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Cloudy land surface temperature retrieval from three-channel microwave data

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Abstract: Land surface temperature (LST) plays an important role in land surface processes, and it is a key input for estimating important hydrological states and fluxes, such as soil moisture and evapotranspiration. In this study, a three-channel method is proposed to retrieve cloudy LST values from passive microwave data based on the relationship among surface emissivities at 18.7, 36.5 and 89.0 GHz over a bare soil surface. The performance of the method was evaluated using simulated data, resulting in a root mean square error (RMSE) of approximately 1.4 K over the bare soil surface. This method was further extended to retrieve cloudy LST values over a natural surface. Due to the lack of in situ LST measurements, ground-based air temperatures were used as proxy data to validate the cloudy LST values retrieved from AMSR-E data. The RMSE values of the differences between the retrieved cloudy LST values and the ground-based air temperatures are approximately 3.4 K and 4.3 K for the descending and ascending overpasses, respectively. The results demonstrate that the three-channel method can be used to retrieve cloudy LST values from passive microwave data with reasonable accuracy.

Keyword: Cloudy land surface temperature, passive microwave data, AMSR-E, three-channel method

1 Introduction

Land surface temperature (LST) is a key physical variable in surface energy and water balance processes at regional and global scales (Coll et al. 2016; Duan et al. 2014; Wan and Li 1997). LST plays a key role in various fields, including climatology, hydrology, meteorology, ecology, agriculture, public health, and environmental monitoring (Anderson et al. 2008; Li et al. 2009; Weng and Grody 1998). Compared to traditional ground-based LST measurements, satellite remote sensing techniques provide a unique way to measure LST at regional and global scales.

Satellite thermal infrared (TIR) measurements are widely used to retrieve LST via different algorithms, e.g., single-channel, split-window, and multi-channel algorithms (Becker and Li 1990; Chen et al. 2017; Li et al. 2013; Neteler 2010; Price 1983). The LST values derived from TIR measurements have a relatively high resolution (e.g., 1 km for MODIS data) and a high retrieval accuracy (1-2 K). The main issue associated with the TIR measurements is their inability to penetrate clouds, which limits their practical applications. This limitation is considerable because, on average, 60% of the land surface is covered by clouds, which alter the radiative energy exchange, reduce surface insolation and increase downward longwave radiation (Duan, Li, and Leng 2017).

Compared to TIR signals, passive microwave signals are much less affected by clouds and water vapor; thus, passive microwave measurements are attractive for retrieving LST values, especially under cloudy conditions (Han et al. 2017; Liu et al. 2013). Several methods have been proposed to estimate LST from passive microwave observations (Aires et al. 2001; Chen et al. 2011; Fily et al. 2003; Gao et al. 2008; Jones et al. 2007; Njoku and Li 1999).

These methods can be grouped into three categories: empirical methods, physical based methods and artificial neural network methods. The empirical method first proposed by Mcfarland et al. (1990) directly related all the SSM/I channels (19, 22, 37 and 85 GHz) to the minimum screen air temperatures and an accuracy of 2-3 K was obtained at the study area for the surface without water, snow and falling rain. The simplified regression method relies on the relationship between air temperatures and the vertically polarized brightness temperatures at 37 GHz for different well-defined study sites (Holmes et al. 2009; Owe and Griend 2001). The accuracy varies for different surfaces and it was about 2.5 K for forests and 3.5 K for low vegetation. The main advantage of this procedure is that the inputs are only satellite-measured brightness temperatures, which are easy to obtain. The obvious weakness is that the need to determine the site-specific relationship between LST and air temperature has limited the application of this method at regional scales with variable surface conditions. Additionally, Weng and Grody (1998) presented a physical based method for LST estimation under the assumption that two adjacent frequencies (19 and 22 GHz) have approximately the same surface emissivity. This method was proposed based on the radiative transfer model and has a clear physical foundation. Its accuracy was 4.4 K when the algorithm was applied for the actual SSM/I measurements. However, atmospheric water vapor, one of the input variables, is difficult to obtain or has a low level of accuracy, which restricts the application of this method. Basist et al. (1998) proposed another physically based LST retrieval method based on the theoretical relationship of emissivity over a spectrum of microwave frequencies for different magnitudes of soil moisture. Its accuracy was about 2 K for the independent case ("Blizzard of 1996"). However, the emissivity of the dry surface, which is one of the input variables of this method, is difficult to

measure. For the artificial neural network method, Davis et al. (1995) took advantage of the inverse problems, which was considered ill-posed, by adding additional informative constraints to the problem solution using Bayesian methodology, then used the neural networks to retrieve soil moisture, surface air temperature and vegetation moisture. This is a mathematical method without clear physical foundation and the accuracy of this method depends on the training dataset.

