RESPONSES TO THE REFEREES

We thank the reviewers for the comments. Below are our responses (in **blue** font) to the reviewers' comments and questions (in **black** font).

Anonymous Referee #1

Received and published: 9 February 2016

General Comments:

This manuscript compares two different approaches to retrieve energy budget components (including sensible and latent heat flux) at the land surface using satellite data from the Chinese HJ-1B. One approach (IPUS) uses information aggregated to the 300m resolution as given by the thermal channel; the second approach (TSFA) uses a temperature sharpening approach, making use of a NDVI – TS relationship and downscaling 300m Ts information to the 30m scale. Authors illustrate the differences between both approaches and demonstrate within a validation exercise the advantages and improved prediction capacities of the latter approach. I think this comparison and the results obtained are in principle worth publishing and will be of use for the readership of HESS. However, before a possible publication, author need to address and solve some significant concerns and questions that came up when working through the manuscript.

1. One of the major deficits of the manuscript is the following: The satellite data available are the 30m resolution data in the VIS/NIR spectral region and the 300m thermal information. As a "standard/normal" remote sensing user, I would try to make use of this available information. That means in a "reference application" (as it appears to me the IPUS scheme is meant to be) I would try to make use of the 30m data to derive NDVI and land use information (and all the other relevant parameters such as vegetation height, vegetation cover, roughness length etc., but also the simplification of individual fluxes for given LU type). Why are these parameters aggregated in the IPUS approach? Why don't use the high resolution information with an aggregated 300m Ts-signal. This should be compared to the TSFA approach in order to be able to evaluate the effect of purely temperature sharpening. Here actually the baseline situation is first worsened by aggregating information that is available in much higher resolution. In case the intention of the authors was to show what can happen when also in the VIS/NIR range only 300m resolution data were available, then all the (300m) average land surface parameters should have been derived from the aggregated reflectance information. So, I personally feel here are different aspects mixed and not properly separated.

Response: Thank you for your valuable comments. We assume that the ET estimation errors mainly come from inhomogeneity of surface landscape and variables. We aimed to reduce the uncertainties in estimated ET that caused by surface heterogeneities, and the TSFA is our final scheme. To evaluate the ability of the TSFA method to capture surface heterogeneity and reveal the scale effect, we used the IPUS method because it does not consider the effects of mixed pixels at all. According to your comments, we added the TRFA (temperature resampling and flux aggregation) method, which uses 30 m visible/near infrared band data with 300 m thermal infrared band data to estimate ET. In this method, simple spatial resampling (300 m to 30 m) of LST was used instead of spatial sharpening according to NDVI information. Comparisons between the TFSA and TRFA methods can be used to evaluate the effects of temperature sharpening on estimating ET, as well as the significance of separating inhomogeneity of landscape from that of surface variables (such as LST), and that would make our logic clearer.

2. The title of the manuscript suggests that the focus of the paper is on evapotranspiration – when looking through the manuscript and figures and tables, it seems to me that sensible heat flux is dominating the content and discussion. As a result, I would suggest to either change the title or put some more emphasis on ET in the presentation and discussion of results. As a result of my evaluation I would suggest major revisions of the manuscript before a possible publication in HESS.

Response: Thank you for your suggestion. We revised the manuscript by placing more emphasis on LE with a balance analysis and discussion of H.

Specific Comments/Questions

- In general, there are a very large number of abbreviations used in the manuscript – not all of them are intuitive and it is painful to always try and find the first position where they are explained. So I would suggest generating a list of abbreviations.

Response: Thank you for your suggestion. A table of abbreviations and the usage of input data were added in the appendix.

- Figure and table legends are not self-explaining throughout the manuscript and need extension!

Response: The figure and table legends were revised.

P2L14-22: While this paragraph is ok in principle, we as hydrologist all know how important ET – so in order to come quicker to the point it should be omitted.

Response: Thank you for your suggestion. We agree with your suggestion and have deleted this paragraph.

P6L17: Why choosing the 25% fractions having the lowest CV? Please explain in the text!

Response: We have added our justification for this decision in the manuscript.

According to the temperature sharpening method "DisTrad" proposed by Kustas et al. (2003), 25% of the pure pixels with the lowest CV are selected from each class. Regarding heterogeneity, lower CVs correspond with more homogeneous land surfaces. In addition, a fraction should guarantee that a sufficient number of pixels was obtained to fit a least-squares expression between $NDVI_{300}$ and T_{300}; thus, we choose 25% of the fractions with the lowest CVs.

P9L11: How is Ld calculated in the scheme?

Response: The Ld calculation method was introduced in Section 3.2.1.1. (P14L10).

Reference: Yu, S., Xin, X., and Liu, Q.: Estimation of clear-sky longwave downward radiation from HJ-1B thermal data, Sci. China Earth Sci., 56, 829-842, 10.1007/s11430-012-4507-z, 2013.

P12L21ff: It remains unclear how albedo is calculated

Response: The expression of the surface albedo computing method was modified as follows:

"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."

Reference: Liang, S., Stroeve, J., and Box, J. E.: Mapping daily snow/ice shortwave broadband albedo from Moderate Resolution Imaging Spectroradiometer (MODIS): The improved direct retrieval algorithm and validation with Greenland in situ measurement, Journal of Geophysical Research: Atmospheres, 110, D10109, 10.1029/2004JD005493, 2005.

Liu, Q., Qu, Y., Wang, L. Z., Liu, N. F., and Liang, S. L.: Glass-Global Land Surface Broadband Albedo Product: Algorithm Theoretical Basis Document. Version, 1, 1-50, College of Global Change and Earth System Science, Beijing Norman University, 2011.

P14L11: briefly describe how this is expressed/described (Ref)

Response: The top-of-atmosphere (TOA) brightness temperature of the HJ-1B thermal channel was used as the atmospheric effective temperature.

As shown in Yu et al. (2013), "To investigate the relation between TOA brightness temperature of the HJ-1B thermal channel and near-surface air temperature, TOA brightness temperature of HJ-1B is simulated using the Thermodynamic Initial Guess Retrieval (TIGR) atmospheric profile database TIGR2002 (http://ara.abct.lmd.Polytechnique.fr/index.php?page=tigr) and MODTRAN radiative transfer model; it has high correlation with near-surface air temperature."

Reference: Yu, S., Xin, X., and Liu, Q.: Estimation of clear-sky longwave downward radiation from HJ-1B thermal data, Sci. China Earth Sci., 56, 829-842, 10.1007/s11430-012-4507-z, 2013.

P16L2: What reliable methods? This needs to be more specific and with references.

Response: The methods were added as follows:

"Reliable methods were used to ensure the quality of the turbulent heat flux data. Before the main campaign, an intercomparison of all instruments was conducted in the Gobi Desert (Xu et al., 2013). After basic processing, including spike removal and corrections for density fluctuations (WPL-correction), a four-step procedure (data were rejected when (1) the sensor was malfunctioning, (2) precipitation occurred within 1 h before or after collection, (3) the missing ratio was greater than 3% in the 30-min raw record and (4) the friction velocity was below 0.1 ms-1 at night) was performed to control the quality of the EC data, and EC outputs were available every 30 min (for more details see Liu et al., 2011; Xu et al., 2013)."

P17ff: In the section 4.1 surface parameter and fluxes derived are evaluated against measurements. In order to put those results into a general context I think a discussion and comparison in relation to other international Remote sensing/Flux measurement campaigns should be given.

Response: Thank you for your comments. Introduction and discussion of the other ground campaigns was given.

Introduction of the study area:

The Heihe River Basin has long served as a test bed for integrated watershed studies as well as land surface or hydrological experiments. Comprehensive experiments, such as Watershed Allied Telemetry Experimental Research (WATER) (Li et al., 2009), and an international experiment - the Heihe Basin Field Experiment (HEIFE) in World Climate Research Programme (WCRP) have taken place in the Heihe River Basin. One major objective of HiWATER is to capture the strong land surface heterogeneities and associated uncertainties within a watershed (Li et al., 2013).

Discussion:

Our surface variable retrieval methods were validated against other areas considered in remote sensing measurement campaigns. For example, the albedo algorithm was previously applied to retrieve Global Land Surface Satellite (GLASS) Products (Liang et al., 2014), the LST retrieval algorithm was validated in the Haihe River Basin in northern China (Li et al., 2011), and the soil heat flux correction algorithm was validated in the GAME-Tibet campaign (Yang and Wang, 2008). Since the surface of the Heihe River Basin is extreme heterogeneous, additional comparisons of our algorithm in other areas of research would be better.

References:

Hu Y Q, Gao Y X, Wang J M, Ji G L, Shen Z B, Chen L C, Chen J Y and Li S Q: Some achievements in scientific research during HEIFE, Plateau Meteorology, (03), 2-13, 1994.

Li, H., Liu, Q., Jiang, J., Wang, H., and Sun, L.: Validation of the land surface temperature derived from HJ-1B/IRS data with ground measurements, Geoscience and Remote Sensing Symposium (IGARSS), 2011 IEEE International, Vancouver, Canada, 293-296, 2011.

Li, X., Cheng, G. D., Liu, S. M., Xiao, Q., Ma, M. G., Jin, R., Che, T., Liu, Q. H., Wang, W. Z., Qi, Y., Wen, J. G., Li, H. Y., Zhu, G. F., Guo, J. W., Ran, Y. H., Wang, S. G., Zhu, Z. L., Zhou, J., Hu, X. L., and Xu, Z. W.: Heihe Watershed Allied Telemetry Experimental Research (HiWATER): Scientific Objectives and Experimental Design, Bulletin of the American Meteorological Society, 94, 1145-1160, 10.1175/BAMS-D-12-00154.1, 2013.

Liang, S. L., Zhang, X. T., Xiao, Z. Q., Cheng, J., Liu , Q., and Zhao, X.: Global LAnd Surface Satellite (GLASS) Products: Algorithms, Validation and Analysis, 1 ed., SpringerBriefs in Earth Sciences, Springer International Publishing, 2014.

Yang, K., and Wang, J.: A temperature prediction-correction method for estimating surface soil heat flux from soil temperature and moisture data, Sci. China Ser. D-Earth Sci., 51, 721-729, 10.1007/s11430-008-0036-1, 2008.

P20L9-10: This statement about errors is not very specific!

Response: We deleted this statement because it was repetitive with the sentence preceding it.

P22L5: How do you justify a ground heat flux of 0 for buildings?

Response: In our study area, ‘buildings’ contain residents and roads. Influenced by local climate situation, special materials with low heat conductance are used for residential buildings to maintain cool conditions during the summer and warm conditions during the winter. Thus, we justified using a ground heat flux of 0 for buildings. According to your comments, the buildings of these residents were not prevalent. Thus, we recalculated all the data, and $G = 0.4R_n$ for buildings during the summer (Kato, 2005).

