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Estimation of Soil Evaporation and Vegetation Transpiration Using Two Trapezoidal Models from MODIS Data

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Key Points:

- Soil evaporation and vegetation transpiration were estimated using two trapezoidal models.
- Land surface temperature of MODIS pixel was decomposed into soil and vegetation component temperatures.
- Analysis was made over three test sites.

Abstract

Soil evaporation (ET_s) and vegetation transpiration (ET_v) are essential in evaporative demand analyses and agricultural applications. This study estimated ET_s and ET_v using two trapezoidal models, i.e. the conventional trapezoidal model and the end-member-based soil and vegetation energy partitioning (ESVEP) model, at three AmeriFlux tower sites. First, the land surface temperature (LST) of a Moderate Resolution Imaging Spectroradiometer (MODIS) pixel was decomposed into soil and vegetation temperatures (T_s and T_v , respectively) which involve important information related to ET_s and ET_v and were compared with corresponding temperatures from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). Then ET_s and ET_v were parameterized, and the total evapotranspiration (ET) was validated with the eddy covariance (EC) system measurements after energy imbalance corrections via the residual energy (RE) and Bowen ratio (BR) methods. The results showed that the ESVEP model partitioned T_s , with a root mean square error (RMSE) of 1.56-2.70 K (4.98-10.16 %), and T_v , with an RMSE of 2.54-2.80 K (9.73-11.11 %); indicating a higher accuracy than that from the conventional trapezoidal model, where the RMSE was 2.26-3.64 K (7.31-13.40 %) for T_s separation and 2.82-4.62 K (9.80-15.49 %) for T_v separation. For the ET estimation, the ESVEP model still performed better. The estimation RMSE was 49.8-58.4 W/m² (22.8-27.2 %) for the ESVEP model and 72.0-89.5 W/m² (29.8-41.1 %) for the conventional trapezoidal model, compared to the RE corrected measurements; the RMSE was 42.6-53.3 W/m² (24.4-28.1 %) for the ESVEP model and 57.5-78.1 W/m² (32.3-37.9 %) for the conventional trapezoidal model, compared to the BR corrected measurements.

1 Introduction

Evapotranspiration (ET , soil evaporation + vegetation transpiration) is a key component in the water cycle and energy exchange between the land surface and atmosphere, and it affects the availability of water and partition of turbulent energy fluxes on Earth's surface (Anderson et al., 2007; Li et al., 2009; Wang & Dickinson, 2012; Long et al., 2012; Schlesinger & Jasechko, 2014). Compared to the total ET , soil evaporation (ET_s) may have more significant effects on crop/vegetation water use by decreasing the air vapor pressure deficit and reducing the overall evaporative demand, and vegetation transpiration (ET_v) is more critical in agricultural applications for better allocating water resources and improving water use efficiency (Crow et al., 2008; Song et al., 2015; Tang & Li 2017; Good et al., 2017). Remote sensing-based models play a dominant role in ET research and global implications (Tang et al., 2015a; Anderson et al., 2017; Zhang et al., 2017; Fisher et al., 2017), and the spatially distributed land surface temperature (LST) estimated from thermal infrared remote sensing data is widely used in the study of ET (Wang et al., 2006; Anderson et al., 2012).

LST /fraction vegetation cover (FVC) feature model is one of widely used ET estimation models, which is based on the interpretation of the contextual relationship between remotely sensed LST and FVC (Jiang & Islam, 2003; Carlson, 2007; Zhang et al., 2016). At the first development of this method, if there exist a sufficient number of pixels representing a broad range of soil wetness and fractional vegetation cover in an image, and the outliers (e.g., clouds and sloped terrains) are removed, the envelope of these pixels could constitute a physically meaningful triangle or trapezoid. The vertices in the triangle or trapezoid are called dry or wet end-members with extreme temperatures which are related to extreme ET_s or ET_v .

To separate ET_s and ET_v , two-source LST/FVC models have been put forward and developed. Nishida et al. (2003) proposed a two-source LST/FVC model in which the complementary relationship of the actual and potential ET with a canopy conductance model was used to estimate ET_v , and the triangle space was used to estimate ET_s . By quasi-linear interpolation in the LST/FVC space, Zhang et al. (2008) developed a two-source energy separation algorithm to estimate the fraction of ET_s and ET_v . Later, for avoiding the complex calculation of canopy conductance in the study of Nishida et al. (2003), Long and Singh (2012) developed a two-source LST/FVC trapezoidal model. For further enhancing of the parameterizations of ET_s and ET_v , Yang et al. (2015) combined the conceptual trapezoidal space and the concept of the crop water stress index into the two-source LST/FVC model. Due to the fact that it is very subjective and prone to error and it requires the study areas to contain full vegetation and bare soil with extreme wet and dry conditions, two-source LST/FVC model usually theoretically calculates the boundaries from an energy balance equation of land surface and does not rely on the study area generating the LST/FVC spaces, allowing the determination of dry and wet end-members independently from the study area (Moran et al., 1994; Long and Singh, 2012, Sun et al, 2017).

With respect to these widely applied conventional trapezoidal models, there is a conventional interpretation that has been used in estimating ET_s and ET_v . These trapezoidal models assume that the T_v and T_s vary simultaneously with the variation in soil moisture availability (Wang et al, 2010; Long & Singh, 2012; Yang et al, 2015), and the ET_s and ET_v are estimated based on the assumption that they vary synchronously with the variation of T_s and T_v in the trapezoid, respectively (Sun, 2016). The decomposition method used to derive ET_s and ET_v in these conventional models would result that the soil evaporation fraction is approximately equal to the vegetation transpiration fraction (Tang & Li, 2017). However, it has been reported that the ET_s process primarily exploits water in the thin upper soil layer, whereas the ET_v process usually uses water from the deep root zone layer. It means that there should exist a difference in the speed of the variation between ET_v and ET_s because vegetation can absorb deep layer soil moisture to maintain transpiration, while the surface soil dries out. Therefore, the response of the soil water content to ET_s should be different from that to ET_v (Carlson et al., 2013), and the assumption that ET_s and ET_v vary simultaneously in conventional trapezoidal models may be not always appropriate (Sun 2016; Tang & Li, 2015b, 2017).

