geoland

Integrated Project geoland

GMES products & services, integrating **EO** monitoring capacities
to support the implementation of European directives and policies
related to "**land** cover and vegetation"

CSP – Algorithm Theoretical Basis Document (ATBD)

WP 8317 – Soil Moisture

CSP-0350-RP-0008-ATBDWP8317

Issue 1.00

EC Proposal Reference No. **FP-6-502871**

Book Captain: **Ralf Lindau (Uni Bonn)**
Contributing Authors:

Document Release Sheet

Book captain:	**Ralf Lindau (Uni Bonn)**		Sign	Date
Approval	**Ralf Lindau (Uni Bonn)**		Sign	Date
Endorsement:	Co-ordinator (ITD)		Sign	Date
Distribution:	CSP Task Manager CSP Partners Global Observatories Task Managers			

Change Record

Issue/Rev	*Date*	*Page(s)*	*Description of Change*	*Release*
	20.12.2004	All	Description of the algorithm used to derive soil moisture from passive microwave data.	

TABLE OF CONTENTS

List of Figures

List of Tables

1 BACKGROUND OF THE DOCUMENT

1.1 EXECUTIVE SUMMARY

This document describes the theoretical basis of a soil moisture retrieval used to generate soil moisture fields from microwave observations of AMSR-E (Advanced Microwave Scanning Radiometer – Earth Observing System). The deliverables will be global 10-daily fields of soil moisture within the uppermost meter of soil on a spatial resolution of 50 km for the years 2003 and 2004.

1.2 SCOPE AND OBJECTIVES

In this document an algorithm for the determination of root zone soil moisture from passive microwave measurements is presented. Global fields of the soil moisture within the uppermost meter of soil are derived with a temporal resolution of 10 days. For calibration, longterm soil moisture observations from the former Soviet Union are used. The variance of the measurements is largely dominated by the spatial variability of the longterm mean soil moisture, while the temporal variability gives comparatively small contribution. Consequently, the algorithm is organized into two steps. The first step concentrates on the retrieval of the spatial variance of the longterm means, which comprises more than 85% of the total soil moisture variability. A major part of the spatial variance can be explained by four easily available fields: the climatological precipitation, land use, soil texture and terrain slope. The second step of the algorithm is dedicated to the local temporal variability. This part of variability is recovered is by using passive microwave data from AMSR-E. Both 6-GHz and 10 GHz channels of AMSR are shown to be severely disturbed by Radio Frequency Interference (RFI), so that information from the 18-GHz-channel is used instead. The algorithm provides reasonable soil moisture fields, which is confirmed by a comparison with independent measurements from Illinois.

1.3 CONTENT OF THE DOCUMENT

This document is structured as following. Chapter 2 states the users' requirements. In chapter 3 the methodology of the soil moisture algorithm is described. After an overview the retrieval algorithm is discussed in four subsections. First, we present the data sets used for calibration and as input of the algorithm. Then, the variance structure of soil moisture is discussed and at last the derivation of the algorithm is delineated. First comparisons with independent soil moisture measurements are presented in chapter 3.4. Due to Radio Frequency Interference some risks of failure existed at the beginning of the project. However, these are overcome by a modification of the original algorithm.

1.4 RELATED DOCUMENTS

1.4.1 Input

Overview of former deliverables acting as inputs to this document.

Document ID	**Descriptor**
CSP-0350-RP-0005	Service Portfolio

1.4.2 Output

Overview of other deliverables for which this document is an input.

Document ID	**Descriptor**
CSP-0350-RP-0010	Test and Benchmarks report
CSP-0350-RP-0012	The input and output data sets used for tests and benchmarks
CSP-0350-COD-0000	A prototype
CSP-0350-COD-0009	A source code (breadboard or processing line)
CSP-0350-RP-0011	The processing line test report
CSP-0350-PRD-0000	CSP Product WP8317

2 REVIEW OF USERS REQUIREMENTS

The Global Observatories ONC and OFM need global soil moisture fields for the years 2003 and 2004. Temporal and spatial resolutions of 100 km and 10 days are required. As date of delivery June 2005 is agreed. The complete list of product characteristics is described in the Service Portfolio Document.

3 METHODOLOGY DESCRIPTION

3.1 OVERVIEW

Soil moisture acts as a kind of memory for the weather of the past weeks. Wet soils are able to maintain an increased evaporation over several days despite lacking precipitation. There is no doubt that soil moisture plays an important role within the complex interactions between the different components of the climate system on almost all scales (Dirmeyer et al., 1999), (Douville, 2002). The adequate treatment of soil moisture is therefore crucial for any climate modelling (Viterbo and Betts, 1999). However, area-covering measurements of soil moisture appropriate for assimilation or model validation are not available. In this respect, microwave measurements from satellite can be useful (Jackson and Schmugge, 1982), but reliable retrieval algorithms for soil moisture have been derived so far only for semi-arid regions where the disturbing signal from the vegetation remains small (Drusch et al., 2004). Further limitations for microwave satellite data are caused by their small penetration depth which allows to detect soil moisture only within the uppermost centimetres of the soil. Information from the underneath soil is only indirectly attainable (Wagner et al., 1999). However, for hydrological purposes the soil moisture within a considerably thicker layer, typically the uppermost meter of soil, is of much higher interest. Thus, supplementary data is required in addition to satellite measurements.