Reference: Kato, S., and Yamaguchi, Y.: Analysis of urban heat-island effect using ASTER and ETM+ Data: Separation of anthropogenic heat discharge and natural heat radiation from sensible heat flux, Remote Sensing of Environment, 99, 44-54, http://dx.doi.org/10.1016/j.rse.2005.04.026, 2005.

P23L22ff: This statement is actually a result of what is summarized under point 1 in the general conclusion.

Response: We did not observe any relations between the statement at P23L22 and the general conclusion.

P24L25ff: Why do you use these specific day for calculating the sensitivities! In fig. 12 the x-axis shows variations in %. This makes it difficult to follow the interpretations of the curves in the section.

Response: Sensitivity analysis is a general mathematic analysis procedure, and the presented input data for a specific day can indicate the influences of surface variables. We calculated the sensitivity results using large amounts of data from different phenophases, and our input data illustrated the sensitivities of our ET algorithm. To make the sensitivity analysis results universal, we drew a figure with % on the x-axis. We revised the paragraph and the x-axis in Figure 12 (Figure 13 in latest revised version) to make it easier to understand, especially for LST, because the discussed manuscript did not describe the x axis of LST variation clear, as follows:

"Since LE is calculated as a residual item in energy balance equations, the sensitivity of H is analyzed at first. Land surface variables (including LST, LAI, canopy height, and FVC) and meteorological variables (including wind speed, air temperature, air pressure and relative humidity) are needed to estimate H in this paper. To locate the error source when retrieving H, a sensitivity 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), 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 with a step size of 0.1 m), FVC=0.5, wind speed u=2.48 $m \cdot s^{-1}$, air temperature Ta=297.9 K, air pressure = 97.2 kPa, and RH=40.29%. In addition, the land use type is maize, and the reference H is 230.2 $W \cdot m^{-2}$."

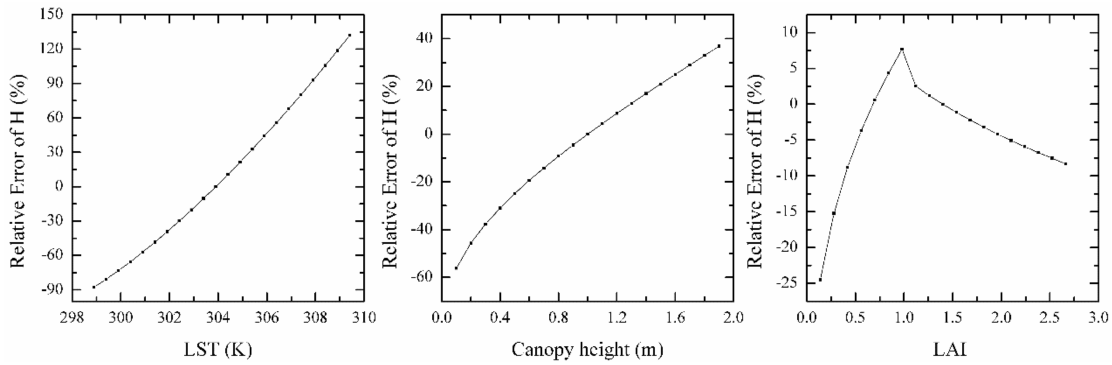

Figure 13. Sensitivity analysis of the surface variables for sensible heat flux

P29L5: Why do authors suddenly come up with the two source model – why didn't they use it initially?

Response: This sentence was deleted because it was not related to the objective of our study.

P30: While the difference between Ts and Taero has been mentioned in the introduction, why isn't that problem discussed here!

Response: Yes, we agree that the difference between Ts and Tareo should be discussed in this paper. "Excess" resistance r_{ex} was added to r_a to correct the discrepancy between Ts and Tareo in most remotely sensed evapotranspiration models. Thus, the error caused by the difference between Ts and Tareo was shifted to the parameterization scheme error of "excess" resistance, which we discussed in the discussion. We revised this section as follows to clarify the discussion.

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

Reference: Jiao, J. J, Xin, X. Z., Yu S. S., Zhou, T. and Peng, Z. Q.: Estimation of surface energy balance from HJ-1 satellite data. Journal of Remote Sensing, 18(5), 1048-1058, doi:10.11834/jrs.20143322, 2014

P50: Table 13 – there is an error in the definition of the relative error (twice the same expression in the difference)

Response: The mistake regarding the definition of relative error was corrected.

Minor Comments:

P3L4: Surface resistance is also needed for schemes classified under (1) because closure schemes need to calculate H where ra is required as well.

Response: We classified these remotely sensed models to discuss their drawbacks when used for heterogeneous surfaces. In addition, surface resistance is also needed for Penman-Monteith equations. Thus, we do not think surface resistance needs to be classified in this paper because it would disturb the flow of the manuscript and is not a focal point of our study.

P3L20: Which models? All those listed in (1) - (5) or only those in (5)

Response: All those models listed in (1) – (5).

P3L24-25: I do not understand ": : : inhomogeneity is a relative concept of homogeneity: : :!???

Response: We tried to express comparison concept of heterogeneous surface and weak heterogeneous surface and homogeneous surface. And we removed this sentence.

P3L26: Density of what?

Response: The density of the vegetation variations. We revised this paragraph for clarity as follows: "Surface landscape inhomogeneity can be classified using two scenarios: nonlinear vegetation density variations between sub-pixels (e.g., different types of vegetation mixed with each other or with bare soil) and coarse pixels containing total different landscapes (e.g., vegetation or bare soil mixed with buildings or water)."

P4L4ff: I do not understand that sentence/statement!

Response: We have revised this sentence as follows:

“However, it is difficult to develop linear operational models due to the complexity of mass and heat transfer processes between the atmosphere and land surface.”

P13L18: what is <dε> in equation (15)?

Response: <dε> is an effective value of the cavity effect of emissivity and is the mean dε of all vegetation species. In this paper, <dε>=0.015. The definition of <dε> was updated in the manuscript.

P14L1: Sentence (: : : H Li et al : : :) does not make sense.

Response: The names of the authors were located incorrectly due to typesetting. We corrected this problem as follows:

“A single-channel parametric model for retrieving LST based on HJ-1B/IRS TIR data developed by H. Li et al. (2010) was applied.”

P14L7: What is 6SLUT? Reference!

Response: 6SLUT is a look up table that was generated by the 6S (Second Simulation of a Satellite Signal in the Solar Spectrum) radiation transfer mode (Vermote et al., 2006). The following reference was added in the paper.

Reference: Vermote E F, Tanre D, Deuze J L, et al. Second Simulation of a Satellite Signal in the Solar Spectrum-Vector. 6S User Guide Version 3, 2006.

P28L1: Sentence (: : : greatly decreased the heterogeneity) does not make sense

Response: We have corrected this expression as follows:

“The temperature sharpening algorithm in TSFA uses the NDVI at 30 m to monitor the LST at 30 m and is capable of decreasing the influences of the heterogeneity of the LST.”

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General Comments:

In this manuscript, the authors compared two different spatial aggregation approaches to retrieve and evaluate the land surface energy balance fluxes using remote sensing data from the Chinese HJ-1B. One approach (IPUS) uses information aggregated to the 300m resolution as given by the thermal channel while the second approach (TSFA) uses a thermal sharpening approach by utilizing NDVI – TS relationship and downscaling 300m Ts into the 30m. Authors showed the differences between both approaches. Validation exercise is also performed to demonstrate the advantages and improved prediction capacities of the TSFA approach. This study is very useful to the community and worth publishing. However, the authors need to address the following concerns before a possible publication.

The sentence constructions also need to be better in some part of the manuscript.

(1) A clear hypothesis and research question is missing in the manuscript.

Response: Our basic hypothesis is that the inhomogeneity of surface landscapes and variables in the mixed pixels would result in large ET estimation error. In this study, we aimed to reduce the uncertainty of ET estimations caused by landscape and surface variables. We revised the introduction to clarify our hypothesis and goals.

(2) Is it really necessary to aggregate the NDVI from 30 m to 300 m as described in the IPUS method? Why not using the 30 m NDVI with 300 m LST?

Response: Thank you for your valuable comments. Although it is important to compare the TSFA method with the IPUS method, this comparison is not sufficient. We assume that ET estimation errors mainly result from the inhomogeneity of surface landscapes and variables. We aim to reduce the uncertainties of ET estimations due to surface heterogeneities and use the TSFA method as our final method. To evaluate the ability of the TSFA method to capture surface heterogeneity and reveal the scale effect, we used the IPUS method because it does not consider the effects of mixed pixels at all. According to your comments, we added the TRFA (temperature resampling and flux aggregation) method, which uses 30 m visible/near infrared and 300 m thermal infrared band data to estimate ET and simple spatial LST resampling (300 m to 30 m) instead of spatial sharpening based on NDVI information. Comparisons of the TFSA and TRFA methods can be used to evaluate the effects of temperature sharpening on estimating ET, as well as the significance of separating inhomogeneity of landscape from that of surface variables (such as LST), and that would make our logic clearer.

(3) More emphasis is given on discussing the sensible heat flux (For example Table 11, 12, 13 and 14). A balanced discussion involving both LE and H would read better and rational.

Response: We revised the manuscript by placing more emphasis on discussing the LE with a balance analysis and discussion of H.

(4) Suggest including a table on different input data, their source and for what purpose they were used.

Response: Thank you for your suggestion. A table of abbreviations and the usage of input data were added in the appendix.

(5) The table and figure captions need to be explicit.

Response: We revised the table and figure captions.

(6) Abstract: Some statistics need to be added in the abstract. At this moment it reads too general.

Response: We revised the abstract by adding and updating statistical results as follows:

“Evapotranspiration (ET) plays an important role in surface-atmosphere interactions and can be monitored using remote sensing data. However, surface heterogeneity including inhomogeneity of landscapes and surface variables affects the accuracy of ET estimated from satellite data significantly. The objective of this study is to assess and reduce the uncertainties resulted from surface heterogeneity in remotely sensed ET using Chinese HJ-1B satellite data, which is of 30m spatial resolution in VIS/NIR bands and 300m spatial resolution in TIR band. A temperature sharpening and flux aggregation scheme (TSFA) was developed to obtain accurate heat fluxes from the HJ-1B satellite data. Two methods employing different upscaling policies of surface variables and fluxes were used to compare with TSFA, i.e., IPUS (input parameter upscaling) and TRFA (temperature resampling and flux aggregation). Moreover, the three methods can also be regarded as representing three typical schemes handling mixed pixels from the simplest to the most complex, i.e., all surface variables are at coarse resolution (300 m in this study) in IPUS and fine resolution (30 m in this study) in TSFA, while TRFA is in the middle (both 30m and 300m variables are used). Analysis and comparison between them can help us to get better understandings about spatial scale errors in remote sensing of surface heat fluxes. In situ data collected during HiWATER-MUSOEXE (Multi-Scale Observation Experiment on Evapotranspiration over heterogeneous land surfaces of The Heihe Watershed Allied Telemetry Experimental Research) were used for the validation and analysis of the methods. ET estimated by TSFA is of best agreement with in-situ observations, the footprint validation results show that the R2, MBE, and RMSE of the sensible heat flux (H) were 0.61, 0.90 $W \cdot m^{-2}$ and 50.99 $W \cdot m^{-2}$, respectively, and the corresponding terms for the latent heat flux (LE) were 0.82, -20.54 $W \cdot m^{-2}$ and 71.24 $W \cdot m^{-2}$, respectively, and IPUS showed the largest errors in ET estimation. The RMSE of LE between the TSFA and IPUS methods was 51.30 $W \cdot m^{-2}$, and the RMSE of LE between the TSFA and TRFA methods was 16.48 $W \cdot m^{-2}$. Furthermore, additional analysis shows that the TSFA method can capture the sub-pixel variations of land surface temperature and integrate the effects of overlooked landscapes in mixed pixels."