To consider different responses of the soil water content in the upper surface layer to ET_s and in the deeper root zone layer to ET_v , Tang & Li (2015b, 2017) developed another trapezoidal model, an end-member-based soil and vegetation energy partitioning model (i.e., the ESVEP model). The ESVEP model separates ET_s and ET_v based on two-phase ET dynamics with the variations in soil moisture in different layers. First, with the decrease in the soil water content in the upper soil layer from sufficiency to zero, ET_s varies from the maximum to zero, but ET_v keeps potential due to the soil water content in the deep root zone remaining sufficient. Second, when the soil moisture availability in the root zone gradually decreases from sufficiency to the threshold value for the wilting point, ET_v varies from the potential value to zero due to the fact that vegetation is water-stressed, and ET_s remains at zero because the soil water content in the upper soil layer remains at zero. With the similar interpolation process of ET estimation, Sun (2016) also indicated that T_v should vary after T_s because vegetation can absorb soil moisture in deep layer to maintain transpiration, and a two-stage trapezoid is suggested to estimate soil evaporation fraction and vegetation transpiration fraction.

It is clear that the conventional trapezoidal model and the ESVEP model developed by Tang & Li (2015b, 2017) have different interpretation processes in terms of separating ET_s and ET_v . Two interpretation processes related to different trapezoidal models may result in totally different results and it is necessary to evaluate the differences from them. In addition, how the temperatures of the dry and wet end-members are determined also differs in the conventional trapezoidal model and the ESVEP model. The surface temperatures of the dry and wet end-members in the conventional trapezoidal models are usually determined either semi-empirically from the scatterplot of the LST/FVC model (Tang et al., 2010) or theoretically using the surface energy balance theory (Long & Singh, 2012; Sun et al., 2016). Specially, three main theoretical methods for determining dry and wet edges of the LST/FVC spaces were discussed in Sun et al (2017). Some models also used the near-surface air temperature as the temperature of the wet end-members (Long & Singh, 2012). Whereas in the ESVEP model, the net radiation was first diverged into soil and vegetation components by considering the transmission of direct and diffuse shortwave radiation separately from the transmission of longwave radiation through the canopy, then, the temperature of four end-members were calculated with the separated soil and vegetation net radiations.

Therefore, the objective of this study is to estimate ET_s and ET_v using the ESVEP model and the conventional trapezoidal model at three AmeriFlux tower sites with different climate types in the USA, to investigate a two-source model with better performance based on the same remote sensing data inputs. To focus on two different interpretation processes related to the two trapezoidal models and simplify the analysis, only the different processes for separating ET_s and ET_v are investigated, and the end-members are determined by the same method that the ESVEP model used. For the conventional trapezoidal model, the near-surface air temperature is also regarded as the temperature of the wet end-members, which is discussed as another situation of this model. The present study is organized as follows; Section 2 presents the methods of this study and Section 3 gives the introduction of test sites and materials. The results and discussion are shown in Section 4, and the conclusions are provided in Section 5.

2 Materials and Methods

2.1 The conventional two-source trapezoidal model

The conventional two-source trapezoidal model is based on the interpretation of the LST/FVC space. Figure 1(a) illustrates the LST/FVC space and concepts of the isopleths for soil surface moisture. Theoretically, there are four critical points (i.e., end-members) within the trapezoidal framework: A, B, C, and D, or trapezoid ABCD. Point A ($FVC=0$, $LST=T_{s,d}$) represents the driest bare surface with the highest soil temperature ($T_{s,d}$); point B ($FVC=0$, $LST=T_{s,w}$) represents the wettest bare surface with the lowest soil temperature ($T_{s,w}$); point C ($FVC=1$, $LST=T_{v,w}$) indicates the fully vegetated surface with the lowest vegetation temperature ($T_{v,w}$); point D ($FVC=1$, $LST=T_{v,d}$) indicates the fully vegetated surface with the highest vegetation temperature ($T_{v,d}$). The line AD is the so called dry edge, which represents surfaces with the largest amount of water stress for the full range of the FVC , and the ET of these surfaces is equal to zero. Analogously, the line BC is the wet edge, which represents wet surfaces at equilibrium ET rates ($ET_{s,w}$ and $ET_{v,w}$) without water stress. The dry and wet edges constitute the boundary conditions of the trapezoidal model (Allen et al., 2007).

The conventional trapezoidal model for ET estimation virtually is an interpolating scheme between the potential ET at the wet edge and the minimum ET at the dry edge. To prepare for the interpolation, the corresponding temperatures of the dry (T_{s_dry}) and wet (T_{s_wet}) edges of a give point P (LST , FVC) are calculated first:

$$T_{s_dry} = T_{s,d} + FVC * (T_{v,d} - T_{s,d}) \quad (1a)$$

$$T_{s_wet} = T_{s,w} + FVC * (T_{v,w} - T_{s,w}) \quad (1b)$$

The composite LST is decomposed to the soil and vegetation component temperatures (T_s and T_v , respectively) by interpolating the temperatures from four critical points:

$$T_s = T_{s,w} + (LST - T_{s_wet}) / (T_{s_dry} - T_{s_wet}) * (T_{s,d} - T_{s,w}) \quad (2a)$$

$$T_v = T_{v,w} + (LST - T_{s_wet}) / (T_{s_dry} - T_{s_wet}) * (T_{v,d} - T_{v,w}) \quad (2b)$$

Then, ET_s and ET_v are parameterized as follows:

$$ET_s = ((T_{s,d} - LST) / (T_{s,d} - T_{s,w})) * ET_{s,w} \quad (3a)$$

$$ET_v = ((T_{v,d} - LST) / (T_{v,d} - T_{v,w})) * ET_{v,w} \quad (3b)$$

$ET_{s,w}$ and $ET_{v,w}$ represent the equilibrium ET rates for soil and vegetation without water stress, respectively.

The total ET is the sum of ET_s and ET_v :

$$ET = ((T_{s,d} - LST) / (T_{s,d} - T_{s,w})) * ET_{s,w} + ((T_{v,d} - LST) / (T_{v,d} - T_{v,w})) * ET_{v,w} \quad (4)$$

For the conventional trapezoidal model, the near-surface air temperature is sometimes treated as an alternative for the temperature of the wet edge, which is analyzed as another situation for this model in this study; namely,

$$ET_{Ta} = ((T_{s,d} - LST) / (T_{s,d} - T_a)) * ET_{s,w} + ((T_{v,d} - LST) / (T_{v,d} - T_a)) * ET_{v,w} \quad (5)$$

where ET_{Ta} represents the total ET , where the near-surface air temperature is treated as the temperature of the wet edge.