In this document, a pure statistical approach is suggested to derive the root zone soil moisture on the continental scale. Operational soil moisture measurements have had a long tradition in the former Soviet Union, so that long time series are available mainly from this region. We will use such observations as literal ground truth. Our aim is a statistical algorithm, which is able to explain a maximum of the observed soil moisture variability. Consequently, the first step is to analyse the variance of the observations (chapter 3.2.3). This analysis of variance will identify candidates suitable to serve as input parameters for the soil moisture estimation.

Although the soil moisture within a deeper soil layer will be retrieved, the microwave emission will contribute useful information. The most promising microwave frequency is the L-band, where the disturbance through vegetation and atmosphere remains small. Measurements from space at such low frequencies (1–2 GHz) will, however, not be available before 2006 (Kerr et al., 2001). C-band measurements have a lower potential for soil moisture detection, but they are available again through AMSR-E (Advanced Microwave Scanning Radiometer Eos) since the launch of the Aqua satellite in 2002. AMSR has closed a data gap in C-band measurements existing since the termination of the SMMR (Scanning Multichannel Microwave Radiometer) mission in 1987. The historical SMMR data is so far the only available long-term C-band time series. Moreover, it covers large parts of the existing soil moisture data sets gathered in the former Soviet Union. Therefore, SMMR data is a prominent candidate to test the capability of microwave measurements for soil moisture retrievals in general, and evaluate their use especially for deep layer soil moisture.

Unfortunately, the lowest and most suitable frequency available from SMMR (6.6 GHz) is strongly influenced by Radio Frequency Interference (RFI). This disturbing noise stems from various emitters of our technical society and is difficult to eliminate. Even for the historical SMMR it turns out that at least Europe is completely contaminated by RFI. However, the 10 GHz channel was found to be undisturbed in those times, so that we originally planned to use this channel to derive soil moisture. However, for modern AMSR data the RFI problem is expanded also to the 10-GHz channel. Therefore, only 18-GHz can be used as input data.

3.2 THE RETRIEVAL ALGORITHM

3.2.1 Calibration data

Two data sets of soil moisture are used to calibrate and evaluate the soil moisture algorithm; both are available from the Global Soil Moisture Data Bank (Robock et al, 2000). The first set stems from the former Soviet Union and is used here to derive the soil moisture algorithm. The second set consists of measurement from Illinois, USA, (Hollinger and Isard, 1994) and is used as independent data set to verify the skill of the derived algorithm (chapter 3.4). For both data sets, the location of stations is given is Fig 1.

The Russian calibration data is compiled by Vinnikov and Yeserkepova (1991) and covers a broad spectrum of climate zones ranging from the Asian subtropical deserts to the arctic tundra. The data set comprises soil moisture measurements of the uppermost meter of soil at 50 stations with natural vegetation. The original data set contains only the plant available soil moisture excluding that fraction of water corresponding to the wilting level, but Vinnikov and Yeserkepova (1991) provided also the wilting levels for each of the 50 stations. An updated version of this information available via the Global Soil Moisture Data Bank is used to reconstruct the entire amount of soil moisture content. The data set contains measurements taken each 10 days during the period 1952 to 1985. Only a few stations are reporting in the early years, however, reducing the potential data volume from about 50000 to 17748. We further restricted our calculations to the period 1979 to 1985, in which all additional supplementary data sets used later are available. 7009 observations in total at 48 stations are the basis of the algorithm.

3.2.2 Algorithm input data

In the following, the five data sets are described, which are used to explain the observed soil moisture variance in the retrieval algorithm. These are precipitation, soil texture, terrain slope, land use, and the 18-GHz brightness temperature from satellite. Precipitation is the most important input

