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Evaluating soil evaporation parameterizations at near-instantaneous scales using surface dryness indices

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\textbf{A B S T R A C T}

Soil evaporation is an important component in the water and energy cycles on land, especially for areas that are moderately or densely covered by bare soil. Soil evaporation parameterizations that scale down potential evaporation with the soil surface temperature ($T_s$) and/or the air humidity are regionally applicable because of the advantage of omitting pixel-scale near-surface soil moisture. In this paper, we provide an intercomparison study among these parameterizations. Potential evaporation indices are estimated from the Priestley-Taylor method, the Penman method, and the mass transfer method (with or without $T_s$). The surface dryness indices that indicate the water availability of the soil surface are based on $T_s$ and/or the air humidity. We establish and evaluate ten such soil evaporation parameterizations through combinations of different types of potential evaporation indices and surface dryness indices at near-instantaneous scales (30 min). The results show that incorporating the soil temperature in the surface dryness index instead of the potential evaporation index can improve soil evaporation estimations. Poorer but still reasonable estimations are achieved when only the air humidity-based surface dryness index is used. In addition, the energy balance factor is crucial in the surface dryness indices. Our study indicates that the potential evaporation indices that are based on the Penman equation are generally more useful and robust than those that are based on the Priestley-Taylor approach or the mass transfer method. However, when the surface dryness index is only based on air humidity data, the Priestley-Taylor potential evaporation index performs as well as the index that is estimated from the Penman equation. In contrast, a soil evaporation parameterization that estimates the potential evaporation through the mass transfer method (with $T_s$) and the surface dryness index from the soil moisture content did not perform as well as the above ten parameterizations.

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1. Introduction

Evapotranspiration (ET), which includes evaporation from soil and water and transpiration from plants, is a major component in the land surface water cycle and energy balance (Oki and Kanae, 2006; Trenberth et al., 2009, 2007). The spatial estimation of daily ET, especially its partitioning between the canopy and soil layers is therefore useful to improve irrigation design (Colaizzi et al., 2004), climate simulations (Lawrence et al., 2007) and environmental assessments (Newman et al., 2006). Transpiration at daily or smaller time scales has been successfully estimated by using remote-sensing based vegetation indices (VIs) and physiological canopy conductance models (Gan and Gao, 2015; Leuning et al., 2008; Mu et al., 2011; Zhang et al., 2010). However, estimating soil evaporation is more complicated and less constrained compared to transpiration calculations, which may cause great estimation errors in moderately and sparsely vegetative areas.

Evaporation at remote-sensing-pixel scales is usually estimated by tuning down the potential rate of evaporation with the soil moisture availability at the near surface. For example, the Penman hypothesis assumes that the actual evaporation is proportional to the potential evaporation, and one method to estimate the relative evaporation $LE/LE_p$, where $LE$ and $LE_p$ are the actual and potential ET, respectively, is introducing a function of soil water availability...
(Yang et al., 2006). However, the operational retrievals of regional soil moisture at moderate resolution (approximately 1 km) remain a challenge even with the great development of microwave remote sensing techniques because passive microwave systems measure the soil moisture at relatively coarse resolution (e.g., 25 km) and active microwave systems require local calibration to minimize the effects of vegetation and surface roughness on radar signals (Wagner et al., 2007). In addition, the surface soil moisture may experience rapid changes over short time scales, so the difficulty of this method is further highlighted at near-instantaneous scales (e.g., 30 min in this study).

A possible way to avoid using the pixel-scale soil moisture content is to estimate the actual ET directly from the potential ET. For example, Bouchet (1963) stated that the actual ET is not necessarily proportional to the potential ET; in contrast, as the surface dries, a decrease in the actual ET is accompanied by an identical increase in the potential ET if the total available energy is constant. This is known as the complementary relationship. Thus the actual ET can be readily estimated from the potential ET by using such complementary models (Brutsaert and Stricker, 1979; Granger, 1989a; Morton, 1983). However, such models usually require a hypothesis on the exact relationship between the changes in the energy that is used in the actual ET and the energy that is available for the potential ET, which may not be valid in all spatial and temporal scales.

Another way to directly estimate the actual ET from the potential ET is to return to the relative evaporation perspective but explore the usage of potential evaporation in indicating the surface dryness. The actual evaporation is estimated as the product of the potential evaporation and the relative evaporation, and the latter is estimated from the surface dryness index (SDI), which is parameterized as a function of the potential ET. The key of such parameterizations is to model the SDI from the potential evaporation.

Granger and Gray (1989) modeled the SDI as a dimensionless index that combines the available energy at the land surface and the drying power of the air. The drying power of the air is an index that indicates the potential ET and is estimated from the mass transfer method by using the air humidity. The air humidity is influenced by land-atmosphere feedbacks through ET (Brutsaert and Stricker, 1979), and thus reflects the surface dryness to some extent (Granger and Gray, 1989). Compared to the soil moisture, the air humidity is a more readily available variable that can be obtained from weather station measurements or regional atmospheric simulations. However, the coupling between the atmospheric humidity and the near-surface soil moisture deviates from the equilibrium state because of the large-scale advection effect, in which case the atmospheric humidity is no longer a good indicator of the near-surface soil moisture content.

Compared to the air humidity, the soil surface temperature is more directly linked to the near surface soil moisture conditions. This factor can be used to scale down the potential evaporation to estimate the actual evaporation, for example, within the LST-VI framework (Long and Singh, 2012; Merlin et al., 2014; Nishida et al., 2003) and the PT-JPL model (Garcia et al., 2013), which was first proposed by Fisher et al. (2008). In addition, a potential evaporation index can be estimated by using the mass transfer method with the land surface temperature thanks to the development of thermal remote sensing techniques. Crago and Crowley (2005) compared several versions of complementary ET models that use different combinations of potential ET indices (with and without land surface temperature) at near-instantaneous time scales. However, their models were applied to estimate the total ET instead of the soil evaporation.

