EXPERIMENTAL I KM SOIL MOISTURE PRODUCTS FROM ENVISAT ASAR FOR SOUTHERN AFRICA

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ABSTRACT

Soil moisture is an important environmental variable and a key element in the Earths energy, water and carbon cycle. Monitoring soil moisture over large areas is only feasible using remote sensing.

In this paper, a change detection approach based on an extensive Envisat ASAR Global Mode data archive is presented. Actual backscatter measurements are compared to two reference values representing dry and wet soil conditions. Maps showing the surface soil moisture are generated. First validation showed a good agreement with precipitation data and soil moisture measurements. However, the lack of large scale soil moisture monitoring sites makes validation difficult.

1 INTRODUCTION

The water content of the soil layer forming the boundary between the solid earth and the atmosphere is highly variable in space and time. The knowledge of the spatio-temporal evolution of soil moisture is an important parameter in many environmental disciplines.

Monitoring of soil moisture using in-situ measurements at continental or global scales is not feasible. Besides hydrologic modelling, remote sensing can provide spatially extended data. Remote sensing techniques exploiting the microwave region of the electromagnetic spectrum are regarded to have the largest potential to yield soil moisture estimates. The search for an operational soil moisture retrieval algorithm has been one of the driving forces of the active microwave remote sensing community since the 1970s [1]. Unfortunately, there is still no widely accepted method that delivers soil moisture data at spatial scales of 1 km or better [2].

There are a number of methodological and technical reasons for this deficiency. Although it is generally accepted, that microwaves show a unique sensitivity to the moisture content of soils, the information contained in the backscattered radar signals is ambiguous. Besides the dielectrical properties of the soils controlled by the soil moisture content, also the geometrical properties of the soil surfaces have a profound effect on the radar backscattering process. Research has shown that the influence of surface roughness on the backscattered signal is in the same order or larger than the influence of soil moisture [3]. Thus, it is important to adequately model the scattering of coherent electromagnetic waves by a rough, natural soil surface. Theoretically this would be possible by solving Maxwell's equations, but given the complex shapes of natural surfaces, an exact mathematical solution is not feasible. Therefore theoretical backscatter models have been developed, which contain approximate solutions of the surface scattering problem, e.g. the Integral Equation Model, Small Perturbation Model, Geometric Optics Model, Physical Optics Model. Unfortunately, the applicability of these models for operational applications is limited. Firstly, natural surfaces often do not fall within the validity ranges of such models, given by the statistical surface roughness descriptors r.m.s. height and autocorrelation length [4-7]. Secondly, theoretical models often require a large number of observables, e.g. backscatter measurements at different frequencies and polarizations. Operational Synthetic Aperture Radar (SAR) sensors do not provide multi-parametric data and the number of independent observables of such systems is small. Therefore, simplified mathematical models must be used for soil moisture retrieval [8].

The presence of vegetation reduces the sensitivity of microwaves to soil moisture. Different approaches to model the effect of vegetation on the radar backscattering process have been developed but there accuracy is not known. Laboratory experiments showed, that the backscattering contribution of C-band data from a soil covered by wheat of 50 cm height are much higher than predicted by vegetation models [9].

Instead of building complex models requiring extensive input data sets to provide a physical description of the radar backscattering process, change detection methods showed their potential in a number of studies. They exploit variations in radar backscattering measurements over time and are based on the assumption, that variations due to surface roughness and vegetation cover act on much longer time scales than soil moisture related changes in radar backscatter [10, 11].

Besides the methodological issues, also the technical specifications of operational space borne SAR sensors do not always meet the requirements for soil moisture

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mapping. The technical specifications of the ERS SAR sensor were originally chosen for oceanographic applications. Orbit configurations and ground swath widths of most active SAR sensors only allow repeat cycles in the order of one month. From an applications point of view, frequent SAR observations at spatial resolutions of 1 km or better are required. Only SAR techniques can deliver such data.
In this paper, a data driven change detection approach is presented, using Envisat ASAR data acquired using the ScanSAR technique, which provides image data at medium spatial and temporal scales.

2 DATA

2.1 Study Area

The study area covers the African continent south of the equator. The area is characterized by different climates ranging from tropical rain forest climate at the equator to Mediterranean climates in the south. The south-eastern part shows very dry desert climates. Land cover reflects the diverse climatic conditions and comprises dense tropical rain forest, savanna, steppe, deciduous forests to evergreen Mediterranean forests and hard leaf shrubs. Precipitation patterns show either distinct seasonal patterns with a dry and wet season or arid conditions.

