Remotely sensed soil temperatures beneath snow-free skin-surface using thermal observations from tandem polar-orbiting satellites: An analytical three-time-scale model

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Abstract

Subsurface soil temperature is a key variable of land surface processes and not only responds to but also modulates the interactions of energy fluxes at the Earth’s surface. Thermal remote sensing has traditionally been regarded as incapable of detecting the soil temperature beneath the skin-surface. This study shows that thermal remote sensing can be used to estimate soil temperatures. Our results provide insights into thermal observations collected with tandem polar-orbiting satellites when used toward obtaining soil temperatures under clear-sky conditions without the use of any ground-based information or field-measured soil properties.

We designed an analytical three-time-scale (3-scale, for short) model, dividing the annual cycle of soil temperatures into three subcycles: the annual temperature cycle (ATC), which represents the daily-averaged temperature; the diurnal temperature cycle (DTC), which represents the instantaneous temperature; and the weather-change temperature cycle (WTC), which is divided into two parts to represent both the daily-averaged (WTCavg) and the instantaneous temperature (WTCinst). The DTC and WTCinst were further parameterized into four undetermined variables, including the daily-averaged temperature, thermal inertia, upward surface flux factor, and day-to-day change rate. Thus, under clear-sky conditions, the four thermal measurements in a diurnal cycle recorded with tandem polar-orbiting satellites are sufficient for reconstructing the DTC of both land surface and soil temperatures. Polar-orbiting satellite data from MODIS are used to show the model’s capability. The results demonstrate that soil temperatures with a spatial resolution of 1 km under snow-free conditions can be generated at any time of a clear-sky day. Validation is performed by using a comparison between the MODIS-inverted and ground-based soil temperatures. The comparison shows that the accuracy of inverted soil temperatures lies between 0.3 and 2.5 K with an average of approximately 1.5 K. These results open a new frontier in the application of thermal remote sensing wherein soil temperatures with high spatial and temporal resolutions can be remotely estimated.

1. Introduction

When the sun radiates energy onto a location on Earth, a portion of the absorbed solar radiation at the Earth’s surface is conducted downward, changing the subsurface soil temperatures periodically at multiple temporal scales. Soil temperature within the shallow layers is an important variable for biophysicochemical soil processes, such as microbial activity, evaporation, aeration, seed germination, and root development (Hillel, 1998). Soil temperature from a relatively deep layer can be used to model land surface processes (Best, Cox, & Warrilow, 2005), to monitor subsurface urban heat islands and subsurface geothermal systems (Ferguson & Woodbury, 2007), and to optimally design underground pipes (Dalla Rosa, Ll, & Svendsen, 2011).

Soil temperature can be obtained from both observations and models. Observed soil temperatures are usually measured by thermometers installed within the soil near the surface (e.g., the Soil Climate Analysis Network sites). These measurements are characterized by high accuracy, as well as high cost, but low representativeness over extensive and heterogeneous areas. Modeling has the advantage of providing the soil temperature at any depth and time. However, this
approach requires the construction of equations that are capable of describing all of the possible physical processes in addition to a reason-
able parameterization strategy for the soil parameters (such as the soil texture, pores, structure, water, fauna, organism interactions, and thermal properties), which is generally difficult in practice.

In spite of these challenges, soil temperature has been modeled for general planetary surfaces (Hapke, 1996; Yan, Chassefière, Leblanc, & Sarkissian, 2006) and for soil under a crop layer (Luo, Loomis, & Hsiao, 1992), a forest canopy (Bond-Lamberty, Wang, & Gower, 2005; Graham, Lam, & Yuen, 2010; Paul et al., 2004), or a snow cover (Hiroti, Pomeroy, Granger, & Maule, 2002). Numerous methods have been proposed to simulate soil temperature, including numerical methods (Herb, Janke, Mohseni, & Stefan, 2008; Zoras, Dimoudi, & Kosmopoulos, 2012), analytical models (Lin, 1980), semi-empirical methods (Al-Temeemi & Harris, 2001; Drouila et al., 2009; Elias, Cichota, Torriani, & De Jong Van Lier, 2004), purely empirical methods (Zheng, Hunt, & Running, 1993), and statistical methods that employ intelligent algorithms, such as the neural network algorithm (Tabari, Westermann, Heikenfeld, Dorn, & Boike, 2013), and these methods can be adapted to complex urban environments in which heterogeneous soils containing multiple layers and irregular geometric structures are considered (Zoras et al., 2012). However, numerical methods require the use of many subsurface physical and chemical parameters and various meteorological variables that constrain the boundary conditions of soil heat conduction, resulting in weak extensibility. Analytical methods regularly use two approaches, including the Fourier equation (Carslaw & Jaeger, 1959) and the force-restore technique (Bhumralkar, 1975), to derive the soil heat flux and temperature. Such methods are suitable for parameterization and thus have been widely adopted in land surface models (Deardorff, 1978). Semi-empirical and empirical methods are easy to implement (Chow, Long, Mok, & Li, 2011) and provide an effective supplement for periods when there are no records of measured soil temperature due to an unexpected instrument breakdown. Among these methods, special interest has been given to estimations of soil temperature based on the air temperature and other soil-temperature-related variables (Beltrami, 2001; Kang, Kim, Oh, & Lee, 2000; Smardon et al., 2006; Zheng et al., 1993).

Although progresses have been made, obtaining soil temperatures over extensive areas remains a challenge due to the high heterogeneity of land surfaces (Zhan, Chen, Zhou, Li, & Liu, 2011). Thermal remote sensing is a promising technique to combat this challenge and has yielded credible land surface temperature (LST) products (Wan, 2008). However, satellite thermal sensors can only detect the skin-surface temperature to a depth of several micrometers (Kerr, 2007; Norman & Becker, 1995), and they cannot obtain subsurface thermal status directly with an instantaneous observation. Fortunately, there is more than one thermal measurement per daily cycle for most of the current LST products generated from tandem polar-orbiting sensors (e.g., MODIS detects a majority of the Earth’s surface four times per day) and geostationary satellite observations (e.g., SEVIRI-MSG provides thermal data at 15-minute intervals) (Rasmussen, Gottsch, Olesen, & Sandholm, 2011).

The multi-temporal sampling of LSTs has long been used to estimate the physical properties of soil (e.g., the thermal inertia and the correlated soil moisture) and the soil heat flux (Murray & Verhoef, 2007a,b). Progress in estimating soil physical properties based on satellite data has continued since the launch of the first generation of satellites in the 1970s (Kahle, 1977; Watson, 1975), with continuing improvements in the 1980s (Price, 1985), 1990s (Sobrino & El Kharrar, 1999; Xue & Cracknell, 1995), 2000s (Verhoef, 2004; Murray & Verhoef, 2007a), and 2010s (Zhan et al., 2012b). The physical properties of soils rather than soil temperatures have been the foci of these studies. Other research has attempted to estimate the soil heat flux by combining multi-temporal LSTs and limited knowledge of the surface or soil properties (Murray & Verhoef, 2007b; van der Tol, 2012; Verhoef, 2004; Verhoef et al., 2012; Wang & Bras, 1999). These studies require temporally quasi-continuous (e.g., sub-hourly) LSTs, which can be obtained from geostationary thermal observations.