In this study, we focus on the parameterization of soil evaporation. We attempt to directly establish the relationships between the relative evaporation and the surface dryness indices for different situations with different data availability by using model simulations and in-situ measurements. First, we incorporate the land surface temperature (LST) in potential evaporation indices and surface dryness indices and then determine the best incorporation method by comparing the strength of six combinations of potential evaporation indices and surface dryness indices when estimating the soil evaporation. Such formulations can be useful in diagnostic and process-based models, in which energy fluxes and the LST are simultaneously determined. Second, we evaluate the usage of air humidity data in estimating the near-instantaneous soil evaporation and determine the best formulation out of four parameterizations for modeling soil evaporation. When LST data are not available or when the LST is not considered in the surface energy balance, such formulations can be used together with a canopy conductance model to estimate total the ET. Third, the parameterization that uses the soil moisture content is also used for comparison. In this study, the above-mentioned evaluations are performed at pixel scales, in which case a sound thermal-based two-source energy balance model (TSEBTR) is used to determine the “actual” evaporation and transpiration at the pixel scale by using the remotely sensed LST, measured energy fluxes and atmospheric conditions.

2. Methods

2.1. Parameterizations of the soil evaporation

The soil evaporation is usually estimated by tuning down the potential rate of evaporation \( LE_\text{s} \) according to the surface dryness index, i.e., \( LE_\text{s\_predicted} = LE_\text{s} \times \text{fun}(\text{SDI}) \), in which fun(SDI) is the relative evaporation. First, we introduce three parameterizations of the potential evaporation and then the formulations of the SDI and relative evaporation with respect to the SDI. A summary of all the variables that are used in the soil evaporation parameterizations is shown in Table 1.

The concept of potential ET, which refers to the evapotranspiration rate that would occur for a large uniform surface with an adequate water supply, was first proposed and used by Thornthwaite (1948) for climate classifications. However, as Brutsaert (1982) had indicated, the water/heat feedbacks of the saturated surface to the air are unknown, so the potential rate that is calculated under actual air conditions is not the same as what would occur for a saturated surface. Granger (1989b) noted that the potential rate is indeterminable under the original definition of Thornthwaite.
(1948), but defining useful potential ET indices that represent real and attainable situations is more important.

We applied the potential ET indices that were summarized by Granger (1989b) to the soil layer of a mosaic pixel of the land surface. The first index, which is known as the equilibrium evaporation, refers to the evaporation rate that would occur for a surface that becomes saturated with the available energy. The equilibrium evaporation is mainly constrained by the available energy and thus represents a minimal advection situation. The Priestley-Taylor (PT) approach (Priestley and Taylor, 1972) is often used to estimate this potential rate. We apply the PT approach to estimate the equilibrium evaporation for the soil layer (LEs_pm) of a partially vegetated surface, where \( \alpha \) is set to 1.26:

\[
LEs_{pm} = \frac{\alpha}{\Delta + \gamma} (R_{ns} - G) \tag{1}
\]

where \( \gamma \) is the psychrometric constant (0.667 hPa/K) and \( \Delta \) is the slope of the saturated vapor pressure to the air temperature. \( R_{ns} \) is the net radiation in the soil layer and \( G \) is the soil heat flux.

The second index, which is known as the wet environment evaporation, refers to the evaporation rate that would occur for a surface that becomes saturated with the energy supply and the atmospheric conditions unchanged. This index is usually estimated through the Penman equation (Penman, 1948), which is denoted as LEs_pm:

\[
LEs_{pm} = \frac{\Delta (R_{ns} - G) + \rho c_p (e_c(T_a) - e_s)/(r_a + r_s)}{\Delta + \gamma} \tag{2}
\]

where \( \rho \) is the air density (1.25 kg/m³) and \( c_p \) is the specific heat of the air (1005 J/kgK) at a constant pressure. \( e_s \) is the atmospheric water vapor pressure (hPa) and \( e_c(T_a) \) is the saturated water vapor pressure of the air at the given air temperature \( T_a \). \( LEs_{pm} \) considers the effects of both the available energy and advection on the potential evaporation. Therefore, this function is larger than LEs_pr and the actual evaporation. \( r_a \) and \( r_s \) are the aerodynamic and under-canopy resistances in TSEB, respectively, which will be shown in Section 2.2.

The third index refers to the evaporation rate that would occur for a surface that becomes saturated with the current atmospheric conditions and the surface temperature remaining unchanged. This potential evaporation is calculated by the mass transfer equation, which is denoted as LEs_mnt. Because no energy limit exists for such cases, \( LEs_{mnt} \) represents the upper limit for the potential evaporation:

\[
LEs_{mnt} = \frac{\rho c_p (e_c(T_a) - e_s)/(r_a + r_s)}{\gamma} \tag{3}
\]

where \( e_c(T_a) \) is the saturated vapor pressure at the soil surface temperature \( T_a \).

Surface dryness indices have usually been based on atmospheric humidity data in previous studies to model the ET with minimal data. For example, the surface dryness indices that were proposed by Granger and Gray (1989) and Fisher et al. (2008) are shown in Eqs. (4) and (5), respectively. Granger and Gray (1989) modeled the SDI as a dimensionless index that consists of the available energy at the land surface and the drying power of the air. Higher actual ET and rising soil moisture tends to increase the vapor pressure in the air, thus decreasing the drying power \( E_s \) (Eq. (6)), and vice versa. As a result, the drying power reflects the surface soil moisture content to some extent. Furthermore, Granger and Gray (1989) noted that the sum of the available energy and the drying power describes the upper limit of ET, so the surface dryness index can be formulated as a dimensionless variable, \( E_s/(E_s + R_{ns} - G) \). This index falls into the range of 0–1. As the land surface becomes saturated, the SDI in Eq. (4) approaches 0 because \( E_s \) tends to be 0. On the other hand, if the land surface is completely dry, \( E_s \) reaches its maximum value for the given air conditions, as does the surface dryness index.

\[
SDI = \frac{E_s}{E_s + R_{ns} - G} \tag{4}
\]

\[
SDI = (RH)^{(e_s(T_a) - e_s)}/C_0 \tag{5}
\]

Fisher et al. (2008) also used the air humidity to model the SDI, although their formulation did not consider the surface’s available energy (Eq. (5)). The basic logic was also that the air humidity can reflect the surface soil moisture conditions, but, they found that the relative humidity (RH) of the air is lower than the expected relative evaporation at a high vapor pressure deficit (VPD) and higher than the expected relative evaporation at a low VPD, so they modeled \( LEs_{pm}/LEs \), as \( RH^{(1-\beta)} \), where \( \beta \) is a parameter.

