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1    **Response to the Referee**

2    We thank the reviewer for the comments. Below are our responses (in **blue** font) to the review's  
3    comments (in **black** font).

4

5    **Anonymous Referee**

6    I think the authors have done a very good job in addressing almost all of the reviewer comments  
7    and have significantly approved the manuscript!

8    Before final acceptance however, I would still like to see 2 topics addressed in the discussion  
9    and conclusion part of manuscript that are essential when comparing ground observed fluxes  
10   and RS derived fluxes: a) the different footprints of measurements and RS, and b) the non-  
11   closure of the measured energy balance and their correction. Both aspects might have a signif-  
12   icant impact on possible differences and biases - and should at least be taken into consideration  
13   in the evaluation of the results.

14   **Response:** Thank you for your suggestion. We added some discussion about the two topics in the  
15   discussion, following as:

16   **a) The different footprints of measurements and RS.**

17   Since a footprint model was used in the validation, the footprints discrepancy between in situ  
18   measurements and remote sensing pixel may cause biases. For example, model validation results  
19   were calculated by the relative weights of the footprint model, and multiply heat flux results of the  
20   coarse pixels which were covered by source area from upwind direction. However, the heat fluxes  
21   of coarse pixels included the contribution of not-overlapped sub-pixels within the coarse pixel. In-  
22   fluenced by the heterogeneity of underlying surface, it would cause uncertainties in the validation.

23   **b) The non-closure of the measured energy balance and their correction.**

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

34

35   **Reference:**

36   Charuchittipan, D., Babel, W., Mauder, M., Leps, J.-P., and Foken, T.: Extension of the Aver-  
37   aging Time in Eddy-Covariance Measurements and Its Effect on the Energy Balance Closure,  
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43   ance of maize and soybean, *Agricultural and Forest Meteorology*, 125, 105-115,  
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2 Pherson, J. I., Eichinger, W. E., and Cooper, D. I.: Tower and Aircraft Eddy Covariance Measure-  
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7 tural and Forest Meteorology*, 148, 680-690, <http://dx.doi.org/10.1016/j.agrformet.2007.11.011>,  
8 2008.

9 **Relevant Changes**

10 All the changes were marked as **navy blue** color in the manuscript.

11 1. We have added two topics: a) the footprint discrepancy between measurements and remote sens-

12 ing, and b) the non-closure of the measured energy balance and their correction in the discussion.

13 2. New references were added.

14

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# 1      **Remote-sensing algorithm for surface evapotranspiration**

## 2      **considering landscape and statistical effects on mixed-pixels**

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### 8      **Abstract**

9      Evapotranspiration (ET) plays an important role in surface-atmosphere interactions and can be  
10     monitored using remote sensing data. However, surface heterogeneity including inhomogeneity of  
11     landscapes and surface variables affects the accuracy of ET estimated from satellite data signifi-  
12     cantly. The objective of this study is to assess and reduce the uncertainties resulted from surface  
13     heterogeneity in remotely sensed ET using Chinese HJ-1B satellite data, which is of 30m spatial  
14     resolution in VIS/NIR bands and 300m spatial resolution in 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. Two methods employing different upscaling policies of surface variables and fluxes  
17     were used to compare with TSFA, i.e., IPUS (input parameter upscaling) and TRFA (temperature  
18     resampling and flux aggregation). Moreover, the three methods can also be regarded as representing  
19     three typical schemes handling mixed pixels from the simplest to the most complex, i.e., all surface  
20     variables are at coarse resolution (300 m in this study) in IPUS and fine resolution (30 m in this  
21     study) in TSFA, while TRFA is in the middle (both 30m and 300m variables are used). Analysis and  
22     comparison between them can help us to get better understandings about spatial scale errors in re-  
23     mote sensing of surface heat fluxes. In situ data collected during HiWATER-MUSOEXE (Multi-  
24     Scale Observation Experiment on Evapotranspiration over heterogeneous land surfaces of The  
25     Heihe Watershed Allied Telemetry Experimental Research) were used for the validation and analy-  
26     sis of the methods. ET estimated by TSFA is of best agreement with in-situ observations, the foot-  
27     print validation results show that the  $R^2$ , MBE, and RMSE of the sensible heat flux (H) were 0.61,  
28      $0.90 \text{ W}\cdot\text{m}^{-2}$  and  $50.99 \text{ W}\cdot\text{m}^{-2}$ , respectively, and the corresponding terms for the latent heat flux (LE)  
29     were 0.82,  $-20.54 \text{ W}\cdot\text{m}^{-2}$  and  $71.24 \text{ W}\cdot\text{m}^{-2}$ , respectively, and IPUS showed the largest errors in ET  
30     estimation. The RMSE of LE between the TSFA and IPUS methods was  $51.30 \text{ W}\cdot\text{m}^{-2}$ , and the  
31     RMSE of LE between the TSFA and TRFA methods was  $16.48 \text{ W}\cdot\text{m}^{-2}$ . Furthermore, additional  
32     analysis shows that the TSFA method can capture the sub-pixel variations of land surface tempera-  
33     ture and integrate the effects of overlooked landscapes in mixed pixels.

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

### 36      **1. Introduction**

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

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

17 All these ET estimation models are usually developed for simple and homogeneous surface  
18 conditions. When these remotely sensed models are applied to calculate the regional ET via satellite  
19 data, large spatial scale errors occur. **Because heterogeneity is a natural attribute of the Earth's surface**,  
20 non-linear operational model is another important issue of remotely sensed spatial scale error.  
21 However, it is difficult to develop linear operational models due to the complexity of mass and heat  
22 transfer processes between the atmosphere and land surface.

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

32 Studies have shown that different landscapes (Blyth and Harding, 1995; Moran et al., 1997;  
33 Bonan et al., 2002; McCabe and Wood, 2006) and the sub-pixel variations of surface variables, such as  
34 stomatal conductance (Bin and Roni, 1994), leaf area index (Bonan et al., 1993; Maayar and Chen, 2006)  
35 can cause errors in turbulent heat flux estimations. Surface variables inhomogeneity is rather difficult  
36 to evaluate as the sub-pixel variation of surface variables could be large even in the pure pixel. For example,  
37 generally, temperatures over the land surfaces vary strongly in space and time, and it is not unusual for the LST  
38 to vary by more than 10 K over just a few centimeters of distance or by more than 1 K in less than a minute over certain cover types (Z. Li et al., 2013). But in mixed pixels, surface variables such as land surface temperature are set as singular to represent  
39 the entire pixel area in ET estimation models.

40 The focus of this study is on the effects of surface heterogeneity when estimating ET. According  
41 to the current satellites operation situation, three methods were used to analyze the uncertainty

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1 produced by surface heterogeneity. Input parameter upscaling (IPUS) does not consider the surface  
2 heterogeneities at all. It was designed to simulate the satellites that have identical spatial resolution  
3 both in visible near-infrared (VNIR) and thermal infrared bands (TIR), such as the land surface  
4 products of Moderate-Resolution Imaging Spectroradiometer (MODIS) satellites. Temperature  
5 resampling and flux aggregation (TRFA) only does not consider the heterogeneity of LST, and tem-  
6 perature sharpening and flux aggregation (TSFA) consider all the surface heterogeneities. They  
7 were designed for the majority of satellites data or products that have inconsistent spatial resolution  
8 between VNIR and TIR, such as Landsat and HJ-1B satellites.

9 Surface variables in this paper mainly derived from HJ-1B satellite data were used for this  
10 purpose. The Chinese HJ-1A/B satellites were launched on September 6, 2008, and were designed  
11 for disaster and environmental monitoring, as well as other applications. The HJ-1B satellites are  
12 equipped with two charge-coupled device (CCD) cameras and one infrared scanner (IRS) with spa-  
13 tial resolutions of 30 m and 300 m, respectively. Compared with high-temporal-resolution satellites,  
14 such as the MODIS satellite, or high-spatial-resolution satellites, such as the Landsat 7 or 8 satellites,  
15 HJ-1B has the advantage of a high spatial-temporal 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), H. Li et al. (2010, 2011) and Yu et al. (2013), respectively. These variables lay the foundation  
21 for ET research.

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

## 25 **2. Methodology**

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

27 Surface thermal dynamics are a driving force of ET. The spatial resolution of TIR images is  
28 usually not as high as the spatial resolution of visible near-infrared bands (VNIR) because the energy  
29 of VNIR photons is higher than the energy of thermal photons. Thus, the inhomogeneity of TIR  
30 images would be greater than the inhomogeneity of VNIR images. Once the inhomogeneity of TIR  
31 images is enhanced, the uncertainty of the variables is calculated in the TIR band, and variables  
32 such as the land surface temperature become unpredictable. Therefore, we would like to derive land  
33 surface temperature data with a high spatial resolution.

34 The different spatial resolutions of TIR and VNIR images make it possible to obtain the land  
35 surface temperature at the spatial resolution of the VNIR images, which is referred to as tempera-  
36 ture-sharpening. Kustas et al. (2003) proposed a statistical temperature-sharpening method that  
37 could be applied to remotely sensed evapotranspiration models. This method assumes that the neg-  
38 ative correlation between the Normalized Difference Vegetation Index (NDVI) and LST is invariant.  
39 The NDVI reflects vegetation growth and cover, and the LST reflects surface thermal dynamics.  
40 The LST decreases with increasing vegetation cover. The resulting scatter plots form a feature space  
41 that is applicable at different scales when enough pixels exist.

42 HJ-1B satellite images can provide vegetation and thermal information at spatial resolutions of

30 m and 300 m, respectively. However, the 300 m resolution thermal data cannot be used to discriminate the surface temperatures of small targets within pixels. This deficiency can be addressed by using the functional relationship between NDVI and LST. A flowchart of temperature sharpening is shown in Fig. 1, and the LST at the NDVI pixel resolution can be derived based on the following steps (Kustas et al., 2003):

(1) The selection of a subset of pixels from the scene where the NDVI is the most uniform at a pixel resolution of 300 m. Calculate the coefficient of variation (CV) by using the original NDVI data ( $NDVI_{30}$ ) with a resolution of 30 m and sort the values from smallest to largest. The CV is calculated as follows:

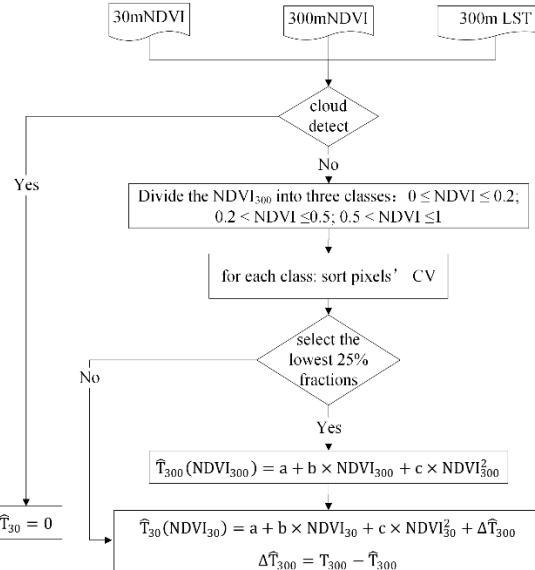
$$CV = \frac{STD}{mean} \quad (1)$$

where STD and mean are the standard deviation and the average values, respectively, among the 10×10 pixels that make up each 300-m NDVI ( $NDVI_{300}$ ) aggregated from  $NDVI_{30}$ .

(2) Next, the  $NDVI_{300}$  is divided into several classes ( $0 \leq NDVI_{300} < 0.2$ ,  $0.2 \leq NDVI_{300} < 0.5$  and  $0.5 \leq NDVI_{300}$ ). Lower CV values correspond with more homogeneous land surface values, and a specific fraction should guarantee that a sufficient number of pixels is available for fitting a least-squares expression between  $NDVI_{300}$  and  $T_{300}$ . Then, the fractions (25%) of the pixels having the lowest CV are selected from each class.

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

$$\hat{T}_{300}(NDVI_{300}) = a + b \times NDVI_{300} + c \times NDVI_{300}^2 \quad (2)$$



**Figure 1.** Flowchart of temperature sharpening.

(4) For each 30-m pixel within the 300-m pixel,  $\hat{T}_{30}$  can be computed according to Eq. (2) as follows:

$$\hat{T}_{30}(NDVI_{30}) = a + b \times NDVI_{30} + c \times NDVI_{30}^2 + \Delta\hat{T}_{300} \quad (3)$$

where  $\Delta\hat{T}_{300} = T_{300} - \hat{T}_{300}$  is the deviation between the regressed temperature and the temperature that was observed by the satellite at 300 m.

## 2.2. Area-weighting method based on landscape information

Coarse pixels are inhomogeneous because various types of land use may be included. Using a dominant type to represent such a large landscape is irrational. When a sharpened temperature is

1 obtained, the spatial details could be provided by surface **variables** at a high resolution, and the  
2 inhomogeneous problem could be greatly diminished as the landscape is divided into finer pixels.

