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Submitted to:
Journal of Hydrometeorology

Date of first submission
19 November 2007

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Abstract

This paper presents a study undertaken in preparation of the work leading up to the assimilation of SMOS observations into the land surface model (LSM) ISBA at Météo France. This study consists of an inter-comparison experiment of different space-borne platforms providing surface soil moisture information (AMSR-E and ERS-Scat) with the reanalysis soil moisture predictions over France from the model suite SIM (SAFRAN-ISBA-MODCOU) of Météo France for the years 2003 to 2005. Both modelled and remotely sensed data are initially validated against in-situ observations obtained at the experimental soil moisture monitoring site SMOSREX in south-western France. Two different AMSR-E soil moisture products are compared in the course of this study (the official AMSR-E product from the National Snow and Ice Data Centre (NSIDC) and a new product developed at the Vrije Universiteit Amsterdam and NASA (VUA-NASA)), which were obtained using two different retrieval algorithms. This allows an additional assessment of the different algorithms, while using identical brightness temperature data sets. This study shows that a good correlation exists between AMSR-E (VUA-NASA), ERS-Scat, and SIM, generally for low altitudes and low-to-moderate vegetation covers (1.5 to 3kg m^2 vegetation water content), with a reduction in the correlation in mountainous regions. It is also shown that the AMSR-E (NSIDC) soil moisture product has significant differences, when compared to the other data sets.

1. Introduction

Soil moisture is the governing variable for modelling soil surface-to-atmosphere energy exchanges and land surface model (LSM) initialisation, as it controls both evaporation and transpiration from bare soil surfaces and vegetation covers. Consequently, a significant amount of studies have been and are currently being conducted to obtain soil moisture estimates through land surface modelling (e.g. Dirmeyer et al. 1999; Georgakakos and Carpenter 2006) and remotely sensed surface soil moisture observations (e.g. Wagner et al. 1999ab; Kerr et al. 2001; Njoku et al. 2003).

For the purpose of soil moisture remote sensing, observations in the microwave bands have been found to produce the best results. The optimal wavelength lies within the L-band range (~1-2GHz), as interference through vegetation water content at this frequency range is lower than at higher frequencies.. However, instruments have in the past been and are currently operated at higher frequencies (above 5GHz), mainly because none of these missions were dedicated soil moisture missions. The first such dedicated soil moisture mission will be the Soil Moisture and Ocean Salinity mission (SMOS), to be launched in 2009. The first microwave instrument operated for an extensive time and within adequate wavelengths was the Scanning Multichannel Microwave Radiometer (SMMR) on Nimbus-7 (operational from 1978 to 1987), which operated at bands at and above 6.6GHz. SMMR was followed by the Special Sensor Microwave/Imager (SSM/I; since 1987) and the similar Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI; since 1997), which operate at frequencies above 10GHz. Instruments which are currently operational at frequencies similar to SMMR (and therefore closer to L-band), are the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) on board NASA's Aqua satellite, WindSat on board the American Navy's Coriolis satellite, and the scatterometers on board the European Remote Sensing satellites (ERS-1 & -2). Finally, a new scatterometer

(ASCAT) was launched on board ESA's MetOp satellite in 2006 and its data will soon be available operationally (Bartalis et al. 2007).

Despite almost 30 years of experience with these microwave remote sensing instruments, it is still necessary to validate the soil moisture products obtained from these instruments through in-situ soil moisture observations. However, such ground-truthing has only been achieved over small temporal and spatial scales (eg. the Soil Moisture Experiments (SMEX) or the Campaign for validating the Operation of SMOS (CoSMOS)), as it is economically and practically infeasible to observe soil moisture at high spatial and temporal resolution over large scales using in-situ observations, mainly because of its high spatial variability. Only in the present decade there have been attempts to establish long-term and large scale soil moisture observation networks or data banks such as the Global Soil Moisture Data Bank (Robock et al. 2000), the Goulburn River experimental catchment in Australia (Rüdiger et al. 2007), or SMOSMANIA in south-western France (Calvet et al. 2005). However, these data sets only represent single points in space. This lack of spatial extent limits the usefulness of such data sets for assimilation into large scale land surface models and also for disaggregation studies, as the large scale, but also subpixel variability is not captured with single point measurements. Moreover, satellite products are generally available at scales of about 0.25° or 25km, which leads to problems in their validation process, due to the different spatial scales (spatially averaged satellite products are compared to point measurements). Consequently, new validation methods complementing the existing soil moisture networks have to be conceived (Wagner et al. 2007). Under the assumption that LSMs, forced with high quality atmospheric forcing data, adequately represent the surface soil moisture dynamics, the scale issues can be reduced. This assumption in turn will then allow the large-scale and long-term evaluation of the satellite products in terms of their temporal dynamics, as the products considered are essentially independent models.

In this paper, both the need for large scale ground-truthing and understanding of the subpixel heterogeneity of soil moisture are addressed. First, the temporal correlation of satellite products at a large scale with a synthetic high-resolution surface soil moisture data base is presented. The high-resolution meteorological observation network throughout France (more than 1000 surface meteorological stations and more than 3500 daily rain gauges) has resulted in a high-quality atmospheric forcing data base (Quintana-Seguí et al. 2008) for the operational land surface model ISBA of Météo-France, within the modelling system SIM (SAFRAN-ISBA-MODCOU; Habets et al., 2008). The SIM model simulates the soil moisture dynamics.

The satellite products used for this study were obtained from AMSR-E and ERS-2. Furthermore, the recent development of a new retrieval algorithm for AMSR-E (Owe et al. 2007) allowed to compare the official AMSR-E product (Njoku et al. 2003) with this new data base. In the first part of this study, the different data sets used are discussed, followed by a brief comparison of those remotely sensed data sets and SIM with in-situ observations of the SMOSREX experimental site near Toulouse, France (de Rosnay et al. 2006), to determine their capability to represent the temporal soil moisture dynamics of a point or pixel. The good results of this analysis between the land surface model, in-situ observations, and satellite data also shows that previous results obtained over Spain (Wagner et al. 2007; one single satellite pixel), or over Australia (Draper et al. 2007; several in-situ observations for a number of pixels) can be extrapolated to a national or even continental scale, as they show the same tendencies. The differences between the various soil type data bases used in the satellite retrieval schemes and the model data base, make it difficult to compare absolute values. Consequently, the discussion of this paper will focus on the normalised data sets. In the second part, the inter-comparison study then presents the correlations and mean differences between all data sets (ie. also between the different satellite products).

2. Data Sets

Due to the limitation in the spatial extent of SIM, this study is limited to watersheds of mainland France. Nevertheless, the surface and climatic conditions throughout the country are sufficiently variable (ranging from sub-humid to alpine), to give a statistically sound data basis for a representative analysis. The years 2003-2005 were chosen for this study, as data exists for all sources (SIM – 1970 to 2006; ERS-Scat – 1992 to 2006; AMSR-E – 2003 to date; and SMOSREX – 2001 to date). Moreover, this 3-year period includes both very dry and very wet climatic conditions, which are necessary to determine the dynamic range of the soil moisture observations within each pixel. The following sections briefly outline the various data sets, used for this study.

a. SAFRAN-ISBA-MODCOU (SIM)

The modelled surface soil moisture data base was obtained from the modelling system SAFRAN-ISBA-MODCOU (SAFRAN – atmospheric forcing data base; ISBA – land surface model; MODCOU – hydrological routing model). Of these three model chain segments, only SAFRAN and ISBA were of importance for the present study.

SAFRAN (Système d'analyse fournissant des renseignements atmosphériques pour la nivologie) is a reanalysis forcing data base, initially developed to improve snowfall and avalanche forecasting. Within SAFRAN, the main atmospheric forcing parameters are analysed. Each atmospheric parameter is analysed individually using an optimal interpolation method. The final size of a grid cell within SAFRAN is 8x8 km^2. For precipitation, however, the actual pixel sizes of SAFRAN vary, as they represent zones of climatic conditions rather than regularly gridded areas. Each climatic zone covers about 1000km^2, resulting in about 600 such pixels over France. The forcing parameters are in principle assumed to be homogeneous within one such pixel, however, they vary on a sub-pixel scale with topography. Apart from precipitation the SAFRAN forcing data is available at 6-hourly intervals. Precipitation is obtained using daily observations at the rain gauges and then interpolated into hourly time steps as a function of the relative humidity during the day. The SAFRAN data base has recently been validated against in-situ observations and found to be well correlated (Quintana-Seguí et al. 2008).

The land surface model used in SIM is ISBA (Interactions of the Soil, Biosphere and Atmosphere; Noilhan and Planton 1989; Mahfouf and Noilhan 1996), which is used operationally as the land surface scheme within the numerical weather prediction system at Météo-France. The soil layer and soil moisture dynamics are modelled within a 3-soil-layer model (Boone et al. 1999), which is based on the force-restore approach, where the three soil layers are a surface layer of 1cm depth, forming part of a root zone layer above the third, deep layer.

