An Empirical Algorithm for Retrieving Land Surface Temperature From AMSR-E Data Considering the Comprehensive Effects of Environmental Variables

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Abstract Microwave (MW) remote sensing has the potential to obtain all-weather land surface temperature (LST) and serves as a complement to the thermal-infrared (TIR) LST under cloudy sky conditions. However, the accuracy of MW LST is generally lower than that of TIR LST, making the retrieval of highly accurate all-weather LST a challenging task. We propose an empirical algorithm for retrieving LST from the Advanced Microwave Scanning Radiometer (AMSR-E) brightness temperature (BT) data. First, we constructed a comprehensive classification system of environmental variables (CCSEV), allowing for the influence of topography, land cover, solar radiation, and atmospheric condition on the spatiotemporal distribution of LST, then the LST was expressed as a function of the combination of different AMSR-E channels for each CCSEV class. When performing the testing with the data from 2005, 2009 and 2011, the accuracy is 3.27 K, 2.65 K and 3.48 K in the daytime and 2.94 K, 2.63 K, 2.15 K at nighttime, respectively. The proposed algorithm was compared to an existing algorithm developed for China without considering the topography. The result shows that the accuracy of LST has improved by 2.81 K in the daytime and 2.14 K at nighttime in China, compared with the Moderate Resolution Imaging Spectroradiometer (MODIS) LST. The verification at the Naqu sites in the Qinghai-Tibet Plateau shows that the accuracy has improved by 1–2 K in the daytime and 0.7–1 K at nighttime. These results indicate that the developed algorithm is universal and accurate and benefits the retrieval of accurate all-weather LST.

1. Introduction

Land surface temperature (LST) is one of the critical environmental indicators for the study of energy balance and material exchange near the Earth’s surface. It is extensively employed in fields such as evapotranspiration estimation, hydrologic cycle research, vegetation monitoring, urban heat island research, disaster prediction, and crop yield estimation (Anderson et al., 2008; Cheng & Kustas, 2019; Kalma et al., 2008; Li et al., 2009; Trenberth et al., 2007; Zhang & Cheng, 2019; Zhou et al., 2011).

Remote sensing is a unique means for acquiring LST on the regional and global scales. Generally, we can derive LST from thermal-infrared (TIR) and microwave (MW) observations with specifically designed retrieval algorithms. It is well recognized that the TIR algorithm is much more developed and the retrieved LST has a relatively high spatial resolution and accuracy (Li et al., 2013b). There are already some released TIR LST products, including the Moderate Resolution Imaging Spectroradiometer (MODIS) LST (https://lpdaac.usgs.gov/), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) LST (http://asterweb.jpl.nasa.gov/), the Visible Infrared Imaging Radiometer (VIIRS) LST (https://lpdaac.usgs.gov/), and Spinning Enhanced Visible and Infrared Imager (SEVIRI) LST (http://www.esa.int/), etc. However, the TIR signal is sensitive to the atmosphere and cannot penetrate the clouds, which prevents the onboard TIR sensor from capturing the land surface information and results in a serious data gap in the produced LST products (Jin, 2000). In contrast, MW can penetrate clouds, making the retrieval of all-weather LST possible. According to the literature review, many studies have been conducted to retrieve the LST from the observations of the Scanning Multichannel Microwave Radiometer (SMMR), the Special Sensor Microwave/Image (SSM/I), the Tropical Rainfall Measuring Mission Microwave Imager (TMI), the Advanced Microwave Scanning Radiometer (AMSR, named AMSR-E on satellite Aqua and AMSR2 on satellite GCOM-W), etc.
The algorithms used to retrieve the LST from MW observations can be grouped into the following three categories: the physical models, the semiempirical models, and the empirical statistical models.

A physical model has a solid foundation and is theoretically universal to various environmental conditions. However, a physical model requires numbers of inputs that are difficult to obtain in most real applications, including land surface emissivity and some atmospheric parameters. The reanalysis data or simulation database with relatively low accuracy and a simplified pattern are usually used to establish the physical model as an alternative. For example, Huang et al. (2018) first used the Global Forecast System (GFS) reanalysis data and the Thermodynamic Initial Guess Retrieval (TIGR) data to simulate the land surface emissivity and atmospheric parameters, and then used the simulated data to retrieve the LST from AMSR2 observations.

Based on the simplified radiative transfer equation (RTE), the semiempirical model establishes the regression relationships to determine the inputs in the RTE using other parameters that are convenient to obtain. For example, Zhou et al. (2018) proposed a two-step algorithm for retrieving the AMSR-E LST in which the land surface emissivity parameter was first determined by its relationship with the brightness temperature (BT) data in the channels of dual-polarized frequency, and then, the LST was retrieved using the simplified RTE, ignoring the atmospheric effects.

The empirical statistical model retrieves the LST by establishing the regression relationship between the MW BT and the reference LST. The reference LST usually comes from the in-situ measurements or existing TIR products. The empirical statistical model does not consider the complex process of radiative transfer and is free from preparing hard-to-obtain parameters in the RTE. To ensure its accuracy, the empirical statistical model is usually constructed for the separate environmental conditions. The empirical statistical model is recognized as the most applied MW LST retrieval method due to its simplicity and acceptable accuracy. The study of empirical statistical models is focused on the following two aspects: the combination of MW channels and the model’s applicability. For the first aspect, many studies indicated that the vertical polarized channel approximately 37 GHz or 89 GHz is the best channel to retrieve the MW LST (McFarland et al., 1990). Further studies indicated that the influence of soil moisture and water vapor can be corrected by adding the difference of the vertical polarized BT between 36.5 GHz and 23.8 GHz channels as well as between 36.5 GHz and 18.7 GHz channels into the regression model (Holmes et al., 2009; Mao et al., 2007; McFarland et al., 1990; Owe & Van De Griend, 2001). Additionally, the incorporation of quadratic correction items could improve the model’s accuracy (Mao et al., 2007). Regarding the second aspect, the LST is affected by the complex and comprehensive effects of the topography, land cover (LC), soil moisture, and solar and atmospheric radiation, etc., and varies greatly in space and time. Thus, a single empirical regression model cannot be applied to all conditions with high accuracy. The integration of multiple regression models with each model designed for a certain specific environmental condition is preferred by various researchers. For example, McFarland et al. (1990) established a MW LST retrieval algorithm by integrating the regression models for the farmland/pasture, wet soil, and dry soil in the Great Plains of the United States. Hollinger (1991) and Owe and Van De Griend (2001) modified McFarland’s algorithm by separating the time scale into seasons and day-and-night. Zhou et al. (2015) proposed a more detailed classification system that retrieves the LST for different seasons, day-and-night, and LC types. A sufficient consideration of different environmental conditions ensures the applicability of the empirical statistical model. However, the existing literature shows that the impact of the topography has not been explicitly incorporated into the developed algorithms.

