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Assessment of soil moisture fields from imperfect climate models with uncertain satellite observations

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Abstract

We demonstrate that global satellite products can be used to evaluate climate model soil moisture predictions but conclusions should be drawn with care. The quality of a limited area climate model (LAM) was compared to a general circulation model (GCM) using soil moisture data from two different Earth observing satellites within a model validation scheme that copes with the presence of uncertain data. Results showed that in the face of imperfect models and data, it is difficult to investigate the quality of current land surface schemes in simulating hydrology accurately. Nevertheless, a LAM provides, in general, a better representation of spatial patterns and dynamics of soil moisture. However, in months when data uncertainty is higher, particularly in colder months and in periods when vegetation cover and soil moisture are out of phase (e.g. August in the case of Western Europe), it is not possible to draw firm conclusions about model acceptability. Our work indicates that a higher resolution LAM has more benefits to soil moisture prediction than are due to the resolution alone and can be attributed to an overall intensification of the hydrological cycle relative to the GCM.

Introduction

The land surface is a key component in climate models (CMs) and controls the partitioning of available energy at the surface between sensible and latent heat (ground flux), and of available water between evaporation and runoff (Pitman, 2003). The control of soil moisture on the partitioning of the heat fluxes is a key mechanism because the dynamics of soil moisture content thereby influence the variability in both weather and climate (Entekhabi et al., 1996). Simulations from climate models are increasingly being used in other applications. In particular for hydrological models being applied to assess future or past changes in hydrological behaviour, land surface schemes (LSSs) in CMs need to be evaluated against some sort of data. Given that these models are run over scales for which ground data collection is hardly possible, evaluation of land

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surface variables is difficult to perform. It is argued by Cornwell Cornwell and Harvey (2007) that while the quality of CM-LSSs seems to be improving (although there still are large inconsistencies in predictions), without high-quality long-term observations there remains significant uncertainty in the evolution of CM predictions of soil moisture 5 change.

However, satellites acquire data over very similar scales to climate models, and thus present an invaluable source of validation data. Many different techniques exist to derive soil moisture from passive as well as active microwave sensors. These range from less complex change detection algorithms (Wagner et al., 1999) to more sophisticated integration of land parameter retrieval models (Owe et al., 2001). It is important to note the many differences in definition of soil moisture that exist. LSSs are most concerned with heat and energy fluxes and soil moisture is treated and defined differently by different CM-LSSs (Cornwell and Harvey, 2007). Although efforts are being made to improve soil moisture retrieval from remote sensing, in some existing algorithms, soil moisture is represented as a wetness index whereby changes with depth or the effects of heat and moisture fluxes are only partially represented.

We use the global soil moisture products from the Advanced Microwave Scanning Radiometer onboard the Earth Observation satellite (AMSR-E) and the scatterometer sensor on the European Remote Sensing satellite (ERS-2) to propose a scheme to assess the quality and value of soil moisture simulated by a limited area model (LAM), HadRM (Jones et al., 1995), and a general circulation model (GCM), HadAM3 (Pope et al., 2000). By doing so, it is the aim to justify the development and use of a LAM. For instance, more reliable higher resolution limited area models could provide valuable input data for large scale hydrological modeling under different climate change scenarios.

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Data

Active scatterometer data

Global, coarse-resolution soil moisture data (25-50 km) are derived from backscatter measurements from active scatterometers on-board ERS-1 and ERS-2 (1991 to present) and the three MetOp satellites (2006-2020). Surface soil moisture data are derived using a change detection method for radar backscatter that relies upon the multi-incidence observation capabilities of the scatterometer to model the effects of vegetation phenology (Wagner et al., 1999). This technique retrieves topsoil moisture content (<5 cm) in a relative quantity ranging between 0 and 1 (respectively, 0–100%), scaled between zero soil moisture and saturation. The data can be obtained free of charge at http://www.ipf.tuwien.ac.at/radar/.

