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Accounting for soil porosity improves a thermal inertia model for estimating surface soil water content

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ABSTRACT

Soil thermal inertia (P), a property that controls the temporal variation of near-surface temperature, has been used to estimate surface water content (θ) in remote sensing studies. The accuracy of θ estimates, however, is affected by surface soil porosity (*n*). We hypothesize that *n* can be derived using a simple linear *n*-P relationship of a dry surface soil layer, and that accounting for *n* improves the accuracy of θ estimation using a P(θ) model. The P of a surface layer was measured by using the heat pulse method during a drying period, and the feasibility of estimating θ with a P(θ) model that included *n* was explored. The approach was also tested with published *P* values derived from meteorological data and MODIS data against *in situ* θ measurements at two field sites in Arizona, USA. The results on a partially vegetated shrubland indicated that by using the P-derived *n*, the P(θ) model provided more accurate θ estimates than by using the literature *n* values. Discrepancies between modeled θ and *in situ* θ measurements were observed at small θ values, which were caused in part by the fact that the modeled θ represented soil layers a few millimeters thick, while the *in situ* measurements represented θ at the 5-cm depth. The new *n*-P function has potential for estimating surface θ accurately using multi-scale P data on bare soils or on sparsely vegetated lands.

1. Introduction

Soil water content (θ, $m^3\,m^{-3}$) is a key environmental variable that affects water and energy exchanges at the land-atmosphere interface (Robinson et al., 2008; Ochsner et al., 2013). Recently large-scale θ monitoring techniques have been advanced for better understanding the dynamics and patterns of θ and θ-related land surface processes (Ochsner et al., 2013). Among these techniques, the optical/microwave remote sensing (RS) methods allow for spatial and temporal mapping of surface θ for large areas (Wagner et al., 1999; Moran et al., 2004; Leng et al., 2016; Sadeghi et al., 2017). The microwaves can penetrate into soil (about 0–5 cm) and are only slightly disturbed by clouds or vegetation cover, making the microwave RS methods suitable for global θ mapping. The passive microwave methods have a fairly coarse spatial resolution but a broad coverage, while the radar methods (active microwave methods) are of high spatial resolution but with long repeat pass (Moran et al., 2004; Entekhabi et al., 2014; Uebbing et al., 2017). Compared to microwave methods, the reflective and thermal RS methods, which use the correlations between optical reflectance/thermal emission and θ, have the advantage of estimating θ with relatively high spatial resolutions and regular revisit frequencies (Verstraeten et al., 2006; Ciani et al., 2005; Haubrock et al., 2008; Tian and Philpot, 2015; Zhang and Zhou, 2016), despite the fact that they are influenced significantly by vegetation, darkness (at night) and atmospheric conditions. Several researchers have proposed that the optical RS methods can be integrated with the microwave methods as a downscaling approach for improving the spatial resolution of microwave θ estimates (Piles et al., 2011; Jackson et al., 2012; Merlin et al., 2013; Sadeghi et al., 2015, 2017).

The thermal RS methods estimate θ based on the dependence of land surface temperature at the thermal infrared wavebands (3 to 14 μm) or the relations between soil thermal properties and θ (Carlson et al., 1994; Moran et al., 1994). Zhang and Zhou (2016) conducted a full literature review on optical and thermal remote sensing methods for estimating θ. The surface temperature-based relationships that usually include vegetation index are mostly empirical, and the θ results are often interfered by near-surface atmospheric conditions, such as wind speed, surface albedo, and net radiation (Carlson, 2007; Mallick et al., 2009; Piles et al., 2011). The thermal property-based approach, on the other hand, relates θ to soil thermal inertia (P, $J\,m^{-2}\,s^{-1/2}\,K^{-1}$),