Figure 1. Schematic diagrams of (a) the conventional two-source trapezoidal model based on the LST/FVC space and (b) the ESVEP model

2.2 The end-member-based soil and vegetation energy partitioning model (ESVEP model)

The ESVEP model can be regarded as another conventional two-source LST/FVC trapezoidal model that is composed of two triangles (triangle 1 and triangle 2), as shown in Figure 1 (b). However, in the ESVEP model (Tang & Li, 2015b; 2017), the ET_s and ET_v vary differently rather than simultaneously. The two triangles in this model are related to the two stages of ET estimation, where stage 1 corresponds to the lower triangle and stage 2 corresponds to the upper triangle. In stage 1, for a given FVC , with the decrease of the soil water content in the upper soil layer from sufficiency in the wet edge to zero in dry edge I, the ET_s varies from a maximum to zero. Dry edge I represents the case of dry soil in the upper layer, with sufficient water content in the root zone

and ET_v keeps potential value. In stage 2, with the soil moisture availability in the root zone gradually decreasing from 1 to the threshold value of the wilting point, the ET_v varies from the potential value to zero. Dry edge II represents the same case as the dry edge in the conventional trapezoidal model, including surfaces with the largest water stress.

In theory, a given pixel can be located in either triangle 1 (e.g., Q1 (LST, FVC)) or triangle 2 (e.g., Q2 (LST, FVC)). A critical surface temperature (T^*) is used to identify which triangle the point is in (Tang & Li, 2017):

$$T^* = [(T_{s,w}^4 (1 - FVC) + FVC * T_{v,w}^4)]^{1/4} \quad (6)$$

If the given pixel is found in triangle 1 ($LST \leq T^*$), the T_s and T_v can be estimated as:

$$T_v = T_{v,w} \quad (7a)$$

$$T_s = [(LST_R^4 - FVC * T_v^4) / (1 - FVC)]^{1/4} \quad (7b)$$

In this case, the ET_v is close to the potential value and the ET_s varies from a maximum to zero. The ET_s and ET_v can be derived as follows:

$$ET_s = \frac{T_{s,d} - T_s}{T_{s,d} - T_{s,w}} ET_{s,w} \quad (8a)$$

$$ET_v = ET_{v,w} \quad (8b)$$

Similarly, if the pixel is located in triangle 2 ($LST > T^*$), the T_s and T_v can be separated as follows:

$$T_s = T_{s,d} \quad (9a)$$

$$T_v = \{[LST^4 - (1 - FVC)T_s^4] / FVC\}^{1/4} \quad (9b)$$

In this situation, the ET_s should be close to zero and the ET_v varies from the potential value to zero. The ET_s and ET_v can be calculated as

$$ET_s = 0 \quad (10a)$$

$$ET_v = \frac{T_{v,d} - T_v}{T_{v,d} - T_{v,w}} ET_{v,w} \quad (10b)$$

where $T_{s,d}$, $T_{s,w}$, $T_{v,d}$ and $T_{v,w}$ represent the temperatures of the four end-members, which have same meanings as those in the conventional trapezoidal model. $ET_{s,w}$ and $ET_{v,w}$ represent the same variables as those in the conventional trapezoidal model, which are the maximum ET values for soil and vegetation during a situation without water stress, respectively.

2.3 Divergence of surface net radiation and soil heat flux

As stated above, to focus on different interpretation processes in the two trapezoidal models and simplify the analysis, the temperatures of the four end-members are calculated using the same method as that in the ESVEP model, in which the net radiations of the soil and vegetation components ($R_{n,s}$ and $R_{n,v}$, respectively) are separated at first. The divergence of surface net radiation was conducted with an algorithm which is applied by Kustas & Norman (2000) to replace the exponential extinction of net radiation (i.e., Beer's Law) that is originally used in the two-source N95 model. In detail, the $R_{n,s}$ and $R_{n,v}$ are separated by considering the transmission of direct

and diffuse shortwave radiation separately from the transmission of longwave radiation through the canopy (Norman & Kustas, 1998; Tang & Li, 2017):

$$R_{n,v} = (1 - \tau_{sw})(1 - \alpha_v)R_g + [1 - \exp(-k_L LAI)](L_{sky} + L_s - 2L_v) \quad (11a)$$

$$R_{n,s} = \tau_{sw}(1 - \alpha_s)R_g + \exp(-k_L LAI)L_{sky} + [1 - \exp(-k_L LAI)]L_v - L_s \quad (11b)$$

where τ_{sw} represents the canopy transmittance for shortwave radiation; α_v and α_s represent soil and vegetation albedo, respectively; R_g represents solar radiation (W/m^2); L_{sky} , L_v , and L_s represent longwave emissions from the sky, vegetation, and soil, respectively; and k_L represents the extinction coefficient, which is approximately 0.95.

The soil heat flux (G , W/m^2) is estimated following the work of Tang and Li (2017):

$$G = \Gamma * R_{n,s} \quad (12)$$

where Γ represents the fraction of the soil heat flux to soil net radiation and is equal to 0.296 in this study.

2.4 Estimation of the temperatures of the end-members

Then the temperatures of the four end-members in the two trapezoidal models are calculated using an adapted method that proposed by Moran et al. (1994) and applied in the study of Tang and Li (2017), according to the surface energy balance theory and Penman-Monteith equation (Moran et al., 1994):

$$T_{sd} = \frac{r_{as}(R_{n,s} - G_s)}{\rho C_p} + T_a \quad (13a)$$

$$T_{vd} = \frac{r_{av}R_{n,v}}{\rho C_p} \frac{\gamma(1 + r_{vd}/r_{av})}{\Delta + \gamma(1 + r_{vd}/r_{av})} - \frac{VPD}{\Delta + \gamma(1 + r_{vd}/r_{av})} + T_a \quad (13b)$$

$$T_{sw} = \frac{r_{as}(R_{n,s} - G_s)}{\rho C_p} \frac{\gamma}{\Delta + \gamma} - \frac{VPD}{\Delta + \gamma} + T_a \quad (13c)$$

$$T_{vw} = \frac{r_{av}R_{n,v}}{\rho C_p} \frac{\gamma(1 + r_{vw}/r_{av})}{\Delta + \gamma(1 + r_{vw}/r_{av})} - \frac{VPD}{\Delta + \gamma(1 + r_{vw}/r_{av})} + T_a \quad (13d)$$

where T_a represents air temperature (K); ρ is the density of air (kg/m^3); C_p represents the volumetric heat capacity of air ($\text{J}/(^{\circ}\text{Cm}^3)$); γ represents the psychrometric constant ($\text{kPa}/^{\circ}\text{C}$); Δ represents the slope of saturated vapor pressure versus air temperature ($\text{kPa}/^{\circ}\text{C}$); VPD represents the vapor pressure deficit of air (kPa); r_{vd} represents the canopy resistance of nearly closed stomata (set as 2,000 s/m), and r_{vw} represents the canopy resistance under well-watered condition and is estimated to be 100/LAI (Liang et al., 1994, Allen et al., 1998). r_a represents the aerodynamic resistance and can be calculated as

$$r_{av} \text{ (or } r_{as}) = \frac{[\ln(\frac{z_u - d}{z_{om}}) - \psi_m][\ln(\frac{z_t - d}{z_{oh}}) - \psi_h]}{k^2 u} \quad (14)$$

where z_u and z_t represent the heights of the wind speed and T_a measurements (m), respectively; k represents the von Karman's constant; u represents the wind speed (m); Ψ_m and Ψ_h represent the stability correction functions for momentum and heat transfer, respectively; d represents the zero plane displacement height (m); z_{oh} represents the roughness height for the surface heat transfer (m); and z_{om} represents the surface momentum roughness height (m) (Norman et al, 1995).

