Soil moisture from operational meteorological satellites

Wolfgang Wagner · Vahid Naeimi · Klaus Scipal · Richard de Jeu · José Martínez-Fernández

Abstract In recent years, unforeseen advances in monitoring soil moisture from operational satellite platforms have been made, mainly due to improved geophysical retrieval methods. In this study, four recently published soil-moisture datasets are compared with in-situ observations from the REMEDHUS monitoring network located in the semi-arid part of the Duero basin in Spain. The remotely sensed soil-moisture products are retrieved from (1) the Advanced Microwave Scanning Radiometer (AMSR-E), which is a passive microwave sensor on-board NASA's Aqua satellite, (2) European Remote Sensing satellite (ERS) scatterometer, which is an active microwave sensor on-board the two ERS satellites and (3) visible and thermal images from the METEOSAT satellite. Statistical analysis indicates that three satellite datasets contribute effectively to the monitoring of trends in surface soil-moisture conditions, but not to the estimation of absolute soil-moisture values. These sensors, or rather their successors, will be flown on operational meteorological satellites in the near future. With further improvements in processing techniques, operational meteorological satellites will increasingly deliver high-quality soil-moisture data. This may be of particular interest for hydrogeological studies that investigate long-term processes such as groundwater recharge.

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Résumé Ces dernières années des avancées inespérées ont été faites dans l'étude de l'humidité du sol à partir de plateformes satellites opérationnelles, principalement grâce à des méthodes de géophysique avancées. Dans cette étude, quatre séries de données récemment publiées sur l'humidité du sol sont comparées avec des observations in-situ issues du réseau d'observation REMEDHUS situé dans la partie semi-aride du bassin de Duero en Espagne. Les données d'humidité du sol issues de la télédétection proviennent (1) d'un radiomètre micro-ondes (AMSR-E), qui est un détecteur de micro-ondes passives embarqué à bord du satellite Aqua de la NASA, (2) du scatteromètre des satellites européens de télédétection (ERS), qui est un détecteur de micro-ondes actives embarqué sur les deux satellites ERS, et (3) des images dans le visible et le thermique enregistrées par le satellite METEOSAT. Une analyse statistique montre que trois séries de données satellites contribuent à l'observation de tendances pour les conditions d'humidité du sol en surface, mais ne permettent pas d'estimer des valeurs absolues d'humidité du sol. Ces détecteurs, ou plutôt leurs successeurs, seront à l'avenir embarqués sur des satellites météorologiques opérationnels. Ces derniers, grâce à des améliorations supplémentaires des techniques de traitement des données, fourniront davantage de données de haute qualité sur l'humidité du sol. Ceci peut être particulièrement intéressant dans le cas d'études hydrogéologiques demandant l'étude de processus à long terme comme la recharge des eaux souterraines.

Resumen En años recientes se han hecho avances imprevistos en el monitoreo de la humedad del suelo a partir de plataformas operacionales de satélite, principalmente debido al mejoramiento de métodos de recuperación geofísica. En este estudio se comparan tres grupos de datos de humedad del suelo recientemente publicados con observaciones in-situ de la red de monitoreo REMEDHUS que se localiza en la parte semi-árida de la cuenca Duero en España. Los productos de sensores remotos sobre humedad del suelo se recuperan de (1) Radiómetro Avanzado de Exploración con Microondas (AMSR-E) el cual es un sensor pasivo de microondas a bordo del satélite Aqua de NASA, (2) dispersómetro de

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satélite de Sensores Remotos Europeo (ERS) el cual es un sensor activo de microondas a bordo de los dos satélites ERS, y (3) imágenes visibles y termales del satélite METEOSAT. Los análisis estadísticos indican que los tres grupos de datos de satélite contribuyen efectivamente al monitoreo de tendencias en las condiciones superficiales de humedad del suelo, pero no en la estimación de valores absolutos de humedad del suelo. Estos sensores, o más bien sus sucesores, volarán en satélites meteorológicos operacionales en el futuro cercano. Con un mejoramiento posterior de las técnicas de procesamiento los satélites meteorológicos operacionales continuarán distribuyendo datos de humedad del suelo de alta calidad. Esto puede ser de particular interés para estudios hidrogeológicos que investigan procesos a largo plazo tal como recarga de agua subterránea.

Keywords Remote sensing · Soil moisture · Unsaturated zone · Scale effects · Satellites

Introduction

The retrieval of soil moisture from satellite data is a challenging problem due to the confounding influences of other surface variables such as vegetation or surface roughness, and the complex structure of the Earth's surface (Jackson 2002). For a successful retrieval of soil moisture, one ideally employs remote sensing techniques that exhibit a high sensitivity to soil moisture while minimising instrument noise and the perturbing impacts of other surface variables on the measured signal. Also important is the choice of the retrieval algorithms that must describe the physical measurement process with sufficient detail, yet be simple enough in order to allow a robust inversion of the satellite measurements.

The optimum design for a soil-moisture sensor has been the subject of many remote sensing studies in the 1980s and 1990s. These studies indicated that low-frequency microwave radiometers should offer the best performance (Jackson et al. 1999). As a result, recent proposals for dedicated soil-moisture missions have chiefly relied on passive microwave techniques in the frequency band from 1 to 2 GHz (L-band). The first approved mission is the Soil Moisture and Ocean Salinity (SMOS) satellite, which is scheduled for launch in 2007 (Kerr et al. 2001). SMOS has a spatial resolution of about 40 km and a revisit time of about 2 days. The second soil-moisture satellite was foreseen to be the Hydrosphere State (Hydros) mission (Entekhabi et al. 2004). Unfortunately, this mission was recently cancelled due to a change in US space policy.

