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From near-surface to root-zone soil moisture using an exponential filter: an assessment of the method based on in-situ observations and model simulations

C. Albergel[1], C. Rüdiger[1,*], T. Pellarin[2], J.-C. Calvet[1], N. Fritz[1], F. Froissard[1], D. Suquia[1], A. Petitpa[1], B. Piguet[1], and E. Martin[1]

[1]CNRM/GAME (Météo-France, CNRS), Toulouse, France
[2]LTHE (UMR 5564), Grenoble, France
[*]now with: Department of Civil and Environmental Engineering, The University of Melbourne, Melbourne, Australia

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Correspondence to: J.-C. Calvet (calvet@meteo.fr)

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Abstract

A long term data acquisition effort of profile soil moisture is under way in southwestern France at 13 automatic weather stations. This ground network was developed in order to validate remote sensing and model soil moisture estimates. In this paper, both those in situ observations and a synthetic data set covering continental France are used to test a simple method to retrieve the root zone soil moisture from a time series of surface soil moisture information. A recursive exponential filter equation using a time constant, T, is used to compute a soil water index. The Nash and Sutcliff coefficient is used as a criterion to optimise the T parameter for each ground station and for each model pixel of the synthetic data set. In general, the soil water indices derived from the surface soil moisture observations and simulations agree well with the reference root-zone soil moisture. Overall, the results show the potential of the exponential filter equation and of its recursive formulation to derive a soil water index from surface soil moisture estimates. This paper further investigates the correlation of the time scale parameter T with soil properties and climate conditions. While no significant relationship could be determined between T and the main soil properties (clay and sand fractions, bulk density and organic matter content), the modelled spatial variability and the observed inter-annual variability of T suggest that a climate effect exists.

1 Introduction

Microwave remote sensing provides a means to quantitatively describe the water content of a shallow near-surface soil layer, w_g (Schmugge, 1983). However, the variable of interest for applications in short- and medium-range meteorological modelling and hydrological studies over vegetated areas is the root-zone soil moisture content (w_2), which controls plant transpiration. Since the near-surface soil moisture is related to the root-zone soil moisture through diffusion processes, assimilation algorithms may allow the retrieval of w_2 from observed w_g (Entekhabi et al., 1994;, Houser et al., 1998; Calvet and Noilhan, 2000; Walker et al., 2001a, 2001b). Estimation of profile soil moisture from intermittent remotely sensed soil moisture data has focused on the assimilation of such data into land surface models (Ragab, 1995; Walker, 2001a; Sabater et al., 2007). Land surface models with a thin topsoil layer, consistent with the nature of the remotely sensed observations are required in such an approach. Several authors concluded that the Kalman Filter (Kalman, 1960), an optimal sequential assimilation method extensively used in various environmental problems, is well suited for profile soil moisture estimation (Walker et al., 2001b). Other assimilation techniques such as 1DVAR also provide good results under controlled conditions (Sabater et al., 2007). However, the lack of high quality information on the model parameters at a global scale (soil properties, atmospheric forcing) and the uncertainties related to the physical description of the water and energy balance are a disadvantage. Moreover, the analysed profile soil moisture is model-dependent, and the chosen assimilation method may also affect the results (Sabater et al., 2007).

In contrast to data assimilation approaches, simpler methods to estimate the root-zone soil moisture rely solely on the remotely sensed surface soil moisture. Wagner et al. (1999) proposed to use an exponential filter to estimate the soil water index (SWI) of the root-zone from remotely sensed surface soil moisture time series. A number of studies have already shown the potential of this method using data from the scatterometer on board the European Remote Sensing Satellite (Wagner, 1999; Ceballos et al., 2005; Pellarin et al., 2006). Consequently, this approach may be tested using other existing or future remotely sensed data sets.

The SMOS satellite (Soil Moisture and Ocean Salinity, ESA/CNES), scheduled for launch in 2009, consists of a spaceborne L-band interferometric radiometer able to provide global estimates of surface soil moisture with a sampling time step of 2–3 days (Kerr et al., 2001). It is the first satellite exclusively designed for measuring soil moisture over land. Ground-truth measurements of soil moisture at various locations and covering large climatic gradients (several hundreds of km) will permit to validate the SMOS surface soil moisture products and to analyse w_2, once the SMOS data are available at a global scale. This will be achieved by making use of several soil moisture observation networks, such as the SMOSMANIA (Soil Moisture Observing System-Meteorological Automatic Network Integrated Application) network in southwestern France (Calvet et al., 2007). With SMOSMANIA soil moisture profile measurements at 12 locations of the automatic weather station network of Météo-France, the RADOME (Réseau d'Acquisition de Données d'Observations Météorologiques Etendu) network have been obtained since early 2007. This group of stations forms a 400 km transect along the climatic gradient between the Atlantic Ocean and the Mediterranean Sea, with all stations being equipped with probes measuring the volumetric soil moisture content at various depths.

SMOSMANIA is a long-term data acquisition effort of profile soil moisture observations that will be used to support the validation of soil moisture estimates derived from SMOS observations. Other remote sensing products from AMSR-E (Advanced Microwave Scanning Radiometer for Earth Observing System), WindSAT (a satellite-based polarimetric microwave radiometer), or ASCAT (Advanced Scatterometer on METOP) may be validated by SMOSMANIA as well, together with model soil moisture estimates over France (Rüdiger et al., 2008[1]). The SMOSREX (Surface Monitoring Of the Soil Reservoir EXperiment) experimental site (De Rosnay et al., 2006) is located along the same transect and may also be included in the validation effort, as SMOSREX includes profile soil moisture measurements.

In this paper, the SMOSMANIA project and its scientific objectives are first presented. This is followed by a definition of an exponential filter (Wagner et al., 1999) which allows to estimate the SWI from intermittent surface soil moisture measurements, as well as its recursive formulation (Stroud, 1999). The exponential filter equation uses a single tuning parameter: a time constant, T. In this study, the recursive formulation is used and the filter is applied to the surface soil moisture measurements ob-

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tained with SMOSMANIA and SMOSREX to estimate the root-zone soil moisture at a depth of 30 cm. In order to investigate the link between T and the local environmental characteristics (such as soil properties, depth, etc.), a similar study is performed with synthetic data from the SAFRAN-ISBA-MODCOU (SIM; SAFRAN atmospheric forcing data base; ISBA land surface model; MODCOU hydrological routing model) model suite applied over continental France (Habets et al., 2008).

2 Materials and methods

2.1 SMOSMANIA

The main objective of the SMOSMANIA network is to validate remote sensing soil moisture products. However, the use of observations obtained from SMOSMANIA are not limited to satellite validation and other objectives include: (i) the validation of the operational soil moisture products of Météo-France, produced by the hydrometeorological model SIM (Habets et al., 2005; Habets et al., 2008), (ii) the validation of new versions of the land surface model of Météo-France (ISBA), and (iii) ground-truthing of future airborne Cal/Val campaigns in support of the SMOS mission. For the first time, automatic measurements of soil moisture have been integrated in an operational meteorological network which results in a unique data set.

The SMOSMANIA network is based on the existing automatic weather station network of Météo-France (RADOME). The RADOME stations observe air temperature and relative humidity, wind speed and precipitation. At some stations the downwelling shortwave radiation is also measured. Twelve existing stations of RADOME in south-western France were chosen. They are listed in Table 1, from East to West. The stations form a Mediterranean-Atlantic transect (Fig. 1) following the marked climatic gradient between the two coastlines. The locations of the chosen stations are in relatively flat areas (mountainous areas are avoided as much as possible) and the altitude of the highest station (MTM) is 538m above sea level. The three most eastward stations

(NBN, LZC and MTM) are representative of a Mediterranean climate. The average distance between two neighbouring stations is approximately 45 km which is consistent with the spatial resolution of the future SMOS footprints. The vegetation cover at those sites consists of natural fallow, cut once or twice a year.

The main innovation of SMOSMANIA is the use of soil moisture probes in conjunction with an operational weather station network. Four soil moisture probes were horizontally installed per station at depths of 5, 10, 20, 30 cm to allow the reconstitution of a soil moisture profile. The ThetaProbe ML2X of Delta-T Devices was chosen because it has successfully been used during previous long-term campaigns of Météo-France and because it can easily be interfaced with the RADOME stations. The ThetaProbe is a capacitance probe using the dielectric permittivity properties of the soil to estimate the volumetric soil moisture content (White et al., 1994). The impedance of its array of four prongs varies with the two components of the soil impedance: the apparent dielectric constant and the ionic conductivity. As output, the ThetaProbe provides a voltage signal in unit of V (White et al., 1994) and its variation is virtually proportional to changes in the soil moisture content over a large dynamic range.