(7) Page 2, line 16: Evapotranspiration is a variable, not a 'parameter' as stated by the authors. Authors should know the difference between a parameter and a variable.

Response: We agree with your opinion that evapotranspiration is a variable rather than a 'parameter'. We have revised this phrasing throughout the manuscript.

(8) Page 2, line 16: Reference is too old. Many recent references are available.

Response: Thank you for this reminder. We agree that the presented references are old. This paragraph was mainly introduced to highlight the importance of ET. We deleted this paragraph because hydrologists should already understand the importance of ET.

(9) Page 2, line 22-22: This sentence does not carry anything meaningful. Please make your statement clear.

Response: We agree with your opinion and have deleted this meaningless sentence to introduce the models directly.

(10) Page 3, line 37: it should be 'landscapes' instead of 'landscape'.

Response: We have made this suggested correction.

(11) Page 3 (line 23 onwards to page 4): The last paragraph is quite confusing to understand.

Response: We have revised this paragraph.

(12) Page 4, L26: 'Land based parameters': : :..LAI, LST, DLR are not parameters, these are variables. This is becoming confusing now.

Response: Thank you for your suggestion. We have revised our use of ‘parameters’ throughout the manuscript.

(13) Page 5, L10: The resolution: : :: : :. Need to be explicit on what is intended here by ‘resolution’.

Response: We revised this sentence as follows:

“The spatial resolution of TIR images is usually not as high as the spatial resolution of visible near-infrared bands (VNIR) because the energy of VNIR photons is higher than the energy of thermal photons. Thus, the inhomogeneity of TIR images would be greater than the inhomogeneity of VNIR images.”

(14) Throughout the entire manuscript, the authors are confused about ‘parameter’.

Response: Thank you for your suggestion. We have revised our use of ‘parameter’ throughout the manuscript.

(15) Section 4.3.2, paragraph 3: The authors have not mentioned anything about the LE statistics of the two methods.

Response: We revised this paragraph and emphasized the LE.

(16) Spatial comparison of surface fluxes (as mentioned in section 4.3.2) should be done at least for 2 different vegetation cover conditions.

Response: Thank you for your suggestion. We added comparisons of the turbulent heat fluxes for the two following weak heterogeneity conditions: (1) different vegetation cover conditions and (2) vegetation mixed with bare soil.

(17) I made some edits and comments in the manuscript pdf (attached here), which the authors should consider.

Response: The provided edits and comments were addressed in the manuscript.

Specific comments in attached pdf:

How did you assign the crop height and ancillary parameter information in the stability corrections.

Response: A widely used parameterization scheme was used for stability correction. The equations used are listed below.

From the Monin-Obukhov similarity theory (MOST), the aerodynamic resistance r_a can be calculated as follows:

$$r_a = \frac{1}{ku_*}[\ln(\frac{z-d}{z_{0m}}) - \psi_H(\frac{z-d}{L})] \quad (1)$$

$$u_* = ku[\ln(\frac{z-d}{z_{0m}}) - \psi_M(\frac{z-d}{L})]^{-1} \quad (2)$$

$$L = -\rho c_p \frac{u_*^3\theta_v}{kgH} \quad (3)$$

where $k = 0.4$ and is the von Karman’s constant, u_* is the friction velocity, u is the wind speed at a reference height of z above the surface, d and z_{0m} are the zero plane displacement height and the roughness length for momentum transfer, respectively, L is the Monin-Obukhov length, g is the acceleration due to gravity and θ_v is the potential virtual temperature near the surface. In addition, ψ_M and ψ_H are stability functions, where $\psi_M = \psi_H = 0$ under neutral conditions and ψ_M and ψ_H can be parameterized as follows under unstable conditions (Paulson, 1970; Ambast et al., 2002):

$$\psi_M = 2\ln\left[\frac{1+x}{2}\right] + \ln\left[\frac{1+x^2}{2}\right] - 2\tan^{-1}x + \frac{\pi}{2} \tag{4}$$

$$\psi_H = 2\ln[(1+x^2)/2] \tag{5}$$

where $x = (1-16z/L)^{1/4}$. Under stable conditions, ψ_M is equal to ψ_H as follows (Webb, 1970):

$$\psi_M = \psi_H = -5 \cdot \frac{z-d}{L} \tag{6}$$

The parameterization of the zero plane displacement height d and the roughness length z_{0m} are determined as follows (Choudhury and Monteith, 1988):

$$d = 1.1h\ln(1 + (c_d LAI)^{1/4}) \tag{7}$$

$$z_{0m} = \begin{cases} z_{0s} + 0.3h(c_d LAI)^{1/2} & 0 \le c_d LAI \le 0.2 \\ 0.3h\left(1 - \frac{d}{h}\right) & 0.2 < c_d LAI \le 1.5 \end{cases} \tag{8}$$

where h is the canopy height and was set according to the area phenophase, classification and a priori knowledge. c_d is the mean drag coefficient and is assumed uniform within the canopy, LAI is the leaf area index, and z_{0s} is the substrate roughness length (for the bare soil surface, z_{0s} = 0.01).

References:

Ambast, S. K., Keshari, A. K., and Gosain, A. K.: An operational model for estimating Regional Evapotranspiration through Surface Energy Partitioning (RESEP), International Journal of Remote Sensing, 23, 4917-4930, 10.1080/01431160110114501, 2002.

Choudhury, B. J., and Monteith, J. L.: A four-layer model for the heat budget of homogeneous land surfaces, Quarterly Journal of the Royal Meteorological Society, 114, 373-398, 10.1002/qj.49711448006, 1988.

Paulson, C. A.: The mathematical representation of wind speed and temperature profiles in the unstable atmospheric surface layer, Journal of Applied Meteorology, 9, 857-861, 1970.

Webb, E. K.: Profile relationships: The log-linear range, and extension to strong stability, Quarterly Journal of the Royal Meteorological Society, 96, 67-90, 10.1002/qj.49709640708, 1970.

How can you infer "The quadrangular with a relatively large bias in Fig. 9a and b is caused by DLR, i.e. it is influenced by the MOD05 water vapor."

Response: Bad lines appeared in the images scanned by MODIS Terra due to an instrumental malfunction that occurred beginning in 2002. After preprocessing the original data by interpolation, a weak quadrangular remained in the image. In addition, the MOD05 water vapor product was used to calculate downward longwave radiation in this paper, which is an important and sensitive variable of net radiation. We compared the results with the processed MOD05 product and observed that the quadrangular overlapped well. In addition, the order of magnitude at the quadrangular was within ±5 $W \cdot m^{-2}$, which matches the bias caused by the downward longwave radiation between IPUS and TSFA.

We revised the expression as follows (Fig. 9 becomes Fig. 11 in the latest revised manuscript, in next page):

"The quadrangular with a relatively unstable bias shown in Fig. 11(a) is caused by the L_d that was calculated from the MOD05 water vapor product which exists quadrangular even after preprocessing the instrument malfunction gap."

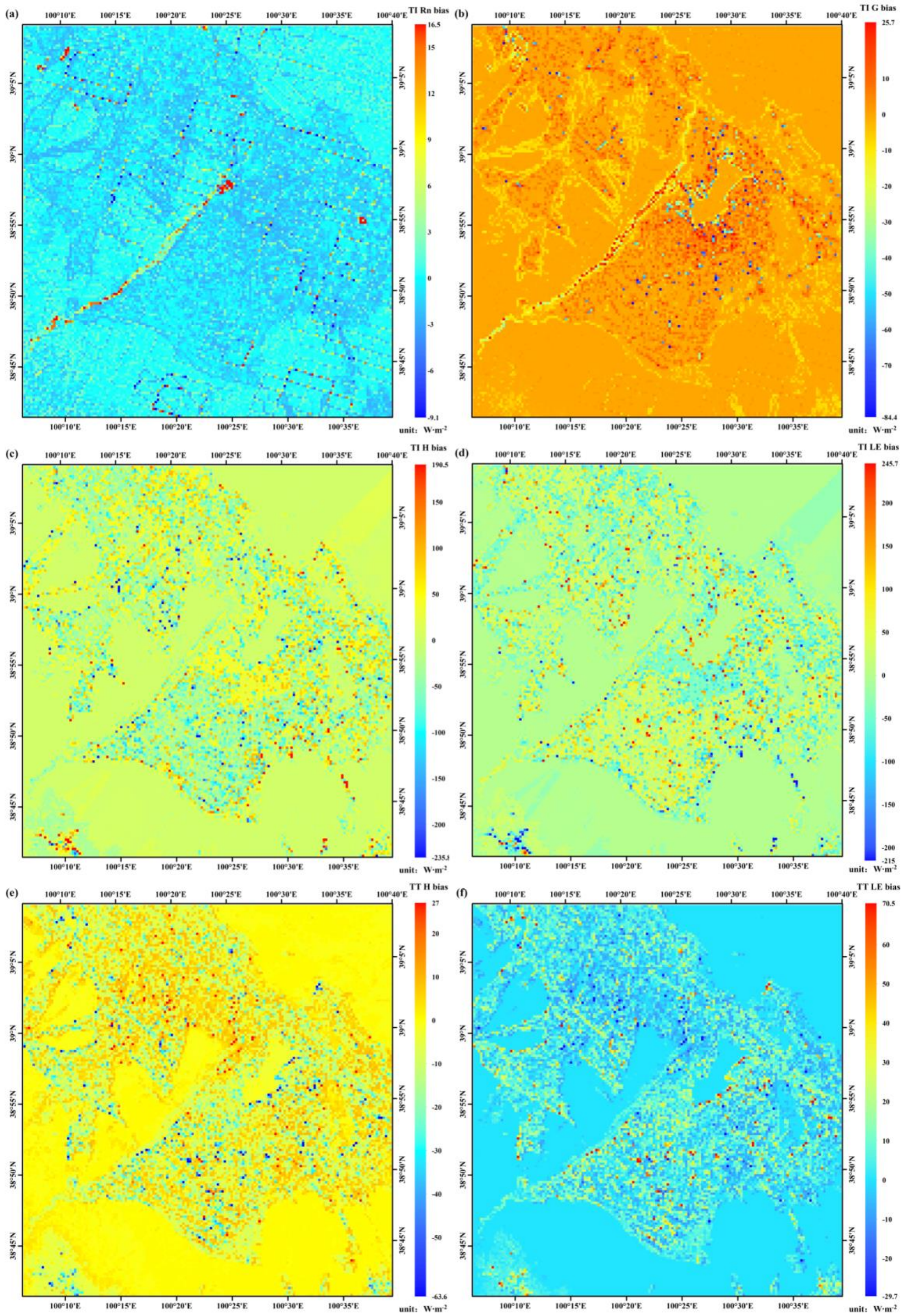

Figure 11. Maps of the bias of the energy balance components calculated using the TSFA method minus the IPUS method: (a) R_n, (b) G, (c) H, (d) LE, TSFA minus TRFA: (e) H and (f) LE.