After the calculation of the related parameters, the potential soil evaporation ($ET_{s,w}$) and vegetation transpiration ($ET_{v,w}$) mentioned in the two trapezoidal models are estimated using the following equations:

$$ET_{s,w} = \frac{\Delta \times (R_{n,s} - G_s) + \rho C_p VPD / r_{as}}{\Delta + \gamma} \quad (15a)$$

$$ET_{v,w} = \frac{\Delta \times R_{n,v} + \rho C_p VPD / r_{av}}{\Delta + \gamma(1 + r_{vw} / r_{av})} \quad (15b)$$

3 Test sites and datasets

3.1 Test sites and flux data

This study is conducted at three AmeriFlux tower sites named US-Bol (in Illinois state), US-ARM (in Oklahoma state), and US-Aud (in Arizona state). These three sites are evenly distributed from east to west across the contiguous USA, as shown in Figure 2. The vegetation types around these sites are crops and grass, and the climates are classified as humid continental (warm summers), mid-latitude desert, and humid subtropical, respectively, which are the three main climate types in the USA. The mean annual precipitation at these sites ranges from 368 mm/year to 727 mm/year, and the mean annual temperature ranges from 11.55 °C to 16.08 °C. The details on these flux sites are listed in Table 1.

Figure 2. The location of the test sites (the map is from ESRI)

The AmeriFlux tower datasets are available every 30 min, and the datasets for the measured meteorological data and surface flux data at these three test sites are downloaded from the AmeriFlux File Transfer Protocol servers (<http://ameriflux.lbl.gov/>). The datasets have been standardized and passed quality assurance and quality control (QA/QC) checks (Di et al., 2015). The meteorological variables used in this study include wind speed, relative humidity, air temperature, and atmospheric pressure. The flux data include latent heat flux (LE) and sensible heat flux (H), which are measured regularly by an eddy covariance (EC) system. A series of data quality control steps have been conducted to obtain reliable EC-measured LE and H (remove the data larger than 700 W/m² or less than -100W/m²) (Tang et al., 2013; Di et al., 2015). Downward/upward shortwave and longwave radiations and the soil heat flux (G) are also collected.

The EC-measured surface energy components (LE and H) are subject to errors in the energy budget closure (i.e., $R_n - G > LE + H$) (Stoy et al., 2013) which are mainly from the measurement error, the length of the sampling intervals, the dispersive fluxes not being sampled by the EC system. For effective validation of the results, the residual energy (RE) and Bowen ratio (BR) correction methods have been widely applied in a number of papers to validate the LE and H from diverse ET models (Anderson et al., 2008; Sánchez et al., 2008). In the RE correction method, the imbalanced energy is completely included in the LE (Twine et al., 2000). In the BR method, the

surface available energy is repartitioned into H and LE by conserving the original Bowen ratio measured by the EC system. The two correction methods are also used in this study to correct the energy imbalance in the surface energy measurements, and the corrected LE corresponding to the satellite overpass time is used to validate the estimated ET from the two trapezoidal models.

Table 1. The information of test sites on location, vegetation, and climate

Site name	State	Elevation (m)	Latitude (°N)	Longitude (°)	Vegetation	Climate	Mean annual precipitation (mm)	Mean annual temperature (°C)
US-Bo1	Illinois	219	40.0062	-88.2904	Crop	Humid continental	724	11.55
US-ARM	Oklahoma	129	36.6058	-97.4884	Crop	Mediterranean	504	16.08
US-Aud	Arizona	1469	31.5907	-110.5092	Grass	Mid-latitude desert	368	15.82

3.2 MODIS data

The MODIS products used in this study include the calibrated radiance product (MOD021KM), LST and emissivity product (MOD11_L2), surface reflectance product (MOD09GA), geolocation product (MOD03), leaf area index product (MOD15A2) and cloud mask product (MOD35_L2). The MOD021KM product consists of calibrated and geolocated radiances and reflectance at the top of the atmosphere (TOA) in 36 bands, to be used for the estimation of the net radiation. The level 2 MOD11_L2 product is generated daily using the generalized split window algorithm (Wan & Dozier, 1996), with a 1 km spatial resolution, to provide the surface temperature. The MOD03 product outputs a dataset that mainly includes geodetic coordinates (latitude and longitude), solar zenith and azimuth angles, satellite zenith and azimuth angles, and ground elevation in each 1 km pixel for the geo-calibration of the MOD11_L2 product. The surface spectral reflectance for bands 1-7, with a spatial resolution of 500 m extracted from MOD09GA, is first resampled to 1km with a bilinear resampling method, which is then used to estimate the albedo. The leaf area index is extracted from the MOD15A2 product to estimate the canopy resistance and separate the soil and vegetation net radiations. The MOD35 product is used to guarantee the clear-sky selections in which only the days with highest quality (the quality assurance flag is “11”) are selected.

3.3 ASTER data

The ASTER data used in this study include the surface kinetic temperature (AST_08) and ASTER surface reflectance VNIR and SWIR (AST_07) data products. AST_08 is a product generated using the five thermal infrared (TIR) bands between the 8 and 12 μm spectral ranges, and this product contains surface temperatures at a 90 m spatial resolution for land areas only. The AST_07 data product contains measures of reflectance in both the visible and near infrared (VNIR) and shortwave infrared (SWIR) bands. The data from AST_07 are resampled to 90 m from 15 m with a bilinear resampling method in this study.