3 Combined with a high-resolution classification map, sub-pixel scale parameters can be applied  
4 to the ET algorithm, which is more rational than using a dominate-class type because different land-  
5 scapes might require different ET algorithms. The surface energy flux can be averaged linearly due  
6 to the conservation of energy (Kustas et al., 2003), and a simple average that calculates the arithmetic  
7 mean over sub-pixels is the best choice for flux upscaling approaches (Ershadi et al., 2013b).  
8 Thus, the aggregated flux at a low resolution  $F(x, y)$  is the arithmetic mean of all of the  $n \times n$   
9 sub-pixel fluxes that constitute the contributing flux  $F(x_i, y_j)$  at coordinate  $(x_i, y_j)$  as follows:

10

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

11 Because the average of the sub-pixels fluxes is equal to the area-weighted sum of each land-  
12 type result, the final coarse result can be derived by the area-weighted sum of each land-type result  
13 within the landscape. The main steps of the area-weighting process are shown below (Xin et al.,  
14 2012):

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

16 (2) Count area ratio of different land-cover types within each pixel of a low-spatial-resolution  
17 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 net radiation ( $R_n$ ), soil heat flux ( $G$ ) and  
20 sensible heat flux ( $H$ ).

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

23

$$F = \sum_{i=1}^n w_i \cdot F_i \quad (5)$$

24 where  $w_i$  is the fractional area contributing flux  $F_i$  of class type  $i$ , and  $F$  is the aggregated flux  
25 at the coarse resolution. The LE is computed as a residual of the surface energy balance in the TSFA  
26 (Temperature Sharpening and Flux Aggregation, see Sect. 2.3) process, in which a high-spatial-  
27 resolution image is used to reduce the 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:

31

$$R_n = LE + H + G \quad (6)$$

32 where  $R_n$  is the net radiation,  $G$  is the soil heat flux,  $H$  is the sensible heat flux, and  $LE$  is the  
33 latent heat flux absorbed by water vapor when it evaporates from the soil surface and transpires  
34 from plants through stomata. The widely used one-source energy balance model considers the ho-  
35 mogeneous SPAC medium and **ignores** the inhomogeneity and structure. The  $LE$  can be expressed  
36 as follows:

37

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

38 where  $\gamma$  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 re-

sistance and canopy resistance. The surface resistance is influenced by the physiological characteristics of the vegetation and the water supply of roots. Thus, it is difficult to obtain surface resistance by using remote sensing, and surface resistance is highly uncertain, particularly over heterogeneous surfaces. To avoid error introduced by the uncertainty of the surface resistance, the LE is computed as a residual of the surface energy balance equation.

$R_n$  is the difference between incoming and outgoing radiation and is calculated as follows:

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

where  $S_d$  is the downward shortwave radiation,  $\alpha$  is the surface broadband albedo,  $\varepsilon_s$  is the 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 temperature.

$G$  is commonly estimated by deriving empirical equations that consider surface **variables**, such as  $R_n$ . Because the canopy exerts a significant influence on  $G$ , the fractional canopy coverage FVC is used to determine the ratio of  $G$  to  $R_n$  as follows:

$$G = R_n \times [\Gamma_c + (1 - FVC) \times (\Gamma_s - \Gamma_c)] \quad (9)$$

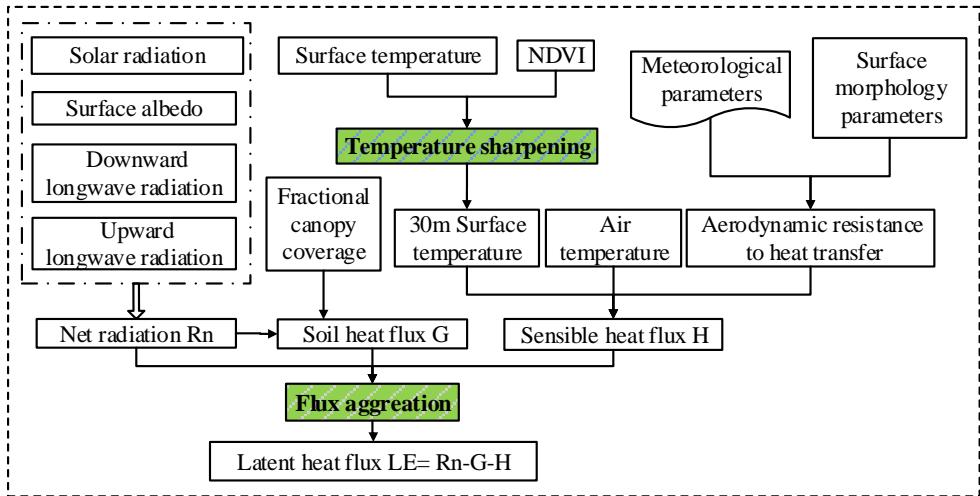
where  $\Gamma_s$  is 0.315 for bare soil and  $\Gamma_c$  is 0.05 for a full vegetation canopy (Su, 2002).  $H$  is the transfer of turbulent heat between the surface and atmosphere that is driven by a **temperature difference** and is controlled by resistances that depend on local atmospheric conditions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

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

where  $\rho$  is the density of the air;  $c_p$  is the specific heat of the air at a constant pressure;  $T_{aero}$  is the aerodynamic surface temperature obtained by extrapolating the logarithmic air-temperature profile to the roughness length for heat transport;  $T_a$  is the air temperature at a reference height; and  $r_a$  is the aerodynamic resistance, which influences the heat transfer between the source of turbulent heat flux and the reference height. Aerodynamic resistance was calculated based on the Monin-Obukhov similarity theory (MOST) using a stability correction function (Paulson, 1970; Ambast et al., 2002). The zero-plane displacement height,  $d$ , and roughness length,  $z_{0m}$ , were parameterized by the **schemes** proposed by Choudhury (Choudhury and Monteith, 1988).

In this approach,  $H$  must be accurately estimated. However, calculating  $H$  by using Eq. (10) is difficult. Because remote sensing cannot obtain  $T_{aero}$ , the value of  $T_{aero}$  is usually replaced by the radiative surface temperature  $T_{rad}$ , which is not always equal to  $T_{aero}$ . The difference between these terms for homogeneous and fully covered vegetation is approximately 1-2°C (Choudhury et al., 1986), or up to 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  $r_{ex} = 4/u_*$ , which was proposed by Chen (1988), to calculate  $r_{ex}$ .

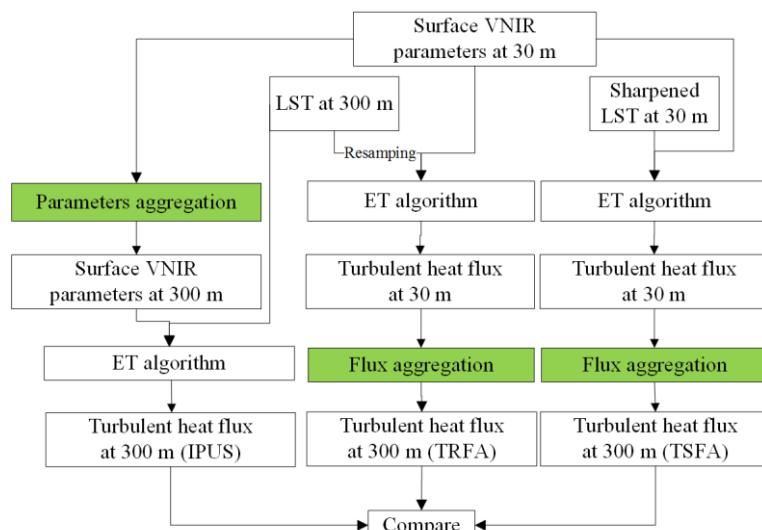
Fig. 2 shows a flowchart for merging ET retrieval and temperature sharpening based on HJ-1B satellites.



1

2 **Figure 2.** Flowchart of ET retrieval using the “Temperature Sharpening and Flux Aggregation” method.

3 The spatial scale effect is usually revealed by a discrepancy between different upscaling methods:  
 4 the upscaling of aggregate parameters to the large scale to calculate the heat flux and the cal-  
 5 culation of the heat flux at the small scale before upscaling it to the large scale. In this paper, the  
 6 resolution of the final output result is 300 m. To evaluate the reduced heterogeneity effect of TSFA,  
 7 two other upscaling methods called IPUS and TRFA were used (see Fig. 3). When using IPUS, the  
 8 surface-parameter retrieving algorithms (see Sect. 3.2.1.1) are applied to HJ-1 CCD data. Then, the  
 9 variable results are aggregated at a spatial resolution of 300 m. These 300 m outputs are used as  
 10 input parameters in the one-source energy balance model to obtain the four energy-balance compo-  
 11 nents at 300 m. In TRFA, the LST at 300 m is resized to 30 m using nearest neighbor sampling.  
 12 Then, the resampled LST and surface VNIR variables at 30 m are applied to ET algorithm. The  
 13 outputs of the four energy-balance components of the TRFA are obtained using the area-weighting  
 14 method shown in Sect. 2.2.

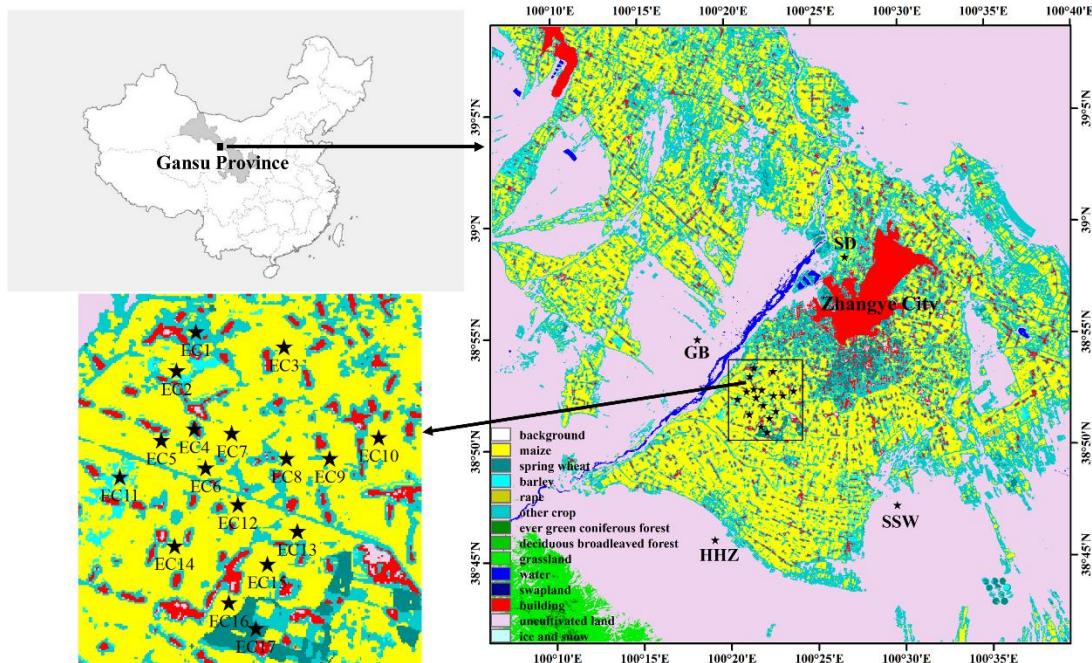
15  
1615 **Figure 3.** Flowchart of the three upscaling methods for retrieving evapotranspiration.  
16

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1 **3. Study area and Dataset**

2 **3.1. Study area**

3 Our study was conducted in the middle stream of the Heihe River Basin (HRB), which is lo-  
4 cated near the city of Zhangye in the arid region of Gansu Province in northwestern China  
5 (100.11°E-100.16°E, 39.10°N-39.15°N). The middle reach of the HRB is a typical desert-oasis ag-  
6 riculture ecosystem dominated by maize and wheat. A large portion of the Gobi Desert and the  
7 alpine vegetation of Qilian Mountain are located near the study area (see Fig. 4). The artificial oasis  
8 is highly heterogeneous, which impacts the thermal-dynamic and hydraulic features. Consequently,  
9 the water use efficiency and ET are variable. The Heihe River Basin has long served as a test bed  
10 for integrated watershed studies as well as land surface or hydrological experiments. Comprehen-  
11 sive experiments, such as Watershed Allied Telemetry Experimental Research (WATER) (Li et al.,  
12 2009), and an international experiment - the Heihe Basin Field Experiment (HEIFE) in World Cli-  
13 mate Research Programme (WCRP) have taken place in the Heihe River Basin. One major objective  
14 of HiWATER is to capture the strong land surface heterogeneities and associated uncertainties  
15 within a watershed (Li et al., 2013).



