Remote-sensing algorithm for surface evapotranspiration

2 considering landscape and statistical effects on mixed-pixels

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8 Abstract

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9 Evapotranspiration (ET) plays an important role in surface-atmosphere interactions and can be 10 monitored using remote sensing data. However, surface heterogeneity, including the inhomogeneity 11 of landscapes and surface variables, significantly affects the accuracy of ET estimated from satellite 12 data. The objective of this study is to assess and reduce the uncertainties resulting from surface heterogeneity in remotely sensed ET using Chinese HJ-1B satellite data, which is of 30 m spatial 13 14 resolution in VIS/NIR bands and 300 m spatial resolution in the TIR band. A temperature sharpening 15 and flux aggregation scheme (TSFA) was developed to obtain accurate heat fluxes from the HJ-1B 16 satellite data. The IPUS (input parameter upscaling) and TRFA (temperature resampling and flux 17 aggregation) methods were used to compare with the TSFA in this study. The three methods represent three typical schemes used to handle mixed pixels from the simplest to the most complex. IPUS 18 19 handles all surface variables at coarse resolution of 300 m in this study, TSFA handles them at 30 m 20 resolution, and TRFA handles them at 30m and 300m resolution, which depends on the actual spatial 21 resolution. Analyzing and comparing the three methods can help us to get a better understanding of 22 spatial scale errors in remote sensing of surface heat fluxes. In situ data collected during HiWATER-23 MUSOEXE (Multi-Scale Observation Experiment on Evapotranspiration over heterogeneous land 24 surfaces of The Heihe Watershed Allied Telemetry Experimental Research) were used to validate and analyze the methods. ET estimated by TSFA exhibited the best agreement with in situ observa-25 26 tions, and the footprint validation results showed that the R², MBE, and RMSE values of the sensible 27 heat flux (H) were 0.61, 0.90 W·m⁻² and 50.99 W·m⁻², respectively, and those for the latent heat flux 28 (LE) were 0.82, -20.54 W·m⁻² and 71.24 W·m⁻², respectively. IPUS yielded the largest errors in ET 29 estimation. The RMSE of LE between the TSFA and IPUS methods was 51.30 W·m⁻², and the RMSE of LE between the TSFA and TRFA methods was 16.48 W·m⁻². Furthermore, additional 30 31 analysis showed that the TSFA method can capture the sub-pixel variations of land surface temper-32 ature and the influences of various landscapes within mixed pixels. 33 Index Terms: surface heterogeneity, temperature sharpening, area weighting, energy balance, evapo-

Index Terms: surface heterogeneity, temperature sharpening, area weighting, energy balance, evapo transpiration, spatial scale, HJ-1B satellite

35 1. Introduction

Five types of methods have been developed to estimate evapotranspiration (ET) or latent heat flux (LE) via remote sensing. (1) Surface energy balance models calculate LE as a residual term. According to the partitioning of the sources and sinks of the Soil-Plant-Atmosphere Continuum (SPAC), surface energy balance models can be classified as one-source (Bastiaanssen et al., 1998;

1 Su, 2002; Allen et al., 2007; Long and Singh, 2012a) or two-source models (Shuttleworth and Wal-2 lace, 1985; Norman et al., 1995; Xin and Liu, 2010; Zhu et al., 2013). (2) Penman-Monteith models 3 are used to calculate LE by using the Penman-Monteith equation and numerous surface resistance 4 parameterization schemes that control the diffusion of evaporation from soil surfaces and transpira-5 tion from plant canopies. These two-source Penman-Monteith models separate soil evaporation 6 from plant transpiration (Cleugh et al., 2007; Mu et al., 2011; Leuning et al., 2008; Chen et al., 2013; 7 Sun et al., 2013; Mallick et al., 2015). (3) Land surface temperature-vegetation index (LST-VI) space 8 methods assign the dry and wet edges of the LST-VI feature space as minimum and maximum ET, 9 respectively. These methods interpolate the media, and use the Penman-Monteith or Priestley-Taylor 10 equation to calculate the LE (Jiang and Islam, 1999, 2001; Sun et al., 2011; Long and Singh, 2012b; 11 Yang and Shang, 2013; Fan et al., 2015; Zhang et al., 2005). (4) Priestley-Taylor models expand the 12 range of the Priestley-Taylor coefficient in the Priestley-Taylor equation (Jiang and Islam, 2003; Jin 13 et al., 2011) or combine the physiological force factors with the energy component of ET (Fisher et 14 al., 2008; Yao et al., 2013). (5) Additional methods include empirical/statistical methods (Wang and 15 Liang, 2008; Yebra et al., 2013) and the use of complementary based models (Venturini et al., 2008) 16 and land-process models with data assimilation schemes (Bateni and Liang, 2012; Xu et al., 2015).

17 If the operational algorithm can be described as a linear combination of inputs, or if the surface 18 variables and landscapes are homogeneous at the pixel scale, scale error does not exist (Hu and 19 Islam, 1997). However, it is difficult to develop linear operational models due to the complexity of 20 mass and heat transfer processes between the atmosphere and land surface. ET estimation models 21 have been generally developed for simple and homogeneous surface conditions. However, hetero-22 geneity is a natural attribute of the surface of the Earth. Therefore, larger spatial scale errors occur 23 when these remotely sensed models are applied to calculate the regional ET using satellite data.

24 In previous studies, researchers have coupled high- and low-resolution satellite data and statis-25 tically quantified the inhomogeneity of mixed pixels to correct the scale error in ET estimations using (1) temperature downscaling, which converts images from a lower (coarser) to higher (finer) 26 27 spatial resolution using statistical-based models with regression or stochastic relationships among 28 parameters (Kustas et al., 2003; Norman et al., 2003; Cammalleri et al., 2013; Ha et al., 2013), (2) 29 the correction-factor method, which uses sub-pixel landscapes information to determine the correc-30 tion factor of scale bias (Maayar and Chen, 2006) and (3) the area-weighting method, which calcu-31 lates roughness length and sensible heat flux based on sub-pixel landscapes (Xin et al., 2012). These 32 correction methods mainly focus on two problems: inhomogeneity of landscapes and inhomogene-33 ity of surface variables.

34 Studies have shown that different landscapes (Blyth and Harding, 1995; Moran et al., 1997; 35 Bonan et al., 2002; McCabe and Wood, 2006) and the sub-pixel variations of surface variables, such 36 as stomatal conductance (Bin and Roni, 1994), or leaf area index (Bonan et al., 1993; Maayar and 37 Chen, 2006), can cause errors in turbulent heat flux estimations. Surface variables inhomogeneity 38 is rather difficult to evaluate, as the sub-pixel variation of surface variables can be large, even in the 39 pure pixels. For example, generally, temperatures over land surfaces vary strongly in space and time, 40 and it is common for the LST to vary by more than 10 K over just a few centimeters of distance or 41 by more than 1 K in less than a minute over certain cover types (Li et al., 2013b). However, in case 42 of mixed pixels, surface variables such as land surface temperature are commonly considered as a 43 single value to represent the entire pixel area in ET estimation models, which results in large errors. 44 The focus of this study is on the effects of surface heterogeneity when estimating ET. Based on the satellite products that are currently available, three methods were used to analyze the uncer tainties produced by surface heterogeneity: (1) input parameter upscaling (IPUS) does not consider

- 3 the surface heterogeneities at all. It was designed to simulate the satellites that have identical spatial
- 4 resolutions both the visible near-infrared (VNIR) and thermal infrared (TIR) bands; (2) temperature
- 5 resampling and flux aggregation (TRFA) does not consider the heterogeneity of LST; and (3) tem-
- 6 perature sharpening and flux aggregation (TSFA) considers all the surface heterogeneities. These
- methods were designed for use with the majority of satellite data or products that have inconsistent
- 8 spatial resolutions between the VNIR and TIR bands, such as the Landsat and HJ-1B satellites.

9 The surface variables in this paper were mainly derived from HJ-1B satellite data. The Chinese 10 HJ-1A/B satellites were launched on September 6, 2008, and were designed for disaster and envi-11 ronmental monitoring, as well as other applications. The HJ-1B satellites are equipped with two 12 charge-coupled device (CCD) cameras and one infrared scanner (IRS) with spatial resolutions of 30 13 m and 300 m, respectively. Compared to high-temporal-resolution satellite data, such as the MODIS 14 satellite data, or high-spatial resolution satellite data, such as the Landsat 7 or 8 satellites data, HJ-15 1B data has the advantage of a high spatiotemporal resolution. Since the satellites were launched, 16 the HJ-1/CCD time series data have been widely used in China to accurately classify land cover 17 (Zhong et al., 2014a) and monitor various environmental disasters (Wang et al., 2010). Land-based 18 variables, such as leaf area index (LAI), land surface temperature (LST), and downward longwave 19 radiation (L_d), have been retrieved by the HJ-1 satellites using algorithms developed by Chen et al. 20 (2010), Li et al. (2010a, 2011a) and Yu et al. (2013), respectively. These variables lay the foundation 21 for ET research.

Although the HJ-1B satellites provide CCD data with a high spatial resolution of 30 m, the spatial resolution of the thermal infrared (TIR) band is only 300 m. Thus, surface heterogeneity effects must be considered when estimating the heat flux.

25 2. Methodology

26 **2.1. Temperature-sharpening method based on statistical relationships**

Surface thermal dynamics affect ET. The spatial resolution of TIR images is usually not as high as the spatial resolution of visible near-infrared (VNIR) bands because the energy of VNIR photons is higher than the energy of thermal photons. Thus, the inhomogeneity of TIR images would be larger than the inhomogeneity of VNIR images. Since the land surface temperature is calculated from the TIR band, the uncertainty of the variables becomes unpredictable when the inhomogeneity of TIR images is enhanced. Therefore, land surface temperature data should be derived with a high spatial resolution.

The land surface temperature can be reconstructed at the spatial resolution of the VNIR images by using a statistical temperature-sharpening strategy proposed by Kustas et al. (2003). This method assumes that the negative correlation between the Normalized Difference Vegetation Index (NDVI) and LST is invariant. The NDVI reflects vegetation growth and coverage, and the LST reflects surface thermal dynamics. The LST decreases with increasing vegetation cover. The scatter plot between the LST and NDVI values forms a feature space that is applicable at different scales when sufficient number of pixels exist.

HJ-1B satellite images can provide vegetation and thermal information at spatial resolutions of
30 m and 300 m, respectively. The 300 m resolution thermal data cannot sufficiently distinguish the

1 surface temperatures of small targets within pixels. However, this issue can be addressed by tem-

2 perature sharpening based on the functional relationship between NDVI and LST. A flowchart of 3 temperature sharpening is shown in Fig. 1, and LST at the NDVI pixel resolution can be derived 4 based on the following steps (Kustas et al., 2003):

5 (1) The NDVI₃₀ is aggregated to 300 m NDVI (NDVI₃₀₀). Then, the NDVI₃₀₀ is divided into 6 three classes ($0 \le NDVI_{300} < 0.2$, $0.2 \le NDVI_{300} < 0.5$ and $0.5 \le NDVI_{300}$).

7 (2) A subset of pixels is selected from the scene where the NDVI is as homogeneous as possible 8 at a pixel resolution of 300 m based on the coefficient of variation (CV). The CVs are calculated 9 using the original 30 m NDVI data (NDVI₃₀) as follows:

11 where STD and mean are the standard deviation and the average values of 10×10 pixels of NDVI₃₀, respectively. The CVs are sorted from smallest to largest. Lower CVs corresponds to more homo-12 13 geneous land surface values, and a threshold should be determined to guarantee that a sufficient 14 number of pixels is available for least squares fitting between NDVI₃₀₀ and T₃₀₀. Therefore, the 15 fractions of 25% of the lowest CVs are selected from each class.

