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# A practical algorithm for estimating surface soil moisture using combined optical and thermal infrared data



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#### ABSTRACT

Surface soil moisture (SSM) is a critical variable for understanding the energy and water exchange between the land and atmosphere. A multi-linear model was recently developed to determine SSM using ellipse variables, namely, the center horizontal coordinate  $(x_0)$ , center vertical coordinate  $(y_0)$ , semi-major axis (a) and rotation angle ( $\theta$ ), derived from the elliptical relationship between diurnal cycles of land surface temperature (LST) and net surface shortwave radiation (NSSR). However, the multi-linear model has a major disadvantage. The model coefficients are calculated based on simulated data produced by a land surface model simulation that requires sufficient meteorological measurements. This study aims to determine the model coefficients directly using limited meteorological parameters rather than via the complicated simulation process, decreasing the dependence of the model coefficients on meteorological measurements. With the simulated data, a practical algorithm was developed to estimate SSM based on combined optical and thermal infrared data. The results suggest that the proposed approach can be used to determine the coefficients associated with all ellipse variables based on historical meteorological records, whereas the constant term varies daily and can only be determined using the daily maximum solar radiation in a prediction model. Simulated results from three FLUXNET sites over 30 cloud-free days revealed an average root mean square error (RMSE) of 0.042 m<sup>3</sup>/m<sup>3</sup> when historical meteorological records were used to synchronously determine the model coefficients. In addition, estimated SSM values exhibited generally moderate accuracies (coefficient of determination  $R^2 = 0.395$ , RMSE = 0.061 m<sup>3</sup>/m<sup>3</sup>) compared to SSM measurements at the Yucheng Comprehensive Experimental Station.

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#### 1. Introduction

Soil moisture content usually refers to the water contained in the unsaturated soil zone (Seneviratne et al., 2010). As a crucial part of the soil moisture content, land surface soil moisture (SSM) is a critical parameter that largely controls the energy and water exchange between the land and atmosphere (Eltahir, 1998; Entekhabi and Rodriquez-Iturbe, 1994). Accurately estimating SSM is of high relevance to a number of bio-physical processes that closely related to various fundamental research and practical applications, especially for the energy, mass and water between the atmosphere, bio-

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http://dx.doi.org/10.1016/j.jag.2016.07.004 0303-2434/© 2016 Elsevier B.V. All rights reserved. sphere and hydrosphere (Johnsson and Jansson, 1991; Li et al., 2009, 2013a,b; Sanchez-Mejia and Papuga, 2014; Duan et al., 2014a; Ferguson et al., 2016). For instance, SSM is widely recognized as a key variable in climate systems, playing a major role in climate change projections (Seneviratne et al., 2010; Mittelbach et al., 2011; Al-Yaari et al., 2014) and global change studies (Henderson-Sellers, 1996; Falloon et al., 2011; Dorigo and de Jeu, 2016). In the agricultural application, accurate monitoring of SSM is quite benefit to almost all stages of crop growth, and is also of great importance to detect agricultural drought and for yield estimates (Holzman et al., 2014; Carrão et al., 2016). Moreover, SSM is also considered as a significant component of the hydrological cycle, effectively controlling the partition of rainfall into infiltration and runoff (Anderson et al., 2009; Tuttle and Salvucci, 2014; Laiolo et al., 2016).

Quantitative SSM values, particularly at the regional and global scales, are useful in the aforementioned context. Therefore, a number of studies have focused on obtaining regional or global

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Fig. 1. Sketch of the ellipse parameters and elliptical relationship between the diurnal cycles of dimensionless LST and NSSR from 08:00 to 16:00 with an interval of 30 min.

scale SSM values, especially in recent decades due to advances in the acquisition of remote sensing observations and algorithm development. These remote sensing methods for SSM retrieval can be simply divided into two categories: the one is singleband based algorithms. In this category, the optical band-derived spectral reflectance and the thermal infrared band-derived thermal inertia are two most commonly used methods (Price, 1977; Adegoke and Carleton, 2002; Lesaignoux et al., 2013); the other is using multi-band remote sensing data. This category mainly includes three forms of multi-band combination, namely, combining optical and thermal infrared data (Wetzel et al., 1984; Sandholt et al., 2002), combining optical and microwave data (Mattar et al., 2012; Santamaría-Artigas et al., 2016), and combining thermal infrared and microwave data (Chauhan et al., 2003; Sobrino et al., 2012; Notarnicola et al., 2012). In these algorithms, the feature space between optical-derived vegetation index (VI) and thermal infrared-derived surface temperature and the following indices developed on the basis of the feature space, have been widely implemented for estimating SSM with various images all over the world. In addition to these algorithms, many polar orbit and geostationary satellites have been successfully launched into space and are currently in operation, providing a variety of data for SSM estimation across the world. Specifically, several global SSM products have been successfully developed and can be publicly accessed (http://www.esa-soilmoisture-cci.org/ , http://nsidc.org/data/amsre/, http://www.catds.fr/, http://www. nasa.gov/smap/). Although these SSM data sets have been previously used in many fields, the currently available SSM data sets are primarily based on microwave observations, and several limitations have prevented further use of SSM products in various applications. Using the Advanced Scatterometer (ASCAT) soil moisture product as an example, only count values from zero to one hundred (rather than the real volumetric water content) are provided to represent the extremely dry to extremely wet conditions. Consequently, these values must generally be converted into absolute soil moisture content using time series analysis or auxiliary data such as soil porosity or other soil moisture data sets (Wagner et al., 1999; Ceballos et al., 2005; Draper et al., 2011; Pierdicca

et al., 2013). Although SSM data sets such as the commonly used Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) and Soil Moisture and Ocean Salinity (SMOS) have been developed based on radiative transfer models, the challenge is that they require the input of many physical parameters, some of which are currently not well-defined, *e.g.* vegetation cover in target frequencies and the emission properties of the soil surface (Pan et al., 2014). This challenge is most likely to make the accuracies of the currently available passive microwave-based SSM products must be further verified and improved (Coopersmith et al., 2015). Moreover, the coarse spatial resolution is also a critical issue that has greatly limited the application of these SSM products in relatively small regions, often leading to difficulties detecting sub-pixel variations (Merlin et al., 2010).

Compared with microwave-based SSM products, optical and thermal infrared remotely sensed observations typically possess finer spatial resolutions that are better for various applications. Moreover, the theoretical basis associated with the commonly used optical and thermal infrared SSM retrieval methods is generally more advanced than microwave remote sensing retrieval methods. Nevertheless, a prominent issue associated with these optical and thermal infrared-based algorithms is that the real volumetric water content cannot be directly obtained. Empirical or statistical relationships between the remotely sensed proxies and ground SSM measurements are generally needed to estimate regional SSM. Consequently, no actual, operational thermal infrared- and/or optical-based SSM products are currently available.

A novel SSM retrieval model that combines diurnal cycles of land surface temperature (LST) and net surface shortwave radiation (NSSR) on cloud-free days has recently been developed based on these limitations. The simulated data are produced *via* a land surface model simulation process (Leng et al., 2014). Specifically, this model has been used to directly and quantitatively estimate SSM without establishing empirical relationships between remotely sensed proxies and SSM measurements, differing from other commonly used optical and thermal infrared observation-based SSM retrieval methods. Nevertheless, this SSM retrieval model suffers from a major problem. Although the five model coefficients in the Download English Version:

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