Besides these innovations in satellite technology, a less-visible revolution has taken place in algorithmic research. This revolution became possible thanks to the increasing availability of computer power, disk space, and powerful programming languages at affordable costs. This has allowed more students and researchers to develop and test algorithms on regional to global scales than in the past. This has lead to a greater diversity of methods and consequently more successful algorithms.

In line with the above-described developments, several global and continental-scale soil-moisture datasets have recently been published and shared openly with the international community (e.g. Njoku et al. 2003; Wagner et al. 2003). Because the product characteristics vary, depending on the satellite technique and retrieval approach, it is difficult for users to judge the fitness of use of the various datasets for their applications. Without going into the details of sensor specifications and algorithms, a first impression of the information content of different soil-moisture products can be obtained by comparing them to in-situ soil-moisture observations and against each other. In this study, four published remotely sensed soil-moisture datasets of coarse spatial resolution (5–56 km) are compared to in-situ observations over a test site in Spain. All selected sensor types are or will in the near future be operated on-board operational meteorological satellite platforms. Therefore, the long-term availability of these data is guaranteed, which is of high importance for hydrogeology and many other applications.

Datasets

An important criterion for the selection of the satellite datasets and the test site was that at least 3 years of data be available to analyse multi-annual soil-moisture variations. Additionally, it was required that several in-situ stations be located within the satellite footprint, in order to be able to compute area-representative soil-moisture values. Unfortunately, worldwide, there are only a few in-situ networks that satisfy these two criteria. To our knowledge, the only European site which complies with these criteria is the REHMEDUS network in Spain where the University of Salamanca has collected bi-weekly data from 23 stations since 1999. With respect to the satellite observations, it was additionally required that the retrieved soil-moisture data be available at continental to global scales. This implies that no specific tuning of the algorithm took place to achieve a best fit to the specific test site conditions. The following satellite datasets were compiled for this study: (1) two soil-moisture datasets derived from the Advanced Microwave Scanning Radiometer (AMSR-E) on-board NASA's Aqua satellite (its successor, the Conical Microwave Imager/Sounder (CMIS) will be flown on the National Polar-orbiting Operational Environment Satellite System (NPOESS) operated by NOAA); (2) one soil-moisture dataset derived from the scatterometer on-board of the European Remote Sensing Satellites ERS-1 and ERS-2 (its successor, the Advanced Scatterometer, (ASCAT) will be flown on the Meteorological Operational (METOP) satellites operated by EUMETSAT); (3) one dataset derived from METEOSAT geostationary satellite imagery and precipitation data using an Energy and Water Balance Monitoring System (EWBMS). The first three datasets are available globally, the latter for Europe, Africa and parts of Asia. An overview of important character-

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Table 1 Specifications of the five soil-moisture datasets used in this study

	TDR (in-situ)	ERS-SCAT (TU Wien)	AMSR-E (NSIDC)	AMSR-E (VUA-NASA)	METEOSAT (EARS)
Available observation period	June 99–Dec. 05	June 99–Dec. 05[a]	Feb. 03–Dec. 05	Feb. 03–Dec. 05	June 99–July 04
Frequency bands	–	5.6 GHz	10.7 GHz	6.9 and 36.5 GHz	Visible and infrared
Spatial resolution	Mean of 20 stations[b]	50 km	56 km	56 km	5 km
Temporal interval (days)	14	2–8 (irregular)	~1	~1	10
Observation time	9 am–3 pm[c]	10:30 am and 10:30 pm[d]	1:30 am and 1:30 pm[d]	1:30 am and 1:30 pm[d]	Irregular within last 10 days[e]
Soil layer (cm)	2–8	0–2	0–1	0–2	Surface

[a] No data between Jan. 2001 and Aug. 2003

[b] Mean value of point-like in-situ measurements from 20 stations distributed over an area of about 1285 km^2

[c] TDR readings are spread out over 1 day

[d] Equatorial crossing times of ascending and descending satellite pass

[e] Depending on cloud coverage

istics of these soil-moisture datasets is given in Table 1. A short description of the each dataset is provided in the following sections.

In-situ soil moisture

The REMEDHUS network covers an area of about 1,285 km^2 and is located in the central sector of the Duero basin in Spain (Fig. 1). The climate is semi-arid continental Mediterranean, with a mean annual rainfall of 385 mm, a mean temperature of 12°C, and an annual potential evapotranspiration of 908 mm. The most abundant soils are Luvisols and Cambisols (FAO classification), with a predominantly sandy texture (mean sand content, 71%), especially at the surface horizons. Occasionally, there are clayey horizons at the bottom of the profiles. The organic matter content is very low (mean, 0.9%). Throughout almost all the territory, the soil is used for agricultural purposes, rain-fed crops being the norm (80% cereals).

In the spring of 1999, a network of 23 soil-moisture measuring stations was set up in the area (Ceballos et al.