Site-specific calibration curves were developed using in-situ gravimetric soil samples in order to convert the voltage signal into volumetric soil moisture content ($m^3 m^{-3}$). As calibrations have to be performed for each soil type (i.e. for all stations) and for each depth, 48 calibrations curves were obtained for the SMOSMANIA network. The calibration was performed both in-situ (through regular gravimetric sampling around the station performed in 2006 and 2007) and in a laboratory set-up (monitoring of a given sample in various controlled conditions). Exponential calibration curves were found to represent best the relationship between the volumetric soil moisture content and the voltage measured by the sensor. The ThetaProbes are set to perform measurements at regular intervals of 12 min. They were installed in 2006 and have been operational since then, so that data covering the whole 2007 annual cycle are available.

Figures 2 and 3 show the 5 cm and 30 cm volumetric soil moisture content for the 12 SMOSMANIA stations, respectively, over a period of 14 months (January 2007–

February 2008) and at 12 min time intervals.

During the installation of the soil moisture probes, soil samples where collected for each of the four depths of the soil moisture profile (5, 10, 20, 30 cm). Those samples were used to determine soil texture, soil organic matter and bulk density (see Table 1).

2.2 SMOSREX

Located at the ONERA (Office National d'Etudes et de Recherches Aérospatiales) site of Fauga-Mauzac, near Toulouse in southwestern France (Fig. 1), the SMOSREX experiment (De Rosnay et al., 2006) aims at improving the modelling of the microwave L-band emission of the soil-vegetation system as well as improving the understanding of soil-plant-atmosphere interactions. The SMOSREX site consists of two plots (one of bare soil, one with fallow), observed by an L-band radiometer (LEWIS) installed at the top of a central structure, 15 m a.g.l. Operations began in January 2001 with the monitoring of soil moisture and temperature profiles. Soil moisture measurements are taken at depths of 0–6 cm, 10, 20, 30, 40, 50, 60, 70, 80, 90 cm and are available from January 2001 to December 2007 with an half-hourly time step. Using the soil moisture observations at each depth the integrated soil moisture in the root-zone is defined as the arithmetic average of those observations.

2.3 SIM

In the present study, the SIM model suite SAFRAN-ISBA-MODCOU is used to compute a surface w_g and a root-zone w_2 soil moisture data base over continental France from 1 August 2002 to 31 August 2004.

SAFRAN (Système d'analyse fournissant des renseignements atmosphériques à la neige) (Durand et al., 1993) is a mesoscale atmospheric analysis system for surface variables and was initially developed in order to provide an analysis of the atmospheric forcing in mountainous areas for snow depth and avalanche forecasting. The SAFRAN analysis provides the main atmospheric forcing parameters (precipitation, air temperature, air humidity, wind speed, incident radiation) using information from more than 1000 meteorological stations and more than 3500 daily rain gauges throughout France. An optimal interpolation method is used to assign values for each analysed variable. It was shown that a good correlation between the SAFRAN data base and in-situ observations exists (Quintana-Segui et al., 2008).

The land surface scheme in SIM is ISBA (Interaction between Soil, Biosphere and Atmosphere) in which the hydrology is based on the equations of the force-restore approach (Noilhan and Planton, 1989; Noilhan and Mahfouf, 1996). The soil layer and soil moisture dynamics are modelled within a 3-soil-layer model (Boone et al., 1999) with the soil and vegetation parameters being derived from a global data base of soils and ecosystems (ECOCLIMAP; Masson et al., 2003). For the purpose of the land surface simulations, the ISBA parameters, provided by ECOCLIMAP at a resolution of 1km, were aggregated to the model resolution of 8 km.

MODCOU is a hydrogeological model and was not used in the current study.

SIM was extended to the whole of continental France in 2002 in order to monitor the water resources at the national scale in near real-time (Habets et al., 2008). In total, SIM consists of a 9892 pixel data base. For each pixel, data such as surface and root-zone soil moisture, the thickness of the soil layer, fraction of clay and sand, LAI (Leaf Area Index), and the atmospheric forcing are available. For hydrological purposes, the database exceeds the political borders and covers, in particular, regions of Germany and Switzerland (over these regions, the quality of the atmospheric forcing is reduced as no ground observation is used in the analysis).

The w_g data set is used to derive a spatially and temporally distributed SWI product, described in Sect. 3.4, which is based on the exponential filter. In Sect. 4, the retrieved SWI is compared with the reference w_2.

2.4 The exponential filter

Past studies have shown that the profile soil moisture content is often reasonably well correlated with the surface soil moisture. The problem is that no clear relationship be-

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tween the regression coefficients and the characteristics of the site could be identified (Jackson, 1986). Recognising the need for a more physical approach, Jackson (Jackson et al., 1980) suggested the use of a water movement simulation model to compute the vertical moisture distribution in the soil profile. Assuming that hydrologic equilibrium conditions are satisfied, and provided soil properties are known, it is possible to estimate the profile soil moisture content from instantaneous surface observations. However, this assumption of near-equilibrium does not occur after rainfall and is not likely to be valid at daytime due to the high variability of the energy and water budget. To avoid the decoupling between w_g and w_2 after rainfall events, long time series may be correlated to the root-zone, and to avoid the daytime decoupling, surface soil moisture measurements should be taken during the morning (Jackson et al., 1980).

Several approaches can be used in order to relate profile soil moisture to surface soil moisture (Houser et al., 1998; Walker et al., 2001b; Sabater et al., 2007). In a simplified two-layer water-balance approach, the root-zone soil moisture can be estimated by convoluting the surface soil moisture time series with an exponential filter (Wagner et al., 1999). The top layer w_g is regarded as the remotely sensed surface layer and the second layer w_2 as a "reservoir" below. Once assuming that the water flux between those two layers is proportional to the difference in soil moisture content between the two layers, a simple water balance equation Eq. (1) can be used to establish a connection between w_2, and w_g:

$$L\frac{dw_2(t)}{dt} = C \cdot \left[w_g(t) - w_2(t)\right] \quad (1)$$

where L is the depth of the second layer, t represents time and C is an area-representative pseudo-diffusivity constant. Under the assumption that C is constant and $T{=}L/C$, the integration of Eq. (1) is:

$$w_2(t) = \frac{1}{T}\int_{-\infty}^{t} w_g(\tau)\exp\left[-\frac{t-\tau}{T}\right]d\tau \quad (2)$$

In this case, the parameter T represents a characteristic time length. This parameter can be considered as a surrogate parameter for all the processes affecting the temporal dynamics of soil moisture, such as the thickness of the soil layer, soil hydraulic properties, evaporation, run-off and vertical gradient of soil properties (texture, density). T represents the time scale of soil moisture variation, in units of day (Ceballos et al., 2005). Different important processes such as transpiration are not considered in Eq. (2). Additionally, it is assumed that the soil hydraulic conductivity is constant while it may vary in reality by several orders of magnitude depending on the soil moisture conditions (Wagner et al., 1999).

Remotely sensed data provides measurements at irregular time intervals, thus the continuous formulation of Eq. (2) is replaced by a discrete equation (Wagner et al., 1999):

$$\mathrm{SWI}(t_n) = \frac{\sum_{i}^{n} \mathrm{ms}(t_i) e^{-\frac{t_n - t_i}{T}}}{\sum_{i}^{n} e^{-\frac{t_n - t_i}{T}}} \quad (3)$$

where $\mathrm{ms}(t_i)$ is a normalised surface soil moisture, estimated from remote sensing at time t_i. This discontinuous time series replaces the continuous parameter $w_g(t)$. The quantity $w_2(t)$ is replaced by the Soil Water Index (SWI). The SWI is calculated if there is at least one measurement in the time interval $[t_n - T, t_n]$ and at least 3 measurements in the interval $[t_n - 3T, t_n]$ (Pellarin et al., 2006).

Equation (3) was validated against in situ measurements by Ceballos et al. (2005) in the semi-arid region of the Duero Basin in Spain. They found a statistically significant coefficient of determination (r^2=0.75) by comparing the SWI to 0–1 m soil moisture data from a measuring site, and a root mean square error of 0.022 $m^3 m^{-3}$.

