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# Regional surface soil heat flux estimate from multiple remote sensing data in a temperate and semiarid basin

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**Abstract.** The regional surface soil heat flux ($G_0$) estimation is very important for the large-scale land surface process modeling. However, most of the regional $G_0$ estimation methods are based on the empirical relationship between $G_0$ and the net radiation flux. A physical model based on harmonic analysis was improved (referred to as "HM model") and applied over the Heihe River Basin northwest China with multiple remote sensing data, e.g., FY-2C, AMSR-E, and MODIS, and soil map data. The sensitivity analysis of the model was studied as well. The results show that the improved model describes the variation of $G_0$ well. Land surface temperature (LST) and thermal inertia ($\Gamma$) are the two key input variables to the HM model. Compared with *in situ* $G_0$, there are some differences, mainly due to the differences between remote-sensed LST and the *in situ* LST. The sensitivity analysis shows that the errors from $-7$ to $-0.5$ K in LST amplitude and from $-300$ to 300 $\mathrm{J\,m^{-2}\,K^{-1}\,s^{-0.5}}$ in $\Gamma$ will cause about 20% errors, which are acceptable for $G_0$ estimation.
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**Keywords:** harmonic analysis model; regional soil heat flux; thermal inertia; remote sensing data; arid and semiarid area.

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## 1 Introduction

The at-surface soil heat flux, $G_0$, is an important component of the land surface energy balance, particularly in the condition of dry soil or sparse canopies where $G_0$ can be as large as 50% of net radiation flux ($R_n$).[1,2] $G_0$ can be comparable with the maximum sensible heat flux ($H$) for well-watered conditions and be nearly the same as the maximum latent heat flux ($LE$) for senescent vegetation.[3] Many studies have proved that the incorrect estimation of $G_0$ is also an important factor leading to the surface energy imbalance problem. For example, Wilson et al.[4] revealed that the energy balance closure error for agricultural, grassland, and chaparral land surfaces was reduced by 20% when $G_0$ was used instead of being measured by soil heat flux plate buried in some depth in the soil. Heusinkveld et al.[5] proved that the energy balance closure error in an arid region became negligible with correct $G_0$ measurement. Wang et al.[6] found that the energy balance closure underestimation decreased from 32% to 14% when using $G_0$ (which was calculated by thermal diffusion equation) instead of using the heat flux plate measurements in depth of soil. Thus, the correct determination of $G_0$ is very important for improving the closure of surface energy balance.[7,8] The regional estimation of $G_0$ is urgently needed for the regional evapotranspiration estimation and the verification of regional or global circulation models.[9] Many empirical methods have been developed to derive regional $G_0$ from remotely sensed variables such as net radiation,[10–12] vegetation index,[11,13] land surface temperature (LST),[14] and land surface albedo.[14] The majority of the methods focused on developing the relationship between the ratio of $G_0/R_n$

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and remote sensing variables. For example, Reginato et al.[15] built a linear relationship between $G_0/R_n$ and vegetation height; Choudhury et al.[10] related $G_0/R_n$ to leaf area index using Beer's law; Su[13] estimated $G_0/R_n$ from fractional vegetation cover. However, those methods ignored the important effect of soil thermal properties on $G_0$ explicitly, and did not consider the effect of the LST on $G_0$. Santanello and Friedl[12] determined the diurnal course of $G_0/R_n$ using a cosine model that relates the maximum daytime $G_0/R_n$ to the daily maximum and minimum LSTs. Although LST (usually defined as a composite temperature of vegetation canopy and soil when vegetation exists) was utilized, this method is only applicable to dry and bare soil or dry and sparse canopy areas.[8,16] Bastiaanssen et al.[14] developed another empirical approach to estimate $G_0/R_n$ from LST, normalized difference vegetation index (NDVI), and land surface albedo assuming both LST and albedo reflect land surface wetness. However, neither the land surface albedo nor LST retrieved from remote sensing data can accurately reflect the soil wetness under dense vegetation conditions. However, the soil wetness is important for soil thermal properties and soil temperature. Cammalleri et al.[17] introduced a correction factor to explicitly incorporate the soil water content behavior. Based on the previous work (e.g., Carslaw and Jaeger,[18] Van Wijk and DeVries,[19] Horton and Wierenga[20]), Murray and Verhoef[8,16] proposed a physically based model using the harmonic analysis of soil surface temperature to estimate $G_0$ (HM model hereinafter), which is independent of net radiation flux $R_n$. In the HM model, the input variables include soil surface temperature, soil surface moisture, and fractional vegetation cover. These variables can be obtained from satellite observations, which make the model promising for the regional $G_0$ estimate. In addition, errors and uncertainties on $G_0$ are more transparent and more easily interpreted in Murray's HM model. However, there are still some disadvantages in the HM model. First, a fixed value of phase shift between canopy composite temperature and below-canopy soil surface temperature is used in the HM model, while it may vary with the underlying surfaces. Second, the HM model uses empirical and simulated soil properties, so it needs more discussion since soil properties vary with time and space. Moreover, in addition to the study of Verhoef et al.,[9] the HM model has not yet been applied at the regional scale using remote sensing data.

To improve the application of the HM model at the regional scale, the objectives of this study are: (1) to develop a parameterization of the phase shift between canopy composite temperature and below-canopy soil surface temperature rather than using a fixed value as in the original scheme; (2) to obtain soil properties (soil porosity and sand fraction) from a soil map to replace the empirical and simulated ones; (3) to estimate regional $G_0$ in the Heihe River Basin (HRB) using multisource remote sensing data including visible, thermal infrared, and microwave remote sensing data; (4) to perform a sensitivity analysis of the HM model to input variables and clarify which variables are significant for $G_0$ estimate.

## 2 Materials and Methods

### 2.1 *Study Area*

The HRB is located in arid and semiarid regions of northwest China. The study area is located in the upper and middle reach of HRB (Fig. 1). The HRB is a typical inland river basin in China with a geographic range between 37.5 to 42.2°N and 97.1 to 102.0°E, and with an area of about $14 \times 10^4$ km$^2$. It has a unique mixed landscape of "ice/frozen soil–forest–river and wetland–oasis–desert" and complicated ecohydrological processes.[21] The upper reach lies in the Qilian Mountains with an elevation of about 3000 to 5000 m and is mainly covered by forest, shrubs, and alpine meadows with an average annual air temperature, annual precipitation, and relative humidity of 2.0°C, 350 mm, and 60% (from 1960 to 2000), respectively.[22] The middle reach is flat with an elevation between 1400 and 1700 m and is mainly irrigated farmland; from east to west the mean annual air temperature is about 2.8°C to 7.6°C and precipitation is 250 to 50 mm (1960 to 2000). Ground measurements in two experimental sites were used in this study. The Yingke site (100° 24' 37" E, 38° 51' 26" N) is located in the middle reach of the HRB with maize and spring wheat from May to July, maize only in August to September, and bare soil (loamy soils) in the remaining period. The maximum height of maize canopy is 1.8 m and that of spring wheat is about 1 m in the growing season.[23,24] The Arou site lies in the upper reach of the HRB and is covered with grass in the growing season from May to September with 0.2 to 0.3 m height on sandy soils.