Relevant changes

All the changes were marked as **red** color in the manuscript.

1. We have revised the abstract and introduction with hypothesis and research question stated.
2. We revised the manuscript by placing more emphasis on discussing the LE with a balance analysis and discussion of H.
3. Figure and table legends and names were revised.
4. A table of abbreviations and the usage of input data were added in the appendix.
5. New references were added.

Remote-sensing algorithm for surface evapotranspiration considering landscape and statistical effects on mixed-pixels

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Abstract

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

Index Terms: heterogeneous surface, temperature sharpening, area weighting, energy balance, evapotranspiration, spatial scale, HJ-1B satellite

1. Introduction

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

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

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

Studies have shown that different landscapes (Blyth and Harding, 1995; Moran et al., 1997; Bonan et al., 2002; McCabe and Wood, 2006) and the sub-pixel variations of surface variables, such as stomatal conductance (Bin and Roni, 1994), leaf area index (Bonan et al., 1993; Maayar and Chen, 2006) can cause errors in turbulent heat flux estimations. Surface variables inhomogeneity is rather difficult to evaluate as the sub-pixel variation of surface variables could be large even in the pure pixel. For example, generally, temperatures over the land surfaces vary strongly in space and time, and it is not unusual for the LST 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 the entire pixel area in ET estimation models.

The focus of this study is on the effects of surface heterogeneity when estimating ET. According to the current satellites operation situation, three methods were used to analyze the uncertainty produced by surface heterogeneity. Input parameter upscaling (IPUS) does not consider the surface heterogeneities at all. It was designed to simulate the satellites that have identical spatial resolution both in visible near-infrared (VNIR) and thermal infrared bands (TIR), such as the land surface products of Moderate-Resolution Imaging Spectroradiometer (MODIS) satellites. Temperature resampling and flux aggregation (TRFA) only does not consider the heterogeneity of LST, and temperature sharpening and flux aggregation (TSFA) consider all the surface heterogeneities. They were designed for the majority of satellites data or products that have inconsistent spatial resolution between VNIR and TIR, such as Landsat and HJ-1B satellites.

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

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

2. Methodology

2.1. Temperature-sharpening method based on statistical relationships

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

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

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 use 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:

$$\mathrm{CV} = \frac{\mathrm{STD}}{\mathrm{mean}} \tag{1}$$

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 ($0 \leq \mathrm{NDVI}_{300} < 0.2$, $0.2 \leq \mathrm{NDVI}_{300} < 0.5$ and $0.5 \leq \mathrm{NDVI}_{300}$). 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.

$$\hat{\mathrm{T}}_{300}(\mathrm{NDVI}_{300}) = \mathrm{a} + \mathrm{b} \times \mathrm{NDVI}_{300} + \mathrm{c} \times \mathrm{NDVI}_{300}^{2} \tag{2}$$

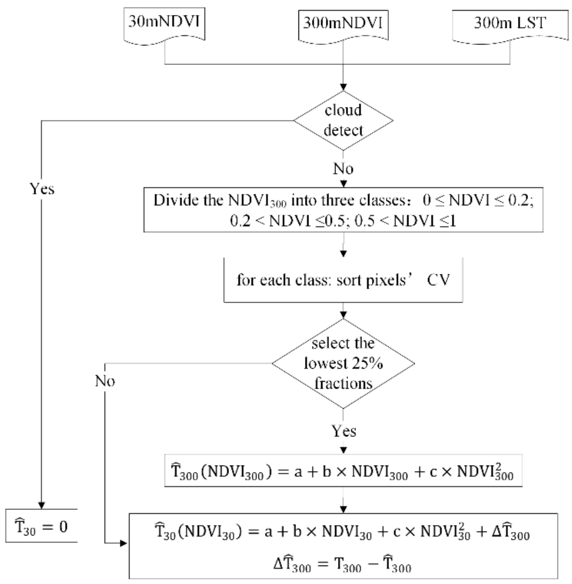

Figure 1. Flowchart of temperature sharpening.

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

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

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

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

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

(2) Count area ratio of different land-cover types within each pixel of a low-spatial-resolution classification image.

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

sensible heat flux (H).

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

$$F = \sum_{i=1}^{n} w_i \cdot F_i \tag{5}$$

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

2.3. Pixel ET algorithm

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

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

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

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

where γ is the psychometric constant; e_s and e_a are the aerodynamic saturation vapor pressure and atmospheric water vapor pressure, respectively; and r_a and r_s are the water vapor transfer aerodynamic resistance and surface resistance, respectively. Surface resistance includes soil resistance 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:

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

where S_d is the downward shortwave radiation, α is the surface broadband albedo, ε_s is the emissivity of the land surface, L_d is the downward atmospheric longwave radiation, $\sigma = 5.67 \times 10^{-8} W \cdot m^{-2} \cdot K^{-4}$ 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:

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

where Γ_s is 0.315 for bare soil and Γ_c is 0.05 for a full vegetation canopy (Su, 2002). H is the transfer of turbulent heat between the surface and atmosphere 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,

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

where ρ 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℃ (Choudhury et al., 1986), or up to 10℃ 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.

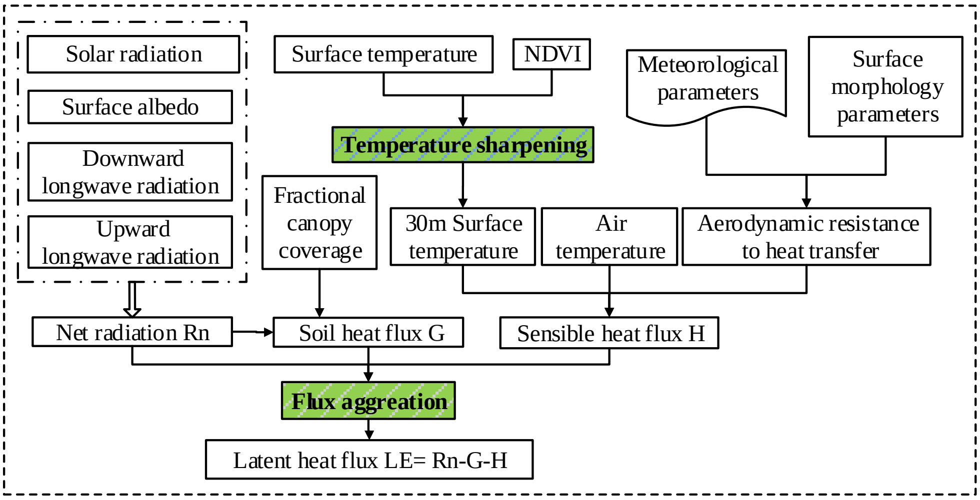

Figure 2. Flowchart of ET retrieval using the "Temperature Sharpening and Flux Aggregation" method.

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

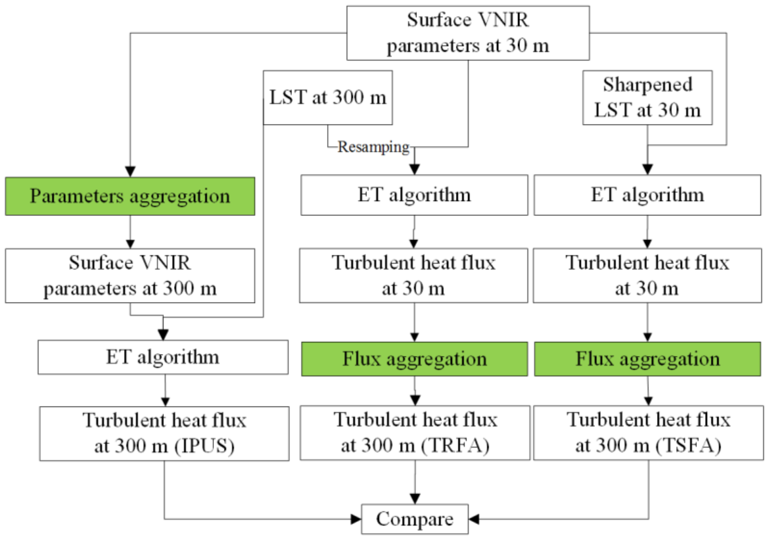

Figure 3. Flowchart of the three upscaling methods for retrieving evapotranspiration.

3. Study area and Dataset

3.1. Study area

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

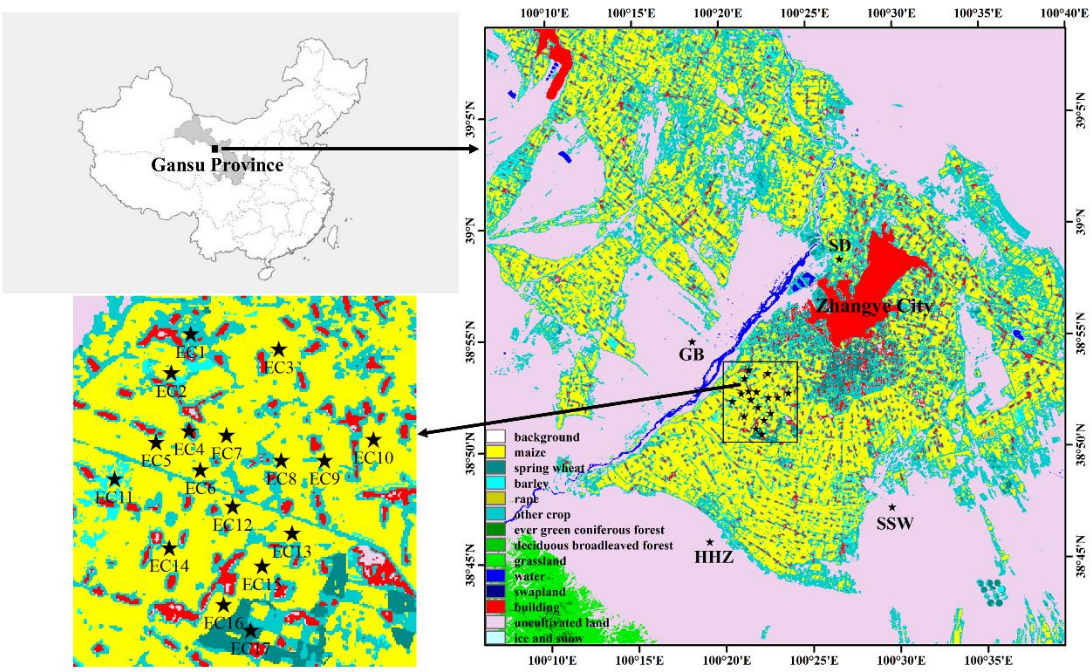

Figure 4. Study area and distribution of EC towers in HiWATER-MUSOEXE

3.2. Dataset

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

3.2.1. Remote sensing data

3.2.1.1. HJ-1B satellite data

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

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

Sensor	Band	Spectral range (μm)	Spatial resolution (m)	Swath width (km)	Revisit time (days)
	1	0.43-0.52			