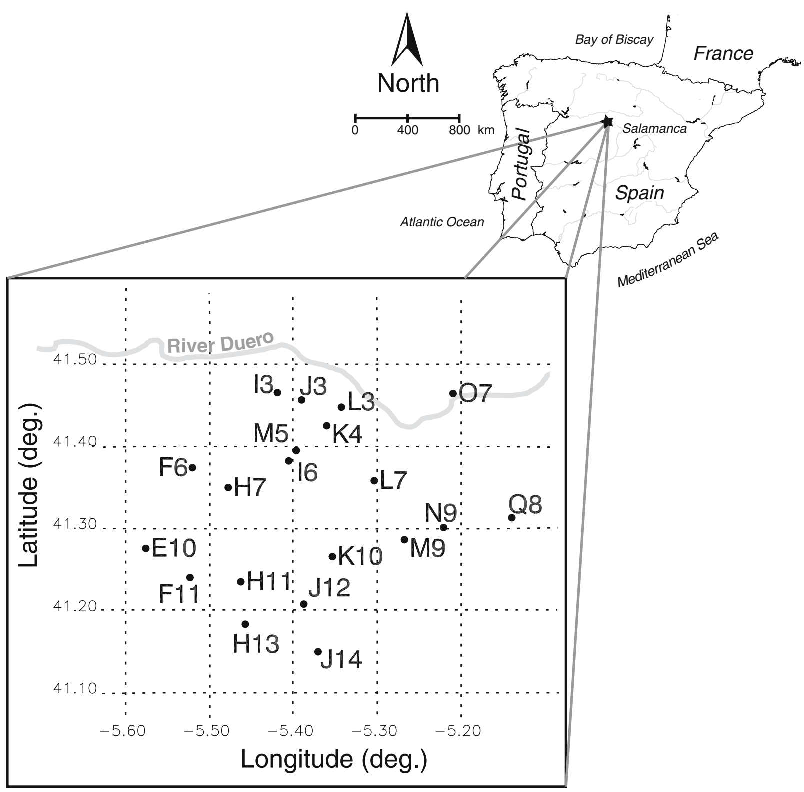

Fig. 1 Map of REMEDHUS soil-moisture station network in Spain operated by the University of Salamanca

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2002). The distribution of the stations was irregular and was based on the distribution of the main physiographic and pedological units of the area. With the exception of three stations located at the bottoms of valleys used for grazing, all the rest were located in areas used for non-irrigated crops (cereals and grape vines). In this study, because the land is used chiefly for agriculture, only the 20 stations from the agricultural sites were used. Each station is equipped with two-wire Time Domain Reflectometry (TDR) probes measuring 265 mm in length, installed horizontally at depths of 5, 25, 50 and 100 cm. In this study, the only probes that were used were those installed at 5 cm depth, which represents approximately the 2–8 cm soil-moisture layer. Measurements were taken fortnightly at each of the stations. All stations can be considered to be hydrologically independent even though they are all included within the same climatic context.

For TDR soil-moisture measurements, a Tektronix 1502C was used as a waveform generator. The waveforms were analysed visually in the field, following the method described by Cassel et al. (1994), and soil moisture was obtained using the formula proposed by Topp et al. (1980). Prior to this, the method was calibrated at the laboratory by measurements in monoliths of the main soil types present in the study area. The gravimetric and TDR methods were used to test the applicability of the formula, as suggested by Zegelin et al. (1992).

A previous study by Martínez-Fernández and Ceballos (2003) has demonstrated that the REMEDHUS network is characterised by a high temporal stability. According to the methodology proposed by Vauchaud et al. (1985), it is possible to identify points that systematically over- or under-estimate the mean soil-moisture value. In general, in REMEDHUS, the stations maintain their status, regardless of the periods, even though, from the pluviometric point of view, these periods are different (Fig. 2). The groupings of stations characterising the dry and wet locations are always identical. The stations showing the most marked temporal instability maintained this characteristic, regardless of the period considered.

AMSR-E soil moisture

The Advanced Microwave Scanning Radiometer (AMSR-E) instrument provides global passive microwave measurements at 6.9 GHz (C-band), 10.7 GHz (X-band) and four higher frequency bands including the 36.5 GHz (Ka-band) observations during ascending (1:30 pm) and descending (1:30 am) satellite passes. The spatial resolution of the measurements is 56 km at C-band, 38 km at X-band, and 12 km at Ka-band. The instrument measures the microwave radiation emitted by the Earth's surface in vertical and horizontal polarisation, expressed in terms of brightness temperature. Microwave radiometer measurements are sensitive to soil moisture because soil moisture strongly influences the emissivity of a soil.

Brightness temperature measurements of land surfaces, as made by spaceborne microwave radiometers, are most often described with radiative transfer models (e.g. Mo et al. 1982). These models express the observed brightness temperature as a function of soil moisture and a set of atmospheric, soil and vegetation variables, including the thermodynamic temperature of the soil and the vegetation canopy, the single scattering albedo and transmissivity of the canopy, and the atmospheric opacity. Some of these variables are estimated with physically based models while others are just defined as fixed input parameters. For example, the canopy transmissivity is described as a function of the vegetation optical depth, which in turn is often related to the vegetation water content.

In this paper, two techniques that use AMSR-E microwave observations to retrieve soil moisture are analysed: (1) the soil-moisture product published by the National Snow and Ice Data Centre (NSIDC; Njoku et al. 2003) and (2) the Land Surface Parameter Model (LPRM) that was developed by researchers of NASA and the department of Hydrology and GeoEnvironmental Sciences at the Vrije Universiteit Amsterdam (VUA), the Netherlands (Owe et al. 2001). Both the NSIDC and the VUA-NASA models use similar parameterisations to solve for soil moisture. The main difference between the two techniques can primarily be found in the use of different sensor frequencies, the method for modelling