There is no previous study presenting a verification of the SIM surface soil moisture product. On the other hand, the ISBA model has been extensively validated for various biomes. In particular, a number of studies exist comparing a point-specific calibrated ISBA version to actual in-situ soil moisture observations in France (Calvet et al. 1998a,b, Boone et al. 1999, Calvet and Noilhan 2000, and Sabater et al. 2007). The latter case corresponds to SMOSREX, and the former to a previous experiment (MUREX) in the same region. The RMSE for those cases is, respectively, 0.06 and 0.07 m^3m^{-3}, with a mean difference in the order of 0.01 and 0.03 m^3m^{-3}. In both cases the Nash efficiency was calculated with 0.65/0.59. Based on the results of Prigent et al. (2005), this level of error between in-situ observations and model predictions is expected, while maintaining a good correlation despite the different observation and model layer depths. The land surface parameters for ISBA are obtained from

ECOCLIMAP (Masson et al. 2003). The parameters provided by ECOCLIMAP are originally provided at 1km resolution and are aggregated to the model resolution of 8km.

b. AMSR-E

AMSR-E is a passive microwave scanning radiometer, operating at six wavelengths within the microwave spectrum (6.925, 10.65, 18.7, 23.8, 36.5, and 89GHz) in horizontal and vertical polarisations, flown on NASA's Aqua satellite. The total swath width during an overpass is approximately 1445km, with footprint resolutions ranging from 56km (6.925GHz) to 5km (89GHz). Aqua is a sun-synchronous satellite orbiting Earth approximately 14 times each day, with morning/descending and afternoon/ascending overpasses, at around 1.30am/pm. This configuration results in a repeat coverage of approximately every three days in the equatorial latitudes and more frequent coverage in higher latitudes. For the particular case of France, Aqua overpasses take place at 4 out of 5 days for both ascending and descending orbits.

Currently, two different data products are freely available. The official product can be obtained through the National Snow and Ice Data Center (NSIDC, hereafter AMSR-E (NSIDC)), while a new product has recently been made available through the Vrije Universiteit Amsterdam in collaboration with NASA (hereafter AMSR-E (VUA-NASA)). Both products are briefly described in the following sections.

i. AMSR-E (NSIDC)

The AMSR-E (NSIDC) data used for this study were obtained from the operational Level 3 B03 AMSR-E data set (Njoku 2006). While the original resolution at 10.65GHz is ~38km, the data is binned into regular 0.25°x0.25° pixels, through oversampling at 10km intervals.

The NSIDC method uses two low frequency dual polarized channels to optimize the three parameters (soil moisture, vegetation optical depth and the effective soil temperature) simultaneously. Originally, the method was developed and tested for the C- and X- band channels. Unfortunately, severe radio-frequency interference (RFI) was discovered within C-band (6.925GHz) over the USA and Japan and X-band over Italy and Great Britain (Li et al 2004, 2006). For this reason, the retrieval algorithm was applied to the X-band (10.65GHz) and Ku-band (18.7 GHz) brightness temperatures. This has some important disadvantages: 1) the 18 GHz channel introduces atmospheric influences and, 2) the observation depth of the soil moisture product is reduced to 5-10mm, which is approximately half the potential range of C-band and 3) vegetation attenuation effects are more significant than at lower frequencies.

ii. AMSR-E (VUA-NASA)

The VUA-NASA retrieval products from AMSR-E are derived according to the Land Surface Parameter Model (LPRM) (Owe et al. 2007). The LPRM is a three-parameter retrieval model for passive microwave data, using one dual polarized channel (either 6.925 or 10.65GHz) for the retrieval of both surface soil moisture and vegetation water content (VWC). The land surface temperature is derived separately from the vertically polarized 36.5GHz channel.

The forward radiative transfer model in LPRM is based on one vegetation layer (τ-ω approach) and the vegetation optical depth is parameterized as a function of the Microwave Polarization Difference Index (MPDI) and soil moisture according to Meesters et al. (2005). This method is applied globally, and requires no regional calibration or fitting parameters to aid the retrieval process.

The main differences with the AMSR-E (NSIDC) soil moisture product lies in the use of a higher frequency band for the retrieval of the land surface temperature (LST), and the parameterization of the vegetation optical depth, leaving only the soil moisture to be optimized.

c. ERS-Scat

The ERS-Scat data is obtained through active microwave remote sensing, ie. an energy pulse is sent to the surface and the intensity of the returned signal is then used within the retrieval algorithm to derive a relative soil moisture state. ERS-Scat is operated at 5.3GHz (C-band), observing only the vertically polarised backscatter within this band, thus resulting in a similar observation depth as AMSR-E. RFI has been found to have little impact on active microwave remote sensing at this frequency. ERS-Scat has a morning/descending and evening/ascending orbit at 10.30am/pm, with a varying repeat coverage of about 2 to 8 days. The spatial resolution of an ERS-Scat footprint is in the order of 50km, while the soil moisture product is binned into pixels of 0.25° (north-south extent) and 25km (west-east extent).

The soil moisture product is provided in relative values, ranging from 0 to 100%. The normalisation of the backscatter signal is done, using the minimum and maximum observed backscatter from the 1992-2000 period, as dry and wet references. The retrieval algorithm is described in detail in Wagner et al. (1999, 2003).

d. SMOSREX

SMOSREX is an experimental field site for in-situ and remotely sensed soil moisture observations jointly operated by various research institutes in France and located to the south of Toulouse (43°23'N, 1°17'E) in south-western France (De Rosnay et al. 2006). The overall size of SMOSREX is approximately 6000m² separated into two areas with either bare soil or fallow. The climate is temperate with monthly mean maximum temperatures of 5°C in winter and 24°C in summer and an average annual cumulative precipitation of about 650mm. The surface soil consists of a sandy loam, with 16% clay, 47% silt, and 37% sand.

Most instruments installed at the site have been in operation since 2001. The main feature of this site is a tower-mounted L-band radiometer for the production of multi-angle brightness temperatures. Other instrumentation include a weather station, and soil temperature and moisture sensors, installed at various points and depths. The soil moisture sensors (Theta Probes ©) used for this study are located at four points within the fallow section of the site (most representative for the overall region and therefore the model simulations), with a spacing of only a few metres. The sensors are vertically inserted at the surface, therefore integrating the soil moisture content from 0 to 6cm, and a temporally averaged soil moisture content is stored every 30 minutes individually for all sensors. The calibration of the sensors is presented in (De Rosnay et al. 2006).

For the purpose of this study, the in-situ observations were aggregated into daily averages and compared to the respective data sets obtained through the model and remote sensing. Spatially averaging the observations of those four probes reduces the effect of spatial variability within and increases the representativity of the soil moisture observations, and also reduces the individual observations to one point in space.

e. Data Preparation

The results presented in this paper are based solely on the data sets from descending orbits (nighttime) to avoid overly solar effects in the satellite data, due to sun glint and strong temperature gradients between the vegetation and the surface, and also within the surface layer, but also due to Faraday rotation and temperature gradients within the sensor which are more pronounced during daytime overpasses (Kerr and Njoku 1990). Other effects such as quick dry-down or the lack thereof due to local changes in solar radiation, which can not be adequately represented in an LSM and in reality may be affected by cloud coverage and wind, among other factors play a significant role in the daytime evolution of surface soil moisture. While the in-situ observations were spatially and temporally averaged, the soil moisture simulations were extracted for the time steps close to the overpass times of the satellites. A comparison of the differences between the individual measurements of the soil moisture probes and their spatial average at 6am and also between the daily average with the spatial average at 6am resulted in an RMSE of 0.036 m^3m^{-3} in both cases. This shows that spatial and diurnal variabilities contribute to the same extent to the uncertainty in the in-situ observations. The use of a spatially and temporally daily average is therefore justifiable.

All data have been reprojected from their original coordinate systems onto a regular 0.25°x0.25° grid using a nearest neighbour approach. As the overall footprints of AMSR-E and ERS-Scat are in the order of 50km with a spacing of about 10km between the centre points, and the gridded products used in this study are binned at 25km or 0.25°, respectively, a spatial shift in the data due to the reprojection process (a maximum of 12km) is not expected to add any additional noise to the data or affect the data quality, as a footprint with its centre 12km from the pixel centre would still include information from more than half of the land surface corresponding to the pixel area due to its size. To obtain an average pixel value within the reprojected pixels, all original pixels with their centre falling into one reprojected pixel were averaged to one single value. This average value was then assumed to be the representative soil moisture of the reprojected pixel. In the case of the satellite observations, only one original pixel would generally fall into a reprojected pixel, due to the similarity in size, so that no errors are introduced due to the averaging of two satellite pixels. For all data sets, the same general rule applied for the reprojection process, to avoid inconsistencies between the data sets introduced through the reprojection and aggregation process.