CCD	2	0.52-0.60	30	360 (single) 700 (two）	4
	3	0.63-0.69			
	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	300		

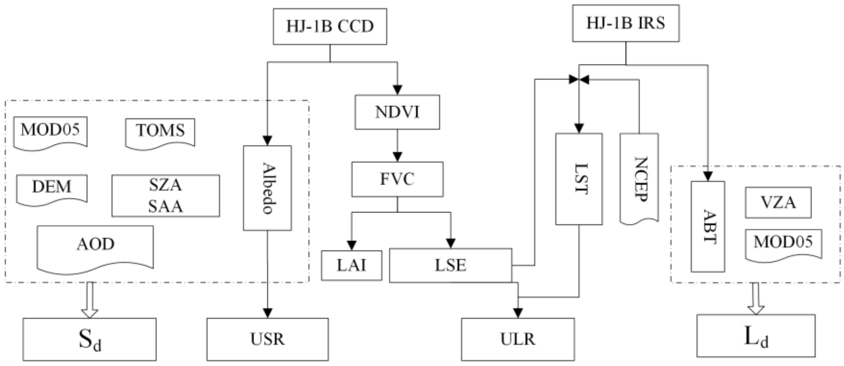

Figure 5. Flowchart of the land surface variable retrieval. The abbreviations are defined as follows: SZA: solar zenith angle; SAA: solar azimuth angle; VZA: view zenith angle; AOD: aerosol optical depth; ABT: at-nadir brightness temperature; S_d: downward shortwave radiation; USR: upward shortwave radiation,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

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

The HJ-1B satellite data 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:

$$\mathrm{NDVI} = \frac{\rho_{nir}-\rho_{red}}{\rho_{nir}+\rho_{red}} \tag{11}$$

and

$$\mathrm{FVC} = \frac{\mathrm{NDVI} - \mathrm{NDVI_s}}{\mathrm{NDVI_v} + \mathrm{NDVI_s}} \tag{12}$$

where ρ_{nir} and ρ_{red} are the reflectances in the near-infrared and red band, respectively, and $\mathrm{NDVI_v}$ and $\mathrm{NDVI_s}$ 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):

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

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

where θ is the zenith angle, $\mathrm{P}(\theta)$ is the angular distribution of the canopy gap fraction, $G(\theta)$ is the projection coefficient (0.5), and Ω 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):

$$\varepsilon = \varepsilon_v \cdot \mathrm{FVC} + \varepsilon_g(1 - \mathrm{FVC}) + 4 < d\varepsilon > \cdot\, \mathrm{FVC} \cdot (1 - \mathrm{FVC}) \tag{15}$$

where ε 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 ε_v and ε_g are the vegetation and ground emissivity, respectively.

(4) Land surface temperature. A single-channel parametric model for retrieving LST based on HJ-1B/IRS TIR data developed by 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 was performed by using products of the ASTER DEM.

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

3.2.1.2. Ancillary data

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

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

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

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

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

3.2.2. HiWATER experiment dataset

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

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

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

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

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

4. Results and analysis

4.1. Evaluation of surface variables

To control the model input variables and analyze sources of error, the coarse-resolution land surface temperature, downward shortwave radiation, downward longwave radiation, R_n and G were evaluated using in situ data.

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

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

in which $L^{\uparrow}$ and $L^{\downarrow}$ are in situ surface upwelling and atmospheric downwelling longwave radiation, respectively, and ε_s is the surface broadband emissivity, which is regarded as the pixel value of the 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 $W{\cdot}m^{-2}$, and 25.35 $W{\cdot}m^{-2}$, 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 $W{\cdot}m^{-2}$ and 21.13 $W{\cdot}m^{-2}$, respectively.

Table 4. Station validation results of downward shortwave radiation

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

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

Table 5. Station validation results of downward longwave radiation

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

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				

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

Table 6. Station net radiation validation results

station	R^2	MBE (W·m^{-2})	RMSE (W·m^{-2})	station	R^2	MBE (W·m^{-2})	RMSE (W·m^{-2})
EC1	0.76	-2.55	30.61	EC11	0.86	-15.13	28.05
EC2	0.79	2.52	25.24	EC12	0.90	-8.46	19.38
EC3	0.86	-35.84	42.97	EC13	0.88	-25.73	32.34
EC4	0.84	76.64	80.25	EC14	0.90	4.23	18.18
EC5	0.85	-24.41	32.34	EC15	0.84	8.33	23.01
EC6	0.82	4.35	23.44	EC17	0.89	-62.62	68.11
EC7	0.61	-58.66	67.83	GB	0.77	-10.40	38.86
EC8	0.83	-20.62	32.45	SSW	0.44	23.05	62.93
EC9	0.87	-29.60	36.27	SD	0.75	19.98	35.24
EC10	0.83	-24.35	33.51				

The R^2, MBE, and RMSE of the G in the HRB were 0.57, 8.51 W·m^{-2}, and 29.73 W·m^{-2}, respectively. The station R_n 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_n was overestimated. After removing the data on July 27, the R^2, MBE, and RMSE of the G at SSW were 0.17, 19.34 $W \cdot m^{-2}$, and 33.30 $W \cdot m^{-2}$, respectively.

Table 7. Station validation results of the soil heat flux

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

4.2. Validation of heat fluxes by TSFA

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

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

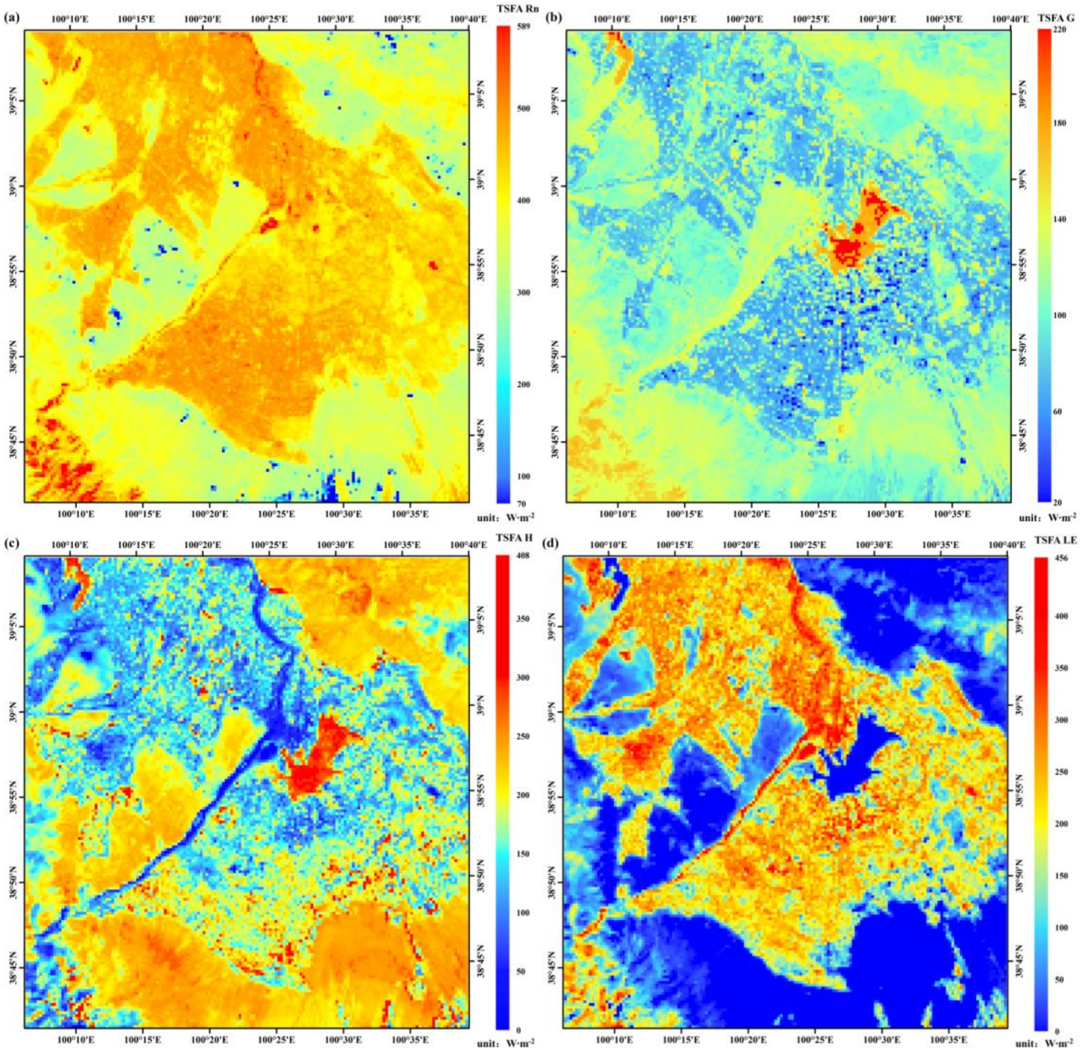

Figure 6. Maps of the four energy components, (a) Rn, (b) G, (c) H and (d) LE, calculated by TSFA on September 13, 2012.