16 (3) A least squares expression is established between $NDVI_{300}$ and T_{300} using the selected 17 pixels.



20

21 (4) For each 30 m pixel within a 300 m pixel, \hat{T}_{30} can be calculated according to Eq. (2) as 22 follows:

23 $\widehat{T}_{30}(\text{NDVI}_{30}) = a + b \times \text{NDVI}_{30} + c \times \text{NDVI}_{30}^2 + \Delta \widehat{T}_{300}$ (3)24 where $\Delta \widehat{T}_{300} = \overline{T}_{300} - \widehat{T}_{300}$ is the deviation between the regressed temperature and the temperature that was observed by the satellite at 300 m. 25

26 2.2. Area-weighting method based on landscape information

27 Coarse pixels are inhomogeneous because various types of land use may be included. Using a 28 dominant type to represent such a large landscape is irrational. The spatial resolution of LST is 29 significantly increased by temperature sharpening in section 2.1. Consequently, all inputs of ET algorithms can be obtained at high spatial resolutions. Then, inhomogeneity issues can be greatly
 diminished by dividing the landscape into finer pixels.

- Combined with a high-resolution classification map, sub-pixel scale parameters can be used in the ET algorithm, which is more rational than using a dominant class type because different landscapes may require different ET algorithms. The surface energy fluxes can be averaged linearly due to the conservation of energy (Kustas et al., 2003), and a simple average that calculates the arithmetic mean over sub-pixels is the best choice for flux upscaling (Ershadi et al., 2013b). Thus, the aggregated flux at a low resolution F(x, y) is the arithmetic mean of all the n × n sub-pixel fluxes that constitute the contributing flux $F(x_i, y_j)$ at coordinate (x_i, y_j) :
- 10

15

$$F(x, y) = \frac{1}{n \times n} \sum_{i=1}^{n} \sum_{j=1}^{n} F(x_i, y_j)$$
(4)

Because the average of the sub-pixels fluxes is equal to the area-weighted sum of each landtype result, the final coarse result can be derived from the area-weighted sum of each land type result within the landscape. The main steps in the area-weighting process are shown below (Xin et al., 2012):

(1) Geometric correction and registration of the VNIR and TIR input datasets.

(2) Count the area ratios of different land cover types within each pixel of a low-spatial-reso-lution classification image.

18 (3) According to the fine-classification data, different parameterization schemes can be used in 19 the ET algorithm to calculate the sub-pixel flux, such as the net radiation (R_n) , soil heat flux (G) and 20 sensible heat flux (H).

(4) To calculate the regional flux, the flux of the large pixel is calculated by the area-weightingmethod as follows:

23

$$\mathbf{F} = \sum_{i=1}^{n} \mathbf{w}_i \cdot \mathbf{F}_i \tag{5}$$

where w_i is the fractional area contributing flux F_i of class type i and F is the aggregated flux at the coarse resolution. The LE is computed as a residual of the surface energy balance in the TSFA (see section 2.3) process, in which a high-spatial resolution image is used to reduce the number of mixed pixels.

28 2.3. Pixel ET algorithm

29 The surface energy balance describes the energy between the land surface and atmosphere. The 30 energy budget is commonly expressed as follows:

 $R_n = LE + H + G \tag{6}$

where R_n is the net radiation, G is the soil heat flux, H is the sensible heat flux, and LE is the latent heat flux absorbed by water vapor when it evaporates from the soil surface and transpires from plants through stomata. The widely used one-source energy balance model considers a homogeneous SPAC medium and ignores the inhomogeneity and structure. In this case, LE can be expressed as follows:

37

$$LE = \frac{\rho c_p}{\gamma} \cdot \frac{e_s - e_a}{r_a + r_s}$$
(7)

38 where γ is the psychometric constant; e_s and e_a are the aerodynamic saturation vapor pressure 39 and atmospheric water vapor pressure, respectively; and r_a and r_s are the water vapor transfer 40 aerodynamic resistance and surface resistance, respectively. Surface resistance includes soil re1 sistance and canopy resistance. The surface resistance is influenced by the physiological character-

- istics of the vegetation and the water supply of roots. Thus, it is difficult to obtain surface resistance
 via remote sensing, and surface resistance is highly uncertain, particularly over heterogeneous surfaces. To avoid error introduced by the uncertainty of the surface resistance, LE is computed as a
- 5 residual of the surface energy balance equation.
- 6
- R_n is the difference between incoming and outgoing radiation and is calculated as follows:
- 7

$$R_n = S_d(1 - \alpha) + \varepsilon_s L_d - \varepsilon_s \sigma T_{rad}^4$$
(8)

8 where S_d is the downward shortwave radiation, α is the surface broadband albedo, ε_s is the 9 emissivity of the land surface, L_d is the downward atmospheric longwave radiation, $\sigma = 5.67 \times 10^{-8} \text{W} \cdot \text{m}^{-2} \cdot \text{K}^{-4}$ is the Stefan-Boltzmann constant and T_{rad} is the surface radiation tempera-11 ture.

12 G is commonly estimated using the empirical relationship with R_n . Because the canopy exerts 13 a significant influence on G, the fractional canopy coverage FVC is used to determine the ratio of 14 G to R_n as follows:

$$G = R_n \times [\Gamma_c + (1 - FVC) \times (\Gamma_s - \Gamma_c)]$$

where Γ_s is 0.315 for bare soil and Γ_c is 0.05 for a full vegetation canopy (Su, 2002). H is the transfer of turbulent heat between the surface and atmosphere, which is driven by a temperature difference and controlled by resistances that depend on local atmospheric conditions and land cover properties (Kalma et al., 2008). According to gradient diffusion theory, the equation for H is as follows:

15

$$H = \rho c_p \frac{T_{aero} - T_a}{r_a}$$
(10)

(9)

22 where ρ is the density of the air; c_p is the specific heat of the air at a constant pressure; T_{aero} is 23 the aerodynamic surface temperature obtained by extrapolating the logarithmic air temperature pro-24 file to the roughness length for heat transport; T_a is the air temperature at a reference height; and 25 r_a is the aerodynamic resistance, which influences the heat transfer between the source of the tur-26 bulent heat flux and the reference height. Aerodynamic resistance was calculated based on the 27 Monin-Obukhov similarity theory (MOST) using a stability correction function (Paulson, 1970; 28 Ambast et al., 2002). The zero-plane displacement height, d, and roughness length, z_{0m}, were pa-29 rameterized by the schemes proposed by Choudhury and Monteith (1988).

In this approach, H must be accurately estimated. However, calculating H using Eq. (10) is difficult. Because remote sensing cannot obtain T_{aero} , the value of T_{aero} is generally replaced with the radiative surface temperature T_{rad} , which is not always equal to T_{aero} . The difference between these terms for homogeneous and full-coverage vegetation is approximately 1-2°C (Choudhury et al., 1986), and it can reach 10°C in sparsely vegetative areas (Kustas, 1990). The method that corrects for this discrepancy adds "excess" resistance r_{ex} to r_a . We used the brief method proposed by Chen (1988) to calculate r_{ex} : $r_{ex} = 4/u_*$.

Fig. 2 shows the flowchart for merging ET retrieval and temperature sharpening based on HJ-1B satellites.





Figure 2. Flowchart of ET retrieval using the "Temperature Sharpening and Flux Aggregation" method.

3 The spatial scale effect is generally revealed by a discrepancy between different upscaling methods. In one method, parameters are upscaled to a large scale before calculating the heat flux. 4 5 In the other method, heat flux is calculated at a small scale, and the results are then upscaled. In this 6 study, the resolution of the final output result is 300 m. To evaluate the heterogeneity reducing effect 7 of TSFA, two other upscaling methods called IPUS and TRFA were implemented (see Fig. 3). In 8 the case of IPUS, the inputs of the energy balance model are first retrieved at 30 m resolution (see 9 section 3.2.1.1) and then aggregated to 300 m resolution. Subsequently, these 300 m inputs are used 10 in the one-source energy balance model to obtain the four energy balance components at 300 m 11 resolution. In TRFA, the LST at 300 m is first resampled to 30 m using the nearest neighbour method 12 and the 30 m resolution inputs are used for estimating ET. The outputs of the four energy-balance 13 components of the TRFA are obtained using the area-weighting method shown in section 2.2.





14 15

Figure 3. Flowchart of the three upscaling methods for retrieving evapotranspiration

16 3. Study area and Dataset

17 **3.1. Study area**

18 Our study was conducted in the middle stream of the Heihe River Basin (HRB), which is lo-19 cated near the city of Zhangye in the arid region of Gansu Province in northwestern China

(100.11 E-100.16 E, 39.10 N-39.15 N). The middle reach of the HRB is a typical desert-oasis ag-1 2 riculture ecosystem dominated by maize and wheat. Areas of the Gobi Desert and the alpine vege-3 tation in the Qilian Mountains are located near the study area (see Fig. 4). The artificial oasis is 4 highly heterogeneous, which impacts the thermal-dynamics and hydraulic features. Consequently, 5 the water use efficiency and ET are variable. The Heihe River Basin has long served as a test bed 6 for integrated watershed studies, as well as land surface and hydrological experiments. Comprehen-7 sive experiments, such as the Watershed Allied Telemetry Experimental Research (WATER) project 8 (Li et al., 2009), and an international experiment - the Heihe Basin Field Experiment (HEIFE) as 9 part of the World Climate Research Programme (WCRP), have been conducted in this basin. One 10 major objective of HiWATER was to capture the strong land surface heterogeneities and associated

11 uncertainties within a watershed (Li et al., 2013a).



12 13

Figure 4. Study area and distribution of EC towers in HiWATER-MUSOEXE

14 **3.2. Dataset**

In this study, data are mainly derived from the HJ-1B satellite. We combined these data with ancillary data and *in situ* "Multi-Scale Observation Experiment on Evapotranspiration over heterogeneous land surfaces of The Heihe Watershed Allied Telemetry Experimental Research" (Hi-WATER-MUSOEXE) data to estimate and validate the HJ-B land surface variables and heat fluxes.

19 3.2.1. Remote sensing data

20 3.2.1.1. HJ-1B satellite data

The specifications of HJ-1B are shown in Table 1. The satellite has quasi-sun-synchronous orbits at an altitude of 650 km, a swath width of 700 km and a revisit period of 4 days. Combined, the revisit period of the satellites is 48 h. Because HJ-1 CCDs lack an onboard calibration system, cross-calibration methods were proposed to calibrate the CCD instruments (Zhang et al., 2013; Zhong et al., 2014b). The image quality of the HJ-1A/B CCD is stable, the performances of each band are balanced (Zhang et al., 2013) and the radiometric performance of the HJ-1A/B CCD sensors is similar to the performances of the Landsat-5 TM, Observer-1 (EO-1) Advanced Land Imager and Terra ASTER. The image quality of the HJ-1 CCD is very similar to the image quality of Landsat-5 TM (Jiang et al., 2013). In addition, the accuracy of the TIR band's onboard calibration meets the land surface temperature retrieval requirements but not the sea surface temperature retrieval requirements (Li et al., 2011b). The Center for Resources Satellite Data and Application (CRESDA) in China releases calibration coefficients annually on its website (http://www.cresda.com). These

8 data are freely available from the CRESDA website (http://218.247.138.121/DSSPlatform/in-

9 10 dex.html).