In a brief study it was examined whether the variability between the soil moisture of high resolution SIM pixels with their averaged low resolution equivalent resulted in any errors within the analysis. However, no relationship between the this subpixel heterogeneity and the spatial distribution of the correlation coefficients between the different soil moisture products presented in the following section was found.

The soil moisture data from the satellites and SMOSREX were normalised following the approach presented by Pellarin et al. (2006), where the maximum and minimum of the soil moisture range was not determined by the soil type, but rather by the observed dynamic range within each individual pixel within the full study period (2003-2005). To exclude any abnormal outliers due to observational errors or instrument noise, the 90% confidence interval was chosen to define the upper and lower soil moisture content, respectively, using (1) and (2).

$$int^{+}(SM) = \mu(SM) + 1.64 * \sigma(SM) \quad (1)$$

and

$$int^{-}(SM) = \mu(SM) - 1.64 * \sigma(SM) \quad (2)$$

where int^{+} and int^{-} are the upper and lower confidence limits; $\mu(SM)$ is the average soil moisture content for the pixel; and $\sigma(SM)$ the standard deviation of the soil moisture content for each pixel. With the knowledge of the upper and lower soil moisture content the absolute soil moisture value is then normalised using (3):

$$\theta_{n} = \frac{SM_{obs} - int^{-}}{int^{+} - int^{-}} \quad (3)$$

where SM_{obs} is the individual soil moisture observation and θ_n is its normalised soil moisture value. As a simplification it is assumed that the data are normally distributed, so that 90% of the data lie by definition within a range of $\mu \pm 1.64\sigma$. All data outside of this range were discarded. Also, pixel values were excluded from the overall analysis, where SIM predicted frozen soil water. As model simulations as such have no outliers due to instrumentation errors, no screening of extreme values is required. The soil moisture from SIM is therefore normalised using the modelled maxima and minima of each individual pixel, instead of int^+ and int^-.

Pixels located over major urban agglomerations (ie. Lille, Paris, Lyon, Bordeaux, Toulouse, and Marseille) were not excluded. However, the correct representation of the soil moisture is doubtful, as SIM is not capable to give realistic soil moisture conditions over urban (and consequently sealed) areas, and moreover, the possibility of pixels subjected to potential radio-frequency interference (Li et al. 2004) is higher in these areas. Nevertheless, the number of these pixels is small (<0.5% of the total), compared to the total over France and their overall effect on the statistical analyses was found to be negligible.

3. Comparison of the soil moisture products with in-situ observations

An evaluation of the surface soil moisture products obtained from SIM and the satellites was undertaken, using the same three years of in-situ soil moisture observations as for the remainder of this study (2003-2005). The in-situ data were obtained from the observations at the experimental site SMOSREX. The data from the four surface soil moisture sensors installed at SMOSREX, were averaged both spatially and over time, so that one daily averaged observation was obtained for each day. This approach reduced the existing noise levels in the in-situ observations, as discussed in the previous section. The model and satellite data used here are the binned and reprojected data as for the large scale study in section 4, as described above. SIM was not especially calibrated to the conditions at SMOSREX. For this evaluation study various statistical parameters were calculated: the root mean square error

(RMSE), the mean difference or bias between two data sets, the correlation coefficient (r) between two data sets, and the Nash efficiency coefficient (N). All statistics presented in the following sections were calculated for the normalised soil moisture values and are therefore dimensionless.

In a first step, the absolute values of the soil moisture products were compared with the in-situ data. For this purpose, the already normalised ERS-Scat data were transferred into absolute values, using the known maximum and minimum surface soil moisture observations at SMOSREX. While a good correlation exists between SIM and SMOSREX data sets, a severe lack of soil moisture dynamics is observed for the AMSR-E (NSIDC) data set (not shown). However, the AMSR-E (VUA-NASA) data is well correlated despite an apparent wet bias. Finally, the ERS-Scat observations are also well correlated in terms of their temporal dynamics. In contrast to the AMSR-E (VUA-NASA) data, the ERS-Scat data exhibits a dry bias. Due to the different soil moisture dynamics and biases, it is difficult to compare the various data sets in detail, consequently, all comparison in the remainder of this paper will be undertaken with normalised data (Fig. 1).

The comparison of the normalised SIM and SMOSREX data sets shows a good temporal correlation ($r = 0.755$; $N=0.478$), with a bias (-0.083) towards the in-situ observations (ie. the in-situ observations tend to be drier), with the exceptions of very dry conditions, when the model has the tendency to overestimate the soil moisture at this site (Fig. 2). Throughout the years, a higher level of surface soil moisture dynamics is observed within the model data (Fig. 1), which results in a root mean square error (RMSE) of 0.198. This phenomenon is explained by inaccuracies in the forcing data due to the spatial interpolation process within SIM and the differences in the thickness of the observed soil layers (1cm for SIM against 0-6cm for the ThetaProbes). However, there are only few data points causing this noise and this is consequently deemed acceptable.

The normalised AMSR-E (NSIDC) data display a very high variation, with interchanging peaks and troughs every three months (Fig. 1). Every year, minimal values are reached during winter and their maximum in summer. This recurring negative correlation with the in-situ data results in a high RMSE and low overall correlation (r = 0.132; N=-0.734; bias = 0.132; RMSE = 0.356). In contrast to the comparison of the absolute data, the persistent wet bias in the AMSR-E (VUA-NASA) data has been reduced due to the normalisation. Similar to the SIM predictions, a strong correlation between in-situ and remotely sensed data is found in this case with a wet bias towards the AMSR-E data (r = 0.775; N=0.471; bias = 0.072; RMSE = 0.194). Finally, the ERS-Scat observations are also well correlated over time with the in-situ data (r = 0.618; N=0.125), however a dry bias (-0.085) results in a more significant RMSE of 0.244 than for the AMSR-E (VUA-NASA) data. As ERS-Scat data are only available from August 2003 onwards, the identical periods of data cover (ie. August 2003 – December 2005) for the other surface soil moisture products was undertaken (not shown), in order to verify that the first seven months did not introduce significant biases in the statistical analyses, which then would not be seen in the ERS-Scat comparisons. The differences in correlation, RMSE, and bias did not change significantly for any of the inter-comparisons covering either the full three years or the period August 2003 – December 2005. Consequently, all comparisons shown in the remainder of this paper are based on the full period. The Nash efficiency coefficient for SIM and AMSR-E (VUA-NASA) are acceptable. They are also similar to each other suggesting that the two data sets perform equally well compared to the in-situ observations, while the low Nash efficiency of ERS-Scat is due to the relatively strong bias in the satellite data. In the case of the AMSR-E (NSIDC) data, the negative Nash efficiency suggests by definition that an average value of the in-situ observations would compare better with the overall observations than the remotely sensed observations. This is an important finding as it shows the extreme difference between the in-situ observations and the satellite product.

Four aspects have to be considered for the cause of the differences observed in this evaluation: i) the scale difference (8km and 0.25° for the model and the satellite, respectively, against a single point observation), as the comparison or validation of soil moisture products at different spatial scales will remain difficult in most cases, unless a representative catchment average soil moisture monitoring site (Grayson and Western 1998) can be identified; ii) the soil data base, as the model soil information constitutes an average of the soil particle size distribution within an 8km/0.25° pixel, which may result in significant differences compared to the soil conditions at the point of observation (the particle size analysis for SMOSREX yielded 16% clay, 47% silt, and 37% sand; the particle size distribution within ECOCLIMAP is 25%/25%/50%), iii) the forcing data, as it is obtained by interpolation between observations and atmospheric predictions, which may miss localised events, iv) the observation depth, with the model layer of 1cm and approximately the same depth for the satellite observations against the integrated soil moisture content at 0-6cm for the in-situ observations, may result in different dynamics.

Considering the above four aspects, SIM, AMSR-E (VUA-NASA) and ERS-Scat perform well when compared to the SMOSREX in-situ observations, and also show a good representation of the dynamic behaviour of the soil moisture content. For SIM, an RMSE of 0.198 with a dynamic range of the surface soil moisture at the site of ~0.3 m^3m^{-3}, can be translated into an absolute error in the soil moisture of just under 0.06 m^3m^{-3}. This result is particularly good, as SIM was not calibrated to the conditions at SMOSREX, but rather used the vegetation and soil conditions obtained from ECOCLIMAP. Moreover, despite the differences in scale these errors are identical to the performance of the site-specific calibrated model.

