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Near real time de-noising of satellite-based soil moisture retrievals: An intercomparison among three different techniques

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ABSTRACT

Real-time de-noising of satellite-derived soil moisture observations presents opportunities to deliver more accurate and timely satellite data for direct satellite users. So far, the most commonly used techniques for reducing the impact of noise in the retrieved satellite soil moisture observations have been based on moving average filters and Fourier based methods. This paper introduces a new alternative wavelet based approach called Wiener-Wavelet-Based Filter (WiW), which uses an entropy based de-noising method to design a causal version of the filter. WiW is used as a post-retrieval processing tool to enhance the quality of observations derived from one active (the Advanced Scatterometer, ASCAT) and one passive (the Advanced Microwave Scanning Radiometer for Earth Observing System, AMSRE) satellite sensors. The filter is then compared with two candidate de-noising techniques, namely: i) a Wiener causal filter introduced by Su et al. (2013) and ii) a conventional moving average filter. The validation is carried out globally at 173 (for AMSRE) and 243 (for ASCAT) soil moisture stations. Results show that all the three de-noising techniques can increase the agreement between satellite and in situ measurements in terms of correlation and signal-to-noise ratio. The Wiener-based methods show least signal distortion and demonstrate to be conservative in retaining the signal information in de-noised data. Importantly, the Wiener filters can be calibrated with the data at hand, without the need for auxiliary data.

1. Introduction

An increasing availability of satellite-derived soil moisture (SM) observations provides new opportunities for enhancing drought monitoring and flood forecasting and informs climatic studies. Indeed, many satellite products are now available at high spatial and temporal resolution (Nichols et al., 2011; Ochsner et al., 2013), closing the gaps between spatiotemporal scales of the observations and those of practical applications. These observational products are important complements to modelled data (with or without land data assimilation of satellite SM), as independent data for model initialization and evaluation. Despite the increased data availability, error characterization of the satellite SM products reveals systematic errors relative to reference in situ or modelled SM, and random error in the product (Dorigo et al., 2010; Su et al., 2016). The random error or noise can arise from instrumental radiometric inaccuracy, stray background contributions to sensors' field-of-view, spatial resampling, and imperfect retrieval model parameterization, among other reasons. Such error undermines our ability to properly interpret the true SM dynamics, namely the rapid wetting by precipitation and loss via infiltration and evapotranspiration. To this end, de-noising has the potential to greatly improve the quality of the satellite SM derived from instantaneous retrieval algorithms as it exploits the properties of autocorrelation in the SM signal to distinguish true signal from noise. On this basis, several methods have been considered to reduce the noise content in satellite SM.

Fourier based methods have been used to de-noise satellite SM retrievals by filtering either the observed emissivity time series (Du, 2012) or the retrieved SM observations (Su et al., 2013). In particular, the latter used a linearized water balance model to develop physically-based Wiener filters. Both causal and non-causal versions of the Wiener filter were developed to de-noise satellite SM derived

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from AMSRE and the ASCAT sensors. These two types of filters are distinguished by their applicability for real-time operations. The causal filtering uses only SM information in previous and current time steps to estimate the current value of SM, while the SM information in future time steps are also used in non-causal filtering. Thus, for the purpose of providing timely denoised satellite data, this work focuses on the former methods.

The most commonly used and simplest de-noising filter is a moving average filter (Draper et al., 2009; Rebel et al., 2012; Kumar et al., 2015), which is a part of the techniques known as smoothing models. It assumes that the signal in a noisy time series is locally stationary with a slow-varying mean, and thus the mean of the SM values within a moving window is taken as the best estimate of SM for an intra-window time step. The degree of smoothing, controlled by adjusting the width of the moving window, can lead to data degradation as a result of over-smoothing and distortion.

Wavelet shrinkage is another approach of de-noising that is based on wavelet analysis (Donoho, 1995). Wavelet analysis allows representations of non-stationary characteristics of a time series, enabling studies of time evolution of the processes or signals at different time scales (Daubechies, 1992) and discrimination of signal and noise (Donoho, 1995). De-noising is achieved by reducing the magnitudes of the wavelet coefficients, which are representations of the time series in the wavelet domain, using a priori estimated threshold. Over-smoothing and signal loss can therefore occur when the threshold is too high. This technique has been applied to de-noise satellite SM (Su and Ryu, 2015) with the threshold estimated via triple collocation (TC) analysis, although three coincident SM data are needed for TC.