18 **3.2. Dataset**

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

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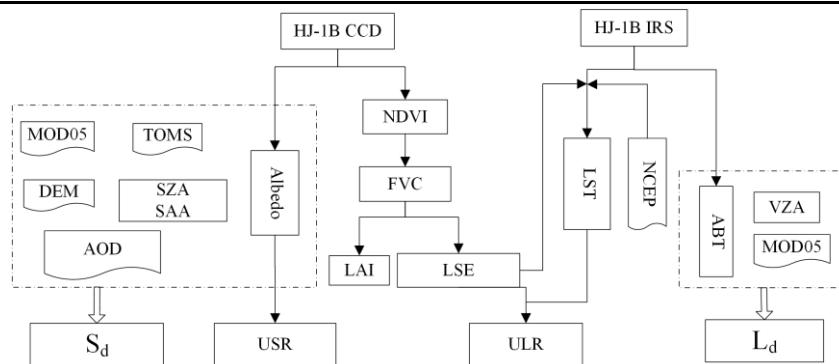
1    **3.2.1. Remote sensing data**

2    **3.2.1.1. HJ-1B satellite data**

3    The specifications of HJ-1B are shown in Table 1. These satellites have quasi-sun-synchronous  
 4    orbits at an altitude of 650 km, a swath width of 700 km and a revisit period of 4 days. Together, the  
 5    revisit period of the satellites is 48 h. Because HJ-1 CCDs lack an onboard calibration system,  
 6    scholars have proposed cross-calibration methods for calibrating the CCD instruments (Zhong et al.,  
 7    2014b; Zhang et al., 2013). The image quality of HJ-1A/B CCDs is stable, the performances of each  
 8    band are balanced (Zhang et al., 2013), and the radiometric performance of the HJ-1A/B CCD sen-  
 9    sors is similar to the performances of the Landsat-5 TM, Advanced Land Imager, and ASTER sen-  
 10    sors. The image quality of HJ-1 CCDs is very similar to the image quality of Landsat-5 TM (Jiang  
 11    et al., 2013). In addition, the accuracy of the TIR band's onboard calibration meets land surface  
 12    temperature retrieval requirements but not sea surface temperature retrieval requirements (J. Li et  
 13    al., 2011). China Center for Resources Satellite Data and Application (CRESDA) releases calibra-  
 14    tion coefficients once each year on its website (<http://www.cresda.com>). These data are freely avail-  
 15    able from the CRESDA website (<http://218.247.138.121/DSSPlatform/index.html>).

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

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



17    **Figure 5.** Flowchart of the land surface variable retrieval. The abbreviations are defined as follows: SZA: solar  
 18    zenith angle; SAA: solar azimuth angle; VZA: view zenith angle; AOD: aerosol optical depth; ABT: at-nadir bright-  
 19    ness temperature;  $S_d$ : downward shortwave radiation; USR: upward shortwave radiation, ULR: upward longwave  
 20    radiation; and  $L_d$ : downward longwave radiation.

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

The HJ-1B satellite data from the HRB were pre-processed and included geometric correction, radiometric calibration, and atmosphere correction. For Eq. (1) to (10), the following surface **variables** are needed: downward shortwave radiation, downward longwave radiation, emissivity, albedo, fractional vegetation coverage (FVC), cloud mask data, meteorological data, LAI and LST. Fig. 5 contains a flowchart showing the retrieval of these **variables**.

(1) Surface albedo. According to the algorithm proposed by Liang et al. (2005) and Q. Liu et al. (2011), surface albedo was obtained from the top of the atmosphere (TOA) reflectance by the HJ-1 satellite with a lookup table based on an angular bin regression relationship. The surface albedo and bidirectional reflectance distribution function (BRDF) of the HJ-1 satellite in the regression procedure were monitored by using POLDER-3/PARASOL BRDF datasets, and BRDF was used to obtain the TOA reflectance using the 6S (Second Simulation of a Satellite Signal in the Solar Spectrum) radiation transfer mode.

(2) NDVI, FVC and LAI. The NDVI is the central regression of temperature sharpening and was used to calculate the FVC. Atmospherically corrected surface reflectance values were used to calculate the NDVI as follows:

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

and

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

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

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

$$P(\theta) = 1 - FVC \quad (14)$$

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

(3) Land surface emissivity (LSE). LSE is needed to calculate the  $R_n$  and is extremely important for retrieving LST. In this paper, LSE was calculated using the FVC as follows (Valor and Caselles, 1996):

$$\varepsilon = \varepsilon_v \cdot FVC + \varepsilon_g (1 - FVC) + 4 < d\varepsilon > \cdot FVC \cdot (1 - FVC) \quad (15)$$

where  $\varepsilon$  is the LSE,  $< d\varepsilon >$  is an effective value of the cavity effect of emissivity, the mean  $d\varepsilon$  of all vegetation species in this study is  $< d\varepsilon > = 0.015$ , and  $\varepsilon_v$  and  $\varepsilon_g$  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 H. Li et al. (2010) was applied. This model was developed from a parametric model based on MODTRAN4 using NCEP atmospheric profile data.

(5) Downward shortwave radiation. The algorithm proposed by L. Li et al. (2010) was applied. MOD05, TOMS, aerosol, and solar angle data were used to estimate the direct light flux and diffuse light flux by using a lookup table that was generated using the 6S radiation transfer mode (Vermote et al., 2006). This method considered the influences of complex terrain, and a topographic correction

1 was performed by using products of the ASTER DEM.

2 (6) Downward longwave radiation ( $L_d$ ). The TOA brightness temperature of the HJ-1B thermal  
3 channel was used to substitute the atmospheric effective temperature. Effective atmospheric emis-  
4 sivity was parameterized as an empirical function of the water vapor content. These values were  
5 substituted for atmospheric temperature and atmospheric emissivity to estimate the value of  $L_d$ .  
6 Because this  $L_d$  retrieval method proposed by Yu et al. (2013) was only valid for clear-sky conditions,  
7 cloud masking information was used to determine clear skies. When cloud contamination existed in  
8 the image, the brightness temperature was relatively low, causing the  $L_d$  to be lower than that in the  
9 cloudless images.

10 **3.2.1.2. Ancillary data**

11 Ancillary data were used because the bands of the satellite could not invert all of the variables  
12 needed for retrieving ET.

13 (1) Atmospheric water vapor data. MODIS provides water vapor data (MOD05), including a  
14 1-km near-infrared product and a 5-km thermal-infrared product, every day. The 1-km near-infrared  
15 water vapor product was used to retrieve  $L_d$  in this study.

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

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

21 (4) Atmosphere profile data. Global reanalysis data from the National Centers for Environmen-  
22 tal Prediction (NCEP) were used to derive LST. These data were generated globally every 6 hours  
23 (0:00, 06:00, 12:00, 18:00 UTC) for every 1° of latitude and longitude (Li et al., 2010a).

24 **3.2.2. HiWATER experiment dataset**

25 The in situ HRB observation data were provided by HiWATER. From June to September 2012,  
26 HiWATER designed two nested observation matrices over 30 km×30 km and 5.5 km×5.5 km within  
27 the middle stream oasis in Zhangye to focus on the heterogeneity of the scale effect in the so-called  
28 HiWATER-MUSOEXE.

29 In a larger observation matrix, four eddy covariance (EC) systems and one superstation were  
30 installed in the oasis–desert ecosystem. Each station was supplemented with an automatic meteor-  
31 ological station (AMS) to record meteorological and soil variables and monitor the spatial–temporal  
32 variations of ET and its impact factors (Li et al., 2013). The station information is shown in Table  
33 2, and the distribution of the stations is shown in Fig. 4. Within the artificial oasis, an observation  
34 matrix composed of 17 EC towers and ordinary AMSs exists where the superstation was located.  
35 The land surface was heterogeneous and dominated by maize, maize inter-cropped with spring  
36 wheat, vegetables, orchards, and residential areas (Li et al., 2013). Because the EC16 and HHZ  
37 stations lacked  $R_n$  and G observation data, they were excluded from this study.

38 **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
EC9	100.39E	38.87N	3.9	1543.34	maize
EC10	100.40E	38.88N	4.8	1534.73	maize
EC11	100.34E	38.87N	3.5	1575.65	maize
EC12	100.37E	38.87N	3.5	1559.25	maize
EC13	100.38E	38.86N	5	1550.73	maize
EC14	100.35E	38.86N	4.6	1570.23	maize
EC15	100.37E	38.86N	4.5	1556.06	maize
EC17	100.37E	38.85N	7	1559.63	orchard
GB	100.30E	38.91N	4.6	1562	uncultivated land-Gobi
SSW	100.49E	38.79N	4.6	1594	uncultivated land-desert
SD	100.45E	38.98N	5.2	1460	swamp land

1 The ground observation data include 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 (data were  
 5 rejected when (1) the sensor was malfunctioning, (2) precipitation occurred within 1 h before or  
 6 after collection, (3) the missing ratio was greater than 3% in the 30-min raw record and (4) the  
 7 friction velocity was below  $0.1 \text{ ms}^{-1}$  at night) was performed to control the quality of the EC data,  
 8 and EC outputs were available every 30 min (for more details see Liu et al., 2011b; Xu et al., 2013;  
 9 Liu et al., 2016). G was measured by using three soil heat plates at a depth of 6 cm at each site, and  
 10 the surface G was calculated using the method proposed by Yang and Wang(2008) based on the soil  
 11 temperature and moisture above the plates. Surface meteorological variables, such as wind speed,  
 12 wind direction, relative humidity and air pressure, were used to interpolate images using the inverse-  
 13 distance weighted method. Researchers can obtain these data from the websites of the Cold and Arid  
 14 Regions Science Data Center at LanZhou <http://card.westgis.ac.cn/> or the Heihe Plan Data Manage-  
 15 ment Center <http://www.heihedata.org/>.

16 An energy imbalance is common in ground flux observations. The conserving Bowen ratio  
 17 (H/LE) and residual closure technique are often used to force energy balance. Computing the LE as  
 18 a residual variable may be a better method for energy balance closure under conditions with large  
 19 LEs (small or negative Bowen ratios due to strong advection) (Kustas et al., 2012). Thus, the resid-  
 20 ual closure method was applied because the “oasis effect” was distinctly observed in the desert-  
 21 oasis system on clear days during the summer (Liu et al., 2011b).

22 **4. Results and analysis**

23 **4.1. Evaluation of surface variables**

24 To control the model input variables and analyze sources of error, the coarse-resolution land  
 25 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:

$$T_s = \left[ \frac{L^\uparrow - (1 - \varepsilon_s) \cdot L^\downarrow}{\varepsilon_s \cdot \sigma} \right]^{\frac{1}{4}} \quad (16)$$

in which  $L^\uparrow$  and  $L^\downarrow$  are in situ surface upwelling and atmospheric downwelling longwave radiation, respectively, and  $\varepsilon_s$  is the surface broadband emissivity, which is regarded as the pixel value of the HJ-1B at the AMS. The coefficient of determination  $R^2$ , mean bias error (MBE) and root mean square error (RMSE) of the LST are 0.71, -0.14 K and 3.37 K, respectively. As seen in Table 3, the accuracy of EC4 is low. The main causes of the large errors are as follows: (1) because buildings and soil/vegetation are distinct materials, the LSE algorithm may not be suitable for buildings and (2) the EC4 foundation is non-uniform and is not suitable for validation. After removing the EC4 data, the  $R^2$ , MBE, and RMSE of the LSTs were 0.83, 0.69 K and 2.51 K, respectively. The LST errors of SSW and SD were large due to large errors on particular days. For example, although it was briefly cloudy above station SSW on July 27, this area was not identified as cloudy in the cloud detection process.

**Table 3.** Station validation results of land surface temperature

station	$R^2$	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				

The  $R^2$ , MBE, and RMSE values of  $S_d$  were 0.81, 13.80  $\text{W}\cdot\text{m}^{-2}$ , and 25.35  $\text{W}\cdot\text{m}^{-2}$ , respectively. The station validation results are shown in Table 4. The accuracy of SSW is low. Because cloudy conditions occurred briefly on July 27, few ground observations were obtained, and  $S_d$  was significantly overestimated. After removing these data, the  $R^2$ , MBE, and RMSE values of  $S_d$  at SSW were 0.87, 10.90  $\text{W}\cdot\text{m}^{-2}$  and 21.13  $\text{W}\cdot\text{m}^{-2}$ , respectively.