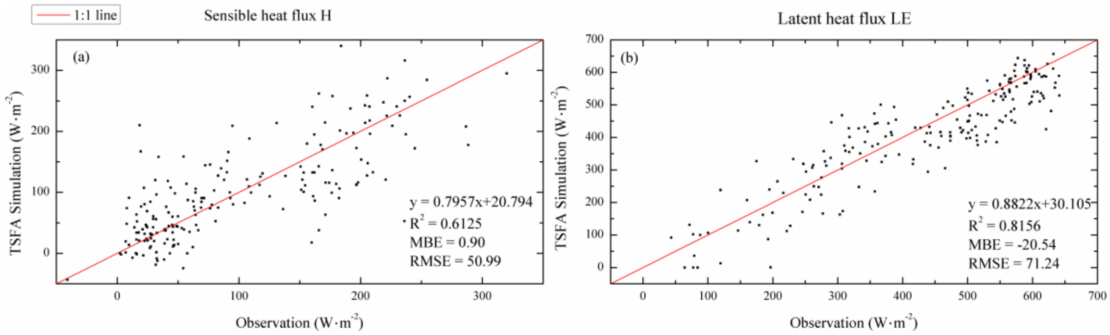

Figure 7. Scatter plot of the TSFA turbulent heat flux results

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

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

	TSFA-H(W·m^{-2})			TSFA-LE(W·m^{-2})		
date	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

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

4.3. Comparison between TSFA, TRFA and IPUS

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

4.3.1. Validation of TRFA and IPUS heat fluxes

Table 9 provides the footprint in situ validation results of the H and LE calculated using the IPUS and TRFA methods. The R^2, MBE, and RMSE of the LE between TSFA and TRFA were 0.99, -7.81 W·m^{-2} and 16.48 W·m^{-2}, respectively. And the R^2, MBE, and RMSE of the LE between TSFA and IPUS were 0.91, -4.10 W·m^{-2} and 51.30W·m^{-2}, respectively. Comparing with validation results of TSFA in Table 8, the TSFA method had a better retrieval accuracy than the TRFA method, and TRFA method was better than the IPUS method on all days, because the MBE and RMSE of TSFA decreased and the R^2 of TSFA increased on most days. Table 9 shows that the improvement in the accuracy that resulted from temperature resampling (TRFA) when comparing with the IPUS method was relatively higher than the improvement observed from temperature sharpening (TSFA) when comparing with the TRFA method. Compared with the IPUS method, the TRFA results were similar to the TSFA results since the sub-pixel landscapes and sub-pixel variations of most variables were considered. Thus, TRFA could effectively decrease the scale error that resulted from heterogeneity because the VNIR data of satellite were fully used. However, the performance of the TRFA method is unstable. For example, on August 3 and August 29, the TRFA results were slightly worse than the IPUS results, and the TSFA results were obviously better. This difference occurred because the different sub-pixel landscape temperatures were treated as equal to the values estimated at the 300-m resolution. Thus, when the 300-m-resolution LST has large retrieving errors, the turbulent heat flux retrieving error may be amplified by the sub-pixel landscapes.

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

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

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

EC4 is used as an example because its land cover and sub-pixel variation of temperature were complicated. Table 11 compares the turbulent heat fluxes calculated using the IPUS, TRFA and TSFA methods. Significant differences were observed between the TSFA and IPUS results and between the TRFA and IPUS results due to the heterogeneity of the surface. The LE calculated using the TSFA method was more consistent with in situ measurements than the LE calculated using the IPUS method because the MBE and RMSE decreased greatly, the R^2 increased, and the accuracy was improved by approximately 40 $W \cdot m^{-2}$. However, the LE calculated by using the TRFA was more accurate than the LE calculated by using the TSFA, as discussed below.

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 $\Delta\widehat{T}_{300}$ 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 W·m^{-2}, but the scale effect of R_n was not obvious, as discussed in Sect. 4.3.1, and the G was overestimated by approximately 20 W·m^{-2}. These results would lead to low accuracy of the available energy and overestimate the error by 60 W·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(W·m^{-2})				LE(W·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: W·m^{-2}

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

Fig. 8 shows that the classes and temperatures of 10×10 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 sensitivity and 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-sharpening results for the EC4 pixel on August 29. The temperature achieved at a resolution of 300 m was 303.49 K. Compared with the in situ measurement of 313.24 K, the temperature at a resolution of 300 m was underestimated. Even when substituting the in situ temperature into the ET model, the value of H reached 399.60 W·m^{-2} and the LE became 0 W·m^{-2}. When substituting the in situ temperature in the TRFA method, H was 396.49 W·m^{-2} and LE was 18.7 W·m^{-2}, indicating that the LE was underestimated and the H was overestimated with large errors. After processing by temperature sharpening, the distribution of the temperature at the 30-m resolution agreed with the classification. Temperature sharpening improved the description of heterogeneity based on the thermodynamic-driven force of the turbulent heat flux. These results apply to the ET model with the classification map and high-resolution variables and correspond with more accurate sensible heat flux estimations.

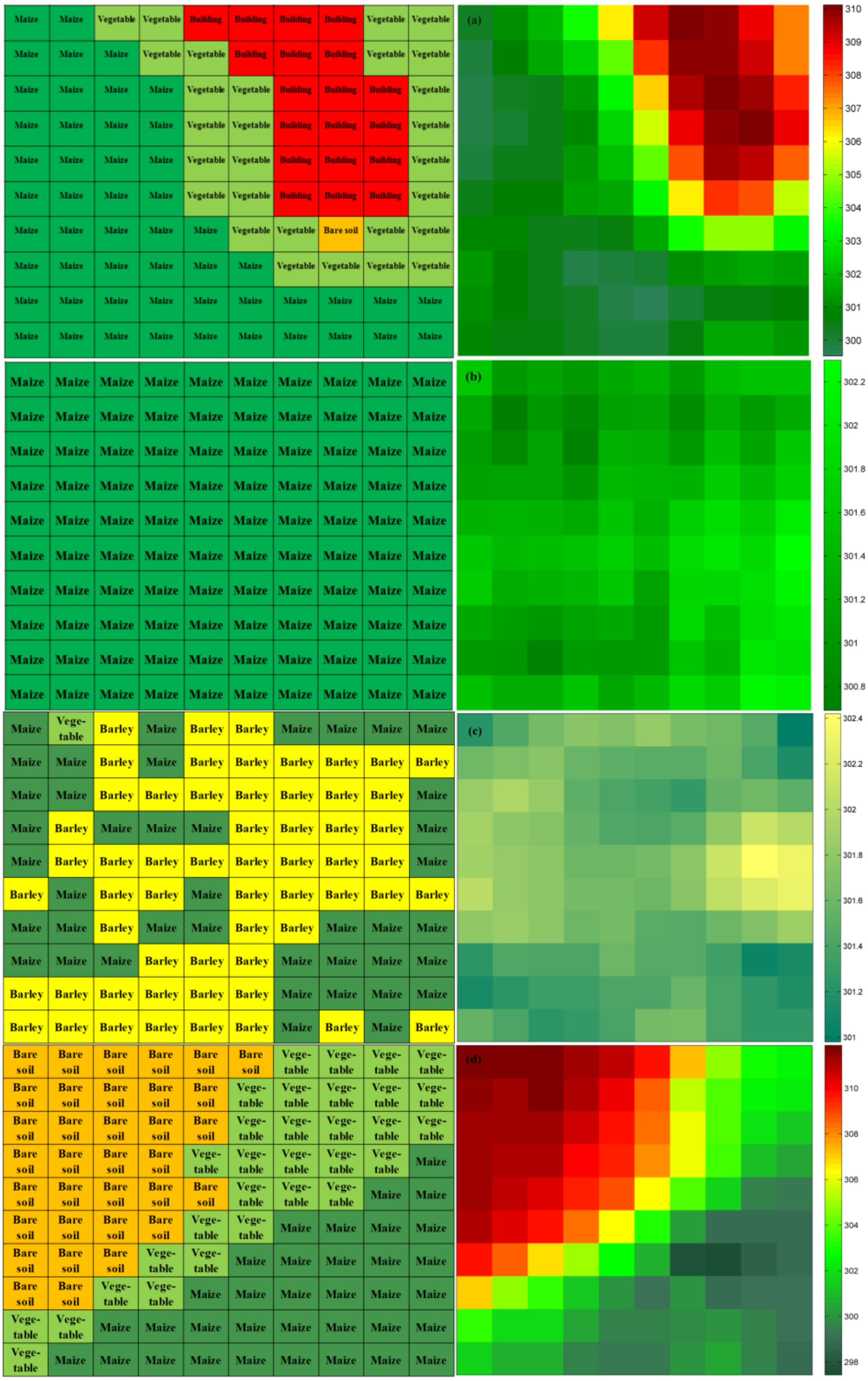

Figure 8. Distribution of classes and temperatures over the extreme heterogeneous surface (a) EC4, homogeneous surface (b) EC15, weak heterogeneous surface (c) EC11 and (d) a typical pixel on August 29, 2012.

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 W·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 (W·m^{-2})				LE (W·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: W·m^{-2}

	IPUS			TRFA			TSFA		
Variable	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE
EC15-H	0.40	40.64	74.64	0.33	45.93	80.81	0.40	40.36	72.88
EC15-LE	0.74	-52.11	83.48	0.71	-48.80	82.51	0.74	-49.00	81.94

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).

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

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

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

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

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

	IPUS			TRFA			TSFA		
Variable	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

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

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

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

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

	IPUS			TRFA		
Variable	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

4.3.2. Comparison of TRFA and IPUS methods

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

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

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

The quadrangular with a relatively unstable bias shown in Fig. 11(a) is caused by the L_d that was calculated from the MOD05 water vapor product which exists quadrangular even after preprocessing the instrument malfunction gap. From Fig. 11, the differences of the four energy components of the pure pixels between these three methods are within 5 W·m^{-2}, and the mixed pixels have different ranges.

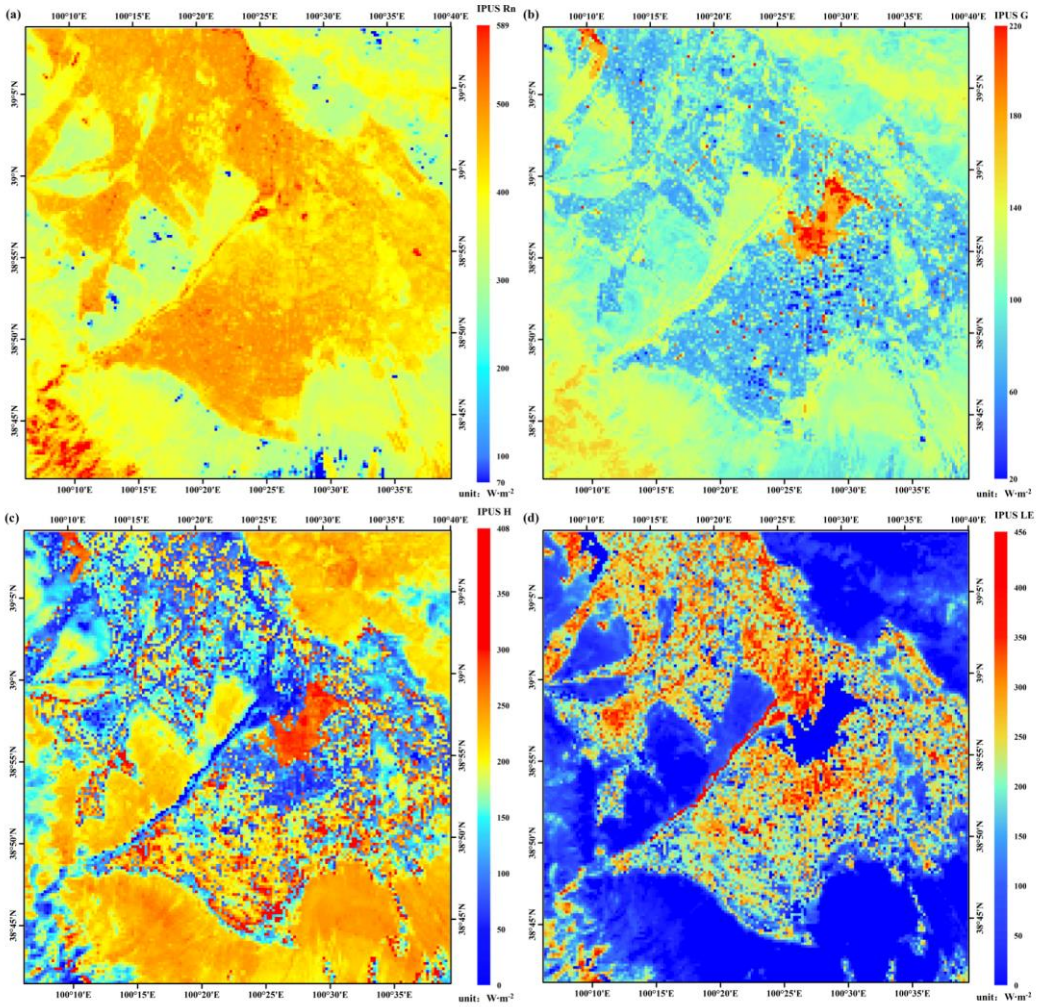

Figure 9. Maps of the four energy components, (a) R_n, (b) G, (c) H and (d) LE, calculated using the IPUS method on September 13, 2012.