Depending on the application, the calculated error may be considered large or acceptable. For atmospheric studies, it is more important to obtain a good representation of the temporal dynamics, while the absolute soil moisture state is less important. On the other hand, an error of 0.06 m^3m^{-3} exceeds the validation goals of future satellite missions (Kerr et al, 2001). In the first case, the evaluation of satellite data against any benchmark is necessary, shown by the lack of temporal dynamics in the AMSR-E (NSIDC) data. In the second case, two factors influencing the RMSE have to be considered to qualify the above value of 0.06 m^3m^{-3}: i) the mean difference or bias between SIM and SMOSREX and ii) the spatial uncertainty of the in-situ observation. Biases, in the case of the normalised data 0.084 (or 0.025 m^3m^{-3}), may be removed using various techniques (eg. Drusch et al., 2005), while the uncertainty in the spatial averaging of the four in-situ observations is in the order of 0.036 m^3m^{-3}. In particular the removal of the bias would lead to a significant decrease of the RMSE. Consequently, it is concluded that SIM may be used with reasonable confidence for a large scale model intercomparison study, assuming that ECOCLIMAP provides similarly good information for all other model pixels.

While the correlations derived from Fig. 1 are relatively large for SIM, AMSR-E (VUA-NASA) and ERS-Scat, much of the captured variability is seasonal (dry in summer, wet in winter). In order to assess the coherence with the in-situ observations and to avoid seasonal effects, monthly anomalies are calculated. The difference to the mean is calculated for a sliding window of five weeks, and the difference is scaled to the standard deviation. Table 1 shows seasonal scores, including the Kendall statistics and p-value. All the products are significantly correlated to the in-situ observations, except for satellite products at specific periods of the year. While SIM presents significant correlations throughout the year, all the satellite products are not significantly correlated to in-situ observations at wintertime (DJF). This may be explained by the sensitivity of the microwave signal (either active or passive) to soil freezing and by the reduced dynamics of the surface soil moisture at wintertime. Both VUA-NASA and NSIDC products present high correlations of the anomalies for the other seasons. On the other hand, ERS-Scat has significant correlations at springtime (MAM), only. The lack of significance of ERS-Scat during the summer and autumn seasons (JJA and SON, respectively), may be explained by the small number of observations over the SMOSREX site (28 and 41, respectively), compared with AMSR-E (184 and 175, respectively, for the VUA-NASA product).

4. Inter-Comparison (all Data Sets)

a. General Correlation (all data)

Fig. 3 shows correlation maps of the different remote sensing and modelled data sets for all surface conditions and all years. A good correlation exists between the three data sets AMSR-E (VUA-NASA), ERS-Scat, and SIM, in particular for regions of herbaceous vegetation over regions with little relief, with a range of the coefficient of correlation from 0.2 to 0.9. Areas with denser vegetation, such as the forest of Les Landes in the South-West along the Atlantic coast show a lower level of correlation, which would have to be expected due to the masking effect on the microwave emissions of the soil moisture through vegetation. Similarly, low correlations are found in regions with strong relief such as the Massif Central and the Alps. The good correlation of ERS-Scat with SIM in the Italian Alps should be ignored, as only a few data points were available due to the overpass rate of ERS over the region and the filtering of days with frozen soils or snow. Mountainous regions cause errors in both the modelling of soil moisture and its retrieval from satellite observations. First, there exists a high level of uncertainty in the soil depth and its variability in those regions, which impacts on the predictions of the soil moisture dynamics in the SIM model. Secondly, relief interferes with the retrieval of low resolution remotely sensed soil moisture observations and may cause considerable levels of errors (Mätzler and Standley 2000). The AMSR-E (NSIDC) product has virtually only low correlations with any of the other data sets, even producing negative correlations overall (Table 2).

This analysis also shows that previous results obtained over Spain (Wagner et al. 2007; one single satellite pixel), or over Australia (Draper et al. 2007; several in-situ observations for a number of pixels) can be extrapolated to a national or even continental scale, as they show the same tendencies. In particular, the lack of soil moisture dynamics within the AMSR-E (NSIDC) data set are apparent and are shown in all studies.

The data used to derive the spatial plots of Fig. 3 are summarised in Table 2 as showing the respective coefficient of correlation (r), root mean square error (RMSE) and bias between the data sets. Compared to SIM, the ERS-Scat data set has the highest overall correlation (r = 0.728) and lowest RMSE (0.201), followed by AMSR-E (VUA-NASA) with an r = 0.491 and an RMSE of 0.297. As mentioned before, AMSR-E (NSIDC) has a negative correlation of –0.014 with an RMSE of 0.370. The RMSE presented here is the RMSE obtained from the normalised results, ie. it represents the relative error of the soil moisture dynamical range. Assuming an average dynamic range of 0.3 m^3m^{-3} and that SIM gives accurate in-situ observations, this would translate into an average error of 0.056 m^3m^{-3} for ERS-Scat, which is higher than the design accuracy of SMOS (0.04 m^3m^{-3}).

Like the bias between the SIM and SMOSREX data sets, the biases shown between SIM and the three satellite products are all positive. This suggests that a consistent dry bias exists within SIM. A first explanation for the bias between SIM and SMOSREX are the different thickness of the observed soil layers (1cm in the model against 0-6cm in-situ), as the deeper profile of the in-situ observations is likely to maintain a higher soil moisture content, as it is less affected by evaporation than the thin surface layer in the model. Furthermore, other aspects such as erroneous soil type information, biased forcing data, and biases in the soil moisture retrieval for the satellites may result in consistent biases.

b. Correlations Specific to Land Surface Cover

A comparison of vegetation maps with the results of Fig. 3 suggested a connection between the accuracy of the remotely sensed soil moisture information and the land cover. Therefore, the dominant land surface cover within each satellite-type pixel was determined, using the information from ECOCLIMAP, in order to identify vegetation specific correlations for each data product. For this purpose, the different vegetation types within each 0.25° pixel were aggregated into three dominant cover types: i) cultivated soils, ii) grasslands, and iii) forests (Fig. 4). Relatively good correlations exist between SIM, ERS-Scat and AMSR-E (VUA-NASA) for the two herbaceous vegetation covers (Fig. 5a & b). Like in the analysis of the overall data set, ERS-Scat and SIM have the highest correlation coefficient and lowest RMSE. Similarly, the pairs SIM/AMSR-E (VUA-NASA) and AMSR-E (VUA-NASA)/ERS-Scat have slightly lower correlation coefficients and higher RMSEs, and AMSR-E (NSIDC) having negative correlations throughout. These results (with the exception of the AMSR-E (NSIDC) data) are not surprising given that remotely sensed soil moisture information should theoretically be retrievable with a high level of accuracy over herbaceous vegetation types. In herbaceous vegetation covers, active and passive methodologies are expected to show similar performances, especially when using a similar frequency. The higher correlations of ERS-Scat and SIM as compared to AMSR-E (VUA-NASA) and SIM, shows potential for improvement of the AMSR-E (VUA-NASA) product. Part of the difference might be explained by the limited range of moisture values in the optimization routine for the AMSR-E (VUA-NASA) product (0-50%). For the retrieval of the current AMSR-E (VUA-NASA) data, the soil moisture content is limited to a maximum of 0.5 m^3m^{-3}. However, it was found that the surface soil moisture states often reached this point of saturation (Fig. 1). Consequently, if this constraint were to be relaxed, and the retrieval process were allowed to produce higher values, a quasi-normalised soil moisture product may be obtained (this aspect has been considered for the next version of soil moisture data, which has recently been made available). However, as a consequence of this constraint, the maximum soil moisture is currently underestimated, which leads to an underestimation of the dynamic range, and consequently a wet bias in the AMSR-E (VUA-NASA) data. The methodology behind the ERS product avoids this caveat, by scaling between minimum and maximum observed signal over the period 1992-2000.

The comparison of the various data sets for forested regions (Fig. 5c) overall shows lower correlations and higher RMSEs. Again, ERS-Scat produces the best correlation with SIM, followed by AMSR-E (VUA-NASA) and AMSR-E (NSIDC). Moreover, the ERS-Scat soil moisture product appears to conserve its good correlation with SIM from the analysis of the herbaceous vegetation types. Under the assumption that SIM is equally valid for forested regions as for regions with low vegetation, it may be concluded that two effects may influence the consistency of ERS-Scat for different vegetation types. Firstly, the retrieval process of ERS-Scat implicitly takes into consideration the vegetation type by scaling the current signal between the wet end dry ends of its long-term data base. This statement has significance for other soil moisture missions in both active and passive microwave remote sensing, as the approach taken for the retrieval of ERS-Scat soil moisture may be applied along with more sophisticated radiative transfer models. Secondly, the ERS-Scat is well calibrated and has a low radiometric noise of about 0.15 dB, which allows estimating soil moisture even in areas where abundant forest cover reduces the effective sensitivity of backscatter to soil moisture.