2.5 Recursive formulation of the exponential filter

Stroud (1999) shows that the recursive formulation of the exponential filter resembles a Kalman filter (Kalman, 1960). In the case of soil moisture, the following recursive equation can be written:

$$\mathrm{SWI}_n = \mathrm{SWI}_{n-1} + K_n(\mathrm{ms}\,(t_n) - \mathrm{SWI}_{n-1}) \quad (4)$$

where the gain K at time t_n is given by:

$$K_n = \frac{1}{1 + \sum_i^n e^{-\frac{(t_n - t_i)}{T}}} \quad (5)$$

This gain may also be written in a recursive form as:

$$K_n = \frac{K_{n-1}}{K_{n-1} + e^{-\frac{(t_n - t_{n-1})}{T}}}. \quad (6)$$

The range of the gain K is [0,1]. In the presence of extensive temporal data gaps (relative to the filter time scale), Eq. (6) tends toward unity. In that particular case, the previous estimates are disregarded when new observations are obtained and the new estimate takes on the value of the new observation. For the initialisation of the filter, K_1=1 and SWI_1=ms(t_1).

This recursive formulation can handle data more easily than the original exponential filter, as the only requirement for an update of the SWI is (apart from the previous SWI and K values) the availability of a new ms(t_n) observation and the time interval since the last observation (t_n−t_{n-1}).

In this study, the recursive formulation of the exponential filter, as proposed by Stroud (1999), was used. It was checked (not shown) that this method yields the same results for the SMOSMANIA network and at the SMOSREX station as those obtained with Eq. (3).

3 Application of the exponential filter

In this study, only in-situ surface soil moisture observations taken at 0600 Local Standard Time (LST) at the 12 SMOSMANIA stations and at SMOSREX are used. Similarly, only the 6 a.m. simulations were extracted from the SIM data base. The 6 a.m. time was chosen as this will be the morning/descending overpass time of SMOS. Moreover, undesired effects in the real data base due to local climatic incidences are more pronounced in the afternoon, and were therefore avoided. The recursive filter Eqs. (4)–(6) were applied to the surface soil moisture values, normalised between the minimum and maximum values observed during the whole period considered.

3.1 Statistical scores

In order to assess the quality of the exponential filter, the correlation coefficient (r), the root mean square error (RMSE) and the Nash-Sutcliffe coefficient (N) were determined. The Nash-Sutcliffe coefficient N is defined as

$$N = 1 - \frac{\sum_{i=1}^{p} (\mathrm{SWI_{obs}}(i) - \mathrm{SWI_m}(i))^2}{\sum_{i=1}^{p} (\mathrm{SWI_{obs}}(i) - \mu \mathrm{SWI_{obs}})^2}, \tag{7}$$

where $\mathrm{SWI}_m(i)$ and $\mathrm{SWI_{obs}}(i)$ are the modelled and observed SWI at time i. The μ $\mathrm{SWI_{obs}}$ value is the overall average of the observed (reference) SWI. N can range from $-\infty$ to 1. A value of 1 corresponds to a perfect match between modelled and observed data. A value of 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas a value of less than 0 occurs when the observed mean is a better predictor than the model (Nash and Sutcliffe, 1970).

3.2 SMOSMANIA

For each SMOSMANIA station, the soil moisture observations at a depth of 5cm are used to calculate the SWI. The calculated SWI is then compared to soil moisture observations at 30 cm (the deepest observation at the SMOSMANIA stations), for different values of T (up to 40 days). Previous analyses of SMOSREX data (not shown) indicate that local soil moisture observations at depths ranging from 20 cm to 50 cm are significantly correlated to the root-zone soil moisture integrated over 1m depth. The r^2 values over a period of three years (2001–2003) exceed 0.9. Consequently, in this study, the 30 cm soil moisture observations are considered as a good indicator of the root zone soil moisture.

For each station the T parameter corresponding to the best value of a statistical score (N or r) is determined and is called T_{opt}. In general the N value was used to optimise T, except for the stations of MTM and SBR. While the highest N value retrieved for the former is negative for any value of T, the retrievals of the latter always result in an underestimation of the root-zone soil moisture and is very low, 0.02. Consequently, the T values at those stations were optimised using r between the retrieved SWI and the soil moisture observations at 30 cm.

3.3 SMOSREX

Surface (0–6 cm) soil moisture observations at SMOSREX are used to calculate the SWI over a 7 year period (2001–2007) using the exponential filter for different values of T (up to 40 days). The SWI values are compared to the soil moisture observations at 30 cm and at other depths (from 10 cm down to 90 cm) and to the soil moisture integrated over the root-zone.

3.4 SIM

Surface soil moisture information from the 9892 grid cells of the SIM database are used to compute the SWI. In SIM, w_g corresponds to a skin soil moisture (a few mm at the soil surface), and the SWI corresponds to the total soil moisture content w_2 of the second soil layer of ISBA. The thickness of this layer may vary from one grid cell to another. For each grid cell, different T values are used in order to retrieve T_{opt} corresponding to the highest value of N. T_{opt} was optimised over the two year period of the data base

(2003–2004). Negative values of N are sometimes observed over mountainous and dense urban areas (not shown). Over mountainous areas, perturbing physical factors (snow, soil freezing) affect the sensitivity of w_g to w_2. Over dense urban areas, the soil moisture simulated by SIM is not relevant. The grid cells for which the maximum N is negative are excluded from the database. As a consequence, a 9258 grid cell database is available with T_{opt}, and the scores of the SWI retrieval (r, RMSE, bias and N) versus the reference simulated w_2.

4 Analysis of the results

In this section, the T_{opt} values obtained with the methodology described in Sect. 3 are presented, along with the corresponding r, RMSE and N, in Tables 2 and 3 for SMOSMANIA (the 12 stations) and SMOSREX, respectively. Figures 4 to 11 illustrate the results obtained with the in situ data of SMOSMANIA and SMOSREX, and with the synthetic data of SIM.

4.1 Performance of the exponential filter

The performance of the exponential filter for retrieving the root-zone soil moisture from the available surface soil moisture information shows was investigated for the 12 SMOSMANIA stations, for 7 annual cycles of SMOSREX, and for the SIM simulations.

4.1.1 SMOSMANIA

Table 2 shows good SWI retrieval results for the majority of the SMOSMANIA stations, at a depth of 30 cm: 7 stations present N values higher than 0.7 (SFL, MNT, SVN, LHS, CDM, PRG, URG). Fair values of N are obtained for NBN and CRD (0.675 and 0.635, respectively). Results for LZC are poor (N=0.376) and negative or very low values of N are obtained for MTM and SBR (see Sect. 3.2). Despite the biased retrieval of MTM and SBR, seasonal dynamics in the root-zone soil moisture are well retrieved. It is interesting to note that most N values lower than 0.7 are observed at the stations presenting the highest fraction of sand (Table 1): the average fraction of sand at LZC, MTM, CRD, SBR is higher than 40%.

The values of r and RMSE are less contrasting than N, from one station to another. The average r and RMSE are 0.88 and 0.16, respectively. The RMSE represents the relative error of the soil moisture dynamical range. With an average dynamic range of $0.4\,m^3m^{-3}$ for the SMOSMANIA network at 5cm depth, and an average RMSE value of 0.16, an estimate of the average error of the root-zone soil moisture retrieval is about $0.065\,m^3m^{-3}$.

The retrieved T_{opt} values presented in Table 2 range from 1 to 23 days, with an average of 6 days. In order to test the sensitivity of the exponential filter to changes in T_{opt} (or to the use of a single T_{opt} value for all the stations), T was set to 6 days for all sites. The new value of N for each site is also shown in Table 2. The SWI for all stations of the SMOSMANIA network, calculated with T_{opt} set to 6 days, are presented on Fig. 4 along with the soil moisture observations at 30 cm. Although the initial T_{opt} ranges from 1 to 23 days, peaks and troughs are still well represented with the averaged T_{opt}=6 days. The majority of the sites maintain a high value of N, which suggests that the sensitivity to changes in T is limited.

The evolution of N as a function of T for the 12 SMOSMANIA stations is shown in Fig. 5. It is obvious that several monitoring sites have a large range of possible T_{opt} values with a high N. These results support the findings of Wagner (1998), who stated that the approach may be relatively insensitive to T.

4.1.2 SMOSREX

As the SMOSREX time series of soil moisture covers 7 annual cycles, T_{opt} was determined for each individual year, to gain an understanding of the inter-annual variability of this parameter. Table 3 presents T_{opt} for each year and for the whole period (T_{opt}=6 days), and the corresponding statistical scores, at a depth of 30cm. The value of N ranges from 0.557 to 0.935, with a mean of 0.845. For T_{opt}=6 days a N value of 0.858

is obtained. The average r and RMSE are 0.946 and 0.113, respectively. The difference between the N values corresponding to the annual T_{opt} or to T_{opt}=6 days is low, which is consistent with the results obtained with the data from the SMOSMANIA network (Sect. 4.1.1). The optimisation of the calculated SWI on the basis of the SWI obtained from the integrated soil moisture observations over the complete root-zone depth at SMOSREX yields a T_{opt} of 11 days and an N value of 0.837, which is only marginally lower than the N value for 30 cm.