Although the atmospheric humidity is a good indicator of the soil moisture conditions when the surface is in an equilibrium state with the overlying air, such an equilibrium state rarely occurs because of the large-scale advection effect. Instead, the soil surface temperature is strongly influenced by evaporation and can serve as a good indicator of the soil moisture conditions. As a result, we modified the surface dryness indices that were first proposed by Granger and Gray (1989) and Fisher et al. (2008) to incorporate the soil surface temperature. The surface dryness indices are denoted as SDI1 and SDI2, as shown in Eqs. (7) and (8), respectively.

In this study, a constant of 100 in Eq. (8) was used to scale the range of SDI2 to conveniently map the relationship between SDI2 and relative evaporation. This choice does not alter the fitting relationship between SDI2 and the relative evaporation because \( \beta \) would change correspondingly if a constant other than 100 was chosen. In addition, Fisher et al. (2008) modeled soil evaporation at monthly scales and used the midday rather than daily mean atmospheric conditions because the link between the surface moisture status and the evaporative demand of the atmosphere is the strongest at midday. Here, we use the near-instantaneous atmospheric measurements to estimate SDI2 because we intend to resolve soil evaporation at sub-daily scales. As with SDI1, SDI2 can be seen as a function of LEs_mnt.

\[
SDI_1 = \frac{LEs_{mnt}}{LEs_{mpt} + R_{ns} - G} \tag{7}
\]

\[
SDI_2 = (RH)^{(e_s(T_a) - e_s)/100} \tag{8}
\]

The relative evaporation \( f \) is calculated as follows:

\[
f = \frac{LEs}{LEs_{mpt}} \tag{9}
\]

\[
LEs_{mpt} = \frac{1}{1 + a \exp(b \cdot SDI_1)} \tag{10}
\]

\[
LEs_{mnt} = SDI_2^{10} \tag{11}
\]

Under adequate water supply conditions, the relative evaporation approaches 1, which indicates that a small coefficient \( a \) in Eq. (12) is appropriate. In contrast, when the surface becomes completely dry, SDI1 and the relative evaporation tend to be 1 and 0, respectively, which indicates that \( b \) must be a relatively large number (Eq. (12)). In addition, \( a \) is negative when \( LEs/LEs_{mpt} \) is < 1. Therefore, the range of \( a \) was set to \([-0.5, 0.1] \) and the range of \( b \) was set to \([0, 15] \), for \( LEs/LEs_{mpt} = \text{fun}(SDI_1) \). For \( LEs/LEs_{mpt} = \text{fun}(SDI_1) \) and \( LEs_{mpt}/LEs_{mnt} = \text{fun}(SDI_1) \), the range of \( a \) was set to \([0, 0.1] \) and the range of \( b \) was set to \([0, 15] \). Similarly, we set the range of \( \beta \) to be \([0, 10] \).

These three types of potential evaporation indices (Eqs. (1)-(3)) and two types of surface dryness indices (Eqs. (10) and (11))
produce six combinations of parameterizations of soil evaporation if the soil surface temperature is available. These combinations can be written in two general forms, which are shown in Eqs. (12) and (13), where $a$, $b$ and $\beta$ are the aforementioned parameters. Table 2 shows the details of all these combinations.

$$LE_s = LE_{s_\text{pt}} \cdot \frac{LE_s}{LE_{s_\text{pt}}} = LE_{s_\text{pt}} \cdot \frac{1}{1 + a \exp(b \cdot SDI_1)}$$  \hspace{1cm} (12)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \cdot \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (13)

The two forms of soil evaporation parameterizations that correspond to Eqs. (12) and (13) are shown in Eqs. (14)–(16) and in Eqs. (17)–(19), respectively.

$$LE_s = LE_{s_\text{pt}} \cdot \frac{LE_s}{LE_{s_\text{pt}}} = LE_{s_\text{pt}} \frac{1}{1 + a \exp(b \cdot SDI_1)}$$  \hspace{1cm} (14)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (15)

$$LE_s = LE_{s_\text{pt}} \cdot \frac{LE_s}{LE_{s_\text{pt}}} = LE_{s_\text{pt}} \frac{1}{1 + a \exp(b \cdot SDI_1)}$$  \hspace{1cm} (16)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (17)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (18)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (19)

The above equations (Eqs. (14)–(19)) attempt to establish the relationship between the potential evaporation and the actual evaporation directly without using the pixel-scale soil moisture content as input. For example, we can obtain Eq. (20) if we substitute Eq. (7) into Eq. (16). $LE_s$ is then a function of $LE_{s_\text{pm}}$. In Section 4, we will evaluate the fitness of the parameterizations for actual evaporation data and determine the parameterization with the best performance.

$$LE_s = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot \frac{SDI_1 - \theta_{air}}{\theta_{air} + \theta_{r_0} - \theta})}$$  \hspace{1cm} (20)

For conditions in which the soil surface temperature is unavailable, we apply the original formulations of the surface dryness indices that were proposed by Granger and Gray (1989) and Fisher et al. (2008) to the soil layer, as shown in Eqs. (21) and (22), respectively. The ranges of the parameters for SDI_1 and SDI_2 were the same as for SDI_1 and SDI_2, respectively.