In addition, it is a practical way to generate a spatial continuous LST with higher resolution by blending the MW and TIR LSTs, which has received increasing attention in recent years (Duan et al., 2017; Jang et al., 2014; Kou et al., 2016; Shwetha & Kumar, 2016; Wang et al., 2014; Xu et al., 2019). Two critical issues are related to the quality of the blended LST, i.e., the accuracy of the MW LST, especially under cloudy conditions, and the scale difference between the MW and TIR LSTs. The scale difference can be alleviated by downscaling the MW LST. However, the performance of downsampling is affected by the accuracy of the MW LST. Thus, continuing to improve the accuracy of the MW LST plays a decisive role in improving the quality of the blended all-weather LST.

China has a varied and complex near-surface environment, where the topography, LC and climate in different subregions are remarkably distinctive, making the LST retrieval more challenging. Taking the landmass
of China as the study area, we explore the possibility of improving the LST accuracy by explicitly incorporating the effects of topography, and propose an empirical algorithm for LST retrieval from AMSR-E BT data. A comprehensive classification system of environmental variables (CCSEV) is first constructed, and then, a linear function of the combination of AMSR-E BT data in different channels is established for each CCSEV class. Finally, the algorithm is verified by comparing the retrieved LST with the reference MODIS LST and field observations in China.

2. Study Area and Data

2.1. Study Area

The landmass of China is selected as the study area for retrieving the AMSR-E LST, and the Naqu area and the Heihe River Basin (HRB) are selected as the verification regions (Figure 1) to assess the accuracy of the retrieved LST. The two verification regions are the major areas of concern for ecological, hydrological and climate change research in China, in which large numbers of experiments have been carried out and a great deal of data have been accumulated. These two regions are located in the Qinghai-Tibet Plateau and the surrounding areas with a profound influence on the climate changes at the regional and global scale. Specifically, the Naqu area is in the southern part of the Qinghai-Tibet Plateau, within the range of 31°11' - 32°08' N and 91°45' - 92°40' E. It belongs to the alpine climate, with the LC dominated by grassland. The topography is relatively flat with an average slope of 7.12°. The HRB region is in the middle Qilian Mountain and its northern foot, within the range of 37°44' - 39°08' N and 99°38' - 101°09' E. It belongs to the transition zone between the arid continental climate and the alpine and semihumid climate, with the LC dominated by bare land, grassland and coniferous forest. The topographies of the northwestern part and the southeastern part of the HRB region are distinctly different. The former is flat with an average slope of 3.1°, while the latter is mountainous with an average slope of 14.75°.

2.2. Data

The data used for developing and testing the LST retrieval algorithm primarily include the MODIS LST product and the AMSR-E BT data in different channels. In addition, the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) data, the MODIS LC data, the MODIS snow cover data, and the desert data of China are introduced into the construction of the CCSEV. Moreover, the soil temperature observations at the sites of the HRB and Naqu verification regions are used as the reference to verify the accuracy of the proposed algorithm. The basic information of these data is listed in Table 1.

2.2.1. Satellite Data

AMSR-E is a MW sensor onboard the satellite Aqua, which started operation in 2002 and stopped running in September 2011. AMSR-E observes the Earth at approximately 1:30 am and 1:30 pm local time. It contains 12 channels that are spread over six frequencies (i.e., 6.9 GHz, 10.7 GHz, 18.7 GHz, 23.8 GHz, 36.5 GHz and 89 GHz) and two polarization states (horizontal and vertical). The AMSR-E BT data used in this study belong to the level 3 product (NISDC-0302) and were downloaded from the National Snow & Ice Data Center (NSIDC) (http://nsidc.org).

MODIS is the sensor onboard the satellites Terra and Aqua. The products derived from the MODIS/Aqua are adopted because it is on the same platform as the AMSR-E. They share the identical orbital geometry and overpass time, so there is no need to consider the time difference of data acquisition. The MODIS products used in this study include the LST product (MYD11A1), the LC product (MCD12Q1), and the snow cover product (MYD10C1). All of them are downloaded from the Land Processes Distributed Active Archive Center (https://ladsweb.modaps.eosdis.nasa.gov/). MYD11A1 is the level 3 standard product of LST, which consists of the daily data layers, including the daytime and nighttime LST and other ancillary data. The accuracy of the MODIS LST data is proven to be better than 1 K over a homogeneous surface under clear sky (Wan, 2008). MCD12Q1 is the level 3 standard product of the LC type provided under five different classification systems, including the International Geosphere-Biosphere Programme (IGBP) system, the University of Maryland (UMD) system, the MODIS LAI/IPAR algorithm system, the biome classification (BGC) system, and the plant functional type (PFT) system. Among these systems, IGBP is adopted in this study because it contains the most complete LC types and has the better classification accuracy of 75% (Friedl et al., 2010). MYD10C1 is the level 3 standard product of daily snow cover. The pixel value of the data indicates the percentage of snow coverage in the entire grid.
SRTM data was collected by the radar onboard the space shuttle Endeavor in February 2000. The SRTM data records the elevation of the land surface on the continent between 60°N to 56°S, accounting for 80% of the land areas on the Earth's surface. Due to its higher accuracy and spatial resolution compared with

Figure 1. The verification regions of the Naqu and HRB areas in China. Green dots represent the field measurement sites.
other contemporaneous elevation datasets, SRTM data have been used in many fields since its release (Yang et al., 2011; Zandbergen, 2008). Zhang et al. (2016b) indicated that the bias of 3″ SRTM data in China is −0.35 m, and 90% error (i.e., the average absolute error for the 90% area, an index that SRTM designed) is 7.4 m, which is better than the designed mission objective of 16 m. SRTM data has two spatial resolution types, namely, 1″ and 3″, in which the 3″ resolution data is adopted for its more extensive applications.

2.2.2. The Desert Distribution Data

The map of the desert distribution in China (LIGGD, 1974) comes from the Cold and Arid Regions Science Data Center (http://westdc.westgis.ac.cn). These data are based on the aerial survey and field investigation conducted in the 1970s and was created through the cooperation of the Institute of Cold and Arid Regions Environmental and Engineering Research and the Institute of Geographic Sciences and Natural Resources Research. The data mainly includes the 9 major desert regions across northern China from the west to the east.

2.2.3. Soil Temperature Data

Many studies used soil temperature rather than skin temperature as the reference to assess the accuracy of the satellite MW LST due to the more widespread observation networks of soil temperature (Kou et al., 2016; Sun & Pinker, 2003; Xu et al., 2019). A large number of networks provide field soil temperature observations at different depths, among which the Central Tibet Plateau Soil Moisture and Temperature Monitoring Network (CTP-SMTMN, http://ismn.geo.tuwien.ac.at/) and the Automatic Weather Stations from the Watershed Allied Telemetry Experimental Research (AWS-WATER, http://www.heiheidata.org/) were selected in this study. The CTP-SMTMN consists of 57 stations spread across the Naqu area, and each of them collects the soil temperature at the depths of 0–5 cm, 10 cm, 20 cm and 40 cm every 30 minutes. The data provider categorized these stations into three subsets with different spatial scales (large: 1.0°, medium: 0.3°, and small: 0.1°) and suggested users choose appropriate one for the applications in different spatial scales. The large-scale set containing 38 stations and evenly distributed in the Naqu area were selected as the verification sites in this study for its smallest difference with the satellite data used in this study. The AWS-WATER consists of 12 stations spreading the HRB, and each of them collects the soil temperature at the depths of 5 cm, 10 cm, 20 cm, 40 cm, 80 cm, 120 cm and 160 cm every 30 minutes. The Huazhaizi (HZZ) desert station, the Dayekou (DYK) Guantan forest station, and the Arou (AR) freeze/thaw station are selected as the verification sites in this study.

