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Research papers

Evaluating controls of soil properties and climatic conditions on the use of an exponential filter for converting near surface to root zone soil moisture contents

Tiejun Wang [a,b,*], Trenton E. Franz [b], Jinsheng You [b], Martha D. Shulski [b], Chittaranjan Ray [c]

[a] Institute of Surface-Earth System Science, Tianjin University, Weijin Road 92, Tianjin 300072, PR China
[b] School of Natural Resources, University of Nebraska-Lincoln, Hardin Hall, 3310 Holdrege Street, Lincoln, NE 68583, USA
[c] Nebraska Water Center, University of Nebraska-Lincoln, Lincoln, NE 68588, USA

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ABSTRACT

Root zone soil moisture (RZSM) is an important state variable for understanding various land surface and ecohydrological processes. Due to the lack of field measurements, different methods have been proposed to estimate RZSM, including the use of exponential filters to predict RZSM from remotely sensed near surface soil moisture data. However, inconsistent findings about the controls on the optimal characteristic time length T_{opt}, which is used in the exponential filter method, have been reported in the literature. To reconcile these inconsistent findings and further improve the use of the method, the impacts of soil properties and climatic conditions on T_{opt} were assessed in this study using observed and modelled soil moisture datasets. Daily soil moisture data, daily meteorological records, and soil properties were retrieved from the Automated Weather Data Network (AWDN) and the Soil Climate Analysis Network (SCAN) within the continental United States. Data from the AWDN stations showed that T_{opt} was mostly controlled by soil texture (e.g., a negative correlation with the sand fraction and a positive one with the clay fraction) as compared to climatic conditions. However, at SCAN stations, T_{opt} was mostly affected by precipitation (P), and no significant correlation was found between T_{opt} and soil texture. The difference in controlling factors between ADWN and SCAN stations can be largely attributed to the higher spatial variability in P across the SCAN stations, which overrode the impacts of soil properties on T_{opt}. A 1-D vadose zone model was also utilized to simulate soil moisture at selected SCAN sites using a generated soil hydraulic parameter dataset. The simulation results further demonstrated the negative relationship between T_{opt} and P observed for the SCAN stations. Moreover, the simulation results revealed that T_{opt} was larger under vegetated conditions than under bare surface conditions. Under the same climatic conditions at each simulated site, which could be deemed as reduced variability in P, significant correlations existed between T_{opt} and van Genuchten parameters. In particular, T_{opt} was shown to be smaller for coarser soils, which was consistent with the results observed from AWDN stations. The findings of this study offer additional insights into the use of the exponential filter method for estimating RZSM from near surface soil moisture measurements.

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1. Introduction

Soil moisture is an important state variable as it interacts with a variety of land surface and ecohydrological processes in complex feedback mechanisms (Jung et al., 2010; Seneviratne et al., 2010; Vereecken et al., 2014; Wang and Franz, 2015; Wang et al., 2015a). In particular, knowledge of root zone soil moisture (RZSM) over different spatiotemporal scales is crucial for understanding land surface and ecohydrological processes, predicting agricultural production, and making rational water management policies. Although a range of techniques (e.g., gravimetric method, time domain reflectometry, ground penetration radar, and capacitance method) are available for measuring soil moisture contents with reasonable accuracy (Dobriyal et al., 2012), most of those techniques are not suitable for mapping soil moisture at large spatial scales (Vereecken et al., 2008), with only few exceptions (e.g., using large-scale soil moisture monitoring networks (Ochsner et al., 2013) and roving cosmic ray neutron probes (Franz et al., 2015)).

* Corresponding author at: Institute of Surface-Earth System Science, Tianjin University, Weijin Road 92, Tianjin 300072, PR China.
E-mail address: tiejun.wang@tju.edu.cn (T. Wang).

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By comparison, airborne and satellite remote sensing techniques can provide large spatial coverage of soil moisture, but their penetration depths are limited to several centimeters (e.g., $\sim$5 cm) below the soil surface (Njoku and Entekhabi, 1996). The shallow penetration depth greatly limits the use of remotely sensed soil moisture data for various research and application purposes. To overcome this issue, it is necessary to infer deeper RZSM from information on near surface soil moisture (NSSM) obtained from remote sensing techniques.

Field and modelling studies have shown strong correlations between NSSM and RZSM (Pachepsky et al., 2005; Mahmood and Hubbard, 2007; Albergel et al., 2008; Ford et al., 2014). Those studies offer the rationale for relating NSSM to RZSM. Meanwhile, analytical, statistical, and modelling approaches have been used to develop relationships between NSSM and RZSM (Jackson, 1980; Entekhabi et al., 1994; Ragab, 1995; Wagner et al., 1999; Sabater et al., 2007; Albergel et al., 2008; Manfreda et al., 2014). For instance, based on a conceptual two-layer soil water balance model, Wagner et al. (1999) proposed to use an exponential filter (i.e., $e^{-t/T}$, where t is time and T is the characteristic time length) to convert NSSM to soil water index (SWI) in deeper soil layers. Later, Albergel et al. (2008) modified the discrete form of the exponential filter proposed by Wagner et al. (1999) to a recursive form. Because of its simplicity, the exponential filter method has been applied to estimate RZSM under different climatic and land surface conditions (e.g., Wagner et al., 1999; Ceballos et al., 2005; Albergel et al., 2008; Zhao et al., 2008; Manfreda et al., 2011; Ford et al., 2014; Paulik et al., 2014). For example, Ceballos et al. (2005) and Zhao et al. (2008) evaluated SWI derived from the European Remote Sensing Satellite (ERS) scatterometer in Spain and China, respectively. Ford et al. (2014) applied the exponential filter method for estimating RZSM in the Unites States Great Plains, with SWI derived from the Soil Moisture and Ocean Salinity (SMOS) satellite.

