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Mapping soil moisture with the OPtical TRApezoid Model (OPTRAM) based on long-term MODIS observations

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ABSTRACT

The OPtical TRApezoid Model (OPTRAM) has recently been proposed for estimation of soil moisture using only optical remote sensing data. The model relies on a physical linear relationship between the soil moisture content and shortwave infrared transformed reflectance (STR) and can be parameterized universally (i.e., a single calibration for a given area) based on the pixel distribution within the STR-Normalized Difference Vegetation Index (NDVI) trapezoidal space. The main motivation for this study was to evaluate how the universal parameterization of OPTRAM works for long periods of time (e.g., several decades). This is especially relevant for uncovering the soil moisture and agricultural drought history in response to climate change in different regions. In this study, MODIS satellite observations from 2001 to 2017 were acquired and used for the analysis. Cosmicray neutron (CRN) soil moisture data, collected with the COsmic-ray Soil Moisture Observing System (COSMOS) at five different sites in the U.S. covering diverse climates, soil types, and land covers, were applied for evaluation of the MODIS-OPTRAM-based soil moisture estimates. The OPTRAM soil moisture estimates were further compared to the Soil Moisture Active and Passive (SMAP) (L-band), the Soil Moisture Ocean Salinity (SMOS) (Lband), and the Advanced AScatterometer (ASCAT) (C-band) soil moisture retrievals. OPTRAM soil moisture data were also analyzed for potential monitoring of agricultural drought through comparison of the OPTRAM-based Soil Water Deficit Index (OPTRAM-SWDI) with the widely-applied Crop Moisture Index (CMI). Evaluation results indicate that OPTRAM-based soil moisture estimates provide overall unbiased RMSE and R between 0.050 and 0.085 cm3 cm−³ and 0.10 to 0.70, respectively, for all investigated sites. The performance of OPTRAM is comparable with the ASCAT retrievals, but slightly less accurate than SMAP and SMOS. OPTRAM and the three microvave satellites captured CRN soil moisture temporal dynamics very well for all five investigated sites. A close agreement was observed between the OPTRAM-SWDI and CMI drought indices for most selected sites. In conclusion, OPTRAM can estimate temporal soil moisture dynamics with reasonable accuracy for a range of climatic conditions (semi-arid to humid), soil types, and land covers, and can potentially be applied for agricultural drought monitoring.

1. Introduction

Soil moisture is a highly dynamic state variable that controls fundamental hydrological processes such as evaporation, infiltration, and runoff. It is also critical for management and allocation of water resources, prediction and monitoring of drought, agricultural production, mitigation of natural disasters and monitoring of ecosystem response to climate change ([Robinson et al., 2008;](#page--1-0) [Vereecken et al., 2014](#page--1-1); [Babaeian](#page--1-2) [et al., 2016](#page--1-2)).

Remote sensing techniques provide powerful means for characterizing and monitoring the high spatiotemporal variability of soil moisture. During the past decade, several satellites with various spatiotemporal resolutions have been launched for monitoring near surface (0–5 cm) soil moisture, including the European Soil Moisture and Ocean Salinity (SMOS) Satellite, launched in 2009 ([Kerr et al., 2001](#page--1-3)), the Advanced Microwave Scanning Radiometer 2 (AMSR-2) on the Global Change Observation Mission-Water (GCOM-W1) Satellite, launched in 2012, the Advanced Scatterometer (ASCAT) launched in 2006 on the EUMETSAT MetOp-A and MetOp-B satellites, the ESA Sentinel-1 Satellite launched in 2014 ([Bartalis et al., 2007](#page--1-4)), and NASA's Soil Moisture Active-Passive (SMAP) Satellite, launched in 2015 [\(Entekhabi et al.,](#page--1-5) [2010\)](#page--1-5). These microwave satellites yield the most accurate

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measurements of soil moisture ([Mattikalli et al., 1998](#page--1-6)) because of the high dielectric permittivity of soil water within the microwave domain ([Hallikainen et al., 1985\)](#page--1-7) and the greater penetration of microwaves through vegetation canopy and underlying soil [\(Escorihuela et al.,](#page--1-8) [2010;](#page--1-8) [Chapin et al., 2012;](#page--1-9) [Tabatabaeenejad et al., 2015\)](#page--1-10).

Passive microwave satellites commonly provide high temporal resolution observations (e.g., daily), but suffer from low spatial resolution. Within this context, optical and thermal remote sensing observations provide higher spatial resolution information and thus are often used to enhance the passive microwave soil moisture maps through data fusion and downscaling approaches (e.g., [Piles et al., 2014;](#page--1-11) [Merlin](#page--1-12) [et al., 2012](#page--1-12)). Hence, development of robust optical and thermal methods, in concert with microwave techniques, can improve remote sensing of soil moisture.

The trapezoid (or triangle) model is a widely-applied approach to remote sensing of soil moisture based on thermal (land surface temperature, LST) and optical data [\(Carlson et al., 1994;](#page--1-13) [Gillies and](#page--1-14) [Carlson, 1995;](#page--1-14) [Owen et al., 1998](#page--1-15); [Rahimzadeh-Bajgiran et al., 2013](#page--1-16); Shafi[an and Maas, 2015](#page--1-17); [Sun, 2016\)](#page--1-18). Despite the trapezoid model's obvious success discussed in [Sadeghi et al. \(2017\),](#page--1-19) it suffers from two inherent limitations. The first is the requirement of concurrent optical and thermal data, which renders the model inapplicable to satellites that do not provide thermal data (e.g., ESA Sentinel-2). The second limitation is that the land surface temperature is not only affected by soil moisture content but also by ambient atmospheric conditions (e.g., wind speed, air temperature, and air humidity). Hence, the conventional trapezoid model needs time consuming and computationally demanding individual parameterization (calibration) for each individual observation date. To overcome these two limitations, [Sadeghi](#page--1-19) [et al. \(2017\)](#page--1-19) proposed the physically-based OPtical TRApezoid Model (OPTRAM) for estimation of surface soil moisture. The OPTRAM trapezoid is formed by distribution of the normalized difference vegetation index (NDVI) as a measure of vegetation fraction versus shortwaveinfrared (SWIR) transformed reflectance to obtain soil moisture content. This concept was introduced by [Sadeghi et al. \(2015\)](#page--1-20). The OP-TRAM does not require a thermal band, hence, it is applicable to satellites providing optical bands only (this resolves the first limitation of the conventional trapezoid model). Because SWIR reflectance does not significantly change with ambient atmospheric conditions, OPTRAM can be universally parameterized for a given location (this resolves the second limitation of the conventional trapezoid model).