Since passive microwave measurements suffer from a relatively coarser spatial resolution (10-25 km) and a lower retrieval accuracy (4-6 K) than TIR measurements, the LST values derived from passive microwave data is mainly used to complement the gaps resulting from the inability of TIR data to provide LST values under cloudy conditions (Andre et al. 2015; Duan, Li, and Leng 2017; Shwetha and Kumar 2016).

The objective of this study is to develop a simple but physically based cloudy LST retrieval method based on the method proposed by Basist et al. (1998). This paper is organized as follows. Section 2 describes the study area and the data used in this study. Section 3 presents the development of the three-channel method. Section 4 provides the applications of the proposed method over the bare soil surfaces and the natural surfaces, and the conclusions are presented in the last section.

2 Study area and data

2.1 Study area

In this study, China's landmass, which features considerable changes in the landscape, was selected as the study area (Liu and Diamond 2005). The eastern part of the landmass is characterized by extensive alluvial plains, whereas the north is predominantly covered with grasslands. The southern portion features hills and low mountain ranges, and the western part contains major mountain ranges. Furthermore, China's climate differs from region to region due to its highly complex topography.

The south is warm, the north is cold, the east is humid, and the west is dry. The north has four obvious seasons, including dry and windy springs, hot and rainy summers, cool autumns, and cold and dry winters, and the south has four weak seasons but clear rainy and dry seasons (Fu et al. 2008; Wang et al. 2013; Wu et al. 2013). Moreover, the underlying surface is complicated by different land cover types (Figure 1).

Figure 1. Land cover types in China generated from the MODIS land cover type product MCD12Q1.

2.2 Simulated data

To develop the LST retrieval method, a dataset was generated from the advanced integral equation model (AIEM) and monochromatic radiative transfer model (MonoRTM) and included the brightness temperatures at the top of atmosphere,

upwelling and downwelling atmospheric brightness temperatures, atmospheric transmittance, LST and emissivity.

The AIEM was used to simulate the surface emissivity (Chen et al. 2003). To consider all the land surface types, reasonable variations in the input variables (sand volume content, clay volume content, soil bulk density, surface roughness, soil moisture and LST) are necessary. Thus, 6 typical types of soil with different sand and clay volume contents and soil bulk densities were selected (Table 1); the surface root mean square height was varied from 1.25 to 3 cm at intervals of 0.25 cm; surface correlation length was varied from 12.5 to 30 cm at intervals of 2.5 cm; soil moisture was varied from 0.02 to 0.38 m³/m³ at intervals of 0.06 m³/m³; and the LST was set equal to the atmospheric bottom temperature. The output of AIEM was the surface emissivity.

Table 1. The soil texture of 6 soil types.

No.	Sand volume contents	Clay volume contents	Soil bulk densities(g cm ⁻³)
1	0.46	0.24	1.24
2	0.33	0.37	1.32
3	0.59	0.18	1.38
4	0.34	0.25	1.12
5	0.21	0.36	1.06
6	0.14	0.57	1.01

The MonoRTM was used to simulate the atmospheric parameters (upwelling and downwelling atmospheric brightness temperatures and atmospheric transmittance). To ensure that the dataset was representative, the Thermodynamic Initial Guess Retrieval (TIGR) dataset from the Laboratory of Dynamic Meteorology (LMD) was used. The

TIGR dataset is a climatological library of 2311 representative atmospheric situations that were selected using statistical methods from 80,000 radiosonde reports (Chedin et al. 1985). Each profile is divided into 40 layers and described from the surface to the top of atmosphere (TOA) by the temperature, water vapor, and ozone concentrations on a given pressure grid. In this study, sixty atmospheric profiles with nearly uniformly distributed water vapor values ranging from 0.1 to 6.0 cm were selected from the TIGR dataset; the bottom temperatures of these atmospheric profiles varied from 273.15 to 308.3 K. To describe the cloudy atmospheric conditions, reasonable cloud liquid water was added to the atmospheric layers at a height of less than 5 km, and it was added to a single atmospheric layer for each situation. Cloud liquid water ranged from 0-0.5 mm at intervals of 0.1 mm for the atmospheric layers at heights less than 2 km, 0-0.4 mm at intervals of 0.1 mm for the atmospheric layers at heights of 2 to 4 km, and 0-0.3 mm at intervals of 0.1 mm for the atmospheric layers at heights of 4 to 5 km. As a result, there are 34 or 35 cases of added CLW for each profile, this depends on the number of layers lower than 5 km in each profile. The main outputs of the MonoRTM were the upwelling and downwelling atmospheric brightness temperatures and atmospheric transmittance.

