \( \Theta \) (i.e., moisture, standard deviation and correlation length roughness parameters) conditioned to the measurements vector \( Z \) (i.e., the radar observations at different polarizations and possibly at different times). Considering the availability of a temporal series of measurements acquired at the current time \( t \) and at \( M \) previous times \( t-M, \ldots, t-1 \), the pdf to be maximized is:

\[
p(\Theta^t | Z^{-M, \ldots, Z^t})
\]

In (2)-(3), \(|·|\) indicates the determinant, \( Tr(·) \) represents the trace operator, \( n \) is the number of looks of the SAR image and \( C=C(\Theta) \) is the covariance matrix that describes the surface scattering for the general case of a polarimetric radar. Subscript mono is used because it represents the cost function for a standard monomtemporal MAP algorithm [4], while the summation is related to the multi-temporal approach.

The minimum of \( d \) is found using a Monte Carlo approach and is searched in a randomly generated database, i.e., a look-up-table where at each realization of surface parameter \( \Theta \) corresponds an expected covariance matrix \( C \). The forward surface scattering model proposed by Oh et al. [5] is used for combining \( \Theta \) with \( C \) in the database. The effects of vegetation on the radar signal are taken into account by applying a well-established semi-empirical model of scattering from vegetation canopy as done in [4], useful at least when the vegetation is not very much developed.

3 Available data and processing

The first dataset to which MLTA is applied is the time series of ERS-1 images acquired over Central Italy throughout the period February–April 1994, at 23° of incidence angle, vertical polarization, during ten satellite descending passes (February 6, 9, 12, 15, 18, 21, 24, March 8, April 7, 10). The other dataset is formed by the acquisitions (23° of incidence angle, vertical polarization) over Denmark performed by ERS-2 in 2011 on May 1, 4, 13, 16, 19, 25, 28, 31 and June 3, 6, 9, 12. All the available SAR data have been multilooked (a pixel size of 60m in both ground range and azimuth, corresponding to 45 looks, has been chosen) and geocoded (the SRTM DEM has been used). To infer the vegetation conditions the, CORINE land cover has been used.
together with optical data derived, for 1994, from the Advanced Very High Resolution Radiometer (AVHRR) and, for 2011, from the MODerate Imaging Spectroradiometer (MODIS). From the optical data, the Normalized Difference Vegetation Index (NDVI) has been derived.

To assess the ERS-1 derived SM, the outputs of the SWB model have been used. SWB has been specifically calibrated over the considered area of interest (Central Italy), so that it provides a reliable reference for the comparison. Conversely, to assess the ERS-2 derived estimates, the availability of a number of ISMN stations has been exploited. In addition, SAR-derived SM have been compared with the SWB model output and SAR retrievals, the agreement between the two datasets is very good (determination coefficient $R^2=0.943$, and root mean square difference $RMSD=0.009\ m^3/m^3$) showing that, by using a time series of satellite images, the temporal evolution of soil moisture can be estimated satisfactorily. In the future it is expected to apply the model for each point where meteorological data are available to test the capability of ERS-1 to reproduce also the spatial variability of soil moisture. We plan also to use satellite SM as inputs to the land surface models, to verify the impact of the assimilation on model predictions, similarly to what has been done for a Numerical Weather Prediction model in [8].

4 Results

4.1 Comparison between ERS-derived and model-derived soil moisture

Figure 1: Soil moisture provided by the model (red line) compared with multitemporal retrievals from ERS-1 images (green dots).

In order to run the model, it was required to select the rain-gauge and thermometers in the study area for the period of interest (February-April 1994). Figure 1 shows the comparison between ERS-1 (green dots) and modelled (red line) soil moisture data. After calibration of the model output and SAR retrievals, the agreement between the two datasets is very good (determination coefficient $R^2=0.943$, and root mean square difference $RMSD=0.009\ m^3/m^3$) showing that, by using a time series of satellite images, the temporal evolution of soil moisture can be estimated satisfactorily. In the future it is expected to apply the model for each point where meteorological data are available to test the capability of ERS-1 to reproduce also the spatial variability of soil moisture. We plan also to use satellite SM as inputs to the land surface models, to verify the impact of the assimilation on model predictions, similarly to what has been done for a Numerical Weather Prediction model in [8].

4.2 Comparison between satellite and in situ soil moisture

Figure 2 shows the comparison between ISMN measurements over Denmark (May-June 2011) and the estimates derived from ERS-2, ASCAT and SMOS data. It can be noted that although the correlation coefficient ($R$) is quite small, SAR presents the best scores ($R=0.41$, $RMSD=6.99\ m^3/m^3$ and slope of the best fit line equal to 0.43). The poor performances can be due to the fact that we are comparing point measurements with areal ones. It must be also underlined that the Denmark 2011 case study is not very favourable for satellite estimates of SM since vegetation was well developed (NDVI generally exceeds 0.4) and accounting for its effects by using the water cloud model represents a difficult task. Nonetheless, the results indicate that by using MLTA and taking also advantage of its high spatial resolution (although some spatial averaging is required to reduce noise), SAR provides the most accurate SM product among the satellite ones.

By averaging the satellite data over the area where the ground stations are placed, we have also compared the
temporal trends of SM products with in situ ones. The results are shown in Figure 3 only for ERS and ISMN data. It can be noted that ERS is able to detect the temporal variations of SM as measured by ISMN stations. This ability apparently improves by adjusting the temporal mean value and the standard deviation of satellite SM in each pixel associated to a ground station, in order of match mean and standard deviation of in situ ones (green line in Figure 3). This approach is often used in the literature, when the ability to detect changes in SM is considered important.

Figure 2: Comparison between satellite and in situ ISMN. Upper panel: SAR; lower left panel: ASCAT; lower right panel: SMOS.

Figure 3: Comparison between ERS-2/SAR, and ISMN (blue line) temporal trends of daily spatial averages.

Worse result are obtained by computing the spatial correlation between daily satellite SM and in situ SM. Even the spatial correlation between different satellite data is quite poor, a fact which demands for further analysis and a better correction of the vegetation effect.

5 Conclusions

In anticipation of the upcoming availability of Sentinel-1 data, an algorithm designed to exploit the short revisit time of this satellite to retrieve soil moisture has been applied to three-day repeat ERS/SAR data. SAR derived soil moisture have been compared to model and in situ data, as well as to soil moisture products derived from low resolution satellite data (ASCAT and SMOS). Over a large scale, the multitemporal algorithm produces estimates that agree with model and in situ data, while at finer scale SAR presents slightly better performances than other satellite instruments when compared to in situ data, although the spatial correlation is not very high.

References