2.2 Envisat ASAR ScanSAR Modes

The presented study exploits a comprehensive archive of the European environmental satellite Envisat. Envisat was launched on 1st March 2002 into a sun synchronous orbit with an inclination angle of 98.55° at an altitude of about 800 km with 14 orbits per day and a nominal repetition rate of 35 days. Besides other earth observation instruments, it carries an active C-band SAR sensor, the Advanced SAR instrument (ASAR).
The ASAR sensor provides image data at different spatial and temporal resolutions and at different polarizations. With its active-phased array SAR antenna the ASAR sensor can be operated in two ScanSAR modes. Image data acquired in the ScanSAR modes Wide Swath (WS) or Global Monitoring (GM) are covering swaths of 405 km width under varying incidence angles. A combination of ascending and descending orbits allows image acquisitions of a region up to 10 times a month [12].
Swath width of conventional strip-map SAR sensors like the ERS SAR is limited by the antenna beam pattern, sampling requirements to avoid ambiguities in the received signals, beam-forming requirements as well as data rate limitations [13-15].
To achieve wider ground swaths, the ScanSAR imaging technique has been developed, which is based on rapid beam steering of the antenna beam and sharing the radar operational time between two or more sub-swaths. The imaging process is divided into several blocks of pulses, where the ScanSAR sensor scans through adjacent subswaths. Each subswath is illuminated only for a certain period of time. The cost of having a much wider swath is the degradation of the spatial resolution [15-17]. Table 1 lists the technical specifications of the ASAR Global Mode.

Table 1: Technical characteristics of Envisat ASAR Global Mode

Polarization	VV or HH
Spatial Resolution	≤ 1000 m, > 7 looks
Temp. Resolution	≤ 3 days, (desc. + asc. orbits)
Radiom. Resolution	≤ 1.6 dB
Swath Width	≥ 405 km, 5 sub-swaths
Incidence angle range	15-45°
Centre Frequency	5.331 GHz (λ=5.67 cm)
Duty cycle	≈ 100%
Data rate	≤ 0.9 Mbit/s

2.3 Preprocessing of ASAR GM Data

The Envisat ASAR GM data and DORIS precise orbit information are automatically downloaded from ESA via FTP. Preprocessing comprises geocoding, radiometric calibration, resampling to a regular spatial grid and local incidence angel normalization. For geocoding and radiometric calibration, the commercial software package SARscape© developed by the Swiss company SARmap was used together with in-house software solutions based on ENVI/IDL. The geocoding procedure based on the so called Range-Doppler-Approach performs a backward geocoding and allows fully automatic geocoding and radiometric calibration without any user interaction. Incorporating precise DORIS orbit information and digital elevation data (SRTM improved GTOPO30), geocoded backscatter image data are produced with sub pixel accuracy. A local incidence angle is assigned to each ASAR GM backscatter pixel value
Individual geocoded and calibrated ASAR GM scenes are resampled to a regular grid and ingested into a

spatial data base to simplify time series analysis. A global grid with a sampling interval of 15 arc seconds, corresponding to a distance of about 500 m at the equator, was defined. The chosen datum is WGS-84 with the origin set to 180°W/90°S. The grid was divided into cells of 0.5° x 0.5°, which resulted in 720 columns and 360 rows globally. The database is automatically updated as new ASAR GM data are received.

In the last preprocessing step a local incidence angle normalization has been applied to remove the incidence angle dependency caused by the large swath width. Assuming a linear relation between radar backscatter and local incidence angle, as it has been observed by [18-20], a linear model is used to remove the local incidence angle dependency for the backscatter measurements. The ASAR GM radar backscatter measurements are adjusted to a medium incidence angle of 30° using the formula:

$$\sigma^0(30°) = \sigma^0(\theta) - a(\theta - 30°) \qquad (1)$$

where $\sigma^0(30°)$ is the normalized backscatter expressed in decibels, $\sigma^0(\theta)$ is the uncorrected radar backscatter, a is the slope of the regression line of the linear model fitted to $\sigma^0(\theta)$ time series data and θ is the local incidence angle.

3 METHOD

Based on comprehensive time series data of ASAR GM, a data driven change detection algorithm for soil moisture retrieval was developed. It builds upon the same theoretical basis as a method developed originally for soil moisture retrieval from global ERS-1/2 C-band scatterometer data. A detailed description of this approach can be found in [21] and [22]. Model parameters are estimated from long time series of radar measurements to have a number of observations exceeding the model parameters by far. The model compares actual backscatter measurements to the two reference values σ^0_{dry} and σ^0_{wet}, representing dry and wet soil conditions at which the lowest and highest radar backscatter has been recorded. Assuming a linear relationship between σ^0, expressed in logarithmic units (dB), and soil moisture, the relative moisture content m_s of the thin soil surface layer (< 2cm) ranging between 0 and 100% is estimated from [21]:

$$m_s(t) = \frac{\sigma^0(t) - \sigma^0_{dry}(t)}{\sigma^0_{wet}(t) - \sigma^0_{dry}(t)} \qquad (2)$$

Because – regarded from a temporal perspective – the seasonal vegetation signal in C-band time series is much weaker than the soil moisture signal [21] seasonal vegetation effects are neglected in a first approximation, i.e. σ^0_{dry} and σ^0_{wet} are assumed to be constant over the year.