The brightness temperatures at the top of the atmosphere were calculated based on the radiative transfer model using the output variables from AIEM and MonoRTM. The incidence angle at the surface was set to 55 ° according to the configuration of the microwave radiometer used in this study, and the passive microwave channels of 6.93, 10.65 18.7, 23.8, 36.5 and 89.0 GHz were selected when conducting the simulation.

2.3 AMSR-E data

The Advanced Microwave Scanning Radiometer for EOS (AMSR-E) on the Aqua satellite was launched in May 2002. It measures vertically and horizontally

polarized brightness temperatures at 6.93, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz. Two measurements per day are available for each channel: the ascending overpass (equatorial crossing time of 1:30 pm local solar time) and descending overpass (equatorial crossing time of 1:30 am local solar time). The AMSR-E brightness temperature product (NSIDC-0301) in the EASE-grid projection at a 25-km resolution between May and October (the first ten days of each month) from 2010 was used in this study.

2.4 Ground-based measurements

To evaluate the retrieval accuracy of the proposed method, ground-based measurements over different land cover types were collected from the global hourly Integrated Surface Data (ISD) database, which includes numerous parameters such as wind speed and direction, wind gust, air temperature, dew point, cloud data, sea level pressure, altimeter setting, station pressure, present weather, visibility, precipitation amounts for various time periods, snow depth, and various other elements that are observed at each station. In this study, 139 sites were selected based on elevation. To ensure that the terrain of the selected stations is relatively flat, the standard deviation of the elevation is less than 100 m over a 25*25 km area around each site. The geographical locations of the sites used in this study are shown in Figure 2. Ninety-three sites were used to calibrate the estimated LST to the air temperature, and 46 sites were used to assess the accuracy of the LST retrieval method.

Figure 2. Geographical locations of 139 sites (93 sites for calibration and 46 sites for assessment).

3 Development of the three-channel method for retrieving cloudy LST

To derive LST values from passive microwave observations, the variation in surface emissivity must be addressed. For a given frequency, the major factor influencing the variation in emissivity is soil moisture, which can reduce emissivity by 33% for the 18.7 GHz vertically polarized channel (Basist et al. 1998). Therefore, it is necessary to quantitatively determine the perturbation due to soil moisture on the surface emissivity when deriving LST. Figure 3 shows how emissivity changes as a function of frequency and soil moisture using the simulated data. As the soil moisture increases, the emissivity decreases and the slope of the emissivity between low and high frequencies increases. For a given soil moisture, the emissivity increases with increases in frequency. Thus, the lowest emissivity occurs when the surface becomes saturated with water, whereas the highest emissivity occurs when the surface is dry; in comparison, surface emissivity has negligible variation for different frequencies in this situation. The surface with a soil moisture of $0.02 \text{ m}^3/\text{m}^3$ was a dry surface in the

simulated data. Since the channel at 18.7 GHz is much less affected by the atmosphere than the channels at 23.8, 36.5 and 89.0 GHz and more effective for LST retrieval than 6.93 and 10.65 GHz, this channel was chosen as the main channel for retrieving LST. The soil moisture perturbation of the surface emissivity at 18.7 GHz can be expressed as follows:

$$\varepsilon_0(u_1) - \varepsilon_s(u_1) = [\varepsilon_0(v_3) - \varepsilon_s(v_3)] + [\varepsilon_s(v_3) - \varepsilon_s(v_2)] + [\varepsilon_s(v_2) - \varepsilon_s(u_1)] + [\varepsilon_0(u_1) - \varepsilon_0(v_3)] \quad (0)$$

where v_1 , v_2 and v_3 represent the channels at 18.7, 36.5 and 89.0 GHz, respectively; ε_s is the surface emissivity; and ε_0 is the emissivity of the dry surface. Since the impact of soil moisture on emissivity at 89.0 GHz is relatively small compared to other frequencies and since the emissivity at 36.5 GHz is less affected by clouds than 23.8 GHz, the emissivities of 36.5 and 89.0 GHz were used to express the variation in emissivity at 18.7 GHz.