$$SDI_1 = \frac{LE_{s_\text{pm}}}{LE_{s_\text{pm}} + R_{soil} - \theta}$$  \hspace{1cm} (21)

$$SDI_2 = \frac{(RH) \cdot (T_{air}) \cdot (T_{air})}{(T_{air}) \cdot (T_{air})}$$  \hspace{1cm} (22)

$LE_{s_\text{pm}}$ is calculated as follows:

$$LE_{s_\text{pm}} = \frac{\theta_{soil} - \theta_{air}}{\theta_{soil} + \theta_{air}}$$  \hspace{1cm} (23)

| Case | Potential evaporation index $LE_{s_\text{pm}}$ | Surface dryness index SDI | Relationships between relative evaporation and SDI |
|------|---------------------------------|------------------|---------------------------------|
| 1    | $LE_{s_\text{pt}}$              | SDI_1            | $LE_{s_\text{pt}}$ = $SDI_1$   |
| 2    | $LE_{s_\text{pm}}$              | SDI_1            | $LE_{s_\text{pm}}$ = $SDI_1$   |
| 3    | $LE_{s_\text{pt}}$              | SDI_2            | $LE_{s_\text{pt}}$ = $SDI_2$   |
| 4    | $LE_{s_\text{pm}}$              | SDI_2            | $LE_{s_\text{pm}}$ = $SDI_2$   |
| 5    | $LE_{s_\text{pt}}$              | SDI_1            | $LE_{s_\text{pt}}$ = $SDI_1$   |
| 6    | $LE_{s_\text{pm}}$              | SDI_2            | $LE_{s_\text{pm}}$ = $SDI_2$   |

Because the soil surface temperature is unavailable, two potential evaporation indices ($LE_{s_\text{pt}}$ and $LE_{s_\text{pm}}$) and two surface dryness indices (SDI_1 and SDI_2) provide four parameterization combinations for soil evaporation. These combinations can also be written in two general forms, which are shown in Eqs. (12) and (13). The two forms of soil evaporation parameterizations that correspond to Eqs. (12) and (13) are shown in Eqs. (24) and (25) and in Eqs. (26) and (27), respectively. Table 3 shows the details of all these combinations.

$$LE_s = LE_{s_\text{pt}} \cdot \frac{LE_s}{LE_{s_\text{pt}}} = LE_{s_\text{pt}} \frac{1}{1 + a \exp(b \cdot SDI_1)}$$  \hspace{1cm} (24)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (25)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (26)

$$LE_s = LE_{s_\text{pm}} \cdot \frac{LE_s}{LE_{s_\text{pm}}} = LE_{s_\text{pm}} \frac{1}{1 + a \exp(b \cdot SDI_2)}$$  \hspace{1cm} (27)

2.2. ET partitioning method for evaluating the soil evaporation

The true values of the near-instantaneous soil evaporation at MODIS pixel scales are required to evaluate the parameterizations that were established in Section 2.1. A detailed review of ET partitioning methods can be found in Kool et al. (2014). In this study, we used the TSEBTR model to compute the soil evaporation as a reference to test our soil evaporation parameterizations. The capability of the TSEBTR model to estimate ET components has been validated by Colalizzi et al. (2012), who used sap flow data. In addition, the TSEBTR model has been used to partition observed LE measurements from an eddy covariance system into transpiration and soil evaporation (Agam et al., 2010). Agam et al. (2010) iteratively ran the TSEBTR model at each time point with a series of $\alpha$ to achieve minimal error in LE prediction (compared to the LE measurements). Then, the reference LE components that were considered the “true” values were obtained from the minimal error case. We used their method to estimate LE components by using detailed measurements of the atmospheric conditions, the energy fluxes (including soil heat flux), and the land surface temperature.

The calculation procedure is shown in Fig. 1. The net radiation ($R_n$) and its partitioning between the canopy layer ($R_{can}$) and soil ($R_{soil}$) layers are determined by the atmospheric forcings, the LST and the leaf area index. Then the transpiration ($LE_s$) is estimated for each leaf area index through the PT approach, and the sensible heat flux in the canopy layer ($H_c$) is calculated as the residue of the energy balance equation for the canopy layer. The canopy temperature can then be estimated by inverting the heat transfer equation for $H_c$. The component temperature of the soil layer ($T_s$) can be determined by decomposing the LST with the vegetative cover ($f_c$) and $T_c$. The sensible heat flux in the soil layer ($H_s$) can then be calculated by the heat transfer equation, and the latent heat flux in the soil layer ($LE_s$) can be estimated as the residue of the energy balance equation for the soil layer, given that soil heat flux measurements...
are available. The aerodynamic resistance \( r_a \) is estimated from the wind speed and the surface roughness (Li et al., 2005). The under-canopy resistance \( r_s \) is the resistance to sensible and latent heat fluxes between the soil surface and the canopy displacement height. A detailed description of calculating \( r_s \) can be found in Gan and Gao (2015).

At this derivation stage, the soil evaporation \( (LE_s) \), the potential evaporation indices \( (LE_{s_{pt}}, LE_{s_{pm}}, \text{and } LE_{s_{mt}}) \), the corresponding relative evaporation, the surface dryness indices \( (SDI_{1}, SDI_{2}, SDI_{3} \text{ and } SDI_{4}) \) and the soil surface resistance \( (r_{ss}) \) to water vapor can be estimated. The soil evaporation from the optimized TSEB is considered as the reference \( LE_s \), which is used as the approximation of the actual evaporation. We then use the reference LEs to evaluate each parameterization that was established in Section 2.1 to estimate the soil evaporation.

3. Study sites and data description

We evaluated the soil evaporation parameterizations at two crop sites, i.e., the Daxing site and Tongyu site, which are located in semi-humid and semi-arid areas in China, respectively. Assessing and improving agricultural water use efficiency are important for water resource sustainability in these areas. In-situ measurements from the Daxing site were provided by the Cold and Arid Regions Science Data Center at Lanzhou (http://westdc.westgis.ac.cn/haihe/daxing) (Liu and Xu, 2013), and the data from the Tongyu site were obtained from the Coordinated Energy and Water Cycle Observations Project’s (CEOP) reference site data archive (http://www.ceop.net/).