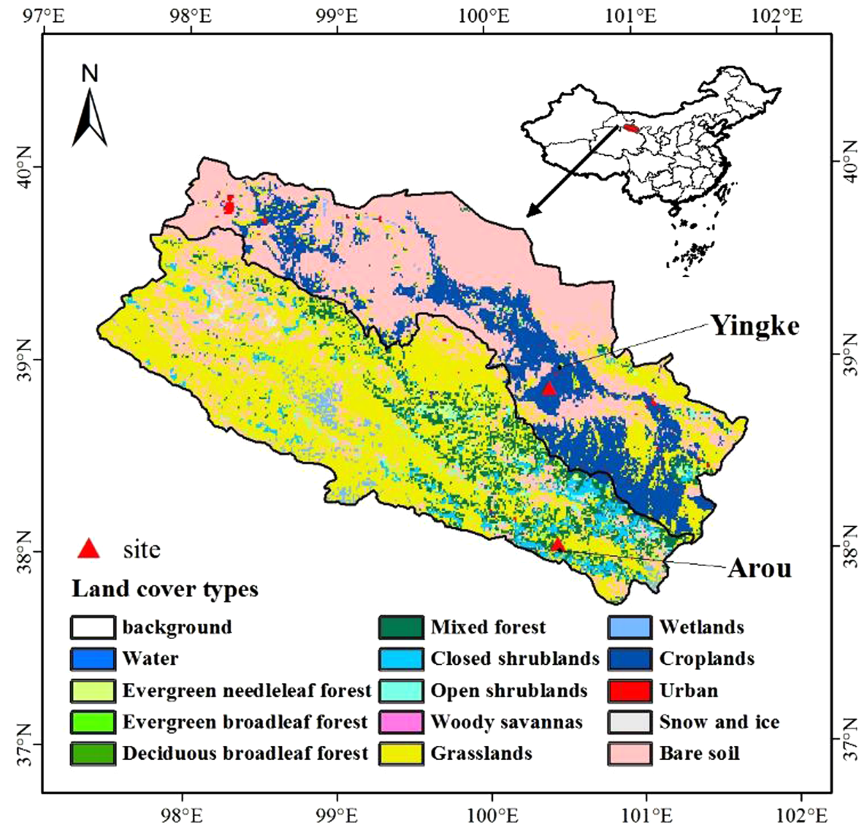


**Fig. 1** The land cover map of upper and middle reaches of the HRB in 2010.

## 2.2 *Data*

### 2.2.1 *Remote sensing data and soil map*

The forcing data of the HM model include LST, surface soil moisture, and fractional vegetation cover $f_c$, which can be derived from remote sensing data. Relevant surface properties are soil porosity and soil texture, which can be obtained from a soil map. Table 1 gives the summary of the remote sensing data and soil map used for regional scale application in this paper. The LST was retrieved from Chinese Geostationary Meteorological Satellite Feng Yun (FY-2C) using a generalized split-window algorithm[25,26] and gap-filled by applying the harmonic analysis of time series (HANTS) and multichannel singular spectrum analysis methodology.[27,28] The dataset was provided by the EU-FP7 project CEOP-AEGIS.[29] The hourly LST was then linearly interpolated to 30-min intervals in this study. The soil moisture product produced by Liu et al.[30] is retrieved from the observations by AMSR-E (Advanced Microwave Scanning Radiometer for EOS) sensor using a new dual-channel algorithm based on the $Q_p$ model developed by Shi et al.[31,32] Compared with ground measurements, the new soil moisture product performs better than the NASA product of AMSR-E, with a root mean square error (RMSE) improved from 0.066 to 0.048 $cm^3 cm^{-3}$ and a coefficient of determination ($R^2$) from 0.08 to 0.59. Moreover, the new soil moisture product reveals the seasonal variation of soil moisture better than the NASA product. The cloud-free NDVI time series are reconstructed based on the MODIS NDVI product using the improved HANTS method (iHANTS),[33,34] and the data can be found in the Cold and Arid Regions Science Data Center at Lanzhou.[35] This gap-free NDVI dataset is employed in this paper to calculate $f_c$ as $f_c = 1 - [(\mathrm{NDVI}_{\max} - \mathrm{NDVI})/(\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min})]^{0.7}$, where $\mathrm{NDVI}_{\max}$ and $\mathrm{NDVI}_{\min}$ are NDVI values for full vegetation cover and bare soil, respectively.[36] The soil properties are taken from a soil map produced by Shangguan et al.[37] The remote sensing data in May and July of 2009 were selected and unified to 1-km spatial resolution with a bilinear interpolation method.

**Table 1** Remote sensing data and soil map used in the present study.

| Data | Satellite/other source | Spatial resolution | Temporal resolution |
|---|---|---|---|
| NDVI | MODIS-Terra | 1 km | Daily |
| Soil moisture | AMSR-E | 0.25 deg | Twice a day |
| Land surface temperature | FY-2C | 5 km | Hourly |
| Soil texture and porosity | Soil map | 30 arc sec | Perennially |

**Table 2** Variables measured and the depths/heights of the sensors at the Yingke and Arou sites in the HRB in 2009 (according to Liu et al.[23,24]).

| Variables | Yingke site (m) | Arou site (m) |
|---|---|---|
| Soil temperature | 0.1, 0.2, 0.4, 0.8, 1.2, 1.6 (109, Campbell) | 0.1, 0.2, 0.4, 0.8, 1.2, 1.6 (107, Campbell) |
| Soil moisture | 0.1, 0.2, 0.4, 0.8, 1.2, 1.6 (CS616, Campbell) | 0.1, 0.2, 0.4, 0.8, 1.2, 1.6 (CS616, Campbell) |
| Upward/downward long wave radiation fluxes | 4 (CG3, Kipp, and Zonen) | 1.5 (PIR, Eppley) |

### 2.2.2 *In situ data*

Since the 1980s, many comprehensive hydrological and ecological experiments have been carried out in the HRB, e.g., the HRB field experiment (HEIFE),[38,39] Watershed Allied Telemetry Experimental Research (WATER),[40–42] and the Heihe Watershed Allied Telemetry Experimental Research (HiWATER).[21,43] The *in situ* micrometeorological data at the Yingke and Arou sites are from WATER in 2009 with 30-min intervals and are provided by the Cold and Arid Regions Science Data Center at Lanzhou.

The *in situ* $G_0$ measurements in this study were calculated by the thermal diffusion equation[44] with measurements of soil temperature and moisture profiles at the Yingke and Arou sites (Table 2). The *in situ* LST required in the thermal diffusion equation is derived from upward and downward longwave radiation fluxes [Eq. (7)].

## 2.3 *Methods*

### 2.3.1 *HM model*

The physical model for the land surface soil heat flux estimate based on the harmonic analysis of soil surface temperature (HM model) is described by Murray and Verhoef[8,16] as follows:

$$G_0 = \Gamma \cdot \sum_{n=1}^{M} A_n \sqrt{n\omega} \sin\left(n\omega t + \phi_n + \frac{\pi}{4}\right) = \Gamma \cdot J_s, \tag{1}$$

where $G_0$ (W m$^{-2}$) is the at-surface soil heat flux, $\Gamma$ (J m$^{-2}$ K$^{-1}$ s$^{-0.5}$) is the soil thermal inertia, $M$ is the total number of harmonics used ($M = 10$ in this study), $A_n$ is the amplitude of the $n$'th soil surface temperature ($T_s$) harmonic, $\omega$ (rad s$^{-1}$) is the angular frequency, $t$ is the time (s), $\phi_n$ (rad) is the phase shift of the $n$'th soil surface temperature harmonic, and $J_s$ is the summation of harmonic terms of soil surface temperature.