Figure 3. The relationship of emissivity over commonly used frequencies for 8 different surface soil moistures (SM). $\varepsilon_0(v_1)$ and $\varepsilon_0(v_3)$ are the emissivities of dry surface at 18.7 and 89.0 GHz respectively; $\varepsilon_s(v_1)$, $\varepsilon_s(v_2)$ and $\varepsilon_s(v_3)$ are the emissivities of wet surface at 18.7 GHz, 23.8 and 89.0 GHz respectively (the sand volume content is 0.14, the clay volume content is 0.57, the land surface temperature is 273.15 K, the correlation length is 12.5 cm and the root mean square height is 1.25 cm).

Figure 3 also demonstrates that the values of $[\varepsilon_0(\nu_1) - \varepsilon_0(\nu_3)]$ and $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$ are relatively small compared to the other items in equation (1). Moreover, the emissivities of the dry surface ($\varepsilon_0(\nu_1)$ and $\varepsilon_0(\nu_3)$) are difficult to obtain. To simplify equation (1), we parameterize the items $[\varepsilon_0(\nu_1) - \varepsilon_0(\nu_3)]$ and $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$. The item $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$ represents the impact of soil moisture on the emissivity at 89.0 GHz, which is related to the slope of emissivity between the two frequencies. Figure 4 shows the scatter plot of $[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)]$, which indicates the slope of emissivity between the two frequencies and $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$. This demonstrates that the relationship between $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$ and $[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)]$ can be approximated by a quadratic relationship as follows.

$$[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)] = \alpha[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)]^2 + \beta[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)] + \gamma \quad (0)$$

The coefficients ($\alpha=5.9227$, $\beta=0.4002$, $\gamma=0.0011$) were determined by the polynomial fitting method using simulated data. A favorable accuracy with a root mean square error (RMSE) of 0.003 was achieved.

Figure 4. Scatter plots of $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$ vs $[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)]$, here $[\varepsilon_0(\nu_3) - \varepsilon_s(\nu_3)]$ is the emissivity difference at 89.0 GHz between dry and wet surface, $[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)]$ is the emissivity difference of wet surface between 89.0 and 36.5 GHz.

The histogram of $[\varepsilon_0(\nu_1) - \varepsilon_0(\nu_3)]$ shown in Figure 5 indicates that this item varies from -0.01 to 0, with an average value of -0.003 for all surface conditions; thus, it can be replaced using the averaged value $C = -0.003$ without resulting in a large error.

Figure 5. Histogram of the differences between emissivities over dry surfaces at 18.7 ($\varepsilon_0(\nu_1)$) and 89.0 ($\varepsilon_0(\nu_3)$) GHz.

Consequently, the emissivity of ν_1 can be written as follows:

$$\varepsilon_s(\nu_1) = \varepsilon_0(\nu_1) - [\varepsilon_s(\nu_2) - \varepsilon_s(\nu_1)] - (\beta + 1)[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)] - \alpha[\varepsilon_s(\nu_3) - \varepsilon_s(\nu_2)]^2 - (\gamma + C) \quad (0)$$

Assuming that the atmospheric effects are negligible compared to the variations in surface temperature and emissivity, we expressed the brightness temperature measurement as follows:

$$T_b(\nu) = \varepsilon_s(\nu)T_s \quad (0)$$

where $T_b(\nu)$ is the brightness temperature at frequency ν and T_s is the LST. Since the smallest variation in emissivity occurs for the vertical polarization, this polarization is preferred when deriving the LST. Thus, substituting equation (4) into equation (3) and solving for T_s , yields the following:

$$T_s = \frac{T_b(\nu_1) + [T_b(\nu_2) - T_b(\nu_1)] + (\beta + 1)[T_b(\nu_3) - T_b(\nu_2)] + \alpha[T_b(\nu_3) - T_b(\nu_2)]^2}{\varepsilon_0(\nu_1) - (\gamma + C)} \quad (0)$$