The proper observations for verifying the LST are the ones nearest to the land surface, so the soil temperature at a depth of 0–5 cm in the Naqu area was adopted. Because some sites in the HRB region lack soil temperature observations at 5 cm depth, the verification there adopts the 10 cm depth observations in all three stations for the convenience of comparison. In addition, only the observations at the time closest to the overpass
time of the corresponding AMSR-E pixels were retained. If multiple sites are located inside one AMSR-E pixel, their soil temperatures were averaged to match the AMSR-E LST.

3. Methodology

3.1. The Principle of the MW LST Retrieval Algorithm

The RTE is the foundation for retrieving MW LST, which describes the composition of the MW radiation received by the satellite sensor. Compared with that in the TIR spectral domain, the effects of atmospheric scattering and absorption on the electromagnetic radiation in the MW spectral range is very small, especially in the higher frequency range. Therefore, the MW RTE can be expressed as follows:

\[ B_p(T_{up}) = \tau_p(\theta)e_pB_p(T_s) + (1-e_p)[1-\tau_p(\theta)]\tau_p(\theta)B_p(T_{a\ down}) + [1-\tau_p(\theta)]B_p(T_{a\ up}) \]  

(1)

where the subscript \( p \) represents the frequency; \( T_s \) and \( T_{up} \) are the LST and BT in Kelvin (K) at a given frequency, respectively; \( B_p(T_{up}) \) and \( B_p(T_s) \) are the sensor-received and the surface-emitted radiation in W \( \cdot \) m\(^{-2}\) \cdot sr\(^{-1}\) \cdot Hz\(^{-1}\), respectively; \( B_p(T_{a\ down}) \) and \( B_p(T_{a\ up}) \) are the downward and the upward atmospheric radiation variables in W \( \cdot \) m\(^{-2}\) \cdot sr\(^{-1}\) \cdot Hz\(^{-1}\), respectively; \( \tau_p(\theta) \) is the atmospheric transmissivity at the satellite viewing angle \( \theta \); \( e_p \) is the land surface emissivity; \( T_{a\ down} \) and \( T_{a\ up} \) are the downward and the upward equivalent atmospheric temperatures in K, respectively. Planck’s law describes the radiation emitted by a black body at frequency \( p \) and a given thermodynamic temperature \( T \), as follows:

\[ B_p(T) = \frac{2hp^3}{c^2(e^{hp/kT} - 1)} \]  

(2)

where \( B_p(T) \) is the radiation intensity of the black body; \( h \) is the Planck constant; \( c \) is the light speed; \( e \) is the natural constant; and \( k \) is the Boltzmann constant. Planck’s law can be expanded by the Taylor formula as follows:

\[ B_p(T) = \frac{2kT_p^2}{c^2} \cdot \frac{1}{1 + (hp/kT) + (hp/kT)^2 + \ldots + (hp/kT)^n} \]  

(3)

According to the Rayleigh-Jeans approximation, Equation (3) is reduced to Equation (4) in the small frequencies, as follows:

\[ B_p(T) \approx \frac{2kT_p^2}{c^2} \]  

(4)

where \( 2kp^2/c^2 \) is a constant at a given frequency, so Equation (1) can be rewritten as follows:

\[ T_{up} = \tau_p(\theta)e_pT_s + (1-e_p)[1-\tau_p(\theta)]\tau_p(\theta)T_{a\ down} + [1-\tau_p(\theta)]T_{a\ up} \]  

(5)

Equation (5) indicates the five parameters required to calculate the LST, namely, \( T_{bp} \), \( \tau_p(\theta) \), \( e_p \), \( T_{a\ down} \), and \( T_{a\ up} \). \( T_{bp} \) is received by the sensor. \( e_p \) is an inherent property of a certain LC type related to its composition, texture, and physical properties. In addition, \( e_p \) is directional, where even the emissivity of the same LC type changes due to the variation of the topographic relief and satellite viewing angle. \( \tau_p(\theta) \), \( T_{a\ down} \) and \( T_{a\ up} \) are related to the factors such as the atmospheric composition and the solar radiation. Solar radiation is the direct heat source of the earth surface and rises the temperature of land surface and air by thermal radiation. In the daytime with clear sky, the solar radiation warms the land surface and air, while at nighttime, the earth surface radiates heat outward and LST and air temperature drop. Hence, \( T_{a\ down} \) and \( T_{a\ up} \) are changing in the spatial and time scales. Among these parameters, \( T_{bp} \) is received by the sensor, but the other four parameters are difficult to obtain in the regional or global scales.

Further analysis on Equation (5) reveals a linear relationship between the LST and the sensor BT given the \( e_p \) and atmospheric parameters. Therefore, the LST can be estimated by establishing the regression relationship between the reference LST and the MW BT under different environmental conditions. This relationship is affected by the other parameters (\( e_p \), \( \tau_p(\theta) \), \( T_{a\ down} \) and \( T_{a\ up} \)) in Equation (5), and these parameters are
closely related to the topography (Topo), land cover (LC), time (t), and space (s) (Holmes et al., 2009; McFarland et al., 1990; Prigent et al., 1999). Moreover, besides the radiance of single terrain element (one pixel), adjacent terrain contributes to the terrain radiance as well, especially over the relief area. Therefore, topography affects LST via directional emissivity and adjacent terrain effect. The environmental variables of topography, LC and solar radiation vary greatly in different parts of China and different time periods; therefore, they effect the spatiotemporal variation of LST in different combination forms. Although these relationships are complex and intermixed, Topo and LC are considered to be mainly connected with emissivity, and t and s are mainly connected with the atmospheric parameters and solar radiation. Therefore, the relationship between LST and BT can be described by the following equation:

\[ T_s = f(T_b, \text{Topo}, \text{LC}, t, s) \]  

where \( f \) is the function used to estimate the LST. The commonly used regression equation is relatively simple (e.g., linear equation) and not qualified to model the distributions of the LST under complex environmental conditions. Therefore, a CCSEV including the four variables (Topo, LC, t and s) is first constructed, and each class in the CCSEV is ensured to be as inner homogeneous as possible. Then, the regression model is established for each class to retrieve the LST.

Considering the complex near-surface environment throughout China, all the 12 channels of AMSR-E are employed to construct the regression model. In addition, the second order of the difference of the vertical polarized BT between 36.5 GHz and 18.7 GHz, as well as between 36.5 GHz and 23.8 GHz are also introduced as the predictors to correct the inhomogeneity of emissivity, and\( T_b \) and \( T_s \) represent the horizontal and vertical polarization of each frequency, and \( A_0, A_i, (i = 1, 2, ..., 6) \), \( B, C \) are the coefficients of each prediction term in the model. The best retrieval under different environmental conditions may not always be achieved using all the prediction terms, so the stepwise regression is adopted. The stepwise regression automatically conducts the significance test and removes the redundant prediction terms so that the optimum combination of prediction terms is finally acquired for each class in the CCSEV.

\[ T_s = A_0 + \sum_{i=1}^{6} (A_h T_{bh} + A_v T_{bv}) + B(T_{b36.5v} - T_{b18.7v})^2 + C(T_{b36.5v} - T_{b23.8v})^2 \]  

3.2. Construction of the CCSEV

The process for establishing the CCSEV is divided into four steps. Figure 2 and the following sections illustrate the details.