An aspect of the data visible within the scatterplots of Fig. 5 is the apparent bi-modality of the SIM data with data clouds forming for the lower and upper value ranges. Fig. 6 and 7 show histograms of the surface soil moisture from the four different low-resolution data sources (SIM, AMSR-E (VUA-NASA), AMSR-E (NSIDC), and ERS-Scat) for SMOSREX and for the whole of France, respectively. The histograms of the various data sources show different patterns at the local scale (Fig. 6). While SIM and ERS-Scat show clear bi-modalities, this is not the case for the two AMSR-E products, with AMSR-E (VUA-NASA) having several peaks with a saturation at 1, and AMSR-E (NSIDC) data being almost normally distributed, though all data sets, have a minima in the range of 0.4 to 0.6. The histogram of the in-situ data at SMOSREX (Fig. 6e) also shows a bi-modality, although with its maximum in the wet spectrum. This would suggest that preferred soil moisture states exist at SMOSREX, but that the distribution is not correctly captured by the various models.

The non-normal distribution of the histograms have significance for the normalisation process, as it was previously assumed that the soil moisture distribution was sufficiently normal at each point. A violation of the assumption of normality would mean that the 90% confidence interval could not be calculated with the equations (1) and (2). To assess this, the distribution of the soil moisture states at the national scale was studied (Fig. 7).

An exception here is SIM with a clear peak in the dry spectrum (0.2) and AMSR-E (VUA-NASA) being skewed towards the wet end (Fig. 7). The overall distributions show that SIM retains its clear bi-modality with a peak in the dry spectrum, while the ERS-Scat and AMSR-E data become more normally distributed. For the AMSR-E data sets, the distribution of AMSR-E (NSIDC) data becomes almost Gaussian with a slight skew towards the wet end, while the AMSR-E (VUA-NASA) data is more evenly distributed. As the normalisation procedure of Pellarin et al. (2006) is only applied to the AMSR-E data, it is concluded that the normalisation process is still applicable to the majority of the pixels throughout France.

The results shown here are in line with other studies. For example, Teuling et al. (2005) showed that preferred soil moisture states may exist locally. However, they found that this effect could not be observed at all sites studied and that it could not be linked to local soil conditions and may therefore be a random effect. This conclusion is supported by Fig. 6 and 7, where the histograms for the data at SMOSREX suggest that local preferred wet and dry states exist, while the distribution of all observations over France is not bimodal.

c. *Intra-seasonal Correlation*

The bi-modality presented in the previous section is unlikely to be caused by differences in the soil types, as the soil moisture data were normalised, and SMOSREX also appears to have this distribution (Fig. 6e). The bi-modality is related to the varying soil moisture states, which are caused by either precipitation events or seasons. As the effect of precipitation events on the soil moisture distribution is difficult to obtain, the results obtained for the cultivated soils in Fig. 5 were separated according to the various seasons. This analysis (Fig. 8) clearly shows the different preferred soil moisture states in summer (dry) and winter (wet), which are consequently the main reason for the creation of the data clouds in Fig. 5. Similar results of preferred soil moisture states during the various seasons has been shown by Settin et al. (2007), where they were largely attributed to the precipitation intervals and intensities during the various seasons. Interestingly, the two AMSR-E products have nearly the same correlations with SIM during springtime, which would suggest that the two radiative transfer models work similarly well during this period.

5. Conclusion

In this paper, an intercomparison study of several remotely sensed surface soil moisture products with the re-analysis LSM predictions over France has been presented. First, the LSM predictions, and the satellite observations were compared with a 3-year in-situ surface soil moisture data set from an experimental site in south-western France (SMOSREX) to determine their capability to represent the temporal dynamics of a point or pixel. A good correlation was found between the model predictions and the in-situ data, despite a slight dry bias within the model predictions. Based on this evaluation, it was then assumed that the land surface model predictions over France may be used as a credible approximate estimate in the absence of more direct surface soil moisture observations for the whole country.

The analyses of this study, have shown that two of the three satellite data sets (AMSR-E (VUA-NASA) and ERS-Scat) have generally a good correlation with the model predictions, while the AMSR-E (NSIDC) data set did not correlate well with any of the other data sets. Generally, the AMSR-E (NSIDC) data showed a significant lack of seasonal soil moisture dynamics, which was well captured by the other data sets. These results suggest that the AMSR-E (NSIDC) data set is not correct, as three other independent models (a physically based radiative transfer model, an empiric soil moisture retrieval scheme, and a land surface model) show a good correlation with each other. This is further supported by the good correlation between SIM, AMSR-E (VUA-NASA), ERS-Scat and the in-situ observations at SMOSREX. It is possible that those three models are all wrong and coincidentally produce the same results, though the comparison with SMOSREX suggest that this is not likely. The results of the observations obtained from the scatterometer additionally highlights the potential use of active microwave data sets, which will be continued by the MetOp ASCAT observations.

The analysis of de-trended time series (monthly anomalies) of surface soil moisture over the SMOSREX site shows that short term variations of SIM and all the satellite products (included the NSIDC AMSR-E product) are meaningful. The significance is less for ERS-Scat, which has a high sampling time.

For the moment it has to be acknowledged that there exists a good correlation between some products for densely vegetated areas, but further studies are required to validate their physical meaning or relevance. Given that the we present only the temporal dynamics in this paper, it is interesting to learn that some satellite products appear to represent those dynamics better than others, even for forested areas.

While in-situ observations averaged to the land surface model or remotely sensed pixel scale may be better suited for the evaluation of both land surface or radiative transfer models, these observations are still sparse and difficult to obtain. This study presents an alternative to the use of in-situ observations for such large scale evaluations through the inter-comparison of independent and apparently similar soil moisture estimates from different models.

Finally, the good correlations between point observations and the low resolution model predictions and satellite observations also show the importance of single point observations for the verification of LSM and remotely sensed soil moisture products. They also support the need of the installation of new and the maintenance of existing soil moisture monitoring networks. This is particularly true for forested and mountainous regions, which in the past have been neglected when new soil moisture monitoring sites were established. With the need for the evaluation of land surface model performances and satellite validation campaigns, the relatively few existing networks are not sufficient.

Acknowledgments

The authors acknowledge the NSIDC for the AMSR-E (NSIDC) data set. Eric Martin and Jean-François Mahfouf from the CNRM are thanked for providing access to the SIM data base and fruitful discussions. During the course of this study, Christoph Rüdiger was financed through a post-doctoral fellowship with the Centre National d'Etudes Spatiales (CNES). The SMOSREX project was co-funded by the «Programme National de Télédétection Spatiale» and by the «Programme Terre Océan Surface Continentales et Atmosphère» (CNES), and by participants to the experiment: CESBIO (CNES, CNRS, IRD, UPS), CNRM/GAME (Météo-France, CNRS), INRA, and ONERA, all in the framework of the SMOS science preparatory program.

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Figures

Figures

Figure 1. Time series plots (2003-2005) of the normalised values of the in-situ observations at SMOSREX (black lines) and the four surface soil moisture products, SIM, AMSR-E (NSIDC), AMSR-E (VUA), and ERS-Scat (+). The model predictions and satellite observations were obtained from respective low-resolution pixels covering SMOSREX.

Figure 2. Scatterplot of the normalised in-situ soil moisture observations at SMOSREX (vertical axis) with the four low-resolution data sets (SIM, AMSR-E (VUA), AMSR-E (NSIDC), and ERS-Scat) for the years 2003-2005. Darker regions show a higher density of data points.

Figure 3. Maps of the coefficient of correlation between the various soil moisture products (normalised values) over mainland France. The circles highlight the 6 major metropolitan areas of France.

Figure 4. Location of pixels with the different dominant land cover types (cultivated soils, grasslands, and forests), based on the fractional covers obtained from Ecoclimap and aggregated to 0.25° resolution.

Figure 5. Vegetation type specific comparison of the different soil moisture products for the three dominant vegetation types (a) cultivated soils, b) grasslands, c) forests), using the data from the period 2003-2005. The scatterplots and their corresponding statistics are located on opposite sides of each figure, ie. the scatterplot of the data pair SIM-AMSR (VUA) is in the

top left hand corner, while the respective statistical values are found in the bottom right hand corner. Darker regions show a higher density of data points.

Figure 6. Histograms showing the relative frequency (vertical axis) of the various normalised soil moisture observations (horizontal axis) and predictions for the years 2003-2005 for the SMOSREX site: SIM model, AMSR-E product of VUA-NASA, AMSR-E product of NSIDC, ERS-Scat product of University of Vienna, in situ observations.

Figure 7. Histograms showing the relative frequency (vertical axis) of the various normalised soil moisture observations (horizontal axis) and predictions for the years 2003-2005 for whole of France: SIM model, AMSR-E product of VUA-NASA, AMSR-E product of NSIDC, ERS-Scat product of University of Vienna.