2.2 Passive AMSR-E data

Parameters for soil moisture retrieval are derived from passive microwave remote sensing data using the Land Parameter Retrieval Model (LPRM). The LPRM is based on a forward radiative transfer model to retrieve surface soil moisture and vegetation optical depth (VOD), i.e. vegetation wetness (Owe et al., 2001). A unique feature of this method is that it may be applied at any microwave frequency (<20 GHz), making it very suitable to exploit all the available passive microwave data from historic satellites (Owe et al., 2008). This dataset describes volumetric soil moisture (in m³ m⁻³) of the first top centimeters (1–2 cm) with an average accuracy of 0.06 m³ m⁻³ for sparse to moderate vegetated regions (de Jeu et al., 2008). For direct data use, five years (2002-2007) of daily 0.25 degree surface soil moisture data from AMSR-E C-band are available free of charge at http://www.geo.vu.nl/~jeur/lprm/.

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2.3 Soil moisture from climate models

Soil moisture is simulated within both CMs using MOSES (Meteorological Office Surface Exchange Scheme) from the UK Meteorological Office (UKMO) (Cox et al., 1999). MOSES is a land surface scheme that reproduces terrestrial processes according to a simplified surface flux partitioning scheme. For moisture flux, the surface hydrology is defined in terms of the soil moisture vertical profile, snow lying on the ground and water on plant leaves or on the soil surface. The soil hydrology component of MOSES is based on a finite difference approximation to Richards' equation (Cox et al., 1999) and moisture content is output for four vertical profiles (0.1, 0.25, 0.65 and 2.0 m), of which the top one (10 cm) is used for comparison in this study. Both CMs generate atmospheric conditions that interact with MOSES to output soil moisture.

HadAM3, with a grid resolution of 2.5 degrees latitude by 3.75 degrees longitude, is an improved version of the former Hadley Centre atmospheric model HadAM2b (Stratton, 1999) and is based on the Unified Model (UM) system. The HadAM3 simulations assessed in this paper are identical to the modern control simulations of Jost et al. (2005). The atmospheric model is initialized by observed climatological monthly mean sea surface temperatures (SSTs) (over 30 years), and so simulations do not correspond to any particular year. In other words, this study compares the seasonal cycle between data sets and not individual years.

HadRM is a limited area atmospheric model also belonging to the UM system, which is driven at its lateral boundaries and at the sea surface by a time series of data archived from a previous integration of HadAM3. Locatable over any part of the globe, it is typically run for short periods (i.e. <20 years) at a horizontal grid resolution of 0.44 degrees, as opposed to global simulations of long periods of time, which generates high-resolution climate change information for particular regions, however, the relative computational cost is high (Jones et al., 1995). Again, the HadRM simulations are identical to the modern control simulations of Jost et al. (2005).

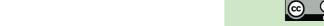
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3 Methods

3.1 Data pre-processing

For data quality assessment, both remote sensing data sets were translated onto a common grid over the chosen study area of Western Europe (Fig. 1). The Delaunay Triangulation method (Guibas and Stolfi, 1985) was used to plot data onto a common grid resolution of 0.5 degrees, as it does not assume any special arrangement of the data points used. Thereafter, soil moisture values were scaled between 0 and 1 (fractional soil moisture) in the spatial domain for sake of comparing different sources of soil moisture (Fig. 1).

Given that climate model outputs are available on a monthly basis for six years constrained by climatological mean SSTs (with an additional eight years spin-up time) for both the LAM and GCM, averaging all daily remote sensing values over a month for 3–4 years from 2004 to 2006/2007 for each sensor separately was assumed sensible. Although AMSR-E data are available on a daily basis whilst ERS data are acquired every 3 days, it is assumed that this difference is assumed negligible for monthly averaging. It is worth noting that although remote sensing data from both sensors are also available for the entire year of 2003, this year was omitted because (a) the ERS sensor was switched off a number of times and (b) the strong abnormal heat wave over Europe that summer had considerable effects on soil moisture conditions (Fischer et al., 2007), and as a result, both climate models (for normal atmospheric conditions) would be inappropriately penalized during evaluation.