This study compares T_s and T_v separated from the LST of a MODIS pixel with corresponding temperatures from ASTER. In detail, A MODIS mixed temperature pixel, with a 1 km spatial resolution, corresponds to 11*11 pixels from AST_08. These corresponding AST_08 pixels are soil or vegetation pixels, and the average temperatures of each category are used to validate the T_s or T_v separated from a MODIS temperature pixel. The identification of the soil or vegetation category of an AST_08 pixel is conducted according to the FVC of the pixel. Specifically, when

the *FVC* is larger than 0.8, the related pixel is identified as vegetation; when the *FVC* is smaller than 0.2, the related pixel is identified as soil (Song et al., 2015). The *FVC* is calculated from normalized difference vegetation index (*NDVI*) values, which are estimated from the surface reflectance with AST_07 bands 2 and 3. The value of the *FVC* is calculated from the following equation (Gebremichael et al., 2009):

$$FVC = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (16)$$

where $NDVI_{min}$ represents the minimum value of the *NDVI* and $NDVI_{max}$ represents the maximum value of the *NDVI*.

The flowchart for the estimation and validation of T_s , T_v , ET_s and ET_v with meteorological data, MODIS data and ASTER data are displayed in Figure 3. And the spatial and temporal resolutions of different ASTER and MODIS data products used in this study are shown in Table 2.

Figure 3. Flowchart of the estimation and validation of soil temperature (T_s), vegetation temperature (T_v), soil evaporation (ET_s) and vegetation transpiration (ET_v)

Table 2. The spatial and temporal resolutions of different ASTER and MODIS data products used in this study

Sensor	Product	Description	Spatial resolution	Temporal resolution
			n	
MODIS	MOD021KM	Calibrated radiance product	1000 m	Daily
	MOD11_L2	LST and emissivity product	1000 m	Daily
	MOD03	Geolocation product	1000 m	Daily
	MOD35_L2	Cloud mask product	1000 m	Daily
	MOD09GA	Surface reflectance product	500 m	Daily
	MOD15A2	Leaf area index product	500 m	8-day
ASTER	AST_07	Surface reflectance product	30m	Daily (but may not cover the study area)
	AST_08	Surface kinetic temperature product	90m	Daily (but may not cover the study area)

Although the ASTER standard products for *LST* and emissivity have been widely used, significant uncertainty in the temperature and emissivity algorithm often occur (Jiménez-Muñoz et al., 2006), which could introduce relatively large errors in *LST* estimation. Therefore, the data are removed when a large difference (5 K) between the MODIS mixed pixel *LST* and the corresponding ASTER averaged *LST* occurs in this paper. Finally, by combining the gaps in the MODIS data, ASTER data, meteorological data and ET data, a total number of 26 days, 15 days and 17 days at the three test sites are selected, as shown in Table 3.

Table 3. Selected days at the three test flux sites

Site	Selected days
US-Bo1 N=26	2001238; 2001270; 2001302; 2001318; 2002001; 2002033; 2003068; 2003285; 2003292; 2003324; 2003333; 2004071; 2004208; 2004263; 2004304; 2005018; 2005105; 2005114; 2005210; 2005322; 2006069; 2006076; 2006124; 2006197; 2006204; 2006213
US-ARM N=15	2010058; 2010131; 2010202; 2010234; 2011004; 2011013; 2011044; 2011070; 2011124; 2011132; 2011173; 2011214; 2011221; 2011262; 2011294
US-Aud N=17	2007051; 2007074; 2007083; 2007090; 2007099; 2007147; 2007282; 2008109; 2009015; 2009031; 2009088; 2009191; 2009271; 2009319; 2010098; 2010107; 2010322

4 Results and Discussion

4.1 Validation of net radiation with measured data

In these two trapezoidal models, the $R_{n,s}$ and $R_{n,v}$ determine the surface temperature estimation of the four end-members and influence the accuracy in the estimations of ET_s and ET_v . Figure 4 shows the comparison of estimated net radiation (R_n) and the corresponding ground-based measurements at these three flux sites. The R_n has a wide range of variations between 269.8 W/m² and 697.5 W/m² for the model estimates and between 254.3 W/m² and 698.1 W/m² for the ground-based measurements at the three flux sites. It is clear that, overall, the model-estimated R_n agrees well with the ground-based measurement, with a small bias of -10.5 W/m² and an RMSE of 37.7 W/m² at the US_Bo1 site, a bias of -3.4 W/m² and an RMSE of 42.4 W/m² at the US_ARM site, and a bias of -8.7 W/m² and an RMSE of 39.1 W/m² at the US_Aud site, respectively. This good performance provides the reliability of determining the dry/wet end-members and, subsequently, the retrieval of ET_s and ET_v .

Figure 4. Comparison of estimated R_n and ground-based measurements at three flux sites

4.2 Estimations of the surface temperatures of the end-members

The accurate estimation of the surface temperatures of the four end-members is significant for the separation of the T_s and T_v and the subsequent parameterization of ET_s and ET_v . Figure 5 shows the surface temperatures of four end-members estimated using Eqs.(13a-13d), together with the MODIS LST and near-surface air temperature measurements at three flux sites. In the figure, Ts_{ds} and Ts_{dv} represent the surface temperature estimated in dry soil and dry vegetation, respectively; similarly, Ts_{ws} and Ts_{wv} represent the surface temperature estimated in wet soil and wet vegetation, respectively, and Ts_{rs} and Ta represent the MODIS LST and near-surface air temperature measurements, respectively.

Overall, the temporal variations in Ts_{ds} , Ts_{dv} , Ts_{ws} , Ts_{wv} and the MODIS LST have similar trends to that in Ta , and these variations vary considerably over the course of the season due to seasonally different radiations and atmospheric conditions. At all three flux sites, the surface temperature estimated in the dry soil is the highest, followed by the surface temperature of the dry vegetation, as all available energies during these two conditions are partitioned into sensible heat flux for heating the near-surface air (Tang & Li, 2017). The surface temperature estimated in the wet soil is slightly higher or lower than that in the wet vegetation. The MODIS LST on different days fell between the maximum and minimum temperatures of the four end-members. The near-

surface air temperature is larger than the surface temperature estimated in the wet end-members on most days, especially at the US_ARM site and US_Aud site. At the US_Bo1 sites, they are similar on most days. The differences may result from the different vegetation types at different flux sites which, in turn, lead to variations in the photosynthesis, water use and fraction of incoming solar radiation and the interaction between air and surfaces.

Figure 5. Temporal variations in the surface temperature estimated in the dry soil (T_{s_ds}), dry vegetation (T_{s_dv}), wet soil (T_{s_ws}), wet vegetation (T_{s_wv}), MODIS LST (T_{s_rs}) and near-surface air temperature (T_a) at the (a)US_Bo1, (b) US_ARM and (c) US_Aud sites.