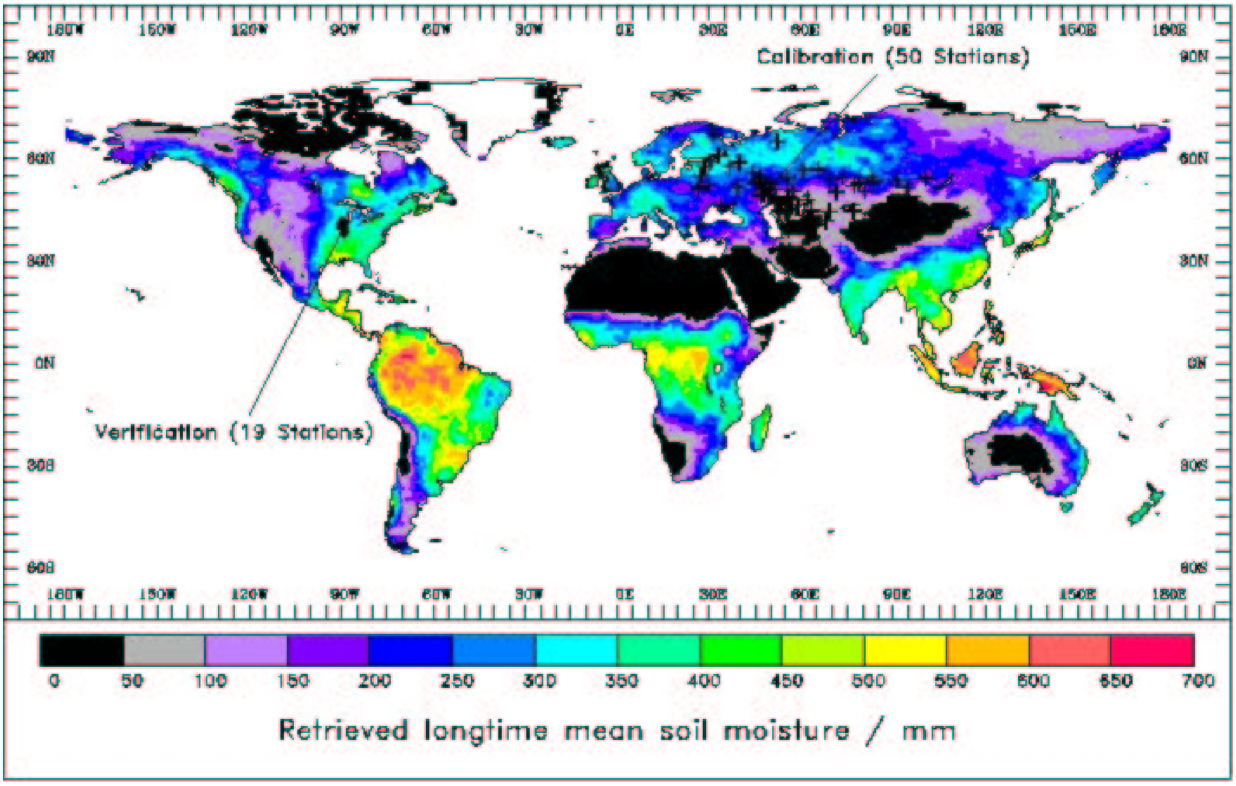


Fig. 1: *Locations of the soil moisture stations plus the retrieved longtime mean soil moisture. 50 stations in the former Soviet Union are used as calibration (large crosses); at 19 stations in Illinois (USA) the derived algorithm is tested (small crosses). The shading gives the long-time mean soil moisture as it results from a global application of the soil moisture algorithm.*

parameter for soil moisture. We use data from GPCP (Global Precipitation Climatology Project, Adler et al., 2003) providing the global distribution of monthly mean precipitation on a resolution of 2.5° in latitude and longitude. The GPCP product is a combined satellite ground-based data set covering the period from 1979 to the present.

Information about soil texture and slope is based on the Soil Map of the World, produced in twelve volumes by the Food and Agriculture Organisation (FAO, 1970-1978) between 1970 and 1978. Zobler (1986) digitised these maps into a gridded format on 1° resolution. Soil texture is given in five classes from loamy sand to clay loam, plus an additional class for organic soils. The terrain slope is given as average slope within an area of 1° by 1°, which is reconstructed from the fractional coverage of three original classes of steepness.

The land cover is another important parameter for soil moisture retrievals, which is taken from the UMD-1km-Global-Land-Cover data set (Hansen et al., 2000). It is produced by the University of Maryland and is based on measurements of AVHRR (Advanced Very High Resolution Radiometer). On a spatial resolution of 1 km, the vegetation type is given in 12 classes with decreasing vegetation density from evergreen forest to bare ground plus an additional class for urban areas.

As fifth and last input information, passive microwave data is used. The passive microwave emission from the earth's surface has been measured by SMMR from October 1978 to August 1987. We use it in EASE-grid format (Knowles, 2002) providing near-global brightness temperatures on a nominal spatial resolution of 25 km for all frequencies. The true resolution is, depending on frequency, considerably lower. At 18-GHz, an original footprint is 69 km by 43 km large.

For historical SMMR data, Radio frequency Interference was restricted to the 6-GHz channel. Although this is the most promising frequency for soil moisture, it could be replaced by information from 10 GHz in our original algorithm. However, for modern AMSR data it turns out that also the 10 GHz measurements are strongly affected by RFI. Over England and Italy even the mean brightness temperatures of this channel are considerably increased. Thus, a use of low frequency data from AMSR seems to be problematical so that the algorithm is modified. The new version uses 18 GHz measurements as input data instead of 10 GHz.