The Daxing site (39.6123°N, 116.4270°E) is located in a crop-land with very flat terrain (Jia et al., 2012; Liu et al., 2013) in the Hai River Basin in the northern plain of China. The mean annual precipitation in the Hai River Basin (1956–2000) is 527 mm, which only constitutes 1.5% of the national total water resources but supplies water to 10% of the population of the country (Liu et al., 2013; Sun, 2013). Winter wheat, maize, and vegetables are planted at this crop site, with maximum heights of 0.7 m, 2.2 m, and 0.5 m, respectively (Liu et al., 2013).

The Tongyu site is located on the SongNen plain, which is the second largest plain and one of the most important areas of grain production in China. The SongNen plain, which is located in northeastern China, is characterized by a temperate, semi-arid continental monsoon climate (Yu et al., 2014). The sustainable development of agriculture in this area has long been restricted because of drought and water shortage (Wang et al., 2003). The annual mean air temperature at the Tongyu site is 5.2 °C, and the annual mean precipitation is 404.3 mm. Corn is planted at this crop site (44.5921°N, 122.8773°E) and reaches its maximum height (~1.8 m) in September (Tu, 2007).

All the data that were used in this study are summarized in Table 4. The land surface temperature, albedo, and leaf area index data at the study sites were obtained from the MODIS products, which were downloaded from the Goddard Space Flight Center (http://ladsweb.nascom.nasa.gov/data/). The data sets that were used to evaluate the soil evaporation parameterizations were collected when the highest quality MOD11L2/MYD11L2 LST data were available, i.e., the quality control (qc) flags equalled 0, during the study periods (2009 at the Daxing site, and 2003 and 2004 at the Tongyu site). These data sets include remotely sensed products, atmospheric forcing, and soil moisture and energy flux measurements.

All the in-situ measurements at both sites were recorded at an interval of 30 min, except for the atmospheric and sub-surface measurements at the Daxing site, which were recorded every 10 min. However, these data were averaged to match the 30-min scale.

The EC systems measured fluxes at the spatial scale of the MODIS LST (approximately 0.01°) because the stations were surrounded by homogeneous flat terrain and were not sheltered by tall obstacles. Closure corrections were performed on the sensible and latent heat fluxes from the EC systems before the flux measurements could be used. We partitioned the available energy \( (R_n - G) \) between the sensible and latent heat fluxes by using the 30-min average evaporative fraction \( LE/(H + LE) \) that was calculated from the EC measurements (Twine et al., 2000).

Soil heat flux measurements below the surface usually do not equal the corresponding surface values. At the Tongyu site, we used the calorimetric method (Heusinkveld et al., 2004) to esti-
mate the soil heat flux at the surface by combining the heat storage in the top 0.05-m soil layer and the soil heat flux at 0.05 m below the surface. However, both the soil heat flux and the soil temperature at the Daxing site were measured at a depth of 0.02 m, so we used the original measurements of the soil heat flux as a surrogate of the surface values.

4. Results and discussion

4.1. TSEBTR model performances

We iteratively ran the TSEBTR model at the timings in which the MODIS LST data with the highest quality were available to obtain the total LE and its partitioning between the canopy and soil layers. In addition, we calculated a series of potential evaporation indices by using the PT approach, the Penman approach, and the mass transfer method, for all the timings (qc = 0 for LST) of the study periods. The drying power of the air, $\text{LE}_{\text{air}}$, was also determined by using the mass transfer equation with the atmospheric water vapor deficit. Table 5 shows the minimum, maximum and mean values of the above-mentioned variables and the EC measurements. The relative evaporation and the surface dryness indices (SDI1, SDI2, SDI3, and SDI4) could also be determined.

Soil evaporation comprised a considerable fraction of the total ET, i.e., 53.4% and 34.0%, at the Daxing and Tongyu sites, respectively (Table 6). Therefore, the ratios of the RMSEs to the mean EC measurements, which are called “relative RMSEs” in the rest of the paper, were quite small, which indicate the capability of the optimized TSEBTR model to reproduce the energy fluxes.

We compared the performances of the model that used the qualified LST data (qc = 0) and the un-qualified LST data (qc > 0) over the entire study periods to further evaluate the capability of the optimized TSEBTR model. At the Daxing site, the fraction of LST data that were qualified was relatively high (78%), and the relative RMSEs were only 8.1% and 11.0% for the timings when qc > 0 and qc = 0, respectively (Table 6). In contrast, the fraction of LST data at the Tongyu site that were qualified was only 48.7%. In addition, the relative RMSE for the model that used the unqualified LST data (32.9%) was much higher than that for the model that used the qualified LST data (12.9%) (Table 6). Thus, we only selected the timings when the qualified LST data were available.

Figs. 2–4 show that the optimized TSEBTR model that used quality-controlled LST data reproduced the LE values throughout the range of fractional vegetation cover at both sites. These good performances, especially during periods with low vegetation cover, during which the effects of adjusting $x$ were quite minor, indicated that the parameterizations of net radiation partitioning and the resistance terms of heat transfer in TSEBTR were reasonable. Therefore, LE partitioning is assumed to be reasonable after iteratively running the TSEBTR model with both flux measurements and the land surface temperature serving as constraints to force closure on the LE partitioning.

4.2. Evaluating the soil evaporation parameterizations that incorporated the LST

In this section, we establish and evaluate the relationships between the relative evaporation and the surface dryness indices (SDI1 and SDI2) that incorporate LST and determine how well the soil evaporation parameterizations (Eqs. (14)–(19)) that are based on the potential evaporation and relative evaporation concepts can fit the observation data. The fitted curve between $\text{LE}_{\text{pr}}/\text{LE}$ and
SDI\(_1\) was denoted as \(\text{LE}_{s/LEs_{pt}} = \text{fun}(SDI_1)\). Similar notations are used in the rest of this study.

