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SOIL MOISTURE ESTIMATION AND ANALYSIS IN WESTERN AFRICA BASED ON ERS SCATTEROMETER

M. Zribi⁽¹⁾, M. Pardé⁽²⁾, P. De Rosnay^(1,3), F. Baup⁽¹⁾, E. Mougin⁽¹⁾, L. Descroix⁽⁴⁾, T. Pellarin⁽⁴⁾, N. Boulain⁽⁵⁾, C. Ottlé⁽⁶⁾

⁽¹⁾ CNRS/IRD/UPS/CNES/CESBIO, 18 avenue. Edouard Belin, bpi 2801, 31401 Toulouse cedex 9 email: Mehrez.Zribi@ird.fr
⁽²⁾ CNRS/IPSL/LATMOS, 10-12 av. de l'Europe, 78140 Vélizy, France
⁽³⁾ ECMWF, Reading, RG2 9AX, United Kingdom

⁽⁴⁾ LTHE, BP 53 Domaine Universitaire, 38041 GRENOBLE cedex 9, France

⁽⁵⁾ HSM, BP_5045 Agropolis 34032 Montpellier France

⁽⁶⁾ CNRS / IPSL / Laboratoire des Sciences du Climat et de l'Environnement, Gif-sur-Yvette, France

ABSTRACT

The present paper presents a new methodology for the estimation of surface soil moisture over Western Africa, based on data provided by the European Remote sensing Wind SCatterometer (WSC) instrument, in which an empirical model is used to estimate volumetric soil moisture. This approach takes into account the effects of vegetation and soil roughness in the soil moisture estimation process. The proposed estimations have been validated using different methods, and a good degree of coherence has been observed between satellite estimations and ground truth measurements. Comparison with the multi-model analysis product provided by the Global Soil Wetness Project, Phase 2 (GSWP-2) indicates that their estimations are well correlated.

1. INTRODUCTION

Surface soil moisture plays a crucial role in the continental water cycle because it controls the partitioning of precipitation between runoff, infiltration and evaporation [1], controls the partitioning of incoming radiation between latent and sensible heat fluxes, influences the vegetation's condition, and modulates the soil's thermal and hydraulic properties. Soil moisture thus influences atmospheric water vapour fluxes and precipitation as a consequence. Various numerical weather forecasting models have demonstrated the high sensitivity of predicted rainfall to the ambient conditions of soil moisture ([2], [3]).

In the case of African Monsoons, the feedback effects arising from the influence of continental surfaces on monsoon dynamics, are commonly thought to have played an important role in the drought of the 70's and 80's. In order to fully understand the role played by continental surfaces, it is important to identify the main hydrological processes involved in the continental water cycle, together with their variation and sensitivity as a function of climatic or geological region. Whereas the regular measurement of soil surface characteristics (moisture and vegetation) in these regions poses a substantial challenge, considerable efforts have been made over the past three decades to develop remote sensing techniques to characterise the spatial and temporal variability of soil moisture over large regions [9]. In particular, active and passive microwave techniques as well as interpretation tools have been developed [4].

The active microwave studies reported in recent years were based mainly on the use of a low resolution scatterometer ([5]-[6]). The backscattered contribution from vegetation is determined using physical or empirical models. ([7]-[8]) developed a global methodology for the estimation of a relative soil surface moisture index. In the present paper we introduce a methodology in which soil moisture is estimated from ERS wind scatterometer radar data, acquired using both ERS1 and ERS2 over the period from 1991 to 2000. With this approach, processed radar data is combined with Normalized Difference Vegetation Index (NDVI) auxiliary data in order to estimate the mean soil moisture with a resolution of 25 km.

Our paper is organised as follows: in section II, the studied site and satellite data are presented. Section III describes the proposed methodology. Validation and derived results, including mapping of soil moisture, are provided in section IV. Finally, our conclusions are presented in Section V.

2. STUDIED AREA AND SATELLITE DATA

2.1 Study area (vegetation, rainfall, ...)

Western Africa (Fig. 1) is characterised by three climatic zones, distinguished by their mean annual rainfall levels:

* The north: a desert-like regime prevails (less than 300mm of annual precipitation), with one rainy season of less than three months (from midi-July to mid-September).