Figure 8. Scatterplots showing the comparison of the various soil moisture products for pixels with herbaceous vegetation only (cultivated soils and grasslands) for the four seasons a) spring, b) summer, c) autumn, and d) winter. The scatterplots and their corresponding statistics are located on opposite sides of each figure, ie. the scatterplot of the data pair SIM-AMSR (VUA) is in the top left hand corner, while the respective statistical values are found in the bottom right hand corner. Darker regions show a higher density of data points.

Tables

Table 1 – Comparison of monthly anomalies of surface soil moisture products (SIM, AMSR-E, ERS-Scat) with in-situ 0-6cm observations at the SMOSREX site, for three pooled annual cycles (2003 to 2005).

Product	Season	Number	Correlation	Bias	RMSE	Kendall τ	Kendall p-value
SIM	All	794	0.61	0.01	0.79	0.63	****
SIM	DJF	121	0.44	-0.03	0.93	0.53	**
SIM	MAM	219	0.74	0.01	0.65	0.73	****
SIM	JJA	255	0.58	0.03	0.78	0.58	****
SIM	SON	199	0.65	0.04	0.79	0.66	****
AMSR-E (NSIDC)	All	698	0.46	0.01	0.88	0.39	****
AMSR-E (NSIDC)	DJF	95	0.27	-0.20	0.99	0.17	NS
AMSR-E (NSIDC)	MAM	192	0.62	0.11	0.77	0.54	****
AMSR-E (NSIDC)	JJA	219	0.23	0.02	1.03	0.21	**
AMSR-E (NSIDC)	SON	192	0.54	0.01	0.88	0.48	****
AMSR-E (VUA-NASA)	All	606	0.38	0.01	0.97	0.38	****
AMSR-E (VUA-NASA)	DJF	75	0.12	-0.07	1.05	0.01	NS
AMSR-E (VUA-NASA)	MAM	172	0.49	0.09	0.90	0.53	****
AMSR-E (VUA-NASA)	JJA	184	0.28	0.01	1.00	0.28	***
AMSR-E (VUA-NASA)	SON	175	0.42	0.00	1.01	0.44	****
ERS-Scat	All	133	0.34	-0.08	0.85	0.30	**
ERS-Scat	DJF	32	0.57	-0.12	0.51	0.39	NS
ERS-Scat	MAM	32	0.55	-0.06	0.54	0.57	*
ERS-Scat	JJA	28	0.28	-0.10	0.64	0.30	NS
ERS-Scat	SON	41	0.19	0.02	0.81	0.07	NS

The monthly anomaly is the difference to the mean divided by the standard deviation, for a period of 5 weeks. The Kendall τ is a non-parametric measure of correlation that assesses how well an arbitrary monotonic function could describe the relationship between two variables, without making any assumptions about the frequency distribution of the variables. It is used to measure the degree of correspondence between two rankings and assessing the significance of this correspondence. The p-value indicates the significance of the test, if it is small (below 0.05 at least), it means that the correlation is not a coincidence. The following thresholds on p-values are used: (i) NS (non significant) for p-value greater than 0.05, (ii) * between 0.05 and 0.01, (iii) ** between 0.01 and 0.001, (iv) *** between 0.001 and 0.0001 and (v) * below a value of 0.0001.***

Table 2 – Statistics of the inter-comparison between the difference data sets (normalised surface soil moisture data). The values in each cell correspond to the coefficient of correlation, bias, and RMSE, respectively.

		SIM	ERS-Scat	AMSR-E (VUA-NASA)
AMSR-E (NSIDC)	r bias RMSE	-0.014 0.215 0.370	-0.099 0.040 0.363	-0.115 0.043 0.361
AMSR-E (VUA-NASA)	r bias RMSE	0.491 0.177 0.297	0.397 0.099 0.296	
ERS-Scat	r bias RMSE	0.728 0.093 0.201		

Figures

Fig. 1 Time series plots (2003-2005) of the normalised values of the in-situ observations at SMOSREX (black lines) and the four surface soil moisture products, SIM, AMSR-E (NSIDC), AMSR-E (VUA), and ERS-Scat (+). The model predictions and satellite observations were obtained from respective low-resolution pixels covering SMOSREX.

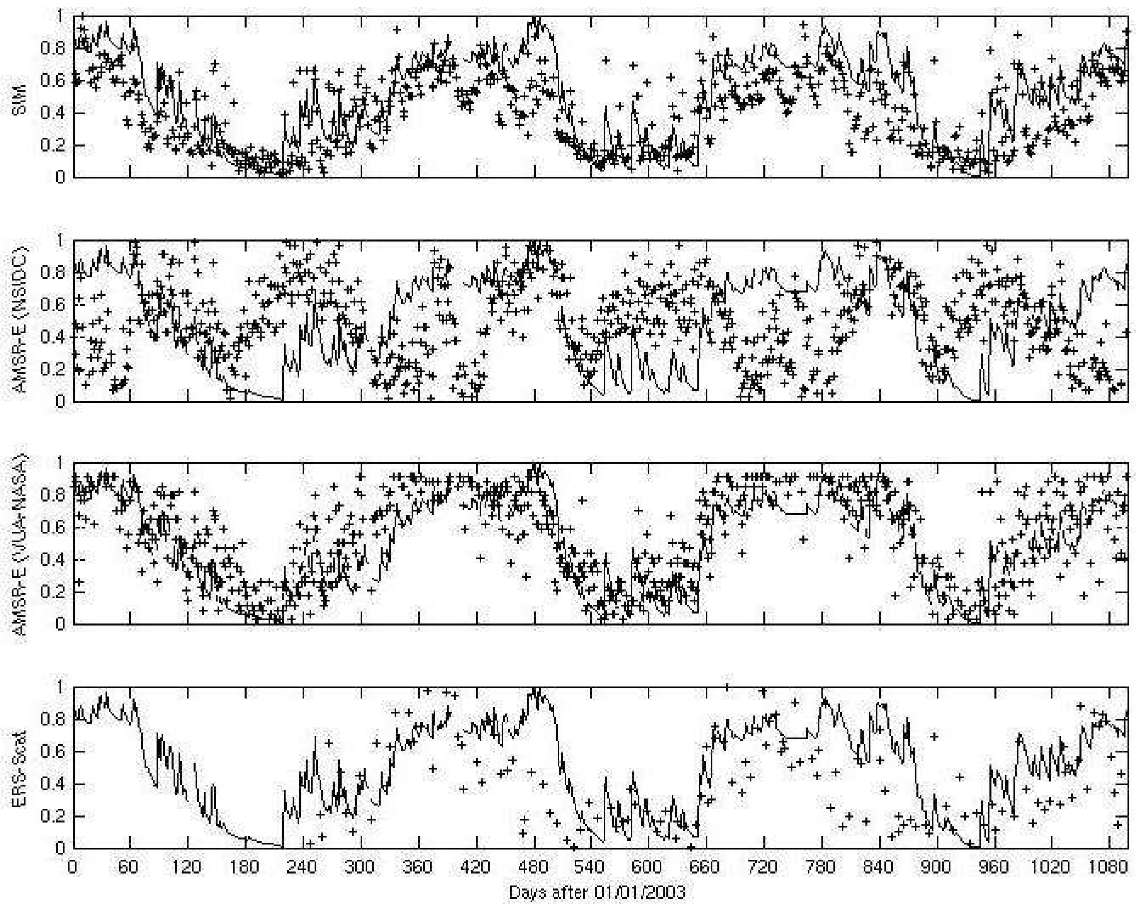


Fig. 2 Scatterplot of the normalised in-situ soil moisture observations at SMOSREX (vertical axis) with the four low-resolution data sets (SIM, AMSR-E (VUA), AMSR-E (NSIDC), and ERS-Scat) for the years 2003-2005. Darker regions show a higher density of data points.

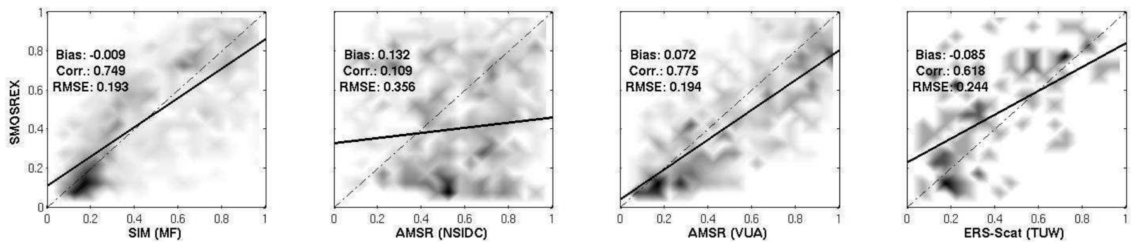


Fig. 3 Maps of the coefficient of correlation between the various soil moisture products (normalised values) over mainland France. The circles highlight the 6 major metropolitan areas of France.