However, the spatial resolution of geostationary observations is relatively low. Polar-orbiting thermal observations, possessing a spatial resolution several times higher, may be an alternative. The tandem arrangement of polar-orbiting satellites allows for the reconstruction of diurnal surface temperatures (Duan, Li, Wang, Wu, & Tang, 2012; Zhou, Chen, Zhang, & Zhan, 2013) and, thus, may indirectly detect the soil thermal status. Additionally, most previous investigations have attempted to incorporate the LSTs in a diurnal temperature cycle (DTC) but disregarded the full utilization of the LSTs in an annual temperature cycle (ATC), which are important for the estimation of relatively deeper soil temperatures. Therefore, an analytical method was developed to determine the soil temperature beneath the skin-surface. This process requires combining all the available LSTs in each DTC during an ATC, in addition to the visible and near infrared (VNIR) observations from polar-orbiting satellites.

This study follows the steps of using temporal thermal measurements to retrieve soil thermal properties and heat flux. We propose that the soil temperature under snow-free conditions can be estimated using satellite thermal observations. We believe that this approach can demonstrate the potential for satellite-based thermal observations to provide data that will complement and extend the current ground-based observation networks of soil temperature.

2. Problem and background

2.1. Problem

Both surface properties (e.g., land cover and surface geometry) and meteorological driving variables (e.g., air temperature) are required to determine the boundary conditions and, therefore, to drive the modeling of heat transfer. However, soil properties over extensive areas are highly heterogeneous. It is not easy to obtain both the soil properties at the pixel scale of satellite images and the climatic and meteorological status simultaneously. Satellite-observed multi-temporal LSTs result from the surface energy budget, and they already contain information on meteorological conditions. To determine the evolution of the upper boundary, we propose a three-time-scale model (3-scale, for short) to estimate soil temperatures using temporally sporadic satellite LSTs (see Sections 2.2, and 3.1 to 3.3.). To determine the soil thermal properties, a method was constructed using samples collected from previous studies (see Section 3.4).

2.2. Background

Soil temperature dynamics are governed by multiple periodic or quasi-periodic cycles (see Fig. 1). Over a temporal scale longer than one year (e.g., decades), the annually averaged soil temperature at a specific site is constant in the absence of climate change. At a very short temporal scale (e.g., minutes), the soil temperature changes rapidly due to the downward conduction of surface heat, and the heat budget is further impacted by microscopic turbulence and horizontal advection (Meier & Scherer, 2012). The present study does not consider the aforementioned two scales because (1) the soil temperature variation due to the advection and advection can be weakened at the pixel scale, and (2) we only focus on estimating the annual and diurnal soil temperatures. Soil temperatures at depths greater than approximately 10 m (the actual depth at which the ATC has an impact depends on soil thermal properties and LST variations) barely change during an annual cycle (Schaetzl & Anderson, 2005); this depth was termed the zero annual range by Oke (1987). The aim of this study is to reconstruct the soil temperature profile between the skin-surface and the zero annual range, i.e., the soil temperature between 0 and approximately 10 m.

Within the zero annual range, several other cycles control the soil temperature dynamics. The diurnal temperature cycle (DTC) dominates
shallow soil temperatures and contributes the high-frequency component of soil temperature variations. The annual temperature cycle (ATC) proceeds downward into deeper layers, representing the low-frequency component. Between the high-frequency DTC and the low-frequency ATC, the soil temperature is further affected by short-term weather changes, such as cloudiness or precipitation. We define the temperature variation due to weather variations using a general nomenclature: the weather-change temperature cycle (WTC). The WTC exerts influence on both the daily-averaged temperature (WTCavg) and the instantaneous temperature (WTCinst). A clear-sky is required because thermal observations cannot penetrate to clouds. Under clear-sky conditions, the WTCinst induces the day-to-day difference (DTD) of surface and soil temperature (Göttsche & Olsen, 2001).

Soil temperature dynamics $T_s(t)$ within the zero annual range are a combination of the above three temperature cycles, expressed as:

$$T_s(z, t) = \frac{T_w^{\text{var}}}{\text{ATC}} + \frac{T_w^{\text{d}}}{\text{DTC}} + \frac{T_w^{\text{inst}}}{\text{WTC}}$$

where $T_s$ represents the annually averaged temperature; $T_w^{\text{var}}$ is the annual temperature variation; $T_w^{\text{d}}$ is the diurnal temperature variation; and $T_w^{\text{inst}}$ is the instantaneous temperature variation. The modeling of soil temperatures can be resolved through the parameterization of $\Delta T_w^{\text{var}}, \Delta T_w^{\text{d}}, \Delta T_w^{\text{inst}}$, and $\Delta T_d$ using clear-sky observations.

3. Parameterization strategy

The heat conduction within soil is described by the following:

$$\partial T(z, t)/\partial t = D \cdot \partial^2 T(z, t)/\partial z^2 = k \cdot \rho \cdot c^{-1} \cdot \partial^2 T(z, t)/\partial z^2,$$

where $T$, $z$, and $t$ are the temperature, depth, and time, respectively; and $D$, $k$, $\rho$, and $c$ are the thermal diffusivity, thermal conductivity, density, and specific heat, respectively.

The ATC and WTCavg are parameterized for the estimation of the daily-averaged temperature, and the DTC and WTCinst are parameterized for the estimation of the instantaneous temperature.

3.1. Daily-averaged soil temperature

3.1.1. Annual temperature cycle (ATC)

The thermal field of deep soil is more strongly influenced by the ATC than by the other two cycles. Ideally, the boundary condition of the ATC is considered harmonic (Kang et al., 2000). An analytical solution to Eq. (2) for the harmonic boundary condition is written as follows (Carslaw & Jaeger, 1959):

$$\bar{T}_d(z, t) = T_d + \Delta T_d = T_d + A_d \cdot \exp(-H_d z) \cdot \sin(\omega_d t - H_d z + \phi_d),$$

where $\bar{T}_d$ is the initial guess of the daily-averaged temperature (hereafter abbreviated as daily temperature); $A_d$ is the ATC amplitude; $H_d$ is equal to $\sqrt{0.5 \omega_d / D}$, in which $\omega_d$ is equal to $2\pi / (365 \cdot t_p)$ ($t_p = 86,400 \text{ s}$; unit: s$^{-1}$); and $\phi_d$ is the phase offset.