3.2.1. The Topography Classification System

Previous studies showed that the spatial distribution of the LST is related to the topographic parameters, such as the elevation, slope, aspect, etc. (Chen et al., 2018; Dozier & Frew, 1990; Hutengs & Vohland, 2016; Liu et al., 2006; Sandmeier & Itten, 1997; Shepherd & Dymond, 2003; You et al., 2010; Zhang et al., 2016a). Unfortunately, with the increase of the spatial scale, it is no longer appropriate to describe the topography by the slope and aspect (Tang, 2000). Topographic relief is an important quantitative indicator of topography at a large spatial scale, which refers to the maximum elevation difference within a certain spatial extent and plays an important role in the research of the Earth and environmental sciences (Pachauri et al., 1998; Saha et al., 2005). Conceptually, topographic relief is an extension of slope, and both parameters describe the variation of elevation in a given range (Moser et al., 2007; Wolf et al., 2011). Therefore, topographic relief is adopted to describe the relationship between the LST and topography in such a large scale of the AMSR-E pixel size. For the relationship between LST and elevation, the average elevation is adopted. The key point in calculating the topographic relief is to determine the size of the “certain spatial extent”. This extent is not a fixed value but varies with the spatial scale, topographical features, and the purpose of the research. Various pixel window sizes (e.g., \(5 \times 5 \text{ km}^2, 10 \times 10 \text{ km}^2, 16 \times 16 \text{ km}^2\)) have been used as the “certain spatial extent” for the particular purposes in different studies (Feng et al., 2007; Iwahashi & Pike, 2007; Liu et al., 2001; Smith, 2014; Tang et al., 2006). A size of 0.25° × 0.25° same as the spatial
resolution of AMSR-E data is adopted to calculate the topographic relief and average elevation. These two topographic parameters are both derived from the SRTM data.

Moreover, elevation and topographic relief are also the parameters for the classification of basic landform types (Li et al., 2013a). The elevation is used to divide the different levels in the vertical direction, and the topographic relief is used to distinguish between the mountains with different undulations. Several strategies have been proposed for the classification of basic landform types in China (Li et al., 2013a; Zhou et al., 2009). Although these strategies are different in details due to factors such as the technical conditions, data sources, spatial scales, etc., they are generally similar at the large spatial scale. A classification system of basic landform types that considers the spatial scale of AMSR-E data is developed in this study, in which the elevation is classified into three levels, i.e., low elevation (< 300 m), middle elevation (300–2800 m), and high elevation (> 2800 m), while the topographic relief is classified into four levels, i.e., plain (0–270 m), hill (270–1000 m), moderate mountain (1000–2300 m), and steep mountain (> 2300 m). The map of the basic landform types in China was derived by overlapping the classified elevation and topographic relief data (Figure 3). The basic landform types of China are considered unchanged in the long term in the CCSV.

3.2.2. Integrating the Vegetated and Other LC Types

The MODIS LC product (MCD12Q1) was provided on an annual time scale, so that each LC type in this product can be considered unchanged over the whole year.

As the proportion 1 in Table 2 shows, there are 13 LC types associated with vegetation (including the barren or sparsely vegetated), and the total proportion reaches 97.4%. These vegetated LC and the basic landform types are first integrated to construct the topography and vegetation classification system. Similar to the topographic parameters, the LC data was resampled to the resolution of the AMSR-E data before integration. The rule is to take the LC type accounting for the largest proportion in the 0.25° × 0.25° range as the LC type at the large scale. Although mixed pixels inevitably exist in the large pixel size, it is reasonable to consider...
that the relationship between the LST and BT in this spatial scale is influenced by the dominant LC type. The proportion and distribution of each LC type after resampling (Proportion 2) are illustrated in Table 2 and Figure 4. Note that deciduous needleleaf forest and savannas disappeared after resampling due to their very small proportions.

The IGBP system provides a detailed division of the vegetated LC. According to our experiment in this study, in the regions with large terrain fluctuations, the accuracy of AMSR-E LST derived from the regression models of different vegetated LC zones is almost same as that derived from those of merged vegetated LC zone. We inferred that the influence of the topography on the LST is more obvious than that of the vegetation in these kinds of regions. The similar vegetated LC types are therefore merged in these types of regions, such as the Yunnan-Guizhou Plateau (zone 15 in Figure 5), the Hengduan Mountains (zone 68 in Figure 5), South

Figure 3. The classification of basic landform types in China.

Table 2
The Proportion of the Area of Each LC Type in China

| ID | LC type           | Proportion 1 * | Proportion 2 ** | ID         | LC type                     | Proportion 1 * | Proportion 2 ** |
|----|------------------|----------------|-----------------|------------|----------------------------|----------------|-----------------|
| 0  | Water            | 0.70%          | 0.23%           | 9          | Savannas                   | 0.05%          | -               |
| 1  | Evergreen needleleaf forest | 0.46%          | 0.03%           | 10         | Grasslands                 | 30.53%         | 31.68%          |
| 2  | Evergreen broadleaf forest | 1.75%          | 2.07%           | 11         | Permanent wetlands         | 0.34%          | 0.01%           |
| 3  | Deciduous needleleaf forest | 0.23%          | -               | 12         | Croplands                  | 16.31%         | 17.51%          |
| 4  | Deciduous broadleaf forest | 0.87%          | 0.42%           | 13         | Urban and built-up         | 0.85%          | 0.14%           |
| 5  | Mixed forests    | 14.43%         | 17.23%          | 14         | Cropland/natural vegetation | 3.86%          | 2.66%           |
| 6  | Closed shrublands| 0.19%          | 0.02%           | 15         | Snow and ice               | 0.71%          | 0.34%           |
| 7  | Open shrublands  | 1.23%          | 0.48%           | 16         | Barren or sparsely vegetated| 22.72%         | 23.35%          |
| 8  | Woody savannas   | 4.75%          | 3.83%           |            |                            |                |                 |

Note. * represents the proportion of the area of each LC type in the original MCD12Q1 data; ** represents the proportion after resampling.
Tibet (zone 66 in Figure 5), etc. The classification system of topography and vegetation is then constructed by integrating the merged vegetated LC types and the basic landform types and merging the scattered independent vegetated pixels into their surrounding large size zones, which includes 71 zones, as Figure 5 shows.

The other LC types in Table 2 including water, permanent wetlands, urban and built-up areas, and snow and ice are then introduced into the CCSEV. Although the areas of these LC types are small, their LST usually differs substantially from the surroundings. In view of their similarity, permanent wetlands are incorporated into the water. Different from the vegetated LC, the water (including the permanent wetlands), urban and built-up areas, and snow and ice are not only small in area but also very scattered in distribution (Figure 4). It is therefore not suitable to establish the regression models for these LC types following the topography and vegetation classification system. According to the features of topography and climate, the 71 zones are grouped into eight large regions, i.e., the eastern part of Northeast China, the western part of Northeast China, North China, South China, the eastern part of Northwest China, the western part of Northwest China, Southwest China, and the Qinghai-Tibet Plateau. The LSTs of these LC types with small areas are retrieved from these large regions separately.