The parameter soil thermal inertia, $\Gamma$, is a key variable for estimating $G_0$ using Eq. (1). Murray and Verhoef[8] adopted the concept of normalized thermal conductivity[45] and developed a physical method to calculate $\Gamma$ as

$$\Gamma = \exp[\gamma \cdot (1 - S_r^{\gamma-\delta})] \cdot (\Gamma_* - \Gamma_0) + \Gamma_0, \tag{2}$$

where $\Gamma_*$ and $\Gamma_0$ are the thermal inertia for saturated and air-dry soil ($\mathrm{J\,m^{-2}\,K^{-1}\,s^{-0.5}}$), respectively, and can be calculated as $\Gamma_* = 788.2 \cdot \theta_*^{-1.29}$ and $\Gamma_0 = -1062.4 \cdot \theta_* + 1010.8$ with $\theta_*$ ($\mathrm{cm^3\,cm^{-3}}$) as soil porosity (equal to the saturated soil moisture content); $\gamma$ ($-$) is a parameter depending on soil texture; $S_r$ ($\mathrm{cm^3\,cm^{-3}}$) is relative saturation and is equal to $\theta/\theta_*$, with $\theta$ ($\mathrm{cm^3\,cm^{-3}}$) as actual soil moisture; and $\delta$ ($-$) is a shape parameter.

With remote sensing observations by space-borne or ground-based radiometers, usually the composite temperature of soil and vegetation canopy is measured for vegetated land surfaces other than soil only. Assuming the same time offset $\Delta t$ (s) applies to all harmonics, $J_s$ is written as

$$J_s(t) = \left(1 - \frac{1}{2} \cdot f_c\right) \cdot \sum_{n=1}^{M} \left[A_n' \sqrt{n\omega} \cdot \sin\left(n\omega t + \Phi_n' + \frac{\pi}{4} - \frac{\pi \cdot \Delta t}{12}\right)\right], \tag{3}$$

where $f_c$ is fractional vegetation cover, $A_n'$ (K) and $\phi_n'$ (rad) are the daily amplitude and phase shift of the $n$'th canopy composite temperature harmonic, respectively. $\Delta t$ (s) is the time offset between the canopy composite temperature and the below-canopy soil surface temperature and is found as 1.5 h in Murray and Verhoef based on their data.[8] In this paper, we propose a simple parameterization to estimate this time offset $\Delta t$ by taking into account the effect of vegetation condition (see Sec. 2.3.2).

### 2.3.2 *Parameterization of time offset*

Murray and Verhoef[16] and Verhoef et al.[9] showed that the below-canopy soil surface temperature arrived at the daily maximum a few hours later than canopy composite temperature according to their field data due to the extinction by the vegetation canopy. Such time offset between the canopy composite temperature and the below-canopy soil surface temperature results in the delayed maximum daily surface soil flux $G_0$ for vegetated surface when compared with bare soil surface. They also showed that a constant value 1.5 h was sufficient for various canopy densities (observed $f_c$ ranged from 0.6 to 0.99) and canopy types (oilseed rape, winter wheat, spring wheat, and borage). Theoretically, the time offset depends on canopy density and canopy structure.[9] According to measurements in July at the Yingke site in the HRB, the time offset ($\Delta t$) value of 1.5 h is applicable for full covered vegetation canopy (i.e., $f_c = 1$) but not for sparse canopy, and $\Delta t$ is equal to zero for bare soil ($f_c = 0$). Although canopy structure influences the radiation extinction, only fractional vegetation cover $f_c$ is used to represent the canopy condition in the present study. With the two boundary values (i.e., $\Delta t = 1.5$ h for $f_c = 1$ and $\Delta t = 0$ h for $f_c = 0$), a linear approach is proposed here to describe the time offset $\Delta t$ as a function of $f_c$:

$$\Delta t = 1.5 \cdot f_c \tag{4}$$

### 2.3.3 *Sensitivity coefficient*

Sensitivity analysis is important for understanding the source of uncertainties in hydrological and ecological modeling studies;[46,47] in particular, in this study it can identify which input parameter most affects $G_0$ estimate. A simple method is to plot the relative changes of a dependent variable against the relative changes of an independent variable as a curve.[48,49] Nevertheless, a mathematically defined sensitivity coefficient is mostly used in sensitivity analysis.[47,50–53] It is difficult to compare the sensitivity of variables by partial derivatives for a multivariables model (e.g., Penman–Monteith method). A nondimensional sensitivity coefficient is a transform of the partial derivative approach, which has been widely used in evapotranspiration studies.[52–55] The sensitivity coefficient is as follows:[52]

$$S_{V_i} = \lim_{\Delta V_i \to 0} \left( \frac{\Delta G_0 / G_0}{\Delta V_i / V_i} \right) = \frac{\partial G_0}{\partial V_i} \cdot \frac{V_i}{G_0}, \tag{5}$$

where $S_{Vi}$ is the sensitivity coefficient and $V_i$ is the $i$'th variable. A positive/negative sensitivity coefficient indicates $G_0$ will increase/decrease as the variable increases. The larger the sensitivity coefficient is, the larger effect of the given variable on $G_0$.

The relative error (RE) is used to evaluate variation in $G_0$, as follows:

$$\mathrm{RE} = \frac{G_0' - G_0}{G_0} \times 100\%, \tag{6}$$

where RE is the RE of $G_0$, $G_0'$ is $G_0$ with varying LST or $\Gamma$, and $G_0$ is the original value.

### 2.3.4 *In situ LST*

The *in situ* LST is calculated as follows:

$$T(z_0) = \left[ \frac{R_{L\uparrow} - (1 - \varepsilon) R_{L\downarrow}}{\varepsilon \sigma} \right]^{1/4}, \tag{7}$$

where $R_{L\uparrow}$ and $R_{L\downarrow}$ are the upward and downward longwave radiation fluxes ($\mathrm{W\,m^{-2}}$), respectively, $\varepsilon$ is the land surface emissivity (taken as 0.987 at the Yingke and Arou sites),[23,24] and the Stefan–Boltzmann constant $\sigma = 5.67 \times 10^{-8}$ ($\mathrm{W\,m^{-2}\,K^{-4}}$).