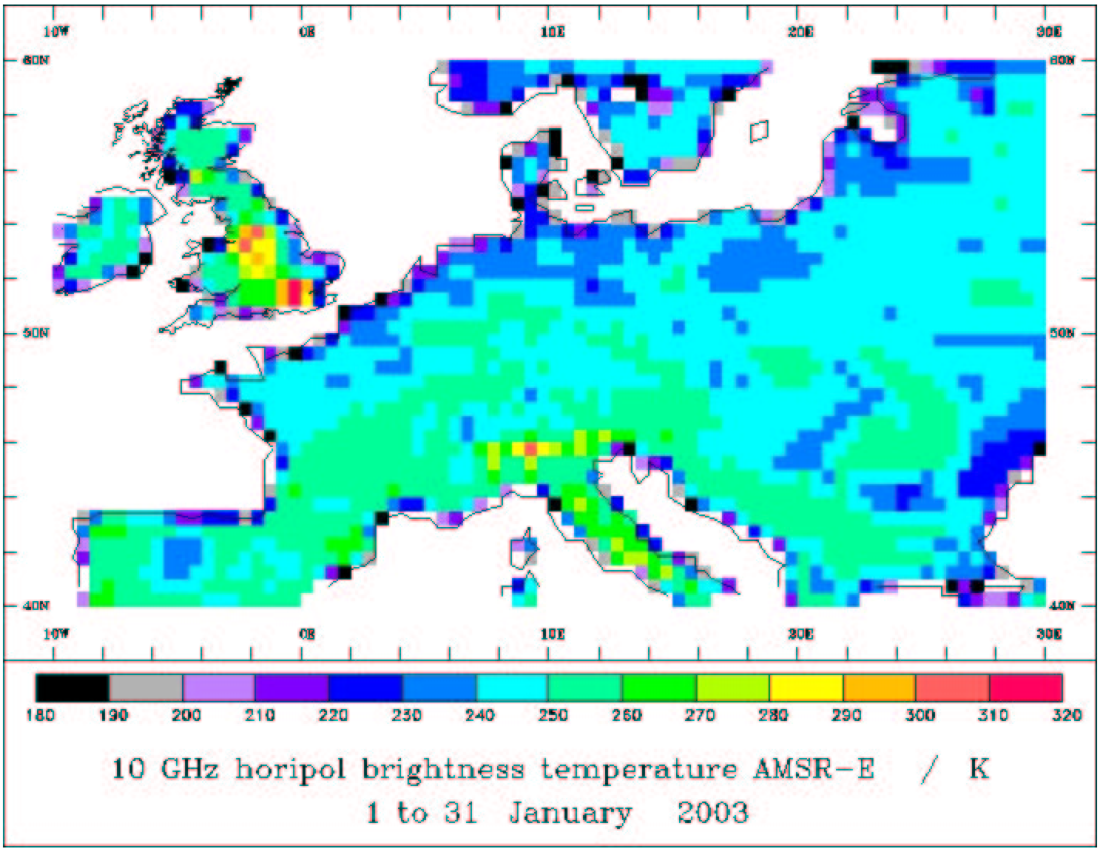


Fig. 2: *Monthly mean brightness temperature of 10 GHz horizontal polarized microwave emission over Europe for January 2003. Over England and Italy the radiation is strongly increased due Radio Frequency Interference.*

3.2.3 Analysis of soil moisture variance

The Russian soil moisture data set compiled by Vinnikov and Yeserkepova (1991) serves as calibration for the retrieval algorithm. First, the soil moisture variance of this data set is analysed according to the technique suggested by Lindau (2003). The underlying idea is that the total variance of a sample can be decomposed into an external and an internal part. The separation is performed by subdividing the complete sample into several sub-samples. The variance of sub-sample means constitutes the external variance. The remaining internal variance of the whole data set is equal to the weighted mean variance of the sub-samples. By performing three different kinds of sub-division, the spatial variance of the long-term means, the variance of the mean annual cycle and the interannual variability are separated.

In addition, the effects of sampling errors have to be taken into account. For the decomposition into internal and external variance, averages are computed, which are of course not free of error due to the limited sample size. E.g., the external variance is overestimated due to errors when estimating the sub-sample means. Assuming random errors, this additional error variance is easy to determine since it depends only on the internal variance and on the number of observations. This error component can then be subtracted from the seeming external variance yielding an estimate for the true external variance. A forth and last component of the variance accounts for the errors of the total mean. However, this component remains small as several thousands of independent observations are considered. In summary, the total variance is decomposed into four components: Error of the total mean (1a), seeming external variance (1b), mean error of external means (1c), and internal variance (1d):

$$\frac{1}{m-1}\sum_{k=1}^{N}\sum_{i=1}^{n_k}\left(x_{ki}-\bar{x}\right)^2 = \frac{1}{m\left(m-1\right)}\sum_{k=1}^{N}\sum_{i=1}^{n_k}\left(x_{ki}-\bar{x}\right)^2 \tag{1a}$$

$$+ \frac{1}{m}\sum_{k=1}^{N} n_k\left(\bar{x}_k-\bar{x}\right)^2 \tag{1b}$$

$$- \frac{1}{m}\sum_{k=1}^{N}\frac{n_k}{n_k\left(n_k-1\right)}\sum_{i=1}^{n_k}\left(x_{ki}-\bar{x}_k\right)^2 \tag{1c}$$

$$+ \frac{1}{m}\sum_{k=1}^{N}\frac{n_k}{n_k-1}\sum_{i=1}^{n_k}\left(x_{ki}-\bar{x}_k\right)^2 \tag{1d}$$

where m is the total number of observations and $\bar{x}=\frac{1}{m}\sum x_{ki}=\frac{1}{N\,n_k}\sum_{k=1}^{N}\sum_{i=1}^{n_k}x_{ki}$ the total mean. x_{ki} denotes the i-th individual value in the k-th subsample. N is the number of subsamples and n_k the number of observations in the k-th subsample.

The subdivision of the entire data set is performed in three different ways. Firstly, all measurements of a station constitute one sub-sample resulting in 48 long-term means, one for each station. In this case, the external variance describes the spatial variance of the long-term mean soil moisture. Secondly, one sub-sample contains all measurements for one specific 10-day period of the year. The sub-sample mean is now the spatial average soil moisture for a particular 10-day period of the year averaged over all 8 years. In this case, the external variance comprises the mean annual cycle of soil moisture. In the third kind of subdivision all measurements of one individual year are grouped together, regardless of location and season, thus the mean interannual variability is obtained.

The entire data set (7009 observations) has a total mean of 179 mm water within the uppermost meter of soil. The total variance is 10682 mm^2, corresponding to a standard deviation of about 103 mm. The variance is now decomposed following the procedure outlined above (Tab.1). The first row of Tab. 1 gives the number of sub-samples. In the following four rows the magnitudes of the above defined variance components (eq.1) are shown. The true external variance is concluded by subtracting term (1c) (the error of external means) from term (1b) (the seeming external variance), which is then expressed in absolute values and relative to the total variance.