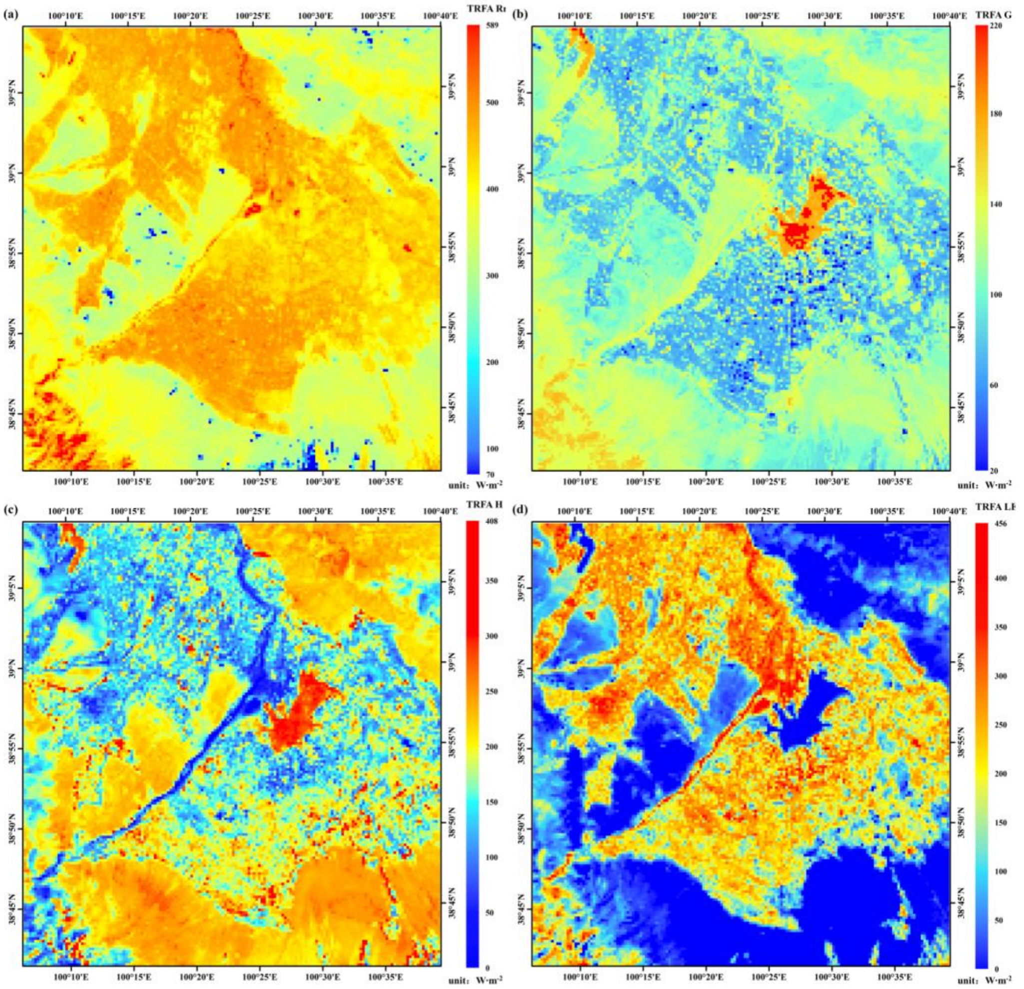

Figure 10. Maps of the four energy components, (a) R_n, (b) G, (c) H and (d) LE, calculated using the TRFA method on September 13, 2012.

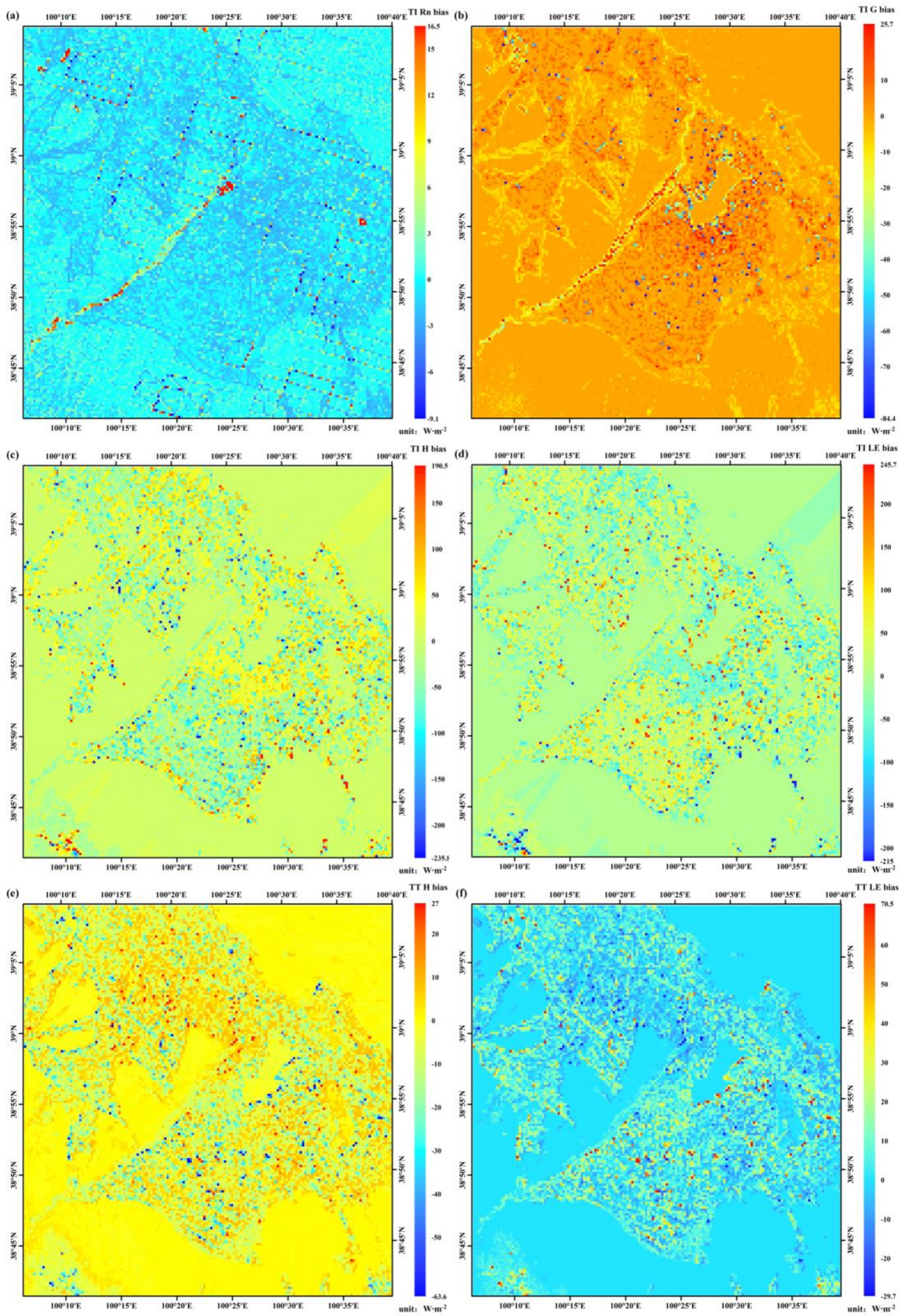

Figure 11. Maps of the bias of the energy balance components calculated using the TSFA method minus the IPUS method: (a) R_n, (b) G, (c) H, (d) LE, TSFA minus TRFA: (e) H and (f) LE.