To use the exponential filter method at a specific site, an optimum T (T_{opt}) is needed to calculate SWI, which is usually obtained through optimizations based on observed soil moisture data at different depths. A wide range of T_{opt} values has been reported from previous studies (Ceballos et al., 2005; Albergel et al., 2008; De Lange et al., 2008; Ford et al., 2014). Given the mathematical formulation of the exponential filter, Ceballos et al. (2005) showed that T_{opt} reflected the combined effect of local conditions on the temporal persistence of soil moisture. Therefore, to use the exponential filter method in areas with limited or no soil moisture observations, it is necessary to understand the local controls on T_{opt}. Several attempts have been made to evaluate the impacts of different environmental factors on T_{opt} but with conflicting results (Ceballos et al., 2005; Albergel et al., 2008; De Lange et al., 2008). Based on soil moisture data from Spain, Ceballos et al. (2005) showed that T_{opt} tended to be larger for deeper soil layers and was also affected by soil texture. De Lange et al. (2008) utilized a 1-D vadose zone model to compile a synthetic T_{opt} dataset for different soil textures. Their results revealed that T_{opt} highly depended on soil texture and the sampling interval of NSSM. Albergel et al. (2008) analyzed the impacts of soil depth, soil texture, and climatic conditions on T_{opt}, using observed and modelled soil moisture data from France. The authors reached a similar conclusion that soil depth played a significant role in determining T_{opt}; however, they did not find any significant relationships of T_{opt} with clay and sand fractions. In addition, Albergel et al. (2008) suggested that T_{opt} was affected by climatic conditions, although their results were inconclusive. Ford et al. (2014) analyzed soil moisture data measured in Oklahoma and Nebraska of the United States. The authors found that the accuracy of RZSM estimates was dependent on wetness conditions. Paulik et al. (2014) assessed the SWI product from the Copernicus Global Land Service using in-situ soil moisture data from 23 monitoring networks around the global, and showed that T_{opt} was affected by an array of factors (e.g., soil depth and topography).

While previous studies have shown that T_{opt} was affected by a range of environmental factors, the inconsistent findings from those studies still warrant further investigations to improve the use of the exponential filter method for estimating RZSM. Therefore, the primary goal of this study was to assess the impacts of various soil and climatic variables on T_{opt}. It should be emphasized here that assessing the accuracy of soil moisture estimates derived from remote sensing techniques was not the focus of this study, as such analyses have been already carried out in numerous studies. Observed soil moisture data from two widely used monitoring networks within the continental United States were retrieved to compute T_{opt}. A comprehensive dataset, including soil and climatic variables, was compiled to analyze the impacts of different environmental factors on T_{opt}. Moreover, a modelling approach was adopted to further evaluate the controls of soil hydraulic parameters on T_{opt}. The results of this study can provide additional insights into the use of the exponential filter method for estimating RZSM.

2. Materials and methods

2.1. Exponential filter method

Wagner et al. (1999) first proposed the use of an exponential filter to predict RZSM dynamics from NSSM measurements. In this study, the recursive exponential filter from Albergel et al. (2008) was used to analyze the effects of different environmental factors on T_{opt} and a brief description of the method is given here. The recursive exponential filter of Albergel et al. (2008) can be given as

$$SWI_{m,t_n} = SWI_{m,t_{n-1}} + K_{t_n}(ms_{t_n} - SWI_{m,t_{n-1}}) \tag{1}$$

where SWI_{m,t_n} and $SWI_{m,t_{n-1}}$ are the estimated soil water index (SWI) in root zones at time t_n and t_{n-1}, respectively, ms_{t_n} is normalized NSSM measured at time t_n, and K_{t_n} is the gain at time t_n and given as:

$$K_{t_n} = \frac{K_{t_n-1}}{K_{t_n-1} + e^{-\frac{t_n - t_{n-1}}{T}}} \tag{2}$$

where K_{t_n-1} is the gain at time t_{n-1} and T is the characteristic time length in days.

Before filtering, daily volumetric soil moisture contents were normalized to obtain ms using the maximum and minimum values from each time series of NSSM measurements (e.g., 10 cm for the Automated Weather Data Network-AWDN and 5 cm for the Soil Climate Analysis Network-SCAN; see the following section for details). Following Albergel et al. (2008), the filter (i.e., Eqs. (1) and (2)) was initialized with $SWI_{m,t_1} = ms_{t_1}$ and $K_{t_1} = 1$. Daily data on RZSM were also scaled between 0 and 1 to obtain observed SWI (SWI_{obs}) using the maximum and minimum values from each time series of RZSM measurements (e.g., 25 cm, 50 cm, and profile average for the AWDN stations; 10 cm, 20 cm, 50 cm, and profile average for the SCAN stations). Different T values (up to 60 days in this study, which was larger than the one of 40 days used by Albergel et al. (2008) and Ford et al. (2014)) were tested to compute SWI_{m}. The Nash-Sutcliffe (NS) score (Nash and Sutcliffe, 1970) was adopted to evaluate the filter performance (e.g., Albergel et al., 2008; Ford et al., 2014). At each site, T_{opt} was equal to the T value corresponding to the highest NS score. Additional metrics, including root mean square error (RMSE), correlation coefficient (r), and mean bias (MB), were also calculated to assess the filter performance.

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