4.3 Comparison of component temperatures from two trapezoidal models and those from ASTER

The T_s and T_v are compared with the corresponding temperatures from ASTER in this study. To validate the accuracy of the LST from the ASTER data (AST_08), temperature calculated from the upwelling longwave radiation measured at the three flux towers is used as true temperature value, because that the site temperature measurement has limited spatial representation (Li et al., 2013). A comparison between the LST from ASTER and the computed LST from the radiation measurements is displayed in Figure 6. The results indicate that the ASTER LST is in acceptable agreement with that from the ground observations, with biases of 0.81 K, 1.38 K and 0.58 K and RMSEs of 2.33 K, 2.14 K and 2.16 K at the US_Bo1 site, US_ARM site and US_Aud site, respectively. The accuracy related to the ASTER LST demonstrated at these three sites is similar to that (2.25 K) from a previous study (Song et al., 2015). The differences between the ASTER LST and that from the measurements are mainly from uncertainties or errors in the sensor calibration, assumed emissivity, and spatial heterogeneity. The comparable accuracy of the ASTER LST makes it possible and credible to validate the T_s and T_v separated from the two trapezoidal models.

Figure 6. Comparison of LST from ASTER and that computed from radiation measurements

The two-dimensional plots of the separated T_s and T_v and those from ASTER at three test sites are demonstrated in Figure 7. In the plots, T_s separations are shown in Figure 7 (a) (c) (e), and T_v separations are shown in Figure 7 (b) (d) (f). The statistical bias, RMSE and the relative RMSE (RMSE value presented as percentage of mean temperature value ($^{\circ}\text{C}$)) are displayed in Table 4.

Regarding to the T_s separations, the ESVEP model performs better than the conventional model. Specially, the biases related to the ESVEP model are 0.19 K, -0.10 K, and 0.42 K at the US_Bo1 site, US_ARM site and US_Aud site, respectively, and the RMSEs are 2.76 K (10.16 %), 2.04 K (7.46 %), and 1.56 K (4.98 %), respectively. When referring to the conventional trapezoidal model, the biases are -1.86 K, 0.29 K, and 0.61 K at the US_Bo1 site, US_ARM site and US_Aud site, respectively, and the RMSEs are 3.64 K (13.40 %), 2.37 K (8.66 %), and 2.29 K (7.31 %), respectively. For the T_v separations, the negative biases at all three sites revealed underestimations of the T_v from both two models. Specifically, the biases related to the ESVEP model are -0.83 K, -1.63 K, and -1.71 K and related to the conventional trapezoidal model are -0.91 K, -0.54 K, and -3.09 K, respectively. The ESVEP model performs similar with the conventional model at the US_Bo1 site, where the RMSE is 2.80 K (9.73 %) for the ESVEP model and is 2.82 K (9.80 %) for the conventional trapezoidal model. At other two sites, the ESVEP model performed better. At the US_ARM site, the RMSE for the ESVEP model is 2.54 K (10.17 %) and for the conventional trapezoidal model is 3.51 K (14.06 %). At the US_Aud site, the RMSE of the ESVEP model is

2.80 K (11.11 %) and the RMSE of the conventional trapezoidal model is 4.62 K (15.49 %). As for different sites which have different climates, the two trapezoidal models separate T_s with high accuracy at the US_Aud site which has mid-latitude desert climate, and separate T_v with high accuracy at the US_Bo1 site which has humid continental climate. This reason for this difference is that high humidity generates high FVC which leads to better T_v separation, vice versa. And the different T_s and T_v separations at the same site further reveals that the assumption that T_s and T_v vary simultaneously in the conventional trapezoidal model is not always appropriate.

Figure 7. Comparison of soil and vegetation temperatures from the two models and ASTER

Table 4. The statistical items from the comparison of soil and vegetation temperatures from the two models and ASTER

Site	Model	Ts			Tv		
		Bias(K)	RMSE (K)	RMSE (%)	Bias(K)	RMSE (K)	RMSE (%)
US_Bo1	ESVEP	0.19	2.76**	10.16	-0.83	2.80**	9.73
	Conventional model	-1.86	3.64**	13.40	-0.91	2.82**	9.80
	ESVEP	-0.10	2.04**	7.46	-1.63	2.54**	10.17
US_ARM	Conventional model	0.29	2.37**	8.66	-0.54	3.51**	14.06
	ESVEP	0.42	1.56**	4.98	-1.74	2.80**	11.11
US_Aud	Conventional model	0.61	2.29**	7.31	-3.09	4.62**	15.49

** means the result passed the significance test $\alpha=0.01$.

In total, the T_s and T_v are successfully separated using the two trapezoidal models, and the deviations are acceptable, which provide necessary preparation for the accurate estimation of ET_s and ET_v . Specifically, the ESVEP model performs better and is more stable than the conventional trapezoidal model in both the T_s and T_v separations. Recall that some similar performances of the two models may result from the fact that the shape of the LST/FVC space in the conventional trapezoidal model in this situation approximates a triangle shape, which corresponds with the first stage of ET in the ESVEP model. The better performance of the ESVEP model may result from considering the different responses of the soil water content to the ET_s and ET_v , which might be closer to reality.

4.4 ET estimations from the two trapezoidal models

With the determination of the available surface energy flux and calculation of the corresponding temperatures, ET_s and ET_v are parameterized by the two trapezoidal models. The total ET ($ET_s + ET_v$) from the two trapezoidal models is evaluated with the EC measurement corrected with the RE and BR methods, respectively. For the conventional trapezoidal model, another situation is also discussed, in which the near-surface air temperature is regarded as an alternative to the temperatures of the wet edges. Figure 8 depicts the scatterplots between the estimated ET and the EC measurement at these three sites, in which the ESVEP model, the conventional trapezoidal model and the model in another situation are represented by *ESVEP*, *conventional model*, and

conventional model_Ta, respectively. From the figure, estimates from the ESVEP model show closer agreement with the EC measurements than that of the conventional trapezoidal model and the estimated ET from the ESVEP model and measured values are distributed around the 1:1 line on most days, regardless of when the results are compared to the measurements corrected by the RE method or the BR method. Figure 9 shows the statistical biases and RMSEs. The statistical bias, RMSE and the relative RMSE (RMSE value presented as percentage of mean ET) are displayed in Table 5.