Due to the high noise level in the ASAR GM data and the uncertainty connected with the question, if the ASAR GM time series data for one location really captured the lowest and highest radar backscatter, the estimation of the reference values σ^0_{dry} and σ^0_{wet} is not straightforward. The estimation of the reference values is based on the assumption, that the probabilities p_{dry} and p_{wet} of acquiring backscatter measurements during dry and wet conditions are known. To calculate the number of measurements N taken during dry and wet conditions, the following formulas are used:

$$N_{dry} = N \cdot p_{dry} \qquad (3)$$

$$N_{wet} = N \cdot p_{wet} \qquad (4)$$

The reference values σ^0_{dry} and σ^0_{wet} are calculated by averaging the driest and wettest measurements, selected with formulas (3) and (4):

$$\sigma^0_{dry} \approx \frac{1}{N_{dry}} \sum_{i=1}^{N_{dry}} \sigma^0_i \qquad (5)$$

$$\sigma^0_{wet} \approx \frac{1}{N_{wet}} \sum_{i=1}^{N_{wet}} \sigma^0_i \qquad (6)$$

The probabilities p_{dry} and p_{wet} depend on the climatic conditions and on other properties of the land surface (e.g. soil type, vegetation, ect.). Based on global ERS scatterometer time series data covering the years 1992 – 2000, the probabilities have been estimated. Due to the different spatial resolutions, the probabilities have been interpolated to the spatial ASAR GM grid resolution.

It is not possible to retrieve soil moisture from all areas within the study area. Tropical rainforests, deserts, water bodies and areas not meeting a quality threshold are masked out. This threshold relates pixel backscatter measurements to area averaged backscatter data to characterize natural noise levels and the sensitivity to soil moisture changes [23].

4 RESULTS

A set of 2350 Envisat ASAR GM scenes has been processed and analyzed. Maps showing the surface soil moisture conditions covering the study area were generated. They can be viewed at http://www.ipf.tuwien.ac.at/radar/index.php?go=s_data3. An analysis of the model parameters sensitivity, dry reference and wet reference was carried out as a preliminarily assessment of the quality of the retrieval method. The retrieved surface soil moisture maps were compared with precipitation records. Despite the fact that the retrieval algorithm does not account for seasonal vegetation effects, spurious effects due to vegetation growth and senescence could visually not be identified.

Sensitivity of backscatter to surface soil moisture (Figure 1) is calculated as the difference between the wet and the dry reference and characterizes the dynamic range of the backscatter measurements for a certain location. It is based on Envisat ASAR GM data from December 2004 – December 2006. Areas not meeting the quality threshold are masked out and appear as white areas in the maps.

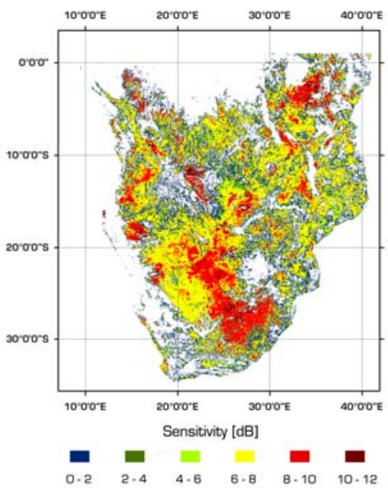

Figure 1: ENVISAT ASAR GM dynamic range in dB for Africa south of equator

Sensitivity has been analyzed for different land cover classes defined by the USGS Global land use/land cover dataset. Highest sensitivities can be observed for savanna, grassland, pastures and cropland with values of more than 6dB. Low sensitivities can be found for wetlands, mixed forest and barren ground. Evergreen broadleaf forests (rain forest) show the lowest sensitivities to temporal changes in the radar backscatter measurements.

Figure 2 shows the wet reference for the study area. The wet reference by land cover type varies between -2 – -4 dB. The variation of the dry reference (Figure 3) is much larger with values ranging between -6 and -11 dB, what has been expected based on experience with ERS scatterometer time series. The denser the vegetation cover, the higher is the backscatter during dry conditions. The highest dry reference is therefore determined for rain forest (evergreen broadleaf forest).