**Table 4.** Station validation results of downward shortwave radiation

station	$R^2$	MBE ( $\text{W}\cdot\text{m}^{-2}$ )	RMSE ( $\text{W}\cdot\text{m}^{-2}$ )	station	$R^2$	MBE ( $\text{W}\cdot\text{m}^{-2}$ )	RMSE ( $\text{W}\cdot\text{m}^{-2}$ )
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				

1 The  $R^2$ , MBE, and RMSE of the HRB  $L_d$  were 0.73,  $0.28 \text{ W}\cdot\text{m}^{-2}$ , and  $21.24 \text{ W}\cdot\text{m}^{-2}$ , respectively.  
 2 As seen in Table 5, the accuracies at EC3, SD and SSW were low. The low accuracies at EC3 and  
 3 SD potentially resulted from (1) high humidity, which resulted in low at-nadir brightness tempera-  
 4 tures and low retrieved  $L_d$ , or (2) instrument error, which occurred because the EC3 ground obser-  
 5 vations were always greater than those of the other stations during the same period. Although SSW  
 6 was located in a desert, the ground-air temperature difference was large. The  $L_d$  retrieval may have  
 7 a large error because the models use surface temperature when estimating  $L_d$  to approximate or  
 8 substitute the near-surface temperature (Yu et al., 2013). The corrected error of our  $L_d$  retrieving  
 9 algorithm resulted from the ground-air temperature difference in non-vegetated areas. The inaccu-  
 10 racy of the SSW LST may influence the  $L_d$  results.

11 **Table 5.** Station validation results of downward longwave radiation

station	$R^2$	MBE ( $\text{W}\cdot\text{m}^{-2}$ )	RMSE ( $\text{W}\cdot\text{m}^{-2}$ )	station	$R^2$	MBE ( $\text{W}\cdot\text{m}^{-2}$ )	RMSE ( $\text{W}\cdot\text{m}^{-2}$ )
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				

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

27 **Table 6.** Station net radiation validation results

station	R <sup>2</sup>	MBE (W·m <sup>-2</sup> )	RMSE (W·m <sup>-2</sup> )	station	R <sup>2</sup>	MBE (W·m <sup>-2</sup> )	RMSE (W·m <sup>-2</sup> )
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
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				

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

10

**Table 7.** Station validation results of the soil heat flux

station	R <sup>2</sup>	MBE (W·m <sup>-2</sup> )	RMSE (W·m <sup>-2</sup> )	station	R <sup>2</sup>	MBE (W·m <sup>-2</sup> )	RMSE (W·m <sup>-2</sup> )
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				

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 spatial distribution of the turbulent heat flux is obvious. The H of buildings and uncultivated land, including the Gobi Desert, barren areas and other deserts, was high, in addition to the LEs of the water and agricultural areas in the oasis. The southern areas of the images show uncultivated barren land bordering the Qilian Mountains that resulted from snowmelt and the downward movement of water. In these areas, the groundwater levels are high and the soil moisture content is approximately 30% based on in situ measurements at a depth of 2 cm. Therefore, the LE is higher in the south than

13

14

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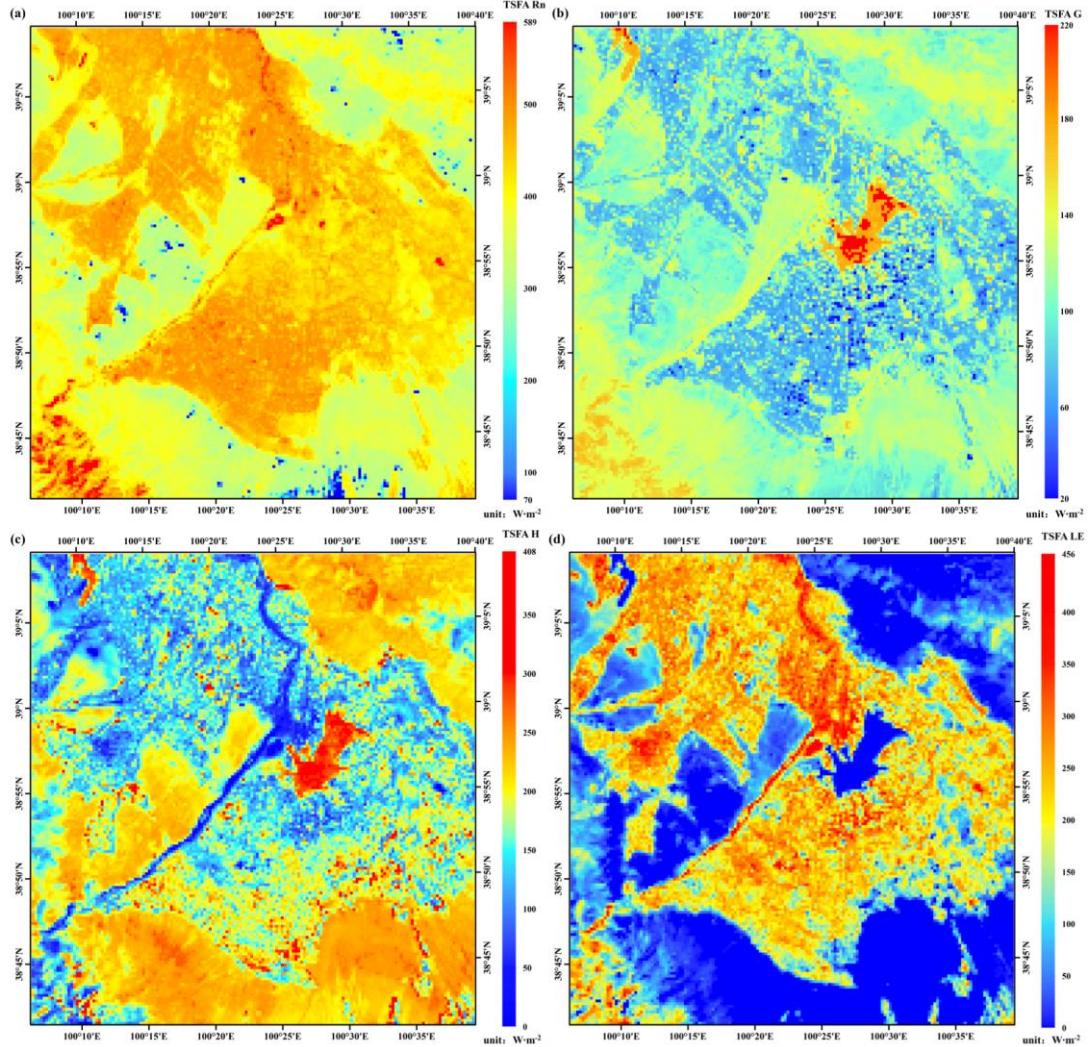
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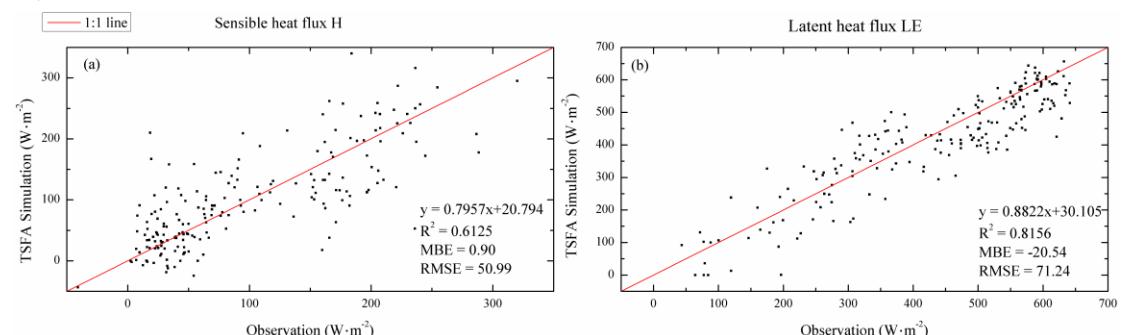
18

1 in the southeast desert, although both areas were classified as uncultivated land.

2 Studies have shown that validation methods that consider the source area are more appropriate  
 3 for evaluating ET models than traditional validation methods based on a single pixel (Jia et al., 2012;  
 4 Song et al., 2012). In this study, a user-friendly tool presented by Neftel et al. (2008) and based on  
 5 the Eulerian analytic flux footprint model proposed by Kormann and Meixner (2001) was used to  
 6 calculate the footprints of the function parameters. The continuous footprint function was dispersed  
 7 based on the relative weights of the pixels on which the source area fell.



9 **Figure 6.** Maps of the four energy components, (a) Rn, (b) G, (c) H and (d) LE, calculated by TSFA on September  
 10 13, 2012.



11 **Figure 7.** Scatter plot of the TSFA turbulent heat flux results  
 12

1 The footprint validation results of the TSFA turbulent heat fluxes are shown in Fig. 7 and Table  
 2 8. The  $R^2$ , MBE, and RMSE of the H were 0.61,  $0.90 \text{ W}\cdot\text{m}^{-2}$  and  $50.99 \text{ W}\cdot\text{m}^{-2}$ , respectively, and the  
 3 corresponding terms for the LE were 0.82,  $-20.54 \text{ W}\cdot\text{m}^{-2}$  and  $71.24 \text{ W}\cdot\text{m}^{-2}$ , respectively. Because  
 4 the LE was calculated as a residual term, it was impacted by the  $R_n$ , surface G and H. The errors  
 5 of all of these variables may contribute to the LE, which complicates the error source of the LE and  
 6 is discussed in Sects. 4.3.2 and 4.4.

7 **Table 8.** In situ validation results of heat flux of TSFA

date	TSFA-H( $\text{W}\cdot\text{m}^{-2}$ )			TSFA-LE( $\text{W}\cdot\text{m}^{-2}$ )		
	$R^2$	MBE	RMSE	$R^2$	MBE	RMSE
0619	0.39	44.73	66.38	0.69	-44.15	80.60
0630	0.73	23.71	38.96	0.88	-63.81	77.83
0708	0.55	32.70	58.72	0.85	-43.02	72.32
0727	0.90	-34.34	43.59	0.92	26.74	57.60
0803	0.80	-4.77	18.92	0.78	-4.58	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

8 As seen in Fig. 7, most of the H values are small because June, July, August and September  
 9 constitute the growing season when ET greatly cools the air. The differential temperature between  
 10 the land surface and air is small, leading to a low H. The points with large H values are influenced  
 11 by uncultivated land. In our study area, bare soil, the Gobi Desert, and desert areas compose the  
 12 uncultivated land. The points in the scatter plot with large H values represent desert, where the H  
 13 values reach approximately  $300 \text{ W}\cdot\text{m}^{-2}$ . Some points in the H scatter plot are less than 0 due to  
 14 inversion from the “oasis effect” or irrigation. For example, HiWATER’s soil moisture data show  
 15 that irrigation occurred on August 22, 2012. Irrigation is the main source of water within the oasis  
 16 and cools the land surface to temperatures below the air temperature. In addition, irrigation leads to  
 17 errors in LST retrieval because it increases the atmospheric water vapor content, as discussed in  
 18 Sect. 4.1. The model error is further analyzed in Sect. 4.4.

### 19 **4.3. Comparison between TSFA, TRFA and IPUS**

20 To verify whether the TSFA method can simulate the heterogeneities of the land surface, the  
 21 TRFA and IPUS methods were compared for estimating the ET. These three methods were evaluated  
 22 using (1) validation of TRFA and IPUS based on in situ measurements and (2) qualitative analysis  
 23 based on the spatial distribution and scatter plots of the four energy balance components.

#### 24 **4.3.1. Validation of TRFA and IPUS heat fluxes**

25 Table 9 provides the footprint in situ validation results of the H and LE calculated using the  
 26 IPUS and TRFA methods. The  $R^2$ , MBE, and RMSE of the LE between TSFA and TRFA were 0.99,  
 27  $-7.81 \text{ W}\cdot\text{m}^{-2}$  and  $16.48 \text{ W}\cdot\text{m}^{-2}$ , respectively. And the  $R^2$ , MBE, and RMSE of the LE between TSFA  
 28 and IPUS were 0.91,  $-4.10 \text{ W}\cdot\text{m}^{-2}$  and  $51.30 \text{ W}\cdot\text{m}^{-2}$ , respectively. Comparing with validation results  
 29 of TSFA in Table 8, the TSFA method had a better retrieval accuracy than the TRFA method, and

1 TRFA method was better than the IPUS method on all days, because the MBE and RMSE of TSFA  
 2 decreased and the  $R^2$  of TSFA increased on most days. Table 9 shows that the improvement in the  
 3 accuracy that resulted from temperature resampling (TRFA) when comparing with the IPUS method  
 4 was relatively higher than the improvement observed from temperature sharpening (TSFA) when  
 5 comparing with the TRFA method. Compared with the IPUS method, the TRFA results were similar  
 6 to the TSFA results since the sub-pixel landscapes and sub-pixel variations of most variables were  
 7 considered. Thus, TRFA could effectively decrease the scale error that resulted from heterogeneity  
 8 because the VNIR data of satellite were fully used. However, the performance of the TRFA method  
 9 is unstable. For example, on August 3 and August 29, the TRFA results were slightly worse than the  
 10 IPUS results, and the TSFA results were obviously better. This difference occurred because the dif-  
 11 ferent sub-pixel landscape temperatures were treated as equal to the values estimated at the 300-m  
 12 resolution. Thus, when the 300-m-resolution LST has large retrieving errors, the turbulent heat flux  
 13 retrieving error may be amplified by the sub-pixel landscapes.