The relative external variance attains more than 85% when it is defined as variance between long-term means at each station, showing the strong dominance of spatial variability. The annual cycle contains only 3% of the total variance and the interannual variability is another order of magnitude smaller. This means that the knowledge of the long-term mean soil moisture at each station is crucial for the capture of soil moisture variability in general. Thus, aiming at a soil moisture algorithm, the first and most important step is to explain this temporally constant variance. Therefore, we will first concentrate on the retrieval of the long-time mean soil moisture. For this purpose, temporally constant fields of global climatogical means are of prime importance. The temporal variance will be included in a second step, when the major part of the variance is already explained.

Table 1: Decomposition of the observed soil moisture variance in mm^2 into the four components given in Eq.(1). The true external variance is obtained by subtracting the error variance of external means from the seeming external variance. The procedure is applied three times to retrieve the variance contributions by the annual cycle, the interstation variability and the interannual variability.

	Interstation	Annual Cycle	Interannual
Number of sub-samples	48	36	8
Error of the total mean in mm^2	2	2	2
Seeming external variance in mm^2	9133	388	39
Error variance of external means in mm^2	10	51	12
Internal variance in mm^2	1558	10343	10654
True external variance in mm^2	9123	338	26
Relative external variance in %	85.40	3.16	0.25

3.2.4 Derivation of the algorithm

We first tested several data sets concerning their spatial correlation with the long-time mean soil moisture distribution given by the 48 stations in the former Soviet Union. As expected, a high correlation (correlation coefficient 0.766) is found with the long-time mean precipitation field of GPCP. A linear regression estimate explains accordingly 58.6% of the long-term spatial soil moisture variance.

In the following, only the unexplained part of soil moisture variability is considered and the capability of further data sets is tested to explain this remaining variance fraction. Three additional data sets are successively included in a multiple linear regression estimation (table.2). The inclusion of soil texture information increases the explained variance by more than 10%, despite soil texture itself shows almost no correlation with soil moisture. On the contrary, the temporal mean vegetation density explains 37.7% of the temporal mean soil moisture variance, but adds only 3.8% due to the correlation of vegetation density with mean precipitation and soil texture. After the inclusion of four data sets, no significant improvement could be obtained by adding further information. We end up with the following linear regression estimation:

Tab.2: The explained variance (in percent) of the climatological 1m soil moisture for each of the four parameters used in Eq.(2). In the first column the performance of the parameters are considered separately, the second shows the successive increase of explained variance as actually obtained by the algorithm.

	Separate	cumulative
Climatological rain	58.6	58.6
Soil texture	0.5	69.0
Vegetation density	37.7	72.8
Terrain slope	2.8	73.0

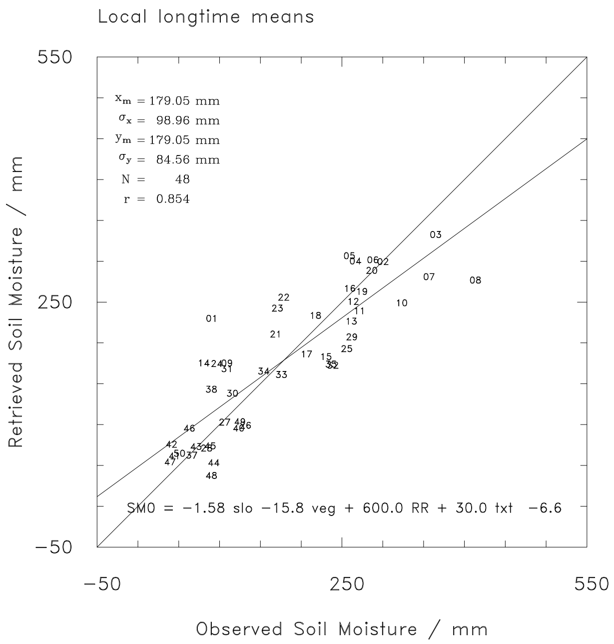
$$SM_0 = 600\ R - 1.56\ S + 30.0\ T - 15.8\ V - 6.6 \qquad (2)$$

where SM_0 denotes the local climatological mean soil moisture within the uppermost meter in mm. The right-hand side variables denote the long-term mean annual precipitation index R (see Eq.3), the terrain slope S, the soil texture T and the vegetation class V, respectively. The slope S is expressed in %, as given in the FAO raw data. Also the original soil texture classes T, spanning from 1 for coarse soils over 5 for fine textures to 7 for organic soils, are directly adopted, as well as the vegetation density classification of UMD data reaching from 1 for tropical rain forest to 12 for bare ground. Only the values for precipitation are pre-processed before being used in Eq. (2). The idea is that the storage capacity of a 1 meter soil layer is of course limited, while precipitation may ascend to arbitrary high values without increasing soil moisture further. Thus, we use a precipitation index based on an exponential function damping the nominal increase for extreme wet climates:

$$R = 1 - e^{-p/p0} \tag{3}$$

with p denoting the actual mean annual precipitation and p_0 being a constant of 1000 mm/a.