Table 1. Specifications of the HJ-1B main payloads

		1	1	5	
Sensor	Band	Spectral range (µm)	Spatial resolution (m)	Swath width (km)	Revisit time (days)
	1 2	0.43-0.52 0.52-0.60		360 (single)	
CCD	3	0.63-0.69	30	700 (two)	4
	4	0.76-0.90		700 (0.00)	
	5	0.75-1.10			
IDC	6	1.55-1.75	150	720	4
IKS	7	3.50-3.90		720	4
	8	10.5-12.5	300		



11

Figure 5. Flowchart of land surface variable retrieval. The abbreviations are defined as follows: SZA: solar zenith angle; SAA: solar azimuth angle; VZA: view zenith angle; AOD: aerosol optical depth; ABT: at-nadir brightness temperature; S_d: downward shortwave radiation; USR: upward shortwave radiation, ULR: upward longwave radia-

15 tion; and Ld: downward longwave radiation.

We used the HJ-1B satellite data from the HRB region in 2012. Because many variable-retrieving algorithms require clear-sky conditions when calculating ET, we combined data quality information with visual interpretation to select satellite images without clouds. Considering the period of ground observations discussed in section 3.2.2, we obtained data for 11 days: June 19, June 30, July 8, July 27, August 2, August 15, August 22, August 29, September 2, September 13 and September 14.

The HJ-1B satellite data of the HRB were pre-processed, including geometric correction, radiometric calibration, and atmospheric correction. The following surface variables are needed in Eqs. (1) to (10): downward shortwave radiation, downward longwave radiation, emissivity, albedo, fractional vegetation coverage (FVC), cloud mask data, meteorological data, LAI and LST. Fig. 5 illustrates a flowchart of the retrieval of these variables.

(1) Surface albedo. According to the algorithm proposed by Liang et al. (2005) and Liu et al.
(2011a), surface albedo was obtained from the top of the atmosphere (TOA) reflectance by the HJ-

1 satellite using a lookup table based on an angular bin regression relationship. The surface albedo
 2 and bidirectional reflectance distribution function (BRDF) of the HJ-1 satellite in the regression
 3 procedure were monitored using POLDER-3/PARASOL BRDF datasets, and BRDF was used to
 4 obtain the TOA reflectance in the 6S (Second Simulation of a Satellite Signal in the Solar Spectrum)

5 radiation transfer mode.

6 (2) NDVI, FVC and LAI. The NDVI is the regression kernel of the temperature-sharpening
7 procedure and is used to calculate the FVC. Atmospherically corrected surface reflectance values
8 were used to calculate the NDVI as follows:

 $NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$ (11)

10 and

11

12

$$FVC = \frac{NDVI - NDVI_s}{NDVI_v + NDVI_s}$$
(12)

13 where ρ_{nir} and ρ_{red} are the reflectances in the near-infrared and red band, respectively, and 14 NDVI_v and NDVI_s are the fully vegetated and bare soil NDVI values, respectively. As an im-15 portant input for the parameterization of surface roughness length and aerodynamic resistance, the 16 LAI was determined using the following equation (Nilson, 1971):

$$P(\theta) = e^{-G(\theta) \cdot \Omega \cdot LAI/\cos(\theta)}$$
(13)

25

$$P(\theta) = 1 - FVC \tag{14}$$

19 where θ is the zenith angle, P(θ) is the angular distribution of the canopy gap fraction, G(θ) is 20 the projection coefficient (0.5) and Ω is the total foliage clumping index, which can be obtained 21 from the GLC global clumping index database according to the land use type (He et al., 2012).

$$\varepsilon = \varepsilon_{\rm v} \cdot {\rm FVC} + \varepsilon_{\rm g} (1 - {\rm FVC}) + 4 < d\varepsilon > \cdot {\rm FVC} \cdot (1 - {\rm FVC})$$
(15)

where ε is the LSE, $\langle d\varepsilon \rangle$ is an effective value of the cavity effect of emissivity, the mean d ε of all vegetation species in this study is $\langle d\varepsilon \rangle = 0.015$, ε_v and ε_g are the vegetation and ground emissivity, respectively.

(4) Land surface temperature. A single-channel parametric model for retrieving LST based on
 HJ-1B/IRS TIR data developed by Li et al. (2010a) was employed to obtain the LST. This model
 was developed from a parametric model based on MODTRAN4 using NCEP atmospheric profile
 data.

(5) Downward shortwave radiation. In this study, the algorithm proposed by Li et al. (2010b)
was applied. MOD05, TOMS, aerosol and solar angle data were used to estimate the direct light
flux and diffuse light flux using a lookup table that was generated via the 6S radiation transfer mode
(Vermote et al., 2006). This method considered the influences of complex terrain, and a topographic
correction was performed by using products of the ASTER digital elevation model (DEM).

(6) Downward longwave radiation (L_d). The TOA brightness temperature of the HJ-1B thermal
channel was used to substitute the atmospheric effective temperature. Effective atmospheric emissivity was parameterized as an empirical function of the water vapor content. These values were
substituted for atmospheric temperature and atmospheric emissivity to estimate the value of L_d.
Because this L_d retrieval method proposed by Yu et al. (2013) was only valid for clear-sky conditions,

1 cloud masking information was used to determine clear skies. When cloud contamination existed in

2 the image, the brightness temperature was relatively low, causing the L_d to be lower than that in the

3 cloudless images.

4 3.2.1.2. Ancillary data

5 Ancillary data were used because the bands of the satellite could not invert all of the variables 6 needed to retrieve ET.

7 (1) Atmospheric water vapor data. MODIS provides water vapor data (MOD05), including a
1-km near-infrared product and a 5-km thermal-infrared product, every day. The 1-km near-infrared
9 water vapor product was used to retrieve L_d in this study.

(2) Surface elevation data. We used the 30 m resolution Global Digital Elevation Model
(GDEM) based on ASTER, which covers 83 N-83 S, to derive S_d.

12 (3) Atmosphere ozone data. A Total Ozone Mapping Spectrometer (TOMS), which was carried 13 on an Earth Probe (EP) satellite, was used to derive S_d . The TOMS-EP provided daily global at-14 mospheric ozone data at a resolution of 1 °×1.25 ° (Li et al., 2010b).

(4) Atmosphere profile data. Global reanalysis data from the National Centers for Environmental Prediction (NCEP) were used to derive LST. These data were generated globally every 6 hours
(0:00, 06:00, 12:00, 18:00 UTC) for every 1 °of latitude and longitude (Li et al., 2010a).

18 **3.2.2. HiWATER experiment dataset**

The *in situ* HRB observation data were provided by HiWATER. From June to September 2012,
HiWATER designed nested observation matrices over 30 km×30 km and 5.5 km×5.5 km within the
middle stream oasis in Zhangye to focus on the heterogeneity of the scale effect in HiWATERMUSOEXE.

23 In the larger observation matrix, four eddy covariance (EC) systems and one superstation were 24 installed in the oasis-desert ecosystem. Each station was supplemented with an automatic meteor-25 ological station (AMS) to record meteorological and soil variables and monitor the spatial-temporal 26 variations of ET and its associated factors (Li et al., 2013a). The station information is shown in 27 Table 2, and the distribution of the stations is shown in Fig. 4. Within the artificial oasis, an obser-28 vation matrix composed of 17 EC towers and ordinary AMSs exists where the superstation was 29 located. The land surface was heterogeneous and dominated by maize, maize inter-cropped with 30 spring wheat, vegetables, orchards and residential areas (Li et al., 2013a). Because the EC16 and 31 HHZ stations lacked R_n and G observation data, they were excluded from this study.

32

Table 2. The in situ HiWATER-MUSOEXE station information

Station	Longitude ()	Latitude ()	Tower height (m)	Altitude (m)	Land cover
EC1	100.36E	38.89N	3.8	1552.75	vegetation
EC2	100.35E	38.89N	3.7	1559.09	maize
EC3	100.38E	38.89N	3.8	1543.05	maize
EC4	100.36E	38.88N	4.2	1561.87	building
EC5	100.35E	38.88N	3	1567.65	maize
EC6	100.36E	38.87N	4.6	1562.97	maize
EC7	100.37E	38.88N	3.8	1556.39	maize
EC8	100.38E	38.87N	3.2	1550.06	maize

3.34 maize
34.73 maize
75.65 maize
i9.25 maize
i0.73 maize
70.23 maize
6.06 maize
i9.63 orchard
562 uncultivated land-Gobi
594 uncultivated land-desert
swamp land

1 The ground observation data included the H and LE. Reliable methods were used to ensure the 2 quality of the turbulent heat flux data. Before the main campaign, an intercomparison of all instru-3 ments was conducted in the Gobi Desert (Xu et al., 2013). After basic processing, including spike 4 removal and corrections for density fluctuations (WPL correction), a four-step procedure was per-5 formed to control the quality of the EC data. In this procedure, data were rejected when (1) the 6 sensor had been malfunctioning, (2) precipitation occurred within 1 h before or after collection, (3) 7 the ratio of missing data was greater than 3% in the 30 min raw record and (4) the friction velocity 8 was below 0.1 ms⁻¹ at night (for more details see Liu et al., 2011b; Xu et al., 2013; Liu et al., 2016). 9 EC outputs are available every 30 min. G was measured by using three soil heat plates at a depth of 10 6 cm at each site, and the surface G was calculated using the method proposed by Yang and 11 Wang(2008) based on the soil temperature and moisture above the plates. Surface meteorological 12 variables, such as wind speed, wind direction, relative humidity and air pressure, were used to in-13 terpolate images using the inverse distance weighting. Researchers can obtain these data from the 14 websites of the Cold and Arid Regions Science Data Center at Lanzhou (http://card.westgis.ac.cn/) 15 or the Heihe Plan Data Management Center (http://www.heihedata.org/).

Energy imbalances are common in ground flux observations. The conserving Bowen ratio (H/LE) and residual closure technique are often used to force the energy balance. Computing the LE as a residual variable may be a better method for energy balance closure under conditions with large LEs (small or negative Bowen ratios due to strong advection) (Kustas et al., 2012). Thus, the residual closure method was applied because the "oasis effect" was distinctly observed in the desertoasis system on clear days during the summer (Liu et al., 2011b).

22 4. Results and analysis

23 **4.1. Evaluation of surface variables**

To control model inputs and analyse error sources, the coarse-resolution land surface temperature, downward shortwave radiation, downward longwave radiation, R_n and G were evaluated using *in situ* data.

The ground-based land surface temperature, T_s , was calculated using the Stefan-Boltzman Law from the AMS measurements of the longwave radiation fluxes (Li et al., 2014) as follows:

29
$$T_{s} = \left[\frac{L^{\uparrow} - (1 - \varepsilon_{s}) \cdot L^{\downarrow}}{\varepsilon_{s} \cdot \sigma}\right]^{\frac{1}{4}}$$
(16)

30 in which L^{\uparrow} and L^{\downarrow} are *in situ* surface upwelling and atmospheric downwelling longwave radiation,

respectively, and ε_s is the surface broadband emissivity, which is regarded as the pixel value of the 1 2 HJ-1B at the AMS. The coefficient of determination R², mean bias error (MBE) and root mean 3 square error (RMSE) of the LST are 0.71, -0.14 K and 3.37 K, respectively. As shown in Table 3, 4 the accuracy of EC4 is low. The main causes of the large errors are as follows: (1) buildings and 5 soil/vegetation are distinct materials, the LSE algorithm may not be suitable for buildings and (2) 6 the EC4 foundation is non-uniform and is not suitable for validation. After removing the EC4 data, 7 the R², MBE and RMSE values of the LSTs were 0.83, 0.69 K and 2.51 K, respectively. The LST 8 errors of SSW and SD were large due to large errors on particular days. For example, although it 9 was briefly cloudy above station SSW on July 27, this area was not identified as cloudy in the cloud 10 detection process.