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an intrinsic property that represents the ability of a surface soil to resist temperature change (Cracknell and Xue, 1996a, 1996b). According to the definition, P is determined by the volumetric heat capacity (C, $J\,m^{-3}\,K^{-1}$) and thermal conductivity (λ, $W\,m^{-1}\,K^{-1}$) of the surface layer,

$$P = \sqrt{C\lambda}. \tag{1}$$

Surface P can be retrieved remotely using operational satellites on a daily basis (Price, 1980; Cracknell and Xue, 1996a). Several studies have proposed P-based empirical equations for estimating θ (Verstraeten et al., 2006; Matsushima et al., 2012), but most of them are site-specific and require vast ground data for model calibration. Other studies have related P to θ by using the $C(\theta)$ and $\lambda(\theta)$ models that use surface porosity (n, unitless) and soil texture information (Kahle et al., 1975; Pratt and Ellyett, 1979; Cai et al., 2007; Lu et al., 2009; Minacapilli et al., 2009, 2012). Murray and Verhoef (2007) proposed a normalized $P(\theta)$ model with n as the main variable for estimating soil heat flux density, but failed to consider the effects of soil texture on P. Considering that P varied across soils and changed with θ, Lu et al. (2009) improved the Murray and Verhoef (2007) P model by including n and soil textural information. The Lu et al. (2009) model is physically based, easy to use, and only requires prior knowledge of soil textural information and n, thus it has the potential for deriving θ by applying the thermal RS method across different soil types without calibration requirements. However, there is a lack of evaluation of the Lu et al. (2009) P model for field use across multiple scales and for various surface conditions.

The P-based models for retrieving θ require soil texture and n as inputs. Soil texture information can often be obtained conveniently from soil survey data. *In situ* n measurements, however, are tedious and are often limited to the point scale, which restricts the application of the Lu et al. (2009) P method. Moreover, n usually exhibits strong temporal and spatial variations due to agricultural practices and wetting and drying cycles (Sun et al., 2009; Leng et al., 2017; Zhang et al., 2018). Uncertainties in n can lead to large errors in θ estimates (Murray and Verhoef, 2007; Lu et al., 2009). There exists a need to develop advanced methods that determine n accurately and quickly, which will improve the accuracy of θ estimations using the P models.

In this paper, we present a new method for estimating n from soil surface P measurements by extending the Lu et al. (2009) model. The new method for estimating surface θ is evaluated using micro-scale heat-pulse measurements, mesoscale mesonet data and large-scale RS imagery datasets for various soil types, locations, vegetation covers and moisture conditions.

2. Theoretical considerations

Lu et al. (2009) established the following relationship to represent the dependences of P on soil type, porosity and θ (hereafter referred to as the LU model),

$$P = P_{dry} + (P_{sat} - P_{dry})K_P, \tag{2}$$

where P_{dry} ($J\,m^{-2}\,s^{-1/2}\,K^{-1}$) and P_{sat} ($J\,m^{-2}\,s^{-1/2}\,K^{-1}$) are the thermal inertia values of dry and saturated soils, respectively, and K_p represents the Kersten function (Murray and Verhoef, 2007).

According to the LU model, K_p is calculated as,

$$K_P = \exp[\varepsilon(1 - S_r^{-\mu})], \tag{3}$$

where S_r (unitless) is the degree of water saturation, which equals to the ratio of θ and n, ε and μ are soil texture-specific parameters (unitless): 2.95 and 0.16 for coarse soils with sand fraction > 40%, and 0.60 and 0.71 for fine soils with sand fraction < 40% (Lu et al., 2009).

By definition, P_{sat} ($J\,m^{-2}\,s^{-1/2}\,K^{-1}$) is calculated as,

$$P_{sat} = \sqrt{\lambda_{sat} C_{sat}}, \tag{4}$$

where λ_{sat} ($W\,m^{-1}\,K^{-1}$) and C_{sat} ($J\,m^{-3}\,K^{-1}$) are the saturated soil thermal conductivity and volumetric heat capacity, respectively. The values of λ_{sat} are estimated using the following geometric mean equation (Côté and Konrad, 2005),

$$\lambda_{sat} = (\lambda_q^q \lambda_o^{1-q})^{1-n} \lambda_w^n, \tag{5}$$

where λ_q and λ_w are the thermal conductivities of quartz ($7.70\,W\,m^{-1}\,K^{-1}$) and water ($0.594\,W\,m^{-1}\,K^{-1}$), respectively. The quartz content of total solids (q, unitless) is taken as the sand fraction (Peters-Lidard et al., 1998; Bristow, 1998). The thermal conductivity of other minerals (λ_o, $W\,m^{-1}\,K^{-1}$) is taken as $2.0\,W\,m^{-1}\,K^{-1}$ for soils when $q > 0.2$, and $3.0\,W\,m^{-1}\,K^{-1}$ for soils when $q \le 0.2$ (Lu et al., 2009).