## 3 Results and Discussion

### 3.1 *In Situ Soil Heat Fluxes with Different Time Offsets*

The surface soil heat flux estimated by the HM model [Eq. (1) with $M = 10$], with time offset of 1.5 h and $1.5 f_c$ h using *in situ* micrometeorological measurements in May and July of 2009 at the Yingke site, were compared with the *in situ* $G_0$ measurements. To show the difference in the estimated $G_0$ with different time offsets more clearly, only some days with varying $f_c$ (14, 22, 23, 25, 28, 29, 30 in May and 17, 19, 21, 23, 24, 26, 28 in July of 2009) were selected, as shown in Fig. 2. $G_0$ estimation with time offset of 1.5 h are lagged $G_0$ with $1.5 f_c$ h in May, and they are nearly the same in July (Fig. 2). RMSE is improved from 80.8 to 52.8 $\mathrm{W \cdot m^{-2}}$ when using time offset of $1.5 f_c$ h instead of 1.5 h in whole May [Fig. 3(a)], and $R^2$ increases from 0.59 to 0.83. However, the improvement is not obvious in July, with nearly the same RMSE and $R^2$ [Fig. 3(b)]. Thus, the improved model improves the accuracy of $G_0$ for sparse vegetation in May when the mean $f_c$ was about 0.3. Furthermore, the results in July are not better than May, and the HM model for vegetated surface should be improved further in our following work. At the Arou site, $f_c$ had less variation over the whole year than that at the Yingke site. In conclusion, the improvement performs better at the Yingke site than at the Arou site, which is not shown here.

### 3.2 *Spatial Distribution of $G_0$*

The improved HM model [Eqs. (3) and (4)] was applied to remote sensing data in the HRB region, as listed in Table 1. To analyze the spatial patterns of the estimated $G_0$ in different seasons, $G_0$ at the same time on different days over a month were averaged to avoid the

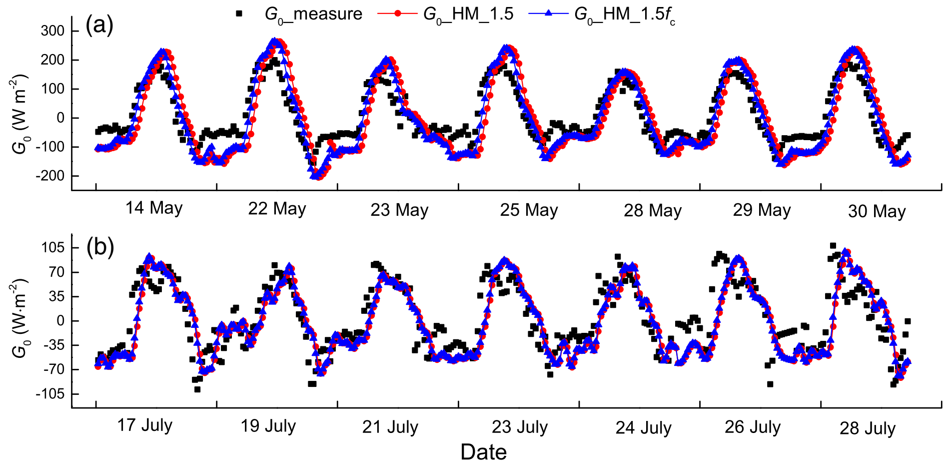


**Fig. 2** The diurnal variations of $G_0$ on some days in (a) May and (b) July of 2009 at the Yingke site. $G_0$_measure is the *in situ* measurements of surface soil heat flux, $G_0$_HM_1.5 and $G_0$_HM_1.5$f_c$ are calculated by HM model with time offset of 1.5 h and 1.5$f_c$ h, respectively, using *in situ* measurements of LST.

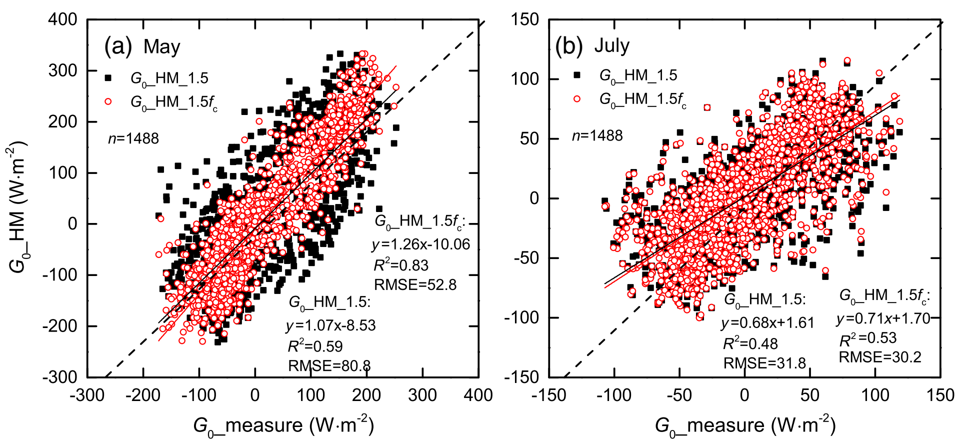


**Fig. 3** Scatter plot of $G_0$ measurement and $G_0$ estimation by HM model in the whole (a) May and (b) July of 2009 at the Yingke site. $G_0$_measure, $G_0$_HM_1.5, and $G_0$_HM_1.5$f_c$ are the same as in Fig. 2.

contingency caused by gaps in the remote sensing data due to cloud cover and other reasons. The mean monthly $G_0$ maps at 10:30 am in May and July are shown in Fig. 4. As expected, it is found that the $G_0$ values are generally higher in bare soil than in vegetated surfaces [Figs. 4(a) and 4(b)] in both May and July of 2009. More energy was transferred into the soil directly for bare surfaces, while for vegetated surface the energy is intercepted by vegetation canopy for transpiration, so less energy was conducted into the soil. The $G_0$ values over the desert area in the center of the middle reach are significantly higher than the values in the surrounding bare soil in both May and July of 2009 due to higher sand fraction and lower porosity in desert area, according to the soil map, which gives higher thermal inertia according to Eq. (2) [Figs. 4(c) and 4(d)].

For the same land cover type, the $G_0$ values vary with $f_c$ from May to July. The mean $G_0$ values in May are 222 W m$^{-2}$ at the Yingke site and 156 W m$^{-2}$ at the Arou site, while the mean values of $G_0$ in July are 103 and 87 W m$^{-2}$ at the two sites, respectively. In both sites, the $G_0$ values are lower in July due to higher $f_c$ over maize and grass land surfaces in May than in July. The $f_c$ increased from 0.32 to 0.77 from May to July at the Yingke site and from 0.46 to 1.0 at the Arou site in 2009.