14 **Table 9.** In situ validation results of turbulent heat fluxes of IPUS and TRFA

IPUS-H(W·m <sup>-2</sup> )				IPUS-LE (W·m <sup>-2</sup> )				TRFA-H (W·m <sup>-2</sup> )				TRFA-LE (W·m <sup>-2</sup> )			
date	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	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			

15 Surface landscape inhomogeneity can be classified using two conditions: nonlinear vegetation  
 16 density variations between sub-pixels (e.g., different types of vegetation mixed with each other or  
 17 with bare soil) and coarse pixels containing different landscapes (e.g., vegetation or bare soil mixed  
 18 with buildings or water). And landscapes variation always corresponding to inhomogeneity of sur-  
 19 face variable. To evaluate the effects of TSFA, stations with a typical severe heterogeneous surface,  
 20 such as EC4, a weak heterogeneous surface, such as EC11 and a typical pixel (called “TP” hereafter)  
 21 at the boundary of the oasis and bare soil (sample 62, line 102 in the image of study area), and a  
 22 uniform surface, such as EC15, were selected to analyze the temperature sharpening results.

23 EC4 is used as an example because its land cover and sub-pixel variation of temperature were  
 24 complicated. Table 11 compares the turbulent heat fluxes calculated using the IPUS, TRFA and  
 25 TSFA methods. Significant differences were observed between the TSFA and IPUS results and be-  
 26 tween the TRFA and IPUS results due to the heterogeneity of the surface. The LE calculated using  
 27 the TSFA method was more consistent with in situ measurements than the LE calculated using the  
 28 IPUS method because the MBE and RMSE decreased greatly, the  $R^2$  increased, and the accuracy  
 29 was improved by approximately 40 W·m<sup>-2</sup>. However, the LE calculated by using the TRFA was  
 30 more accurate than the LE calculated by using the TSFA, as discussed below.

31 The H calculated by using the TSFA method was more accurate than the H calculated by using

the TRFA and IPUS methods. The accuracy of the results from the TRFA method was relatively close to the accuracy 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 were always greater than those obtained from the TSFA method. Because the TSFA turbulent heat flux results are the same as the TRFA turbulent heat flux results for buildings and water bodies in our pixel ET algorithm, so the difference between TSFA and TRFA depends on the vegetation and bare soil. And the 300-m-resolution LST is larger than the LST of the sub-pixels, such as pixels containing vegetation or bare soil, for two reasons: (1) the coarse pixels contain buildings and result in a larger 300-m-resolution LST and (2) the LSTs were underestimated at EC4 (as shown in Table 3), which would underestimate the value of  $\Delta\hat{T}_{300}$  in Eq.(3) and, consequently, the sharpening temperature at 30 m and  $H$ . Because the LE was calculated as a residual item in the energy balance equation, the errors of the other three energy balance components would accumulate in the LE. At EC4, the  $R_n$  was overestimated by approximately  $80 \text{ W}\cdot\text{m}^{-2}$ , but the scale effect of  $R_n$  was not obvious, as discussed in Sect. 4.1, and the  $G$  was overestimated by approximately  $20 \text{ W}\cdot\text{m}^{-2}$ . These results would lead to low accuracy of the available energy and overestimate the error by  $60 \text{ W}\cdot\text{m}^{-2}$ . As TRFA overestimates  $H$ , the underestimation of  $H$  in TSFA would result in larger overestimation of LE than TRFA. Consequently, the LE calculated by using the TSFA method is less accurate than the LE calculated by using the TRFA method.

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

EC4		H( $\text{W}\cdot\text{m}^{-2}$ )				LE( $\text{W}\cdot\text{m}^{-2}$ )			
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	
0815	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	

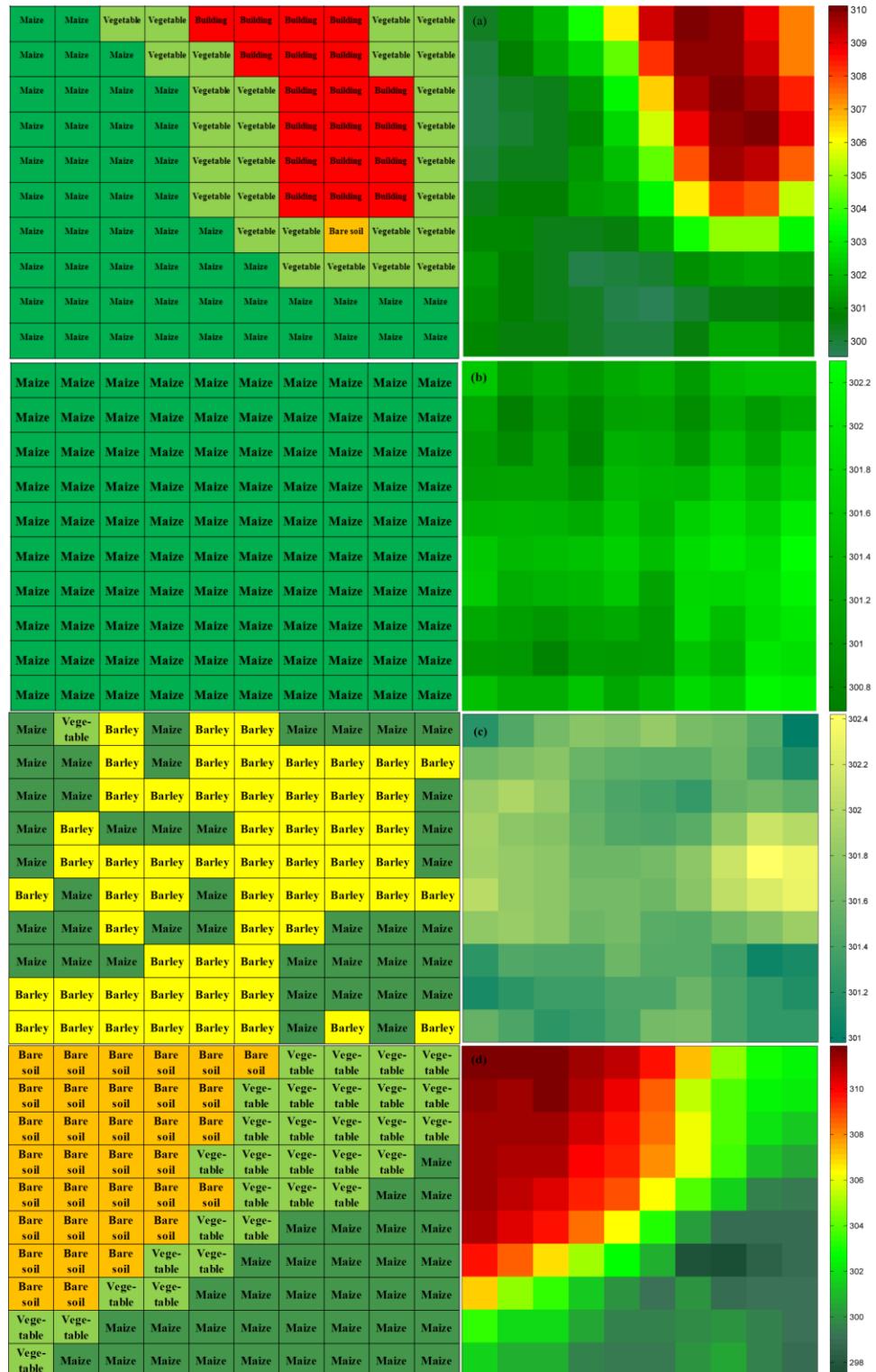
units:  $\text{W}\cdot\text{m}^{-2}$

Variable	IPUS			TRFA			TSFA		
	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	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

Fig. 8 shows that the classes and temperatures of  $10\times10$  sub-pixels at 30 m correspond to the pixels with a resolution of 300 m at the EC tower. In the IPUS upscaling scheme, the 300-m pixels included buildings and maize and vegetable crops at the 30-m resolution and were identified as maize. The canopy height gap between maize and vegetables was large during our study period, resulting in the overestimation of the canopy height. For more details see the error analysis in Sect. 4.4. However, because buildings corresponded with  $H = 0.6R_n$  in this paper, ignoring the contributions of buildings would result in the underestimation of  $H$ . Fig. 8(a) shows the temperature-

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1 sharpening results for the EC4 pixel on August 29. The temperature achieved at a resolution of 300  
2 m was 303.49 K. Compared with the in situ measurement of 313.24 K, the temperature at a resolu-  
3 tion of 300 m was underestimated. Even when substituting the in situ temperature into the ET model,  
4 the value of H reached 399.60  $\text{W}\cdot\text{m}^{-2}$  and the LE became 0  $\text{W}\cdot\text{m}^{-2}$ . When substituting the in situ  
5 temperature in the TRFA method, H was 396.49  $\text{W}\cdot\text{m}^{-2}$  and LE was 18.7  $\text{W}\cdot\text{m}^{-2}$ , indicating that the  
6 LE was underestimated and the H was overestimated with large errors. After processing by temper-  
7 ature sharpening, the distribution of the temperature at the 30-m resolution agreed with the classifi-  
8 cation. Temperature sharpening improved the description of heterogeneity based on the thermody-  
9 namic-driven force of the turbulent heat flux. These results apply to the ET model with the classifi-  
10 cation map and high-resolution variables and correspond with more accurate sensible heat flux es-  
11 timations.



**Figure 8.** Distribution of classes and temperatures over the extreme heterogeneous surface (a) EC4, homogeneous surface (b) EC15, weak heterogeneous surface (c) EC11 and (d) a typical pixel on August 29, 2012.

The land surface of EC15 was uniform and comprised of pure pixels covered by maize. The temperature distribution at the 30-m resolution was as homogeneous as the land cover, and the variation range of the surface temperature was small (approximately 1.6 K). Table 11 shows the in situ validation results of EC15, for which the overall accuracy is not high due to the low LST retrieval

accuracy on July 8, which is discussed in Sect. 4.4.1. For the homogeneous surface, the gaps between IPUS, TRFA and TSFA were not large (within  $10 \text{ W}\cdot\text{m}^{-2}$ ), and the accuracy did not improve (MBE and RMSE did not have obvious variations). Statistically sharpening the temperature may increase the uncertainty of the model results for a homogeneous surface; however, this influence could be omitted.

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

EC15		H ( $\text{W}\cdot\text{m}^{-2}$ )				LE ( $\text{W}\cdot\text{m}^{-2}$ )		
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

units:  $\text{W}\cdot\text{m}^{-2}$

Variable	IPUS			TRFA			TSFA		
	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	MBE	RMSE	R <sup>2</sup>	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

The weak heterogeneous land surface EC11 contained barley, maize and vegetables in a coarse pixel with a fractional area of 48:41:1 and was classified as barley at the 300-m resolution. The distributions of the classes and temperatures are shown in Fig. 8(c), and the pixel belongs to the first conditions of heterogeneity (nonlinear vegetation density variation between sub-pixels) that are classified in the introduction. Table 12 shows the in situ validation results of EC11, for which the improvements in the accuracies of H and LE by temperature resampling or sharpening were not as obvious as the improvements at EC4, which contained total different landscapes (the other inhomogeneous scenario in introduction).

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

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

9 The excess errors resulted from the relatively low LST accuracy, with  $R^2$ , MBE, and RMSE  
 10 values of 0.42, 1.59 K and 2.98 K, respectively. On August 29, the temperature at a resolution of  
 11 300 m was 301.6 K, and the observed temperature of the ground was 300.20 K. The LST at the 300-  
 12 m resolution was slightly overestimated. When the in situ temperature was substituted into the IPUS  
 13 algorithm, the value of H decreased to  $16.06 \text{ W}\cdot\text{m}^{-2}$  and the LE became  $467.43 \text{ W}\cdot\text{m}^{-2}$ . When sub-  
 14 stituting the in situ temperature in the TRFA scheme, the value of H was  $22.43 \text{ W}\cdot\text{m}^{-2}$  and the LE  
 15 was  $461.58 \text{ W}\cdot\text{m}^{-2}$ , which were more similar to the ground observations.

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

EC11		H( $\text{W}\cdot\text{m}^{-2}$ )				LE( $\text{W}\cdot\text{m}^{-2}$ )			
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	

17 units:  $\text{W}\cdot\text{m}^{-2}$

Variable	IPUS			TRFA			TSFA		
	$R^2$	MBE	RMSE	$R^2$	MBE	RMSE	$R^2$	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

18 Another typical pixel located at the boundary of the bare soil and the oasis with no flux mea-  
 19 surements was used to evaluate the correction effects of landscapes and temperature sharpening. The  
 20 land surface of TP contained maize, vegetables and bare soil at a fraction of 35:31:34. Table 13  
 21 shows that when neither the heterogeneity of the landscape nor the LST are considered, the relative  
 22 error of LE could reach  $180 \text{ W}\cdot\text{m}^{-2}$ . In addition, if only the LST heterogeneity is not considered, the  
 23 LE relative error could reach  $48 \text{ W}\cdot\text{m}^{-2}$ . This result also reveals that the influences of landscape  
 24 inhomogeneity are greater than the influences of inhomogeneity on the LST in mixed pixels.