3.1.2. Weather-change temperature cycle on daily temperature (WTCavg)

The dynamics of soil temperature, as illustrated by Eq. (3), are obtained in ideal cases when no precipitation or abrupt weather changes have occurred. The WTC acts quasi-periodically. From the beginning, a temperature drop occurs usually caused by precipitation, which is then followed by a temperature increase due to lasting clear-skies. Diurnal LSTs for a series of days can be used to quantify the impact of the WTCavg but thermal remote sensing of LSTs is frequently blocked by clouds, making the quantitative description of the WTC difficult. To adjust the soil temperatures modeled in an ideally harmonic ATC, we assess the WTCavg effect using a correction factor $\Delta T_w^{\text{var}}$, and the WTCavg-adjusted daily soil temperature is then provided as follows:

$$T_d(z, t) = \bar{T}_d + \Delta T_w^{\text{var}}$$

where $T_d$ is the satellite-observed temperature; $z_{\text{obs}}$ is the observation depth, which is equal to zero for thermal remote sensing; and $H_w$ is estimated through $\sqrt{0.5 \omega_w / D}$, in which $\omega_w$ is the equivalent angular
velocity in a \( \text{WTC}_{\text{avg}} \) and is equal to \( 2\pi / (L_w \cdot t_p) \) (unit: \( \text{s}^{-1} \)), where \( L_w \) is the typical number of days of a \( \text{WTC}_{\text{avg}} \) and is related to the local climatic background.

We provide a semi-empirical estimation of \( L_w \) using the most typical duration of a \( \text{WTC}_{\text{avg}} \), which, following a Fast Fourier Transform (FFT) of all the daily temperatures in an ATC, is simply the frequency at which the Fourier amplitude reaches the maximum. The daily temperatures measured at any certain ground-based site within the study area are adequate to quantify the typical duration of a \( \text{WTC}_{\text{avg}} \) because the background climate and weather changes are similar in a local area.

### 3.2. Instantaneous soil temperature

Nonetheless, \( T_d \) is a daily average and is not instantaneous. Instantaneous temperatures can only be modeled using the thermal observations within a DTC.

#### 3.2.1. Diurnal temperature cycle (DTC)

For a pair of tandem polar-orbiting satellites, there are commonly only four observations in a DTC (Fig. 1b). Many previous semi-empirical DTC models attempted to model the surface temperature with simple coefficients (Göttische & Olesen, 2001; Inamdar, French, Hook, Vaughan, & Luckett, 2008; Jiang, Li, & Nerry, 2006; van den Bergh, van Wyk, van Wyk, & Udahemuka, 2007). However, these methods may be unsuitable for the inversion of soil temperatures for two reasons. (1) These models require five to six thermal observations to fit the DTC. This is easy to implement for field records or GOES data but is difficult to satisfy for tandem polar-orbiting satellites, which observe the surface four times daily atmost. (2) These models have no variable (e.g., thermal inertia or conductivity) that can describe not only the skin property but also the bulk property of subsurface layers with any significant thickness. To address this limitation, we provide a DTC model modified from Zhan et al. (2012a); this model is capable not only of interpolating sporadically observed LSTs but also of modeling soil temperature. This DTC model is illustrated as follows (further details are in Appendix A):

\[
T_s(z, t) = T_d + \sum_{n=1}^{\infty} M_n(h_1, P) \cdot \exp(-H_n^2z) \cdot g(t),
\]

(5)

where \( T_s \) represents the average temperature during a DTC; \( H_n^2 \) is written as \( D \cdot \sqrt{0.5n - \omega^2} \); \( M_n \) is an intermediate variable related to the thermal inertia \( P \) and the upward flux coefficient \( h_1 \); and \( g \) is an intermediate function, provided as:

\[
\begin{align*}
  g(t) &= A_n \cos(\omega_n t - H_n^2 z - \varphi_n) + B_n \sin(\omega_n t - H_n^2 z - \varphi_n) \\
  A_n &= (1/2\pi) \int_{-\omega_n t}^{\omega_n t} f(\omega_n t) \cos(\omega_n t - H_n^2 z - \varphi_n) \, d\omega_n \\
  B_n &= (1/2\pi) \int_{-\omega_n t}^{\omega_n t} f(\omega_n t) \sin(\omega_n t - H_n^2 z - \varphi_n) \, d\omega_n \\
  \varphi_n &= \arctan\left( \frac{P/\sqrt{H_n^2}}{(\sqrt{2}h_1 + P/\sqrt{H_n^2})^{-1}} \right).
\end{align*}
\]

(6)

where \( A_n \) and \( B_n \) are the Fourier coefficients of the solar radiation (i.e., \( f(t) \)) received by surface, which are given as Eqs. (A2) and (A3) (see Appendix A); and \( \varphi_n \) is the phase difference of the \( n \)th order.

Through Eq. (5), the DTC dynamics are linked to only three undetermined coefficients, i.e., \( P, T_d \), and \( h_1 \). In comparison with most of the previous DTC models, which usually require at least four coefficients for DTC modeling, Eq. (5) reduces at least one coefficient by using a physical rather than semi-empirical representation, with \( P \) denoting the soil thermal property, \( T_d \) reflecting the climate and weather background, and \( h_1 \) quantifying the upward heat fluxes.

#### 3.2.2. Weather-change temperature cycle on instantaneous temperature (\( \text{WTC}_{\text{inst}} \))

The aforementioned modeling of the DTC disregards the \( \text{WTC}_{\text{inst}} \) (i.e., the day-to-day temperature difference). The parameterization of the DTC using only three coefficients leaves only one thermal observation, enabling the quantification of \( \text{WTC}_{\text{inst}} \). Eq. (5) can be converted into the following:

\[
T_s(z, t) = T_d + \sigma(t - 0.5 \cdot t_p) + \sum_{n=1}^{\infty} M_n \cdot \exp(-H_n^2z) \cdot g(t),
\]

(7)

where \( \sigma \) is the DTC change rate, which is related to the temperature difference by coupling with time \( t \); and \( t_p \) is the total number of seconds per day. The introduction of \( 0.5 \cdot t_p \) aims to guarantee that the average of \( T_d(z, t) \) during a DTC will be equal to \( T_d \).