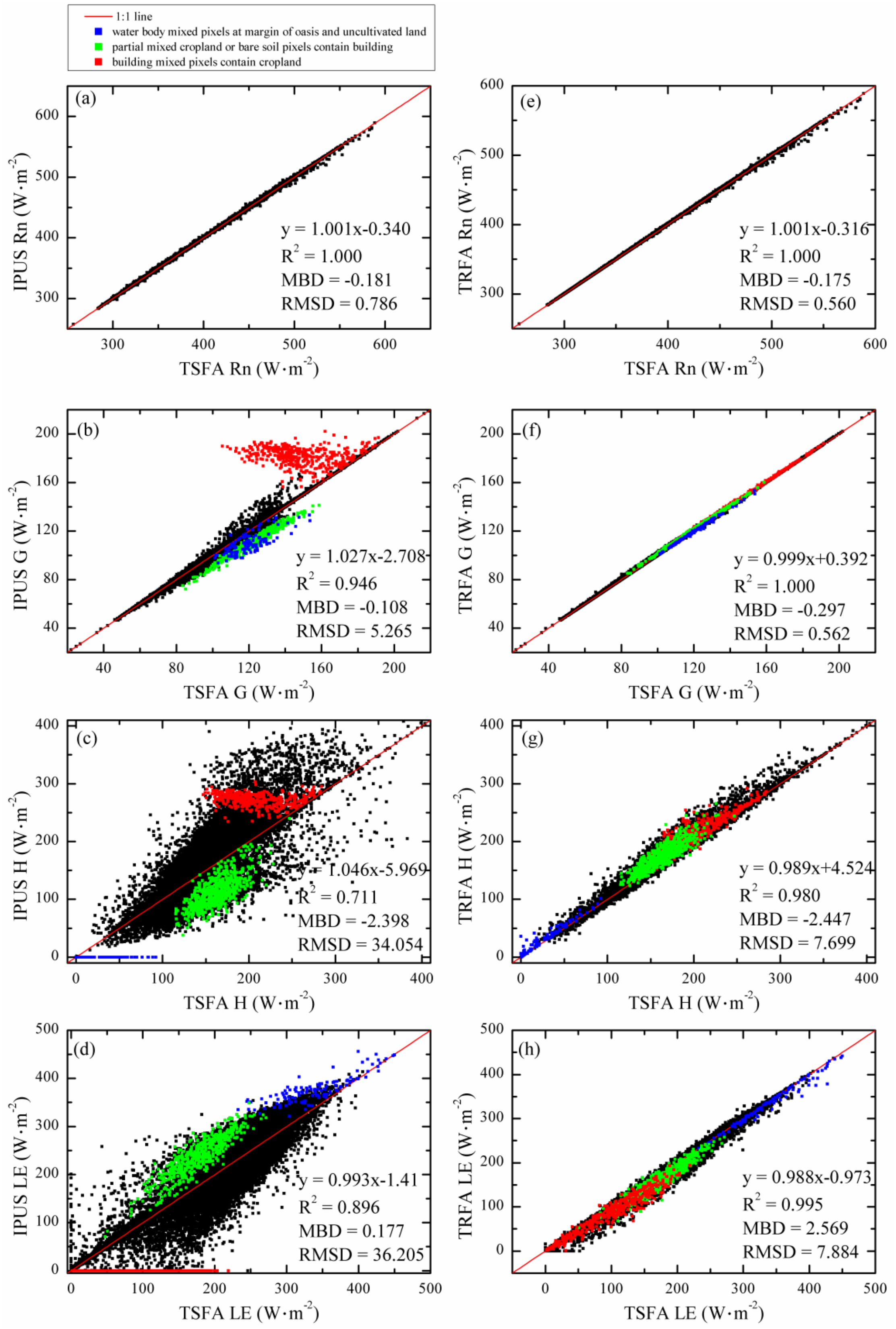

Figure 12. Scatter plots between the TSFA and IPUS results: (a) R_n, (b) G, (c) H and (d) LE; TSFA and TRFA (e) R_n, (f) G, (g) H and (h) LE. MBD and RMSD are the mean bias deviation and root mean square deviation between the TSFA and IPUS results, respectively.

Fig. 12 shows the scatter plots between the results from the TSFA method and the other two methods for all four energy balance components in the image. Fig. 11(a)(e) shows that R_n does not vary much between the three methods because the scatter is centralized around the 1:1 line. However, regarding the spatial scale effect, the differences in G, H and LE calculated by using the IPUS and TSFA methods are obvious: the scatter plots are dispersed at the mixed pixels, and the differences between the TRFA and TSFA results are relatively smaller. When using the TSFA method, the temperature sharpening results can be divided into results that are higher and lower than the LST retrieved at 300 m. Compared with the LST retrieved at 300 m when using the TRFA method, a higher LST would be counterbalanced by a lower LST when calculating H. Thus, the heterogeneous effect of temperature is neutralized in this case. This observation potentially resulted from the temperature sharpening algorithms because they tend to overestimate the sub-pixel LST for cooler landscapes and underestimate the sub-pixel LST for warmer areas in the image (Kustas et al., 2003).

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

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

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

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

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

TSFA methods because it depends on R_n.

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

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

Number of class types in pixels	IPUS (W·m^{-2})			TRFA (W·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

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

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

Types of mixed pixels	IPUS (W·m^{-2})			TRFA (W·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

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

4.4. Error analysis

Since LE is calculated as a residual term in the energy balance equations, the sensitivity of H was analyzed at first. Land surface variables (including LST, LAI, canopy height, and FVC) and meteorological variables (including wind speed, air temperature, air pressure and relative humidity) are needed to estimate H in this paper. To locate the error source when retrieving H, a sensitivity 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), 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 with a step size of 0.1 m), FVC=0.5, wind speed u=2.48 m·s^{-1}, air temperature Ta=297.9 K, air pressure = 97.2 kPa, and RH=40.29%. In addition, the land use type is maize, and the reference H is 230.2 W·m^{-2}.

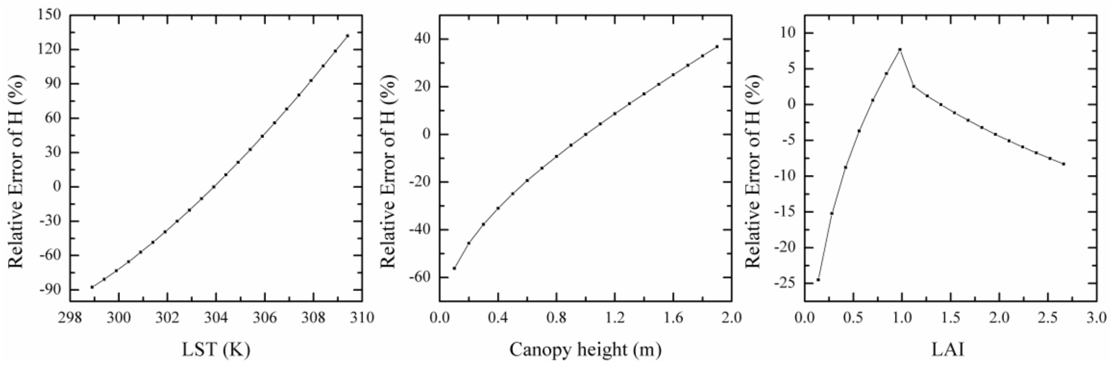

Figure 13. Sensitivity analysis of the surface variables for sensible heat flux

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

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

4.4.1. The error of LST

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

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

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

Station	Date	retrieved LST (K)	observed LST (K)	LST bias (K)	EC-LE ($W \cdot m^{-2}$)	LE from retrieved LST ($W \cdot m^{-2}$)	LE from observed LST ($W \cdot m^{-2}$)	LE relative error (%)	H 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

Notes: "LST bias" is calculated as the retrieved LST minus the observed LST; "EC-LE" is the in situ latent heat flux; "LE relative error" is the relative error between the retrieved and observed LST and is expressed as ((LE from retrieved LST)-(LE from observed LST))/(LE from observed LST)×100%, "H relative error" is calculated in the same way.

4.4.2. The error of canopy height

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

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

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

Date	EC-LE ($W \cdot m^{-2}$)	LE from incorrect canopy height ($W \cdot m^{-2}$)	LE from correct canopy height ($W \cdot m^{-2}$)	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

Except for the error source discussed before, the following sources of error were unavoidable: (1) Although the remotely sensed turbulent heat flux is instantaneous, the EC data are averaged over time. Thus, the time scales do not match in the validation.

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

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

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

5. Discussion

As mentioned in the results and analysis, the TSFA method describes the surface heterogeneity more clearly than the IPUS and TRFA methods. The IPUS method aggregates the land surface parameters achieved by CCDs from 30 m to 300 m, which results in the loss of surface information and leads to the scale effect. Although the TRFA method uses VNIR information and partially decreases the heterogeneity caused by landscape and VNIR variables, it treats the pivotal variable LST as homogeneous within mixed pixels, which results in considerable error. In summary, the superiority of the TSFA method is described as follows:

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

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

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

Our surface variable retrieval methods were validated against other areas considered in remote sensing measurement campaigns. For example, the albedo algorithm was previously applied to retrieve Global Land Surface Satellite (GLASS) Products (Liang et al., 2014), the LST retrieval algorithm was validated in the Haihe River Basin in northern China (Li et al., 2011), and the soil heat flux correction algorithm was validated in the GAME-Tibet campaign (Yang and Wang, 2008). Since the surface of the Heihe River Basin is extreme heterogeneous, additional comparisons of our algorithm in other areas of research would be better.

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

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

6. Conclusion

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

Compared with the IPUS and TRFA methods, the TSFA method is more consistent with in situ measurements. If ET estimating algorithm does not consider surface heterogeneity at all (i.e. IPUS), it would cause significant error (i.e. 186 W·m^{-2}) of heat fluxes. If ET estimating algorithm does not consider heterogeneity of LST only (i.e. TRFA), it would cause non-negligible error (i.e. 49 W·m^{-2}) in heat fluxes calculating. The TSFA method reduces the uncertainties produced by surface landscapes and LST inhomogeneity. As a sensitive variable of the ET model, canopy height is mainly determined by classification, and the application of classification at a 30-m resolution can improve the accuracy of the canopy height. As another sensitive variable, the sharpened surface temperature at a resolution of 30 m decreases the thermodynamic uncertainty caused by land surface heterogeneities. The TSFA method can capture the heterogeneities of the land surface and integrate the effects of landscapes in mixed pixels that are neglected at coarse spatial resolutions.

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

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Appendix

Notation		Application (for calculating)
6S radiation transfer mode	Second Simulation of a Satellite Signal in the Solar Spectrum radiation transfer mode	Albedo, S_d
α	Surface broadband albedo	S_d, R_n
ABT	At-nadir brightness temperature (K)	L_d
AMS	Automatic meteorological station	
AOD	Aerosol optical depth	S_d
BRDF	Bidirectional reflectance distribution function	α
CCD	Charge-coupled device	
CV	Coefficient of variation	Sharpened LST
EC	Eddy covariance	
FVC	Fractional vegetation coverage	LSE, G, LAI
G	Soil heat flux ($W \cdot m^{-2}$)	
$G(\theta)$	G function, Foliage angle distribution	LAI
H	Sensible heat flux ($W \cdot m^{-2}$)	
HRB	The Heihe River Basin	
IPUS	Input parameter upscaling scheme	
IRS	Infrared scanner	
L_d	Downward atmospheric longwave radiation ($W \cdot m^{-2}$)	R_n
LSE/ε	Land surface emissivity	LST
$\varepsilon_v/\varepsilon_g$	The vegetation/ground emissivity	
LST/T_{rad}	Land surface temperature/Surface radiation temperature (K)	H
MBE/MBD	Mean bias error (deviation)	
NCEP	National Centers for Environmental Prediction	LST
NDVI/$NDVI_{30}$	Normalized difference vegetation index	FVC, Sharpened LST
$NDVI_{300}$	300-m NDVI aggregated from NDVI	Sharpened LST
$NDVI_s/NDVI_v$	Normalized difference vegetation index of bare soil/fully covered vegetation	FVC
$P(\theta)$	Angular distribution of the canopy gap fraction	LAI
r_a	Aerodynamic resistance ($s \cdot m^{-1}$)	H
r_{ex}	“Excess” resistance ($s \cdot m^{-1}$)	heat transfer resistance
R_n	Net radiation ($W \cdot m^{-2}$)	
RMSE/RMSD	Root mean square error (deviation)	
S_d	Downward shortwave radiation ($W \cdot m^{-2}$)	R_n
SPAC	The soil-plant-atmosphere continuum	
SZA	Solar zenith angle	S_d
T_a	Air temperature (K)	H

T_{aero}	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_d
TRFA	Temperature resampling and flux aggregation	
TSFA	Temperature sharpening and flux aggregation	
ULR	Upward longwave radiation ($W \cdot m^{-2}$)	R_n
USR	Upward shortwave radiation ($W \cdot m^{-2}$)	R_n
VNIR	Visible/near-infrared	
VZA/θ	View zenith angle	L_d, LAI

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