The simulated annealing technique (Dekkers and Aarts, 1991; Kirkpatrick et al., 1983) was used to estimate the parameters in the relationships between the relative evaporation and SDI. The simulated annealing technique can achieve global optima by so-called hill-climbing moves to avoid being trapped in local minima. The estimated parameters, RMSEs and biases of the predicted relative evaporation values are shown in Table 7. For SDI\(_1\), the results at both sites indicated that \(\text{LE}_{s/LEs_{mt}} = \text{fun}(SDI_1)\) performed the best, followed by \(\text{LE}_{s/LEs_{pm}} = \text{fun}(SDI_1)\), whereas \(\text{LE}_{s/LEs_{pt}} = \text{fun}(SDI_1)\) performed the worst. Similar results were found for SDI\(_2\).

In addition, SDI\(_1\) was generally better than SDI\(_2\) for modeling the same \(\text{LE}_{s/LEs}\) at the same site for most cases, except for the bias in \(\text{LE}_{s/LEs_{pt}} = \text{fun}(SDI_1)\) at the Daxing site, which was much larger than those in the other cases (Table 7). Both surface dryness indices SDI\(_1\) and SDI\(_2\) include the factor \(e(T_s)/C_0\) to indicate the water availability of the surface. However, the soil temperature itself is the result of the surface energy balance and can change if the available energy changes under the same water supply conditions. This indicates that no one-to-one matching relationship exists between the soil temperature and the soil water availability. Compared to SDI\(_2\), SDI\(_1\) is a normalized factor that considers both the soil temperature and the energy balance effect of the surface when indicating the surface dryness.

We also examined whether \(\text{LE}_s\) can be expressed as a function of a potential evaporation index and a surface dryness index (Eqs. (14)–(19)). Such functions can be denoted as, e.g., \(\text{LE}_s = \text{fun}(\text{LEs_{mt}}, SDI_1)\) for Eq. (14). Similar notations are used in the rest of the paper. Although \(\text{LE}_{s/LEs_{mt}}\) can be modeled quite well with both surface dryness indices SDI\(_1\) and SDI\(_2\), the accuracy of reproducing the evaporation by using \(\text{LEs_{mt}}\) as the potential evaporation index may be unsatisfactory (Tables 7 and 8, Figs. 5 and 6). For example, the case \(\text{LE}_s = \text{fun}(\text{LEs_{mt}}, SDI_2)\) performed the worst at both sites compared to the other parameterizations. The main reason was that \(\text{LEs_{mt}}\) was much larger than the other potential evaporation indices (Table 5), which means that relatively small errors in \(\text{LE}_{s/LEs_{mt}}\) could induce large errors in the predicted \(\text{LE}_s\). Although the \(\text{LE}_s\) estimation was found to be quite accurate at both sites for \(\text{LE}_s = \text{fun}(\text{LEs_{mt}}, SDI_1)\), where the RMSEs for \(\text{LE}_{s/LEs_{mt}} = \text{fun}(SDI_1)\) were the lowest, our results indicated that \(\text{LEs_{mt}}\) was not a robust potential evaporation index to estimate the soil

![Fig. 2. Time series of the soil moisture content, LAI, latent heat flux predictions and EC measurements at the Daxing site in 2009.](image1)

![Fig. 3. Time series of the soil moisture content, LAI, latent heat flux predictions and EC measurements at the Tongyu site in 2003.](image2)
evaporation estimation. However, if LE$_{s_{pt}}$ is used, the surface dryness index SDI$_1$ is suggested.

When LE$_{s_{pt}}$ was used as the potential evaporation index, the LE$_s$ estimation was generally reasonable, except for LE$_s = \text{Fun}(\text{LE}_{s_{pt}}, \text{SDI}_1)$, which resulted in a relatively large bias ($/C0 20.7 \text{W/m}^2$) at the Daxing site. The major advantage of LE$_{s_{pt}}$ is that this factor requires minimal data as input, compared to other potential evaporation indices. In contrast, both LE$_s = \text{Fun}(\text{LE}_{s_{pm}}, \text{SDI}_1)$ and LE$_s = \text{Fun}(\text{LE}_{s_{mt}}, \text{SDI}_1)$ performed quite well, which suggests that LE$_{s_{pm}}$ is a robust potential evaporation index for soil evaporation estimation. The relative RMSEs in LE$_s$ for LE$_s = \text{Fun}(\text{LE}_{s_{pm}}, \text{SDI}_1)$ were relatively low, i.e., 29.9% and 28.0% at the Daxing and Tongyu sites, respectively.

Incorporating the soil temperature into the estimation of soil evaporation and evaluating such parameterizations with a thermal-based ET model are not meaningless. The limited availability of high-quality LST images remains an obstacle to continuous daily ET estimation because of the effects of clouds on thermal remote sensing. In contrast, the soil evaporation parameterizations that were formulated in this section could still be used to solve LE$_s$ when the LST is unavailable through the use of the soil surface energy balance equation (i.e., $H_s(T_s) + LE_s(T_s) + G = R_{ns}$), in which only $T_s$ is unknown. Thus, the method that was proposed here shows potential in diagnostic or process-based ET models.