Figure 8. Validation of estimated ET from the two trapezoidal models with EC measurements corrected with the RE method (a) (c) (e) and the BR method (b) (d) (f) at the three test sites

Table 5. The RMSE and relative RMSE of ET estimation from the two trapezoidal models compared with EC measurements corrected by the RE and the BR method

Site	Model	Bias _RE (W/m ²)	RMSE_R E correction s (W/m ²)	Relative RMSE_RE corrections (%)	Bias _BR (W/m ²)	RMSE_B R correction s (W/m ²)	Relative RMSE_BR corrections (%)
US_Bo1	ESVEP	-6.8	49.8**	22.8	-19.4	51.7**	24.4
	Conventional model	35.4	89.5**	41.1	35.8	78.1**	36.8
	Conventional model_Ta	-22.3	75.1**	34.5	-37.9	84.9**	40.1
US_ARM	ESVEP	-15.6	58.4**	24.0	8.6	53.3**	24.3
	Conventional model	-13.1	72.5**	29.8	5.6	70.8**	32.3
	Conventional model_Ta	-61.0	82.0**	33.7	48.6	77.5**	45.4
US_Aud	ESVEP	12.7	50.6**	27.2	2.4	42.6**	28.1
	Conventional model	15.9	72.0**	38.7	-7.6	57.5**	37.9
	Conventional model_Ta	-26.1	69.0**	37.1	-32.1	56.2**	37.1

** means the result passed the significance test $\alpha=0.01$.

Figure 9. Statistical measures for the validation of ET from the two trapezoidal models, with EC measurements corrected by the RE (a) method and the BR (b) method at the three test sites

When the results are validated by the RE corrected measurements (Figure 9(a)), ET produced by the ESVEP model has an overall bias of -6.8 W/m² and an RMSE of 49.8 W/m² (22.8 %) at the US_Bo1 site, a bias of -15.6 W/m² and an RMSE of 58.4 W/m² (24.0 %) at the US_ARM site, and a bias of 12.7 W/m² and an RMSE of 50.6 W/m² (27.2 %) at the US_Aud site. For the conventional trapezoidal model, the estimation biases are 35.4 W/m², -13.1 W/m² and -15.9 W/m² at these three sites, with RMSEs of 89.5 W/m² (41.1 %), 72.5 W/m² (29.8 %) and 72.0 W/m² (98.7 %), respectively. In another situation of this model, the results have similar RMSEs; however, in this situation, ET is more seriously underestimated, with biases of -22.3 W/m², -61.0 W/m² and -26.1 W/m² and RMSEs of 75.1 W/m² (34.5 %), 82.0 W/m² (33.7 %) and 69.0 W/m² (37.1 %) at the US_Bo1 site, US_ARM site and US_Aud site, respectively.

When the results are validated with the BR corrected measurements (Figure 9(b)), the ESVEP model performs with biases of -19.4 W/m², 8.6 W/m² and 2.4 W/m² and with RMSEs of 51.7 W/m²

(24.4 %), 53.3 W/m² (24.3 %) and 42.6 W/m² (28.1 %) at three test sites, respectively. For the conventional trapezoidal model, the biases are 35.8 W/m², 5.6 W/m² and -7.6 W/m², with RMSEs of 78.1 W/m² (36.8 %), 70.8 W/m² (32.3 %) and 57.5 W/m² (37.9 %) at the US_Bo1 site, US_ARM site and US_Aud site, respectively. In another situation of the model, the estimation biases are -37.9 W/m², -48.6 W/m² and -32.1 W/m², with RMSEs of 84.9 W/m² (40.1 %), 77.5 W/m² (45.4 %) and 56.2 W/m² (37.1 %) at three test sites, respectively, still indicating serious underestimations. It was pointed out in a previous study (Tang & Li, 2017) that the use of the area-averaged air temperature would overestimate the temperature of the wet end-member/edge if the underlying surface was water-stressed, which might be the reason for the more serious underestimations. In addition, at the US_Aud site, the ET estimations are less than 0 W/m² in Figure 9(c) on the three days (2007051, 2007090, and 2007099) when the T_s are seriously underestimated (Figure 7 (f)). As for different sites with different climates and vegetation types, the ESVEP model performed better and more stably, showing that the ESVEP model is capable of discriminating *ET* for different crop types.

Further, a sensitivity analysis is performed in this study. We analyzed the relative change of ET estimation from the two trapezoidal models with the change of T_s or T_v by -3 K, -2 K, -1 K, +1 K, +2 K, +3 K to its initial value, respectively. 14 days are selected when the RMSE related to the ET estimation is less than 10 W/m² compared to the BR corrected measurements and the results are presented in Figure 10. It can be found that a slight perturbation of T_v would bring greater variation of ET than T_s in the conventional trapezoidal model. As for the ESVEP model, the ET estimation is sensitive to T_s in most selected days while insensitive to T_v in most days. In the conventional trapezoid model, a ± 1 K perturbation in T_s and T_v produce about 10 % and 20 % variation in ET estimation, respectively; a ± 2 K perturbation in T_s and T_v produce 11 % - 28 % and 22 % - 65 % variation in ET estimation, respectively; a ± 3 K perturbation in T_s and T_v cause 20 % - 49 % and 30 % - 89 % variation in ET estimation, respectively. As for the ESVEP model, approximate sensitivity to T_s is found compared to the conventional trapezoid model in the days when ET estimation is sensitive to T_s ; while the perturbation in T_v would not cause ET estimation variation in most selected days. The reason for the insensitivity to T_v in the ESVEP model may be that the ET process is in first stage of the model in which ET_v is estimated using ET under extremely wet condition directly rather than with T_v (Eq. (8b)).

Figure 10 Sensitivity analysis of ET estimation to the variations in T_s and T_v in (a) (b) the conventional trapezoid model and (c) (d) the ESVEP model

4.5 Discussion

The ESVEP model and conventional trapezoidal model used in this study are both two-source models, and their greatest merit lies in their ability to discriminate vegetation transpiration from soil surface evaporation when compared with single-source models. Therefore, they are more practical in agricultural applications for better allocating water resources and improving water use efficiency (Crow et al., 2008; Long et al., 2012). The results from this study and other previous studies (Zhang et al., 2008; Yang et al., 2012; Tang & Li, 2017) have indicated that these two models both have acceptable accuracies. In fact, long term ET can also be well simulated by many models already (Miralles et al., 2016; Mueller et al., 2013; Schlesinger et al., 2014; Sutanto et al., 2014; Wei et al., 2017), however, these ETs are usually simulated with coarse resolution which are more than 50 km or 100 km. Compared to two-source energy balance models, such as N95 model, the ESVEP model has slightly lower but comparable accuracy (Tang & Li, 2017). However,

the two-source energy balance models usually need the estimation of the parallel or series resistance network, which somewhat complicates the application of them over a wide range of surface fractional vegetation cover and soil water availability conditions. A sensitivity analysis from previous studies (Long & Singh, 2012; Tang & Li, 2017) suggested that the two models are most sensitive to LST from remote sensing data and are relatively not sensitive to a range of derived meteorological observations and variables (wind speed, air vapor pressure, vegetation height). However, the meteorological data requirement is still a challenge when these two models are used over large areas. Currently, several globally or regionally gridded meteorological reanalysis products may provide data inputs for the two models, indicating promise for mapping ET over large areas.