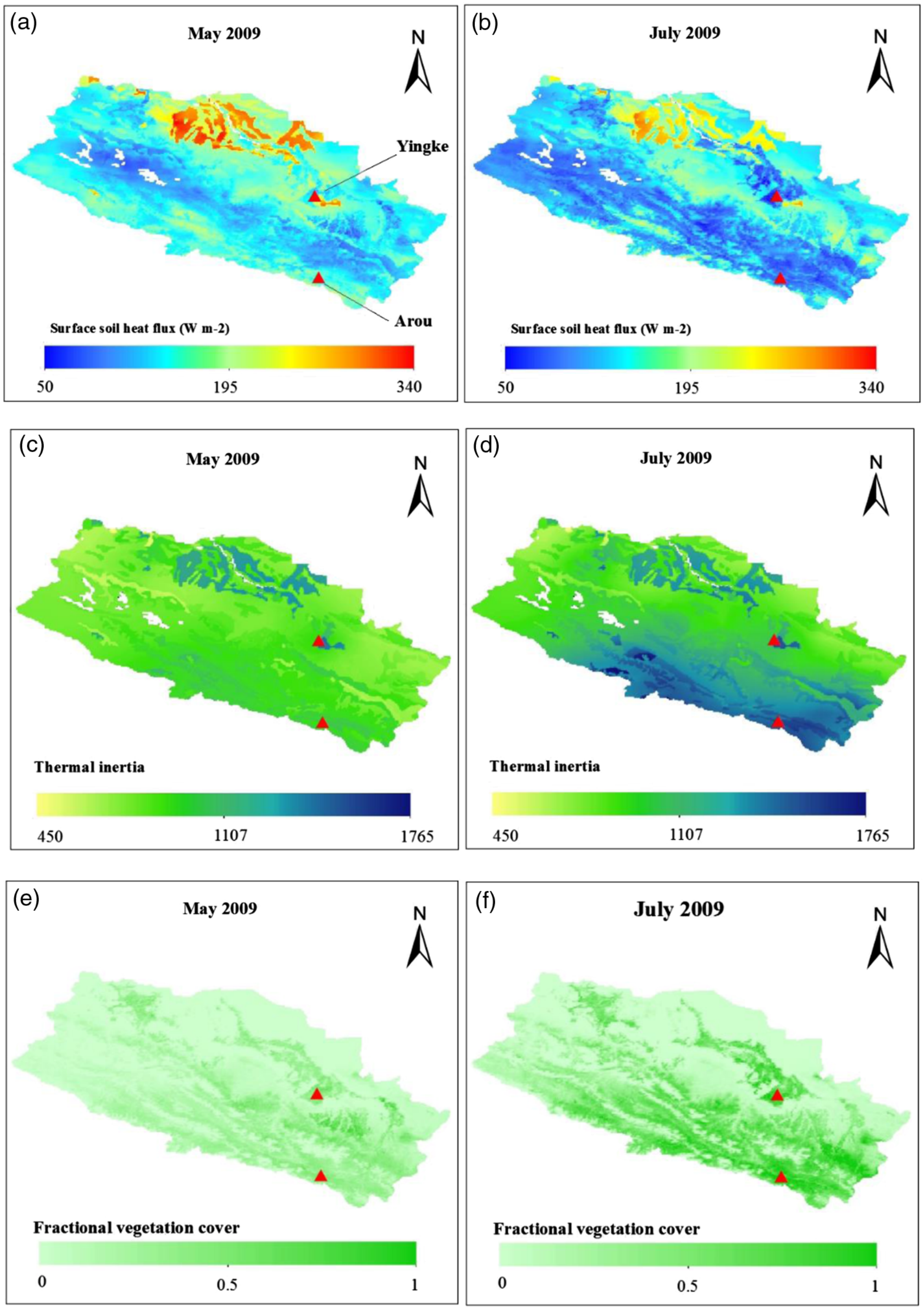


**Fig. 4** The distribution of mean monthly $G_0$ estimation at 10:30 am local time (a) in May and (b) in July, the distribution of mean monthly thermal inertia (c) in May and (d) in July, and the distribution of monthly $f_c$ (e) in May and (f) in July in 2009 in the upper and middle reaches of the HRB.

In July of 2009, the maximum of monthly $G_0$ value in the study area at 10:30 am can reach to 329 $\mathrm{W\,m^{-2}}$ in desert area in the middle reach of HRB, where $R_n$ is about 600 $\mathrm{W\,m^{-2}}$. This leads to $G_0$ being up to 50% of $R_n$. The $G_0$ for the cropland in the middle reach is higher in May than that in July as the cropland is at the emergence stage in May with a lower $f_c$ [Fig. 4(e)]. The $G_0$ for the vegetated surfaces in the upper reach in July is lower than in May, which is attributed to higher $f_c$ for grass land in the growing season [Fig. 4(f)].

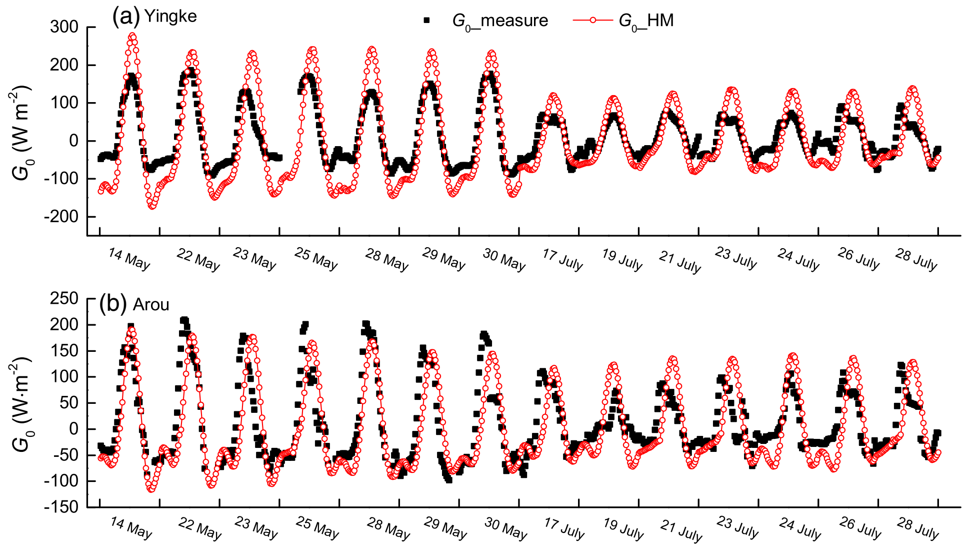


**Fig. 5** The diurnal variations of land surface soil heat flux $G_0$ in May and July of 2009: (a) at the Yingke site and (b) at the Arou site. $G_0$_HM is calculated by the improved HM model using remote sensing data and soil map data.

## 3.3 *Validation of Estimated Soil Heat Flux from Remote Sensing*

The calculated $G_0$ by the improved HM model using remote sensing data and soil map was evaluated at the Yingke and Arou sites by comparing *in situ* $G_0$ measurements. It was found that the estimated $G_0$ is overestimated in both daytime and nighttime at the Yingke site [Fig. 5(a)]. At the Arou site, the estimated daytime $G_0$ (positive) is underestimated in May and overestimated in July [Fig. 5(b)]. The deviations are mainly caused by remote sensing data, which are different from ground measurements. To investigate which remote sensing data lead to $G_0$ errors the most, cross-calculation with remote sensing data and *in situ* measurements were performed in this study.

As shown in Table 3, four different variables were applied to the HM model. $A$, $B$, $C$, and $D$ in Table 3 represent LST from FY-2C, the *in situ* LST derived from the observed longwave radiation, the thermal inertia from AMSR-E data and soil map, and the *in situ* thermal inertia derived from the observed soil properties, respectively. It is important to know which forcing data caused the overestimation or underestimation in the calculated $G_0$ when applying the HM model to remote sensing data. Equation (1) shows that the thermal inertia and LST affect $G_0$ directly. Compared to $G_0$ estimated with $A$ and $C$, the $G_0$ estimated with $B$ and $C$ is more consistent with *in situ* $G_0$ measurements (Fig. 6). The $R^2$ increased from 0.80 to 0.84 at the Yingke site and from 0.54 to 0.72 at the Arou site. The RMSE also increased from 48.2 to 37.4 $\mathrm{W\,m^{-2}}$ at the Yingke site and from 52.4 to 33.2 $\mathrm{W\,m^{-2}}$ at the Arou site. Although $G_0$ estimated with $A$ and $D$ is also improved, the improvement is not so obvious. It shows that the deviation of estimated $G_0$ using remote sensing data is mainly caused by the difference between remotely sensed LST and ground-measured LST, and the AMSR-E soil moisture and soil texture bring fewer errors.