#### 3.2.3. Aboveground vegetation

Vegetation can block solar radiation from the soil and attenuate the amplitude of the soil DTC. To estimate the soil temperature under vegetation, the impact of vegetation should be removed because satellite thermal sensors only measure the status of the leaves of the upper layers. Through the fractional surface coverage calculated from the leaf area index (LAI), Murray and Verhoef (2007b) used a physical method to derive the subsurface heat flux from the observed composite temperature. Similarly, we model the soil temperatures under vegetation by inducing an extinction coefficient (Zheng et al., 1993), given by the following:

\[
T_s(z, t) = T_d + \exp(-\kappa Z \cdot \exp(\varphi_L)) \cdot \left[ \sigma(t - 0.5 \cdot t_p) + \sum_{n=1}^{\infty} M_n \exp(-H_n^2z) g(t) \right],
\]

(8)

where \( \kappa \), \( L \), and \( Z \) are the extinction coefficient, LAI, and solar zenith angle, respectively. A typical value for \( \kappa \) is 0.5 (Zheng et al., 1993), corresponding to the spherical leaf angle distribution and usually adequate in simple cases (Murray & Verhoef, 2007b). During heat transfer, the vegetation layer plays a role similar to that of a layer of soil, which functions as an exponential attenuator of temperature variation through \( \exp(-\kappa L) \). However, there are major differences between these components: the vegetation still allows the transmission of solar radiation, but the soil is impenetrable to sunlight, and thus, radiation vanishes, but heat conduction occurs. Herein, the soil not only attenuates temperature but also functions as a phase time-delay of soil temperature (i.e., \( \phi_n \)).

#### 3.3. Combination of ATC, \( \text{WTC}_{\text{avg}} \), DTC, and \( \text{WTC}_{\text{inst}} \)

The soil temperature dynamics are a combination of the actions of ATC, WTC, and DTC. We rewrite Eq. (1) as follows:

\[
T_s(z, t) = T_d + \Delta T_d + \Delta T_{\text{w-avg}} + \Delta T_{\text{w-inst}}.
\]

(9)

where

\[
\begin{align*}
  (i) \quad & \Delta T_d = A_d \cdot \exp(-H_d z) \cdot \sin(\omega_d t - H_d z + \varphi_d) \\
  (ii) \quad & \Delta T_{\text{w-avg}} = \exp(-H_w z) \cdot \left[ \Delta T_d \cdot \left( \frac{\Delta T_d}{T_d + \Delta T_d} \right) \right] \\
  (iii) \quad & \Delta T_{\text{w-inst}} = \exp(-\kappa Z \cdot \exp(\varphi_L)) \cdot \left[ \sigma(t - 0.5 \cdot t_p) + \sum_{n=1}^{\infty} M_n \exp(-H_n^2z) g(t) \right] \\
  (iv) \quad & \Delta T_{\text{w-inst}} = \exp(-\kappa Z \cdot \exp(\varphi_L)) \cdot \left[ \sigma(t - 0.5 \cdot t_p) + \sum_{n=1}^{\infty} M_n \exp(-H_n^2z) g(t) \right].
\end{align*}
\]

(10)

Considering the large number of variables that must be used, which may generate confusion when Eqs. (9) and (10) are used, further clarification is provided below.
3.3.1. Clarification of ATC and WTCavg intended to represent daily soil temperature

In an ATC, the abundant thermal observations under clear-sky conditions allow for the estimation of the four undetermined coefficients of $\Delta T_0$ including $T_a$, $A_0$, $D_0$, and $\phi_0$. In a WTC, $\Delta T_{w-avg}$ is empirically estimated using Eq. (10).

The daily temperature is the basic variable of $\Delta T_0$ and $\Delta T_{w-avg}$ (Fig. 1a), but satellites can only obtain the instantaneous status. The average of the four LSTs observed in a DTC is an option for estimating the daily temperature. However, this direct average of the four observations has a systematic error that is higher than the real daily temperature. This error has been confirmed and discussed by practical validations (see Section 6.1). Alternatively, we provide a theoretically devised average temperature using Eq. (8), by which $T_{d}$ is solved with the four observations in a DTC.

3.3.2. Clarification of DTC and WTCinst intended to represent instantaneous soil temperature

The instantaneous soil temperature is the basic variable of $\Delta T_0$ and $\Delta T_{w-inst}$. Again, four undetermined coefficients (i.e., $T_d$, $P$, $h_1$, and $\sigma$) have been used to model the DTC and WTCinst, which correspond to the four thermal observations in a DTC. There may be doubts as to whether the atmospheric transmittance $\tau$ is another unknown that requires additional satellite-observed or ground information in addition to the four observations. However, the information contained in $\tau$ is unnecessary because $\tau$ can be incorporated into $P$ and $h_1$, producing two surrogate coefficients, namely, $P$ (i.e., $P \cdot \tau^{-1}$) and $h_1$ (i.e., $h_1 \cdot \tau^{-1}$), that can replace $P$ and $h_1$, respectively. Note that in this case, the inverted surrogate thermal inertia and upward flux coefficient include the information regarding $\tau$ and thus are more difficult to interpret.

3.3.3. Clarification of assumptions

The aforementioned parameterizations are based on three assumptions. First, this study assumes that the coefficients of the ATC model are annually invariant; however, annual variations do occur. This fact is suggested by the minor oscillations among the annually averaged soil temperatures at different depths (see Table 1). Nevertheless, this oscillation is so low (usually less than 1 K) that this assumption is generally acceptable. Second, no snow accumulates on the ground. Snow is significantly warmer than the snow surface or air temperature (Kohn & Roeyer, 2010). The snow cover, together with the subsurface soil, undermines the heat conduction process within the semi-infinite and homogeneous media described by Eq. (2). The unsuitability of the 3-scale model with snow-covered ground is evidenced by the analysis in Section 6.1. Third, the model assumes a uniform layer of vegetation. The model’s instability due to the within-pixel heterogeneity is termed the scaling effect, which is affected by most nonlinear remote sensing models (Liang, 2005). We examine the scaling effect on the 3-scale model in Section 6.3.

3.4. Estimation of soil thermal properties

The soil thermal properties, including the thermal diffusivity $D$, conductivity $k$, inertia $P$, and volumetric heat capacity $\rho \cdot c$ are important for the estimation of soil temperature. These four properties are connected through $D = k/\rho c$ and $P = \sqrt{\kappa \rho c}$ (Oke, 1987). Eqs. (9) and (10) enable the estimation of soil temperatures using polar-orbiting satellite observations. However, the thermal diffusivity is difficult to obtain through remote observations when $z = 0$. A simple and practical method to overcome this hurdle is to assign a fixed thermal diffusivity of approximately $5.0 - 6.0 \times 10^{-7} m^2 s^{-1}$ (Dudhia, 1996; Kang et al., 2000; Wang, 2012; Wang & Bras, 1999). Previous studies have shown that a fixed thermal diffusivity does not lead to large prediction errors (Kang et al., 2000). Nevertheless, thermal diffusivity might change with surface and subsurface status. As a more precise alternative, this subsection proposes an approach to determine the thermal diffusivity through its physical relationship with the thermal conductivity and inertia.