The problems related to the distortion and over-smoothing of the satellite SM time series highlighted above, are undesirable for many applications like flood forecasting, landslides and particularly for rainfall estimation from SM (Crow and Bolten, 2007; Pellarin et al., 2013; Brocca et al., 2014; Zhan et al., 2015) where the timing of SM response to rainfall is particularly important. Indeed, the high-frequency components of SM observations are not only related to noise but are also the result of rapid SM changes following rainfall events. In this respect, a trade-off has to be determined between the need to remove noise and the necessity of retaining SM information (Su et al., 2013). Identifying this trade-off is not new in signal processing and in the hydrology literature. Specifically, Sang et al. (2010) developed a filtering technique, called Entropy-Based Wavelet De-noising Method (EBWDM), which uses the information entropy theory to describe the different characteristics of noises and observed time series and allows an efficient separation of white noise from the original time series. However, the filter cannot be applied in near real time applications because it can induce undesirable signal distortions at the edge (or ends) of time series. In this study, EBWDM was used to train a causal Wiener filter in a new approach, termed Wiener Wavelet (WiW) filter. This filter combines the robustness of EBWDM and the real-time applicability of causal Wiener filter. By exploiting a formal mathematical characterization of noise used in EBWDM, such a real-time method is potentially less susceptible to the problems of over-smoothing and distortion.

Within this context, the objective of this study is twofold. First, it provides a formal introduction of the WiW and its underlying formalism. Second, it reports an extensive global-scale evaluation of WiW and the first inter-comparisons against other candidate de-noising methods, namely the physically-based Wiener filter of Su et al. (2013) (referred to as Wiener Water Balance, WiWB, filter henceforth) and the moving average filter (MVAVG). The three candidate methods reflect three contrasting de-noising filter design paradigms such that this study can inform the best practices in de-noising of satellite SM data. In particular, we apply the methods to two prominent microwave satellite SM products, derived from AMSRE and ASCAT. The evaluation are conducted in the similar manner as Su et al. (2015), against in situ measurements from over 270 monitoring stations using a range of validation metrics.

The paper is organised as follows. Section 2 describes the three types of de-noising filters under investigations. Section 3 contains the description of the datasets used while Section 4 provides a description the filter setup and the data handling. Results are contained in Section 5, followed by discussion and conclusions in Section 6.

2. Methods

Passive and active microwave SM retrievals are generally erroneous for several reasons. Main errors include instrument noise, structural model errors, inaccuracies in the auxiliary data used on the retrieval and uncertainties in the model parameters (Su and Ryu, 2015). It is expected that these processes can impart different types of errors and noises on the retrieved SM. Different de-noising filters can therefore perform differently based on how realistic their underlying assumptions pertaining to noise are. For WiW and WiWB, the noise is assumed to be white and additive; by ontrast for MVAVG, it assumes that nearly all the high-frequency components below some frequency threshold are all noise. While more sophisticated error models can be used to describe the other types of errors such as autocorrelated or non-orthogonal error models, the noise in instantaneous satellite SM retrievals is still typically assumed to be orthogonal and uncorrelated (Dorigo et al., 2010).

2.1. Wiener filter implementation: general concepts

A common approach to Wiener filter implementation is the minimization of the mean-squared error between some desired signal response and the actual filter output. In practice, this requires the knowledge of the auto-correlation functions or equivalently the power spectra of the signal and the noise. The noise power spectrum can be obtained by comparing the desired (noise-free) power spectrum of the signal with the one of the noisy signals, or from the (signal-inactive) noise-only periods – that are not feasible with operational satellites. In summary, the challenge of implementing a Wiener filter is that the desired signal is often observed with noise, and that the autocorrelation or the power spectra of the desired signal are not readily available. Su et al. (2013) addressed this by using a simple water balance model to define a theoretical power spectra of the desired signal (Section 2.3). By contrast, WiW uses EBWDM output to calibrate a Wiener filter; this ensures best white noise extraction (see Section 2.2.2) because EBWDM was specifically built for removing this type of noise.

2.2. The Wiener wavelet based filter (WiW)

2.2.1. Entropy-Based Wavelet De-noising Method (EBWDM) for time series analysis

Wavelet based de-noising methods can offer effective means for removing noise from an observed signal as a time series. Contrary to Fourier methods, where the signal is described as a sum of sinusoids (the basis functions) weighted by variable coefficient values, the wavelet analysis uses a different class of basis functions, known as wavelets. These coefficients are determined by taking the inner product of the signal and wavelet functions. Accordingly, the signal is represented by the wavelet coefficients and the frequencies and locations of these constituent wavelets functions. A key step in de-noising is to use this frequency-time profile of the observed signal to distinguish between its noise and the signal components and thus is our objective of using EBWDM (Sang et al., 2014, 2009, 2012).

A general implementation of wavelet-based denoising (also known as wavelet shrinkage) comprises of three steps. First, the signal time series is projected to the wavelet domain. Here, the signal