The retrieval of the SWI at 30 cm for the SMOSREX site is shown on Fig. 6 for T_{opt}=6 days along with the observations at 30 cm for the period of January 2001 to December 2007. The two time series compare generally well but two shortcomings are observed:

- At wintertime, while the observations reach saturation, a saturation of the retrieved SWI is not achieved every year. Better results are obtained if the surface soil moisture observations are normalised yearly. In order to assess the impact of the interannual variability on the method, the normalisation was applied to the whole 7 year period.

- At summertime, the retrieved SWI overestimates the observations during the relatively wet years of 2001 and 2002. These periods display strong, but short precipitation events that resulted in a wet surface and consequently a high estimated SWI, whereas the in situ soil moisture profile observations show that those precipitation were not strong enough to increase soil moisture at 30cm.

4.1.3 SIM

The spatial variability of T_{opt} over continental France was investigated thanks to the SIM database. Figure 7 shows maps of N and T_{opt} over the SIM domain for all the grid cells (i.e. for spatially varying values of thickness of the root-zone and soil texture). Median values of N and T_{opt} are 0.689 and 15 days, respectively.

An example of retrieval is given in Fig. 8 for one grid cell (4.96° E, 43.68° N) of the SIM data base. This case was chosen among the 9258 grid cells for which the exponential filter performs well (N=0.86). For this grid cell T_{opt}=10 days, less than the average value (14.2), the thickness of the root-zone is 1.4 m and the fractions of clay and sand are 0.32 and 0.38, respectively. The SWI derived from w_g and the corresponding root-zone soil moisture content are shown.

Overall, the performance of the filter is good (N is higher than 0.7 for about 50% of the grid cells), and the variability of T_{opt} throughout the SIM domain is rather small with 50% of the values ranging mostly from 10 to 15 days. The highest values of T_{opt} are found in the mountainous areas of the Alps and Pyrenees, and this may be explained by contrasting climatic conditions (snow cover, freezing, thawing etc.) compared to the plain areas.

4.2 Impact of soil depth/thickness

Equation 1 shows that T_{opt} does depend on the soil depth or thickness for which the SWI is computed. Soil moisture observations at SMOSREX are available at depths between 10 and 90 cm, and the SIM derived SWI may correspond to contrasting soil thickness values. Therefore, it is possible to compare the SWI derived from the surface soil moisture observations at several depths or for several soil thickness values and to obtain the corresponding T_{opt} values.

Figure 9a presents T_{opt} for different depths at SMOSREX. It appears that T_{opt} is strongly correlated with the depth of the observation. Similar results are shown for SIM in Fig. 9b. In this case, binned and averaged values of T_{opt} are presented, for different soil thickness values (19 classes of soil thickness are used). Figure 9a shows that for soil depths ranging from 30 cm to 50 cm, SMOSREX T_{opt} varies from 6 to 23 days. Figure 9b shows that this range of T_{opt} values corresponds in the SIM simulations to root-zone thickness values ranging from 0.55 to 2 m. This is consistent with the observation at SMOSREX that soil moisture observations between 20 cm and 50 cm correlate well with the integrated soil water content over a thickness of 1 m (Sect. 3.2).

4.3 Impact of soil characteristics

Other parameters with a potential impact on T_{opt} are soil texture (clay and sand fraction), the bulk density, and the organic matter content, as they influence the infiltration capacity of the soil. Observed soil characteristics are available for SMOSMANIA (Table 1). For SIM, the model simulations account for soil texture, only.

In the case of SMOSMANIA, although the sand fraction seems to influence the N value (Sect. 4.1.1), no significant correlation between T_{opt} and soil characteristics could be established (not shown).

In the case of SIM, over France, soil texture has little influence on T_{opt}, as shown by Fig. 10. In Fig. 10, the retrieved T_{opt} is displayed as a function of clay and sand fractions, for the dominant soil thickness class (1.50±0.05 m). In order to reduce the influence of climatic conditions on the retrieval of T_{opt}, attempts were made to analyse the correlation over regions of 80×80 km. The results obtained (not shown) were similar to those presented in Fig. 10. Consequently, it is concluded that soil texture may not play a significant role in the determination of T_{opt}.

4.4 Impact of climate

As mentioned earlier, T_{opt} may be affected by local climate conditions. This assumption is further supported by the results in Table 3, where a rather large inter-annual variability of T_{opt} is observed for SMOSREX.

In order to explore this climate impact on T_{opt}, the SIM data base was used. All the T_{opt} values of the main depth class (1.50±0.05 m) were extracted over a south-north transect extending from the Mediterranean part of the Rhône valley to the Saône plain (44.8° N–46.9° N, 4.6° E–5.4° E). This transect presents a strong climatic gradient, with higher temperatures in the southern part (subject to a Mediterranean climate) than in the northern part (subject to a more temperate, continental climate), and a different precipitation regime. The average wind speed is also stronger in the southern part (Troen and Patersen, 1989). The extracted T_{opt} values were binned and averaged over regular intervals of 50 km. Figure 11 shows that T_{opt} tends to increase from the Mediterranean region to the Saône plain. Lower values of T_{opt} are representative of a faster response of the SWI to w_g and this is consistent with the higher evaporation demand (higher temperatures and wind speed) and the less frequent, but more intense, precipitation events observed in the southern part of the transect.

5 Discussion

This study provides several insights into the use of the semi-empirical approach developed by Wagner et al. (1999) to retrieve the root-zone soil moisture from remote sensing surface soil moisture estimates. It is shown that two main factors impacting on the retrieval exist: (i) the soil depth as T increases with the depth and (ii) the dominant climatic conditions within a region. It was also found that this study does not permit to establish a link between T_{opt} and soil texture (fraction of clay or sand). Climatic factors on drying/wetting characteristics have been found to have stronger effects than soil texture alone. An example of this climate impact was presented with Fig. 10 on the Rhône valley with an increasing T_{opt} from South to North corresponding to a climatic gradient. It was found that the soil layer depth plays a key role in the retrieval of T as it controls soil moisture variation which reacts slower with depth (see Figs. 2 and 3) and, consequently, increases T. On the other hand, regions in which phenomenon which reduce soil moisture (such as wind, high temperature, and evapotranspiration) dominate the climatic conditions appear to have lower T values.

The exponential filter was shown to significantly lack sensitivity to T_{opt}. The results presented in Tables 2 and 3 have different Nash-Sutcliffe coefficients corresponding to different T values (T_{opt} and averaged T_{opt}). Particularly the results of Table 3 show this lack of sensitivity. While an interannual variability of T_{opt} exists, the difference between the two values of N calculated for each year with T_{opt} or T=6 days at SMOSREX is low. The actual difference between the values of N is less than 2% and therefore N remains at a high level. Similarly, using the averaged T_{opt} for the twelve stations of the

SMOSMANIA network instead of their station-specific T_{opt} values causes a difference of less than 4%. The high accuracy of the result using either T_{opt} or a globally averaged T and the apparent insensibility of the retrieval method to changes in T_{opt} are interpreted as an advantage of this method, as a range of T values may be applied to obtain good estimates of the SWI. However these results may also lead to the interpretation that this insensitivity shows that the method is not fully adequate.

6 Conclusions

In this paper, an exponential filter is applied in order to retrieve root-zone soil moisture information (SWI) from surface soil moisture measurements. Generally, the use of this method results in good retrievals, after the characteristic time length of the filter (T) has been optimised (T_{opt}). The recursive formulation of the exponential filter was implemented as it reduces computational time and eliminates the need to store and reprocess long data records (all data in the interval $[t_n - 3T, t_n]$) each time a new observation is available.

Combining the rich SMOSMANIA and SMOSREX in situ data sets with synthetic data from land surface simulations over France, the impact of different factors on the single parameter of this approach (T_{opt}) could be assessed.

While no clear link between T_{opt} and various site-specific properties (except for depth) is found, its inter-annual variability at SMOSREX and its spatial variability over France allows the assumption that the local climate may affect T_{opt}. However, it was found that the exponential filter is not very sensitive to interannual or spatial variations of T, and that the application of a constant average value of T does not significantly affect the quality of the retrievals. The main features of the seasonal and interannual variability are captured.