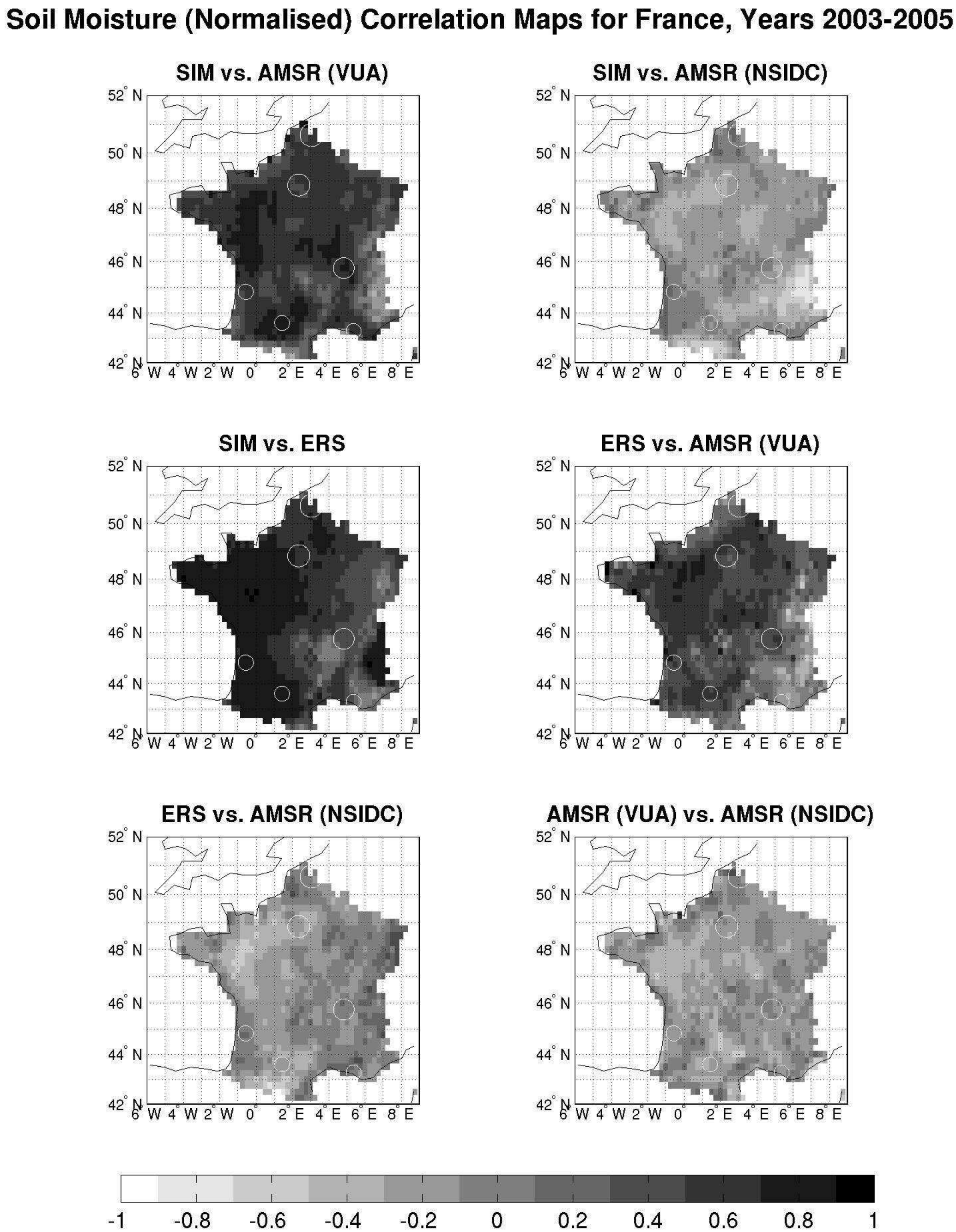


Fig. 4 Location of pixels with the different dominant land cover types (cultivated soils, grasslands, and forests), based on the fractional covers obtained from Ecoclimap and aggregated to 0.25° resolution.

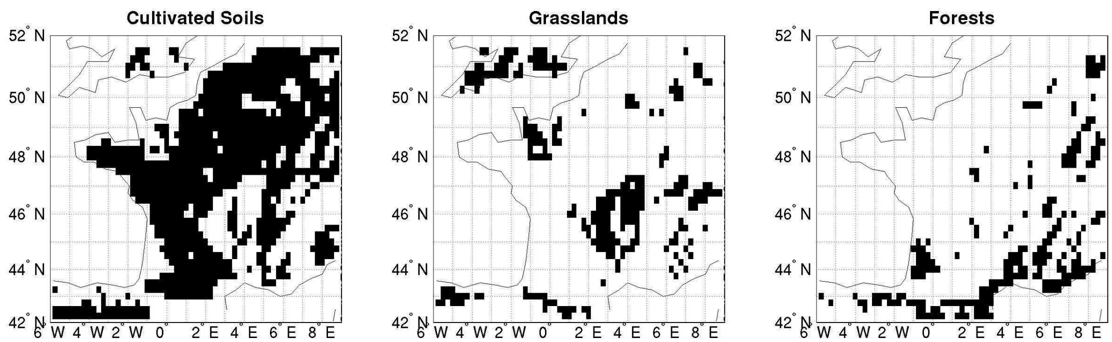


Fig. 5 Vegetation type specific comparison of the different soil moisture products for the three dominant vegetation types (a) cultivated soils, b) grasslands, c) forests), using the data from the period 2003-2005. The scatterplots and their corresponding statistics are located on opposite sides of each figure, ie. the scatterplot of the data pair SIM-AMSR (VUA) is in the top left hand corner, while the respective statistical values are found in the bottom right hand corner. Darker regions show a higher density of data points.

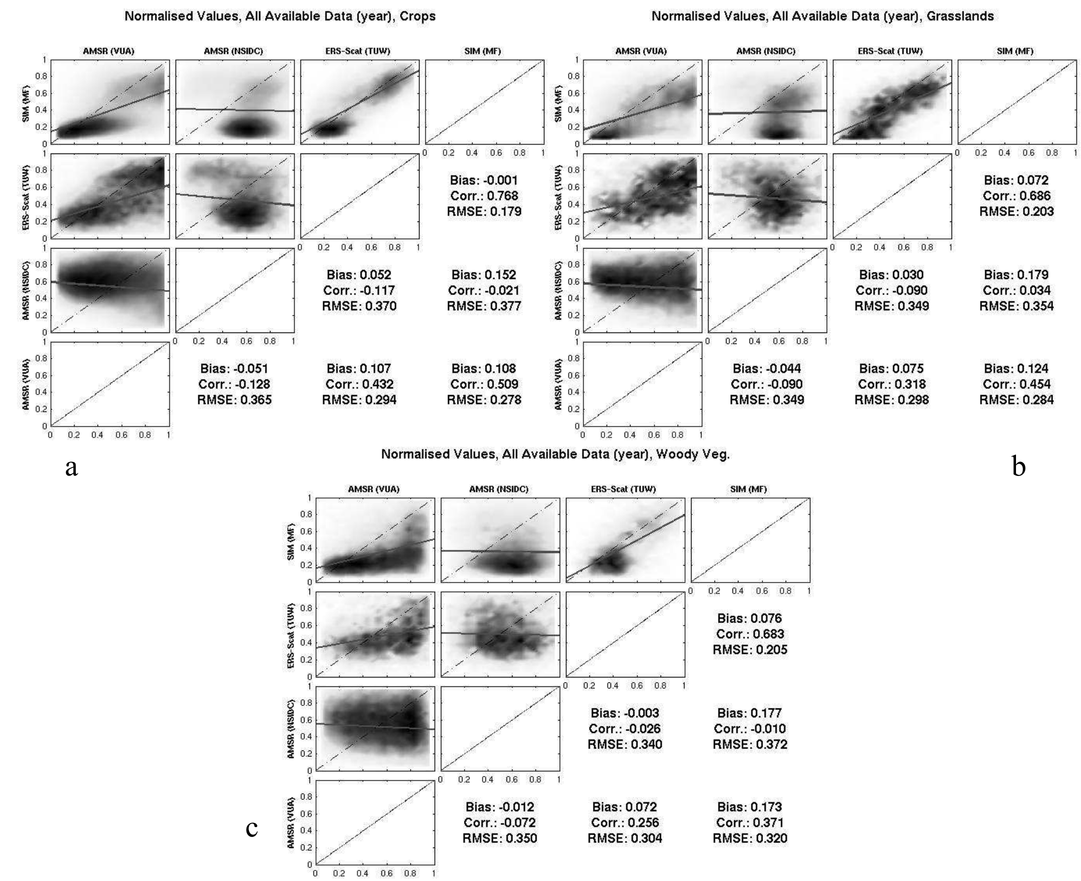


Fig 6. Histograms showing the relative frequency (vertical axis) of the various normalised soil moisture observations (horizontal axis) and predictions for the years 2003-2005 for the SMOSREX site: SIM model, AMSR-E product of VUA-NASA, AMSR-E product of NSIDC, ERS-Scat product of University of Vienna, in situ observations.