Station	\mathbb{R}^2	MBE (K)	RMSE (K)	Station	R ²	MBE (K)	RMSE (K)
EC1	0.82	0.18	1.74	EC11	0.42	1.59	2.98
EC2	0.82	0.59	1.54	EC12	0.87	0.62	1.51
EC3	0.69	0.38	1.90	EC13	0.83	0.44	1.48
EC4	0.83	-9.87	10.04	EC14	0.73	1.43	2.44
EC5	0.83	1.71	2.34	EC15	0.74	1.53	2.41
EC6	0.61	0.30	2.44	EC17	0.78	1.20	2.32
EC7	0.82	0.39	1.40	GB	0.69	0.12	2.33
EC8	0.83	0.45	1.55	SSW	0.59	1.38	3.82
EC9	0.63	2.31	3.15	SD	0.76	-3.83	4.84
EC10	0.68	1.32	2.45				

Table 3. The station validation results of land surface temperature

12 The R², MBE and RMSE values of S_d were 0.81, 13.80 W·m⁻², and 25.35 W·m⁻², respectively. 13 The station validation results are shown in Table 4. The accuracy of SSW is low. Because cloudy 14 conditions occurred briefly on July 27, few ground observations were obtained, and S_d was signif-15 icantly overestimated. After removing these data, the R², MBE and RMSE values of S_d at SSW 16 were 0.87, 10.90 W·m⁻² and 21.13 W·m⁻², respectively.

17

11

Table 4. The station validation results of downward shortwave radiation

C4-4:	D ²	MBE	RMSE	Ctation.	D2	MBE	RMSE
Station	K²	$(W \cdot m^{-2})$	$(W \cdot m^{-2})$	Station	K2	(W·m ⁻²)	$(W \cdot m^{-2})$
EC1	0.97	25.23	27.73	EC11	0.90	30.11	33.76
EC2	0.84	28.29	33.57	EC12	0.96	24.35	26.43
EC3	0.97	17.56	19.25	EC13	0.93	12.41	17.92
EC4	0.98	6.07	9.34	EC14	0.98	32.40	33.49
EC5	0.98	10.60	12.29	EC15	0.94	26.71	29.71
EC6	0.93	27.68	30.71	EC17	0.94	-20.25	24.54
EC7	0.89	-17.69	27.59	GB	0.89	25.34	30.63
EC8	0.83	15.63	25.50	SSW	0.63	18.51	34.93
EC9	0.96	-2.27	9.96	SD	0.98	5.70	13.82
EC10	0.94	-3.50	11.97				

18

The R², MBE and RMSE values of the HRB L_d were 0.73, 0.28 W·m⁻², and 21.24 W·m⁻²,

19 respectively. As seen in Table 5, the accuracies at EC3, SD and SSW were low. The low accuracies

1 at EC3 and SD potentially resulted from (1) high humidity, which resulted in low at-nadir brightness 2 temperatures and low retrieved L_d, or (2) instrument error, which occurred because the EC3 ground 3 observations were always greater than those of the other stations during the same period. Although 4 SSW was located in a desert, the ground-air temperature difference was large. The L_d retrieval may 5 have a large error because the models use surface temperature when estimating L_d to approximate 6 or substitute the near-surface temperature (Yu et al., 2013). The corrected error of our Ld retrieving 7 algorithm resulted from the ground-air temperature difference in non-vegetated areas. The inaccu-8 racy of the SSW LST may influence the L_d results. 9

G ()	D ²	MBE	RMSE	а .	D ²	MBE	RMSE
Station	R²	(W·m ⁻²)	(W·m ⁻²)	Station	R²	(W·m ⁻²)	(W·m ⁻²)
EC1	0.85	4.16	17.21	EC11	0.93	-2.72	10.55
EC2	0.88	0.11	14.23	EC12	0.87	-0.84	14.80
EC3	0.91	-35.65	37.88	EC13	0.86	-7.28	15.98
EC4	0.88	3.36	16.38	EC14	0.82	4.07	16.42
EC5	0.88	-0.79	15.02	EC15	0.85	17.67	23.06
EC6	0.84	2.55	15.43	EC17	0.90	-1.11	12.87
EC7	0.75	-5.90	19.72	GB	0.88	9.50	27.82
EC8	0.80	-1.35	17.49	SSW	0.85	25.33	34.50
EC9	0.86	10.44	17.99	SD	0.85	-26.54	34.08
EC10	0.87	7.98	16.05				

Table 5. The station validation results of downward longwave radiation

The R², MBE and RMSE values of the HRB R_n were 0.70, -9.64 W·m⁻², and 42.77 W·m⁻², 10 11 respectively. The station-validated results of R_n are shown in Table 6, which indicates that the 12 accuracies of EC4, EC7, EC17 and SSW were relatively low. According to the sensitivity analysis 13 of Eq. (8), L_d and S_d are highly sensitive variables when calculating R_n , while the albedo, LSE 14 and LST are not as sensitive. Although LST was not a sensitive variable, the MBE and RMSE values 15 of LST at EC4 reached -9.87 K and 10.04 K because the land cover of EC4 was maize at 300 m 16 resolution. However, the observation tower was located in a built-up area, which potentially caused errors when estimating R_n . The accuracies of S_d and L_d at EC7 were low on several days, and 17 18 MBE=-43.40 W·m⁻² and RMSE=50.50 W·m⁻² after removing these data. EC17 was located in an 19 orchard, and the signal that was received by the sensors at EC17 was affected by the complex ver-20 tical structure of the orchard ecosystem. The information of substrate plants may be ignored, leading 21 to albedo retrieval errors. An albedo bias of 0.03 can lead to an R_n error of approximately 20 W·m⁻ 22 ² when the solar incoming radiation is large. As previously discussed, it was briefly cloudy on July 27, and after removing those data, the R^2 , MBE and RMSE values of the R_n obtained at station 23 SSW were 0.72, 8.20 W·m⁻², and 37.60 W·m⁻², respectively. 24



Station \mathbf{R}^2		MBE RMSE		St-4:	D2	MBE	RMSE
Station	K	$(W \cdot m^{-2})$	(W·m ⁻²)	Station	K²	$(W \cdot m^{-2})$	$(W \cdot m^{-2})$
EC1	0.76	-2.55	30.61	EC11	0.86	-15.13	28.05
EC2	0.79	2.52	25.24	EC12	0.90	-8.46	19.38
EC3	0.86	-35.84	42.97	EC13	0.88	-25.73	32.34
EC4	0.84	76.64	80.25	EC14	0.90	4.23	18.18

Table 6. The station net radiation validation results

EC5	0.85	-24.41	32.34	EC15	0.84 8.33	23.01
EC6	0.82	4.35	23.44	EC17	0.89 -62.62	68.11
EC7	0.61	-58.66	67.83	GB	0.77 -10.40	38.86
EC8	0.83	-20.62	32.45	SSW	0.44 23.05	62.93
EC9	0.87	-29.60	36.27	SD	0.75 19.98	35.24
EC10	0.83	-24.35	33.51			

The R², MBE and RMSE values of the G in the HRB were 0.57, 8.51 W·m⁻², and 29.73 W·m⁻ 1 2 ², respectively. The station-validated G results are shown in Table 7. At EC5, the soil temperature 3 and moisture were the same at different depths after July 19, which resulted in a surface G that was 4 equal to the G at a depth of 6 cm. G below the surface was usually less than the G at the soil surface; 5 thus, the validation results of G at EC5 indicate that G was overestimated. At SSW, the brief cloudy 6 period decreased the observed soil surface temperature, which decreased the calculated surface G. 7 However, the remotely sensed G did not reflect this situation. In this case, the G was overestimated because the R_n was overestimated. After removing the data on July 27, the R^2 , MBE and RMSE 8 9 values of the G at SSW were 0.17, 19.34 W·m⁻², and 33.30 W·m⁻², respectively.

10

tation R ²		MBE	RMSE	RMSE Station		MBE	RMSE
tation	K²	(W·m ⁻²)	$(W \cdot m^{-2})$	Station	K2	(W·m ⁻²)	(W·m ⁻²)
EC1	0.50	19.73	31.53	EC11	0.71	4.23	19.23
EC2	0.24	20.78	28.72	EC12	0.53	20.29	24.79
EC3	0.03	-1.15	36.28	EC13	0.91	-0.89	17.27
EC4	0.45	18.50	22.29	EC14	0.82	-1.89	18.72
EC5	0.38	41.87	60.19	EC15	0.78	6.68	15.80
EC6	0.83	-5.91	14.57	EC17	0.49	8.26	33.59
EC7	0.28	7.50	24.65	GB	0.29	-17.86	26.81
EC8	0.68	-5.73	20.15	SSW	0.01	30.41	51.87
EC9	0.61	6.83	26.96	SD	0.71	-4.79	13.71
EC10	0.41	7.68	28.67				

Table 7. The station validation results of the soil heat flux

11 4.2. Validation of heat fluxes by TSFA

12 Fig. 6 provides the turbulent heat flux results calculated by TSFA on September 13, 2012. The 13 spatial distribution of the turbulent heat flux is obvious. The H values of buildings and uncultivated 14 land, including land patches in the Gobi region, barren areas and desert areas, were high, in addition 15 to the LEs of water and agricultural areas in the oasis. The southern areas of the images show un-16 cultivated barren land bordering the Qilian Mountains that resulted from snowmelt and the down-17 ward movement of water. In these areas, the groundwater levels are high and the soil moisture con-18 tent is approximately 30% based on *in situ* measurements at a depth of 2 cm. Therefore, the LE 19 values of barren areas in the south are higher than the LE values of desert areas in the southeast, 20 although both areas were classified as uncultivated land.

Studies have shown that validation methods that consider the source area are more appropriate for evaluating ET models than traditional validation methods based on a single pixel (Jia et al., 2012; Song et al., 2012). In this study, a user-friendly tool presented by Neftel et al. (2008), which is based on the Eulerian analytic flux footprint model proposed by Kormann and Meixner (2001) was used

- 1 to calculate the footprints of the function parameters. The continuous footprint function was dis-
- 2 persed based on the relative weights of the pixels in which the source area was located.



3

4 **Figure 6.** Maps of the four energy components, (a) Rn, (b) G, (c) H and (d) LE, calculated by TSFA on September

5 13, 2012.





Figure 7. Scatter plot of the TSFA turbulent heat flux results

8 The footprint validation results of the TSFA turbulent heat fluxes are shown in Fig. 7 and Table 9 8. The R², MBE and RMSE of H were 0.61, 0.90 W·m⁻² and 50.99 W·m⁻², respectively, and those 10 of LE were 0.82, -20.54 W·m⁻² and 71.24 W·m⁻², respectively. Because LE was calculated as a 11 residual term, it was impacted by R_n, surface G and H. The errors of all inputs may contribute to

- 1 the LE, which complicates the error sources of the LE. These errors are discussed in detail in sec-
- 2 tions 4.3.2 and 4.4.

3

Table 8. In situ validation results of heat flux using the TSFA TSFA-H(W·m⁻²) TSFA-LE(W·m⁻²) \mathbb{R}^2 \mathbb{R}^2 Date MBE RMSE MBE RMSE 0619 0.39 44.73 66.38 0.69 -44.15 80.60 0630 23.71 38.96 -63.81 77.83 0.73 0.88 0708 0.55 32.70 58.72 0.85 -43.02 72.32 0.90 -34.34 43.59 0727 0.92 26.74 57.60 0.80 -4.77 -4.58 0803 18.92 0.78 47.86 0815 0.74 -18.37 38.82 0.93 4.75 35.41 0822 0.40 31.64 66.21 0.65 -44.44 93.81 0829 0.79 23.01 38.36 0.79 -50.45 77.99 0902 0.21 -45.10 74.81 0.54 24.39 69.31 0913 0.25 -9.64 41.01 0.59 -59.36 82.77 0914 0.31 -34.11 50.88 0.47 27.99 67.50

As shown in Fig. 7, the majority of the H values are small because June, July, August and 4 5 September constitute the growing season when ET greatly cools the air. The temperature difference 6 between the land surface and air is small, leading to a low H. The points with large H values are 7 influenced by uncultivated land. In our study area, Gobi region, barren area and desert area comprise 8 the uncultivated land. The points in the scatter plot with large H values represent desert, where the 9 H values reach approximately 300 W·m⁻². Some points in the H scatter plot are less than 0 due to 10 inversion from the "oasis effect" or irrigation. For example, the HiWATER soil moisture data show 11 that irrigation occurred on August 22, 2012. Irrigation is the main source of water within the oasis 12 and cools the land surface to temperatures below the air temperature. In addition, irrigation leads to 13 errors in LST retrieval because it increases the atmospheric water vapor content, as discussed in

14 section 4.1. The model error is further analyzed in section 4.4.