Desert accounts for approximately 7.3% of China’s land area (LIGGD, 1974), but the IGBP system does not separate the desert from the other LC types. According to the desert distribution data of China, the desert is assigned as barren or sparsely vegetated, grasslands, and croplands in the IGBP system. However, there are significant differences in the radiation characteristics of desert and other LC types due to factors such as the size and density of surface rock and gravel, and their moisture contents and mineral components (Hulley & Hook, 2009; Zhang et al., 2018). The desert is therefore separated out to improve the accuracy of the LST retrieval. The deserts in China are mainly distributed in the form of large areas (Figure 5), so a regression model for the LST retrieval is established for each desert area. The distribution of desert in the scale of the AMSR-E data is treated as unchanged in the long term.

Figure 4. The LC types in China.
Snow cover is another important factor that affects the LST distribution but is not included in the IGBP system. Snow cover is not the same as snow and ice in the IGBP system. The former is caused by the snowfall and is widely distributed in most parts of China in winter, while the latter refers to the permanent glaciers in high mountains. Snow cover changes quickly in the spatial and time scales and replaces the original LC, leading to the large variation of the LST. The MODIS daily snow cover product (MYD10C1) is therefore introduced into the construction of the CCSEV to improve its rationality. In view of its rapid change and discrete distribution in the spatial scale, the snow cover across China is divided into the eight large regions in which to retrieve the LST.

The classification system of topography and vegetation overlaid with water, urban and built-up areas, snow and ice, and desert is shown in Figure 5, in which the eight large regions are distinguished from each other by color. All the elements in this classification system are considered unchanged for one year. However, after being further overlaid with the daily snow cover, this classification system becomes unique every day. The water, urban and built-up area, snow and ice, desert, and snow cover data are upscaled to the resolution of the AMSR-E data before the overlaying process. The rule for upscaling is as follows: count the area of each LC in the area of one AMSR-E pixel first; if any LC type occupies more than 60% of the area of the AMSR-E pixel, this pixel will be treated as a ‘pure’ pixel of this LC type; otherwise, this pixel will be treated as a mixed pixel. The threshold of 60% comes from the scheme in Zhou et al. (2015).

3.2.3. Integrating the Time Interval

In addition to the classification in the spatial scale, the CCSEV also incorporates the classification in the time scale. In previous studies, AMSR-E LST retrieval algorithms were usually developed by the time scale of day-and-night, season, or long term (Zhou et al., 2015; Zhou et al., 2018). The diurnal cycle of solar radiation usually makes the LST in daytime and nighttime obviously different from each other, so it is reasonable to develop LST retrieval algorithms for daytime and nighttime separately. However, the uniform seasonal

Figure 5. The classification system by integrating the topography, vegetation, and other LC types (without daily snow cover), as well as the eight large regions. The zones of topography and vegetation are numbered from 1 to 71.
division of one year across the whole landmass of China can bring errors because the climate change inside a year shows various patterns in different places, let alone the long-term scale. The monthly division of one year could avoid the irrational merging of the months that have different climatic characteristics. The experiment in this study has confirmed this point. That is, the accuracy of the AMSR-E LST derived from the monthly CCSEV is better than that derived from the seasonal CCSEV in China. Therefore, day-and-night and monthly time scales are introduced into the classification system of topography, vegetation, and other LC types to complete the CCSEV.

3.3. Algorithm Development

Data preprocessing before the development of the AMSR-E LST retrieval algorithm mainly includes the quality control of the MODIS LST product and the AMSR-E BT data, and the upscaling of the MODIS LST data. For the data quality control, the MODIS LST product (MYD11A1) provides a pixel-by-pixel data layer for quality screening. The LST pixels marked with “Good quality” and “Average emissivity error < 0.02” are retained to ensure the accuracy of the regression model. The AMSR-E BT product (NISDC-0302) has no quality control data layer, therefore the polarization ratio (PR), defined as the ratio of the horizontal polarized BT to the vertical polarized BT at the same frequency, is used to realize a simple quality control of the AMSR-E BT data. The pixels with PR values greater than 1 are removed because the PR is less than 1 under normal conditions (Gao et al., 2008); therefore, the data upscaling, the 0.01° MODIS LST was aggregated to 0.25° to match the AMSR-E data in model construction. In previous studies, the regression models are usually constructed in the areas with relatively flat terrains to avoid the topographic effect on the upscaling of MODIS LST; therefore, simply averaging the MODIS LST pixels in an AMSR-E BT pixel meets the requirement of accuracy (Lakshmi & Zehrufhs, 2002). However, in the areas with large terrain fluctuations, the topographic effect should be considered. LST upscaling in such complex regions has always been a difficult issue, in which many theoretical problems have not been resolved yet. Liu et al. (2006) argued that the topographic effect on upscaling the LST in a region with a large undulating terrain is less than 1 K, taking the ASTER LST on the Loess Plateau as an example. Therefore, the simple averaging method is a compromise in upsampling the MODIS LST in this study. Due to the cloud cover and data quality control, there could be some MODIS pixels with invalid values in the area of one AMSR-E pixel. Therefore, any aggregated MODIS LST with the percentage of available pixels greater than 60% is retained, a threshold the same as that in the resampling of LC data.

The upscaled MODIS LST and corresponding AMSR-E BT data in 2010 are used to train the regression model, and the AMSR-E LST is retrieved by inputting the all-weather AMSR-E BT into the model. Affected by the factors such as cloud cover, data quality control, and the class size, some classes may not have enough number of samples available for training (e.g., water, urban and built-up areas). To eliminate this defect, the CCSEV was also constructed on the seasonal and annual time scales as a complement. The seasons are divided according to the following rules: March to May belong to spring, June to August belong to summer, September to November belong to autumn, December, January, and February belong to winter. If the proportion of training samples (PTS) in a monthly class (defined as the ratio between the number of available pixels in a class and the number of all pixels that this class occupies in space) is less than 1, then its regression model is replaced by the complement model of the season that this month is in. If the proportion of the pixel samples in this seasonal class is still less than 3, then the regression model is replaced by the complement model of the year. For the mixed pixels in the CCSEV, their LST is the weighted sum of the LST of each LC type, in which the weight is the area proportion. The regression models of these LC types adopt those constructed using the ‘pure’ pixels.