The coefficients in (2) indicate that a decrease of the vegetation class will increase the mean soil moisture SM_0. This is plausible since low classes denote dense vegetation. A two classes denser vegetation (e.g. from Open Scrubland to Wooded Grassland) have the same effect as a one class finer soil texture (from: sandy loam to loam): Both increase the estimated soil moisture by about 30 mm, corresponding to 0.3 standard deviations of the Russian soil moisture data used as calibration. For the same increase in soil moisture the terrain slope has to be levelled from 20% to 0% or the normalized precipitation R has to be increased by 0.2, which corresponds to an intensification of mean rainfall from e.g. 500 mm/a to 900 mm/a.



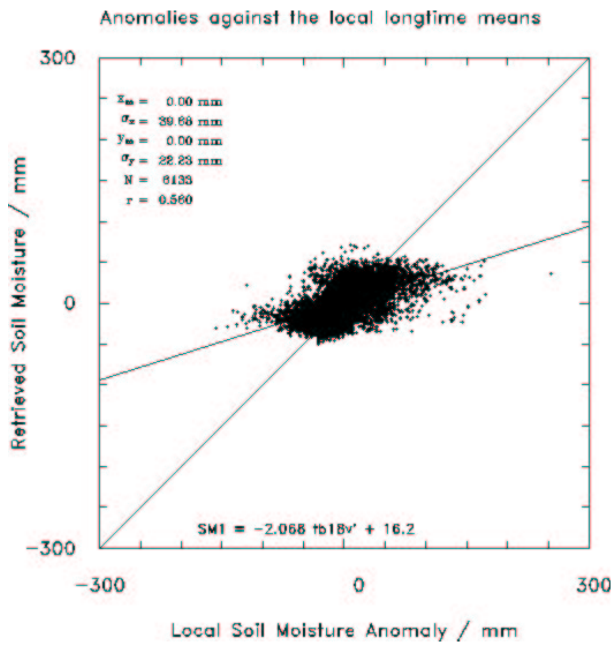


Fig.2: *Local long-time mean 1m soil moisture as observed at 48 Russian stations (the station number are plotted) compared to the theoretical value SM_0 as retrieved by the first part of the algorithm given in (2).*

Fig.3: *Local soil moisture anomaly against the longtime mean at each station compared to the theoretical value SM1 as retrieved by the second part of the retrieval, given in (4), which explains the remaining temporal part of the variance.*

With (2), we are able to estimate the long-term mean soil moisture from four easily available fields with a linear correlation coefficient of 0.854 for the dependent data set (Fig.2). A global application of this algorithm yields reasonable results as shown in figure 1.

Although the major part of the total variance is explained by (2), SM_0 can only provide temporally constant soil moisture at each station. By the second step the temporal variability is added. We use the 18 GHz brightness temperature from satellite to estimate the temporal variance at each station:

$$SM_1 = - 2.068 \text{ tb18v} + 16.2 \tag{4}$$

where tb18v denotes the anomaly of vertical polarized brightness temperature against the long-time local mean averaged over the last 2 months in K. The averaging period for the brightness temperature is in good agreement with the time-constants found for soil moisture. Using Belarusian observations, Lindau et al. (2002) determined the temporal correlation length of soil moisture to about 60 days. The averaging period used in (4) is not prescribed, but resulted empirically as the optimal settings from different test runs.