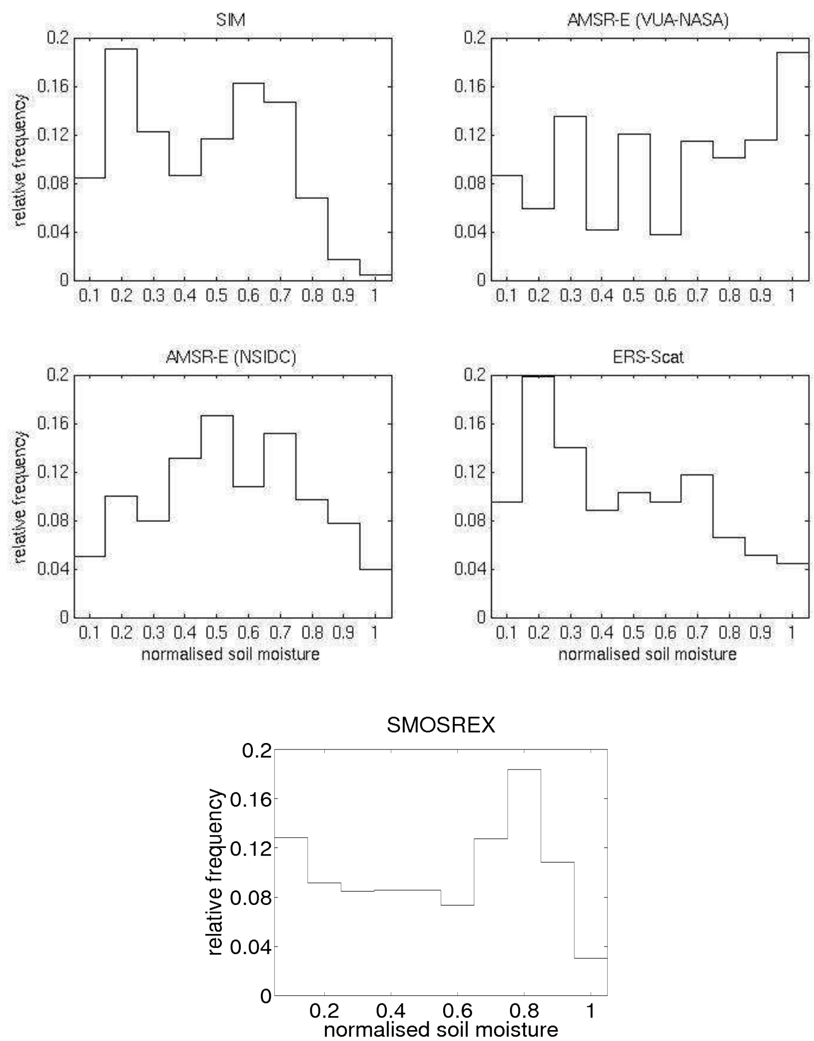


Fig 7. Histograms showing the relative frequency (vertical axis) of the various normalised soil moisture observations (horizontal axis) and predictions for the years 2003-2005 for whole of France: SIM model, AMSR-E product of VUA-NASA, AMSR-E product of NSIDC, ERS-Scat product of University of Vienna.

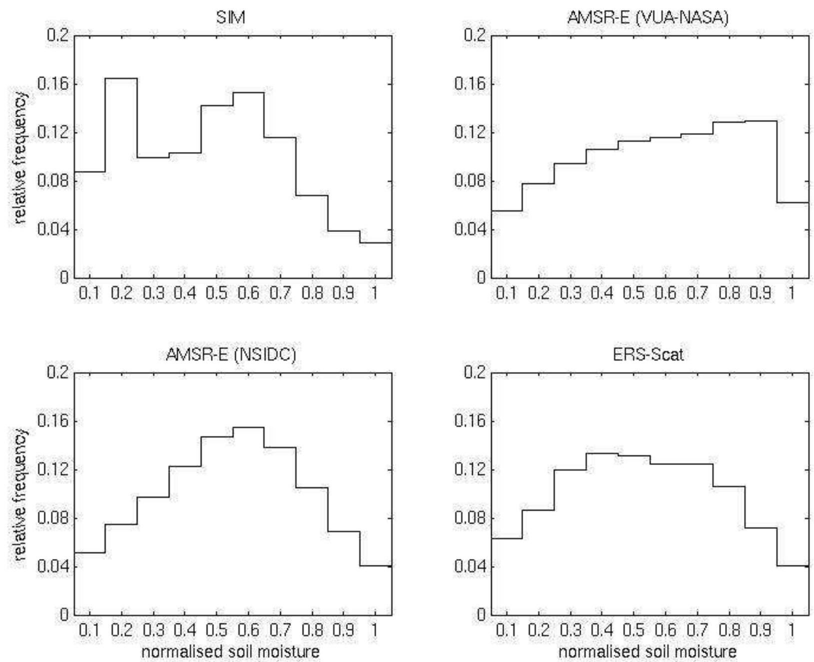
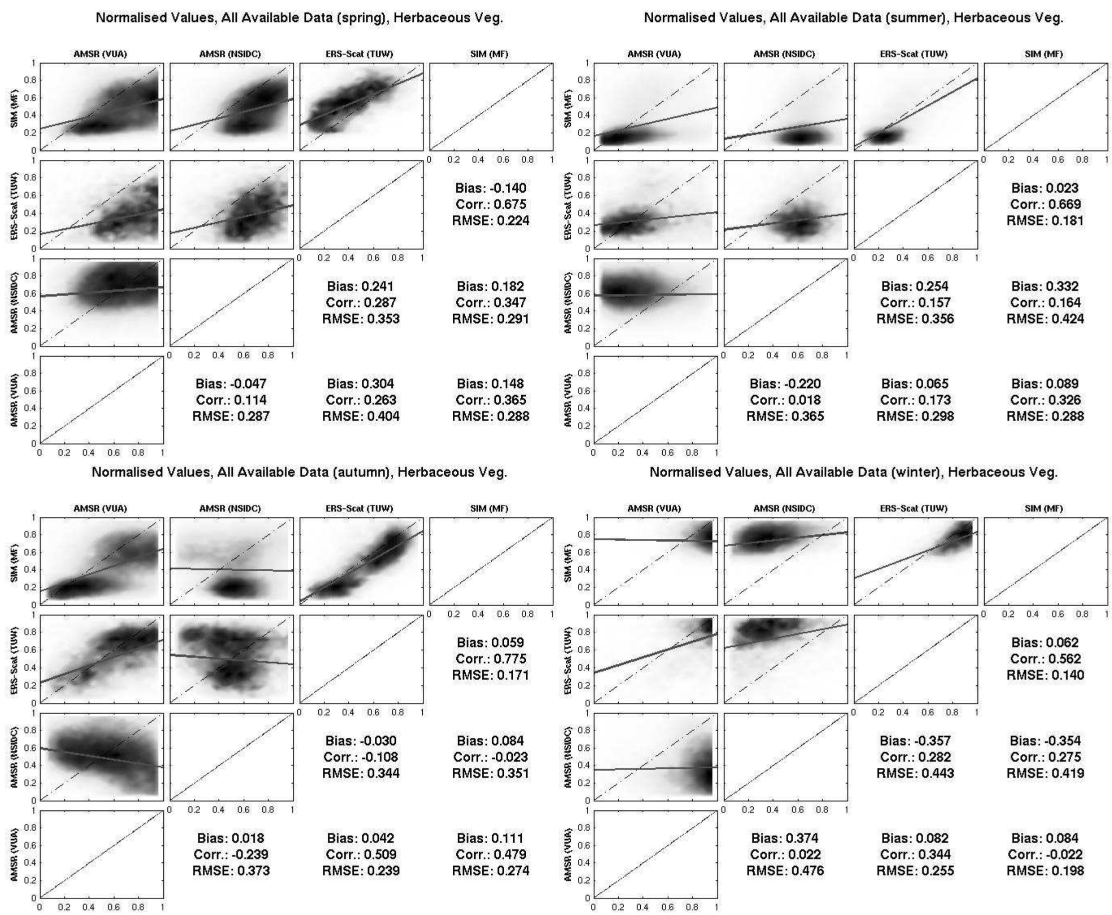


Fig. 8 Scatterplots showing the comparison of the various soil moisture products for pixels with herbaceous vegetation only (cultivated soils and grasslands) for the four seasons a) spring, b) summer, c) autumn, and d) winter. The scatterplots and their corresponding statistics are located on opposite sides of each figure, ie. the scatterplot of the data pair SIM-AMSR (VUA) is in the top left hand corner, while the respective statistical values are found in the bottom right hand corner. Darker regions show a higher density of data points.

a b



c d