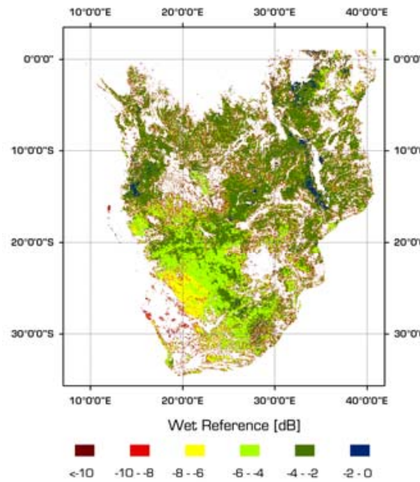

Figure 2: Wet reference in dB for Africa south of the equator

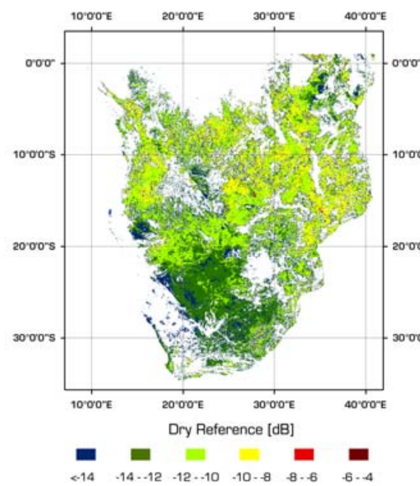

Figure 3: Dry reference in dB for Africa south of the equator

In sequences of surface soil moisture maps, which can be viewed at http://www.ipf.tuwien.ac.at/radar/index.php?go=s_data3, the influence of moving frontal systems and the impact of precipitation on the backscatter properties of the Earths surface become evident. Climatic conditions with wet and dry seasons as well as the movement of the ITC can be seen. The study area is characterized either by regions with clear

rainy and dry season patterns or by very arid regions. The latter have a very low dynamic range as soil moisture does not change over time. A high dynamic range or sensitivity is mostly caused by the seasonal patterns.
Precipitation events shortly before acquisition can be spatially captured in detail if the preceding days have been comparably dry. Figure 4 and 5 give an example for December 2004. The resulting high surface soil moisture from rainfall events on the $21^{st}/22^{nd}$ in the Eastern Cape is clearly visible. Relative soil moisture values of 50% and higher are detected.

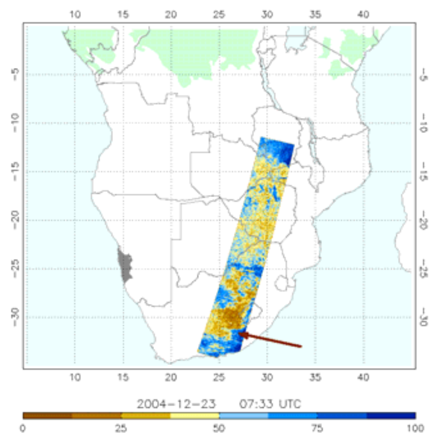

Figure 4: Relative soil moisture map from the 23rd of December 2004, arrow indicates meteorological station

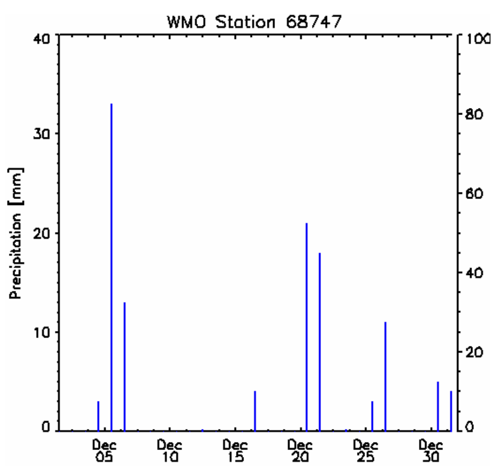

Figure 5: Precipitation record for Fort Beaufort (26.63 E, 32.78 S) December 2004

5 DISCUSSION

The presented study provides relative surface soil moisture maps based on Envisat ASAR GM time series data. First comparisons showed the potential of the ASAR GM data to monitor the surface soil moisture conditions at a spatial resolution of 1000 m over Africa south of the equator. Model parameters coincide with land cover patterns and reflect SAR theory.
A validation of the surface soil moisture maps is hampered by the non-availability of large scale in-situ soil moisture measurements in the study area. Therefore comparisons with other data like meteorological records or hydrologic models are necessary. The development of a dedicated validation scheme will be an important step forward.
Further research work will be necessary to develop quantitative methods for recognising the theoretically expected vegetation errors.
Nevertheless, this study is one example of the large potential of ScanSAR data. All-weather and all-day mapping capabilities of space borne active microwave sensors at medium temporal and spatial resolutions are a valuable tool for monitoring geophysical parameters.

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