**Table 3** The combinations of LST and $\Gamma$ derived from remote sensing data and *in situ* measurements, respectively.

| Variable | Remote sensing data | *In situ* measurement |
|---|---|---|
| LST | $A$: FY-2C | $B$: field LST |
| $\Gamma$ | $C$: AMSR-E, soil map | $D$: field soil moisture, soil texture |

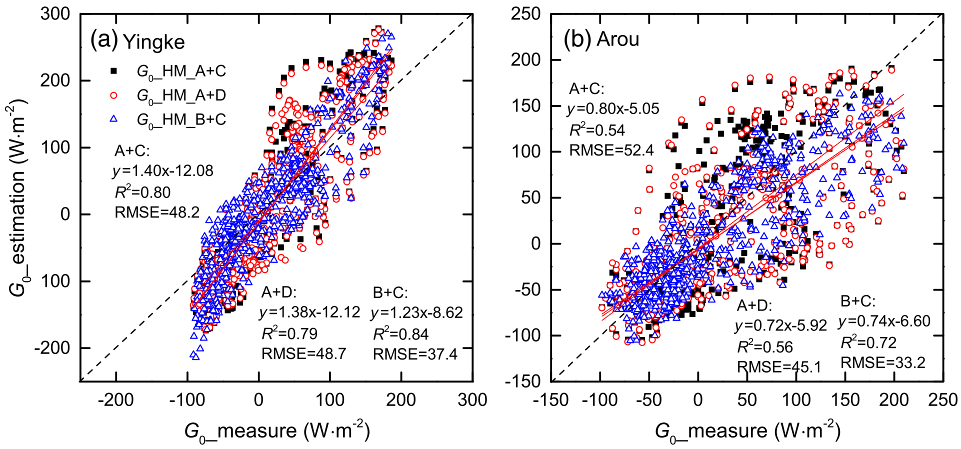


**Fig. 6** Scatterplot of $G_0$ estimation for cases *A*, *B*, *C*, and *D* in Table 3 versus *in situ* $G_0$ measurement, respectively, on 14 days (14, 22, 23, 25, 28, 29, 30 in May and 17, 19, 21, 23, 24, 26, 28 in July of 2009) (a) at the Yinke site and (b) at the Arou site.

## 3.4 *Sensitivity of Estimated $G_0$ to Input Variables*

### 3.4.1 *Sensitivity coefficients for each variable*

The estimated $G_0$ is related to LST, soil moisture, $f_c$, and soil properties, which have different dimensions and different ranges of values. The input variables are interrelated and the question arises as to which parameter is more influential on the estimated $G_0$. Sensitivity analysis can answer the question. According to Eq. (5), the sensitivity coefficients for the input variables were evaluated and are listed in Table 4. The data used to perform the sensitivity analysis are from the Yingke site. The LST, soil moisture, and sand fraction are positively correlated to $G_0$, while $f_c$ and porosity are negatively correlated to $G_0$. Notably, the porosity is the most influential on $G_0$, and sand fraction is the least important with a sensitivity coefficient of 0.06. $f_c$ is more related to $G_0$ for dense vegetation, which shows that the relationship of $f_c$ and $G_0$ is nonlinear.

### 3.4.2 *Sensitivity of $G_0$ to LST and thermal inertia*

According to the HM model, $G_0$ values depend on the amplitude of LST and thermal inertia. The sensitivity coefficients give the qualitative dependence of $G_0$ on input variables. This section presents the quantitative sensitivity analysis of $G_0$ to the amplitude of LST and thermal inertia. With a fixed thermal inertia, $G_0$ was calculated using varied LST with daily amplitude $(A) \pm dA$ ($dA = -12, -11, -9, -7, -6, -2, -0.5, 1, 3, 5$ K). Similarly, with a fixed LST, $G_0$ was calculated using varied thermal inertia values $\Gamma \pm d\Gamma$ ($d\Gamma = -1000, -800, -600, -400, -200, 0, 200, 400, 600, 800, 1000\ \mathrm{J\,m^{-2}\,K^{-1}\,s^{-0.5}}$) by the HM model. The RE is used to evaluate $G_0$ variation based on Eq. (6).

**Table 4** The sensitivity coefficients of input variables in the HM model.

| Variables | $S_{Vi}$ |
|---|---|
| Amplitude of LST | 0.99 |
| Soil moisture | 0.44 to 0.46 |
| $f_c$ | −0.18 to −0.69 |
| Porosity | −1.3 |
| Sand fraction | 0.06 |

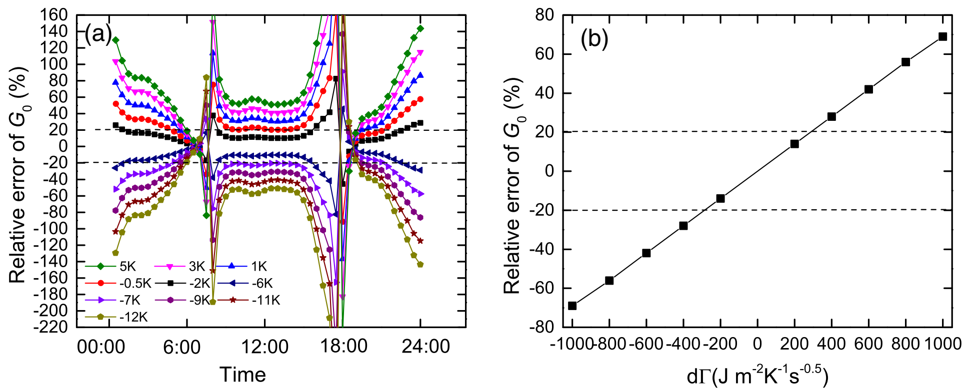


**Fig. 7** The mean RE on $G_0$ in 14 days (14, 22, 23, 25, 28, 29, 30 in May and 17, 19, 21, 23, 24, 26, 28 in July of 2009) with (a) varied amplitude of LST and (b) varied thermal inertia at the Yingke site.

$G_0$ is nonlinearly correlated to LST amplitude and linearly correlated to thermal inertia. Therefore, RE value is constant in each day with the same $d\Gamma$. However, RE is varied with the same $dA$. An error of 20% on $G_0$ evaluation is acceptable.[56–58] When $dA$ is varied from $-0.5$ to $-7$ K, and $d\Gamma$ is varied from $-300$ to $300\ \mathrm{J\,m^{-2}\,K^{-1}\,s^{-0.5}}$, respectively, the mean RE on $G_0$ in the 14 days (14, 22, 23, 25, 28, 29, 30 in May and 17, 19, 21, 23, 24, 26, 28 in July of 2009) is less than 20% at the Yingke site (Fig. 7).