25 **Table 13.** Comparison of the turbulent heat flux results at TP

Date	H ( $\text{W}\cdot\text{m}^{-2}$ )			LE ( $\text{W}\cdot\text{m}^{-2}$ )		
	IPUS	TRFA	TSFA	IPUS	TRFA	TSFA

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0619	186.31	149.73	143.98	321.04	358.22	364.79
0630	383.65	191.59	158.79	67.03	259.36	292.89
0708	498.36	240.20	204.18	0.29	259.25	293.41
0727	276.79	136.06	84.01	206.52	347.64	402.23
0803	214.14	75.45	53.72	252.37	392.08	416.41
0815	214.14	98.24	72.05	252.37	368.64	393.68
0822	436.48	369.28	276.70	0.00	67.79	162.80
0829	235.29	117.16	67.21	183.62	302.41	356.75
0902	423.61	212.15	180.92	0.00	211.77	241.36
0913	338.00	285.04	216.26	0.00	53.62	122.58
0914	270.44	148.20	100.19	115.19	238.43	286.51

1       units:  $\text{W}\cdot\text{m}^{-2}$

Variable	IPUS			TRFA		
	$R^2$	MBE	RMSE	$R^2$	MBE	RMSE
TP-H	0.62	174.47	185.49	0.95	42.28	48.01
TP-LE	0.71	-175.91	186.63	0.97	-43.11	49.04

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

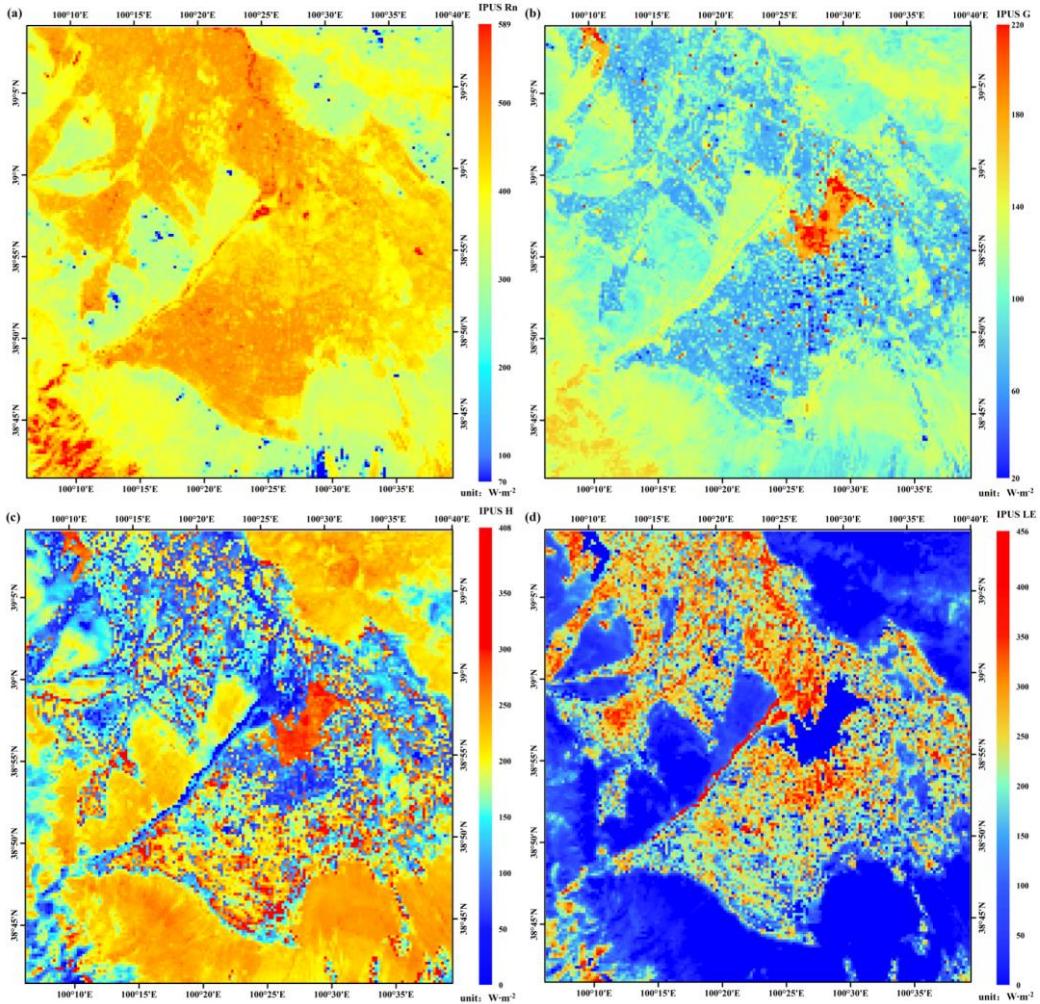
3       Using September 13 as an example, the spatial distributions of the four components of the  
4       energy balance calculated by IPUS and TRFA are shown in Fig. 9 and Fig. 10, respectively. TSFA  
5       minus IPUS and TSFA minus TRFA, which show the spatial distributions of the heterogeneity ef-  
6       fect, are shown in Fig. 11. Scatterplots of TSFA versus IPUS and TRFA are shown in Fig. 12.

7       Comparing Fig. 6 with Fig. 9, the spatial distribution of the fluxes greatly changes, except for  
8        $R_n$ . The TSFA results are synoptically smoother than the IPUS results because the land types and  
9       temperature distributions in mixed pixels that cannot be considered in IPUS appear in TSFA. For  
10      example, the boundary between the oasis and uncultivated land becomes a belt of intermediate G,  
11      H and LE because mixed pixels include uncultivated land and vegetation. However, mixed pixels  
12      are classified as the dominant land use type in the parameterization process of IPUS. This result  
13      overlooks the contributions of heat flux from complex land use types and overestimates or underes-  
14      timates the heat flux by approximately  $50 \text{ W}\cdot\text{m}^{-2}$ . However, TSFA can integrate the effects of these  
15      land areas and reveals the relative actual surface conditions. The results of this analysis vary less  
16      dramatically than the results obtained using IPUS, as shown in the figures. The results are similar  
17      in the oasis.

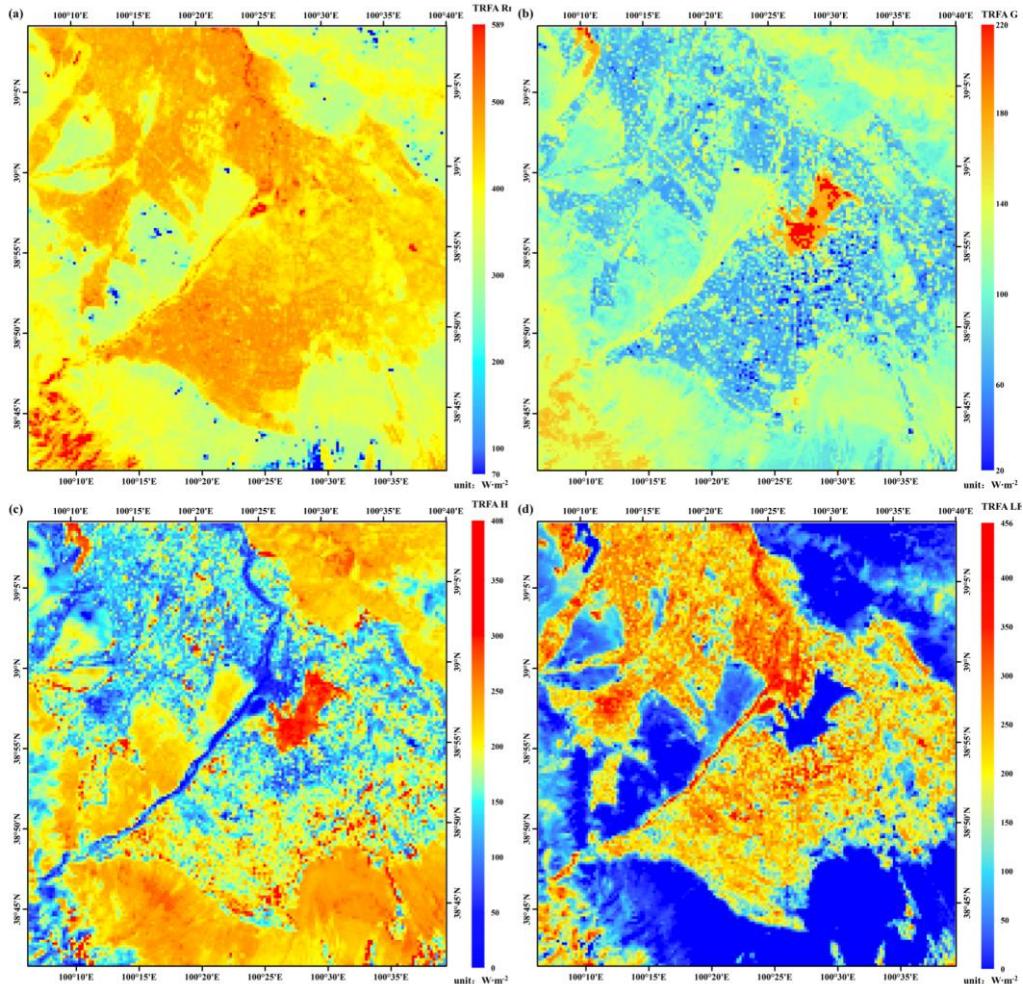
18      Based on the overviews presented in Fig. 6 and Fig. 10, the TRFA and TSFA methods are  
19      similar. Because the TRFA method considers the sub-pixel landscapes that could be a significant  
20      source of error in ET models, the difference between the TSFA and TRFA methods result from the  
21      differences between the sharpened and retrieved LST for the sub-pixels at the 300 m resolution. In  
22      addition, the bias between the TSFA and TRFA is not as obvious as the bias between the TSFA and  
23      IPUS methods, as shown in Fig. 11(c)(d)(e)(f). Furthermore, Fig. 11(f) shows that the LEs calcu-  
24      lated by using the TSFA method for most oasis areas were slightly greater than the LEs calculated  
25      by using the TRFA method, which were approximately  $20 \text{ W}\cdot\text{m}^{-2}$ .

26      The quadrangular with a relatively unstable bias shown in Fig. 11(a) is caused by the  $L_d$  that  
27      was calculated from the MOD05 water vapor product which exists quadrangular even after prepro-  
28      cessing the instrument malfunction gap. From Fig. 11, the differences of the four energy components

1 of the pure pixels between these three methods are within  $5 \text{ W}\cdot\text{m}^{-2}$ , and the mixed pixels have dif-  
2 ferent ranges.