In this study, the ESVEP model performs better and is more stable than the conventional trapezoidal model in separating ET_s and ET_v . The improvement in the ESVEP model comes from the consideration for different responses of the soil water content to ET_s and ET_v . The difference of the two trapezoidal models which are studied in this paper is only the interpretation process for separating ET_s and ET_v . The temperatures of four end-members in the two trapezoidal models are determined by the same method that used in the ESVEP model. And it is different in other papers in which the two models use different ways for the calculation of end-members. This is to say, the conventional trapezoidal model in our paper only use the conventional interpretation processes of ET but not the conventional method for determining the four dry/wet soil/vegetation end-members. According to the principle of the ESVEP model, it has a greater potential to enhance the effects of partitioning evapotranspiration and monitoring deep soil moisture. Thus, this model is suitable for deep root vegetation which highly depends on the soil moisture at the root zone. In addition, other previous studies (Karnieli et al., 2006; 2010) showed that when water is the limiting factor for vegetation growth, the LST/FVC relationship correlation is negative. Therefore, the ESVEP model based on LST/FVC relationship is more suitable for the areas and periods where water is the limiting factor for vegetation growth, such as in arid and semiarid areas and during the midseason (Sun et al. 2016).

As for the validation of the ET_s and ET_v separations, a small amount of reliable data exists. Although limited field datasets are used in some studies (Talsma et al., 2018), it has also been pointed out that it is difficult to draw definite conclusions given the paucity of the field datasets. In this study, the validations T_s and T_v derived from the two trapezoidal models are used as the first proof for the separation of ET_s and ET_v . The results show that T_s and T_v are in good agreement with those from the ASTER data. The relatively large errors from the T_v separations might derive from the overestimation of ASTER LST compared with the calculations from the longwave radiation measurements. In fact, the measured longwave radiations are manually observed on the ground and their measured times cannot exactly match the ASTER overpass times. Therefore, it is important to have accurate component temperatures for validation. Some studies (Song et al., 2015) have tried using simulated temperatures from the diurnal temperature cycle (DTC) model to validate the separated T_s and T_v , which may be tested in further studies.

The total ET from the two trapezoidal models is evaluated with the EC measurements, which is regarded as another validation for the estimations of ET_s and ET_v . For the differences between the estimated ET and measured values, several error sources cannot be neglected. The primary source should be the scale mismatch between the ET datasets, namely, the spatial representativeness of the EC-derived ET is different with a MODIS pixel resolution of 1 km. However, the flux data (LE and H) used in this study are all from EC systems which are located about 2 m height above

the ground. Therefore, the foot prints of the measured flux data are overall all within the MODIS pixel and the uncertainty caused by the foot print from the EC measurements is relatively small. Moreover, the observation time is not totally matched. In general, MODIS-based prediction is usually instantaneous value at the satellite overpass time, while the ET measurement is usually half-hour averaged value. Errors in the remotely sensed data and meteorological records can also lead to errors. The results of the available energy retrievals showed that, there is a fairly close agreement between the retrievals and the measurements, but the RMSE values are almost half of those related to the ET estimations. Therefore, there is still room to improve the estimation accuracies of remote sensing parameters. Neglecting of interception evaporation maybe also one of the reasons for the errors of total ET estimates in some models, however, only clear days are selected for the estimations of ET when using the two trapezoidal models and there is no precipitation, thus, the interception is very small in this study.

In addition, ASTER data is used to validate estimated T_s and T_v from the two trapezoidal models in this study, and the two trapezoidal models are applied at three flux sites and not large spatial regions due to the insufficient data from the ASTER. The compounding effects from the spatial heterogeneity of the soil moisture content and vegetation cover may also affect the estimations, which may also need further investigation.

5 Summary and conclusion

In this study, the ET_s and ET_v are estimated using the conventional trapezoidal model and the ESVEP model. These two trapezoidal models are applied at three AmeriFlux sites with different climate types in the USA. Due to lack of reliable data for the validation of these individual fluxes, the T_s and T_v , which include important information related to ET_s and ET_v , are separated first using the two trapezoid models and compared with the corresponding temperatures from ASTER. In addition, the total ET is validated with the EC measurements after correction of the energy imbalance with the RE and BR methods. The results show that the ESVEP model reproduces T_s , with an RMSE of 1.56-2.7 K (4.98-10.16 %), and T_v , with an RMSE of 2.54-2.80 K (9.73-11.11 %). The conventional trapezoidal model has an RMSE of 2.26-3.64 K (7.31-13.40 %) for T_s separation and an RMSE of 2.82-4.62 K (9.80-15.49 %) for T_v separation. Compared to the RE corrected measurements, the ESVEP model estimates ET with overall RMSEs of 49.8 W/m² (22.8 %), 58.4 W/m² (24.0 %) and 50.6 W/m² (27.2 %) at three test sites; and the conventional trapezoidal model estimates ET with RMSEs of 89.5 W/m² (41.1 %), 72.5 W/m² (29.8 %) and 72.0 W/m² (38.7 %). Compared to the BR corrected measurements, the RMSEs are 51.7 W/m² (24.4 %), 53.3 W/m² (24.3 %) and 42.6 W/m² (28.1 %) for the ESVEP model, and 78.1 W/m² (36.8 %), 70.8 W/m² (32.3 %) and 57.5 W/m² (37.9 %) for the conventional trapezoidal model. When the wet edges are calculated using the near-surface air temperatures, the conventional trapezoidal model has more serious underestimations of the ET . The sensitivity analysis shows that ET estimation is similar sensitive to T_s in both two trapezoidal model and is less sensitive to T_v in the ESVEP model than in the conventional trapezoidal model.

Therefore, the ESVEP model performs better and is more stable than the conventional trapezoid and less sensitive to T_v variation in ET estimation. For the wide range of applications of the ESVEP model in the future, globally or regionally gridded meteorological reanalysis products may be taken as input data; the accuracy related to the remote sensing data parameterization should be improved, and space and time matching among all data should also be taken into further consideration.

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Figure 5

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Figure 9

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