OPTRAM has been initially evaluated in [Sadeghi et al. \(2017\)](#page--1-19) based on ESA Sentinel-2 and NASA Landsat-8 satellite observations for mapping of soil moisture in the Walnut Gulch and Little Washita watersheds in Arizona and Oklahoma, respectively. Because Sentinel-2 was only recently launched (i.e., in summer 2015), the time period covered in the [Sadeghi et al. \(2017\)](#page--1-19) study was limited to a few months in 2015 and 2016. Hence, the main motivation for this current study was to evaluate how the universal parameterization of OPTRAM (i.e., a single calibration for a given area) works for long periods of time (e.g., several decades). This is especially important with regard to expanding our ability to uncover the soil moisture history in response to climate change in different regions.

Long-term soil moisture data provide a useful measure for monitoring agricultural drought ([Chakrabarti et al., 2014\)](#page--1-21), which is defined based on the soil water deficit and its effects on crop production. Recently, several studies have shown the potential of remotely sensed soil moisture data for agricultural drought monitoring [\(Chakrabarti et al.,](#page--1-21) [2014;](#page--1-21) [Martinez-Fernandez et al., 2016](#page--1-22); [Carrao et al., 2016](#page--1-23); [Mishra](#page--1-24) [et al., 2017;](#page--1-24) [Liu et al., 2017\)](#page--1-25). Several soil moisture-based drought indices have also been introduced for agricultural drought monitoring including the Soil Moisture Index (SMI) ([Sridhar et al., 2008](#page--1-26)), Soil Water Deficit (SWD) [\(Torres-Ruiz et al., 2013](#page--1-27)), Plant Available Water (PAW) [\(McPherson et al., 2007](#page--1-28)), Drought Severity Index (DSI) ([Cammalleri et al., 2016\)](#page--1-29), Soil Moisture Drought Index (SMDI) ([Sohrabi](#page--1-30) [et al., 2015\)](#page--1-30), and Soil Water Deficit Index (SWDI) [\(Martinez-Fernandez](#page--1-31)

[et al., 2015\)](#page--1-31). Among these drought indices, SWDI is a simple agricultural drought index that is computed based on plant water availability, which is assumed to not change over long time periods. The SWDI has been recently used in conjunction with remotely sensed soil moisture estimates from SMAP and SMOS for monitoring agricultural drought [\(Martinez-Fernandez et al., 2016](#page--1-22); [Mishra et al., 2017](#page--1-24)). The application of microwave-based soil moisture retrievals (e.g., SMAP, SMOS, Sentinel-1) for long-term monitoring of agricultural drought is limited due to the lack of soil moisture data for long periods of time. The optical satellites such as Landsat and MODIS, launched many years before SMAP, SMOS, and Sentinel-1, provide a unique opportunity for such analysis in order to fill this critical observational gap.

The specific objectives of this study were to: (i) evaluate the universally-parameterized OPTRAM for estimation of soil moisture with long-term MODIS data for four watersheds in the United States, which exhibit diverse climates, soil types, and land covers, (ii) compare the accuracy of OPTRAM soil moisture estimates with retrievals from microwave satellites (i.e., SMAP, SMOS, ASCAT), and (iii) explore the feasibility of applying long-term OPTRAM soil moisture data for agricultural drought monitoring.

2. Background: the Optical TRApezoid Model (OPTRAM)

[Sadeghi et al. \(2017\)](#page--1-19) proposed a physically-based trapezoidal space termed the "OPtical TRApezoid Model" (OPTRAM) for remote sensing of soil moisture based on optical data only. The concept is based on the pixel distribution within the STR-NDVI space, where STR is the SWIR transformed reflectance and NDVI is the normalized difference vegetation index, thereby replacing LST in the conventional trapezoid model. Considering a linear relationship between soil saturation degree, W (0 for completely dry and 1 for saturated soil) and *STR* ([Sadeghi](#page--1-20) [et al., 2015](#page--1-20)) results in:

$$
W = \frac{STR - STR_d}{STR_w - STR_d} \tag{1}
$$

where:

$$
STR = \frac{(1 - R)^2}{2R} \tag{2}
$$

where STR_d and STR_w are STR at dry (e.g., $\theta \sim 0$ cm³ cm⁻³, where θ is volumetric moisture content) and wet (e.g., $\theta = \theta_s$ cm³ cm⁻³, where θ_s is saturated moisture content) states, respectively, and R is surface reflectance for the SWIR electromagnetic domain (i.e., 2130 nm, MODIS band 7). Assuming an empirical linear relationships of STR_d and STR_w with vegetation fraction, the dry and wet edges of the optical trapezoid are defined as follows (see [Fig. 1](#page-1-0)):

$$
STR_d = i_d + s_d NDVI \tag{3}
$$

Fig. 1. The OPtical TRApezoid Model (OPTRAM) relating STR [Eq. [\(2\)\]](#page-1-1) and NDVI.

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