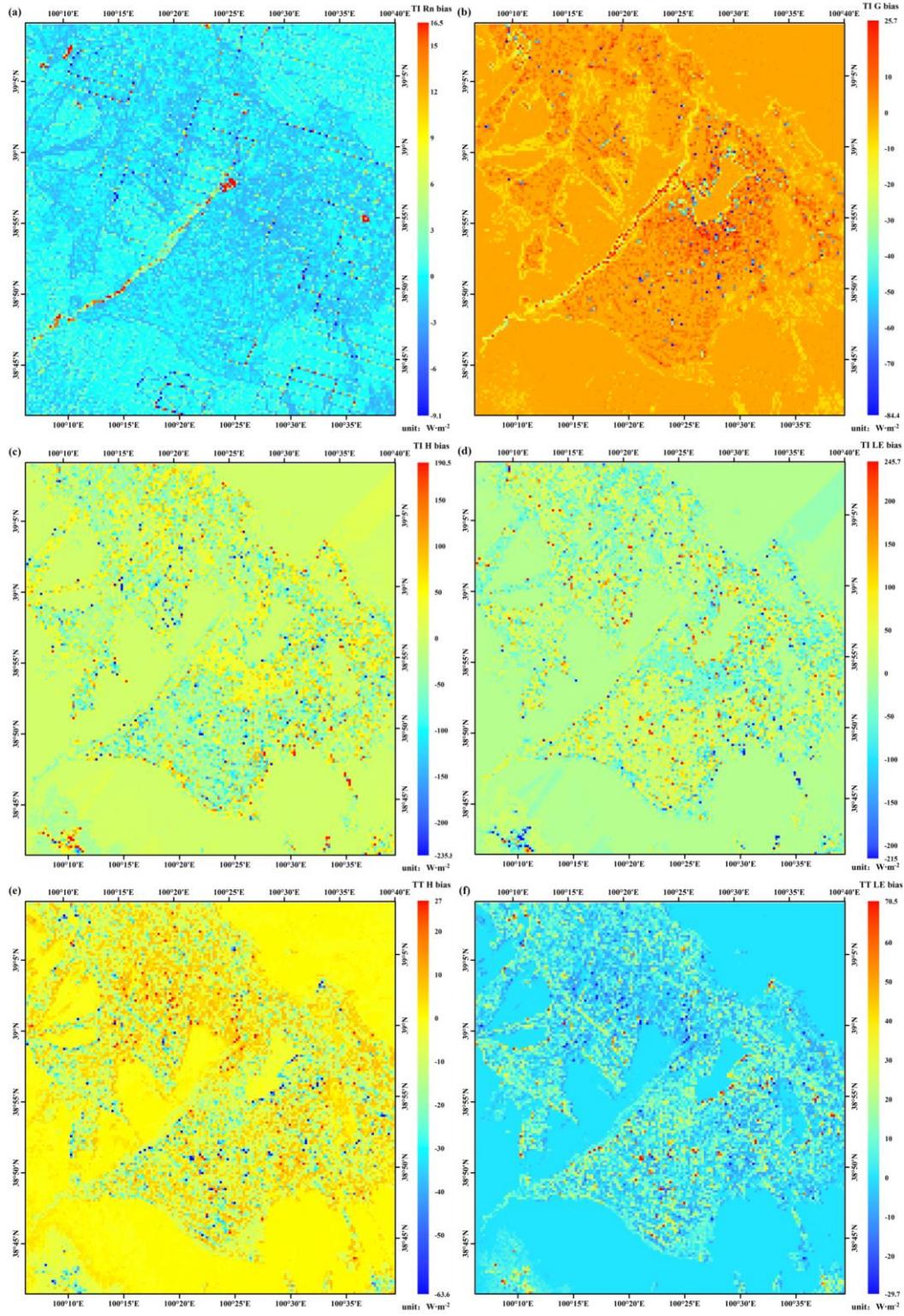


3  
4 **Figure 9.** Maps of the four energy components, (a) R<sub>n</sub>, (b) G, (c) H and (d) LE, calculated using the IPUS method  
5 on September 13, 2012.



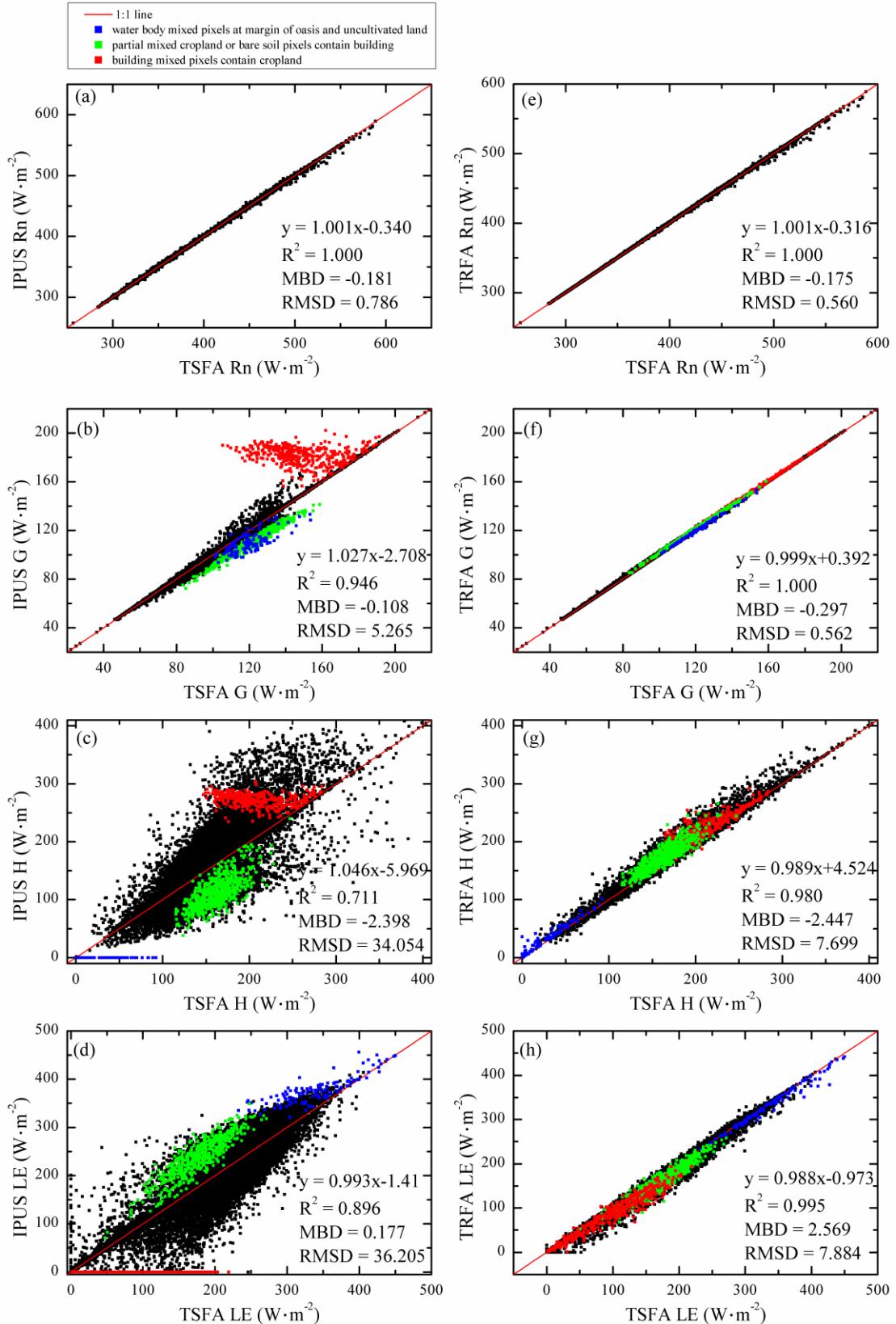
1

2 **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)  $LE$ , TSFA minus TRFA: (e)  $H$  and (f)  $LE$ .



1

2 **Figure 12.** Scatter plots between the TSFA and IPUS results: (a) R<sub>n</sub>, (b) G, (c) H and (d) LE; TSFA and TRFA (e)  
3 R<sub>n</sub>, (f) G, (g) H and (h) LE. MBD and RMSD are the mean bias deviation and root mean square deviation between  
4 the TSFA and IPUS results, respectively.

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

---

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

12 However,  $LE$  is calculated as a residual; thus, the difference of  $LE$  resulted from the  $G$  and  $H$ .  
13 When the 300 m mixed pixels contain various types of land, they may be categorized as one type of  
14 land because of the coarse resolution of the IPUS results and because a single temperature value is  
15 used to evaluate the thermal dynamic effects when using the TRFA method. Pixels with highly dif-  
16 ferent  $G$ ,  $H$  and  $LE$  values are mainly distributed near the mixed pixels, as shown in Fig. 10. An  
17 explanation for these deviations is provided below.

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

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

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

40 (3) In mixed pixels that contain various crops, such as maize and vegetables, the  $LE$  is under-  
41 estimated if the area of maize within the pixel is overestimated because the canopy height of the  
42 maize would be taller than that of vegetables, which would result in the overestimation of  $H$  when  
43 using the IPUS and TRFA methods. In addition,  $G$  depends on the FVC of the crops when using  
44 the IPUS method, and is nearly the same as the values of  $G$  obtained when using the TRFA and

1 TSFA methods because it depends on  $R_n$ .

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

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

Number of class types in pixels	IPUS ( $\text{W}\cdot\text{m}^{-2}$ )			TRFA ( $\text{W}\cdot\text{m}^{-2}$ )			Pixel number
	$R^2$	MBD	RMSD	$R^2$	MBD	RMSD	
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

15 Notes: Number of class types in mixed pixels means the number of classification types that were contained in  
16 the pixels. For example, 1 represents the pure pixels, 2 represents mixed pixels containing two land use types, etc.  
17 MBD and RMSD are the mean bias deviation and root mean square deviation, respectively, between the TSFA  
18 results and the TRFA and IPUS results.

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

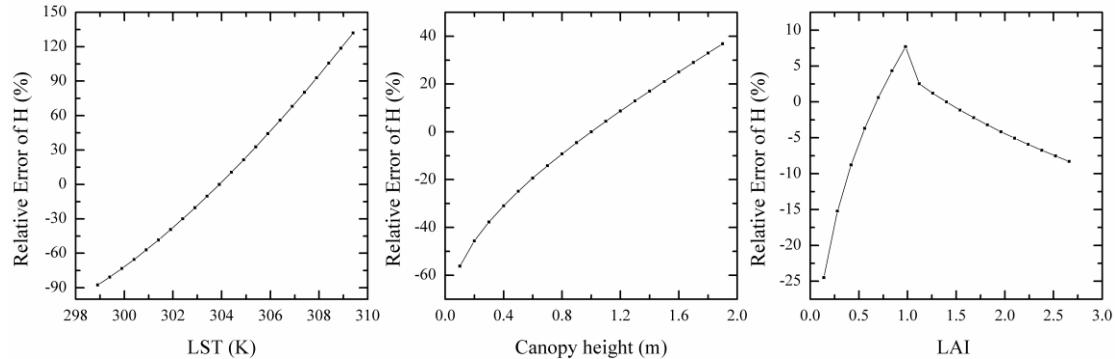
Types of mixed pixels	IPUS ( $\text{W}\cdot\text{m}^{-2}$ )			TRFA ( $\text{W}\cdot\text{m}^{-2}$ )			Pixel number
	$R^2$	MBD	RMSD	$R^2$	MBD	RMSD	
mixed pixels contain buildings	0.58	-1.02	61.94	0.97	-9.64	14.66	4918
mixed pixels do not contain buildings	0.81	-5.49	39.21	0.99	-2.12	7.60	10,884
mixed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

20 Considering the landscapes and inhomogeneous distribution of LST, the TSFA method ensures  
21 that none of the end members (30 m pixel) are ignored or exaggerated. Thus, the distribution of LE  
22 calculated using the TSFA method is smoother and more rational than the distributions of LE cal-  
23 culated using the other methods. At the regional scale, the TSFA method describes the heterogeneity  
24 of the land surface more precisely. And how much the estimation accuracy can be improved is dis-  
25 cussed in the following sections.

#### 26 **4.4. Error analysis**

27 Since LE is calculated as a residual term in the energy balance equations, the sensitivity of H  
28 was analyzed at first. Land surface variables (including LST, LAI, canopy height, and FVC) and  
29 meteorological variables (including wind speed, air temperature, air pressure and relative humidity)  
30 are needed to estimate H in this paper. To locate the error source when retrieving H, a sensitivity

1 analysis was performed by adding errors at each 10% step (except LST). Fig. 13 presents the sensitivity analysis results: LST = 303.9 K (ranging from 298.4~309.4 K with a step size of 0.5 K),  
 2 LAI=1.4 (ranging 0.14~2.66 with a step size of 0.14), canopy height equals 1 m (ranging 0.1~1.9 m  
 3 with a step size of 0.1 m), FVC=0.5, wind speed  $u=2.48 \text{ m}\cdot\text{s}^{-1}$ , air temperature  $T_a=297.9 \text{ K}$ , air  
 4 pressure = 97.2 kPa, and RH=40.29%. In addition, the land use type is maize, and the reference H  
 5 is  $230.2 \text{ W}\cdot\text{m}^{-2}$ .



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.

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

20 **4.4.1. The error of LST**

21 As shown in Fig. 13 using monitoring data, a 1 K LST bias would result in 21% error of H,  
 22 about  $48.3 \text{ W}\cdot\text{m}^{-2}$ . However, the sensitivity of the LST is unstable and depends on the strength of  
 23 the turbulence. The strength of the turbulence determines the mass and energy transport and the  
 24 resistance of heat transfer, which influences the sensitivity of the LST. A weaker turbulence corre-  
 25 sponds to a weaker LST sensitivity and vice versa.

26 The influence of LST was analyzed based on the sensitivity analysis and LE results. We chose  
 27 homogeneous stations to analyze the LST error so that other errors could be ignored. These results  
 28 are shown in Table 16. The LE results obtained from the observed LST are consistent with the in  
 29 situ observations but have less bias. The LE was overestimated when the LST was underestimated  
 30 and vice versa. Because the magnitude of LE was greater than H, the relative error of LE was less  
 31 than the relative error of H. However, 1 K of LST bias would result in an average LE error of 30  
 32  $\text{W}\cdot\text{m}^{-2}$ , which is consistent with the sensitivity analysis of H shown in Fig. 13. Specifically, 1 K of  
 33 LST bias would result in LE biases of  $8.7 \text{ W}\cdot\text{m}^{-2}$  (in desert, SSW) to  $84.4 \text{ W}\cdot\text{m}^{-2}$  (in oasis, EC8),  
 34 which may prove that the sensitivity of LST is unstable.