This study underlines the potential of the exponential filter and its recursive formulation for root zone soil moisture retrieval. The discussed method is satisfactory and relies solely on surface soil moisture estimates. No land surface model or meteoro-

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logical observations (like precipitation) are needed to retrieve a SWI. As surface soil moisture can be observed from space by remote sensing techniques, the performance of the exponential filter is particularly interesting in data poor areas.

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References

Boone, A., Calvet, J.-C., and Noilhan, J.: Inclusion of a third soil layer in a land surface scheme using the force-restore method, J. Appl. Meteorol., 38, 1611–1630, 1999.

Calvet, J.-C. and Noilhan, J.: From near-surface to root-zone soil moisture using year-round data, J. Hydrometeorol., 1, 393–411, 2000.

Calvet, J.-C., Fritz, N., Froissard, F., Suquia, D., Petitpa, A., and Piguet, B.: In situ soil moisture observations for the CAL/VAL of SMOS: the SMOSMANIA network, International Geoscience and Remote Sensing Symposium, IGARSS, Barcelona, Spain, 23–28 July 2007, 1196–1199, doi:10.1109/IGARSS.2007.4423019, 2007.

Ceballos A., Scipal, K., Wagner, W., and Martinez-Fernandez, J.: Validation of ERS scatterometer derived soil moisture data in the central part of the Duero Basin, Spain, Hydrol. Process., 19, 1549–1566, 2005.

De Rosnay, P., Calvet, J.-C., Kerr, Y., Wigneron, J.-P., Lemaître, F., et al.: SMOSREX: A long term field campaign experiment for soil moisture and land surface processes remote sensing, Remote Sens. Environ., 102, 377–389, 2006.

Durand, Y., Brun E., Merindol, L., Guyomarc'h, G., Lesaffre, B., and Martin, E.: A meteorologi-

cal estimation of relevant parameters for snow models, Ann. Geophys., 18, 65–71, 1993, http://www.ann-geophys.net/18/65/1993/.
Entekhabi, D., Nakamura, H., and Njoku, E. G.: Solving the Inverse problem for soil moisture and temperature profiles by sequential assimilation of multifrequency remotely sensed observations, IEEE Trans. Geosci. Remote. Sens., 32, 438–448, 1994.
Habets, F., Ducrocq, V., and Noilhan, J.: Prévisions hydrologiques et échelles spatiales: l'exemple des modèles opérationnelles de Météo-France, C. R. Geosci., 337, 181–192, 2005.
Habets, F., Boone, A., Champeaux, J.-L., Etchevers, P., Franchisteguy, L., et al.: The SAFRAN-ISBA-MODCOU hydrometeorological model applied over France, J. Geophys. Res., 113, D06113, doi:10.1029/2007JD008548, 2008.
Houser, P. R., Shuttleworth, W. J., Famiglietti, J. S., Gupta, H. V., Syed, K. H., et al.: Integration of Soil Moisture Remote Sensing and Hydrologic Modelling Using Data Assimilation, Water Resour. Res., 34(12), 3405–3420, 1998.
Jackson, T. J.: Profile soil moisture from space measurements, J. Irr. Drain. Div.- ASCE, 106, 81–92, 1980.
Jackson, T. J.: Soil water modelling and remote sensing, IEEE T. Geosci. Remote, GE-24, 37–46, 1986.
Kalman, R. E.: A new approach to linear filtering and prediction problems, J. Basic Eng.-T. Asme., 82, no. Series D, 35–45, 1960.
Kerr, Y., Waldteufel, P., Wigneron, J.-P., Martinuzzi, J.-M., Font, J., and Berger, M.: Soil Moisture retrieval from space: the Soil Moisture and Ocean Salinity (SMOS) mission, IEEE Trans. Geosci. Remote, 39, 1729–1736, 2001.
Kerr, Y.: Soil moisture from space: Where are we?, Hydrogeol. J., 15, 117–120, 2007.
Masson, V., Champeaux, J.-L., Chauvin, F., Meriguet, C., and Lacaze, R.: A global database of land surface parameters at 1 km resolution in meteorological and climate models, J. Climate, 9, 1261–1282, 2003.
Nash J. and Sutcliffe, J.: River flow forecasting through conceptual models, part Ii – a discussion and principles, J. Hydrol., 10, 282–290, 1970.
Noilhan, J. and Planton, S.: A simple parameterisation of Land Surface Processes for meteorological model, Mon. Weather Rev., 117, 356–549, 1989.
Noilhan, J. and Mahfouf, J.-F.: The ISBA land surface parameterisation scheme, Global Planet. Change, 13, 145–149, 1996.

Pellarin, T., Calvet, J.-C., and Wagner, W.: Evaluation of ERS scatterometer soil moisture products over a half-degree region in southwestern France, Geophys. Res. Lett., 33, L17401, doi:10.1029/2006GL027231, 2006.

Quintana Segui P., Lemoigne, P., Durand, Y., Martin, E., Habets, F., et al.: Analysis of near surface atmospheric variables: Validation of the SAFRAN analysis over France, J. Appl. Meteorol. Clim., 47, 92–107, 2008.

Ragab, R.: Towards a continuous operational system to estimate the root-zone soil moisture from intermittent remotely sensed surface soil moisture, J. Hydrol., 173, 1–4, 1–25, 1995.

Robinson, D. A., Campbell, C. S., Hopmans, J. W., Hornbuckle, B. K., Jones, S. B., et al.: Soil moisture measurement for ecological and hydrological watershed-scale observatories: a review, Vadose Zone J., 7, 358–389, doi:10.2136/vzj2007.0143, 2008.

Sabater, J. M., Jarland, L., Calvet, J.-C., Bouyssel, F., and De Rosnay, P.: From near surface to root zone soil moisture using different assimilation techniques, J. Hydrometeorol., 8, 94–206, 2007.

Schmugge, T. J.: Remote Sensing of Soil Moisture: Recent Advances, IEEE T. Geosci. Remote, GE21, 145–146, 1983.

Stroud, P. D.: A recursive exponential filter for time-sensitive data, Los Alamos national Laboratory, LAUR-99-5573, public.lanl.gov/stroud/ExpFilter/ExpFilter995573.pdf, 1999.

Troen, I. and Petersen, E. L.: European Wind Atlas. ISBN 87-550-1482-8, Risbø National Laboratory, Roskilde, 656, 1989.

Wagner, W.: Soil moisture retrieval from ERS scatterometer data, Ph.D. thesis, University of Technology, Vienna, 101 pp.,1998.

Wagner, W., Lemoine, G., and Rott, H.: A method for estimating soil moisture from ERS scatterometer and soil data, Remote Sens. Environ., 70, 191–207, 1999.

Wagner, W., Scipal, K., Pathe, C., Gerten, D., Lutch W., and Rudolph, B.: Evaluation of the agreement between the first global remotely sensed soil moisture data with model and precipitation data, J. Geophys. Res.-Atmos., 108, 19, doi:10.1029/2003JD003663, 4611, 2003.

Walker, J. P., Willgoose, G. R., and Kalma, J. D.: One-dimensional soil moisture profile retrieval by assimilation of near-surface measurements: A simplified soil moisture model and field application, J. Hydrometeorol., 2, 356–373, 2001a.

Walker, J. P., Willgoose, G. R., and Kalma, J. D.: One-dimensional soil moisture profile retrieval by assimilation of near-surface observations: a comparison of retrieval algorithms, Advanced in Water Resources, 24, 6, 631–650, 2001b.

White I., Knight, J. H., Zegelin, S. J.- and Topp, G. C.: Comments on “Considerations on the use of time-domain reflectometry (TDR) for measuring soil water content”, edited by: Whalley, W. R., Response, Eur. J. Soil. Scvi., 45, 503–510, 1994.

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Table 1. Soil characteristics of the 12 stations of the SMOSMANIA network at four depths (5 10, 20, 30 cm): clay and sand fractions, organic matter, and bulk density. The stations are listed from East to West (Narbonne to Sabres).