4. Results and Discussion

4.1. The Performance of the AMSR-E LST Retrieval Algorithm

Figure 6 shows the statistics of some attributes of the regression models used for deriving the AMSR-E LST. These attributes include the PTS, the coefficient of determination ($R^2$), and the root mean square error (RMSE). The classes in the CCSEV are first divided into 24 categories according to the month and day-night scale, and then the number of classes in each category that fall into the different ranges of the indicators is counted to evaluate the quality of the AMSR-E LST retrieval algorithm. The horizontal axis in each month represents the intervals of the indicator ranges and the vertical axis represents the number of classes.
PTS is one of the criteria used for measuring the model’s representativeness. The spatiotemporal variation of cloud cover and the quality of MODIS LST are the two factors leading to the change of PTS across the classes. Figure 6(a) indicates that the number of classes in the PTS range of less than 1 is relatively small in all 24 categories of different months and day-nights, accounting for 1% to 23% of the total number of classes in each category, with an average percentage of 10%. Therefore, the regression models in most classes are representative. From the perspective of the month, there are more classes in the larger PTS ranges in both daytime and nighttime.
and nighttime during the period from June to October, which indicates that the cloud cover is less and the quality of MODIS LST is higher in these months throughout China. From the perspective of day-night, the PTs during the nighttime of all months are greater than those in the daytime, indicating that the cloud cover is less and the MODIS LST quality is higher at nighttime throughout China.

$R^2$ reflects the fitting quality of regression model. In Figure 6(b), most classes in each category are in the higher $R^2$ ranges with the averages of 0.66–0.85 and the standard deviations (STDs) of 0.1–0.18, which indicates that the quality of the regression models are generally good. From the perspective of the month, the qualities of the regression models from January to March and September to December are better than those from April to August, especially in the daytime. From the perspective of day-night, the qualities of the regression models in the daytime fluctuate more gently than those at nighttime throughout the year; however, the qualities of the nighttime regression models are better than those in the daytime, especially in the months from April to October. The reasons for the above phenomena are as follows: 1) the large amount of cloud cover in the daytime and warm months leads to a small number of training samples for the regression models; 2) due to the influence of solar radiation, the variation of the LST in the daytime and warm months is generally larger than that at nighttime and in the cold months, and therefore its relationship with the BT is more complex.

The RMSE reflects the accuracy of regression model, which is calculated from the difference between the retrieved AMSR–E LST and reference MODIS LST. Figure 6(c) shows that the average RMSE (1.45–2.85 K) and the STD of the RMSE (0.57–1.04 K) are both in the lower value ranges, indicating that the accuracies of the regression models in different months and day-nights are generally good. From the perspective of the month, the accuracies of the models show opposite trends in the daytime and nighttime. The models in the daytime from January to February and September to December are better than those from April to August, especially in the daytime. From the perspective of day-night, the accuracies of the regression models in the daytime fluctuate more gently than those at nighttime throughout the year; however, the accuracies of the nighttime regression models are better than those in the daytime, especially in the months from April to October. The reasons for these variation patterns of the models’ accuracies are basically consistent with those for $R^2$, i.e., the spatiotemporal changes of cloud cover and solar radiation.

Figure 7 shows the statistics of the same attributes of the regression models as those in Figure 6, except that they are counted according to the day-night scale and spatial zones. The annual average and STD of each attribute in the spatial zones are distinguished by color. Note that the snow cover is distributed into the other classes in the spatial scale due to its daily variations.

In Figure 7(a), the PTs values of the zones in northwestern China (equals the eastern part of Northwest China plus the western part of Northwest China) and the Qinghai-Tibet Plateau (in the range of 6–10 in the daytime and 9–15 at nighttime) are higher than those in South China and the Sichuan Basin (zone number 16 in Figure 5, in the range of 0–1 in the daytime and 0–3 at nighttime), which indicates a relatively more cloud cover in South China and the Sichuan Basin. In addition, the annual STD values of the PT at northwestern China and the Qinghai-Tibet Plateau (in the range of 2–6 in the daytime and 2–5 at nighttime) are generally higher than those in South China and the Sichuan Basin (in the range of 0–3 in the daytime and 1–3 at nighttime), which reflects a larger variation of cloud cover in northwestern China and the Qinghai-Tibet Plateau compared with other regions in China.

As shown in Figures 7(b) and 7(c), the average $R^2$ values in central and eastern China (including the eastern part of Northeast China, North China, South China, the eastern part of Northwest China, and Southwest China) are generally higher than 0.6 and 0.7 in the daytime and nighttime, respectively, while the average $R^2$ values in the Qinghai-Tibet Plateau and the western part of Northwest China are in the lower range of 0.1–0.7 and 0.2–0.8 in the daytime and nighttime, respectively. The average RMSE values in central and eastern China are generally less than 2 K and 1.5 K in the daytime and nighttime, respectively, while the average RMSE values in the Qinghai-Tibet Plateau and the western part of Northwest China are in the higher range of 2–5 K and 1–4 K in the daytime and nighttime, respectively. Therefore, the regression models in the zones of central and eastern China are more accurate than those in the zones of the Qinghai-Tibet Plateau and the western part of Northwest China, which is mainly related to the topography and LC. Figures 3 and 4 show that in central and eastern China, the topography is dominated by plains, hills, and moderate mountains, and the vegetation cover is dominated by croplands and other forests. The relatively flat terrain and
Figure 7. Evaluation of the regression models for AMSR-E LST retrieval by the spatial zones and day-night scale.
simple vegetation cover in these areas result in a higher quality and accuracy of the regression models. In the Qinghai-Tibet Plateau and the western part of Northwest China, the topography includes almost all the types from plains to steep mountains, in which the moderate-to-steep mountains are widely distributed. The LC types here include desert, grassland, bare land, and snow and ice, etc. The relatively steep terrain and complex LC lead to the lower quality and accuracy of regression models here. Moreover, the STD of $R^2$ and the RMSE values among the different zones are slightly different from each other compared with the average $R^2$ and RMSE values. The STD of $R^2$ in the daytime and at nighttime are both in the range of 0.05–0.15, while the STD of RMSE values are in the range of 0.2–0.8 K in the daytime and 0–0.6 K at nighttime. Figure 8 shows the scatter plot of the AMSR-E LST and MODIS LST in both daytime and nighttime of 2010 in the landmass of China. For both daytime and nighttime scatters, the $R^2$ values are higher than 0.97 and the RMSE values are lower than 2.7 K, which indicates an overall good performance of the developed algorithm in 2010.

4.2. The Universality of the AMSR-E LST Retrieval Algorithm

To verify the universality of the proposed algorithm, we compared the AMSR-E LST in the years of 2005, 2009, and 2011 with the collocated MODIS LST data. Figure 9 shows the scatter plots of the AMSR-E LST and MODIS LST data in the daytime and at nighttime in these years. The performance of the proposed algorithm degrades slightly when applied to the other years, indicating that the proposed algorithm is universal. Specifically, the $R^2$ values of all the scatter plots exceed 0.94, which is slightly smaller than that in 2010. In these years, the RMSEs of AMSR-E LST are 3.27 K, 2.65 K and 3.48 K in the daytime and 2.94 K, 2.63 K, 2.15 K at nighttime, which is not much higher than the RMSEs in the daytime and nighttime of 2010. Similar to the results in Section 4.1, the RMSEs of AMSR-E LST at nighttime of these years are all smaller than that in the daytime, which also confirms that the accuracies of the developed models are better at nighttime.