### 3.4.3 *Sensitivity of thermal inertia to soil properties and soil moisture*

The soil porosity and soil sand fraction, together with soil moisture were used to calculate thermal inertia in the HM model [Eq. (2)]. According to the China soil map used in this study, the soil porosity varies from 0.43 to 0.67 when the sand fraction is less than 0.4, and the sand fraction value is mostly less than 0.8 for soil. The relative saturation $S_r$ ($\theta/\theta*$) describes the soil moisture conditions. The variations of $\Gamma$ from dry to wet soil conditions are shown in Fig. 8. Different values of soil porosity (0.43, 0.55, and 0.67) when the sand fraction is less than 0.4 were used to calculate $\Gamma$ under different soil moisture conditions [Fig. 8(a)]. Different values of sand fraction and a fixed soil porosity of 0.46 were also used to calculate $\Gamma$ [Fig. 8(b)]. It is shown that $\Gamma$ increases with the increasing soil moisture. $\Gamma$ varies largely under wet soil conditions (with larger $S_r$) than dry soil conditions (with smaller $S_r$) with the same soil porosity variation [Fig. 8(a)], which means that $\Gamma$ under wet conditions (i.e., when $S_r$ is larger) is more sensitive to soil porosity. $\Gamma$ is sensitive to smaller porosity, according to Fig. 8(a), because there is greater change of $\Gamma$

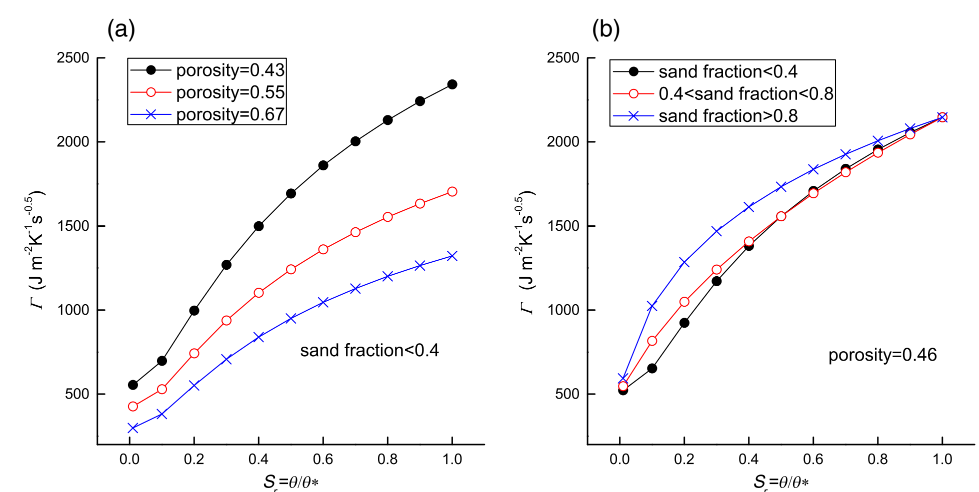


**Fig. 8** The sensitivity of thermal inertia as a function of relative saturation ($S_r$) to (a) porosity and (b) sand fraction.

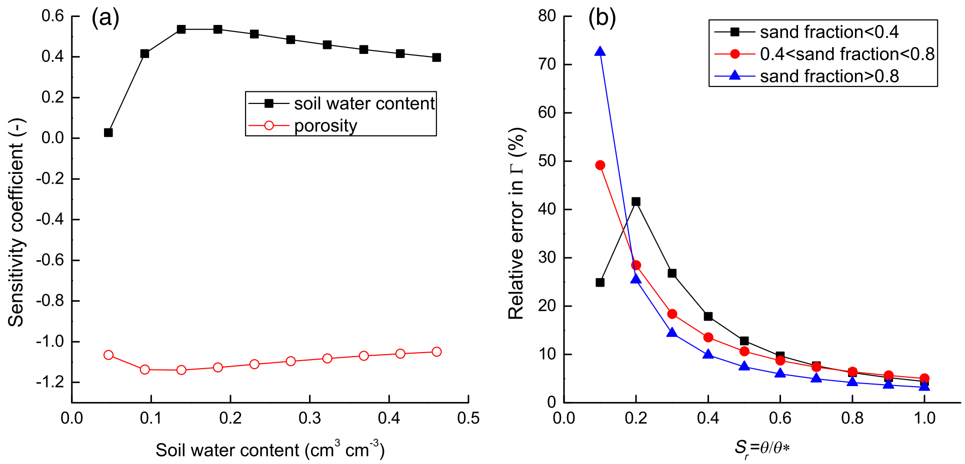


**Fig. 9** (a) The sensitivity coefficients of Γ for soil moisture and soil porosity under conditions of sand fraction less than 0.4 soil, (b) the RE in Γ as a function of relative saturation, and (c) the sensitivity coefficients of Γ for sand fraction and soil porosity [the porosity is same as in (a)].

with porosity from 0.43 to 0.55 than that from 0.55 to 0.67 under the same $S_r$. Figure 8(b) shows that the difference in thermal inertia with varied sand fraction becomes smaller with increasing soil moisture. There is little change in Γ with sand fraction less than 0.8 (which is the dominant case in the Chinese sand fraction distribution). Thus, Γ is more sensitive to porosity than sand fraction in any soil moisture conditions.

The sensitivity coefficients of thermal inertia for soil moisture with a porosity of 0.46 and for porosity varying from 0.46 to 0.67 were calculated under different soil moisture content with a sand fraction less than 0.4 [Fig. 9(a)]. The sensitivity coefficient is positive for soil water content and negative for porosity. Thermal inertia is more sensitive to porosity than soil water content with a maximum sensitivity coefficient of 1.14 versus 0.54. Thus, accurate porosity is most important to estimate thermal inertia. This is also consistent with the results of Lu et al.[59] Figure 9(b) shows the RE in Γ estimate as a function of $S_r$. The largest RE in Γ is found for soil with sand fraction greater than 0.8 under dry soil conditions ($S_r < 0.1$), whereas the error rapidly declines with increasing values of $S_r$. The soil with sand fraction between 0.4 and 0.8 shows a steady decline in error. The error for other soils reaches a maximum at $S_r = 0.2$ then drops and under dry soil conditions is smaller than in soils with sand fraction greater than 0.4. This conclusion is consistent with the study of Murray and Verhoef.[8] The thermal inertia has a stronger sensitivity to soil moisture at low values of $S_r$ ($S_r < 0.3$ for soil of sand fraction less than 0.4; $S_r < 0.2$ for other soils) with a more than 20% RE. An RE of 20% in Γ will cause a error of 20% in $G_0$ based on the HM model. According to the soil moisture category by Murray and Verhoef[8] (dry with $S_r < 0.1$; dry-moist with $0.1 < S_r < 0.25$; moist with $0.26 < S_r < 0.5$; moist-wet with $0.51 < S_r < 0.75$; wet with $0.76 < S_r < 0.1$), for the same soil type, the accurate soil moisture is important for $G_0$ estimates in dry and dry-moist soil conditions. The sand fraction has a greater effect on Γ for dry and dry-moist soil because the RE in Γ varies largely when different sand fraction is applied [Fig. 9(b)]. That can also be seen obviously in Fig. 9(c): the sensitivity coefficient for sand fraction decreases with increasing $S_r$ and the value is less than 0.2, which is smaller than that for porosity.