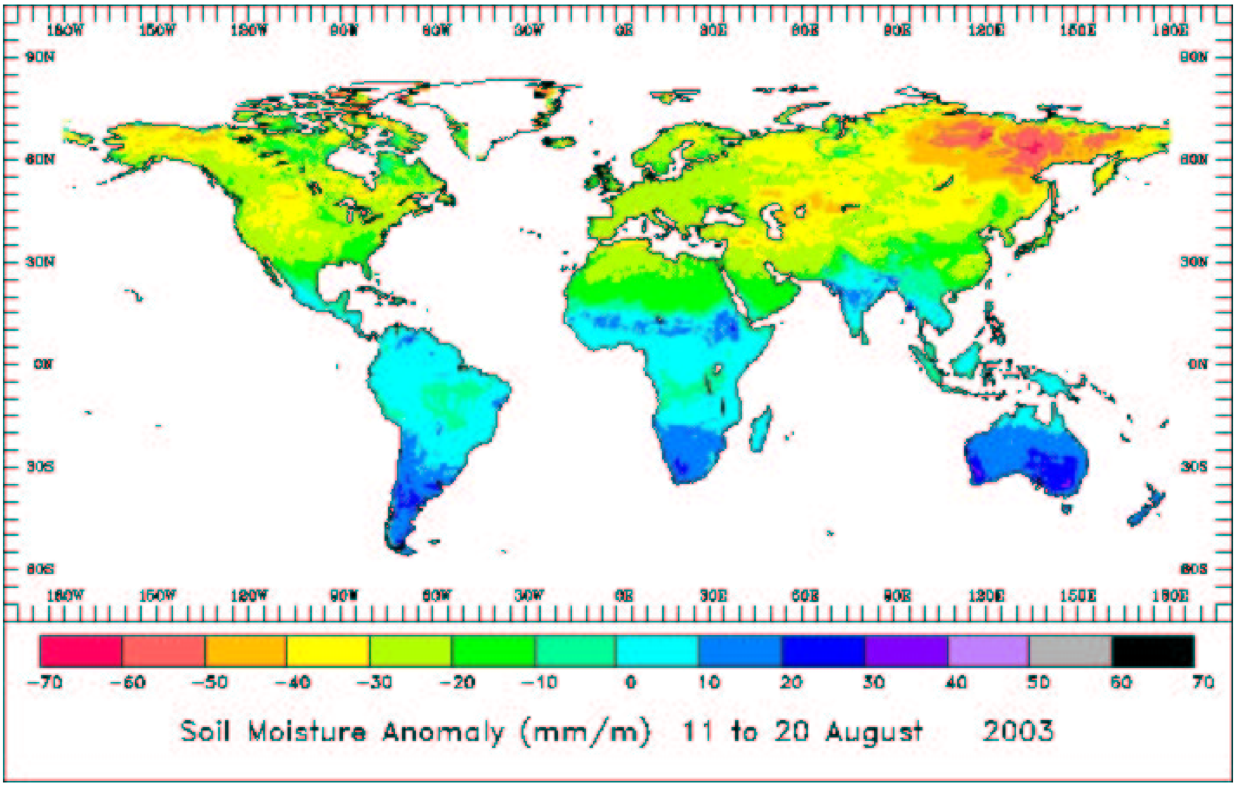


Fig.4: *Soil moisture anomaly for the ten day period in mid August 2003 as retrieved by (4) . For the total soil moisture at each location the longterm mean given in figure 1 has to be added*

By application of (4), a correlation of 0.560 is attained for the temporal anomalies at each station (Fig. 3), which seems to be weak at a first glance. But we have to keep in mind that only the remaining part of the variance (about 15% of the total variance) is considered here, which includes also nearly the complete error variance of the soil moisture observations themselves. Hence, it is far more difficult to explain a larger part of this variability.

By combining (2) and (4), soil moisture can be derived with a correlation of 0.786. About three quarters of the spatial variance is explained in this way, as it is treated explicitly in (2) (see Fig. 2). For the temporal variance the circumstances are more difficult since observation errors, annual cycle and interannual variability are lumped together. To asses the performance of the algorithm in this respect, we computed the mean monthly soil moisture for the entire region and compared these 12 values to the observations. The mean annual cycle is reproduced with an excellent correlation of 0.979. An analogous procedure provides for the inter-annual variability a value of 0.525.

Figure 4 shows an exemplary map for the soil moisture retrieval. For the period August 11 to 20, 2003, the soil moisture anomaly is given as retrieved by the second part of the algorithm (Eq.4). For the absolute soil moisture the long-term mean has to be added (Fig.1).

3.3 THE PRODUCT QUALITY

Errors of individual soil moisture estimates as retrieved by the presented algorithm are easily assessable by considering that part of the variance, which is unexplained by the algorithm. The total variance of the calibration data set is 10682 mm^2. The retrieved soil moisture shows a correlation of 0.786. Thus, about 38% of the variance is unexplained by the algorithm. The corresponding error variance for individual soil moisture estimates, representing a 10 day and a 50 by 50 km mean, is therefore: 0.38 10682 mm^2 = 4059 mm^2. In terms of standard deviation the error is 63.7 mm. However, if several of such individual soil moisture estimates are averaged in time or space, the resulting error will be reduced.

3.4 THE VALIDATION PROCEDURE

In order to assess the algorithm's quality, it has to be applied to independent data. Spread over Illinois, 19 soil moisture stations operate since several decades. We extracted measurements from the period 1979 to 1999 and computed the long-time mean soil moisture in the uppermost meter at each station. Such temporal averages are then alternatively derived with our proposed retrieval algorithm by using globally available information of the four climatological parameters needed in (2). An excellent agreement between algorithm and measurement is found. The measured total mean of 330 mm is reproduced with a deviation of only 4 mm (Fig.5). The accomplished quality control is quite an acid test since the algorithm is transferred to another continent and into a climate region with soil moistures much higher than those prevailing in the former Soviet Union where the algorithm has been derived.

At first glance, however, the correlation between measurements and retrieval appears rather low (0.235). The explanation becomes obvious when we compare the error variance of the algorithm with the variability covered by the Illinois measurements. The error variance of long-term means of the algorithm appears as unexplained variance in Fig. 2, according to:

$$\sigma_e = \sigma \sqrt{1-r^2} \tag{5}$$

The error σ_e amounts to about 51 mm which is even larger than the standard deviation of the Illinois data set (46 mm, Fig.5). Thus, on a continental scale all 19 stations in Illinois are located in immediate mutual proximity, and represent effectively only a single site. Hence, the detected low correlation is a pure corollary of the limited spatial coverage of the Illinois data. However, the good agreement between the predicted and the observed total means lends some prove to the skill of our algorithm.

In the next future, we plan to perform an intercomparison with the soil moisture product from active microwaves provided by IPF.

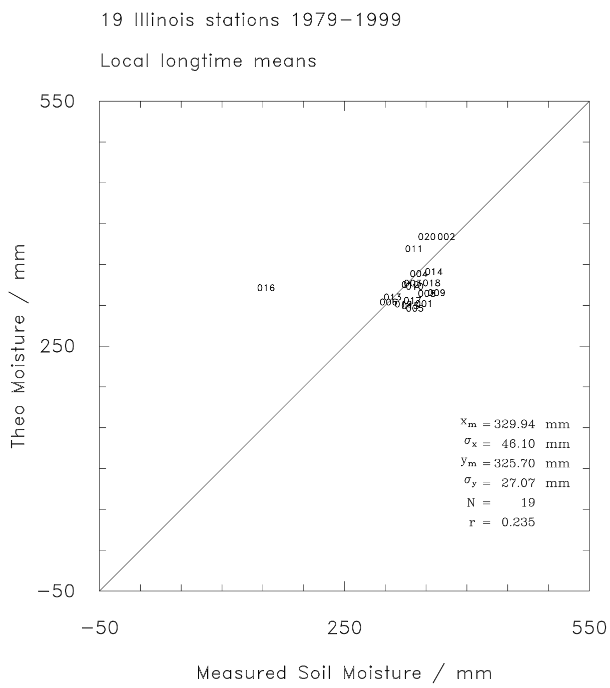


Fig.5: *Independent comparison between the measured longtime mean soil moisture from 19 stations in Illinois (station numbers are plotted) and the theoretically derived value.*