Although the algorithm is universal, there are some anomalies in the scatter plots. For example, at the nighttime of 2011, the LST of some AMSR-E pixels are significantly lower than the MODIS LST in the higher temperature range. Therefore, there remains room for further improvement of the proposed algorithm. The biases of all the scatter plots are negative, indicating that the proposed algorithm has underestimated the LST in general. This is mainly related to the difference of the thermal sampling depth (TSD, the depth that the electromagnetic wave penetrates the land surface) between TIR radiation and MW radiation (Parinussa et al., 2008; Zhou et al., 2015). The TSD is only at the micrometer level in the TIR range, while it varies to a larger extent in the MW range according to the LC, the soil moisture, and the frequency of the MW channels.

4.3. Comparison With the Existing Algorithms

To further evaluate the performance of the developed algorithm, a comparison with two existing algorithms was conducted. One algorithm is proposed by Zhou et al. (2015), in which the landmass of China was first divided into eight regions according to the LC types, and then the regression models for retrieving the daytime and nighttime AMSR-E LST of each season were constructed in each region. The other algorithm is proposed by Holmes et al. (2009), in which a simple universal linear regression model using one MW channel was constructed based on the field observations in 17 representative stations across the world. Table 3 shows
the error statistics of the AMSR-E LST in 2011 derived by the three algorithms, in which the RMSE is counted based on the classification system adopted by Zhou et al. (2015). All the pixels with LST values below 273.15 K are excluded from the statistics to meet the requirement of Holmes's algorithm. The first numbers in the cells are the RMSE of Zhou's algorithm; the numbers in the brackets are the RMSEs of Holmes's algorithm; and the numbers after the slashes are the RMSEs of the algorithm in this study. The underlined number means the accuracy of the algorithm in this study is equal to or lower than that of Zhou's algorithm. The dash means the algorithms does not retrieve the LST in the corresponding classes.

As shown in Table 3, the accuracy of the algorithm in this study did not exceed that of Holmes's algorithm only in a few classes, i.e., the water and permanent wetland and the evergreen forest. The reason is that the training samples for the LC types with small areas are not sufficient to construct a representative regression model. Regarding the classes where the accuracy of AMSR-E LST is improved, the average improvement is 2.81 K in the daytime 2.14 K at nighttime. The reason for the higher improvement in the daytime is that the accuracy of Zhou’s algorithm is better at nighttime than in the daytime, so the improvement at nighttime is limited. From the perspective of the LC type, the improvements in the shrubland and the savanna and grassland are the greatest in the daytime (1.5–4 times), and the improvements in the barren land and the savanna and grassland are the greatest at nighttime (1.5–10 times). The reason for this phenomenon is that these LC types are large in area or are widely dispersed. The LST values in different regions are impacted not only by

Figure 9. The scatter plot of the AMSR-E and MODIS LSTs in China in both daytime and nighttime for 2005, 2009, and 2011.
the LC but also by the topography and atmospheric condition. In Zhou’s algorithm, the combination of the same LC type in different regions brings about errors in the LST retrieval, while the algorithm in this study separates the landscape according to the different environmental variables. From the perspective of the season, the average improvements are relatively high in the daytime in autumn and winter (2.9 K and 3.4 K) and at nighttime in winter and spring (3.0 K and 3.4 K). The reason for the higher improvement in the colder seasons is that the accuracy of Zhou’s algorithm is lower in these seasons which provides room for the improvement of the accuracy of AMSR-E LST. In addition, the algorithm in this study is superior to Holmes’s algorithm in all classes, with average improvements of 4.8 K in the daytime and 4.7 K at nighttime. It can be concluded that fully considering the influences of topography, LC, and the atmospheric condition brings a significant improvement in the accuracy of LST retrieval.

From the perspective of the accuracy of the AMSR-E LST in this study itself, a similar trend of the RMSE across the classes is presented when compared with Zhou’s algorithm. The accuracy of the algorithm in the evergreen forest and the deciduous forest is generally higher than that in other LC types. The reason is that the MW captures the canopy temperature in the dense vegetation area, which is the same as the TIR sensors (Holmes et al., 2009; Zhou et al., 2015). In shrubland, barren land, cropland, and the savanna and grassland, the accuracy of algorithm varies greatly across the seasons and day and night, which is related to the TSD, soil moisture, and other factors (Zhou et al., 2015).

4.4. Verification of AMSR-E LST With Field Observation

The comparison with reference MODIS LST only indicates the situation in clear sky because of the limitation of MODIS LST. For the all-weather condition, it is appropriate to compared the AMSR-E LST with in-situ data. However, there exist differences in the physical meaning and spatial scale between the field-measured soil temperature and the satellite-observed LST, it is necessary to calibrate the soil temperature before verification, making these two types of values comparable. The MODIS LST data is first upscaled to the pixel size of the AMSR-E data, and then a linear regression model between the upscaled MODIS LST and the soil temperature is constructed to adjust the soil temperature. The HRB sites provide the soil temperature observations for the whole year of 2010, while the Naqu sites provide the soil temperature observations from mid-July to December in 2010.

Figure 10 shows the scatter plots of the soil temperature and the upscaled MODIS LST in both daytime and nighttime at the validation sites, as well as the calibration formulas and the RMSEs. Site groups 1–12 are connected with the AMSR-E pixels containing multiple sites. These site groups involve all the 38 stations in the Naqu area. The other three stations in HRB are connected with only one site of observation, individually. RMSE1 and RMSE2 are between the upscaled MODIS LST and the soil temperature before and after calibration, respectively. In most sites, the high R² values of the regression equations (above 0.6 in daytime, and
Figure 10. Calibration of the soil temperature at the sites in the Naqu and HRB areas.
Figure 11. The scatter plots of the calibrated soil temperature and the AMSR-E LST at the sites in the Naqu and HRB areas.
Figure 12. The time series of the AMSR-E LST, calibrated soil temperature, and upscaled MODIS LST at the Naqu and HRB sites in 2010.
Figure 13. The images of the daytime and nighttime AMSR-E LST in China on the 15th day of each month in 2010.
above 0.9 at nighttime), indicates a strong correlation between the soil temperature and LST. The RMSEs at all the sites are significantly decreased after calibration, with a range of 1.85–5.52 K in the daytime and 1.60–3.51 K at nighttime.

Figure 11 shows the scatter plots of the calibrated soil temperature and the AMSR-E LST in both daytime and nighttime at the validation sites. The RMSEs of the AMSR-E LST at the 12 Naqu site groups are in the range of 2.57–4.43 K in daytime, with an average of 3.37 K, and they are in the range of 2.53–3.06 K at nighttime, with an average of 2.85 K. The RMSEs of the AMSR-E LST at the AR, DYK, HZZ stations are 7.49 K, 10.56 K, and 5.10 K in daytime, respectively, and they are 2.75 K, 2.9 K, and 2.0 K at nighttime, respectively. The accuracies of the AMSR-E LST at most sites are higher at nighttime than in daytime, which is consistent with the result drawn from the reference MODIS LST in Section 4.2. Among the all sites, the accuracies of the AMSR-E LST in the Naqu sites are higher and more stable, which is related to factors including the simple LC types and the flat terrain there. These factors lead to the spatiotemporal changes of the LST in the Naqu area to be relatively small and the scale effect between the field observations and AMSR-E LST to be weak. In the HRB area, the accuracy of the nighttime AMSR-E LST is comparable to that in the Naqu area, while the accuracy of the daytime AMSR-E LST is relatively low. This result is related to the various LC types and the complex terrain there. In particular, the large topographic relief in the AR and DYK sites leads to a huge difference of solar radiation between the sunny slope and shady slope and between the valley and ridge, which significantly affects the spatial distribution of the LST around these two sites, causing the obvious difference of the observations between the site-scale and pixel-scale. This phenomenon demonstrates that the topography is an important factor affecting the spatial distribution of LST.