15 **4.3. Comparison between TSFA, TRFA and IPUS**

To verify whether the TSFA method can simulate the heterogeneity of the land surface, the TRFA and IPUS methods were also implemented for comparison purposes. These three methods were evaluated using (1) validation of TRFA and IPUS based on *in situ* measurements and (2) quantitative analysis based on the spatial distribution and scatter plots of the four energy balance components.

21 4.3.1. Validation of the TRFA and IPUS heat fluxes

22 Table 9 provides the in situ validation results of H and LE calculated using the IPUS and TRFA 23 methods. Compared to validation results of TSFA in Table 8, the TSFA produced a better retrieval 24 accuracy than the TRFA, and the TRFA was better than the IPUS on all days and the MBE and 25 RMSE values of TSFA decreased and the R² of TSFA increased on most days. Table 9 shows that 26 the improvements in accuracy between TRFA and IPUS were relatively larger than those between 27 TSFA and TRFA. Compared to the IPUS results, the TRFA results were similar to the TSFA results 28 because sub-pixel landscapes and sub-pixel variations of most variables were considered. Thus, 29 TRFA effectively decreased the scale error that resulted from heterogeneity because the 30 m VNIR

1 data were fully used. However, the performance of the TRFA method is unstable. For example, on

2 August 3 and August 29, the TRFA results were slightly worse than the IPUS results. This situation

3 occurred because the different sub-pixel landscape temperatures were considered as equal to the

- 4 values estimated at the 300 m resolution. Thus, when values of LST at 300 m scale have large
 - retrieval errors, the turbulent heat flux retrieval error may be amplified by the sub-pixel landscapes.

	Table 9. In situ validation results of the turbulent heat fluxes of IPUS and TRFA												
	IP	US-H(W	·m ⁻²)	IP	US-LE (W	∕•m ⁻²)	TRFA-H (W·m ⁻²)			TR	TRFA-LE (W·m ⁻²)		
date	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	
0619	0.32	48.53	71.70	0.66	-47.68	86.02	0.39	52.28	70.98	0.65	-46.71	85.93	
0630	0.50	41.45	67.30	0.80	-81.75	102.33	0.69	42.64	60.85	0.86	-78.50	93.98	
0708	0.34	44.17	77.45	0.63	-66.75	118.63	0.44	54.20	76.00	0.82	-63.82	89.11	
0727	0.81	-33.14	50.01	0.83	25.61	74.26	0.84	-23.53	41.76	0.86	14.82	65.21	
0803	0.84	-5.23	33.50	0.74	-3.98	60.49	0.80	7.76	37.51	0.76	-18.23	62.71	
0815	0.64	-23.28	47.89	0.85	10.32	54.98	0.70	-14.77	39.99	0.89	0.59	45.22	
0822	0.31	41.50	74.81	0.61	-53.60	102.12	0.40	40.63	69.94	0.65	-54.17	98.97	
0829	0.72	27.15	44.16	0.76	-54.76	83.20	0.75	30.79	44.97	0.77	-59.43	86.22	
0902	0.28	-52.44	83.25	0.51	32.89	76.48	0.21	-45.77	75.84	0.52	24.37	71.69	
0913	0.08	-11.45	57.50	0.61	-57.38	81.83	0.06	-11.89	49.63	0.54	-57.78	84.58	
0914	0.12	-36.52	67.38	0.28	19.46	89.30	0.03	-34.34	64.85	0.38	25.41	75.96	

7

5

6

Variations in landscape characteristics systematically trigger variations in surface variables. 8 Landscape inhomogeneity can be classified using two conditions: nonlinear vegetation density var-9 iations between sub-pixels (e.g., different types of vegetation mixed with each other or with bare 10 soil) and coarse pixels containing different landscapes (e.g., vegetation or bare soil mixed with buildings or water). To evaluate the effects of TSFA, stations with a typical severe heterogeneous 11 12 surface at EC4, a weak heterogeneous surface at EC11, a typical pixel (called "TP" hereafter) at the 13 boundary of the oasis and bare soil (sample 62, line 102 in the image of study area), and a uniform 14 surface at EC15, were selected to analyze the temperature sharpening results.

15 EC4 is used as an example because its land cover and sub-pixel variations of temperature were 16 complicated. Table 10 compares the turbulent heat fluxes calculated using the IPUS, TRFA and 17 TSFA methods. Significant differences were observed between the TSFA and IPUS results and between the TRFA and IPUS results due to the heterogeneity of the surface. The LE calculated using 18 19 the TSFA method was more consistent with *in situ* measurements than the LE calculated using the 20 IPUS method because the MBE and RMSE decreased considerably, the R² increased, and the accu-21 racy was improved by approximately 40 W·m⁻². However, the LE calculated by the TRFA was more 22 accurate than the LE calculated by the TSFA, as discussed below.

23 The H calculated by using the TSFA method was more accurate than the H calculated by using 24 the TRFA and IPUS methods. The RMSE of the results from the TRFA method was relatively close 25 to the RMSE of the results from the TSFA method because the TRFA method also considers the effects of the heterogeneity of landscapes. In addition, the H values obtained from the TRFA method 26 27 were always greater than those obtained from the TSFA method. Because the TSFA turbulent heat 28 flux results are the same as the TRFA turbulent heat flux results for buildings and water bodies in 29 our pixel ET algorithm, the differences between the TSFA and TRFA results depend on the vegeta-30 tion and bare soil. Additionally, the 300 m resolution LST is larger than the LST of the sub-pixels, 31 such as pixels containing vegetation or bare soil. This relationship occurs for two reasons: (1) the

1 coarse pixels contain buildings and result in a larger 300 m resolution LST and (2) the LSTs were 2 underestimated at EC4 (as shown in Table 3), which would underestimate the value of $\Delta \hat{T}_{300}$ in 3 Eq. (3) and, consequently, the sharpening temperature at 30 m and H. Because the LE was calculated 4 as a residual item in the energy balance equation, the errors of the other three energy balance com-5 ponents accumulate in the LE term. At EC4, the Rn was overestimated by approximately 80 W·m-6 ², as discussed in section 4.1, but the scale effect of R_n was not obvious (see section 4.3.2), and the 7 G was overestimated by approximately 20 W·m⁻². These results decreased the accuracy of the avail-8 able energy and overestimated the error by 60 W·m⁻². Because the TRFA overestimates H, the un-9 derestimation of H in the TSFA would result in larger overestimation of LE than that estimated by 10 the TRFA. Consequently, the LE calculated by using the TSFA method is less accurate than the LE 11 calculated by the TRFA method.

12

Table 10. Comparison of the turbulent heat flux results at EC4

	EC4		H(W	·m ⁻²)		$LE(W \cdot m^{-2})$				
	Date	EC	IPUS	TRFA	TSFA	EC	IPUS	TRFA	TSFA	
	0619	150.65	105.86	154.71	142.13	278.55	402.60	344.05	357.79	
	0630	138.32	99.91	153.53	126.88	341.98	419.83	358.12	386.07	
	0708	117.04	63.47	131.79	112.16	361.16	502.60	424.85	444.01	
	0727	136.41	4.87	85.99	72.33	306.53	543.48	452.01	467.96	
	0803	68.97	36.51	111.73	74.76	389.63	498.21	414.67	454.23	
	5	104.60	12.69	88.26	82.56	357.34	522.31	436.43	441.95	
	0822	125.34	85.93	120.68	93.18	318.08	415.15	370.76	400.99	
	0829	82.93	73.06	103.84	74.76	317.68	362.04	322.77	355.16	
	0902	162.05	93.74	144.49	132.60	280.41	375.42	315.16	326.29	
	0913	119.42	151.44	157.07	130.85	263.18	234.93	222.62	249.59	
	0914	110.02	88.24	128.37	99.33	262.33	333.82	285.04	314.91	
units: W	∕•m ⁻²									

13

		IPUS			TRFA		TSFA		
Variable	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE
EC4-H	0.11	-44.65	61.73	0.25	5.88	26.33	0.51	-16.93	26.54
EC4-LE	0.49	99.21	119.55	0.56	42.69	62.40	0.60	63.92	76.78

14

Fig. 8 shows that the classes and temperatures of 10×10 sub-pixels at 30 m correspond to the 15 pixels with a resolution of 300 m at the EC tower. In the IPUS upscaling scheme, the 300 m pixels included buildings, maize and vegetable crops at the 30 m resolution and were identified as maize. 16 17 The canopy height gap between maize and vegetables was large during our study period, resulting 18 in the overestimation of the canopy height. For additional details, see the error analysis in section 19 4.4. However, because buildings corresponded with $H = 0.6R_n$ in this study, ignoring the contri-20 butions of buildings would result in the underestimation of H. Fig. 8(a) shows the temperature-21 sharpening results in the EC4 pixel on August 29. The temperature retrieved at 300 m scale was 22 303.49 K. Compared with the *in situ* measurement of 313.24 K, the temperature was underestimated 23 at a resolution of 300 m. Even when substituting the *in situ* temperature into the ET model, the value 24 of H reached 399.60 W·m⁻² and the LE became 0 W·m⁻². When substituting the *in situ* temperature into the TRFA method, H was 396.49 W·m⁻² and LE was 18.7 W·m⁻², indicating that the LE was 25 26 underestimated and the H was overestimated with large errors. After processing by temperature 27 sharpening, the distribution of the temperature at the 30 m resolution agreed with the classification.

- 1 Temperature sharpening improved the description of heterogeneity based on the thermodynamic-
- 2 driven force of the turbulent heat flux. These results apply to the ET model based on the classifica-
- 3 tion map and high-resolution inputs and correspond to more accurate sensible heat flux estimates.



4

Figure 8. Distribution of classes and temperatures over (a) EC4, (b) EC15, (c) EC11 and (d) TP on August 29, 2012
The land surface of EC15 was uniform and consisted of pure pixels covering maize fields.
Consequently, the temperature distribution at 30 m resolution was very homogeneous, and the surface temperature variations were comprised within a range of 1.6 K. Table 11 shows the *in situ*

1 validation results at EC15, for which the overall accuracy is not high due to the low LST retrieval

2 accuracy on July 8, which is discussed in section 4.4.1. For homogeneous surfaces, the gaps between

3 IPUS, TRFA and TSFA were not large (within 10 W·m⁻²), and the accuracy did not improve (MBE

4 and RMSE did not exhibit obvious variations). Statistically sharpening the temperature may increase

5 the uncertainty of the model results for homogeneous surfaces; however, this influence could be

6 omitted.