3.5 RISK OF FAILURE

The major risk of failure is already identified and eliminated. Radio Frequency Interference has increased considerably during the last years. The quality of microwave measurements from satellite suffers more and more from this perturbation source. Not only 6 GHz, but also the 10 GHz channel is severely disturbed in the modern microwave measurement from AMSR.

Consequently, we modified our original algorithm. As input data, microwave measurements from the 18 GHz channel are used instead of the lower frequencies. First results for the year 2003 are showing reasonable patterns in global soil moisture distribution, which indicates that the modification of the retrieval algorithm has overcome the RFI problematic.

3.6 LINKS TO OTHER GEOLAND ACTIVITIES

To be added in the next versions of the ATBD.

3.7 REFERENCES

Adler RF, Huffman GJ, Chang A, Ferraro R, Xie PP, Janowiak J, Rudolf B, Schneider U, Curtis S, Bolvin D, Gruber A, Susskind J, Arkin P, Nelkin E, 2003: The version-2 global precipitation climatology project (GPCP) monthly precipitation analysis (1979-present), *Journal of Hydrometeorology*, **4** (6), 1147-1167

DeFries, R.S., Hansen, M., Townshend, J.R.G., and Sohlberg, R., 1998, Global land cover classifications at 8km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers, *International Journal of Remote Sensing*, **19** (16), 3141-3168.

Dirmeyer, P.A., A.J. Dolman, and N. Sato, 1999: The Global Wetness Project: A pilot project for global land surface modelling and validation. *Bull. Amer. Meteor. Soc.*, **80**, 851-878.

Douville, H., 2002: Influence of soil moisture on the Asian and African monsoon. Part II: Interannual variability. *J. Climate,* **15**, 701-720.

Drusch M., Wood E.F., Gao H., Thiele A., 2004: Soil moisture retrieval during the Southern Great Plains Hydrology Experiment 1999: A comparison between experimental remote sensing data and operational products. *Water Resources Research* **40** (2) W02504.

Food and Agriculture Organization (FAO) of the United Nations, 1970-78, *Soil map of the world*, scale 1:5,000,000, volumes I- X: United Nations Educational, Scientific, and Cultural Organization, Paris.

Hansen, M.C., DeFries, R.S., Townshend, J.R.G., and Sohlberg, R., 2000: Global land cover classification at 1km spatial resolution using a classification tree approach, *International Journal of Remote Sensing* **21** (6-7), 1331-1364.

Hollinger S.E., Isard S.A., 1994: A Soil-moisture climatology of Illinois, *Journal of Climate* **7** (5), 822-833.

Jackson, T.J., T.J. Schmugge, and J.R. Wang, 1982: Passive microwave remote sensing of soil moisture under vegetation canopies. *Water Resour. Res.*, **18**, 1137-1142.

Kerr, Y.H., P. Waldteufel, P., J.-P. Wigneron, J.-M. Martinuzzi, J. Font, and M.Berger, 2001: Soil moisture retrieval from space: The Soil Moisture and Ocean Salinity (SMOS) mission. *IEEE Trans. Geosci. Remote Sens.*, **39**, 29-35.

Knowles, K., E. Njoku, R. Armstrong, and M.J. Brodzik. 2002: *Nimbus-7 SMMR Pathfinder daily EASE-Grid brightness temperatures*. Boulder, CO: National Snow and Ice Data Center.

Lindau R., 2003: Errors of Atlantic Air-Sea Fluxes Derived from Ship Observations. Journal of Climate, **16** (4), 783-788.

Lindau, R., C. Simmer, and T. Mikhnevich, 2002: Soil Moisture Detection from Satellite BALTEX Newsletter **4**, 11-13.

Robock A, Vinnikov KY, Srinivasan G, Entin J.K., Hollinger, S.E., Speranskaya N.A., Liu, S., and Namkhai, A., 2000: The Global Soil Moisture Data Bank. *Bulletin of the American Met. Soc.* **81** (6): 1281-1299.

Vinnikov, K. Ya. & I. B. Yeserkepova, Soil moisture: empirical data and model results*. J. Climate*, **4**, pp. 66-79, 1991.

Viterbo P. and. A. K. Betts, 1999: Impact of the ECMWF reanalysis soil water on forecasts on the July 1993 Mississippi flood. Journal of Geophysical Research 104 (D16): 19361-19366.

Wagner, W., Lemoine G., and Rott H., 1999: A method for estimating soil moisture from ERS scatterometer and soil data. *Remote Sensing of Environment* **70**, (2), 191-207.

Zobler, L. 1986. *A world soil file for global climate modeling*. NASA TM-87802. National Aeronautics and Space Administration. Washington, D.C.

4 PSEUDO-CODE

Only the derived soil moisture fields will be provided.