3.2 Defining an appropriate LSS assessment scheme

After data pre-processing, the agreement of monthly soil moisture values between the two remote sensing sensors was assessed using histogram distributions in the form of box plots (Fig. 2). This gave an appreciation of data consistency over a full year. A strong positive skewness of the distribution and a mean absolute difference value over

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Interactive Discussion

Europe of ~0.2 in fractional soil moisture for most months indicated a good agreement (pixel by pixel) between the two products. Reciprocally, the degree of disagreement between the two products may be viewed as a measure of the uncertainty associated with the data. This information can be used in an evaluation scheme where both model and observation data are known to be in error. Such schemes have recently gained popularity in hydrological studies (Beven, 2006) and is used here to assess both climate models.

Given that soil moisture is highly variable in its nature, is poorly defined and reproduced differently by climate modeling as well as remote sensing, a fit-for-purpose model evaluation scheme, which copes with errors in both data and models as described above, needed to be defined. In the hydrology literature a number of different fuzzy rules-based membership functions have been used (e.g. Beven, 2006; Pappenberger et al., 2007)). We implemented a trapazoidal non-linear function (Fig. 3) that defines an adequate number of degrees of freedom within a fuzzy membership definition based on an interval of monthly mean remotely sensed soil moisture, the bounds of which are defined by the two satellite observations (RS_1 and RS_2 respectively) from 2004 to 2006/2007. Outside either side of this interval a Gaussian function is defined by $RS\pm\sigma$. In the case of observations from two different sources, the degree of variability (σ) is composed not only of a natural variability of the variable but also the level of disagreement between the sources themselves. The membership function that gives the acceptability (A_{LSS}) of the mean of monthly soil moisture outputs (LSS) from the LAM and GCM over Europe is defined in Eq. (1) below.

$$A_{\text{LSS}} = \begin{cases} 1 & RS_{1} \leq \text{LSS} \leq RS_{2} \\ ae^{-\frac{(\text{LSS}-RS_{1})}{2c_{1}^{2}}} & \text{LSS} < RS_{1} \\ -\frac{(\text{LSS}-RS_{2})}{2c_{2}^{2}} & \text{LSS} > RS_{2} \end{cases}$$
 (1)

Where a equals 1, c_1 equals $RS_1\pm\sigma$ and c_2 equals $RS_2\pm\sigma$ where σ denotes the standard deviation in soil moisture from both satellites. a is the height of the curve's 2739

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peak, RS_1 and RS_2 denote the position of the center of the peak, and c_1 and c_2 control the width of the function. By adopting a conditional membership function, it is ensured that the LSS is given a maximum acceptability of 1 if it falls inside an interval defined by the mean soil moisture of the two satellite instruments over the 3-4 years 5 and decreasing acceptabilities following a Gaussian distribution on either side of the interval $\pm \sigma$.

Results and discussion

4.1 Remote sensing soil moisture

Figure 1 shows that there is a strong spatial consistency between the AMSR-E derived soil moisture and that simulated by both climate models, but in places different spatial patterns are observed in the ERS scatterometer soil moisture. This is most probably because the AMSR-E algorithm and MOSES are physically based whereas the scatterometer data are obtained using a multi-incidence change detection algorithm which may lead to greater spatial inconsistencies.

A more thorough analysis of the data revealed that there is in general a good agreement between the monthly mean soil moisture values of the two sensors. Over Europe, absolute differences are for most months less than 0.15 in fractional soil moisture. This is reflected in Fig. 4b which illustrates that observed data variability is generally of σ <0.15, except for colder months, particularly NDJ. It is believed that alongside the natural variability of soil moisture, differences during colder months are primarily related to difficulties in retrieving soil moisture at lower temperatures and over snow-covered areas, especially for single or extreme events. Disagreement during warmer months may result (i) from differences in retrieval algorithms and also to a certain degree in soil depth (1-2 cm for AMSR-E, <5 cm for ERS and 10 cm for MOSES) especially in summertime, (ii) when vegetation and soil moisture are "out of phase" (for active microwave sensors), and (iii) when vegetation wetness (i.e. VOD) is too high (in case of

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the AMSR-E), resulting in large uncertainties in retrieved soil moisture (de Jeu et al., 2008). Also, at higher altitudes, large topographic variations as well as high vegetation add considerable uncertainties to the retrieval of soil moisture.