7

Table 11. Comparison of the turbulent heat fluxes results at EC15

		_						
EC15		$H (W \cdot m^{-2}) \qquad \qquad LE (W \cdot m^{-2})$						
Date	EC	IPUS	TRFA	TSFA	EC	IPUS	TRFA	TSFA
0619	92.55	106.60	109.25	99.81	419.47	427.19	419.99	429.98
0630	42.37	43.99	45.51	44.67	551.73	527.12	525.17	526.09
0708	18.34	217.53	235.48	209.90	620.95	425.71	397.49	424.86
0727	27.68	21.22	31.11	24.30	597.76	589.58	579.43	586.47
0803	2.33	33.32	-0.07	0.01	592.37	565.20	601.33	601.33
0815	48.81	32.31	46.28	44.62	553.74	561.92	547.48	549.11
0822	54.59	154.34	151.77	158.60	473.68	408.37	410.80	405.07
0829	9.80	94.97	95.01	90.91	473.54	399.25	398.52	402.93
0913	176.96	265.62	209.65	257.81	307.72	165.40	221.68	173.58
0914	188.34	198.15	197.04	196.60	274.98	275.07	276.05	276.56
-								

8

units	W·m⁻²									
			IPUS			TRFA			TSFA	
	Variable	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE
	EC15-H	0.40	40.64	74.64	0.33	45.93	80.81	0.40	40.36	72.88
	EC15-LE	0.74	-52.11	83.48	0.71	-48.80	82.51	0.74	-49.00	81.94

9

The weak heterogeneous land surface at EC11 contained barley, maize and vegetables in a 300 10 m pixel resolution with a fractional area of 58:41:1 and was classified as barley at the 300 m reso-11 lution. The distributions of the classes and temperatures are shown in Fig. 8(c). The pixel belongs 12 to the first conditions of heterogeneity (nonlinear vegetation density variation between sub-pixels). 13 Table 12 shows the *in situ* validation results of EC11. The improvements in the accuracies of H and 14 LE by temperature resampling or sharpening were not as obvious as the improvements at EC4, 15 which contained totally different landscapes (the other inhomogeneous condition).

16 Theoretically, the LE from the TSFA and TRFA at EC11 should be smaller than the IPUS LE 17 values in the energy balance system. The height of maize (ranges from 0.3 to 2 m) was generally 18 higher than the height of barley (ranges from 0.9 to 1.1 m) in the study area from June to August. 19 Taller vegetation resulted in larger surface roughness and smaller aerodynamic resistance, which 20 led to larger H values and smaller LE values, and vice versa (e.g., vegetables with a canopy height 21 of 0.2 m). When using the TSFA and TRFA methods, patch landscapes consisting of different crops, 22 such as maize and vegetables, were considered. Thus, the LE was smaller than the IPUS LE. On 23 June 19, the canopy height of maize was 0.74 m, which was lower than the canopy height of barley 24 (1 m) and indicated that the H values resulted from the TRFA and TSFA methods were less than H 25 resulted from the IPUS method. Because our validation method considered the influence of source 26 area, the *in situ* turbulent heat flux validation results included the effects of neighboring pixels (i.e., 27 on August 3, the turbulent heat flux values of the pixel corresponding to the location of EC11 was 28 only assigned a weight of 37% in the source area).

1 The differences between the TSFA and TRFA methods were small and resulted from the LST 2 differences between the 30 m resolution temperature-sharpening results and the LST retrieved at the 3 300 m resolution, but these differences were not evident at EC11. For example, on August 29, the 4 temperature range was 1.4 K, as shown in Fig. 8(c). This temperature was even less than the tem-5 perature range at EC15 because the observation system at EC15 was a superstation with a 40 m tall 6 tower that may cause large shadow effects and result in a relative large temperature range. Hence, 7 the temperature sharpening effect is not obvious after aggregating the flux at the 300 m resolution 8 under dense vegetation canopies. However, temperature sharpening can still decrease the heteroge-9 neity that resulted from thermal dynamics.

10 The excess errors at EC11 was caused by the relatively low LST accuracy, with R², MBE and 11 RMSE values of 0.42, 1.59 K and 2.98 K, respectively. On August 29, the temperature retrieved at 12 300 m scale was 301.6 K, and the observed ground temperature was 300.20 K. The LST at the 300 13 m resolution was slightly overestimated. When the in situ temperature was substituted into the IPUS algorithm, the value of H decreased to 16.06 W·m⁻² and LE became 467.43 W·m⁻². When the *in situ* 14 temperature was substituted into the TRFA scheme, the value of H was 22.43 W·m⁻² and the LE was 15 16 461.58 W·m⁻², which were similar to the ground observations.

17

Table 12. Comparison of the turbulent heat flux results at EC11

						at Berr		
EC11		H(W	'·m⁻²)			LE(W	∕•m ⁻²)	
Date	EC	IPUS	TRFA	TSFA	EC	IPUS	TRFA	TSFA
0619	33.94	173.69	158.12	158.18	531.46	391.60	407.42	407.40
0630	25.03	3.29	23.12	21.37	635.22	586.37	566.48	568.28
0708	32.29	68.17	97.16	96.13	601.98	567.73	538.77	539.81
0727	21.42	-1.17	-1.58	-3.77	587.70	618.80	619.19	621.46
0803	7.01	24.85	20.34	19.52	614.28	575.03	585.29	586.16
0815	38.94	12.51	15.52	16.02	567.07	584.31	581.31	580.82
0822	69.25	73.45	83.11	84.38	516.07	483.23	473.60	472.40
0829	29.77	48.21	60.9	60.81	473.22	427.92	415.32	415.45
0902	193.97	154.58	197.01	197.49	306.62	361.96	319.54	319.03
0913	288.37	168.42	176.4	177.71	160.29	216.53	208.49	207.19
0914	240.33	268.91	256.29	256.40	199.52	156.00	168.63	168.55

18 units: W·m⁻²

	IPUS			TRFA			TSFA			
Variable	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	\mathbb{R}^2	MBE	RMSE	
EC11-H	0.61	-1.07	61.31	0.57	-0.36	63.24	0.67	-0.21	55.50	
EC11-LE	0.88	-19.83	63.16	0.89	-18.12	60.02	0.90	-21.29	58.11	

19 Another typical pixel located at the boundary of the bare soil and the oasis with no flux meas-20 urements was used to evaluate the correction effects of landscapes and temperature sharpening. The 21 land surface of the TP contained maize, vegetables and bare soil at a fraction of 35:31:34. Table 13 22 shows that when neither the heterogeneity of the landscape nor the LST are considered, the relative error of LE reached 180 W·m⁻². In addition, if only the LST heterogeneity is not considered, the LE 23 24 relative error reached 48 W·m⁻². This result also reveals that the influences of landscape inhomoge-25 neity are greater than the influences of inhomogeneity on the LST in mixed pixels. 26 Та

abl	e 13.	Com	parison	of the	turbulent	heat	flux	results	at	ΤI
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H (W⋅m ⁻²)	LE (W·m ⁻²)

Date	IP	US	TRFA	TSFA	IPUS	TRFA	TSFA
0619	18	6.31	149.73	143.98	321.04	358.22	364.79
0630	38	3.65	191.59	158.79	67.03	259.36	292.89
0708	49	8.36	240.20	204.18	0.29	259.25	293.41
0727	27	6.79	136.06	84.01	206.52	347.64	402.23
0803	21	4.14	75.45	53.72	252.37	392.08	416.41
0815	21	4.14	98.24	72.05	252.37	368.64	393.68
0822	43	6.48	369.28	276.70	0.00	67.79	162.80
0829	23	5.29	117.16	67.21	183.62	302.41	356.75
0902	42	3.61	212.15	180.92	0.00	211.77	241.36
0913	33	8.00	285.04	216.26	0.00	53.62	122.58
0914	27	0.44	148.20	100.19	115.19	238.43	286.51
			IPUS	5		TRFA	
Varia	ble	\mathbb{R}^2	MBE	RMSE	R ²	MBE	RMSE
TP-I	H	0.62	174.47	185.49	0.95	42.28	48.01
TP-L	E	0.71	-175.91	186.63	0.97	-43.11	49.04

units: W·m⁻²

1

2 **4.3.2.** Comparison of the TRFA and IPUS methods

Using data of September 13 as an example, the spatial distributions of the four components of the energy balance calculated by the IPUS and TRFA methods are shown in Fig. 9 and Fig. 10, respectively. TSFA minus IPUS and TSFA minus TRFA, which display the spatial distributions of the scale effect, are shown in Fig. 11. Scatterplots of TSFA versus IPUS and TRFA are shown in Fig. 12.

8 A comparison of Fig. 6 with Fig. 9 shows that the spatial distributions of the fluxes greatly 9 change, except for R_n. The TSFA results are synoptically smoother than the IPUS results because 10 the land cover types and temperature distributions in mixed pixels are not considered in IPUS. For 11 example, the boundary between the oasis and uncultivated land becomes a belt of intermediate G, 12 H and LE because these mixed pixels include uncultivated land and vegetation. However, mixed 13 pixels are classified as the dominant land use type in the parameterization process of IPUS. This 14 result overlooks the contributions of heat flux from complex land use types and overestimates or underestimates the turbulent heat flux by approximately 50 W·m⁻². Since the TSFA can integrate the 15 effects of these land areas and reveals the relative actual surface conditions, the heat flux results of 16 17 TSFA vary less dramatically than those of IPUS, as shown in the figures. The results are similar in 18 the oasis area.

19 Based on Fig. 6 and Fig. 10, the TRFA and TSFA methods are similar. Because the TRFA 20 method considers the sub-pixel landscapes that could be significant source of error in the ET models, 21 the difference between the TSFA and TRFA methods is mainly resulted from the differences between 22 the sharpened LST and retrieved, resampled LST of sub-pixels at the 30 m resolution. In addition, 23 the bias between the TSFA and TRFA is not as obvious as the bias between the TSFA and IPUS 24 methods, as shown in Fig. 11(c)-(f). Furthermore, Fig. 11(f) shows that the LEs calculated by using 25 the TSFA method in most oasis areas were slightly greater than the LEs calculated by using the 26 TRFA method, which yielded values of approximately 20 W·m⁻².

27 The quadrangular with a relatively unstable bias shown in Fig. 11(a) is caused by the L_d that

- 1 was calculated from the MOD05 water vapor product which exists quadrangular even after prepro-
- 2 cessing the instrument malfunction gap. In Fig. 11, the differences of the four energy components
- 3 of the pure pixels between these three methods are within 5 $W \cdot m^{-2}$, and the mixed pixels have dif-
- 4 ferent ranges.



5

⁷ on September 13, 2012



1

 $2 \qquad \mbox{Figure 10. Maps of the four energy components, (a) } R_n, (b) G, (c) H and (d) LE, calculated using the TRFA method$

3 on September 13, 2012



1

2 Figure 11. Maps of the bias of the energy balance components calculated using the TSFA method minus the IPUS

3 method: (a) R_n , (b) G, (c) H, (d) LE, and TSFA minus TRFA: (e) H and (f) LE





Figure 12. Scatter plots between the TSFA and IPUS results: (a) R_n, (b) G, (c) H and (d) LE; and TSFA and TRFA
results: (e) R_n, (f) G, (g) H and (h) LE. MBD and RMSD are the mean bias deviation and root mean square deviation
between the TSFA and IPUS results, respectively



Fig. 12 shows the scatter plots between the results of the TSFA method and the other two

1 methods for all four energy balance components. Fig. 11(a)(e) shows that R_n does not vary much 2 between the three methods and the scatter is centralized around the 1:1 line. However, regarding the 3 spatial scale effect, the differences in G, H and LE calculated by using the IPUS and TSFA meth-4 ods are obvious. The scatter plots disperse at the mixed pixels, and the differences between the 5 TRFA and TSFA results are relatively smaller. When using the TSFA method, the temperature sharp-6 ening results can be divided into results that are higher and lower than the LST retrieved at 300 m. 7 Compared to the LST retrieved at 300 m when using the TRFA method, a higher LST is counterbal-8 anced by a lower LST when calculating H using the TSFA. Thus, the effect of temperature hetero-9 geneity is neutralized in this case. This observation is potentially resulted from the temperature-10 sharpening algorithms because they tend to overestimate the sub-pixel LST for cooler landscapes 11 and underestimate the sub-pixel LST for warmer areas in the image (Kustas et al., 2003).