The dependency among these four thermal properties indicates that identifying any two of the four is sufficient to determine the other two. First, thermal inertia can be resolved using the four thermal measurements in a DTC through Eqs. (5) to (8). Note that apart from the determination of thermal inertia using these equations, Verhoef (2004) adopted a much simpler method to estimate thermal inertia using multi-temporal LSTs during clear nighttime conditions. However, such quasi-continuous clear nighttime LSTs are unavailable for polar-orbiting sensors. Second, this study found that the thermal conductivity is empirically related to the thermal inertia for typical surface and substrate materials (Fig. 2). Studies have shown empirical relationships between the thermal conductivity and moisture content and between the thermal inertia and moisture content (Oke, 1987). It is anticipated that conductivity could be statistically related to thermal inertia, in addition to the physical relation of $P = \sqrt{\kappa \rho c}$. We investigated four main landcover types: rock, bare soil, urban concrete, and vegetation. Samples of thermal conductivity and inertia for these landcover types were retrieved from previous studies, including Cui (1994) (23 types of rocks), Peters-Lidard, Blackburn, Liang, and Wood (1998) and Ochsner (2001) (nine types of soils), Sugawara, Narita, and Mikami (2001) (eight types of urban concrete), and Jayalakshmy and Philip (2010) (14 types of plant leaves).

<table>
<thead>
<tr>
<th>Site</th>
<th>Clear-sky days</th>
<th>Lat./long. (°)</th>
<th>Land cover</th>
<th>Avg. soil temperature in an ATC (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2°</td>
</tr>
<tr>
<td>McCracken</td>
<td>112</td>
<td>37.45, −</td>
<td>Scattered grass</td>
<td>14.8</td>
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<td>37.51, −</td>
<td>Scattered grass</td>
<td>10.9</td>
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<tr>
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<td>37.19, −</td>
<td>Shrub</td>
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</tr>
<tr>
<td>Vermillion</td>
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<td>37.10, −</td>
<td>Scattered grass</td>
<td>17.7</td>
</tr>
<tr>
<td>Sand Hollow</td>
<td>113.36</td>
<td>38.59, −</td>
<td>Scattered grass</td>
<td>12.6</td>
</tr>
<tr>
<td>Hals Canyon</td>
<td>113.75</td>
<td>41.77, −</td>
<td>Scattered grass</td>
<td>10.9</td>
</tr>
</tbody>
</table>

* Note that all these data were obtained in 2011.

Fig. 2. The empirical relationship between the thermal inertia and thermal conductivity of four typical landcovers: concrete, rock, soil, and vegetation. The TI is the unit of thermal inertia, representing $J s^{-1} m^{-2} K^{-1}$. 

---

Table 1

A brief description of the six SCAN stations in Utah used for satellite-ground validation.
Fig. 2 reveals that there is an approximate exponential relationship between thermal inertia and conductivity, given as follows:

\[
\begin{align*}
D & = k^2 p^{-2} \\
D & = k^2 p^{-2} \ln[(4727.0 - P)/3151.6],
\end{align*}
\]  

(11)

through which the fitted \(R^2\) reaches 0.97. Eq. (11) indicates that an estimate of thermal conductivity can be performed using the thermal inertia. Therefore, the thermal diffusivity can be derived and accordingly all of the four thermal properties are calibrated.

4. Methods

The steps followed using the MODIS data are illustrated in Fig. 3, also given as follows:

1. For a single location (or pixel), retrieve all of the valid (clear-sky) pixels in an annual cycle.
2. Estimate the daily LST (i.e., \(T_d\)) using the four MODIS/LSTs in each DTC.
3. Estimate the annually invariant coefficients, including \(T_a, A_w, D,\) and \(\phi_s\) using Eq. (3) and the daily LSTs.
4. Estimate the daily soil temperature variation due to the WTCavg (i.e., \(\Delta T_{soil,avg}\)) through Eq. (10). (ii).
5. Estimate the four undetermined coefficients, including \(T_{d}, \bar{P}, \bar{h}_1,\) and \(\sigma\), using Eq. (8) and the four MODIS/LSTs in a DTC.
6. Predict the soil temperature using Eqs. (9) and (10).

5. Data

The satellite data utilized are the Terra-Aqua/MODIS products from NASA, including the daily LST product (MOD11A1 and MYD11A1, L3 Global 1 km, four measurements per day), the eight-day LAI product (MCD15A2, L4 Global 1 km), and the 16-day albedo product (MCD43B3, L3 Global 1 km). The spatial resolution of these products is 1 km. The validation data are field observations from the Soil Climate Analysis Network (SCAN) in 2011. The soil temperatures from SCAN are measured by encapsulated thermistors at typical measured depths of 2, 4, 8, 20, and 40 inches, corresponding to 5.08, 10.16, 20.32, 50.80, and 101.60 cm, respectively. Validating satellite thermal observations requires field measurements to be performed over homogeneous surfaces and synchronously with the satellite transit time; otherwise, the satellite-based and ground-based temperatures will be incommensurate (1) because what the satellite observes is different from what the ground sensors record and (2) because temperature can change rapidly.

Utah was selected as the validation location because it contains the largest number of SCAN sites (35 sites). However, SCAN is installed mainly for agricultural use, and many of its sites are located in natural grasslands near cropland, which induces high heterogeneity at the spatial scale of 1-km. At these sites, the measured soil temperatures under grasslands cannot represent the subsurface temperature at a larger spatial scale, and thus, invalidates the homogeneity required for the satellite-ground comparison. Through removing the sites at which high heterogeneity occurs at a spatial scale of several kilometers, we chose six sites for satellite-ground validation, including Park Valley, Hals Canyon, Sand Hollow, Spooky, Vermilion, and McCracken Mesa (Table 1). These six sites are located in the semiarid steppe climate (Bsk) and mid-latitude desert climate (Bwh).

6. Validation and temporal results

This study used a satellite-ground comparison to validate the estimated soil temperatures; the validation procedures are illustrated by Fig. 4. Validations were performed for both the ATC and the DTC to evaluate the daily and instantaneous soil temperatures, respectively.

The soil temperatures at 2″, 4″, 8″, 20″, and 40″ estimated from the MODIS data are directly compared with the field measurements at sites where the homogeneity requirement is satisfied (see Fig. 4). To determine the most typical duration of the WTC in the study area, the daily soil temperatures of McCracken Mesa at 2″ were used, and the corresponding frequency spectrogram is described as Fig. 5, which indicates that the most suitable \(L_{soil}\) is approximately ten days.

6.1. Daily soil temperature

In an ATC, the daily temperature is the variable that needs to be intercompared. We estimate the differences of the daily temperature under clear-sky conditions by using the 3-scale method and the average of the four MODIS/LSTs over the six SCAN sites (Fig. 6). The comparison confirms the analysis in Section 3.3.1, i.e., this difference is significant, with a mean absolute error (MAE) of approximately 3.0 K. The daily
temperature estimate is always lower when using the 3-scale model than the average of the four observations of MODIS/LST. This observed systematic difference may arise because the period of temperature drop during the nighttime is longer than that of the temperature increase during the morning.