To reduce the error caused by the above approximate expression, T_s can be rewritten as follows:

$$T_s = \frac{T_b(\nu_1) + a[T_b(\nu_2) - T_b(\nu_1)] + b[T_b(\nu_3) - T_b(\nu_2)] + c[T_b(\nu_3) - T_b(\nu_2)]^2 + d}{\varepsilon_0(\nu_1) - e} \quad (0)$$

The coefficients $a=1.315$, $b=0.896$, $c=0.0315$, $d=0.55$, and $e=-0.004$ were obtained by the nonlinear fitting method using simulated data. Since $\varepsilon_0(\nu_1)$ is related to the soil sand and clay volume contents and the surface roughness, it is difficult to determine accurately. Moreover, the variation in $\varepsilon_0(\nu_1) - e$ is slight, i.e., between 0.96 and 1.0, with a mean of 0.990 and a standard deviation of 0.008. Thus, the value of this item can be replaced with its average value. Consequently, T_s can be rewritten as follows:

$$T_s = AT_b(\nu_1) + B[T_b(\nu_2) - T_b(\nu_1)] + C[T_b(\nu_3) - T_b(\nu_2)] + D[T_b(\nu_3) - T_b(\nu_2)]^2 + E \quad (0)$$

The coefficients $A=0.936$, $B=0.701$, $C=1.694$, $D=0.0125$, and $E=21.40$ were obtained using simulated data. In this form, the channel at 18.7 GHz is the primary channel for retrieving cloudy LST values. Three corrections are made to this estimate. Comparing the actual T_s and the estimated T_s using equations (6) and (7), the accuracies of the estimated T_s are 0.83 and 2.37 K. Figure 6 displays the histogram of the difference between the actual T_s and the estimated T_s using equations (6) and (7), which indicates that the accuracy of equation (7) is slightly worse than that of equation (6) due to the approximate expression of $\varepsilon_0(\nu_1)$.

Figure 6. Histogram of the differences between the actual T_s and estimated T_s using equations (6) and (7).

4 Results and discussion

4.1 Application to the brightness temperature at the top of atmosphere over a bare soil surface

Although the atmospheric impact on the passive microwave data is relatively small compared to the TIR data and the atmospheric impact was neglected when developing the three-channel method in Section 3, the atmospheric impact on the brightness temperature should be considered in order to accurately evaluate the performance of the proposed method in the real earth-atmosphere system.

For the bare soil surface, the brightness temperature at TOA is a sum of 1) soil emissions, 2) atmospheric emissions (upward) and 3) ground-reflected atmospheric emissions and cosmic background (upward). It can be expressed as follows:

$$T_{TOA}(\nu) = T_s \varepsilon_s(\nu) \tau_a(\nu) + T_{ba\uparrow}(\nu) + (T_{ba\downarrow}(\nu) + T_{bc})(1 - \varepsilon_s(\nu)) \tau_a(\nu) \quad (0)$$

where $\tau_a(\nu)$ is the atmospheric transmittance at frequency ν ; $T_{ba\uparrow}(\nu)$ and $T_{ba\downarrow}(\nu)$ are the upwelling and downwelling atmospheric brightness temperatures at frequency ν , respectively; and T_{bc} is the space background brightness temperature, which is approximately 2.725 K and is usually neglected. Thus, we substituted equation (8)

into equation (7) and solved for T_s . In this process, the T_b in equation (7) was replaced by T_{TOA} in equation (8). To improve the accuracy of the estimated T_s , the coefficients in equation (7) were re-determined using the simulated data ($A=0.904$, $B=1.023$, $C=1.070$, $D=0.0040$, $E=28.42$). The retrieval accuracy is 1.35 K, as shown in Figure 7. A comparison of the accuracy of the estimated LST from T_b (the blue histogram in Figure 6) and T_{TOA} (Figure 7) indicates that the retrieval accuracy from T_{TOA} is better than that from T_b . This accuracy difference is because the three corrections in equation (7), which represent the T_{TOA} difference between adjacent frequencies, decrease the atmospheric impact on the estimated LST.

Figure 7. Histogram of the difference between the actual T_s and estimated T_s from the TOA brightness temperature using equations (7) over bare soil surface.

4.2 Application to AMSR-E brightness temperature data over a natural surface

To further assess the applicability of the proposed method over a natural surface, the satellite-measured data were used to retrieve cloudy LST values, and then the estimated LST values were compared with the ground-based air temperature from the ISD database. The satellite-measured brightness temperature represents the sum of 1) soil emissions, 2) direct vegetation emissions, 3) ground-reflected vegetation emissions, 4) direct atmospheric emissions (upward) and 5) ground-reflected

atmospheric emissions and cosmic background (upward); thus, these data describe natural surfaces and differ from the simulated data, which only consider bare soil surfaces.