### 3.4.4 *Influence of fractional vegetation cover and satellite zenith angle on $G_0$*

According to Eqs. (3) and (4), $f_c$ affects not only the amplitude of LST but also the phase of below-canopy soil surface temperature. Thus, if there is a large error on remote sensed $f_c$, the accuracy of $G_0$ will be decreased. According to the 30-min interval data in this study, the phase of soil surface temperature can be regarded as invariant when the difference of $f_c$ between remote sensing data and field measurement is less than 0.1 over sparse or dense vegetated surfaces. $f_c$ affects only the amplitude of soil surface temperature and gives less than 10% RE on

$G_0$. Therefore, if the deviation of $f_c$ is less than 0.1, the impact of the $f_c$ error on $G_0$ can be neglected.

Murray and Verhoef[16] considered different satellite zenith view angles ($\beta$) ranging from 0 deg to 45 deg and found that they bring nearly same $J_s$ and have small effects on $G_0$. In the present study, FY-2C LST has 40 deg to 45 deg zenith view angles in the HRB area. Thus, the zenith view angle has little effect on $G_0$ estimation.

## 4 Conclusions

This study applied the improved physically based HM model based on the one developed by Murray and Verhoef[8,16] to estimate regional $G_0$ in the HRB. The thermal infrared remote sensing data (LST from FY2C), microwave radiation remote sensing data (surface soil moisture from AMSR-E), visible remote sensing data (NDVI from MODIS), and soil map were used in this study. The improvement is on the parameterization for the phase shift between canopy temperature and below-canopy soil surface temperature by introducing the fractional vegetation cover instead of applying a constant value as in the original model. The improved model was then used to calculate spatiotemporal $G_0$ in the HRB using satellite data and a soil map. Furthermore, we also studied qualitatively and quantitatively the sensitivity of $G_0$ to input variables. The main conclusions obtained from the investigation are as follows:

(1) The revised phase of below-canopy soil surface temperature improves the accuracy of $G_0$ estimation especially over sparsely vegetated surfaces, with $R^2$ increasing from 0.59 to 0.83 and RMSE decreased from 80.8 to 52.8 $\mathrm{W\,m^{-2}}$ in May of 2009 at the Yingke site.

(2) $G_0$ varies nonlinearly with the amplitude of LST and linearly with thermal inertia. Compared with $G_0$ measurement over maize, a variation of $-300$ to 300 $\mathrm{J\,m^{-2}\,K^{-1}\,s^{-0.5}}$ in thermal inertia and $-7$ to $-0.5$ K in the amplitude of LST will cause a less than about 20% RE on the $G_0$ estimation, which is acceptable.

(3) The soil porosity is the most influential variable on thermal inertia with a maximum sensitivity coefficient of 1.14 under different soil moisture status. The sensitivity of thermal inertia for sand fraction decreases with increasing $S_r$, and is small when soil is wet. $G_0$ is more sensitive to soil porosity under wet soil conditions than under dry soil conditions. Thus, the accuracy of porosity is most important for the regional estimate of $G_0$, especially for wet soil conditions.

(4) The RE in the thermal inertia estimate decreases with increasing $S_r$. When $S_r$ is less than about 0.3, the RE in the thermal inertia is larger than 20%, which will cause an RE of 20% in $G_0$ estimate.

(5) The $G_0$ estimation is more sensitive to $f_c$ for dense vegetation than for sparse vegetation. Approximately 0.1 error in $f_c$ leads to an RE on $G_0$ of less than 10%. In addition, the effect of the FY-2C view zenith angle of 40 deg to 45 deg on $G_0$ estimation in the HRB can be neglected.

## Appendix: Derivation of LST Amplitudes and Phases of Harmonics

The harmonic analysis of surface temperature is as follows (Horton and Wierenga):[20]

$$T = \bar{T} + \sum_{n=1}^{M} A_n \sin(n\omega t + \phi_n), \tag{8}$$

$$\begin{aligned} A_\mathrm{n} \sin(n\omega t + \phi_n) &= A_n \sin(nwt) \cos \phi_n + A_n \cos(nwt) \sin \phi_n \\ &= a_n \sin(nwt) + b_n \cos(nwt), \end{aligned} \tag{9}$$

where $\bar{T}$ is daily average temperature, $a_n = A_n \cos \phi_n$, $b_n = A_n \sin \phi$. $a_n$ and $b_n$ are unknown parameters; other parameters are known. If $M = 10$ and LST is at 30-min timescale (48 data in one day), the expanding Eq. (8) can be expressed as follows:

$$\begin{bmatrix} \sin(wt_1) & \cos(wt_1) & \sin(2wt_1) & \cos(2wt_1) & \sin(3wt_1) & \cos(3wt_1) & \dots & \sin(10wt_1) & \cos(10wt_1) \\ \sin(wt_2) & \cos(wt_2) & \cos(2wt_2) & \cos(2wt_2) & \sin(3wt_2) & \cos(3wt_2) & \dots & \sin(10wt_2) & \cos(10wt_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \sin(wt_{48}) & \cos(wt_{48}) & \sin(2wt_{48}) & \cos(2wt_{48}) & \sin(3wt_{48}) & \cos(3wt_{48}) & & \sin(10wt_{48}) & \cos(10wt_{48}) \end{bmatrix}$$

$$\cdot \begin{bmatrix} a_1 \\ b_1 \\ \vdots \\ b_{20} \end{bmatrix} = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_{48} \end{bmatrix}, \tag{10}$$

Eq. (10) is written as

$$A \cdot X = Y, \tag{11}$$

where

$A=$

$$\begin{bmatrix} \sin(wt_1) & \cos(wt_1) & \sin(2wt_1) & \cos(2wt_1) & \sin(3wt_1) & \cos(3wt_1) & \dots & \sin(10wt_1) & \cos(10wt_1) \\ \sin(wt_2) & \cos(wt_2) & \cos(2wt_2) & \cos(2wt_2) & \sin(3wt_2) & \cos(3wt_2) & \dots & \sin(10wt_2) & \cos(10wt_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \sin(wt_{48}) & \cos(wt_{48}) & \sin(2wt_{48}) & \cos(2wt_{48}) & \sin(3wt_{48}) & \cos(3wt_{48}) & \dots & \sin(10wt_{48}) & \cos(10wt_{48}) \end{bmatrix}.$$

$$X = \begin{bmatrix} a_1 \\ b_1 \\ \vdots \\ b_{10} \end{bmatrix},$$

$$Y = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_{48} \end{bmatrix}.$$

$$A^T \cdot A \cdot X = A^T \cdot Y, \tag{12}$$

$$X = (A^T \cdot A)^{-1} \cdot (A^T \cdot Y), \tag{13}$$

where $A^T$ is $A$ matrix transpose, $(A^T \cdot A)^{-1}$ is matrix $(A^T \cdot A)$ inverse, $a_n$ and $b_n$ can be obtained from Eq. (13).

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