Based on the predicted daily temperatures, the soil temperatures are modeled, site by site, at 2″, 4″, 8″, 20″, and 40″ (Table 2). Spooky has no recorded data between Aug. and Oct. (Fig. 7), which may have been caused by data transmission breakdowns. The results show the success of modeling the annual amplitude and the phase delay in achieving the maximum temperature for deeper soil layers. Further error analysis shows that the accuracy ranges from 0.75 to 2.75 K, with an average of 1.52 K. This accuracy is tolerable and is comparable to the estimation of soil temperature using air temperature, as well as auxiliary surface and soil parameters (Kang et al., 2000; Paul et al., 2004). However, prior to any detailed analysis, we need to stress that using ground-based measurements to validate the results inverted from satellite observations may be problematic. At a specific site where instruments are installed, the microenvironment is likely to be different from the surface status observed from satellites (Zhou et al., 2013).

The results indicate the four additional phenomena: First, as the soil depth increases, the error of the modeled soil temperature decreases,

<table>
<thead>
<tr>
<th>Site</th>
<th>MAE (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2″</td>
</tr>
<tr>
<td>McCracken Mesa</td>
<td>1.50</td>
</tr>
<tr>
<td>Spooky</td>
<td>0.98</td>
</tr>
<tr>
<td>Vermillion</td>
<td>1.67</td>
</tr>
<tr>
<td>Sand Hollow</td>
<td>1.34</td>
</tr>
<tr>
<td>Hals Canyon</td>
<td>2.75</td>
</tr>
<tr>
<td>Park Valley</td>
<td>1.93</td>
</tr>
</tbody>
</table>

Fig. 5. The frequency spectrogram of the daily temperatures of McCracken Mesa at 2″ in an ATC calculated using the Fast Fourier Transform (FFT). $L_w$ is the most typical duration of a WTC.

Fig. 6. The daily temperature difference between the 3-scale method and the average of the four MODIS/LSTs in a DTC. The temperature difference and the day of year represent the radial and angular coordinates, respectively. The red circle denotes the MAE.
with the exception of Vermillion and the slight increase of error observed at 20°. This relationship makes sense because the soil temperatures of deeper layers are lower in amplitude and they exhibit a smoother variation, allowing the temperature variation to be predicted more accurately by using satellite LSTs.

Second, inducing the WTC improves the modeling accuracy. Without the WTC, the modeled soil temperature evolves harmonically and fails to reproduce the fast fluctuations. This improvement is reflected in the favorable match between the modeled and observed soil temperatures in the short-term temperature variations (see Fig. 7). There may be doubt as to whether quantifying the WTC with an empirical method is reasonable because the WTC is driven by multiple meteorological variables. We resort to the use of an empirical method because a purely model-driven method is inapplicable to satellite thermal data that are constantly interrupted by clouds. Moreover, the amplitude of the WTC is self-adjusted and determined by the difference between the observed MODIS/LST and the fitted soil temperature.

Third, the accuracy is higher in summer than in winter. Relatively large errors were found in winter, especially at Hals Canyon and Park Valley (Fig. 7e and f). This is because the number of image acquisitions of MODIS/LST in summer is significantly higher than that in winter. The coefficients of the ATC model are primarily determined by the

Fig. 7. A comparison between the estimated daily soil temperature using MODIS/LST and the actual ground temperatures at depths of 2° (5.08 cm) and 20° (50.8 cm) in 2011 over six SCAN sites in Utah. (a) McCracken Mesa; (b) Spooky; (c) Vermillion; (d) Sand Hollow; (e) Hals Canyon; and (f) Park Valley.
summer MODIS/LSTs, and the winter soil temperature is not as well predicted. (2) The snow cover in winter changes the thermal regime of the soil and weakens the 3-scale model, which is based on the heat conduction within semi-infinite and homogeneous media.

Finally, at a temporal scale longer than a DTC, the daily soil temperature is controlled more by the ATC and is less influenced by the WTC. The modeling accuracy would likely be higher if the basic variable were set to be the soil temperature averaged during a period longer than a DTC (e.g., weekly, monthly, or seasonal temperature).

6.2. Instantaneous soil temperature

In a DTC, the instantaneous temperature is the basic variable. We performed comparisons between the observed and modeled soil temperatures at three SCAN sites. The prediction errors are given in Fig. 8. For brevity, only the evolution wave of soil temperatures at Sand Hollow is provided (Fig. 9). The prediction MAEs range from 0.33 to 2.55 K, with an average of 1.37 K. The MAE distribution with soil depth exhibits an interesting phenomenon: the MAE decreases with increasing depth when the depth is less than 20"; it increases at the depth of 20" but decreases again with a further increase of soil depth. The combined action of the ATC and DTC may be responsible for this phenomenon.

At depths less than 20" (approximately 50 cm), the DTC plays a greater role than the ATC, and the DTC amplitude shrinks quickly as the soil depth increases. The absolute prediction accuracy therefore decreases. At depths greater than 20", the DTC weakens, and the ATC gradually dominates. Consequently, the MAEs are distributed in a similar pattern as that observed at depths shallower than 20".

These comparisons confirm that reconstruction of a soil thermal field using measurements at a single depth is possible (Holmes, Owe, De Jeu, & Kooi, 2008; Wang, 2012). The results further indicate the following points. First, the uneven change in the day-to-day process shows that the WTC is successfully represented by incorporating the change rate factor $\sigma$. Second, a recurring error between the observed and modeled soil temperatures derives from the amplitude differences.
Gene heterogeneity is negligible because the mapping (e.g., Watson (1975)) is within-pixel heterogeneity of vegetation. The error caused by vegetation heterogeneity is usually conducted over vegetation-sparse areas. Likewise, the 3-scale model may be suitable for other planetary surfaces (e.g., Mars) when the annual and daily cycle lengths are set as those of the planets, mostly due to the absence of vegetation. For example, with THEMIS (thermal emission imaging system) data, the 3-scale model may be revised to investigate the subsurface thermal status of Mars to estimate the soil properties or the subsurface water/ice status of Mars. In urban heat island (UHI) analyses, the 3-scale model has the potential to assist monitoring of the subsurface UHI (Menberg, Bayer, Zosseder, Rumohr, & Blum, 2013). Nevertheless, the spatial heterogeneity of urban surfaces is high and the scaling effect will be intensified. Fortunately, this effect may be weakened to some extent because the temperature difference is the only focus of UHI studies. In the estimation of surface fluxes, the 3-scale model may provide a better estimation of $R_n$ (i.e., net radiation divided by soil heat flux) ($\text{Murray} \& \text{Verhoef}, 2007b$) than setting this ratio as a constant. However, to better estimate surface fluxes, an improved parameterization of the heat transfer within vegetation is needed rather than the use of a simple extinction coefficient.