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* The central zone: characterised by a Sahelian regime (300 to 750 mm of annual precipitation) in which the rainy season lasts between three and four months (August being the wettest month), and the remaining part of the year is generally dry.

* The tropical zone: characterised by 750 to 1200 mm of annual precipitation and a longer rainy season, which can last up to six months in the southern reaches of the zone.

One of the most significant climatic variations experienced in this region was the persistent decline in rainfall which occurred in the Sahel, starting in the late 1960s. The trend was abruptly interrupted by a return of adequate rainfall in 1994, which is considered to be the wettest of the past 30 years, and was thought to signal the end of the preceding drought. However, rainfall in 1994 barely exceeded the region's mean value during the 20th century, and was unusual in that the anomalously wet conditions occurred towards the end of the rainy season and in the following months. Unfortunately, dry conditions returned after 1994.



Figure 1. Study site

2.2 ERS Scatterometer data

The ERS wind scatterometer was initially designed to measure wind speed and direction at the sea's surface. The instrument consists of three antennae which transmit radar beams which are pointed 45° forwards, 45° sideways, and 45° backwards with respect to the satellite's nadir. The incidence angle θ varies over the instrument's swath, from 18° to 47° for the mid-beam antenna, and from 25 to 59° for the fore-beam and aftbeam antennae ([6]) Once the data has been reduced, each resolution cell is thus associated with measurements derived from three different angles of incidence. The sensor operates at 5.3 GHz and VV polarisation, like the ERS/SAR instrument. Its spatial resolution is around 50 km, and measurements are repeated every 3 to 4 days. The data is processed using a grid, and our studied region was divided into elementary 0.25° square cells. All measurements associated with the same cell, but taken at various incidence angles, are recorded together and are associated with the corresponding latitude/longitude co-ordinates.

3. METHODOLOGY

3.1 Radar data normalisation

As the backscattered radar signals are acquired at incidence angles ranging between 18° and 59° signal strength variations can arise, which are affected in particular by soil roughness and surface vegetation characteristics. The angular dependence of the radar signals can thus be expected to have spatial and temporal variations, with the latter being strongly influenced by vegetation dynamics during the rainy season. For all of these reasons, we chose to normalise the radar signal data, using monthly statistics for each elementary cell in the studied site.

The angular variation of backscattering coefficient is modelled with a 2nd order polynomial function:

$$\sigma_{dB}^{0} = A(t)\theta^{2} + B(t)\theta + C(t)$$
(1)

The three parameters A, B, and C are computed for each cell, for each month of the year, using radar data measured during the period 1991-2000 with all incidence angle interval.

Fig. 2 illustrates an example of polynomial fitting of radar data, computed in January and August for one cells.

Using the polynomial fit described above, the data was normalised to 40° using to the following expression:

$$\sigma_{dB}^{0}(40^{\circ}) = \sigma_{dB}^{0}(\theta) - A(t)\left(\theta^{2} - 40^{2}\right) - B(t)\left(\theta - 40\right)$$
(2)

In the present study, after normalisation with all incidence measurements, only signals recorded at incidence angles less than 35° have been considered in soil moisture estimation. At higher incidence angles, the influence of vegetation on radar signal is likely to be strong and to dominate the soil moisture effect. The dynamic range of backscattered radar signals, arising from variations in soil moisture, would then diminish at higher incidence angles, thereby introducing radar normalisation errors, particularly at the data interval extremities. Although only low incidence angle signals are used for soil moisture estimation, we included high incidence angle signals in our normalisation approach, in order to have a precise estimation of processed signals.



Figure 2. Normalisation of radar scatterometer data

3.2 Elimination of roughness effects

After normalisation of the backscattered signals to a single angle of incidence, the dataset remains sensitive to three parameters: soil moisture, soil roughness, vegetation and surface heterogeneity.

The signal received by the instrument from each spatial cell results from the sum of backscattered signals contributed by both bare soil and vegetation cover. These two contributions, weighted by their respective percentages of terrain cover, are added incoherently to give the measured signal.