4.2 LSS acceptability

The analysis of the remote sensing soil moisture products confirms that both the degree of natural variability and the level of disagreement can be used to set limits of acceptability inside which the LAM and GCM need to fall to be acceptable. Figure 4a illustrates the acceptability of the LAM HadRM for each season alongside remote sensing data variability (Fig. 4b). In particular months (e.g. August in the case of Western Europe), with larger data intervals, apparent model performances increase. With higher degrees of freedom to fit the data, higher levels of model acceptability are to be expected, given the nature of the proposed evaluation scheme. In months of higher natural data variability, there is at the same time more uncertainty in the data retrieval because of the factors outlined earlier.

To assess the percentage improvement that is to be gained with the HadRM over Europe as opposed to the global HadAM3, the acceptability of the latter was computed and compared to the LAM translated onto the GCM grid. Equation (2) below gives the percentage improvement, I_{LAM} , that can be achieved with a high resolution CM.

$$I_{\text{LAM}} = \left(\frac{P_{\text{LAM}} - P_{\text{GCM}}}{P_{\text{GCM}}}\right) \times 100 \tag{2}$$

In HadRM, processes are better discretized due to the higher resolution, which results in a more intense reprensentation of the hydrological cycle (Jones et al., 1995). Therefore outputs of highly spatially varying parameters are more heterogeneous, which can lead to a better fit with spatially and temporally varying observations. Figure 5 shows I_{I AM} for the four seasons. For months in which the two satellites disagree most (NDJF and also August), the gain in acceptability is less obvious and conclusions should be drawn with care. However, for months when both observation sources

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give more similar values (MAMJJ) despite often more complex vegetation-soil moisture relations (e.g. March and April), the improvement is striking and exceeds in some occasions 100%. These findings justify the development and use of a LAM.

One possibility to further improve soil moisture simulations in LSSs is laid out by Gedney et al. (2000) who found that differences among CM predictions of changes in surface hydrology are particularly sensitive to how the runoff is parameterized over the active soil moisture range. Variations in the runoff at the critical soil moisture point account for much of the spread in predictions. Reducing the uncertainties in these predictions will require improved treatment of runoff appropriate for the spatial resolution, rather than further sophistication in the treatment of evapotranspiration.

5 Conclusions

In a review of LSSs, Pitman (Pitman, 2003) points out that significant problems remain to be addressed, including difficulties in parameterizing hydrology and sub-grid-scale heterogeneity. Continued development of land surface models requires more multi-disciplinary efforts by scientists with a wide range of skills. In this context, we have presented a possible evaluation scheme for CM-LSSs in the face of imperfect models and uncertain observations. The scheme reflects limitations of both current CM-LSSs and available remote sensing data.

Our work indicates that the use of a higher resolution LAM has more benefits to soil moisture prediction than are due to the resolution alone and can be attributed to improved representation of precipitation and thus the hydrological cycle at an enhanced horizontal resolution (Jones et al., 1995).

We believe that higher resolution CMs need to be evaluated with observations that space-borne remote sensing could potentially provide. However, our results indicate that for some months model differences are around the same order of magnitude as the uncertainty in current data sets. Therefore, further effort is needed to obtain more accurate soil moisture observations. Availability of adequate estimations of uncertainty

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associated with the data, such as presented by de Jeu et al. (2008), is also expected to reveal more. Noteworthy is also the progress researchers currently make with higher resolution soil moisture retrieval from Envisat ASAR observations (<1 km resolution, see e.g. Loew et al., 2006). This is still in an experimental stage, but may become routinely available in the very near future. Also, improved data products from new satellite missions, such as the Soil Moisture and Ocean Salinity (SMOS) mission, may allow us to better assess models.

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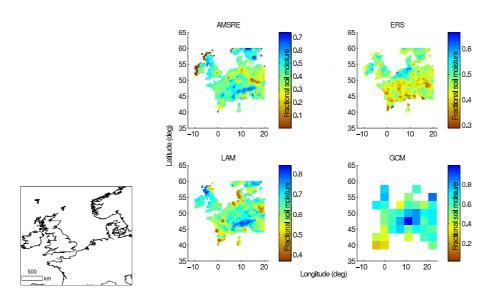


Fig. 1. Selected study area and annual mean soil moisture estimated from space-borne sensors (top) and climate models (bottom). Note that AMSR-E soil moisture along the west coast of Ireland and northern Scotland are caused by pixels with excess water on the surface and values in these parts should thus be interpreted with care or ignored.