35 **Table 16.** Results of the LST error analyses at the homogeneous stations

Station	Date	retrieved	observed	LST bias (K)	EC-LE (W·m <sup>-2</sup> )	LE from	LE from	LE	H
		LST (K)	LST (K)			retrieved	observed	relative error (%)	relative error (%)
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
EC2	0822	299.79	298.05	1.74	501.12	411.43	486.28	-17.90	67.20
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  $((\text{LE from}$   
 3  $\text{retrieved LST}) - (\text{LE from observed LST})) / (\text{LE from observed LST}) \times 100\%$ , “H relative error” is calculated in the  
 4 same way.

#### 5 4.4.2. The error of canopy height

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 at EC17 was orchard. However, in our land classification map, the land use at  
 11 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 results with incorrect canopy heights and correct orchard canopy heights at EC17 are  
 15 shown in Table 17. The days of large LST bias were removed, and the bias between the model and  
 16 ground observations decreased. The excess errors were caused by errors in the LST and other land  
 17 use types, such as buildings and maize in the mixed pixels.

18 **Table 17.** Results of the canopy height error analyses at EC17

Date	EC-LE (W·m <sup>-2</sup> )	LE from incorrect canopy height (W·m <sup>-2</sup> )	LE from correct canopy height (W·m <sup>-2</sup> )	LE relative error (%)
20120815	499.62	562.06	521.83	7.71
20120822	366.27	519.01	396.54	30.88
20120902	377.96	471.68	336.52	40.16
20120914	465.38	352.78	258.07	36.70

19 Except for the error source discussed before, the following sources of error were unavoidable:

20 (1) Although the remotely sensed turbulent heat flux is instantaneous, the EC data are averaged

1 over time. Thus, the time scales do not match in the validation.

2 (2) The calibration coefficient of HJ-1B satellite's CCD and IRS drifts because of the aging  
3 instruments.

4 (3) Geometric correction causes half-pixel bias equal to or less than the deviation of the artifi-  
5 cially subjective interpretation.

6 A one-source model and simplified parameterization schemes for determining surface rough-  
7 ness lengths and heat transfer coefficients were used in this paper. The one-source model combines  
8 soil evaporation and plant transpiration and assumes that SPAC is a one-source continuum for cal-  
9 culating ET. This assumption is reasonable when the surface is densely covered by vegetation but  
10 relies on the accuracy of the difference between the LST and air temperature, as previously men-  
11 tioned. When a one-source model is applied to an area covered by sparse vegetation, such a semi-  
12 arid or arid areas, this assumption is irrational.

## 13 5. Discussion

14 As mentioned in the results and analysis, the TSFA method describes the surface heterogeneity  
15 more clearly than the IPUS and TRFA methods. The IPUS method aggregates the land surface pa-  
16 rameters achieved by CCDs from 30 m to 300 m, which results in the loss of surface information  
17 and leads to the scale effect. Although the TRFA method uses VNIR information and partially de-  
18 creases the heterogeneity caused by landscape and VNIR variables, it treats the pivotal variable LST  
19 as homogeneous within mixed pixels, which results in considerable error. In summary, the superi-  
20 ority of the TSFA method is described as follows:

21 (1) The temperature sharpening algorithm in TSFA uses the NDVI at 30 m to monitor the LST  
22 at 30 m and is capable of decreasing the influences of the heterogeneity of the LST, which agrees  
23 with previous research results (Kustas et al., 2003; Bayala and Rivas, 2014; Mukherjee et al., 2014).  
24 As analyzed in Sect. 4.3, the ignorance of the heterogeneity of LST in mixed pixels is irrational and  
25 causes errors when estimating ET.

26 (2) In the one-source energy balance model, different landscapes used different parameteriza-  
27 tion schemes. In the IPUS method, a single land cover type is assigned to a mixed pixel, which  
28 results in a large error. However, the TSFA method is used to calculate the surface flux at 30 m and  
29 is aggregated to 300 m using the area-weighting method, which considers all of the sub-pixel land-  
30 scapes and improves the retrieval accuracy.

31 Some problems exist in the temperature sharpening algorithms. The temperature-downscaling  
32 method used in this paper caused boxy anomalies in parts of the sharpened-temperature field be-  
33 cause of the constant residual term,  $\Delta\hat{T}_{300}$ , in Eq. (3) within large pixels. This situation also oc-  
34 curred in the temperature sharpening algorithm proposed by Agam et al. (2007). In addition, our  
35 temperature sharpening algorithm tends to overestimate the sub-pixel LST for cooler landscapes  
36 and underestimate the sub-pixel LST for warmer areas (Kustas et al., 2003). This inaccurate estima-  
37 tion causes errors that are difficult to evaluate when estimating turbulent heat flux. For example, the  
38 small turbulent heat flux bias between TSFA and TRFA was caused by the counterbalanced effect  
39 as analyzed in Sect. 4.3.1. The evaluation of more temperature sharpening algorithms under heter-  
40 ogenous surfaces with real datasets when applied in ET models would be helpful (Ha et al., 2011).

41 Our surface variable retrieval methods were validated against other areas considered in remote  
42 sensing measurement campaigns. For example, the albedo algorithm was previously applied to re-

---

1 retrieve Global Land Surface Satellite (GLASS) Products (Liang et al., 2014), the LST retrieval algo-  
2 rithm was validated in the Haihe River Basin in northern China (Li et al., 2011), and the soil heat  
3 flux correction algorithm was validated in the GAME-Tibet campaign (Yang and Wang, 2008).  
4 Since the surface of the Heihe River Basin is extreme heterogeneous, additional comparisons of our  
5 algorithm in other areas of research would be better.

6 In addition, to correct the discrepancy between remotely sensed radiative surface temperature  
7 and aerodynamic temperature at the source of heat transport, a brief and well-performed parameter-  
8 ization scheme (under uniformly flat plant surface) of “excess” resistance was used to calculate the  
9 aerodynamic resistance of heat transfer (Jiao et al., 2014). Since the objects of our study are mixed  
10 pixels, more parameterization methods should be compared to select the optimum method.

11 Because of the sensitive **variables** of the one-source energy balance model used in this paper,  
12 the accuracy of the LST and canopy height greatly influenced the turbulent heat flux. HJ-1B IRS is  
13 a single-thermal channel, the single-channel LST-retrieving algorithm may be unstable under wet  
14 atmospheric conditions (water vapor contents higher than 3 g/cm<sup>2</sup>) (H. Li et al., 2010), which may  
15 create a bottleneck for ET estimations by HJ-1B. The canopy height is a priori knowledge based on  
16 phenophase classifications and would influence the accuracy of the surface roughness, the length of  
17 a heterogeneous surface or the seasonal transition. Multi-source remote sensing data could be used  
18 to improve the accuracy of calibrations and land surface **variable** estimations. Active microwave  
19 and LiDAR data (Colin and Faivre, 2010) could be used to obtain the canopy height, which would  
20 decrease the dependence on the accuracy of the classification.

21 The energy balance closure has significant influence on evaluation of the model calculated heat  
22 flux results. In our study area, the EC energy balance closure ratio was greater than 0.75 (Liu et al.,  
23 2011b). Studies have shown that the not-captured low-frequency eddies(Von Randow et al., 2008),  
24 extension of averaging time (Charuchittipan et al., 2014), and lack of an accurate accounting of heat  
25 storage terms(Meyers and Hollinger, 2004) are potential reasons for the energy imbalance and so  
26 forth. The conserving Bowen ratio and residual closure technique are often used to force energy  
27 balance. We chose the residual closure at last because the conserving Bowen ratio method conducted  
28 irrational sensible heat flux due to small or negative Bowen ratios (large LEs due to “oasis effect”)  
29 in the oasis-desert system. Energy balance closure was problematic at times for turbulent flux sys-  
30 tem and tended to be associated with significant discrepancies in LE (Prueger et al., 2005).

31 Since a footprint model was used in the validation, the footprints discrepancy between in situ  
32 measurements and remote sensing pixel may cause biases. For example, model validation results  
33 were calculated by the relative weights of the footprint model, and multiply heat flux results of the  
34 coarse pixels which were covered by source area from upwind direction. However, the heat fluxes  
35 of coarse pixels included the contribution of not-overlapped sub-pixels within the coarse pixel. In-  
36 fluenced by the heterogeneity of underlying surface, it would cause uncertainties in the validation.

## 37 6. Conclusion

38 We studied the effects of surface heterogeneity in ET estimation by the IPUS, TRFA and TSFA  
39 methods over heterogeneous surface based on spatial resolution characteristic of different satellites,  
40 and applied them to HJ-1B satellite data based on operational satellites’ instrumental characteristics.

41 Compared with the IPUS and TRFA methods, the TSFA method is more consistent with in situ  
42 measurements (energy balance forced by residual closure method) according to the footprint vali-  
43 dation results. If ET estimating algorithm does not consider surface heterogeneity at all (i.e. IPUS),

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1 it would cause significant error (i.e.  $186 \text{ W}\cdot\text{m}^{-2}$ ) of heat fluxes. If ET estimating algorithm does not  
2 consider heterogeneity of LST only (i.e. TRFA), it would cause non-negligible error (i.e.  $49 \text{ W}\cdot\text{m}^{-2}$ )  
3 in heat fluxes calculating. The TSFA method reduces the uncertainties produced by surface land-  
4 scapes and LST inhomogeneity. As a sensitive variable of the ET model, canopy height is mainly  
5 determined by classification, and the application of classification at a 30-m resolution can improve  
6 the accuracy of the canopy height. As another sensitive variable, the sharpened surface temperature  
7 at a resolution of 30 m decreases the thermodynamic uncertainty caused by land surface heteroge-  
8 neities. The TSFA method can capture the heterogeneities of the land surface and integrate the ef-  
9 fects of landscapes in mixed pixels that are neglected at coarse spatial resolutions.

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

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## 21 Appendix

Notation	Application (for calculating)
6S radiation transfer mode	Second Simulation of a Satellite Signal in the Solar Spectrum
$\alpha$	radiation transfer mode
ABT	Surface broadband albedo
AMS	At-nadir brightness temperature (K)
AOD	Automatic meteorological station
BRDF	Aerosol optical depth
CCD	Bidirectional reflectance distribution function
CV	Charge-coupled device
EC	Coefficient of variation
FVC	Eddy covariance
G	Fractional vegetation coverage
$G(\theta)$	Soil heat flux ( $\text{W}\cdot\text{m}^{-2}$ )
H	G function, Foliage angle distribution
HRB	Sensible heat flux ( $\text{W}\cdot\text{m}^{-2}$ )
IPUS	The Heihe River Basin
IRS	Input parameter upscaling scheme
$L_d$	Infrared scanner
LSE/ε	Downward atmospheric longwave radiation ( $\text{W}\cdot\text{m}^{-2}$ )
	Land surface emissivity
	$R_n$
	LST

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$\varepsilon_v/\varepsilon_g$	The vegetation/ground emissivity	
LST/T <sub>rad</sub>	Land surface temperature/Surface radiation temperature (K)	H
MBE/MBD	Mean bias error (deviation)	
NCEP	National Centers for Environmental Prediction	LST
NDVI/NDVI <sub>30</sub>	Normalized difference vegetation index	FVC, Sharpened LST
NDVI <sub>300</sub>	300-m NDVI aggregated from NDVI	Sharpened LST
NDVI <sub>s</sub> /NDVI <sub>v</sub>	Normalized difference vegetation index of bare soil/fully covered vegetation	FVC
P( $\theta$ )	Angular distribution of the canopy gap fraction	LAI
r <sub>a</sub>	Aerodynamic resistance (s·m <sup>-1</sup> )	H
r <sub>ex</sub>	“Excess” resistance (s·m <sup>-1</sup> )	heat transfer resistance
R <sub>n</sub>	Net radiation (W·m <sup>-2</sup> )	
RMSE/RMSD	Root mean square error (deviation)	
S <sub>d</sub>	Downward shortwave radiation (W·m <sup>-2</sup> )	R <sub>n</sub>
SPAC	The soil-plant-atmosphere continuum	
SZA	Solar zenith angle	S <sub>d</sub>
T <sub>a</sub>	Air temperature (K)	H
T <sub>aero</sub>	Aerodynamic surface temperature obtained by extrapolating the logarithmic air-temperature profile to the roughness length for heat transport (K)	H
TOA	Top of the atmosphere	
TOMS	Total ozone mapping spectrometer	S <sub>d</sub>
TRFA	Temperature resampling and flux aggregation	
TSFA	Temperature sharpening and flux aggregation	
ULR	Upward longwave radiation (W·m <sup>-2</sup> )	R <sub>n</sub>
USR	Upward shortwave radiation (W·m <sup>-2</sup> )	R <sub>n</sub>
VNIR	Visible/near-infrared	
VZA/ $\theta$	View zenith angle	L <sub>d</sub> , LAI

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