Zhou et al. (2015) verified their algorithm at the ANNI and BJ sites. These two sites are within the same extent of the Naqu area. The RMSEs of the AMSR-E LST values retrieved by their algorithm are 4.3 K and 5.1 K in daytime, and 3.5 K and 3.8 K at nighttime, respectively. By comparison, the accuracy of the AMSR-E LST in this study has been improved by 1–2 K in the daytime and 0.7–1 K at nighttime.

Figure 12 shows the time series of the AMSR-E LST, the calibrated soil temperature, and the upscaled MODIS LST at the Naqu and HRB sites in 2010. The upper clusters of points in each plot are the time series of the LST in the daytime, while the lower ones are the time series of the LST at nighttime. The time series of the AMSR-E LST in each plot reflects the correct trend of the LST over the whole year, although the accuracy in the daytime is relatively low.

4.5. The Spatial Distribution of AMSR-E LST

Figure 13 shows the images of the retrieved AMSR-E LST in China on the 15th day of each month in 2010. The blank area inside the landmass of China is caused by the orbital gap of the AMSR-E sensor. These images correctly reflect the spatiotemporal trend of the LST, in which the LST experienced a gradual increasing trend from January to July, and a gradual decreasing trend from August to December. The northeastern China area and the Qinghai-Tibet Plateau are the regions with lower LST values across the country, while South China and the desert regions in northwestern China are the regions with higher LST values.

5. Conclusions

An empirical algorithm for retrieving the LST from the AMSR-E data is proposed in this study. In this algorithm, a CCSEV that considers the influence of the topography, LC, solar radiation, and atmospheric condition on the spatiotemporal distribution of the LST is constructed; then, the LST was expressed as a linear function of the AMSR-E BT data for each environmental condition. Compared with previous studies, the influence of the topography is explicitly considered for the first time in the development of the MW LST retrieval algorithm, and the classification of the factors is more reasonable than before. The coefficients of the regression models are stored in a look-up table to derive the LST from the combination of different channels of the AMSR-E BT data. All the AMSR-E channels are employed to take full advantage of the satellite observations. Meanwhile, the stepwise regression method is introduced to remove the redundant prediction terms.

Taking 2010 as an example, the RMSE of the AMSR-E LST in the whole landmass of China is 2.67 K in the daytime and 2.08 K at nighttime. The accuracy of the retrieved AMSR-E LST varies with the environmental conditions. Overall, the accuracy at nighttime is higher than that in the daytime. The accuracies of the
nighttime models are higher in the warm months, while the accuracies of the daytime models are higher in the cold months. The accuracies of the models in eastern China are higher than those in the Qinghai-Tibet Plateau and northwestern China. These differences in accuracies are closely related to the variations of the topography, LC, solar radiation, and atmospheric conditions. According to the test by the MODIS LST in 2005, 2009 and 2011, the algorithm is verified to be universal and accurate. The RMSE of AMSR-E LST values in these years are in the range of 2.65–3.48 K in the daytime and 2.15–2.94 K at nighttime, which is slightly lower than those in 2010. Compared with the LST retrieved by Zhou’s algorithm, the accuracy of the AMSR-E LST in this study has improved by 2.81 K in the daytime and 2.14 K at nighttime. Compared with the algorithm in Holmes et al. (2009), the accuracy of the AMSR-E LST in this study has improved by 4.8 K and 4.7 K in the daytime and at nighttime, respectively. Compared with the field measurements, the accuracies of the retrieved AMSR-E LST values vary in the range of 2–3 K at nighttime, while they vary in the range of 2.57–10.56 K in the daytime. The accuracies at the sites in the Naqu area are generally higher than those in the HRB regions. Compared with the algorithm proposed in Zhou et al. (2015), the developed algorithm has improved the accuracy of the AMSR-E LST by 1–2 K in the daytime and 0.7–1 K at nighttime in the Naqu area. In view of the time series and the images of the retrieved AMSR-E LST, although there exists some large errors and the accuracy in the daytime is lower than that at nighttime, the retrieved AMSR-E LST can accurately reflect the general trend of the spatiotemporal variations of the LST in China.

Although the algorithm proposed in this study has improved the accuracy of retrieved AMSR-E LST in China, the improvement of the accuracy is not uniform in space and time scale due to the changing environmental variables. Different environmental variables have different contribution rate to the LST retrieval. That is the reason why the nighttime LST is more accurate than the daytime LST, and in terrain with large fluctuations the variation of LC has less effect than the topography on the retrieval of LST.

There are some limitations in this study, as follows: (1) The CCSEV contains large numbers of classes, which leads to some classes shorting of training samples. The regression models in these classes are lacking representativeness and result in a lower accuracy of retrieved AMSR-E LST. Further optimization of the CCSEV can be realized by adding more training samples in the time scale or by merging similar classes. (2) The level 3 AMSR-E BT product does not provide quality control data. Although a simple quality control based on the PR is made, there remain some abnormal AMSR-E BT pixels, resulting in some errors in the AMSR-E LST. Therefore, a more effective quality control method for the AMSR-E BT data is necessary. (3) The scale effect should not be ignored in the development and verification of the AMSR-E LST retrieval algorithm. This problem is represented in two aspects: First, when aggregating the MODIS LST from 0.01° to 0.25° to serve as the reference, a simple averaging method is adopted due to the dispute in upscaling the LST in large undulating terrains. However, the simple averaging method may bring about large errors in the complex environmental conditions. Second, there is a large scale effect between the soil temperature and the AMSR-E LST. Therefore, a more effective quality control method for the AMSR-E LST is necessary. (4) The scale effect should not be ignored in the development and verification of the AMSR-E LST retrieval algorithm. This problem is represented in two aspects: First, when aggregating the MODIS LST from 0.01° to 0.25° to serve as the reference, a simple averaging method is adopted due to the dispute in upscaling the LST in large undulating terrains. However, the simple averaging method may bring about large errors in the complex environmental conditions. Second, there is a large scale effect between the soil temperature and the AMSR-E LST, making the comparison between them uncertain to some extent. These scale effects can be improved by further research on the scaling of LST. (4) The difference in the TSD between the TIR and MW signal is an unavoidable problem in the development of the MW LST retrieval algorithm, which results in the general underestimating of the AMSR-E LST. Although this problem has been pointed out in most studies, few explorations have been made to correct the TSD difference except for Zhou et al. (2017), who has tried to address this problem in retrieving the AMSR-E LST over barren land. Zhou et al. (2017) argued that the TSD correction still needs further study to extend it to various LC types and other MW channels. From the above analysis, the accuracy of the retrieval algorithm for the AMSR-E LST has room for further improvement and there is potential for the retrieval of more accurate all-weather LST data.

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