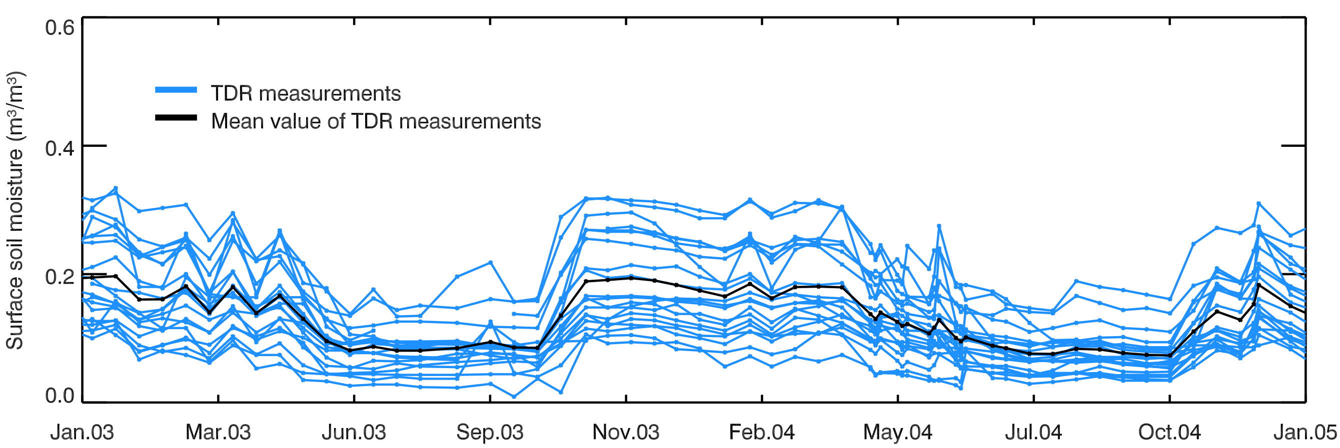

Fig. 2 Time series of TDR measurements from 20 stations and their mean value

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vegetation optical depth and the estimation of soil/canopy temperature.

The soil-moisture product of NSIDC is based on the inversion of microwave radiative transfer models that link surface geophysical variables to the observed brightness temperature at the two low frequency bands (Njoku et al. 2003). However, because in many parts of the world the 6.9 GHz channel is affected by radio frequency interference (RFI) effects (but not over the REHMEDUS network area), the current version of the NSIDC soil-moisture product uses only the 10.7 GHz channel. The geophysical parameters including soil moisture, surface soil/canopy temperature and vegetation water content are adjusted iteratively to minimise the weighted sum of the squared differences between the observed and the computed brightness temperatures. The data can be obtained from the National Snow and Ice Data Centre (2006).

The VUA-NASA model uses either the 6.9 GHz or the 10.7 GHz channel for soil-moisture retrieval. In this paper, only the results for the 6.9 GHz data are shown. Also, the 10.7 GHz soil-moisture data were available but not shown here because they are very similar to the 6.9 GHz data. The vegetation water content is estimated with the optical depth model as described by Meesters et al. (2005) and the surface soil/canopy temperatures are derived offline using the vertical polarised Ka band (36.5 GHz) microwave observations. Both the VUA-NASA and the NSIDC soil-moisture data were smoothed by using a boxcar filter over three measurements to slightly dampen short-term fluctuations.

ERS scatterometer soil moisture

The ERS scatterometer is an active microwave instrument that sends out a short pulse towards the Earth's surface and measures the reflected pulse energy. Since the reflectivity of soil increases strongly with increasing soil-moisture content, scatterometers provide, comparable to microwave radiometers, a rather direct measurement of soil moisture. The ERS scatterometer is operated in C-band (5.3 GHz) and measures the vertically polarised backscatter simultaneously with three antennas at different azimuth and incidence angles around 10:30 am for descending satellite passes and around 10:30 pm for ascending passes. The spatial resolution of the backscatter data is about 50 km. Unfortunately, the temporal coverage of the ERS scatterometer is comparably low over the study area (Table 1) because the instrument was often switched off due to conflicting ERS Synthetic Aperture Radar (SAR) operations over Europe.

Over land surfaces, the backscatter measurements are affected by soil moisture, surface roughness and vegetation. To retrieve soil moisture, the method described in Wagner et al. (2003) is used, which, from its conception, is a change detection technique. Change detection is attractive because it presents a simple, albeit indirect way of accounting for surface roughness effects and heterogeneous land cover. From a temporal viewpoint, these characteristics are highly stable at the spatial scale of tens of kilometres and hence do not need to be modelled separately. Thus, the retrieval can be simplified to account only for the temporally variable soil moisture and vegetation conditions. Since a change in biomass affects backscatter differently at different incidence angles, the multi-incidence angle observations of the ERS scatterometer are used to quantitatively correct for the effects of vegetation phenology (Wagner et al. 1999). Soil moisture is finally retrieved by relating the instantaneous backscatter measurement to a dry and wet backscatter reference. The reference values are determined by selecting the lowest and highest backscatter measurement from vegetation-corrected backscatter time series spanning a 10-year period. This assures the selection of a measurement at completely dry conditions as dry reference and at saturated conditions as wet reference. The retrieved information is a relative measure of the surface soil-moisture content and is assumed to correspond to the degree of saturation. Absolute soil-moisture values can be obtained by multiplying it with the soil porosity. The data can be obtained from the Vienna University of Technology (2006).

METEOSAT soil moisture

The energy and water balance monitoring system (EWBMS) developed by EARS (Environmental Analysis and Remote Sensing), Delft, The Netherlands, provides energy and water balance data of the Earth's surface that are derived from rain-gauge observations and METEOSAT geostationary satellite images by solving the surface energy-balance equation (Roebeling et al. 2004). The basic products of the system are 10-day averaged maps of rainfall, radiation and evapotranspiration at 5-km spatial resolution. Soil moisture is estimated by the ratio of actual and potential evapotranspiration which is assumed to have a linear relationship. The data can be obtained from Environmental Analysis and Remote Sensing (2006).

Within EWBMS, METEOSAT imagery is exploited in different ways. Firstly, hourly METEOSAT thermal infrared images are used in what is generally called a "cloud-indexing" method to spatially interpolate rain-gauge measurements. Very high, high, medium-high, medium-low and low cloud tops are counted for each METEOSAT pixel during a 10-day period. These cloud durations are then compared with point rainfall data, and by means of multiple regression, a first estimate of the rainfall field from the cloud durations is obtained. This result is then locally calibrated so as to match the rainfall point data measured on the ground. Furthermore, METEOSAT visible and thermal infrared imagery at noon and mid-night are processed to derive surface temperature, albedo, and net radiation. Through the use of an energy balance equation, the actual evapotranspiration is derived. Processing is done on a daily basis, but results are averaged for the meteorological decade (10 days). Details on EWBMS are provided in Rosema et al. (2001).