Any temporal evolution of the soil moisture can potentially be monitored through the detection of changes in backscattered signal. If we consider radar signals scattered from the same cell, roughness effects and some vegetation effects could be eliminated by computing the difference between data recorded at different dates. This approach relies on the assumption that the change in backscattered signal is due only to local variations in soil moisture. In order to estimate the absolute value of soil moisture on one particular date we subtract, for each cell, an estimation of the driest signal (with Mv \approx 0%) recorded on the same day of the year, from the 'moist' backscattered signal.

From the processed radar signals we identify, for each cell (i,j) and each month (k), the driest day (d_k) corresponding to the weakest radar signal recorded during the period from 1991 to 2000. In order to take into account the short-term influence of strong vegetation dynamics, in particular during the rainy season between July and September, we retrieve the lowest signal corresponding to the other days of the year by using a simple linear interpolation between the driest days retrieved for each month (k), according to:

$$\begin{aligned} - & \sigma_{dry}^{0}(d) = f\left(\sigma_{dry}^{0}(d_{k-1}), \sigma_{dry}^{0}(d_{k})\right) & \text{if } (d < d_{k}), \text{ or} \\ - & \sigma_{dry}^{0}(d) = f\left(\sigma_{dry}^{0}(d_{k}), \sigma_{dry}^{0}(d_{k+1})\right) & \text{if } (d > d_{k}). \end{aligned}$$

Fig. 3 illustrates the full set of normalised ERS/WSC data, for one cell, with the associated estimations of σ_{dry}^0 for the period ranging between 1996 and 2000. It can clearly be seen that the processed radar signals have a lower limit corresponding to dry conditions. The fully processed signal for a given day *d*, in month *k*, thus becomes:

$$\Delta \sigma = \sigma_{dB}^0(d_k) - \sigma_{dry}^0(d_k) = H(veg, Mv) \quad (3)$$



Figure 3. Illustration of normalised radar data and estimated dry signal

3.3 Modelling of radar signal dependence on vegetation and surface moisture

The proposed approach takes advantage of the approximately linear dependence of radar backscattering on changes in soil moisture.

If we assume that the influence of variations in vegetation canopy is small when compared to that of soil moisture, between a given date for soil moisture estimation and that at which the driest signal is estimated, the difference obtained for each cell could be expressed by:

$$\Delta \sigma = \alpha \quad \Delta M v \ , \tag{4}$$

where $\Delta \sigma$ is the change in VV polarisation radar signal (dB) and ΔMv is the change in soil moisture. The parameter α can be expected to depend on vegetation parameters and on the roughness characteristics of the soil surface. The dependence of α on both vegetation and soil roughness can be expressed using the function

f(veg) and the slope α_{soil} (bare soil), with:

$$\alpha = f(veg) \alpha_{soil} \tag{5}$$

meaning that for soil with vegetation coverage, equation Eq. 5 becomes:

$$\Delta \sigma = f(veg) \alpha_{soil} \Delta M v \quad (6)$$

The bare soil slope α_{soil} was measured and estimated from local measurements made at the Diantandou site in Niger, [9], and is estimated to be approximately 0.28 for mean radar signals at 1km scale, in VV polarisation at 5.3 GHz with low incidence angles. This estimation is based on various experimental measurements made with ASAR-ENVISAT data, acquired during two rainy seasons (2004-2005), and soil moisture ground truth measurements made at different test sites (Wankama, Banizambou, Plateau Sofia, Maourey Kaoura Zeno, Tondi Kiboro, Garbey Tombo) with different soil types in Diantandou site. We consider that α_{soil} is only weakly dependent on variations in soil roughness between cells over the studied region, if we consider no large variations of soil roughness during soil moisture monitoring, which is the case of western Africa, with a small percent of agricultural sites. The latter hypothesis could be validated using backscattering model simulations.

The remaining unknown variable is the function f(veg), which characterises the influence of vegetation on the slope of $\Delta \sigma$.