However, LE is calculated as a residual; thus, the difference of LE is resulted from G and H. When the 300 m mixed pixels contained various types of landcapes, they were categorized as one type of landscape in the IPUS method and a single temperature value was used to evaluate the thermal dynamic effects when using the TRFA method. Pixels with highly different G, H and LE values are mainly distributed near the mixed pixels, as shown in Fig. 10. An explanation for these deviations is provided below.

The parameterization of G and H are based on the land cover type. For example, for buildings, $G = 0.4R_n$ (Kato and Yamaguchi, 2005) (which is usually greater than the G of vegetation and bare soil deduced from Eq.(9)) and $H = 0.6R_n$, and for water, $G = 0.226R_n$ and $LE = R_n -$ G. From the land cover map shown in Fig. 4, four major classes exist in the study area: buildings with a high H, uncultivated land with a relatively high H, cropland with a relatively low H, and water with H = 0.

24 (1) If a pixel contains cropland and buildings and is categorized as cropland, the building area 25 within the pixel is ignored in the IPUS method. In this case, G and H are underestimated and LE 26 is overestimated. In addition, after considering the landscapes using the TRFA method, the LE is 27 underestimated and H is overestimated because the pixels contain buildings that are still reflected 28 indistinctly by LST at 300 m because the detailed temperature heterogeneity cannot be represented 29 by the TRFA method. These points are shown in green in Fig. 11. However, if the pixel is categorized 30 as built-up, the building area within a pixel is exaggerated, which causes G and H to be overesti-31 mated and LE to be underestimated when using the IPUS method. This situation is similar to that 32 illustrated by the green points associated with the TRFA results and is shown by the red points in 33 Fig. 11.

34 (2) At the boundary of the oasis and uncultivated land, the mixed pixels are divided into 35 cropland, LE is overestimated, G and H are underestimated in the IPUS method, and vice versa. 36 LE is also overestimated in the pixels containing water and other types of land cover (generally 37 bare soil in our study area). These pixels are categorized as water and are shown as blue points in 38 Fig. 11. Some of the blue LE points calculated by using the TSFA method are slightly smaller than 39 those calculated using the TRFA method for pixels containing vegetation. At noon, the temperature 40 of vegetation in those pixels is lower than that of water bodies.

(3) In mixed pixels that contain various crops, such as maize and vegetables, LE is underestimated if the area of maize within the pixel is overestimated because the canopy height of the maize
is taller than that of vegetables. This relationship results in the overestimation of H when using the
IPUS and TRFA methods. In addition, G depends on the FVC values of the crops when using the

1 IPUS method. Moreover, G depends on R_n when using the TRFA method and is nearly identical 2 to the values of G obtained using the TSFA method.

3 At the study area, we compared the TRFA and IPUS methods to quantify the ability of the 4 TSFA method to simulate the heterogeneities of the land surface on September 13 (see Table 14). In 5 pure pixels, the LE biases among the IPUS, TRFA and TSFA methods were small. In mixed pixels, 6 the LE bias between the TSFA and IPUS methods varied from 35.36 to 65.66 W·m⁻², and the bias 7 between the TSFA and TRFA methods varied from 4.41 to 22.53 W·m⁻². More class types in mixed 8 pixels correspond to larger biases. Table 15 shows the bias of the mixed pixels that contain buildings 9 and bare soil between the three methods. In mixed pixels with buildings, the IPUS and TRFA meth-10 ods generally underestimated LE and had large bias values compared to those of the TSFA method. 11 In mixed pixels without buildings and bare soil, the bias between TRFA (or IPUS) and TSFA was 12 relatively small, which indicates that the landscape and temperature inhomogeneity were accounted 13 for by the TSFA method. The aforementioned analyses demonstrate that the TSFA method can con-14 sider the heterogeneous effects of mixed pixels.

15

Number of class	IPUS (W·m ⁻²)			Т	Pixel		
types in pixels	\mathbb{R}^2	MBD	RMSD	\mathbb{R}^2	MBD	RMSD	number
1	1.00	0.21	0.21	1.00	0.05	0.61	11,398
2	0.85	-7.18	35.36	1.00	-0.35	4.41	8212
3	0.66	-2.32	52.55	0.98	-7.33	12.56	4762
4	0.49	1.88	65.66	0.96	-11.56	16.55	2824
5	0.98	-30.92	62.69	0.96	-16.90	22.53	4

Table 14. Comparison of the latent heat flux in pixels containing different numbers of class types

16 Notes: The number of class types in mixed pixels represents the number of classification types that were contained in the pixels. For example, 1 represents the pure pixels, 2 represents mixed pixels containing two land use types, etc. MBD and RMSD are the mean bias deviation and root mean square deviation, respectively, between the

- 19 TSFA results and the TRFA and IPUS results.
- 20

 Table 15. Comparison of the latent heat fluxes of typical mixed pixels

Types of mixed pixels		IPUS (W·m ⁻²)			TRFA (W⋅m ⁻²)			
		MBD	RMSD	\mathbb{R}^2	MBD	RMSD	number	
Mixed pixels containing buildings	0.58	-1.02	61.94	0.97	-9.64	14.66	4918	
Mixed pixels do not containing buildings	0.81	-5.49	39.21	0.99	-2.12	7.60	10,884	
Mixed pixels containing bare soil	0.73	-1.52	49.04	0.98	-5.96	11.86	9049	
Mixed pixels do not containing bare soil	0.65	-7.55	45.28	0.98	-2.46	7.83	6753	

Considering the landscapes and inhomogeneous distribution of LST, the TSFA method ensures that none of the end members (30 m pixel) are ignored or exaggerated. Thus, the distribution of LE calculated using the TSFA method is smoother and more rational than the distributions of LE calculated using the other methods. At the regional scale, the TSFA method describes the heterogeneity of the land surface more precisely. The degree of achievable estimation accuracy is discussed hereafter.

27 **4.4. Error analysis**

Since LE is calculated as a residual term in the energy balance equations, the sensitivity of H was analyzed first. Land surface variables (including LST, LAI, canopy height, and FVC) and me-teorological variables including wind speed, air temperature, air pressure and relative humidity are

- the major factors for H sensitive analysis. Fig. 13 presents a case of sensitivity analysis results for
 H. In this case, LST is 303.9 K, and it ranges from 298.4~309.4 K with a step size of 0.5 K, LAI is
 set to 1.4 and it ranges from 0.14~2.66 with a step size of 0.14. Canopy height is 1 m and it ranges
 from 0.1~1.9 m with a step size of 0.1 m. Additionally, FVC=0.5, wind speed u=2.48 m·s⁻¹, air
- 5 temperature Ta=297.9 K, air pressure = 97.2 kPa, and RH=40.29%. In addition, the land cover is
- 6 maize, and the reference H is $230.2 \text{ W} \cdot \text{m}^{-2}$.



7 8

Figure 13. Sensitivity analysis of the surface variables for sensible heat flux

9 The air pressure is stable over a short period and has little effect on the ET results. Although 10 "excess resistance" was calculated from the friction velocity, the meteorological data were provided 11 by ground observations; thus, the meteorological data are relatively accurate. As shown in Fig. 13, 12 LAI, canopy height and LST are sensitive variables.

The parameterization of the momentum roughness length indicates that H is sensitive to LAI, with decreasing sensitivity when the LAI is greater than 1. When the LAI is less than 1, the momentum roughness length increases as the LAI increases, and turbulent exchange are enhanced. However, when the LAI is greater than 1, the plant canopy is regarded as a continuum that is not a sensitive variable. Because our study area is dominated by agriculture and the study period extended from July to September, the crops in the HRB middle stream grew quickly, thus, the LAI was usually greater than 1. Thus, LST and canopy height are the main sources of error.

20 **4.4.1. Errors in LST**

As shown in Fig. 13, 1 K LST bias would result in 21% error of H while H is 230.2 W·m⁻². However, the sensitivity of the LST is unstable and depends on the strength of the turbulence. The strength of the turbulence determines the mass and energy transport and the resistance of heat transfer, which influences the sensitivity to the LST. A weaker turbulence corresponds to a weaker LST sensitivity, and vice versa.

26 A sensitivity analysis of LE induced by LST was also performed. In order to exclude the influ-27 ence of other factors, stations were chosen with homogeneous landscapes within coarse pixels. 28 These results are shown in Table 16. The LE results obtained from the observed LST are consistent 29 with the *in situ* observations and have less bias. LE was overestimated when the LST was underes-30 timated, and vice versa. Because the magnitude of LE was greater than that of H, the relative error of LE was less than the relative error of H. However, 1 K of LST bias resulted in an average LE 31 error of 30 W·m⁻², which is consistent with the sensitivity analysis of H shown in Fig. 13. Specifi-32 33 cally, 1 K of LST bias would resulted in an LE biases of 8.7 W·m⁻² (in desert, SSW) to 84.4 W·m⁻² 34 (in oasis, EC8), which indicates that the sensitivity of LST is unstable.

35 **Table 16.** Th

Table 16. The results of the LST error analyses at the stations with homogeneous landscapes

Station	Date	Re- trieved	Ob- served	LST bias	EC-LE (W·m ⁻²)	LE from retrieved LST	LE from observed LST	LE relative error	H relative error
		LST (K)	LST (K)	(K)		(W·m ⁻²)	(W·m ⁻²)	(%)	(%)
EC8	0619	304.92	301.74	3.18	415.89	321.80	399.78	-22.62	68.58
EC7	0630	302.5	299.35	3.15	611.22	453.59	557.97	-25.79	886.08
EC10	0708	303.58	300.5	3.08	617.83	504.44	549.53	-18.35	390.24
EC15	0708	303.55	300.13	3.42	620.95	425.71	603.73	-31.44	450.57
EC7	0727	298.87	300.55	-1.68	577.59	643.56	566.62	11.42	-132.47
SSW	0727	307.86	316.82	-8.96	119.35	238.07	78.43	99.48	-60.36
EC8	0822	299.58	297.77	1.81	543.56	416.23	467.42	-23.42	88.59
EC10	0822	301.61	298.04	3.57	503.82	398.82	513.67	-20.84	138.61
EC15	0822	300.59	297.69	2.9	473.68	408.37	495.49	-13.79	129.60
EC8	0829	301.54	300.44	1.1	514.31	402.93	428.78	-21.66	63.91
EC15	0829	301.41	299.84	1.57	473.54	399.25	459.66	-15.69	182.34
SSW	0902	304.9	303.42	1.48	226.88	127.96	149.83	-43.60	11.36

1 Notes: "LST bias" is calculated as the retrieved LST minus the observed LST; "EC-LE" is the *in situ* latent heat flux;

2 "LE relative error" is the relative error between the retrieved and observed LST and is expressed as ((LE from

retrieved LST)-(LE from observed LST))/(LE from observed LST)×100% and "H relative error" is calculated in the
 same way.

5 **4.4.2. Errors in canopy height**

18

6 In this paper, canopy height was obtained from a phenophase and classification map. Thus, the 7 accuracy of the canopy height was mainly dependent on the classification accuracy and plant growth 8 state. Even within the same region, the canopy height of a crop can differ due to differences in 9 seeding times and soil attributes, such as soil moisture and fertilization.