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Methods

The comparison of in-situ soil-moisture observations with satellite data is problematic for a number of reasons. Firstly, in-situ observations are essentially point-like data, while the satellite data represent areas ranging from a few to several thousands of square kilometres (25 km^2 in the case of METEOSAT, and 2,500–3,000 km^2 in the case of AMSR-E and the ERS scatterometer). Secondly, the moisture content in the remotely sensed soil-surface layer is highly dynamic because this layer is directly exposed to atmospheric forcing (precipitation, radiation, wind, etc.). Therefore, one would expect that with increasing time lag between observations, the correlation between two different soil-moisture datasets decreases. Thirdly, satellites gather information about the topmost soil layer (from the surface to a few centimetres depending on the sensor's wavelength), while in-situ soil-moisture probes represent a soil layer beneath the surface, depending on the depth at which they are buried. Therefore, high correlations between satellite and in-situ soil-moisture data are in general difficult to obtain. In principle, by investing in more and better in-situ equipment, these problems can be tackled to some extent. However, in practice, funding for in-situ networks is limited and one must find complementary approaches for evaluating the quality of the satellite soil-moisture datasets.

To alleviate some of the problems associated with just using in-situ observations for the evaluation of satellite soil-moisture datasets, it is hereby proposed that a pairwise comparison of all datasets should be made. Even though the errors of the satellite datasets are a-priori not known, and hence subject of this study, the rationale is that each dataset has a different error structure and conveys another aspect of the "true" areal surface soil-moisture conditions. By cross-comparing all datasets, one can learn about the differences between the datasets, which adds to the understanding of the properties of each dataset. Because the datasets used in this study rest upon fundamentally different sensor/retrieval concepts (except for the two AMSR-E datasets), their information content is highly complementary and one may assume that their errors are, in a first approximation, uncorrelated. From this assumption, it follows that datasets, which are in good agreement compared to the other datasets, better reflect the true areal surface soil-moisture conditions than those datasets which deviate more sharply. Note that this assumption would not be valid if, for example, one uses different datasets derived from only one passive microwave sensor using different radiative transfer models. In this case, vegetation and/or temperature effects may be modelled somewhat erroneously in a very similar way with all algorithms. As a result, one would not notice these problems just based on a simple comparison of the different datasets.

For a quantitative comparison, the correlation coefficient, R, and the root mean square error, RMSE, were computed for each dataset pair. Since the temporal sampling intervals and observation times do not match (Table 1), measurements had to be interpolated, whereas the rule was that temporal interpolation was applied to those datasets which contained more points. In other words, all satellite datasets were interpolated to the in-situ measurements. AMSR-E data, which provided daily coverage, were interpolated to ERS scatterometer and EARS data points. For example, to estimate AMSR soil moisture, θ_{AMSR}, at the observation time t of the in-situ measurements, the following computation was performed:

$$\theta_{\mathrm{AMSR}}(t) = \theta_{\mathrm{AMSR}}(t_1) + \left(\frac{t - t_1}{t_2 - t_1}\right)[\theta_{\mathrm{AMSR}}(t_2) - \theta_{\mathrm{AMSR}}(t_1)] \quad (1)$$

where t_1 is the time of the closest AMSR acquisition before the in-situ measurements and t_2 is the one directly after. To minimise the effects of temporal decorrelation due to the highly variable soil-moisture conditions, while retaining sufficient data pairs, it was required that measurements not be taken more than 3 days apart.

For the best possible matching of the spatial scales, the measurements from 20 TDR stations, θ_i, were averaged to

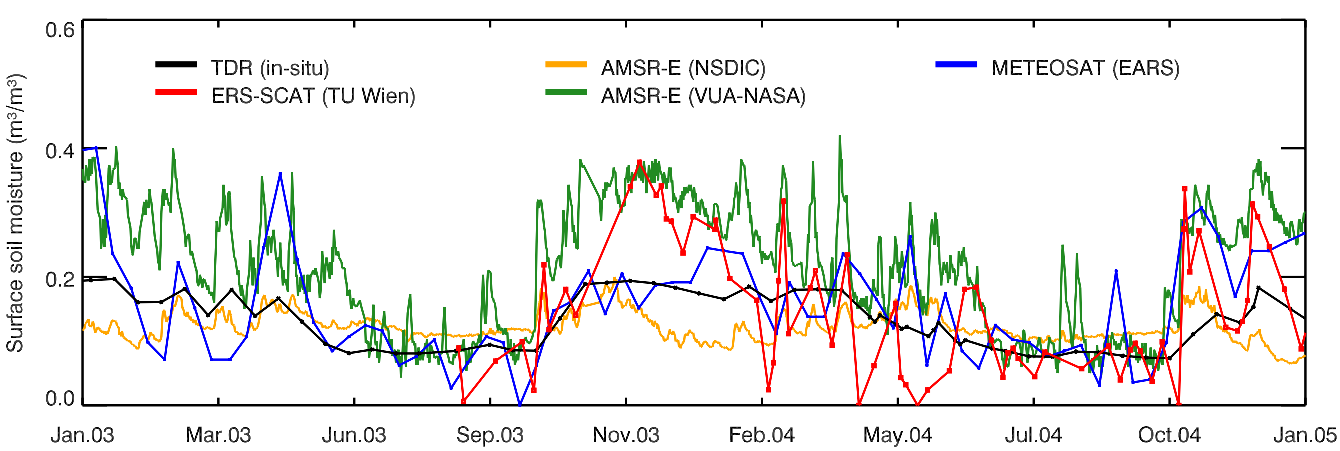

Fig. 3 Time series of in-situ and four satellite soil-moisture datasets for the period 1 January 2003 to 31 December 2005. The satellite data represent the soil surface layer (0–2 cm) and the in-situ measurements represent a thin soil layer directly beneath the Earth's surface (2–8 cm)