Analysis of the effect of vegetation on radar signals The aim of this section is to analyse the relationship between variations in the f(veg) and various characteristics of the vegetation. Although optical thickness has been used to estimate such variations, this is not a practical approach in the present case, as there is either a lack or a total absence of validated satellite products such as optical thickness or LAI over Africa. We therefore choose to study the influence of vegetation by directly using the NDVI index, acquired by NOAA's - Advanced Very High Resolution Radiometer (NOAA-AVHRR). NDVI products are provided by the Africa Data Dissemination Service Website and (http://igskmnwb015.cr.usgs.gov/adds), are computed every 10 days. In the present case they were used after extrapolation of the data from 8 x 8 km² to $25 \text{ x} 25 \text{ km}^2$ resolution.

As vegetation sensitivity cannot be demonstrated during the dry season, in the absence of variations in rain and soil moisture, we analysed data from the studied region recorded during the rainy months only (July, August and September). Fig. 4 illustrates the processed $\Delta\sigma$ signal as a function of NDVI, estimated for each cell during these three months, for all of the studied regions. We first make the assumption that, from the processed data recorded over each region during the ten year interval from 1991 to 2000, the soil moisture varied in the same proportion, independently of the presence or nature of vegetation over each cell. As all of the cells experience periods of total drvness, this means that in all cells the soil moisture would have varied from, say, 0% for driest days in sahel and desert regions to an identical maximum value during the rainy season. For value of NDVI (between 0 and 1), variations in $\Delta\sigma$ are mainly caused by variations in soil moisture. It can also be observed that the maximum values of $\Delta \sigma$ recorded for any given level of NDVI, must correspond to approximately the same maximum value of volumetric moisture - since we take into account the statistics of a full set of data, recorded over the ten year period between 1991 and 1992. As shown in Fig. 4, an increase in vegetation (NDVI) is clearly associated with a reduction in the maximum value of $\Delta \sigma$. This tendency is in agreement with the observed decrease in radar signal sensitivity to soil moisture associated with an increasing of vegetation cover. In order to estimate variations of the slope α without being affected by noise effects due

to rare events, for each value of NDVI we excluded the upper 2% of the corresponding values of $\Delta \tilde{\sigma}$ As illustrated in Fig. 4, when the NDVI increases from 0 to 1, the corresponding estimations of $\Delta \sigma$ decrease in value. This relationship is closely approximated by the following polynomial:

$$\Delta \sigma_{\max} (NDVI) = \xi .NDVI^{2} + \gamma .NDVI + \Delta \sigma_{\max}^{bare}$$
(7)



Figure 4. Analysis of vegetation effect on radar signal

Soil moisture estimation

The results of the last section show that the slope α decreases as a function of *NDVI*. By introducing the expression: $\Delta \sigma_{\max}^{bare} = \alpha_{soil} M v_{\max}$ for bare soil, we can write:

$$\alpha = \alpha_{soil} \left(1 + \frac{\xi}{\Delta \sigma_{max}^{bare}} .NDVI^2 + \frac{\gamma}{\Delta \sigma_{max}^{bare}} .NDVI \right)$$
(8)

One can identify the second term in the above expression with f(veg), described above.

From the analysed data, the following empirical relationship can then be established:

$$\Delta \sigma = 0.28 \times (-1.21 \, NDVI^2 + 0.03 \, NDVI + 1) Mv \ (9)$$

In order to avoid errors due to high effect of dense vegetation cover, particularly in tropical regions, we propose to estimate soil moisture only for cells with a maximum NDVI during the studied period lower than 0.6.

4. VALIDATION AND RESULTS

4.1 Algorithm validation

Because of the absence of sufficient ground truth soil moisture measurements in the studied period, between 1991 and 2000, we propose to validate our approach using several different methods.

<u>Comparison with SAR estimations and in situ soil</u> moisture measurements in Niger site

An approach was developed to estimate soil moisture over Niger site, using ASAR/SAR data [9]. Fig. 5 illustrates an inter-comparison between SAR and ERS scatterometer estimations, showing a good coherence between the two products.

Only a small number of *in situ* measurements were made during the studied period, on the Banizambou site in Niger (lat: $13^{\circ}.53$, long: 2.65° co-ordinates). These measurements were made in different test fields, using TDR and gravimetric measurements. The comparisons between measurements and estimations shown in Fig. 6 are found to have an rms error around 3%. As these measurements were not made specifically for the purposes of remote sensing validation, the may have been made some hours before or after the overhead passage of the radar instrument. It would then be normal for significant errors to occur whenever the measurements were made shortly before or after a rainfall event.