### 4.3. Evaluating the soil evaporation parameterizations that used the atmospheric humidity

In this section, we establish and evaluate the relationships between the relative evaporation and the surface dryness indices (SDI$_1$ and SDI$_2$) that mainly use the atmospheric humidity and test the fitness of the soil evaporation parameterizations (Eqs. (24)–(27)) that are based on the potential evaporation and relative evaporation concepts to the observation data. The calibrated parameters, RMSEs and biases of the predicted relative evaporation are shown in Tables 9 and 10. For SDI$_1$, the results at both sites indicated that LE$_s/\text{LE}_{s_{pm}} = \text{fun(SDI}_1)$ performed better than
Table 9
Evaluation of the fitting of the relative evaporation curve and its usefulness in estimating the soil evaporation. SDI 3 was used as the surface dryness index.

| Relative evaporation parameterizations | a  | b   | RMSE | BIAS |
|---------------------------------------|----|-----|------|------|
| Daxing                                | 0.0215 | 5.07 | 0.284 | −0.002 |
| LE s = Fun(SDI 3)                     | 0.0122 | 7.02 | 0.228 | 0.004 |
| Tongyu                                | 0.0100 | 4.23 | 0.222 | −0.002 |
| LE s = Fun(SDI 3)                     | 0.0535 | 5.80 | 0.181 | 0.002 |

Table 10
Evaluation of the fitting of the relative evaporation curve and its usefulness in estimating the soil evaporation. SDI 4 was used as the surface dryness index.

| Relative evaporation parameterizations | β  | RMSE | BIAS |
|---------------------------------------|----|------|------|
| Daxing                                | 1.452 | 0.309 | 0.027 |
| LE s = Fun(SDI 4)                     | 2.644 | 0.283 | 0.020 |
| Tongyu                                | 4.097 | 0.243 | 0.005 |
| LE s = Fun(SDI 4)                     | 5.474 | 0.203 | −0.005 |

Fig. 5. Results for the cases of LE s = Fun(SDI 1) and LE s = Fun(SDI 2). a, b, and c show the scatter plots and fitting curves of the surface dryness index SDI 1 and the relative evaporation LE s/LE s pt, LE s/LE s pm, and LE s/LE s mt, respectively. d, e, and f show the scatter plots of the reference LE s and the LE s that was predicted by the parameterizations of LE s = Fun(LE s pt, SDI 1), LE s = Fun(LE s pm, SDI 1), and LE s = Fun(LE s mt, SDI 1), respectively.

Fig. 6. Results for the cases of LE s/LE s pt = Fun(SDI 2) and LE s = Fun(SDI 2). a, b, and c show the scatter plots and fitting curves of the surface dryness index SDI 2 and the relative evaporation LE s/LE s pt, LE s/LE s pm, and LE s/LE s mt, respectively. d, e, and f show the scatter plots of the reference LE s and the LE s that was predicted by the parameterizations of LE s = Fun(LE s pt, SDI 2), LE s = Fun(LE s pm, SDI 2), and LE s = Fun(LE s mt, SDI 2), respectively.
LEs/LEs_pt = fun(SDI3). Similar results were found for SDI4. In addition, SDI3 was always better than SDI4 when modeling the same LEs/LEs at the same site (Tables 9 and 10). Both surface dryness indices include the factor \( e_a(t_a) - e_s \) to indicate the water availability of the surface; however, compared to SDI4, SDI3 is a normalized factor that considers both the atmospheric forcing and the energy balance effect when indicating the surface dryness.

The evaporataion was estimated by using the fitted curves of the relative evaporation (Figs. 7 and 8). Although LEs/LEs_pm = fun(SDI4) had better fitting results than LEs/LEs_pt = fun(SDI4) in terms of relative evaporation, the accuracy of estimating the evaporation with this curve proved to be poorer than LEs = Fun(LEs_pt, SDI3) at the Daxing site. However, the accuracies of using LEs_pt and LEs_pm in estimating the soil evaporation were quite close when SDI3 was used.

Although the PT approach is the simplest formulation to estimate the potential evaporation, LEs_pt is a useful potential evaporation index to estimate the soil evaporation. The PT approach represents the lower limit of potential evaporation because this method does not consider the drying power of the air. As a result, the sensitivity of LEs to the error of LEs_pt is the smallest. In addition, the parameterization that used LEs_pt to estimate LEs could be as sound as that with LEs_pm, especially when SDI3 was used because the surface dryness indices in this study include the effect of the drying power of the air.

Table 11 shows the relative differences in the RMSEs of LEs from the parameterizations that incorporated the LST in the surface dryness indices and those that did not. For example, the RMSEs of LEs = Fun(LEs_pm, SDI1) were 38.9% and 49.5% smaller than those of LEs = Fun(LEs_pm, SDI3) at the Daxing site and Tongyu site.
respectively. This result indicates that incorporating the soil temperature in the surface dryness indices had improved the soil evaporation estimation. However, the parameterizations that used SDI 3 or SDI 4 still performed quite well (Tables 9 and 10). In addition, such formulations that used the atmospheric humidity could be used with a canopy conductance model to estimate the total ET when LST data were not available or when the LST was not considered in the surface energy balance.

4.4. Evaluating the soil evaporation parameterizations that were based on the soil surface resistance and near-surface soil moisture

Diagnostic and process-based ET models usually use the concept of soil surface resistance ($r_{ss}$) to consider the degree of unsaturation of the soil water. LE$_s$ is estimated by the mass transfer equation and $r_{ss}$ is simulated by an exponential function of the soil moisture (Sellers et al., 1992). In this paper, $r_{ss}$ includes both the effects of the unsaturation of the soil water on the surface water vapor pressure $e_{s}(T_s)$ and the resistance of the soil surface to water vapor:

$$LE_s = \frac{\rho c_p}{\gamma} \frac{e_s(T_s) - e_a}{r_{ss} + r_s + r_a}$$  \hspace{1cm} (28)

$$\ln(r_{ss}) = a_0 - a_1 \cdot sm$$  \hspace{1cm} (29)

where $sm = \frac{swc}{swc_{sat}}$, $swc$ and $swc_{sat}$ are the actual and saturated soil water content, respectively.