Stations	Depth (cm)	Clay (g kg^{-1})	Sand (g kg^{-1})	Organic matter (g kg^{-1})	Bulk density (kg m^{-3})
Narbonne (NBN)	5	464	262	62.4	1260
	10	492	232	54.6	1545
	20	455	268	45.6	1237
	30	428	315	44.6	1237
Lézignan Corbières (LZC)	5	273	440	29.6	1383
	10	251	490	20.8	1498
	20	262	497	18.3	1468
	30	278	510	17.0	1468
Mouthoumet (MTM)	5	294	420	71.0	1438
	10	305	411	61.8	1540
	20	278	452	59.5	1561
	30	298	419	47.5	1600
St Félix de Lauragais (SFL)	5	228	435	19.6	1575
	10	224	403	14.2	1533
	20	239	397	16.5	1524
	30	294	320	11.9	1553
Montaut (MNT)	5	150	283	33.2	1405
	10	153	313	19.4	1444
	20	146	299	14.2	1562
	30	154	276	10.8	1458
Savenes (SVN)	5	194	361	12.8	1425
	10	193	339	11.6	1453
	20	195	346	10.7	1532
	30	353	239	5.6	1532
Lahas (LHS)	5	353	278	27.2	1518
	10	410	207	25.8	1500
	20	404	223	25.3	1535
	30	395	217	19.2	1370
Condom (CDM)	5	410	148	17.2	1419
	10	442	134	25.5	1522
	20	456	124	20.5	1460
	30	460	133	19.2	1574
Peyrusse Grande (PRG)	5	417	158	39.8	1285
	10	423	156	31.3	1476
	20	440	175	18.1	1449
	30	501	121	15.1	1536
Créon d'Armagnac (CRD)	5	57	881	44.5	1305
	10	53	884	27.1	1435
	20	47	898	28.3	1615
	30	50	878	23.2	1412
Urgons (URG)	5	157	159	27.6	1370
	10	158	154	21.9	1500
	20	152	164	19.8	1530
	30	172	144	8.1	1590
Sabres (SBR)	5	39	932	18.8	1460
	10	42	937	16.5	1680
	20	36	934	18.3	1678
	30	38	946	19.2	1645

Table 2. The retrieved optimum characteristic time length T_{opt} of an exponential filter for each SMOSMANIA station, at a depth of 30 cm. Statistical scores are given for each station: the correlation coefficient r, the root mean square error (RMSE), the Nash-Sutcliffe coefficient (N) corresponding to T_{opt}, and to the average T_{opt} (6 days).

Stations	T_{opt}	r	RMSE	N	N for T_{opt} = 6 days
NBN	4	0.887	0.145	0.675	0.672
LZC	8	0.826	0.231	0.376	0.367
MTM	1	0.495	0.193	negative	negative
SFL	4	0.940	0.102	0.882	0.879
MNT	2	0.958	0.134	0.796	0.777
SVN	5	0.952	0.161	0.762	0.762
LHS	23	0.926	0.180	0.706	0.591
CDM	12	0.888	0.137	0.774	0.743
PRG	2	0.932	0.126	0.818	0.798
CRD	1	0.912	0.151	0.635	0.605
URG	5	0.931	0.183	0.780	0.780
SBR	4	0.895	0.217	0.016	negative

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Table 3. The retrieved optimum characteristic time length T_{opt} of an exponential filter for each year (2001 to 2007) of the SMOSREX data set, and for the pooled (2001–2007) data set, at a depth of 30 cm. Statistical scores are given for each period: the correlation coefficient r, the root mean square error (RMSE), the Nash-Sutcliffe coefficient (N) corresponding to T_{opt}, and to the T_{opt} of the pooled data set (6 days).

Period	T_{opt} (days)	r	RMSE	N	N for T =6 days
2001	11	0.792	0.101	0.557	0.512
2002	11	0.966	0.141	0.863	0.847
2003	9	0.953	0.140	0.839	0.834
2004	5	0.976	0.140	0.880	0.878
2005	3	0.969	0.097	0.904	0.893
2006	6	0.978	0.086	0.927	0.927
2007	6	0.979	0.077	0.935	0.935
2001–2007	6	0.956	0.121	0.858	0.858

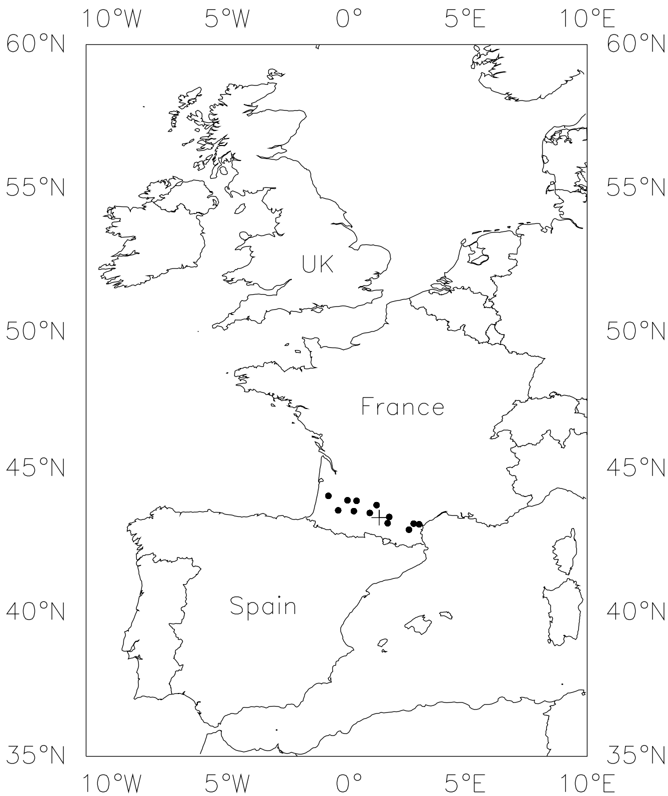

Fig. 1. Map illustrating the SMOSMANIA network located in southwestern France (full dots) forming a 400 km transect between the Atlantic ocean and the Mediterranean sea. The "+" symbol is for SMOSREX station. The stations are equipped with probes measuring volumetric soil moisture content and soil temperature at various depths.

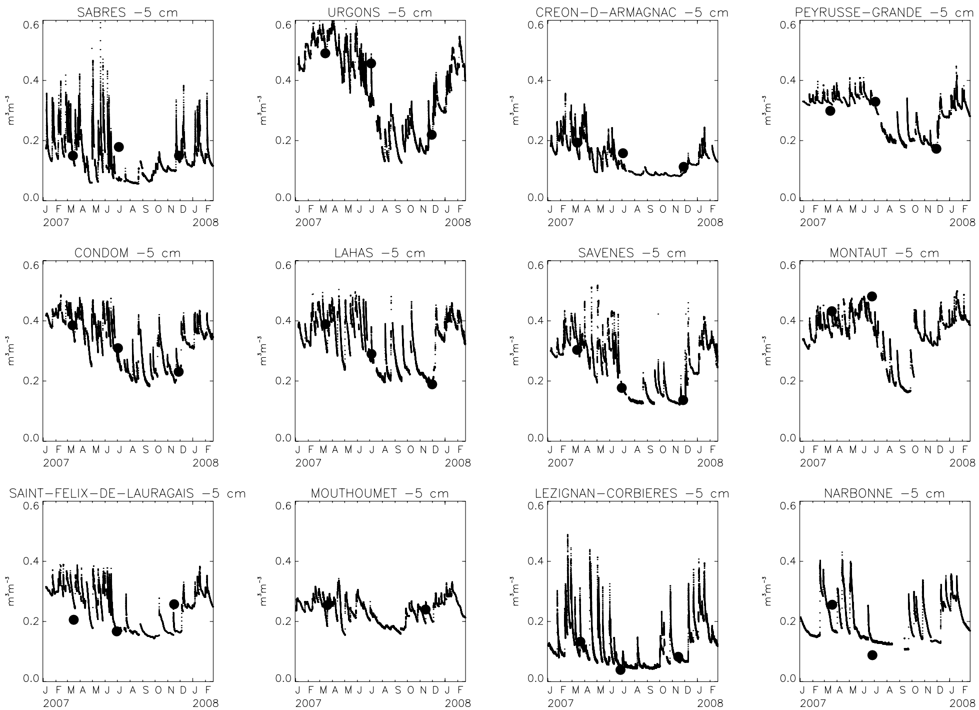

Fig. 2. Volumetric soil moisture measured for the 12 stations of the SMOSMANIA network over a 14 month period (from January 2007 to February 2008), at a depth of 5 cm: continuous observations with an automatic probe (solid line), manual gravimetric measurements on soil samples (dots).