10 The land use type was orchard at EC17. However, in our land classification map, the land use 11 at EC17 was other crops, which includes vegetables and orchards. Thus, it was difficult to set the 12 canopy height. In our study area, most of the other crops were vegetables (canopy height of 0.2 m), 13 and the height of the orchard was approximately 4 m; thus, a value of 0.2 m would overestimate the 14 LE. The LE estimations with incorrect canopy heights and correct orchard canopy height at EC17 15 are shown in Table 17. The days of large LST bias were removed, and the bias between the model 16 and ground observations decreased. The excess errors were caused by errors in the LST and land 17 use, such as buildings and maize in the mixed pixels.

	Table 17. The results of the earlopy height erfor analyses at ECT7						
Data	EC-LE	LE from incorrect	LE-I relative	LE from correct	LE-C relative		
Date	(W·m ⁻²)	canopy height (W·m ⁻²)	error (%)	canopy height (W·m ⁻²)	error (%)		
20120815	499.62	562.06	12.50	521.83	4.45		
20120822	366.27	519.01	41.70	396.54	8.26		
20120902	377.96	471.68	24.80	336.52	-10.96		
20120914	465.38	352.78	-24.20	258.07	-44.55		

Table 17. The results of the canopy height error analyses at EC17

19 Notes: "LE-I relative error" is the relative error between the LE from incorrect canopy height and observed LE and

20 is expressed as ((LE from incorrect canopy height)-(EC-LE))/(EC-LE)×100%, "LE-C relative error" is the relative

- 1 error between the LE from correct canopy height and observed LE and is expressed as ((LE from correct canopy
- 2 height)-(EC-LE))/(EC-LE)×100%.

cially subjective interpretation.

- 3 Except for the error source discussed previously, the following sources of error were unavoid-4 able:
- 5 (1) Although the remotely sensed turbulent heat flux is instantaneous, the EC data are averaged 6 over time. Thus, the time scales do not match in the validation.

7 (2) The calibration coefficients of the HJ-1B satellite's CCD and IRS drifts because of instru-8 ments aging.

(3) Geometric correction causes half-pixel bias equal to or less than the deviation of the artifi-

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11 A one-source model and simplified parameterization schemes were used in this paper to deter-12 mining surface roughness lengths and heat transfer coefficients. The one-source model combines 13 soil evaporation and plant transpiration and assumes that SPAC is a one-source continuum. This 14 assumption is reasonable when the surface is densely covered by vegetation but relies on the accu-15 racy of the difference between the LST and air temperature, as previously mentioned. When a one-16 source model is applied to an area covered by sparse vegetation, such as semi-arid or arid areas, this 17 assumption is irrational.

5. Discussions 18

19 The TSFA describes the surface heterogeneity much better than the IPUS and TRFA. The IPUS 20 aggregates the land surface variables from 30 m to 300 m, which results in the loss of land surface 21 details and leads to the scale effects. Although the TRFA uses 30 m information from VNIR bands 22 and partially decreases the heterogeneity, it treats the pivotal variable LST as homogeneous at 300 23 m resolution, which results in considerable error. In summary, the advantages of the TSFA method 24 are described as follows:

25 (1) The temperature sharpening algorithm in TSFA is capable of decreasing the influences of 26 the heterogeneity of the LST, which is consistent with results from previous studies (Kustas et al., 27 2003; Bayala and Rivas, 2014; Mukherjee et al., 2014). As analyzed in section 4.3, the non-consid-28 eration of the heterogeneity of LST in mixed pixels is ill-founded and causes errors when estimating 29 ET.

30 (2) In the one-source energy balance model, different parameterization schemes were em-31 ployed for different landscapes. In the IPUS, a single land cover is assigned to a mixed pixel, which 32 results in a large error. However, the TSFA method is used to calculate the surface flux at 30 m and 33 is aggregated to 300 m using the area-weighting method, which considers all of the sub-pixel land-34 scapes and improves the accuracy.

35 Some problems exist in the temperature-sharpening algorithms. The temperature-downscaling 36 method used in this paper caused "boxy" anomalies in parts of the sharpened temperature fields in large pixels because of the constant residual term, $\Delta \hat{T}_{300}$, in Eq. (3) within large pixels. This situa-37 tion also occurred in the temperature-sharpening algorithm proposed by Agam et al. (2007). In ad-38 39 dition, our temperature sharpening algorithm tends to overestimate the sub-pixel LST for cooler 40 landscapes and underestimate the sub-pixel LST for warmer areas (Kustas et al., 2003). This inac-41 curate estimation causes errors that are difficult to evaluate when estimating the turbulent heat flux. 42 For example, the small turbulent heat flux bias between TSFA and TRFA was caused by a counter-43 balancing effect as analyzed in section 4.3.1. Additional temperature sharpening algorithms under

heterogeneous surfaces should be evaluated using real datasets when applied in ET models (Ha et
 al., 2011).

The retrieval methods of land surface variables were validated against in other areas. For example, the albedo algorithm was previously applied to retrieve Global Land Surface Satellite (GLASS) Products (Liang et al., 2014), the LST retrieval algorithm was validated in the Haihe River Basin in northern China (Li et al., 2011a), and the soil heat flux correction algorithm was validated in the GAME-Tibet campaign (Yang and Wang, 2008). Since the surface of the Heihe River Basin si very heterogeneous, additional comparisons of our algorithm in other areas would be helpful.

9 In addition, to correct the discrepancy between remotely sensed radiative surface temperature 10 and aerodynamic temperature at the source of heat transport, a brief and well performed parameter-11 ization scheme (under uniformly flat plant surface) of "excess" resistance was used to calculate the 12 aerodynamic resistance of heat transfer (Jiao et al., 2014). Since our study is based on mixed pixels, 13 multiple parameterization methods should be compared to select the optimum method.

14 Because of the sensitive variables of the one-source energy balance model used in this paper, 15 the accuracies of the LST and canopy height greatly influenced the turbulent heat flux. HJ-1B IRS 16 has a single-thermal channel, and the single-channel LST-retrieving algorithm may be unstable un-17 der wet atmospheric conditions (water vapor contents higher than 3 g/cm²) (Li et al., 2010a), which 18 may create a bottleneck for ET estimations by HJ-1B. The canopy height is a priori knowledge 19 based on phenophase classifications and would influence the accuracy of the surface roughness 20 calculation. Multi-source remote sensing data could be used to improve the accuracy of calibrations 21 and land surface variable estimation. Active microwave and LiDAR data (Colin and Faivre, 2010) 22 could be used to obtain the canopy height, which would decrease the dependence on the accuracy 23 of the classification.

24 The energy balance closure has a significant influence on the evaluation of the model calcu-25 lated heat flux results. In our study area, the EC energy balance closure ratio was greater than 0.75 26 (Liu et al., 2011b). Studies have shown that not-captured low-frequency eddies (Von Randow et al., 27 2008), extension of averaging time (Charuchittipan et al., 2014) and lack of an accurate accounting 28 of heat storage terms (Meyers and Hollinger, 2004) are potential reasons for the energy imbalance 29 and so forth. The conserving Bowen ratio and residual closure technique are often used to force 30 energy balance. We chose the residual closure method at last because the conserving Bowen ratio 31 method yields irrational sensible heat flux due to small or negative Bowen ratios (large LEs due to 32 the "oasis effect") in the oasis-desert system. Energy balance closure was problematic at times for 33 turbulent flux system and tended to be associated with significant discrepancies in LE (Prueger et 34 al., 2005).

Since a footprint model was used in the validation, the footprints discrepancies between *in situ* measurements and remote sensing pixel may cause biases. For example, model validation results were calculated based on the relative weights of the footprint model and multiplied by the heat flux results of the coarse pixels in the source area from the upwind direction. However, the heat fluxes of coarse pixels included the contributions of non-overlapped sub-pixels within the coarse pixel. These pixels are influenced by the heterogeneity of underlying surface, it would cause uncertainties in the validation.

42 **6.** Conclusion

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The effects of surface heterogeneity in ET estimation have been studied here by employing the

IPUS, TRFA and TSFA methods over heterogeneous surface. Compared to the IPUS and TRFA 1 2 methods, the TSFA method exhibits more consistent agreement with *in situ* measurements (energy 3 balance forced by the residual closure method) based on the footprint validation results. The IPUS 4 approach does not consider surface heterogeneity at all, which causes significant error in the heat 5 fluxes (i.e., 186 W·m⁻²). The TRFA considers heterogeneity of landscapes besides LST heterogene-6 ity, with a heat flux error (i.e., 49 $W \cdot m^{-2}$) that is less than that of IPUS. However, this error is non-7 negligible. As a sensitive variable of the ET model, canopy height is mainly determined by classifi-8 cation, and the application of classification at a 30 m resolution can improve the accuracy of the 9 canopy height. Additionally, the sharpened surface temperature at a resolution of 30 m decreases 10 the thermodynamic uncertainty caused by the land surface. The TSFA method can capture the het-11 erogeneities of the land surface and integrate the effects of landscapes in mixed pixels that are ne-12 glected at coarse spatial resolutions.

HJ-1B satellite data have advantages because of their high spatiotemporal resolution and free
 access. Because the satellites are still in operation, the long-term data are promising for applications
 of monitoring energy budgets.

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26 Appendix

Notation		Application
Notation		(for calculating)
6S radiation	Second Simulation of a Satellite Signal in the Solar Spectrum	
transfer mode	radiation transfer mode	Albedo, S _d
α	Surface broadband albedo	S _d , R _n
ABT	At-nadir brightness temperature (K)	L_d
AMS	Automatic meteorological station	
AOD	Aerosol optical depth	S _d
BRDF	Bidirectional reflectance distribution function	α
CCD	Charge-coupled device	
CV	Coefficient of variation	Sharpened LST
EC	Eddy covariance	
FVC	Fractional vegetation coverage	LSE, G, LAI
G	Soil heat flux (W·m ⁻²)	
$G(\theta)$	G function, Foliage angle distribution	LAI
Н	Sensible heat flux (W·m ⁻²)	

HRB	The Heihe River Basin	
IPUS	Input parameter upscaling scheme	
IRS	Infrared scanner	
L _d	Downward atmospheric longwave radiation (W·m ⁻²)	R _n
LSE/ϵ	Land surface emissivity	LST
ϵ_v/ϵ_g	The vegetation/ground emissivity	
LST/T _{rad}	Land surface temperature/Surface radiation temperature (K)	Н
MBE/MBD	Mean bias error (deviation)	
NCEP	National Centers for Environmental Prediction	LST
NDVI/NDVI ₃₀	Normalized difference vegetation index	FVC, Sharpened LST
NDVI300	300 m NDVI aggregated from NDVI	Sharpened LST
NDVI _s /NDVI _v	Normalized difference vegetation index of bare soil/fully cov-	FVC
	ered vegetation	
$P(\theta)$	Angular distribution of the canopy gap fraction	LAI
r _a	Aerodynamic resistance (s·m ⁻¹)	Н
r _{ex}	"Excess" resistance (s·m ⁻¹)	heat transfer resistance
R _n	Net radiation (W·m ⁻²)	
RMSE/RMSD	Root mean square error (deviation)	
S _d	Downward shortwave radiation (W·m ⁻²)	R _n
SPAC	The soil-plant-atmosphere continuum	
SZA	Solar zenith angle	S _d
T _a	Air temperature (K)	Н
	Aerodynamic surface temperature obtained by extrapolating the	Н
T _{aero}	logarithmic air-temperature profile to the roughness length for	
	heat transport (K)	
TOA	Top of the atmosphere	
TOMS	Total ozone mapping spectrometer	S _d
TRFA	Temperature resampling and flux aggregation	
TSFA	Temperature sharpening and flux aggregation	
ULR	Upward longwave radiation (W·m ⁻²)	R _n
USR	Upward shortwave radiation (W·m ⁻²)	R _n
VNIR	Visible/near-infrared	
VZA/θ	View zenith angle	L _d , LAI

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