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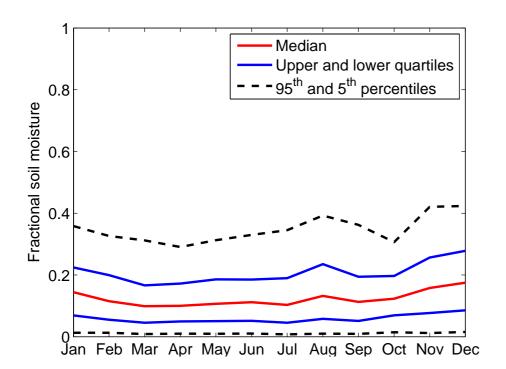


Fig. 2. Line plot showing the distribution of the remote sensing soil moisture interval $[RS_1, RS_2]$ for each month.

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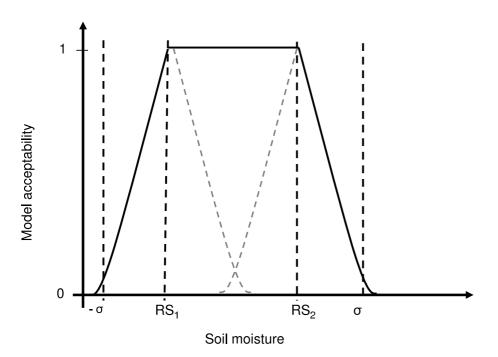


Fig. 3. Evaluation scheme based on a non-linear trapazoidal fuzzy membership function. RS_1 and RS_2 represent monthly soil moisture values from the two satellites, meaning that RS_1 and RS_2 can take the value of either the ERS-2 SAR or the AMSR-E depending on whichever value is larger or smaller, respectively. Note that this acceptability scheme is applied to every pixel in the domain separately.

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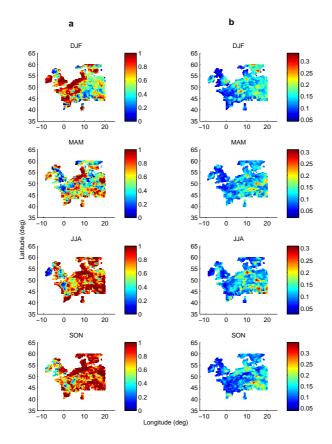


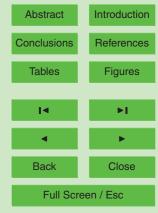
Fig. 4. (a) The plots show LAM acceptabilities for each meteorological season, where a maximum of 1 is attributed to a simulation that falls within the interval $[RS_1, RS_2]$ while a Gaussian function is applied outside that interval $\pm \sigma$ on either side. The plots in (b) give the variability (σ) in remote sensing-observed soil moisture.

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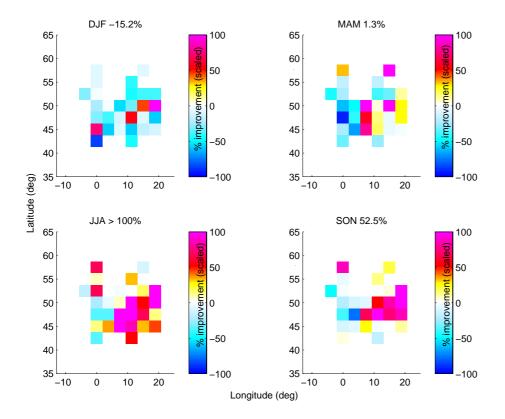
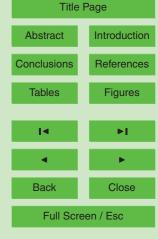


Fig. 5. Percentage improvement of soil moisture simulation when using a LAM instead of a GCM, for each season. The LAM is plotted to the GCM grid, which implicitly reflects the enhancement in surface dynamics representation that is to be gained with a LAM. Positive values indicate that the LAM gives a higher acceptability than the GCM and negative values show a lower acceptability of the LAM. Percentage values at top of plots give average I_{LAM} values over Western Europe.

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