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obtain one value, Θ, which is assumed to be representative for the entire network area:

$$\Theta(t) = \frac{1}{n}\sum_{i=1}^{n}\theta_i(t) \quad (2)$$

with n=20. This averaging has the effect of suppressing local differences in soil moisture due to varying soil types, topography and land use, whereas the large-scale atmosphere-driven soil-moisture component is preserved (Vinnikov et al. 1999; Entin et al. 2000). For the comparison with the average in-situ value, the AMSR-E and the ERS scatterometer pixels located over the centre of the network area were extracted. With respect to the METEOSAT data, the average of 5×5 pixels, which corresponds to an area of about 25×25 km^2, was computed.

Results and discussion

The comparison of time series plots in Fig. 3 shows that the five data sets depict roughly the same seasonal trends. However, significant differences between the five soil-moisture datasets are apparent. In particular, the much higher temporal variability of the satellite datasets compared to the in-situ time series is striking. This is probably partly due to a higher noise level of the satellite data and the longer sampling interval of the in-situ data, not capturing the surface soil-moisture dynamics to a full extent. However, it must also be considered that the TDR measurements and the satellite data represent different soil layers. While the TDR data represent a thin soil layer directly below the Earth's surface (about 2–8 cm), the satellites sense only the topmost soil layer (0–2 cm) that responds very quickly to atmospheric forcing. This explains some fast temporal variations in the satellite data compared to the in-situ data. For example, in the period from mid-February until April 2004, several peaks in the AMSR-E and ERS scatterometer time series are clearly visible, whereas the in-situ dataset does not show them. These peaks were caused by precipitation events which apparently did not significantly raise the moisture content in the sub-surface layer (Fig. 4). This shows that it is problematic to consider in-situ soil-moisture observations as "ground truth". To improve the suitability of the REMEDHUS network for the validation of satellite data even further, all stations have therefore been equipped with data loggers in the year 2005 to significantly improve the temporal sampling interval. However, the problem of satellites and in-situ observations representing different soil layers can hardly be overcome due to practical limitations in the installation of the in-situ probes.

Another apparent difference between the five soil-moisture data sets is that their absolute values differ. While the TDR measurements and the AMSR-E NSIDC dataset vary only within a relatively small interval from 0.05 to 0.25 m^{3}m^{-3}, the ERS scatterometer and AMSR-E VUA-NASA datasets vary between 0 and about 0.43 m^{3}m^{-3}, whereby the latter value corresponds to the average saturated soil water content in the topsoil layer measured in the field. The observed visual disagreement between absolute soil-moisture values was confirmed by the rank-sum-test, which examines the hypothesis that two sample populations have the same mean, and the f-variance test, which computes the f-statistic and the probability that two sample populations have significantly different variances. Both statistical tests indicated significant inconsistencies of the mean and the variance between most of the soil-moisture products. While this may appear to be a remote sensing problem, in reality it is not. To derive absolute soil-moisture values from satellite data, auxiliary information about soil type, structure and hydrologic properties is needed. At local scales, adequate soil data may be available, but at continental to global scales, harmonised soil databases are currently only available at coarse scales from 1:1,000,000 to 1:5,000,000 (Montanarella and Nègre 2001). In other words, differences in the absolute values of the datasets merely reflect different choices of auxiliary soil data and not information stemming from the satellites. For further analysis, all datasets were normalised between their respective minimum and maximum values within the available observation period.

Scatterplots of pairs of the normalised datasets can be seen in Fig. 5. Based on the data points shown in Fig. 5, the correlation, R, and the root mean square error, RMSE, were calculated. Please note that because the data are normalised, the RMSE is identical with the relative RMSE. The results are summarised in Table 2. The

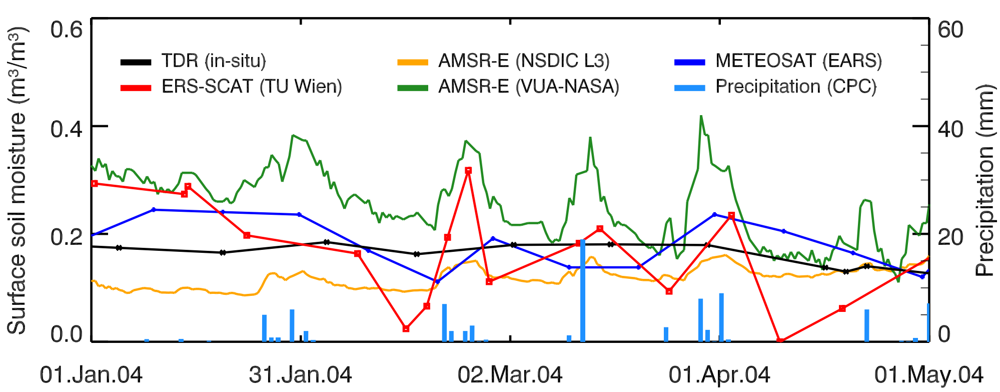

Fig. 4 Time series of precipitation and five soil-moisture datasets for the period 1 January 2004 to 1 May 2004. The precipitation data were recorded at a synoptic weather station located in Salamanca at 40.95°N and 5.65°W