Due to the lack of high-density ground-based LST data and because LST values are similar to the air temperature under cloudy conditions, the ground-based air temperature was used to evaluate the proposed method. We selected 6168 measurements (3041 measurements for descending overpasses and 3127 measurements for ascending overpasses) from 139 sites based on the atmospheric conditions. To achieve the objective of this study, the measurements, which were obtained under a cloudy sky were selected. The ground-based measurement is identified as a cloudy measurement when the land surface temperature of MYD11C1 (MODIS LST product) is not produced due to the cloud effect over 5*5 pixels around the measurement point. Moreover, the air temperature at each site for each day was interpolated to the ascending and descending overpass time of AMSR-E.

Since an intrinsic difference exists between the ground-based air temperatures, which are measured 2 m above the surface, and the estimated LST, which is an ‘effective temperature’ due to the different penetration depths of different frequencies, to compare the estimated cloudy LST with the ground-based air temperature, the coefficients of equation (7) were re-determined using the satellite data and air temperatures from 93 sites, and these are shown in Figure 2. The new coefficients $A=0.990$, $B=0.870$, $C=0.379$, $D=0.0280$, and $E=16.65$ for the descending overpass and $A=0.963$, $B=0.498$, $C=1.451$, $D=0.0056$, and $E=18.02$ for the ascending overpass were obtained using the satellite-measured brightness temperature and the ground-based air temperature. Comparing the estimated T_s and air temperature of 93 sites, the RMSEs of 3.78 and 4.09 K were obtained from equation (7) using the satellite-measured

brightness temperatures of the descending overpass and ascending overpass, respectively. Figure 8 indicates that the retrieval accuracy of the descending overpass is better than that of the ascending overpass due to the relatively small variation in the LST at night (descending overpass). Two reasons can explain the relatively small RMSE value of the descending overpass. One reason is that the subsurface temperature is more uniformly distributed at night (descending overpass) than during the day (ascending overpass); thus, the impact of the penetration depth on the temperature at different frequencies is small at night. The other reason is due to the small spatial heterogeneity of the LST at night.

Figure 8. Scatter plots of T_s , using the satellite measured brightness temperatures of descending overpass (a) and ascending overpass (b), and ground-based air temperature of 93 sites.

The ground-based air temperatures from 46 sites, which are shown in Figure 2, were used to evaluate the accuracy of the estimated T_s over China. In the scatter plots in Figure 9, the T_s values estimated with equation (7) using the satellite-measured brightness temperatures of the descending overpass and ascending overpass are plotted against the ground-based air temperatures from 46 sites. The RMSE values are 3.37 and 4.26 K for the descending and ascending overpasses, respectively. The accuracy of the estimated T_s values at night (descending overpass) is better than that

during the day (ascending overpass) due to the abovementioned explanation of the calibration sites.

Figure 9. Scatter plots of T_s , estimated from equations (7) using the satellite measured brightness temperatures of descending overpass (a) and ascending overpass (b), and ground-based air temperature of 46 sites.

5 Conclusions

The presence of cloud cover greatly limits the practical application of satellite-derived TIR LST methods. In this study, a three-channel method for estimating cloudy LST values was proposed based on the relationships among the emissivities over commonly used frequencies for different surface soil moistures. The method is practical because it is independent of the land surface type, surface emissivity and atmospheric impact, and the input variables are only the brightness temperatures of three vertically polarized channels (18.7, 36.5 and 89.0 GHz). The results demonstrate that the retrieval accuracy is 1.35 K when using simulated data that describe a bare soil surface. For natural surfaces, the values of RMSE are 3.78 and 4.09 K for the descending overpass and ascending overpass, respectively. Comparing the T_s estimated from the satellite data with ground-based air temperatures, the accuracies of the estimated T_s are 3.37 and 4.26 K for the descending overpass and

ascending overpass, respectively. In summary, the proposed method is effective for retrieving the cloudy LST over a natural surface. If ground-based LST data are available, the coefficients of the proposed method should be re-determined using the satellite-measured brightness temperature and ground-based LST values in order to further improve the accuracy of the cloudy LST retrieval.

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