Figure 5. Inter-comparisons between ASAR and ERS estimations over Niger site



Figure 6. Inter-comparison between ERS and ASAR estimations, and ground truth measurements

Correlation with rainfall

Fig. 7 provides a time series comparison of soil moisture and rainfall. The latter is given by the mean value of measurements taken from different rain gauge stations on the Banizambou site. It can be seen that although rainfall and soil moisture are not directly comparable, soil moisture peaks occur after rainfall events during the rainy season. For the studied sites, it has been computed that 92% of volumetric moisture

values higher than 8% correspond to rainfall events which occurred on the same or previous day. Similarly, 89% of volumetric moisture values lower than 4% correspond to an absence of rainfall during the previous two days. These results demonstrate a good degree of correlation between rainfall and variations in soil moisture.



Comparison with GSWP2 multi-model analysis

The soil moisture estimations described here have been compared with soil moisture products provided by GSWP-2 ([10]. GSWP-2 (http://www.iges.org/gswp/) is an international initiative which was launched by the Global Energy and Water Cycle Experiment (GEWEX) to provide global data sets of soil wetness, energy and water fluxes, by driving 13 land surface models with state-of-the-art 1° by 1° atmospheric forcing and land surface parameters over a 10 year period (1986-1995). The baseline meteorological forcing provided by GSWP-2 is based on reanalysis made by the National Centers for Environmental Prediction / Department of Energy (NCEP/DOE). The soil moisture estimations derived in the present study are compared with GSWP-2 modelled (top layer) soil moisture profiles of 0.5° by 0.5° cells, for the period from 1991-1995. If we consider the same lowest value of soil moisture during the dry season, Fig. 8 illustrates temporal variations of the two products in two different cells (the Sahel and the desert region). In the Sahel cell $(13^{\circ}-3^{\circ})$, the wet season starts in June and lasts for approximately 4 months, and in the desert region cell (16°-3°) there is a very short wet season associated with lower soil moisture values. We observe good coherence between estimations based on satellite data and model simulations for the two last regions. Both estimators follow approximately the same variations during the rainy season. In the case of the latter two regions, we observe an rms difference in volumetric soil moisture equal to 2.4% for the desert cell and 3.4% for the Sahel cell.



Figure.8. Inter-comparison between moisture estimations and GSWP-2 outputs

4.2 Maps

Having validated our algorithm, we were able to apply it to each ERS WSC data point in the studied region. Resulting maps of mean soil moisture, averaged over a period of 5 days, are illustrated in Fig. 9 for three dates in the period June1999-october 1999. We estimate soil moisture only in cells with a maximum NDVI lower than 0.6. Therefore maps correspond particularly to sahel and desert regions. Large spatial variations can be observed, which must be due to high rainfall variability with a convective structure. These results also reveal a general behaviour of monsoon dynamic, in agreement with the known regimes of precipitation with larger duration of monsoon in the south.





Figure 9. Illustration of moisture mapping over Western Africa

5. CONCLUSION

A methodology has been developed to enable surface soil moisture to be estimated from ERS radar wind scatterometer data, with a resolution equal to 25Km. The raw data is processed in three stages:

- normalisation of the data to a single incidence angle (40°)
- Elimination of roughness effects using an estimation of the dry soil signal corresponding to the same roughness and vegetation as the acquired radar signal.
- Cancellation of the influence of vegetation on the radar signal's sensitivity to soil moisture, using the NDVI index derived from AVHRR measurements.

The proposed methodology has been validated using different approaches, and a high level of correlation is observed between soil moisture variations and rainfall events. Secondly, comparisons between some ground truth measurements and the soil moisture values estimated using our methodology are characterised by an rms relative difference of 3%. A good degree of coherence is found between the soil moisture output given by GSWP2 multi-model analyses, and our reduction of ERS satellite data, even in those cases where the former is known to overestimate the surface soil moisture, with rms errors for the studied cells equal to 2.4% for desert and 3.4% for sahel cell. Soil moisture maps are proposed for the studied period.

Future work will include more detailed analysis of various climatic anomalies, which occurred during the ten years covered by the present study.

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