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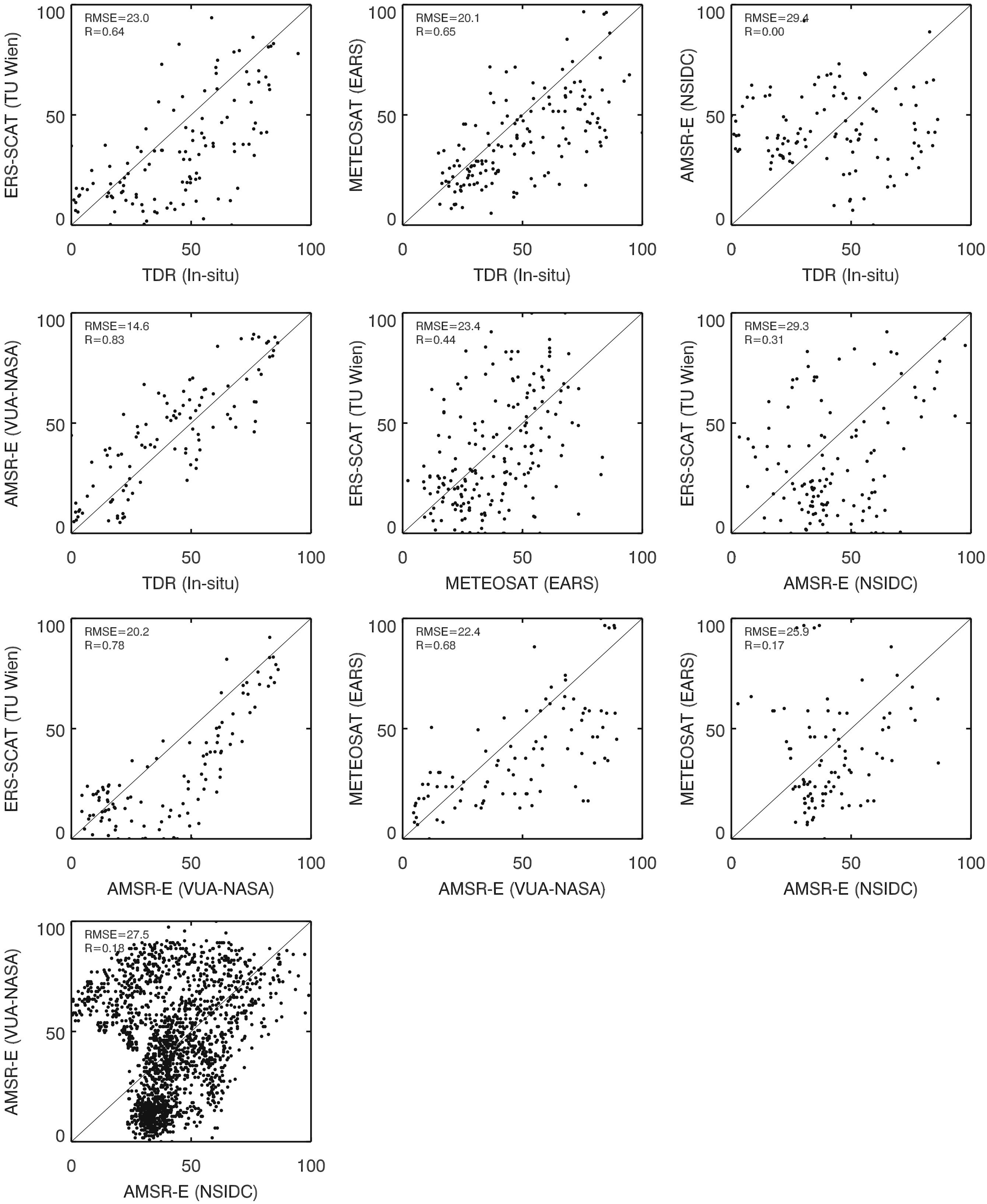

Fig. 5 Scatterplots of pairs from five soil-moisture datasets (given in %) as listed in Table 1. The data were normalised to the range 0–100 to ease the comparison between different pairs

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	TDR (In-situ)	ERS-SCAT (TU Wien)	AMSR-E (NSIDC)	AMSR-E (VUA-NASA)	METEOSAT (EARS)	
Correlation Coefficient	**0.65**	**0.44**	**0.17**	**0.68**		METEOSAT (EARS)
	0.83	**0.78**	**0.18**		**22.4**	AMSR-E (VUA)
	0.00	**0.31**		**27.5**	**25.9**	AMSR-E (NSIDC)
	0.64		**29.3**	**20.2**	**23.4**	ERS-SCAT (TU Wien)
		23.0	**29.4**	**14.6**	**20.1**	TDR (In-situ)

Root Mean Square Error

Table 2 Correlation coefficient (R) and root mean square error (RMSE) between pairs of five soil-moisture datasets

derived R values range between 0 and 0.83, indicating statistically significant correlation with positive covariances for most combinations. The RMSE ranges between 14.6 and 29.4%. Also, calculations for the 10.7 GHz AMSR-E VUA-NASA data set were performed. The comparison with the in-situ observation gave R=0.83 and RMSE=14.7%, i.e. practically identical results as for the 6.9 GHz VUA-NASA dataset. This suggests that for the study area, both C- and X-band radiometer data are equally suited for soil-moisture retrieval, even though lower frequency channels should generally be expected to provide better soil-moisture estimates because longer wavelengths penetrate deeper into vegetation and soil.