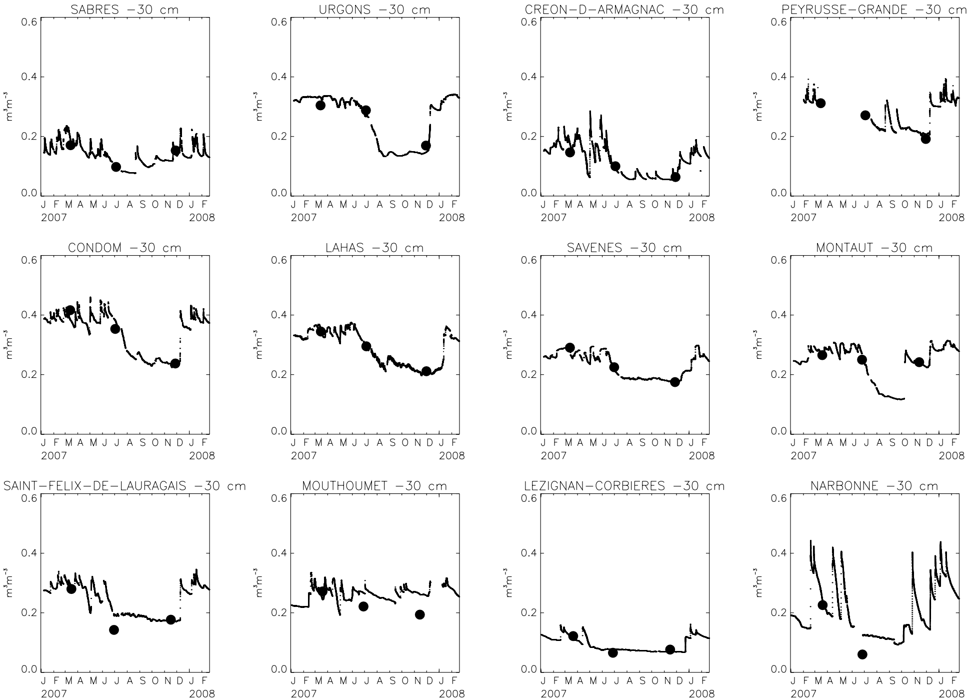

Fig. 3. Volumetric soil moisture measured for the 12 stations of the SMOSMANIA network over a 14 month period (from January 2007 to February 2008), at a depth of 30 cm: continuous observations with an automatic probe (solid line), manual gravimetric measurements on soil samples (dots).

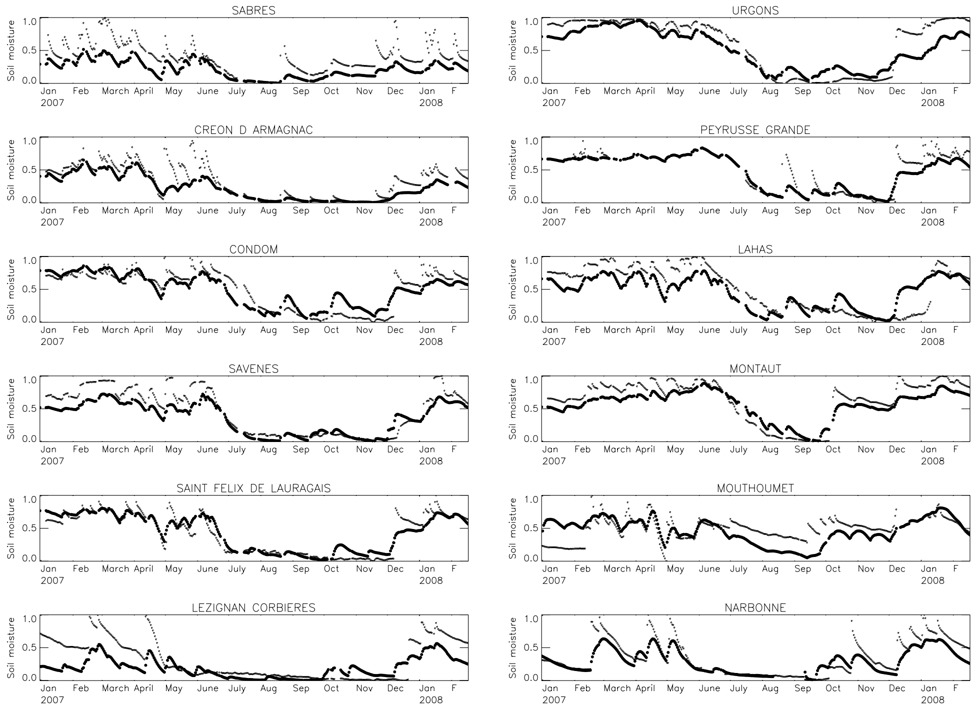

Fig. 4. Soil water index (SWI) at 30 cm derived from filtered surface soil moisture observations at 5 cm (large dots) and soil moisture observations at 30 cm (small dots), for the 12 stations of SMOSMANIA over a 14 month period. The characteristic time length of the exponential filter T=6 days is used, i.e. the mean value of the 12 optimised T parameters.

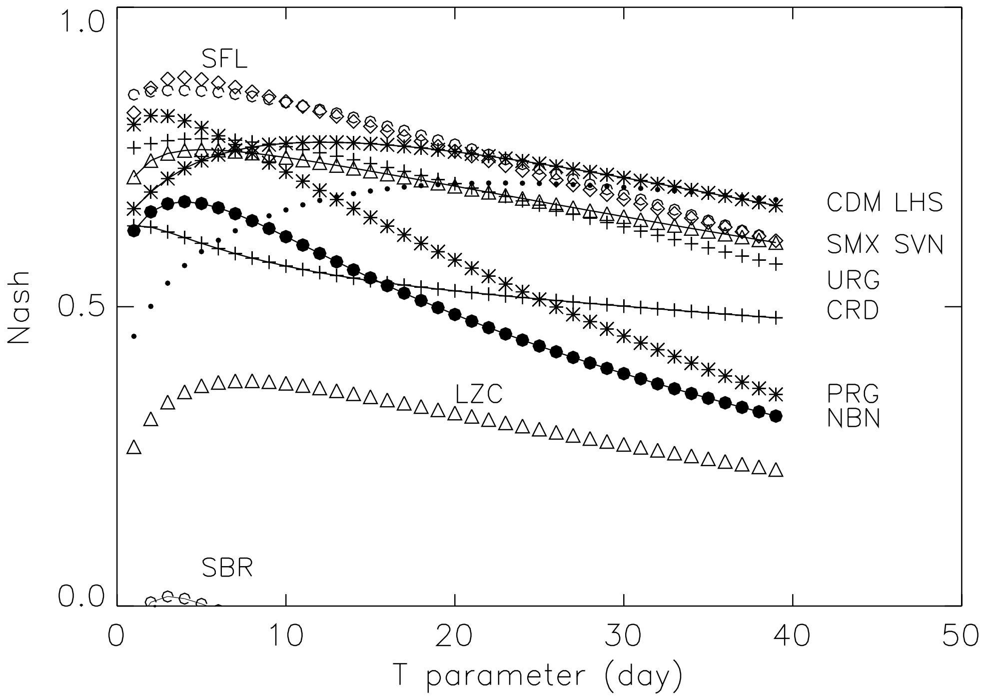

Fig. 5. Nash-Sutcliffe score of the SWI at 30 cm derived from filtered surface soil moisture observations at 5 cm versus the characteristic time length *T* used in the exponential filter for the 12 SMOSMANIA stations (Table 1) and for the SMOSREX station (SMX) from 2001 to 2007.

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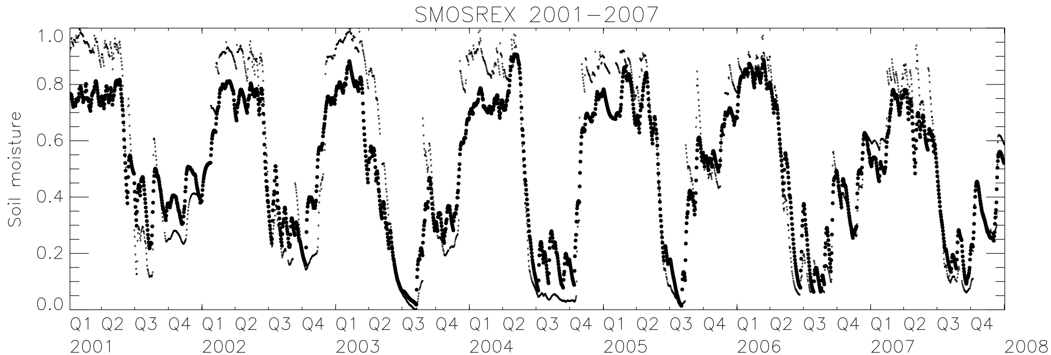

Fig. 6. Soil wetness index (SWI) at 30 cm derived from filtered surface soil moisture observations at 0–6 cm (large dots) and soil moisture observations at 30 cm (small dots), for the SMOSREX station over a 7 year period (from January 2001 to December 2007). The characteristic time length of the exponential filter T=6 days is used, i.e. the best-fit value for the 7-year period.