6.3. Discussion

As proposed in Section 3.3.3, the 3-scale model requires the implicit assumption that the aboveground vegetation is uniform and fully closed. In cases where high heterogeneity exists within a 1-km pixel, such as for sparse canopies or row crop vegetation, this assumption is invalid. The unsuitability of nonlinear models at the pixel scale due to subpixel heterogeneity is termed the ‘scaling effect’.

To assess the scaling effect of the 3-scale model, we retrieved two adjacent pixels in the study area on Oct. 21. Pixel A has a relatively dense canopy with LAI = 3.4, while the LAI of Pixel B is 0.3. Assume that there is a new pixel, one part of which shares the same vegetation status with Pixel A, whereas the remainder is consistent with that of Pixel B. With an increasing dominance of the dense canopy coming from Pixel A, represented by the increase of LAI from 0.3 to 3.4, the soil temperature differences predicted between using the nonlinear 3-scale model and using the direct average of component soil temperatures are provided in Fig. 10. The results indicate that the maximum temperature difference at $2\,^\circ$ is 0.55 K, which appears when the dense vegetation (LAI = 3.4) occupies approximately 40% of the pixel area. As the depth increases, this difference decreases simply because soil temperatures in deeper layers have a lower diurnal variation and they are less impacted by the surface status (e.g., vegetation). These results imply that high heterogeneity within a pixel decreases the prediction accuracy of the 3-scale model because of the scaling effect.

The aforementioned validation shows that the maximum MAE for the inverted soil temperature is approximately 2.75 K, with an average of approximately 1.5 K. The high errors in daily soil temperature are primarily because of the model’s unsuitability in winter when a snow cover exists and because of the empirical representation of the WTC length. The high errors in instantaneous soil temperature may be attributed to the scale mismatch between the MODIS-inverted and ground-based temperatures and to the scaling effect as a consequence of within-pixel heterogeneity of vegetation.

In geological mapping, the high error caused by vegetation heterogeneity is negligible because the mapping (e.g., Watson (1975)) is usually conducted over vegetation-sparse areas. Likewise, the 3-scale model may be suitable for other planetary surfaces (e.g., Mars) when the annual and daily cycle lengths are set as those of the planets, mostly due to the absence of vegetation. For example, with THEMIS (thermal emission imaging system) data, the 3-scale model may be revised to investigate the subsurface thermal status of Mars to estimate the soil properties or the subsurface water/ice status of Mars. In urban heat island (UHI) analyses, the 3-scale model has the potential to assist monitoring of the subsurface UHI (Menberg, Bayer, Zosseder, Rumohr, & Blum, 2013). Nevertheless, the spatial heterogeneity of urban surfaces is high and the scaling effect will be intensified. Fortunately, this effect may be weakened to some extent because the temperature difference is the only focus of UHI studies. In the estimation of surface fluxes, the 3-scale model may provide a better estimation of $R_n$ (i.e., net radiation divided by soil heat flux) ($\text{Murray} \& \text{Verhoef}, 2007b$) than setting this ratio as a constant. However, to better estimate surface fluxes, an improved parameterization of the heat transfer within vegetation is needed rather than the use of a simple extinction coefficient.

7. Spatial and profile results

Using MODIS data, we estimated the soil temperatures in the proximity of McCracken Mesa (37.45°N, –109.34°W, Utah) at a spatial range of 100 km × 100 km. Two typical clear-sky days, i.e., DOY 28 and 204, were chosen to represent the winter and summer, respectively (Fig. 11). To demonstrate the spatial distribution of soil temperatures at different depths, we further provide the soil temperature contours at the depths of 0.02, 0.05, 0.20, 0.50, 2.00, and 5.00 m, all at 12:00 on DOY 105 (Fig. 12). The results confirm the high spatial heterogeneity of the soil temperature, implying that ground-based measurements insufficiently characterize the soil thermal field at a large spatial scale.

Fig. 10. The scaling effect of the soil temperatures modeled using the 3-scale method (Case A), which disregards the heterogeneity within pixels and which uses the direct average of component temperatures within a pixel (Case B).

Fig. 11. The soil temperature contours at a depth of 5 cm at 12:00 in the region near McCracken Mesa (37.45°N, –109.34°W, denoted as M), with a spatial resolution and scale of 1 km and 100 km × 100 km, respectively. (a) and (b) represent DOY 28 and 204, respectively.
These results also illustrate that seasonal variation in soil temperature is significant and that spatial heterogeneity in soil temperature is much higher in summer than in winter (see Fig. 11a and b).

The reconstruction of the soil thermal field contains both soil temperatures and soil heat fluxes. Using the MODIS data, the variations of the soil temperature and heat flux with increasing soil depth were estimated in proximity of McCracken Mesa at a 1-km pixel scale (Fig. 13). The soil heat flux is estimated with $-k \cdot \partial T/\partial z$. To exaggerate and decrease the details of the shallow and deep layers, respectively, a break was set at the depth of 0.6 m, as the diurnal soil temperature and heat flux change insignificantly at depths greater than 0.6 m.

The results show that the variations of the soil temperature with increasing depth are not monotonic. Taking the profile at 18:00 on DOY 204 as an example (Fig. 13a), the soil temperature first increases with increasing depth and reaches a maximum at 0.1 m. The soil temperature then decreases and reaches a relatively low value at 0.3 m, followed by a similar pattern of increase and decrease from 0.3 to 10 m, between which the profile changes more slowly. This behavior is caused by the multiple external periodic and quasi-periodic forces, which include the ATC, WTC, and DTC. These forces exert different patterns on the soil temperature field as a function of depth.

Fig. 12. The soil temperature contours across the region near McCracken Mesa (spatial resolution = 1 km, DOY = 105, and time = 12:00). (a), (b), (c), (d), (e), and (f) denote the soil temperatures at 0.02, 0.05, 0.20, 0.50, 2.00, and 5.00 m, respectively.
At depths shallower than 0.5 m, the DTC and WTC\textsubscript{inst} prevail. The profiles of soil temperature during a DTC gradually converge with depth (Fig. 13). The soil temperatures on DOY 24 (i.e., winter) and 204 (i.e., summer) meet at 1.5 °C and 28.0 °C, respectively; while the soil heat fluxes meet at 4.0 and −2.5 W m\(^{-2}\), respectively. This suggests that in winter, the soil at relatively shallower layers is heated by the deep-layer soil, whereas in summer, the shallow-layer soil is the heat source for deep layers.

At depths between 0.5 m and the zero annual range, the ATC and WTC\textsubscript{inst} become predominant. The corresponding profiles from summer and winter steadily converge, with the soil temperature converging at 14.3 °C (relative to the ground-based measurement of 14.6 °C, see Table 1) and the soil heat flux converging at 0.0 W m\(^{-2}\). These values indicate that, at depths greater than 10 m, the soil temperature field is rarely influenced by inner-annual forces but might be impacted by forces at a temporal scale longer than an ATC (e.g., long-term climate change), which is exemplified by the common utilization of soil temperatures from extremely deep boreholes to reconstruct historical climates (Pollack, Huang, & Shen, 1998).