We fit the curve of $\ln(r_{ss})$ to $sm$ and then evaluated the parameterization of $LE_s = Fun(r_{ss}, sm)$. Fig. 9 shows that the scatter points were divided into two categories approximately by the line $sm = 0.31$ for the Daxing site. The time when $sm$ was smaller than 0.31 at the Daxing site mainly lay in two periods, i.e., DOY 1–58 and DOY 286–365. A similar phenomenon was found at the Tongyu site when all the LST data ($qc = 0$ and $qc > 0$) were used (not shown in Fig. 9). However, the data points when $sm$ was small were basically ruled out because the LST at such timings was not qualified at the Tongyu site (see Figs. 3 and 4). In general, the timings of the points when $sm$ was small at both sites mainly lay in winter and spring, when soil moisture would experience freezing and thawing cycles because of the cold weather. The relationships between the soil surface resistance and soil moisture would therefore be different under different weather conditions. Thus, we fit the curve into separate groups at the Daxing site. The parameters and statistical results at both sites are shown in Table 12 and Fig. 9.

Fig. 9. Results for the case of $\ln(r_{ss}) = Fun(sm)$. a and b show the scatter-plots and fitting curves of the dryness index $swc/swc_{sat}$ and $\ln(r_{ss})$ for the Daxing and Tongyu sites, respectively. d and e show the scatter-plots of the reference LE$_s$ and the LE$_s$ that was predicted by the parameterizations of $LE_s = Fun(r_{ss}, sm)$ for the Daxing and Tongyu sites, respectively.

Table 11

|                | Relative differences in LE, RMSEs (%) |
|----------------|--------------------------------------|
|                | PT SDI 1 vs. SDI 3 SDI 2 vs. SDI 4 PM SDI 1 vs. SDI 3 SDI 2 vs. SDI 4 |
| Daxing         | -5.1 -18.5 -38.9 -21.6               |
| Tongyu         | -38.6 -26.2 -49.5 -23.0               |

Table 12

|                | $a_0$ | $a_1$ | RMSE (W/m$^2$) | BIAS (W/m$^2$) |
|----------------|-------|-------|----------------|----------------|
| Daxing         | $\ln(r_{ss}) = Fun(sm)$ $sm < 0.31$ | 9.08 | 13.18 | 1.212 | 0.005 |
|                |       |       |                |                |
|                | $\ln(r_{ss}) = Fun(sm)$ $0.31 < sm < 1$ | 9.48 | 6.00 | 1.551 | 0.030 |
| Tongyu         | $\ln(r_{ss}) = Fun(sm)$ | 8.04 | 1.69 | 1.153 | -0.02 |

|                | LE$_s$ parameterizations | RMSE (W/m$^2$) | BIAS (W/m$^2$) |
|----------------|-------------------------|----------------|----------------|
| Daxing         | $LE_s = Fun(r_{ss}, sm)$ | 123.3 | -2.3 |
| Tongyu         | $LE_s = Fun(r_{ss}, sm)$ | 63.8 | -3.8 |
The RMSEs of $\ln(r_{ss})$ in the three cases at both sites exceeded 1, with the maximum value being 1.551, which indicates that $r_{ss}$ and therefore the estimated $LE_s$ could be several times greater than the actual values. The RMSEs in $LE_s$ from the parameterization of $LE_s = \text{Fun}(r_{ss}, sm)$ were 203.7% greater and 199.5% greater than those from the parameterization of $LE_s = \text{Fun}(LE_{s, pm}, SDI_1)$ at the Daxing and Tongyu sites, respectively. At the same time, the RMSEs in $LE_s$ from the parameterization of $LE_s = \text{Fun}(r_{ss}, sm)$ were 110.4% greater and 54.9% greater than those from the parameterization of $LE_s = \text{Fun}(LE_{s, pt}, SDI_1)$ at the Daxing and Tongyu sites, respectively.

The parameterization of $LE_s = \text{Fun}(r_{ss}, sm)$ performed worse than those of $LE_s = \text{Fun}(LE_{s, pm}, SDI_1)$ and $LE_s = \text{Fun}(LE_{s, pt}, SDI_1)$, which indicates that accurate estimations were difficult to achieve even with the soil moisture measurements. One of the drawbacks of the parameterization of $LE_s = \text{Fun}(r_{ss}, sm)$ was that the soil moisture at 2 cm and 5 cm may have been unable to represent the surface moisture conditions because of the decoupling effect of the soil moisture at different depths (Capehart and Carlson, 1997) and because the soil surface energy balance is more strongly coupled to the surface's (several millimeters) moisture conditions than at deeper layers (2 cm and 5 cm) (Kustas et al., 2003).

5. Conclusions

In this study, we evaluated 11 parameterizations of soil evaporation at near-instantaneous scales at two semi-humid and semiarid crop sites, where detailed measurements of heat fluxes and atmospheric conditions were available. The relationships between the relative evaporation and SDI and their usefulness in estimating soil evaporation were studied.

Incorporating the soil temperature in the surface dryness indices improved the soil evaporation estimation. However, the parameterizations that used the LST-based potential evaporation index sometimes produced less accurate soil evaporation values. Therefore, the soil temperature should be used in the surface dryness indices instead of the potential evaporation indices when estimating soil evaporation.

The evaporation that was estimated by using the fitted curve of the relative evaporation, which used the air humidity, showed reasonable results for the potential evaporation indices that were calculated by both the PT approach and the Penman equation. The PT approach represented the lower limit of potential evaporation, and the sensitivity of $LE_s$ to the errors of $LE_{s, sm}$ was also the smallest. In addition, the parameterization of $LE_s = \text{Fun}(LE_{s, pm}, SDI_1)$ was as sound as that of $LE_s = \text{Fun}(LE_{s, pt}, SDI_1)$ because the dryness indices in this study included the effect of the drying power of the air. In contrast, the RMSEs in $LE_s$ from the parameterization of $LE_s = \text{Fun}(r_{ss}, sm)$ were much larger than those from the cases that used atmospheric humidity data at both sites.

The surface dryness indices that considered the surface energy balance ($SDI_1$, $SDI_3$) were generally better than those that only used the water vapor deficits ($SDI_2$, $SDI_4$) for the same potential evaporation index at the same site, however, the latter indices required less data and were easier to use. Our study indicated that the potential evaporation indices that were based on the Penman equation were the most useful and robust.

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