According to Campbell (1985), C_{sat} is obtained from,

$$C_{sat} = \rho_b c_s + \rho_w c_w n, \tag{6}$$

where ρ_b is soil bulk density ($g\,cm^{-3}$), c_s is the specific heat of soil solids, which is taken as $0.80\,J\,g^{-1}\,K^{-1}$ (Lu et al., 2009), c_w is the specific heat of water ($4.18\,J\,g^{-1}\,K^{-1}$), and ρ_w is the density of water ($1.0\,g\,cm^{-3}$).

The term P_{dry} can be estimated from $\rho_b c_s$ (C of dry soils in Eq. (1)) and λ_{dry}. In this study, we used a fixed c_s value of $0.80\,J\,g^{-1}\,K^{-1}$ because differential scanning calorimetry measurements indicated that c_s varied in a narrow range (Lu et al., 2013). Several studies have shown that there is a linear relationship between λ_{dry} and n (Johansen, 1975; Lu et al., 2007). In fact, Murray and Verhoef (2007) proposed a linear equation to calculate P_{dry} from n,

$$P_{dry} = -1.0624n + 1.0108. \tag{7}$$

Fig. 1 shows the P_{dry} estimates *versus* n (line) using Eq. (7) and measured values (dots) with heat pulse sensors for 12 soils of various textures (Lu et al., 2007). The n values ranged from 0.40 to 0.55, which produced a P_{dry} range of 0.45- to $0.59\text{-}kJ\,m^{-2}\,s^{-1/2}\,K^{-1}$. Despite the variability of soil texture, a strong linear correlation between P_{dry} and n was observed, indicating that Eq. (7) provided fairly good P_{dry} estimations. Inversely, n can be calculated from P_{dry} using the following equation,

$$n = \frac{1.0108 - P_{dry}}{1.0624}. \tag{8}$$

As an example, Fig. 2a presents the $P(\theta)$ curves of a loamy sand soil (with 80% sand and 12% clay) at n of 0.52, 0.48, and 0.44. The P data were obtained using heat pulse sensors on repacked soil cores with

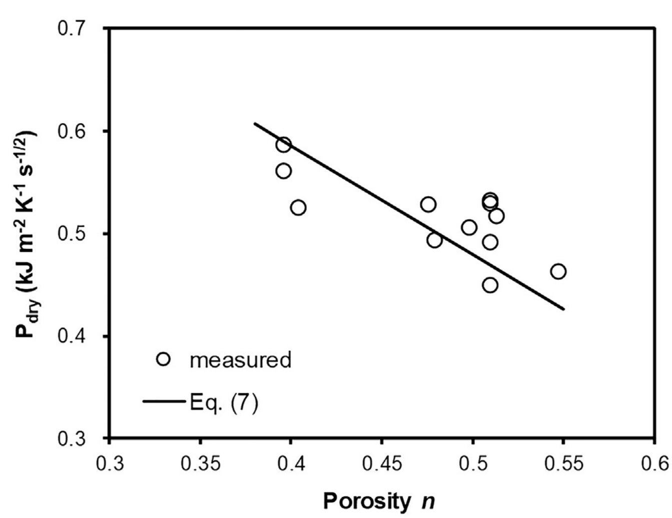

Fig. 1. Thermal inertia (P) of dry soils measured with the heat pulse method as a function of porosity n for 12 soils of varying textures. The solid line represents the results from Eq. (7) (Murray and Verhoef, 2007). The measured soil thermal property data are from Lu et al. (2007).