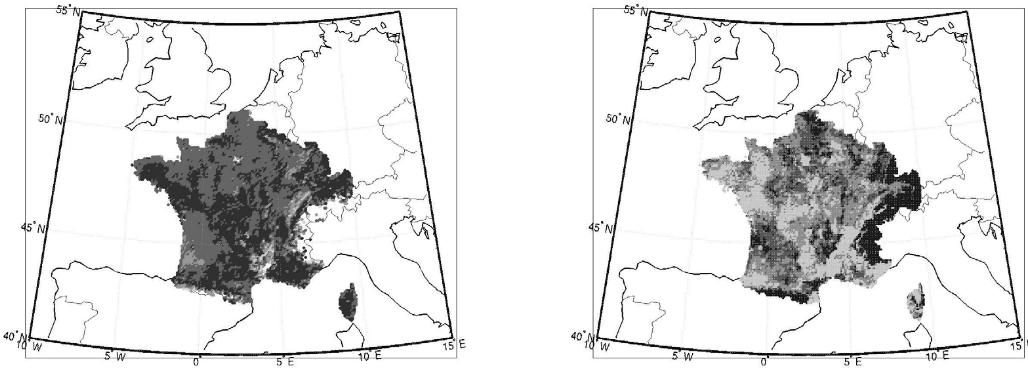

Fig. 7. Results of the exponential filter over the SIM domain for a 2-year period: Nash-Sutcliffe score N of the SWI derived from filtered surface soil moisture simulations (left), optimised characteristic time length T_{opt} of the exponential filter (right). The results are given for variable values of the soil thickness (from 0.2 to 2.0 m). Dark to light-grey classes correspond to values of N and T_{opt} binned in 4 intervals of decreasing value: [good (N>0.7), fair (0.5>N>0.7), poor (0.2>N>0.5), inadequate (N<0.2)] and [>15d, 12–15d, 10–15d, <10d], respectively.

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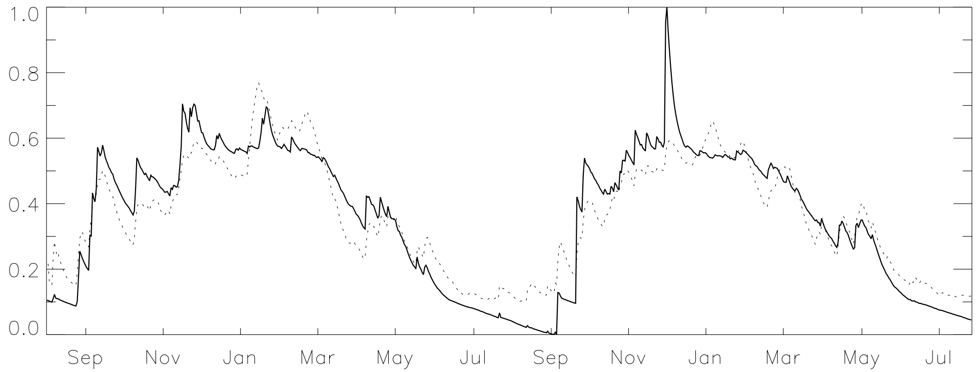

Fig. 8. Results of the exponential filter over a SIM grid cell (chosen among the 9258 pixels of the SIM database) for a 2-year period: SWI derived from filtered surface soil moisture simulations (dotted line) and the reference root-zone soil water content simulated by SIM (solid line) for one pixel on a two year period.

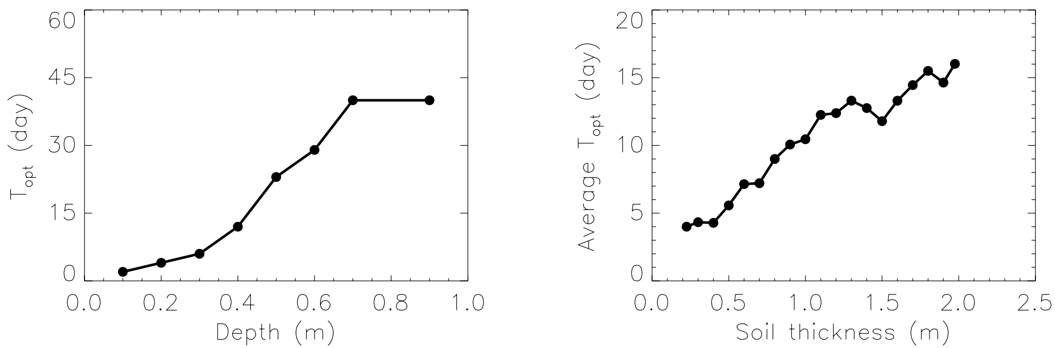

Fig. 9. Optimised characteristic time length of the exponential filter (T_{opt}) versus the corresponding (left) depth of the reference root-zone observations of SMOSREX, (right) thickness of the root-zone soil layer of SIM. In the latter case, averaged values are plotted.

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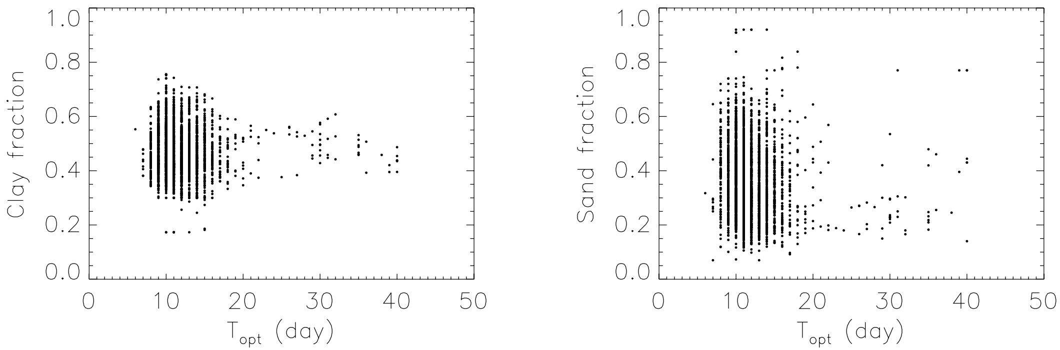

Fig. 10. Results of the exponential filter over the SIM domain for a 2-year period: clay and sand fraction versus the optimised characteristic time length of the exponential filter (T_{opt}) for the most frequent thickness of the root-zone soil layer of SIM (1.50 m±0.05 m).

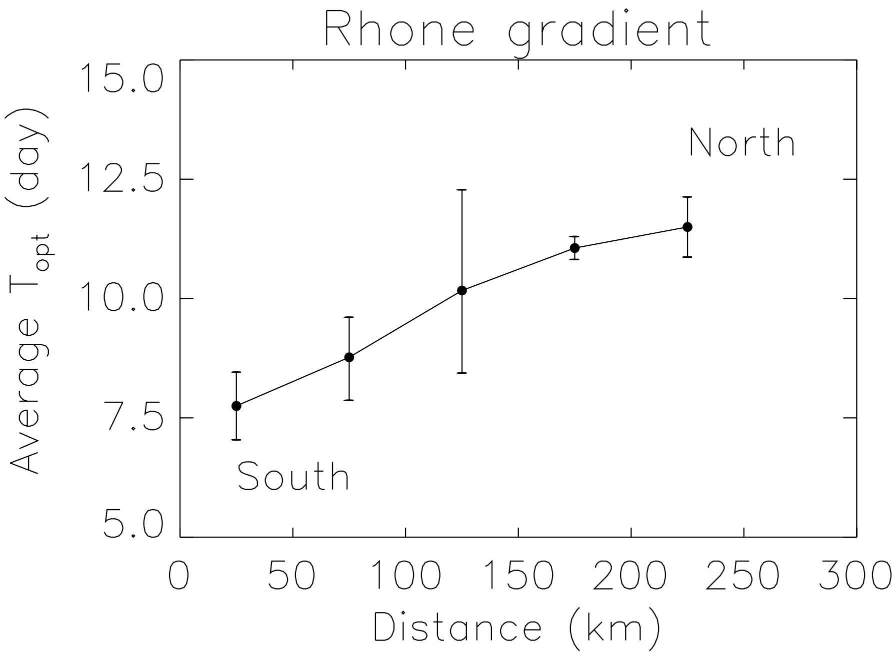

Fig. 11. Results of the exponential filter over the SIM domain for a 2-year period: average optimised characteristic time length of the exponential filter (T_{opt}) along a South-North transect from the Rhône valley to the Saône plain. Binned values are presented each 50 km for the most frequent thickness of the root-zone soil layer of SIM (1.50 m±0.05 m) and the most frequent fraction of clay (12 to 21%). The vertical bars indicate the standard deviation of the binned T_{opt}.

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