Overall, the scattering of data as shown in Fig. 5 is relatively high. If the AMSR-E data from NSIDC are excluded, the RMSE ranges between 14.6 and 23.4% and R ranges between 0.44 and 0.83. The "true" RMSE between each individual satellite product and the "true" surface soil moisture is, however, smaller than the above-cited values because the noise of the various datasets can safely be assumed to be uncorrelated due to the fundamentally different measurement approaches. If it is assumed that the noise level of two products is equal, then the "true" RMSE of both products can be estimated by dividing the RMSE from Table 2 by $\sqrt{2}$. For example, the RMSE between the ERS scatterometer and the VUA-NASA data is 20.2%. Assuming equal noise levels, the true RMSE for both datasets can be estimated to be around 14.3%. For the REMEDHUS network area, where the saturated soil-moisture content is 0.43 m^3m^{-3}, this translates into an absolute RMSE of 0.062 m^3m^{-3}. This value is higher than the specified error of 0.04 m^3m^{-3} for SMOS, but probably still of an acceptable magnitude to be of use for various applications. For example, Ceballos et al. (2005) use the scatterometer-derived surface soil-moisture time series to derive estimates of the soil-moisture content in the 0–1-m soil profile. They compared it to the REMEDHUS measurements averaged over the 0-1-m soil profile and obtained a significant coefficient of determination (R^2=0.75) and a low RMSE (0.022 m^3m^{-3}). These much better results for the profile soil-moisture values compared to the surface data is most likely a result of the lower spatial and temporal variability of the profile soil-moisture content. Also, the infiltration model employed by Ceballos et al. (2005) uses several dozen scatterometer-derived surface values to estimate one profile value, which, besides the intended physical effects, had the additional effect of suppressing the measurement noise to some extent.

To identify those datasets which show good agreement compared to the others, the mean R and RMSE values were calculated for each dataset by averaging the product-specific values from Table 2. The results are shown in Table 3. It is very interesting to see that the AMSR-E soil-moisture dataset from VUA-NASA has the highest mean correlation (R=0.62) and the lowest mean RMSE value (RMSE=21.2%) compared to all other datasets, including the TDR measurements. From the other three satellite datasets, the ERS scatterometer and the METEOSAT datasets show somewhat poorer, but still comparable skill to the VUA-NASA data, while the AMSR-E data from NSIDC clearly deviate the most of all other data. This is further confirmed by calculating the anomaly correlation coefficient between the four satellite data sets and the in-situ time series (Table 3). While for AMSR-E from VUA-NASA, ERS scatterometer and METEOSAT the anomaly correlation coefficient is in the range of 0.38–0.49, it is negative for AMSR-E from NSIDC. The time series plots in Fig. 3 reveals that the NSIDC product is characterised by a low variability of soil moisture and, more importantly, it shows a different long-term trend for the period November to March which persists for all years. Reasons for the weaker performance of the NSIDC product might be manifold and it is not possible to identify the exact reason without analysing the NSIDC algorithm and intermediate products in detail. Nevertheless, one can confidently exclude that the use of the 10.7 GHz channel

Table 3 Summary of statistical analysis

	TDR (in-situ)	ERS-SCAT (TU Wien)	AMSR-E (NSIDC)	AMSR-E (VUA-NASA)	METEOSAT (EARS)
Mean of observation time difference to in-situ data (days)	–	3.11	0.15	0.18	2.58
Mean of correlation coefficients to the other four time series[a]	0.53	0.54	0.17	0.62	0.49
Mean of RMSE to other four time series[a,b]	21.8	24.0	28.0	21.2	23.0
Anomaly correlation coefficient to in-situ data[b]	–	0.44	–0.05	0.49	0.38

[a] Obtained by averaging the values of Table 2

[b] After normalisation

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was the problem because in the case of the VUA-NASA algorithm, the 6.9 and 10.7 GHz results were practically identical. Therefore, it appears likely that the NSIDC algorithm does not properly describe the confounding effects of vegetation and/or surface temperature upon the AMSR-E measurements over the test area.

One limitation of the current study is that global satellite datasets were evaluated based on data from only one test site, representing a particular kind of soil and land cover. It may well be that, due to algorithmic reasons, the different datasets perform differently over other sites with different vegetation and soil characteristics. Therefore, there is now a strong need for establishing a global network of in-situ soil-moisture stations for validating the upcoming low-resolution data as provided by meteorological satellites such as METOP, NPOESS or Meteosat Second Generation (MSG), and by the dedicated soil-moisture satellite (SMOS).

Conclusions

In recent years, major advances in retrieving soil moisture from different sensor systems have been made. These advances have been made possible primarily because of improvements in algorithms and retrieval methods. As a result, several soil-moisture datasets have recently become available. In this study, four published satellite datasets were compared to high-quality soil-moisture data from a test site located in the Duero basin in Spain. The remotely sensed data were not tuned to the specific site conditions. Three of the satellite products contribute effectively to the monitoring of trends in surface soil-moisture conditions despite the fact that they rest upon fundamentally different measurement and retrieval concepts (AMSR-E, ERS scatterometer, METEOSAT). Similar observations were made in a recent study by Verstraeten et al. (2006) where METEOSAT and ERS scatterometer soil-moisture data were compared to in-situ measurements over ten sites across Europe. A surprising finding was that the best and worst results were obtained for two datasets derived from the same sensor (AMSR-E). Even though this result may be specific for the study area, this demonstrates that the retrieval algorithm plays an equally important role for the quality of a soil-moisture dataset as the technical specifications and performance of the satellite system.

The successor instruments of the sensors used in this study will be operated on-board operational satellite systems such as METOP, MSG and NPOESS. With further improvements in processing techniques, operational meteorological satellites will increasingly deliver high-quality soil-moisture data, which may be of particular interest for hydrogeological studies that investigate long-term processes such as groundwater recharge. Thereby, operational meteorological satellites will complement the experimental SMOS satellite, which will allow testing of the current limits of satellite technology for soil-moisture sensing.

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