8. Conclusions

The remote estimation of daily and instantaneous soil temperatures remains difficult due to the high heterogeneity of land surfaces, which makes ground-based measurements far from representative at large spatial scales. This study exhibits the potential of LSTs from tandem polar-orbiting satellites in an annual cycle to estimate soil temperatures under snow-free conditions. An analytical three-time-scale model (i.e., 3-scale, including the ATC, WTC, and DTC) was designed to estimate soil temperature at depths above the zero annual range. We demonstrate that thermal remote sensing is capable of obtaining the soil thermal field without the use of ground-based measurements.

Validations were performed using both satellite-ground comparisons and indirect modeling, with an average accuracy of approximately 1.5 K. The daily and instantaneous soil temperatures were generated with spatial resolutions of 1 km at any time of day under a clear sky. We find that four thermal observations are sufficient to determine the skin-surface DTC, facilitating the production of LSTs with high temporal resolution, especially when GOES LSTs are unavailable. We also emphasize that it is generally problematic to validate satellite-derived soil temperatures using ground-based measurements because the scale differs. One solution to this problem involves validations over an extensive highly homogeneous area, such as a desert or dense canopy. Another solution may be the disaggregation of LST (Zhan et al., 2013), which downscals the LST to a much higher spatio-temporal resolution at which homogeneous land covers are easier to find.

Although this work makes progress on the estimation of soil temperature using thermal remote sensing, unsolved problems remain. (1) Thermal remote sensing fails to provide the soil temperatures on non-clear-sky days. In such cases, microwave satellite observation might provide a complement. (2) Using an extinction coefficient to represent the heat transfer within vegetation may be insufficient because wind can also penetrate the vegetation and drive heat transfer. (3) The soil thermal property is assumed vertically homogeneous. This assumption might be problematic because soil is often layered and soil moisture may vary with depth. Nevertheless, we believe this investigation expands the frontier of thermal remote sensing when used to estimate the soil temperature beneath the skin-surface.

Acknowledgments

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Appendix A. A physically based model capable of predicting both surface and soil temperatures within a DTC

In a diurnal temperature cycle (DTC), the upward fluxes, including the surface emitted thermal radiance and sensible and latent heat fluxes, can be parameterized as a linear function of LST (Xue & Cracknell, 1995). An inhomogeneous boundary condition that constrains Eq. (2) can be obtained according to the surface energy balance:

$$-k \cdot \frac{\partial T(z, t)}{\partial z_{|z=0}} = f(t) - [h_0 + h_1 T_d(0, t)],$$

where $f$ is the solar radiation received by surface in a DTC; and $h_0$ and $h_1$ are the constant and linear coefficient of the upward fluxes, which include the longwave radiation, sensible and latent heat fluxes, respectively. $f(t)$ is written as follows under solar radiation:

$$f(t) = (1 - \alpha) \cdot S_0 \cdot \cos \theta - \tau$$

$$\alpha_d = W_{\text{rad}} = [0, 2\pi/|\cos \theta > 0.04],$$

Fig. 13. The soil temperature and heat flux variations with increasing soil depth at a 1-km spatial scale in proximity of McCracken Mesa (37°45′N, −109°34′W). (a) and (b) represent the soil temperatures and heat fluxes on DOY 28 and 204, respectively. The zero annual range temperature and heat flux are 14.3 °C and 0.0 W m\(^{-2}\), respectively. A negative heat flux means that the heat is transferred from the surface downward. This work was supported in part by the National Natural Science Foundation of China (grant number 41301360), by the Natural Science Foundation of Jiangsu Province (grant number BK20130566), by the Chinese State Key Basic Research Project (grant number 2013CB733406), by the Open Fund of State Key Laboratory of Earth Surface Processes and Resource Ecology (grant number: 2013-KF-01), by the Open Fund of State Key Laboratory of Remote Sensing Science (grant numbers OFSRRS201214 and OFSRRS201313), and by the National 863 Plan under grant 2013AA122801. We thank the Natural Resources Conservation Service for providing ground-based soil temperatures through the Soil Climate Analysis Network.
where $\alpha$ is the surface albedo; $S_0$, $Z$, and $T$ represent the solar constant, solar incident zenith angle, and atmospheric transmittance respectively; $\omega_B$ is the angular velocity of the Earth’s rotation; and $W_{\text{shaded}}$ denotes the period when the sun radiates on surface. Alternatively, $f(t)$ is provided as follows without solar radiation:

$$f(t) = 0$$

$$A_0 = \left[0.2\pi \right]^2 \sin (0.04 \tau)$$

where $W_{\text{shaded}}$ is the period without solar radiation; and $Z$ and $\tau$ are given by:

$$\tau = 1 - 0.25 \sec^2 \theta$$

$$Z = \cos \theta \cos \omega \cos \omega t + \sin \theta \sin \omega t \left(1 - 0.25 \sec^2 \theta \right)$$

where $\theta$ and $\lambda$ are the sun declination and local latitude, respectively.

The solution of Eq. (2) under the boundary condition of Eq. (A1) is offered as Zhan et al. (2012a):

$$T_s(t, z) = T_d + \sum_{n=1}^{\infty} M_n \exp \left( -H_n^2 \right) \cdot g(t)$$

where $P$ is the thermal inertial; $T_d$ represents $-h_0 / h_1$ and implies the average temperature in a DTC; and $g(t)$, $A_n$, $B_n$, $M_n$, $H_n$, and $\phi_n$ are given as Eqs. (A6) to (A8):

$$g(t) = A_n \cos \left( \omega_n t - H_n^2 \phi_n \right) + B_n \sin \left( \omega_n t - H_n^2 \phi_n \right)$$

$A_n$ and $B_n$ are the Fourier coefficients of $f(t)$, expressed as:

$$A_n = \left(1/2\pi \right) \int_{0}^{2\pi} f(\omega t) \cos \omega_n \omega dt$$

$$B_n = \left(1/2\pi \right) \int_{0}^{2\pi} f(\omega t) \sin \omega_n \omega dt$$

$H_n$ and $M_n$ are two intermediate variables and $\phi_n$ is the phase difference of the nth order, estimated using:

$$M_n = \left( \text{no}_A^2 P + \sqrt{\text{no}_A \text{no}_B} h_2 + h_1^2 \right)^{1/2}$$

$$H_n = D_n \cdot 0.5n - \frac{1}{2} \omega$$

$$\phi_n = \arctan \left[ P / \text{no}_B \left( \sqrt{2} h_2 + P / \text{no}_A \right) \right]$$

Through Eq. (A5), satellite-observed LSTs are connected with three undetermined parameters including $P$, $h_0$, and $h_1$.

References


